Best Model Selection and Hyperparamter Tunning

```
In [1]:
        # Import the loan data as a data frame and ensure that the data is loaded properly.
         # Load package first
         import numpy as np
         import pandas as pd
         from sklearn.model_selection import train_test_split
         from sklearn.preprocessing import MinMaxScaler
         # Load the data frame
        loanset = pd.read_csv('Loan_Train.csv')
         #Check load is successful
        loanset.head()
Out[1]:
            Loan ID Gender Married Dependents Education Self Employed ApplicantIncome CoapplicantIncome LoanAmount Loan Amount Tern
        0 LP001002
                       Male
                                 No
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                                                                                   5849
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         4 LP001008
                       Male
                                 No
                                                 Graduate
                                                                    No
                                                                                   6000
                                                                                                                 141.0
                                                                                                                                   360.
        # prep the data
In [2]:
         # drop column "Load ID"
        loan = loanset.drop(['Loan_ID'], axis=1)
         #Find out rows with missing data
         #noempty = pd.notnull(loan)
         #cleanloan = loan[noempty]
         #cleanloan
         cleanloan = loan.dropna()
        print('variables with NA values', cleanloan.isna().sum())
In [3]:
         cleanloan.shape
```

```
variables with NA values Gender
                                                          0
         Married
                               0
         Dependents
         Education
                               0
         Self Employed
                               0
         ApplicantIncome
         CoapplicantIncome
         LoanAmount
         Loan_Amount_Term
         Credit_History
         Property Area
                               0
         Loan_Status
                               0
         dtype: int64
         (480, 12)
Out[3]:
         #Convert the categorical features into dummy variables.
In [4]:
         cat = cleanloan.select_dtypes(exclude=np.number)
         print(cat.keys())
         Index(['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed',
                 'Property Area', 'Loan Status'],
               dtype='object')
         newdf = pd.get_dummies(cleanloan, columns=cat.keys(), drop_first=True)
In [5]:
         newdf.shape
         (480, 15)
Out[5]:
         newdf.head()
In [6]:
Out[6]:
            ApplicantIncome CoapplicantIncome LoanAmount Loan_Amount_Term Credit_History Gender_Male Married_Yes Dependents_1 Depende
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                                       4196.0
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```

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newdf.rename(columns = {'Loan_Status_Y':'Loan_Status'}, inplace = True)
In [6]:
         newdf
In [8]:
Out[8]:
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        480 rows × 15 columns
         # Split the data into a training and test set, where the "Loan_Status" column is the target.
In [7]:
         X=newdf.drop(columns=['Loan_Status'],axis=1)
         y=newdf['Loan_Status']
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)
        #Create a pipeline with a minmax scaler and a KNN classifer
In [9]:
         from sklearn.pipeline import Pipeline
         from sklearn.neighbors import KNeighborsClassifier
         scaler = MinMaxScaler(feature range=(0, 1))
```

pipe = Pipeline([('std', scaler), ('classifier', KNeighborsClassifier(n_neighbors=2))], verbose = True)

```
In [37]: # Fit a default KNN classifier to the data with this pipeline
         model = pipe.fit(X_train, y_train)
         [Pipeline] ...... (step 1 of 2) Processing std, total=
         [Pipeline] ...... (step 2 of 2) Processing classifier, total=
                                                                          0.0s
In [21]: # scoring data
         from sklearn.metrics import accuracy_score
         print('accuracy of first KNN classifier is:', accuracy score(y test, model.predict(X test)))
         accuracy of first KNN classifier is: 0.6041666666666666
 In [8]: # Create a search space where the n_neighbors vareis from 1 to 10
         from sklearn.model selection import GridSearchCV
         scaler = MinMaxScaler()
         knn = KNeighborsClassifier(n_neighbors=5, n_jobs=-1)
         pipe2 = Pipeline([('std', scaler), ('classifier', knn)], verbose = True)
         # Create search space
         search_space = [{"classifier__n_neighbors": [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]}]
         # Fit a grid search with the pipeline, with 5 fold and find the best value for n neighbors parameter
         #Create grid search
         classifier = GridSearchCV(pipe2, search space, cv=5, verbose=0).fit(X train, y train)
         NameError
                                                   Traceback (most recent call last)
         Cell In[8], line 6
               2 from sklearn.model selection import GridSearchCV
               4 scaler = MinMaxScaler()
         ---> 6 knn = KNeighborsClassifier(n_neighbors=5, n_jobs=-1)
               8 pipe2 = Pipeline([('std', scaler), ('classifier', knn)], verbose = True)
              10 # Create search space
         NameError: name 'KNeighborsClassifier' is not defined
In [69]: # # Best neighborhood size (k)
         print ('best value is:', classifier.best estimator .get params()["classifier n neighbors"])
         best value is: 5
```

```
# repeat steps 6 and 7 with the same pipeline, but expand your search space
In [10]:
         # include logistic regression and random forest models
         from sklearn.linear model import LogisticRegression
         from sklearn.ensemble import RandomForestClassifier
         from sklearn.model selection import GridSearchCV
         from sklearn.pipeline import Pipeline
         #build pipe
         scaler = MinMaxScaler()
         pipe3 = Pipeline([('std', scaler), ("classifier", RandomForestClassifier())])
         # Create disctionary for 2 classifier
         search_space = [{"classifier": [LogisticRegression()],
                          "classifier__penalty": ['l1', 'l2'],
                          "classifier C": np.logspace(0, 4, 10)},
                         {"classifier": [RandomForestClassifier()],
                          "classifier__n_estimators": [10, 100, 1000],
                          "classifier max features": [1, 2, 3]}]
In [11]: # What are the best model and hyperparameters found in the grid search?
         gridsearch = GridSearchCV(pipe, search space, cv=5, verbose=0)
         #Fit grid search
         best_model = gridsearch.fit(X_train, y_train)
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C:\Users\Daisy\anaconda3\Lib\site-packages\sklearn\model selection\ validation.py:425: FitFailedWarning:
         50 fits failed out of a total of 145.
         The score on these train-test partitions for these parameters will be set to nan.
         If these failures are not expected, you can try to debug them by setting error score='raise'.
         Below are more details about the failures:
         50 fits failed with the following error:
         Traceback (most recent call last):
           File "C:\Users\Daisy\anaconda3\Lib\site-packages\sklearn\model_selection\_validation.py", line 732, in _fit_and_score
            estimator.fit(X train, y train, **fit params)
           File "C:\Users\Daisy\anaconda3\Lib\site-packages\sklearn\base.py", line 1151, in wrapper
            return fit method(estimator, *args, **kwargs)
                   ^^^^^^
           File "C:\Users\Daisy\anaconda3\Lib\site-packages\sklearn\pipeline.py", line 420, in fit
             self._final_estimator.fit(Xt, y, **fit_params_last_step)
           File "C:\Users\Daisy\anaconda3\Lib\site-packages\sklearn\base.py", line 1151, in wrapper
            return fit method(estimator, *args, **kwargs)
                   ^^^^^
           File "C:\Users\Daisy\anaconda3\Lib\site-packages\sklearn\linear model\ logistic.py", line 1168, in fit
            solver = check solver(self.solver, self.penalty, self.dual)
                     ^^^^^
           File "C:\Users\Daisy\anaconda3\Lib\site-packages\sklearn\linear model\ logistic.py", line 56, in check solver
            raise ValueError(
         ValueError: Solver lbfgs supports only '12' or 'none' penalties, got 11 penalty.
           warnings.warn(some_fits_failed_message, FitFailedWarning)
         C:\Users\Daisy\anaconda3\Lib\site-packages\sklearn\model selection\ search.py:976: UserWarning: One or more of the test
         scores are non-finite: [
                                   nan 0.79955571
                                                           nan 0.79692413
                                                                                nan 0.79692413
                nan 0.79692413
                                     nan 0.79429255
                                                          nan 0.79429255
                nan 0.79429255
                                     nan 0.79429255
                                                          nan 0.79429255
                nan 0.79429255 0.7213944 0.77091593 0.77881066 0.7291866
         0.78133971 0.78920027 0.74227614 0.78393712 0.7917635 ]
          warnings.warn(
In [12]: #View best model
         best model.best estimator .get params()["classifier"]
         ▼ LogisticRegression
Out[12]:
         LogisticRegression()
In [17]: #Find the accuracy of this model on the test set.
```

predicted = best model.predict(X test)

```
from sklearn.metrics import accuracy_score
print('accuracy of Logistic Regression classifier is:', round(accuracy_score(y_test, predicted),2))
```

accuracy of Logistic Regression classifier is: 0.82

Summary

In this exercise, I tried to use hyperparamter grid search to fine tune the KNN classifier, as well as compare 3 different models (KNN, Logistic regression and Random forest classifiers). The winner is logistic regression, its accuracy is 0.82 vs the KNN classifier is only 0.60

Another observation is the build in gridsearch make the model comparision and selection much easier and visible. different models with different parameters can be easily tried out for model selection purpose.

In []: