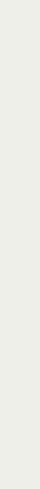
# Instagram Data Analysis

By Haripriya and Taryn





### **Background on Data**

- ★ We used data of 11692 instagram posts.
  - We extracted relevant data, which would include the following:
    - Username
    - Following
    - Followers
    - Multiple\_images
    - ls\_video

is_video	caption	comments	likes	created_at	location	imageUrl	multiple_images	username	followers	following
False	I'm a brunch & Iced Coffee girlie ● Q \n\nTop @	268	16382.0	1.709327e+09	NaN	https://instagram.flba2- 1.fna.fbcdn.net/v/t39	True	christendominique	2144626.0	1021.0
True	Brow tips I really wish I would have know w	138	9267.0	1.709241e+09	NaN	https://instagram.flba2- 1.fna.fbcdn.net/v/t51	False	christendominique	2144626.0	1021.0
True	OMG I can't believe it's already been 1 yr sin	1089	10100.0	1.709155e+09	NaN	https://instagram.flba2- 1.fna.fbcdn.net/v/t51	False	christendominique	2144626.0	1021.0
True	90's Glam was Pam! \n\nMakeup \n@smashboxcosme	271	6943.0	1.709065e+09	NaN	https://instagram.flba2- 1.fna.fbcdn.net/v/t51	False	christendominique	2144626.0	1021.0
True	Chiseled & Sculptured	145	17158.0	1.7087 <b>1</b> 8e+09	NaN	https://instagram.flba2- 1.fna.fbcdn.net/v/t51	False	christendominique	2144626.0	1021.0

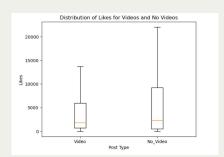
	created_at	followers	following
count	3.744000e+03	3.744000e+03	3.744000e+03
mean	1.681608e+09	1.894394e+06	1.031337e+04
std	4.969690e+07	6.845989e+06	1.198092e+05
min	1.450283e+09	1.000000e+00	0.000000e+00
25%	1.685892e+09	1.971580e+05	4.200000e+02
50%	1.705337e+09	4.990260e+05	7.850000e+02
75%	1.708531e+09	1.117678e+06	1.296000e+03
max	1.709526e+09	7.180750e+07	1.568394e+06

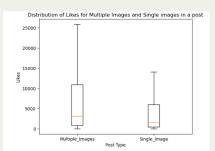
Goal: Clean the data by removing NA values and scaling it for better results

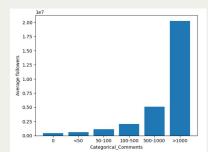
```
# Convert columns to numeric types
instagram_df['likes'] = pd.to_numeric(instagram_df['likes'], errors='coerce')
instagram_df['comments'] = pd.to_numeric(instagram_df['comments'], errors='coerce')
instagram_df['multiple_images'] = instagram_df['multiple_images'].astype(bool)
```

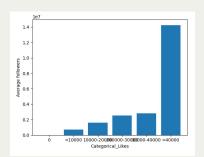
# **Data Preprocessing**

Goal: Trying to visualize the data with various graphs to help identify possible trends









## **Data Visualization**

#### **Naive Bayes Process**

#### **STEPS**

- 1. Create categorical columns of the quantitative data (ex: we encoded all the values greater than 100 comments into a category of 100-200)
  - Converting data accordingly to promote consistency
  - Taking into account values above our range
- 2. Making a column for the ratio between followers and following and another column with the influencer status depending on the ratio (1 following : 6000 followers)
- 3. Splitting data into test and training and having the Gaussian Naive Bayes model train with the training data
- 4. Gaussian model will predict the test data using the knowledge from training data
- 5. Specifying conditions
- 6. Calculating accuracy and the prediction of the model

Categorical_Likes	Categorical_Comments	Followers and Following Ratio	Influencer
10000-20000	100-500	2100.515181	False
<10000	100-500	2100.515181	False
10000-20000	>1000	2100.515181	False
<10000	100-500	2100.515181	False
10000-20000	100-500	2100.515181	False

**Goal:** Identifying how various components affect the possibility of an instagram user being considered an influencer.

#### **Key Takeaways:**

- ★ We have found that the number of likes and comments a person has influences their influencer status more than the components of their posts
- ★ With the specific conditions below, this is what our model predicts with 83.58% accuracy

Accuracy: 83.58%

Prediction for a post who has a video, multiple images, 10000 - 20000 likes, and more than 1000 comments: Influencer = No Prediction for a post who has a video, multiple images, less than 10000, and more than 1000 comments: Influencer = Yes

# Naive Bayes Results

#### **Decision Tree Process**

#### **STEPS**

- Starting the same as Naive Bayes, Create categorical columns of the quantitative data (ex: we encoded all the values greater than 100 comments into a category of 100-200)
  - Converting data accordingly to promote consistency
  - Taking into account values above our range
- 2. Set thresholds for "Influencer" status
  - o Followers to following: 6000:1
  - o Likes per post: 10000
  - Comments per post: 500
  - Number of images: at least one
- Calculate accuracy and precision, print accuracy report based on results

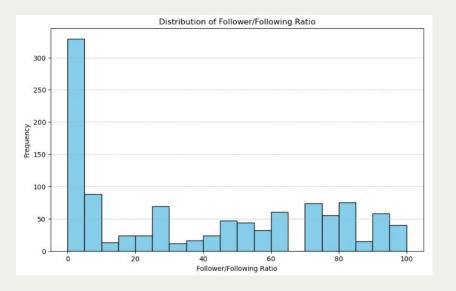
multiple_images	username	followers	following
True	christendominique	2144626.0	1021.0
False	christendominique	2144626.0	1021.0
False	christendominique	2144626.0	1021.0
False	christendominique	2144626.0	1021.0
False	christendominique	2144626.0	1021.0

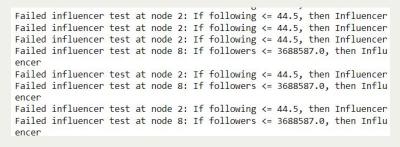
#### **Accuracy Visualization**

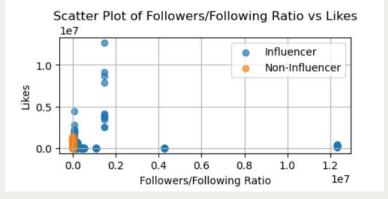
Goal: Determine influencer status based on following ratio, likes, comments, and number of images (all taken from data)

Accuracy: 0.94 Classification		544		
	precision	recall	f1-score	support
False	0.97	0.96	0.97	2950
True	0.82	0.85	0.84	558

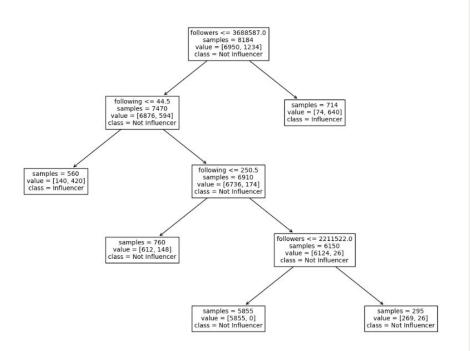
- Accuracy: 94.669%
- Precision: measures accuracy of the positive predictions
  - 97% of "not an influencer" were actually not an influencer
  - 82% of "influencer" were actually influencers
- Recall: percent actually "correct" by the classifier
- F1-Score: mean of precision and recall, shows truth behind predictions
- Support: number of actual occurrences of each category







## **Data Visualization**



## Decision Tree Results

## **Naive Bayes**

- Focuses on conditions of a specific post and tried to determine if the user has the status of "influencer."
  - Predicts whether the person is an influencer
- We created categories that would help classify
- Accuracy at 83.58%

#### **Decision Tree**

- Focused more on follower/following ratio to determine "influencer" status
  - Certain accounts that had massive likes and comments got swept under the rug because of the ratio being too low
- All needs must be met in order to classify as an influencer
- Preset criteria in order to classify
- Higher Accuracy at about 94%

# Thank you for your time!