

Predicting Beer Ratings with in-database machine learning and APEX (in ATP)

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Introduction, Heli

- * Graduated from University of Helsinki (Master of Science, computer science), currently a doctoral student, researcher and lecturer (databases, Big Data, Multi-model Databases, methods and tools for utilizing semi-structured data for decision making) at University of Helsinki
- * Worked with Oracle products since 1993, worked for IT since 1990
- * Data and Database!
- * CEO for Miracle Finland Oy
- * Oracle ACE Director, Oracle Groundbreaker Ambassador
- * Ambassador for EOUC (EMEA Oracle Users Group Community)
- * Listed as one of the TOP 100 influencers on IT sector in Finland (2015, 2016, 2017, 2018)
- * Public speaker and an author
- * Winner of Devvy for Database Design Category, 2015
- * Author of the book Oracle SQL Developer Data Modeler for Database Design Mastery (Oracle Press, 2015), co-author for Real World SQL and PL/SQL: Advice from the Experts (Oracle Press, 2016)



Oracle SQL Developer Data Modeler for Database Design Mastery

Design, Deploy, and Maintain World-Class Databases
on Any Platform

Heli Helskyaho
Oracle ACE Director

Forewords by C.J. Date and Tom Kyte



Real World SQL & PL/SQL

Advice from the Experts

Arup Nanda
Brendan Tierney
Heli Helskyaho
Martin Widlake
Alex Nuijten



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Why in-database?

- * The *DATA*
 - * Why to move the data?
 - * It usually is a lot of data...
 - * No hassle with moving the data
 - * Preparing the data is the hard part (80/20)
 - * Doing it in the database is the easiest way
 - * Database is the natural environment for handling data

Why in-database?

- * The *SKILLS* needed already acquired
 - * You already know SQL and PL/SQL

Why in-database?

- * The database has *APEX*
 - * You can use APEX for visualizing the data and the process

Why in-database?

- * The deployment
 - * table, view, PL/SQL Package, Function, Procedure,... is easily used with many technologies
- * ...

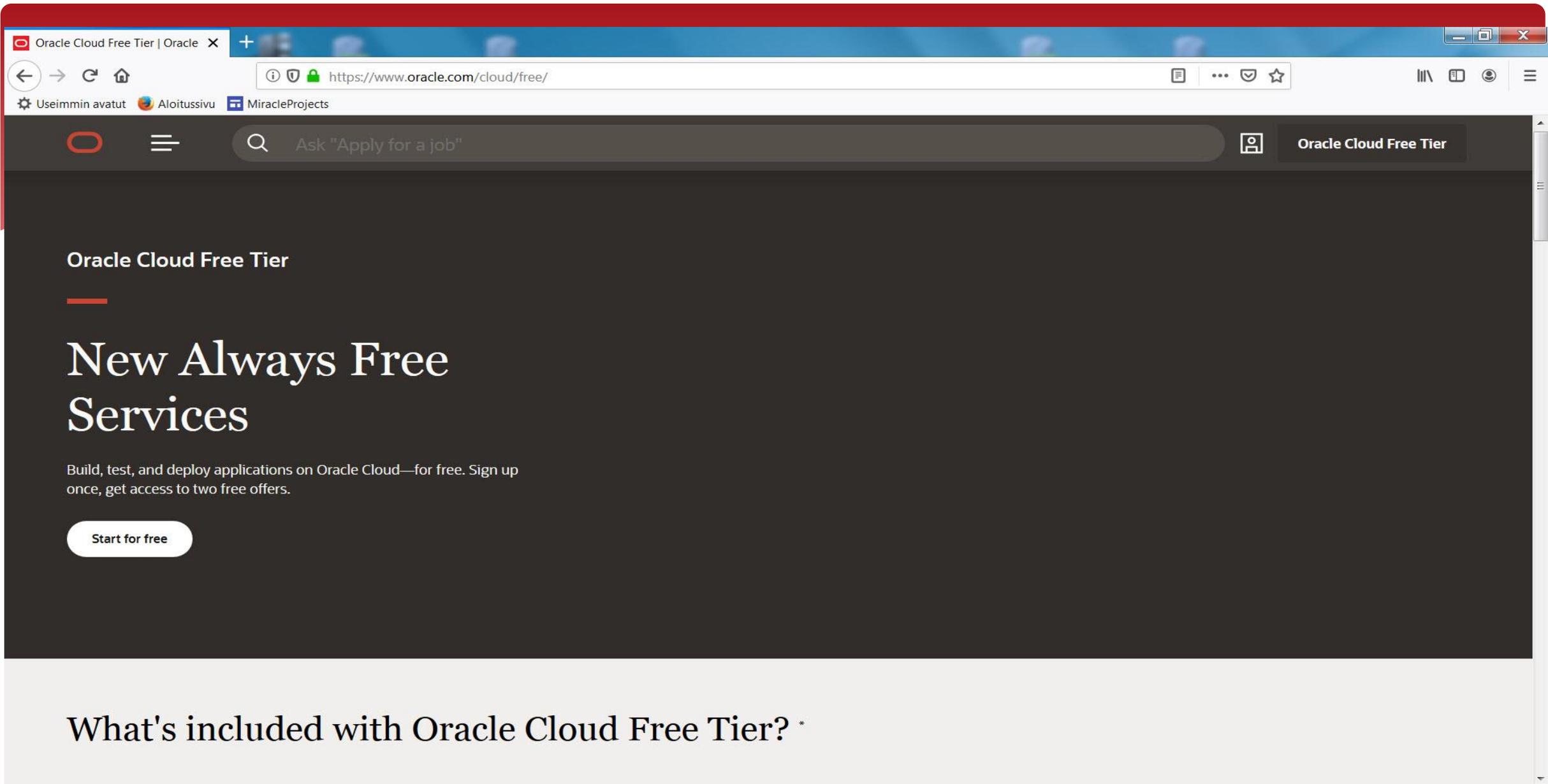
In-database Machine Learning

- * “Oracle Machine Learning” is a Zeppelin based SQL notebook that is available with ADW and ATP
- * Oracle Database Advanced Analytics (OAA) =
 - * Oracle DB + Oracle Data Mining (ODM) (+Data Miner GUI in Oracle SQL Developer) +
 - * Oracle R Enterprise (ORE)
- * Predictive Analytics with Oracle Data Mining (ODM)
- * Predictive Queries with Oracle Analytic Functions

Advanced analytics (and ODM)

- * is a **licensed product**
 - * in the EE database separately licensed
 - * in the Cloud included in: Database Service either High Performance Package or Extreme Performance Package

- * Make sure to check the licenses before using





Search: Ask "Where do I download Java Runtime Environment?"

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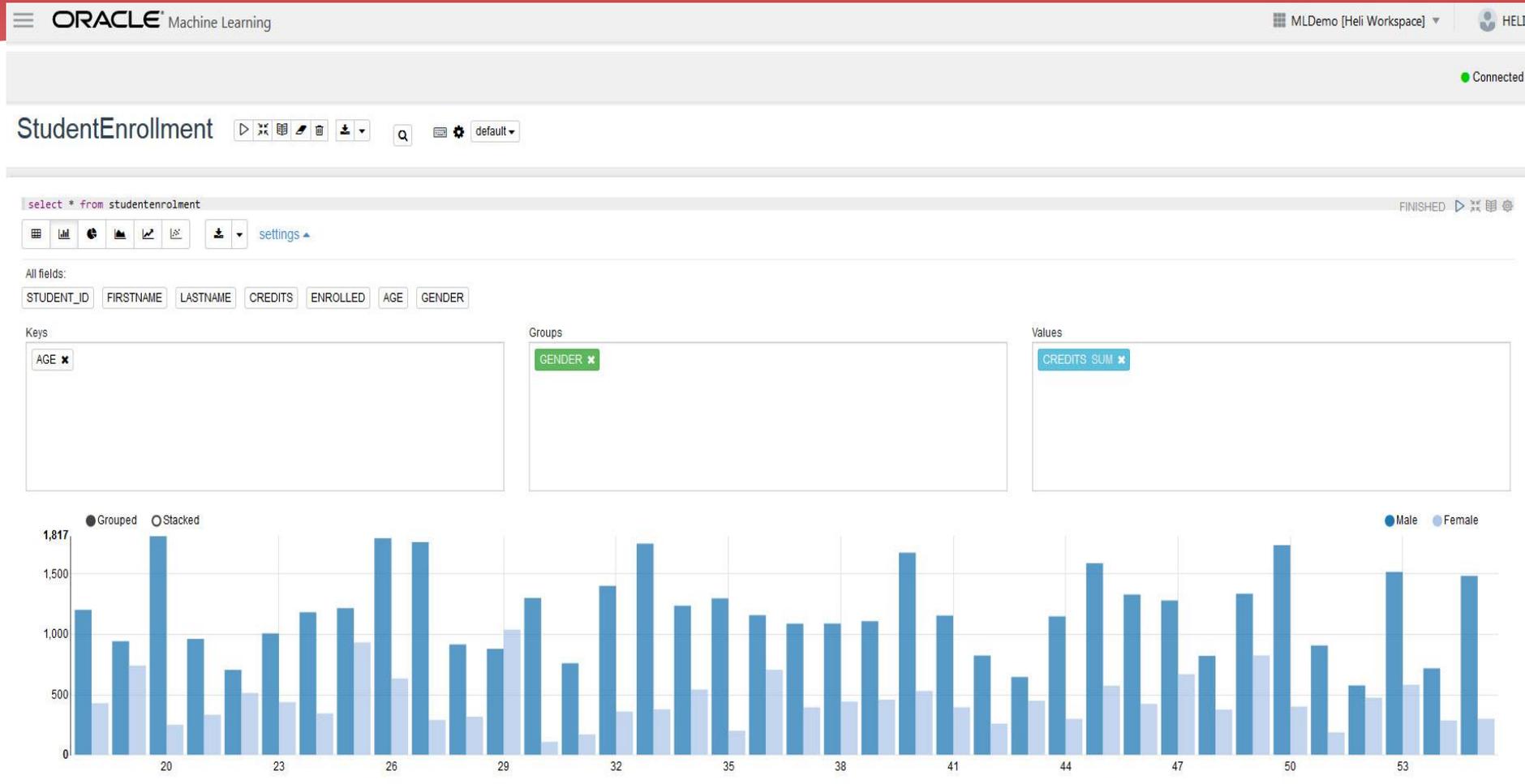
APEX, ORDS, SQL Developer in ATP and ADW

The screenshot shows the Oracle Cloud Infrastructure console for an Autonomous Transaction Processing (ATP) database. The page is titled "Autonomous Transaction Processing" and features a sidebar with navigation options: Overview, Activity, Administration, and Development. The main content area displays four cards:

- Oracle Application Express**: Oracle Application Express (APEX) provides a low-code development environment that enables you to build apps in a single, extensible platform, which is fully supported by Autonomous Database.
- SQL Developer Web**: Oracle SQL Developer Web provides a browser-based integrated development environment and administration interface for Oracle Autonomous Database. It provides a subset of the features available in the desktop product.
- Oracle ML SQL Notebooks**: Oracle Machine Learning SQL notebooks provide easy access to Oracle's parallelized, scalable in-database implementations of a library of Oracle Advanced Analytics' machine learning algorithms (classification, regression, anomaly detection, clustering, associations, attribute importance, feature extraction, times series, etc.), SQL, PL/SQL and Oracle's statistical and analytical SQL functions.
- Download Oracle Instant Client**: This is a free, light-weight set of tools, libraries and SDKs for building and connecting applications. These libraries underly the Oracle APIs of languages including Node.js, Python and PHP and provide access for OCI, OCCI, JDBC, ODBC and Pro*C applications. Tools such as SQL*Plus and Oracle Data Pump are also included - Oracle recommends using this version of Data Pump for moving existing Oracle Database schemas to Autonomous Transaction Processing.

At the bottom of the page, there are links for "Terms of Use and Privacy" and "Send Feedback", and a copyright notice: "Copyright © 2019, Oracle and/or its affiliates. All rights reserved."

Oracle Machine Learning in ATP and ADW



Oracle DB and Python

- * Python
- * Cx_Oracle (pip install)
- * Oracle Instant Client
 - * same version 32/64 as your Python
 - * add to the path
 - * 19 will not work with Windows 7, 18 does
- * Oracle DB/ATP/ADW (TNS_ADMIN, instant client.../network/admin)
 - * Sqlnet.ora
 - * Tnsnames.ora
 - * Wallet

Data Dictionary Views for ODM

Table 2-1 Data Dictionary Views for Oracle Data Mining

View Name	Description
<code>ALL_MINING_MODELS</code>	Provides information about all accessible mining models
<code>ALL_MINING_MODEL_ATTRIBUTES</code>	Provides information about the attributes of all accessible mining models
<code>ALL_MINING_MODEL_PARTITIONS</code>	Provides information about the partitions of all accessible partitioned mining models
<code>ALL_MINING_MODEL_SETTINGS</code>	Provides information about the configuration settings for all accessible mining models
<code>ALL_MINING_MODEL_VIEWS</code>	Provides information about the model views for all accessible mining models
<code>ALL_MINING_MODEL_XFORMS</code>	Provides the user-specified transformations embedded in all accessible mining models.

