

ORACLE[®] Oracle Data Mining — In-Database Data Mining Made Easy!

Charlie Berger Sr. Director Product Management, Data Mining and Advanced Analytics Oracle Corporation charlie.berger@oracle.com www.twitter.com/CharlieDataMine





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



Agenda

- Market Drivers
- Oracle Data Mining
- Exadata and Oracle Data Mining
- Oracle Data Miner 11g Release 2 New GUI
- Oracle Statistical Functions
- Ability to Import 3rd Party e.g. SAS models
- Applications Powered by Oracle Data Mining
- Getting Started with ODM





Analytics: Strategic and Mission Critical

- Competing on Analytics, by Tom Davenport
 - "Some companies have built their very businesses on their ability to collect, analyze, and act on data."
 - "Although numerous organizations are embracing analytics, only a handful have achieved this level of proficiency. But analytics competitors are the leaders in their varied fields—consumer products finance, retail, and travel and entertainment among them."
 - "Organizations are moving beyond query and reporting" IDC 2006
- Super Crunchers, by Ian Ayers
 - "In the past, one could get by on intuition and experience. Times have changed. Today, the name of the game is data." -Steven D. Levitt, author of Freakonomics
 - "Data-mining and statistical analysis have suddenly become *cool....* Dissecting marketing, politics, and even sports, stuff th complex and important shouldn't be this much fun to read."-Wired



Analytics

saking.... Not only is it fun to read, it just may change the way you thin STEVEN D. LEVITT, coauthor of Freak THINKING-BY-NUP



ORACLE

Competitive Advantage

Optimization	What's the best the tear tappen?	Data Mining
Predictive Modeling	What will happen next?	****
Forecasting/Extrapolation	What if these trends continue?	Analytic\$
Statistical Analysis	Why is this happening?	
Alerts	What actions are needed?	
Query/drill down	Where exactly is the problem?	Access &
Ad hoc reports	How many, how often, where?	Reporting
Standard Reports	What happened?	

Degree of Intelligence

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

Copyright 2010 Oracle Corporation

ORACLE

Competitive Advantage



What is In-Database Analytics?

Move the data??

Move the algorithms?







What is In-Database Analytics?

Move the data??

Move the algorithms?





ORACLE

What is In-Database Analytics?

Move the algorithms!!!!!



ORACLE

Traditional Analytics Environment Move Data → Algorithms



- Traditional analytics environment results in:
 - Data movement
 - Data duplication
 - Loss of security



Oracle Architecture Move Data ← Algorithms



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



In-Database Data Mining



Copyright 2010 Oracle Corporation

ORACLE



ORACLE



- 11 years "stem celling analytics" into Oracle
 - Designed advanced analytics into database kernel to leverage relational database strengths
 - Naïve Bayes and Association Rules—1st algorithms added
 - Leverages counting, conditional probabilities, and much more
- Now, analytical database platform
 - 12 cutting edge machine learning algorithms and 50+ statistical functions
 - A data mining model is a schema object in the database, built via a PL/SQL API and scored via built-in SQL functions.
 - When building models, leverage existing scalable technology
 - (e.g., parallel execution, bitmap indexes, aggregation techniques) and add new core database technology (e.g., recursion within the parallel infrastructure, IEEE float, etc.)
 - True power of embedding within the database is evident when scoring models using built-in SQL functions (incl. Exadata)



You Can Think of It Like This...

Traditional SQL

- "Human-driven" queries
- Domain expertise
- Any "*rules*" must be defined and managed

SQL Queries

- SELECT
- DISTINCT
- AGGREGATE
- WHERE
- AND OR
- GROUP BY
- ORDER BY
- RANK



Oracle Data Mining

- Automated knowledge discovery, model building and deployment
- Domain expertise to assemble the "right" data to mine
- ODM "Verbs"
 - PREDICT
 - DETECT
 - CLUSTER
 - CLASSIFY
 - REGRESS
 - PROFILE
 - IDENTIFY FACTORS
 - ASSOCIATE



ORACLE

Copyright 2010 Oracle Corporation

÷

Oracle Data Mining Algorithms



Copyright 2010 Oracle Corporation

ORACLE

Oracle Data Miner 11g Release 2 GUI Free SQL Developer Extension on OTN

- Graphical User Interface for data analyst
- SQL Developer Extension (OTN download)
- Explore data discover new insights
- Build and evaluate data mining models
- Apply predictive models
- Share analytical workflows
- Deploy SQL Apply code/scripts



ORACLE

Oracle Data Miner 11g Release 2 GUI Free SQL Developer Extension on OTN



ORACLE

The Forrester Wave™: Predictive Analytics And Data Mining Solutions, Q1 2010

Oracle Data Mining Cited as a Leader; 2nd place in Current Offering

- Ranks 2nd place in Current Offering
- "Oracle focuses on indatabase mining in the Oracle Database, on integration of Oracle Data Mining into the kernel of that database, and on leveraging that technology in Oracle's branded applications."



The Forrester Wave is copyrighted by Forrester Research, Inc. Forrester and Forrester Wave are trademarks of Forrester Research, Inc. The Forrester Wave is a graphical representation of Forrester's call on a market and is plotted using a detailed spreadsheet with exposed scores, weightings, and comments. Forrester does not endorse any vendor, product, or service depicted in the Forrester Wave. Information is based on best available resources. Opinions reflect judgment at the time and are subject to change.





