In [5]:
```python
# task 3
# import libraries for this task
import pandas as pd
import json
import datetime
```

Step 1: Network overlap: with the "following.json" dataset, write a function that takes any two influencers' user ID's and calculate the fraction of followers these two influencers share over the total number of followers of the less followed influencer. The reference date is April 30, 2022.

In [33]:
```python
# import following.json into the same directory (on anacondas jupyter notebook) and import it into this file
# for analysis.
following_df = pd.read_json('following.json')
```

In [112…
```python
following_df
```

Out[112]:

	follower_uid	influencer_uid	follow_timestamp
0	829451382935531520	902200087	2022-04-26 16:07:33 UTC
1	2872039840	969221141347913728	2022-02-18 15:51:26 UTC
2	1499994241979801600	14709326	2022-04-23 05:40:07 UTC
3	1135376232839864320	836533158669500416	2022-04-28 13:26:38 UTC
4	431066540	16106584	2017-04-14 11:35:28 UTC
...	...	...	...
551130	78333251	158414847	2013-11-11 01:20:59 UTC
551131	2802988291	158414847	2020-01-11 14:50:13 UTC
551132	1519077442006261760	158414847	2022-04-27 01:35:00 UTC
551133	2861786021	158414847	2019-07-21 14:38:03 UTC
551134	1518751896810496000	158414847	2022-04-26 00:48:35 UTC

551135 rows × 3 columns

In [4]:
```python
following_df.head() # look at the structure of the dataframe to see how i can format the function
```

Out[4]:

	follower_uid	influencer_uid	follow_timestamp
0	829451382935531520	902200087	2022-04-26 16:07:33 UTC
1	2872039840	969221141347913728	2022-02-18 15:51:26 UTC
2	1499994241979801600	14709326	2022-04-23 05:40:07 UTC
3	1135376232839864320	836533158669500416	2022-04-28 13:26:38 UTC
4	431066540	16106584	2017-04-14 11:35:28 UTC

In [11]:
```python
following_df.dtypes # check the data types - we can see the 'follow_timestamp' column is a of type str.
```

Out[11]:
```
follower_uid         int64
influencer_uid       int64
follow_timestamp    object
dtype: object
```

In [75]:
```python
# function for step 1)

# the set up of this function assumes that any dataframe u pass in has the same column names
# as the "following_df" dataset.

def shared_followers(df: pd.DataFrame, influencer1_id, influencer2_id):

    # filter data to include only entries from April 30, 2022
    filtered_data = df[df['follow_timestamp'].str.startswith('2022-04-30')]

    # get set of follower IDs for each influencer (each follower is unique)
    influencer1_followers = set(filtered_data[filtered_data['influencer_uid'] == influencer1_id]['follower_uid'])
    influencer2_followers = set(filtered_data[filtered_data['influencer_uid'] == influencer2_id]['follower_uid'])

    # calculate total number of unique followers for each influencer that they both share
    overlap_count = len(influencer1_followers.intersection(influencer2_followers))

    # calculate total number of followers of the less followed influencer
    total_followers = min(len(influencer1_followers), len(influencer2_followers))

    # calculate fraction of followers that two influencers share
    if total_followers > 0: # just in case the total_followers of that influencer are 0, we don't want a
        # ZeroDivError.

        overlap_fraction = overlap_count / total_followers
    else:
        return 0.0

        # just made the function return 0.0 when the lower influencer has 0 followers (no intersection between
        # any followers in this case)

    return overlap_fraction
```

In [78]:
```python
# example usage:
shared = shared_followers(following_df, 158414847, 158414847)
print(shared)
# makes sense that the same influencer has a fraction of 1.0 (all followers are same) on april 30th.
```

```
1.0
```

Step 2: Engagement overlap: with the "engagement.json" dataset, write a function that takes any two influencers' user ID's and calculate the fraction of engagers of these two influencers' tweets as a function of the total number of engagers of the less engaged influencer, over the period of April 22, 2022 to April 30, 2022.

In [79]:
```python
# import engagement.json into the same directory (on anacondas jupyter notebook) and import it into this file
engagement_df = pd.read_json('engagement.json')
```

In [81]:
```python
engagement_df.head()
```

Out[81]:

	follower_uid	influencer_uid	engaged_tweetID	engaged_dt
0	1000041135396433920	1298372735383605248	1520185102143303680	2022-04-29
1	1000041135396433920	158414847	1520185102143303680	2022-04-29
2	1000041135396433920	288277167	1520185102143303680	2022-04-29
3	1000146462112665600	1022693675250249728	1518276445335961600	2022-04-24
4	1000146462112665600	10774652	1518276445335961600	2022-04-24

In [127…
```python
g = engagement_df.groupby('influencer_uid')
```

In [131…
```python
id_ = 158414847
n = g.get_group(id_)
```

In [132…
```python
n # so the tweetid is the tweet of the influencer that is being engaged with.
```

Out[132]:

	follower_uid	influencer_uid	engaged_tweetID	engaged_dt
1	1000041135396433920	158414847	1520185102143303680	2022-04-29
17	1000179949519564800	158414847	1518276445335961600	2022-04-25
31	1000768242594533376	158414847	1520185102143303680	2022-04-30
57	1000889457849978880	158414847	1519375241734197248	2022-04-28
58	1000889457849978880	158414847	1520185102143303680	2022-04-30
...	...	...	...	...
155778	998332081657794560	158414847	1520185102143303680	2022-04-30
155827	999023394845839360	158414847	1519375241734197248	2022-04-28
155898	999958937368780800	158414847	1519375241734197248	2022-04-28
155899	999958937368780800	158414847	1520185102143303680	2022-04-30
155946	999988765664993280	158414847	1520185102143303680	2022-04-30

6426 rows × 4 columns

In [82]:
```python
engagement_df.dtypes # engaged_dt is an object
```

Out[82]:
```
follower_uid        int64
influencer_uid      int64
engaged_tweetID     int64
engaged_dt         object
dtype: object
```

In [83]:
```python
engagement_df.tail()
```

Out[83]:

	follower_uid	influencer_uid	engaged_tweetID	engaged_dt
155961	999988765664993280	807095	1520185102143303680	2022-04-30
155962	999988765664993280	813286	1520185102143303680	2022-04-30
155963	999988765664993280	825476542478303232	1520185102143303680	2022-04-30
155964	999988765664993280	886398296146706432	1520185102143303680	2022-04-30
155965	999988765664993280	970207298	1520185102143303680	2022-04-30

In [136…
```python
# function 2)

def shared_engagements(df: pd.DataFrame, influencer1_id, influencer2_id):

    # Filter data to include only entries between April 22, 2022, and April 30, 2022, for both influencers
    filtered_data = df[(df['engaged_dt'] >= '2022-04-22') & (df['engaged_dt'] <= '2022-04-30') &
                       ((df['influencer_uid'] == influencer1_id) | (df['influencer_uid'] == influencer2_id))]

    influencer1_tweets = set(filtered_data[filtered_data['influencer_uid'] == influencer1_id]['engaged_tweetID'])
    influencer2_tweets = set(filtered_data[filtered_data['influencer_uid'] == influencer2_id]['engaged_tweetID'])

    # calculate total number of unique engaged tweets for each influencer that they both share
    overlap_count = len(influencer1_tweets.intersection(influencer2_tweets))

    # calculate total number of engaged tweets of the less engaged influencer
    total_tweets = min(len(influencer1_tweets), len(influencer2_tweets))

    # calculate fraction of engaged tweets that two influencers share
    if total_tweets > 0: # avoiding zerodiverror
        overlap_fraction = overlap_count / total_tweets
    else:
        return 0.0

    return overlap_fraction
```

In [105…
```python
shared = shared_engagements(engagement_df, 158414847, 158414847)
print(shared)
# 2 same influencers have a 1.0 ratio of shared engagement of tweets within the same period of time.
```

```
1.0
```

Step 3: Produce two histograms of network overlap (Step 2) and engagement overlap (Step 3) measures, respectively, across all influencer pairs

In [107…
```python
import matplotlib.pyplot as plt
```

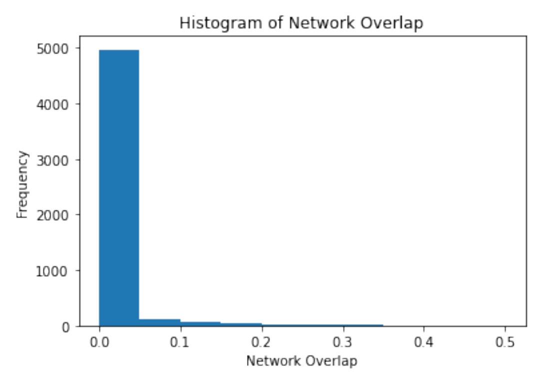
In [ ]:
```python
# network overlap - fraction of same followers on april 30th, bw 2 influencers
# engagement overlap - fraction of engaged tweets bw 22-30 of two influencers
```

In [123…
```python
# network overlap histogram

network_overlap = []
engagement_overlap = []
influencer_ids = list(following_df['influencer_uid'].unique())

# loop through all possible influencer pairs
for i in range(len(influencer_ids)):
    for j in range(i+1, len(influencer_ids)):
        # call shared_followers functions
        network_overlap.append(shared_followers(following_df, influencer_ids[i], influencer_ids[j]))

# create histogram for network overlap
plt.hist(network_overlap)
plt.xlabel('Network Overlap')
plt.ylabel('Frequency')
plt.title('Histogram of Network Overlap')
plt.show()
```

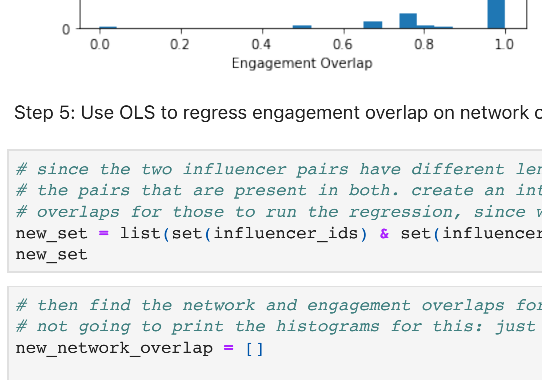


In [137…
```python
# engagement overlap histogram

influencer_ids_2 = list(engagement_df['influencer_uid'].unique())

for i in range(len(influencer_ids_2)):
    for j in range(i+1, len(influencer_ids_2)):
        # call shared_engagements functions
        engagement_overlap.append(shared_engagements(engagement_df, influencer_ids_2[i], influencer_ids_2[j]))

# create histogram for engagement overlap
plt.hist(engagement_overlap, bins=23)
plt.xlabel('Engagement Overlap')
plt.ylabel('Frequency')
plt.title('Histogram of Engagement Overlap')
plt.show()
```



Step 5: Use OLS to regress engagement overlap on network overlap measures for all influencers pairs, and plot the regression results on a two-dimensional graph with standard error bands.

In [ ]:
```python
# since the two influencer pairs have different lengths overthe two dataframes, im going to only use
# the pairs that are present in both. create an intersection between the lists first and then find the
# overlaps for those to run the regression, since we can't run regressions on 2 lists of different lengths.
new_set = list(set(influencer_ids) & set(influencer_ids_2))
new_set
```

In [146…
```python
# then find the network and engagement overlaps for only these influencers.
# not going to print the histograms for this: just the list
new_network_overlap = []

for i in range(len(new_set)):
    for j in range(i+1, len(new_set)):
        # call shared_followers functions
        new_network_overlap.append(shared_followers(following_df, influencer_ids[i], influencer_ids[j]))
```

In [148…
```python
new_engagement_overlap = []

for i in range(len(new_set)):
    for j in range(i+1, len(new_set)):
        # call shared_engagements functions
        new_engagement_overlap.append(shared_engagements(engagement_df, influencer_ids[i], influencer_ids[j]))
```

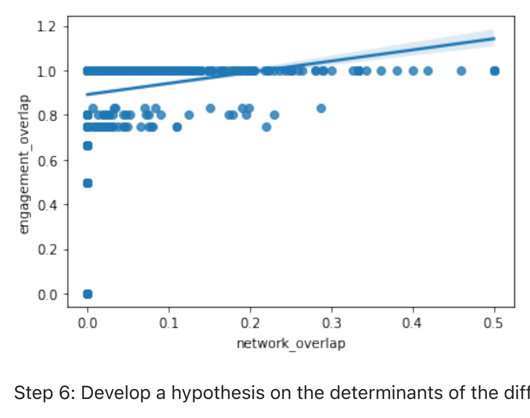
In [159…
```python
import statsmodels.api as sm
import seaborn as sns

# create a dataframe with network overlap and engagement overlap measures
df_overlap = pd.DataFrame({'network_overlap': new_network_overlap,
                           'engagement_overlap':new_engagement_overlap })

# perform OLS regression
X = sm.add_constant(df_overlap['network_overlap'])
model = sm.OLS(df_overlap['engagement_overlap'], X)
results = model.fit()


# plot the results with standard error bands
sns.regplot(x='network_overlap', y='engagement_overlap', data=df_overlap, ci=95) #95th confidence interval
```

Out[159]:
```
<AxesSubplot:xlabel='network_overlap', ylabel='engagement_overlap'>
```



Step 6: Develop a hypothesis on the determinants of the difference between network vs engagement overlaps, i.e. what makes two influencers have high network overlap but low engagement overlap and vice versa?

One possible hypothesis on the determinants of the difference between network vs engagement overlaps could be related to the content and style of the tweets that the influencers are posting. For instance, two influencers might have a high network overlap because they have similar interests and followers, but their engagement overlap might be low if their tweeting styles are different or if they are covering different topics. Similarly, two influencers might have a low network overlap but a high engagement overlap if they are posting about similar topics but have different audiences. Another factor that could impact the difference between network vs engagement overlaps could be the frequency and timing of the tweets, as influencers might have different tweeting schedules and patterns that could affect how their followers engage with their content. Overall, there could be multiple factors that contribute to the difference between network vs engagement overlaps, and further research and analysis would be needed to identify and test these hypotheses.