STATS 3DA3

Homework Assignment 6

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Heart Disease Classification Challenge

Overview

In this assignment, we will analyze the UCI Heart Disease Dataset, which contains medical records used to predict the presence of heart disease in patients. The dataset includes a mix of categorical and numerical variables, some missing values, and class imbalance.

For the context of data science methods for heart disease prediction, refer to - Detrano, R., et., al. (1989). International application of a new probability algorithm for the diagnosis of coronary artery disease. The American journal of cardiology, 64(5), 304-310. DOI:10.1016/0002-9149(89)90524-9.

Dataset Information

The dataset is available at the UCI Machine Learning Repository:
https://archive.ics.uci.edu/ml/datasets/Heart+Disease

- Key Features:
  - The dataset includes 303 observations with 13 features.
  - Features include age, sex, chest pain type, resting blood pressure, cholesterol levels, fasting blood sugar, electrocardiographic results, and others.

  - The response variable is `num`, which will be transformed to binary in the analysis.

Objectives

Analyze the dataset using **two classification algorithms**. Your analysis should include exploratory data analysis, handling of missing values, feature selection, feature engineering, modeling, interpretation, and effective communication. The goal is to draw meaningful and well-supported conclusions from your analysis.

- Classifier requirement: **At least one** of the classifiers must be interpretable to allow for in-depth analysis and inference.

Required Libraries

```python
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.feature_selection import SelectFromModel
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, f1_score
```

Q1 Define and describe a classification problem using the dataset.

```python
df = pd.read_csv('https://archive.ics.uci.edu/static/public/45/data.csv')
df.head()
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	num
0	63	1	1	145	233	1	2	150	0	2.3	3	0.0	6.0	0
1	67	1	4	160	286	0	2	108	1	1.5	2	3.0	3.0	2
2	67	1	4	120	229	0	2	129	1	2.6	2	2.0	7.0	1
3	37	1	3	130	250	0	0	187	0	3.5	3	0.0	3.0	0
4	41	0	2	130	204	0	2	172	0	1.4	1	0.0	3.0	0

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       303 non-null    int64
 1   sex       303 non-null    int64
 2   cp        303 non-null    int64
 3   trestbps  303 non-null    int64
 4   chol      303 non-null    int64
 5   fbs       303 non-null    int64
 6   restecg   303 non-null    int64
 7   thalach   303 non-null    int64
 8   exang     303 non-null    int64
 9   oldpeak   303 non-null    float64
 10  slope     303 non-null    int64
 11  ca        299 non-null    float64
```

```
 12  thal      301 non-null   float64
 13  num       303 non-null   int64
dtypes: float64(3), int64(11)
memory usage: 33.3 KB
```

```
df.describe()
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000
mean	54.438944	0.679868	3.158416	131.689769	246.693069	0.148515	0.990099	149.607261
std	9.038662	0.467299	0.960126	17.599748	51.776918	0.356198	0.994971	22.875003
min	29.000000	0.000000	1.000000	94.000000	126.000000	0.000000	0.000000	71.000000
25%	48.000000	0.000000	3.000000	120.000000	211.000000	0.000000	0.000000	133.500000
50%	56.000000	1.000000	3.000000	130.000000	241.000000	0.000000	1.000000	153.000000
75%	61.000000	1.000000	4.000000	140.000000	275.000000	0.000000	2.000000	166.000000
max	77.000000	1.000000	4.000000	200.000000	564.000000	1.000000	2.000000	202.000000

Answer The data machine contains 303 pieces of data and 14 variables, among which the first 13 are about the basic characteristics of the patient, including physiological features such as age and gender, as well as data about the condition, and num is the final diagnostic result. So, we chose num as the target field. Used to refer to whether the patient has heart disease. It is an integer value from 0 (non-existent) to 4. The experiments in the Cleveland database focused on simply trying to distinguish between existence (values 1, 2, 3, 4) and non existence (value 0).

Q2 Apply any chosen data transformations, or explain why no transformations were necessary.

Answer The dataset consists entirely of numerical variables, without any string or object type variables, so there is no need for data type conversion. However, it is necessary to standardize the continuous variables, Standardization can improve the performance of gradient descent algorithms such as logistic regression.

Q3 Provide a detailed description of the dataset, including variables, summaries, number of observations, data types, and distributions (include at least three statements).