Exadata + Data Mining 11g Release 2 "DM Scoring" Pushed to Storage!



 In 11g Release 2, SQL predicates and Oracle Data Mining models are <u>pushed to storage level for execution</u>

For example, find the US customers likely to churn:



Exadata + Data Mining 11g Release 2 Benefits

- Eliminates data movement
 - 2X-5X+ faster scoring on Exadata
 - Depends on number of joins involved with data for scoring
- Preserves security
- Significant architecture and performance advantages over SAS Institute
 - Years ahead of SAS's road map to move SAS analytics towards RDBMSs (<u>http://support.sas.com/resources/papers/InDatabase07.pdf</u>)
- Netezza performance but using industry standard RDBMS + SQL-based in-database advanced analytics
- Best platform for building enterprise predictive analytics applications e.g. Fusion Applications -> "Analytical iPod for the Enterprise"



TurkCell Prepaid Churn Model Oracle Data Mining on Exadata 11g Release 2



- Churn Problem
 - Churn prediction starts with turning an abundance of data into valuable information and continues as a cyclic process
- Approach
 - Initially we have used a large Solaris (100+ UltraSparc 7 cores and 640 GB memory) box to build our first SVM models:
 - It took 29 hours to complete model build & apply.
- Conclusion
 - On Exadata this reduces to a few hours mainly due to enormous improvement in data preparation stage
 - Churn prediction over various customer groups is and will be the focus of Turkcell
 - Embedded data mining with ODM is faster, more robust (due to stability of SVM algorithm), easier to automate, easier to manage

Excerpts from TurkCell presentation at OOW 2010, September 21, 2010 Necdet Deniz Halicioğlu <u>deniz.halicioglu@turkcellteknoloji.com.tr</u>





Oracle Data Miner 11g Release 2

0000

SOFTWARE. HARDWARE. COMPLETE.

Ú XSCF



Easier

Oracle Data Miner 11g Release 2 GUI

- Predict customer behavior
- Identify key factors
- Predict next-likely product
- Customer profiling
- Detect fraud & anomalies
- Mine "text" and unstructured data





Explore Data

- Thumbnail distributions of every attribute
 - Grouped by another attribute
- Summary statistics for all attributes
 - Min, max, stdev, variance median, mean, skewness, kurtosis, etc.

Name	Histogram	Data Type	Percent NULLs	Distinct Values	Mode	Average
'OR_TRANSFUSIONS"		NUMBER	0	2		0.3139
'SIZE_REDUCTION"	li	NUMBER	0	193		1.3375
'ER_ADMIT"		NUMBER	0	2		0.3751
'INCISION"		VARCHAR2	0	18	LABD	
'RESP_COMORB"		VARCHAR2	0	2	0	
'I_D"		NUMBER	0	1,994		1,255.66
'OR_DC_R"		NUMBER	0	17		16.9092
'MALIGNANCY"		VARCHAR2	0	2	0	
WT_LOSS_TIME"		NUMBER	0	8		0.2342
'ADM_LIPASE"	_ 1	NUMBER	84.3029	79		613.2236
'SMOKE_TYPE"		VARCHAR2	0	3	А	
'CARD_COMORB"		VARCHAR2	0	2	0	
"SIZE_REDUCTION By LYMPH_	STATUS"		156 - 5.185	6.214 - 7.243	3 10.33 - 1	1.359



Build and Evaluate Models

- Comparative model
 performance
 results
- Adjust and tune predictive models





Understand Model Details



ORACLE

Analytical "Work Flow" Methodologies

 Build, share and automate predictive analytics methodologies



2	Patient	Outcomes 🛛 🖉 🛛 🗛	t Risk patients 🛛 🗛	CLAS_DT_1_7	CLAS_GLN	1_1_7				
ଜ	<u>)</u> ∣⊻iew	:Cache Data 🕶 So	ort Filter: Enter Where	Clause				Custome	r Segments Clust	ers
[CLAS SVM 1 7 PR	ED CLAS SVM 1 7 PROB	LYMPH TYPE	SIZE TUMOR MM	MARITAL	ADM ALBUMIN	AMT CHEMO	FREQ CHEMO	CLAS DT
	1	1	0.99865991	Agressive	7,100	М	- 1.6	42.17	1	<u>^</u>
	2	1	0.99865991	Agressive	7,100	м	1.6	42.17	1	
	3	1	0.99865991	Agressive	7,100	м	1.6	42.17	1	
	4	1	0.99351446	Agressive	5,200	м	2.4	52	1	
	5	1	0.99351446	Agressive	5,200	м	2.4	52	1	
	6	1	0.99351446	Agressive	5,200	М	2.4	52	1	
	7	1	0.99149541	Agressive	1,350	S	2.4	37.01	2	
	8	1	0.99149541	Agressive	1,350	S	2.4	37.01	2	
	9	1	0.99149541	Agressive	1,350	S	2.4	37.01	2	
	10	1	0.99149541	Agressive	1,350	S	2.4	37.01	2	
	11	1	0.9912111	Indolent	3,400	W		3.25	2	
	12	1	0.9912111	Indolent	3,400	W		3.25	2	
	13	1	0.9912111	Indolent	3,400	W		3.25	2	
	14	1	0.9912111	Indolent	3,400	W		3.25	2	
	15	1	0.98217842	Indolent	1,000	М	2.4	52.25	1	
	16	1	0.98217842	Indolent	1,000	М	2.4	52.25	1	R



