

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
url = "/content/drive/MyDrive/IdentityResolution.csv"
df = pd.read_csv(url)
```

```
#Visualize data
```

```
df.columns = ['Name', 'Twitter', 'Facebook', 'Instagram']
```

```
df.head()
```

	Name	Twitter	Facebook	
0	Alex Sablan	https://www.twitter.com/AlexSablancom	https://facebook.com/alexsablancom	http://
1	Xavier Gass	https://www.twitter.com/XaviGasso	http://www.facebook.com/xgasso	http://
2	Nicole Lapin	https://www.twitter.com/NicoleLapin	http://www.facebook.com/nicolelapin	http://i
3	Mattan	https://www.twitter.com/mattanriff	https://www.facebook.com/mattanriff	https://i

Extracting Username from profile url of all the social networks sites

```
def getUsername(x):
    x = x.split('/')
    x = x[-1]
    return x.lower();
```

```
for i in range(1,4):
    # print(df.iloc[:,i])
    df.iloc[:,i] = df.iloc[:,i].apply(lambda x: getUsername(x))
```

df

	Name	Twitter	Facebook	Instagram
0	Alex Sablan	alexsablancom	alexsablancom	a_sablan
1	Xavier Gass	xavigasso	xgasso	xavigasso
2	Nicole Lapin	nicolelapin	nicolelapin	nicolelapin
3	Mattan Griffel	mattangriffel	mattangriffel	mattangriffel
4	Shashank Bharadwaj	snk	shashu10	shashu10
...
318	Vasu Chawla	vasuchawla	vasuchawla26	vasuchawla
319	Dayn Wilberding	dayn	daynw	dayn
320	Guillermo Navarro	bildenlex	drguillermomavarro	bildenlex
321	Antonio J. Cuevas	zeroneuronas	antonio.j.cuevas	zeroneuronas
322	Ghibril Ariadna	arighibril	ghibril	ghibril

323 rows × 4 columns

Now we have the username for futher analysis

The Two distance metrics I'll be using are "HAMMING" and "LEVENSHTEIN"

- Hamming distance between two strings of equal length is the number of positions at which the corresponding symbols are different. In other words, it measures the minimum number of substitutions required to change one string into the other.
- The Levenshtein distance is a string metric for measuring the difference between two sequences. Informally, the Levenshtein distance between two words is the minimum number of single-character edits (insertions, deletions or substitutions) required to change one word into the other.

```
pip install textdistance
```

```
import textdistance as td
```

```
tf = df.iloc[:,[1,2]]  ## Twitter-Facbook linkage
ti = df.iloc[:,[1,3]]  ## Twitter-Instagram linkage
fi = df.iloc[:,[2,3]]  ## Facebook-Instagram linkage
```

```
def get_score(df1):
    df1['Hamming'] = ""
    df1['Similarity'] = ""
    df1['levenshtein'] = ""
    df1['lev_Similar'] = ""

    for i in range(0,323):
        df1.iat[i,2] = td.hamming.distance(df1.iat[i,0],df1.iat[i,1])
        df1.iat[i,3] = td.hamming.normalized_similarity(df1.iat[i,0],df1.iat[i,1])

        df1.iat[i,4] = td.levenshtein.distance(df1.iat[i,0],df1.iat[i,1])
        df1.iat[i,5] = td.levenshtein.normalized_similarity(df1.iat[i,0],df1.iat[i,1])
    return df1
```

```
def count_plot(data):
    plt.figure(figsize = (16, 6))
    plt.subplot(1, 2, 1)
    ax = sns.countplot(x='Hamming',data=data, palette = 'dark')
    ax.set_title(label = 'Count of Hamming Distance', fontsize = 20)
    ax.set_xlabel(xlabel = 'Hamming Distance', fontsize = 16)
    ax.set_ylabel(ylabel = 'Count', fontsize = 16)
    # plt.show()

    # plt.figure(figsize = (13, 8))
    plt.subplot(1, 2, 2)
    ax = sns.countplot(x='levenshtein',data=tf, palette = 'dark')
    ax.set_title(label = 'Count of levenshtein Distance', fontsize = 20)
    ax.set_xlabel(xlabel = 'levenshtein Distance', fontsize = 16)
    ax.set_ylabel(ylabel = 'Count', fontsize = 16)
    plt.show()
```

```
def line_plot(data):
    plt.subplots(figsize=(16,6))
    plt.subplot(1, 2, 1)
```

```
plt.subplot(1, 2, 1)
plt.title('Hamming vs Similarity', fontsize = 20, fontweight = 15)
sns.lineplot(x="Hamming",y = 'Similarity',data=tf)

plt.subplot(1, 2, 2)
plt.title('Levenshtein vs Similarity', fontsize = 20, fontweight = 15)
sns.lineplot(x= 'levenshtein',y='lev_Similar',data = tf)
plt.show()
```

Twitter-Facebook

tf

	Twitter	Facebook
0	alexsablancom	alexsablancom
1	xavigasso	xgasso
2	nicolelapin	nicolelapin
3	mattangriffel	mattangriffel
4	snk	shashu10
...
318	vasuchawla	vasuchawla26
319	dayn	daynw
320	bildenlex	drguillermomavarro
321	zeroneuronas	antonio.j.cuevas
322	arighibril	ghibril

323 rows × 2 columns

```
df1 = tf
tf = get_score(df1)
```

tf

	Twitter	Facebook	Hamming	Similarity	levenshtein	lev_Similar
0	alexsablancom	alexsablancom	0	1	0	1
1	xavigasso	xgasso	8	0.111111	3	0.666667
2	nicolelapin	nicolelapin	0	1	0	1
3	mattangriffel	mattangriffel	0	1	0	1
4	snk	shashu10	7	0.125	7	0.125
...
318	vasuchawla	vasuchawla26	2	0.833333	2	0.833333
319	dayn	daynw	1	0.8	1	0.8
320	bildenlex	drguillermonavarro	16	0.111111	14	0.222222
321	zeroneuronas	antonio.j.cuevas	14	0.125	12	0.25
322	arighibril	ghibril	8	0.2	3	0.7

323 rows × 6 columns

```
count_plot(tf)
```

Count of Hamming Distance

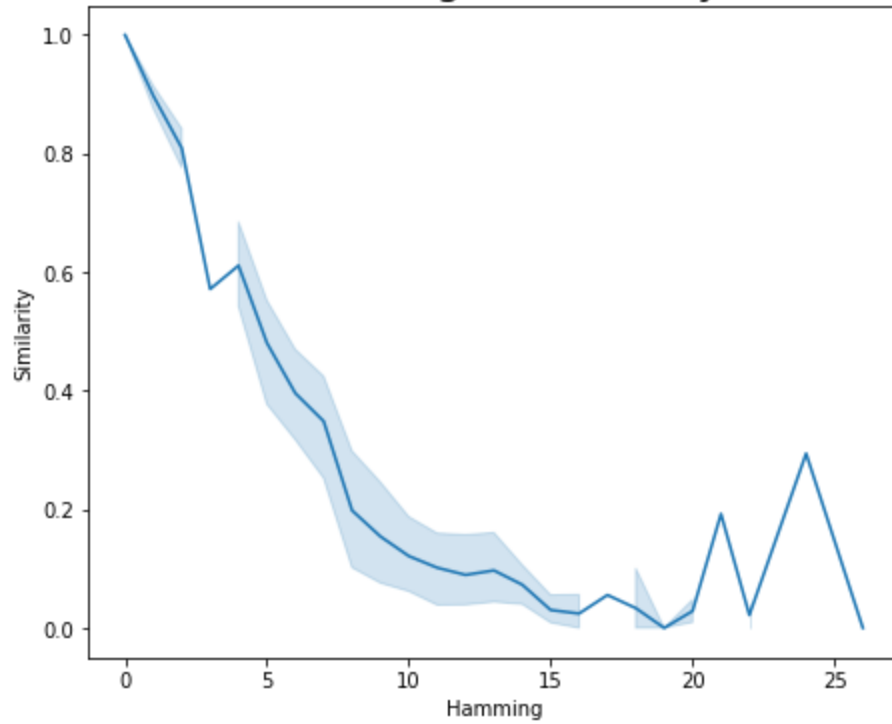


Count of levenshtein Distance

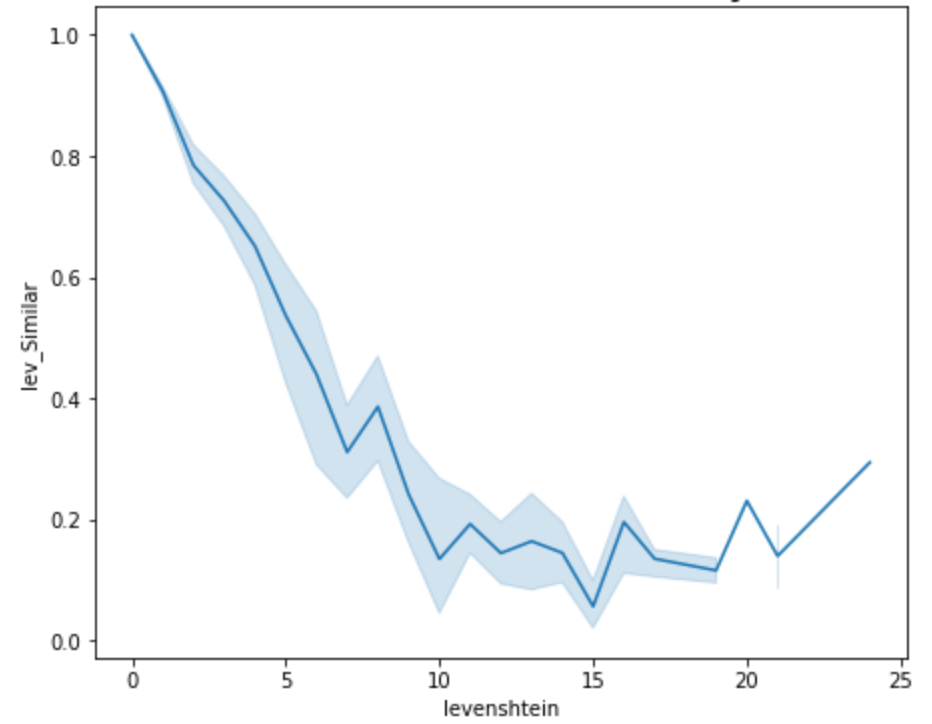


```
line_plot(tf)
```

Hamming vs Similarity



Levenshtein vs Similarity



```
tt = []
```

```
for i in range(0,323):
    tt.append(td.lcsstr.distance(tf.iat[i,0],tf.iat[i,1]))
```

```
tt
```

Twitter-Instagram

```
ti
```

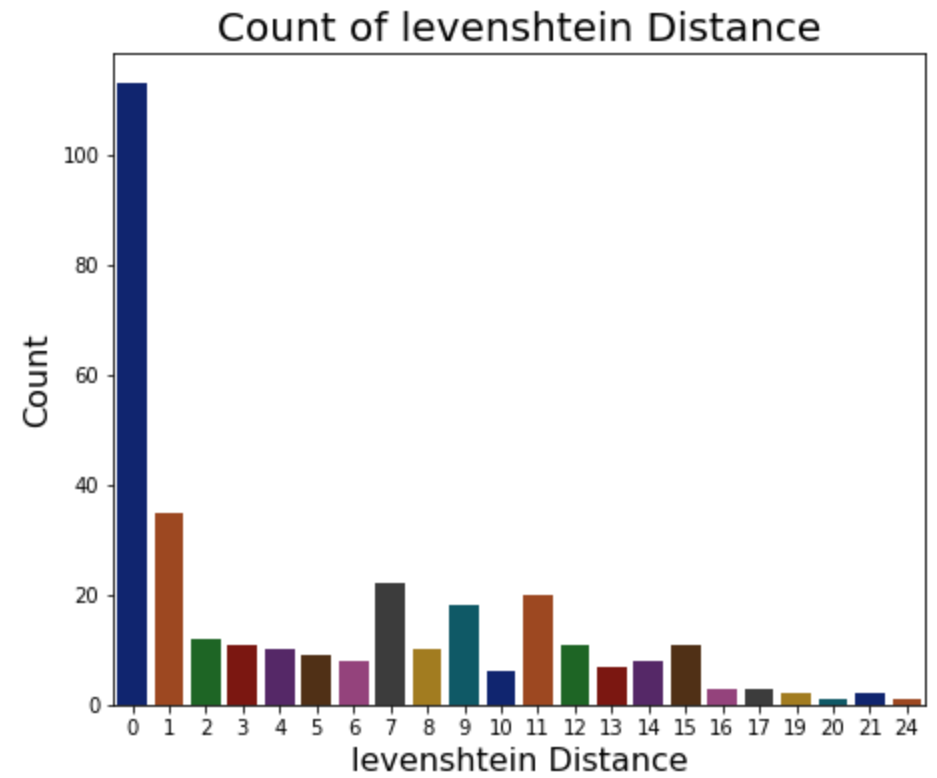
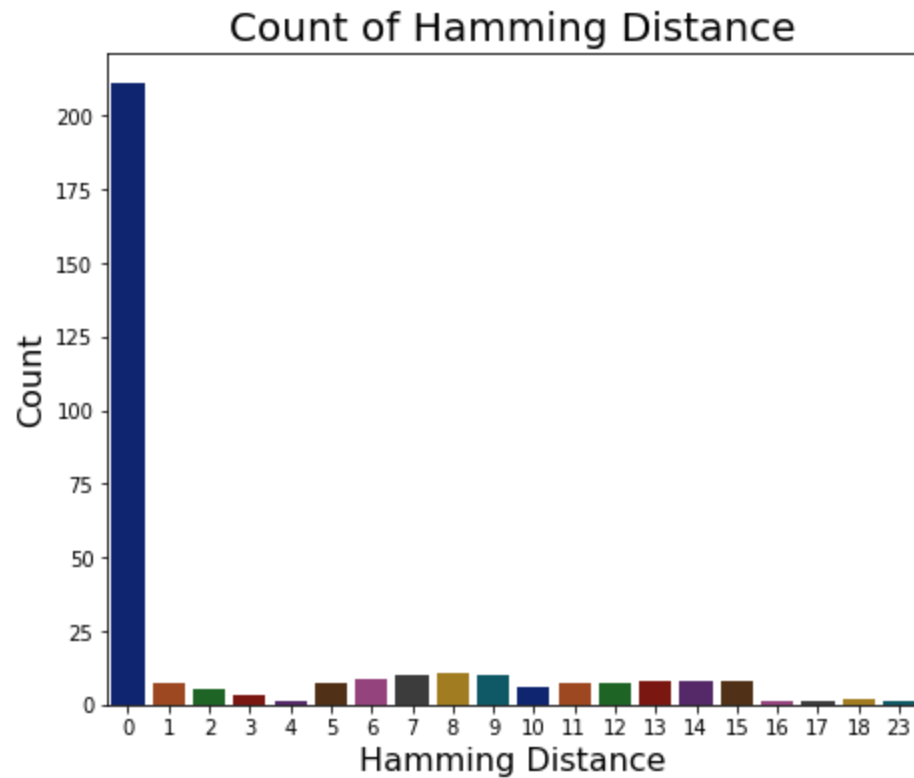
	Twitter	Instagram
0	alexsablancom	a_sablan
1	xavigasso	xavigasso
2	nicolelapin	nicolelapin
3	mattangriffel	mattangriffel
4	snk	shashu10
...
318	vasuchawla	vasuchawla
319	dayn	dayn
320	bildenlex	bildenlex
321	zeroneuronas	zeroneuronas
322	arighibril	ghibril

323 rows × 2 columns

```
df1 = ti
ti = get_score(df1)
ti
```

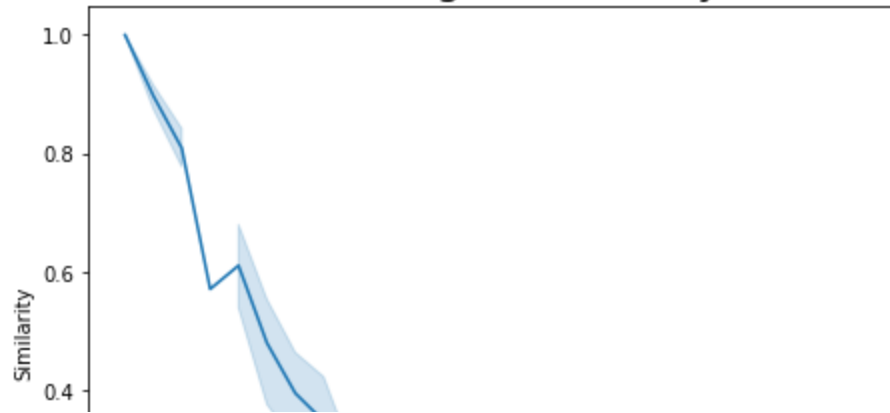
	Twitter	Instagram	Hamming	Similarity	levenshtein	lev_Similar
0	alexsablancom	a_sablan	12	0.0769231	6	0.538462
1	xavigasso	xavigasso	0	1	0	1
2	nicolelapin	nicolelapin	0	1	0	1

```
count_plot(ti)
```

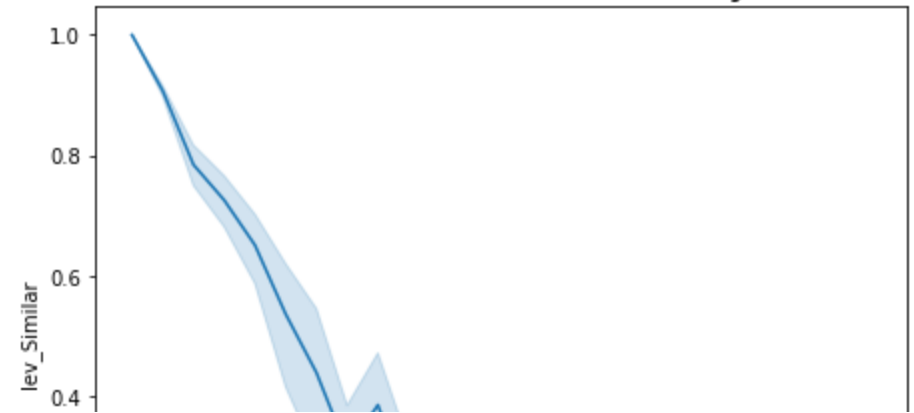


```
line_plot(ti)
```


Hamming vs Similarity



Levenshtein vs Similarity



Facebook-Instagram



fi

	Facebook	Instagram
0	alexsablancom	a_sablan
1	xgasso	xavigasso
2	nicolelapin	nicolelapin
3	mattangriffel	mattangriffel
4	shashu10	shashu10
...
318	vasuchawla26	vasuchawla
319	daynw	dayn
320	drguillermonavarro	bildenlex
321	antonio.j.cuevas	zeroneuronas
322	ghibril	ghibril

323 rows × 2 columns

```
df1 = fi
fi = get_score(df1)
```

fi

	Facebook	Instagram	Hamming	Similarity	levenshtein	lev_Similar
0	alexsablancom	a_sablan	12	0.0769231	6	0.538462
1	xgasso	xavigasso	8	0.111111	3	0.666667
2	nicolelapin	nicolelapin	0	1	0	1
3	mattangriffel	mattangriffel	0	1	0	1
4	shashu10	shashu10	0	1	0	1
...
318	vasuchawla26	vasuchawla	2	0.833333	2	0.833333
319	daynw	dayn	1	0.8	1	0.8
320	drguillermomavarro	bildenlex	16	0.111111	14	0.222222
321	antonio.j.cuevas	zeroneuronas	14	0.125	12	0.25
322	ghibril	ghibril	0	1	0	1

323 rows × 6 columns

```
count_plot(fi)
```

Count of Hamming Distance

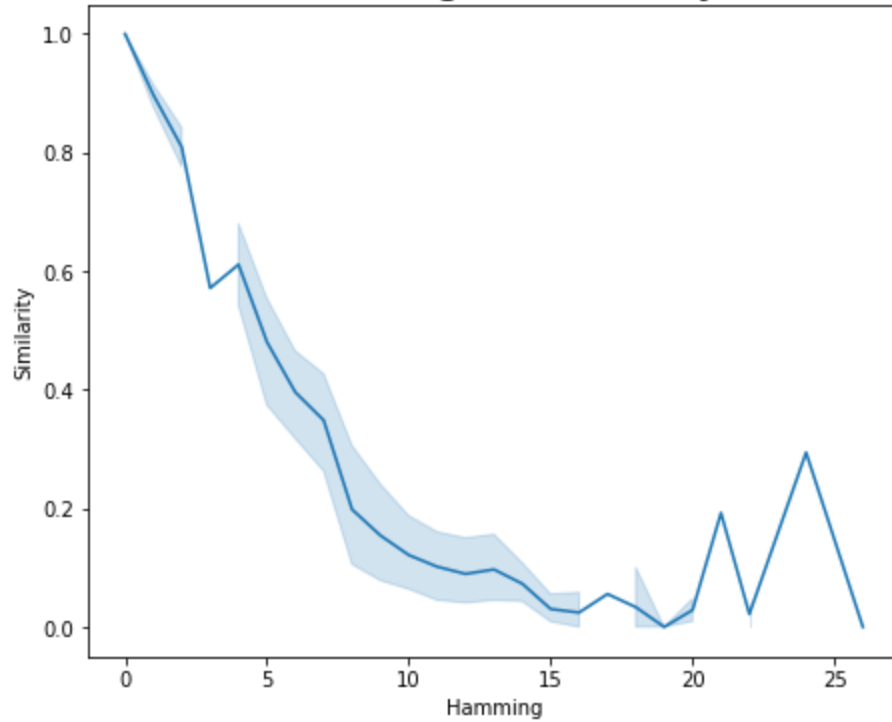


Count of levenshtein Distance

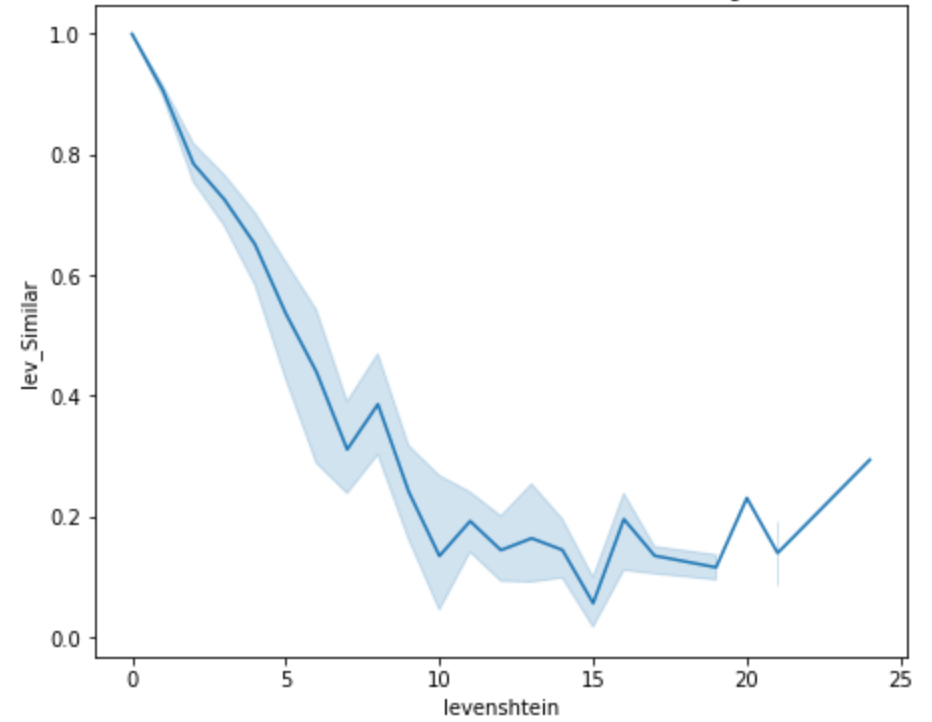


```
line_plot(fi)
```

Hamming vs Similarity



Levenshtein vs Similarity



```
tf['lev_Similar'].value_counts()
```

1.000000	113
0.000000	18
0.153846	6
0.909091	6
0.666667	6
...	
0.071429	1
0.454545	1
0.533333	1
0.857143	1

0.136364 1
Name: lev_Similar Length: 97 dtype: int64

```
ti['lev_Similar'].value_counts()
```

1.000000	211
0.000000	12
0.333333	5
0.111111	4
0.583333	4
0.928571	4
0.222222	4
0.875000	4
0.857143	4
0.200000	3
0.888889	3
0.571429	3
0.166667	3
0.153846	3
0.777778	3
0.230769	3
0.428571	2
0.666667	2
0.714286	2
0.833333	2
0.800000	2
0.133333	2
0.066667	2
0.444444	2
0.272727	2
0.250000	2
0.454545	2
0.125000	2
0.100000	2
0.909091	2
0.625000	1
0.500000	1
0.384615	1
0.529412	1
0.545455	1
0.923077	1
0.142857	1
0.266667	1
0.700000	1
0.818182	1
0.933333	1
0.076923	1
0.900000	1

```

0.260870      1
0.466667      1
0.307692      1
0.285714      1
0.214286      1
0.416667      1
0.357143      1
0.400000      1
0.538462      1
Name: lev_Similar, dtype: int64

```

```
fi['lev_Similar'].value_counts()
```

```

1.000000      114
0.000000       18
0.666667        6
0.916667        6
0.153846         6
...
0.437500         1
0.652174         1
0.615385         1
0.692308         1
0.642857         1
Name: lev_Similar, Length: 86, dtype: int64

```

From above analysis we can conclude that the pair Twitter-Instagram has the max common name username, followed by Facebook-Instagram and then Twitter-Facebook

✓ 0s completed at 10:12 PM

