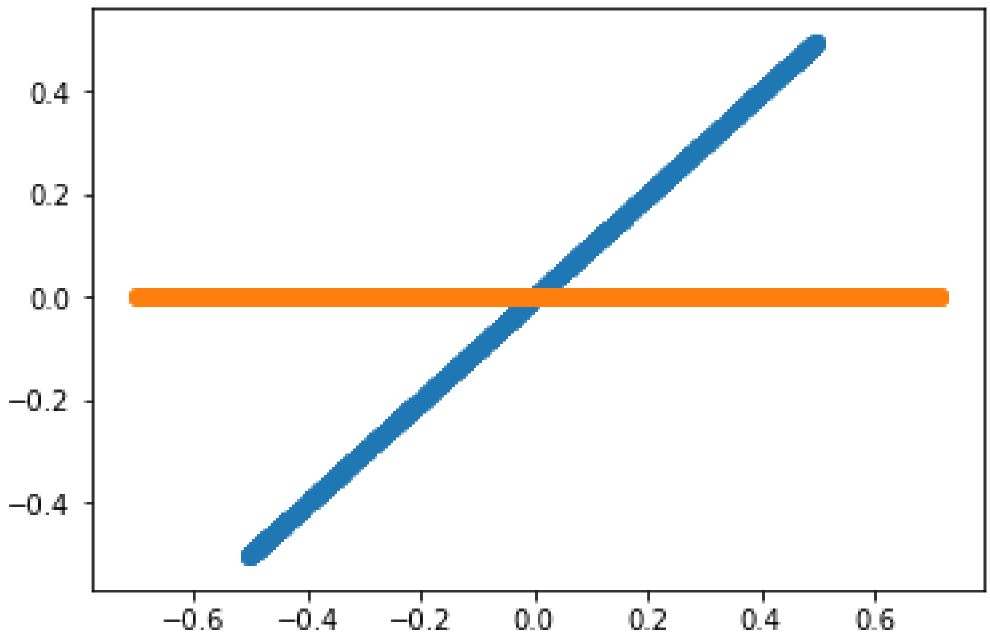
Untitled

October 1, 2020

In [1]:
```
import numpy as np                                # Linear algebra library
import matplotlib.pyplot as plt                   # library for visualization
from sklearn.decomposition import PCA             # PCA library
import pandas as pd                               # Data frame library
import math                                       # Library for math functions
import random                                     # Library for pseudo random numbers
```

In [2]:
```
n = 1  # The amount of the correlation
x = np.random.uniform(1,2,1000) # Generate 1000 samples from a uniform random variable
y = x.copy() * n # Make y = n * x

# PCA works better if the data is centered
x = x - np.mean(x) # Center x. Remove its mean
y = y - np.mean(y) # Center y. Remove its mean

data = pd.DataFrame({'x': x, 'y': y}) # Create a data frame with x and y
plt.scatter(data.x, data.y) # Plot the original correlated data in blue

pca = PCA(n_components=2) # Instantiate a PCA. Choose to get 2 output variables

# Create the transformation model for this data. Internally, it gets the rotation
# matrix and the explained variance
pcaTr = pca.fit(data)

rotatedData = pcaTr.transform(data) # Transform the data base on the rotation matrix o
# # Create a data frame with the new variables. We call these new variables PC1 and PC
dataPCA = pd.DataFrame(data = rotatedData, columns = ['PC1', 'PC2'])

# Plot the transformed data in orange
plt.scatter(dataPCA.PC1, dataPCA.PC2)
plt.show()
```



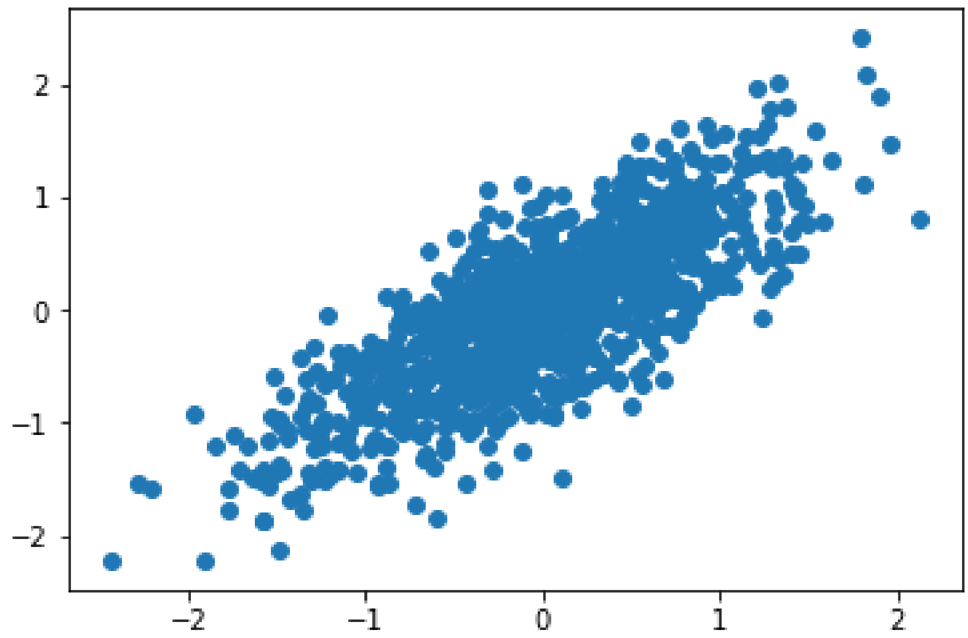

```
In [3]: print('Eigenvectors or principal component: First row must be in the direction of [1, n
        print(pcaTr.components_)

        print()
        print('Eigenvalues or explained variance')
        print(pcaTr.explained_variance_)
```

```
Eigenvectors or principal component: First row must be in the direction of [1, n]
[[-0.70710678 -0.70710678]
 [-0.70710678  0.70710678]]

Eigenvalues or explained variance
[1.72808576e-01 1.94068968e-34]
```

```
In [4]: import matplotlib.lines as mlines
        import matplotlib.transforms as mtransforms

        random.seed(100)

        std1 = 1     # The desired standard deviation of our first random variable
        std2 = 0.333 # The desired standard deviation of our second random variable

        x = np.random.normal(0, std1, 1000) # Get 1000 samples from x ~ N(0, std1)
        y = np.random.normal(0, std2, 1000)  # Get 1000 samples from y ~ N(0, std2)
        #y = y + np.random.normal(0,1,1000)*noiseLevel * np.sin(0.78)
```

```python
# PCA works better if the data is centered
x = x - np.mean(x) # Center x
y = y - np.mean(y) # Center y

#Define a pair of dependent variables with a desired amount of covariance
n = 1 # Magnitude of covariance.
angle = np.arctan(1 / n) # Convert the covariance to and angle
print('angle: ',  angle * 180 / math.pi)

# Create a rotation matrix using the given angle
rotationMatrix = np.array([[np.cos(angle), np.sin(angle)],
                 [-np.sin(angle), np.cos(angle)]])


print('rotationMatrix')
print(rotationMatrix)

xy = np.concatenate(([x] , [y]), axis=0).T # Create a matrix with columns x and y

# Transform the data using the rotation matrix. It correlates the two variables
data = np.dot(xy, rotationMatrix) # Return a nD array

# Print the rotated data
plt.scatter(data[:,0], data[:,1])
plt.show()
```

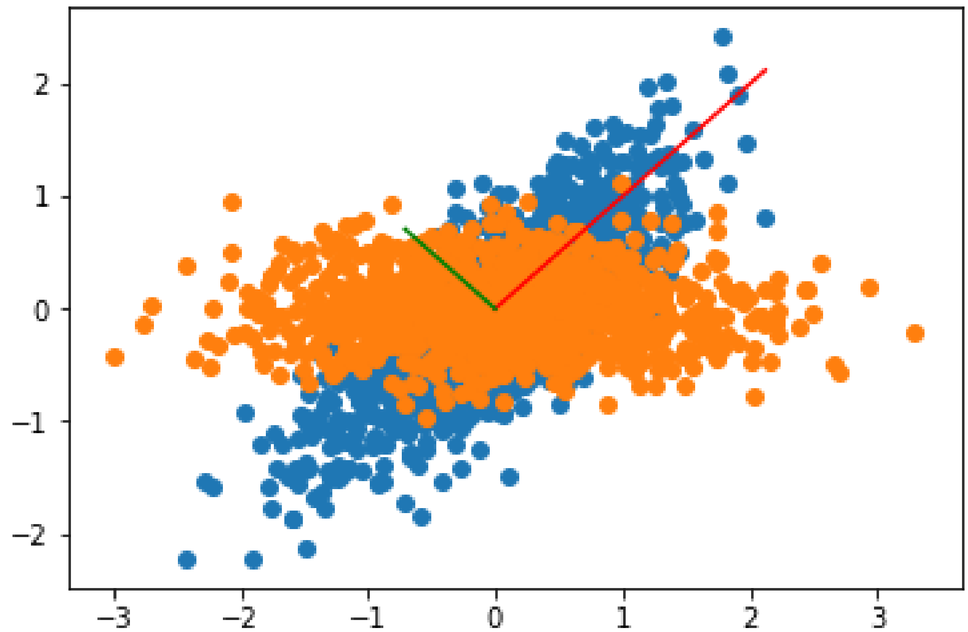
```
angle:  45.0
rotationMatrix
[[ 0.70710678  0.70710678]
 [-0.70710678  0.70710678]]
```



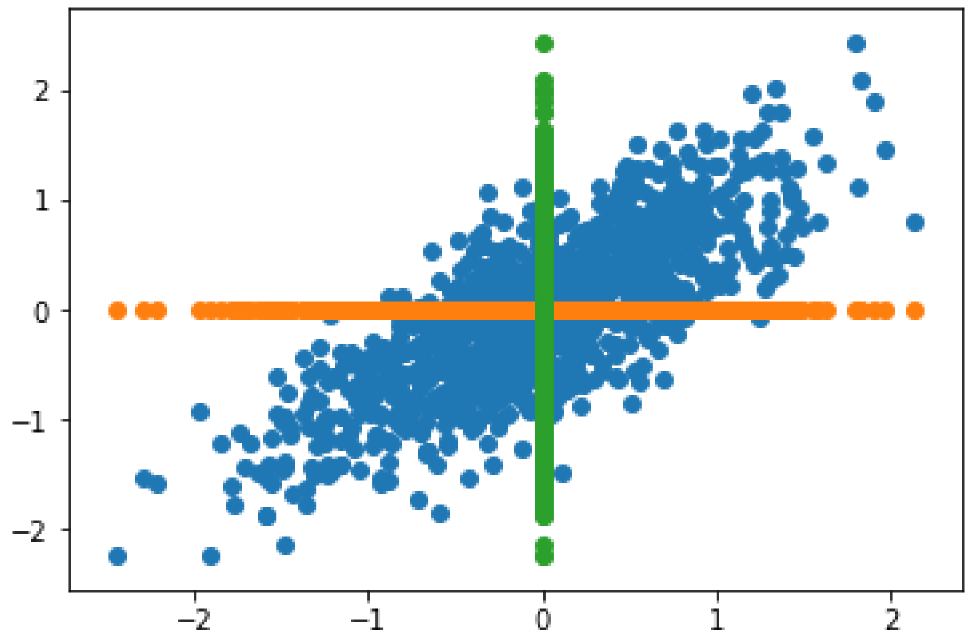
In [5]:
```
plt.scatter(data[:,0], data[:,1]) # Print the original data in blue

# Apply PCA. In theory, the Eigenvector matrix must be the
# inverse of the original rotationMatrix.
pca = PCA(n_components=2)  # Instantiate a PCA. Choose to get 2 output variables

# Create the transformation model for this data. Internally it gets the rotation
# matrix and the explained variance
pcaTr = pca.fit(data)

# Create an array with the transformed data
dataPCA = pcaTr.transform(data)

print('Eigenvectors or principal component: First row must be in the direction of [1, n
print(pcaTr.components_)

print()
print('Eigenvalues or explained variance')
print(pcaTr.explained_variance_)

# Print the rotated data
plt.scatter(dataPCA[:,0], dataPCA[:,1])

# Plot the first component axe. Use the explained variance to scale the vector
plt.plot([0, rotationMatrix[0][0] * std1 * 3], [0, rotationMatrix[0][1] * std1 * 3], 'r
# Plot the second component axe. Use the explained variance to scale the vector
```

```
plt.plot([0, rotationMatrix[1][0] * std2 * 3], [0, rotationMatrix[1][1] * std2 * 3], '

plt.show()
```

```
Eigenvectors or principal component: First row must be in the direction of [1, n]
[[-0.69755375 -0.71653246]
 [ 0.71653246 -0.69755375]]

Eigenvalues or explained variance
[0.92040465 0.10828296]
```




```
In [6]: nPoints = len(data)

        # Plot the original data in blue
        plt.scatter(data[:,0], data[:,1])

        #Plot the projection along the first component in orange
        plt.scatter(data[:,0], np.zeros(nPoints))

        #Plot the projection along the second component in green
        plt.scatter(np.zeros(nPoints), data[:,1])

        plt.show()
```




```
In [ ]:
```