

# PythonByCasviRandom

September 4, 2024

```
[35]: import pandas as pd
!pip install scikit-learn -i https://pypi.tuna.tsinghua.edu.cn/simple
```

```
Looking in indexes: https://pypi.tuna.tsinghua.edu.cn/simple
Requirement already satisfied: scikit-learn in ./config/jupyterlab-
desktop/jlab_server/lib/python3.12/site-packages (1.5.1)
Requirement already satisfied: numpy>=1.19.5 in ./config/jupyterlab-
desktop/jlab_server/lib/python3.12/site-packages (from scikit-learn) (2.1.0)
Requirement already satisfied: scipy>=1.6.0 in ./config/jupyterlab-
desktop/jlab_server/lib/python3.12/site-packages (from scikit-learn) (1.14.1)
Requirement already satisfied: joblib>=1.2.0 in ./config/jupyterlab-
desktop/jlab_server/lib/python3.12/site-packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in ./config/jupyterlab-
desktop/jlab_server/lib/python3.12/site-packages (from scikit-learn) (3.5.0)
```

```
[36]: df=pd.read_csv('https://raw.githubusercontent.com/dataprofessor/data/master/
↳delaney_solubility_with_descriptors.csv')
```

```
[37]: df
```

```
[37]:
```

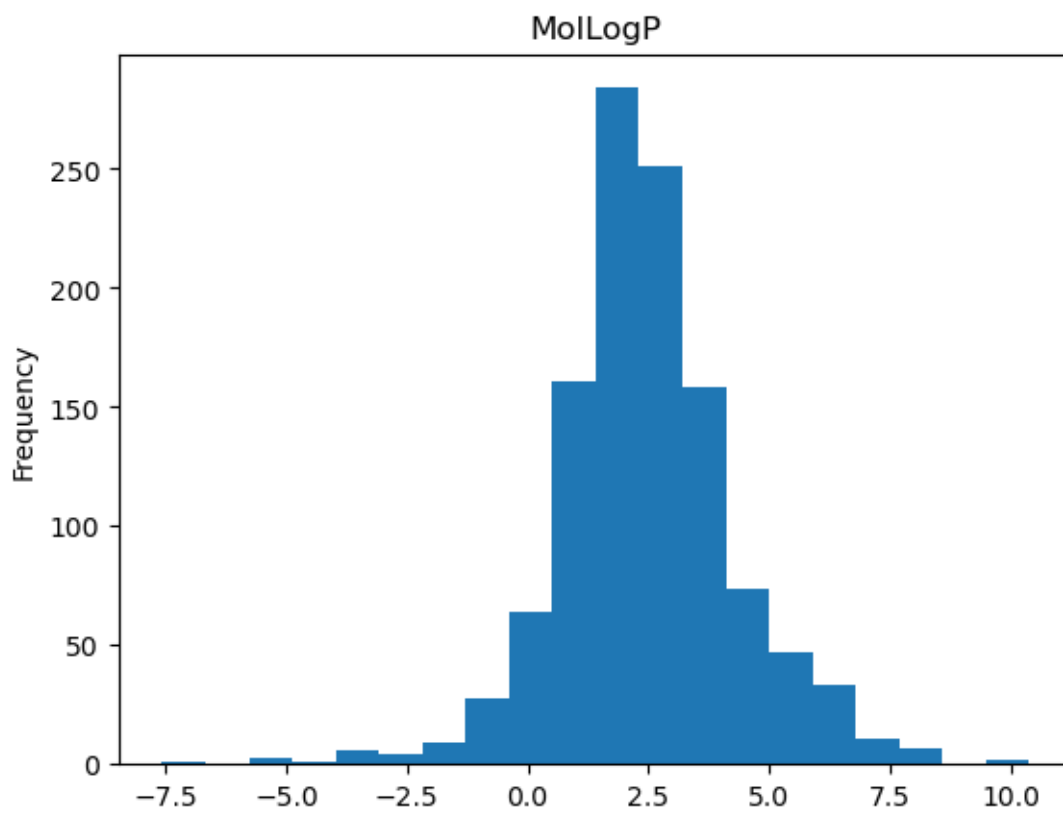
	MolLogP	MolWt	NumRotatableBonds	AromaticProportion	logS
0	2.59540	167.850	0.0	0.000000	-2.180
1	2.37650	133.405	0.0	0.000000	-2.000
2	2.59380	167.850	1.0	0.000000	-1.740
3	2.02890	133.405	1.0	0.000000	-1.480
4	2.91890	187.375	1.0	0.000000	-3.040
...	...	...	...	...	...
1139	1.98820	287.343	8.0	0.000000	1.144
1140	3.42130	286.114	2.0	0.333333	-4.925
1141	3.60960	308.333	4.0	0.695652	-3.893
1142	2.56214	354.815	3.0	0.521739	-3.790
1143	2.02164	179.219	1.0	0.461538	-2.581

```
[1144 rows x 5 columns]
```

