California Housing Prices

June 27, 2019

1 California Housing Prices

Median house prices for California districts derived from the 1990 census.
Photo by Vita Vilcina

1.1 Context

This is the dataset used in the second chapter of Aurélien Géron's recent book 'Hands-On Machine learning with Scikit-Learn and TensorFlow'. It serves as an excellent introduction to implementing machine learning algorithms because it requires rudimentary data cleaning, has an easily understandable list of variables and sits at an optimal size between being to toyish and too cumbersome.

The data contains information from the 1990 California census. So although it may not help you with predicting current housing prices like the Zillow Zestimate dataset, it does provide an accessible introductory dataset for teaching people about the basics of machine learning.

1.2 Acknowledgements

Please refer to the Kaggle challenge web page

1.3 Inspiration

predict a real estate price

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2 Exploratory Data Analysis

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        import os

In [2]: import folium
```

In [3]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.linear_model import Lasso, LinearRegression, Ridge, RANSACRegressor, SGDR
from sklearn.ensemble import AdaBoostRegressor
from sklearn.svm import SVR
```

In [4]:
```
file_path = os.path.join('input', 'house_big.csv')
df = pd.read_csv(file_path)
df.head()
```

Out[4]:
```
   longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
0    -122.23     37.88                41.0        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
4    -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       558.0       219.0         5.6431            341300.0        NEAR BAY
4       565.0       259.0         3.8462            342200.0        NEAR BAY
```

In [5]:
```
df.shape
```

Out[5]: (20640, 10)

2.1 Content

The data pertains to the houses found in a given California district and some summary stats about them based on the 1990 census data. Be warned the data aren't cleaned so there are some preprocessing steps required! The columns are as follows, their names are pretty self explanitory: * longitude * latitude * housing_median_age * total_rooms * total_bedrooms * population * households * median_income * median_house_value * ocean_proximity

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
longitude             20640 non-null float64
latitude              20640 non-null float64
housing_median_age    20640 non-null float64
total_rooms           20640 non-null float64
total_bedrooms        20433 non-null float64
population            20640 non-null float64
households            20640 non-null float64
median_income         20640 non-null float64
```

```
median_house_value    20640 non-null float64
ocean_proximity       20640 non-null object
dtypes: float64(9), object(1)
memory usage: 1.6+ MB
```

There are few missing value int the 'total_bedrooms' column. Now let's see the basic stats for the numerical columns:

```
In [7]: df.describe()
```

```
Out[7]:          longitude      latitude  housing_median_age   total_rooms  \
        count  20640.000000  20640.000000        20640.000000  20640.000000
        mean    -119.569704     35.631861           28.639486   2635.763081
        std        2.003532      2.135952           12.585558   2181.615252
        min     -124.350000     32.540000            1.000000      2.000000
        25%     -121.800000     33.930000           18.000000   1447.750000
        50%     -118.490000     34.260000           29.000000   2127.000000
        75%     -118.010000     37.710000           37.000000   3148.000000
        max     -114.310000     41.950000           52.000000  39320.000000

               total_bedrooms    population    households  median_income  \
        count    20433.000000  20640.000000  20640.000000   20640.000000
        mean       537.870553   1425.476744    499.539680       3.870671
        std        421.385070   1132.462122    382.329753       1.899822
        min          1.000000      3.000000      1.000000       0.499900
        25%        296.000000    787.000000    280.000000       2.563400
        50%        435.000000   1166.000000    409.000000       3.534800
        75%        647.000000   1725.000000    605.000000       4.743250
        max       6445.000000  35682.000000   6082.000000      15.000100

               median_house_value
        count        20640.000000
        mean        206855.816909
        std         115395.615874
        min          14999.000000
        25%         119600.000000
        50%         179700.000000
        75%         264725.000000
        max         500001.000000
```

```
In [8]: df.ocean_proximity.value_counts()
```

```
Out[8]: <1H OCEAN     9136
        INLAND        6551
        NEAR OCEAN    2658
        NEAR BAY      2290
        ISLAND           5
        Name: ocean_proximity, dtype: int64
```

2.2 Cleaning data

```
In [9]: df.duplicated().sum()
```

```
Out[9]: 0
```

```
In [10]: df.isnull().sum()
```

```
Out[10]: longitude               0
         latitude                0
         housing_median_age      0
         total_rooms             0
         total_bedrooms        207
         population              0
         households              0
         median_income           0
         median_house_value      0
         ocean_proximity         0
         dtype: int64
```

