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

Final Project

Group_ID: `7`

Group Members:

1. `Xiaoting_B00685239`
2. `Xuelian_B00977221`
3. `Siqi_B00976996`

1. Dataset Information

Dataset Name: `Adult`

Link to the Dataset: `https://archive.ics.uci.edu/dataset/2/adult`

Dataset Description:

```
 The dataset extraction was done by Barry Becker from the 1994
Census detabash. Prediction task is to determine whether a person
make over 50k a year.
```

2. Task Information

Task Goal: `Prediction task is to determine whether a person make over 50k a year.`

Task Description:

```
 The task is aiming to predict income above or less and equal to
50k/yr based on their age, educaltion level, race, sex, marital
status, etc. Four models are applied for prediction performance
comparison, which are respectively logistic regression, random
forest, KNN and naive bayes.
```

3. Task Implementation: Coding

3.1 Preprocessing

In [ ]:
```python
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings('ignore')
```

In [ ]:
```python
train_data=pd.read_csv('adult_train.csv')
test_data=pd.read_csv('adult_test.csv')
test_data['Income'] = test_data['Income'].str.replace('.', '')
train_data
```

Out[ ]:

	Age	Workclass	Final Weight	Education	Education Number	Marital Status	Occupation	Re
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	No
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	No
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	
...	...	...	...	...	...	...	...	
32556	27	Private	257302	Assoc-acdm	12	Married-civ-spouse	Tech-support	
32557	40	Private	154374	HS-grad	9	Married-civ-spouse	Machine-op-inspct	
32558	58	Private	151910	HS-grad	9	Widowed	Adm-clerical	
32559	22	Private	201490	HS-grad	9	Never-married	Adm-clerical	
32560	52	Self-emp-inc	287927	HS-grad	9	Married-civ-spouse	Exec-managerial	

32561 rows × 15 columns

In [ ]:
```python
discrete_columns = ['Workclass', 'Education', 'Marital Status', 'Occupati
continuous_columns = ['Age', 'Final Weight', 'Education Number', 'Capital
```

In [ ]:
```python
# Checking for missing values
missing_values = train_data.isnull().sum()

# Checking for duplicate rows
duplicate_rows = train_data.duplicated().sum()
```

```
missing_values, duplicate_rows
```

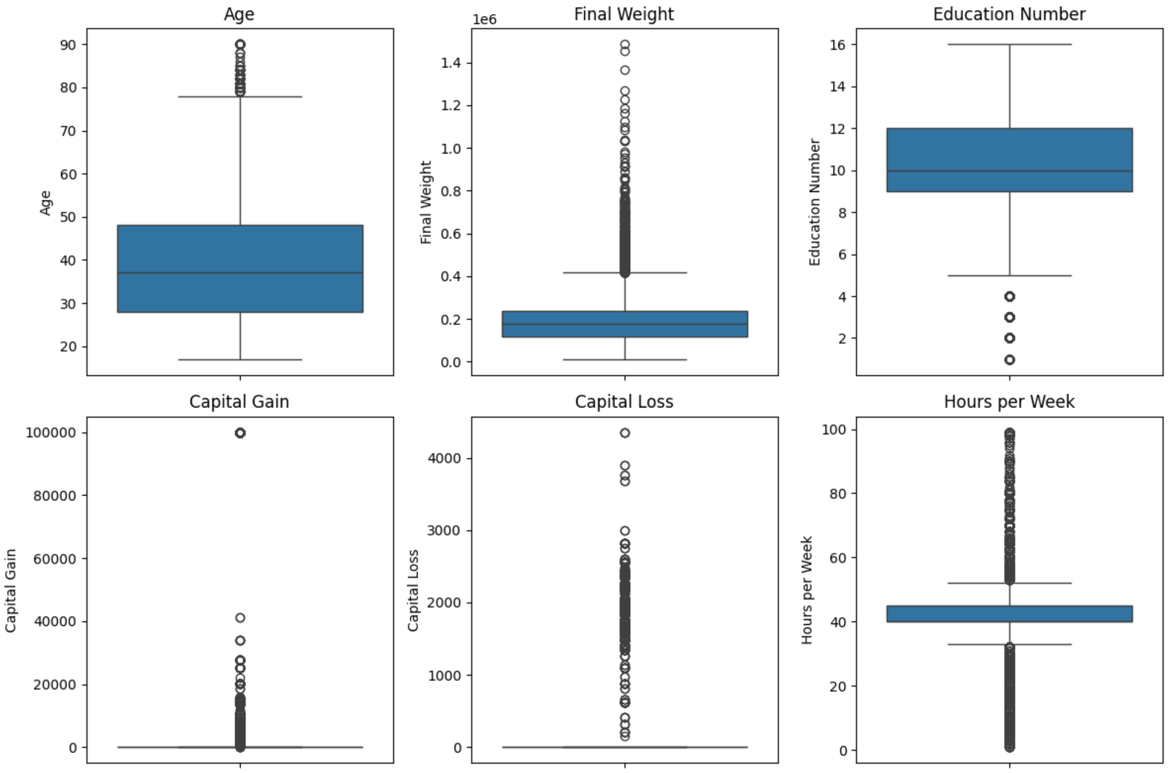
Out[ ]:
```
(Age                0
 Workclass          0
 Final Weight       0
 Education          0
 Education Number   0
 Marital Status     0
 Occupation         0
 Relationship       0
 Race               0
 Sex                0
 Capital Gain       0
 Capital Loss       0
 Hours per Week     0
 Native Country     0
 Income             0
 dtype: int64,
 24)
```

In [ ]:
```python
import matplotlib.pyplot as plt
import seaborn as sns

# Plotting boxplots for continuous columns to identify outliers
plt.figure(figsize=(12, 8))

for i, col in enumerate(continuous_columns, 1):
    plt.subplot(2, 3, i)
    sns.boxplot(y=train_data[col])
    plt.title(col)

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



In [ ]:
```python
from sklearn.preprocessing import OrdinalEncoder, StandardScaler
```

```
scaler = StandardScaler()
scaled_continuous_train = scaler.fit_transform(train_data[continuous_colu
scaled_continuous_test = scaler.transform(test_data[continuous_columns])
```

In [ ]:
```
def binary_encode(column, max_bits=None):
    ordinal_encoder = OrdinalEncoder()
    integer_encoded = ordinal_encoder.fit_transform(column.values.reshape
    max_value = np.max(integer_encoded)
    num_bits = max_bits if max_bits else int(np.ceil(np.log2(max_value +
    binary_encoded = ((integer_encoded.reshape(-1, 1) & (2**np.arange(num
    binary_encoded = binary_encoded[:, ::-1]
    col_names = [f"{column.name}_bit_{i}" for i in range(num_bits)]
    return pd.DataFrame(binary_encoded, columns=col_names)

binary_encoded_train = pd.concat([binary_encode(train_data[col]) for col
binary_encoded_test = pd.concat([binary_encode(test_data[col]) for col in
```

In [ ]:
```
processed_train_data = pd.concat([pd.DataFrame(scaled_continuous_train, c
processed_test_data = pd.concat([pd.DataFrame(scaled_continuous_test, col
processed_train_data
```

Out[ ]:

	Age	Final Weight	Education Number	Capital Gain	Capital Loss	Hours per Week	Workcla
0	0.030671	-1.063611	1.134739	0.148453	-0.21666	-0.035429	
1	0.837109	-1.008707	1.134739	-0.145920	-0.21666	-2.222153	
2	-0.042642	0.245079	-0.420060	-0.145920	-0.21666	-0.035429	
3	1.057047	0.425801	-1.197459	-0.145920	-0.21666	-0.035429	
4	-0.775768	1.408176	1.134739	-0.145920	-0.21666	-0.035429	
...	...	...	...	...	...	...	
32556	-0.849080	0.639741	0.746039	-0.145920	-0.21666	-0.197409	
32557	0.103983	-0.335433	-0.420060	-0.145920	-0.21666	-0.035429	
32558	1.423610	-0.358777	-0.420060	-0.145920	-0.21666	-0.035429	
32559	-1.215643	0.110960	-0.420060	-0.145920	-0.21666	-1.655225	
32560	0.983734	0.929893	-0.420060	1.888424	-0.21666	-0.035429	

32561 rows × 35 columns

In [ ]:
```
processed_test_data
```

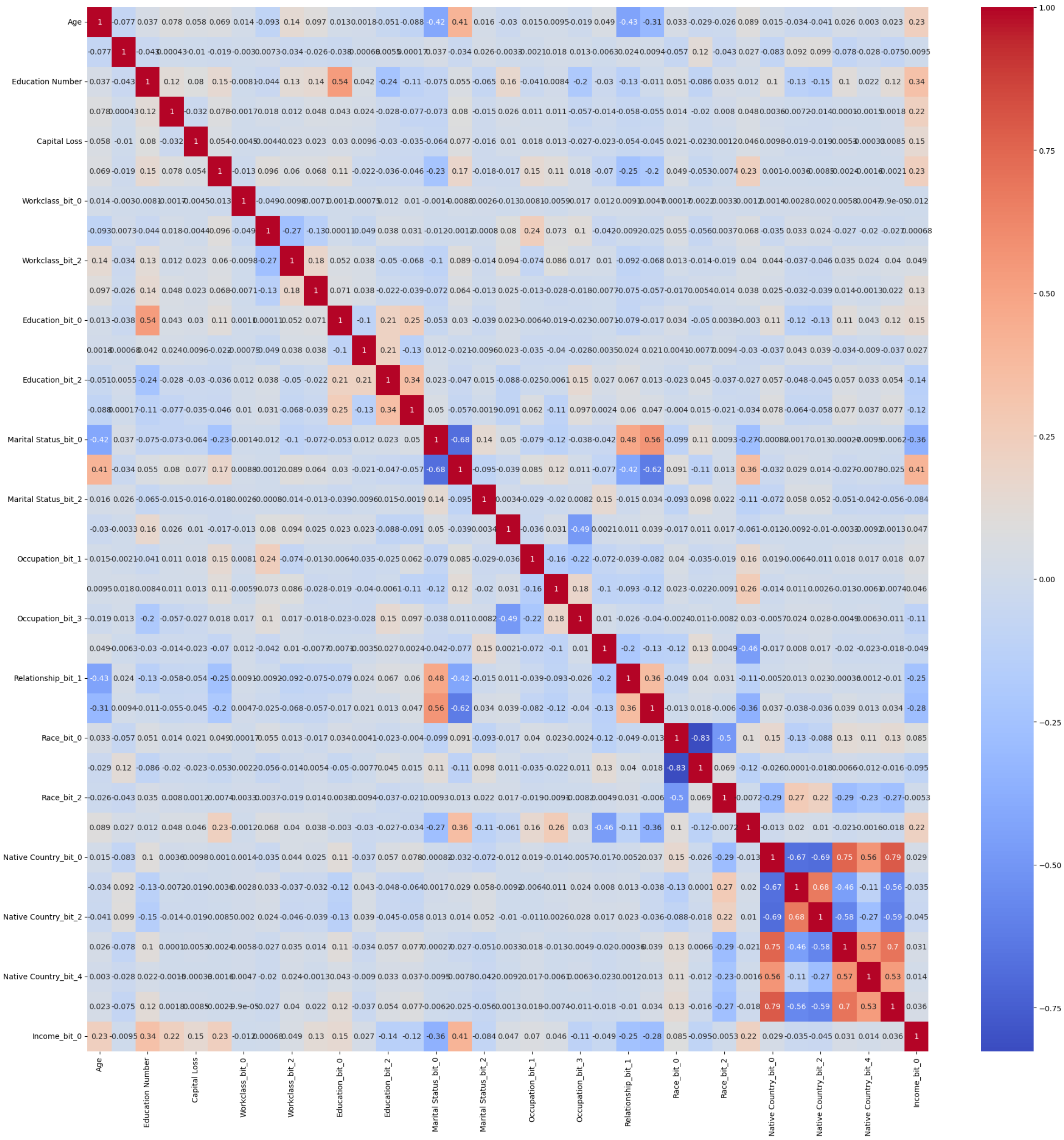
Out[ ]:

	Age	Final Weight	Education Number	Capital Gain	Capital Loss	Hours per Week	Workcla
0	-0.995706	0.350774	-1.197459	-0.145920	-0.21666	-0.035429	
1	-0.042642	-0.947095	-0.420060	-0.145920	-0.21666	0.774468	
2	-0.775768	1.394362	0.746039	-0.145920	-0.21666	-0.035429	
3	0.397233	-0.279070	-0.031360	0.895083	-0.21666	-0.035429	
4	-1.508894	-0.817458	-0.031360	-0.145920	-0.21666	-0.845327	
...	...	...	...	...	...	...	
16276	0.030671	0.242928	1.134739	-0.145920	-0.21666	-0.359389	
16277	1.863485	1.247055	-0.420060	-0.145920	-0.21666	-0.035429	
16278	-0.042642	1.754690	1.134739	-0.145920	-0.21666	0.774468	
16279	0.397233	-1.003212	1.134739	0.592721	-0.21666	-0.035429	
16280	-0.262580	-0.072293	1.134739	-0.145920	-0.21666	1.584366	

16281 rows × 35 columns

In [ ]:

```
heatmap=processed_train_data.corr()
sns.heatmap(heatmap,annot=True,cmap='coolwarm')
plt.gcf().set_size_inches(25, 25)
```



3.2 Model development and evaluation

3.2.1 Logistic Regression

In [ ]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, accuracy_score
X_train = processed_train_data.drop('Income_bit_0', axis=1)
y_train = processed_train_data['Income_bit_0']
X_test = processed_test_data.drop('Income_bit_0', axis=1)
y_test = processed_test_data['Income_bit_0']
```

3.2.1.1 Hyperparameter tune

In [ ]:
```
from sklearn.model_selection import GridSearchCV

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

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

           0       0.87      0.94      0.90     12435
           1       0.74      0.53      0.62      3846

    accuracy                           0.84     16281
   macro avg       0.80      0.74      0.76     16281
weighted avg       0.84      0.84      0.84     16281

Best Parameters: {'C': 10, 'penalty': 'l2', 'solver': 'liblinear', 'tol':
0.0001}
Best Cross-Validation Score: 0.8447531038848404
Test Set Accuracy: 0.8446655610834716
```

3.2.1.2 Model evaluation

In [ ]:

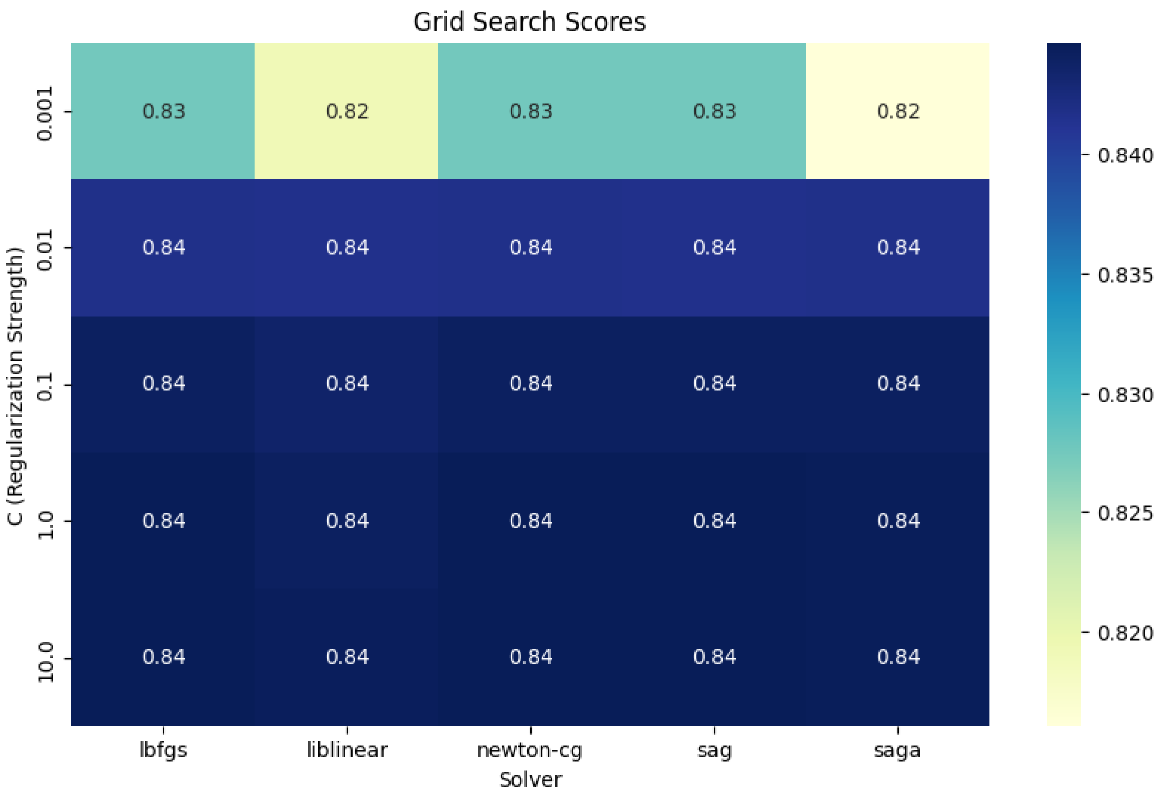
```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

# 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])
```

```python
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 [ ]:
```python
from sklearn.neighbors import KNeighborsClassifier
KNN = KNeighborsClassifier(n_neighbors=20)
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       0.87      0.93      0.90     12435
           1       0.71      0.57      0.63      3846

    accuracy                           0.84     16281
   macro avg       0.79      0.75      0.77     16281
weighted avg       0.84      0.84      0.84     16281
```

3.2.2.1 Hyperparameter tune

In [ ]:
```python
from sklearn.model_selection import cross_val_score

X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_

k_range = range(1,50)
```

```
k_scores = []

