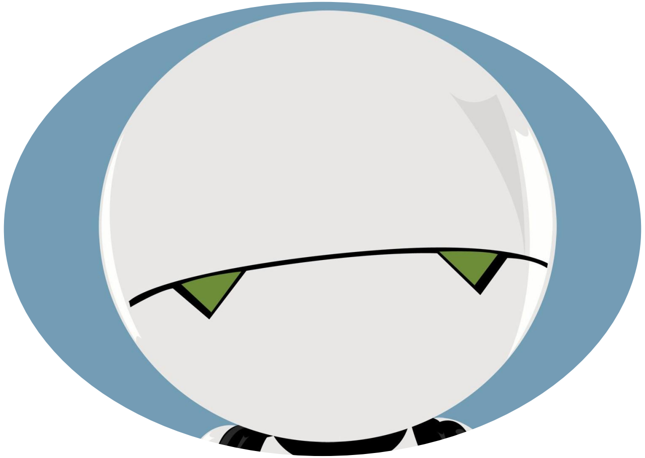
Deeplearning in production

the Data Engineer part

whoami



Scauglog
Data Engineer, Xebia

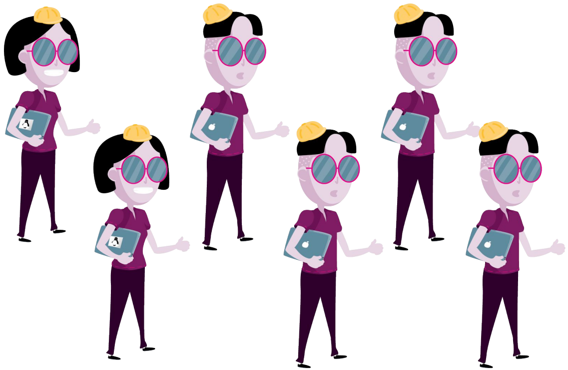
https://github.com/scauglog/prez

init project

Team Astro

Product Owner

Scrum Master

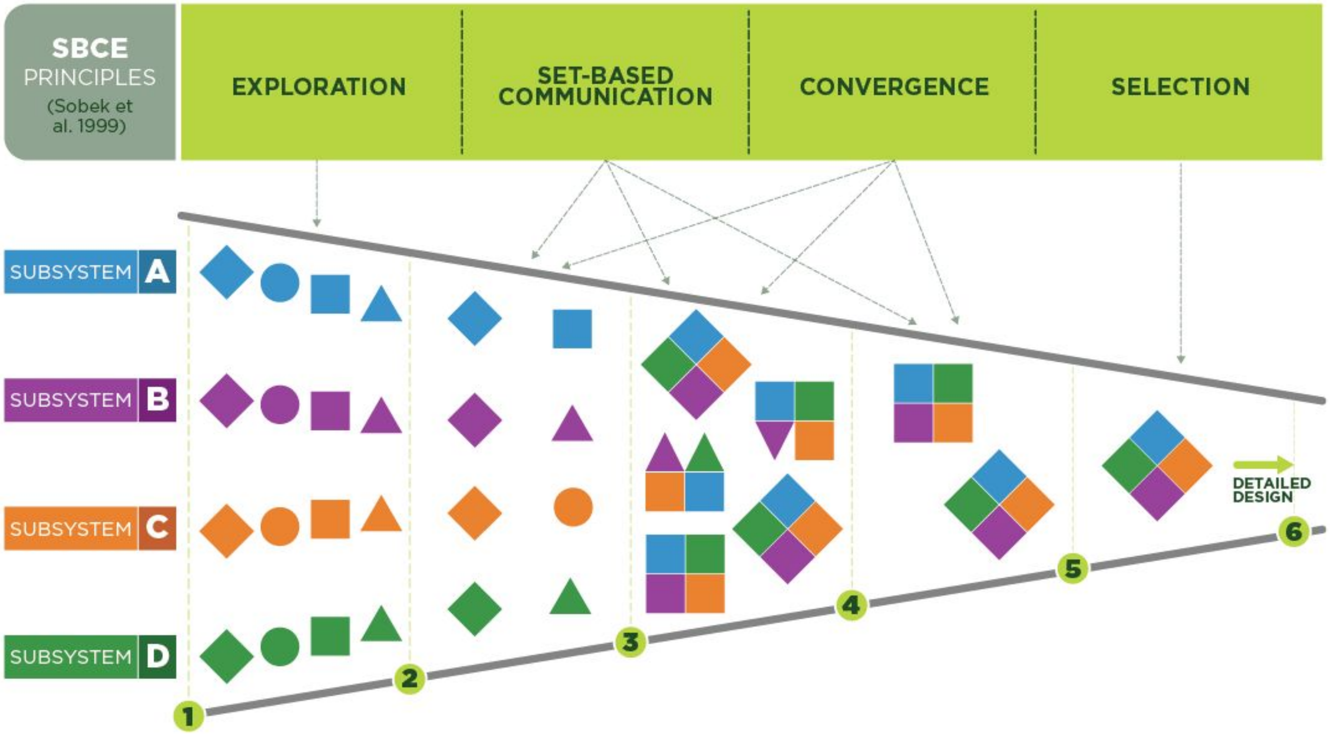


Data Scientists, Data Engineers, Machine Learning Engineers

Business

- Buy sponsored link on google adwords
- 10M Predictions in less than 1 hour (~2700/s)
- Bid each day
- Each bid should cost less than what we earn

Choose your model



And the winner is

XGBoost

And the winner is

What is Deep Learning?

What is a Deep Learning model?

