Working with Missing Data

Utilizing the California Housing dataset

Setup

In [1]:

```
# Import package dependencies
import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
from ml_metrics import rmse
import matplotlib.pyplot as plt
from sklearn import datasets
```

Load Dataset

In [2]:

```
# Load in the dataset
california = datasets.fetch_california_housing()
print(california.data.shape)
```

```
(20640, 8)
```

In [3]:

```
print(california.keys())
```

```
dict_keys(['data', 'target', 'frame', 'target_names', 'feature_names', 'DE
SCR'])
```

In [4]:

```
print(california.DESCR)
```

```
.. _california_housing_dataset:

California Housing dataset
--------------------------

**Data Set Characteristics:**

    :Number of Instances: 20640

    :Number of Attributes: 8 numeric, predictive attributes and the target

    :Attribute Information:
        - MedInc        median income in block
        - HouseAge      median house age in block
        - AveRooms      average number of rooms
        - AveBedrms     average number of bedrooms
        - Population    block population
        - AveOccup      average house occupancy
        - Latitude      house block latitude
        - Longitude     house block longitude

    :Missing Attribute Values: None

This dataset was obtained from the StatLib repository.
http://lib.stat.cmu.edu/datasets/

The target variable is the median house value for California districts.

This dataset was derived from the 1990 U.S. census, using one row per cens
us
block group. A block group is the smallest geographical unit for which the
U.S.
Census Bureau publishes sample data (a block group typically has a populat
ion
of 600 to 3,000 people).

It can be downloaded/loaded using the
:func:`sklearn.datasets.fetch_california_housing` function.

.. topic:: References

    - Pace, R. Kelley and Ronald Barry, Sparse Spatial Autoregressions,
      Statistics and Probability Letters, 33 (1997) 291-297
```

In [5]:

```
print(california.feature_names)
```

```
['MedInc', 'HouseAge', 'AveRooms', 'AveBedrms', 'Population', 'AveOccup',
'Latitude', 'Longitude']
```

In [6]:

```
california.target
```

Out[6]:

```
array([4.526, 3.585, 3.521, ..., 0.923, 0.847, 0.894])
```

In [7]:

```
# Convert the matrix to pandas
cal = pd.DataFrame(california.data)
cal.columns = california.feature_names
cal['MedInc'] = california.target
cal.head()
```

Out[7]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude
0	4.526	41.0	6.984127	1.023810	322.0	2.555556	37.88	-122.23
1	3.585	21.0	6.238137	0.971880	2401.0	2.109842	37.86	-122.22
2	3.521	52.0	8.288136	1.073446	496.0	2.802260	37.85	-122.24
3	3.413	52.0	5.817352	1.073059	558.0	2.547945	37.85	-122.25
4	3.422	52.0	6.281853	1.081081	565.0	2.181467	37.85	-122.25

Exploratory Data Analysis

In [8]:

```
cal.describe()
```

Out[8]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	2.068558	28.639486	5.429000	1.096675	1425.476744	3.070655
std	1.153956	12.585558	2.474173	0.473911	1132.462122	10.386050
min	0.149990	1.000000	0.846154	0.333333	3.000000	0.692308
25%	1.196000	18.000000	4.440716	1.006079	787.000000	2.429741
50%	1.797000	29.000000	5.229129	1.048780	1166.000000	2.818116
75%	2.647250	37.000000	6.052381	1.099526	1725.000000	3.282261
max	5.000010	52.000000	141.909091	34.066667	35682.000000	1243.333333

In [9]:

```
feature_names = cal.columns[1:].values
label_name = cal.columns[0]
print(f"Features: {feature_names}")
print(f"Label: {label_name}")
```

```
Features: ['HouseAge' 'AveRooms' 'AveBedrms' 'Population' 'AveOccup' 'Lati
tude'
 'Longitude']
Label: MedInc
```

Case 3 - Missing Not at Random (MNAR)

Start by fitting a Linear Regression model to the full dataset

Create a training and testing split (ex., 70/30-split)

In [10]:

```
# Create training and testing sets (cross-validation not needed)
train_set = cal.sample(frac=0.7, random_state=100)
test_set = cal[~cal.isin(train_set)].dropna()
print(train_set.shape[0])
print(test_set.shape[0])
```

```
14448
6192
```

In [11]:

```
train_set.head()
```

Out[11]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitud
8151	2.453	36.0	6.276836	1.039548	444.0	2.508475	33.81	-118.1
53	1.042	52.0	4.075000	1.140000	1162.0	2.905000	37.82	-122.2
3039	1.462	13.0	6.746647	1.062593	2170.0	3.233979	35.37	-119.1
9484	1.542	19.0	6.750000	1.348684	424.0	2.789474	39.31	-123.1
9307	3.242	31.0	4.477459	1.073087	2962.0	2.023224	37.98	-122.5

In [12]:

```
# Get the training and testing row indices for later use
train_index = train_set.index.values.astype(int)
test_index = test_set.index.values.astype(int)
```

In [13]:

```
# Demonstration of using the row indices above to select consistent records
cal.iloc[train_index].head()
```