Machine Learning in short

- * Supervised learning
 - * *Regression*, how much? How many?, numbers
 - * *Classification*, Is it this or that?, groups/classes
 - * *Anomaly detection (classification)*, Is this weird?
- * Unsupervised learning
 - * *Clustering*, Which groups? Group them in 5 groups
- * Reinforcement learning
 - * which action? feedback positive/negative

Machine Learning in short

- * Use the right *Features*
 - * with right Algorithms
 - * to build the right *Models*
 - * that achieve the right *Tasks*

Machine Learning

1. Defining the Task, understanding the Task
2. Collecting the data, understanding the data
 1. Attributes (Features, Columns)
 2. Exploring
 3. Preparing the data/Transforming the data
3. Creating a Model
 1. Model (Function)
 2. Algorithm
4. Train, test (validate)
5. Evaluate the models
6. Scoring and Deployment

Beer rating

Define the Task

- * The Task: *Predict the overall rating for a beer*
 - * *Find the beers that will most likely be rated as 5*
 - * *Find the brewers that most likely will make beer rated as 5*

- * We will use *Supervised Learning and Classification*, our target attribute is OVERALL (values 1-5)

Collecting the data

- * www.kaggle.com/c/beer-ratings/data
- * *Beer_train*, all know input and output
- * (*Beer_test*, only known input, output unknown)
- * In the demo we will use *Beer_train* but we call it *Beer_data*
- * For deployment we will use *Beer_Test*

The data

- * For Supervised Learning the data must be divided in two sets:
 - * one for *training* the other one for *testing* the model really works (validation).
 - * In the demo we will split *Beer_data* in to two sets:
 - * *Beer_training_data*
 - * *Beer_testing_data*
- * The data requirements for ODM:
 - * Data must be stored in a *single table or view (a case table)*
 - * Each record must be stored in a *separate row as a case*
 - * Each case can (optionally) be identified by a *unique case ID*

The data for Supervised Learning

```
* Beer_data -> Beer_training_data, Beer_testing_data
-- create training set
CREATE TABLE Beer_training_data
AS SELECT * FROM Beer_data
WHERE ORA_HASH (IDIndex, 99, 5) < 65;

-- create testing set
CREATE TABLE Beer_testing_data
AS SELECT * FROM Beer_data
WHERE ORA_HASH (IDIndex, 99, 5) >= 65;
```

A quick look to APEX (demo)

- * Beer_Train
- * Beer_Training_Data
- * Beer_Testing_Dat

Oracle PL/SQL Packages for Data Mining

- * DBMS_PREDICTIVE_ANALYTICS
 - * Routines for performing *predictive analytics*
- * DBMS_DATA_MINING_TRANSFORMING
 - * Routines for *transforming the data* for mining models
- * DBMS_DATA_MINING
 - * Routines for *creating and managing mining models*

DBMS_PREDICTIVE_ANALYTICS

- * routines that perform an automated data mining known as *predictive analytics*
- * no need to be aware of model building or scoring
 - * All mining activities are handled internally by the procedure.

DBMS_PREDICTIVE_ANALYTICS

- * EXPLAIN
 - * *ranks attributes* in order of influence in explaining the target column
- * PREDICT
 - * *predicts the value of a target* column based on values in the input data
- * PROFILE
 - * *generates rules* that describe the cases from the input data

DBMS_PREDICTIVE_ANALYTICS

```
SQL> describe dbms_predictive_analytics
```

PROCEDURE EXPLAIN

Argument Name	Type	In/Out	Default?
DATA_TABLE_NAME	VARCHAR2	IN	
EXPLAIN_COLUMN_NAME	VARCHAR2	IN	
RESULT_TABLE_NAME	VARCHAR2	IN	
DATA_SCHEMA_NAME	VARCHAR2	IN	DEFAULT

PROCEDURE PREDICT

Argument Name	Type	In/Out	Default?
ACCURACY	NUMBER	OUT	
DATA_TABLE_NAME	VARCHAR2	IN	
CASE_ID_COLUMN_NAME	VARCHAR2	IN	
TARGET_COLUMN_NAME	VARCHAR2	IN	
RESULT_TABLE_NAME	VARCHAR2	IN	
DATA_SCHEMA_NAME	VARCHAR2	IN	DEFAULT

PROCEDURE PROFILE

Argument Name	Type	In/Out	Default?
DATA_TABLE_NAME	VARCHAR2	IN	
TARGET_COLUMN_NAME	VARCHAR2	IN	
RESULT_TABLE_NAME	VARCHAR2	IN	
DATA_SCHEMA_NAME	VARCHAR2	IN	DEFAULT

EXPLAIN

```
BEGIN
```

```
    DBMS_PREDICTIVE_ANALYTICS.EXPLAIN (
```

```
        data_table_name           => 'Beer_training_data',
```

```
        explain_column_name      => 'overall',
```

```
        result_table_name        => 'beer_explain');
```

```
END;
```

```
/
```

EXPLAIN

	ATTRIBUTE_NAME	ATTRIBUTE_SUBNAME	EXPLANATORY_VALUE	RANK
1	TASTE	(null)	0,1369959018036639046488620435087567350302	1
2	PALATE	(null)	0,1033038106866505612466700086317885929612	2
3	AROMA	(null)	0,08791526829406451506523536256475774282	3
4	APPEARANCE	(null)	0,0597994415746425094084278968669637963851	4
5	IDINDEX	(null)	0,0514743174015554311246566591668580953978	5
6	STYLE	(null)	0,0487182850810693894469596131763997020818	6
7	BEERID	(null)	0,0447651730492723089511095141894142199002	7
8	ABV	(null)	0,0282744648145592050251039059166762689924	8
9	BREWERID	(null)	0,0273217823948269630249887964806943058078	9
10	TEXT	(null)	0	10
11	PROFILENAME	(null)	0	10
12	NAME	(null)	0	10
13	GENDER	(null)	0	10
14	AGEINSECONDS	(null)	0	10
15	BIRTHDAYRAW	(null)	0	10
16	TIMEUNIX	(null)	0	10
17	TIMESTRUCT	(null)	0	10
18	BIRTHDAYUNIX	(null)	0	10

PREDICT

```
DECLARE
p_accuracy NUMBER(10,9);
BEGIN
  DBMS_PREDICTIVE_ANALYTICS.PREDICT(
    accuracy          => p_accuracy,
    data_table_name   => 'Beer_training_data',
    case_id_column_name => 'idindex',
    target_column_name => 'overall',
    result_table_name => 'Beer_predict');
  DBMS_OUTPUT.PUT_LINE('Accuracy: ' || p_accuracy);
END;
/
```

Accuracy: .24618951 (a measure of improved maximum average accuracy versus a naive model's maximum average accuracy)

PREDICT

IDINDEX	PREDICTION	PROBABILITY
0	2	.42799808967620911
1	3	.53057676003601528
2	3	.51728627054274079
3	4	.45808326842381863
4	4	.47447188708319082
5	4	.64845475978174982
6	4	.65424415909731026
7	3	.45898266110126107
9	4	.51363296269020753

How did it predict?

- * Total no of rows: 37 303
- * Correct predictions: 25 421
- * Not correct predictions: 11 882

PROFILE

- * creates a Decision Tree model
 - * to identify the characteristics of the *attributes* that predict the target
 - * creates rules (expressed in XML as if-then-else statements) that describe the *decisions* that affect the prediction
- * PROFILE returns XML that is derived from the model details generated by the algorithm.

PROFILE

```
BEGIN
    DBMS_PREDICTIVE_ANALYTICS.PROFILE (
        DATA_TABLE_NAME      => 'Beer_training_data',
        TARGET_COLUMN_NAME    => 'overall',
        RESULT_TABLE_NAME     =>
'beer_profile_result');
END;
/
```

PROFILE

BEER_PROFILE_RESULT		
PROFILE_ID	RECORD_COUNT	DESCRIPTION
1	50	[SYS.XMLTYPE]
2	100	[SYS.XMLTYPE]
3	34	[SYS.XMLTYPE]
4	462	[SYS.XMLTYPE]
5	566	[SYS.XMLTYPE]
6	279	[SYS.XMLTYPE]
7	2445	[SYS.XMLTYPE]
8	1624	[SYS.XMLTYPE]
9	1522	[SYS.XMLTYPE]
10	653	[SYS.XMLTYPE]
11	8024	[SYS.XMLTYPE]
12	3557	[SYS.XMLTYPE]
...	...	[SYS.XMLTYPE]

Now to the process itself

Preparing the data

- * This is usually the most difficult and time consuming part of machine learning... 80/20...

Attributes

- * **Data attributes**

- * columns in the data set used to build, test, or score a model

- * **Model attributes**

- * the data representations used internally by the model

- * **The target attribute**

- * in supervised learning contains the *known values* of output and to which the predictions are compared to

- * *Identify* the columns (features) to include in the case table

Understanding the data

- * go through the data and each attribute and feature
- * datatype (numeric, category, ...)
 - * note Palate/aroma/... is not numeric, it is categorial!
- * type, expectation, missing, outliers, comment
- * linear plot to find data to be removed (outlier)
- * a correlation plot to show the correlation
- * remove nulls on very significant features (somehow)
- * transform features
- * ...

Understanding the data

- * A demo with APEX or Oracle Machine learning (ATP)

Understanding the data

- * The Target is **OVERALL**
- * 0 value in Overall (1-5?)?
 - * Remove?
 - * Accept (0-5)?
 - * ...

A Feature/Attribute

- * Is a Feature/Attribute relevant?
- * Is a Feature/Attribute independent? (the area vs no of rooms)
- * Is a Feature/Attribute simple? (how to compare? GPS coordinates not good, Convert for instance distance from water)

Let's talk about some attributes in our example

- * APPEARANCE,
- * AROMA,
- * PALATE,
- * TASTE,
- * BEERID,
- * TEXT,
- * TIMESTRUCT,
- * TIMEUNIX,
- * AGEINSECONDS,
- * BIRTHDAYRAW,
- * BIRTHDAYUNIX,
- * PROFILENAME,
- * NAME,
- * GENDER

Missing Data

- * Missing Values or Sparse Data?
 - * Missing values
 - * some attribute values are *unknown*
 - * missing values in columns with a simple data type
 - * Sparse data
 - * values that are *assumed to be known*, although they are not represented in the data
 - * missing values in nested columns

Transforming the data

- * Creating Nested Columns
 - * if you want to include transactional data etc.
- * Converting Column Data Types
 - * Age -> Child, Adult
- * Business and Domain-Sensitive Transformations
 - * Date of birth -> age
- * Text Transformation (a text column must be in a table, not a view)
- * ...
- * Write SQL expressions for any transformations not handled by ADP

DBMS_DATA_MINING_TRANSFORM

DBMS_DATA_MINING_TRANSFORM

Understand the routines of DBMS_DATA_MINING_TRANSFORM package.

The DBMS_DATA_MINING_TRANSFORM package contains routines that perform data transformations such as binning, normalization, and outlier treatment. The package includes routines for:

- Specifying transformations in a format that can be embedded in a mining model.
- Specifying transformations as relational views (external to mining model objects).
- Specifying distinct properties for columns in the build data. For example, you can specify that the column must be interpreted as unstructured text, or that the column must be excluded from Automatic Data Preparation.

Normalization

- * Normalization
 - * A technique for *reducing the range of numerical data*
 - * (Model View Details: DM\$VN for Normalization)

Outlier Treatment

- * A value is considered an *outlier* if it deviates *significantly* from most other values in the column
- * Outliers can have a skewing effect on the data
- * Outliers can interfere with the effectiveness of transformations such as normalization or binning.
- * problematic or perfectly valid data?

Creating a Model

DBMS_DATA_MINING

Understand the routines of DBMS_DATA_MINING package.

The DBMS_DATA_MINING package contains routines for creating mining models, for performing operations on mining models, and for querying mining models. The package includes routines for:

- Creating, dropping, and performing other DDL operations on mining models
- Obtaining detailed information about model attributes, rules, and other information internal to the model (model details)
- Computing test metrics for classification models
- Specifying costs for classification models
- Exporting and importing models
- Building models using Oracle's native algorithms as well as algorithms written in R

Creating a Model

- * Choose the mining function
- * Choose the algorithm
- * Create and populate the settings table

Choose the Model (Mining Function)

- * Supervised Learning
 - * Regression
 - * Classification
 - * Anomaly Detection
 - * (Feature Selection)
- * Unsupervised Learning
 - * Clustering
 - * Anomaly Detection
 - * Association
 - * (Feature Extraction)

Choosing the Algorithm

- * Decision Tree (classification)
- * Naive Bayes (classification)
- * Generalized Linear Models (regression and classification)
- * Support Vector Machines (classification, regression, and anomaly detection)
- * k-Means (clustering)
- * O-Cluster (clustering)
- * Minimum Description Length (for calculating attribute importance)
- * Apriori (for calculating association rules)
- * Non-Negative Matrix Factorization, NMF (feature extraction)
- * ... Each version brings more algorithms to choose from...

Table 5-3 Data Mining Algorithms

ALGO_NAME Value	Algorithm	Default?	Mining Model Function
ALGO_AI_MDL	Minimum Description Length	—	attribute importance
ALGO_APRIORI_ASSOCIATION_RULES	Apriori	—	association
ALGO_CUR_DECOMPOSITION	CUR Decomposition	—	Attribute Importance
ALGO_DECISION_TREE	Decision Tree	—	classification
ALGO_EXPECTATION_MAXIMIZATION	Expectation Maximization	—	—
ALGO_EXPLICIT_SEMANTIC_ANALYSIS	Explicit Semantic Analysis	—	feature extraction classification
ALGO_EXPONENTIAL_SMOOTHING	Exponential Smoothing	—	time series
ALGO_EXTENSIBLE_LANG	Language used for extensible algorithm	—	All mining functions are supported
ALGO_GENERALIZED_LINEAR_MODEL	Generalized Linear Model	—	classification and regression
ALGO_KMEANS	k-Means	yes	clustering
ALGO_NAIVE_BAYES	Naive Bayes	yes	classification
ALGO_NEURAL_NETWORK	Neural Network	—	classification
ALGO_NONNEGATIVE_MATRIX_FACTOR	Non-Negative Matrix Factorization	yes	feature extraction
ALGO_O_CLUSTER	O-Cluster	—	clustering
ALGO_RANDOM_FOREST	Random Forest	—	classification
ALGO_SINGULAR_VALUE_DECOMP	Singular Value Decomposition (can also be used for Principal Component Analysis)	—	feature extraction
ALGO_SUPPORT_VECTOR_MACHINES	Support Vector Machine	yes	default regression algorithm regression, classification, and anomaly detection (classification with no target)

Create a model

* CREATE_MODEL procedure in the DBMS_DATA_MINING package

```
PROCEDURE CREATE_MODEL(  
    model_name          IN VARCHAR2,  
    mining_function     IN VARCHAR2,  
    data_table_name    IN VARCHAR2,  
    case_id_column_name IN VARCHAR2,  
    target_column_name IN VARCHAR2 DEFAULT NULL,  
    settings_table_name IN VARCHAR2 DEFAULT NULL,  
    data_schema_name   IN VARCHAR2 DEFAULT NULL,  
    settings_schema_name IN VARCHAR2 DEFAULT NULL,  
    xform_list         IN TRANSFORM_LIST DEFAULT NULL);
```

A Settings table

```
CREATE TABLE Beer_settings_DT (  
  setting_name VARCHAR2(30),  
  setting_value VARCHAR2(4000));  
  
BEGIN  
  INSERT INTO Beer_settings_DT VALUES  
    (dbms_data_mining.algo_name, dbms_data_mining.algo_decision_tree);  
  ...  
END;  
/
```

Other possible settings

- * Cost table and matrix (Decision Tree model)
- * Prior Probabilities (Naive Bayes)
- * Class Weights (Logistic Regression or Support Vector Machine)
- * ...

Create a new model

```
BEGIN
  DBMS_DATA_MINING.CREATE_MODEL(
    model_name          => 'Beer_DT',
    mining_function     => dbms_data_mining.classification,
    data_table_name     => 'Beer_training_data',
    case_id_column_name => 'IDIndex',
    target_column_name  => 'Overall',
    settings_table_name => 'Beer_settings_DT');
END;
/
```

Model Signature

- * **The set of data attributes** that are used to build a model

Model Signature

```
SELECT attribute_name, attribute_type  
FROM TABLE(DBMS_DATA_MINING.GET_MODEL_SIGNATURE('BEER_DT'))  
ORDER BY attribute_name;
```

	ATTRIBUTE_NAME	ATTRIBUTE_TYPE
1	ABV	NUMBER
2	BREWERID	NUMBER
3	STYLE	VARCHAR2

Testing and Evaluating the model

- * Test: the model with new data (known input, known output)
- * Evaluation: depends on the chosen metrics

Accuracy

- * In our task we have chosen that only accuracy is important (this is a simple demo)

Evaluation

- * Demo with APEX or ATP
 - * (Confusion matrices, Beer model comparison, Beer evaluation of models)
- * What algorithm is the best?

Evaluation

- * In our simple example none of the models was very good but Decision Tree was a little bit better than others
- * We are now happy with our model and ready to deploy it

Scoring and Deployment

- * Deployment is implementing the models in the target environment
- * Deployment
 - * Moving a model from the database where it was built to the database where it will be used (export/import)
 - * With scoring data either for real-time or batch results
 - * Extracting model details to produce reports (clustering rules, decision tree rules, ...)

Apply the Model

```
BEGIN
```

```
    DBMS_DATA_MINING.APPLY (  
    model_name          => 'beer_DT',  
    data_table_name     => 'beer_test',  
    case_id_column_name => 'idindex',  
    result_table_name   => 'beer_result_table_DT');
```

```
END;
```

```
/
```

BEER_RESULT_TABLE_DT

Indexes Model Constraints Grants Statistics UI Defaults Triggers Dependencies SQL REST

Get Rows

IDINDEX	PREDICTION	PROBABILITY	COST
13803	4	.61222339304531082	.38777660695468918
13803	5	.25594192717480391	.74405807282519609
13803	3	.11017445264020606	.88982554735979391
13803	2	.01803067556492214	.98196932443507789
13803	1	.0036295515747570544	.99637044842524292
13803	0	0	1
13960	4	.61222339304531082	.38777660695468918
13960	5	.25594192717480391	.74405807282519609
13960	3	.11017445264020606	.88982554735979391

Real-time scoring a prediction, single record scoring

What is the probability for beer 43548 to get overall 5?

```
SELECT PREDICTION_PROBABILITY(Beer_DT, 5 USING *) beer_overall_prob
FROM beer_test
WHERE idindex = 43658;
1.5087463556851313E-001
```

```
SELECT PREDICTION_PROBABILITY(Beer_DT, 5 USING STYLE) beer_overall_prob
FROM beer_test
WHERE idindex = 43658;
2.4140018157974377E-001
```

USING: Predictors and/or Expressions (only if

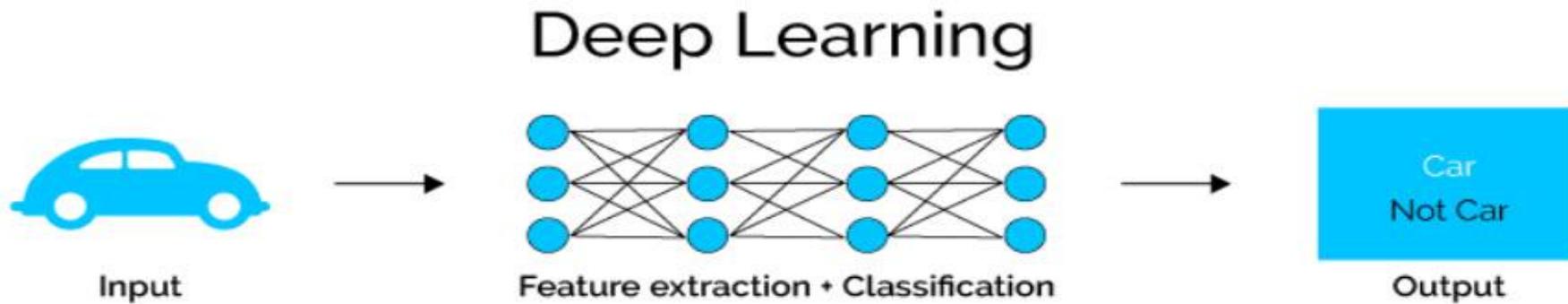
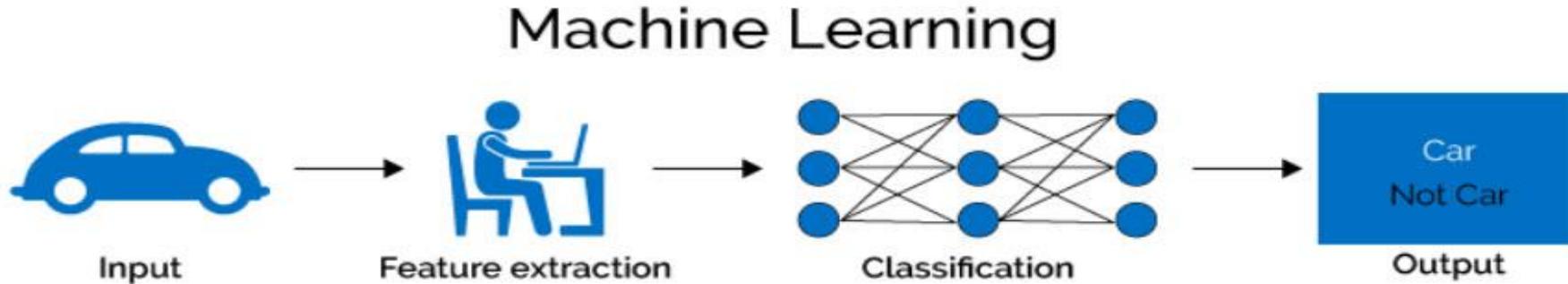
Real-time scoring a prediction, batch scoring

What are the brewers that I should contact (making most of the overall 5 beers)?

```
SELECT brewerid, count(*) as cnt
FROM beer_test
WHERE PREDICTION(Beer_DT USING *) = 5
group by brewerid
order by cnt desc;
```

The deep learning version

What is deep learning?



<https://towardsdatascience.com/why-deep-learning-is-needed-over-traditional-machine-learning-1b6a99177063>

Predicting Beer Ratings with Deep Learning

- * A quick demo in ATP

Conclusion

- * Oracle PL/SQL Packages for Data Mining
 - * DBMS_PREDICTIVE_ANALYTICS
 - * Routines for performing *predictive analytics*
 - * DBMS_DATA_MINING_TRANSFORMING
 - * Routines for *transforming the data* for mining models
 - * DBMS_DATA_MINING
 - * Routines for *creating and managing mining models*

Conclusion

The Process

1. Defining the Task, understanding the Task
2. Collecting the data, understanding the data
3. Attributes (Features, Columns)
4. Preparing the data/Transforming the data
5. Creating a Model
 1. Model (Function)
 2. Algorithm
6. Evaluate the models
7. Scoring and Deployment

THANK YOU!

QUESTIONS?

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