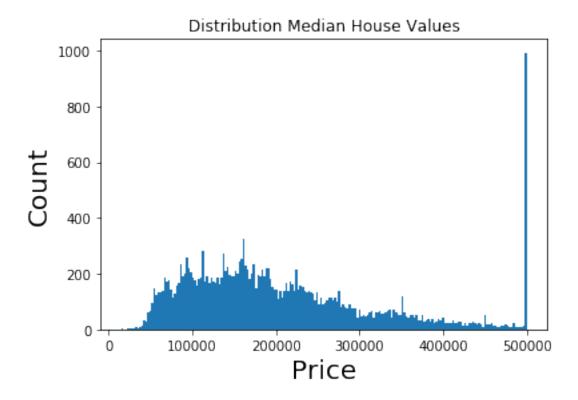
# Housing

## November 6, 2019

```
In [1]: import pandas
        from matplotlib import pyplot
        import seaborn as sns
        from sklearn.model_selection import train_test_split
        from sklearn.linear_model import LinearRegression
        from sklearn.linear_model import BayesianRidge
        from scipy import stats
        import numpy
In [2]: df = pandas.read_csv("datos/housing.csv")
        df.head()
Out[2]:
           longitude latitude housing_median_age total_rooms total_bedrooms \
             -122.23
                                               41.0
        0
                         37.88
                                                           880.0
                                                                            129.0
        1
             -122.22
                         37.86
                                               21.0
                                                           7099.0
                                                                           1106.0
        2
             -122.24
                         37.85
                                               52.0
                                                           1467.0
                                                                            190.0
        3
             -122.25
                         37.85
                                               52.0
                                                           1274.0
                                                                            235.0
             -122.25
                         37.85
                                               52.0
                                                           1627.0
                                                                            280.0
           population households median_income median_house_value ocean_proximity
        0
                322.0
                             126.0
                                           8.3252
                                                              452600.0
                                                                              NEAR BAY
        1
               2401.0
                           1138.0
                                           8.3014
                                                              358500.0
                                                                              NEAR BAY
        2
                496.0
                             177.0
                                           7.2574
                                                              352100.0
                                                                              NEAR BAY
        3
                            219.0
                558.0
                                           5.6431
                                                              341300.0
                                                                              NEAR BAY
        4
                565.0
                            259.0
                                           3.8462
                                                              342200.0
                                                                              NEAR BAY
In [3]: df.shape
Out[3]: (20640, 10)
In [4]: df = df.dropna()
In [5]: df.shape
Out[5]: (20433, 10)
In [6]: df.columns
```

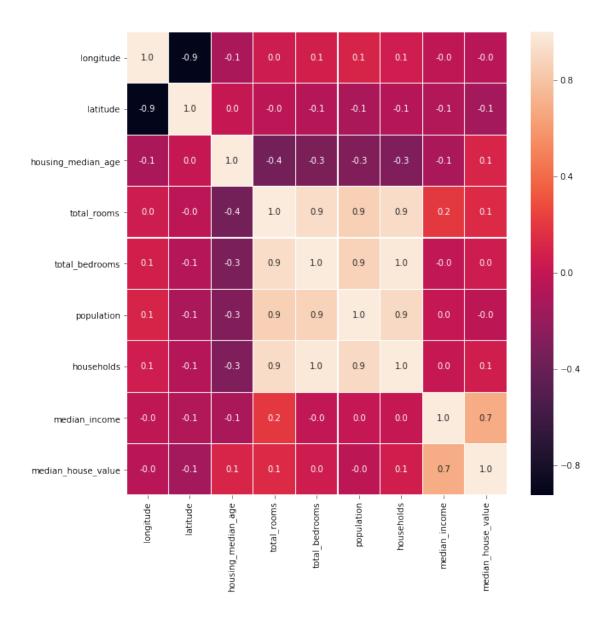
```
Out[6]: Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
               'total_bedrooms', 'population', 'households', 'median_income',
               'median_house_value', 'ocean_proximity'],
              dtype='object')
In [7]: pyplot.hist(df["median_house_value"], bins = 200)
        pyplot.xlabel("Price", fontsize=20)
        pyplot.ylabel("Count", fontsize=20)
        pyplot.title("Distribution Median House Values")
```

## Out[7]: Text(0.5, 1.0, 'Distribution Median House Values')



In [8]: df.corr()["median\_house\_value"].sort\_values() Out[8]: latitude -0.144638 longitude -0.045398 population -0.025300 total\_bedrooms 0.049686 households 0.064894 housing\_median\_age 0.106432 total\_rooms 0.133294 median\_income 0.688355 median\_house\_value 1.000000 Name: median\_house\_value, dtype: float64

```
In [9]: # One hot encode the variables
        dummy_df = pandas.get_dummies(df["ocean_proximity"])
        # Put the grade back in the dataframe
        dummy_df['median_house_value'] = df['median_house_value']
        # Find correlations with grade
        dummy_df.corr()['median_house_value'].sort_values()
Out[9]: INLAND
                             -0.484787
        ISLAND
                              0.023525
        NEAR OCEAN
                              0.140378
        NEAR BAY
                              0.160526
        <1H OCEAN
                              0.257614
                              1.000000
        median_house_value
        Name: median_house_value, dtype: float64
In [10]: f, ax = pyplot.subplots(figsize = (10, 10))
         sns.heatmap(df.corr(), annot = True, linewidth = 0.3, fmt = ".1f", ax = ax)
         pyplot.show()
```



```
In [11]: def format_data(df):
    # Targets are final grade of student
    labels = df['median_house_value']

# One-Hot Encoding of Categorical Variables
    df = pandas.get_dummies(df)

# Find correlations with the Grade
    most_correlated = df.corr().abs()['median_house_value'].sort_values(ascending=False)

# Maintain the top 6 most correlation features with Grade
    most_correlated = most_correlated[:]
```

```
df = df.loc[:, most_correlated.index]
             # Split into training/testing sets with 25% split
             X_train, X_test, y_train, y_test = train_test_split(df, labels,
                                                                   test_size = 0.25,
                                                                   random_state=42)
             return X_train, X_test, y_train, y_test
In [12]: X_train, X_test, y_train, y_test = format_data(df)
         X_train.head()
Out[12]:
                median_house_value median_income ocean_proximity_INLAND
         2830
                           44600.0
                                            1.7109
                                                                          1
         14951
                           155000.0
                                            2.4567
                                                                          0
         8314
                           450000.0
                                            2.1579
                                                                          0
         14271
                            65700.0
                                            1.0531
                                                                          0
         305
                            91200.0
                                            1.8913
                ocean_proximity_<1H OCEAN
                                           ocean_proximity_NEAR BAY
                                                                       latitude \
         2830
                                         0
                                                                          35.40
                                                                    0
         14951
                                         1
                                                                    0
                                                                          32.71
         8314
                                         0
                                                                    0
                                                                          33.35
                                                                          32.70
         14271
                                         0
                                                                    0
         305
                                         0
                                                                    1
                                                                          37.76
                ocean_proximity_NEAR OCEAN
                                             total_rooms housing_median_age \
         2830
                                          0
                                                  8739.0
                                                                         11.0
         14951
                                          0
                                                   2413.0
                                                                         18.0
         8314
                                          0
                                                   1675.0
                                                                         27.0
         14271
                                          1
                                                   818.0
                                                                         38.0
         305
                                                   2018.0
                                                                         43.0
                households total_bedrooms longitude population \
         2830
                                     2190.0
                                               -119.01
                    1919.0
                                                             4781.0
         14951
                     551.0
                                      533.0
                                               -116.96
                                                             1129.0
         8314
                     331.0
                                      521.0
                                               -118.32
                                                             744.0
                                               -117.12
         14271
                     231.0
                                      217.0
                                                              953.0
                     367.0
                                               -122.18
         305
                                      408.0
                                                             1111.0
                ocean_proximity_ISLAND
         2830
                                      0
         14951
                                      0
                                      1
         8314
         14271
                                      0
         305
                                      0
```

In [13]: print(X\_train.shape)

```
print(X_test.shape)
(15324, 14)
(5109, 14)
In [14]: def evaluate(X_train, X_test, y_train, y_test):
             # Names of models
             model_name_list = ['Linear Regression', "Bayesian Ridge"]
             X_train = X_train.drop(columns='median_house_value')
             X_test = X_test.drop(columns='median_house_value')
             # Instantiate the models
             model1 = LinearRegression()
             model2 = BayesianRidge(compute_score=True)
             # Dataframe for results
             results = pandas.DataFrame(columns=['mae', 'rmse'], index = model_name_list)
             # Train and predict with each model
             for i, model in enumerate([model1, model2]):
                 model.fit(X_train, y_train)
                 predictions = model.predict(X_test)
                 coeff = model.coef_
                 score = model.score(X_test, y_test)
                 print("{} Coefficients: ".format(model_name_list[i]), coeff)
                 print("\n")
                 print("{} Score: ".format(model_name_list[i]), score)
                 print("\n")
                 # Metrics
                 mae = numpy.mean(abs(predictions - y_test))
                 rmse = numpy.sqrt(numpy.mean((predictions - y_test) ** 2))
                 # Insert results into the dataframe
                 model_name = model_name_list[i]
                 results.loc[model_name, :] = [mae, rmse]
             # Median Value Baseline Metrics
             baseline = numpy.mean(y_train)
             baseline_mae = numpy.mean(abs(baseline - y_test))
             baseline_rmse = numpy.sqrt(numpy.mean((baseline - y_test) ** 2))
             results.loc['Baseline', :] = [baseline_mae, baseline_rmse]
             return results
In [15]: results = evaluate(X_train, X_test, y_train, y_test)
```

```
Linear Regression Coefficients: [ 3.92330777e+04 -7.36819088e+04 -3.40321348e+04 -4.02817945e+06 -2.55205753e+04 -3.12916376e+04 -6.36691750e+00 1.08813173e+03 4.35107705e+01 1.02597469e+02 -2.68384898e+04 -3.62122333e+01 1.79287476e+05]
```

Linear Regression Score: 0.6547516410329023

```
Bayesian Ridge Coefficients: [ 3.92244863e+04 -5.00655360e+04 -1.05743626e+04 -1.67689497e+04 -2.56126711e+04 -7.85132337e+03 -6.36482591e+00 1.09028421e+03 4.30517739e+01 1.03031260e+02 -2.69134708e+04 -3.62257024e+01 8.52601716e+04]
```

Bayesian Ridge Score: 0.6553914482946943

### In [16]: print(results)

mae rmse Linear Regression 49958.5 68343.3 Bayesian Ridge 49921.4 68279.9 Baseline 92461.7 116314

#### In [17]: X\_test.iloc[50]

Out[17]:	median_house_value	177500.0000
	median_income	2.4827
	${\tt ocean\_proximity\_INLAND}$	0.0000
	ocean_proximity_<1H OCEAN	1.0000
	ocean_proximity_NEAR BAY	0.0000
	latitude	38.3600
	ocean_proximity_NEAR OCEAN	0.0000
	total_rooms	5496.0000
	housing_median_age	6.0000
	households	1189.0000
	total_bedrooms	1374.0000
	longitude	-122.6900
	population	2502.0000
	${\tt ocean\_proximity\_ISLAND}$	0.0000
	Name: 19157, dtype: float64	