Oracle Machine Learning Notebook
Included in Autonomous Data Warehouse Cloud

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Sr. Director Product Management,
Machine Learning, AI and Cognitive Analytics
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Safe Harbor Statement

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ORACLE®

Introducing Oracle Autonomous Data Warehouse Cloud

Value Proposition

Easy

- Provision a data warehouse in as little as 15-seconds
- Automated management of database administration
- Simple Load and Go with Automated Tuning
- Dedicated cloud-ready migration tools including Redshift

Fast

- Up to 14x performance advantage than Redshift[1]
- High concurrency supports multi-user access and workloads
- Based on Exadata for extreme performance

- Only Pay for What you Use with user defined sizing, on-demand scaling & idle shut-off
- Independent scaling of compute and storage
- Instant scaling with zero downtime

Oracle Autonomous Data Warehouse Cloud Key Features

High-Performance Queries and Concurrent Workloads
Optimized query performance with preconfigured resource profiles for different types of users

Oracle SQL
Autonomous DW Cloud is compatible with all business analytics tools that support Oracle Database

Self Driving
Fully automated database for self-tuning patching and upgrading itself while the system is running

Cloud-Based Data Loading
Fast, scalable data-loading from Oracle Object Store, AWS S3, or on-premises

Highly Elastic
Independently scale compute and storage, without having to overpay for fixed blocks of resources

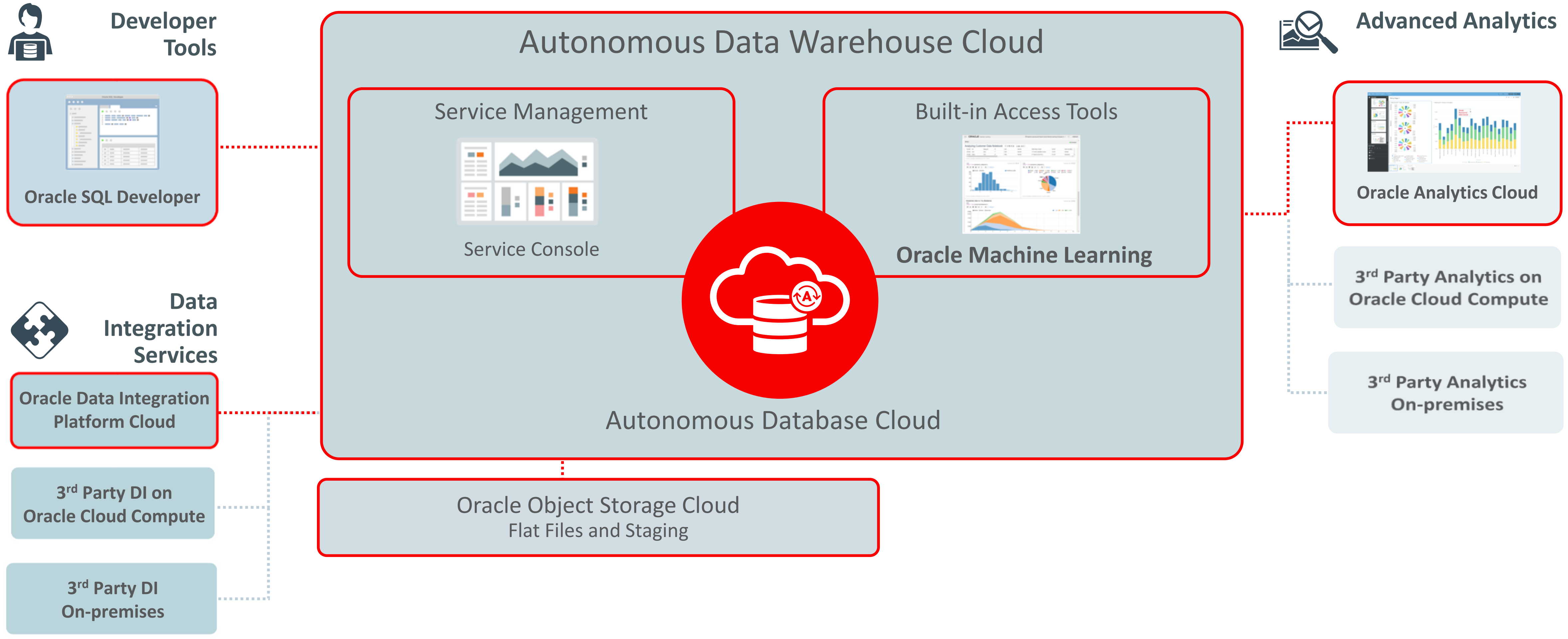
Oracle Machine Learning

Built-in Web-Based SQL ML Tool
Apache Zeppelin Oracle Machine Learning notebooks ready to run ML from browser

Database migration utility
Dedicated cloud-ready migration tools for easy migration from Amazon Redshift, SQL Server and other databases

Enterprise Grade Security
Data is encrypted by default in the cloud, as well as in transit and at rest

Architecture for Modern Cloud Data Warehousing



Introducing:
Oracle Machine Learning SQL Notebook

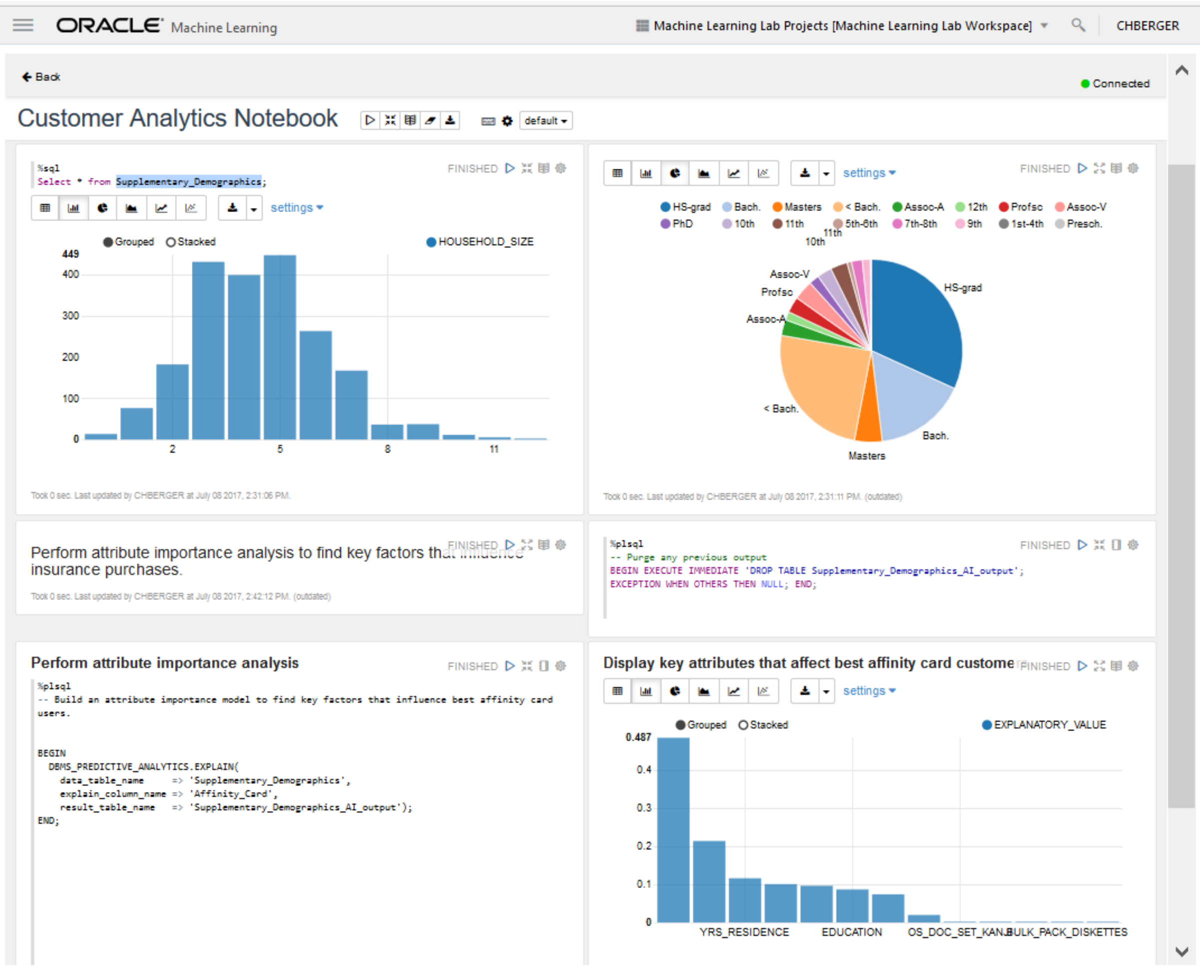
ORACLE

Oracle Machine Learning

Machine Learning Notebook for Autonomous Data Warehouse Cloud

Key Features

- Collaborative UI for data scientists
  - Packaged with Autonomous Data Warehouse Cloud (V1)
  - Easy access to shared notebooks, templates, permissions, scheduler, etc.
  - SQL ML algorithms API (V1)
  - Supports deployment of ML analytics



Oracle Machine Learning

Machine Learning Notebook for Autonomous Data Warehouse Cloud

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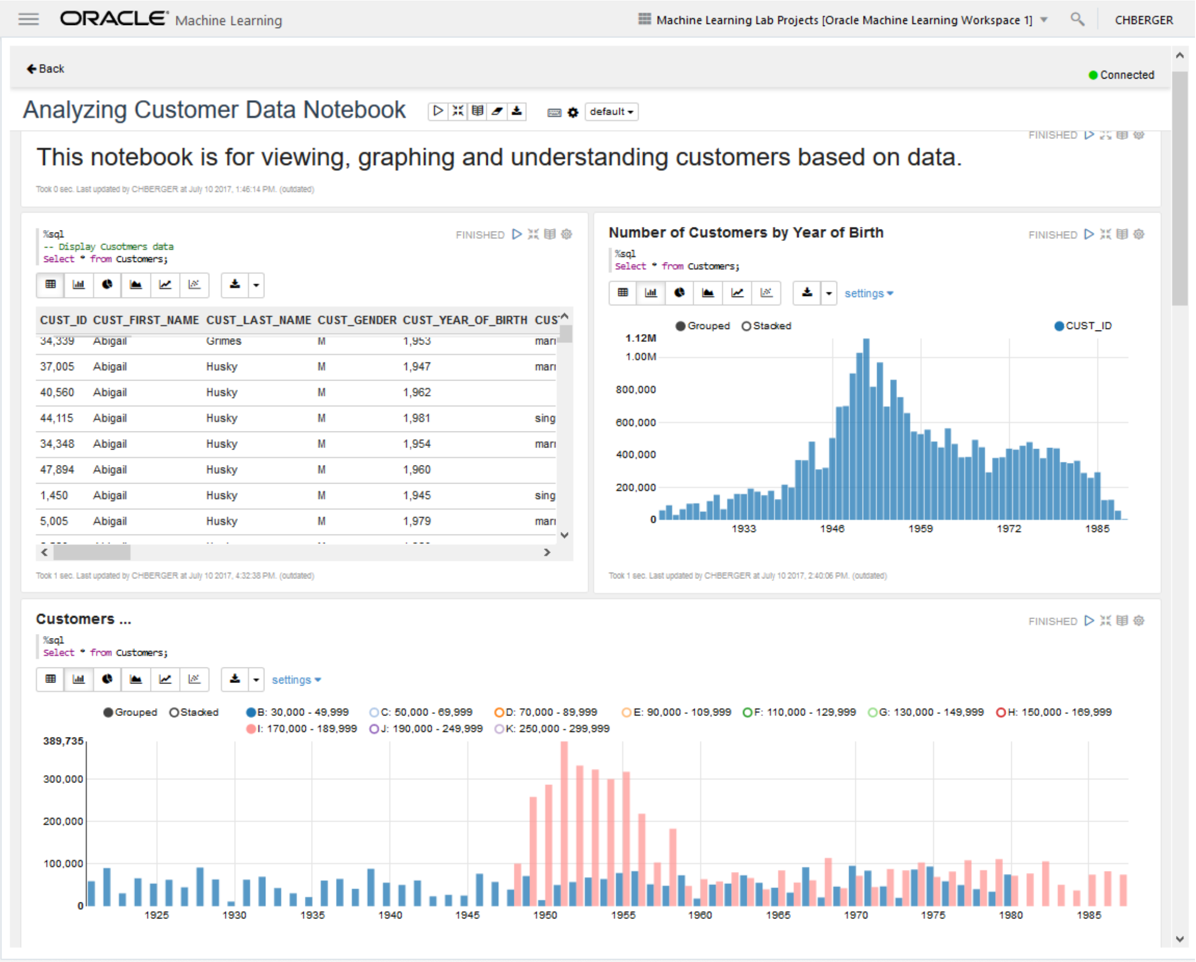
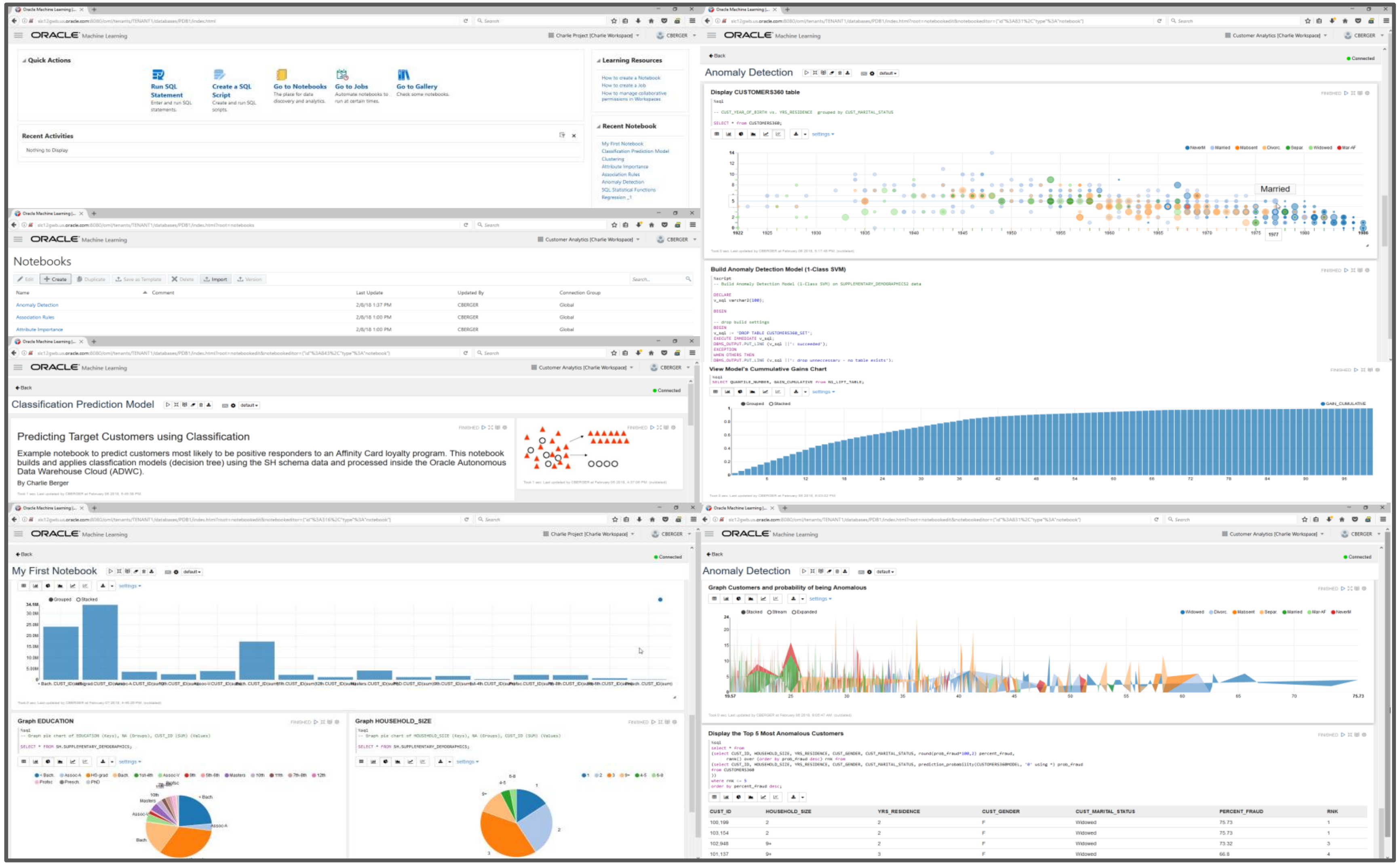


Oracle Machine Learning Quick DEMO



Oracle Machine Learning ...

slc12gwb.us.oracle.com:8080/omlusers/login.html?tenant=TENANT1&database=PDB1&redirect_uri=http://slc12gwb.us.oracle.com:8080/omlusers/api/oauth2/v1/login

Search

ORACLE Machine Learning

Sign In

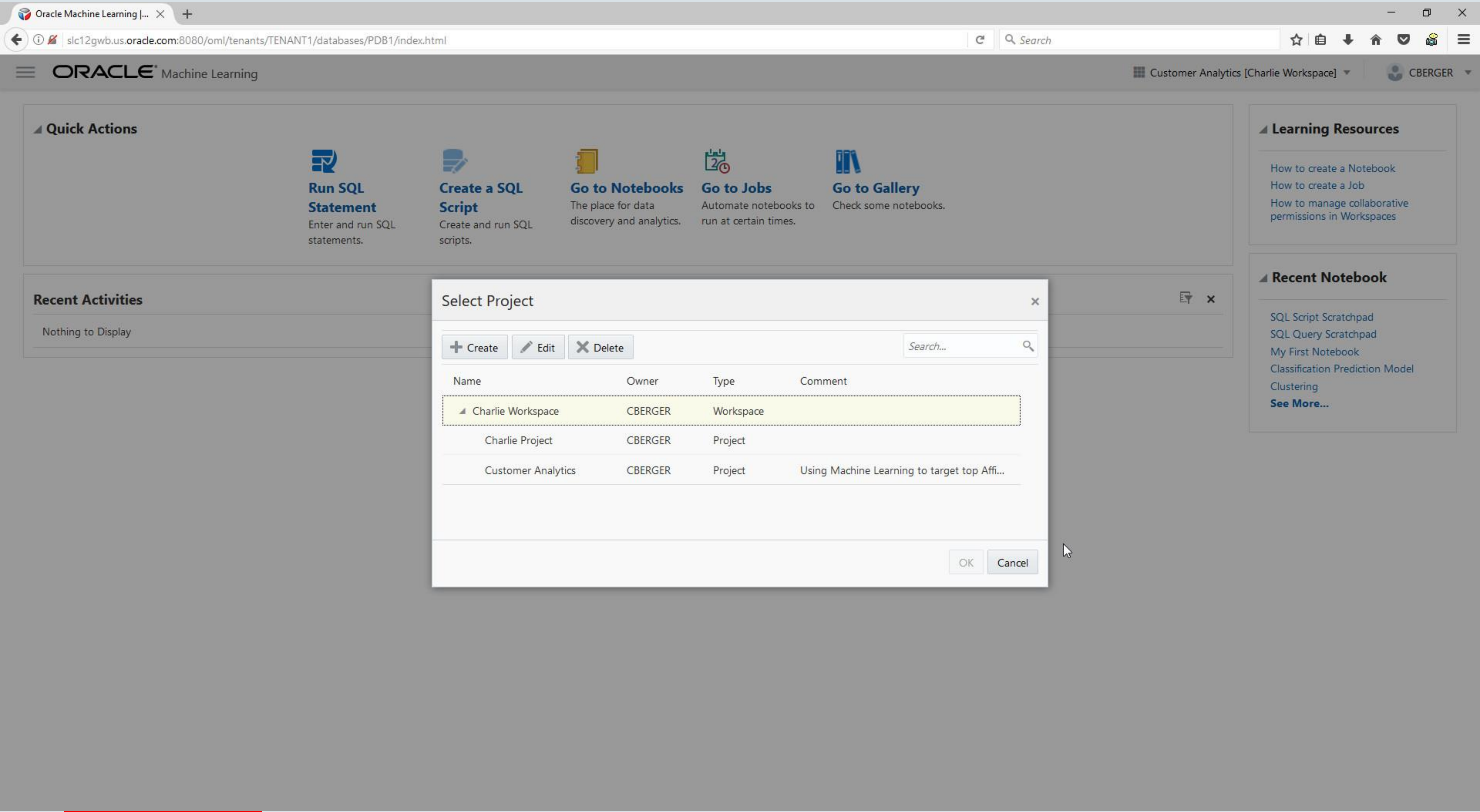
Tenant TENANT1

Database PDB1

* Username CBERGER

* Password ••••••••••••

Sign In


Oracle Machine Learning |...
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Search
ORACLE Machine Learning
Customer Analytics [Charlie Workspace]
CBERGER
Quick Actions
Run SQL Statement
Enter and run SQL statements.
Create a SQL Script
Create and run SQL scripts.
Go to Notebooks
The place for data discovery and analytics.
Go to Jobs
Automate notebooks to run at certain times.
Go to Gallery
Check some notebooks.
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How to create a Notebook
How to create a Job
How to manage collaborative permissions in Workspaces
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Recent Notebook
SQL Script Scratchpad
SQL Query Scratchpad
My First Notebook
Classification Prediction Model
Clustering
See More...
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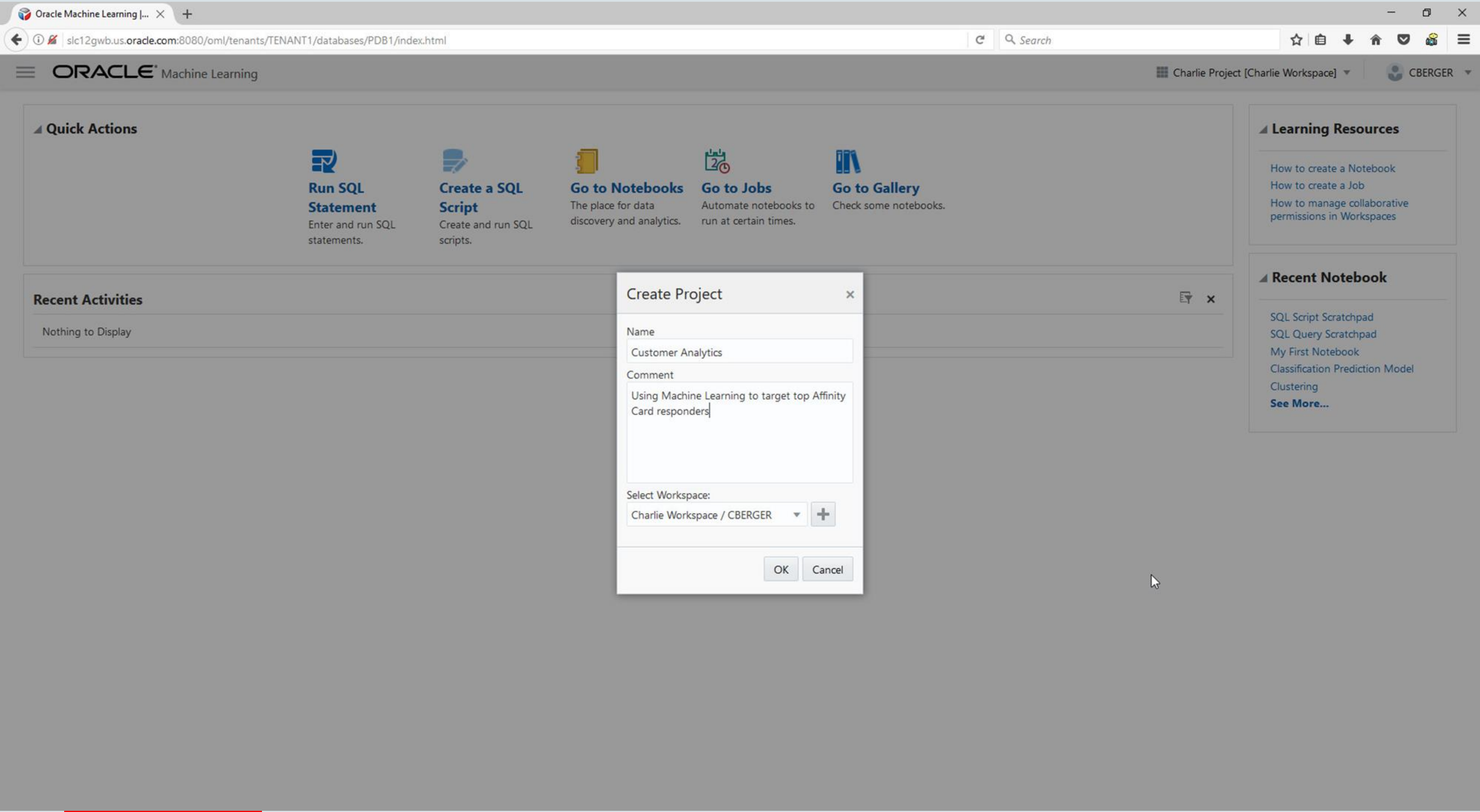
Search...
Name
Owner
Type
Comment
Charlie Workspace
CBERGER
Workspace
Charlie Project
CBERGER
Project
Customer Analytics
CBERGER
Project
Using Machine Learning to target top Affi...
OK
Cancel


Oracle Machine Learning |...
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Search
ORACLE Machine Learning
Charlie Project [Charlie Workspace]
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Quick Actions
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SQL Script Scratchpad
SQL Query Scratchpad
My First Notebook
Classification Prediction Model
Clustering
See More...
Create Project
Name
Customer Analytics
Comment
Using Machine Learning to target top Affinity Card responders
Select Workspace:
Charlie Workspace / CBERGER
OK
Cancel

Oracle Machine Learning |...

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Charlie Project [Charlie Workspace]

CBERGER

Quick Actions

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Enter and run SQL statements.

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Recent Activities

Nothing to Display

Learning Resources

- How to create a Notebook
- How to create a Job
- How to manage collaborative permissions in Workspaces

Recent Notebook

- My First Notebook
- Classification Prediction Model
- Clustering
- Attribute Importance
- Association Rules
- Anomaly Detection
- SQL Statistical Functions
- Regression _1

Oracle Machine Learning |...

slc12gwb.us.oracle.com:8080/oml/tenants/TENANT1/databases/PDB1/index.html?root=notebooks

ORACLE Machine Learning

Customer Analytics [Charlie Workspace] CBERGER

Notebooks

Edit | Create | Duplicate | Save as Template | Delete | Import | Version

Search...

Name	Comment	Last Update	Updated By	Connection Group
Anomaly Detection		2/8/18 1:37 PM	CBERGER	Global
Association Rules		2/8/18 1:00 PM	CBERGER	Global
Attribute Importance		2/8/18 1:00 PM	CBERGER	Global
Classification Prediction Model		2/8/18 1:00 PM	CBERGER	Global
Clustering		2/8/18 12:59 PM	CBERGER	Global
My First Notebook		2/8/18 1:00 PM	CBERGER	Global
Regression _1		2/8/18 1:00 PM	CBERGER	Global
SQL Query Scratchpad		2/8/18 1:00 PM	CBERGER	Global
SQL Script Scratchpad		2/8/18 1:00 PM	CBERGER	Global
SQL Statistical Functions		2/8/18 1:00 PM	CBERGER	Global

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Oracle Machine Learning |... × +

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ORACLE Machine Learning   Charlie Project [Charlie Workspace]   CBERGER

← Back   Connected

SQL Script Scratchpad

default

```
%script
SELECT * FROM SH.CUSTOMERS;
```

FINISHED

```
CUST_ID  CUST_FIRST_NAME  CUST_LAST_NAME  CUST_GENDER  CUST_YEAR_OF_BIRTH  CUST_MARITAL_STATUS  CUST_STREET_ADDRESS          CUST_POSTAL_CODE  CUST_CITY      CUST_CITY_ID  CUST_STATE_PROVINCE        CUST_STATE_PROVINCE_ID  COUNTRY_ID  CUST_MAIN_PHON
E_NUMBER  CUST_INCOME_LEVEL      CUST_CREDIT_LIMIT  CUST_EMAIL              CUST_TOTAL          CUST_TOTAL_ID  CUST_SRC_ID  CUST_EFF_FROM     CUST_EFF_TO    CUST_VALID
   43005 Rosemary         Kane            F                  1951 single          117 West Braxton Avenue      44130             San Mateo           52290 CA                                          52567       52790 661-204-8260
K: 250,000 - 299,999            11000 Kane@company.example.com     Customer total          52772            01-JAN-98                  I
   23248 Rosemary         Kane            F                  1952 married          17 West Gloucester Court    32701             Freising            51522 Bayern                                      52561       52776 538-204-5008
K: 250,000 - 299,999             7000 Kane@company.example.com     Customer total          52772            01-JAN-98                  I
   46784 Rosemary         Kane            F                  1959                  27 Todd Boulevard           48797             Wymondham           52520 England - Norfolk                           52591       52789 369-226-9676
K: 250,000 - 299,999            15000 Kane@company.example.com     Customer total          52772            01-JAN-98                  I
   50339 Rosemary         Kane            F                  1964 married          27 South Kaufman Boulevard  66437             Asten               51075 Noord-Brabant                               52682       52770 125-692-1259
K: 250,000 - 299,999            11000 Kane@company.example.com     Customer total          52772            01-JAN-98                  I
    3895 Rosemary         Kane            F                  1963 married          37 North 5th Street         40365             Tralee              52379 Kerry                                       52637       52772 284-248-2226
K: 250,000 - 299,999             7000 Kane@company.example.com     Customer total          52772            01-JAN-98                  I
    7450 Rosemary         Kane            F                  1966 single           47 East Mckenzie Road       57929             Heilbronn           51656 Baden-Wuerttemberg                          52559       52776 323-711-2933
K: 250,000 - 299,999            15000 Kane@company.example.com     Customer total          52772            01-JAN-98                  I
   11006 Rosemary         Kane            F                  1985                  57 Braxton Drive            63627             Keighley            51722 England - West Yorkshire                    52594       52789 190-716-7148
K: 250,000 - 299,999            11000 Kane@company.example.com     Customer total          52772            01-JAN-98                  I
   14562 Rosemary         Kane            F                  1960 married          57 North Page Drive         46864             Lauret              51788 Languedoc-Roussillon                        52645       52779 221-349-7611
```

Took 8 sec. Last updated by CBERGER at February 08 2018, 12:43:55 PM.

```
%script
```

READY

Oracle Machine Learning |...

slc12gwb.us.oracle.com:8080/oml/tenants/TENANT1/databases/PDB1/index.html

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Charlie Project [Charlie Workspace]

CBERGER

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Learning Resources

Recent Notebook

SQL Query Scratchpad
My First Notebook
Classification Prediction Model
Clustering
Attribute Importance
See More...

Recent Activities

today

Charlie Berger **updated** SQL Query Scratchpad notebook in Charlie Project [Charlie Workspace]
2/8/18 12:14 PM

yesterday

Charlie Berger **updated** Classification Prediction Model notebook in Charlie Project [Charlie Workspace]
2/7/18 5:44 PM

last Tuesday

Charlie Berger **changed** notebook name from Statistical Functions to SQL Statistical Functions in Charlie Project [Charlie Workspace]
2/6/18 10:22 PM

Charlie Berger **changed** notebook name from SQL Statistical Functions to Statistical Functions in Charlie Project [Charlie Workspace]
2/6/18 10:17 PM

Charlie Berger **changed** notebook name from Statistical Functions to SQL Statistical Functions in Charlie Project [Charlie Workspace]
2/6/18 10:17 PM

Charlie Berger **changed** notebook name from SQL Statistical Functions to Statistical Functions in Charlie Project [Charlie Workspace]
2/6/18 10:16 PM

Oracle Machine Learning |...

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ORACLE Machine Learning

Charlie Project [Charlie Workspace] CBERGER

Back

Connected

SQL Query Scratchpad

default

```
SELECT * FROM SH.CUSTOMERS;
```

FINISHED

CUST_ID	CUST_FIRST_NAME	CUST_LAST_NAME	CUST_GENDER	CUST_YEAR_OF_BIRTH	CUST_MARITAL_STATUS	CUST_STREET_ADDRESS	CUST_POSTAL_CODE	CUST_CITY	CUST_CITY_ID	CUST_STATE_PROVINCE	CUST_STATE_PROVINCE_
37,057	Bernard	Wright	M	1,941	married	107 East Catano Avenue	66,361	Velbert	52,436	Nordrhein-Westfalen	52,684
40,612	Bernard	Wright	M	1,947		107 South Prentiss Avenue	33,866	Bergen op Zoom	51,181	Noord-Brabant	52,682
44,167	Bernard	Wright	M	1,974	single	117 North Door Avenue	83,601	San Francisco	52,289	CA	52,567
34,880	Bernard	Wright	M	1,955	married	17 North Lehigh Court	59,862	Malaga	51,894	Malaga	52,661
47,946	Bernard	Wright	M	1,937		27 West Baraga Boulevard	46,864	Lauret	51,788	Languedoc-Roussillon	52,645
1,502	Bernard	Wright	M	1,945	single	37 Mountain View Street	80,841	Wolverhampton	52,514	England - West Midlands	52,593
5,057	Bernard	Wright	M	1,947	married	37 South Catano Street	34,216	Murnau	51,934	Bayern	52,561
8,612	Bernard	Wright	M	1,939		47 West Prentiss Road	72,059	Los Angeles	51,806	CA	52,567

Took 0 sec. Last updated by CBERGER at February 08 2018, 12:13:58 PM.

READY

Oracle Machine Learning |... New Tab

slc12gwb.us.oracle.com:8080/oml/tenants/TENANT1/databases/PDB1/index.html?root=library-examples

ORACLE Machine Learning

Charlie Project [Charlie Workspace] CBERGER

Gallery

New Notebook

Title	Description	Author	Date Added	Tags	Likes
Analyzing Cars Data	Analyzing Cars Data Example	Author:	Date Added: 2/2/18 11:49 AM	Tags: 'Data' 'Graph' 'Attribute Impor...	0 Likes 0 0
Attribute Importance	Attribute Importance Example	Author:	Date Added: 2/2/18 11:49 AM	Tags: 'Attribute Importance' 'Key Fa...	0 Likes 0 0
Auto Insurance Fraud Dete...	Auto Insurance Fraud Detection Exa...	Author:	Date Added: 2/2/18 11:49 AM	Tags: 'Anomaly Detection' 'Fraud'	0 Likes 0 0
Clustering for Identifying C...	Clustering for Identifying Customer ...	Author:	Date Added: 2/2/18 11:49 AM	Tags: 'Clustering' 'Unsupervised' 'Se...	0 Likes 0 0
DT Classification Model	DT Classification Model Example	Author:	Date Added: 2/2/18 11:49 AM	Tags: 'Oracle SQL'	0 Likes 0 0
Market Basket Analysis Not...	Market Basket Analysis Notebook E...	Author:	Date Added: 2/2/18 11:49 AM	Tags: 'Association Rules' 'Market Bas...	0 Likes 0 0
Predicting Insurance Buyers	Predicting Insurance Buyers Example	Author:	Date Added: 2/2/18 11:49 AM	Tags: 'Classification' 'Model Build' 'M...	0 Likes 0 0
Predicting Values (Regressi...	Predicting Values (Regression) Exam...	Author:	Date Added: 2/2/18 11:49 AM	Tags: 'Regression' 'Linear Regression...	0 Likes 0 0
SQL Data Retrieval	SQL Data Retrieval Example	Author:	Date Added: 2/2/18 11:49 AM	Tags: 'Oracle SQL'	0 Likes 0 0
SQL Statistical Functions Ex...	SQL Statistical Functions Examples E...	Author:	Date Added: 2/2/18 11:49 AM	Tags: 'Statistics' 'Descriptive Statistic...	0 Likes 0 0
Simple PL SQL	Simple PL SQL Example	Author:	Date Added: 2/2/18 11:49 AM	Tags: 'Oracle SQL'	0 Likes 0 0

Oracle Machine Learning |...

