import numpy as np import pandas as pd import matplotlib.pyplot as plt import seaborn as sns import warnings warnings.filterwarnings('ignore') In [4]: data = pd.read csv('Social Network Ads (2)-Copy1.csv') data.head() Out[4]: User ID Gender Age EstimatedSalary Purchased **0** 15624510 Male 19 19000 0 **1** 15810944 20000 Male 35 0 **2** 15668575 Female 26 43000 0 **3** 15603246 Female 57000 0 **4** 15804002 0 Male 19 76000 data.drop(columns=['Gender'],inplace=True) data.tail() User ID Age EstimatedSalary Purchased **395** 15691863 41000 1 **396** 15706071 23000 1 **397** 15654296 50 20000 **398** 15755018 0 33000 **399** 15594041 36000 1 data.drop(columns=['User ID'],inplace=True) data.head() Age EstimatedSalary Purchased 0 19 19000 0 1 35 20000 0 43000 0 2 26 3 27 57000 0 19 76000 0 from sklearn.model selection import train test split from sklearn.preprocessing import StandardScaler x = data.drop(columns=['Purchased']) y = data['Purchased'] x train, x test, y train, y test = train test split(x, y, random state=0, train size=0.75) x train = x train.astype('float') x test = x test.astype('float') scaler = StandardScaler() x_train = scaler.fit_transform(x_train) x test = scaler.transform(x_test) from sklearn.model selection import GridSearchCV parameter grid ={ 'n neighbors':np.arange(1,50)} from sklearn.neighbors import KNeighborsClassifier kNN = KNeighborsClassifier() GridSeachCv GridSearchCV is a library function that is a member of sklearn's model_selection package. It helps to loop through predefined hyperparameters and fit your estimator (model) on your training set. So, in the end, you can select the best parameters from the listed hyperparameters. In addition to that, you can specify the number of times for the cross-validation for each set of hyperparameters. Then all you have to do is create an object of GridSearchCV. Here basically you need to define a few named arguments: 1. estimator: estimator object you created 2. params_grid: the dictionary object that holds the hyperparameters you want to try 3. scoring: evaluation metric that you want to use, you can simply pass a valid string/object of evaluation metric 4. cv: number of cross-validation you have to try for each selected set of hyperparameters 5. **verbose**: you can set it to 1 to get the detailed print out while you fit the data to GridSearchCV 6. **n_jobs**: number of processes you wish to run in parallel for this task if it -1 it will use all available processors. In [18]: knn cv=GridSearchCV(kNN,parameter grid,cv=5) knn cv.fit(x train,y train) Out[18]: GridSearchCV(cv=5, estimator=KNeighborsClassifier(), param_grid={'n_neighbors': array([1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49])}) In [19]: y_pred=knn_cv.predict(x_test) y_pred Out[19]: array([0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1], dtype=int64) In [20]: knn_cv.best_params_ Out[20]: {'n neighbors': 5} knn_cv.best_score_ Out[21]: 0.90333333333333333 from sklearn.metrics import confusion matrix, classification report mat = confusion_matrix(y_test,y_pred) Out[23]: array([[64, 4], [3, 29]], dtype=int64) print(classification_report(y_test,y_pred)) In [24]: precision recall f1-score support 0.94 0.96 0.95 68 0.88 0.91 0.89 32 accuracy 0.93 100 0.92 0.92 macro avg 0.92 100 0.93 0.93 100 weighted avg 0.93 RandomSearchCv RandomSearchCV has the same purpose of GridSearchCV: they both were designed to find the best parameters to improve your model. However, here not all parameters are tested. Rather, the search is randomized and all the other parameters are held constant while the parameters we are testing is variable. Pratically, the implementation of RandomSearchCV is very similar to that of the GridSearchCV: from sklearn.model selection import RandomizedSearchCV from sklearn.tree import DecisionTreeClassifier from scipy.stats import randint #setup the parameter and distribution to sample from :- params dict param dist = {'max depth':[3,None],'min samples leaf':randint(1,9),'criterion':['gini','entropy']} #decision Tree tree = DecisionTreeClassifier() #RandomizedSearchCV tree cv = RandomizedSearchCV(tree,param dist,cv=5) tree_cv.fit(x_train,y_train) Out[32]: RandomizedSearchCV(cv=5, estimator=DecisionTreeClassifier(), param distributions={'criterion': ['gini', 'entropy'], 'max_depth': [3, None], 'min samples leaf': <scipy.stats. distn infrastructure.rv frozen object at 0x0000023DE4FC6310>}) tree_cv.predict(x_test) Out[33]: array([0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 1], dtype=int64) In [34]: tree_cv.best_params_ Out[34]: {'criterion': 'gini', 'max_depth': 3, 'min samples leaf': 7} In [35]: tree cv.best score Out[35]: 0.9 mat = confusion_matrix(y_test,y_pred) Out[36]: array([[64, 4], [3, 29]], dtype=int64) import seaborn as sns sns.heatmap(mat,annot=True,fmt='d') plt.show() - 60 50 40 30 20 29 10 Ó 1 print(classification_report(y_test,y_pred)) precision recall f1-score support 0 0.96 0.94 0.95 68 1 0.88 0.91 0.89 32 0.93 100 accuracy macro avo 0.92 0.92 0.92 100 0.93 0.93 0.93 100 weighted avg In [40]: data3 = pd.DataFrame({'Actual':y_test,'Predicted':y_pred}) data3.head() Out[40]: **Actual Predicted** 132 0 0 309 0 341 0 0 196 246 0 0 RandomSearchCV VS Greadsearchcv • With GridSearchCV, by calling the method bestparams you are guaranteed to get the best model results (according to your scoring) within your test values, since it will test every single one of the values you passed. However, with RandomSearchCV, the more samples you test from the value set, the more confident the search will be — but it will never be 100% certain (unless you test every value out of the set of possible values). Statistically speaking, we can be fairly confident that the best parameters found are indeed the best combination of optimal parameters since the search is completely randomized. The running times of RandomSearchCV vs. GridSearchCV on the other hand, are widely different. Depending on the n_iter chosen, RandomSearchCV can be two, three, four times faster than GridSearchCV. However, the higher the n_iter chosen, the lower will be the speed of RandomSearchCV and the closer the algorithm will be to GridSearchCV. GreadsearchCv import numpy as np from sklearn.ensemble import RandomForestClassifier n estimators = [int(x) for x in np.linspace(start = 200, stop = 2000, num = 10)]max depth = [int(x) for x in np.linspace(10, 110, num = 11)]max features = ['auto', 'sqrt'] $min_samples_split = [2, 5, 10]$ min samples leaf = [1, 2, 4]rf_grid = {'n_estimators': n_estimators, 'max features': max features, 'max depth': max depth, 'min_samples_split': min_samples_split, 'min_samples_leaf': min_samples_leaf} model = GridSearchCV(RandomForestClassifier(), rf_grid, scoring = 'accuracy', cv = 5) # fit the model model.fit(x_train, y_train) RandomsearchCv max depth = [int(x) for x in np.linspace(10, 110, num = 11)]max_features = ['auto', 'sqrt'] min samples split = [2, 5, 10] $min_samples_leaf = [1, 2, 4]$ rf_grid = {'n_estimators': n_estimators, 'max_features': max_features, 'max_depth': max_depth, 'min_samples_split': min_samples_split, 'min_samples_leaf': min_samples_leaf} model = RandomizedSearchCV(estimator = RandomForestClassifier(), param_distributions = rf_grid, cv = 5, $n_{iter} = 100$) # fit the model model.fit(x_train, y_train)