Sentiment Analysis On PokemonGo

Objective:

To use algorithm for Prediction, Classification and Clustering of Tweet Sentiments using Microsoft Azure and deploy the project into a web service using AWS

Data Cleansing:

Following are the steps we made to cleanse the pokemon dataset using RStudio.

1. Remove punctuations, control characters and digits.
2. Split sentence into words with str_split function from stringr package
3. Compare words to the dictionaries of positive & negative terms
4. Clean up sentences with R's regex-driven global substitute, gsub() and convert all the sentence to lower case
5. Remove retweet entities, @people, numbers, unnecessary spaces and html links
6. Classify your emotion and get the best fit
7. Substitute NA's by "unknown" and classify your polarity
8. Show your data frame with results
9. Plot distribution of emotions

Running the model:

a) Binary Classification Model

Step 1: Get data

Upload the CSV file of your pokemon dataset. The CSV file should be cleansed with the steps mentioned above.

Each instance in the data set has the following fields:

- pol - the polarity of the tweet (0 = negative, 2 = neutral, 4 = positive)
- tweet_id - the id of the tweet
- time_stamp - the date of the tweet (Sat May 16 23:58:44 UTC 2009)
- user_id - the user who posted the tweet
- tweet_text - the text of the tweet
- Sentiment_score - the sentiment score of each tweet based on its polarity

Step 2: Text preprocessing using R

Unstructured text such as a tweets usually requires some preprocessing before it can be analyzed. We used the following R code to remove punctuation marks, special character and digits, and then performed case normalization:

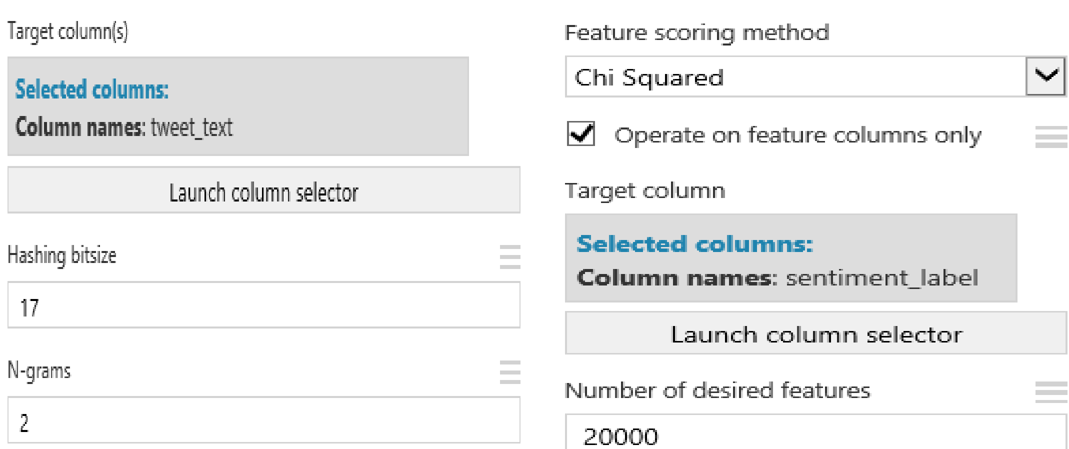
R Script

```
# Map 1-based optional input ports to variables
dataset1 <- maml.mapInputPort(1) # class: data.frame

# Contents of optional Zip port are in ./src/
# source("src/yourfile.R");
# load("src/yourData.rdata");

# Sample operation
pol <- dataset1[[5]]
text <- dataset1[[2]]
text <- gsub("[^a-z]", " ", text, ignore.case = TRUE)

text <- sapply(text, tolower)
data.set <- as.data.frame(cbind(pol, text), stringAsFactors = FALSE)
# You'll see this output in the R Device port.
# It'll have your stdout, stderr and PNG graphics device(s).
plot(data.set);
# Select data.frame to be sent to the output Dataset port
maml.mapOutputPort("data.set");
```

After the text was cleaned, we used the **Metadata Editor** module to change the metadata of the text column as follows.

- We marked the text column as non-categorical column.
- We also marked the text column as a non-feature.

Step 3: Feature engineering

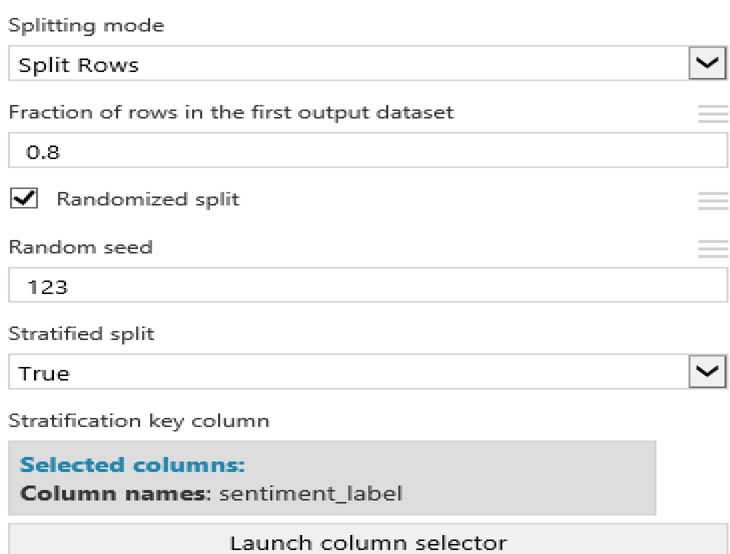


we used the **Filter Based Feature Selection** module to select a compact feature subset from the exhaustive list of extracted hashing features. The aim is to reduce the computational complexity without affecting classification accuracy.

We chose the Chi-squared score function to rank the hashing features in descending order, and returned the top 20,000 most relevant features with respect to the sentiment label, out of the 2^17 extracted features.

Step 4: Split the data into train and test

The *Split* module in Azure ML is used to split the data into train and test sets where the split is stratified. The stratification will maintain the class ratios into the two output groups. We use the first 80% of the pokemon sample tweets for training and the remaining 20% for testing the performance of the trained model.



In the launch column selector, you will be using the variable called pol.

Step 5: Train prediction model

To train the model, we connected the text features created in the previous steps (the training data) to the***Train Model** module. Microsoft Azure Machine Learning Studio supports a number of learning algorithms but we select SVM for illustration.

Two class support Vector entries:

Number of iterations

10

Lambda

0.0001

Normalize features

Project to the unit-sphere

Random number seed

123

Allow unknown categorical levels

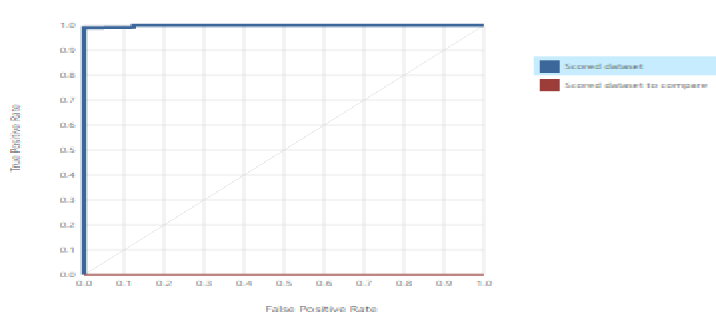
Step 6: Evaluate model performance

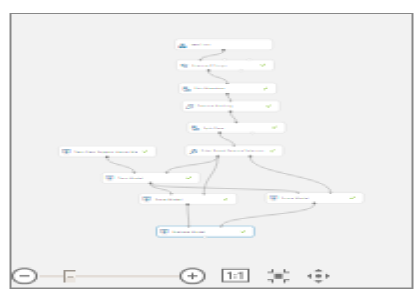
In order to evaluate the generalization ability of the trained Support Vector Machine model on unseen data, the output model and the test data set are connected to the *Score Model* module in order to score the tweets of the test set. Then connect the out predictions to the *Evaluate Model* module in order to get a number of performance evaluation metrics as shown below.

Finally, we added the **Evaluate Model** module, to get the evaluation metrics (ROC, precision/recall, and lift) shown in the following charts.

Classification1 › Evaluate Model › Evaluation results

ROC PRECISION/RECALL LIFT



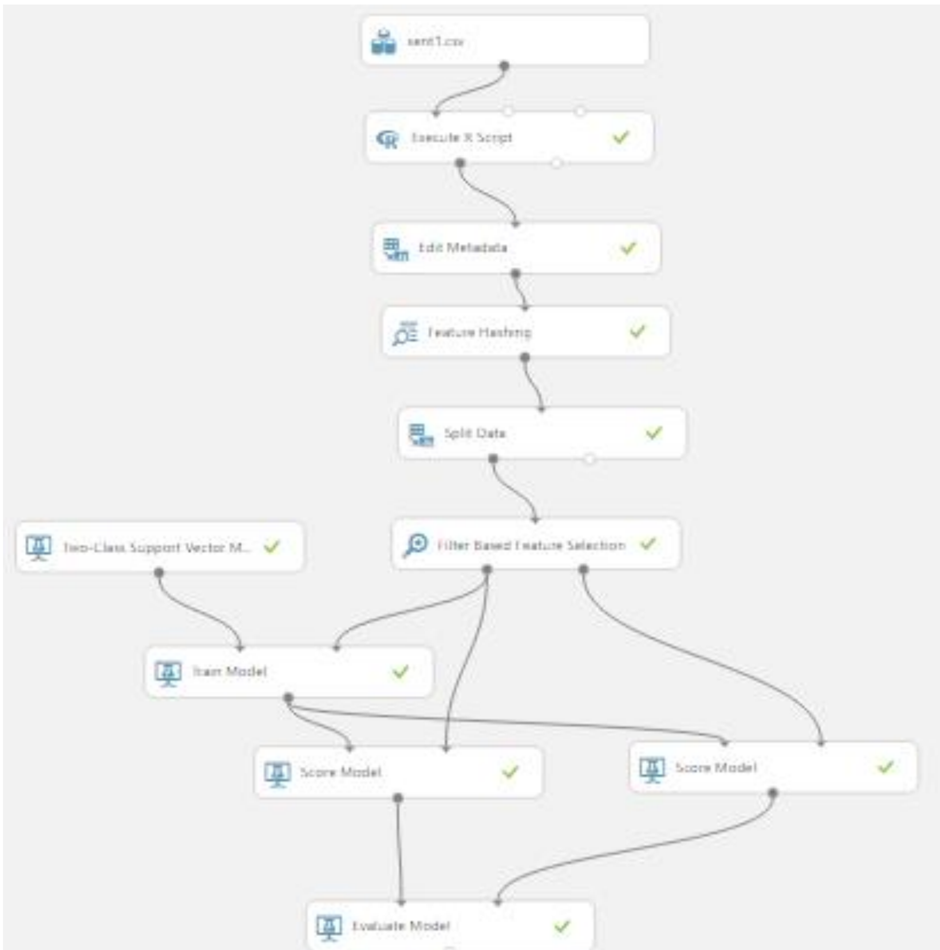


True Positive	False Negative	Accuracy	Precision	Threshold	AUC
1853	1	0.962	0.948	0.5	0.999
False Positive	**True Negative**	**Recall**	**F1 Score**		
101	712	0.999	0.973		
Positive Label	**Negative Label**				
4	0				

Score Bin	Positive Examples	Negative Examples	Fraction Above Threshold	Accuracy	F1 Score	Precision	Recall	Negative Precision	Negative Recall	Cumulative AUC
(0.900,1.000]	1851	101	0.732	0.961	0.973	0.948	0.998	0.996	0.876	0.123
(0.800,0.900]	0	0	0.732	0.961	0.973	0.948	0.998	0.996	0.876	0.123
(0.700,0.800]	0	0	0.732	0.961	0.973	0.948	0.998	0.996	0.876	0.123
(0.600,0.700]	2	0	0.733	0.962	0.973	0.948	0.999	0.999	0.876	0.123
(0.500,0.600]	0	0	0.733	0.962	0.973	0.948	0.999	0.999	0.876	0.123
(0.400,0.500]	0	0	0.733	0.962	0.973	0.948	0.999	0.999	0.876	0.123
(0.300,0.400]	0	1	0.733	0.961	0.973	0.948	0.999	0.999	0.875	0.124
(0.200,0.300]	0	1	0.733	0.961	0.973	0.947	0.999	0.999	0.873	0.126

Step 7: Publish prediction web service

A key feature of Azure Machine Learning is the ability to easily publish models as web services on Windows Azure. In order to publish the trained sentiment prediction model, first we must save the trained model. To do this, just click the output port of the **Train Model** module and select **Save as Trained Model**.



Classification Model

b) Clustering

Step 1: Get data

Same as steps repeated for classification model

Step 2: Text preprocessing using R

Same as steps repeated for classification model

Step3: K-means Clustering

This experiment demonstrates how to use the K-Means clustering algorithm to perform segmentation on sentiment's polarity from the pokemon dataset, based on the text of emotions about each tweet.

Step 4: Train prediction model

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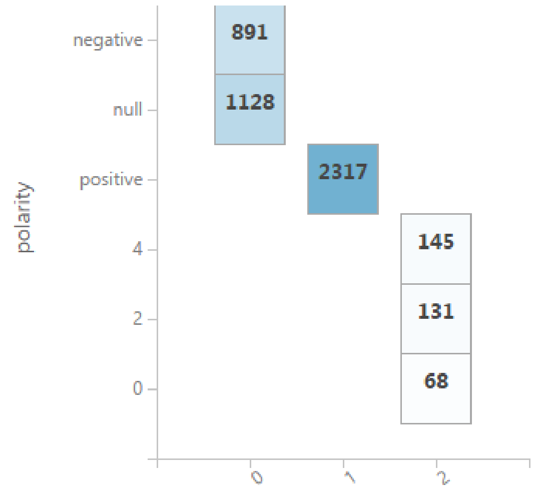
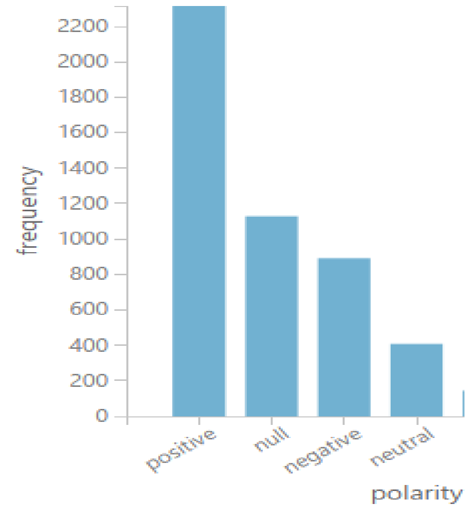
Step 5 Evaluate model performance

Once the data was prepared, we created several different instances of the **K-Means Clustering** module and trained models on the text data. By trial and error, we found that the best results were obtained with 2 clusters, but models using 1 and 3 clusters were also tried.

Finally, we used **Metadata Editor** to change the cluster labels into categorical values, and saved the results in CSV format for downloading, using **Convert to CSV** module.

pol	text	emotion	polarity	Assignments	DistancesToClusterCente no.0
4	i liked avideooverworld mappok mon go music extended	unknown	positive	1	2.135521
4	summer nights are definitely bae weather plays pok mon go instead	unknown	positive	1	2.135521
4	every time the pokemon go music starts playing on my phonegives me the	unknown	positive	1	2.135521





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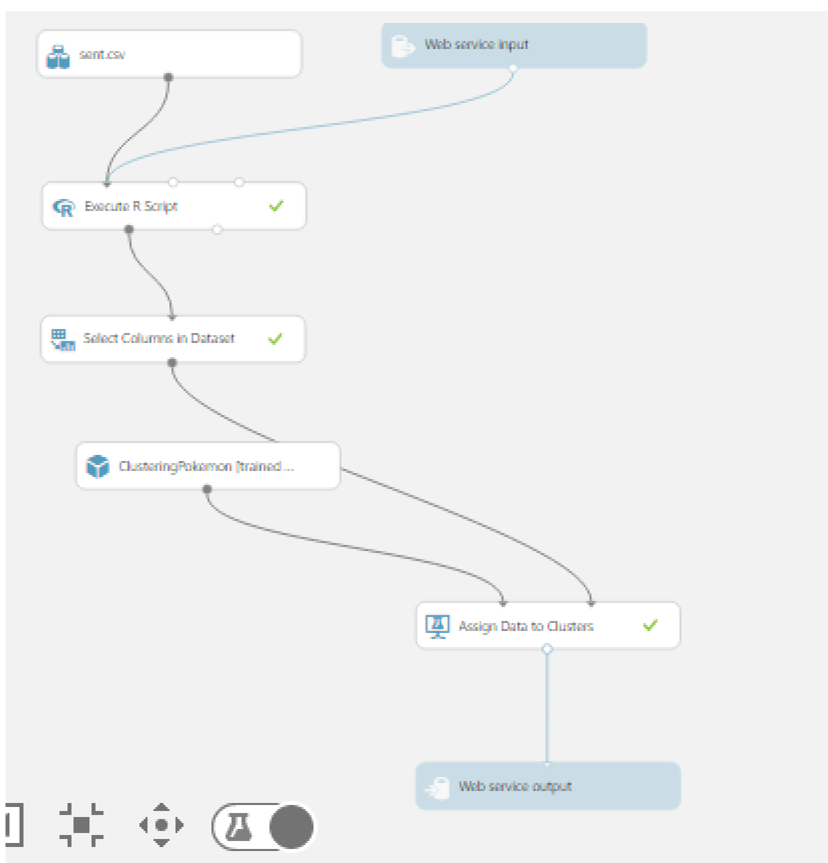
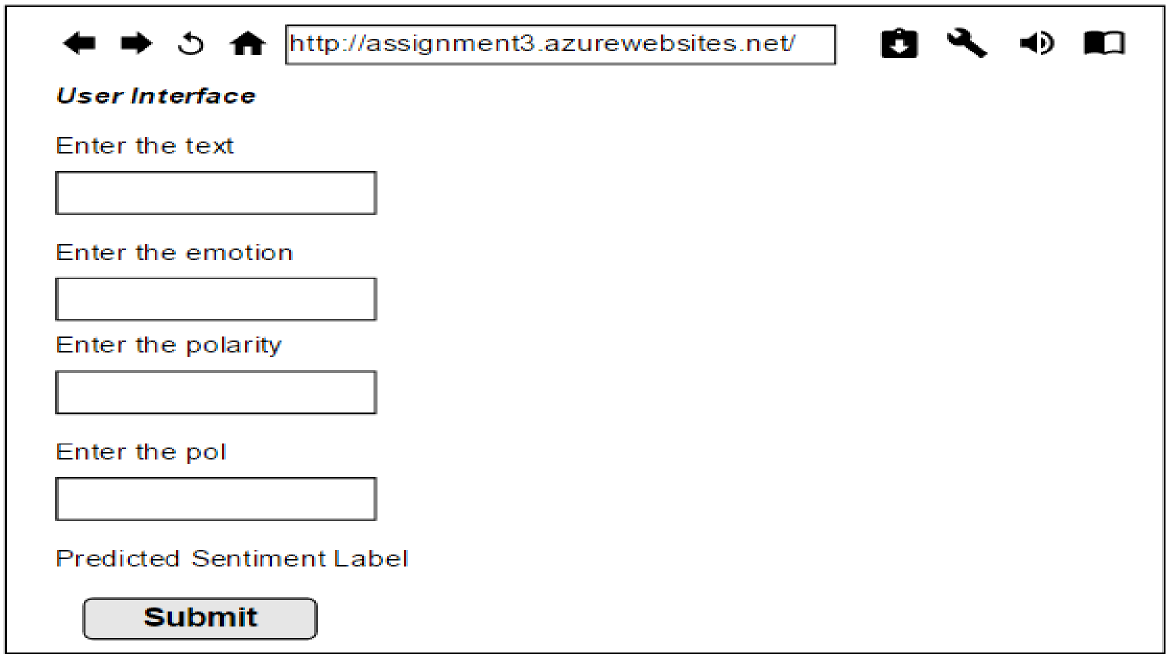


MOCKUPS: (app.moqups.com)

User Interface Page:



Workflow of Azure web services