Lab work week - 2

Task-2A:

In [2]:
```
import seaborn as sns
iris = sns.load_dataset('iris')
iris.head()
```

Out[2]:

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa

In [3]:
```
X_iris = iris.drop('species', axis=1)
X_iris.shape
```

Out[3]:
```
(150, 4)
```

In [4]:
```
y_iris = iris['species']
y_iris.shape
```

Out[4]:
```
(150,)
```

In [5]:
```
from sklearn.model_selection import train_test_split
Xtrain, Xtest, ytrain, ytest = train_test_split(X_iris, y_iris, random_state=1)
```

In [6]:
```
from sklearn.naive_bayes import GaussianNB
model = GaussianNB()
model.fit(Xtrain, ytrain)
y_predict = model.predict(Xtest)
```

In [7]:
```
from sklearn.metrics import accuracy_score
accuracy_score(ytest, y_predict)
```

Out[7]:
```
0.9736842105263158
```

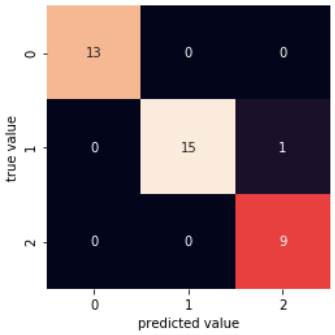
In [9]:
```
from sklearn.model_selection import cross_val_score
cross_val_score(model, X_iris, y_iris, cv=5)
```

Out[9]:
```
array([0.93333333, 0.96666667, 0.93333333, 0.93333333, 1.        ])
```

In [14]:
```
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt

mat = confusion_matrix(ytest, y_predict)

sns.heatmap(mat, square=True, annot=True, cbar=False)
plt.xlabel('predicted value')
plt.ylabel('true value');
```



The accuracy score value of the Gaussian naive Bayes model, that is, the success of predicting untrained data, was calculated as 97 percent.

When we divide the same iris data set into smaller parts and set cv = 5, we can perform train and test operations on small parts. As a result of this crosss validation method, 5 different accuracy values were obtained. In fact, when we calculate the average based on these five values, it again shows us the success rate of the model. As an average, the success rate of the model can be stated as 95 percent.

When we look at the confusion matrix, the model established correctly predicted 13 samples with a real value of 0. Again, the model correctly predicted 15 samples with a real value of 1, namely the label of 1. For an example, it was actually labeled as 1 but model predicted as 2. The 9 samples labeled as 2 are labeled as 2 in the model.

Task-2B:

```
In [15]: from sklearn.datasets import load_digits
         digits = load_digits()

In [16]: X = digits.data
         X.shape

Out[16]: (1797, 64)

In [17]: y = digits.target
         y.shape

Out[17]: (1797,)
```

Isomap

```
In [18]: from sklearn.manifold import Isomap

         iso = Isomap(n_components=5)
         iso.fit(digits.data)
         data_projected = iso.transform(digits.data)
         data_projected.shape

Out[18]: (1797, 5)

In [19]: from sklearn.model_selection import train_test_split
         Xtrain, Xtest, ytrain, ytest = train_test_split(data_projected, y, random_state=0)

In [20]: Xtrain.shape

Out[20]: (1347, 5)

In [21]: ytrain.shape

Out[21]: (1347,)

In [22]: from sklearn.naive_bayes import GaussianNB

         model = GaussianNB()
         model.fit(Xtrain, ytrain)
         y_model = model.predict(Xtest)
```

```
In [23]: from sklearn.metrics import accuracy_score
         accuracy_score(ytest, y_model)

Out[23]: 0.9466666666666667
```

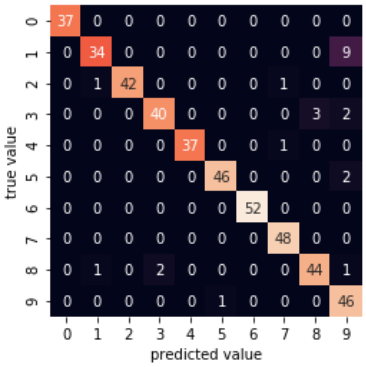
```
In [24]: from sklearn.model_selection import cross_val_score
         cross_val_score(model, data_projected, y, cv=10)

Out[24]: array([0.92222222, 0.97777778, 0.92222222, 0.85      , 0.95      ,
                0.87777778, 0.97777778, 0.99441341, 0.89944134, 0.94972067])
```

```
In [25]: from sklearn.metrics import confusion_matrix

         mat = confusion_matrix(ytest, y_model)

         sns.heatmap(mat, square=True, annot=True, cbar=False)
         plt.xlabel('predicted value')
         plt.ylabel('true value');
```



The success rate of the model we set up over the data set we obtained after dimensionality reduction (5 feature) using the Isomap method is 95 percent.

The train and test results made by dividing the data into 10 parts with cross validation have an average success rate of 93 percent. Tha validation score is 93 percent. Training too much can sometimes cause the model to overfit and the validation score to decrease.

When we look at the confusion matrix, we can say that especially for the value 9; For 9 samples with 9 in the actual dataset, the model predicted as 1.

Principal Component Analysis (PCA)

In [26]:
```
from sklearn.decomposition import PCA
model = PCA(n_components=5)
model.fit(digits.data)
X_5D = model.transform(digits.data)
X_5D.shape
```

Out[26]:
```
(1797, 5)
```

In [27]:
```
Xtrain, Xtest, ytrain, ytest = train_test_split(X_5D, y, random_state=0)
```

In [28]:
```
Xtrain.shape
```

Out[28]:
```
(1347, 5)
```

In [29]:
```
ytrain.shape
```

Out[29]:
```
(1347,)
```

In [30]:
```
from sklearn.naive_bayes import GaussianNB
model = GaussianNB()
model.fit(Xtrain, ytrain)
y_model = model.predict(Xtest)
```

In [31]:
```
from sklearn.metrics import accuracy_score
accuracy_score(ytest, y_model)
```

Out[31]:
```
0.8466666666666667
```

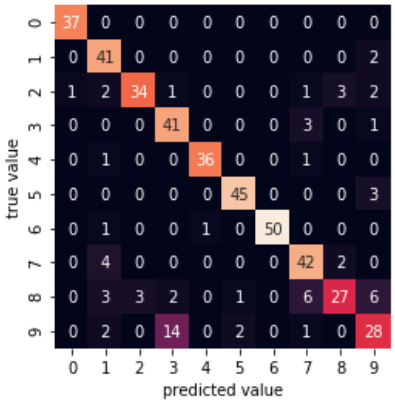
In [32]:
```
from sklearn.model_selection import cross_val_score
cross_val_score(model, X_5D, y, cv=10)
```

Out[32]:
```
array([0.82222222, 0.89444444, 0.81111111, 0.81666667, 0.84444444,
       0.78888889, 0.86111111, 0.82122905, 0.74860335, 0.84916201])
```

In [33]:
```
from sklearn.metrics import confusion_matrix

mat = confusion_matrix(ytest, y_model)

sns.heatmap(mat, square=True, annot=True, cbar=False)
plt.xlabel('predicted value')
plt.ylabel('true value');
```



Likewise, after the dimensionality reduction we made using the pca method, when we put our data into the model, the success rate we achieved was 85 percent.

When compared to the result we obtained using the previous isomap method, we can say that this model has a lower success rate.

When we look at the confusion matrix, this matrix actually shows us how much of the true values are correctly predicted.

For example, for 6, we can say that all were correctly estimated. There is no loss. But when we look at 9, out of 42 samples with a real value of 9, it is estimated as 3 for 14 of them. There are also other values that the model predicts as 9. The value 3 of 5 is called 9. The value 2 of 2 is called 9. the value 2 of 1 and the value 6 of 8 is called 9.

Task-2C:

For the critical issues we will consider in order to choose the best model, we can list the following.

- The established model can be very complex. Or may not be complex enough

- The size of the data set being trained may not be sufficient. It may be necessary to increase the size of the data set.

- The model may be working with less features. It may be necessary to train the model with more features.

Variance occurs when the model performs well in the training dataset but does not perform well in an untrained dataset, such as a test dataset or validation dataset. Variance tells us how dispersed the predicted value from the true value is.

A model with high variance tries to fit most of the data points, which makes the model complex and difficult to model.

Bias is how far predicted values are from true values. If the predicted values are far from the true values, the bias is high.

Underfit : Unlike over-learning, if a model has insufficient learning, it means that the model does not fit the training data and therefore misses trends in the data. It also means that the model cannot be generalized to new data. this problem is usually the result of a very simple model so we can call it a lack of underestimating independent variables.

Models with underfitting problems have a high error rate in both training and test data sets. It has low variance and high bias. Instead of following training data too closely, these models ignore lessons learned from training data and fail to learn the basic relationship between inputs and outputs.

Overfit : If our model has begun to memorize our dataset for training, or if our training set is uniform, the risk of overfitting is high. When we show our test data to this model where we got a high score on the training set, we will probably get a very low score. Because the model memorized the situations in the training set and searches for these situations in the test data set. Since memorized situations cannot be found in the slightest change, you can get very bad prediction scores in the test data set. Models with overfitting problems show high variance and low bias.

Depending on whether the model is underfit or overfit, training and validation scores are also very important. An underfit model is a high-bias model and its training score and validation scores are similar. An overfit model is a high-variance model and its validation score is much worse than the training score.

We wouldn't worry too much about an underfitted model, and we would have proven that the model failed. But since an overfitting model is considered successful, we need to prove how successful it actually is. In such cases, we need to validate the model. For this, we can use the cross validation method.

For a moderately complex model, we can call the best model to the point where the validation score value is optimum.

Learning curve is a curve graph showing the changes in training and validation score values according to the model score and training data set size.

Good fit: As the size of the training data set in the learning curve increases, the point where the validation score and the training score merge are evaluated as good fit.

Task-2D:

For this task we can use the breast_cancer dataset provided by the sklearn library.

In [104]:
```
from sklearn.datasets import load_breast_cancer
cancer = load_breast_cancer()
```

In [105]:
```
X = cancer.data
X.shape
```

Out[105]:
```
(569, 30)
```

In [106]:
```
y = cancer.target
y.shape
```

Out[106]:
```
(569,)
```

In [107]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=5)
```

In [108]:
```
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier()

print("Default Parameters ")
print(model.get_params())
```

```
Default Parameters
{'bootstrap': True, 'ccp_alpha': 0.0, 'class_weight': None, 'criterion': 'gini', 'max_depth': None, 'max_features': 'auto', 'ma
x_leaf_nodes': None, 'max_samples': None, 'min_impurity_decrease': 0.0, 'min_impurity_split': None, 'min_samples_leaf': 1, 'min
_samples_split': 2, 'min_weight_fraction_leaf': 0.0, 'n_estimators': 100, 'n_jobs': None, 'oob_score': False, 'random_state': N
one, 'verbose': 0, 'warm_start': False}
```

In [109]:
```
#for instance 3*4*5 different values for 3 different parameters
bootstrap_v = [True, False, True]
criterion = ['gini', 'entropy']
max_features_v = ['sqrt', 'log2']
n_estimators_v = list(range(100,2000,400))
#min_sample_leaf_v = list(range(1,5,2))
```

In [110]:
```
grid_params  = {
    'bootstrap' : bootstrap_v,
    'criterion' : criterion,
    'max_features' : max_features_v,
    'n_estimators' : n_estimators_v
}

print("Tuning Parameters")
print(grid_params)
```

```
Tuning Parameters
{'bootstrap': [True, False, True], 'criterion': ['gini', 'entropy'], 'max_features': ['sqrt', 'log2'], 'n_estimators': [100, 50
0, 900, 1300, 1700]}
```

In [111]:
```
grid_search = GridSearchCV(estimator=model, param_grid=grid_params, cv=5, verbose=1)
```

In [112]:
```
grid_search.fit(X_train, y_train)

print('Best Parameters for our classsifier')
print(grid_search.best_params_)
```

```
Fitting 5 folds for each of 60 candidates, totalling 300 fits

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done 300 out of 300 | elapsed:  6.0min finished

Best Parameters for our classsifier
{'bootstrap': False, 'criterion': 'entropy', 'max_features': 'sqrt', 'n_estimators': 500}
```

In [115]:
```
#Evaluation of base Model
model = RandomForestClassifier()
model=model.fit(X_train, y_train)
predict = model.predict(X_test)
report = classification_report(y_test, predict)
score = accuracy_score(y_true= y_test, y_pred=predict)
print(report)
print("{} {:0.2f}%".format("Accuracy Score : ", score*100))
```

```
              precision    recall  f1-score   support

           0       0.98      0.94      0.96        48
           1       0.96      0.98      0.97        66

    accuracy                           0.96       114
   macro avg       0.97      0.96      0.96       114
weighted avg       0.97      0.96      0.96       114

Accuracy Score :  96.49%
```

In [116]:
```
#Evaluation of best Estimator Selected from GridSearchCV
from sklearn.metrics import classification_report, accuracy_score
predict = grid_search.best_estimator_.predict(X_test)
report = classification_report(y_test, predict)
score = accuracy_score(y_true= y_test, y_pred=predict)
print(report)
print("{} {:0.2f}%".format("Accuracy Score : ", score*100))
```

```
              precision    recall  f1-score   support

           0       1.00      0.94      0.97        48
           1       0.96      1.00      0.98        66

    accuracy                           0.97       114
   macro avg       0.98      0.97      0.97       114
weighted avg       0.97      0.97      0.97       114

Accuracy Score :  97.37%
```

The Base Model accuracy was 96.49% but after hyperparameter tuning that is selecting best estimator parameters, the accuracy increased to 97.37% on Tuned Model. This is a significant increase in accuracy.