



Continuous Machine and Deep Learning at Scale With Apache Ignite

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- Continuous Machine Learning / Deep Learning Introduction
- Overview of Apache Ignite Continuous ML/DL Capabilities
- Demo & API discussion
- Q & A



Why Machine Learning at Scale?

Scalability

- Data exceed capacity of single server
- Burden for development and business

Models trained & then deployed in different systems

- Move data out for training
- Wait for training to complete
- Redeploy models in production





Machine Learning Pipelines: where is the time spent?





Continuous Machine Learning at Scale





Apache Ignite Is a Top 5 Apache Project





From January 1, 2019 Apache Software Foundation Blog Post: "Apache in 2018 – By The Digits"



Apr-14 Jun-14 Jun-14 Oct-14 Dec-14 Jun-15 Jun-15 Jun-15 Dec-15 Dec-15 Dec-16 Aug-16 Oct-17 Jun-17 Jun-17 Aug-17 Aug-17 Aug-17 Dec-117 Aug-17 Jun-17 Aug-17 Jun-17 Aug-17 Dec-117 Aug-17 Dec-117 Aug-17 Dec-117 Aug-17 Dec-117 Aug-17 Dec-117 Dec-117 Aug-17 Dec-117 Dec-117 Aug-17 Dec-117 Dec-118 Dec-118 Dec-117 Dec-118 Dec-18 Dec-

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Apache Ignite Users







Apache Ignite In-Memory Computing Platform



Apache Ignite Features

GridGain Enterprise Features



Overview of Apache Ignite Continuous ML/DL Capabilities



Apache Ignite Continuous Learning framework





Partitions Distribution and Replication



Continuous Learning enabled with Partitioned Datasets







Apache Ignite Distributed Training: Clustering

- K-means (Centroid Mean)
- GMM (Centroid Mean + Variance)

- Use Cases OLTP and other tabular data that need to be Labeled
 - Customer Segmentation
 - Anomaly Detection
 - Network throughput characterization







Apache Ignite Distributed Training: Classification

- Logistic Regression & Naive Bayes
- SVM, KNN, ANN
- Decision trees & Random Forest
- Use cases Operational (OLTP) data prediction:
 - Fraud detection
 - Credit Card Scoring
 - Clinical Trials
 - Customer Segmentation







Apache Ignite Distributed Training: Regression

- KNN & Linear Regressions
- Decision tree regression
- Random forest regression
- Gradient-boosted tree regression
- Use cases Operational data (OLTP) predictions
 - Trend analysis
 - Financial forecasting
 - Time series prediction
 - Response modeling (pharma etc)

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Apache Ignite: TensorFlow Integration



- Use Cases Operational data "High dimension" data (Images, Text, Audio, speech)
- Image data classification
- Natural Language Processing Clinical notes
- Document Classification, Free Form text

- >>> import tensorflow as tf >>> from tensorflow.contrib.ignite import IgniteDataset >>> >>> dataset = IgniteDataset(cache_name="SQL_PUBLIC_KITTEN_CACHE") >>> iterator = dataset.make_one_shot_iterator() >>> next_obj = iterator.get_next() >>> >>> with tf.Session() as sess: >>> for _ in range(3): >>> print(sess.run(next_obj)) {'key': 1, 'val': {'NAME': b'WARM KITTY'}} {'key': 2, 'val': {'NAME': b'SOFT KITTY'}}
 - {'key': 3, 'val': {'NAME': b'LITTLE BALL OF FUR'}}



Apache Ignite Distributed PreProcessing: Normalization

normalized data original data zero-centered data -5 -10 L -10 -10 L -10 -10 L -10 -5 0 5 -5 -5 5 0 10





Without feature scaling

With feature scaling



https://medium.com/@nsethi610/data-cleaning-scale-and-normalize-data-4a7c781dd628



Apache Ignite Distributed preprocessing: One-Hot Encoder



* Also included: String Encoding



Achieving Continuous ML/DL at Scale: Architectural Considerations / Trade-Offs

- Operational Data Models: from centralized to parallelized
 - De-normalization Data Affinity for parallel Loads, Queries, Updates, Joins
 - Horizontal scale-out
- Done locally in node: data partition + preprocessing + training + inferencing
 - Reduces data shuffling over the network between the cluster and application
- ML pipeline enhancements
 - Co-Located & Distributed processing of all ML steps: ingest to inferencing
 - ML model performance measured, and updatable, with nearby transaction data



Demo & API discussion



package org.apache.ignite.examples.ml

Adding your own Preprocessor and Algorithm to a Dataset

dataset/AlgorithmSpecificDatasetExample.java

Passing custom preprocessor classes to the cluster

• **environment**/TrainingWithCustomPreprocessorsExample.java

TensorFlow data set , inferencing at the cluster nodes

• **inference/**TensorFlowDistributedInferenceExample.java

Decision tree

tree/FraudDetectionExample.java

End-to-End Model Prep & Training Tutorial (shows feature preprocessing, transformation, different algorithm comparisons, accuracy metrics, pipelines)



- > 🚺 package-info.java
- > J Step_1_Read_and_Learn.java
- > 🚺 Step_2_Imputing.java
- > D Step_3_Categorial_with_One_Hot_Encoder.java
- > J Step_3_Categorial.java
- > J Step_4_Add_age_fare.java
- > 🚺 Step_5_Scaling_with_Pipeline.java
- > 🚺 Step_5_Scaling.java
- > J Step_6_KNN.java
- > 🚺 Step_7_Split_train_test.java
- > 🚺 Step_8_CV_with_Param_Grid_and_metrics_and_pipeline.java
- > J Step_8_CV_with_Param_Grid_and_metrics.java
- > 🚺 Step_8_CV_with_Param_Grid.java
- > 🚺 Step_8_CV.java
- > D Step_9_Scaling_With_Stacking.java
- > 🕖 TitanicUtils.java
- > 🚺 TutorialStepByStepExample.java



Ignite ML API to Update the model

SVMLinearClassificationTrainer trainer = new
SVMLinearClassificationTrainer();

SVMLinearClassificationModel mdl1 =
trainer.fit(ignite, dataCache1, vectorizer);

SVMLinearClassificationModel mdl2 =
trainer.update(mdl1, ignite, dataCache2,
vectorizer);

DatasetTraininer interface:

(Some Constraints according to the Algorithm)

Online / Online Batch with new data

- Centroid updates KMeans, ANN
- Add new dataset KNN
- Update with new Gradient NN, Log Regression, Linear Regression
- Increment to Current state SVM, GDB
- Decision Tree retrain
- Random Forest adds new DT, may discard other DTs for size management



Demo tutorial sample

✓ / org.apache.ignite.examples.ml.tutorial .____ ____package-info.java_____/ > J Step_1_Read_and_Learn.java > J Step_2_Imputing.java > 🚺 Step_3_Categorial_with_One_Hot_Encoder.java > J Step_3_Categorial.java Step_4_Add_age_fare.java Step_5_Scaling_with_Pipeline.java > J Step_5_Scaling.java > J Step_6_KNN.java > J Step_7_Split_train_test.java > J Step_8_CV_with_Param_Grid_and_metrics_and_pipeline.java Step_8_CV_with_Param_Grid_and_metrics.java > J Step_8_CV_with_Param_Grid.java > 🚺 Step_8_CV.java Step_9_Scaling_With_Stacking.java > 🔊 Titanic Utils.java > J TutorialStepByStepExample.java

To run this example:

- Import this directory with pom.xml into your favorite IDE as a Maven project
 - <path>\apache-ignite-2.7.6-bin\examples\pom.xml
- I'll run this job on a single node inside my laptop on Eclipse (normally you would run jobs on a cluster of nodes)
 - Each of these Steps can be run independently or all together with TutorialStepByStepExample.java
 - Widely used Titanic data set (we include it here)
- Discussion of how Apache Ignite API can be invoked by 3rd party Auto ML and other application wrappers
- Compare the Accuracy obtained different ML steps
 - Accuracy defined as % correct predictions versus ground truth
 - Different algorithms and different preprocessing
 - Effects of Test / Train split on Overfitting

Apache Ignite Spark integration





Write to Ignite DataFrame from within Spark session

System.out.println("Reading data from Ignite table.");

Dataset<Row> peopleDF = spark.read()
 .format(IgniteDataFrameSettings.FORMAT_IGNITE())
 .option(IgniteDataFrameSettings.OPTION_CONFIG_FILE(), CONFIG)
 .option(IgniteDataFrameSettings.OPTION_TABLE(), "people")
 .load();

peopleDF.createOrReplaceTempView("people");

Dataset <row> sqlDF</row>	= spark.sql	("SELECT	* F1	ROM p	eople	WHERE	id	> 0	AND	id	<	6");
<pre>sqlDF.show();</pre>		<u> </u>	-								-	_ /

Read from same Ignite DataFrame from another Spark Session

- DF (and RDD) shared across sessions
- SQL with Indexing for faster queries
- Ignite DF are mutable



To Summarize: Apache Ignite for Continuous Learning at Scale

Massive Scale for Memory, Storage, Computation

- Massive Throughput with minimal ETL
- Massive operational data sizes + in-place parallel processing
- Faster cycle times from transactions, ML/DL dataset extraction, predictions

Integrates with Existing ML / DL operations

- Low-level Distributed APIs to integrate with Auto ML and other Data Science workflows
- For End-Users: Python API to manage Cache, Datasets, SQL, ML
- Apache Ignite integrations to accelerate Spark, TensorFlow pipelines; including Model imports from other tool sets



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Documentation: •

Resources

- <u>https://apacheignite.readme.io/docs</u>
- Python support
 - https://github.com/gridgain/ml-python-api
- Examples and Tutorials: ٠
 - <u>https://github.com/apache/ignite/tree/master/examples/s</u> <u>rc/main/java/org/apache/ignite/examples/ml</u>
- **Details on TensorFlow** •
 - https://medium.com/tensorflow/tensorflow-on-apacheignite-99f1fc60efeb









