Twits: perusing GNIP Twitter data

By Dodge Coates

Gnip Enterprise Access to Twitter Data

- Provide 1/10 of the twitter firehose

- Accessed for roughly 2 ½ weeks, between late January and mid February, 2012

Lots of data

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- No schema available for the dataset

Data Sample

```
"id_str":"163372337134182401",
"in_reply_to_status_id":null,
"created_at":"Sat Jan 28 21:26:15 +0000 2012",
. . .
"user":
    {
        "id_str":"44153313",
        "favourites_count":25,
        "contributors_enabled":false,
        . . .
        "lang":"en",
        "utc_offset":-21600,
        "profile_sidebar_border_color":"BDDCAD",
        "followers_count":349,
        "url":"http://kingsofkauffman.com/",
        "profile_image_url":"http://a1.twimg.com/profile_images/1442806914/My_Photo__normal.jpg"
    },
"retweet_count":3,
"favorited":false,
"id":163372337134182401,
"entities":
    {"hashtags":[
        {
            "text":"Mizzou",
            . . .
    },
    "retweeted_status":
        {
            "id_str":"163369042332229632",
            "place":null,"geo":null,
            "text":"Funny line from #Mizzou's Kim English about DGB: \"We were 100 percent focused on toda
            "in_reply_to_status_id_str":null,
            "coordinates":null,
            "user":
                {
                    "id_str":"168902884",
                    "favourites_count":0,
                    "profile_use_background_image":true,
                    "screen_name":"tpkcstar",
                        . . .
                    "favorited":false,
                    "id":163369042332229632,
                }
        }
    }
    }
```

Goals

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1. Exploring the data

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2. Developing an interesting prediction

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1. Exploring the data

2. Developing an interesting prediction

3. Get a feel for working with a large dataset

The Data

- A lot to process!

Storage

- SQL

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  - Hardware is too expensive
  - API is too time-consuming

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- Settled on sampling

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- Each file contains 38 rows

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- Therefore sampling must be done carefully to not distort time series data

Inspecting Data Features

- Complete json object contains ~130 attributes
- Components:
  - User data
  - Tweet data
  - Original retweet data (a copy of the outer user/tweet data)
- Reduced to 38 features in the processed data

Developing a Model Target: what to look for?

