CSCI 6515 - Machine Learning for Big Data (Fall 2023)

Final Project

Group_ID: `7`

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1. Dataset Information

Dataset Name: `Credit_approval`

Link to the Dataset: `https://archive.ics.uci.edu/dataset/27/credit+approval`

Dataset Description:

```
 This file concerns credit card applications.  All attribute
names and values have been changed to meaningless symbols to
protect confidentiality of the data. This dataset is interesting
because there is a good mix of attributes -- continuous, nominal
with small numbers of values, and nominal with larger numbers of
values.
```

2. Task Information

Task Goal: `Predict the final decision of credit application.`

Task Description:

```
 The task is designed to predict the final decision on a credit
application based on the applicant's personal and financial
situation (e.g. income, marriage, debt, etc.). Four models were
used for comparison of prediction performance, namely logistic
regression, random forest, KNN and Bayesian model.
```

3. Task Implementation: Coding

3.1 Preprocessing

In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [ ]:
```
import ssl
import warnings
warnings.filterwarnings('ignore')
print(ssl.get_default_verify_paths())
```

```
DefaultVerifyPaths(cafile=None, capath=None, openssl_cafile_env='SSL_CERT_
FILE', openssl_cafile='C:\\Program Files\\Common Files\\SSL/cert.pem', ope
nssl_capath_env='SSL_CERT_DIR', openssl_capath='C:\\Program Files\\Common
Files\\SSL/certs')
```

In [ ]:
```
from ucimlrepo import fetch_ucirepo

# fetch dataset
credit_approval = fetch_ucirepo(id=27)

# data (as pandas dataframes)
X = credit_approval.data.features
y = credit_approval.data.targets
```

In [ ]:
```
X = X.iloc[:, [14,13,12,11,10,9,8,7,6,5,4,3,2,1,0]]
X
```

Out[ ]:

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14
0	b	30.83	0.000	u	g	w	v	1.25	t	t	1	f	g	202.0
1	a	58.67	4.460	u	g	q	h	3.04	t	t	6	f	g	43.0
2	a	24.50	0.500	u	g	q	h	1.50	t	f	0	f	g	280.0
3	b	27.83	1.540	u	g	w	v	3.75	t	t	5	t	g	100.0
4	b	20.17	5.625	u	g	w	v	1.71	t	f	0	f	s	120.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
685	b	21.08	10.085	y	p	e	h	1.25	f	f	0	f	g	260.0
686	a	22.67	0.750	u	g	c	v	2.00	f	t	2	t	g	200.0
687	a	25.25	13.500	y	p	ff	ff	2.00	f	t	1	t	g	200.0
688	b	17.92	0.205	u	g	aa	v	0.04	f	f	0	f	g	280.0
689	b	35.00	3.375	u	g	c	h	8.29	f	f	0	t	g	0.0

690 rows × 15 columns

In [ ]:
```
y
```

Out[ ]:

	A16
0	+
1	+
2	+
3	+
4	+
...	...
685	-
686	-
687	-
688	-
689	-

690 rows × 1 columns

In [ ]:
```
df = X.merge(y,how='outer', left_index=True, right_index=True)
df
```

Out[ ]:

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14
0	b	30.83	0.000	u	g	w	v	1.25	t	t	1	f	g	202.0
1	a	58.67	4.460	u	g	q	h	3.04	t	t	6	f	g	43.0
2	a	24.50	0.500	u	g	q	h	1.50	t	f	0	f	g	280.0
3	b	27.83	1.540	u	g	w	v	3.75	t	t	5	t	g	100.0
4	b	20.17	5.625	u	g	w	v	1.71	t	f	0	f	s	120.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
685	b	21.08	10.085	y	p	e	h	1.25	f	f	0	f	g	260.0
686	a	22.67	0.750	u	g	c	v	2.00	f	t	2	t	g	200.0
687	a	25.25	13.500	y	p	ff	ff	2.00	f	t	1	t	g	200.0
688	b	17.92	0.205	u	g	aa	v	0.04	f	f	0	f	g	280.0
689	b	35.00	3.375	u	g	c	h	8.29	f	f	0	t	g	0.0

690 rows × 16 columns

In [ ]:
```
df = df.rename(columns={"A1":"Gender","A2":"Age","A3":"Debt","A4":"Marrie
                        "A7":"Ethnicity","A8":"YearsEmployed","A9":"Prior
                        "A12":"DriverLicense","A13":"Citizen","A14":"ZipC
df
```

Out[ ]:

	Gender	Age	Debt	Married	BankCustomer	EducationLevel	Ethnicity	Y
0	b	30.83	0.000	u	g	w	v	
1	a	58.67	4.460	u	g	q	h	
2	a	24.50	0.500	u	g	q	h	
3	b	27.83	1.540	u	g	w	v	
4	b	20.17	5.625	u	g	w	v	
...	...	...	...	...	...	...	...	
685	b	21.08	10.085	y	p	e	h	
686	a	22.67	0.750	u	g	c	v	
687	a	25.25	13.500	y	p	ff	ff	
688	b	17.92	0.205	u	g	aa	v	
689	b	35.00	3.375	u	g	c	h	

690 rows × 16 columns

In [ ]:

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

Out[ ]:

```
Gender            12
Age               12
Debt               0
Married            6
BankCustomer       6
EducationLevel     9
Ethnicity          9
YearsEmployed      0
PriorDefault       0
Employed           0
CreditScore        0
DriverLicense      0
Citizen            0
ZipCode           13
Income             0
ApprovalStatus     0
dtype: int64
```

In [ ]:

```
df = df.dropna(axis=0)
df = df.drop_duplicates()
df
```

Out[ ]:

	Gender	Age	Debt	Married	BankCustomer	EducationLevel	Ethnicity	Y
0	b	30.83	0.000	u	g	w	v	
1	a	58.67	4.460	u	g	q	h	
2	a	24.50	0.500	u	g	q	h	
3	b	27.83	1.540	u	g	w	v	
4	b	20.17	5.625	u	g	w	v	
...	...	...	...	...	...	...	...	
685	b	21.08	10.085	y	p	e	h	
686	a	22.67	0.750	u	g	c	v	
687	a	25.25	13.500	y	p	ff	ff	
688	b	17.92	0.205	u	g	aa	v	
689	b	35.00	3.375	u	g	c	h	

653 rows × 16 columns

In [ ]:

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

Out[ ]:

```
Gender            0
Age               0
Debt              0
Married           0
BankCustomer      0
EducationLevel    0
Ethnicity         0
YearsEmployed     0
PriorDefault      0
Employed          0
CreditScore       0
DriverLicense     0
Citizen           0
ZipCode           0
Income            0
ApprovalStatus    0
dtype: int64
```

Encode and Normalization

In [ ]:

```
df['ApprovalStatus'] = df['ApprovalStatus'].map({'+' : 1, '-' : 0})
df
```

Out[ ]:

	Gender	Age	Debt	Married	BankCustomer	EducationLevel	Ethnicity	Y
0	b	30.83	0.000	u	g	w	v	
1	a	58.67	4.460	u	g	q	h	
2	a	24.50	0.500	u	g	q	h	
3	b	27.83	1.540	u	g	w	v	
4	b	20.17	5.625	u	g	w	v	
...	...	...	...	...	...	...	...	
685	b	21.08	10.085	y	p	e	h	
686	a	22.67	0.750	u	g	c	v	
687	a	25.25	13.500	y	p	ff	ff	
688	b	17.92	0.205	u	g	aa	v	
689	b	35.00	3.375	u	g	c	h	

653 rows × 16 columns

In [ ]:

```
from sklearn.preprocessing import LabelEncoder
#Apply label encoding on all columns with type of object
df[list(df.columns[df.dtypes == object])]  = df[list(df.columns[df.dtypes
df
```

Out[ ]:

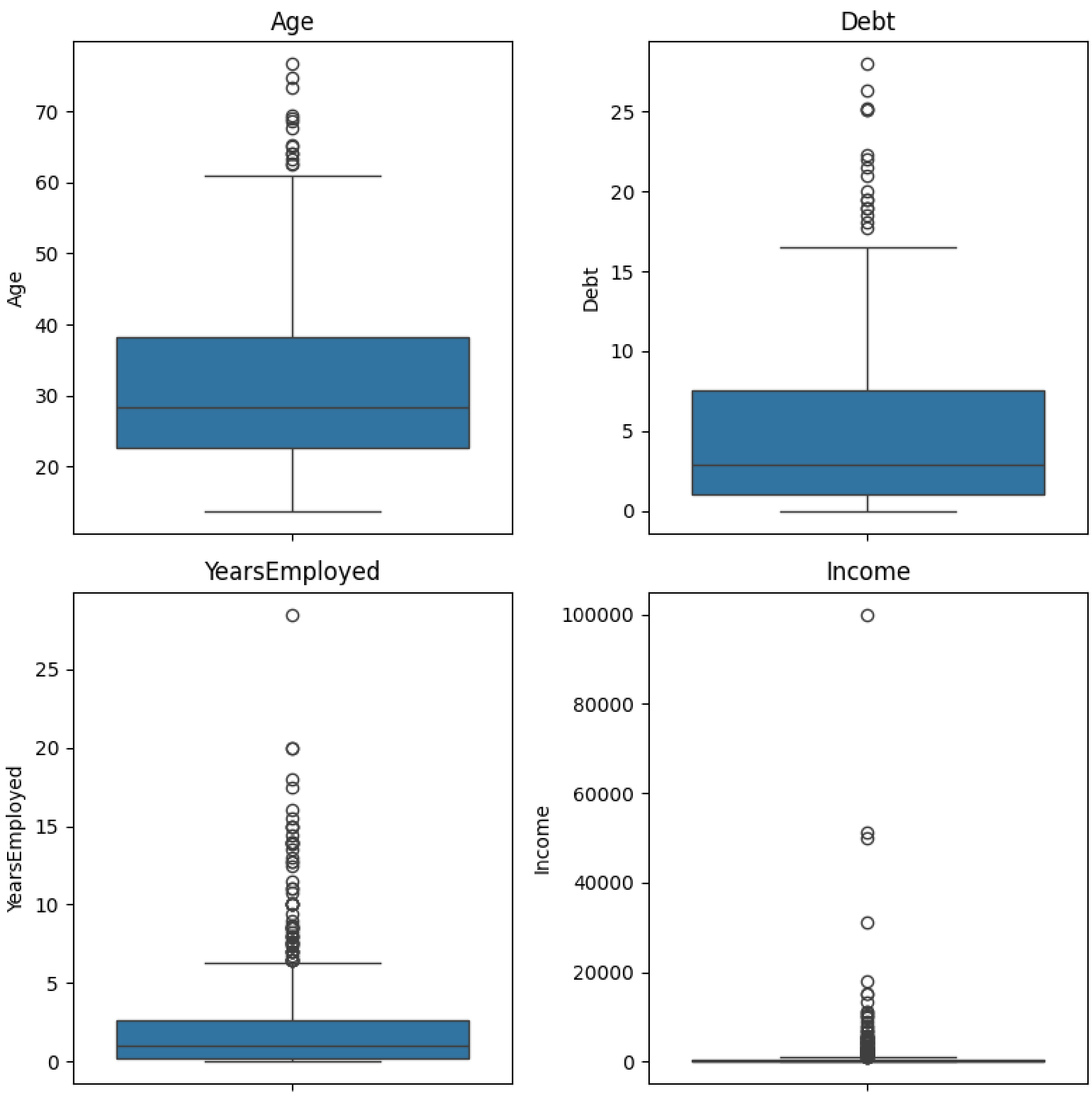
	Gender	Age	Debt	Married	BankCustomer	EducationLevel	Ethnicity	Y
0	1	30.83	0.000	1	0	12	7	
1	0	58.67	4.460	1	0	10	3	
2	0	24.50	0.500	1	0	10	3	
3	1	27.83	1.540	1	0	12	7	
4	1	20.17	5.625	1	0	12	7	
...	...	...	...	...	...	...	...	
685	1	21.08	10.085	2	2	4	3	
686	0	22.67	0.750	1	0	1	7	
687	0	25.25	13.500	2	2	5	2	
688	1	17.92	0.205	1	0	0	7	
689	1	35.00	3.375	1	0	1	3	