for k in k_range:
    KNN = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(KNN, X_val.to_numpy(), y_val.to_numpy(), cv=
    k_scores.append(scores.mean())
print(k_scores)
print(k_scores.index(max(k_scores)))
```

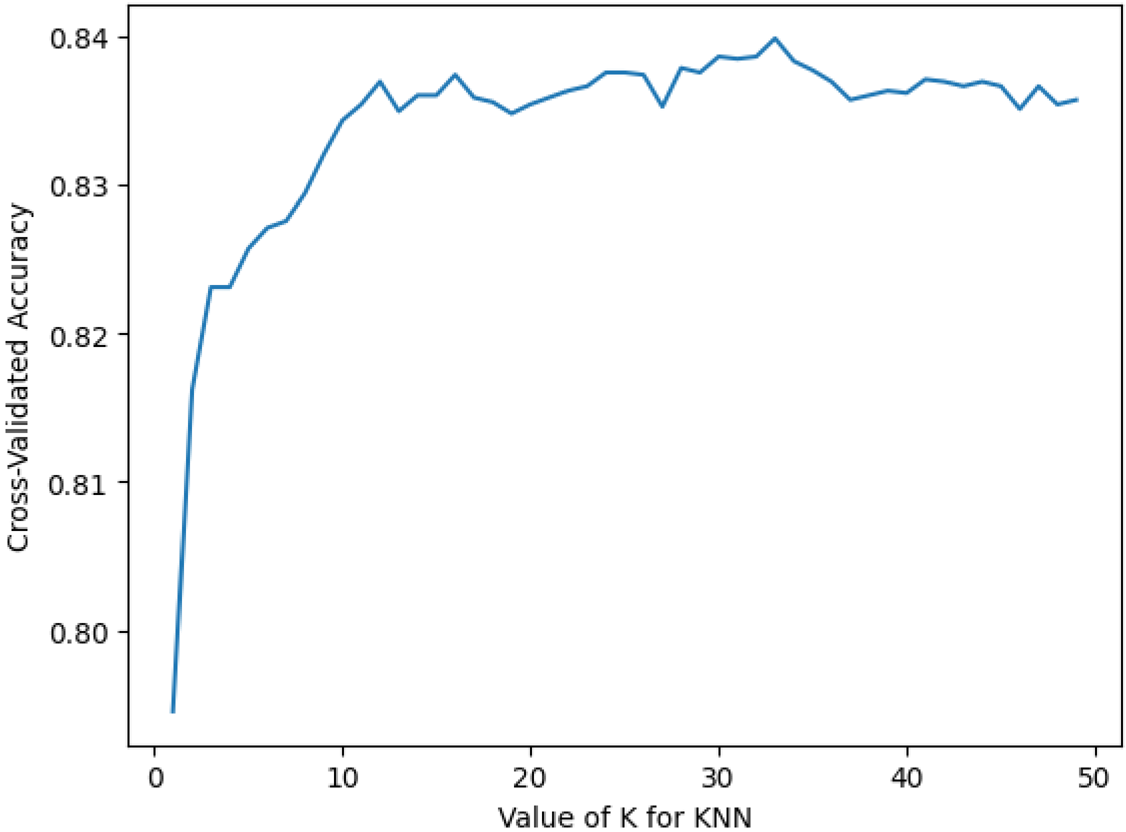
```
[0.7945647564388907, 0.8162105491315861, 0.8231225203320987, 0.82312063554
88959, 0.8257310602847907, 0.8271118995787509, 0.8275741426592406, 0.82941
84030231921, 0.8320276497695852, 0.8343329752245248, 0.8354070660522274,
0.836941043981416, 0.8349448229717377, 0.8360207985826431, 0.8360189137994
402, 0.8374032870619057, 0.8358653039684111, 0.8355587911000537, 0.8347919
199344096, 0.8354065948564265, 0.8358660107621121, 0.8363270758531, 0.8366
338243193578, 0.8375557189034332, 0.8375557189034332, 0.8374011666808027,
0.835251335840095, 0.8378627029675911, 0.8375552477076325, 0.8386302809269
364, 0.8384747863127044, 0.8386295741332355, 0.8398572747919669, 0.8383211
764816751, 0.8377072083533591, 0.8369408083835157, 0.8357126365289831, 0.8
360191493973405, 0.8363254266677975, 0.8361734660220707, 0.837094653812445
2, 0.8369396303940139, 0.8366331175256565, 0.8369393947961136, 0.836631939
5361549, 0.835095134432162, 0.8366321751340553, 0.8354035320837221, 0.8357
100449520795]
32
```

In [ ]:

```
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

Re-build the KNN model with best performed number of neighbors

```
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       0.88      0.92      0.90     12435
           1       0.69      0.59      0.64      3846

    accuracy                           0.84     16281
   macro avg       0.79      0.75      0.77     16281
weighted avg       0.83      0.84      0.84     16281
```

```
In [ ]: from sklearn.model_selection import GridSearchCV
        k_range = list(range(1, 50))
        param_grid = dict(n_neighbors=k_range)
        grid = GridSearchCV(KNN, param_grid, cv=10, scoring='accuracy')
        grid_search = grid.fit(X_train.to_numpy(), y_train.to_numpy())
        print (grid_search.best_score_)
        print (grid_search.best_params_)
        print (grid_search.best_estimator_)
```

```
0.8389895509934517
{'n_neighbors': 45}
KNeighborsClassifier(n_neighbors=45)
```

```
In [ ]: KNN = KNeighborsClassifier(n_neighbors=grid_search.best_index_)
        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       0.87      0.93      0.90     12435
           1       0.70      0.56      0.62      3846

    accuracy                           0.84     16281
   macro avg       0.79      0.74      0.76     16281
weighted avg       0.83      0.84      0.83     16281
```

3.2.3 Naive Bayes Classifier

Three types of Naive Bayers models are used here, which are Gaussian, Bernoulli, and Multinomial Navier Bayers models. Which model fits the dataset best depends on the distribution that the dataset follows.

```
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       0.95      0.67      0.78     12435
           1       0.45      0.88      0.59      3846

    accuracy                           0.72     16281
   macro avg       0.70      0.77      0.69     16281
weighted avg       0.83      0.72      0.74     16281
```

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       0.90      0.82      0.86     12435
           1       0.54      0.70      0.61      3846

    accuracy                           0.79     16281
   macro avg       0.72      0.76      0.74     16281
weighted avg       0.82      0.79      0.80     16281
```

In [ ]:
```
from sklearn.naive_bayes import MultinomialNB

#Negative value is not acceptable for the multinomial Naive Bayers. Thus,
processed_train_data_ = pd.concat([train_data[continuous_columns], binary
processed_test_data_ = pd.concat([test_data[continuous_columns], binary_e
X_train = processed_train_data_.drop('Income_bit_0', axis=1)
y_train = processed_train_data_['Income_bit_0']
X_test = processed_test_data_.drop('Income_bit_0', axis=1)
y_test = processed_test_data_['Income_bit_0']

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       0.80      0.96      0.87     12435
           1       0.62      0.23      0.34      3846

    accuracy                           0.79     16281
   macro avg       0.71      0.59      0.60     16281
weighted avg       0.76      0.79      0.75     16281
```

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

X_train = processed_train_data.drop('Income_bit_0', axis=1)
```

```
y_train = processed_train_data['Income_bit_0']
X_test = processed_test_data.drop('Income_bit_0', axis=1)
y_test = processed_test_data['Income_bit_0']


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': 5, 'min_samples_leaf': 4, 'max_depth': None}
```

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: 0.8654997696913864
```

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

```
Random Search Confusion Matrix:
 [[4701  241]
 [ 635  936]]
```

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       0.88      0.95      0.91      4942
           1       0.80      0.60      0.68      1571

    accuracy                           0.87      6513
   macro avg       0.84      0.77      0.80      6513
weighted avg       0.86      0.87      0.86      6513
```

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

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

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

```
Best Hyperparameters_GridSearch: {'max_depth': 20, 'min_samples_leaf': 2,
'min_samples_split': 2, '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": 10,"n_estimators": 100,
Grid Search: "min_samples_split": 2, "n_estimators:: 150
Compare the performance for the validation set: (Random Search already done) **

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

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

```
Grid Search Validation Accuracy: 0.8661139259941655
 0.8661139259941655
```

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

```
Grid Search Confusion Matrix:
 [[4705  237]
 [ 635  936]]
```

In [ ]:
```python
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       0.88      0.95      0.92      4942
           1       0.80      0.60      0.68      1571

    accuracy                           0.87      6513
   macro avg       0.84      0.77      0.80      6513
weighted avg       0.86      0.87      0.86      6513
```

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: 0.8618635218966894
```

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

```
Confusion Matrix:
 [[11877   558]
 [ 1691  2155]]
```

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      0.96      0.91     12435
           1       0.79      0.56      0.66      3846

    accuracy                           0.86     16281
   macro avg       0.83      0.76      0.79     16281
weighted avg       0.86      0.86      0.85     16281
```