# MSc Data Mining

Topic 05 : Classification

Part 02 : Logistic Regression

Dr Bernard Butler and Dr Kieran Murphy

Department of Computing and Mathematics, WIT.
(bernard.butler@wit.ie; kmurphy@wit.ie)

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Foundation

Data Handling

Exploratory Data Analysis

Data Modelling Fundamentals

Data Modelling Advanced

Rule Based

Association Rules

Recommender Systems

Supervised

Regression

Basic Classification

Deep Learning

## Outline

- Relationship with linear regression
- (Sigmoid) Logistic function

# Outline

# Linear Regression                                                                I

Take the IRIS dataset (4 features, target discrete with 3 levels $[0, 1, 2]$) and simplify it by[*] taking only the
first feature, and merging class 1 ('versicolor') and class 2 ('virginica').

```
1 X, y, target_names = iris.data[:,:1], iris.target, iris.target_names
  y[y>1] = 1
  target_names = np.array([target_names[0], 'other'])
```

So we have target

```
2 y
```

```
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, 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, 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, 1, 1])
```

and target names of

```
3 target_names
```
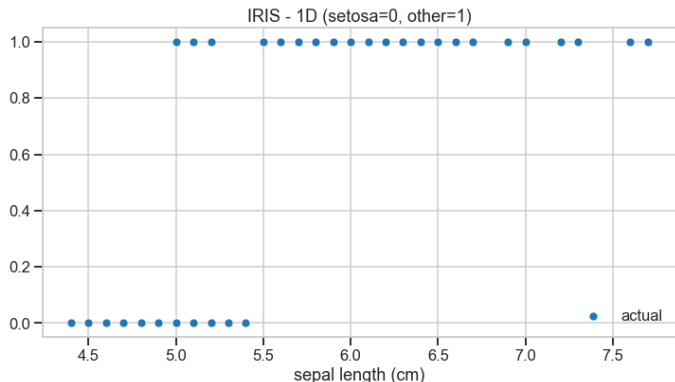
```
array(['setosa', 'other'], dtype='<U6')
```

---

[*]Python for Data Science — Cheat Sheet Numpy Basics

# Linear Regression <span style="float:right">II</span>

```
plt.figure(figsize=(12,6))
sns.scatterplot(x=X_test.T[0],y=y_test, label="actual")
plt.xlabel(iris.feature_names[0])
plt.title("IRIS – 1D (setosa=0, other=1)")
plt.legend(loc="lower right")
plt.show()
```



IRIS - 1D (setosa=0, other=1)

From the graph, it looks like we could predict class using sepal length, in particular if sepal length is <5.5 then predict setosa else predict other.
How many observations will be miss-classified then?

Following standard procedure we split data ...

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.6, random_state=666)
```

... import and create instance of model (`LinearRegression`) ...

```
from sklearn.linear_model import LinearRegression
model = LinearRegression()
```

... fit model (using training data — feature(s) and target) ...

```
model.fit(X_train, y_train)
```

... predict (using feature(s) in test data) ...

```
y_pred = model.predict(X_test)
```

# Linear Regression                                                                    III

Following standard procedure we split data . . .

```
from sklearn.model_selection import train_test_split
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```

# Linear Regression III

Following standard procedure we split data ...

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.6, random_state=666)
```

... import and create instance of model (`LinearRegression`) ...

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from sklearn.linear_model import LinearRegression
model = LinearRegression()
```

... fit model (using training data — feature(s) and target) ...

```
model.fit(X_train, y_train)
```

... predict (using feature(s) in test data) ...

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y_pred = model.predict(X_test)
```

# Linear Regression                                                          III

Following standard procedure we split data ...

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X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.6, random_state=666)
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... import and create instance of model (LinearRegression) ...

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from sklearn.linear_model import LinearRegression
model = LinearRegression()
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... fit model (using training data — feature(s) and target) ...
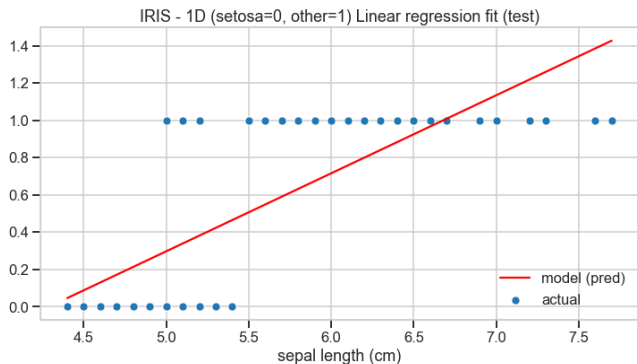
```
model.fit(X_train, y_train)
```

... predict (using feature(s) in test data) ...

```
y_pred = model.predict(X_test)
```

# Linear Regression                                                              III

Following standard procedure we split data . . .

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y_pred = model.predict(X_test)
```

# Linear Regression                                                          III

```
plt.figure(figsize=(12,6))
sns.scatterplot(x=X_test.T[0],y=y_test, label="actual")
sns.lineplot(x=X_test.T[0], y=y_pred, color='red', label="model (pred)")
plt.xlabel(iris.feature_names[0])
plt.title("IRIS – 1D (setosa=0, other=1) Linear regression fit (test)")
plt.legend(loc="lower right")
plt.show()
```
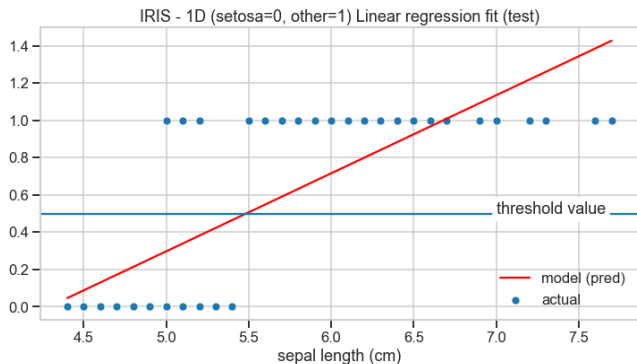


IRIS - 1D (setosa=0, other=1) Linear regression fit (test)

This is called a linear probability model. It has the advantages that much of the regression statistical theory can be applied to it.

But output is in range $(-\infty, \infty)$, we want $0$ or $1$

# Linear Regression <span style="float:right">III</span>

26

```python
plt.figure(figsize=(12,6))
sns.scatterplot(x=X_test.T[0],y=y_test, label="actual")
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```



This is called a linear probability model. It has the advantages that much of the regression statistical theory can be applied to it.
But output is in range $(-\infty, \infty)$, we want $0$ or $1$

Pick a threshold value, default is 0.5.
If $y <$ threshold
    predict 0
else
    predict 1

# ... it would be nice ...

Can we ~~replace~~ map the infinite interval $(-\infty, \infty)$ to a finite interval, say to $(0, 1)$ ?
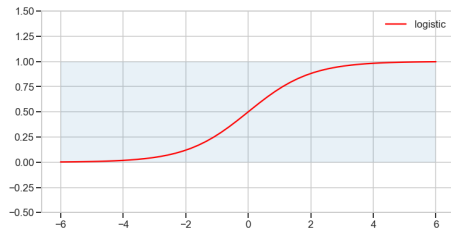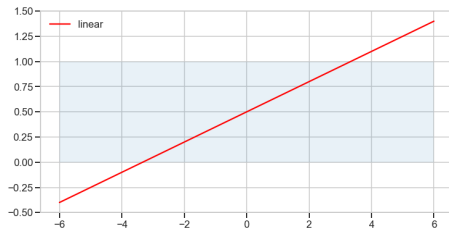


$\rightsquigarrow$

A Sigmoid function[†] is any function that has a stretched S-shaped curve. One example of a sigmoid function is the
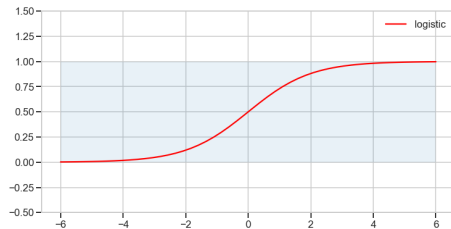
## Logistic function, $\sigma$

$$\sigma(x) = \frac{1}{1 + \exp(-x)} = \frac{1}{1 + e^{-x}} = \frac{e^x}{1 + e^x}$$

[†] Sigmoid function (Wikipedia), and Logistic function (Wikipedia),

# ... it would be nice ...

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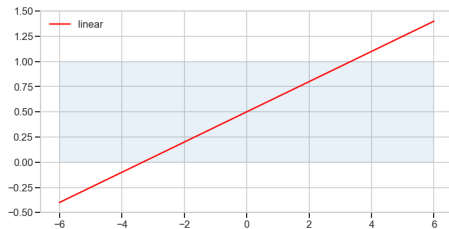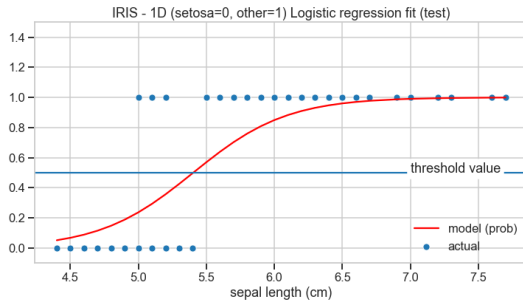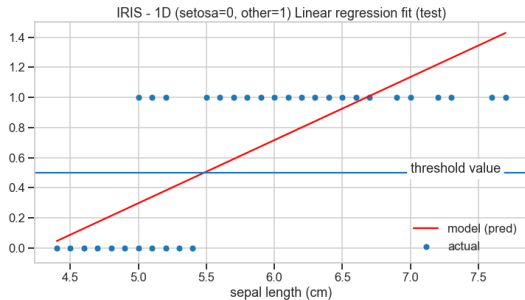
## Logistic function, $\sigma$

$$\sigma(x) = \frac{1}{1 + \exp(-x)} = \frac{1}{1 + e^{-x}} = \frac{e^x}{1 + e^x}$$

[†]Sigmoid function (Wikipedia), and Logistic function (Wikipedia),

# Linear Regression vs Logistic Regression



**Linear Regression Model**

$$y = mx + c$$

$$x \curvearrowright y$$

**Logistic Regression Model**

$$y = \sigma(z) \quad \text{where} \quad z = mx + c$$

$$x \curvearrowright z \curvearrowright y$$

Aside: The function linking, $z$, the output of linear step, to $y$, the model output is called a link function.

# Aside: Of all the Sigmoid functions, why pick Logistic?    I

First a little bit of mathematical manipulation ...

$$y = \sigma(z) = \frac{1}{1 + e^{-z}} \qquad\qquad \text{definition of } \sigma(z)$$

$$y + y e^{-z} = 1 \qquad\qquad \text{multiply both sides by } (1 + e^{-z})$$

$$e^{-z} = \frac{1 - y}{y} \qquad\qquad \text{solve for } e^{-z}$$

$$e^{z} = \frac{y}{1 - y} \qquad\qquad \text{invert both sides}$$

$$z = \ln\left(\frac{y}{1 - y}\right) \qquad\qquad \text{apply logs}$$

So we have

$$y = \frac{1}{1 + e^{-z}} \qquad \Longleftrightarrow \qquad z = \ln\left(\frac{y}{1 - y}\right)$$

# Aside: Of all the Sigmoid functions, why pick Logistic? II

- If $y$ represents a probability, then

$$\frac{y}{1-y}$$

  represent the odds — an alternative measure of the likelihood of a particular outcome[‡].

- Then

$$z = \ln\left(\frac{y}{1-y}\right)$$

  is the log-odds, or the logit.

- This implies that increasing one of the independent variables multiplicatively scales the odds of the given outcome at a constant rate, with each independent variable having its own parameter. So the feature coefficients in a logistic regression have a similar interpretation (but not the same!) as in linear regression.

---

[‡]Odds are defined as the ratio of the number of events that produce that outcome relative to the number that do not.

# Logistic Regression — Probability of being in Predicted Class

Unlike some classifiers, the `LogisticRegression` classifier can also report on the probability of an observation being in the predicted class[§].

27
```
y_prob = model.predict_proba(X_test)
y_prob
```

```
array([[0.36106274, 0.63893726],
       [0.24038055, 0.75961945],
       [0.76292166, 0.23707834],
       [0.24038055, 0.75961945],
       [0.91120554, 0.08879446],
       [0.43024916, 0.56975084],
       [0.29719846, 0.70280154],
       [0.03992405, 0.96007595],
       [0.06912596, 0.93087404],
       [0.43024916, 0.56975084],
       [0.02275676, 0.97724324],
       [0.93203415, 0.06796585],
```

28
```
y_log_prob = model.predict_log_proba(X_test)
y_log_prob
```

```
array([[-1.01870355e+00, -4.47949007e-01],
       [-1.42553199e+00, -2.74937692e-01],
       [-2.70599925e-01, -1.43936465e+00],
       [-1.42553199e+00, -2.74937692e-01],
       [-9.29867864e-02, -2.42143102e+00],
       [-8.43390801e-01, -5.62556133e-01],
       [-1.21335515e+00, -3.52680729e-01],
       [-3.22077634e+00, -4.07428849e-02],
       [-2.67182500e+00, -7.16313014e-02],
       [-8.43390801e-01, -5.62556133e-01],
       [-3.78289290e+00, -2.30196948e-02],
       [-7.03858210e-02, -2.68874994e+00],
```

---

[§]This is a big deal as it allows us to punish learners when they miss-classify based on how confident the classifier was — cross entropy loss functions (week 6 & 7).

# Logistic Regression



IRIS - 1D (setosa=0, other=1) Logistic regression fit (test)
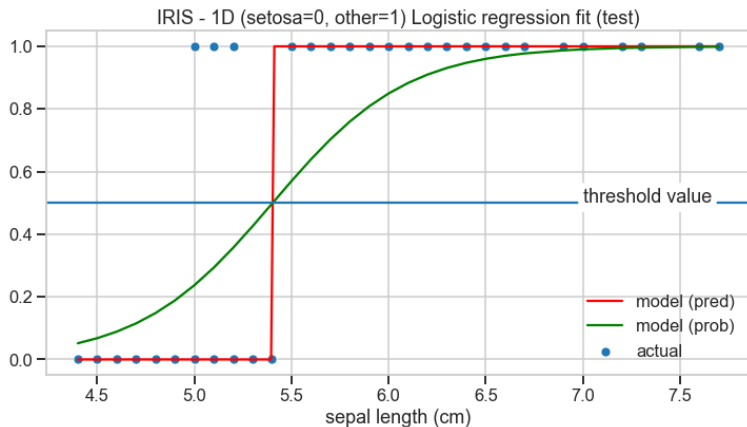
| Predicted | other | setosa |
|---|---|---|
| **Actual** | | |
| **other** | 38 | 3 |
| **setosa** | 0 | 19 |