In [1]:
```
import matplotlib
%matplotlib inline
%config InlineBackend.figure_format = 'svg'
import matplotlib.pyplot as plt
plt.style.use('ggplot')

import pandas as pd
import numpy as np

from tqdm import tqdm #to show the progress in the function for best s
core calculation within range
from sklearn.cluster import KMeans, DBSCAN
from sklearn.metrics import silhouette_score
from sklearn.datasets import make_blobs
from sklearn.neighbors import KNeighborsClassifier

from collections import defaultdict

import hdbscan
import folium
import re

cols = ['#e9194b', '#3cb44b', '#ffe119', '#4363d8', '#f58231', '#911eb
4',
        '#46f0f0', '#f03e26', '#bcf60c', '#fabebe', '#008080', '#e6bef
f',
        '#9a6324', '#fffac8', '#800000', '#aaffc3', '#808000', '#ffd8b
1',
        '#000075','#808000'] * 10  #introducing more colors to differe
ntiate
```

In [2]:
```
df = pd.read_csv("taxi_data.csv")
df.head()
```

Out[2]:

	LON	LAT	NAME
0	28.17858	-25.73882	11th Street Taxi Rank
1	28.17660	-25.73795	81 Bazaar Street Taxi Rank
2	27.83239	-26.53722	Adams Road Taxi Rank
3	28.12514	-26.26666	Alberton City Mall Taxi Rank
4	28.10144	-26.10567	Alexandra Main Taxi Rank

In [3]:
```
df.duplicated(subset=['LON', 'LAT']).values.any() #checking whether du
plicate value exists
df.isna().values.any() #checking whether there is null value
```

Out[3]: True

In [4]:
```
df.dropna(inplace=True) #null value removal
df.drop_duplicates(subset=['LON', 'LAT'], keep = 'first', inplace=True
) #duplicate removal
```

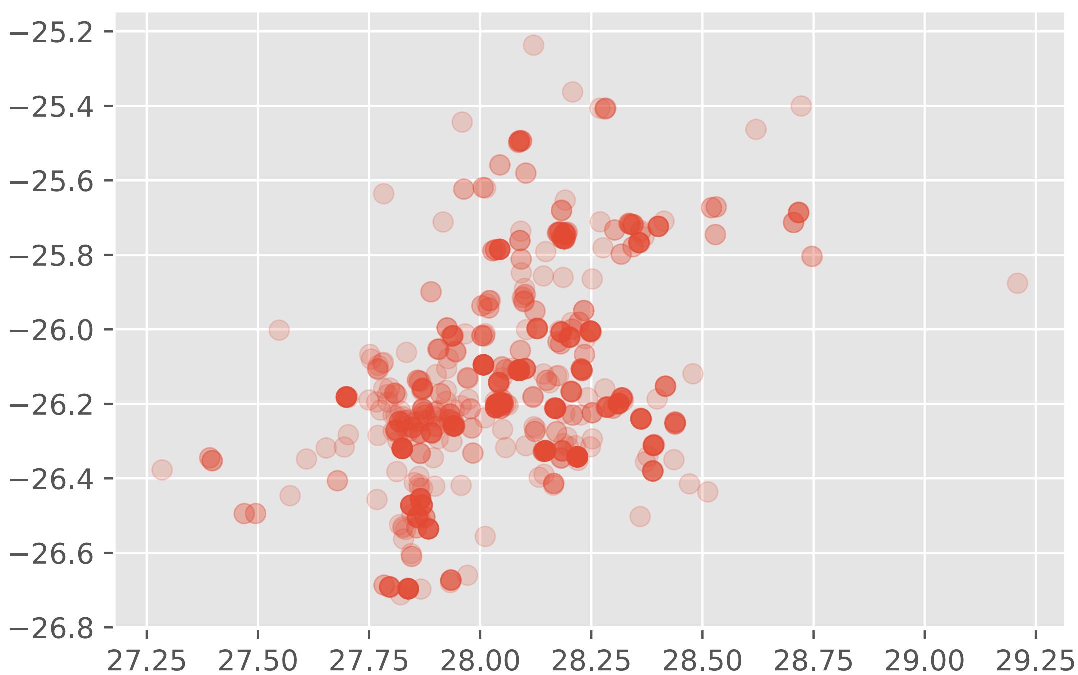
In [5]:
```
X = np.array(df[['LON', 'LAT']], dtype = 'float64')
```

