

# Big Data Predictive Analytics in Oracle Database 12c

Oracle Advanced Analytics Database Option—Extending the Database to an *Analytical* Database

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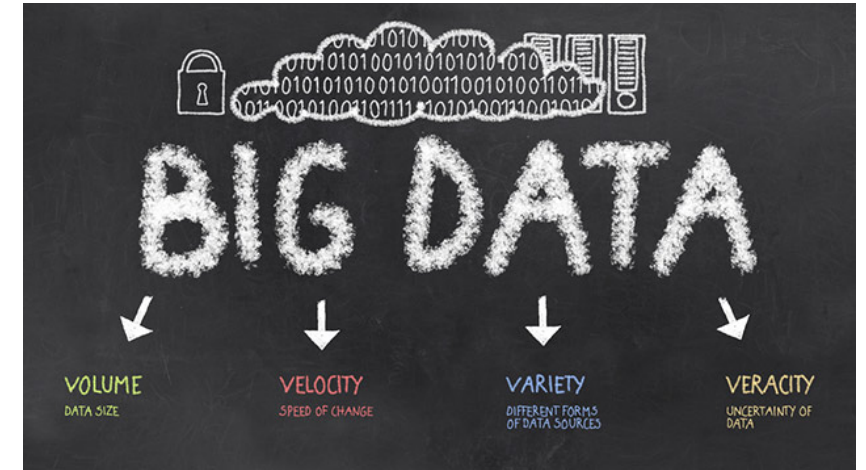
# Safe Harbor Statement

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# Big Data is Big Business

Sources: The Economist, McKinsey & Company, Gartner, Facebook, IBM

- Every day, we create 2.5-quintillion bytes of data.
- 90 per cent of the data in the world today has been created in the past two years.
- Every minute, 100,000 tweets are sent globally.
- Google receives two-million search requests every minute.
- Five-billion mobile phones were in use in 2010.
- 30-billion pieces of content are shared on Facebook every month.
- By one estimate, there will be 5,200 gigabytes of data for every human on the planet by 2020.
- **By 2015, 4.4-million IT jobs globally will be created to support big data, generating 1.9-million IT jobs in the United States alone.**
- 70 per cent of data is created by individuals – but enterprises are responsible for storing and managing 80 per cent of it.
- Big data will drive \$232 billion in spending through 2016.
- There is the potential for a 60 per cent increase in retailers' operating margins with big data.



# Analytics and Big Data



Are Changing the World

## ANALYTICS

Unlock value in data to solve some of the world's most pressing problems



### Transform Communities

Using analytics and big data, U.N. officials will deliver energy to 1.3 billion people



### Save Lives

Scientists protect consumers by pulling deadly medication off the market



### Increase Public Safety

Police increase public safety by predicting crime "hot spots" and pre-deploying officers

## CHANGE YOUR BUSINESS

Imagine what analytics can do for your business

**3x**

Top performers are 3x more likely to use analytics than low performers

**53%**

use analytics to drive strategy

**50%**

use analytics to transform daily operations

## ORGANIZATIONS WHICH USE ANALYTICS GET

**\$10.66**

FOR EVERY

**\$1**

THEY SPEND ON ANALYTICS

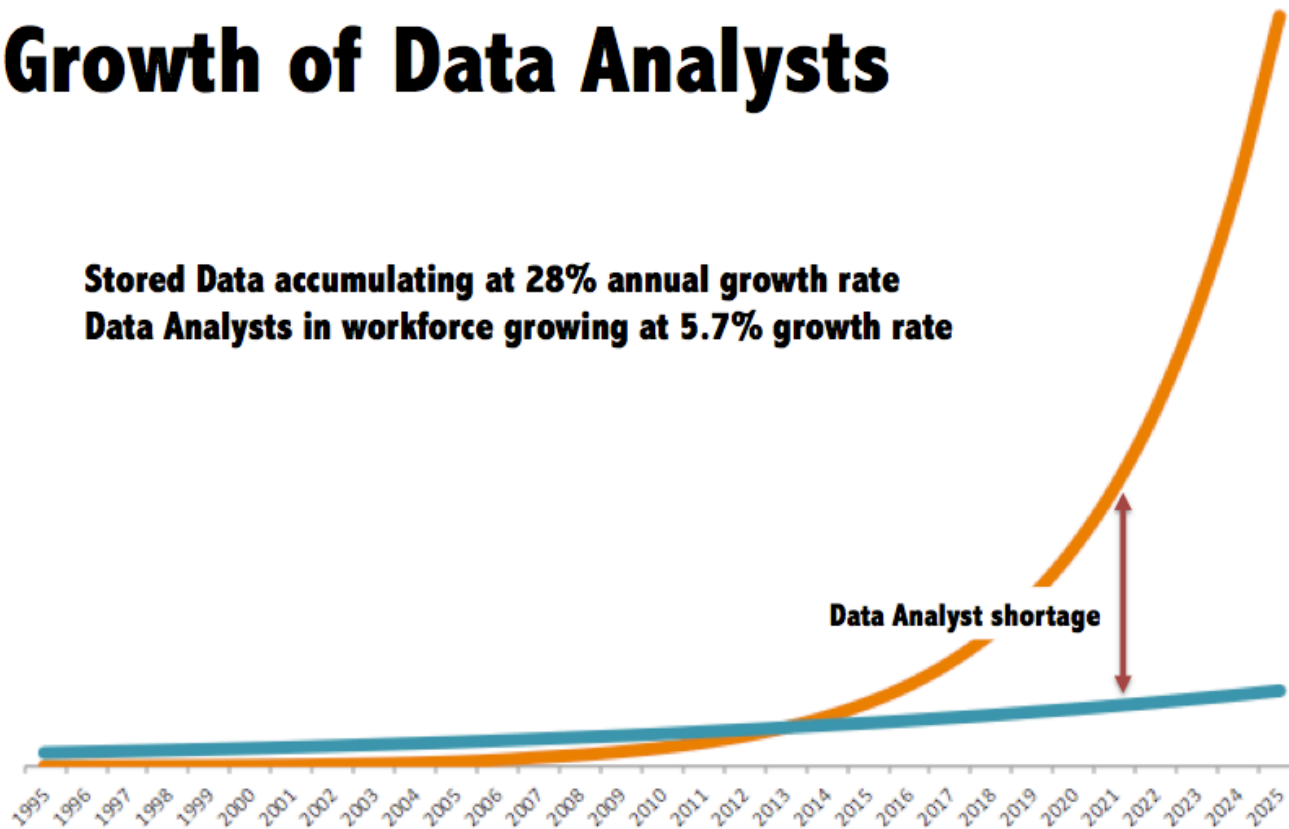
# Planning for Future

Growth of Data Exponentially Greater than Growth of Data Analysts!



## Growth of Data vs. Growth of Data Analysts

**Stored Data accumulating at 28% annual growth rate**  
**Data Analysts in workforce growing at 5.7% growth rate**



### Conclusion

- Data Analysis platforms need to be
  - Extremely **Easy to Learn**, yet..
  - Extremely **Powerful** and
  - **Automated** as much as possible!

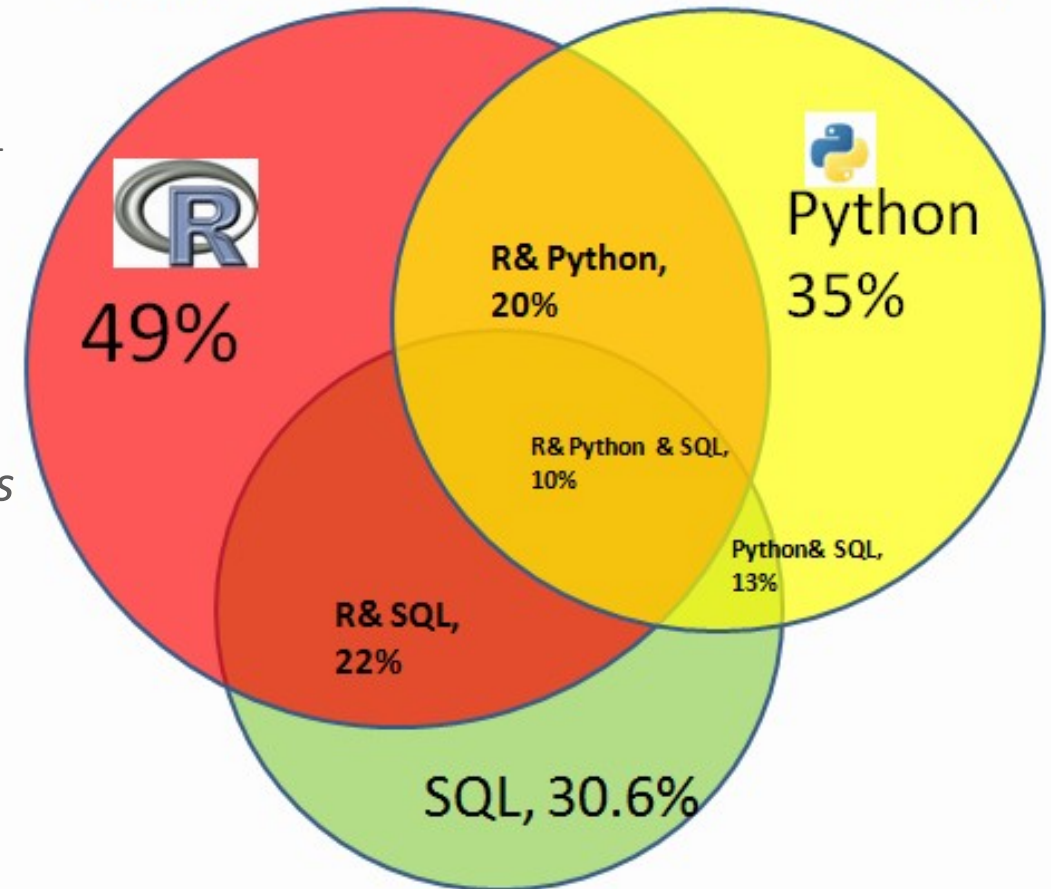
# Four Main Languages for Analytics, Data Mining, Data Science: R, SQL, SAS, Python

SQL is at Core

- BIG DATA'S BIG FLIP-FLOP

- BY BILL FRANKS, Chief Analytics Officer for Teradata, MAR 13, 2014
- *“It wasn’t too long ago that many people espoused the **decline, if not death, of the SQL language** and relational database technology in general.”*
- *“In case you hadn’t noticed, a **huge flip-flop has occurred**. Many of the same people and organizations that were recently dismissing the entire concept of relational environments and SQL are **now racing to ... wait for it ... add SQL-style interfaces on top of non-relational platforms like Hadoop!**”*

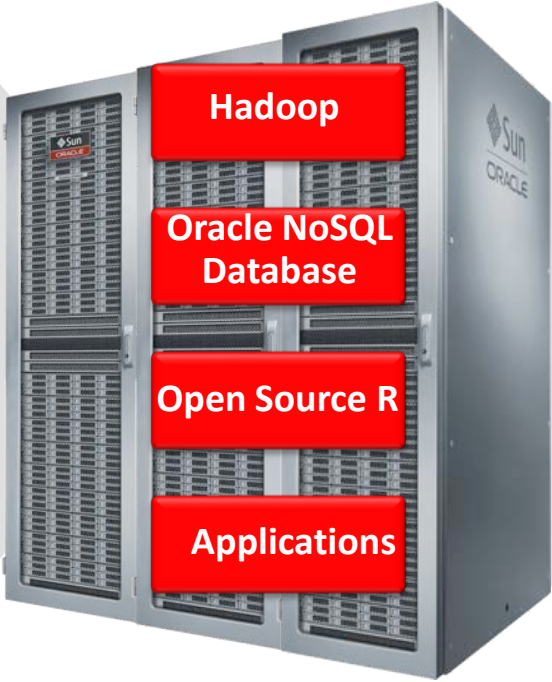
KDnuggets 2014 Poll: Languages used for Analytics/Data Mining



# Oracle Big Data Platform

## Oracle Big Data Appliance

Optimized for Hadoop, R, and NoSQL Processing



## Oracle Big Data Connectors

Oracle Big Data Connectors

Oracle Data Integrator

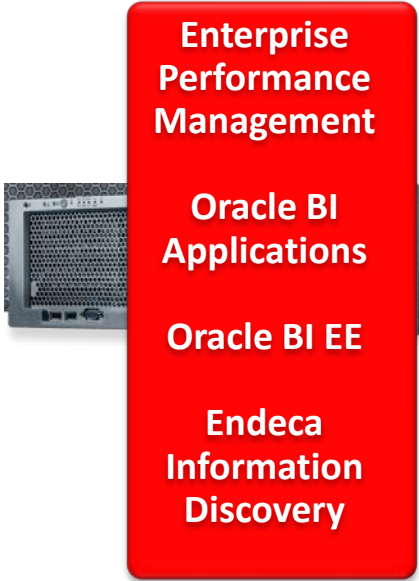
## Oracle Exadata

“System of Record”  
Optimized for DW/OLTP



## Oracle Exalytics

Optimized for Analytics & In-Memory Workloads



Stream

Acquire

Organize

Discover & Analyze

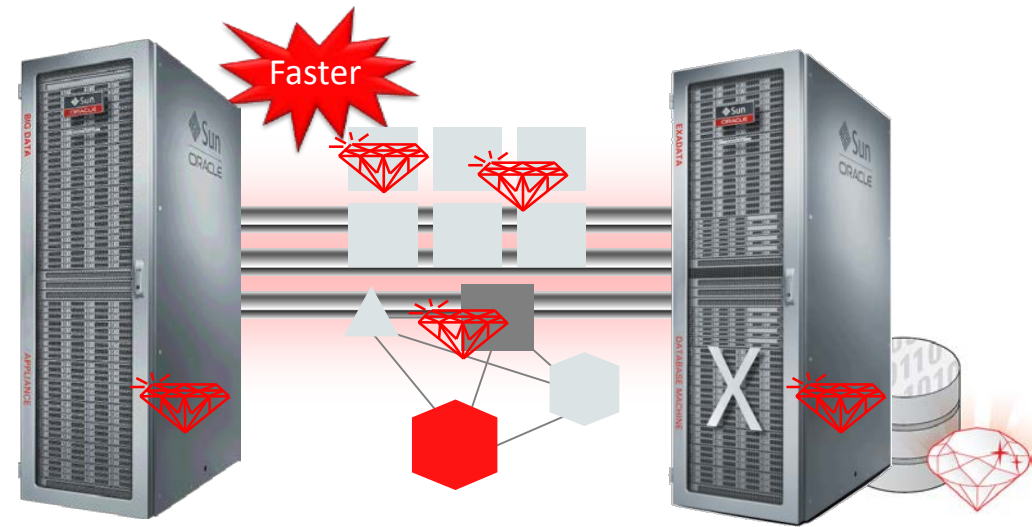


# Oracle Advanced Analytics + Exadata + Big Data SQL

## OAA data mining model “scoring” pushed to Exadata storage tier and BDA

- With Oracle Advanced Analytics, SQL predicates and predictive models get pushed down for execution

- For **Exadata** environments, get pushed to Exadata storage level for execution
- For **BDA** environments, get pushed to BDA for execution



**Big Data Appliance**

+  
Hadoop

**Exadata**

+  
Oracle Database

- 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;
```

Scoring function executed in Exadata or on BDA

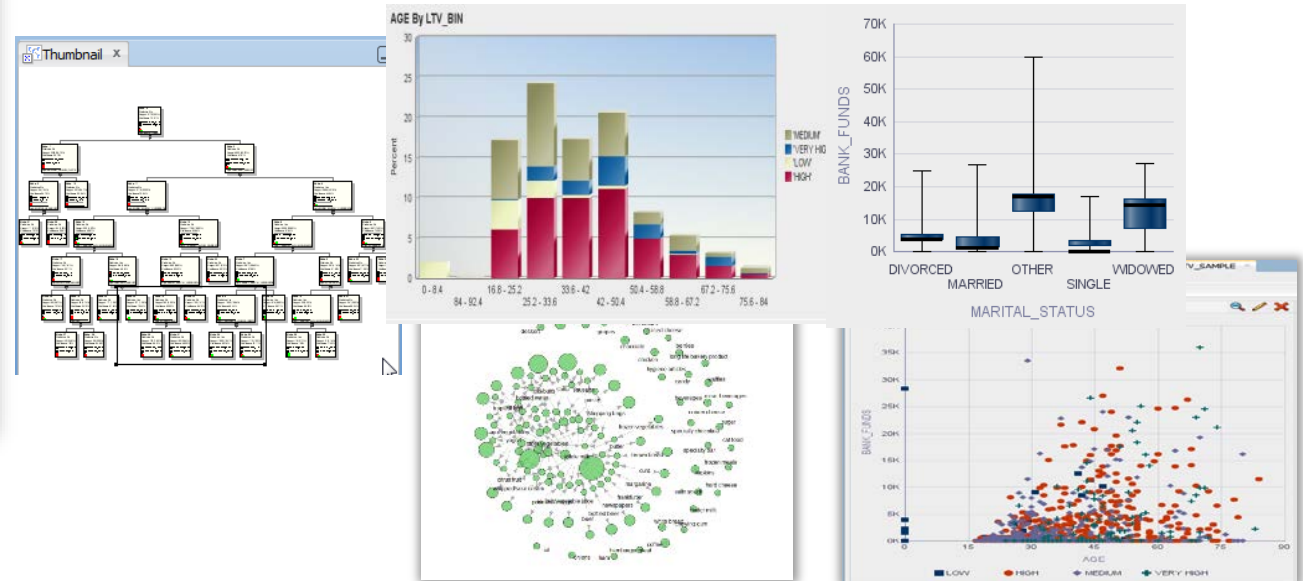
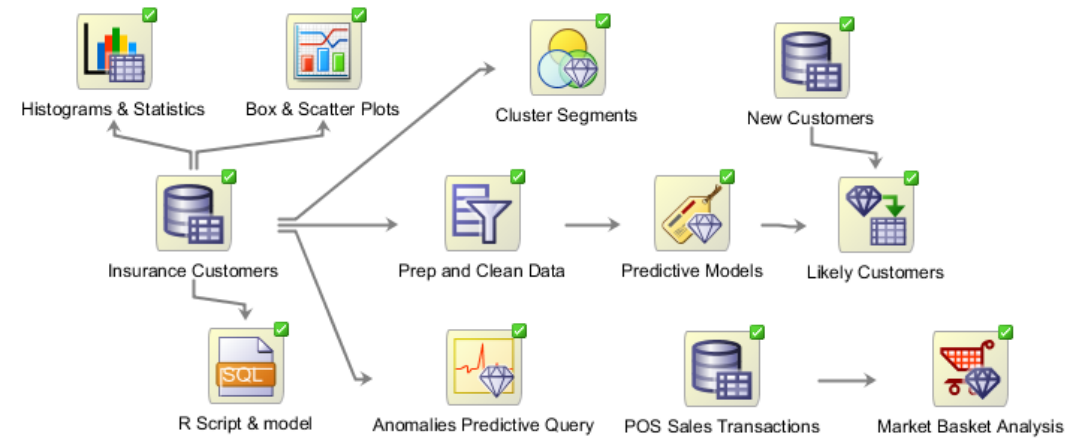


# Oracle Advanced Analytics Database Option

Fastest Way to Deliver Scalable Enterprise-wide Predictive Analytics

## Key Features

- In-database data mining algorithms and open source R algorithms
- SQL, PL/SQL, R languages
- Scalable, parallel in-database execution
- Workflow GUI and IDEs
- Integrated component of Database
- Enables enterprise analytical applications

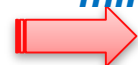


# Oracle Advanced Analytics Database Evolution



- 7 Data Mining “Partners”

1998



1999



- Oracle acquires Thinking Machine Corp’s dev. team + “Darwin” data mining software

2002



2004



2005



2008



2011



2014



- Oracle Data Mining 10g & 10gR2 introduces SQL dm functions, 7 new SQL dm algorithms and new Oracle Data Miner “Classic” wizards driven GUI



- ODM 11g & 11gR2 adds AutoDataPrep (ADP), text mining, perf. improvements
- SQLDEV/Oracle Data Miner adds NN, Stepwise, 3.2 “work flow” GUI launched
- Integration with “R” and introduction/addition of Oracle R Enterprise
- Product renamed “Oracle Advanced Analytics (ODM + ORE)”

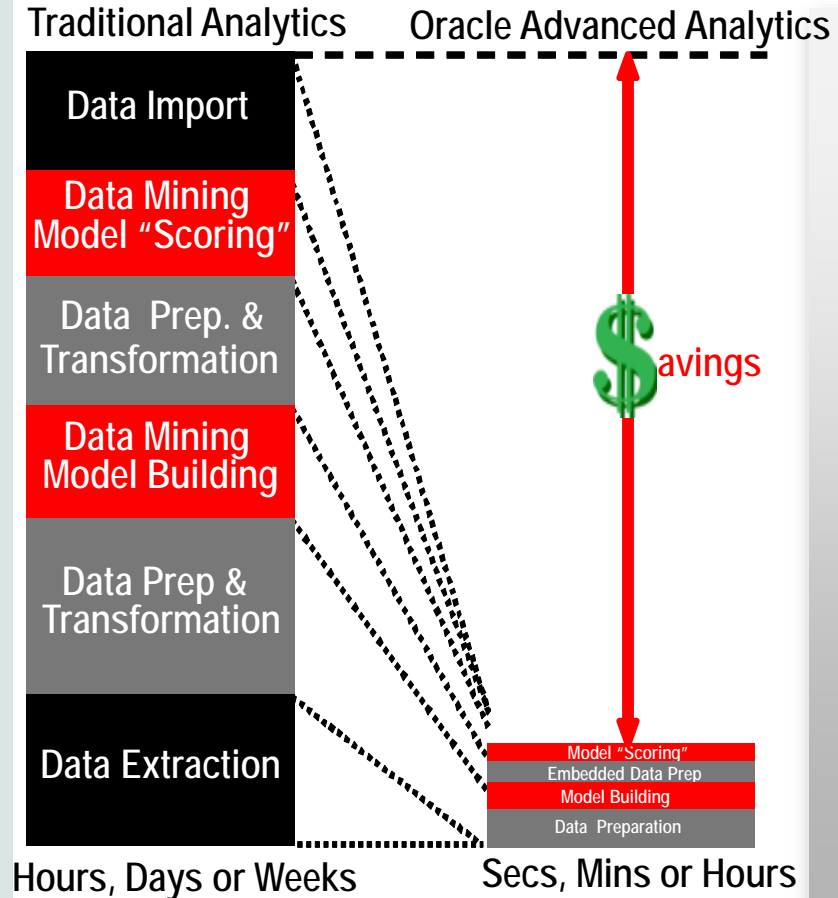


- New algorithms (EM, PCA, SVD)
- Predictive Queries
- SQLDEV/Oracle Data Miner 4.0 SQL script generation and SQL Query node (R integration)
- OAA/ORE 1.3 + 1.4
- Oracle Adv. Analytics for Hadoop Connector launched with scalable BDA algorithms



# Oracle Advanced Analytics

## Performance and Scalability with Low Total Cost of Ownership



### Data remains in the Database

- Scalable, parallel Data Mining algorithms in SQL kernel
- Fast parallelized native SQL data mining functions, SQL data preparation and efficient execution of R open-source packages
- High-performance parallel scoring of SQL data mining functions and R open-source models

### Fastest way to deliver enterprise-wide predictive analytics

- Integrated GUI for Predictive Analytics
- Database scoring engine

### Lowest TCO

- Eliminate data duplication
- Eliminate separate analytical servers
- Leverage investment in Oracle IT

# Turkcell

## Combating Communications Fraud



### Objectives

- Prepaid card fraud—millions of dollars/year
- Extremely fast sifting through huge data volumes; with fraud, time is money

### Solution

- Monitor 10 billion daily call-data records
- Leveraged SQL for the preparation—1 PB
- Due to the slow process of moving data, Turkcell IT builds and deploys models in-DB
- Oracle Advanced Analytics on Exadata for extreme speed. Analysts can detect fraud patterns almost immediately

- “Turkcell manages 100 terabytes of compressed data—or one petabyte of uncompressed raw data—on Oracle Exadata. With Oracle Data Mining, a component of the Oracle Advanced Analytics Option, we can analyze large volumes of customer data and call-data records easier and faster than with any other tool and rapidly detect and combat fraudulent phone use.”  
– Hasan Tonguç Yılmaz, Manager, Turkcell İletişim Hizmetleri A.Ş.



Oracle Advanced Analytics  
In-Database Fraud Models

Exadata



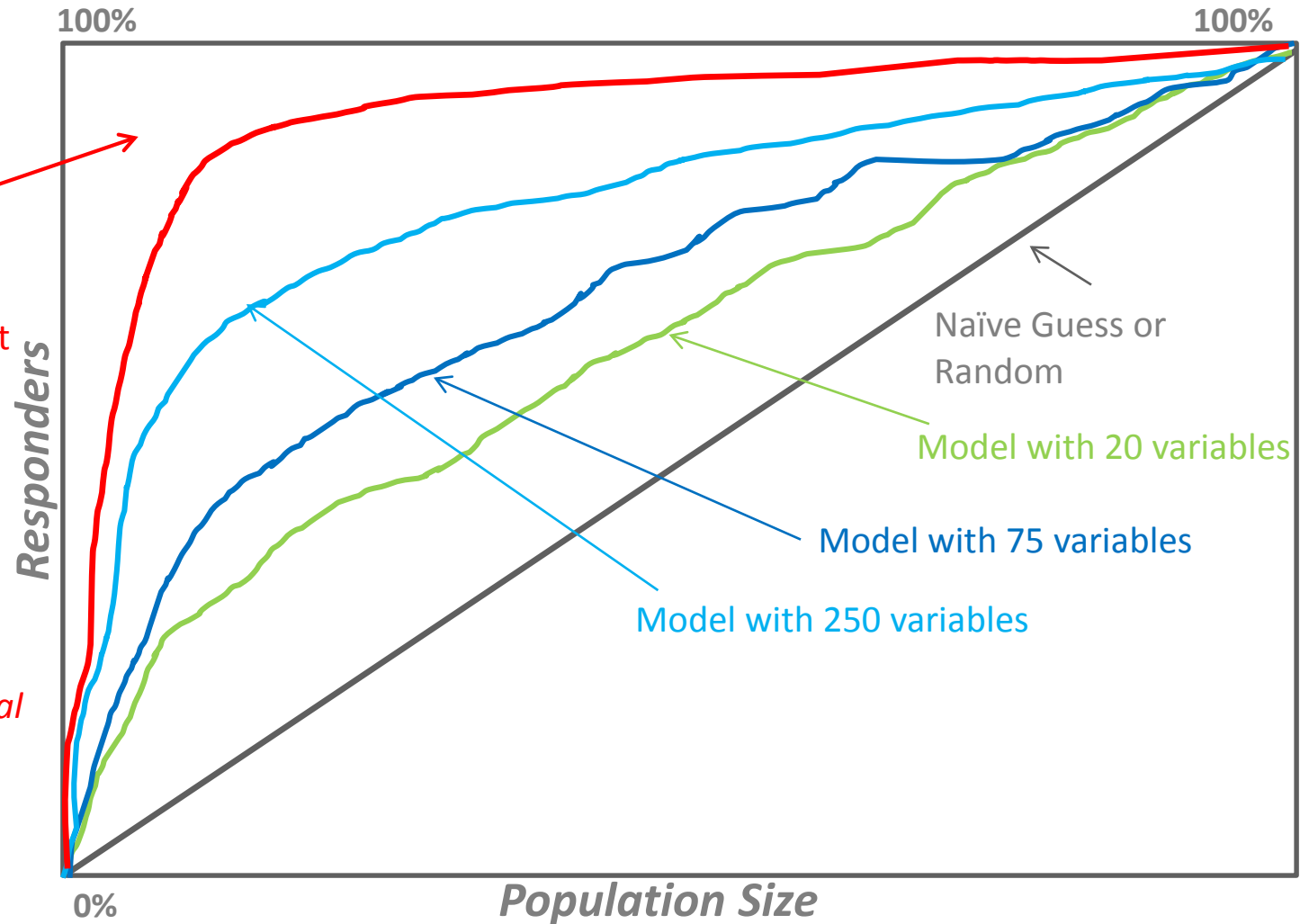
# More Data Variety—Better Predictive Models

- Increasing sources of relevant data can boost model accuracy



Model with "Big Data" and hundreds -- thousands of input variables including:

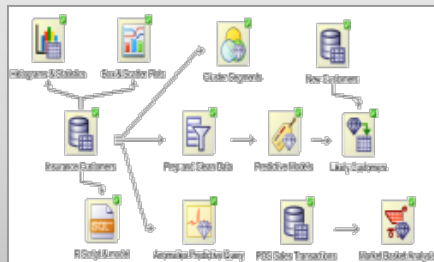
- Demographic data
- Purchase POS transactional data
- "Unstructured data", text & comments
- Spatial location data
- Long term vs. recent historical behavior
- Web visits
- Sensor data
- etc.



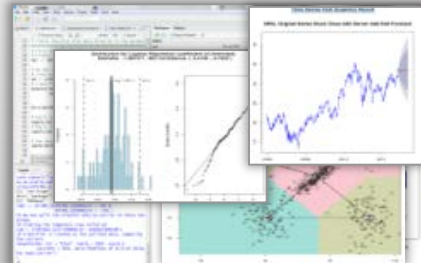
# Oracle Advanced Analytics Database Architecture

## Component of Oracle Database—SQL Functions

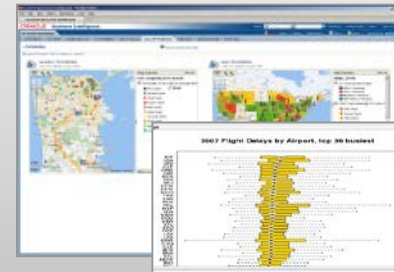
### SQL Developer



### R Client



### OBIEE



### Applications



## Oracle Database Enterprise Edition

### Oracle Advanced Analytics

*Native SQL Data Mining/Analytic Functions + High-performance  
R Integration for Scalable, Distributed, Parallel Execution*



# Fiserv

## Combating Fraud

### Objectives

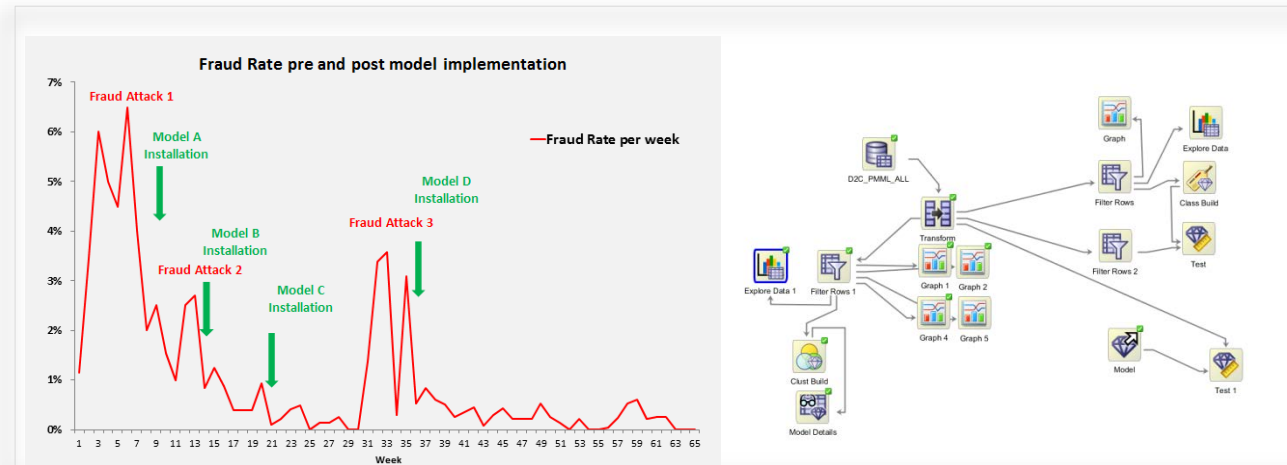
- Build and implement Risk Mitigation Strategies for 2,500 US banks and Financial Institutions
- Fraud revention in online payments performed by organized sophisticated criminal groups
- When dealing with the hectic world of fraud, speed is the most important factor
- Hard to detect...target has low frequency (3 in 10,000)

### Solution

- Oracle Advanced Analytics used by data analysts and deployed by DBA

“Oracle Advanced Analytics has a competitive advantage in terms of time savings, accuracy, cost, ease of use and deployment. When dealing with the hectic world of fraud, the speed to implement a new model is the most important factor. Systems with good algorithms and a fast turnaround have better ROI than systems with complex algorithms with long implementation times.”

– Miguel Barrera, Risk Manager, Julia Minkowski, Risk Analyst, Fiserv Inc,



Excerpted from **Becoming Faster than a Mouse: Turn Data Mining into Action in Fraud Detection using OAA**, presented at Oracle BIWA Summit 2014, [www.biwasumit.org](http://www.biwasumit.org), - Miguel Barrera, Risk Manager, Fiserv Inc, - Julia Minkowski, Risk Analyst, Fiserv Inc.

# What we learned... **fiserv.**



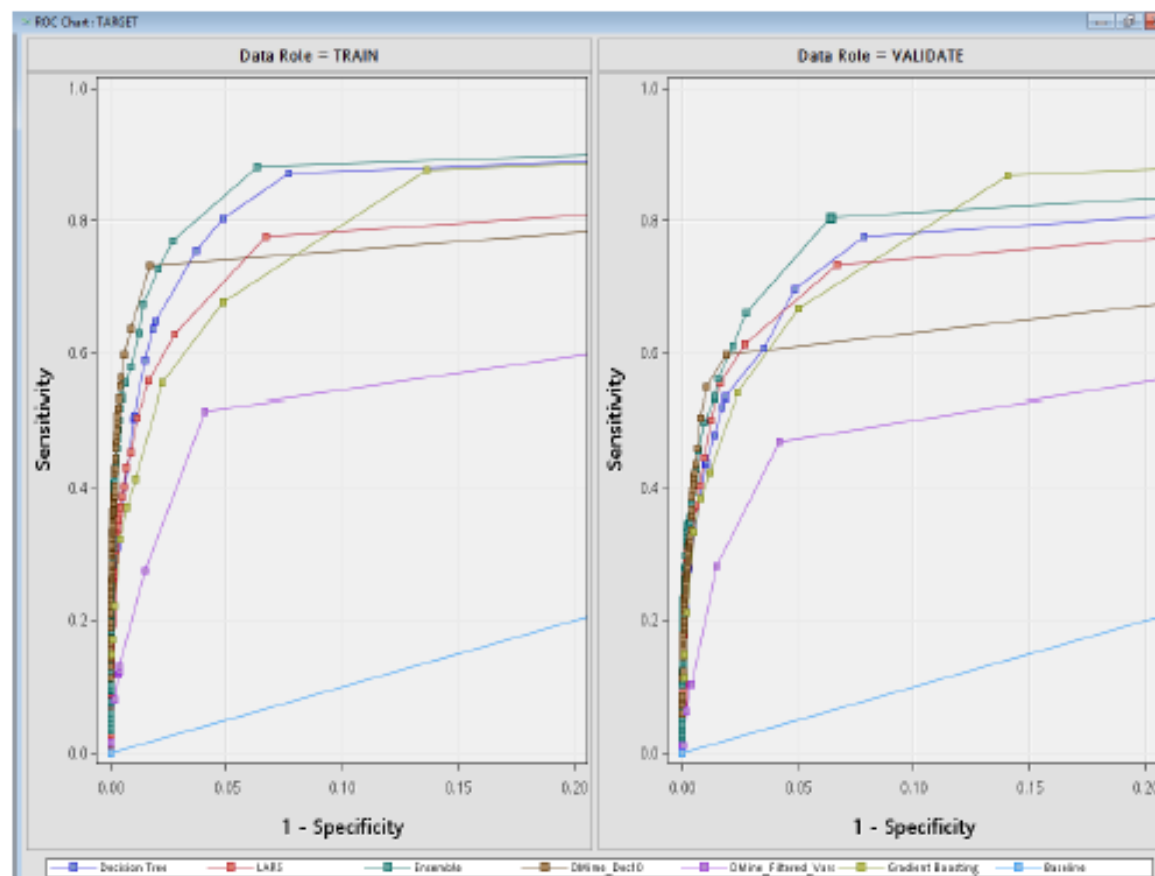
- Complex Methods barely outperform simpler methods:
- Binning makes Trees and GLM almost as good as Ensemble or Gradient Methods



- Complex methods are hard to implement and **require investments in infrastructure**



- The current model building structure (SAS + Angoss) does not scale to grow with large volume

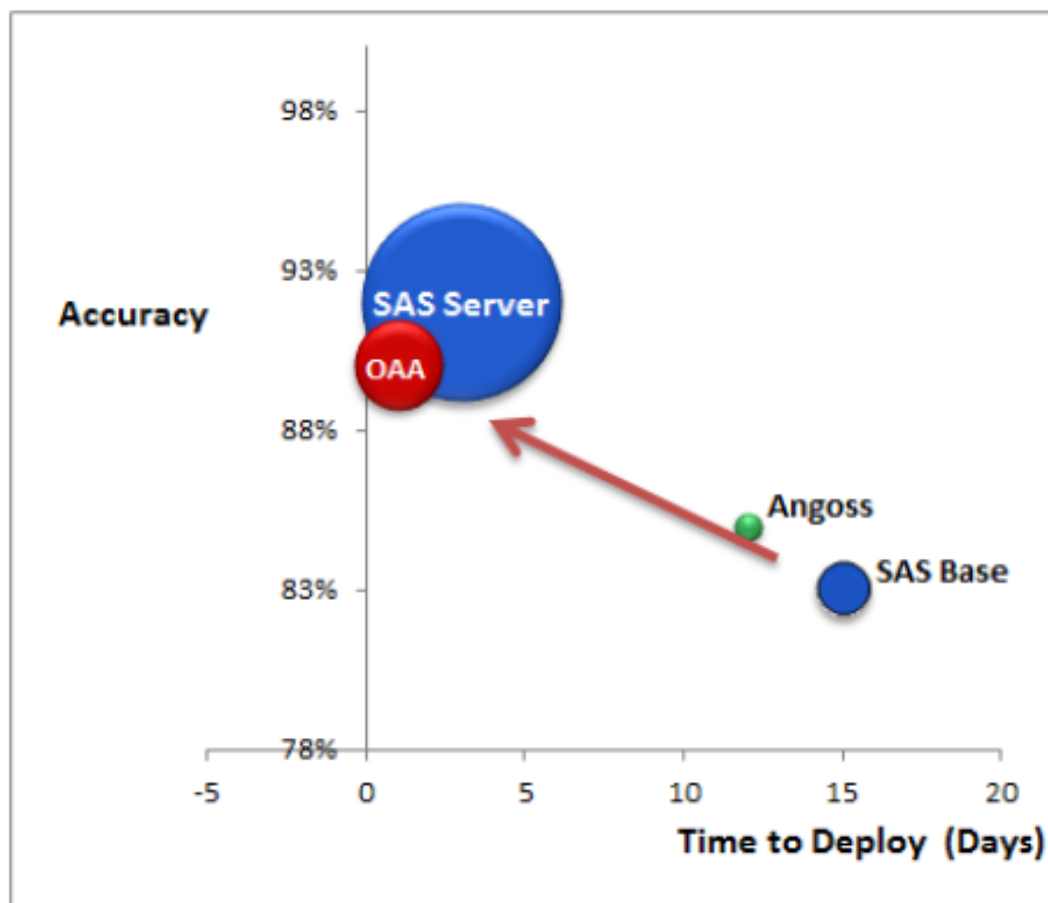




# Accuracy + Agility vs. Cost to Deploy **fiserv.**

Cost Dimension (Size)

Time to Deploy x Accuracy (% Fr Detected)



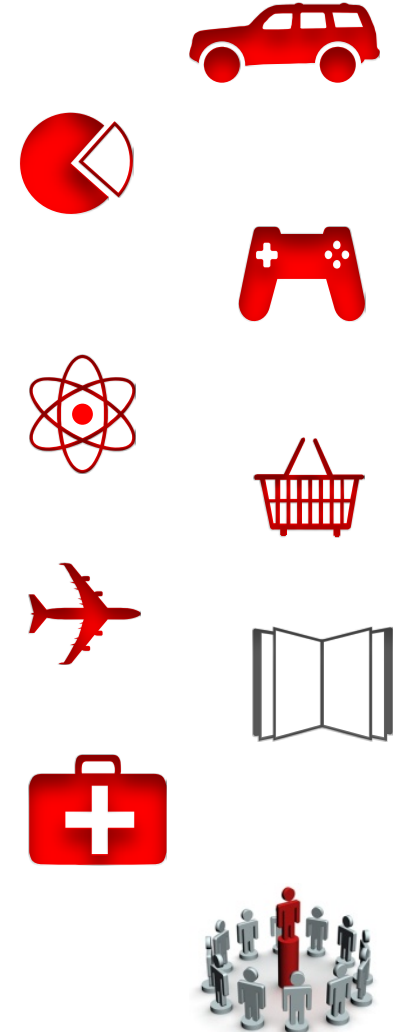
- Pick the best combination of:
  - Less days to deployment
  - High model accuracy
  - Lower Cost

Application	Deploy (Days)	Accuracy	Total Cost
SAS Server	3	0.92	x5
ODM	1	0.90	1
SAS Base	15	0.83	30%
Angoss	12	0.85	10%

# Predictive Analytics & Data Mining

## Typical Use Cases

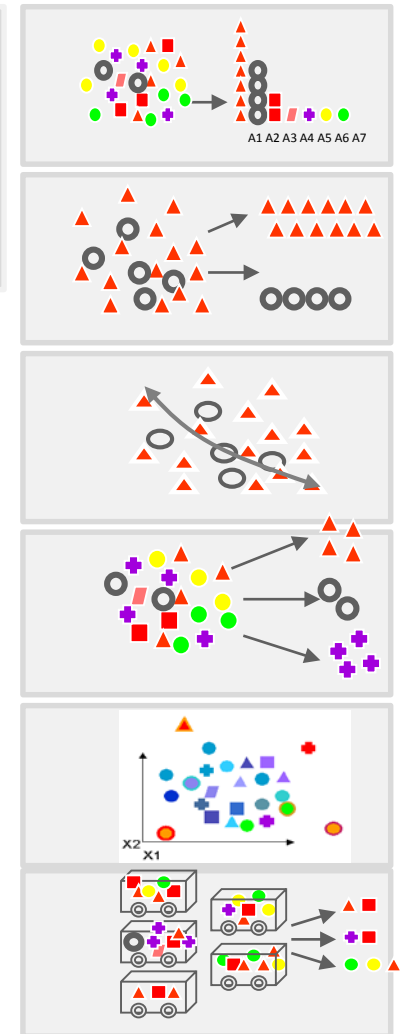
- Targeting the right customer with the right offer
- How is a customer likely to respond to an offer?
- Finding the most profitable growth opportunities
- Finding and preventing customer churn
- Maximizing cross-business impact
- Security and suspicious activity detection
- Understanding sentiments in customer conversations
- Reducing medical errors & improving quality of health
- Understanding influencers in social networks

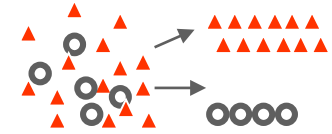


# What is Data Mining?

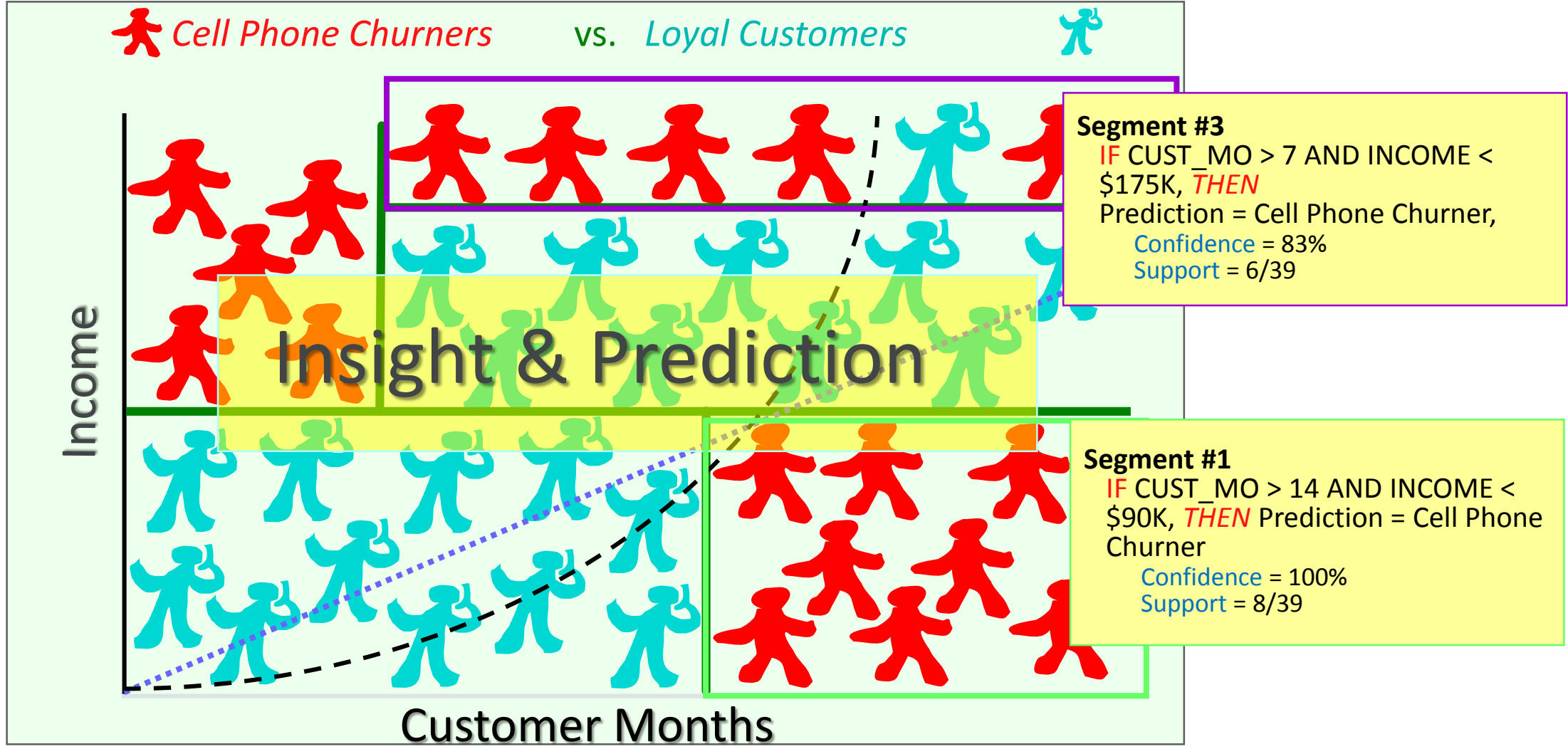
***Automatically*** sifting through **large amounts** of data to find **previously hidden patterns**, discover **valuable new insights** and **make predictions**

- Identify most important factor (*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*)
- Find fraudulent or “rare events” (*Anomaly Detection*)
- Determine co-occurring items in a “baskets” (*Associations*)



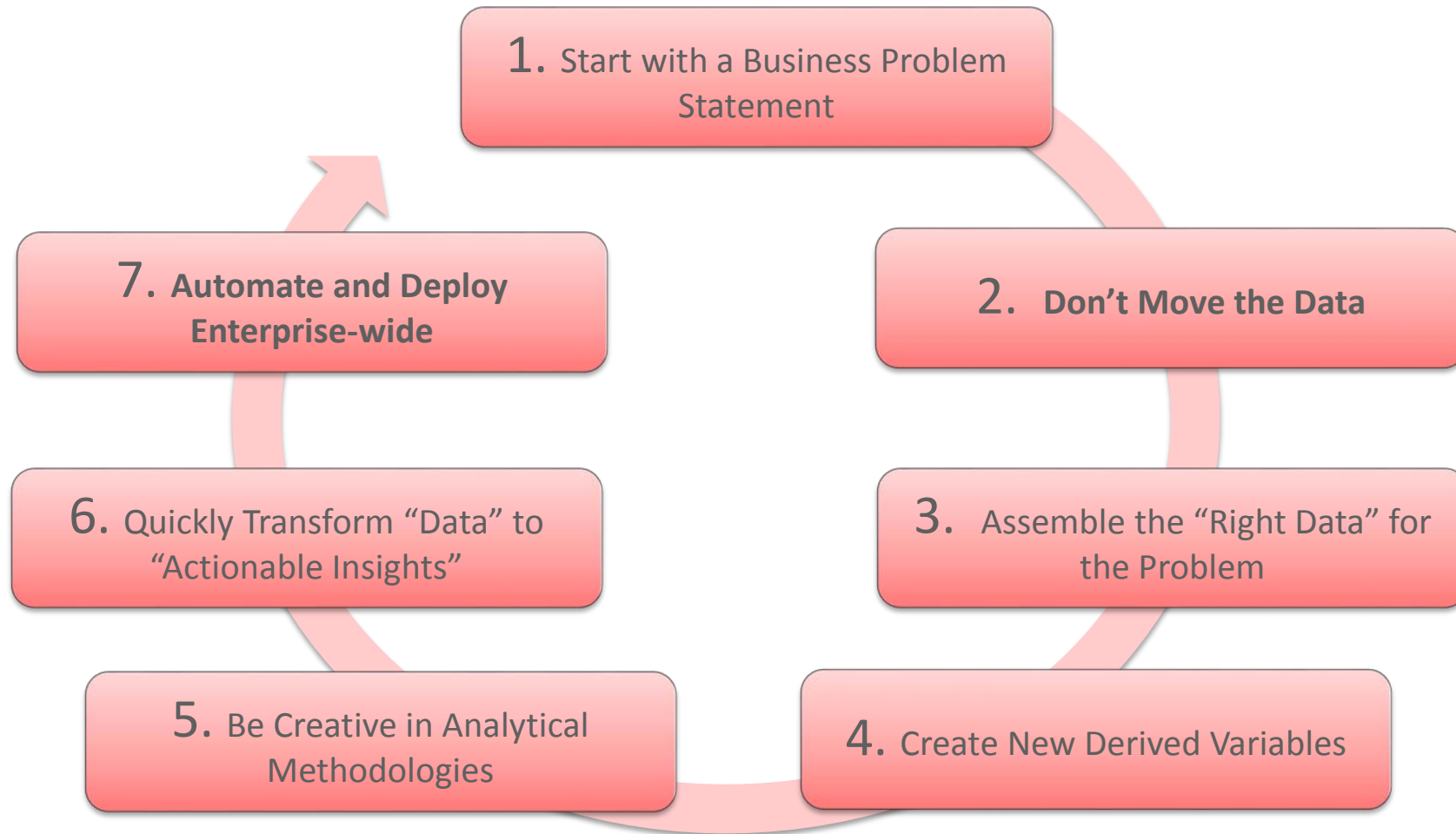


# Data Mining Provides Better Information, Valuable Insights and Predictions



# Oracle Advanced Analytics—*Best Practices*

Nothing is Different; Everything is Different

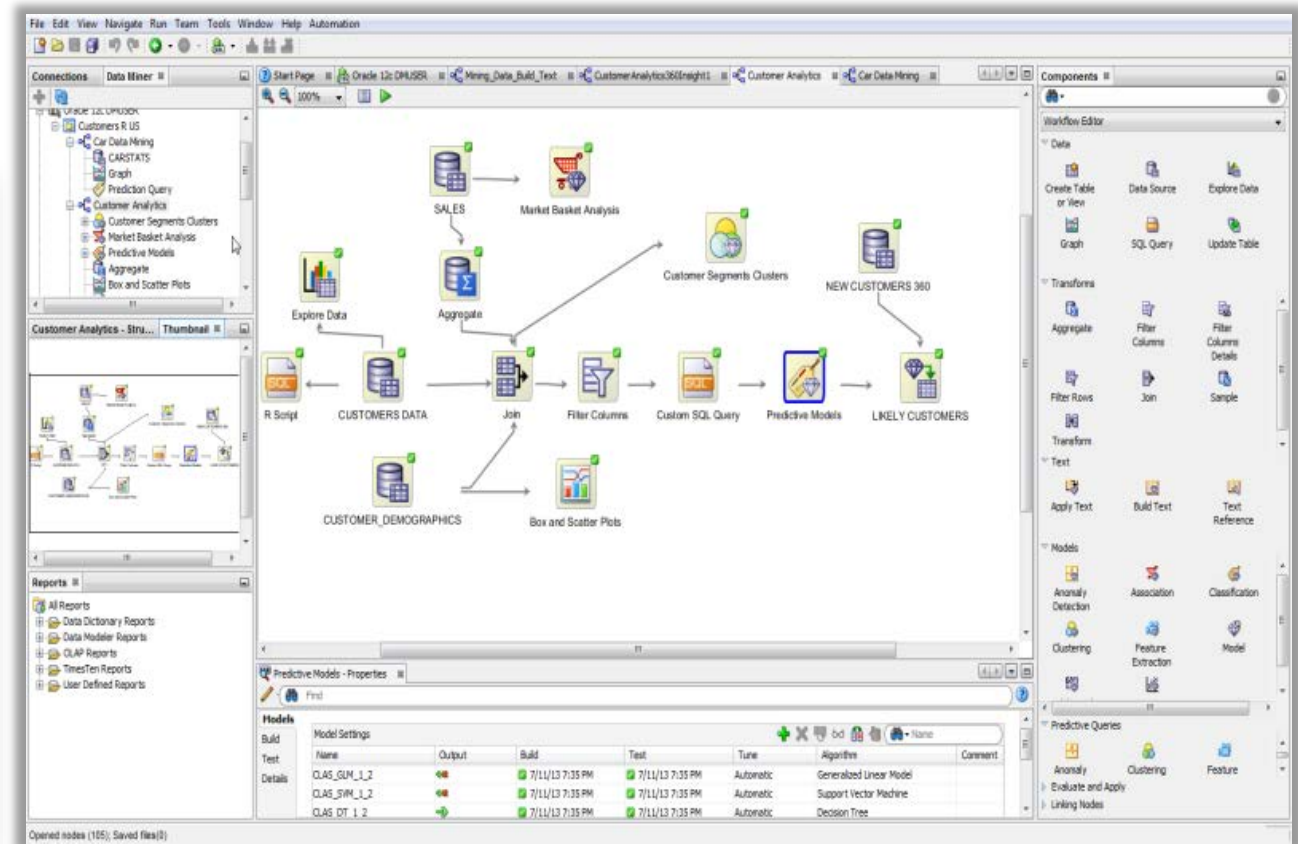


# Oracle Data Miner “Workflow” GUI for Data Analysts

## SQL Developer 4.0 Extension

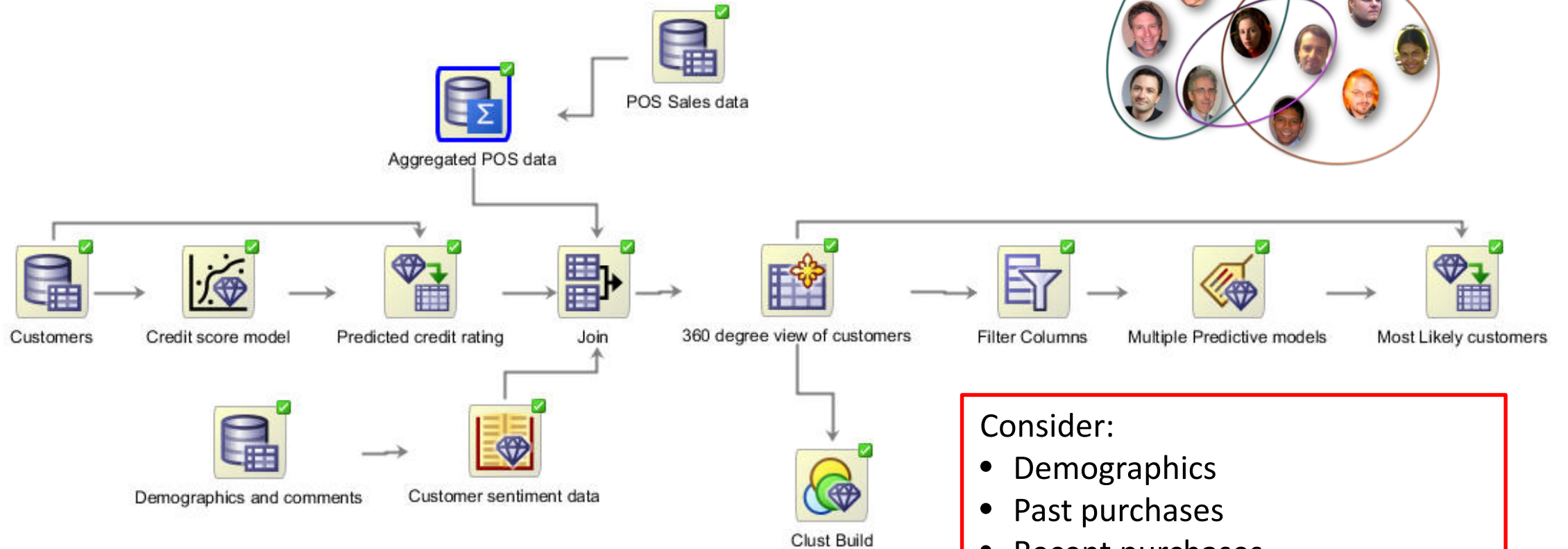
Free OTN Download

- Easy to Use
  - Oracle Data Miner GUI for data analysts
  - “Work flow” paradigm
- Powerful
  - Multiple algorithms & data transformations
  - Runs 100% in-DB
  - Build, evaluate and apply models
- Automate and Deploy
  - Save and share analytical workflows
  - Generate SQL scripts for deployment



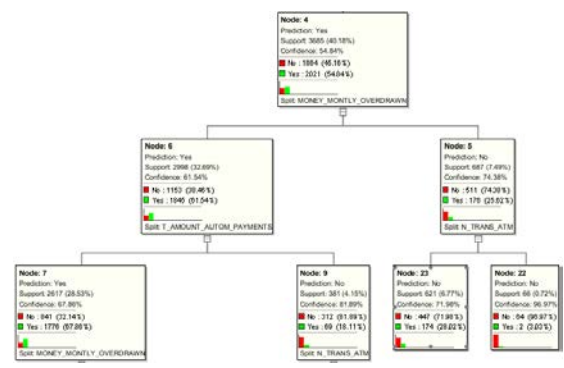
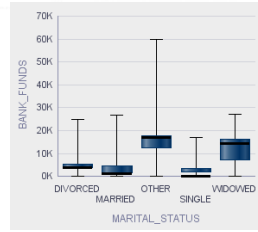
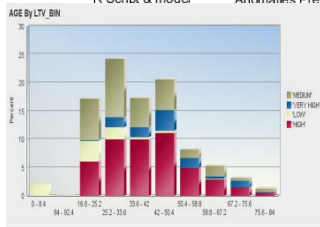
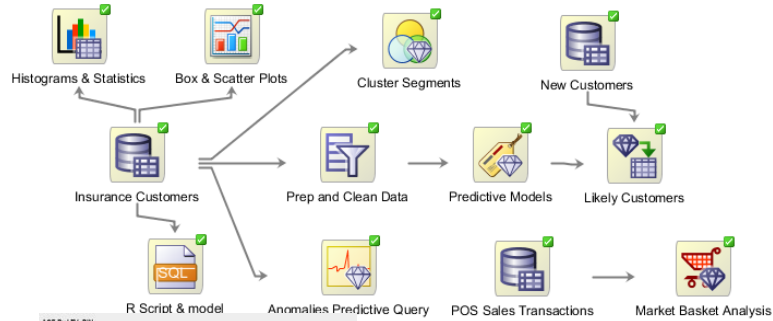
# Predicting Behavior

## Identify “Likely Behavior” and their Profiles



- Consider:
- Demographics
  - Past purchases
  - Recent purchases
  - Customer comments & tweets

# Oracle Advanced Analytics



## OAA/ORACLE DATA MINER QUICK DEMO



# Start with a Business Problem Statement

## Common Examples

- Predict employees that voluntarily churn
- Predict customers that are likely to churn
- Target “best” customers
- Find items that will help me sell more most profitable items
- What is a specific customer most likely to purchase next?
- Who are my “best customers”?
- How can I combat fraud?
- I’ve got all this data; can you “mine” it and find useful insights?

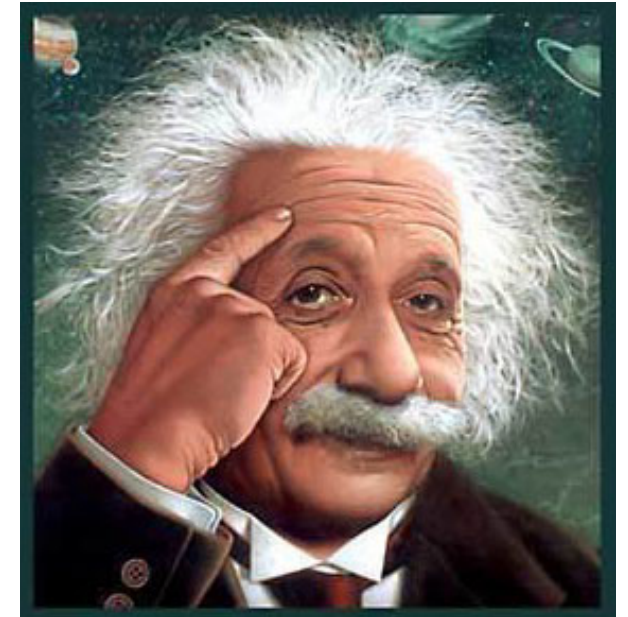


# Start with a Business Problem Statement

## Clearly Define Problem

“If I had an hour to solve a problem I'd spend 55 minutes thinking about the problem and 5 minutes thinking about solutions.”

— Albert Einstein



# Be Specific in Problem Statement

## Poorly Defined

Predict employees that leave

Predict customers that churn

Target “best” customers

How can I make more \$\$?

Which customers are likely to buy?

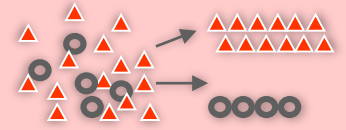
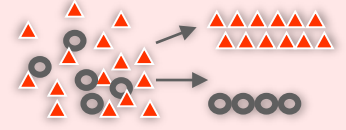
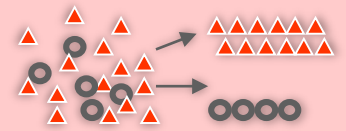
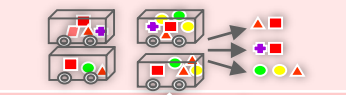
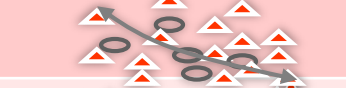
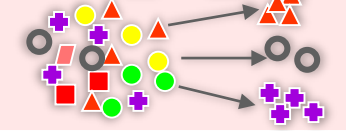

Who are my “best customers”?

How can I combat fraud?

# Be Specific in Problem Statement

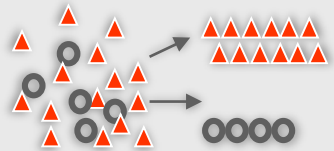

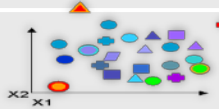
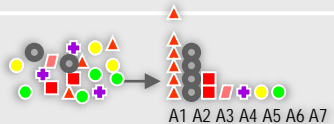
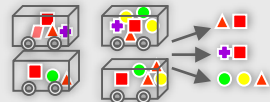
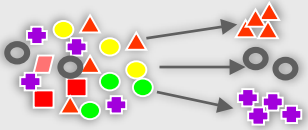
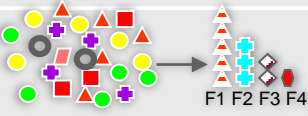
Poorly Defined	Better
Predict employees that leave	<ul style="list-style-type: none"><li>• Based on past employees that voluntarily left:<ul style="list-style-type: none"><li>• Create New Attribute <b>EmplTurnover</b> → 0/1</li></ul></li></ul>
Predict customers that churn	<ul style="list-style-type: none"><li>• Based on past customers that have churned:<ul style="list-style-type: none"><li>• Create New Attribute <b>Churn</b> → YES/NO</li></ul></li></ul>
Target “best” customers	<ul style="list-style-type: none"><li>• Recency, Frequency Monetary (RFM) Analysis</li><li>• Specific Dollar Amount over Time Window:<ul style="list-style-type: none"><li>• Who has spent \$500+ in most recent 18 months</li></ul></li></ul>
How can I make more \$\$?	<ul style="list-style-type: none"><li>• What helps me sell soft drinks &amp; coffee?</li></ul>
Which customers are likely to buy?	<ul style="list-style-type: none"><li>• How much is each customer likely to spend?</li></ul>
Who are my “best customers”?	<ul style="list-style-type: none"><li>• What descriptive “rules” describe “best customers”?</li></ul>
How can I combat fraud?	<ul style="list-style-type: none"><li>• Which transactions are the most anomalous?<ul style="list-style-type: none"><li>• Then roll-up to physician, claimant, employee, etc.</li></ul></li></ul>

# Be Specific in Problem Statement

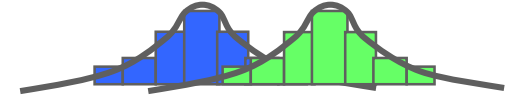
Poorly Defined	Better	Data Mining Technique
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# Oracle Advanced Analytics

## In-Database Data Mining Algorithms—SQL & R & GUI Access

Function		Algorithms	Applicability
Classification		Logistic Regression (GLM) Decision Trees Naïve Bayes Support Vector Machines (SVM)	Classical statistical technique Popular / Rules / transparency Embedded app Wide / narrow data / text
Regression		Linear Regression (GLM) Support Vector Machine (SVM)	Classical statistical technique Wide / narrow data / text
Anomaly Detection		One Class SVM	Unknown fraud cases or anomalies
Attribute Importance		Minimum Description Length (MDL) Principal Components Analysis (PCA)	Attribute reduction, Reduce data noise
Association Rules		Apriori	Market basket analysis / Next Best Offer
Clustering		Hierarchical k-Means Hierarchical O-Cluster Expectation-Maximization Clustering (EM)	Product grouping / Text mining Gene and protein analysis
Feature Extraction		Nonnegative Matrix Factorization (NMF) Singular Value Decomposition (SVD)	Text analysis / Feature reduction

# In-Database Advanced Analytics



## Independent Samples T-Test

- Query compares the mean of AMOUNT\_SOLD between MEN and WOMEN Grouped By CUST\_INCOME\_LEVEL ranges
- Returns observed t value and its related two-sided significance (<.05 = significant)

```
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;
```

Script Output x  
Task completed in 3.872 seconds

INCOME_LEVEL	SOLD_TO_MEN	SOLD_TO_WOMEN	T_OBSERVED	TWO_SIDED_P_VALUE
A: Below 30,000	105.28349	99.4281447	-1.98806289	.0468114816
B: 30,000 - 49,999	102.59651	109.829642	2.84330875	.00234105343
C: 50,000 - 69,999	105.627388	110.127931	2.36148671	.0182042211
D: 70,000 - 89,999	106.630299	110.47287	2.28496443	.0223169973
E: 90,000 - 109,999	103.396741	101.610416	-1.25445773	.209677823
F: 110,000 - 129,999	106.76476	105.981312	-0.604449985	.545545304
G: 130,000 - 149,999	108.877532	107.31377	-0.852982449	.393671218
H: 150,000 - 169,999	110.987258	107.152191	-1.90623631	.056622983
I: 170,000 - 189,999	102.808238	107.43556	2.18477851	.0289085659
J: 190,000 - 249,999	108.040564	115.343356	2.58313425	.00979451611
K: 250,000 - 299,999	112.377993	108.196097	-1.41078707	.158316973
L: 300,000 and above	120.970235	112.216342	-2.06428678	.0390038615
	107.121845	113.80441	.686144393	.492670059
	106.663769	107.276386	1.08013499	.280082357

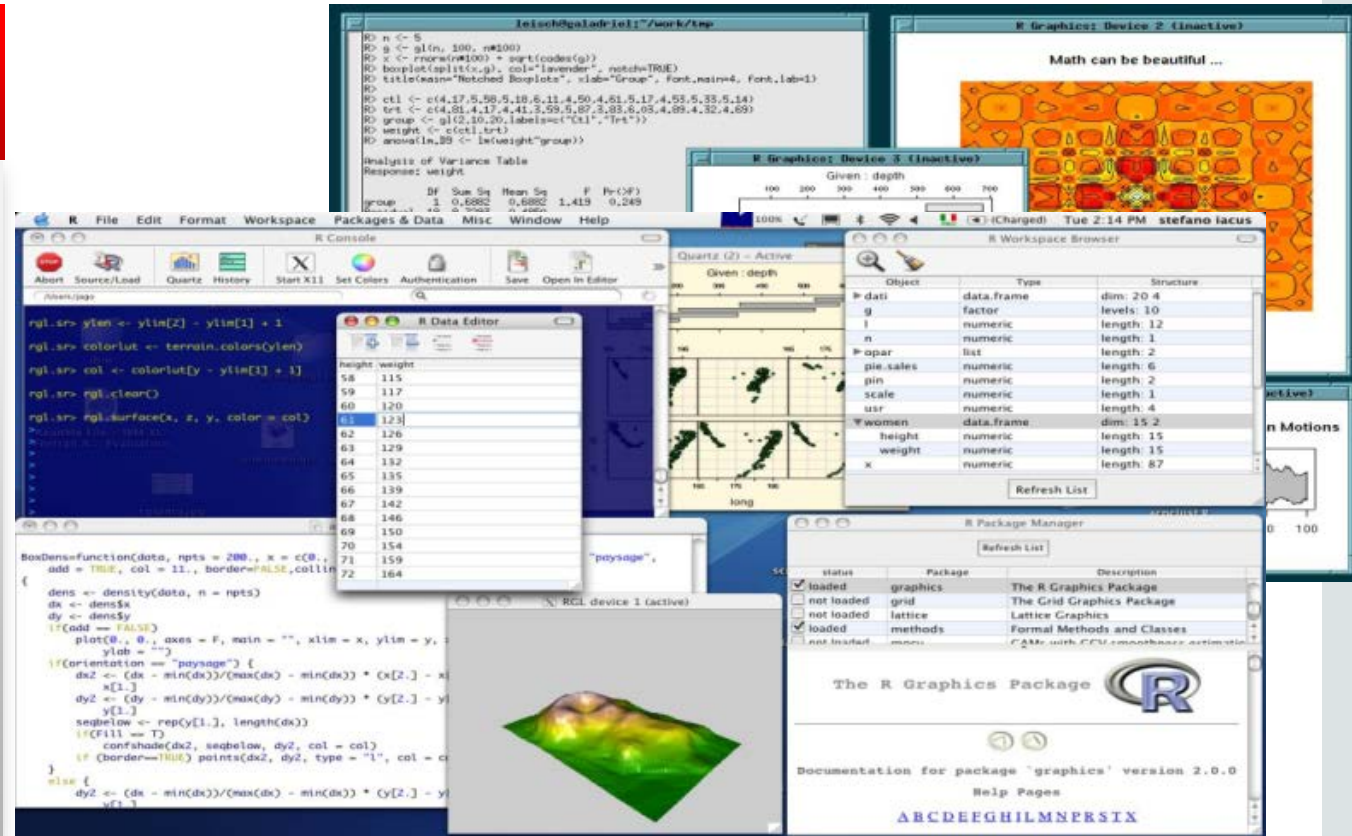
14 rows selected

# R—Widely Popular

R is a statistics language similar to Base SAS or SPSS statistics

## R environment

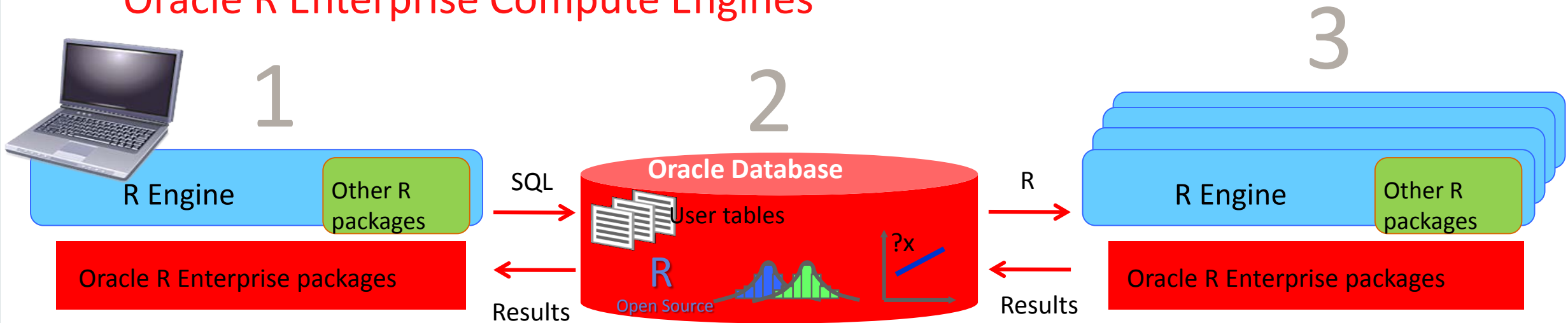
- Strengths
  - Powerful & Extensible
  - Graphical & Extensive statistics
  - Free—open source
- Challenges
  - Memory constrained
  - Single threaded
  - Outer loop—slows down process
  - Not industrial strength





# Oracle Advanced Analytics

## Oracle R Enterprise Compute Engines



### User R Engine on desktop

- R-SQL Transparency Framework intercepts R functions for scalable in-database execution
- Function intercept for data transforms, statistical functions and advanced analytics
- Interactive display of graphical results and flow control as in standard R
- Submit entire R scripts for execution by database

### Database Compute Engine

- Scale to large datasets
- Access tables, views, and external tables, as well as data through DB LINKS
- Leverage database SQL parallelism
- Leverage new and existing in-database statistical and data mining capabilities

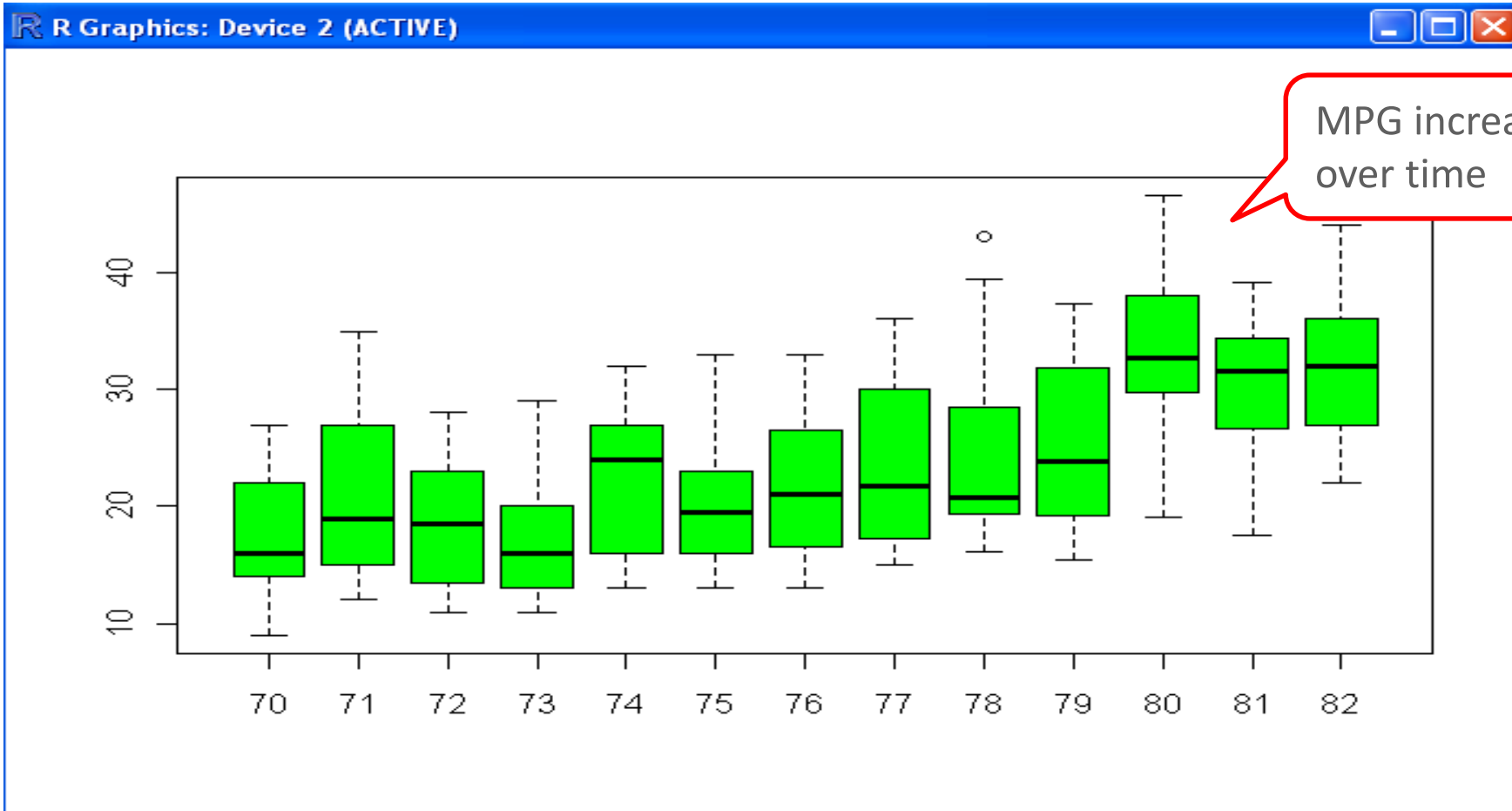
### R Engine(s) spawned by Oracle DB

- Database can spawn multiple R engines for database-managed parallelism
- Efficient data transfer to spawned R engines
- Emulate map-reduce style algorithms and applications
- Enables “lights-out” execution of R scripts

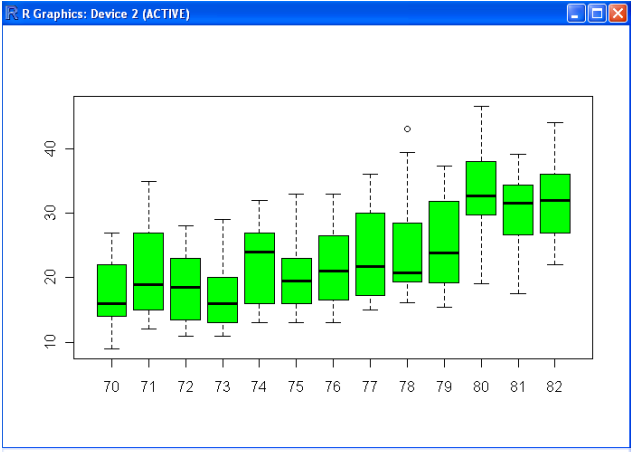
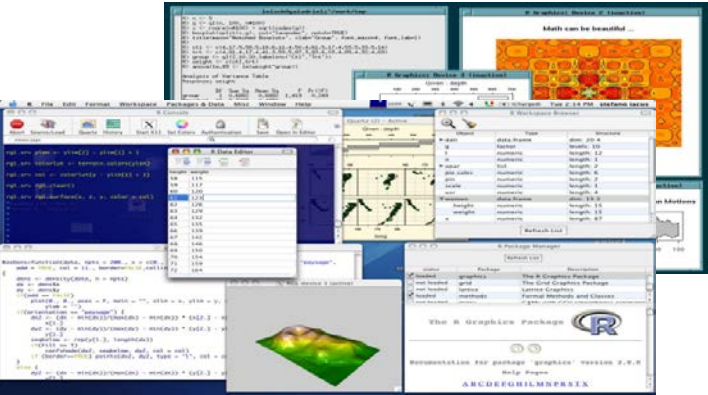
# Oracle Advanced Analytics

## R Graphics Direct Access to Database Data

```
R> boxplot(split(CARSTATS$mpg, CARSTATS$model.year), col = "green")
```



# Oracle Advanced Analytics



## OAA/ORACLE R ENTERPRISE QUICK DEMO



# Oracle Advanced Analytics

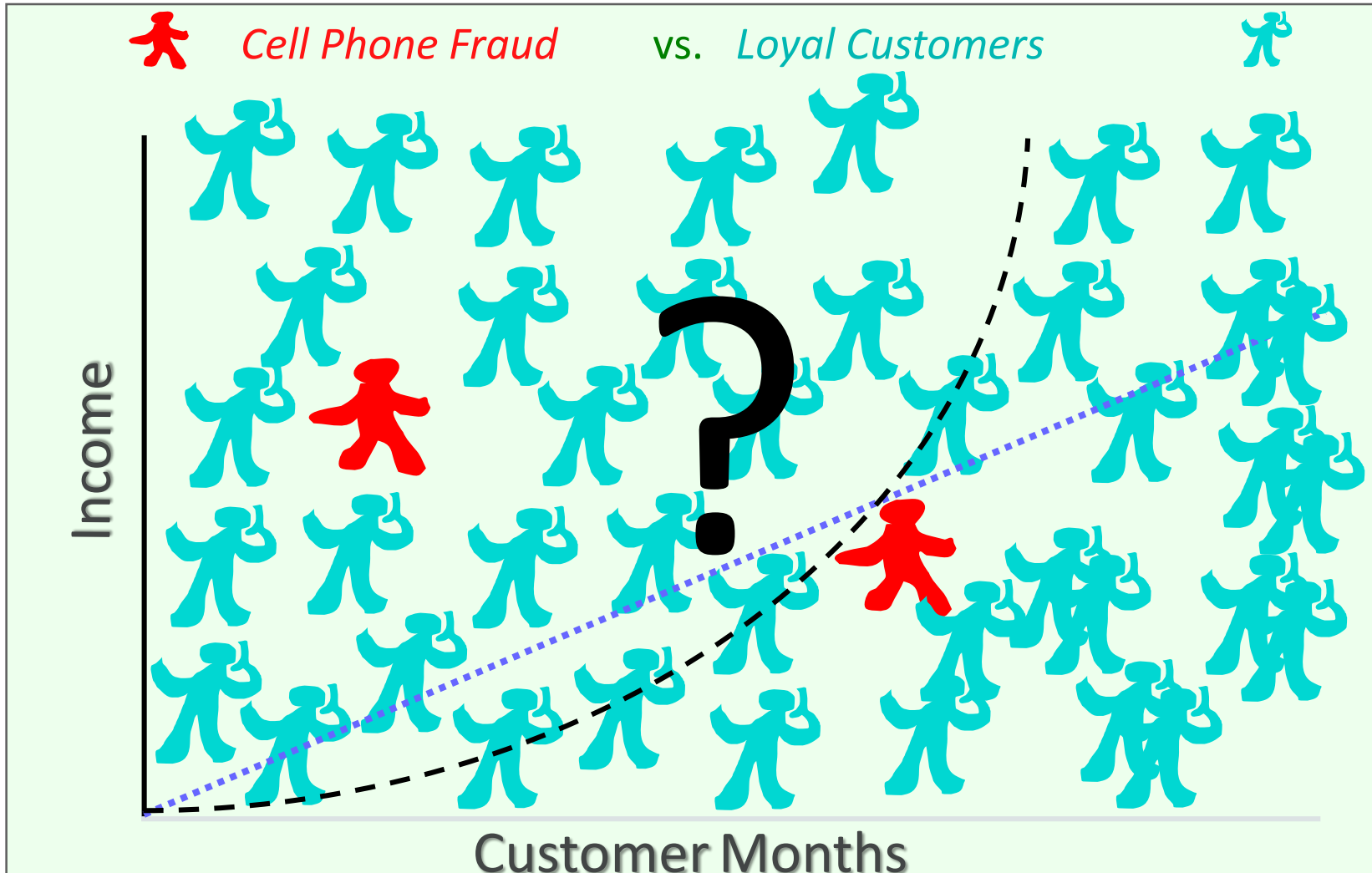
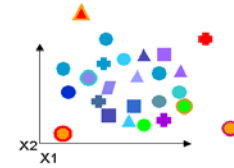
## Wide Range of In-Database Data Mining and Statistical Functions

- Data Understanding & Visualization
  - Summary & Descriptive Statistics
  - Histograms, scatter plots, box plots, bar charts
  - R graphics: 3-D plots, link plots, special R graph types
  - Cross tabulations
  - Tests for Correlations (t-test, Pearson's, ANOVA)
  - Selected Base SAS equivalents
- Data Selection, Preparation and Transformations
  - Joins, Tables, Views, Data Selection, Data Filter, SQL time windows, Multiple schemas
  - Sampling techniques
  - Re-coding, Missing values
  - Aggregations
  - Spatial data
  - SQL Patterns
  - R to SQL transparency and push down
- Classification Models
  - Logistic Regression (GLM)
  - Naive Bayes
  - Decision Trees
  - Support Vector Machines (SVM)
  - Neural Networks (NNs)
- Regression Models
  - Multiple Regression (GLM)
- Clustering
  - Hierarchical K-means
  - Orthogonal Partitioning
  - Expectation Maximization
- Anomaly Detection
  - Special case Support Vector Machine (1-Class SVM)
- Associations / Market Basket Analysis
  - A Priori algorithm
- Feature Selection and Reduction
  - Attribute Importance (Minimum Description Length)
  - Principal Components Analysis (PCA)
  - Non-negative Matrix Factorization
  - Singular Vector Decomposition
- Text Mining
  - Most OAA algorithms support unstructured data (i.e. customer comments, email, abstracts, etc.)
- Transactional Data
  - Most OAA algorithms support transactional data (i.e. purchase transactions, repeated measures over time)
- R packages—ability to run open source
  - Broad range of R CRAN packages can be run as part of database process via R to SQL transparency and/or via Embedded R mode

\* included in every Oracle Database

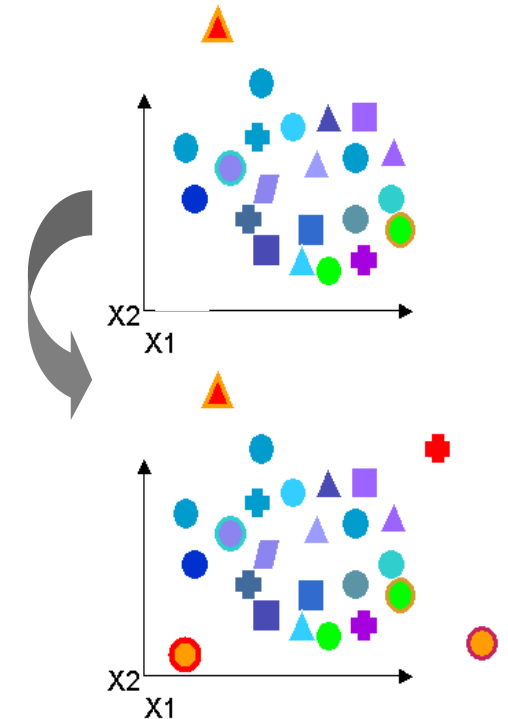
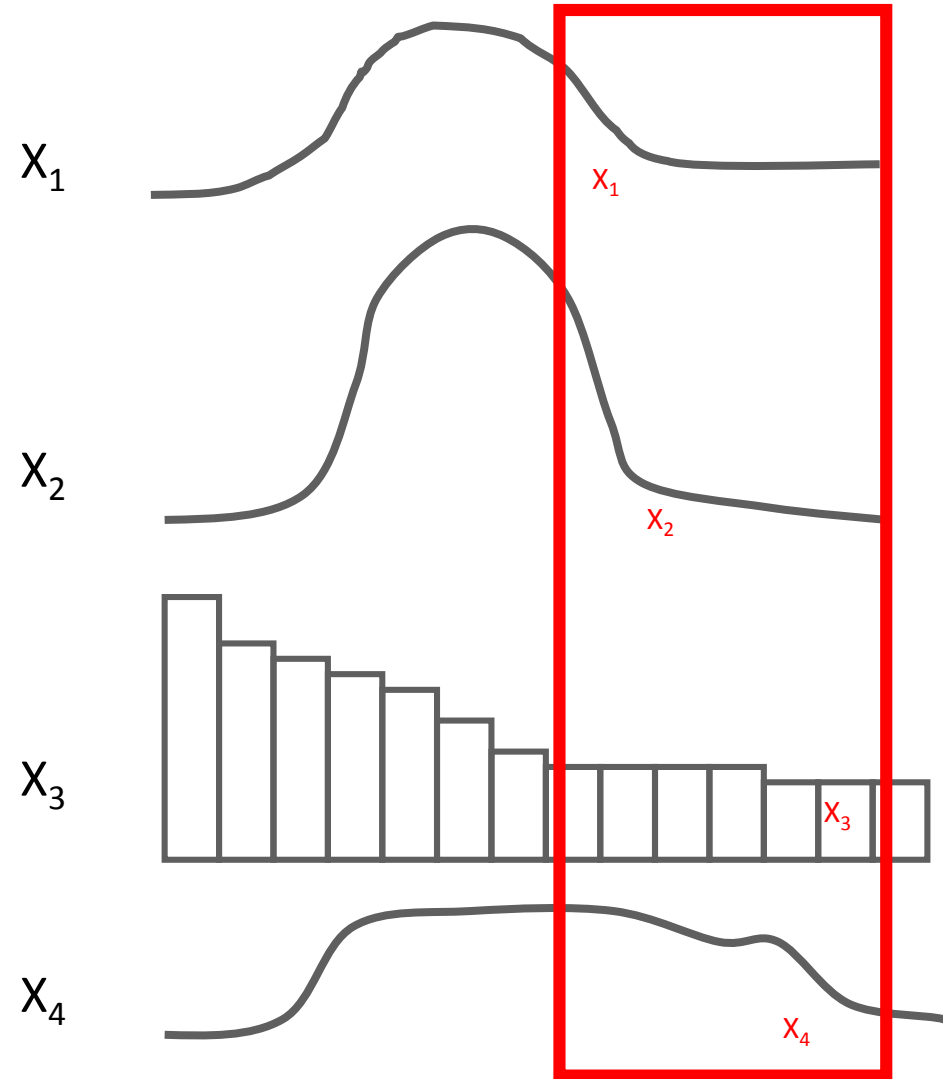
# Data Mining When Lack Examples

Better Information, Valuable Insights and Predictions



# Challenge: Finding Anomalies

- Considering multiple attributes
- Taken alone, may seem “normal”
- Taken collectively, a record may appear to be anomalous
- Look for what is “*different*”



# Fraud Prediction Demo

## Automated In-DB Analytical Methodology



```
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 ('2to4', 'morethan4')))
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

### Automated Monthly “Application”! *Just*

*add:*

Create

View CLAIMS2\_30

As

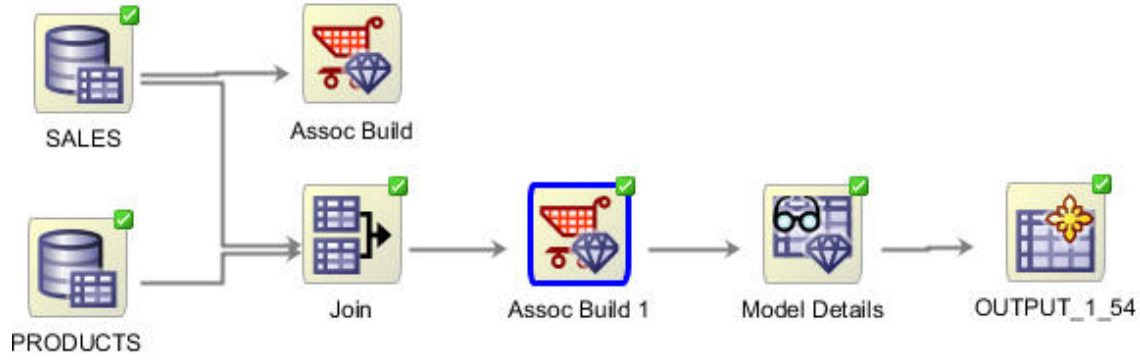
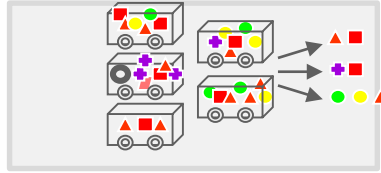
Select \* from CLAIMS2

Where mydate > SYSDATE – 30

Time measure: set timing on;

# Retail

## Market Basket Analysis



Find market baskets,  
product bundles, and next-likely products

Customer Analytics 360 View | Aggregated POS data | CLAS\_SVM\_1\_95 | CLUS\_KM\_2\_2 | ASSOC\_AP\_2\_54 | SH.SALES1

Rules | Itemsets | Settings

Sort by: Lift | Descending

Fetch Size: 1,000

Use Filter

Item Filters

Attribute	Filter
256MB Memory Card	Consequent

Filter

Minimum Lift: 2

Minimum Support(%): 1

Minimum Confidence(%): 10

Maximum Items In Rule: 10

Minimum Items In Rule: 1

Rule Content: Subname

Rules: 102 out of 7,934

ID	Antecedent	Consequent	Lift	Confidence(%)	Support(%)	Item Count
4063	Fly Fishing AND Comic Book Heroes	256MB Memory Card	24.4193	79.4987	1.108	2
3984	Fly Fishing AND Finding Fido	256MB Memory Card	23.6035	76.8431	1.085	2
4066	Fly Fishing AND Martial Arts Champions	256MB Memory Card	23.5529	76.6781	1.2449	2
4050	Fly Fishing AND 128MB Memory Card	256MB Memory Card	23.3091	75.8846	1.3784	2
6329	Comic Book Heroes AND Martial Arts Cham...	256MB Memory Card	23.2682	75.7514	1.5495	2
4023	Fly Fishing AND Smash up Boxing	256MB Memory Card	22.9962	74.8659	1.2673	2
4222	Finding Fido AND Comic Book Heroes	256MB Memory Card	22.9302	74.651	1.1953	2
4069	Fly Fishing AND Adventures with Numbers	256MB Memory Card	22.8958	74.539	1.3274	2

Rule Details:

ID: 4063

IF

Fly Fishing AND  
Comic Book Heroes

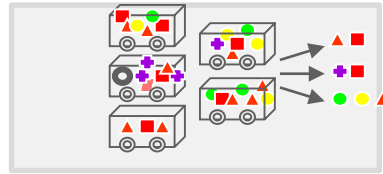
THEN

256MB Memory Card



# Retail

## Market Basket Analysis



- Perform market basket analysis in-database
- Find All “A→B rules”
- Sort by confidence
- Filter out recommendations that already in the customer’s shopping cart
- Finally, query the top 3 recommendations based on the order of highest confidence and support

```
SELECT rownum AS rank, consequent AS recommendation FROM
(
  SELECT
  cons_pred.attribute_subname consequent,
  max(AR.rule_support) max_support,
  max(AR.rule_confidence) max_confidence
  FROM TABLE (
  DBMS_DATA_MINING.GET_ASSOCIATION_RULES (
  'AR_RECOMMENDATION', 10, NULL, 0.5, 0.01, 2, 1,
  ORA_MINING_VARCHAR2_NT (
  'RULE_CONFIDENCE DESC', 'RULE_SUPPORT DESC'),
  DM_ITEMS(DM_ITEM('PROD_NAME', 'Comic Book Heroes', NULL, NULL),
  DM_ITEM('PROD_NAME', 'Martial Arts Champions', NULL, NULL)),
  NULL, 1)) AR,
  TABLE(AR.consequent) cons_pred
  WHERE cons_pred.attribute_subname NOT IN ('Comic Book Heroes', 'Martial Arts
  Champions')
  GROUP BY cons_pred.attribute_subname
  ORDER BY max_confidence DESC, max_support DESC
  )
```

```
WHERE rownum <=3;
RANK RECOMMENDATION
```

- 
- 1 Endurance Racing
  - 2 128MB Memory Card
  - 3 Xtend Memory



## Accelerates Complex Segmentation Queries from Weeks to Minutes—Gains Competitive Advantage

### Objectives

- World's leading customer-science company
- Accelerate analytic capabilities to near real time using Oracle Advanced Analytics and third-party tools, enabling analysis of unstructured big data from emerging sources, like smart phones

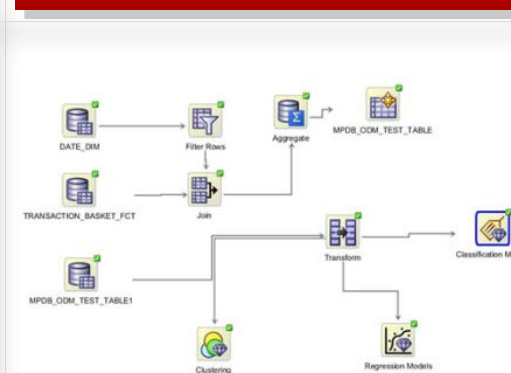
### Solution

- Accelerated segmentation and customer-loyalty analysis from one week to just four hours—enabling the company to deliver more timely information & finer-grained analysis
- Generated more accurate business insights and marketing recommendations with the ability to analyze 100% of data—including years of historical data—instead of just a small sample

- “Improved analysts’ productivity and focus as they can now run queries and complete analysis without having to wait hours or days for a query to process”
- “Improved accuracy of marketing recommendations by analyzing larger sample sizes and predicting the market’s reception to new product ideas and strategies”

— dunnhumby Oracle Customer Snapshot

(<http://www.oracle.com/us/corporate/customers/customersearch/dunnhumby-1-exadata-ss-2137635.html>)



# Oracle Advanced Analytics

## More Details

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

```
Select prediction_probability(CLAS_DT_4_15, 'Yes'  
    USING 7800 as bank_funds, 125 as checking_amount, 20 as  
    credit_balance, 55 as age, 'Married' as marital_status,  
    250 as MONEY_MONTHLY_OVERDRAWN, 1 as house_ownership)  
from dual;
```



**Likelihood to respond:**

Query Result

SQL | All Rows Fetched: 1 in 0 seconds

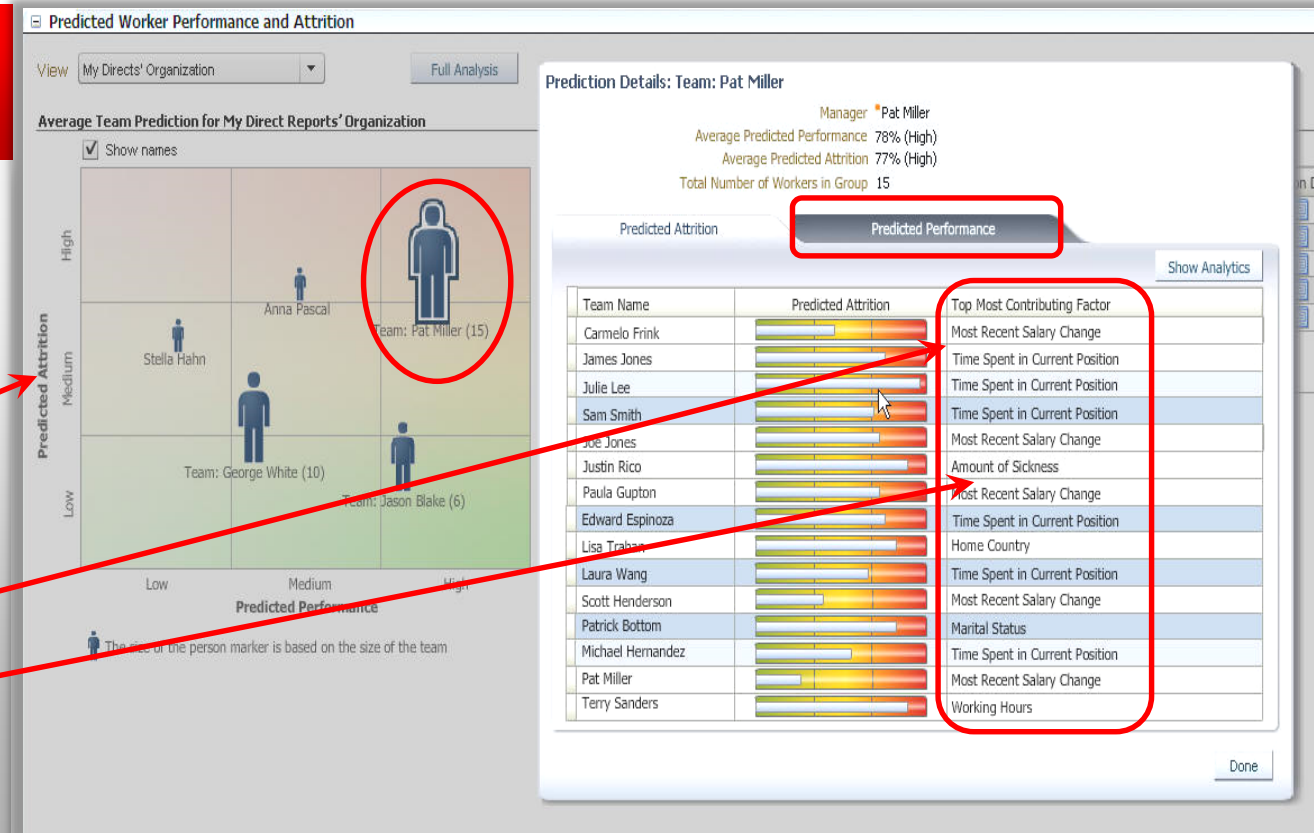
PREDICTION_PROB...
0.8382936507936...

# Fusion HCM Predictive Workforce

## Predictive Analytics Applications

### Fusion Human Capital Management Powered by OAA

- Oracle Advanced Analytics factory-installed predictive analytics
- Employees likely to leave and predicted performance
- Top reasons, expected behavior
- Real-time "What if?" analysis



# Fusion HCM Predictive Workforce

## Predictive Analytics Applications

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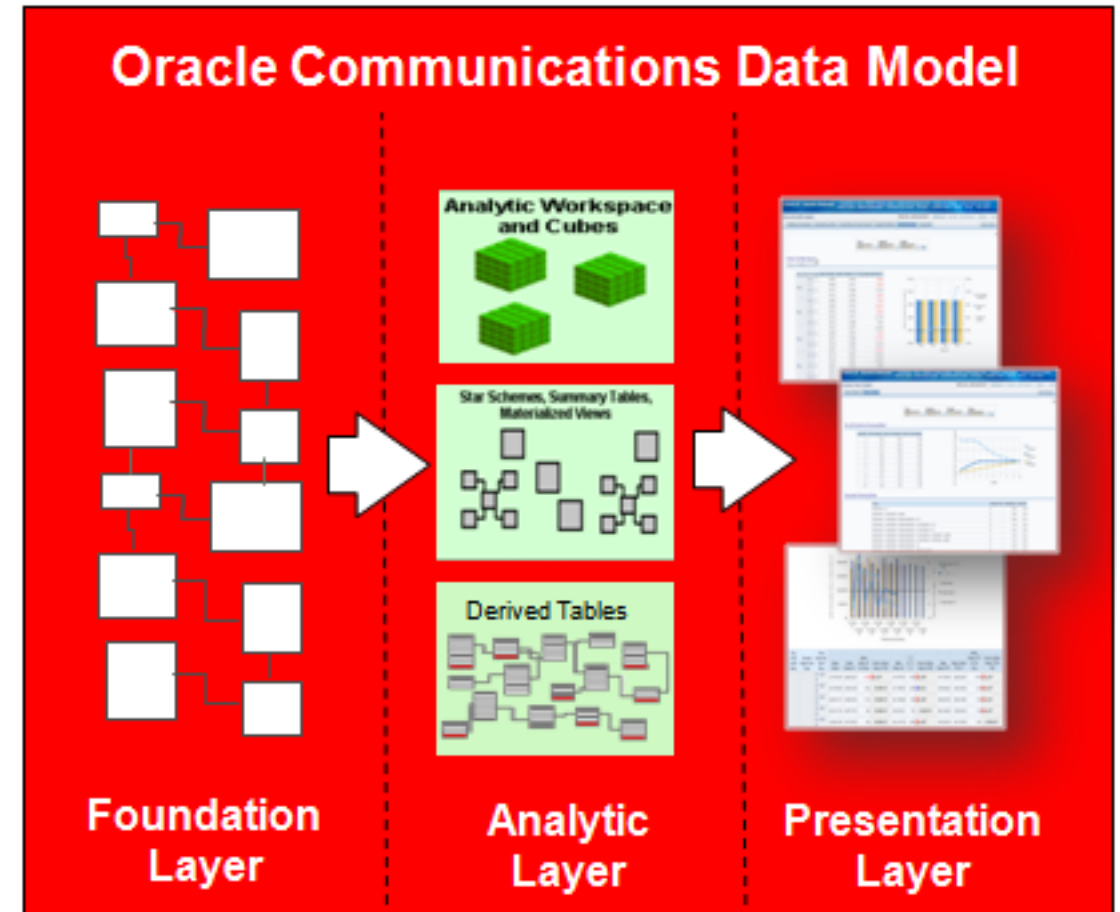
The screenshot displays the Oracle Fusion HCM Predictive Workforce interface. The main view is a heatmap titled "Team Prediction for My Directs' Organizations" with axes for "Predicted Performance" (Low to High) and "Predicted Voluntary Termination" (Low to High). Team markers are shown, with sizes indicating relative team size. A detailed view for "Fiona Arrington" is open, showing her profile, current performance (3-Meets), and predicted performance (87%). A table lists reasons for predicted voluntary termination, such as "Latest salary change" (1%) and "Time in current grade" (23.32 Months). A slider below the table allows for "What if?" analysis, ranging from "Makes less likely" to "Makes more likely".

Contribution	Predicted Voluntary Termination Reason	Current Value
	Latest salary change	1 %
	Current grade	Prof3
	Worker's stock options compared to peers	.45
	Time in current grade	23.32 Months
	Increase in sickness over previous year	1 Days
	Normal working hours	40
	Time since last sickness	5.91 Months
	Potential profit on stock	1
	Ratio of vested to unvested options	1 %

# Oracle Communications Industry Data Model

## Predictive Analytics Applications

- Enterprise wide data model for communications industry
  - Over 1,500 tables and 30,000 columns
  - Over 1,000 industry measures and KPIs
  - TMF SID conformance aligned
- **Prebuilt mining models**, OLAP cubes and sample reports
- Automatic data movement across layers
- Easily extensible and customizable
- Usable within any source application



# Oracle Communications Industry Data Model

## Predictive Analytics Applications

### Pre-Built Predictive Models

- Fastest Way to Deliver Scalable Enterprise-wide Predictive Analytics
- OAA's clustering and predictions available in-DB for OBIEE
- Automatic Customer Segmentation, Churn Predictions, and Sentiment Analysis

Business Intelligence

Customer Segmentation Details

Segment Name

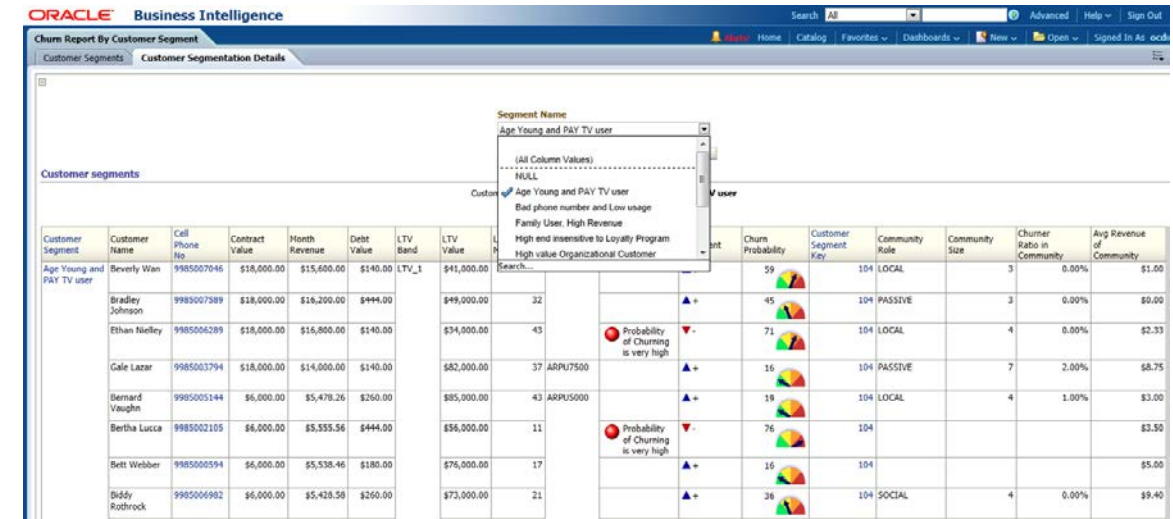
- Age Young and PAY TV user
- (All Column Values)
- Age Young and PAY TV user
- Bad phone number and Low usage
- Family User, High Revenue
- High end insensitive to Loyalty Program
- High value Organizational Customer
- High value and use loyalty program
- Low Revenue

Cell Phone No	Contract Value	Month Revenue	Debt Value	LTV Band	LTV Value	Customer	Churn Probability	Customer Segment Key	Community Role	Community Size	Churn Ratio
9985007046	\$18,000.00	\$15,600.00	\$140.00	LTV_1	\$41,000.00		59	104	LOCAL		3
9985007589	\$18,000.00	\$16,200.00	\$444.00		\$49,000.00	32	45	104	PASSIVE		3
9985006289	\$18,000.00	\$16,800.00	\$140.00		\$34,000.00	43	71	104	LOCAL		4
9985003794	\$18,000.00	\$14,000.00	\$140.00		\$82,000.00	37 ARPU7500	16	104	PASSIVE		7
9985005144	\$6,000.00	\$5,478.26	\$260.00		\$85,000.00	43 ARPU5000	19	104	LOCAL		4
9985002105	\$6,000.00	\$5,555.56	\$444.00		\$56,000.00	11	76	104			
9985000594	\$6,000.00	\$5,538.46	\$180.00		\$76,000.00	17	16	104			

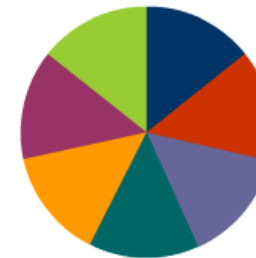
# Oracle Communications Data Model

## Pre-Built Data Mining Models

1. Prepaid Churn Prediction
2. Postpaid Churn Prediction
3. Customer Profiling
4. Targeted Promotion
5. Customer Life Time Value
6. Customer Life Time Survival Value
7. Customer Sentiment



Segment Avg Debt value



- Age Young and PAY TV user, CUST\_TYP\_CD is IND; PAY\_TV\_IND=1; AGE\_ON\_NET\_NBR=626.83; PORT\_OUT\_CNT is NA;; 11
- Family User, High Revenue, CUST\_TYP\_CD is IND; NBR\_OF\_CHLDRN=2.99; AGE\_ON\_NET\_NBR=1205.64; MO\_RVN=233.2, 16
- High end insensitive to Loyalty Program, CUST\_TYP\_CD is IND; LYLTY\_PROG\_BAL=773.81; AGE\_ON\_NET\_NBR=1975.87; MO\_RVN=406;, 13
- High value Organizational Customer, CUST\_TYP\_CD is ORG; SBRP\_CNT=85.3; AGE\_ON\_NET\_NBR=923.72; TOT\_RVN=39,942;, 7
- High value and use loyalty program, CUST\_TYP\_CD is IND; LYLTY\_PROG\_BAL=757.1; AGE\_ON\_NET\_NBR=1675.63; MO\_RVN=516;, 15
- Organizational Customer, CUST\_TYP\_CD is ORG; SBRP\_CNT=155.71; AGE\_ON\_NET\_NBR=859.31; PORT\_OUT\_CNT is NA;; 5
- Troublesome Customer with less revenue, CUST\_TYP\_CD is IND; CMLNT\_LFTM\_CNT=73.52; AGE\_ON\_NET\_NBR=1493.95; PORT\_OUT\_CNT is NA;; 3



# Oracle Communications Data Model

## Pre-Built Prepaid Churn Prediction Data Mining Models

- Prepaid Churn Prediction Definition
  - Customer is recognized as a churner when he stop using any product from the operator
- Sample Input Attributes Used in Model
  - 170 attributes used in total for prepaid churn model

Attribute	Description
ACCPY_NWSLTR_IND	Indicates whether customer accepts News Letter
BRDBND_IND	Indicates whether Customer has Broadband connection
CAR_DRVR_LICNS_IND	Indicates whether customer has driver's license
CAR_TYP_CD	Car Type Code
CHRN_IND	Indicates whether a customer is a Churner or Non-churner
CMPLNT_CNT_LAST_3MO	Number of complaints made by customer in last 3 months
CMPLNT_CNT_LAST_MO	Number of complaints made by customer in this month
CMPLNT_CNT_LFTM	Number of complaints made by customer in his/her life span
CRDT_CTGRY_KEY	Customer Credit Category
CUST_RVN_BND_CD	Customer Revenue Band Code
DAYS_BFR_FIRST_RCHR	Days between first payment and first recharge
DAYS_BFR_FIRST_USE	Days between payment and first use
DRPD_CALLS_CNT_LAST_3MO	Number of dropped calls in last 3 months
DRPD_CALLS_CNT_LAST_MO	Number of dropped calls this month
DRPD_CALLS_CNT_LFTM	Number of dropped calls in customer life span
DWLNG_OWNER	Dwelling Owner
DWLNG_STAT	Dwelling Status
DWLNG_SZ	Dwelling Size
DWLNG_TENR	Dwelling Tenure
DWNLD_DATA_LAST_3MO	Data downloaded in KBs in last 3 months
DWNLD_DATA_LAST_MO	Data downloaded in KBs in last 1 month
DWNLD_DATA_LFTM	Data downloaded in KBs in lifetime
ETHNCTY	Customer Ethnicity
GNDR_CD	Individual Customer Gender Code
HH_SZ	Household Size
HNGUP_CALLS_CNT_LAST_3MO	Number of hangup calls in last 3 months
HNGUP_CALLS_CNT_LAST_MO	Number of hangup calls this month
MMS_CNT_LAST_MO	MMSs sent in last 1 month
OFFNET_CALLS_LAST_MO	Number of offnet calls in last 1 month
PAY_TV_IND	Indicates whether Customer has Pay TV connection

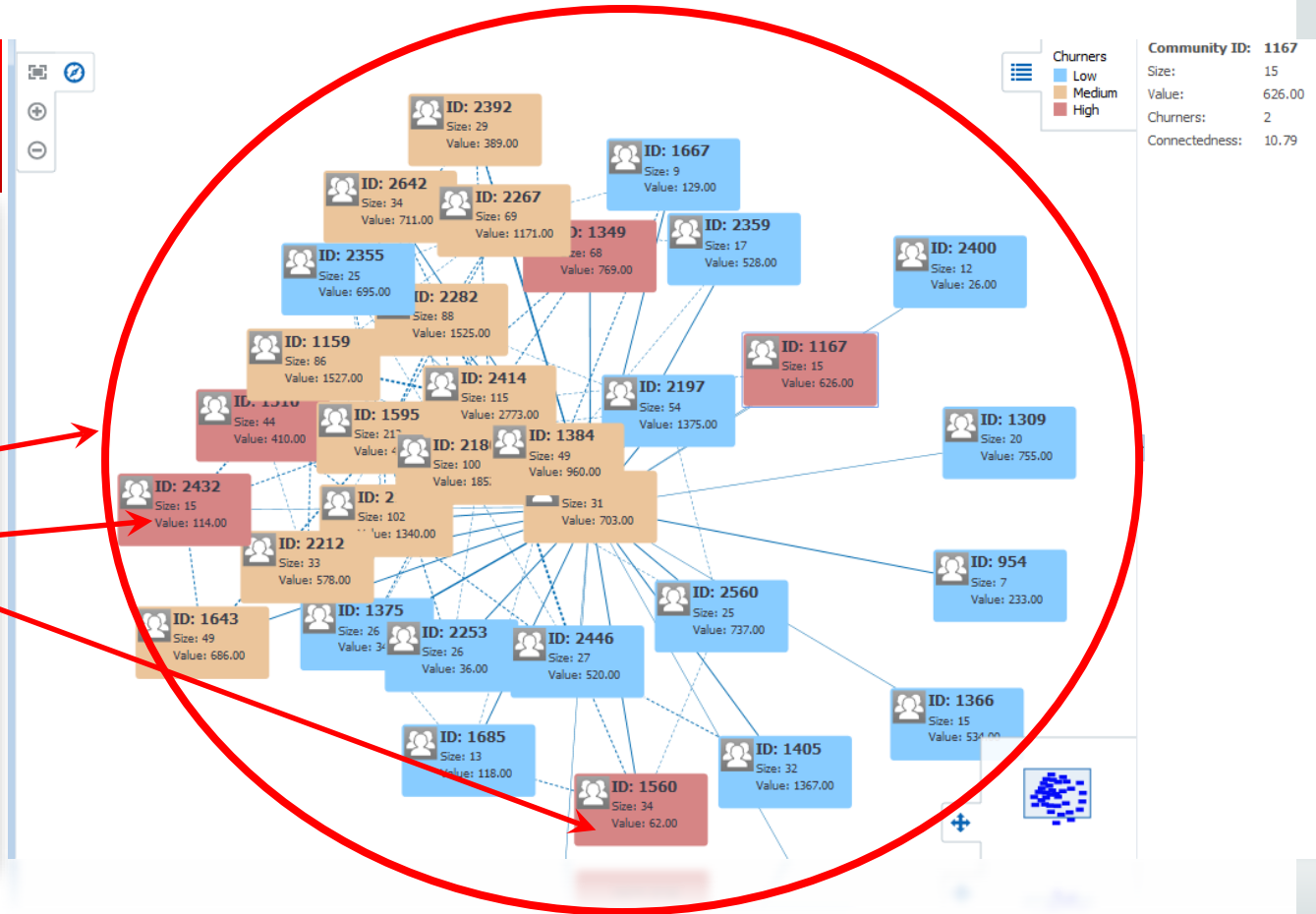


# Oracle Communications Industry Data Model

## Predictive Analytics Applications

### OCDM Telco Churn Enhanced by SNA Analysis

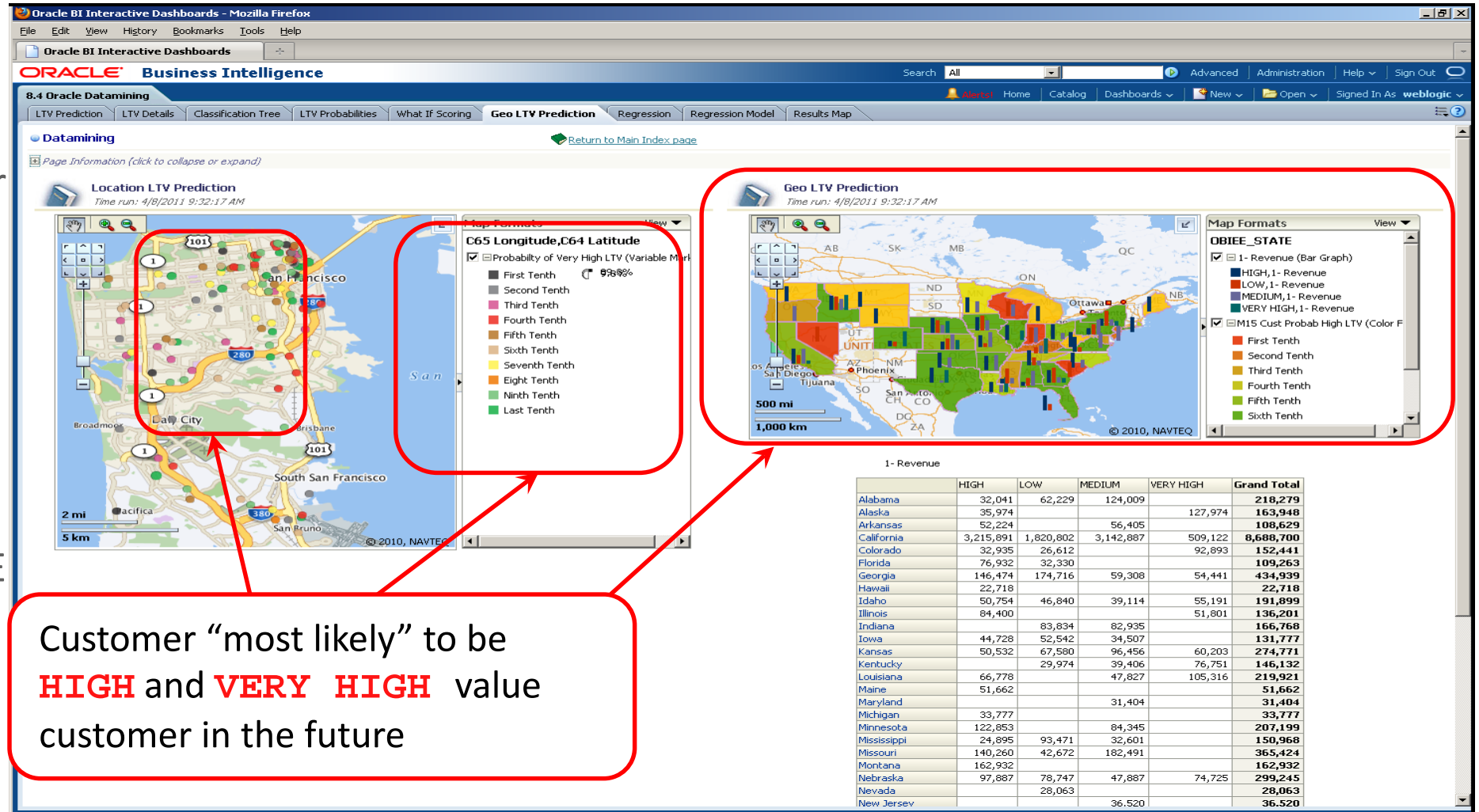
- Integrated with OCDM, OBIEE, and leverages Oracle Data Mining with specialized SNA code
- Identification of social network communities from CDR data
- Predictive scores for churn and influence at a node level, as well as potential revenue/value at risk
- User interface targeted at business users and flexible ad-hoc reporting



# Integrated Business Intelligence

## Enhance Dashboards with Predictions and Data Mining Insights

- In-database predictive models “mine” customer data and predict their behavior
- OBIEE’s integrated spatial mapping shows location
- All OAA results and predictions available in Database via OBIEE Admin to enhance dashboards



# Integrated Business Intelligence

## Enhance Dashboards with Predictions and Data Mining Insights

- In-database predictive models “mine” customer data and predict their behavior
- OBIEE’s integrated spatial mapping shows location
- All OAA results and predictions available in Database via OBIEE Admin to enhance dashboards

The screenshot displays the Siebel Analytics Administration Tool interface, divided into three main sections: Presentation, Business Model and Mapping, and Physical. The Presentation panel shows a tree structure for 'CD\_BUYERS' with sub-items like 'DIM', 'KEY\_FACTOR', 'IMPORTANCE', 'FACT', and 'RANK'. The Business Model and Mapping panel shows a similar tree structure with 'Sources' and 'FACT' sub-items. The Physical panel shows a tree structure for 'Oracle\_10gR2' with sub-items like 'DIM', 'CBERGER', and 'XLS\_Forecast'. Red circles highlight 'KEY\_FACTOR' and 'IMPORTANCE' in the Presentation panel, 'AFFINITY\_CARD' and 'BULK\_PACK\_DISKETS' in the Business Model and Mapping panel, and 'CD\_BUYERS\_PREDICT\_A' and 'KEY\_CD\_BUYER\_ATTRIBUTES' in the Physical panel. A callout box points to the Physical panel with the text 'Oracle Data Mining results available to Oracle BI EE administrators'. Another callout box points to the Business Model and Mapping panel with the text 'Oracle BI EE defines results for end user presentation'.

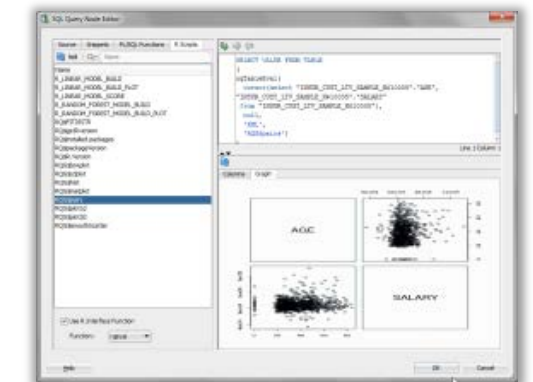
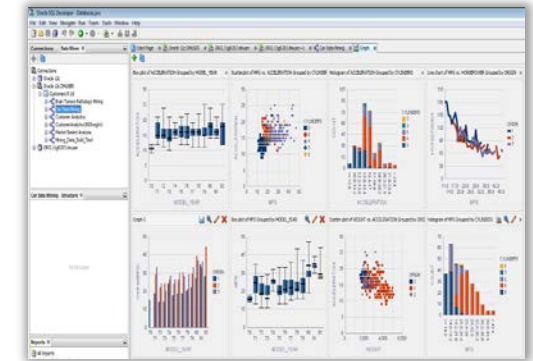
# Oracle Advanced Analytics Database Option

## Oracle Data Miner 4.0 Summary New Features

- Oracle Data Miner/SQLDEV 4.0 (for Oracle Database 11g and 12c)
  - New **Graph node** (box, scatter, bar, histograms)
  - **SQL Query node** + integration of R scripts
  - Automatic **SQL script generation** for deployment



- Oracle Advanced Analytics 12c features exposed in Oracle Data Miner
  - New SQL data mining algorithms/enhancements
    - Expectation Maximization clustering algorithm
    - PCA & Singular Vector Decomposition algorithms
    - Improved/automated Text Mining, Prediction Details and other algorithm improvements)
  - Predictive SQL Queries—automatic build, apply within SQL query

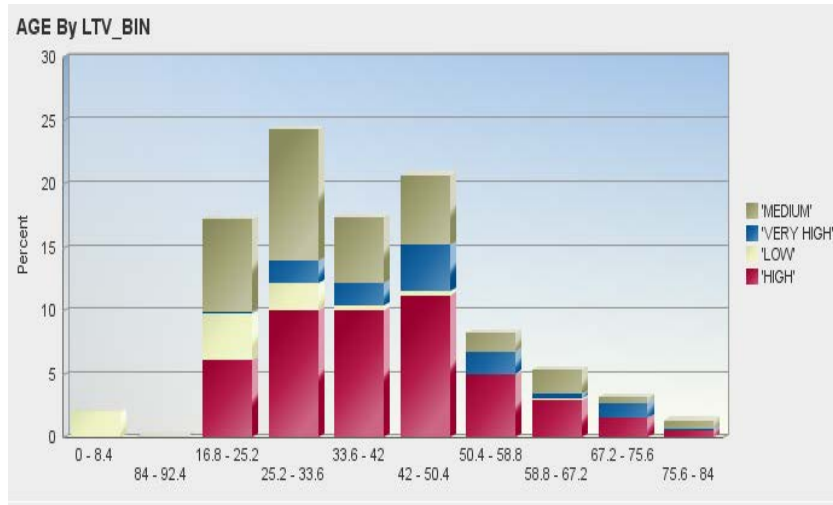
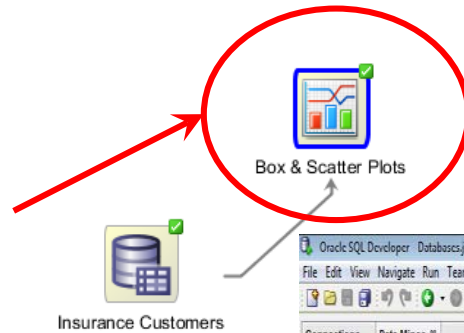


# SQL Developer/Oracle Data Miner 4.0

## New Features

### ■ Graph node

- Scatter, line, bar, box plots, histograms
- Group\_by supported

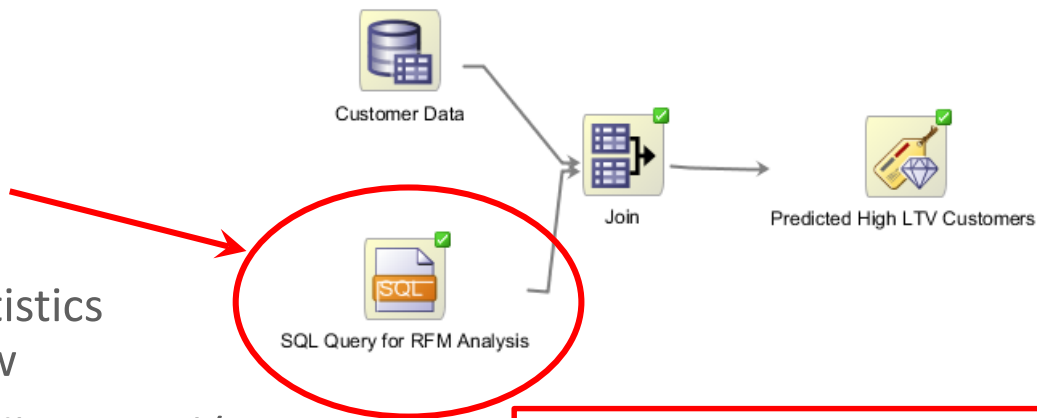


# SQL Developer/Oracle Data Miner 4.0

## New Features

- **SQL Query node**

- Allows any form of query/transformation/statistics within an ODM'r work flow
- Use SQL anywhere to handle special/unique data manipulation use cases
  - Recency, Frequency, Monetary (RFM)
  - SQL Window functions for e.g. moving average of \$\$ checks written past 3 months vs. past 3 days
- Allows integration of R Scripts



```

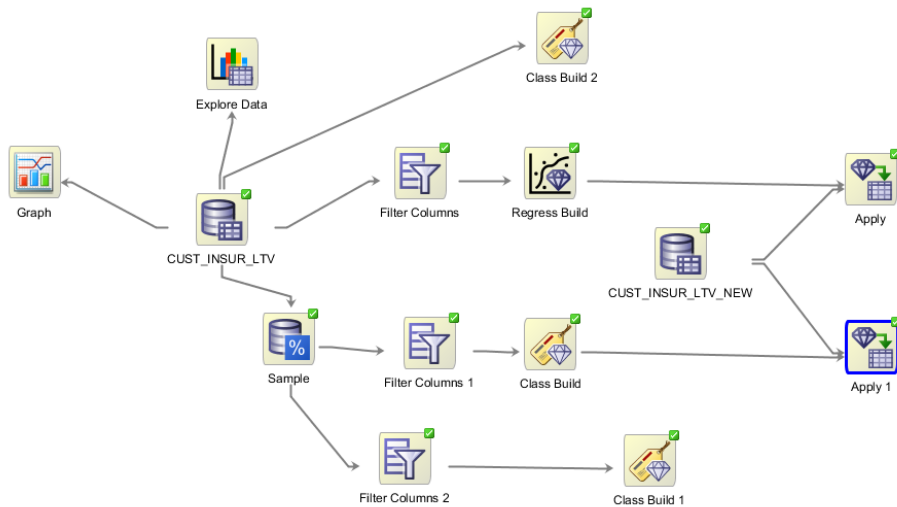
    select cust_id, rfm_recency, rfm_frequency, rfm_monetary,
           rfm_recency*100 + rfm_frequency*10 + rfm_monetary as rfm_combined
    from
    (select cust_id,
           ntile (5) over (order by last_purchase_date) as rfm_recency,
           ntile (5) over (order by count_purchases) as rfm_frequency,
           ntile (5) over (order by total_amount) as rfm_monetary
    from
    (select cust_id,
           max(time_id) as last_purchase_date,
           count(*) as count_purchases,
           sum(amount_sold) as total_amount
     from SH.sales
     group by cust_id)
    )
    order by 5 desc
  
```

# SQL Developer/Oracle Data Miner 4.0

## New Features

### ■ SQL Script Generation

- Deploy entire methodology as a SQL script
- Immediate deployment of data analyst's methodologies



Generate SQL Script - Step 2 of 2


**Script Directory**

Target Database: [Target Database](#)

Script Directory:

Base Directory:

Directory Path: C:\SQLDEV Oracle Data Miner Feb 17 2013\sqldeveloper\sqldeveloper\bin\ODM work flow

Name	Date modified	Type	Size
Apply 1.sql	7/24/2013 4:12 PM	SQL File	3 KB
Class Build.sql	7/24/2013 4:12 PM	SQL File	56 KB
CUST_INSUR_LTV.sql	7/24/2013 4:12 PM	SQL File	4 KB
CUST_INSUR_LTV_NEW.sql	7/24/2013 4:12 PM	SQL File	4 KB
Filter Columns 1.sql	7/24/2013 4:12 PM	SQL File	8 KB
 Predicting LTV_BEST.png	7/24/2013 4:12 PM	PNG image	64 KB
Predicting LTV_BEST_Drop.sql	7/24/2013 4:12 PM	SQL File	3 KB
Predicting LTV_BEST_Run.sql	7/24/2013 4:12 PM	SQL File	6 KB
Sample.sql	7/24/2013 4:12 PM	SQL File	4 KB

Buttons: Help, < Back, Next >, Finish, Cancel

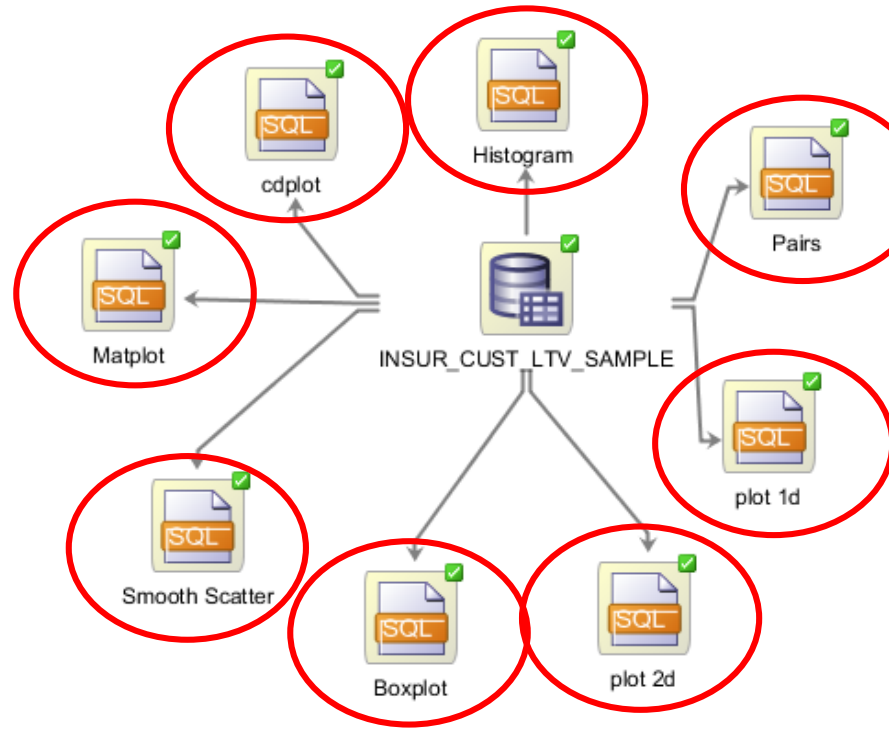


# SQL Developer/Oracle Data Miner 4.0

## New Features

- **SQL Query node**

- Allows integration of R Scripts



SQL Query Node Editor

Source Snippets PL/SQL Functions R Scripts

Name

- R\_LINEAR\_MODEL\_BUILD
- R\_LINEAR\_MODEL\_BUILD\_PLOT
- R\_LINEAR\_MODEL\_SCORE
- R\_RANDOM\_FOREST\_MODEL\_BUILD
- R\_RANDOM\_FOREST\_MODEL\_BUILD\_PLOT
- RQ\$FITDISTR
- RQ\$getRVersion
- RQ\$installed.packages
- RQ\$packageVersion
- RQ\$R.Version
- RQG\$boxplot
- RQG\$cdplot
- RQG\$hist
- RQG\$matplot
- RQG\$pairs**
- RQG\$plot1d
- RQG\$plot2d
- RQG\$smoothScatter

```

SELECT VALUE FROM TABLE
(
  rqTableEval(
    cursor(select "INSUR_CUST_LTV_SAMPLE_N@10005"."AGE",
      "INSUR_CUST_LTV_SAMPLE_N@10005"."SALARY"
    from "INSUR_CUST_LTV_SAMPLE_N@10005"),
    null,
    'XML',
    'RQG$pairs')
)
  
```

Line 1 Column 1

Columns Graph

AGE

SALARY

Use R Interface Function

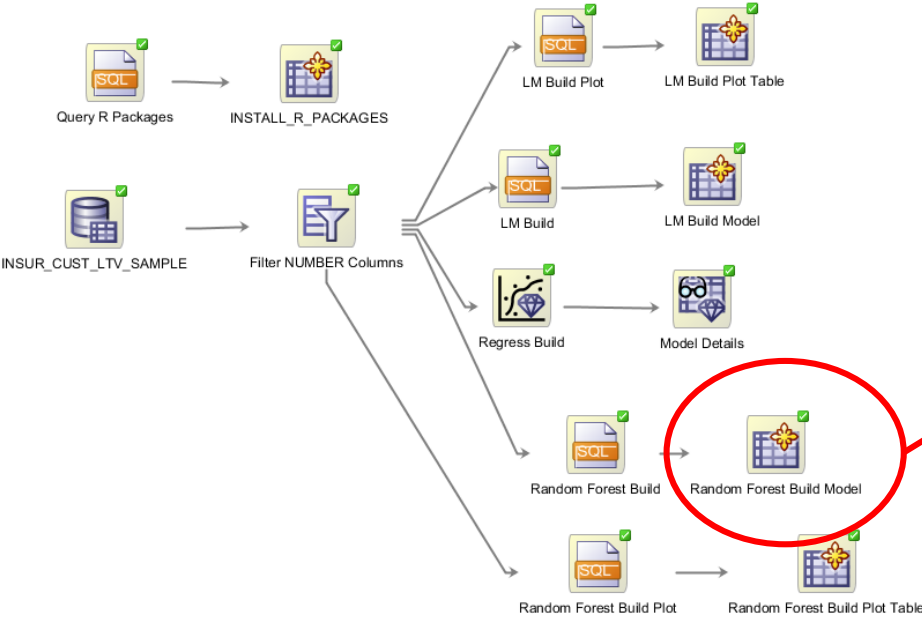
Function: rqEval

Help OK Cancel

# SQL Developer/Oracle Data Miner 4.0

## New Features

- **SQL Query node**
  - Allows integration of R Scripts



SQL Query Node Editor

Source Snippets PL/SQL Functions R Scripts

Name

```

SELECT VALUE FROM TABLE
(
  rqTableEval(
    cursor(select * from "Filter NUMBER Columns_N$10010"),
    NULL,
    'XML',
    'R_RANDOM_FOREST_MODEL_BUILD')
  )
  
```

Line 1 Column 1

Columns Data

Name	Data Type	Mining
VALUE	CLOB	Text

Use R Interface Function

Function:

Help OK Cancel

# 12c New Features

## New Server Functionality



- **3 New Oracle Data Mining SQL functions algorithms**

- **Expectation Maximization (EM) Clustering**

- New Clustering Technique

- Probabilistic clustering algorithm that creates a density model of the data
- Improved approach for data originating in different domains (for example, sales transactions and customer demographics, or structured data and text or other unstructured data)
- Automatically determines the optimal number of clusters needed to model the data.

