Name: \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

# **Do You Have What It Takes to Go Viral?**

In this lesson, we'll investigate what makes TikTok videos successful by analyzing real data. Can we predict which videos will go viral? Let's find out by examining TikTok engagement patterns.

Here is some TikTok data for 10 random videos taken from the TikTok platform:

| **Video** | **Category** | **Duration (sec)** | **Views** | **Likes** | **Engagement Rate (%)** | **Time Posted** | **Hashtags** |
| --- | --- | --- | --- | --- | --- | --- | --- |
| A | Dance | 15 | 105,000 | 12,600 | 12.0 | 8 PM | 4 |
| B | Sports | 45 | 28,500 | 2,280 | 8.0 | 3 PM | 6 |
| C | Comedy | 22 | 89,000 | 9,790 | 11.0 | 7 PM | 3 |
| D | Tutorial | 58 | 15,000 | 900 | 6.0 | 11 AM | 5 |
| E | Dance | 18 | 95,000 | 11,400 | 12.0 | 9 PM | 3 |
| F | Gaming | 31 | 42,000 | 2,940 | 7.0 | 4 PM | 7 |
| G | News | 25 | 68,000 | 4,760 | 7.0 | 8 AM | 4 |
| H | Comedy | 20 | 82,000 | 9,020 | 11.0 | 8 PM | 3 |
| I | Food | 35 | 31,000 | 2,170 | 7.0 | 2 PM | 5 |
| J | Music | 12 | 93,000 | 10,230 | 11.0 | 7 PM | 4 |

1. What patterns do you notice about views and engagement?
2. Make three predictions about what factors lead to higher views. Explain your reasoning.
3. Take a random sample of 5 videos from our dataset and calculate their mean view count. Do this three times.
4. Now let’s take some actual TikTok data to look for trends. Please navigate to <https://webr.r-wasm.org/latest/> and in the top right pane click Upload File and choose the tiktok\_data.csv file provided by your instructor. Before we analyze the data we need to load those capabilities into the platform so please copy and paste the following into the first three lines in the currently empty top left pane.

library(ggplot2)

library(dplyr)

library(tidyr)

 In order for the libraries to load, you may need to look in the bottom left pane and type in

a 1 to select “Yes” to have the program load them. Once you do that three times, let’s make sure the dataset is loaded and that we can read it correctly by pasting the following code underneath:

 tiktok\_data <- read.csv("/tiktok\_data.csv", stringsAsFactors = TRUE)

 str(tiktok\_data)

head(tiktok\_data)

summary(tiktok\_data)

 What are some key summary statistics that stick out to you in your dataset?

1. Now let’s start creating some visuals to help us really look into this data. First let’s just look at a distribution of views:
 ggplot(tiktok\_data, aes(x = Views)) +

 geom\_histogram(bins = 20, fill = "skyblue", color = "black") +

 labs(title = "Distribution of TikTok Video Views",

 x = "Views",

 y = "Frequency") +

 theme\_minimal()

According to your data, what is the approximate range of views of this random sample of videos? From about \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_ views to about \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_ views.

1. Okay, now let’s drill down into some categories. Go ahead and copy and paste this code over the code of the last plot you made:

 ggplot(tiktok\_data, aes(x = Category, y = Views, fill = Category)) +

 geom\_boxplot() +

 labs(title = "Views by Content Category",

 x = "Category",

 y = "Views") +

 theme\_minimal() +

 theme(axis.text.x = element\_text(angle = 45, hjust = 1),

 legend.position = "none")

 What categories seem very popular according to your dataset?

 Which ones seem to have less views?

1. If we define the Engagement Rate as likes/views, let’s see which categories seem to actually cause a viewer to hit that heart button.

 ggplot(tiktok\_data, aes(x = Category, y =

as.numeric(Engagement), fill = Category)) +

 geom\_boxplot() +

 labs(title = "Engagement Rate by Content Category",

 x = "Category",

 y = "Engagement") +

 theme\_minimal() +

 theme(axis.text.x = element\_text(angle = 45, hjust = 1),

 legend.position = "none")

 Do the most viewed categories also have the highest engagement rates? Use specific

 data to back up your claim.

1. Now let’s analyze the data to see if there are any trends in video duration.

 # Create a scatter plot of duration vs. views

ggplot(tiktok\_data, aes(x = Duration, y = Views)) +

 geom\_point(aes(color = Category), alpha = 0.7) +

 geom\_smooth(method = "loess", se = TRUE, color = "black") +

 labs(title = "Relationship Between Video Duration and Views",

 x = "Duration (seconds)",

 y = "Views") +

 theme\_minimal()

# Check correlation

cor.test(tiktok\_data$Duration, tiktok\_data$Views)

 What does this graph tell you about optimal video duration?

1. Now that we know how long our videos should be, let’s look to see if there is an optimal time to post a TikTok video.

 # Extract hour from Time\_Posted for analysis

extract\_hour <- function(time\_str) {

 # Extract components using regex

 parts <- regmatches(time\_str, regexec("(\\d+):(\\d+)\\s+(AM|PM)", time\_str))[[1]]

 if(length(parts) < 4) return(NA) # Return NA if pattern doesn't match

 hour <- as.numeric(parts[2])

 ampm <- parts[4]

 # Convert to 24-hour format

 if(ampm == "PM" && hour < 12) hour <- hour + 12

 if(ampm == "AM" && hour == 12) hour <- 0

 return(hour)

}

# Add a column with the extracted hour

tiktok\_data$hour <- sapply(tiktok\_data$Time\_Posted, extract\_hour)

# Create the plot

ggplot(tiktok\_data, aes(x = factor(hour), y = Views)) +

 geom\_boxplot(fill = "skyblue") +

 labs(title = "Views by Posting Hour",

 x = "Hour of Day (24-hour format)",

 y = "Number of Views") +

 theme\_minimal()

 What trends do you notice about the best times to post a video? How do those trends

 seem to support people’s day to day lifestyles?

1. Lastly, let’s see if there’s any data to support whether we should include a sound clip on our video.

 ggplot(tiktok\_data, aes(x = Uses\_Trending, y = Views,

fill = Uses\_Trending)) +

 geom\_boxplot() +

 labs(title = "Impact of Trending Sounds on Views",

 x = "Uses Trending Sound",

 y = "Views") +

 theme\_minimal() +

 theme(legend.position = "none")

What does the interquartile range tell you about the difference?

What about the median?

What about the maximum?

Based on these findings, what is your recommendation about playing a trending sound clip?

1. Now let’s run a correlation analysis:

 # First, ensure Engagement is numeric

tiktok\_data$Engagement <- as.numeric(tiktok\_data$Engagement)

# Create correlation matrix

correlation\_data <- tiktok\_data %>%

 select(Views, Likes, Shares, Comments, Duration, Hashtags, Engagement\_Rate)

# Calculate correlation matrix

correlation\_matrix <- cor(correlation\_data, use = "complete.obs")

# Install and load the corrplot package if not already available

if (!requireNamespace("corrplot", quietly = TRUE)) {

 install.packages("corrplot")

}

library(corrplot)

# Create correlation plot

corrplot(correlation\_matrix,

 method = "number",

 type = "upper",

 tl.col = "black",

 col = colorRampPalette(c("darkblue", "white", "darkred"))(100),

 diag = FALSE)

 Based on this heatmap, what things does “views” have a strong positive correlation
 with?

 Based on this heatmap, what things does “views” have a strong negative correlation
 with?

1. What are some key insights from this lesson and data that you might use if you were thinking about posting your next video and wanting the most views and likes?

##

## **Exit Ticket**

Using what we've learned about sampling distributions:

1. Why do different samples of 30 videos give us different means?
2. What would happen to our dot plot of sample means if we used samples of 100 videos instead?
3. How could a content creator use this information to improve their TikTok strategy?

## **Homework Problems**

1. If the mean views for dance videos is 50,000 with σ = 15,000, what's the probability a sample of 30 videos will have a mean above 55,000?
2. A content creator's videos have a mean engagement rate of 8% with σ = 2%. If they post 40 videos, what's the probability their average engagement will be between 7.5% and 8.5%?
3. Using the Central Limit Theorem, explain why taking a larger sample of videos gives us a more reliable estimate of true TikTok success rates.