Al Summit 발표 자료

대규모 데이터의 처리를 위한 In-DB Machine Learning과 AutoML

M/L의 쉬운 활용을 통해 Citizen Data Scientist 지원

장성우 전무

Cloud Engineering, Oracle Korea Dec 9, 2021



Overall Message

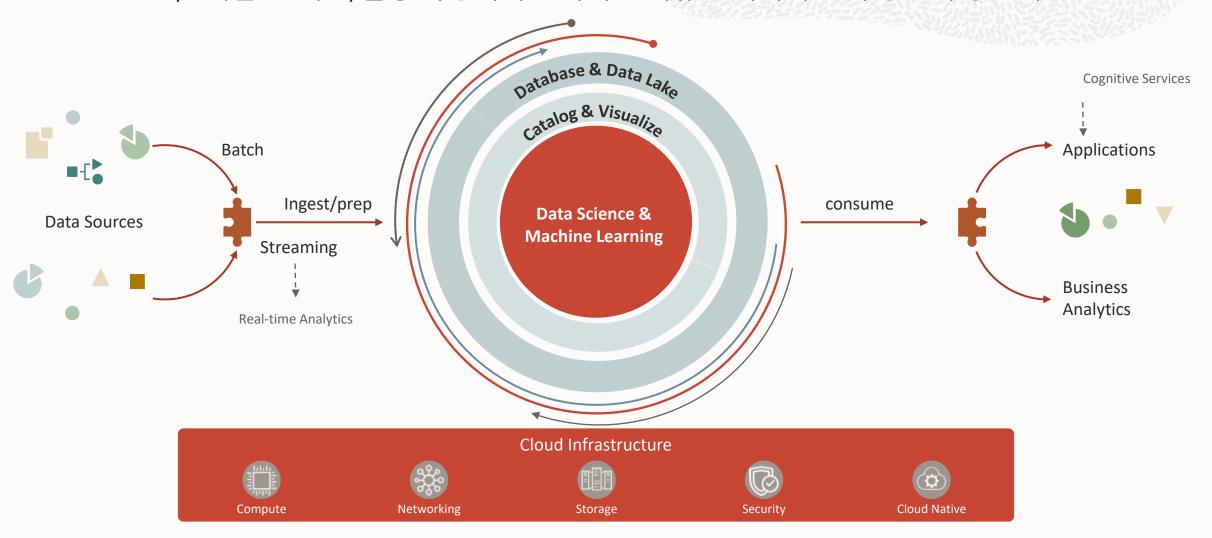
- Data Scientist가 접하는 어려움
 - ✓ 대규모 데이터의 빠른 처리를 통한 생산성 향상 필요
 - ✓ 수많은 데이터 관리 작업과 복잡한 M/L Process 수반
- In-DB Machine Learning
 - ✓ 대규모 데이터의 이동 없이 DB 안에서 M/L 기반 분석/예측 작업 가능
 - ✓ 알고리즘의 병렬 수행 지원을 통한 성능 향상
- AutoML
 - ✓ 예측력/성능이 좋은 M/L 알고리즘을 자동으로 선택
- Autonomous DB
 - ✓ Data Scientist는 모델에만 집중하고 나머지 DB 관리 작업은 ADB가 자율적으로 수행
- Oracle Machine Learning: In-DB M/L + AutoML + Autonomous DB
 - ✓ M/L의 쉬운 활용을 통해 Citizen Data Scientist 지원

Agenda

- Machine Learning Overview
- In-Database Machine Learning
 - Supporting Algorithms
 - Performance
 - Interface Method for Python, R and SQL
- AutoML
 - Methodology
 - Performance Improvement
- Autonomous DB
 - Architecture
 - Auto-Scaling
- Summaries : Oracle Machine Learning

Data Scientist | Machine Learning Process

End-2-End M/L 개발 및 배포/활용 과정에서 효과적인 대규모 데이터 관리 방안이 중요해짐



Factors Affecting Machine Learning Performance

Data volume – the most obvious factor is the amount of data involved

Data movement and loading

- related to data volume is the performance impact of moving data from one environment to another.
- this time needs to be considered when comparing machine learning tools and processes.

Algorithm implementation

- algorithms implemented in a non-parallel or single-threaded manner result in poor performance even when run on multi-processor hardware
- enabling parallelism is often fundamental for improving performance and scalability.

Choice of algorithm – different algorithms can have vastly different computational requirements and results

Concurrent users – # of data scientists working on the system

Load on the system – # of workloads on the system

데이터의 거대화에 따른 HPC 시장의 성장

- 데이터의 거대화는 불가피
 - 과거 20년 동안 빅데이터 시장의 폭발적인 성장
 - 초거대 AI의 출현
 - 클라우드의 성장 및 일반화
- HPC(High Performance Computing) 시장의 성장
 - AI와 Big Data에 따른 HPC 시장의 성장 확대
 - Top500 SC의 성능 증대 → 엑사스케일로 발전 중
 - HPC 수요에 대응하기 위한 민관 투자 증가
 - "국가초고성능컴퓨팅 혁신 전략" 수립 중

"거대 규모 데이터의 빠른 처리를 위한 HPC 시장의 성장 및 확대가 당분간 지속될 것으로 예측됨"

- □ (시 장) 고성능컴퓨터 시장은 '19년 278억 달러에서 '24년 429억 달러로 지속 확대 전망(연평균 9.0% 성장, Hyperion Research, '20)
- 이 데이터 집약적 컴퓨팅의 확산으로 스토리지 시장 급성장 중이며, 슈퍼컴 퓨터급 서버의 비중이 지속 확대(19년 41.8% → '24년 47.7%)
- o 또한, 산학연, 정부기관 각 수요주체별 수요도 안정적으로 증가 중



- □ (기술) 세계 주요국은 차세대 초고성능컴퓨팅 기술로서 인간의 두뇌 처리 능력과 비견되는 엑사스케일급 시스템(1초당 10¹⁸번 연산)" 기술개발 경쟁 중
 - * 현재 가장 빠른 일반PC(200GF) 5백만대 이상의 성능
- o 중앙처리장치 성능은 반도체 집적화('무어의 법칙') 한계로 둔화 상태
- 이기종 멀티코어, 차세대 메모리 구조 등을 통해 연산성능집적도 100배↑
 및 전력효율 3배↑, 높은 확장성·유연성 구현을 위한 기술 개발 중



출처: "국가초고성능컴퓨팅 혁신전략, 2021.5"

대규모 데이터의 빠르고 안정적인 처리를 위한 Oracle Database 기술

단일 엔진 DBMS

- MVCC를 지원하는 DB kernel 기반 위에 지속적으로 새로운 기능을 추가
- 지원 기능별 Version만 상이

Converged Database

- Relational, JSON, Spatial, Graph, Blockchain, XML, Text, LOB 등의 모든 타입의 데이터 모델 지원

• 병렬처리를 위한 RAC(Real Application Cluster)

- H/W 추가(scale-out)를 통한 선형적인 성능 향상 지원

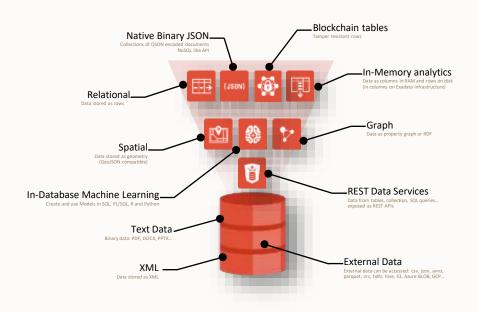
• Extreme Performance를 위한 Exadata DB Machine

- DB 서버와 Storage 서버를 초고속 네트워크로 연결
- 27.6M OLTP Read IOPS 지원(X9M, 8K IO 기준)
- Rack 연결을 통한 수십 PB DB 운영 지원

Autonomous DB

- DB 내에 M/L을 적용하여 auto-management 제공
- Citizen Data Scientist의 기반 제공

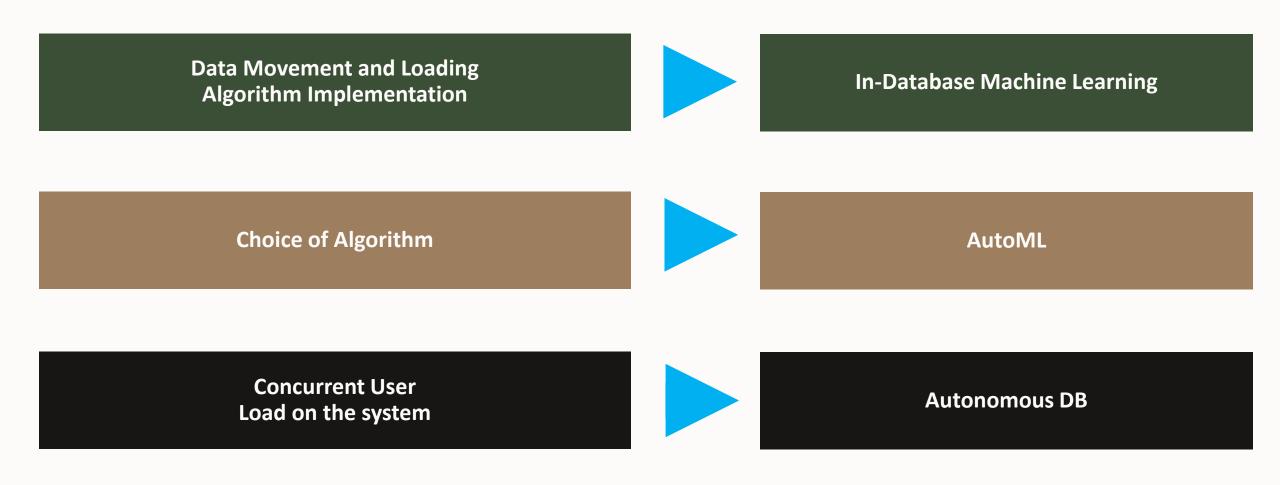






"성능과 안정성의 기반 위에 Emerging Technology를 지속적으로 지원"

Machine Learning Performance 개선을 위한 3가지 방안



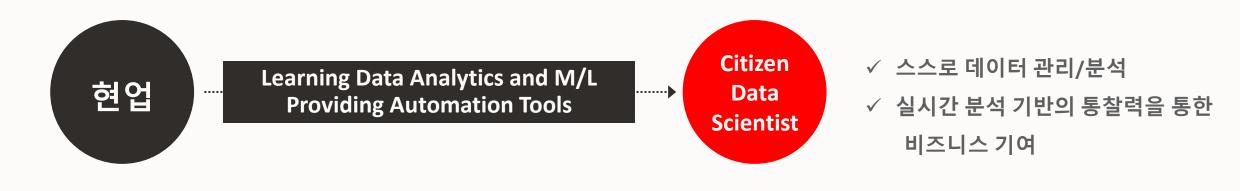
Machine Learning 업무 적용의 현재

현업 담당자는 D/S 조직에 분석 모델을 요청하고, D/S 조직은 모델을 작성/제공하는 과정에서 긴 시간 소요 및 Communication Overhead 발생