SQL Developer Active Query Builder

 New, easy to use, interactive query builder in SQL Developer for assembling and preparing data—for mining

2) Start Page

Worksheet

SELECT

FROM

ON

sh.customers INNER JOIN SH. SALES

A dmuser

Query Builder

sh.customers.CUST ID, sh.customers.CUST FIRST NAME, sh.customers.CUST LAST NAME, sh.customers.CUST GENDER, SH. SALES. TIME_ID, SH. SALES. CHANNEL_ID

sh.customers.CUST ID = SH.SALES.CUST ID

	CUSTOMERS (SH)										
	* CUST_IRST_NAME CUST_CAST_NAME CUST_CAST_NAME CUST_CAST_CAST_NAME CUST_CAST_CAST_NAME CUST_CAST_COSTAL_COD CUST_CITY CUST_CITY_ID CUST_STATE_PROVI CUST_STATE_PROVI CUST_STATE_PROVI CUNTRY_ID CUST_MAIN_PHONE, CUST_MAIN_PHONE,	- 10		SALES (SH)	LD _SOLD SOLD	2					Q
		1	Aline	Sort Tupe	Sort Order	Grauping	Criteria	Cr.			
Ductors	Expression	A CONTRACT AT A	Pulcia	Doitiype	Sortordes	Grouping	Cincenta				
Output	Expression sh.customers.CUST ID	Aggregate				100					
Output	Expression sh.customers.CUST_ID sh.customers.CUST_FIRST_NAME	Aggregate									
Output	Expression sh.customers.CUST_ID sh.customers.CUST_FIRST_NAME sh.customers.CUST_LAST_NAME	Aggregate									
Output	Expression sh.customers.CUST_ID sh.customers.CUST_FIRST_NAME sh.customers.CUST_LAST_NAME sh.customers.CUST_GENDER	Aggregate									
Output	Expression sh.customers.CUST_ID sh.customers.CUST_FIRST_NAME sh.customers.CUST_LAST_NAME sh.customers.CUST_GENDER SH.SALES.TIME_ID	Aggregate									
Output	Expression sh.customers.CUST_ID sh.customers.CUST_FIRST_NAME sh.customers.CUST_LAST_NAME sh.customers.CUST_GENDER SH.SALES.TIME_ID SH.SALES.CHANNEL_ID	Aggregate									
	Expression sh.customers.CUST_ID sh.customers.CUST_FIRST_NAME sh.customers.CUST_LAST_NAME sh.customers.CUST_GENDER SH.SALES.TIME_ID SH.SALES.CHANNEL_ID	Aggregate									
	Expression sh.customers.CUST_ID sh.customers.CUST_FIRST_NAME sh.customers.CUST_LAST_NAME sh.customers.CUST_GENDER SH.SALES.TIME_ID SH.SALES.CHANNEL_ID	Aggregate									
Output	Expression sh.customers.CUST_ID sh.customers.CUST_FIRST_NAME sh.customers.CUST_LAST_NAME sh.customers.CUST_GENDER SH.SALES.TIME_ID SH.SALES.CHANNEL_ID ry Result	Aggregate									
Output	Expression sh.customers.CUST_ID sh.customers.CUST_FIRST_NAME sh.customers.CUST_LAST_NAME sh.customers.CUST_GENDER SH.SALES.TIME_ID SH.SALES.CHANNEL_ID ry Result Stression SQL Fetched 50 rows in 0.2	Aggregate 12 seconds									
Output	Expression sh.customers.CUST_ID sh.customers.CUST_FIRST_NAME sh.customers.CUST_LAST_NAME sh.customers.CUST_GENDER SH.SALES.TIME_ID SH.SALES.CHANNEL_ID ry Result CUST_ID CUST_FIRST_NAME	Aggregate 12 seconds CUST_LAST_N		CUST. GENDER	CUST_YEAR	OF BIRTH	CUST MA	RITAL STATUS	CUST STREET A	ADDRESS	D
Dutput	Expression sh.customers.CUST_ID sh.customers.CUST_FIRST_NAME sh.customers.CUST_LAST_NAME sh.customers.CUST_GENDER SH.SALES.TIME_ID SH.SALES.CHANNEL_ID sh.saLES.CHANNEL_ID SH.SALES.CHANNEL_ID CUST_ID CUST_FIRST_NAME 49671 Abigail	IZ seconds	IAME B	CUST_GENDER	CUST_YEAR.	OF_BIRTH 0	CUST_MA arried	RITAL_STATUS	CUST_STREET_A	ADDRESS ahoc Boulevard	E 0
Dutput	Expression sh.customers.CUST_ID sh.customers.CUST_FIRST_NAME sh.customers.CUST_GENDER SH.SALES.TIME_ID SH.SALES.CHANNEL_ID SH.SALES.CHANNEL_ID st.SALES.CHANNEL_ID SH.SALES.CHANNEL SH.SALES.CHANNEL SH.SALES.CHA	12 seconds CUST_LAST_N Ruddy Ruddy	IAME B	CUST_GENDER	CUST_YEAR	OF_BIRTH 0	CUST_MA arried null)	RITAL_STATUS	CUST_STREET_A 27 North Sagadi 37 West Geneva	ADDRESS ahoc Boulevard Street	C 033
Dutput	Expression sh.customers.CUST_ID sh.customers.CUST_FIRST_NAME sh.customers.CUST_GENDER SH.SALES.TIME_ID SH.SALES.CHANNEL_ID st.SALES.CHANNEL_ID SH.SALES.CHANNEL_ID ST.SALES.CHANNEL ST.SALES.CHANNEL ST.SALES.CHA	12 seconds CUST_LAST_N Ruddy Ruddy Ruddy	AME B	CUST_GENDER	CUST_YEAR.	OF_BIRTH 1976 m 1964 (1942 s	CUST_MA arried null) ingle	RITAL_STATUS	CUST_STREET_A 27 North Sagad 37 West Geneva 47 Toa Alta Roi	ADDRESS ahoc Boulevard Street ad	C 033 5540 3407
Quer Quer 1 2 3 4	Expression sh.customers.CUST_ID sh.customers.CUST_FIRST_NAME sh.customers.CUST_LAST_NAME sh.customers.CUST_GENDER SH.SALES.TIME_ID SH.SALES.CHANNEL_ID ry Result St.SALES.CHANNEL_ID CUST_ID SCUST_FIRST_NAME 49671 Abigail 10388 Abigail 10388 Abigail	12 seconds CUST_LAST_N Ruddy Ruddy Ruddy Ruddy	AME B M M M M	CUST_GENDER	CUST_YEAR.	OF_BIRTH 8	CUST_MA arried null) ingle arried	RITAL_STATUS	CUST_STREET_A 27 North Sagada 37 West Genevat 47 Toa Alta Roi 47 South Kanaba	ADDRESS ahoc Boulevard Street ad ec Road	CI 1 6033 5540 3407 7299
Uutput	Expression sh.customers.CUST_ID sh.customers.CUST_FIRST_NAME sh.customers.CUST_GENDER SH.SALES.TIME_ID SH.SALES.TIME_ID SH.SALES.CHANNEL_ID CUST_ID CUST_FIRST_NAME 49671 Abigai1 6783 Abigai1 10338 Abigai1 13894 Abigai1 10384 Abigai1	12 seconds CUST_LAST_N Ruddy Ruddy Ruddy Ruddy Ruddy	AME B M M M M M	CUST_GENDER	CUST_YEAR	OF_BIRTH 0F_BIRTH 1976 m 1964 () 1942 s 1977 m 1949 ()	CUST_MA arried null) ingle arried null)	RITAL_STATUS	CUST_STREET_A 27 North Sagadi 37 West Geneva 47 Toa Alta Ro 47 South Kanabu 57 North 3rd D	ADDRESS ahoc Boulevard Street ad ec Road rive	CL 1 60332 5540 3407 7299 6764