HDF

protobuf

Protocol Buffers

Deeplearning in Production at Scale

?

Choose your Framework

- Distributed Prediction
- Can create complex network
- Documentation
- Community

TensorFlow

DL4J

mxnet

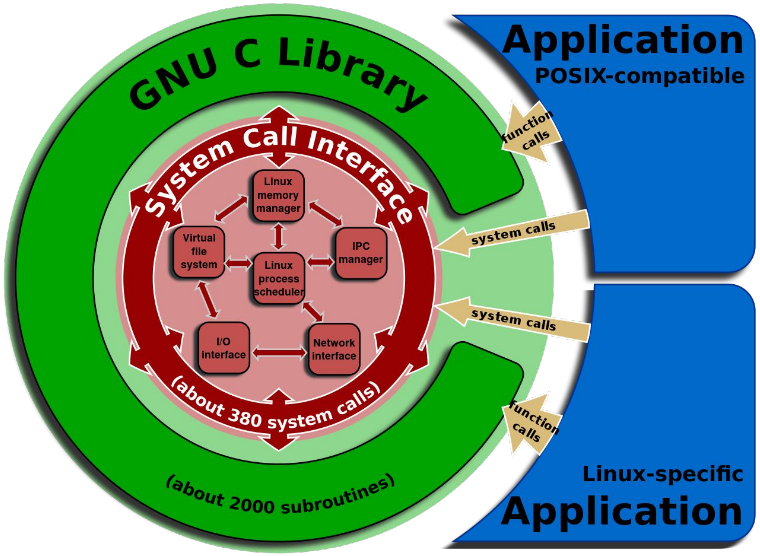
K

And the winner is

TensorFlow

Wait

CentOS

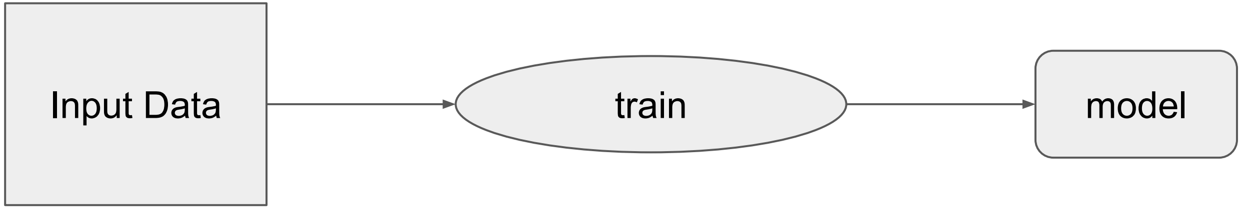

GNU C Library
(about 2000 subroutines)
System Call Interface
(about 380 system calls)
Linux memory manager
Virtual file system
Linux process scheduler
IPC manager
I/O interface
Network interface
Application
POSIX-compatible
function calls
system calls
system calls
function calls
Linux-specific
Application

