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

import datetime

dataset = pd.read_csv('../dataset/access_log.txt/output.csv')
dataset.head()
```

```
                IP          Timestamp
URL  \
0  10.223.157.186  15-07-2009 14:58                      GET /
HTTP/1.1
1  10.223.157.186  15-07-2009 14:58           GET /favicon.ico
HTTP/1.1
2  10.223.157.186  15-07-2009 15:50                      GET /
HTTP/1.1
3  10.223.157.186  15-07-2009 15:50   GET /assets/js/lowpro.js
HTTP/1.1
4  10.223.157.186  15-07-2009 15:50  GET /assets/css/reset.css
HTTP/1.1

   Status
0     200
1     200
2     200
3     200
4     200
```

```
df = dataset.iloc[:580, :]
df.head()
```

```
                IP          Timestamp
URL  \
0  10.223.157.186  15-07-2009 14:58                      GET /
HTTP/1.1
1  10.223.157.186  15-07-2009 14:58           GET /favicon.ico
HTTP/1.1
2  10.223.157.186  15-07-2009 15:50                      GET /
HTTP/1.1
3  10.223.157.186  15-07-2009 15:50   GET /assets/js/lowpro.js
HTTP/1.1
4  10.223.157.186  15-07-2009 15:50  GET /assets/css/reset.css
HTTP/1.1

   Status
0     200
1     200
2     200
```

```
3     200
4     200

data = {
    "IP_Address": ["10.128.2.1"],
    "Time_Difference_Mean": [99],
    "Time_Difference_Variance": [54],
    "Time_Difference_Sum": [105],
    "Time_Difference_Maximum": [15],
    "Character-bigrams": [45],
    "Character-trigrams": [34],
    "Character-ngrams": [74],
    "Count_of_most_visited_page": [14],
    "Status": [200],
    "Number_of_records": [40],
}
work_dataset = pd.DataFrame(data)
work_dataset

   IP_Address  Time_Difference_Mean  Time_Difference_Variance  \
0  10.128.2.1                    99                        54

   Time_Difference_Sum  Time_Difference_Maximum  Character-bigrams  \
0                  105                       15                 45

   Character-trigrams  Character-ngrams  Count_of_most_visited_page
Status  \
0                  34                74                          14
200

   Number_of_records
0                 40

import datetime

# import pandas as pd


def time_stats(dataframe):
    """
    Calculate time-based statistics from weblog time format [DD-MM-
YYYY HH:MM

    Args:
        dataframe: pandas DataFrame with time values in format [DD-MM-
YYYY HH:MM]
    Returns:
        tuple: (max_time_diff, mean_time_diff, sum_time_diff,
variance_time_diff)
    """
    if len(dataframe) <= 1:
```

```
        return 0, 0, 0, 0

    # Extract time from the format [DD-MM-YYYY HH:MM]
    def extract_time(time_str):
        return datetime.datetime.strptime(time_str, "%d-%m-%Y %H:%M")

    # Process all times at once
    try:
        processed_times = [
            extract_time(str(time)) for time in dataframe.iloc[:,
1].values
        ]

        # Calculate time differences in seconds
        time_diffs = [
            (processed_times[i] - processed_times[i -
1]).total_seconds()
            for i in range(1, len(processed_times))
        ]

        if not time_diffs:
            return 0, 0, 0, 0

        # Calculate statistics
        max_time_diff = max(time_diffs)
        sum_time_diff = sum(time_diffs)
        mean_time_diff = sum_time_diff / len(time_diffs)

        # Calculate variance
        variance_time_diff = sum(
            (diff - mean_time_diff) ** 2 for diff in time_diffs
        ) / len(time_diffs)

        return max_time_diff, mean_time_diff, sum_time_diff,
variance_time_diff

    except (ValueError, IndexError) as e:
        print(f"Error processing times: {e}")
        return 0, 0, 0, 0

time_stats(df)
```

```
(1045980.0, 2048.2901554404143, 1185960.0, 1893147251.4805982)
```

```
import re
import string
import nltk
import nltk.corpus
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.util import bigrams
```

```
def most_frequent(List):
    return max(set(List), key=List.count)

def bigram_stats(dataframe):
    url_array = dataframe.iloc[:, 2].values
    full_string = ""
    for url in url_array:
        full_string = full_string + url
    full_string = full_string.lower()
    full_string = re.sub(r"\d+", "", full_string)
    table = str.maketrans({key: None for key in string.punctuation})
    full_string = full_string.translate(table)
    full_string = full_string.strip()
    full_string_tokens = word_tokenize(full_string)
    for char in full_string_tokens:
        if char == "get":
            full_string_tokens.remove("get")
    for char in full_string_tokens:
        if char == "httpget":
            full_string_tokens.remove("httpget")
    for char in full_string_tokens:
        if char == "httppost":
            full_string_tokens.remove("httppost")
    for char in full_string_tokens:
        if char == "post":
            full_string_tokens.remove("post")

