End-To-End Machine Learning with Apache Spark

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End-to-End ML with Apache Spark

Outline

1. ML Project Overview
2. Operationalizing
3. Spark-Based Projects
4. Code Example!

Starting Questions

- Who in here is a Data Professional (e.g., scientist, engineer)?
- How many of you have used Apache Spark? in production?
- How many of you are currently developing/maintaining a ML service?

Acknowledgments

This talk is based and inspired on the following conferences:

- Operationalizing Machine Learning - Serving ML Models by Boris Lublinsky
- Concept Drift: Monitoring Model Quality in Streaming Machine Learning Applications by Emre Velipasaoglu
- R, Scikit-Learn, and Apache Spark ML: What Difference Does It Make? by Villu Ruusmann

Find the complete list of references in the **References** section.

Prerequisites

This talk assumes you are a machine learning enthusiast or a data-professional (e.g. scientist, engineer) that is well aware the basic concepts required to design and execute an ML-project.

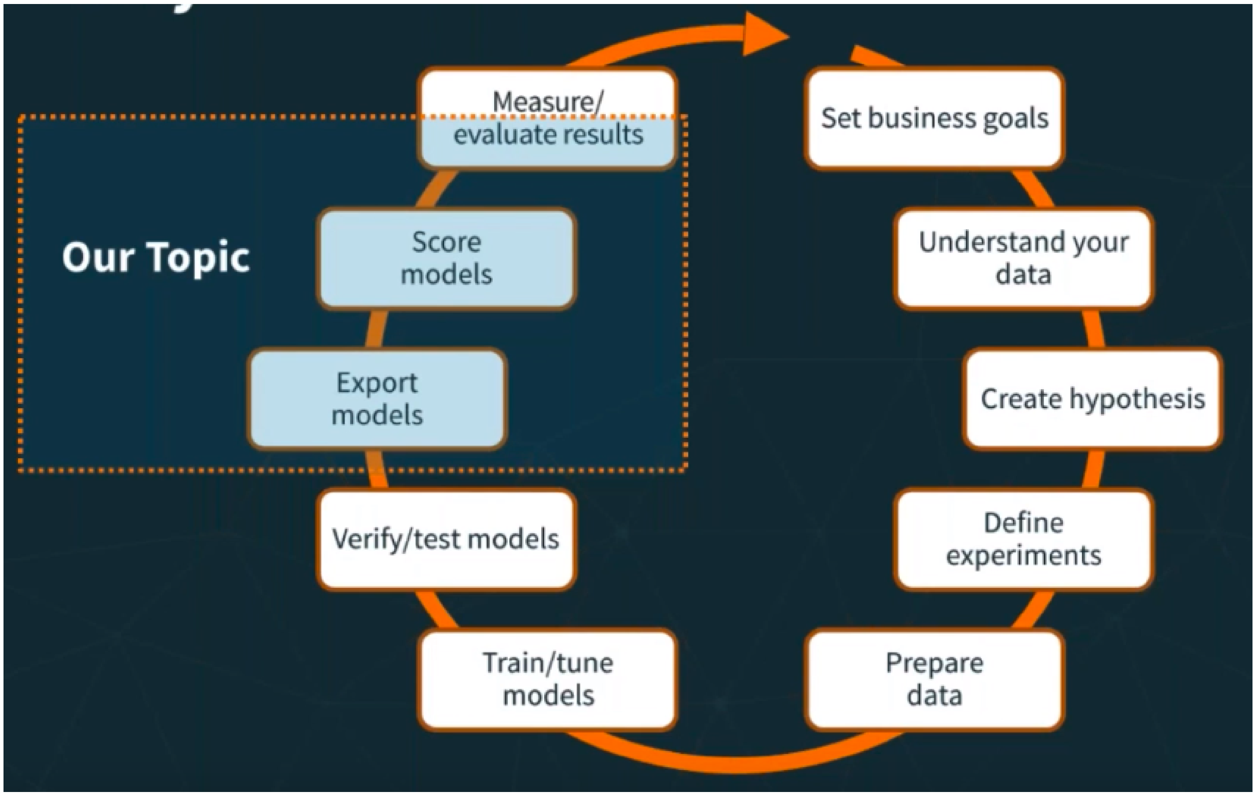
The audience must have a workable understanding of:

- Main programming languages used in the data-sphere (i.e. scala, python, R)
- General understanding of data architecutres (e.g. batch-oriented, streaming)
- Machine Learning theory (i.e., lots of math).
- Machine Learning frameworks (e.g., Spark ML, Tensorflow, PyTorch)
- Data-related skills (e.g., cleaning, visualization)

ML Project Overview

Typically with a ML Project, different groups are responsible for model training and serving. Moreover, the data science toolbox is constantly evolving, pushing software engineers to create more model-serving frameworks and introducing complexity to the development pipeline.

Consider the following machine-learning pipeline:



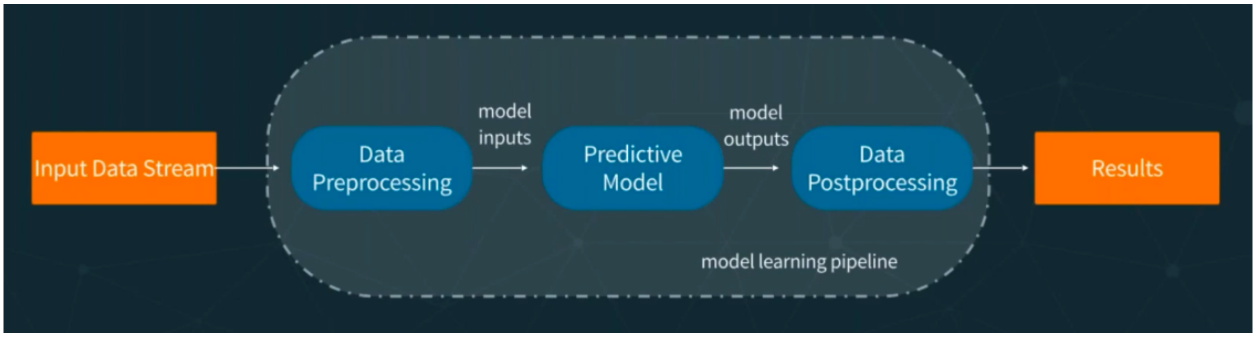
Machine Learning Cycle.

What's a ML Model?

We will use the idea of a model as just a function `f` that transforms a set of inputs `x` into outputs `y` (i.e. `y = f(x)`).

This definition allows us to apply functional composition in the implementation of our ML service.

With this is mind, we can introduce the concept [machine learning pipelines] as a graph defining a chain of operations (e.g., data transformations):

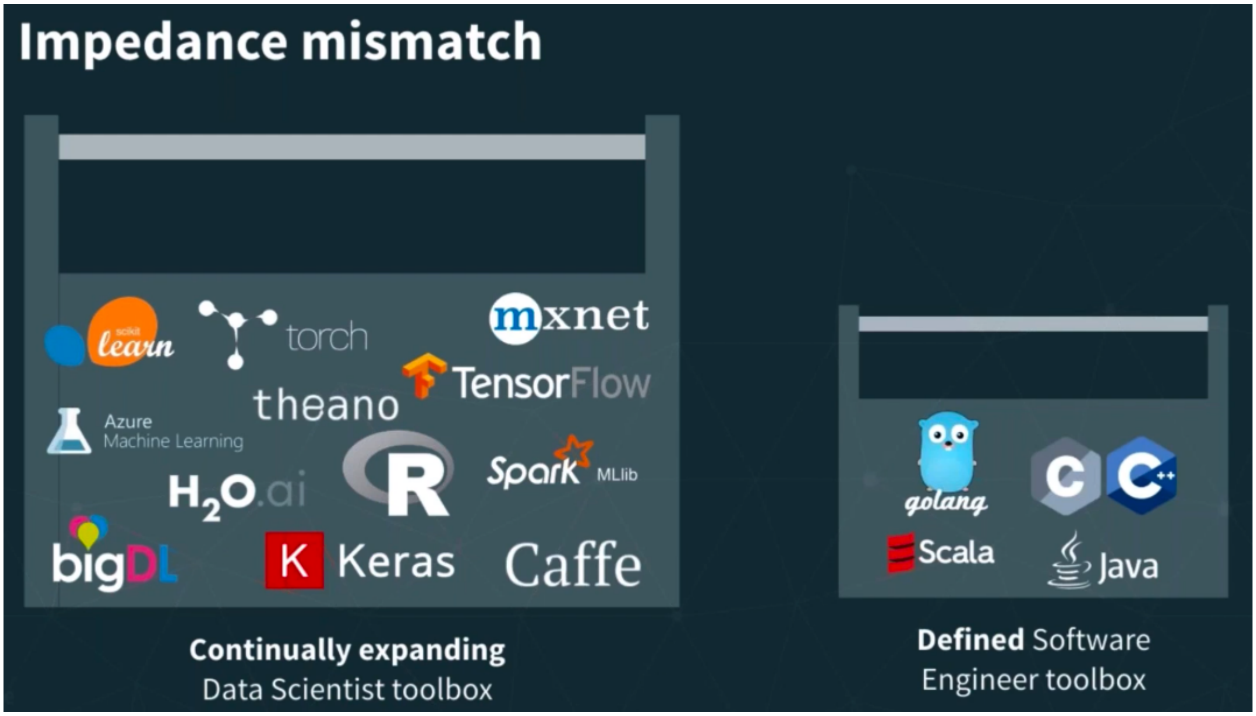


Why is it important to define a pipeline? To encapsulate all the logic needed to serve the machine learning model. This formalizes the pipeline form the input data to the output.

Operationalizing

Traditional Approach

Traditionally, the machine learning model was viewed as code. This code had to be somehow imported for serving in production.



Impedance mismatch

Continually expanding Data Scientist toolbox

Defined Software Engineer toolbox

Impedance mismatch!

A simple solution

We can shift our thinking from a "code" perspective to a "data" perspective and represent the model using a standard specification that's agnostic to the training process. We can use the PMML specification designed by the Data Mining Group to achieve this.

Predictive Markdown Model Language is:

> "an XML-based language that provides a way for applications to define statistical and data-mining models as well as to share models between PMML-compliant applications."

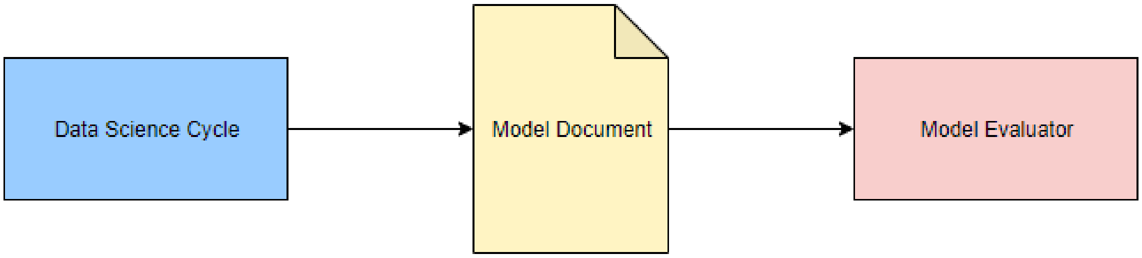
(Ruusmann 2017)

Integration with the most popular ML frameworks via JPMML:

- jpmml-sparkml
- jpmml-sklearn
- jpmml-r
- jpmml-xgboost

- jpmml-tensorflow

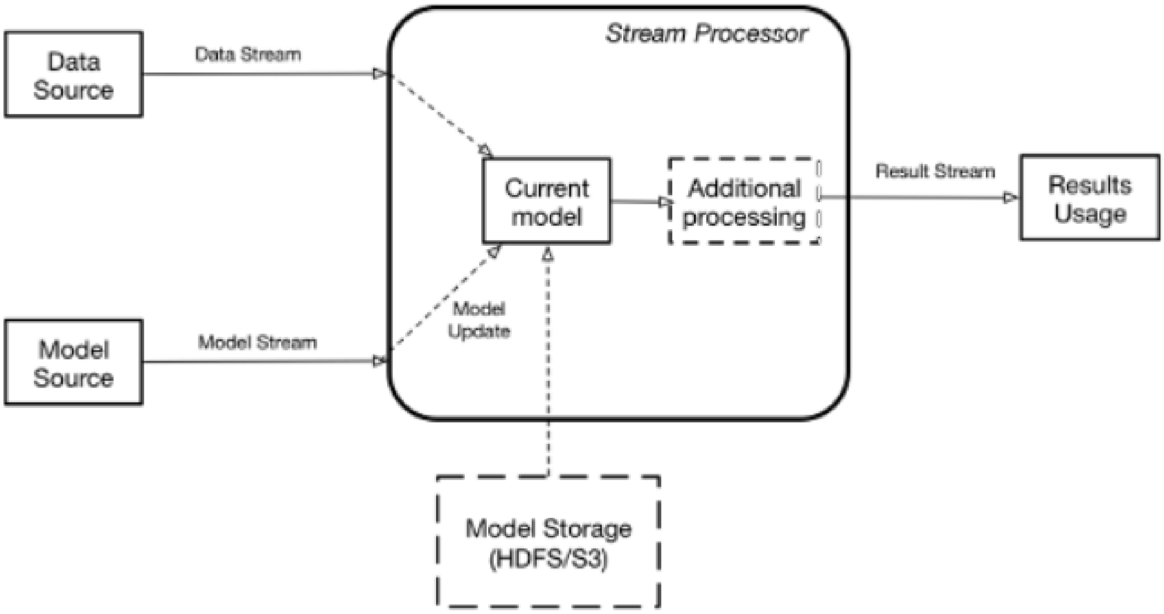
Using these tools we can achieve:



Simple Scoring.

Best Practice

We can use either a stream-processing engine (SPE e.g., Apache Spark, Flink) or a stream-processing library (SPL e.g., Akka Stream, Kafka Stream).



Suggested architecture.

- SPE: Good fit for applications that require features provided out of the box by such engines.
- SPL: Provide a programming model highly customizable and light-weight.

(Lublinsky 2017)

We can use Akka Streams - based on Akka Actors, to implement the proposed architecture (see syntax example). The result would look like this:

Simple Akka Implementation

Furthermore, we can enhance this approach by using Akka Clusters.

Akka Cluster Implementation

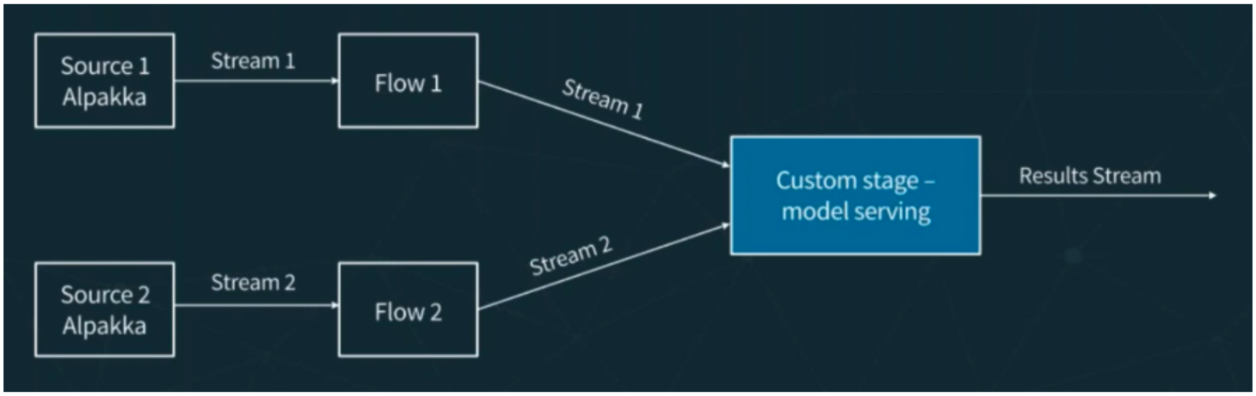


Figure 1: Naive Akka Implementation

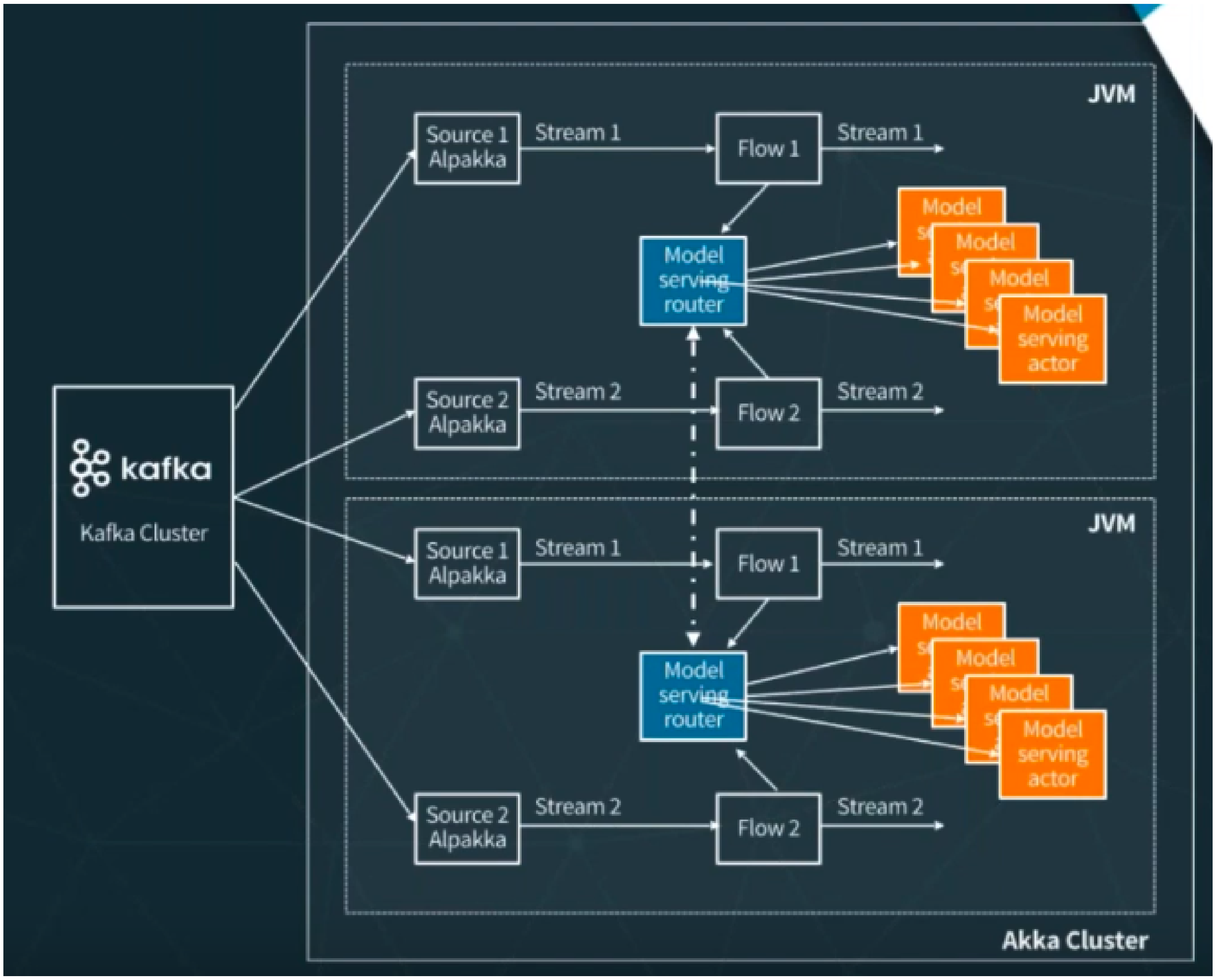
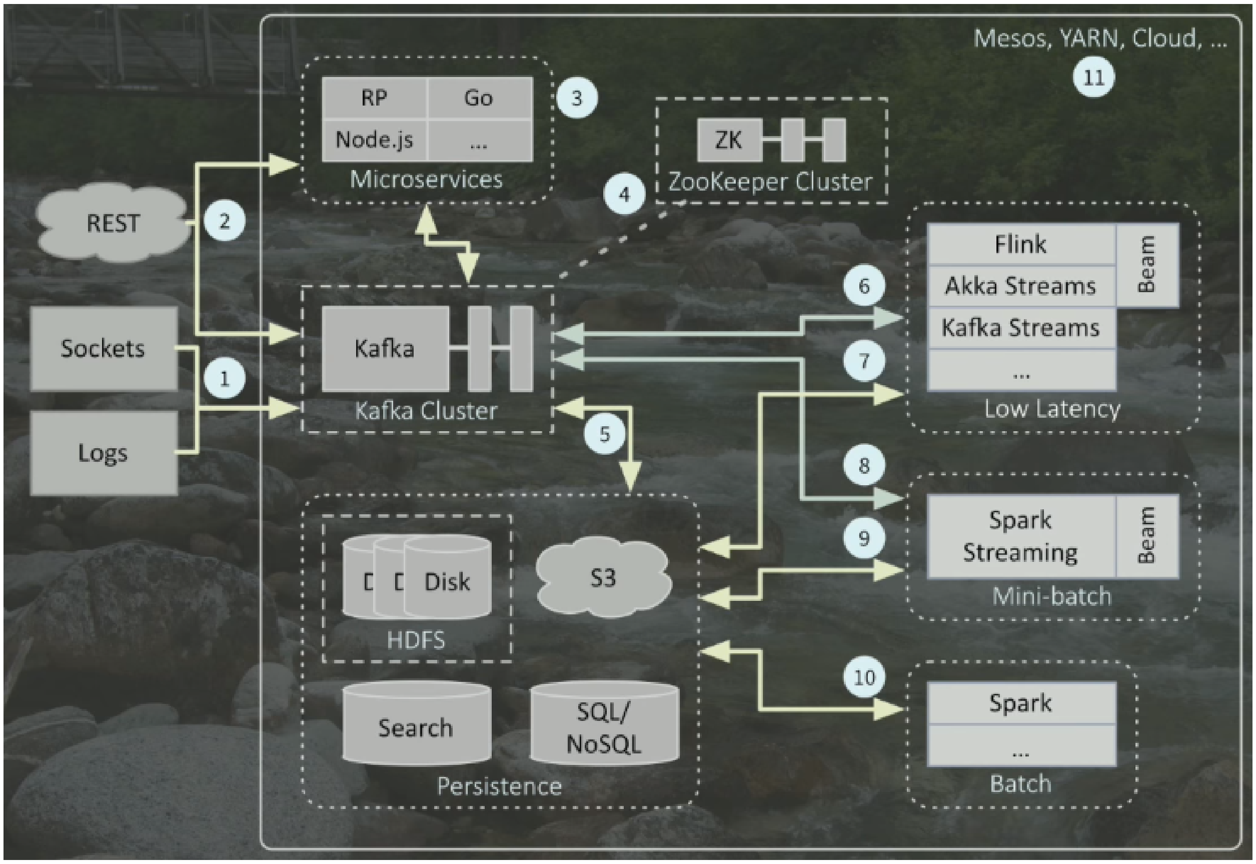


Figure 2: Akka Cluster Implementation

The Big Picture

Dean Wampler does a fantastic job describing the overall picture of a data-driven system architecture.



Big Picture Architecture

(Wampler 2017)

Spark-Based Projects

Why Apache Spark?

According to their website,

> "Apache Spark is a unified analytics engine for large-scale data processing."

According to the book "High Performance Spark - Best Practices for Scaling & Optimizing Apache Spark":

> "Apache Spark is a high-performance, general puropose distributed computer system. Spark enables us to process large quantities of data, beyond what can fit on a sinlge machine, with a high-level, relatively easy-to-use API. Uniquely, Spark allows us to write the logic of data transformations and machine learning algorithms in a way that is parallelizable, but relatively system agnostic."

(Karau and Warren 2017)

Most of the Apache Spark features revolve around a base data-structure called RDDs (resilient distributed datasets). An RDD is a fault-tolerant collection of elements that can be operated on parallel.

Let's initialize an Spark Session (sbt console: `sbt -Dscala.color "content/console"`):

```
import org.apache.spark.sql.SparkSession

val spark =
  SparkSession.builder.appName("Example!").config("spark.master", "local[*]").getOrCreate()

import spark.implicits._
```

By default, the number of partitions is the number of all available cores (Laskowski 2017):

```
spark.sparkContext.defaultParallelism
// res0: Int = 12
```

We can test this by creating a simple Dataset from a list:

```
trait Person

object Person {
  final case class Dead(name: String, birthYear: Int, deadYear: Int) extends Person {
      def kill: Dead = this
    }

  final case class Alive(name: String, birthYear: Int) extends Person {
    def kill: Dead = Dead(name, birthYear, 2019)
  }

  val names: List[String] = List(
    "Data Ninja",
    "Random Developer",
    "Pizza Lover",
    "Beer Lover"
  )

  val years: List[Int] = (1980 to 2000).toList

  def getRandomElement[A](ls: List[A]): A =
    ls(scala.util.Random.nextInt(ls.size))

  def getRandom: Alive = Alive(getRandomElement(names), getRandomElement(years))
}

val people: List[Person.Alive] = (1 to 1000).toList.map(i => Person.getRandom)
```

We can now create a `Dataset[Person]`:

```
import org.apache.spark.sql.Dataset

val alivePeople: Dataset[Person.Alive] = spark.createDataset(people)
```

The number of partitions on this dataset:

```
alivePeople.rdd.partitions.size
// res1: Int = 12
```

```
val deadPeople: Dataset[Person.Dead] =
  alivePeople.filter(_.birthYear > 1994).map(person => person.kill)
// deadPeople: org.apache.spark.sql.Dataset[Person.Dead] = [name: string, birthYear: int ... 1 more fie

deadPeople.show()
// +----------------+---------+--------+
// |            name|birthYear|deadYear|
// +----------------+---------+--------+
// |      Data Ninja|     1998|    2019|
// |Random Developer|     2000|    2019|
// |Random Developer|     1996|    2019|
// |      Data Ninja|     1995|    2019|
// |Random Developer|     1996|    2019|
// |      Beer Lover|     1997|    2019|
// |      Beer Lover|     1997|    2019|
// |     Pizza Lover|     1997|    2019|
// |      Data Ninja|     1999|    2019|
// |      Beer Lover|     1997|    2019|
// |      Data Ninja|     1996|    2019|
// |      Beer Lover|     1996|    2019|
// |      Beer Lover|     1997|    2019|
// |     Pizza Lover|     1997|    2019|
// |      Data Ninja|     1995|    2019|
// |      Beer Lover|     1999|    2019|
// |Random Developer|     1995|    2019|
// |     Pizza Lover|     1995|    2019|
// |      Data Ninja|     1997|    2019|
// |     Pizza Lover|     2000|    2019|
// +----------------+---------+--------+
// only showing top 20 rows
//
```

```
spark.close()
```

For performance reasons, this presentation will use the official Scala API.

Intro to Spark ML

Spark ML is a practical and scalable machine learning library based on a [Dataset]. A Dataset is a distributed collection of data with interesting features such as strong typing, lambda functions, and with the advantages of the Spark SQL's optimized execution engine. We can manipulate a dataset with functional transformantions. The most basic ones:

- map - `Dataset[A].map(fn: A => B): Dataset[B]`
- flatMap - `Dataset[A].flatMap(fn: A => Dataset[B]): Dataset[B]`
- filter - `Dataset[A].filter(fn: A => Boolean): Dataset[A]`

One of the most usefull abstractions available on the Spark ML package are pipelines. Main concepts:

- `Dataset[Row]`: A set of data, also called dataframe. Each row usually represents an observation.
- `Transformer`: an algorithm that takes one `DataFrame` and returns another `DataFrame`.
- `Estimator`: an algorithm that takes a `DataFrame` and returns a `Transformer`.
- `Pipeline`: a chain of multiple `Transformer` or `Estimator`.

Intro to JPMML and Openscoring

Data Scientist might use Python and R for exploration and modeling while software engineers use Scala, Java, or Go for the system architecture. Complexity arises when dealing with multiple runtimes and trying to integrate the data solutions into the system. One way to standardize this interaction is via PMML: Predictive Markdown Model Language.

To use the jpmml-sparkml library, just add the following dependency to your sbt file:

```
"org.jpmml" % "jpmml-sparkml" % "1.4.5"
```

Now we can just take a Spark `PipelineModel` and create a PMML object:

```
val pmmlBuilder = new PMMLBuilder(schema, pipelineModel)
pmmlBuilder.build()
```

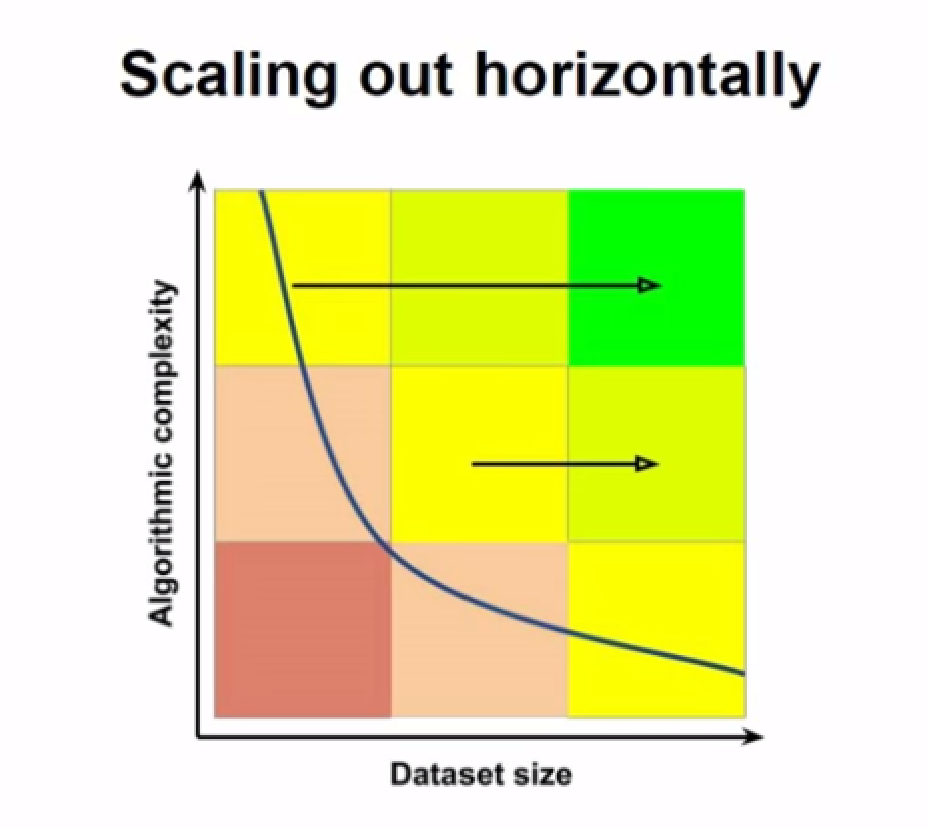
See the official jpmml-sparkml github repo for a complete list of supported `PipelineStages` types.

We can use Openscoring, a java-based REST web-service, as our scoring-engine of the resulting PMML model.

- Simple but powerful API
- Allows for single predictions and for batch predictions.
- Acceptable performance (usually sub-milliseconds respond time)

Model REST API endpoints:

HTTP method	Endpoint	Required role(s)	Description
GET	/model	-	Get the summaries of all models
PUT	/model/${id}	admin	Deploy a model
GET	/model/${id}	-	Get the summary of a model
GET	/model/${id}/pmml	admin	Download a model as a PMML document
POST	/model/${id}	-	Evaluate data in “single prediction” mode
POST	/model/${id}/batch	-	Evaluate data in “batch prediction” mode
POST	/model/${id}/csv	-	Evaluate data in “CSV prediction” mode
DELETE	/model/${id}	admin	Undeploy a model



Complexity vs dataset size.

(Ruusmann 2017)

Code Example!

Download the data

We can use the Gutenberg Project as a data-source for our ML task. To download the complete content of the gutenberg project as a set of txt-files run the following bash-command:

```
curl -sSL https://raw.githubusercontent.com/RHDZMOTA/spark-wordcount/develop/gutenberg.sh | sh
```

Depending on your network speed this can take up to 3 hours.

Let's figure out the "footprint" of this dataset:

- Number of books: `ls -l gutenberg | wc -l`
- Data size: `du -sh gutenberg`

Consider taking a random sample to facilitate local development. The following command generates a sample of 5K books:

```
mkdir gutenberg-sample && ls gutenberg/ | shuf -n 5000 | xargs -I _ cp gutenberg/_ gutenberg-sample/_
```

Printing the results.

```
echo "There are $(ls -l gutenberg | wc -l) books that represent: $(du -sh gutenberg)"
```

Minimum Setup

1. Install [Java 8] or greater.
    - Debain-based OS: `sudo apt install openjdk-8-jdk`
2. Install the [Scala Build Tool] (SBT)
    - Debian-based OS:

```
$ sudo apt install wget
$ wget https://dl.bintray.com/sbt/debian/sbt-1.2.6.deb
$ sudo dpkg -i sbt-1.2.6.deb
$ rm -r sbt-1.2.6.deb
$ sbt about
```

WordCount

Let's do a quick wordcount example on the dataset as a warm-up exercise:

```
import com.rhdzmota.presentations.Settings.S03
import com.rhdzmota.presentations.S03.config.Context
import org.apache.spark.sql._

object WordCount extends Context {
  import spark.implicits._

  final case class WordCount(word: String, count: Long)

  val data: Dataset[String] = spark.read.textFile(S03.Data.source)

  val wordcount: Dataset[WordCount] = data
    .flatMap(_.split("""\s+""")).map(_.toLowerCase.replaceAll("[^A-Za-z0-9]", "")).filter(_.length > 1)
    .groupByKey(identity).count().map({case (w, c) => WordCount(w, c)})
    .sort($"count".desc)

  def main(args: Array[String]): Unit = {
    println("S03 WordCount Application")
    wordcount.show()
    spark.close()
  }
}
```

Run:

```
WordCount.main(Array[String]())
```

Or:

```
sbt "content/runMain com.rhdzmota.presentations.S03.WordCount"
```

Next Word Prediction

The challenge we have consists con taking an n-set of books and create a model that's capable of predicting the next word given a context of the last m-words.

A similar approach is performed for generating word embeddings based on the distributional hypothesis - words that appear in the same contexts share semantic meaning.

Openscoring Container

We can easily leverage Openscoring with Docker.

Consider the following `Dockerfile`:

```
FROM maven:3.5-jdk-8-alpine

RUN apk update && apk upgrade && apk add --no-cache bash ca-certificates wget openssh

RUN wget https://github.com/openscoring/openscoring/releases/download/1.4.3/openscoring-server-executabl

ADD application.conf application.conf

ENTRYPOINT java -Dconfig.file=application.conf -jar openscoring-server-executable-1.4.3.jar

EXPOSE 8080

CMD []
```

And the following `application.conf` file:

```
application {
  // List of JAX-RS Component class names that must be registered
  componentClasses = [
    "org.openscoring.service.filters.NetworkSecurityContextFilter",
    "org.openscoring.service.filters.ServiceIdentificationFilter"
  ]
}

networkSecurityContextFilter {
  // List of trusted IP addresses. An empty list defaults to all local network IP addresses.
  // A client that originates from a trusted IP address (as indicated by the value of the CGI variable
  trustedAddresses = ["*"]
}
```

We can create our custom image with:

```
docker build -t next-word-demo/openscoring resources/provided/docker/
```

Now we can run a docker container with:

```
docker run -p 8080:8080 -d --name next-word-engine next-word-demo/openscoring
```

You can test this service is running by going to: `http://{ip-address}:8080/openscoring` where `ip-address` is your `docker-machine ip` or `localhost`. We can now upload the resulting dataset to the Openscoring API:

```
curl -X PUT --data-binary @resources/output/model/2019-01-25T01-07-14.836-89d19488-3d3d-483c-a2f0-47caf
-H "Content-type: text/xml" \
http://192.168.99.100:8080/openscoring/model/next-word
```

We should see the model in `http://{ip-address}:8080/openscoring/model/next-word-demo`.

Enjoy your scoring!

```
curl -X POST --data-binary @resources/provided/requests/req-01.json \
    -H "Content-type: application/json" \
    http://192.168.99.100:8080/openscoring/model/next-word \
    | jq '.result."pmml(prediction)"'
```

References

Karau, Holden, and Rachel Warren. 2017. *High Performance Spark: Best Practices for Scaling and Optimizing Apache Spark.* “ O’Reilly Media, Inc.”

Laskowski, Jacek. 2017. “Mastering Apache Spark.” *Gitbook: Https://Jaceklaskowski.gitbooks.io/Mastering-Apache-Spark* 25.

Lublinsky, Boris. 2017. *Serving Machine Learning Models - a Guide to Architecture, Stream, Processing Engines, and Frameworks.* “O’Reilly Media, Inc.”

Ruusmann, Villu. 2017. “R, Scikit-Learn, and Apache Spark Ml: What Difference Does It Make?” Youtube - StartApp. https://www.youtube.com/watch?v=CdVXEQgmnfY.

Wampler, Dean. 2017. “Fast Data Architectures for Streaming Applications.” Youtube - GOTO Conferences. https://www.youtube.com/watch?v=oCW5y4_8uGU.