Bias-Variance Decomposition

```
In [56]: import ssl
    ssl._create_default_https_context = ssl._create_unverified_context

In [57]: # Import necessary libraries
    import numpy as np
    import pandas as pd

from sklearn.datasets import fetch_california_housing, load_iris, make_regre
    from sklearn.model_selection import train_test_split
    from sklearn.preprocessing import StandardScaler
    from sklearn.linear_model import LinearRegression
    from sklearn.tree import DecisionTreeRegressor, DecisionTreeClassifier
    from sklearn.metrics import mean_squared_error
    from sklearn.utils import resample

import warnings
warnings.filterwarnings('ignore')
```

Define Bias-Variance Decomposition Function

```
In [58]: def bias_variance_decomp(model, X_train, y_train, X_test, y_test, n_bootstra
             """Simple bias-variance decomposition for regression"""
             # Array to store predictions from each bootstrap model
             predictions = np.zeros((n bootstraps, len(y test)))
             # For each bootstrap sample
             for i in range(n bootstraps):
                 # Create bootstrap sample
                 X boot, y boot = resample(X train, y train, random state=i)
                 # Train model on bootstrap sample
                 model.fit(X boot, y boot)
                 # Predict on test data
                 predictions[i] = model.predict(X test)
             # Average prediction across all bootstrap models
             average pred = np.mean(predictions, axis=0)
             # Calculate squared bias
             bias squared = np.mean((average pred - y test) ** 2)
             # Calculate variance
             variance = np.mean(np.var(predictions, axis=0))
             # Calculate average error
             error = np.mean(np.mean((predictions - y test.reshape(1, -1)) ** 2, axis
```

```
# Noise (irreducible error)
noise = error - bias_squared - variance
return bias_squared, variance, error, noise
```

1. California Housing Dataset

California Housing Dataset: (20640, 8)

```
In [60]: # Define different complexity levels for decision trees
         max depths = [1, 3, 5, 10, None]
         # Store results
         bias values cal = []
         variance values cal = []
         error values cal = []
         # Perform bias-variance decomposition
         print("California Housing Dataset Results:")
         print("-" * 60)
         print(f"{'Max Depth':<10} {'Bias2':<15} {'Variance':<15} {'Total Error':<15}</pre>
         print("-" * 60)
         for depth in max depths:
             model = DecisionTreeRegressor(max depth=depth, random state=42)
             bias, variance, error, noise = bias variance decomp(
                 model, X train cal, y train cal, X test cal, y test cal
             bias values cal.append(bias)
             variance values cal.append(variance)
             error values cal.append(error)
             depth str = str(depth) if depth is not None else "None"
             print(f"{depth str:<10} {bias:<15.4f} {variance:<15.4f} {error:<15.4f}")</pre>
         print("-" * 60)
```

Max Depth	Bias ²	Variance	Total Error
1 1 3 3 5 5 10 10 None	0.9177 0.9177 0.5990 0.5990 0.4615 0.4615 0.2972 0.2972	0.0283 0.0283 0.0482 0.0482 0.0712 0.0712 0.1586 0.1586 0.2999	0.9460 0.9460 0.6472 0.6472 0.5327 0.5327 0.4558 0.4558
None	0.2548	0.2999	0.5547

2. Iris Dataset

```
In [61]: # Define a simplified bias-variance decomposition for classification
         def bias variance decomp clf(model, X train, y train, X test, y test, n boot
             """Simplified bias-variance estimation for classification"""
             predictions = np.zeros((n bootstraps, len(y test)))
             # For each bootstrap sample
             for i in range(n bootstraps):
                 # Create bootstrap sample
                 X boot, y boot = resample(X train, y train, random state=i)
                 # Train model on bootstrap sample
                 model.fit(X boot, y boot)
                 # Predict on test data
                 predictions[i] = model.predict(X test)
             # Mode prediction (most common class) for each test point
             from scipy import stats
             main predictions = stats.mode(predictions, axis=0, keepdims=False)[0]
             # Bias - error between main prediction and true class
             bias = np.mean(main predictions != y test)
             # Variance - disagreement between individual models
             variance = np.mean([np.mean(pred != main predictions) for pred in predictions)
             # Total error - average misclassification rate
             error = np.mean([np.mean(pred != y test) for pred in predictions])
             return bias, variance, error, 0 # Noise is 0 for this simplified approa
```

```
In [62]: # Load Iris dataset
   iris = load_iris()
   X_iris = iris.data
   y_iris = iris.target
```

```
# Scale features
scaler = StandardScaler()
X iris scaled = scaler.fit transform(X iris)
# Split data
X train iris, X test iris, y train iris, y test iris = train test split(
    X_iris_scaled, y_iris, test_size=0.2, random_state=42, stratify=y_iris
print(f"Iris Dataset: {X iris.shape}")
```

Iris Dataset: (150, 4)

```
In [63]: # Define different complexity levels for decision trees
         max depths iris = [1, 2, 3, 5, None]
         # Store results
         bias values iris = []
         variance values iris = []
         error values iris = []
         # Perform bias-variance decomposition
         print("Iris Dataset Results:")
         print("-" * 60)
         print(f"{'Max Depth':<10} {'Bias':<15} {'Variance':<15} {'Total Error':<15}"</pre>
         print("-" * 60)
         for depth in max depths iris:
             model = DecisionTreeClassifier(max depth=depth, random state=42)
             bias, variance, error, = bias variance decomp clf(
                 model, X train iris, y train iris, X test iris, y test iris
             )
             bias values iris.append(bias)
             variance values iris.append(variance)
             error values iris.append(error)
             depth str = str(depth) if depth is not None else "None"
             print(f"{depth str:<10} {bias:<15.4f} {variance:<15.4f} {error:<15.4f}")</pre>
         print("-" * 60)
```

Iris Dataset Results:

Max Depth	Bias	Variance	Total Error
1	0.1000	0.3367	0.3440
2	0.0667	0.0347	0.0720
3	0.0333	0.0287	0.0620
3	0.0333	0.0287	0.0620
5	0.0667	0.0367	0.0727
None	0.0667	0.0367	0.0727
5	0.0667	0.0367	0.0727
None	0.0667	0.0367	0.0727

3. Random Dataset

```
# Store results
bias values random = []
variance values random = []
error values random = []
# Perform bias-variance decomposition
print("Random Dataset Results:")
print("-" * 60)
print(f"{'Max Depth':<10} {'Bias2':<15} {'Variance':<15} {'Total Error':<15}</pre>
print("-" * 60)
for depth in max depths random:
    model = DecisionTreeRegressor(max_depth=depth, random state=42)
    bias, variance, error, noise = bias variance decomp(
        model, X train random, y train random, X test random, y test random
    bias values random.append(bias)
    variance values random.append(variance)
    error values random.append(error)
    depth str = str(depth) if depth is not None else "None"
    print(f"{depth str:<10} {bias:<15.4f} {variance:<15.4f} {error:<15.4f}")</pre>
print("-" * 60)
```

Random Dataset Results:

Max Depth	Bias²	Variance	Total Error
1 1 3 3 5 5 10 10 None	2530.0593 2530.0593 1381.7954 1381.7954 845.9926 845.9926 606.1889 606.1889 615.8563	193.7232 193.7232 748.9352 748.9352 991.4796 991.4796 1180.8849 1180.8849	2723.7825 2723.7825 2130.7307 2130.7307 1837.4723 1837.4723 1787.0738 1787.0738 1786.1445
None	615.8563	1170.2882	1786.1445

This notebook was converted with convert.ploomber.io