TikTok Analysis

How are views affected by followers, likes, shares, and comments?

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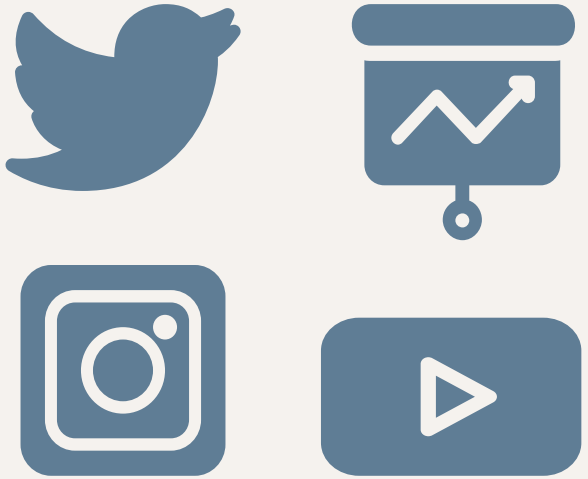
01 Introduction

Motivation

Learning how follower count, average likes, shares, and comments affect views can help influencers determine in which areas they need more engagement and better refine their content.



Dataset

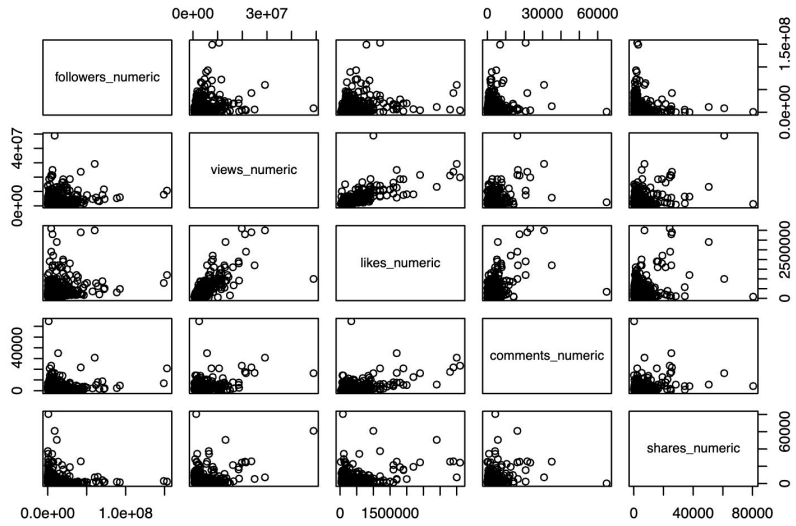
- Kaggle: Social Media Influencers in 2022

  https://www.kaggle.com/datasets/ramjasmaurya/top-1000-social-media-channels

- 1000 observations and 8 variables

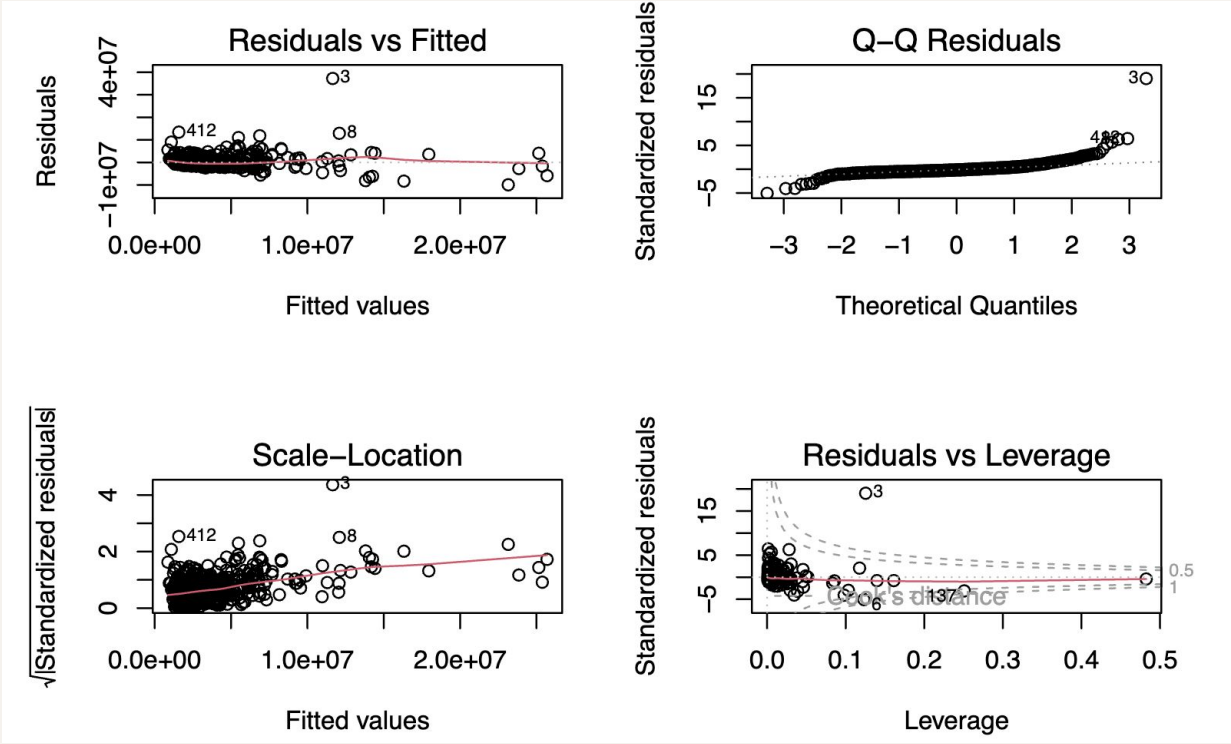
Original Model

```
pairs(tiktok_subset)
```

