Predicting Successful Clips

What's Twitch?

Social video platform for gamers, video game culture, and the creative arts.

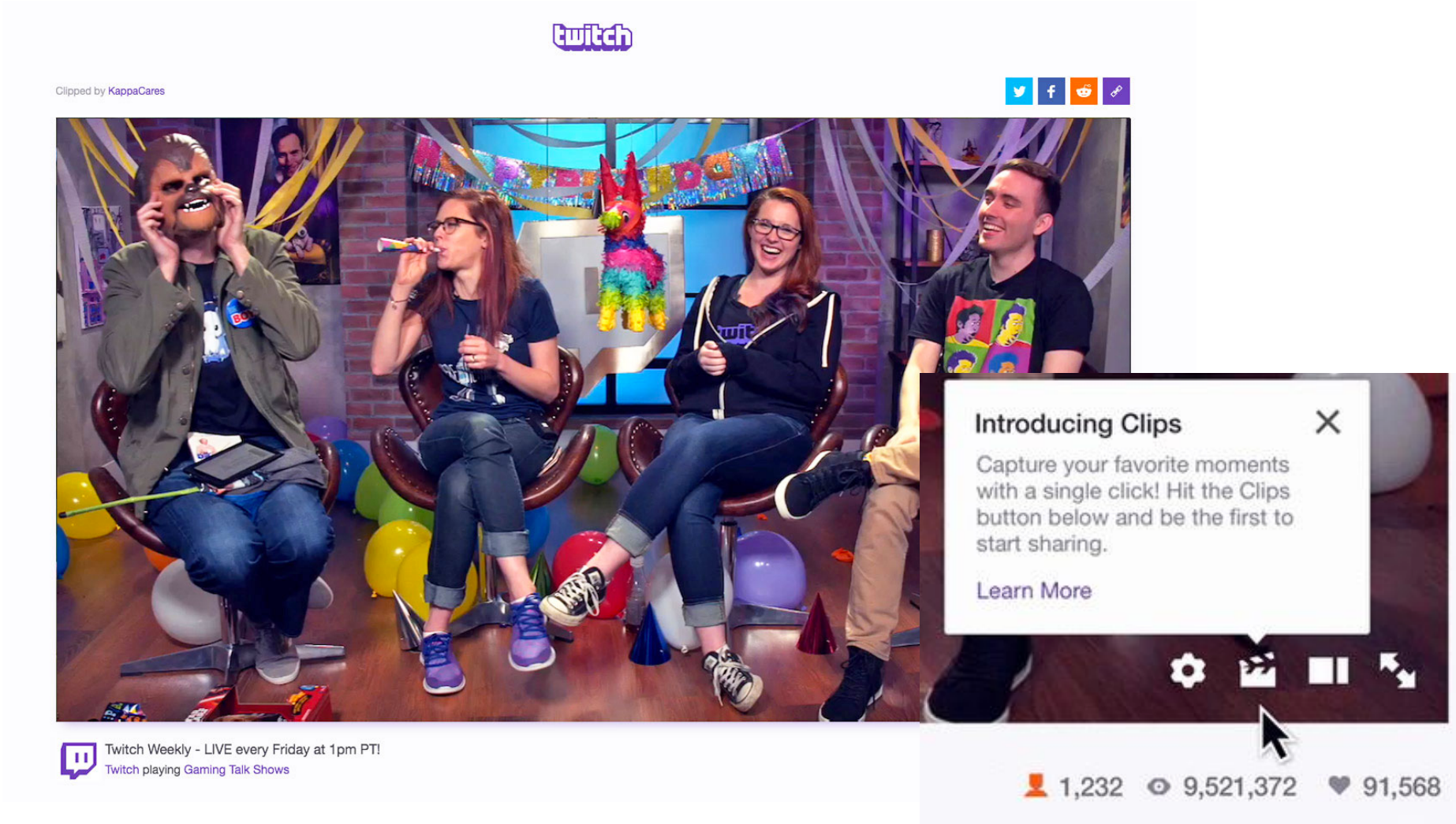
10mm Daily Unique Viewers

106 Minutes Viewed daily per user

9Bn + Chat messages in 2015

35K Twitch Con 2016 attendees

What are Clips?



Goals

- Predict the number of plays a clip will receive when it is created

Application:

- Automatically create Twitch and YouTube VOD content
- Provide editors a better starting place to create highlight reels
- Give content marketing an easy place to find good content
- Feature importance:
  - Popularity (games, geography, platform, broadcaster)
  - Virality (referral platform, spreading patterns, community mapping)

Problem Type

BASIC FORM **4**

	continuous	categorical
supervised	**regression**	**classification**
unsupervised	**dimension reduction**	**clustering**

Initial Data

```
In [6]: #check nulls
        df1.isnull().sum()
```

```
Out[6]: minute                0
        country               0
        region             3570
        asn_id               42
        domain                0
        channel               0
        play_session_id   99405
        url                   0
        app_version       99405
        channel_id            0
        partner             200
        clip_id               0
        login                 0
        platform              0
        device_id          1224
        referrer_url     100000
        game               1023
        host                  0
        source_offset     59484
        duration          58818
        user_id           59484
        total_plays           0
        ccus                  1
        msg_per_min           0
        avg_subs              0
        total_bits            0
        number_of_bits_msgs   0
        dtype: int64
```

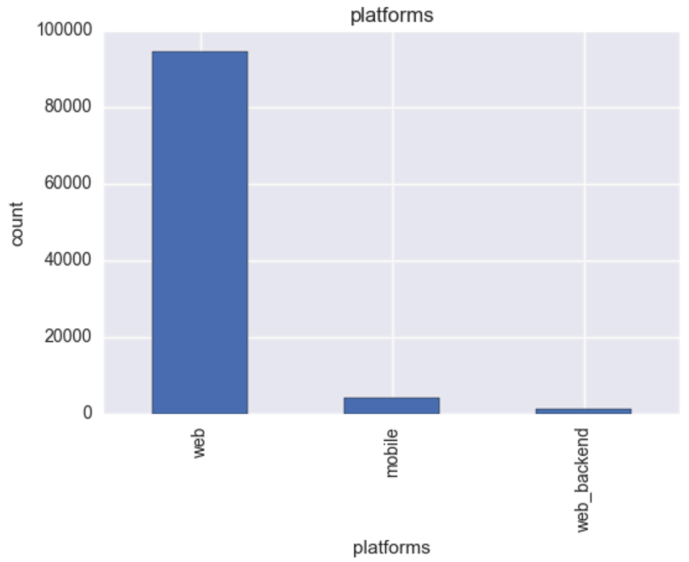
Approximately 50 million clips are created each month

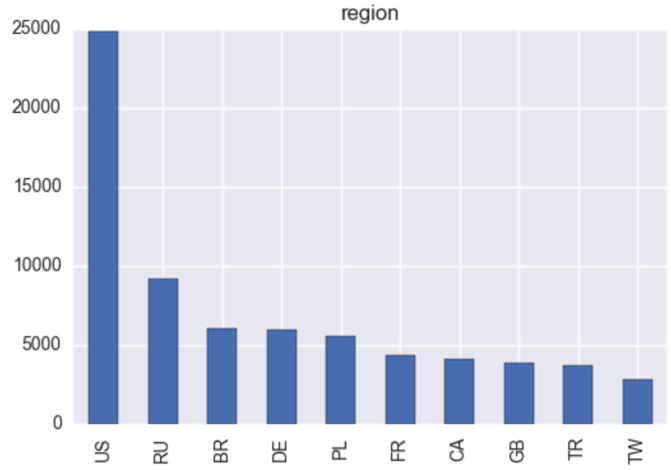
- Randomly sampled 100,000 clips over the past 4 months

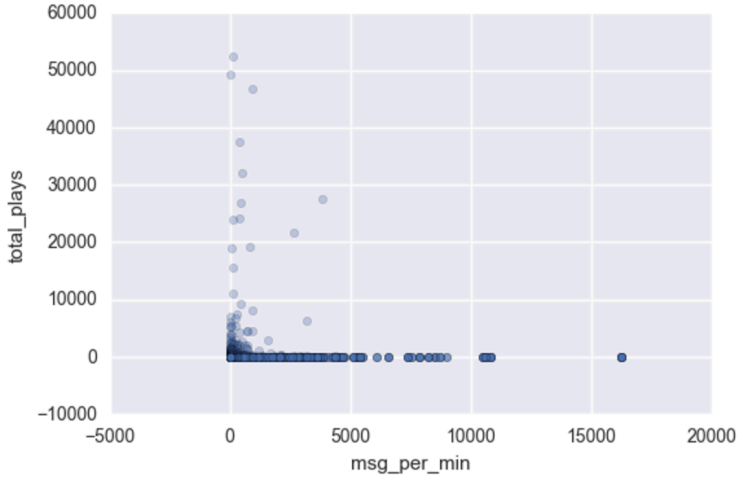
Features Added	
ccus	Number of people that were watching the channel live when the clip was created
msg_per_min	Chat velocity
avg_subs	Number of paid subscribers during the month the clip was made (on that channel)
total_bits	Donations (tips) that occurred during the time of the clip being created
number_of_bits_msgs	Number of msg's that contained a donation/tip

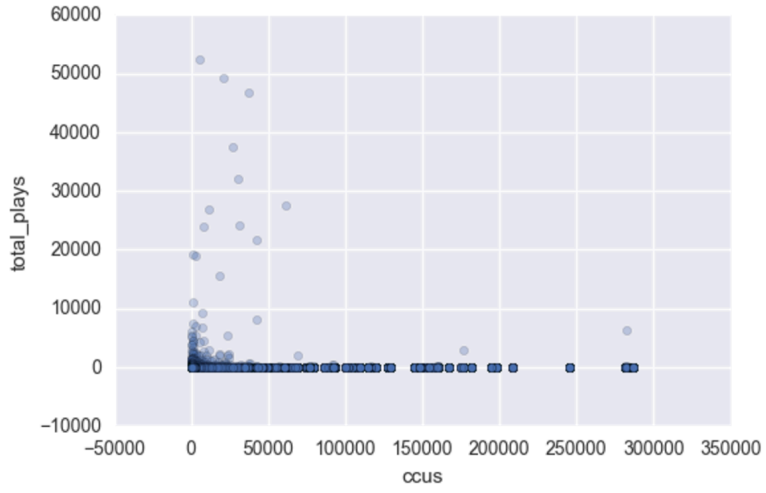
EDA

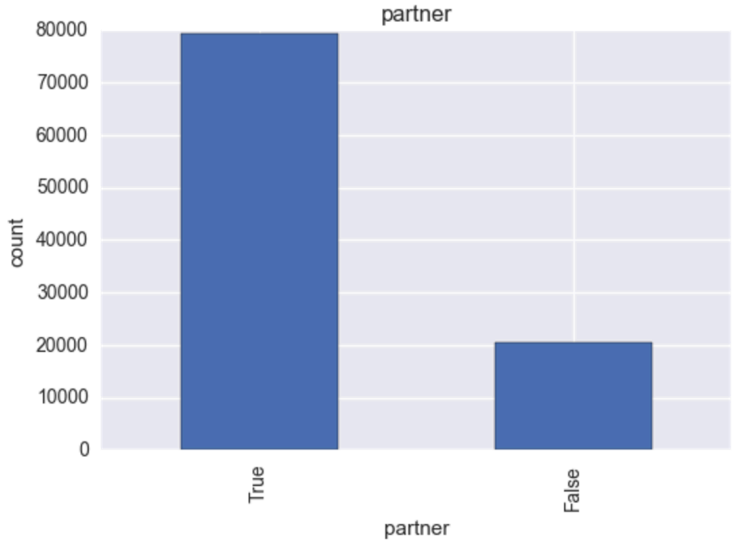
```
In [29]: df1.total_plays.describe()

Out[29]: count     99799.000000
         mean          8.015982
         std         385.588382
         min           0.000000
         25%           0.000000
         50%           0.000000
         75%           1.000000
         max       52290.000000
         Name: total_plays, dtype: float64
```











Results: LinearRegression

Loss Function Used: RMSE

Predicting with the mean of the entire dataset

```
In [23]: np.sqrt(metrics.mean_squared_error(df1.total_plays, df1.total_plays_prediction))
Out[23]: 385.58644994988981
```

Linear Regression with handpicked features: RMSE = 183.66

- Average score of five cross validations

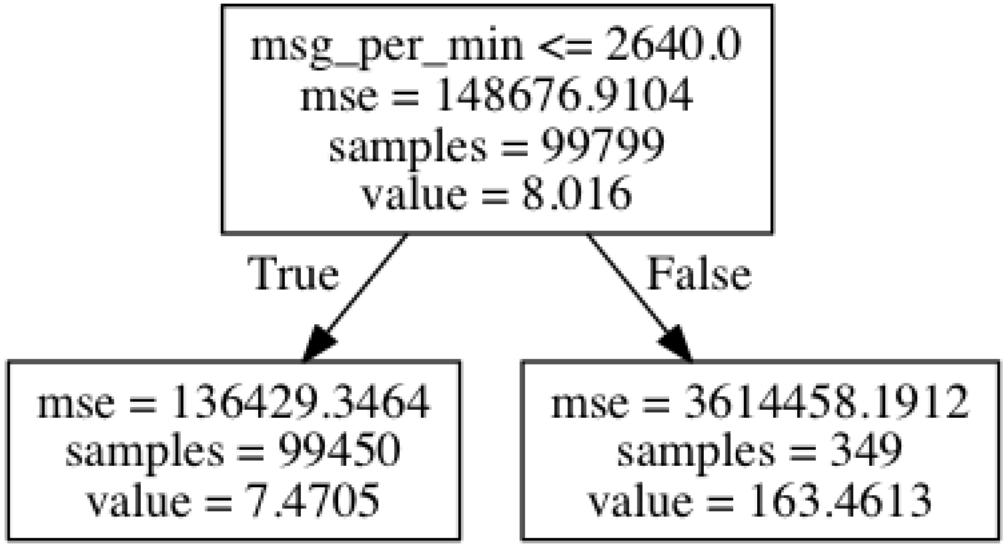
```
In [63]: feature_cols = ['avg_subs', 'msg_per_min', 'total_bits', 'ccus']
         X = df1[feature_cols]
         cross_val_rmse(X, y)
Out[63]: 183.66020497432285
```

Results: DecisionTreeRegressor

All features, RMSE: 228.031

Handpicked features & cv, RMSE: 133.86

- Most useful feature was chat velocity (msg_per_min)

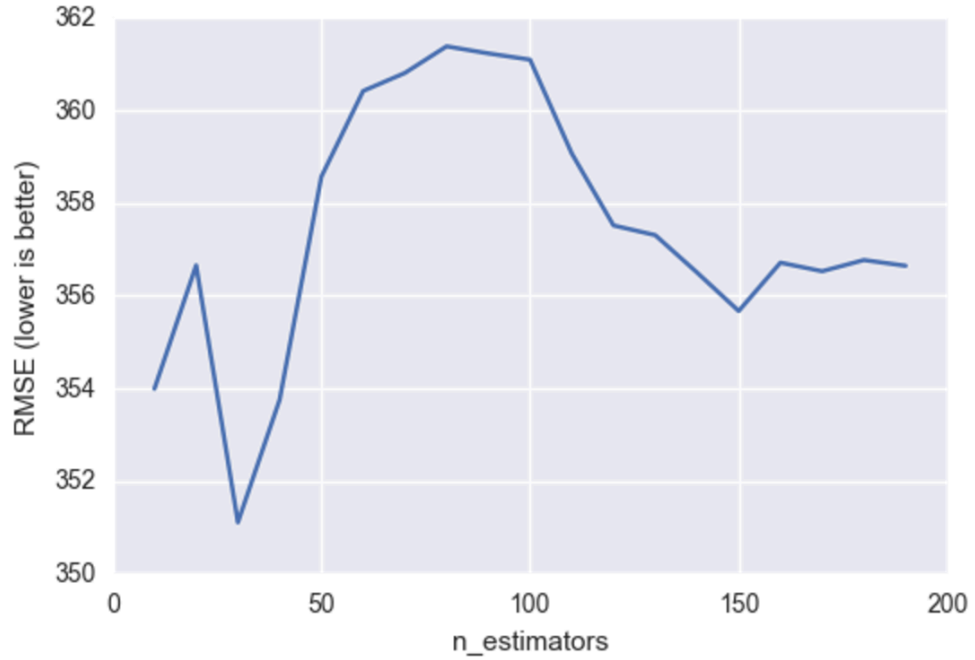


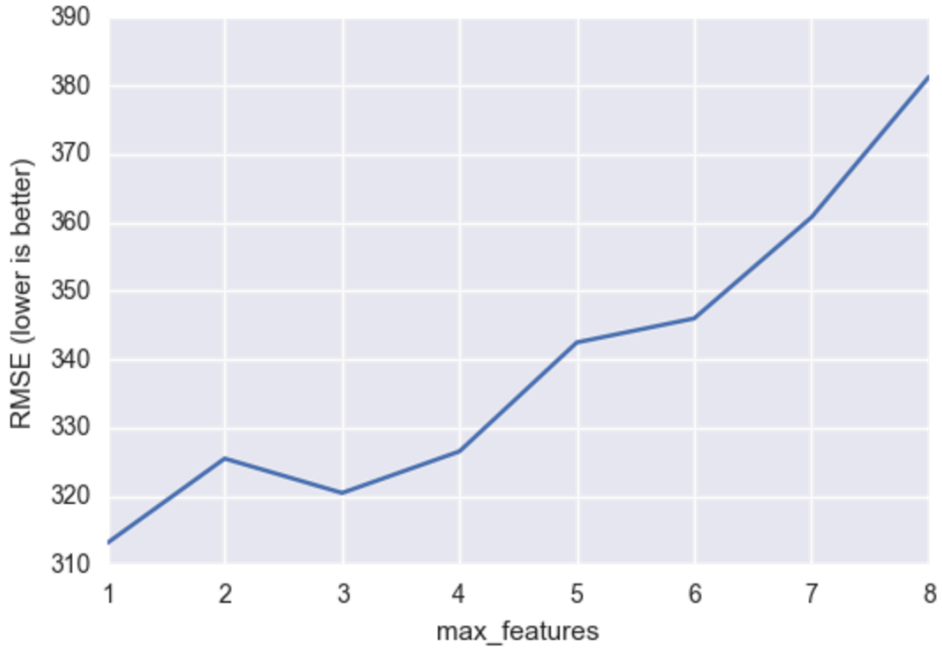
Results: RandomForestRegressor

My random forest performed worse, RMSE = 313.16

- Again, chat velocity was the only thing that didn't introduce noise

```
<matplotlib.text.Text at 0x11e6daf10>
```





Follow-up: BayesianRidge

Investigated using the chat during the clip to predict plays

- Smaller sample (1,000) clips, produced ~150,000 messages
- Used: Body, Tags

```
In [65]: np.sqrt(metrics.mean_squared_error(df3_comb.total_plays, df3_comb.total_plays_prediction))
Out[65]: 93.238281403080364
```

```
In [62]: np.sqrt(metrics.mean_squared_error(y_test, preds))
Out[62]: 11.505129508483178
```

Next Steps

- Better Feature Engineering
  - More flexible with how clip creation time is mapped to engineered features
- Continuous NLP to see if a running sentiment analysis would be useful for identifying clips
  - Tune NLP and use it in conjunction with the the broader model
  - I've hypothesized that emoticons like PogChamp & Kreygasm could indicate highlight worthy moments
    - Internal sentiment scoring may be available
- Features around the person clipping
  - Compare clipper's popularity on the popular social sites
  - Reddit and Twitter API would be the most useful based on my preliminary research

My Takeaways

- Build a MVP feature before investing more time
  - I spent too much time trying to create great features without testing simplified versions first (subs, bits messages, etc.)
- Expand upon promising features
  - Knowing that chat velocity was important, I could have measured the change in chat velocity over a grouping of seconds or whole minutes
- Samples
  - With a bottom heavy distribution, I found it difficult to find a representative sample and reduce my margin of error
- Accuracy vs. Resources

Questions!

www.twitch.tv