현업 담당자가 직접 분석 모델을 만들고 적용하여 분석의 실시간성 및 업무의 효율성을 높일 필요가 있음
→ Citizen Data Scientist의 필요 이유

Citizen Data Scientist 확산의 전제 조건

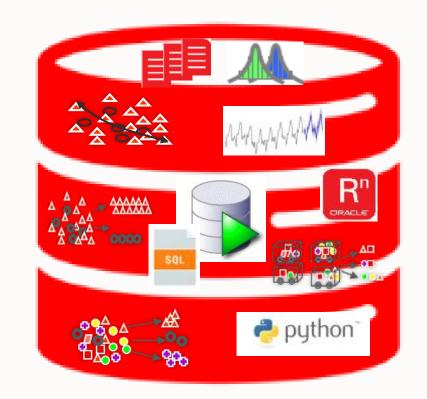


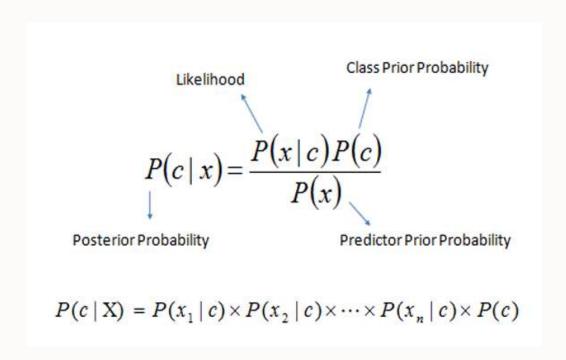
- Machine Learning Process의 간소화 필요
 - 현업 담당자는 데이터 혹은 시스템 관리의 부담 없이
 - 업무에 대한 지식을 기반으로 분석 대상과 목표만 정의하면
 - 쉬운 UI 혹은 Low-Code 환경을 통해
 - M/L 알고리즘의 선택 및 모델 생성 작업을 시스템이 자동적으로 지원해 줄 수 있어야함
- 지원 방안 : In-DB M/L + AutoML + Autonomous DB

In-DB Machine Learning

M/L Algorithms Operate on Data in Database







DB의 성능과 안정성 기반 위에
DB 내 대규모 데이터에 대한 M/L 알고리즘 적용을 지원하여
데이터 이동 최소화 및 병렬 처리를 통한 성능 향상 제공

Machine Learning Algorithms and Analytics in Oracle Database

CLASSIFICATION

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

ANOMALY DETECTION

- One-Class SVM
- MSET-SPRT*

CLUSTERING

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

TIME SERIES

- Forecasting Exponential Smoothing
- Includes popular models

 e.g. Holt-Winters with trends,
 seasonality, irregular time series

REGRESSION

- Generalized Linear Model (GLM)
- Support Vector Machine (SVM)
- Stepwise Linear regression
- Neural Network
- XGBoost*

ATTRIBUTE IMPORTANCE

- Minimum Description Length
- Principal Component Analysis (PCA)
- Unsupervised Pairwise KL Divergence
- CUR decomposition for row & AI

ASSOCIATION RULES

• A priori

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)

ROW IMPORTANCE

CUR Decomposition

RANKING

XGBoost*

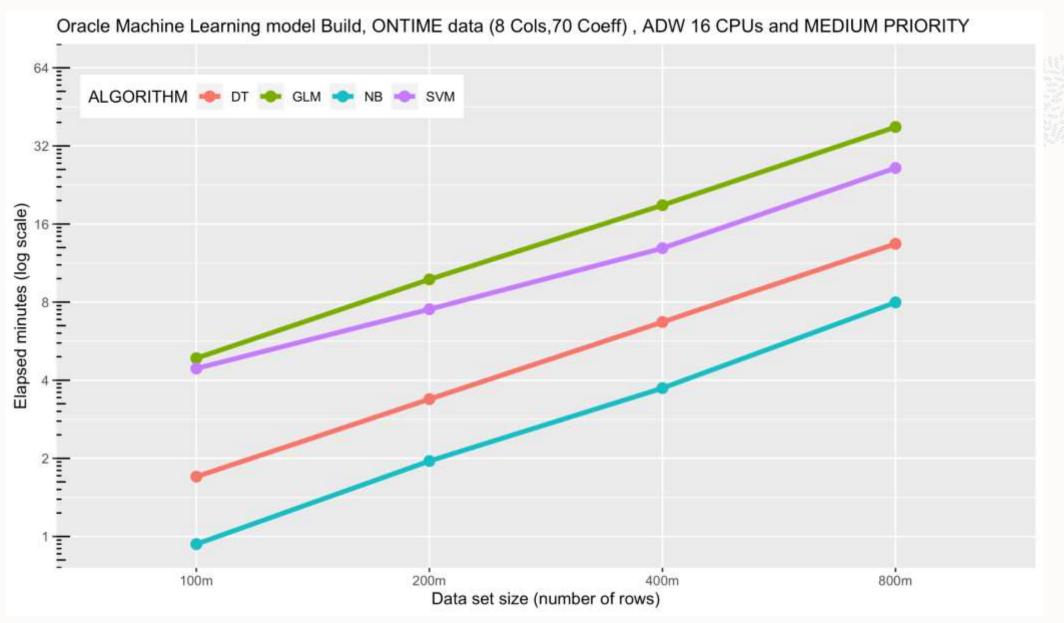
TEXT MINING SUPPORT

- Algorithms support text columns
- Tokenization and theme extraction
- Explicit Semantic Analysis (ESA)

STATISTICAL FUNCTIONS

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

Includes support for Partitioned Models, Transactional data and aggregations

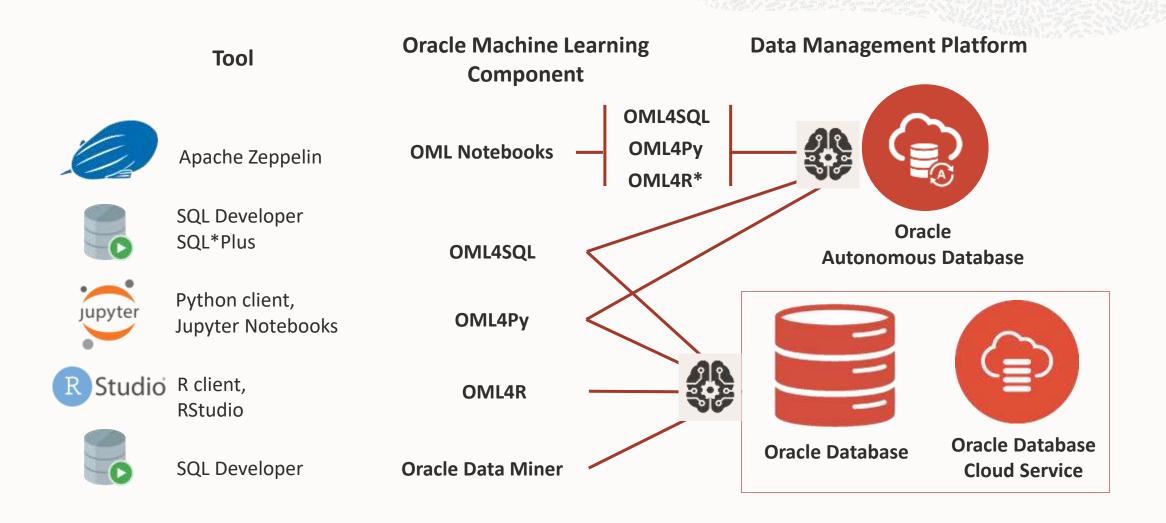


https://blogs.oracle.com/machinelearning/machine-learning-performance-on-autonomous-database



https://blogs.oracle.com/machinelearning/machine-learning-scoring-performance-on-autonomous-database

Oracle Machine Learning interfaces to Oracle Database



Oracle Machine Learning Notebooks

Autonomous Database as a Data Science Platform

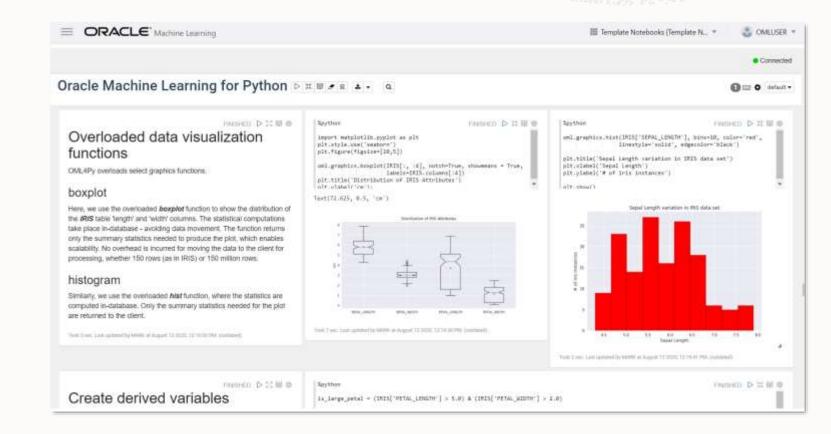


Collaborative UI

- Based on Apache Zeppelin
- Supports data scientists, data analysts, application developers, and DBAs with SQL and Python
- Easy notebook sharing
- Scheduling, versioning, access control

Included with Autonomous Database

- Automatically provisioned and managed
- In-database algorithms and analytics functions
- Explore and prepare, build and evaluate models, score data, deploy solutions



Oracle Machine Learning for R and Python

Empower data scientists with open source environments

Transparency layer

- Leverage proxy objects so data remains in database
- Overload native functions translating functionality to SQL
- Use familiar R / Python syntax on database data

Parallel, distributed algorithms

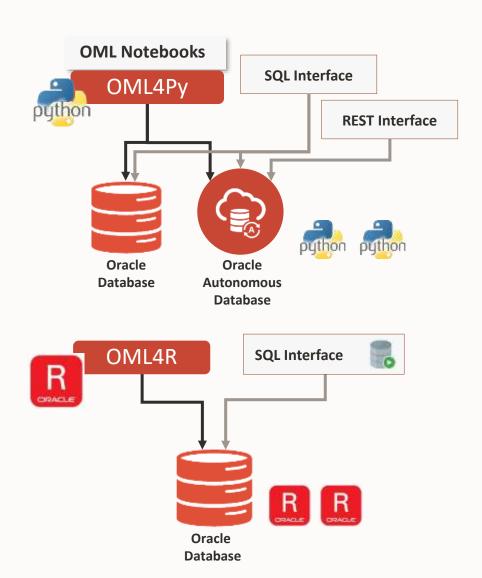
- Scalability and performance
- Exposes in-database algorithms available from OML4SQL

Embedded execution

- Manage and invoke R or Python scripts in Oracle Database
- Data-parallel, task-parallel, and non-parallel execution
- Use open source packages to augment functionality