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90% Search

ORACLE Machine Learning

Charlie Project [Charlie Workspace] CBERGER

Back

Connected

My First Notebook

default

FINISHED

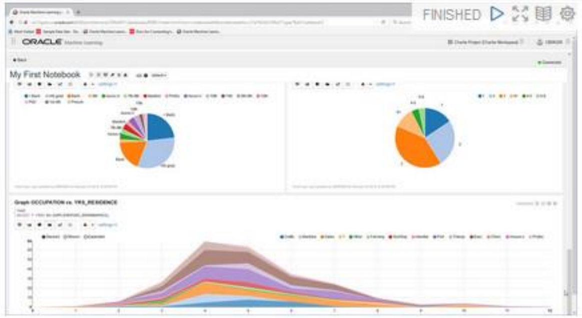
Simple Oracle Machine Learning notebook example

Oracle Machine Learning example notebook for learning basic functions using SH schema data and highlights basic data selection and data vewing using the Oracle Autonomous Data Warehouse Cloud (ADWC).

By Charlie Berger

Took 5 sec. Last updated by CBERGER at February 07 2018, 4:39:39 PM.

FINISHED



Took 0 sec. Last updated by CBERGER at February 07 2018, 4:39:39 PM.

FINISHED

For more information, check the Oracle ADWC Documentation https://docs.oracle.com/en/cloud/paas/autonomous-data-warehouse-cloud/index.html, Oracle Machine Learning folder on Oracle on Github https://github.com/oracle, Oracle Advanced Analytics http://www.oracle.com/technetwork/database/options/advanced-analytics/overview/index.html and Oracle Machine Learning on Oracle Technology Network and Introducing Oracle Machine Learning blog post https://blogs.oracle.com/datamining/introducing-oracle-machine-learning-sql-notebooks-for-the-oracle-autonomous-data-warehouse-cloud on Oracle Machine Learning blog.

Took 0 sec. Last updated by CBERGER at February 07 2018, 4:39:39 PM.

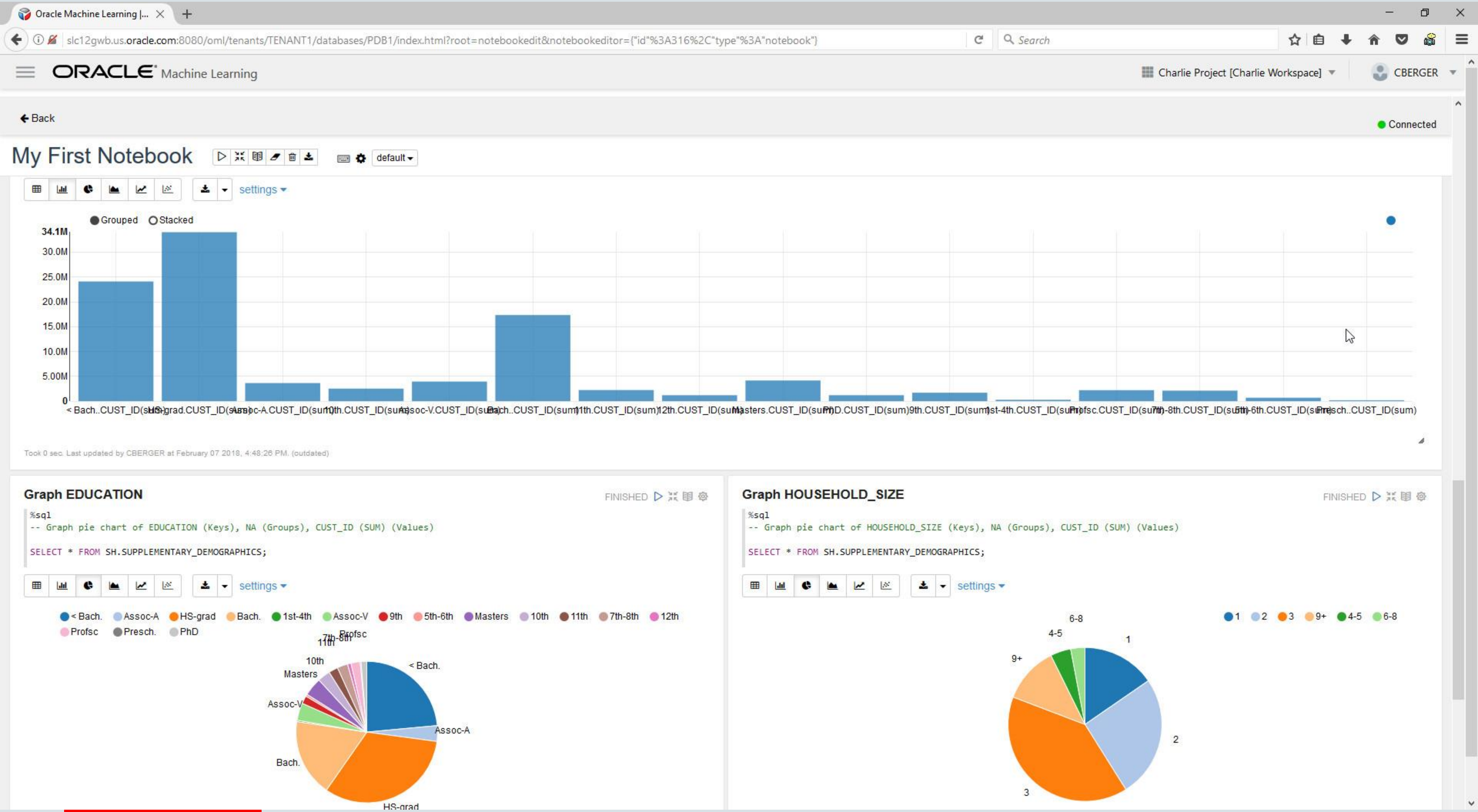
Show all tables

FINISHED

```
%sql
SELECT * FROM all_tables where owner = 'SH';
```

OWNER	TABLE_NAME	TABLESPACE_NAME	CLUSTER_NAME	IOT_NAME	STATUS	PCT_FREE	PCT_USED	INI_TRANS	MAX_TRANS	INITIAL_EXTENT	NEXT_EXTENT	MIN_EXTENTS	MAX_EXTENTS	PCT_INCREASE	FREELISTS	FREELIST_GROUPS	LOGGING	BACKED_UP
SH	SALES	SYSTEM			VALID	10	40	1	255	65,536	1,048,576	1	2,147,483,645		1	1	YES	N
SH	TIMES	SYSTEM			VALID	10	40	1	255	65,536	1,048,576	1	2,147,483,645		1	1	YES	N
SH	CHANNELS	SYSTEM			VALID	10	40	1	255	65,536	1,048,576	1	2,147,483,645		1	1	YES	N
SH	PROMOTIONS	SYSTEM			VALID	10	40	1	255	65,536	1,048,576	1	2,147,483,645		1	1	YES	N
SH	CUSTOMERS	SYSTEM			VALID	10	40	1	255	65,536	1,048,576	1	2,147,483,645		1	1	YES	N
SH	COUNTRIES	SYSTEM			VALID	10	40	1	255	65,536	1,048,576	1	2,147,483,645		1	1	YES	N
SH	SUPPLEMENTARY_DEMOGRAPHICS	SYSTEM			VALID	10	40	1	255	65,536	1,048,576	1	2,147,483,645		1	1	YES	N
SH	SALES_TRANSACTIONS_EXT	SYSTEM			VALID	10	40	1	255								YES	N

Took 9 sec. Last updated by CBERGER at February 07 2018, 4:39:43 PM. (outdated)



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ORACLE Machine Learning
Charlie Project [Charlie Workspace]
CBERGER
Back
Connected
My First Notebook
default
settings
Grouped
Stacked
34.1M
30.0M
25.0M
20.0M
15.0M
10.0M
5.00M
0
Took 0 sec. Last updated by CBERGER at February 07 2018, 4:48:26 PM. (outdated)
Graph EDUCATION
FINISHED
%sql
-- Graph pie chart of EDUCATION (Keys), NA (Groups), CUST_ID (SUM) (Values)
SELECT * FROM SH.SUPPLEMENTARY_DEMOGRAPHICS;
settings
< Bach. Assoc-A HS-grad Bach. 1st-4th Assoc-V 9th 5th-6th Masters 10th 11th 7th-8th 12th
Profsc Presch. PhD
Graph HOUSEHOLD_SIZE
FINISHED
%sql
-- Graph pie chart of HOUSEHOLD_SIZE (Keys), NA (Groups), CUST_ID (SUM) (Values)
SELECT * FROM SH.SUPPLEMENTARY_DEMOGRAPHICS;
settings
1 2 3 9+ 4-5 6-8

Oracle Machine Learning |...

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ORACLE Machine Learning

Charlie Project [Charlie Workspace] CBERGER

Back

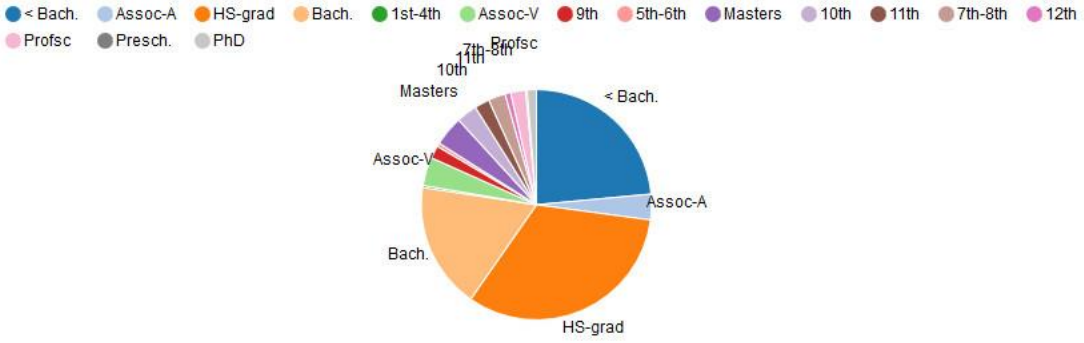
Connected

My First Notebook

default

```
-- Graph pie chart of EDUCATION (keys), NA (groups), CUST_ID (SUM) (values)
SELECT * FROM SH.SUPPLEMENTARY_DEMOGRAPHICS;
```

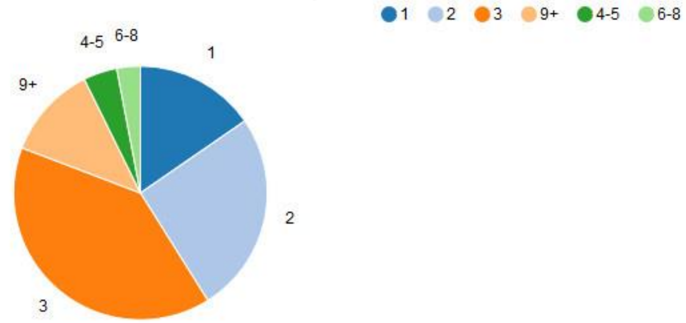
settings



Took 0 sec. Last updated by CBERGER at February 07 2018, 4:39:44 PM. (outdated)

```
-- Graph pie chart of HOUSEHOLD_SIZE (keys), NA (groups), CUST_ID (SUM) (values)
SELECT * FROM SH.SUPPLEMENTARY_DEMOGRAPHICS;
```

settings



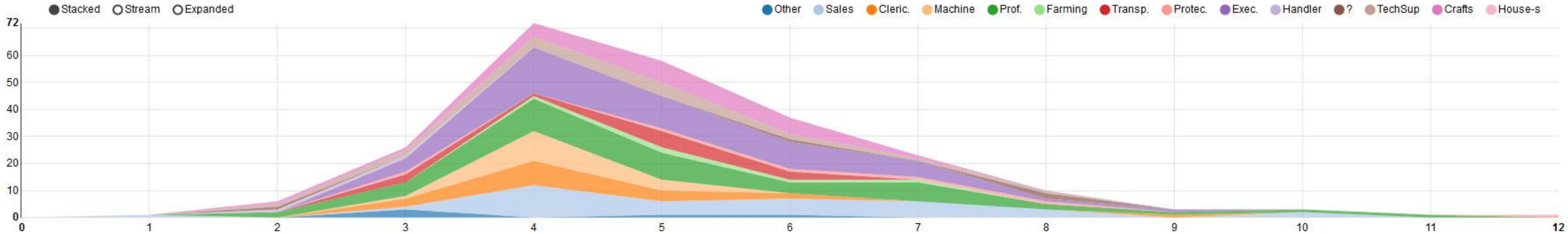
Took 0 sec. Last updated by CBERGER at February 07 2018, 4:39:44 PM. (outdated)

Graph OCCUPATION vs. YRS_RESIDENCE

FINISHED

```
%sql
SELECT * FROM SH.SUPPLEMENTARY_DEMOGRAPHICS;
```

settings



Oracle Machine Learning |...

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ORACLE Machine Learning

Customer Analytics [Charlie Workspace] CBERGER

Back

Connected

Anomaly Detection

default

FINISHED

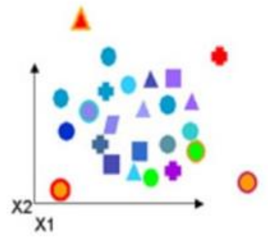
Anomaly Detection to Detect Suspicious or Rare Occurrences

This notebook shows how to detect rare records, customers or transactions using an unsupervised learning algorithm (1-Class Support Vector Machine). The notebook first builds a 1-Class SVM model and then applies the model to flag unusual or suspicious records. The anomaly detection model can also be applied to "score" new records. The entire machine learning methodology runs inside the Oracle Autonomous Data Warehouse Cloud (ADWC).

By Charlie Berger

Took 0 sec. Last updated by CBERGER at February 06 2018, 8:54:19 AM. (outdated)

FINISHED



Took 1 sec. Last updated by CBERGER at February 06 2018, 7:49:16 AM. (outdated)

FINISHED

For more information, check the Oracle ADWC Documentation https://docs.oracle.com/en/cloud/paas/autonomous-data-warehouse-cloud/index.html, Oracle Machine Learning folder on Oracle on Github https://github.com/oracle, Oracle Advanced Analytics http://www.oracle.com/technetwork/database/options/advanced-analytics/overview/index.html and Oracle Machine Learning on Oracle Technology Network and Introducing Oracle Machine Learning blog post

Took 0 sec. Last updated by CBERGER at February 06 2018, 9:25:06 AM. (outdated)

Clean up and drop any table if previously exists for notebook reproducibility

FINISHED

```
%script
BEGIN
      EXECUTE IMMEDIATE 'DROP Table SUPPLEMENTARY_DEMOGRAPHICS2';
  EXCEPTION
      WHEN OTHERS THEN NULL;
END;
```

```
PL/SQL procedure successfully completed.
```

Took 0 sec. Last updated by CBERGER at February 06 2018, 5:12:56 PM.

Create SUPPLEMENTARY_DEMOGRAPHICS2 table that remove COMMENTS unstructured data for simplicity.

FINISHED

```
%sql
CREATE Table SUPPLEMENTARY_DEMOGRAPHICS2
  AS (SELECT AFFINITY_CARD, BOOKKEEPING_APPLICATION, BULK_PACK_DISKETTES, CUST_ID, EDUCATION, FLAT_PANEL_MONITOR, HOME_THEATER_PACKAGE, HOUSEHOLD_SIZE, OCCUPATION, OS_DOC_SET_KANJI, PRINTER_SUPPLIES, YRS_RESIDENCE, Y_BOX_GAMES
      FROM SH.SUPPLEMENTARY_DEMOGRAPHICS);
```

```
Updated 4500 row(s).
```

Took 1 sec. Last updated by CBERGER at February 06 2018, 5:13:01 PM.

