Oracle In-Database ML with OML4SQL/OML4PY in Autonomous DB







Agenda

- Machine Learning Enabling Business Applications
- Machine Learning in Oracle Database: OML4SQL and OML4Py
- > Running Machine Learning with Oracle Autonomous Database
- > An Example: Building Machine Learning Model with OML
- Summary/Q & A

About Me: Kai Yu

D¢LLTechnologies



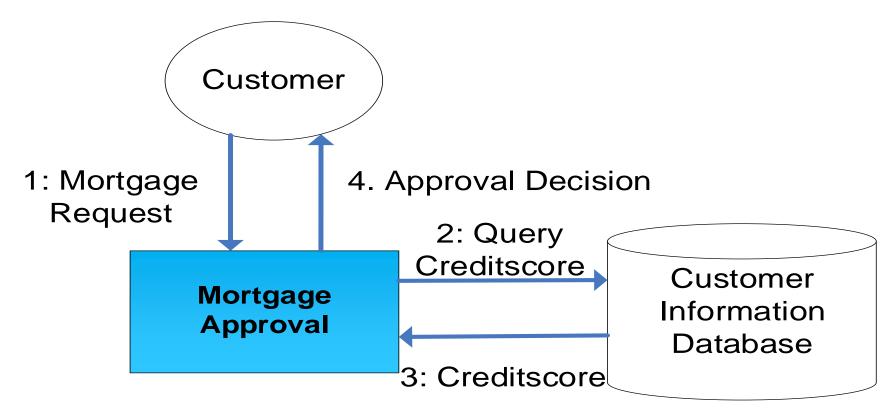
- Distinguished Engineer, Dell Technical Leadership Community
 Dell Database Solutions Engineering
- 28+ years working in Tech Industry
- Specializing in Oracle Database, Virtualization/Cloud and Machine Learning
- Author and Frequent Speaker at IEEE and Oracle Conferences
- IOUG Cloud Computing SIG Co-founder and VP
- Oracle ACE Director since 2010
- Co-recipient of the OAUG Innovator of Year Award
- Oracle Technologist of the Year: Cloud Architect by Oracle Magazine
- My Blog: http://kyuoracleblog.wordpress.com/



A simple mortgage request approval application

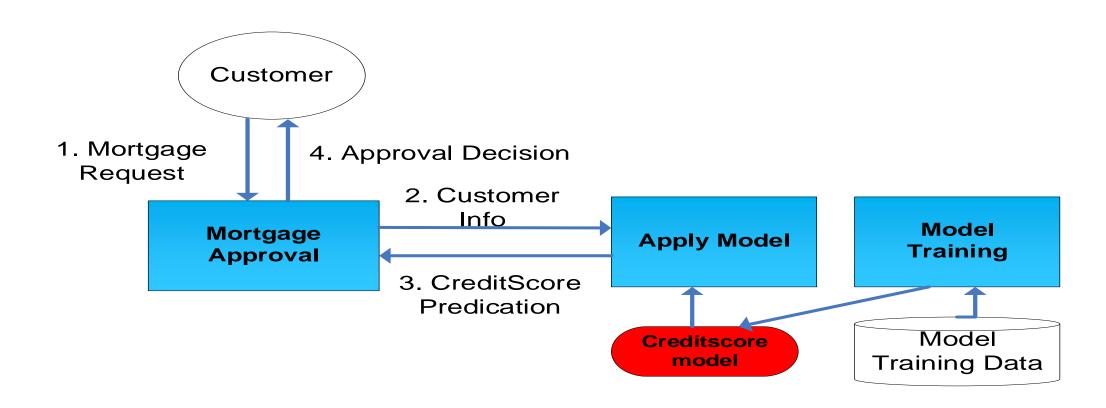
Mortgage approval decisions made based on the customer credit scores.

- A simple business process for customers with known credit scores.
- Limitation: What if the customer's credit score is unknown?



An intelligent mortgage approval application for customers with unknown credit score

- Predict customer credit scores based on pre-trained credit score model.
- Add intelligence to the traditional business applications with predictive capability through Machine Learning.



Next generation enterprise applications are more data driven and more intelligent.

- Transform massive volumes of data into meaningful insights
- Using AI and ML methods in business applications.

84% of organizations are using at least one emerging technology — AI, IoT, digital assistants, blockchain according to a recent survey by Oracle.

(https://www.oracle.com/a/ocom/docs/esg-research-oracle-emerging-technologies.pdf)



Top emerging technology statistics:

Finance

Offload to the cloud:



SaaS enablement:

92% of respondents see SaaS finance applications as enablers for the adoption of emerging technologies.



Prebuilt capabilities:

Organizations that add emerging technology capabilities to finance applications by purchasing prebuilt solutions outnumber those that build solutions by two to one.

Offload to the cloud:



SaaS enablement:

88% of respondents see SaaS SCM applications as enablers for the adoption of emerging technologies.



Supply chain management

Top emerging technology statistics:

Prebuilt capabilities:

Organizations that add emerging technology capabilities to SCM applications by purchasing solutions outnumber those that build solutions by three to one.

Take advantage of emerging technology benefits:



Al effectiveness:

Users of AI within financial systems report an average improvement of 33% in productivity and 37% reduction in errors.



Al efficiency:

Organizations have reduced the time needed to complete the monthly financial close process by about four days on average thanks to the incorporation of AI into their finance systems.

Specific impacts by emerging tech:



Al efficiency:

76% of organizations cite increased employee productivity as a realized benefit of Al-powered SCM.

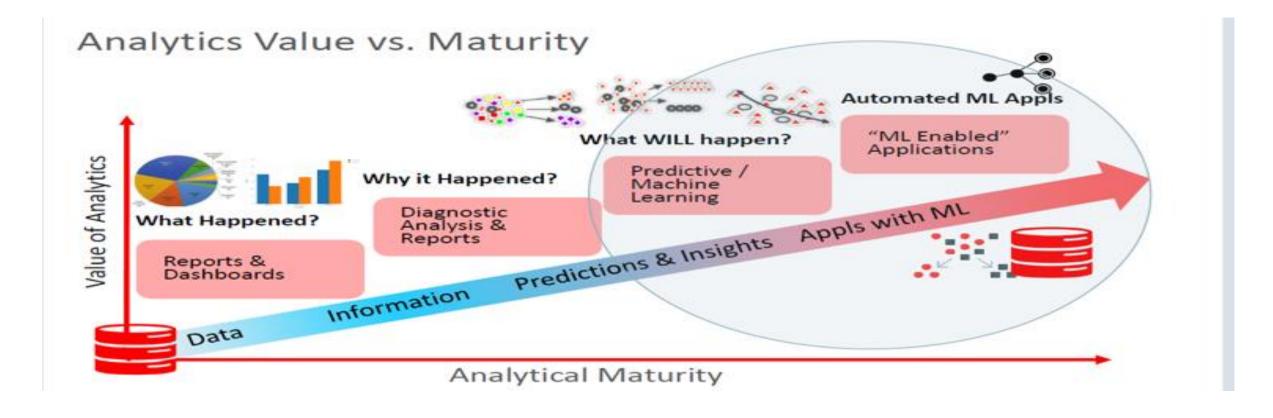
75%

Increase adoption:

75% of respondents credit chatbots and intelligent voice assistants with increasing the use of SCM apps by suppliers and customers.

Advanced Analytics and Machine Learning bring great business values

- Transform massive volumes of data into meaningful insights:
 Started with historical report and moved to advanced analytics such as
 Prediction, Pattern Discovery, Grouping and Actionable information
- ML enabled applications.



Business Problems involving machine learning

- Pattern discovery: discovers certain patterns or trends from a large set of data
- Prediction: predict the probability of a future event based on historical data
- Grouping : find the nature group of data
- Actionable information: generate actionable decision from a large set of data

Supervised Learning vs unsupervised learning

Supervised learning:

- Directed by previously known output target and its dependent input attributes
- ML model: the target value as a function of a set of independent attributes based on a known data set .
- Supervised Learning Functions: Attribute Importance, Classification, Regression

Unsupervised Learning:

- Used when we do not know the target value.
- There is no previously known results like the ones in supervised learning to train the model and test the model.
- Unsupervised learning functions:

Anomaly Detection: for example, finding customer's different purchasing pattern

Association Rules: discover the rules that defines the items that tend to occur

together, for example, the products that customers tend to buy together.

Clustering: groups the items

Feature Extraction: creates new attributions using liner combinations of the

original attributions

Some special challenges and considerations:

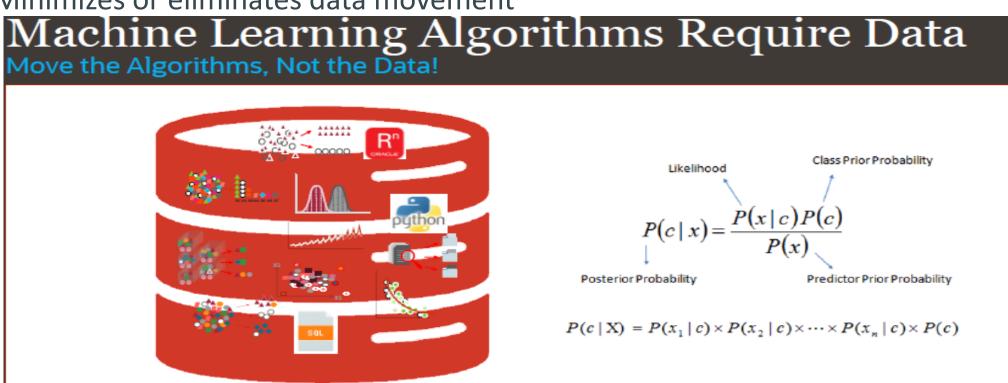
- Enterprise data may be generated by transactional applications
- Large Data set used for model training and model validation
- Data are stored in structured format like in relational database tables.
- Data preparation and data exploratory on large data set
- Real time data may be needed
- The ML models may be deployed with traditional applications

Machine Learning in Oracle Database OML4SQL and OML4Py

Move the Algorithm, Not the Data → In Database Machine Learning

Oracle "moves the algorithms to the data": Make the machine learning algorithms available within Oracle Database

Minimizes or eliminates data movement



An "Al Database" or "Thinking Database"? -> It Changes Everything!

Built-in machine learning functions in database process large data sets

- Built-in functions in Oracle database support supervised and unsupervised ML functions such as classification, clustering, prediction, regression etc.
- Provide over 30 ML algorithms: Decision tree, k-means, linear regression, logistic regression,
- Data processing tool SQL interface for data gathering and preparation
- Support entire major machine learning process: Data Gathering and Preparation, Model Training,
 Model Evaluation, Model Scoring and deployment with SQL and/or database built-in functions & procedures.

Machine Learning: algorithms automatically examine large amount of data to identify patterns, discover new insight am make predications

Machine learning algorithms implemented as SQL functions inside Oracle DB

CLASSIFICATION

- Naïve Bayes
- Logistic Regression (GLM)
- Decision Tree
- Random Forest
- Neural Network
- Support Vector Machine
- Explicit Semantic Analysis

CLUSTERING

- Hierarchical K-Means
- Hierarchical O-Cluster
- Expectation Maximization (EM)

ANOMALY DETECTION

One-Class SVM

TIME SERIES

- Forecasting Exponential Smoothing
- Includes popular models

 e.g. Holt-Winters with trends, seasonality, irregularity, missing data

REGRESSION

- Linear Model
- Generalized Linear Model
- Support Vector Machine (SVM)
- Stepwise Linear regression
- Neural Network
- LASSO

ATTRIBUTE IMPORTANCE

- Minimum Description Length
- Principal Comp Analysis (PCA)
- Unsupervised Pair-wise KL Div
- CUR decomposition for row & AI

ASSOCIATION RULES

- A priori/ market basket

PREDICTIVE QUERIES

Predict, cluster, detect, features

SQL ANALYTICS

- SQL Windows
- SQL Patterns
- SOI Apprepates

FEATURE EXTRACTION

- Principal Comp Analysis (PCA)
- Non-negative Matrix Factorization
- Singular Value Decomposition (SVD)
- Explicit Semantic Analysis (ESA)

TEXT MINING SUPPORT

- Algorithms support text
- Tokenization and theme extraction
- Explicit Semantic Analysis (ESA) for document similarity

STATISTICAL FUNCTIONS

 Basic statistics: min, max, median, stdev, t-test, F-test, Pearson's, Chi-Sq, ANOVA, etc.

R AND PYTHON PACKAGES

- Third-party R and Python Packages through Embedded Execution
- Spark MLlib algorithm integration

Oracle Machine Learning for SQL (OML4SQL)

Simple SQL Syntax – Classification Model:

Setting mode parameter values with insert statements Model build(PL/SQL):

```
/* Create a Build Setting (DT) for Model Build */

EXECUTE IMMEDIATE 'CREATE TABLE n1_build_settings (setting_name VARCHAR2(30),setting_value VARCHAR2(4000))';

EXECUTE IMMEDIATE 'INSERT INTO n1_build_settings (setting_name, setting_value) VALUES (''ALGO_NAME'', ''ALGO_DECISION_TREE'')';

EXECUTE IMMEDIATE 'INSERT INTO n1_build_settings (setting_name, setting_value) VALUES (''PREP_AUTO'', ''ON'')';

DBMS_OUTPUT.PUT_LINE ('Created model build settings table: n1_build_settings ');

/*

-- Populate and Adjust Model Setting (DT) for Model Build

EXECUTE IMMEDIATE 'INSERT INTO n1_build_settings VALUES (''TREE_TERM_MAX_DEPTH'', 7)';

EXECUTE IMMEDIATE 'INSERT INTO n1_build_settings VALUES (''TREE_TERM_MINREC_SPLIT'', 20)';

EXECUTE IMMEDIATE 'INSERT INTO n1_build_settings VALUES (''TREE_TERM_MINPCT_SPLIT'', .1)';

EXECUTE IMMEDIATE 'INSERT INTO n1_build_settings VALUES (''TREE_TERM_MINPCT_NODE'', 0.05)';

*/
```

BEGIN

```
DBMS_DATA_MINING.CREATE_MODEL(
model_name =>'N1_CLASS_MODEL',
mining_function =>'dbms_data_mining.classification,
data_table_name =>'N1_TRAIN_DATA',
case_id_column_name => 'CUSTOMER_ID',
target_column_name => 'CREDIT_SCORE_BIN',
setting_table_name => 'N1_BUILD_SETTINGS')

END;
```

Real-time scoring(SQL query):

```
select prediction_probability(N1_CLASS_MODEL, 'Good Credit' USING 'Rich' as WEALTH, 2000 as income, 'Silver' as customer_value_segment) Prediction_Probability from dual;
```

Oracle Machine Learning for SQL (OML4SQL)

In-database, parallel, distributed algorithms

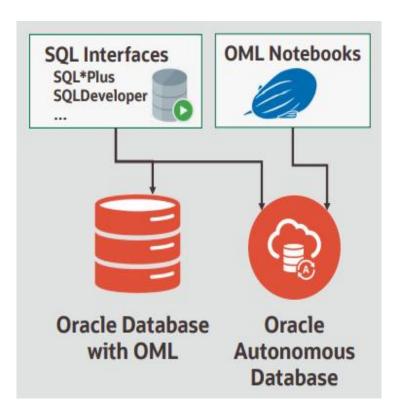
- No extracting data to separate ML engine
- Fast and scalable
- Batch and real-time scoring
- Explanatory prediction details

ML models as first class database objects

- Access control via permissions
- Audit user actions
- Export / import models across databases

