About Dataset

Context

The data contains information from the 1990 California census. It does provide an accessible introductory dataset for teaching people about the basics of machine learning.

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.The columns are as follows:

1. longitude: A measure of how far west a house is; a higher value is farther west
2. latitude: A measure of how far north a house is; a higher value is farther north
3. housingMedianAge: Median age of a house within a block; a lower number is a newer building
4. totalRooms: Total number of rooms within a block
5. totalBedrooms: Total number of bedrooms within a block
6. population: Total number of people residing within a block
7. households: Total number of households, a group of people residing within a home unit, for a block
8. medianIncome: Median income for households within a block of houses (measured in tens of thousands of US Dollars)
9. medianHouseValue: Median house value for households within a block (measured in US Dollars)
10. oceanProximity: Location of the house w.r.t ocean/sea

In [134…

```
# Load needed libraries
import numpy as np
```

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.datasets import fetch_california_housing

california_df = fetch_california_housing(as_frame=True)
california_df = pd.read_csv("housing[1].csv")

print("Data Imported Successfully")
```

```
Data Imported Successfully
```

In [135…

```
# Get the first 5 rows of data
california_df.head(5)
```

Out[135…

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	popul
0	-122.23	37.88	41.0	880.0	129.0	
1	-122.22	37.86	21.0	7099.0	1106.0	2
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	

In [136…

```
# Get the last 5 rows of data
california_df.tail(5)
```

Out[136…

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	
20635	-121.09	39.48	25.0	1665.0	374.0	
20636	-121.21	39.49	18.0	697.0	150.0	
20637	-121.22	39.43	17.0	2254.0	485.0	
20638	-121.32	39.43	18.0	1860.0	409.0	
20639	-121.24	39.37	16.0	2785.0	616.0	

In [137…

```
# Some info about the dataset
california_df.info()

# ||ANALYSIS||
# We see that the total_bedrooms has a few NULL(MISSING) values. And the varia
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   longitude           20640 non-null  float64
 1   latitude            20640 non-null  float64
 2   housing_median_age  20640 non-null  float64
 3   total_rooms         20640 non-null  float64
 4   total_bedrooms      20433 non-null  float64
 5   population          20640 non-null  float64
 6   households          20640 non-null  float64
 7   median_income       20640 non-null  float64
 8   median_house_value  20640 non-null  float64
 9   ocean_proximity     20640 non-null  object 
dtypes: float64(9), object(1)
memory usage: 1.6+ MB
```

In [138…

```
# Some description about the dataset
california_df.describe()

# ||ANALYSIS||
# Just a few columns dicating the mean, standard devation and showing the 25th
# As well the smallest and largest value in each category
```

Out[138…

	longitude	latitude	housing_median_age	total_rooms	total_bec
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.
mean	-119.569704	35.631861	28.639486	2635.763081	537.
std	2.003532	2.135952	12.585558	2181.615252	421.
min	-124.350000	32.540000	1.000000	2.000000	1.
25%	-121.800000	33.930000	18.000000	1447.750000	296.
50%	-118.490000	34.260000	29.000000	2127.000000	435.
75%	-118.010000	37.710000	37.000000	3148.000000	647.
max	-114.310000	41.950000	52.000000	39320.000000	6445.

In [139…

```
# Get the Null values in our dataset
pd.DataFrame(california_df.isnull().sum())

# ||ANALYSIS||
# total_bedrooms has 207 missing values, we shall deal with this below
```

Out[139…

	0
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

In [140…

```
# Fix the total_bedrooms, replace the NULL values with the MEAN or AVERAGE val
total_bedrooms_mean_value = california_df["total_bedrooms"].mean()
california_df["total_bedrooms"].replace(np.nan, total_bedrooms_mean_value, inp

print("Successfully changed all NULL values to the mean value")
```

```
Successfully changed all NULL values to the mean value
/tmp/ipython-input-3536752185.py:3: FutureWarning: A value is trying to be set
on a copy of a DataFrame or Series through chained assignment using an inplace
method.
The behavior will change in pandas 3.0. This inplace method will never work bec
ause the intermediate object on which we are setting values always behaves as a
copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.me
thod({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, t
o perform the operation inplace on the original object.


  california_df["total_bedrooms"].replace(np.nan, total_bedrooms_mean_value, in
place  = True)
```

In [141…

```
# Calculating mean of every column
column_count = 0
for i in california_df.columns:
  print(f"The mean value of {i} = {california_df[i].mean()}")

  # Incrementing the Counter
  column_count += 1
  if column_count == 9: # I have used 9 because there are 10 columns
    break
```

```
The mean value of longitude = -119.56970445736432
The mean value of latitude = 35.63186143410853
The mean value of housing_median_age = 28.639486434108527
The mean value of total_rooms = 2635.7630813953488
The mean value of total_bedrooms = 537.8705525375617
The mean value of population = 1425.4767441860465
The mean value of households = 499.5396802325581
The mean value of median_income = 3.8706710029069766
The mean value of median_house_value = 206855.81690891474
```

Visualization

I have analysed and visualised many relationships and connections between different columns to get interesting insights from our dataset.

What have I done?

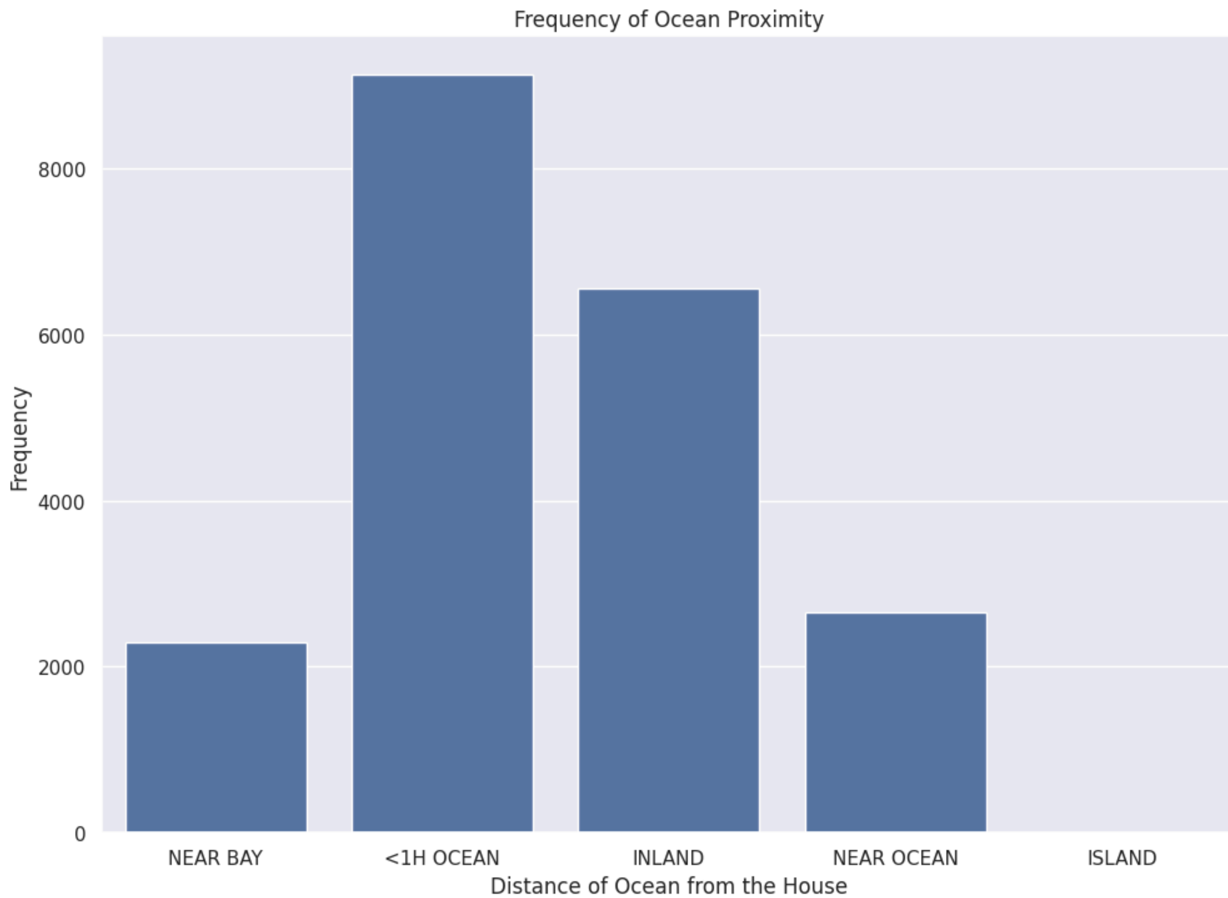
I have Explored the correlation & relationship between different data columns.

I have noted a few of the interesting insights from the exploratory analysis.

UNIVARIATE ANALYSIS

In [142…

```python
# Frequency of Ocean Proximity
sns.set(rc={'figure.figsize':(11.7,8.27)})

# Plot
sns.countplot(data=california_df, x="ocean_proximity").set(
    title = "Frequency of Ocean Proximity",
    xlabel = "Distance of Ocean from the House",
    ylabel = "Frequency"
)

# Show
plt.show()
```



In [143…

```
for col in california_df.columns:
    print("\n\n===============================")
    print("COLUMN:", col)
    print("===============================")

    # Check type
    if pd.api.types.is_numeric_dtype(california_df[col]):
        print("Type: Numeric")
        print("Missing values:", california_df[col].isnull().sum())
        print("Mean:", california_df[col].mean())
        print("Median:", california_df[col].median())
        print("Std:", california_df[col].std())
        print("Skew:", california_df[col].skew())
```

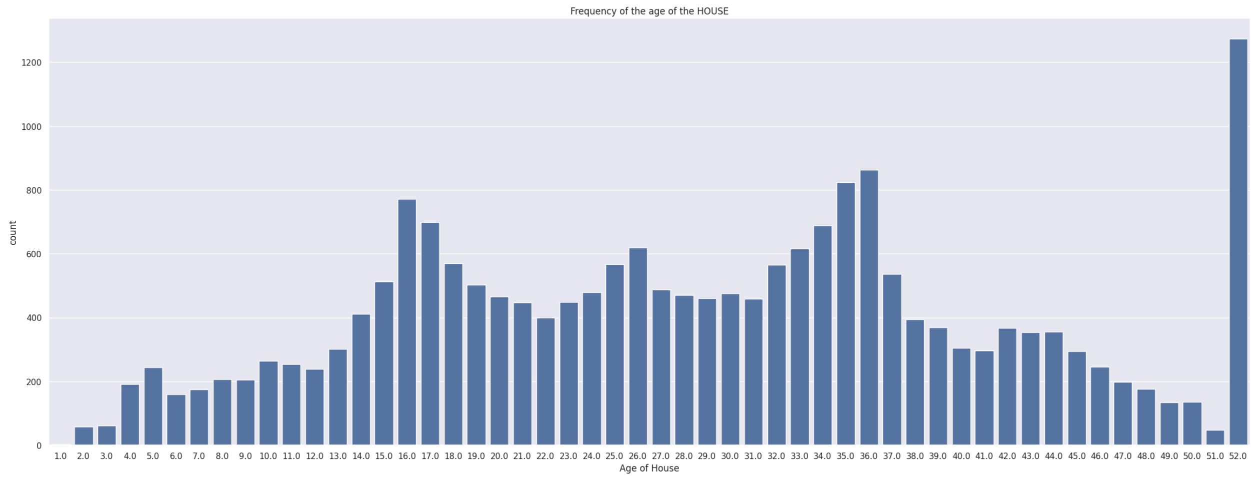
```
==============================
COLUMN: longitude
==============================
Type: Numeric
Missing values: 0
Mean: -119.56970445736432
Median: -118.49
Std: 2.003531723502581
Skew: -0.2978012079524362


==============================
COLUMN: latitude
==============================
Type: Numeric
Missing values: 0
Mean: 35.63186143410853
Median: 34.26
Std: 2.1359523974571117
Skew: 0.46595300370997006


==============================
COLUMN: housing_median_age
==============================
Type: Numeric
Missing values: 0
Mean: 28.639486434108527
Median: 29.0
Std: 12.585557612111637
Skew: 0.060330637599136865


==============================
COLUMN: total_rooms
==============================
Type: Numeric
Missing values: 0
Mean: 2635.7630813953488
Median: 2127.0
Std: 2181.615251582787
Skew: 4.147343450632158


==============================
COLUMN: total_bedrooms
==============================
Type: Numeric
Missing values: 0
Mean: 537.8705525375617
Median: 438.0
Std: 419.26659232552385
Skew: 3.4770233756335105
```

```
===============================
COLUMN: population
===============================
Type: Numeric
Missing values: 0
Mean: 1425.4767441860465
Median: 1166.0
Std: 1132.4621217653375
Skew: 4.93585822672712


===============================
COLUMN: households
===============================
Type: Numeric
Missing values: 0
Mean: 499.5396802325581
Median: 409.0
Std: 382.3297528316099
Skew: 3.410437711667147


===============================
COLUMN: median_income
===============================
Type: Numeric
Missing values: 0
Mean: 3.8706710029069766
Median: 3.5347999999999997
Std: 1.8998217179452732
Skew: 1.6466567021344465


===============================
COLUMN: median_house_value
===============================
Type: Numeric
Missing values: 0
Mean: 206855.81690891474
Median: 179700.0
Std: 115395.6158744132
Skew: 0.9777632739098341


===============================
COLUMN: ocean_proximity
===============================
```

In [144…

```
# Frequency of the age of the HOUSE
sns.set(rc={'figure.figsize':(28.7,10.27)})

# Plot
```

```python
sns.countplot(data=california_df, x="housing_median_age").set(
    title = "Frequency of the age of the HOUSE",
    xlabel = "Age of House"
)

# Show
plt.show()
```



In [145…

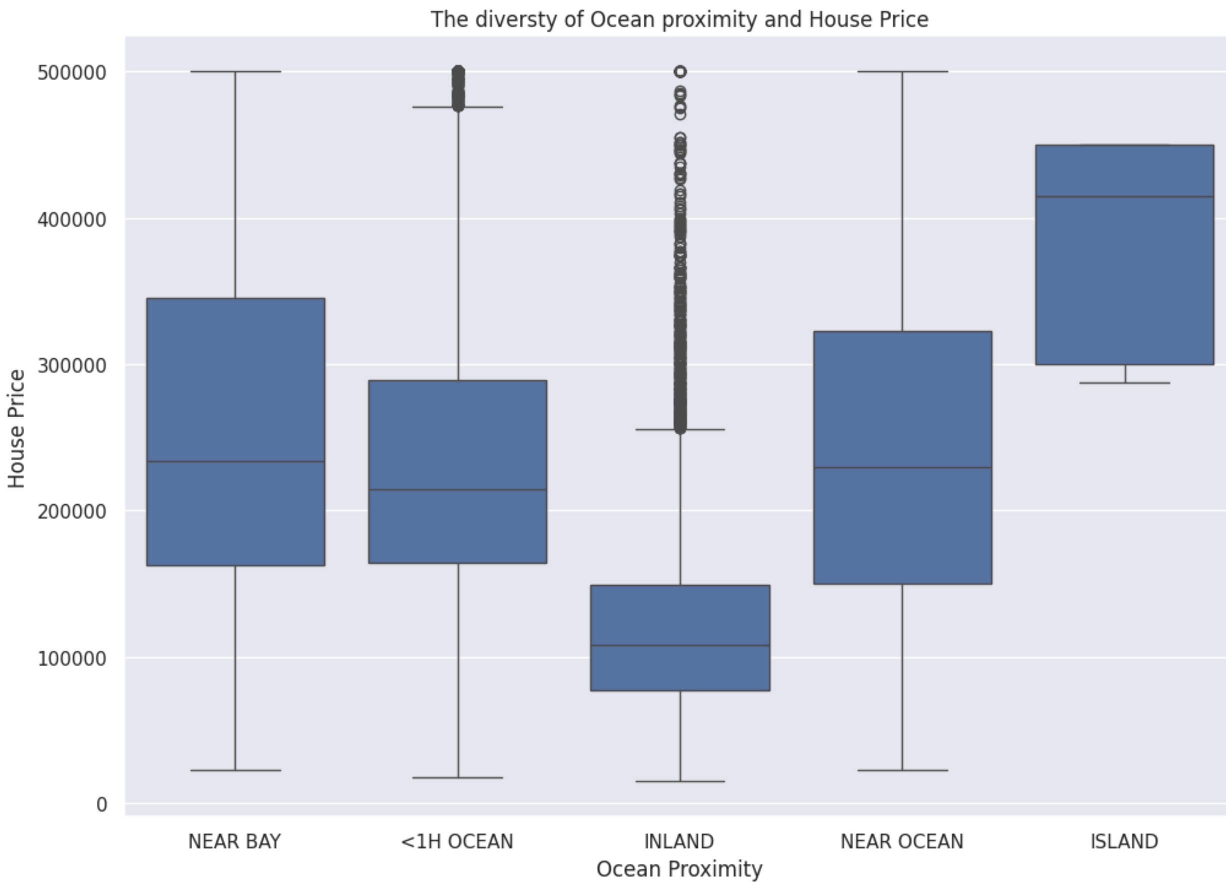
```python
print("\n===== CATEGORICAL SUMMARY =====\n")

categorical_cols = california_df.select_dtypes(exclude=[np.number]).columns.tc

for col in categorical_cols:
    print(f"\n### {col} ###\n")
    print(california_df[col].value_counts(dropna=False))
```

```
===== CATEGORICAL SUMMARY =====


### ocean_proximity ###

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

In [146…

```python
# The diversty of Ocean proximity and House Price
sns.set(rc={'figure.figsize':(11.7,8.27)})

sns.boxplot(x='ocean_proximity',y='median_house_value',data=california_df).set
    title = "The diversty of Ocean proximity and House Price",
    xlabel = "Ocean Proximity",
    ylabel = "House Price"
)

# Show
```

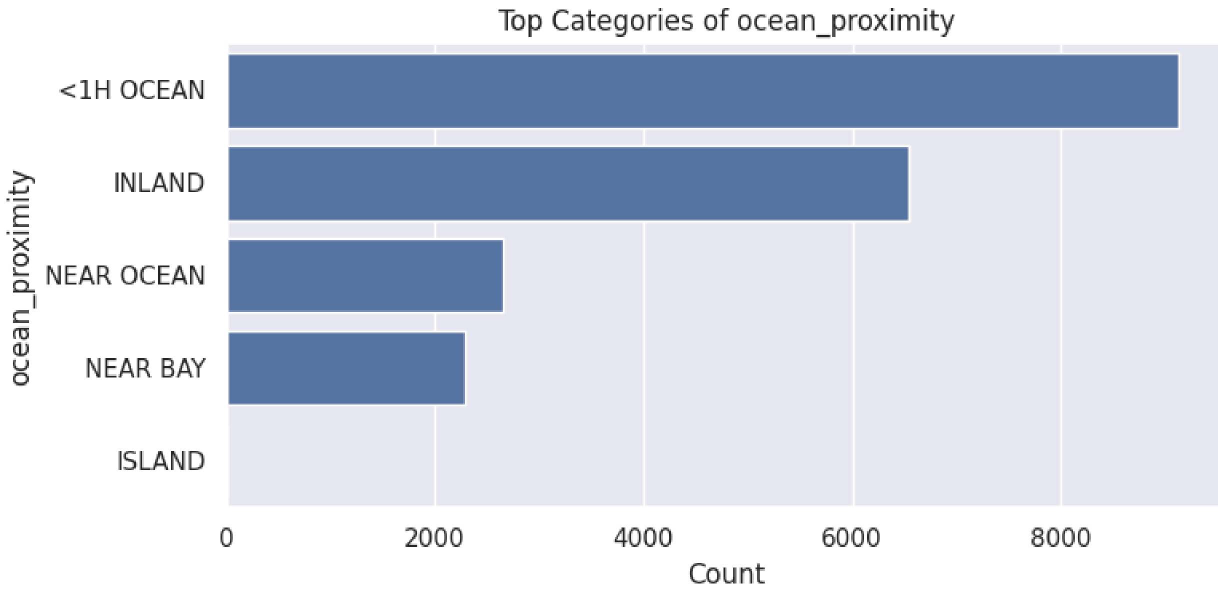
```
plt.show()
```



In [147…

```
for col in categorical_cols:
    print(f"\n\n### {col} ###")
    vc = california_df[col].value_counts().head(20)

    plt.figure(figsize=(8,4))
    sns.barplot(x=vc.values, y=vc.index)
    plt.title(f"Top Categories of {col}")
    plt.xlabel("Count")
    plt.ylabel(col)
    plt.tight_layout()
    plt.show()
```

```
### ocean_proximity ###
```



BI VARIATE ANALYSIS

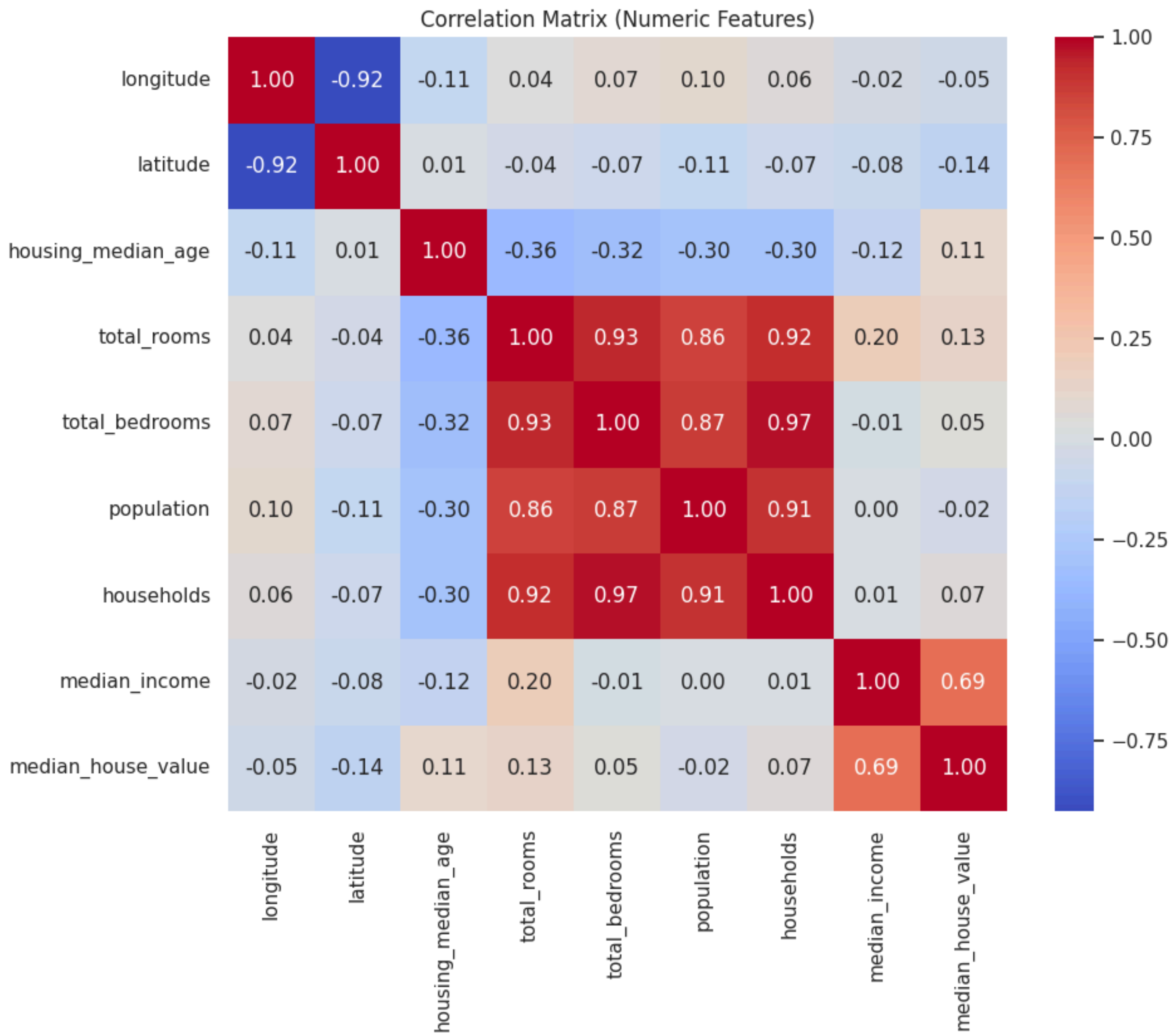
In [148…

```
numeric_cols = california_df.select_dtypes(include=[np.number]).columns.tolist
categorical_cols = california_df.select_dtypes(exclude=[np.number]).columns.tc

print("Numeric columns:", numeric_cols)
print("Categorical columns:", categorical_cols)
```

```
Numeric columns: ['longitude', 'latitude', 'housing_median_age', 'total_rooms',
'total_bedrooms', 'population', 'households', 'median_income', 'median_house_va
lue']
Categorical columns: ['ocean_proximity']
```

In [149…

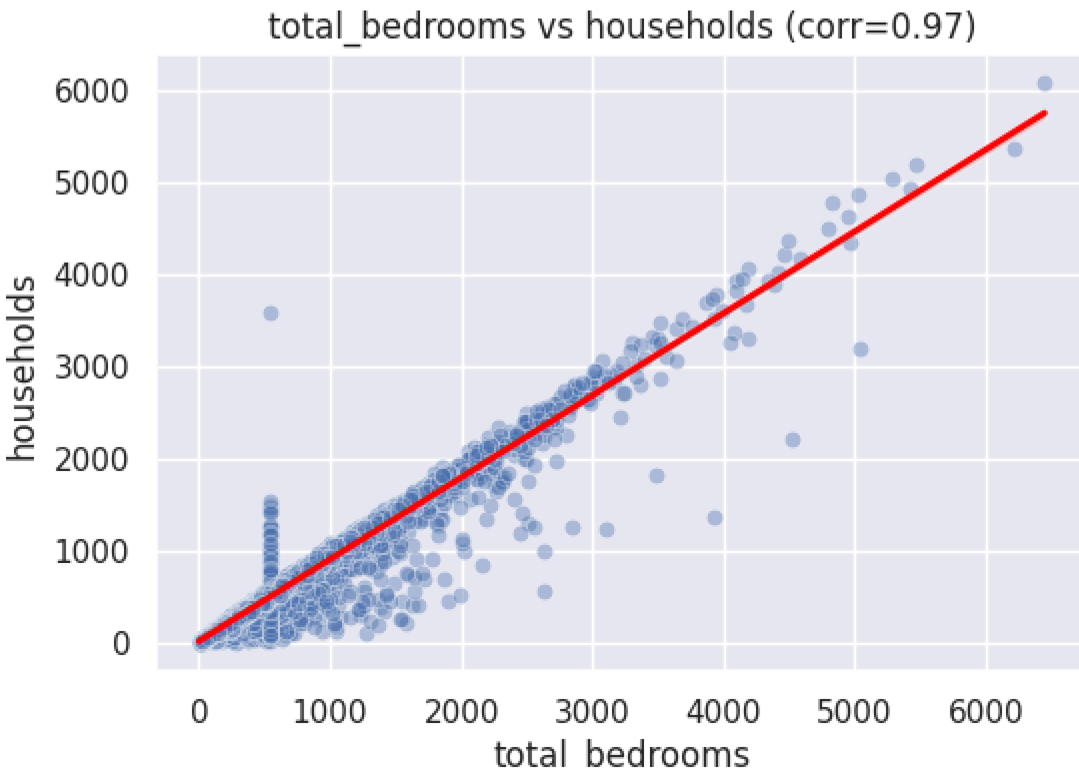
```
plt.figure(figsize=(10,8))
sns.heatmap(california_df[numeric_cols].corr(), annot=True, cmap="coolwarm", f
plt.title("Correlation Matrix (Numeric Features)")
plt.show()
```

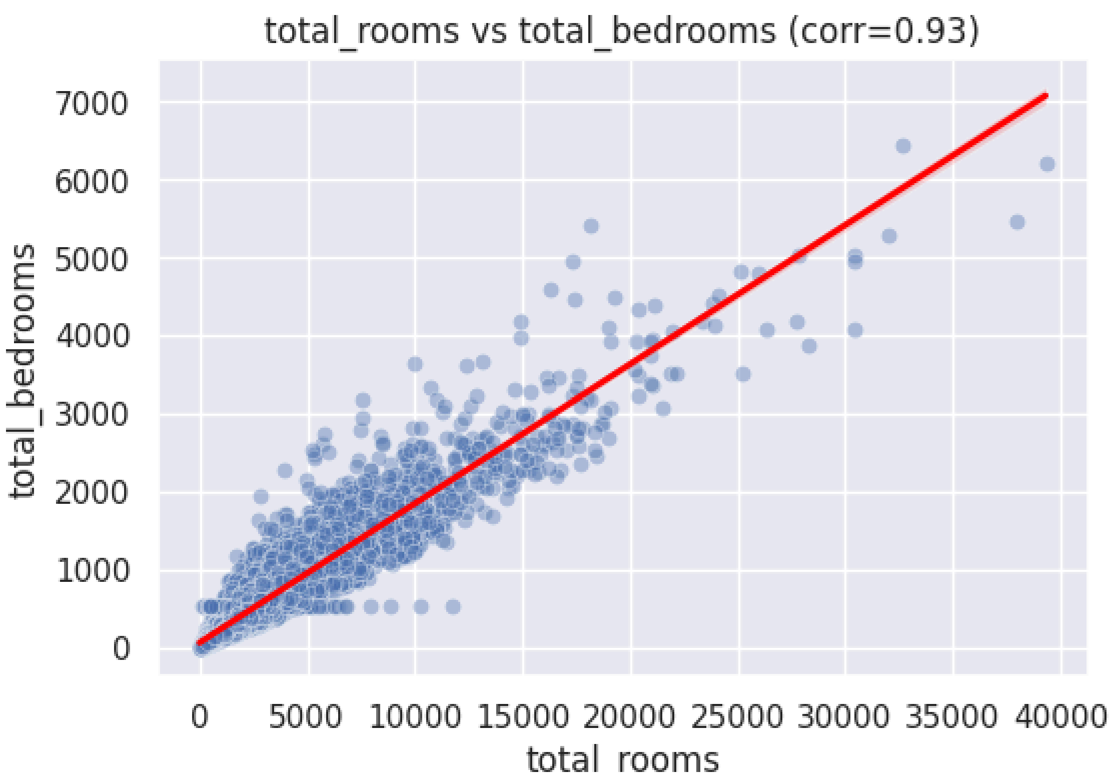


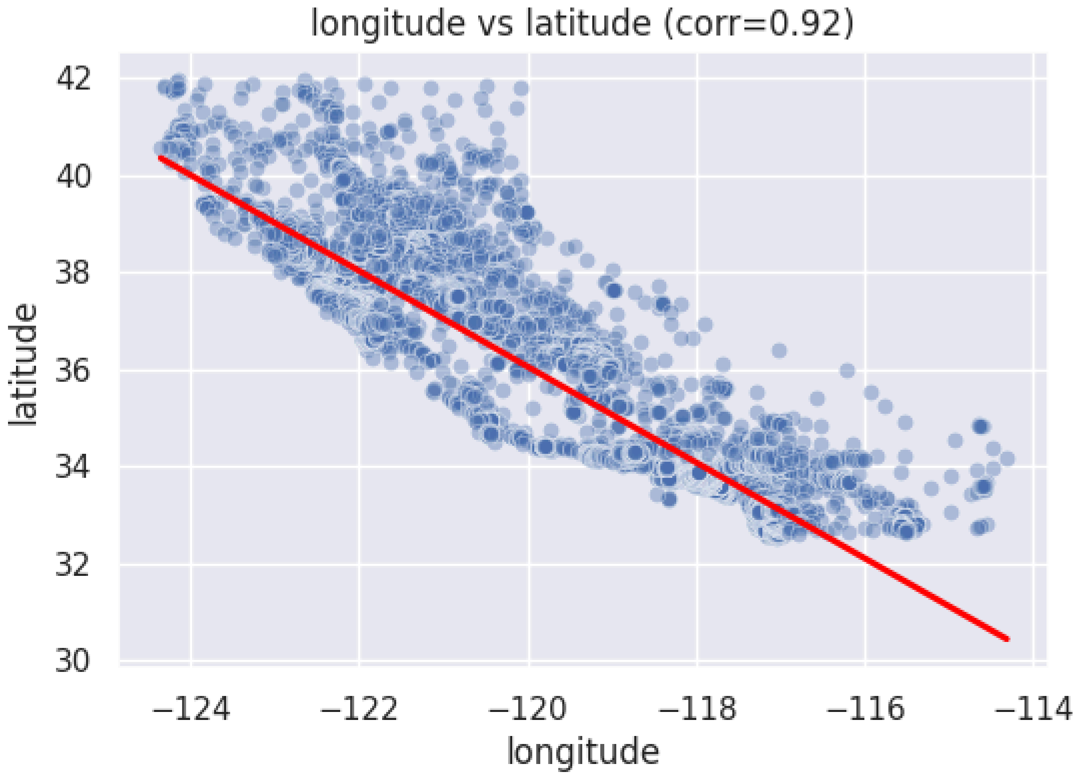
In [150…

```
corr = california_df[numeric_cols].corr().abs()

# get top 5 correlated pairs
pairs = (
    corr.where(np.triu(np.ones(corr.shape), k=1).astype(bool))
    .stack()
    .sort_values(ascending=False)
    .head(5)
)

print(pairs)

for (col1, col2), val in pairs.items():
    plt.figure(figsize=(6,4))
    sns.scatterplot(x=california_df[col1], y=california_df[col2], alpha=0.4)
    sns.regplot(x=california_df[col1], y=california_df[col2], scatter=False, c
    plt.title(f"{col1} vs {col2} (corr={val:.2f})")
    plt.show()
```

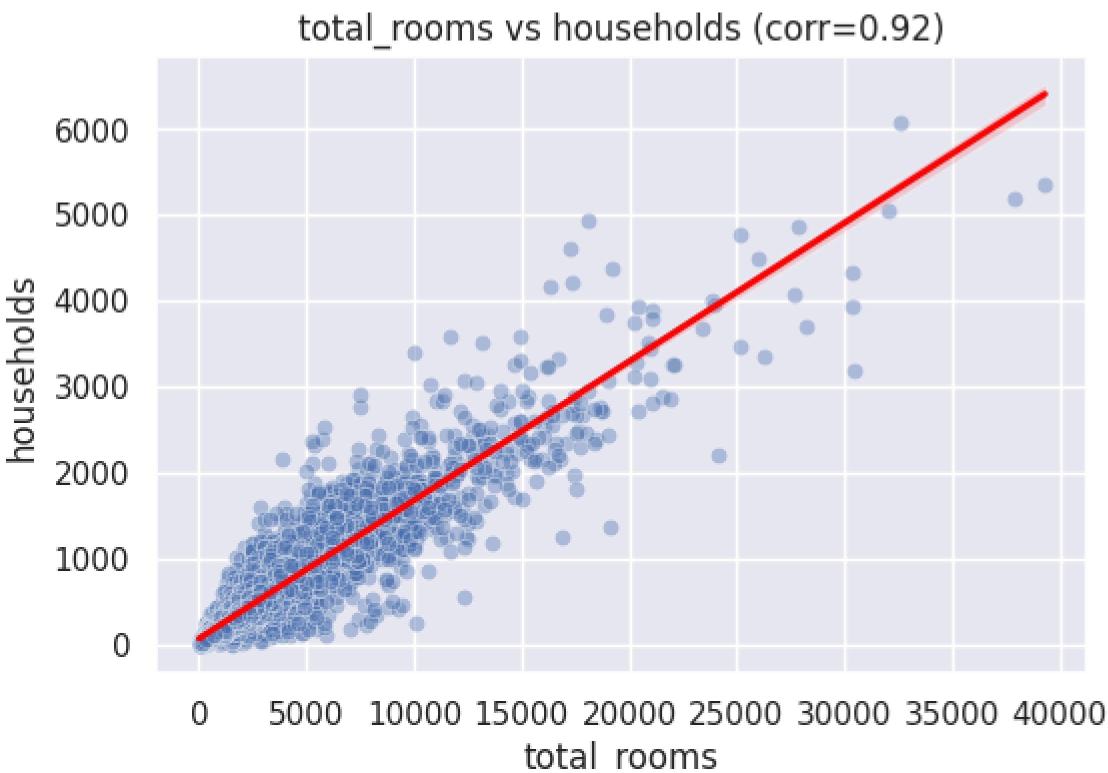
```
total_bedrooms  households        0.974725
total_rooms     total_bedrooms    0.927253
longitude       latitude          0.924664
total_rooms     households        0.918484
population      households        0.907222
dtype: float64
```







longitude vs latitude (corr=0.92)
latitude
42
40
38
36
34
32
30
−124
−122
−120
−118
−116
−114
longitude



total_rooms vs households (corr=0.92)
households
6000
5000
4000
3000
2000
1000
0
0
5000
10000
15000
20000
25000
30000
35000
40000
total_rooms

In [151…

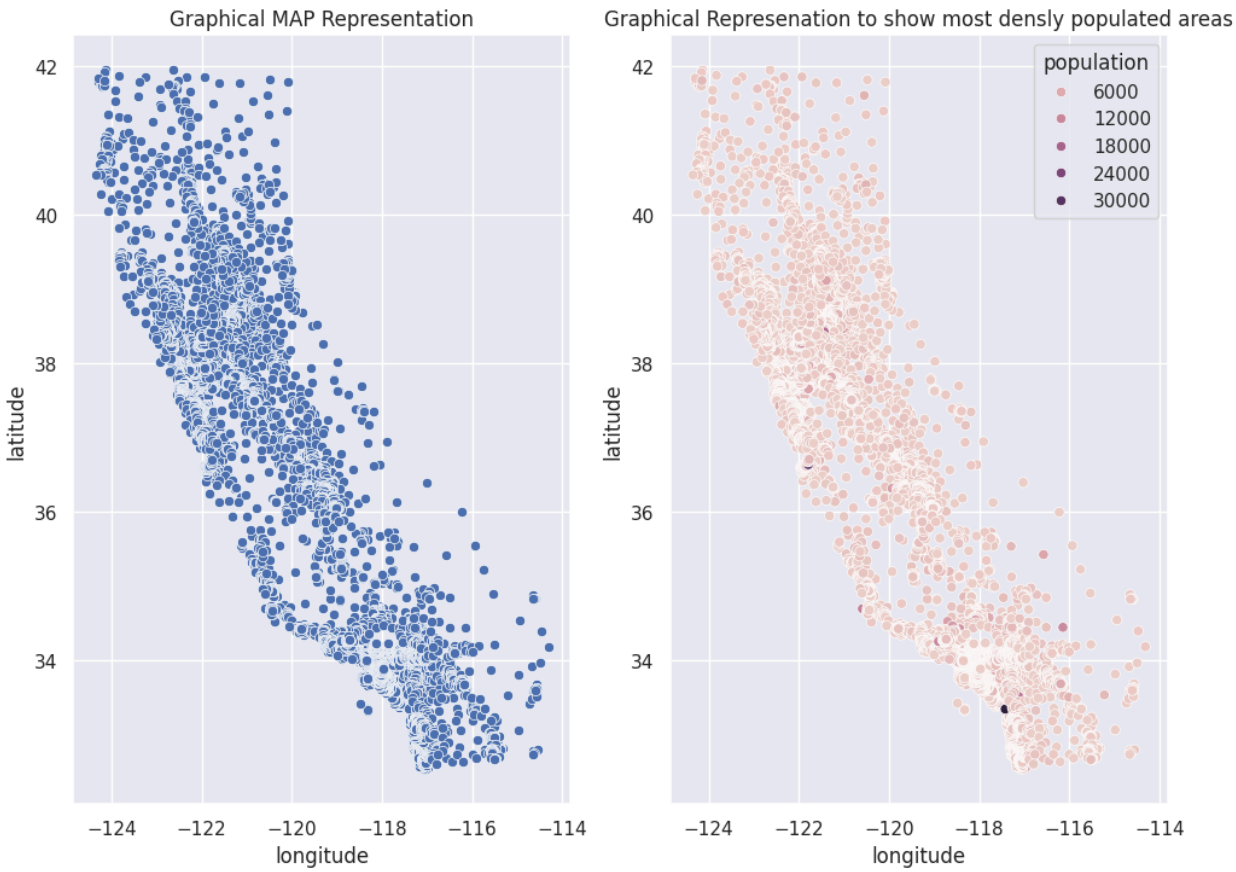
```
# Get pair values
plt.figure(figsize=(25,15))

# Plot
sns.pairplot(california_df)

# Sho
plt.show()
```

```
<Figure size 2500x1500 with 0 Axes>
```

In [152…

```
# Get the longitudinal & latitudinal graph
sns.set(rc={'figure.figsize':(11.7,8.27)})
fig, axes = plt.subplots(1, 2)

# Plot
sns.scatterplot(data=california_df, x="longitude", y="latitude", ax=axes[0]).s
    title = "Graphical MAP Representation"
)
sns.scatterplot(data=california_df, x="longitude", y="latitude", hue="populati
    title = "Graphical Represenation to show most densly populated areas"
)

# Show
plt.show()

# |||ANALYSIS|||
```

```
# We obeserve that the mostly densly populated areas are near San Diago & Los
```

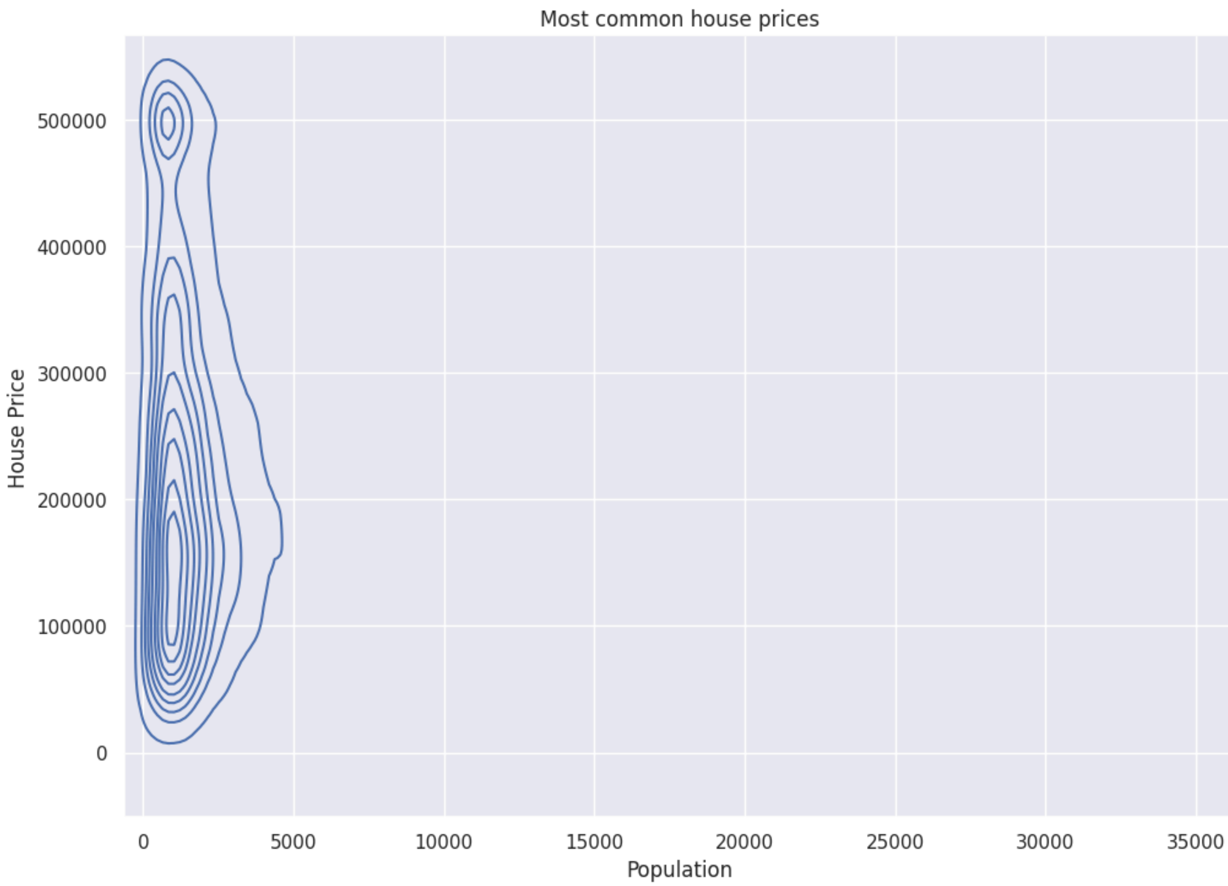


In [153…

```
# The relation between the Ocean Proximity and Population - PLOT 1
sns.set(rc={'figure.figsize':(11.7,8.27)})

# Plot
sns.scatterplot(data=california_df, x="population", y="median_house_value").se
    title = "How does price of house change with population and ocean proxmity
    xlabel = "Population",
    ylabel = "House Price"
)
# Show
plt.show()

# |||ANALYSIS|||
# We obeserve that most of the houses are Inland, with a price between 30,000
```

In [154…

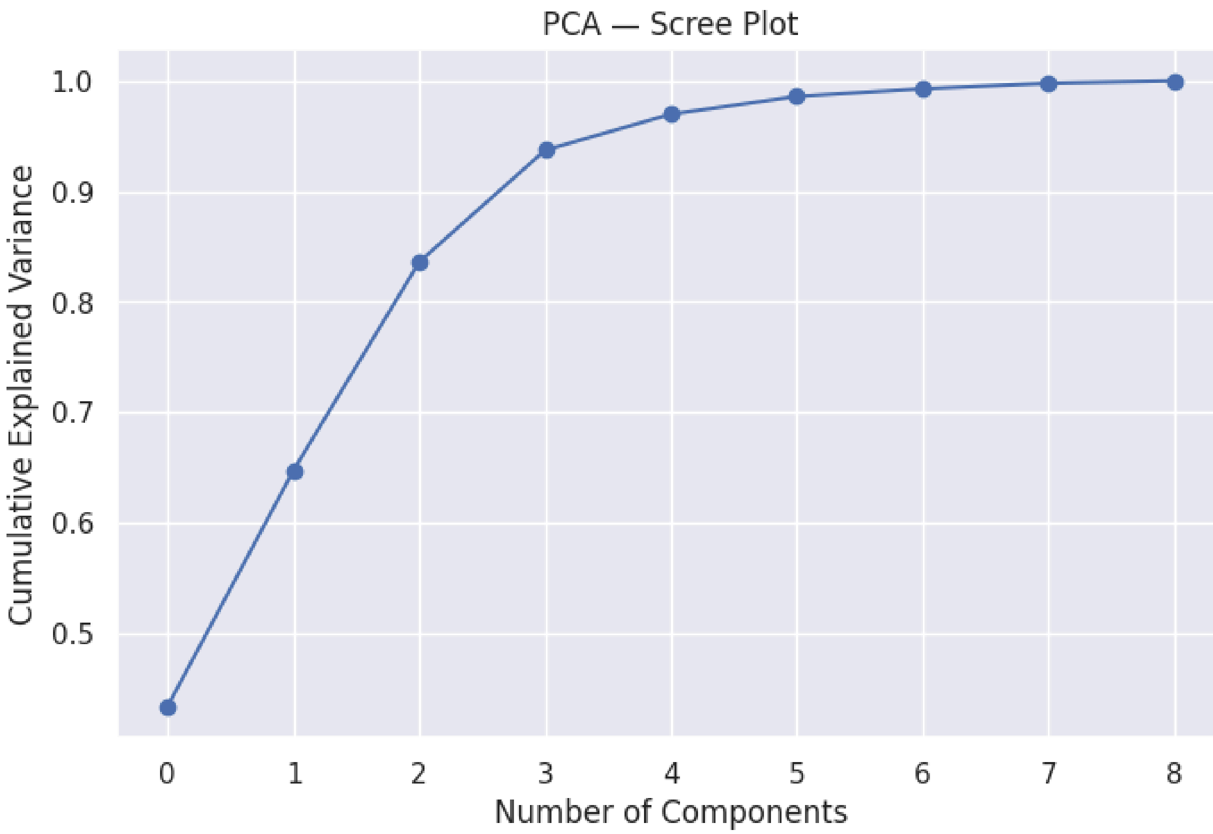
```
# The most common house prices
sns.set(rc={'figure.figsize':(11.7,8.27)})

# Plot
sns.kdeplot(x='population', y='median_house_value', data=california_df).set(
    title = "Most common house prices",
    xlabel = "Population",
    ylabel = "House Price"
)

# Show
plt.show()

# |||ANALYSIS|||
# We observe that mostly house prices in CA, lie between 50,000-280,000.
```



MULTI VARIATE ANALYSIS

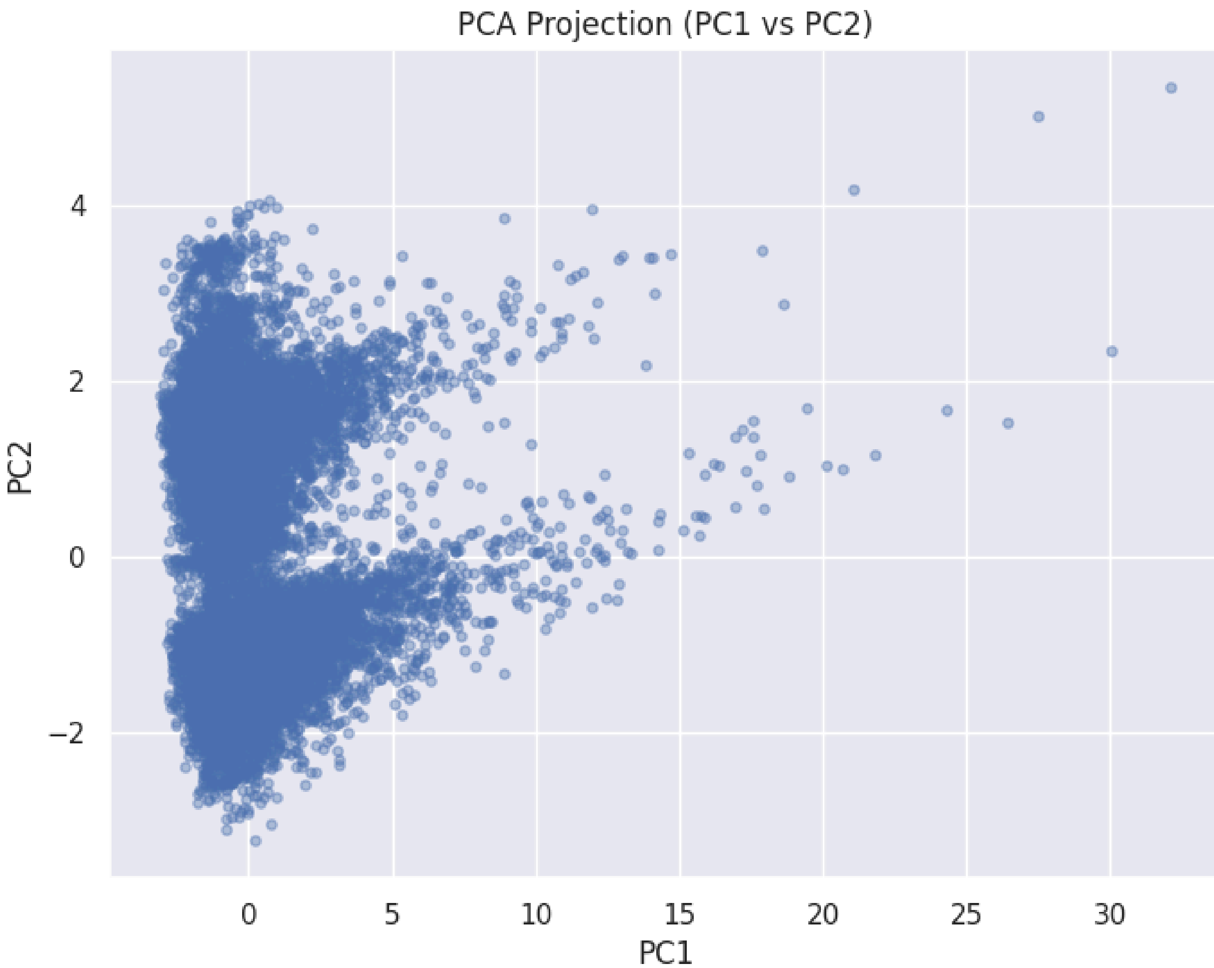
In [155…

```
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA

# Standardize numeric features
X_scaled = StandardScaler().fit_transform(california_df[numeric_cols].fillna(c

# PCA
pca = PCA()
pca.fit(X_scaled)

# Explained variance plot (scree)
plt.figure(figsize=(8,5))
plt.plot(np.cumsum(pca.explained_variance_ratio_), marker="o")
plt.xlabel("Number of Components")
plt.ylabel("Cumulative Explained Variance")
plt.title("PCA — Scree Plot")
plt.grid(True)
plt.show()
```



In [156…

```
X_pca = pca.transform(X_scaled)

plt.figure(figsize=(8,6))
plt.scatter(
    X_pca[:, 0],
    X_pca[:, 1],
    alpha=0.4,
    s=15
)
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.title("PCA Projection (PC1 vs PC2)")
plt.grid(True)
plt.show()
```



SIMPLE LINEAR REGRESSION

In [157…
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

In [158…
```
df = pd.read_csv("housing[1].csv")
```

In [159…
```
X = df[["median_income"]]        # independent variable
y = df["median_house_value"]
```

In [160…
```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)
```

In [161…
```
model = LinearRegression()
model.fit(X_train, y_train)
```

Out[161…

▾ LinearRegression

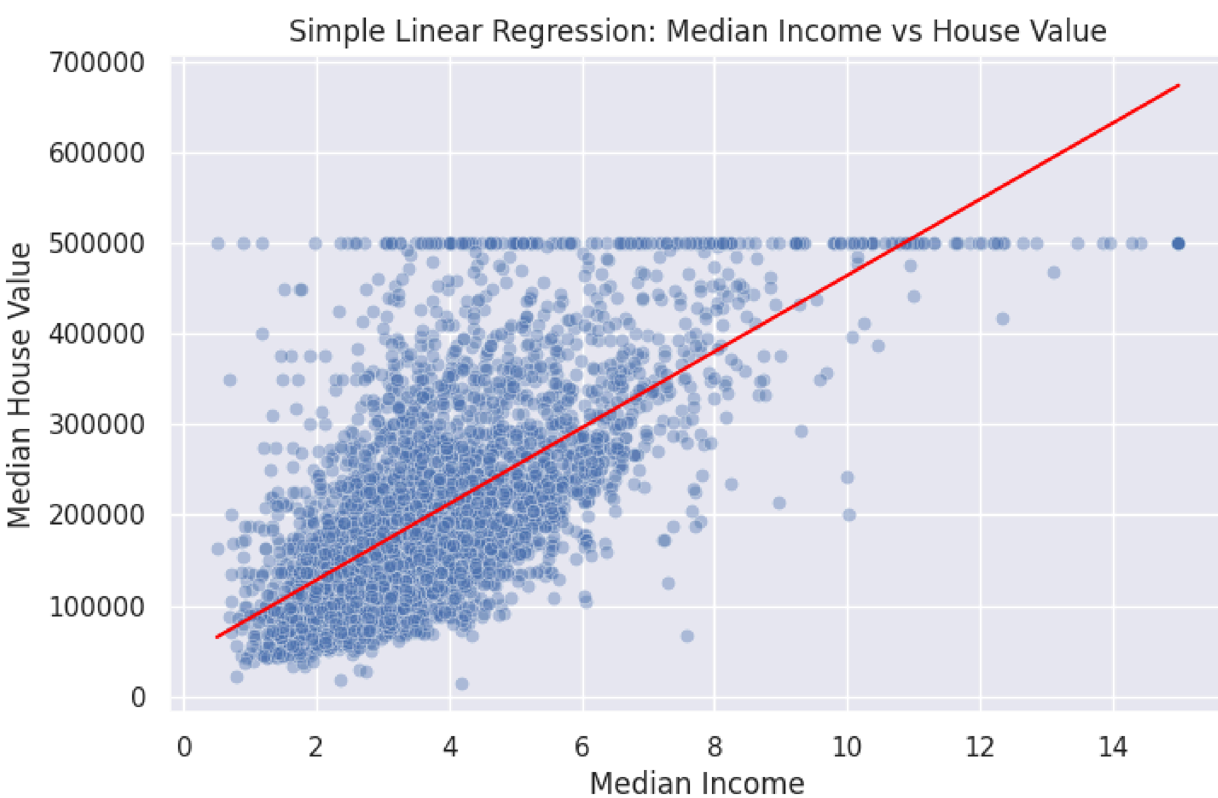
LinearRegression()

In [162…
```
y_pred = model.predict(X_test)
```

In [163…
```
print("Coefficient:", model.coef_[0])
print("Intercept:", model.intercept_)
print("MAE:", mean_absolute_error(y_test, y_pred))
print("R²:", r2_score(y_test, y_pred))
```

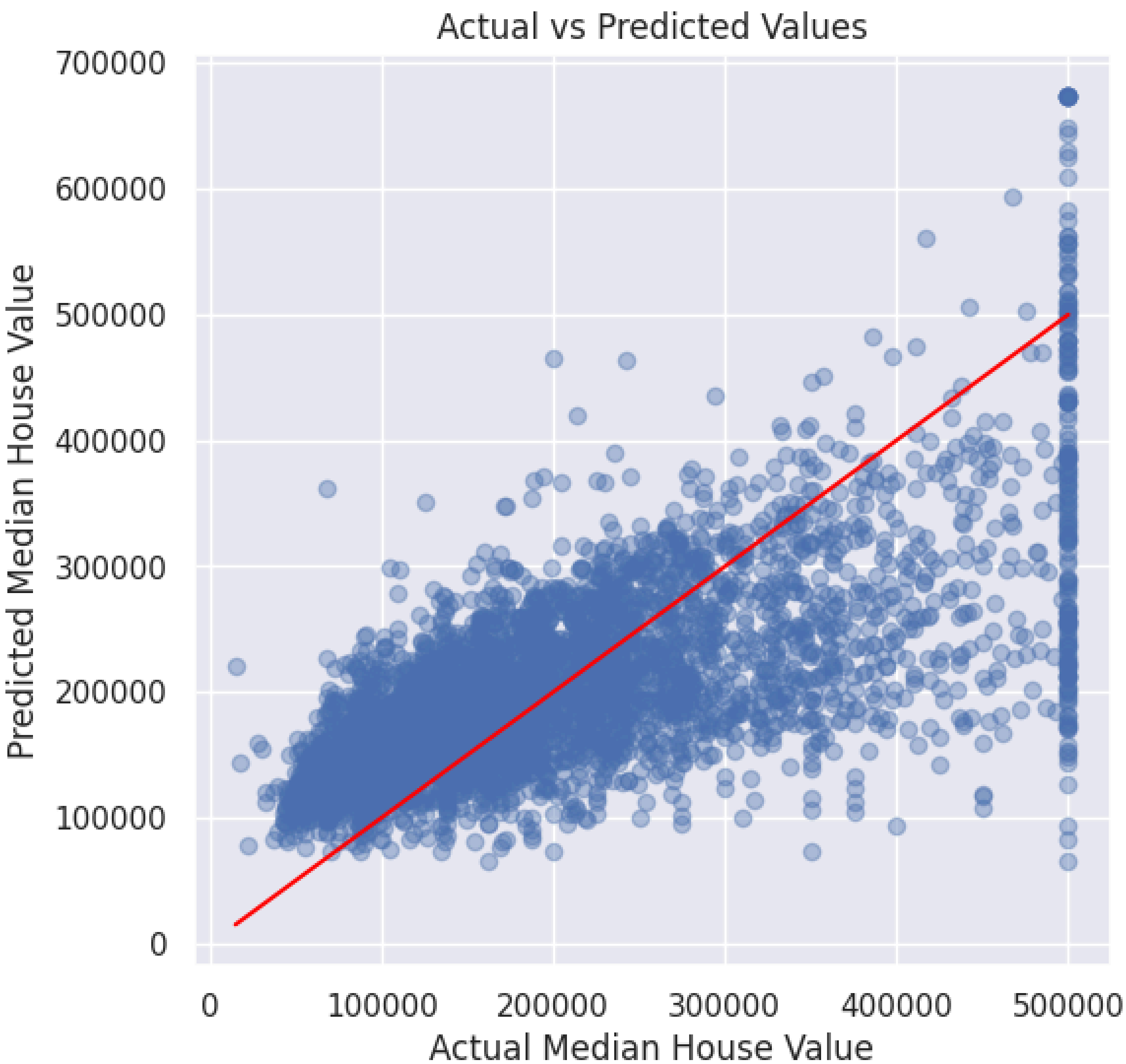
```
Coefficient: 41933.84939381272
Intercept: 44459.72916907875
MAE: 62990.86530093761
R²: 0.45885918903846656
```

In [164…
```
plt.figure(figsize=(8,5))
sns.scatterplot(x=X_test["median_income"], y=y_test, alpha=0.4)
sns.lineplot(x=X_test["median_income"], y=y_pred, color='red')
plt.xlabel("Median Income")
plt.ylabel("Median House Value")
plt.title("Simple Linear Regression: Median Income vs House Value")
plt.show()
```



In [165…
```
plt.figure(figsize=(6,6))
plt.scatter(y_test, y_pred, alpha=0.4)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], color="re
```

```python
plt.xlabel("Actual Median House Value")
plt.ylabel("Predicted Median House Value")
plt.title("Actual vs Predicted Values")
plt.show()
```



MULTIPLE LINEAR REGRESSION

In [166…
```python
from sklearn.impute import SimpleImputer
```

In [167…
```python
numeric_df = df.select_dtypes(include=['number'])
```

In [168…
```python
# Set the target variable
target = "median_house_value"        # your dataset's target
```

In [169…
```python
# Define X and y
X = numeric_df.drop(columns=[target])   # all numeric features except target
y = numeric_df[target]
```

In [170…
```
imputer = SimpleImputer(strategy="median")
X_imputed = imputer.fit_transform(X)
```

In [171…
```
X_train, X_test, y_train, y_test = train_test_split(
    X_imputed, y, test_size=0.2, random_state=42
)
```

In [172…
```
model = LinearRegression()
model.fit(X_train, y_train)
```

Out[172…

▾ LinearRegression ⓘ ?

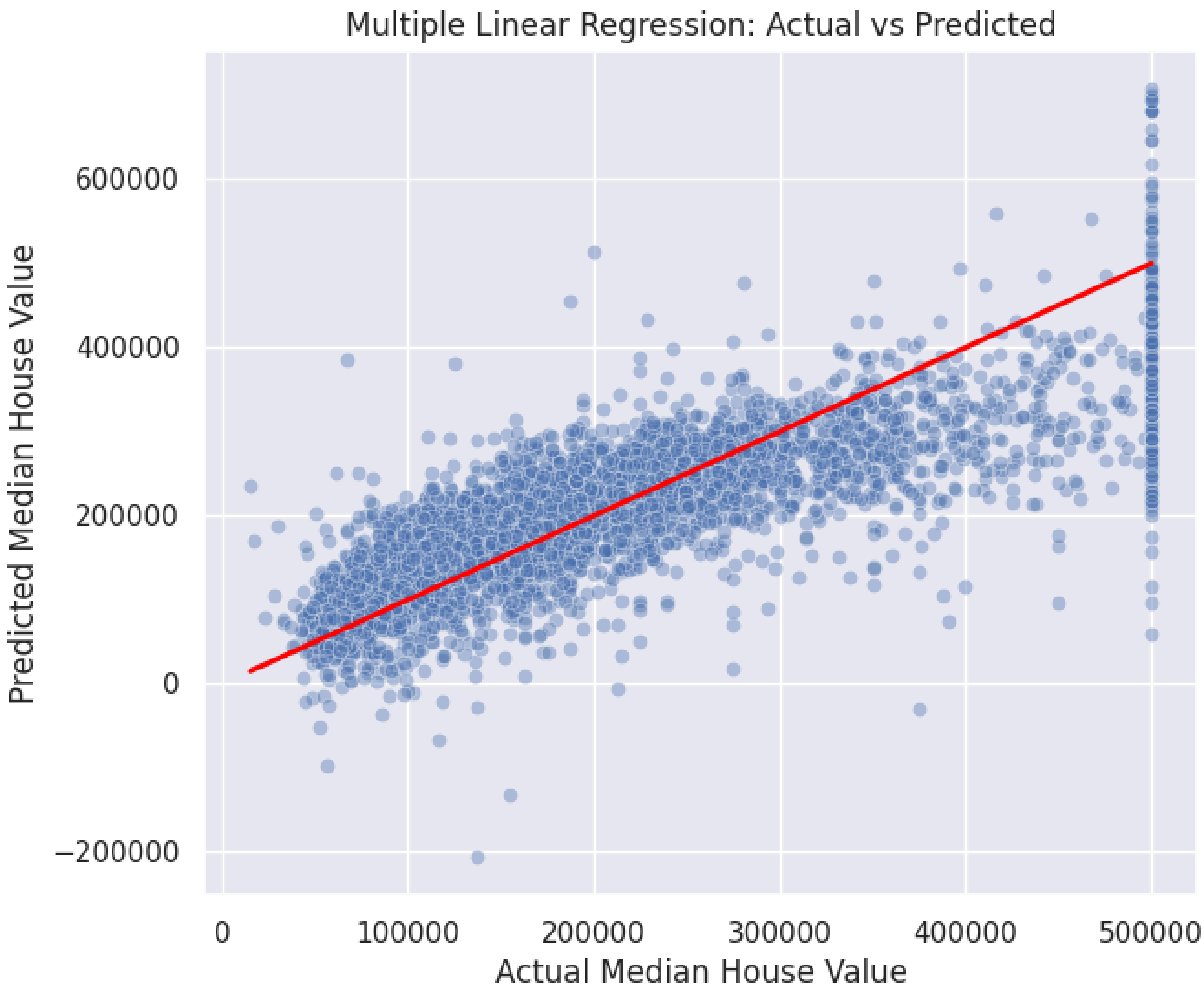
LinearRegression()

In [173…
```
y_pred = model.predict(X_test)
```

In [174…
```
print("Intercept:", model.intercept_)
print("\n=== MODEL PERFORMANCE ===")
print("MAE:", mean_absolute_error(y_test, y_pred))
print("R²:", r2_score(y_test, y_pred))
```

```
Intercept: -3578224.234818384

=== MODEL PERFORMANCE ===
MAE: 51810.483628046866
R²: 0.6138664756435175
```

In [175…
```
plt.figure(figsize=(7,6))
sns.scatterplot(x=y_test, y=y_pred, alpha=0.4)
plt.plot([y_test.min(), y_test.max()],
         [y_test.min(), y_test.max()],
         color='red', linewidth=2)

plt.xlabel("Actual Median House Value")
plt.ylabel("Predicted Median House Value")
plt.title("Multiple Linear Regression: Actual vs Predicted")
plt.show()
```



Multiple Linear Regression: Actual vs Predicted
Predicted Median House Value
Actual Median House Value
600000
400000
200000
0
−200000
0
100000
200000
300000
400000
500000