Oracle Machine Learning |...

slc12gwb.us.oracle.com:8080/oml/tenants/TENANT1/databases/PDB1/index.html?root=notebookedit&notebookeditor={"id"%3A831%2C"type"%3A"notebook"}

ORACLE Machine Learning

Customer Analytics [Charlie Workspace] CBERGER

Back

Connected

Anomaly Detection

default

Build Anomaly Detection Model (1-Class SVM)

FINISHED

```
%script
-- Build Anomaly Detection Model (1-Class SVM) on SUPPLEMENTARY_DEMOGRAPHICS2 data

DECLARE
v_sql varchar2(100);

BEGIN

-- drop build settings
BEGIN
v_sql := 'DROP TABLE CUSTOMERS360_SET';
EXECUTE IMMEDIATE v_sql;
DBMS_OUTPUT.PUT_LINE (v_sql ||': succeeded');
EXCEPTION
WHEN OTHERS THEN
DBMS_OUTPUT.PUT_LINE (v_sql ||': drop unneccessary - no table exists');
END;

-- drop any previous model.
BEGIN
v_sql := 'CALL DBMS_DATA_MINING.DROP_MODEL(''CUSTOMERS360MODEL'')';
EXECUTE IMMEDIATE v_sql;
DBMS_OUTPUT.PUT_LINE (v_sql ||': succeeded');
EXCEPTION
WHEN OTHERS THEN
DBMS_OUTPUT.PUT_LINE (v_sql ||': drop unneccessary - no model exists');
END;

-- Create a Build Setting table for Model Build

EXECUTE IMMEDIATE 'CREATE TABLE CUSTOMERS360_SET (setting_name VARCHAR2(30),setting_value VARCHAR2(4000))';
EXECUTE IMMEDIATE 'INSERT INTO CUSTOMERS360_SET (setting_name, setting_value) VALUES (''ALGO_NAME'', ''ALGO_SUPPORT_VECTOR_MACHINES'')';
EXECUTE IMMEDIATE 'INSERT INTO n1_build_settings (setting_name, setting_value) VALUES (''PREP_AUTO'', ''ON'')';
DBMS_OUTPUT.PUT_LINE ('Created model build settings table: CUSTOMERS360_SET ');


-- Build the 1-Class SVM model.

EXECUTE IMMEDIATE 'CALL DBMS_DATA_MINING.CREATE_MODEL(''CUSTOMERS360MODEL'', ''CLASSIFICATION'', ''CUSTOMERS360'', ''CUST_ID   '', null, ''CUSTOMERS360_SET'')';
DBMS_OUTPUT.PUT_LINE ('Created model: CUSTOMERS360_MODEL ');

End;
```

```
DROP TABLE CUSTOMERS360_SET: succeeded
CALL DBMS_DATA_MINING.DROP_MODEL('CUSTOMERS360MODEL'): succeeded
Created model build settings table: CUSTOMERS360_SET
Created model: CUSTOMERS360_MODEL
PL/SQL procedure successfully completed.
```

Took 3 sec. Last updated by CBERGER at February 06 2018, 5:19:03 PM.

Oracle Machine Learning |...

slc12gwb.us.oracle.com:8080/oml/tenants/TENANT1/databases/PDB1/index.html?root=notebookedit&notebookeditor={"id"%3A831%2C"type"%3A"notebook"}

ORACLE Machine Learning

Customer Analytics [Charlie Workspace] CBERGER

Back

Connected

Anomaly Detection

default

Display CUSTOMERS360 table

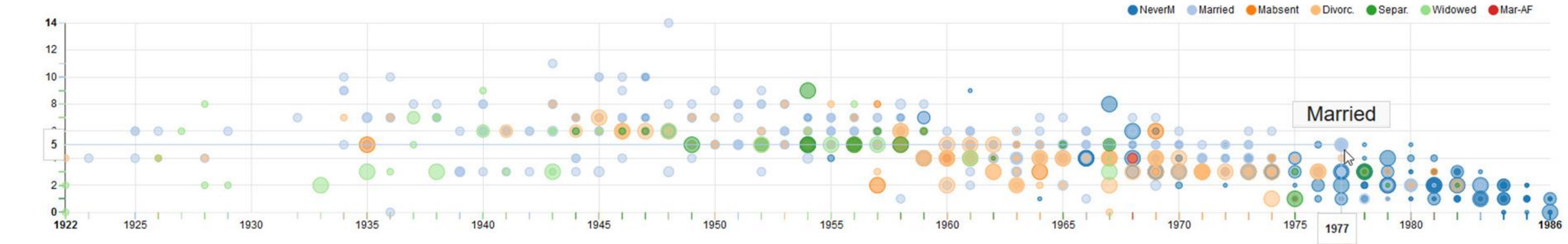
FINISHED

```
%sql

-- CUST_YEAR_OF_BIRTH vs. YRS_RESIDENCE  grouped by CUST_MARITAL_STATUS

SELECT * from CUSTOMERS360;
```

settings



Took 0 sec. Last updated by CBERGER at February 06 2018, 5:17:48 PM. (outdated)

Build Anomaly Detection Model (1-Class SVM)

FINISHED

```
%script
-- Build Anomaly Detection Model (1-Class SVM) on SUPPLEMENTARY_DEMOGRAPHICS2 data

DECLARE
v_sql varchar2(100);

BEGIN

-- drop build settings
BEGIN
v_sql := 'DROP TABLE CUSTOMERS360_SET';
EXECUTE IMMEDIATE v_sql;
DBMS_OUTPUT.PUT_LINE (v_sql ||': succeeded');
EXCEPTION
WHEN OTHERS THEN
DBMS_OUTPUT.PUT_LINE (v_sql ||': drop unneccessary - no table exists');
```

Oracle Machine Learning |...

slc12gwb.us.oracle.com:8080/oml/tenants/TENANT1/databases/PDB1/index.html?root=notebookedit&notebookeditor={"id"%3A831%2C"type"%3A"notebook"}

Search

ORACLE Machine Learning

Customer Analytics [Charlie Workspace]

CBERGER

Back

Connected

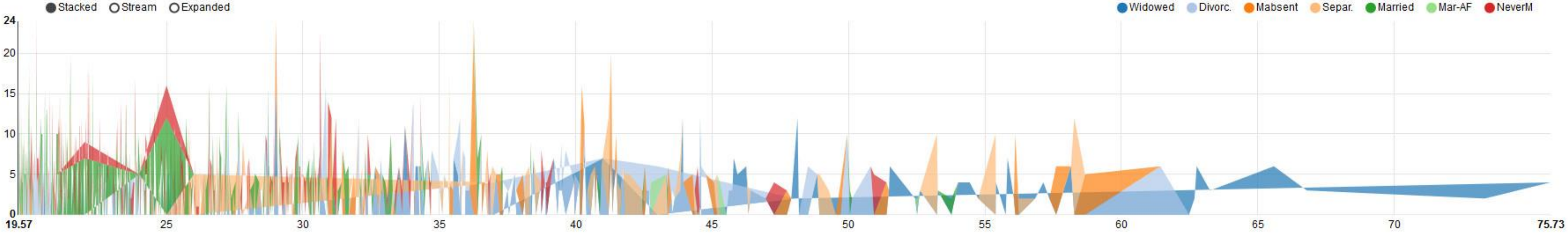
Anomaly Detection

default

Graph Customers and probability of being Anomalous

FINISHED

settings



Took 0 sec. Last updated by CBERGER at February 06 2018, 9:05:47 AM. (outdated)

Display the Top 5 Most Anomalous Customers

FINISHED

```
%sql
select * from
(select CUST_ID, HOUSEHOLD_SIZE, YRS_RESIDENCE, CUST_GENDER, CUST_MARITAL_STATUS, round(prob_fraud*100,2) percent_fraud,
      rank() over (order by prob_fraud desc) rnk from
(select CUST_ID, HOUSEHOLD_SIZE, YRS_RESIDENCE, CUST_GENDER, CUST_MARITAL_STATUS, prediction_probability(CUSTOMERS360MODEL, '0' using *) prob_fraud
from CUSTOMERS360
))
where rnk <= 5
order by percent_fraud desc;
```

CUST_ID	HOUSEHOLD_SIZE	YRS_RESIDENCE	CUST_GENDER	CUST_MARITAL_STATUS	PERCENT_FRAUD	RNK
100,199	2	2	F	Widowed	75.73	1
103,154	2	2	F	Widowed	75.73	1
102,948	9+	2	F	Widowed	73.32	3
101,137	9+	3	F	Widowed	66.8	4

Oracle Machine Learning |... New Tab

slc12gwb.us.oracle.com:8080/oml/tenants/TENANT1/databases/PDB1/index.html?root=notebookedit&notebookeditor={"id"%3A441%2C"type"%3A"notebook"}

ORACLE Machine Learning

Charlie Project [Charlie Workspace] CBERGER

Back

Connected

Classification Prediction Model

default

FINISHED

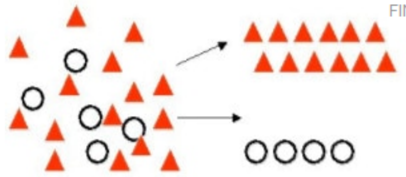
Predicting Target Customers using Classification

Example notebook to predict customers most likely to be positive responders to an Affinity Card loyalty program. This notebook builds and applies classfication models (decision tree) using the SH schema data and processed inside the Oracle Autonomous Data Warehouse Cloud (ADWC).

By Charlie Berger

Took 1 sec. Last updated by CBERGER at February 06 2018, 5:45:38 PM.

FINISHED



Took 1 sec. Last updated by CBERGER at February 05 2018, 4:37:06 PM. (outdated)

FINISHED

For more information, check the Oracle ADWC Documentation https://docs.oracle.com/en/cloud/paas/autonomous-data-warehouse-cloud/index.html, Oracle Machine Learning folder on Oracle on Github https://github.com/oracle, Oracle Advanced Analytics http://www.oracle.com/technetwork/database/options/advanced-analytics/overview/index.html and Oracle Machine Learning on Oracle Technology Network and Introducing Oracle Machine Learning blog post https://blogs.oracle.com/datamining/introducing-oracle-machine-learning-sql-notebooks-for-the-oracle-autonomous-data-warehouse-cloud on Oracle Machine Learning blog.

Took 1 sec. Last updated by CBERGER at February 03 2018, 9:48:09 PM. (outdated)

Display the SH.SUPPLEMENTARY_DEMOGRAPHICS data

FINISHED

```
%sql
Select * from SH.SUPPLEMENTARY_DEMOGRAPHICS;
```

CUST_ID	EDUCATION	OCCUPATION	HOUSEHOLD_SIZE	YRS_RESIDENCE	AFFINITY_CARD	BULK_PACK_DISKETTES	FLAT_PANEL_MONITOR	HOME_THEATER_PACKAGE	BOOKKEEPING_APPLICATION	PRINTER_SUPPLIES	Y_BOX_GAMES	OS_DOC_SET_KANJI	CC
100,931	< Bach.	Crafts	3	6	1	1	1	1	1	1	0	0	Sh
100,932	HS-grad	Machine	1	5	0	0	0	0	1	1	0	0	I ar
100,933	HS-grad	Sales	3	7	1	1	1	1	1	1	0	0	Aff
100,934	Bach.	?	2	4	0	0	0	0	1	1	1	0	Aff
100,935	< Bach.	Other	2	2	0	0	0	0	1	1	1	0	Gr
100,936	9th	Crafts	3	3	0	0	0	1	0	1	0	0	I ar
100,937	HS-grad	Crafts	2	4	0	1	1	0	1	1	1	0	Aff
100,938	HS-grad	Farming	1	1	0	1	1	1	1	1	0	0	I pı

Oracle Machine Learning |... ×

slc12gwb.us.oracle.com:8080/oml/tenants/TENANT1/databases/PDB1/index.html?root=notebookedit&notebookeditor={"id"%3A441%2C"type"%3A"notebook"}

ORACLE Machine Learning

Charlie Project [Charlie Workspace] CBERGER

← Back

Connected

Classification Prediction Model

default

Real-time prediction

FINISHED

```
%sql
Select prediction_probability(N1_CLASS_MODEL, '1'
  USING '3' as HOUSEHOLD_SIZE, 5 as YRS_RESIDENCE, 1 as Y_BOX_GAMES)
from dual;
```

PREDICTION_PROBABILITY(N1_CLASS_MODEL,'1'USING'3'ASHOUSEHOLD_SIZE,5ASYRS_RESIDENCE,1ASY_BOX_GAMES)
0.45058

Took 0 sec. Last updated by CBERGER at February 08 2018, 4:51:11 PM.

Interactive selection of likely Affinity_Card reponders selected by HOUSEHOLD_SIZE

FINISHED

```
%sql
SELECT A.*, B.* FROM N1_APPLY_RESULT A, N1_TEST_DATA B WHERE HOUSEHOLD_SIZE = ${HOUSEHOLD_SIZE='1','1'|'3'| '9+'} and a.CUST_ID = b.CUST_ID;
```

HOUSEHOLD_SIZE

'3'

CUST_ID	PREDICTION	PROBABILITY	COST	CUST_ID	CUST_GENDER	CUST_MARITAL_STATUS	CUST_YEAR_OF_BIRTH	CUST_INCOME_LEVEL	CUST_CREDIT_LIMIT	EDUCATION	AFFINITY_CARD	HOUSEHOLD_SIZE	OCCUPATION	YRS_RESIDENCE	Y_BOX_GAM
100,302	0	0.5928	0.4072	100,302	M	Married	1,975	J: 190,000 - 249,999	11,000	10th	0	3	Crafts	4	1
100,302	1	0.4072	0.5928	100,302	M	Married	1,975	J: 190,000 - 249,999	11,000	10th	0	3	Crafts	4	1
100,612	1	0.5375	0.4625	100,612	M	Married	1,974	H: 150,000 - 169,999	7,000	Assoc-A	1	3	Sales	4	1
100,612	0	0.4625	0.5375	100,612	M	Married	1,974	H: 150,000 - 169,999	7,000	Assoc-A	1	3	Sales	4	1
100,950	0	0.5928	0.4072	100,950	M	Married	1,958	G: 130,000 - 149,999	5,000	HS-grad	1	3	Sales	6	0
100,950	1	0.4072	0.5928	100,950	M	Married	1,958	G: 130,000 - 149,999	5,000	HS-grad	1	3	Sales	6	0
101,203	1	0.5375	0.4625	101,203	M	Married	1,968	I: 170,000 - 189,999	9,000	Bach.	1	3	Sales	4	0
101,203	0	0.4625	0.5375	101,203	M	Married	1,968	I: 170,000 - 189,999	9,000	Bach.	1	3	Sales	4	0

Table of Contents

How to Get Started with Oracle Machine Learning

Here is how you can get started with Oracle Machine Learning.

1. Request access to Oracle Machine Learning. Contact your Service Administrator to provide access to your Oracle Machine Learning account.
2. Access the Oracle Machine Learning account by using your credentials. In case you forget your password, then request the Administrator to reset it.

   > **Note:**
   > Once you receive your new password, you must change it immediately. Refer to the Oracle Machine Learning password policy for more information.

3. Once you log in for the first time, a workspace and project will be created for you. You can start creating your notebook and assign it to the default project and workspace. You can also create your own project and workspace.

Related Topics

- Password Policy

Accessing Oracle Machine Learning User Management Page

From Autonomous Data Warehouse Cloud you can access the Oracle Machine Learning **Mange Oracle ML Users** page.

To access Oracle Machine Learning **Mange Oracle ML Users** page:

1. Sign in to your Cloud Account and navigate to the **My Services** Dashboard.
2. Click the navigation menu icon in the top corner of the My Services Dashboard and then click **Autonomous Data Warehouse Cloud**.
3. Select a service and click the and select **Service Console**.
4. At the prompt, enter ADMIN for the username and enter the password for the ADMIN user.

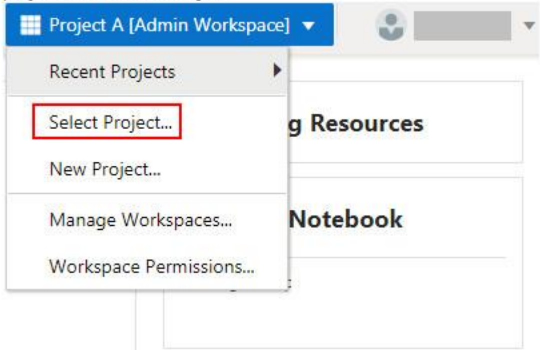
Table of Contents

Creating Projects and Workspaces

A project is a container for your notebooks, and a workspace is a container for your projects. You can own multiple projects in a workspace.

The initial workspace and the default project is created by the Oracle Machine Learning service automatically when you log in to Oracle Machine Learning for the first time. To create a new project and a workspace:

1. On the top right corner of Oracle Machine Learning home page, click the project workspace drop-down list. The project name and the workspace, in which the project resides, are displayed here. In this screenshot, the project name is Project A, and the workspace name is Admin. If a default project exists, then the default project name is displayed here. To choose a different project, click **Select Project.**



Description of the illustration select_project.eps

> **Note:**
> The last project that you have worked on is stored in the browser cache and is the default project. If you clear the cache, then no default exists and you must select a project.

