## **Exercise Week 38**

## **Analytical part**

Show that

$$\mathbb{E}[(\mathbf{y} - \tilde{\mathbf{y}})^2] = \operatorname{Bias}[\tilde{y}] + \operatorname{var}[\tilde{y}] + \sigma^2$$

With:

$$\mathrm{Bias}[ ilde{y}] = \mathbb{E}[(\mathbf{y} - \mathbb{E}[ ilde{y}])^2]$$

and

$$ext{var}[ ilde{y}] = \mathbb{E}[(\mathbf{ ilde{y}} - \mathbb{E}[ ilde{y}])^2] = 1/n \sum_i ( ilde{y_i} - \mathbb{E}[\mathbf{ ilde{y}}])^2$$

We begin by rewriting the squared difference  $\mathbb{E}[(\mathbf{y}-\mathbf{ ilde{y}})^2]$  by adding and subtracting  $\mathbb{E}[ ilde{y}]$ 

$$\mathbb{E}[(\mathbf{y} - \mathbf{\tilde{y}})^2] = \mathbb{E}[(\mathbf{y} - \mathbb{E}[\tilde{y}] + \mathbb{E}[\tilde{y}] - \mathbf{\tilde{y}})^2]$$

Then expand the expression

$$\mathbf{E} = \mathbb{E}[(\mathbf{y} - \mathbb{E}[ ilde{y}])^2 + 2(\mathbf{y} - \mathbb{E}[ ilde{y}])(\mathbb{E}[ ilde{y}] - ilde{\mathbf{y}}) + (\mathbb{E}[ ilde{y}] - ilde{\mathbf{y}})^2]$$

The second term involves the product of  $(\mathbf{y} - \mathbb{E}[\tilde{y}])$  and  $(\mathbb{E}[\tilde{y}] - \mathbf{\tilde{y}})$ . Since  $\mathbf{y}$  and  $\mathbf{\tilde{y}}$  are independent, then:

$$\mathbb{E}[(\mathbf{y} - \mathbb{E}[ ilde{y}])(\mathbb{E}[ ilde{y}] - \mathbf{ ilde{y}})] = 0$$

And we are left with

$$\mathbb{E}[(\mathbf{y} - \mathbf{\tilde{y}})^2] = \mathbb{E}[(\mathbf{y} - \mathbb{E}[\tilde{y}])^2] + \mathbb{E}[(\mathbf{\tilde{y}} - \mathbb{E}[\tilde{y}])^2]$$

The first term  $\mathbb{E}[(\mathbf{y} - \mathbb{E}[ ilde{y}])^2]$ , represents the bias

$$\mathrm{Bias}[ ilde{y}] = \mathbb{E}[(f(x) - \mathbb{E}[ ilde{y}])^2]$$

The second term,  $\mathbb{E}[(\mathbf{ ilde{y}} - \mathbb{E}[ ilde{y}])^2]$ , represents the variance

$$ext{Var}[ ilde{y}] = \mathbb{E}[(\mathbf{ ilde{y}} - \mathbb{E}[ ilde{y}])^2]$$

In equation,  $\mathbf{y}=f(x)+\epsilon$ ,  $\epsilon$  is the noise term with variance  $\sigma^2$ , and it must be included

And so the final result is

$$\mathbb{E}[(\mathbf{y} - \mathbf{\tilde{y}})^2] = \mathrm{Bias}^2[\tilde{y}] + \mathrm{Var}[\tilde{y}] + \sigma^2$$

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In [6]: import matplotlib.pyplot as plt
        import numpy as np
        from sklearn.linear_model import LinearRegression
        from sklearn.preprocessing import PolynomialFeatures
        from sklearn.model_selection import train_test_split
        from sklearn.pipeline import make_pipeline
        from sklearn.utils import resample
        np.random.seed(0)
        n = 500
        n_boostraps = 100
        max degree = 15
        noise = 0.1
        x = np.linspace(-1, 3, n).reshape(-1, 1)
        y = np.exp(-x**2) + 1.5 * np.exp(-(x-2)**2) + np.random.normal(0, 0.1, x.shape)
        x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2)
        errors = []
        biases = []
        variances = []
        degrees = range(1, max_degree+1)
        for degree in degrees:
            model = make_pipeline(PolynomialFeatures(degree=degree), LinearRegression(fit_intercept=False))
            y_pred = np.empty((y_test.shape[0], n_boostraps))
            for i in range(n_boostraps):
                x_{, y_{}} = resample(x_{train}, y_{train})
                y_pred[:, i] = model.fit(x_, y_).predict(x_test).ravel()
            error = np.mean(np.mean((y_test - y_pred)**2, axis=1, keepdims=True))
            bias = np.mean((y_test - np.mean(y_pred, axis=1, keepdims=True))**2)
            variance = np.mean(np.var(y_pred, axis=1, keepdims=True))
            errors.append(error)
            biases.append(bias)
            variances.append(variance)
            print(f'Degree: {degree}, Error: {error:.3f}, Bias^2: {bias:.3f}, Variance: {variance:.5f}')
        # Plot results as a function of polynomial degree
        plt.plot(degrees, errors, label='Error (MSE)', marker='o')
        plt.plot(degrees, biases, label='Bias^2', marker='o')
        plt.plot(degrees, variances, label='Variance', marker='o')
        plt.xlabel('Polynomial Degree')
        plt.ylabel('Error/Bias^2/Variance')
        plt.title('Bias-Variance Trade-off')
        plt.legend()
        plt.grid(True)
        plt.show()
```

```
Degree: 1, Error: 0.060, Bias^2: 0.059, Variance: 0.00042
Degree: 2, Error: 0.041, Bias^2: 0.041, Variance: 0.00032
Degree: 3, Error: 0.034, Bias^2: 0.034, Variance: 0.00035
Degree: 4, Error: 0.016, Bias^2: 0.016, Variance: 0.00027
Degree: 5, Error: 0.016, Bias^2: 0.016, Variance: 0.00029
Degree: 6, Error: 0.011, Bias^2: 0.011, Variance: 0.00016
Degree: 7, Error: 0.011, Bias^2: 0.011, Variance: 0.00021
Degree: 8, Error: 0.011, Bias^2: 0.011, Variance: 0.00023
Degree: 9, Error: 0.011, Bias^2: 0.011, Variance: 0.00027
Degree: 10, Error: 0.011, Bias^2: 0.011, Variance: 0.00028
Degree: 11, Error: 0.011, Bias^2: 0.011, Variance: 0.00029
Degree: 12, Error: 0.011, Bias^2: 0.011, Variance: 0.00031
Degree: 13, Error: 0.011, Bias^2: 0.011, Variance: 0.00032
Degree: 14, Error: 0.011, Bias^2: 0.011, Variance: 0.00042
Degree: 15, Error: 0.011, Bias^2: 0.011, Variance: 0.00042
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