Logistic Regression

Unlike other algorithms, Logistic Regression is easily misguided by young developers. Maybe because people still think that it is a regression machine learning algorithm.

Logistic regression is a statistical machine learning algorithm that classifies the data by considering outcome variables on extreme ends and tries makes a logarithmic line that distinguishes between them.

Imports

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

Loading Dataset

In [2]:
```
from sklearn.datasets import load_iris
```

In [3]:
```
iris = load_iris()
```

In [4]:
```
type(iris)
```

Out[4]:
```
sklearn.utils.Bunch
```

See all the keys

In [5]:
```
iris.keys()
```

Out[5]:
```
dict_keys(['data', 'target', 'frame', 'target_names', 'DESCR', 'feature_names', 'filenam
e'])
```

Description

In [6]:
```
print(iris["DESCR"])
```

```
.. _iris_dataset:

Iris plants dataset
--------------------

**Data Set Characteristics:**

    :Number of Instances: 150 (50 in each of three classes)
    :Number of Attributes: 4 numeric, predictive attributes and the class
    :Attribute Information:
        - sepal length in cm
        - sepal width in cm
        - petal length in cm
        - petal width in cm
        - class:
```

```
                - Iris-Setosa
                - Iris-Versicolour
                - Iris-Virginica

    :Summary Statistics:

    ============== ==== ==== ======= ===== ====================
                    Min  Max   Mean    SD   Class Correlation
    ============== ==== ==== ======= ===== ====================
    sepal length:   4.3  7.9   5.84   0.83    0.7826
    sepal width:    2.0  4.4   3.05   0.43   -0.4194
    petal length:   1.0  6.9   3.76   1.76    0.9490  (high!)
    petal width:    0.1  2.5   1.20   0.76    0.9565  (high!)
    ============== ==== ==== ======= ===== ====================

    :Missing Attribute Values: None
    :Class Distribution: 33.3% for each of 3 classes.
    :Creator: R.A. Fisher
    :Donor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)
    :Date: July, 1988

The famous Iris database, first used by Sir R.A. Fisher. The dataset is taken
from Fisher's paper. Note that it's the same as in R, but not as in the UCI
Machine Learning Repository, which has two wrong data points.

This is perhaps the best known database to be found in the
pattern recognition literature.  Fisher's paper is a classic in the field and
is referenced frequently to this day.  (See Duda & Hart, for example.)  The
data set contains 3 classes of 50 instances each, where each class refers to a
type of iris plant.  One class is linearly separable from the other 2; the
latter are NOT linearly separable from each other.

.. topic:: References

   - Fisher, R.A. "The use of multiple measurements in taxonomic problems"
     Annual Eugenics, 7, Part II, 179-188 (1936); also in "Contributions to
     Mathematical Statistics" (John Wiley, NY, 1950).
   - Duda, R.O., & Hart, P.E. (1973) Pattern Classification and Scene Analysis.
     (Q327.D83) John Wiley & Sons.  ISBN 0-471-22361-1.  See page 218.
   - Dasarathy, B.V. (1980) "Nosing Around the Neighborhood: A New System
     Structure and Classification Rule for Recognition in Partially Exposed
     Environments".  IEEE Transactions on Pattern Analysis and Machine
     Intelligence, Vol. PAMI-2, No. 1, 67-71.
   - Gates, G.W. (1972) "The Reduced Nearest Neighbor Rule".  IEEE Transactions
     on Information Theory, May 1972, 431-433.
   - See also: 1988 MLC Proceedings, 54-64.  Cheeseman et al"s AUTOCLASS II
     conceptual clustering system finds 3 classes in the data.
   - Many, many more ...
```

Data

In [7]:
```
iris["data"][:5] # Independent columns
```

Out[7]:
```
array([[5.1, 3.5, 1.4, 0.2],
       [4.9, 3. , 1.4, 0.2],
       [4.7, 3.2, 1.3, 0.2],
       [4.6, 3.1, 1.5, 0.2],
       [5. , 3.6, 1.4, 0.2]])
```

In [8]:
```
iris["feature_names"] # Column names
```

Out[8]:
```
['sepal length (cm)',
 'sepal width (cm)',
 'petal length (cm)',
 'petal width (cm)']
```

In [9]:
```
np.array(iris["target"]) # Dependent column
```

Out[9]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2])
```

In [10]:
```
iris["target_names"]
# So, 0 is setosa, 1 is versicolor and 2 is virginica
```

Out[10]:
```
array(['setosa', 'versicolor', 'virginica'], dtype='<U10')
```

Create Dataframe

In [11]:
```
df = pd.DataFrame(data=iris["data"], columns=iris["feature_names"])
df["target"] = iris["target"]
df.head()
```

Out[11]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
0	5.1	3.5	1.4	0.2	0
1	4.9	3.0	1.4	0.2	0
2	4.7	3.2	1.3	0.2	0
3	4.6	3.1	1.5	0.2	0
4	5.0	3.6	1.4	0.2	0

In [12]:
```
df["target"].unique()
```

Out[12]:
```
array([0, 1, 2])
```

In [13]:
```
df["target"].replace(range(3), iris["target_names"], inplace=True)
```

In [14]:
```
df.head()
```

Out[14]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
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 [15]:
```
df["target"].unique()
```

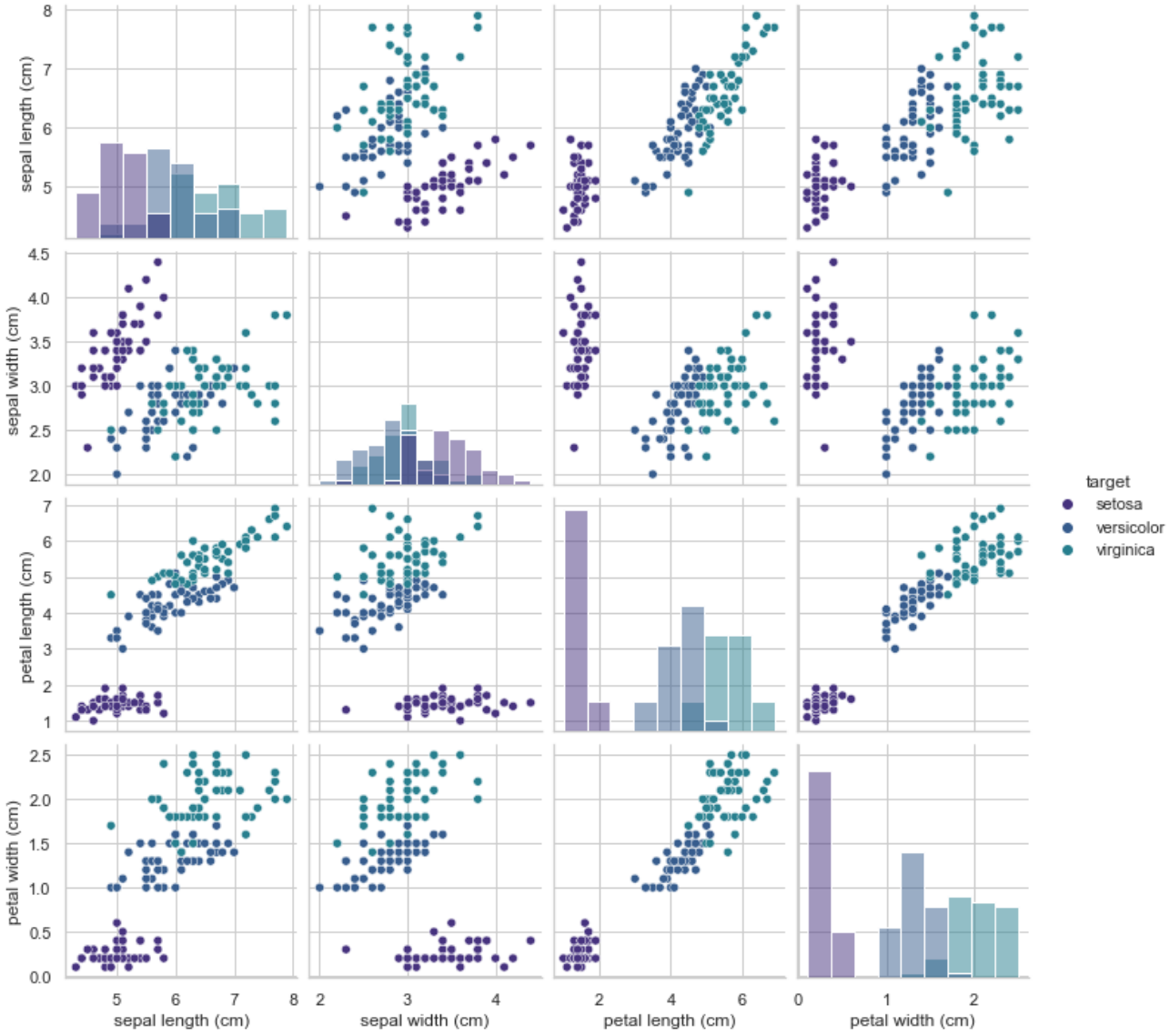
Out[15]:
```
array(['setosa', 'versicolor', 'virginica'], dtype=object)
```

EDA

In [16]:
```
sns.set(style="whitegrid", palette="viridis")
```

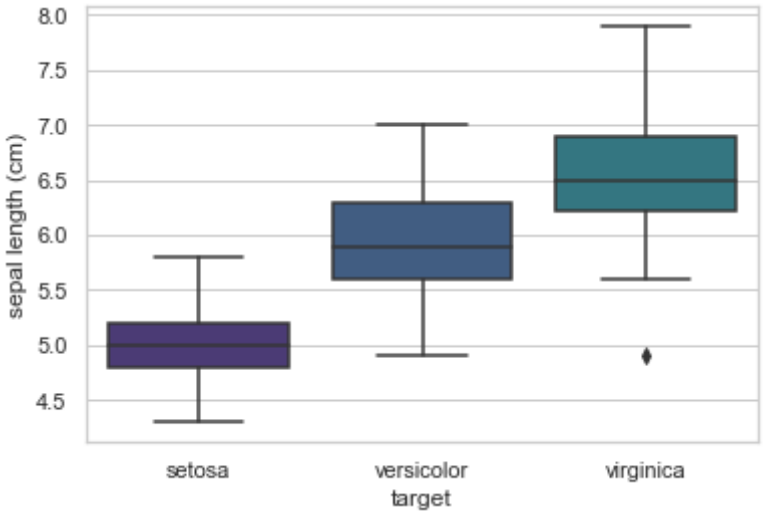
In [17]:
```
sns.pairplot(df, hue="target", diag_kind='hist')
```

Out[17]:
```
<seaborn.axisgrid.PairGrid at 0x1dab9d27670>
```



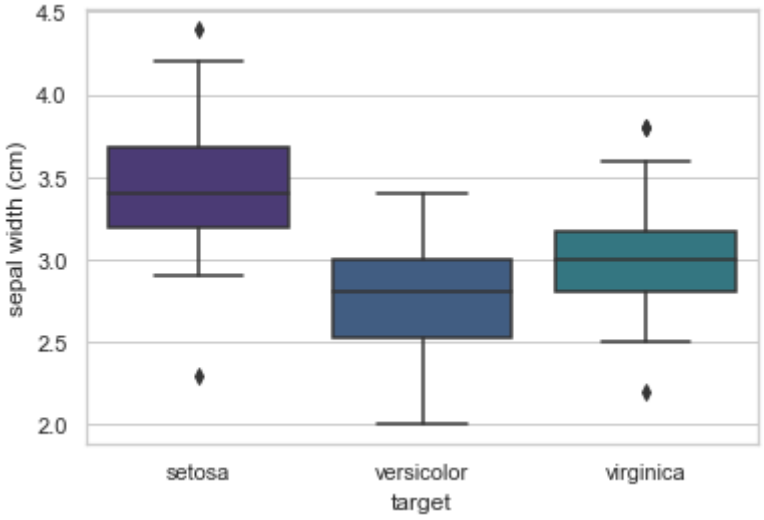
In [18]:
```
sns.boxplot(x="target", y="sepal length (cm)", data=df)
```

Out[18]:
```
<AxesSubplot:xlabel='target', ylabel='sepal length (cm)'>
```



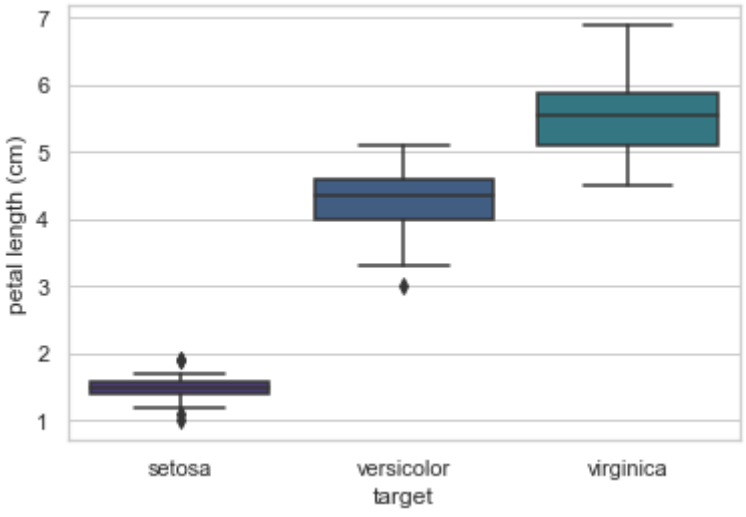
In [19]:
```
sns.boxplot(x="target", y="sepal width (cm)", data=df)
```

Out[19]: <AxesSubplot:xlabel='target', ylabel='sepal width (cm)'>



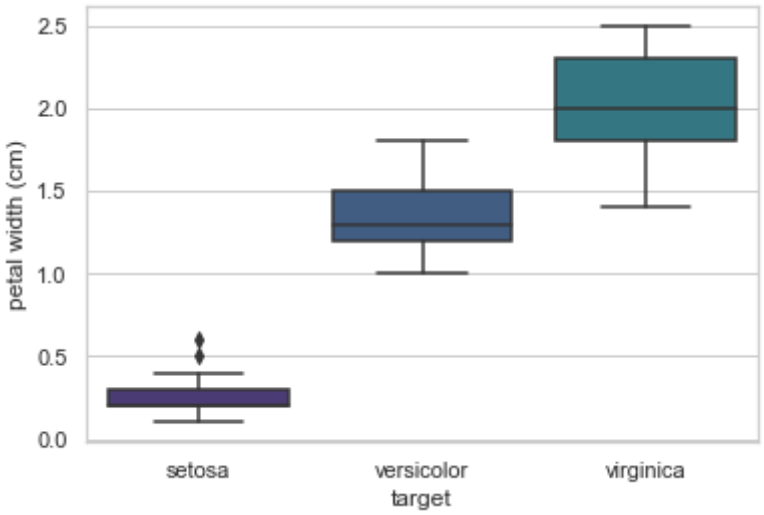
In [20]:
```
sns.boxplot(x="target", y="petal length (cm)", data=df)
```

Out[20]: <AxesSubplot:xlabel='target', ylabel='petal length (cm)'>



In [21]:
```
sns.boxplot(x="target", y="petal width (cm)", data=df)
```

Out[21]: <AxesSubplot:xlabel='target', ylabel='petal width (cm)'>



Feature Selection

In [22]:
```
df.head()
```

Out[22]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
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 [23]:
```
X = df.drop("target", axis=1) # Independent
y = df["target"] # Dependent
```

Train Test Split

In [24]:
```
from sklearn.model_selection import train_test_split
```

In [25]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=202
```

In [26]:
```
X_train[:5]
```

Out[26]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
120	6.9	3.2	5.7	2.3
117	7.7	3.8	6.7	2.2
76	6.8	2.8	4.8	1.4
86	6.7	3.1	4.7	1.5
57	4.9	2.4	3.3	1.0

In [27]:
```
y_train[:5]
```

Out[27]:
```
120     virginica
117     virginica
76     versicolor
86     versicolor
57     versicolor
Name: target, dtype: object
```

Logistic Regression

Logistic regression produces a logistic curve, which is limited to values between 0 and 1. Logistic regression is similar to a linear regression, but the curve is constructed using the natural logarithm of the odds of the target variable, rather than the probability.

Sigmoid Function / Logistic Function: $f(x) = \frac{1}{1+e^{-x}}$

The range of sigmoid function is (0, 1).

Equation of Logistic Regression: $\hat{y} = \frac{1}{1+e^{-\Sigma\beta_i.X_i}}$

Error = $y - \hat{y}$ (for each and every row individually)
Total squared error = $\Sigma(y - \hat{y})^2$ (The error is squared to punish larger values of error)

The derivation of cost function and also the method for optimizing the beta values is almost same as that of linear regression.

If you want to learn more about Logistic Regression, go watch this great video on the topic.

Model

In [28]:
```
from sklearn.linear_model import LogisticRegression
```

In [29]:
```
log_model = LogisticRegression(max_iter=100)
# Increase max_iter if your model fails to converge
```

In [30]:
```
log_model.fit(X_train, y_train)
```

Out[30]:
```
LogisticRegression()
```

In [31]:
```
log_pred = log_model.predict(X_test)
```

In [32]:
```
print(list(log_pred))
```

```
['virginica', 'setosa', 'versicolor', 'versicolor', 'versicolor', 'versicolor', 'virginic
a', 'versicolor', 'setosa', 'setosa', 'virginica', 'versicolor', 'setosa', 'virginica',
'virginica', 'setosa', 'versicolor', 'versicolor', 'virginica', 'setosa', 'setosa', 'virg
inica', 'virginica', 'setosa', 'virginica', 'versicolor', 'versicolor', 'virginica', 'set
osa', 'setosa', 'virginica', 'setosa', 'setosa', 'setosa', 'virginica', 'setosa', 'setos
a', 'versicolor', 'setosa', 'virginica', 'setosa', 'virginica', 'versicolor', 'setosa',
'versicolor']
```

In [33]:
```
print(list(y_test))
```

```
['virginica', 'setosa', 'versicolor', 'versicolor', 'versicolor', 'virginica', 'virginic
a', 'versicolor', 'setosa', 'setosa', 'virginica', 'virginica', 'setosa', 'virginica', 'v
irginica', 'setosa', 'versicolor', 'versicolor', 'virginica', 'setosa', 'setosa', 'virgin
ica', 'versicolor', 'setosa', 'virginica', 'versicolor', 'versicolor', 'versicolor', 'set
osa', 'setosa', 'virginica', 'setosa', 'setosa', 'setosa', 'virginica', 'setosa', 'setos
a', 'versicolor', 'setosa', 'virginica', 'setosa', 'virginica', 'versicolor', 'setosa',
'versicolor']
```

Performance Evaluation

In [34]:
```
from sklearn.metrics import confusion_matrix, classification_report
```

Confusion Matrix

n=165	**Predicted: NO**	**Predicted: YES**	
Actual: NO	TN = 50	FP = 10	60
Actual: YES	FN = 5	TP = 100	105
	55	110	

Rows: Actually Setosa, Actually Versicolor, Actually Virginica

Columns: Predicted Setosa, Predicted Versicolor, Predicted Virginica

In [35]:
```
print(confusion_matrix(y_test, log_pred))
```

```
[[18  0  0]
 [ 0 11  2]
 [ 0  2 12]]
```

In [36]:
```
pd.DataFrame(
    data=confusion_matrix(y_test, log_pred),
    columns=["Predicted Setosa", "Predicted Versicolor", "Predicted Virginica"],
    index=["Actually Setosa", "Actually Versicolor", "Actually Virginica"]
)
```

Out[36]:

	Predicted Setosa	Predicted Versicolor	Predicted Virginica
Actually Setosa	18	0	0
Actually Versicolor	0	11	2
Actually Virginica	0	2	12

Classification Report

In [37]:
```
print(classification_report(y_test, log_pred))
```

```
              precision    recall  f1-score   support
```

```
              precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        18
  versicolor       0.85      0.85      0.85        13
   virginica       0.86      0.86      0.86        14

    accuracy                           0.91        45
   macro avg       0.90      0.90      0.90        45
weighted avg       0.91      0.91      0.91        45
```

- **Support:** Number of rows that belong to each of the classes of the dependent categorical feature.
- **Accuracy:** Fraction of predictions that are correct.
- **Precision:** True Positive / Total Predicted Positive (Ability of the model to find all relevant data points)
- **Recall:** True Positive / Total Actual Postive (Ability of model to find all relevant cases)
- **F1-Score:** $\frac{1}{f1-score} = \frac{1}{2}\left(\frac{1}{precision} + \frac{1}{recall}\right)$ (Harmonic mean of precision and recall)