

group-b-1-facebook

May 2, 2024

0.1 Perform the following operations using Python on the Facebook metrics data sets

- Create data subsets
- Merge Data
- Sort Data
- Transposing Data
-

0.2 Shape and reshape Data

0.3 Dataset Description:

Credit: (Moro et al., 2016) S. Moro, P. Rita and B. Vala. Predicting social media performance metrics and evaluation of the impact on brand building: A data mining approach. Journal of Business Research, Elsevier, In press.

Available at: <http://dx.doi.org/10.1016/j.jbusres.2016.02.010>

1. Title: Facebook performance metrics
2. Sources Created by: Sérgio Moro, Paulo Rita and Bernardo Vala (ISCTE-IUL) @ 2016
3. Past Usage:

The full dataset was described and analyzed in:

S. Moro, P. Rita and B. Vala. Predicting social media performance metrics and evaluation of the impact on brand building: A data mining approach. Journal of Business Research, Elsevier, In press, Available online since 28 February 2016.

4. Relevant Information:

The data is related to posts' published during the year of 2014 on the Facebook's page of a renowned cosmetics brand. This dataset contains 500 of the 790 rows and part of the features analyzed by Moro et al. (2016). The remaining were omitted due to confidentiality issues.

5. Number of Instances: 500
6. Number of Attributes: 19
7. Attribute information:

It includes 7 features known prior to post publication and 12 features for evaluating post impact (see Tables 2 and 3 from Moro et al., 2016 - complete reference in the “Citation Request”)

8. Missing Attribute Values: None

```
[1]: import pandas as pd
```

```
[2]: df = pd.read_csv('dataset_Facebook.csv',delimiter=';')
```

```
[3]: df
```

```
[3]:
```

	Page total likes	Type	Category	Post Month	Post Weekday	Post Hour	\
0	139441	Photo	2	12	4	3	
1	139441	Status	2	12	3	10	
2	139441	Photo	3	12	3	3	
3	139441	Photo	2	12	2	10	
4	139441	Photo	2	12	2	3	
..	
495	85093	Photo	3	1	7	2	
496	81370	Photo	2	1	5	8	
497	81370	Photo	1	1	5	2	
498	81370	Photo	3	1	4	11	
499	81370	Photo	2	1	4	4	

	Paid	Lifetime Post Total	Reach	Lifetime Post Total Impressions	\
0	0.0		2752	5091	
1	0.0		10460	19057	
2	0.0		2413	4373	
3	1.0		50128	87991	
4	0.0		7244	13594	
..	
495	0.0		4684	7536	
496	0.0		3480	6229	
497	0.0		3778	7216	
498	0.0		4156	7564	
499	NaN		4188	7292	

	Lifetime Engaged Users	Lifetime Post Consumers	\
0	178	109	
1	1457	1361	
2	177	113	
3	2211	790	
4	671	410	
..	
495	733	708	
496	537	508	
497	625	572	

498	626	574
499	564	524

	Lifetime Post Consumptions \
0	159
1	1674
2	154
3	1119
4	580
..	...
495	985
496	687
497	795
498	832
499	743

	Lifetime Post Impressions by people who have liked your Page \
0	3078
1	11710
2	2812
3	61027
4	6228
..	...
495	4750
496	3961
497	4742
498	4534
499	3861

	Lifetime Post reach by people who like your Page \
0	1640
1	6112
2	1503
3	32048
4	3200
..	...
495	2876
496	2104
497	2388
498	2452
499	2200

	Lifetime People who have liked your Page and engaged with your post \
0	119
1	1108
2	132
3	1386

```

4                                     396
..                                     ...
495                                   392
496                                   301
497                                   363
498                                   370
499                                   316

```

```

      comment    like  share  Total Interactions
0           4     79.0   17.0             100
1           5    130.0   29.0             164
2           0     66.0   14.0              80
3          58   1572.0  147.0            1777
4          19    325.0   49.0             393
..         ...     ...   ...             ...
495         5     53.0   26.0              84
496         0     53.0   22.0              75
497         4     93.0   18.0             115
498         7     91.0   38.0             136
499         0     91.0   28.0             119

```

[500 rows x 19 columns]

```
[4]: df.describe()
```

```

[4]:      Page total likes    Category  Post Month  Post Weekday  Post Hour  \
count      500.000000    500.000000    500.000000    500.000000    500.000000
mean    123194.176000     1.880000     7.038000     4.150000     7.840000
std     16272.813214     0.852675     3.307936     2.030701     4.368589
min      81370.000000     1.000000     1.000000     1.000000     1.000000
25%     112676.000000     1.000000     4.000000     2.000000     3.000000
50%     129600.000000     2.000000     7.000000     4.000000     9.000000
75%     136393.000000     3.000000    10.000000     6.000000    11.000000
max     139441.000000     3.000000    12.000000     7.000000    23.000000

      Paid  Lifetime Post Total Reach  Lifetime Post Total Impressions  \
count    499.000000             500.00000             5.000000e+02
mean      0.278557             13903.36000             2.958595e+04
std       0.448739             22740.78789             7.680325e+04
min       0.000000             238.00000             5.700000e+02
25%       0.000000             3315.00000             5.694750e+03
50%       0.000000             5281.00000             9.051000e+03
75%       1.000000             13168.00000             2.208550e+04
max       1.000000             180480.00000             1.110282e+06

      Lifetime Engaged Users  Lifetime Post Consumers  \
count              500.000000              500.000000

```

mean	920.344000	798.772000
std	985.016636	882.505013
min	9.000000	9.000000
25%	393.750000	332.500000
50%	625.500000	551.500000
75%	1062.000000	955.500000
max	11452.000000	11328.000000

Lifetime Post Consumptions \

count	500.000000
mean	1415.130000
std	2000.594118
min	9.000000
25%	509.250000
50%	851.000000
75%	1463.000000
max	19779.000000

Lifetime Post Impressions by people who have liked your Page \

count	5.000000e+02
mean	1.676638e+04
std	5.979102e+04
min	5.670000e+02
25%	3.969750e+03
50%	6.255500e+03
75%	1.486050e+04
max	1.107833e+06

Lifetime Post reach by people who like your Page \

count	500.000000
mean	6585.488000
std	7682.009405
min	236.000000
25%	2181.500000
50%	3417.000000
75%	7989.000000
max	51456.000000

Lifetime People who have liked your Page and engaged with your post \

count	500.000000
mean	609.986000
std	612.725618
min	9.000000
25%	291.000000
50%	412.000000
75%	656.250000
max	4376.000000

	comment	like	share	Total Interactions
count	500.00000	499.00000	496.00000	500.00000
mean	7.48200	177.945892	27.266129	212.120000
std	21.18091	323.398742	42.613292	380.233118
min	0.00000	0.00000	0.00000	0.00000
25%	1.00000	56.50000	10.00000	71.00000
50%	3.00000	101.00000	19.00000	123.50000
75%	7.00000	187.50000	32.25000	228.50000
max	372.00000	5172.00000	790.00000	6334.00000

1 Create Data Subsets

```
[5]: # First subset: Like and Share
df_subset_1 = df[['like', 'share']]
df_subset_1
```

```
[5]:      like  share
0      79.0   17.0
1     130.0   29.0
2      66.0   14.0
3    1572.0  147.0
4     325.0   49.0
..      ...   ...
495     53.0   26.0
496     53.0   22.0
497     93.0   18.0
498     91.0   38.0
499     91.0   28.0

[500 rows x 2 columns]
```

```
[6]: # second subset: Comment and Type
df_subset_2 = df[['comment', 'Type']]
df_subset_2
```

```
[6]:      comment  Type
0          4  Photo
1          5  Status
2          0  Photo
3         58  Photo
4         19  Photo
..      ...   ...
495         5  Photo
496         0  Photo
497         4  Photo
```

```
498          7  Photo
499          0  Photo
```

```
[500 rows x 2 columns]
```

2 Merge Data

```
[7]: merged_data = pd.merge(df_subset_2, df_subset_1, left_on='comment', right_on='like')
merged_data
```

```
[7]:
```

	comment	Type	like	share
0	4	Photo	4.0	2.0
1	4	Photo	4.0	1.0
2	4	Photo	4.0	0.0
3	4	Photo	4.0	1.0
4	4	Status	4.0	2.0
...
1462	56	Photo	56.0	17.0
1463	56	Photo	56.0	8.0
1464	56	Photo	56.0	12.0
1465	56	Photo	56.0	9.0
1466	56	Photo	56.0	25.0

```
[1467 rows x 4 columns]
```

2.1 Example for merge

```
[8]: # Define a dictionary containing employee data
data1 = {
    'key': ['K0', 'K1', 'K2', 'K3'],
    'Name': ['Jai', 'Princi', 'Gaurav', 'Anuj'],
    'Age': [27, 24, 22, 32],
}
# Define a dictionary containing employee data
data2 = {
    'key': ['K0', 'K1', 'K2', 'K3'],
    'Address': ['Nagpur', 'Kanpur', 'Allahabad', 'Kannuaj'],
    'Qualification': ['Btech', 'B.A', 'Bcom', 'B.hons']}
# Convert the dictionary into DataFrame
data1 = pd.DataFrame(data1)
# Convert the dictionary into DataFrame
data2 = pd.DataFrame(data2)

# print(df, "\n\n", df1)
res = pd.merge(data1, data2, on='key')
res
```

```
[8]:
```

	key	Name	Age	Address	Qualification
0	K0	Jai	27	Nagpur	Btech
1	K1	Princi	24	Kanpur	B.A
2	K2	Gaurav	22	Allahabad	Bcom
3	K3	Anuj	32	Kannuaj	B.hons

3 Sort Data

```
[9]: # Sorting merged_data in descending order wrt 'Like'
merged_data.sort_values(by=['like'], ascending=False)
```

```
[9]:
```

	comment	Type	like	share
1461	146	Photo	146.0	15.0
1460	146	Photo	146.0	9.0
1438	144	Photo	144.0	10.0
1439	144	Photo	144.0	29.0
1448	64	Photo	64.0	22.0
...
563	0	Photo	0.0	0.0
564	0	Photo	0.0	0.0
565	0	Photo	0.0	0.0
566	0	Photo	0.0	0.0
380	0	Photo	0.0	0.0

[1467 rows x 4 columns]

4 Transposing Data

```
[10]: # Method 1
merged_data.transpose()
```

```
[10]:
```

	0	1	2	3	4	5	6	7	8	\
comment	4	4	4	4	4	4	4	4	4	
Type	Photo	Photo	Photo	Photo	Status	Status	Status	Status	Status	
like	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0	
share	2.0	1.0	0.0	1.0	2.0	1.0	0.0	1.0	2.0	

	9	...	1457	1458	1459	1460	1461	1462	1463	1464	\
comment	4	...	51	51	51	146	146	56	56	56	
Type	Status	...	Photo	Photo	Photo	Photo	Photo	Photo	Photo	Photo	
like	4.0	...	51.0	51.0	51.0	146.0	146.0	56.0	56.0	56.0	
share	1.0	...	11.0	6.0	6.0	9.0	15.0	17.0	8.0	12.0	

	1465	1466
comment	56	56
Type	Photo	Photo
like	56.0	56.0
share	9.0	25.0

[4 rows x 1467 columns]

```
[11]: # Method 2
merged_data.T
```

```
[11]:
```

	0	1	2	3	4	5	6	7	8	\
comment	4	4	4	4	4	4	4	4	4	
Type	Photo	Photo	Photo	Photo	Status	Status	Status	Status	Status	
like	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0	4.0	
share	2.0	1.0	0.0	1.0	2.0	1.0	0.0	1.0	2.0	

	9	...	1457	1458	1459	1460	1461	1462	1463	1464	\
comment	4	...	51	51	51	146	146	56	56	56	
Type	Status	...	Photo	Photo	Photo	Photo	Photo	Photo	Photo	Photo	
like	4.0	...	51.0	51.0	51.0	146.0	146.0	56.0	56.0	56.0	
share	1.0	...	11.0	6.0	6.0	9.0	15.0	17.0	8.0	12.0	

	1465	1466
comment	56	56
Type	Photo	Photo
like	56.0	56.0
share	9.0	25.0

[4 rows x 1467 columns]

5 Shape And Reshape Data

[12]: df

```
[12]:      Page total likes      Type Category Post Month Post Weekday Post Hour \
0          139441      Photo          2          12          4          3
1          139441      Status          2          12          3         10
2          139441      Photo          3          12          3          3
3          139441      Photo          2          12          2         10
4          139441      Photo          2          12          2          3
..          ...          ...          ...          ...          ...          ...
495          85093      Photo          3          1          7          2
496          81370      Photo          2          1          5          8
497          81370      Photo          1          1          5          2
498          81370      Photo          3          1          4         11
499          81370      Photo          2          1          4          4
```

```
      Paid Lifetime Post Total Reach Lifetime Post Total Impressions \
0      0.0          2752          5091
1      0.0         10460         19057
2      0.0          2413          4373
3      1.0         50128         87991
4      0.0          7244         13594
..      ...          ...          ...
495     0.0          4684          7536
496     0.0          3480          6229
497     0.0          3778          7216
498     0.0          4156          7564
499     NaN          4188          7292
```

```
      Lifetime Engaged Users Lifetime Post Consumers \
0          178          109
1         1457         1361
2          177          113
3         2211          790
4          671          410
..          ...          ...
495          733          708
496          537          508
497          625          572
498          626          574
499          564          524
```

```
      Lifetime Post Consumptions \
0          159
1         1674
2          154
```

3	1119
4	580
..	...
495	985
496	687
497	795
498	832
499	743

Lifetime Post Impressions by people who have liked your Page \

0	3078
1	11710
2	2812
3	61027
4	6228
..	...
495	4750
496	3961
497	4742
498	4534
499	3861

Lifetime Post reach by people who like your Page \

0	1640
1	6112
2	1503
3	32048
4	3200
..	...
495	2876
496	2104
497	2388
498	2452
499	2200

Lifetime People who have liked your Page and engaged with your post \

0	119
1	1108
2	132
3	1386
4	396
..	...
495	392
496	301
497	363
498	370
499	316

	comment	like	share	Total Interactions
0	4	79.0	17.0	100
1	5	130.0	29.0	164
2	0	66.0	14.0	80
3	58	1572.0	147.0	1777
4	19	325.0	49.0	393
..
495	5	53.0	26.0	84
496	0	53.0	22.0	75
497	4	93.0	18.0	115
498	7	91.0	38.0	136
499	0	91.0	28.0	119

[500 rows x 19 columns]

```
[13]: df.Type.unique()
```

```
[13]: array(['Photo', 'Status', 'Link', 'Video'], dtype=object)
```

```
[17]: # Reshape
# Comment is id_vars and Type is value_vars
pd.melt(df, id_vars = ['Type'], value_vars = ['comment'])
```

```
[17]:
```

	Type	variable	value
0	Photo	comment	4
1	Status	comment	5
2	Photo	comment	0
3	Photo	comment	58
4	Photo	comment	19
..
495	Photo	comment	5
496	Photo	comment	0
497	Photo	comment	4
498	Photo	comment	7
499	Photo	comment	0

[500 rows x 3 columns]

5.1 Examples

```
[15]: # Reshape
df_temp = pd.DataFrame({'foo': ['one', 'one', 'one', 'two', 'two', 'two'],
                          'bar': ['A', 'B', 'C', 'A', 'B', 'C'],
                          'baz': [1, 2, 3, 4, 5, 6],
                          'zoo': ['x', 'y', 'z', 'q', 'w', 't']})
df_temp
```

```
[15]:      foo bar  baz zoo
      0 one  A    1  x
      1 one  B    2  y
      2 one  C    3  z
      3 two  A    4  q
      4 two  B    5  w
      5 two  C    6  t
```

```
[16]: df_temp.pivot(index='foo', columns='bar', values='baz')
```

```
[16]: bar  A  B  C
      foo
      one  1  2  3
      two  4  5  6
```

```
[ ]:
```

```
[ ]:
```