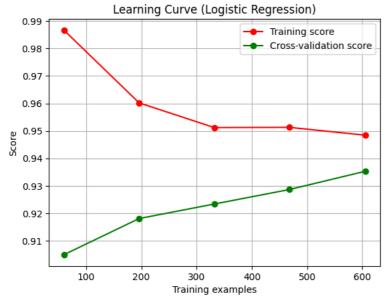
```
import numpy as np
import pandas as pd
from sklearn.preprocessing import StandardScaler, RobustScaler
df = pd.read_csv('/kaggle/input/creditcardfraud/creditcard.csv')
print(df.head())
class_0_data = df[df['Class'] == 0]
class 1 data = df[df['Class'] == 1]
print("Class 0 Data Shape:", class_0_data.shape)
print("Class 1 Data Shape:", class_1_data.shape)
print('No Frauds:', round(df['Class'].value_counts(normalize=True)[0] * 100, 2), '% of the dataset')
print('Frauds:', round(df['Class'].value_counts(normalize=True)[1] * 100, 2), '% of the dataset')
rob scaler = RobustScaler()
df['scaled_amount'] = rob_scaler.fit_transform(df['Amount'].values.reshape(-1, 1))
df['scaled_time'] = rob_scaler.fit_transform(df['Time'].values.reshape(-1, 1))
df.drop(['Time', 'Amount'], axis=1, inplace=True)
scaled_amount = df['scaled_amount']
scaled_time = df['scaled_time']
df.drop(['scaled_amount', 'scaled_time'], axis=1, inplace=True)
df.insert(0, 'scaled_amount', scaled_amount)
df.insert(1, 'scaled_time', scaled_time)
print(df.head())
(2)
                              V2
                                        V3
       Time
                    V1
                                                  ٧4
                                                             V5
                                                                       V6
        0.0 -1.359807 -0.072781 2.536347 1.378155 -0.338321 0.462388 0.239599
        0.0 1.191857 0.266151 0.166480 0.448154 0.060018 -0.082361 -0.078803
        1.0 -1.358354 -1.340163 1.773209 0.379780 -0.503198 1.800499 0.791461
     3
        1.0 -0.966272 -0.185226 1.792993 -0.863291 -0.010309 1.247203 0.237609
       2.0 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592941
                                      V21
                                                V22
                                                           V23
              V۶
                        V9 ...
                                                                     V24
                                                                               V25 \
     0 \quad 0.098698 \quad 0.363787 \quad \dots \quad -0.018307 \quad 0.277838 \quad -0.110474 \quad 0.066928 \quad 0.128539
     1 0.085102 -0.255425 ... -0.225775 -0.638672 0.101288 -0.339846 0.167170
     2 0.247676 -1.514654 ... 0.247998 0.771679 0.909412 -0.689281 -0.327642
     3 0.377436 -1.387024 ... -0.108300 0.005274 -0.190321 -1.175575 0.647376
     4 -0.270533 0.817739 ... -0.009431 0.798278 -0.137458 0.141267 -0.206010
             V26
                       V27
                                 V28 Amount Class
    0 -0.189115  0.133558 -0.021053  149.62
                                                  0
     1 0.125895 -0.008983 0.014724
                                        2.69
                                                   0
     2 -0.139097 -0.055353 -0.059752 378.66
                                                   0
     3 -0.221929 0.062723 0.061458 123.50
                                                   0
     4 0.502292 0.219422 0.215153 69.99
     [5 rows x 31 columns]
     Class 0 Data Shape: (284315, 31)
    Class 1 Data Shape: (492, 31)
     No Frauds: 99.83 % of the dataset
     Frauds: 0.17 % of the dataset
        scaled_amount scaled_time
                                          V1
                                                    V2
     0
            1.783274
                       -0.994983 -1.359807 -0.072781 2.536347 1.378155
                         -0.994983 1.191857 0.266151 0.166480 0.448154
     1
            -0.269825
                        -0.994972 -1.358354 -1.340163 1.773209 0.379780
             4.983721
     3
             1.418291
                         -0.994972 -0.966272 -0.185226 1.792993 -0.863291
             0.670579
                        -0.994960 -1.158233  0.877737  1.548718  0.403034
                                  V7
                        V6
                                            V8 ...