- **Principal Components Analysis (PCA)**

- Data Reduction & improved modeling capability

- Based on SVD, powerful feature extraction method use orthogonal linear projections to capture the underlying variance of the data

- **Singular Value Decomposition (SVD)**

- Big data “workhorse” technique for matrix operations

- Scales well to very large data sizes (both rows and attributes) for very large numerical data sets (e.g. sensor data, text, etc.)

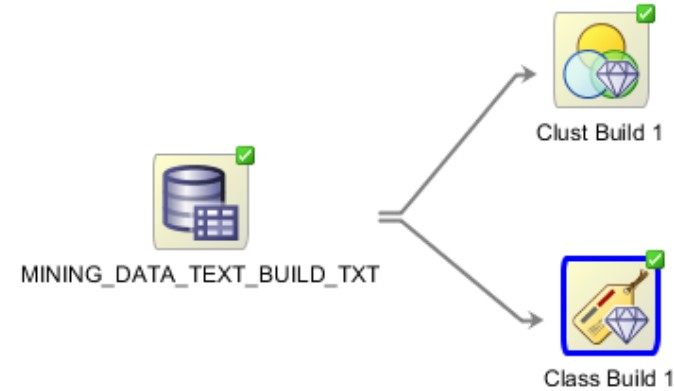
# 12c New Features

## New Server Functionality

- **Text Mining Support Enhancements**

- This enhancement greatly simplifies the data mining process (model build, deployment and scoring) when text data is present in the input:

- Manual pre-processing of text data is no longer needed.
- No text index needs to be created
- Additional data types are supported: CLOB, BLOB, BFILE
- Character data can be specified as either categorical values or text



Edit Classification Build Node

Build Input Text

Determine inputs automatically (using heuristics) [Show](#)

Columns: 17 included out of 19.

Name	Data Type	Input	Mining Type	Auto Prep	Rules
AFFINITY_CARD	NUMBER	→		<input checked="" type="checkbox"/>	
AGE	NUMBER	→		<input checked="" type="checkbox"/>	
BOOKKEEPING_APPLICATION	NUMBER	→		<input checked="" type="checkbox"/>	
BULK_PACK_DISKETTES	NUMBER	→		<input checked="" type="checkbox"/>	
COMMENTS	CLOB	→	Text	<input checked="" type="checkbox"/>	
COUNTRY_NAME	VARCHAR2	→	Text	<input checked="" type="checkbox"/>	
CUST_GENDER	CHAR	→	Text Custom	<input checked="" type="checkbox"/>	
CUST_ID	NUMBER	⇄		<input checked="" type="checkbox"/>	
CUST_INCOME_LEVEL	VARCHAR2	→		<input checked="" type="checkbox"/>	
CUST_MARITAL_STATUS	VARCHAR2	→		<input checked="" type="checkbox"/>	
EDUCATION	VARCHAR2	→		<input checked="" type="checkbox"/>	

# 12c New Features

## New Server Functionality

### • Predictive Queries

- Immediate build/apply of ODM models in SQL query
  - Classification & regression
    - Multi-target (nested) problems
  - Clustering query
  - Anomaly query
  - Feature extraction query

OAA automatically creates multiple anomaly detection models “Grouped\_By” and “scores” by partition via powerful SQL query



Results/Predictions!

	CLAS_DT_1_13_PROB_Yes	MARITAL_STATUS	CREDIT_BALANCE	STATE	N_OF_DEPENDENTS	SALARY
1	0.13417190775681342	SINGLE	2,836	NY	0	64,175
2	0.8963051251489869	DIVORCED	0	CA	1	63,148
3	0.6569555717407137	MARRIED	0	MN	1	61,777
4	0.0014831294030404152	MARRIED	0	MI	2	92,173
5	0.13417190775681342	DIVORCED	0	CA	1	58,917
6	0.01639344262295082	MARRIED	5,100	MI	2	49,668
7	0.13417190775681342	MARRIED	0	CA	1	65,194
8	0.6569555717407137	SINGLE	0	CA	0	59,418
9	0.0014831294030404152	MARRIED	0	MI	3	60,958
10	0.6569555717407137	DIVORCED	0	WI	1	61,181
11	0.8963051251489869	WIDOWED	0	MI	1	69,066
12	0.1566265060240964	DIVORCED	0	NY	6	69,716

Predictive Queries

- Anomaly Detection Query
- Clustering Query
- Feature Extraction Query
- Prediction Query

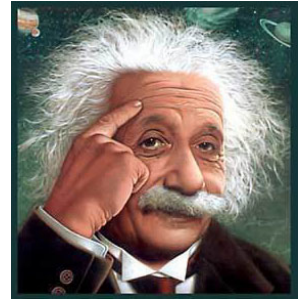
# The Four Traps of Predictive Analytics

- The First Trap: Magical Thinking

- The need to **really understand what you want to decide using analytics** before you develop them

*“If I had an hour to solve a problem I'd spend 55 minutes thinking about the problem and 5 minutes thinking about solutions.”*

— Albert Einstein



- The Second Trap: Starting at the Top

- The need to begin with operational decisions not strategic ones
- **Predictive analytics works best for prompting decisions about operations**, rather than initiating their use at the executive level.
- **Operational decisions**, such as those in which companies choose a supplier or **determine whether to extend credit**, lend themselves well to predictive analytics
- Companies also need to frame their predictive analytics around actions. “Don’t look at how good a customer is.”
  - **Look at, what action should I offer to a customer?**
  - Should I change suppliers?”



# The Four Traps of Predictive Analytics

- The Third Trap: Building Cottages, Not Factories

- Need to industrialize analytics not treat it as a cottage industry Creating analytic models that don't scale. Analytics specialists are no more connected to the business than technology specialists
- Otherwise, **analytics specialists are prone to create the equivalent of a cottage industry, where the models built apply to only one thing, or are too complex and expensive to be reused easily.**
  - Netflix's famous challenge, where it gave \$1 million for a better algorithm to make movie recommendations. Its million-dollar model "was never deployed," Taylor said. "They got a fabulous model, but ask them, and they will tell you that the resources weren't available to use it. What they meant to fund was 'a model that was more predictive that we can realistically deploy and run on our service in Earth time.' They didn't ask for that."

- The Fourth Trap: Seeking Purified Data

- Avoid being paralyzed by weakness in your data
  - "Garbage in, garbage out" is the cliché of data-haters everywhere. "It is not true that companies need good data to use predictive analytics," Taylor said. "The techniques can be robust in the face of terrible data, because they were invented by people who had terrible data," he noted.
- **Companies should start with the business decision they want to make, and then look for data that might help them predict outcomes.**



# OAA Links and Resources

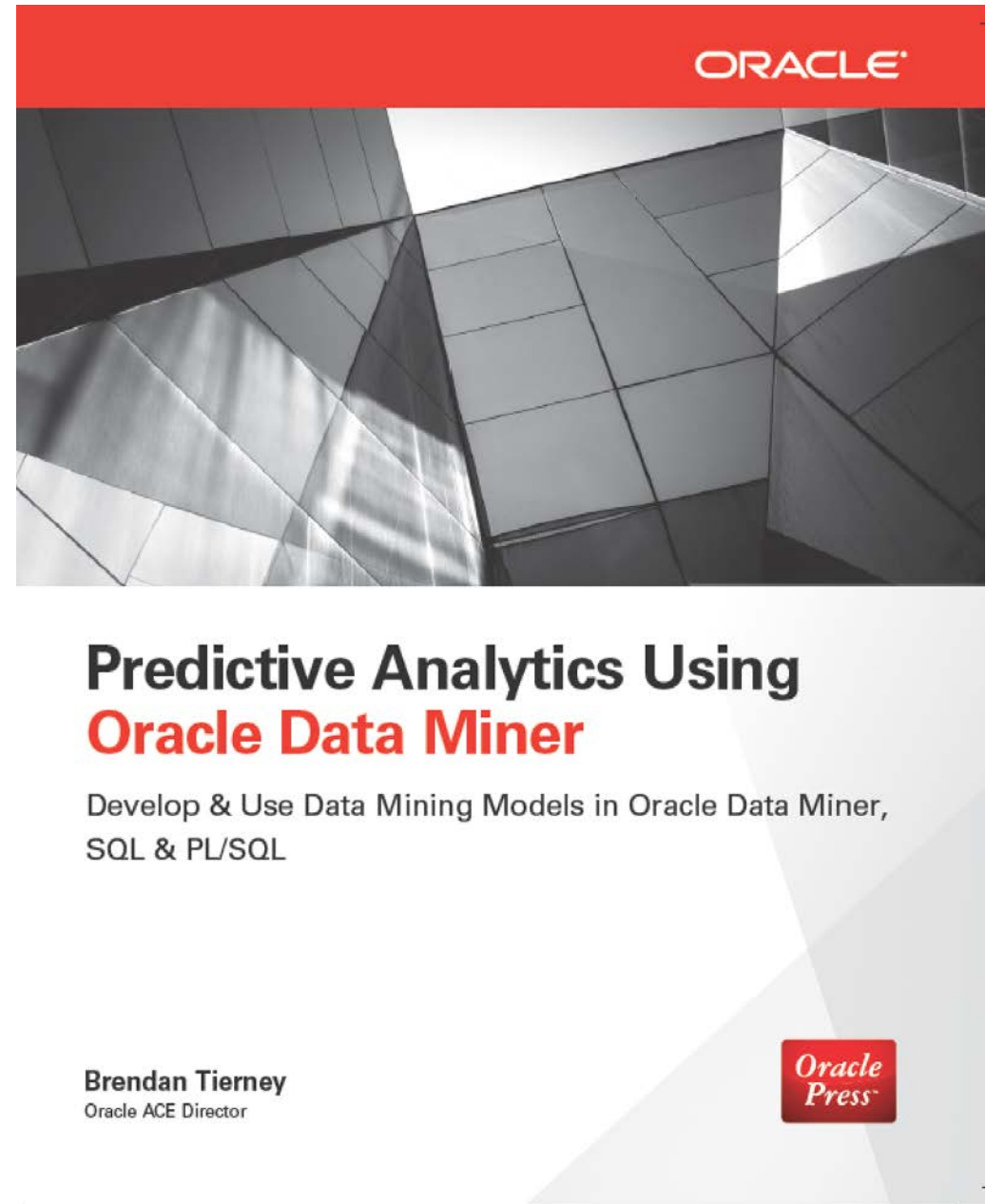
- **Oracle Advanced Analytics Overview:**
  - Link to presentation—[Big Data Analytics using Oracle Advanced Analytics In-Database Option](#)
  - [OAA data sheet](#) on OTN
  - *Oracle Internal* [OAA Product Management Wiki and Workspace](#)
- **YouTube recorded OAA Presentations and Demos:**
  - [Oracle Advanced Analytics and Data Mining at the YouTube Movies](#) (6 + OAA “live” Demos on ODM’r 4.0 New Features, Retail, Fraud, Loyalty, Overview, etc.)
- **Getting Started:**
  - Link to [Getting Started w/ ODM blog entry](#)
  - Link to [New OAA/Oracle Data Mining 2-Day Instructor Led Oracle University course](#).
  - Link to [OAA/Oracle Data Mining 4.0 Oracle by Examples \(free\) Tutorials](#) on OTN
  - Take a [Free Test Drive of Oracle Advanced Analytics \(Oracle Data Miner GUI\) on the Amazon Cloud](#)
  - Link to [SQL Developer Days Virtual Event w/ downloadable VM of Oracle Database + ODM/ODMr and e-training for Hands on Labs](#)
  - Link to [OAA/Oracle R Enterprise \(free\) Tutorial Series](#) on OTN
- **Additional Resources:**
  - [Oracle Advanced Analytics Option on OTN page](#)
  - [OAA/Oracle Data Mining on OTN page](#), [ODM Documentation](#) & [ODM Blog](#)
  - [OAA/Oracle R Enterprise page on OTN page](#), [ORE Documentation](#) & [ORE Blog](#)
  - [Oracle SQL based Basic Statistical functions](#) on OTN
  - Business Intelligence, Warehousing & Analytics—[BIWA Summit’15, Jan 27-29, 2015](#) at Oracle HQ Conference Center



# New book on Oracle Advanced Analytics available

Book available on Amazon

[Predictive Analytics Using Oracle Data Miner: Develop for ODM in SQL & PL/SQL](#)



# Take a Test Drive!

## Vlamis Software, Oracle Partner Offers FREE Test Drives on the Amazon Cloud

- Step 1—Fill out request

- Go to <http://www.vlamis.com/testdrive-registration/>

- Step 2—Connect

- Connect with Remote Desktop

- Step 3—Start Test Drive!

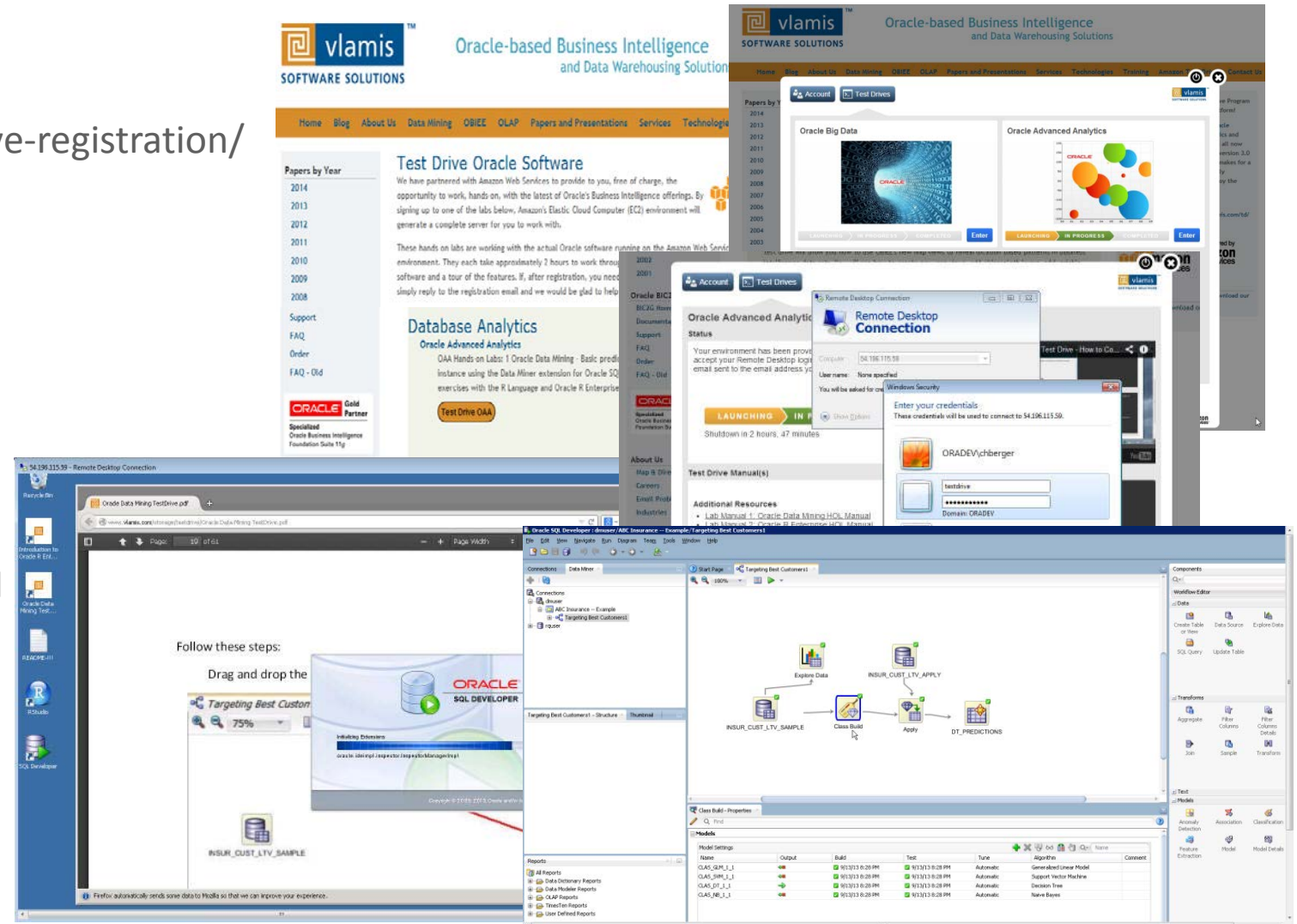
- Oracle Database +

- Oracle Advanced Analytics Option

- SQL Developer/Oracle Data Miner GUI

- Demo data for learning

- Follow Tutorials





[Home Page](#) [Hotel and Travel](#) [Agenda](#) [Sponsorship](#) [Registration](#) [Abstract Submission](#)

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January 27-29th 2015

Oracle Conference Center at Oracle HQ Campus, Redwood Shores, CA

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[Example talks from last year](#)

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