retweet_count

- The current retweet number for a given tweet

retweet_count

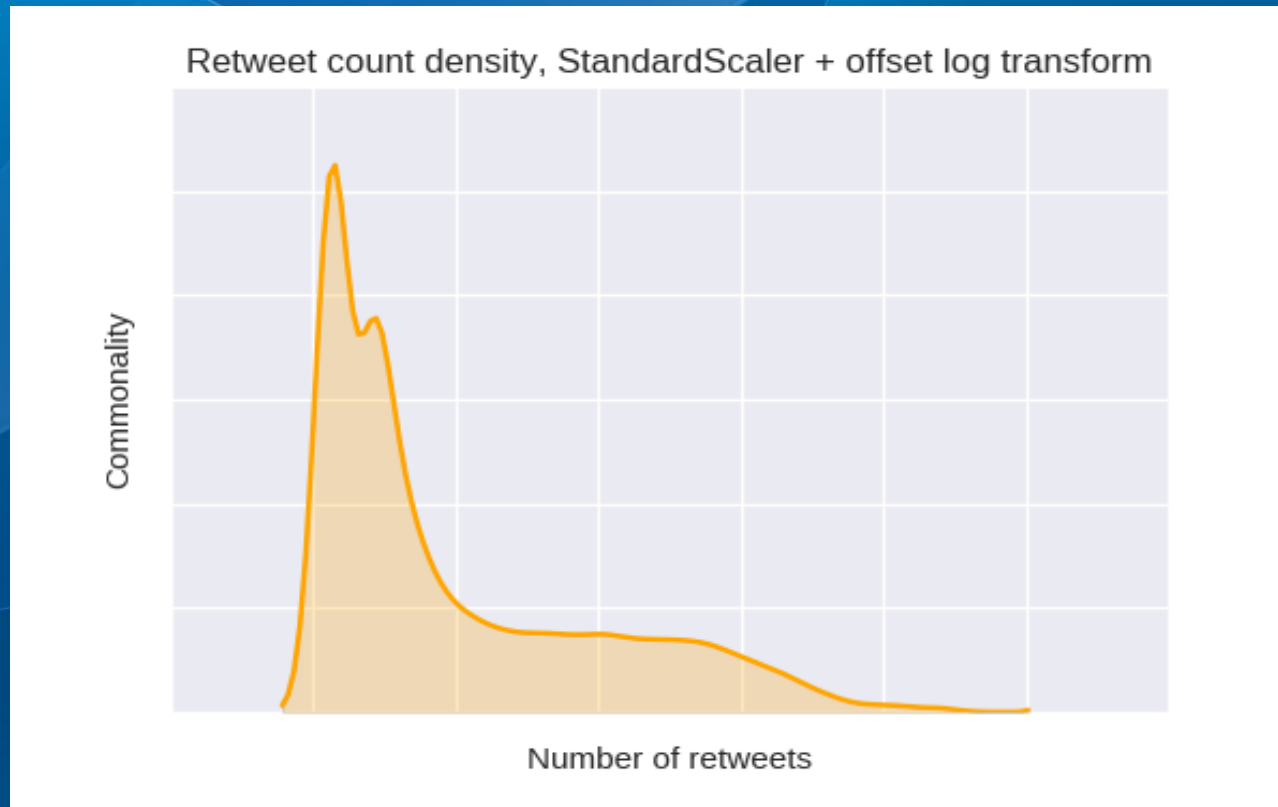- The current retweet number for a given tweet
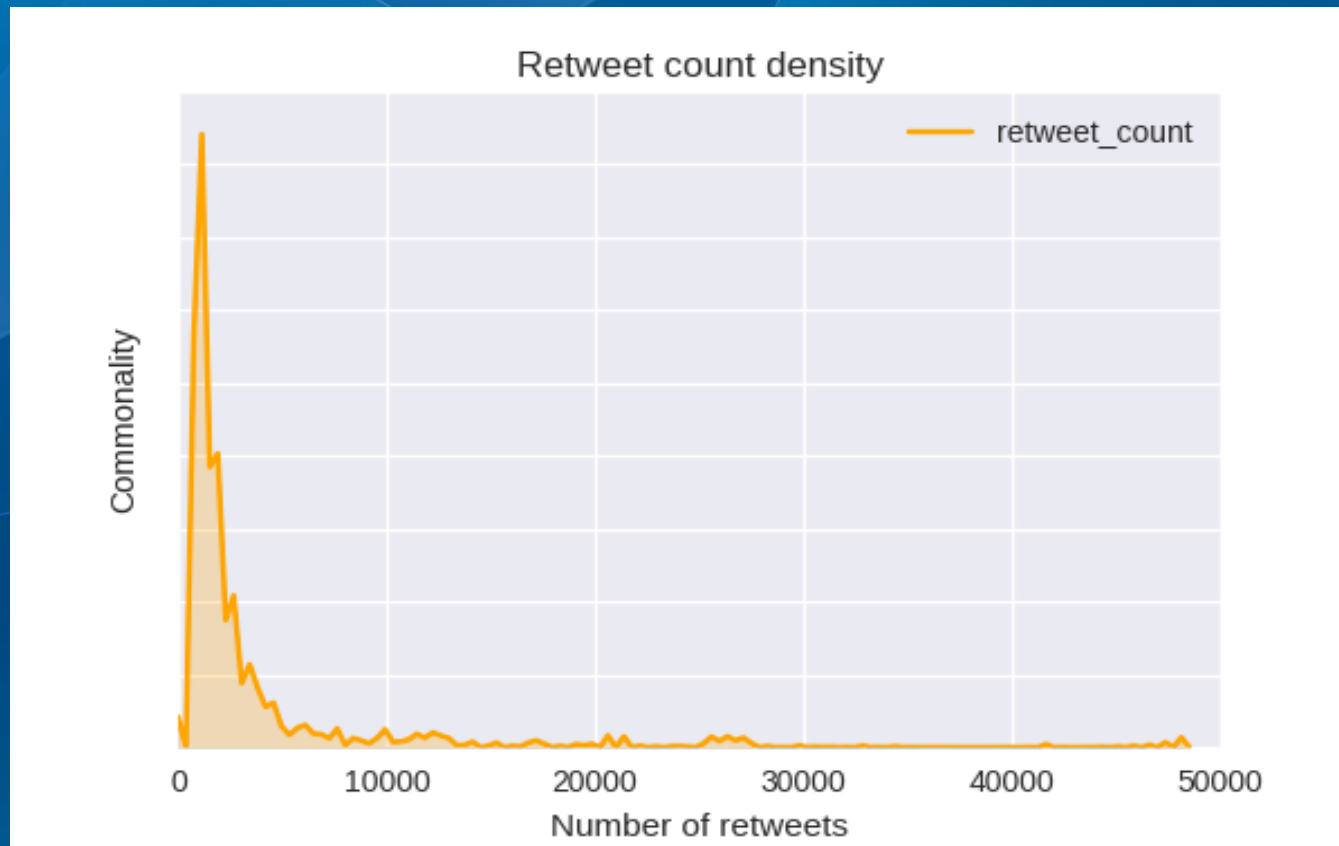
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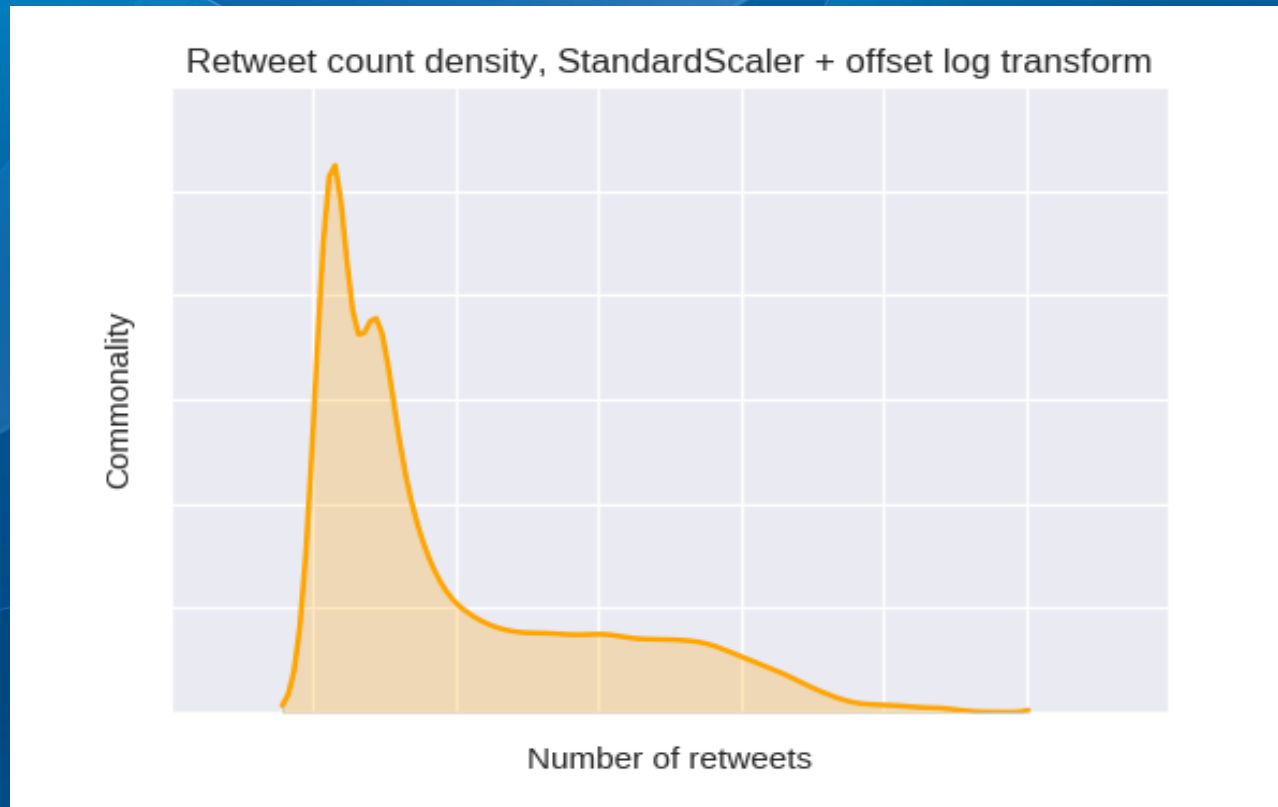
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- Partitioning the tweets and encoding them yields the labels for classification

Transforming retweet_count

Doesn't work.

retweet_count is a bad target

- Very highly correlated with number of followers

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- Very highly correlated with number of followers

- Very easy to predict

- Not very interesting

Tweetability

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- More interesting idea for getting at the "goodness" of a tweet

- Foolish to presume that tweetability corresponds with "goodness"?
 - Probably.

Target Penalty

- Add a constant penalty
  - Low retweet counts should be disproportionately rewarded for high retweet/followers ratio
  - Goal is not to maximize predictability

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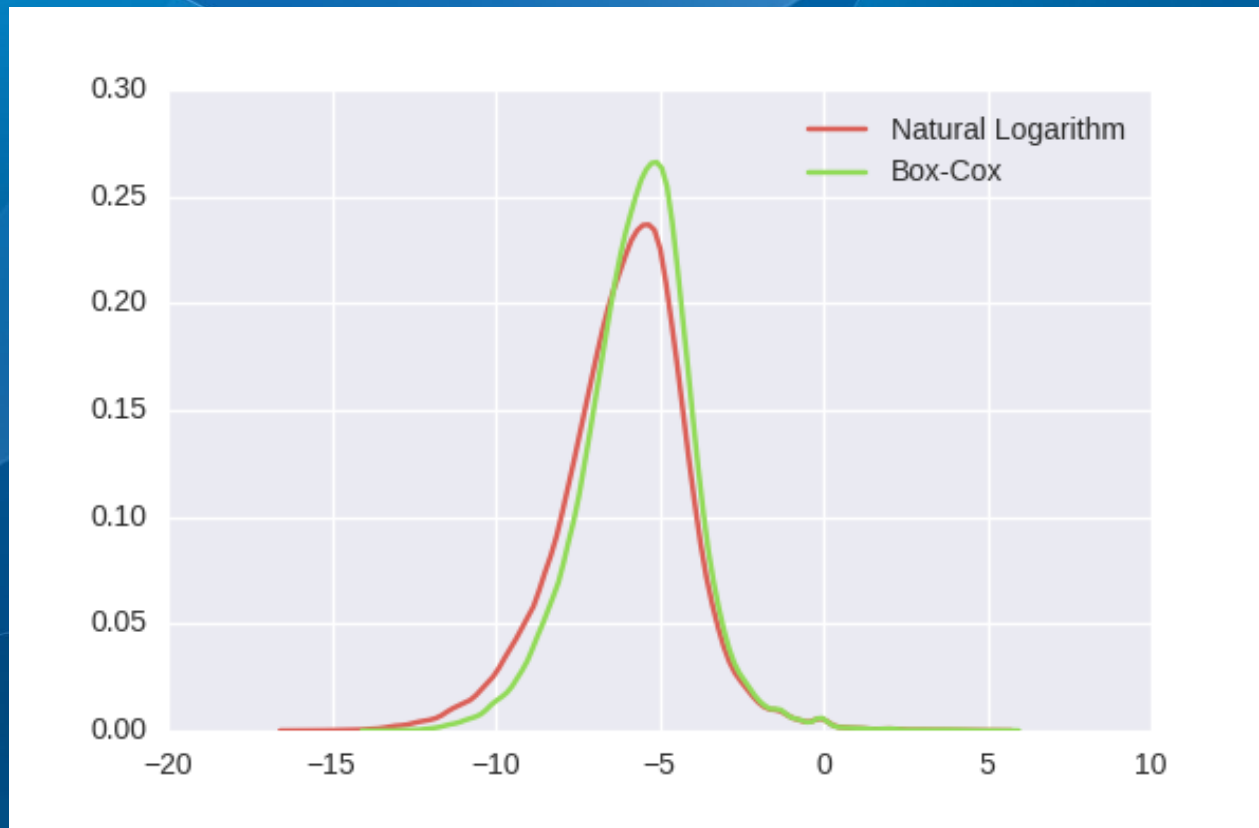
- Add a penalty for diminishing returns

$$\frac{retweetcount + \log(followerscount)}{followerscount + C/retweetcount}$$

Tranforming Tweetability
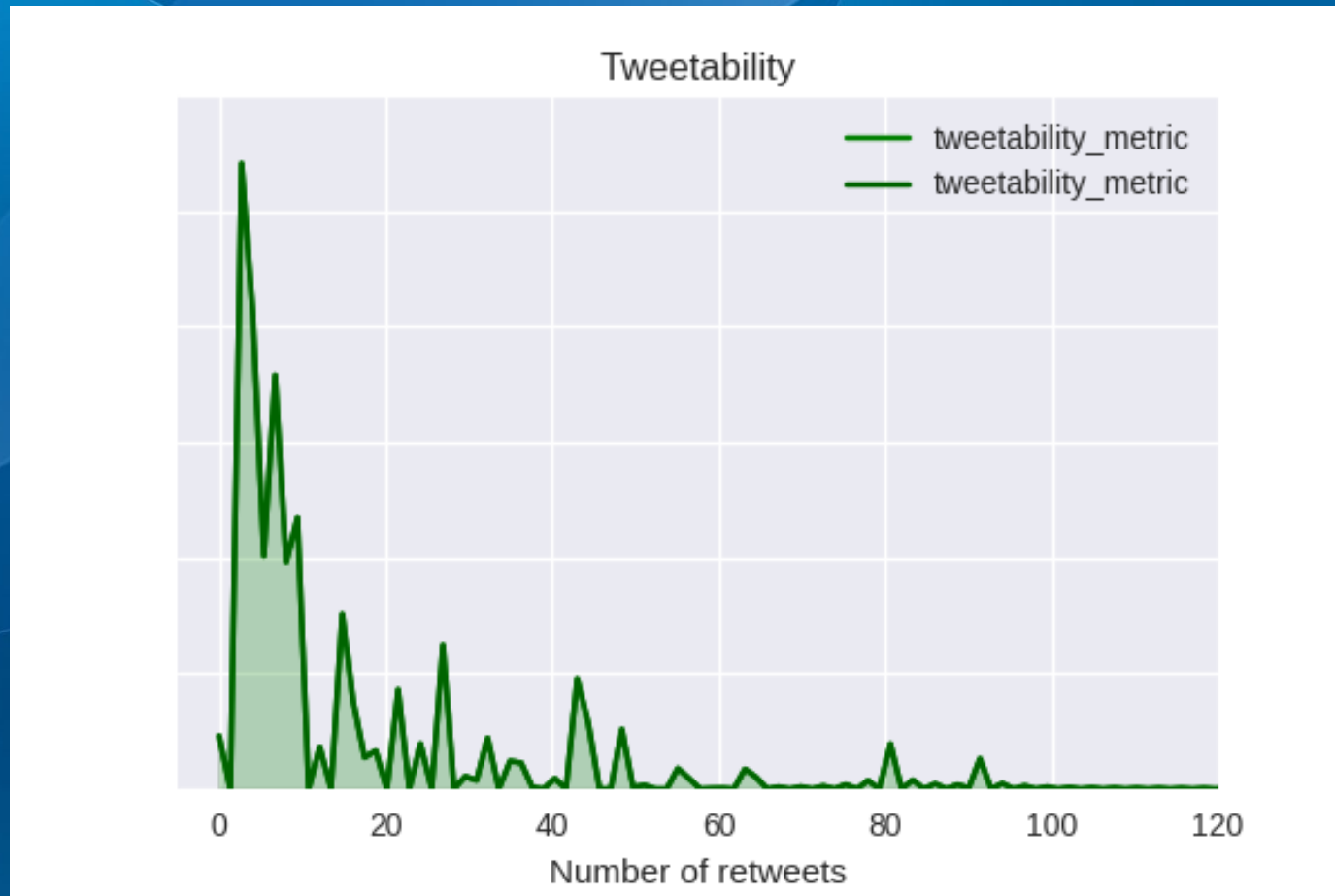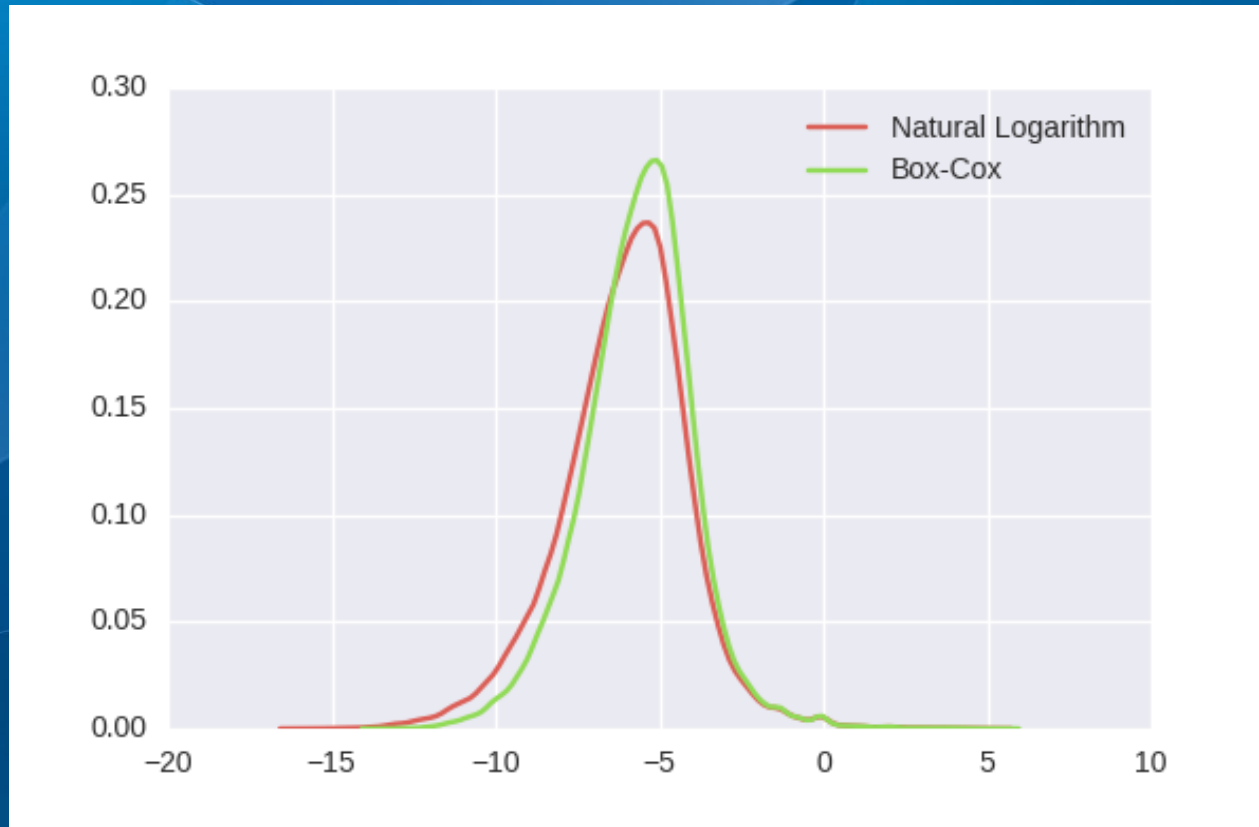
Transforming Tweetability

- After Transformations

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- Minimized variance made partitioning better than k-means clustering for

Engineered features

- Hashtag count, user mention count
- sentiment polarity
- text diversity
- punctuation score
- word count
- hashtag popularity
- Etc.

Models

- RandomForest and simple decision trees quite well

- Both achieve about 70% accuracy, but high log loss

- Interestingly, the additional features past three or four core features (statuses count, favorites count, etc) barely improved accuracy (~1 point) and often harmed log loss.

Models (cont.)

- Voting classifier
  - Consists of Random forest, Naive Bayes, and Logistic regression estimators
  - Originally reduced log loss
  - Yet to run again on corrected data

Takeaways and thoughts

- Large datasets are brutal.
- Carefully examine foreign data, particularly variable json, for structure and message, not just content
  - The invested time is worth it.
- Feature engineering can be very unintuitive
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