This notebook is used as a "first look" of the kaggle competition "Google Landmark Recognition 2019" test set.

Because the available test set of the 2020 comeptition is witouth its ground truth table we will use 2019 competition test set to evaluate our algorithm.

The 2019 competition test set was released as CSV file with three columns: id (16-character string), landmarks (space-separated list of integer landmark IDs, or empty if no landmark from the dataset is depicted) and Usage (either "Public" or "Private", referring to which subset the image belongs to).

It can be found here.

In [291…

```
# imports for code
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import cv2
```

In [292…

```
# load the test data csv file as data frame
test_df = pd.read_csv("C:/Users/Matan/Desktop/projectB/data/2019/recognition_solution_v2.1.csv")
test_df
```

Out[292…

	id	landmarks	Usage
0	e324e0f3e6d9e504	NaN	Private
1	d9e17c5f3e0c47b3	NaN	Private
2	1a748a755ed67512	NaN	Public
3	537bf9bdfccdafea	NaN	Private
4	13f4c974274ee08b	NaN	Private
...	...	...	...
117572	e351c3e672c25fbd	190441	Public
117573	5426472625271a4d	NaN	Public
117574	7b6a585405978398	NaN	Public
117575	d885235ba249cf5d	NaN	Public
117576	c7f657e8d0f7fafb	NaN	Private

117577 rows × 3 columns

As we can see there are a lot of NaN values in the landmarks column. That mean that a lot of the objects in the test set are not landmarks but non-landmarks.

We would like to look at the images from the train set:

In [293…

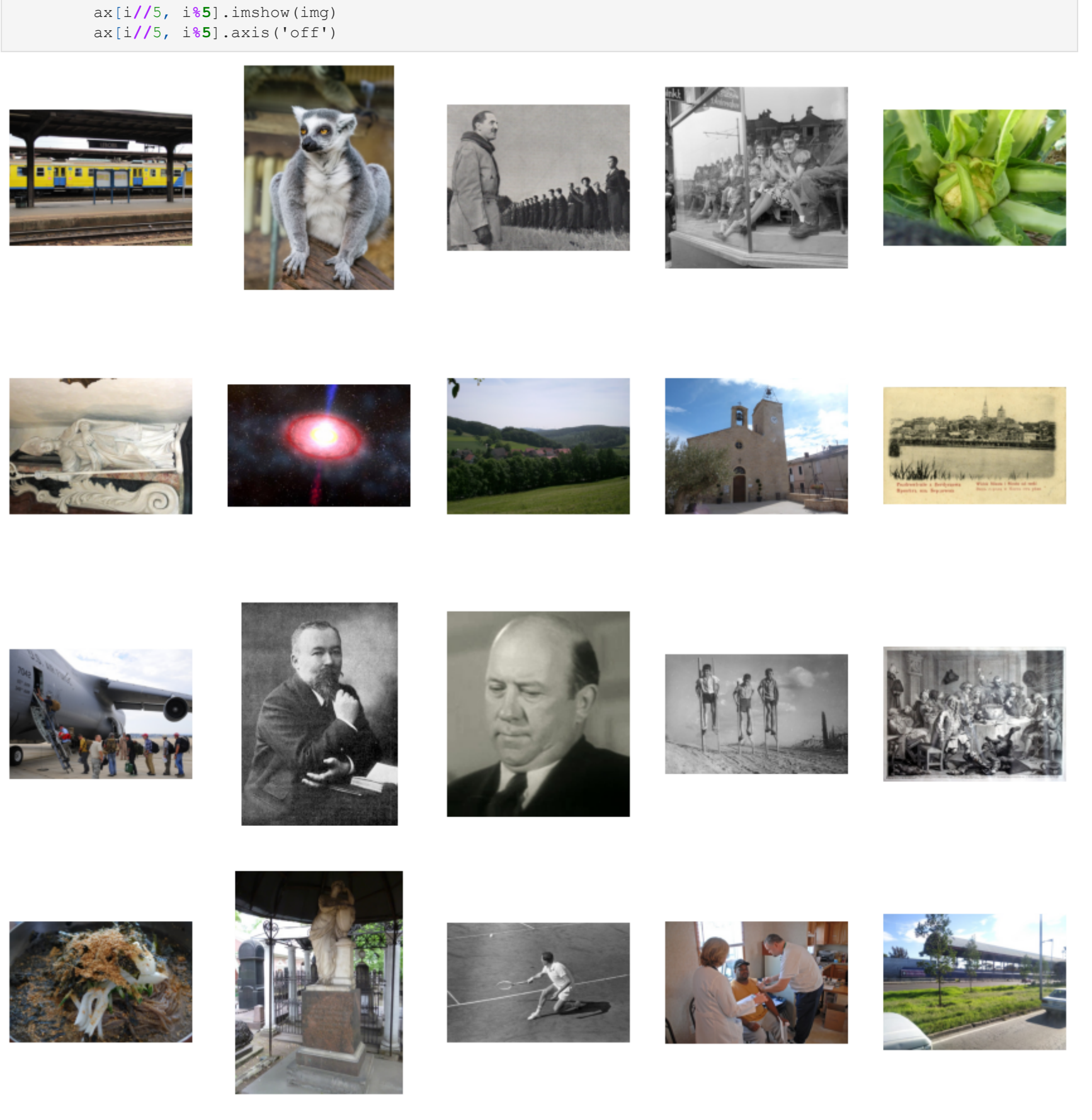
```
# load test image path and labels as a dictionary and then convet to dataframe
test_path_label_dict = {'image': [], 'target': []}
for i in range(test_df.shape[0]):
    test_path_label_dict['image'].append(
        "D:/dataset/test" + '/' +
        test_df['id'][i][0] + '/' +
        test_df['id'][i][1] + '/' +
        test_df['id'][i][2] + '/' +
        test_df['id'][i] + ".jpg")
    test_path_label_dict['target'].append(test_df['landmarks'][i])

test_path_label_df = pd.DataFrame(test_path_label_dict)
```

In [294…

```
images = []

for i in range(1,21):
    img = cv2.imread(test_path_label_df.image[1:21][i])
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    images.append(img)
f, ax = plt.subplots(4,5, figsize=(15,15))
for i, img in enumerate(images):
        ax[i//5, i%5].imshow(img)
        ax[i//5, i%5].axis('off')
```



As we saw from the dataframe, the train set contain a lot of images that are not landmark at all but a variety of images including protrait, group of people, animals, plants, food, etc..

We will look now only on the landmarks inside the test set.

In [295…

```
test_df_no_NaN = test_df.dropna()
test_df_no_NaN = test_df_no_NaN.reset_index()
test_df_no_NaN = test_df_no_NaN.drop('index', axis=1)
test_df_no_NaN
```

Out[295…

	id	landmarks	Usage
0	ed85edf01da02f26	179171	Public
1	4d5d0e6264e6c7e0	124703	Public
2	e153105026e18260	150977	Public
3	db635e33c17229bb	92607	Private
4	03b1294a0fa46763	184268	Private
...	...	...	...
1967	4e4e7fdca971442f	95197	Private
1968	efd80af423defb09	162786	Public
1969	90e066e0d0ac2827	188823	Private
1970	ee95080bf6187d9a	127232	Public
1971	e351c3e672c25fbd	190441	Public

1972 rows × 3 columns

As we can see, most of the objects in the test set are non-landmarks.

We would like to look at the images from the test set that identified as landmarks:

In [296…

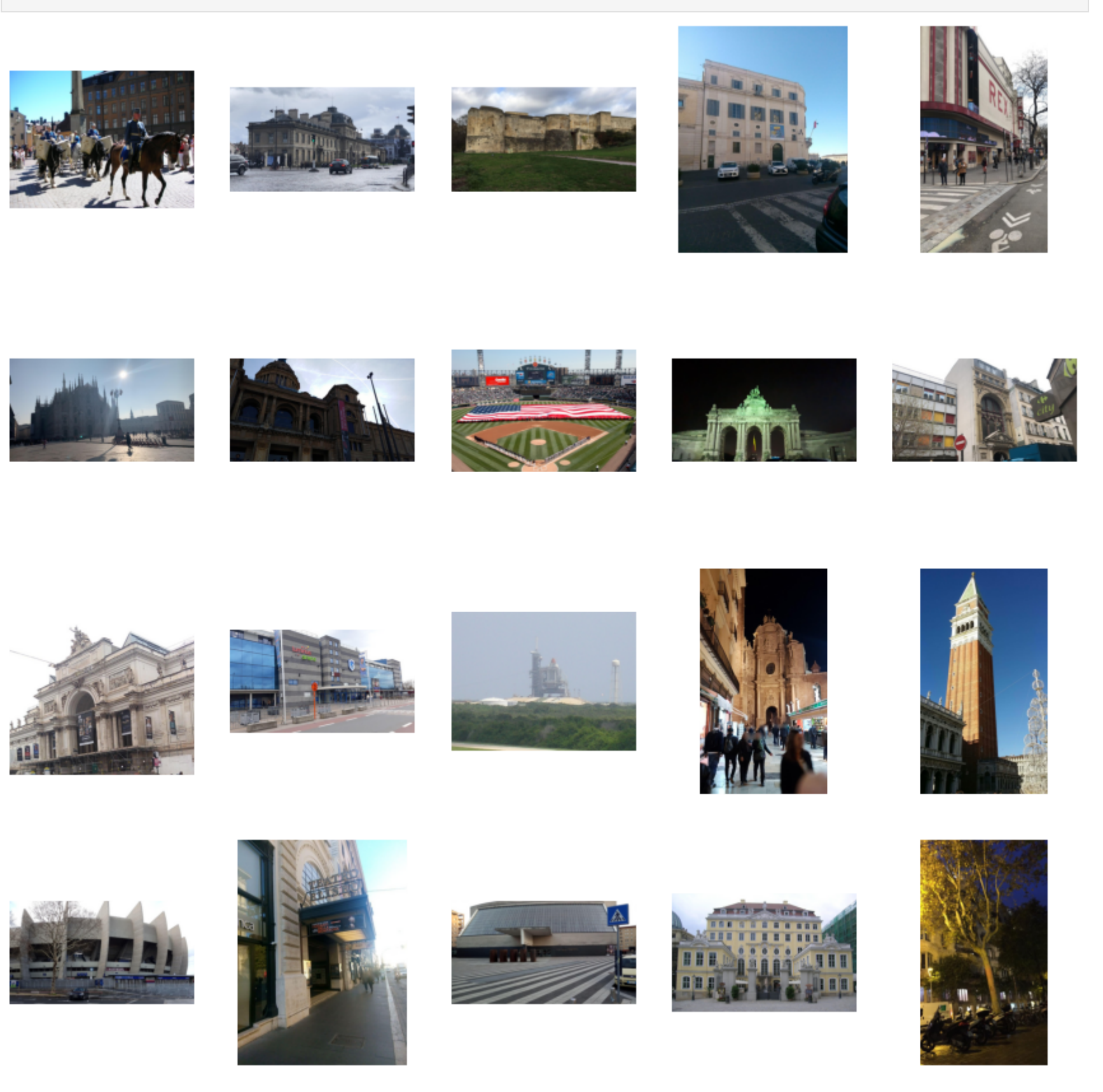
```
# load test image (without NaN) path and labels as a dictionary and then convet to dataframe
test_no_NaN_path_label_dict = {'image': [], 'target': []}
for i in range(test_df_no_NaN.shape[0]):
    test_no_NaN_path_label_dict['image'].append(
        "D:/dataset/test" + '/' +
        test_df_no_NaN['id'][i][0] + '/' +
        test_df_no_NaN['id'][i][1] + '/' +
        test_df_no_NaN['id'][i][2] + '/' +
        test_df_no_NaN['id'][i] + ".jpg")
    test_no_NaN_path_label_dict['target'].append(test_df_no_NaN['landmarks'][i])

test_no_NaN_path_label_df = pd.DataFrame(test_no_NaN_path_label_dict)
```

In [297…

```
images = []

for i in range(1,21):
    img = cv2.imread(test_no_NaN_path_label_df.image[1:21][i])
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    images.append(img)
f, ax = plt.subplots(4,5, figsize=(15,15))
for i, img in enumerate(images):
        ax[i//5, i%5].imshow(img)
        ax[i//5, i%5].axis('off')
```



As we can see, all the images above shows a variety of landmarks

We'll now check few of the test set properties:

In [298…

```
print("number of ids is: {}" .format(test_df['id'].size))
print("\nnumber of landmarks ids is: {}" .format(test_df_no_NaN['id'].size))
print("\nnumber of unique values in landmarks column is: {}" .format(test_df['landmarks'].nunique()))
```

```
number of ids is: 117577

number of landmarks ids is: 1972

number of unique values in landmarks column is: 849
```

As we can see, the test set composed out of **117,577 images** that divided into **849 classes**. Only **1972 pictures** out of the 117,577 images in the test set are actually landmarkd, e.i. only **1.67 %**

We would like to look at the different classes in the test set, we we'll start with the top classes:

In [299…

```
print("top 10 classes:\n")
print(test_df_no_NaN['landmarks'].value_counts().head(10))
```

```
top 10 classes:

114046 171629    13
158276           12
100782           11
74275            10
556              10
15223            10
169083           10
161396           10
179453           10
149453           10
Name: landmarks, dtype: int64
```

As we can see from the top result, some images can relate to more than one class. We would like to know how many images can realte to more than one

In [300…

```
# We'll creata new data frame thus if one image relate to more then one class we'll split the classes to oth
new_df = test_df_no_NaN["landmarks"].str.split(" ", n = 10, expand = True)
print(new_df.shape)
```

```
(1972, 4)
```

As we can see, one image can relate to different classes (up to 4).

In [301…

```
# now we'll concat the four columns to 1 and drop the NaN
concat_df = pd.concat([new_df[0], new_df[1], new_df[2], new_df[3]]).dropna()
concat_df = concat_df.to_frame('landmarks').reset_index()
concat_df = concat_df.drop('index', axis=1)
print("The classes that appear in the test set, seperated:")
concat_df
```

```
The classes that appear in the test set, seperated:
```

Out[301…

	landmarks
0	179171
1	124703
2	150977
3	92607
4	184268
...	...
2309	52006
2310	76017
2311	52006
2312	48571
2313	9463

2314 rows × 1 columns

In [302…

```
print(concat_df['landmarks'].value_counts().head(10))

print("\nnumber of unique values in landmarks column is: {}" .format(concat_df['landmarks'].nunique()))
```

```
185558    16
100782    16
114046    15
171629    13
121008    12
158276    12
47378     12
132969    12
178061    11
146388    11
Name: landmarks, dtype: int64

number of unique values in landmarks column is: 852
```

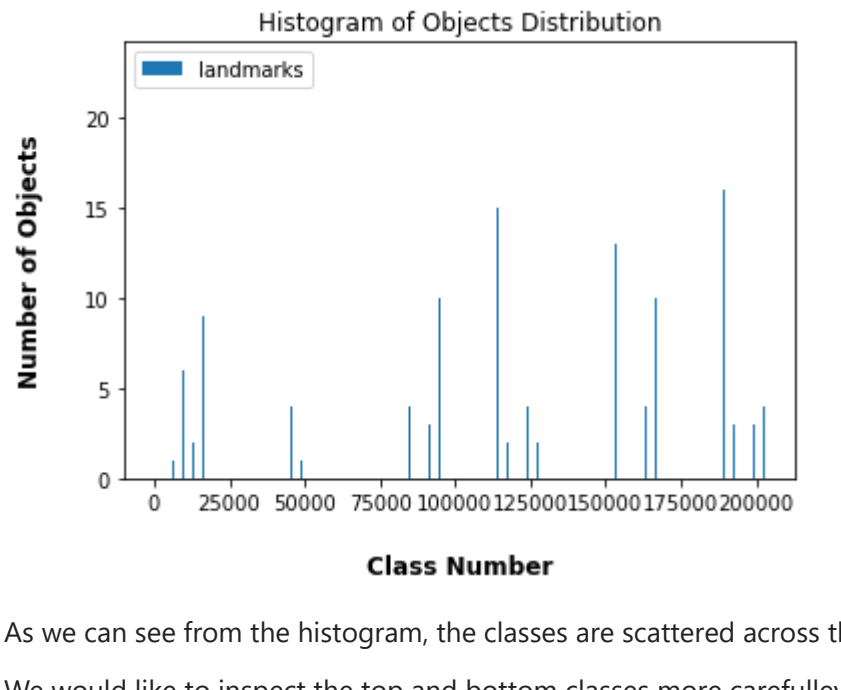
As we can see from the above, when we first split and then concatenate the landmarks coulmn, it changed the amount of recurrence of some classes. It also changed the amount of classes to **852 classes**.

We would like to plot the classes histogram:

In [303…

```
concat_df_float = concat_df.astype(float)
fig = plt.figure()
ax = concat_df_float.plot.hist(bins=852, grid=False, rwidth=0.1)
ax.set_xlabel("Class Number", labelpad=20, weight='bold', size=12)
ax.set_ylabel("Number of Objects", labelpad=20, weight='bold', size=12)
ax.set_title("Histogram of Objects Distribution")
plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```

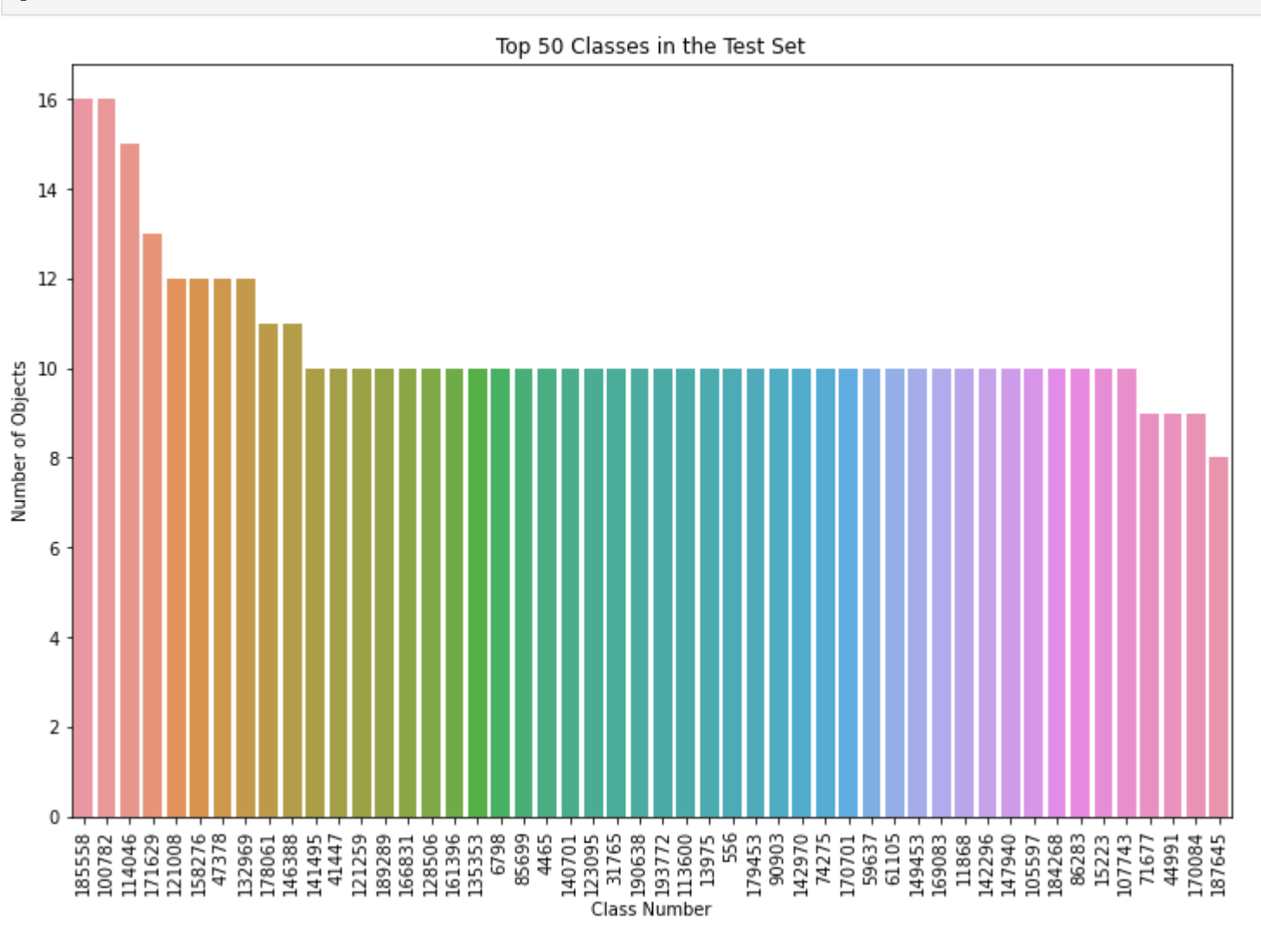


As we can see from the histogram, the classes are scattered across the x axis.

We would like to inspect the top and bottom classes more carefulley:

In [304…

```
fig2 = plt.figure(figsize = (12,8))
sns.countplot(x=concat_df.landmarks, order = concat_df['landmarks'].value_counts().head(50).index)
plt.xlabel("Class Number")
plt.ylabel("Number of Objects")
plt.title("Top 50 Classes in the Test Set")
plt.xticks(rotation = 90)
plt.show()
```

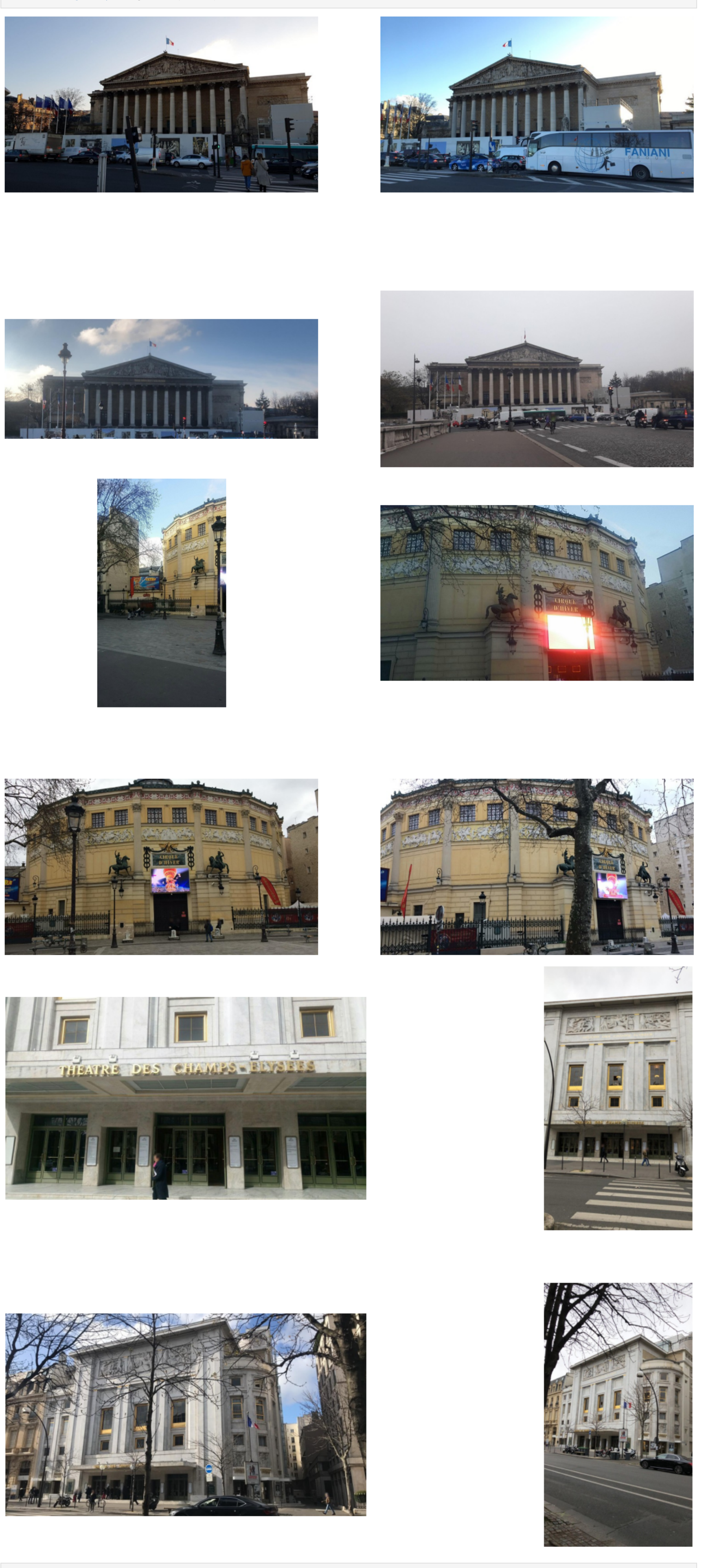


We will display some images from some of the top classes:

In [305…

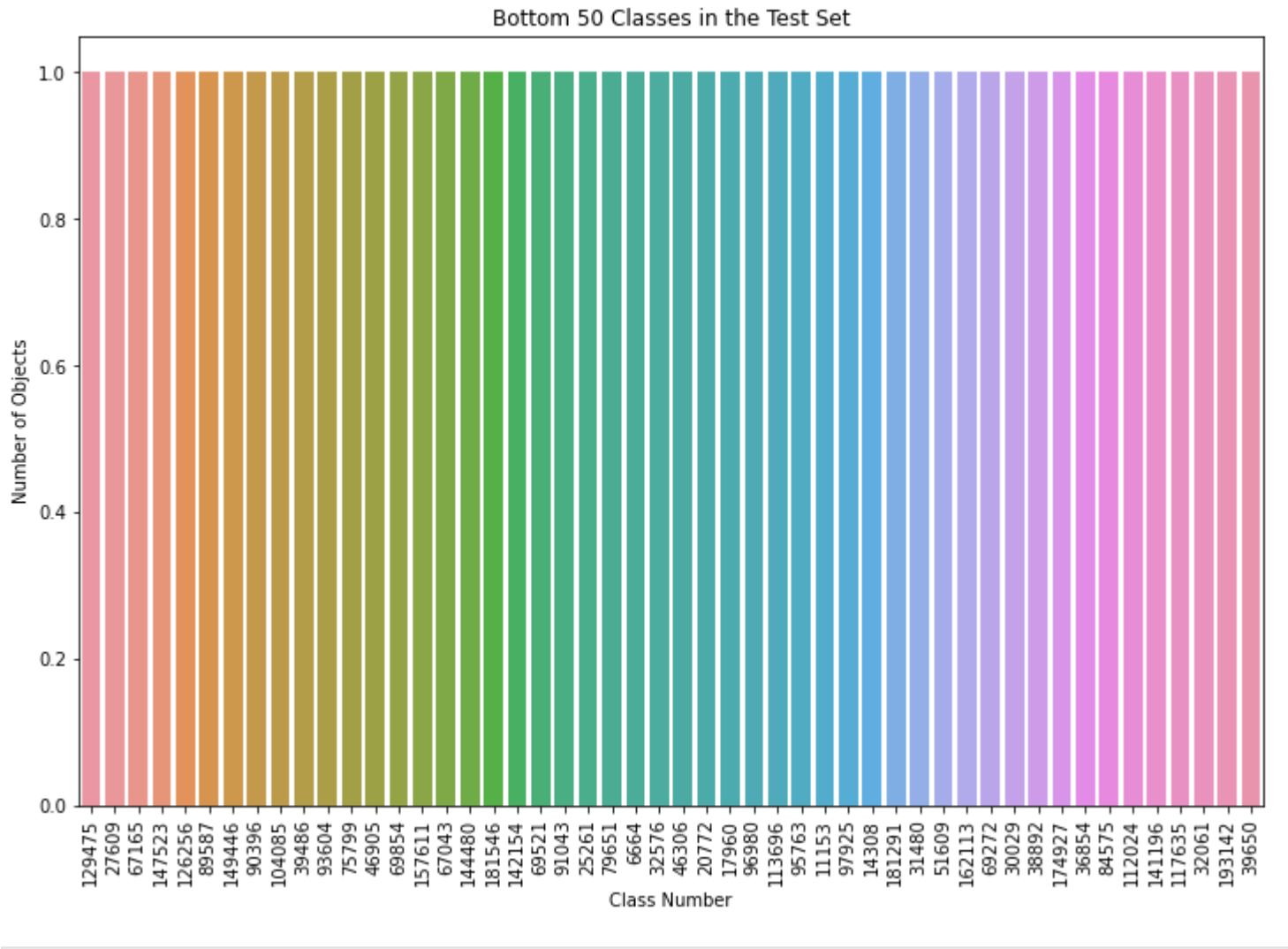
```
top_classes = (158276, 161396, 6798) # some top classes

for i in range(len(top_classes)):
    images = []
    for j in range(4):
        img = cv2.imread(test_no_NaN_path_label_df[test_no_NaN_path_label_df.target == str(top_classes[i])][
        img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
        images.append(img)
    f, ax = plt.subplots(2,2,figsize=(20,15))
    for k, img in enumerate(images):
        ax[k//2, k%2].imshow(img)
        ax[k//2, k%2].axis('off')
```



In [306…

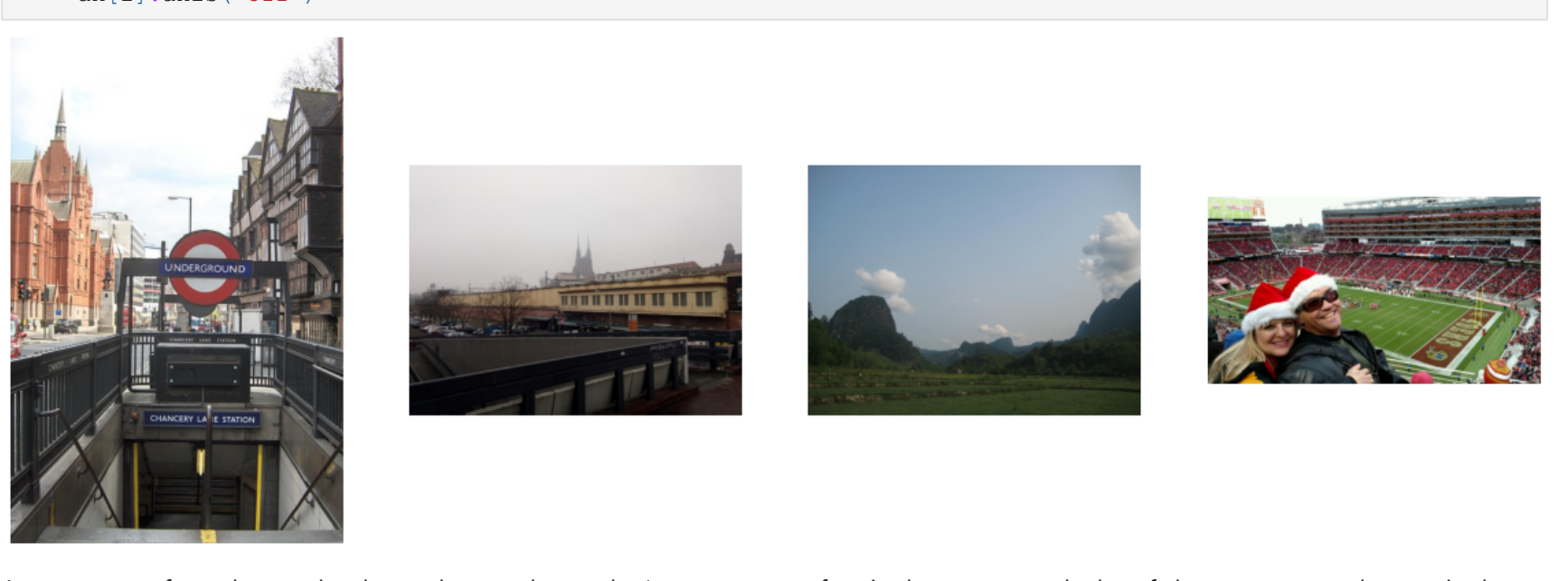
```
fig2 = plt.figure(figsize = (12,8))
sns.countplot(x=concat_df.landmarks, order = concat_df['landmarks'].value_counts().tail(50).index)
plt.xlabel("Class Number")
plt.ylabel("Number of Objects")
plt.title("Bottom 50 Classes in the Test Set")
plt.xticks(rotation = 90)
plt.show()
```



In [307…

```
bottom_classes = (70439, 69521, 69272, 38892) # some bottom classes
fig = plt.figure(figsize=(20,15))
img = [0] * len(bottom_classes) # a zeros array with bottom_classes len
ax = [0] * len(bottom_classes)

for i, class_ in enumerate(bottom_classes):
    img[i] = cv2.imread(test_no_NaN_path_label_df[test_no_NaN_path_label_df.target == str(class_)]['image'].
    img[i] = cv2.cvtColor(img[i], cv2.COLOR_BGR2RGB)
    ax[i] = fig.add_subplot(1, len(bottom_classes), i+1)
    ax[i].imshow(img[i])
    ax[i].axis('off')
```



As we can see from the graphs above, the top classes don't appear very often in the test set and a lot of classes appear only once in the train set.

This is the 2019 test set we will use to evaluate our algorithm.