BIDAF Workshop:
Platform for distributed and streaming machine learning

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RISE
The State-of-the-Art Machine Learning Platforms
Why We Need a Platform for Data Intensive ML?

Hidden Technical Debt in Machine Learning Systems

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Abstract

Machine learning offers a fantastically powerful toolkit for building useful complex prediction systems quickly. This paper argues it is dangerous to think of these quick wins as coming for free. Using the software engineering framework of technical debt, we find it is common to incur massive ongoing maintenance costs in real-world ML systems. We explore several ML-specific risk factors and account for in system design. These include boundary erosion, entanglement,

Figure 1: Only a small fraction of real-world ML systems is composed of the ML code, as shown by the small black box in the middle. The required surrounding infrastructure is vast and complex.
End-to-End ML Pipelines?

TFX: A TensorFlow-Based Production-Scale Machine Learning Platform

Denis Baylor, Eric Breck, Heng-Tze Cheng, Noah Fiedel, Chan Yu Fu, Salma Haykal, Mustafa Ispr, Viran Jain, Levent Koc, Chia Yuen Koo, Clemen Meswalm, Akshay Naresh Modi, Neoklis Polyzotis, Saurabh Rastogi, Steven Enlue Weng, Martin Wicht, Jarek Wilkiewicz, Xin Zhang

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ABSTRACT

Creating and maintaining a platform for reliably producing and deploying machine learning models requires careful orchestration of many components—a learner for generating models based on training data, metrics for analyzing and valuating both data as well as models, and finally infrastructure for serving models in production. This becomes particularly challenging when data changes over time and fresh models need to be produced continuously. Unfortunately, such orchestration is often done ad-hoc using glue code and custom scripts developed by individual teams for specific use cases, leading to duplicated effort and fragile systems with high technical debt.

Knowledge Discovery and Data Mining KDD 2017
That is Great! But ...

- Focuses on automating in batches
  - ingest new **data batch** -> validate/transform -> train -> evaluate -> serve ->
  - repeat
- Tightly coupled to the Tensorflow echo system
- Focus on Neural Networks

In BIDAF ...

- **Continuous** learning and evolving models
- **One-pass** streaming algorithms and models
  - scans the data only once
Hopsworks Platform
Hopsworks Platform

- The platform for data intensive AI
  - **Big Data**: Spark, Flink, Beam, Kafka, HDFS, ...
  - **ML**: Tensorflow, PyTorch, Keras, Feature Store, TFX, ...
  - **Secure**, Multi-tenant, Scalable

- Collaboration between:
  - Researchers at RISE and KTH
  - Logical Clocks (Startup)

- Hosted service at RISE Datacenter in Luleå
  - Try it at [https://hops.site](https://hops.site) (contact me for an account)

- **Open-source** development + Enterprise features
What is Hopsworks?

Elasticity & Performance
- Feature Store
  Data warehouse for ML
- Distributed Deep Learning
  Faster with more GPUs
- HopsFS
  NVMe speed with Big Data
- Horizontally Scalable
  Ingestion, DataPrep, Training, Serving

Development & Operations
- Notebooks for Development
  First-class Python Support
- Version Everything
  Code, Infrastructure, Data
- Model Serving on Kubernetes
  TF Serving, MLeap, SkLearn
- End-to-End ML Pipelines
  Orchestrated by Airflow

Governance & Compliance
- Secure Multi-Tenancy
  Project-based restricted access
- Encryption At-Rest, In-Motion
  TLS/SSL everywhere
- AI-Asset Governance
  Models, experiments, data, GPUs
- Data/Model/Feature Lineage
  Discover/track dependencies
Hopsworks Technical Milestones

- **World’s fastest HDFS** Published at USENIX FAST with Oracle and Spotify
- **World’s first** Hadoop platform to support GPUs-as-a-Resource
- **World’s First** Open Source Feature Store for Machine Learning
- **World’s most scalable** POSIX-like Hierarchical Filesystem with Multi Data Center Availability with 1.6m ops/sec on GCP

- Winner of IEEE Scale Challenge 2017 with HopsFS - 1.2m ops/sec
- **World’s First** Distributed Filesystem to store small files in metadata on NVMe disks
- **World’s First** Unified Hparam, Ablation Study Framework - Maggy

“HopsFS is a huge win.”
- Adrian Colyer, The Morning Paper
BIDAF Architecture Overview
BIDAF End-to-End Pipeline
BIDAF End-to-End Pipeline

- Preprocessing
- Anomaly
- Causality
- Clustering
- Replay from File
- streaming
- Kafka
- Hopworks REST API

...
Advantages

● Robust & Fault Tolerant
  ○ Spark tracks processed data & resume after failure
  ○ Kafka decouples components

● Scalable
  ○ Spark auto scaling & partition kafka topics

● Event-time based stream processing
  ○ Advanced windowing semantics
  ○ Delayed and out-of-order events
Preprocessing: Align and Expand Features

- **Align feature data frequencies:**
  - Sampled at irregular intervals
  - Interpolation and smoothing

- **Expand features**
  - Smoothing at different scales
  - Slopes
  - Variance

- **Help to better understand and explore structures in data**
More at following sessions
Demo at the end ....