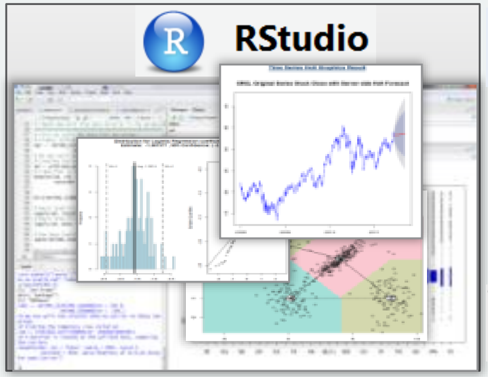
2. To create a new project, click **New Project.**
   The Create Project dialog box opens.
3. In the **Name** field, provide a name for your project.
4. In the **Comments** field, enter comments, if any.
5. In the **Select Workspace** field, select a workspace from the drop-down list. Your project is assigned to the selected workspace. If you want to create a new workspace, then click +.
6. In the Create Workspace dialog box, enter a name for the workspace in the **Name** field.
7. In the **Comments** field, enter comments, if any.
8. Click **OK.**
   This creates your workspace, and navigates back to the Create Project dialog box. The project that you are creating is now assigned to the newly created workspace.
9. Click **OK.**

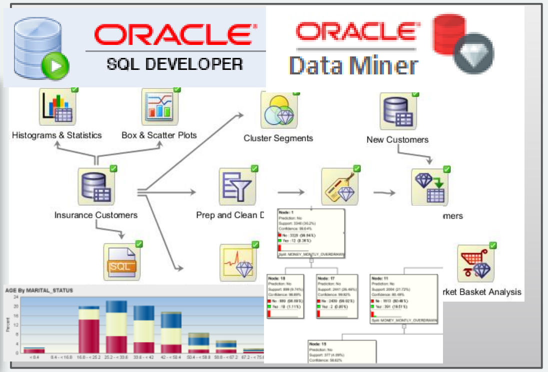
Oracle’s Machine Learning/Advanced Analytics Platforms

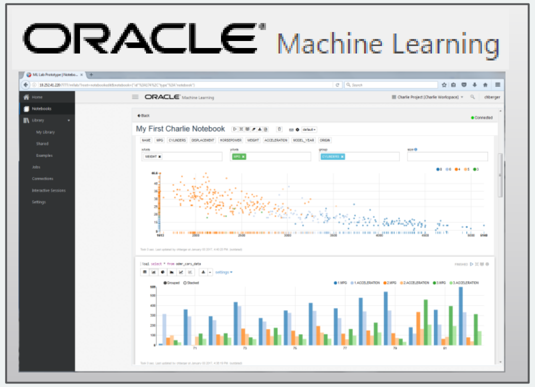
Machine Learning Algorithms Embedded in the Data Management Platforms

“Analytics Producers”

Data Scientists, R Users, Citizen Data Scientists







New Zeppelin notebook based UI for data scientists collaborating and sharing ML analytical methodologies in Clouds

ORACLE Data Management + Advanced Analytical Platform

Big Data SQL

ORACLE Big Data Cloud Service

“Oracle Machine Learning” Big Data Cloud

HIVE

ORAAH—Machine Learning Algorithms

Statistical Functions + R Integration

for Scalable, Parallel, Distributed Execution

ORACLE Database Cloud

“Oracle Machine Learning” Database Edition

Machine Learning Algorithms,

Statistical Functions + R Integration

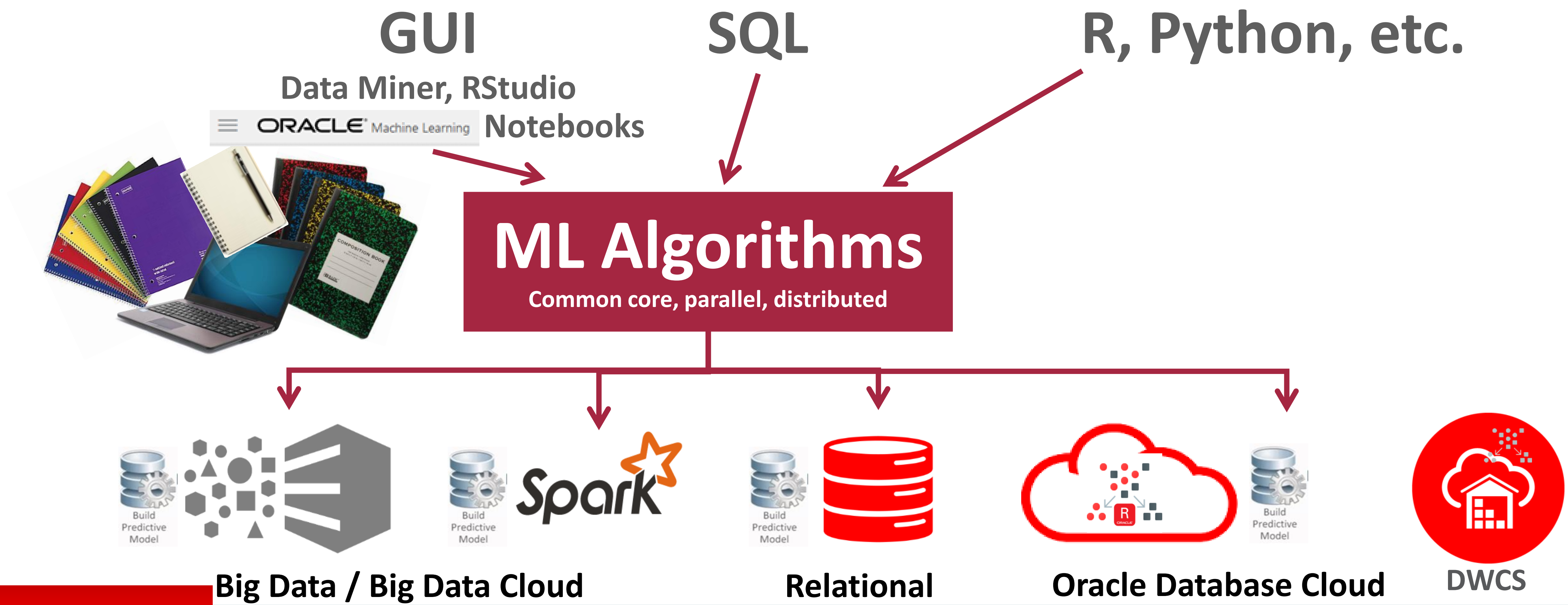
for Scalable, Parallel, Distributed, in-DB Execution

ORACLE

Oracle Machine Learning and Advanced Analytics

Strategy and Road Map

- Support multiple data platforms, analytical engines, languages, UIs and deployment strategies



More Information on Oracle’s ML/AA Functionality

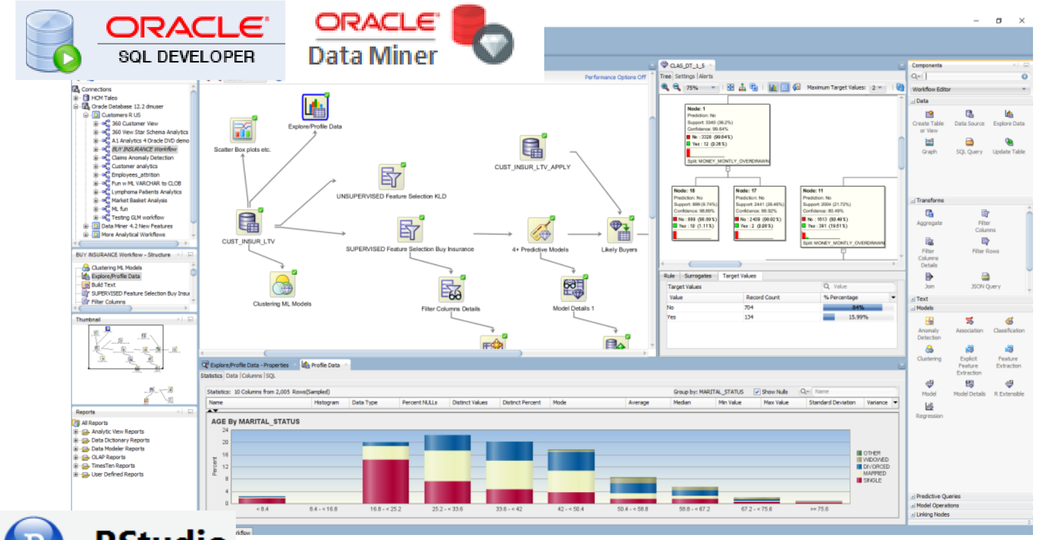
ORACLE

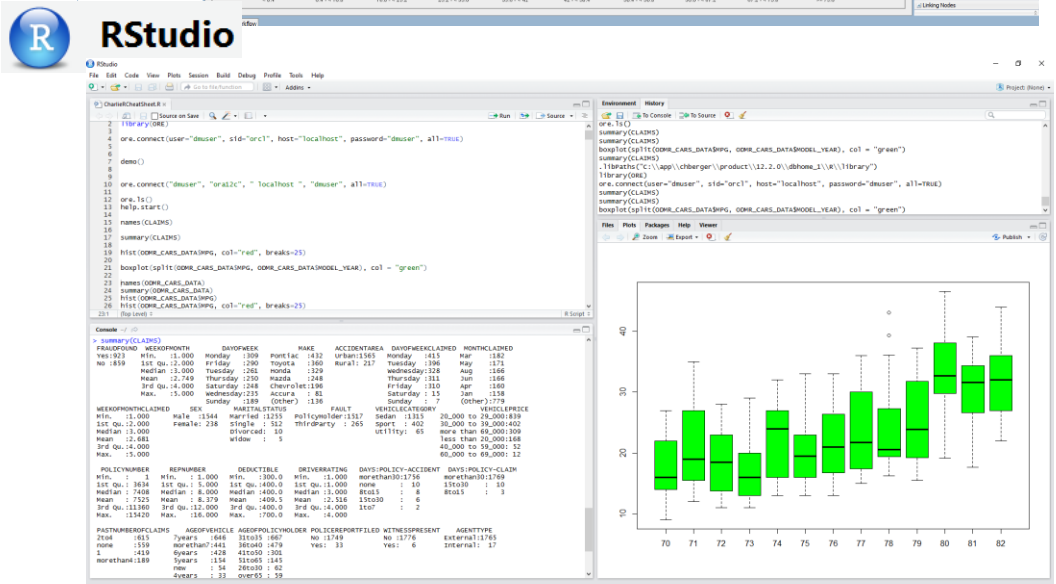
Oracle's Machine Learning/Advanced Analytics

Fastest Way to Deliver Scalable Enterprise-wide Predictive Analytics

Key Features

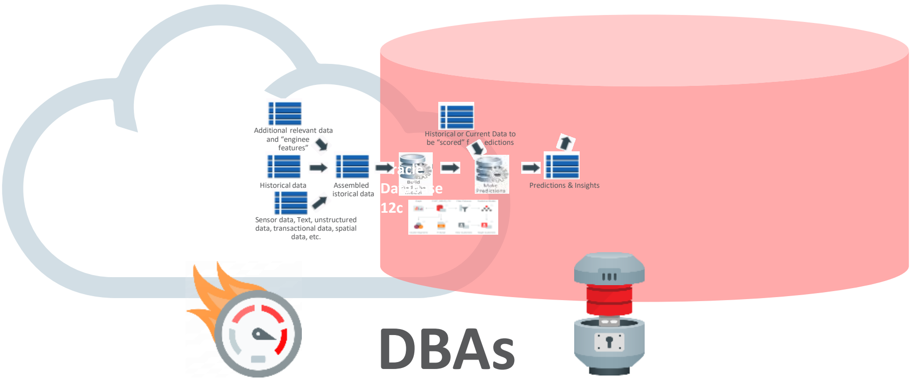
- Parallel, scalable machine learning algorithms and R integration
- In-Database + Hadoop—Don't move the data
- Data analysts, data scientists & developers
- Drag and drop workflow, R and SQL APIs
- Extends data management into powerful advanced/predictive analytics platform
- Enables enterprise predictive analytics deployment + applications



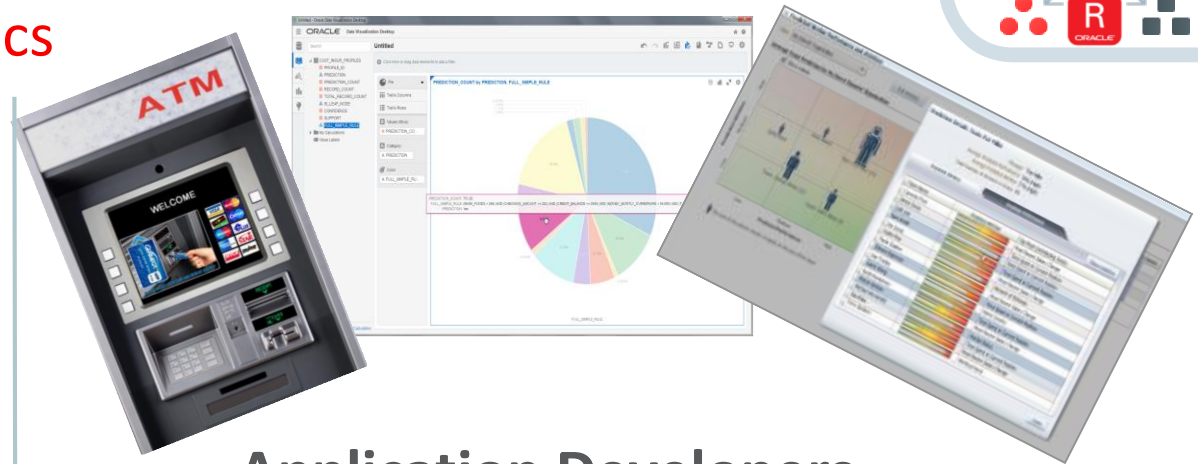


Multiple Data Scientist User Roles Supported

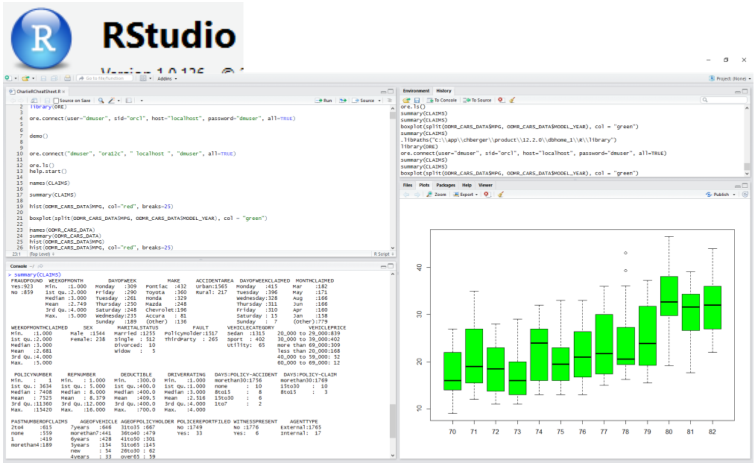
Oracle's Machine Learning/Advanced Analytics



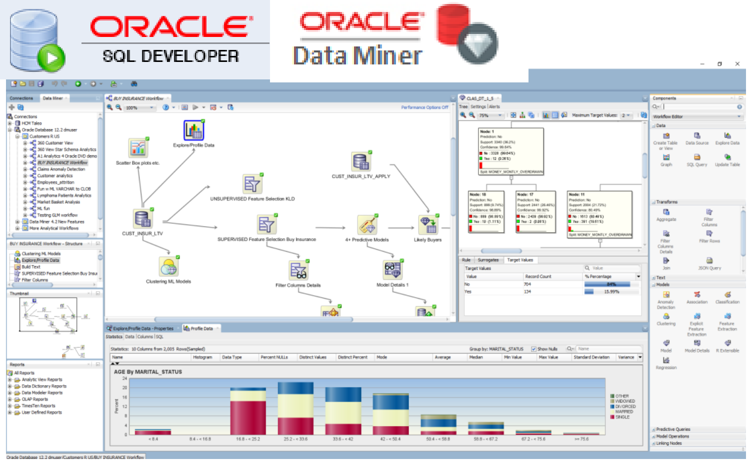
DBAs



Application Developers



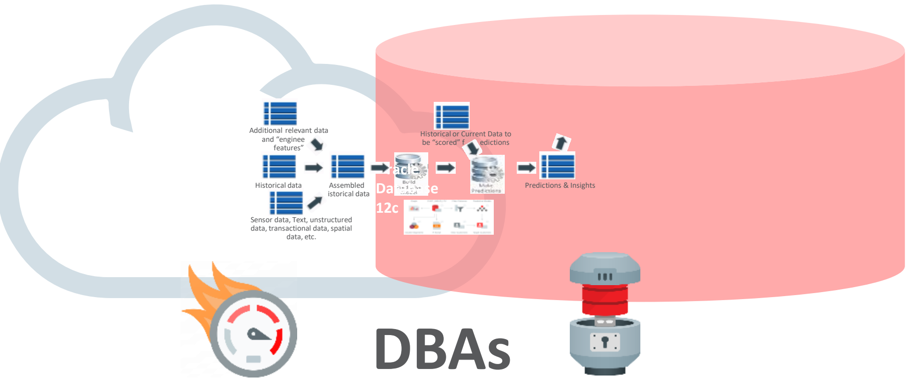
R Users, Data Scientists



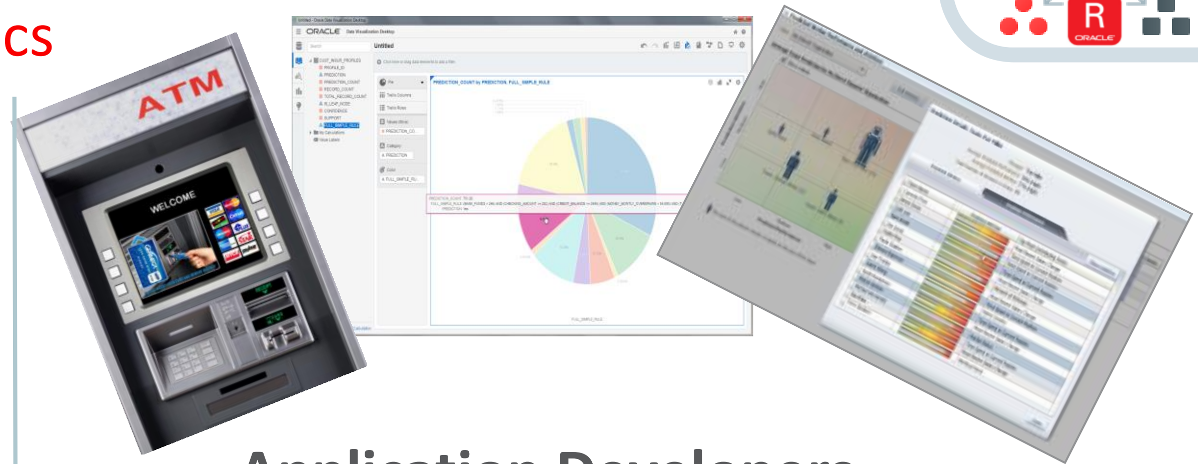
Data Analysts, Citizen Data Scientists

Multiple Data Scientist User Roles Supported

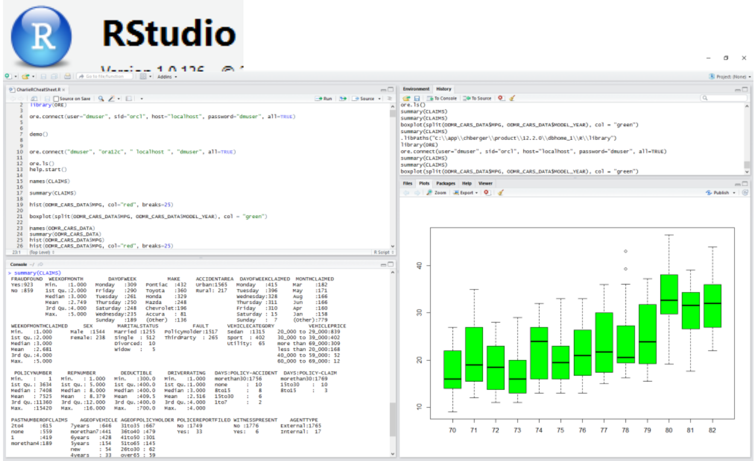
Oracle's Machine Learning/Advanced Analytics



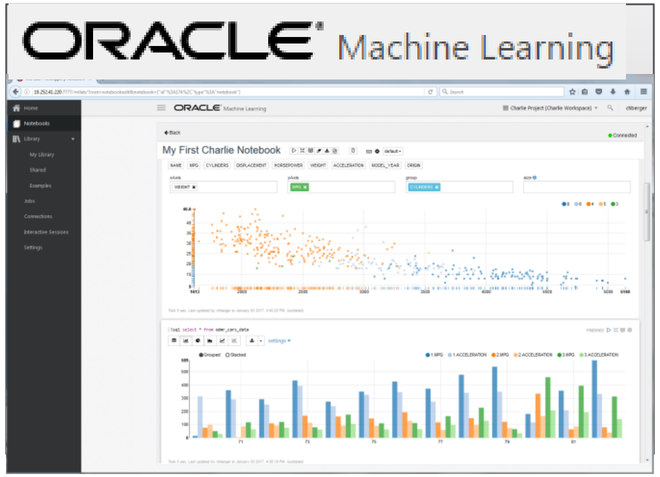
DBAs



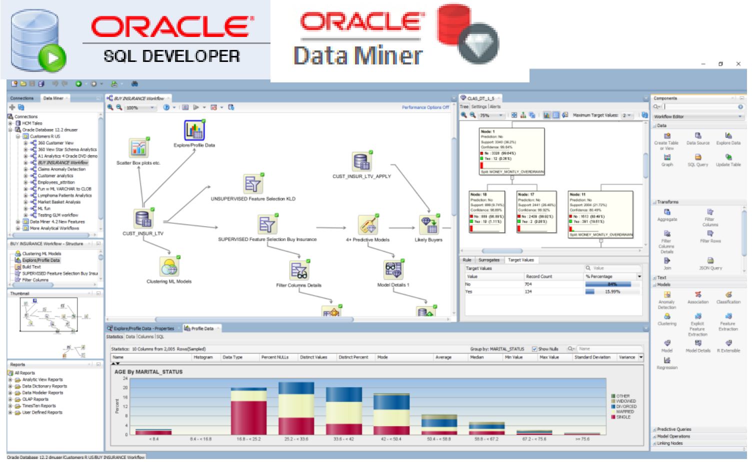
Application Developers



R Users, Data Scientists



OML SQL Notebook Users

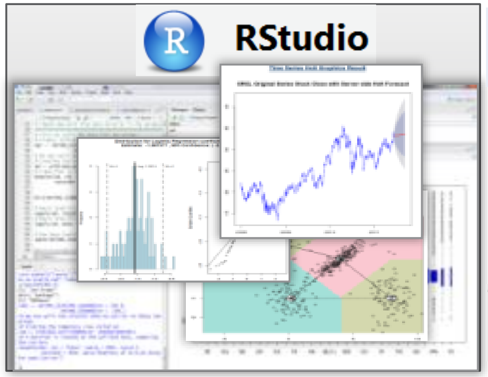


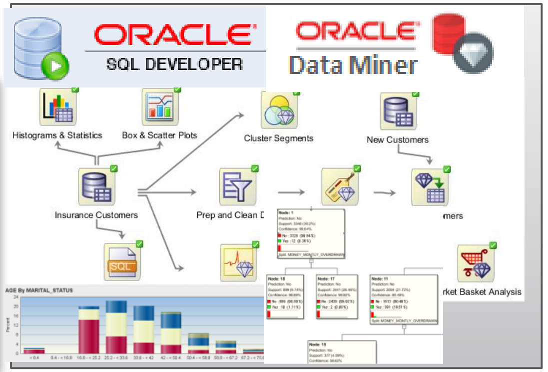
Data Analyst, Citizen Data Scientists

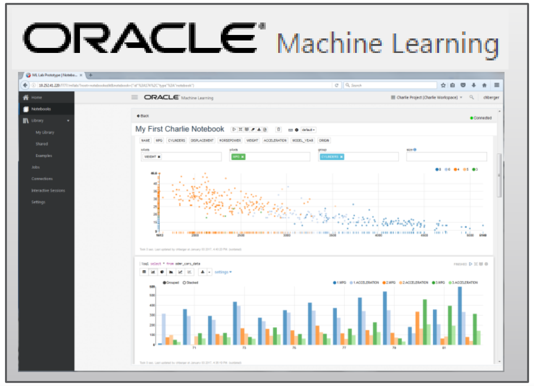
ORACLE

Manage and Analyze All Your Data

Data Scientists, R Users, Citizen Data Scientists







Architecturally, Many Options and Flexibility

SQL / R

Boil down the Data Lake

Big Data SQL / R

"Engineered Features"

– Derived attributes that reflect domain knowledge—key to best models e.g:

- Counts
- Totals
- Changes over time

Object Store

NoSQL

ORACLE

kafka

ORACLE

Oracle's Machine Learning & Adv. Analytics Algorithms

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
- Holt-Winters, Regular & Irregular, with and w/o trends & seasonal
- Single, Double Exp Smoothing

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, SQL Aggregates

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

Text Mining Support
- Algorithms support text type
- 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 Packages
- CRAN R Algorithm Packages through Embedded R Execution
- Spark MLlib algorithm integration

Exportable ML Models
- C and Java code for deployment

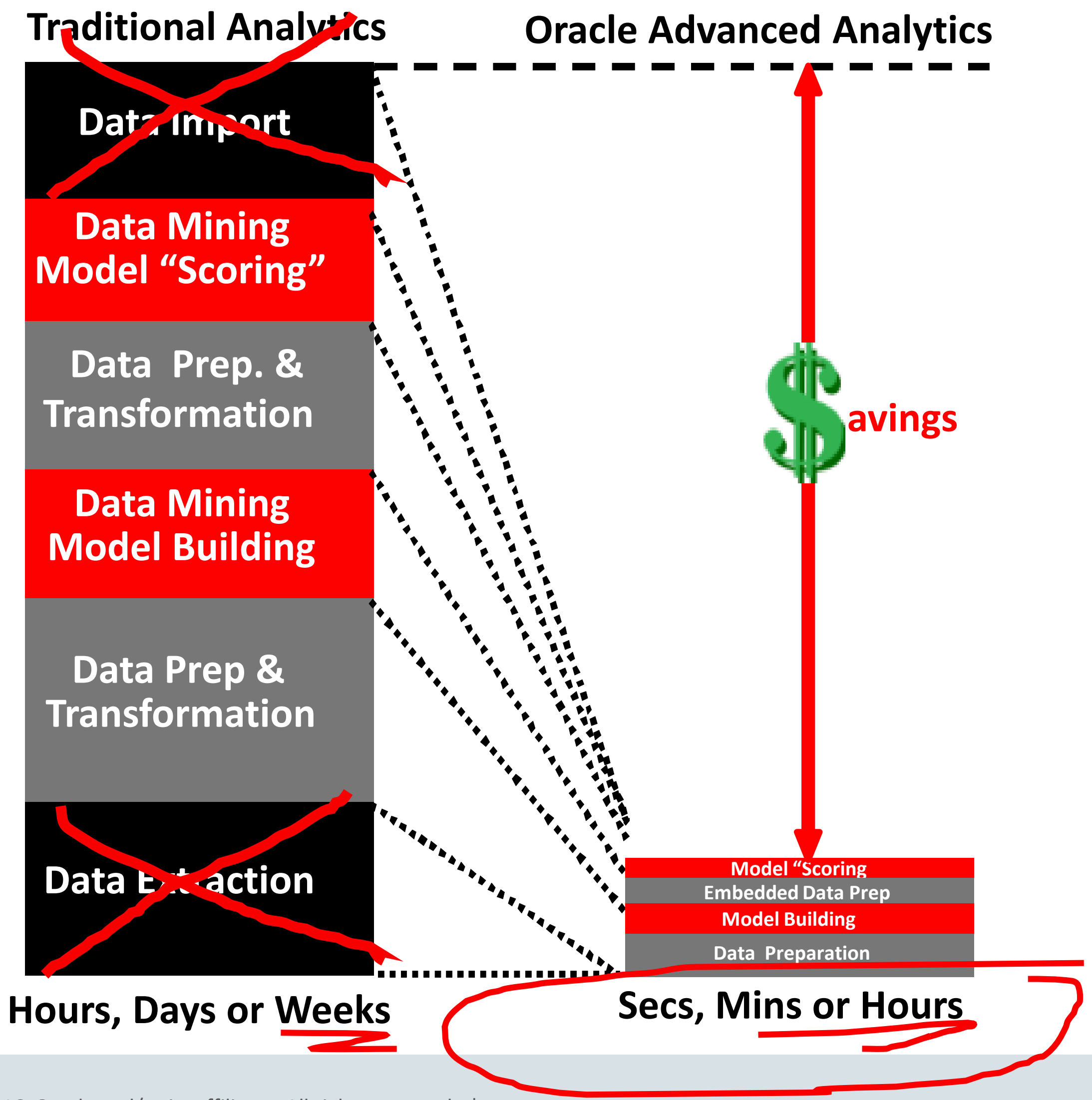
- OAA (Oracle Data Mining + Oracle R Enterprise) and ORAAH combined
- OAA includes support for Partitioned Models, Transactional, Unstructured, Geo-spatial, Graph data. etc,

Oracle's Machine Learning/Advanced Analytics

Fastest Way to Deliver Enterprise-wide Predictive Analytics

Major Benefits

- Data remains in Database & Hadoop
  - Model building and scoring occur in-database
  - Use R packages with data-parallel invocations
- Leverage investment in Oracle IT
  - Eliminate data duplication
  - Eliminate separate analytical servers
- Deliver enterprise-wide applications
  - GUI for ML/Predictive Analytics & code gen
  - R interface leverages database as HPC engine



Oracle Advanced Analytics 12.2

Model Build Time Performance

Unofficial

NEW IN 12.2

OAA 12.2 Algorithms	Rows (Ms)	T7-4 (Sparc & Solaris) Model Build Time (Secs / Degree of Parallelism)	X5-4 (Intel and Linux)
Attributes Importance	640	28s / 512	44s / 72
K Means Clustering	640	161s / 256	268s / 144
Expectation Maximization	159	455s / 512	588s / 144
Naive Bayes Classification	320	17s / 256	23s / 72
GLM Classification	640	154s / 512	363s / 144
GLM Regressior			
Support Vector			
Support Vector Machine (SGD solver)	[illegible]	[illegible] / 256	[illegible] / 72

Wow! That's *Fast!*

In 24 hours, could build new predictive models for entire United States Population, for 400 attributes, 4 times!

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The way to read their results is that they compare 2 chips: X5 (Intel and Linux) and T7 (Sparc and Solaris). They are measuring scalability (time in seconds) with increase degree of parallelism (dop). The data also has high cardinality categorical columns which translates in 9K mining attributes (when algorithms require explosion). There are no comparisons to 12.1 and it is fair to say that the 12.1 algorithms could not run on data of this size.

Fraud Prediction Demo

Automated In-DB Analytical Methodology

```
drop table CLAIMS_SET;
exec dbms_data_mining.drop_model('CLAIMSMODEL');
create table CLAIMS_SET (setting_name varchar2(30), setting_value varchar2(4000));
insert into CLAIMS_SET values ('ALGO_NAME','ALGO_SUPPORT_VECTOR_MACHINES');
insert into CLAIMS_SET values ('PREP_AUTO','ON');
commit;
```

```
begin
dbms_data_mining.create_model('CLAIMSMODEL', 'CLASSIFICATION',
  'CLAIMS', 'POLICYNUMBER', null, 'CLAIMS_SET');
end;
/
```

```
-- Top 5 most suspicious fraud policy holder claims
select * from
(select POLICYNUMBER, round(prob_fraud*100,2) percent_fraud,
     rank() over (order by prob_fraud desc) rnk from
(select POLICYNUMBER, prediction_probability(CLAIMSMODEL, '0' using *) prob_fraud
from CLAIMS
where PASTNUMBEROFCLAIMS in ('2to4', 'morethan4')))
where rnk <= 5
order by percent_fraud desc;
```

Script Output × Query Result ×

SQL | All Rows Fetched: 5 in 0.064 seconds

	POLICYNUMBER	PERCENT_FRAUD	RNK
1	654	61.87	1
2	11068	57.37	2
3	7435	55.47	3
4	3599	55.4	4
5	14877	55.37	5

Automated Monthly "Application"! *Just add:*

Create
View CLAIMS2_30
As
Select * from CLAIMS2
Where mydate > SYSDATE – 30

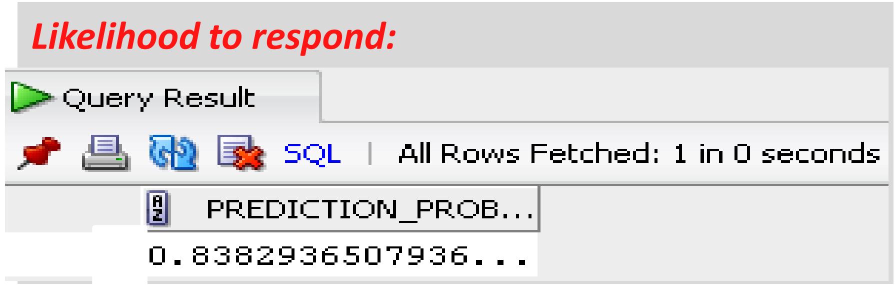
Time measure: set timing on;

Oracle Advanced Analytics

Real-Time Scoring, Predictions and Recommendations

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

```
Select prediction_probability(CLAS_DT_1_15, 'Yes'
   USING 7800 as bank_funds, 125 as checking_amount, 20 as
   credit_balance, 55 as age, 'Married' as marital_status,
   250 as MONEY_MONTLY_OVERDRAWN, 1 as house_ownership)
from dual;
```



Oracle Cloud

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Build Predictive Models on an Attribute

Oracle's Machine Learning Accelerates New Possibilities

Machine Learning Model ➔ Function(X_1, X_2, ….X) ➔ Y (LTV_BIN); Probability

	CUST_ID	AGE	SEX	MARITAL_STATUS	N_TRANS_ATM	LTV	CHECKING_AMOUNT	BANK_FUNDS	SALARY	HOUSE_OWNERSHIP	PROFESSION	LTV_BIN	Probability
1	CU8617	46.0000	M	MARRIED	2.0000	34,040.0000	25.0000	0.0000	63,760...	2.0000	Cashier	VERY HIGH	.91
2	CU7115	27.0000	M	DIVORCED	5.0000	20,843.2500	25.0000	0.0000	58,573...	1.0000	PROF-14	MEDIUM	.77
3	CU7117	30.0000	F	DIVORCED	5.0000	28,306.5000	349.0000	6,300.0000	65,226...	2.0000	Administrator	HIGH	.64
4	CU7118	33.0000	M	DIVORCED	1.0000	26,480.2500	25.0000	0.0000	68,721...	1.0000	Nurse	HIGH	.78
5	CU7120	21.0000	M	DIVORCED	3.0000	22,012.0000	25.0000	0.0000	57,648...	1.0000	Professor	HIGH	.52
6	CU7121	32.0000	F	MARRIED	2.0000	20,904.5000	999.0000	201.0000	60,818...	1.0000	PROF-38	MEDIUM	.93
7	CU7123	35.0000	M	MARRIED	2.0000	22,330.5000	92.0000	8,200.0000	61,322...	1.0000	Clerical	HIGH	.83
8	CU7124	44.0000	F	DIVORCED	5.0000	23,085.5000	25.0000	2,000.0000	60,742...	1.0000	PROF-1	HIGH	.54
9	CU7125	63.0000	M	MARRIED	1.0000	25,383.0000	25.0000	0.0000	62,332...	1.0000	Waiter/Waitress	HIGH	.74
10	CU7127	58.0000	M	WIDOWED	2.0000	29,106.0000	25.0000	0.0000	69,224...	1.0000	Nurse	HIGH	.68
11	CU7128	26.0000	M	SINGLE	1.0000	15,084.7500	708.0000	1,100.0000	65,939...	0.0000	Programmer/...	MEDIUM	.55
12	CU7129	28.0000	M	MARRIED	0.0000	30,351.7500	25.0000	0.0000	66,207...	1.0000	Nurse	VERY HIGH	.78
13	CU7131	47.0000	F	DIVORCED	4.0000	25,222.7500	1,186.0000	2,800.0000	68,091...	1.0000	School Teacher	HIGH	.93
14	CU7132	39.0000	M	SINGLE	0.0000	32,064.7500	25.0000	0.0000	68,659...	1.0000	Nurse	VERY HIGH	.98
15	CU7133	26.0000	F	MARRIED	3.0000	15,425.2500	25.0000	0.0000	61,301...	1.0000	Fireman	MEDIUM	.89
16	CU7134	38.0000	M	SINGLE	1.0000	20,695.2500	25.0000	0.0000	63,581...	0.0000	Nurse	MEDIUM	.90
17	CU7135	42.0000	M	SINGLE	1.0000	21,900.7500	25.0000	0.0000	66,803...	0.0000	Nurse	MEDIUM	.76
18	CU7136	36.0000	M	SINGLE	1.0000	22,064.7500	25.0000	0.0000	69,859...	0.0000	Nurse	HIGH	.92
19	CU7137	23.0000	M	SINGLE	0.0000	20,237.2500	25.0000	0.0000	67,749...	0.0000	Nurse	MEDIUM	.65
20	CU7138	38.0000	F	MARRIED	5.0000	24,152.5000	25.0000	2,150.0000	67,410...	1.0000	Veterinarian	HIGH	.93

