# Oracle Machine Learning

Introduction Move the Algorithms – Not the Data



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### **Building on a converged database**

In cloud and on premises – integrated, not fragmented



Supports any Data Relational, JSON, graph, spatial, text, OLAP, XML, multimedia

**Supports any Workload** Transactions, analytics, ML, IoT, streaming, blockchain

**Most Productive for Developers and Analysts** Integrated microservices, events, REST, SaaS, ML, CI/CD, Low-Code

### **Contrasting Architectures**

Oracle – Simpler, integrated. Dramatically simpler for developers to invoke declarative SQL, Python and R to run machine learning, spatial, graph, JSON, unstructured, IoT, blockchain, etc. in one "Converged" Database

Others – Fragmented. Multiple fragmented databases, platforms, tools, and distributed execution and data movement across them





EVENT RPC

### **Oracle Autonomous Database is an ecosystem**

Autonomous Database with built-in tool suite

#### **Data Sources** Visualization & Development **Applications** Application Express ORACLE ORACLE ORACLE Fusion Applications Siebel PeopleSoft Oracle EBS Oracle NetSuite SAD Oracle ML 働 Notebook Catalog -129 NoSQL Databases Data Machine Oracle Insights Learning **Analytics Cloud** Business CSV Files Graph Models {**‡**} **IDEs** Streaming o kafka Services **Spreadsheets** Data Load & APEX: Data-Transforms Driven App Dev 42 Data Lake **3rd Party Bl** ۴¢ OCI Object Amazon S3 Microsoft Azure Tools **Blob Storage** Storage

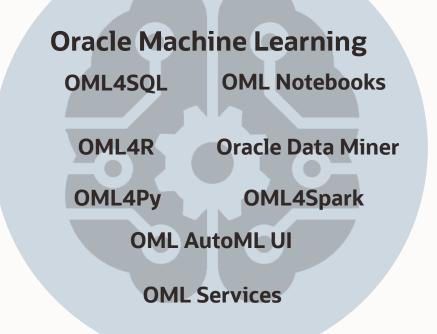
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### **Oracle Machine Learning**

Move the algorithms – not the data

Oracle Machine Learning extends Oracle Database and enables users to augment applications and dashboards with machine learning-based intelligence

OML delivers 30+ powerful in-database machine learning algorithms with automated functionality via SQL, R and Python APIs



Oracle Machine Learning database features included with Oracle Database and Oracle Autonomous Database

### **Oracle Machine Learning Algorithms and Analytics**

### 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, irregularity, missing data

#### REGRESSION

- Linear Model
- 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 & Al

#### **ASSOCIATION RULES**

• A priori/ market basket

#### **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.

#### **R** AND **P**YTHON **PACKAGES**

Third-party R and Python Packages
 through Embedded Execution

### Oracle Machine Learning for SQL OML4SQL



### What it is

- SQL and PL/SQL interface for in-database ML
- Build, evaluate, deploy models and score data using over 30 in-database parallelized algorithms
- Automatic data preparation that is algorithm-specific
- Score data using prediction operators directly in SQL queries
- Partition models, text mining, and prediction details
- Supports numeric, categorical, text, and nested columns

### Benefits

- Scalable in-database ML algorithms
- Faster time-to-market through immediate solution deployment
- Score data on a scalable platform
- In-database models exist as first-class database objects for ease of backup, recovery, and security
- Supports R and Python interfaces

## 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\_setlst('ALGO\_NAME') := 'ALGO\_SUPPORT\_VECTOR\_MACHINES'; V\_setlst('PREP\_AUTO') := 'ON'; DBMS\_DATA\_MINING.CREATE\_MODEL2(

```
MODEL_NAME => 'BUY_TRVL_INSUR',
MINING_FUNCTION => 'CLASSIFICATION',
DATA_QUERY => 'select * from CUSTOMERS',
SET_LIST => v_setlst,
CASE_ID_COLUMN_NAME => 'CUST_ID',
TARGET_COLUMN_NAME => BUY_TRAVEL_INSURANCE');
```



-- 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

## **Oracle Autonomous Database and OML Notebooks**

#### Notebook with model created in SQL

ORACLE<sup>®</sup> Machine Learning



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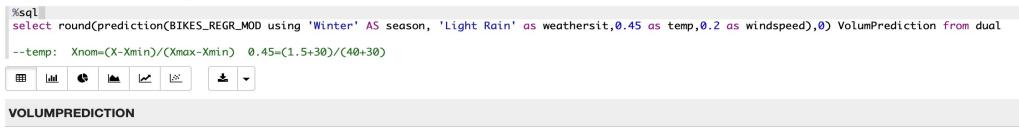
### Using Support Vector Machine Regression to Predict Volume of Bikes

This notebook shows how to predict numerical values using Support Vector Machine (SVM) Regression. Given demographic information when renting bikes to predict the volume of bikes rented out in column Volume.

#### - Build the SVM regression model

DBMS_DATA_MINING.CREATE_MODEL( MODEL_NAME => 'BIKES_REGR_MOD', MINING_FUNCTION => DBMS_DATA_MINING.REGRESSION,	%sql select * from BIKES_REGR_SETTINGS;					
DATA_TABLE_NAME => 'BIKES_TRAIN',	SETTING_NAME	SETTING_VALUE				
CASE_ID_COLUMN_NAME => 'DAY_ID',	ALGO_NAME	ALGO_SUPPORT_VECTOR_MACHINES				
TARGET_COLUMN_NAME => 'VOLUME',	SVMS_KERNEL_FUNCTION	SVMS_GAUSSIAN				
SETTINGS_TABLE_NAME => 'BIKES_REGR_SETTINGS',	PREP_AUTO	ON de				
XF0RM_LIST => V_XLST); Jpdated March 2020 by Renée Wikestad.						

#### Apply the model to a singel record



#### 2620



# Oracle Machine Learning for R

#### OML4R

R Language API to OML Algorithms and Integration with R

Key features

- Use Oracle Database as HPC environment via R→SQL transparency layer
- Access in-database parallelized machine learning algorithms
- Manage scripts and objects in Oracle Database
- Integrate results into applications and dashboards via SQL
- Use third-party packages with Embedded R Execution

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# **Oracle Machine Learning for Python**

#### **OML4Py** Supported in Oracle Autonomous Database with OML Notebooks

### Use Oracle Database as HPC environment

• Explore, transform, and analyze data faster and at scale

#### Use in-database parallelized and distributed ML algorithms

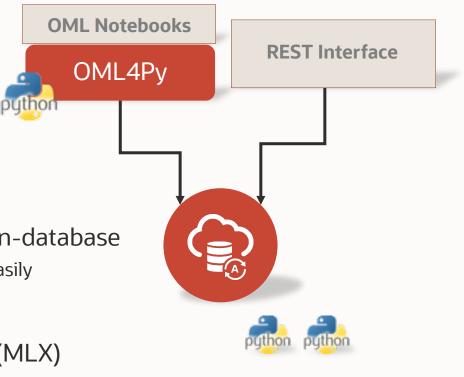
- Build more models on more data, and score large volume data faster
- Use in-database algorithms from OML4SQL via natural Python API
- Increased productivity from automatic data preparation, partitioned models, and integrated text mining capabilities

### Run user-defined Python functions and manage Python objects in-database

- Collaborate: hand-off data science products from data scientist to developers easily
- Return structured and image results in Python and REST API

#### Automated machine learning (AutoML) and model explainability (MLX)

- Algorithm selection, feature selection, hyperparameter tuning, model selection
- Model-agnostic identification of important features that impact model predictions



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## **Oracle Machine Learning for Python Notebooks UI**

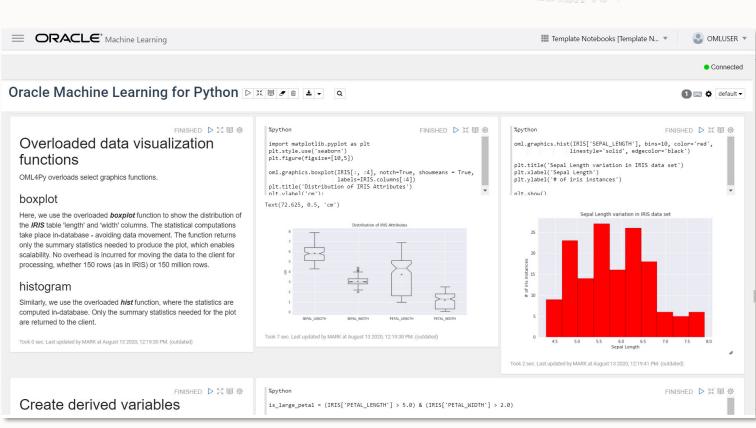
### Autonomous Database as a Data Science Platform

#### Collaborative UI

- Based on Apache Zeppelin
- Supports data scientists, data analysts, application developers, DBAs with SQL and Python
- Easy notebook sharing
- Permissions, versioning, and scheduling of notebooks

### 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





### **Transparency Layer** In-database performance – indexes, query optimization, parallelism, partitioning



Leverages proxy objects for database data: oml.DataFrame

```
# Create table from Pandas DataFrame data
DATA = oml.create(data, table = 'CUSTOMER')
```

```
# Get proxy object to DB table boston
DATA = oml.sync(table = 'CUSTOMER')
```

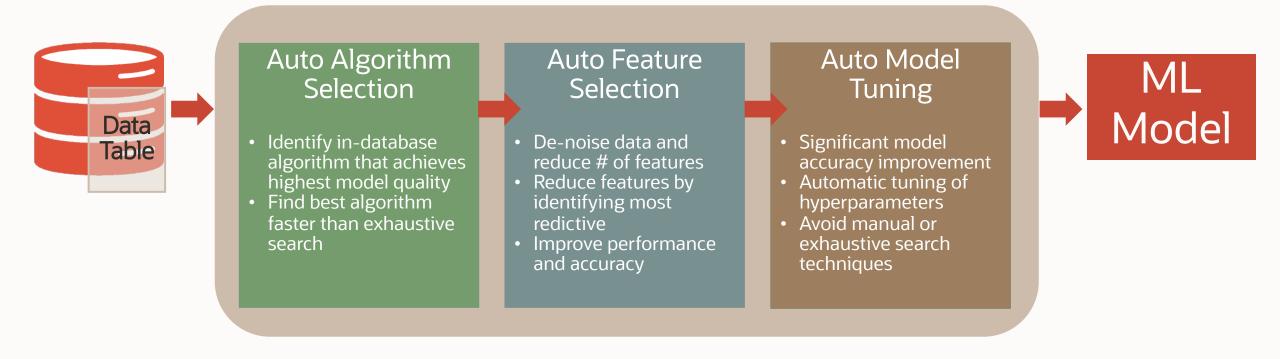
Uses familiar Python syntax to manipulate database data

Overloads Python functions translating functionality to SQL

## AutoML – with OML4Py

### Faster and Easier Machine Learning for Data Scientists, Non-Experts and Developers





### Enables non-expert users to leverage Machine Learning

## **OML** AutoML UI

No-code AutoML-based user interface supporting automatic machine learning

Powerful, easy to use UI

Enable non-expert users to use ML

Automates model building, tuning, and deployment

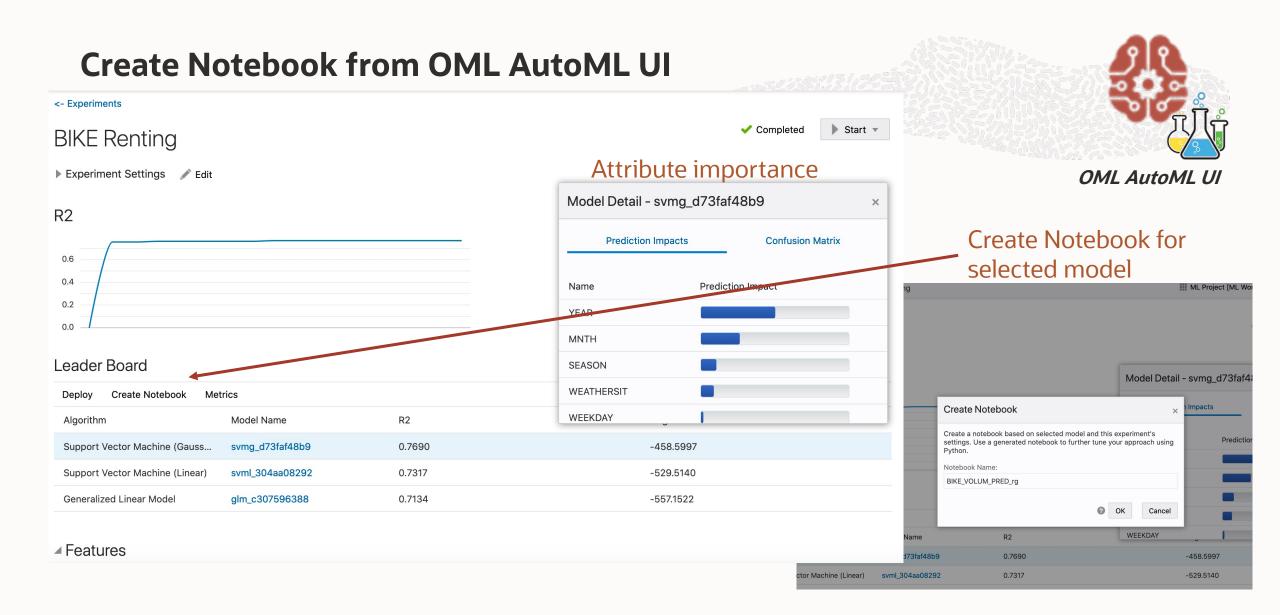
- Enhance data scientist productivity
- Support model management
- Empower non-expert users

### Featuring

- Minimal
- Model let
- Model c

<ul> <li>Minimal user input: data, target</li> <li>Model leaderboard</li> </ul>	
• Model deployment via REST endpoints Copyright © 2021 Oracle and/or its affiliates.	

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## **Oracle Autonomous Database and OML Notebooks**

#### Generated Notebook

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		Connected
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Build Data %python import oml columns = 'INSTANT', 'ATEMP', 'HOLIDAY', 'HUM', 'MNTH', 'SEASON', 'TEMP', 'WEATHERSIT', 'WEEKDAY', 'WINDSPEED', 'WORKINGDAY', 'YEAR', ' schema='MLUSER' toble='BIKE_RENTING_TRAINING' column = ','_join(columns) query = 'SELECT '+ column +' FROM '+ schema + '.' + table data_build = oml.sync(query=query) z.show(data_build)	COUNT	READY D X 單 ⊕
Create Train Data %python import oml X_train = data_build[:,['INSTANT', 'ATEMP', 'HOLIDAY', 'HUM', 'MNTH', 'SEASON', 'TEMP', 'WEATHERSIT', 'WEEKDAY', 'WINDSPEED', 'WORKINGDAY', 'YEAR'] y_train = data_build[:,'COUNT']	1	READY D X 團 @
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<pre>import oml svm_settings = {     'ALGO_NAME': 'ALGO_SUPPORT_VECTOR_MACHINES', 'SVMS_COMPLEXITY_FACTOR': '66.700000000002', 'SVMS_EPSILON': '0.3975300444430571', 'SVMS_KER     .345207879911715', 'SVMS_NLM_PIVOTS': '200', '00MS_DETAILS': '0DMS_DISABLE'   } svm_mod = oml.svm('regression',**svm_settings)</pre>	NEL_FUNCTION' : 'SVMS_GAUSSIAN' , 'SVM	IS_STD_DEV' : '2
<pre>svm_mod = svm_mod.fit(X_train, y_train)</pre>		_
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OML4Py Model (Regression with svmg)

### **OML Services**

REST API – deploy models outside the database

Model Management and Deployment Services

- Deploy in-database models and using ONNX format, third-party models
- Import ONNX for Tensorflow, PyTorch, MXNet, scikitlearn, etc.
- Store, version, compare ML models

**Cognitive Text Services** 

- Extract topics and keywords
- Sentiment analysis
- Text summary and similarity





## **Oracle Machine Learning Services - Methods**

Components with built-in Oracle Machine Learning



Admin	Repository	Deployment	<b>Cognitive Text</b>
POST	POST	POST	POST
<ul> <li>Token using ADB user and password</li> </ul>	<ul><li>Store Model</li><li>Update Model Namespace</li></ul>	<ul> <li>Create Model Endpoint</li> <li>Score Model using</li> </ul>	<ul><li>Get Most Relevant Topics</li><li>Get Most Relevant</li></ul>
Generic	GET	Endpoint	<ul><li>Keywords</li><li>Get Summaries</li></ul>
GET	Models list	GET	<ul><li>Get Summaries</li><li>Get Sentiments</li></ul>
<ul> <li>Metadata for all Versions: Version 1 Metadata</li> <li>Open API Specification</li> </ul>	<ul> <li>Model Info</li> <li>Model Metadata</li> <li>Model Content</li> </ul> DELETE	<ul> <li>Endpoints</li> <li>Endpoint Details</li> <li>Open API Specification for Endpoint</li> </ul>	<ul> <li>Get Semantic Similarities</li> <li>Numeric Features</li> </ul>
	<ul> <li>Model</li> </ul>	Endpoint DELETE	<ul><li>GET</li><li>Get Endpoints</li></ul>

Endpoint

•

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none	form	n-data 🔍 x-www-form-urlencoded 💿 raw 🌑 binary 🜑 GraphQL JSON 🔻			Bea	utify

1	4	
2	"topNdetails":5,	
3	"inputRecords": [	
4	{	
5	"AGE":41,	
6	"BOOKKEEPING_APPLICATION": 1,	
7	"CUST_GENDER":"M",	
8	"CUST_MARITAL_STATUS":"NeverM",	
9	"EDUCATION": "HS-grad",	
10	"HOME_THEATER_PACKAGE":1,	
11	"HOUSEHOLD_SIZE":"4",	
12	"OCCUPATION":"Crafts",	
13	"YRS_RESIDENCE":6,	
14	"Y_BOX_GAMES":1	
15	}	
16	]	
17	3	

Response

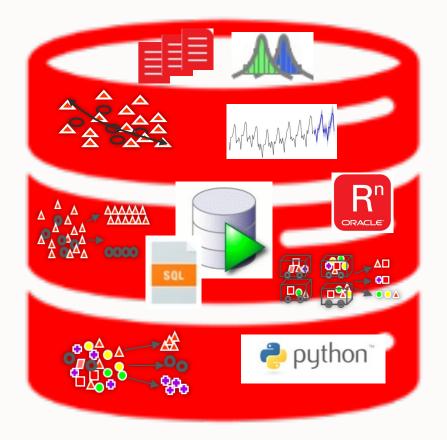


Hit Send to get a response

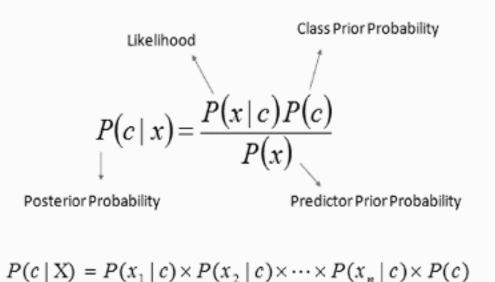
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### Why Oracle for Machine Learning?

Move the Algorithms, Not the Data!







### **Helpful Links**

#### **ORACLE MACHINE LEARNING ON O.COM**

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

#### **OML TUTORIALS**

OML LiveLab: <a href="https://apexapps.oracle.com/pls/apex/dbpm/r/livelabs/view-workshop?p180\_id=560">https://apexapps.oracle.com/pls/apex/dbpm/r/livelabs/view-workshop?wid=560</a> OML4Py LiveLab: <a href="https://apexapps.oracle.com/pls/apex/dbpm/r/livelabs/view-workshop?wid=786">https://apexapps.oracle.com/pls/apex/dbpm/r/livelabs/view-workshop?wid=786</a> Interactive tour: <a href="https://docs.oracle.com/en/cloud/paas/autonomous-database/oml-tour">https://apexapps.oracle.com/en/cloud/paas/autonomous-database/oml-tour</a> Picking a Good Wine Using ADW, OML and OAC Workshop: <a href="https://go.oracle.com/LP=109257?elqCampaignId=293121">https://go.oracle.com/LP=109257?elqCampaignId=293121</a>

#### **OML OFFICE HOURS**

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

#### **ORACLE ANALYTICS CLOUD**

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

#### **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





https://www.oracle.com/cloud/free/

# Thank you

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