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

Overview of the dataset

In [2]:
```
housing = pd.read_csv("housing.csv")
housing.head()
```

Out[2]:

	status	bed	bath	acre_lot	city	state	zip_code	house_size	prev_sold_date	price
0	for_sale	3.0	2.0	0.12	Adjuntas	Puerto Rico	601.0	920.0	NaN	105000.0
1	for_sale	4.0	2.0	0.08	Adjuntas	Puerto Rico	601.0	1527.0	NaN	80000.0
2	for_sale	2.0	1.0	0.15	Juana Diaz	Puerto Rico	795.0	748.0	NaN	67000.0
3	for_sale	4.0	2.0	0.10	Ponce	Puerto Rico	731.0	1800.0	NaN	145000.0
4	for_sale	6.0	2.0	0.05	Mayaguez	Puerto Rico	680.0	NaN	NaN	65000.0

In [3]:
```
housing.shape
```

Out[3]:
```
(904966, 10)
```

In [4]:
```
housing.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 904966 entries, 0 to 904965
Data columns (total 10 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   status          904966 non-null  object 
 1   bed             775126 non-null  float64
 2   bath            791082 non-null  float64
 3   acre_lot        638324 non-null  float64
 4   city            904894 non-null  object 
 5   state           904966 non-null  object 
 6   zip_code        904762 non-null  float64
 7   house_size      612080 non-null  float64
 8   prev_sold_date  445865 non-null  object 
 9   price           904895 non-null  float64
dtypes: float64(6), object(4)
memory usage: 69.0+ MB
```

As seen above the housing dataset has 9 variables. The target variable is price and the other variables are its features. Among these 9 features we can distinguish 5 numerical variables and 4 categorical variables. Note that there are some variables that are in numerical format, but actually should be categorial variables, like zip code.

In [5]:
```
print(f"Numerical variables in dataset: {housing.select_dtypes(exclude = ['object']).columns.tolist()}")
print(f"Categorical variables in dataset: {housing.select_dtypes(include = ['object']).columns.tolist()}")
```

```
Numerical variables in dataset: ['bed', 'bath', 'acre_lot', 'zip_code', 'house_size', 'price']
Categorical variables in dataset: ['status', 'city', 'state', 'prev_sold_date']
```

Below are presented statistics indicators for numerical and categorical variables (in separated tables).

In [6]:
```
housing.describe()
```

Out[6]:

	bed	bath	acre_lot	zip_code	house_size	price
count	775126.000000	791082.000000	638324.000000	904762.000000	6.120800e+05	9.048950e+05
mean	3.332190	2.484236	17.317292	6519.464582	2.138437e+03	8.774382e+05
std	2.065312	1.931622	970.707378	3816.713093	3.046600e+03	2.457698e+06
min	1.000000	1.000000	0.000000	601.000000	1.000000e+02	0.000000e+00
25%	2.000000	2.000000	0.110000	2908.000000	1.132000e+03	2.685000e+05
50%	3.000000	2.000000	0.290000	6811.000000	1.650000e+03	4.750000e+05
75%	4.000000	3.000000	1.150000	8854.000000	2.495000e+03	8.300000e+05
max	123.000000	198.000000	100000.000000	99999.000000	1.450112e+06	8.750000e+08

In [7]:
```
housing.describe(include = 'object')
```

Out[7]:

	status	city	state	prev_sold_date
count	904966	904894	904966	445865
unique	2	2487	18	9870
top	for_sale	New York City	New Jersey	2018-07-25
freq	903373	47502	231958	317

Data Cleaning

In order of conducting Exploratory Data Analysis and Model Development we need to be sure that the dataset can be usable, otherwise it will produce problems. So we have to do checks related to missing values in the dataset and ways of handling with it. Based on the variables we will decide which of them to keep for this project, which to drop, which to fill with imputations mode.

In [8]:
```
values_missing = housing.isna().sum()*100/len(housing)
print('Percentage Missing Values %')
values_missing
```

Out[8]:
```
Percentage Missing Values %
status             0.000000
bed               14.347500
bath              12.584340
acre_lot          29.464311
city               0.007956
state              0.000000
zip_code           0.022542
house_size        32.364310
prev_sold_date    50.731298
price              0.007846
dtype: float64
```

As seen above there are variables that have missing values. First we will remove columns city, zip_code and prev_sold_date, because they will be not used.

In [9]:
```
housing = housing.drop(["city","zip_code","prev_sold_date"], axis=1)
```

From Out[8] we can see that the target variables price has 0.78% missing values, so it is better to just remove the missing values from it.

In [10]:
```
housing = housing.drop(housing[housing['price'].isnull()].index)
```

Also we will remove the rows that have 2 or more missing values.

In [11]:
```
housing = housing[~(housing.isna().sum(axis=1) >= 2)]
```

Below we will make a check to see the state of missing values in the variables.

In [12]:
```
((housing.isna().sum() / len(housing)) * 100).sort_values(ascending=False)
```

Out[12]:
```
acre_lot      24.884798
house_size    15.764261
bed            0.576647
bath           0.408540
status         0.000000
state          0.000000
price          0.000000
dtype: float64
```

Also we will remove the missing values from variables bed and bath as they are < 1 %.

In [13]:
```
housing = housing.drop(housing[housing['bed'].isnull()].index, axis=0)
housing = housing.drop(housing[housing['bath'].isnull()].index, axis=0)
```

Now we will do a check related to status variable and we will remove it as it has only one value "for_sale".

In [14]:
```
housing["status"].value_counts()
```

Out[14]:
```
for_sale    700912
Name: status, dtype: int64
```

In [15]:
```
housing = housing.drop("status", axis=1)
```

For variables like acre_lot and house_size we will use Median imputation to handle missing values. Median is more reccommended to be used with numeric variables.

In [16]:
```
housing['acre_lot'].fillna(housing['acre_lot'].median(), inplace=True)
housing['house_size'].fillna(housing['house_size'].median(), inplace=True)
```

In [17]:
```
housing.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 700912 entries, 0 to 904965
Data columns (total 6 columns):
 #   Column      Non-Null Count   Dtype  
---  ------      --------------   -----  
 0   bed         700912 non-null  float64
 1   bath        700912 non-null  float64
 2   acre_lot    700912 non-null  float64
 3   state       700912 non-null  object 
 4   house_size  700912 non-null  float64
 5   price       700912 non-null  float64
dtypes: float64(5), object(1)
memory usage: 37.4+ MB
```

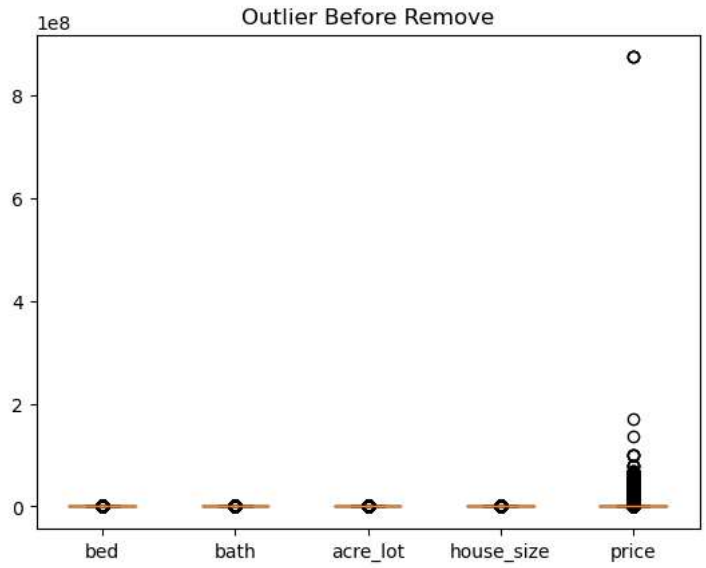
We will make another check if we have missing values.

In [18]:
```
housing.isnull().sum()
```

Out[18]:
```
bed           0
bath          0
acre_lot      0
state         0
house_size    0
price         0
dtype: int64
```

Data cleaning has not finished yet. We need to detect for outliers and remove them.

