Artist Recognition from Audio Features of Songs

An attempt to analyse the Million Song Dataset using MapReduce

The Team

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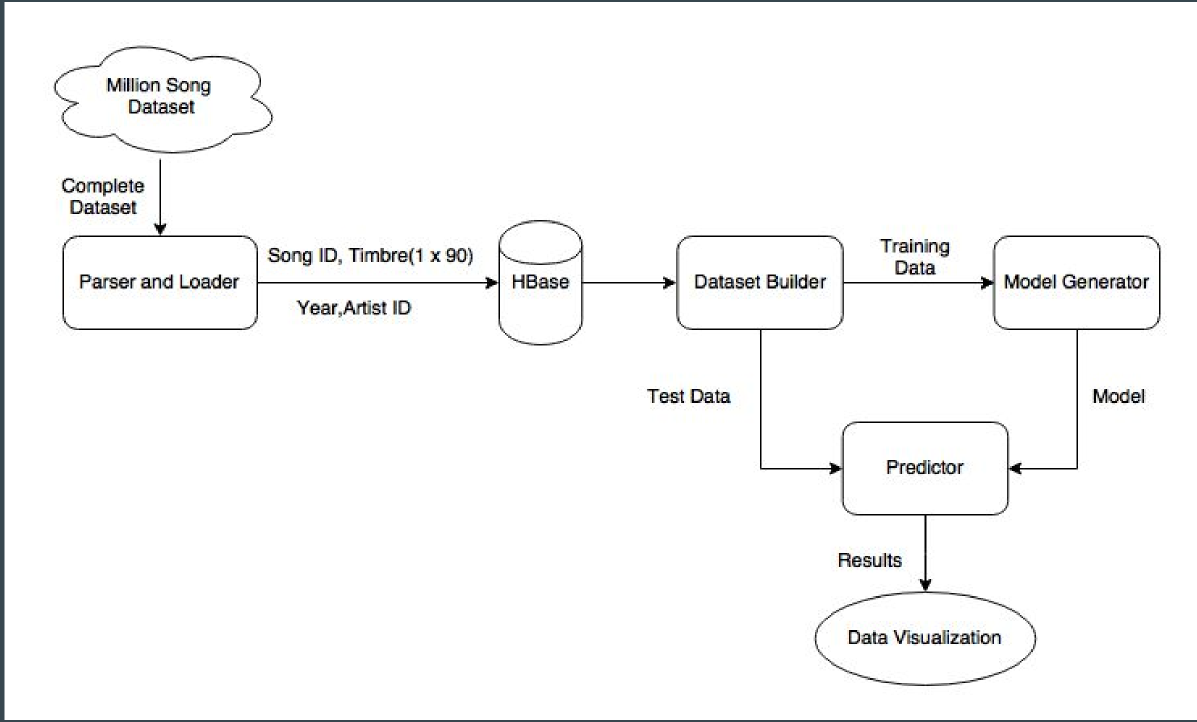
Introduction

- **Problem Statement:**
  To predict the artist of a particular song based on the audio features of the song.

- **Million Song Dataset:**
  - 273 GB of data
  - 1 million songs (from 1920 - 2010)
  - 44,745 unique artists
  - 42 attributes for each song
  - Key Fields: song id, timbre, year, artist id

https://aws.amazon.com/datasets/million-song-dataset/

Approach



Technology Stack

- Hadoop 2.6
- HBase 0.98.15
- Spark 1.5.0
- Scala 2.10
- Thrift 0.9.3
- Anaconda Python 2.7
- AWS EC2
- AWS EMR
- AWS S3

Implementation

Parsing & Loading Data	• Parse HDF5 Data ⇒ Extract Key Features • Load Data into HBase
Preparation of Train & Test Data	• Scan HBase ⇒ Filter Data • Store in LibSVM Format
Machine Learning	• Deciding ML algorithm • Spark's MLlib Logistic Regression
Analysis of Results	• Confusion matrix by year • Most and Least Predictable Artists
Insights & Trends	• Song Popularity & Artist Familiarity • Tempo & Song Popularity

Task 1:
Parsing and Loading Data

Parsing and Loading Data

- Data was in HDF5 format
- Python to parse HDF5 files and extract
  - ArtistID(String)
  - SongID(String)
  - Year(Int)
  - Timbre(2D array of Float Values)
- Key Feature: Timbre
  - Timbre represents the spectral surface of the song.
  - 12 Rows and hundreds of columns (one for each segment of the song)
  - Average and covariance of this 2D array to get 90 columns.