                                                           V20
                                                                     V21
     0 \ -0.338321 \quad 0.462388 \quad 0.239599 \quad 0.098698 \quad \dots \quad 0.251412 \ -0.018307 \quad 0.277838
     1\quad 0.060018\ -0.082361\ -0.078803\quad 0.085102\quad \dots\ -0.069083\ -0.225775\ -0.638672
     2 \ -0.503198 \ 1.800499 \ 0.791461 \ 0.247676 \ \dots \ 0.524980 \ 0.247998 \ 0.771679
     3 - 0.010309 \ 1.247203 \ 0.237609 \ 0.377436 \ \dots - 0.208038 \ - 0.108300 \ 0.005274
     4 -0.407193 0.095921 0.592941 -0.270533 ... 0.408542 -0.009431 0.798278
             V23
                                 V25
                       V24
                                           V26
                                                     V27
                                                                V28 Class
     0 -0.110474  0.066928  0.128539 -0.189115  0.133558 -0.021053
     1 0.101288 -0.339846 0.167170 0.125895 -0.008983 0.014724
                                                                         0
     2 0.909412 -0.689281 -0.327642 -0.139097 -0.055353 -0.059752
                                                                         0
     3 -0.190321 -1.175575 0.647376 -0.221929 0.062723 0.061458
                                                                         0
     4 -0.137458 0.141267 -0.206010 0.502292 0.219422 0.215153
                                                                         0
     [5 rows x 31 columns]
```

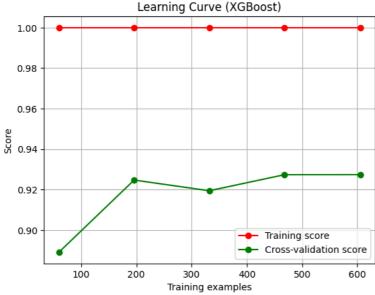
```
from sklearn.model_selection import StratifiedKFold
print('No Frauds:', round(df['Class'].value_counts(normalize=True)[0] * 100, 2), '% of the dataset')
print('Frauds:', round(df['Class'].value_counts(normalize=True)[1] * 100, 2), '% of the dataset')
X = df.drop('Class', axis=1)
y = df['Class']
sss = StratifiedKFold(n_splits=5, random_state=None, shuffle=False)
for train_index, test_index in sss.split(X, y):
    print("Train:", train_index, "Test:", test_index)
    original_Xtrain, original_Xtest = X.iloc[train_index], X.iloc[test_index]
    original_ytrain, original_ytest = y.iloc[train_index], y.iloc[test_index]
original_Xtrain = original_Xtrain.values
original_Xtest = original_Xtest.values
original ytrain = original ytrain.values
original_ytest = original_ytest.values
train label distribution = np.bincount(original ytrain) / len(original ytrain)
test_label_distribution = np.bincount(original_ytest) / len(original_ytest)
print('-' * 100)
print('Label Distributions: \n')
print("Train set:", train_label_distribution)
print("Test set:", test_label_distribution)
     No Frauds: 99.83 % of the dataset
     Frauds: 0.17 % of the dataset
     Train: [ 30473 30496 31002 ... 284804 284805 284806] Test: [ 0 1 2 ... 57017 57018 57019] Train: [ 0 1 2 ... 284804 284805 284806] Test: [ 30473 30496 31002 ... 113964 113965 113966]
     Train: [
                  0
                         1
                                2 ... 284804 284805 284806] Test: [ 81609 82400 83053 ... 170946 170947 170948]
     Train: [
                                2 ... 284804 284805 284806] Test: [150654 150660 150661 ... 227866 227867 227868]
                  0
                                2 ... 227866 227867 227868] Test: [212516 212644 213092 ... 284804 284805 284806]
     Train: [
     Label Distributions:
     Train set: [0.99827076 0.00172924]
     Test set: [0.99827952 0.00172048]
#Subsampling
df = df.sample(frac=1)
fraud_df = df.loc[df['Class'] == 1]
non_fraud_df = df.loc[df['Class'] == 0][:492]
normal_distributed_df = pd.concat([fraud_df, non_fraud_df])
new_df = normal_distributed_df.sample(frac=1, random_state=42)
print('Distribution of the Classes in the subsample dataset')
print(new_df['Class'].value_counts()/len(new_df))
     Distribution of the Classes in the subsample dataset
     Class
        0.5
     0
     1
         0.5
     Name: count, dtype: float64
```

```
# Code taken from kaggle removing the outliers in the data
v14_fraud = new_df['V14'].loc[new_df['Class'] == 1].values
q25, q75 = np.percentile(v14_fraud, 25), np.percentile(v14_fraud, 75)
print('Quartile 25: {} | Quartile 75: {}'.format(q25, q75))
v14_iqr = q75 - q25
print('iqr: {}'.format(v14_iqr))
v14 cut off = v14 iqr * 1.5
v14_lower, v14_upper = q25 - v14_cut_off, q75 + v14_cut_off
print('Cut Off: {}'.format(v14_cut_off))
print('V14 Lower: {}'.format(v14 lower))
print('V14 Upper: {}'.format(v14_upper))
outliers = [x \text{ for } x \text{ in } v14\_\text{fraud if } x < v14\_\text{lower or } x > v14\_\text{upper}]
print('Feature V14 Outliers for Fraud Cases: {}'.format(len(outliers)))
print('V10 outliers:{}'.format(outliers))
new df = new df.drop(new df['V14'] > v14 upper) | (new df['V14'] < v14 lower)].index)
print('----' * 44)
v12_fraud = new_df['V12'].loc[new_df['Class'] == 1].values
q25, q75 = np.percentile(v12_fraud, 25), np.percentile(v12_fraud, 75)
v12_{iqr} = q75 - q25
v12_cut_off = v12_iqr * 1.5
v12 lower, v12 upper = q25 - v12 cut off, q75 + v12 cut off
print('V12 Lower: {}'.format(v12_lower))
print('V12 Upper: {}'.format(v12_upper))
outliers = [x \text{ for } x \text{ in } v12\_fraud \text{ if } x < v12\_lower \text{ or } x > v12\_upper]
print('V12 outliers: {}'.format(outliers))
print('Feature V12 Outliers for Fraud Cases: {}'.format(len(outliers)))
\label{eq:new_df} new_df = new_df.drop(new_df[(new_df['V12'] > v12\_upper) \mid (new_df['V12'] < v12\_lower)].index)
print('Number of Instances after outliers removal: {}'.format(len(new_df)))
print('----' * 44)
v10_fraud = new_df['V10'].loc[new_df['Class'] == 1].values
q25, q75 = np.percentile(v10_fraud, 25), np.percentile(v10_fraud, 75)
v10_{iqr} = q75 - q25
v10_cut_off = v10_iqr * 1.5
v10_lower, v10_upper = q25 - v10_cut_off, q75 + v10_cut_off
print('V10 Lower: {}'.format(v10_lower))
print('V10 Upper: {}'.format(v10_upper))
outliers = [x \text{ for } x \text{ in } v10\_\text{fraud if } x < v10\_\text{lower or } x > v10\_\text{upper}]
print('V10 outliers: {}'.format(outliers))
print('Feature V10 Outliers for Fraud Cases: {}'.format(len(outliers)))
new_df = new_df.drop(new_df[(new_df['V10'] > v10_upper) | (new_df['V10'] < v10_lower)].index)
print('Number of Instances after outliers removal: {}'.format(len(new_df)))
     Quartile 25: -9.692722964972386 | Quartile 75: -4.282820849486865
     iar: 5.409902115485521
     Cut Off: 8.114853173228282
     V14 Lower: -17.807576138200666
     V14 Upper: 3.8320323237414167
     Feature V14 Outliers for Fraud Cases: 4
     V10 outliers:[-18.0499976898594, -19.2143254902614, -18.4937733551053, -18.8220867423816]
     V12 Lower: -17.3430371579634
     V12 Upper: 5.776973384895937
     V12 outliers: [-18.6837146333443, -18.0475965708216, -18.5536970096458, -18.4311310279993]
     Feature V12 Outliers for Fraud Cases: 4
     Number of Instances after outliers removal: 975
     V10 Lower: -14.89885463232024
     V10 Upper: 4.92033495834214
     V10 outliers: [-22.1870885620007, -14.9246547735487, -15.2399619587112, -16.6496281595399, -22.1870885620007, -24.4031849699728, -22
     Feature V10 Outliers for Fraud Cases: 27
     Number of Instances after outliers removal: 947
    4
X = new_df.drop('Class', axis=1)
y = new_df['Class']
from sklearn.model_selection import train_test_split
 \textit{X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.2, random\_state=42) } 
X_train = X_train.values
X_test = X_test.values
y_train = y_train.values
y_test = y_test.values
```

```
from sklearn.model selection import cross val score
from sklearn.linear_model import LogisticRegression
import xgboost as xgb
from sklearn.neural_network import MLPClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
import numpy as np
import warnings
warnings.filterwarnings("ignore")
# Define models
models = {
    "Logistic Regression": LogisticRegression(),
    "XGBoost": xgb.XGBClassifier(),
    "MLP": MLPClassifier(),
    "KNN": KNeighborsClassifier(),
    "SVM": SVC()
}
# Perform cross-validation for each model
for name, model in models.items():
    scores = cross\_val\_score(model, X\_train, y\_train, cv=5) \\ \  \  \, \text{$\#$ 5-fold cross-validation}
   print(f"{name} Cross-Validation Mean Accuracy:", np.mean(scores))
    Logistic Regression Cross-Validation Mean Accuracy: 0.9352823283373999
    XGBoost Cross-Validation Mean Accuracy: 0.9326420355524572
    MLP Cross-Validation Mean Accuracy: 0.9379400487974904
     KNN Cross-Validation Mean Accuracy: 0.9194057162774486
    SVM Cross-Validation Mean Accuracy: 0.9259933774834437
from sklearn.model_selection import GridSearchCV
warnings.filterwarnings("ignore")
param_grids = {
    "Logistic Regression": {'C': [0.001, 0.01, 0.1, 1, 10, 100]},
    "XGBoost": {'max_depth': [3, 5, 7], 'n_estimators': [50, 100, 200]},
    "MLP": {'hidden_layer_sizes': [(50,), (100,), (50, 50)]},
    "KNN": {'n_neighbors': [3, 5, 7, 9]},
    "SVM": {'C': [0.1, 1, 10], 'gamma': [0.1, 1, 10]}
}
for name, model in models.items():
   grid_search = GridSearchCV(model, param_grids[name], cv=5, scoring='accuracy', n_jobs=-1)
    grid_search.fit(X_train, y_train)
   print(f"Best parameters for {name}: {grid_search.best_params_}")
   print(f"Best cross-validation accuracy for {name}: {grid_search.best_score_}")
   best_model = grid_search.best_estimator_
    scores = cross_val_score(best_model, X_train, y_train, cv=5)
    print(f"{name} Cross-Validation Mean Accuracy with Best Parameters:", np.mean(scores))
```

```
import matplotlib.pyplot as plt
from sklearn.model_selection import learning_curve
def plot_learning_curve(model, title, X, y, cv=5, train_sizes=np.linspace(.1, 1.0, 5)):
    train_sizes, train_scores, test_scores = learning_curve(model, X, y, cv=cv, train_sizes=train_sizes, scoring='accuracy', n_jobs=-1)
    train_scores_mean = np.mean(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    plt.figure()
    plt.title(title)
    plt.xlabel("Training examples")
    plt.ylabel("Score")
    plt.grid()
    plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Training score")
plt.plot(train_sizes, test_scores_mean, 'o-', color="g", label="Cross-validation score")
    plt.legend(loc="best")
    return plt
models = {
    "Logistic Regression": LogisticRegression(C=1), # Use best parameters found from grid search
    "XGBoost": xgb.XGBClassifier(max_depth=3, n_estimators=100),
    "MLP": MLPClassifier(hidden_layer_sizes=(50,)), # Use best parameters found from grid search
    "KNN": KNeighborsClassifier(n_neighbors=5), # Use best parameters found from grid search
    "SVM": SVC(C=1, gamma=0.1) \ \ \mbox{\# Use best parameters found from grid search}
for name, model in models.items():
    plot_learning_curve(model, f"Learning Curve ({name})", X_train, y_train)
    plt.show()
```





/opt/conda/lib/python3.10/site-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Opti /opt/conda/lib/python3.10/site-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Opti warnings.warn(/opt/conda/lib/python3.10/site-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Opti warnings.warn(/opt/conda/lib/python3.10/site-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Opti warnings.warn(opt/conda/lib/python3.10/site-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Opti warnings.warn(/opt/conda/lib/python3.10/site-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Opti warnings.warn(

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/opt/conda/lib/python3.10/site-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Opti warnings.warn(
/opt/conda/lib/python3.10/site-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Opti warnings.warn(