```
In [11]: print(f'percentage of missing values: {df.total_bedrooms.isnull().sum() / df.shape[0]
```

```
percentage of missing values: 1.00%
```

```
In [12]: df = df.fillna(df.median())
         df.isnull().sum()
```

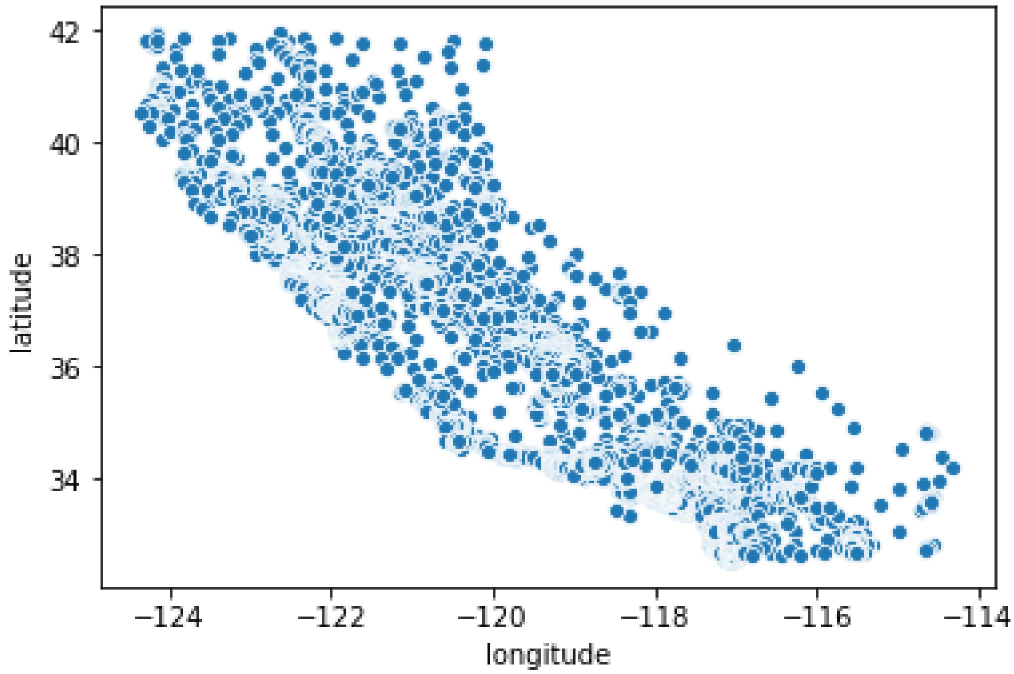
```
Out[12]: longitude             0
         latitude              0
         housing_median_age    0
         total_rooms           0
         total_bedrooms        0
         population            0
         households            0
         median_income         0
         median_house_value    0
         ocean_proximity       0
         dtype: int64
```

2.3 Dealing with geospatial infos

Visualization of the data in a scatter plot in a "geographic way"

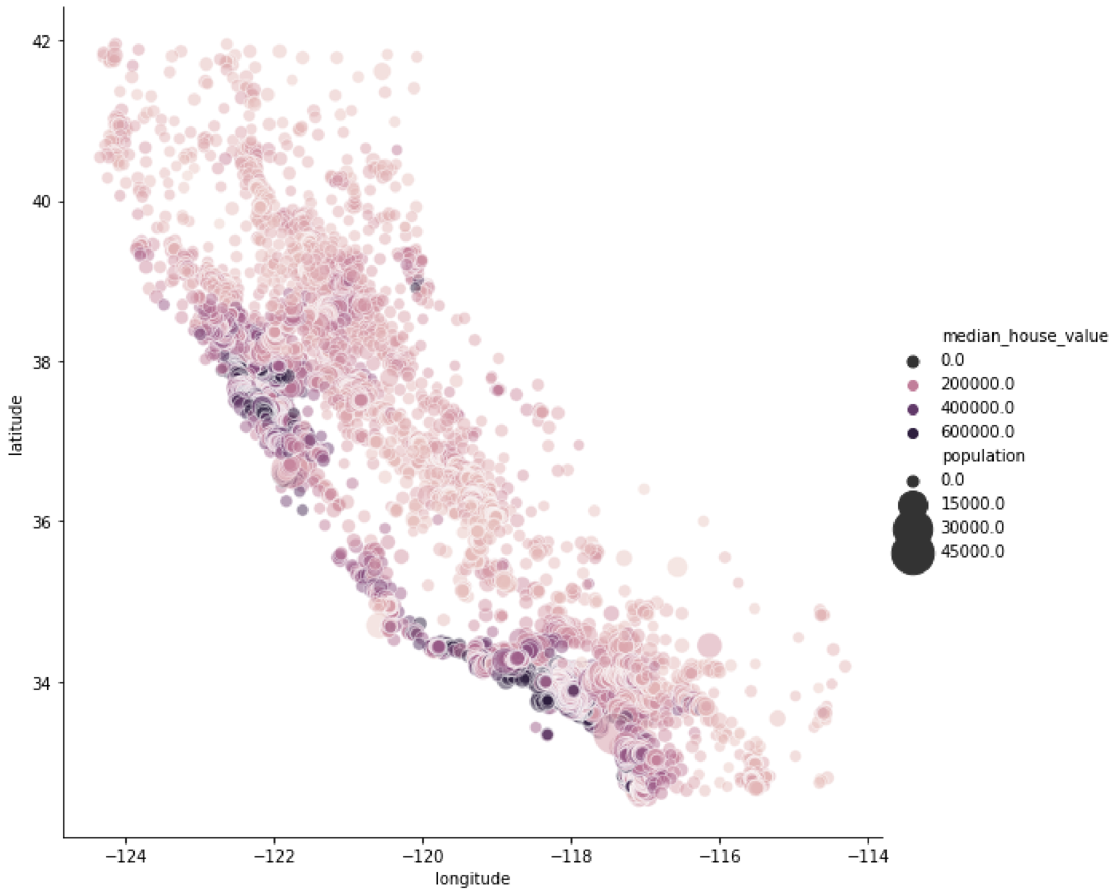
```
In [13]: sns.scatterplot(df.longitude, df.latitude)
```

```
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7f244cbecb00>
```



Same plot but this time with a varying size of the data points based on `population` variable and a different color depending of the real estate price (`median_house_value`)

```
In [14]: sns.relplot(x="longitude", y="latitude", hue="median_house_value", size="population",
                     sizes=(50, 700), data=df, height=8)
         plt.show()
```




```
In [15]: # Create a map with folium centered at the mean latitude and longitude
         cali_map = folium.Map(location=[35.6, -117], zoom_start=6)

         # Display the map
         display(cali_map)
```

```
<folium.folium.Map at 0x7f244c886d68>
```

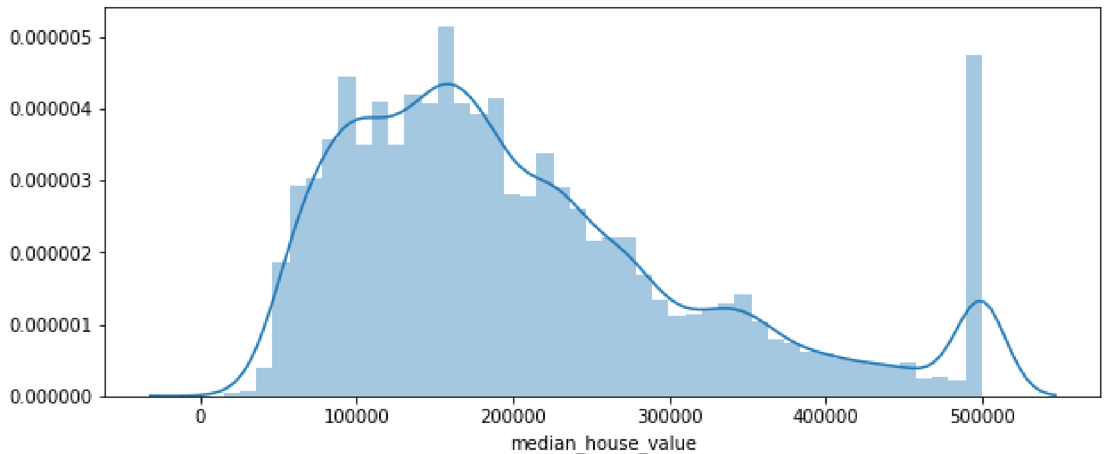
```
In [16]: # Add markers for each rows
         for i in range(df.shape[0]):
             folium.Marker((float(df.iloc[i, 1]), float(df.iloc[i, 0]))).add_to(cali_map)

         # Display the map
         display(cali_map)
```

```
<folium.folium.Map at 0x7f244c886d68>
```

2.4 Target analysis

In [17]:
```
plt.figure(figsize=(10, 4))
sns.distplot(df.median_house_value)
plt.show()
```

```
/home/sunflowa/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWarning:
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

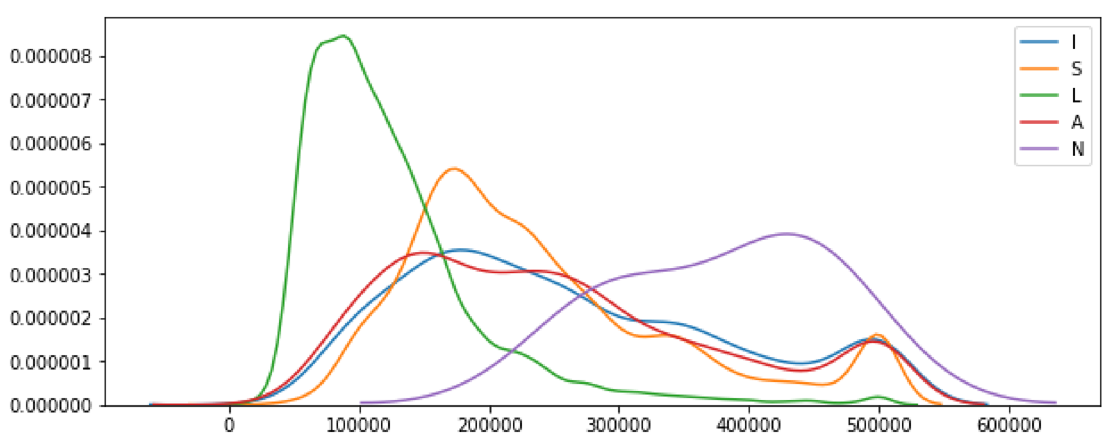


Variations depending on the proximity with ocean

In [18]:
```
df.ocean_proximity.unique()
```

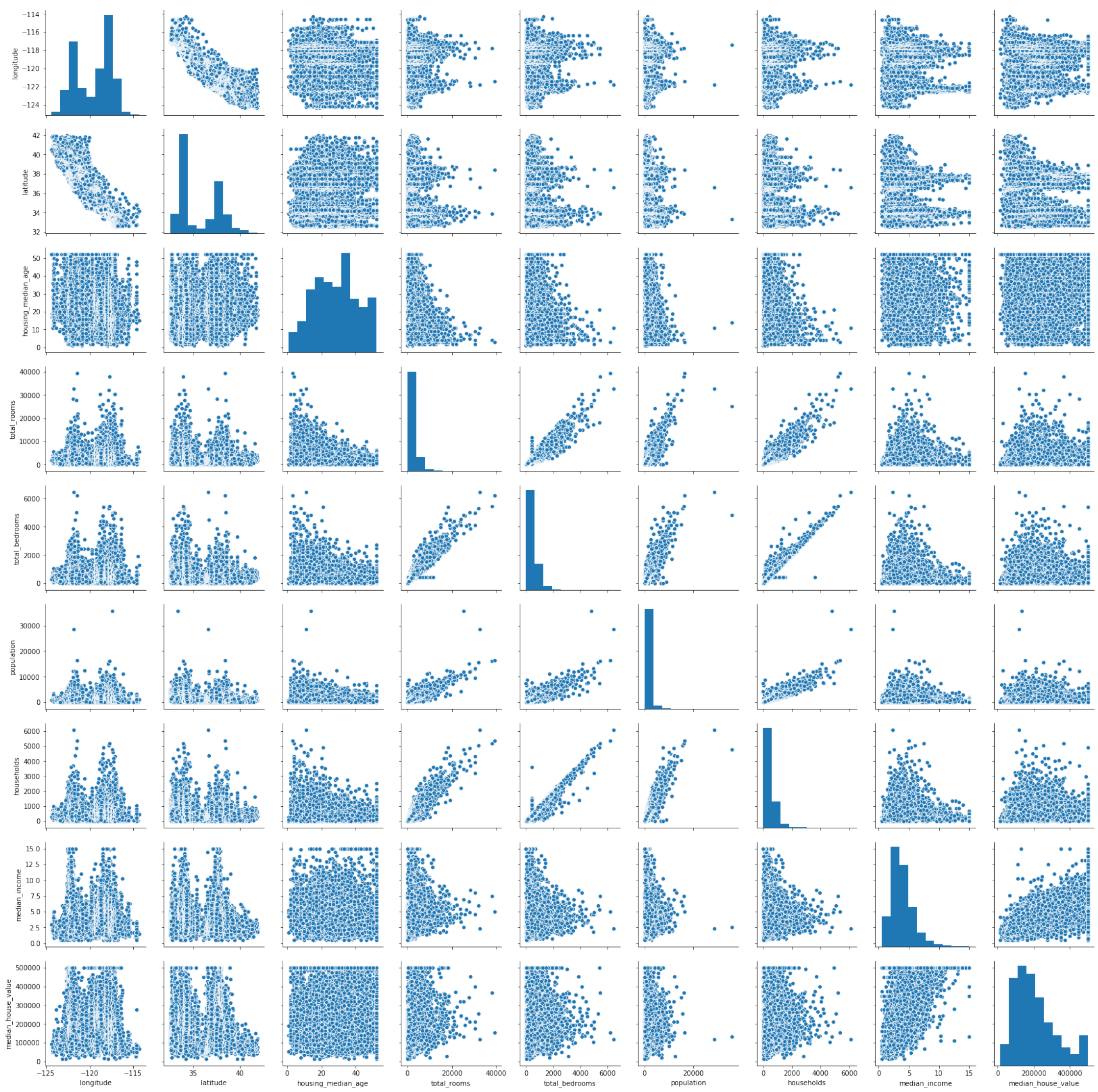
Out[18]:
```
array(['NEAR BAY', '<1H OCEAN', 'INLAND', 'NEAR OCEAN', 'ISLAND'],
      dtype=object)
```

In [19]:
```
plt.figure(figsize=(10, 4))
for prox in df.ocean_proximity.unique():
    sns.kdeplot(data=df[df.ocean_proximity == prox].median_house_value)
    plt.legend(prox)
plt.show()
```

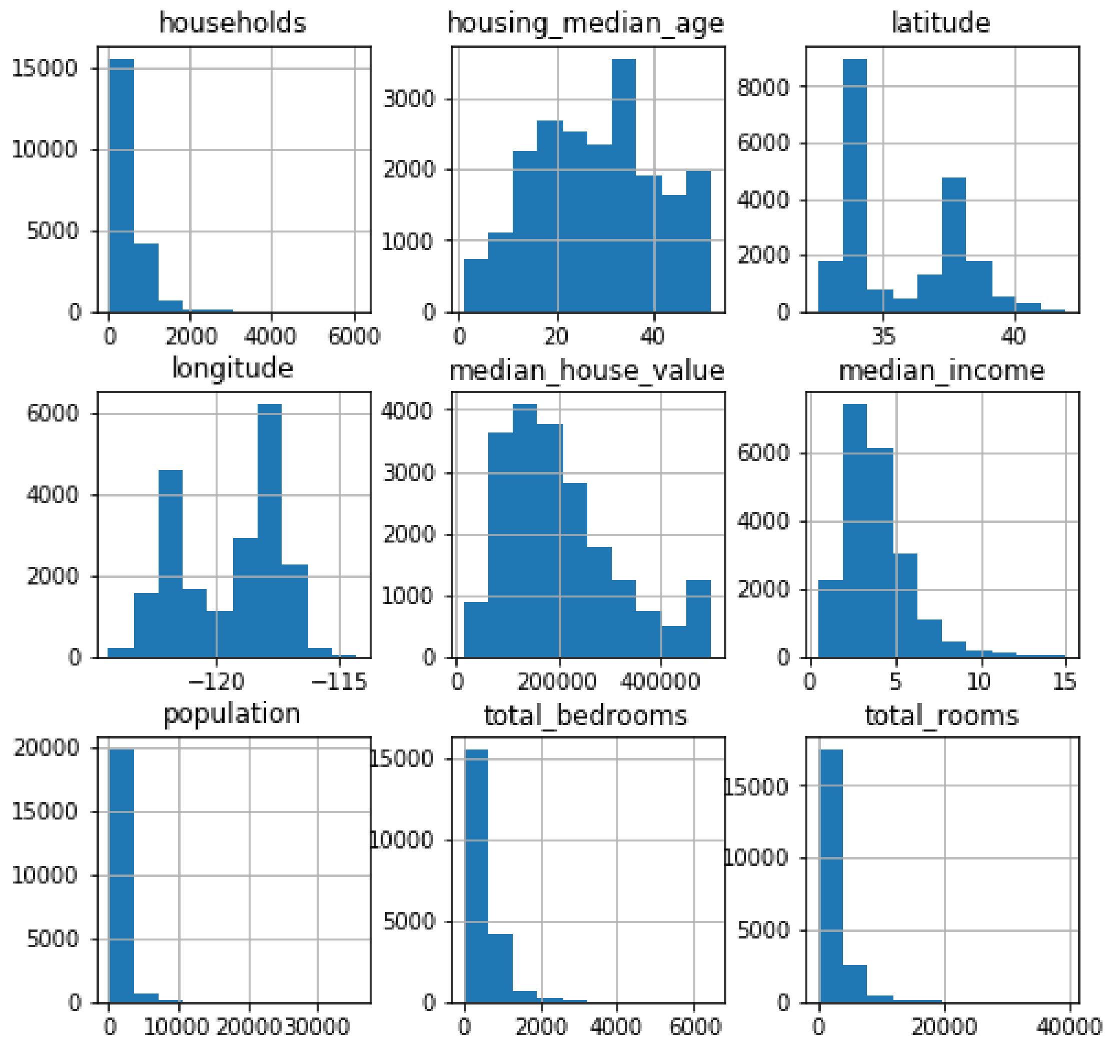


2.5 Other analysis

In [20]:
```
sns.pairplot(df)
plt.show()
```



In [21]:
```
df.hist(figsize=(8, 8))
plt.show()
```



2.6 Correlations

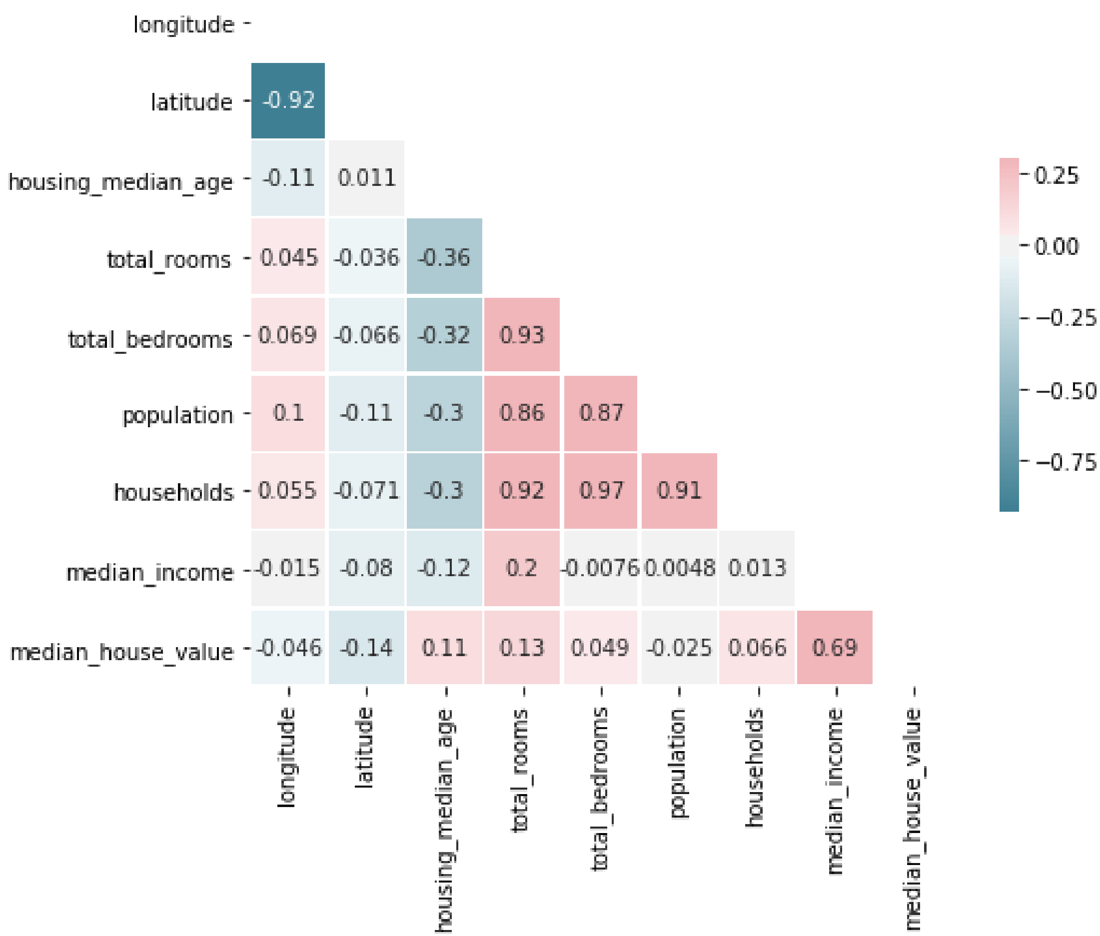
In [22]:
```
corr = df.corr()
corr
```

Out[22]:
```
                    longitude  latitude  housing_median_age  total_rooms  \
longitude            1.000000 -0.924664           -0.108197     0.044568
latitude            -0.924664  1.000000            0.011173    -0.036100
housing_median_age  -0.108197  0.011173            1.000000    -0.361262
total_rooms          0.044568 -0.036100           -0.361262     1.000000
total_bedrooms       0.069120 -0.066484           -0.319026     0.927058
population           0.099773 -0.108785           -0.296244     0.857126
households           0.055310 -0.071035           -0.302916     0.918484
median_income       -0.015176 -0.079809           -0.119034     0.198050
median_house_value  -0.045967 -0.144160            0.105623     0.134153
```

```
                    total_bedrooms  population  households  median_income  \
longitude                 0.069120    0.099773    0.055310      -0.015176
latitude                 -0.066484   -0.108785   -0.071035      -0.079809
housing_median_age       -0.319026   -0.296244   -0.302916      -0.119034
total_rooms               0.927058    0.857126    0.918484       0.198050
total_bedrooms            1.000000    0.873535    0.974366      -0.007617
population                0.873535    1.000000    0.907222       0.004834
households                0.974366    0.907222    1.000000       0.013033
median_income            -0.007617    0.004834    0.013033       1.000000
median_house_value        0.049457   -0.024650    0.065843       0.688075

                    median_house_value
longitude                    -0.045967
latitude                     -0.144160
housing_median_age            0.105623
total_rooms                   0.134153
total_bedrooms                0.049457
population                   -0.024650
households                    0.065843
median_income                 0.688075
median_house_value            1.000000
```

In [23]:
```
# Generate a mask for the upper triangle
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(8, 6))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5}, annot=True)
```

Out[23]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f243ec37898>
```



- lat and log are highly positively correlated
- total_bedrooms, population and householdsare highly positively correlated too
- median_income and median_house_value are also positively correlated

which make sense.

---

3 Models training and predictions

3.1 Data preparation

Label encoding of categorical feature (ocean proximity)

```
In [24]: df = pd.get_dummies(data=df, columns=['ocean_proximity'], drop_first=False)
         df.head()
```

```
Out[24]:    longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
         0    -122.23     37.88                41.0        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
         4    -122.25     37.85                52.0       1627.0           280.0

            population  households  median_income  median_house_value  \
         0       322.0       126.0         8.3252            452600.0
         1      2401.0      1138.0         8.3014            358500.0
         2       496.0       177.0         7.2574            352100.0
         3       558.0       219.0         5.6431            341300.0
         4       565.0       259.0         3.8462            342200.0

            ocean_proximity_<1H OCEAN  ocean_proximity_INLAND  ocean_proximity_ISLAND  \
         0                          0                       0                       0
         1                          0                       0                       0
         2                          0                       0                       0
         3                          0                       0                       0
         4                          0                       0                       0

            ocean_proximity_NEAR BAY  ocean_proximity_NEAR OCEAN
         0                         1                           0
         1                         1                           0
         2                         1                           0
         3                         1                           0
         4                         1                           0
```

```
In [63]: feat_removed = ['median_house_value']

         # removed
         #['longitude', 'latitude', 'housing_median_age', 'total_rooms', 'total_bedrooms', 'po
         #'median_house_value', 'ocean_proximity']
```

```
In [64]: y = df.median_house_value
         X = df.drop(columns=feat_removed)
         X.shape, y.shape
```

```
Out[64]: ((20640, 13), (20640,))
```

```
In [65]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

3.2 Metric RMSE root mean squared error

Root Mean Square Error (RMSE) is the standard deviation of the residuals (prediction errors). Residuals are a measure of how far from the regression line data points are; RMSE is a measure of how spread out these residuals are. In other words, it tells you how concentrated the data is around the line of best fit. Root mean square error is commonly used in climatology, forecasting, and regression analysis to verify experimental results.

```
In [66]: def calculate_rmse(model, model_name):
             model.fit(X_train, y_train)
             y_pred, y_pred_train = model.predict(X_test), model.predict(X_train)
             rmse_test, rmse_train = np.sqrt(mean_squared_error(y_test, y_pred)), np.sqrt(mean_
             print(model_name, f' RMSE on train: {rmse_train:.0f}, on test: {rmse_test:.0f}')
             return rmse_test
```

3.3 Linear Regression

```
In [67]: lr = LinearRegression()
         lr_err = calculate_rmse(lr, 'Linear Reg')
```

```
Linear Reg  RMSE on train: 68533, on test: 69932
```

3.4 RANSAC Regressor

```
In [68]: ra = RANSACRegressor()
         ra_err = calculate_rmse(ra, 'RANSAC Reg')
```

```
RANSAC Reg  RMSE on train: 78281, on test: 78795
```

3.5 Lasso

```
In [69]: la = Lasso()
         la_err = calculate_rmse(la, 'Lasso Reg')
```

```
Lasso Reg  RMSE on train: 68533, on test: 69932
```

```
/home/sunflowa/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/coordinate_descent.py
  ConvergenceWarning)
```

3.6 SGD Regressor

```
In [70]: sg = SGDRegressor()
         sg_err = calculate_rmse(sg, 'SGD Reg')
```

```
SGD Reg  RMSE on train: 2939589866401599, on test: 2954302199978100
```

```
/home/sunflowa/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/stochastic_gradient.
  FutureWarning)
```

3.7 Ridge

```
In [71]: ri = SGDRegressor()
         ri_err = calculate_rmse(ri, 'Ridge')
```

```
Ridge  RMSE on train: 24125952802617160, on test: 24256192059939448


/home/sunflowa/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/stochastic_gradient.p
  FutureWarning)
```

3.8 AdaBoostRegressor

```
In [72]: ad = AdaBoostRegressor()
         ad_err = calculate_rmse(ad, 'AdaBoostRegressor')
```

```
AdaBoostRegressor  RMSE on train: 86734, on test: 86345
```

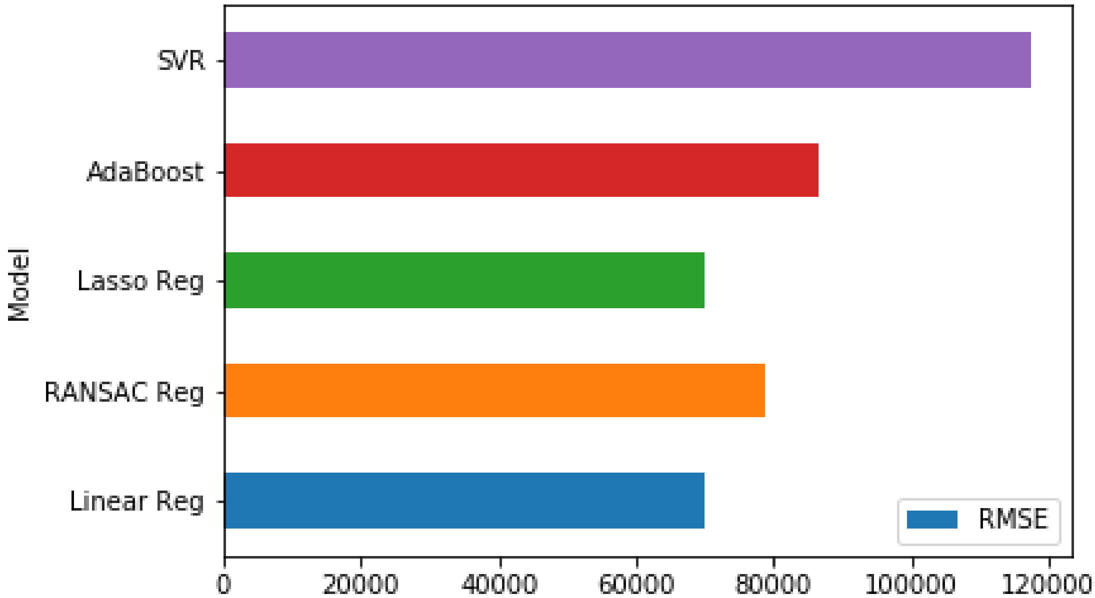
3.9 SVR

```
In [73]: sv = SVR()
         sv_err = calculate_rmse(sv, 'SVR')
```

```
/home/sunflowa/anaconda3/lib/python3.7/site-packages/sklearn/svm/base.py:196: FutureWarning: Th
  "avoid this warning.", FutureWarning)


SVR  RMSE on train: 118660, on test: 117282
```

3.10 Results comparison

```
In [74]: df_score = pd.DataFrame({'Model':['Linear Reg', 'RANSAC Reg', 'Lasso Reg', 'AdaBoost'
                                  'RMSE':[lr_err, ra_err, la_err, ad_err, sv_err]})
         ax = df_score.plot.barh(y='RMSE', x='Model')
```



Lasso and the Linear Reg are the winners ! Surprisingly the RSME is a little lower for the best models when we keep features such as lat/long and 'total_bedrooms', 'population'.

```
In [ ]:
```