2023/6/25 09:28 Python1

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In [2]: # 导入操作系统库
       import os
       # 更改工作目录
       os.chdir(r"D:\softwares\applied statistics\pythoncodelearning\chap6\sourcecode")
       # 导入基础计算库
        import numpy as np
        # 导入绘图库
        import matplotlib.pyplot as plt
        # 导入bagging回归器
       from sklearn.ensemble import BaggingRegressor
        # 导入决策树回归
       from sklearn.tree import DecisionTreeRegressor
        # 导入绘图库中的字体管理包
        from matplotlib import font_manager
        # 实现中文字符正常显示
       font = font_manager.FontProperties(fname=r"C:\Windows\Fonts\SimKai.ttf")
        # 使用seaborn风格绘图
       plt.style.use("seaborn-v0_8")
       # 计算期望的迭代次数
       n_repeat = 50
        # 训练集样本量
       n_{train} = 50
        # 测试集样本量
       n test = 1000
        # 标准差
       noise = 0.1
       np.random.seed(0)
        # 构造模型
       estimators = [
           ("Tree", DecisionTreeRegressor()),
           ("Bagging(Tree)", BaggingRegressor(DecisionTreeRegressor())),
        # 回归器的长度
       n_estimators = len(estimators)
        # 生成x数据
        def f(x):
           x = x.ravel()
           return np.exp(-(x**2)) + 1.5 * np.exp(-((x - 2) ** 2))
        # 生成XY数据
       def generate(n_samples, noise, n_repeat=1):
           X = np.random.rand(n samples) * 10 - 5
           X = np.sort(X)
           if n_repeat == 1:
               y = f(X) + np.random.normal(0.0, noise, n_samples)
           else:
               y = np.zeros((n_samples, n_repeat))
               for i in range(n repeat):
                   y[:, i] = f(X) + np.random.normal(0.0, noise, n_samples)
           X = X.reshape((n_samples, 1))
           return X, y
        # 训练集列表
       X train = []
       y train = []
        # 多个训练集
       for i in range(n_repeat):
           X, y = generate(n_samples=n_train, noise=noise)
           X_train.append(X)
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2023/6/25 09:28 Python1

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y train.append(y)
# 生成一个测试集
X_test, y_test = generate(n_samples=n_test, noise=noise, n_repeat=n_repeat)
# 开始绘图
fig, axs = plt.subplots(2, 2, figsize=(10, 8), tight layout=True)
for n, (name, estimator) in enumerate(estimators):
   # 初始化预测值
   y predict = np.zeros((n test, n repeat))
   for i in range(n_repeat):
       #模型拟合
       estimator.fit(X_train[i], y_train[i])
       #模型预测
       y_predict[:, i] = estimator.predict(X_test)
   # 误差分解,初始化误差值
   y_error = np.zeros(n_test)
   for i in range(n_repeat):
       for j in range(n repeat):
           # 计算预测值和真实值之间的误差
           y_error += (y_test[:, j] - y_predict[:, i]) ** 2
   # rescale─下
   y_error /= n_repeat * n_repeat
   # test数据集的噪声, 方差
   y_noise = np.var(y_test, axis=1)
   # 偏差平方和
   y_bias = (f(X_test) - np.mean(y_predict, axis=1)) ** 2
   # 预测值的方差
   y_var = np.var(y_predict, axis=1)
   print(
       "\{0\}: \{1:.4f\} (error) = \{2:.4f\} (bias^2) "
       " + {3:.4f} (var) + {4:.4f} (noise)".format(
           name, np.mean(y error), np.mean(y bias),
           np.mean(y_var), np.mean(y_noise)
   )
   # Plot figures
   ax1=axs.flatten()[n]
   # 绘制测试集的真实值, 无噪声
   ax1.plot(X_test, f(X_test), "b", label="$f(x)$")
   #绘制训练集散点图,有噪声
   ax1.plot(X_train[0], y_train[0], ".b", label="LS \sim y = f(x) + noise")
   for i in range(n repeat):
       if i == 0:
           # 测试集上的预测值
           ax1.plot(X_{test}, y_{predict}[:, i], "r", label=r"$\^y(x)$")
       else:
           # 测试集上的预测值
           ax1.plot(X_test, y_predict[:, i], "r", alpha=0.05)
   # 测试集上的预测值的均值
   ax1.plot(X_test, np.mean(y_predict, axis=1), "c", label=r"$\mathbb{E}_{LS} \
   ax1.set_xlim([-5, 5])
   ax1.set_title(name)
   if n == n estimators - 1:
       ax1.legend(loc=(1.1, 0.5))
   ax2 = axs.flatten()[n_estimators + n]
   # 测试集上的误差,偏差,方差,噪声
   ax2.plot(X_test, y_error, "r", label="$error(x)$")
   ax2.plot(X_test, y_bias, "b", label="$bias^2(x)$"),
   ax2.plot(X_test, y_var, "g", label="$variance(x)$"),
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2023/6/25 09:28 Python1

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ax2.plot(X_test, y_noise, "c", label="$noise(x)$")
ax2.set_xlim([-5, 5])
ax2.set_ylim([0, 0.1])
if n == n_estimators - 1:
    ax2.legend(loc=(1.1, 0.5))

plt.show()
fig.savefig("../codeimage/code1.pdf")
```

Tree: 0.0255 (error) = 0.0003 (bias^2) + 0.0152 (var) + 0.0098 (noise) Bagging(Tree): 0.0196 (error) = 0.0004 (bias^2) + 0.0092 (var) + 0.0098 (nois e)

