1. Main objective of the analysis that specifies whether your model will be focused on prediction or interpretation

- We want both model prediction and model interpretation

1. Model summary and brief data description

In [144]:

```
import pandas as pd ,numpy as np ,matplotlib.pyplot as plt
data = pd.read_csv("breast-cancer.csv" ,header = None)
col_name = ['Class' ,'age' ,'menopause' ,'tumor-size' ,'inv-nodes' ,
 'node-caps' ,'deg-malig' ,'breast' ,'breast=quad' ,'irradiat']
data.columns = col_name
data.head()
```

Out[144]:

	Class	age	menopause	tumor-size	inv-nodes	node-caps	deg-malig	breast	breast=quad	irradiat
0	no-recurrence-events	30-39	premeno	30-34	0-2	no	3	left	left_low	no
1	no-recurrence-events	40-49	premeno	20-24	0-2	no	2	right	right_up	no
2	no-recurrence-events	40-49	premeno	20-24	0-2	no	2	left	left_low	no
3	no-recurrence-events	60-69	ge40	15-19	0-2	no	2	right	left_up	no
4	no-recurrence-events	40-49	premeno	0-4	0-2	no	2	right	right_low	no

- Data related to breast cancer and we have to build a model that can classify given attribute whether these are recurrent event or not

In [145]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 286 entries, 0 to 285
Data columns (total 10 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   Class        286 non-null    object
 1   age          286 non-null    object
 2   menopause    286 non-null    object
 3   tumor-size   286 non-null    object
 4   inv-nodes    286 non-null    object
 5   node-caps    286 non-null    object
 6   deg-malig    286 non-null    int64 
 7   breast       286 non-null    object
 8   breast=quad  286 non-null    object
 9   irradiat     286 non-null    object
dtypes: int64(1), object(9)
memory usage: 22.5+ KB
```

In [122]:

```
cat_col = data.columns[data.dtypes == np.object]
data[cat_col].describe()
```

Out[122]:

	Class	age	menopause	tumor-size	inv-nodes	node-caps	breast	breast=quad	irradiat
count	286	286	286	286	286	286	286	286	286
unique	2	6	3	11	7	3	2	6	2
top	no-recurrence-events	50-59	premeno	30-34	0-2	no	left	left_low	no
freq	201	96	150	60	213	222	152	110	218

1. Data cleaning and feature engineering.

In [146]:

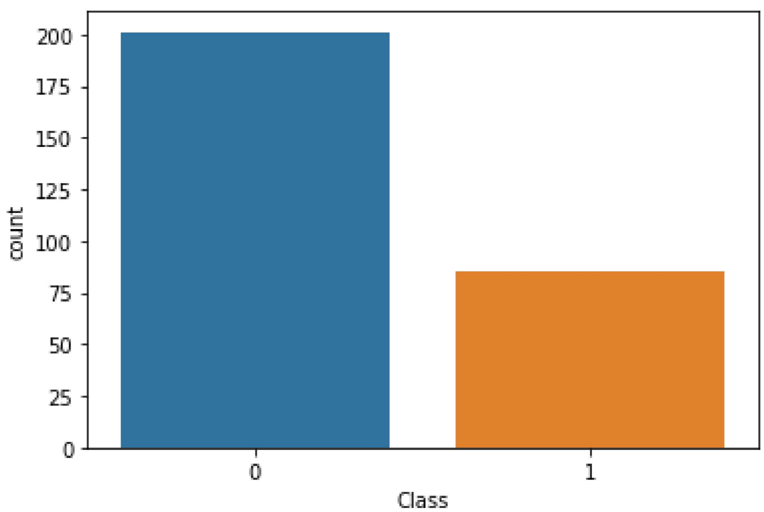
```
from sklearn.preprocessing import LabelEncoder
le =  LabelEncoder()
for col in cat_col:
    data[col] = le.fit_transform(data[col])
data.head()
```

Out[146]:

	Class	age	menopause	tumor-size	inv-nodes	node-caps	deg-malig	breast	breast=quad	irradiat
0	0	1	2	5	0	1	3	0	2	0
1	0	2	2	3	0	1	2	1	5	0
2	0	2	2	3	0	1	2	0	2	0
3	0	4	0	2	0	1	2	1	3	0
4	0	2	2	0	0	1	2	1	4	0

In [147]:

```
import seaborn as sns
ax = sns.countplot(data.Class)
```



In [148]:

```
data.Class.value_counts()/len(data.Class)
```

Out[148]:

```
0    0.702797
1    0.297203
Name: Class, dtype: float64
```

In [149]:

```
### BEGIN SOLUTION
from sklearn.model_selection import StratifiedShuffleSplit

# Get the split indexes
strat_shuf_split = StratifiedShuffleSplit(n_splits=1,
                                          test_size=0.3,
                                          random_state=42)
X = data.drop(columns = ['Class'])
y = data.loc[:,'Class']
train_idx, test_idx = next(strat_shuf_split.split(X ,y))

# Create the dataframes
X_train =X.loc[train_idx,:]
y_train = y.loc[train_idx]

X_test  = X.loc[test_idx, :]
y_test  = y.loc[test_idx]
```

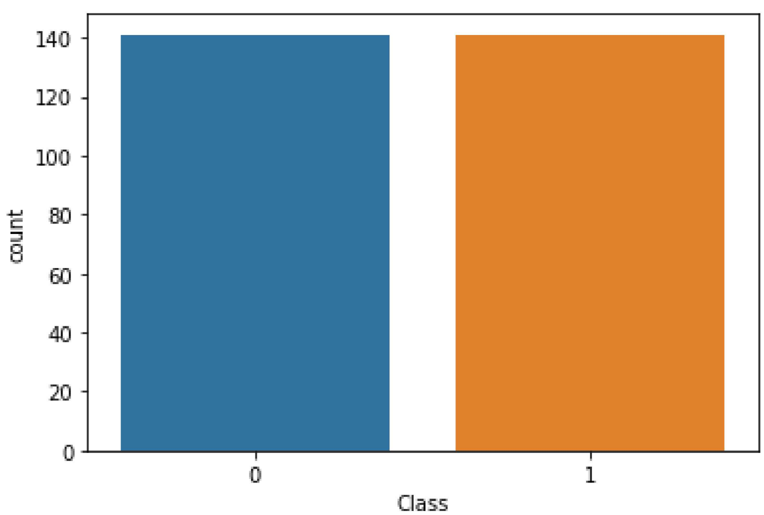
- Handling Class imbalance of training dataset

In [150]:

```
from imblearn.over_sampling import SMOTE
oversample = SMOTE()
X_train, y_train = oversample.fit_resample(X_train, y_train)
sns.countplot(y_train)
```

Out[150]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2539e77b1c0>
```



1. Fitting at least three different classifier models (KNN , Logistics Regression ,Logistic Regression with L1 or L2 penalty), preferably of different nature in explainability and predictability.

- Fitting K-Nearest Neighbours Classifiers

In [177]:

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report, f1_sc
ore


# Estimate KNN model and report outcomes
knn = KNeighborsClassifier(n_neighbors=3)
knn = knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
# Preciision, recall, f-score from the multi-class support function
print(classification_report(y_test, y_pred))
print('Accuracy score: ', round(accuracy_score(y_test, y_pred), 2))
print('F1 Score: ', round(f1_score(y_test, y_pred), 2))
```

```
              precision    recall  f1-score   support

           0       0.79      0.63      0.70        60
           1       0.42      0.62      0.50        26

    accuracy                           0.63        86
   macro avg       0.61      0.62      0.60        86
weighted avg       0.68      0.63      0.64        86

Accuracy score:  0.63
F1 Score:  0.5
```

- Fitting Logistic Regression model

In [152]:

```
### BEGIN SOLUTION
from sklearn.linear_model import LogisticRegression

# Standard logistic regression
lr = LogisticRegression(solver='liblinear').fit(X_train, y_train)
lr.fit(X_train, y_train)
y_pred = lr.predict(X_test)
# Preciision, recall, f-score from the multi-class support function
print(classification_report(y_test, y_pred))
print('Accuracy score: ', round(accuracy_score(y_test, y_pred), 2))
print('F1 Score: ', round(f1_score(y_test, y_pred), 2))
```

```
              precision    recall  f1-score   support

           0       0.80      0.65      0.72        60
           1       0.43      0.62      0.51        26

    accuracy                           0.64        86
   macro avg       0.61      0.63      0.61        86
weighted avg       0.69      0.64      0.65        86

Accuracy score:  0.64
F1 Score:  0.51
```

- Fitting Logistic regression with L1 penalty

In [153]:

```
from sklearn.linear_model import LogisticRegressionCV

# L1 regularized logistic regression
lr_l1 = LogisticRegressionCV(Cs=10, cv=4, penalty='l1', solver='liblinear').fit(X_train, y
_train)


lr_l1.fit(X_train, y_train)
y_pred = lr_l1.predict(X_test)
# Preciision, recall, f-score from the multi-class support function
print(classification_report(y_test, y_pred))
print('Accuracy score: ', round(accuracy_score(y_test, y_pred), 2))
print('F1 Score: ', round(f1_score(y_test, y_pred), 2))
```

```
              precision    recall  f1-score   support

           0       0.79      0.88      0.83        60
           1       0.63      0.46      0.53        26

    accuracy                           0.76        86
   macro avg       0.71      0.67      0.68        86
weighted avg       0.74      0.76      0.74        86

Accuracy score:  0.76
F1 Score:  0.53
```

- Fitting Logistic regression with L2 penalty

In [154]:

```
# L2 regularized logistic regression
lr_l2 = LogisticRegressionCV(Cs=10, cv=4, penalty='l2', solver='liblinear').fit(X_train, y
_train)
lr_l2.fit(X_train, y_train)
y_pred = lr_l2.predict(X_test)
# Preciision, recall, f-score from the multi-class support function
print(classification_report(y_test, y_pred))
print('Accuracy score: ', round(accuracy_score(y_test, y_pred), 2))
print('F1 Score: ', round(f1_score(y_test, y_pred), 2))
### END SOLUTION
```

```
              precision    recall  f1-score   support

           0       0.80      0.67      0.73        60
           1       0.44      0.62      0.52        26

    accuracy                           0.65        86
   macro avg       0.62      0.64      0.62        86
weighted avg       0.69      0.65      0.66        86

Accuracy score:  0.65
F1 Score:  0.52
```

In [180]:

```
result = pd.DataFrame({'Model Desc': ['KNN' ,'Logistic_Regression','Logistic_L1','Logistic_L2']
                       ,'Accuracy':[0.63 ,0.64,0.76,0.65]
                       ,'F1 Score':[0.5,0.51,0.53,0.52]})
result
```

Out[180]:

	Model Desc	Accuracy	F1 Score
0	KNN	0.63	0.50
1	Logistic_Regression	0.64	0.51
2	Logistic_L1	0.76	0.53
3	Logistic_L2	0.65	0.52

SUMMARY

- The final model for prediction is Logistic regression with L1 penalty . we can use this model both for prediction and model interpretability. The reason for Logistic regression with L1 penalty is best is because it has highest accuracy and F1 Score compare to all other model we have fitted
- Further analysis can be done based on hyperparameter tunning of model using Grid Search approach

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