Analysis of Trending YouTube Videos

Presented by
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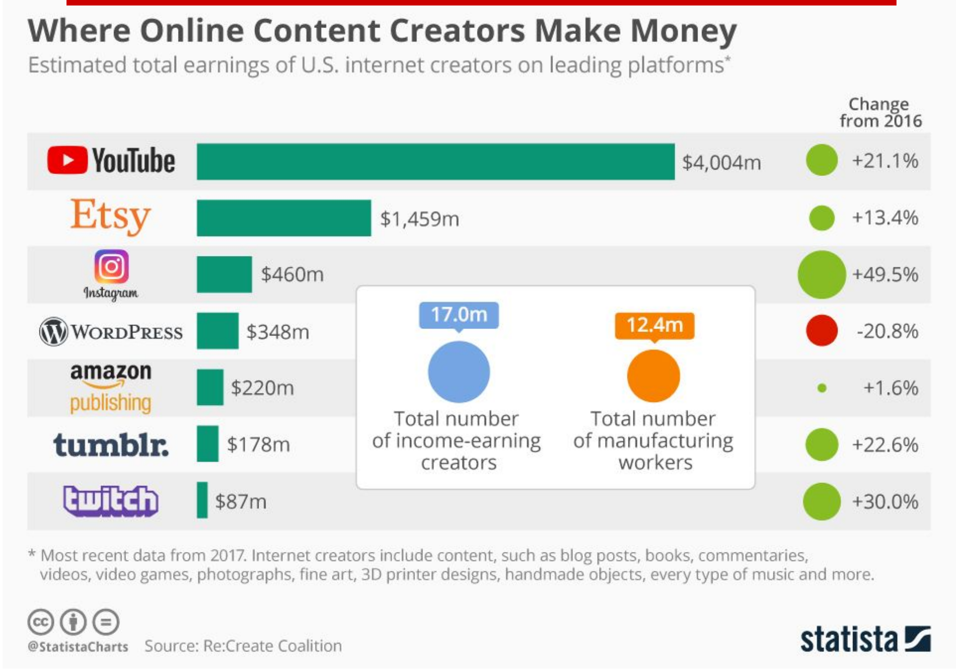
Introduction & Key Question

Publishing videos on Youtube is highly profitable



Trending Videos

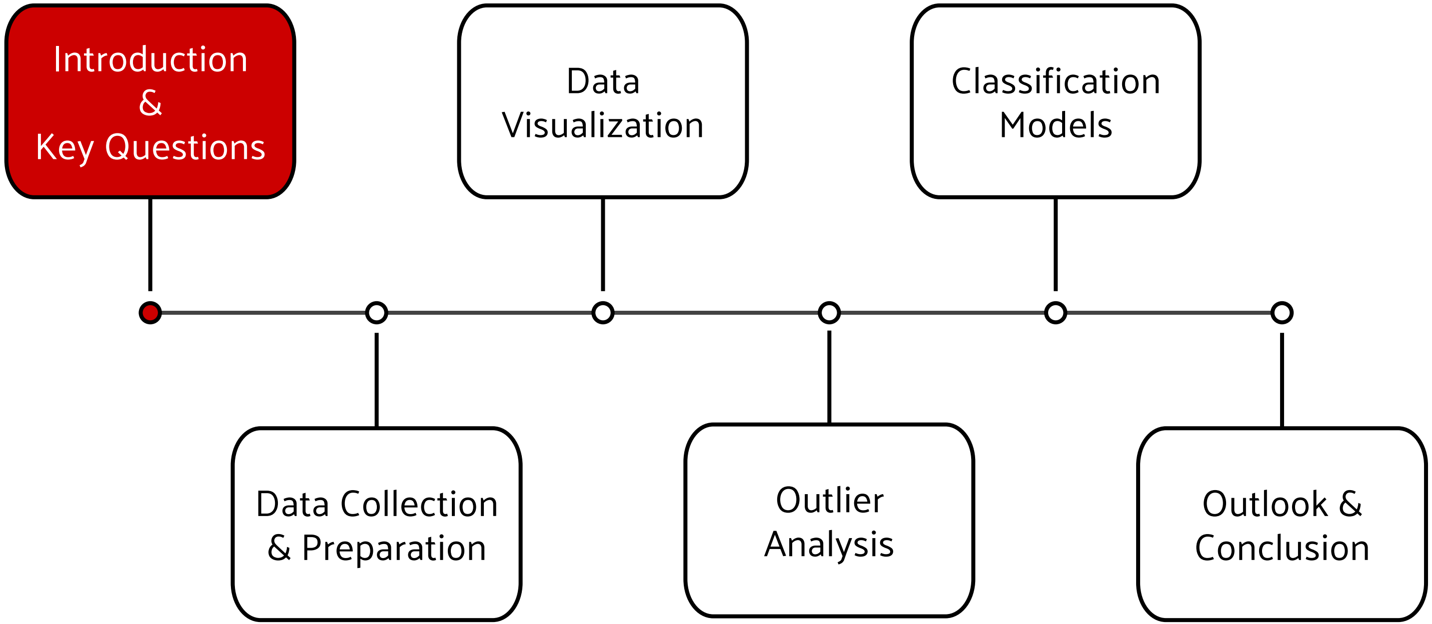
Trending aims to surface videos that:

- Are appealing to a wide range of viewers
- Are not misleading, clickbaity, or sensational
- Capture the breadth of what's happening on YouTube and in the world
- Showcase a diversity of creators
- Ideally, are surprising or novel

Key question:

- What factors make an immediately trending video?

Presentation Outline



Prepare the Dataset

Attributes	Missing Values
video_id	0
trending_date	0
title	0
channel_title	0
category_id	0
publish_time	0
tags	0
views	0
likes	0
dislikes	0
comment_count	0
thumbnail_link	0
comments_disabled	0
ratings_disabled	0
video_error_or_removed	0
description	570

16 attributes, 40949 observations

Key step: constructing dependent variable

1. Create a new variable “pre-trending time ”

pre-trending time = trending date - publish time

2. Keeps the first pre-trending time of each video

3. Remove the upper outliers of pre-trending time via IQR

count	6334.000000
mean	22.041048
std	205.918572
min	0.000000
25%	1.000000
50%	2.000000
75%	3.000000
max	4215.000000

```
def only_outlier(cleaned, col_name):
    q1 = cleaned['pretrending_time'].quantile(0.25)
    q3 = cleaned['pretrending_time'].quantile(0.75)
    iqr = q3-q1 #Interquartile range
    fence_low  = q1-1.5*iqr
    fence_high = q3+1.5*iqr
    only_out = cleaned.loc[(cleaned['pretrending_time'] > fence_high)]
    return only_out
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Source: Trending YouTube Video Statistics. Retrieved from https://www.kaggle.com/datasnaek/youtube-new

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4. Create a new variable "immediate trending"

   pre-trending time average = 1.86

   pre-trending time <= 1.86 ⟶ immediate trending = 1

   pre-trending time > 1.86 ⟶ immediate trending = 0

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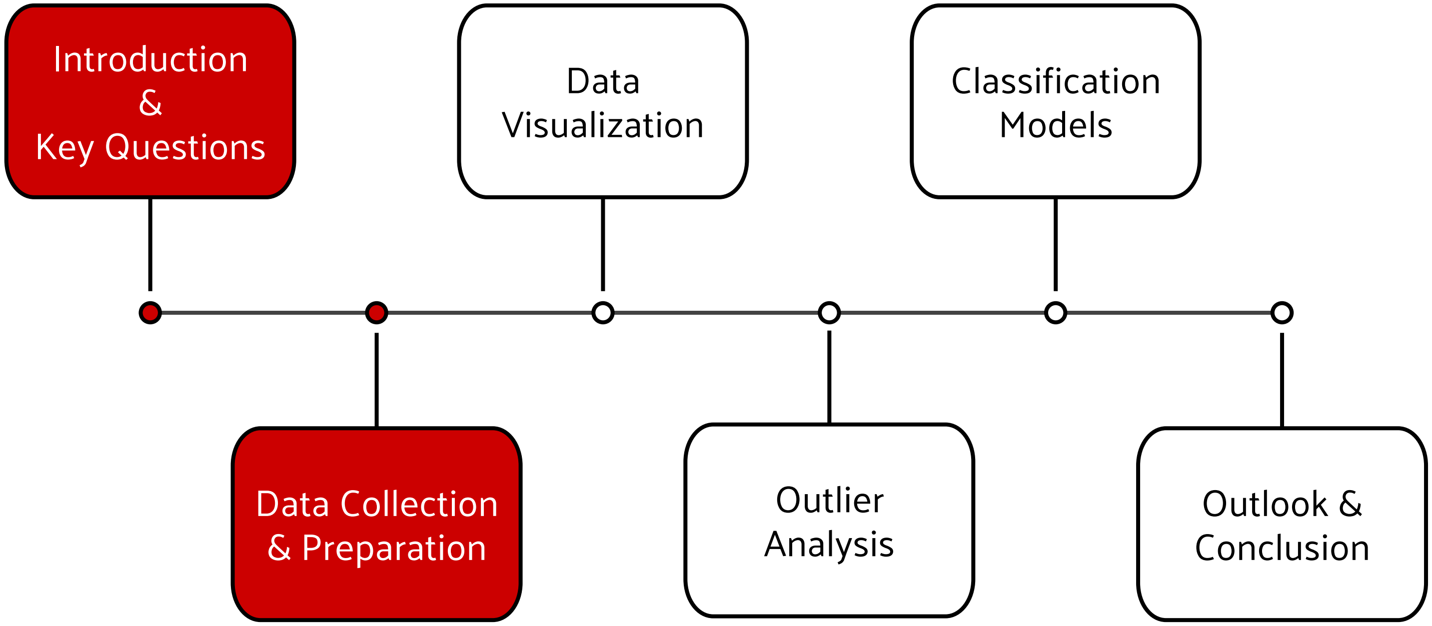
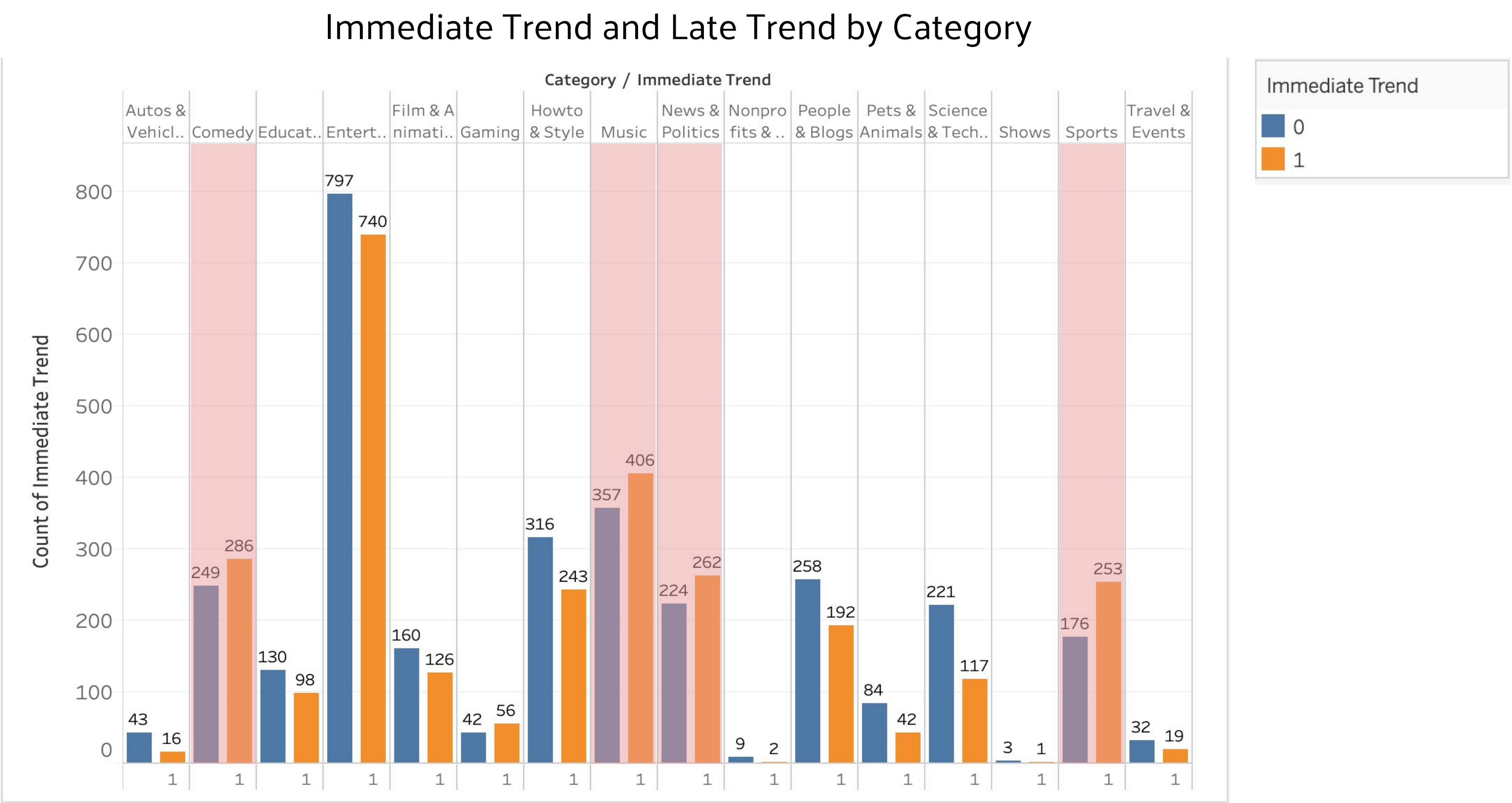
Presentation Outline

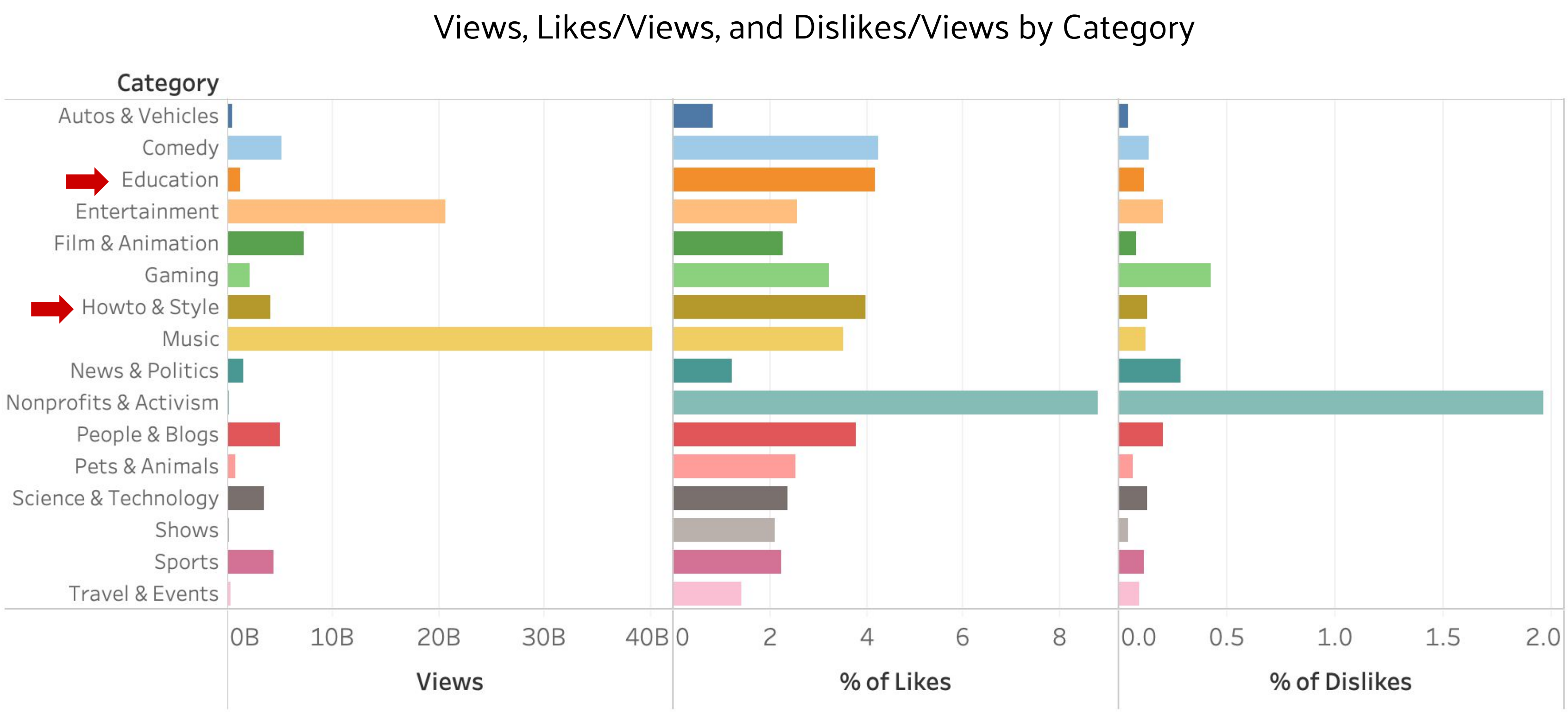


Compare Immediate Trend and Late Trend by Category



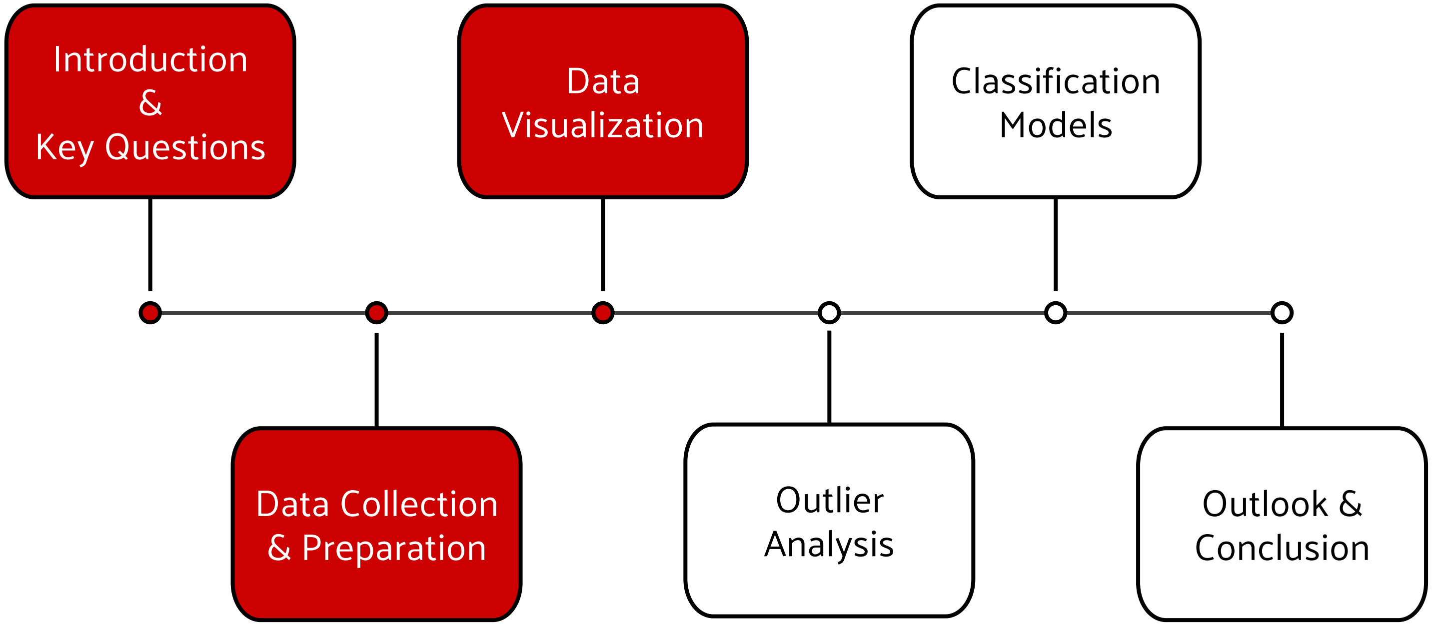
Takeaway: publish current events videos to be immediately trending

Compare Views, Likes, Dislikes by Category

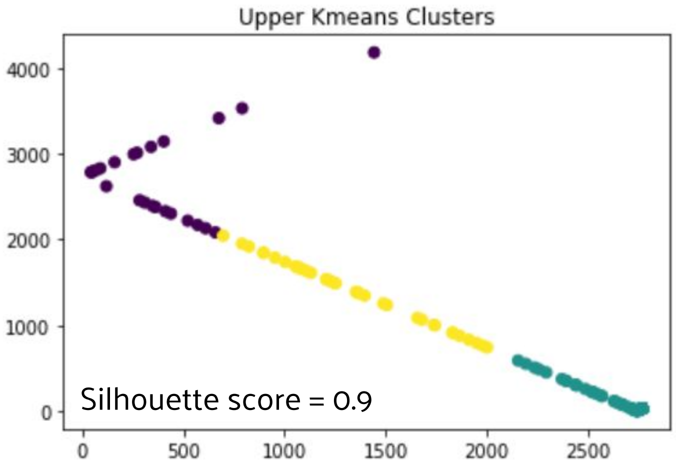


Takeaway: explore opportunities in Education and Howto & Style categories

Presentation Outline



Study the Upper Outliers via Clustering



Cluster 0

video_id	views	likes	dislikes	comment_count	pretrending_time	cluster_labels
-37nlo_tLnk	2863.0	2.0	0.0	0.0	2933.0	0
2vQ_fnlvvr8	45096.0	287.0	9.0	59.0	3113.0	0
5WUDfviiKRE	16823.0	93.0	275.0	172.0	2463.0	0
76c_nxhuVdM	163780.0	826.0	10.0	167.0	2839.0	0
9L4-DV1nVek	25796.0	64.0	4.0	22.0	2823.0	0
K9kVsnTQh-g	73685.0	260.0	55.0	96.0	2816.0	0
MJO3FmmFuh4	258506.0	459.0	152.0	82.0	4215.0	0
P2I7hQHOqNI	2896.0	30.0	0.0	3.0	2489.0	0
Tn5OBFgiExQ	51984.0	215.0	8.0	31.0	2163.0	0
UQtt9I6c-YM	49942.0	46.0	6.0	26.0	3563.0	0

Cluster 1

video_id	views	likes	dislikes	comment_count	pretrending_time	cluster_labels
-BQJo3vK8O8	48431654.0	609101.0	52259.0	29172.0	6.0	1
-CS84oCtjvc	994662.0	21094.0	714.0	3212.0	6.0	1
-QR-TB_k20M	23877.0	93.0	30.0	20.0	6.0	1
-hg_VRwS5RI	110470.0	7366.0	69.0	1247.0	7.0	1
-t1q78GYNww	127481.0	4865.0	234.0	1117.0	6.0	1
...	...	...	...	...	...	...
yFRPhi0jhGc	635806.0	35790.0	864.0	2857.0	6.0	1
z5JQMBcVFns	161532.0	1272.0	45.0	54.0	7.0	1
zYWt2mnalP8	160477.0	8388.0	691.0	950.0	6.0	1
zbV1zyg_4qU	5965.0	186.0	8.0	52.0	26.0	1
zzQsGL_F9_c	154206.0	1180.0	107.0	55.0	6.0	1

Cluster 2

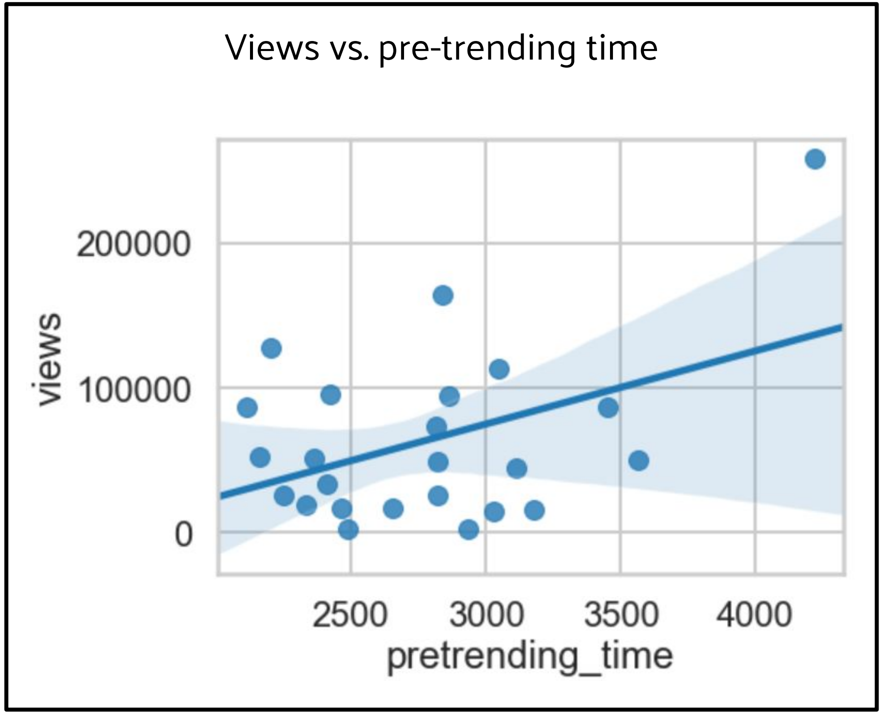
video_id	views	likes	dislikes	comment_count	pretrending_time	cluster_labels
0f7CuSU_huU	6491.0	15.0	0.0	8.0	1770.0	2
1x77e4XvqZ4	8502.0	42.0	0.0	4.0	1094.0	2
4Ek6UCI0YQs	2302.0	2.0	0.0	0.0	862.0	2
6A3cHzFQsql	112310.0	612.0	7.0	95.0	1878.0	2
6nJw-jPQYVI	192609.0	1345.0	24.0	126.0	908.0	2
7sEKooUZi7I	2992.0	28.0	0.0	1.0	1520.0	2
9o2FXVhjLyY	18264.0	315.0	29.0	122.0	1267.0	2
9vIKOFd73XM	10283.0	49.0	23.0	25.0	1719.0	2
A6owSHYjOiE	28954.0	74.0	9.0	11.0	1661.0	2
GDUncuEErzQ	7188.0	29.0	2.0	2.0	1820.0	2

Cluster 0: Significant Impact From Views on Pre-trending Time

Cluster 0

pretrending_time ~ views + likes + dislikes + comment_count

```
                            OLS Regression Results
==============================================================================
Dep. Variable:       pretrending_time   R-squared:                       0.486
Model:                            OLS   Adj. R-squared:                  0.378
Method:                 Least Squares   F-statistic:                     4.499
Date:                Sat, 30 Nov 2019   Prob (F-statistic):             0.0100
Time:                        11:33:10   Log-Likelihood:                -174.87
No. Observations:                  24   AIC:                             359.7
Df Residuals:                      19   BIC:                             365.6
Df Model:                           4
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
Intercept      2700.8934    131.134     20.596      0.000    2426.428    2975.359
views             0.0058      0.002      2.840      0.010       0.002       0.010
likes            -0.0479      0.732     -0.065      0.949      -1.580       1.484
dislikes          1.8776      1.707      1.100      0.285      -1.694       5.450
comment_count    -4.5664      2.686     -1.700      0.105     -10.188       1.055
=================================================================================
Omnibus:                        0.203   Durbin-Watson:                   2.057
Prob(Omnibus):                  0.904   Jarque-Bera (JB):                0.086
Skew:                           0.122   Prob(JB):                        0.958
Kurtosis:                       2.835   Cond. No.                     1.39e+05
==============================================================================
```



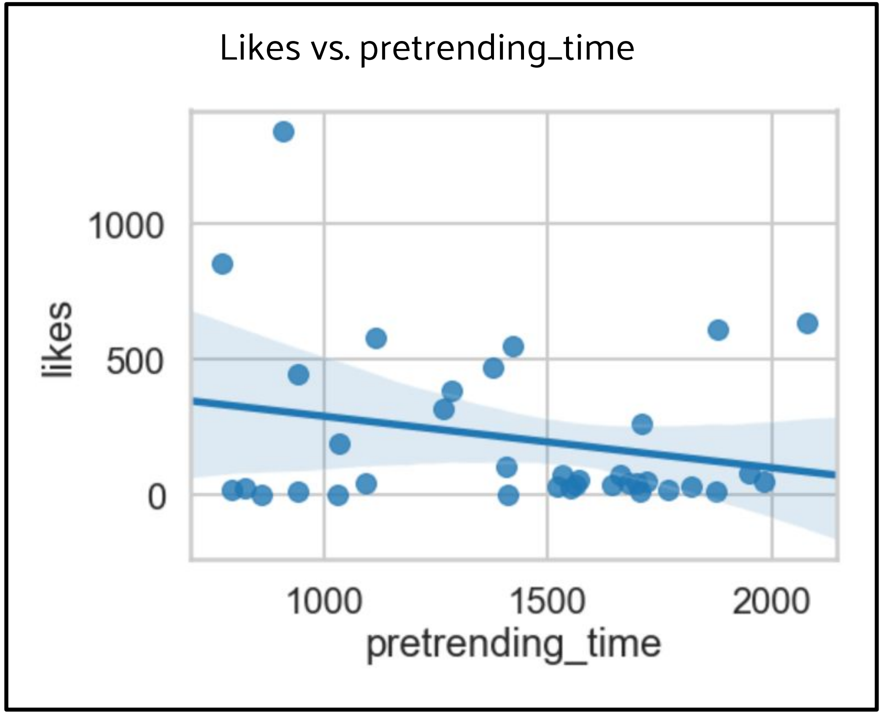
Observation: videos cumulate views before they actually get on the trending list

Cluster 2: Significant Impact From Likes on Pre-trending Time

Cluster 2

pretrending_time ~ views + likes + dislikes + comment_count

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        pretrending_time   R-squared:                       0.155
Model:                             OLS   Adj. R-squared:                  0.046
Method:                  Least Squares   F-statistic:                     1.425
Date:                 Sat, 30 Nov 2019   Prob (F-statistic):              0.249
Time:                         11:34:39   Log-Likelihood:                -261.36
No. Observations:                   36   AIC:                             532.7
Df Residuals:                       31   BIC:                             540.6
Df Model:                            4
Covariance Type:             nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
Intercept      1457.4035     79.373     18.361      0.000    1295.521    1619.286
views             0.0027      0.002      1.435      0.161      -0.001       0.007
likes            -0.8888      0.471     -1.886      0.069      -1.850       0.072
dislikes          1.4120      9.097      0.155      0.878     -17.142      19.966
comment_count     1.5655      3.199      0.489      0.628      -4.959       8.090
==============================================================================
Omnibus:                         3.158   Durbin-Watson:                   2.489
Prob(Omnibus):                   0.206   Jarque-Bera (JB):                1.999
Skew:                           -0.357   Prob(JB):                        0.368
Kurtosis:                        2.093   Cond. No.                     9.07e+04
==============================================================================
```



Observation: the higher the like count, the shorter pre-trending time will be

Cluster 1: No Significant Relationship Observed

Cluster 1

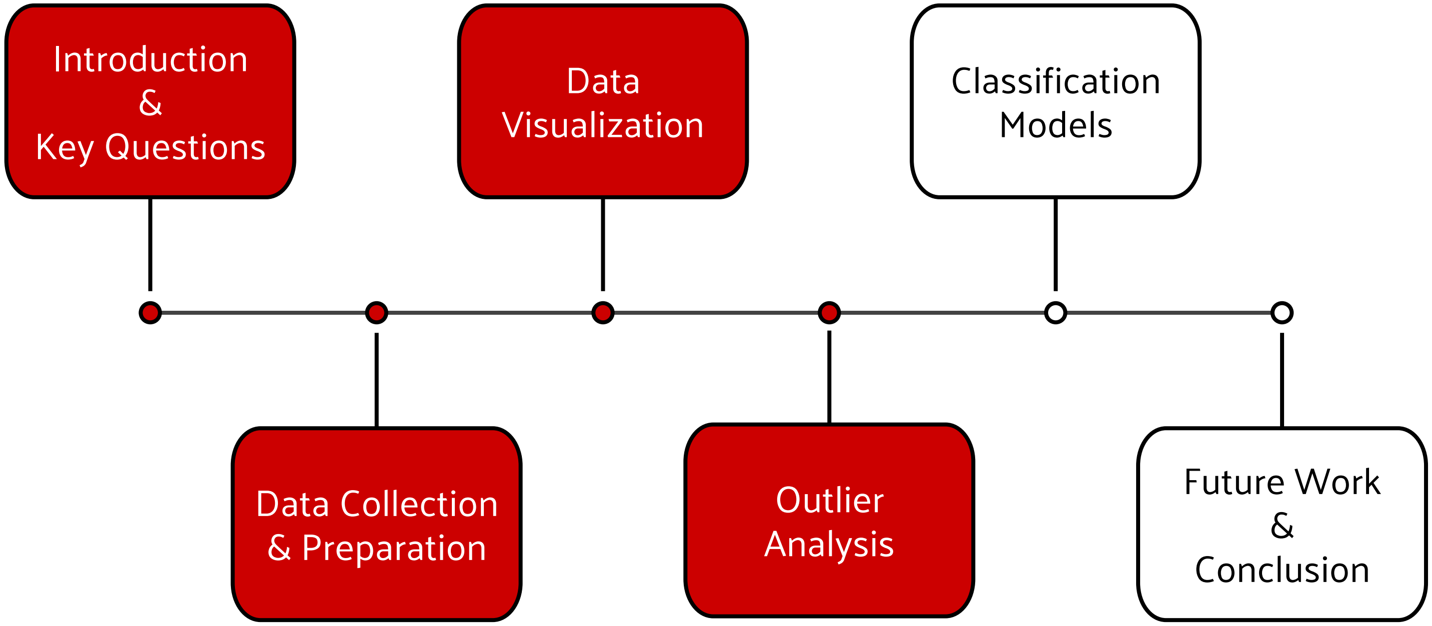
pretrending_time ~ views + likes + dislikes + comment_count

```
                            OLS Regression Results
==============================================================================
Dep. Variable:       pretrending_time   R-squared:                       0.010
Model:                            OLS   Adj. R-squared:                 -0.002
Method:                 Least Squares   F-statistic:                    0.8117
Date:                Sat, 30 Nov 2019   Prob (F-statistic):              0.518
Time:                        11:34:05   Log-Likelihood:                -1942.1
No. Observations:                 330   AIC:                             3894.
Df Residuals:                     325   BIC:                             3913.
Df Model:                           4
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
Intercept        35.3264      5.125      6.893      0.000      25.245      45.408
views         -5.644e-07   2.43e-06     -0.233      0.816   -5.34e-06    4.21e-06
likes         -4.426e-05      0.000     -0.361      0.718      -0.000       0.000
dislikes      -5.587e-05      0.000     -0.138      0.890      -0.001       0.001
comment_count    -0.0004      0.001     -0.540      0.589      -0.002       0.001
==============================================================================
Omnibus:                      327.036   Durbin-Watson:                   2.090
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             6884.267
Skew:                           4.427   Prob(JB):                         0.00
Kurtosis:                      23.550   Cond. No.                     3.49e+06
==============================================================================
```

Rationale

- Skewness for Cluster 1 linear regression is high compared to other two groups of clusters, which means containing data that has various of pre-trending time
- Cluster 1 has the highest average views, likes and dislikes, despite they are not significant for pre-trending time
- Cluster 1 has similar characteristics as “inner” dataset

Presentation Outline



Feature Engineering

Variable Transformation

Tags (object)	→	Tag number (integer)
Title (object)	→	Title length (integer)
Comments_disabled (bool)	→	Comments_no (float)
Video_error_or_removed (bool)	→	Video_error_or_removed_no (float)

New Variable Creation

Like ratio = likes/(likes + dislikes)

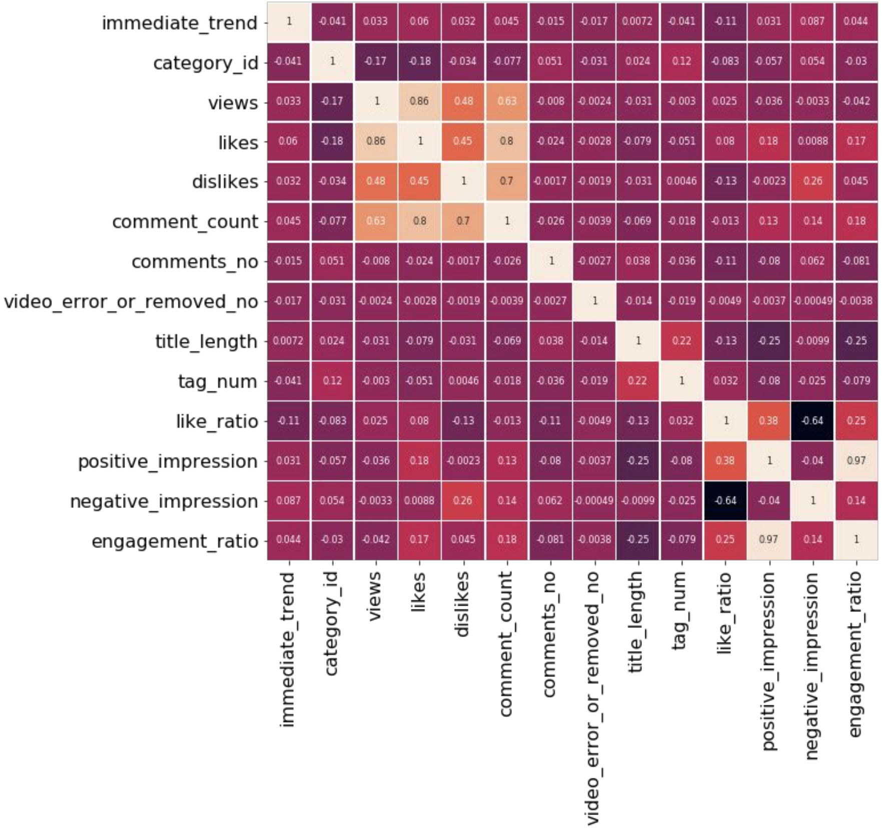
Positive impression = likes/views

Negative impression = dislikes/views

Engagement ratio = (comment count + likes + dislikes)/views

14 attributes, 39281 observations

Feature Selection via Correlation Analysis

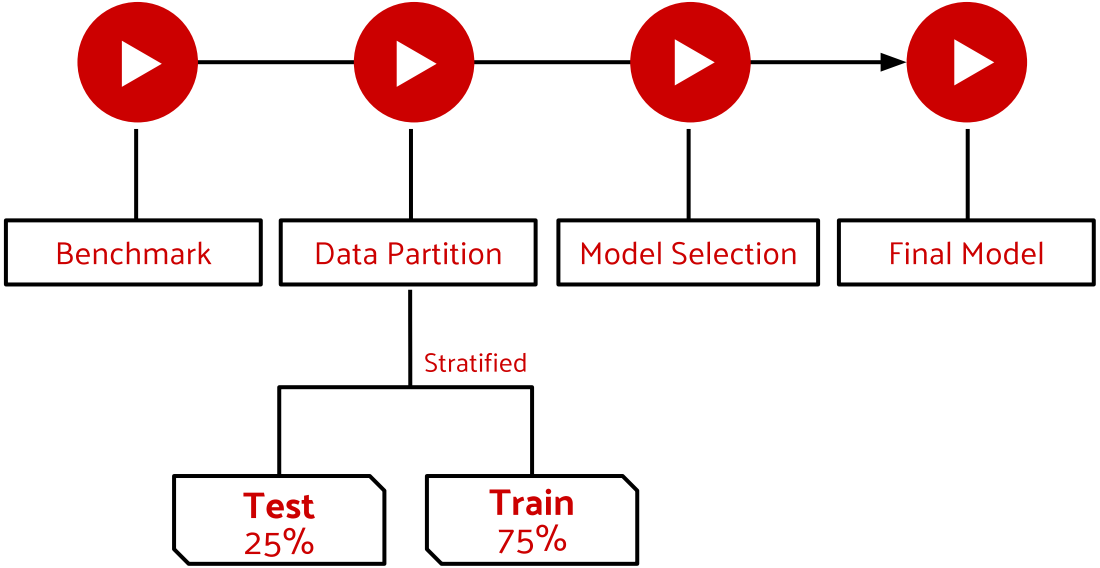


Correlation with *Immediate_trend* attribute

Attributes	Corr. Coeff.	p-Value
category_id	−0.041042	4.033523e−16
views	0.033477	3.208751e−11
likes	0.060450	3.940152e−33
dislikes	0.032090	1.997401e−10
comment_count	0.044811	6.367884e−19
comments_no	−0.015116	2.735510e−03
video_error_or_removed_no	−0.017156	6.729631e−04
title_length	0.007221	1.524000e−01
tag_num	−0.041054	3.959438e−16
like_ratio	−0.113157	4.285877e−112
positive_impression	0.030669	1.203739e−09
negative_impression	0.086773	1.586447e−66
engagement_ratio	0.043715	4.402762e−18

11 attributes, 39281 observations
Label: *Immediate_trend*
Features: the other 10 attributes

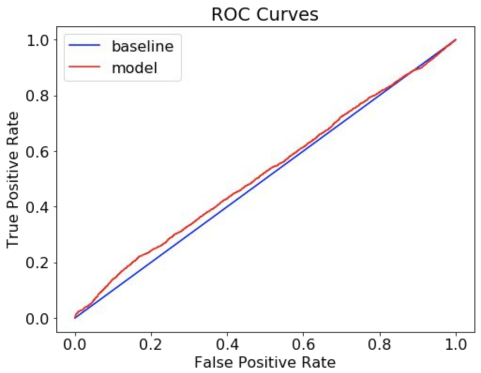
Modeling Process Overview



Modeling Optimization

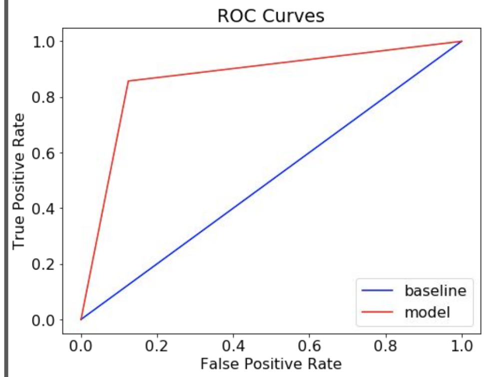
Benchmark model (GNB)
Recall: 0.05 Precision: 0.54 ROC: 0.50 Accuracy: 0.52

Naive Bayes



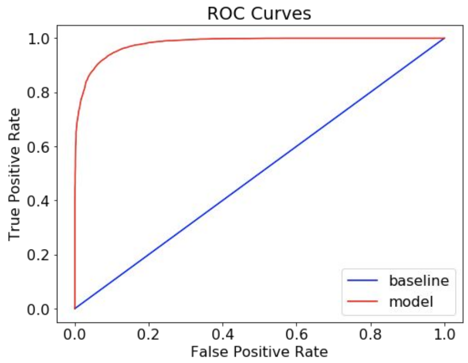
Recall: 0.05
Precision: 0.53
Roc: 0.52
Accuracy: 0.52

Decision Tree



Recall: 0.86
Precision: 0.87
Roc: 0.87
Accuracy: 0.52

Random Forest



Recall: 0.91
Precision: 0.93
Roc: 0.98
Accuracy: 0.92

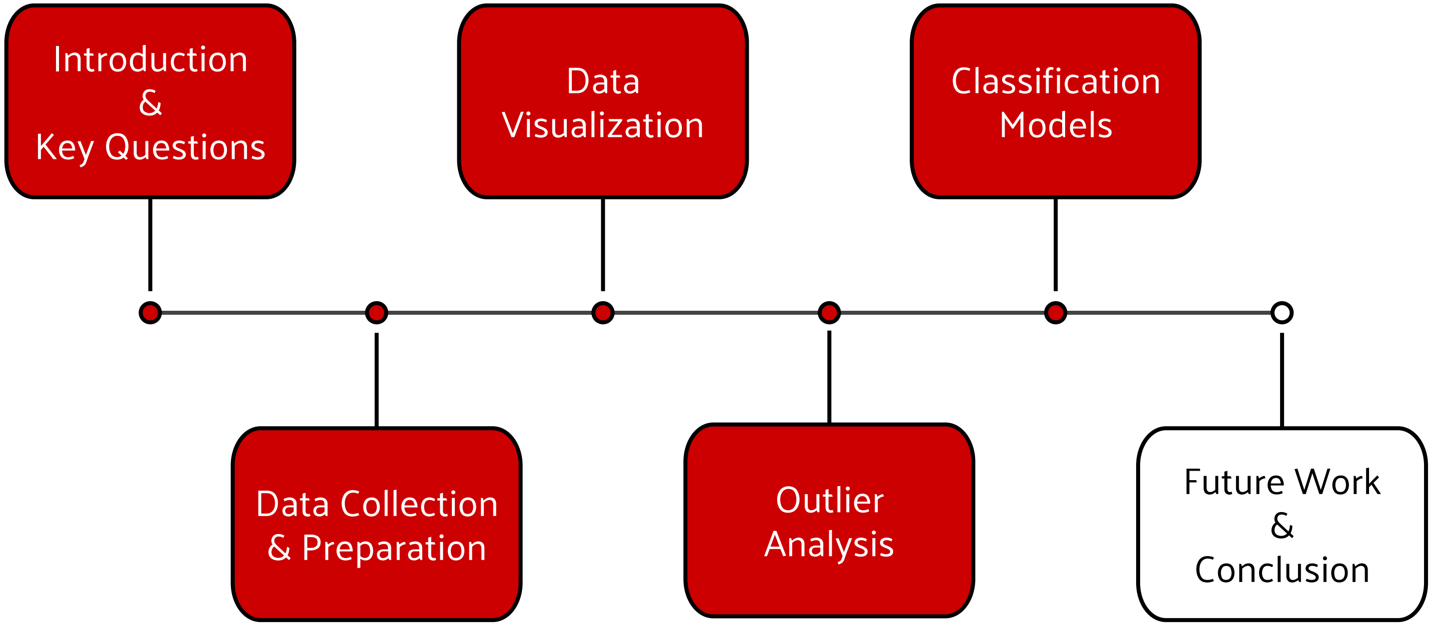
Tag Number is the Most Important Factor

Results from random forest model		
Attributes	**Importance**	**Impact Direction**
tag_num	0.133807	Negative
comment_count	0.119388	Positive
like_ratio	0.115624	Negative
negative_impression	0.114163	Positive
likes	0.098008	Positive
dislikes	0.096474	Positive
postive_impression	0.087713	Positive
engagement_ratio	0.086578	Positive
views	0.080964	Positive
category_id	0.067280	Negative

Takeaways

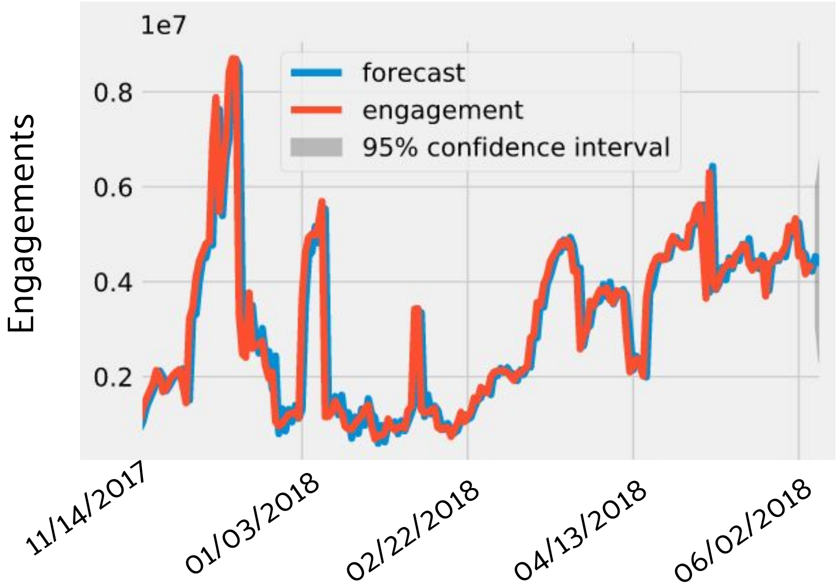
- Reduce tag number to make the video more focused
- More comments, more likely to be immediately trending
- Both like and dislike are important to make immediate trending

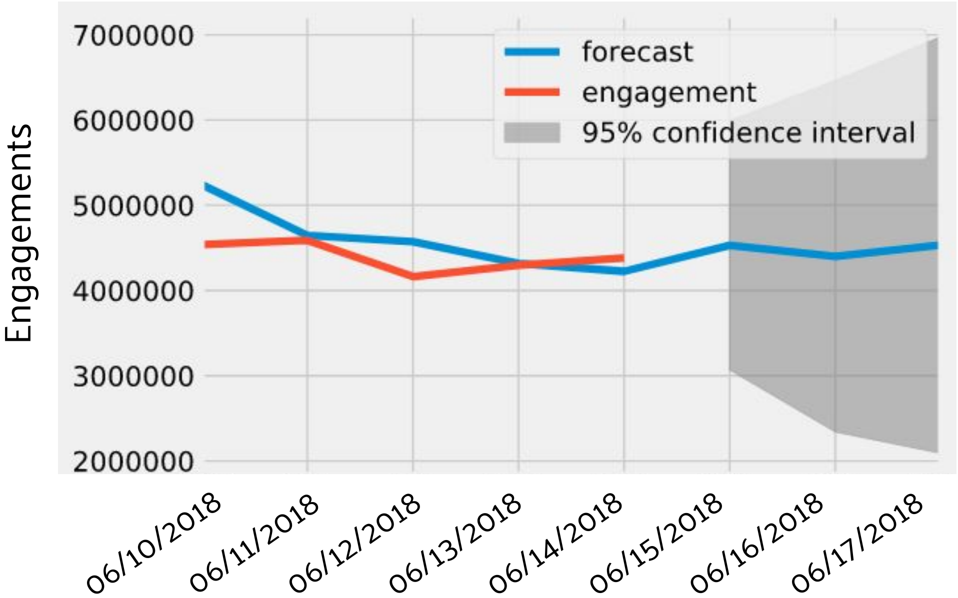
Presentation Outline



Future Work: Time Series Analysis - Preliminary Results

Time series analysis for trending entertainment videos





Recommendation: not publish video in next 3 days due to slightly decrease in predicted engagement

Summary

What we did

- Conducted EDA to understand the difference between immediate trend and late trend by category, and difference in views, positive impression and negative impression between each category
- Performed clustering and linear regression analysis to study the videos with long pre-trending time (outliers)
- Constructed classification models to predict immediate trend videos and to figure out important features

What we found

To make an immediately trending video

- Publish current events videos
- Make the video more focused by reducing tag number
- Encourage leaving comments
- Both like and dislike are important

Other insights for content creators

- Explore opportunities in Education and Howto & Style categories

Future work

- Construct the time series models to predict the engagement changes in trending videos for recommending video publish time

Thank You

Supplementary Information

Remove Upper Outliers via IQR

Pretreding time overview

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    iqr = q3-q1 #Interquartile range
    fence_low  = q1-1.5*iqr
    fence_high = q3+1.5*iqr
    only_out = cleaned.loc[(cleaned['pretrending_time'] > fence_high)]
    return only_out
```

```python
def remove_outlier(cleaned, col_name):
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    fence_high = q3+1.5*iqr
    cleaned_out = cleaned.loc[(cleaned['pretrending_time'] < fence_high)]
    return cleaned_out
```
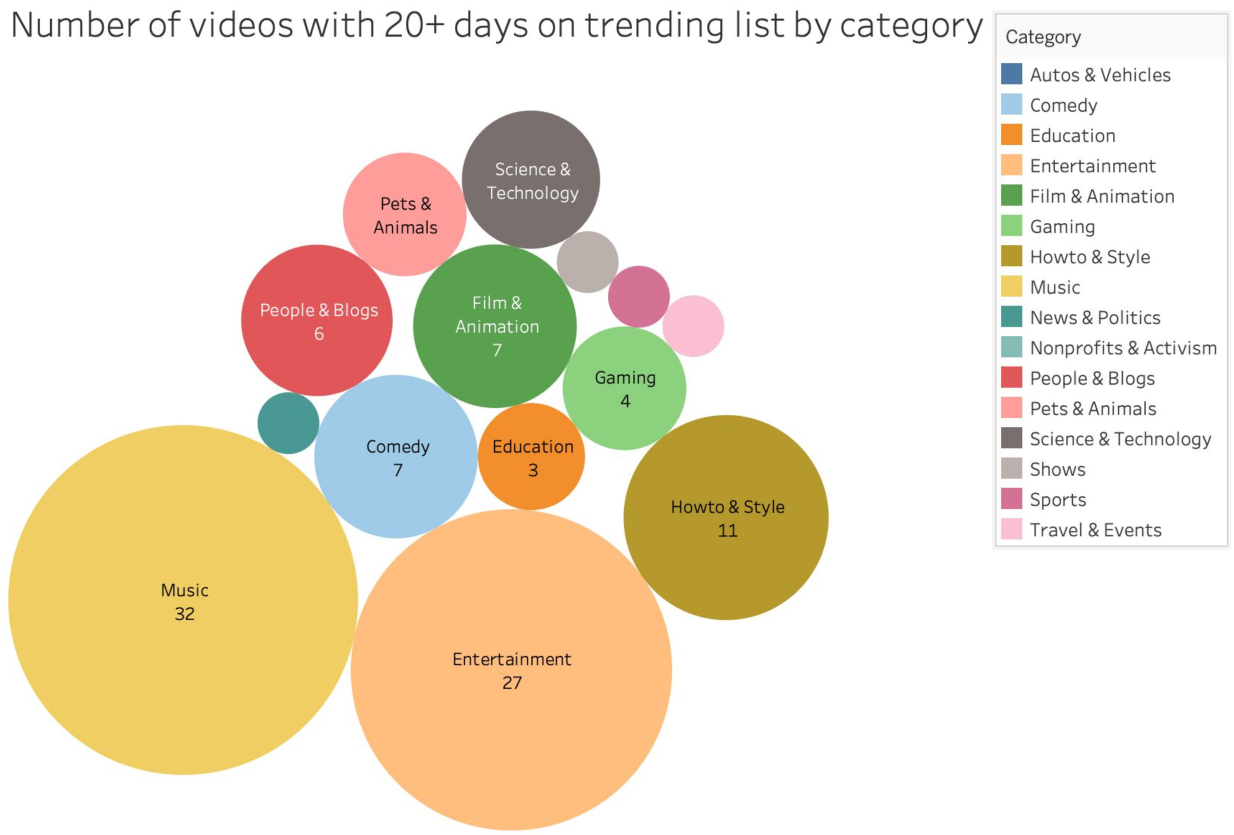
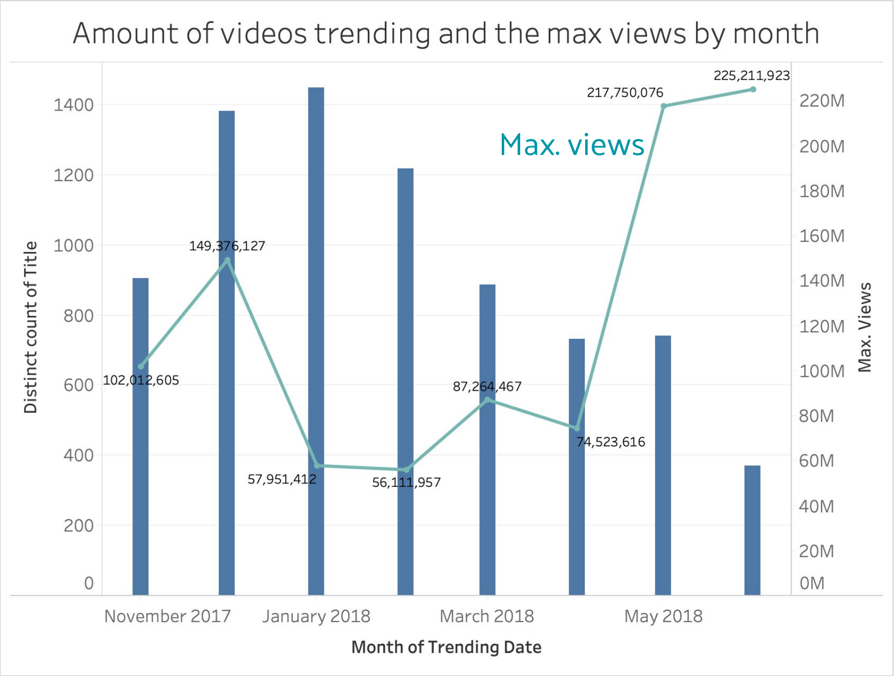
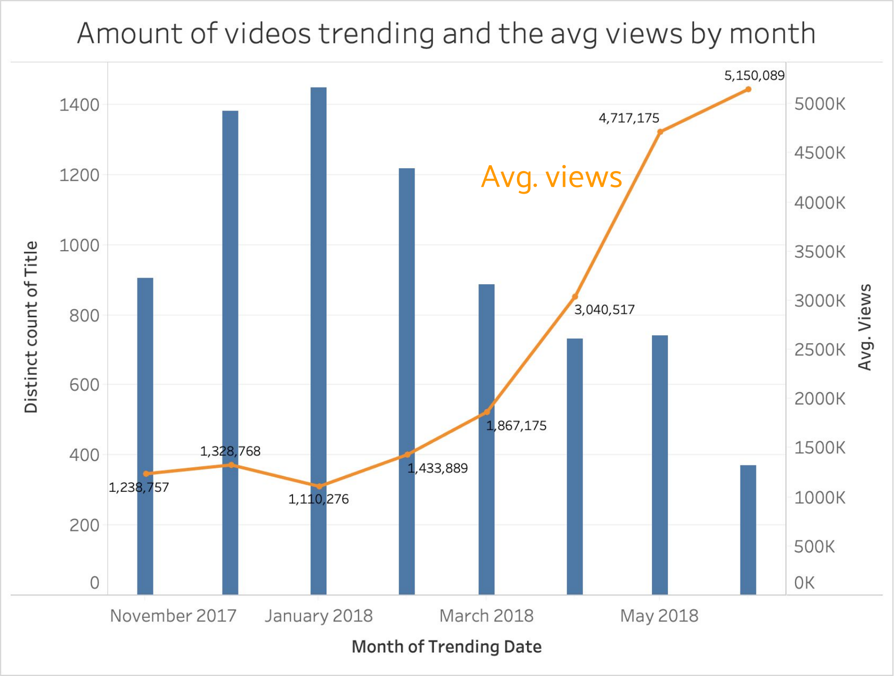

Long-Trending Videos



Dramatic Increase in Views in May 2018





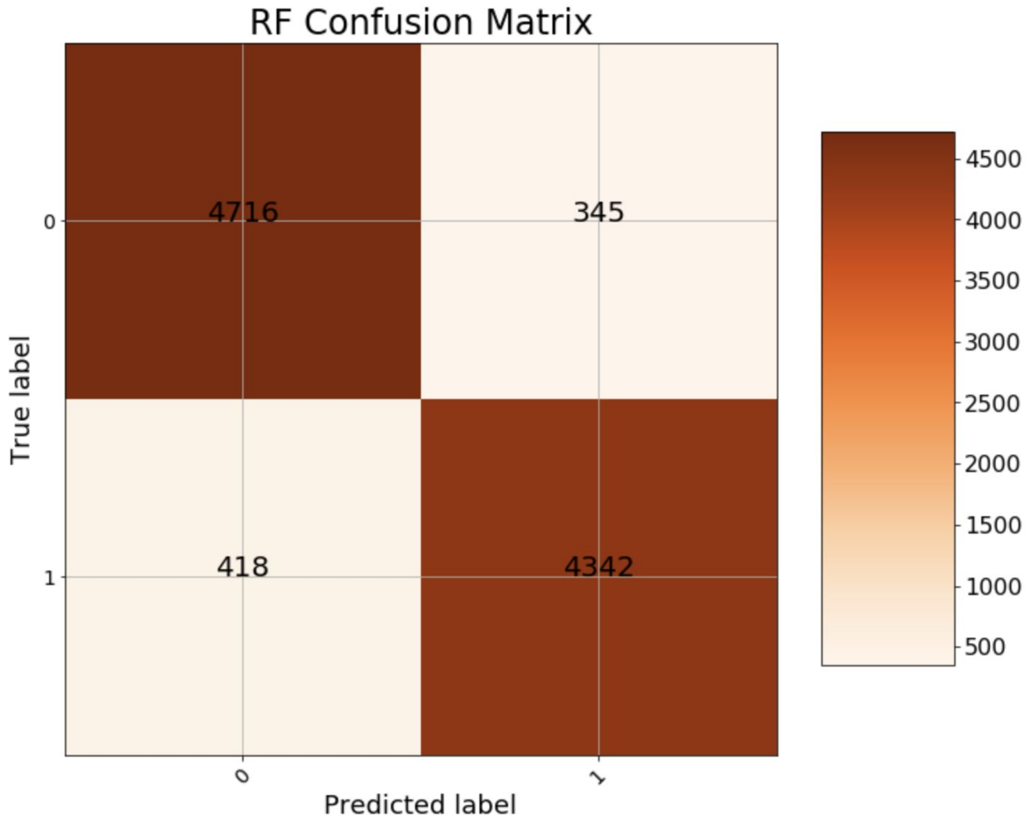
May 2018: “Childish Gambino - This Is America” was published

Identifying Cluster Number via Silhouette Score

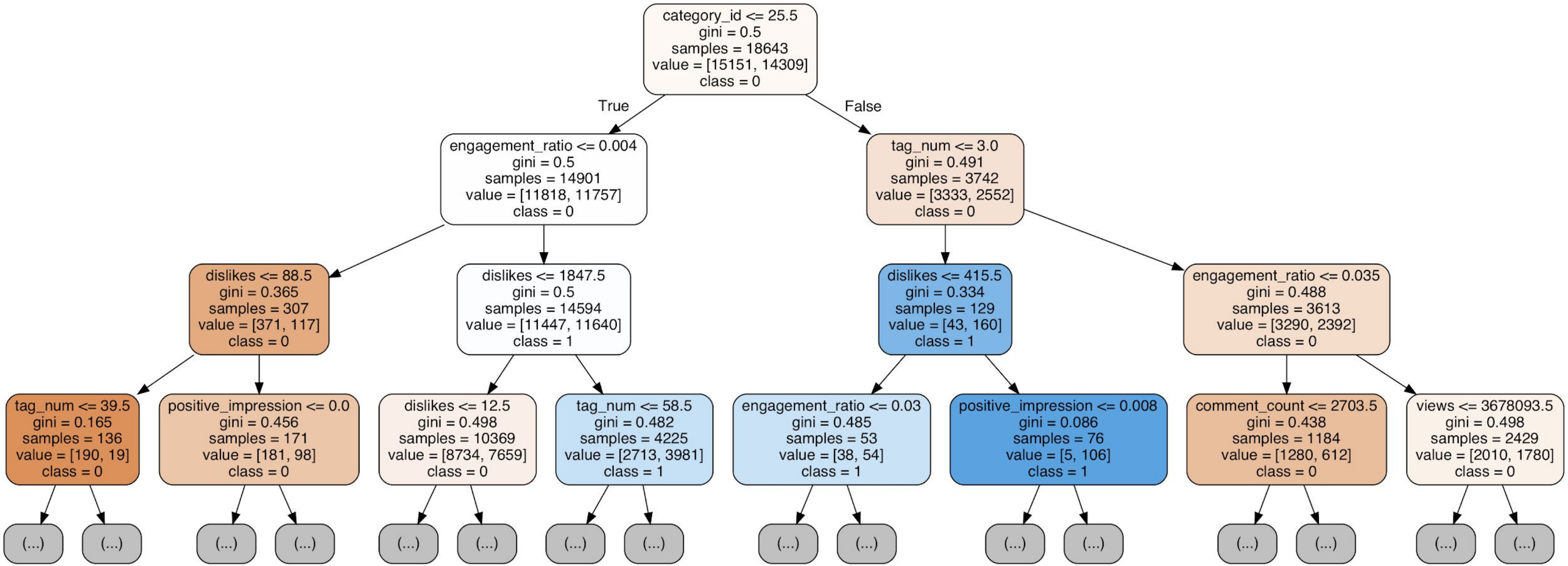
```
# Print out `s_score_dict`
print(s_score_dict)
```

```
{2: [0.9009486705900968], 3: [0.8971033378954894], 4: [0.8853091053839264], 5: [0.885842839667557], 6: [0.8887056890145145], 7:
[0.8833120752778203], 8: [0.882921629467595], 9: [0.8796317163090666], 10: [0.8768285388044179]}
```

Confusion Matrix For Random Forest



One Tree from Random Forest Model



ARIMA: AutoRegressive Integrated Moving Average

If d=0: $y_t = Y_t$

If d=1: $y_t = Y_t - Y_{t-1}$

If d=2: $y_t = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2}) = Y_t - 2Y_{t-1} + Y_{t-2}$

d: the number of non seasonal differences
y: original series
Y: stationaized (differenced) series

Forecasting Equation

$$\hat{y}_t = \overbrace{\mu}^{\text{constant}} + \overbrace{\phi_1 y_{t-1} + \ldots + \phi_p y_{t-p}}^{\text{AR terms (lagged values of } y)}$$

$$\underbrace{-\theta_1 e_{t-1} \ldots - \theta_q e_{t-q}}_{\text{MA terms (lagged errors)}}$$

By convention, the AR terms are + and the MA terms are –

Source: https://towardsdatascience.com/unboxing-arima-models-1dc09d2746f8