Predicting High-Priced Rental Apartments in the USA

Milestone 1 – Group_26

In [1]:
```
# Install needed packages if not available
#!pip install ucimlrepo seaborn scikit-learn

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pandera as pa

from ucimlrepo import fetch_ucirepo
from pandera import Column, Check, DataFrameSchema
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score,
    f1_score, ConfusionMatrixDisplay
)


sns.set(style="whitegrid")
plt.rcParams["figure.figsize"] = (8, 5)
```

Summary

This project investigates whether it is possible to predict when an apartment listing in the United States is **high-priced relative to other listings in the same state**. Using the *Apartment for Rent Classified* dataset from the UCI Machine Learning Repository, we defined a binary target indicating whether each listing's price was above the state-level median. We developed a logistic regression model to classify listings as either high-priced or not. The final classifier achieved an accuracy of 0.7 on unseen data, indicating that it correctly predicts a listing as high-priced in most cases.

The notebook includes:

- Data loading from the web
- Data cleaning and wrangling
- Exploratory data analysis

- Visualizations
- Classification modeling
- Results, discussion, and conclusions

Introduction

Homeownership in the United States has become somewhat less attainable for many Americans due to increasing housing prices, rising mortage rates and other increases in the cost of living. As a result, according to recent surveys, around 84% of Gen Z adults report delaying major life milestones in order to afford a home, with many turning to long-term renting instead. Nearly 75% of Gen Z say they prefer renting to owning, which is important to note as this generation represents more than 20% of the U.S. population. Growing rental demand is driving new construction as developers across the country are expected to add more than 500,000 new apartment units across the country.

These trends lead us to wonder if apartment rental prices vary dramatically across the U.S. A price considered as “expensive” in Texas may be considered “cheap” in New York. As many Gen Z adults are relocating to higher-cost states and more than 75% of them rent, understanding these price differences is increasingly important. Additionally, rental prices are influenced by a variety of listing features. For example, apartments with more bedrooms or bathrooms are generally associated with higher-prices. Other features such as whether pets are allowed or whether the apartment includes additional fees, may also signal higher quality or prices. These features will be incorporated into our model to assess their impact on whether an apartment is classified as high-priced or not. To create a meaningful comparison across regions, we evaluated whether each apartment is **high-priced relative to the median rent within its own state**.

Research Question

Can a machine learning algorithm accurately predict whether an apartment listing is high-priced relative to the median rental price in its state, using features such as square footage, number of bedrooms and bathrooms, and various listing attributes?

Dataset

We use the **Apartment for Rent Classified** dataset from the UCI Machine Learning Repository. The dataset contains:

- 10,000+ apartment listings
- Structural and listing details
- Geographic information
- Price and square footage

Data Cleaning & Wrangling

We prepared the dataset by:

1. Loading the data from the UCI ML Repository
2. Selecting relevant columns
3. Removing rows with missing or invalid values
4. Computing the median rental price for each state
5. Creating a binary target variable `high_price`

In [2]:
```python
# Load dataset directly from the UCI ML Repository
apartment_ds = fetch_ucirepo(id=555)

df = apartment_ds.data.original.copy()

df.head()
```

```
/Users/shanzekhemani/miniforge3/envs/Group_26/lib/python3.12/site-packages/u
cimlrepo/fetch.py:97: DtypeWarning: Columns (0,5,6,12,14,15) have mixed type
s. Specify dtype option on import or set low_memory=False.
  df = pd.read_csv(data_url)
```

Out[2]:

	id	category	title	body	amenities	bathrooms
0	5668640009	housing/rent/apartment	One BR 507 & 509 Esplanade	This unit is located at 507 & 509 Esplanade, R...	NaN	1
1	5668639818	housing/rent/apartment	Three BR 146 Lochview Drive	This unit is located at 146 Lochview Drive, Ne...	NaN	1.5
2	5668639686	housing/rent/apartment	Three BR 3101 Morningside Drive	This unit is located at 3101 Morningside Drive...	NaN	2
3	5668639659	housing/rent/apartment	Two BR 209 Aegean Way	This unit is located at 209 Aegean Way, Vacavi...	NaN	1
4	5668639374	housing/rent/apartment	One BR 4805 Marquette NE	This unit is located at 4805 Marquette NE, Alb...	NaN	1