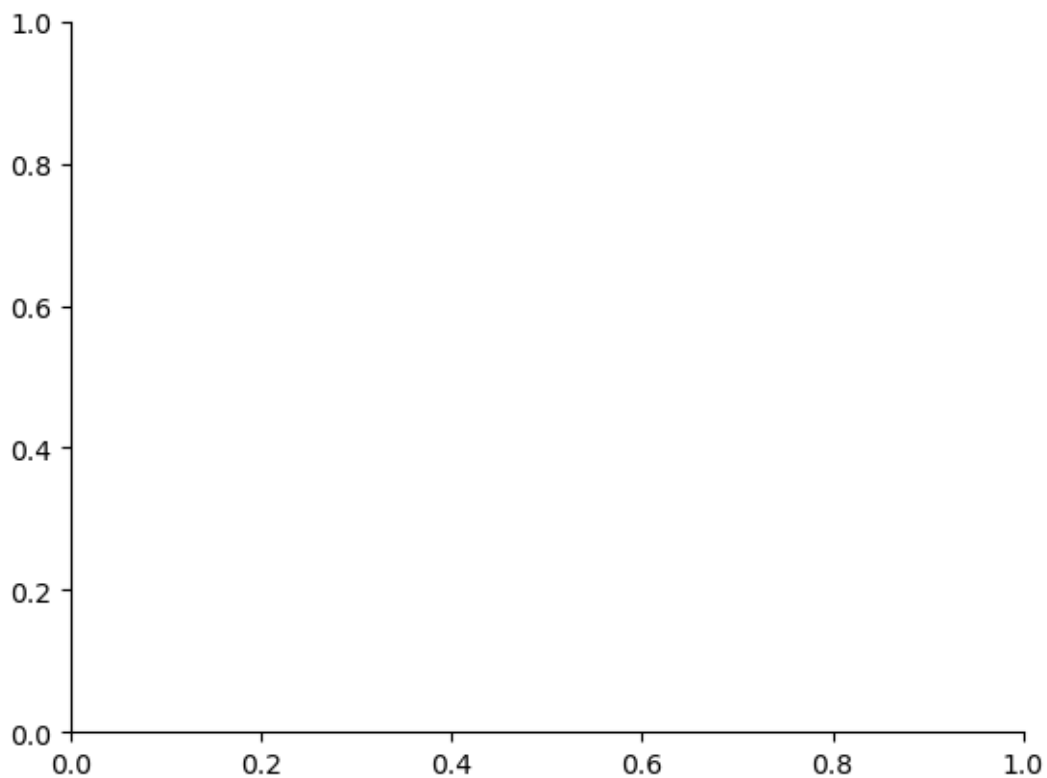
```
[38]: from matplotlib import pyplot as plt
```

```
[39]: df['MolLogP'].plot(kind='hist', bins=20, title='MolLogP')
```

```
[39]: <Axes: title={'center': 'MolLogP'}, ylabel='Frequency'>
```



```
[40]: plt.gca().spines[['top', 'right',]].set_visible(False)
```



```
[41]: import pandas as pd
from sklearn.model_selection import train_test_split

y= df['logS']
x= df.drop('logS', axis=1)

from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,
↳random_state=100)
```

```
[42]: x_train
```

```
[42]:
```

	MolLogP	MolWt	NumRotatableBonds	AromaticProportion
107	3.14280	112.216	5.0	0.000000
378	-2.07850	142.070	0.0	0.000000
529	-0.47730	168.152	0.0	0.000000
546	-0.86740	154.125	0.0	0.000000
320	1.62150	100.161	2.0	0.000000
..	...	...	...	...
802	3.00254	250.301	1.0	0.842105

53	2.13860	82.146	3.0	0.000000
350	5.76304	256.348	0.0	0.900000
79	3.89960	186.339	10.0	0.000000
792	2.52334	310.297	3.0	0.300000

[915 rows x 4 columns]

```
[43]: x_test
```

```
[43]:      MolLogP      MolWt  NumRotatableBonds  AromaticProportion
822  2.91000  172.268                7.0            0.000000
118  7.27400  360.882                1.0            0.666667
347  1.94040  145.161                0.0            0.909091
1123 1.98640  119.378                0.0            0.000000
924  1.70062  108.140                0.0            0.750000
...
1114 1.76210  478.513                4.0            0.000000
427  6.32820  276.338                0.0            1.000000
711  0.04430  218.205                5.0            0.000000
4    2.91890  187.375                1.0            0.000000
948  3.56010  318.328                2.0            0.750000
```

[229 rows x 4 columns]

```
[44]: from sklearn.linear_model import LinearRegression
```

```
lr = LinearRegression()
lr.fit(x_train, y_train)
```

```
[44]: LinearRegression()
```

```
[45]: y_train_pred = lr.predict(x_train)
y_test_pred = lr.predict(x_test)
```

```
[46]: y_lr_test_pred = lr.predict(x_test)
y_lr_test_pred # Now you can display the predictions
```

```
[46]: array([-3.05722870e+00, -7.77785827e+00, -2.55016650e+00, -2.01523582e+00,
-2.06375990e+00, -9.99672215e-01, -5.94603364e-01, -5.53626003e-01,
-5.72200956e+00, -3.94006681e+00, -3.95496755e+00, -2.29737009e+00,
-1.48980354e+00, -1.48988982e+00, -4.64510806e+00, -1.90396018e+00,
-1.51566313e+00, -3.16424605e+00, -3.70863920e+00, -5.58105660e+00,
-3.25038467e+00, -5.04235077e+00, -5.69194881e+00, -2.14339849e+00,
-4.35689341e+00, -5.03964756e+00, -3.10383618e+00, -4.40286964e+00,
-4.21276272e+00,  5.56508349e-01, -1.45537678e+00, -4.41027396e+00,
-2.59668773e+00, -1.53336276e+00, -5.55749874e-01, -1.67111795e+00,
-2.78163675e+00, -3.15395565e+00, -5.27083361e+00, -1.75321446e+00,
```

-1.53350725e+00, -2.01255666e+00, -6.57559167e+00, -7.89433046e+00,  
-5.76437127e+00, -4.16422068e+00, -3.43694663e+00, 1.43834212e+00,  
-1.12679105e-02, -2.34521849e+00, -1.86480046e+00, -5.03964756e+00,  
8.55886378e-01, -3.17679292e+00, -5.06764094e+00, -1.99464442e+00,  
-7.77785827e+00, -1.21764693e+00, -9.09541075e-01, -5.04235077e+00,  
-2.43898748e+00, -2.84034045e+00, -2.53403538e+00, -2.36170311e+00,  
-1.63103729e+00, -1.53182046e+00, -3.23931568e+00, -2.88008616e+00,  
-1.88300518e+00, -3.21582220e+00, -3.40245202e+00, -9.01813905e-01,  
-4.82308940e+00, -7.69116343e-01, -7.12894308e+00, -1.05440427e+01,  
-1.95444152e+00, -3.50194744e+00, -7.18167736e+00, -6.01555673e+00,  
-2.08189806e+00, -2.31652280e+00, -3.44556948e+00, -2.05480142e+00,  
-6.01555673e+00, -2.88308299e+00, -4.84867198e+00, -3.51006495e-01,  
-3.54726250e+00, -1.21057919e+00, -4.36658559e+00, -4.21815903e-01,  
-1.63103729e+00, -2.51604291e+00, -2.16707077e+00, -1.48726025e+00,  
-3.20864450e+00, -1.51411141e+00, -1.65033691e+00, -3.66287663e+00,  
-3.26968347e+00, -3.94492313e+00, -4.22509088e+00, -3.68794650e+00,  
-5.98734972e+00, -1.43710934e+00, -1.97653920e+00, -1.85076729e+00,  
-1.14179382e+00, -3.07730828e+00, -4.84867198e+00, -2.19679345e+00,  
-1.68737438e+00, -2.20390218e+00, 1.89408269e+00, -3.61322115e+00,  
-2.79173430e+00, -2.41564138e+00, -7.53910534e-01, -8.54744860e-01,  
-9.20407401e-02, -6.14209981e+00, -3.79386016e+00, -7.77785827e+00,  
-1.79874130e+00, -2.50544035e+00, -3.77102985e+00, -2.25250766e+00,  
-2.57788713e+00, -2.06375990e+00, -3.33843958e+00, -1.03912484e+00,  
-6.68946164e+00, -1.91112045e+00, -2.58735850e+00, -2.19902800e+00,  
-1.90219551e+00, -2.81396751e+00, -4.16972153e+00, -5.72200956e+00,  
-1.60816482e+00, -3.68121117e+00, -4.60929775e+00, -2.45888480e+00,  
1.13185484e+00, -1.69279625e+00, -7.09025955e+00, -3.79386016e+00,  
-2.99712058e+00, -5.79600137e+00, -2.44845780e+00, -5.29399242e+00,  
-5.29389899e-01, -3.53652118e+00, -3.51200413e+00, -2.02419300e+00,  
-4.47466933e+00, -3.63836536e+00, -4.56596939e+00, -5.57842703e+00,  
-5.30676136e+00, -2.39225449e+00, -4.88290144e+00, -2.61359308e+00,  
-3.11841945e+00, -2.05580278e+00, -1.64987419e+00, -4.91881901e+00,  
-3.93774254e+00, -4.26411548e+00, -3.15082845e+00, -3.49352203e+00,  
-3.81768831e+00, -3.77197350e+00, -2.55016650e+00, -1.97653920e+00,  
-2.59432621e+00, -5.38480406e+00, -5.44932525e+00, -3.04107137e+00,  
-1.87252408e+00, -2.25124657e+00, -2.89215707e+00, -3.46087334e+00,  
-6.06861986e+00, -1.89916369e+00, -1.98035105e+00, -2.45036038e+00,  
-2.79393037e+00, -4.76010415e+00, -1.72379306e+00, -7.09025955e+00,  
-2.86880150e+00, -2.70674744e+00, -4.36825704e+00, -3.11841945e+00,  
-3.85805633e+00, 9.78662246e-03, -4.47466933e+00, -6.08708502e+00,  
-5.19970454e+00, -6.40483191e+00, -4.10155218e+00, -1.07044752e+00,  
1.99249372e+00, -3.63698515e+00, -8.50933009e-01, -3.26770298e+00,  
-4.78343575e+00, -1.48988982e+00, -2.24629276e+00, -4.13247222e+00,  
-4.36873484e+00, -1.89724815e+00, -1.50596465e+00, -1.16713539e-02,  
-1.73602998e+00, -2.34521849e+00, -4.54942814e-01, -4.18812419e+00,  
-1.87770440e+00, -3.70838271e+00, -1.59899899e+00, -3.26143822e+00,  
-4.17623614e+00, -6.67872053e+00, -1.23069039e+00, -3.14545964e+00,

-4.79863925e+00])

