More Machine Learning

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```
In [1]: import numpy as np
  import pandas as pd
  import matplotlib.pyplot as plt
  import seaborn as sns
  sns.set_style('whitegrid')
  colors = sns.color_palette()
```





An example of overfitting with a random forest





A nonlinear model with noise





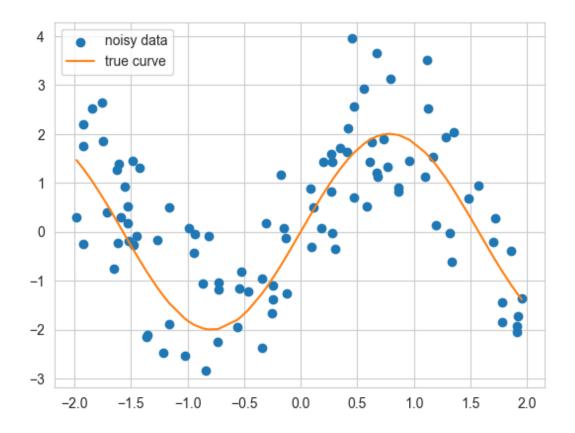
```
In [2]: # Nonlinear model
def curve(x):
    return 2 * np.sin(2 * x)

# Generate data
np.random.seed(0)
x = np.random.uniform(low=-2, high=2, size=100)
x = np.sort(x)
y = curve(x) + np.random.normal(size=100)
X = x.reshape(-1, 1)
```





```
In [3]: # View data
        plt.scatter(x, y, label="noisy data")
        plt.plot(x, curve(x), label="true curve", c=colors[1])
        plt.legend()
        plt.show()
```





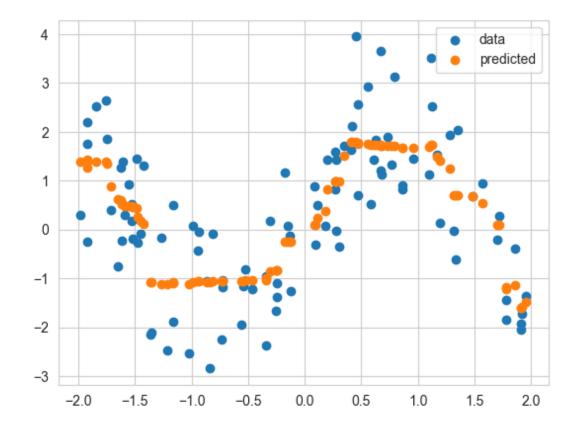
A shallow random forest





```
In [4]: from sklearn.ensemble import RandomForestRegressor

forest1 = RandomForestRegressor(max_depth=3, random_state=0)
forest1.fit(X=X, y=y)
predict1 = forest1.predict(X=X)
plt.scatter(x, y, label="data")
plt.scatter(x, predict1, label="predicted")
plt.legend()
plt.show()
```



 R^2 of the model





```
In [5]: print(f"R squared is {forest1.score(X=X, y=y): .2%}")
```

R squared is 67.63%





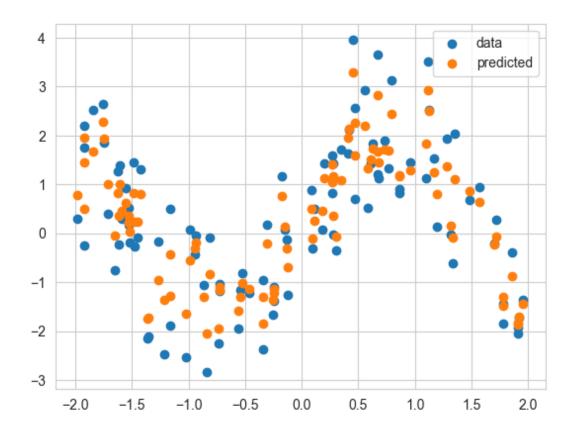
A More Complex Model

Set max_depth higher.