5 rows × 22 columns

In [3]:
```
cols_needed = [
    "price", "square_feet", "bathrooms", "bedrooms",
    "state", "pets_allowed", "fee", "has_photo"
]

df_subset = df[cols_needed].copy()

# Convert price and square_feet to numeric (coerce invalid values to NaN)
df_subset["price"] = pd.to_numeric(df_subset["price"], errors="coerce")
df_subset["square_feet"] = pd.to_numeric(df_subset["square_feet"], errors="c

# Also convert bathrooms and bedrooms to numeric
df_subset["bathrooms"] = pd.to_numeric(df_subset["bathrooms"], errors="coerc
df_subset["bedrooms"] = pd.to_numeric(df_subset["bedrooms"], errors="coerce"

# Remove non-positive or missing price/square_feet
df_subset = df_subset[
    (df_subset["price"] > 0) &
    (df_subset["square_feet"] > 0)
]

# Drop rows with missing values in other key areas
df_subset = df_subset.dropna(subset=cols_needed)
```

```
# Compute median price per state
state_medians = df_subset.groupby("state")["price"].median()
df_subset["state_median_price"] = df_subset["state"].map(state_medians)

# Remove duplicates
df_subset = df_subset.drop_duplicates().reset_index(drop=True)

# Create binary target
df_subset["high_price"] = (df_subset["price"] > df_subset["state_median_pric

df_subset.head()
```

Out[3]:

	price	square_feet	bathrooms	bedrooms	state	pets_allowed	fee	has_photo
0	2195.0	542.0	1.0	1.0	CA	Cats	No	Thumbnail
1	1250.0	1500.0	1.5	3.0	VA	Cats,Dogs	No	Thumbnail
2	1600.0	820.0	1.0	2.0	CA	Cats,Dogs	No	Thumbnail
3	975.0	624.0	1.0	1.0	NM	Cats,Dogs	No	Thumbnail
4	1250.0	965.0	1.5	2.0	NM	Cats,Dogs	No	Thumbnail

In [4]:

```
# Data Validation Checks

numeric_cols = ["price", "square_feet", "bathrooms", "bedrooms", "state_medi

target = "high_price"
threshold = 0.9  # correlation threshold

allowed_states = [
    'CA','VA','NM','CO','WV','WA','TX','IL','MS','OR','FL','MO','PA','IA',
    'WI','NC','GA','OK','RI','NJ','IN','MD','OH','ND','NE','DC','AZ','MA',
    'MI','SC','ID','MN','KS','TN','UT','KY','SD','LA','AK','AR','AL','CT',
    'NY','NV','HI','WY','VT','NH','MT','DE','ME'
]

allowed_pets = ['Cats', 'Cats,Dogs', 'Dogs', 'Cats,Dogs,None']
allowed_fee = ['No', 'Yes']
allowed_has_photo = ['Thumbnail', 'Yes', 'No']

def check_no_outliers(df):
    has_outliers = False

    for col in numeric_cols:
        q1 = df[col].quantile(0.25)
        q3 = df[col].quantile(0.75)
        iqr = q3 - q1
        lower = q1 - 1.5 * iqr
        upper = q3 + 1.5 * iqr

        outliers = df[(df[col] < lower) | (df[col] > upper)]
        if not outliers.empty:
            has_outliers = True
            print(f"Outliers detected in column '{col}':")
            print(outliers[[col]])
            print("-"*40)

    return not has_outliers  # True if no outliers, False otherwise

def check_categories(df):
    invalid_found = False  # track if any invalid category exists

    category_mapping = {
        "state": allowed_states,
        "pets_allowed": allowed_pets,
        "fee": allowed_fee,
        "has_photo": allowed_has_photo
    }

    for col, allowed in category_mapping.items():
        invalid_rows = df[~df[col].isin(allowed)]
        if not invalid_rows.empty:
            invalid_found = True
            print(f"Unexpected values in column '{col}':")
            print(invalid_rows[[col]])
            print("-"*40)

    return not invalid_found  # True if all categories valid, False otherwis

def check_target_distribution(df):
    # Only 0 or 1 allowed
    unique_vals = set(df["high_price"].unique())
    if not unique_vals.issubset({0, 1}):
        print(f"Unexpected target values found: {unique_vals}")
        return False

    # Check class balance
    ratio = df["high_price"].mean()  # proportion of 1s
    if ratio <= 0.05 or ratio >= 0.95:
        print(f"Target distribution is extremely imbalanced: {ratio:.2f} pro
        return False

    return True

result = check_target_distribution(df_subset)
print("Target distribution check passed?", result)

def check_corr_target(df):
    corr = df[numeric_cols + [target]].corr()[target].drop(target)
    return (abs(corr) < threshold).all()

def check_corr_feats(df):
    for i in range(len(numeric_cols)):
        for j in range(i + 1, len(numeric_cols)):
            corr = df[numeric_cols[i]].corr(df[numeric_cols[j]])
            if abs(corr) >= threshold:
                return False
    return True
```

```
schema = DataFrameSchema(
    {
        "price": Column(pa.Float, nullable=False,
            checks=[Check.greater_than(0),
                    Check(lambda s: s.isna().mean() <= 0.05)]),

        "square_feet": Column(pa.Float, nullable=False,
            checks=[Check.greater_than(0),
                    Check(lambda s: s.isna().mean() <= 0.05)]),

        "bathrooms": Column(pa.Float, nullable=False,
            checks=[Check.greater_than_or_equal_to(0),
                    Check(lambda s: s.isna().mean() <= 0.05)]),

        "bedrooms": Column(pa.Float, nullable=False,
            checks=[Check.greater_than_or_equal_to(0),
                    Check(lambda s: s.isna().mean() <= 0.05)]),

        "state": Column(pa.String, nullable=False,
            checks=[Check.isin(allowed_states),
                    Check.str_length(min_value=1)]),

        "pets_allowed": Column(pa.String, nullable=True,
            checks=[Check.isin(allowed_pets)]),

        "fee": Column(pa.String, nullable=True,
            checks=[Check.isin(allowed_fee)]),

        "has_photo": Column(pa.String, nullable=False,
            checks=[Check.isin(allowed_has_photo)]),

        "state_median_price": Column(pa.Float, nullable=False,
            checks=[Check.greater_than(0),
                    Check(lambda s: s.isna().mean() <= 0.05)]),

        "high_price": Column(pa.Int, nullable=False,
            checks=[Check.isin([0, 1])]),
    },

    checks=[
        Check(lambda df: df.duplicated().sum() == 0, error="Duplicate rows c
        Check(lambda df: ~df.isna().all(axis=1)),
        Check(check_no_outliers, error="Outliers detected in numeric columns
        Check(check_categories, error="Unexpected categorical values."),
        Check(check_target_distribution, error="Target variable distribution
        Check(check_corr_target, error="Anomalous correlation between target
        Check(check_corr_feats, error="Anomalous correlation between feature
    ])

try:
    validated_df = schema.validate(df_subset, lazy=True)
    print("All checks passed!")
except pa.errors.SchemaErrors as e:
    print("Some checks failed:")
    print(e.failure_cases)
```

```
Target distribution check passed? True
Outliers detected in column 'price':
        price
13     3250.0
20     4950.0
27     3580.0
62     3200.0
63     3399.0
...       ...
35521  3140.0
35603  2902.0
35638  3275.0
35649  3850.0
35666  3002.0

[1713 rows x 1 columns]
----------------------------------------
Outliers detected in column 'square_feet':
       square_feet
27          2100.0
56          1850.0
63          1721.0
64          2598.0
65          2200.0
...            ...
35369       2756.0
35387       2196.0
35392       2080.0
35470       2160.0
35652       1900.0

[846 rows x 1 columns]
----------------------------------------
Outliers detected in column 'bathrooms':
       bathrooms
636          4.5
748          4.0
1014         4.0
1314         5.0
1324         4.5
1452         4.0
1547         4.0
1574         4.0
1692         4.0
1812         4.0
1835         5.0
1840         4.0
1876         4.0
2029         4.0
2130         7.0
2180         4.0
2740         4.5
2870         6.0
3064         4.0
3439         4.0
3470         4.0
```

```
3747         4.0
3789         4.0
3796         5.0
3936         4.5
3951         4.0
4150         4.0
4247         5.0
4261         4.0
4393         4.0
4466         4.0
4506         4.0
4520         4.5
9431         4.0
9836         4.0
10836        4.5
16376        5.0
17168        4.0
17977        4.0
23571        4.0
26986        4.0
29979        4.0
31518        4.0
31682        5.0
32450        4.0
34767        4.5
----------------------------------------
Outliers detected in column 'bedrooms':
       bedrooms
27          4.0
33          4.0
62          4.0
64          4.0
65          4.0
...         ...
35387       4.0
35392       4.0
35407       4.0
35436       4.0
35470       4.0

[549 rows x 1 columns]
----------------------------------------
Some checks failed:
  column  failure_case index   schema_context  \
0   None         False  None  DataFrameSchema

                                   check  check_number
0  Outliers detected in numeric columns.             2
```

```
/Users/shanzekhemani/miniforge3/envs/Group_26/lib/python3.12/site-packages/p
andera/_pandas_deprecated.py:146: FutureWarning: Importing pandas-specific c
lasses and functions from the
top-level pandera module will be **removed in a future version of pandera**.
If you're using pandera to validate pandas objects, we highly recommend upda
ting
your import:

```

# old import
import pandera as pa

# new import
import pandera.pandas as pa
```

If you're using pandera to validate objects from other compatible libraries
like pyspark or polars, see the supported libraries section of the documenta
tion
for more information on how to import pandera:

https://pandera.readthedocs.io/en/stable/supported_libraries.html

To disable this warning, set the environment variable:

```
export DISABLE_PANDERA_IMPORT_WARNING=True
```

  warnings.warn(_future_warning, FutureWarning)
```

Exploratory Data Analysis (EDA)

We explored:

- Summary statistics
- Class balance
- Price distribution
- Relationship between size and price

In [7]:
```
df_subset[["price", "square_feet", "bathrooms"]].describe()
```

Out[7]:

	price	square_feet	bathrooms
count	35700.000000	35700.000000	35700.000000
mean	1487.928235	940.632157	1.440294
std	722.414581	338.539094	0.533467
min	285.000000	200.000000	1.000000
25%	1025.000000	720.750000	1.000000
50%	1327.000000	897.000000	1.000000
75%	1745.000000	1105.000000	2.000000
max	19500.000000	12000.000000	7.000000

In [8]:

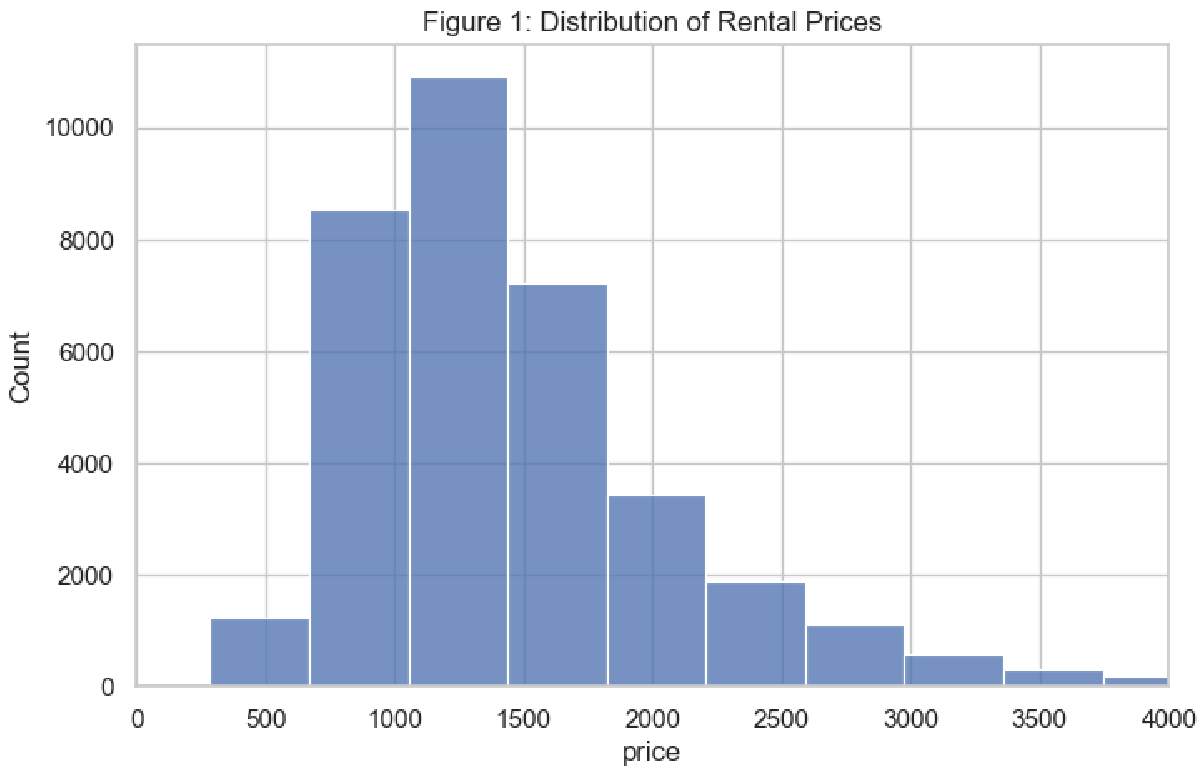
```
df_subset["high_price"].value_counts(normalize=True)
```

Out[8]:

```
high_price
1    0.510728
0    0.489272
Name: proportion, dtype: float64
```

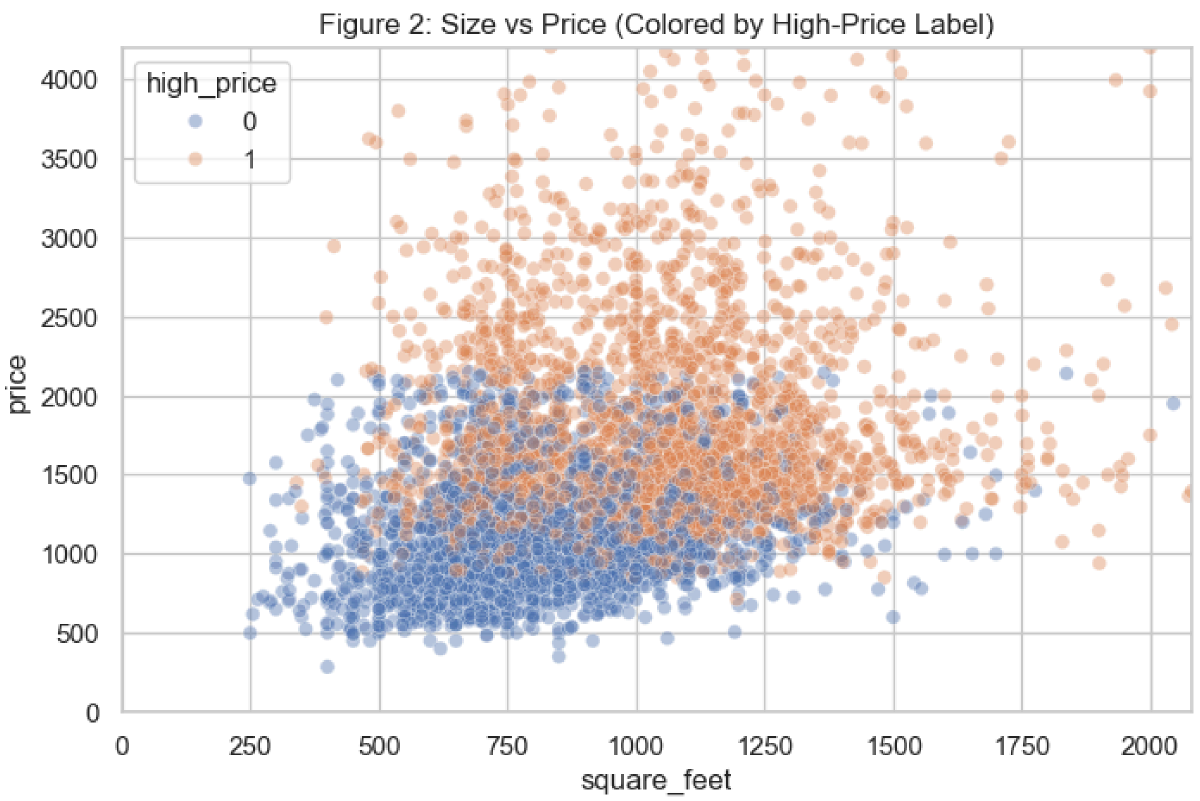
In [9]:

```
sns.histplot(df_subset["price"], bins=50)
plt.xlim(0, df_subset["price"].quantile(0.99))
plt.title("Figure 1: Distribution of Rental Prices")
plt.show()
```



In [10]:

```
sample_df = df_subset.sample(n=min(5000, len(df_subset)), random_state=123)

sns.scatterplot(
    data=sample_df,
    x="square_feet",
    y="price",
    hue="high_price",
    alpha=0.4
)
plt.xlim(0, sample_df["square_feet"].quantile(0.99))
plt.ylim(0, sample_df["price"].quantile(0.99))
plt.title("Figure 2: Size vs Price (Colored by High-Price Label)")
plt.show()
```



Modeling: Logistic Regression Classifier

We predict `high_price` using:

Numeric features

- square_feet
- bathrooms

Categorical features

- bedrooms
- state
- pets_allowed
- fee
- has_photo

We use a train-test split and a preprocessing pipeline.

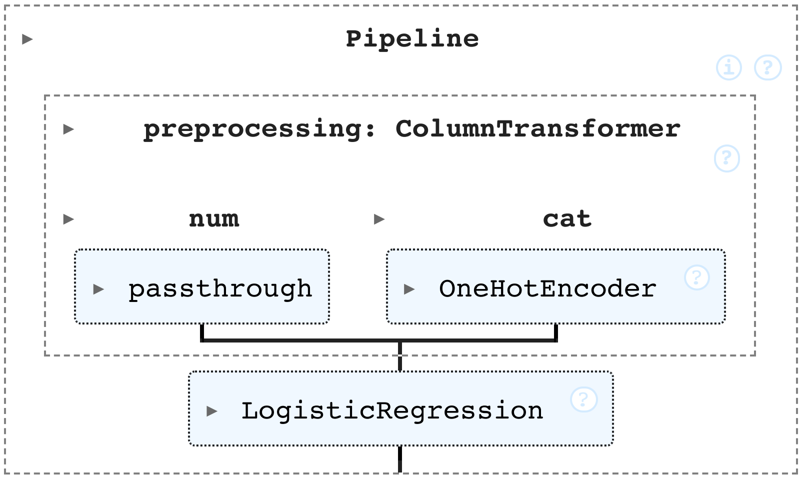
In [11]:
```
numeric_features = ["square_feet", "bathrooms"]
categorical_features = ["bedrooms", "state", "pets_allowed", "fee", "has_pho

model_df = df_subset[numeric_features + categorical_features + ["high_price"

X = model_df[numeric_features + categorical_features]
y = model_df["high_price"]

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, stratify=y, random_state=123
)

(len(X_train), len(X_test))
```

Out[11]:
```
(28560, 7140)
```

In [12]:
```
numeric_transformer = "passthrough"
categorical_transformer = OneHotEncoder(handle_unknown="ignore")

preprocessor = ColumnTransformer(
    transformers=[
        ("num", numeric_transformer, numeric_features),
        ("cat", categorical_transformer, categorical_features)
    ]
)

model = Pipeline(
    steps=[
        ("preprocessing", preprocessor),
        ("classifier", LogisticRegression(max_iter=1000))
    ]
)

model.fit(X_train, y_train)
```

```
/Users/shanzekhemani/miniforge3/envs/Group_26/lib/python3.12/site-packages/s
klearn/linear_model/_logistic.py:473: ConvergenceWarning: lbfgs failed to co
nverge after 1000 iteration(s) (status=1):
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT

Increase the number of iterations to improve the convergence (max_iter=100
0).
You might also want to scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regre
ssion
  n_iter_i = _check_optimize_result(
```

Out[12]:



In [13]:

```
y_pred = model.predict(X_test)

metrics = {
    "Accuracy": accuracy_score(y_test, y_pred),
    "Precision": precision_score(y_test, y_pred),
    "Recall": recall_score(y_test, y_pred),
    "F1-score": f1_score(y_test, y_pred)
}

pd.DataFrame(metrics, index=["Logistic Regression"])
```

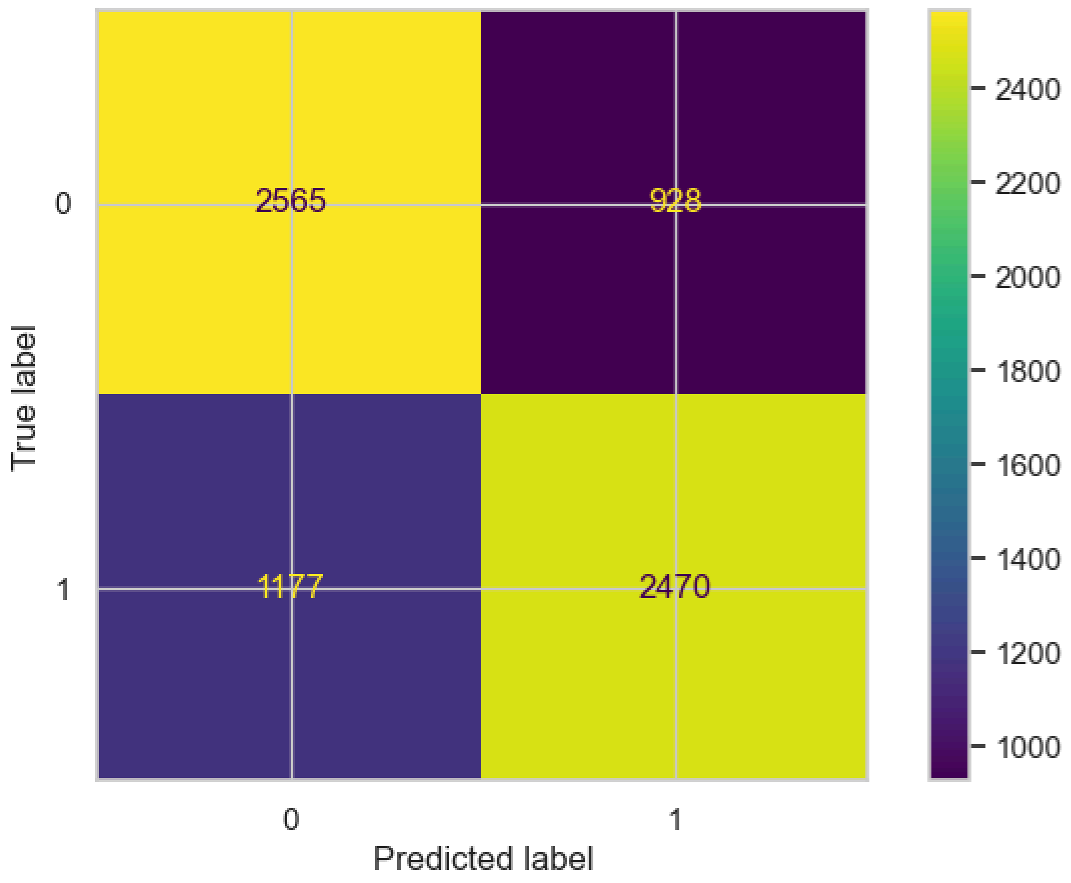
Out[13]:

	Accuracy	Precision	Recall	F1-score
Logistic Regression	0.705182	0.726898	0.677269	0.701207

In [14]:

```
ConfusionMatrixDisplay.from_predictions(y_test, y_pred)
plt.title("Figure 3: Confusion Matrix")
plt.show()
```

Figure 3: Confusion Matrix



Discussion

Summary of Findings

The logistic regression classifier performed reasonably well in predicting whether an apartment is high-priced relative to its state’s median rental price. Our logistic regression model achieved an accuracy of approximately 0.7, indicating that the model correctly classified 70% of apartment listings as either high-priced or not relative to their state's median rent. The model has a precision score of 0.715 which means the model was correct about 71% of the time when predicting an apartment to be high-priced. The recall score of approximately 0.660 shows the model was able to correctly identify about 66% of actually high-priced listings. Combined, these values resulted in a F1-score of 0.686.

- Overall, these metrics suggest that the model provides a reasonably balanced performance, though there is room for improvement in correctly identifying all high-priced apartments.

Analysis

The model performed well when identifying low-priced listings as indicated by the large number of true negatives (2,893). However, it was slightly less successful at identifying high-priced listings misclassifying 1,323 of them as not high-priced when they in fact were. These results align reasonably well with our expectations. We anticipated that apartment prices would vary across the country and the model's high precision of 0.72 suggests that it is usually correct when predicting a listing as high-priced, supporting the idea that certain features contribute meaningfully to the classification. The F1-score of ~0.69 indicates that the model is not overfitting to one class and maintains a balanced trade-off between identifying high-priced listings and avoiding false positives.

Overall, the results suggest that rental price classification at the state level is predictable to a moderate degree, but not with perfect accuracy. This is likely due to the variability of housing markets across the country. The model performs as expected for a logistic regression approach and provides a useful baseline for predicting whether a listing is high-priced relative to its state’s median rent.

Limitations and Future Work

A key limitation of this analysis is that logistic regression may be too simple to capture the full complexity of rental markets, which vary widely across and within states. The model's moderate accuracy (0.70) and recall (0.66) indicate that many high priced listings remain misclassified, suggesting that important predictive features were not included.

Future work could expand this analysis by incorporating more advanced models such as random forests, as well as extracting additional insights through NLP features derived from apartment descriptions. It may also be valuable to explore state by state differences in greater depth and to perform regression modelling to predict exact prices rather than broader categories. Further improvements could come from adding location specific features like the neighbourhood characteristics, building age, or available amenities which may contribute more meaningfully to overall model performance.

References

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2. Newsweek. (2023). Gen Z is renting, not buying: What it means for the country’s future. https://www.newsweek.com/gen-z-renting-not-buying-what-means-country-future-2120726

3. PR Newswire. (2023). Top 10 states to which Gen Zers are moving and the states they are leaving. https://www.prnewswire.com/news-releases/top-10-states-to-which-gen-zers-are-moving-and-the-states-they-are-leaving-302058380.html

4. Starmer, J. (n.d.). Classification metrics educational videos [YouTube channel]. StatQuest. https://www.youtube.com/user/joshstarmer

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