[47]: y\_lr\_test\_pred

```
[47]: array([-3.05722870e+00, -7.77785827e+00, -2.55016650e+00, -2.01523582e+00,
-2.06375990e+00, -9.99672215e-01, -5.94603364e-01, -5.53626003e-01,
-5.72200956e+00, -3.94006681e+00, -3.95496755e+00, -2.29737009e+00,
-1.48980354e+00, -1.48988982e+00, -4.64510806e+00, -1.90396018e+00,
-1.51566313e+00, -3.16424605e+00, -3.70863920e+00, -5.58105660e+00,
-3.25038467e+00, -5.04235077e+00, -5.69194881e+00, -2.14339849e+00,
-4.35689341e+00, -5.03964756e+00, -3.10383618e+00, -4.40286964e+00,
-4.21276272e+00, 5.56508349e-01, -1.45537678e+00, -4.41027396e+00,
-2.59668773e+00, -1.53336276e+00, -5.55749874e-01, -1.67111795e+00,
-2.78163675e+00, -3.15395565e+00, -5.27083361e+00, -1.75321446e+00,
-1.53350725e+00, -2.01255666e+00, -6.57559167e+00, -7.89433046e+00,
-5.76437127e+00, -4.16422068e+00, -3.43694663e+00, 1.43834212e+00,
-1.12679105e-02, -2.34521849e+00, -1.86480046e+00, -5.03964756e+00,
8.55886378e-01, -3.17679292e+00, -5.06764094e+00, -1.99464442e+00,
-7.77785827e+00, -1.21764693e+00, -9.09541075e-01, -5.04235077e+00,
-2.43898748e+00, -2.84034045e+00, -2.53403538e+00, -2.36170311e+00,
-1.63103729e+00, -1.53182046e+00, -3.23931568e+00, -2.88008616e+00,
-1.88300518e+00, -3.21582220e+00, -3.40245202e+00, -9.01813905e-01,
-4.82308940e+00, -7.69116343e-01, -7.12894308e+00, -1.05440427e+01,
-1.95444152e+00, -3.50194744e+00, -7.18167736e+00, -6.01555673e+00,
-2.08189806e+00, -2.31652280e+00, -3.44556948e+00, -2.05480142e+00,
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-3.20864450e+00, -1.51411141e+00, -1.65033691e+00, -3.66287663e+00,
-3.26968347e+00, -3.94492313e+00, -4.22509088e+00, -3.68794650e+00,
-5.98734972e+00, -1.43710934e+00, -1.97653920e+00, -1.85076729e+00,
-1.14179382e+00, -3.07730828e+00, -4.84867198e+00, -2.19679345e+00,
-1.68737438e+00, -2.20390218e+00, 1.89408269e+00, -3.61322115e+00,
-2.79173430e+00, -2.41564138e+00, -7.53910534e-01, -8.54744860e-01,
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-1.79874130e+00, -2.50544035e+00, -3.77102985e+00, -2.25250766e+00,
-2.57788713e+00, -2.06375990e+00, -3.33843958e+00, -1.03912484e+00,
-6.68946164e+00, -1.91112045e+00, -2.58735850e+00, -2.19902800e+00,
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-1.60816482e+00, -3.68121117e+00, -4.60929775e+00, -2.45888480e+00,
1.13185484e+00, -1.69279625e+00, -7.09025955e+00, -3.79386016e+00,
-2.99712058e+00, -5.79600137e+00, -2.44845780e+00, -5.29399242e+00,
-5.29389899e-01, -3.53652118e+00, -3.51200413e+00, -2.02419300e+00,
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-5.30676136e+00, -2.39225449e+00, -4.88290144e+00, -2.61359308e+00,
-3.11841945e+00, -2.05580278e+00, -1.64987419e+00, -4.91881901e+00,
-3.93774254e+00, -4.26411548e+00, -3.15082845e+00, -3.49352203e+00,
```

```

-3.81768831e+00, -3.77197350e+00, -2.55016650e+00, -1.97653920e+00,
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-1.87252408e+00, -2.25124657e+00, -2.89215707e+00, -3.46087334e+00,
-6.06861986e+00, -1.89916369e+00, -1.98035105e+00, -2.45036038e+00,
-2.79393037e+00, -4.76010415e+00, -1.72379306e+00, -7.09025955e+00,
-2.86880150e+00, -2.70674744e+00, -4.36825704e+00, -3.11841945e+00,
-3.85805633e+00, 9.78662246e-03, -4.47466933e+00, -6.08708502e+00,
-5.19970454e+00, -6.40483191e+00, -4.10155218e+00, -1.07044752e+00,
1.99249372e+00, -3.63698515e+00, -8.50933009e-01, -3.26770298e+00,
-4.78343575e+00, -1.48988982e+00, -2.24629276e+00, -4.13247222e+00,
-4.36873484e+00, -1.89724815e+00, -1.50596465e+00, -1.16713539e-02,
-1.73602998e+00, -2.34521849e+00, -4.54942814e-01, -4.18812419e+00,
-1.87770440e+00, -3.70838271e+00, -1.59899899e+00, -3.26143822e+00,
-4.17623614e+00, -6.67872053e+00, -1.23069039e+00, -3.14545964e+00,
-4.79863925e+00])

```

```
[48]: from sklearn.metrics import mean_squared_error, r2_score
```

```

# Make predictions (if you haven't already)
y_lr_train_pred = lr.predict(x_train)
y_lr_test_pred = lr.predict(x_test)

# Calculate metrics
lr_train_mse = mean_squared_error(y_train, y_lr_train_pred)
lr_train_r2 = r2_score(y_train, y_lr_train_pred)
lr_test_mse = mean_squared_error(y_test, y_lr_test_pred)
lr_test_r2 = r2_score(y_test, y_lr_test_pred)

# Print the results
print('LR MSE (Train): ', lr_train_mse)
print('LR R2 (Train): ', lr_train_r2)
print('LR MSE (Test): ', lr_test_mse)
print('LR R2 (Test): ', lr_test_r2)

```

```

LR MSE (Train): 1.0075362951093687
LR R2 (Train): 0.7645051774663391
LR MSE (Test): 1.0206953660861033
LR R2 (Test): 0.7891616188563282

```

```
[49]: print('LR MSE (Train): ', lr_train_mse)
print('LR R2 (Train): ', lr_train_r2)
print('LR MSE (Test): ', lr_test_mse)
print('LR R2 (Test): ', lr_test_r2)
```

```

LR MSE (Train): 1.0075362951093687
LR R2 (Train): 0.7645051774663391
LR MSE (Test): 1.0206953660861033
LR R2 (Test): 0.7891616188563282

```

```
[50]: lr_results = pd.DataFrame([ 'Linear regression' , lr_train_mse, lr_train_r2,
↳lr_test_mse, lr_test_r2]).transpose()
```

```
[51]: lr_results = pd.DataFrame([ 'Linear regression' , lr_train_mse, lr_train_r2,
↳lr_test_mse, lr_test_r2]).transpose()
lr_results.columns = ['Method' , 'Training MSE' , 'Training R2', 'Test MSE' ,
↳'Test r2']
```

```
[52]: from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score

rf = RandomForestRegressor()
rf.fit(x_train, y_train)

y_rf_train_pred = rf.predict(x_train)
y_rf_test_pred = rf.predict(x_test)

rf_train_mse = mean_squared_error(y_train, y_rf_train_pred)
rf_train_r2 = r2_score(y_train, y_rf_train_pred)
rf_test_mse = mean_squared_error(y_test, y_rf_test_pred)
rf_test_r2 = r2_score(y_test, y_rf_test_pred)

rf_results = pd.DataFrame([ 'Random Forest' , rf_train_mse, rf_train_r2,
↳rf_test_mse, rf_test_r2]).transpose()
rf_results.columns = ['Method', 'Training MSE', 'Training R2', 'Test MSE',
↳'Test R2']
```

```
[53]: rf_results
```

```
[53]:          Method Training MSE Training R2  Test MSE  Test R2
0  Random Forest    0.085346    0.980052  0.634092  0.86902
```

```
[54]: lr_results.columns = ['Method' , 'Training MSE' , 'Training R2', 'Test MSE' ,
↳'Test R2']
```

```
[55]: lr_results
```

```
[55]:          Method Training MSE Training R2  Test MSE  Test R2
0  Linear regression    1.007536    0.764505  1.020695  0.789162
```

```
[56]: from sklearn.ensemble import RandomForestRegressor
rf = RandomForestRegressor() #create the RandomForestRegressor object
rf.fit(x_train, y_train)
```

```
[56]: RandomForestRegressor()
```

```
[57]: # prompt: import random numpy or pandas
```

```
import pandas as pd
import numpy as np
```

```
[58]: y_rf_train_pred = rf.predict(x_train)
y_rf_test_pred = rf.predict(x_test)
```

```
[59]: # prompt: 10 random numbers using numpy
```

```
import numpy as np
random_numbers = np.random.rand(10)
print(random_numbers)
```

```
[0.01292749 0.59930049 0.64971771 0.92813352 0.98965713 0.96061211
 0.45377325 0.16806282 0.60949223 0.6867629 ]
```

```
[60]: from sklearn.metrics import mean_squared_error, r2_score
rf_train_mse = mean_squared_error(y_train, y_rf_train_pred)
rf_train_r2 = r2_score(y_train, y_rf_train_pred)
rf_test_mse = mean_squared_error(y_test, y_rf_test_pred)
rf_test_r2 = r2_score(y_test, y_rf_test_pred)
```

```
[61]: # prompt: a slider using jupyter widgets
```

```
import ipywidgets as widgets
from IPython.display import display
```

```
# Create a slider
```

```
slider = widgets.IntSlider(
    value=7,
    min=0,
    max=10,
    step=1,
    description='Value:',
    disabled=False,
    continuous_update=False,
    orientation='horizontal',
    readout=True,
    readout_format='d'
)
```

```
# Display the slider
```

```
display(slider)
```

```
IntSlider(value=7, continuous_update=False, description='Value:', max=10)
```

```
[62]: y_train
```

```
[62]: 107    -4.440
      378    -1.250
      529    -1.655
      546    -1.886
      320    -0.740
      ...
      802    -2.925
      53     -2.680
      350    -7.020
      79     -4.800
      792    -3.240
      Name: logS, Length: 915, dtype: float64
```

```
[63]: new_var0 = df_models = pd.concat([ lr_results, rf_results], axis=0)
      df_models # remove any extra spaces before this line
      new_var0
```

```
[63]:
```