And the winner is

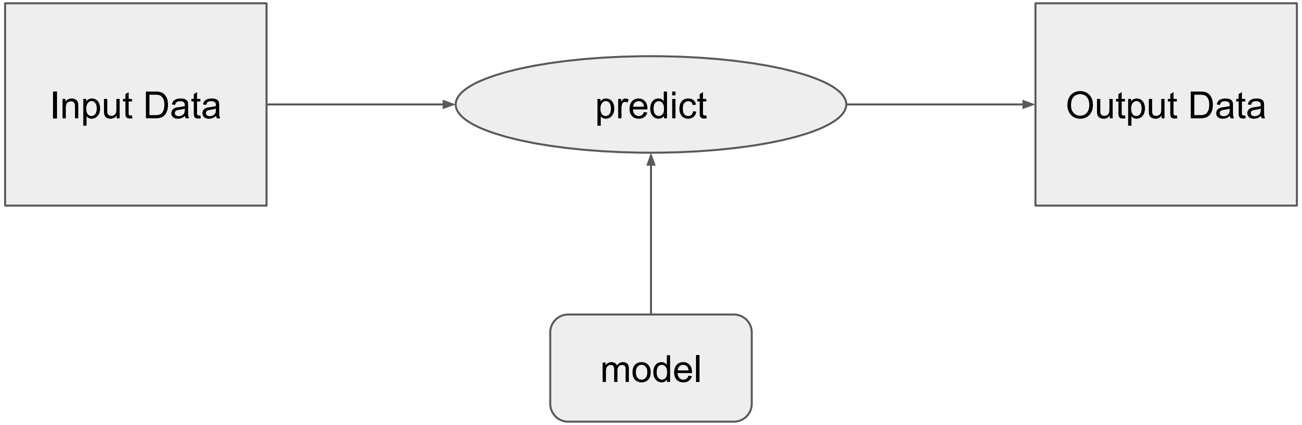
DL4J

How to Deep Learn

Train Workflow



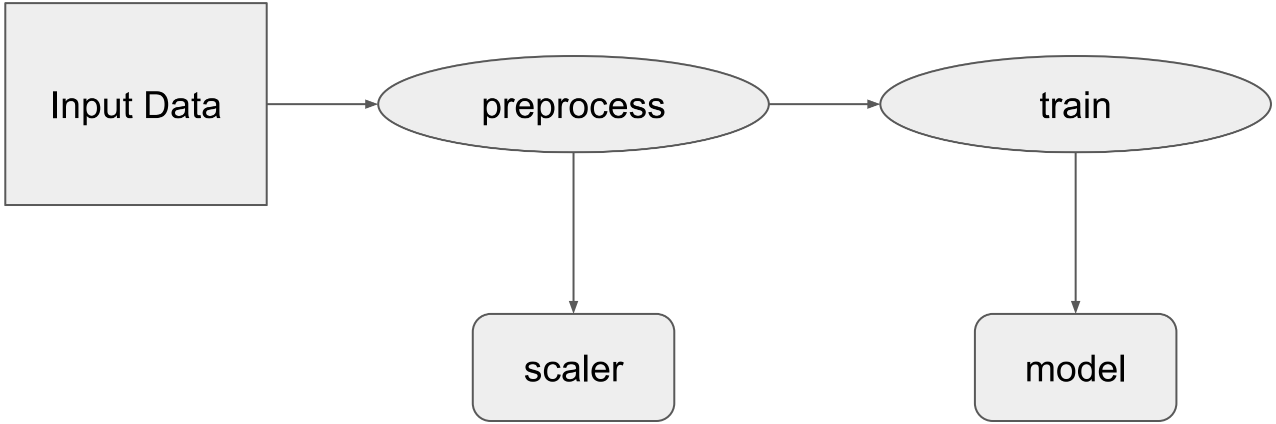
Predict Workflow



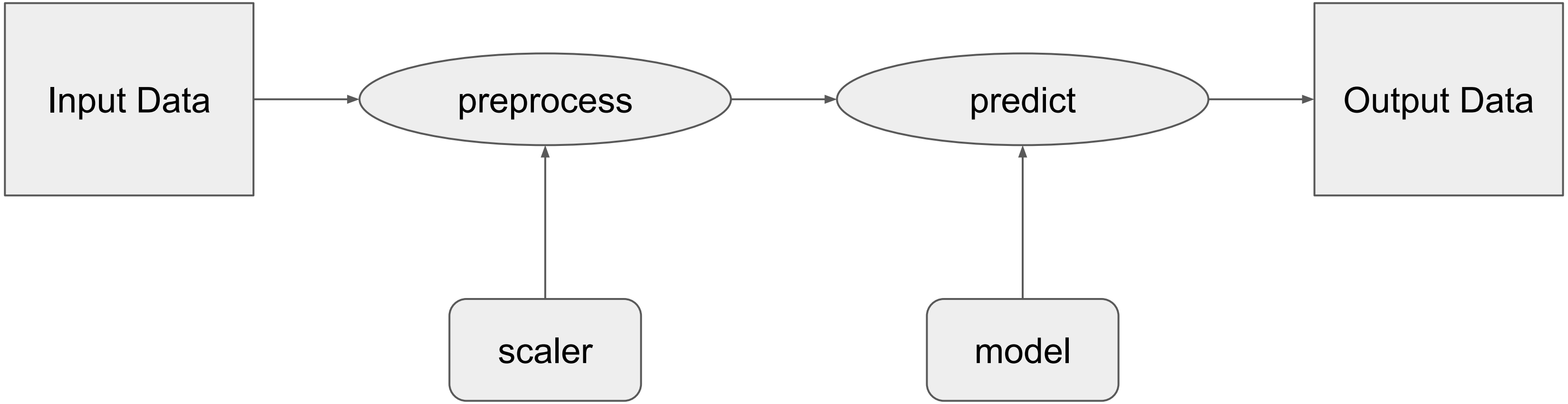
Preprocessing

- Scaling (normalisation, min max, …)
- Replace null
- Lagging

Train Workflow



Predict Workflow



Predict at scale

Scaling Prediction: naïve approach

```
def predict(input: RDD[PreprocessRow], modelPath: String): RDD[SinglePredictionRow]
= {
 input.map { row =>
   // load model
   val hdfs = FileSystem.get(new Configuration())
   val source  = new Path(modelPath)
   val model = ModelSerializer.restoreComputationGraph(hdfs.open(source), true)

   // make prediction
   val prediction = model.output(row.features)(0).getColumn(0).toFloatVector

   // return prediction
   SinglePredictionRow.fromPreprocessRow(row, prediction(0))
 }
}
```

Scaling Prediction: faster

```
def predict(input: RDD[PreprocessRow], modelPath: String): RDD[SinglePredictionRow]
= {
 // load model
 lazy val hdfs = FileSystem.get(new Configuration())
 lazy val source  = new Path(modelPath)
 lazy val model = ModelSerializer.restoreComputationGraph(hdfs.open(source), true)

 input.map { row =>
   // make prediction
   val prediction = model.output(row.features)(0).getColumn(0).toFloatVector

   // return prediction
   SinglePredictionRow.fromPreprocessRow(row, prediction(0))
 }
}
```

Scaling Prediction: fastest

```
def predict(input: RDD[PreprocessRow], modelPath: String):
RDD[SinglePredictionRow] = {
 // load model
 lazy val hdfs = FileSystem.get(new Configuration())
 lazy val source  = new Path(modelPath)
 lazy val model = ModelSerializer.restoreComputationGraph(hdfs.open(source),
true)

 input.mapPartitions { partition =>
   val partitionSeq = partition.toSeq
   if (partitionSeq.isEmpty) {
     Iterator(): Iterator[SinglePredictionRow]
   } else {
     val features = partitionSeq.map(_.features).reduce( (x, y) => Nd4j.concat(0,
x, y))

     val predictions = model.output(features)(0).getColumn(0).toFloatVector
     partitionSeq.zip(predictions).map { case (row, prediction) =>
       SinglePredictionRow.fromPreprocessRow(row, prediction)
     }.toIterator
   }
 }
}
```

OOM

- ND4J Array are C++ offheap object
- Cache your dataframe or look stage details to estimate memory usage
- Set `spark.yarn.executor.memoryOverhead`
- Use ND4J workspace to properly manage memory deallocation
- Repartition your dataframe before prediction to ensure equals partition
- Set `spark.sql.shuffle.partitions`

OOM

```scala
def predict(input: RDD[PreprocessRow], modelPath: String, numFeatures: Int, timeSteps: Int): RDD[SinglePredictionRow] =
{
   // load model ...
  lazy val basicConfig: WorkspaceConfiguration = WorkspaceConfiguration.builder().initialSize(0)
    .policyLearning(LearningPolicy.NONE).policyAllocation(AllocationPolicy.STRICT).build()
  lazy val workspace = Nd4j.getWorkspaceManager.getAndActivateWorkspace(basicConfig, "myWorkspace")

  input.mapPartitions { partition =>
    val partitionSeq = partition.toSeq
    if (partitionSeq.isEmpty) {
      Iterator(): Iterator[SinglePredictionRow]
    } else {
      workspace.notifyScopeEntered()
      val features = Nd4j.create(partitionSeq.flatMap(_.features).toArray, Array(partitionSeq.size, numFeatures,
timeSteps))
      val predictions = model.output(false, workspace, features)(0).toFloatVector
      workspace.notifyScopeLeft()

      partitionSeq.zip(predictions).map { case (row, prediction) =>
        SinglePredictionRow.fromPreprocessRow(row, prediction)
      }.toIterator
    }
  }
}
```

Compile

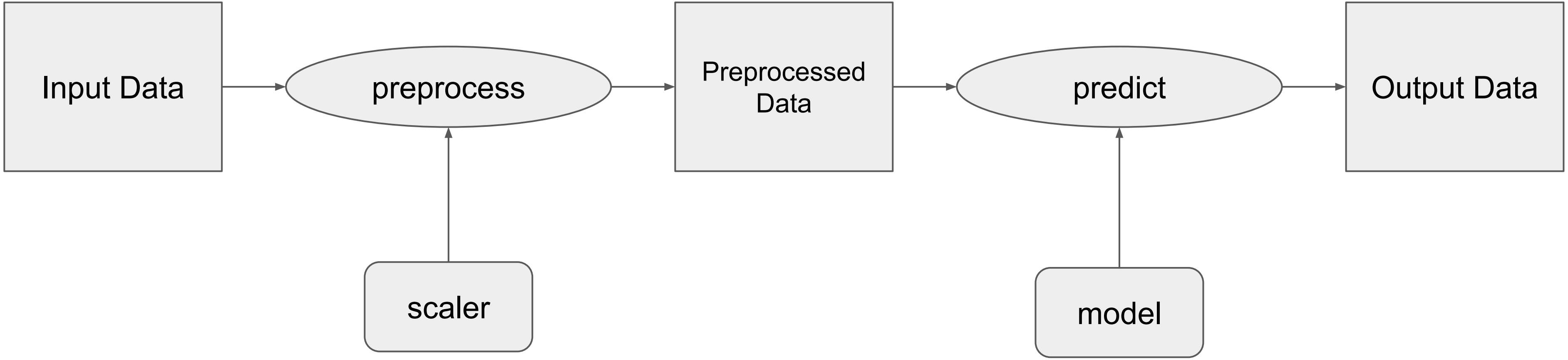
- Maven
- `-Djavacpp.platform=linux-x86_64`
- Exclude
  - `deeplearning4j-datasets`
  - `deeplearning4j-datavec-iterators`
  - `deeplearning4j-ui-components`

Training at scale

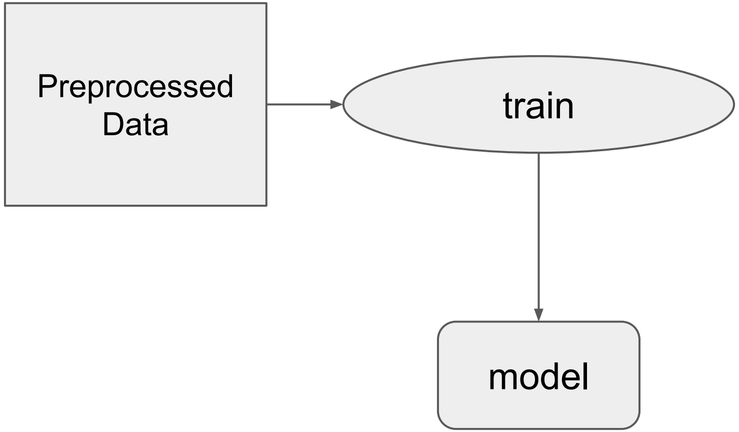
Retrain again and again and again...

- Model performance decline over time
- Hyperparameter tuning
- Deep Learning model rarely comes alone (clustering)

Predict Workflow



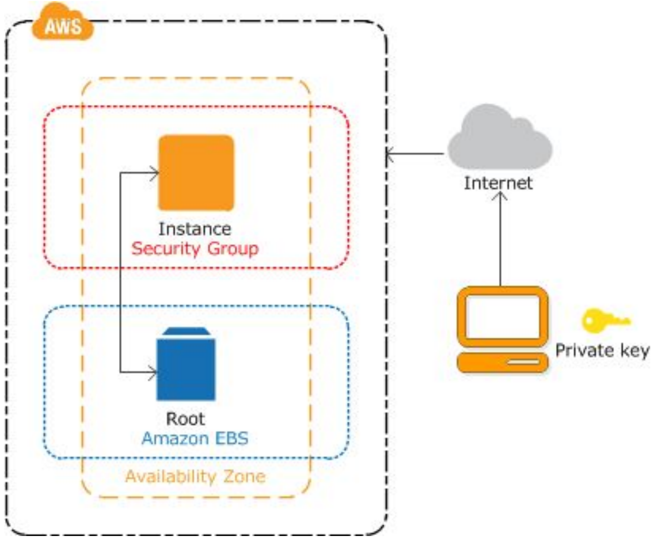
Train Workflow



Training at scale: AWS EC2

Training at scale: AWS EC2

- Create VPC
- Create Subnet associated to VPC
- Create an IGW associated to VPC
- Create a route table associated to IGW
- Create a Security Group associated to VPC
    - Authorize ssh only for my IP
- Create a key pair
- Create EC2 server with EBS volume



Training at scale: AWS EC2

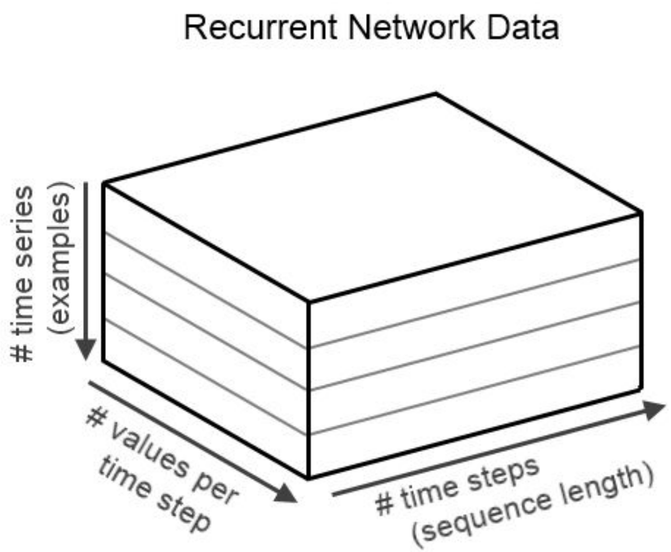
- Add ssh keys of team members
- Install cuda, cudnn, nccl and configure them
- Deploy train jar to EC2 instance
- Deploy train pipeline to EC2 instance
- Deploy preprocessed data to EC2 instance
- Deploy auto shutdown script

Training at scale: AWS EC2

- Ansible
- Transfert preprocess data to S3
- Store model in S3
- Check CPU vs GPU training time
- Keep track of training config and performance
- Share knowledge with Data Scientist
- Put your data in EBS volume if they fit

Training with DL4J: Lessons learned

- Beware of tensor order
- Prefetch data in memory (InMemoryDatasetIterator)
- Add listener to monitor your training compute performance
- Use the UI

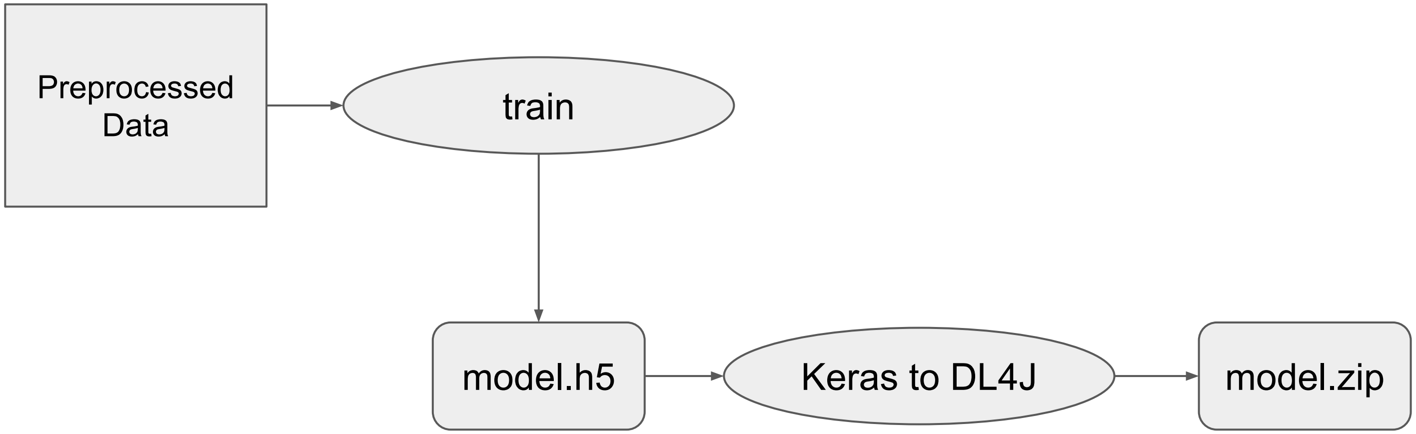


Keras to DL4J

- Data Scientist loves Keras
- Keras is easier to import on notebook
- Training on Keras is faster
- Keras is compliant with cloud training (Sagemaker, CloudML)

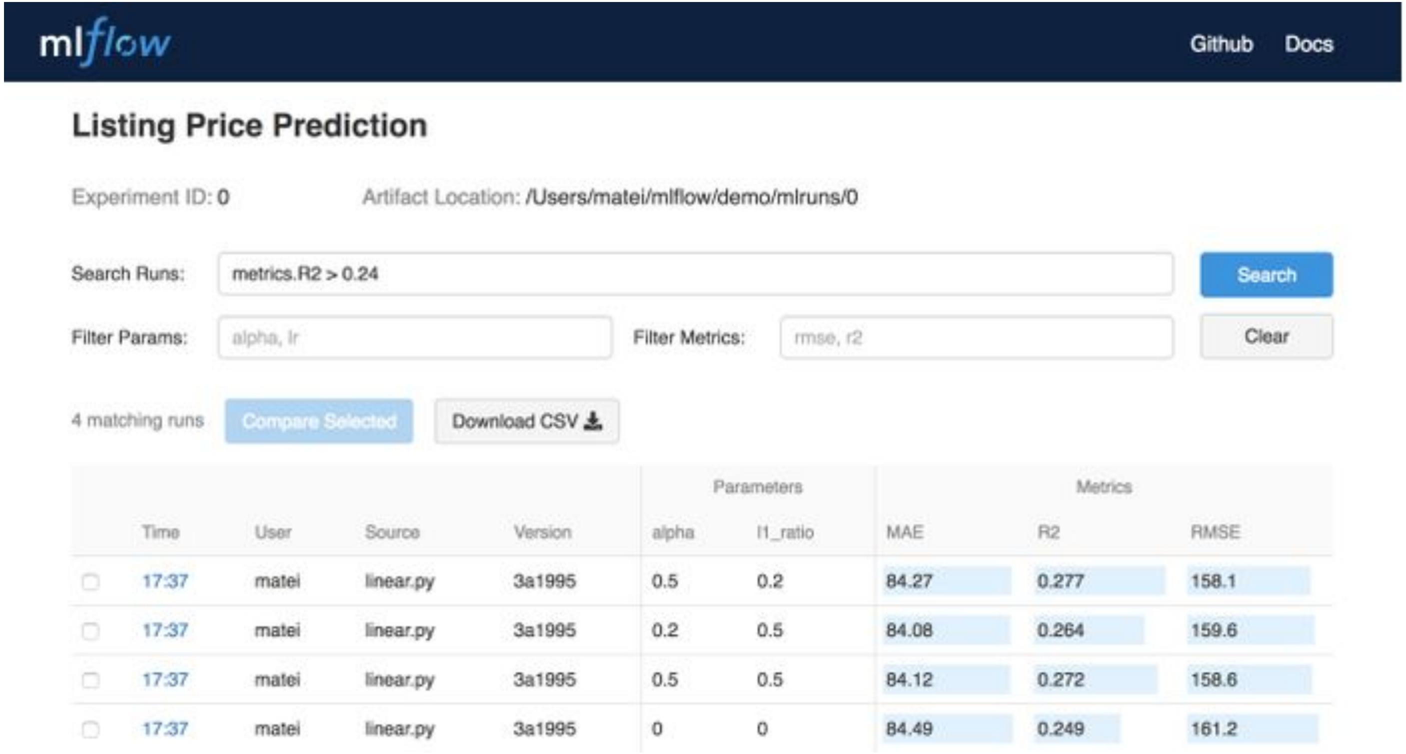
```
def execute(config: Config): Unit = {
 val kerasModel = KerasModelImport.importKerasModelAndWeights(
  config.kerasModelPath, false)
 ModelSaver.writeModel(kerasModel, config.outputModelPath)
}
```

Workflow Train



Monitoring

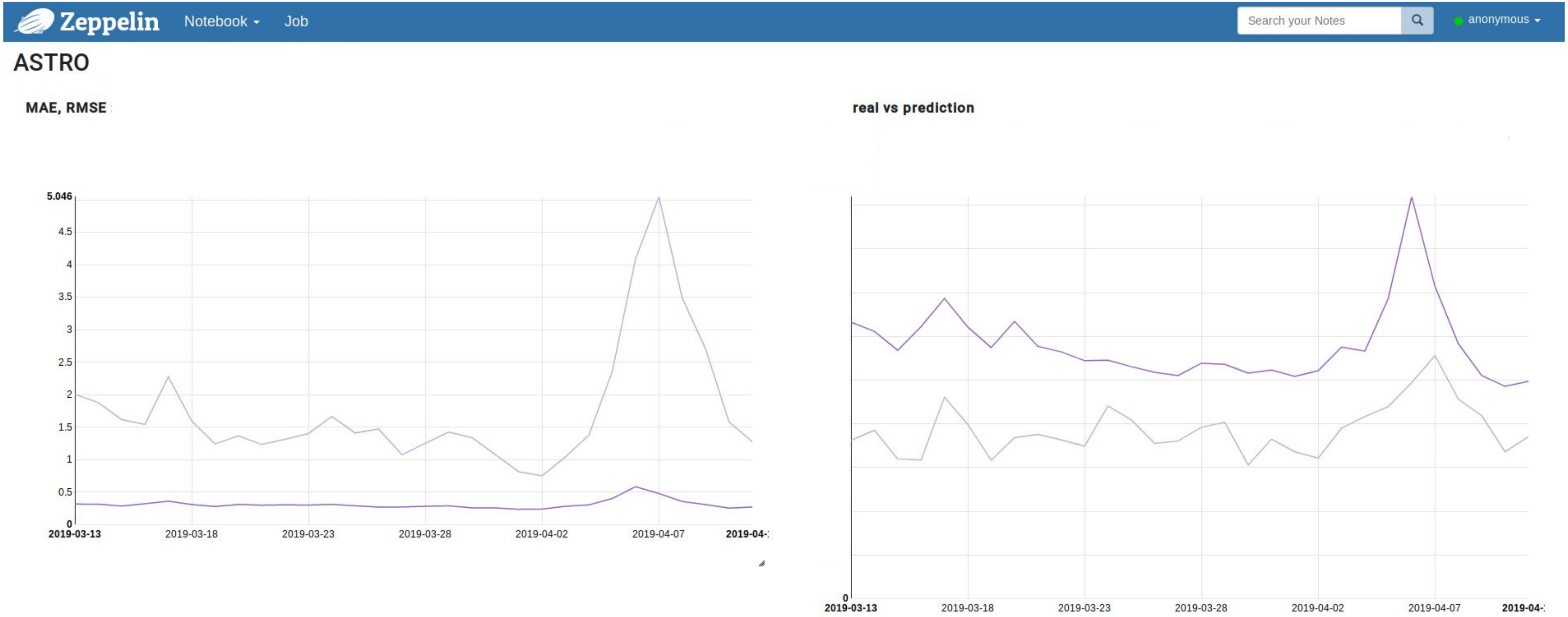
Monitoring: mlflow



Monitoring: mlflow

- Ensure your training machine can reach mlflow server
- Keep track of your experiment
  - Training parameter
  - Performance
- Compare results
- (model repository, standardize model packaging, easy deployment)

Monitoring: Zeppelin



Monitoring: Zeppelin

- Already in HDP
- Authentication
- Scheduling
- Report View
- Auto shutdown
- Can mix sources (Scala, JDBC, C*, ...)
- API to automate deployment

Apache Zeppelin

Thank you for your attention

Any questions?