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Oracle Machine Learning: Scaling R and Python for the Enterprise

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Oracle Machine Learning Product Management

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Why data scientists and data analysts use R and Python

Powerful

Extensible

Graphical

Extensive statistics

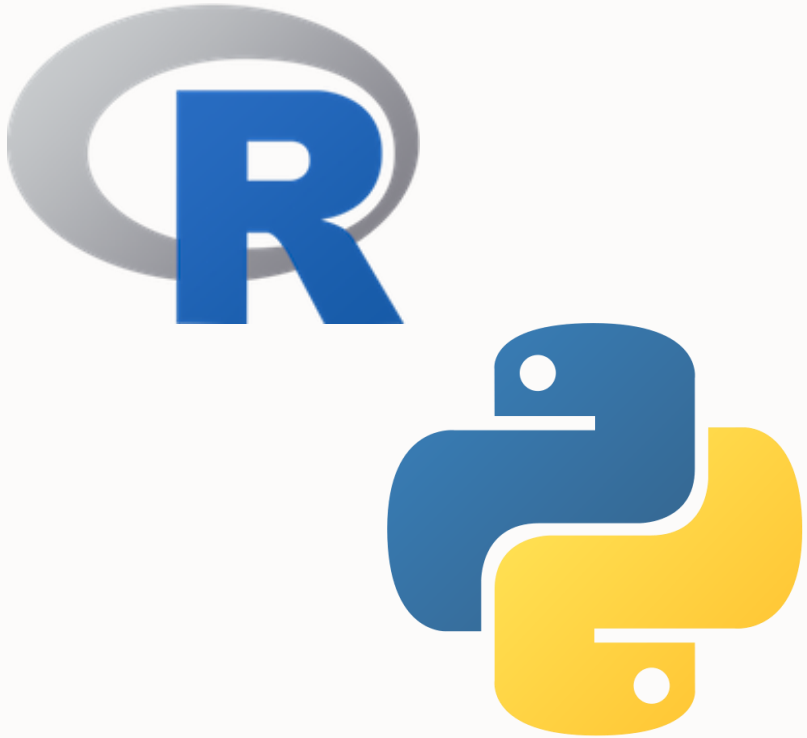
Ease of installation and use

Rich ecosystem

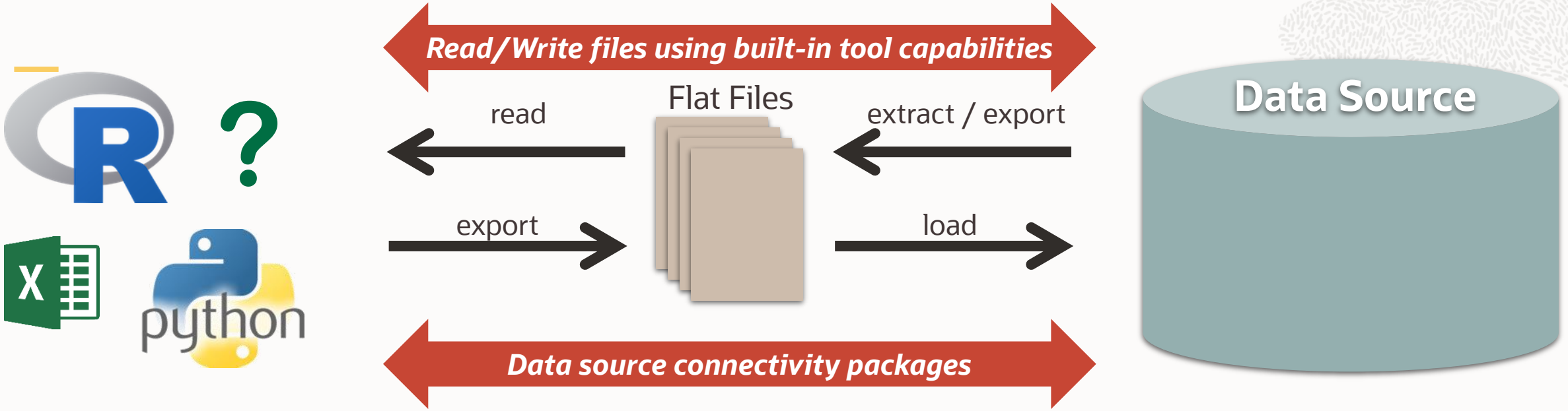
- 1000s of open source packages
- Millions of users worldwide

Heavily used by data scientists

Free



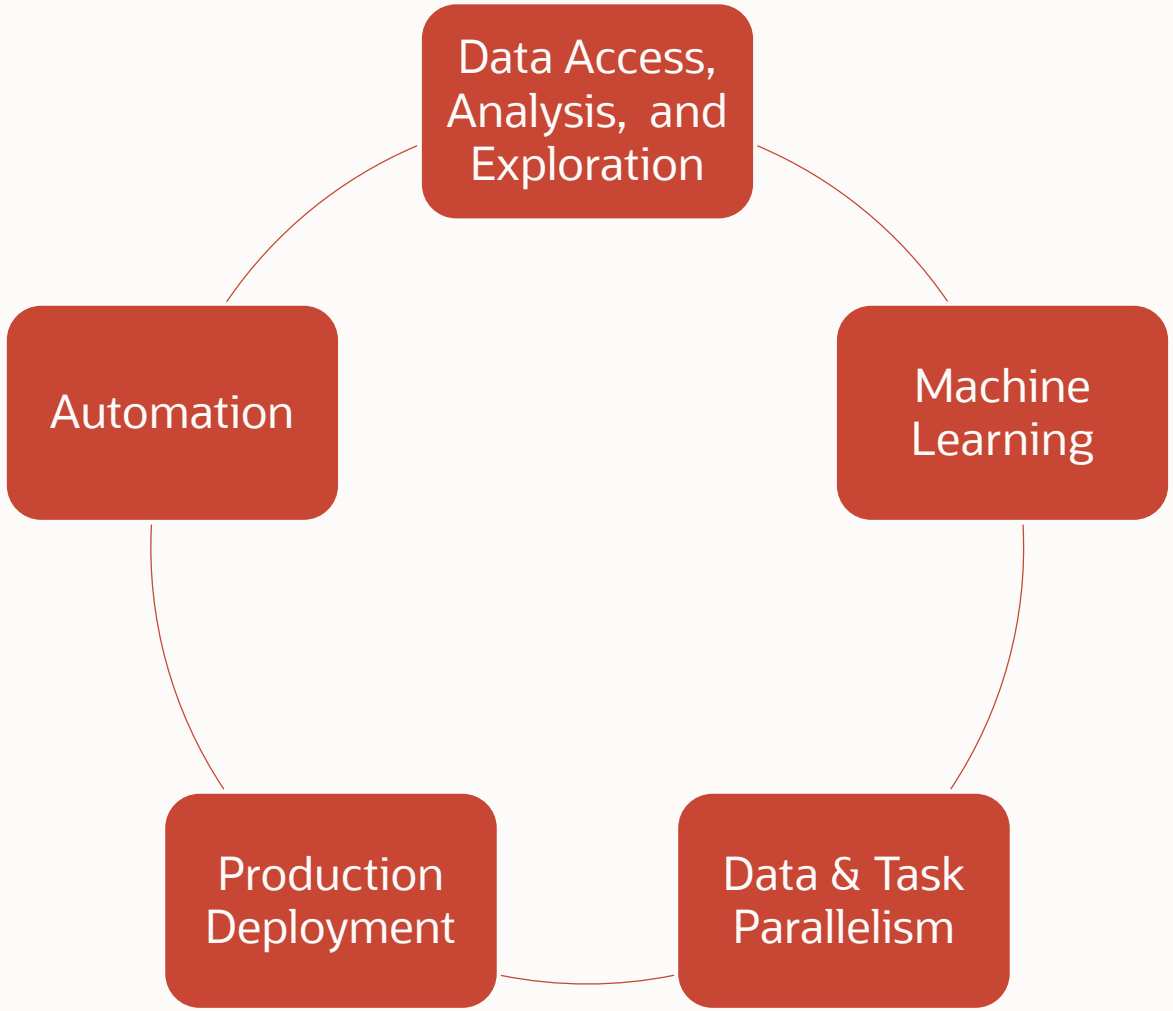
Traditional Analytics and Data Source Interaction



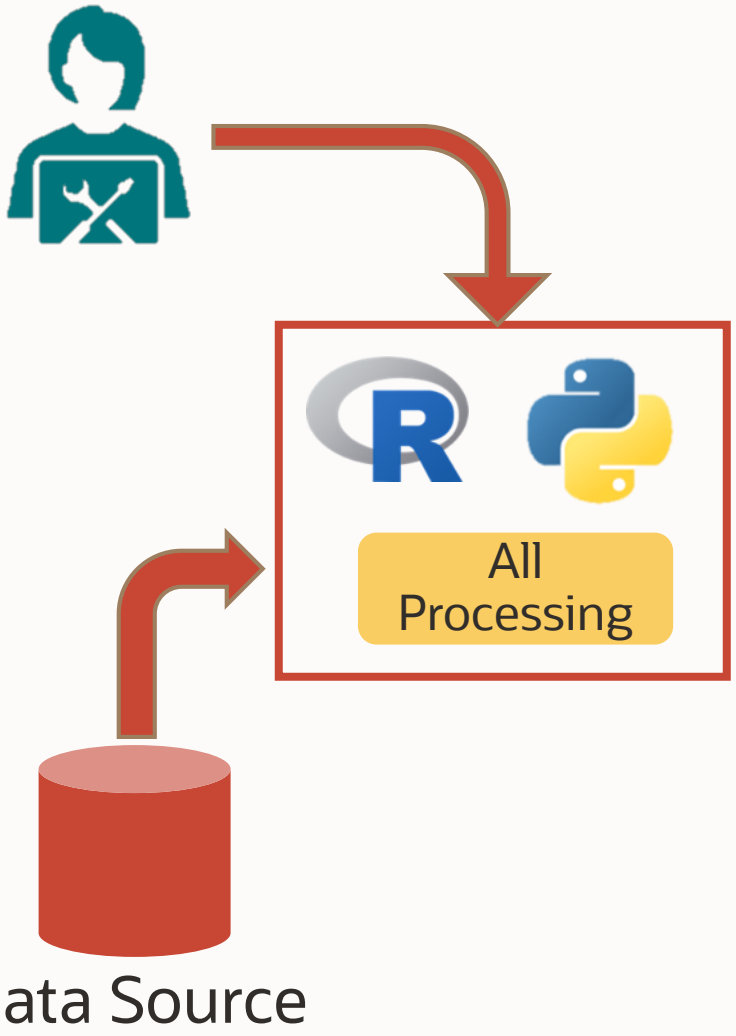
Deployment
Ad hoc
cron job

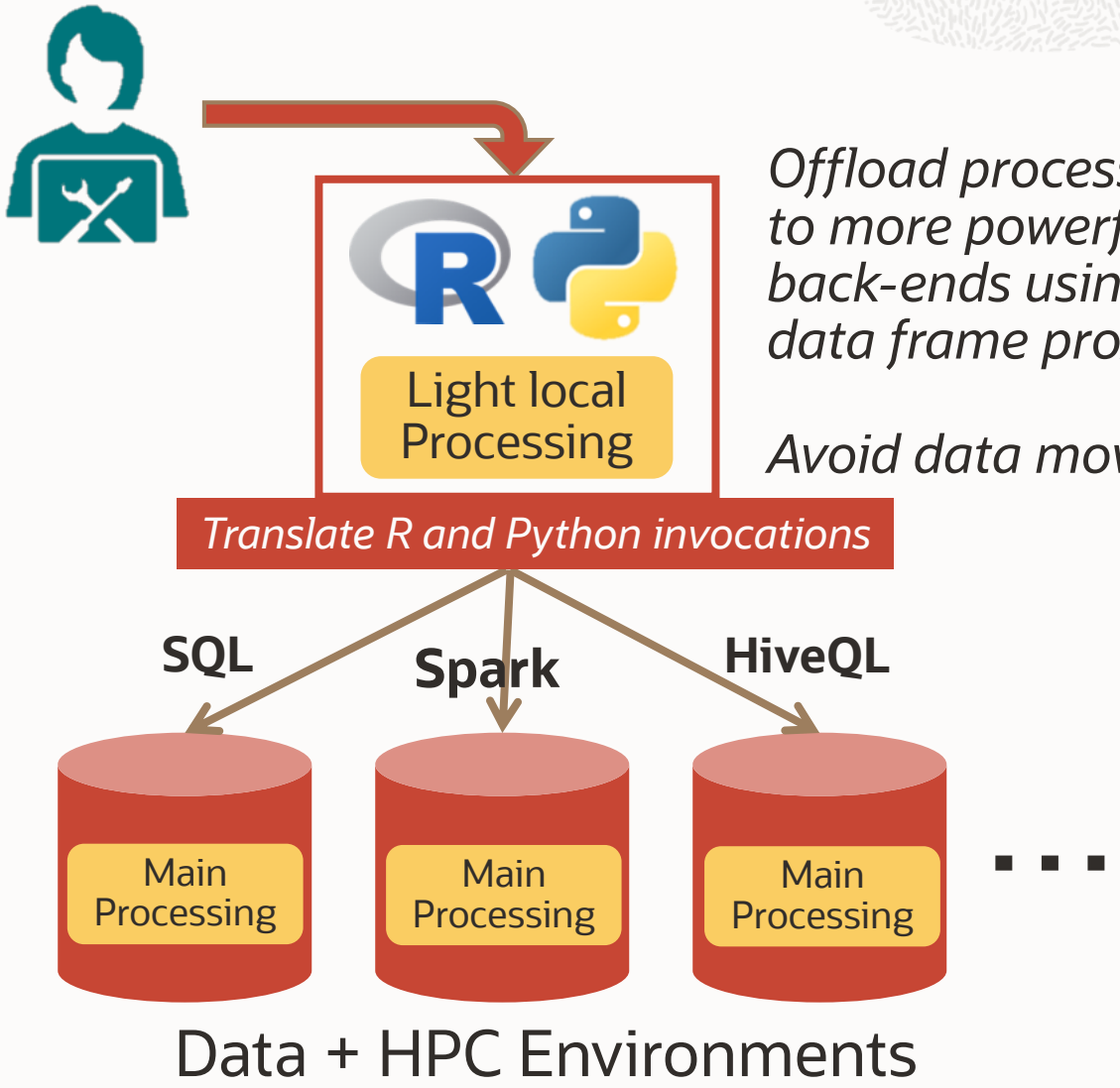
Access latency
Paradigm shift: R/Python → *Data Access Language* → R/Python
Memory limitation – data size, in-memory processing
Single threaded
Issues for backup, recovery, security
Ad hoc production deployment

Elements affecting enterprise scalability for R and Python



Data access, analysis, and exploration





Offload processing to more powerful back-ends using data frame proxies

Avoid data movement

Data access, analysis, and exploration

- Maintain language features and interface
- Reference data via proxy objects to eliminate data movement
- Overload functions that translate the open source invocations to the language of data processing engine
- Execute at the data processing engine

Analyze all of your data, faster

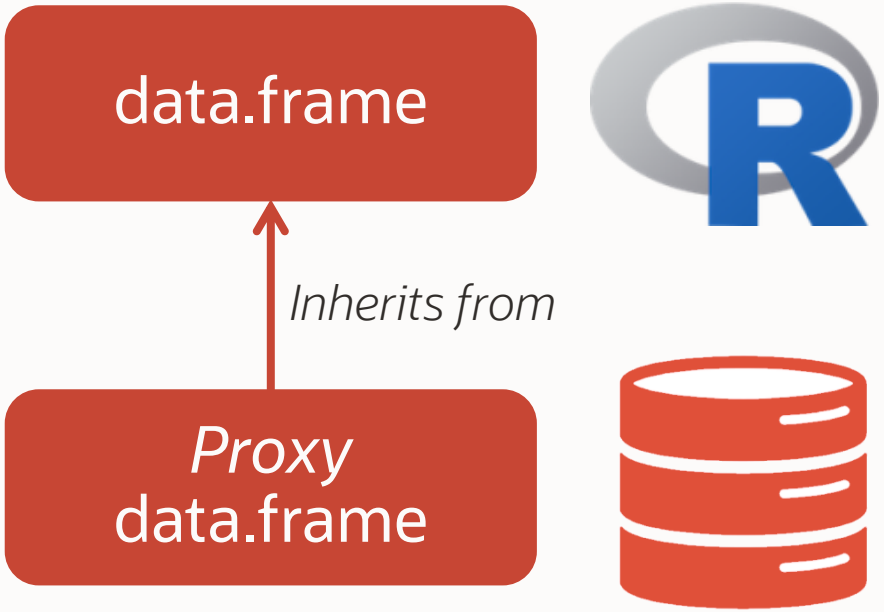
No data access latency

Leverage performance optimizations of data processing engine

Proxy objects

Example using OML4R interface

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
1	5.1	3.5	1.4	0.2	setosa
2	4.9	3.0	1.4	0.2	setosa
3	4.7	3.2	1.3	0.2	setosa
4	4.6	3.1	1.5	0.2	setosa
5	5.0	3.6	1.4	0.2	setosa
6	5.4	3.9	1.7	0.4	setosa




```
> str(iris)
'data.frame':   150 obs. of  5 variables:
 $ Sepal.Length: num  5.1 4.9 4.7 4.6 5 5.4 4.6 5 4.4 4.9 ...
 $ Sepal.Width : num  3.5 3 3.2 3.1 3.6 3.9 3.4 3.4 2.9 3.1 ...
 $ Petal.Length: num  1.4 1.4 1.3 1.5 1.4 1.7 1.4 1.5 1.4 1.5 ...
 $ Petal.Width : num  0.2 0.2 0.2 0.2 0.2 0.4 0.3 0.2 0.2 0.1 ...
 $ Species     : Factor w/ 3 levels "setosa","versicolor",..: 1 1 1 1 1 1 1 1 1 1 ...
```

```
> str(IRIS)
'data.frame':   150 obs. of  5 variables:
Formal class 'ore.frame' [package "OREbase"] with 12 slots
  ..@ .Data    : list()
  ..@ dataQry  : Named chr "( select /*+ no_merge(t) */  \"Sepal.Length\" VAL001,\"Sepal.Wid
th\" VAL002,\"Petal.Length\" VAL003,\"Petal.Width\" VAL004,\"Sp"| __truncated__
  .. ..- attr(*, "names")= chr "2539_1"
  ..@ dataObj  : chr "2539_1"
  ..@ desc     :'data.frame':   5 obs. of  2 variables:
  .. ..$ name  : chr  "Sepal.Length" "Sepal.Width" "Petal.Length" "Petal.Width" ...
  .. ..$ Sclass: chr  "numeric" "numeric" "numeric" "numeric" ...
  ..@ sqlName  : chr
  ..@ sqlValue : chr  "\"Sepal.Length\"" "\"Sepal.Width\"" "\"Petal.Length\"" "\"Petal.Width
```

```
"( select /*+ no_merge(t) */  \"Sepal.Length\" VAL001,\"Sepal.Width\" VAL
002,\"Petal.Length\" VAL003,\"Petal.Width\" VAL004,\"Species\" VAL005 fro
m \"RQUSER\".\"IRIS\" t  )"
```

Open Source Language access to Oracle Database

OML4R

```
library(ORE)


ore.connect("oml_user", ...)
```

```
ore.sync()
ore.attach()
ore.ls()
head(ONTIME_S)
TMP_ONTIME <- ore.get("ONTIME_S")
```

```
dim(ONTIME_S)
summary(ONTIME_S)
cor(ONTIME_S[,c('ARRDELAY','DEPDELAY')],
  use="complete.obs")
```

OML4Py*

```
import oml
import pandas as pd
import matplotlib.pyplot as plt
oml.connect("oml_user", ...)
```

```
t = oml.sync(table="*",regex_match=True)
t.keys()
oml.dir()
ONTIME_S = t.get("ONTIME_S","none")
ONTIME_S.head()
```

```
ONTIME_S.shape()
ONTIME_S.describe()
ONTIME_S[['ARRDELAY','DEPDELAY']].corr()
```


* Python coming soon

Open Source Language access to Oracle Database

OML4R

```
DF <-
  ONTIME_S[ONTIME_S$DEST=="SFO",1:21])
```

```
hist(DF$ARRDELAY,breaks=100,color="green",
     main= 'Histogram of Arrival Delay',
     xlab = 'Arrival Delay (minutes)',
     ylab = '# of flights')
```

```
boxplot(SEPAL_WIDTH ~ Species, data=IRIS,
    notch=TRUE, ylab='cm',
    main= 'Distribution of IRIS Attributes')
```

OML4Py*

```
DF =
  ONTIME_S[ONTIME_S["DEST"]=="SFO",1:21]
```

```
_ = oml.graphics.hist(DF['ARRDELAY'],
                      100, color='green')
plt.title('Histogram of Arrival Delay')
plt.xlabel('Arrival Delay (minutes)')
plt.ylabel('# of flights')
```

```
oml.graphics.boxplot(IRIS[:, :4], notch=True,
   showmeans = True, labels=['Sepal Length',
   'Sepal Width','Petal Length', 'Petal
   Width'])
plt.title('Distribution of IRIS Attributes')
plt.ylabel('cm');
```

Open Source Language access to Oracle Database

OML4R

```
df1 <-data.frame(x1=1:5,y1=letters[1:5])

df2 <-data.frame(x1=5:1,y2=letters[11:15])

ore.drop(table="TEST_DF1")
ore.drop(table="TEST_DF2")

ore.create(df1, table="TEST_DF1")
ore.create(df2, table="TEST_DF2")
```

```
merge(TEST_DF1, TEST_DF2, by="x1")
```

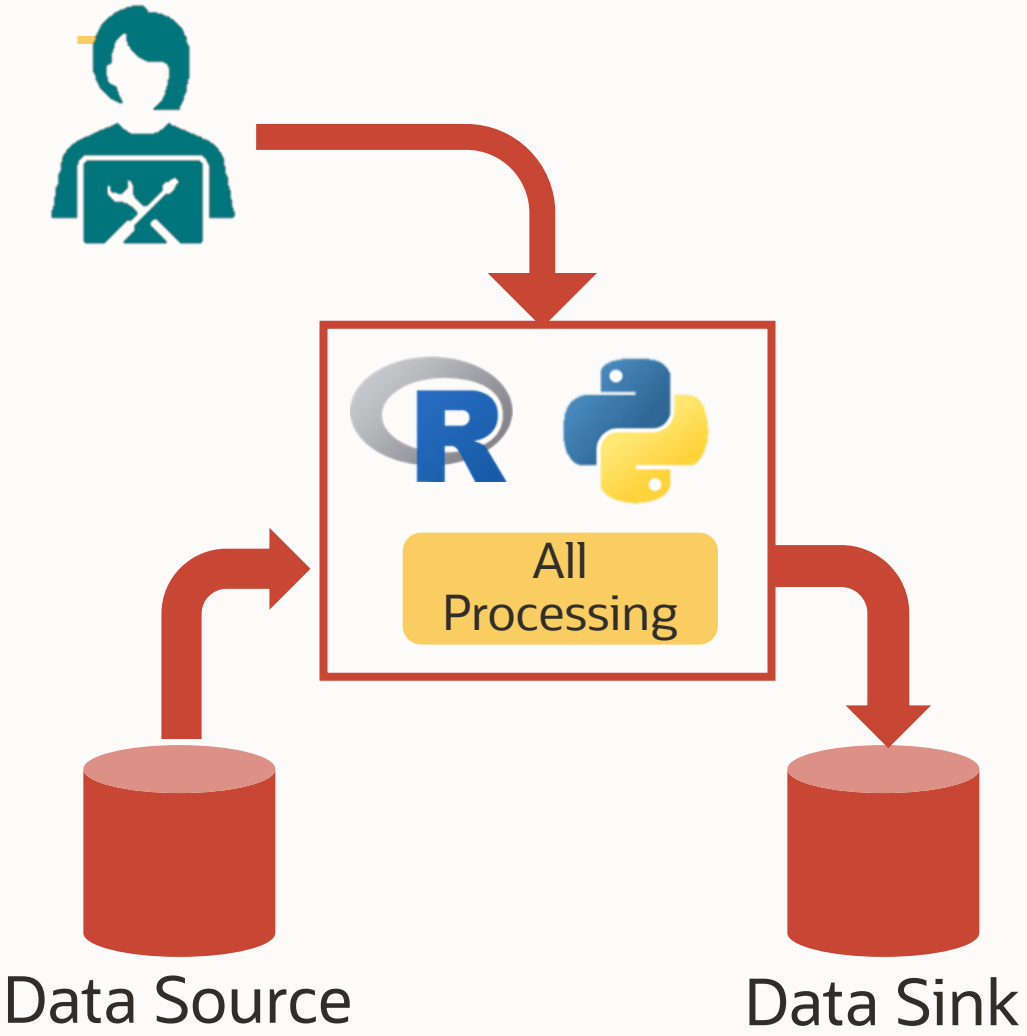
OML4Py*

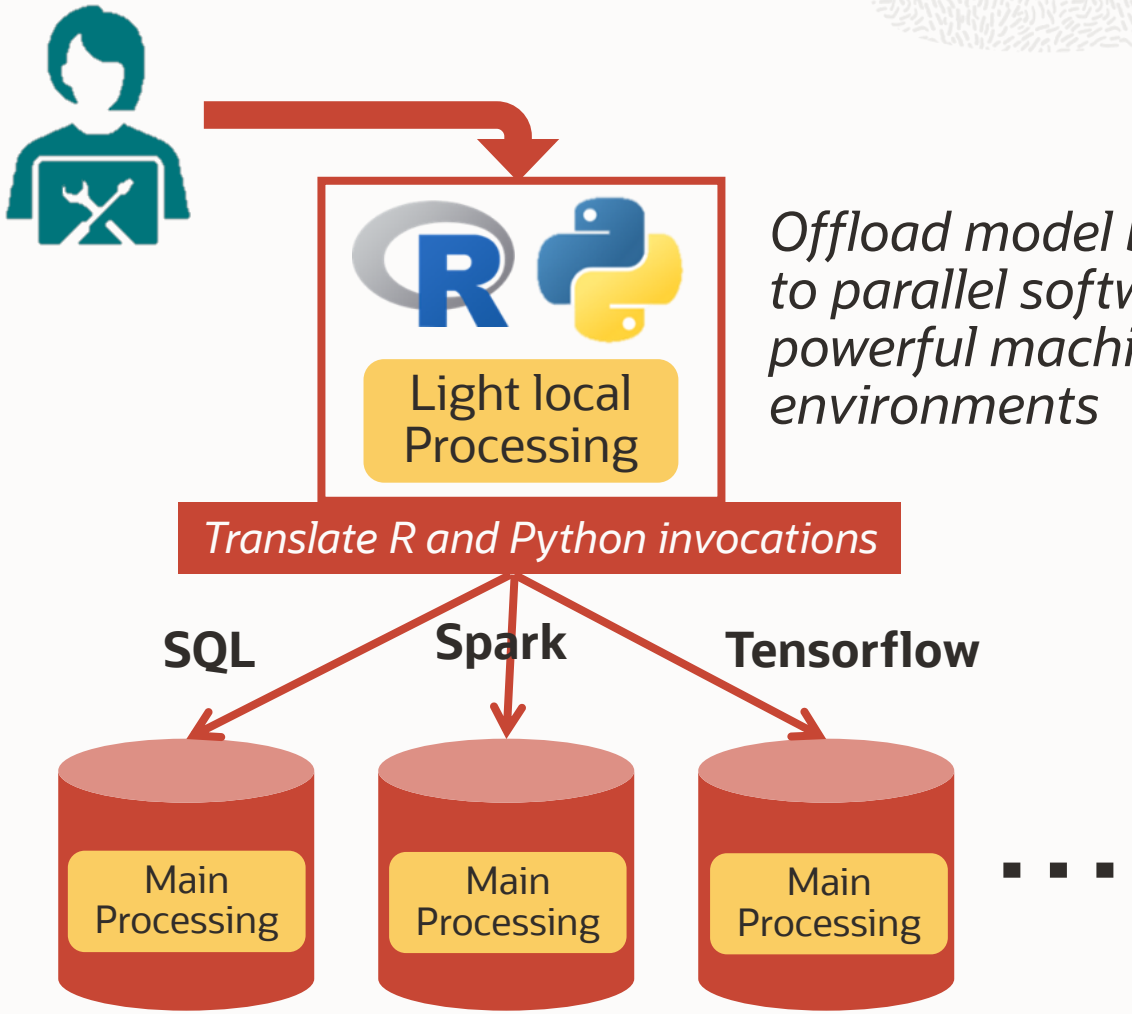
```
letters = list(map(chr, range(97, 123)))
df1 = pd.DataFrame({'x1':range(1,6),
                    'x2':letters[1:6]})
df2 = pd.DataFrame({'x1':range(1,6),
                    'x2':letters[11:16]})
oml.drop("TEST_DF1")
oml.drop("TEST_DF2")

TEST_DF1 = oml.create(df1, table="TEST_DF1")
TEST_DF2 = oml.create(df2, table="TEST_DF2")
```

```
df2.merge(df1,on='x1')
```

Scalable Machine Learning





Offload model building to parallel software and powerful machines and environments

Scalable Machine Learning

Maintain open source machine learning interface

- OML4R - easy to specify R formula – minimal lines of code including transformations, interaction terms, etc.
- OML4Py – familiar Python predictors/target interface with fit() and predict()

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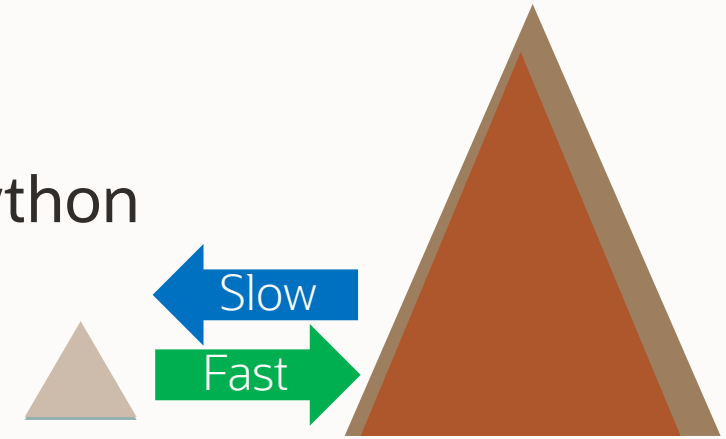
Bring the algorithm to the data

- Eliminate or minimize data movement
- Leverage proxy objects to reference data from R/Python



Scalable Machine Learning

Maintain open source machine learning interface

- OML4R - easy to specify R formula – minimal lines of code including transformations, interaction terms, etc.
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Bring the algorithm to the data

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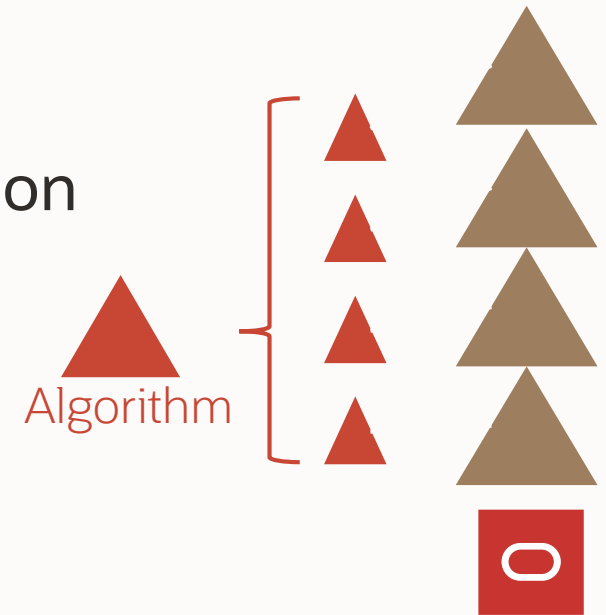
- Leverage proxy objects to reference data from R/Python

Parallel, distributed algorithm implementations

- Custom state-of-the-art integrated implementations
- Supplement with open source packages and toolkits



Offload Model Build and Score to Oracle Database

OML4R

```
n.rows <- nrow(IRIS)
row.names(IRIS) <- IRIS$Species
my.smpl <- sample(1:n.rows, ceiling(n.rows*0.7))
train.dat <- IRIS[my.smpl,]
test.dat <- IRIS[setdiff(1:n.rows, my.smpl),]

rf_mod <- ore.randomForest(Species~.,train.dat)
```

```
pred <- predict(rf_mod, test.dat, type="all",
   supplemental.cols=c("SEPAL_LENGTH","Species"))


table(pred$Species, pred$prediction)
```

OML4Py*

```
from oml import rf

train_dat, test_dat = IRIS.split()
train_x = train_dat.drop('Species')
train_y = train_dat['Species']

rf_mod = rf()
rf_mod = rf_mod.fit(train_x, train_y)
```

```
pred = rf_mod.predict(test_dat.drop('Species'),
   supplemental_cols = test_dat[:,['SEPAL_LENGTH',
                                   'Species']])
res_ct =
   pred.crosstab('Species','PREDICTION',pivot=True)
res_ct.sort_values(by='Species')
```

Benefits of parallelism and *not* moving data

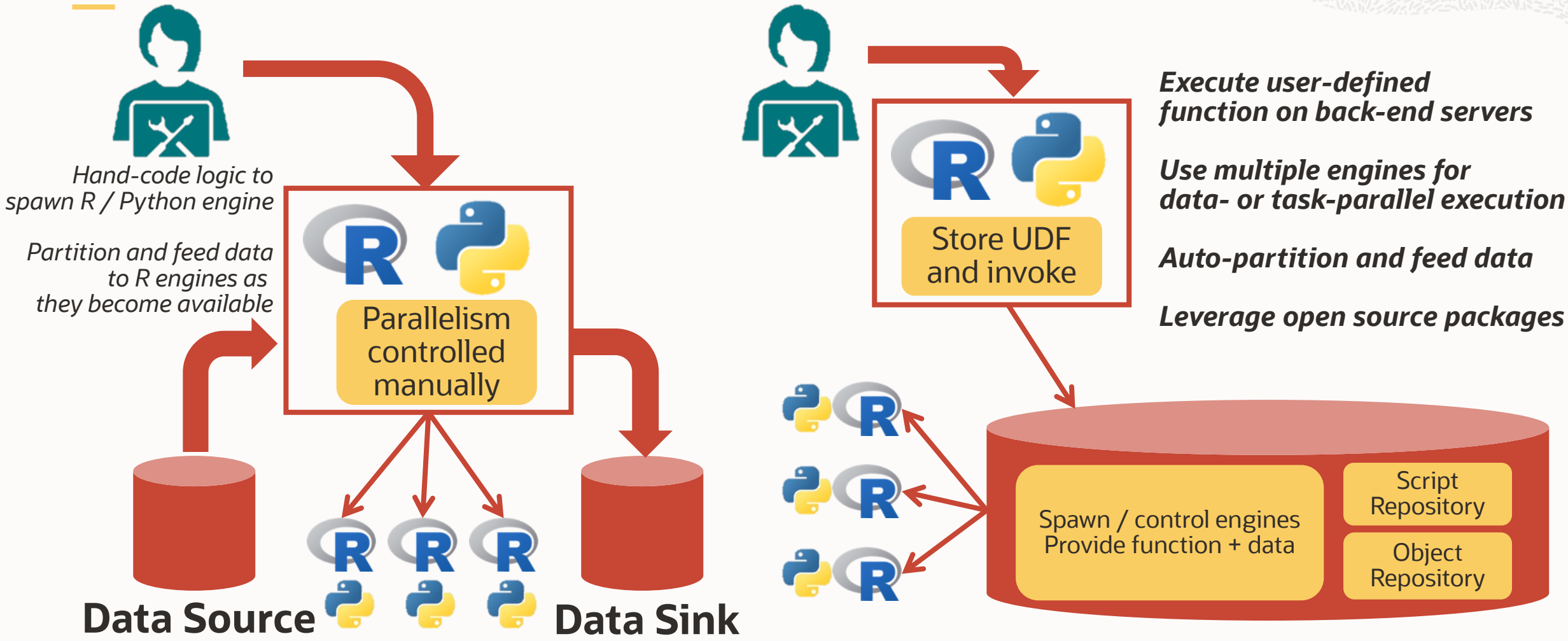
Data remains at Oracle Database Server Machine

- Predict "Total Revenue" of a customer
- 184 million records, 31 numeric predictors
- Data stored in an Oracle Database table

Algorithm	Threads Used*	Memory required**	Time for Data Loading***	Time just for Computation	Total Elapsed	Relative Performance
Open-Source R Linear Model (lm)	1	220Gb	1h3min	43min	1h46min	1x
OML4R lm (ore.lm)	1	-	-	42.8min	42.8min	2.47X
OML4R lm (ore.lm)	32	-	-	1min34s	1min34s	67.7X
OML4R lm (ore.lm)	64	-	-	57.97s	57.97s	110X
OML4R lm (ore.lm)	128	-	-	41.69s	41.69s	153X

* Open-source R lm() is single threaded
** Data moved into R Session memory, since open-source lm() requires all data to be in-memory
*** Time to load 40Gb of raw data into the open-source R Session's memory

Data and Task Parallel Execution



Execute user-defined function on back-end servers

Use multiple engines for data- or task-parallel execution

Auto-partition and feed data

Leverage open source packages

Data and Task Parallel Execution

Easily specify parallelism and data partitioning

- Simplified API – all-in-one
- Build and score with large number of open source models
- Partition data by value or count
- Invoke user-defined functions in parallel with index input

Automated management of R and Python engines

- Insulation from hardware details
- Limit memory and compute resources, as possible

Automated load of data and user-defined functions into R and Python engines

Leverage packages from open source ecosystems

Comparing OML4R and OML4Py – Table Apply

OML4R

```
library(e1071)
buildNB <-
  function(dat,dsname) {
    library(e1071)
    dat$Species <- as.factor(dat$Species)
    mod<-naiveBayes(Species ~ ., dat)
    ore.save(mod,name=dsname,overwrite=TRUE)
    mod
  }
```

```
mod <- ore.tableApply(IRIS, buildNB,
                      dsname='NB_Model-1',
                      ore.connect=TRUE)
```

OML4Py*

```
def build_nb(dat, dsname):
    import oml
    from sklearn.naive_bayes import GaussianNB
    from sklearn import preprocessing
    le = preprocessing.LabelEncoder()
    raw_labels = dat["Species"].values
    le.fit(raw_labels)
    y = le.transform(raw_labels)
    X = dat["SEPAL_LENGTH","SEPAL_WIDTH",
  "PETAL_LENGTH","PETAL_WIDTH"].values
    mod = GaussianNB().fit(X, y)
    oml.ds.save(objs={'mod':mod},name=dsname,
                overwrite=True)
```

```
mod = oml.table_apply(IRIS, build_nb,
                      dsname = 'NB_Model-1',
                      oml_connect=True)
```


Comparing OML4R and OML4Py – Row Apply

OML4R

```
scoreNBmodel <- function(dat, dsname) {
     library(e1071)
     ore.load(dsname)
     dat$PRED <- predict(mod, newdata = dat)
     dat
   }
```

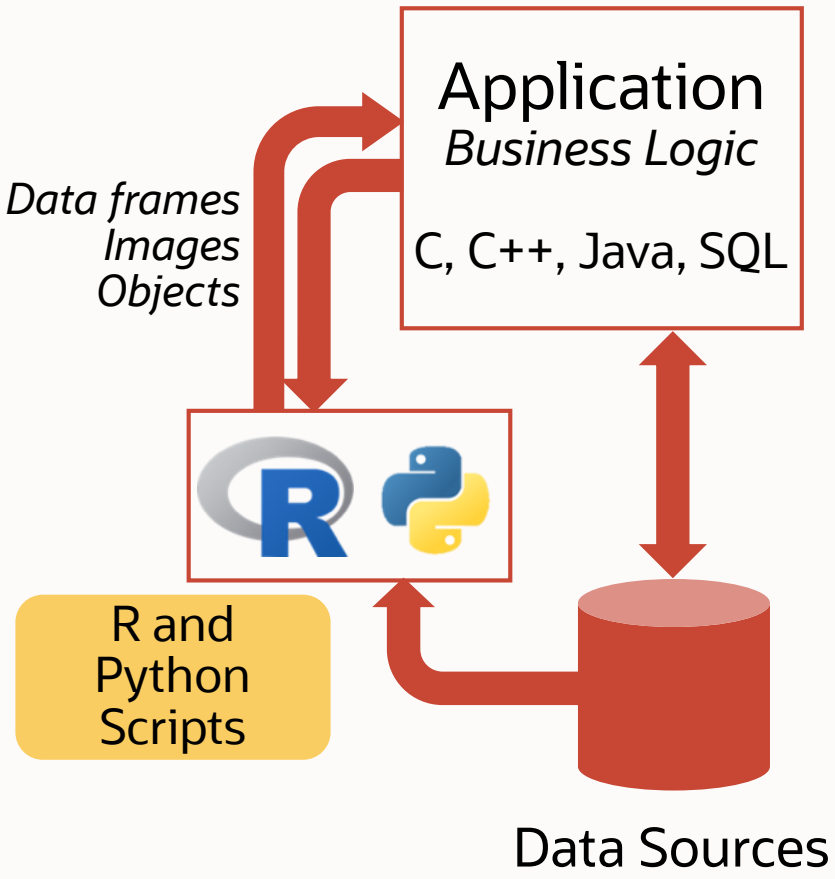
```
IRIS_PRED      <- IRIS[1,]
IRIS_PRED$PRED <- "A"

res <- ore.rowApply(IRIS, scoreNBmodel,
                    dsname = 'NB_Model-1',
                    parallel = 4, rows = 10,
                    FUN.VALUE = IRIS_PRED,
                    ore.connect = TRUE)
```

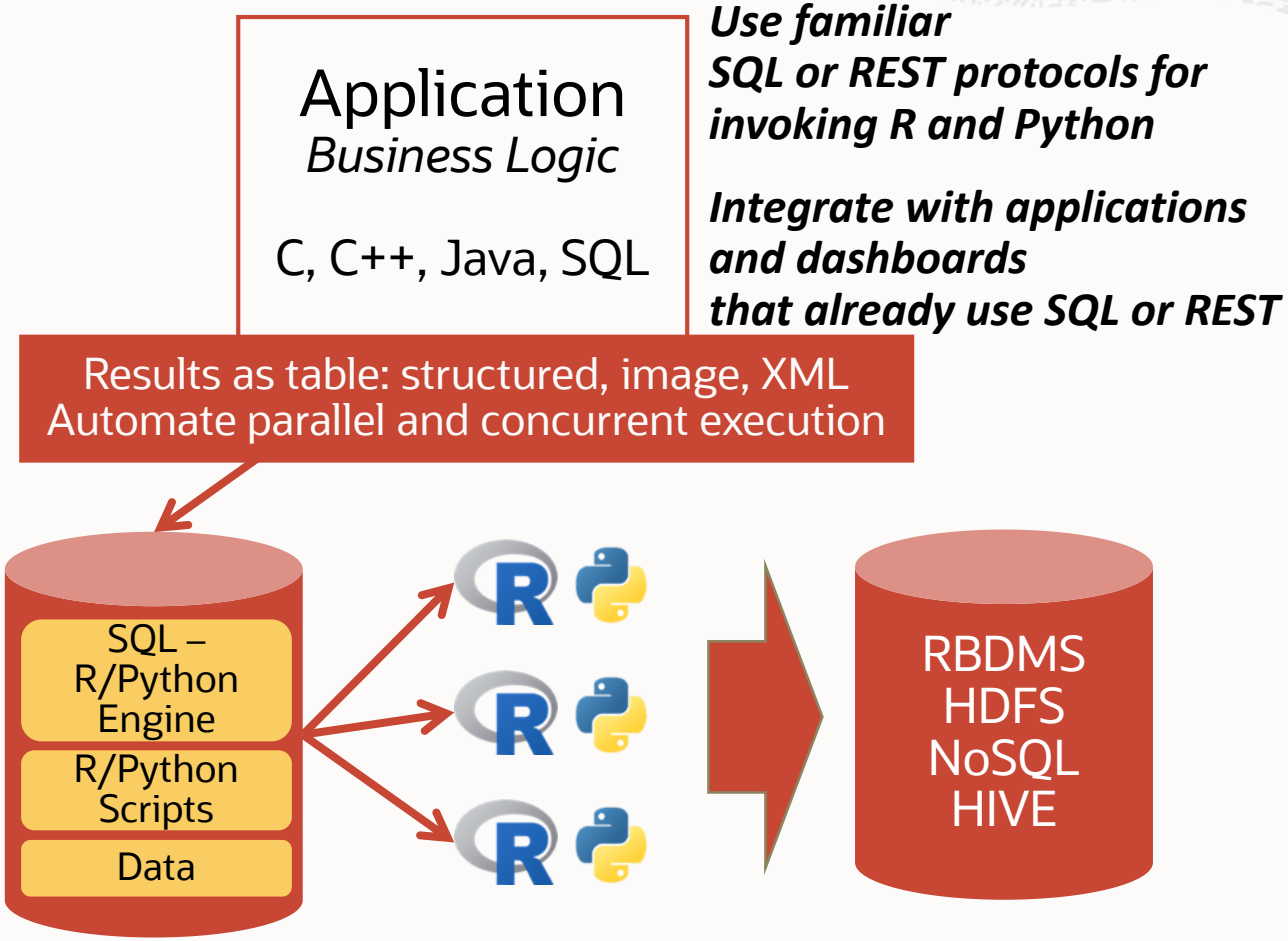
OML4Py*

```
def score_nb_mod(dat, dsname):
     import oml
     from sklearn.naive_bayes import GaussianNB
     objs = oml.ds.load(dsname,to_globals=False)
     mod = objs['mod']
      dat['PREDICTION'] =
         mod.predict(dat.drop('Species',axis=1))
     return dat
```

```
IRIS_PRED = pd.DataFrame([(1,1,1,1,'a',1)],
   columns=["SEPAL_LENGTH","SEPAL_WIDTH",
            "PETAL_LENGTH","PETAL_WIDTH",
            "Species","PREDICTION"]))
res = oml.row_apply(IRIS,score_nb_mod,
                    dsname = 'NB_Model-1',
                    parallel = 4, rows = 10
                    func_value = IRIS_PRED,
                    oml_connect = True)
```

Deployment





Use familiar SQL or REST protocols for invoking R and Python

Integrate with applications and dashboards that already use SQL or REST

Deployment

- Invoke user-defined R and Python functions easily from environments that readily use SQL or REST
- Automated mapping of data structures and types
- Seamlessly return data frames, images, XML as database rowsets
- Schedule execution of user-defined functions for “lights-out” operation

Create user-defined functions from SQL (or use from R/Python)

OML4R

```
BEGIN
  sys.rqScriptDrop('RandomRedDots');
  sys.rqScriptCreate('RandomRedDots',
 'function(){
       id <- 1:10
       plot( 1:100, rnorm(100), pch = 21,
             bg = "red", cex = 2,
             main="Random Red Dots" )
       data.frame(id=id, val=id / 100)
       }');
END;
```

OML4Py*

```
BEGIN
   sys.pyqScriptDrop('RandomRedDots');
   sys.pyqScriptCreate('RandomRedDots',
'def RandomRedDots ():
    import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt

    d = {''id'': range(1,10),
         ''val'': [x/100 for x in range(1,10)]}
    df = pd.DataFrame(data=d)
    fig = plt.figure(1)
    ax = fig.add_subplot(111)
    ax.scatter(range(0,100),
               np.random.rand(100),c=''r'')
    fig.suptitle("Random Red Dots")
    return df', NULL, TRUE);
END;
```

Invoke user-defined functions from SQL

OML4R

```
select ID, IMAGE from
  table(rqEval(NULL,'PNG','RandomRedDots'))
```

```
select ID, VAL from
  table(rqEval(NULL,
               'select 1 id, 1 val from dual',
               'RandomRedDots'))
```

```
select dbms_lob.substr(VALUE,4000,1) from
  table(rqEval(NULL,'XML',RandomRedDots'))
```

```
# In R, invoke same function by name
ore.doEval(FUN.NAME='RandomRedDots')
```

OML4Py*

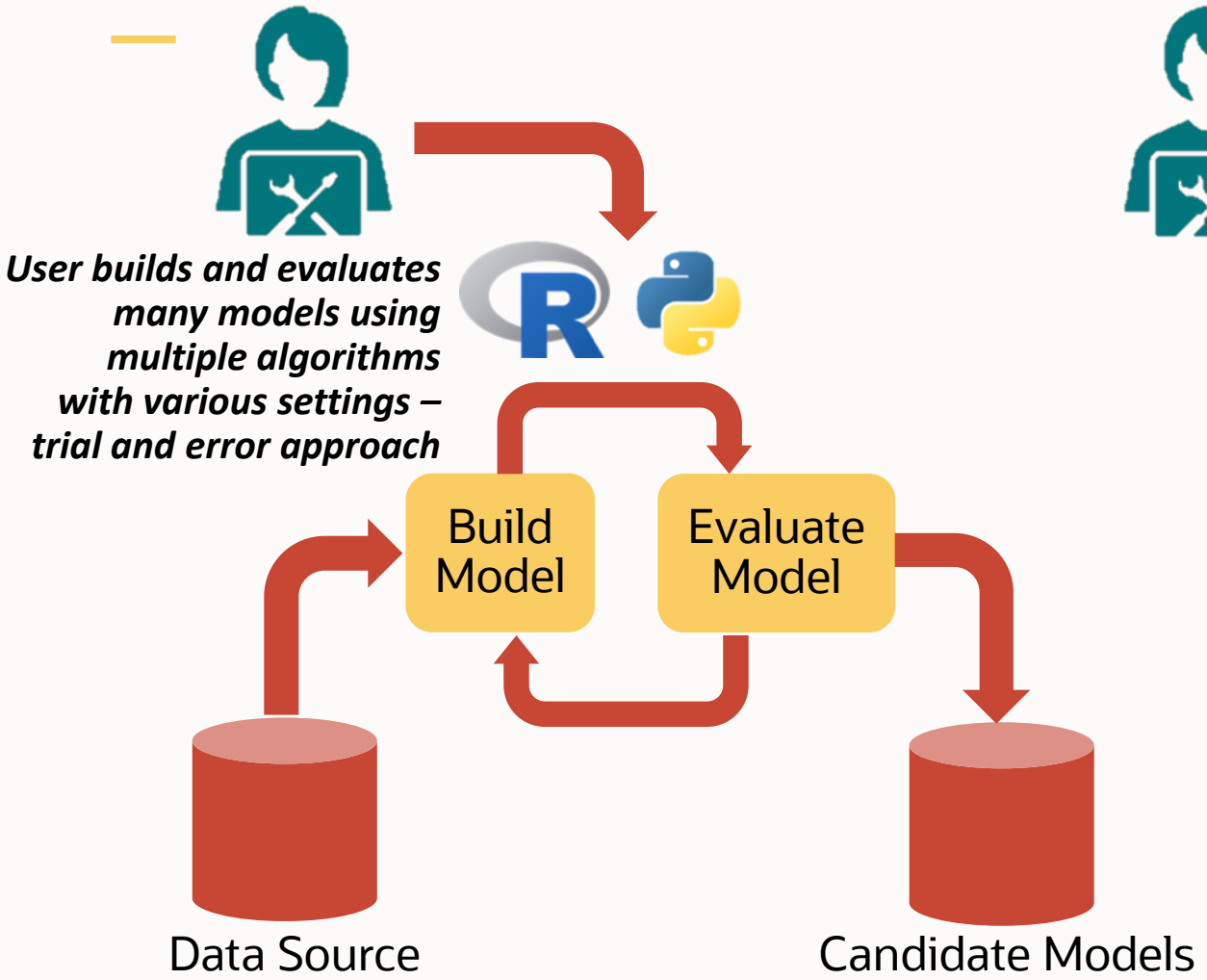
```
select ID, IMAGE from
   table(pyqEval(NULL,'PNG','RandomRedDots'))
```

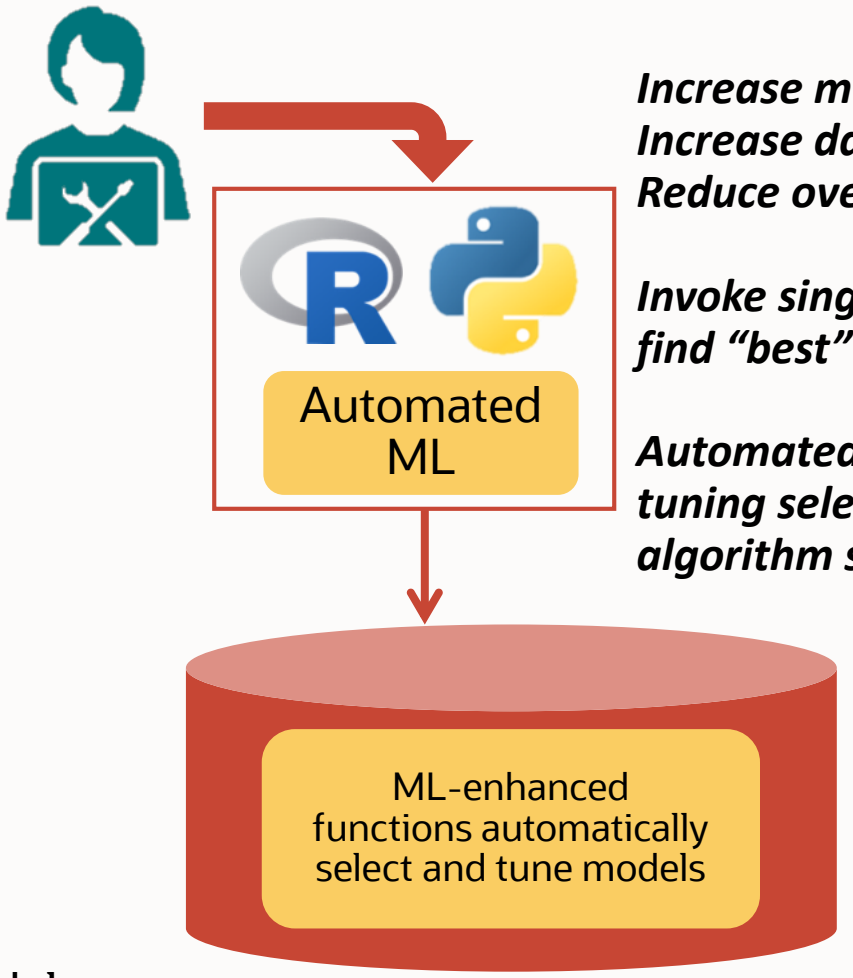
```
select ID, VAL from
  table(pyqEval(NULL,
               'select 1 id, 1 val from dual',
               'RandomRedDots'))
```

```
select dbms_lob.substr(VALUE,4000,1) from
  table(pyqEval(NULL,'XML','RandomRedDots'))
```

```
# In Python, invoke same function by name
res = oml.do_eval(func='RandomRedDots')
```

Automation





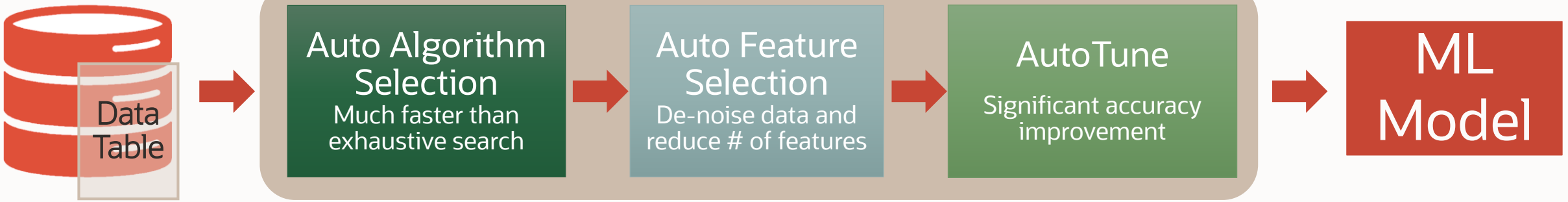
Increase model quality
Increase data scientist productivity
Reduce overall compute time

Invoke single function to find "best" algorithm and model

Automated hyperparameter tuning selects "best" algorithm settings

AutoML – *new* with OML4Py

Increase data scientist productivity – reduce overall compute time



Auto Algorithm Selection

- Identify in-database algorithm that achieves highest model quality
- Find best model faster than with exhaustive search

Auto Feature Selection

- Reduce # of features by identifying most predictive
- Improve performance and accuracy

Auto Tune Hyperparameters

- Significantly improve model accuracy
- Avoid manual or exhaustive search techniques

Enables non-expert users to leverage Machine Learning

Auto Algorithm Selection

Identify best algorithm to achieve maximum score metric guided by ML
Find best model many times faster than with exhaustive search techniques

OML4Py

```
ms = AlgorithmSelection(mining_function = 'classification',
                        score_metric = 'accuracy',
                        parallel = 4)

best_model = ms.select(X_train, y_train)

all_models = ms.select(X_train, y_train, tune=False)
```

Auto Feature Selection

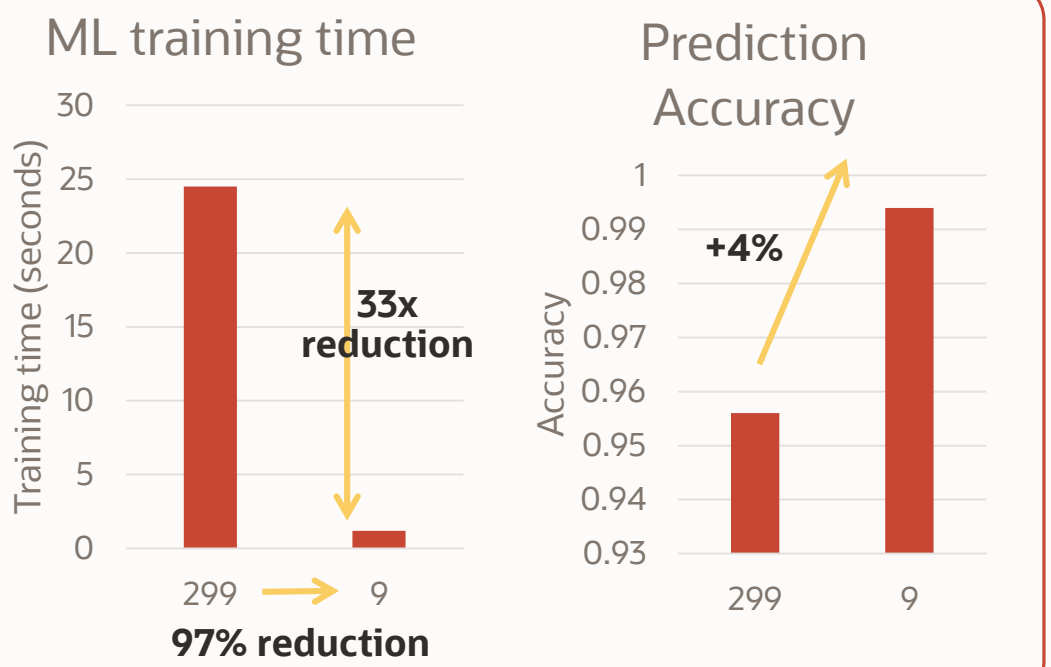
Speed-up ML pipeline by selecting most relevant features

OML4Py

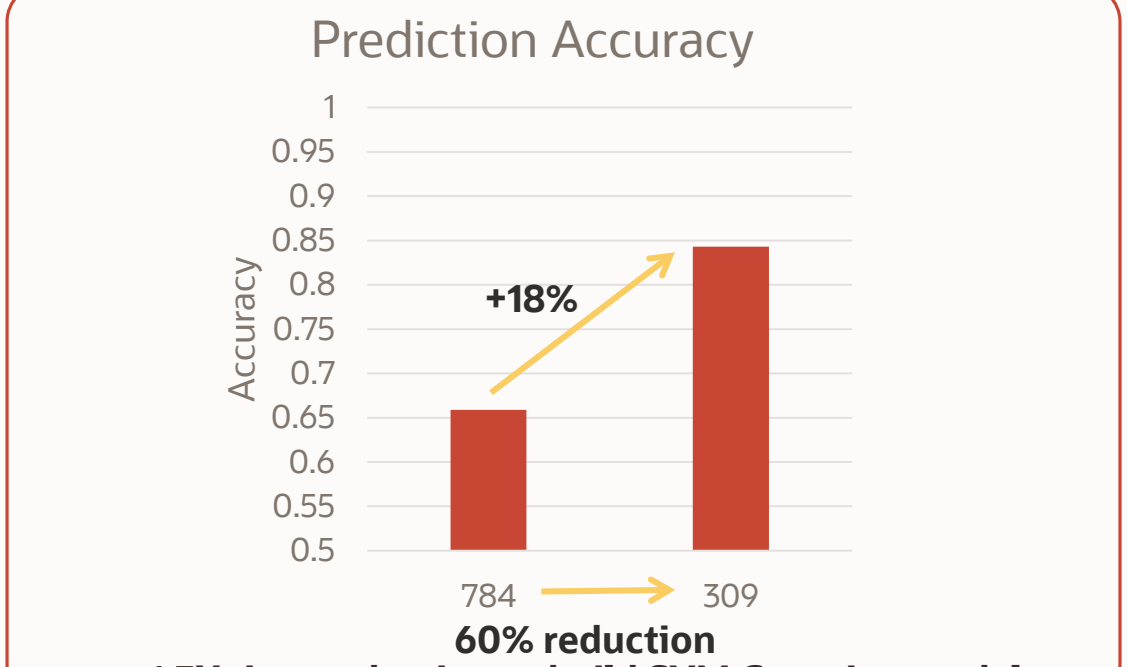
```
fs = FeatureSelection(mining_function = 'classification',
                      score_metric = 'accuracy',
                      parallel = 4)

selected_features = fs.reduce('dt', X_train, y_train)

X_train = X_train[:,selected_features]
```

OML4Py Auto Feature Selection: examples

Reduce # of features by identifying most relevant, improving performance and accuracy



OpenML dataset 312 with 1925 rows, 299 columns



OpenML dataset 40996 with 56K rows, 784 columns

Auto Tune

Significantly improve model accuracy guided by ML

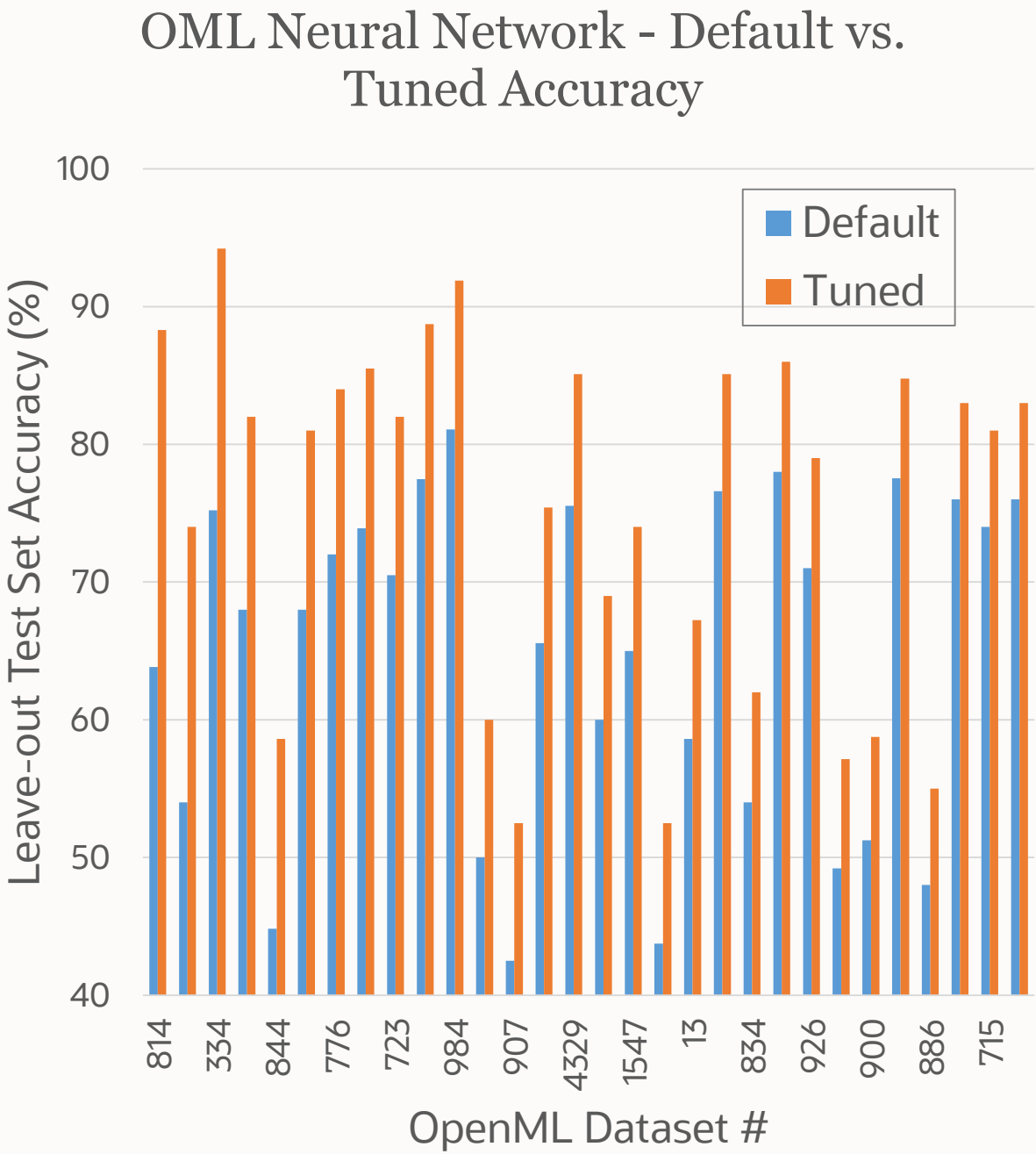
Avoid manual or exhaustive search techniques

OML4Py

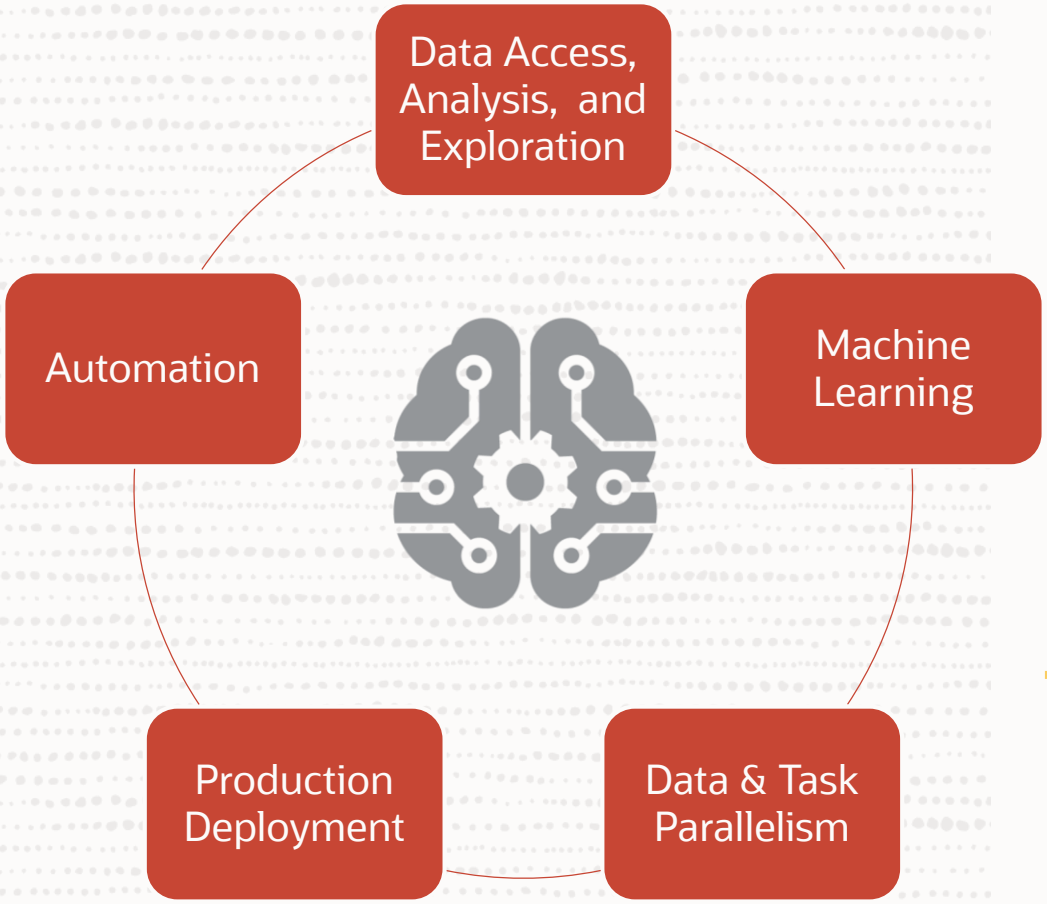
```
at = Autotune(mining_function = 'classification',
              score_metric = 'accuracy',
                   parallel = 4)

results = at.tune('dt', X_train, y_train)

best_mod = results['best_model']
all_evals = results['all_evals']
```

Mean improvement 1.7%
Across ~300 datasets
8-24% improvement for several datasets

Auto Tune:
Evaluation for OML Neural Network



Enabling R and Python for the Enterprise

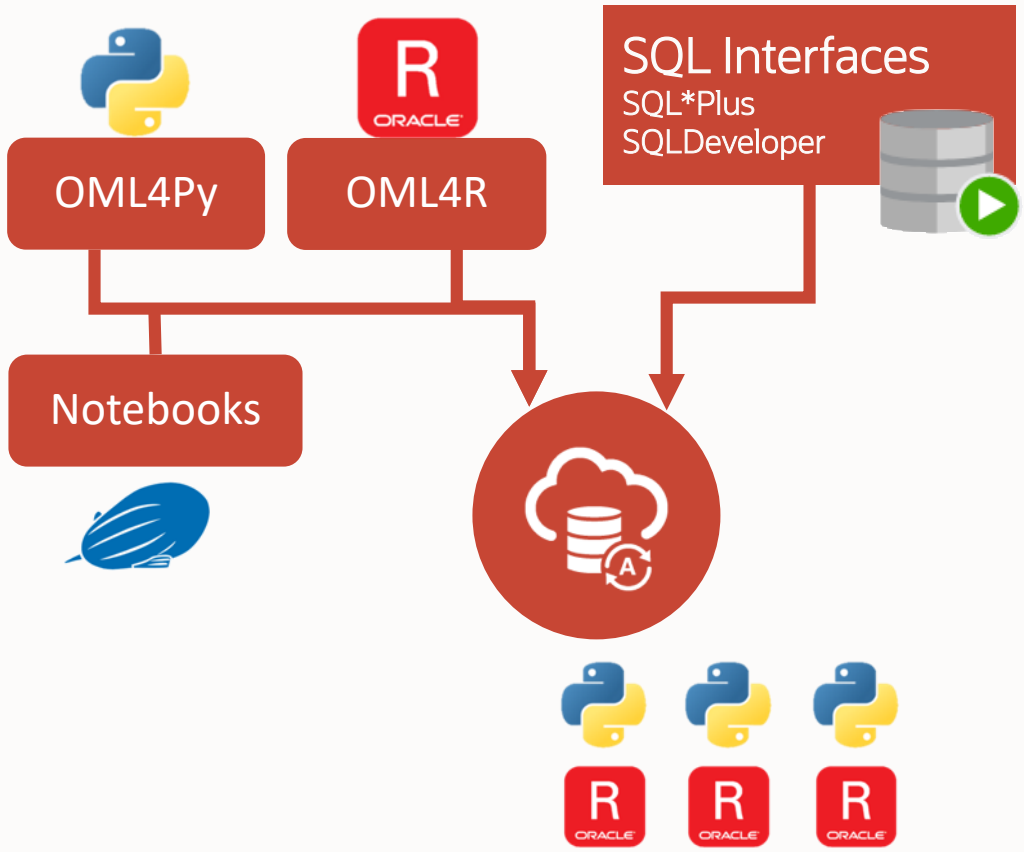


1. Leverage new, more powerful ML back-ends and libraries more easily as they arise
2. Enable data- and task-parallel execution quickly and easily for big data processing
3. Offload processing to powerful back-ends for the heavy lifting… transparent scalability
4. Immediately leverage data scientist R and Python scripts and results in production environments
5. Enhance user productivity through automation

Oracle Machine Learning for R / Python

Coming soon to Oracle Autonomous Database

- Use Oracle Database as HPC environment
- Use in-database parallel and distributed machine learning algorithms
- Manage R and Python scripts and objects in Oracle Database
- Integrate open source results into applications and dashboards via SQL
- In OML4Py, automated machine learning – AutoML



Oracle Machine Learning for R / Python

Coming soon to Oracle Autonomous Database

Transparency layer

- Leverage proxy objects so data remain in database
- Overload native functions translating functionality to SQL
- Use familiar R / Python syntax to manipulate database data

Parallel, distributed algorithms

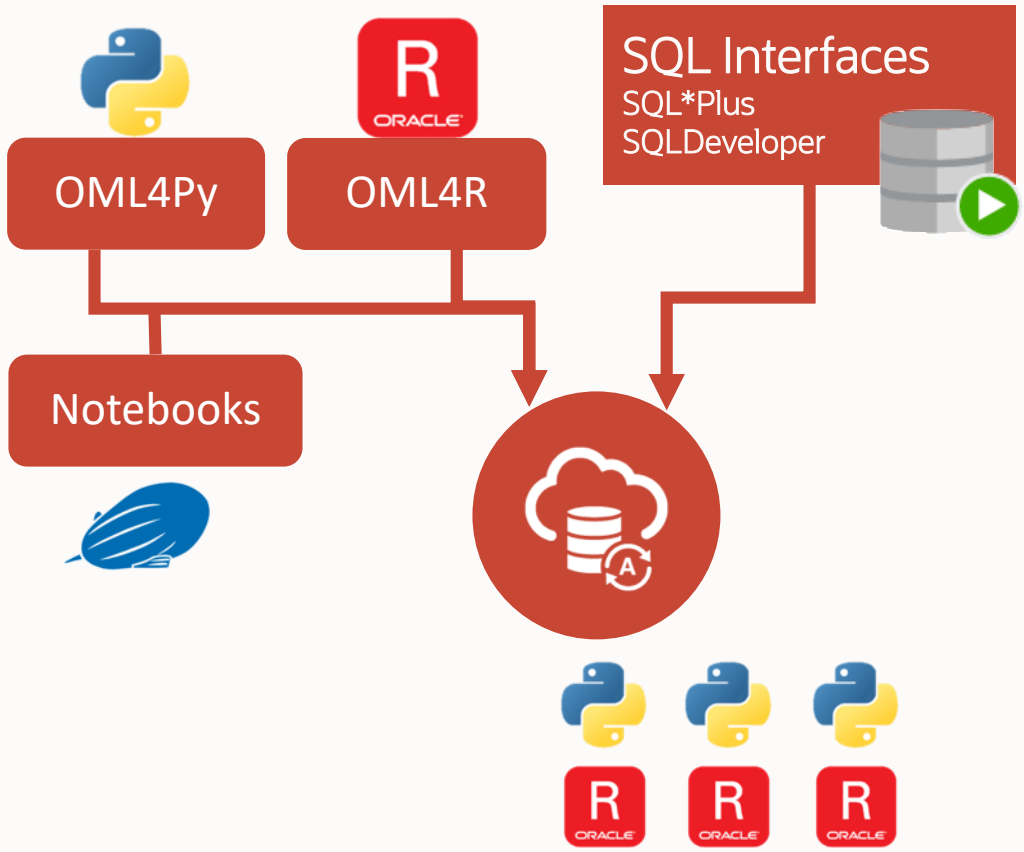
- Scalability and performance
- Exposes in-database algorithms available from OML4SQL

Embedded execution

- Manage and invoke R or Python scripts in Oracle Database
- Data-parallel, task-parallel, and non-parallel execution
- Use open source packages to augment functionality

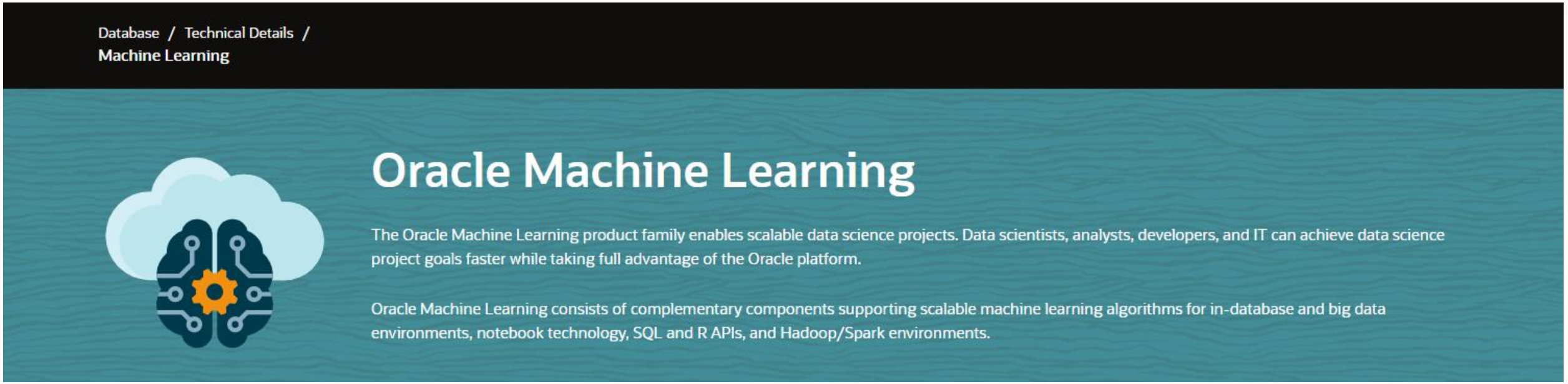
OML4Py Automated Machine Learning - AutoML

- Model selection, feature selection, hyper-parameter tuning



For more information…

oracle.com/machine-learning



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Speaker: Todd Bottger
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