pca_conference_room

January 18, 2022

1 Principal Component Analysis

Below are the Principal Component Analysis on the first 13 features:

- 1. index: Index for each data point
- 2. sim: Index for each simulation
- 3. tem: Temperature of air supplied to the zone (°C)
- 4. mass: Total mass flow rate of air supply to the zone (kg/s)
- 5. n: North Wall Temperature (°C)
- 6. w: West Wall Temperature (°C)
- 7. s: South Wall Temperature (°C)
- 8. sw: South Window Temperature (°C)
- 9. e: East Wall Temperature (°C)
- 10. ew: East Window Temperature (°C)
- 11. floor: Floor Temperature (°C)
- 12. ceiling: Ceiling Temperature (°C)
- 13. n occ: Number of occupants in zone
- 14. x: location of occupant of interest on x-axis (m)
- 15. y: location of occupant of interest on y-axis (m)

The last 3 features are treated as target predictions for evaluation purpose.

- 1. MRT: Mean radiant temperature of the occupant of interest's head and chest (°C)
- 2. T: Average temperature of air surrounding the occupant of interest (°C)
- 3. V: Average speed of air surrounding the occupant of interest occupant (°C)

```
[9]: data_loc = '../data/preprocessed/'
```

1.1 Conference Room

1.1.1 1. Standardize the data

```
[10]: import pandas as pd
from sklearn.preprocessing import StandardScaler

con_room_data = pd.read_csv(data_loc+"conference_room.csv")

# Remove the index column
con_room_data.drop(columns=['index', 'sim'], inplace=True)
```

```
# Seperate the data into features and labels
     X = con_room_data.drop(columns=['MRT', 'T', 'V'])
     y_MRT = con_room_data['MRT']
     y_T = con_room_data['T']
     y_V = con_room_data['V']
     # Standardize the data
     scaler = StandardScaler()
     scaler.fit(X)
     X std = pd.DataFrame(scaler.transform(X), columns=X.columns)
     X_std.describe()
Γ10]:
                     t.em
                                                                                 \
                                  mass
                                                   n
                                                                               S
     count 2.095800e+04 2.095800e+04 2.095800e+04 2.095800e+04 2.095800e+04
     mean -4.310471e-17 -4.757569e-17 8.324540e-16 2.804879e-16 -3.261234e-16
     std
            1.000024e+00 1.000024e+00 1.000024e+00 1.000024e+00 1.000024e+00
           -1.475736e+00 -1.580859e+00 -2.757295e+00 -2.813610e+00 -2.518167e+00
     min
     25%
          -8.367246e-01 -7.712921e-01 -4.492384e-01 -6.161947e-01 -4.785246e-01
     50%
          -1.977131e-01 -1.930300e-01 1.277757e-01 4.825129e-01 3.373321e-01
     75%
           7.608042e-01 7.321895e-01 7.047898e-01 4.825129e-01 7.452605e-01
            4.275367e+00 1.888714e+00 1.281804e+00 1.581220e+00 1.561117e+00
     max
                      SW
                                     е
                                                  ew
                                                             floor
                                                                        ceiling \
            2.095800e+04 2.095800e+04 2.095800e+04 2.095800e+04 2.095800e+04
     count
            1.493481e-16 -6.394761e-16 8.086702e-17 -3.902229e-16 8.464716e-16
     mean
     std
            1.000024e+00 1.000024e+00 1.000024e+00 1.000024e+00 1.000024e+00
           -2.552468e+00 -2.492894e+00 -2.478706e+00 -2.867409e+00 -2.893951e+00
     min
     25%
           -5.250738e-01 -5.087353e-01 -4.909610e-01 -4.279673e-01 -4.354616e-01
     50%
           8.314466e-02 2.849281e-01 1.053624e-01 5.992101e-02 5.479341e-01
     75%
            6.913631e-01 6.817599e-01 7.016859e-01 5.478093e-01 5.479341e-01
            2.516018e+00 1.475423e+00 2.490656e+00 1.523586e+00 1.039632e+00
     max
                   n occ
                                     Х
     count 2.095800e+04 2.095800e+04 2.095800e+04
     mean -3.272447e-14 3.813283e-14 -9.820309e-15
            1.000024e+00 1.000024e+00 1.000024e+00
     std
           -1.674496e+00 -1.133249e+00 -1.282534e+00
     min
     25%
           -8.380860e-01 -1.133249e+00 -1.282534e+00
     50%
            8.347336e-01 -2.697370e-01 -2.252214e-01
            8.347336e-01 9.039089e-01 1.160499e+00
     75%
     max
            8.347336e-01 1.773502e+00 1.160499e+00
```

1.1.2 2. Perform PCA

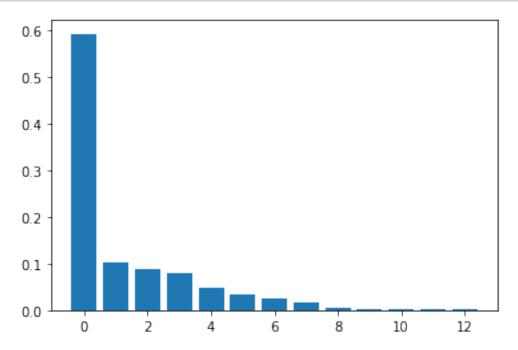
```
[11]: # Perform PCA
    from sklearn.decomposition import PCA
    import matplotlib.pyplot as plt
    import numpy as np
    from numpy import savetxt

pca = PCA()
    pca.fit(X_std)

e_vectors = pca.components_ # The eigenvectors
    evr = pca.explained_variance_ratio_ # The variance explained by each eigenvector

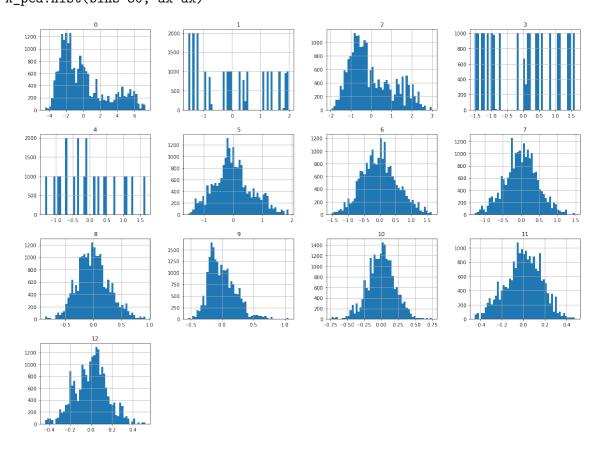
# Save the eigenvectors to a text file
    savetxt("../reports/data/pca_conference_room_eigenvectors.csv", e_vectors,u_delimiter=',')

plt.bar(range(len(evr)), evr)
    plt.savefig('../figures/evr_pca_conference_room.png')
```



```
[12]: # Tramsform the data
X_pca = pd.DataFrame(pca.transform(X_std))
fig, ax = plt.subplots(figsize=(20,15))
X_pca.hist(bins=50, ax=ax)
fig.savefig('../figures/hist_pca_conference_room.png')
```

/tmp/ipykernel_54312/4093233920.py:4: UserWarning: To output multiple subplots,
the figure containing the passed axes is being cleared
 X_pca.hist(bins=50, ax=ax)



After performing PCA on the features, the distribution graph shows more normal distribution features (8 features).

1.1.3 3. Compare models' results with and without PCA on predicting MRT

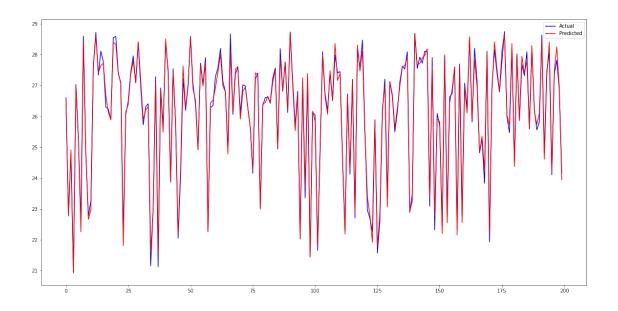
3.1 Split the data into training and testing

3.2 Train and evaluate the Linear Regression model

3.2.1 Without PCA

```
[14]: from sklearn.linear_model import LinearRegression
      from sklearn.metrics import mean_squared_error
      import pickle
      import time
      # Train linear regression model on training data
      model = LinearRegression()
      start = time.time()
      model.fit(X_train, y_train)
      stop = time.time()
      lr_train_time = stop - start
      print(f"Training time: {lr_train_time}s")
      # Save the model to a pickle file
      filename = '../reports/models/lr_MRT_conference_room_model.pkl'
      pickle.dump(model, open(filename, 'wb'))
      # Predict on test data
      y_pred = model.predict(X_test)
      # Evaluate the model
      mse = mean_squared_error(y_test, y_pred)
      print(f'Mean squared error: {mse}')
      # Plot the predictions and actual values
      plt.figure(figsize=(20,10))
      plt.plot(range(200), y_test[:200], color='blue', label='Actual')
      plt.plot(range(200), y_pred[:200], color='red', label='Predicted')
      plt.legend()
      plt.show()
```

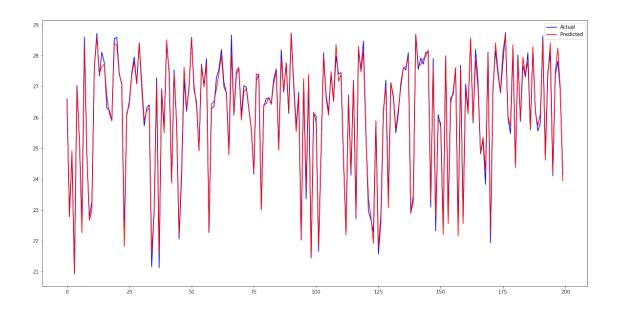
Training time: 0.01263737678527832s Mean squared error: 0.036303047735584584



3.2.2 With PCA

```
[15]: # Train linear regression model on training data
      start = time.time()
      model.fit(X_train_pca, y_train_pca)
      stop = time.time()
      lr_pca_train_time = stop - start
      print(f"Training time: {lr_pca_train_time}s")
      # Predict on test data
      y_pred_pca = model.predict(X_test_pca)
      # Save the model to a pickle file
      filename = '../reports/models/lr_MRT_pca_conference_room_model.pkl'
      pickle.dump(model, open(filename, 'wb'))
      # Evaluate the model
      mse = mean_squared_error(y_test_pca, y_pred_pca)
      print(f'Mean squared error: {mse}')
      # Plot the predictions and actual values
      plt.figure(figsize=(20,10))
      plt.plot(range(200), y_test_pca[:200], color='blue', label='Actual')
      plt.plot(range(200), y_pred_pca[:200], color='red', label='Predicted')
      plt.legend()
     plt.show()
```

Training time: 0.014313220977783203s Mean squared error: 0.03630304773558465



3.3 Train and evaluate the Feedforward Neural Network model

```
[16]: # Create neural network model
      from keras.models import Sequential
      from keras.layers import Dense
      N_NEURONS = 1024
      N_LAYERS = 4
      model = Sequential()
      model.add(Dense(units=N_NEURONS, input_dim=X.shape[1], activation='relu'))
      for i in range(N_LAYERS-1):
          model.add(Dense(units=N_NEURONS, activation='relu'))
      model.add(Dense(units=1, activation='linear')) # Output layer
      model.compile(loss='mean_squared_error', optimizer='adam')
      # Train the model
      start = time.time()
      model.fit(X_train, y_train, epochs=100, verbose=0)
      stop = time.time()
      nn_train_time = stop - start
      print(f"Training time: {nn_train_time}s")
      # Predict on test data
      y_pred_nn = model.predict(X_test)
      model.save('../reports/models/nn_MRT_conference_room_model.pkl')
```

```
# Evaluate the model
mse = mean_squared_error(y_test, y_pred_nn)
print(f'Mean squared error: {mse}')

# Plot the predictions and actual values
plt.figure(figsize=(20,10))
plt.plot(range(200), y_test[:200], color='blue', label='Actual')
plt.plot(range(200), y_pred_nn[:200], color='red', label='Predicted')
plt.legend()
plt.show()
```

Training time: 190.46492838859558s

WARNING:tensorflow:From /home/khiem/anaconda3/lib/python3.8/site-

packages/tensorflow/python/training/tracking/tracking.py:111:

Model.state_updates (from tensorflow.python.keras.engine.training) is deprecated and will be removed in a future version.

Instructions for updating:

This property should not be used in TensorFlow 2.0, as updates are applied automatically.

WARNING:tensorflow:From /home/khiem/anaconda3/lib/python3.8/site-packages/tensorflow/python/training/tracking/tracking.py:111: Layer.updates (from tensorflow.python.keras.engine.base_layer) is deprecated and will be removed in a future version.

Instructions for updating:

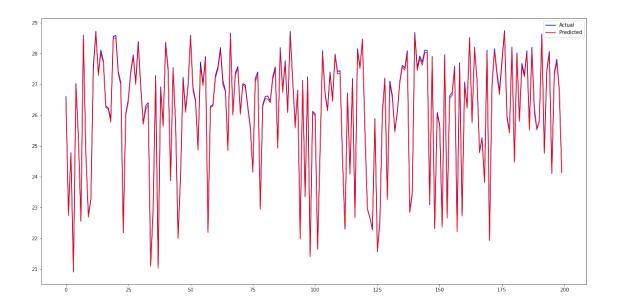
This property should not be used in TensorFlow 2.0, as updates are applied automatically.

2022-01-18 14:04:03.738644: W tensorflow/python/util/util.cc:348] Sets are not currently considered sequences, but this may change in the future, so consider avoiding using them.

INFO:tensorflow:Assets written to:

 $../reports/models/nn_MRT_conference_room_model.pkl/assets$

Mean squared error: 0.005940737672679868



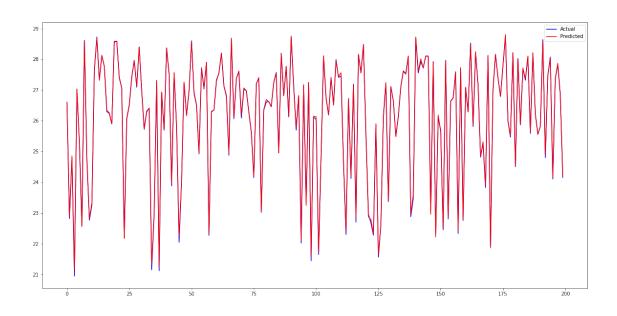
3.3.2 With PCA

```
[17]: # Train the model
      start = time.time()
      model.fit(X_train_pca, y_train_pca, epochs=100, verbose=0)
      stop = time.time()
      nn_pca_train_time = stop - start
      print(f"Training time: {nn_pca_train_time}s")
      # Predict on test data
      y_pred_nn_pca = model.predict(X_test_pca)
      model.save('../reports/models/nn_MRT_pca_conference_room_model.pkl')
      # Evaluate the model
      mse = mean_squared_error(y_test_pca, y_pred_nn_pca)
      print(f'Mean squared error: {mse}')
      # Plot the predictions and actual values
      plt.figure(figsize=(20,10))
      plt.plot(range(200), y_test_pca[:200], color='blue', label='Actual')
      plt.plot(range(200), y_pred_nn_pca[:200], color='red', label='Predicted')
      plt.legend()
      plt.show()
```

Training time: 200.48521423339844s

INFO:tensorflow:Assets written to:
../reports/models/nn_MRT_pca_conference_room_model.pkl/assets

Mean squared error: 0.0023151260541025287



1.1.4 4. Compare models' results with and without PCA on predicting T

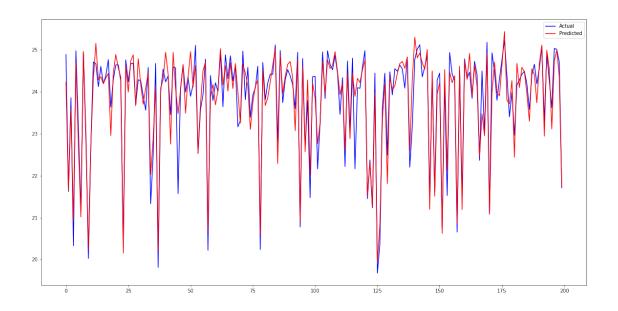
4.1 Split the data into training and testing

4.2 Train and evaluate the Linear Regression model

4.2.1 Without PCA

```
[20]: from sklearn.linear_model import LinearRegression
      from sklearn.metrics import mean_squared_error
      import pickle
      import time
      # Train linear regression model on training data
      model = LinearRegression()
      start = time.time()
      model.fit(X_train, y_train)
      stop = time.time()
      lr_train_time = stop - start
      print(f"Training time: {lr_train_time}s")
      # Save the model to a pickle file
      filename = '../reports/models/lr_T_conference_room_model.pkl'
      pickle.dump(model, open(filename, 'wb'))
      # Predict on test data
      y_pred = model.predict(X_test)
      # Evaluate the model
      mse = mean_squared_error(y_test, y_pred)
      print(f'Mean squared error: {mse}')
      # Plot the predictions and actual values
      plt.figure(figsize=(20,10))
      plt.plot(range(200), y_test[:200], color='blue', label='Actual')
      plt.plot(range(200), y_pred[:200], color='red', label='Predicted')
      plt.legend()
     plt.show()
```

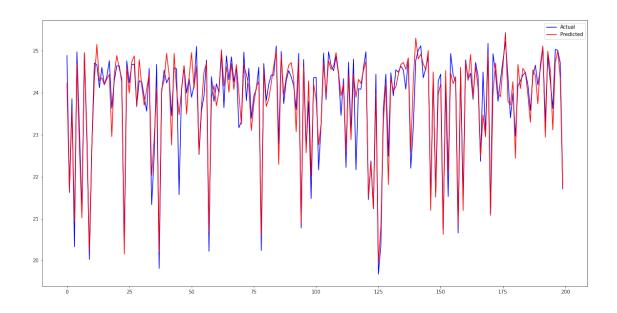
Training time: 0.009361028671264648s Mean squared error: 0.1324888237360454



4.2.2 With PCA

```
[21]: # Train linear regression model on training data
      start = time.time()
      model.fit(X_train_pca, y_train_pca)
      stop = time.time()
      lr_pca_train_time = stop - start
      print(f"Training time: {lr_pca_train_time}s")
      # Predict on test data
      y_pred_pca = model.predict(X_test_pca)
      # Save the model to a pickle file
      filename = '../reports/models/lr_T_pca_conference_room_model.pkl'
      pickle.dump(model, open(filename, 'wb'))
      # Evaluate the model
      mse = mean_squared_error(y_test_pca, y_pred_pca)
      print(f'Mean squared error: {mse}')
      # Plot the predictions and actual values
      plt.figure(figsize=(20,10))
      plt.plot(range(200), y_test_pca[:200], color='blue', label='Actual')
      plt.plot(range(200), y_pred_pca[:200], color='red', label='Predicted')
      plt.legend()
     plt.show()
```

Training time: 0.011274337768554688s Mean squared error: 0.13248888237360457



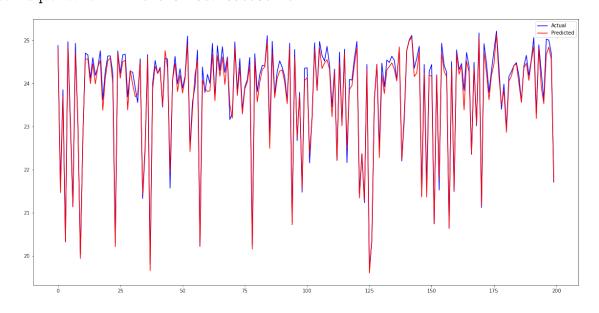
4.3 Train and evaluate the Feedforward Neural Network model

```
[22]: # Create neural network model
      from keras.models import Sequential
      from keras.layers import Dense
      N NEURONS = 1024
      N_LAYERS = 4
      model = Sequential()
      model.add(Dense(units=N_NEURONS, input_dim=X.shape[1], activation='relu'))
      for i in range(N_LAYERS-1):
          model.add(Dense(units=N_NEURONS, activation='relu'))
      model.add(Dense(units=1, activation='linear')) # Output layer
      model.compile(loss='mean_squared_error', optimizer='adam')
      # Train the model
      start = time.time()
      model.fit(X_train, y_train, epochs=100, verbose=0)
      stop = time.time()
      nn_train_time = stop - start
      print(f"Training time: {nn_train_time}s")
      # Predict on test data
      y_pred_nn = model.predict(X_test)
      model.save('../reports/models/nn_T_conference_room_model.pkl')
```

```
# Evaluate the model
mse = mean_squared_error(y_test, y_pred_nn)
print(f'Mean squared error: {mse}')

# Plot the predictions and actual values
plt.figure(figsize=(20,10))
plt.plot(range(200), y_test[:200], color='blue', label='Actual')
plt.plot(range(200), y_pred_nn[:200], color='red', label='Predicted')
plt.legend()
plt.show()
```

Training time: 198.21673274040222s
INFO:tensorflow:Assets written to:
../reports/models/nn_T_conference_room_model.pkl/assets
Mean squared error: 0.028228071596030416



4.3.2 With PCA

```
[23]: # Train the model
start = time.time()
model.fit(X_train_pca, y_train_pca, epochs=100, verbose=0)
stop = time.time()
nn_pca_train_time = stop - start
print(f"Training time: {nn_pca_train_time}s")

# Predict on test data
y_pred_nn_pca = model.predict(X_test_pca)
model.save('../reports/models/nn_T_pca_conference_room_model.pkl')
```

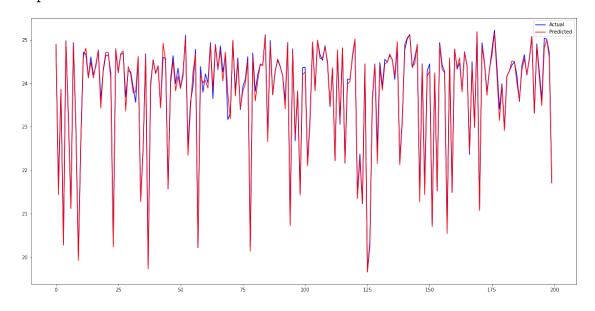
```
# Evaluate the model
mse = mean_squared_error(y_test_pca, y_pred_nn_pca)
print(f'Mean squared error: {mse}')

# Plot the predictions and actual values
plt.figure(figsize=(20,10))
plt.plot(range(200), y_test_pca[:200], color='blue', label='Actual')
plt.plot(range(200), y_pred_nn_pca[:200], color='red', label='Predicted')
plt.legend()
plt.show()
```

Training time: 199.61321687698364s

INFO:tensorflow:Assets written to:
../reports/models/nn_T_pca_conference_room_model.pkl/assets

Mean squared error: 0.01676264223699558



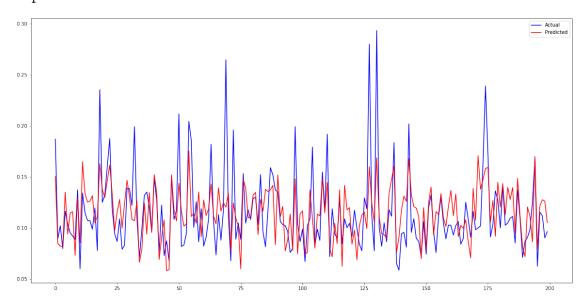
1.1.5 5. Compare models' results with and without PCA on predicting V

5.1 Split the data into training and testing

5.2 Train and evaluate the Linear Regression model

```
[26]: from sklearn.linear_model import LinearRegression
      from sklearn.metrics import mean_squared_error
      import pickle
      import time
      # Train linear regression model on training data
      model = LinearRegression()
      start = time.time()
      model.fit(X_train, y_train)
      stop = time.time()
      lr_train_time = stop - start
      print(f"Training time: {lr_train_time}s")
      # Save the model to a pickle file
      filename = '../reports/models/lr_V_conference_room_model.pkl'
      pickle.dump(model, open(filename, 'wb'))
      # Predict on test data
      y_pred = model.predict(X_test)
      # Evaluate the model
      mse = mean_squared_error(y_test, y_pred)
      print(f'Mean squared error: {mse}')
      # Plot the predictions and actual values
      plt.figure(figsize=(20,10))
      plt.plot(range(200), y_test[:200], color='blue', label='Actual')
      plt.plot(range(200), y_pred[:200], color='red', label='Predicted')
      plt.legend()
      plt.show()
```

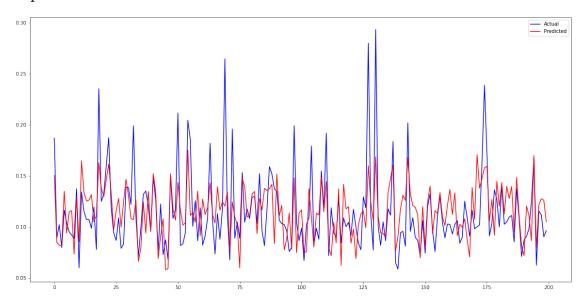
Training time: 0.014678001403808594s
Mean squared error: 0.001118630731868217



5.2.2 With PCA

```
[27]: # Train linear regression model on training data
      start = time.time()
      model.fit(X_train_pca, y_train_pca)
      stop = time.time()
      lr_pca_train_time = stop - start
      print(f"Training time: {lr_pca_train_time}s")
      # Predict on test data
      y_pred_pca = model.predict(X_test_pca)
      # Save the model to a pickle file
      filename = '../reports/models/lr_V_pca_conference_room_model.pkl'
      pickle.dump(model, open(filename, 'wb'))
      # Evaluate the model
      mse = mean_squared_error(y_test_pca, y_pred_pca)
      print(f'Mean squared error: {mse}')
      # Plot the predictions and actual values
      plt.figure(figsize=(20,10))
      plt.plot(range(200), y_test_pca[:200], color='blue', label='Actual')
      plt.plot(range(200), y_pred_pca[:200], color='red', label='Predicted')
      plt.legend()
      plt.show()
```

Training time: 0.012313365936279297s
Mean squared error: 0.001118630731868217



5.3 Train and evaluate the Feedforward Neural Network model

```
[28]: # Create neural network model
      from keras.models import Sequential
      from keras.layers import Dense
      N_NEURONS = 1024
      N_LAYERS = 4
     model = Sequential()
      model.add(Dense(units=N_NEURONS, input_dim=X.shape[1], activation='relu'))
      for i in range(N_LAYERS-1):
          model.add(Dense(units=N_NEURONS, activation='relu'))
      model.add(Dense(units=1, activation='linear')) # Output layer
      model.compile(loss='mean_squared_error', optimizer='adam')
      # Train the model
      start = time.time()
      model.fit(X_train, y_train, epochs=100, verbose=0)
      stop = time.time()
      nn_train_time = stop - start
      print(f"Training time: {nn_train_time}s")
      # Predict on test data
```

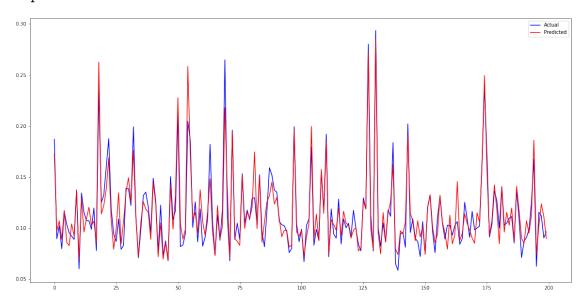
```
y_pred_nn = model.predict(X_test)
model.save('../reports/models/nn_V_conference_room_model.pkl')

# Evaluate the model
mse = mean_squared_error(y_test, y_pred_nn)
print(f'Mean squared error: {mse}')

# Plot the predictions and actual values
plt.figure(figsize=(20,10))
plt.plot(range(200), y_test[:200], color='blue', label='Actual')
plt.plot(range(200), y_pred_nn[:200], color='red', label='Predicted')
plt.legend()
plt.show()
```

Training time: 203.27048873901367s
INFO:tensorflow:Assets written to:
../reports/models/nn_V_conference_room_model.pkl/assets

Mean squared error: 0.0003013890718162625



5.3.2 With PCA

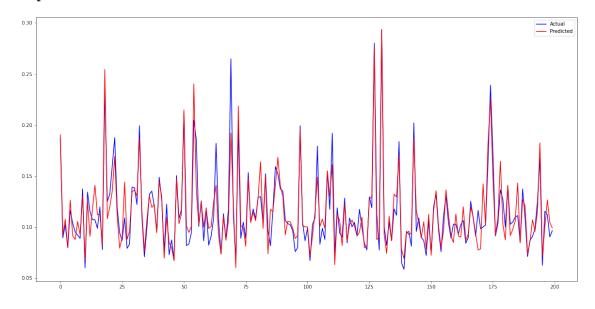
```
[29]: # Train the model
start = time.time()
model.fit(X_train_pca, y_train_pca, epochs=100, verbose=0)
stop = time.time()
nn_pca_train_time = stop - start
print(f"Training time: {nn_pca_train_time}s")
# Predict on test data
```

```
y_pred_nn_pca = model.predict(X_test_pca)
model.save('../reports/models/nn_V_pca_conference_room_model.pkl')

# Evaluate the model
mse = mean_squared_error(y_test_pca, y_pred_nn_pca)
print(f'Mean squared error: {mse}')

# Plot the predictions and actual values
plt.figure(figsize=(20,10))
plt.plot(range(200), y_test_pca[:200], color='blue', label='Actual')
plt.plot(range(200), y_pred_nn_pca[:200], color='red', label='Predicted')
plt.legend()
plt.show()
```

Training time: 193.58191180229187s
INFO:tensorflow:Assets written to:
../reports/models/nn_V_pca_conference_room_model.pkl/assets
Mean squared error: 0.00030001247540154495



writer.writerow(['Neural network with PCA', nn_pca_train_time])