

# Source code

```
import streamlit as st

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.model_selection import train_test_split

from sklearn.linear_model import LogisticRegression

from sklearn.metrics import classification_report, confusion_matrix, accuracy_score

from sklearn.preprocessing import StandardScaler, LabelEncoder

from io import StringIO


# Set up the app

st.title("Housing Data Analysis Dashboard")


# Load data once and store in session_state

if "data" not in st.session_state:

    st.session_state.data = pd.read_csv("housing.csv")


data = st.session_state.data # always work on this reference


options = st.selectbox(

    "Select processing",

    ["Data Cleaning", "Data Visualization", "Logistic Regression Analysis(ML model)"]

)
```

```

if options == 'Data Cleaning':
    # Data Cleaning Section
    st.header("1. Data Cleaning")

    st.subheader("Raw Data Preview")
    st.write(data.head())
    st.write("Shape:", data.shape)
    st.write("Description:")
    st.write(data.describe())
    st.subheader("Data Information")
    buffer = StringIO()
    data.info(buf=buffer)
    info_str = buffer.getvalue()
    st.text(info_str)

    # Encoding categorical columns
    if st.checkbox("Encoding object columns"):
        cat_cols = data.select_dtypes(include=['object']).columns
        if len(cat_cols) > 0:
            for col in cat_cols:
                le = LabelEncoder()
                data[col] = le.fit_transform(data[col])
            st.success("Label encoding applied.")

    # Show updated info after encoding

```

```

    buffer = StringIO()

    data.info(buf=buffer)

    info_str = buffer.getvalue()

    st.text(info_str)

else:

    st.info("No categorical columns to encode.")

# Missing values

st.subheader("Missing Values")

st.write(data.isnull().sum())

if st.checkbox("Handle missing values"):

    for col in data.columns:

        if data[col].isnull().sum() > 0:

            data[col].fillna(data[col].mean(), inplace=True)

    st.success("Missing values handled!")

    st.write("Remaining missing values:", data.isnull().sum())


# Duplicate values

st.subheader("Duplicate Values")

st.write(f"Number of duplicates: {data.duplicated().sum()}")

if st.checkbox("Handle duplicated values"):

    data.drop_duplicates(inplace=True)

    st.success("Duplicate rows removed!")

    st.write(f"Remaining duplicates: {data.duplicated().sum()}")


# Outlier detection

st.subheader("Check Outliers (IQR method)")

```

```

outlier_counts = {}

numeric_cols = data.select_dtypes(include=['int64', 'float64']).columns

for col in numeric_cols:

    Q1 = data[col].quantile(0.25)

    Q3 = data[col].quantile(0.75)

    IQR = Q3 - Q1

    lower_bound = Q1 - 1.5 * IQR

    upper_bound = Q3 + 1.5 * IQR

    outlier_counts[col] = ((data[col] < lower_bound) |

                           (data[col] > upper_bound)).sum()

st.write(pd.DataFrame(list(outlier_counts.items()), columns=["Column", "Outlier
Count"]))

```

# Handle outliers by capping

```
def handle_outliers(df):
```

```
    for col in df.select_dtypes(include=['int64', 'float64']).columns:
```

```
        Q1 = df[col].quantile(0.25)
```

```
        Q3 = df[col].quantile(0.75)
```

```
        IQR = Q3 - Q1
```

```
        lower_bound = Q1 - 1.5 * IQR
```

```
        upper_bound = Q3 + 1.5 * IQR
```

```
        df[col] = np.where(df[col] < lower_bound, lower_bound,
```

```
                           np.where(df[col] > upper_bound, upper_bound, df[col]))
```

```
    return df
```

```
if st.checkbox("Handle outliers"):
```

```

data = handle_outliers(data)

st.success("Outliers handled (capped to IQR limits)!")

# Recalculate and show new counts

new_outlier_counts = {}

for col in numeric_cols:

    Q1 = data[col].quantile(0.25)

    Q3 = data[col].quantile(0.75)

    IQR = Q3 - Q1

    lower_bound = Q1 - 1.5 * IQR

    upper_bound = Q3 + 1.5 * IQR

    new_outlier_counts[col] = ((data[col] < lower_bound) |

                               (data[col] > upper_bound)).sum()

    st.write(pd.DataFrame(list(new_outlier_counts.items()), columns=["Column", "Outlier
Count"]))

elif options == 'Data Visualization':

    # Data Visualization Section

    st.header("2. Data Visualization")

    # Select visualization type

    viz_type = st.selectbox("Select Visualization Type",

                             ["Histogram", "Box Plot", "Scatter Plot", "Correlation Heatmap"])

    if viz_type == "Histogram":

        col = st.selectbox("Select column for histogram", data.select_dtypes(include=['int64',
'float64']).columns)

        bins = st.slider("Number of bins", 5, 100, 20)

```

```
fig, ax = plt.subplots()

ax.hist(data[col], bins=bins, edgecolor='black')

ax.set_title(f"Histogram of {col}")

ax.set_xlabel(col)

ax.set_ylabel("Frequency")

st.pyplot(fig)
```

```
elif viz_type == "Box Plot":
```

```
    col = st.selectbox("Select column for box plot", data.select_dtypes(include=['int64',
'float64']).columns)
```

```
    fig, ax = plt.subplots()

    sns.boxplot(x=data[col], ax=ax)

    ax.set_title(f"Box Plot of {col}")

    st.pyplot(fig)
```

```
elif viz_type == "Scatter Plot":
```

```
    col1 = st.selectbox("Select X-axis column", data.select_dtypes(include=['int64',
'float64']).columns)
```

```
    col2 = st.selectbox("Select Y-axis column", data.select_dtypes(include=['int64',
'float64']).columns)
```

```
    fig, ax = plt.subplots()

    ax.scatter(data[col1], data[col2], alpha=0.5)

    ax.set_title(f"Scatter Plot: {col1} vs {col2}")

    ax.set_xlabel(col1)

    ax.set_ylabel(col2)

    st.pyplot(fig)
```

```
elif viz_type == "Correlation Heatmap":  
    numeric_data = data.select_dtypes(include=['int64', 'float64'])  
    fig, ax = plt.subplots(figsize=(10, 8))  
    sns.heatmap(numeric_data.corr(), annot=True, cmap='coolwarm', ax=ax)  
    ax.set_title("Correlation Heatmap")  
    st.pyplot(fig)
```

```
elif options == 'Logistic Regression Analysis(ML model)':
```

```
# Logistic Regression Section
```

```
st.header("3. Logistic Regression Analysis")
```

```
# Create a binary target variable
```

```
median_value = data['median_house_value'].median()
```

```
data['high_value'] = (data['median_house_value'] > median_value).astype(int)
```

```
# Feature Selection
```

```
st.subheader("Feature Selection")
```

```
available_features = data.select_dtypes(include=['int64', 'float64']).columns.tolist()
```

```
columns_to_remove = ['median_house_value', 'high_value']
```

```
selected_features = st.multiselect(
```

```
    "Select features for the model",
```

```
    [col for col in available_features if col not in columns_to_remove],
```

```
    default=['median_income', 'housing_median_age', 'total_rooms']
```

```
)
```

```
if len(selected_features) > 0:
```

```
# Prepare data

X = data[selected_features]
y = data['high_value']


# Split data

test_size = st.slider("Test set size", 0.1, 0.5, 0.2)

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


# Scale features

scaler = StandardScaler()

X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)


# Train model

model = LogisticRegression(max_iter=1000)

model.fit(X_train_scaled, y_train)


# Predictions

y_pred = model.predict(X_test_scaled)


# Evaluation

st.subheader("Model Evaluation")

st.write("### Classification Report")

report = classification_report(y_test, y_pred, output_dict=True)

st.table(pd.DataFrame(report).transpose())
```



```
st.write("### Confusion Matrix")

cm = confusion_matrix(y_test, y_pred)

fig, ax = plt.subplots()

sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', ax=ax)

ax.set_xlabel('Predicted')

ax.set_ylabel('Actual')

st.pyplot(fig)
```

# Coefficients

```
st.subheader("Model Coefficients")

coef_df = pd.DataFrame({

    'Feature': selected_features,

    'Coefficient': model.coef_[0]

})

st.table(coef_df.sort_values('Coefficient', ascending=False))
```

# Prediction on new data

```
st.subheader("Make Predictions")

st.write("Enter values for the selected features to predict if a house is high value:")

input_values = {}

col1, col2 = st.columns(2)

for i, feature in enumerate(selected_features):

    if i % 2 == 0:

        with col1:
```

```
        input_values[feature] = st.number_input(feature,  
value=float(data[feature].median()))
```

```
    else:
```

```
        with col2:
```

```
            input_values[feature] = st.number_input(feature,  
value=float(data[feature].median()))
```

```
if st.button("Predict"):
```

```
    input_df = pd.DataFrame([input_values])
```

```
    input_scaled = scaler.transform(input_df)
```

```
    prediction = model.predict(input_scaled)[0]
```

```
    probability = model.predict_proba(input_scaled)[0][1]
```

```
    st.write(f"### Prediction: {'High Value' if prediction == 1 else 'Not High Value'}")
```

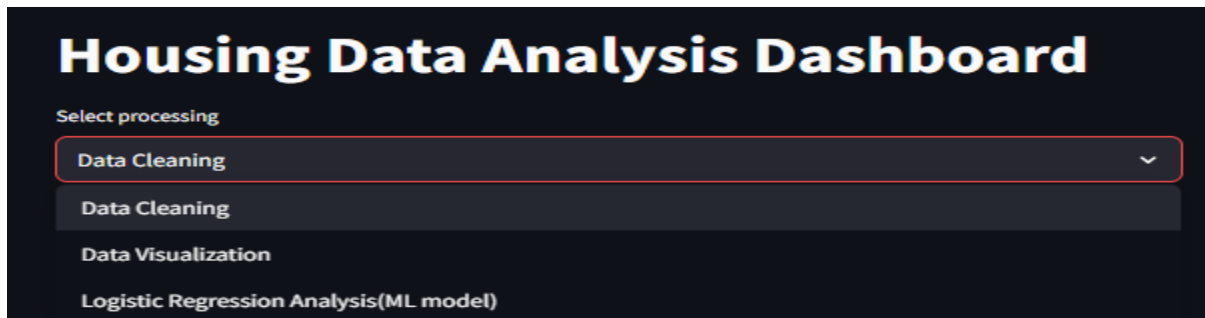
```
    st.write(f"Probability of being high value: {probability:.2f}")
```

```
else:
```

```
    st.warning("Please select at least one feature for the model.")
```

# Streamlit app

## Selection menu



## Data cleaning

### 1. Data Cleaning

#### Raw Data Preview

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households
0	-122.23	37.88	41	880	129	322	126
1	-122.22	37.86	21	7099	1106	2401	1138
2	-122.24	37.85	52	1467	190	496	177
3	-122.25	37.85	52	1274	235	558	219
4	-122.25	37.85	52	1627	280	565	259

Shape: (20640, 10)

Description:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households
count	20640	20640	20640	20640	20433	20640	20640
mean	-119.5697	35.6319	28.6395	2635.7631	537.8706	1425.4767	499.5397
std	2.0035	2.136	12.5856	2181.6153	421.3851	1132.4621	382.3298
min	-124.35	32.54	1	2	1	3	1
25%	-121.8	33.93	18	1447.75	296	787	280
50%	-118.49	34.26	29	2127	435	1166	409
75%	-118.01	37.71	37	3148	647	1725	605
max	-114.31	41.95	52	39320	6445	35682	6082

## Data Information

<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

### ✓ Encoding object columns

Label encoding applied.

<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	int32

dtypes: float64(9), int32(1)  
memory usage: 1.5 MB

## Duplicate Values

Number of duplicates: 0

☐ Handle duplicated values

## Check Outliers (IQR method)

	Column	Outlier Count
0	longitude	0
1	latitude	0
2	housing_median_age	0
3	total_rooms	1287
4	total_bedrooms	1306
5	population	1196
6	households	1220
7	median_income	681
8	median_house_value	1071

☒ Handle outliers

Outliers handled (capped to IQR limits):

	Column	Outlier Count
0	longitude	0
1	latitude	0
2	housing_median_age	0
3	total_rooms	0
4	total_bedrooms	0
5	population	0
6	households	0
7	median_income	0
8	median_house_value	0

# Sample of Data visualization

## 2. Data Visualization

Select Visualization Type

Histogram

Select column for histogram

longitude

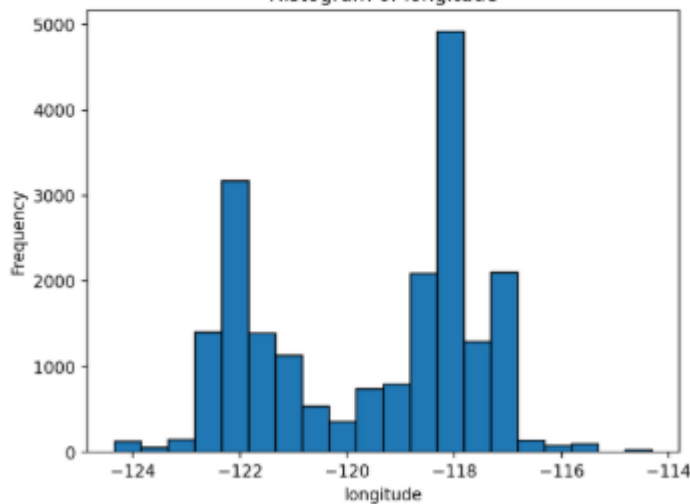
Number of bins

20

5

180

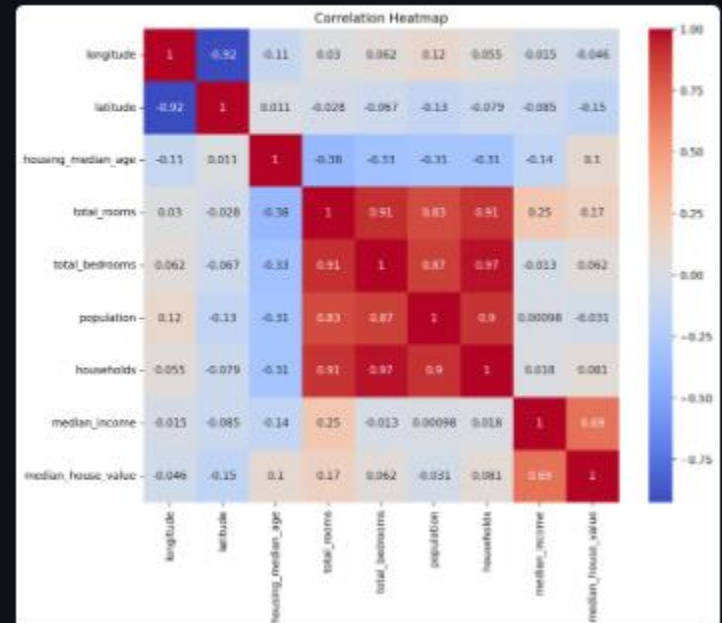
Histogram of longitude



## 2. Data Visualization

Select Visualization Type

Correlation Heatmap



## 2. Data Visualization

Select Visualization Type

Scatter Plot

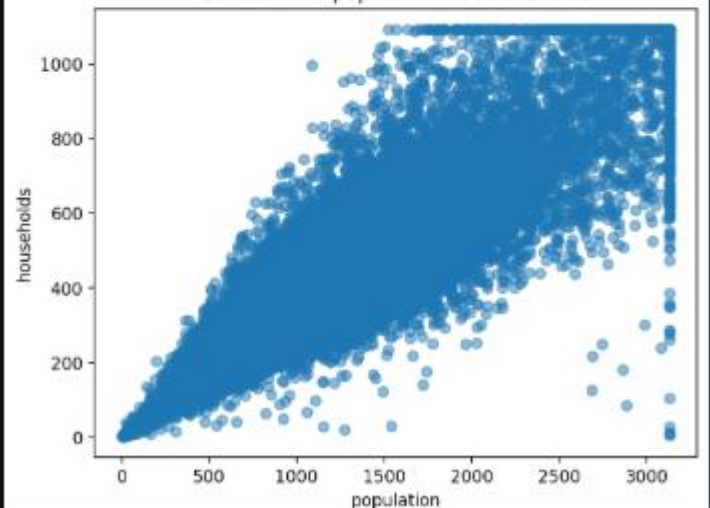
Select X-axis column

population

Select Y-axis column

households

Scatter Plot: population vs households



# Model

## 3. Logistic Regression Analysis

### Feature Selection

Select features for the model

median\_income × housing\_median... × total\_rooms × |

longitude

latitude

total\_bedrooms

population

households

### Classification report

	precision	recall	f1-score	support
0	0.7484	0.7963	0.7716	2,077.0000
1	0.7795	0.7289	0.7533	2,051.0000
accuracy	0.7628	0.7628	0.7628	0.7628
macro avg	0.7639	0.7626	0.7625	4,128.0000
weighted avg	0.7638	0.7628	0.7625	4,128.0000

### Feature Selection

Select features for the model

median\_income × housing\_median... × total\_rooms × population ×

longitude ×

Test set size

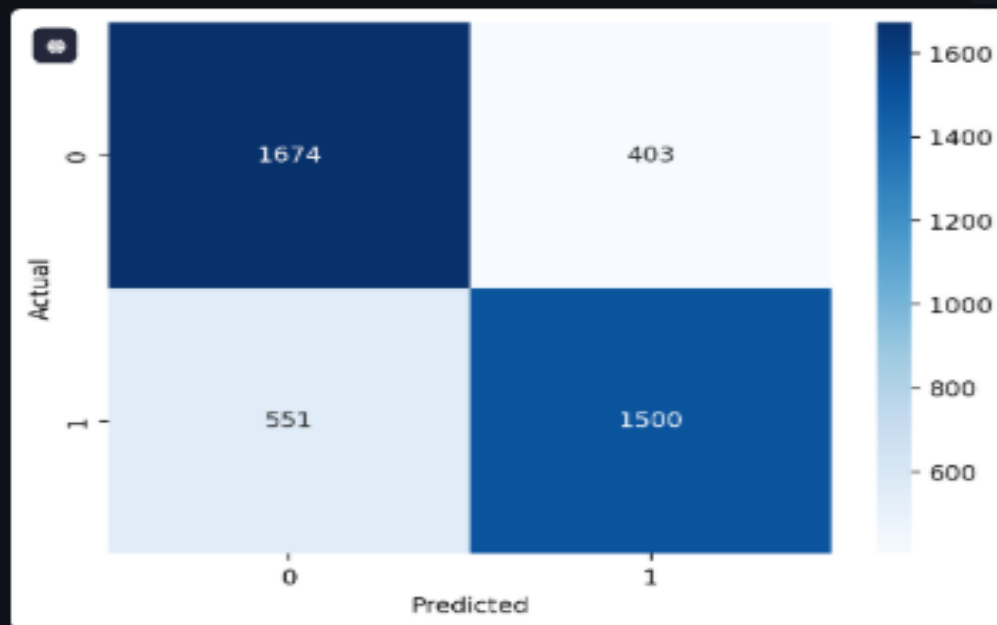


### Model Evaluation

### Classification Report

	precision	recall	f1-score	support
0	0.7524	0.8060	0.7782	2,077.0000
1	0.7882	0.7314	0.7587	2,051.0000
accuracy	0.7689	0.7689	0.7689	0.7689
macro avg	0.7703	0.7687	0.7685	4,128.0000
weighted avg	0.7702	0.7689	0.7685	4,128.0000

### Confusion Matrix



### Model Coefficients

	Feature	Coefficient
0	median_income	1.7952
1	housing_median_age	0.6100
2	total_rooms	0.4806
4	longitude	-0.0400
3	population	-0.2304

# Prediction model

## Make Predictions

Enter values for the selected features to predict if a house is high value:

median_income	housing_median_age
<input type="text" value="3.53"/>	<input type="text" value="29.00"/>
total_rooms	population
<input type="text" value="2127.00"/>	<input type="text" value="1166.00"/>
longitude	
<input type="text" value="-118.49"/>	

### Prediction: Not High Value

Probability of being high value: 0.45