Copyright	2010 Oracle Corporation	

Example: Simple, Predictive SQL

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

Ele thep Enter SQL Statement SELECT A CUSTOMER ID, A AGE, MORTGAGE AMOUNT, PREDICTION PROBABILITY(INSUR CUST LT35466 DT, VERY HIGH USING A^) prob FROM CBERGER INSUR_CUST_LTV A) (VHERE prob > 0.85) Results Fetch Size 100 Fetch Next Betresh CUSTOMER_D AGE MORTGAGE. PROB CUI523 50 1158 9806451612 CU1523 50 19806451612 CU1523 50 9806451612 CU1523 50 9806451612 CU1523 50 9806451612 CU1523 50 9806451612 CU1523 50 9806451612 CU1523 50 9806451612 CU1754 54 2000 9806451612 CU1755 51 3000 9806451612 CU1336 34 1300 9806451612 CU1360 35 1600 9806451612	🍲 SQL Worl	kshee	t			
Enter SQL Statement SELECT A CUSTOMER ID, AAGE, MORTGAGE AMOUNT, PREDICTION PROBABILITY(INSUR CUST LI735466 DT, VERY HIGH) USING A*) prob FROM CBERGER.INSUR_CUST_LITY A) WHERE prob > 0.85; Results Fetch Size 100 Fetch Next Betresh CUSTOMER_D AGE MORTGAGE. PROB CUI523 50 1158 9806451612 CU1523 50 1158 9806451612 CU153 67 1500 9806451612 CU1755 51 3000 9806451612 CU1336 34 1300 9806451612 CU1346 35 1600 9806451612 CU1346 35 1600 9806451612 CU1346 35 1600 9806451612 CU1347 55 1600 9806451612 CU1348	<u>File H</u> elp					
SELECT A CUSTOMER ID. A AGE. MORTGAGE AMOUNT. PREDICTION PROBABILITY (INSUR CUST LT35466 DT, VERY HIGH) USING A.*) prob FROM CBERGER.INSUR_CUST_LTV A) WHERE prob > 0.85; Fetch Size Image: Customer_ID AGE MORTGAGE. Prob Customer_ID AGE MORTGAGE.	Enter SQL	Stater	ment			
SELECT A CUSTOMER ID. A AGE, MORTGAGE AMOUNT. PREDICTION PROBABILITY(INSUR CUST LT35466 DT, VERY HIGH) USING A ") prob FROM CBERGER.INSUR_CUST_LTV A) WHERE prob > 0.85; Results Fetch Size 100 Fetch Next Befresh Fetch Size 100 Fetch Next Befresh Fetch Size 100 9806451612 CU1523 50 11158 9806451612 CU1523 70 7000 9806451612 CU1533 70 7000 9806451612 CU153 767 1150 9806451612 CU153 78 1100 9806451612 CU153 78 1100 9806451612 CU153 78 1100 9806451612 CU1336 34 1300 9806451612 CU1338 78 1100 9806451612 CU1344 53 1200 9806451612 CU1345 51 1500 9806451612 CU1345 78 1100 9806451612 CU						
SELECT A COSTOMER ID, AAGE_MONTGAGE AMOUNT, PREDICTION PROBABILITY(INSUR CUST LI35466 DT, VERY HIGH) USING A.*) prob FROM CBERGER INSUR_CUST_LITV A) WHERE prob > 0.85 Results Results CUSTOMER_D AGE MORTGAGE PROB CUSTOMER_D AGE MORTGAGE PROB CU1523 50 1158 9806451612 CU1533 70 7000 9806451612 CU157 44 50 9806451612 CU157 67 150 9806451612 CU1324 2000 9806451612 CU1338 78 1100 9806451612 CU1338 78 1100 9806451612 CU1338 78 1100 9806451612 CU1324 2167 9806451612 2167	SELECT A CUSTOMER ID, A AGE, MORTGAGE AMOUNT,					
USING A*) prob FROM CBERGER.INSUR_CUST_LITV A) WHERE prob > 0.85 Image: State	File Help Enter SQL Statement SELECT A CUSTOMER ID, A.AGE, MORTGAGE AMOUNT, PREDICTION PROBABILITY(INSUR CUST LT35466 DT, VERY HIGH') USING A.*) prob FROM CBERGER.INSUR_CUST_LTV A) WHERE prob > 0.85; Image: Customer and the statement of the statemen					
FROM CBERGER.INSUR_CUST_LIVA) USING A.*) prob WHERE prob > 0.85; FROM CBERGER.CUST_INSUR Image: Customer in the strength of the strengt of the strength of the strength of the strength of th	USING A.*) prob					
WHERE prob > 0.85; FROM CBERGER.CUST_INSUR Results Frech Next Refresh CUSTOMER_D AGE MORTGAGE. PROB CU1523 50 70 9806451612 CU1653 70 70 9806451612 CU1653 70 70 9806451612 CU1757 51 300 9806451612 CU1753 67 150 9806451612 CU1734 50 9806451612 9806451612 CU1735 51 3000 9806451612 CU1324 27 1150 9806451612 CU1324 20 20 9806451612 CU1324 2100 9806451612 1100 CU1324 2100 9806451612 1100 CU1324 2100 9806451612 1100 201686 35 100 9806451612 CU13242 1100 98	FROM CBERGER INSUR CUST LTV A)					
Image: Constraint of the constraint	VHERE prob > 0.85;					
Image: Control of the control of th	· · · · ·				-	
Results Fetch Next Befresh CUSTOMER_D AGE MORTGAGE. PROB CU1523 50 1158 .9806451612 CU1663 70 7000 .9806451612 CU1057 49 5000 .9806451612 CU17059 36 3500 .9806451612 CU1775 51 3000 .9806451612 CU1753 67 1500 .9806451612 CU17324 50 2000 .9806451612 CU1336 34 1300 .9806451612 CU1338 78 1100 .9806451612 CU1334 53 1200 .9806451612 CU1334 53 1200 .9806451612 CU1324 29 2187 .9806451612			55555			
Fetch Size: 100 Fetch Next Refresh CUSTOMER_D AGE MORTGAGE. PROB CU1523 50 1158 9806451612 CU1663 70 7000 9806451612 CU1057 49 5000 9806451612 CU1764 54 2800 9806451612 CU1775 51 3000 9806451612 CU1537 67 1500 9806451612 CU1537 67 1500 9806451612 CU1324 50 2000 9806451612 CU1336 34 1300 9806451612 CU1336 1100 9806451612 19806451612 CU1336 78 1100 9806451612 CU1337 78 1100 9806451612 CU1341 53 1200 9806451612 CU1341 53 1200 9806451612 CU1342 59 1600 9806451612 CU1342 53 1800 9806451612 CU1344 53 1800	Results					
CUSTOMER_ID AGE MORTGAGE PROB CU1523 50 1158 9806451612 CU1653 70 7000 9806451612 CU1057 49 5000 9806451612 CU1059 36 3500 9806451612 CU1775 51 3000 9806451612 CU1537 67 1500 9806451612 CU1324 50 2000 9806451612 CU1336 34 1300 9806451612 CU1336 78 1110 9806451612 CU1336 78 1100 9806451612 CU1341 53 1200 9806451612 CU13242 49 2187 9806451612	Fetch Size: 4	00	Fatch Next Refresh			
CUSTOMER_ID AGE MORTGAGE. PROB CU1523 50 1158 9806451612 CU1653 70 7000 9806451612 CU1057 49 5000 9806451612 CU1059 36 3500 9806451612 CU1764 54 2800 9806451612 CU1755 51 3000 9806451612 CU1537 67 1500 9806451612 CU1544 27 1150 9806451612 CU1324 50 2000 9806451612 CU1336 34 1300 9806451612 CU1336 78 1100 9806451612 CU1341 53 1200 9806451612 CU1341 53 1200 9806451612 CU1686 35 1600 9806451612 CU13242 49 2187 9806451612					L	
CU1325 30 1130 1300431612 CU1653 70 7000 .9806451612 CU1057 49 5000 .9806451612 CU1059 36 3500 .9806451612 CU1764 54 2800 .9806451612 CU1755 51 3000 .9806451612 CU1537 67 1500 .9806451612 CU1537 67 1500 .9806451612 CU1324 50 .2000 .9806451612 CU1336 34 1300 .9806451612 CU1338 78 1100 .9806451612 CU1341 53 1200 .9806451612 CU1686 35 1600 .9806451612 CU13242 49 .2187 .9806451612	CUSTOMER_	_ID 50	AGE MORTGAGE	PROB		
CU1057 49 5000 9806451612 CU1059 36 3500 9806451612 CU1764 54 2800 9806451612 CU1775 51 3000 9806451612 CU1537 67 1500 9806451612 CU2544 27 1150 9806451612 CU1324 50 2000 9806451612 CU1336 34 1300 9806451612 CU1338 78 1100 9806451612 CU1384 53 1200 9806451612 CU1384 53 1200 9806451612 CU1384 53 1200 9806451612 CU1866 35 1600 9806451612 CU3242 49 2187 9806451612	CU1653	70	7000	.9806451612		
CU1059 36 3500 .9806451612 CU1764 54 2800 .9806451612 CU1775 51 3000 .9806451612 CU1537 67 1500 .9806451612 CU2544 27 1150 .9806451612 CU1324 50 2000 .9806451612 CU1336 34 1300 .9806451612 CU1338 76 1100 .9806451612 CU1384 53 1200 .9806451612 CU1384 53 1200 .9806451612 CU1384 53 1200 .9806451612 CU1384 53 1600 .9806451612 CU3242 49 2187 .9806451612	CU1057	49	5000	.9806451612		
CU1764 54 2800 .9806451612 CU1775 51 3000 .9806451612 CU1537 67 1500 .9806451612 CU2534 27 1150 .9806451612 CU1324 50 2000 .9806451612 CU1336 34 1300 .9806451612 CU1338 78 1100 .9806451612 CU1341 53 1200 .9806451612 CU1686 35 1600 .9806451612 CU3242 49 .2187 .9806451612	CU1059	36	3500	.9806451612		
CU1775 S1 S000 S000451612 CU1537 67 1500 .9806451612 CU2544 27 1150 .9806451612 CU1324 50 2000 .9806451612 CU1336 34 1300 .9806451612 CU1338 78 1100 .9806451612 CU1341 53 1200 .9806451612 CU1686 35 1600 .9806451612 CU3242 49 2187 .9806451612	CU1764	54	2800	.9806451612		
CU2544 27 1150 .9806451612 CU1324 50 2000 .9806451612 CU1336 34 1300 .9806451612 CU1338 78 1100 .9806451612 CU1341 53 1200 .9806451612 CU1686 35 1600 .9806451612 CU3242 49 2187 .9806451612	CU1775	51 67	1500	.9806451612		
CU1324 50 2000 .9806451612 CU1336 34 1300 .9806451612 CU1338 78 1100 .9806451612 CU1341 53 1200 .9806451612 CU1686 35 1600 .9806451612 CU3242 49 .2187 .9806451612	CU2544	27	1150	.9806451612		
CU1336 34 1300 .9806451612 CU1338 78 1100 .9806451612 CU1341 53 1200 .9806451612 CU1686 35 1600 .9806451612 CU3242 49 .2187 .9806451612	CU1324	50	2000	.9806451612		
CU1338 78 1100 J8806451612 CU1341 53 1200 J8806451612 CU1686 35 1600 J8806451612 CU3242 49 2187 J8806451612	CU1336	34	1300	.9806451612		
CU1686 35 1600 .9806451612 CU3242 49 2187 .9806451612	CU1338	78	1100	.9806451612		
CU3242 49 2187 .9806451612	CU1686	35	1600	.9806451612		
	CU3242	49	2187	.9806451612	▼	



Fraud Prediction Demo

drop table CLAIMS_SET;			
exec dbms_data_mining.drop_model('CLAIMSMODEL');	POLICYNUMBER	PERCENT_FRAUD	RNK
create table CLAIMS_SET (setting_name varchar2(30), setting_value varchar2(4000));			
insert into CLAIMS_SET values	6532	64.78	1
('ALGO_NAME','ALGO_SUPPORT_VECTOR_MACHINES');	2749	64.17	2
insert into CLAIMS_SET values ('PREP_AUTO','ON');	3440	63.22	3
commit;	654	63.1	4
	12650	62.36	5
begin			
dbms_data_mining.create_model('CLAIMSMODEL', 'CLASSIFICATION',	Automated Month	ly "Application"!	Just add:
'CLAIMS2', 'POLICYNUMBER', null, 'CLAIMS_SET');	Create		
end;	View CLAIMS2_3	30	
	As		
Top 5 most suspicious fraud policy holder claims	Select * from CLA	AIMS2	
select * from	Where mydate >	SYSDATE – 30	
(select POLICYNUMBER, round(prob_fraud*100,2) percent_fraud, rank() over (order by prob_fraud desc) rnk from	L		
(select POLICYNUMBER, prediction_probability(CLAIMSMODEL, '0' using *) prob_fraud			
from CLAIMS2		0040	
where PASTNUMBEROFCLAIMS in ('2 to 4', 'more than 4')))		ORAC	LE.
where rnk <= 5			
order by percent_fraud desc;		10100	



Real-time Prediction

with records as (select **On-the-fly, single record** 78000 SALARY. 250000 MORTGAGE AMOUNT. apply with new data (e.g. 6 TIME AS CUSTOMER, 12 MONTHLY CHECKS WRITTEN, from call center) 55 AGE. 423 BANK_FUNDS, 'Married' MARITAL STATUS. 'Nurse' PROFESSION, 'M' SEX, 4000 CREDIT CARD LIMITS, 2 N OF DEPENDENTS, HOUSE OWNERSHIP from dual) 1 select s.prediction prediction, s.probability probability from (select PREDICTION_SET(CUST_INSUR_LT46939_DT, 1 USING *) pset from records) t, TABLE(t.pset) s;

PREDICTION PROBABILITY HIGH .65123504738232096





SOFTWARE. HARDWARE. COMPLETE.

Ú XSCF

Oracle Statistical Functions (Free)

Window Aggregate functions Count, min, max, range stats_mode, variance,

11g Statistics & SQL Analytics (Free)

(moving and cumulative)

percent_rank, ntile

rank, dense_rank, cume_dist,

Ranking functions

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

Descriptive Statistics

- DBMS_STAT_FUNCS: summarizes numerical columns of a table and returns count, min, max, range, mean, median, stats_mode, variance, standard deviation, 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





Split Lot A/B Offer testing



- Offer "A" to one population and "B" to another
- Over time period "t" calculate median purchase amounts of customers receiving offer A & B





- Perform t-test to compare
- <u>If</u> statistically significantly better results achieved from one offer over another, offer everyone higher performing offer



Independent Samples T-Test (Pooled Variances)

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

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







Ability to Import 3rd Party DM Models

 Capability to import 3rd party dm models, import, and convert to native ODM models



- Benefits
 - SAS, SPSS, R, etc. data mining models can be used for scoring inside the Database
 - Imported dm models become native ODM models and inherit all ODM benefits <u>including scoring at Exadata storage layer</u>, 1st class objects, security, etc.

ORACLE

In-Database SAS Scoring

Score the SAS_ODM Model

- SAS models become native ODM models
 - No loss of information
- Original source data for scoring remains in Database
- "Exadata scoring" of SAS models







In-Database SAS Scoring

Import the SAS Model

🕂 🚯	ا 🗗 🖌 🏈 😫 ا 😓 ا 🖓 ڬ	8	adc2100781.us.oracle.com 11.2.0.2
Connection	begin dbms_data_mining.import_model		
🗟 🎦 🕢	'SAS_Log_Reg_Model2',		
قە 🗙	XMLType(bfilename('PMML_DIR', 'SAS_Logistic_Regres	<pre>sion_PMML_Model.xml'), nl;</pre>	s_charset_id('AL32UTF8'))
🕀 🚰 Recent Files 🛛 🗘	end;	т	
Thumbnail	/	1	
	Query Result Statement Output		
	📌 🥔 🖃 📇 📃 I		
🗣 Workflow J	anonymous block completed		4
CBERGER Laptop			
		Line 4 Column 24 Insert	Modified Windows: CR/LF Editir

ORACLE

ask Tort

In-Database SAS Scoring Score the SAS_ODM Model

```
select
   prediction(SAS_Log_Reg_Model4 using *),
   prediction_probability(SAS_Log_Reg_Model using *)
from
   sas_dataset where id < 10;</pre>
```

<u>File E</u> dit <u>Y</u> iew <u>N</u> avigate <u>R</u> un Versi <u>o</u> ning <u>T</u> ools <u>H</u> elp								
🔊 🖓 🔚 🕄 🖓 🕲	💥 🗐 💼 🔾 • 🛇 • 🚵 •	ask Tom						
🛃 Data Miner	AAA Customer Analytics Add C2100781.us.oracle.com 11.2.0.2							
🕂 🚯		adc2100781.us.oracle.com 11.2.0.2 -						
Connection	<pre>select prediction(SAS_Log_Reg_Model using *), prediction_probability(SAS_Log_Reg_Model using *) from sas_dataset where id < 10;</pre>							
E-Cant Files	Statement Output							
Thumbnail	📌 📇 🔞 🙀 SQL All Rows Fetched: 9 in 0.062 seconds							
	PREDICTION(SAS_LOG_REG_MODELUSING*) PREDICTION_PROBABILITY(SAS_LOG_REG_MODELUSING*)	NG*)						
	1 0 0.6405639512367	8522						
🔂 Workflow J	2 0 0.5919261962282	1852						
CBERGER Laptop	3 0 0.5929514495617	8569						
	4 0 0.6596575208781	2879 👻						
	Line 1 Column 1 Inser	t Modified Windows: CR/LF Editing						





Integration with Oracle BI EE

🥙 (Online) Siebel Analytics Administration Tool - AnalyticsWeb





ORACLE

_ @ X

Example

Better Information for OBI EE Reports and Dashboards





Predictive Analytics Applications

Powered by Oracle Data Mining



(Partial List as of March 2010)

Fusion HCM Predictive Analytics

					Search All	M		€ .		💄 You ar	e logged in as l
🟠 N	avigator~ Recent Ite	ems~ Favorite	es∨ Tags∨ Watchlis	t∨						Preferences	Help 4
Wa		ounting Man	Pager Recourses								
we	General Acc		lager Resources								
🗆 My (Organization										⊻ %
🚠 Org	ganization Chart 隆 Hierard	thy Grid 🛄 Table	Number of Levels to be Displa	ayed 2 🔁							
6	Seneral Employment	Availability	Budget Compens	sation Performance							
Action	ns 🔻 View 👻 🍸 Filter	/									
									Predicted Risk		
Name				Job Title		Phone	Email	Id	Individual	annan an ann an an an an an an an an an	Group
<u> </u>	🔁 • Leslie Hann			Finance Director		(813) 419-0861	lhann@vision.com	12345			
	Anna Pascal			Senior Accountant Manager		(986) 819-8861	apascal@vision.com	23456			<u> </u>
	🗄 🛁 George White			Finance Manager		(542) 465-6424	gwhite@vision.com	74342			<u> </u>
-	🗄 🛁 Jason Blake			Senior Manager		(251) 331-1816	jblake@vision.com	67890			<u> </u>
	🗄 🔤 Pat Miller			Accounting Manager		(793) 465-3470	pmiller@vision.com	34567			
	Stella Hahn			Manager		(700) 796-6338	shahn@vision.com	90123			
Pred	icted Worker Performa	ance and Attriti	on Eul Archeric								V
view (My Directs' Organization	•	Full Analysis								
Averag	ge Team Prediction for M	ly Direct Reports	'Organization								
1	✓ Show names										
				Team Name Total Numl	er of Team Members Aver	age Predicted Attrit	on Average Predic	ted Performance	Prediction Details		
_				Anna Pascal	0						
figh				Team: George White	10						
-			1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	Team: Jason Blake	6						
		Anna Pascal		Team: Pat Miller	15						
			Team: Pat Miller (15)	Stella Hahn	0						
ĒΕ	Stella Hahn										
edit edit											
⊇ Cte											
red											
۵	Team: G	eorge White (10)									
3	realli, G	corge write (10)	Toomu Jacon Plaka (6)								
Po			ream: Dason Blake (6)								

ORACLE

Fusion HCM Predictive Analytics



ORACLE

Copyright 2010 Oracle Corporation



Getting Started

- Oracle Data Miner Cue Cards—part of client install
- Oracle By Example Online Learning on OTN



Using Oracle Data Miner for Oracle Database 11g Release 2

Purpose

This tutorial covers the use of Oracle Data Miner to perform data mining against Oracle Database 11g Release2. I Data Miner graphical user interface (GUI). The Oracle Data Miner GUI is included as an extension of Oracle SQL D

Oracle SQL Developer is a free graphical tool for database development. With SQL Developer, you can browse dat statements. Starting with SQL Developer, version 3.0, you can also access the Oracle Data Miner GUI, which provi

DISCLAIMER: This tutorial has been developed with pre-production software, and is not available for external audi

Time to Complete

Approximately 30 mins

Overview

Data mining is the process of extracting useful information from masses of data by extracting patterns and trends

B Predict individual behavior, for example, the customers likely to respond to a promotional offer or the customer

- I Find profiles of targeted people or items (Classification using Decision Trees)
- Find natural segments or clusters (Clustering)
- Identify factors more associated with a target attribute (Attribute Importance)
- E Find co-occurring events or purchases (Associations, sometimes known as Market Basket Analysis)
- E Find fraudulent or rare events (Anomaly Detection)

The phases of solving a business problem using Oracle Data Mining are as follows:

- 1. Problem Definition in Terms of Data Mining and Business Goals
- 2. Data Acquisition and Preparation
- 3. Building and Evaluation of Models
- 4. Deployment

Compare the Models

After you build/train the selected models, you can view and evaluate the results for all of the models in a comparative for

Follow these steps:

1. Right-click the build node and select Compare from the menu



Results: A Class Build display tab opens, showing a graphical comparison of the four models, as shown here:











"This presentation is for informational purposes only and may not be incorporated into a contract or agreement."