# Music Popularity Prediction

CSYE7200 - Final Project

# Our team

3 members!

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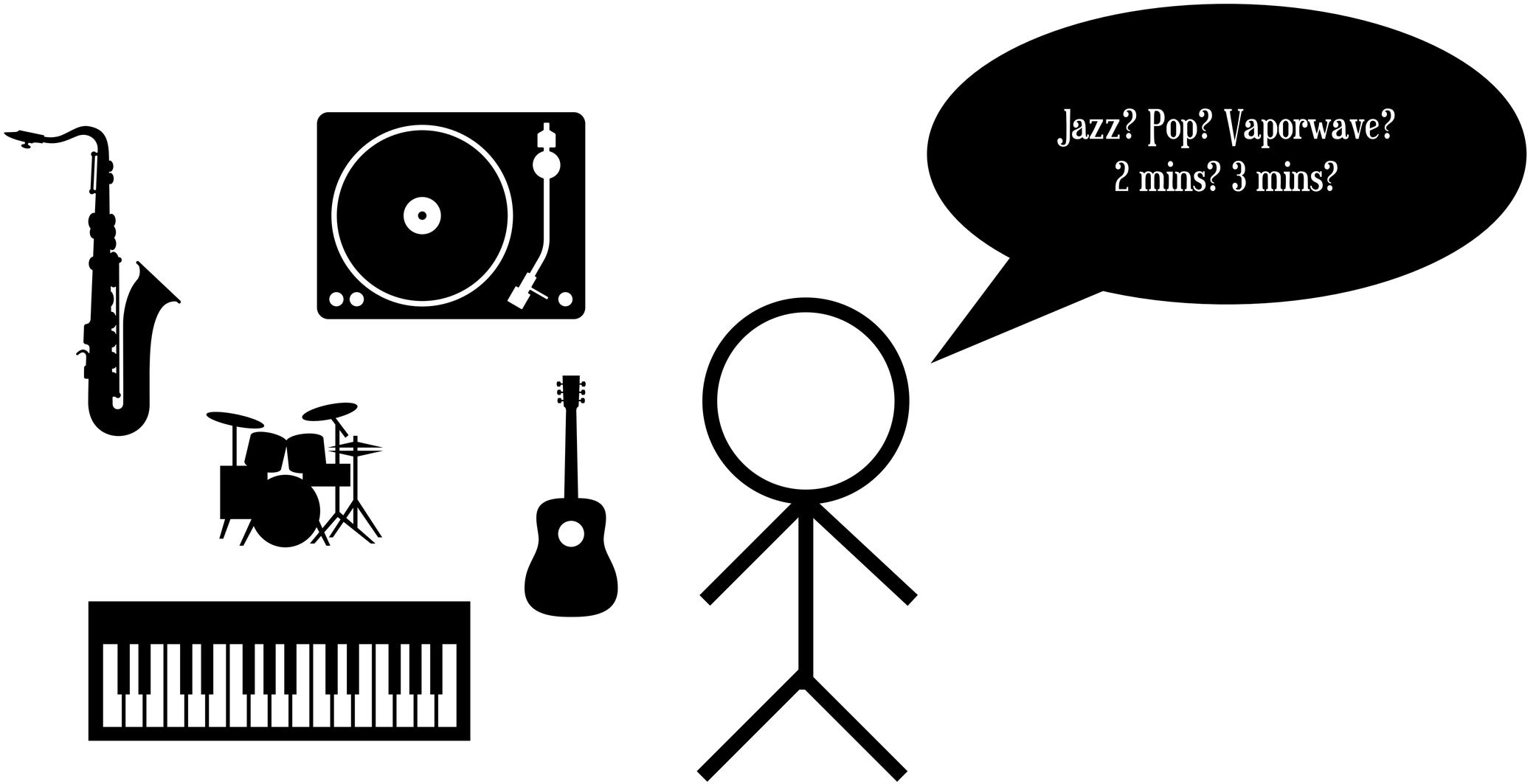



(Music producer who is trying to write next song)

Title
Artist
Duration
Energy
Loudness
...

Music Features

# Music Popularity Prediction

Yes!
Your song will be popular!

