Million Song Database Analysis

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1 Problem Statement

The objective of this group coursework assignment was to demonstrate large data set processing and analysis techniques in a parallel computation environment using Apache Hadoop and/or Spark.

Perform detailed analysis on the Million Song Data using Spark and Scala to understand

- The nature of the data
- Key correlations
- Key insights

The objective set of deliverables was agreed to be:

- 1. Spearman correlation key fields
- 2. Song Tempo and Song 'Hotness Heat map
- 3. Linear Regression classifier

The Million Song Dataset can be downloaded at http://labrosa.ee.columbia.edu/millionsong/

2 Approach

The following approach was used

- 1. High-level data analysis to understand data structure and to inform further analysis
- 2. Set-up development environment
- 3. Develop and unit test Scala/Spark code to analyze the data
- 4. Review results to feed into further analysis and development

3 Raw Dataset Analysis

From an initial inspection of the dataset comprised on Hadoop, the data comprised of 26 csv files containing a total of 1 million data records.

The dataset itself had no metadata, so this had to be determined before detailed analysis could commence. Meta data was constructed by comparing the data to various examples on the MSD and EchoNest sites and looking at field position.

A high-level summary analysis was performed on the fields in order to understand data quality and completeness, key observations are listed below

Understanding Track Data

- Each field per row was contained within "" , e.g. *"1","Progressively Funky","401198","0.0","*
  - this would require a well-thought "regex" to select the features into correct columns for RDDs
- 1 million total records exist within the data

Feature Analysis

- 50% of Artist latitude and longitude were missing
- Dance ability was meaningless – all values where 0
- Musical features such as mode, key and time signature whilst looking promising provided very little value and differentiation within the dataset. The values were so aggregated/coarse that they provided almost no musical analysis value.

4 Implementation Approach

4.1 Development Environment

The team adopted a collaborative development approach by hosting Scala source code, analysis artefacts and the report itself on the Queen Mary EECS Enterprise Github. The project repository is available here: https://github.research.its.qmul.ac.uk/ec15541/million-song

Whilst a Maven build was provided, the team chose the Scala Build Tool (SBT) build process. The team developed their own SBT build, including dependencies to support the specific development and testing requirements. In particular, the Breeze library was used for matrix and vector operations to support regression based machine learning whilst ScalaTest was used for unit/integration testing. The project dependencies are listed below:

```
val mockitoAll    = "org.mockito"      %  "mockito-all"     % Version.mockito
val scalaTest     = "org.scalatest"    %% "scalatest"       % Version.scalaTest
val sparkCore     = "org.apache.spark"                 % "spark-core_2.10"  % Version.sparkCore //% "provided"
val breezeCore    = "org.scalanlp"     %% "breeze" % Version.breeze
val breezeNative  = "org.scalanlp"     %% "breeze-natives" % Version.breeze
val breezeViz     = "org.scalanlp"     %% "breeze-viz" %  Version.breeze
```

4.1.1 Testing

The team believed in a structured approach to testing the Spark drivers and relied on a ScalaTest library for unit testing and local Spark cluster integration testing. This allowed the team to develop and test against a real subset of the million song dataset containing 2000 tracks hosted in RDDs on a local (single node) Spark cluster without adversely affecting the moonshot cluster. This allowed driver and all supporting functionality to be developed and tested in isolation before being promoted and executed on the Moonshot cluster against the entire dataset. The test tracks were loaded from /src/test/resources/TestTracks.csv by the BaseDriverSpec class which provided common functions to all descendent unit test suites.

4.2 A Framework for Spark Analysis of MSD

To assist the team in working on multiple aspects of analysis at the same time we created a framework of helper objects and abstract classes that performed common behaviors:

- Common base class for all drivers to handle loading of the dataset and the instantiation of helper classes that represent the song data

- The creation of ‘model’ classes that represent key aspects of the data e.g. Track, Artist, GeoLocation and Places. The objects would take the raw text record and produce an instance of a given class with a set of attributes representing the fields, which were then used in RDD’s
- Data cleansing strategy was to ignore records that had an incomplete set of fields. Where there were missing values we provided defaults, within the model classes.
- To ensure that multiple changes to the code base from the team did not break the overall code, a suite of unit tests were added.

5 Data Analysis and Results

5.1 Feature Correlation Analysis

There are a number of numeric features within the Million Song Dataset that we expected would demonstrate some correlation. To explore this hypothesis we developed a correlation calculation based on the Spearman approach which makes no assumption about the distribution of the dataset. This is a single value between -1 and 1 where a value near either limit shows a correlation: as one feature value increases, so does the other (or decreases). A value close to 0 indicates no correlation.

5.1.1 Tracks

The first track relationship we chose was between song tempo and song “hotness”.

An initial Scala object called “BasicCorrelations” was coded [without much consideration for performance] which performed the following:

1. Load RDD from Million Song Dataset mapped to named 'Track' features (see Track.scala)
2. Map an RDD of non-zero tempos as a tuple of track id and tempo (track7IDd , tempo)
3. Map an RDD of non-zero hotnesses as a tuple of track id and hotness (track7Id, songHotness)
4. Create an RDD join of tempo and hotness by track id -> (track7ID, (tempo,songHotness))
5. Persist this RDD
6. Project the RDD several times to collect numeric values for calculations (e.g. sum of tempo * hotness)
7. Calculate the Spearman correlation and print to console *(No result data was required to be saved back to HDFS)*

This was later improved by a re-write that employed an accumulator to aggregate the column values per RDD partition and then combine each to a single summed set of values. This removed the need for the intermediate RDDs and proved to be much faster. In tests, the first correlation job completed in 319146 milliseconds from the original track mapping to completion whereas the second job using accumulators completed in just 63020 milliseconds. To gain these metrics, a simple grab of “System.currentTimeMillis” was employed.

The actual result of the correlation shows almost zero correlation between song hotness and tempo:

```
#DancingDads : Spearman correlation, r(tempo, hotness) = 0.026070182686774128 in
63020 milliseconds
```

A later correlation between year and hotness was explored but this again showed very little correlation:

```
#DancingDads : Spearman correlation, r(year, hotness) = 0.09286060647056213
```

We then looked at an R scatter plot of Artist familiarity against Song hotness on a small subset of data and saw a broadly linear relationship.

```
#DancingDads : Spearman correlation, r(familiarity, hotness) = 0.47956310486659387
```
The result, on the full dataset, confirmed there was a degree of correlation.

In total, we ran correlation checks against the following:

	Tempo	Song Hotness	Familiarity	Year
Tempo	1			
Song Hotness	0.026	1		
Familiarity	0.028	**0.480**	1	
Year	0.016	0.093	0.023	1

The next section takes a deeper dive into the seemingly uninteresting tempo/hotness correlation to uncover some hidden patterns.

5.1.2 Song Tempo and Song 'Hotness' Heat Map

To understand the relationship between two fields (Tempo and Song Hotness) a heat map was created using Spark. The Song Tempo was binned in groups of 0.1 and plotted in the columns of an array. Song Hotness was binned in groups of 15 and plotted on the rows of the array. Each cell represents the count of songs for the related tempo and hotness. The results were then plotted as heat using Excel.

The visual results help to understand that the data and show some interesting insight that mid tempo songs between 105 – 135 bpm have a hotness rating between 0.3 and 0.6.

	Song Hotness									
Song Tempo	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1**
15	0	0	6	1	7	2	3	1	1	0
30	0	2	57	42	45	32	13	8	0	0
45	0	14	435	322	353	283	145	65	22	1
60	0	38	908	720	760	651	345	158	46	4
75	0	106	3332	2538	2939	2336	1505	605	176	33
90	0	341	9938	8512	9892	8658	5472	2464	741	131
105	0	487	16438	13889	16646	14444	9414	4052	1191	204
120	0	521	14612	12362	14908	12752	8185	3877	1119	203
135	0	750	18108	15856	18340	15441	10119	4764	1417	233
150	0	437	11887	10541	12440	10786	7195	3423	978	146
165	0	306	8468	7549	9180	8327	5537	2580	815	144
180	0	216	5228	4596	5909	5168	3332	1558	407	59
195	0	118	3226	2994	3609	3193	2154	887	200	31
210	0	58	1755	1596	2014	1861	1216	545	117	23
225	0	32	863	807	1103	1006	647	273	70	12
240	0	16	411	394	477	491	272	119	35	3
255	0	11	203	171	179	178	84	50	7	1
270	0	0	6	5	9	5	6	1	1	0
285	0	1	2	1	3	0	2	0	0	0
300	0	0	0	0	0	0	0	0	0	0
315	0	0	0	0	0	0	0	0	0	0

Table 1: Tempo vs Hotness Heatmap

5.2 Linear Regression

The driver pre-processing for linear regression adopted a map/reduce technique to sum several attribute values in one RDD transformation.
A class called "Artist" was used to encapsulate methods to produce elements for labelling training and test datasets.

- Map set to "Track" class (named attributes) per element
- Map artist-only features to (key,(values tuple)) where key is ArtistID
- Reduce by adding one tuple to the previous (using overloaded "+" method of Artist class)
- Split resultant RDD into training and test with labels
- Fit and predict a linear regressor, by computing the cost via map and summing via a reduce.

A linear regression model was developed to experiment with prediction of track and artist features from the MSD. The model training logic is encapsulated in LinearRegressor and prediction in the LinearRegressionModel. The objective of linear regression is to minimize the r*esidual sum of squares* (RSS) or sum of squared errors (SSE) between predicated and actual continuous values:

$$(\boldsymbol{w}'\boldsymbol{x_i} - \boldsymbol{y_i})^2$$

where **w** is the vector of weights or coefficients,
x is the vector of features values (inputs) and
y is the actual values (labels).

Model training was based on iterating over the training dataset and computing the cost or error on each iteration:

$$trainCost = \sum_{i}^{N} (\boldsymbol{w}'\boldsymbol{x_i} - \boldsymbol{y_i})\boldsymbol{x_i} - \lambda w$$

where λ acts as a configurable regulariser to control model over fitting.

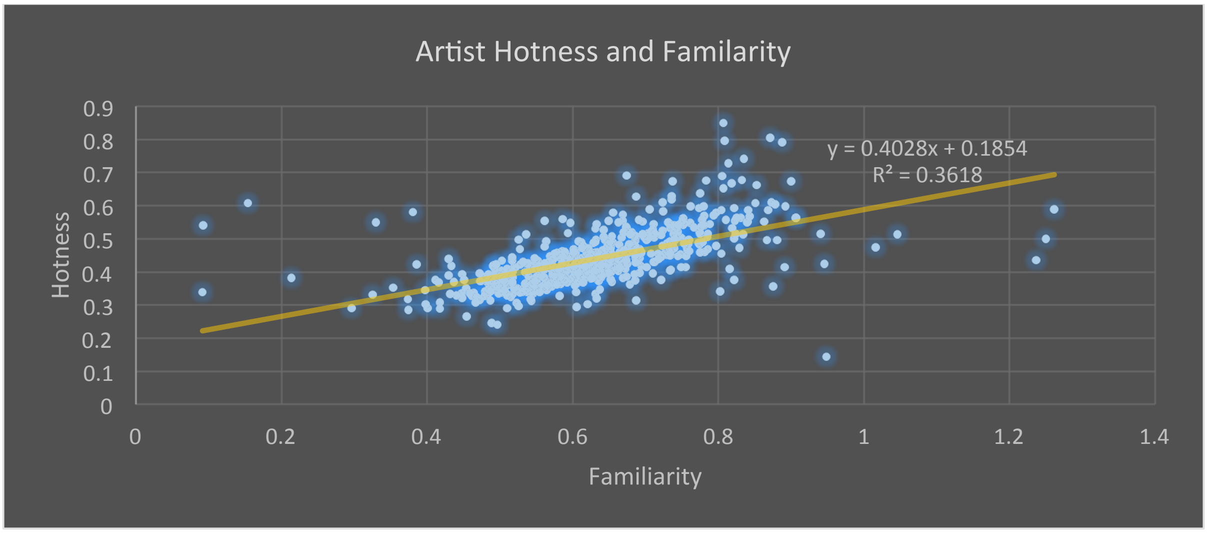
A gradient descent optimization process was used for training the model weights. Costs were computed for each iteration over the training set and adjusted in the direction of the minima (where the differentiated cost function = 0) using a gradient descent approach

$$\boldsymbol{w} = \boldsymbol{w} + \frac{\alpha}{m}\boldsymbol{trainCost}$$

where α is the learning rate or gradient descent rate and *m* = the number of features

Experimentation with the 2000 track test subset

The scatter plot below shows artist hotness and familiarity along with an Excel trend line (linear regression model). The trend line is based on fit against the artists from the entire 2000 track subset.

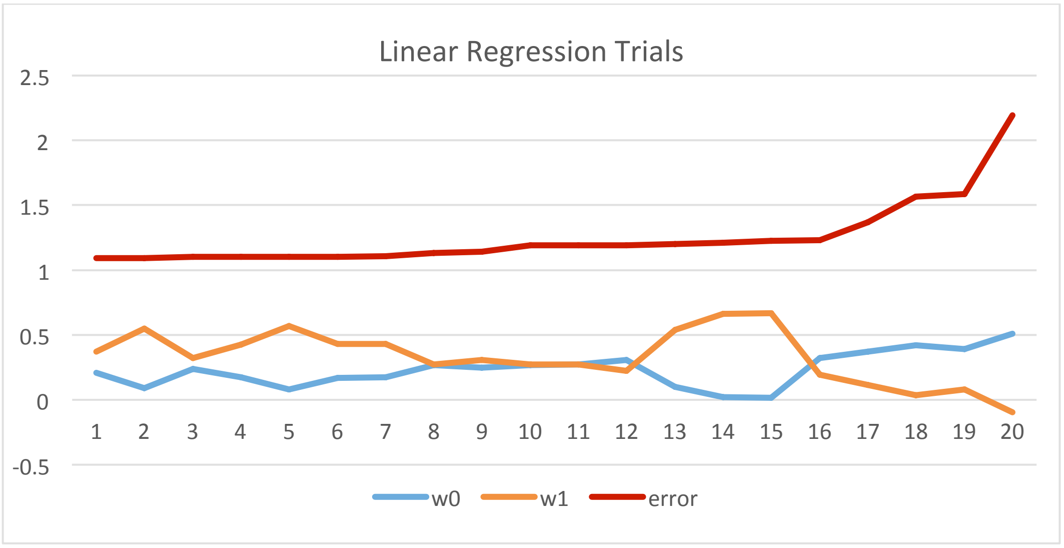


We then used the linear regressor to train the model weights against a 60% split of the subset. The remaining 40% was used to evaluate the trained model by making predictions and measure the error between predictions and actual values.

Using the target model (based on Excel linear trend with coefficients, w_0= 0.1854 and w_1= 0.4028 the following error rates were achieved against the training and test sets.

Training error	1.7082741133758377
Test error	1.0919065052694035

The chart below shows the model error and coefficients using our linear regressor with gradient descent and regularization.



5. Summary and Conclusions

This group exercise has been challenging on a number of fronts. Essentially, the collaboration has worked well with each member being able to contribute to the project. Most of the team was inexperienced in the use of GitHub and so this has been a valuable skill to acquire along with an increased awareness of Apache Spark and the Scala language. We have also used SBT and have learned of its importance in a Scala development environment.

Some lessons have been learned with regards to the performance aspects of running jobs in a Spark cluster environment. Whilst RDDs provide a useful abstraction from the underlying parallelism, the method of processing large data sets still needs to be considered. In particular, the initial correlation task where many RDDs were created and an expensive join performed, highlight the need to look for ways to derive intermediate and final data in more efficient ways (in our case through accumulators).

The Million Song Dataset has proved to be reluctant to give up its secrets. The validity of features such as "hotness" are brought into question and musical data perhaps requires more domain knowledge than any of the group possess. Regression exercises have shown that we can use the concepts of RDD transformations with cost and gradient descent functions to produce an error metric to assess the efficacy of the model.

We all now have an appreciation of code-control, collaboration tools, IDEs and understand the potential of Scala, SBT and Apache Spark.

Key observations:

- It is easy to "slay" a Spark cluster
- Agree on a development environment (IDEs, build tools, unit-test) as early as possible and make sure everyone is up-to-speed on the technology
- Data is Data; make sure you can turn it into information in spite of gaps and inconsistencies
- Background knowledge in parallel processing is essential
- If you're a hot artist, your songs are likely to be hot too

Directions for future efforts (given more time):

- Investigate the Geospatial aspect of the data (we started on this but ran out of time)
- More effort on filling in the gaps (for example extrapolating coordinates from artist location text)
- Classification exercises (can we predict the year or cluster by genre)

6. References

Apache Foundation (2015) *Spark Programming Guide*.[online] Available at: http://spark.apache.org/docs/latest/programming-guide.html [Accessed 5 December 2015].

ScalaNLP (2015) *Breeze Quick start* Numeric Processing for Scala [online] Avaialble at https://github.com/scalanlp/breeze/wiki/Quickstart [Accessed 10 December 2015].

Murphy, K (2012) *Machine Learning – A Probabilistic Perspective* MIT Press, Cambridge, Mass. USA