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## Assignment 6

# **Human Activity Recognition Using Smartphones dataset**

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

train\_data.describe()

	tBodyAcc- mean()-X	tBodyAcc- mean()-Y	tBodyAcc- mean()-Z	tBodyAcc- std()-X	tBodyAcc- std()-Y	tBodyAcc- std()-Z	tBodyAcc- mad()-X	tBodyAcc- mad()-Y	tBodyAcc- mad()-Z	tBodyAcc- max()-X
count	7352.000000	7352.000000	7352.000000	7352.000000	7352.000000	7352.000000	7352.000000	7352.000000	7352.000000	7352.000000
mean	0.274488	-0.017695	-0.109141	-0.605438	-0.510938	-0.604754	-0.630512	-0.526907	-0.606150	-0.468604
std	0.070261	0.040811	0.056635	0.448734	0.502645	0.418687	0.424073	0.485942	0.414122	0.544547
min	-1.000000	-1.000000	-1.000000	-1.000000	-0.999873	-1.000000	-1.000000	-1.000000	-1.000000	-1.000000
25%	0.262975	-0.024863	-0.120993	-0.992754	-0.978129	-0.980233	-0.993591	-0.978162	-0.980251	-0.936219
50%	0.277193	-0.017219	-0.108676	-0.946196	-0.851897	-0.859365	-0.950709	-0.857328	-0.857143	-0.881637
75%	0.288461	-0.010783	-0.097794	-0.242813	-0.034231	-0.262415	-0.292680	-0.066701	-0.265671	-0.017129
max	1.000000	1.000000	1.000000	1.000000	0.916238	1.000000	1.000000	0.967664	1.000000	1.000000
8 rows × 563 columns										

```
train_data.duplicated().sum()

# 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()
```

```
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:
    dtype='object')
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
# Extract the top 10 features based on importance scores
'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
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
```

## GitHub Link

https://colab.research.google.com/drive/1ZRmRBZG0mfnS7UiSYZ9zbAQAjDX2IWNJ? usp=sharing

### learning outcome

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

#### 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.