New OML4SQL features added in 21c

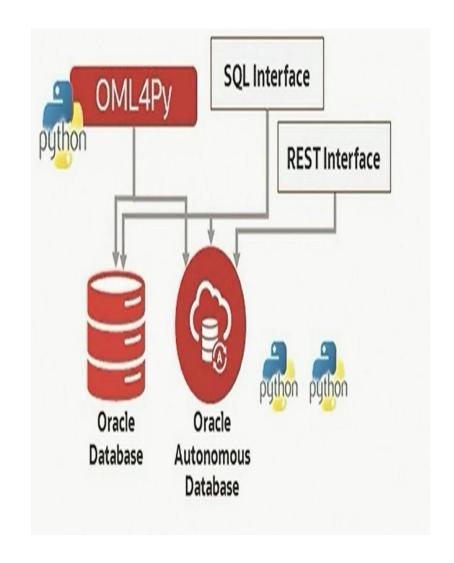
- OML MSET-SPRT Algorithm for Sequential Probability Ratio Test;
- OML XGBoost Algorithm: a highly-efficient, scalable gradient tree boosting machine learning algorithm for regression and classification.
- Adam Optimization Solver for the Neural Network Algorithm; new Neural Network Algorithm Settings



Oracle Machine Learning for Python (OML4Py)

Oracle Machine Learning for Python (OML4Py)

- Enables the opensource Python environment to operate on database data at scale.
- Allow you to run Python commands and scripts for statistical analysis and machine learning on data stored in Oracle Database.
- Use in-database machine learning algorithms with OML4Py
- Leverage database server and minimizing data movement
- Use AutoML for automatic algorithm selection, feature selection, and model tuning
- Execute user-defined Python functions in non-parallel, data-parallel, and task-parallel fashion
- Store and manage Python objects in the database



Oracle Machine Learning for Python (OML4Py)

OML4Py OML Classes that provide access to In-Database Machine Learning Algorithm, example:

1 .Create an OML SVM model object

- 2. Train the model with training data
- 3. Export the model to svm_model table
- 4. Import the model

5. Apply the model to make predictions on new data

```
BEGIN

SELECT SERVAL INTO v_blob FROM "svm_sermod";

dbms_data_mining.import_sermodel(v_blob, 'my_iris_svm_classifier');

END;
```

```
-- Make predictions and display cases where mod(ID,3) equals 0.

SELECT ID, "Species" AS TARGET_SPECIES,

PREDICTION(my_iris_svm_classifier USING "Sepal_Length",

"Sepal_Width",

"Petal_Length", "Petal_Width")

AS PREDICT_SPECIES

FROM "IRIS_TEST_DATA" WHERE MOD(ID,3) = 0;
```

Oracle Machine Learning for Python (OML4Py)

OML4Py OML classes that provide access to In-Database Machine Learning Algorithm:

Class	Algorithm	Function of Algorithm	Description
oml.ai	Minimum Description Length	Attribute importance for classification or regression	Ranks attributes according to their importance in predicting a target.
oml.ar	Apriori	Association rules	Performs market basket analysis by identifying co-occurring items (frequent itemsets) within a set.
oml.dt	Decision Tree	Classification	Extracts predictive information in the form of human-understandable rules. The rules are ifthen-else expressions; they explain the decisions that lead to the prediction.
oml.em	Expectation Maximization	Clustering	Performs probabilistic clustering based on a density estimation algorithm.
oml.esa	Explicit Semantic Analysis	Feature extraction	Extracts text-based features from a corpus of documents. Performs document similarity comparisons.
oml.glm	Generalized Linear Model	Classification Regression	Implements logistic regression for classification of binary targets and linear regression for continuous targets.
oml.km	<i>k</i> -Means	Clustering	Uses unsupervised learning to group data based on similarity into a predetermined number of clusters.
oml.nb	Naive Bayes	Classification	Makes predictions by deriving the probability of a prediction from the underlying evidence, as observed in the data.
oml.nn	Neural Network	Classification Regression	Learns from examples and tunes the weights of the connections among the neurons during the learning process.
oml.rf	Random Forest	Classification	Provides an ensemble learning technique for classification of data.
oml.svd	Singular Value Decomposition	Feature extraction	Performs orthogonal linear transformations that capture the underlying variance of the data by decomposing a rectangular matrix into three matrices.
oml.svm	Support Vector Machine	Anomaly detection Classification Regression	Builds a model that is a profile of a class, which, when the model is applied, identifies cases that are somehow different from that profile.

Use popular languages

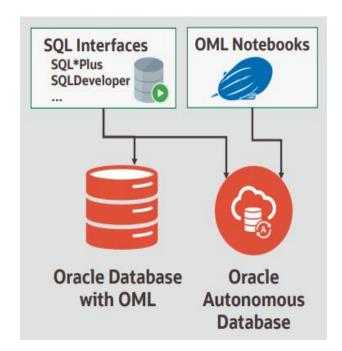
- SQL: Oracle Machine Learning for SQL: (OML4SQL)
- Python: Oracle Machine Learning for Python (OML4Py)
- R: Oracle Machine Learning for R (OML4R)
- REST :API interface

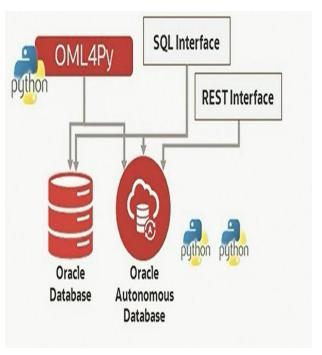
GUI Interfaces

- Oracle Machine Learning Notebooks
- Oracle Data Miner User Interface (Oracle SQL)
- Developer extension)
- Oracle Machine Learning AutoML User Interface

Support entire major machine learning process:

- Data Gathering and Preparation,
- Model Training, Model Evaluation,
- Model Scoring and deployment with SQL and/or database built-in functions & procedures.





Automated Machine Learning (AutoML)

Automated Machine Learning in OLM4Py

- . Introduced in Oracle 21c
- . Provided the following AutoML capabilities:

Automate algorithm selection,

Automate feature selection

Automated hyperparameter

Machine Learning Algorithms Supported by AutoML **

Algorithm Abbreviation	Algorithm Name
dt	Decision Tree
glm	Generalized Linear Model
glm_ridge	Generalized Linear Model with ridge regression
nb	Naive Bayes
nn	Neural Network
rf	Random Forest
svm_gaussian	Support Vector Machine with Gaussian kernel
svm_linear	Support Vector Machine with linear kernel

The Automated Machine Learning classes **

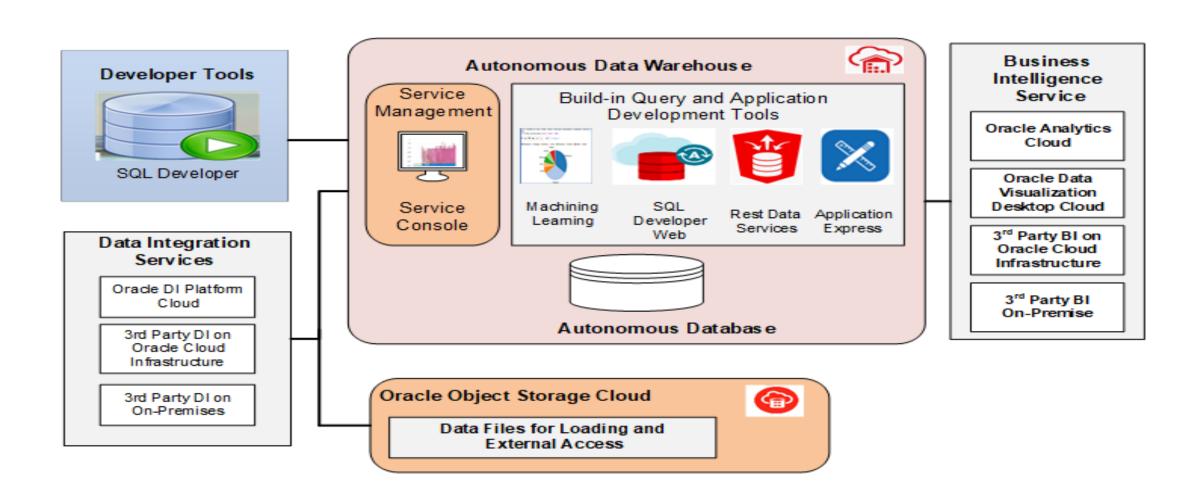
Class	Description
oml.automl.Algori thmSelection	Using only the characteristics of the data set and the task, automatically selects the best algorithms from the set of supported Oracle Machine Learning algorithms.
	Supports classification and regression functions.
oml.automl.Featur eSelection	Uses meta-learning to quickly identify the most relevant feature subsets given a training data set and an Oracle Machine Learning algorithm.
	Supports classification and regression functions.
oml.automl.ModelT uning	Uses a highly parallel, asynchronous gradient-based hyperparameter optimization algorithm to tune the algorithm hyperparameters.
	Supports classification and regression functions.
oml.automl.ModelS election	Selects the best Oracle Machine Learning algorithm and then tunes that algorithm.
	Supports classification and regression functions.