```python
df.shape
```

```
(303, 14)
```

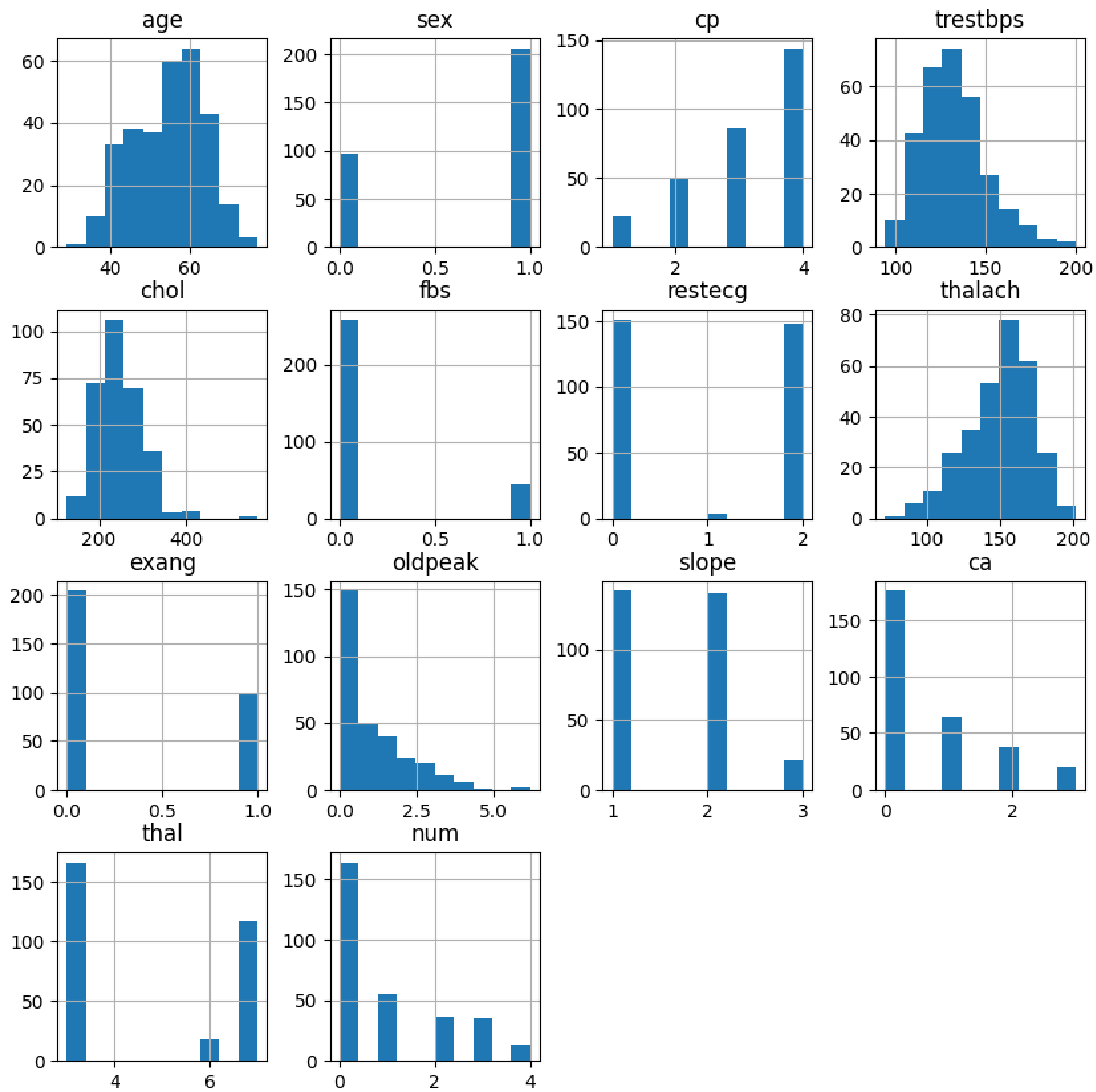
```python
print(df.dtypes)
```

```
age           int64
sex           int64
cp            int64
trestbps      int64
chol          int64
fbs           int64
restecg       int64
thalach       int64
exang         int64
oldpeak     float64
slope         int64
ca          float64
thal        float64
num           int64
dtype: object
```

```python
df.hist(figsize=(10,10))
```

```
array([[<Axes: title={'center': 'age'}>, <Axes: title={'center': 'sex'}>,
        <Axes: title={'center': 'cp'}>,
        <Axes: title={'center': 'trestbps'}>],
```

```
 [<Axes: title={'center': 'chol'}>,
  <Axes: title={'center': 'fbs'}>,
  <Axes: title={'center': 'restecg'}>,
  <Axes: title={'center': 'thalach'}>],
 [<Axes: title={'center': 'exang'}>,
  <Axes: title={'center': 'oldpeak'}>,
  <Axes: title={'center': 'slope'}>,
  <Axes: title={'center': 'ca'}>],
 [<Axes: title={'center': 'thal'}>,
  <Axes: title={'center': 'num'}>, <Axes: >, <Axes: >]],
dtype=object)
```



Answer: (1) there are 303 samples and 14 attributes.

(2) there are only int64 and float64 data type, They are all numerical variables.

(3) The variables of age, testbps, chol, and Thalach are relatively close to a normal distribution, while the number of categories in the target variable num is uneven.

Q4 Transform the response num into a binary outcome: 1 for heart disease and 0 for no heart disease. So combine 1, 2, 3, and 4 into 1 and 0 for 0. For Questions 4-16, use the transformed binary outcome.

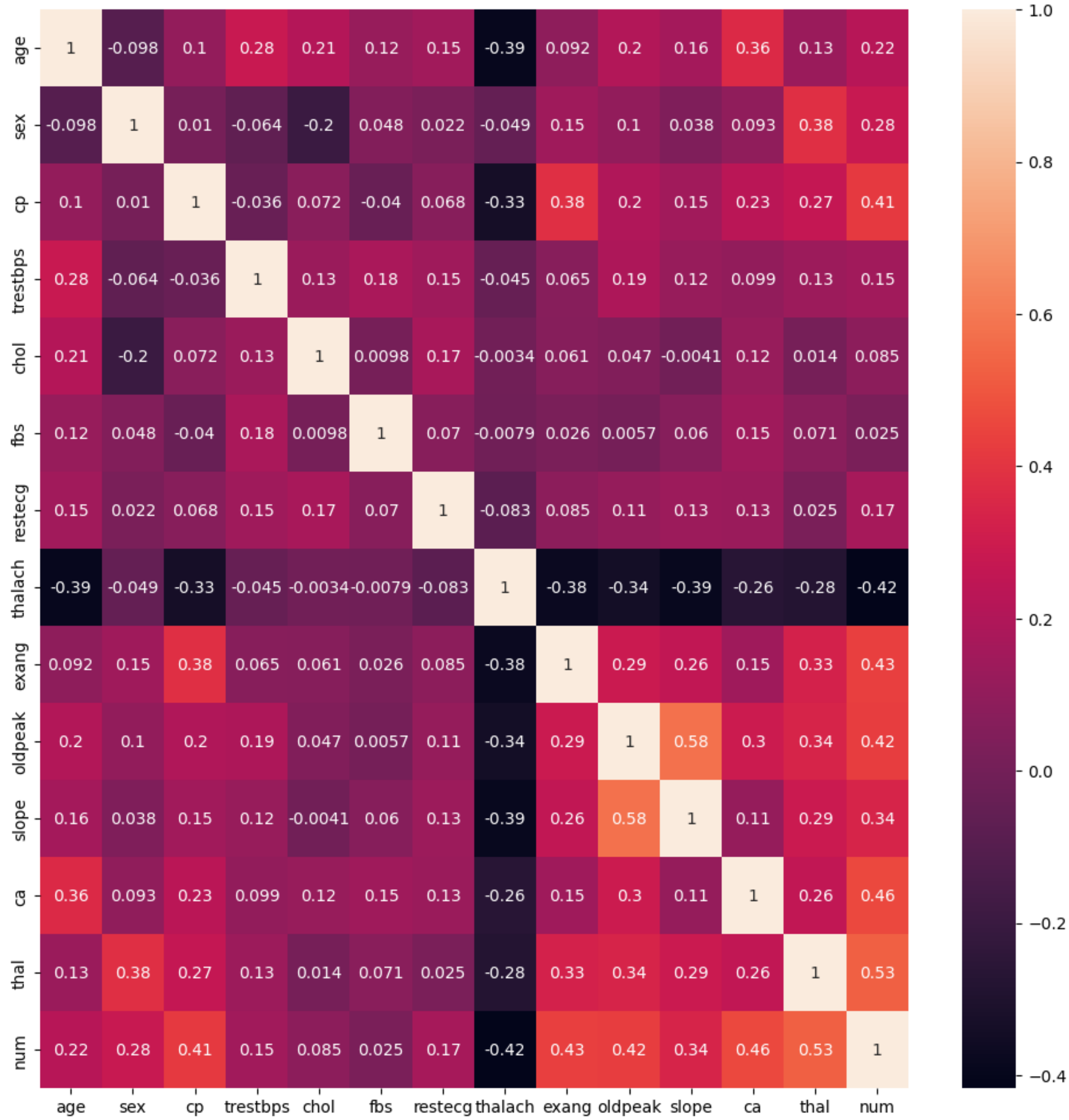
```
def binary_process(data):


    if data<1:
        return 0
    else:
        return 1


df['num'] = df['num'].apply(binary_process)
```

Q5 5.Analyze relationships between variables and discuss their implications for feature selection or extraction (include at least two statements).

```
corrmat = df.corr()
top_corr_features = corrmat.index
plt.figure(figsize=(12,12))
g=sns.heatmap(df[top_corr_features].corr(),annot=True)
```


age
sex
cp
trestbps
chol
fbs
restecg
thalach
exang
oldpeak
slope
ca
thal
num
1 -0.098 0.1 0.28 0.21 0.12 0.15 -0.39 0.092 0.2 0.16 0.36 0.13 0.22
-0.098 1 0.01 -0.064 -0.2 0.048 0.022 -0.049 0.15 0.1 0.038 0.093 0.38 0.28
0.1 0.01 1 -0.036 0.072 -0.04 0.068 -0.33 0.38 0.2 0.15 0.23 0.27 0.41
0.28 -0.064 -0.036 1 0.13 0.18 0.15 -0.045 0.065 0.19 0.12 0.099 0.13 0.15
0.21 -0.2 0.072 0.13 1 0.0098 0.17 -0.0034 0.061 0.047 -0.0041 0.12 0.014 0.085
0.12 0.048 -0.04 0.18 0.0098 1 0.07 -0.0079 0.026 0.0057 0.06 0.15 0.071 0.025
0.15 0.022 0.068 0.15 0.17 0.07 1 -0.083 0.085 0.11 0.13 0.13 0.025 0.17
-0.39 -0.049 -0.33 -0.045 -0.0034 -0.0079 -0.083 1 -0.38 -0.34 -0.39 -0.26 -0.28 -0.42
0.092 0.15 0.38 0.065 0.061 0.026 0.085 -0.38 1 0.29 0.26 0.15 0.33 0.43
0.2 0.1 0.2 0.19 0.047 0.0057 0.11 -0.34 0.29 1 0.58 0.3 0.34 0.42
0.16 0.038 0.15 0.12 -0.0041 0.06 0.13 -0.39 0.26 0.58 1 0.11 0.29 0.34
0.36 0.093 0.23 0.099 0.12 0.15 0.13 -0.26 0.15 0.3 0.11 1 0.26 0.46
0.13 0.38 0.27 0.13 0.014 0.071 0.025 -0.28 0.33 0.34 0.29 0.26 1 0.53
0.22 0.28 0.41 0.15 0.085 0.025 0.17 -0.42 0.43 0.42 0.34 0.46 0.53 1
age sex cp trestbps chol fbs restecg thalach exang oldpeak slope ca thal num
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4

Q6 Drop the rows with the missing values. How many osbervations after dropping the missing values. Skip the outlier analysis.

```
df.isnull().sum()
```

```
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          4
thal        2
num         0
dtype: int64
```

```
df = df.dropna()


df.shape
```

```
(297, 14)
```

Answer:there are 6 rows with the missing values. and there are 297 osbervations after dropping the missing values

Q7 Sub-group analysis: Explore potential sub-groups within the data using appropriate data science methods. Identify and visualize these sub-groups without using the labels and categorical variables. Categroical variables already define sub groups so we don't need to include them for this analysis.

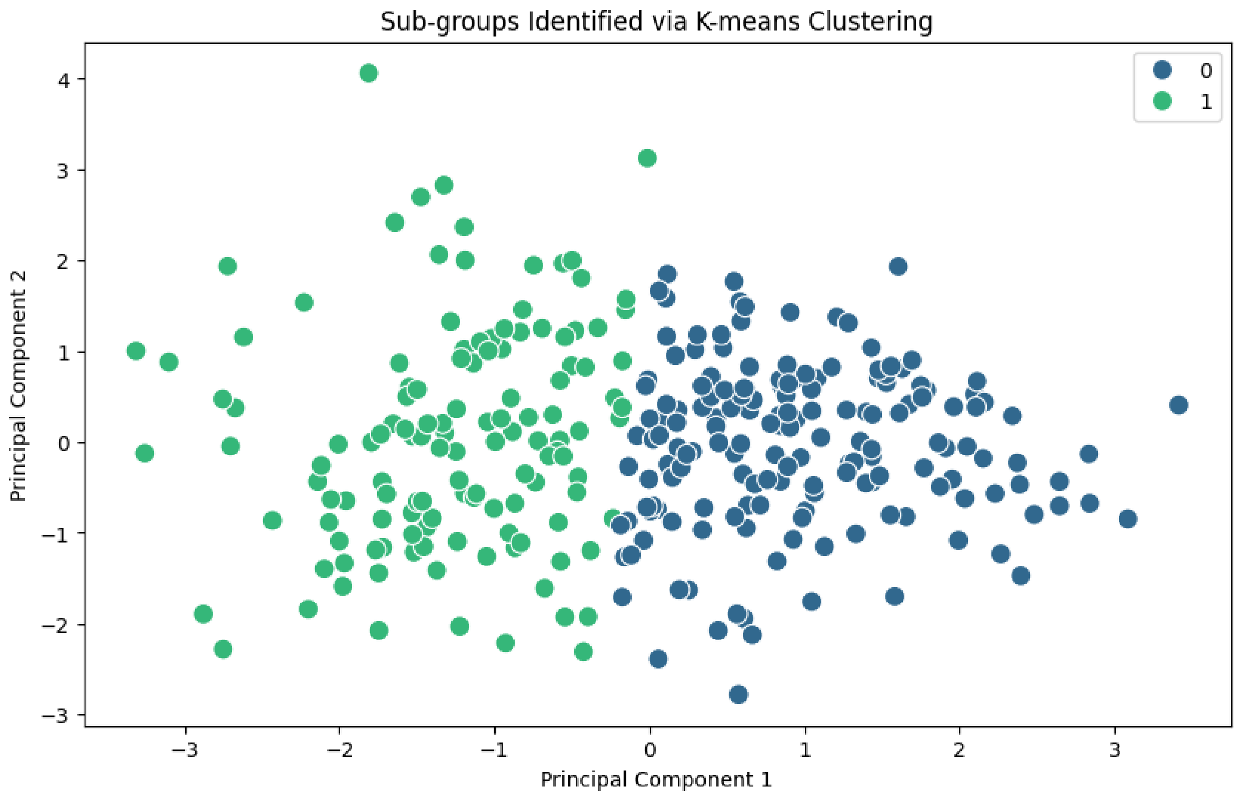
```
cont_features = ['age', 'trestbps', 'chol', 'thalach', 'oldpeak']
df_sub = df[cont_features]

# Standardize data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(df_sub)

pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

kmeans = KMeans(n_clusters=2,n_init='auto', random_state=42)
clusters = kmeans.fit_predict(X_scaled)

# Plot PCA results with clusters
plt.figure(figsize=(10,6))
sns.scatterplot(x=X_pca[:,0], y=X_pca[:,1], hue=clusters, palette='viridis', s=100)
plt.title('Sub-groups Identified via K-means Clustering')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.show()
```



Answer: we using k-means clustering and pca to identify and visualize these sub-groups without using the labels and categorical variables.

Q8 Split 30% of the data for testing using a random seed of 1. Use the remaining 70% for training and model selection.

```
X = df.drop(['num'],axis=1)
y = df['num']


X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1)
```

Q9 Identify the two classifiers you have chosen. Justify your selections based on the classifier requirement for this assignment.

Logistic regression

Logistic regression is a commonly used classification algorithm with high computational efficiency, fast training and prediction speed, and is suitable for processing large-scale datasets; The algorithm has low memory usage, and the model parameters only store feature weights and intercept terms. The model has strong interpretability; The output probability has clear statistical significance (probability values between 0-1) The influence of features can be directly explained by weight coefficients (positive weights promote positive classes, negative weights suppress positive classes); The algorithm is based on maximum likelihood estimation and has a solid foundation in probability statistics to calculate confidence intervals and p-values for statistical testing. It performs well on linearly separable data.

Random Forest

Random Forest is an ensemble learning algorithm that can handle complex nonlinear relationships; The algorithm automatically captures the interaction between features through the combination of multiple decision trees, without the need to manually construct feature cross terms. It has excellent anti overfitting ability; By using bagging (self sampling) and random subspace methods to reduce variance, parallel training is naturally supported, and performance can be improved by increasing the number of trees. The algorithm does not require features to follow a normal distribution, but instead quantifies feature contribution through permutation of importance to support feature selection and data understanding. It has strong robustness and is insensitive to missing values. It has a wide range of applicable scenarios and performs well on both small sample and large-scale data

Q10 Specify two metrics to compare classifier performance. Provide technical details on how each metric is computed.

Accuracy

Accuracy can directly reflect the proportion of correct predictions made by the model as a whole (correct sample size/total sample size), which non-technical personnel can quickly understand (such as “model accuracy of 90%”). When the distribution of categories is balanced (such as positive and negative samples 50:50), it can reliably reflect the high computational efficiency of the model performance, which is suitable for quickly evaluating the advantages of application scenarios in large datasets. It is suitable for scenarios where the cost of misjudgment is similar for various categories, and is the easiest to understand indicator for evaluating classification algorithms.

F1 score

F1 score is the harmonic mean of precision and recall, which can cope with imbalanced categories; When data is skewed (such as only 1% positive samples in fraud detection), misjudging cost sensitive scenarios is more reliable than accuracy

Precision: Focus on the proportion of samples predicted as positive that are actually positive (reducing false positives)

Recall: Focus on the proportion of samples that are actually positive and predicted to be positive (reduce false positives)

Q11 Train two selected classifiers in (9) and identify optimal tuning parameters (if applicable) using the training set.

```
model_lr = LogisticRegression(max_iter=1000)
model_lr.fit(X_train,y_train)
```

```
LogisticRegression(max_iter=1000)
```

```
param_grid = {
    'n_estimators': [50, 100, 300],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10],
}
rf = RandomForestClassifier(random_state=42, n_jobs=-1)

grid_search = GridSearchCV(
    estimator=rf,
    param_grid=param_grid,
    scoring='f1',
    cv=3,
    n_jobs=-1,
    verbose=2,
    return_train_score=True
)
grid_search.fit(X_train, y_train)

print("Best parameter combination:", grid_search.best_params_)
print("Best Cross Validation Score:", grid_search.best_score_)
```

```
Fitting 3 folds for each of 27 candidates, totalling 81 fits
Best parameter combination: {'max_depth': None, 'min_samples_split': 10, 'n_estimators': 50}
Best Cross Validation Score: 0.7953158837248043
```

```
model_rf = grid_search.best_estimator_
```

Q12.Apply a feature selection or extraction method to one of the classifiers in (9). Train this third classifier on the training set and identify optimal tuning parameters (if applicable) using the training set.

```
selector = SelectFromModel(rf, threshold='median')
X_train_selected = selector.fit_transform(X_train, y_train)
X_test_selected = selector.transform(X_test)

# Get selected feature names
selected_features = X.columns[selector.get_support()]
print(f"Selected {len(selected_features)} features:", list(selected_features))
```

```
Selected 7 features: ['age', 'cp', 'trestbps', 'thalach', 'oldpeak', 'ca', 'thal']
```

```
param_grid = {
    'n_estimators': [50, 100, 300],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10],
}
rf = RandomForestClassifier(random_state=42, n_jobs=-1)

grid_search = GridSearchCV(
    estimator=rf,
    param_grid=param_grid,
    scoring='f1',
    cv=3,
    n_jobs=-1,
    verbose=2,
    return_train_score=True
)
grid_search.fit(X_train_selected, y_train)
```

```python
print("Best parameter combination:", grid_search.best_params_)
print("Best Cross Validation Score:", grid_search.best_score_)
```

```
Fitting 3 folds for each of 27 candidates, totalling 81 fits
Best parameter combination: {'max_depth': 10, 'min_samples_split': 2, 'n_estimators': 100}
Best Cross Validation Score: 0.7833519137866963
```

```python
model_rf_selcetF = grid_search.best_estimator_
```

Q13 Use the selected metrics to evaluate three classifiers in (11) and (12) on the test set.

- Discuss your findings (at least two statements).
- Discuss the impact of feature selection or extraction on the performance of the classifier (at least one statement).

```
lr_pred=model_lr.predict(X_test)


print("the accuracy of Logistic Regression:",accuracy_score(y_test,lr_pred))
print("the f1 score of Logistic Regression:",f1_score(y_test,lr_pred))
```

```
the accuracy of Logistic Regression: 0.8111111111111111
the f1 score of Logistic Regression: 0.7951807228915663
```

```
rf_pred_tune = model_rf.predict(X_test)


print("the accuracy of  tuning parameters Random Forest:",accuracy_score(y_test,rf_pred_tune))
print("the f1 score of  tuning parameters Random Fores:",f1_score(y_test,rf_pred_tune))
```

```
the accuracy of  tuning parameters Random Forest: 0.8555555555555555
the f1 score of  tuning parameters Random Fores: 0.8354430379746836
```

```
select_pred = model_rf_selcetF.predict(X_test_selected)


print("the accuracy of selected features:",accuracy_score(y_test,select_pred))
print("the f1 score of selected features:",f1_score(y_test,select_pred))
```

```
the accuracy of selected features: 0.8
the f1 score of selected features: 0.7692307692307693
```

(1) The predictive performance of the parameter optimized random forest model is better than that of logistic regression, indicating that the random forest has a strong ability to fit data.

(2) After feature extraction, the predictive performance of the model deteriorated..

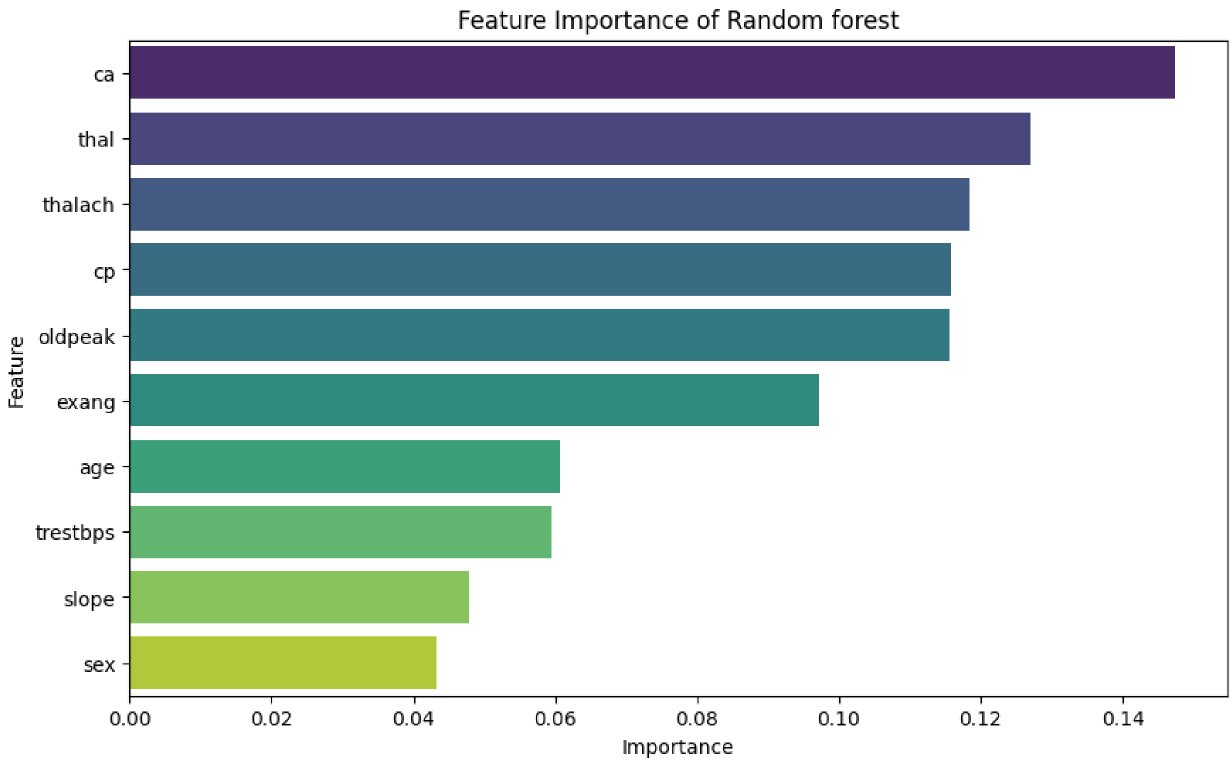
After feature dimensionality reduction, the data actually deteriorates, indicating that the information carried by the data contributes to the classifier. The richer the data information, the more helpful it may be for classification; Although dimensionality reduction can reduce computational complexity, it may not necessarily improve performance.

Q14 For the best interpretable model identified in (13), analyze and interpret the most important predictor variables in the context of the classification challenge (at least two statements).

```
feature_importances = model_rf.feature_importances_
feature_names = X_train.columns
importance_df = pd.DataFrame({"feature": feature_names, "importance": feature_importances})
importance_df = importance_df.sort_values(by="importance", ascending=False)
print(importance_df)
```

```
     feature  importance
11        ca    0.147453
12      thal    0.127048
7    thalach    0.118370
2         cp    0.115805
9    oldpeak    0.115618
8      exang    0.097222
0        age    0.060713
3   trestbps    0.059472
10     slope    0.047826
1        sex    0.043250
4       chol    0.041523
6    restecg    0.017566
5        fbs    0.008133
```

```
plt.figure(figsize=(10, 6))
sns.barplot(x="importance", y="feature", data=importance_df[:10], palette="viridis",hue="featu
plt.title("Feature Importance of Random forest")
plt.xlabel("Importance")
plt.ylabel("Feature")
plt.show()
```



(1) The variables ca and that contribute the most to disease prediction. In the heart disease dataset, ca and thal are two key clinical variables that are often used as important reference indicators for diagnosing the condition.

(2) Consistent with the previous correlation analysis results, the two variables with the strongest correlation contribute the most to classification

Q15 [Bonus] Sub-group improvement strategy: If sub-groups were identified, propose and implement a method to further improve the performance of one classifier. Compare the fourth classifier performance with the results from (13).

```
cont_features = ['age', 'trestbps', 'chol', 'thalach', 'oldpeak']
df_sub = df[cont_features]

scaler = StandardScaler()
X_scaled = scaler.fit_transform(df_sub)
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)
y = df['num'].values

X_train, X_test, y_train, y_test = train_test_split(X_pca, y, test_size=0.3, random_state=1)



rf = RandomForestClassifier(random_state=42, n_jobs=-1)

rf.fit(X_train,y_train)
```

```
RandomForestClassifier(n_jobs=-1, random_state=42)
```

```
sub_pred = rf.predict(X_test)

print("the accuracy of selected features:",accuracy_score(y_test,sub_pred))
print("the f1 score of selected features:",f1_score(y_test,sub_pred))
```

```
the accuracy of selected features: 0.6777777777777778
the f1 score of selected features: 0.6329113924050633
```

It can be seen that although the feature data reduced by PCA can be clustered to separate labels, its contribution to the prediction results in the classifier is not better than that of all features. There is no noise in the feature data, and the information carried by the variables is useful.

Q16 Team Contributions: Document each team member's specific contributions to the questions above. For group submissions, this should match the GitHub commit history. Individual submissions do not need to address this question.

Howard Wang(wangh397): Question 1-8

Yiming Xia(xiay67): Question 9-17

Since this was our first time using GitHub, we were unfamiliar with its workflow. Therefore, we completed the work locally and uploaded our parts individually to the repository.

Q17 Link to the public GitHub repository. This is optional for the individual submissions.

https://github.com/HW397/STATS-3DA3-A6/tree/main