COMPANY STOCKS PREDICTION

CMPE 239 Web And Data Mining

SAN JOSÉ STATE UNIVERSITY

By: Team- Data Crunchers

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ABSTRACT:
Forecasting stock return is an important financial subject that has attracted researcher's attention for many years. It involves an assumption that fundamental information publicly available in the past has some predictive relationships to the future stock returns. This study tries to help the investors in the stock market to decide the better timing for buying or selling stocks based on the knowledge extracted from the historical prices of such stocks. The decision taken will be based on the data mining techniques such as K-Means Clustering, TF-IDF, Single Value Decomposition and Vector Space Model.

This project focuses on the predicting future stocks of companies in IT sector based on the company's past 3 years of data and Twitter data. The purpose is to provide a systematic analysis of the company's financial data and determine company's future stocks. In twenty first century, stocks have become the most prominent factor to determine the growth for companies. Therefore forecasting their stocks will help them in the world of globalization and increasing economy, and to compete with other companies to achieve optimum share in the market. This prediction will also be helpful for those who wish to invest in stock market.

Contents

1. PROJECT DESCRIPTION:

In this project, we have implemented the Data mining techniques, which have been applied for stock trading to predict the rise and fall of stock prices before the actual event of an increase, or decrease in the stock price occurs. In particular the project will demonstrate the application of Support Vector Machines, Linear Regression, Prediction using Naïve Bayes Algorithm, State vector model, Vector Space Model and k-means in detail along with the benefits and pitfalls of each method. The project introduces the parameters and variables that can be used in order to recognize the patterns in stock prices which can be helpful in the future prediction of stocks and how they can be combined with other algorithms to improve the accuracy of such prediction systems. Note: The main goal of the project was to study and apply as many data mining algorithms as possible on a dataset involving a particular domain, namely the Stock Market, as opposed to coming up with a newer (and/or better) algorithm that is more efficient in predicting the price of a stock. We have tried to briefly research the background which is essential to the study of the domain of financial prediction systems. We have showcased the results obtained from the application of the algorithms we have used by plotting various kinds of graphs which are simpler and amenable to an end user understanding on the financial dataset in the project.

The stock market is an essential way for companies to raise money. Companies can raise additional financial capital by being publicly traded in order to expand their business by selling shares of ownership. Historically it is known that share prices can have a major influence on economic activities and can be an indicator of social mood. The stock market movements has always been a rich and interesting subject with such many factors to be analyzed that for a long time it would be considered unpredictable. The application of new computerized mathematical methods over the past few decades developed by companies such as Merrill Lynch and other financial management companies have created models that can maximize their returns while minimizing their risks. Stock market prediction has been around for years but it has been giving a new method of prediction thanks to the rise of social media. The objective of this project is to analyze Twitter feeds for activities and trends associated with a brand and to see how their stock market shares are related and if they are affected to the twitter activity. This analysis will look at the relationship of the amount of tweets for specific brands on NASDAQ such as IBM, FB, and Picasa etc. These brands where chosen since they are innovative technology companies that are on the same stock exchange. Therefore gathering of the twitter data was not time zone dependent. Sample stock market data was collected from the Yahoo Finance website, there they provide historical data for the NASDAQ. Java scripts were used to acquire the tweets through Twitters API service. The Tweets for each brand were then counted using Amazon Web Service and Text Wrangler. The

counted tweets were subsequently analyzed using R studio. The Data was the visualized using high charts and a user friendly analysis using various kinds of graphs will be presented to the end user.

Figure 1: Stock Market Prediction

2. REQUIREMENTS:

1. Twitter Feeds:
   Feed pages should be present in the system to update the latest feeds continuously, based on the user preferences and search history.

2. Hashtag Sentiment Streaming:
   Streaming of tweets could be done based on keywords that are most popularly tweeted.

3. Financial Data:
   Financial Data of companies are required in order to process the data.

3. UI DESIGN PRINCIPLES-STORYBOARD, WIREFRAMES:

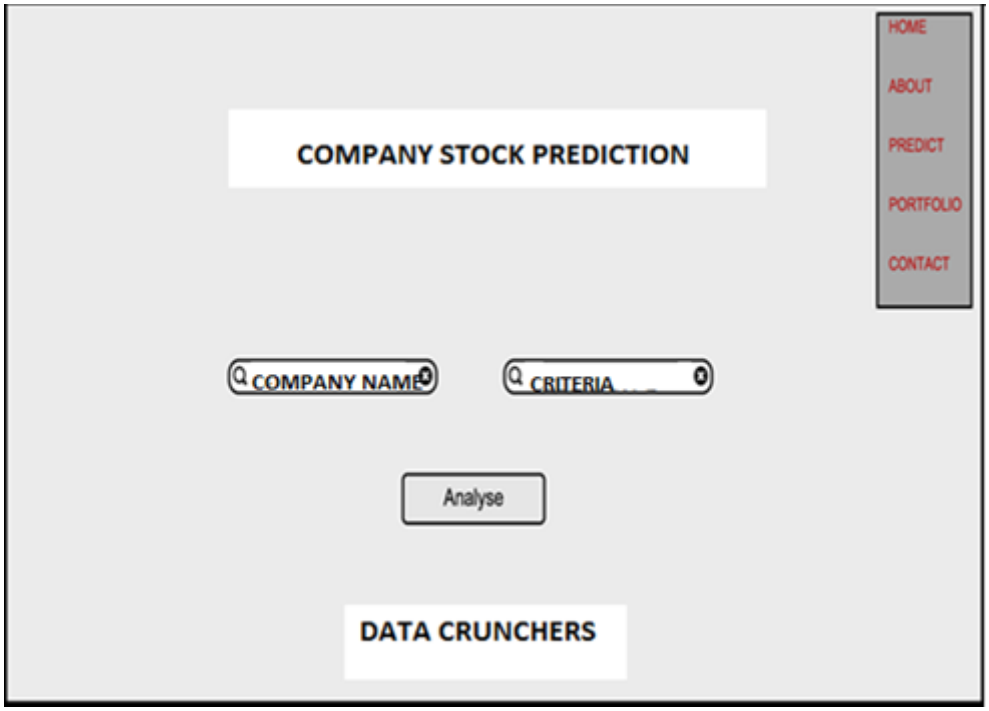


Figure 3.1: Wireframe

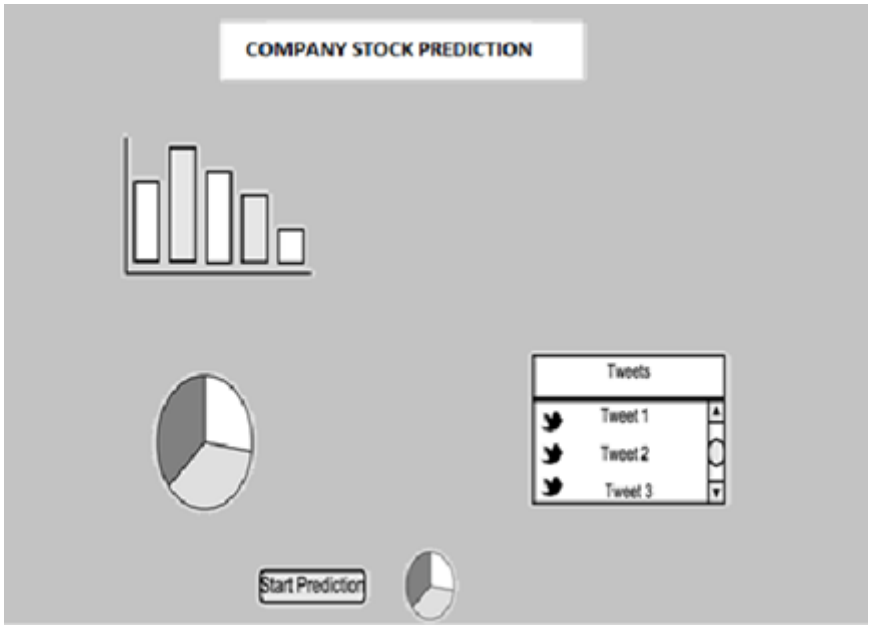


Figure 3.2: Wireframe

Storyboard Events:

1. User browses through our website
2. Selects the Predict tab where you enter the company's name and the criteria which talks about the company
3. Click on Analyze button.

4. HighChart would be displayed for that company
5. Click on Start Prediction.
6. Bar graph is displayed with positive, negative and neutral twitter sentiments.

3.1 ANDROID APP:

We have Created Web-Hybrid Android App. Hybrid applications are coded in HTML, CSS and JavaScript. They are run through the invisible browser that is packaged into a native application.

- Can access Native APIs
- Distribute through App Stores
- Can run on multiple platforms

Tools Used:

- Android Studio
- GenyMotion for emulation

Screenshots:

Figure 3.3: Home Screen

Figure 3.4: Team Information

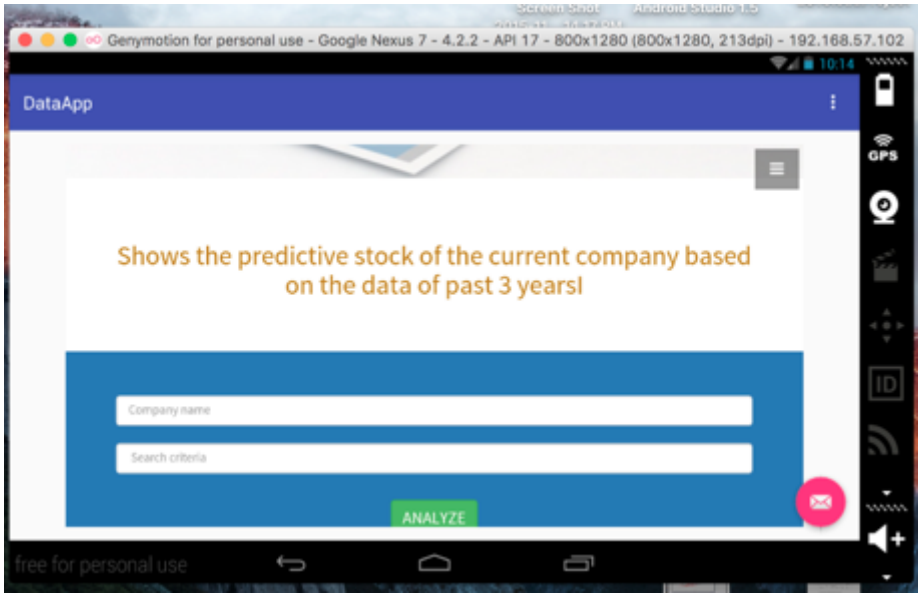


Figure 3.5: Enter Company to predict its Stocks

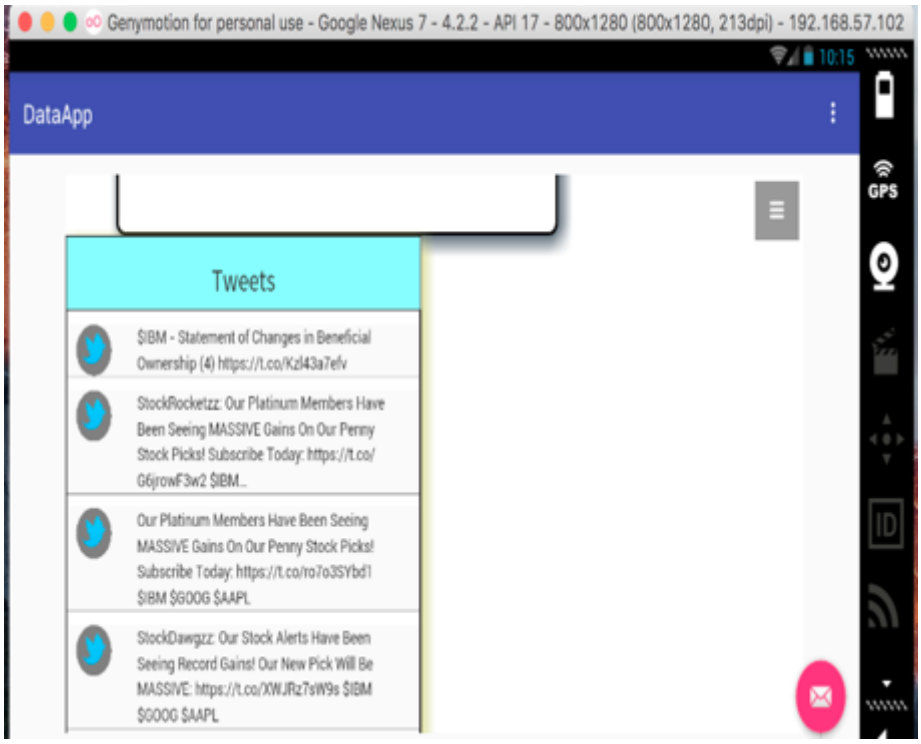


Figure 3.6: Data from Twitter

Source Code:

```
 import android.os.Bundle;
import android.support.design.widget.FloatingActionButton;
import android.support.design.widget.Snackbar;
import android.support.v7.app.AppCompatActivity;
import android.support.v7.widget.Toolbar;
import android.view.View;
import android.view.Menu;
import android.view.MenuItem;
import android.webkit.WebView;

public class Main extends AppCompatActivity {

        @Override
        protected void onCreate(Bundle savedInstanceState) {
        super.onCreate(savedInstanceState);
        setContentView(R.layout.activity_main);
        Toolbar toolbar = (Toolbar) findViewById(R.id.toolbar);
        setSupportActionBar(toolbar);

        String url = "http://10.189.107.200:3000/";
        WebView view = (WebView) this.findViewById(R.id.webView);
        view.loadUrl(url);
```

```
        FloatingActionButton fab = (FloatingActionButton)
findViewById(R.id.fab);
        fab.setOnClickListener(new View.OnClickListener() {
        @Override
        public void onClick(View view) {
                Snackbar.make(view, "Replace with your own action",
Snackbar.LENGTH_LONG)
                .setAction("Action", null).show();
        }
        });
        }

        @Override
        public boolean onCreateOptionsMenu(Menu menu) {
        // Inflate the menu; this adds items to the action bar if it is present.
      getMenuInflater().inflate(R.menu.menu_main, menu);
        return true;
        }

        @Override
        public boolean onOptionsItemSelected(MenuItem item) {
          // Handle action bar item clicks here. The action bar will
        // automatically handle clicks on the Home/Up button, so long
        // as you specify a parent activity in AndroidManifest.xml.
        int id = item.getItemId();

        //noinspection SimplifiableIfStatement
        if (id == R.id.action_settings) {
        return true;
        }

        return super.onOptionsItemSelected(item);
        }
}
```

AndroidManifest.xml

```
<?xml version="1.0" encoding="utf-8"?>
<manifest xmlns:android="http://schemas.android.com/apk/res/android"
   package="com.example.chhavigupta.dataapp">

   <uses-permission android:name="android.permission.INTERNET"/>

   <application
      android:allowBackup="true"
      android:icon="@mipmap/ic_launcher"
      android:label="@string/app_name"
      android:supportsRtl="true"
      android:theme="@style/AppTheme">
      <activity
```

```
        android:name=".Main"
        android:label="@string/app_name"
        android:theme="@style/AppTheme.NoActionBar">
        <intent-filter>
                <action android:name="android.intent.action.MAIN" />

                <category   android:name="android.intent.category.LAUNCHER"
/>
        </intent-filter>
      </activity>
   </application>

</manifest>
```

4. HIGH LEVEL ARCHITECTURE DESIGN:

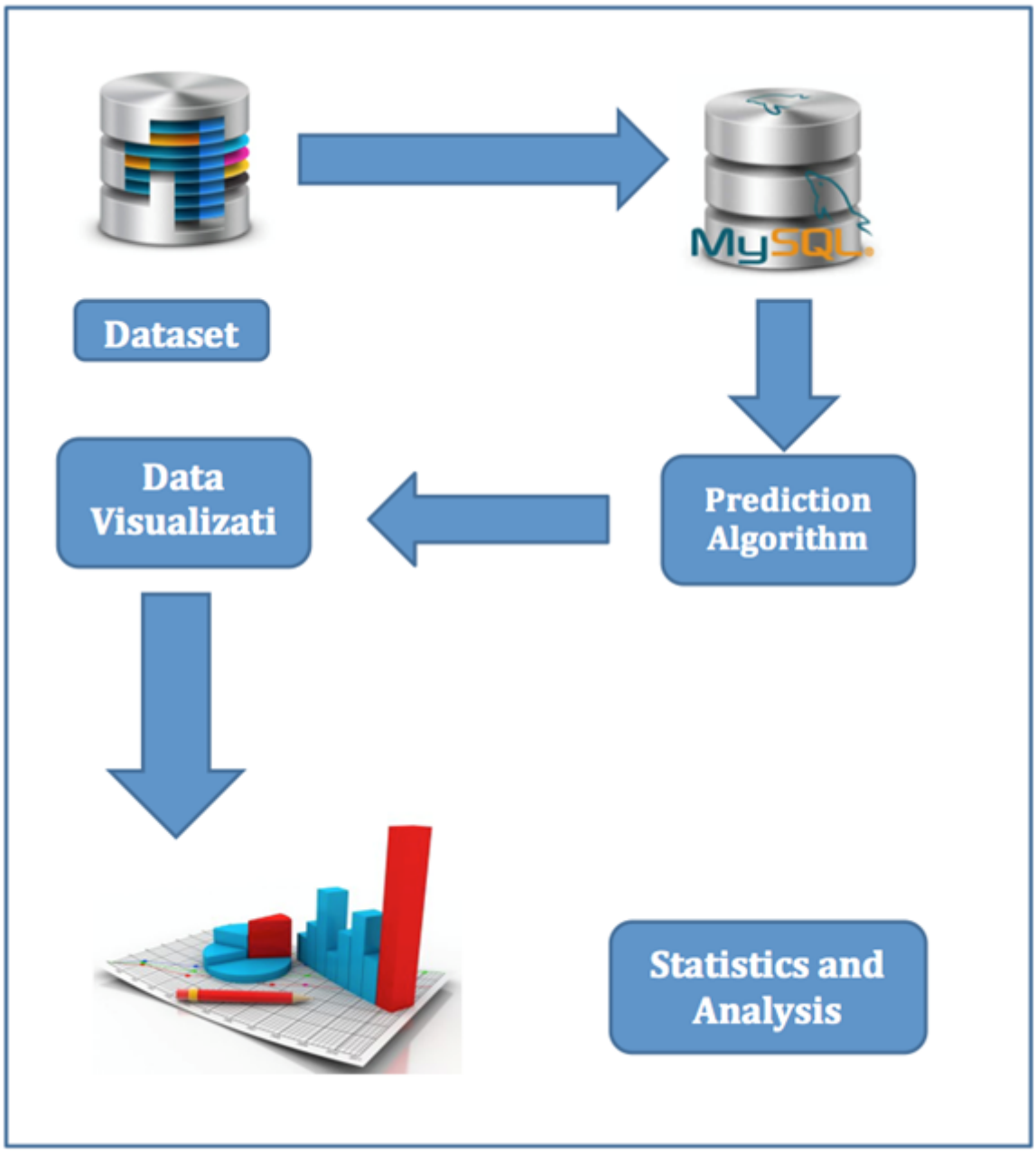


Figure 4.1: High Level Architecture

Description:

1. Data are stored in MySQL database.
2. Dataset from MySQL is fetched to perform computation.
3. We are running predictive algorithm on the fetched data.
4. The algorithm scans through all the fetched data and predicts the result.
5. The result is passed to the visualization tool.
6. Using high charts, the data is represented on our web application.

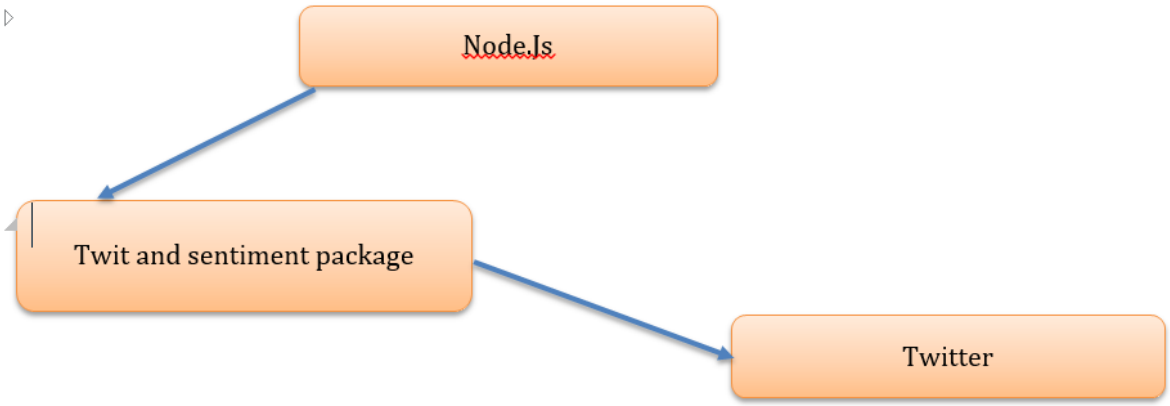


Figure 4.2: Flow: High Level Architecture

5. DATASETS AND DATA PATTERNS:

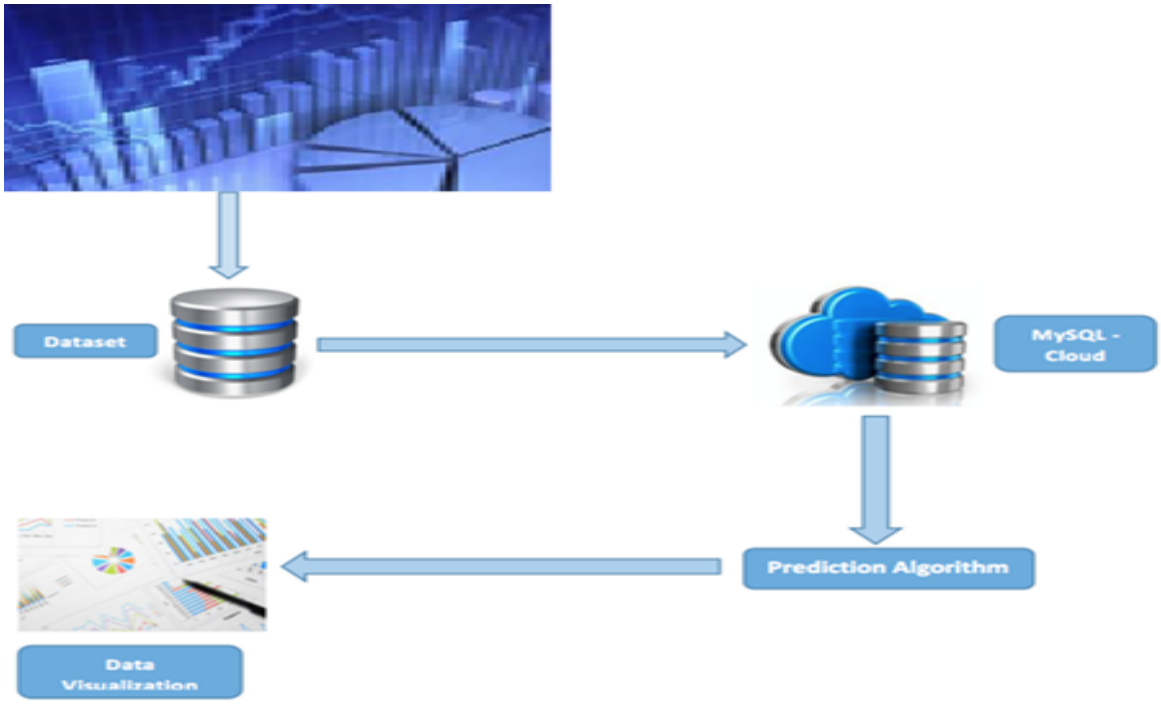


Figure 5.1: Data Patterns

6. DATA ARCHITECTURE:

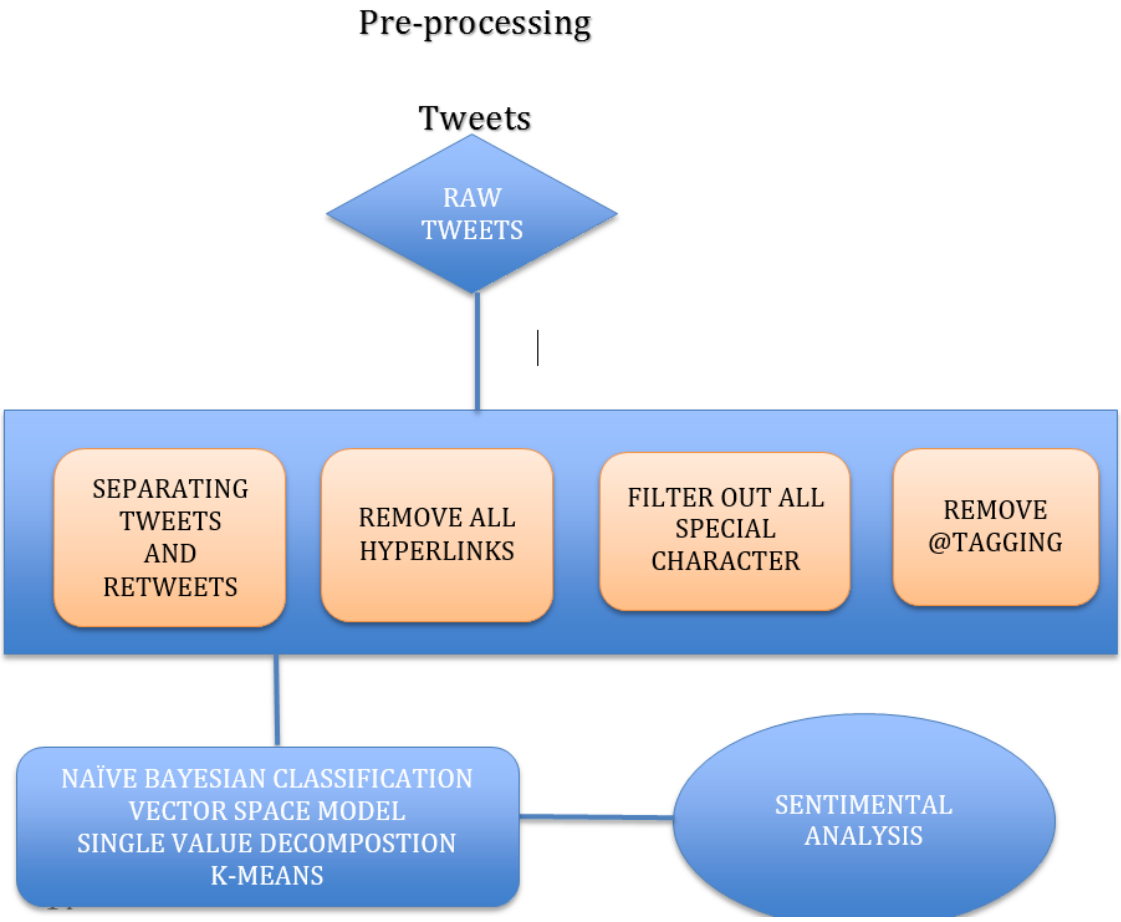


Figure 6.1: Architecture for twitter sentiment analysis

Description:

1. Need to do twitter authentication so that one can access twitter data.
2. Pull out the tweets from twitter which are based on user input
3. As we only need text we have to filter out the tweets
4. Retweets are not necessary we have to remove them
5. Delete all special character and digits
6. Delete hyperlinks and spaces
7. Delete all tagging i.e @ people
8. This will all result in the preprocessed data
9. Now apply SVD, K-Means Clustering, SVM, TF-IDF

This algorithm displays a bar graph with positive, negative and neutral sentiments as shown above.

