Milestone 1: Project Proposal and Data Selection/Preparation

1: Preparing for Your Project Proposal

1.1: Client/Dataset Selection

Client: Lobbyists4America

Dataset name: Congressional Tweets Dataset (2008–2017)

Source (example): https://www.dropbox.com/sh/qrq1pcjsji0v03u/AAC639WcH58tM0YZperwY388a?dl=0

Why this dataset was selected:

- The dataset directly aligns with Lobbyists4America's goal: understanding topics, key members, and relationships within U.S. Congress to inform lobbying strategy.
- Ten years (2008–2017) gives a broad temporal span to detect topic trends, shifts around major political events (e.g., elections, legislation bursts), and persistent influencers.
- Tweets include text, timestamps, user metadata, mentions/retweets — useful for NLP topic modeling, network analysis (mentions/retweets), and member-level summary statistics.

1.2: Data Import & Cleaning

1.2.1: Importing the Data

```
import json
import os
import pandas as pd

tweets = "data/tweets.json"
users = "data/users.json"

tweets_path = os.path.join(os.getcwd(), tweets)
users_path = os.path.join(os.getcwd(), users)

tweets_data = []
user_data = []

with open(tweets_path, "r", encoding="utf-8") as f:
    for line in f:
        if line.strip():  # skip empty lines
            tweets_data.append(json.loads(line))

with open(users_path, "r", encoding="utf-8") as f:
    for line in f:
        if line.strip():  # skip empty lines
            user_data.append(json.loads(line))

tweets_df = pd.DataFrame(tweets_data)
user_df = pd.DataFrame(user_data)
```

1.2.2: Removing unwanted columns

```
tweets_columns_needed = [
    "created_at",
    "screen_name",
    "user_id",
    "text",
    "lang",
    "retweet_count",
    "favorite_count",
    "entities",
    "in_reply_to_user_id",
    "in_reply_to_screen_name",
    "source",
    "is_quote_status",
    "quoted_status_id"
]
```

```
user_columns_needed = [
    "id",
    "id_str",
    "screen_name",
    "name",
    "description",
    "followers_count",
    "friends_count",
    "favourites_count",
    "statuses_count",
    "verified",
    "protected",
    "created_at",
    "location"
]

tweets_clean = tweets_df[tweets_columns_needed]
user_clean = user_df[user_columns_needed]
```

1.2.2: Data Cleaning

```
# Drop completely empty rows
tweets_clean = tweets_clean.dropna(how="all")
user_clean = user_clean.dropna(how="all")

# Fill or drop specific important columns
tweets_clean = tweets_clean.dropna(subset=["text", "created_at"])
user_clean = user_clean.dropna(subset=["id", "screen_name"])

tweets_clean.drop_duplicates(subset=["text", "created_at"], inplace=True)
user_clean.drop_duplicates(subset=["id"], inplace=True)
```

1.3: Initial exploration of data

```
# Number of rows and columns
print("Tweets dataset shape:", tweets_clean.shape)
print("User dataset shape:", user_clean.shape)

# Column names
print("\nTweets columns:", tweets_clean.columns.tolist())
print("User columns:", user_clean.columns.tolist())

# Data types and nulls
print("\nTweets info:")
tweets_clean.info()
print("\nUser info:")
user_clean.info()
```

```
Tweets dataset shape: (1243322, 13)
User dataset shape: (548, 13)

Tweets columns: ['created_at', 'screen_name', 'user_id', 'text', 'lang', 'retweet_count', 'favorite_count', 'entitie
User columns: ['id', 'id_str', 'screen_name', 'name', 'description', 'followers_count', 'friends_count', 'favourites

Tweets info:
<class 'pandas.core.frame.DataFrame'>
Index: 1243322 entries, 0 to 1243369
Data columns (total 13 columns):
 #   Column                  Non-Null Count    Dtype
---  ------                  --------------    -----
 0   created_at              1243322 non-null  datetime64[ns]
 1   screen_name             1243322 non-null  object
 2   user_id                 1243322 non-null  int64
 3   text                    1243322 non-null  object
 4   lang                    1243322 non-null  object
 5   retweet_count           1243322 non-null  int64
 6   favorite_count          1243322 non-null  int64
 7   entities                1243322 non-null  object
 8   in_reply_to_user_id     65411 non-null    float64
 9   in_reply_to_screen_name  65411 non-null    object
 10  source                  1243322 non-null  object
 11  is_quote_status         1243322 non-null  bool
 12  quoted_status_id        56417 non-null    float64
dtypes: bool(1), datetime64[ns](1), float64(2), int64(3), object(6)
memory usage: 124.5+ MB

User info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 548 entries, 0 to 547
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype
```

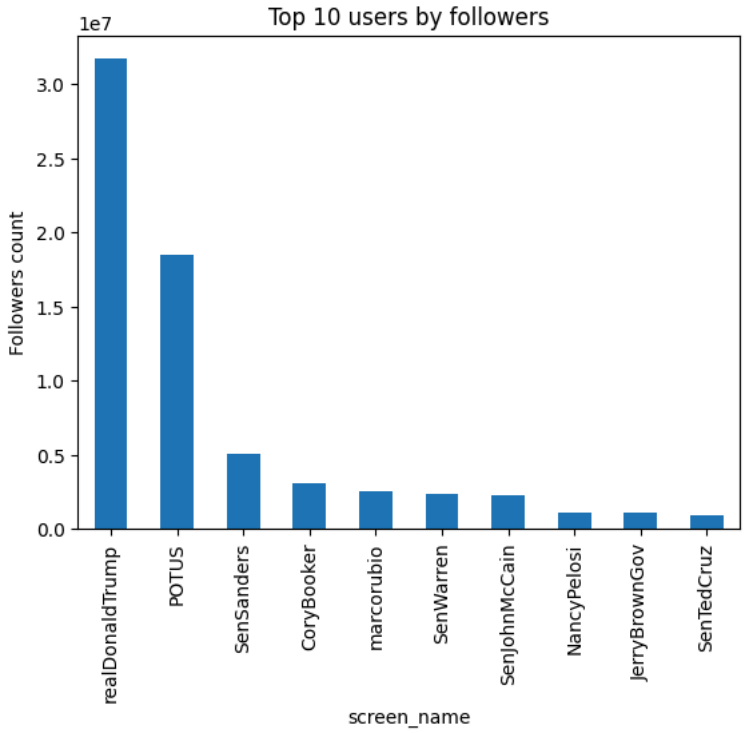
```
---  ------            --------------  -----
 0   id                548 non-null    int64
 1   id_str            548 non-null    object
 2   screen_name       548 non-null    object
 3   name              548 non-null    object
 4   description       548 non-null    object
 5   followers_count   548 non-null    int64
 6   friends_count     548 non-null    int64
 7   favourites_count  548 non-null    int64
 8   statuses_count    548 non-null    int64
 9   verified          548 non-null    bool
 10  protected         548 non-null    bool
 11  created_at        548 non-null    object
 12  location          548 non-null    object
dtypes: bool(2), int64(5), object(6)
memory usage: 48.3+ KB
```

```
# Numeric stats
tweets_clean.describe()
user_clean.describe()
```

	id	followers_count	friends_count	favourites_count	statuses_count
count	5.480000e+02	5.480000e+02	548.000000	548.000000	548.000000
mean	7.236303e+16	1.634339e+05	2033.731752	413.912409	3658.959854
std	2.312213e+17	1.597357e+06	6278.436076	965.151440	4259.273134
min	5.558312e+06	4.000000e+00	0.000000	0.000000	0.000000
25%	5.768882e+07	8.960250e+03	368.000000	32.750000	1387.500000
50%	2.470519e+08	1.673200e+04	751.500000	120.500000	2684.000000
75%	1.212627e+09	3.308100e+04	1670.500000	379.750000	4509.250000
max	8.547151e+17	3.171258e+07	92934.000000	12507.000000	59535.000000

```
import matplotlib.pyplot as plt

# Top 10 users by followers
user_clean.nlargest(10, 'followers_count')[['screen_name','followers_count']].plot.bar(x='screen_name', y='follower
plt.title("Top 10 users by followers")
plt.ylabel("Followers count")
plt.show()
```

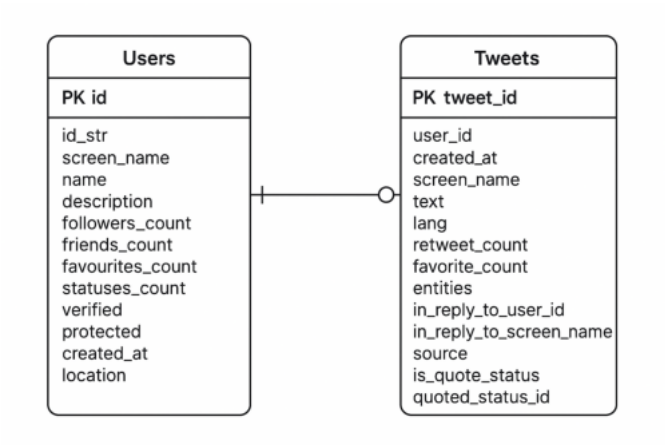


1.4 : Proposed ERD

```
import matplotlib.pyplot as plt
import matplotlib.image as mpimg

# Load the image
img = mpimg.imread('./data/ERD.png')

# Display the image
plt.imshow(img)
plt.axis('off')  # Hide axes
plt.show()
```



Project Proposal - Lobbyists4America

Description

This project aims to analyze congressional tweets from 2008 to 2017 to uncover trends in topics, member activity, and relationships within the U.S. Congress. By examining tweet content, engagement metrics, and interactions between members, we hope to identify which legislators are most influential, which topics dominate discussions, and how members are connected through mentions, replies, and quotes. These insights will be valuable to Lobbyists4America and their clients, who want to strengthen their lobbying strategies by understanding legislative communication patterns. Political analysts, advocacy organizations, and policy-focused researchers may also find the findings useful to better understand the social media behavior of Congress. The project will provide actionable intelligence that can inform strategic decisions, identify key influencers, and reveal emerging trends in legislative priorities.

Questions

1. Which topics, hashtags, and keywords are most frequently discussed by members of Congress, and how have these trends shifted from 2008 to 2017?
2. Which Congress members are the most active or influential on Twitter based on tweets, retweets, mentions, and follower engagement?
3. How are members connected to each other through replies, mentions, and quotes, and can we identify clusters or alliances based on these interactions?

Hypotheses

1. Members with higher follower counts and more statuses will have higher engagement on their tweets.
2. Specific topics (e.g., healthcare, finance, legislation) will dominate discussion during certain years or political events.
3. Members within the same political party or committees are more likely to interact with each other via mentions and replies.

Approach

We will start by cleaning and exploring the tweets and user datasets, focusing on key columns such as `created_at`, `text`, `screen_name`, `user_id`, `retweet_count`, `favorite_count`, `entities`, and reply/quote relationships. Topic analysis will be performed using hashtags, keywords, and natural language processing techniques, while user influence will be assessed via follower counts and engagement metrics. Interaction networks will be constructed using replies, mentions, and quotes to visualize relationships and identify clusters. We will track trends over time to understand shifts in focus and engagement, and evaluate hypotheses using descriptive statistics, network metrics (e.g., centrality), and time-series analysis. Overall, this approach aims to provide both high-level insights and actionable details for stakeholders.