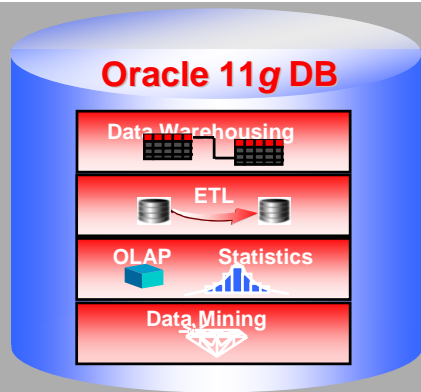


ORACLE[®] DATABASE 11^g



Oracle Data Mining 11g Release 2 Overview and Demo


ORACLE[®]

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ORACLE[®]





The following is intended to outline our general product direction. It is intended for information purposes only, and may not be incorporated into any contract. It is not a commitment to deliver any material, code, or functionality, and should not be relied upon in making purchasing decisions. The development, release, and timing of any features or functionality described for Oracle's products remains at the sole discretion of Oracle.

Outline

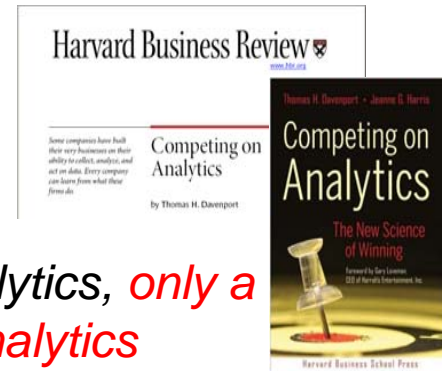
- Today's BI must go beyond simple reporting
- To succeed, companies must
 - Eliminate data movement
 - Collapse information latency
 - Deliver better BI through analytics
- ODM makes the Database an “Analytical Database”
 - Enables applications *“Powered by Oracle Data Mining”*
- Brief demonstrations
 1. Oracle Data Mining
 2. OBI EE Dashboards with ODM Results
 3. Oracle Sales Prospector with embedded ODM



Analytics: Strategic and Mission Critical

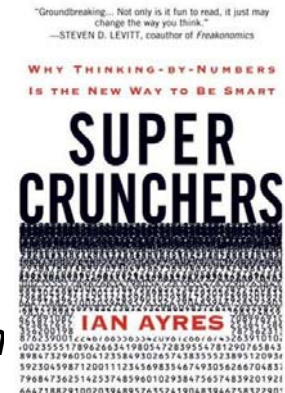
- *Competing on Analytics*, by Tom Davenport

- “Some companies have built their very businesses on their ability to collect, analyze, and act on data.”
- “Although numerous organizations are embracing analytics, **only a handful have achieved this level of proficiency. But analytics competitors are the leaders in their varied fields—consumer products finance, retail, and travel and entertainment among them.**”
- “Organizations are moving beyond query and reporting” - IDC 2006

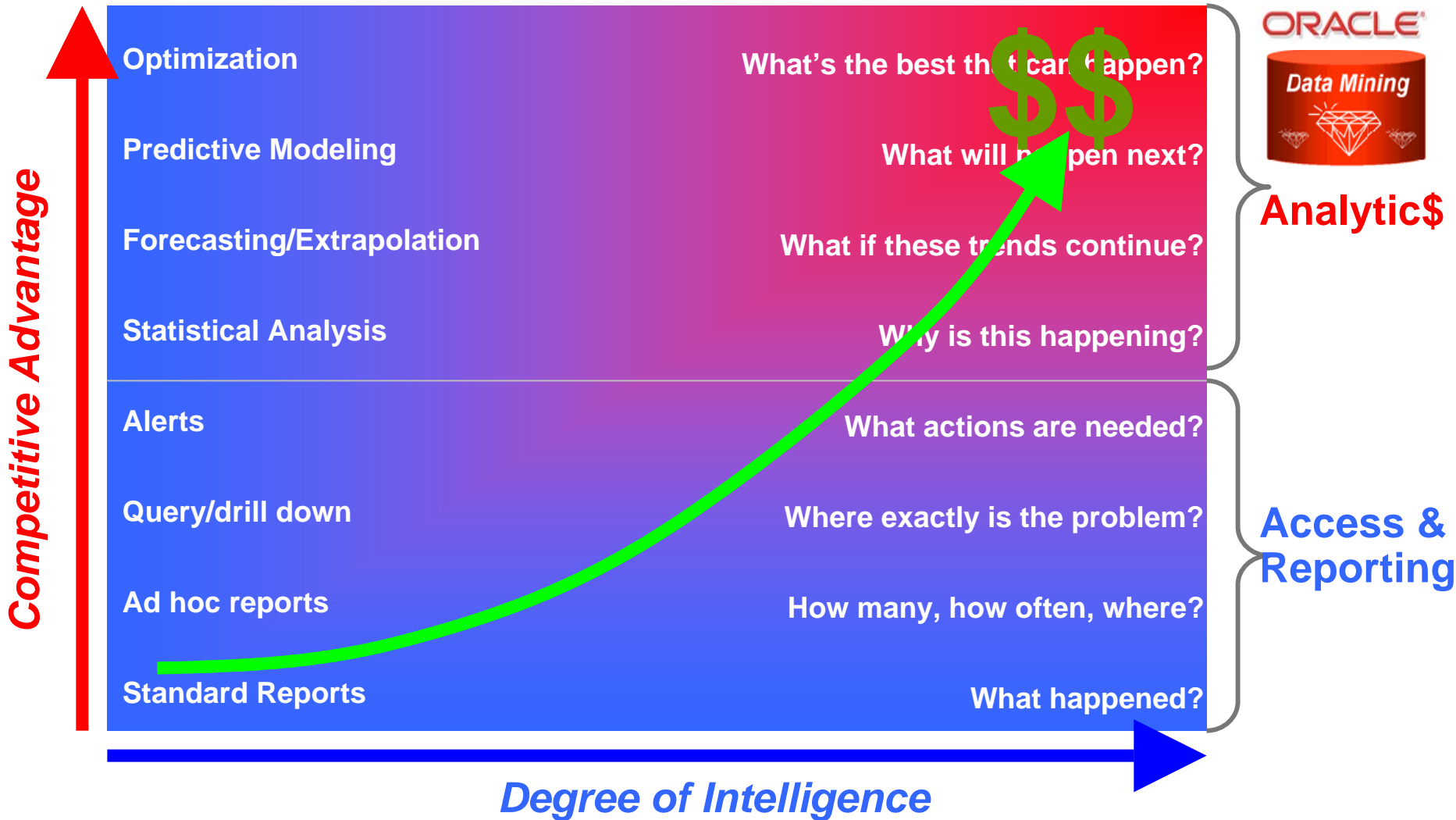


- *Super Crunchers*, by Ian Ayres

- “In the past, one could get by on intuition and experience. Times have changed. **Today, the name of the game is data.**”
—Steven D. Levitt, author of *Freakonomics*
- “**Data-mining and statistical analysis have suddenly become cool....** Dissecting marketing, politics, and even sports, stuff th complex and important shouldn't be this much fun to read.” —Wired

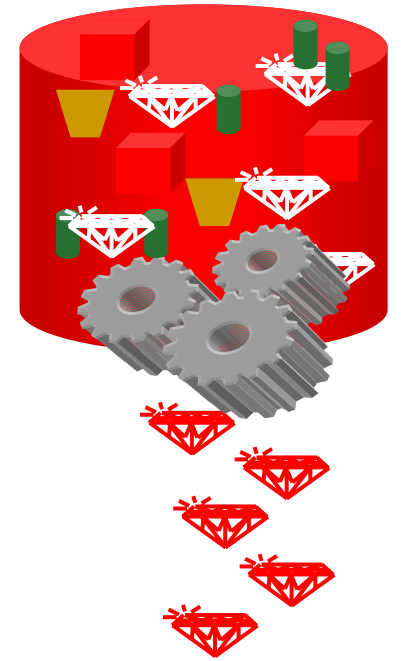


Competitive Advantage





Oracle Data Mining Option



What is Data Mining?

- Automatically sifts through data to find hidden patterns, discover new insights, and make predictions
- Data Mining can provide valuable results:
 - Predict customer behavior (*Classification*)
 - Predict or estimate a value (*Regression*)
 - Segment a population (*Clustering*)
 - Identify factors more associated with a business problem (*Attribute Importance*)
 - Find profiles of targeted people or items (*Decision Trees*)
 - Determine important relationships and “market baskets” within the population (*Associations*)
 - Find fraudulent or “rare events” (*Anomaly Detection*)

Oracle Data Mining Example Use Cases

- **Retail**

- Customer segmentation
- Response modeling
- Recommend next likely product
- Profile high value customers

- **Banking**

- Credit scoring
- Probability of default
- Customer profitability
- Customer targeting

- **Insurance**

- Risk factor identification
- Claims fraud
- Policy bundling
- Employee retention

- **Higher Education**

- Alumni donations
- Student acquisition
- Student retention
- At-risk student identification

- **Healthcare**

- Patient procedure recommendation
- Patient outcome prediction
- Fraud detection
- Doctor & nurse note analysis

- **Life Sciences**

- Drug discovery & interaction
- Common factors in (un)healthy patients
- Cancer cell classification
- Drug safety surveillance

- **Telecommunications**

- Customer churn
- Identify cross-sell opportunities
- Network intrusion detection

- **Public Sector**

- Taxation fraud & anomalies
- Crime analysis
- Pattern recognition in military surveillance

- **Manufacturing**

- Root cause analysis of defects
- Warranty analysis
- Reliability analysis
- Yield analysis

- **Automotive**

- Feature bundling for customer segments
- Supplier quality analysis
- Problem diagnosis

- **Chemical**

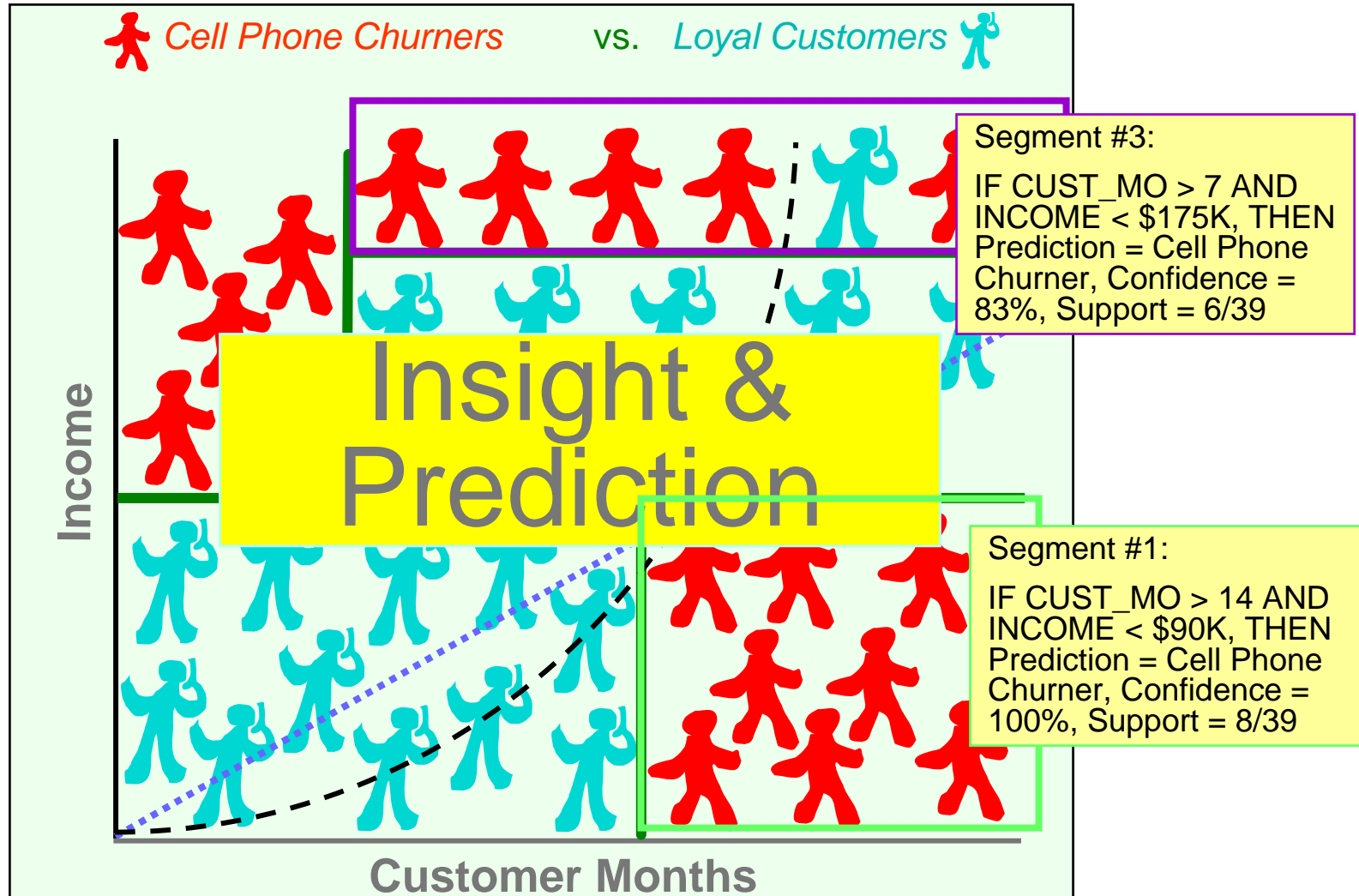
- New compound discovery
- Molecule clustering
- Product yield analysis

- **Utilities**

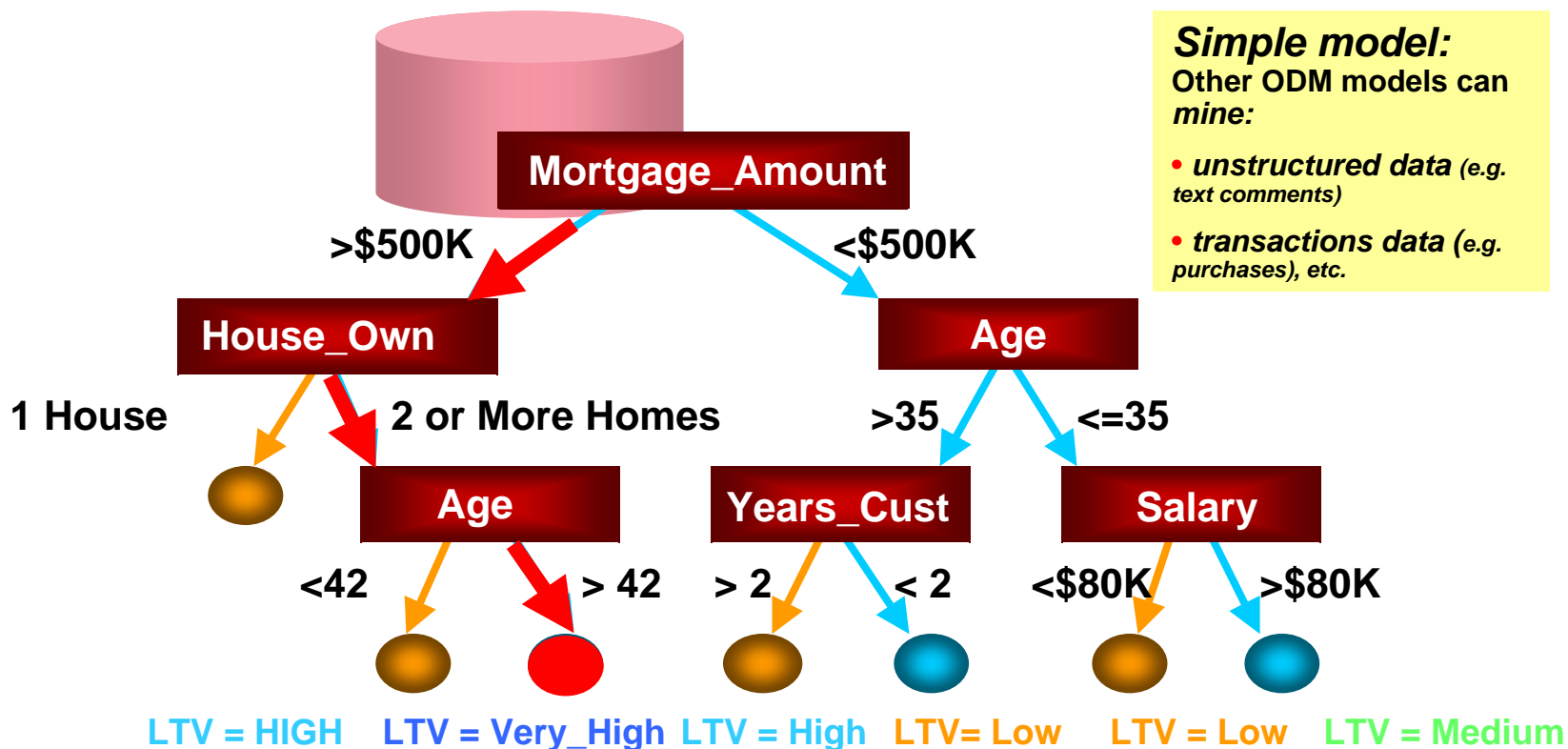
- Predict power line / equipment failure
- Product bundling
- Consumer fraud detection

Data Mining Provides

Better Information, Valuable Insights and Predictions



Predicting High LTV Customers Using a Decision Tree Model



Simple model:
Other ODM models can mine:

- *unstructured data* (e.g. text comments)
- *transactions data* (e.g. purchases), etc.

IF (Mortgage_Amount > \$500K AND House_Own = 2 or more AND Age = >42)
THEN Probability(Lifetime Customer Value is "VERY HIGH" = 77%, Support = 15%)



**“Essentially, all
models are wrong, but
some are useful.”**

- George Box

(one of the most influential statisticians of the 20th century and a pioneer in the areas of quality control, time series analysis, design of experiments and Bayesian inference.)

Oracle Data Mining

Overview (Classification)



Cases

Input Attributes

Target

Model

<i>Historic Data</i>			<u>Respond?</u> 1 = Yes, 0 = No	
<u>Name</u>	<u>Income</u>	<u>Age</u>		
Jones	30,000	30		1
Smith	55,000	67		1
Lee	25,000	23		0
Rogers	50,000	44		0
<i>New Data</i>				
Campos	40,500	52	?	1 .85
Horn	37,000	73	?	0 .74
Habers	57,200	32	?	0 .93
Berger	95,600	34	?	1 .65

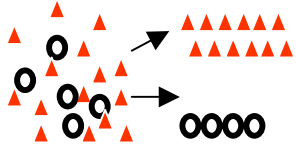
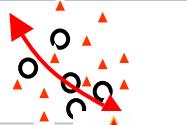
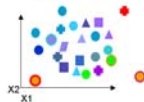
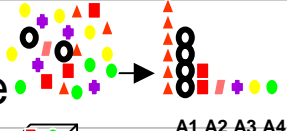
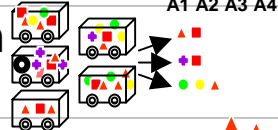
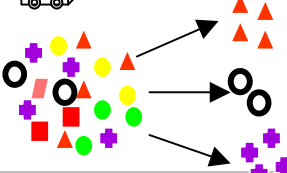
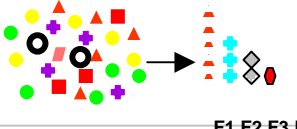
Functional Relationship:
 $Y = F(X_1, X_2, \dots, X_m)$



Prediction Confidence

Oracle Data Mining

Algorithm Summary 11g

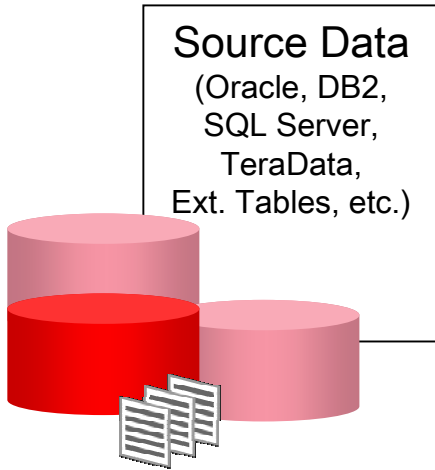
Problem	Algorithm	Applicability
Classification 	Logistic Regression (GLM) Decision Trees Naïve Bayes Support Vector Machine	Classical statistical technique Popular / Rules / transparency Embedded app Wide / narrow data / text
Regression 	Multiple Regression (GLM) Support Vector Machine	Classical statistical technique Wide / narrow data / text
Anomaly Detection 	One Class SVM	Lack examples
Attribute Importance 	Minimum Description Length (MDL)	Attribute reduction Identify useful data Reduce data noise
Association Rules 	Apriori	Market basket analysis Link analysis
Clustering 	Hierarchical K-Means Hierarchical O-Cluster	Product grouping Text mining Gene and protein analysis
Feature Extraction 	NMF	Text analysis Feature reduction

Traditional Analytics (SAS) Environment



- SAS environment requires:
 - Data movement
 - Data duplication
 - Loss of security

Oracle Architecture



- Oracle environment:
 - Eliminates data movement
 - Eliminates data duplication
 - Preserves security

In-Database Data Mining

Traditional Analytics

Oracle Data Mining



Results

- Faster time for "Data" to "Insights"
- Lower TCO—Eliminates
 - Data Movement
 - Data Duplication
- Maintains Security

- Model "Scoring" Data remains in the Database
- Embedded data preparation
- Cutting edge machine learning algorithms inside the SQL kernel of Database
- SQL—Most powerful language for data preparation and transformation
- Data remains in the Database

Hours, Days or Weeks

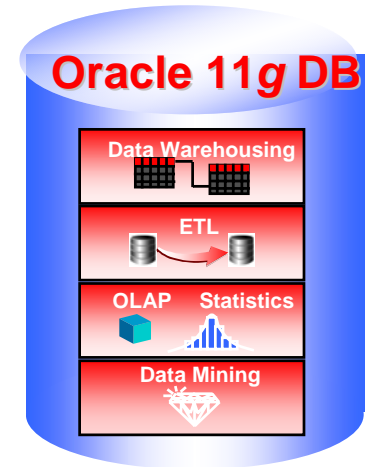
Secs. Mins or Hours



In-Database Data Mining

Advantages

- ODM architecture provides greater
 - Performance, scalability, and data security
- Data remains in the database
 - Fewer moving parts; shorter information latency
- Straightforward inclusion within interesting and arbitrarily complex queries
 - “SELECT Customers WHERE Income > 100K, AND **Probability(Buy Product A) > .85;**”
- Real-world scalability—available for mission critical appls
- Enables pipelining of results without costly materialization
- Performant and scalable:
 - Fast scoring: 2.5 million records scored in 6 seconds on a single CPU system
 - Real-time scoring: 100 models on a single CPU: 0.085 seconds



HP Oracle Database Machine & ODM



- Integrated data warehouse solution
- Extreme Performance
 - 10-100X faster than conventional DW systems
- Scalability to Petabytes
- Enterprise-Ready
 - Complete data warehouse functionality
 - Enterprise-level availability and security
- Scoring of Oracle Data Mining models
 - Blazingly fast performance
 - For example, find the US customers likely to churn:

```
select cust_id
from customers
where region = 'US'
and prediction_probability(churnmod, 'Y' using *) > 0.8;
```

HP Oracle Database Machine & ODM



- In 11gR2, SQL predicates and Oracle Data Mining models are pushed to storage level for execution

For example, find the US customers likely to churn:


```
select cust_id
from customers
where region = 'US'
and prediction_probability(churnmod, 'Y' using *) > 0.8;
```

ODM 11gR2 Scoring: Offloaded to Exadata


- Data mining scoring executed in Exadata:

```
select cust_id
from customers
where region = 'US'
and prediction_probability(churnmod, 'Y' using *) > 0.8;
```

Scoring
function
executed in
Exadata



- All scoring functions offloaded to Exadata
- Benefits
 - Reduces data returned from Exadata to Database server
 - Reduces CPU utilization on Database Server
 - Up to 10x performance gains



**“If I had one hour to
save the world, I would
spend fifty-five minutes
defining the problem
and only five minutes
finding the solution”**

- Albert Einstein

(see also <http://www.wikihow.com/Define-a-Problem>)

Where to Start?

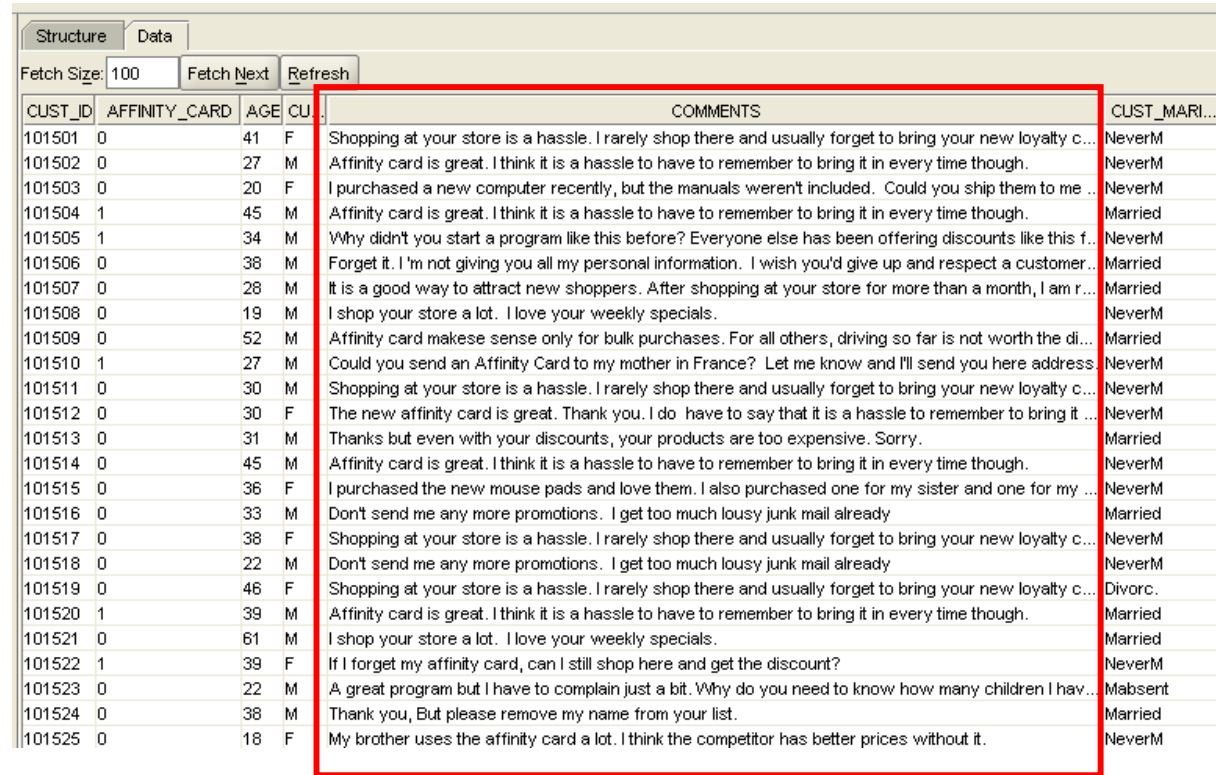
“Wrong: Catalog everything you have, and decide what data is important.

Right: Work backward from the solution, **define the problem explicitly, and map out the **data needed** to populate the investigation and models.”**

- James Taylor with Neil Raden, authors,
Smart (Enough) Systems

Oracle Data Mining and Unstructured Data

- Oracle Data Mining mines unstructured i.e. “text” data
- Include free text and comments in ODM models
- Cluster and Classify documents
- Oracle Text used to preprocess unstructured text

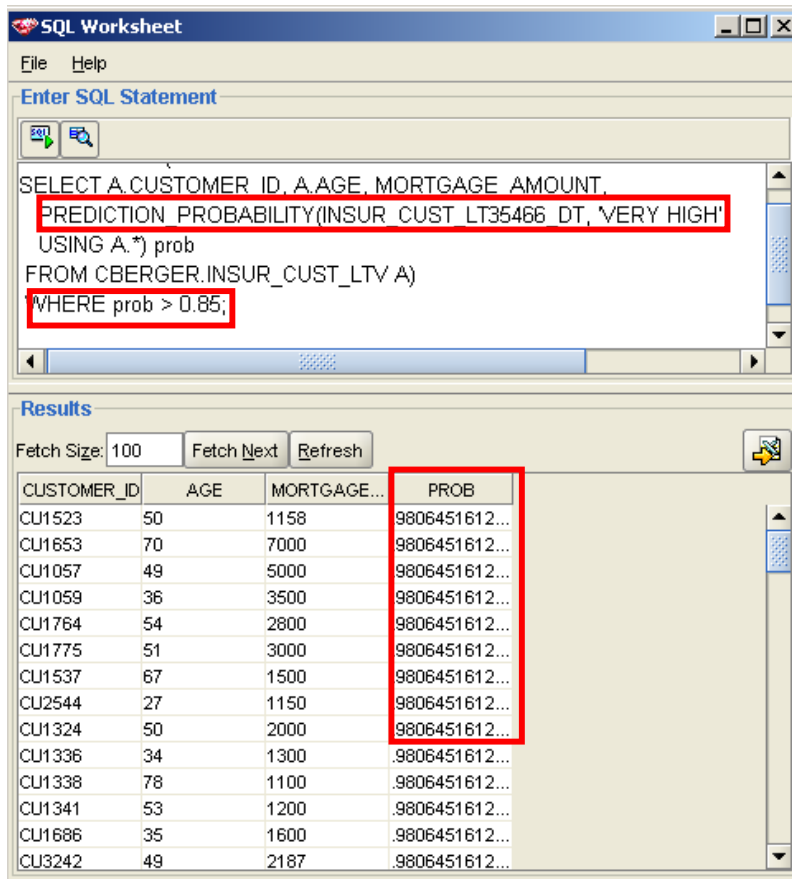


The screenshot shows the Oracle Data Mining interface with a table of customer data. The table has columns for CUST_ID, AFFINITY_CARD, AGE, GENDER, and COMMENTS. The COMMENTS column is highlighted with a red box, indicating it is the focus of the data mining process. The table contains 25 rows of data, each representing a customer's feedback or comment.

CUST_ID	AFFINITY_CARD	AGE	CU...	COMMENTS	CUST_MARI...
101501	0	41	F	Shopping at your store is a hassle. I rarely shop there and usually forget to bring your new loyalty c...	NeverM
101502	0	27	M	Affinity card is great. I think it is a hassle to have to remember to bring it in every time though.	NeverM
101503	0	20	F	I purchased a new computer recently, but the manuals weren't included. Could you ship them to me ...	NeverM
101504	1	45	M	Affinity card is great. I think it is a hassle to have to remember to bring it in every time though.	Married
101505	1	34	M	Why didn't you start a program like this before? Everyone else has been offering discounts like this f...	NeverM
101506	0	38	M	Forget it. I'm not giving you all my personal information. I wish you'd give up and respect a customer..	Married
101507	0	28	M	It is a good way to attract new shoppers. After shopping at your store for more than a month, I am r...	Married
101508	0	19	M	I shop your store a lot. I love your weekly specials.	NeverM
101509	0	52	M	Affinity card makes sense only for bulk purchases. For all others, driving so far is not worth the di...	Married
101510	1	27	M	Could you send an Affinity Card to my mother in France? Let me know and I'll send you here address.	NeverM
101511	0	30	M	Shopping at your store is a hassle. I rarely shop there and usually forget to bring your new loyalty c...	NeverM
101512	0	30	F	The new affinity card is great. Thank you. I do have to say that it is a hassle to remember to bring it ...	NeverM
101513	0	31	M	Thanks but even with your discounts, your products are too expensive. Sorry.	Married
101514	0	45	M	Affinity card is great. I think it is a hassle to have to remember to bring it in every time though.	NeverM
101515	0	36	F	I purchased the new mouse pads and love them. I also purchased one for my sister and one for my ...	NeverM
101516	0	33	M	Don't send me any more promotions. I get too much lousy junk mail already	Married
101517	0	38	F	Shopping at your store is a hassle. I rarely shop there and usually forget to bring your new loyalty c...	NeverM
101518	0	22	M	Don't send me any more promotions. I get too much lousy junk mail already	NeverM
101519	0	46	F	Shopping at your store is a hassle. I rarely shop there and usually forget to bring your new loyalty c...	Divorc.
101520	1	39	M	Affinity card is great. I think it is a hassle to have to remember to bring it in every time though.	Married
101521	0	61	M	I shop your store a lot. I love your weekly specials.	Married
101522	1	39	F	If I forget my affinity card, can I still shop here and get the discount?	NeverM
101523	0	22	M	A great program but I have to complain just a bit. Why do you need to know how many children I hav...	Mabsent
101524	0	38	M	Thank you, But please remove my name from your list.	Married
101525	0	18	F	My brother uses the affinity card a lot. I think the competitor has better prices without it.	NeverM

Example: Simple, Predictive SQL

- Select customers who are **more than 85% likely to be HIGH VALUE customers** & display their AGE & MORTGAGE_AMOUNT



The screenshot shows an SQL Worksheet window with the following content:

```
SQL Worksheet
File Help
Enter SQL Statement
SELECT A.CUSTOMER_ID, A.AGE, MORTGAGE_AMOUNT,
PREDICTION_PROBABILITY(INSUR_CUST_LT35466_DT, 'VERY HIGH'
USING A.*) prob
FROM CBERGER.INSUR_CUST_LTV A)
WHERE prob > 0.85;
```

The Results section shows a table with the following data:

CUSTOMER_ID	AGE	MORTGAGE...	PROB
CU1523	50	1158	9806451612...
CU1653	70	7000	9806451612...
CU1057	49	5000	9806451612...
CU1059	36	3500	9806451612...
CU1764	54	2800	9806451612...
CU1775	51	3000	9806451612...
CU1537	67	1500	9806451612...
CU2544	27	1150	9806451612...
CU1324	50	2000	9806451612...
CU1336	34	1300	.9806451612...
CU1338	78	1100	9806451612...
CU1341	53	1200	.9806451612...
CU1686	35	1600	.9806451612...
CU3242	49	2187	9806451612...

```
SELECT * from(
SELECT A.CUSTOMER_ID, A.AGE,
MORTGAGE_AMOUNT, PREDICTION_PROBABILITY
(INSUR_CUST_LT13126_DT, 'VERY HIGH'
USING A.*) prob
FROM CBERGER.INSUR_CUST_LTV A)
WHERE prob > 0.85;
```

Fraud Prediction Demo

```
drop table CLAIMS_SET;
exec dbms_data_mining.drop_model('CLAIMSMODEL');
create table CLAIMS_SET (setting_name varchar2(30), setting_value varchar2(4000));
insert into CLAIMS_SET values
('ALGO_NAME','ALGO_SUPPORT_VECTOR_MACHINES');
insert into CLAIMS_SET values ('PREP_AUTO','ON');
commit;
```

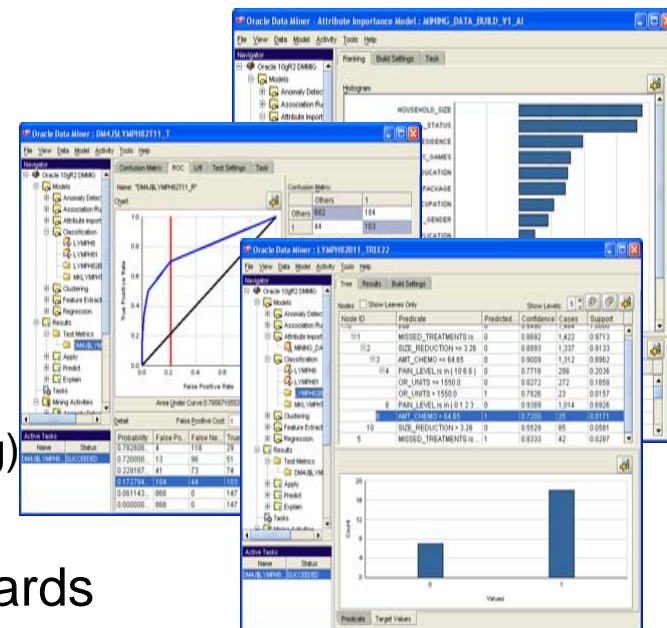
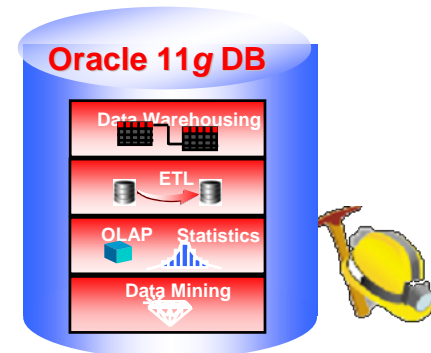
```
begin
dbms_data_mining.create_model('CLAIMSMODEL', 'CLASSIFICATION',
'CLAIMS', 'POLICYNUMBER', null, 'CLAIMS_SET');
end;
/
```

```
-- Top 5 most suspicious fraud policy holder claims
select * from
(select POLICYNUMBER, round(prob_fraud*100,2) percent_fraud,
rank() over (order by prob_fraud desc) rnk from
(select POLICYNUMBER, prediction_probability(CLAIMSMODEL, '0' using *) prob_fraud
from CLAIMS
where PASTNUMBEROFCLAIMS in ('2 to 4', 'more than 4')))
where rnk <= 5
order by percent_fraud desc;
```

POLICYNUMBER	PERCENT_FRAUD	RNK
6532	64.78	1
2749	64.17	2
3440	63.22	3
654	63.1	4
12650	62.36	5

Oracle Data Mining 11g

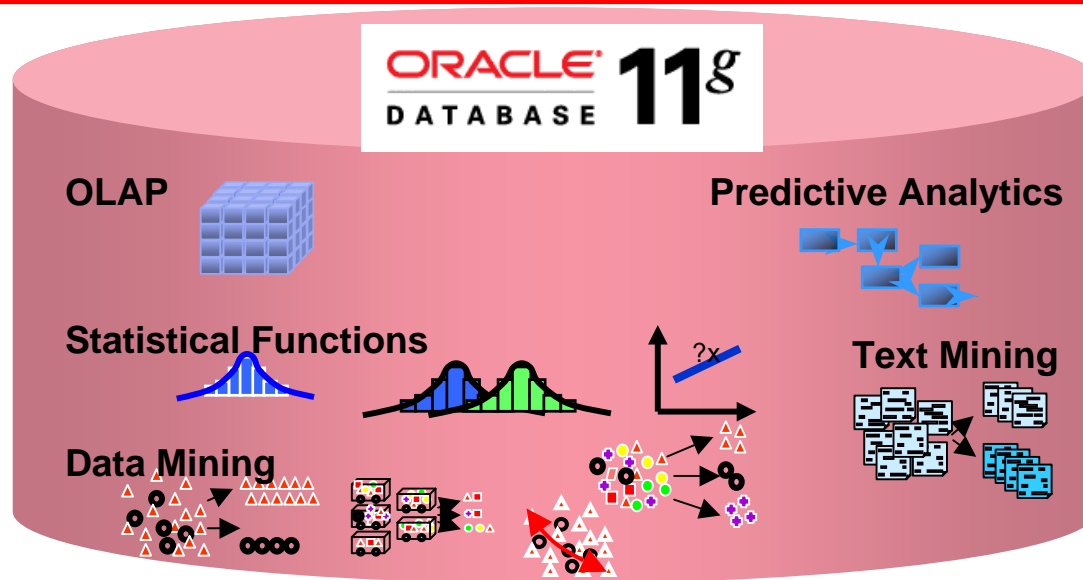
- Data Mining Functions (Server)
 - PL/SQL & Java APIs
 - Develop & deploy predictive analytics applications
- Wide range of DM algorithms (12)
 - Classification & regression
 - Clustering
 - Anomaly detection
 - Attribute importance
 - Feature extraction (NMF)
 - Association rules (Market Basket analysis)
 - Structured & unstructured data (text mining)
- Oracle Data Miner (GUI)
 - Simplified, guided data mining using wizards
- Predictive Analytics
 - “1-click data mining” from a spreadsheet



Analytical Database Changes **Everything**

It boils down to this:

Less data movement = **faster** analytics, and
faster analytics = **better** BI throughout the
enterprise



Integration with Oracle BI EE

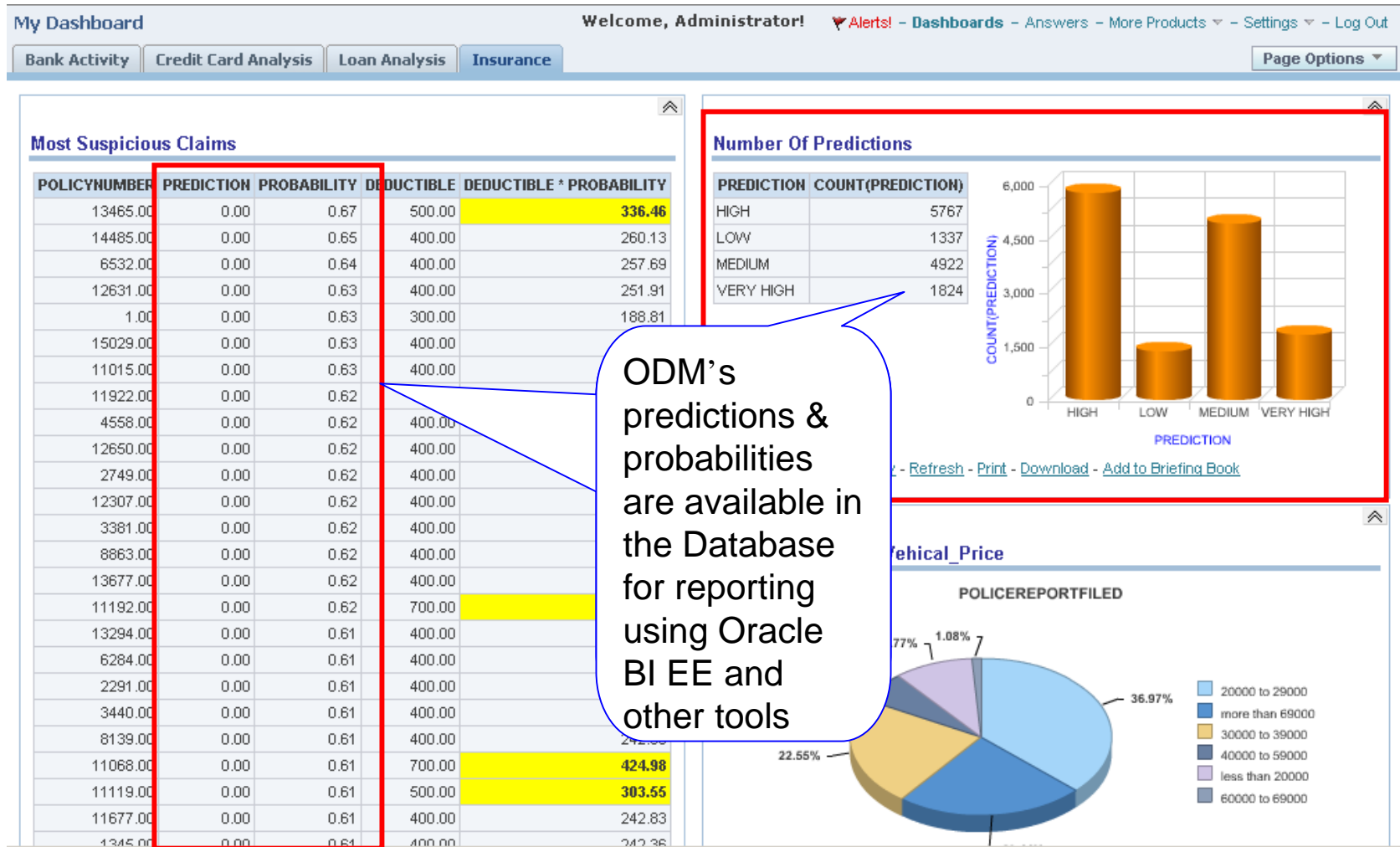
The screenshot displays the Siebel Analytics Administration Tool interface, divided into three main panels: Presentation, Business Model and Mapping, and Physical. The Presentation panel shows a hierarchy for 'CD_BUYERS' with 'DIM' and 'FACT' folders. 'KEY_FACTOR' and 'IMPORTANCE' are circled in red. The Business Model and Mapping panel shows a similar hierarchy with 'Sources' and 'Sales Facts' folders. The Physical panel shows the underlying data sources, including 'Oracle_10gR2', 'Oracle_cberger', and 'CBERGER'. A red circle highlights the 'CD_BUYERS' data source in the Physical panel. A blue callout box points to the 'YRS_RESIDENCE' and 'AFFINITY_CARD' dimensions in the Presentation panel, stating: "Oracle BI EE defines results for end user presentation". Another blue callout box points to the 'CD_BUYERS' data source in the Physical panel, stating: "Oracle Data Mining results available to Oracle BI EE administrators".

Oracle BI EE defines results for end user presentation

Oracle Data Mining results available to Oracle BI EE administrators

Example

Better Information for OBI EE Reports and Dashboards

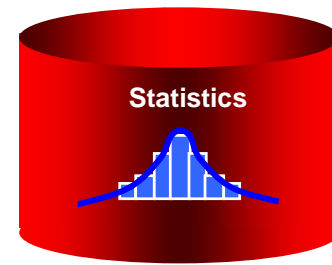




Oracle SQL Statistical Functions

(Free in Every Oracle Database)

11g Statistics & SQL Analytics



- Ranking functions
 - rank, dense_rank, cume_dist, percent_rank, ntile
- Window Aggregate functions (moving and cumulative)
 - Avg, sum, min, max, count, variance, stddev, first_value, last_value
- LAG/LEAD functions
 - Direct inter-row reference using offsets
- Reporting Aggregate functions
 - Sum, avg, min, max, variance, stddev, count, ratio_to_report
- Statistical Aggregates
 - Correlation, linear regression family, covariance
- Linear regression
 - Fitting of an ordinary-least-squares regression line to a set of number pairs.
 - Frequently combined with the COVAR_POP, COVAR_SAMP, and CORR functions

Descriptive Statistics

- DBMS_STAT_FUNCS: summarizes numerical columns of a table and returns count, min, max, range, mean, stats_mode, variance, standard deviation, median, quantile values, +/- n sigma values, top/bottom 5 values
- Correlations
 - Pearson's correlation coefficients, Spearman's and Kendall's (both nonparametric).
- Cross Tabs
 - Enhanced with % statistics: chi squared, phi coefficient, Cramer's V, contingency coefficient, Cohen's kappa
- Hypothesis Testing
 - Student t-test, F-test, Binomial test, Wilcoxon Signed Ranks test, Chi-square, Mann Whitney test, Kolmogorov-Smirnov test, One-way ANOVA
- Distribution Fitting
 - Kolmogorov-Smirnov Test, Anderson-Darling Test, Chi-Squared Test, Normal, Uniform, Weibull, Exponential

Descriptive Statistics

- MEDIAN & MODE

> SQL

- Median: takes numeric or datatype values and returns the middle value
- Mode: returns the most common value

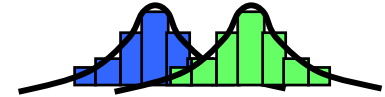
A. `SELECT STATS_MODE(AGE) from LYMPHOMA;`

B. `SELECT MEDIAN(AGE) from LYMPHOMA;`

C. `SELECT TREATMENT_PLAN, STATS_MODE(LYMPH_TYPE)
from lymphoma GROUP BY TREATMENT_PLAN;`

D. `SELECT LYMPH_TYPE, MEDIAN(SIZE_REDUCTION) from
LYMPHOMA GROUP BY LYMPH_TYPE ORDER BY
MEDIAN(SIZE_REDUCTION) ASC;`

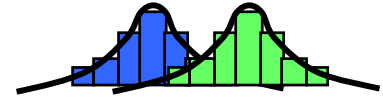
Split Lot A/B Offer testing



- Offer “A” to one population and “B” to another
- Over time period “t” calculate **median** purchase amounts of customers receiving offer A & B
- Perform **t-test** to compare
- If statistically significantly better results achieved from one offer over another, offer everyone higher performing offer



Independent Samples T-Test (Pooled Variances)

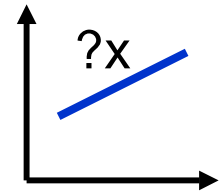


- Query compares the mean of AMOUNT_SOLD between MEN and WOMEN within CUST_INCOME_LEVEL ranges

```
SELECT substr(cust_income_level,1,22) income_level,  
       avg(decode(cust_gender,'M',amount_sold,null)) sold_to_men,  
       avg(decode(cust_gender,'F',amount_sold,null)) sold_to_women,  
       stats_t_test_indep(cust_gender, amount_sold, 'STATISTIC','F')  
       t_observed,  
       stats_t_test_indep(cust_gender, amount_sold) two_sided_p_value  
FROM sh.customers c, sh.sales s  
WHERE c.cust_id=s.cust_id  
GROUP BY rollup(cust_income_level)  
ORDER BY 1;
```

SQL Worksheet

Correlation Functions



- The CORR_S and CORR_K functions support nonparametric or rank correlation (finding correlations between expressions that are ordinal scaled).
- Correlation coefficients take on a value ranging from -1 to 1 , where:
 - 1 indicates a perfect relationship
 - -1 indicates a perfect inverse relationship
 - 0 indicates no relationship
- The following query determines whether there is a correlation between the AGE and WEIGHT of people, using Spearman's correlation:

```
select CORR_S(AGE, WEIGHT)
       coefficient,
       CORR_S(AGE, WEIGHT,
             'TWO_SIDED_SIG')
       p_value,
       substr(TREATMENT_PLAN, 1,15)
as TREATMENT_PLAN
from CBERGER.LYMPHOMA
GROUP BY TREATMENT_PLAN;
```

COEFFICIENT	P_VALUE	TREATMENT_PLAN
.1862586290028...	.019908367365...	Chemo&Radiation
-.0575579915035...	.072279268481...	Chemo_only
-.0746488538574...	.288631463930...	Experimental
-.1254971583227...	.000018140526...	Radiation

ORACLE® Analytics vs. SAS

1. In-Database Analytics Engine

Basic Statistics (*Free*)

Data Mining

Text Mining

2. Costs (ODM: \$23K cpu)

Simplified environment

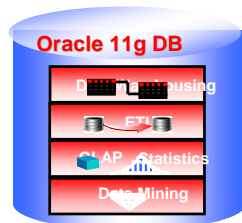
Single server

Security

3. IT Platform

SQL (standard)

Java (standard)



1. External Analytical Engine

Basic Statistics

Data Mining

Text Mining (*separate: SAS EM for Text*)

Advanced Statistics

2. Costs (SAS EM: \$150K/5 users)

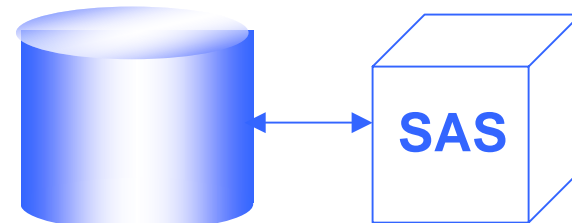
Duplicates data

Annual Renewal Fee (AUF)

(~45% each year)

3. IT Platform

SAS Code (proprietary)



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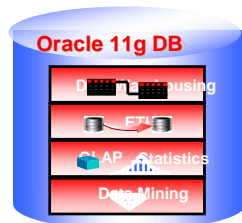
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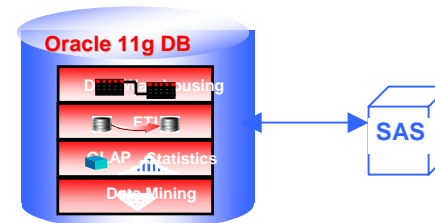
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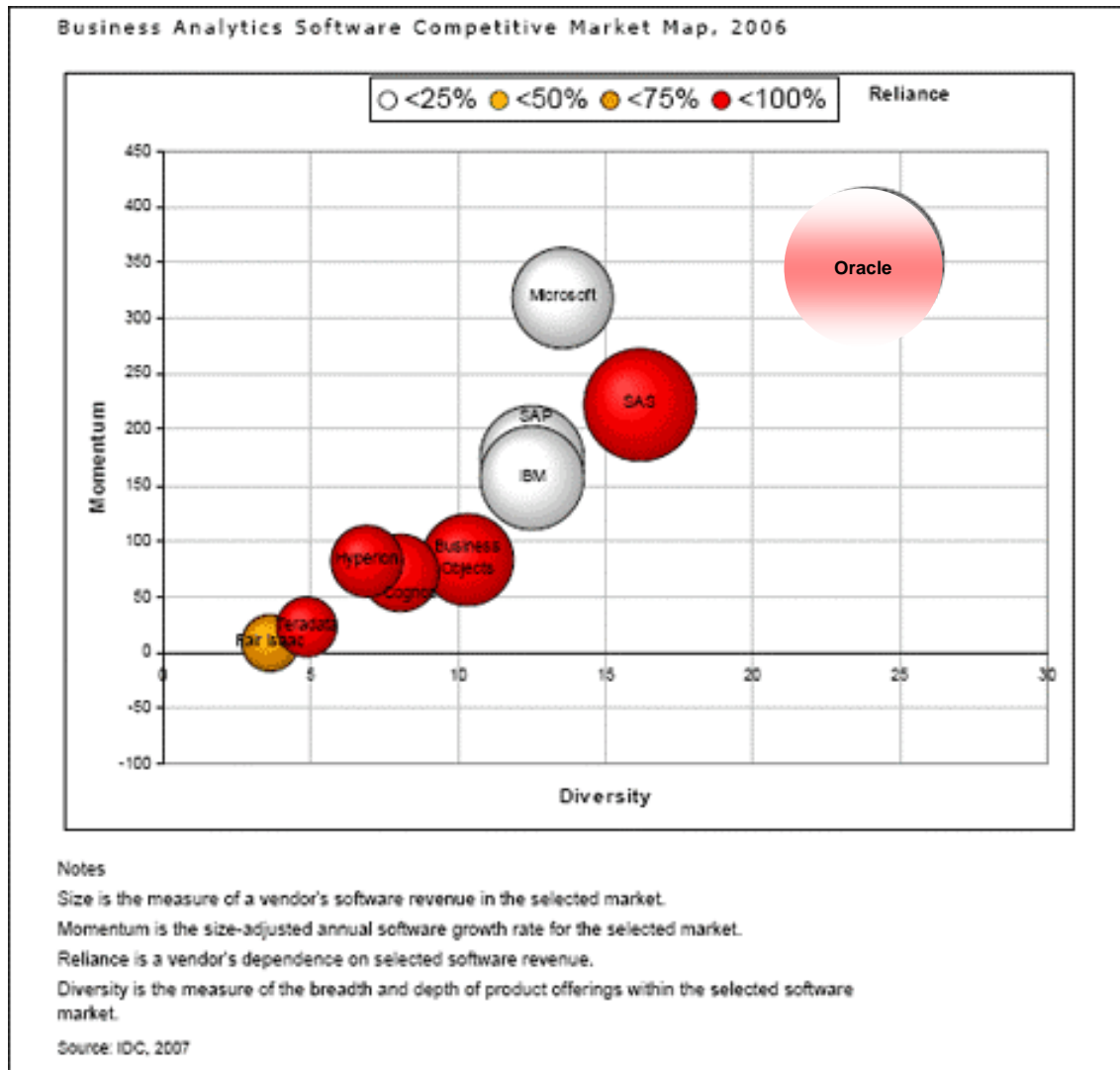
SAS In-Database Processing

3-Year Road Map



- “The goal of the SAS In-Database initiative is ... to achieve deeper technical integration with database providers..
- ..., the SAS engine often must load and extract data over a network to and from the DBMS. This presents a series of challenges:
 - ...Network bottlenecks between SAS and the DBMS constrain access to large volumes of data
 - ... the results of the SAS processing must be transferred back to the DBMS for final storage, which further increases the cost.

IDC Worldwide Business Analytics Software



http://www.oracle.com/corporate/analyst/reports/infrastructure/bi_dw/208699e.pdf

ORACLE

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Brief Demonstrations

1. Oracle Data Mining
2. Oracle Business Intelligence EE
3. CRM Sales Prospector



Oracle Data Mining + OBI EE

Quick Demo: Oracle Data Mining

- Scenario: Insurance Company
- Business problem(s):
 1. Better understand the business by looking at graphs of the data
 2. Identify the factors (attributes) most associated with Customer who BUY_INSURANCE
 3. Target Best Customers
 - a. Build a predictive model to understand who will be a VERY_HIGH VALUE Customer And WHY (IF... THEN.. Rules that can describe them)
 - b. Predict who is likely to be a VERY_HIGH VALUE Customer in the future
 - c. View results in an **OBI EE Dashboard**
 - Including other business problems e.g. Fraud, Cross-Sell, etc.
 - (Entire process **can be automated** w/ PL/SQL and/or Java APIs)

Oracle Data Mining + OBI EE

Understand the Data

Oracle Data Miner - Table : INSUR_CUST_LTV

File View Data Activity Tools Help

Navigator

- Oracle_CB
 - Mining Activities
 - Anomaly Detection
 - Association Rules
 - Attribute Importance
 - Classification
 - Clustering
 - Feature Extraction
 - Regression
 - Data Sources
 - CBERGER
 - Views
 - Tables
 - AAA_INSUR_CLAIMS
 - AAA_INSUR_CLAIMS_VKS20_52
 - AAA_INSUR_CLAIMS171536183...
 - AAA_INSUR_CLAIMS765132333
 - AAA_I...
 - AAA_I...
 - AAA_I...
 - AGE_G...
 - BANK...
 - BANK1
 - BLADD
 - BOSTO
 - BOSTO
 - BPRES
 - BPRES
 - BPRES
 - BPRES
 - bpress
 - BRAIN
 - BRAIN
 - BRAIN
 - CAR_S
 - CD_BU
 - CD_BU
 - CD_BU
 - CD_BU

Structure Data

Fetch Size: 100 Fetch Next Refresh

CUSTOMER_ID	LAST	STA...	REGION	SEX	PROFESSION	BUY_INS...	AGE	HAS_CHILD...	LTV_BIN	SALARY	LTV
CU2409	MARGIT	CA	West	F	Not specified	No	57	1	LOW	5887	13921.75
CU2411	GRAHAM	NY	NorthEast	M	Construction...	No	60	1	HIGH	69335	23833.75
CU2412	KALEIGH	FL	South	F	Medical Doctor	Yes	44	1	HIGH	58342	22485.5
CU2413	MITCH	NY	NorthEast	M	Accountant	Yes	61	1	MEDIUM	67061	18865.25
CU2414	ELDEN	CA	West	M	Software En...	No	68	0	HIGH	67489	29672.25
CU2416	SANDY	NY	NorthEast	M	PROF-22	No	32	0	MEDIUM	63963	20190.75
CU2417	ALEX	NY	NorthEast	M	Sales Repre...	No	27	0	MEDIUM	64964	19941
CU2418	ALI	MI	Midwest	F	Construction...	No	47	0	HIGH	58771	27892.75
CU2420	MERLE	NY	NorthEast	M	Clerical	No	38	1	MEDIUM	60946	19536.5
CU2421	ASLEY	CA	West	F	Clerical	No	52	0	HIGH	67694	29123.5
CU2422	GUADAL...	MI	Midwest	F	PROF-40	Yes	52	0	HIGH	61781	29145.25
CU2423	LIVIA	NY	NorthEast	F	IT Staff	No	64	1	HIGH	63875	25868.75
CU3100	SIOBHAN	MI	Midwest	F	PROF-15	No	62	1	MEDIUM	65359	17539.75
CU3101	REVA	MI	Midwest	F	Software En...	Yes	43	1	HIGH	61513	23178.25

Data Summarization Viewer: CBERGER.INSUR_CUST_LTV

File Help

Sample Count: 10014
Attribute Count: 31

Name	Mining ...	Attrib...	Average	Max	Min	Variance	Ni
AGE	numerical	NUMBER	37.34	84	0	214.23	0
BANK_FUNDS	numerical	NUMBER	2,562.97	105,000	0	23,068,...	0
BUY_INSURANCE	categori...	VARCH...					0
CAR_OWNERSHIP	categori...	NUMBER	0.93	1	0	0.06	0
CHECKING_AMOUNT	numerical	NUMBER	1,068.71	24,760	25	10,100,...	0
CREDIT_BALANCE	numerical	NUMBER	2,793.31	571,088	0	341,598,...	0
CREDIT_CARD_LIMITS	numerical	NUMBER	1,266.43	5,000	500	673,981.1	0
CUSTOMER_ID	categori...	VARCH...					0
FIRST	categori...	VARCH...					0
HAS_CHILDREN	categori...	NUMBER	0.49	1	0	0.25	0
HOUSE_OWNERSHIP	categori...	NUMBER	0.8	2	0	0.26	0
LAST	categori...	VARCH...					0
LTV	numerical	FLOAT	22,260.43	47,501.75	0	46,480,...	0
LTV_BIN	categori...	VARCH...					0
MARITAL_STATUS	categori...	VARCH...					0
MONEY_MONTHLY_OVERDRA...	numerical	FLOAT	53.63	93.64	-77.34	9.42	0
MONTHLY_CHECKS_WRITTEN	numerical	NUMBER	4.55	18	0	23.59	0
MORTGAGE_AMOUNT	numerical	NUMBER	2,005.7	90,000	0	10,274,...	0
N_MORTGAGES	categori...	NUMBER	0.8	2	0	0.26	0
N_OF_DEPENDENTS	numerical	NUMBER	2.06	6	0	2.4	0
N_TRANS_ATM	numerical	NUMBER	2.87	8	0	3.48	0
N_TRANS_KIOSK	numerical	NUMBER	1.95	10	0	3.66	0
N_TRANS_TELLER	numerical	NUMBER	1.8	9	0	2.17	0
N_TRANS_WEB_BANK	numerical	NUMBER	1,331.31	45,000	0	3,873,1...	0
PROFESSION	categori...	VARCH...					0

Activity Tasks

Activities Server

Oracle Data Mining helps to visualize the data

Histogram for selected attribute

Data Source: CBERGER.INSUR_CUST_LTV Attribute: AGE

Histogram for: AGE

Statistics:

- Sample count: 10014
- Minimum value: 0
- Maximum value: 84
- Average value: 37.34
- Variance: 214.23
- Sigma: 14.64
- Skewness: 0.35
- Kurtosis: 0.47

Group	Value(s)	Bin Count	% of Total
0	< 8.4	250	2.5
1	8.4 - 16.8	0	0.0
2	16.8 - 25.2	1940	19.37
3	25.2 - 33.6	2241	22.38
4	33.6 - 42	2011	20.08
5	42 - 50.4	1819	18.16
6	50.4 - 58.8	884	8.83

Binning Strategy: Equal Width...

Graph orientation: Vertical Horizontal

Help OK

Oracle Data Mining + OBI EE

Target the Right Customers

Oracle Data Miner guides the analyst through the data mining process

New Activity Wizard - Step 3 of 4: Data Usage

Review Data Usage Settings

Select the target column, and review the column settings. You can change the column settings to better match your understanding of the data. The default settings have been determined for each column based on the activity type and the characteristics of the data. The options of changing input and mining type vary based on the algorithm chosen. Click Help for more details.

[Data Summary](#)

Name	Alias	Target	Input	Data Type	Mining Type	Sparsity
CBERGER.INSUR_C...		<input type="radio"/>	<input checked="" type="checkbox"/>			
AGE	AGE	<input type="radio"/>	<input checked="" type="checkbox"/>	NUMBER	numerical	<input type="checkbox"/>
BANK_FUNDS	BANK_FUNDS	<input type="radio"/>	<input checked="" type="checkbox"/>	NUMBER	numerical	<input type="checkbox"/>
BUY_INSURANCE	BUY_INSURANCE	<input checked="" type="radio"/>	<input checked="" type="checkbox"/>	VARCHAR2	categorical	<input type="checkbox"/>
CAR_OWNERSHIP	CAR_OWNERSHIP	<input type="radio"/>	<input checked="" type="checkbox"/>	NUMBER	categorical	<input type="checkbox"/>
CHECKING_AMOU...	CHECKING_AMOU...	<input type="radio"/>	<input checked="" type="checkbox"/>	NUMBER	numerical	<input type="checkbox"/>
CREDIT_BALANCE	CREDIT_BALANCE	<input type="radio"/>	<input checked="" type="checkbox"/>	NUMBER	numerical	<input type="checkbox"/>
CREDIT_CARD_LI...	CREDIT_CARD_LI...	<input type="radio"/>	<input checked="" type="checkbox"/>	NUMBER	numerical	<input type="checkbox"/>
CUSTOMER_ID	CUSTOMER_ID	<input type="radio"/>	<input type="checkbox"/>	VARCHAR2	categorical	<input type="checkbox"/>
FIRST	FIRST	<input type="radio"/>	<input type="checkbox"/>	VARCHAR2	categorical	<input type="checkbox"/>
HAS_CHILDREN	HAS_CHILDREN	<input type="radio"/>	<input checked="" type="checkbox"/>	NUMBER	categorical	<input type="checkbox"/>
HOUSE_OWNERS...	HOUSE_OWNERS...	<input type="radio"/>	<input checked="" type="checkbox"/>	NUMBER	categorical	<input type="checkbox"/>
LAST	LAST	<input type="radio"/>	<input type="checkbox"/>	VARCHAR2	categorical	<input type="checkbox"/>
LTV	LTV	<input type="radio"/>	<input checked="" type="checkbox"/>	NUMBER	numerical	<input type="checkbox"/>
LTV_BIN	LTV_BIN	<input type="radio"/>	<input checked="" type="checkbox"/>	VARCHAR2	categorical	<input type="checkbox"/>
MARITAL_STATUS	MARITAL_STATUS	<input type="radio"/>	<input checked="" type="checkbox"/>	VARCHAR2	categorical	<input type="checkbox"/>
MONEY_MONTLY_...	MONEY_MONTLY_...	<input type="radio"/>	<input checked="" type="checkbox"/>	NUMBER	numerical	<input type="checkbox"/>
MONTHLY CHEC...	MONTHLY CHEC...	<input type="radio"/>	<input checked="" type="checkbox"/>	NUMBER	numerical	<input type="checkbox"/>

Include All Exclude All

Help < Back Next > Finish Cancel

Oracle Data Mining + OBI EE

Targeting High Value Customers

Oracle Data Mining builds a model that differentiates HI_VALUE_CUSTOMERS from others

The screenshot displays the Oracle Data Miner interface for a mining activity named 'INSUR_CUST_LTV833819485_BA'. The interface is divided into several sections:

- Navigator:** A tree view on the left showing the project structure, including Mining Activities, Anomaly Detection, Association Rules, Attribute Importance, and Classification. The Classification folder is expanded, showing various mining activities like 'AMAZ_AFF_CARD_BA', 'AMAZ_MINING_BUILD_TEXT_BA', etc.
- Activity Configuration:** The main area shows the activity name, type (Decision Tree Mining Activity), case table (CBERGER.INSUR_CUST_LTV), unique identifier (CUSTOMER_ID), and target (CBERGER.INSUR_CUST_LTV.LTV_BIN).
- Activity Steps:** A list of steps including 'Sample', 'Split', 'Build', and 'Test Metrics', each with a brief description of its function.
- Results:** A table showing the predicted target values and confidence for various nodes. The table has columns for Node ID, Predicate, Predicted Value, Confidence, Cases, and Support.
- Summary:** A section at the bottom right providing overall statistics: Predicted Target Value (VERY HIGH), Support (6.17%), Confidence (56.51%), Cases (538), and Level (5).
- Split Rules:** A list of rules used for splitting the data, such as 'MORTGAGE_AMOUNT > 0.5 AND HOUSE_OWNERSHIP is in 1 AND N_OF_DEPENDENTS <= 1.5 AND HAS_CHILDREN is in 0 AND SALARY > 64588.0'.

Node ID	Predicate	Predicted Value	Confidence	Cases	Support
0	true	HIGH	0.4849	8,722	1.0000
21	MORTGAGE_AMOUNT <= 0.5	MEDIUM	0.5780	2,154	0.2470
21	MORTGAGE_AMOUNT > 0.5	HIGH	0.6200	6,568	0.7530
22	HOUSE_OWNERSHIP is in 2	VERY HIGH	0.7921	433	0.0496
60	AGE <= 20.5	LOW	0.5000	12	0.0014
23	AGE > 20.5	VERY HIGH	0.8052	421	0.0483
24	N_OF_DEPENDENTS <= 3.5	VERY HIGH	0.8991	347	0.0398
25	AGE <= 26.5	HIGH	0.5283	38	0.0044
61	HAS_CHILDREN is in 0	VERY HIGH	1.0000	12	0.0014
62	HAS_CHILDREN is in 1	HIGH	0.7892	26	0.0030
63	AGE > 26.5	VERY HIGH	0.9515	309	0.0354
64	N_OF_DEPENDENTS > 3.5	HIGH	0.6351	74	0.0085
26	HOUSE_OWNERSHIP is in 1	HIGH	0.6500	6,135	0.7034
27	N_OF_DEPENDENTS <= 1.5	HIGH	0.7774	2,879	0.3301
28	HAS_CHILDREN is in 0	HIGH	0.6519	1,086	0.1245
29	SALARY <= 64588.0	HIGH	0.8759	548	0.0628
65	TIME_AS_CUSTOMER is in (2 4 5)	VERY HIGH	0.5875	80	0.0092
66	TIME_AS_CUSTOMER is in 1	HIGH	0.9615	468	0.0537
80	SALARY > 64588.0	VERY HIGH	0.5661	538	0.0617
67	AGE <= 23.5	HIGH	0.6250	16	0.0018
68	AGE > 23.5	VERY HIGH	0.5824	522	0.0598
31	HAS_CHILDREN is in 1	HIGH	0.8533	1,793	0.2056
32	SALARY <= 79990.0	HIGH	0.8778	1,711	0.1962
69	SALARY <= 59841.0	HIGH	0.5347	346	0.0397
70	SALARY > 59841.0	HIGH	0.9648	1,365	0.1565
71	SALARY > 79990.0	VERY HIGH	0.6585	82	0.0094
33	N OF DEPENDENTS > 1.5	HIGH	0.5375	3,256	0.3733

Oracle Data Mining + OBI EE

Targeting High Value Customers

Oracle Data Mining creates a prioritized list of customer who are likely to be high value

Activity: INSUR_CUST_LTV1330924475007_AA: Result Viewer: "INSUR_CUST_LTV_A15728619_A"

File Publish Help

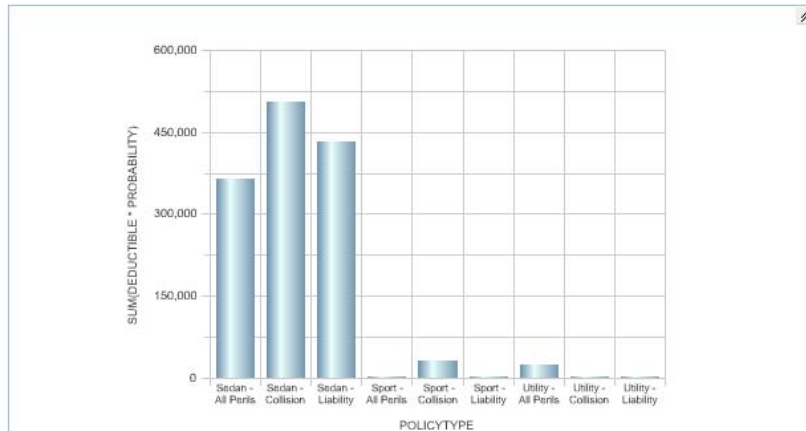
Apply Output Apply Settings Task

Apply Output Table: INSUR_CUST_LTV_A15728619_A

Fetch Size: 100 Refresh

DMR\$CAS...	PREDICTION	PROBABILITY	COST	RANK	NODE	LAST	AGE1	MARITAL_STATUS1	N_MORTGAGE...
CU3111	HIGH	0.9933	0.0067	1	66	CLIFFORD	47	DIVORCED	1
CU3113	MEDIUM	0.9933	0.0067	1	48	HUMBERTO	38	SINGLE	0
CU3116	HIGH	0.9648	0.0352	1	70	EUNA	39	DIVORCED	1
CU3117	MEDIUM	0.9933	0.0067	1	48	HOYT	45	SINGLE	0
CU3119	HIGH	0.9615	0.0385	1	66	LIZBETH	42	DIVORCED	1
CU3121	HIGH	0.9615	0.0385	1	66	BORIS	46	DIVORCED	1
CU3123	HIGH	1	0	1	52	DANA	52	SINGLE	0
CU3125	MEDIUM	0.8722	0.1278	1	73	TIM	49	DIVORCED	1
CU3126	HIGH	0.9648	0.0352	1	70	LASHAWN	61	DIVORCED	1
CU3127	MEDIUM	0.8127	0.1873	1	49	BUCK	41	SINGLE	0
CU3128	MEDIUM	0.8127	0.1873	1	49	WALTON	46	SINGLE	0
CU3129	VERY HIGH	0.9515	0.0485	1	63	ALDEN	49	MARRIED	2
CU3130	VERY HIGH	0.5824	0.4176	1	68	ANGELICA	41	DIVORCED	1
CU3132	HIGH	0.9648	0.0352	1	70	LIZZETTE	34	DIVORCED	1
CU3133	HIGH	0.9648	0.0352	1	70	ISABELLA	30	DIVORCED	1
CU3134	HIGH	0.9648	0.0352	1	70	DELPHA	46	DIVORCED	1
CU3136	LOW	1	0	1	39	GEORGE	0	SINGLE	0
CU3137	HIGH	0.9648	0.0352	1	70	RAUL	39	MARRIED	1
CU3138	VERY HIGH	0.5875	0.4125	1	65	ANGELO	44	DIVORCED	1
CU3139	MEDIUM	0.9933	0.0067	1	48	GARRET	43	SINGLE	0
CU3141	MEDIUM	0.9933	0.0067	1	48	BRYON	39	SINGLE	0
CU3142	HIGH	0.9648	0.0352	1	70	TAMMI	52	DIVORCED	1
CU3143	HIGH	0.9648	0.0352	1	70	LEEANN	46	DIVORCED	1

Integration with Oracle BI EE



Deductible by Policy Type -bar chart

POLICYTYPE	SUM(DEDUCTIBLE * PROBABILITY)
Sedan - All Perils	365451.59
Sedan - Collision	505398.98
Sedan - Liability	433042.90
Sport - All Perils	1640.33
Sport - Collision	30686.23
Sport - Liability	188.68
Utility - All Perils	25113.26
Utility - Collision	
Utility - Liability	



Oracle Data Mining provides more information and better insight

[products/bi/odm/index.html](#)

Oracle Data Mining

Know More, Do More, Spend Less

Business Decision Makers

- **Make Better Decisions**
- **Extract More Value from Your Data**
- **Lower Your Total Cost of Ownership**



Data Analysts

- **Get Results Faster**
- **Get More Results**
- **Easy to Use**



Integrators and IT

- **Create More Value for Your Organization**
- **Make Your Work Easier**
- **Transform IT from a Cost to a Profit Center**





Oracle Data Mining (SQL & Java) APIs

HCM Prediction Demo

```
drop table HCM_SET;  
exec dbms_data_mining.drop_model('HCMMODEL');
```

```
create table HCM_SET (setting_name varchar2(30), setting_value varchar2(4000));  
insert into HCM_SET values ('ALGO_NAME','ALGO_SUPPORT_VECTOR_MACHINES');  
insert into HCM_SET values ('PREP_AUTO','ON');  
commit;
```

```
begin  
dbms_data_mining.create_model('HCMMODEL', 'CLASSIFICATION',  
'EMPL_DATA', 'EMPL_ID', 'CURR_EMPL', 'HCM_SET');  
end;
```

```
-- accuracy (per-class and overall)  
col actual format a6  
select actual, round(corr*100/total,2) percent, corr, total-corr incorr, total from  
(select actual, sum(decode(actual,predicted,1,0)) corr, count(*) total from  
(select CURR_EMPL actual, prediction(HCMMODEL using *) predicted  
from EMPL_DATA_JUNE07)  
group by rollup(actual));
```

```
-- top 5 very high value, current employees most likely to leave  
select * from  
(select empl_id, round(prob_leave*100,2) percent_leave,  
rank() over (order by prob_leave desc) rnk from  
(select empl_id, prediction_probability(HCMMODEL, 'NO' using *) prob_leave  
from EMPL_DATA_JUNE07  
where CURR_EMPL = 'YES' and LTV_BIN = 'VERY HIGH'))  
where rnk <= 5  
order by percent_leave desc;
```

ACTUAL	PERCENT	CORR	INCORR	TOTAL
NO	84.04	3133	595	3728
YES	80.61	8159	1963	10122
	81.53	11292	2558	13850

Elapsed: 00:00:01.51

SQL>

EMPL_ID	PERCENT_LEAVE	RNK
772858	96.84	1
775441	95.65	2
777992	92.1	3
773473	91.51	4
771813	90.21	5

Elapsed: 00:00:00.29

SQL>

Predictive Analytics Use Case



- The cast:
 - Peter: a data mining analyst
 - Sally: a marketing manager
- Peter builds a decision tree classification model, `tree_model`
- Peter grants the ability to view/score the tree model to Sally

```
GRANT SELECT MODEL ON tree_model TO Sally;
```

- Sally inspects the model, likes it, and wants it deployed
- Sally scores the customer database using the new model and his understanding of the cost of contacting a customer and sends the new contact list to the head of the sales department

```
CREATE TABLE AS SELECT cust_name, cust_phone FROM  
customers  
WHERE prediction(Peter.tree_model cost matrix (0,5,1,0) using *) =  
'responder';
```

Real-time Prediction

with

```
records as (select
  78000 SALARY,
  250000 MORTGAGE_AMOUNT,
  6 TIME_AS_CUSTOMER,
  12 MONTHLY_CHECKS_WRITTEN,
  55 AGE,
  423 BANK_FUNDS,
  'Married' MARITAL_STATUS,
  'Nurse' PROFESSION,
  'M' SEX,
  4000 CREDIT_CARD_LIMITS,
  2 N_OF_DEPENDENTS,
  1 HOUSE_OWNERSHIP from dual)
```

```
select s.prediction prediction, s.probability probability
```

```
from (
```

```
select PREDICTION_SET(INSUR_CUST_LT68054_DT, 1 USING *) pset
from records) t, TABLE(t.pset) s;
```

**On-the-fly, single record
apply with new data (e.g.
from call center)**

PREDICTION	PROBABILITY
HIGH	.65123504738232096

Prediction Multiple Models/Optimization

```
➤ with records as (select
  178255 ANNUAL_INCOME,
  30 AGE,
  'Bach.' EDUCATION,
  'Married' MARITAL_STATUS,
  'Male' SEX,
  70 HOURS_PER_WEEK,
  98 PAYROLL_DEDUCTION from dual)
select t.*
from (
  select 'CAR_MODEL' MODEL, s1.prediction prediction, s1.probability probability, s1.probability*25000 as
  expected_revenue from (
    select PREDICTION_SET(NBMODEL_JDM, 1 USING *) pset
    from records ) t1, TABLE(t1.pset) s1
  UNION
  select 'MOTOCYCLE_MODEL' MODEL, s2.prediction prediction, s2.probability probability, s1.probability*2000 as
  expected_revenue from (
    select PREDICTION_SET(ABNMODEL_JDM, 1 USING *) pset
    from records ) t2, TABLE(t2.pset) s2
  UNION
  select 'TRICYCLE_MODEL' MODEL, s3.prediction prediction, s3.probability probability, s1.probability*50 as
  expected_revenue from (
    select PREDICTION_SET(TREEMODEL_JDM, 1 USING *) pset
    from records ) t3, TABLE(t3.pset) s3
  UNION
  select 'BICYCLE_MODEL' MODEL, s4.prediction prediction, s4.probability probability, s1.probability*200 as
  expected_revenue from (
    select PREDICTION_SET(SVMCMODEL_JDM, 1 USING *) pset
    from records ) t4, TABLE(t4.pset) s4
  ) t
order by t.expected_revenue desc;
```

**On-the-fly, multiple models;
then sort by expected revenues**



Oracle Sales Prospector

Larry Ellison Oracle Open World Keynote

November 2007

- Announces Fusion Edge CRM On-Demand Hosted Application with integrated data mining to mine customer database

on SFA Applications

ent 1G SFA Applica
ke Siebel, Salesforce.com

Oracle Data Mining

on 2G SFA Applications help you sell more
a Mines your customer database

What types of customers are buying what products?
What prospects most resemble those customers?

Business Intelligence for Sales People
The science of selling more
With best-fit references

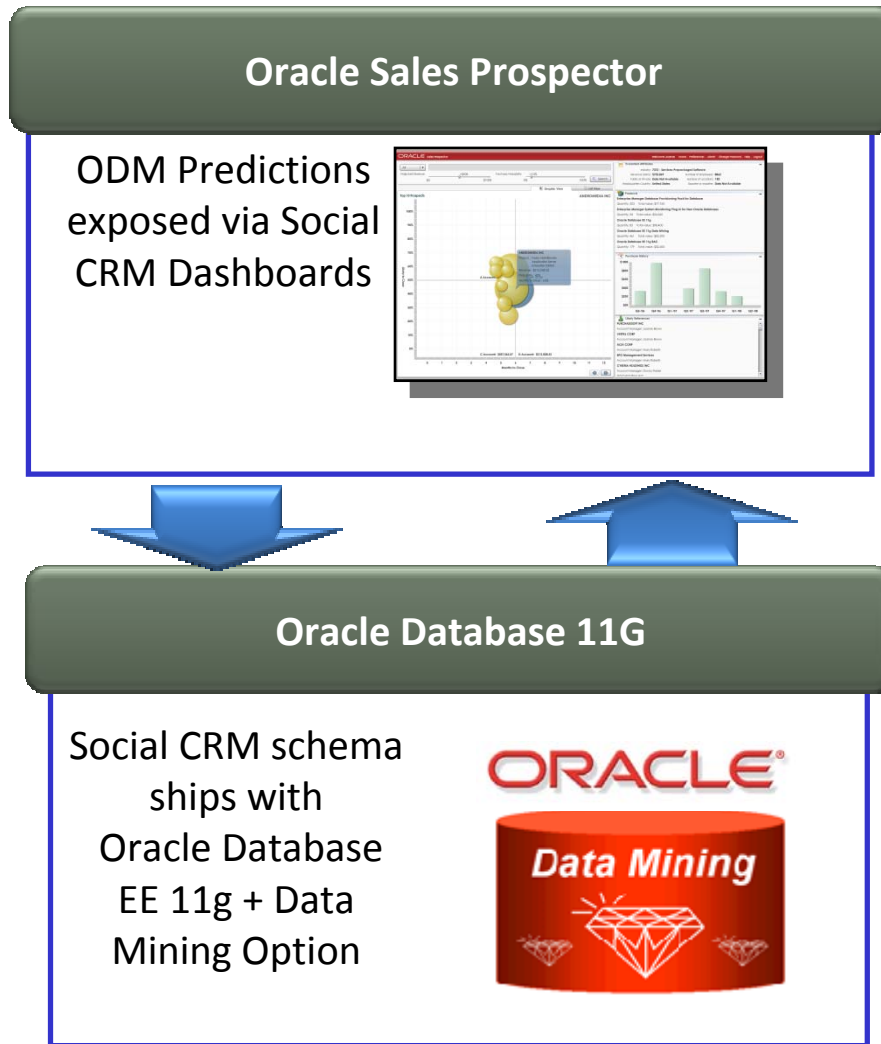
aS



How Can I Sell More?



Oracle Data Mining = the Science of Selling



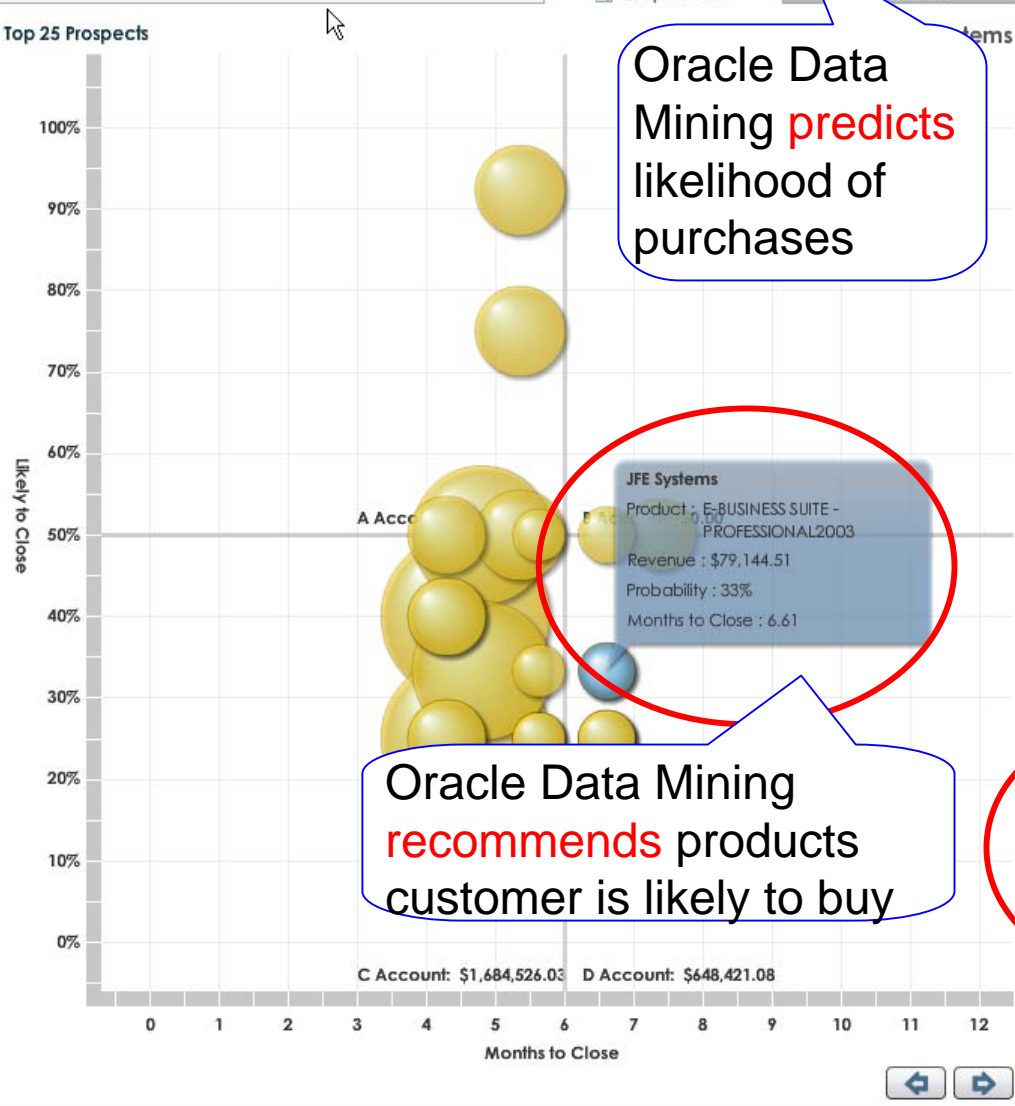
All Search

\$0 \$1M 0% 100%

Evaluated Attributes

Industry: **Electronics**
 Revenue (000's): **\$337,420**
 Public or Private: **Private**
 Headquarters Country: **Japan**

Number of Employees: **1538**
 Number of Locations: **13**
 Exporter or Importer: **Export**

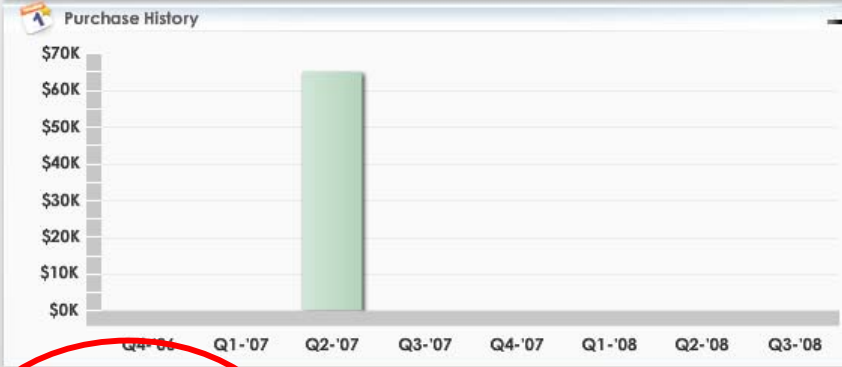


Oracle Data Mining **predicts** likelihood of purchases

Oracle Data Mining **recommends** products customer is likely to buy

Products

91 APP SVR SE	Quantity: 3	Total value: \$0
APP SVR EE	Quantity: 1	Total value: \$0
DATABASE EE	Quantity: 3	Total value: \$0
DATABASE SE	Quantity: 3	Total value: \$3,000,000
DIAGNOSTICS PACK	Quantity: 2	Total value: \$0



- Likely References**
- Aspen Aerogels Inc**
Account Manager: Dima Skorikov
 - FIRST CHURCH OF CHRIST SCIENTIST**
Account Manager: Dima Skorikov
 - Stratus Technologies Inc**
Account Manager: Dima Skorikov

Oracle Data Mining **suggests** likely references



Oracle Retail Data Model

Oracle Retail Data Model

The screenshot displays the Oracle Interactive Dashboards interface. At the top, there are navigation tabs for 'My Dashboard', 'OLAP', 'ORDM Demo Analytics', 'ORDM Demo KPIs', and 'ORDM MetaData'. Below this, a 'Mining Analysis' section is visible, with a navigation bar containing several analysis categories: Associate Basket Analysis, Associate Loss Analysis, Associate Sales Analysis, Product Category Mix, Customer Loyalty Analysis, Frequent Shopper Category Mix, Item Basket Analysis, Item POS Loss, and Store Loss. A red oval highlights this navigation bar. Below the navigation bar, there are filters for 'Year' (2007), 'Month' (BY 2007 M2), 'Division' (Pittsburgh Division), 'District', and 'Store Name' (PITTSBURGH 109). A 'Performance Measure' dropdown is set to 'Customer Loyalty Type'. A blue callout bubble points to the 'Customer Loyalty Analysis' tab, stating: 'Out-of-the box, Oracle Data Mining generates profiles of customers'. Another blue callout bubble points to the 'Item POS Loss' tab, stating: 'Oracle Data Mining automatically mines data for analysis reports'. The main content area shows a table titled 'Customer Profile' with columns for 'Customer Profile', 'Performance Measure Value', '% of Supporting Transaction', and 'Probability'. A red oval highlights the table content.

Customer Profile	Performance Measure Value	% of Supporting Transaction	Probability
Years Of Residence = '1', '2', '3', '4', '5' and YearS_OF_RESIDENCE = '1', '2', '3' and Household Size = '3+' and YearS_OF_RESIDENCE = '1'	LEAST LOYAL	2.45%	84.76%
Years Of Residence = '1', '2', '3', '4', '5' and YearS_OF_RESIDENCE = '1', '2', '3' and Household Size = '3+' and YearS_OF_RESIDENCE = '1' and Marital Status = 'DIVORCED', 'SEPARATED'	LEAST LOYAL	0.13%	100.00%
Years Of Residence = '1', '2', '3', '4', '5' and YearS_OF_RESIDENCE = '1', '2', '3' and Household Size = '3+' and YearS_OF_RESIDENCE = '1' and Marital Status = 'MARRIED', 'SINGLE'	LEAST LOYAL	1.60%	87.85%
Years Of Residence = '1', '2', '3', '4', '5' and YearS_OF_RESIDENCE = '4', '5' and Household Size = '3+'	PRETTY LOYAL	10.93%	83.17%
Years Of Residence = '1', '2', '3', '4', '5' and YearS_OF_RESIDENCE = '4', '5' and Household Size = '3+' and Marital Status = 'MARRIED', 'SINGLE'	PRETTY LOYAL	7.32%	81.58%
Years Of Residence = '1', '2', '3', '4', '5' and YearS_OF_RESIDENCE = '4', '5' and Household Size = 'LESS THAN 3'	MARGINALLY LOYAL	9.00%	86.29%
Years Of Residence = '1', '2', '3', '4', '5' and YearS_OF_RESIDENCE = '4', '5' and Household Size = 'LESS THAN 3' and Marital Status = 'MARRIED', 'SINGLE'	MARGINALLY LOYAL	6.52%	84.17%
Years Of Residence = '10', '6', '7', '8', '9' and Household Size = '3+'	MOST LOYAL	25.01%	88.28%
Years Of Residence = '10', '6', '7', '8', '9' and Household Size = '3+' and Marital Status = 'MARRIED', 'SINGLE'	MOST LOYAL	17.11%	86.10%
Years Of Residence = '10', '6', '7', '8', '9' and Household Size = 'LESS THAN 3'	PRETTY LOYAL	26.20%	80.88%

Summary

Oracle Data Mining Summary

- Powers Next-Generation Predictive Applications
 - Rapidly Build Applications that Automatically Mine Data
 - Code Once, Run Anywhere
 - Parallel and Distributed Processing
 - Industry Standard SQL and Java APIs
- Industry Leader in In-Database Data Mining
 - Option to the Industry Leading RDBMS—Oracle Database
 - Classification, Regression, Attribute Importance
 - Clustering, Market Basket Analysis, Anomaly Detection, Feature Extraction
 - Cutting Edge Algorithms: SVM, One-Class SVM, NMF, Scalable GLM



Oracle Data Mining Summary

- More Information from More Data
 - Easy to use Oracle Data Miner Graphical User Interface
 - Wide Range of In-Database Data Mining Algorithms and Statistics
 - Mine Text, Transactional, and Star Schema Data
 - Mine XML, Semantic RDF, Spatial, and OLAP Data
- Eliminate Barriers Between Analysts and IT
 - Quickly Disseminate Analytical Results and Models Throughout the Organization
 - Include Real-Time Predictive Models and New Insights in SQL queries
 - Eliminate Data Movement, Maximize Security

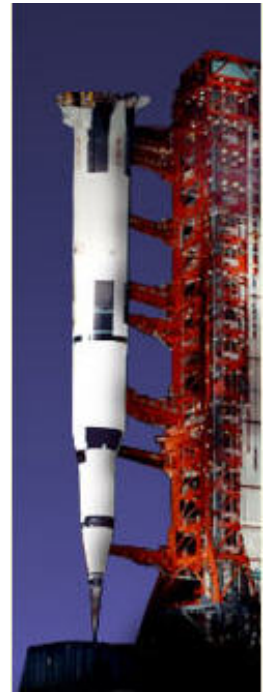




Getting Started

Data Mining Projects

- “The vast majority of BI professionals are excited about the prospects of data mining, but are fully mystified about where to begin or even how to prepare”
- “Of those who did initiate a modeling initiative, ...51% of data mining projects either never left the ground, did not realize value or the ultimate results were not measurable”
- “In most cases, those who attempted an implementation ended up building excellent predictive models that answer the wrong questions”
- “For any organization with annual revenues more than \$50 million, employing data mining technology is not a matter of whether, but when”



<http://www.the-modeling-agency.com>



ORACLE®

Getting Started with Oracle Data Mining

- You can download a **free evaluation copy** of Oracle Data Mining and try it out on your own computer. See the [Oracle Data Mining Administrators Guide](#), which tells how to install a database and set up a user account. Download the Oracle Database Enterprise Edition (10gR2 or 11g) from the [Oracle Technology Network](#). The Oracle Data Mining Option is installed by default with Oracle Database EE. For data analysts or those new to data mining, you will also want to download and install [Oracle Data Miner](#), the free, optional graphical user interface. A summary of algorithms supported by ODM with links to the documentation is posted [here](#).
- To get started quickly, Part I of [ODM Concepts](#) introduces you to the features and terminology of Oracle Data Mining. Then, use the [Oracle Data Mining Tutorial](#) to provide step-by-step guidance for using the Oracle Data Miner graphical interface. ... You can use the Oracle Data Miner (*Data --> Import...*) to import your own data in .csv text files and begin mining.
- For application developers, the [ODM Application Developer's Guide](#) along with the Oracle Data Mining sample programs gets you started writing SQL- or Java-based data mining applications.
- Some additional datasets for learning Oracle Data Mining include:
 - [CUST_INSUR_LTV](#) (dmp file), [CD_BUYERS](#) (dmp file), [EMPL_DATA](#) (dmp file), [LYMPHOMA](#) (dmp file)
- Application developers can integrate predictive analytics into any report or enterprise application using ODM's server-based PL/SQL or Java APIs. See [ODM Sample Programs](#) for demo sample code.
- **Oracle Data Mining Education through Oracle University**
 - [Installing Data Miner](#) (Oracle By Example)
 - [Solving Business Problems with Data Mining](#) (Oracle By Example)



More Information:

Oracle Data Mining 11g

- oracle.com/technology/products/bi/odm/index.html

Oracle Statistical Functions

- http://www.oracle.com/technology/products/bi/stats_fns/index.html

Oracle Business Intelligence Solutions

- oracle.com/bi

<http://search.oracle.com>



Contact Information: Email: Charlie.berger@oracle.com



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