Build Predictive Models on an Attribute

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Machine Learning Model ➔ Function(X_1, X_2, ….X) ➔ Y (LTV_BIN); Probability

	CUST_ID	AGE	SEX	MARITAL_STATUS	N_TRANS_ATM	LTV	CHECKING_AMOUNT	BANK_FUNDS	SALARY	HOUSE_OWNERSHIP	PROFESSION	LTV_BIN	Probability
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Build Predictive Models on an Attribute

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Machine Learning Models ➔ Function(X_1, X_2, ….X) ➔ Y2 (BankFunds ➔ Y (LTV_BIN); Probability

	CUST_ID	AGE	SEX	MARITAL_STATUS	N_TRANS_ATM	LTV	CHECKING_AMOUNT	BANK_FUNDS	P(BankFunds)	SALARY	HOUSE_OWNERSHIP	PROFESSION	LTV_BIN	Probability
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3	CU7117	30.0000	F	DIVORCED	5.0000	28,306.5000	349.0000	6,300.0000	35,000,000	65,226…	2.0000	Administrator	HIGH	.64
4	CU7118	33.0000	M	DIVORCED	1.0000	26,480.2500	25.0000	0.0000	150,000	68,721…	1.0000	Nurse	HIGH	.78
5	CU7120	21.0000	M	DIVORCED	3.0000	22,012.0000	25.0000	0.0000	-5,000	57,648…	1.0000	Professor	HIGH	.52
6	CU7121	32.0000	F	MARRIED	2.0000	20,904.5000	999.0000	201.0000	210,000	60,818…	1.0000	PROF-38	MEDIUM	.93
7	CU7123	35.0000	M	MARRIED	2.0000	22,330.5000	92.0000	8,200.0000	8,500,000	61,322…	1.0000	Clerical	HIGH	.83
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4	CU7118	33.0000	M	DIVORCED	1.0000	26,480.2500	25.0000	0.0000	75	150,000	68,721...	1.0000	Nurse	HIGH	.78
5	CU7120	21.0000	M	DIVORCED	3.0000	22,012.0000	25.0000	0.0000	5,000	-5,000	57,648...	1.0000	Professor	HIGH	.52
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11	CU7128	26.0000	M	SINGLE	1.0000	15,084.7500	708.0000	1,100.0000	-75	1,200,000	65,939...	0.0000	Programmer/...	MEDIUM	.55
12	CU7129	28.0000	M	MARRIED	0.0000	30,351.7500	25.0000	0.0000	225	17,000	66,207...	1.0000	Nurse	VERY HIGH	.78
13	CU7131	47.0000	F	DIVORCED	4.0000	25,222.7500	1,186.0000	2,800.0000	860	2,750,000	68,091...	1.0000	School Teacher	HIGH	.93
14	CU7132	39.0000	M	SINGLE	0.0000	32,064.7500	25.0000	0.0000	268	0	68,659...	1.0000	Nurse	VERY HIGH	.98
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18	CU7136	36.0000	M	SINGLE	1.0000	22,064.7500	25.0000	0.0000	5,000	12,000	69,859...	0.0000	Nurse	HIGH	.92
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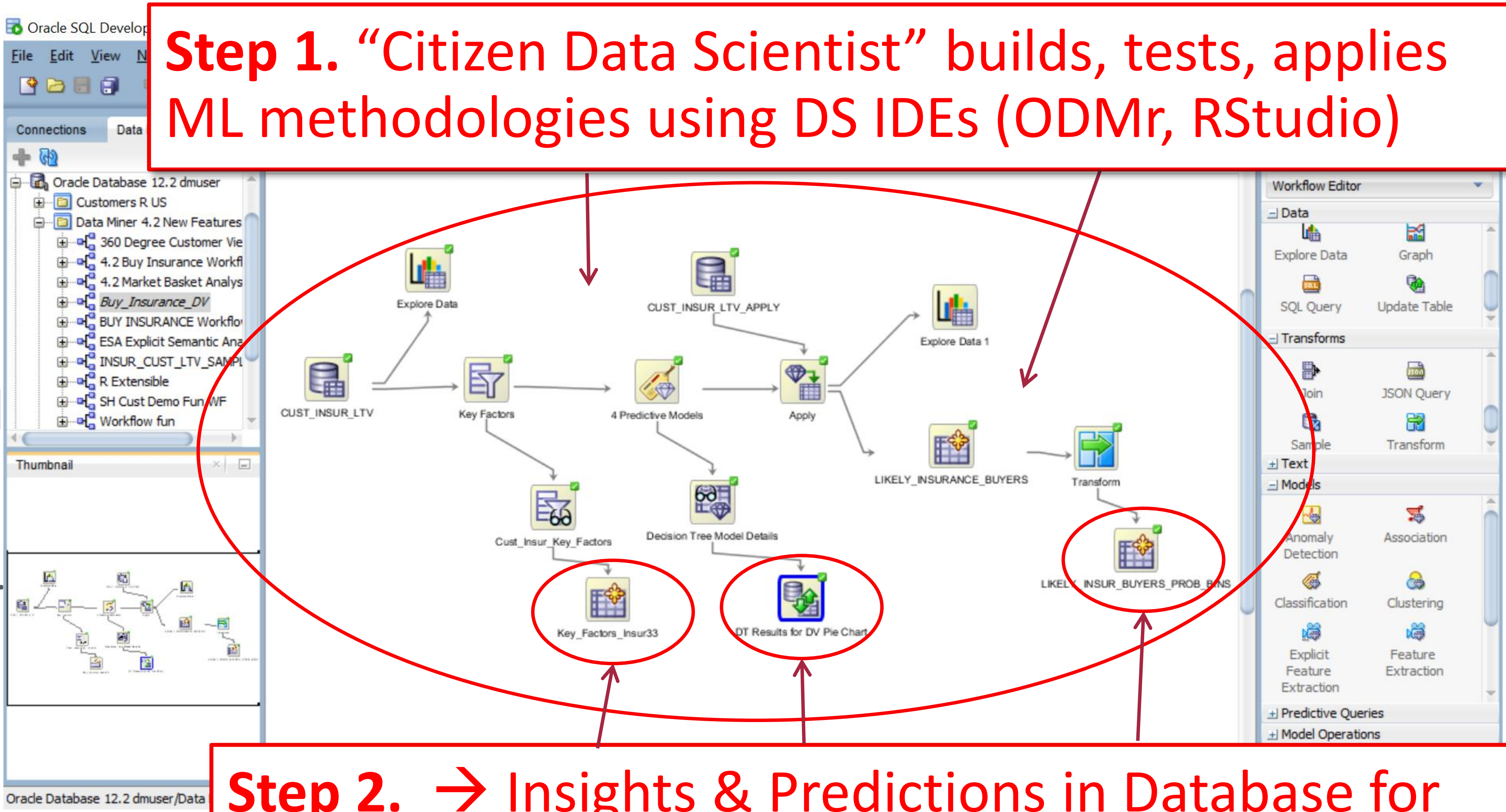
20	CU7138	38.0000	F	MARRIED	5.0000	24,152.5000	25.0000	2,150.0000	497	2,200,000	67,410...	1.0000	Veterinarian	HIGH	.93

Oracle Data Miner "Workflow" UI

Easy to use for "Citizen Data Scientist"; Fast to Deploy via SQL and PL/SQL Scripts

- SQL Developer Extension
- Easy to use to define analytical methodologies that can be shared
- Workflow API and generates SQL code for deployment



Step 1. "Citizen Data Scientist" builds, tests, applies ML methodologies using DS IDEs (ODMr, RStudio)

Step 2. → Insights & Predictions in Database for OAC/DV user additional Viz/Analytics

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Oracle Cloud

Targeting High Credit Customers - Oracle Data Visualization Desktop

ORACLE Data Visualization Desktop

Targeting High Credit Customers - Project

Prepare | Visualize | Narrate | Save

ATTRIBUTE_NAME
CONSUMER_FINDEX_SCORE, WEALTH, +15

Pivot

Columns

Rows
ATTRIBUTE_...

Values
IMPORTANC...
RANK

Color

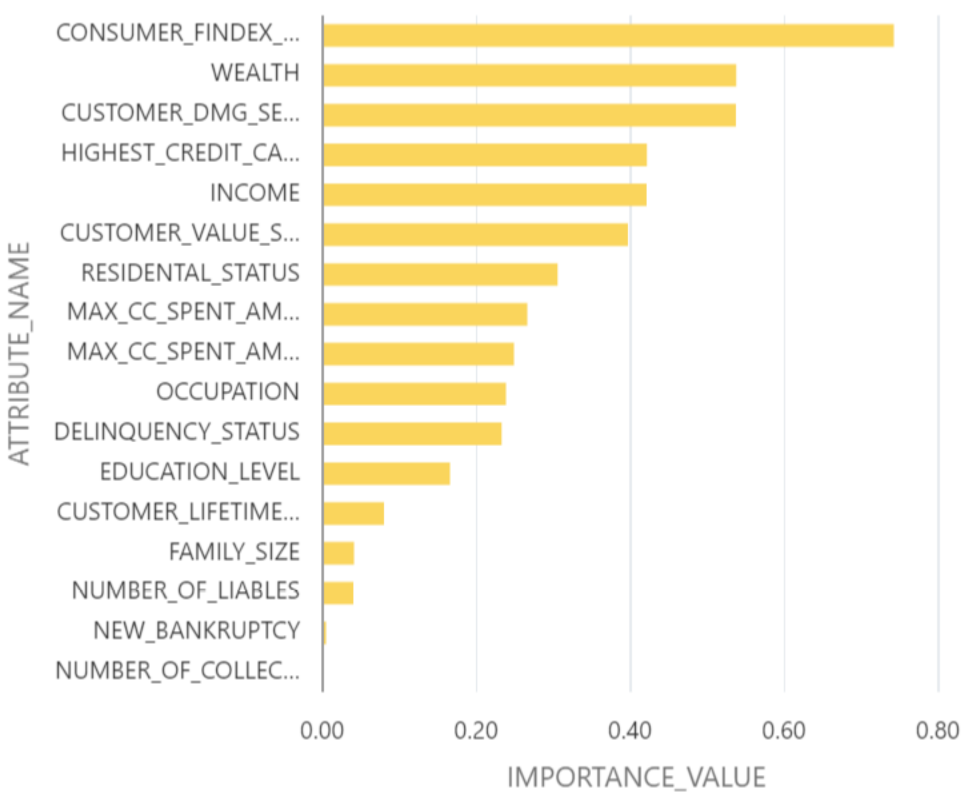
Size

Shape

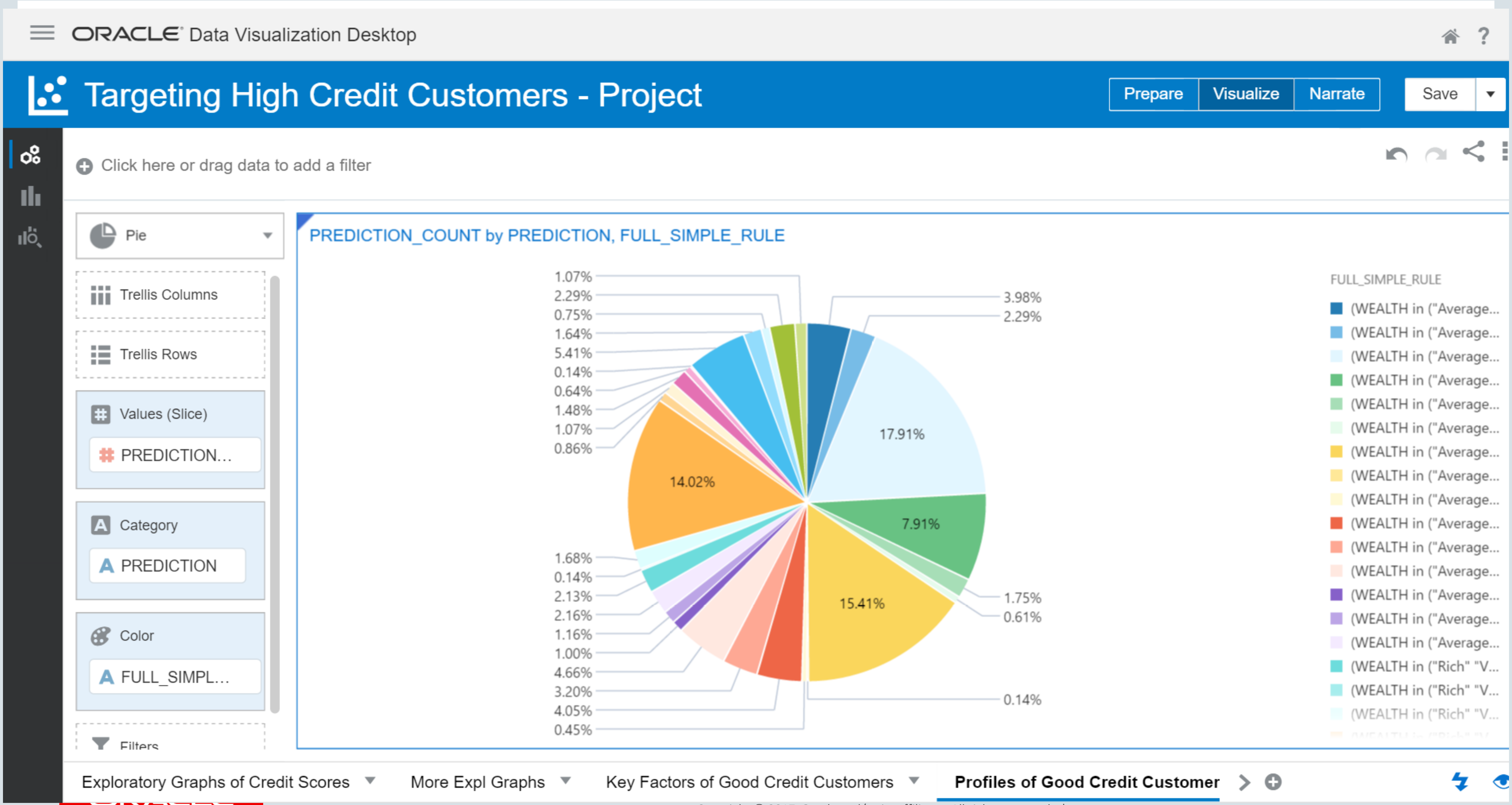
IMPORTANCE_VALUE, RANK by ATTRIBUTE_NAME

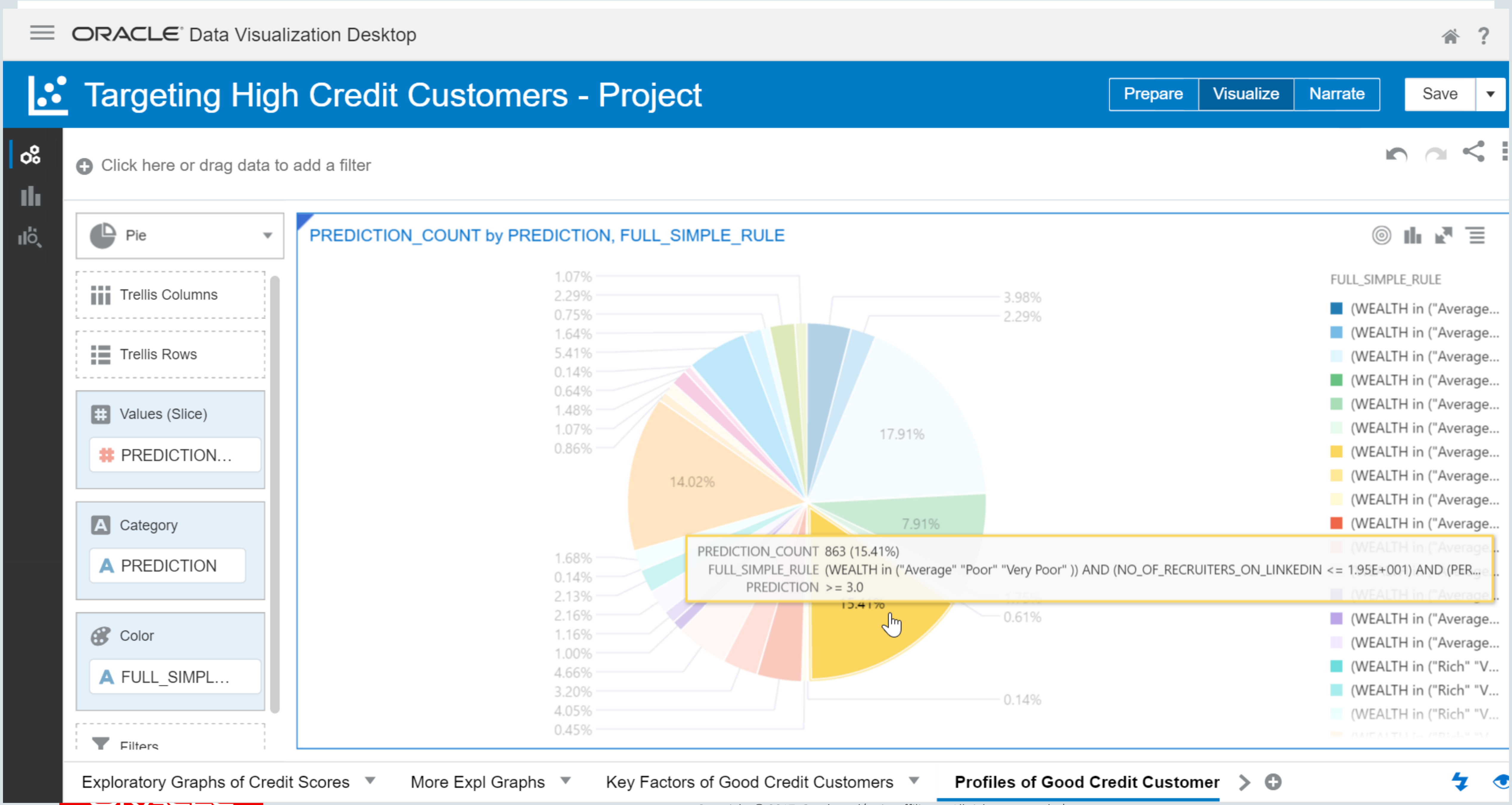
	IMPORTANCE_VALUE	RANK
CONSUMER_FINDEX_SCORE	0.74	1
CUSTOMER_DMG_SEGMENT	0.54	3
CUSTOMER_LIFETIME_VALUE	0.08	13
CUSTOMER_VALUE_SEGMENT	0.40	6
DELINQUENCY_STATUS	0.23	11
EDUCATION_LEVEL	0.17	12
FAMILY_SIZE	0.04	14
HIGHEST_CREDIT_CARD_LIMIT	0.42	4
INCOME	0.42	5
MAX_CC_SPENT_AMOUNT	0.25	9
MAX_CC_SPENT_AMOUNT_PREV	0.27	8
NEW_BANKRUPTCY	0.00	16
NUMBER_OF_COLLECTIONS	0.00	17
NUMBER_OF_LIABLES	0.04	15
OCCUPATION	0.24	10

IMPORTANCE_VALUE by ATTRIBUTE_NAME



Exploratory Graphs of Credit Scores | More Expl Graphs | **Key Factors of Good Credit Customers** | Profiles of Good Credit Customer


ORACLE Data Visualization Desktop
Targeting High Credit Customers - Project
Prepare
Visualize
Narrate
Save
Click here or drag data to add a filter
Pie
Trellis Columns
Trellis Rows
Values (Slice)
PREDICTION...
Category
PREDICTION
Color
FULL_SIMPL...
Filters
PREDICTION_COUNT by PREDICTION, FULL_SIMPLE_RULE
1.07%
2.29%
0.75%
1.64%
5.41%
0.14%
0.64%
1.48%
1.07%
0.86%
3.98%
2.29%
17.91%
14.02%
7.91%
15.41%
1.68%
0.14%
2.13%
2.16%
1.16%
1.00%
4.66%
3.20%
4.05%
0.45%
1.75%
0.61%
0.14%
FULL_SIMPLE_RULE
(WEALTH in ("Average...
(WEALTH in ("Rich" "V...
Exploratory Graphs of Credit Scores
More Expl Graphs
Key Factors of Good Credit Customers
Profiles of Good Credit Customer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Prepare
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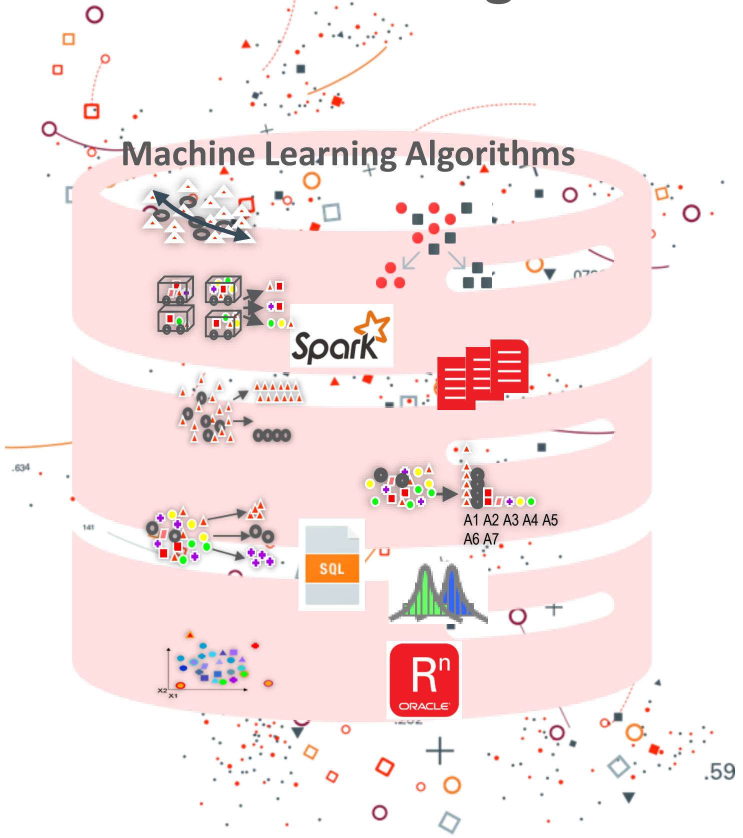
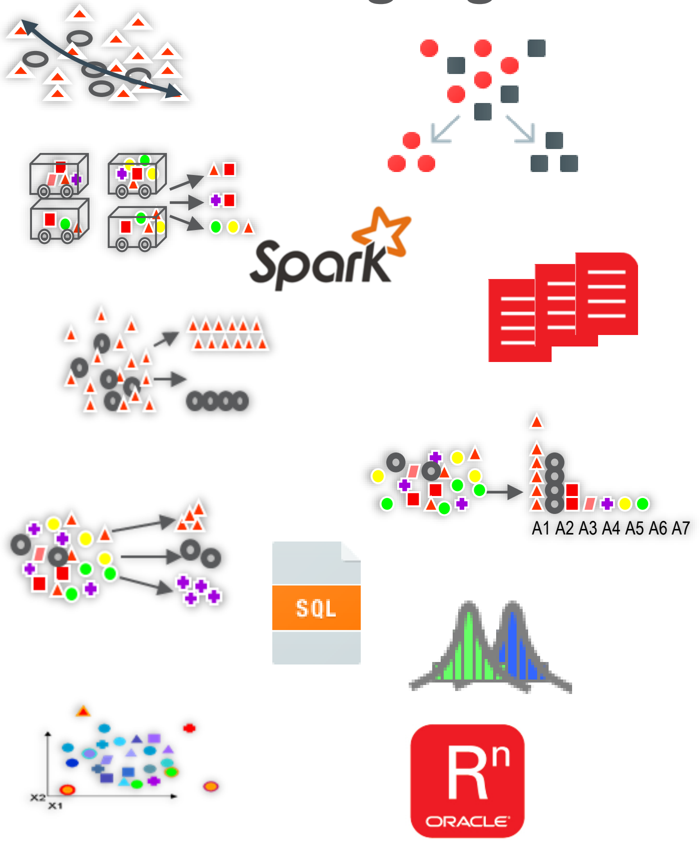
Click here or drag data to add a filter
Pie
Trellis Columns
Trellis Rows
Values (Slice)
PREDICTION...
Category
PREDICTION
Color
FULL_SIMPL...
Filters
PREDICTION_COUNT by PREDICTION, FULL_SIMPLE_RULE
FULL_SIMPLE_RULE
(WEALTH in ("Average...
(WEALTH in ("Rich" "V...
PREDICTION_COUNT 863 (15.41%)
FULL_SIMPLE_RULE (WEALTH in ("Average" "Poor" "Very Poor")) AND (NO_OF_RECRUITERS_ON_LINKEDIN <= 1.95E+001) AND (PER...
PREDICTION >= 3.0
17.91%
14.02%
7.91%
Exploratory Graphs of Credit Scores
More Expl Graphs
Key Factors of Good Credit Customers
Profiles of Good Credit Customer

The Core Ingredients of Good Machine Learning

Domain Knowledge + Data



Machine Learning Algorithms



Insights, Predictions

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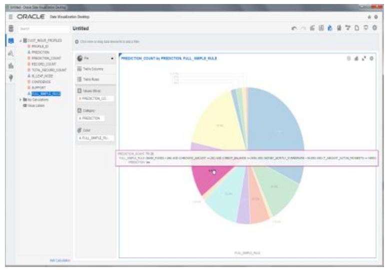
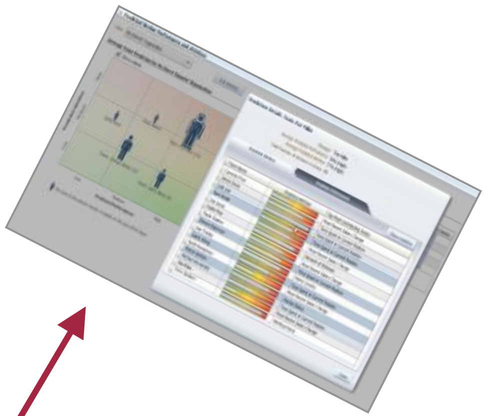
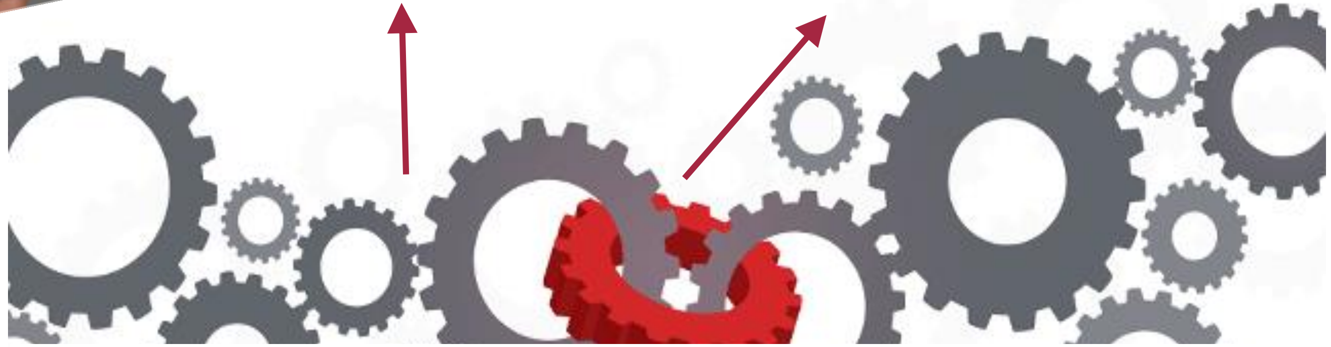
Most Important Factor in Machine Learning? <u>**Deployment!!**</u>

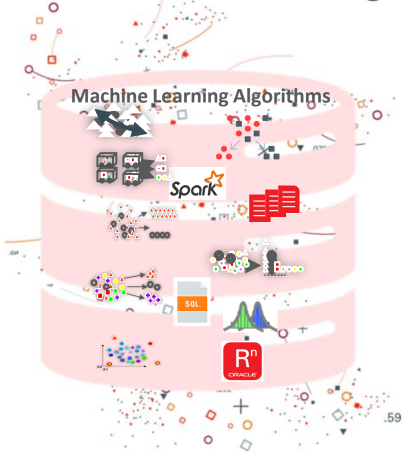




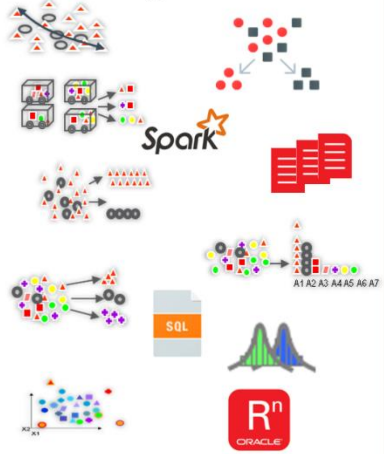


A *"Thinking"* Database

Data + Domain Knowledge



ML Algorithms



Models, Insights, Predictions

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Summary & Next Steps

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Oracle's Machine Learning & Advanced Analytics Data Management Platforms

Summary

- Machine learning, predictive analytics & "AI" have become *must-have* requirements
- Enterprises whose data science teams most rapidly extract predictions and insights win
- Separate islands for data management and for data science don't work
- Evolve towards combined data management + advanced analytics environ that can analyze data, perform machine learning and essentially to "think"
- "Operationalize" ML methodologies and discovered insights & predictions thru organizations for process automation and customer behavior anticipation

Getting Started—Oracle ML/AA Resources & Links

ORACLE Oracle Advanced Analytics Overview Information

- Oracle's Machine Learning and Advanced Analytics 12.2c and Oracle Data Miner 4.2 New Features *preso*
- Oracle Advanced Analytics Public Customer References
- Oracle’s Machine Learning and Advanced Analytics Data Management Platforms white paper on OTN
- *Oracle INTERNAL ONLY* OAA Product Management Wiki and Beehive Workspace (contains latest presentations, demos, product, etc. information)

YouTube recorded Oracle Advanced Analytics Presentations and Demos, White Papers

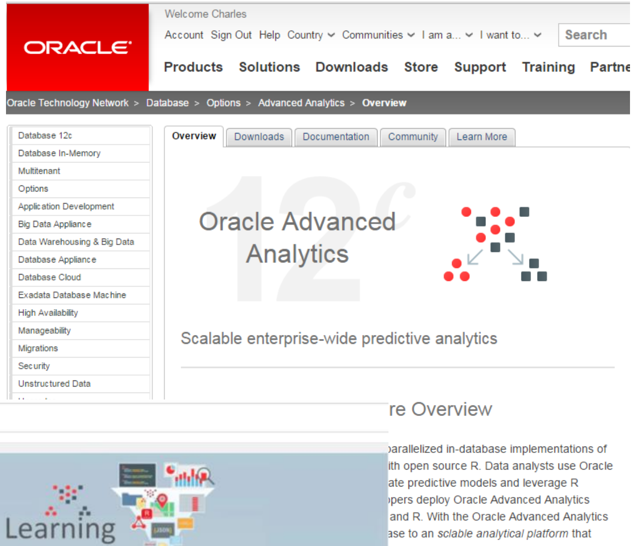
- Oracle's Machine Learning & Advanced Analytics 12.2 & Oracle Data Miner 4.2 New Features YouTube video
- Library of YouTube Movies on Oracle Advanced Analytics, Data Mining, Machine Learning (7+ “live” Demos e.g. Oracle Data Miner 4.0 New Features, Retail, Fraud, Loyalty, Overview, etc.)
- Overview YouTube video of Oracle’s Advanced Analytics and Machine Learning

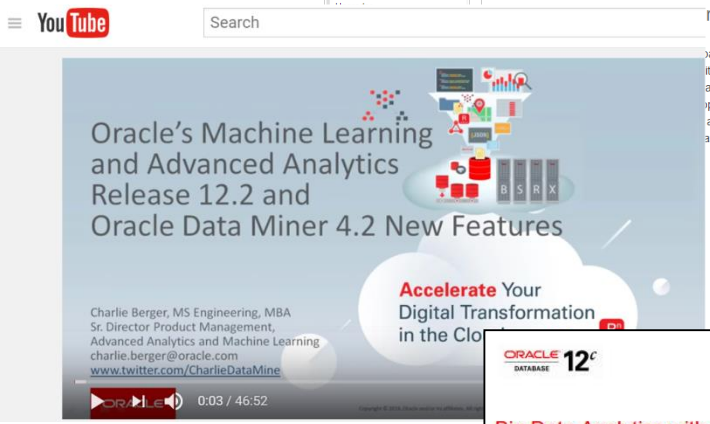
ORACLE UNIVERSITY Getting Started/Training/Tutorials

- Link to OAA/Oracle Data Miner Workflow GUI Online (free) Tutorial Series on OTN
- Link to OAA/Oracle R Enterprise (free) Tutorial Series on OTN
- Link to Try the Oracle Cloud Now!
- Link to Getting Started w/ ODM blog entry
- Link to New OAA/Oracle Data Mining 2-Day Instructor Led Oracle University course.
- Oracle Data Mining Sample Code Examples

ORACLE Help Center Additional Resources, Documentation & OTN Discussion Forums

- Oracle Advanced Analytics Option on OTN page
- OAA/Oracle Data Mining on OTN page, ODM Documentation & ODM Blog
- OAA/Oracle R Enterprise page on OTN page, ORE Documentation & ORE Blog
- Oracle SQL based Basic Statistical functions on OTN
- Oracle R Advanced Analytics for Hadoop (ORAAH) on OTN





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