model

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0.3 Assignment 6

1 Human Activity Recognition Using Smartphones dataset

https://www.kaggle.com/datasets/uciml/human-activity-recognition-with-smartphones?resource=download

[14]:
```
import warnings
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
```

[8]:
```
train_data = pd.read_csv("archive/train.csv")
test_data = pd.read_csv("archive/test.csv")
```

[4]:
```
train_data.shape
```

[4]:
```
(7352, 563)
```

[25]:
```
train_data.describe()
```

[25]:
```
       tBodyAcc-mean()-X  tBodyAcc-mean()-Y  tBodyAcc-mean()-Z  \
count        7352.000000        7352.000000        7352.000000
mean            0.274488          -0.017695          -0.109141
std             0.070261           0.040811           0.056635
min            -1.000000          -1.000000          -1.000000
25%             0.262975          -0.024863          -0.120993
50%             0.277193          -0.017219          -0.108676
75%             0.288461          -0.010783          -0.097794
max             1.000000           1.000000           1.000000

       tBodyAcc-std()-X  tBodyAcc-std()-Y  tBodyAcc-std()-Z  tBodyAcc-mad()-X  \
count       7352.000000       7352.000000       7352.000000       7352.000000
```

```
mean        -0.605438          -0.510938          -0.604754          -0.630512
std          0.448734           0.502645           0.418687           0.424073
min         -1.000000          -0.999873          -1.000000          -1.000000
25%         -0.992754          -0.978129          -0.980233          -0.993591
50%         -0.946196          -0.851897          -0.859365          -0.950709
75%         -0.242813          -0.034231          -0.262415          -0.292680
max          1.000000           0.916238           1.000000           1.000000

       tBodyAcc-mad()-Y  tBodyAcc-mad()-Z  tBodyAcc-max()-X  …  \
count       7352.000000       7352.000000       7352.000000  …
mean          -0.526907         -0.606150         -0.468604  …
std            0.485942          0.414122          0.544547  …
min           -1.000000         -1.000000         -1.000000  …
25%           -0.978162         -0.980251         -0.936219  …
50%           -0.857328         -0.857143         -0.881637  …
75%           -0.066701         -0.265671         -0.017129  …
max            0.967664          1.000000          1.000000  …

       fBodyBodyGyroJerkMag-kurtosis()  angle(tBodyAccMean,gravity)  \
count                      7352.000000                  7352.000000
mean                         -0.625294                     0.008684
std                           0.307584                     0.336787
min                          -0.999765                    -0.976580
25%                          -0.845573                    -0.121527
50%                          -0.711692                     0.009509
75%                          -0.503878                     0.150865
max                           0.956845                     1.000000

       angle(tBodyAccJerkMean),gravityMean)  angle(tBodyGyroMean,gravityMean)  \
count                           7352.000000                       7352.000000
mean                               0.002186                          0.008726
std                                0.448306                          0.608303
min                               -1.000000                         -1.000000
25%                               -0.289549                         -0.482273
50%                                0.008943                          0.008735
75%                                0.292861                          0.506187
max                                1.000000                          0.998702

       angle(tBodyGyroJerkMean,gravityMean)  angle(X,gravityMean)  \
count                           7352.000000           7352.000000
mean                              -0.005981             -0.489547
std                                0.477975              0.511807
min                               -1.000000             -1.000000
25%                               -0.376341             -0.812065
50%                               -0.000368             -0.709417
75%                                0.359368             -0.509079
max                                0.996078              1.000000
```

```
       angle(Y,gravityMean)  angle(Z,gravityMean)      subject      Cluster
count           7352.000000           7352.000000  7352.000000  7352.000000
mean               0.058593             -0.056515    17.413085     1.482182
std                0.297480              0.279122     8.975143     0.759438
min               -1.000000             -1.000000     1.000000     0.000000
25%               -0.017885             -0.143414     8.000000     1.000000
50%                0.182071              0.003181    19.000000     2.000000
75%                0.248353              0.107659    26.000000     2.000000
max                0.478157              1.000000    30.000000     2.000000

[8 rows x 563 columns]
```

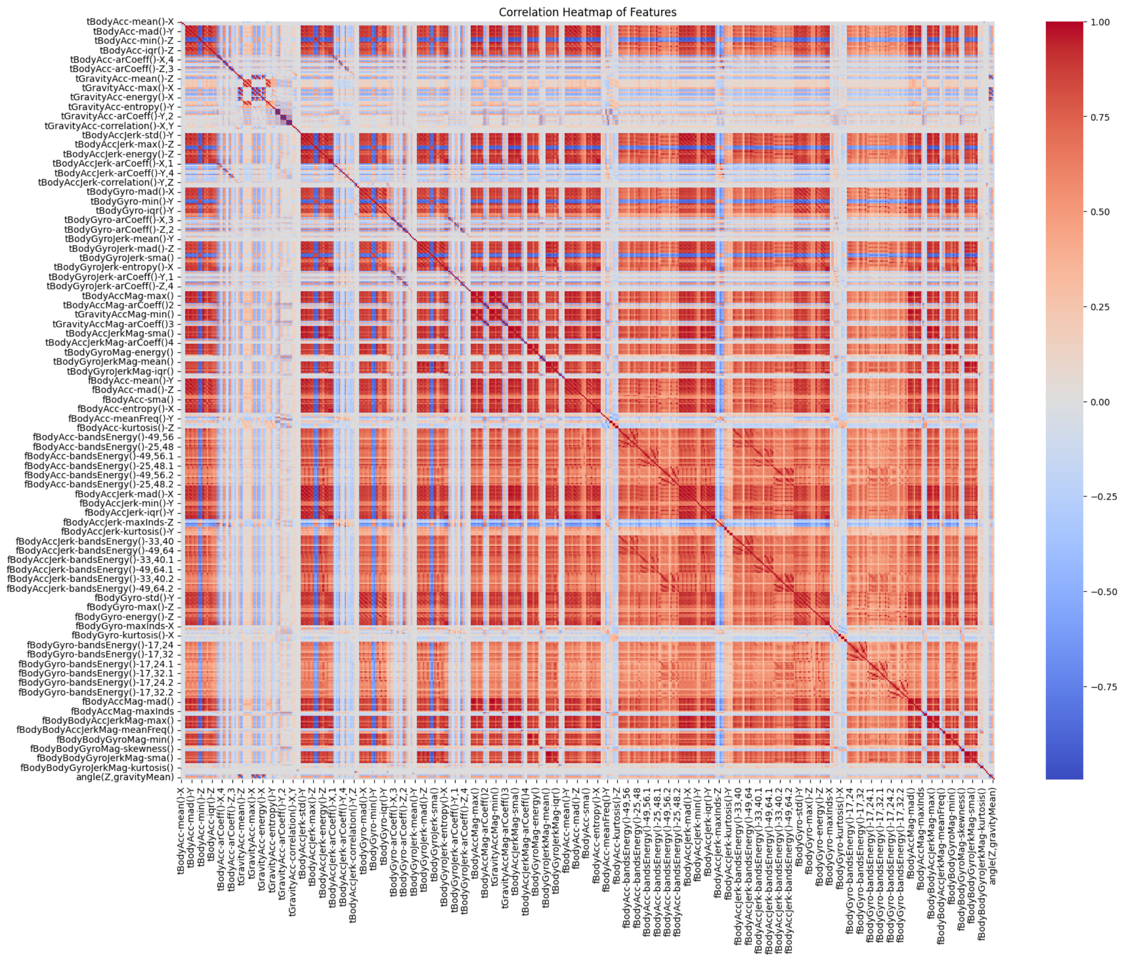
[28]:
```
train_data.duplicated().sum()
```

[28]: 0

[9]:
```
# Exclude non-numeric columns
numeric_columns = train_data.select_dtypes(include=[np.number]).columns
train_data_numeric = train_data[numeric_columns]

# Calculate the correlation matrix
corr_matrix = train_data_numeric.corr()

# Plot the heatmap
plt.figure(figsize=(20, 15))
sns.heatmap(corr_matrix, annot=False, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Heatmap of Features')
plt.show()
```



[10]:
```python
from sklearn.ensemble import RandomForestClassifier

# Separate features and target variable
X = train_data.drop(columns=["subject", "Activity"])
y = train_data["Activity"]

# Feature importance using Random Forest
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X, y)

# Get feature importances
importances = rf.feature_importances_

# Sort feature importances in descending order
indices = np.argsort(importances)[::-1]

# Select top 10 features
```

```
top_features = X.columns[indices][:10]

print("Top 10 features based on importance scores:")
print(top_features)
```

```
Top 10 features based on importance scores:
Index(['tGravityAcc-mean()-X', 'tGravityAcc-max()-X', 'angle(X,gravityMean)',
       'tGravityAcc-mean()-Y', 'tGravityAcc-energy()-X',
       'angle(Y,gravityMean)', 'tGravityAcc-min()-X', 'tGravityAcc-max()-Y',
       'tGravityAcc-min()-Y', 'tGravityAcc-energy()-Y'],
      dtype='object')
```

[17]:
```
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler

# Extract the top 10 features based on importance scores
top_features = ['tGravityAcc-mean()-X', 'tGravityAcc-max()-X',␣
 ↪'angle(X,gravityMean)',
                'tGravityAcc-mean()-Y', 'tGravityAcc-energy()-X',
                'angle(Y,gravityMean)', 'tGravityAcc-min()-X',␣
 ↪'tGravityAcc-max()-Y',
                'tGravityAcc-min()-Y', 'tGravityAcc-energy()-Y']

# Create a new DataFrame with only the top features
X = train_data[top_features]

# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Train the K-means model
kmeans = KMeans(n_clusters=3, random_state=42)  # You need to choose the number␣
 ↪of clusters
kmeans.fit(X_scaled)

# Predict cluster labels
cluster_labels = kmeans.labels_

# Add cluster labels to the DataFrame
train_data['Cluster'] = cluster_labels

# Filter out non-numeric columns
numeric_columns = train_data.select_dtypes(include=[np.number]).columns
```

[23]:
```
from sklearn.metrics import silhouette_score

# After fitting the kmeans model
```

```
silhouette_coeff = silhouette_score(X_scaled, kmeans.labels_)
print("Silhouette Coefficient: ", (silhouette_coeff * 100) ,"% Higher␣
↪silhouette scores indicate better clustering")
```

```
Silhouette Coefficient: %.3f 56.60532382348744 % Higher silhouette scores
indicate better clustering
```

2 GitHub Link https://github.com/KKBUGHUNTER/Machine-Learning-Lab/tree/main/Assignment-06

2.0.1 learning outcome

- Understanding of K-means clustering algorithm
- Data preprocessing
- Feature visualization
- Interpretation of clustering results

2.0.2 Inference

- Feature importance analysis: Identifies key variables driving model predictions.
- Clustering: Uncovers patterns by grouping similar data points together.
- Silhouette scores: Quantify clustering effectiveness by assessing cluster separation and cohesion.