K-means Clustering Model on Facebook Live Sellers in Thailand Data Set

Nyasha M, 28 Apr 2021

Background: This dataset consists of 7050 Facebook posts of various types (live video, photos, status updates, links) from the Facebook pages of 10 Thai fashion and cosmetics retail sellers between March 2012 and June 2018.

Each Facebook post had its engagement metrics (coonsisting of shares, comments, likes, or emoji reactions--namely, “love”, “wow”, “haha”, “sad” and “angry”) recorded into the dataset, along with a timestamp of when each engagement occurred.

The dataset came from the following webpage at the University of California Irvine (UCI): https://archive.ics.uci.edu/ml/datasets/Facebook+Live+Sellers+in+Thailand.

Objective: The goal of this notebook was to determine if the Facebook posts of the sellers could be clustered in some way into distinct categories, such as by the type of media they posted, the types of engagement they generated from Facebook users, or by the year/month that the posts were made.

Conclusions from the data: The sellers generally fell into 3 groups:

- Clusters 0 and 1 belonged to sellers who posted mostly photos or links on Facebook.
  - Cluster 0 were sellers who generally obtained poor engagement from the public.
  - Cluster 1 generally obtained a very high number of reactions--mostly likes--from their posts.
- Cluster 2 belonged to sellers who posted mostly live videos.
  - These sellers generated a very high number of comments, as well as quite a few reactions, shares, and likes from the public.

Citation: Nassim Dehouche and Apiradee Wongkitrungrueng. Facebook Live as a Direct Selling Channel, 2018, Proceedings of ANZMAC 2018: The 20th Conference of the Australian and New Zealand Marketing Academy. Adelaide (Australia), 3-5 December 2018.

Data Exploration and Pre-processing

In [1]:
```python
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import seaborn as sns
import scipy as sc

# Modeling
import sklearn.preprocessing as preprocess
from sklearn.cluster import KMeans as kmeans
from sklearn.metrics import silhouette_score
```

In [48]:
```python
# Change plotting style.
plt.style.use('bmh')
```

Let's first load and preview our dataset.

In [3]:
```python
# load the dataset.
df = pd.read_csv("Live_20210128.csv")
df.head(3)
```

Out[3]:

	status_id	status_type	status_published	num_reactions	num_comments	num_shares	num_likes	num_loves	num_wows	num_hahas
0	1	video	4/22/2018 6:00	529	512	262	432	92	3	1
1	2	photo	4/21/2018 22:45	150	0	0	150	0	0	0
2	3	video	4/21/2018 6:17	227	236	57	204	21	1	1

In [4]:
```python
len(df)
```

Out[4]: 7050

The last 4 columns look like they all just consist of missing values. Is this true?

In [5]:
```python
df.iloc[:,-4:].describe()
```

Out[5]:

	Column1	Column2	Column3	Column4
count	0.0	0.0	0.0	0.0
mean	NaN	NaN	NaN	NaN
std	NaN	NaN	NaN	NaN
min	NaN	NaN	NaN	NaN
25%	NaN	NaN	NaN	NaN
50%	NaN	NaN	NaN	NaN
75%	NaN	NaN	NaN	NaN
max	NaN	NaN	NaN	NaN

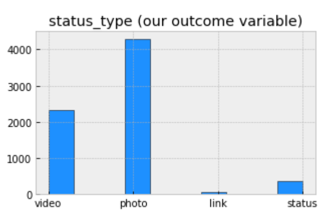
In [6]:
```python
# Remove the missing data columns
df = df.drop(df.iloc[:,-4:], axis=1)
df.head(4)
```

Out[6]:

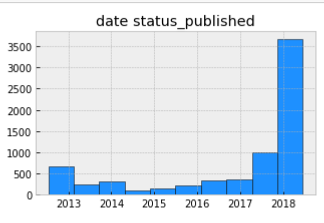
	status_id	status_type	status_published	num_reactions	num_comments	num_shares	num_likes	num_loves	num_wows	num_hahas
0	1	video	4/22/2018 6:00	529	512	262	432	92	3	1
1	2	photo	4/21/2018 22:45	150	0	0	150	0	0	0
2	3	video	4/21/2018 6:17	227	236	57	204	21	1	1
3	4	photo	4/21/2018 2:29	111	0	0	111	0	0	0

In [8]:
```python
# status_type looks like a categorical variable. Is this true?
plt.figure(figsize=(5, 3))
df.status_type.hist(color='dodgerblue', edgecolor='black'), plt.title('status_type (our outcome variabl
e)')
print(df.status_type.value_counts())
```

```
photo     4288
video     2334
status     365
link        63
Name: status_type, dtype: int64
```



In [10]:
```python
plt.figure(figsize=(5, 3))
df.status_published.astype('datetime64[s]').hist(color='dodgerblue', edgecolor='black'), plt.title('dat
e status_published')
plt.show()
```

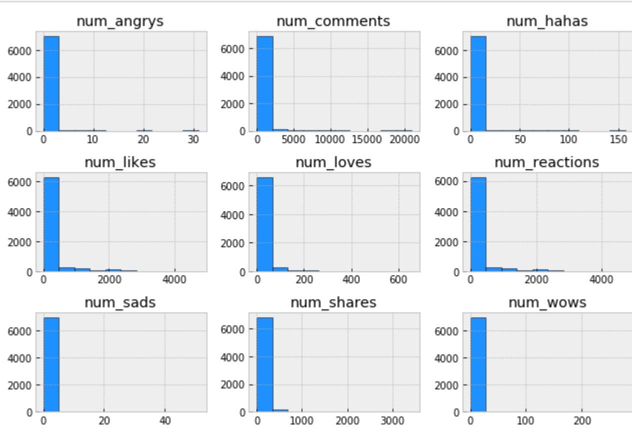


In [11]:
```python
# How many columns are there excluding the first two columns (status and date)?
len(df.iloc[:,3:].columns)
```

Out[11]: 9

Checking the distributions of the data in the 9 remaining columns.

In [12]:
```python
df[df.columns[3:]].hist(figsize=(9,6), color='dodgerblue', edgecolor='black')
plt.tight_layout()
plt.show()
```



Is there any other missing data in the dataset?

In [13]:
```python
df[df.isna().any(axis=1)]
```

Out[13]:

status_id	status_type	status_published	num_reactions	num_comments	num_shares	num_likes	num_loves	num_wows	num_hahas

Let's remove the `status_id` variable since it seems to be just an arbitrary feature.

`status_published` seems like it might have some interesting data that we could try feeding into our clustering algorithm. Let's try extracting the months and years out of this variable, in case these might provide some interesting results.

In [14]:
```python
df = df.drop(['status_id'], axis=1)
```

Extracting the months and years from `status_published` returned an error, because it appears that this variable isn't actually in a datetime format. Let's check the format:

In [15]:
```python
df['status_published'].dtypes
```

Out[15]: dtype('O')

Odd. What happens if we try changing it into a datetime object? Would this work?

In [16]:
```python
df['date'] = pd.to_datetime(df['status_published'], errors='coerce')
```

In [17]:
```python
# It did, so now let's extract the years and month from our new datetime column of 'status_published'.
 We can also now drop
# the old timestamp columns that we don't need anymore.
df['year'] = df['date'].dt.year
df['month'] = df['date'].dt.month

df = df.drop(['status_published', 'date'], axis=1)
```

Finally, K-means can only work on integers, so let's change `status_type` into an int-type feature.

In [18]:
```python
le = preprocess.LabelEncoder()
df['status_type'] = le.fit_transform(df['status_type'])
df.head(4)
```

Out[18]:

	status_type	num_reactions	num_comments	num_shares	num_likes	num_loves	num_wows	num_hahas	num_sads	num_angrys	ye
0	3	529	512	262	432	92	3	1	1	0	20
1	1	150	0	0	150	0	0	0	0	0	20
2	3	227	236	57	204	21	1	1	0	0	20
3	1	111	0	0	111	0	0	0	0	0	20

In [19]:
```python
# Standardizing the data.
clust_array = preprocess.StandardScaler().fit_transform(df)
clust_df = pd.DataFrame(data = clust_array, columns = df.columns)
clust_df.head(4)
```

Out[19]:

	status_type	num_reactions	num_comments	num_shares	num_likes	num_loves	num_wows	num_hahas	num_sads	num_angrys	
0	1.374288	0.646104	0.323350	1.686879	0.482727	1.983266	0.196196	0.076713	0.473570	-0.155748	0.
1	-0.748106	-0.173192	-0.252206	-0.304144	-0.144720	-0.318454	-0.147879	-0.176010	-0.152587	-0.155748	0.
2	1.374288	-0.006738	0.013089	0.129017	-0.024571	0.206938	-0.033187	0.076713	-0.152587	-0.155748	0.
3	-0.748106	-0.257499	-0.252206	-0.304144	-0.231495	-0.318454	-0.147879	-0.176010	-0.152587	-0.155748	0.

Model Deployment

Let's run our clustering model on the data across a range of test/dummy cluster numbers and record which number of clusters lead to the best division of data/distinct groups in the dataset.

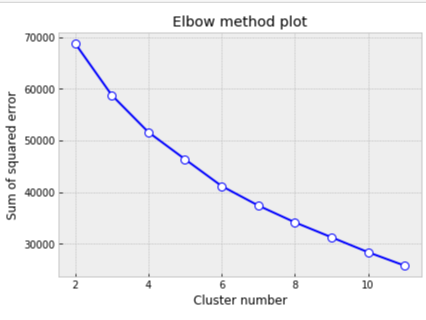
We will plot the sum of squared errors after each cluster (i.e., the elbow method) as well as use the silhouette method to help us determine the ideal number of clusters for our dataset.

In [20]:
```python
ss_dist = [np.nan]*10
for k in range(2, 12):
    # random_state = set.seed to determine where cluster centroids are placed--allows for reproducible
 results
    k_means = kmeans(n_clusters = k, init = 'k-means++', n_init = 12, random_state = 2)
    k_means.fit(clust_df)
    # Record sum of squared errors from each cluster iteration. Find the number of clusters that explai
ns the greatest
    # amount of variation in the data, withoout overfitting.
    ss_dist[k-2] = k_means.inertia_

    # Get silhouette score from each attempted cluster number
    labels = k_means.labels_
    silhouette_avg = silhouette_score(clust_df, labels)
    print("For n_clusters =", k,
          "The average silhouette_score is :", silhouette_avg)
```

```
For n_clusters = 2 The average silhouette_score is : 0.6639750186216327
For n_clusters = 3 The average silhouette_score is : 0.5149693930635386
For n_clusters = 4 The average silhouette_score is : 0.31252549147051584
For n_clusters = 5 The average silhouette_score is : 0.26349116489928504
For n_clusters = 6 The average silhouette_score is : 0.3499857807955862
For n_clusters = 7 The average silhouette_score is : 0.35490824197305587
For n_clusters = 8 The average silhouette_score is : 0.35535464221158986
For n_clusters = 9 The average silhouette_score is : 0.35572238329166356
For n_clusters = 10 The average silhouette_score is : 0.3577116943825716
For n_clusters = 11 The average silhouette_score is : 0.37200366071156815
```

In [42]:
```python
plt.figure(figsize=(6.5, 4.5))
#plt.plot(range(2, 12), ss_dist, '.b-', color='mediumblue')
#plt.scatter(range(2,12), ss_dist, edgecolors='black')
plt.plot(range(2,12), ss_dist, color='blue', marker='.', markerfacecolor='white', markersize=16)
plt.title('Elbow method plot'), plt.xlabel('Cluster number'), plt.ylabel('Sum of squared error')
plt.show()
```



The elbow method plot and our average silhouette scores post-modeling both suggest that perhaps 3 or 6 clusters might be best. Let's rerun our k-means model on just 3 clusters for now, apply the labels to our dataset, and see if we observe any interesting trends.

In [52]:
```python
# pick a random cluster number for now. Run algorithm on the standardized dataset, then save the result
ing cluster labels.
clust_num = 3

k_means = kmeans(init = "k-means++", n_clusters = clust_num, n_init = 12, random_state=2)
print(k_means.fit(clust_df))

labels = k_means.labels_
print(f"\n{labels}")
```

```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=3, n_init=12, n_jobs=None, precompute_distances='auto',
       random_state=2, tol=0.0001, verbose=0)

[0 0 0 ... 0 0 0]
```

In [53]:
```python
# apply the cluster labels to our original dataset.
df["clust_lab"] = labels
df.head(3)
```

Out[53]:

	status_type	num_reactions	num_comments	num_shares	num_likes	num_loves	num_wows	num_hahas	num_sads	num_angrys	ye
0	3	529	512	262	432	92	3	1	1	0	20
1	1	150	0	0	150	0	0	0	0	0	20
2	3	227	236	57	204	21	1	1	0	0	20

How many observations belonged to each cluster?

In [54]:
```python
df.groupby('clust_lab').size()
```

Out[54]:
```
clust_lab
0    6354
1     371
2     325
dtype: int64
```

In [55]:
```python
df.groupby('clust_lab').mean()
```

Out[55]:

clust_lab	status_type	num_reactions	num_comments	num_shares	num_likes	num_loves	num_wows	num_hahas	num_sads	num_a
0	1.652188	112.326881	92.434529	19.541706	104.439723	6.845924	0.538873	0.313031	0.137551	0.0
1	1.555256	1825.568733	61.463612	11.676550	1819.776280	3.113208	2.442049	0.199461	0.032345	0.0
2	2.907692	711.738462	2989.470769	472.796923	545.560000	138.716923	14.646154	8.760000	2.560000	1.4

Show what the original `status_type` labels were, as strings.

In [56]:
```python
print(le.inverse_transform([0, 1, 2, 3]),
      "\n  0,\t 1,\t 2,\t  3")
```

```
['link' 'photo' 'status' 'video']
  0,     1,      2,        3
```

Conclusions

From looking at our aggregated dataframe, we can conclude that the Thai fashion and cosmetics sellers seemed to fall into 3 clusters:

- Clusters 0 and 1 belonged to sellers who posted mostly photos or links on Facebook.
  - Cluster 0 were sellers who generally obtained poor engagement from the public.
  - Cluster 1 generally obtained a very high number of reactions--mostly likes--from their posts.
- Cluster 2 belonged to sellers who posted mostly live videos.
  - These sellers generated a very high number of comments, as well as quite a few reactions, shares, and likes from the public.

Bonus Data Exploration Area Below:

In [73]:
```python
colours = ["#581845", "#FF5733", "#FFE000"] # Red, green, blue

# Exploring some of the data.
fig,axs = plt.subplots(1,2, figsize=(8,3))

sns.scatterplot('month', 'num_reactions', data=df, hue='clust_lab', palette=colours, edgecolor='#35353
5', ax=axs[0], alpha=.6)
sns.scatterplot('num_likes', 'num_reactions', data=df, hue='clust_lab', edgecolor='#353535', palette=co
lours, ax=axs[1], alpha=.6)
axs[0].legend(facecolor='white'), axs[1].legend(facecolor='white')
fig.tight_layout()
```