Out[13]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitud
8151	2.453	36.0	6.276836	1.039548	444.0	2.508475	33.81	-118.1
53	1.042	52.0	4.075000	1.140000	1162.0	2.905000	37.82	-122.2
3039	1.462	13.0	6.746647	1.062593	2170.0	3.233979	35.37	-119.1
9484	1.542	19.0	6.750000	1.348684	424.0	2.789474	39.31	-123.1
9307	3.242	31.0	4.477459	1.073087	2962.0	2.023224	37.98	-122.5

In [14]:

```
# Converting the training and testing datasets back to matrix-formats
X_train = train_set.iloc[:, 1:].values # returns the data; excluding the target
Y_train = train_set.iloc[:, 0].values # returns the target-only
X_test = test_set.iloc[:, 1:].values # ""
Y_test = test_set.iloc[:, 0].values # ""
```

In [15]:

```
def print_model_stats(model, X_train, Y_train, feature_names):
    print(f"Train R2: {model.score(X_train, Y_train)}")
    for feature, coef in zip(feature_names, model.coef_):
        print(f"\tFeature: {feature}, Coef: {round(coef,2)}")
    print(f"Model Intercept: {model.intercept_}")
    print(f"Model Parameters: {model.get_params()}")

    # Find the variable with the largest "normalized" coefficient value
    # print('The positive(max) coef-value is {}'.format(max(reg.coef_))) # Positive Max
    print('The abs(max) coef-value is {}'.format(max(model.coef_, key=abs))) # ABS Max
    # max_var = max(reg.coef_) # Positive Max
    max_var = max(model.coef_, key=abs) # ABS Max
    var_index = model.coef_.tolist().index(max_var)
    print('The variable associated with this coef-value is {}'.format(feature_names[var
_index]))
```

In [16]:

```
# Fit a linear regression to the training data
reg = LinearRegression(normalize=True).fit(X_train, Y_train)
print_model_stats(model=reg, X_train=X_train, Y_train=Y_train, feature_names=feature_na
mes)
```

```
Train R2: 0.4021408992488681
        Feature: HouseAge, Coef: 0.01
        Feature: AveRooms, Coef: 0.36
        Feature: AveBedrms, Coef: -1.38
        Feature: Population, Coef: -0.0
        Feature: AveOccup, Coef: -0.0
        Feature: Latitude, Coef: -0.73
        Feature: Longitude, Coef: -0.72
Model Intercept: -59.014861272508604
Model Parameters: {'copy_X': True, 'fit_intercept': True, 'n_jobs': None,
'normalize': True}
The abs(max) coef-value is -1.381296266178564
The variable associated with this coef-value is AveBedrms
```

In [17]:

```
def return_metrics(model, X_test, Y_test, nround=3):
    Y_pred = model.predict(X_test)
    mae = round(mean_absolute_error(Y_test,Y_pred),nround)
    mse = round(mean_squared_error(Y_test,Y_pred),nround)
    rmse_val = round(rmse(Y_test,Y_pred),nround)
    r2 = round(r2_score(Y_test,Y_pred), nround)
    print(f"MAE: {mae}, MSE: {mse}, RMSE: {rmse_val}, R2: {r2}")
    return mae, mse, rmse_val, r2
```

In [18]:

```
orig_mae, orig_mse, orig_rmse_val, orig_r2 = return_metrics(reg, X_test, Y_test)
res_frame = pd.DataFrame({
    'data':'original',
    'imputation':'none',
    'mae': orig_mae,
    'mse': orig_mse,
    'rmse': orig_rmse_val,
    'R2': orig_r2,
    'mae_diff': np.nan,
    'mse_diff': np.nan,
    'rmse_diff': np.nan,
    'R2_diff': np.nan}, index=[0])
res_frame
```

```
MAE: 0.678, MSE: 0.808, RMSE: 0.899, R2: 0.39
```

Out[18]:

	data	imputation	mae	mse	rmse	R2	mae_diff	mse_diff	rmse_diff	R2_diff
0	original	none	0.678	0.808	0.899	0.39	NaN	NaN	NaN	NaN

Round 1 of Imputation

Here we can randomly sample the full dataset and replace a single column's values

In [19]:

```
cal.describe()
```

Out[19]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	2.068558	28.639486	5.429000	1.096675	1425.476744	3.070655
std	1.153956	12.585558	2.474173	0.473911	1132.462122	10.386050
min	0.149990	1.000000	0.846154	0.333333	3.000000	0.692308
25%	1.196000	18.000000	4.440716	1.006079	787.000000	2.429741
50%	1.797000	29.000000	5.229129	1.048780	1166.000000	2.818116
75%	2.647250	37.000000	6.052381	1.099526	1725.000000	3.282261
max	5.000010	52.000000	141.909091	34.066667	35682.000000	1243.333333

In [20]:

```
## Choose a variable to replace
var = 'AveBedrms'
```

In [21]:

```
# 25% Nullified not at Random
sum(cal[var] > 1.0995)/len(cal)
```

Out[21]:

```
0.2500968992248062
```

In [22]:

```
in_sample = cal[cal[var] > 1.0995]
in_sample.shape
```

Out[22]:

```
(5162, 8)
```

In [23]:

```
out_sample = cal[~cal.isin(in_sample)].dropna()
out_sample.shape
```

Out[23]:

```
(15478, 8)
```

In [24]:

```
print(out_sample.shape[0] + in_sample.shape[0])
print(cal.shape[0])
```

```
20640
20640
```