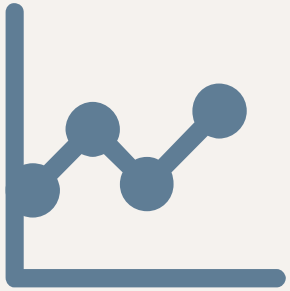



```
## Call:
## lm(formula = views_numeric ~ followers_numeric + likes_numeric +
##     comments_numeric + shares_numeric, data = tiktok_subset)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -9951230  -870340  -336551   445022 37243203
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       5.250e+05  9.955e+04   5.274 1.64e-07 ***
## followers_numeric 2.308e-02  5.707e-03   4.043 5.67e-05 ***
## likes_numeric     6.439e+00  2.374e-01  27.128  < 2e-16 ***
## comments_numeric  5.726e+00  2.300e+01   0.249    0.803
## shares_numeric    7.232e+01  1.344e+01   5.380 9.29e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2092000 on 995 degrees of freedom
## Multiple R-squared:  0.5768, Adjusted R-squared:  0.5751
## F-statistic:   339 on 4 and 995 DF,  p-value: < 2.2e-16
```

```
## Analysis of Variance Table
##
## Response: views_numeric
##                    Df     Sum Sq    Mean Sq   F value    Pr(>F)
## followers_numeric   1 6.4308e+14 6.4308e+14  146.9142 < 2.2e-16 ***
## likes_numeric       1 5.1585e+15 5.1585e+15 1178.4909 < 2.2e-16 ***
## comments_numeric    1 6.7755e+12 6.7755e+12    1.5479    0.2137
## shares_numeric      1 1.2669e+14 1.2669e+14   28.9438  9.29e-08 ***
## Residuals         995 4.3554e+15 4.3772e+12
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```


Residuals vs Fitted
Residuals
Fitted values
3
412
8
−1e+07
4e+07
0.0e+00
1.0e+07
2.0e+07
Q−Q Residuals
Standardized residuals
Theoretical Quantiles
30
−3
−2
−1
0
1
2
3
−5
5
15
Scale−Location
√|Standardized residuals|
Fitted values
0
2
4
Residuals vs Leverage
Standardized residuals
Leverage
137
6
Cook's distance
0.5
1
0.0
0.1
0.2
0.3
0.4
0.5

02 Methods



Handling Outliers

- Remove extreme anomalies to make more reliable model for understanding general TikTok trends
- Regression models were extremely poor when outliers and leverage points were included
- Use new cleaned dataset to create more useful model

```
residuals <- rstudent(model)
cooks_distance <- cooks.distance(model)
n <- nrow(tiktok_subset)
outliers <- which(abs(residuals) > 2 | cooks_distance > 4 / (n - 2))
cleaned_data <- tiktok_subset[-outliers, ]
```

Box-Cox Transformation

```
cleaned_data$comments_numeric[cleaned_data$comments_numeric == 0] <- 1
summary(tranxy <- powerTransform(cbind(views_numeric, followers_numeric, likes_numeric,
                                       comments_numeric, shares_numeric) ~ 1, data = cleaned_data))
```

```
## bcPower Transformations to Multinormality
##                    Est Power Rounded Pwr Wald Lwr Bnd Wald Upr Bnd
## views_numeric       -0.0803        0.00      -0.1694       0.0089
## followers_numeric    0.1860        0.19       0.1497       0.2222
## likes_numeric        0.1286        0.13       0.0515       0.2058
## comments_numeric     0.1928        0.19       0.1536       0.2319
## shares_numeric      -0.0757       -0.08      -0.1275      -0.0240
##
## Likelihood ratio test that transformation parameters are equal to 0
##  (all log transformations)
##                                     LRT df       pval
## LR test, lambda = (0 0 0 0 0) 266.0291  5 < 2.22e-16
##
## Likelihood ratio test that no transformations are needed
##                                     LRT df       pval
## LR test, lambda = (1 1 1 1 1) 4812.938  5 < 2.22e-16
```

```
cleaned_data$transformed_views <- log(cleaned_data$views_numeric)
cleaned_data$transformed_followers <- log(cleaned_data$followers_numeric)
cleaned_data$transformed_likes <- log(cleaned_data$likes_numeric)
cleaned_data$transformed_comments <- log(cleaned_data$likes_numeric)
cleaned_data$transformed_shares <- log(cleaned_data$shares_numeric)
```

- Used Box-Cox to address nonconformities to linear assumptions and create better model fit
- Opted to use log transformation for all variables since the lambdas were all close to zero

Forward Stepwise Variable Selection

- Address multicollinearity by doing variable selection

```
## Start:  AIC=-1158.15
## transformed_views ~ 1
##
##                          Df Sum of Sq    RSS     AIC
## + transformed_likes       1   122.896 156.58 -1706.0
## + transformed_comments    1   122.896 156.58 -1706.0
## + transformed_followers   1    26.303 253.17 -1250.0
## + transformed_shares      1     4.731 274.74 -1172.3
## <none>                                279.48 -1158.2
##
## Step:  AIC=-1705.95
## transformed_views ~ transformed_likes
##
##                          Df Sum of Sq    RSS     AIC
## + transformed_followers   1    4.2463 152.33 -1730.0
## + transformed_shares      1    1.3383 155.24 -1712.1
## <none>                                156.58 -1706.0
##
```

- AIC is lowest for the model that includes all predictor variables except comments

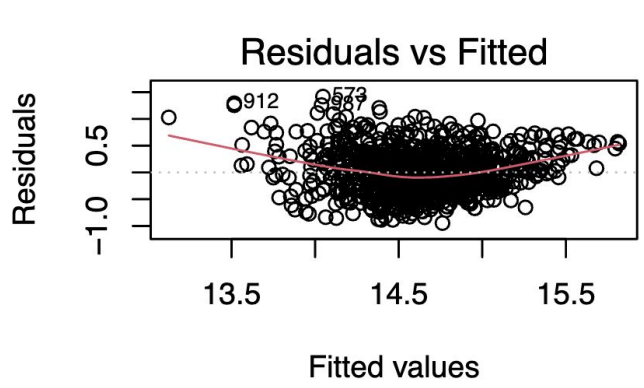
```
## transformed_views ~ transformed_likes + transformed_followers
##
##                          Df Sum of Sq    RSS     AIC
## + transformed_shares      1   0.41734 151.91 -1730.7
## <none>                                152.33 -1730.0
##
## Step:  AIC=-1730.65
## transformed_views ~ transformed_likes + transformed_followers +
##     transformed_shares
##
##        Df Sum of Sq    RSS     AIC
## <none>              151.91 -1730.7
```

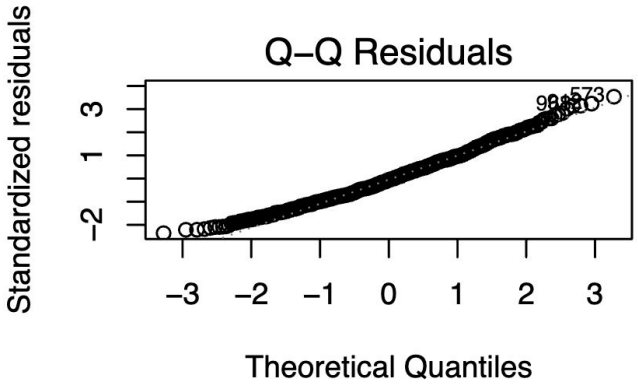
```
## Call:
## lm(formula = transformed_views ~ transformed_followers + transformed_likes,
##     data = cleaned_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.94614 -0.29981 -0.02219  0.26205  1.41715
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)            6.46052    0.29147  22.165  < 2e-16 ***
## transformed_followers  0.05150    0.01003   5.135 3.42e-07 ***
## transformed_likes      0.59473    0.02377  25.024  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4013 on 946 degrees of freedom
## Multiple R-squared:  0.4549, Adjusted R-squared:  0.4538
## F-statistic: 394.8 on 2 and 946 DF,  p-value: < 2.2e-16
```

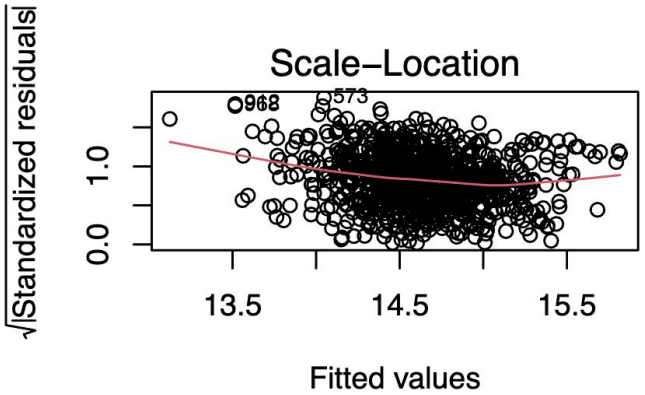
Numerical Output for Final Model

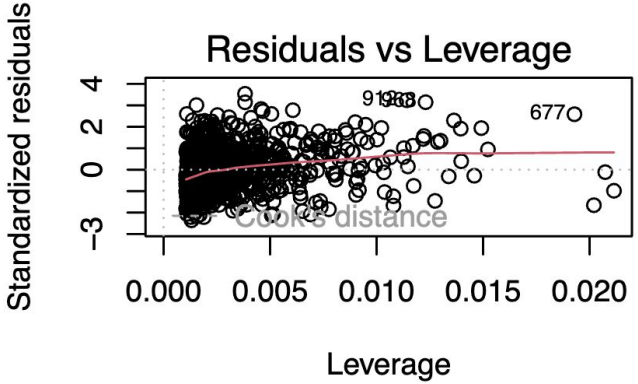
- All predictor variables are significant except “shares”
- Further investigation shows that shares don’t meaningfully contribute to the model and AIC with and without shares are nearly identical

```
## Analysis of Variance Table
##
## Response: transformed_views
##                           Df  Sum Sq Mean Sq F value    Pr(>F)
## transformed_followers      1  26.303  26.303  163.35 < 2.2e-16 ***
## transformed_likes          1 100.839 100.839  626.22 < 2.2e-16 ***
## Residuals                946 152.333   0.161
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```


Residuals vs Fitted
Residuals
Fitted values
912
573
13.5
14.5
15.5
−1.0
0.5


Q–Q Residuals
Standardized residuals
Theoretical Quantiles
573
−3
−2
−1
0
1
2
3


Scale–Location
√|Standardized residuals|
Fitted values
573
13.5
14.5
15.5
0.0
1.0


Residuals vs Leverage
Standardized residuals
Leverage
Cook's distance
677
0.000
0.005
0.010
0.015
0.020
−3
0
2
4

03 Conclusion

Final Model Equation:

$$\ln(\text{Views}) = 6.461 + 0.052 * \ln(\text{Followers}) + 0.595 * \ln(\text{Likes})$$

- A 1% increase in followers leads to a 0.052% increase in views
- A 1% increase in average likes increases views by 0.595%

What does this mean?

- It indicates a positive relationship for followers and especially views, reinforcing the value of growing a dedicated audience and underscoring likes as the main priority for content popularity and engagement.

Because of the challenges faced while developing the model:

- Normality of errors
- Homoscedasticity
- Influence points

The model may not account for all factors, such as content quality or external trends.

- Despite challenges, the final model offers insights into the influence of likes, followers, and shares on view counts as 45.38% (R-squared value) of the variation in the view counts can be explained by the model.

- The overall model significance, as indicated by the F-statistic's p-value, is less than 2.2e-16, which is far below the alpha level of 0.05. This shows that the model is statistically significant at predicting views for tiktokers.