OML4Py also includes AutoML and MLX

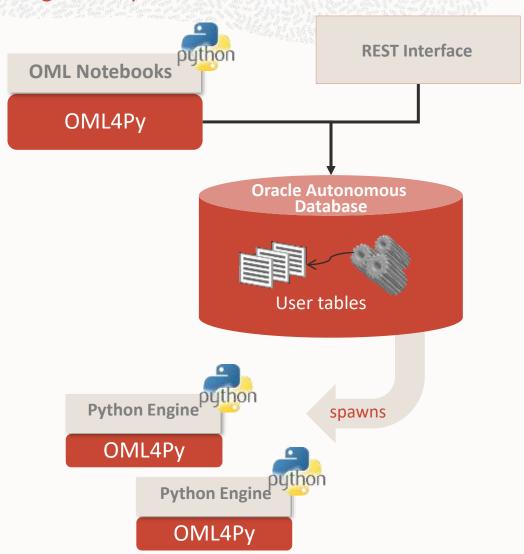
- Automated algorithm selection, feature selection, model tuning
- Algorithm-agnostic model explainability (MLX) for feature ranking



Embedded Execution

Example of parallel partitioned data flow using third party package using OML4Py

```
# user-defined function using sklearn
def build_lm(dat):
  from sklearn import linear model
  lm = linear model.LinearRegression()
  X = dat[['PETAL WIDTH']]
  y = dat[['PETAL LENGTH']]
  lm.fit(X, y)
  return 1m
# select column(s) for partitioning data
index = oml.DataFrame(IRIS['SPECIES'])
# invoke function in parallel on IRIS table
mods = oml.group apply(IRIS, index,
                       func=build lm,
                       parallel=2)
mods.pull().items()
```



Oracle Machine Learning for SQL

Empower SQL users with immediate access to ML included with Oracle Database and Oracle Autonomous Database

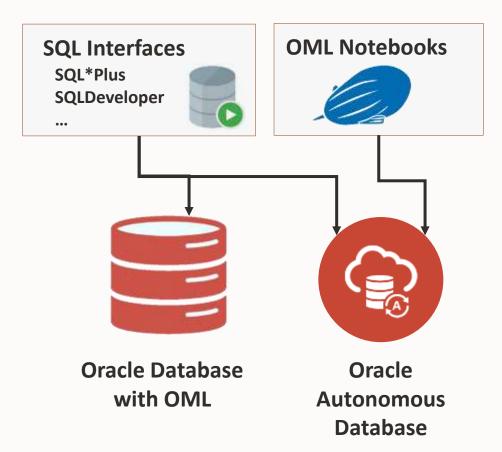
In-database, parallelized, distributed algorithms

- No extracting data to separate ML engine
- Fast and scalable
- Batch and real-time scoring at scale that leverages
 Exadata storage-tier function pushdown
- Algorithm-specific automatic data preparation
- Explanatory prediction details

ML models as first-class database objects

- Access control per model
- Audit user actions
- Export / import models across databases
- Ease of backup, recovery, and security

Faster time-to-market through immediate solution deployment



Intuitive SQL API—OML4SQL

OML to Predict Customer Behavior

```
-- Build a machine learning model to determine which customers are likely buy Travel Insurance
DECLARE
    v set1st DBMS DATA MINING.SETTING LIST;
BEGIN
    v_set1st('ALGO_NAME') := 'ALGO_SUPPORT_VECTOR_MACHINES';
    V set1st('PREP AUTO') := 'ON';
    DBMS DATA MINING.CREATE MODEL2 (
         MODEL_NAME => 'BUY_TRVL_INSUR',
MINING_FUNCTION => 'CLASSIFICATION',
DATA_QUERY => 'select * from CUSTOMERS',
SET_LIST => v_set1st,
         CASE_ID_COLUMN_NAME => 'CUST_ID',
         TARGET COLUMN NAME => BUY TRAVEL_INSURANCE');
END;
-- Apply a machine learning model to predict which customers are likely to buy
SELECT prediction probability (BUY TRVL INSUR, 'Yes'
           USING 3500 as bank funds, 37 as age, 'Married' as marital status, 2 as num previous cruises)
FROM dual;
 SQL | All Rows Fetched: 1 in 0.043 seconds
      ♠ PREDICTION_PROBABILITY(BUY_INSUR 1, YES'USING3500ASBANK_FUNDS, 825ASCHECKING_AMOUNT, 400ASCREDIT_BALANCE
     1 0.9276956709910801
```

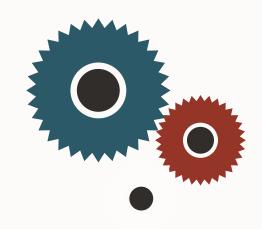
Automation for Machine Learning Modeling

Pain points with traditional ML

- Rapid model development cycles
- Machine learning process can be complex and iterative
- Advanced knowledge of ML algorithms is normally required to get high quality models
- Developing machine learning models is often time intensive to manually explore space of algorithms and hyperparameters

Solution

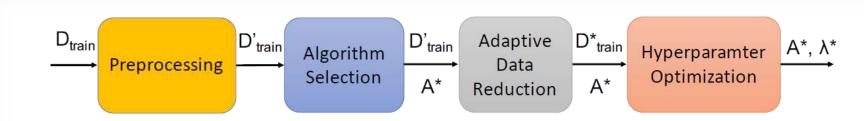
- Introduce an efficient ML pipeline to address rapid model development cycles
- Eliminate repetitive modeling tasks to increase user productivity to reduce compute time



AutoML

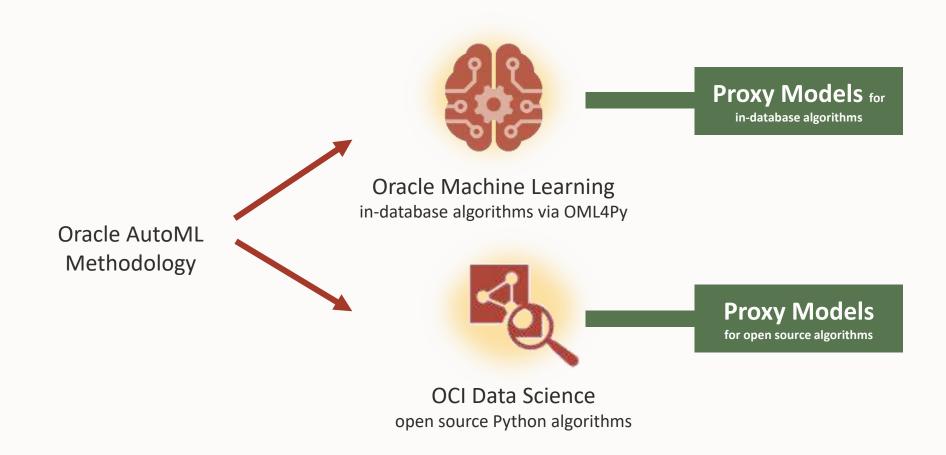
A novel, iteration-free machine learning modeling pipeline

- Designed to provide accurate models in a shorter runtime
- Achieved by eliminating the need to repeatedly iterate over various pipeline configurations
- Each pipeline stage makes decisions based on meta-learned proxy models
- Proxy models predict candidate pipeline configuration performance before building the full final model
- Builds and tunes only the best candidate pipeline
- Achieves better results in a fraction of the time compared to state-of-the-art open source AutoML tools



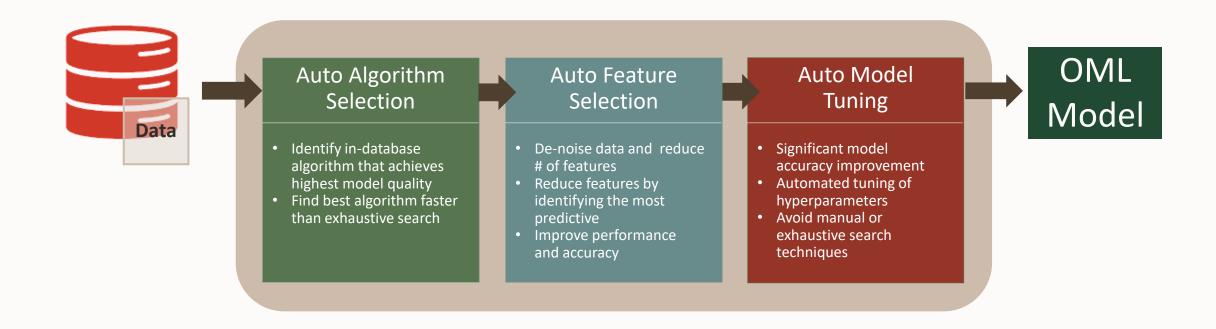
Pipeline stages

Oracle AutoML methodology supports in-database and open source algorithms



AutoML – *new* with OML4Py

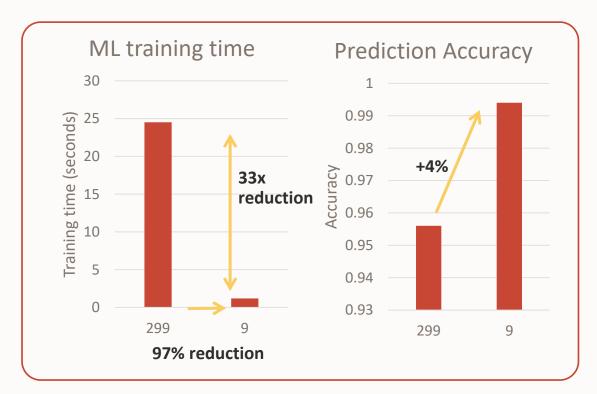
Increase data scientist productivity – reduce overall compute time



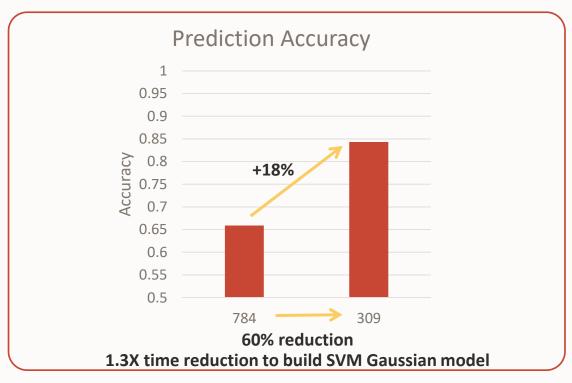
Enables non-expert users to leverage Machine Learning

Improve performance and accuracy with AutoML

Reduce # features by identifying most relevant



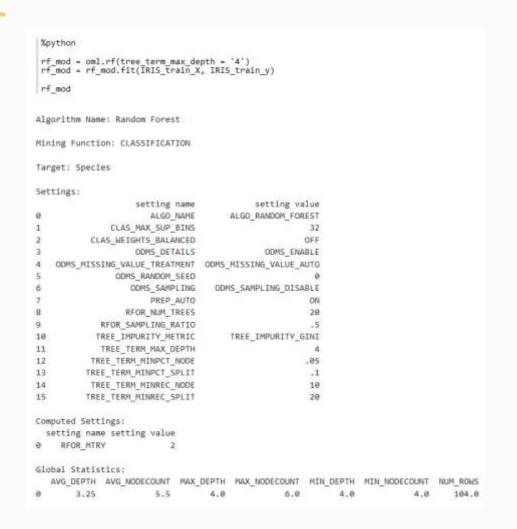
OpenML dataset 312 with 1925 rows, 299 columns