Stats before and after nullifying

In [25]:

```
out_sample.describe()
```

Out[25]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup
count	15478.000000	15478.000000	15478.000000	15478.000000	15478.000000	15478.000000
mean	2.138273	29.377762	5.218842	1.020622	1463.513115	3.053651
std	1.136705	12.222164	1.179026	0.054446	1134.568246	10.044541
min	0.266000	1.000000	0.846154	0.333333	5.000000	0.970588
25%	1.310000	19.000000	4.408637	0.992660	825.000000	2.469555
50%	1.875000	30.000000	5.167558	1.028169	1200.000000	2.854323
75%	2.713000	37.000000	5.950183	1.059217	1760.000000	3.310223
max	5.000010	52.000000	10.370656	1.099490	35682.000000	1243.333333

In [26]:

```
in_sample.describe()
```

Out[26]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	I
count	5162.000000	5162.000000	5162.000000	5162.000000	5162.000000	5162.000000	5162
mean	1.859520	26.425804	6.059148	1.324717	1311.426579	3.121642	35
std	1.179872	13.376301	4.447684	0.905483	1118.504226	11.349494	2
min	0.149990	1.000000	1.260870	1.099502	3.000000	0.692308	32
25%	0.978250	16.000000	4.537158	1.120518	664.000000	2.313486	33
50%	1.530000	25.000000	5.438661	1.152621	1050.000000	2.701410	34
75%	2.356000	36.000000	6.384640	1.233075	1618.750000	3.187990	37
max	5.000010	52.000000	141.909091	34.066667	16305.000000	599.714286	41

In [27]:

```
in_sample[var] = np.nan
```

```
C:\Users\Nikhil\.conda\envs\ds7337_cs3\lib\site-packages\ipykernel_launche
r.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.
```

In [28]:

```
in_sample.describe()
```

Out[28]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	L
count	5162.000000	5162.000000	5162.000000	0.0	5162.000000	5162.000000	5162.
mean	1.859520	26.425804	6.059148	NaN	1311.426579	3.121642	35.
std	1.179872	13.376301	4.447684	NaN	1118.504226	11.349494	2.
min	0.149990	1.000000	1.260870	NaN	3.000000	0.692308	32.
25%	0.978250	16.000000	4.537158	NaN	664.000000	2.313486	33.
50%	1.530000	25.000000	5.438661	NaN	1050.000000	2.701410	34.
75%	2.356000	36.000000	6.384640	NaN	1618.750000	3.187990	37.
max	5.000010	52.000000	141.909091	NaN	16305.000000	599.714286	41.

In [29]:

```
in_sample.head()
```

Out[29]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude
5	2.697	52.0	4.761658	NaN	413.0	2.139896	37.85	-122.25
8	2.267	42.0	4.294118	NaN	1206.0	2.026891	37.84	-122.26
20	1.475	40.0	4.524096	NaN	409.0	2.463855	37.85	-122.27
22	1.139	52.0	5.096234	NaN	1015.0	2.123431	37.84	-122.27
30	1.223	49.0	5.068783	NaN	863.0	2.283069	37.84	-122.28

Choose an imputation method

In [30]:

```
out_sample[var].median()
```

Out[30]:

```
1.028169014084507
```

In [31]:

```
in_sample[var] = in_sample[var].fillna(out_sample[var].median())
in_sample.head()
```

```
C:\Users\Nikhil\.conda\envs\ds7337_cs3\lib\site-packages\ipykernel_launche
r.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.
```

Out[31]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude
5	2.697	52.0	4.761658	1.028169	413.0	2.139896	37.85	-122.25
8	2.267	42.0	4.294118	1.028169	1206.0	2.026891	37.84	-122.26
20	1.475	40.0	4.524096	1.028169	409.0	2.463855	37.85	-122.27
22	1.139	52.0	5.096234	1.028169	1015.0	2.123431	37.84	-122.27
30	1.223	49.0	5.068783	1.028169	863.0	2.283069	37.84	-122.28

In [32]:

```
in_sample[var].describe()
```

Out[32]:

```
count    5.162000e+03
mean     1.028169e+00
std      2.220661e-16
min      1.028169e+00
25%      1.028169e+00
50%      1.028169e+00
75%      1.028169e+00
max      1.028169e+00
Name: AveBedrms, dtype: float64
```

Rejoin the imputed and original datasets

In [33]:

```
imputed_data = pd.concat([in_sample, out_sample])
imputed_data = imputed_data.sort_index()
imputed_data.head(10)
```

Out[33]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude
0	4.526	41.0	6.984127	1.023810	322.0	2.555556	37.88	-122.23
1	3.585	21.0	6.238137	0.971880	2401.0	2.109842	37.86	-122.22
2	3.521	52.0	8.288136	1.073446	496.0	2.802260	37.85	-122.24
3	3.413	52.0	5.817352	1.073059	558.0	2.547945	37.85	-122.25
4	3.422	52.0	6.281853	1.081081	565.0	2.181467	37.85	-122.25
5	2.697	52.0	4.761658	1.028169	413.0	2.139896	37.85	-122.25
6	2.992	52.0	4.931907	0.951362	1094.0	2.128405	37.84	-122.25
7	2.414	52.0	4.797527	1.061824	1157.0	1.788253	37.84	-122.25
8	2.267	42.0	4.294118	1.028169	1206.0	2.026891	37.84	-122.26
9	2.611	52.0	4.970588	0.990196	1551.0	2.172269	37.84	-122.25

Use the same training and testing indices to fit the model

In [34]:

```
train_set = imputed_data.iloc[train_index]
test_set = imputed_data.iloc[test_index]
train_set.head()
```

Out[34]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitud
8151	2.453	36.0	6.276836	1.039548	444.0	2.508475	33.81	-118.1
53	1.042	52.0	4.075000	1.028169	1162.0	2.905000	37.82	-122.2
3039	1.462	13.0	6.746647	1.062593	2170.0	3.233979	35.37	-119.1
9484	1.542	19.0	6.750000	1.028169	424.0	2.789474	39.31	-123.1
9307	3.242	31.0	4.477459	1.073087	2962.0	2.023224	37.98	-122.5

In [35]:

```
# Converting the training and testing datasets back to matrix-formats
X_train = train_set.iloc[:, 1:].values # returns the data; excluding the target
Y_train = train_set.iloc[:, 0].values # returns the target-only
X_test = test_set.iloc[:, 1:].values # ""
Y_test = test_set.iloc[:, 0].values # ""
```

Fit a new model to the imputed dataset

In [36]:

```
reg2 = LinearRegression().fit(X_train, Y_train)
print_model_stats(model=reg2, X_train=X_train, Y_train=Y_train, feature_names=feature_n
ames)
```

```
Train R2: 0.32637770552796863
        Feature: HouseAge, Coef: 0.0
        Feature: AveRooms, Coef: 0.16
        Feature: AveBedrms, Coef: -0.04
        Feature: Population, Coef: -0.0
        Feature: AveOccup, Coef: -0.0
        Feature: Latitude, Coef: -0.78
        Feature: Longitude, Coef: -0.78
Model Intercept: -64.87324065657128
Model Parameters: {'copy_X': True, 'fit_intercept': True, 'n_jobs': None,
'normalize': False}
The abs(max) coef-value is -0.7848961459998272
The variable associated with this coef-value is Longitude
```

In [37]:

```
mae, mse, rmse_val, r2 = return_metrics(reg2, X_test, Y_test)
temp_frame = pd.DataFrame({
    'data':'25% MNAR',
    'imputation':'Median',
    'mae': mae,
    'mse': mse,
    'rmse':rmse_val,
    'R2':r2,
    'mae_diff':mae-orig_mae,
    'mse_diff':mse-orig_mse,
    'rmse_diff':rmse_val-orig_rmse_val,
    'R2_diff':r2-orig_r2
    }, index=[0])
res_frame = pd.concat([res_frame, temp_frame])
res_frame
```

```
MAE: 0.717, MSE: 0.989, RMSE: 0.995, R2: 0.253
```

Out[37]:

	data	imputation	mae	mse	rmse	R2	mae_diff	mse_diff	rmse_diff	R2_diff
0	original	none	0.678	0.808	0.899	0.390	NaN	NaN	NaN	NaN
0	25% MNAR	Median	0.717	0.989	0.995	0.253	0.039	0.181	0.096	-0.137

Round 2 of Imputation (KNN)

In [38]:

```
in_sample = cal[cal['AveBedrms'] > 1.0995]
in_sample.shape
```

Out[38]:

```
(5162, 8)
```

In [39]:

```
out_sample = cal[~cal.isin(in_sample)].dropna()
out_sample.shape
```

Out[39]:

```
(15478, 8)
```

In [40]:

```
print(out_sample.shape[0] + in_sample.shape[0])
print(cal.shape[0])
```

```
20640
20640
```

In [41]:

```
in_sample[var] = np.nan
```

```
C:\Users\Nikhil\.conda\envs\ds7337_cs3\lib\site-packages\ipykernel_launche
r.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.
```

In [42]:

```
in_sample.describe()
```

Out[42]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	L
count	5162.000000	5162.000000	5162.000000	0.0	5162.000000	5162.000000	5162.
mean	1.859520	26.425804	6.059148	NaN	1311.426579	3.121642	35.
std	1.179872	13.376301	4.447684	NaN	1118.504226	11.349494	2.
min	0.149990	1.000000	1.260870	NaN	3.000000	0.692308	32.
25%	0.978250	16.000000	4.537158	NaN	664.000000	2.313486	33.
50%	1.530000	25.000000	5.438661	NaN	1050.000000	2.701410	34.
75%	2.356000	36.000000	6.384640	NaN	1618.750000	3.187990	37.
max	5.000010	52.000000	141.909091	NaN	16305.000000	599.714286	41.

In [43]:

```
imputed_data = pd.concat([in_sample, out_sample])
imputed_data = imputed_data.sort_index()
imputed_data.head(10)
```

Out[43]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude
0	4.526	41.0	6.984127	1.023810	322.0	2.555556	37.88	-122.23
1	3.585	21.0	6.238137	0.971880	2401.0	2.109842	37.86	-122.22
2	3.521	52.0	8.288136	1.073446	496.0	2.802260	37.85	-122.24
3	3.413	52.0	5.817352	1.073059	558.0	2.547945	37.85	-122.25
4	3.422	52.0	6.281853	1.081081	565.0	2.181467	37.85	-122.25
5	2.697	52.0	4.761658	NaN	413.0	2.139896	37.85	-122.25
6	2.992	52.0	4.931907	0.951362	1094.0	2.128405	37.84	-122.25
7	2.414	52.0	4.797527	1.061824	1157.0	1.788253	37.84	-122.25
8	2.267	42.0	4.294118	NaN	1206.0	2.026891	37.84	-122.26
9	2.611	52.0	4.970588	0.990196	1551.0	2.172269	37.84	-122.25

In [44]:

```
from sklearn.impute import KNNImputer
imputer = KNNImputer(n_neighbors=21, )
imputed_data = imputer.fit_transform(imputed_data)
imputed_data = pd.DataFrame(imputed_data, columns=california.feature_names)
```

In [45]:

```
imputed_data.describe()
```

Out[45]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	2.068558	28.639486	5.429000	1.019259	1425.476744	3.070655
std	1.153956	12.585558	2.474173	0.049644	1132.462122	10.386050
min	0.149990	1.000000	0.846154	0.333333	3.000000	0.692308
25%	1.196000	18.000000	4.440716	0.998463	787.000000	2.429741
50%	1.797000	29.000000	5.229129	1.024663	1166.000000	2.818116
75%	2.647250	37.000000	6.052381	1.049569	1725.000000	3.282261
max	5.000010	52.000000	141.909091	1.099490	35682.000000	1243.333333

Use the same training and testing indices to fit the model

In [46]:

```
train_set = imputed_data.iloc[train_index]
test_set = imputed_data.iloc[test_index]
train_set.head()
```

Out[46]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitud
8151	2.453	36.0	6.276836	1.039548	444.0	2.508475	33.81	-118.1
53	1.042	52.0	4.075000	1.033517	1162.0	2.905000	37.82	-122.2
3039	1.462	13.0	6.746647	1.062593	2170.0	3.233979	35.37	-119.1
9484	1.542	19.0	6.750000	0.995947	424.0	2.789474	39.31	-123.1
9307	3.242	31.0	4.477459	1.073087	2962.0	2.023224	37.98	-122.5

In [47]:

```
# Converting the training and testing datasets back to matrix-formats
X_train = train_set.iloc[:, 1:].values # returns the data; excluding the target
Y_train = train_set.iloc[:, 0].values # returns the target-only
X_test = test_set.iloc[:, 1:].values # ""
Y_test = test_set.iloc[:, 0].values # ""
```

Fit a new model to the imputed dataset

In [48]:

```
reg3 = LinearRegression().fit(X_train, Y_train)
print_model_stats(model=reg3, X_train=X_train, Y_train=Y_train, feature_names=feature_n
ames)
```

```
Train R2: 0.32662108482540664
        Feature: HouseAge, Coef: 0.0
        Feature: AveRooms, Coef: 0.16
        Feature: AveBedrms, Coef: 0.38
        Feature: Population, Coef: -0.0
        Feature: AveOccup, Coef: -0.0
        Feature: Latitude, Coef: -0.78
        Feature: Longitude, Coef: -0.78
Model Intercept: -65.2786492885054
Model Parameters: {'copy_X': True, 'fit_intercept': True, 'n_jobs': None,
'normalize': False}
The abs(max) coef-value is -0.7847978535729381
The variable associated with this coef-value is Longitude
```

In [49]:

```
mae, mse, rmse_val, r2 = return_metrics(reg3, X_test, Y_test)
temp_frame = pd.DataFrame({
    'data':'25% MNAR',
    'imputation':'KNN',
    'mae': mae,
    'mse': mse,
    'rmse':rmse_val,
    'R2':r2,
    'mae_diff':mae-orig_mae,
    'mse_diff':mse-orig_mse,
    'rmse_diff':rmse_val-orig_rmse_val,
    'R2_diff':r2-orig_r2
    }, index=[0])
res_frame = pd.concat([res_frame, temp_frame])
res_frame
```

```
MAE: 0.717, MSE: 0.988, RMSE: 0.994, R2: 0.254
```

Out[49]:

	data	imputation	mae	mse	rmse	R2	mae_diff	mse_diff	rmse_diff	R2_diff
0	original	none	0.678	0.808	0.899	0.390	NaN	NaN	NaN	NaN
0	25% MNAR	Median	0.717	0.989	0.995	0.253	0.039	0.181	0.096	-0.137
0	25% MNAR	KNN	0.717	0.988	0.994	0.254	0.039	0.180	0.095	-0.136

Using scikit example

In [50]:

```
from sklearn.impute import SimpleImputer, KNNImputer
from sklearn.model_selection import cross_val_score
from sklearn.pipeline import make_pipeline
```

In [51]:

```
from sklearn.model_selection import KFold
```

In [52]:

```
def get_scores_for_imputer(imputer, model, X_missing, y_missing, scoring = 'neg_mean_sq
uared_error', cv=5):
    estimator = make_pipeline(imputer, model)
    impute_scores = cross_val_score(estimator, X_missing, y_missing, scoring=scoring, c
v=cv)
    return impute_scores

def get_impute_zero_score(model, X_missing, y_missing, scoring = 'neg_mean_squared_erro
r', cv=5):
    imputer = SimpleImputer(missing_values=np.nan, add_indicator=True, strategy='consta
nt', fill_value=0)
    zero_impute_scores = get_scores_for_imputer(
        imputer=imputer, model=model, X_missing=X_missing, y_missing=y_missing, scoring
=scoring, cv=cv
    )
    return zero_impute_scores.mean(), zero_impute_scores.std()

def get_impute_knn_score(model, X_missing, y_missing, scoring = 'neg_mean_squared_erro
r', cv=5):
    imputer = KNNImputer(missing_values=np.nan, add_indicator=True)
    knn_impute_scores = get_scores_for_imputer(
        imputer=imputer, model=model, X_missing=X_missing, y_missing=y_missing, scoring
=scoring, cv=cv
    )
    return knn_impute_scores.mean(), knn_impute_scores.std()

def get_impute_mean(model, X_missing, y_missing, scoring = 'neg_mean_squared_error', cv
=5):
    imputer = SimpleImputer(missing_values=np.nan, strategy="mean", add_indicator=True)
    mean_impute_scores = get_scores_for_imputer(
        imputer=imputer, model=model, X_missing=X_missing, y_missing=y_missing, scoring
=scoring, cv=cv
    )
    return mean_impute_scores.mean(), mean_impute_scores.std()

def get_impute_median(model, X_missing, y_missing, scoring = 'neg_mean_squared_error',
cv=5):
    imputer = SimpleImputer(missing_values=np.nan, strategy="median", add_indicator=Tru
e)
    mean_impute_scores = get_scores_for_imputer(
        imputer=imputer, model=model, X_missing=X_missing, y_missing=y_missing, scoring
=scoring, cv=cv
    )
    return mean_impute_scores.mean(), mean_impute_scores.std()

def get_full_score(model, X_full, y_full, scoring='neg_mean_squared_error', cv=5):
    full_scores = cross_val_score(model, X_full, y_full, scoring=scoring, cv=cv)
    return full_scores.mean(), full_scores.std()
```

Original Data

In [53]:

```
X_full = cal.iloc[:, 1:]
y_full = cal.iloc[:, 0]
print(X_full.shape, y_full.shape)
```

```
(20640, 7) (20640,)
```

Add Missing Data

In [54]:

```
in_sample = cal[cal['AveBedrms'] > 1.0995]
in_sample.shape
```

Out[54]:

```
(5162, 8)
```

In [55]:

```
out_sample = cal[~cal.isin(in_sample)].dropna()
out_sample.shape
```

Out[55]:

```
(15478, 8)
```

In [56]:

```
print(out_sample.shape[0] + in_sample.shape[0])
print(cal.shape[0])
```

```
20640
20640
```

In [57]:

```
in_sample[var] = np.nan
```

```
C:\Users\Nikhil\.conda\envs\ds7337_cs3\lib\site-packages\ipykernel_launche
r.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
s/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.
```

In [58]:

```
missing_data = pd.concat([in_sample, out_sample])
missing_data = missing_data.sort_index()
missing_data.head(10)
```

Out[58]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude
0	4.526	41.0	6.984127	1.023810	322.0	2.555556	37.88	-122.23
1	3.585	21.0	6.238137	0.971880	2401.0	2.109842	37.86	-122.22
2	3.521	52.0	8.288136	1.073446	496.0	2.802260	37.85	-122.24
3	3.413	52.0	5.817352	1.073059	558.0	2.547945	37.85	-122.25
4	3.422	52.0	6.281853	1.081081	565.0	2.181467	37.85	-122.25
5	2.697	52.0	4.761658	NaN	413.0	2.139896	37.85	-122.25
6	2.992	52.0	4.931907	0.951362	1094.0	2.128405	37.84	-122.25
7	2.414	52.0	4.797527	1.061824	1157.0	1.788253	37.84	-122.25
8	2.267	42.0	4.294118	NaN	1206.0	2.026891	37.84	-122.26
9	2.611	52.0	4.970588	0.990196	1551.0	2.172269	37.84	-122.25

In [59]:

```
X_missing = missing_data.iloc[:, 1:].values
y_missing = missing_data.iloc[:, 0].values
```

Various Imputed Scores

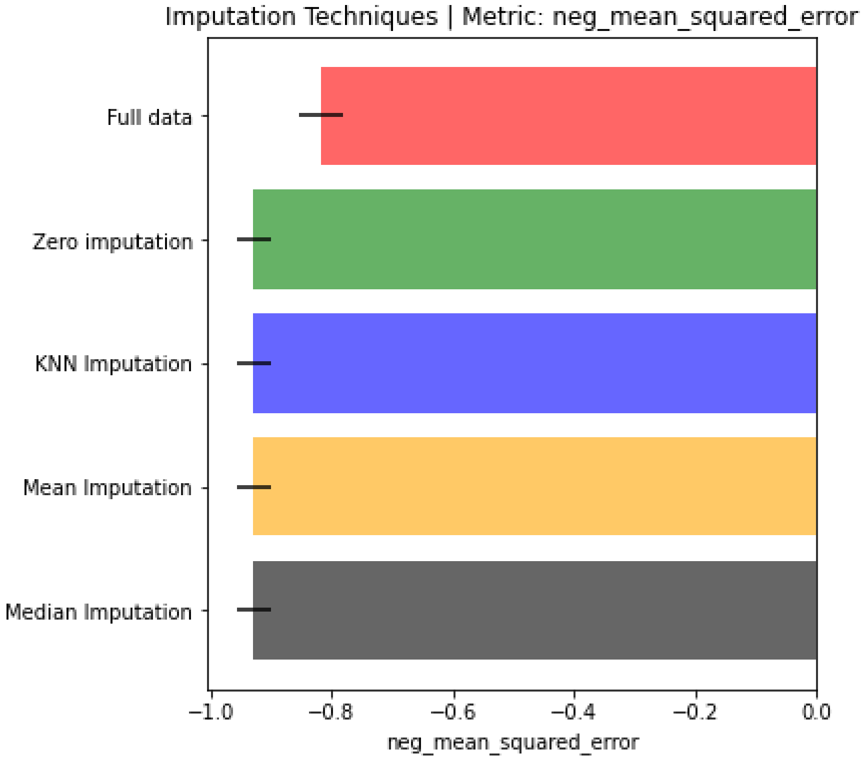
In [60]:

```
def perform_all_analysis(scoring):
    model = LinearRegression(normalize=True)

    x_labels = ['Full data', 'Zero imputation', 'KNN Imputation', 'Mean Imputation', 'M
edian Imputation']
    num = len(x_labels)

    cv = KFold(n_splits=5, shuffle=True, random_state=42)

    metric_means = np.zeros(num)
    metric_stds = np.zeros(num)

    # Original
    metric_means[0], metric_stds[0] = get_full_score(model, X_full, y_full, scoring=sco
ring, cv=cv)

    # Various Imputed
    metric_means[1], metric_stds[1] = get_impute_zero_score(model, X_missing, y_missing
, scoring=scoring, cv=cv)
    metric_means[2], metric_stds[2] = get_impute_knn_score(model, X_missing, y_missing,
scoring=scoring, cv=cv)
    metric_means[3], metric_stds[3] = get_impute_mean(model, X_missing, y_missing, scor
ing=scoring, cv=cv)
    metric_means[4], metric_stds[4] = get_impute_median(model, X_missing, y_missing, sc
oring=scoring, cv=cv)

    print(f"Mean Metric Values: {metric_means}, Std Dev of Metric: {metric_stds}")

    ## Plot Data
    xval = np.arange(num)

    colors = ['r', 'g', 'b', 'orange', 'black']

    # plot results
    plt.figure(figsize=(12, 6))
    ax1 = plt.subplot(121)
    for j in xval:
        ax1.barh(j, metric_means[j], xerr=metric_stds[j], color=colors[j], alpha=0.6, a
lign='center')

    ax1.set_title(f'Imputation Techniques | Metric: {scoring}')
    ax1.set_yticks(xval)
    ax1.set_xlabel(scoring)
    ax1.invert_yaxis()
    ax1.set_yticklabels(x_labels)

    plt.show()

    return metric_means, metric_stds
```

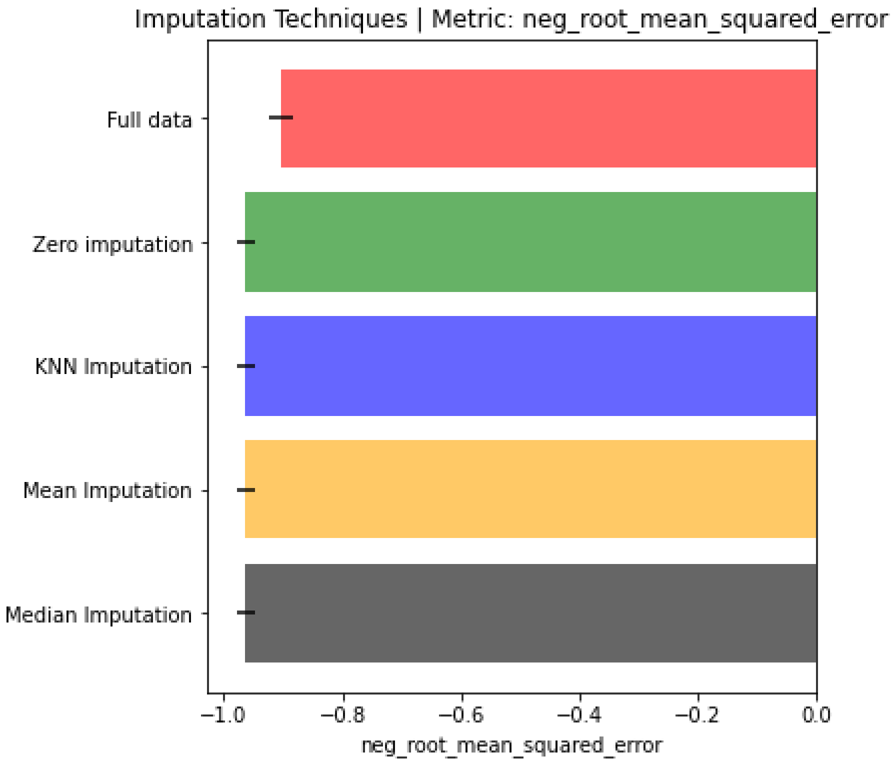
In [61]:

```
perform_all_analysis(scoring = 'neg_mean_squared_error')
perform_all_analysis(scoring = 'neg_root_mean_squared_error')
perform_all_analysis(scoring = 'neg_mean_absolute_error')
perform_all_analysis(scoring = 'r2')
```

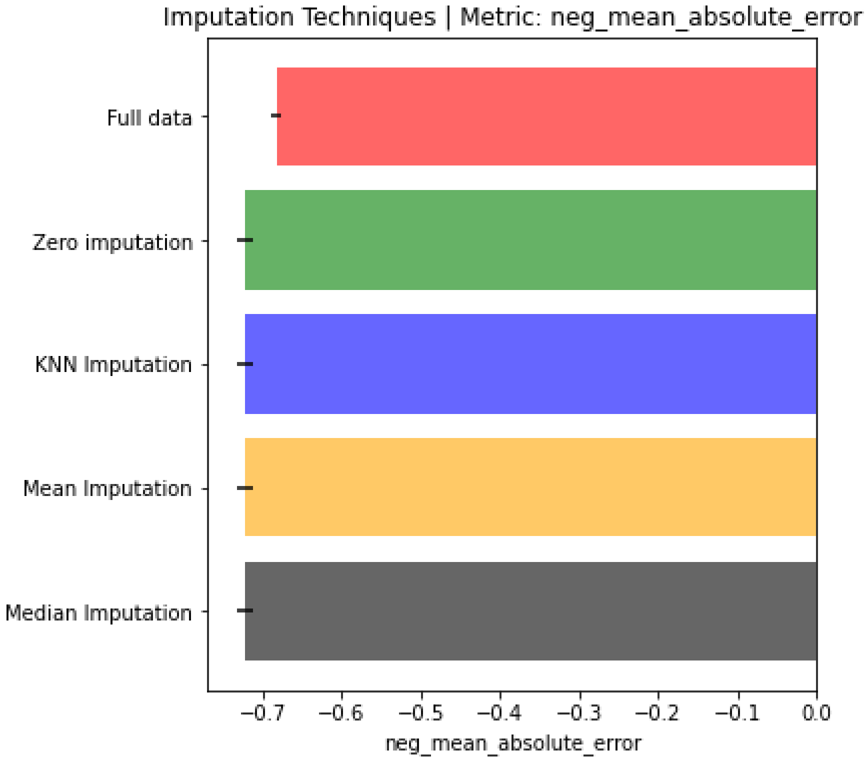
```
Mean Metric Values: [-0.81723216 -0.92887607 -0.92862265 -0.92887607 -0.92
887607], Std Dev of Metric: [0.03543389 0.0291951  0.02914652 0.0291951
0.0291951 ]
```



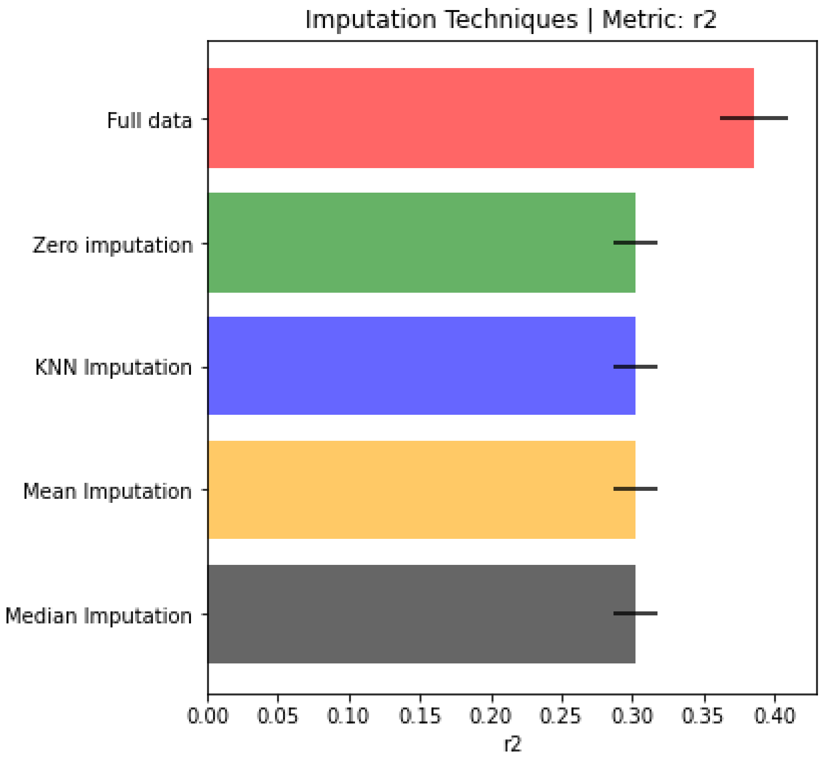

```
Mean Metric Values: [-0.90379834 -0.96366189 -0.96353077 -0.96366189 -0.96
366189], Std Dev of Metric: [0.01951194 0.01522624 0.01520213 0.01522624
0.01522624]
```




```
Mean Metric Values: [-0.68183741 -0.72252395 -0.72244713 -0.72252395 -0.72
252395], Std Dev of Metric: [0.00693352 0.01026593 0.01035667 0.01026593
0.01026593]
```




```
Mean Metric Values: [0.38617075 0.30235608 0.30254518 0.30235608 0.3023560
8], Std Dev of Metric: [0.02364216 0.0152221  0.01522821 0.0152221  0.0152
221 ]
```



Out[61]:

```
(array([0.38617075, 0.30235608, 0.30254518, 0.30235608, 0.30235608]),
 array([0.02364216, 0.0152221 , 0.01522821, 0.0152221 , 0.0152221 ]))
```