

# Chapter 9 - Ex2: Iris - Multiple Linear Regression

Cho dữ liệu Iris.xls

**Yêu cầu: Thực hiện linear regression để từ sepalength, sepalwidth, petallength => dự đoán petalwidth**

1. Đọc dữ liệu, trực quan hóa dữ liệu.
2. Tạo X\_train, X\_test, y\_train, y\_test từ dữ liệu đọc được là sepalength, sepalwidth, petallength (inputs) và petalwidth (outputs) với tỷ lệ dữ liệu test là 0.2
3. Áp dụng linear regression
4. Vẽ hình. Nhận xét kết quả
5. Nếu sepalength, sepalwidth, petallength là 4.5, 3.1, 1.6 => petalwidth là bao nhiêu?
6. Áp dụng lựa chọn thuộc tính quan trọng cho model. Xây dựng lại model sau khi lựa chọn các thuộc tính quan trọng.

```
In [1]: #!pip install pandas-profiling==2.7.1
```

```
In [2]: # from google.colab import drive
# drive.mount("/content/gdrive", force_remount=True)
# %cd '/content/gdrive/My Drive/MDS5_2022/Practice_2022/Chapter9/'
```

```
In [3]: import pandas as pd
import pandas_profiling as pp
```

```
In [4]: iris = pd.read_excel("Iris.xls")
iris.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
#   Column          Non-Null Count  Dtype
---  -
0   sepalength      150 non-null   float64
1   sepalwidth      150 non-null   float64
2   petallength     150 non-null   float64
3   petalwidth      150 non-null   float64
4   iris            150 non-null   object
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```



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

```
Out[5]:
```

	sepal.length	sepal.width	petal.length	petal.width	iris
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa



```
In [6]: profile = pp.ProfileReport(iris)
profile
```

Summarize

19/? [00:05<00:00, 3.01it/s,

dataset:

Completed]

Generate report structure:

1/1 [00:01<00:00,

100%

1.34s/it]

Render HTML: 100%

1/1 [00:00<00:00, 1.72it/s]





# Overview

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## Dataset statistics

Number of variables	5
Number of observations	150
Missing cells	0
Missing cells (%)	0.0%
Duplicate rows	3
Duplicate rows (%)	2.0%
Total size in memory	15.1 KiB
Average record size in memory	103.2 B

## Variable types

NUM	4
CAT	1

# Variables

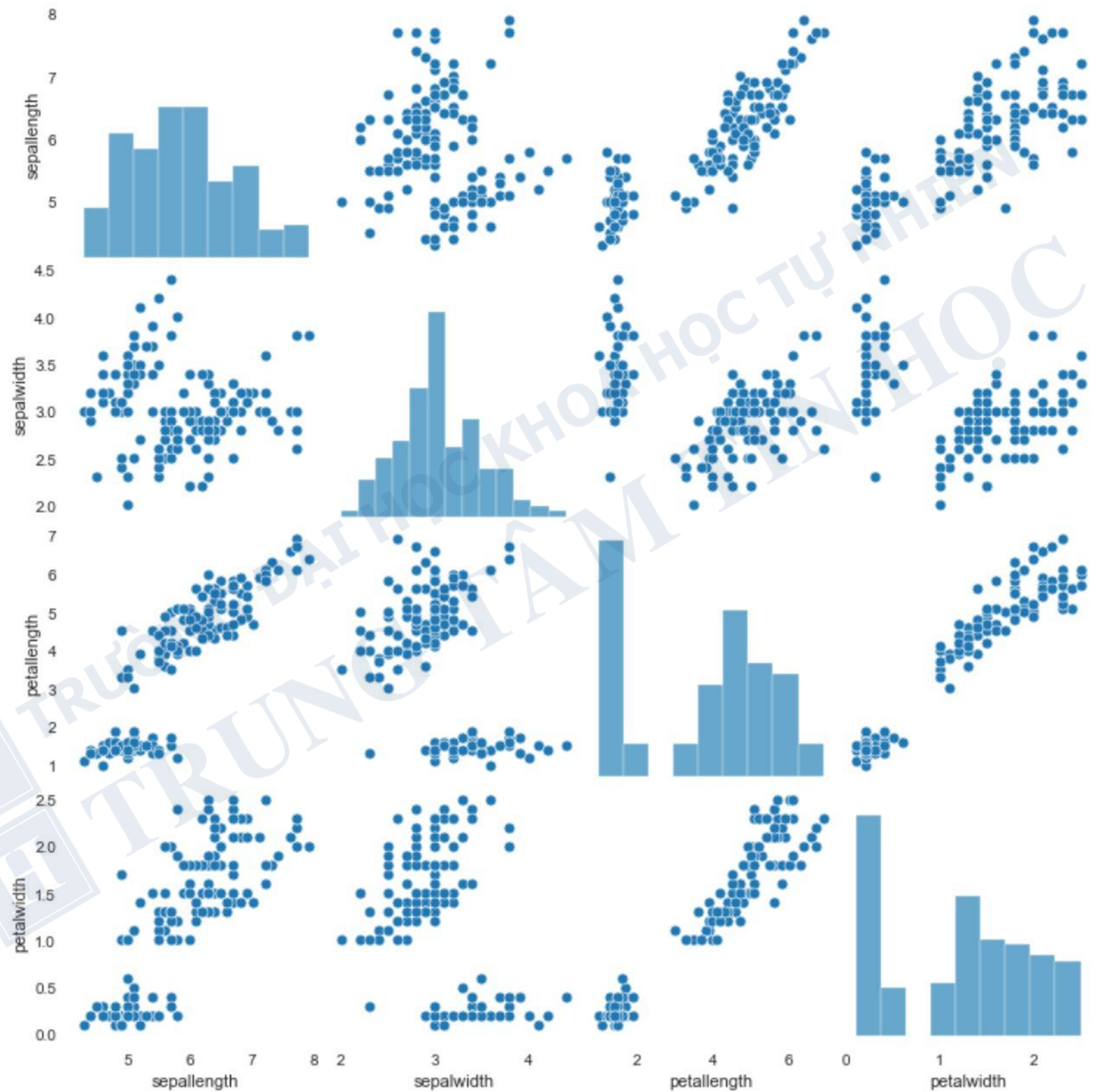
Out[6]:

```
In [7]: profile.to_file("output.html")
```



```
In [8]: import matplotlib.pyplot as plt
import seaborn as sns
```

```
In [9]: sns.pairplot(iris)
plt.show()
```





```
In [10]: inputs = iris[['sepalength', 'sepalwidth', 'petallength']]
inputs.head()
```

Out[10]:

	sepalength	sepalwidth	petallength
0	5.1	3.5	1.4
1	4.9	3.0	1.4
2	4.7	3.2	1.3
3	4.6	3.1	1.5
4	5.0	3.6	1.4

```
In [11]: outputs = iris[['petalwidth']]
outputs.head()
```

Out[11]:

	petalwidth
0	0.2
1	0.2
2	0.2
3	0.2
4	0.2

```
In [12]: import numpy as np
from sklearn import datasets, linear_model
from sklearn.metrics import mean_squared_error, r2_score
```

```
In [13]: from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(inputs, outputs,
                                                    test_size=0.20)

regr1 = linear_model.LinearRegression()
regr1 = regr1.fit(X_train, y_train)
```

```
In [14]: y_pred = regr1.predict(X_test)
```

```
In [15]: # The mean squared error
print("Mean squared error: %.2f"
      % mean_squared_error(outputs, regr1.predict(inputs)))
# Explained variance score: 1 is perfect prediction
print('Variance score: %.2f' % regr1.score(inputs, outputs))
```

Mean squared error: 0.04  
Variance score: 0.94

```
In [16]: # Score = 94% => model fits with ~ 94% data => This is suitable model.
```



```
In [17]: print('Variance score: %.2f' % r2_score(y_test, y_pred)) # y real, y predict
```

Variance score: 0.94

```
In [18]: # Check the score of train and test
```

```
In [19]: regr1.score(X_train, y_train)
```

```
Out[19]: 0.9357294091323384
```

```
In [20]: regr1.score(X_test, y_test)
```

```
Out[20]: 0.9436762270965792
```

```
In [21]: # Both training data and testing data have high score.  
# => Choose this model.
```

```
In [22]: # The coefficients  
m=regr1.coef_  
b=regr1.intercept_  
print('Coefficients: \n', m)  
print('Intercept: \n', b)
```

Coefficients:  
[[-0.16565783 0.17339064 0.50356191]]  
Intercept:  
[-0.25647234]

```
In [23]: # Visualization  
y_train_hat = regr1.predict(X_train)  
y_test_hat = regr1.predict(X_test)
```



```
In [24]: plt.figure(figsize=(10,5))
plt.subplot(1, 2, 1)
ax1 = sns.distplot(y_train, hist=False, color="b", label='Train Actual')
sns.distplot(y_train_hat, hist=False, color="r", label='Train Predict', ax=ax1)
plt.subplot(1,2,2)
ax2 = sns.distplot(y_test, hist=False, color="b", label='Test Actual')
sns.distplot(y_test_hat, hist=False, color="r", label='Test Predict', ax=ax2)
plt.show()
```

c:\program files\python36\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `kdeplot` (an axes-level function for kernel density plots).

warnings.warn(msg, FutureWarning)

c:\program files\python36\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `kdeplot` (an axes-level function for kernel density plots).

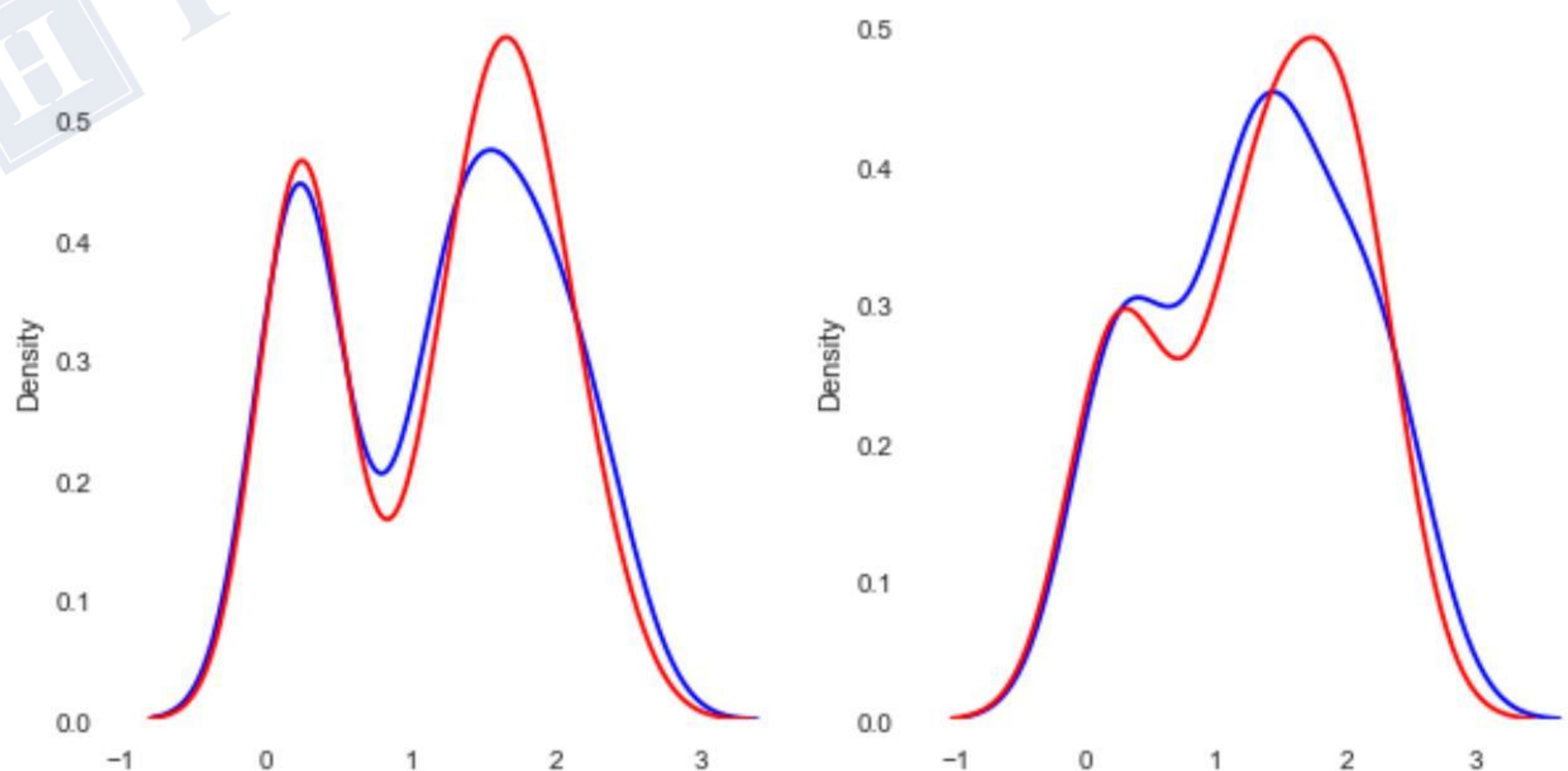
warnings.warn(msg, FutureWarning)

c:\program files\python36\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `kdeplot` (an axes-level function for kernel density plots).

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warnings.warn(msg, FutureWarning)





```
In [25]: # Make new prediction
x_now = [[4.5, 3.1, 1.6]]
y_now = regr1.predict(x_now)
print(y_now)
```

```
[[0.34127746]]
```

## Select important features

### Solution 1: SelectKBest

```
In [26]: # Univariate Selection
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import f_regression
```

```
In [27]: # Apply SelectKBest class to extract all best features
bestfeatures = SelectKBest(score_func=f_regression, k='all')
fit = bestfeatures.fit(inputs, outputs)
dfscores = pd.DataFrame(fit.scores_)
dfcolumns = pd.DataFrame(inputs.columns)
```

c:\program files\python36\lib\site-packages\sklearn\utils\validation.py:73: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n\_samples, ), for example using ravel().

```
return f(**kwargs)
```

```
In [28]: #concat two dataframes for better visualization
featureScores = pd.concat([dfcolumns,dfscores],axis=1)
featureScores.columns = ['Specs', 'Score'] # naming the dataframe columns
print(featureScores.nlargest(3,'Score')) # print 3 best features
```

	Specs	Score
2	petallength	1876.657813
0	sepalength	299.194957
1	sepalwidth	21.554378

```
In [29]: # 2 features have highest scores
X_now = inputs[['petallength', 'sepalength']]
```

```
In [30]: X_train_n, X_test_n, y_train_n, y_test_n = train_test_split(X_now, outputs,
                                                                    test_size=0.20)

regr_n = linear_model.LinearRegression()
regr_n = regr1.fit(X_train_n, y_train_n)
```



```
In [31]: # The mean squared error
print("Mean squared error: %.2f"
      % mean_squared_error(outputs, regr_n.predict(X_now)))
# Explained variance score: 1 is perfect prediction
print('Variance score: %.2f' % regr_n.score(X_now, outputs))
```

Mean squared error: 0.04  
Variance score: 0.93

```
In [32]: print("Train's score:", regr_n.score(X_train_n, y_train_n))
```

Train's score: 0.9318674342068523

```
In [33]: print("Test's score:", regr_n.score(X_test_n, y_test_n))
```

Test's score: 0.9115055217267548

## Solution 2: Correlation Matrix with Heatmap

```
In [34]: # get correlations of each features in dataset
data_sub = iris.iloc[:,0:4]
corrmat = data_sub.corr()
top_corr_features = corrmat.index
```

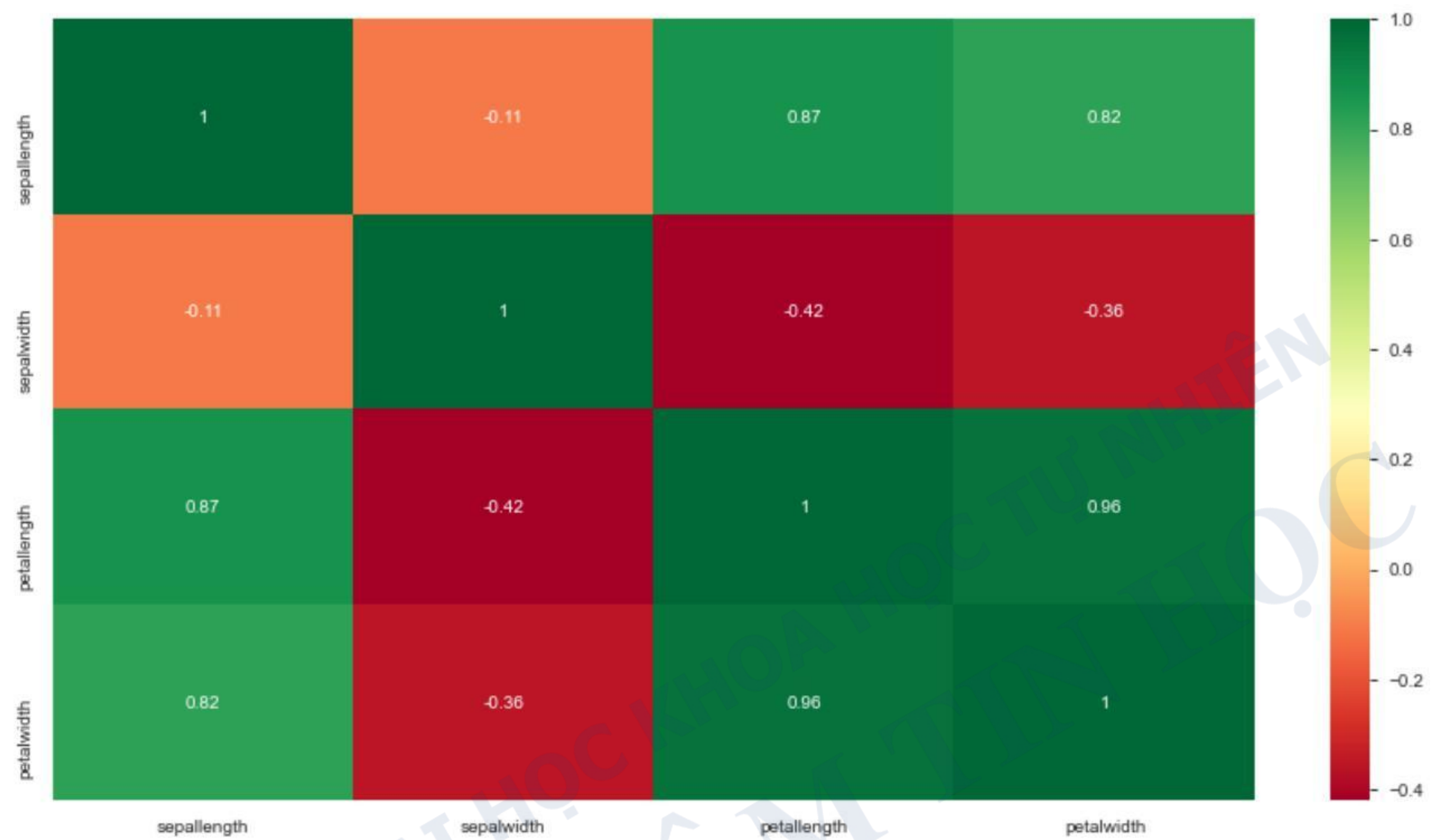
```
In [35]: data_sub.corr()
```

Out[35]:

	sepalength	sepalwidth	petallength	petalwidth
sepalength	1.000000	-0.109369	0.871754	0.817954
sepalwidth	-0.109369	1.000000	-0.420516	-0.356544
petallength	0.871754	-0.420516	1.000000	0.962757
petalwidth	0.817954	-0.356544	0.962757	1.000000



```
In [36]: plt.figure(figsize=(15,8))  
#plot heat map  
g=sns.heatmap(data_sub[top_corr_features].corr(),cmap="RdYlGn", annot=True) # ani
```



In [ ]: