```
In [1]: # 随机森林例子
         from sklearn.datasets import load_boston
         from sklearn.model_selection import cross_val_score
         from sklearn.ensemble import RandomForestRegressor
         boston = load_boston()
         rfr = RandomForestRegressor(n_estimators=100, random_state=0)
         cross_val_score(rfr, boston.data, boston.target, cv=10
                         , scoring="neg_mean_squared_error")
         /usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87: FutureWarning: Functi
         on load_boston is deprecated; `load_boston` is deprecated in 1.0 and will be removed in 1.2.
             The Boston housing prices dataset has an ethical problem. You can refer to
             the documentation of this function for further details.
             The scikit-learn maintainers therefore strongly discourage the use of this
             dataset unless the purpose of the code is to study and educate about
             ethical issues in data science and machine learning.
             In this special case, you can fetch the dataset from the original
             source::
                 import pandas as pd
                 import numpy as np
                 data_url = "http://lib.stat.cmu.edu/datasets/boston"
                 raw_df = pd.read_csv(data_url, sep="\s+", skiprows=22, header=None)
                 data = np.hstack([raw_df.values[::2, :], raw_df.values[1::2, :2]])
                 target = raw_df.values[1::2, 2]
             Alternative datasets include the California housing dataset (i.e.
             :func:`~sklearn.datasets.fetch_california_housing`) and the Ames housing
             dataset. You can load the datasets as follows::
                 from sklearn.datasets import fetch_california_housing
                 housing = fetch_california_housing()
             for the California housing dataset and::
                 from sklearn.datasets import fetch_openml
                 housing = fetch_openml(name="house_prices", as_frame=True)
             for the Ames housing dataset.
           warnings.warn(msg, category=FutureWarning)
Out[1]: array([-11.22504076, -5.3945749 ,
                                            -4.74755867, -22.54699078,
                -12.31243335, -17.18030718, -6.94019868, -94.14567212,
                -28.541145 , -14.6250416 ])
In [2]: # 导入库
         import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt
         from sklearn.impute import SimpleImputer
In [3]: # 以波士顿数据集为例,导入完整的数据集并探索
         n_samples, n_features = boston.data.shape
         print(n_samples)
         print(n_features)
         506
         13
In [4]: # 为完整数据集放入缺失值
         rng = np.random.RandomState(0)
         missing_rate = 0.5
         n_missing_samples = int(np.floor(n_samples * n_features * missing_rate))
         n_missing_samples
Out[4]: 3289
In [5]: X_missing = boston.data.copy()
         missing_samples = rng.randint(0, n_samples, n_missing_samples)
         missing_features = rng.randint(0, n_features, n_missing_samples)
         X_missing[missing_samples, missing_features] = np.nan
         X_missing = pd.DataFrame(X_missing)
In [6]: # 使用O和均值填补缺失值
         imp_mean = SimpleImputer(missing_values=np.nan, strategy='mean')
         X_missing_mean = imp_mean.fit_transform(X_missing)
         imp_0 = SimpleImputer(missing_values=np.nan, strategy='constant', fill_value=0)
         X_missing_0 = imp_0.fit_transform(X_missing)
In [7]: # 使用随机森林填补缺失值
         X_missing_reg = X_missing.copy()
         sortindex = np.argsort(X_missing_reg.isnull().sum(axis=0)).values
         y = boston.target
         print(pd.concat([X_missing_reg.isnull().sum(axis=0), np.argsort(X_missing_reg.isnull().sum(ax
         is=0))], axis=1))
         for i in sortindex:
           # 构建新新标签和新数据集
           df = X_missing_reg
           fillc = df.iloc[:,i]
           df = pd.concat([df.iloc[:,df.columns!=i], pd.DataFrame(y)], axis=1)
           # 填补新数据集
           df_0 = imp_0.fit_transform(df)
           # 拆分训练集和测试集
           Ytrain = fillc[fillc.notnull()]
           Ytest = fillc[fillc.isnull()]
           Xtrain = df_0[fillc.notnull(),:]
           Xtest = df_0[fillc.isnull(),:]
           # 用随机森林回归来填补缺失值
           rfr = RandomForestRegressor(n_estimators=100)
           rfr = rfr.fit(Xtrain, Ytrain)
           Ypredict = rfr.predict(Xtest)
           X_missing_reg.loc[fillc.isnull(),i] = Ypredict
               0
                   1
         0
             200
                   7
             193
         1
                   2
             189
                   1
         3
             196
                   3
             202
         4
                   8
         5
             206
                   0
             213
                   9
         7
             182
                  4
             199 12
         8
             200
         9
                  5
         10
            206
                 10
         11 211
                 11
            203
         12
                   6
In [8]: # 对填补好的数据进行建模
         X = [boston.data, X_missing_mean, X_missing_0, X_missing_reg]
         for x in X:
           rfr = RandomForestRegressor(random_state=0, n_estimators=100)
           score = cross_val_score(rfr, x, boston.target, cv=10
                                   , scoring='neg_mean_squared_error').mean()
           mse.append(score * -1)
In [17]: # 绘出条形图
         x_labels = ['Full data',
                     'Zero Imputation',
                     'Mean Imputation',
                     'Regressor Imputation']
         colors = ['red', 'green', 'blue', 'orange']
         plt.figure(figsize=(12,6))
         ax = plt.subplot(111)
         for i in np.arange(len(mse)):
           ax.barh(i, mse[i], color=colors[i], alpha=0.6, align='center')
         ax.set_title('Imputation Techniques with Boston Data')
         ax.set_xlim(left=np.min(mse)*0.9, right=np.max(mse)*1.1)
         ax.set_xlabel('MSE')
         ax.set_yticks(range(len(mse)))
         ax.set_yticklabels(x_labels)
         plt.show()
                                                Imputation Techniques with Boston Data
          Regressor Imputation
            Mean Imputation
```

Zero Imputation

Full data

15

25

30

MSE

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