    count_most_visited_page = 0
    if len(full_string_tokens) != 0:
        most_visited_page = most_frequent(full_string_tokens)
        count_most_visited_page =
full_string_tokens.count(most_visited_page)

    count_most_appearing_bigram = 0
    bigrams = list(nltk.bigrams(full_string_tokens))
    if len(bigrams) != 0:
        most_appearing_bigram = most_frequent(bigrams)
        count_most_appearing_bigram =
bigrams.count(most_appearing_bigram)

    count_most_appearing_trigram = 0
    trigrams = list(nltk.trigrams(full_string_tokens))
    if len(trigrams) != 0:
        most_appearing_trigram = most_frequent(trigrams)
        count_most_appearing_trigram =
trigrams.count(most_appearing_trigram)

    count_most_appearing_ngram = 0
    ngrams = list(nltk.ngrams(full_string_tokens, 6))
    if len(ngrams) != 0:
```

```
        most_appearing_ngram = most_frequent(ngrams)
        count_most_appearing_ngram =
ngrams.count(most_appearing_ngram)

    return (
        count_most_visited_page,
        count_most_appearing_bigram,
        count_most_appearing_trigram,
        count_most_appearing_ngram,
    )

bigram_stats(df)
```

```
(68, 21, 7, 2)
```

```
from collections import Counter

def most_visited_ip(dataframe):
    ip = dataframe.iloc[:, 0].values
    x = Counter(ip)
    return x.most_common(1)[0][0]

most_visited_ip(df)
```

```
'10.216.113.172'
```

```
def most_freq_status(dataframe):
    status = dataframe.iloc[:, 3].values
    x = Counter(status)
    return x.most_common(1)[0][0]

most_freq_status(df)
```

```
200
```

```
print(dataset.columns)
```

```
Index(['IP', 'Timestamp', 'URL', 'Status'], dtype='object')
```

```
# Process dataset
startindex = 0
endindex = 0
prevdate = ""
p = 1

work_dataset = pd.DataFrame(
    columns=[
        "Character-bigrams",
        "Character-ngrams",
        "Character-trigrams",
        "Count_of_most_visited_page",
        "IP_Address",
```

```
        "Number_of_records",
        "Status",
        "Time_Difference_Maximum",
        "Time_Difference_Mean",
        "Time_Difference_Sum",
        "Time_Difference_Variance",
    ]
)

for i, row in dataset.iterrows():
    date = row["Timestamp"][:10]  # Extract the date part from the
Timestamp
    if i == 0:
        prevdate = date
    else:
        if date == prevdate:
            endindex += 1
        else:
            data = dataset.iloc[startindex : endindex + 1, :]
            max_time_diff, mean_time_diff, sum_time_diff,
variance_time_diff = time_stats(data)
            count_most_visited_page, count_most_appearing_bigram,
count_most_appearing_trigram, count_most_appearing_ngram =
bigram_stats(data)
            most_vis_ip = most_visited_ip(data)
            most_frequent_status = most_freq_status(data)
            most_vis_ip = most_vis_ip if most_vis_ip else "10.130.2.1"
            most_frequent_status = most_frequent_status if
most_frequent_status else 200

            work_dataset.loc[p] = [
                count_most_appearing_bigram,
                count_most_appearing_ngram,
                count_most_appearing_trigram,
                count_most_visited_page,
                most_vis_ip,
                endindex - startindex + 1,
                most_frequent_status,
                max_time_diff,
                mean_time_diff,
                sum_time_diff,
                variance_time_diff,
            ]
            startindex = endindex + 1
            endindex = startindex
            prevdate = date
            p += 1

# Process the last date range
data = dataset.iloc[startindex : endindex + 1, :]
```

```
max_time_diff, mean_time_diff, sum_time_diff, variance_time_diff =
time_stats(data)
count_most_visited_page, count_most_appearing_bigram,
count_most_appearing_trigram, count_most_appearing_ngram =
bigram_stats(data)
most_vis_ip = most_visited_ip(data)
most_frequent_status = most_freq_status(data)
most_vis_ip = most_vis_ip if most_vis_ip else "10.130.2.1"
most_frequent_status = most_frequent_status if most_frequent_status
else 200

work_dataset.loc[p] = [
    count_most_appearing_bigram,
    count_most_appearing_ngram,
    count_most_appearing_trigram,
    count_most_visited_page,
    most_vis_ip,
    endindex - startindex + 1,
    most_frequent_status,
    max_time_diff,
    mean_time_diff,
    sum_time_diff,
    variance_time_diff,
]

work_dataset
```

```
     Character-bigrams  Character-ngrams  Character-trigrams  \
1                    4                 1                   4
2                    7                 2                   4
3                   11                 1                   5
4                   20                 3                   7
5                    1                 1                   1
..                 ...               ...                 ...
315                 99                60                  87
316                169                49                 120
317                152                94                 118
318                215               115                 176
319                127                97                 119

     Count_of_most_visited_page      IP_Address  Number_of_records
Status  \
1                            20  10.223.157.186                115
200
2                            16  10.216.113.172                131
200
3                            32  10.216.113.172                331
200
4                            41    10.153.239.5                605
200
```

```
5                                4  10.216.113.172                  34
200
..                             ...             ...                 ...
...
315                            219  10.208.114.224                3353
200
316                            275    10.220.112.1                3417
200
317                            336  10.216.113.172                6946
200
318                            417  10.216.113.172                7991
200
319                            141  10.216.113.172                4927
200

     Time_Difference_Maximum  Time_Difference_Mean
Time_Difference_Sum  \
1                    18000.0            203.157895
23160.0
2                     3540.0             38.769231
5040.0
3                    33180.0            124.181818
40980.0
4                    31680.0             91.390728
55200.0
5                    37800.0           1376.363636
45420.0
..                       ...                   ...                  ..
.
315                   1140.0             25.739857
86280.0
316                   1260.0             25.222482
86160.0
317                    900.0             12.414687
86220.0
318                   1260.0             10.783479
86160.0
319                    840.0              6.699147
33000.0

     Time_Difference_Variance
1                2.897527e+06
2                1.019000e+05
3                3.478052e+06
4                2.260375e+06
5                4.229628e+07
..                        ...
315              8.794978e+03
316              7.775770e+03
```

```
317              2.587474e+03
318              3.044868e+03
319              1.492758e+03

[319 rows x 11 columns]
```

```
Ip_rep = []
for i, row in work_dataset.iterrows():
    ip = str(row.iloc[4])  # Convert to string
    if ip == "nan":  # Handle missing values
        ip = "0.0.0.0"  # Assign a default IP like "0.0.0.0"
    ip = ip.replace(".", "")  # Remove dots
    a = int(ip)  # Convert to integer
    Ip_rep.append(a)  # Append to list

# Convert list to NumPy array and add to DataFrame
work_dataset["IP_rep"] = np.array(Ip_rep)

work_dataset
```

```
     Character-bigrams  Character-ngrams  Character-trigrams  \
1                    4                 1                   4
2                    7                 2                   4
3                   11                 1                   5
4                   20                 3                   7
5                    1                 1                   1
..                 ...               ...                 ...
315                 99                60                  87
316                169                49                 120
317                152                94                 118
318                215               115                 176
319                127                97                 119

     Count_of_most_visited_page      IP_Address  Number_of_records
Status  \
1                            20  10.223.157.186                115
200
2                            16  10.216.113.172                131
200
3                            32  10.216.113.172                331
200
4                            41    10.153.239.5                605
200
5                             4  10.216.113.172                 34
200
..                          ...             ...                ...
...
315                         219  10.208.114.224               3353
200
316                         275    10.220.112.1               3417
```

```
200
317                          336  10.216.113.172               6946
200
318                          417  10.216.113.172               7991
200
319                          141  10.216.113.172               4927
200

     Time_Difference_Maximum  Time_Difference_Mean
Time_Difference_Sum  \
1                    18000.0            203.157895
23160.0
2                     3540.0             38.769231
5040.0
3                    33180.0            124.181818
40980.0
4                    31680.0             91.390728
55200.0
5                    37800.0           1376.363636
45420.0
..                       ...                   ...                   ..
.
315                   1140.0             25.739857
86280.0
316                   1260.0             25.222482
86160.0
317                    900.0             12.414687
86220.0
318                   1260.0             10.783479
86160.0
319                    840.0              6.699147
33000.0

     Time_Difference_Variance       IP_rep
1                2.897527e+06  10223157186
2                1.019000e+05  10216113172
3                3.478052e+06  10216113172
4                2.260375e+06    101532395
5                4.229628e+07  10216113172
..                        ...          ...
315              8.794978e+03  10208114224
316              7.775770e+03    102201121
317              2.587474e+03  10216113172
318              3.044868e+03  10216113172
319              1.492758e+03  10216113172

[319 rows x 12 columns]

work_dataset.drop("IP_Address", axis=1, inplace=True)
```

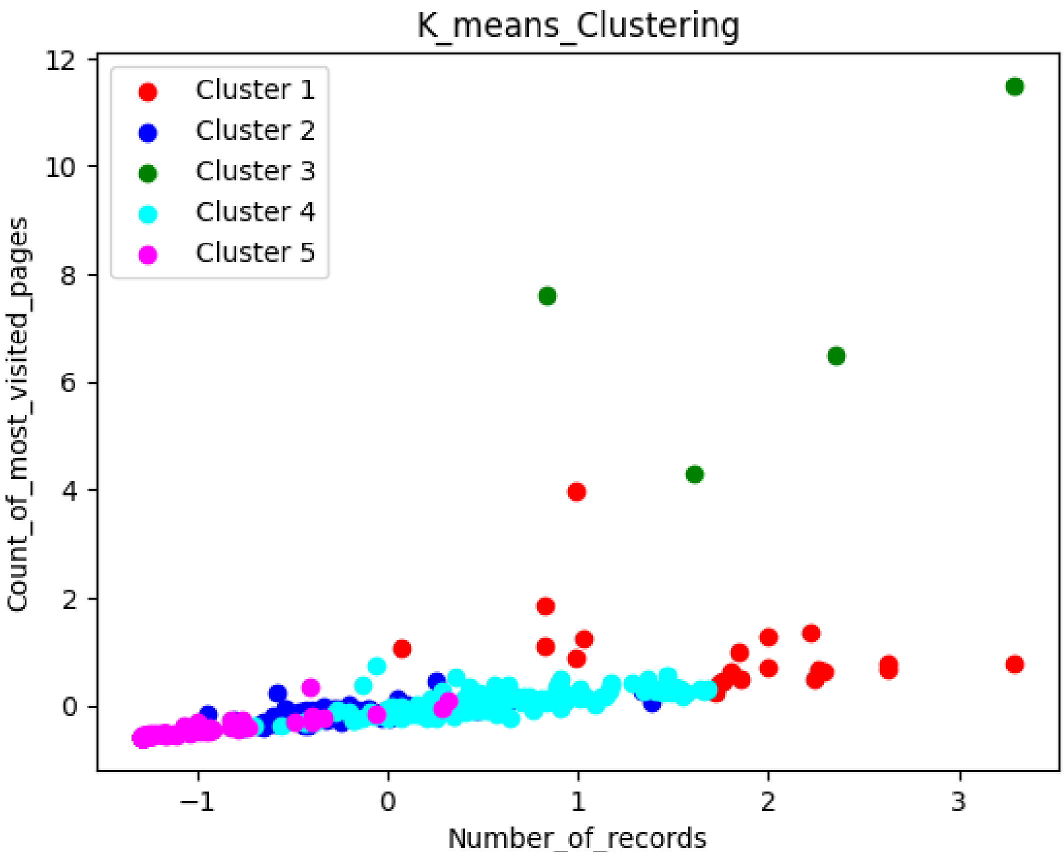
```
work_dataset
```

```
     Character-bigrams  Character-ngrams  Character-trigrams  \
1                    4                 1                   4
2                    7                 2                   4
3                   11                 1                   5
4                   20                 3                   7
5                    1                 1                   1
..                 ...               ...                 ...
315                 99                60                  87
316                169                49                 120
317                152                94                 118
318                215               115                 176
319                127                97                 119

     Count_of_most_visited_page  Number_of_records  Status  \
1                            20                115     200
2                            16                131     200
3                            32                331     200
4                            41                605     200
5                             4                 34     200
..                          ...                ...     ...
315                         219               3353     200
316                         275               3417     200
317                         336               6946     200
318                         417               7991     200
319                         141               4927     200

     Time_Difference_Maximum  Time_Difference_Mean
Time_Difference_Sum  \
1                    18000.0            203.157895
23160.0
2                     3540.0             38.769231
5040.0
3                    33180.0            124.181818
40980.0
4                    31680.0             91.390728
55200.0
5                    37800.0           1376.363636
45420.0
..                       ...                   ...                   ..
.
315                   1140.0             25.739857
86280.0
316                   1260.0             25.222482
86160.0
317                    900.0             12.414687
86220.0
318                   1260.0             10.783479
86160.0
```

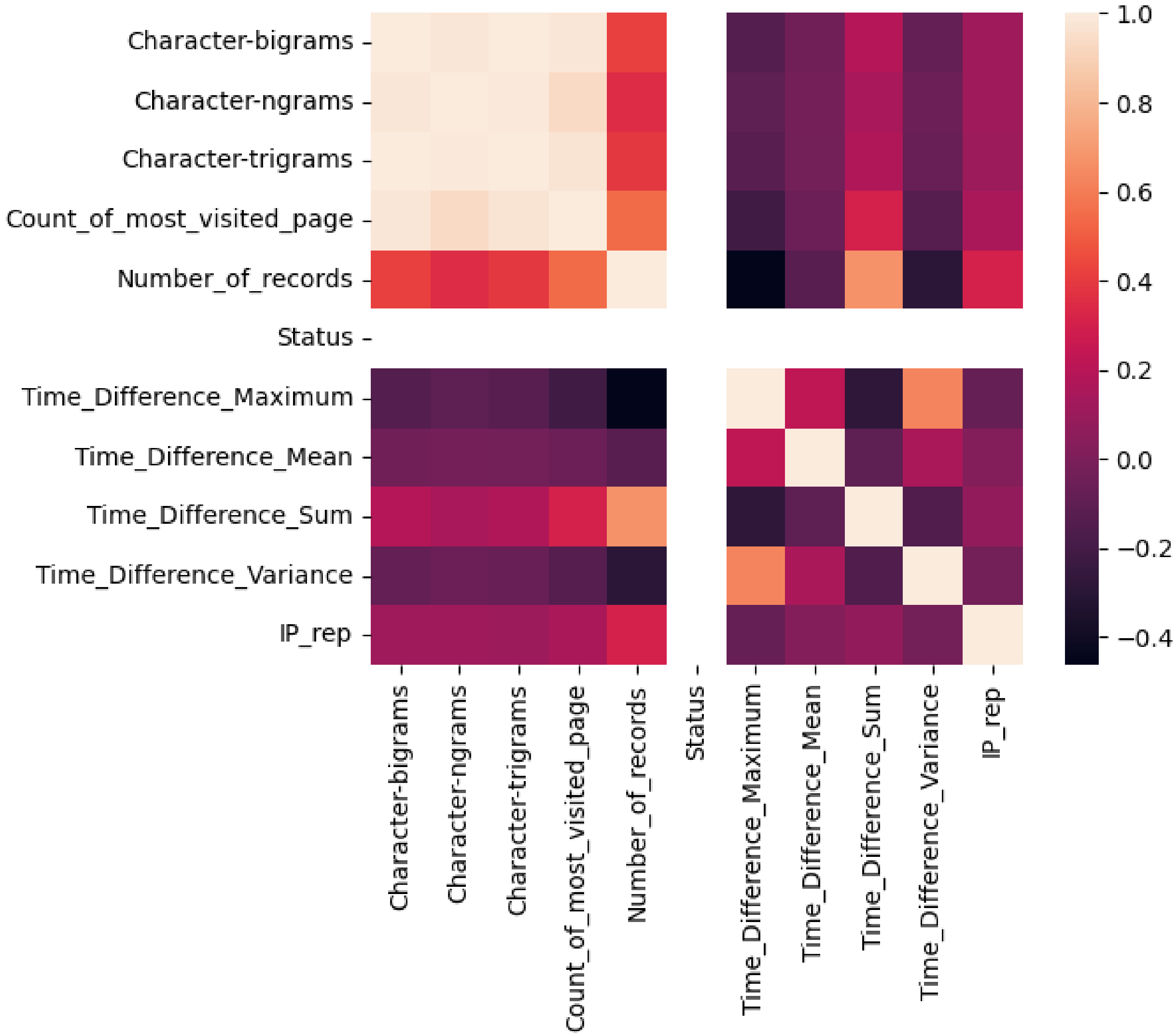
```
319                       840.0              6.699147
33000.0

     Time_Difference_Variance       IP_rep
1                2.897527e+06  10223157186
2                1.019000e+05  10216113172
3                3.478052e+06  10216113172
4                2.260375e+06    101532395
5                4.229628e+07  10216113172
..                        ...          ...
315              8.794978e+03  10208114224
316              7.775770e+03    102201121
317              2.587474e+03  10216113172
318              3.044868e+03  10216113172
319              1.492758e+03  10216113172

[319 rows x 11 columns]

X = work_dataset.iloc[:, :].values

from sklearn.preprocessing import StandardScaler

sc_X = StandardScaler()
X = sc_X.fit_transform(X)
X

array([[-0.34918829, -0.2514142 , -0.30262535, ..., -1.4513591 ,
         0.15823905,  0.76783463],
       [-0.33913374, -0.24585779, -0.30262535, ..., -2.0480536 ,
        -0.22087729,  0.7663166 ],
       [-0.32572767, -0.2514142 , -0.29871537, ..., -0.86454366,
         0.2369643 ,  0.7663166 ],
       ...,
       [ 0.14683643,  0.26533133,  0.14311274, ...,  0.62521676,
        -0.23434511,  0.7663166 ],
       [ 0.35798209,  0.38201581,  0.36989177, ...,  0.62324095,
        -0.23428308,  0.7663166 ],
       [ 0.06304847,  0.28200054,  0.14702273, ..., -1.12732633,
        -0.23449357,  0.7663166 ]])

from sklearn.cluster import KMeans

kmeans = KMeans(n_clusters=5, random_state=0)

kmeans.fit(X)

KMeans(n_clusters=5, random_state=0)

y_kmeans = kmeans.predict(X)
y_kmeans
```

```
array([4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
4,
       4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
4,
       4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
4,
       4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
4,
       4, 1, 1, 3, 3, 3, 3, 3, 1, 1, 3, 3, 1, 1, 3, 1, 1, 3, 3, 3, 3,
3,
       1, 3, 3, 3, 3, 3, 3, 1, 1, 3, 3, 3, 3, 3, 1, 1, 3, 3, 3, 3, 4,
4,
       4, 4, 4, 4, 3, 1, 1, 3, 0, 0, 3, 3, 3, 1, 3, 3, 3, 3, 1, 1, 1,
3,
       3, 3, 1, 3, 1, 1, 0, 3, 3, 1, 3, 1, 3, 3, 3, 3, 3, 3, 3, 3, 3,
0,
       3, 0, 0, 3, 1, 3, 3, 3, 3, 1, 1, 1, 3, 3, 3, 1, 3, 1, 1, 3, 3,
3,
       1, 3, 1, 1, 3, 3, 3, 3, 3, 1, 3, 3, 3, 3, 0, 3, 1, 1, 3, 1, 3,
1,
       1, 1, 3, 3, 3, 3, 3, 1, 3, 1, 3, 3, 3, 3, 3, 1, 1, 3, 3, 1, 3,
3,
       1, 1, 1, 3, 3, 3, 1, 0, 2, 4, 4, 0, 3, 3, 3, 1, 1, 1, 3, 3, 3,
1,
       1, 1, 1, 1, 3, 3, 3, 3, 1, 0, 3, 3, 3, 3, 3, 1, 1, 3, 3, 0, 0,
3,
       1, 1, 0, 3, 0, 3, 3, 1, 1, 2, 2, 0, 0, 2, 3, 1, 0, 3, 0, 0, 3,
3,
       1, 3, 3, 0, 3, 3, 3, 1, 3, 0, 3])
```

```
plt.scatter(X[y_kmeans == 0, 4], X[y_kmeans == 0, 3], c="red",
label="Cluster 1")
plt.scatter(X[y_kmeans == 1, 4], X[y_kmeans == 1, 3], c="blue",
label="Cluster 2")
plt.scatter(X[y_kmeans == 2, 4], X[y_kmeans == 2, 3], c="green",
label="Cluster 3")
plt.scatter(X[y_kmeans == 3, 4], X[y_kmeans == 3, 3], c="cyan",
label="Cluster 4")
plt.scatter(X[y_kmeans == 4, 4], X[y_kmeans == 4, 3], c="magenta",
label="Cluster 5")
# plt.scatter(kmeans.cluster_centers_[:, 0],
kmeans.cluster_centers_[:, 1], s = 300, c = 'yellow', label =
'Centroids')
plt.title("K_means_Clustering")
plt.xlabel("Number_of_records")
plt.ylabel("Count_of_most_visited_pages")
plt.legend()
plt.show()
```



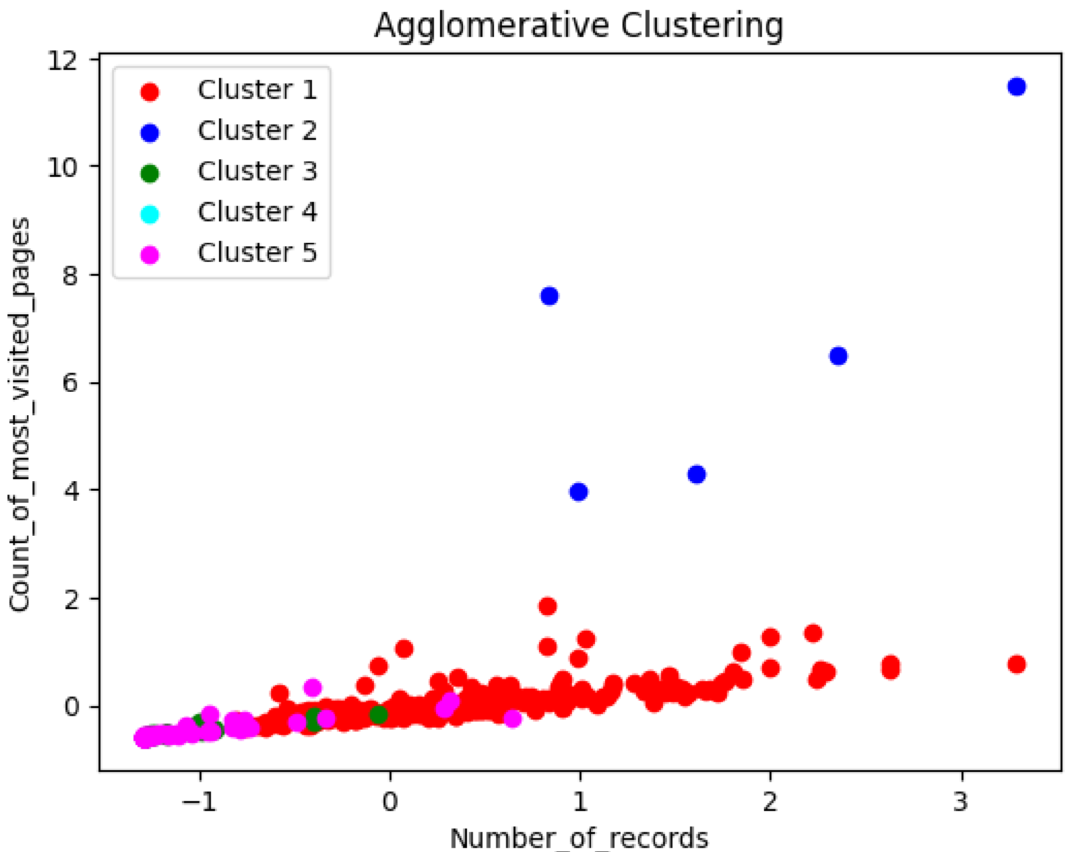

```python
import seaborn as sns

cor = work_dataset.corr()
sns.heatmap(cor, square=True)
plt.show()
```




```
from sklearn.cluster import AgglomerativeClustering,
AffinityPropagation

model = AgglomerativeClustering(n_clusters=5, metric="euclidean",
linkage="ward")
clust_labels1 = model.fit_predict(X)
clust_labels1

array([2, 4, 2, 2, 2, 2, 4, 2, 3, 4, 2, 2, 2, 2, 2, 4, 2, 2, 4, 2, 2,
4,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 4, 4, 2, 2, 4, 4, 4, 2, 2, 4,
4,
       4, 4, 2, 2, 4, 4, 4, 4, 4, 4, 4, 4, 2, 4, 2, 2, 2, 2, 2, 2, 4,
4,
       4, 4, 2, 2, 2, 4, 2, 4, 4, 4, 4, 4, 2, 4, 4, 4, 4, 4, 4, 2, 4,
2,
       4, 4, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
```

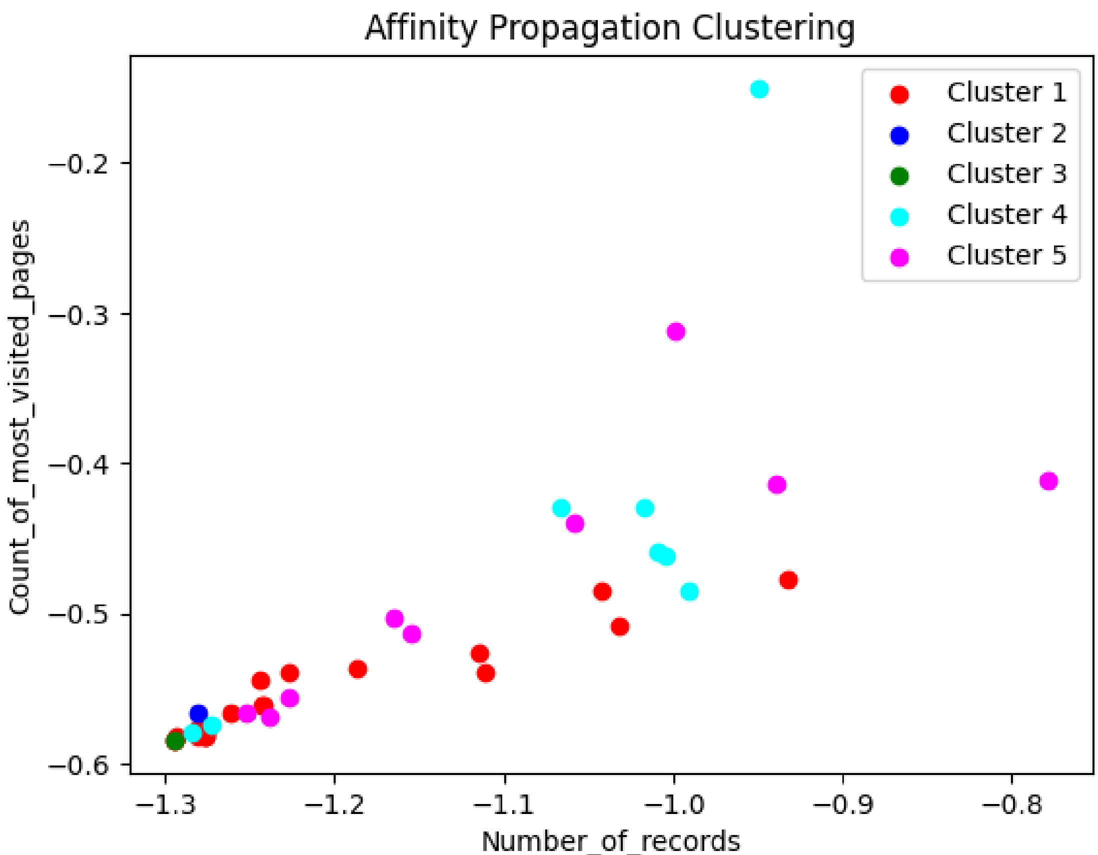
```
0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 4,
4,
        4, 4, 4, 4, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
        0, 0, 0, 0, 0, 0, 0, 0, 1, 4, 4, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
0,
        0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 4], dtype=int64)
```

```
agglomerative = pd.DataFrame(clust_labels1)

plt.scatter(
    X[clust_labels1 == 0, 4], X[clust_labels1 == 0, 3], c="red",
label="Cluster 1"
)
plt.scatter(
    X[clust_labels1 == 1, 4], X[clust_labels1 == 1, 3], c="blue",
label="Cluster 2"
)
plt.scatter(
    X[clust_labels1 == 2, 4], X[clust_labels1 == 2, 3], c="green",
label="Cluster 3"
)
plt.scatter(
    X[clust_labels1 == 3, 4], X[clust_labels1 == 3, 3], c="cyan",
label="Cluster 4"
)
plt.scatter(
    X[clust_labels1 == 4, 4], X[clust_labels1 == 4, 3], c="magenta",
label="Cluster 5"
)
plt.title("Agglomerative Clustering")
plt.xlabel("Number_of_records")
plt.ylabel("Count_of_most_visited_pages")
plt.legend()
plt.show()
```




```
model_affinity = AffinityPropagation(damping=0.5, max_iter=250,
affinity="euclidean")
model_affinity.fit(X)
clust_labels2 = model_affinity.predict(X)
cent2 = model_affinity.cluster_centers_
affinity = pd.DataFrame(clust_labels2)

plt.scatter(
    X[clust_labels2 == 0, 4], X[clust_labels2 == 0, 3], c="red",
label="Cluster 1"
)
plt.scatter(
    X[clust_labels2 == 1, 4], X[clust_labels2 == 1, 3], c="blue",
label="Cluster 2"
)
plt.scatter(
    X[clust_labels2 == 2, 4], X[clust_labels2 == 2, 3], c="green",
label="Cluster 3"
)
plt.scatter(
    X[clust_labels2 == 3, 4], X[clust_labels2 == 3, 3], c="cyan",
label="Cluster 4"
)
```

```
plt.scatter(
    X[clust_labels2 == 4, 4], X[clust_labels2 == 4, 3], c="magenta",
label="Cluster 5"
)
plt.title("Affinity Propagation Clustering")
plt.xlabel("Number_of_records")
plt.ylabel("Count_of_most_visited_pages")
plt.legend()
plt.show()
```




```
from sklearn.cluster import SpectralClustering

clustering = SpectralClustering(
    n_clusters=5, assign_labels="discretize", random_state=0
).fit(X)
clust_labels3 = clustering.labels_

clust_labels3

array([0, 0, 0, 3, 0, 0, 0, 0, 1, 3, 3, 3, 0, 0, 0, 3, 3, 3, 0, 3, 0,
3,
       3, 3, 3, 3, 0, 0, 3, 0, 3, 3, 0, 3, 0, 0, 3, 0, 3, 3, 3, 3, 0,
3,
```

```
       0, 3, 0, 0, 0, 0, 0, 3, 0, 0, 0, 0, 3, 0, 0, 3, 0, 0, 3, 0, 0,
3,
       0, 0, 3, 3, 0, 3, 3, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 3, 0, 3, 0,
0,
       3, 3, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0,
0,
       1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 3,
3,
       3, 3, 3, 3, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1,
0,
       0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
1,
       0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0,
0,
       1, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0,
1,
       1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0,
0,
       1, 1, 1, 0, 0, 0, 1, 0, 4, 0, 3, 2, 0, 0, 0, 1, 1, 1, 0, 0, 0,
1,
       1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
0,
       1, 1, 1, 0, 1, 0, 0, 1, 1, 2, 2, 0, 0, 4, 0, 1, 0, 0, 0, 0, 0,
0,
       1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0], dtype=int64)

plt.scatter(
    X[clust_labels3 == 0, 4], X[clust_labels3 == 0, 3], c="red",
label="Cluster 1"
)
plt.scatter(
    X[clust_labels3 == 1, 4], X[clust_labels3 == 1, 3], c="blue",
label="Cluster 2"
)
plt.scatter(
    X[clust_labels3 == 2, 4], X[clust_labels3 == 2, 3], c="green",
label="Cluster 3"
)
plt.scatter(
    X[clust_labels3 == 3, 4], X[clust_labels3 == 3, 3], c="cyan",
label="Cluster 4"
)
plt.scatter(
    X[clust_labels3 == 4, 4], X[clust_labels3 == 4, 3], c="magenta",
label="Cluster 5"
)
plt.title("Spectral Clustering")
plt.xlabel("Number_of_records")
plt.ylabel("Count_of_most_visited_pages")
```

```
plt.legend()
plt.show()
```