```
In [8]: forest2 = RandomForestRegressor(max_depth=20, random_state=0)
    forest2.fit(X=X, y=y)
    predict2 = forest2.predict(X=X)
    plt.scatter(x, y, label="data")
    plt.scatter(x, predict2, label="predicted")
    plt.legend()
    plt.show()
```



```
In [10]: print(f"R squared of more complex model is {forest2.score(X=X, y=y):.2%}")
```

R squared of more complex model is 90.89%





Apply the models to new data





```
In [11]: np.random.seed(0)
    xnew = np.random.uniform(low=-2, high=2, size=50)
    ynew = curve(xnew) + np.random.normal(size=50)
    Xnew = xnew.reshape(-1, 1)

    print(f"R-squared of model 1 on new data is {forest1.score(X=Xnew, y=ynew):.25
    print(f"R-squared of model 2 on new data is {forest2.score(X=Xnew, y=ynew):.25
    R-squared of model 1 on new data is 62.20%
    R-squared of model 2 on new data is 54.81%
```



Avoid overfitting





Train, validate, test

- Split data into three sets: train, validate, and test
- For each hyperparameter in some set of possible choices,
 - Train on the training data
 - Compute \mathbb{R}^2 on the validation data
 - Choose the hyperparameter value that performs best on the validation data
 - This maximizes "out of sample" performance
- ullet To forecast performance on new data, compute the \mathbb{R}^2 on the test data
- Test data was not used to choose the hyperparameter, so it provides an unbiased test.





Cross validation

- A better method
- Split data into two sets: train and test (maybe 80% and 20%).
- The following is done by usng GridSearchCV on the training data:
 - Split the training data into five sets (could make more or fewer sets).
 - Combine four sets for training and use the fifth for validation.
 - Then choose a different one of the five sets for validation and repeat.
 - End up with five validation scores. Average them.
 - Choose hyperparameter value with highest average validation score.
- ullet To forecast performance on new data, compute the \mathbb{R}^2 on the test data.



Cross validation explained again

- Split the training data into 5 randomly chosen subsets A, B, C, D, and E.
- Use $A \cup B \cup C \cup D$ as training data and validate on E.
- Then use $B \cup C \cup D \cup E$ as training data and validate on A.
- Then, ..., until we have trained and validated 5 times.
- Average the 5 validation scores for each model.
- Choose the hyperparameter value that gives the highest average validation score.
- Then test on the testing data to estimate performance on new data.





Train-test split

- scikit-learn has a function for randomly splitting X, y data into training and test sets
- Let's re-do the example by first generating the whole sample (x + xnew, y + ynew) and then using train-test-split





Cross-validate on the training data and test on test data





```
In [13]: from sklearn.model_selection import GridSearchCV

param_grid = {"max_depth": range(2, 22, 2)}
cv = GridSearchCV(
    RandomForestRegressor(random_state=0),
    param_grid=param_grid,
)
cv.fit(X=X_train, y=y_train)
print(f"best hyperparameter is {cv.best_params_}")
print(f"score on the test data is {cv.score(X=X_test, y=y_test)}")

best hyperparameter is {'max_depth': 4}
score on the test data is 0.3902562772500102
```



Second example









Split into train and test





```
In [15]: 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=0
)
```





```
In [16]: param_grid = {"max_depth": range(2, 22, 2)}
cv = GridSearchCV(
    RandomForestRegressor(random_state=0),
    param_grid=param_grid,
)
cv.fit(X=X_train, y=y_train)
print(f"best hyperparameter is {cv.best_params_}")
print(f"score on the test data is {cv.score(X=X_test, y=y_test)}")

best hyperparameter is {'max_depth': 2}
score on the test data is 0.4433286538475445
```



Example 1 with a neural net







```
In [21]: from sklearn.neural_network import MLPRegressor

net = MLPRegressor(hidden_layer_sizes=[100, 100, 100], random_state=0)
net.fit(X=X_train, y=y_train)
predict = net.predict(X=X_train)
plt.scatter(X_train, y_train, label="training data")
plt.scatter(X_train, predict, label="predicted")
plt.legend()
plt.show()
```



```
In [22]:
         param_grid = {"hidden_layer_sizes": [[100], [100, 100], [100, 100, 100]]}
         cv = GridSearchCV(
             MLPRegressor(random state=0),
             param_grid=param_grid,
         cv.fit(X=X_train, y=y_train)
         print(f"best hyperparameter is {cv.best params }")
         print(f"score on the test data is {cv.score(X=X test, y=y test)}")
          c:\Users\kerry\AppData\Local\Programs\Python\Python310\lib\site-packa
          ges\sklearn\neural network\ multilayer perceptron.py:702: Convergence
          Warning: Stochastic Optimizer: Maximum iterations (200) reached and t
          he optimization hasn't converged yet.
            warnings.warn(
          c:\Users\kerry\AppData\Local\Programs\Python\Python310\lib\site-packa
          ges\sklearn\neural network\ multilayer perceptron.py:702: Convergence
          Warning: Stochastic Optimizer: Maximum iterations (200) reached and t
          he optimization hasn't converged yet.
            warnings.warn(
          c:\Users\kerry\AppData\Local\Programs\Python\Python310\lib\site-packa
          ges\sklearn\neural network\ multilayer perceptron.py:702: Convergence
          Warning: Stochastic Optimizer: Maximum iterations (200) reached and t
          he optimization hasn't converged yet.
            warnings.warn(
          c:\Users\kerry\AppData\Local\Programs\Python\Python310\lib\site-packa
          ges\sklearn\neural network\ multilayer perceptron.py:702: Convergence
          Warning: Stochastic Optimizer: Maximum iterations (200) reached and t
          he optimization hasn't converged yet.
```

warnings warn(

Example 2 with a neural net





```
In [23]: # Generate 50 features (predictors) and 1000 data points
         np.random.seed(0)
         X = pd.DataFrame(
             np.random.normal(size=(1000, 50))
         # only the first feature will matter
         y = X[0] + np.random.normal(size=1000)
```







```
In [24]: 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=0
)
```





```
In [25]: param_grid = {"hidden_layer_sizes": [[100], [100, 100], [100, 100]]}
    cv = GridSearchCV(
        MLPRegressor(random_state=0),
        param_grid=param_grid,
    )
    cv.fit(X=X_train, y=y_train)
    print(f"best hyperparameter is {cv.best_params_}")
    print(f"score on the test data is {cv.score(X=X_test, y=y_test)}")

    best hyperparameter is {'hidden_layer_sizes': [100]}
    score on the test data is 0.1332835337054339
```



Some real data

- Boston house prices
- Try to predict median house price in different neighborhoods of Boston based on characteristics of the houses and characteristics of the residents
- University of California-Irvine Machine Learning Repository and Kaggle
- See https://www.kaggle.com/datasets/fedesoriano/the-boston-houseprice-data for a description of the data.





```
In [39]: url = "https://www.dropbox.com/scl/fi/g9uzsntv93waniyw9pkc2/boston.csv?rlkey=0
    df = pd.read_csv(url)
    df.head(3)
```

Out[39]:		CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIC
	0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296.0	15.
	1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242.0	17.
	2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242.0	17.





```
In [40]: X = df.drop(columns=["MEDV"])
y = df.MEDV
```





Tasks

- 1. Split into train and test
- 2. Run GridSearchCV on training data to find best hyperparameter
- 3. Test the model on the test data





Do this for

1. Random forest with

```
param_grid = {"max_depth": range(2, 22, 2)}
```

2. Neural network with

```
param_grid = {"hidden_layer_sizes": [[100], [100, 100], [100, 100,
100]]}
```

Can chatGPT help?