7. DATA FLOW DIAGRAM:

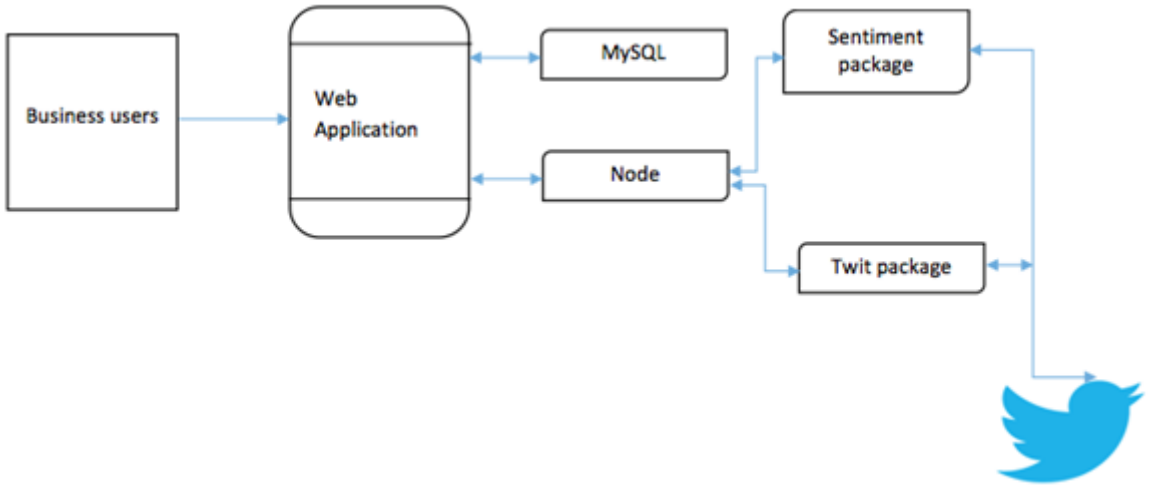


Figure 7.1: Data Flow Diagram

Twitter Data Analysis: Source Code:

```
/**
 * AFINN-based sentiment analysis for Node.js
 *
 * @package sentiment
 * @author Shubhi Yede <shubhi.yede@gmail.com>
 */

/**
 * Dependencies
 */
var extend = require('extend-object');
var afinn = require('../build/AFINN.json');

/**
 * Tokenizes an input string.
 *
 * @param {String} Input
 *
 * @return {Array}
 */
function tokenize (input) {
   //console.log(input);
   var result = input
          .replace(/[^a-zA-Z- ]+/g, '')
          .replace('/ {2,}/',' ')
          .toLowerCase()
          .split(' ');
    //console.log(result);
    return result;
```

```
}
function log10(val) {
  return Math.log(val) / Math.LN10;
}

function TF(freq){
  var tf=1+log10(1+log10(freq));
  return tf;
}

function IDF(d,dt){
  var idf=log10((1+d)/dt);
  return idf;
}

function cosineDistance(v1, v2){
    var numerator=0,sqrt_v1=0,sqrt_v2=0;
          for(var i=0; i<v1.length; i++){
                  numerator+=v1[i]*v2[i];
                  sqrt_v1+=Math.pow(v1[i],2);
                  sqrt_v2+=Math.pow(v2[i],2);
          }
          sqrt_v1 = Math.sqrt(sqrt_v1);
          sqrt_v2 = Math.sqrt(sqrt_v2);
          var denominator = sqrt_v1 * sqrt_v2;
          if(denominator > 0){
            var cosineDistance = numerator / denominator;
            return cosineDistance;
          }
          else
            return 0;

}
function cosineSimilarity(v1,v2){
    var angle=Math.acos(cosineDistance(v1, v2));
    angle=Math.round(angle * 100) / 100;
    return angle;
}

function mult(X, Y){
  //X (r1 x c1)  Y(r2 x c2)
  //c1 == r2
  console.log("X rows = "+ X.length + " X columns = "+ X[0].length+ " Y rows
= " + Y.length + " Y columns = " + Y[0].length);
          if(X[0].length != Y.length){
            console.log('Invalid dimension!');
            return null;
          }
          // dimensions
          var m = X.length, n = Y[0].length, d = Y.length;
```

```
        // multiplication
        var Z = new Array(X.length);
        for(var i = 0; i < X.length; ++i){
                Z[i] = new Array(Y[0].length);
                for(var j = 0; j < Y[0].length; ++j){
                        Z[i][j] = X[i].map(function(x, k){
                                return x * Y[k][j];
                        }).reduce(function(a, b){ return a + b; }, 0);
                }
        }
        return Z;
}

/**
 * Performs sentiment analysis on the provided input "phrase".
 *
 * @param {String} Input phrase
 * @param {Object} Optional sentiment additions to AFINN (hash k/v pairs)
 *
 * @return {Object}
 */
module.exports = function (phrase, inject, callback) {
    // Parse arguments
    if (typeof phrase === 'undefined') phrase = '';
    if (typeof inject === 'undefined') inject = null;
    if (typeof inject === 'function') callback = inject;
    if (typeof callback === 'undefined') callback = null;

    // Merge
    if (inject !== null) {
        afinn = extend(afinn, inject);
    }

    // Storage objects
    /*
    column=words
    rows=tweets_word_freq
        stock, equity, asset, liability, revenue, EBITDA, profit, loss, cash, up, down
    tw1
    tw2
    tw3
    tw4
    tw5
    */
    var counter = [0,0,0,0,0,0,0,0,0,0,0];
    var vsm = [];
    //stock equity asset liability revenue EBITDA profit loss cash up down
    var relevant_words = ["stock", "equity", "asset", "liability", "revenue",
"EBITDA", "profit", "loss", "cash", "up","down"];
    var relevant_words_weight = [3,3,3,3,3,3,3,3,3,3,3];
```

```
var score=0;
console.log("VSM:");
//console.log("phrase.length:"+phrase.length);
var new_row_vector = [];
for(var i=0; i<phrase.length ; ++i){

  //Tokenization

  var tokens = tokenize(phrase[i]);
  var len = tokens.length;
  new_row_vector = [0,0,0,0,0,0,0,0,0,0,0];
  while (len--) {
    var word = tokens[len];

    if (!afinn.hasOwnProperty(word)){
      continue;
    }
    var weight = afinn[word];

    //to measure if tweet is positive or negative
    score += weight;

    //Vector Space Model
    //to find if tweet is relevant or irrelevant
    var index = relevant_words.indexOf(word);
    if(index > -1){
      new_row_vector[index]+=relevant_words_weight[index];
      counter[index]+=1;
    }
  }
  vsm.push(new_row_vector);
  //console.log(new_row_vector);
  //console.log("score="+score);
}

//Display Vector Space Model
for(var i=0; i<vsm.length; ++i){
  console.log(vsm[i]);
}


//TF-IDF
var idf_array = [];
var d=vsm.length;
for(var i=0; i<11; ++i){
  var dt=counter[i];
  idf_array.push(IDF(d,dt));
}
var TD_IDF_matrix = vsm;
console.log("TF-IDF");
```

```
  var tweetTF_IDF_Weight = [];
  var maxWeight = -1000;
  var minWeight = 1000;
  var maxWeightTweet = -1;
  var minWeightTweet = -1;
  var weightSum=0;
  for(i=0; i<vsm.length; ++i){
    weightSum=0;
    for(j=0; j<11; ++j){
      if(vsm[i][j] > 0){
        //tf-idf weight of relevant_word[j] in tweet[i] is given by:
        TD_IDF_matrix[i][j]=TF(vsm[i][j])*idf_array[j];
        TD_IDF_matrix[i][j]=Math.round(TD_IDF_matrix[i][j] * 100) / 100;

        weightSum+=TD_IDF_matrix[i][j];
      }
      console.log(TD_IDF_matrix[i]);
    }
    tweetTF_IDF_Weight.push(weightSum);
    if(weightSum < minWeight){
      minWeightTweet=i;
      minWeight=weightSum;
    }
    if(weightSum > maxWeight){
      maxWeightTweet=i;
      maxWeight=weightSum;
    }
  }
  console.log("maxWeightTweet="+maxWeightTweet+ " and its
weight="+maxWeight);
  console.log("minWeightTweet="+minWeightTweet+ " and its
weight="+minWeight);


  //Cosine similarity
  console.log("Cosine similarity:");
  /*
  var cosineAngle_matrix = [];

  console.log("totalTweets="+totalTweets);
  for(i=0; i<totalTweets-1; ++i){
    var v1 = vsm[i];
    for(j=i+1; j<totalTweets ; ++j){
      var v2 = vsm[j];
      cosineAngle_matrix.push([i,j,cosineSimilarity(v1,v2)]);
    }
  }
  //Display Cosine Similarity
  for(var i=0; i<cosineAngle_matrix.length; ++i){
    console.log(cosineAngle_matrix[i]);
```

```
}
*/
var vector1 = vsm[maxWeightTweet];
var vector2 = vsm[minWeightTweet];
var maxAngle = cosineSimilarity(vector1,vector2);
console.log("Opposite tweets deflect by "+maxAngle);

//LSA using SVD
var svd = require('node-svd').svd;
console.log('-----calculating svd-----');
var res = svd(vsm, 0, { U: true, V: true, debug: 2});
console.log('---');
var U = res.U;
var S = res.S;
var V = res.V;


console.log('U = %s', JSON.stringify(U));
console.log('S = %s', JSON.stringify(S));
console.log('V = %s', JSON.stringify(V));


var rows, columns;
rows=vsm.length;
columns = vsm[0].length;
console.log('vsm is a '+rows+' by '+columns+' matrix');
rows=U.length;
columns = U[0].length;
console.log('U is a '+rows+' by '+columns+' matrix');
//console.log('U = %s', JSON.stringify(U));

//Displaying U
for (i=0; i<rows; ++i){
  for (j=0; j<columns; ++j){
    //U[i][j]=Math.round(U[i][j] * 100) / 100;
    process.stdout.write(U[i][j]+', ');
  }
  process.stdout.write('\n');
}


var newS = [];
console.log("Creating New S ");
for (i=0; i<S.length; ++i){
  var tuple = [];
  for(j=0; j<S.length; ++j){
    tuple.push(0);
  }
  var temp = tuple;
  temp[i] = S[i];
```

```
  newS.push(temp);
 }
 rows=newS.length;
 columns = newS[0].length;
 console.log('!!!!!!!     newS is a '+rows+' by '+columns+' matrix');

 //Displaying newS
 for (i=0; i<rows; ++i){
  for (j=0; j<columns; ++j){
   process.stdout.write(newS[i][j]+', ');
  }
  process.stdout.write('\n');
 }

 rows=V.length;
 columns = V[0].length;
 console.log('V is a '+rows+' by '+columns+' matrix');

 //Displaying V
 for (i=0; i<rows; ++i){
  for (j=0; j<columns; ++j){
   //V[i][j]=Math.round(V[i][j] * 100) / 100;
   process.stdout.write(V[i][j]+', ');
  }
  process.stdout.write('\n');
 }

  //features in decending order in S ...
 var feature1 = S[0];  //strongest
 var feature2 = S[1];  //next strongest

 var VS = mult(V,newS);
 rows=VS.length;
 columns = VS[0].length;
 console.log('VS is a '+rows+' by '+columns+' matrix that describes relation
between relevant words and features');
 //Displaying VS
 for (i=0; i<rows; ++i){
  for (j=0; j<columns; ++j){
   process.stdout.write(VS[i][j]+', ');
  }
  process.stdout.write('\n');
 }

 //Determining which relevant word is part of which of the two stongest
features.
 var feature1Words = [];
 var feature2Words = [];
 var feature1Sentiment=0;
 var feature2Sentiment=0;
```

```
  for (i=0; i<rows; ++i){
    if(VS[i][0] > VS[i][1]){
      feature1Words.push(relevant_words[i]);
      if(afinn.hasOwnProperty(relevant_words[i])){
        var weight = afinn[relevant_words[i]];
        feature1Sentiment+=weight;
      }
    }
    else if(VS[i][0] < VS[i][1]){
      feature2Words.push(relevant_words[i]);
      if(afinn.hasOwnProperty(relevant_words[i])){
        var weight = afinn[relevant_words[i]];
        feature2Sentiment+=weight;
      }
    }
  }

  console.log("Feature1 words = "+feature1Words);
  console.log("Feature2 words = "+feature2Words);
  var US = mult(U,newS);
  rows=US.length;
  columns = US[0].length;
  console.log('US is a '+rows+' by '+columns+' matrix that describes relation
between tweets and features');
  var tweetCoordinates = [];
  for (i=0; i<rows; ++i){
    for (j=0; j<columns; ++j){
      process.stdout.write(US[i][j]+', ');
    }
    //                  f1:x-axis,f2:y-axis
    tweetCoordinates.push([US[i][0],US[i][1]]);
    process.stdout.write('\n');
  }

  rows=tweetCoordinates.length;
  columns = tweetCoordinates[0].length;
  console.log('tweetCoordinates is a '+rows+' by '+columns+' matrix');
  for (i=0; i<rows; ++i){
    for (j=0; j<columns; ++j){
      process.stdout.write(tweetCoordinates[i][j]+', ');
    }
    process.stdout.write('\n');
  }


  //k-means clustering
  var clusterfck = require("clusterfck");
  var kmeans = new clusterfck.Kmeans();
  // Calculate clusters.
```

```
    var clusters = kmeans.cluster(tweetCoordinates, 2);

    console.log('clusters matrix');

    for (i=0; i<clusters.length; ++i){
      console.log("cluster "+i+1);
      for (j=0; j<clusters[i].length; ++j){
        process.stdout.write(clusters[i][j]+'   ;   ');
      }
      process.stdout.write('\n');
    }

    console.log("CLUSTERING RESULT");
    console.log("Cluster 1 for words: ["+feature1Words+"] is of
density="+clusters[0].length+" and sentimentScore="+feature1Sentiment);
    console.log("Cluster 2 for words: ["+feature2Words+"] is of
density="+clusters[1].length+" and sentimentScore="+feature2Sentiment);

    var result = {
       score:          score,
       vsm:            vsm,
       feature1Words:  feature1Words,
       feature2Words:  feature2Words,
       feature1Sentiment:  feature1Sentiment,
       feature2Sentiment:  feature2Sentiment,
       VS:             VS,
       US:             US,
       clusters:       clusters
    };

    if (callback === null) return result;
    process.nextTick(function () {
       callback(null, result);
    });
};
```

8. DATA MINING PRINCIPLES AND ALGORITHMS:

Company Stock Prediction- The project is using Predictive Analysis.

Predictive Analytics:
Predictive analytics is not the actual outcome that would take place in future. It is just a method or form of extracting/generating useful information, from the existing data sets, so as to regulate patterns that could help us determine, or in other words, 'predict' the future trends and outcomes.
For this purpose of analyzing and predicting the unknown future trends, we make use of variety of techniques from data mining, modeling and machine learning. These techniques understand and analyze both, the past and current data, to make analysis and predictions for future.
Ample of industries make use of this predicated analysis in there day-to-day work and its demand is increasing in other fields as well.
Marketing, health-cares, travel, retailers, insurance, fraud detection and many other fields have also realized the usefulness of predictive analysis.
Predictive Modeling or Predictive analytics is nothing but an area of data mining where its objective is to extract useful knowledge from the available data (past and present) and use the same knowledge for identifying patterns and predict behavior of future.

Predictive Models Usage:
Predictive Models are used to predict the future outcome by performing comparison of the values with huge data sets. In our project, we are predicting company's stocks based on its past year's data.

Benefits of Predictive Modeling:
- It enhances the efficiency and truthfulness of our predictions
- Helps us get accurate and reliable results.
- Helps in building efficient models that work more with the limited data provided
- Reduces pain of adjusting and calculating values each time, saving time.
- It provides better diagnostics that help in better managing, controlling and decision-making process.

8.1 Vector Space Model:

In order to find similarity and relationship between each query interface, we use a Vector Space Model representation of these interfaces. The query interfaces in the deep web can be represented as a set of interfaces and a set of attributes of these interfaces [1].

$$A = \{a_1, a_2, ...a_m\} \quad (1)$$

$$F = \{f_1, f_2, ...f_n\} \quad (2)$$

Where F is a set of n query interfaces and A is a set of m attributes of query interfaces. To represent query interface in the form of a Vector Space Model we take F as the column index of the VSM matrix and A as row index of VSM. It compares query interface with attributes and hence ranks the query interfaces based on their similarity with each other. The query interfaces are represented in the form of a vector and the attributes are the dimensions of the vector space. The Vector Space Model is a high dimensional m x n matrix denoted by $C_{(m \times n)}$.

$$\overrightarrow{v_{f_n}} = \left(tf\left(a_1, f_n\right), tf\left(a_2, f_n\right), tf\left(a_3, f_n\right), ..., tf\left(a_m, f_n\right)\right) \quad (3)$$

Here $\overrightarrow{v_{f_n}}$ is the query interface vector.

$C_{(m \times n)}$	f_1	f_2	…	f_n	
a_1	$tf\left(a_1, f_n\right)$	$tf\left(a_1, f_n\right)$	…	$tf\left(a_1, f_n\right)$	
a_2	$tf\left(a_1, f_n\right)$	$tf\left(a_1, f_n\right)$	…	$tf\left(a_1, f_n\right)$	
…	…	…		…	
a_m	$tf\left(a_1, f_n\right)$	$tf\left(a_1, f_n\right)$		…	$tf\left(a_1, f_n\right)$

Table. 1. Represents high dimensional VSM matrix $C_{(m \times n)}$ plotting query interface vectors against their attributes. Here $tf\left(a_m, f_n\right)$ is the term frequency of attribute a_m in query interface f_n.

- **Calculate TF-IDF weight**

Now that we have the Vector Space Model of interfaces in Deep Web, we have to find a way to measure the importance of an attribute with respect to another attribute in a deep web query interface. For this, we use the TF-IDF weights [1].

TF-IDF weight is calculated based on the VSM as follows:

- **Calculate Term Frequency**

Term Frequency $TF(f, a)$ is calculated as follows:

$$TF(f,a) = \begin{cases} 0 & freq(f,a) = 0 \\ 1 + \log(1 + \log(freq(f,a))) & otherwise. \end{cases} \quad (4)$$

where $freq(f, a)$ is the number of occurrences of attribute f in query interface a.

- **Calculate Inverse Document Frequency**

The inverse document frequency computes the importance of an attribute on basis of its occurrence in the query interface vector. The greater its occurrence, the more important it is with reference to context. IDF is calculated as:

$$IDF(a) = \log \frac{1+|f|}{|f_a|} \quad (5)$$

where $|f|$ is the query interface collection and $|f_a|$ is the number of query interfaces in which the attribute a appears.

- **Calculate TF-IDF weight**

The $TF - IDF(f,a)$ weight is calculated as:

$$TF - IDF(f,a) = TF(f,a) \times IDF(a) \quad (6)$$

where $TF(f,a)$ is the term frequency of attribute a in query interface f and $IDF(a)$ is inverse document frequency of attribute a.

- **Calculate Cosine Similarity distance between cluster objects**

Now that we have the query interfaces in the form of vectors in a high dimensional vector space, we need to be able to calculate the similarity between two vectors. For this we use the Cosine similarity to measure the similarity or dissimilarity between pair of query interfaces [3-4].

To illustrate the cosine similarity between two query interfaces, refer to the vector representation of the query interfaces below:

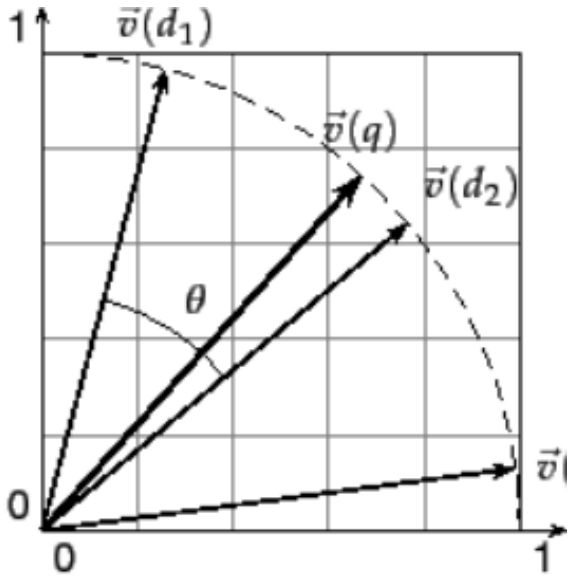


Figure 8.1: Graph showing vectors of query interfaces d_1, d_2 plotted in the vector space. The angle θ shows the deflection between the two vectors [4].

Lets consider $\vec{v}(d_1), \vec{v}(d_2)$ to be the two query interface vectors that we want to calculate similarity for. The Cosine Similarity is the cosine of the angle between the two vectors calculates as:

$$sim(d_1,d_2) = \frac{\vec{V}(d_1) \cdot \vec{V}(d_2)}{|\vec{V}(d_1)||\vec{V}(d_2)|}, \quad (7)$$

Where numerator is the *dot product* of the two query interface vectors.

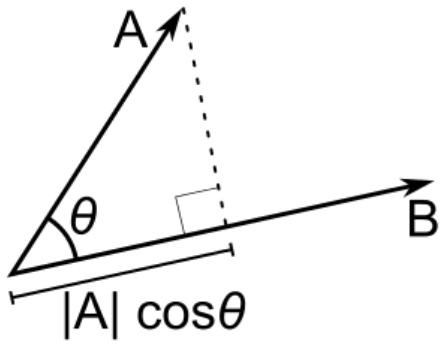


Figure 8.2: Graph showing vectors A and B plotted in the vector space. The angle θ shows the deflection between the two vectors [4].

Dot Product of any two vectors A and B is calculated as follows:

$$\vec{a} \cdot \vec{b} = |a||b|\cos\theta \qquad (8)$$

The Denominator is the Euclidean distance, which is calculated as:

$$\sqrt{\sum_{i=1}^{n} \overrightarrow{V_i^2}(d)} \qquad (9)$$

where V_i represents the vector for which we are calculating the Euclidean distance in an n dimensional space.

Thus the Cosine Similarity will determine how much two query interface vectors deflect from each other. A large value of cosine angle suggests that the query interfaces are very similar and a smaller value suggest dissimilar vetors.

8.2 Latent Semantic Relationship:

The VSM gives a complete picture of similarity between two query interfaces. The next challenge is to be able to use this knowledge of similarity to determine the relationship between two query interfaces. For this purpose, the vectorial semantics in Natural Language Processing provides a technique called LSA that is Latent Semantic Analysis. This technique is used for analyzing the relationships between query interfaces and the attribute terms in them by producing another set of related query interfaces and attributes [1-2].

- **Single Value Decomposition**

Let d1, d2, d3, d4 represent query interfaces among which we want to determine relationship. Let a, b, c, d, e, f be set of attributes of these query interfaces. Then the VSM model will look like follows:

	d1	d2	d3	d4
a	2	2	0	0
b	2	2	0	0
c	3	3	0	0
d	0	0	2	2
e	0	0	1	1
f	0	0	2	2

Table. 2. Showing VSM matrix A plotting query vectors d_i against attributes a, b, etc [2].

VSM is a high dimensional matrix and in order to determine relationship, we need a low dimensional matrix. For this purpose, we need a decomposition algorithm that preserves the columns structure of simulator while reducing the amount of rows in the matrix. Here we use Single Value Decomposition algorithm (SVD) to achieve the same.

The SVD algorithm reduces the VSM matrix into three smaller matrices U, S and V_t. There is a new scale to measure relationship called *feature.* Feature can be defined as a set of attributes that refer to a particular feature of the query interface. For instance, attribute words like "Linux, computation, processor" could correspond to feature like "computers". This new scale feature will be used in the decomposed matrices and will help reduce the amount of rows by grouping attributes.

The decomposition is shown as follows:

$$A = U \times S \times V^T \tag{10}$$

	f1	f2	f3	f4
a	0.48	0	0	0
b	0.48	0	0	0
c	0.72	0	0	0
d	0	-0.66	0	0
e	0	-0.33	0	0
f	0	-0.66	0	0

Table. 3. Showing VSM matrix U plotting features f_i against attributes a, b, etc [2].

	f1	f2	f3	f4
f1	5.83	0	0	0
f2	0	4.24	0	0
f3	0	0	0	0
f4	0	0	0	0

Table. 4. Showing VSM matrix S plotting features f_i against features f_i [2]

	d1	d2	d3	d4
f1	0.70	0.38	0	0
f2	0	0	-0.70	-0.70
f3	0	0	0	0
f4	0	0	0	0

Table. 5. Showing VSM matrix V_t plotting features f_i against query interfaces [2].

In order to interpret the relationship between query interfaces, we calculate product of pairs of decomposed matrices.

	f1	f2	f3	f4
d1	4.123	0.000	0.000	0.000
d2	4.123	0.000	0.000	0.000
d3	0.000	-3.000	0.000	0.000
d4	0.000	-3.000	0.000	0.000

Table. 6. Showing VSM matrix V_tS plotting features f_i against query interfaces d_i [2].

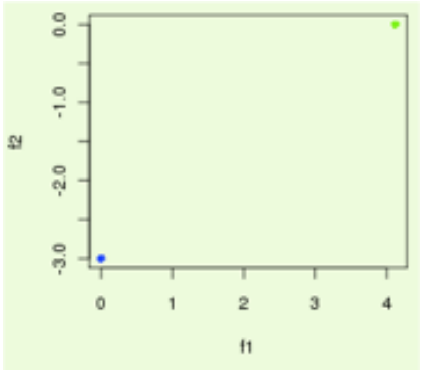


Figure 8.3: Plotting point in V_tS matrix [2]

This matrix shows how two query interfaces d_1 and d_2 are different from d_3 and d_4. The blue and the green points plotted on the graph are way apart which shows the dissimilarity between them.

	f1	f2	f3	f4
a	2.82	0	0	0
b	2.82	0	0	0
c	4.24	0	0	0
d	0	-2.82	0	0
e	0	-1.41	0	0
f	0	-2.82	0	0

Table. 7. Showing VSM matrix US plotting features f_i against attributes a, b, etc [2].

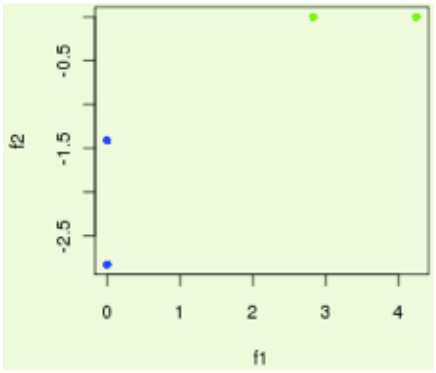


Figure 8.3: Plotting points in US matrix [2].

This matrix shows how three attributes *a, b, c* are aligned with feature *f1*. It also highlights that the attribute c has stronger association with feature *f1* as compared to *a* and *b*. The blue and the green points plotted on the graph represent the pictographically relationship derived from the matrix.

8.3 Clustering using K-mean algorithm:

Clustering of Deep Web Query Interfaces is an important step in this process. Query interfaces in the same group will refer to the same domain and those in different groups will refer to different domains [1].

The k-Means clustering algorithm is an efficient unsupervised learning algorithm. In a k-Means clustering we start with *n* data points that are to be clustered in a *d-dimensional* space denoted by R^d [5].

Our goal is to determine a set of *k* center points such that the mean square distance of each of these *n* data points is reduced to a minimum from its nearest center. This mean square distance is donated as:

$$J(V) = \sum_{i=1}^{c} \sum_{j=1}^{c_i} (\| x_i - v_j \|)^2 \qquad (11)$$

where $\| x_i - v_j \|$ represents Euclidean distance from x_i to v_j, c_i denotes the number of data points that are in cluster *I* and *c* denotes number of cluster centers.

1) From the set of Cluster enters, randomly select a center say ‘c’
2) For each data point in the set, calculate distance from the data point to the cluster centers.
3) Assign a data point to a cluster based on the minimum distance between the data point and respective cluster center as compared to distance from all the cluster centers.
4) Recalculate the new cluster centers using following equation:

$$v_i = (1/c_i)\sum_{j=1}^{c_i} x_j \qquad (12)$$

5) For each data point in the set, recalculate distance from the data point to the new set of cluster centers.

Check if a data point was reassigned to another cluster, if so then repeat from step 3, if not then stop.

8.4 Clustering:

Clustering is the process of examining a collection of “points,” and grouping the points into “clusters” according to some distance measure. The goal is that points in the same cluster have a small distance from one another, while points in different clusters are at a large distance from one another.

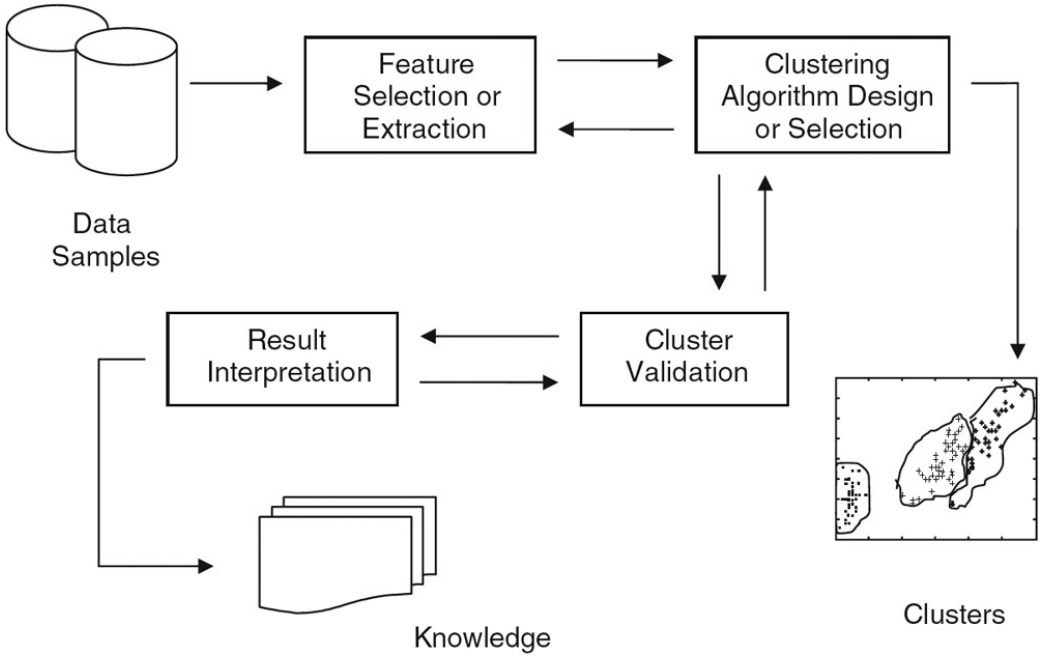


Figure 8.4: Clustering Procedure

Stocks Prediction Algorithm:

We have used following terms in making the prediction for stocks:

Category, Equity, Total Assets, Total Liability, Operating Margin Ratio, Current Asset, Gross Profit, Share Value, Debt Equity, EBITDA, Total Revenue, Full Time Employee, Gross Margin, Cash and Cash Equivalence.

Algorithm:

1. Fetching values for the above terms from the dataset and Twitter for specified company.
2. To make prediction following Data Mining Techniques were applied:
    a) Representation of tweets in Vector Space Model
    b) Calculate TF-IDF weights of above terms to determine relative strength of tweets based on these terms
    c) Calculate Cosine Similarity between any pair of tweets to find the maximum deflection between strongest positive tweet and strongest negative tweet.
    d) Latent Symantic Analysis of Tweets is done using Single Value Decomposition to determine the following:
        - Which is the strongest feature
        - Relation between tweets and feature
        - To map tweets on x-y plane
    e) Calculate K-means Clustering for tweet co-ordinates to form two distinct clusters that suggest if stock rates of company will go up or down in future.
3. The algorithm uses past 3 years of financial records of the company and K-Means clustering result for final prediction.

9. KDD PRINCIPLES:

KDD or Knowledge Discovery in Databases is a multidisciplinary branch of science that deals with data storage and data access, algorithms that are highly scalable and has huge data sets. The processes that are usually included in KDD are: Selection, Processing, Transformation, Data Mining and Evaluation. The overall process of finding and interpreting patterns from data involves recursive application of these steps.

The overall process of finding and interpreting patterns from data involves the repeated application of the following steps:

1. Developing an understanding of
   - the application domain
   - the relevant prior knowledge
   - the goals of the end-user
2. Creating a target data set: selecting a data set, or focusing on a subset of variables, or data samples, on which discovery is to be performed
3. Data cleaning and preprocessing.
   - Removal of noise or outliers
   - Collecting necessary information to model or account for noise
   - Strategies for handling missing data fields.
   - Accounting for time sequence information and known changes.
4. Data reduction and projection.
   - Finding useful features to represent the data depending on the goal of the task: Reduced the sentences into arrays of words.
   - Using dimensionality reduction or transformation methods to reduce the effective number of variables under consideration or to find invariant representations for the data: Transformed the data using SVD into matrices.
5. Choosing the data mining task.
   - Deciding whether the goal of the KDD process is classification, regression, clustering, etc
6. Choosing the data mining algorithms.
   - Selecting method(s) to be used for searching for patterns in the data.
   - Deciding which models and parameters may be appropriate.
   - Matching a particular data mining method with the overall criteria of the KDD process.
7. Data mining
   - Searching for patterns of interest in a particular representational form or a set of such representations as classification rules or trees, regression, clustering, and so forth.
8. Interpreting mined patterns.
9. Consolidating discovered knowledge.

This knowledge can be used for further processing of data.

Make a note of these observations and conclusions to prepare a document that can be put forward to different stakeholders.

We have been using KDD approach in our project for extracting useful information (tweet feeds) from the database. This knowledge involved exploring and analyzing large amounts of data to find patterns for big data based on positive, negative, neutral sentiments. Each tweet belongs to either of these sentiment classes. Inclusion of the neutral class has been in the model in order to classify those tweets that did not belong to positive or negative class.

All the steps used and applied were in accordance with KDD principles. These steps were observed, analyzed and put to use to arrive at a conclusion of getting clean data. Here are the steps that were evenly followed in our project on similar grounds after which we were able to classify the tweet feeds (positive, negative, neutral).

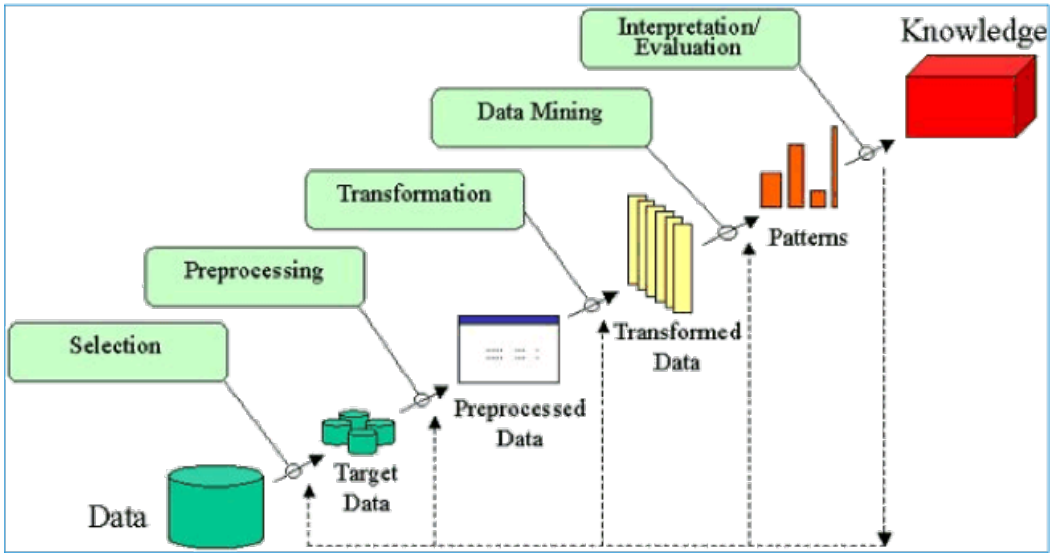


Figure 9: KDD Model

- Selecting tweets of the company by its company name and stocks **(Selection),**
- Tokenizing and Separating the Tweets **(Pre-processing),**
- Filtering special characters **(Cleaning),**
- Separating html links, removing hashtags # from the data used **(Feature Selection and Extraction),**
- Transforming the tweets into Vector Space Model **(Transformation),**
- **(Data Mining):**
    a) Calculate TF-IDF weights to determine relative strength of tweets
    b) Calculate Cosine Similarity between any pair of tweets to find the maximum deflection between strongest positive tweet and strongest negative tweet.
    c) Latent Symantic Analysis of Tweets is done using Single Value Decomposition to determine the following:
        - Which is the strongest feature
        - Relation between tweets and feature
        - To map tweets on x-y plane

d) Calculate K-means Clustering for tweet co-ordinates to form two distinct clusters that suggest if stock rates of company will go up or down in future.

- Used past 3 years of data of the company and K-Means clustering result for final prediction using high charts **(Interpretation and Evaluation),**
- Stock Rate Prediction **(Knowledge)**

10. DATA TOOLS:

Data Analytics using NodeJS libraries and Data mining concepts:
We have used NodeJS libraries like:

- **npm svd** - This library takes the input as a VSM that we create for twitter tweets. It then applies the Single Value Decomposition algorithm on this matrix. It allows us to specify if we want transpose of any of the decomposed matrices. It also allows to specify the verbosity of output. It gives us 3 decomposed matrices U,S and V. We use these matrices to compare tweets against relevant words.
- **npm clusterfck** - This library performs k-means clustering on given data points. We have converted twitter tweets into x,y coordinates and are using this library to cluster these data points and show them on a scatter graph. These clusters help us determine if a stock value is likely to increase or decrease and by how much amount.
- **npm-twit** - This library is used as the twitter api to get desired tweets. We use this library to perform search on the twitter api. We take the company's name and get tweets related to its stocks.

Data Mining Steps:
a) Data extraction
b) Data cleaning
c) Data loading
d) Data transformation
e) Predictive modeling
f) Data visualization

With its growing list of packages, NodeJS libraries can now connect with other data stores such as MySQL, SQLite, Hadoop and MongoDB for data storage activities. NodeJS allows performing Data Analytics by various statistical and machine learning operation as follows:
a) Regression
b) Classification
c) Clustering
d) Recommendation
e) Text Mining.

High Charts
High Charts are used to create interactive charts on the web. We have used high charts for data visualization. Highcharts is a charting library in JavaScript, offering us an easy way of adding interactive charts to our web site or web application. Highcharts supports line, spline, area, areaspline, column, bar, pie, scatter, angular gauges, arearange, areasplinerange, columnrange, bubble, box plot, error bars, funnel, waterfall and polar chart types. We have used high charts for plotting bar graphs and pie charts.

11. DESIGN PATTERNS

11.1 Node JS Express MVC framework:

Express is a minimal and flexible Node.js web application framework that provides a robust set of features for web application. We have Node JS express MVC framework since it provides a lot of in built packages for different functionalities which we plan to achieve. Since it has a great support and bunch of features, Express is one of the best framework for Node.

11.2 Front End – EJS:

EJS stands for Embedded JavaScript, it is essentially HTML with JavaScript based features embedded for templating. EJS is primarily HTML but with additional features which allows us to reuse pieces of our components. If we have any HTML project, then all we need to do is to rename it to .ejs extension and we can start using EJS.

For Highchart-1

```
<!DOCTYPE html>
<html lang="en">
<head>
<meta charset="utf-8">
<meta name="viewport" content="width=device-width, initial-scale=1.0">
<meta name="description" content="">
<meta http-equiv="X-UA-Compatible" content="IE=edge">
<meta name="viewport" content="width=device-width, initial-scale=1">
<meta name="author" content="">
<link href="css/bootstrap.min.css" rel="stylesheet">
<!-- Custom CSS -->
<link href="css/stylish-portfolio.css" rel="stylesheet">
<!-- Custom Fonts -->
<link href="font-awesome/css/font-awesome.min.css" rel="stylesheet"
type="text/css">
<link
href="http://fonts.googleapis.com/css?family=Source+Sans+Pro:300,400,700,30
0italic,400italic,700italic"
rel="stylesheet" type="text/css">
<script
src="http://ajax.googleapis.com/ajax/libs/jquery/1.10.2/jquery.min.js"></script>
<script src="http://code.highcharts.com/highcharts.js"></script>
<script src="http://code.highcharts.com/highcharts-3d.js"></script>
<script src="http://code.highcharts.com/highcharts-more.js"></script>
<script src="http://code.highcharts.com/modules/solid-gauge.js"></script>
```

```
<script src="http://code.highcharts.com/modules/exporting.js"></script>
<!--<link rel="shortcut icon" href="assets/images/gt_favicon.png">-->
<style type="text/css">
.chartSize {
height: 100%;
width: 50%;
position: relative;
}
.scrollit {
overflow: scroll;
height: 350px;
}
</style>
<script type="text/javascript">
function generateMeterResults() {
var gaugeOptions = {
chart: {
type: 'solidgauge'
},
title: null,
pane: {
center: ['50%', '85%'],
size: '140%',
startAngle: -90,
endAngle: 90,
background: {
backgroundColor: (Highcharts.theme && Highcharts.theme.background2) ||
'#EEE',
innerRadius: '60%',
outerRadius: '100%',
shape: 'arc'
}
},
tooltip: {
enabled: false
},
// the value axis
yAxis: {
stops: [
[0.1, '#DF5353'], // red
[0.5, '#DDDF0D'], // yellow
[0.9, '#55BF3B'] // green
],
lineWidth: 0,
```

```
minorTickInterval: null,
tickPixelInterval: 400,
tickWidth: 0,
title: {
y: -70
},
labels: {
y: 16
}
},
plotOptions: {
solidgauge: {
dataLabels: {
y: 5,
borderWidth: 0,
useHTML: true
}
}
}
};
```

twitterSearch.js

```
var util = require('util'),
        twit = require('twit'),
        sentimentAnalysis = require('./twitterSentimentAnalysis.js');

var config = {
        consumer_key: 'WhYExrBdjaQKyArMvJhxjHiHt',
        consumer_secret:
'WZ81G6ADuk2RJgGRVMsRZMGgJcUudbC7W2xdhTTx1Miqbhr68y',
        access_token:                                    '2433226039-
ALNzRIdqRR3StA2GZSXyPDuMJMhp5rm604BWktz',
        access_token_secret:
'nwUXQJsFraf4wd2SB8ls3BKQiB5uAWVEWO1Ea6cLk9ifB'
};


exports.getTweets = function getTweets(comp1, criteria, callback) {
        var twitterClient = new twit(config);
        var tweetsPolarity = [];
        var positive = 0;
        var negative = 0;
        var neutral = 0;
```

```
        var twitQuery = comp1 + ' ' + criteria + ' since:2015-01-01';
        var analysisResult;

        twitterClient.get('search/tweets', {q: twitQuery, count: 100}, function
(err, data) {
        var totalTweets = data.statuses;
        var tweets = [];
        console.log(JSON.stringify(totalTweets));
       console.log("totalTweets.length="+totalTweets.length);
        for (var i = 0; i < totalTweets.length; i++) {
        totalTweets[i].text = totalTweets[i].text.replace(/^RT/, "");
        totalTweets[i].text = totalTweets[i].text.replace(/^ReTw/, "");
        tweets.push(totalTweets[i].text);
        }
       console.log("tweets.length="+tweets.length);
       analysisResult=sentimentAnalysis(tweets);
        /*
        tweetsPolarity.push(positive);
        tweetsPolarity.push(negative);
        tweetsPolarity.push(neutral);
        callback(err, tweetsPolarity, tweets);
        */
        callback(err, analysisResult, tweets);
        }
        );
}
```

twitterSentimentAnalysis.js

```
var sentiment = require('sentiment');
module.exports = function(text) {
        return sentiment(text);
};
```

11.3 Middle tier – Express:

We have used Express as a middleware for Node JS framework. An express application is a series of middleware calls. Middleware is a function with access to the request object(req), response object(res) and the next middleware in line in the request-response cycle of an Express application. Middleware can do the following:

1. Execute code
2. Make changes to the request
3. End the request response cycle

4. Call the next middleware in the stack

An express application can use following kinds of middleware:

1. Application level middleware
2. Router level middleware
3. Error handling middleware
4. Built in middleware
5. Third party middleware

We have used application level middleware. Application level middleware are bound to an instance of express.

App.js

```
var express = require('express');
var path = require('path');
var logger = require('morgan');
var cookieParser = require('cookie-parser');
var bodyParser = require('body-parser');
var routesBase = require('./routes/index');
var analysis = require('./routes/analysis');
var app = express();
// view engine setup
app.set('views', path.join(__dirname, 'views'));
app.set('view engine', 'ejs');
app.use(logger('dev'));
app.use(bodyParser.json());
app.use(bodyParser.urlencoded({extended: false}));
app.use(cookieParser());
app.use(express.static(path.join(__dirname, 'public')));
app.use('/', routesBase);
app.post('/getStats', analysis.getStats);
// catch 404 and forward to error handler
app.use(function (req, res, next) {
var err = new Error('Not Found');
err.status = 404;
next(err);
});
// error handlers
// development error handler
// will print stacktrace
if (app.get('env') === 'development') {
app.use(function (err, req, res, next) {
res.status(err.status || 500);
res.render('error', {
```

```
message: err.message,
error: err
});
});
}
// production error handler
// no stacktraces leaked to user
app.use(function (err, req, res, next) {
res.status(err.status || 500);
res.render('error', {
message: err.message,
error: {}
});
});
module.exports = app;
```

Analysis.js

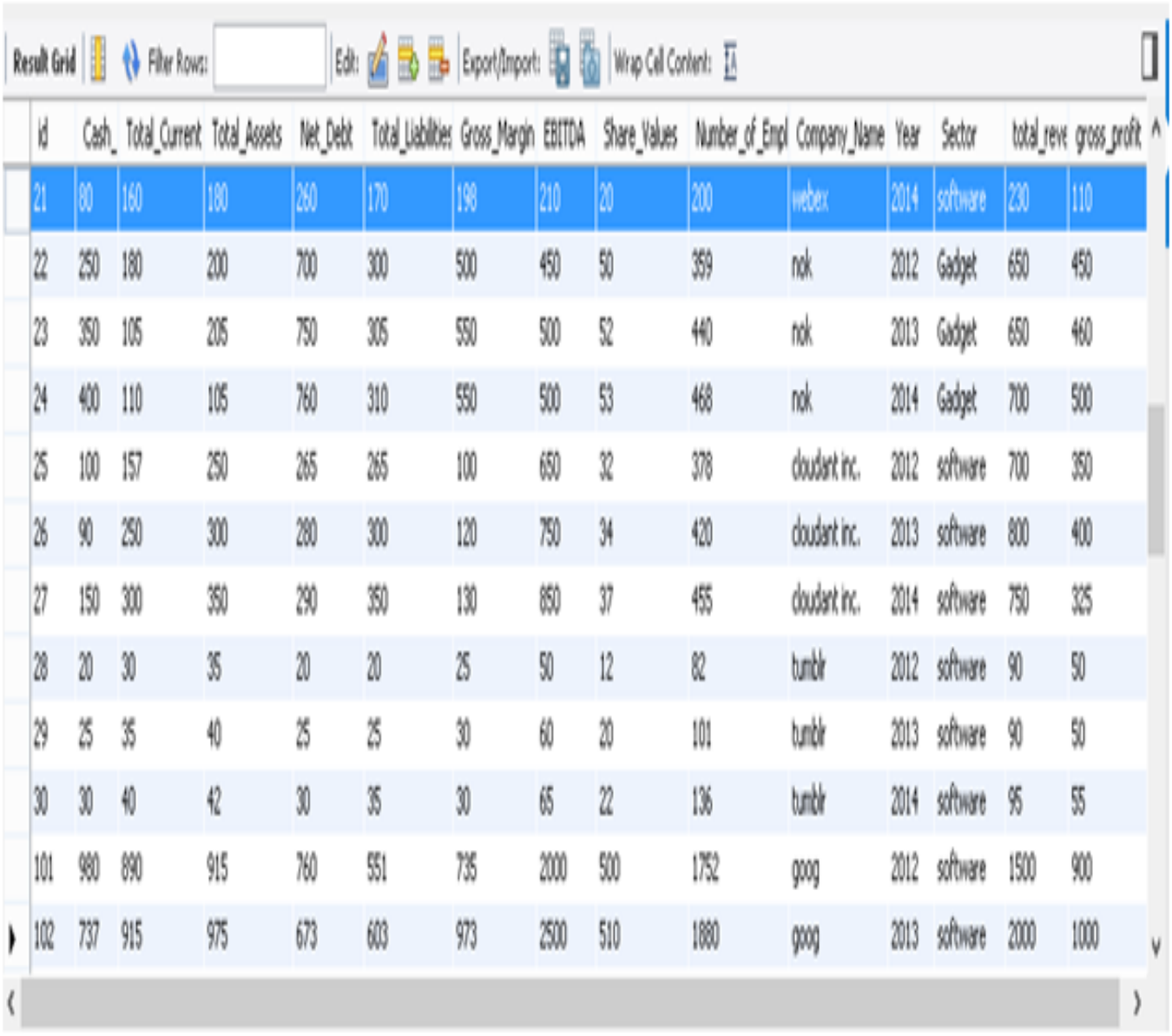
```
var mysql = require('./mysql');
var tweetStats = require('./twitterSearch');
exports.getStats = function (req, res) {
var compFirst = req.param("comp1").toLowerCase().trim();
var criteria = "stock";//"stock equity asset liability revenue EBITDA profit loss
cash up down";
var compSecond = req.param("comp2").toLowerCase().trim();
var getStats = "select * from mytable1 where Company_Name='" + compFirst +
"' OR Company_Name='" + compSecond + "'";
var polarity = [0,0,0];
var analysisResult;
tweetStats.getTweets(compFirst, criteria, function (err, result, twits) {
if (err) {
throw err;
}
analysisResult = result;
var tweets = twits;
console.log("score="+analysisResult.score);
mysql.fetchData(getStats, function (err, rows) {
console.log("rows="+rows.length);
if (rows.length < 6) {
res.render('index', {error: "Error"});
console.log(err);
}
else {
```

```
//console.log("pol..." + polarity);
var year2012="2012";
var year2013="2013";
var year2014="2014";
var i;
var comp1 = [];
var comp2 = [];
var current_Share_Value=1;
for (var i = 0; i < rows.length; i++) {
if (rows[i].Company_Name.toUpperCase() === compFirst.toUpperCase()) {
comp1.push(rows[i]);
console.log(rows[i].Share_Values);
if(rows[i].Year.toUpperCase() === year2014.toUpperCase()){
current_Share_Value=rows[i].Share_Values;
}
}
else if (rows[i].Company_Name.toUpperCase() ===
compSecond.toUpperCase()) {
comp2.push(rows[i]);
}
}
var avg =
(comp1[0].Share_Values+comp1[1].Share_Values+comp1[2].Share_Values)/3;
var increase_by = avg-current_Share_Value;
var predict_share_value = parseInt((increase_by*100)/current_Share_Value);
/*
var result = {
score: score,
vsm: vsm,
feature1Words: feature1Words, //X-axis f1(w1,w4,w7)
feature2Words: feature2Words, //Y-axis f2(w1,w2,w3)
VS: VS,
US: US,
clusters: clusters
//clusters[0] - red array of (x,y) -ve <X< +ve
//clusters[1] - green array of (x,y) -ve <Y< +ve
};
*/
res.render('viewStats', {
data: rows,
comp1: comp1,
comp2: comp2,
polarity: polarity,
tweets: tweets,
```

```
finalPercent: predict_share_value
});
}
// render or error
});
});
}
```

12. DATA STORE:

MySQL is used for data storage. We have created a mock data for a set of companies. It is a relational database that stores data in the form of rows and columns i.e. tabular representation of data.



Result Grid | Filter Rows: | Edit: | Export/Import: | Wrap Cell Content:

id	Cash_	Total_Current	Total_Assets	Net_Debt	Total_Liabilities	Gross_Margin	EBITDA	Share_Values	Number_of_Empl	Company_Name	Year	Sector	total_reve	gross_profit
21	80	160	180	260	170	198	210	20	200	webex	2014	software	230	110
22	250	180	200	700	300	500	450	50	359	nok	2012	Gadget	650	450
23	350	105	205	750	305	550	500	52	440	nok	2013	Gadget	650	460
24	400	110	105	760	310	550	500	53	468	nok	2014	Gadget	700	500
25	100	157	250	265	265	100	650	32	378	doudant inc.	2012	software	700	350
26	90	250	300	280	300	120	750	34	420	doudant inc.	2013	software	800	400
27	150	300	350	290	350	130	850	37	455	doudant inc.	2014	software	750	325
28	20	30	35	20	20	25	50	12	82	tumblr	2012	software	90	50
29	25	35	40	25	25	30	60	20	101	tumblr	2013	software	90	50
30	30	40	42	30	35	30	65	22	136	tumblr	2014	software	95	55
101	980	890	915	760	551	735	2000	500	1752	goog	2012	software	1500	900
102	737	915	975	673	603	973	2500	510	1880	goog	2013	software	2000	1000

Figure 12: Data store in MySQL

13. CLOUD:

We have used IBM Bluemix DevOps Services for hosting our web application and database. It is software as a service (SaaS) on the cloud that supports continuous delivery. With DevOps Services, you can develop, track, plan, and deploy software in one place.

Bluemix is the platform where you deploy your app and add services. The Bluemix Catalog contains services for data management, mobile apps, cloud integration, web apps, and security. The DevOps services in the Catalog are Delivery Pipeline and Track & Plan.

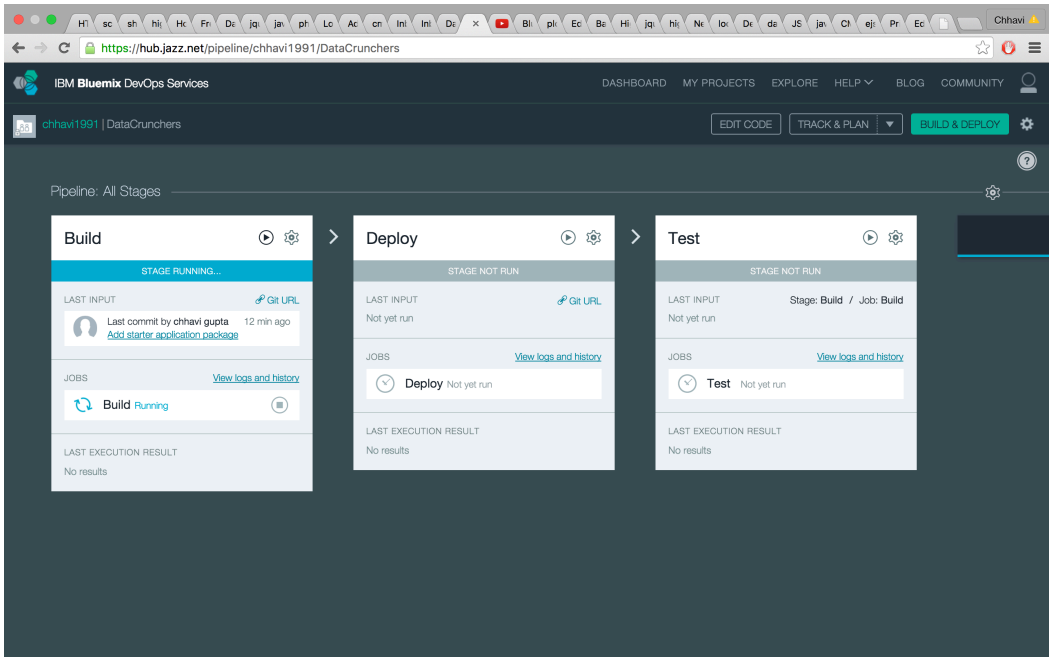


Figure 13.1: Screenshot1

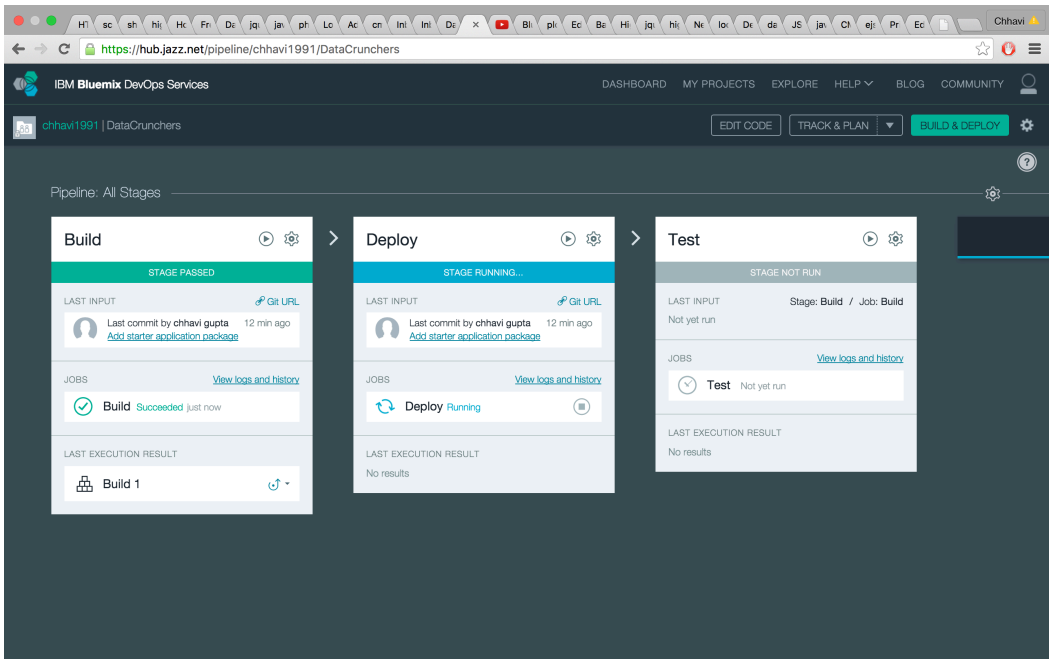


Figure 13.2: Screenshot2

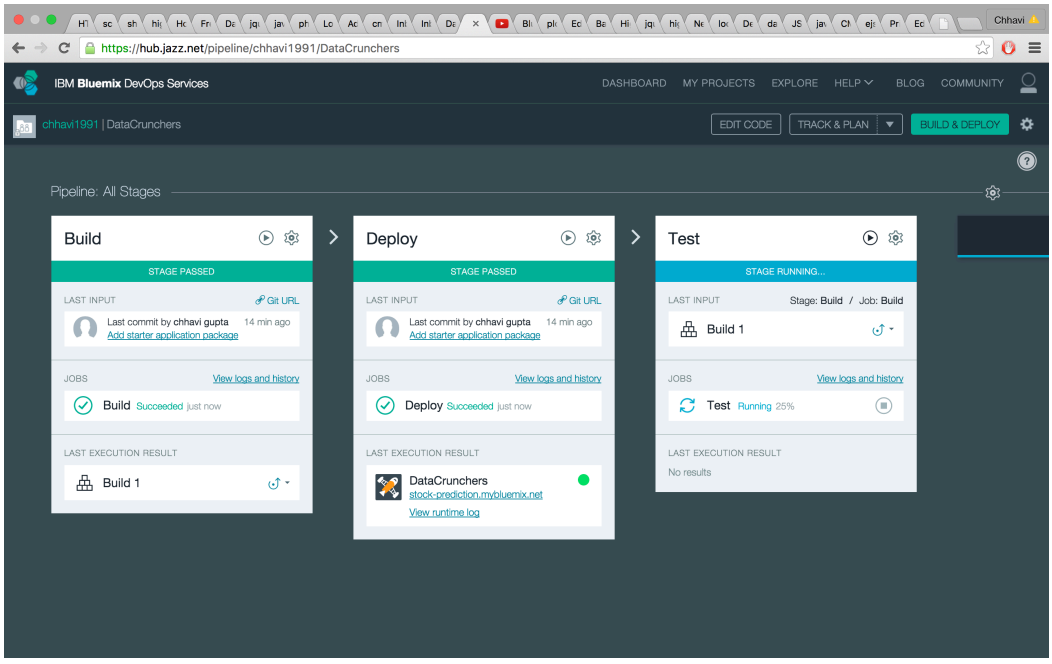


Figure 13.3: Screenshot3

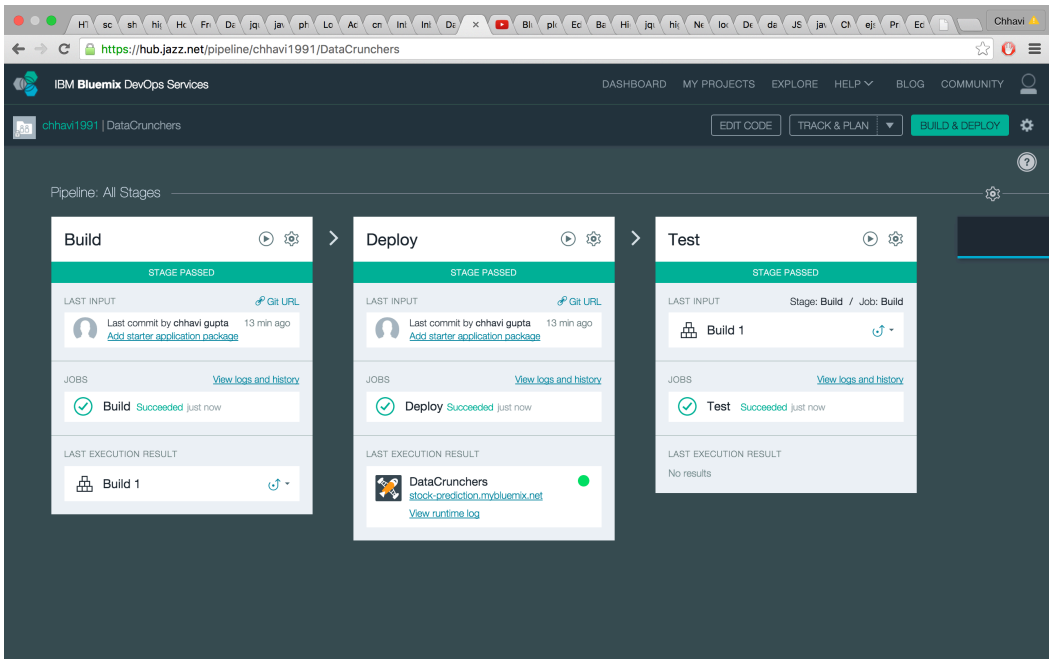


Figure 13.4: Screenshot4

14. CLIENT SIDE DESIGN:

Figure 14.1: Screenshot

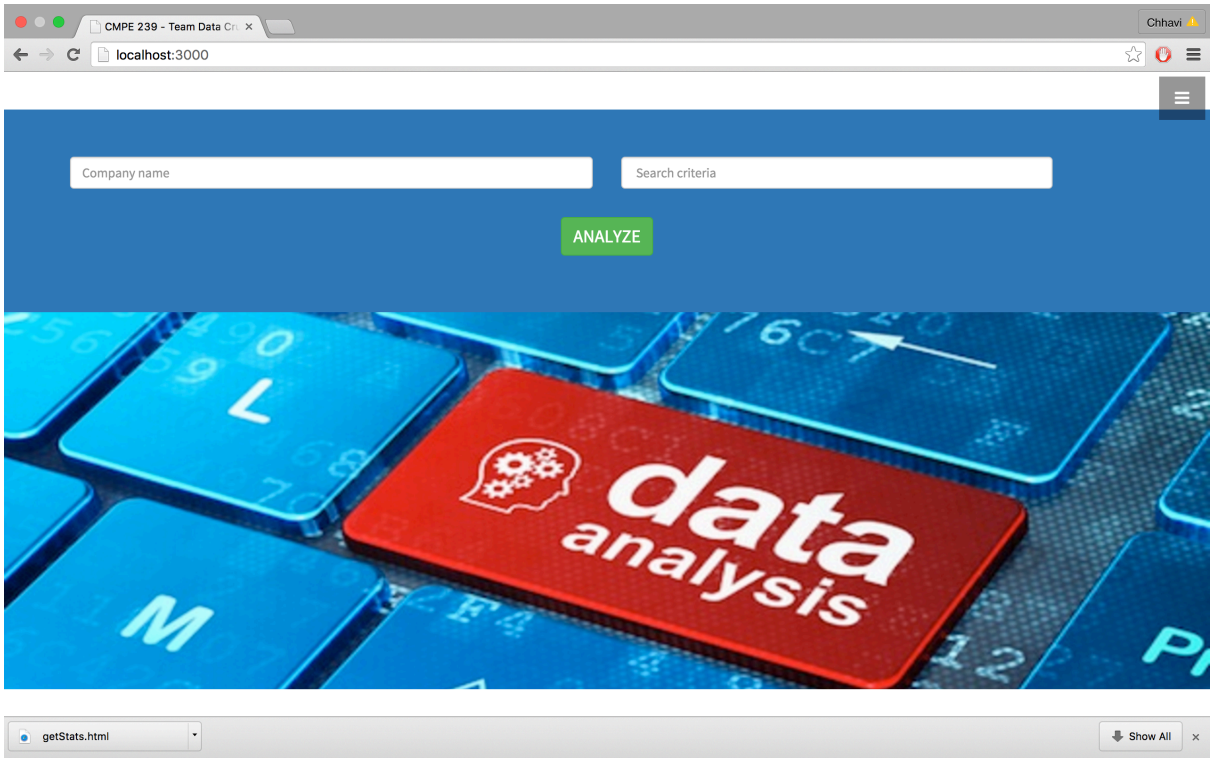


Figure 14.2: Screenshot

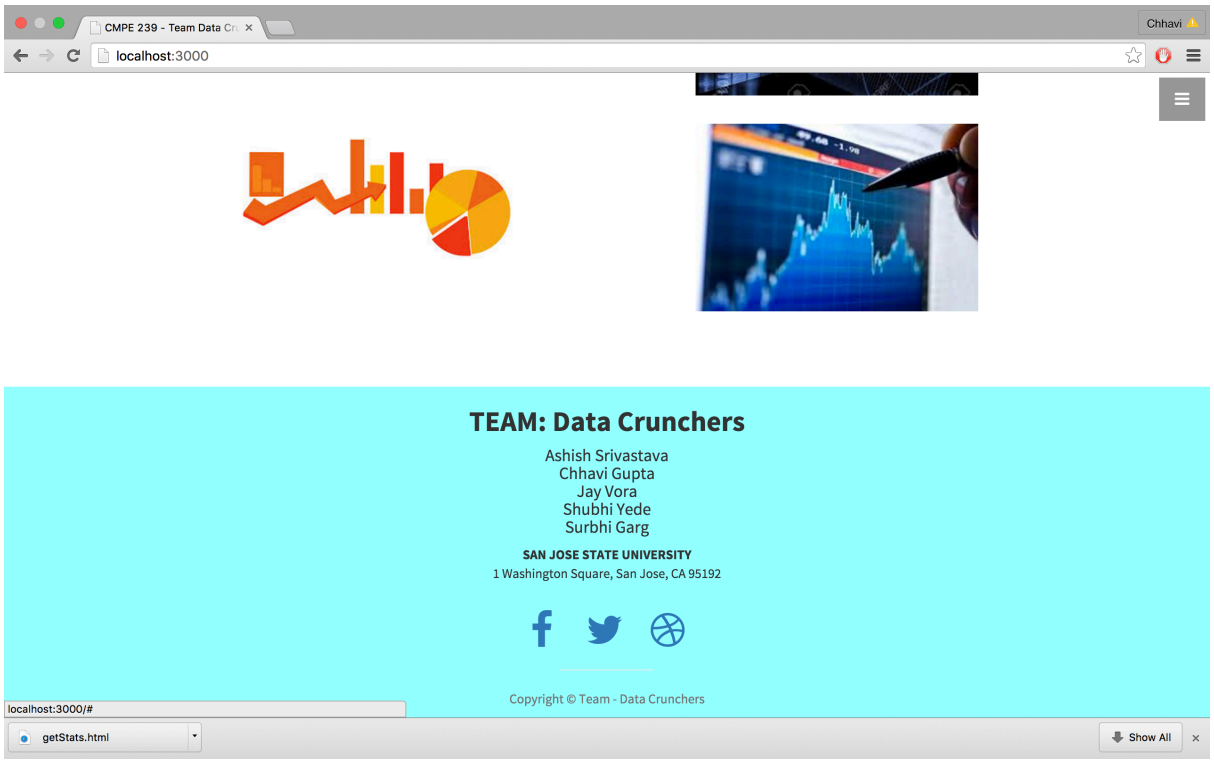


Figure 14.3: Screenshot

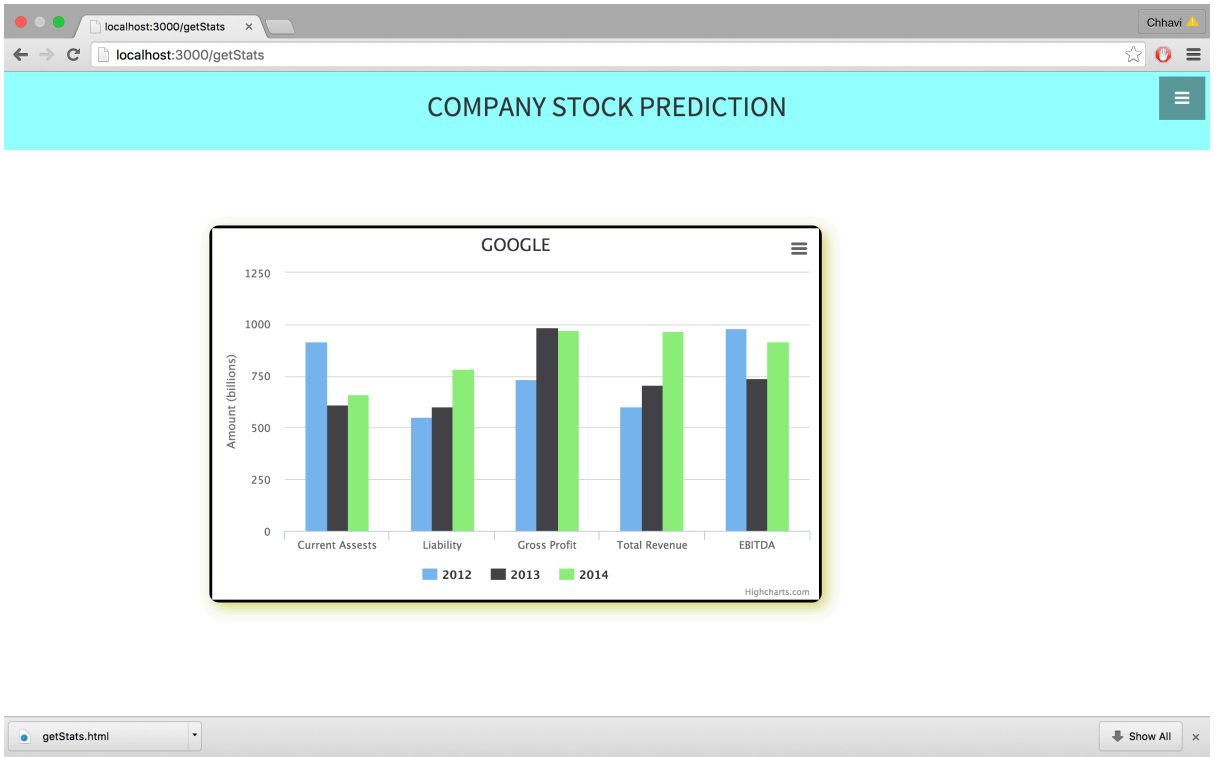


Figure 14.3: Screenshot

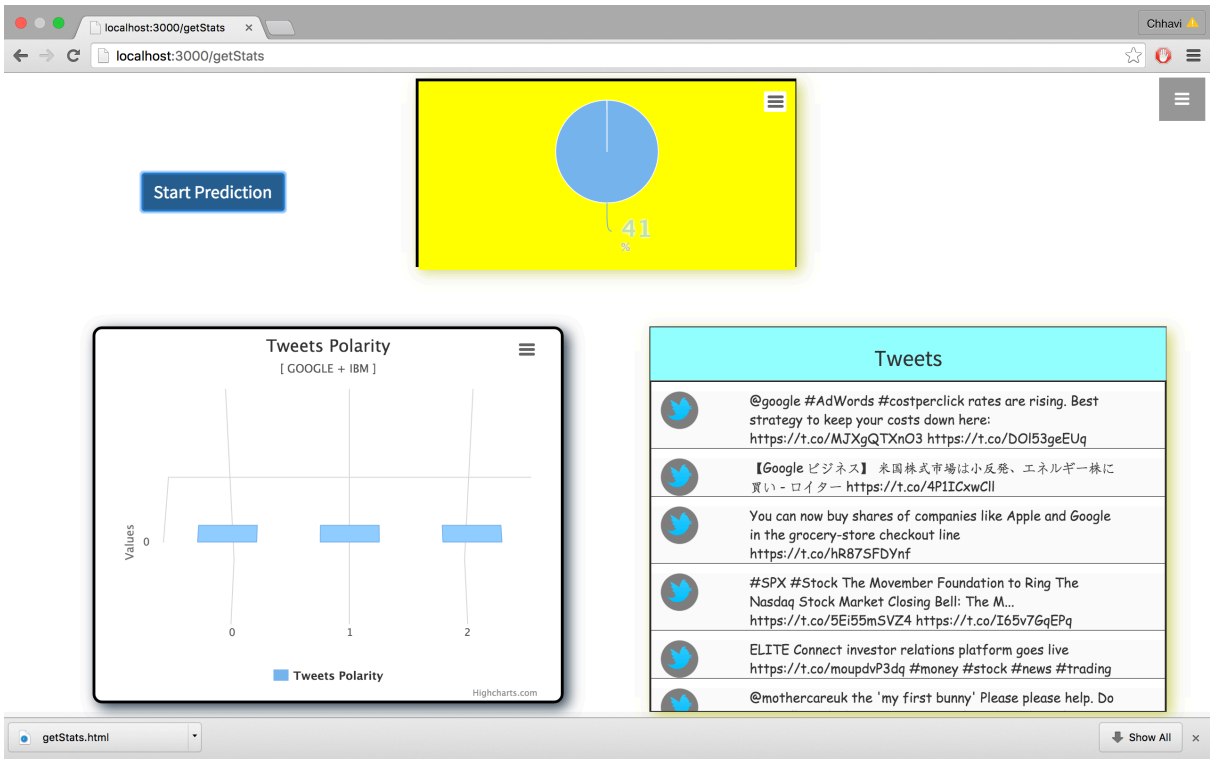


Figure 14.4: Screenshot

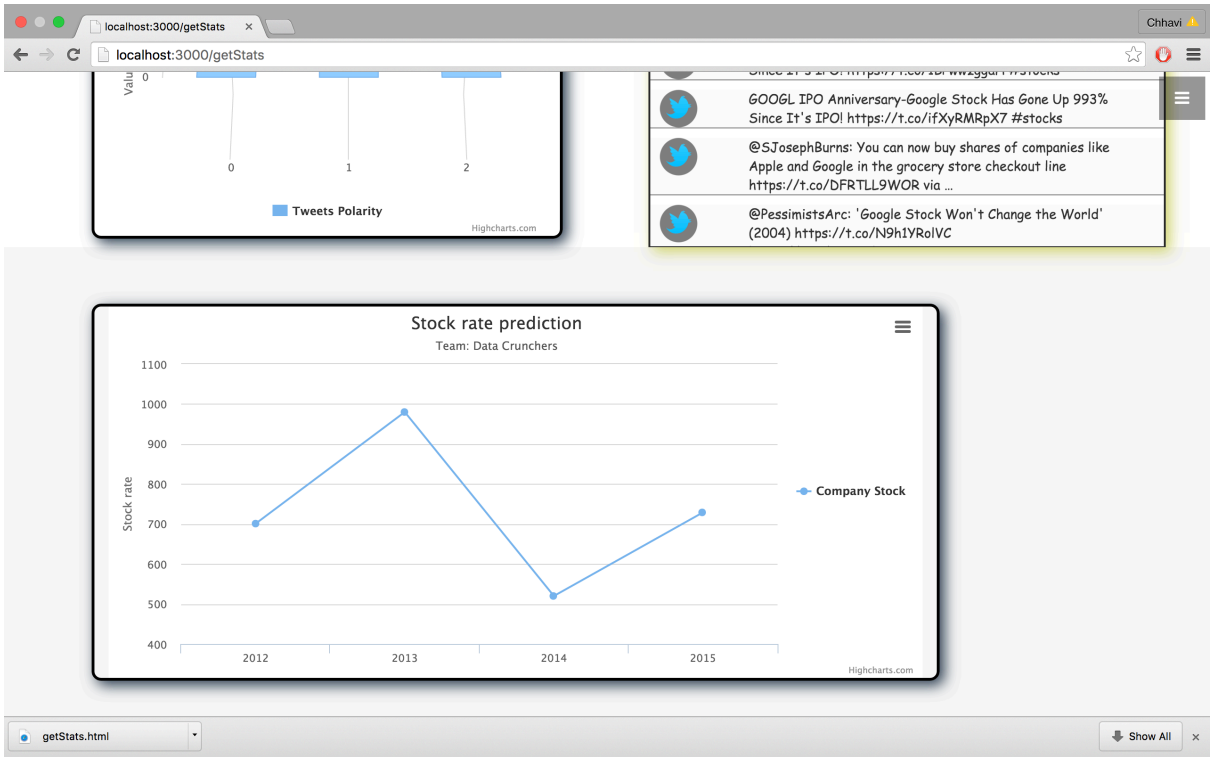


Figure 14.5: Screenshot

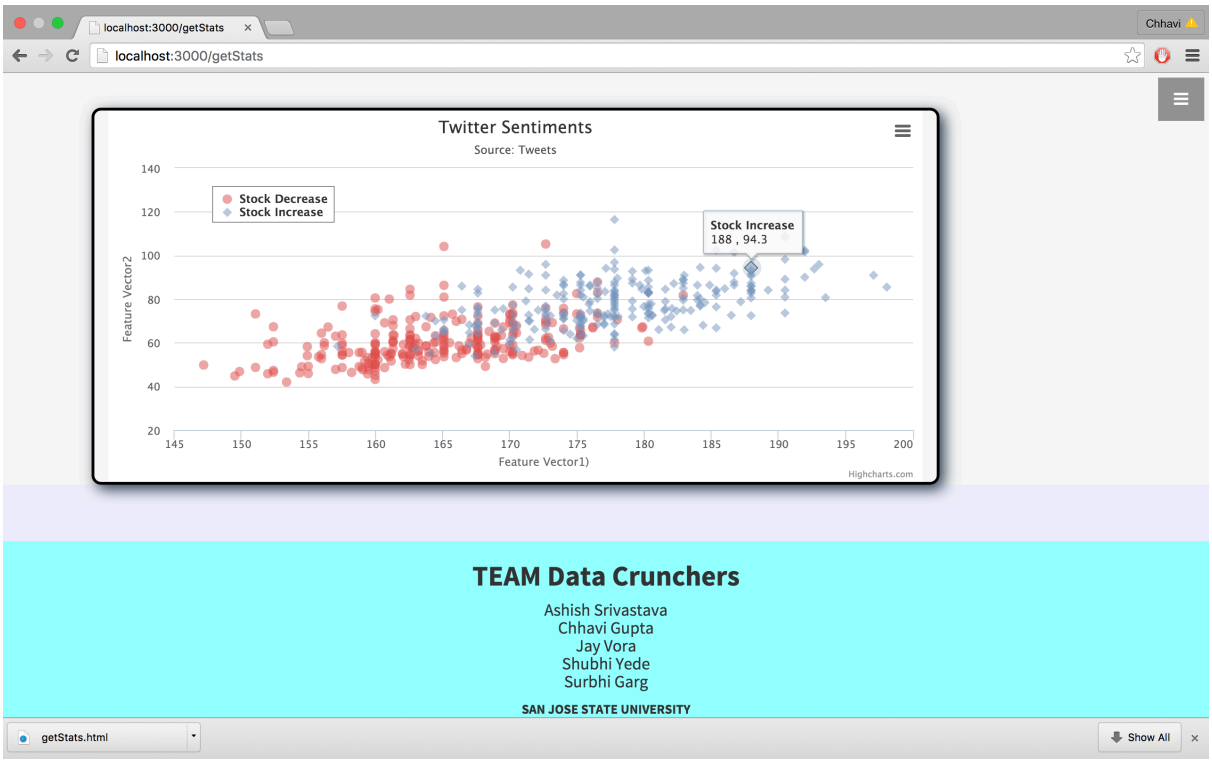


Figure 14.6: Screenshot

15. LOAD TESTING:

The load testing was conducted on our web application using the following tool:

Load Impact tool:

In this tool we tried load testing our web application by supplying 25 virtual users on our application and checking its performance. We tested our application for 5 minutes by giving different number of users and monitoring its performance. Below images will give you the detail overview of the performance of our application with different number of users.

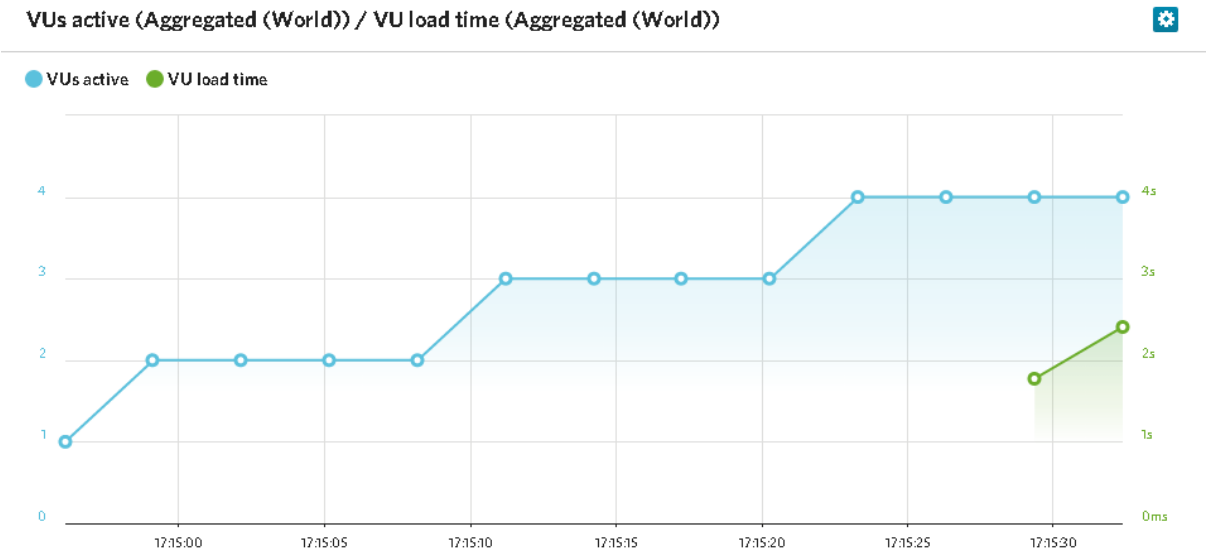


Figure 15.1: Load Testing

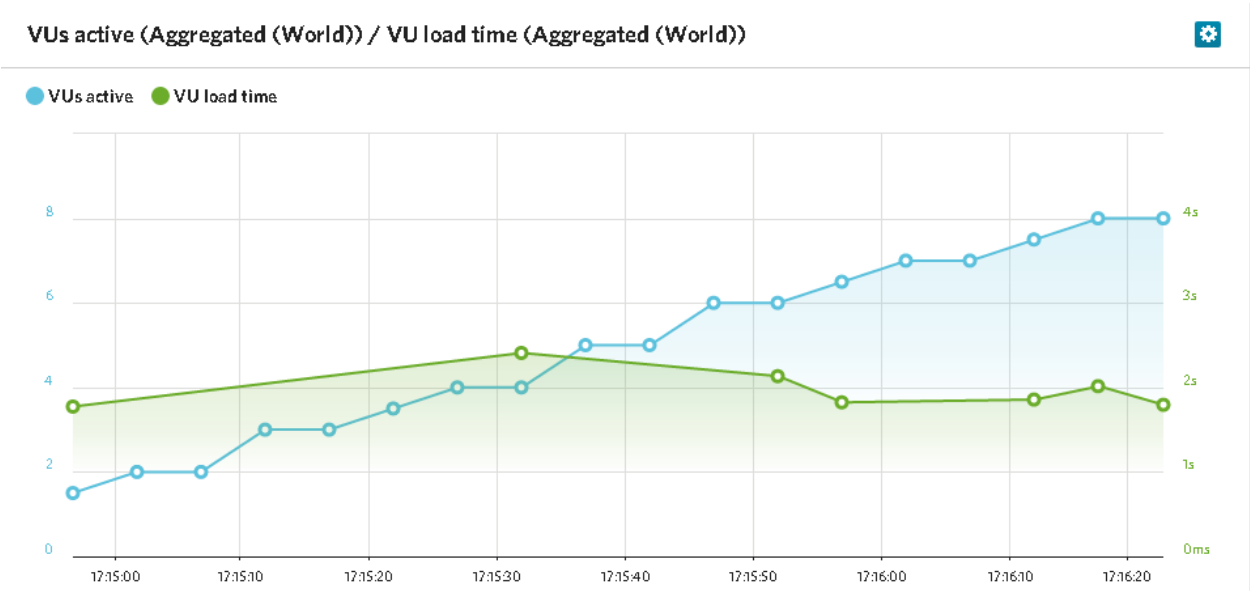


Figure 15.2: Load Testing

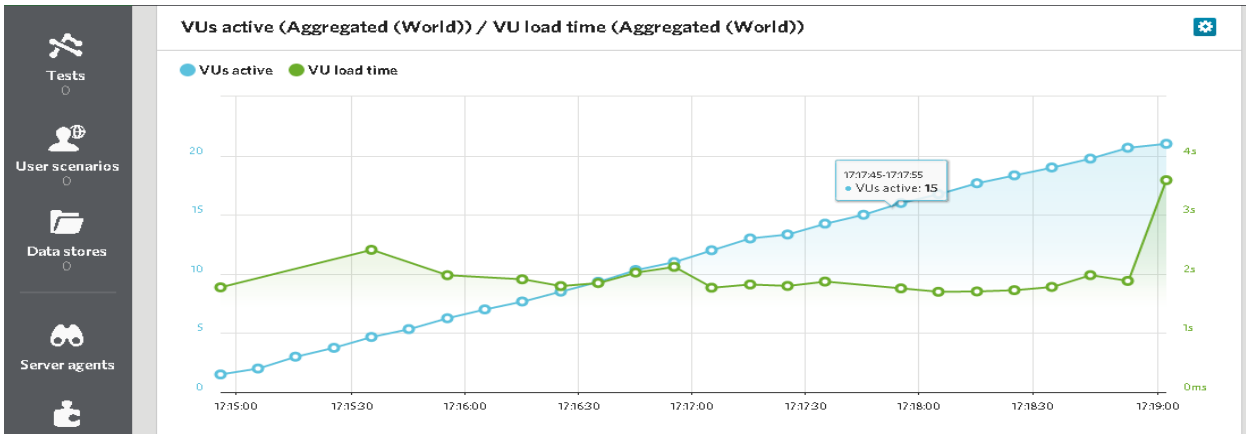


Figure 15.3: Load Testing

Following screenshot shows the result of 25 virtual machines.
These virtual machines were tested on auto generated scenarios. As you can see, there were 138 auto-generated scenarios and all are passed successfully.

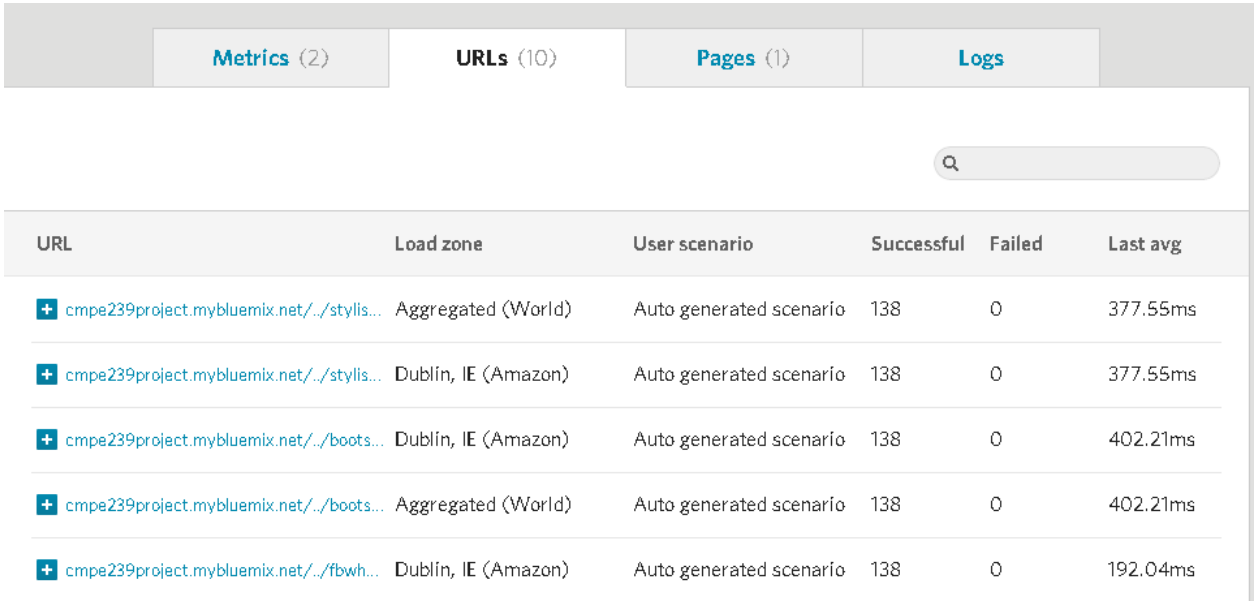
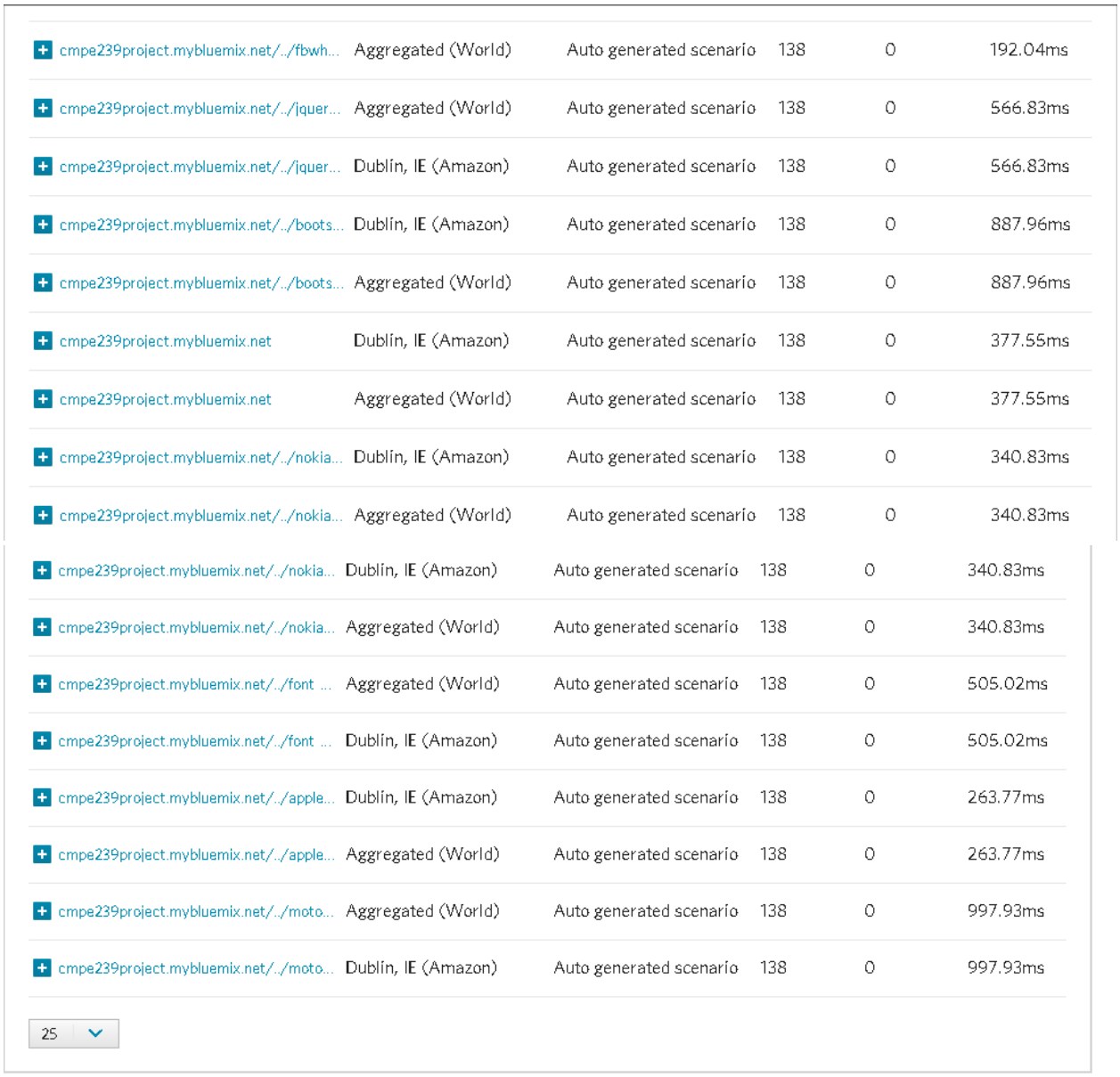


Figure 15.4: Load Testing

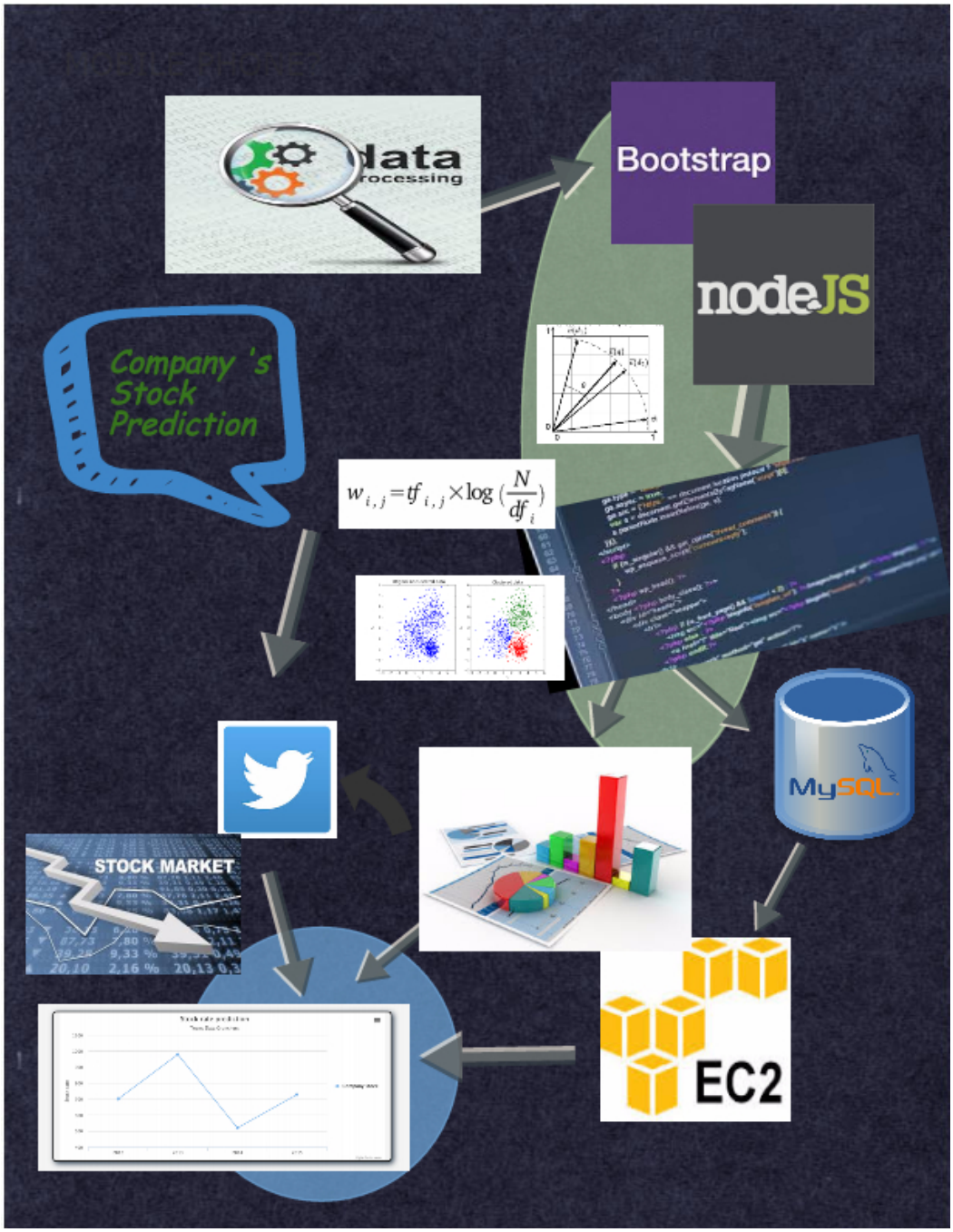


cmpe239project.mybluemix.net/../fbwh...	Aggregated (World)	Auto generated scenario	138	0	192.04ms
cmpe239project.mybluemix.net/../jquer...	Aggregated (World)	Auto generated scenario	138	0	566.83ms
cmpe239project.mybluemix.net/../jquer...	Dublin, IE (Amazon)	Auto generated scenario	138	0	566.83ms
cmpe239project.mybluemix.net/../boots...	Dublin, IE (Amazon)	Auto generated scenario	138	0	887.96ms
cmpe239project.mybluemix.net/../boots...	Aggregated (World)	Auto generated scenario	138	0	887.96ms
cmpe239project.mybluemix.net	Dublin, IE (Amazon)	Auto generated scenario	138	0	377.55ms
cmpe239project.mybluemix.net	Aggregated (World)	Auto generated scenario	138	0	377.55ms
cmpe239project.mybluemix.net/../nokia...	Dublin, IE (Amazon)	Auto generated scenario	138	0	340.83ms
cmpe239project.mybluemix.net/../nokia...	Aggregated (World)	Auto generated scenario	138	0	340.83ms
cmpe239project.mybluemix.net/../nokia...	Dublin, IE (Amazon)	Auto generated scenario	138	0	340.83ms
cmpe239project.mybluemix.net/../nokia...	Aggregated (World)	Auto generated scenario	138	0	340.83ms
cmpe239project.mybluemix.net/../font ...	Aggregated (World)	Auto generated scenario	138	0	505.02ms
cmpe239project.mybluemix.net/../font ...	Dublin, IE (Amazon)	Auto generated scenario	138	0	505.02ms
cmpe239project.mybluemix.net/../apple...	Dublin, IE (Amazon)	Auto generated scenario	138	0	263.77ms
cmpe239project.mybluemix.net/../apple...	Aggregated (World)	Auto generated scenario	138	0	263.77ms
cmpe239project.mybluemix.net/../moto...	Aggregated (World)	Auto generated scenario	138	0	997.93ms
cmpe239project.mybluemix.net/../moto...	Dublin, IE (Amazon)	Auto generated scenario	138	0	997.93ms

25

Figure 15.5: Load Testing

16. INFOGRAPH:



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