	Method	Training MSE	Training R2	Test MSE	Test R2
0	Linear regression	1.007536	0.764505	1.020695	0.789162
0	Random Forest	0.085346	0.980052	0.634092	0.86902

```
[64]: # @title Test MSE vs Test R2

from matplotlib import pyplot as plt
!pip install seaborn -i https://pypi.tuna.tsinghua.edu.cn/simple
import seaborn as sns
import pandas as pd
plt.subplots(figsize=(8, 8))
df_2dhist = pd.DataFrame({
    x_label: grp['Test R2'].value_counts()
    for x_label, grp in df_models.groupby('Test MSE')
})
sns.heatmap(df_2dhist, cmap='viridis')
plt.xlabel('Test MSE')
_ = plt.ylabel('Test R2')
```

```
Looking in indexes: https://pypi.tuna.tsinghua.edu.cn/simple
Requirement already satisfied: seaborn in ./config/jupyterlab-
desktop/jlab_server/lib/python3.12/site-packages (0.13.2)
Requirement already satisfied: numpy!=1.24.0,>=1.20 in ./config/jupyterlab-
desktop/jlab_server/lib/python3.12/site-packages (from seaborn) (2.1.0)
Requirement already satisfied: pandas>=1.2 in ./config/jupyterlab-
desktop/jlab_server/lib/python3.12/site-packages (from seaborn) (2.2.2)
Requirement already satisfied: matplotlib!=3.6.1,>=3.4 in ./config/jupyterlab-
desktop/jlab_server/lib/python3.12/site-packages (from seaborn) (3.9.2)
Requirement already satisfied: contourpy>=1.0.1 in ./config/jupyterlab-
desktop/jlab_server/lib/python3.12/site-packages (from
matplotlib!=3.6.1,>=3.4->seaborn) (1.2.1)
```

Requirement already satisfied: cyclor>=0.10 in ./config/jupyterlab-  
desktop/jlab\_server/lib/python3.12/site-packages (from  
matplotlib!=3.6.1,>=3.4->seaborn) (0.12.1)

Requirement already satisfied: fonttools>=4.22.0 in ./config/jupyterlab-  
desktop/jlab\_server/lib/python3.12/site-packages (from  
matplotlib!=3.6.1,>=3.4->seaborn) (4.53.1)

Requirement already satisfied: kiwisolver>=1.3.1 in ./config/jupyterlab-  
desktop/jlab\_server/lib/python3.12/site-packages (from  
matplotlib!=3.6.1,>=3.4->seaborn) (1.4.5)

Requirement already satisfied: packaging>=20.0 in ./config/jupyterlab-  
desktop/jlab\_server/lib/python3.12/site-packages (from  
matplotlib!=3.6.1,>=3.4->seaborn) (24.1)

Requirement already satisfied: pillow>=8 in ./config/jupyterlab-  
desktop/jlab\_server/lib/python3.12/site-packages (from  
matplotlib!=3.6.1,>=3.4->seaborn) (10.4.0)

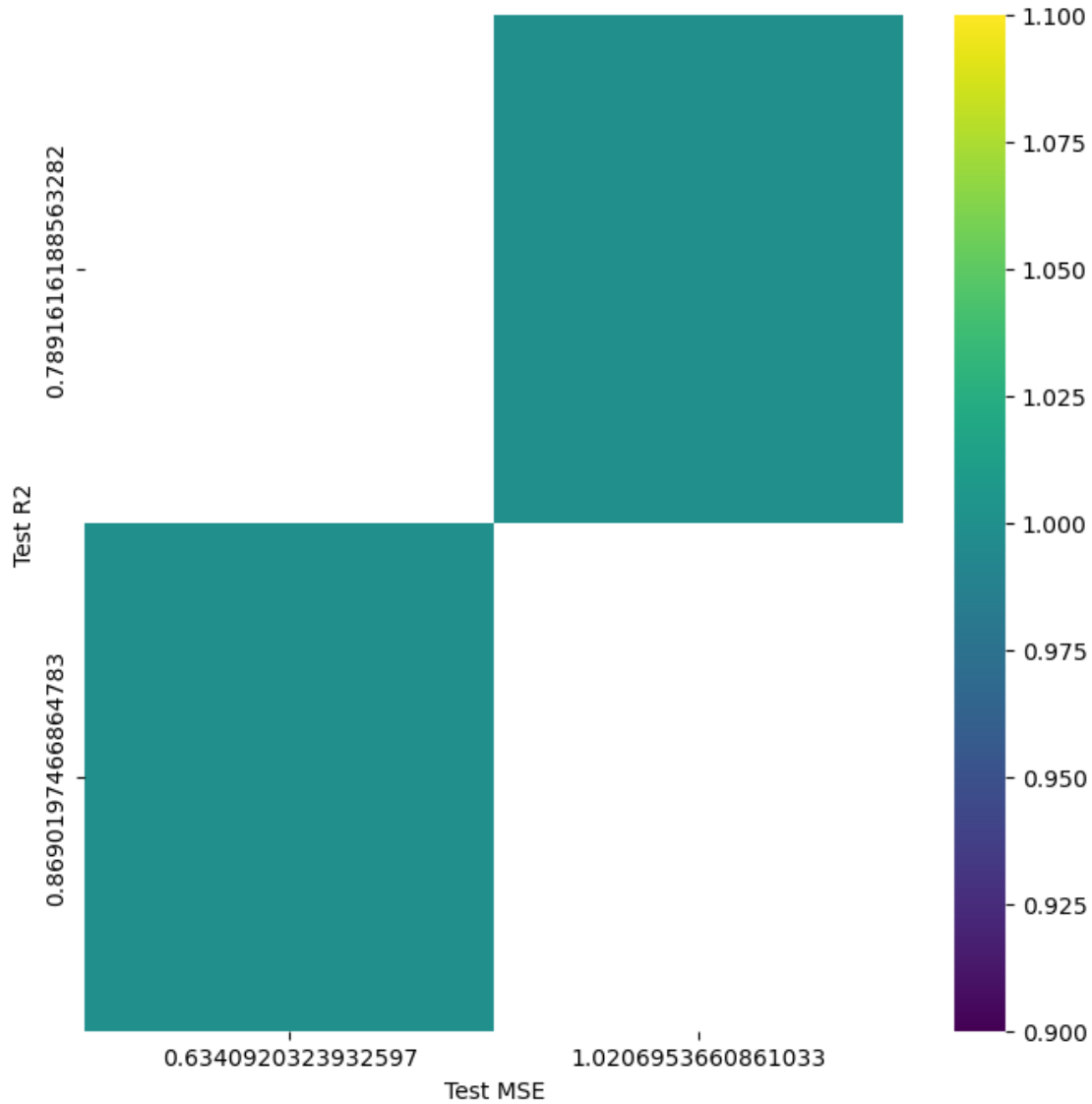
Requirement already satisfied: pyparsing>=2.3.1 in ./config/jupyterlab-  
desktop/jlab\_server/lib/python3.12/site-packages (from  
matplotlib!=3.6.1,>=3.4->seaborn) (3.1.4)

Requirement already satisfied: python-dateutil>=2.7 in ./config/jupyterlab-  
desktop/jlab\_server/lib/python3.12/site-packages (from  
matplotlib!=3.6.1,>=3.4->seaborn) (2.9.0)

Requirement already satisfied: pytz>=2020.1 in ./config/jupyterlab-  
desktop/jlab\_server/lib/python3.12/site-packages (from pandas>=1.2->seaborn)  
(2024.1)

Requirement already satisfied: tzdata>=2022.7 in ./config/jupyterlab-  
desktop/jlab\_server/lib/python3.12/site-packages (from pandas>=1.2->seaborn)  
(2024.1)

Requirement already satisfied: six>=1.5 in ./config/jupyterlab-  
desktop/jlab\_server/lib/python3.12/site-packages (from python-  
dateutil>=2.7->matplotlib!=3.6.1,>=3.4->seaborn) (1.16.0)



```
[65]: # prompt: Using dataframe df_models: convert Pandas to LaTeX
print(df_models.to_latex(index=False)) #Converts the dataframe to a LaTeX table
↳and prints the output.
```

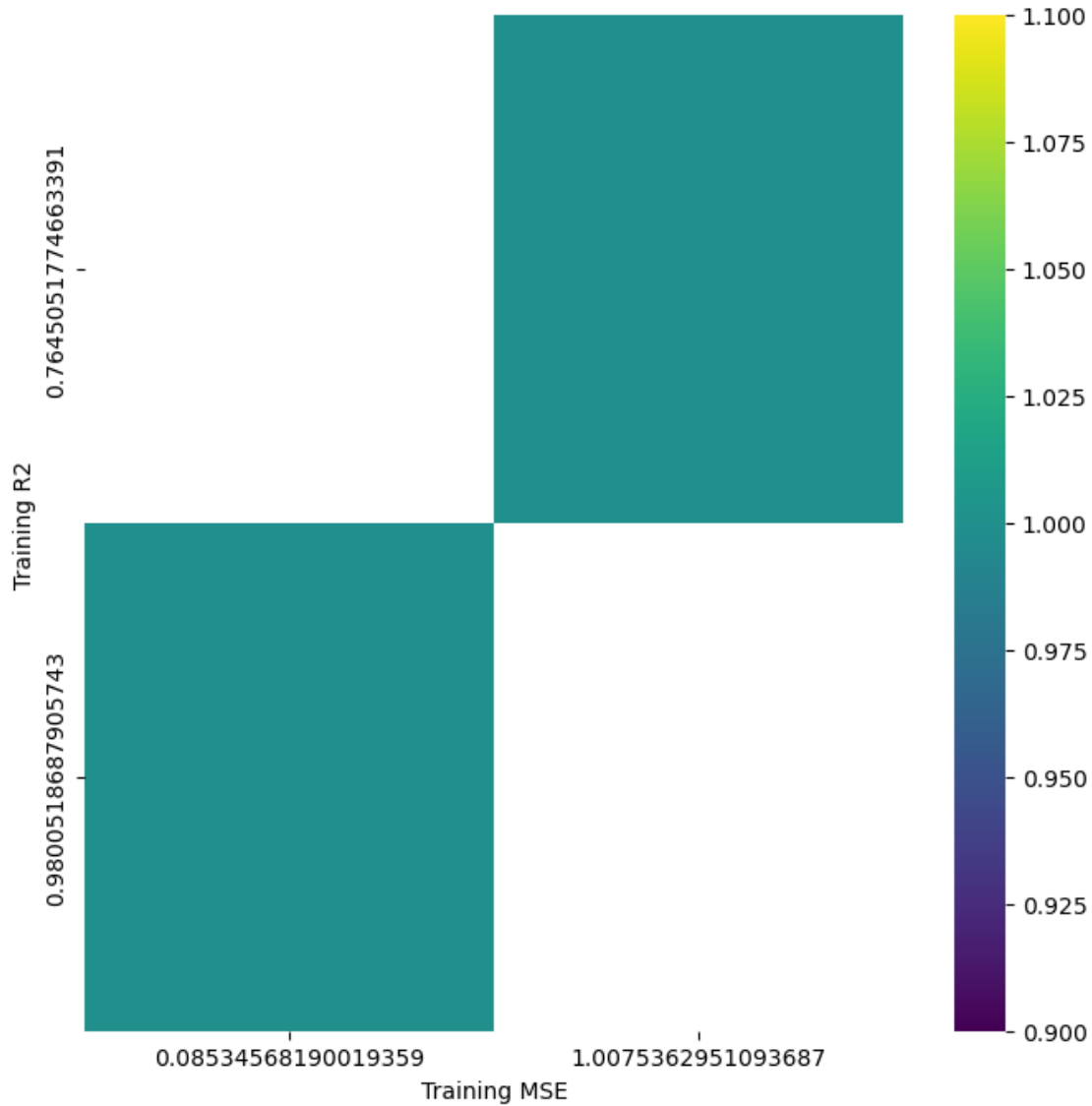
```
\begin{tabular}{llllll}
\toprule
Method & Training MSE & Training R2 & Test MSE & Test R2 & \\
\midrule
Linear regression & 1.007536 & 0.764505 & 1.020695 & 0.789162 & \\
Random Forest & 0.085346 & 0.980052 & 0.634092 & 0.869020 & \\
\bottomrule
\end{tabular}
```

```
[66]: df_models.reset_index(drop=True)
```

```
[66]:
```

