Predicting Tik-Tok User Data Based on Video Data

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Introduction and data

With over 1 billion users globally, TikTok is one of the fastest growing social platforms in the world. Understanding ubiquitous algorithm, which is said to generally account for account factors (likes and comments) and video information (captions, sounds, hashtags), is critical to understanding the app's many critiques, from declining youth mental health outcomes and its addictive nature of its explore page. To better understand TikTok's social impact, we decided to explore TikTok's data and how follower count (a huge driver of engagement) is impacted by other aspects of a user's account, like average number of videos, average number of likes, and average number of comments.

The dataset comes from the 'top_users_vids.csv' file (under folder 'Trending Videos Data Collection') of the Github repository found at: https://github.com/ivantran96/TikTok_famous/tree/main. The data was originally collected as part of the DataResolutions's Data Blog project exploring Tiktok's demographics and trending video analytics.

The original data curators collected the data using David Teather's open-source Unofficial Tiktok API (found at https://github.com/davidteather/TikTok-Api), which uses Python to scrape Tiktok data and fetch the most trending videos, specific user information, and much more. Using the list of top Tiktokers, the curators expanded the list of users by collecting suggested users with the API's getSuggestedUsersbyIDCrawler method. They then collected video data of the 25 most recent posts of each user using the byUsername method, and used the bySound method to collect videos using some of the most famous songs on TikTok.

EDA

We begin our EDA process by first examining the dataset.

Currently, our dataset tiktok has 13 columns and 12,559 observations. Each row is a video. The columns cover attributes of each video such as video length, hashtags used, songs/sounds used, and statistics (number of likes, shares, comments, plays, followers, and total number of likes

and videos across the account). Variables id, create_time, video_length, n_likes, n_shares, n_comments, n_plays, n_followers, n_total_likes, and n_total_vids are numerical while the others are categorical.

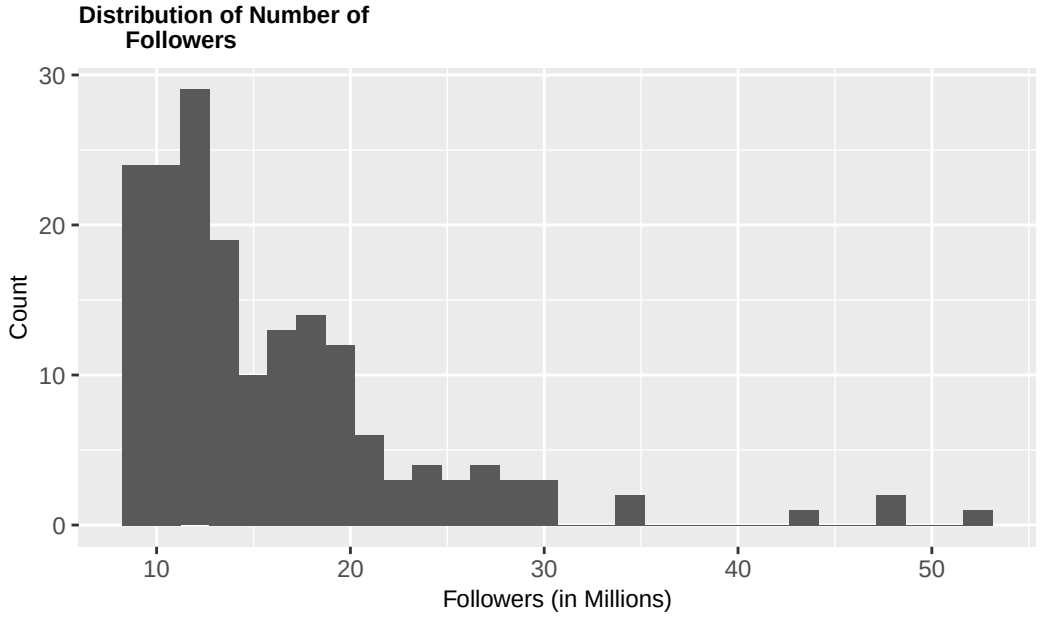
There's a potential for severe multicollinearity if we choose to just drop user_name, since the number of plays or likes a video would have a strong relationship with the user who posted it. Therefore, any analysis without user and its related features would have to consider the user's account as confounding variables. In addition, we'd be forced to drop valuable features directly related to a user such as user followers, user total likes and user total videos (n_followers, n_total_likes, n_total_vids).

The less relevant variables are create time, video ID, hashtags and songs. Most videos don't include a hashtag and there are too many unique instances of them for it to be valuable in our analysis. We could consider binning hashtag into none and at least 1 hashtag(s), however that wouldn't be useful for our analysis since its rare for tiktok followers to mind the number of hashtags. The same is true for songs; it wouldn't be useful to categorize all original songs as similar since most of them could just be user-edited snippets of actual songs.

To address the issues mentioned above, we grouped the data by users and summarized relevant predictor variables by taking their mean. Our modified dataset has 8 columns and 254 observations, with each row being a user.

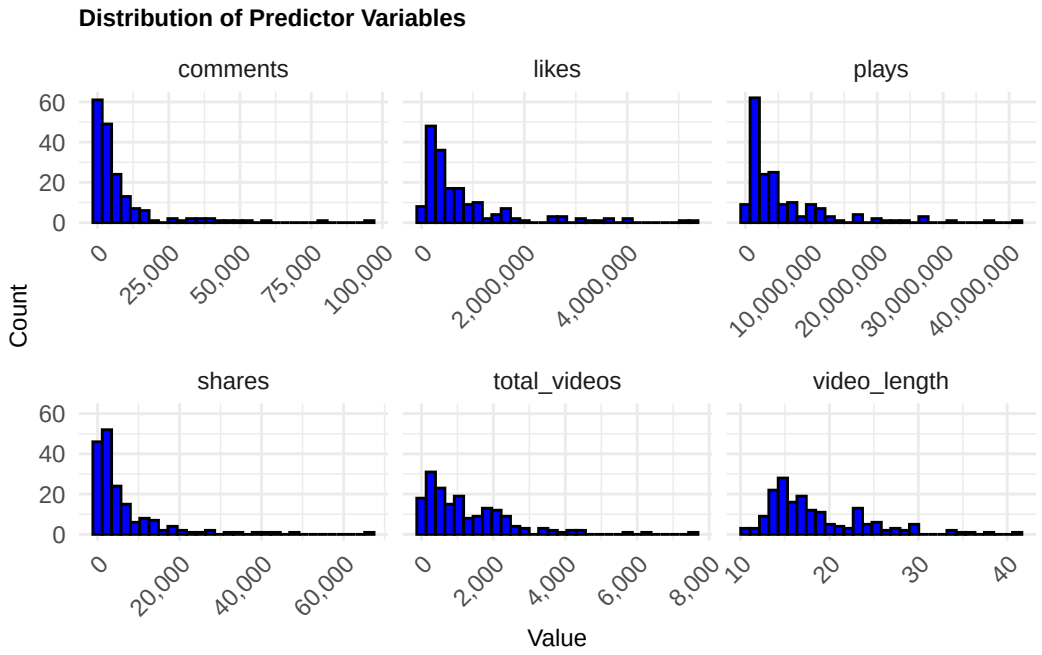
No data leakage is introduced in this process since we are just summarizing by the means of the predictor variable per user. When we split, it'll split based on observations, which are users.

Here's a distribution of our response variable, user followers, from our training set.

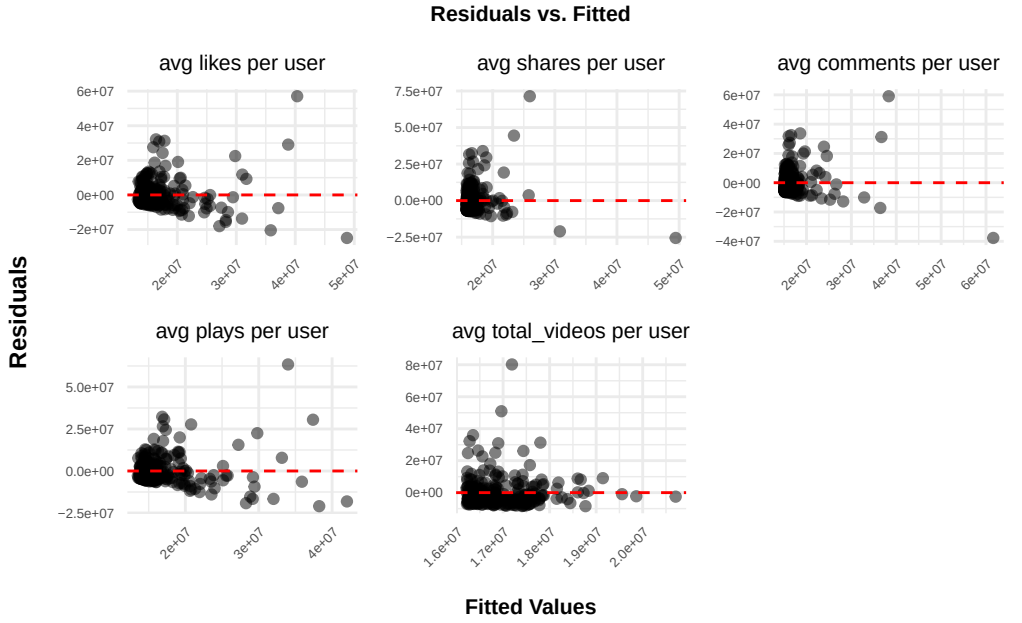


The distribution of our response variable follows, is unimodal and heavily right skewed. The mean is 16,220,526.3 and the standard deviation is 7,710,869.8. The minimum is 8,900,000 and the maximum is 52,300,000. Based on our standard deviation, there seems to be a lot of variation in our dataset; and from our plot, we can see major outliers.

Here are the distributions for the predictor variables we are interested in:



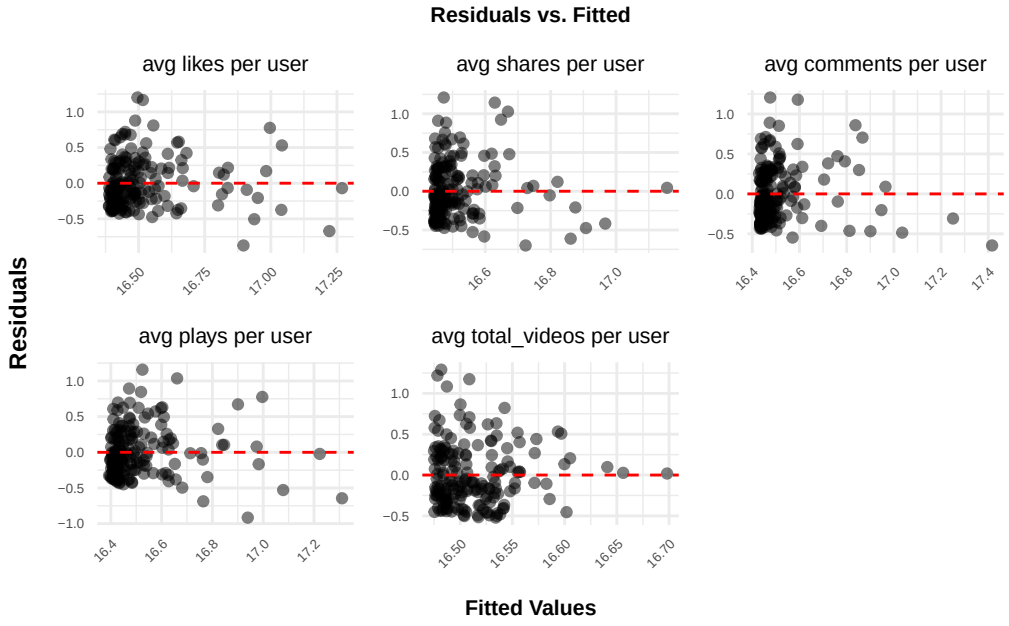
Judging by the number of outliers in our dataset, we are interested in knowing how this might influence our model conditions. Hence, we have the following residual plots for each of them.



All our predictors variables violate constant variance, because there's a clear outward fan

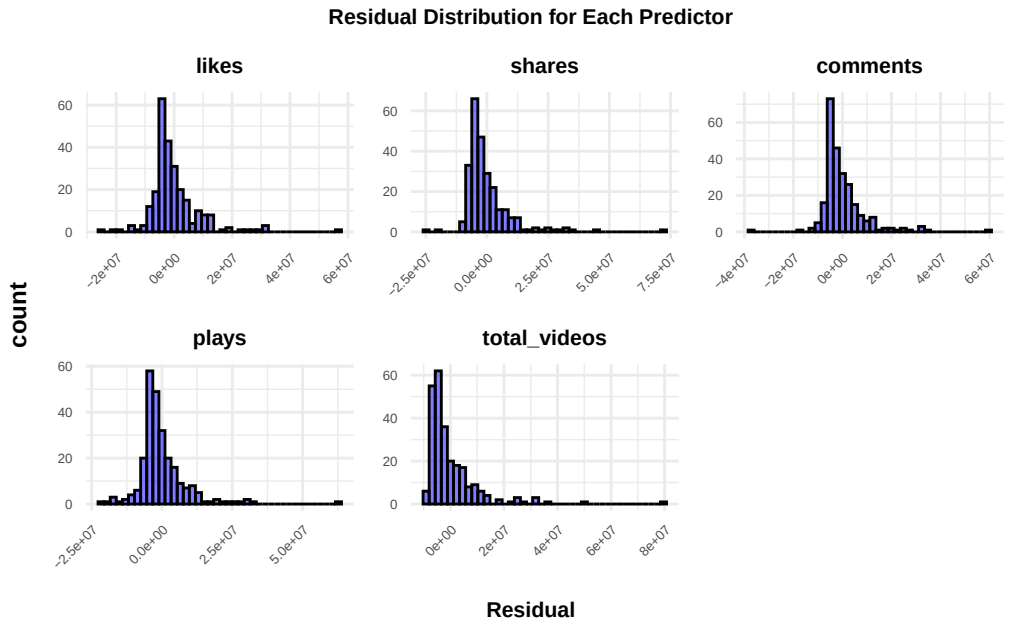
spread for likes, shares, comments, plays and video_length, and an inward spread for total_videos. As a result, we log transformed our response variable of followers.

Because Tiktok videos are commonly divided into 15-second, 1 minute, or 3 minute videos, it also makes sense to process average bin video length into levels, corresponding to "short", "medium" and "long." Now, we can search for interactions effects video_length might have with other predictors such as likes. Therefore, we'll add step_discretize() into the recipe for video_length. We also mean-centered all our numerical variables to make our intercept meaningful and normalized them to reduce standardize them and reduce multicollinearity produced by higher-order terms.



Fanning is a lot less noticeable now. The residual plots don't seem to suggest any underlying patterns. As such, we conclude the predictors satisfy linearity and constant variance.

We can also assume independence is met. Each of the videos are by individual creators, therefore the videos are independent of each other.



Normality seems to be satisfied for each of the predictors except total_videos and possibly shares. However, even though total_videos and shares do not have completely normal distributions, because we have more than 30 observations in the dataset, we can conclude that normality is satisfied regardless of the distribution.

We use the transformed dataset to split our data into testing and training. Before constructing our model, we chose to log transform our response variable 'followers' because, prior to the transformation, the variables were not to scale and returned coefficients of 0.000. We also mean-centered all our predictor variables to make our intercept meaningful.

Methodology

In honing our final model, we used the transformed dataset to reduce multicollinearity and conduct a cross-validation test on tiktok_train.

Detecting Multicollinearity & Model Comparison

Upon conducting a VIF test, we found that likes and plays had the highest vif values (11.614 and 9.82 respectively).

```
      likes       shares     comments        plays total_videos
 11.595466     3.507545     2.598273     9.798934     1.168067
```

Therefore, we constructed two linear regression model fitting variable 'followers' with predictor variables 'likes', 'shares', 'comments', 'plays', 'video_length_bin', and 'total_videos.' Our first model m1 had all the previously indicated predictor variables excluding variable 'likes' while our second model m2 had those predictor variables excluding variable 'plays.' We compared these two models because meaning they have the highest likelihood for multicollinearity.

term	estimate	std.error	statistic	p.value
(Intercept)	16.492	0.043	385.562	0.000
shares	-0.119	0.046	-2.582	0.011
comments	0.105	0.035	2.982	0.003
plays	0.224	0.046	4.885	0.000
video_lengthbin2	0.002	0.061	0.027	0.979
video_lengthbin3	0.059	0.061	0.973	0.332
total_videos	0.113	0.027	4.243	0.000

term	estimate	std.error	statistic	p.value
(Intercept)	16.496	0.043	384.488	0.000
likes	0.238	0.050	4.753	0.000
shares	-0.098	0.044	-2.247	0.026
comments	0.060	0.039	1.533	0.127
video_lengthbin2	-0.003	0.061	-0.043	0.966
video_lengthbin3	0.050	0.061	0.831	0.407
total_videos	0.110	0.027	4.142	0.000

Model Comparison with 5-fold CV

To determine which between m1 and m2, we performed 5-fold cross validation and extract the resulting BIC and AIC scores along with additional evaluations.

Model 1: (without likes):

RMSE:

```
# A tibble: 1 x 4
  mean_rmse mean_adj_rsq mean_aic mean_bic
      <dbl>        <dbl>    <dbl>    <dbl>
1     0.340        0.266     90.7     114.
```

Model 2 (without plays):

RMSE:

```
# A tibble: 1 x 4
  mean_rmse mean_adj_rsq mean_aic mean_bic
      <dbl>        <dbl>    <dbl>    <dbl>
1     0.333        0.259     92.1     116.
```

The difference between the model's evaluations aren't large. Model 1 has a slightly higher RMSE, but it has a lower AIC and BIC, and a higher adjusted r-squared. In this case, we would consider model 1 (the model without likes) to be a better model since it's able to explain more of the variance while also maintaining lower AIC and BIC scores. Therefore, we choose to remove likes and leave plays in the model .

Determining whether video_length_bin are necessary

The p-values associated with video length bins are high, indicating that the variables aren't significant. Because of this, we can do once again do cross validation to test to see how a model without video_length and likes performs against m1 (our chosen model without likes but contains video length).

Model 3 (without video length and likes):

```
# A tibble: 1 x 4
  mean_rmse mean_adj_rsq mean_aic mean_bic
      <dbl>        <dbl>    <dbl>    <dbl>
1     0.339        0.269     88.2     106.
```

We can see that when we remove video_length, it makes sense that AIC and BIC both decrease. We also see that adjusted r-squared only slightly increased by approximately 0.002. Therefore, we prefer the parsimonious model without video length bins.

Determining whether interaction terms are needed

We used domain knowledge to hypothesize several potential interaction variables, including: .connecting average plays and likes (or other engagement metrics) to detect bot activities, connecting likes and total number of videos to evaluate the relationship between user engagement and activity, and connecting average likes and shares to evaluate the viewer's reason for shares (to detect potential negative sentiments). All interaction terms had low p-values, but the first and third interaction terms showed signs of multicollinearity by increasing the p-value of other variables in the model.

This is a table with the second interaction term:

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	16.562	0.029	570.025	0.000	16.505	16.620
likes	0.193	0.084	2.280	0.024	0.026	0.359
plays	0.152	0.075	2.033	0.044	0.004	0.300
shares	-0.100	0.045	-2.218	0.028	-0.189	-0.011
comments	0.066	0.038	1.707	0.090	-0.010	0.142
total_videos	0.171	0.032	5.318	0.000	0.107	0.234
likes:total_videos	0.137	0.046	2.996	0.003	0.047	0.227

We can see from the p-values in the table that all variables seem to be statistically significant with the interaction term. Therefore, those terms should certainly be in our model. The new p-value for comments is not less than our significance level of 0.05, but it is still low. We can perform CV on a model with likes:total_videos.

Model 4 (with likes:total_videos interaction terms):

```
# A tibble: 1 x 4
  mean_rmse mean_adj_rsq mean_aic mean_bic
      <dbl>        <dbl>    <dbl>    <dbl>
1     0.328        0.316     81.8     108.
```

The mean RMSE (0.3282339) is barely smaller than that of model3, one without likes and video_length_bin (0.3389576). However given we are have included more terms, our adj r-square shows a clear increase (0.26883 to 0.3157319), BIC shows a slight increase (105.9608 to 108.3907), and AIC shows a slight decrease (88.243 to 81.8137). Because the increase in our adj r-square is very significant, AIC decreases, and BIC only increases by a small amount, we choose the new model, model 4.

Results

Model 4 performance on test:

```
# A tibble: 2 x 3
  .metric .estimator .estimate
  <chr>   <chr>          <dbl>
1 rmse    standard       0.398
2 rsq     standard       0.385
```

Note that we log transformed our response variable. In order to evaluate the meaning of our RMSE of 0.4067, we take $\exp(0.4067) \sim 1.502$. This value is the multiplicative square difference. For example, if have log followers of 16.04552, our model will be more or less off by $16.04552 \pm .4067^2 \implies \exp(16.04552 \pm 0.1654) \implies 7882219 < 9,299,954 < 10,972,689$. This means our model does a fairly poor at predicting a tiktok user's followers. We also have an RSQ of 0.3615, indicating only 36.2% of the variability in followers can be explained by our predictor variables.

The number of total videos, comments, and plays seems to have a clear positive relationship with follower count. This aligns with our expectationsL the more videos you make, the more engagement your profile is likely to have and more followers you may gain. However, shares had a suprising negative relationship with follower count. We hypothesize that users counter-intuitively may share a video because they dislike it, resulting in them not following the user.

When observing the video length bin variable, the middle video length bin (2) has statistically significant difference from the other two video length bins, as well as a statistically significant interaction term with total videos. This shows that not only do medium length videos generate the most followers, but medium length videos combined with a higher number of total videos significantly increase follower count as well. This is certainly an interesting finding from our analysis, as it isn't the most expected result.

Conclusion

We originally decided to look at how TikTok follower counts are impacted by other aspects of a user's account. It is extremely difficult to correctly predict follower count, given our model only captures 36.2% of the variability in the dataset.

Our dataset was extremely difficult to work with, given that it did not meet the conditions for linear regression (linearity and constant variance), and contained multicollinearity. The variables were also extremely large, and needed to be scaled down to have meaningful coefficients - which made late interpretation significantly more difficult. There also may be underlying relationships between follower count, and other portions of the TikTok algorithm that are not contained in the dataset. In the real world, users have reported that TikTok enforces policies differently from user-to-user, and uses different algorithms from region to region.

In order to improve our analysis, it would be helpful to comb TikTok for a dataset that potentially contains more variables. Three potential options include: finding a meaningful way to capture hashtags (which may require manually looking at TikTok videos), finding a meaningful way to capture whether a user typically utilizes trending music, and using the demographic statistics for users (to account for human decisionmaking).