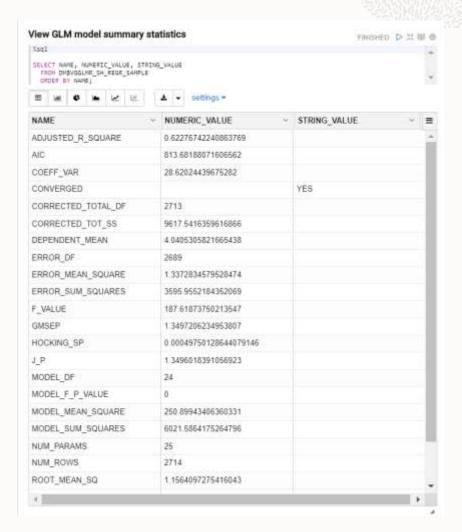


OpenML dataset 40996 with 56K rows, 784 columns

Model Evaluation

Algorithms automatically compute standard metrics





Model Explanation

Prediction Details

Identify the features or predictors that most influence a given prediction Important where model transparency necessary to justify action Useful during model evaluation, as well as for end-users to understand

Influential predictors with actual value and weight

CUST_ID ~	PRED_YRS_RES ~	LOWER_BOUND ~	UPPER_BOUND ~	FIRST_ATTRIBUTE ~	SECOND_ATTRIBUTE	THIRD_ATTRIBUTE ~	FOURTH_ATTRIBU.:.	=
100002	4.219	4.1	4.4	"Y_BOX_GAMES" actualValue="0" weight=".031"	"CUST_YEAR_OF_BIR TH" actualValue="1962" weight=".013"	"AFFINITY_CARD" actualValue="0" weight="956"		^
100003	4.392	4.3	4.5	"Y_BOX_GAMES" actualValue="0" weight=".026"	"CUST_YEAR_OF_BIR TH" actualValue="1969" weight=".007"	"AFFINITY_CARD" actualValue="0" weight="967"		
100005	5.273	5.2	5.4	"Y_BOX_GAMES" actualValue="0" weight="047"	"CUST_YEAR_OF_BIR TH" actualValue="1957" weight="151"	"AFFINITY_CARD" actualValue="1" weight="157"	"OCCUPATION" actualValue="Crafts" weight="644"	
100009	2.22	2	2.4	"AFFINITY_CARD"	"CUST_YEAR_OF_BIR	"Y_BOX_GAMES"		>

OML AutoML UI

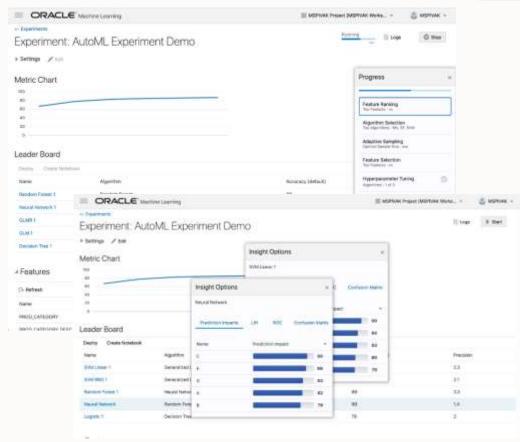
Enhance data scientist productivity and enable non-expert data professionals



Accelerate new ML projects
Automate repetitive and time-consuming tasks
Generate editable notebooks for selected models
Deploy models as REST endpoints

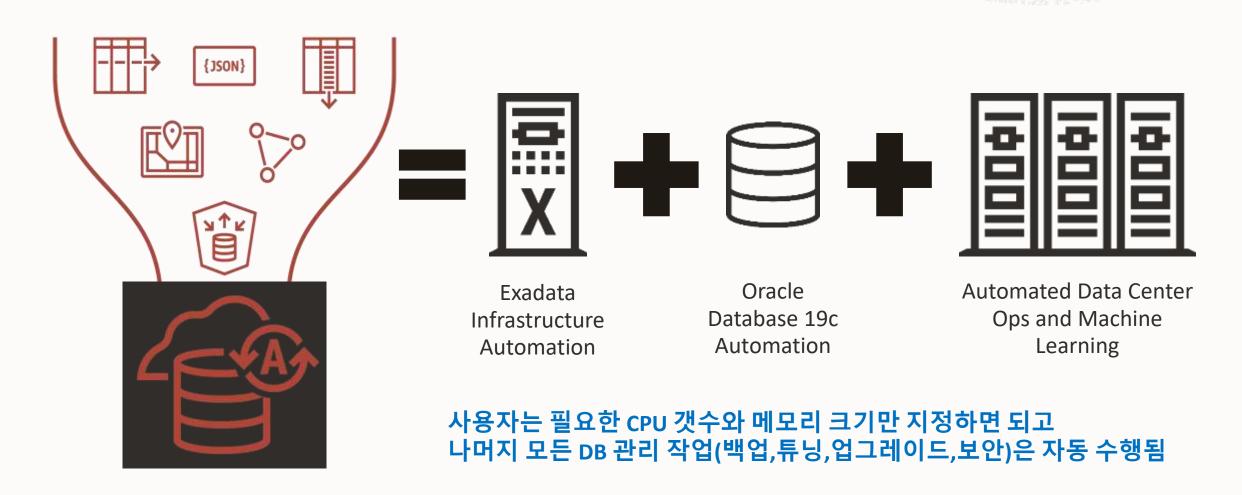
Featuring

- Monitor experiment progress
- Customize selection quality metric and metrics display
- Even faster data scoring performance for streaming and real-time applications



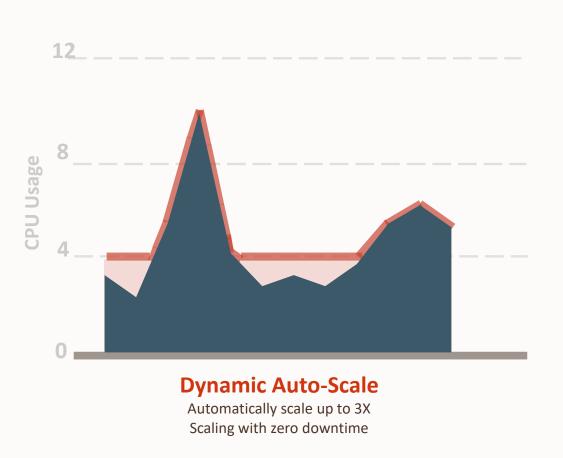
Oracle Autonomous Database is a Fully Managed Cloud Service

With automation across all components driven by AI and ML



Auto Scaling in Oracle Autonomous Database

Automatically scales CPU/IO resources up to 3x when needed by workload



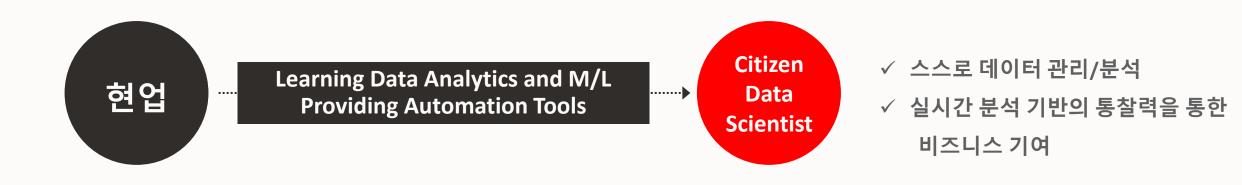
All scaling occurs online, while the application continuously runs.

Up to 3x better throughput for CPU/IO intensive workloads

사용자가 지정한 CPU 갯수와 메모리 크기의 최대 3배까지 자동적으로 Scale-up 되어짐

현업 사용자도 쉽게 M/L을 수행할 수 있는 기술적 토대 지원

Citizen Data Scientist로의 초대



- 필요한 작업 : "Just Do It"
 - 데이터 분석과 Machine Learning의 기본 이해
 - Domain Knowledge를 기반으로 분석 대상과 목표를 정의
 - 편리한/익숙한 클라우드 벤더 선택 (데이터 관리의 부담이 최소화 되는 환경으로)
 - 업무 데이터 수집 및 적재
 - In-DB + AutoML의 "Hands-on" 수행
 - 분석 결과의 공유 및 확산

Summary

- Citizen Data Scientist의 필요성
 - ✓ 현업과 D/S 조직의 분리에 따른 Long Lead Time 및 Communication Overhead 최소화
 - ✓ 업에 대한 통찰력과 실시간 분석을 통한 비즈니스 기여 증대
- Machine Learning Process 간소화의 도구들
 - In-DB Machine Learning
 - ✓ 대규모 데이터의 이동 없이 DB 안에서 M/L 기반 분석/예측 작업 가능
 - ✓ 알고리즘의 병렬 수행 지원을 통한 성능 향상
 - AutoML
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 - ✓ Data Scientist는 모델에만 집중하고 나머지 DB 관리 작업은 ADB가 자율적으로 수행
- Oracle Machine Learning: In-DB M/L + AutoML + Autonomous DB
 - ✓ M/L의 쉬운 활용 여건을 제공하여 Citizen Data Scientist 지원

Helpful Links

ORACLE MACHINE LEARNING ON O.COM

https://www.oracle.com/machine-learning

Oracle Machine Learning

Oracle Machine Learning accelerates the creation and deployment of machine learning models for data scientists by eliminating the need to move data to dedicated machine learning systems.



OML LiveLab: https://apexapps.oracle.com/pls/apex/dbpm/r/livelabs/view-workshop?p180_id=560_

OML4Py LiveLab: https://apexapps.oracle.com/pls/apex/dbpm/r/livelabs/view-workshop?wid=786

Interactive tour: https://docs.oracle.com/en/cloud/paas/autonomous-database/oml-tour

Machine Learning on Autonomous Database Workshop

Oracle Machine Learning for Python on Autonomous Database Workshop

OML OFFICE HOURS

https://asktom.oracle.com/pls/apex/asktom.search?office=6801#sessionss

Oracle Machine Learning Office Hours Free tips and basing every month? Subscribe for monodors and more from Office Hours. EAQ

ORACLE ANALYTICS CLOUD

https://www.oracle.com/solutions/business-analytics/data-visualization/examples.html

Oracle Analytics Library Custom DV examples to enhance your data visualization experience. Standalone .dva projects that can be re-used with your own data.

OML4PY

OML4Py (2m video)
OML4Py Introduction (17m video)
OML4Py Technical Brief
OML4Py User's Guide
Blog: Introducing OML4Py

GitHub Repository with Python notebooks

ORACLE AUTOML UI

Oracle Machine Learning AutoML UI (2m video)
Oracle Machine Learning Demonstration (6m video)
OML AutoML UI Technical Brief
Blog: Introducing Oracle Machine Learning AutoML UI

OML SERVICES

Oracle Machine Learning Services (2m video)
OML Services Technical Brief
Oracle Machine Learning Services Documentation
Blog: Introducing Oracle Machine Learning Services
GitHub Repository with OML Services examples

감사합니다

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