^{**} Refer to Oracle® Machine Learning for Python User's Guide Release 1.0 E97014-16 December 2021

Running Machine Learning with Oracle Autonomous Databases

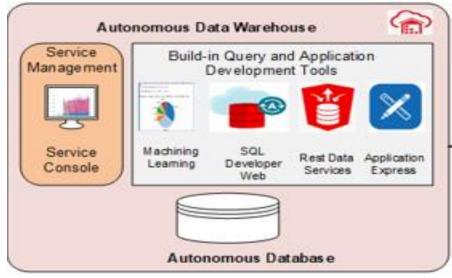
OML in Oracle Autonomous Databases Overview

Oracle Autonomous Database Environment:



Oracle Machine Learning: a part of Autonomous Database collaborate environment

- A web-based development to create data mining notebook
- Used by data scientists, developer and business to users to perform data analytics, data discover and data virtualizations.
- Leverage the ADW scalability and performance in Oracle cloud
 Key Features:
- Collaborative UI for data scientists
- Packaged with Autonomous Data Warehouse Cloud Easy access to shared notebooks, templates, permissions, scheduler, etc.
- SQL ML algorithms API



Machine Learning: algorithms automatically examine large amount of data to identify patterns, discover new insight am make predications

Machine learning algorithms implemented as SQL functions inside Oracle DB

CLASSIFICATION

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- Logistic Regression (GLM)
- Decision Tree
- Random Forest
- Neural Network
- Support Vector Machine
- Explicit Semantic Analysis

CLUSTERING

- Hierarchical K-Means
- Hierarchical O-Cluster
- Expectation Maximization (EM)

ANOMALY DETECTION

- One-Class SVM

TIME SERIES

- Forecasting Exponential Smoothing
- Includes popular models

 e.g. Holt-Winters with trends, seasonality, irregularity, missing data

REGRESSION

- Linear Model
- Generalized Linear Model
- Support Vector Machine (SVM)
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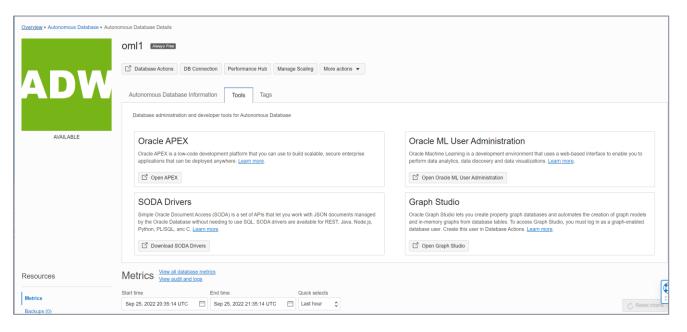
STATISTICAL FUNCTIONS

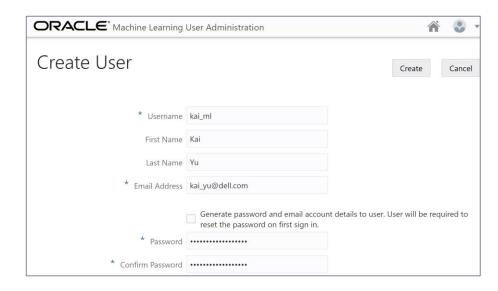
 Basic statistics: min, max, median, stdev, t-test, F-test, Pearson's, Chi-Sq, ANOVA, etc.

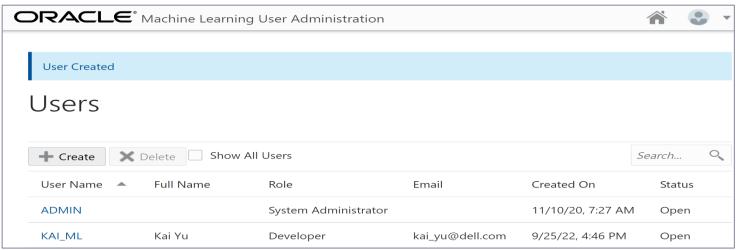
R AND PYTHON PACKAGES

- Third-party R and Python Packages through Embedded Execution
- Spark MLlib algorithm integration

Use Oracle Machine Learning: start with Oracle ML users from Oracle ML Admin

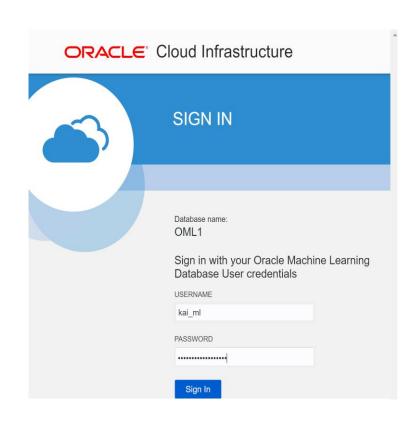


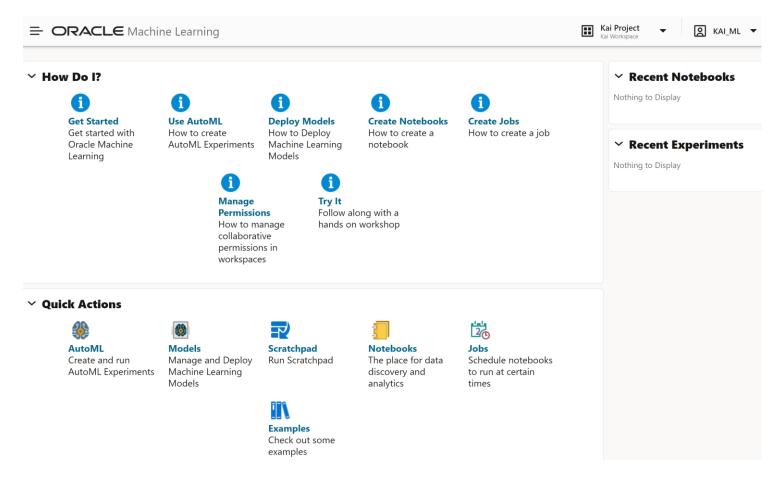




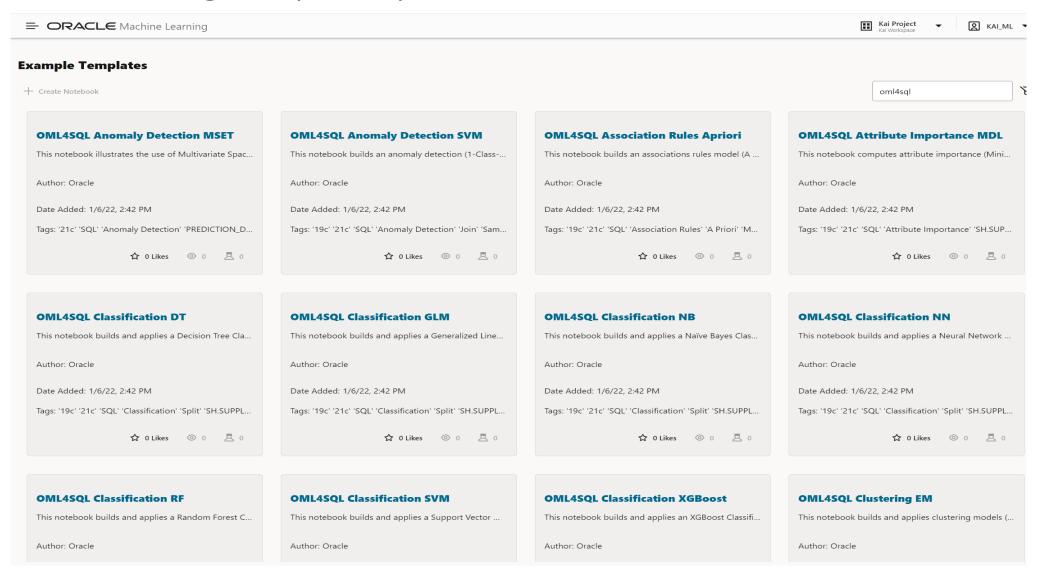
Use Oracle Machine Learning: Login to Oracle ML, taken into OML home

page

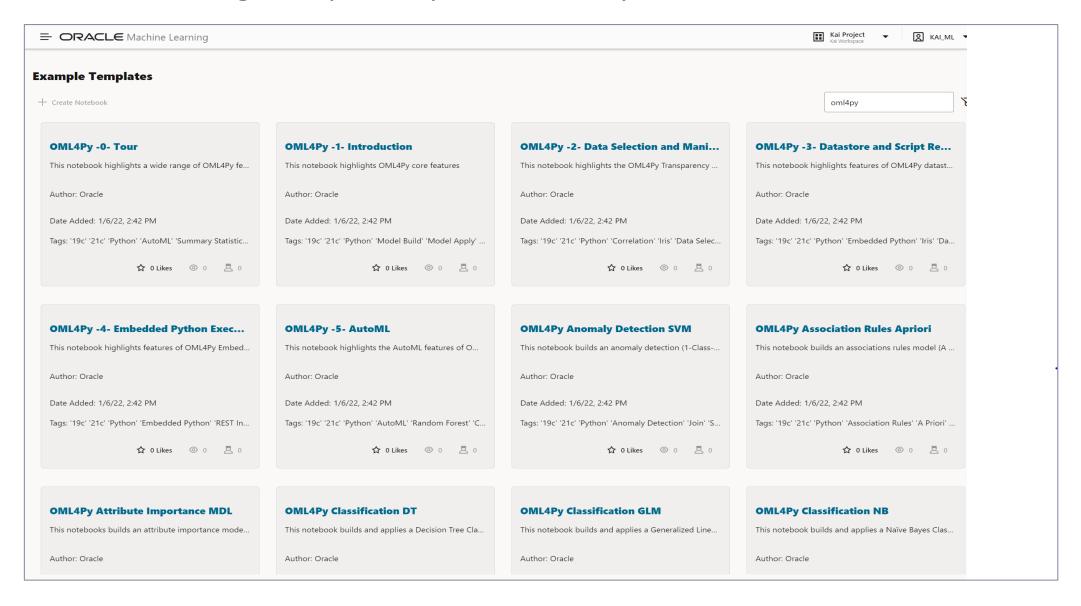




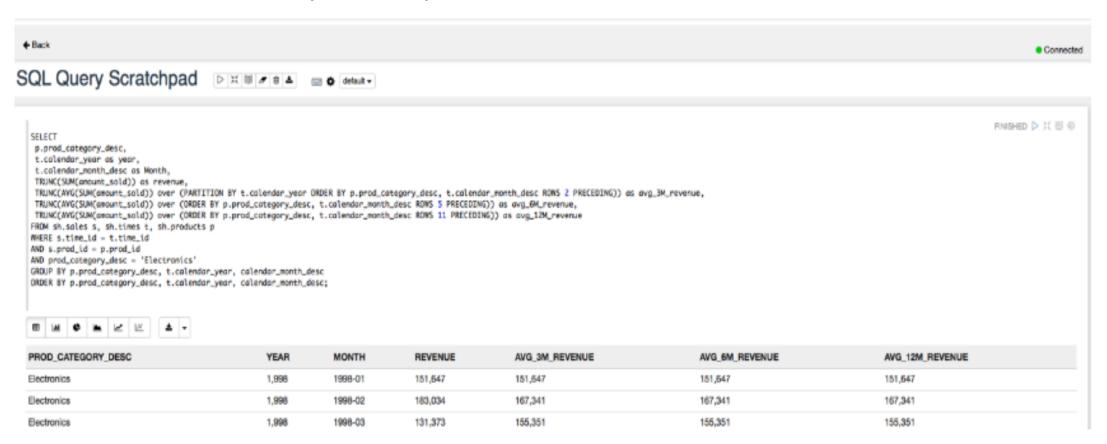
Machine Learning Example Templates: OML4SQL



Machine Learning Example Templates: OML4Py



Use Oracle Machine Learning: Login to Oracle ML, taken into OML home page; Run SQL Statement in SQL Query Scratchpad

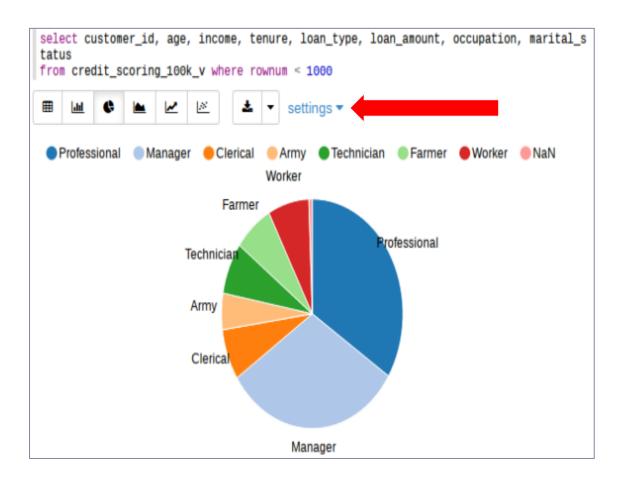


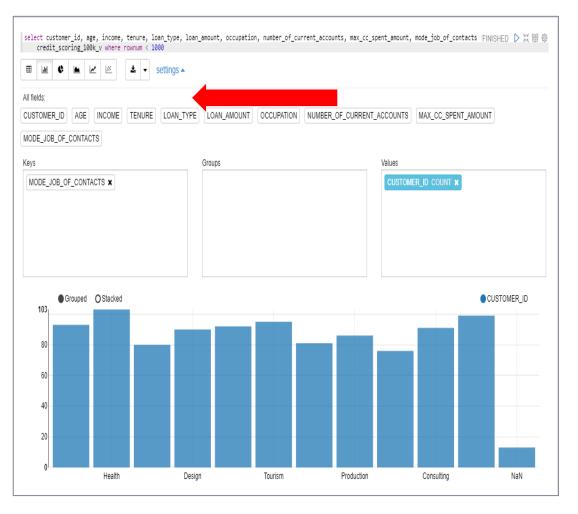
Oracle Machine Learning SQL Notebook

The report menu bar lets you change the result to a graph and/or export result

Changing the display

Specify the statistical functions





Oracle Machine Learning for Python(OML4Py)

OML4Py is a Python module that enables Python users to manipulate data in database tables and views using Python syntax.

Available in two environments:

- In Oracle Autonomous Database, we can use the Python interpreter in Oracle machine Learning notebook.
- In an on-premises database, we can install OML4Py client connecting to OML4Py in database. need to install Python, the required Python libraries, anOML4Py client, the OML4Py server components in the db

Learn OML4Py with Oracle Autonomous Database through examples











Oracle Machine Learning for Python (OML4Py)

Oracle Machine Learning for Python (OML4Py) makes the open source Python scripting language and environment ready for the enterprise and big data. Designed for problems involving both large and small data volumes, OML4Py integrates Python with Oracle Autonomous Database, allowing users to run Python commands and scripts for statistical, machine learning, and visualization analyses on database tables and views using Python syntax. Many familiar Python functions are overloaded that translate Python behavior into SQL for running in-database, as well as new automatic machine learning capabilities.

In this notebook, we highlight a few of the OML4Py features:

- Load OML library
- Create database tables
- Use the transparency layer
- Rank attributes for predictive value using the in-database attribute importance algorithm
- · Build predictive models
- · Score data using these models

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Oracle Machine Learning for Python(OML4Py)

Import libraries supporting OML4Py

```
%python
import warnings
warnings.filterwarnings('ignore')
import pandas as pd
import oml
from oml import automl
pd.set option('display.max rows', 500)
pd.set_option('display.max_columns', 500)
pd.set option('display.width', 1000)
```

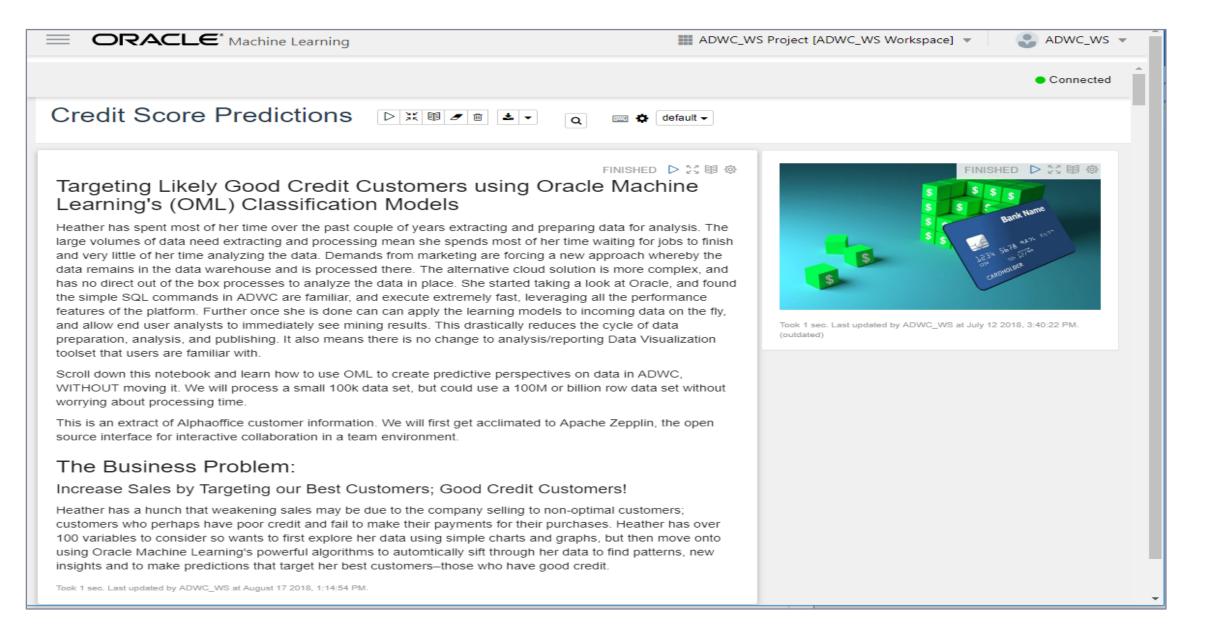
Took 0 secs. Last updated by ML_USER at December 18 2021, 10:34:01 PM.

Creating a new table with *oml.create* based on data from sklearn datasets.

```
FINISHED
%pvthon
from sklearn import datasets
import pandas as pd
pd.set option('display.width',1000)
breastcancer = datasets.load breast cancer()
bc data = breastcancer.data.astype(float)
X = pd.DataFrame(bc_data, columns = breastcancer.feature_names)
y = pd.DataFrame(breastcancer.target, columns = ['TARGET'])
try:
    oml.drop(table='BREASTCANCER')
except:
    pass
BREASTCANCER = oml.create(pd.concat([X, y], axis=1), table =
    'BREASTCANCER') # returns proxy object
print("Shape:",BREASTCANCER.shape)
print("Description:\n", breastcancer.DESCR)
```

An Example: Building Machine Learning Model with OML

Building Machine Learning Model with OML



Building Machine Learning Model with OML

OML Example: predicate customer credit score:

Based on existing customer information with known credit_sore in customer table

- Customer id
- Age
- Income
- Tenure
- Loan_type
- Loan amount
- Occupation
- Marital_status
- Wealth
- Credit limit
- 0

0

Credit_score_bin

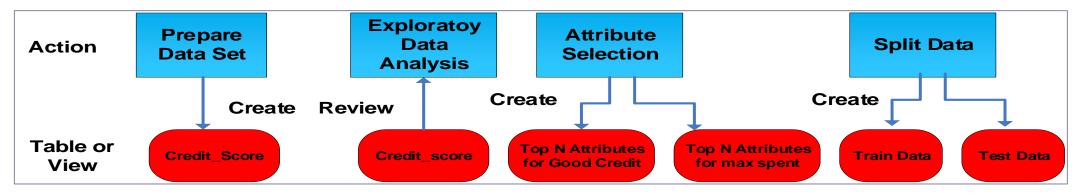
To create a machine learning model that can predict the potential credit scores for new customers whose credit scores are unknown

You can try this by yourself by following this link:

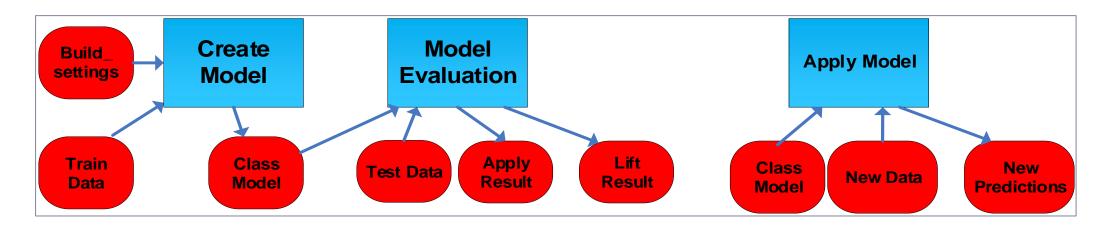
(https://github.com/oracle/learning-library/blob/master/workshops/adwc4dev/L300.md)

Building Machine Learning Model with OML

Data Gathering and Preparation



ML Model Building, Evaluation and Application

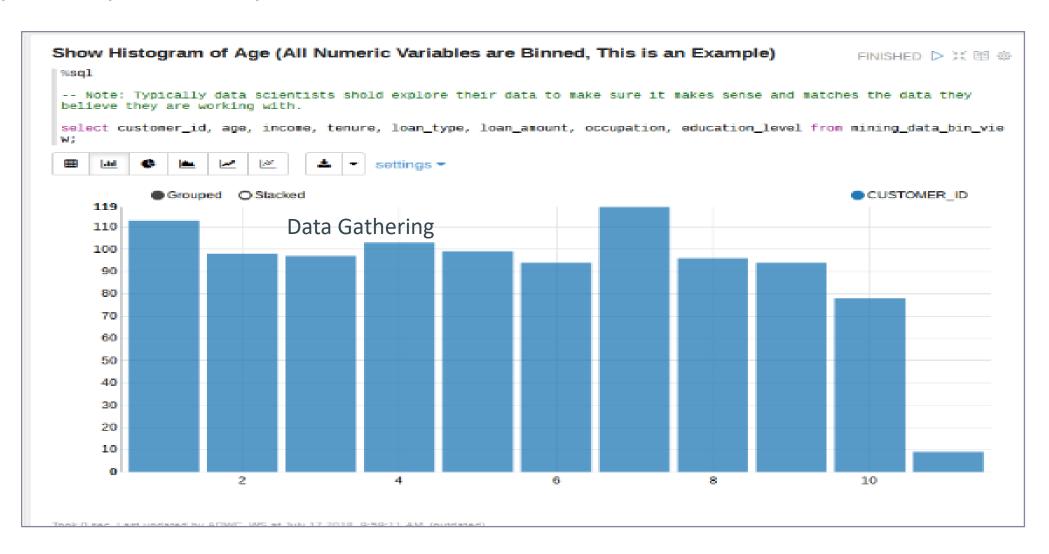


Prepare Data set:

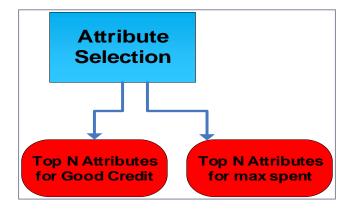
```
create view credit_scoring_100k as select * from credit_score Exploratory Data Analysis: bin the variable PL/SQL code:
```

```
dbms data mining transform.create bin num(
               bin table name => 'bin num tbl');
dbms_data_mining_transform.insert_autobin_num_eqwidth(
     bin table name => 'bin num tbl',
     data_table_name => 'CREDIT_SCORING_100K_V',
     bin num
                  => 5.
     max_bin_num => 10,
     exclude list => dbms data mining transform.COLUMN LIST('CUSTOMER ID'));
dbms_data_mining_transform.xform_bin_num(
     bin_table_name => 'bin_num_tbl',
     data_table_name => 'CREDIT_SCORING_100K_V',
     xform view name => 'mining data bin view');
```

Exploratory Data Analysis: bin the variable



Attribute Selection aka Feature Engineering/Feature Selection Create attribute importance Machine Learning model for Good Credit



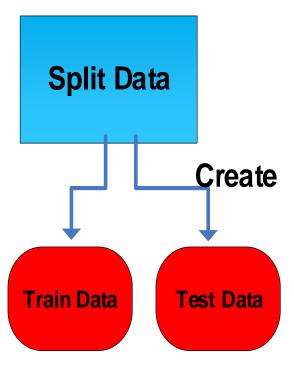
```
%script
 DECLARE
 v_sql varchar2(100);
 BEGIN
 BEGIN EXECUTE IMMEDIATE 'DROP TABLE ai explain output credit score bin';
 EXCEPTION WHEN OTHERS THEN NULL;
 END;
 BEGIN
   DBMS_PREDICTIVE_ANALYTICS.EXPLAIN(
     data_table_name => 'CREDIT_SCORING_100K_V',
     explain_column_name => 'CREDIT_SCORE_BIN',
     result table name => 'AI EXPLAIN OUTPUT CREDIT SCORE BIN');
 END;
 End;
PL/SQL procedure successfully completed.
```

Attribute Selection aka Feature Engineering/Feature Selection Create attribute importance Machine Learning model for Good Credit



Top attributes for good credit customer

. Split Data into Train data (60% data): N1_TRAIN_DATA Test Data (40% data): N1_TEST_DATA

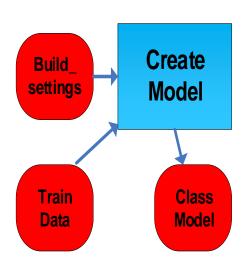


Create or replace view N1_TRAIN_DATA as SELECT * from CREDIT_scoring_100k_V SAMPLE (60) SEED (1)

Create or replace view N2_TEST_DATA
as SELECT * from CREDIT_scoring_100k MINUS
SELECT * FROM N1_ TRAIN_DATA

Create Predictive Model to Target Good Credit Customers

Add parameter settings to n1_build_settings table



```
/* Create a Build Setting (DT) for Model Build */
EXECUTE IMMEDIATE 'CREATE TABLE n1 build settings (setting name VARCHAR2(30), setting value VARCHAR2(4000))';
EXECUTE IMMEDIATE 'INSERT INTO n1_build_settings (setting_name, setting_value) VALUES (''ALGO_NAME'', ''ALGO_DECISION_TREE'')';
EXECUTE IMMEDIATE 'INSERT INTO n1_build_settings (setting_name, setting_value) VALUES (''PREP_AUTO'', ''ON'')';
DBMS OUTPUT.PUT LINE ('Created model build settings table: n1 build settings ');
-- Populate and Adjust Model Setting (DT) for Model Build
EXECUTE IMMEDIATE 'INSERT INTO n1_build_settings VALUES (''TREE_TERM_MAX_DEPTH'', 7)';
EXECUTE IMMEDIATE 'INSERT INTO n1 build settings VALUES (''TREE TERM MINREC SPLIT'', 20)';
EXECUTE IMMEDIATE 'INSERT INTO n1_build_settings VALUES (''TREE_TERM_MINPCT_SPLIT'', .1)';
EXECUTE IMMEDIATE 'INSERT INTO n1_build_settings VALUES (''TREE_TERM_MINREC_NODE'', 10)';
EXECUTE IMMEDIATE 'INSERT INTO n1 build settings VALUES (''TREE TERM MINPCT NODE'', 0.05)';
```

Create Predictive Model to Target Good Credit Customers

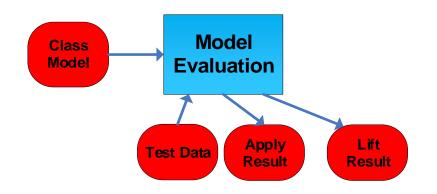
Build a Classification model

```
Create
                                                          Build
                                                          settings
                                                                       Model
BEGIN
                                                                           Class
                                                           Train
                                                           Data
                                                                          Model
DBMS_DATA_MINING.CREATE_MODEL(
   model name
                         =>'N1_CLASS_MODEL',
   mining_function
                         =>'dbms data mining.classification,
   data_table_name
                         =>'N1 TRAIN DATA',
   case id column name
                         => 'CUSTOMER ID',
   target_column_name
                          =>'CREDIT_SCORE_BIN',
                          =>'N1_BUILD_SETTINGS')
   setting table name
 END;
```

Model Evaluation

Test the Model by generating an apply result

Execute DBMS_DATA_MINING.APPLY Procedure: DBMS_DATA_MINING.APPLY('N1_CLASS_MODEL','N1_TEST_DATA','CUSTOMER_ID','N1_APPLY_RESULT')



Test Data: N1 TEST DATA

Apply Result: N1_APPLY_RESULT

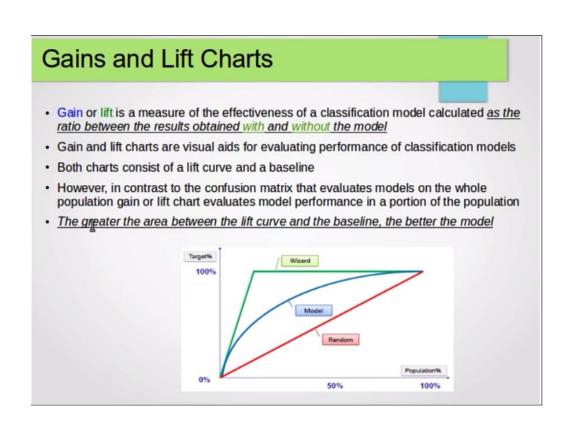
Lift Result: N1_LIFT_TABLE

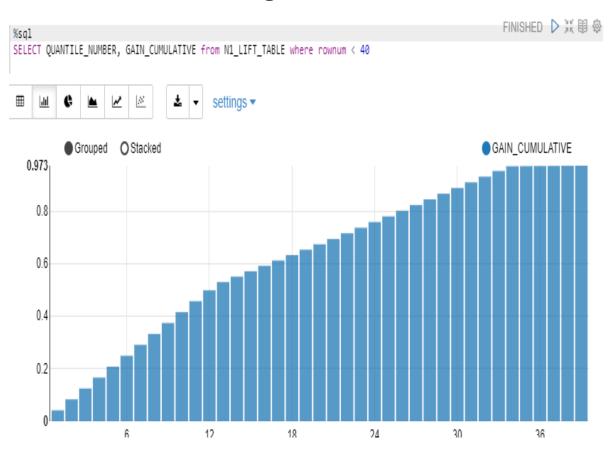
• Create a lift result : Execute DBMS DATA MINING.COMPUTE LIFT Procedure:

DBMS_DATA_MINING. COMPUTE_LIFT ('N1_APPLY_RESULT', 'N1_TEST_DATA', 'CUSTOMER_ID', 'CREDIT_SCORE_BIN', 'N1_LEFT_TABLE', 'GOOD CREDIT', 'PREDICATION', 'PROBABILITY', 100)

Model Evaluation

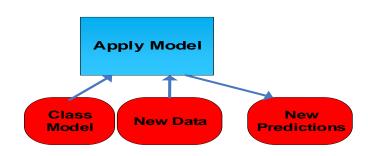
Review Lift result :View Model's Cumulative Gains Chart and decide if its a good model





Apply Model to New data:

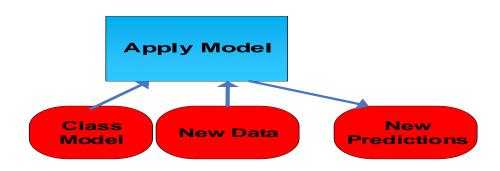
Apply the Oracle Machine Learning Model to New Customers to Show Customers Most Likely to Have Good Credit (for new customers in credit_scoring_new_cust_v)



%sql

Apply Model to New data:

Put the predication results into credit_score_new_predictions table

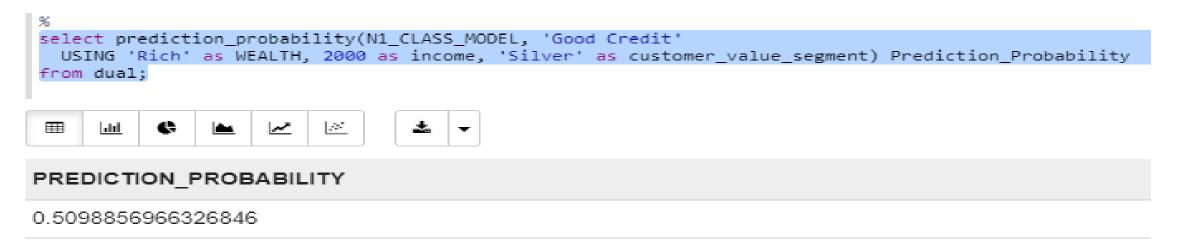


```
create table credit_score_new_predictions as
select a.customer_id
    , a.prob_good_credit
    , b.age, b.income, b.tenure, b.loan_type, b.loan_amount, b.occupation, b.education_level, b.marital_status
from (select * from (select Customer_id, round(prob_good_credit *100,2) prob_good_credit from (select Customer_ID,
    prediction_probability(N1_CLASS_MODEL, 'Good Credit' using *) prob_good_credit from credit_scoring_new_cust_v))) a
, credit_scoring_100k_v b
where a.customer_id = b.customer_id
```

Apply Model to New data:

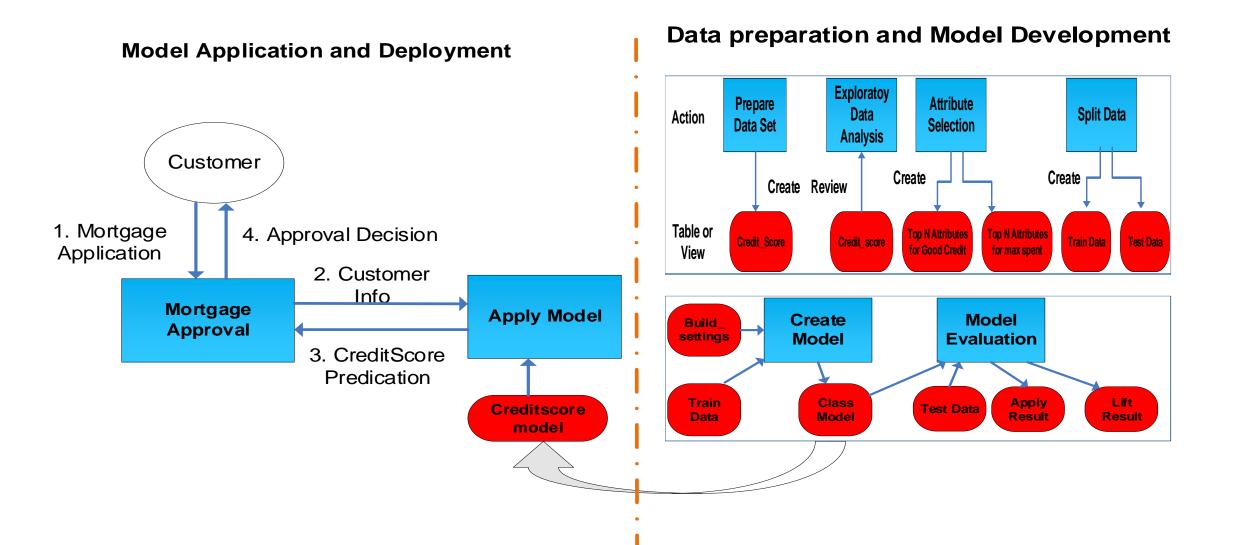
Apply a ML Model to a Single Record in a Transactional Application.

select prediction_probability(N1_CLASS_MODEL, 'Good Credit' USING 'Rich' as WEALTH, 2000 as income, 'Silver' as customer_value_segment) Prediction_Probability from dual;



Enabling Business Applications with machine Learning

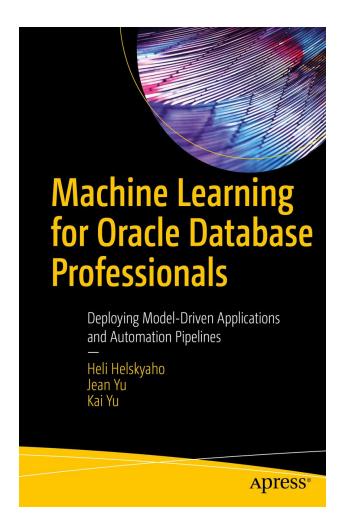
An example: Using Machine Learning for a mortgage approval application



Summary and QA

- Machine Learning Enabling Business Applications
- Machine Learning in Oracle Database
 - Move Algorithm, Not Data
 - Oracle Machine Learning for SQL (OML4SQL)
 - Oracle Machine Learning for Python (OML4Py)
- Running Oracle Machine Learning with Oracle Autonomous Database
 - Machine Learning Algorithms in Oracle Autonomous Database
 - SQL Query Scratchpad
 - Oracle Machine Learning SQL Notebook
 - OML4SQL and OML4Py in Oracle Autonomous Database
- An Example: Building a Machine Learning Model with OML in Autonomous Database
 - Data Gathering and Preparation
 - ML Model Building, Evaluation and Application

Related Publication



About the Authors



Heli Helskyaho is the CEO of Miracle Finland Oy. She holds a master's degree in computer science from the University of Helsinki and specializes in databases. She is currently working on her doctoral studies, researching and teaching at the University of Helsinki. Her research areas cover big data, multi-model databases, schema discovery, and methods and tools for utilizing semi-structured data for decision making.

Heli has been working in IT since 1990. She has held several positions, but every role has included databases and database designing. She believes that understanding your data makes using the data much easier. She is an Oracle ACE Director. an Oracle Groundbreaker Ambassador, and a

frequent speaker at many conferences. She is the author of several books and has been listed as one of the top 100 influencers in the IT sector in Finland for each year from 2015 to 2020.

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ABOUT THE AUTHORS

as well as in leading development teams. Her recent awards include an Outstanding Technical Achievement Award for significant innovation in Cloud Brokerage Cost and Asset Management products in 2019 as well as an Outstanding Technical Achievement Award for Innovation in the Delivery of Remote Maintenance Upgrade for Tivoli Storage Manager in 2011.

Jean is a master inventor with 14 patents granted. She has been a voting member of the IBM Invention Review Board from 2006 to 2020. She has been a speaker at conferences such as North Central Oracle Apps User Group Training Day 2019 and Collaborate 2020.

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Kai has been a frequent speaker at various IT/Oracle conferences, with over 200 presentations in more than 20 countries. He has authored 36 articles in technical journals such as *IEEE Transactions on Big Data* and co-authored the

book Expert Oracle RAC 12c (Apress, 2013). He has been an Oracle ACE Director since 2010. He has served on the IOUG/Quest Conference committee, as the IOUG RAC SIG president, and as the IOUG CLOUG SIG co-founder and vice president. He received the 2011 OAUG Innovator of Year award and the 2012 Oracle Excellence Award for Technologist of the Year: Cloud Architect by Oracle Magazine. He holds master's degrees in computer science and engineering from the Huazhong University of Science and Technology and the University of Wyoming.

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