Parsing and Loading Data

- Mapper
  - Input : Absolute path to HDF5 files (1 File for each song. Total: 1,000,000)
  - Map Partitions - 8
    - Each Partition establishes and maintains a connection to HBase via Thrift Server
    - Each Partition is responsible for opening the HDF5 files and extracting SongId, Timbre, Year, Artist Id.
    - Insert the row into HBase via Thrift
  - HBase Row Identifier: SongId.
- Technologies Used: PySpark, Thrift , HBase (3 HMasters and 8 HRegionServers)

Task 2:
Preparing Test & Train Data

Preparing Test & Train Data - High Level Description

- Scan the entire HBase table
- Filter Records that did not have release year.
- Filter Artists who have at least 50 songs in the dataset.
- For each Artist who has at least 50 songs
  - Get the entire row from HBase
- Test Dataset : 5 Songs of each artist is randomly picked.
- Train Dataset: All the remaining songs of the artist is used for training.
- Train Data: 120,000+;Test Data: 9000+
- Output the data in LibSVM format.

Preparing Test & Train Data - Implementation

- Hadoop RDD of the HBase table
  - Input 1: HBase IP address and Port
  - Input 2: HBase Table Name
- Create an RDD with ArtistId,SongId,Year
- Mapper - For each Row, get the ArtistId, SongId and Year.
- Filter Records that don’t have a valid year
- Output: KeyValuePair RDD Format : (ArtistId,(SongId,Year))
- ReduceByKey - ArtistId
  - RDD Format : (ArtistId, [(SongId,Year),(SongId,Year),(SongId,Year).....])

Preparing Test & Train Data - Implementation

- Filter Artists who don't have at least 50 songs.
- Prepare Train RDD and Test RDD
  - TestRDD - Pick 5 songs from each Artist in the filtered RDD
  - TrainRDD - All remaining songs of the artists go into the TrainRDD
  - RDD Format - (ArtistId, SongId)
- Get all features from HBase for both TrainRDD and TestRDD
  - For each ArtistId, apply a map on all of his songs(SongId) to get all the features of a song.
  - RDD format: (ArtistId,Feature1,Feature2...,Feature90,Year)
  - Output the result in LibSVM format
  - Format: Label 1:Feature1 2:Feature2 ....91:Feature91

Task 3:
Predicting the Artists

Applying Machine Learning

- Deciding ML algorithm
  - Multi-Class ML algorithm
  - Considerations: KNN, PCA and Naive Bayes
  - Our Choice: Logistic Regression
- Training the model and Predicting
  - Apache Spark's MLlib library
  - Multinomial logistic regression algorithm
- Performance comparison on AWS (m3.xlarge)

1 Master, 2 Core	2 hour, 39 minutes
1 Master, 5 Core	1 hour, 17 minutes

Task 4:
Analysis of Results

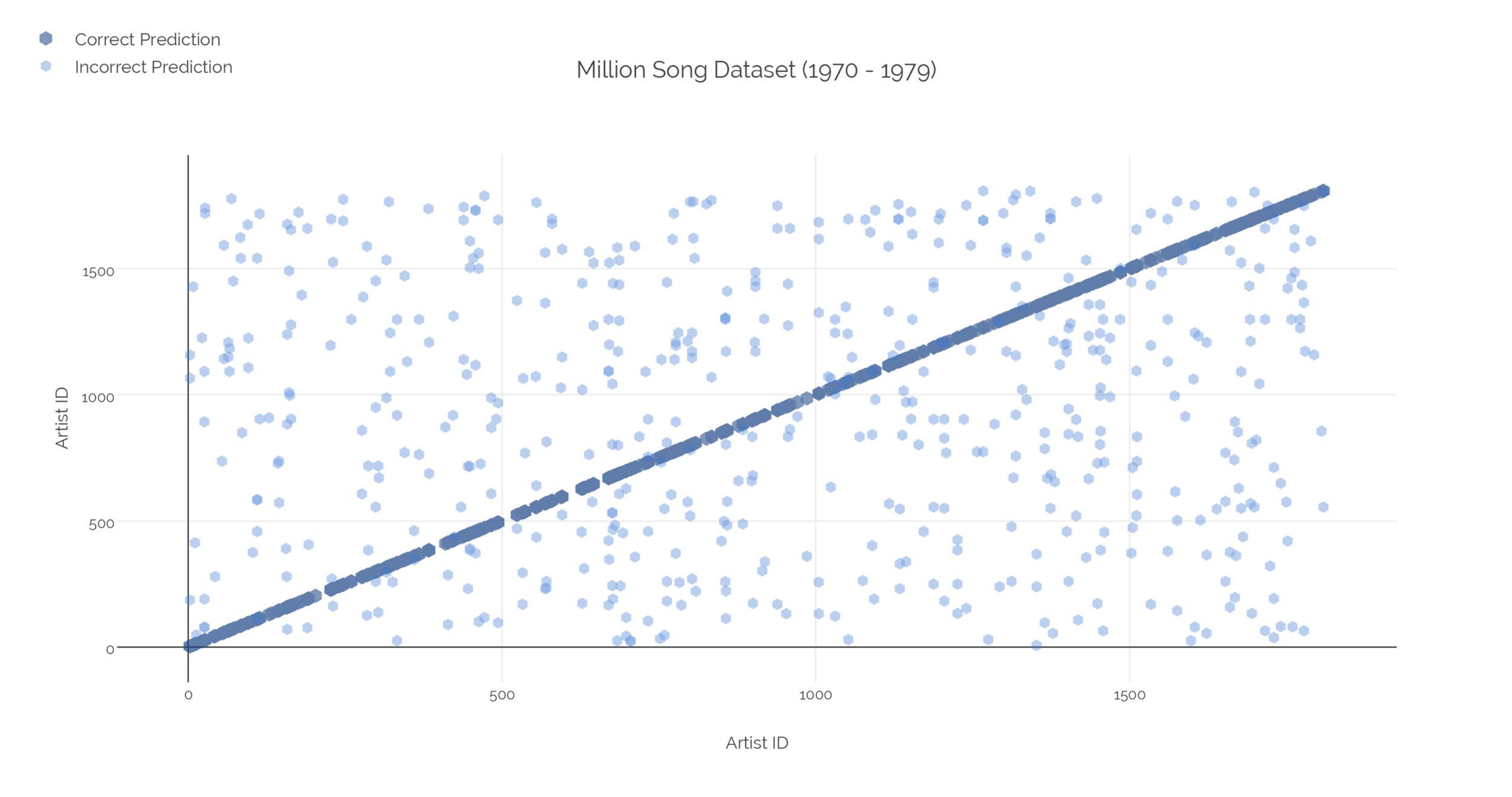
Breakdown of Results

The scattered plot of the actual vs predicted artists are categorized per decade.

The various ranges are:

- 1920 - 1929
- 1930 - 1939
- 1940 - 1949
- 1950 - 1959
- 1960 - 1969
- 1970 - 1979
- 1980 - 1989
- 1990 - 1999
- 2000 - 2009
- 2010

Year 1970 - 1979 (actual vs predicted)



