

# Location-based assignment

This is a location-based assignment in San Francisco. I chose an interesting symbol in front of the place I usually pick up lunch from.

## 1. Resize image to 512 pixels

```
In [ ]: # Import libraries

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

from glob import glob
from PIL import Image
from resizeimage import resizeimage

from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.decomposition import PCA
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
```

```
In [ ]: photos = glob('*.jpeg')
        PHOTO_SIZE = 512
```

```
In [ ]: photos_flattened = []
        # for each image path
        for path in photos:
            # open it as a read file in binary mode
            with open(path, 'r+b') as f:
                # open it as an image
                with Image.open(f) as image:
                    # resize the image to be more manageable
                    cover = resizeimage.resize_cover(image, [PHOTO_SIZE, PHOTO_SIZE])
                    # flatten the matrix to an array and append it to all flattened images
                    photos_flattened.append(np.array(cover).flatten())
```

```
In [ ]: # Flatten it once more
photos_flattened = np.asarray(photos_flattened)
```

```
In [ ]: X = np.stack(i for i in photos_flattened)
```

```
/home/khanh/Documents/cs156-pcw-khanhtmlmn/venv/lib/python3.8/site-packages/IPython/core/interactiveshell.p
y:3191: FutureWarning: arrays to stack must be passed as a "sequence" type such as list or tuple. Support
for non-sequence iterables such as generators is deprecated as of NumPy 1.16 and will raise an error in th
e future.
```

```
    if await self.run_code(code, result, async_=asy):
```

```
In [ ]: X.shape
```

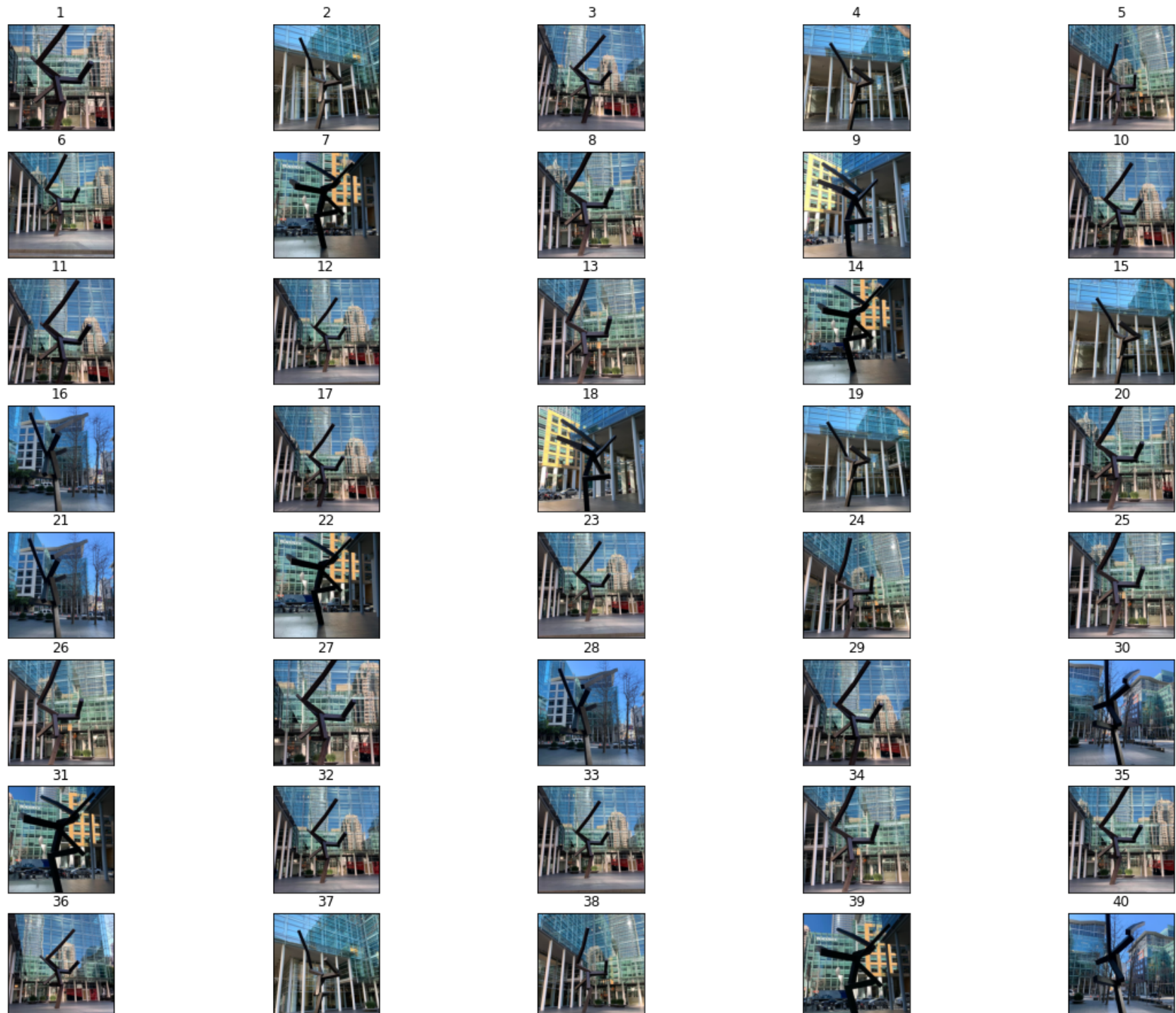
```
Out[ ]: (48, 786432)
```

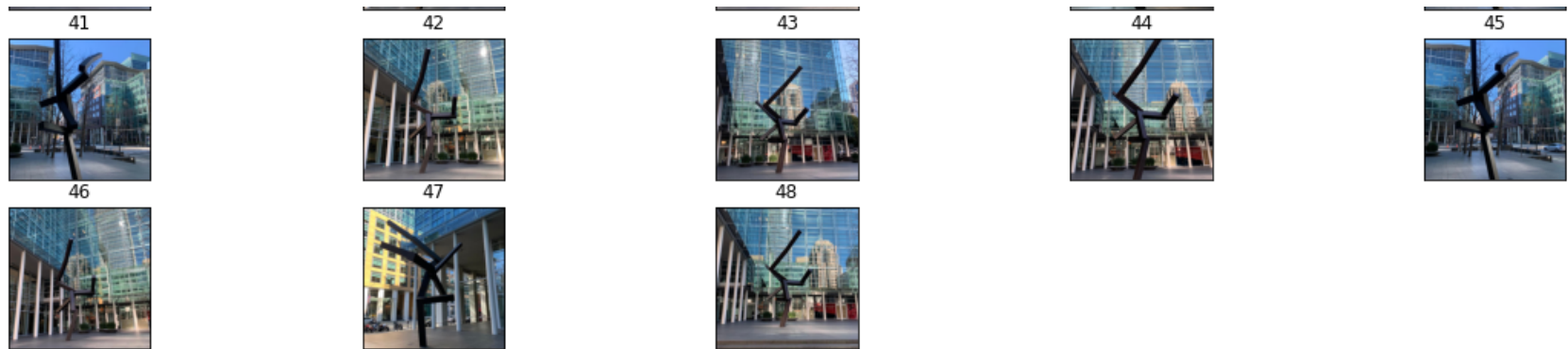
Let's take a look at the original photos. I took them at different angles!

```
In [ ]: # Original photos
```

```
nrows = len(X)//5 + 1
ncols = 5
```

```
plt.figure(figsize=[20, 20])
plt.title("Original photos")
for i in range(len(X)):
    plt.subplot(nrows, ncols, i+1, xticks=[], yticks=[])
    plt.imshow(X[i].reshape(PHOTO_SIZE, PHOTO_SIZE, 3).astype(np.uint8))
    plt.title(f"{i+1}")
plt.show()
```





## 2. Use PCA to project the images down to a 2D representation

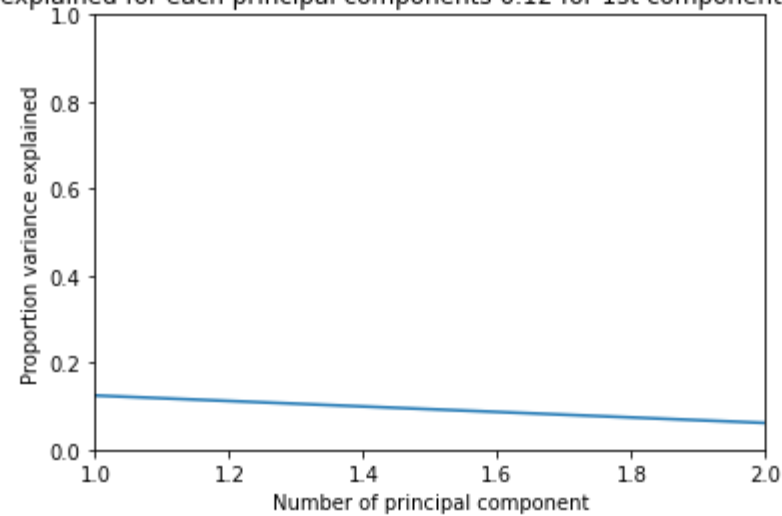
```
In [ ]: pca = PCA(n_components=2)
pca.fit(X)
X_2d = pca.transform(X)
print(X_2d.shape)
```

```
(48, 2)
```

```
In [ ]: variance_explained = pca.explained_variance_ratio_
```

```
In [ ]: plt.plot(range(1,3,1), variance_explained)
plt.title(f'Proportion of variance explained for each principal components {round(variance_explained[0], 2)
plt.xlabel('Number of principal component')
plt.ylabel('Proportion variance explained')
plt.ylim(0, 1)
plt.xlim([1, 2])
plt.show()
```

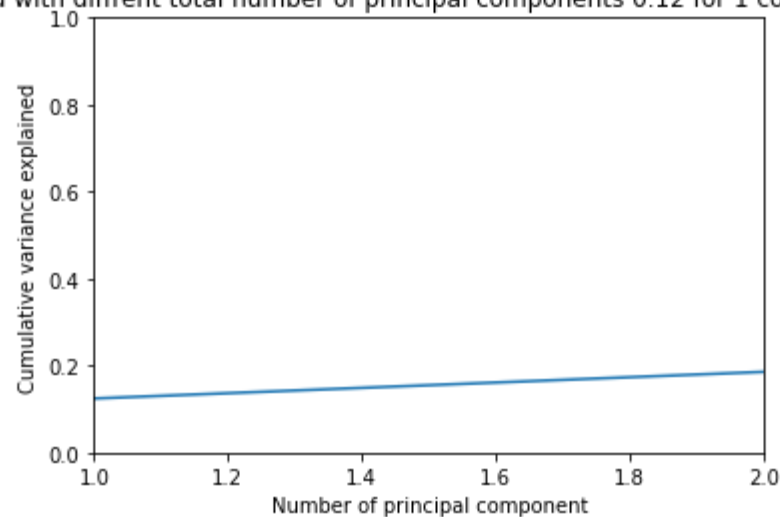
Proportion of variance explained for each principal components 0.12 for 1st component and 0.06 for 2nd component



```
In [ ]: cum_sum_variance_explained = np.cumsum(variance_explained)
```

```
In [ ]: plt.plot(range(1,3,1), cum_sum_variance_explained)
plt.title(f'Cumulative variance explained with diffrent total number of principal components {round(cum_sum_variance_explained[-1], 2)}')
plt.xlabel('Number of principal component')
plt.ylabel('Cumulative variance explained')
plt.ylim(0, 1)
plt.xlim([1, 2])
plt.show()
```

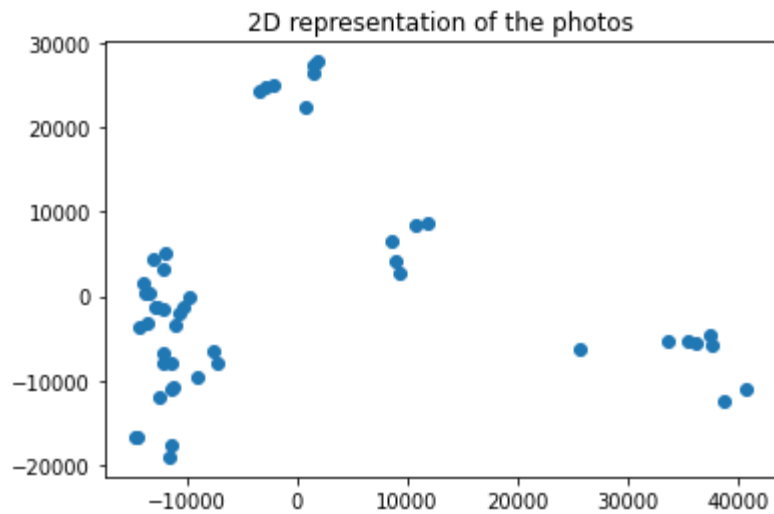
Cumulative variance explained with different total number of principal components 0.12 for 1 component and 0.19 for 2 components



It seems like the two components together can only explain 19% variation in the data, which makes sense given that our object has a very unusual shape. In addition, the photos were taken from a lot of angles!

### 3. Visually inspect the 2D locations in the new space

```
In [ ]: plt.scatter(X_2d[:,0], X_2d[:,1])  
plt.title(f'2D representation of the photos')  
plt.show()
```



Seems like the 2D locations cluster into 4 different groups, which were also the different angles (front, back, left, right) that I took the photos from!

We can also represent the information in a table:

```
In [ ]: pca_df = pd.DataFrame(data=X_2d, columns=['1', '2'])
pca_df.head()
```

```
Out[ ]:
```

	1	2
0	-7246.326090	-7918.640678
1	9350.144377	2814.114686
2	-9705.062618	-124.327807
3	10766.790330	8391.582263
4	-10653.344788	-1874.696437

## 4. Show reconstruction from each low-dimensional representation

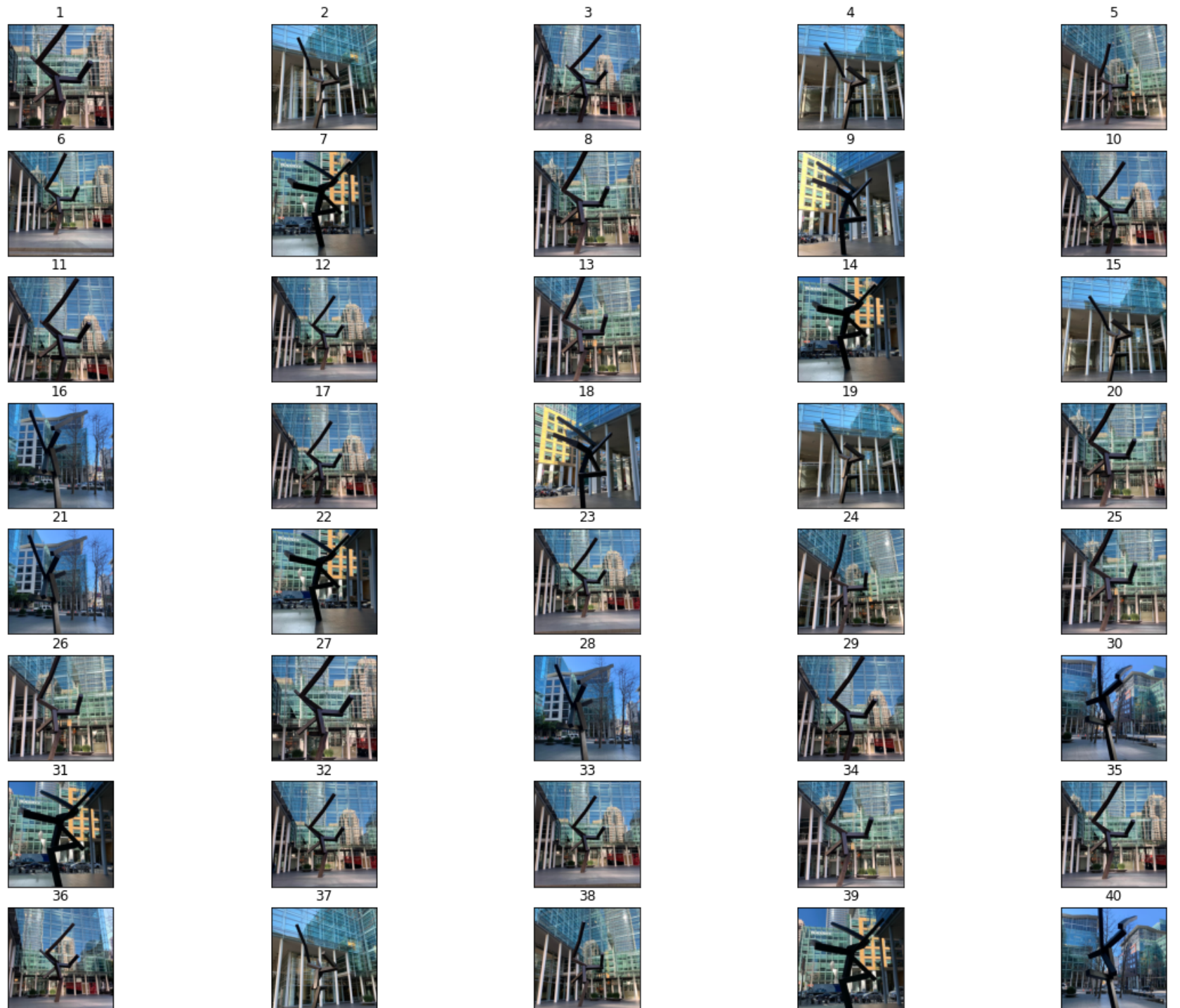
Let's view the original photos again to compare with the reconstructed photos

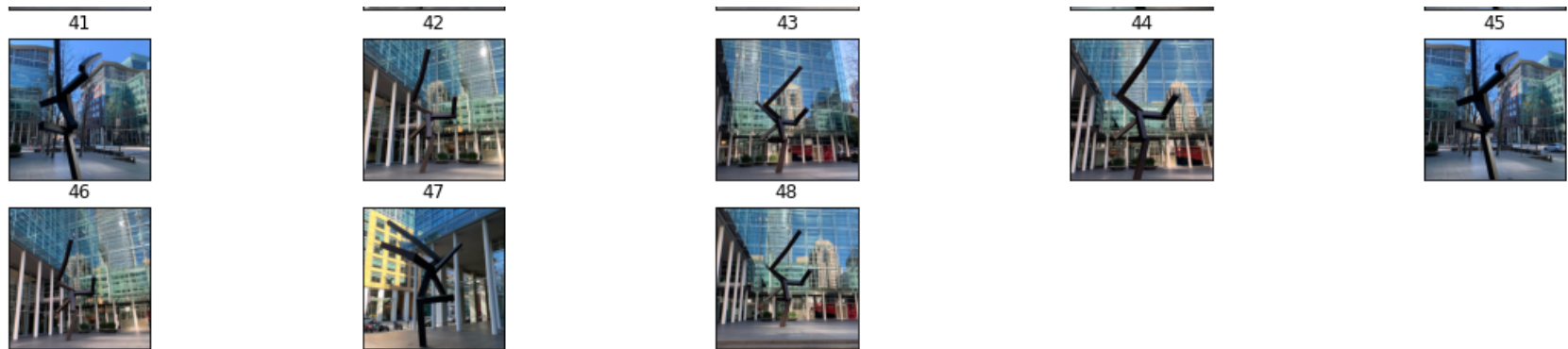
```
In [ ]: # Original photos

nrows = len(X)//5 + 1
ncols = 5

plt.figure(figsize=[20, 20])
plt.title("Original photos")
for i in range(len(X)):
    plt.subplot(nrows, ncols, i+1, xticks=[], yticks=[])
    plt.imshow(X[i].reshape(PHOTO_SIZE, PHOTO_SIZE, 3).astype(np.uint8))
    plt.title(f"{i+1}")
plt.show()
```





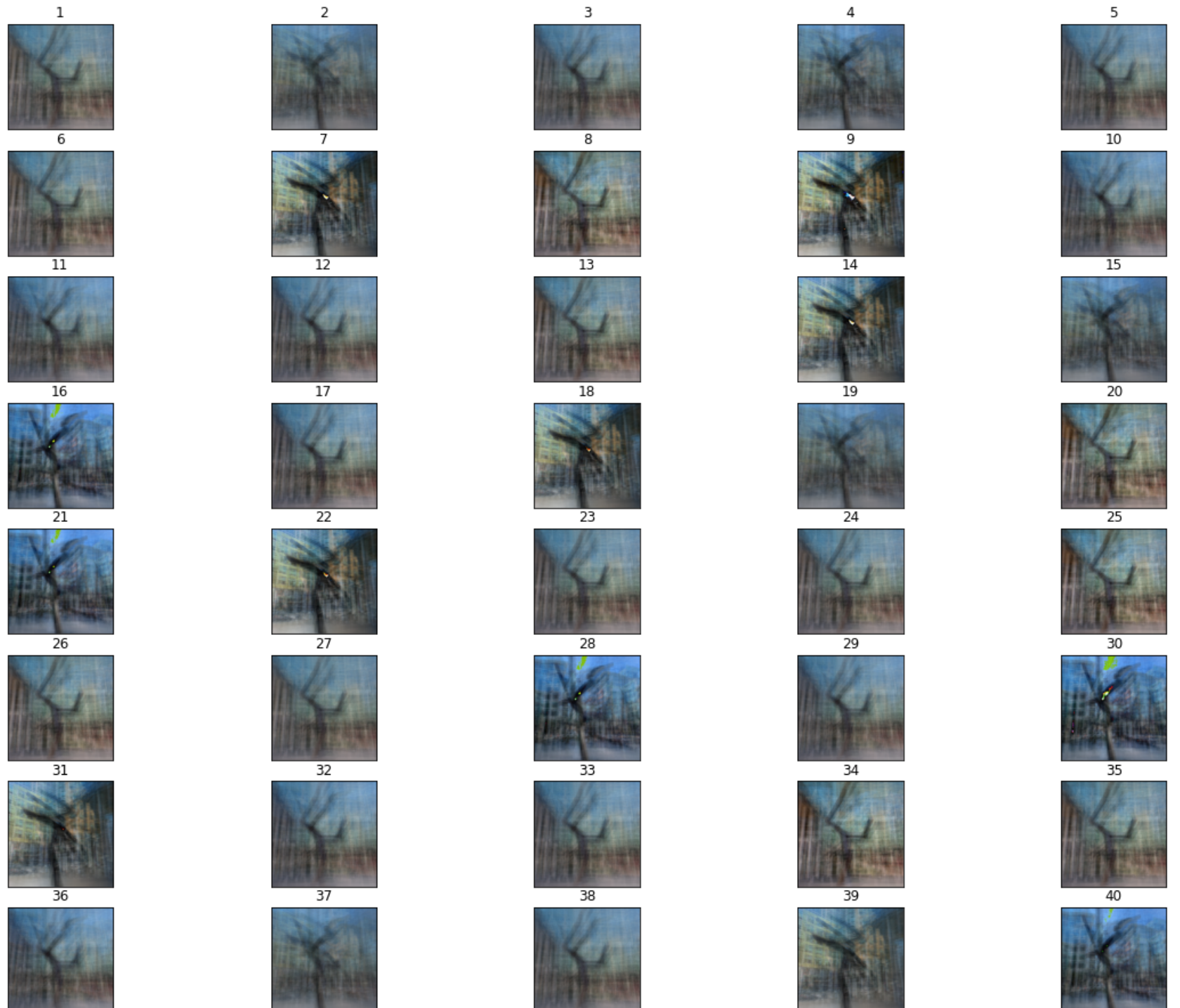


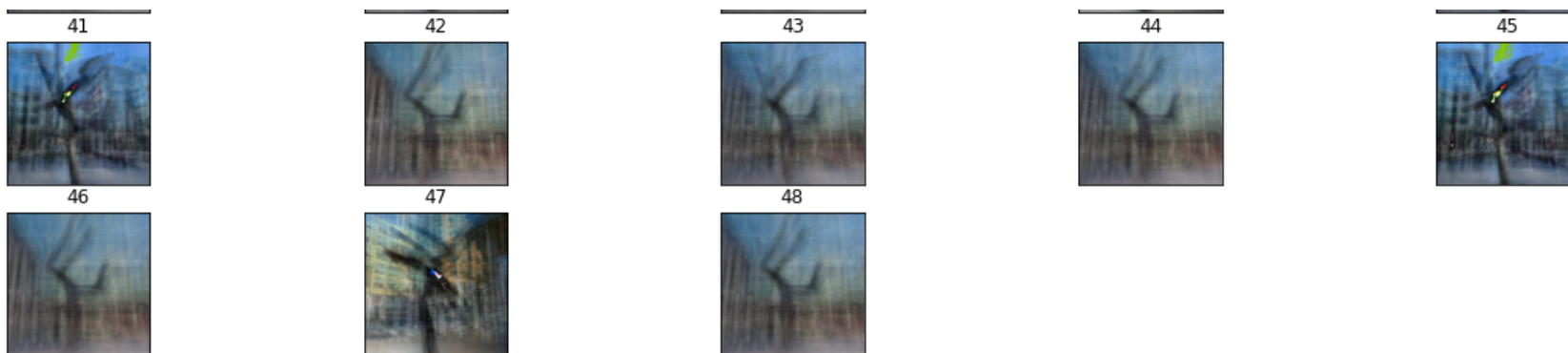
```
In [ ]: reconstructed = pca.inverse_transform(X_2d)
```

```
In [ ]: # Reconstructed photos
```

```
nrows = len(X)//5 + 1
ncols = 5

plt.figure(figsize=[20, 20])
for i in range(len(X)):
    plt.subplot(nrows, ncols, i+1, xticks=[], yticks=[])
    plt.imshow(reconstructed[i].reshape(PHOTO_SIZE, PHOTO_SIZE, 3).astype(np.uint8))
    plt.title(f"{i+1}")
plt.show()
```



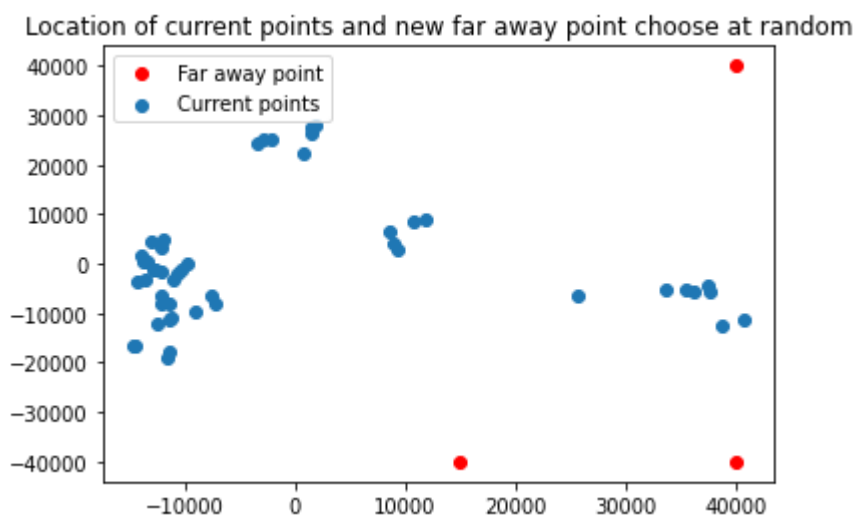


## 5. Plot the reconstruction from a point far away

Let's pick 3 far away points to compare their reconstructions

```
In [ ]: far_away_points = np.array([[40000, 40000], [40000, -40000], [15000, -40000]])

plt.plot(far_away_points[:, 0], far_away_points[:, 1], 'ro', label="Far away point")
plt.scatter(X_2d[:, 0], X_2d[:, 1], label="Current points")
plt.title("Location of current points and new far away point choose at random")
plt.legend()
plt.show()
```

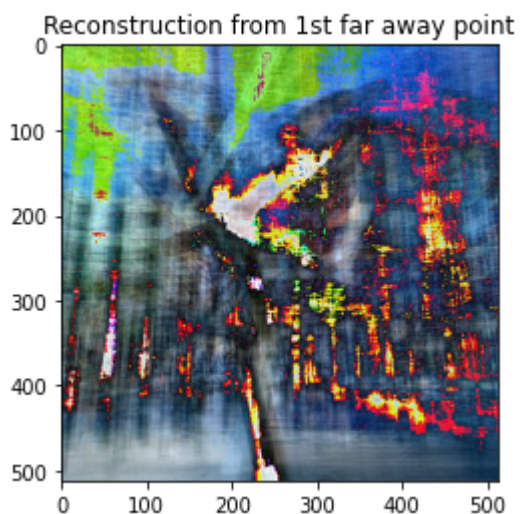




```
In [ ]: current_far_away_point = np.reshape(np.array(far_away_points[0]), (1, -1))
        far_away_point_inversed = pca.inverse_transform(current_far_away_point)

        plt.title("Reconstruction from 1st far away point")
        plt.imshow(np.reshape(far_away_point_inversed, (PHOTO_SIZE, PHOTO_SIZE, 3)).astype(np.uint8))
```

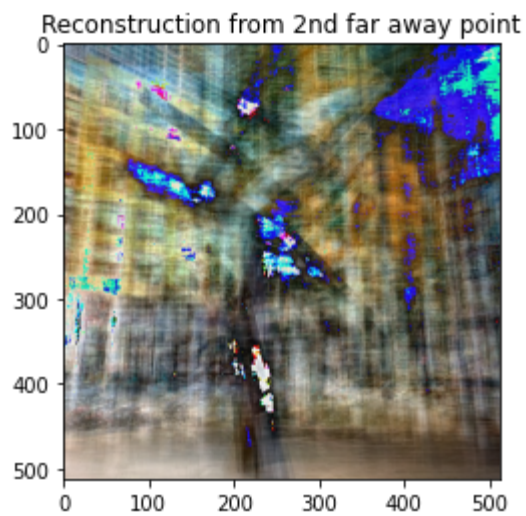
Out[ ]: <matplotlib.image.AxesImage at 0x7fd01e4e2dc0>



```
In [ ]: current_far_away_point = np.reshape(np.array(far_away_points[1]), (1, -1))
        far_away_point_inversed = pca.inverse_transform(current_far_away_point)

        plt.title("Reconstruction from 2nd far away point")
        plt.imshow(np.reshape(far_away_point_inversed, (PHOTO_SIZE, PHOTO_SIZE, 3)).astype(np.uint8))
```

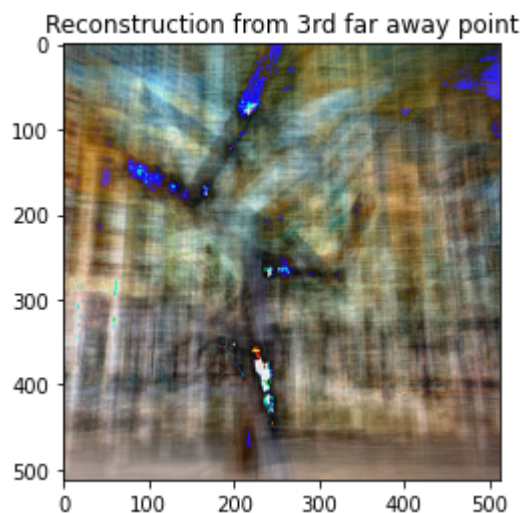
Out[ ]: <matplotlib.image.AxesImage at 0x7fd01e60dc10>



```
In [ ]: current_far_away_point = np.reshape(np.array(far_away_points[2]), (1, -1))
        far_away_point_inversed = pca.inverse_transform(current_far_away_point)

        plt.title("Reconstruction from 3rd far away point")
        plt.imshow(np.reshape(far_away_point_inversed, (PHOTO_SIZE, PHOTO_SIZE, 3)).astype(np.uint8))
```

Out[ ]: <matplotlib.image.AxesImage at 0x7fd01e38c9d0>



There's a little difference between the reconstruction at different far away points, perhaps in lighting!

## Reflection

- Overall, not so much variation is explained (~19%) with 2 components.
- Because of the low variation, the reconstruction is not really close to the original one. The reconstruction also got distracted because of the background building noise.