653 rows × 16 columns

In [ ]:

```
# Plotting boxplots for continuous columns to identify outliers
plt.figure(figsize=(8, 8))
columns = ['Age','Debt','YearsEmployed','Income']

for i, col in enumerate(columns, 1):
    plt.subplot(2, 2, i)
    #sns.boxplot(y=train_data[col])
    #sns.boxplot(data = df , x = 'ApprovalStatus' , y = col)
```

```
    sns.boxplot(data = df , y = col)
    plt.title(col)

plt.tight_layout()
plt.show()
```



In [ ]:

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
df[columns] = scaler.fit_transform(df[columns])
df.head()
```

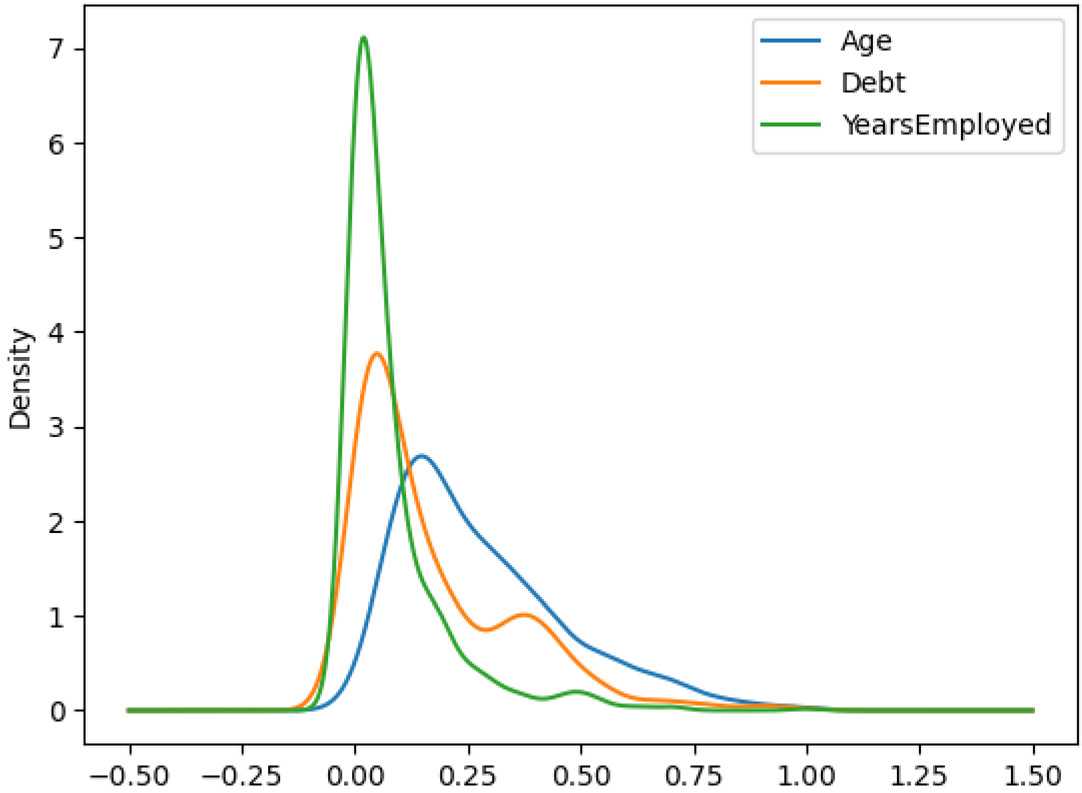
Out[ ]:

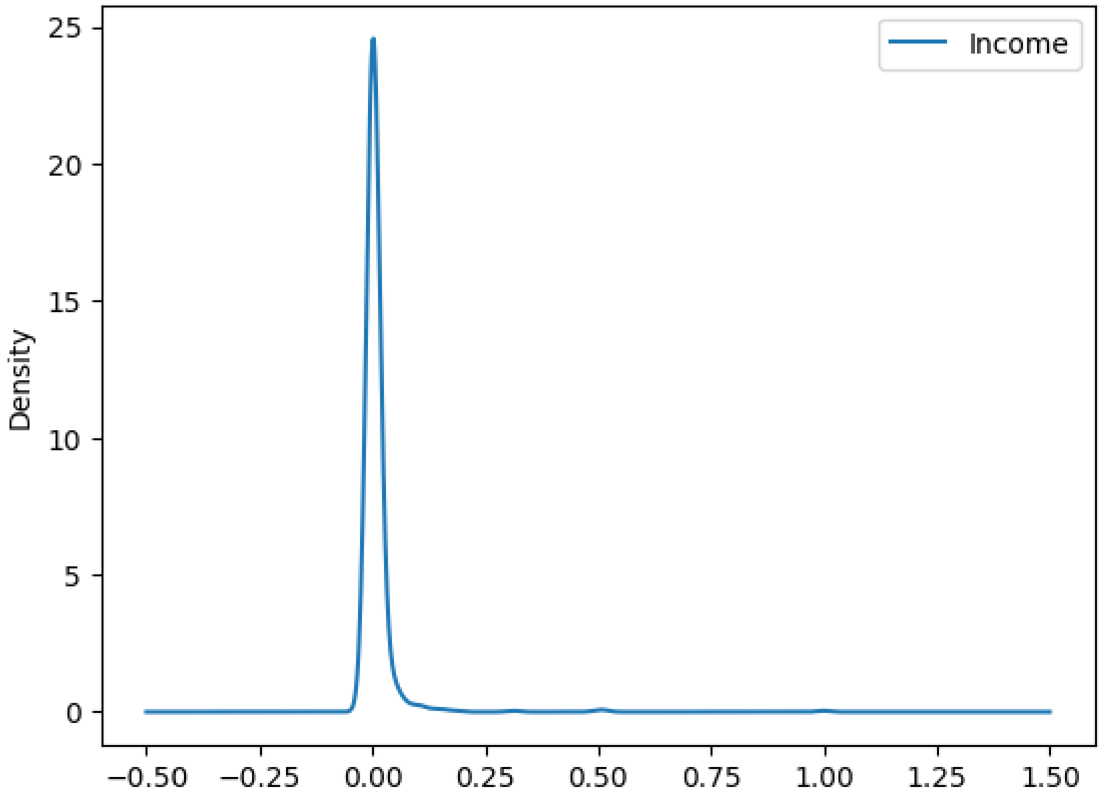
	Gender	Age	Debt	Married	BankCustomer	EducationLevel	Ethnicity
0	1	0.271111	0.000000	1	0	12	7
1	0	0.713016	0.159286	1	0	10	3
2	0	0.170635	0.017857	1	0	10	3
3	1	0.223492	0.055000	1	0	12	7
4	1	0.101905	0.200893	1	0	12	7

Check the distribution of variables

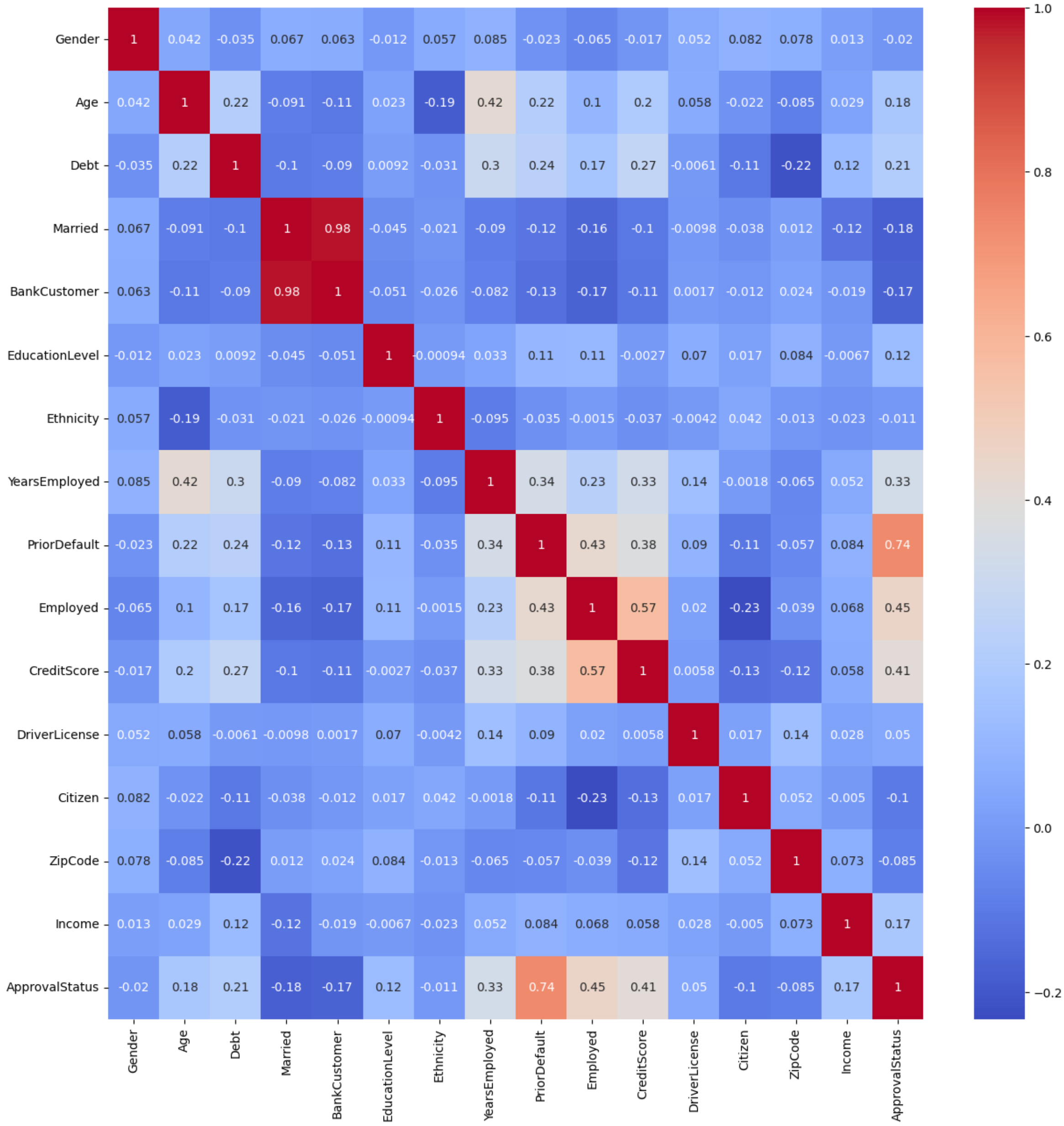
In [ ]:
```
df.iloc[:,[1,2,7]].plot.kde()
df.iloc[:,[14]].plot.kde()
```

Out[ ]: <Axes: ylabel='Density'>





In [ ]:
```
sns.heatmap(df.corr(),annot=True,cmap='coolwarm')
plt.gcf().set_size_inches(15, 15)
plt.show()
```



3.2 Model development and evaluation

3.2.1 Logistic Regression

In [ ]:
```
from sklearn.model_selection import train_test_split,cross_val_score
from sklearn.metrics import classification_report, accuracy_score

X = df.iloc[:,0:15]
y = df.iloc[:,-1:]

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

3.2.1.1 Hyperparameter tune

In [ ]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, accuracy_score
# define param grid
param_grid = {
```

```
    'C': [0.001, 0.01, 0.1, 1, 10],
    'penalty': ['l1', 'l2','elasticnet'],
    'tol': [1e-4, 1e-3, 1e-2],
    'solver': ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga']
}

# build model
logistic = LogisticRegression(max_iter=1000)

# GridSearchCV
grid_search = GridSearchCV(logistic, param_grid, cv=5, scoring='accuracy'
grid_search.fit(X_train, y_train)

# get best params and score
best_params = grid_search.best_params_
best_score = grid_search.best_score_

# use best params
best_logistic = LogisticRegression(**best_params, max_iter=1000)
best_logistic.fit(X_train, y_train)
y_pred_best = best_logistic.predict(X_test)
accuracy_best = accuracy_score(y_test, y_pred_best)
class_report = classification_report(y_test, y_pred_best)



print("Best Parameters:", best_params)
print("Best Cross-Validation Score:", best_score)
print("Test Set Accuracy:", accuracy_best)
print("Classification Report:\n", class_report)
```

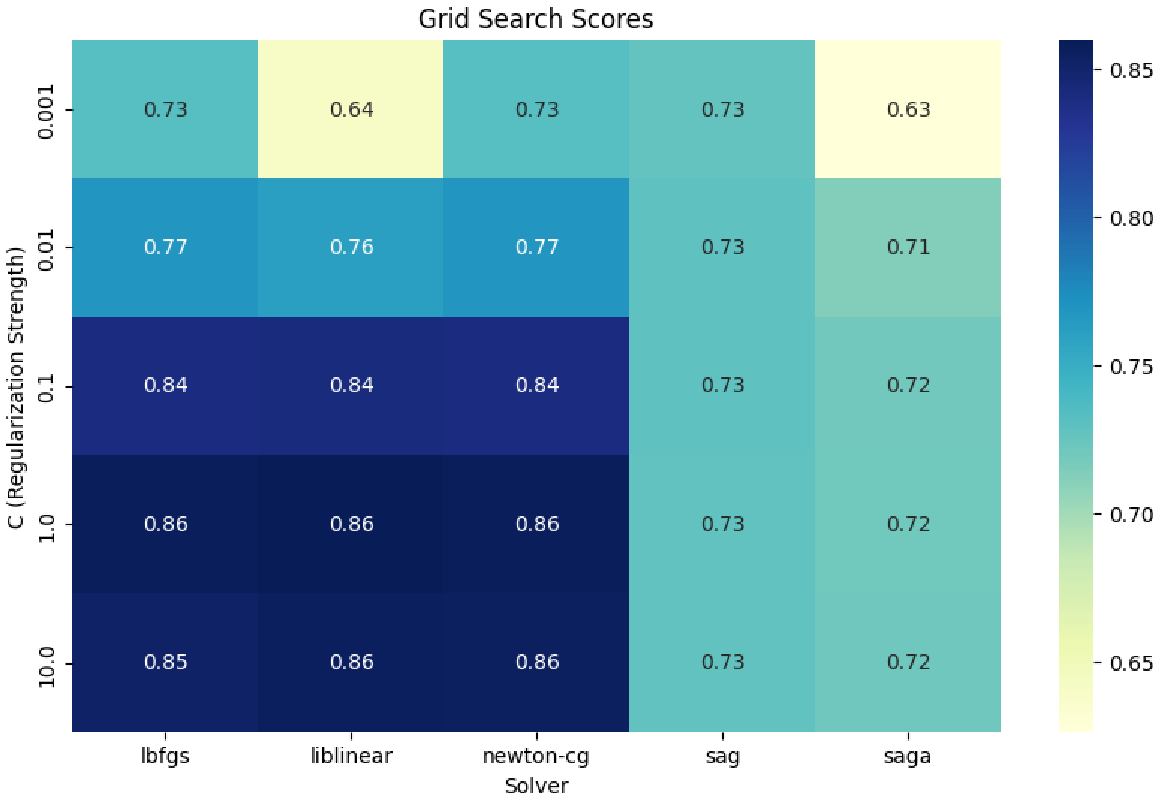
```
Best Parameters: {'C': 1, 'penalty': 'l1', 'solver': 'liblinear', 'tol':
0.001}
Best Cross-Validation Score: 0.8642618251313904
Test Set Accuracy: 0.8877551020408163
Classification Report:
               precision    recall  f1-score   support

           0       0.92      0.88      0.90       112
           1       0.84      0.90      0.87        84

    accuracy                           0.89       196
   macro avg       0.88      0.89      0.89       196
weighted avg       0.89      0.89      0.89       196
```

3.2.1.2 Model evaluation

In [ ]:

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

# get result
results = pd.DataFrame(grid_search.cv_results_)

# choose parameters
param_1 = 'param_C'
param_2 = 'param_solver'

# plot
```

```
pivot_table = results.pivot_table(values='mean_test_score',
                                  index=[param_1],
                                  columns=[param_2])

plt.figure(figsize=(10, 6))
sns.heatmap(pivot_table, annot=True, cmap='YlGnBu')
plt.title('Grid Search Scores')
plt.xlabel('Solver')
plt.ylabel('C (Regularization Strength)')
plt.show()
```



3.2.2 KNN Classifier

In [ ]:
```
from sklearn.model_selection import train_test_split,cross_val_score
from sklearn.metrics import classification_report, accuracy_score
from sklearn.neighbors import KNeighborsClassifier

X = df.iloc[:,0:15]
y = df.iloc[:,-1:]

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

KNN = KNeighborsClassifier(n_neighbors=10)
KNN.fit(X_train.to_numpy(), y_train.to_numpy())
y_pred = KNN.predict(X_test.to_numpy())

cm = classification_report(y_test.to_numpy(),y_pred)
print(cm)
```

```
              precision    recall  f1-score   support

           0       0.64      0.86      0.73       109
           1       0.69      0.39      0.50        87

    accuracy                           0.65       196
   macro avg       0.67      0.63      0.62       196
weighted avg       0.66      0.65      0.63       196
```

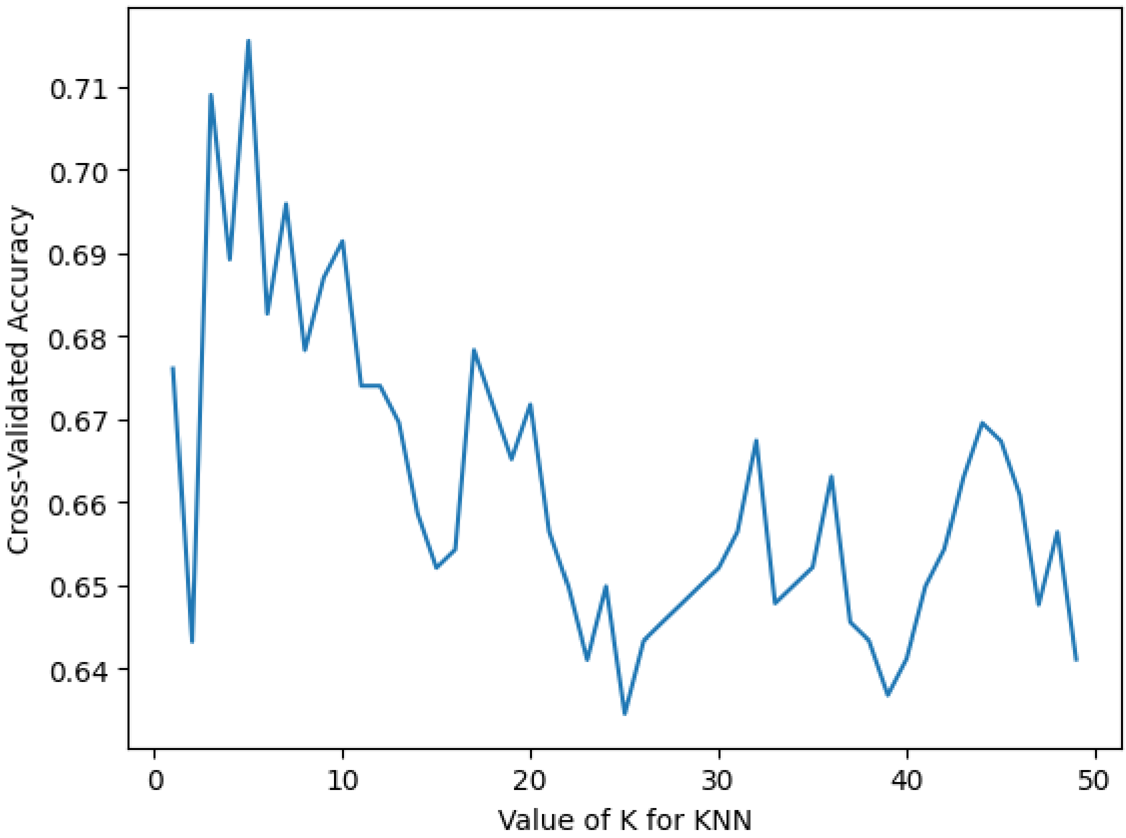
3.2.2.1 Hyperparameter tune

In [ ]:
```python
k_range = range(1,50)
cv_range = [2,3,4,5,6,7,8,9,10]
k_scores = []
cv_scores = []


#for i in cv_range:
for k in k_range:
    KNN = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(KNN, X_train.to_numpy(), y_train.to_numpy(),
    k_scores.append(scores.mean())
    #cv_scores[i,:] = k_scores
print(k_scores)
print(k_scores.index(max(k_scores)))
```

```
[0.6761108456760629, 0.6432632584806497, 0.7090301003344482, 0.68927376970
85524, 0.715551839464883, 0.6827281414237938, 0.6958910654562829, 0.678332
5370281892, 0.6870520783564262, 0.6914715719063544, 0.6740324892498805, 0.
6740324892498805, 0.6696368848542761, 0.6586478738652651, 0.65210224558050
64, 0.6543000477783086, 0.678356426182513, 0.6717391304347826, 0.665193502
1500238, 0.6717869087434305, 0.6564739608217869, 0.6498805542283803, 0.641
0654562828475, 0.6498805542283803, 0.6345676063067367, 0.6433349259436215,
0.6455566172957478, 0.6477305303392259, 0.6499283325370282, 0.652078356426
1825, 0.6564739608217869, 0.6674390826564739, 0.6478260869565218, 0.65, 0.
6521739130434783, 0.6631151457238414, 0.6455566172957478, 0.64335881509794
56, 0.6368131868131869, 0.6412087912087913, 0.6498805542283803, 0.65434782
60869566, 0.6629956999522217, 0.6695652173913043, 0.6673674151935021, 0.66
08695652173913, 0.6476588628762541, 0.6564261825131391, 0.641137123745819
3]
4
```

In [ ]:
```python
plt.plot(k_range, k_scores)
plt.xlabel('Value of K for KNN')
plt.ylabel('Cross-Validated Accuracy')
```

Out[ ]:
```
Text(0, 0.5, 'Cross-Validated Accuracy')
```



3.2.2.2 Model evaluation

In [ ]:
```
KNN = KNeighborsClassifier(n_neighbors=k_range[k_scores.index(max(k_score
KNN.fit(X_train.to_numpy(), y_train.to_numpy())
y_pred = KNN.predict(X_test.to_numpy())

cm = classification_report(y_test.to_numpy(),y_pred)
print(cm)
```

```
              precision    recall  f1-score   support

           0       0.66      0.78      0.72       109
           1       0.65      0.51      0.57        87

    accuracy                           0.66       196
   macro avg       0.66      0.64      0.64       196
weighted avg       0.66      0.66      0.65       196
```

3.2.3 Naive Bayes Classifier

In [ ]:
```
from sklearn.naive_bayes import GaussianNB
GaussNB = GaussianNB()
GaussNB.fit(X_train, y_train)
y_pred = GaussNB.predict(X_test)
cm = classification_report(y_test,y_pred)
print(cm)
```

```
              precision    recall  f1-score   support

           0       0.77      0.97      0.86       109
           1       0.95      0.63      0.76        87

    accuracy                           0.82       196
   macro avg       0.86      0.80      0.81       196
weighted avg       0.85      0.82      0.81       196
```

In [ ]:
```
from sklearn.naive_bayes import BernoulliNB
BernoNB = BernoulliNB(force_alpha=True)
BernoNB.fit(X_train, y_train)
y_pred = BernoNB.predict(X_test)
cm = classification_report(y_test,y_pred)
print(cm)
```

```
              precision    recall  f1-score   support

           0       0.80      0.90      0.84       109
           1       0.85      0.71      0.77        87

    accuracy                           0.82       196
   macro avg       0.82      0.81      0.81       196
weighted avg       0.82      0.82      0.81       196
```

In [ ]:
```
from sklearn.naive_bayes import MultinomialNB
MultiNomNB = MultinomialNB()
MultiNomNB.fit(X_train, y_train)
y_pred = MultiNomNB.predict(X_test)
cm = classification_report(y_test,y_pred)
print(cm)
```

```
              precision    recall  f1-score   support

           0       0.73      0.76      0.74       109
           1       0.68      0.64      0.66        87

    accuracy                           0.71       196
   macro avg       0.71      0.70      0.70       196
weighted avg       0.71      0.71      0.71       196
```

3.2.4 Random Forest Classifier

In [ ]:
```
from sklearn.model_selection import train_test_split, RandomizedSearchCV,
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confus
```

In [ ]:
```
X = df.iloc[:,0:15]
y = df.iloc[:,-1:]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_
```

3.2.4.3 Hyperparameter tune

In [ ]:
```
rf_classifier = RandomForestClassifier(random_state=42)
```

In [ ]:
```
param_dist = {
    'n_estimators': [50, 100, 150],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
#     'max_features': ['auto', 'sqrt', 'log2']
}
```

In [ ]:
```
random_search = RandomizedSearchCV(rf_classifier, param_distributions=par
random_search.fit(X_train, y_train)
```

Out[ ]:
```
▸ RandomizedSearchCV
▸ estimator: RandomForestClassifier
    ▸ RandomForestClassifier
```

In [ ]:
```
print("Best Hyperparameters_RandomSearch:", random_search.best_params_)
```

```
Best Hyperparameters_RandomSearch: {'n_estimators': 100, 'min_samples_spli
t': 2, 'min_samples_leaf': 1, 'max_depth': 10}
```

In [ ]:
```
best_rf_model_Random = random_search.best_estimator_
y_pred = best_rf_model_Random.predict(X_val)
```

In [ ]:
```
accuracy = accuracy_score(y_val, y_pred)
print("Random Search Validation Accuracy:", accuracy)
```

```
Random Search Validation Accuracy: 0.8913043478260869
```

In [ ]:
```
confusion_mat = confusion_matrix(y_val, y_pred)
print("Random Search Confusion Matrix:\n", confusion_mat)
```

```
Random Search Confusion Matrix:
 [[47  5]
 [ 5 35]]
```

In [ ]:
```
class_report = classification_report(y_val, y_pred)
print("Random Search Classification Report:\n", class_report)
```

```
Random Search Classification Report:
               precision    recall  f1-score   support

           0       0.90      0.90      0.90        52
           1       0.88      0.88      0.88        40

    accuracy                           0.89        92
   macro avg       0.89      0.89      0.89        92
weighted avg       0.89      0.89      0.89        92
```

In [ ]:
```
param_grid = {
    'n_estimators': [50, 100, 150],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
#     'max_features': ['auto', 'sqrt', 'log2']
}
```

In [ ]:
```
grid_search = GridSearchCV(rf_classifier, param_grid, cv=5, scoring='accu
grid_search.fit(X_train, y_train)
```

Out[ ]:
```
▸ GridSearchCV
▸ estimator: RandomForestClassifier
  ▸ RandomForestClassifier
```

In [ ]:
```
print("Best Hyperparameters_GridSearch:", grid_search.best_params_)
```

```
Best Hyperparameters_GridSearch: {'max_depth': None, 'min_samples_leaf':
2, 'min_samples_split': 5, 'n_estimators': 100}
```

**The processing time of Grid Search is much slower than Random Search.The different results of these two kinds of hyperparameter tuning methods are:

Random Search: "min_samples_split": 2,"n_estimators": 50,

Grid Search: "min_samples_split": 10, "n_estimators:: 150

Compare the performance for the validation set: (Random Search already done) **

In [ ]:
```
best_rf_model_Grid = grid_search.best_estimator_
y_pred = best_rf_model_Grid.predict(X_val)
```

In [ ]:
```
accuracy = accuracy_score(y_val, y_pred)
print("Grid Search Validation Accuracy:", accuracy)
```

```
Grid Search Validation Accuracy: 0.8695652173913043
```

In [ ]:
```
confusion_mat = confusion_matrix(y_val, y_pred)
print("Grid Search Confusion Matrix:\n", confusion_mat)
```

```
Grid Search Confusion Matrix:
 [[47  5]
 [ 7 33]]
```

In [ ]:
```
class_report = classification_report(y_val, y_pred)
print("Grid Search Classification Report:\n", class_report)
```

```
Grid Search Classification Report:
               precision    recall  f1-score   support

           0       0.87      0.90      0.89        52
           1       0.87      0.82      0.85        40

    accuracy                           0.87        92
   macro avg       0.87      0.86      0.87        92
weighted avg       0.87      0.87      0.87        92
```

3.2.4.3 Model evaluation

The performances from the random grid is better. Just use the hyperparameter from random grid to train the test dataset

In [ ]:
```
best_rf_model_Random = random_search.best_estimator_
y_test_pred = best_rf_model_Random.predict(X_test)
```

In [ ]:
```
accuracy = accuracy_score(y_test, y_test_pred)
print("Test Accuracy:", accuracy)
```

```
Test Accuracy: 0.8775510204081632
```

In [ ]:
```
confusion_mat = confusion_matrix(y_test, y_test_pred)
print("Confusion Matrix:\n", confusion_mat)
```

```
Confusion Matrix:
 [[105   9]
 [ 15  67]]
```

In [ ]:
```
class_report = classification_report(y_test, y_test_pred)
print("Classification Report:\n", class_report)
```

```
Classification Report:
               precision    recall  f1-score   support

           0       0.88      0.92      0.90       114
           1       0.88      0.82      0.85        82

    accuracy                           0.88       196
   macro avg       0.88      0.87      0.87       196
weighted avg       0.88      0.88      0.88       196
```