

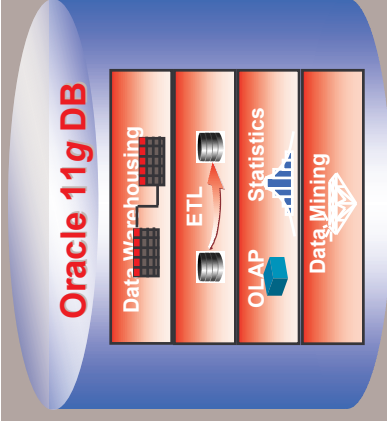
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November 11–15, 2007

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DATABASE **11g**



Predictive Analytics with Oracle Data Mining & Oracle BI EE



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Charlie Berger
Sr. Director Product Management,
Data Mining Technologies & Life Sciences & Healthcare Industries
Oracle Corporation
charlie.berger@oracle.com

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Harvard Business Review

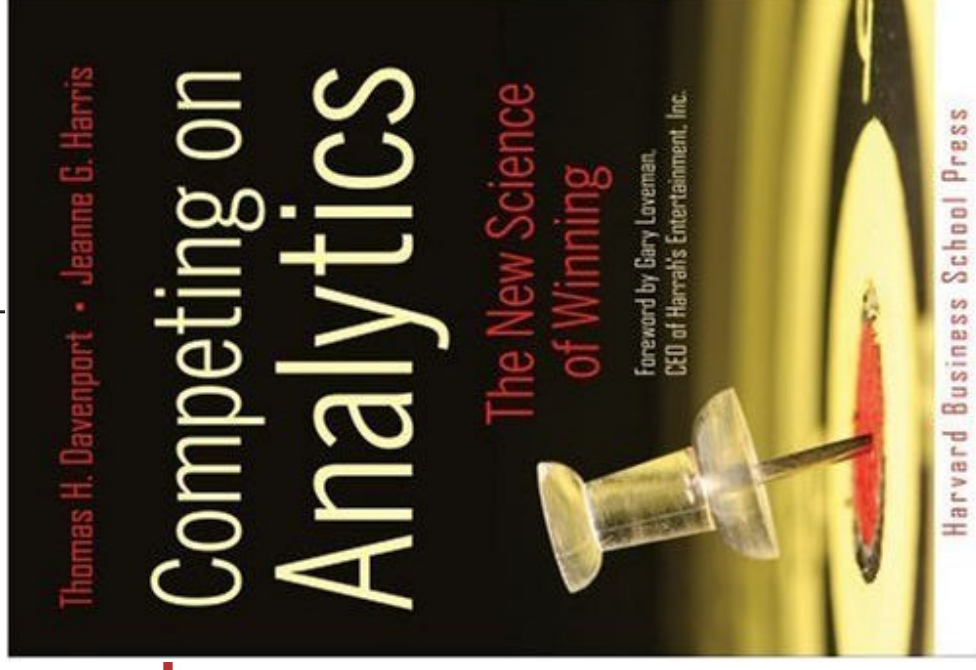


www.hbr.org

Some companies have built their very businesses on their ability to collect, analyze, and act on data. Every company can learn from what these firms do.

Competing on Analytics

by Thomas H. Davenport



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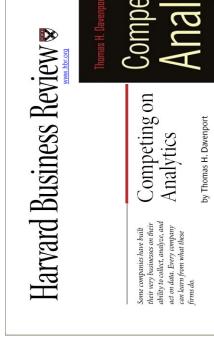
Competing on Analytics

- *“Some companies have built their very businesses on their ability to collect, analyze, and act on data. Every company can learn from what these firms do.”*

Competing on Analytics, by Thomas H. Davenport

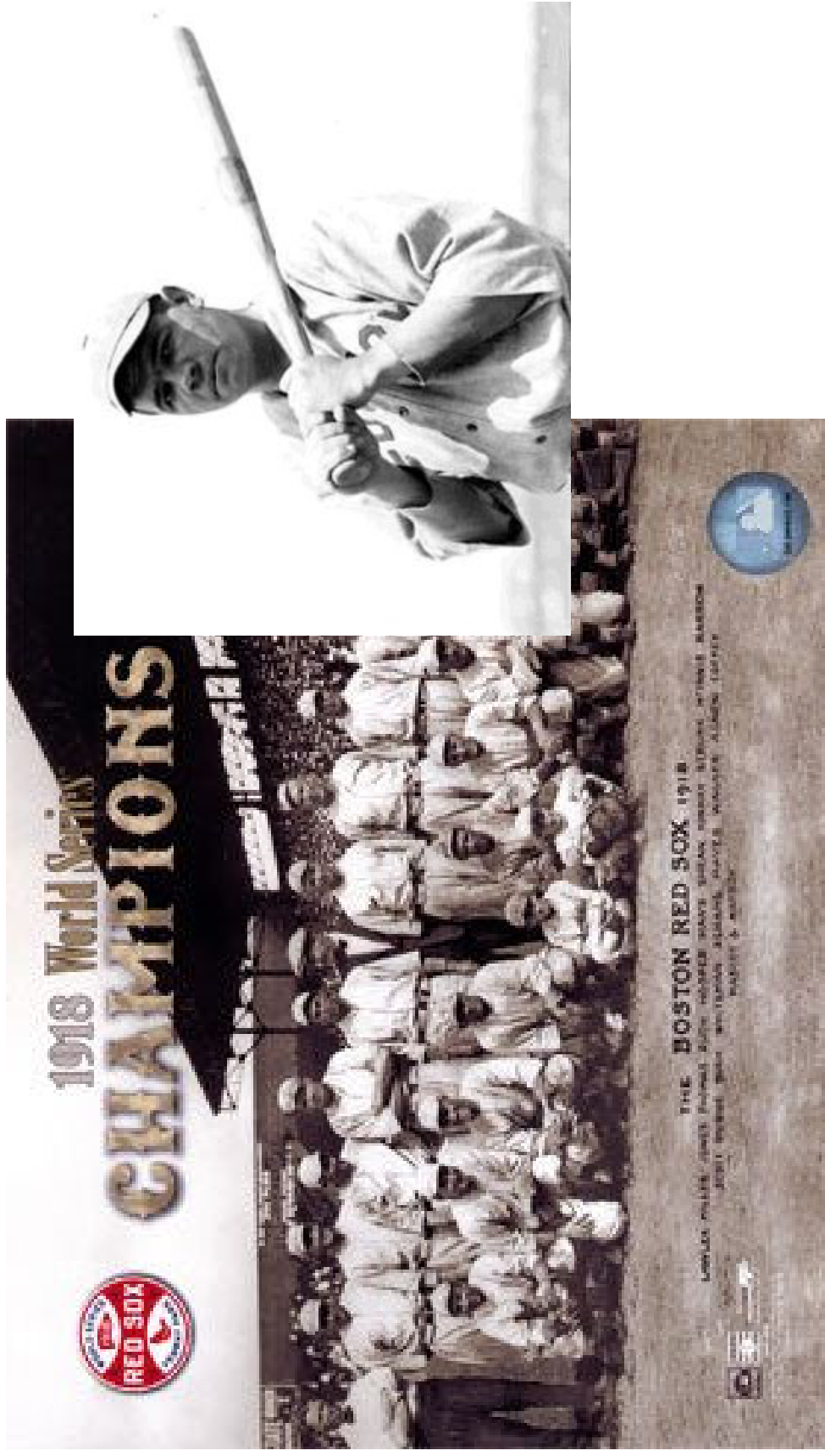
- *“Although numerous organizations are embracing analytics, only a handful have achieved this level of proficiency. But analytics competitors are the leaders in their varied fields—consumer products, finance, retail, and travel and entertainment among them.”* Competing on Analytics, by Thomas H. Davenport

- Business intelligence cited as the **top technology priority for CIOs in 2006** (surpassing security) - Gartner 2006
- **Sizable market - 11.5% growth** in 2005 for a market size of **\$5.7 billion** in worldwide software revenue - IDC 2006
- **“Organizations are moving beyond query and reporting”** - IDC 2006





Boston Red Sox 1918 World Series Champions





2003 Red Sox AL Championship Series



October 16, 2003: Holding a 5-2 lead in the eighth inning of Game 7 at Yankee Stadium, Red Sox manager Grady Little elects to leave starter Pedro Martinez on the mound. Martinez proceeds to give up four hits and three runs in the inning, allowing the Yankees to tie the game. In the bottom of the eleventh inning, leadoff hitter Aaron Boone hits a solo home run off of Tim Wakefield to left field, ending the game and the series, giving the Yankees their 39th American League pennant.





Florida Marlins Win 2003 World Series

Josh Beckett pitches a complete game shut out



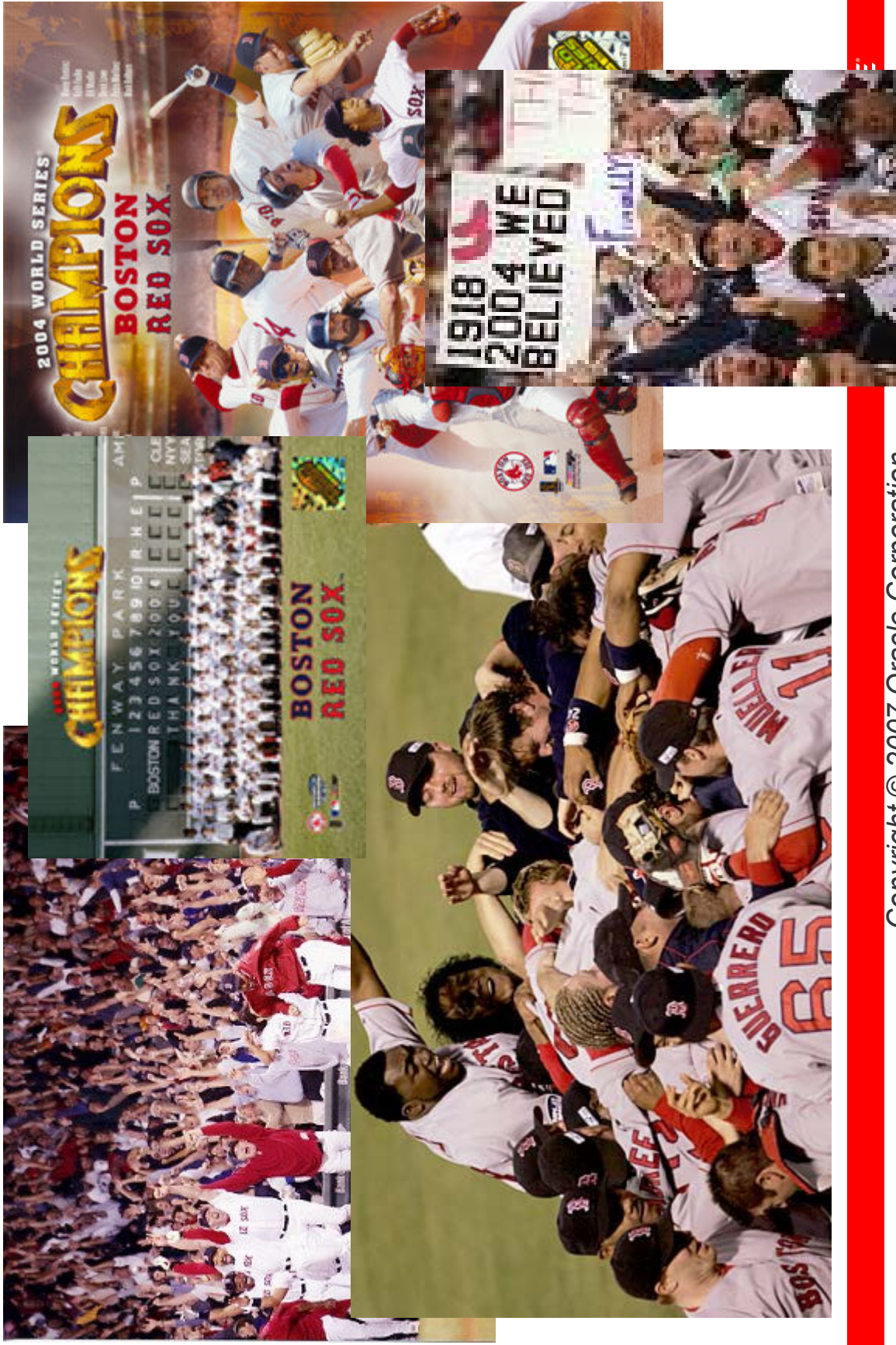
In the World Series, the Marlins put up their young roster with a \$54 million payroll up against the storied Yankees and their \$164 million payroll.

The Data Analyst



- George William "Bill" James is a baseball writer, historian, and statistician whose work has been widely influential. ... His approach, ... scientifically analyzes and studies baseball, often through the use of **statistical data**....
- In 2006, Time magazine named him as one of the **100 Most Influential People in the World**
- In 2003, James was **hired by former reader, John Henry, new owner of the Boston Red Sox**
- **Innovations e.g.:**
 - Runs Created. A statistic intended to quantify a player's contribution to runs scored, as well as a team's expected number of runs scored. Runs created is calculated from other offensive statistics. James' first version of it:
$$\text{Runs Created} = ((\text{Total Bases} * (\text{Hits} + \text{Walks})) / (\text{Plate Appearances})).$$

2004 World Series Champions!!





Talent + Experience + Analytics = Red Sox are 2004 World Champions!

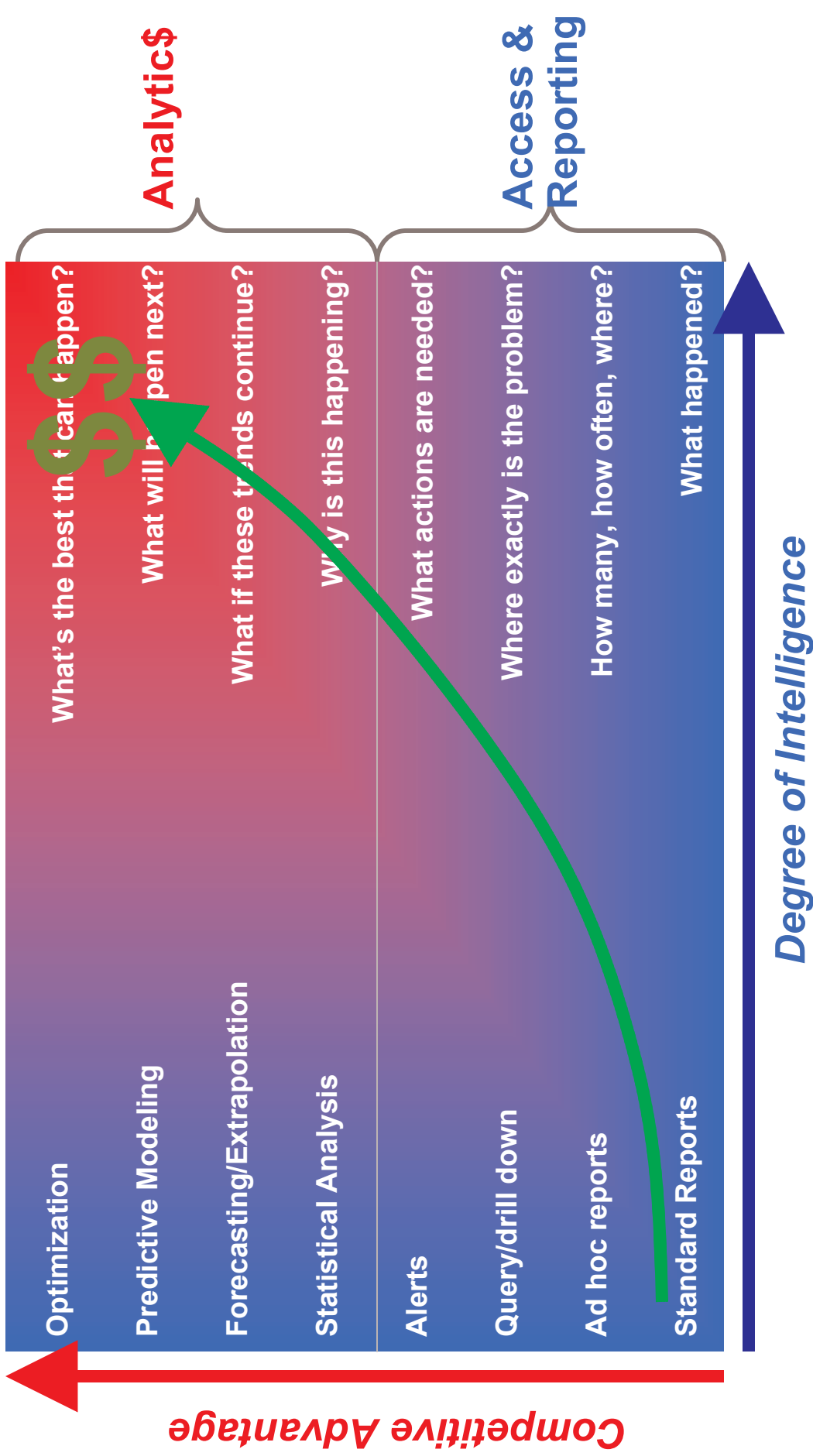
(1st time in 86 years!)



+



Competitive Advantage of BI & Analytics



Source: Competing on Analytics, by T. Davenport & J. Harris

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ORACLE®

on SFA Applications

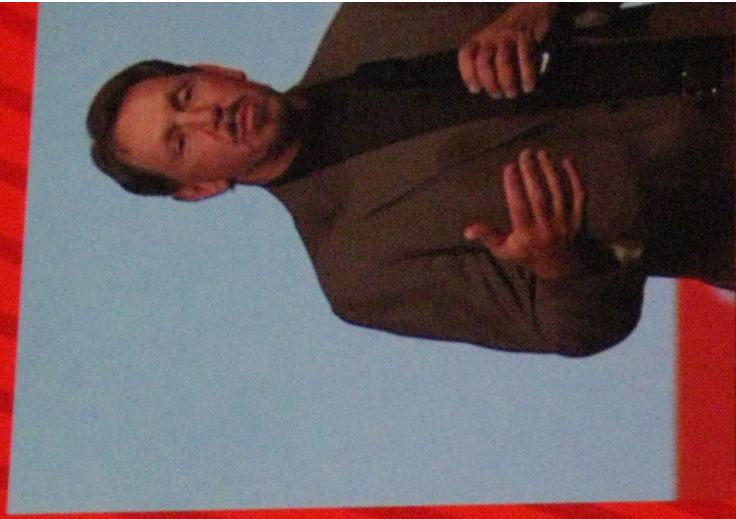
ent 1G SFA Applica
ke Siebel, Salesforce.com

Oracle Data Mining

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

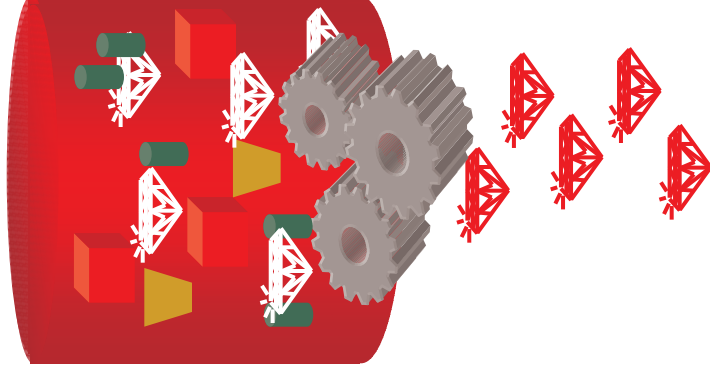
What types of customers are buying what products?
What prospects most resemble those customers?

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



What is Data Mining?

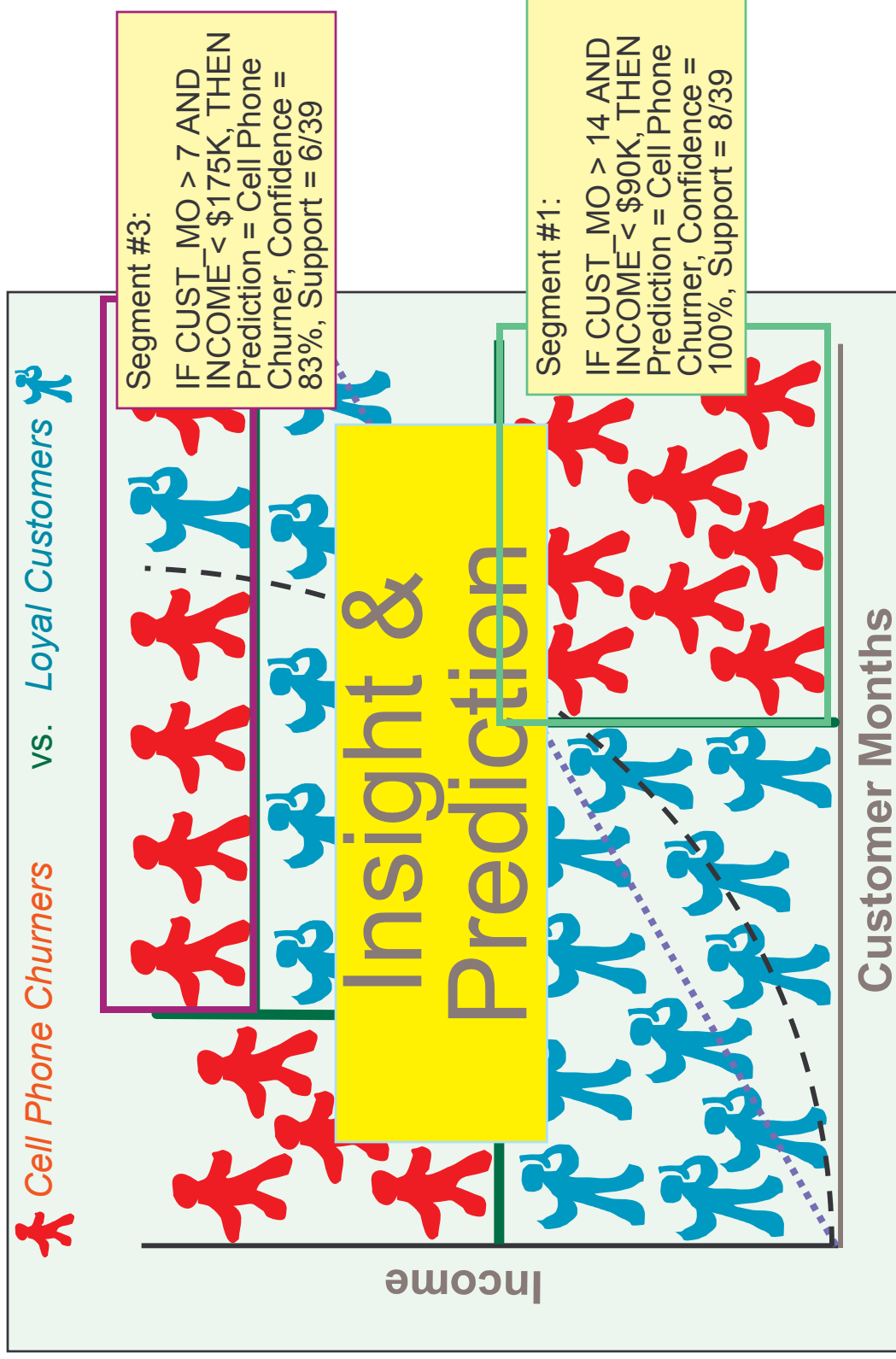
ORACLE[®] DATABASE 11g



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

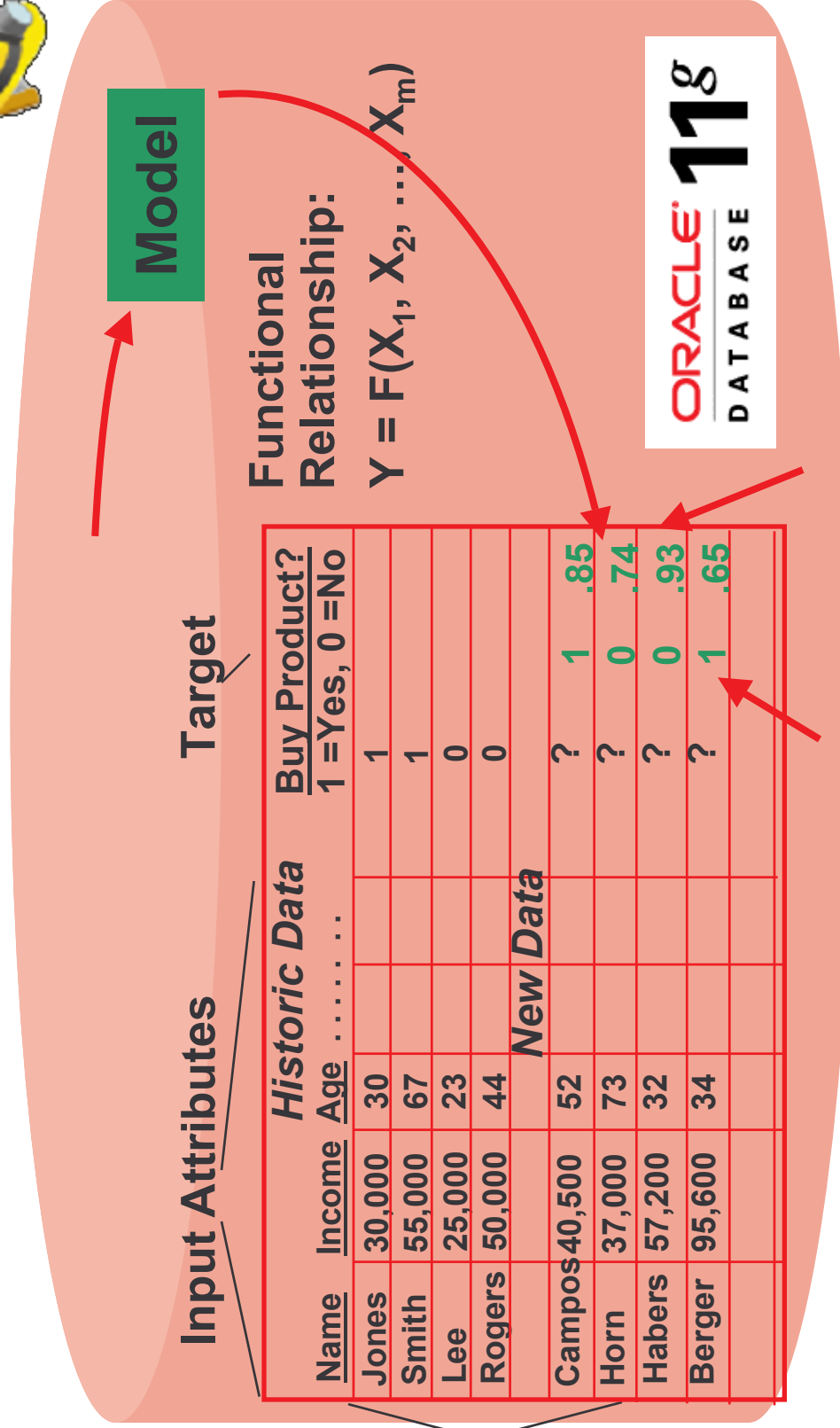
Data Mining Provides

Better Information, Valuable Insights and Predictions



Oracle Data Mining

Overview (Classification)



Input Attributes		Target
Name	Income Age	Buy Product? 1 = Yes, 0 = No
Jones	30,000 30	1
Smith	55,000 67	1
Lee	25,000 23	0
Rogers	50,000 44	0
New Data		
Campos	40,500 52	? .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

Cases

Business Intelligence & Analytics



Query and Reporting OLAP Data Mining

Extraction of detailed and roll up data

“Information”

Who purchased mutual funds in the last 3 years?

Summaries, trends and forecasts

“Analysis”

What is the average income of mutual fund buyers, by region, by year?

Knowledge discovery of hidden patterns

“Insight & Prediction”

Who **will buy** a mutual fund in the next 6 months and why?

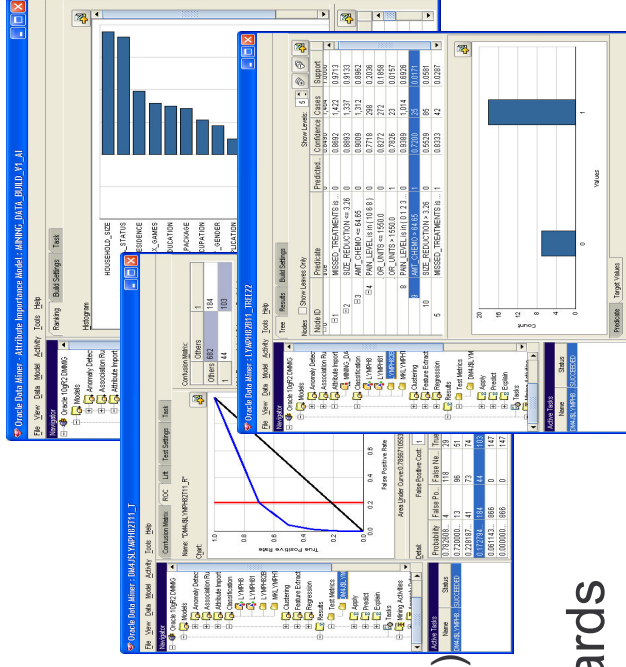
Example Data Mining Applications

Financial Services <ul style="list-style-type: none">– Combat attrition (churn)– Fraud detection– Loan default (Basel II)– Identify selling opportunities	Database Marketing <ul style="list-style-type: none">– Buy product x– More targeted & successful campaigns– Identify cross-sell & up-sell opportunities
Telecommunications <ul style="list-style-type: none">– Identify customers likely to leave– Target highest lifetime value customers– Identify cross-sell opportunities	Insurance, Government <ul style="list-style-type: none">– Flag accounting anomalies (Sarbanes-Oxley)– Reduce cost of investigating suspicious activity or false claims
Retail <ul style="list-style-type: none">– Loyalty programs– Cross-sell– Market-basket analysis– Fraud detection	Life Sciences <ul style="list-style-type: none">– Find factors associated with healthy or unhealthy patients– Discover gene and protein targets– Identify leads for new drugs

Oracle Data Mining 11g

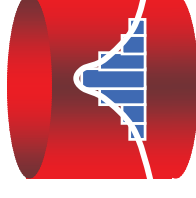
Oracle in-Database Mining Engine

- Data Mining Functions (Server)
 - PL/SQL & Java APIs
 - Develop & deploy predictive analytics applications
- Wide range of DM algorithms
 - 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



11g Statistics & SQL Analytics

FREE (Included in Oracle SE & EE)



- **Ranking functions**
 - rank, dense_rank, cum_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**
 - average, standard deviation, variance, min, max, median (via percentile_count), mode, group-by & roll-up
 - 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

Note: Statistics and SQL Analytics are included in Oracle Database Standard Edition

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**



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;
```

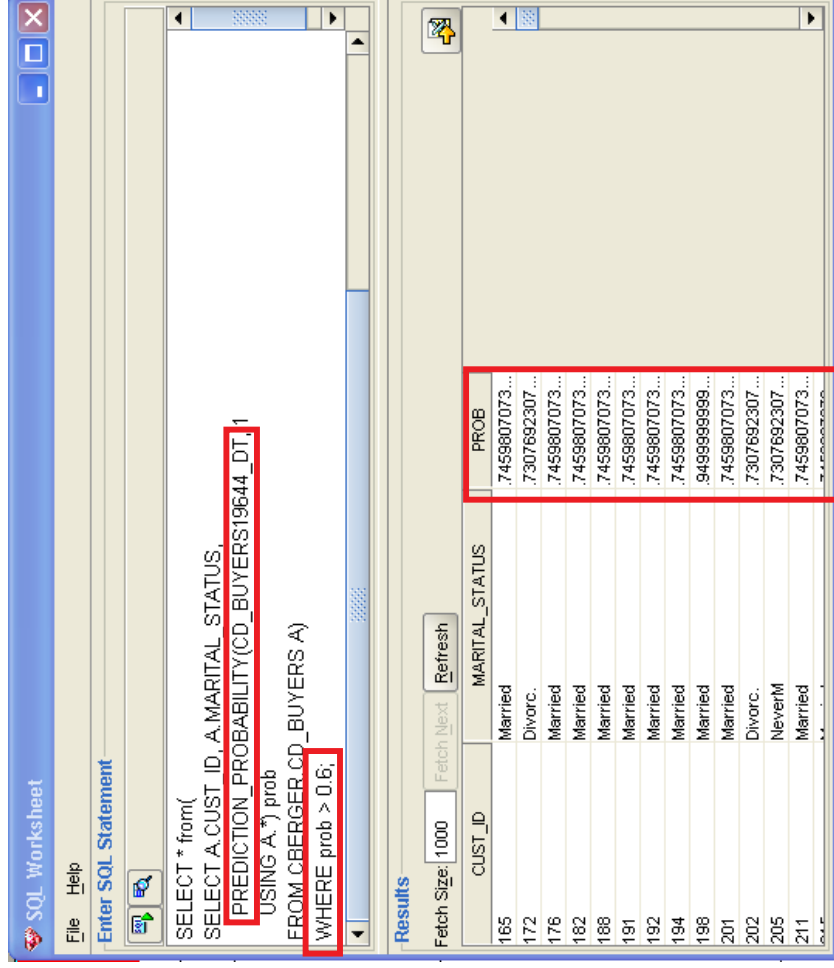
- Sally inspects the model, likes it, and wants it deployed
- Sally scores the customer database using the new model and his understanding of the cost of contacting a customer and sends the new contact list to the head of the sales department

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

Example

Simple, Predictive SQL

- Select customers who are **more than 60% likely to purchase a product** and display their marital status



The screenshot shows a SQL Worksheet window with the following SQL query entered:

```
SELECT * from(  
SELECT A.CUST_ID, A.MARITAL_STATUS,  
PREDICTION_PROBABILITY(CD_BUYERS19644_DT,1  
USING A.*) prob  
FROM CBERGER_CD_BUYERS A)  
WHERE prob > 0.6;
```

The results pane displays a table with the following data:

CUST_ID	MARITAL_STATUS	PROB
165	Married	.7459807073...
172	Divorc.	.7307692307...
176	Married	.7459807073...
182	Married	.7459807073...
188	Married	.7459807073...
191	Married	.7459807073...
192	Married	.7459807073...
194	Married	.7459807073...
198	Married	.9499999999...
201	Married	.7459807073...
202	Divorc.	.7307692307...
205	NeverM	.7307692307...
211	Married	.7459807073...

```
SELECT * from(  
SELECT A.CUST_ID, A.MARITAL_STATUS,  
PREDICTION_PROBABILITY(CD_BUYERS77  
117_DT, 1 USING A.*) prob  
FROM CBERGER_CD_BUYERS A)  
WHERE prob > 0.6;
```

Example

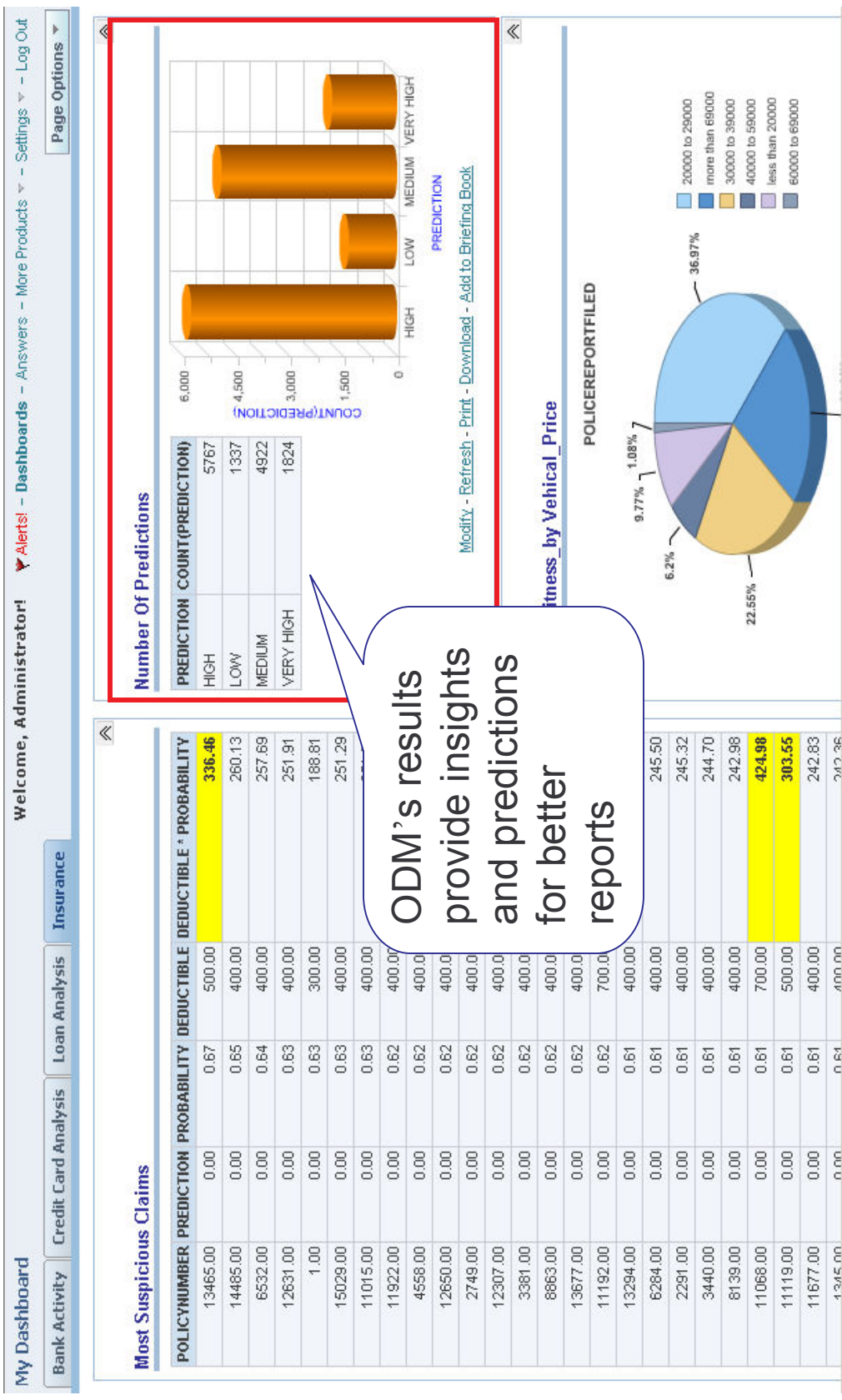
Better Information for OBI EE Reports and Dashboards

The screenshot displays the Oracle BI EE interface. On the left, a tree view shows the 'INSUR_CLAIMS' table with various columns listed. The main area shows a table with the following columns: POLICYNUMBER, VEHICLEPRICE, NUMBEROF CARS, WITNESSPRESENT, AGE OF VEHICLE, and PROBABILITY. A red box highlights the 'PROBABILITY' column, which contains values ranging from 0.60 to 0.63. A callout box points to this column with the text: 'ODM's Prediction probabilities available in Database for Oracle BI EE and other reporting tools'.

POLICYNUMBER	VEHICLEPRICE	NUMBEROF CARS	WITNESSPRESENT	AGE OF VEHICLE	PROBABILITY
11015.00	30000 to 39000	1 vehicle	No	more than 7	0.63
1.00	more than 69000	3 to 4	No	3 years	0.63
12650.00	30000 to 39000	1 vehicle	No	2 years	0.63
11922.00	more than 69000	1 vehicle	No	5 years	0.62
11192.00	30000 to 39000	1 vehicle	Yes	7 years	0.62
13294.00	20000 to 29000	2 vehicles	Yes	5 years	0.61
6284.00	40000 to 59000	1 vehicle	No	more than 7	0.61
8139.00	30000 to 39000	1 vehicle	Yes	6 years	0.61
11119.00	more than 69000	1 vehicle	No	7 years	0.61
11677.00	20000 to 29000	2 vehicles	No	5 years	0.61
8561.00	less than 20000	1 vehicle	No	4 years	0.61
11068.00	20000 to 29000	2 vehicles	No	7 years	0.61
11130.00	20000 to 29000	1 vehicle	Yes	more than 7	0.60
13967.00	20000 to 29000	1 vehicle	No	5 years	0.60
9673.00	20000 to 29000	1 vehicle	Yes	4 years	0.60
3471.00	30000 to 39000	1 vehicle	No	3 years	0.60
4365.00	30000 to 39000	1 vehicle	No	6 years	0.60
14101.00	20000 to 29000	1 vehicle	Yes	more than 7	0.60
7918.00	20000 to 29000	2 vehicles	No	6 years	0.60
11532.00	more than 69000	1 vehicle	No	2 years	0.60

Example

Better Information for OBI EE Reports and Dashboards



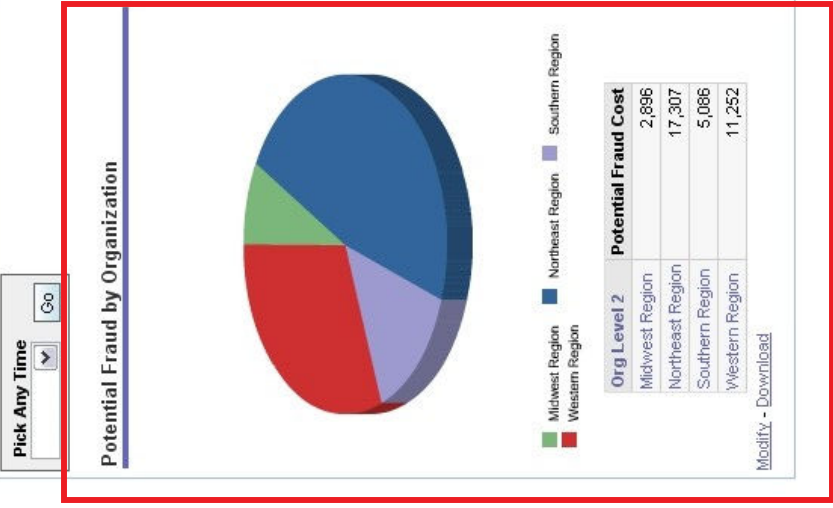
Integration with Oracle BI EE

ODM provides likelihood of expense reporting fraudand other important questions.

Oracle Business Intelligence Dashboard

My Dashboard | Organization Analysis | Category Analysis

Welcome, John Smith | Dashboards - Answers - Advanced Report



Most Suspicious Activities

Employee	Item	Day	Amount	Probability	Potential Fraud Cost
Louis Hagode	Misc. Employee Expenses	31-Dec-2003	15,740	59	9,265
Paul Laker	Misc. Employee Expenses	17-Dec-2003	4,996	56	2,792
Louis Hagode	Misc. Employee Expenses	30-Dec-2003	4,259	60	2,537
Dave Lindquist	Misc. Employee Expenses	01-Jan-2004	2,253	63	1,422
Steven Daniel	Hotel-Lodging	14-Dec-2004	2,304	52	1,205
Paul Laker	Hotel-Lodging	19-Dec-2004	2,219	54	1,201
Steven Daniel	Hotel-Lodging	22-Dec-2004	1,896	52	979
Christina Donohue	Hotel-Lodging	21-Dec-2004	1,744	53	919
Michael Cheng	Hotel-Lodging	21-Dec-2004	1,598	53	842
Dennis Haas	Hotel-Lodging	14-Dec-2004	1,539	52	805

Modify - Download

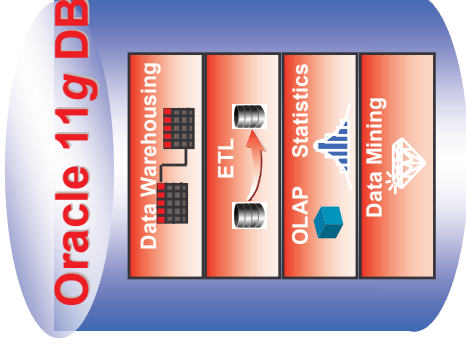
Trends by Organization

Org Level 2	Quarter	Amount	Amt Parent Share	Amt % Chg Prior Per	Potential Fraud Cost	PFC Parent Share	PFC % Chg Prior Per
Midwest Region	Q1 2004	12,173	14	-9	1,056	17	37
	Q2 2004	6,528	14	-46	0	0	-100
	Q3 2004	7,427	13	14	0	0	0
	Q4 2004	15,642	8	111	1,841	6	0
Northeast Region	Q1 2004	28,182	32	-11	537	9	-75
	Q2 2004	14,986	33	-47	0	0	-100
	Q3 2004	21,287	38	42	742	100	0
	Q4 2004	95,027	49	346	16,028	54	2,061
Southern Region	Q1 2004	15,773	18	13	2,003	33	155
	Q2 2004	7,458	16	-53	0	0	-100
	Q3 2004	8,674	15	16	0	0	0
	Q4 2004	27,154	14	213	3,083	10	0
Western Region	Q1 2004	30,909	36	-45	2,487	41	-84
	Q2 2004	16,863	37	-45	0	0	-100
	Q3 2004	18,612	33	10	0	0	0

In-Database Data Mining

Advantages

- ODM architecture provides greater performance, scalability, and data security
- Data remains in the database at all times...with appropriate access security control mechanisms—**fewer moving parts**
- Straightforward inclusion within interesting and arbitrarily complex queries
- Real-world scalability—available for mission critical apps
- 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



Industry Analysts



PREDICTIVE ANALYTICS: Extending the Value of Your

Data Warehousing Investment, By Wayne W. Eckerson

“...According to our survey, **most organizations plan to significantly increase the analytic processing within a data warehouse database in the next three years, particularly for model building and scoring, which show 88% climbs.** The amount of data preparation done in databases will only climb 36% in that time, but it will be done by almost two-thirds of all organizations (60%)—double the rate of companies planning to use the database to create or score analytical models.”

“...it’s surprising that about **one-third of organizations plan to build analytical models in databases within three years.**”

“**We leverage the data warehouse database when possible,**” says one analytics manager. He says most analysts download a data sample to their desktop and then upload it to the data warehouse once it’s completed. **‘Ultimately, however, everything will run in the data warehouse,’** the manager says.”

Industry Analysts Bloor

Oracle data mining: not only good but affordable too!

Published: 30th November, 2006, Bloor Research 2007

“...the Oracle data mining option is one of the **great bargains** available today because it is affordable and ... is a real **Rolls Royce of capability** and features. ...redesigned from scratch and **put the algorithms into the database** to ensure that, not only is the execution of the algorithms efficient, but the vast amounts of data handling that typifies traditional datamining is minimised. ... Oracle are leaving the database in situ and mining it there, which **saves a lot of effort and will greatly increase productivity**.”

This is a **fully featured, highly sophisticated data mining capability** to enable professionals to operate against Oracle data sets with productivity and precision. Oracle data mining has a broad range of available algorithms, which enable it to undertake virtually every kind of business and scientific analysis that one can think of. ...

...Oracle are giving the data mining professional **a real alternative to SAS and SPSS** with an offering that is equally as well featured, but which promises to **outperform any standalone offering**.

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ORACLE® Analytics



vs.

1. In-Database Analytics Engine

Basic Statistics (Free)

Data Mining

Text Mining



2. Standards Based Development Platform

Java (standard)

SQL (standard)

J2EE (standard)

3. Costs (ODM: \$20K cpu)

Simplified environment

Single server

Security

1. External Analytical Engine

Basic Statistics

Data Mining

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

Advanced Statistics

2. Proprietary Development Platform

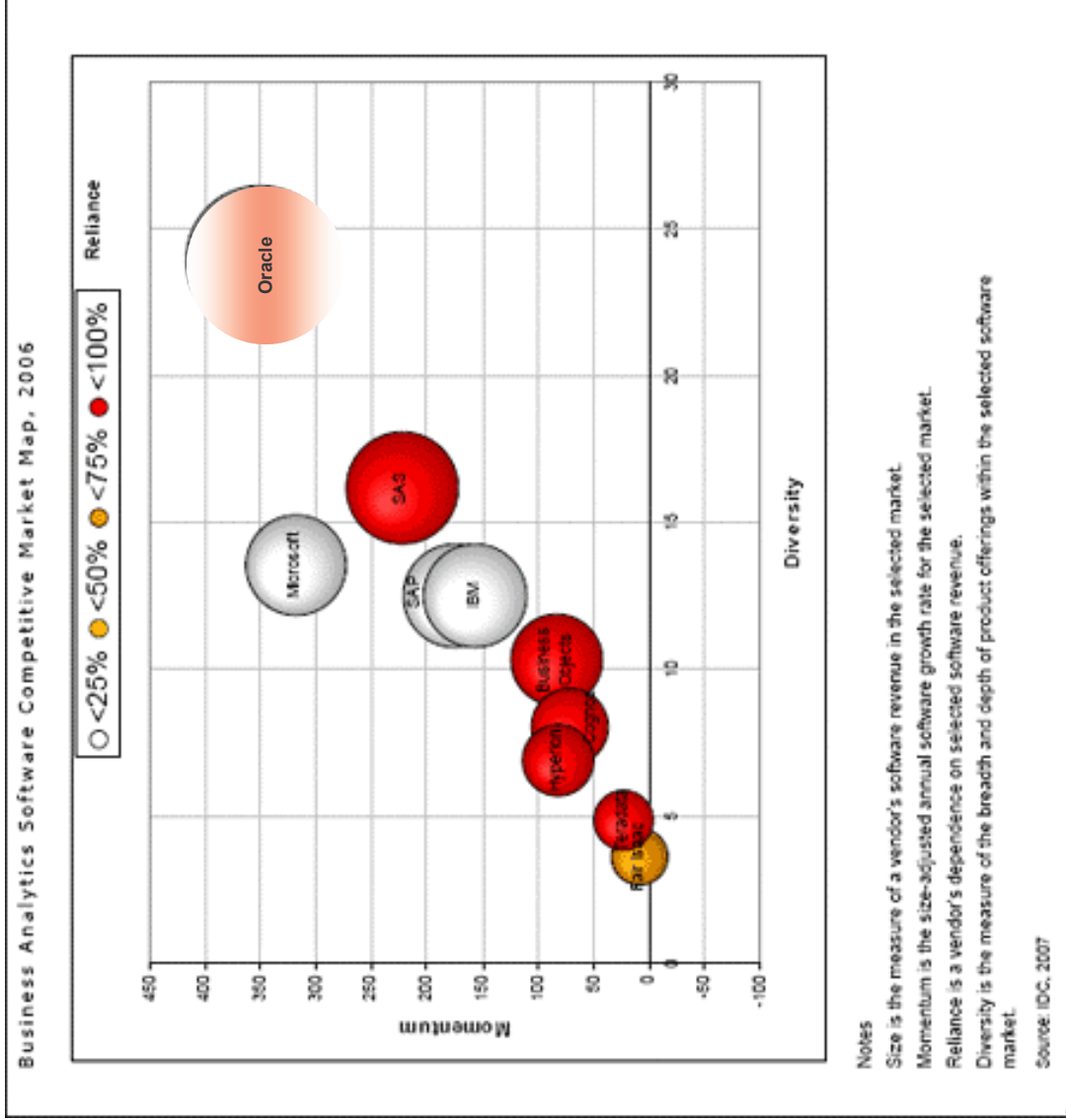
SAS Code (proprietary)

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

Annual Renewal Fee

(~40% each year)

IDC Worldwide Business Analytics Software



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

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DATABASE **11g**



ODM Algorithms, Predictive Analytics & Statistical Functions



Oracle Data Mining

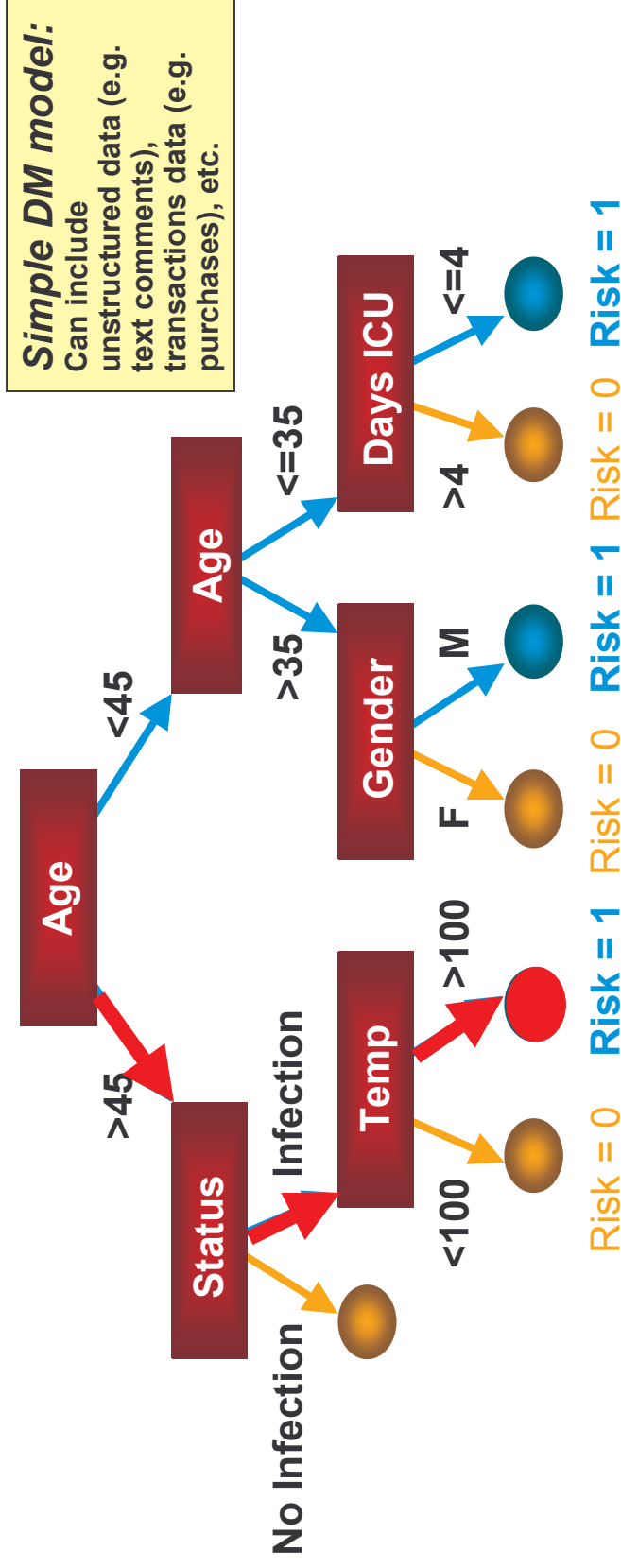
Algorithm Summary 11g

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

Oracle Data Mining 10gR2

Decision Trees

- Classification, Prediction, Patient “profiling”



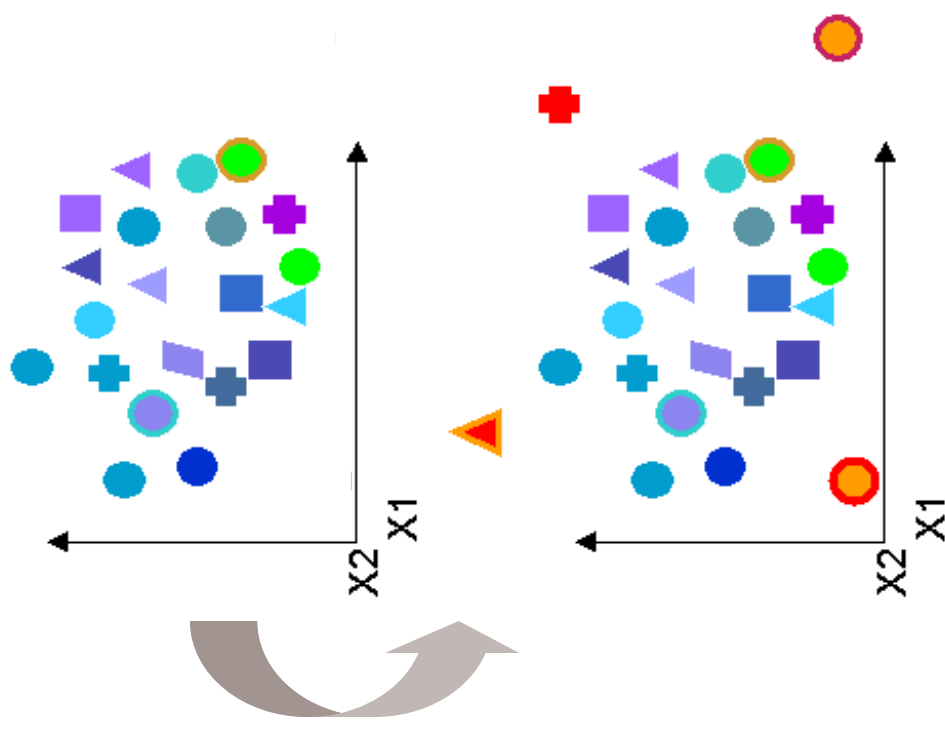
**IF (Age > 45 AND Status = Infection AND Temp = >100)
THEN P(High Risk=1) = .77 Support = 250**

Oracle Data Mining 11g

Anomaly Detection

- “One-Class” SVM Models
 - Fraud, noncompliance
 - Outlier detection
 - Network intrusion detection
 - Disease outbreaks
 - Rare events, true novelty

Problem: Detect rare cases

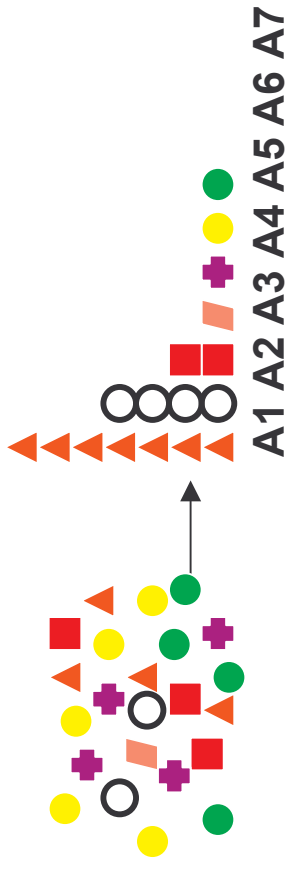


Oracle Data Mining

Algorithms & Example Applications

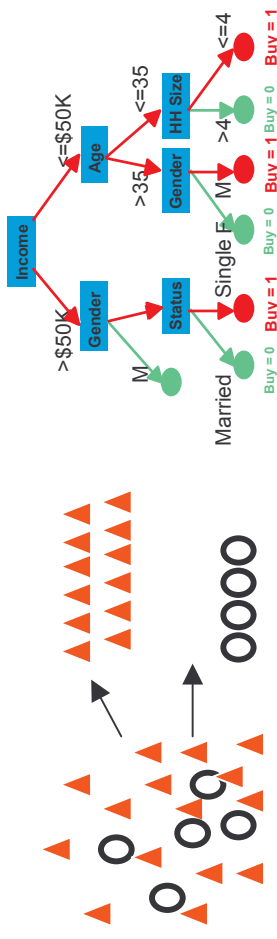
Attribute Importance

- Identify most influential attributes for a target attribute
 - Factors associated with high costs, responding to an offer, etc.



Classification and Prediction

- Predict customers most likely to:
 - Respond to a campaign or offer
 - Incur the highest costs
- Target your best customers
- Develop customer profiles



Regression

- Predict a numeric value
 - Predict a purchase amount or cost
 - Predict the value of a home

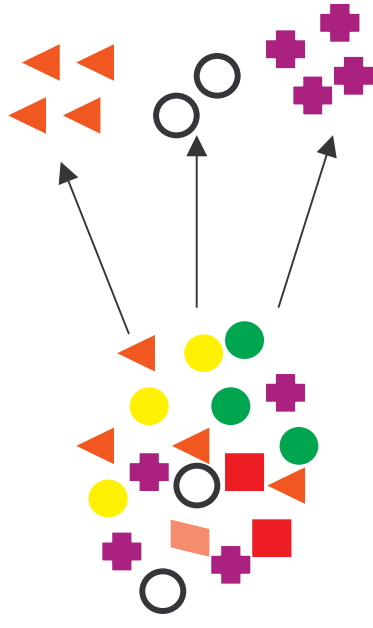


Oracle Data Mining

Algorithms & Example Applications

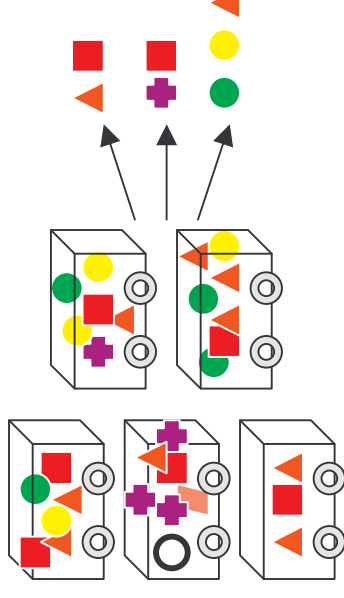
Clustering

- Find naturally occurring groups
 - Market segmentation
 - Find disease subgroups
 - Distinguish normal from non-normal behavior



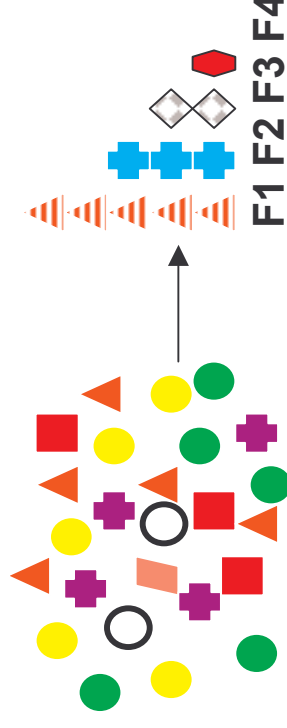
Association Rules

- Find co-occurring items in a market basket
 - Suggest product combinations
 - Design better item placement on shelves



Feature Extraction

- Reduce a large dataset into representative new attributes
 - Useful for clustering and text mining

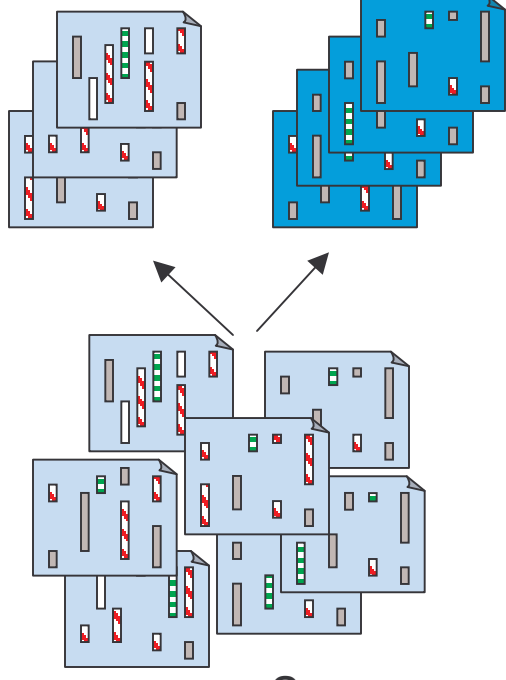


Oracle Data Mining

Algorithms & Example Applications

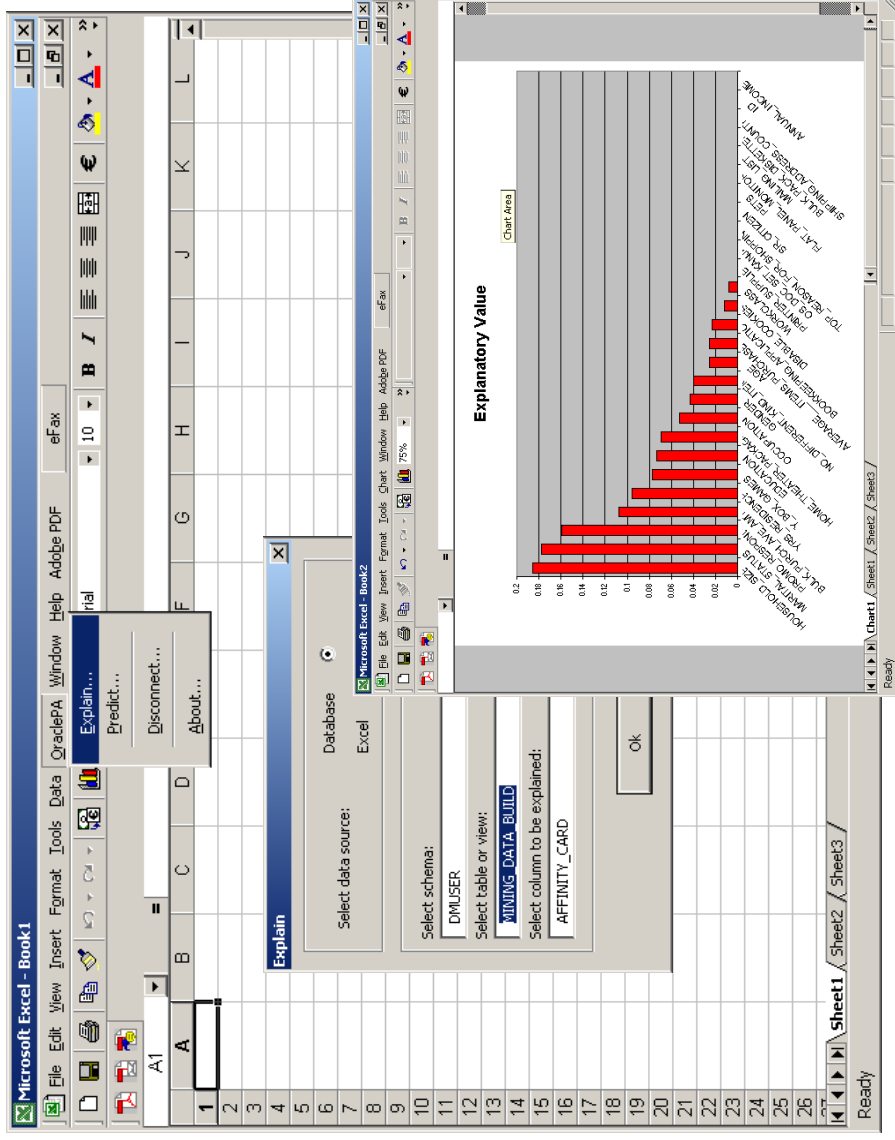
Text Mining

- Combine data and text for better models
 - Add unstructured text e.g. physician's notes to structured data e.g. age, weight, height, etc., to predict outcomes
- Classify and cluster documents
 - Combined with Oracle Text to develop advanced text mining applications e.g. Medline



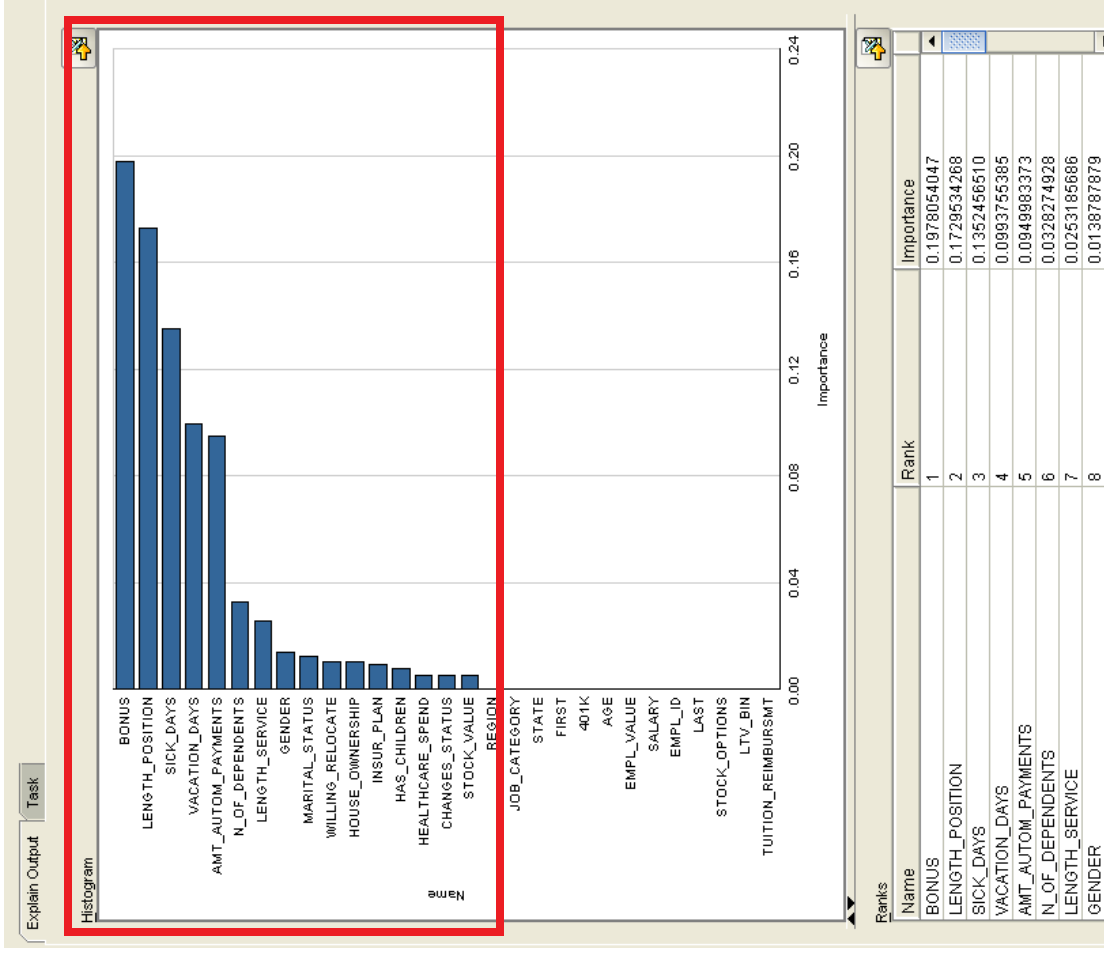
Predictive Analytics

- “One-click data mining”
 - Automates methodology used by expert data miners
- PL/SQL packages
 - PREDICT
 - EXPLAIN
 - PROFILE



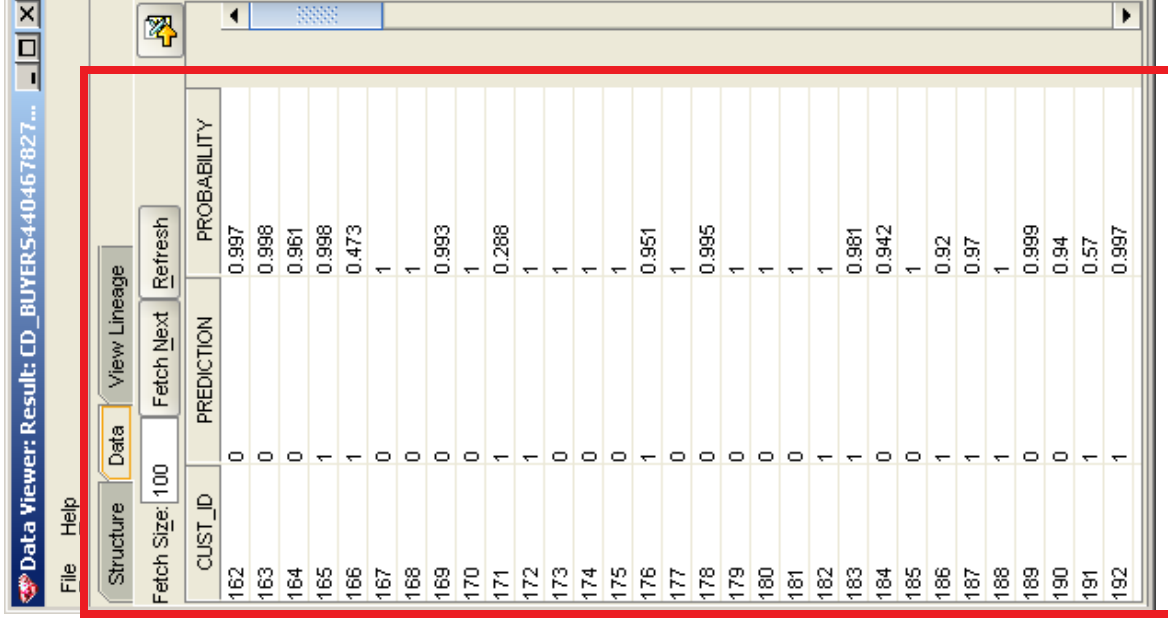
EXPLAIN PA

- Automated Attribute Importance
- Identifies key factors that have the strongest influence on the target variable
- Satisfied customers
- Hi-Value customers
- Healthy patients
- Responders
- etc.



PREDICT PA

- Automated model build and model score
- Produces predictions:
 - People likely to respond
 - Customers likely to buy a product
 - Hi-Value customers
 - Likely Fraud
 - etc.



Data Viewer: Result: CD_BUYERS440467827...

File Help

Structure Data View Lineage

Fetch Size: 100 Fetch Next Refresh

CUST_ID	PREDICTION	PROBABILITY
162	0	0.997
163	0	0.998
164	0	0.961
165	1	0.998
166	1	0.473
167	0	1
168	0	1
169	0	0.993
170	0	1
171	1	0.288
172	1	1
173	0	1
174	0	1
175	0	1
176	1	0.951
177	0	1
178	0	0.995
179	0	1
180	0	1
181	0	1
182	1	1
183	1	0.981
184	0	0.942
185	0	1
186	1	0.92
187	1	0.97
188	1	1
189	0	0.999
190	0	0.94
191	1	0.57
192	1	0.997

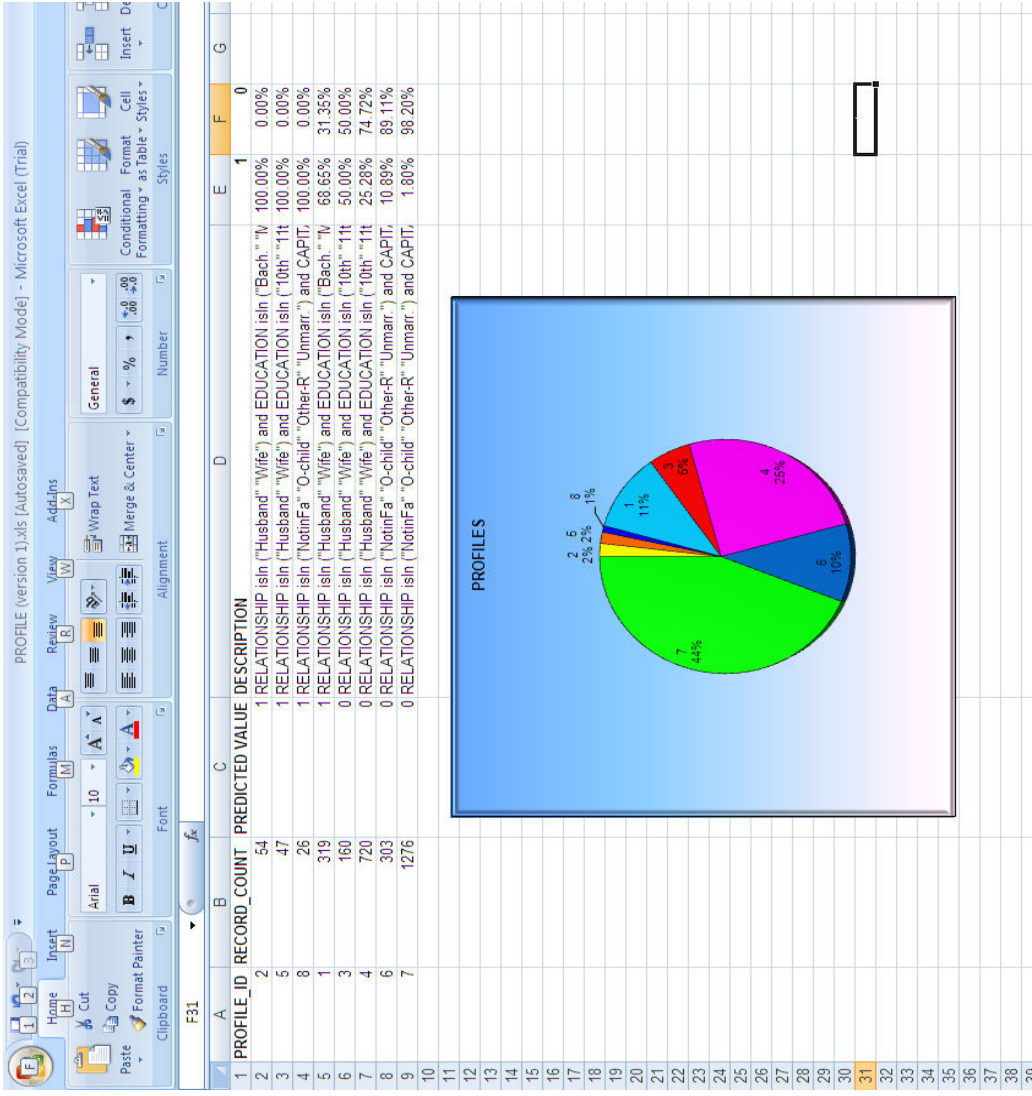
PROFILE PA

- PROFILE finds targeted customer segments, size and confidence and IF... THEN.... “rules” that describe them

PROFILE_ID	RECORD_COUNT	PREDICTED_VALUE	DESCRIPTION
1	319	68.7%	RELATIONSHIP isin ("Husband" "Wife") and EDUCATION isin ("Bach." "Masters" "PhD" "profsc") and 1. CAPITAL_GAIN <= 5095.5
2	54	100.0%	RELATIONSHIP isin ("Husband" "Wife") and EDUCATION isin ("Bach." "Masters" "PhD" "profsc") and 1. CAPITAL_GAIN > 5095.5
3	100	50.0%	RELATIONSHIP isin ("Husband" "Wife") and EDUCATION isin ("10th" "11th" "12th" "1st-4th" "5th-6th" "7th-8th" "9th" < Bach." "Assoc-A" "Assoc-V" "HS-grad" "presch.") and CAPITAL_GAIN <= 5095.5 and 0. OCCUPATION isin ("ArmedF" "Exec." "Prof." "TechSup")
4	720	25.3%	RELATIONSHIP isin ("Husband" "Wife") and EDUCATION isin ("10th" "11th" "12th" "1st-4th" "5th-6th" "7th-8th" "9th" < Bach." "Assoc-A" "Assoc-V" "HS-grad" "presch.") and CAPITAL_GAIN <= 5095.5 and OCCUPATION isin ("Cleric." "Crafts" "Farming" "Handler" "House-s" "Machine" "Other" "Protect." "Sales" "Transp.")
5	47	100.0%	RELATIONSHIP isin ("Husband" "Wife") and EDUCATION isin ("10th" "11th" "12th" "1st-4th" "5th-6th" "7th-8th" "9th" < Bach." "Assoc-A" "Assoc-V" "HS-grad" "presch.") and 1. CAPITAL_GAIN > 5095.5
6	303	10.5%	RELATIONSHIP isin ("NotInFg" "O-child" "Other-R" "Unmarr.") and CAPITAL_GAIN <= 7565.5 and 0. EDUCATION isin ("Bach." "Masters" "PhD" "profsc") and RELATIONSHIP isin ("NotInFa" "O-child" "Other-R" "Unmarr.") and CAPITAL_GAIN <= 7565.5 and EDUCATION isin ("10th" "11th" "12th" "1st-4th" "5th-6th" "7th-8th" "9th" < Bach." "Assoc-A" "Assoc-V" "HS-grad"

PROFILE PA

- PROFILE finds targeted customer segments, size and confidence and IF... THEN.... “rules” that describe them



Links below point to Oracle 10g Release 2 SQL Reference documentation for database functions.

Numeric	Character	Aggregate	Aggregate (contd)	Analytic (contd)	Date Time	Conversion
ABS	CHR	AVG	STATS_MW_TEST	PERCENTILE_CONT	ADD_MONTHS	ASCISTR
ACOS	CONCAT	COLLECT	STATS_T_TEST *	PERCENTILE_DISC	CURRENT_DATE	BIN_TO_NUM
ASIN	INITCAP	CORR	STATS_WSR_TEST	RANK	CURRENT_TIMESTAMP	CAST
ATAN	LOWER	CORR_*	STDDEV	RATIO_TO_REPORT	DBTIMEZONE	CHARTOROWID
ATAN2	LPAD	CORR_S	STDDEV_POP	REGR_ (Linear Regr) *	EXTRACT (datetime)	COMPOSE
BITAND	LTRIM	CORR_K	STDDEV_SAMP	ROW_NUMBER	FROM_TZ	CONVERT
CEIL	NLS_INITCAP	COUNT	SUM	STDDEV *	LAST_DAY	DECOMPOSE
COS	NLS_LOWER	COVAR_POP	VAR_POP	STDDEV_POP *	LOCALTIMESTAMP	HEXTORAW
COSH	NLSSORT	COVAR_SAMP	VAR_SAMP	STDDEV_SAMP *	MONTHS_BETWEEN	NUMTODSINTERVAL
EXP	NLS_UPPER	CUME_DIST	VARIANCE	SUM *	NEW_TIME	NUMTOYMINTERVAL
FLOOR	REGEXP_REPLACE	DENSE_RANK	Analytic	VAR_POP *	NEXT_DAY	RAWTOHEX
LN	REGEXP_SUBSTR	FIRST	AVG *	VAR_SAMP *	NUMTODSINTERVAL	RAWTONHEX
LOG	REPLACE	GROUP_ID	CORR *	VARIANCE *	NUMTOYMINTERVAL	ROWIDTOCHAR
MOD	RPAD	GROUPING	COVAR_POP *	Data Mining	ROUND (date)	ROWIDTONCHAR
NANVL	RTRIM	GROUPING_ID	COVAR_SAMP *	CLUSTER_ID	SESSIONTIMEZONE	SCN_TO_TIMESTAMP
POWER	SOUNDEX	LAST	COUNT *	CLUSTER_PROBABILITY	SYS_EXTRACT_UTC	TIMESTAMP_TO_SCN
REMAINDER	SUBSTR	MAX	CUME_DIST	CLUSTER_SET	SYSDATE	TO_BINARY_DOUBLE
ROUND (number)	TRANSLATE	MEDIAN	DENSE_RANK	FEATURE_ID	SYSTIMESTAMP	TO_BINARY_FLOAT
SIGN	TREAT	MIN	FIRST	FEATURE_SET	TO_CHAR (character)	TO_CHAR (character)
SIN	TRIM	PERCENTILE_CONT	FIRST_VALUE *	FEATURE_VALUE	TO_TIMESTAMP	TO_CHAR (datetime)
SINH	UPPER	PERCENTILE_DISC	LAG	PREDICTION	TO_TIMESTAMP_TZ	TO_CHAR (number)
SQRT		PERCENT_RANK	LAST	PREDICTION_COST	TO_DSINTERVAL	TO_CLOB
TAN	ASCII	RANK	LAST_VALUE *	PREDICTION_DETAILS	TO_DATE	TO_DATE
TANH	INSTR	REGR_ (Linear Regr)	LEAD	PREDICTION_PROBABILITY	TRUNC (date)	TO_DSINTERVAL
TRUNC (number)	LENGTH	STATS_BINOMIAL_TEST	MAX *	PREDICTION_SET	TZ_OFFSET	TO_LOB
WIDTH_BUCKET	REGEXP_INSTR	STATS_CROSSTAB	MIN *		Comparison	TO_MULTI_BYTE
		STATS_MODE	NTILE		GREATEST	TO_NCHAR (character)
		STATS_ONE_WAY_ANOVA	PERCENT_RANK		LEAST	TO_NCHAR (datetime)
		STATS_F_TEST				
		STATS_KS_TEST				

Note: * next to certain Analytic functions indicates that they support moving window specifications.

Descriptive Statistics



- **MEDIAN & MODE**

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

> SQL

```
A. SELECT STATS_MODE(EDUCATION) from CD_BUYERS;  
B. SELECT MEDIAN(ANNUAL_INCOME) from CD_BUYERS;  
C. SELECT EDUCATION, MEDIAN(ANNUAL_INCOME) from  
   CD_BUYERS GROUP BY EDUCATION;  
D. SELECT EDUCATION, MEDIAN(ANNUAL_INCOME) from  
   CD_BUYERS GROUP BY EDUCATION ORDER BY  
   MEDIAN(ANNUAL_INCOME) ASC;
```

One-Sample T-Test



STATS_T_TEST_*

The t-test functions are:

STATS_T_TEST_ONE: A one-sample t-test

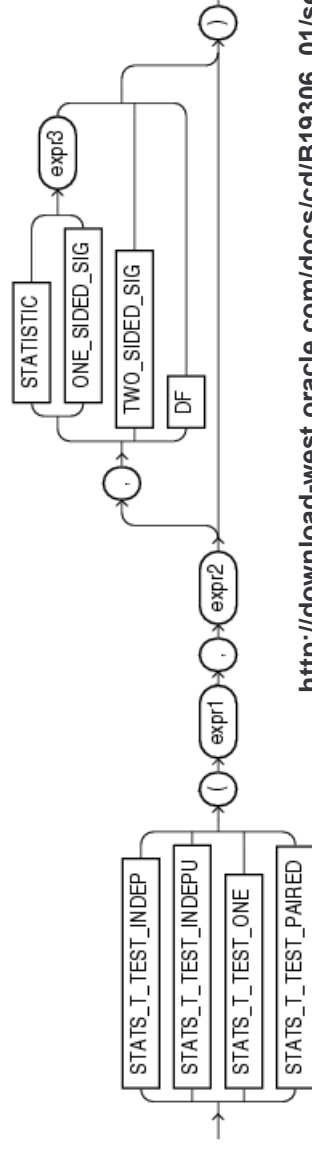
STATS_T_TEST_PAIRED: A two-sample, paired t-test (also known as a crossed t-test)

STATS_T_TEST_INDEP: A t-test of two independent groups with the same variance (pooled variances)

STATS_T_TEST_INDEPU: A t-test of two independent groups with unequal variance (unpooled variances)

Syntax

`stats_t_test:=`



http://download-west.oracle.com/docs/cd/B19306_01/server.102/b14200/functions157.htm



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Independent Samples T-Test



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

The screenshot shows an Oracle SQL Worksheet window. The title bar reads "SQL Worksheet". The menu bar includes "File", "Help", and "Enter SQL Statement". The main text area contains the following SQL query:

```
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;
```

Below the query, the "Results" section is visible. It includes a "Fetch Size: 100" dropdown, "Fetch Next" and "Refresh" buttons, and a table of results. The table has columns: INCOME_LEVEL, SOLD_TO_MEN, SOLD_TO_WOMEN, T_OBSERVED, and TWO_SIDED_P_VALUE. The results are grouped by income level from A to J.

INCOME_LEVEL	SOLD_TO_MEN	SOLD_TO_WOMEN	T_OBSERVED	TWO_SIDED_P_VALUE
A: Below 30,000	1.05283489772952...	9.94281446665347...	-1.9880628862965...	.046811481623777469
B: 30,000 - 49,999	1.02596509506751...	1.09829641827200...	3.04330875305933...	.0023410534279906534
C: 50,000 - 69,999	1.05627588073092...	1.10127931012124...	2.36148671478380...	.0182042221087140492
D: 70,000 - 89,999	1.06630299489770...	1.10472869932602...	2.28496442938685...	.022316997323373052
E: 90,000 - 109,999	1.03396741493733...	1.01610416258370...	-1.2544577321777...	.20967782263168744
F: 110,000 - 129,999	1.06764759620596...	1.05981311948214...	-6.0444998485409...	.54554530367779175
G: 130,000 - 149,999	1.08877532181064...	1.073137698657029...	-8.5298244925517...	.3936712177482169
H: 150,000 - 169,999	1.10987257925271...	1.07152191179957...	-1.9062363114356...	.056622982960629141
I: 170,000 - 189,999	1.02808237970970...	1.07435560141216...	2.18477851179480...	.028908565891614835
J: 190,000 - 249,999	1.08040563837250...	1.15343356029762...	2.58313424607376...	.0097945161125223348

Comparison results grouped by gender with statistical level of significance

Customer Example



248 rows selected.

```
SQL> select peak_id peak, avg(decode(E.sample_group, 'CNS', s.intensity, null)) avg_CNS, avg(decode(E.sample_group, 'ND', s.intensity, null)) avg_ND, stats_ks_test(E.sample_group, s.intensity, 'STATISTIC') ks_stat, stats_ks_test(E.sample_group, s.intensity) ks_p_value, stats_t_test_indep(E.sample_group, s.intensity) t_test_p_value, avg(subs_mass) AVG_MASS from exp_descriptor E, celd_spectrum s where E.exp_id = s.exp_id and E.chip_id = s.chip_id and E.spot_number = s.spot_number and (sample_group = 'CNS' or sample_group = 'ND') Group By peak_id order by stats_t_test_indep(E.sample_group, s.intensity);
```

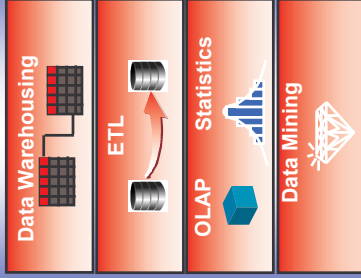
PEAK	AUG_CNS	AUG_ND	KS_STAT	KS_P_VALUE	T_TEST_P_VALUE	AUG_MASS
178	1.3314339	2.17817187	.673333333	7.2556E-16	2.6544E-17	5952.91674
181	5.0996028	7.89194275	.626666667	8.4480E-14	1.4848E-14	6075.9581
180	2.27649538	3.47917519	.606666667	5.8453E-13	8.8539E-14	6055.14643
182	1.82166302	2.70982458	.586666667	3.7986E-12	1.7684E-13	6093.52256
112	1.43756807	.415726202	.6	1.0984E-12	4.5081E-13	4033.66603
179	.470304995	.71366692	.546666667	1.3289E-10	6.0678E-13	5976.18528
162	.32065549	.48811947	.606666667	5.8453E-13	6.3174E-13	5384.91078
176	1.71447936	2.70554235	.553333333	7.4775E-11	1.7747E-12	5914.53224
185	.336895407	.472142857	.55	9.9772E-11	1.9222E-12	6260.71013
186	.401995708	.562915017	.506666667	3.6175E-09	2.1445E-12	6281.69466
177	2.3623861	3.80160199	.586666667	3.7986E-12	4.1808E-12	5933.83033

".. Our experience suggests that Oracle 10g Statistics and Data Mining features can **reduce development effort of analytical systems by an order of magnitude.**"

Sumeet Muju

Senior Member of Professional Staff, SRA International (SRA supports NIH bioinformatics development projects)

Oracle 11g DB



Oracle Data Mining + Oracle BI EE

D E M O N S T R A T I O N



ORACLE®

Oracle Data Mining + OBI EE

Auto Claims Fraud Demo

Oracle Data Miner - Table : CLAIMSB

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
 - ABN_APPLY_OUTUT
 - ABN_TEST_APPLY_OUTUT
 - ABNBUILDSETTINGS_J
 - ABNCOMPUTESTMET
 - ABNCOMPUTESTMET

Structure Data

Fetch Size: 100 Fetch Next Refresh

MONTH	WEEKOFMO...	DAYOFWEEK	ACCIDENTA...	MAVE	VEHICLEPRICE	SEX	MAR
Jan	3	Wednesday	Urban	Honda	4	Male	Single
Oct	5	Friday	Urban	Honda	2	Male	Married
Jun	2	Saturday	Rural	Toyota	1	Male	Married
Feb	4	Saturday	Urban	Honda	3	Male	Married
Dec	1	Sunday	Urban	Mazda	5	Male	Single
Mar	2	Sunday	Urban	Ford	3	Male	Single
Aug	4	Tuesday	Urban	Mazda	5	Male	Single
Apr	2	Friday	Urban	Mazda	4	Male	Married
Aug	3	Friday	Urban	Mazda	4	Male	Married
Mar	3	Monday	Urban	Po...	3	Male	Married
May	3	Monday	Urban	Po...	3	Male	Married
Mar	2	Friday	Urban	Do...	3	Male	Married
Jan	4	Monday	Urban	Ho...	3	Male	Married
Jan	4	Monday	Urban	Ho...	3	Male	Married
Oct	2	Tuesday	Urban	Ch...	3	Male	Married
Sep	2	Friday	Urban	Ma...	3	Male	Married

Data Summarization Viewer: CBERGER.CLAIMSB

Sample Count: 978
Attribute Count: 33

Name	Mining...	Attribut...	Average	Max	Min
FAULT	category...	VARCH...			
FRAUDFOUND_P	category...	NUMB...	0.07	1	0
MAKE	category...	VARCH...			
MARITALSTATUS	category...	VARCH...			
MONTH	category...	VARCH...			
MONTHCLAIMED	category...	VARCH...			
NUMBEROFCAPS	category...	VARCH...			
NUMBEROFSUPPLIMENTS	category...	VARCH...			
PASTNUMBEROFCLAIMS	category...	VARCH...			
POLICEREPORFILED	category...	VARCH...			
POLICYNUMBER	numer...	NUMB...	7,660.34	15,385	11
POLICYTYPE	category...	VARCH...			
REPNUMBER	numer...	NUMB...	8.5	16	1
SEX	category...	VARCH...			
VEHICLECATEGORY	category...	VARCH...			
VEHICLEPRICE	category...	VARCH...			
WEEKOFMONTH	category...	VARCH...			
WEEKOFMONTHCLAIMED	category...	NUMB...	2.73	5	1
WITNESSPRESENT	category...	VARCH...			
YEAR	category...	NUMB...	1,994.87	1,996	1,994

Histogram for: VEHICLEPRICE

Bin range: 20000 to 29000, 30000 to 39000, 40000 to 49000, 50000 to 59000, 60000 to 69000, other

Group	Values(S)	Bin Count	% of Total
20000 to 29000	20000 to 29000	507	51.84
30000 to 39000	30000 to 39000	220	22.49
more than 69000	more than 69000	159	16.26
less than 20000	less than 20000	58	5.93
40000 to 59000	40000 to 59000	31	3.17
60000 to 69000	60000 to 69000	3	0.31
other	nulls	0	0.0

Statistics: Sample count: 978, Mode: 20000

Binning Strategy: Top N...

Graph orientation: Vertical (selected), Horizontal

OK

Data analyst mines automobile insurance claims data to find suspicious claims

Oracle Data Mining + OBI EE

Auto Claims Fraud Demo

Oracle Data Miner guides the analyst through the data mining process

New Activity Wizard - Step 3 of 4: Data Usage

Review Data Usage Settings

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.

Name	Alias	Input	Data Type	Mining Type
ICBERGER_CLAIMSB				
ACCIDENTAREA	ACCIDENTAREA	<input checked="" type="checkbox"/>	VARCHAR2	categorical
ADDRESSCHANGE_CL...	ADDRESSCHANGE_CL...	<input checked="" type="checkbox"/>	VARCHAR2	categorical
AGE	AGE	<input checked="" type="checkbox"/>	NUMBER	numerical
AGENTTYPE	AGENTTYPE	<input checked="" type="checkbox"/>	VARCHAR2	categorical
AGEOFPOLICYHOLDER	AGEOFPOLICYHOLDER	<input checked="" type="checkbox"/>	VARCHAR2	categorical
AGEOFVEHICLE	AGEOFVEHICLE	<input checked="" type="checkbox"/>	VARCHAR2	categorical
BASEPOLICY	BASEPOLICY	<input checked="" type="checkbox"/>	VARCHAR2	categorical
DAYOFWEEK	DAYOFWEEK	<input checked="" type="checkbox"/>	VARCHAR2	categorical
DAYOFWEEKCLAIMED	DAYOFWEEKCLAIMED	<input checked="" type="checkbox"/>	VARCHAR2	categorical
DAYS_POLICY_ACCIDE...	DAYS_POLICY_ACCIDE...	<input checked="" type="checkbox"/>	VARCHAR2	categorical
DAYS_POLICY_CLAIM	DAYS_POLICY_CLAIM	<input checked="" type="checkbox"/>	VARCHAR2	categorical
DEDUCTIBLE	DEDUCTIBLE	<input checked="" type="checkbox"/>	NUMBER	categorical
DRIVERRATING	DRIVERRATING	<input checked="" type="checkbox"/>	NUMBER	categorical
FAULT	FAULT	<input checked="" type="checkbox"/>	VARCHAR2	categorical
FRAUDFOUND_P	FRAUDFOUND_P	<input type="checkbox"/>	NUMBER	categorical
MAKE	MAKE	<input checked="" type="checkbox"/>	VARCHAR2	categorical
MARITALSTATUS	MARITALSTATUS	<input checked="" type="checkbox"/>	VARCHAR2	categorical

Buttons: < Back, Next >, Include All, Exclude All, Finish, Cancel, Help

Oracle Data Mining + OBI EE

Auto Claims Fraud Demo

Oracle Data Mining builds a model that differentiates normal claims from anomalous claims

The screenshot displays the Oracle Data Mining (ODM) interface. The main window shows a mining activity named 'CLAIMSB_FRAUD1_BA' with the following details:

- Name: CLAIMSB_FRAUD1_BA
- Type: Anomaly Detection Mining Activity
- Case Table: CBERGER.CLAIMSB
- Unique Identifier: POLICYNUMBER
- Comment: [Medical Data](#)

The 'Activity Steps' section includes:

- Sample: This step samples the mining data. Although not shown in the screenshot, this step typically handles missing values.
- Missing Values: This transformation step handles missing values.
- Normalize: This transformation step normalizes the mining data.
- Build: This step builds the mining model. To complete this step, the 'Build' button is visible.

The 'Result Viewer' window shows the following table:

Attribute Name	Value	Coefficient
DAYS_POLICY_CLAIM	more than 30	0.8027934054
WITNESSPRESENT	No	0.8012060147
DAYS_POLICY_ACCIDENT	more than 30	0.7797931778
AGENTTYPE	External	0.7634373420
POLICEREPORTFILED	No	0.7273740213
DEDUCTIBLE	400	0.6809346641
ACCIDENTAREA	Urban	0.6254708586
SEX	Male	0.5711776011
NUMBEROFFCARS	1 vehicle	0.5256697063
ADDRESSCHANGE_CLAIM	no change	0.5239510031
FAULT	Policy Holder	0.4893237195
MARITALSTATUS	Married	0.4478115841
VEHICLECATEGORY	Sedan	0.3411958137
MARITALSTATUS	Single	0.3395731141
NUMBEROFSUPPLIMENTS	none	0.3157147624
VEHICLECATEGORY	Sport	0.3085732178
FAULT	Third Party	0.3080140532
YEAR	1994	0.3057861295
VEHICLEPRICE	20000 to 29000	0.2918697577
BASEPOLICY	Collision	0.2781269003
YEAR	1995	0.2753534895
BASEPOLICY	Liability	0.2689752505
POLICYTYPE	Sedan - Liability	0.2689752505

Oracle Data Mining + OBI EE

Auto Claims Fraud Demo

Oracle Data Mining creates a prioritized list of suspicious claims for investigation

Result Viewer: "CLAIMST768348894_A"

File Publish Help

Apply Output Apply Settings Task

Apply Output Table:

Fetch Size: 10000 Refresh

DMRSCAS...	VEHICLEP...	POLICYTY...	NUMBER...	REPNUM...	AGEI	DRIVERR...	AGEOFVE...	POLICER...	WITNESS...	DEDUCTI...	ACCIDEN...	PREDICTI...	PROBAB...
11,015	30000 to 3...	Sedan - All ...	1 vehicle	7	45	1	more than 7	No	No	400	Urban	0	0.6311
1	more than ...	Sport - Lia...	3 to 4	12	21	1	3 years	No	No	300	Urban	0	0.6289
12,650	30000 to 3...	Sedan - Co...	1 vehicle	15	25	3	2 years	No	No	400	Urban	0	0.6278
11,922	more than ...	Utility - All ...	1 vehicle	15	46	1	5 years	No	No	400	Rural	0	0.6238
11,192	30000 to 3...	Sedan - Li...	1 vehicle	7	43	2	7 years	Yes	Yes	700	Rural	0	0.6162
13,294	20000 to 2...	Sedan - Co...	2 vehicles	7	28	2	5 years	No	Yes	400	Rural	0	0.6149
6,284	40000 to 5...	Sedan - Li...	1 vehicle	5	47	3	more than 7	No	No	400	Rural	0	0.6134
8,139	30000 to 3...	Sedan - Co...	1 vehicle	4	34	2	6 years	Yes	Yes	400	Rural	0	0.6115
11,119	more than ...	Sedan - All ...	1 vehicle	1	33	3	7 years	No	No	500	Rural	0	0.6078
11,677	20000 to 2...	Sedan - All ...	2 vehicles	15	49	1	5 years	No	No	400	Urban	0	0.6078
8,561	less than 2...	Sedan - All ...	1 vehicle	9	22	4	4 years	No	No	400	Urban	0	0.6056
11,068	20000 to 2...	Sedan - Co...	2 vehicles	3	54	2	7 years	Yes	No	700	Rural	0	0.6052
11,130	20000 to 2...	Sedan - All ...	1 vehicle	1	50	1	more than 7	Yes	Yes	700	Urban	0	0.6029
13,967	20000 to 2...	Sedan - Co...	1 vehicle	15	24	3	5 years	No	No	400	Rural	0	0.6025
9,673	20000 to 2...	Sedan - Co...	1 vehicle	7	22	2	4 years	Yes	Yes	400	Urban	0	0.6011
3,471	30000 to 3...	Sedan - Li...	1 vehicle	1	40	3	3 years	No	No	400	Urban	0	0.6005
4,395	30000 to 3...	Sedan - Co...	1 vehicle	6	60	3	6 years	No	No	400	Urban	0	0.5995
14,101	20000 to 2...	Sedan - Co...	1 vehicle	7	56	3	more than 7	Yes	Yes	400	Urban	0	0.5985
7,918	20000 to 2...	Sedan - All ...	2 vehicles	5	35	4	6 years	Yes	No	400	Urban	0	0.5965
11,532	more than ...	Sport - Coll...	1 vehicle	13	32	2	2 years	No	No	400	Urban	0	0.5964
11,229	30000 to 3...	Sedan - All ...	1 vehicle	7	54	3	5 years	No	No	400	Urban	0	0.5953
2,931	more than ...	Sport - Coll...	1 vehicle	10	42	4	7 years	No	No	400	Urban	0	0.5941
3,044	30000 to 3...	Sedan - Li...	1 vehicle	8	44	2	more than 7	Yes	No	400	Urban	0	0.5938
5,797	20000 to 2...	Sedan - Co...	2 vehicles	2	26	2	6 years	No	No	400	Urban	0	0.5924
9,398	20000 to 2...	Sedan - Co...	1 vehicle	1	59	4	7 years	Yes	Yes	400	Urban	0	0.5917
4,642	30000 to 3...	Sedan - Co...	2 vehicles	6	50	1	more than 7	No	No	500	Rural	0	0.5908
1,599	more than ...	Sport - Coll...	1 vehicle	7	22	4	5 years	No	No	400	Urban	0	0.5878
627	20000 to 2...	Sedan - Co...	1 vehicle	15	33	3	7 years	No	No	400	Urban	1	0.5873
12,041	20000 to 2...	Sedan - Co...	1 vehicle	11	33	1	7 years	No	No	400	Urban	1	0.5867
2,989	20000 to 2...	Sedan - Co...	1 vehicle	14	30	3	7 years	No	No	400	Urban	1	0.5865
2,092	20000 to 2...	Sedan - Li...	3 to 4	13	36	2	7 years	No	No	500	Urban	0	0.5864

Integration with Oracle BI EE

The screenshot displays the Siebel Analytics Administration Tool interface, divided into three main sections:

- Presentation:** Shows a list of data sources and dimensions. A callout box highlights 'KEY_FACTOR_IMPORTANCE' and states: "Oracle BI EE defines results for end user presentation".
- Business Model and Mapping:** Shows a hierarchical view of data sources and dimensions. A callout box points to 'KEY_FACTOR_IMPORTANCE' and states: "Oracle Data Mining results available to Oracle BI EE administrators".
- Physical:** Shows a list of physical data sources. A callout box points to 'KEY_FACTOR_IMPORTANCE' and states: "Oracle Data Mining results available to Oracle BI EE administrators".

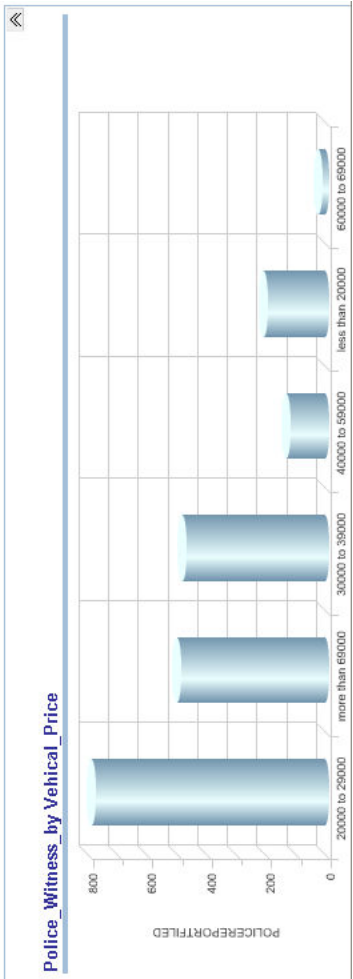
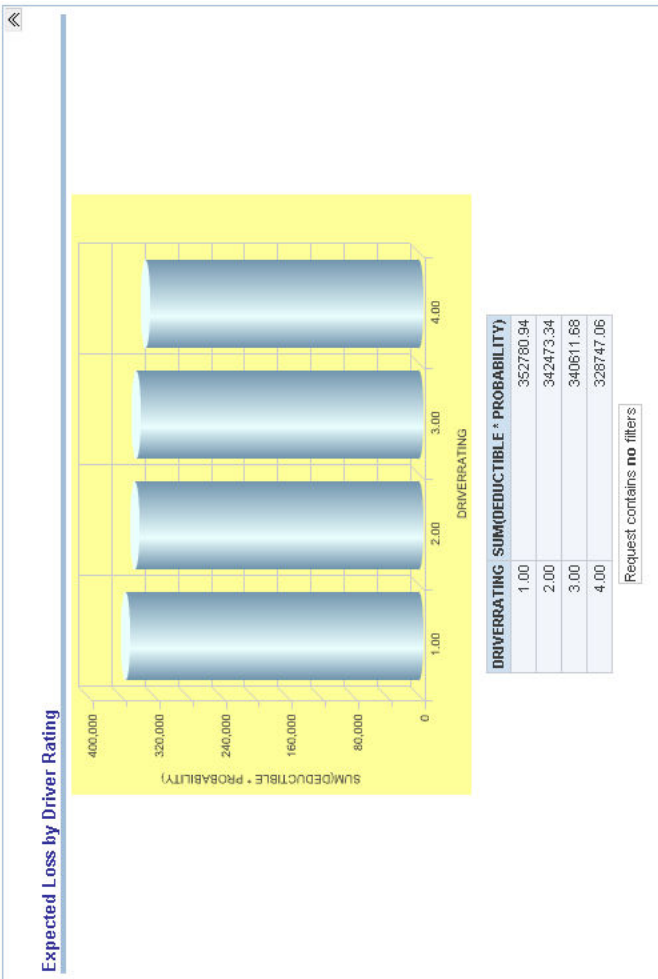
For help, press F1

Integration with Oracle BI EE

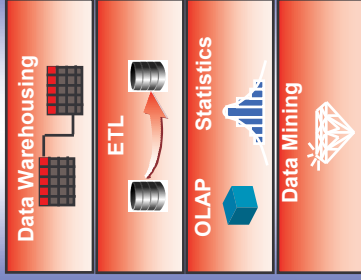
Most Suspicious Claims

POLICYNUMBER	PREDICTION	PROBABILITY	DEDUCTIBLE	DEDUCTIBLE * PROBABILITY	PROBABILITY
13465.0	0.00	0.67	500.00	336.46	0.67
14485.0	0.00	0.65	400.00	260.13	0.65
6532.0	0.00	0.64	400.00	257.69	0.64
12631.0	0.00	0.63	400.00	251.91	0.63
1.0	0.00	0.63	300.00	188.81	0.63
15029.0	0.00	0.63	400.00	251.29	0.63
11015.0	0.00	0.63	400.00	251.25	0.63
11922.0	0.00	0.62	400.00	249.84	0.62
4558.0	0.00	0.62	400.00	249.31	0.62
12650.0	0.00	0.62	400.00	249.17	0.62
2749.0	0.00	0.62	400.00	248.72	0.62
12307.0	0.00	0.62	400.00	248.56	0.62
3381.0	0.00	0.62	400.00	248.23	0.62
8863.0	0.00	0.62	400.00	247.51	0.62
13677.0	0.00	0.62	400.00	246.72	0.62
11192.0	0.00	0.62	700.00	430.72	0.62
13294.0	0.00	0.61	400.00	245.86	0.61
6284.0	0.00	0.61	400.00	245.50	0.61
2291.0	0.00	0.61	400.00	245.32	0.61
3440.0	0.00	0.61	400.00	244.70	0.61
8139.0	0.00	0.61	400.00	242.98	0.61
11068.0	0.00	0.61	700.00	424.98	0.61
11119.0	0.00	0.61	500.00	303.55	0.61
11677.0	0.00	0.61	400.00	242.83	0.61
1345.0	0.00	0.61	400.00	242.38	0.61

Oracle Data Mining provides more information and better insight



Oracle 11g DB



Text Mining, Code Generation



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Oracle Data Mining and Unstructured Data

- Oracle Data Mining includes unstructured i.e. “text” data
- Build classification and clustering models
- Oracle Text used to preprocess unstructured text

Structure		Data		
CUST_ID	AFFINITY_CARD	AGE	CUSTOMER_COMMENT	
101501	0	41	F	Shopping at your store is a hassle. I rarely shop there and usually forget to bring your new loyalty c...
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.
101503	0	20	F	I purchased a new computer recently, but the manuals weren't included. Could you ship them to me.
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.
101505	1	34	M	Why didn't you start a program like this before? Everyone else has been offering discounts like this f...
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.
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...
101508	0	19	M	I shop your store a lot. I love your weekly specials.
101509	0	52	M	Affinity card makes sense only for bulk purchases. For all others, driving so far is not worth the di...
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
101511	0	30	M	Shopping at your store is a hassle. I rarely shop there and usually forget to bring your new loyalty c...
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 ...
101513	0	31	M	Thanks but even with your discounts, your products are too expensive. Sorry.
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.
101515	0	36	F	I purchased the new mouse pads and love them. I also purchased one for my sister and one for my ...
101516	0	33	M	Don't send me any more promotions. I get too much lousy junk mail already
101517	0	38	F	Shopping at your store is a hassle. I rarely shop there and usually forget to bring your new loyalty c...
101518	0	22	M	Don't send me any more promotions. I get too much lousy junk mail already
101519	0	46	F	Shopping at your store is a hassle. I rarely shop there and usually forget to bring your new loyalty c...
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.
101521	0	61	M	I shop your store a lot. I love your weekly specials.
101522	1	39	F	If I forgot my affinity card, can I still shop here and get the discount?
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...
101524	0	38	M	Thank you, But please remove my name from your list.
101525	0	18	F	My brother uses the affinity card a lot. I think the competitor has better prices without it.

Custom Oracle Data & Text Mining Applications

- Oracle Text (included in Oracle Database Standard Edition) preprocesses unstructured text
- Custom applications to mine:
 - Emails
 - Police reports
- Handles large volumes of “documents” or text

The screenshot displays the BioOracle Text Mining application interface. The main window shows search results for the query 'angio' with 4318 MED documents found. The results are displayed in a table with columns for PMID, Fetch, and Score. The top result is PMID 11728927 with a score of 49. The document content is displayed below the table, showing a snippet about 'Angiogenesis is healing process block new blood currently under c powerful tools to fracture healing. inhibitor TNP-471 model system. E angiogenesis ir adjusted amount assessed at wet assessment wat criteria treatment'. The interface also includes a 'Document Clusters' section with a heatmap and a 'Score Contents' section with a tree diagram showing document counts for different clusters.

PMID	Fetch	Score
[1] 11728927	Fetch	49
[2] 12473562	Fetch	32

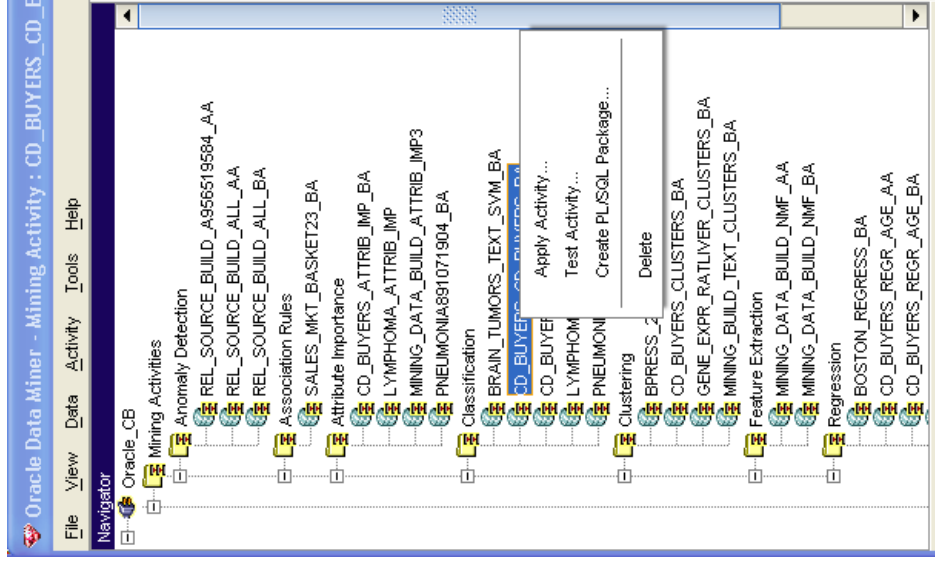
Clusters	NMF Features
#	F1 F2 F3 F4
11254674	
11775025	
11404464	
11862172	
1675513	
10945966	
11805326	
11387186	
12454286	
12816951	
10365025	

Score Contents

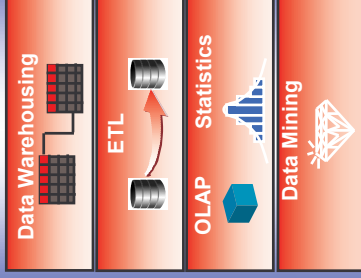
- 1 <18 docs>
- 2 <16 docs>
- 3 <5 docs>
- 4 <35 docs>

Oracle Data Miner (gui) Code Generation

- PL/SQL code generation for Mining Activities



Oracle 11g DB



In-Database Analytics SQL Examples



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Example #2

Better Insights & Information

- Select all customers who have a high propensity to attrite (> 80% chance) and have a customer value rating of more than 90 and have had a recent conversation with customer service regarding a Checking Plus account.

```
SELECT A.cust_name, A.contact_info
FROM customers A
WHERE PREDICTION_PROBABILITY(tree_model,
        'attrite' USING A.*) > 0.8
AND A.cust_value > 90
AND A.cust_id IN
(SELECT B.cust_id
        FROM call_center@HQ_DB B
        WHERE B.call_date BETWEEN '01-Jan-2005'
                AND '30-Jun-2005'
        AND CONTAINS(B.notes, 'Checking Plus', 1) > 0);
```

Real-time Prediction

```
with
records as (select
178255 ANNUAL_INCOME,
0 CAPITAL_GAIN,
83 SAVINGS_BALANCE,
246 AVE_CHECKING_BALANCE,
30 AGE,
'Bach.' EDUCATION,
'SelfENI' WORKCLASS,
'Married' MARITAL_STATUS,
'Sales' OCCUPATION,
'Husband' RELATIONSHIP,
'White' RACE,
'Male' SEX,
70 HOURS_PER_WEEK,
'? ' NATIVE_COUNTRY,
98 PAYROLL_DEDUCTION from dual)
```

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

```
from (
```

```
select PREDICTION_SET(CD_BUYERS76485_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)**

Real-time Prediction Multiple Models

```
> with records as (select
178255 ANNUAL_INCOME,
0 CAPITAL_GAIN,
83 SAVINGS_BALANCE,
246 AVE_CHECKING_BALANCE,
30 AGE,
'Bach.' EDUCATION,
'Selfeni' WORKCLASS,
'Married' MARITAL_STATUS,
'Sales' OCCUPATION,
'Husband' RELATIONSHIP,
'White' RACE,
'Male' SEX,
70 HOURS_PER_WEEK,
'?' NATIVE_COUNTRY,
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, single record
apply with multiple
models; sort by
expected revenues**

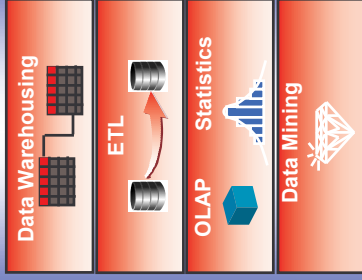
Example #3

Launch & Evaluate a Marketing Campaign

1. Given a previously built response model,...**predict who will respond to a campaign, ...and why**
2.**find out how much each customer spent 3 months before and after the campaign**
3.**how much for just DVDs?**
4. **Is the success statistically significant?**

```
select responder, cust_region, count(*) as cnt,
       sum(post_purch - pre_purch) as tot_increase,
       avg(post_purch - pre_purch) as avg_increase,
       stats_t_test_paired(pre_purch, post_purch) as
       significance
from (
select cust_name,
       prediction(campaign_model using *) as responder,
       sum(case when purchase_date < 15-Apr-2005 then
           purchase_amt else 0 end) as pre_purch,
       sum(case when purchase_date >= 15-Apr-2005 then
           purchase_amt else 0 end) as post_purch
from customers, sales, products@PRODDB
where sales.cust_id = customers.cust_id
and purchase_date between 15-Jan-2005 and 14-Jul-2005
and sales.prod_id = products.prod_id
and contains(prod_description, 'DVD') > 0
group by cust_id, prediction(campaign_model using *) )
group by rollup responder, cust_region order by 4 desc;
```

Oracle 11g DB



Partners



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SPSS Clementine



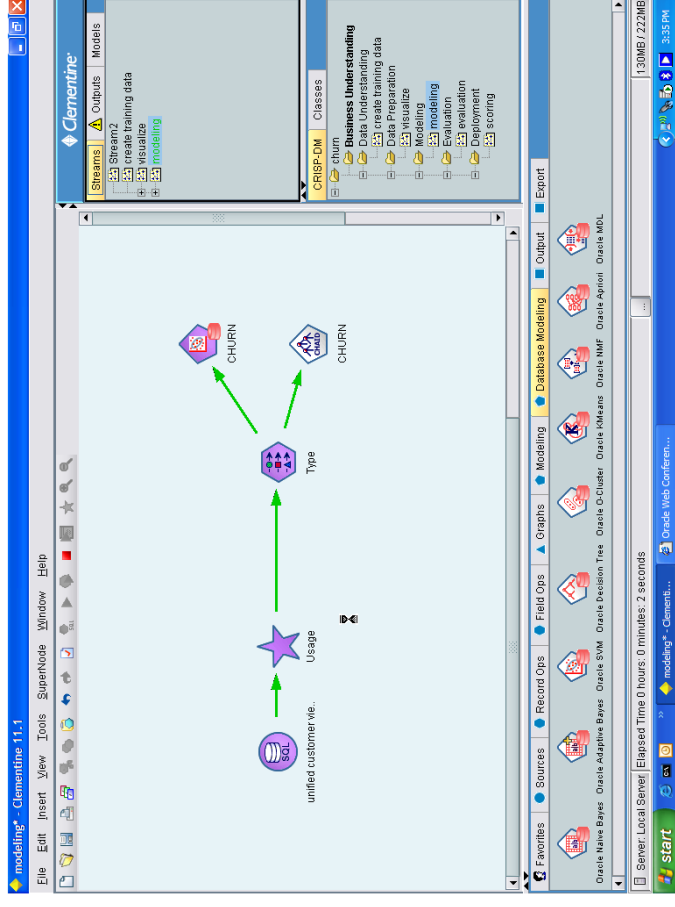
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- Combine SPSS Clementine ease of use with ODM in-Database functionality & scalability
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- For more information :

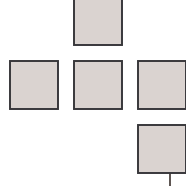
- SPSS – Mike Bittner, Strategic Alliance Manager, 770.329.3870 or mbittner@spss.com
- Oracle – Alan Manewitz, TBU, (925) 984-9910 or alan.manewitz@oracle.com

- Oracle – Charlie Berger, Product Management (781) 744-0324 or charlie.berger@oracle.com

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InforSense -- A Single Optimized Environment for Real Time Business Analytics within the Database



The screenshot displays a complex dataflow workflow within the InforSense application. The workflow includes several tasks: '1. Score new data with (market response model)', '2. Join scores and profiles', '3. Explore results', '4. Identify most valuable customers', and '5. Join with "future high value" and store target list to Oracle database'. Visualizations such as a Pie Chart, Bar Chart, and Scatter Plot are integrated into the workflow. A 'Market Response Model (Cache?)' is also visible. The interface includes a 'Tasks' pane on the left with components like 'Assess', 'TextSense', 'Oracle', 'Data Mining', 'Preprocess', 'Statistics', 'Visualization', 'SDK Examples', 'ControlFlow', 'SparseVector', 'Utilities', 'Perl', and 'Reporting'. A 'View Filter' pane on the right shows 'HY_CAMPAIGN_OUT_MUM <= 6'. The bottom status bar indicates 'Tasks pending: 0' and 'Tasks running: 1'.

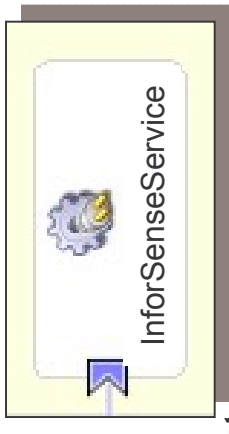
Oracle Decision Tree Model

Oracle Data Sources

Interact with (visualize) data at any step in the workflow

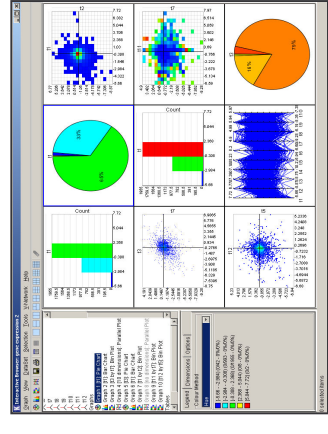
- Oracle Functionalities:**
- Data Mining
 - Preprocess
 - Statistics
 - Text
 - OLAP
 - Scheduler

Deploy the analytic workflow as a service embedding to BPEL, SFA, CRM



Deployment

Deploy the analytic workflow as an Oracle Portal



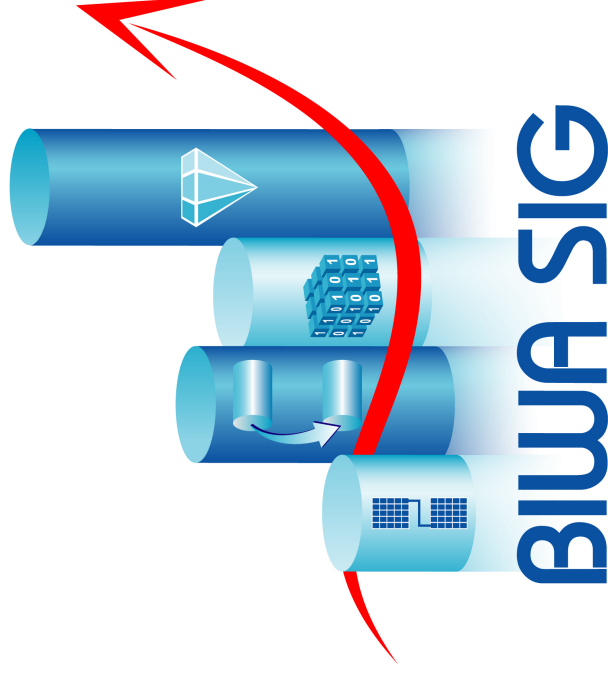
SAS free analytics: leverage Oracle analytics
SQL free analytics: drag-drop application build
Visual analytics: interactive visualisation

Integrative analytics: unified analytical environment
Automated analytics: deploy to Oracle Portal and BPEL

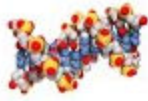
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Better Information—Better Results

- Dec. 2-3, 2008 in San Francisco at Oracle HQ Conference Center
- 2nd BIWA Summit—presentations available at www.olsug.org)
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- IOUG SIG for users who share expertise and vision dedicated to mutual success in leveraging:
 - Oracle Database-centric BI, Warehousing and Analytics
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OLSUG 2008

April 27-28, 2008
World Trade Center
Boston, MA



CONFERENCE ANNOUNCEMENT AND CALL FOR SPEAKER PROPOSALS

OLSUG-2008 INTERNATIONAL ORACLE LIFE SCIENCES AND HEALTHCARE USER GROUP MEETING

April 27-28, 2008 | World Trade Center | Boston, MA

Venue: World Trade Center, Boston, MA, USA
in conjunction with [Bio-IT 2008](#)

Oracle Life Science User Group

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Last date for submission of abstracts: **November 16, 2007**

Presentation notification: **December 7, 2007**

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Healthcare IT: Molecular profiling (Bedside to Benchside)

Healthcare IT: Evidence-based practice

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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

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