In [6]:
```
X
```

Out[6]:
```
array([[ 28.17858, -25.73882],
       [ 28.1766 , -25.73795],
       [ 27.83239, -26.53722],
       ...,
       [ 27.83991, -26.24235],
       [ 27.86166, -26.23624],
       [ 28.39097, -26.30931]])
```

In [7]:
```
plt.scatter(X[:, 0], X[:, 1], alpha = 0.2, s = 50)
```

Out[7]:
```
<matplotlib.collections.PathCollection at 0x12afd6d90>
```



Performance Metric

K means

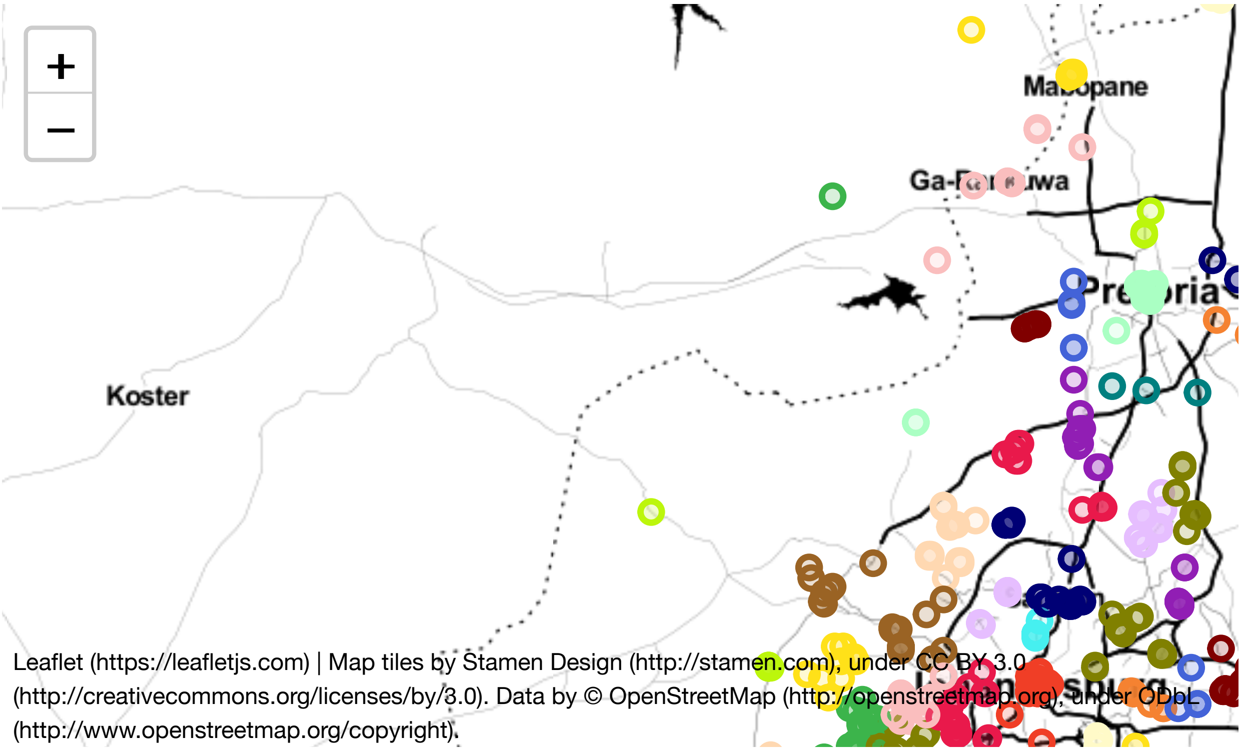
```
In [8]: X = np.array(df[['LON', 'LAT']], dtype = 'float64')
        k = 70
        model = KMeans(n_clusters=k, random_state=17).fit(X)
        class_predictions = model.predict(X)
        df[f'CLUSTER_KMeans{k}'] = class_predictions #new column in dataframe
        showing the predicted clusters for k-means
```