In [19]:
```
var_num = ['bed','bath','acre_lot','house_size','price']
plt.boxplot(housing[var_num])
plt.xticks([1, 2, 3, 4, 5], var_num)
plt.title('Outlier Before Remove')
plt.show()
print(f'Total Row With Outlier: {housing.shape[0]}')
```

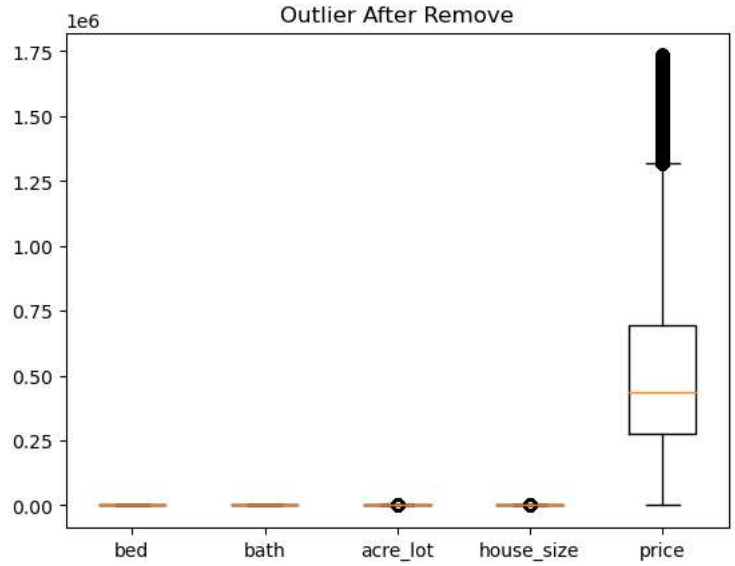



```
Total Row With Outlier: 700912
```

As seen outliers are detected for price in the visualization above, so we will remove.

In [20]:
```
Q1 = housing[var_num].quantile(0.25)
Q3 = housing[var_num].quantile(0.75)
IQR = Q3 - Q1

housing = housing[~((housing[var_num] < (Q1 - 1.5 * IQR)) | (housing[var_num] > (Q3 + 1.5 * IQR))).any(axis=1)]
```

In [21]:
```
var_num = ['bed','bath','acre_lot','house_size','price']
plt.boxplot(housing[var_num])
plt.xticks([1, 2, 3, 4, 5], var_num)
plt.title('Outlier After Remove')
plt.show()
print(f'Total Row Without Outlier: {housing.shape[0]}')
```




```
Total Row Without Outlier: 494209
```

Exploratory Data Analysis and Visualizations

In [22]:
```
housing.describe()
```

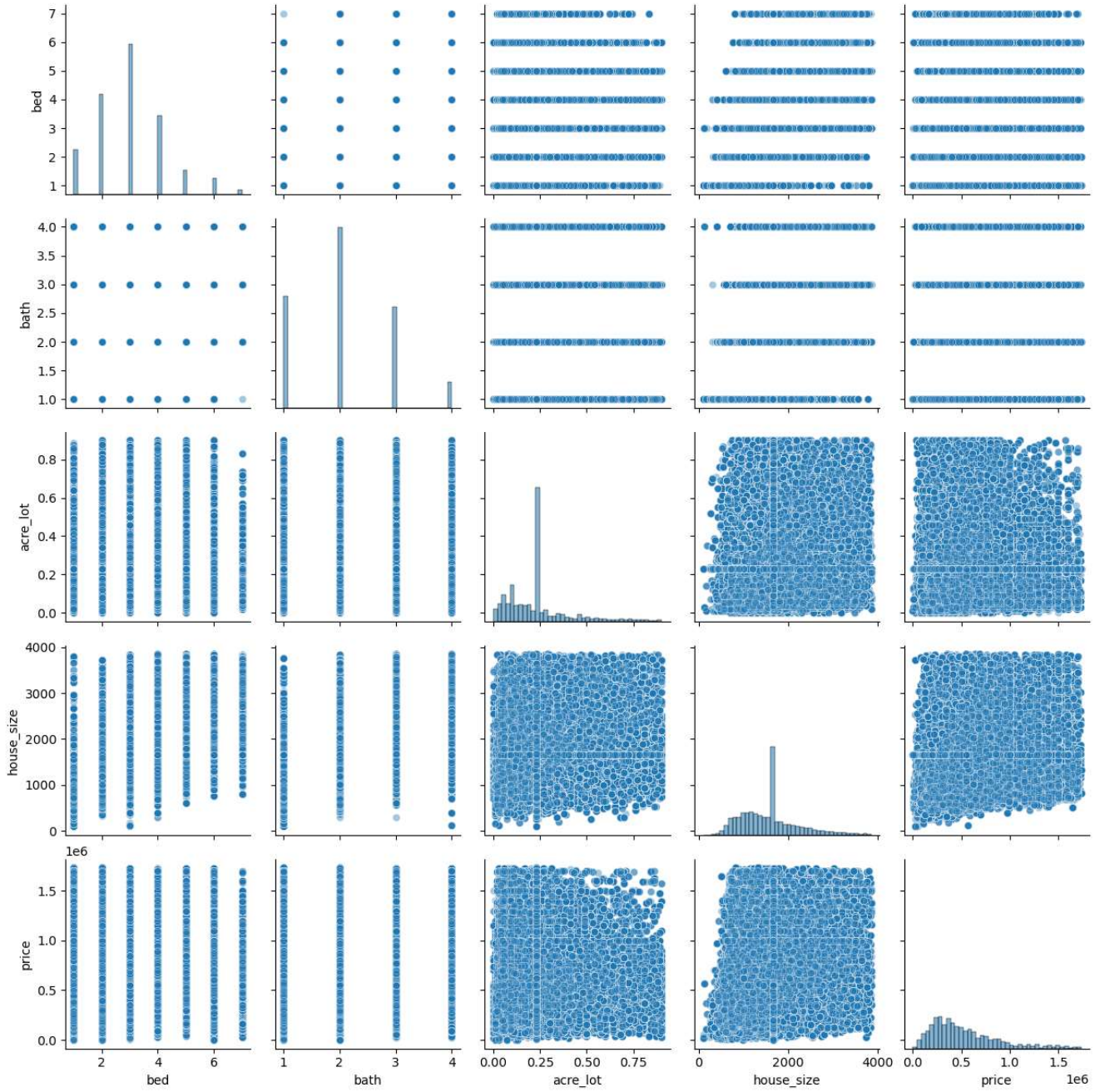
Out[22]:

	bed	bath	acre_lot	house_size	price
count	494209.000000	494209.000000	494209.000000	494209.000000	4.942090e+05
mean	3.007060	2.098831	0.226893	1569.741067	5.217125e+05
std	1.263706	0.863229	0.162786	631.238299	3.400852e+05
min	1.000000	1.000000	0.000000	100.000000	1.000000e+00
25%	2.000000	1.000000	0.110000	1100.000000	2.749000e+05
50%	3.000000	2.000000	0.230000	1600.000000	4.350000e+05
75%	4.000000	3.000000	0.230000	1808.000000	6.919650e+05
max	7.000000	4.000000	0.900000	3852.000000	1.735000e+06

Below it is presented the pairplot of each of 2 variables which show the relationship between them. As presented there is no indication for lienar regression between the variables.

In [23]:
```
sns.pairplot(housing,
             kind='scatter',
             plot_kws={'alpha':0.4},
             diag_kws={'alpha':0.55, 'bins':40})
```

Out[23]:
```
<seaborn.axisgrid.PairGrid at 0x17270eddf90>
```



Below it is presented the correlation matrix for the variables. Considering price as target, there is no evidence for strong correlation between its features.

In [24]:
```
sns.heatmap(housing.corr(), annot=True, linewidths=0.5);
```

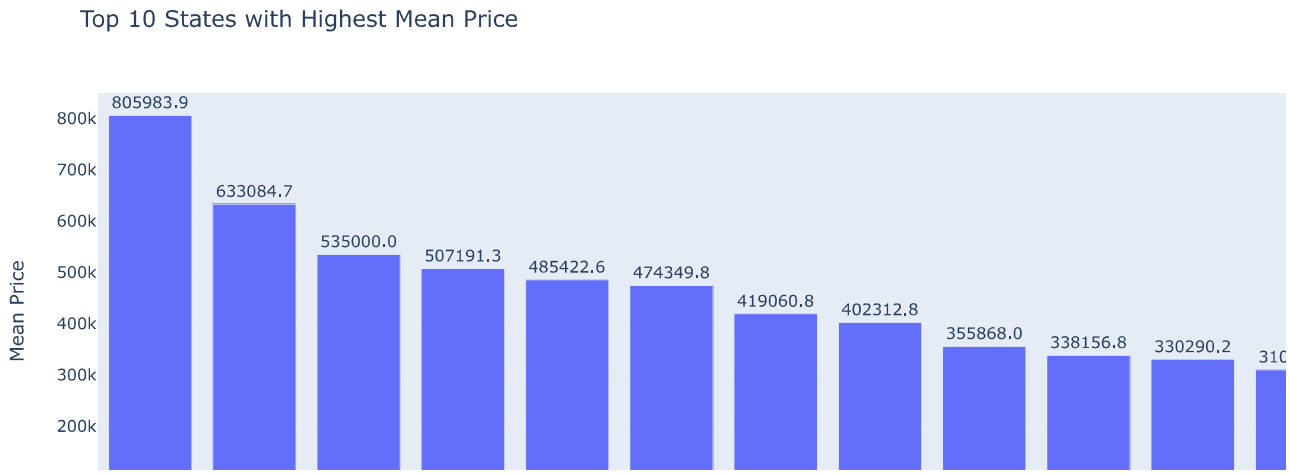
```
C:\Users\HP\AppData\Local\Temp\ipykernel_11424\1901337508.py:1: FutureWarning: The default value of numeric_only in DataFrame.corr is dep
recated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this wa
rning.
  sns.heatmap(housing.corr(), annot=True, linewidths=0.5);
```

Below it is presented the Distribution of Price.

In [25]:
```
fig = px.histogram(housing, x="price", nbins=25, template="plotly")
fig.update_layout(title="Distribution of Price")
fig.show()
```

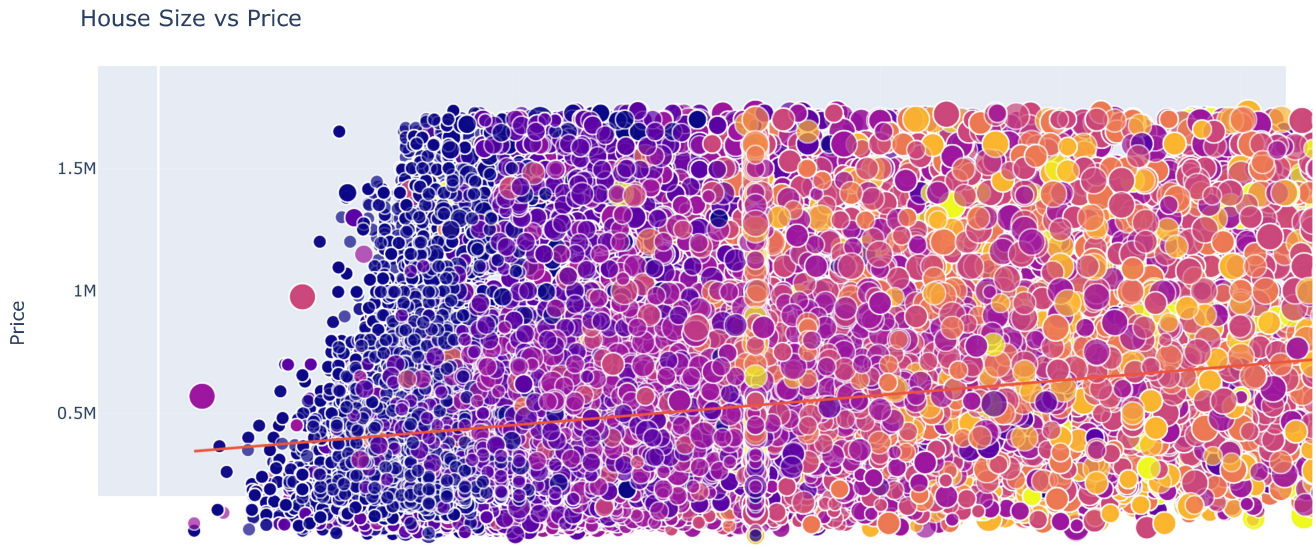
Below it is presented the chart of Top 10 States with Highest Mean Price

In [26]:
```
df_mean = housing.groupby('state')['price'].mean().reset_index()

df_mean_sort = df_mean.sort_values(by='price', ascending=False)

fig = px.bar(df_mean_sort, x='state', y='price',
             title='Top 10 States with Highest Mean Price',
             labels={'state': 'State', 'price': 'Mean Price'})
fig.update_traces(texttemplate='%{y:.1f}', textposition='outside')
fig.show()
```



Below it is presented the chart of House Size, Bed, Bath to Price.

In [27]:
```
fig = px.scatter(housing, x='house_size', y='price', color='bed', size='bath',trendline='ols')
fig.update_layout(title='House Size vs Price',
                  xaxis_title='House Size',
                  yaxis_title='Price')
fig.show()
```



Keeping the unique values of state, removing the ones that have less than 50 counts and fitting and transforming the "state" column to obtain numeric labels.

In [28]:
```
housing["state"].value_counts()
```

Out[28]:
```
New Jersey        153223
Massachusetts     103135
New York           86723
Connecticut        53410
Rhode Island       21126
New Hampshire      18140
Puerto Rico        17488
Pennsylvania       13579
Vermont            13357
Maine              11804
Delaware            1780
Virgin Islands       390
Georgia               48
Wyoming                3
West Virginia          3
Name: state, dtype: int64
```

In [29]:
```
housing = housing.drop(housing[housing["state"].map(housing["state"].value_counts()) < 50]["state"].index)
```

In [30]:
```
housing["state"].unique()
```

Out[30]:
```
array(['Puerto Rico', 'Virgin Islands', 'Massachusetts', 'Connecticut',
       'New Jersey', 'New Hampshire', 'Vermont', 'New York',
       'Rhode Island', 'Maine', 'Pennsylvania', 'Delaware'], dtype=object)
```

In [31]:
```
from sklearn.preprocessing import LabelEncoder

label_encoder = LabelEncoder()
housing['state_numeric'] = label_encoder.fit_transform(housing['state'])
housing = housing.drop("state", axis=1)
housing
```

Out[31]:

	bed	bath	acre_lot	house_size	price	state_numeric
0	3.0	2.0	0.12	920.0	105000.0	8
1	4.0	2.0	0.08	1527.0	80000.0	8
2	2.0	1.0	0.15	748.0	67000.0	8
3	4.0	2.0	0.10	1800.0	145000.0	8
4	6.0	2.0	0.05	1655.0	65000.0	8
...	...	...	...	...	...	...
904958	1.0	1.0	0.23	700.0	245000.0	6
904959	1.0	1.0	0.23	720.0	265000.0	6
904960	2.0	2.0	0.23	1200.0	399000.0	6
904962	2.0	2.0	0.23	1200.0	299000.0	6
904965	3.0	3.0	0.23	1677.0	850000.0	6

494155 rows × 6 columns

In [32]:
```
housing.describe()
```

Out[32]:

	bed	bath	acre_lot	house_size	price	state_numeric
count	494155.00000	494155.000000	494155.000000	494155.000000	4.941550e+05	494155.000000
mean	3.00686	2.098690	0.226893	1569.560421	5.217166e+05	4.566901
std	1.26362	0.863148	0.162794	631.011452	3.401018e+05	2.377142
min	1.00000	1.000000	0.000000	100.000000	1.000000e+00	0.000000
25%	2.00000	1.000000	0.110000	1100.000000	2.749000e+05	3.000000
50%	3.00000	2.000000	0.230000	1600.000000	4.350000e+05	5.000000
75%	4.00000	3.000000	0.230000	1807.000000	6.930000e+05	6.000000
max	7.00000	4.000000	0.900000	3852.000000	1.735000e+06	11.000000

Training the Model with multivariable regression using Scikit Learn

In [33]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import OneHotEncoder, StandardScaler, MinMaxScaler
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
import math
```

Standardizing data

In [34]:
```
housing['house_size'] = StandardScaler().fit_transform(housing['house_size'].values.reshape(len(housing), 1))
housing['price'] = StandardScaler().fit_transform(housing['price'].values.reshape(len(housing), 1))
```

In [35]:
```
housing['bed'] = MinMaxScaler().fit_transform(housing['bed'].values.reshape(len(housing), 1))
housing['bath'] = MinMaxScaler().fit_transform(housing['bath'].values.reshape(len(housing), 1))
housing['acre_lot'] = MinMaxScaler().fit_transform(housing['acre_lot'].values.reshape(len(housing), 1))
```

Splitting the data

X are the predictores, and y is the output. What we want to do is create a model that will take in the values in the X variable and predict y with a linear regression algorithm and random forest regressor algorithm. We will use the SciKit Learn library to create the model.

In the model we will use even categarorical variable state, by using One-hot encoding, in order to use them as dummy varuables in the model.

In [36]:
```
X = housing[['bed', 'bath', 'acre_lot', 'house_size', 'state_numeric']]
y = housing['price']

X = pd.get_dummies(X, columns=['state_numeric'])

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Linear Regression

In [37]:
```
lm = LinearRegression()
```

In [38]:
```
lm.fit(X_train, y_train)
```

Out[38]:
```
▾ LinearRegression
LinearRegression()
```

In [39]:
```
lm.coef_
```

Out[39]:
```
array([-0.37218256,  1.130083  ,  0.0772693 ,  0.1351292 , -0.37376231,
       -0.41614545, -0.13809235,  0.62272378, -0.0503748 ,  0.09431653,
        1.23621904, -0.22260922, -0.49691699, -0.0396621 , -0.29976771,
        0.08407156])
```

In [40]:
```
lm.score(X, y)
```

Out[40]:
```
0.39915832588727773
```

In [41]:
```
# The coefficients in a dataframe
cdf = pd.DataFrame(lm.coef_,X.columns,columns=['Coef'])
print(cdf)
```

```
                    Coef
bed              -0.372183
bath              1.130083
acre_lot          0.077269
house_size        0.135129
state_numeric_0  -0.373762
state_numeric_1  -0.416145
state_numeric_2  -0.138092
state_numeric_3   0.622724
state_numeric_4  -0.050375
state_numeric_5   0.094317
state_numeric_6   1.236219
state_numeric_7  -0.222609
state_numeric_8  -0.496917
state_numeric_9  -0.039662
state_numeric_10 -0.299768
state_numeric_11  0.084072
```

In [42]:
```
predictions = lm.predict(X_test)
```

In [43]:
```
print('Mean Absolute Error:',mean_absolute_error(y_test, predictions))
print('Mean Squared Error:',mean_squared_error(y_test, predictions))
print('Root Mean Squared Error:',math.sqrt(mean_squared_error(y_test, predictions)))
```

```
Mean Absolute Error: 0.5594266344647285
Mean Squared Error: 0.5995482472664143
Root Mean Squared Error: 0.7743050091962561
```

In [45]:
```
print(predictions)
```

```
[-0.19227954 -1.07777078 -0.58209547 ... -0.15342556 -0.10717391
 -1.05121261]
```

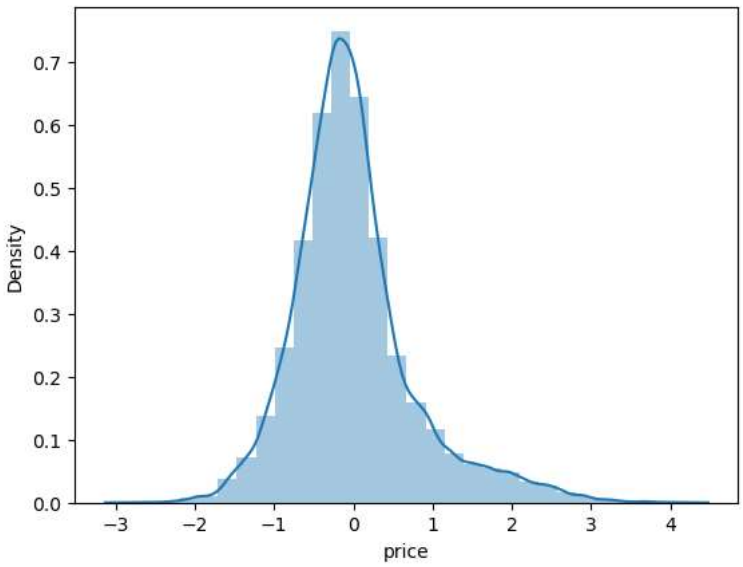
Residuals

Distribution plot of the residuals of the model's predictions. They should be normally distributed.

In [46]:
```
residuals = y_test-predictions
sns.distplot(residuals, bins=30)
```

```
C:\Users\HP\AppData\Local\Temp\ipykernel_11424\339810671.py:2: UserWarning:



`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751
```

Out[46]: <Axes: xlabel='price', ylabel='Density'>



The Linear Regression shows a value of R^2 in the value 39.9% (that is not a very good value). On the other hand the value of MAE and MSE are near 0, which is a very good value.

Random Forest Regressor

In [47]:
```
# creating a Random Forest model and train it using training data
model_RF = RandomForestRegressor(n_estimators=100, random_state=42)
model_RF.fit(X_train, y_train)

# Make predictions using testing data
y_pred = model_RF.predict(X_test)

# calculate average error value using MSE metrics
mse_RF = mean_squared_error(y_test, y_pred)
rmse_RF = mean_squared_error(y_test, y_pred, squared=False)
mae_RF = mean_absolute_error(y_test, y_pred)
r2_RF = r2_score(y_test, y_pred)
```

In [48]:
```
result = {'Random Forest': {'MSE': mse_RF, 'RMSE': rmse_RF, 'MAE': mae_RF, 'R^2': r2_RF}
}
```

In [49]:
```
data = pd.DataFrame.from_dict(result, orient='index')
data = data.applymap(lambda x: f'{x:.2f}')
print(data)
```

```
                MSE  RMSE   MAE   R^2
Random Forest  0.14  0.37  0.16  0.86
```

The Random Forest Regressor shows that all indicators MSE, RMSE, MAE, R^2 are very good and this algorithm is appropriate for the relationship of the varibles.

Training the model with multivariable regression using OLS

In [50]:
```
import  statsmodels.api as sm
X = sm.add_constant(X_train)
model = sm.OLS(y_train, X)
model_fit = model.fit()
print(model_fit.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.399
Model:                            OLS   Adj. R-squared:                  0.399
Method:                 Least Squares   F-statistic:                 1.749e+04
Date:                Sat, 21 Oct 2023   Prob (F-statistic):               0.00
Time:                        15:39:58   Log-Likelihood:            -4.6035e+05
No. Observations:              395324   AIC:                         9.207e+05
Df Residuals:                  395308   BIC:                         9.209e+05
Df Model:                          15
Covariance Type:            nonrobust
==============================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const             -0.5575      0.005   -106.549      0.000      -0.568      -0.547
bed               -0.3722      0.008    -46.622      0.000      -0.388      -0.357
bath               1.1301      0.006    194.094      0.000       1.119       1.141
acre_lot           0.0773      0.007     10.612      0.000       0.063       0.092
house_size         0.1351      0.002     73.699      0.000       0.132       0.139
state_numeric_0   -0.4202      0.005    -78.992      0.000      -0.431      -0.410
state_numeric_1   -0.4626      0.019    -23.980      0.000      -0.500      -0.425
state_numeric_2   -0.1846      0.008    -21.944      0.000      -0.201      -0.168
state_numeric_3    0.5763      0.005    123.131      0.000       0.567       0.585
state_numeric_4   -0.0968      0.007    -13.517      0.000      -0.111      -0.083
state_numeric_5    0.0479      0.004     10.655      0.000       0.039       0.057
state_numeric_6    1.1898      0.005    245.409      0.000       1.180       1.199
state_numeric_7   -0.2691      0.008    -33.787      0.000      -0.285      -0.253
state_numeric_8   -0.5434      0.007    -74.821      0.000      -0.558      -0.529
state_numeric_9   -0.0861      0.007    -12.693      0.000      -0.099      -0.073
state_numeric_10  -0.3462      0.008    -43.480      0.000      -0.362      -0.331
state_numeric_11   0.0376      0.040      0.932      0.351      -0.041       0.117
==============================================================================
Omnibus:                    68868.226   Durbin-Watson:                   1.997
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           146406.691
Skew:                           1.033   Prob(JB):                         0.00
Kurtosis:                       5.149   Cond. No.                     1.57e+15
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 2.5e-25. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

In [ ]: