Regression: Hands-on Session

Ditty Mathew

Machine Learning Camp

22nd June 2018

- NumPy stands for Numerical Python
- To import numpy in python
 - import numpy

array: N-dimensional array; collection of items of same type

array: N-dimensional array; collection of items of same type import numpy as np

array: N-dimensional array; collection of items of same type import numpy as np a= np.array([1,2,3])

array: N-dimensional array; collection of items of same type import numpy as np a= np.array([1,2,3]) print a

```
array: N-dimensional array; collection of items of same type
import numpy as np
a= np.array([1,2,3])
print a
print a.shape
```

```
array: N-dimensional array; collection of items of same type import numpy as np a= np.array([1,2,3]) print a print a.shape
```

• array of more than one dimensions

```
a = np.array([[1, 2], [3, 4]])
print a
```

NumPy also provides a reshape function to resize an array.

```
\begin{array}{l} a = np.array([[1,2,3],[4,5,6]]) \\ b = a.reshape(3,2) \\ print \ b \end{array}
```

To append a column to a numpy array

```
a = np.array([[1,2,3],[4,5,6]])

np.column\_stack((a,[7,8]))
```

To return a new array of specified size, filled with zeros np.zeros((5,2))

To return a new array of specified size, filled with ones np.ones((5,2))

```
\begin{aligned} \mathbf{a} &= \text{np.array}([[1,2,3],[4,5,6]]) \\ \text{To fetch value of } i^{th} \text{ row and } j^{th} \text{ colummn} \\ \mathbf{a}[\mathbf{i},\mathbf{j}] \end{aligned}
```

To fetch all values in j^{th} column

• a[:,j]

a = np.array([[1,2,3],[4,5,6]])

To fetch value of i^{th} row and j^{th} columnn a[i,j]

To fetch all values in j^{th} column

 $\bullet \ a[:,j]$

To fetch all values in i^{th} row

 $\bullet \ a[i,:]$

To multiply two matrices

```
 \begin{array}{l} x \!\!=\!\! np.array([[1,\!2],\![3,\!4]]) \\ y \!\!=\!\! np.array([[1,\!2,\!3],\![3,\!4,\!5]]) \\ np.dot(x,\!y) \end{array}
```

To multiply two matrices

```
x=np.array([[1,2],[3,4]])

y=np.array([[1,2,3],[3,4,5]])

np.dot(x,y)
```

To find a transpose of a matrix

```
y=np.array([[1,2,3],[3,4,5]])
y.transpose()
```

```
To multiply two matrices
```

```
x=np.array([[1,2],[3,4]])
y=np.array([[1,2,3],[3,4,5]])
np.dot(x,y)
```

To find a transpose of a matrix

```
y=np.array([[1,2,3],[3,4,5]])
y.transpose()
```

To find inverse of a matrix

```
y=np.array([[1,2,3],[3,4,5]])

np.linalg.inv(y)
```

• To load data from file data =np.loadtxt(open("data.csv", "rb"), delimiter = ',')

• Import : from sklearn import linear_model

- Import : from sklearn import linear_model
- Select Model

 $regr = linear_model.LinearRegression(fit_intercept = True)$

- Import : from sklearn import linear_model
- Select Model

 regr = linear_model.LinearRegression(fit_intercept=True)
- Train the model using training data regr.fit(X_train, y_train)
- Make predictions using test data
 y_pred = regr.predict(X_test)

- To retrieve coefficients: $\theta_1, t\theta_2, \dots$ regr.coef_
- To retrieve coefficient θ_0 regr.intercept_

Assignment 1: Single Variable Linear Regression

Load file "data_train_sv.csv" to train_data Load file "data_test_sv.csv" to train_data

- Train linear regression model using train_data and predict the target values of test_data
- Compute Mean squared error
- Plot the model

Linear Regression: Evaluation Metrics

• Import from sklearn.metrics import mean_squared_error

Linear Regression: Evaluation Metrics

- Import from sklearn.metrics import mean_squared_error
- \bullet mean_squared_error(y_test, y_pred)

Linear Regression

Training the model

```
\begin{aligned} &\operatorname{regr.fit}(\mathbf{X}\_\operatorname{train}, \, \mathbf{y}\_\operatorname{train}) \\ &\theta = (X\_\operatorname{train}^T * X\_\operatorname{train})^{-1} * X\_\operatorname{train}^T * y\_\operatorname{train} \end{aligned}
```

Linear Regression

```
Training the model  \begin{array}{l} \operatorname{regr.fit}(\mathbf{X}\_\operatorname{train},\,\mathbf{y}\_\operatorname{train}) \\ \theta = (X\_\operatorname{train}^T * X\_\operatorname{train})^{-1} * X\_\operatorname{train}^T * y\_\operatorname{train} \end{array}  Prediction of target value of test data  \begin{array}{l} \mathbf{y}\_\operatorname{pred} = \operatorname{regr.predict}(\mathbf{X}\_\operatorname{test}) \\ y\_\operatorname{pred} = X\_\operatorname{test}\theta \end{array}
```

Matplotlib

• import matplotlib.pyplot as plt plt.scatter(X_test, y_test, color='black')

Matplotlib

• import matplotlib.pyplot as plt plt.scatter(X_test, y_test, color='black') plt.plot(X_test, y_pred, color='blue', linewidth=3)

Matplotlib

• import matplotlib.pyplot as plt plt.scatter(X_test, y_test, color='black') plt.plot(X_test, y_pred, color='blue', linewidth=3) plt.show()

Assignment 1: Multiple Variable Linear Regression

Load file "housing_data.csv" to data Split 80% of data to training data and 20% of data to test data Normalize features (Feature scaling)

- Train linear regression model using train_data and predict the target values of test_data
- Compute Mean squared error

Training and Testing Data Split

from sklearn.model_selection import train_test_split X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=42)

Feature Scaling

```
\begin{split} & \text{from sklearn.preprocessing import StandardScaler} \\ & \text{scaler} = \text{StandardScaler}() \\ & \text{scaler.fit}(X\_\text{train}) \\ & X\_\text{train} = \text{scaler.transform}(X\_\text{train}) \\ & X\_\text{test} = \text{scaler.transform}(X\_\text{test}) \end{split}
```

Assignment 3: Polynomial Curve Fitting

Dataset Generation

Let the underlying function be

$$y_actual = cos^2 2\pi X$$

Plot the function y_actual

$$X = \text{np.linspace}(0, 0.5, 100)$$

y_actual = np.cos(2 * np.pi * X)**2

Assignment 3: Polynomial Curve Fitting

Dataset Generation

Let the underlying function be

$$y_actual = cos^2 2\pi X$$

Plot the function y_actual

$$X = \text{np.linspace}(0, 0.5, 100)$$

 $y_{\text{actual}} = \text{np.cos}(2 * \text{np.pi} * X)**2$

Generate the dataset by adding noise to the underlying function

Assignment 3: Polynomial Curve Fitting

Dataset Generation

Let the underlying function be

$$y_actual = cos^2 2\pi X$$

Plot the function y_actual

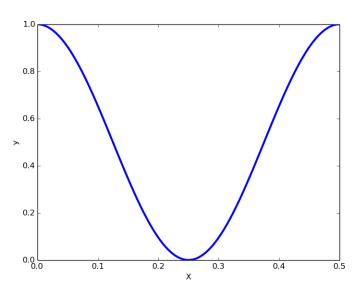
$$X = \text{np.linspace}(0, 0.5, 100)$$

 $y_{\text{actual}} = \text{np.cos}(2 * \text{np.pi} * X)**2$

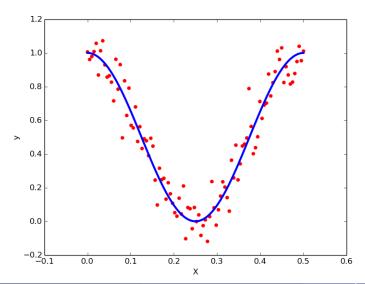
Generate the dataset by adding noise to the underlying function noise = np.random.normal(0, 0.1, 100) $y=y_{actual+noise}$

Plot underlying function y_actual and y

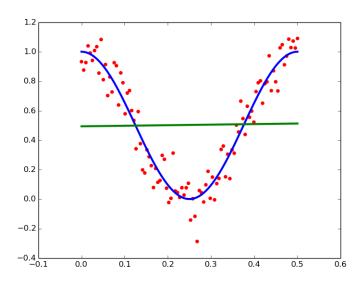
Assignment 3: Polynomial Curve Fitting Dataset Generation



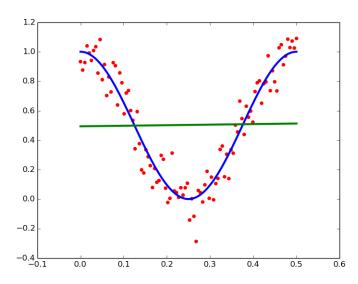
Dataset Generation



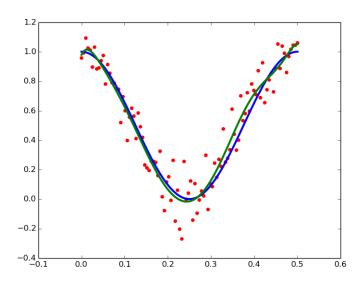
Fit linear regression model

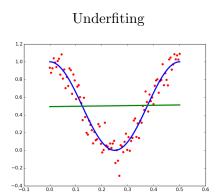


- Import
 - from sklearn.preprocessing import PolynomialFeatures from sklearn.pipeline import Pipeline
- \bullet deg=2
- polynomial_features =
 PolynomialFeatures(degree=deg,include_bias=True)
- linear_regression = linear_model.LinearRegression()
- pipeline = Pipeline([("polynomial_features", polynomial_features),
 ("linear_regression", linear_regression)])
- pipeline.fit(X_train, y_train)

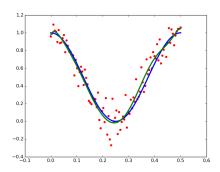


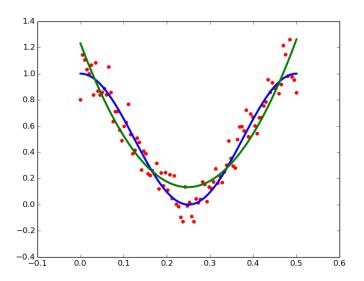
Assignment 3: Polynomial Curve Fitting $_{\text{deg}=10}$





Overfiting





Regularization

$$J(\theta) = \frac{1}{2m} \sum_{i=1}^{m} (h_{\theta}(x^{(i)}) - y(i))^{2} + \lambda \theta^{T} \theta$$

 λ is the regularization parameter

Regularization

 $model = linear_model.Ridge(alpha=0.001, fit_intercept=True)$

To use sample datasets in Sklearn

$$\label{eq:continuous} \begin{split} & \text{from sklearn import datasets} \\ & \text{data} = \text{datasets.load_breast_cancer()} \\ & X {=} \\ & \text{data.data} \\ & y {=} \\ & \text{data.target} \end{split}$$

Logistic Regression

```
classifier = linear_model.LogisticRegression()
classifier.fit(X_train, y_train)
y_pred = classifier.predict(X_test)
```