	Method	Training MSE	Training R2	Test MSE	Test R2
0	Linear regression	1.007536	0.764505	1.020695	0.789162
1	Random Forest	0.085346	0.980052	0.634092	0.86902

```
[67]: from matplotlib import pyplot as plt
import seaborn as sns
import pandas as pd
plt.subplots(figsize=(8, 8))
df_2dhist = pd.DataFrame({
    x_label: grp['Training R2'].value_counts()
    for x_label, grp in df_models.groupby('Training MSE') # Use df_models here
})
sns.heatmap(df_2dhist, cmap='viridis')
plt.xlabel('Training MSE')
_ = plt.ylabel('Training R2')
```

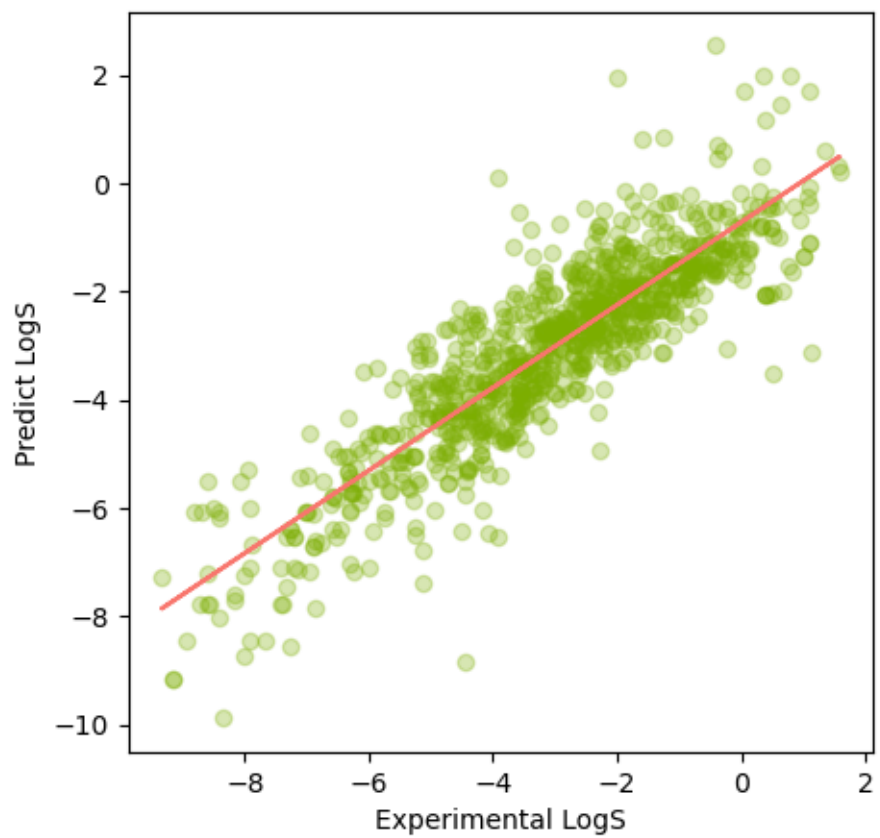


```
[68]: import matplotlib.pyplot as plt
import numpy as np
plt.figure(figsize=(5,5) )
plt.scatter(x=y_train, y=y_lr_train_pred, c="#7CAE00", alpha=0.3)

z = np.polyfit(y_train, y_lr_train_pred, 1)
p = np.poly1d(z)

plt.plot(y_train, p(y_train), '#F8766D')
plt.ylabel('Predict LogS')
plt.xlabel('Experimental LogS')
```

[68]: Text(0.5, 0, 'Experimental LogS')



[ ]:

[ ]: