Tell me how you really feel?

Tweet Customer Sentiment Algorithm: Mod 4 Project

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Problem Statement:

We are aiming to better understand what determines what emotional sentiments that a given tweet contains. We are specifically interested in consumer tweets that are discussing tech products made by businesses.

In this presentation, we will explain results from the algorithm we have created.

Business Value:

By creating a model that can accurately predict the type of sentiment that a consumer product-related tweet contains:

Your new tech company can effectively use PR resources to create auto-responses, and possibly real responses, to negative-sentiment tweets about your products. You can also focus on negative tweets that are valid to you [ie filtering out those who aren't target users or are simply looking to complain]

Your company can capitalize on demographics who are most likely to provide positive-sentiment tweets, in your marketing strategies to gain first-time customers

A significant amount of time across PR/marketing human capital will be saved and profit will increase

Methodology:

Analyze past customer-sentiment tweet data aimed towards Apple and Google products, to make recommendations for your new tech company, on how to most efficiently retain customers and market to new ones

Some of the topics we will explore in our algorithm:

Model Results V1 - Focus on Precision: Positive vs Negative Sentiment

Precision = Reduce False Positives

We believe the tweet is positive-sentiment, but it actually is not

```
Multinomial Naive Bayes
Training Accuracy: 0.9626                Testing Accuracy: 0.8305

[[ 98  36]
 [114 637]]
0.8305084745762712
98 36 114 637
Classification Matrix:
              precision    recall  f1-score   support

           0       0.46      0.73      0.57       134
           1       0.95      0.85      0.89       751

    accuracy                           0.83       885
   macro avg       0.70      0.79      0.73       885
weighted avg       0.87      0.83      0.84       885
```

Model Results V2 - Focus on Precision: Positive, Neutral or Negative Sentiment

Precision = Reduce False Positives

We believe the tweet is positive-sentiment, but it actually is not

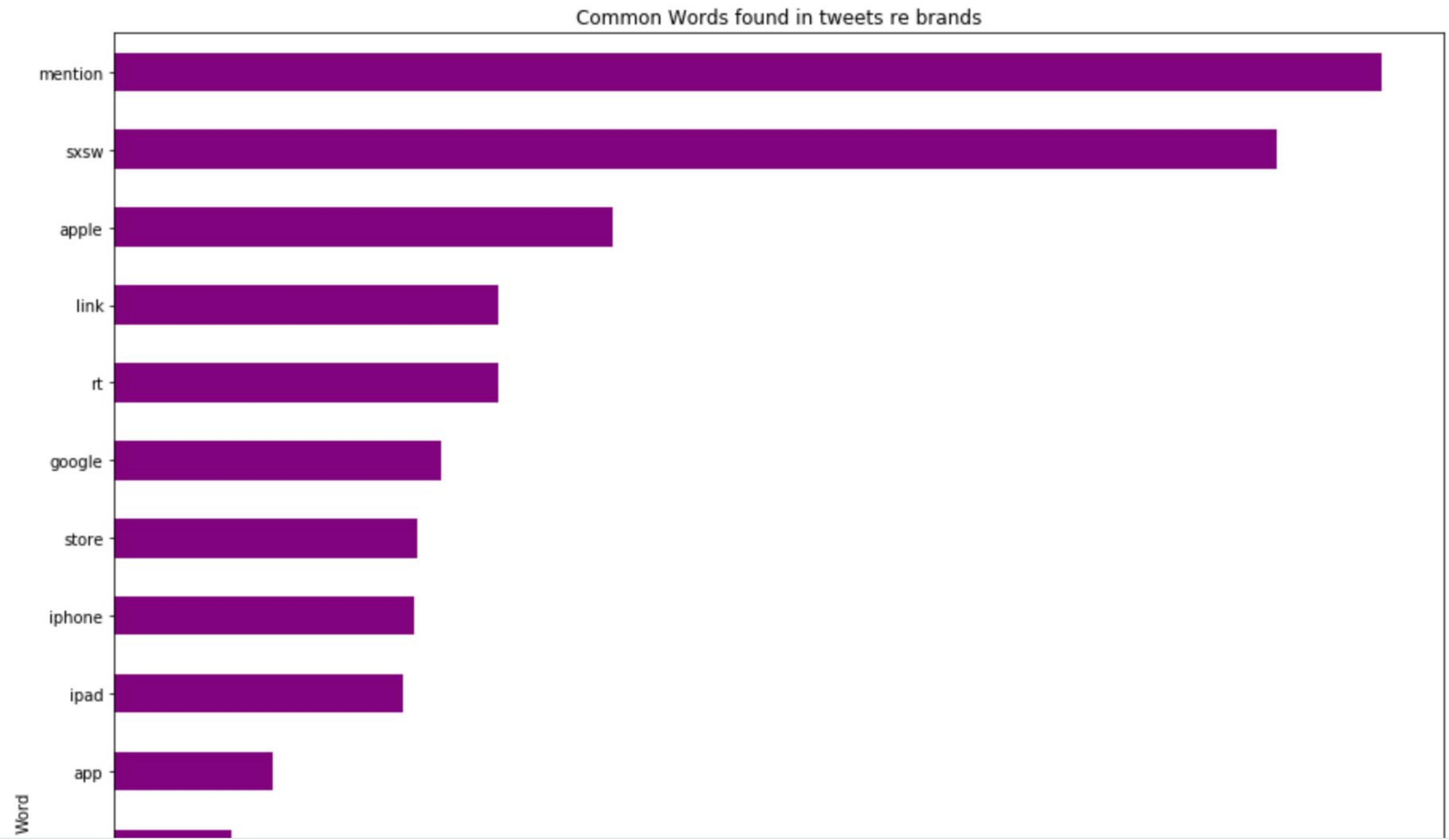
```
Random Forest
Training Accuracy: 0.9889                    Testing Accuracy: 0.6752

[[  37   84   17]
 [  20 1148  188]
 [  13  402  320]]
0.6751906684611934
Classification Matrix:
              precision    recall  f1-score   support

           0       0.53      0.27      0.36       138
           1       0.70      0.85      0.77      1356
           2       0.61      0.44      0.51       735

    accuracy                           0.68      2229
   macro avg       0.61      0.52      0.54      2229
weighted avg       0.66      0.68      0.66      2229
```

Recommendation 1:

Promoting launch events seems to drive a significant proportion of product-related tweets

Recommendation 2:

Using social media giveaways to encourage re-tweets or links to your product, also seems to drive a significant amount of product-related tweets


Common Words found in tweets re brands
mention
sxsw
apple
link
rt
google
store
iphone
ipad
app
Word

Recommendation 3:

Focus PR resources on analyzing negative-sentiment tweets and deciding which types of negative tweets are worth addressing

Future Considerations

Use additional resources to fine-tune the current models

Calculate a new model based on a list of specific, important words that have strong sentiment one way or another [ie tweets with “great”, “awful”, or “terrible” in them]

Obtain more tweet-data from other tech companies, particularly small startups and PR companies

Thank You!