The Bachelor(ette)

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Abstract

Twitter and the TV shows the Bachelor and the Bachelorette are key components of American culture. This projects seeks to better understand the relationship between these two media forms. Using text analysis, we explore the polarity of tweet content as well as associated words that people use to describe the show. These trends are visualized and vary by state, show season, and time. Using all of this information, we begin the process of creating a predictive model. Though the current state of the model yields uninterpretable results, we build the foundation of a potentially promising way to use Twitter data to predict the outcome of each show.

Data

This project utilizes two years worth of Twitter data, which was generated shared with use by Professor Mike Izbicki. Data is stored on a supercomputer as a series of JSON files but parsed into smaller CSVs using a Python script. Data for each season was extracted by looking at the dates between times contestants were announced and one week after the final episode was aired. For each season, a set of key words were used to identify relevant tweets. Key words included the twitter handle of each contestant, as well as 'thebachelor', 'thebachelorette', and 'bachelorabc'. Intially, words like 'bachelor' were included, but this led to high amounts of noise. By narrowing the key words to contestants' twitter handles, the data set became significnatly smaller, but we are more confident that the tweets are relevant to the show of interest. In addition to parsing tweets into geographic location, time, and tweet content, we were also able to measure the sentiment of each tweet. A package called TextBlob was used to assign sentiment from a scale of -1 to 1, with -1 being negative, 0 being neutral, and 1 being positive.

A critical problem of this method is dealing with contestants who do not have Twitter. This was extremely problematic for the Bachelorette 2018, because the winner of the season had no Twitter account. To compensate for this, we parsed a second dataset for this season. This is likely to be a noisy dataset, but the results of the model can be compared to see if the noise made a significant impact. Another flaw in the data was the varying size of each data set. For instance, the Bachelor 2018 was very large, consisting of 1,914 tweets. This is likely due to the fact that this season had a unique ending where the Bachelor ended up leaving the finalist for the runner-up in a very short time frame. Other seasons had very few, nearly 300 tweets. This is something to be mindful of when interpreting results. I

Example of parsed twitter data from the Bachelor 2018:

```
cleaned_data <- read.csv(file = 'Bachelor_2018.csv')
head(cleaned_data)
```

```
##   X             city                           date polarity state
## 1 0 South Burlington Fri May 18 03:48:18 +0000 2018   0.0000    VT
## 2 1        Manhattan Thu May 17 18:40:39 +0000 2018  -0.0625    NY
## 3 2           Queens Thu May 17 22:43:36 +0000 2018   0.0000    NY
## 4 0            Hooks Sat May 19 01:48:48 +0000 2018   0.0000    TX
## 5 1            Hooks Sat May 19 01:50:59 +0000 2018   0.0000    TX
## 6 2      Lindenhurst Sat May 19 00:03:15 +0000 2018   0.3125    NY
##
## 1                                                                 Mike Johnson is not the her
## 2 This is the dumbest show in the world. IT's all fake everyone saying they love each other after sc
```

```
## 3                                                                                                  @JohnPaulWebe
## 4 @MarkWoodsmall @packersfan86 @mushwear @jimmyjamny @Babchik @EvCoRadio @jpwilson1982 @JohnPaulFAL (
## 5 @MarkWoodsmall @packersfan86 @mushwear @jimmyjamny @Babchik @EvCoRadio @jpwilson1982 @JohnPaulFAL (
## 6                  The most underrated Led Zeppelin member! John Baldwin aka John Paul Jones. Musical
```

For the visualizations, the data was wrangled this way....

```
#CHANGE THIS
#wrangled_data <- read.csv(file = 'data/car-speeds.csv')
#head(wrangled_data)
```

For the predictive model, we used a dataset that summarized contestant information of total tweet count and average tweet sentiment. We only looked at 3 seasons of data, which included the Bachelor (2018-2019) and the Bachelorette (2019). Example of predictive model data.

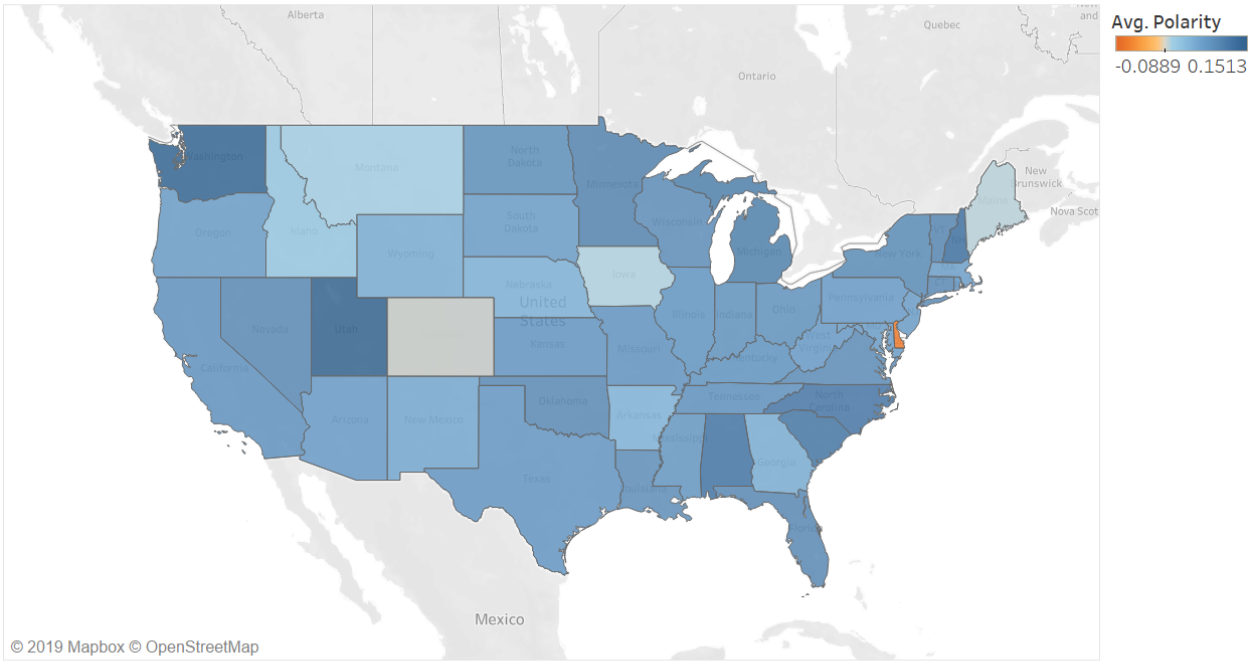
```
generated_data <- read.csv(file = 'model_data.csv')
head(generated_data)
```

```
##   X              X0        X1  X2 status
## 1 0        thebkoof 0.1840278 297 winner
## 2 1 laurenburnham91 0.1250230  66  loser
## 3 2  KendallPatrice 0.2456223 186  loser
## 4 3     tiarachel91 0.1430435 501  loser
## 5 4  whats_ur_sign_ 0.1433547 439  loser
## 6 5   seinnefleming 0.2112450  66  loser
```

Visualizations

The visualizations associated with this project were generated in Tableau and published on Tableau public.

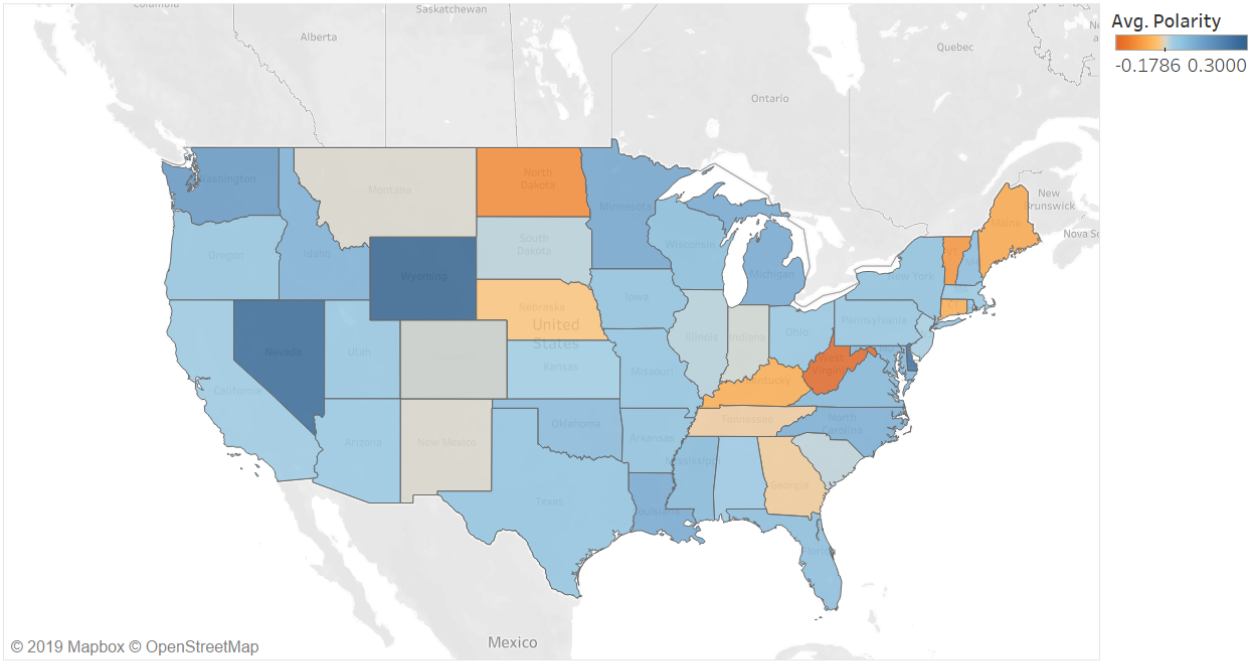
Polarity by State



Map based on Longitude (generated) and Latitude (generated). Color shows average of Polarity. Details are shown for State. The data is filtered on Weeks, Season and Action (State). The Weeks filter keeps 11 of 11 members. The Season filter keeps Bachelor 2018, Bachelor 2019, Bachelorette 2018 and Bachelorette 2019. The Action (State) filter keeps 53 members.

For visualizations, we wanted to first understand how polarity varies occcurs across the United States. Above is a map displaying average polarity of tweets related to The Bachelor/Bachelorette in 2018 and 2019 across all weeks the show is aired. We can see that, on average, tweet sentiment is generally positive across all states, indicated by the blue indicator color. On the other hand, across both shows during 2018 and 2019, it seems that Twitter sentiment in Delaware is on average negative, indicated by the red indicator color.

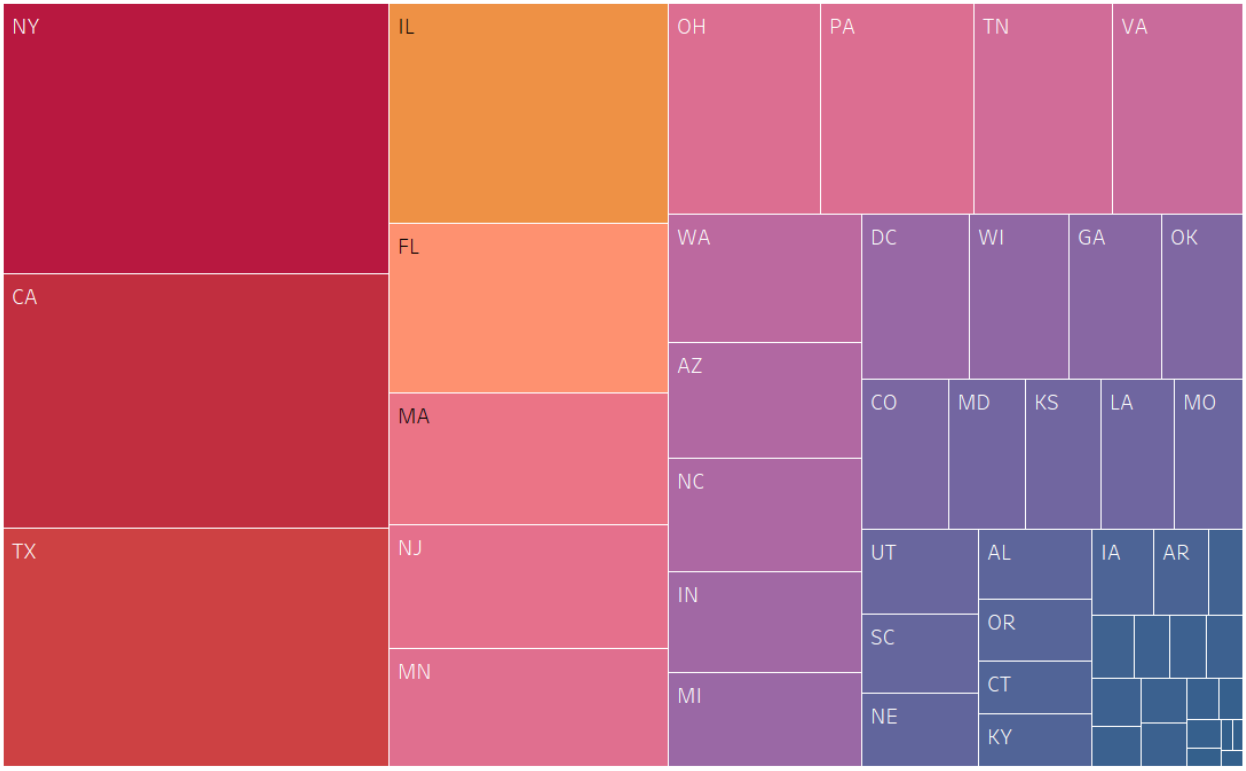
Polarity by State



Map based on Longitude (generated) and Latitude (generated). Color shows average of Polarity. Details are shown for State. The data is filtered on Weeks, Season and Action (State). The Weeks filter keeps week 10. The Season filter keeps Bachelor 2018. The Action (State) filter keeps 53 members.

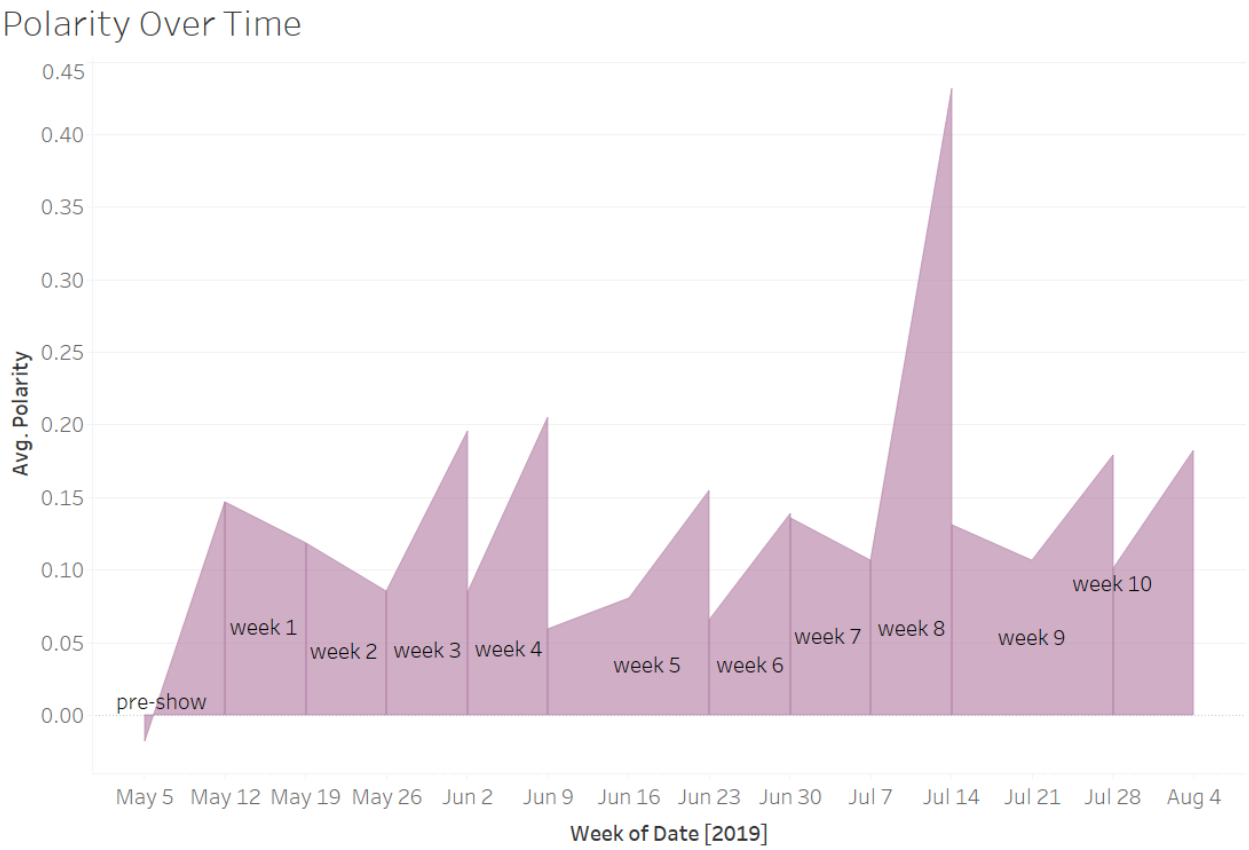
For our map visualizations, our online pulbished version has an interactive feature where the user can toggle the map's display by show season and week. Above is a map displaying average polarity of tweets related to The Bachelor in 2018 on the airing of the last episode and the following week after. We can see that, based on the deep blue indicator color, tweets about the show from Nevada and Wyoming, on average, had the most positive sentiment. On the other hand, tweets about the show from West Virginia and North Dakota, on average, had the most negative sentiment, indicated by the more saturated red indicator color.

Tweet Volume by State



State. Color shows sum of Number of Records. Size shows sum of Number of Records. The marks are labeled by State. The data is filtered on Weeks and Season. The Weeks filter keeps week 10. The Season filter keeps Bachelor 2018.

To accompany the map visualizations, we created an accompanying visualization that represents Tweet volume by state. On the online interactive version, the user can toggle show season and week to compare polarity by state and Tweet volume by state simultaneously. Above is a block graphic displaying Tweet volume for The Bachelor 2018 on the airing of the last episode and the following week after. We can see that, New York, California and Texas dominate in Tweet volume related to The Bachelor this particular week. This helps the user carefully consider the map visualizations by recognizing how many Tweets are considered for caluculating average polarity between states.



The plot of average of Polarity for Date Week. The marks are labeled by Weeks. The data is filtered on Season, which keeps Bachelorette 2019.

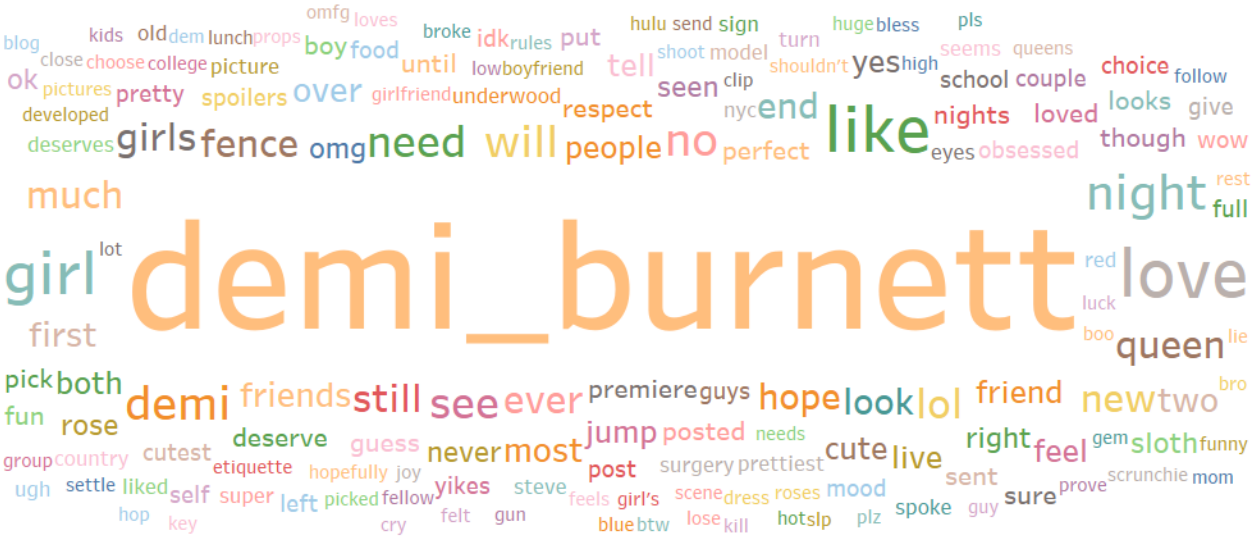
In understanding how polarity varied during the airing of each show season, we created a visualization that plots polarity as a function of time, which the user can filter by show season. Above is an area graphic displaying Tweet polarity across the United States for The Bachelorette 2019 during the entire airing of the show. Furthermore, each area graphic is sectioned by week. This enables the user to interpret polarity episode by episode and the direct impact of an episode. In the above graphic, we can see that sentiment was generally positive about the show with a noticeable spike in positive sentiment during week 8. From conducting brief market research, we conclude that viewers start to express stronger positive sentiment in their Tweets around week 8 due to contestants having more intimate conversations which is a catalyst for chemistry and drama.

Word Count Over 4 Seasons

Word. Color shows details about Word. Size shows sum of N. The data is filtered on N, Word (bachelor_2018_word_count), Word (bachelor_2019_word_count), Word (bachelorette_2018_word_count) and Word (bachelorette_2019_word_count). The N filter includes values greater than or equal to 100. The Word (bachelor_2018_word_count) filter keeps 153 of 200 members. The Word (bachelor_2019_word_count) filter keeps 161 of 200 members. The Word (bachelorette_2018_word_count) filter keeps 156 of 200 members. The Word (bachelorette_2019_word_count) filter keeps 172 of 200 members.

To understand what viewers are tweeting about the most, we created an interactive word cloud visualization that formats the most frequently used words in Tweets in a cloud format, excluding nonsensical and filler words. Above is a word cloud across all show seasons. We can see that words such as `like`, `love`, `need`, and `omg` are often used words in tweets, as indicated by their large size, related to The Bachelor and The Bachelorette. On the online interactive version, the user can also toggle the word cloud to only include words that have a certain minimum word count.

Word Count of The Bachelor 2019



Word. Color shows details about Word. Size shows sum of N. The data is filtered on N, which includes values greater than or equal to 200. The view is filtered on Word, which keeps 161 of 200 members.

To follow up a word cloud that visualizes word frequencies across all show seasons, we also created individual word clouds by show season. Each word cloud also included the feature to toggle the word cloud to only include words that have a certain minimum word count. Above is a word cloud representing frequently used words about The Bachelor 2019. Words such as `demi_burnett`, `fence`, `sloth`, and `love` are some examples of words that are frequently used, as indicated by the word cloud. Furthermore, high word frequencies can help us determine notable moments in a particular show season. Further market research can easily be done to understand the causal and resultant factors of certain high word frequencies.

Ethical Considerations for predictive models

It is critical to point out that no interpretation should be made about these models. We were only able to train this model on 3 seasons worth of data (not 4 because one season's winner had no twitter handle). A better model would have included data from all seasons of the bachelor and bachelorette. We are framing this model as an approach to how the model would look with all of the seasons of data.

The 5 classification models

These models were implemented using Python's scikit learn library. A quick overview of each model is attached below:

Algorithim for predictive models

1. Bootstrapp parsed twitter data for one season

2. Get average tweet sentiment and total tweet count per contestant
3. Shuffle contestant order
4. Repeat steps 1-2
5. Repeat steps 1-3 for all seasons of interest

Therfore, if we repeat step for 1000 times for 3 seasons, the data used for the model will have 3000 entries.

Based on the way dataset was created, the classification model will have 30 classes (contestants), 60 dimensions/features (avg sentiment + total tweets for each contestant), and a binary outcome (winner or not winner).

The 5 classification models

These 5 classification models were implemented using Python's scikit learn library. A quick overview of each model is attached below:

- Naive Bayes is a supervised classification model that uses Bayes' theorem of conditional probability and also uses the 'naive' assumption that feautures are independent. In this case, the Naive Bayes model is trying to predict whether or not a contestant will given their tweet count and average sentiment, under the assumption that tweet count and sentiment are independent (which they are not). Therefore, as more data is inputted into a model, accuracy is expected to go down because the independence assumption does not always hold true, as in this case. In general, a Naive Bayes model creates overly-simplified assumptions, which make it a poor model to use on real world data. It is included in this project in order to compare performance with other models.
- Linear Discriminant Analysis is a supervised classification model that creates a linear decision boundary that seperates multiple classes. LDA has two main uses: dimensionality reduction and linear classification. For dimensionality reductions, LDA tries to project the data into another space/dimension that minmimzes distance from the mean while minimizing variance of each class; this projection can make the data linearly seperable in a lower space when it was not linearly serperable in its original space.
- Logistic Regression is a classification algorithim that generates the probability of binary dependent variables. In our case, the dependent variable is whether or not a contestant will win or not win based on total tweet count and avergae tweet sentiment. It is similar to linear regession, except the outcome is binary (not continuous) and the seperating boundary is 'S' shaped.
- Linear Support Vector Classification tries to linearly seperate training data into classes. A linear SVC can be though of as a SVM. with a linear kernel. Linear SVC tends to perform better with larger sample sizes and is more computationally efficient because it is using a linear kernel.
- Stochastic Gradient Descent Classifier is a linear classifier that utilizes SGD for training. This means that for each data point, the gradient (or minima) of loss is estimated. The SGD classifier has a similar loss function as compared to Logistic Regression, but the solver each one uses is different. Since Logistic Regression uses GD and not SGD, we expect the SGD classifier to be the most computationally efficient out of these 5 models. Like the Naive Bayes model, SGD Classifier is not commonly used in practice.

Model with 3 seasons worth of data

Based on the way dataset was created, the classification model will have 89 classes (contestants), 2 dimensions/features (avg sentiment + total tweets), and a binary outcome (winner or not winner).

The results are highly questionable.

```
knitr::include_graphics("chart.png")
```

	name	accuracy
0	nb	[0.9444444444444444]
1	lda	[0.8888888888888888]
2	lr	[0.9444444444444444]
3	svc	[0.8888888888888888]
4	sgd	[0.9444444444444444]

```
knitr::include_graphics("chart.png")
```


	name	accuracy
0	nb	[0.9444444444444444]
1	lda	[0.8888888888888888]
2	lr	[0.9444444444444444]
3	svc	[0.8888888888888888]
4	sgd	[0.9444444444444444]

Conclusions

Reminder that **no conclusions** can be drawn from the predictive model. It is mainly here in order to setup a model that has access to more seasons of data.

From the visuals, we gain a clear understanding on the geographic distribution of the tweets and how polarity varies across states.

Next Steps

For the predictive model, more seasons' worth of data can be added. This would require Twitter data from 2002 - 2017 to be available. Furthermore, hyperparameters in each classification model can be tuned to yield better results.

New Insights

Completing this project required gaining a better understanding of the 5 classification models mentioned above. Furthermore, generating the visualizations required learning Tableau, which none of the team members had experience in. Accessing data through a supercomputer (ssh-ing through the machine) was also new to the group members abd represeted a major hurdle in intially collecting data.