create_map() functions shows the interactive map of clusters with different colors

```
In [9]: def create_map(df, cluster_column):
            m = folium.Map(location=[df.LAT.mean(), df.LON.mean()], zoom_start
        = 9, tiles = 'Stamen Toner')

            for _, row in df.iterrows(): #return touple of the row number and
        information in the rows
                if row[cluster_column] == -1:
                    cluster_color = '#000000' #to mark the outliers point as b
        lack to identify
                else:
                    cluster_color = cols[row[cluster_column]]

                folium.CircleMarker(
                    location = [row['LAT'], row['LON']],
                    radius = 5,
                    popup = row[cluster_column],
                    color = cluster_color,
                    fill = True,
                    fill_color = cluster_color
                ).add_to(m)
            return m

        m = create_map(df, 'CLUSTER_KMeans70')
        print(f'K = {k}')
        print(f'Silhouette Score: {silhouette_score(X, class_predictions)}')

        m.save('Kmeans70.html') # for saving the result into a html page

        K = 70
        Silhouette Score: 0.6367300948961482
```

In [10]:
```
m
```

Out[10]:



In [11]:
```
# this code snippet explores the best silhouette score within given ra
nge of cluster size, in this case from 2 to 100
best_silhouette, best_k = -1, 0
for k in tqdm(range(2, 100)):
    model = KMeans(n_clusters=k, random_state=1).fit(X)
    class_predictions = model.predict(X)

    curr_silhouette = silhouette_score(X, class_predictions)
    if curr_silhouette > best_silhouette:
        best_k = k
        best_silhouette = curr_silhouette

print(f'K={best_k}')
print(f'Silhouette Score: {best_silhouette}')
```

```
100%|██████████| 98/98 [00:16<00:00,  5.82it/s]

K=98
Silhouette Score: 0.6971995093340411
```

DBSCAN

In [12]:

```python
model = DBSCAN(eps = 0.01, min_samples=5).fit(X) #radius,eps I will consider to make a potential cluster, hyperparameter
class_predictions = model.labels_ #how many samples need to be in the cluster

df['CLUSTERS_DBSCAN'] = class_predictions
```

In [13]:

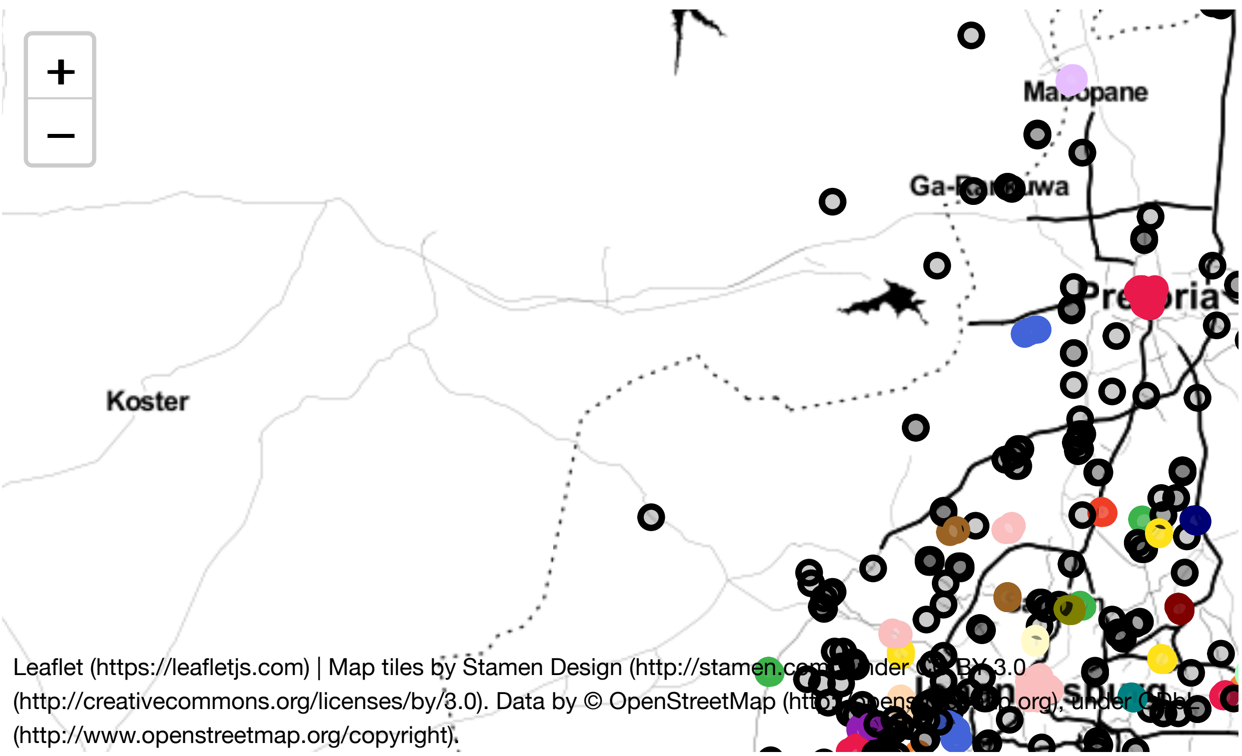
```python
m = create_map(df, 'CLUSTERS_DBSCAN')

print(f'Number of clusters found: {len(np.unique(class_predictions))}')  #how many clusters dbscan found
print(f'Number of outliers found: {len(class_predictions[class_predictions == -1])}')  #number of -1's which has been considered as

print(f'Silhouette ignoring outliers: {silhouette_score(X[class_predictions != -1], class_predictions[class_predictions != -1])}')
no_outliers = 0
no_outliers = np.array([(counter+2)*x if x == -1 else x for counter, x in enumerate(class_predictions)]) #modifying all -1's to some other values so that same noise values don't repeat too often
print(f'Silhouette outliers as singletons: {silhouette_score(X, no_outliers)}') #which suggests we might make some improvements
```

```
Number of clusters found: 51
Number of outliers found: 289
Silhouette ignoring outliers: 0.9232138250288208
Silhouette outliers as singletons: 0.5667489350583482
```

In [14]:

```python
m
```

Out[14]:



HDBSCAN

In [15]:
```
model = hdbscan.HDBSCAN(min_cluster_size=5, min_samples=2,
                        cluster_selection_epsilon=0.01)

class_predictions = model.fit_predict(X)
df['CLUSTER_HDBSCAN'] = class_predictions
```

In [17]:
```
df.tail()
```

Out[17]:

	LON	LAT	NAME	CLUSTER_KMeans70	CLUSTERS_DBSCAN	CLUSTER_HD
832	28.04441	-26.19727	Zimbabwe Taxi Rank	7	9	
833	27.82999	-26.24445	Zola Clinic Taxi Rank	1	25	
834	27.83991	-26.24235	Zola Taxi Rank	1	-1	
835	27.86166	-26.23624	Zondi Taxi Rank	49	-1	
836	28.39097	-26.30931	kwaThema Taxi Rank	10	19	

In [18]:
```
m = create_map(df, 'CLUSTER_HDBSCAN')

print(f'Number of clusters found: {len(np.unique(class_predictions))}'
)  #how many clusters dbscan found
print(f'Number of outliers found: {len(class_predictions[class_predict
ions == -1])}')  #number of -1's

print(f'Silhouette ignoring outliers: {silhouette_score(X[class_predic
tions != -1], class_predictions[class_predictions != -1])}')
no_outliers = 0
no_outliers = np.array([(counter+2)*x if x == -1 else x for counter, x
in enumerate(class_predictions)])
print(f'Silhouette outliers as singletons: {silhouette_score(X, no_out
liers)}') #which suggests we might make some improvements
```

```
Number of clusters found: 67
Number of outliers found: 102
Silhouette ignoring outliers: 0.7670504356844786
Silhouette outliers as singletons: 0.638992483305273
```

outlier addressing

In [19]:
```
classifier = KNeighborsClassifier(n_neighbors=1)
```

In [20]:
```
df_train = df[df.CLUSTER_HDBSCAN != -1]
df_predict = df[df.CLUSTER_HDBSCAN == -1]
```

In [21]:
```
X_train = np.array(df_train[['LON', 'LAT']], dtype = 'float64')
Y_train = np.array(df_train['CLUSTER_HDBSCAN'])

X_predict = np.array(df_predict[['LON', 'LAT']], dtype = 'float64') #o
utlier labels
```

In [22]:
```
classifier.fit(X_train, Y_train)
```

Out[22]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkows
ki',
                     metric_params=None, n_jobs=None, n_neighbors=1,
p=2,
                     weights='uniform')
```

In [23]:
```
predictions = classifier.predict(X_predict)
```

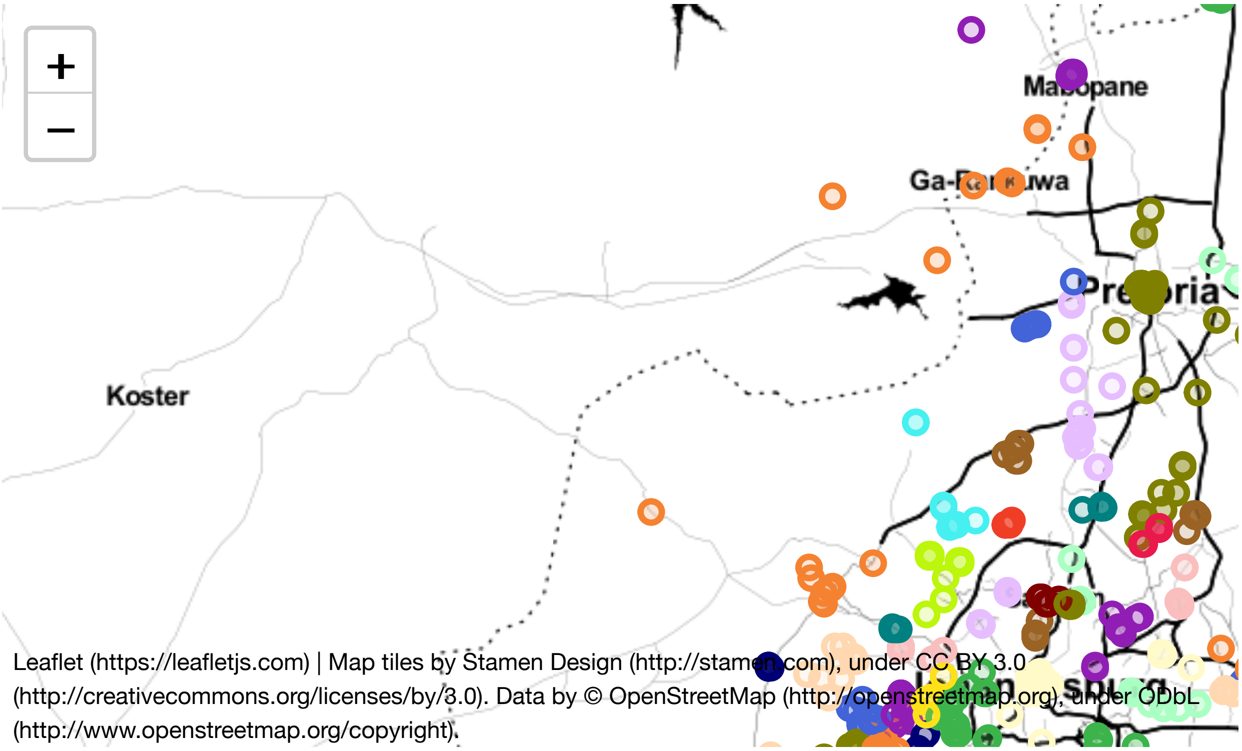
In [24]:
```
df['CLUSTER_hybrid'] = df['CLUSTER_HDBSCAN']
```

In [25]:
```
df.loc[df.CLUSTER_HDBSCAN == -1, 'CLUSTER_hybrid'] = predictions
```

In [26]:
```
m = create_map(df, 'CLUSTER_hybrid')
```

In [27]:
```
m
```

Out[27]:

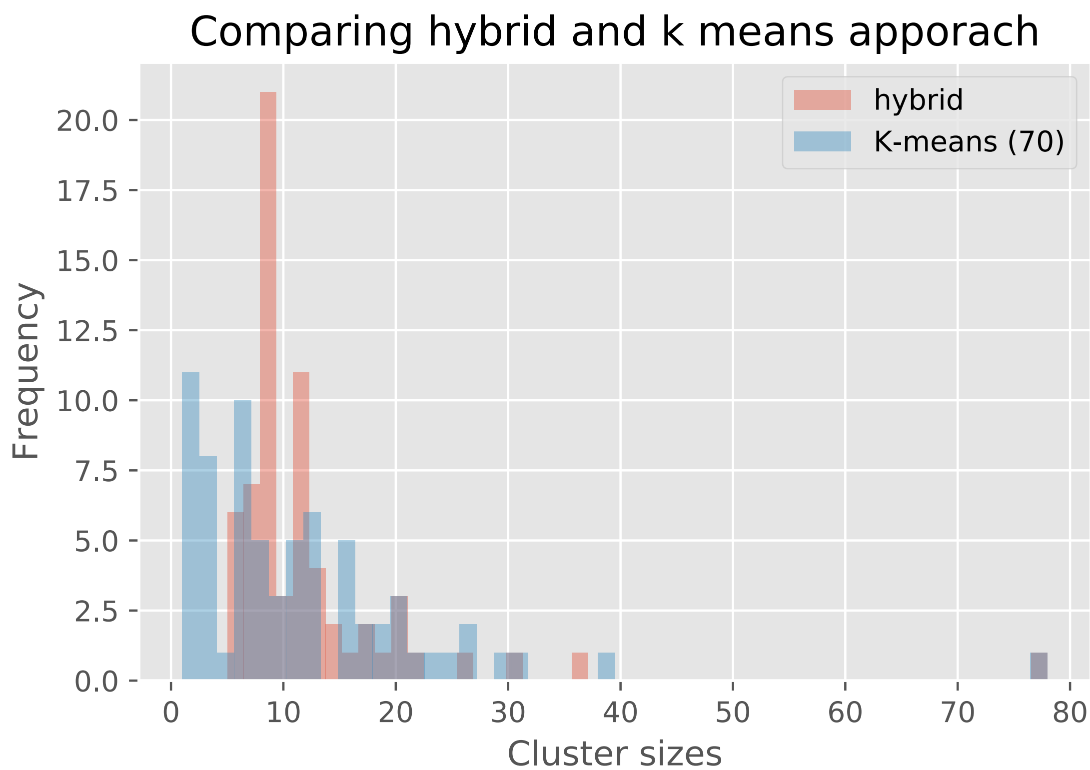


In [28]:
```
class_predictions = df['CLUSTER_hybrid']
print(f'Number of clusters found: {len(np.unique(class_predictions))}'
)  #how many clusters hybrid hdbscan found
print(f'Silhouette Score: {silhouette_score(X, class_predictions)}')

m.save('hrbrid.html')
```

```
Number of clusters found: 66
Silhouette Score: 0.5849126494706486
```

In [29]:
```
df['CLUSTER_hybrid'].value_counts().plot.hist(bins = 50, alpha = 0.4,
label = 'hybrid')
df['CLUSTER_KMeans70'].value_counts().plot.hist(bins = 50, alpha = 0.4
, label = 'K-means (70)')

plt.legend()
plt.title('Comparing hybrid and k means apporach')
plt.xlabel('Cluster sizes')
```

Out[29]:
```
Text(0.5, 0, 'Cluster sizes')
```



In [ ]: