Session 5:
Oracle Machine Learning for R
Machine Learning Algorithms

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Agenda

1. Package Overview
2. OREdm package
3. OREmodels package
4. OREpredict package
5. OREeda package
OML4R Analytics Packages

OREbase
OREedm
  • Oracle Data Mining algorithms exposed through R interface
  • Attribute Importance, Decision Trees, GLM, KMeans, O-Cluster, Naïve Bayes, SVD, SVM, NMF, Association Rules, Explicit Semantic Analysis
OREeda
  • Functions for exploratory data analysis for Base SAS equivalents
OREgraphics
OREmodels
  • ore.lm, ore.stepwise, ore.neural, ore.glm, ore.randomForest
OREpredict
  • Score R models in the database
OREstats
  • In-database statistical computations exposed through R interface
ORExml

List package contents:
lsf.str("package:OREedm")
ls("package:OREedm")
help(package = OREedm)
High performance in-database ML algorithms

**OREdm**
- Support Vector Machine
- GLM
- Naïve Bayes
- Decision Trees
- k-Means clustering
- O-Cluster clustering
- Expectation Maximization
- Explicit Semantic Analysis
- Singular Value Decomposition
- Association Rules
- Attribute Importance

**OREmodels**
- Random Forest
- Principal Component Analysis (overloaded)
- Singular Value Decomposition (overloaded)
- Neural Networks
- Linear Regression
- Stepwise Regression
- Generalized Linear Model
OREdm Package
OREdm Features

Function signatures conform to R norms
• Use formula for specifying target and predictor variables
• Use ore.frame objects as input data set for build and predict
• Creates R objects for models and ore.frames for prediction results
• Use parameter names similar to corresponding R functions
• Function parameters provide explicit default values to corresponding ODM settings, where applicable

As in R, models are treated as transient objects
• Automatically delete ODM model when corresponding R object no longer exists
• Can be explicitly saved using datastore, via ore.save

Implicit variable selection for specific models
Automatic data preparation available
Supports *partitioned* models based on values of one or more columns
Enables text column analytics for select algorithms
Algorithms supporting Implicit Variable Selection

Decision tree performs automatic variable selection as part of the building process itself
- Variables that are not used in the tree are effectively removed
- Takes into account the relationship of the variables with the target

Naïve Bayes performs automatic variable selection when ADP is enabled
- Takes into account relationship of each variable with target

GLM performs variable selection (and creation) when the corresponding settings for feature selection/creation are used
Automatic Data Preparation (ADP)

Automatic variable transformation is handled by auto data preparation for OREdm algorithms

- Auto data preparation takes into account the algorithm and data characteristics to prepare data
- Each algorithm may have different preparation requirements

**Binning:** ADP for Naïve Bayes and Decision Tree use the supervised binning transformation in the `dbms_data_minig_transform` package to generate bins prior to model building (that take into account the target)

**Normalization:** ADP for SVM and GLM uses normalization transformations in the `dbms_data_minig_transform` package to generate a variety of normalization parameters prior to model building

Simplest approach - turn on ADP when building a model and inspect results after

- If user needs more control over preparation stages before model building, transform the data explicitly using OML4R transparency layer
Partition Models
Automates a typical machine learning task for data scientists

Builds an ensemble model composed of multiple sub-models, one built for each partition of data
  • Potentially achieve better accuracy through multiple targeted models – managed and used as one

Set parameter `ODMS_PARTITION_COLUMNS` to the name(s) of the partition column(s)
  • For example, `odm.setting = list(odms_partition_columns = "part")`

Simplifies scoring by allowing user to provide the top level model only
  • Proper sub-model chosen by system based on row of data to be scored

---

**Oracle Database**

Specify Partition Column(s)

```
Partition-1
Partition-2
Partition-3
... 
Partition-n
```

In-DB Algorithm

```
Top Level Model
  Sub-Model-1
  Sub-Model-2
  Sub-Model-3
  ...
  Sub-Model-n
```

Score data using top level model

**New Data**
Extensible R Algorithm Models

Creates an *Extensible R Algorithm* model using Oracle Data Mining in Oracle Database 12.2 or later

Extensible R Algorithm enables build, score, and view of R model using the user-provided R scripts stored in R Script Repository

Supports classification, regression, clustering, feature_extraction, attribute_importance, and association mining functions

Predict method executes the `score.function` specified for the model build and returns an `ore.frame` containing the predictions along with the columns specified by the `supplemental.cols` argument

- Function `predict` applicable to classification, regression, clustering, and feature_extraction models, only
ore.odmRAlg

Extensible R Algorithm Models

ore.odmRAlg(data,
    mining.function = c("classification", "regression", "clustering",
                        "feature_extraction", "attribute_importance", "association"),
    formula = NULL,
    build.function,
    build.parameter = NULL,
    score.function = NULL,
    detail.function = NULL,
    detail.value = NULL,
    odm.setting = NULL)

predict(object, newdata, supplemental.cols = NULL,
        type = c("class","raw"), na.action = na.pass,...)

summary(object,...)
Basic Argument Concepts

data – ore.frame object used for model building

mining.function – A scalar string to specify the type of mining function: classification, regression, clustering, feature_extraction, attribute_importance, and association

formula – An R formula object or a string representing a formula in characters. This formula can be named or take the default name ‘formula’. This name is used to pass the specified formula to the R build.function. If formula is NULL, the user-specified R build.function does not take a formula.

build.function – The name of the user-defined R function in the R Script Repository used to build the model. The R function uses the first argument for input data, optionally the second argument for weight numeric vector when parameter odms_row_weight_column_name is specified in odm.setting, and matches the remaining arguments by name with the values from build.parameter. The R function returns an R model.

build.parameter – A list containing build.function parameters excluding input data and weight vector if applicable. The list element names must match the name of build.function script input parameter names. Only scalar numeric and character values are valid as parameters.

score.function – The name of the user-defined R function in the R Script Repository used to score the model. The script takes two arguments: model and new data. It returns a data.frame containing prediction results. For regression, the results are predicted values. In classification, clustering, and feature exaction, the results are probabilities for each class, cluster, and feature, respectively. Rows of the results match the rows of input data.

detail.function – The name of the user-defined R function in the R Script Repository used to obtain model details and return them in a data.frame

detail.value – A data.frame object used to specify the data types of columns in the returned data.frame from the detail.function

odm.setting – A list to specify Oracle Data Mining parameter settings. This argument is applicable to building models in Database 12.2 or later. Each list element’s name/value refers to the parameter setting name/value. The setting value must have type numeric or character. When parameter ODMS_PARTITION_COLUMNS is set to the names of the partition columns, a partition model is created from the input data.
**ore.odmRAlg – model object**

**ore.odmRAlg object**

- **name**
  - name of model in database

- **mining.function**
  - The type of the data mining function for the model.

- **details**
  - An ore.frame returned by the R detail.function script

- **settings**
  - data.frame with settings used to build model

- **attributes**
  - data.frame of variable/columns used to build model

- **formula**
  - formula used to build the model

- **call**
  - specific invocation of the function with arguments
IRIS <- ore.push(iris)
ore.scriptCreate("glm_build", function(data, form, family) {
    glm(formula = form, data = data, family = family))
ore.scriptCreate("glm_score", function(mod, data) {
    res <- predict(mod, newdata = data); data.frame(res))
ore.scriptCreate("glm_detail", function(mod) {
    data.frame(name=names(mod$coefficients), coef=mod$coefficients))

ralg.mod <- ore.odmRAlg(IRIS, mining.function = "regression",
    formula = c(form="Sepal.Length ~ ."),
    build.function = "glm_build", build.parameter = list(family="gaussian"),
    score.function = "glm_score",
    detail.function = "glm_detail", detail.value = data.frame(name="a", coef=1))

summary(ralg.mod)
ralg.mod$details

predict(ralg.mod, newdata = head(IRIS), supplemental.cols = "Sepal.Length")
<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Main R Function</th>
<th>Mining Type / Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Association Rules</td>
<td>ore.odmAssocRules</td>
<td>Association Rules</td>
</tr>
<tr>
<td>Minimum Description Length</td>
<td>ore.odmAI</td>
<td>Attribute Importance for Classification or Regression</td>
</tr>
<tr>
<td>Decision Tree</td>
<td>ore.odmDT</td>
<td>Classification</td>
</tr>
<tr>
<td>Expectation Maximization (12.2)</td>
<td>ore.odmEM</td>
<td>Clustering</td>
</tr>
<tr>
<td>Explicit Semantic Analysis (12.2)</td>
<td>ore.odmESA</td>
<td>Feature Extraction</td>
</tr>
<tr>
<td>Generalized Linear Models</td>
<td>ore.odmGLM</td>
<td>Classification</td>
</tr>
<tr>
<td>K-Means</td>
<td>ore.odmKMeans</td>
<td>Clustering</td>
</tr>
<tr>
<td>Naïve Bayes</td>
<td>ore.odmNB</td>
<td>Classification</td>
</tr>
<tr>
<td>Non-negative Matrix Factorization</td>
<td>ore.odmNFM</td>
<td>Feature Extraction</td>
</tr>
<tr>
<td>Orthogonal Partitioning</td>
<td>ore.odmOC</td>
<td>Clustering</td>
</tr>
<tr>
<td>Singular Value Decomposition</td>
<td>ore.odmSVD</td>
<td>Feature Extraction</td>
</tr>
<tr>
<td>Support Vector Machine</td>
<td>ore.odmSVM</td>
<td>Classification</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Regression</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Anomaly Detection</td>
</tr>
</tbody>
</table>
Attribute Importance

Compute the relative importance of predictor variables for predicting a response (target) variable

Gain insight into relevance of variables to guide manual variable selection or reduction, with the goal to reduce predictive model build time and/or improve model accuracy

Attribute Importance uses a Minimum Description Length (MDL) based algorithm that ranks the relative importance of predictor variables in predicting a specified response (target) variable

Pairwise only – each predictor with the target

Supports categorical target (classification) and numeric target (regression)
ore.odmAI

*Attribute Importance*

```r
ore.odmAI(
  formula, # formula specifying attributes for model build
  data, # ore.frame of the training dataset
  auto.data.prep = TRUE, # Setting to perform automatic data preparation
  na.action = na.pass, # Allows missing values (na.pass), or removes rows with
  # missing values (na.omit)
  odm.setting = NULL) # A list to specify Oracle Data Mining parameter settings
)```

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Basic Argument Concepts

**formula**

- **Form** `response ~ terms` where 'response' is the numeric or character response vector and 'terms' is a series of terms, i.e., column names, to include in the analysis.
- Multiple terms are specified using '+' between column names.
- **Use** `response ~ .` if all columns in 'data' should be used for model building. Functions can be applied to 'response' and 'terms' to realize transformations. To exclude columns, use '-' before each column name to exclude.
Basic Argument Concepts

**auto.data.prep**
- If TRUE, automatically performs the data transformations required by the algorithm
- Transformation instructions are embedded in the in-database model

Types of transformations
- **Binning**
  - reduces cardinality of continuous and discrete data
  - improve resource utilization and model build response time dramatically without significant loss in model quality
  - can improve model quality by strengthening relationships between attributes
- **Normalization**
  - reduces range of numerical data, e.g., between 0 and 1
Basic Argument Concepts

**na.action**
- By default, allows missing values ('na.pass'), or removes rows with missing values ('na.omit')

**odm.setting**
- Use to build a *partition model*
- Set parameter `ODMS_PARTITION_COLUMNS` to the name(s) of the partition column(s)
- For example, `odm.setting = list(odms_partition_columns = "part")`
ore.odmAI - Example

Attribute Importance

R> LONGLEY <- ore.push(longley)
R> head(LONGLEY)

<table>
<thead>
<tr>
<th>Year</th>
<th>GNP.deflator</th>
<th>GNP</th>
<th>Unemployed</th>
<th>Armed.Forces</th>
<th>Population</th>
<th>Year</th>
<th>Employed</th>
</tr>
</thead>
<tbody>
<tr>
<td>1947</td>
<td>83.0</td>
<td>234.289</td>
<td>235.6</td>
<td>159.0</td>
<td>107.608</td>
<td>1947</td>
<td>60.323</td>
</tr>
<tr>
<td>1948</td>
<td>88.5</td>
<td>259.426</td>
<td>232.5</td>
<td>145.6</td>
<td>108.632</td>
<td>1948</td>
<td>61.122</td>
</tr>
<tr>
<td>1949</td>
<td>88.2</td>
<td>258.054</td>
<td>368.2</td>
<td>161.6</td>
<td>109.773</td>
<td>1949</td>
<td>60.171</td>
</tr>
<tr>
<td>1950</td>
<td>89.5</td>
<td>284.599</td>
<td>335.1</td>
<td>165.0</td>
<td>110.929</td>
<td>1950</td>
<td>61.187</td>
</tr>
<tr>
<td>1951</td>
<td>96.2</td>
<td>328.975</td>
<td>209.9</td>
<td>309.9</td>
<td>112.075</td>
<td>1951</td>
<td>63.221</td>
</tr>
<tr>
<td>1952</td>
<td>98.1</td>
<td>346.999</td>
<td>193.2</td>
<td>359.4</td>
<td>113.270</td>
<td>1952</td>
<td>63.639</td>
</tr>
</tbody>
</table>

R> head(STATE)

<table>
<thead>
<tr>
<th>GNP.deflator</th>
<th>GNP</th>
<th>Unemployed</th>
<th>Armed.Forces</th>
<th>Population</th>
<th>Year</th>
<th>Employed</th>
</tr>
</thead>
<tbody>
<tr>
<td>1947</td>
<td>83.0</td>
<td>234.289</td>
<td>235.6</td>
<td>159.0</td>
<td>107.608</td>
<td>1947</td>
</tr>
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<td>88.5</td>
<td>259.426</td>
<td>232.5</td>
<td>145.6</td>
<td>108.632</td>
<td>1948</td>
</tr>
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<td>258.054</td>
<td>368.2</td>
<td>161.6</td>
<td>109.773</td>
<td>1949</td>
</tr>
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<td>335.1</td>
<td>165.0</td>
<td>110.929</td>
<td>1950</td>
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<td>1951</td>
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<td>328.975</td>
<td>209.9</td>
<td>309.9</td>
<td>112.075</td>
<td>1951</td>
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<td>346.999</td>
<td>193.2</td>
<td>359.4</td>
<td>113.270</td>
<td>1952</td>
</tr>
</tbody>
</table>

R> ore.odmAI(Employed ~ ., LONGLEY)

Call:
ore.odmAI(formula = Employed ~ ., data = LONGLEY)

Importance:

<table>
<thead>
<tr>
<th>importance</th>
<th>rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year</td>
<td>0.4901166</td>
</tr>
<tr>
<td>Population</td>
<td>0.4901166</td>
</tr>
<tr>
<td>GNP</td>
<td>0.4901166</td>
</tr>
<tr>
<td>GNP.deflator</td>
<td>0.4901166</td>
</tr>
<tr>
<td>Armed.Forces</td>
<td>0.3648186</td>
</tr>
<tr>
<td>Unemployed</td>
<td>0.1318046</td>
</tr>
</tbody>
</table>
ore.odmAI - Example

Attribute Importance

R> STATE <- ore.push(as.data.frame(state.x77))
R> head(STATE)

<table>
<thead>
<tr>
<th>Population</th>
<th>Income</th>
<th>Illiteracy</th>
<th>Life Exp</th>
<th>Murder</th>
<th>HS Grad</th>
<th>Frost</th>
<th>Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alabama</td>
<td>3615</td>
<td>3624</td>
<td>2.1</td>
<td>69.05</td>
<td>15.1</td>
<td>41.3</td>
<td>20 50708</td>
</tr>
<tr>
<td>Alaska</td>
<td>365</td>
<td>6315</td>
<td>1.5</td>
<td>69.31</td>
<td>11.3</td>
<td>66.7</td>
<td>152 566432</td>
</tr>
<tr>
<td>Arizona</td>
<td>2212</td>
<td>4530</td>
<td>1.8</td>
<td>70.55</td>
<td>7.8</td>
<td>58.1</td>
<td>15 113417</td>
</tr>
<tr>
<td>Arkansas</td>
<td>2110</td>
<td>3378</td>
<td>1.9</td>
<td>70.66</td>
<td>10.1</td>
<td>39.9</td>
<td>65 51945</td>
</tr>
<tr>
<td>California</td>
<td>21198</td>
<td>5114</td>
<td>1.1</td>
<td>71.71</td>
<td>10.3</td>
<td>62.6</td>
<td>20 156361</td>
</tr>
<tr>
<td>Colorado</td>
<td>2541</td>
<td>4884</td>
<td>0.7</td>
<td>72.06</td>
<td>6.8</td>
<td>63.9</td>
<td>166 103766</td>
</tr>
</tbody>
</table>

R> ore.odmAI(Murder ~ ., STATE)

Call:
ore.odmAI(formula = Murder ~ ., data = STATE)

Importance:

<table>
<thead>
<tr>
<th>Importance</th>
<th>rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Life Exp</td>
<td>0.10872845</td>
</tr>
<tr>
<td>HS Grad</td>
<td>0.06915643</td>
</tr>
<tr>
<td>Illiteracy</td>
<td>0.05760828</td>
</tr>
<tr>
<td>Frost</td>
<td>0.05051389</td>
</tr>
<tr>
<td>Area</td>
<td>-0.04538736</td>
</tr>
<tr>
<td>Income</td>
<td>-0.06720964</td>
</tr>
<tr>
<td>Population</td>
<td>-0.12554537</td>
</tr>
</tbody>
</table>
Attribute Importance - results

**importance**
- Relative metric indicating how much the variable contributes to predicting the target
- Values $> 0$ contribute to prediction
- Values $\leq 0$ do not contribute or add noise

**rank**
- Ordering of variables / attributes from most significant to least
Naïve Bayes

Classification algorithm – simple probabilistic classifier
Relies on Bayes’ theorem \[ P(A|B) = \frac{P(B|A) P(A)}{P(B)} \].

Assumes independence of predictors
• May not be the case, but works well in practice

Conditional probabilities between each predictor and target multiplied to obtain prediction
ore.odmNB & predict.ore.odmNB

Naïve Bayes

ore.odmNB(
  formula, # formula specifying attributes for model build
  data, # ore.frame of the training dataset
  auto.data.prep = TRUE, # Setting to perform automatic data preparation
  class.priors = NULL, # Numeric vector with named elements for target class priors
  na.action = na.pass, # Allows missing values (na.pass), or removes rows with
                      # missing values (na.omit)
  odm.setting = NULL) # A list to specify Oracle Data Mining parameter settings

predict(
  object, # Object of type "ore.naiveBayes"
  newdata, # Data used for scoring
  supplemental.cols = NULL, # Columns to retain in output
  type = c("class","raw"), # "raw" – cond. a-posteriori probs for each class returned
  na.action = na.pass) # "class" – class with max prob
Basic Argument Concepts

class.priors

- Optional user-specified priors for the target classes
- Specifying prior probabilities offsets distribution differences between training data and real population (scoring data)

Use when one target value dominates in frequency

- For example
  - telephone marketing campaign positive responses may be < 2%
  - occurrence of fraud in credit card transactions may be < 1%.

- A classification model built with so few positive cases may not be able to distinguish characteristics of the two classes, resulting in a model that predicts the frequent class every time → use stratified sampling to balance the data set and set priors

- Such models may be accurate, but not be very useful

- Do not rely solely on accuracy when judging the quality of a classification model

Stratified sampling and anomaly detection are alternatives to compensating for data distribution issues
library(ORE)
ore.connect("rquser","orcl","localhost","rquser",all=TRUE)

data(titanic3,package="PASWR")
t3 <- ore.push(titanic3)
t3$survived <- ifelse(t3$survived == 1, "Yes", "No")

n.rows <- nrow(t3)
set.seed(seed=6218945)
random.sample <- sample(1:n.rows, ceiling(n.rows/2))
t3.train <- t3[random.sample,]
t3.test <- t3[setdiff(1:n.rows,random.sample),]

set.seed(6218945)
random.sample <- sample(1:n.rows, ceiling(n.rows/2))
t3.train <- t3[random.sample,]
t3.test <- t3[setdiff(1:n.rows,random.sample),]

priors <- c(Yes=0.1, No=0.9)

nb <- ore.odmNB(survived ~ pclass+sex+age+fare+embarked,
                t3.train, class.priors=priors)

scoredata <- predict(nb, t3.test,"survived")

head(scoredata,10)
with(scoredata, table(survived,PREDICTION,
dnn = c("Actual","Predicted")))

Score data using ore.frame with OREdm model object.

library(verification)
res <- ore.pull(scoredata)

auc.auc <- roc.area(ifelse(res$survived == 1, "Yes", "No"), res$"Yes")
auc.p <- signif(perf.auc$p.value, digits=3)

roc.plot(ifelse(res$survived == "Yes", 1, 0), res$"Yes", binormal=T, plot="both",
        xlab="False Positive Rate",
ylab="True Positive Rate", main="Titanic survival ODM NB model ROC Curve")
text(0.7, 0.4, labels= paste("AUC ROC:"signature(perf.auc$A, digits=3))
text(0.7, 0.3, labels= paste("p-value:"signature(perf.auc$p.value, digits=3))

summary(nb)

Disconnect from database

Model, train and test objects are automatically removed when session ends or R objects are removed
R> summary(nb)

Call:
  glm(formula = survived ~ pclass + sex + age + fare + embarked,
      data = titanic[, class,priors = priors])

Settings:
  value
  prep.auto  on

$apriori
  No  Yes
  0.3  0.7

$tables
  Pclass revenue 'Queenstown', 'Southampton'
  No 0.1569820 0.6821705
  Yes 0.3178235 0.6821705

$fare
  , [51.931249600000001], [51.93124960000001; 51.93124960000001]
  (51.93124960000001;  )
  No 0.315705888 0.6843442
  Yes 0.315705888 0.6843442

$pclass
  '1st', '2nd'  '3rd'
  No 0.3417722 0.6582278
  Yes 0.3417722 0.6582278

$sex
  female  male
  No 0.6789231 0.3210769
  Yes 0.6789231 0.3210769

Levels:
  [1] "No"  "Yes"

AUC ROC: 0.603
p-value: 3.38e-40
Naïve Bayes – model object

**ore.odmNB object**

- **name** of the model
- **settings** used to build the model
- **attributes** used to build the model: name, type (numerical or categorical), data type, data length (size), precision and scale for numeric data, and whether the variable is the target
- **apriori** table with class distribution for the dependent variable
- **tables** is a list with one for each predictor variable with conditional probabilities
- **levels** is a vector of unique target class values
Support Vector Machine

Suite of algorithms, adaptable for use with a variety of problems and data
By swapping one *kernel* for another, SVM can fit diverse problem spaces

Concept
- Data records with N attributes can be thought of as points in N-dimensional space
- SVM attempts to separate the points into subsets with homogeneous target values, by hyperplanes in the linear case, and in the non-linear case (Gaussian) by non-linear separators
- SVM finds the vectors that define the separators giving the widest separation of classes (the “support vectors”).

SVM solves regression problems by defining an N-dimensional “tube” around the data points, determining the vectors giving the widest separation

SVM can emulate some traditional methods, such as linear regression and neural networks, but goes far beyond those methods in flexibility, scalability, and speed
- For example, SVM can act like a neural net in calculating predictions, while a neural net might mistake a local change in direction as a point of minimum error, SVM works to find the global point of minimum error

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ore.odmSVM

Support Vector Machine

ore.odmSVM(
  formula,
  data,
  mining.function, "anomaly.detection"
  auto.data.prep = TRUE,
  class.priors = NULL,
  active.learning = TRUE,
  complexity.factor = "system.determined", # Setting for complexity factor for SVM
  conv.tolerance = 0.0001, # Setting for convergence tolerance for SVM
  epsilon = "system.determined", # Setting for epsilon for SVM Regression
  kernel.function = "system.determined", # Setting for kernel function (SVMS_GAUSSIAN or SVMS_LINEAR)
  std.dev = "system.determined", # Setting for standard deviation for SVM Gaussian kernel
  outlier.rate = 0.1, # Setting for desired rate of outliers in dataset (1class SVM)
  na.action = na.pass # Allow missing values in rows by default, or na.omit
  odm.setting = NULL, # A list to specify ODM parameter settings
  ctx.setting = NULL  # A list to specify Oracle Text attribute-specific settings
)
Basic Argument Concepts

class.priors
active.learning - enabled by default

• optimization method to control model growth and reduce model build time
• without active learning, SVM models grow as the size of the build data set increases, which effectively limits SVM models to small and medium size training sets (less than 100,000 cases)
• with active learning, SVM models can be built on very large training sets.
• active learning forces the SVM algorithm to restrict learning to the most informative training examples and not to attempt to use the entire body of data. In most cases, the resulting models have predictive accuracy comparable to that of a standard (exact) SVM model
• active learning provides a significant improvement in both linear and Gaussian SVM models, whether for classification, regression, or anomaly detection. However, active learning is especially advantageous for the Gaussian kernel, because nonlinear models can otherwise grow to be very large and can place considerable demands on memory and other system resources
Basic Argument Concepts

**complexity.factor**
- regularization setting that balances complexity of the model against model robustness to achieve good generalization on new data
- data-driven approach to automatically determine the complexity factor

**conv.tolerance**
- convergence tolerance criterion for completing the model training process, default .001

**epsilon**
- regularization setting for regression, similar to complexity factor
- specifies the allowable residuals, or noise, in the data
Basic Argument Concepts

**kernel.function** – linear or Gaussian
- a kernel is a function that transforms the input data to a high-dimensional space where the problem is solved. Kernel functions can be linear or nonlinear.
- algorithm automatically uses the kernel function that is most appropriate to the data if not specified
- linear kernel when # attributes > 100 in training data, else Gaussian kernel
  - # attributes reflects categorical columns exploded to numeric attributes

**kernel.cache.size**
- memory allocated to Gaussian kernel cache maintained in memory to improve model build time, default 50 MB

**std.dev**
- controls spread of Gaussian kernel function

**outlier.rate**
- for anomaly detection
- expected outlier rate in anomaly detection, default 0.1
Basic Argument Concepts

**odm.setting** – A list to specify Oracle Data Mining parameter settings. This argument is applicable to building a model in Database 12.2 or later. Each list element’s name and value refer to the parameter setting name and value, respectively. The setting values must be numeric or string. To perform text mining, parameter `ODMS_TEXT_POLICY_NAME` must be set to a text policy name. When parameter `ODMS_PARTITION_COLUMNS` is set to the name(s) of the partition column(s), a partition model with a sub-model in each partition is created from the input data.

**ctx.setting** – A list to specify Oracle Text attribute-specific settings. This argument is applicable to building model in Database 12.2 or later. The name of each list element refers to the text column while the list value specifies the text transformation.

(See ODM documentation for specific settings options.)
predict.ore.odmSVM
Support Vector Machine

predict (object, newdata, supplemental.cols = NULL, # Columns to retain in the output
type = c("class","raw"), # "raw" – cond. a-posteriori probs for each class returned,
# else class with max prob (TBD for compatibility with e1071)
na.action = na.pass,...) # allow missing value in rows by default, or na.omit
Basic Argument Concepts

**supplemental.cols**
- Columns from `newdata` to include as columns in the `ore.frame` prediction result
- Use to include specific columns in the prediction result for easier analysis

**type = c("class","raw"), if a classification model...**
- "raw" provides probability for each class returned
- "class" returns the class with the maximum probability
- default c("class","raw") returns both
ore.odmSVM – Example

Support Vector Machine

```r
x <- seq(0.1, 5, by = 0.02)
y <- log(x) + rnorm(x, sd = 0.2)
dat <- ore.push(data.frame(x=x, y=y))

# Regression
svm.mod <- ore.odmSVM(y~x, dat,"regression", kernel.function="linear")
summary(svm.mod)
coef(svm.mod)
svm.res <- predict(svm.mod, dat, supplemental.cols="x")
head(svm.res,6)
```
# Set up data set

```r
m <- mtcars
m$gear <- as.factor(m$gear)
m$cyl <- as.factor(m$cyl)
m$vs <- as.factor(m$vs)
m$ID <- 1:nrow(m)
MTCARS <- ore.push(m)
```

# Classification

```r
# Classification
svm.mod <- ore.odmSVM(gear ~ .-ID, 
    MTCARS,"classification", 
    kernel.function="linear")
summary(svm.mod)
coef(svm.mod)
svm.res <- predict (svm.mod, MTCARS,"gear")
head(svm.res)
svm.res <- predict (svm.mod, MTCARS,"gear",type="raw")
head(svm.res)
svm.res <- predict (svm.mod, MTCARS,"gear",type="class")
head(svm.res)
with(svm.res, table(gear,PREDICTION))  # confusion matrix

# Anomaly Detection
svm.mod <- ore.odmSVM(~ .-ID, MTCARS,"anomaly.detection", 
    kernel.function="system.determined")
summary(svm.mod)
svm.res <- predict (svm.mod, MTCARS, "ID")
head(svm.res)
table(svm.res$PREDICTION)
```
SVM – model object

ore.odmSVM object

• **name** of the model
• **settings** used to build the model
• **attributes** used to build the model: name, type (numerical or categorical), data type, data length (size), precision and scale for numeric data, and whether the variable is the target
• **fit.values** is an ore.frame of the actual column and predicted column. For regression, the columns are 'ACTUAL' and 'PREDICTED'. For classification, the columns are 'ACTUAL','PREDICTED','PROBABILITY'. For anomaly detection, the columns are 'PREDICTED' and 'PROBABILITY'.
• **residuals** for regression models, an ore.numeric vector containing the residual values (PREDICTED - ACTUAL).
• **formula** is the symbolic description of the model fitted
• **call** is the invocation parameters of the function

If built with a linear kernel, the following are also returned

• **coefficients** of the SVM model, one for each predictor variable. If auto.data.prep is set to TRUE, these coefficients will be in the transformed space (after automatic outlier-aware normalization is applied)
Cluster Description

Centroids

Histograms

INCOME

AGE

C1

C2

INCOME

AGE

C1

C2

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Cluster Rules

Cluster 1:
\[0 < \text{age} \leq 35 \text{ AND } 0 < \text{income} \leq 50K\]
Cluster 2:
\[30 < \text{age} \leq 55 \text{ AND } 40K < \text{income} \leq 80K\]
Clustering Hierarchy

Binary tree
- balanced
- unbalanced

Splitting predicates

MALE

FEMALE

SMOKE

~SMOKE

AGE < 40

AGE ≥ 40

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K-Means clustering

Identify distinct segments of a population
Explain the common characteristics of members of a cluster
Determine what distinguishes members of one cluster from members of another cluster
Partitions a set of observations into $k$ partitions, or clusters
Each observation belongs to the cluster with the nearest centroid or center, which is the mean of the observations variables
Distance can be computed in various ways, e.g., Euclidean or cosine
ore.odmKMeans

*K-Means Clustering*

```r
ore.odmKMeans(
  formula,
  data,
  auto.data.prep = TRUE,
  num.centers = 10,
  block.growth = 2,
  conv.tolerance = 0.01,
  distance.function = "euclidean",
  iterations = 3,
  min.pct.attr.support = 0.1,
  num.bins = 10,
  split.criterion = "variance",
  na.action = na.pass,
  odm.setting = NULL)
```

# Setting to perform automatic data preparation
# number of clusters
# Numeric growth factor for memory to hold cluster data
# Numeric convergence tolerance setting
# Distance function: cosine, euclidean, or fast.cosine
# Maximum number of iterations
# Minimum percent required for variables to appear in rules
# Number of histogram bins
# Split clusters by variance or size
# Allow missing values in rows by default, or na.omit
# A list to specify ODM parameter settings
Basic Argument Concepts

**num.centers** – number of clusters to create, > 1, default 10

**block.growth** – numeric growth factor for memory to hold cluster data, [1..5], default 2

**conv.tolerance** – numeric convergence tolerance setting, (0..0.5], default 0.01

**distance.function**
- distance function between instances and centroids
- options: cosine, euclidean, or fast.cosine
- default: euclidean

**iterations** – maximum number of iterations, [1..20], default 3
Basic Argument Concepts

**min.pct.attr.support**
- minimum percent required for variables to appear in rules, [0,1], default 0.1
- The fraction of attribute values that must be non-null for variable to be included in rule description for cluster
- Setting the parameter value too high in data with missing values can result in very short or even empty rules

**num.bins**
- number of histogram bins, > 0, default 10
- specifies the number of bins in the variable histogram produced by k-Means
- bin boundaries for each variable are computed globally on entire training data set
- binning method is equi-width
- all attributes have same number of bins except variables with a single value, which have only one bin

**split.criterion**
- split clusters by variance or size, default variance
- use size for more balanced clusters, e.g., with text mining
ore.odmKMeans

*K-Means Clustering*

```r
x <- rbind(matrix(rnorm(100, sd = 0.3), ncol = 2),
    matrix(rnorm(100, mean = 1, sd = 0.3), ncol = 2))
colnames(x) <- c("x", "y")
X <- ore.push(data.frame(x))
km.mod1 <- ore.odmKMeans(~., X, num.centers=2, num.bins=5)
summary(km.mod1)
rules(km.mod1)
clusterhists(km.mod1)
histogram(km.mod1)
```

`R> summary(km.mod1)`

Call:
`ore.odmKMeans(formula = ~., data = X, num.centers = 2, num.bins = 5)`

Settings:

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<th></th>
<th>value</th>
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Centers:

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ore.odmKMeans – results

```r
R> rules(km,mod1)

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$'1'$
```}

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### ore.odmKMeans – results

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<th>variable</th>
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<td>0.3191587</td>
<td>0.8467357</td>
<td>3.12E-01</td>
<td>8.47E-01</td>
</tr>
<tr>
<td>24</td>
<td>3</td>
<td>x</td>
<td>0.8467357</td>
<td>1.3744207</td>
<td>8.47E-01</td>
<td>1.37E+00</td>
</tr>
<tr>
<td>25</td>
<td>3</td>
<td>x</td>
<td>1.3744207</td>
<td>1.9026375</td>
<td>1.37E+00</td>
<td>1.90E+00</td>
</tr>
<tr>
<td>26</td>
<td>3</td>
<td>y</td>
<td>-0.7426519</td>
<td>-0.2598869</td>
<td>-7.42E-01</td>
<td>2.59E-01</td>
</tr>
<tr>
<td>27</td>
<td>3</td>
<td>y</td>
<td>-0.2598869</td>
<td>0.2248581</td>
<td>-2.59E-01</td>
<td>2.25E-01</td>
</tr>
<tr>
<td>28</td>
<td>3</td>
<td>y</td>
<td>0.2248581</td>
<td>0.7065331</td>
<td>2.25E-01</td>
<td>7.07E-01</td>
</tr>
<tr>
<td>29</td>
<td>3</td>
<td>y</td>
<td>0.7065331</td>
<td>1.1925380</td>
<td>7.07E-01</td>
<td>1.19E+00</td>
</tr>
<tr>
<td>30</td>
<td>3</td>
<td>y</td>
<td>1.1925380</td>
<td>1.6761350</td>
<td>1.19E+00</td>
<td>1.67E+00</td>
</tr>
</tbody>
</table>

![Cluster Histograms](image.png)
ore.odmKMeans

K-Means Clustering

```r
km.res1 <- predict(km.mod1,X,type="class",supplemental.cols=c("x","y"))
head(km.res1,3)
km.res1.local <- ore.pull(km.res1)

plot(data.frame(x=km.res1.local$x, y=km.res1.local$y), col=km.res1.local$CLUSTER_ID)
points(km.mod1$centers2, col=rownames(km.mod1$centers2), pch = 8, cex=2)

head(predict(km.mod1,X))
head(predict(km.mod1,X,type=c("class","raw"),supplemental.cols=c("x","y")),3)
head(predict(km.mod1,X,type="raw",supplemental.cols=c("x","y")),3)
```
ore.odmKMeans – results

```r
R> km.res1 <- predict(km.mod1,X,type="class",supplemental.cols=c("x","y"))
R> head(km.res1,3)
   x        y  CLUSTER_ID
1 -0.0399935 -0.3029228    3
2  0.5048611  0.3145332    3
3 -0.20133745 0.3497027    3
R> km.res1.local <- ore.pull(km.res1)
R> plot(data.frame(x=km.res1.local$x, y=km.res1.local$y), col=km.res1.local$CLUSTER_ID)
R> points(km.mod1.centers2, col=rownames(km.mod1.centers2), pch = 8, cex=2)
R>
R> head(predict(km.mod1,X))
   '3'   '2'  CLUSTER_ID
1 0.999998 1.844763e-07    3
2 0.9338791 6.612089e-02    3
3 0.9999185 8.154833e-05    3
4 0.9999520 4.798267e-05    3
5 0.9999885 1.153331e-05    3
6 0.9995041 4.959004e-04    3
R> head(predict(km.mod1,X,type=c("class","raw"),supplemental.cols=c("x","y")),3)
   '3'   '2'  x        y  CLUSTER_ID
1 0.999998 1.844763e-07 -0.0399935 -0.3029228    3
2 0.9338791 6.612089e-02 0.5048611  0.3145332    3
3 0.9999185 8.154833e-05 -0.20133745 0.3497027    3
R> head(predict(km.mod1,X,type="raw",supplemental.cols=c("x","y")),3)
   x       y  '3'   '2'
1 -0.0399935 -0.3029228 1.844763e-07
2 0.5048611  0.3145332 0.9338791 6.612089e-02
3 -0.20133745  0.3497027 0.9999185 8.154833e-05
```
K-Means – model object

ore.odmKMeans object

- **name** ...
- **settings** ...
- **attributes** ...
- **cluster** contain general per-cluster information
- **leaf.cluster.count** leaf clusters with support
- **taxonomy** is the parent-child cluster relationship
- **centers** are per cluster-attribute center (centroid) information
- **formula** ...
- **call** ...
ore.odmKMeans with text mining

*K-Means Clustering*

```r
dat <- scan("SOTU-2009.txt", what=character(), sep="\n")
df <- data.frame(ID = seq(length(dat)), PARAGRAPH = dat)
SOTU_TEXT <- ore.push(df)
ore.exec("begin ctx_ddl.create_policy('MY_TXTPOL'); end;") # CTXSYS.CTX_DDL privilege required

km.mod <- ore.odmKMeans(~PARAGRAPH, data = SOTU_TEXT, num.centers = 10L,
   odem.settings = list(ODMS_TEXT_POLICY_NAME = "MY_TXTPOL",
    ODMS_TEXT_MINDOCUMENTS = 2,
    ODMS_TEXT_MAXFEATURES = 20,
    kmns_distance ="dbms_data_mining.kmns_cosine",
    kmns_details = "kmns_details_all"),
   ctx.settings = list(PARAGRAPH="TEXT(TOKEN_TYPE:STEM)"))
```
Orthogonal Partitioning Clustering

*O-Cluster*

- Uses grid-based approach
- Finds natural data clusters
- Creates unbalanced hierarchical trees
- Uses active sampling
O-Cluster Grid-Based Partitioning
When to Use O-Cluster?

High number of records
  • needed for detailed histogram computation
High number of attributes
Presence of noise
Numeric and categorical attributes
Multi-modal density data
  • finds “natural” clusters, may not reach max number of clusters
    set by the user
Orthogonal Partitioning Clustering

Creates a hierarchical grid-based clustering model
- creates axis-parallel (orthogonal) partitions in the input attribute space
- operates recursively
- resulting hierarchical structure represents irregular grid that tessellates attribute space into clusters
- resulting clusters define dense areas in the attribute space

Clusters described by intervals along the attribute axes and corresponding centroids and histograms

Parameter 'sensitivity' defines a baseline density level
- Only areas with peak density above this baseline level can be identified as clusters

O-Cluster separates areas of high density by placing cutting planes through areas of low density
- O-Cluster needs multi-modal histograms (peaks and valleys)
- If an area has projections with uniform or monotonically changing density, O-Cluster does not partition it
Orthogonal Partitioning Clustering

O-Cluster reads the data in batches (the default batch size is 50000)

- Only read another batch if, based on statistical tests, there may still exist clusters that it has not yet uncovered.
- Since O-Cluster may stop the model build before it reads all of the data, it is highly recommended that the data be randomized.
- Binary attributes should be declared as categorical.
- O-Cluster maps categorical data to numerical values.
- Recommend to use ODM’s equi-width binning transformation with automated estimation of the required number of bins.
- Outliers can significantly impact clustering algorithms.
  - Use a clipping transformation before binning or normalizing.
  - Outliers with equi-width binning can prevent O-Cluster from detecting clusters - as a result, the whole population appears to falls within a single cluster.
ore.odmOC

*Orthogonal Partitioning Clustering*

```r
ore.odmOC(formula,
    data,
    auto.data.prep = TRUE,
    num.centers = 10,
    max.buffer = 50000,
    sensitivity = 0.5,
    na.action = na.pass,
    odm.setting = NULL
)
```

```r
## S3 method for class 'ore.odmOC'
predict(object,
    newdata,
    supplemental.cols = NULL,
    type = c("class","raw"),
    na.action = na.pass,...)
```
Basic Argument Concepts

**num.centers** – number of clusters to create, > 1, default 10

**max.buffer** – maximum buffer size, >0, default 50000

**sensitivity** – A fraction that specifies the peak density required for separating a new cluster. The fraction is related to the global uniform density. Value [0,1]. (default: 0.5)
OCluster – model object

ore.odmOC object

- **name**  name of model in database
- **settings**  data.frame with settings used to build model
- **attributes**  data.frame of variable/columns used to build model
- **clusters**  contain general per-cluster information
- **leaf.cluster.count**  data.frame of leaf clusters with support
- **taxonomy**  parent-child cluster relationship
- **centers**  per cluster-attribute center (centroid) information
- **centers2**  simplified cluster centroids (means)
- **histogram**  per cluster attribute histogram information
- **rules**  rules defining clusters
- **formula**  formula used to build the model
- **call**  specific invocation of the function with arguments
x <- rbind(matrix(rnorm(100, sd = 0.3), ncol = 2),
            matrix(rnorm(100, mean = 2, sd = 0.3), ncol = 2))
colnames(x) <- c("x", "y")
X <- ore.push(data.frame(x))

oc.mod1 <- ore.odmOC(~., X, num.centers=2)
summary(oc.mod1)
rules(oc.mod1)
clusterhists(oc.mod1)
histogram(oc.mod1)
ore.odmOC

\textit{O-Cluster Clustering}

\begin{verbatim}
oc.res1 <- predict(oc.mod1,X,type="class",
                   supplemental.cols=c("x","y"))
head(oc.res1,3)
oc.res1.local <- ore.pull(oc.res1)
plot(data.frame(x=oc.res1.local$x,
                y=oc.res1.local$y),
     col=oc.res1.local$CLUSTER_ID)
points(oc.mod1$centers2,
       col = rownames(oc.mod1$centers2),
       pch = 8, cex=2)
\end{verbatim}
Expectation Maximization Clustering

Popular probability density estimation technique
EM used to implement a distribution-based clustering algorithm (EM-clustering)
Expectation Maximization Clustering

ore.odmEM

Automated model search to find number of clusters / components (enabled via EMCS_MODEL_SEARCH)
Protection against overfitting
Supports numeric and multinomial distributions
High quality probability estimates
Generates cluster hierarchy, rules, and other statistics
Supports both Gaussian and multi-value Bernoulli distributions
Includes heuristics that automatically choose distribution types
When to Use EM?

In general, EM is a significantly more expensive algorithm than k-Means. If you have a large dataset, k-Means should be the first choice. However, Oracle’s EM is very scalable relative to other EM implementations.

Parallel implementation allows this EM algorithm to scale linearly with the number of rows. High column dimensionality is handled through the feature selection or random projections.

Provides a component clustering capability to group overlapping EM components into higher level clusters, enabling discovery of arbitrarily shaped clusters. This feature is on by default and may result in fewer clusters than the maximum size. It is also important to distinguish between EM components and the concept of clusters which can include multiple components.

Performs automatic feature selection by removing statistically independent columns, which effectively removes irrelevant noisy columns

Nested columns (ODM SQL only) and text use random projections and are modeled in a lower dimensional space
ore.odmEM

*Expectation Maximization Clustering*

```r
ore.odmEM(formula,
    data,
    num.centers = NULL,
    auto.data.prep = TRUE,
    na.action = na.pass,
    odm.setting = NULL)
```

```r
histogram(x,
    data=NULL,
    cluster.id="all",...)
```

```r
predict (object,
    newdata,
    supplemental.cols = NULL,
    type = c("class","raw"),
    na.action = na.pass,...)
```
Basic Argument Concepts

**num.centers** – number of clusters to create, > 1, default NULL – system determined  
**auto.data.prep** – default TRUE  
**odm.setting** – A list to specify Oracle Data Mining parameter settings. This argument is applicable to building a model in Database 12.2 or later. Each list element's name and value refer to the parameter setting name and value, respectively. The setting values must be numeric or string. When parameter **ODMS_PARTITION_COLUMNS** is set to the name(s) of the partition column(s), a partition model with a sub-model in each partition is created from the input data. (See ODM documentation for specific settings options.)
EM – model object

**ore.odmEM object**

- **name**
  - name of model in database
- **settings**
  - data.frame with settings used to build model
- **attributes**
  - data.frame of variable/columns used to build model
- **clusters**
  - contain general per-cluster information
- **leaf.cluster.count**
  - data.frame of leaf clusters with support
- **taxonomy**
  - parent-child cluster relationship
- **centers**
  - per cluster-attribute center (centroid) information
- **centers2**
  - simplified cluster centroids (means)
- **formula**
  - formula used to build the model
- **call**
  - specific invocation of the function with arguments
ore.odmEM

Expectation Maximization Clustering

```r
x <- rbind(matrix(rnorm(100, sd = 0.3), ncol = 2),
            matrix(rnorm(100, mean = 1, sd = 0.3), ncol = 2))
colnames(x) <- c("x", "y")

X <- ore.push(cbind(data.frame(x),
                  part = as.integer(x[,2] * 100) %% 2))
em.mod <- ore.odmEM(~. -part, X, num.centers = 3)
em.mod
summary(em.mod)
rules(em.mod)
clusterhists(em.mod)
histogram(em.mod)
```

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ore.odmEM

*Expectation Maximization Clustering*

```r
em.res1 <- predict(em.mod,X,type="class",
                     supplemental.cols=c("x","y"))
head(em.res1,3)
em.res1.local <- ore.pull(em.res1)
plot(data.frame(x=em.res1.local$x,
                 y=em.res1.local$y),
     col=em.res1.local$CLUSTER_ID)
points(em.mod$centers2, col =rownames(em.mod$centers2),
       pch = 8, cex=2)
head(predict(em.mod,X))
head(predict(em.mod,X,type=c("class","raw"),
            supplemental.cols=c("x","y")),3)
```
ore.odmEM

Expectation Maximization Clustering with partitioned model

```r
em.pmod <- ore.odmEM(~. , X, num.centers = 3,
                   odm.setting = list(odms_partition_columns = "part"))
partitions(em.pmod)
summary(em.pmod)
rules(em.pmod)
clusterhists(em.pmod)
histogram(em.pmod, part = "DM$P1")

head(predict(em.pmod, X))
head(predict(em.pmod, X,type=c("class","raw"),
            supplemental.cols=c("x","y")),3)
head(predict(em.pmod, X,type="raw",
            supplemental.cols=c("x","y")),3)
```
Decision Tree

Classification algorithm
  • Predicts a discrete value for each case: 0 or 1, Yes or No, Low Medium or High, with corresponding probability
  • Based on classification component of well-known C&RT algorithm
  • Enhancement of supplying Surrogate splitting attributes, if possible, at each node

Uses include
  • Prediction
  • Segmentation
  • Understanding predictions
Decision Tree Example

Segment #1
IF CUST_MO > 14 AND INCOME < $90K, THEN Prediction = Cell Phone Churner,
Confidence = 100%
Support = 8/39

Segment #3
IF CUST_MO > 7 AND INCOME < $175K, THEN Prediction = Cell Phone Churner,
Confidence = 83%
Support = 6/39

Source: Inspired from *Data Mining Techniques: For Marketing, Sales, and Customer Relationship Management* by Michael J. A. Berry, Gordon S. Linoff

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ore.odmDT

Decision Tree

ore.odmDT(
    formula,
    data,
    auto.data.prep = TRUE,
    cost.matrix = NULL,
    impurity.metric = "gini",
    max.depth = 7,
    min.rec.split = 20,
    min.pct.split = 0.1,
    min.rec.node = 10,
    min.pct.node = 0.05,
    na.action = na.pass,
    odm.setting = NULL)
)

# formula specifying attributes for model build
# ore.frame of the training dataset
# Setting to perform automatic data preparation
# numerical sq matrix for costs of incorrect prediction
# gini or entropy
# maximum depth of tree from root to leaf inclusive [2..20]
# minimum number of cases required to split a node
# minimum percent of cases required to split a node
# minimum number of cases required in a child node
# minimum percent of cases required in child node
# Allows missing values (na.pass), or removes rows with
# missing values (na.omit)
# A list to specify Oracle Data Mining parameter settings
Basic Argument Concepts

**cost.matrix** – default NULL

**impurity.metric**
- options: gini or entropy, default "gini"
- measure of node purity
- tree algorithms seek the best test question for splitting data at each node. The best splitter and split value are those that result in the largest increase in target value homogeneity (purity) for the entities in the node

**max.depth**
- default 7
- Criteria for splits: maximum tree depth (the maximum number of nodes between the root and any leaf node, including the leaf node)

**min.rec.split** – default 20

**min.pct.split** – default 0.1

**min.rec.node** – default 10

**min.pct.node** – default 0.05
```r
m <- mtcars
m$gear <- as.factor(m$gear)
m$cyl <- as.factor(m$cyl)
m$vs <- as.factor(m$vs)
m$ID <- 1:nrow(m)
MTCARS <- ore.push(m)
row.names(MTCARS) <- MTCARS

dt.mod <- ore.odmDT(gear ~ ., MTCARS)
summary(dt.mod)
dt.res <- predict(dt.mod, MTCARS,"gear")
# confusion matrix
with(dt.res, table(gear,PREDICTION))
```

```
> dt.mod <- ore.odmDT(gear ~ ., MTCARS)
> summary(dt.mod)
Call:
ore.odmDT(formula = gear ~ ., data = MTCARS)
n = 32
Nodes:
  parent node.id row.count prediction split
1   NA         32          3 <NA>
2   0          16          4 (disp <= 196.299999999999995) (disp > 196.299999999999995)
3   0          16          3 <NA>
surrogate full.splits
1   <NA> <NA>
2 (cyl in ("4" "6" )) (disp <= 196.299999999999995) (disp > 196.299999999999995)
Settings:

<table>
<thead>
<tr>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>prep.auto on</td>
</tr>
<tr>
<td>impurity.metric impurity.gini</td>
</tr>
<tr>
<td>term.max.depth 7</td>
</tr>
<tr>
<td>term.minpct.node 0.05</td>
</tr>
<tr>
<td>term.minpct.split 0.1</td>
</tr>
<tr>
<td>term.minrec.node 10</td>
</tr>
<tr>
<td>term.minrec.split 20</td>
</tr>
</tbody>
</table>

> dt.res <- predict(dt.mod, MTCARS,"gear")
> with(dt.res, table(gear,PREDICTION))
PREDICTION
  gear 3 4 3 14 1 4 0 12 5 2 3
```
Decision Tree – model object

**ore.odmDT object**

- **name** …
- **settings** …
- **attributes** …
- **costs**  
  a data.frame containing the cost matrix supplied at model build
- **Distributions** target class distributions at each tree node
- **nodes**  
  a data.frame with tree node details, including: parent node id, node id, number of rows assigned to that node, predicted value, split predicate, surrogate variables (if applicable), and full split predicates from current node to root node
- **formula** …
- **call** …
Generalized Linear Models

Linear Models

Assumes $Y$ is normally distributed with constant variance
Linear models fit
\[ \mu_Y = \beta_0 + \sum_{j=1}^{p} \beta_j X_j \]
No assumptions about predictors $X_j$ distributions, e.g., need not be normally distributed
Nonlinear functions on predictors allowed
Advantages
- Computational simplicity
- Interpretable model form
- Ability to compute certain diagnostic information about the quality of the fit

Generalized Linear Models

Addresses target variables that are non-normal
- Assume $Y$ follows distribution from exponential family
- Specify link function and probability distribution, or variance function
GLM fits models of the form
\[ g(\mu_Y) = \beta_0 + \sum_{j=1}^{p} \beta_j X_j \]
$g(\mu_Y)$ is a function of the conditional mean, a.k.a. link function

http://en.wikipedia.org/wiki/Exponential_family
ore.odmGLM

Generalized Linear Model

ore.odmGLM(
  formula,              # formula specifying attributes for model build
  data,                # ore.frame of the training dataset
  weights = NULL,      
  type = c("normal", "logistic"),
  na.treatment = c("delete.row", "mean.or.mode"),
  reference = NULL,    
  ridge = FALSE,       
  ridge.value = NULL,  
  ridge.vif = FALSE,   
  auto.data.prep = TRUE,  # Setting to perform automatic data preparation
  odm.setting = NULL)  # A list to specify Oracle Data Mining parameter settings
)
Basic Argument Concepts

weights
• An optional character string representing the column name in the data argument to use as analytical weights in the model fit, Default NULL

type
• the type of generalized linear model, default “normal”
  - "normal" (Gaussian) - identify link function and variance function = 1 (constant over range of response values)
  - "logistic" (binomial) - logit link function and binomial variance function

na.treatment
• The missing value treatment; either "delete.row" (delete entire row) or "mean.or.mode" (replace missing values with the mean in numeric predictors and the mode in categorical predictors), Default "delete.row"

reference
• An optional response variable category to use as the reference value (non-case/failure code) in a binary logistic regression model
• By default, reference is taken to be the category with the highest prevalence, default NULL
Basic Argument Concepts

ridge
• Compensates for multicollinearity
• TRUE to enable ridge estimation of the coefficients, FALSE otherwise, default FALSE
• Applies both to regression and classification
• When enabled, no prediction bounds can be produced

ridge.value
• The value for the ridge parameter used by the algorithm
• Used when ridge regression explicitly enabled
• If ridge regression is enabled internally by the algorithm, the ridge parameter is determined by the algorithm, default NULL

ridge.vif
• (Linear regression only) Optional logical indicator for whether to produce Variance Inflation Factor (VIF) statistics for the ridge estimates
• VIFs can only be produced if enough Oracle database system resources are available
• Default FALSE
# Linear regression using the longley data set
LONGLEY <- ore.push(longley)
longfit1 <- ore.odmGLM(Employed ~ ., data = LONGLEY)
summary(longfit1)
# Ridge regression using the longley data set

longfit2 <- ore.odmGLM(Employed ~ ., data = LONGLEY,
                         ridge = TRUE,
                         ridge.vif = TRUE)

summary(longfit2)
Generalized Linear Model Regression

# Logistic regression using the infert data set

INFERT <- ore.push(infert)

infit1 <- ore.odmGLM(
  case ~ age+parity+education+spontaneous+induced,
  data = INFERT,
  type = "logistic"
)

R> # Logistic regression using the infert data set
R> INFERT <- ore.push(infert)
R> infit1 <- ore.odmGLM(case ~ age+parity+education+spontaneous+induced,
+    data = INFERT, type = "logistic")
R> infit1

Response:
case == "1"

Call:  ore.odmGLM(formula = case ~ age + parity + education + spontaneous +
induced, data = INFERT, type = "logistic")

Coefficients:
        (Intercept)          age         parity education0-5yrs
    -2.19348  0.03958  -0.82828          1.04424
education12+ yrs spontaneous   induced
    -0.35896  2.04590  1.28876

Degrees of Freedom: 247 Total (i.e. Null); 241 Residual
Null Deviance: 316.2
Residual Deviance: 257.8    AIC: 271.8
ore.odmGLM – other functions

**Generalized Linear Model**

- `residuals(object, type = c("deviance", "pearson", "response"), ...)`
- `fitted(object, ...)`
- `predict(object, newdata, supplemental.cols = NULL, confint = FALSE, level = 0.95, na.action = na.pass, ...)`
- `confint(object, parm, level = 0.95, ...)`
- `deviance(object, ...)`
- `extractAIC(fit, scale = 0, k = 2, ...)`
- `logLik(object, ...)`
- `nobs(object, ...)`

- **confint**: A logical indicator for whether to produce confidence intervals for the predicted values.
- **level**: A numeric value within [0, 1] to use for the confidence level.
- **na.action**: Function to use for missing value handling; either 'na.pass' (allow missing values) or 'na.omit' (remove rows with missing values).
- **parm**: An optional character vector that specifies which coefficients to include in the set of confidence intervals.
- **scale**: An optional numeric scale parameter.
- **k**: An optional numeric weight of the equivalent degrees of freedom.
Generalized Linear Model Prediction

```r
res <- predict(infit1, newdata = INFERT, confint=TRUE, level = 0.97)
head(res)

head(residuals(infit1))
extractAIC(infit1)
logLik(infit1)
nobs(infit1)
```

```
R> res <- predict(infit1, newdata = INFERT, confint=TRUE, level = 0.97)
R> head(res)
PREDICTION LOWER.CONF UPPER.CONF
1 0.5721917 0.1767983 0.8928118
2 0.7258536 0.2887066 0.9452694
3 0.1194461 0.5546963 0.9775927
4 0.3684102 0.2546444 0.8958629
5 0.5104286 0.3632442 0.6558268
6 0.6322268 0.4007028 0.8154924
R>
R> head(residuals(infit1))
[1] 1.0566751 0.8005085 2.0614994 1.4131937 1.1597452 0.9576085
R> extractAIC(infit1)
[1] 7.0000 271.7977
R> logLik(infit1)
'log Lik.' -128.8988 (df=7)
R> nobs(infit1)
[1] 248
```
# Changing the reference value to 1
infit2 <- ore.odmGLM(
  case ~ age+parity+education+spontaneous+induced,
  data = INFERT,
  type = "logistic",
  reference = 1)

infit2

R> # Changing the reference value to 1
R> infit2 <- ore.odmGLM(case ~ age+parity+education+spontaneous+induced,
                        +    data = INFERT, type = "logistic", reference = 1)
R> infit2

Response:
case == "0"

Call: ore.odmGLM(formula = case ~ age + parity + education + spontaneous +
                   induced, data = INFERT, type = "logistic", reference = 1)

Coefficients:
                     (Intercept)        age        parity education0-5yrs
             2.19348     -0.03958     0.82828    -1.04424
education12+ yrs spontaneous induced
             0.35896     -2.04590    -1.28876

Degrees of Freedom: 247 Total (i.e. Null); 241 Residual
Null Deviance: 316.2
Residual Deviance: 257.8    AIC: 271.8
### Generalized Linear Model – model object

**ore.odmGLM object**

- **name**
  - ...
- **settings**
  - ...
- **attributes**
  - ...
- **coefficients**
  - a named vector of coefficients
- **residuals**
  - ore.frame containing 3 types of residuals: "deviance", "pearson", and "response"
- **fitted.values**
  - an ore.vector containing the fitted values
- **rank**
  - numeric rank of the fitted model
- **type**
  - type of model fit
- **deviance**
  - minus twice the maximized log-likelihood, up to a constant
- **aic**
  - same version of Akaike's An Information Criterion as used by glm
- **null.deviance**
  - deviance for the null (intercept only) model
- **prior.weights**
  - weights initially supplied or 1 if none were
- **df.residual**
  - residual degrees of freedom

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Generalized Linear Model – model object (2)

**ore.odmGLM object**
- **df.null** residual degrees of freedom for the null model
- **y** ore.vector containing the response variable
- **converged** indicator for whether the model converged
- **model** ore.frame containing the model frame
- **na.treatment** how missing values were treated
- **na.action** number of rows with missing values that were removed
- **terms** terms object used
- **data** data argument
- **nonreference** in logistic regression, the response values that represents success
- **ridge** ridge argument
- **auto.data.prep** whether or not auto data preparation should be used
- **fit.name** internal name for the in-database model
- **fit.details** model details
- **formula** ...
- **call** ...
To Ridge or not to Ridge

If the data has a large number of attributes AND accuracy is more important than a compact model ridge is the preferred approach
If having a compact model is important, then feature selection is the preferred approach
If the problem is believed to be non-linear in nature or the user does not know, then it is also a good idea to create a model with feature generation on
  • Will generate compact polynomial (quadratic or cubic) models that may fit the data better
User can also easily create these 3 types of models in a single model build node in Oracle Data Miner and then compare models to select best model
GLM Analysis of Variance tables (SQL)

Stats from Analysis can be obtained from the global statistics:

```sql
SELECT * 
FROM TABLE(dbms_data_mining.get_model_details_global('<model_name>')) 
order by global_detail_name;
```

The stats from the parameter table can be obtained through attribute level details

```sql
SELECT * 
FROM TABLE(dbms_data_mining.get_model_details_glm('<model_name>'));
```
Association Rules – Market Basket Analysis

Apriori algorithm (Agrawal and Srikant 1994)
Finds frequent itemsets and generates association models
• Finds co-occurrence of items in large volumes of data: both transactional and relational

Produces rules
• Set of items in a transactional record implies the existence of another set of items
• Groups of items form rules if they pass a minimum threshold
• Thresholds include: how frequently they occur (support) and how often the consequent follows the antecedent (confidence)

Apriori algorithm is efficient, and scales well with respect to the number of transactions, number of items, and number of itemsets and rules produced
Association (Market Basket Analysis)

**Transactional Data and Rule Example**

**Input Data:**

<table>
<thead>
<tr>
<th>User ID</th>
<th>Movies Viewed</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>{Movie1, Movie2, Movie3}</td>
</tr>
<tr>
<td>2</td>
<td>{Movie1, Movie4}</td>
</tr>
<tr>
<td>3</td>
<td>{Movie1, Movie3}</td>
</tr>
<tr>
<td>4</td>
<td>{Movie2, Movie5, Movie6}</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>N</td>
<td>{Movie3, Movie4, Movie6}</td>
</tr>
</tbody>
</table>

**Movie1 and Movie2 → Movie3**

with support of .12 and confidence .78
## Association Rules

### Support and Confidence

<table>
<thead>
<tr>
<th>User ID</th>
<th>Movies Viewed</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>{1, 2, 3}</td>
</tr>
<tr>
<td>2</td>
<td>{1, 4}</td>
</tr>
<tr>
<td>3</td>
<td>{1, 3}</td>
</tr>
<tr>
<td>4</td>
<td>{2, 5, 6}</td>
</tr>
</tbody>
</table>

Support (A → B)  
= $P(AB)$  
= count (A & B) / totalCount

Confidence (A → B)  
= $P(AB) / P(A)$  
= count (A & B) / count (A)

1 → 3:  
Support = 2/4 = 50%  
Confidence = 2/3 = 66%

3 → 1:  
Support = 2/4 = 50%  
Confidence = 2/2 = 100%
ore.odmAssocRules

Association Rules

ore.odmAssocRules(formula,
    data,
    case.id.column,
    item.id.column = NULL,
    item.value.column = NULL,
    min.support = 0.05,
    min.confidence = 0.05,
    max.rule.length = 2,
    na.action = na.pass,
    odm.setting = NULL)

## S3 method for class 'ore.odmAssocRules'
rules(object, ...)

## S3 method for class 'ore.odmAssocRules'
itemsets(object, ...)
Basic Argument Concepts

**case.id.column**
- Column name in 'data' that contains unique case identifiers

**item.id.column**
- Column in 'data' that contains item IDs. If NULL (default), 'data' treated as single-record case relational table, where each row considered a transaction and column values of that row are converted to items for that transaction; if specified, treated as transactional or multi-record case table where each row corresponds to an item in transaction, and model ignores any columns in 'data' other than item ID and item value.

**item.value.column**
- Column name in 'data' that contains the value of the item. (default: NULL)

**min.support**
- Numeric value that specifies the minimum support for rules in the model

**min.confidence**
- Numeric value that specifies the minimum confidence for rules in the model

**max.rule.length**
- Numeric value that specifies the maximum number of items in rule
Association Rules – model object

**ore.odmAssocRules object**
- **name** – name of in-database model
- **settings** - data.frame of settings used to build model
- **attributes** - named 'vector' of the types of input item values
- **inputType**: The type of input data table. It is "trans","tranWithValue", or "relational" for a multi-record case table, a multi-record case table with the values specified, or a single-record case table, respectively
- **formula**: A formula specified by users
Association Rules – model object

**ore.itemsets object** - returned by itemsets() that describes the property of each itemset
- **ITEMSET_ID**: numerical identifier associated with each itemset
- **NUMBER_OF_ITEMS**: number of items in the itemset
- **ITEMS**: names of items in the itemset
- **SUPPORT**: number of transactions containing this itemset

**ore.rules object** - returned by rules() that describes the property of each rule
- **RULE_ID**
- **NUMBER_OF_ITEMS**
- **LHS**: left hand side of rule (antecedent)
- **RHS**: right hand side of rule (consequent)
- **SUPPORT**
- **CONFIDENCE**
- **LIFT**
ore.odmAssocRules

**Association Rules**

```r
id <- c(1, 1, 1, 2, 2, 2, 3, 3, 3, 3)
item <- c("b", "d", "e", "a", "b", "c", "b", "c", "d", "e")
data.ore <- ore.push(data.frame(ID = id, ITEM = item))

ar.mod1 <- ore.odmAssocRules(~., data.ore, case.id.column = "ID", item.id.column = "ITEM", min.support = 0.6, min.confidence = 0.6, max.rule.length = 3)

# Generate itemsets and rules of the model
itemsets <- itemsets(ar.mod1)
rules <- rules(ar.mod1)

# subsetting
sub.itemsets <- subset(itemsets, min.support=0.7, items=list("b"))
sub.rules <- subset(rules, min.confidence=0.7, lhs=list("b", "c"))

library(arules)

# Convert the rules to the rules object in arules package
rules.arules <- ore.pull(rules)
inspect(rules.arules)
```

<table>
<thead>
<tr>
<th>Rule</th>
<th>Support</th>
<th>Confidence</th>
<th>Lift</th>
</tr>
</thead>
<tbody>
<tr>
<td>{b} =&gt; {e}</td>
<td>1.0000000</td>
<td>1.0000000</td>
<td>1</td>
</tr>
<tr>
<td>{e} =&gt; {b}</td>
<td>1.0000000</td>
<td>1.0000000</td>
<td>1</td>
</tr>
<tr>
<td>{c} =&gt; {e}</td>
<td>0.6666667</td>
<td>1.0000000</td>
<td>1</td>
</tr>
<tr>
<td>{d, e} =&gt; {b}</td>
<td>0.6666667</td>
<td>1.0000000</td>
<td>1</td>
</tr>
<tr>
<td>{c, e} =&gt; {b}</td>
<td>0.6666667</td>
<td>1.0000000</td>
<td>1</td>
</tr>
<tr>
<td>{b, d} =&gt; {e}</td>
<td>0.6666667</td>
<td>1.0000000</td>
<td>1</td>
</tr>
<tr>
<td>{b, c} =&gt; {e}</td>
<td>0.6666667</td>
<td>1.0000000</td>
<td>1</td>
</tr>
<tr>
<td>{d} =&gt; {b}</td>
<td>0.6666667</td>
<td>1.0000000</td>
<td>1</td>
</tr>
<tr>
<td>{d} =&gt; {e}</td>
<td>0.6666667</td>
<td>1.0000000</td>
<td>1</td>
</tr>
<tr>
<td>{c} =&gt; {b}</td>
<td>0.6666667</td>
<td>1.0000000</td>
<td>1</td>
</tr>
<tr>
<td>{b, e} =&gt; {d}</td>
<td>0.6666667</td>
<td>1.0000000</td>
<td>1</td>
</tr>
<tr>
<td>{b, e} =&gt; {c}</td>
<td>0.6666667</td>
<td>1.0000000</td>
<td>1</td>
</tr>
<tr>
<td>{e} =&gt; {d}</td>
<td>0.6666667</td>
<td>1.0000000</td>
<td>1</td>
</tr>
<tr>
<td>{e} =&gt; {c}</td>
<td>0.6666667</td>
<td>1.0000000</td>
<td>1</td>
</tr>
<tr>
<td>{b, e} =&gt; {d}</td>
<td>0.6666667</td>
<td>1.0000000</td>
<td>1</td>
</tr>
<tr>
<td>{b, e} =&gt; {c}</td>
<td>0.6666667</td>
<td>1.0000000</td>
<td>1</td>
</tr>
</tbody>
</table>
```
## ore.odmAssocRules

### Association Rules

```r
# Convert itemsets to the itemsets object in arules package
texts <- ore.odmAssocRules
itemsets.arules <- ore.pull(itemsets)
inspect(itemsets.arules)

library(arulesViz)
plot(rules.arules, method = "graph", interactive=TRUE)
```

R> inspect(itemsets.arules)

<table>
<thead>
<tr>
<th>items</th>
<th>support</th>
</tr>
</thead>
<tbody>
<tr>
<td>{b}</td>
<td>1.0000000</td>
</tr>
<tr>
<td>{e}</td>
<td>1.0000000</td>
</tr>
<tr>
<td>{b, e}</td>
<td>1.0000000</td>
</tr>
<tr>
<td>{c}</td>
<td>0.6666667</td>
</tr>
<tr>
<td>{d}</td>
<td>0.6666667</td>
</tr>
<tr>
<td>{b, c}</td>
<td>0.6666667</td>
</tr>
<tr>
<td>{b, d}</td>
<td>0.6666667</td>
</tr>
<tr>
<td>{c, e}</td>
<td>0.6666667</td>
</tr>
<tr>
<td>{d, e}</td>
<td>0.6666667</td>
</tr>
<tr>
<td>{b, c, e}</td>
<td>0.6666667</td>
</tr>
<tr>
<td>{b, d, e}</td>
<td>0.6666667</td>
</tr>
</tbody>
</table>
```
ore.odmAssocRules – multi-record case with value

**Association Rules**

```r
id <- c(1, 1, 2, 2, 3, 3, 4, 4, 5, 5, 6, 6, 7, 8, 8, 9, 9, 10, 11, 12, 12, 13, 14, 15, 16, 17)
item <- c("a","b","a","b","a","c","d","c","d","c","d","d","a","d","e","a",
"a","d","e","d","e","d","d","d")
value <- c(1, 1, 1, 1, 1, 2, 2, 1, 2, 1, 2, 3, 2, 1, 2, 2, 3, 2, 3, 2, 3, 3)
data2.ore <- ore.push(data.frame("ID" = id, "ITEM" = item, "VALUE" = value))

ar.mod2 <- ore.odmAssocRules(~., data2.ore, case.id.column = "ID",
item.id.column = "ITEM", item.value.column = "VALUE", max.rule.length = 3)

rules <- rules(ar.mod2)
itemsets <- itemsets(ar.mod2)

itemsets.arules <- ore.pull(itemsets)
inspect(itemsets.arules)

rules.arules <- ore.pull(rules)

plot(rules.arules, method = "graph",interactive=TRUE)
```

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# Relational data in a single-record case table.

```r
ar.mod3 <- ore.odmAssocRules(~., NARROW, 
    case.id.column = "ID", 
    min.support=0.25, min.confidence=0.15, 
    max.rule.length = 2)
```

```r
rules = rules(ar.mod3) 
itemsets = itemsets(ar.mod3)
```

```r
itemsets.arules <- ore.pull(itemsets) 
inspect(itemsets.arules) 
```

```r
rules.arules <- ore.pull(rules) 
```

```r
plot(rules.arules, method = "graph",interactive=TRUE)
```

---

<table>
<thead>
<tr>
<th>items</th>
<th>support</th>
</tr>
</thead>
<tbody>
<tr>
<td>{COUNTRY=United States of America}</td>
<td>0.8960000</td>
</tr>
<tr>
<td>{CLASS=0}</td>
<td>0.7466667</td>
</tr>
<tr>
<td>{CLASS=0, COUNTRY=United States of America}</td>
<td>0.6646667</td>
</tr>
<tr>
<td>{GENDER=M}</td>
<td>0.5866667</td>
</tr>
<tr>
<td>{COUNTRY=United States of America, GENDER=M}</td>
<td>0.5273333</td>
</tr>
<tr>
<td>{MARITAL_STATUS=Married}</td>
<td>0.4133333</td>
</tr>
<tr>
<td>{CLASS=0, GENDER=M}</td>
<td>0.3986667</td>
</tr>
<tr>
<td>{COUNTRY=United States of America, MARITAL_STATUS=Married}</td>
<td>0.3646667</td>
</tr>
<tr>
<td>{GENDER=M, MARITAL_STATUS=Married}</td>
<td>0.3140000</td>
</tr>
<tr>
<td>{GENDER=F}</td>
<td>0.2806667</td>
</tr>
<tr>
<td>{EDUCATION=HS-grad}</td>
<td>0.2806667</td>
</tr>
<tr>
<td>{MARITAL_STATUS=NeverM}</td>
<td>0.2793333</td>
</tr>
<tr>
<td>{CLASS=0, MARITAL_STATUS=NeverM}</td>
<td>0.2633333</td>
</tr>
<tr>
<td>{COUNTRY=United States of America, EDUCATION=HS-grad}</td>
<td>0.2586667</td>
</tr>
<tr>
<td>{CLASS=1}</td>
<td>0.2533333</td>
</tr>
<tr>
<td>{COUNTRY=United States of America, MARITAL_STATUS=NeverM}</td>
<td>0.2533333</td>
</tr>
<tr>
<td>{CLASS=0, GENDER=F}</td>
<td>0.2520000</td>
</tr>
<tr>
<td>{COUNTRY=United States of America, GENDER=F}</td>
<td>0.2520000</td>
</tr>
</tbody>
</table>

---

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plot(rules.arules, method = "graph", interactive = TRUE)
Feature Extraction
Singular Value Decomposition

Feature extraction algorithm
Orthogonal linear transformations capture the underlying variance of data by decomposing a rectangular matrix into three matrixes: U, D and V
Matrix D is a diagonal matrix and its singular values reflect the amount of data variance captured by the bases
Singular Value Decomposition

*ore.odmSVD*

Supports narrow data via Tall and Skinny solvers
Supports wide data via stochastic solvers
Provides eigensolvers for faster analysis with sparse data
Provides traditional SVD for more stable results
ore.odmSVD

*Singular Value Decomposition*

```r
ore.odmSVD(formula,  
  data,  
  auto.data.prep = TRUE,  
  na.action = na.pass,  
  odm.setting = NULL,  
  ctx.setting = NULL)
```

```r
features(object,...)
```

```r
feature_compare(object,  
  newdata,  
  compare.cols = NULL,  
  supplemental.cols = NULL)
```

```r
predict(object,  
  newdata,  
  supplemental.cols = NULL,  
  type = c("class","raw"),  
  na.action = na.pass,...)
```

```r
u(object)
```

```r
v(object)
```

```r
d(object)
```
Basic Argument Concepts

**num.centers** – number of clusters to create, > 1, default NULL – system determined

**auto.data.prep** – default TRUE

**odm.setting** – A list to specify Oracle Data Mining parameter settings. This argument is applicable to building a model in Database 12.2 or later. Each list element's name and value refer to the parameter setting name and value, respectively. The setting values must be numeric or string. To perform text mining, parameter `ODMS_TEXT_POLICY_NAME` must be set to a text policy name. When parameter `ODMS_PARTITION_COLUMNS` is set to the name(s) of the partition column(s), a partition model with a sub-model in each partition is created from the input data

**ctx.setting** – A list to specify Oracle Text attribute-specific settings. This argument is applicable to building model in Database 12.2 or later. The name of each list element refers to the text column while the list value specifies the text transformation. See ODM documentation for specific settings options.
SVD – model object

**ore.odmSVD object**
- **name**  
  name of model in database
- **settings**  
  data.frame with settings used to build model
- **attributes**  
  data.frame of variable/columns used to build model
- **formula**  
  formula used to build the model
- **call**  
  specific invocation of the function with arguments
ore.odmSVD

Singular Value Decomposition

IRIS <- ore.push(cbind(ID = seq_along(iris[[1L]]), iris))

svd.mod <- ore.odmSVD(~. -ID, IRIS)
summary(svd.mod)
d(svd.mod)
v(svd.mod)
head(predict(svd.mod, IRIS, supplemental.cols = "ID"))

svd.pmod <- ore.odmSVD(~. -ID, IRIS,
                        odm.setting = list(odms_partition_columns = "Species"))
summary(svd.pmod)
d(svd.pmod)
v(svd.pmod)
head(predict(svd.pmod, IRIS, supplemental.cols = "ID"))
Non-negative Matrix Factorization

State-of-the-art algorithm for Feature Extraction
Dimensionality reduction technique
• Creates new features of existing attributes
• Compare to AI which reduces attributes by taking a subset
• NMF derives fewer new “features” taking into account interactions among original attributes
Supports text mining, life sciences, marketing applications
NMF, intuitively...

Useful where there are many attributes

- Each has weak predictability, even ambiguous
- But when taken in combination, produce meaningful patterns, topics, or themes

Example: Text

- Same word can predict different documents
e.g., “hike” can be applied to the outdoors or interest rates
- NMF introduces context which is essential for predictive power
e.g., “hike” + “mountain” -> “outdoors sports”
  “hike” + “interest” -> “interest rates”
Conceptual view...

Attributes values

- a
- b
- c
- d
- e
- f
- g
- h
- ...
- x
- y
- z

Target values

- 1
- 2

Attributes values

- a
- b
- c
- d
- e
- f
- g
- h
- ...
- x
- y
- z

Extracted features

- f1
- f2
- f3
- f4

Target values

- 1
- 2

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Feature Extraction
Face representation with Vector Quantization

VQ

original

\[(0,0,0,\ldots,1,\ldots,0,0)\]

encoding

\[\times\]

reconstruction
Feature Extraction
Face representation with Principal Component Analysis

PCA

original

encoding

reconstruction

\[
(0.9, 0.6, -0.5, \ldots, 0.9, -0.3) \times \text{encoding} = \text{reconstruction}
\]
Feature Extraction
Face representation with NMF

NMF

(0, .5, .3, 0, 1, ..., 3, 0)

encoding

= reconstruction
ore.odmNMF

Non-negative Matrix Factorization

ore.odmNMF(formula,
    data,
    auto.data.prep = TRUE,
    num.features = NULL,
    conv.tolerance = NULL,
    num.iter = NULL,
    rand.seed = NULL,
    nonnegative.scoring = TRUE,
    na.action = na.pass,
    odm.setting = NULL,
    ctx.setting = NULL)

predict(object,
        newdata,
        supplemental.cols = NULL,
        type = c("class","raw"),
        na.action = na.pass,...)
Basic Argument Concepts

num.features – number of features to be extracted

conv.tolerance – convergence tolerance

num.iter – maximum number of iterations

rand.seed – random seed

nonnegative.scoring – non-negative values allowed in scoring
ore.odmNMF
Non-negative Matrix Factorization

training.set <- ore.push(npk[1:18, c("N","P","K")])
scoring.set <- ore.push(npk[19:24, c("N","P","K")])
nmf.mod <- ore.odmNMF(~., training.set, num.features = 3)
features(nmf.mod)
summary(nmf.mod)
predict(nmf.mod, scoring.set)
### Non-negative Matrix Factorization

**R> predict(nmf.mod, scoring.set)**

<table>
<thead>
<tr>
<th>FEATURE_ID</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>19</td>
<td>0.1972489</td>
<td>1.2400782</td>
<td>0.03280919</td>
</tr>
<tr>
<td>20</td>
<td>0.7298919</td>
<td>0.0000000</td>
<td>1.29438165</td>
</tr>
<tr>
<td>21</td>
<td>0.1972489</td>
<td>1.2400782</td>
<td>0.03280919</td>
</tr>
<tr>
<td>22</td>
<td>0.0000000</td>
<td>1.0231268</td>
<td>0.98567623</td>
</tr>
<tr>
<td>23</td>
<td>0.7298919</td>
<td>0.0000000</td>
<td>1.29438165</td>
</tr>
<tr>
<td>24</td>
<td>1.5703239</td>
<td>0.1523159</td>
<td>0.00000000</td>
</tr>
</tbody>
</table>

---

**Call:**

R> summary(nmf.mod)

**Settings:**

- `feat.num.features`: 3
- `nmfs.conv.tolerance`: 0.05
- `nmfs.nonnegative.scoring`: True
- `nmfs.num.iterations`: 50
- `nmfs.random.seed`: -1
- `prep.auto`: on

**Features:**

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Explicit Semantic Analysis (ESA)

Oracle Advanced Analytics 12.2+
Explicit Semantic Analysis (ESA)

In NLP and information retrieval, ESA is a **vectorial representation** of text (individual words or entire documents) that uses a document corpus as a knowledge base

- A word is represented as a column vector in the TF-IDF matrix of the text corpus
- A document (string of words) is represented as the centroid of the vectors representing its words

Text corpus often is English Wikipedia, though other corpora can be used

**Designed to improve text categorization**

- Computes "semantic relatedness" using cosine similarity between aforementioned vectors, collectively interpreted as a **space of "concepts explicitly defined and described by humans"**
- Wikipedia articles are equated with concepts

The name "explicit semantic analysis" contrasts with latent semantic analysis (LSA), because use of a knowledge base makes possible to **assign human-readable labels** to concepts comprising the vector space
Explicit Semantic Analysis (ESA)

Data
• Text documents
• Data with mixed set of columns, i.e., text + categorical + numerical

Examples
• Calculate semantic similarity between text documents or between mixed data
• Explicit topic modeling for text
Case 1: Calculate semantic similarity between text documents or between mixed data

Requires Wikipedia or another encyclopedic source to create a model
Model source data should cover all aspects of language usage
  • E.g., number of articles in the source data should be comparable to dictionary size
  • A dictionary of size 200K is often sufficient
  • Ideally source data is ~orthogonal, i.e. without overlapping articles
Case 1: Example

The following two paragraphs score a high similarity at 0.695 according to a Wikipedia-based ESA model:

• The Securities and Exchange Commission sued Tesla’s CEO on Thursday for making ‘false and misleading’ statements to investors. It’s asking a federal judge to prevent Musk from serving as an officer or a director of a public company, among other penalties. The complaint hinges on a tweet Musk sent on August 7 about taking Tesla private. ‘Am considering taking Tesla private at $420,’ Musk said. ‘Funding secured.’ The SEC said he had not actually secured the funding. ‘In truth and in fact, Musk had not even discussed, much less confirmed, key deal terms, including price, with any potential funding source,’ the SEC said in its complaint. That tweet, and subsequent tweets from Musk over the next three hours, caused ‘significant confusion and disruption in the market for Tesla’s stock,’ as well as harm to investors, the SEC said. On the day of Musk’s tweet, Tesla’s stock shot up nearly 9%. It has declined substantially since then.

• The Securities and Exchange Commission filed a lawsuit Thursday against Elon Musk, the chief executive of Tesla, accusing him of making false public statements with the potential to hurt investors. The lawsuit, filed in federal court in New York, seeks to bar Mr. Musk from serving as an executive or director of publicly traded companies. Tesla, the electric-car maker of which Mr. Musk was a co-founder, is publicly traded. The suit relates to an Aug. 7 Twitter post by Mr. Musk, in which he said he had ‘funding secured’ to convert Tesla into a private company. The S.E.C. said Mr. Musk ‘knew or was reckless in not knowing’ that his statements were false or misleading. ‘In truth and in fact, Musk had not even discussed, much less confirmed, key deal terms, including price, with any potential funding source,’ the S.E.C. said in its lawsuit.

In contrast, similarity between the first paragraph and this paragraph is only 0.051:

• If humans had lived 200 million years ago, they would have marveled at the largest dinosaur of its time. It’s name means ‘a giant thunderclap at dawn.’ The recently discovered fossil of a new dinosaur species in South Africa revealed a relative of the brontosaurus that weighed 26,000 pounds, about double the size of a large African elephant. The researchers have named it Ledumahadi mafube, which is Sesotho for ‘a giant thunderclap at dawn.’ Sesotho is an official South African language indigenous to the part of the country where the dinosaur was found. ‘The name reflects the great size of the animal as well as the fact that its lineage appeared at the origins of sauropod dinosaurs,’ said Jonah Choiniere, study author and paleontology professor at the University of the Witwatersrand in Johannesburg, South Africa. ‘It honors both the recent and ancient heritage of southern Africa.’
Case 2: Explicit topic modeling for text

Discover the most relevant topics for a given text document
  • Not really applicable to mixed data
Using Wikipedia as the model source data is typical
Explicit topic modeling benefits from domain-specific data
  • E.g., medicine, biology, physics and all other science branches
Requires that data source is encyclopedic for the selected domain
  • If domain topic coverage is insufficient, results will be poor
Case 2: Example

"The more things change... Yes, I'm inclined to agree, especially with regards to the historical relationship between stock prices and bond yields. The two have generally traded together, rising during periods of economic growth and falling during periods of contraction. Consider the period from 1998 through 2010, during which the U.S. economy experienced two expansions as well as two recessions: Then central banks came to the rescue. Fed Chairman Ben Bernanke led from Washington with the help of the bank’s current $3.6T balance sheet. He’s accompanied by Mario Draghi at the European Central Bank and an equally forthright Shinzo Abe in Japan. Their coordinated monetary expansion has provided all the sugar needed for an equities moonshot, while they vowed to hold global borrowing costs at record lows“

Top topics (concepts, people, organizations, events) discovered by ESA using Wikipedia as model source data

- Recession, Ben Bernanke, Lost Decade Japan, Mario Draghi, Quantitative easing, Long Depression, Great Recession, Federal Open Market Committee, Bank of Canada, Monetary policy, Japanese asset price bubble, Money supply, Great Depression, Central bank, Federal Reserve System

If instead of using the entire Wikipedia, we limit ourselves to the source dataset comprised of concepts only, this result would translate to:

- Recession, Quantitative easing, Monetary policy, Money supply, Central bank, Federal Reserve System
ESA vs. LDA (Latent Dirichlet Allocation)

**ESA is more interpretable than LDA**

Topics discovered by LDA are *latent*, meaning difficult to interpret:
- Topics are defined by their keywords, i.e., they have no names, no abstract descriptions.
- To give meaning to topics, keywords can be extracted by LDA.
- Definitions solely based on keywords are fuzzy, and keywords for different topics usually overlap.
- Extracted keywords can be just generic words.
- Set of automatically extracted keywords for a topic does not map to a convenient English topic name.

Biggest problem with LDA: set of topics is fluid:
- Topic set changes with any changes to the training data.
- Any modification of training data changes topic boundaries.
- Topics cannot be mapped to existing knowledge base or topics understood by humans if training data not static.
- Training data is almost never static.

ESA discovers topics from a given set of topics in a knowledge base:
- Topics are defined by humans → topics are well understood.
- Topic set of interest can be selected and augmented if necessary → full control of the selection of topics.
- Set of topics can be geared toward a specific task, e.g., knowledge base for topic modeling of online messages possibly related to terrorist activities, which is different than one for topic modeling of technical reports from academia.
- Can combine multiple knowledge bases, each with its own topic set, which may or may not overlap.
- Topic overlapping does not affect ESA's capability to detect relevant topics.
ore.odmESA

Explicit Semantic Analysis

ore.odmESA(formula,  
    data,  
    auto.data.prep = TRUE,  
    na.action = na.pass,  
    odm.setting = NULL,  
    ctx.setting = NULL)

features(object,...)

feature_compare(object, newdata, compare.cols = NULL, supplemental.cols = NULL)

predict(object,  
    newdata,  
    supplemental.cols = NULL,  
    type = c("class","raw"),  
    na.action = na.pass,...)
Basic Argument Concepts

**odm.setting** – A list to specify Oracle Data Mining parameter settings. This argument is applicable to building a model in Database 12.2 or later. Each list element's name and value refer to the parameter setting name and value, respectively. The setting values must be numeric or string. Parameter `CASE_ID_COLUMN_NAME` must specify the name of the column containing unique identifier. Parameter `ODMS_TEXT_POLICY_NAME` specifies the name of a valid Oracle text policy used for text mining. When parameter `ODMS_PARTITION_COLUMNS` is set to the names of the partition columns, then a partition model with sub-model in each partition is created from the input data.

**ctx.setting** – A list to specify Oracle Text attribute-specific settings. This argument is applicable to building model in Database 12.2 or later. The name of each list element refers to the text column while the list value specifies the text transformation.

(See ODM documentation for specific settings options.)
ESA – model object

ore.odmESA object

- **name**: name of model in database
- **settings**: data.frame with settings used to build model
- **attributes**: data.frame of variable/columns used to build model
- **formula**: formula used to build the model
- **call**: specific invocation of the function with arguments
ores.odmESA
Explicit Semantic Analysis

title <- c('Aids in Africa: Planning for a long war',
            'Mars rover maneuvers for rim shot',
            'Mars express confirms presence of water at Mars south pole',
            'NASA announces major Mars rover finding',
            'Drug access, Asia threat in focus at AIDS summit',
            'NASA Mars Odyssey THEMIS image: typical crater',
            'Road blocks for Aids')

ESA_TEXT <- ore.push(data.frame(CUST_ID = seq(length(title)),
                                  TITLE = title))

# create text policy (CTXSYS.CTXDDL privilege is required)
ore.exec("begin ctx_ddl.create_policy('ESA_TXTPOL'); end;")
ore.odmESA

Explicit Semantic Analysis

```r
esa.mod <- ore.odmESA(~., data = ESA_TEXT,
    odm.setting = list(case_id_column_name = "CUST_ID",
        ODMS_TEXT_POLICY_NAME = "ESA_TXTPOL",
        ESAS_MIN_ITEMS = 1),
    ctx.setting = list(TITLE = c("MIN_DOCUMENTS:1", "MAX_FEATURES:3"))
)

class(esa.mod)
summary(esa.mod)
settings(esa.mod)
predict(esa.mod, ESATEXT, type = "class", supplemental.cols = "CUST_ID")

ore.exec("begin ctx_ddl.drop_policy('ESA_TXTPOL'); end;")
```
OREmodels Package
OREmodels Algorithms

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Main R Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear Regression</td>
<td>ore.lm</td>
</tr>
<tr>
<td>Stepwise Linear Regression</td>
<td>ore.stepwise</td>
</tr>
<tr>
<td>Generalized Linear Models</td>
<td>ore.glm</td>
</tr>
<tr>
<td>Feedforward Neural Networks</td>
<td>ore.neural</td>
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<td>Random Forest</td>
<td>ore.randomForest</td>
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<td>Singular Value Decomposition</td>
<td>svd  overloaded</td>
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<tr>
<td>Principal Component Analysis</td>
<td>prcomp  overloaded  princomp  overloaded</td>
</tr>
</tbody>
</table>
ore.lm and ore.stepwise

Overview

ore.lm performs least squares regression
ore.stepwise performs stepwise least squares regression with marginal t-tests for variable selection – similar to SAS

Uses database data represented by ore.frame objects

In-database algorithm

- Estimates model using block update QR decomposition with column pivoting
- Once coefficients have been estimated, a second pass of the data estimates model-level statistics
- If collinear terms in data, ore.lm and ore.stepwise will not estimate coefficient values for the collinear set of terms
- For ore.stepwise, this collinear set of terms will be excluded throughout the procedure
# Fit full model

```r
fit1 <- lm(Employed ~ ., data = longley)
summary(fit1)
```

Coefficient `Armed.Forces` significant at $p < .001$ indicates for a 1 unit increase in `Armed.Forces`, `Employed` decreases by 0.01 units when all other predictors held constant.

Multiple R-squared of 0.9955 indicates the model accounts for 99.55% of the variance in the target.

Adjusted R-squared takes into account the number of predictors to account for chance improvement of R-squared simply be increasing number of predictors.

Residual standard error is the average error in predicting the target.

F-statistic indicates if predictors predict target beyond chance.

---

R> fit1 <- lm(Employed ~ ., data = longley)  
R> summary(fit1)

Call:
`lm(formula = Employed ~ ., data = longley)`

Residuals:
```
          Min        1Q  Median        3Q       Max
-0.41011   -0.15767  -0.02816   0.10155   0.45539
```

Coefficients:

```
            Estimate  Std. Error   t value  Pr(>|t|)
(Intercept) -3.482e+03  8.904e+02   -3.911    0.00356 **
GIP deflator  1.506e-02  8.492e-02    0.177    0.86314
GIP          -3.582e-02  3.349e-02   -1.070    0.31288
Unemployed   -2.020e-02  4.884e-03   -4.136    0.00253 **
Armed.Forces -1.033e-02  2.143e-03   -4.822    0.000944 ***
Population   -5.110e-02  2.261e-01   -0.226    0.826212
Year          1.829e+00  4.555e-01    4.018    0.003037 **
```

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3049 on 9 degrees of freedom
Multiple R-squared: 0.9955,  Adjusted R-squared: 0.9925
F-statistic: 330.3 on 6 and 9 DF,  p-value: 4.984e-10

---
# To limit overhead caused by parallelism
options(ore.parallel=1)

LONGLEY <- ore.push(longley)

# Fit full model
oreFit1 <- ore.lm(Employed ~ ., data = LONGLEY)

summary(oreFit1)

Since data is small, turn off parallelism by setting ore.parallel to 1
lm and ore.lm results side-by-side

They’re identical

R> fit1 <- lm(Employed ~ ., data = longley)
R> summary(fit1)

Call:
  lm(formula = Employed ~ ., data = longley)

Residuals:
   Min     1Q    Median     3Q     Max
-0.41011 -0.15767 -0.02816  0.10155  0.45539

Coefficients:
                              Estimate Std. Error t value Pr(>|t|)
(Intercept)          -3.482e+03  8.904e+02  -3.911 0.003560 **
GNP.deflator         1.506e+02  8.492e-02   1.770 0.0863141
GNP                 -3.582e-02  3.349e-02  -1.070 0.28681
Unemployment         -2.020e-02  4.884e-03   -4.136 0.0002550 **
Armed.Forces         -1.033e-02  2.143e-03   -4.822 0.0009440 ***
Population           -5.110e-02  2.626e-01  -0.226 0.826212
Year                1.829e+00  4.556e-01    4.016 0.003037 **

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3049 on 9 degrees of freedom
Multiple R-squared: 0.9945,  Adjusted R-squared: 0.9925
F-statistic: 930.3 on 8 and 9 DF,  p-value: 4.984e-10

R> LONGLEY <- ore.push(longley)
R> # Fit full model
R> oreFit1 <- ore.lm(Employed ~ ., data = LONGLEY)
R> summary(oreFit1)

Call:
  ore.lm(formula = Employed ~ ., data = LONGLEY)

Residuals:
   Min     1Q    Median     3Q     Max
-0.41011 -0.15980 -0.02816  0.15681  0.45539

Coefficients:
                              Estimate Std. Error t value Pr(>|t|)
(Intercept)          -3.482e+03  8.904e+02  -3.911 0.003560 **
GNP.deflator         1.506e+02  8.492e-02   1.770 0.0863141
GNP                 -3.582e-02  3.349e-02  -1.070 0.28681
Unemployment         -2.020e-02  4.884e-03   -4.136 0.0002550 **
Armed.Forces         -1.033e-02  2.143e-03   -4.822 0.0009440 ***
Population           -5.110e-02  2.626e-01  -0.226 0.826212
Year                1.829e+00  4.556e-01    4.016 0.003037 **

---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3049 on 9 degrees of freedom
Multiple R-squared: 0.9945,  Adjusted R-squared: 0.9925
F-statistic: 930.3 on 8 and 9 DF,  p-value: 4.984e-10
Other functions on ore.lm model

`summary(object, correlation = FALSE, symbolic.cor = FALSE, ...)`
- Return the call, residuals, coefficients, and various statistics

`predict(object, newdata, se.fit = FALSE, scale = NULL, df = Inf, interval = c("none", "confidence", "prediction"), level = 0.95, type = c("response", "terms"), terms = NULL, na.action = na.pass, pred.var = NULL, weights = NULL, ...)`

`vcov(object, ...)`
- Returns the variance-covariance matrix of the main parameters of a fitted model object

`logLik(object, ...)`
- Returns object of class `logLik` – a number with at least one attribute, "df" (degrees of freedom), giving number of (estimated) parameters in model

`hatvalues(model, ...)`
- Returns measure of high leverage for observations. Observations with value > 2x or 3x average hat value should be examined for possible removal. Average hat value = p / n, where p is number of parameters (including intercept) and n is number of observations

`add1(object, scope, scale = 0, test = c("none", "Chisq", "F"), x = NULL, k = 2, ...)`
`drop1(object, scope, scale = 0, all.cols = TRUE, test = c("none", "Chisq", "F"), k = 2, ...)`
- Compute all single terms in scope argument that can be added to / dropped from model, fit those models and compute table of changes in fit

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Other functions on ore.lm model

**anova(object, ...)**
- Returns the coefficients for the model

**confint(object, parm, level = 0.95, ...)**
- Return the confidence interval of the coefficients

**deviance(object, ...)**
- Returns the deviance of the model

**extractAIC(fit, scale, k = 2, ...)**
- Returns the (generalized) Akaike Information Criterion for a fitted parametric model

**fitted(object, ...) & fitted.values(object, ...)**
- Returns the predicted values on each of the training data observations/rows

**formula(x, ...)**
- Returns the formula used to specify the model

**model.frame(formula, ...)**
- Returns the training data used to build the model

**nobs(object, ...)**
- Returns the number of observations in the training data

**resid(object, ...) & residuals(object, ...)**
- Returns the residual values from the predictions (predicted – actual) for each observation

**plot(object, ...)**
- Produces diagnostic plots to assess model fit
  - Plot of residuals against fitted values, a Scale-Location plot of $\sqrt{| residuals |}$ against fitted values, a Normal Q-Q plot, a plot of Cook’s distances versus row labels, a plot of residuals against leverages, and a plot of Cook’s distances against leverage/(1-leverage)
Stepwise Regression: ore.stepwise

Motivation

Automatically selects predictive variables
Produces models with fewer terms
Enable handling data with complex patterns
  • Even for relatively small data sets (e.g., < 1M rows) R may not yield satisfactory results
Increases performance
  • Side benefit of handling complex patterns is to dramatically boost performance
  • No need to pull data into memory from database
  • Leverage more powerful database machine
Provide a stepwise regression that maps to SAS PROC REG
  • Uses marginal t-tests for variable selection as opposed to AIC, which is used for R's step() function. Note R's step function can be used with ore.lm.
ore.stepwise – parameters

ore.stepwise(formula, data, scope,
    direction = c("both", "backward", "forward", "alternate", "none"),
    add.p = 0.50, drop.p = 0.10, nbest = 1, steps = 1000,
    contrasts = NULL, xlev = NULL, ...)

**scope** – range of models to examine, either single formula object, or list containing lower and upper formula object elements

**direction** – The stepwise search mode; one of "'both'" (first try to add a term using the 'add.p' argument value and then try repeatedly to drop terms using the 'drop.p' argument value), "'backward'"", "'forward'", "'alternate'" (similar to "'both'" but only one drop is attempted per add attempt) or "'none'" with a default of "'both'"

**add.p** – F-test p-value threshold for adding term to model

**drop.p** – F-test p-value threshold for dropping term from model

**nbest** – number of best models to report at each step

**steps** – maximum number of steps

**contrasts** – named list to be supplied to the contrasts.arg argument of model.matrix

**xlev** – a named list of character vectors specifying the levels for each ore.factor variable
ore.stepwise – example

```r
LONGLEY <- ore.push(longley)

# Using ore.stepwise
oreStep1 <-
  ore.stepwise(Employed ~ .^2, data = LONGLEY,
                add.p = 0.1, drop.p = 0.1)

oreStep1

# Using R step with ore.lm
oreStep2 <-
  step(ore.lm(Employed ~ 1, data = LONGLEY),
       scope = terms(Employed ~ .^2, data = LONGLEY))

oreStep2
```

Build model with interaction terms
R> oreStep1 <-
+   ore.stepwise(Employed ~ .^2, data = LONGLEY,
+                  add.p = 0.1, drop.p = 0.1)
R> oreStep1

Aliased:

Steps:

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<th>Drop</th>
<th>RSS</th>
<th>Rank</th>
</tr>
</thead>
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</tr>
<tr>
<td>2</td>
<td>GNP:Year &lt;NA&gt;</td>
<td>218,957</td>
<td>3</td>
</tr>
<tr>
<td>3</td>
<td>GNP.deflator:GNP &lt;NA&gt;</td>
<td>130,525</td>
<td>4</td>
</tr>
<tr>
<td>4</td>
<td>GNP.deflator:Population &lt;NA&gt;</td>
<td>81,244</td>
<td>5</td>
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<tr>
<td>5</td>
<td>GNP:Armed.Forces &lt;NA&gt;</td>
<td>18,244</td>
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<tr>
<td>6</td>
<td>Year &lt;NA&gt;</td>
<td>14,492</td>
<td>7</td>
</tr>
</tbody>
</table>

Call:
ore.stepwise(formula = Employed ~ .^2, data = LONGLEY, add.p = 0.1,
              drop.p = 0.1)

Coefficients:

<table>
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<th></th>
<th></th>
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<td></td>
</tr>
<tr>
<td>GNP:Armed.Forces &lt;NA&gt;</td>
<td>2.303e-05</td>
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<tr>
<td>GNP:Year &lt;NA&gt;</td>
<td>6.875e-06</td>
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</tbody>
</table>

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step with ore.lm – results

Akaike information criterion (AIC)
• Measure of quality of a model
• Used for model selection

```r
> oreStep2 <-
+ step(ore.lm(employed ~ 1, data = LONGLEY),
+ scope = terms(ore.lm ~ .2, data = LONGLEY))
Start: AIC=41.17
Employed ~ 1

    DF Sum of Sq RSS AIC
+ GNP          1 178.973  6.056 -11.597
+ Year         1 174.652 10.457 -2.806
+ GNP:Year     1 174.337 10.611 -2.571
+ Population   1 170.643 14.356  2.278
+ Unemployed   1  46.718 128.293 33.599
+ Armed.Forces 1  38.691 146.318 33.411
<none>        1 186.009 41.165
Step: AIC=11.6
Employed ~ GNP

    DF Sum of Sq RSS AIC
+ Unemployed  1  2.457 3.572 -17.980
+ Population  1  2.162 3.874 -15.691
+ Year        1  1.125 4.911 -12.838
<none>       1  6.056 -11.597
+ GNP:Year    1  0.212 5.924 -10.189
+ Armed.Forces 1  0.077 6.395 -9.682
+ GNP          1 170.973 185.008 41.165
Step: AIC=17.36
Employed ~ GNP + Unemployed

    DF Sum of Sq RSS AIC
+ Armed.Forces 1 0.222 2.757 -20.137
+ Year         1 0.340 3.239 -17.995
+ GNP:Unemployed 1 0.182 3.397 -16.736
+ Population   1 0.097 3.402 -16.399
+ GNP:Year     1 0.013 3.559 -16.044
+ Unemployed   1 2.457 6.056 -11.597
+ GNP          1 134.714 138.293 30.509
<none>        1 186.009 41.165
```

```
> Step: AIC=20.14
Employed ~ GNP + Unemployed + Armed.Forces

     DF Sum of Sq RSS AIC
+ Year           1 1.898  0.859 -36.799
+ GNP:Unemployed 1 0.614  2.143 -22.198
+ Population     1 0.390  2.367 -20.578
<none>          1 2.757 -50.172
+ GNP:Year       1 0.083  2.673 -18.629
+ GNP:Deflator   1 0.073  2.684 -18.556
+ GNP:Armed.Forces 1 0.060  2.697 -18.489
+ Armed.Forces   1 0.022  3.657 -17.950
+ Unemployed     1  3.263  5.389 -9.802
+ GNP            1 78.494 81.250 21.995
```

```
> Step: AIC=36.8
Employed ~ GNP + Unemployed + Armed.Forces + Year

     DF Sum of Sq RSS AIC
<none>          1 0.859 -36.799
+ Unemployed:Year 1 0.0749  0.783 -36.203
+ GNP:Unemployed  1 0.0678  0.790 -36.118
+ GNP:Armed.Forces 1 0.0515  0.807 -35.738
+ GNP:Armed.Forces:Year 1 0.0367  0.822 -35.439
+ Population     1 0.0193  0.833 -35.153
+ GNP:Deflator   1 0.0175  0.841 -35.129
+ Armed.Forces:Year 1 0.0136  0.845 -35.054
+ GNP:Year       1 0.0084  0.852 -34.957
+ GNP            1 0.4647  1.324 -31.879
+ Year           1 1.6800  2.757 -20.137
+ Armed.Forces   1 2.3986  3.239 -17.950
+ Unemployed     1 4.0491  4.907 -10.908
<none>          1 186.009 41.165
```

```
> summary(orelm2)

Call:
ore.lm(formula = Employed ~ GNP + Unemployed + Armed.Forces +
Year, data = LONGLEY)

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 4.049e+01 1.898e+02  2.13e+01   0.036
GNP          3.897e-02 4.026e-02  9.71e-01   0.339
Unemployed  -4.018e-02 9.098e-02 -4.38e-01   0.667
Armed.Forces-1.015e-02 9.997e-02 -1.02e-01   0.915
Year        -1.087e+00 6.288e+00 -1.72e+00   0.087
```

```
How to use Akaike's Information Criterion (AIC) as a selection criterion for stepwise regression

AIC cannot be used with `ore.stepwise`, since the `ore.stepwise` function uses marginal t-tests for variable selection. `ore.lm` integrates with R's `step` function, which does use AIC.

It is not as fast as `ore.stepwise`, but will get the job done.

R> LONGLEY <- ore.push(longley)
R> mod <- ore.lm(Employed ~ ., data = LONGLEY)
R> step(mod)
Start:  AIC= -33.22
Employed ~ GNP.deflator + GNP + Unemployed + Armed.Forces + Population + Year

<table>
<thead>
<tr>
<th>Df</th>
<th>Sum of Sq</th>
<th>RSS</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>GNP.deflator</td>
<td>1</td>
<td>0.00292</td>
<td>0.83935</td>
</tr>
<tr>
<td>Population</td>
<td>1</td>
<td>0.00475</td>
<td>0.84117</td>
</tr>
<tr>
<td>GNP</td>
<td>1</td>
<td>0.10631</td>
<td>0.94273</td>
</tr>
<tr>
<td>&lt;none&gt;</td>
<td></td>
<td>0.83642</td>
<td>-33.219</td>
</tr>
<tr>
<td>Year</td>
<td>1</td>
<td>1.49881</td>
<td>2.33524</td>
</tr>
<tr>
<td>Unemployed</td>
<td>1</td>
<td>1.59014</td>
<td>2.42656</td>
</tr>
<tr>
<td>Armed.Forces</td>
<td>1</td>
<td>2.16091</td>
<td>2.99733</td>
</tr>
</tbody>
</table>

Step:  AIC= -35.16
Employed ~ GNP + Unemployed + Armed.Forces + Population + Year

Df Sum of Sq | RSS      | AIC        |
------------|----------|------------|
Population | 1         | 0.01933  | 0.8587     |
<none>     |           | 0.8393   | -35.163    |
GNP        | 1         | 0.14637  | 0.9857     |
Year       | 1         | 1.52725  | 2.3666     |
Unemployed | 1         | 2.18989  | 3.0292     |
Armed.Forces | 1                 | 2.39752  | 3.2369     |

Step:  AIC= -36.8
Employed ~ GNP + Unemployed + Armed.Forces + Year

Df Sum of Sq | RSS      | AIC        |
-------------|----------|------------|
<none>      |          | 0.8587    | -36.799    |
GNP         | 1         | 0.4647   | 1.3234     |
Year        | 1         | 1.8980   | 2.7567     |
Armed.Forces | 1                 | 2.3806   | 3.2393     |
Unemployed  | 1         | 4.0491   | 4.9077     |

Call:
ore.lm(formula = Employed ~ GNP + Unemployed + Armed.Forces + Year, data = LONGLEY)

Coefficients:
(Intercept) GNP Unemployed Armed.Forces Year
-3.599e+03 -4.019e-02 -2.088e-02 -1.015e-2 1.887e+00
Linear Model Example
An example using the R state.x77 data set

```r
library(car)
?state.x77
state.df <- as.data.frame(state.x77)
scatterplotMatrix(state.df)
```

Scatterplot of pairs of variables (bivariate analysis)
Fitted loess curve (red)
Fitted linear model (green)
Diagonals show density and run plot per variable
An example using the R state.x77 data set

```r
options(digits=3)
cor(state.df)
# also with in-database execution
STATE <- ore.push(state.df)
cor(STATE)
```

<table>
<thead>
<tr>
<th></th>
<th>Population</th>
<th>Income</th>
<th>Illiteracy</th>
<th>Life Exp</th>
<th>Murder</th>
<th>HS Grad</th>
<th>Frost</th>
<th>Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population</td>
<td>1.0000</td>
<td>0.208</td>
<td>0.1076</td>
<td>-0.0681</td>
<td>0.344</td>
<td>-0.0985</td>
<td>-0.3322</td>
<td>0.0225</td>
</tr>
<tr>
<td>Income</td>
<td>0.2082</td>
<td>1.000</td>
<td>-0.4371</td>
<td>0.3403</td>
<td>-0.230</td>
<td>0.6199</td>
<td>0.2263</td>
<td>0.3633</td>
</tr>
<tr>
<td>Illiteracy</td>
<td>0.1076</td>
<td>-0.4371</td>
<td>1.0000</td>
<td>-0.5885</td>
<td>0.703</td>
<td>-0.6572</td>
<td>-0.6719</td>
<td>0.0773</td>
</tr>
<tr>
<td>Life Exp</td>
<td>-0.0681</td>
<td>0.340</td>
<td>-0.5885</td>
<td>1.0000</td>
<td>-0.781</td>
<td>0.5822</td>
<td>0.2621</td>
<td>-0.1073</td>
</tr>
<tr>
<td>Murder</td>
<td>0.3436</td>
<td>-0.230</td>
<td>0.7030</td>
<td>-0.7808</td>
<td>1.000</td>
<td>-0.4880</td>
<td>-0.5389</td>
<td>0.2284</td>
</tr>
<tr>
<td>HS Grad</td>
<td>-0.0985</td>
<td>0.620</td>
<td>-0.6572</td>
<td>0.5822</td>
<td>-0.488</td>
<td>1.0000</td>
<td>0.3668</td>
<td>0.3335</td>
</tr>
<tr>
<td>Frost</td>
<td>-0.3322</td>
<td>0.226</td>
<td>-0.6719</td>
<td>0.2621</td>
<td>-0.539</td>
<td>0.3668</td>
<td>1.0000</td>
<td>0.0592</td>
</tr>
<tr>
<td>Area</td>
<td>0.0225</td>
<td>0.363</td>
<td>0.0773</td>
<td>-0.1073</td>
<td>0.228</td>
<td>0.3335</td>
<td>0.0592</td>
<td>1.0000</td>
</tr>
</tbody>
</table>
Interpreting correlation

An example using the R state.x77 data set

```
fit <- lm(Murder ~ ., state.df)
summary(fit)
```

Life Exp is significant, but we would expect this

Remove it from the model, then HS Grad and Income
# Rename vars to remove space
names(state.df)[4] <- "LifeExp"
names(state.df)[6] <- "HSGrad"

fit <- lm(Murder ~ ., state.df)
summary(fit)

fit <- lm(Murder ~ .-LifeExp-Income-HSGrad, state.df)
summary(fit)
An example using the R state.x77 data set

```r
fit2 <- lm(Murder ~ .^2, state.df)
summary(fit2)
```
An example using the R state.x77 data set

```r
STATE <- ore.push(state.df)
fit3 <- ore.stepwise(Murder ~ .^2, STATE)
summary(fit3)
```

Call:
`ore.stepwise(formula = Murder ~ .^2, data = STATE)`

Residuals:
```
           Min         1Q     Median         3Q        Max
-3.53999   -1.11278  -0.08235  1.24966  3.51400
```

Coefficients: ~ `Linear` model

```text
Estimate Std. Error t value Pr(>|t|)
(Intercept)          1.203e+02 1.631e+01   7.380 3.19e-09 ***
LifeExp             -1.621e+00 2.236e-01  -7.248 4.95e-09 ***
Population:Illiteracy 1.669e-04 4.479e-05   3.726 0.000551 ***
Illiteracy:LifeExp   2.590e-02 7.559e-03   3.426 0.001337 **
Illiteracy:Frost     -1.500e-02 5.625e-03  -2.666 0.010701 *
Frost:Area           -5.508e-08 2.138e-08  -2.576 0.013433 *
```

---
Signif. codes:  `0 `***` `0.001 `**` `0.01 `*` `0.05 `.` `1`

Residual standard error: 1.682 on 44 degrees of freedom
Multiple R-squared: 0.8137, Adjusted R-squared: 0.7925
F-statistic: 38.43 on 5 and 44 DF, p-value: 5.541e-15
# Formula specification option

Class `formula` accepts the following options

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>~</td>
<td>separates response/target variables from explanatory/predictor variables</td>
<td>y ~ x</td>
</tr>
<tr>
<td>+</td>
<td>separates predictors</td>
<td>y ~ a + b + c</td>
</tr>
<tr>
<td>:</td>
<td>specify interaction terms between predictors</td>
<td>y ~ a + c + a:c</td>
</tr>
<tr>
<td>*</td>
<td>Specify all possible interactions between specific predictors</td>
<td>y ~ a * b * c</td>
</tr>
<tr>
<td>^</td>
<td>Specify interactions up to a specific degree</td>
<td>y ~ (a + b + c)^2 \rightarrow y ~ a + b + c + a:b + a:c + b:c</td>
</tr>
<tr>
<td>.</td>
<td>Represents all other variables beside target variable</td>
<td>y ~ .</td>
</tr>
<tr>
<td>-</td>
<td>Remove the specified predictor(s)</td>
<td>y ~ (a + b + c)^3 \rightarrow y ~ a + b + c + a:c + a:b:c</td>
</tr>
<tr>
<td>-1</td>
<td>Suppresses the intercept from the model, forcing the regression line through the origin at $a = 0$</td>
<td>y ~ a + b - 1</td>
</tr>
<tr>
<td>l()</td>
<td>Interpret contents arithmetically</td>
<td>y ~ a + l(b-c)^3 \rightarrow y ~ a + v, where $v = (b-c)^3$</td>
</tr>
<tr>
<td>function</td>
<td>Mathematical function</td>
<td>$\sqrt{y} \sim a + \log(b)$</td>
</tr>
</tbody>
</table>
Fitting Linear Models
Ordinary Least Squares Regression Assumptions

**Normality** – for fixed values of predictor variables, target variable is normally distributed

**Independence** – target values are independent of each other – one does not influence others

**Linearity** – target is linearly related to the predictor variables

**Homoscedasticity** – target variance doesn’t change with different ranges of predictor variables

Violating assumptions may mean statistical significance tests and confidence intervals may be inaccurate
Assessing the quality of a linear model

```r
confint(fit)
par(mfrow=c(2,2))
plot(fit)
```

**Interpreting results:**
The interval 2.26 to 5.47 is 95% likely to contain the true Murder rate change given a 1% change in illiteracy

```r
> confint(fit)

2.5 %   97.5 %
(Intercept) -2.25e+00  5.554052
Population  4.48e-05  0.000385
Illiteracy  2.26e+00  5.473176
Frost      -2.22e-02  0.017426
Area       -8.15e-07  0.000016
```
Assessing Normality

Normal Q-Q plot should be a straight line if the data meets the normality assumption. Data do not fall on this line, so normality assumption violated.
Assessing Linearity

Residuals should be randomly distributed if target is linearly related to predictors.
Only “random noise” should remain.
There appears to be a curved relationship, indicating the need for quadratic terms.
Assessing Homoscedasticity

$\sqrt{\text{of standardized residuals}}$ should be randomly distributed about a horizontal line.
There appears to be a curved relationship, indicating the need for quadratic terms.
Should some data be removed from the data set?

Outliers
• Have large residual value
• Model doesn’t predict well

High Leverage Values
• Predictor values are unusual relative to other observations

Influential Observations
• row has unusually high impact on model parameters
• Indicated by Cook’s distance
Package **car** and **qqPlot** and **outlierTest**

More accurate assessment of normality assumption
95% confidence bound drawn around 45° line
Outliers can be manually selected
Iteratively remove outliers and reinvoke **outlierTest**

```r
library(car)
qqPlot(fit,
    labels=row.names(state.df),
    id.method="identify",
    simulate=TRUE,
    main="state.df Q-Q Plot")
outlierTest(fit)
# Select points and hit ESC
```
Other options...

See package `gvlma` and function `gvlma` for overall assessment of model assumptions.
More on Multicollinearity

One variable is closely correlated (or determined by) another
  • E.g., age & data of birth
    year & population

Use variance inflation factor (VIF)
  • Use car package function vif
  • Use sqrt(vif) > 2, then there is a multicollinearity problem

Problematic for interpreting individual predictor variables, but not for prediction
library(car)
vif(fit)
sqrt(vif(fit)) > 2

fit2 <- lm(Murder~., state.df)
vif(fit2)
sqrt(vif(fit2)) > 2
Remedies for common problems

Multicollinearity
• Deleting one of the predictors involved or where $\sqrt{\text{vif}} > 2$
• Use ridge regression

Transform target and/or predictor variables
• $Y^\lambda$, where, for example, $\lambda$ in {-2, -1, -0.5, 0, log, .5, none, 2}
• $\log(Y)$
• Remember – a transformation should “make sense” for interpretation of result

Normality assumption
• Use a non-parametric algorithm; Use GLM
• In car package, use `powerTransform` on target to get estimate of power $\lambda$

Linearity assumption
• Use a non-linear regression algorithm
• In car package, use `boxTidwell` on predictors to get estimate of power $\lambda$

Homoscedasticity assumption – homogeneity of variance
• In car package, use `spreadLevelPlot` on model to get estimate of power $\lambda$ on for $Y^\lambda$
Parametric vs. non-parametric algorithms

**Parametric**

- Fixed family of functions
- Fixed number of parameters that are independent of the number of observations
- E.g., linear regression

**Non-parametric**

- Learned function based on observation data
- E.g. KNN classifier, SVM

http://www.iro.umontreal.ca/~lisa/twiki/bin/view.cgi/Public/NonParametric
Is one model better than another?

```r
> anova(fit, fit2)
Analysis of Variance Table

Model 1: Murder ~ Population + Illiteracy + Area + Frost
Model 2: Murder ~ Population + Income + Illiteracy + LifeExp + HSGrad + 
                Frost + Area

             Res.Df RSS Df Sum of Sq  F    Pr(>F)
1            45 269          
2            42 128          141 15.5 6.4e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
> > AIC(fit, fit2)
   df AIC
fit  6  238
fit2  9  207
```

ANOVA requires nested models
Look for significant p-value

AIC does not require nested models
Models with smaller AIC values are better

http://en.wikipedia.org/wiki/Akaike_information_criterion
RandomForest
Random Forest Algorithm

Ensemble learning technique for classification and regression
Known for high accuracy models
Constructs many “small” decision trees
For classification, predicts mode of classes predicted by individual trees
For regression, predicts mean prediction of individual trees
Avoids overfitting, which is common for decision trees

Developed by Leo Breiman and Adele Cutler combining the ideas of “bagging” and random selection of variables resulting in a collection of decision trees with controlled variance
ore.randomForest supports classification

Enables performance and scalability for larger data sets
Executes in parallel for model building and scoring
  • ore.parallel global option used for preferred DOP

*Oracle R Distribution new randomForest* function
  • Reduces memory requirements over standard R (~7X)
  • As a result, reduces memory requirements for ore.randomForest
  • ORD randomForest supports *classification* only

Can use Oracle R Distribution’s or R’s randomForest package
Random Forest

ore.randomForest(formula, data, ntree=500, mtry = NULL,
replace = TRUE, classwt = NULL, cutoff = NULL,
sampsize = if(replace) nrow(data) else ceiling(0.632*nrow(data)),
nodesize = 1L, maxnodes = NULL, confusion.matrix = FALSE,
na.action = na.fail, ...)

grabTree(object, k = 1L, labelVar = FALSE, ...)
predict(object, newdata,
  type = c("response", "prob", "vote", "all"),
norm.votes = TRUE,
  supplemental.cols = NULL,
cache.model = TRUE, ...)

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Random Forest

**ntree** – total number of trees to grow

**mtry** – number of variables randomly sampled as candidates at each tree node split

**replace** – a logical value indicating whether to execute sampling with replacement

**classwt** – a vector of priors of the classes. If specified, the length of the vector should be equal to the number of classes in the target column. The vector does not need to add up to 1.

**cutoff** – a vector of cutoff values. If specified, the length of the vector should be equal to the number of classes in the target column. When determining the prediction class for an observation, the one with the maximum ratio of proportion of votes to cutoff is selected. If not specified, the default is '1/k' where 'k' is the number of classes.

**sampsize** – size of the sample to draw for growing trees

**nodesize** – minimum size of terminal nodes

**maxnodes** – maximum number of terminal nodes of each tree to be grown. If not specified, trees can be grown to the maximum size subject to the limits of 'nodesize'.

**confusion.matrix** – a logical value indicating whether to calculate the confusion matrix. Note that this confusion matrix is not based on OOB (out-of-bag), it is the result of applying the built random forest model to the entire training data.
Random Forest

**na.action** – the manner in which 'NA' values are handled. With the default 'na.fail', it fails if the training data contains 'NA'.

**k** – an integer indicating which tree's information to extract

**labelVar** – a logical value indicating whether the 'split var' and 'prediction' columns in the returned frame use meaningful labels.

**newdata** – an 'ore.frame' object, the test data

**type** – specifies the type of the output: 'response', 'prob', 'votes', or 'all' returning predicted values, matrix of class probabilities, matrix of vote counts, or both the vote matrix and predicted values, respectively.

**norm.votes** – a logical value indicating whether the vote counts in the output vote matrix should be normalized. The argument is ignored if 'type' is 'response' or 'prob'.

**supplemental.cols** – additional columns to include in the prediction result from the 'newdata' data set

**cache.model** – a logical value indicating whether the entire random forest model is cached in memory during prediction
ore.randomForest

ore.randomForest() builds a random forest model by growing trees in parallel
Scoring method 'predict' runs in parallel

```
options(ore.parallel=4)

IRIS <- ore.push(iris)
mod <- ore.randomForest(Species~., IRIS)

tree10 <- grabTree(mod, k = 10, labelVar = TRUE)

ans <- predict(mod,IRIS,type="all",supplemental.cols="Species", cache.model=FALSE)
table(ans$Species, ans$prediction)
```
ore.randomForest Results

```r
R> options(ore.parallel=4)
R> IRIS <- ore.push(iris)
R> mod <- ore.randomForest(Species ~ ., IRIS)
R> tree10 <- grabTree(mod, k = 10, labelVar = TRUE)
R> ans <- predict(mod, IRIS, type="all", supplemental.cols="Species")
R> table(ans$Species, ans$prediction) # learns perfectly

<table>
<thead>
<tr>
<th></th>
<th>setosa</th>
<th>versicolor</th>
<th>virginica</th>
</tr>
</thead>
<tbody>
<tr>
<td>setosa</td>
<td>50</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>versicolor</td>
<td>0</td>
<td>50</td>
<td>0</td>
</tr>
<tr>
<td>virginica</td>
<td>0</td>
<td>0</td>
<td>50</td>
</tr>
</tbody>
</table>
```

```
R> tree10
  node.id left.sister right.sister split.var split.point status prediction
  1       1        2            3 Sepal.Length 5.55    1 <NA>
  2       4        1            5 Petal.Width  0.70    1 <NA>
  3       6        7            7 Petal.Length 4.75    1 <NA>
  4       0        0            <NA>        0.00    -1 setosa
  5       8        9            9 Sepal.Length 4.95    1 <NA>
  6       10       11           11 Sepal.Width 3.70    1 <NA>
  7       12       13           13 Petal.Length 5.05    1 <NA>
  8       0        0            <NA>        0.00    -1 virginica
  9       0        0            <NA>        0.00    -1 versicolor
 10      10       0            <NA>        0.00    -1 versicolor
 11      11       0            <NA>        0.00    -1 setosa
 12      12       14           15 Petal.Width 1.75    1 <NA>
 13      0        0            <NA>        0.00    -1 virginica
 14      14       16           17 Sepal.Length 6.15    1 <NA>
 15      0        0            <NA>        0.00    -1 virginica
 16      0        0            <NA>        0.00    -1 virginica
 17      0        0            <NA>        0.00    -1 versicolor
```
Memory vs. Speed

ore.randomForest for 1.5 is architected for speed

- Relying on OML4R embedded R, parallelism of ore.randomForest achieves many times speedup, but at the cost of memory
- ore.randomForest loads a copy of the training data for each extproc

For example, building 100M rows with DOP=72

- Needs at least 72 x C x datasetSize, where C is a small constant (3-5) required by the algorithm
- Hitting memory limitations with a 10M or 100M dataset with DOP=72 is expected for most machines

ORD's randomForest improves memory usage over R's randomForest (~7X less)

Recommendations

- Reduce ore.parallel for large datasets to complete
- Set memory limit to prevent system memory overrun
- Recommendation for all embedded R-based OML4R algorithms, though particularly critical for current version of ore.randomForest
ore.randomForest – how it works

ore.randomForest() builds a random forest model by growing trees in parallel

Returns an 'ore.randomForest' object

Requires Oracle R Distribution (ORD) or 'randomForest' package be installed

• Oracle R Distribution is preferred to the package 'randomForest' for better performance and compatibility.
• A warning is issued if the package 'randomForest' is used

Scoring method 'predict' runs in parallel

• The default value of cache.model 'TRUE' is recommended when sufficient memory is available
• Otherwise, 'cache.model' should be set to 'FALSE' to prevent memory overuse

ore.parallel global option is used by 'ore.randomForest' to determine preferred DOP
Neural Network
Artificial Neural Networks

Neural network (NN) is a mathematical model inspired by biological neural networks and in some sense mimics the functioning of a brain

- Consists of an interconnected group of artificial neurons (nodes)
- Non-linear statistical data modeling tools
- Model complex nonlinear relationships between input and output variables

Find patterns in data:

- Function approximation: regression analysis, including time series prediction, fitness approximation, and modeling
- Classification: including pattern and sequence recognition, novelty detection and sequential decision making
- Data processing: including filtering, clustering, blind source separation and compression
- Robotics: including directing manipulators, computer numerical control
Artificial Neural Networks

Well-suited to data with noisy and complex sensor data

Problem characteristics
- Potentially many (numeric) predictors, e.g., pixel values
- Target may be discrete-valued, real-valued, or a vector of such
- Training data may contain errors – robust to noise
- Fast scoring
- Model transparency not required – models difficult to interpret

Universal approximator
- Adding more neurons can lower error to be as small as desired
- Not always the desired behavior
Steps to Neural Network modeling

Architecture specification
Data preparation
Building the model
  • Stopping criteria: iterations, error on validation set within tolerance
Viewing statistical results from model
Improving the model
Architecture Specification

Input Layer
- Numerical or categorical
- No automatic normalization of data
- Supports up to 1000 actual columns (due to database table limit)
- No fixed limit on interactions
- No fixed limit on cardinality of categorical variables

Hidden Layers
- Any number of hidden layers - \( k \)
- All nodes from previous layer are connected to nodes of next
- Activation function applies to one layer
  - Bipolar Sigmoid default for hidden layers

Output Layer
- Currently single numeric target or binary categorical
- Linear activation function default, all others also supported

Calculate number of weights
- \((\# \text{ input units}) \times (\# \text{ L1 nodes}) + (\# \text{ L1 nodes bias}) +
  (\# \text{ L1 nodes}) \times (\# \text{ L2 nodes}) + (\# \text{ L2 nodes bias}) +
  \cdots
  (\# \text{ Lk nodes}) \times (\# \text{ output nodes})\)

Initialize weights
- Change initialization with random seed
- Set lower and upper bound, typically -0.25, 0.25
Unique aspects of ore.neural

Hidden layer structure complexity
Wide range of activation functions - 15
Support for categorical variables and transformations of all variables – predictors and targets
Support for logistic regression through entropy activation function
No competitive CRAN package available for neural networks
Extraordinary scalability on several dimensions including HYPER SPARSE data sets
  • Scale-up and Scale-out
Compared to SAS’s HPNeural, ore.neural can work with data sets that do not fit in memory
  • SAS requires complete data set to fit into distributed memory before it can solve any HP* models
Architecture Guidelines

Start

• one hidden layer with one neuron/node
• number of nodes less than $\sqrt{\text{#observations} \times \text{#variables}}$

Test different number of hidden nodes and number of layers
Test different activation functions
Restart (rebuild) model multiple times with different weight initializations to escape local minima, keep model with lowest objective function value, e.g., fit$objValue$

Perfecting neural networks is an art
Data Preparation

Data preparation may be unnecessary if appropriate activation functions are used - especially for targets (outputs)

- Bipolar sigmoid can model values from -1 ... 1 range
- Hyperbolic tangent can model values from -1 ... 1 range
- Logistic sigmoid can model values from 0 ... 1 range

Output preparation

- If target (output) is not scaled (normalized) into ranges above, then linear activation function is appropriate
- If output activation function is non-linear, targets must be scaled

Scaling is recommended for faster convergence, however experimentation is key

For predictors (input data), choose standard R facilities, for instance

- data <- iris
data$Petal.Length <- scale(data$Petal.Length)

- To normalize Petal.Length around 0
  > sd(data$Petal.Length)
  [1] 1
  > mean(data$Petal.Length)
  [1] -2.895326e-17
<table>
<thead>
<tr>
<th>Activation Function</th>
<th>Activation Setting</th>
<th>Definition</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arctangent</td>
<td>atan</td>
<td>( f(x) = \arctan x )</td>
<td></td>
</tr>
<tr>
<td>Bipolar Sigmoid</td>
<td>bSigmoid</td>
<td>( f(x) = (1 - e^{-x})/(1 + e^{-x}) )</td>
<td>Use in input data with different signs or unscaled</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Use on output layer when values ([-1, 1])</td>
</tr>
<tr>
<td>Cosine</td>
<td>cos</td>
<td>( f(x) = \cos x )</td>
<td></td>
</tr>
<tr>
<td>Gaussian</td>
<td>gaussian</td>
<td>( f(x) = e^{-x^2} )</td>
<td></td>
</tr>
<tr>
<td>Gauss error</td>
<td>gaussError</td>
<td>( f(x) = 2/\sqrt{\pi} ) integral ( e^{-t^2} ) ( dt )</td>
<td></td>
</tr>
<tr>
<td>Gompertz</td>
<td>gompertz</td>
<td>( f(x) = e^{-e^{-x}} )</td>
<td></td>
</tr>
<tr>
<td>Linear</td>
<td>linear</td>
<td>( f(x) = x )</td>
<td>Applicable across all data ranges</td>
</tr>
<tr>
<td>Logistic Sigmoid</td>
<td>sigmoid</td>
<td>( f(x) = 1 / (1 + e^{-x}) )</td>
<td>Use on output layer when values ([0..1])</td>
</tr>
<tr>
<td>Reciprocal</td>
<td>reciprocal</td>
<td>( f(x) = 1 / x )</td>
<td>Value should not include 0 value</td>
</tr>
<tr>
<td>Sigmoid Modulus</td>
<td>sigmoidModulus</td>
<td>( f(x) = x / (1 +</td>
<td>x</td>
</tr>
<tr>
<td>Sigmoid Square Root</td>
<td>sigmoidSqrt</td>
<td>( f(x) = x / (1 + \sqrt{1+x^2}) )</td>
<td></td>
</tr>
<tr>
<td>Sine</td>
<td>sin</td>
<td>( f(x) = \sin x )</td>
<td></td>
</tr>
<tr>
<td>Square</td>
<td>square</td>
<td>( f(x) = x^2 )</td>
<td></td>
</tr>
<tr>
<td>Hyperbolic Tangent</td>
<td>tanh</td>
<td>( f(x) = \tanh x )</td>
<td></td>
</tr>
<tr>
<td>Wave</td>
<td>wave</td>
<td>( f(x) = x / (1 + x^2) )</td>
<td></td>
</tr>
<tr>
<td>Entropy (output only)</td>
<td>entropy</td>
<td>( f(x) = \log(1 + \exp(x)) – yx )</td>
<td>Use with logistic regression</td>
</tr>
</tbody>
</table>

If specified, must include one for each hidden layer and output layer.
ore.neural
Artificial Neural Network

ore.neural(
  formula,          # initial vector of weights
  data,             # named list of character vectors specifying levels for each ore.factor var
  weight = NULL,    # vector of nodes per layer, or none, e.g., 2 layers c(20,5)
  xlev = NULL,      # vector activation functions, including one for output
  hiddenSizes = NULL,  # numerical optimization stopping crit.
  activations = NULL,    # select value >= 5
  gradTolerance = 1E-1,  # Stopping criterion: \( \frac{|f_{current} - f_{previous}|}{1 + |f|} \)
  maxIterations = 200L,    # weight initialization range
  objMinProgress = 1E-6,  # weight initialization range
  lowerBound = -0.7,  # number of L-BFGS update pairs
  upperBound = 0.7,       # logical whether to scale inverse of Hessian matrix in L-BFGS updates
  nUpdates = 20L,         # repot iteration log for big data solver
  scaleHessian = TRUE,
  trace = FALSE)

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Stopping Criteria

gradTolerance
- Affects how quickly model can converge
- Valid values: > 10^{-9}
- If > 1M observations, set to 1
- If # observations < 1000, set to between .01 and .001

objMinProgress
- Valid values [10^{-1}, 10^{-6}]
- Indicates required change from one iteration to next
- Computed as \( \frac{|f_{current} - f_{previous}|}{1 + |f|} \)

maxIterations
- Valid values >= 5
- Upper limit on the number of iterations
Local Minima

Local Minima are non-optimal states that can improve no further with current settings and weights. To determine if a neural network is possibly in a local minima, rebuild model with different weights:

- Change random seed to different value
- Change upper/lower bound of weight initialization values
- Select model with best objective function value, e.g., `fit$objValue`
Local Minima

```r
d <- data.frame(A=c(0,1,0,1),
                 B=c(1,0,0,1),
                 T=c(1,1,0,0))

# Run the model below 5 ~ 10 times and observe the resulting objective
# function value - the smaller, the better
library(nnet)
fit.nn <- nnet(formula = T ~ A + B, data = d, size=2)
predict(fit.nn,d)

fit.ore <- ore.neural(formula = T ~ A + B, data = ore.push(d),
                      hiddenSizes = c(5000, 10, 10),
                      lowerBound=-1, upperBound=1)
predict(fit.ore,ore.push(d))
```
Local Minima - results

R> fit.nn <- nnet(formula = T ~ A + B, data = d, size=2)
# weights:  9
initial  value 1.046487
iter 10 value 0.997966
iter 20 value 0.569304
iter 30 value 0.502784
iter 40 value 0.500426
iter 50 value 0.500050
final  value 0.500041
converged
R> predict(fit.nn,d)
[,1]
1  0.499970251
2  0.999986345
3  0.002586049
4  0.500004855

R> fit.ore <- ore.neural(formula = T ~ A + B, data = ore.push(d),
+    hiddenSizes = c(5000, 10, 10),
+    lowerBound=-1, upperBound=1)
R> predict(fit.ore,ore.push(d))
pred_T
1  0.913355525
2  1.035549253
3 -0.020444140
4 -0.001179834

R> fit.nn <- nnet(formula = T ~ A + B, data = d, size=2)
# weights:  9
initial  value 1.042918
iter 10 value 0.992396
iter 20 value 0.682306
iter 30 value 0.666802
iter 40 value 0.666718
final  value 0.666709
converged
R> predict(fit.nn,d)
[,1]
1  0.666687
2  0.666650
3  0.000337
4  0.666700

R> fit.ore <- ore.neural(formula = T ~ A + B, data = ore.push(d),
+    hiddenSizes = c(5000, 10, 10),
+    lowerBound=-1, upperBound=1)
R> predict(fit.ore,ore.push(d))
pred_T
1  1.00488
2  0.99595
3 -0.00718
4 -0.00165
Optimization argument: nUpdates

Optimization parameter for \textit{L-BFGS} solver
Indicates number of matrix adjustments to occur before updating Hessian matrix

Recommended ranges
\begin{itemize}
\item Usual models: 7..25
\item If \# weights > 1M: 3..25
\item If highly non-linear behavior, use > 10
\end{itemize}

If you’re unfamiliar with underlying techniques, don’t touch
Example

```r
IRIS <- ore.push(iris)

fit <- ore.neural(Petal.Length ~ Petal.Width + Sepal.Length,
                   data = IRIS, hiddenSizes = c(20, 5),
                   activations = c('bSigmoid', 'tanh', 'linear'))

print(fit)

R> print(fit)
Number of input units 2
Number of output units 1
Number of hidden layers 2
Objective value 6.431877E+00
Solution status Optimal
Hidden layer [1] number of neurons 20, activation 'bSigmoid'
Hidden layer [2] number of neurons 5, activation 'tanh'
Output layer number of neurons 1, activation 'linear'
Optimization solver L-BFGS
Scale Hessian inverse 1
Number of L-BFGS updates 20

ans <- predict(fit, newdata = IRIS,
                supplemental.cols = 'Petal.Length')
localPredictions <- ore.pull(ans)

# Inspect some predictions
head(localPredictions)

# Compute RMSE
ore.rmse <- function (pred, obs) {
  sqrt(mean((pred-obs)^2, na.rm=TRUE))
}

R> ore.rmse(localPredictions$pred_Petal.Length, localPredictions$Petal.Length)
[1] 0.00148768
```

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Example – linear regression

No hidden structure in network

```r
fit <- ore.neural(Petal.Length ~ Petal.Width + Sepal.Length, data = IRIS)
print(fit)

# Print fit object
R> print(fit)
Number of input units  2
Number of output units  1
Number of hidden layers  0
Objective value  1.311757E+01
Solution status  Optimal
Output layer  number of neurons 1, activation 'linear'
Optimization solver  L-BFGS
Scale Hessian inverse  1
Number of L-BFGS updates  20
```
Model Details: Solution Status

optimal
  • meets all stopping criteria
numerical difficulties encountered
  • TBD
maximum iterations reached
  • more iterations may be needed to improve model
insufficient memory
  • could not build model with current settings due to memory
no progress
  • change in objective function insufficient to make process
unbounded
  • one of model parameters (weights) is greater than 1E+24
    (check input data, unlikely to happen)
Model Details: Objective Value

Error statistic on the model ore.neural tries to minimize this value
Calculated as $\text{sum}((\text{predicted} - \text{actual})^2)$
ore.neural vs. nnet

OML4R...
- Is scalable
- Allows choosing wide range of activation functions
- Provides generic topology
  - unrestricted number of hidden layers, including none
- Has a parallel implementation
Generalized Linear Models
Generalized Linear Models

Fits generalized linear models using a Fisher scoring iteratively re-weighted least squares (IRLS) algorithm for logistic regression, probit regression, and poisson regression.

Instead of the traditional step halving to prevent the selection of less optimal coefficient estimates, a line search is used to select new coefficient estimates at each iteration starting from the current coefficient estimates and moving through the Fisher scoring suggested estimates using the formula $(1 - \alpha) \times \text{old} + \alpha \times \text{suggested}$ where $\alpha$ is in $[0, 2]$.

When the 'interp' control argument is 'TRUE', the deviance is approximated by a cubic spline interpolation; and when 'FALSE', the deviance is calculated using a follow-up data scan.

Each iteration consists of two or three embedded R map/reduce operations: an IRLS operation, an initial line search operation, and an optional follow-up line search operation if 'interp = FALSE'.

The IRLS map/reduce operations are on the matrix cross-products based off of 'model.matrix' or 'sparse.model.matrix' function calls depending on the underlying scarcity of the model matrix.

After the algorithm has either converged or reached the maximum number of iterations, a final embedded R map/reduce operation is used to generate the complete set of model-level statistics.
ore.glm

Generalized Linear Model

ore.glm(formula, data, weights, family = gaussian(), start = NULL, control = list(...), contrasts = NULL, xlev = NULL, ylev = NULL, yprob = NULL, ...)

# 'formula' object representing the model to be fit
# 'ore.frame' object specifying the data for the model
# optional 'ore.number' object specifying the model’s analytic weights
# 'family' object specifying the generalized linear model family details.
# Same type of object used for 'glm' function in the 'stats' package
# optional 'numeric' vector specifying initial coefficient estimates in
# the linear predictor
# optional 'list' object containing a list of fit control parameters to
# be interpreted by the 'ore.glm.control' function
# optional named 'list' to be supplied to 'contrasts.arg' argument of 'model.matrix'
# optional named 'list' of 'character' vectors specifying the 'levels'
# for each 'ore.factor' variable
# optional 'character' vector to specify the response variable levels
# in 'binomial' generalized linear models
# optional numeric value between 0 and 1 specifying overall probability
# of 'y != ylev[1]' in 'binomial' linear models
ore.glm examples

Generalized Linear Model

```r
library(rpart)

# Logistic regression
KYPHOSIS <- ore.push(kyphosis)
kypFit1 <- ore.glm(Kyphosis ~ ., data = KYPHOSIS, family = binomial())
kypFit2 <- glm(Kyphosis ~ ., data = kyphosis, family = binomial())
summary(kypFit1)
summary(kypFit2)

# Poisson regression
SOLDER <- ore.push(solder)
solFit1 <- ore.glm(skips ~ ., data = SOLDER, family = poisson())
solFit2 <- glm(skips ~ ., data = solder, family = poisson())
summary(solFit1)
summary(solFit2)
```
ore.glm results
Generalized Linear Model

R> summary(kyphFit1)

Call:
ore.glm(formula = Kyphosis ~ ., data = KYPHOSIS, family = binomial())

Deviance Residuals:
Min 1Q Median 3Q Max
-2.3124 -0.5484 -0.3632 -0.1659 2.1613

Coefficients:
Estimate Std. Error z value Pr(>|z|)
(Intercept) -2.03693 1.44962 -1.405 0.15998
Age 0.01093 0.00645 1.696 0.08997 .
Number 0.41060 0.22487 1.826 0.06786 .
Start -0.20651 0.06770 -3.050 0.00229 **
---
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 83.234 on 80 degrees of freedom
Residual deviance: 61.380 on 77 degrees of freedom
AIC: 69.38

Number of Fisher Scoring iterations: 4

R> summary(kyphFit2)

Call:
glm(formula = Kyphosis ~ ., family = binomial(), data = kyphosis)

Deviance Residuals:
Min 1Q Median 3Q Max
-2.3124 -0.5484 -0.3632 -0.1659 2.1613

Coefficients:
Estimate Std. Error z value Pr(>|z|)
(Intercept) -2.03693 1.44957 -1.405 0.15996
Age 0.01093 0.00645 1.696 0.08996 .
Number 0.41060 0.22486 1.826 0.06785 .
Start -0.20651 0.06769 -3.050 0.00229 **
---
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 83.234 on 80 degrees of freedom
Residual deviance: 61.380 on 77 degrees of freedom
AIC: 69.38

Number of Fisher Scoring iterations: 5
### Compare ore.glm results

**R> summary(solFit1)**

Call: 
ore.glm(formula = skips ~ ., data = SOLDER, family = poisson())

Deviance Residuals:
```
                       Min          1Q  Median          3Q         Max
-3.4105      -1.0897     -0.4408     0.6406      3.7927
```

Coefficients:
```
                               Estimate Std. Error z value Pr(>|z|)
(Intercept)                 -1.25506   0.10069  -12.465  < 2e-16 ***
OpeningM                     0.25851   0.06656   3.884   0.000103 ***
OpeningS                    1.89349   0.05363  35.305  < 2e-16 ***
SolderThin                  1.09973   0.03864  28.465  < 2e-16 ***
MaskA3                       0.42819   0.07547   5.674   1.40e-08 ***
MaskB3                      1.20225   0.06697  17.953  < 2e-16 ***
MaskB6                      1.86648   0.06310  29.580  < 2e-16 ***
PadTypeD6                   -0.36865   0.07138  -5.164   2.41e-07 ***
PadTypeD7                   -0.09844   0.06620  -1.487   0.137001     
PadTypeL4                   0.26236   0.06071   4.321   1.55e-05 ***
PadTypeL6                   -0.66845   0.07841  -8.525  < 2e-16 ***
PadTypeL7                   -0.49021   0.07406  -6.619   3.61e-11 ***
PadTypeL8                   -0.27115   0.06939  -3.907   9.33e-05 ***
PadTypeL9                   -0.63645   0.07759  -8.203  2.35e-16 ***
PadTypeW4                   -0.11000   0.06640  -1.657   0.097591     
PadTypeW9                   -1.43759   0.10419  -13.798  < 2e-16 ***
Panel                       0.11818   0.02056   5.749   8.97e-09 ***
```

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 1

(Dispersion parameter for poisson family taken to be 1)

Null deviance: 6855.7 on 719 degrees of freedom
Residual deviance: 1165.4 on 703 degrees of freedom
AIC: 2781.6

Number of Fisher Scoring iterations: 4

---

**R> summary(solFit2)**

Call: 
glm(formula = skips ~ ., family = poisson(), data = solder)

Deviance Residuals:
```
                       Min          1Q  Median          3Q         Max
-3.4105      -1.0897     -0.4408     0.6406      3.7927
```

Coefficients:
```
                               Estimate Std. Error z value Pr(>|z|)
(Intercept)                 -1.25506   0.10069  -12.465  < 2e-16 ***
OpeningM                     0.25851   0.06656   3.884   0.000103 ***
OpeningS                    1.89349   0.05363  35.305  < 2e-16 ***
SolderThin                  1.09973   0.03864  28.465  < 2e-16 ***
MaskA3                       0.42819   0.07547   5.674   1.40e-08 ***
MaskB3                      1.20225   0.06697  17.953  < 2e-16 ***
MaskB6                      1.86648   0.06310  29.580  < 2e-16 ***
PadTypeD6                   -0.36865   0.07138  -5.164   2.41e-07 ***
PadTypeD7                   -0.09844   0.06620  -1.487   0.137001     
PadTypeL4                   0.26236   0.06071   4.321   1.55e-05 ***
PadTypeL6                   -0.66845   0.07841  -8.525  < 2e-16 ***
PadTypeL7                   -0.49021   0.07406  -6.619   3.61e-11 ***
PadTypeL8                   -0.27115   0.06939  -3.907   9.33e-05 ***
PadTypeL9                   -0.63645   0.07759  -8.203  2.35e-16 ***
PadTypeW4                   -0.11000   0.06640  -1.657   0.097591     
PadTypeW9                   -1.43759   0.10419  -13.798  < 2e-16 ***
Panel                       0.11818   0.02056   5.749   8.97e-09 ***
```

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 1

(Dispersion parameter for poisson family taken to be 1)

Null deviance: 6855.7 on 719 degrees of freedom
Residual deviance: 1165.4 on 703 degrees of freedom
AIC: 2781.6

Number of Fisher Scoring iterations: 5
Singular Value Decomposition (SVD)
Singular Value Decomposition

**svd** overloaded

- Execute in parallel
- Accept ore.frame objects

In-database execution to improve scalability and performance

No data movement
SVD

See `?svd`

- `svd(x, nu = min(n, p), nv = min(n, p))`
- `x`: a numeric `ore.frame`
- `nu`: number of left singular vectors to be computed
  \(0 < nu < n = \text{nrow}(x)\)
- `nv`: number of right singular vectors to be computed
  \(0 < nv < p = \text{ncol}(x)\)

```r
hilbert <- function(n) {
  i <- 1:n
  1 / outer(i - 1, i, "+")
}

X <- ore.push(as.data.frame(hilbert(9)[, 1:6]))
(s <- svd(X))
```

R> hilbert <- function(n) { i <- 1:n; 1 / outer(i - 1, i, "+") }
R> X <- ore.push(as.data.frame(hilbert(9)[, 1:6]))
R> (s <- svd(X))

$d$
```
[1,] 1.668433e+00 2.773727e-01 2.237222e-02 1.084693e-03 3.243788e-05 5.234864e-07
```

$v$
```
[1,] 0.7364928 -0.6225002 -0.2550021 0.06976287 -0.01328234 -0.001588146
[2,] 0.4432826 0.1818705 0.6866860 -0.50860089 0.19626669 0.041116974
[3,] 0.3274789 0.3508553 0.2611139 0.50473697 -0.61605641 -0.259215626
[4,] 0.2626469 0.3921783 -0.1043599 0.43747940 0.40833605 0.638901622
[5,] 0.2204199 0.3945644 -0.3509658 -0.01612426 0.46427916 -0.675826789
[6,] 0.1904420 0.3831871 -0.5110654 -0.53856351 -0.44663632 0.257248908```
SVD example using ore.frame

# Set up the data
dat <- iris[, -5]; mat <- as.matrix(dat); dat$IDX <- seq_len(nrow(dat))
ore.create(dat, table = "DAT")
ore.exec("alter table DAT add constraint DAT primary key ("IDX")")
ore.sync(table = "DAT", use.keys = TRUE)

# Compute svd on ore.frame
sol <- svd(DAT[, -5])
plot(cumsum(sol$d^2/sum(sol$d^2)), col = "red")  # % explained variance

# Derive the U matrix since not provided with model
sol.U <- as.matrix(DAT[, -5]) %*% (sol$v) %*% diag(1./sol$d)
class(sol.U)  # ore.tblmatrix

k <- 1  # use one singular vector
recon1 <- (sol.U)[, 1:k, drop = FALSE] %*% diag((sol$d)[1:k, drop = FALSE], nrow = k, ncol = k) %*% t((sol$v)[, 1:k, drop = FALSE])
class(recon1)  # ore.tblmatrix

myviz(mat, ore.pull(recon1), lab1 = "Iris data", lab2 = "Recon 1")
Visualization function

```r
myviz <- function(m1, m2, lab1, lab2) {
    x11(6,6)
    par(mfcol=c(1,2), mar=c(1,1,1,1), oma=c(0,3,1,0))
    zlim=range(m1, m2)
    image(m1, zlim=zlim, yaxt="n", xaxt="n", ylab="", xlab="", main=lab1)
    axis(2, at=seq(0,1,,ncol(m1)), labels=colnames(m1))
    image(m2, zlim=zlim, yaxt="n", xaxt="n", ylab="", xlab="", main=lab2)
}
```

Example inspiration: StackExchange Cross Validated
prcomp and princomp
Principal Component Analysis

See `prcomp` and `princomp`  
Overloaded `prcomp` uses ORE’s parallel SVD 
Overloaded `princomp` uses Eigen decomposition of the correlation matrix, and an ORE-specific scheme to calculate a small correlation matrix, and call R’s Eigen decomposition
OREpredict Package
Exadata storage tier scoring for R models

Fastest way to operationalize R-based models for scoring in Oracle Database

Go from model to SQL scoring in one step
  • No dependencies on PMML or any other plugins

R models supported out-of-the-box include
  • glm, glm.nb, hclust, kmeans, lm, multinom, nnet, rpart

Models can be managed in-database using OML4R datastore
OREpredict Package

Provide a commercial grade scoring engine
• High performance
• Scalable
• Simplify application workflow

Use R-generated models to score in-database on ore.frame

Maximizes use of Oracle Database as compute engine

Function ore.predict
• S4 generic function
• A specific method for each model OML4R supports
## ore.predict supported algorithms

<table>
<thead>
<tr>
<th>Class</th>
<th>Package</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>glm</td>
<td>stats</td>
<td>Generalized Linear Model</td>
</tr>
<tr>
<td>negbin</td>
<td>MASS</td>
<td>Negative binomial Generalized Linear Model</td>
</tr>
<tr>
<td>hclust</td>
<td>stats</td>
<td>Hierarchical Clustering</td>
</tr>
<tr>
<td>kmeans</td>
<td>stats</td>
<td>K-Means Clustering</td>
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<tr>
<td>lm</td>
<td>stats</td>
<td>Linear Model</td>
</tr>
<tr>
<td>multinom</td>
<td>nnet</td>
<td>Multinomial Log-Linear Model</td>
</tr>
<tr>
<td>nnet</td>
<td>nnet</td>
<td>Neural Network</td>
</tr>
<tr>
<td>rpart</td>
<td>rpart</td>
<td>Recursive Partitioning and Regression Tree</td>
</tr>
</tbody>
</table>
# lm, based on stats:::predict.lm
ore.predict(object, newdata, se.fit = FALSE, scale = NULL, 
df = Inf, interval = c("none","confidence","prediction"), level = 0.95, na.action = na.pass, pred.var = NULL, weights = NULL, ...)

# glm, based on stats:::predict.glm
ore.predict(object, newdata, type = c("link", "response"), se.fit = FALSE, dispersion = NULL, na.action = na.pass, ...)

# rpart, based on rpart:::predict.rpart
ore.predict(object, newdata, type = c("vector", "prob", "class", "matrix"), na.action = na.pass, ...)

# matrix (for use in hclust problems)
ore.predict(object, newdata, type = c("classes", "distances"), method = "euclidean", p = 2, na.action = na.pass, ...)

# kmeans
ore.predict(object, newdata, type = c("classes", "distances"), na.action = na.pass, ...)

# nnet, based on nnet:::predict.nnet
ore.predict(object, newdata, type = c("raw", "class"), na.action = na.pass, ...)

# multinom, based on nnet:::predict.multinom
ore.predict(object, newdata, type = c("class", "probs"), na.action = na.pass, ...)
Example using `lm`

```r
irisModel <- lm(Sepal.Length ~ ., data = iris)
IRIS <- ore.push(iris)
IRISpred <- ore.predict(irisModel, IRIS, se.fit = TRUE,
                        interval = "prediction")
IRIS <- cbind(IRIS, IRISpred)
head(IRIS)
```

Build a typical R `lm` model
Use `ore.predict` to score data in Oracle Database using `ore.frame`, e.g., `IRIS`
Example using glm

Build an R glm model
Use `ore.predict` to score data in Oracle Database using `ore.frame`, e.g., INFERT

```r
infertModel <- glm(case ~ age + parity + education + spontaneous + induced, 
                    data = infert, family = binomial())
INFERT <- ore.push(infert)
INFERTpred <- ore.predict(infertModel, INFERT, type = "response", se.fit = TRUE)
INFERT <- cbind(INFERT, INFERTpred)
head(INFERT)
```

<table>
<thead>
<tr>
<th>education</th>
<th>age</th>
<th>parity</th>
<th>induced</th>
<th>spontaneous</th>
<th>stratum</th>
<th>pooled.stratum</th>
<th>PRED</th>
<th>SE.PRED</th>
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<tbody>
<tr>
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<td>1</td>
<td>1</td>
<td>2</td>
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<tr>
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<td>2</td>
<td>1</td>
<td>0</td>
<td>3</td>
<td>4</td>
<td>0.1194459</td>
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<tr>
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<td>2</td>
<td>1</td>
<td>0</td>
<td>4</td>
<td>2</td>
<td>0.3684102</td>
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<tr>
<td>6-11yrs</td>
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<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>5</td>
<td>32</td>
<td>0.5104285</td>
</tr>
<tr>
<td>6-11yrs</td>
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<td>4</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>6</td>
<td>36</td>
<td>0.6322269</td>
</tr>
</tbody>
</table>
OREeda Package: Exponential Smoothing
Time Series Exponential Smoothing

Used to produce smoothed data for presentation or for forecasting, i.e., making predictions
Assigns exponentially decreasing weights over time

Commonly applied to financial market and economic data

Simplest form

\[
\begin{align*}
s_1 &= x_0 \\
s_t &= \alpha x_{t-1} + (1 - \alpha)s_{t-1} = s_{t-1} + \alpha(x_{t-1} - s_{t-1}), t > 1
\end{align*}
\]

http://en.wikipedia.org/wiki/Exponential_smoothing
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\end{align*}
\]

http://en.wikipedia.org/wiki/Exponential_smoothing
ore.esm function signature

ore.esm(x,
        interval = NULL,
        model = "simple",
        accumulate = "NONE",
        setmissing = "PREV",
        optim.start = c(alpha=0.3, beta=0.1),
        optim.control = list())

fitted(object, start = NULL, end = NULL, ...)

predict(object, n.ahead = 12L, ...)

forecast.ore.esm(object, h = 12L, ...)
ore.esm arguments

x – An ordered 'ore.vector' of time series data or transactional data. The ordering column could be either integers from 1 to the length of the time series or of type 'ore.datetime'.

interval – The interval of the time series, or the time interval by which the transactional data is to be accumulated. If the ordering column of the argument 'x' is of type 'ore.datetime', 'interval' must be specified.

- Possible values: ""YEAR"", ""QTR"", ""MONTH"", ""WEEK"", ""DAY"", ""HOUR"", ""MINUTE"", ""SECOND"

model – The exponential smoothing model name. Possible values: ""simple"", ""double"

accumulate – The method of accumulation. Possible values:

- NONE No accumulation occurs. Argument 'x' is required to be equally spaced time series observations.
- TOTAL Accumulation based on the sum of the observed values
- AVERAGE Accumulation based on the average of the observed values. The value could be abbreviated to ""AVG"".
- MINIMUM Accumulation based on the minimum of the observed values. The value could be abbreviated to ""MIN"".
- MAXIMUM Accumulation based on the maximum of the observed values. The value could be abbreviated to ""MAX"".
- NOBS Accumulation based on the number of observations
- NMISS Accumulation based on the number of missing observations
ore.esm arguments

**setmissing:** The method of treating missing values. Possible values:
- **AVERAGE** Missing values are set to average of the accumulated values. The value could be abbreviated to "AVG"
- **MINIMUM** Missing values are set to minimum of the accumulated values. The value could be abbreviated to "MIN"
- **MAXIMUM** Missing values are set to maximum of the accumulated values. The value could be abbreviated to "MAX"
- **MEDIAN** Missing values are set to median of the accumulated values. The value could be abbreviated to "MED"
- **FIRST** Missing values are set to first accumulated non-missing value
- **LAST** Missing values are set to last accumulated non-missing value
- **PREVIOUS** Missing values are set to previous accumulated non-missing value. The value could be abbreviated to "PREV"
- **NEXT** Missing values are set to the next accumulated non-missing value.

**optim.start:** A vector with named components 'alpha' and 'beta' containing the starting values for the optimizer. Ignored in the 'simple' model case.

**optim.control:** Optional list with additional control parameters passed to 'optim' in the 'double' model case. Ignored in the 'simple' model case.
predict and forecast arguments for ore.esm

predict(object, n.ahead = 12L, ...)  
forecast.ore.esm(object, h = 12L, ...)

**object**: object of type 'ore.esm'
**n.ahead**: number of time periods to forecast
**h**: number of time periods to forecast
library(TTR)
library(zoo)
# Get data for selected stocks in XTS format
stocks <- c("orcl","ibm","sap","msft")
list.data <- vector("list",length(stocks))
for(s in stocks) {
  xts.data <- getYahooData(s, 20050101, 20180206)
  df.data <- data.frame(xts.data)
  df.data$date <- index(xts.data)
  df.data$symbol <- s
  df.data$Split <- NULL
  list.data[[s]] <- df.data
}
stock.data <- data.frame(do.call("rbind",list.data))
ore.drop("STOCKS")
ore.create(stock.data,table="STOCKS")
rownames(STOCKS) <- STOCKS$date
head(STOCKS)
```
# Importing the data
orcl.stock <- ore.pull(STOCKS[STOCKS$symbol=='orcl',c("date","Close","symbol")])

ts.orcl.stock <- ts(orcl.stock$Close)

ts.sm.orcl <- ts(SMA(ts.orcl.stock,n=30),frequency=365, start=c(2008,1) )

# Plotting the stock data
plot(orcl.stock$date,orcl.stock$Close,type="l",col="red",xlab="Date",ylab="US$", main="ORCL Stock Close CLIENT-side Smoothed Series n=30 days")
lines(orcl.stock$date,ts.sm.orcl,col="blue")
legend("topleft", c("Closing","MA(30) of Closing"),
   col=c("red","blue"),lwd=2,title = "Series",bty="n")

orcl.stock <- STOCKS[STOCKS$symbol=='orcl',c("date","Close")]

dESM.mod <- ore.esm(orcl.stock$Close, "DAY", model = "double")
dESM.predict <- predict(dESM.mod, 30)
plot(orcl.stock,type="l")
lines(dESM.predict,col="red",lwd=4)
```
Using supplemental functions

dESM.mod <- ore.esm(orcl.stock$Close, "DAY",
                     model = "double",
                     optim.start=c(alpha=0.5,beta=0.5))

dESM.predict <- predict(dESM.mod, 30)
dESM.fitted <- fitted(dESM.mod)

plot(orcl.stock,type="l",lwd=2)
lines(dESM.predict,col="red",lwd=2)
lines(orcl.stock[,1], dESM.fitted, col='red',lwd=1)

row.idx = 1500:2722
plot(orcl.stock[row.idx,], type="l",lwd=3)
lines(orcl.stock[row.idx,1], dESM.fitted[row.idx], col='red')
lines(dESM.predict,col="red",lwd=2)
Summary

OREdm
- Oracle Data Mining algorithms exposed through R interface
- Attribute Importance, Decision Trees, GLM, KMeans, O-Cluster, Naïve Bayes, SVD, SVM, NMF, Association Rules, Explicit Semantic Analysis

OREeda
- Functions for exploratory data analysis for Base SAS equivalents

OREmodels
- ore.lm, ore.stepwise, ore.neural, ore.glm, ore.randomForest

OREpredict
- Score R models in the database

OREstats
- In-database statistical computations exposed through R interface
For more information...

oracle.com/machine-learning

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See also AskTOM OML Office Hours
Thank You

Mark Hornick
Oracle Machine Learning Product Management