Or

No!
Most people won’t like your song

# Data sources

- Million Song Dataset
  - http://millionsongdataset.com/
- ~1,000,000 rows of data
- Has “song_hotttnesss” attribute for popularity

Because the data size is too large(more than 300 GB), we finally used a subset of the source data(about 380,000 rows)

Some attributes

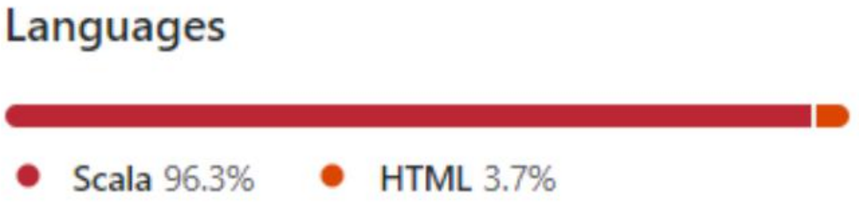
end_of_fade_in
start_of_fade_out
loudness
tempo
title
year
song_hotttness
...

# Use cases

- User calls the API with music features, and receives prediction value.
- User calls the API and system validates user input, informs user if there is any error.
- User calls the API and system processes the input data, runs ML model on it and returns the prediction value.

# Scala in our project

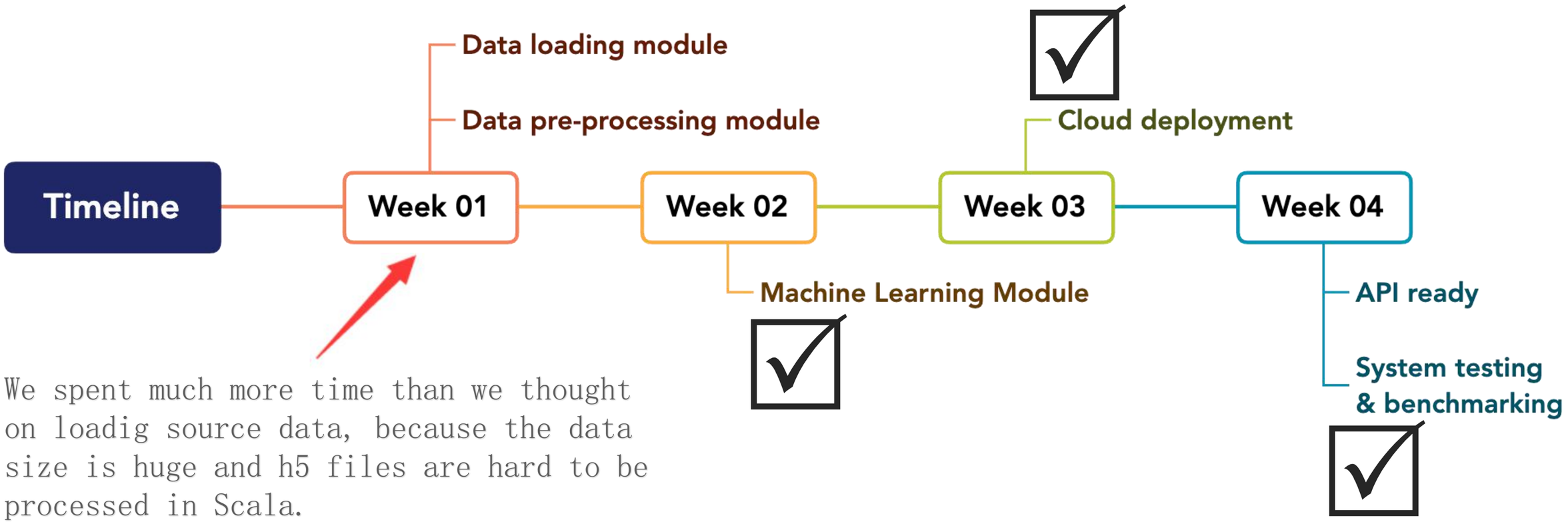
- Planning to write all codes in Scala ☑
  - Data loading and pre-processing — Scala & Spark
  - Machine learning — Spark build-in ML library
  - API web service — Scala Play! Framework




Library used for reading h5 file in scala: https://github.com/jamesmudd/jhdf

- Our repo: https://github.com/NiftyMule/csye7200-bigdata-project

# Milestones




We spent much more time than we thought on loadig source data, because the data size is huge and h5 files are hard to be processed in Scala.
Fortunately, we finished this milestone at Week 02 and didn’t break our timeline

# Methodology

## Big data

- Whole application is a big-data application
- 2 loops
  - **Training**: Ingest -> Feature extraction -> Machine learning
  - **Inference**: Ingest -> Feature extraction -> Model inference -> Return

# Ingesting - Implementation

```scala
def loadRowFromH5(h5FilePath: String): Try[Option[Row]] = Try (...)

def loadDataFromFolder(folderPath: String, spark: SparkSession): Try[DataFrame] = Try (...)

def loadCsv(filepath: String, spark: SparkSession): Try[DataFrame] = Try {
  spark.read
    .option("delimiter", ",")
    .schema(getSchema())
    .csv(filepath)
}

def dfFromJson(json: JsValue, spark: SparkSession): Try[DataFrame] = Try {
  spark.read
    .schema(getSchema(isTrainData = false))
    .json(
      spark.createDataset(List(json.toString()))(Encoders.STRING)
    )
}
```

# Ingesting - Unit Test

```
behavior of "loadDataFromH5"

it should "successfully load sample .h5 file" in {...}

it should "skip the row if hotness field is missing" in {...}

it should "return failure when given invalid filepath" in {...}

behavior of "loadDataFromFolder"

it should "successfully load data from h5 folders" in {...}

it should "fail when given wrong filepath" in {...}

behavior of "loadCSV"

it should "successfully load data from CSV file" in {...}

behavior of "Json converter"

it should "successfully convert JsValue to DataFrame" in {...}
```

# Methodology

## Machine learning

- Spark built-in ML library
- Algorithms planning to be used:
  - Logistic regression
  - Random forest
  - Bag of Words

We didn’t use this technic because we end out dropping all StringType features and the accuracy still get up to the Acceptance criteria.

# Preproccesing

```scala
def columnProcessing(df: DataFrame, isTrainData: Boolean = true): Try[DataFrame] = Try {
  // drop songs before 1920 and those with nan values
  logger.info( message = s"raw dataframe size: ${df.count()}")
  val df1 = df.filter(df("year") > 1920)
    .na.drop(List("artist_latitude", "artist_longitude"))
    .drop( colNames = "artist_id", "artist_name", "title", "artist_terms", "artist_terms_freq", "artist_terms_weight")
    .withColumn( colName = "year", df("year") - 1920)
  // logger.info(s"Batch year = ${df1.select("year").head(4).map(x => x.getInt(0)).mkString("Array(", ", ", ")")}")

  if (isTrainData) {
    val avgHotness = df1.select(expr( expr = "AVG(song_hotness)"))
      .collect().head.getDouble(0)

    // set training label & shift years
    df1.withColumn( colName = "label", when(df1("song_hotness") >= avgHotness, value = 1).otherwise( value = 0))
  } else df1
}
```

Drop invalid data and useless features

Calculate Avg hotness for decieding if a song is popular

Generate labels for training

# Assembler & Standard Scaler

```
def assembleScalePipeline(df: DataFrame): Pipeline ={
  val vectorAssembler = new VectorAssembler()
    .setInputCols(df.dtypes
      .filter(x => !List("song_hotness", "label").contains(x._1) && List("DoubleType", "IntegerType").contains(x._2))
      .map(_._1)
    )
    .setOutputCol("raw_features")

  val standardScaler = new StandardScaler()
    .setInputCol("raw_features")
    .setOutputCol("features") // MUST set here "features", Model will find this col by specific name to train

  new Pipeline().setStages(Array(vectorAssembler, standardScaler))
}
```

Choose Double and Int type of data as training features

Data Normalization

Construct as a pipeline

# Model training

```scala
def fit(df: DataFrame,
        modelName: String,
        evaluate: Boolean = false
       ): Try[PipelineModel] = Try {
  val dataSplit = df.randomSplit(Array(0.8, 0.2), seed = 11L)
  val trainSet = dataSplit(0).cache()

  val assemble_scale_pipeline = assembleScalePipeline(df)

  val model = modelName match {
    case ModelName_LR => new LogisticRegression()
    case ModelName_RF => new RandomForestClassifier()
    case _ => throw new Exception("Invalid model name")
  }

  val whole_pipeline = new Pipeline().setStages(Array(assemble_scale_pipeline, model))

  logger.info( message = s"Fitting with $modelName...")
  val trainedPipelineModel = whole_pipeline.fit(trainSet)
  logger.info( message = s"Fitting complete! [$modelName]")

  // evaluate model performance
  if (evaluate) {...}

  trainedPipelineModel
}
```

80% for training, 20% for validation

Construct whole pipeline with assemble, scale and model

Evaluation part

# Machine Learning - Unit test

```
behavior of "ML Pipeline"

it should "successfully preprocess dataframe" taggedAs Slow in {...}

it should "successfully train and predict" taggedAs Slow in {...}
```

# Methodology

## Cloud

A Master with 2 Slaves on AWS

- Deploy Spark cluster on AWS
- To leverage the power of parallel computing
- Expose an API

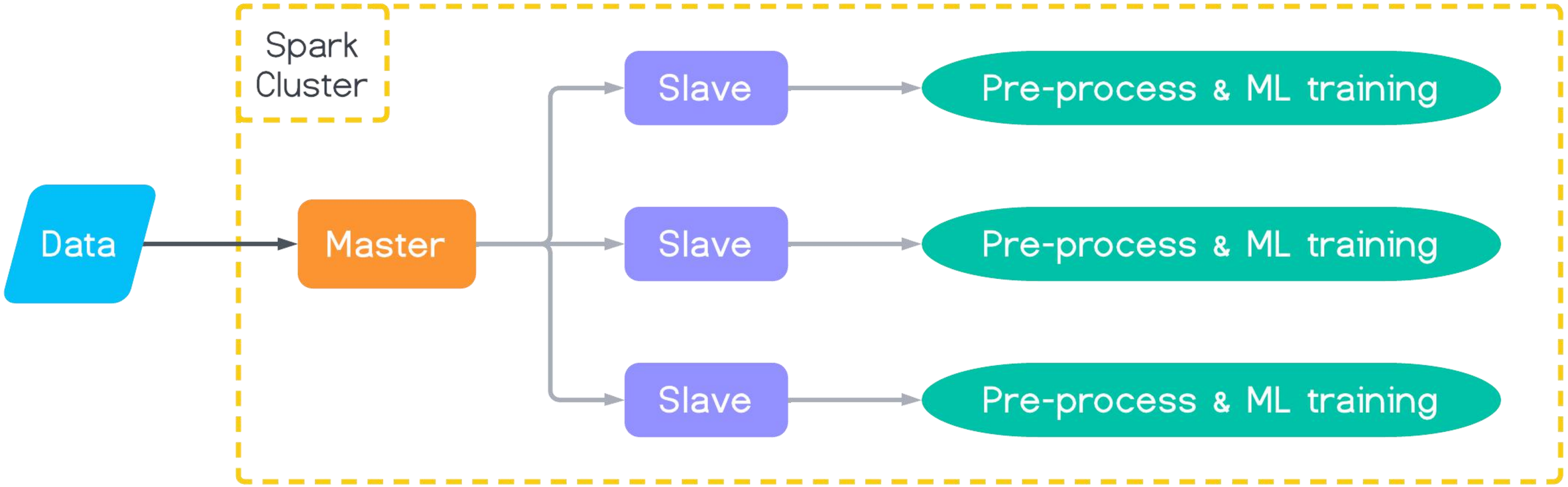
We finally designed 5 APIs exposed to users using Play FrameWork:

```
# Spark
GET     /spark/train
POST    /spark/infer/lr
POST    /spark/infer/rf
POST    /spark/infer_batch/lr
POST    /spark/infer_batch/rf
```

# Methodology

## Training pipeline

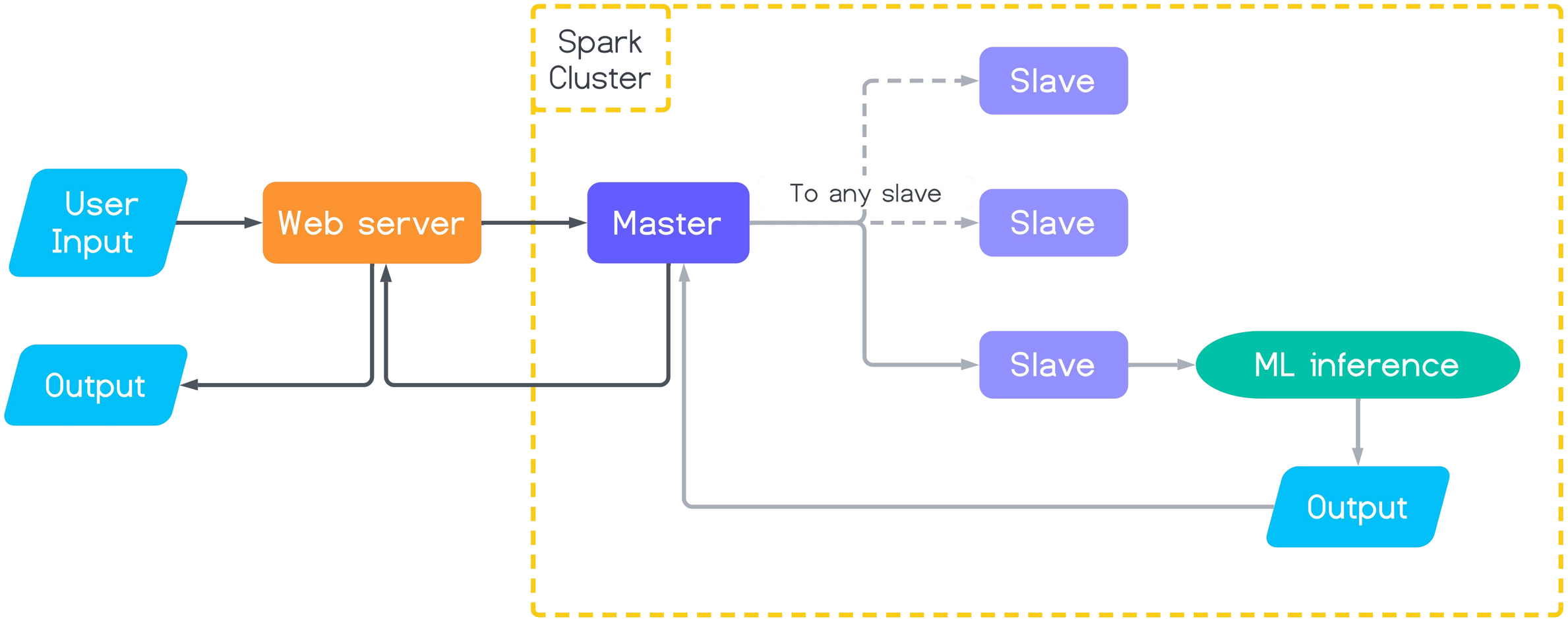
Made use of spark.ml.Pipeline to achieve



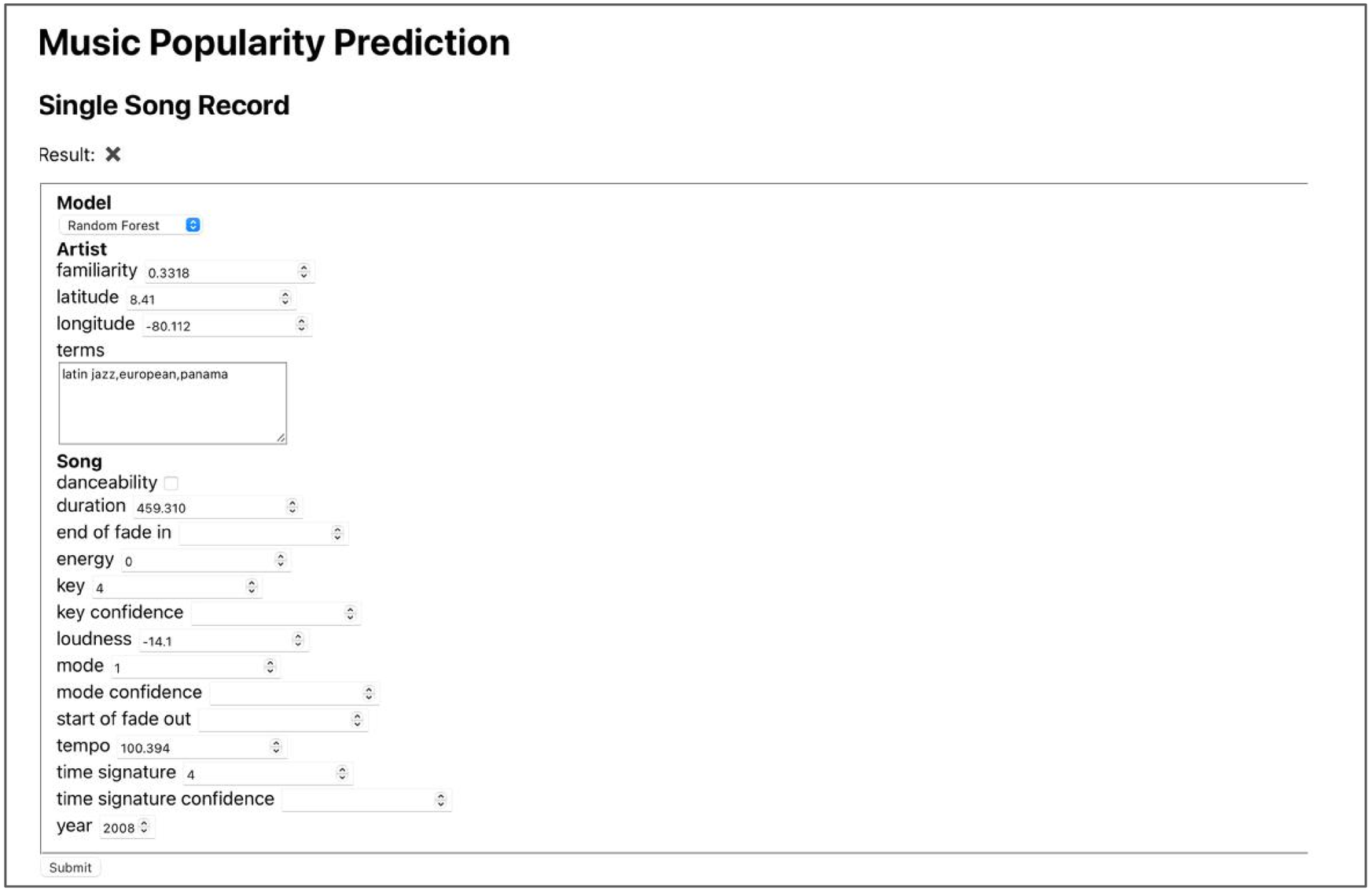
# Methodology

## Inference pipeline

Made use of spark.ml.PipelineModel to achieve



# GUI - Single record



# GUI - Batch record

# Acceptance criteria

- User queries responding time:
  - Single record: **<5s** ☑
  - Batch records: **<1s** per record (on average) ☑
    - (batch has >5 records)
- Model predicting time: **<4s** ☑
- Precision & recall of the ML model: **>60%** ☑

| | Resonding time (Single) | Resonding time (per record on Avg) (Batch size=50) | Resonding time (per record on Avg) (Batch size=500) | Validation Accuracy | Recall |
|---|---|---|---|---|---|
| Logistic Regression | 417.28ms | 12.32ms | **3.23ms** | 78.29% | **79.12%** |
| Random Forest | 542.39ms | 10.46ms | **4.26ms** | **79.07%** | 78.02% |

# Our goal

- Learn how to:
  - Process & load data in Spark and Scala ☑
  - Train a machine learning model and use it for prediction ☑
  - Deploy a Spark cluster to cloud environment ☑
  - Implement a simple web server in Scala ☑
- Apply these knowledges to build a real-world application! ?

Front web page...
High concurrent request...
Larger Data...
To be continued...

# DEMO