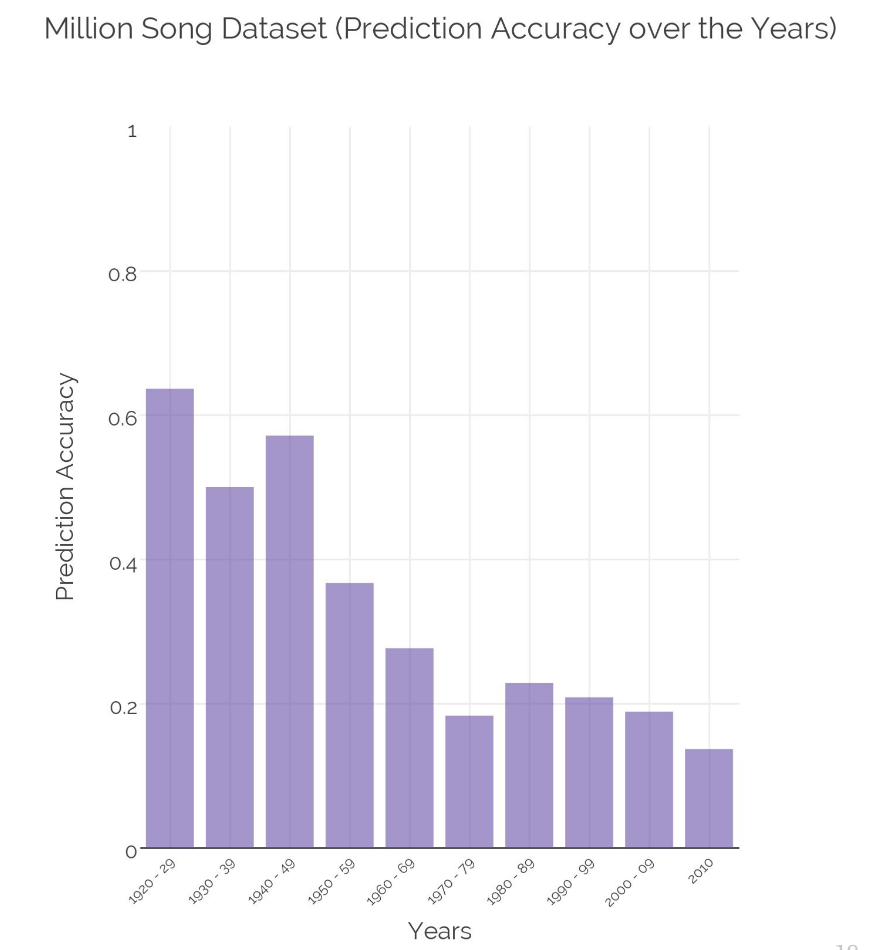
Prediction Accuracy

Findings

The prediction accuracy over the year varies due to the quantity and quality of data available throughout the years in the dataset.

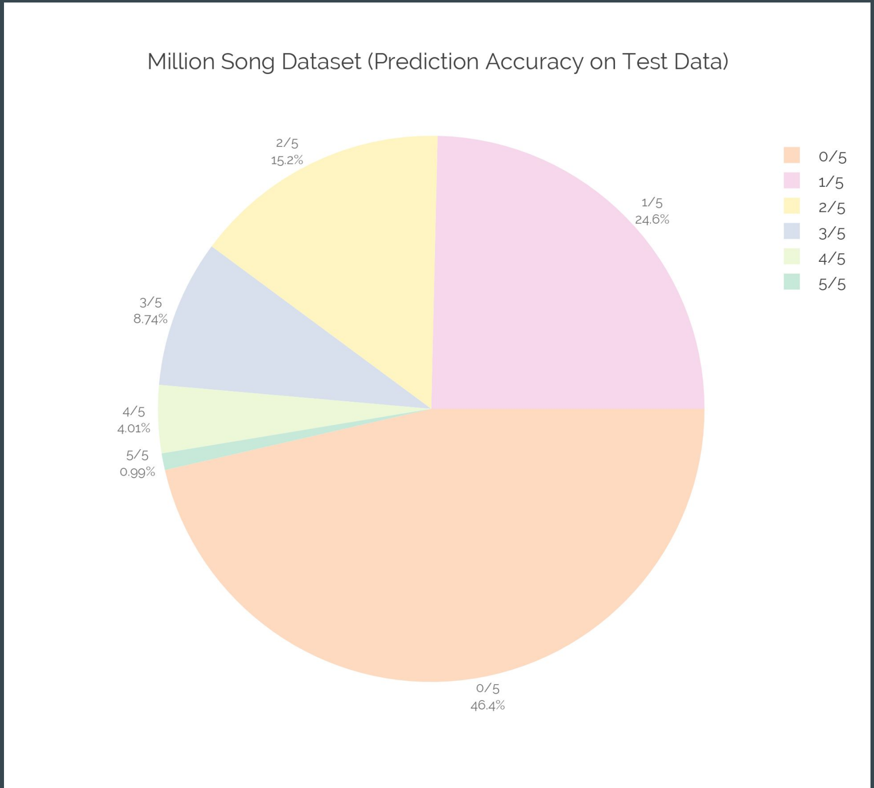
Statistics:

- Correct Predictions = 1861
- Overall Prediction Accuracy = **20.45%**



Predictability of Artists

- **Most Predictable Artists**
  - George Lopez
  - Yonder Mountain String Band
  - Down to the Bone
- **Least Predictable Artists**
  - Jimmy LaFave
  - The Turtles
  - Peter Dennis Blandford Townshend

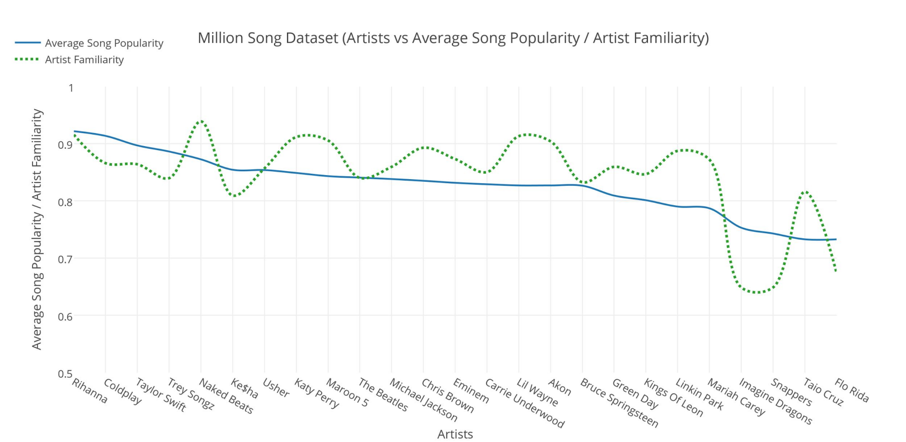


Insights

Trend 1 - Song Popularity & Artist Familiarity

The song popularity affects artist's familiarity.

Mapper : <offset of the line, text of the line>
Reducer : <Artist Name, <Song Popularity, Artist Familiarity>>

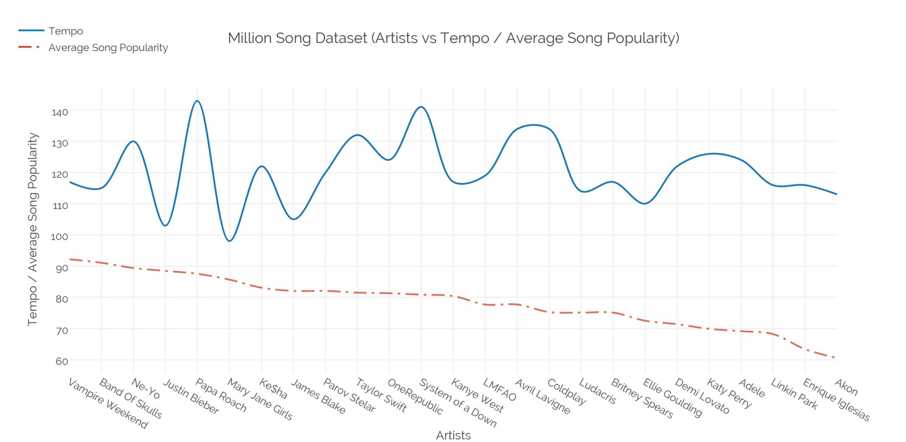


*** Top 25 artists displayed in the visualization*

Trend 2 - Tempo & Song Popularity

The tempo doesn't affect the song popularity.

Mapper : <offset of the line, text of the line>
Reducer : <Artist Name, <Tempo, Song Popularity>>



*** Top 25 artists displayed in the visualization*

Thank You!