BÀI TUẦN 04: EVALUATING REGRESSION MODELS PERFORMANCE

1. Thông tin sinh viên

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2.Source

1. Linear Regression

```
1. import matplotlib.pyplot as plt
2. import pandas as pd
3.
4. # dataset = pd.read_csv('Position_Salaries.csv')
5. dataset_train = pd.read_csv('Position_SalariesTrain.csv')
6. dataset_test = pd.read_csv('Position_SalariesTest.csv')
7. X = dataset_train.iloc[:, 1:-1].values
8. Y = dataset_train.iloc[:, -1].values
9. X_test = dataset_test.iloc[:, 1:-1].values
10. Y_test = dataset_test.iloc[:, -1].values
11.
12. from sklearn.linear_model import LinearRegression
13. lin_reg = LinearRegression()
14. lin_{reg.fit}(X, Y)
15. Y_pred = lin_reg.predict(X)
16. Y_pred_test = lin_reg.predict(X_test)
17. plt.scatter(X_test, Y_test, color = "red")
18. plt.scatter(X_test, Y_pred_test, color = "black")
19. plt.plot(X, Y_pred, color = "blue")
20. plt.title("Position Level vs Salary (Linear Regression)")
21. plt.xlabel("Position Level")
22. plt.ylabel("Salary (dollars/year)")
23. plt.show()
25. from sklearn.metrics import mean_squared_error
26. from math import sqrt
27. print("SSE",len(X_test)*mean_squared_error(Y_test, Y_pred_test))
28. print("RMSE", sqrt(mean_squared_error(Y_test, Y_pred_test)))
29. from sklearn.metrics import r2_score
30. r2=r2_score(Y_test, Y_pred_test)
31. print("r2= ",r2)
```

```
32. adjusted_r_squared = 1 - (1-r2)*((len(Y_test)-1)/(len(Y_test)-X_test.shape[1]-
1))
33. print("adjusted_r_squared",adjusted_r_squared)
34. import statsmodels.regression.linear_model as sm
35. regressor_OLS = sm.OLS(endog = Y, exog = X).fit()
36. print(regressor_OLS.summary())
```

2. Polynomial Regression

```
1. import numpy as np
2. import matplotlib.pyplot as plt
3. import pandas as pd
4.
5. # dataset = pd.read csv('Position Salaries.csv')
6. dataset_train = pd.read_csv('Position_SalariesTrain.csv')
7. dataset test = pd.read csv('Position SalariesTest.csv')
8. X = dataset_train.iloc[:, 1:-1].values
9. Y = dataset_train.iloc[:, -1].values
10. X_test = dataset_test.iloc[:, 1:-1].values
11. Y test = dataset test.iloc[:, -1].values
12.
13. from sklearn.preprocessing import PolynomialFeatures
14. poly_transform = PolynomialFeatures(degree=4)
15. X poly = poly transform.fit transform(X)
16. X_poly_test = poly_transform.fit_transform(X_test)
17.
18. from sklearn.linear_model import LinearRegression
19. poly lin reg = LinearRegression()
20. poly_lin_reg.fit(X_poly, Y)
21.
22. Y_poly_pred = poly_lin_reg.predict(X_poly)
23. Y_poly_pred_test = poly_lin_reg.predict(X_poly_test)
24. plt.scatter(X_test, Y_test ,color = "red")
25. plt.plot(X, Y_poly_pred, color = "blue")
26. plt.scatter(X_test, Y_poly_pred_test ,color = "black")
27. plt.title("Position Level vs Salary(Polynomial Regression)")
28. plt.xlabel("Position Level")
29. plt.ylabel("Salary (dollars/year)")
30. plt.show()
31.
32. X_grid = np.arange(0, max(X)+1, 0.1)
33. X_grid = X_grid.reshape((len(X_grid), 1))
34. plt.scatter(X_test, Y_test, color = "red")
35. plt.plot(X_grid, poly_lin_reg.predict(poly_transform.fit_transform(X_grid)),
   color = 'blue')
36. plt.scatter(X test, Y poly pred test, color = "black")
```

```
37. plt.title("Position Level vs Salary(Polynomial Regression)")
38. plt.xlabel("Position Level")
39. plt.ylabel("Salary (dollars/year)")
40. plt.show()
41.
42.
43. # from sklearn.metrics import mean absolute error
44. # print("MAE", mean_absolute_error(Y_test, Y_poly_pred_test))
45. from sklearn.metrics import mean_squared_error
46. from math import sqrt
47. print("SSE",len(X_test)*mean_squared_error(Y_test, Y_poly_pred_test))
48. print("RMSE", sqrt(mean_squared_error(Y_test, Y_poly_pred_test)))
49. from sklearn.metrics import r2_score
50. r2=r2 score(Y test, Y poly pred test)
51. print("r2=",r2)
52. adjusted_r_squared = 1 - (1-r^2)*((len(Y_test)-1)/(len(Y_test)-X_test.shape[1]-1))
53. print("adjusted_r_squared= ",adjusted_r_squared)
54. import statsmodels.regression.linear_model as sm
55. regressor_OLS = sm.OLS(endog = Y, exog = X).fit()
56. print(regressor_OLS.summary())
```

3. Support Vector Regression (SVR)

```
1. import numpy as np
2. import matplotlib.pyplot as plt
3. import pandas as pd
4.
5. # dataset = pd.read_csv('Position_Salaries.csv')
6. dataset_train = pd.read_csv('Position_SalariesTrain.csv')
7. dataset test = pd.read csv('Position SalariesTest.csv')
8. X = dataset_train.iloc[:, 1:-1].values
9. Y = dataset_train.iloc[:, -1].values
10. X_test = dataset_test.iloc[:, 1:-1].values
11. Y_test = dataset_test.iloc[:, -1].values
12. Y = Y.reshape(len(Y),1)
13. Y_test = Y_test.reshape(len(Y_test),1)
14. from sklearn.preprocessing import StandardScaler
15. sc X = StandardScaler()
16. sc_y = StandardScaler()
17. X trans = sc X.fit transform(X)
18. Y_trans = sc_y.fit_transform(Y)
19. from sklearn.svm import SVR
20. regressor = SVR(kernel = 'rbf')
21. regressor.fit(X_trans, Y_trans)
```

```
22. def predict(model, X, SC_X, SC_Y):
     X_{trans} = SC_{X.transform}(X)
23.
      Y_trans_pred = model.predict(X_trans)
24.
25.
      Y_pred = SC_Y.inverse_transform(Y_trans_pred)
26. return Y_pred
27. Y_pred_train = predict(regressor, X, sc_X, sc_y)
28. Y pred test = predict(regressor, X test, sc X, sc y)
29. plt.scatter(X test, Y test, color = 'red')
30. plt.scatter(X_test, Y_pred_test, color = 'black')
31. plt.plot(X, Y pred train, color = 'blue')
32. plt.title('Truth or Bluff (SVR)')
33. plt.xlabel('Position level')
34. plt.ylabel('Salary')
35. plt.show()
36.
37. X grid = np.arange(0, 11, 0.1)
38. X grid= X grid.reshape((len(X grid), 1))
39. Y_pred_grid = predict(regressor, X_grid, sc_X, sc_y)
40. plt.scatter(X_test, Y_test, color = 'red')
41. plt.scatter(X_test, Y_pred_test, color = 'black')
42. plt.plot(X_grid, Y_pred_grid, color = 'blue')
43. plt.title('Truth or Bluff (SVR)')
44. plt.xlabel('Position level')
45. plt.ylabel('Salary')
46. plt.show()
47.
48. from sklearn.metrics import mean_squared_error
49. from math import sqrt
50. print("SSE",len(X test)*mean squared error(Y test, Y pred test))
51. print("RMSE", sqrt(mean_squared_error(Y_test, Y_pred_test)))
52. from sklearn.metrics import r2_score
53. r2=r2_score(Y_test, Y_pred_test)
54. print("r2=",r2)
55. adjusted r squared = 1 - (1-r^2)*((len(Y test)-1)/(len(Y test)-X test.shape[1]-1))
56. print("adjusted_r_squared= ",adjusted_r_squared)
```

4. Decision Tree Regression

- 1. import numpy as np
- 2. import matplotlib.pyplot as plt
- 3. import pandas as pd
- 4.
- 5. # dataset = pd.read_csv('Position_Salaries.csv')
- 6. dataset_train = pd.read_csv('Position_SalariesTrain.csv')
- 7. dataset_test = pd.read_csv('Position_SalariesTest.csv')

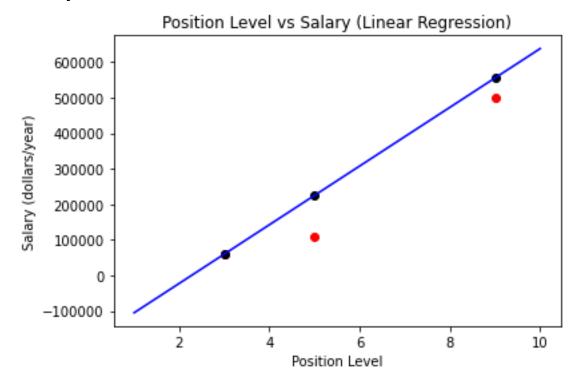
```
8. X = dataset_train.iloc[:, 1:-1].values
9. Y = dataset_train.iloc[:, -1].values
10. X_test = dataset_test.iloc[:, 1:-1].values
11. Y_test = dataset_test.iloc[:, -1].values
12. Y = Y.reshape(len(Y), 1)
13. Y_test = Y_test.reshape(len(Y_test),1)
14. from sklearn.tree import DecisionTreeRegressor
15. regressor = DecisionTreeRegressor(random_state = 0)
16. regressor.fit(X, Y)
17. Y_pred_test=regressor.predict(X_test)
18. X_{grid} = np.arange(min(X), max(X), 0.01)
19. X_grid = X_grid.reshape((len(X_grid), 1))
20. plt.scatter(X_test, Y_test, color = 'red')
21. plt.scatter(X_test, Y_pred_test, color = 'black')
22. plt.plot(X_grid, regressor.predict(X_grid), color = 'blue')
23. plt.title('Truth or Bluff (Decision Tree Regression)')
24. plt.xlabel('Position level')
25. plt.ylabel('Salary')
26. plt.show()
27.
28. from sklearn.metrics import mean_squared_error
29. from math import sqrt
30. print("SSE",len(X_test)*mean_squared_error(Y_test, Y_pred_test))
31. print("RMSE", sqrt(mean_squared_error(Y_test, Y_pred_test)))
32. from sklearn.metrics import r2_score
33. r2=r2_score(Y_test, Y_pred_test)
34. print("r2=",r2)
35. adjusted_r_squared = 1 - (1-r^2)*((len(Y_test)-1)/(len(Y_test)-1))
   X \text{ test.shape}[1]-1)
36. print("adjusted_r_squared= ",adjusted_r_squared)
```

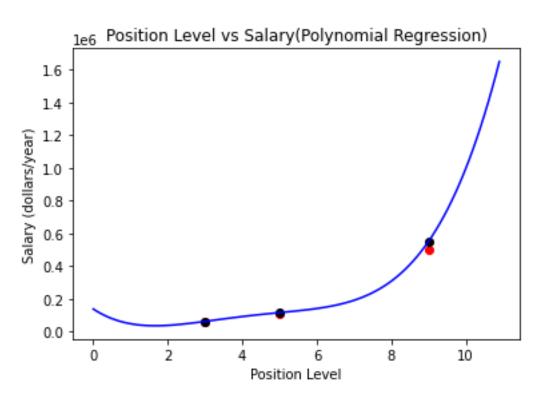
5. Random Forest Regression

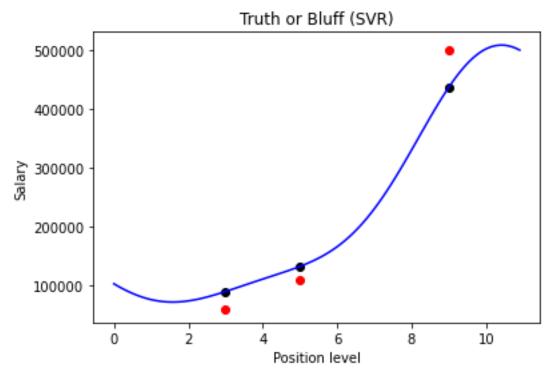
- 1. import numpy as np
- 2. import matplotlib.pyplot as plt
- 3. import pandas as pd
- 4.
- 5. # dataset = pd.read_csv('Position_Salaries.csv')

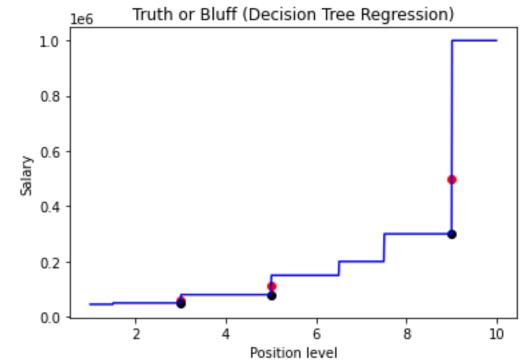
```
6. dataset_train = pd.read_csv('Position_SalariesTrain.csv')
7. dataset_test = pd.read_csv('Position_SalariesTest.csv')
8. X = dataset_train.iloc[:, 1:-1].values
9. Y = dataset_train.iloc[:, -1].values
10. X_test = dataset_test.iloc[:, 1:-1].values
11. Y_test = dataset_test.iloc[:, -1].values
12. Y = Y.reshape(len(Y), 1)
13. Y_test = Y_test.reshape(len(Y_test),1)
14.
15. from sklearn.ensemble import RandomForestRegressor
16. regressor = RandomForestRegressor(n_estimators = 7, random_state =
   0)
17. regressor.fit(X, Y)
18. Y_pred_test=regressor.predict(X_test)
19. X_{grid} = np.arange(min(X), max(X), 0.1)
20. X_grid = X_grid.reshape((len(X_grid), 1))
21. plt.scatter(X_test, Y_test, color = 'red')
22. plt.scatter(X_test, Y_pred_test, color = 'black')
23. plt.plot(X_grid, regressor.predict(X_grid), color = 'blue')
24. plt.title('Truth or Bluff (Random Forest Regression)')
25. plt.xlabel('Position level')
26. plt.ylabel('Salary')
27. plt.show()
28.
29. from sklearn.metrics import mean_squared_error
30. from math import sqrt
31. print("SSE",len(X_test)*mean_squared_error(Y_test, Y_pred_test))
32. print("RMSE", sqrt(mean_squared_error(Y_test, Y_pred_test)))
33. from sklearn.metrics import r2 score
34. r2=r2_score(Y_test, Y_pred_test)
35. print("r2=",r2)
36. adjusted_r\_squared = 1 - (1-r2)*((len(Y_test)-1)/(len(Y_test)-1))
   X_{\text{test.shape}}[1]-1)
37. print("adjusted_r_squared= ",adjusted_r_squared)
```

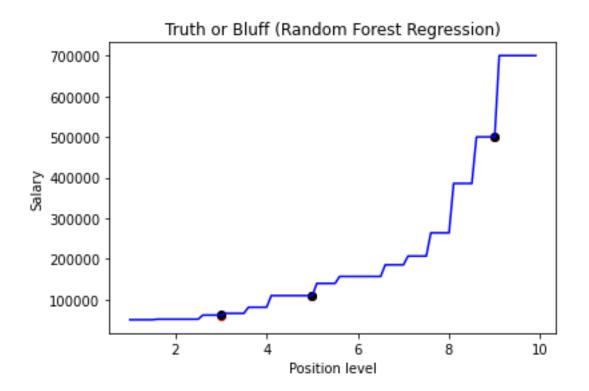
3. Kết quả











	Squared Sum (SSE	RMSE	R^2	R_adjusted^2
Linear Regression	16378430468.137295	73888.27256549196	0.8588877328994489	0.7177754657988977
Polynomial Regression	2839073339.221048	30762.928660001624	0.9755392877149249	0.9510785754298499
Support Vector Regression (SVR)	5277090661.4986925	41940.79422828762	0.9545339690278688	0.9090679380557376
Decision Tree Regression	41000000000.0	116904.5194450012	0.6467547386559449	0.2935094773118898

Random	4591836.734693887	1237.179148263485	0.999960437937380	0.9999208758747611
Forest				
Regression				

Nhân xét:

- Với Hàm lỗi Squared Sum (SSE) thì phương pháp Random Forest Regression là tốt nhất.
- Với Hàm lỗi Root Mean Squared (RMSE) thì phương pháp Random Forest Regression là tốt nhất.
- Với Hàm đánh giá R^2 thì phương pháp Random Forest Regression là tốt nhất.
- Với Hàm đánh giá R adjusted^2 thì phương pháp Random Forest Regression là tốt nhất.
- Với tập dữ liệu và test trên thì với phương pháp Random Forest Regression thì cho tất cả các đánh giá độ đo là tốt nhất.
- -Với việc random_state = 0 thì cho ta thấy được phương pháp Random Forest Regression là tốt nhất.
- Với tập dữ liệu và test trên thì với phương pháp Decision Tree Regression thì cho tất cả các đánh giá độ đo là tệ nhất.
- -Nếu không có random_state = 0 thì sẽ cho những kết quả khác nhau sau mỗi lần chạy.

Run 1:

```
SSE 2177551020.408165

RMSE 26941.60982822027

r2= 0.9812387907489245

adjusted_r_squared= 0.962477581497849
```

Run 2:

```
SSE 206632653.0612244
RMSE 8299.25002758732
r2= 0.9982197071821262
adjusted_r_squared= 0.9964394143642523
```

Run 3:

```
SSE 45922959183.67346
RMSE 123724.10056745002
r2= 0.6043398117431924
adjusted_r_squared= 0.2086796234863848
```

Run 4:

```
SSE 13163265306.122444
RMSE 66240.13211068358
r2= 0.8865887538243328
adjusted_r_squared= 0.7731775076486656
```

Run 5:

```
SSE 10002040816.32653
RMSE 57740.917947692666
r2= 0.9138250360454349
adjusted_r_squared= 0.8276500720908697
```

- Với việc chạy ngẫu nhiên 5 lần với việc không dùng random_state = 0 thì kết quả hoàn toàn khác nhau không tốt nhất với một số lần chạy trên. Với Run 3 thì có lẽ là kết quả tệ nhất với 5 phương pháp.