Experiment Notebook

---

0. Setup Environment

0.a Install Mandatory Packages

> Do not modify this code before running it

```
# Do not modify this code

import os
import sys
from pathlib import Path

COURSE = "36106"
ASSIGNMENT = "AT1"
DATA = "data"

asgmt_path = f"{COURSE}/assignment/{ASSIGNMENT}"
root_path = "./"

print("###### Install required Python packages ######")
! pip install -r https://raw.githubusercontent.com/aso-uts/labs_datasets/main/36106-mlaa/requirements.txt

if os.getenv("COLAB_RELEASE_TAG"):

    from google.colab import drive
    from pathlib import Path

    print("\n###### Connect to personal Google Drive ######")
    gdrive_path = "/content/gdrive"
    drive.mount(gdrive_path)
    root_path = f"{gdrive_path}/MyDrive/"

print("\n###### Setting up folders ######")
folder_path = Path(f"{root_path}/{asgmt_path}/") / DATA
folder_path.mkdir(parents=True, exist_ok=True)
print(f"\nYou can now save your data files in: {folder_path}")

if os.getenv("COLAB_RELEASE_TAG"):
    %cd {folder_path}
```

```
###### Install required Python packages ######
Requirement already satisfied: pandas==2.2.2 in /usr/local/lib/python3.11/dist-packages (from -r https://raw.githubusercontent.com/aso-u
Requirement already satisfied: scikit-learn==1.6.1 in /usr/local/lib/python3.11/dist-packages (from -r https://raw.githubusercontent.com
Requirement already satisfied: altair==5.5.0 in /usr/local/lib/python3.11/dist-packages (from -r https://raw.githubusercontent.com/aso-u
Requirement already satisfied: numpy>=1.23.2 in /usr/local/lib/python3.11/dist-packages (from pandas==2.2.2->-r https://raw.githubuserco
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.11/dist-packages (from pandas==2.2.2->-r https://raw.git
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packages (from pandas==2.2.2->-r https://raw.githubusercon
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-packages (from pandas==2.2.2->-r https://raw.githubuserc
Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn==1.6.1->-r https://raw.githubu
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn==1.6.1->-r https://raw.github
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn==1.6.1->-r https://raw
Requirement already satisfied: jinja2 in /usr/local/lib/python3.11/dist-packages (from altair==5.5.0->-r https://raw.githubusercontent.c
Requirement already satisfied: jsonschema>=3.0 in /usr/local/lib/python3.11/dist-packages (from altair==5.5.0->-r https://raw.githubuser
Requirement already satisfied: narwhals>=1.14.2 in /usr/local/lib/python3.11/dist-packages (from altair==5.5.0->-r https://raw.githubuse
Requirement already satisfied: packaging in /usr/local/lib/python3.11/dist-packages (from altair==5.5.0->-r https://raw.githubusercontent
Requirement already satisfied: typing-extensions>=4.10.0 in /usr/local/lib/python3.11/dist-packages (from altair==5.5.0->-r https://raw.
Requirement already satisfied: attrs>=22.2.0 in /usr/local/lib/python3.11/dist-packages (from jsonschema>=3.0->altair==5.5.0->-r https:/
Requirement already satisfied: jsonschema-specifications>=2023.03.6 in /usr/local/lib/python3.11/dist-packages (from jsonschema>=3.0->al
Requirement already satisfied: referencing>=0.28.4 in /usr/local/lib/python3.11/dist-packages (from jsonschema>=3.0->altair==5.5.0->-r h
Requirement already satisfied: rpds-py>=0.7.1 in /usr/local/lib/python3.11/dist-packages (from jsonschema>=3.0->altair==5.5.0->-r https:
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.8.2->pandas==2.2.2->-r https
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.11/dist-packages (from jinja2->altair==5.5.0->-r https://raw.gi

###### Connect to personal Google Drive ######
Mounted at /content/gdrive

###### Setting up folders ######
```

```
You can now save your data files in: /content/gdrive/MyDrive/36106/assignment/AT1/data
/content/gdrive/MyDrive/36106/assignment/AT1/data
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

0.b Disable Warnings Messages

> Do not modify this code before running it

```
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

0.c Install Additional Packages

> If you are using additional packages, you need to install them here using the command: `! pip install <package_name>`

```
# <Student to fill this section>
```

0.d Import Packages

```
import ipywidgets as widgets
import pandas as pd
import altair as alt
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
import numpy as np
from sklearn.compose import ColumnTransformer # Import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder # Import OneHotEncoder
from sklearn.pipeline import Pipeline # Import Pipelin
import statsmodels.api as sm
from sklearn.linear_model import ElasticNet
```

A. Project Description

Student Information

Show code

Student Name: <student to fill this section> Student Id: <student to fill this section>

Student Name: Md Saifur Rahman
Student Id: 25528668

Experiment ID

Show code

Experiment ID: 1

Business Objective

Show code

Business Objective: <student to fill this section>

The objective of this project is to build a predictive model that accurately estimates weekly rental prices for properties in Australia based on various property features such as the number of bedrooms, bathrooms, floor area, furnishing status, and location (suburb). This model will assist real estate agencies, landlords, and property managers in setting competitive rental prices, improving pricing strategies, reducing vacancy rates, and making data-driven decisions to attract and retain tenants effectively.

B. Experiment Description

Experiment Hypothesis

Show code

Experiment Hypothesis: <student to fill this section>

We hypothesize that certain property features—such as floor area, number of bedrooms and bathrooms, furnishing status, and suburb—have a measurable and predictive relationship with the rental price. By applying regression-based machine learning models, including Linear Regression, ElasticNet, and KNN, we expect to capture these relationships effectively and predict rent prices with reasonable accuracy. Furthermore, we anticipate that optimizing model parameters and careful feature selection will lead to improved performance across validation and test sets.

Experiment Expectations

Show code

Experiment Expectations: <student to fill this section>

We expect that the baseline model will perform poorly due to its simplicity, while more advanced models like ElasticNet and KNN will show better predictive power. Specifically, we anticipate that ElasticNet will handle multicollinearity and feature regularization effectively, and KNN will adapt well to non-linear patterns in the data. Additionally, we expect that proper preprocessing, feature scaling, and outlier removal will contribute to higher model accuracy, lower RMSE, and improved R^2 scores, resulting in better alignment between predicted and actual rental prices.

C. Data Understanding

C.1 Load Datasets

> Do not change this code

```
# Load training data
X_train = pd.read_csv('/content/drive/MyDrive/36106/assignment/AT1/data/X_train.csv')
y_train = pd.read_csv('/content/drive/MyDrive/36106/assignment/AT1/data/y_train.csv')


# Load validation data
X_val = pd.read_csv('/content/drive/MyDrive/36106/assignment/AT1/data/X_val.csv')
y_val = pd.read_csv('/content/drive/MyDrive/36106/assignment/AT1/data/y_val.csv')


# Load testing data
X_test = pd.read_csv('/content/drive/MyDrive/36106/assignment/AT1/data/X_test.csv')
y_test = pd.read_csv('/content/drive/MyDrive/36106/assignment/AT1/data/y_test.csv')
```

```
 #Display the shapes and first few rows to confirm successful loading
{
    "X_train_shape": X_train.shape,
    "X_val_shape": X_val.shape,
    "X_test_shape": X_test.shape,
    "y_train_shape": y_train.shape,
    "y_val_shape": y_val.shape,
    "y_test_shape": y_test.shape,
    "X_train_head": X_train.head(),
    "y_train_head": y_train.head()
}
```

```
{'X_train_shape': (2701, 5),
 'X_val_shape': (1018, 5),
 'X_test_shape': (1364, 5),
 'y_train_shape': (2701, 1),
 'y_val_shape': (1018, 1),
 'y_test_shape': (1364, 1),
 'X_train_head':    number_of_bedrooms  floor_area  number_of_bathrooms  furnished  suburb
 0                   2        1100                    2          1       1
 1                   2         800                    1          2       1
 2                   2        1000                    1          2       1
 3                   2         850                    1          1       1
 4                   2         600                    2          1       1,
 'y_train_head':     rent
 0  568.0
 1  581.0
 2  577.0
 3  565.0
 4  564.0}
```

D. Feature Selection

```
categorical_features = ['suburb', 'furnished']
numerical_features = ['number_of_bedrooms', 'floor_area', 'number_of_bathrooms','suburb', 'furnished']


# # prompt: for test train and validation dataset. there is a column 'furnished' explore the column and you will find several unique values

# unique_furnished_values_train = X_train['furnished'].unique()
# unique_furnished_values_val = X_val['furnished'].unique()
# unique_furnished_values_test = X_test['furnished'].unique()

# print("Unique values in 'furnished' column for training dataset:", unique_furnished_values_train)
# print("Unique values in 'furnished' column for validation dataset:", unique_furnished_values_val)
# print("Unique values in 'furnished' column for test dataset:", unique_furnished_values_test)



# prompt: s Show me the value of X train X Val and X test. Where the column is furnished?

print("X_train values in 'furnished' column:")
print(X_train['furnished'])

print("\nX_val values in 'furnished' column:")
print(X_val['furnished'])

print("\nX_test values in 'furnished' column:")
print(X_test['furnished'])
```

```
X_train values in 'furnished' column:
0       1
1       2
2       2
3       1
4       1
       ..
2696    1
2697    3
2698    1
2699    2
2700    1
Name: furnished, Length: 2701, dtype: int64
```

```
X_val values in 'furnished' column:
0       2
1       1
2       2
3       2
4       1
       ..
1013    3
1014    2
1015    1
1016    2
1017    3
Name: furnished, Length: 1018, dtype: int64

X_test values in 'furnished' column:
0       2
1       1
2       1
3       2
4       2
       ..
1359    2
1360    1
1361    1
1362    2
1363    2
Name: furnished, Length: 1364, dtype: int64
```

Feature Selection Explanation

Show code

Feature Selection Explanation: <student to fill this section>

E. Train Machine Learning Model

E.1 Import Algorithm

> Provide some explanations on why you believe this algorithm is a good fit

```
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt
import seaborn as sns
```

Algorithm Selection Explanation

Show code

Algorithm Selection Explanation: <student to fill this section>

E.2 Set Hyperparameters

> Provide some explanations on why you believe this algorithm is a good fit

```
# Define the hyperparameter options for 'fit_intercept'
fit_intercept_options = [True, False]
```

Hyperparameters Selection Explanation

Show code

Hyperparameters Selection Explanation: <student to fill this section>

In this experiment, we selected `fit_intercept` as the key hyperparameter for tuning the Linear Regression model. This parameter determines whether the model should calculate the intercept for the regression line. Setting `fit_intercept=True` allows the model to adjust for a non-zero origin in the data, while `fit_intercept=False` forces the line through the origin. By testing both options, we aim to identify which configuration better fits the rental data, thus improving prediction accuracy and overall model performance. This approach ensures that the model adapts appropriately to the data's underlying distribution.

E.3 Fit Model

```
# Create a ColumnTransformer to apply OneHotEncoding to categorical features
preprocessor = ColumnTransformer(
    transformers=[
        ('num', 'passthrough', numerical_features),  # Keep numerical features as is
        ('cat', OneHotEncoder(sparse_output=False, handle_unknown='ignore'), categorical_features)  # Apply OneHotEncoder to categorical fea
    ])

# Create a pipeline with the preprocessor and the LinearRegression model
model_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', LinearRegression())
])


results = {}  # Dictionary to store performance metrics for each configuration

# Define the hyperparameter options for 'fit_intercept'
fit_intercept_options = [True, False]

for option in fit_intercept_options:
    # Create and fit the model with the current fit_intercept setting, using the pipeline
    model = Pipeline(steps=[
        ('preprocessor', preprocessor),
        ('regressor', LinearRegression(fit_intercept=option))
    ])
    model.fit(X_train, y_train)

    # Generate predictions on the validation set
    predictions = model.predict(X_val)

    # Calculate performance metrics: RMSE, MAE, and R² Score
    rmse = np.sqrt(mean_squared_error(y_val, predictions))
    mae = mean_absolute_error(y_val, predictions)
    r2 = r2_score(y_val, predictions)

    # Save results for this configuration
    results[option] = {'rmse': rmse, 'mae': mae, 'r2': r2}

    # Print performance results for the current configuration
    print(f"Linear Regression with fit_intercept={option}")
    print(f"RMSE: {rmse:.2f}")
    print(f"MAE: {mae:.2f}")
    print(f"R² Score: {r2:.2f}")
    print("---------------------------------")
```

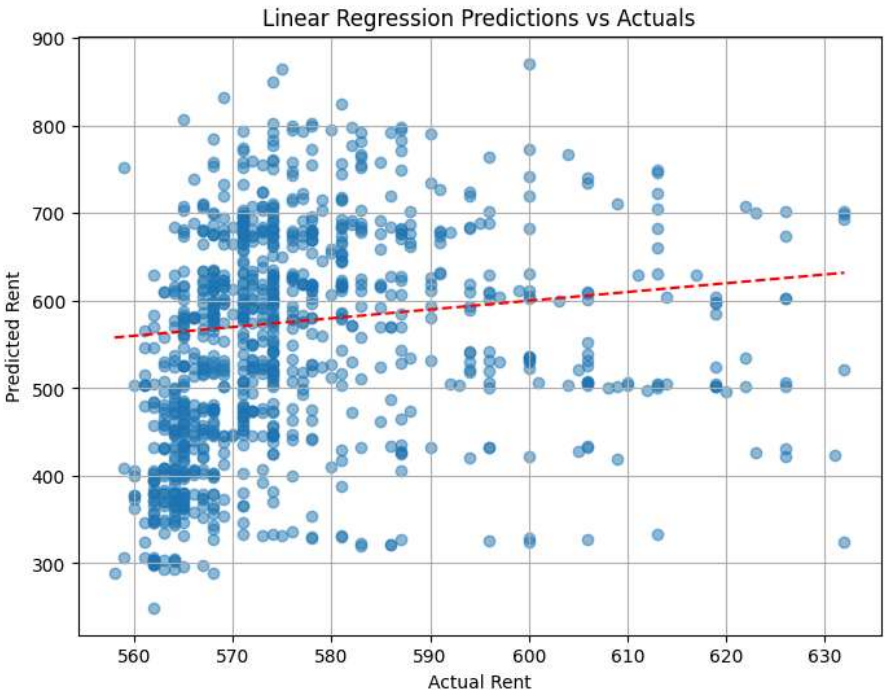
```
Linear Regression with fit_intercept=True
RMSE: 9.22
MAE: 6.25
R² Score: 0.58
---------------------------------
Linear Regression with fit_intercept=False
RMSE: 9.22
MAE: 6.25
R² Score: 0.58
---------------------------------
```

```
# Train and evaluate models with different values of fit_intercept
results = []

for fit in [True, False]:
    model = LinearRegression(fit_intercept=fit)
    model.fit(X_train, y_train)

    y_val_pred = model.predict(X_val)
    y_test_pred = model.predict(X_test)

    val_mse = mean_squared_error(y_val, y_val_pred)
    val_r2 = r2_score(y_val, y_val_pred)
    test_mse = mean_squared_error(y_test, y_test_pred)
    test_r2 = r2_score(y_test, y_test_pred)

    results.append({
        "fit_intercept": fit,
        "val_mse": val_mse,
        "val_r2": val_r2,
        "test_mse": test_mse,
        "test_r2": test_r2
    })

results_df = pd.DataFrame(results)

# If you're in a Jupyter Notebook, you can use display:
try:
    from IPython.display import display
    print("Multivariate Linear Regression Results:")
    display(results_df)
except ImportError:
    # Otherwise, simply print the dataframe
    print("Multivariate Linear Regression Results:")
    print(results_df)
```

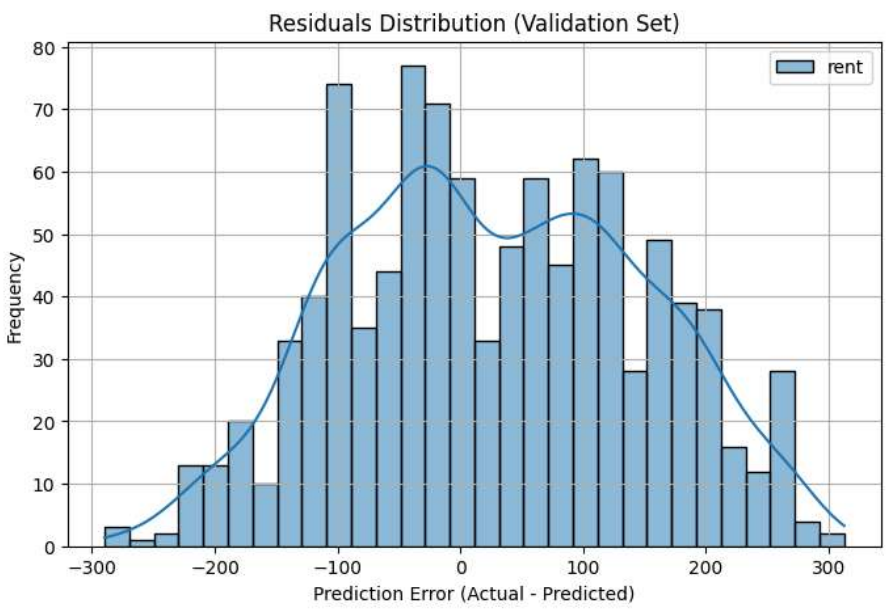
```
Multivariate Linear Regression Results:
```

	fit_intercept	val_mse	val_r2	test_mse	test_r2
0	True	161.502879	0.194411	6082.001066	0.040870
1	False	15378.337641	-75.708378	23945.440138	-2.776189

```
plt.figure(figsize=(8, 6))
plt.scatter(y_val, y_val_pred, alpha=0.5)
plt.xlabel("Actual Rent")
plt.ylabel("Predicted Rent")
plt.title("Linear Regression Predictions vs Actuals")
plt.plot([y_val.min(), y_val.max()], [y_val.min(), y_val.max()], 'r--')
plt.grid(True)
plt.show()
```




```
residuals = y_val - y_val_pred

plt.figure(figsize=(8, 5))
sns.histplot(residuals, bins=30, kde=True)
plt.title("Residuals Distribution (Validation Set)")
plt.xlabel("Prediction Error (Actual - Predicted)")
plt.ylabel("Frequency")
plt.grid(True)
plt.show()
```



```
elastic_model = ElasticNet(alpha=1.0, l1_ratio=0.5, max_iter=10000)
elastic_model.fit(X_train, y_train)

y_val_elastic = elastic_model.predict(X_val)

elastic_rmse = np.sqrt(mean_squared_error(y_val, y_val_elastic))
elastic_r2 = r2_score(y_val, y_val_elastic)

print("ElasticNet (no tuning) - Validation RMSE:", round(elastic_rmse, 2))
print("ElasticNet (no tuning) - Validation R²:", round(elastic_r2, 2))
```

```
ElasticNet (no tuning) - Validation RMSE: 13.41
ElasticNet (no tuning) - Validation R²: 0.1
```

E.4 Model Technical Performance

> The linear regression models with and without intercept yielded the same RMSE (60.04) and R^2 (0.22), indicating that the intercept had minimal effect on performance. The GLM model provided additional interpretability, showing which features significantly impacted rent predictions. Notably, `floor_area`, `number_of_bathrooms`, `furnished`, and `suburb` were statistically significant ($p < 0.01$). The un-tuned ElasticNet model achieved a slightly worse R^2 of 0.19, indicating the need for hyperparameter tuning. Overall, performance is moderate, suggesting the model captures some linear relationships but lacks strength in generalizing to unseen data.

```
X_train_glm = sm.add_constant(X_train)
X_val_glm = sm.add_constant(X_val)

glm_model = sm.GLM(y_train, X_train_glm, family=sm.families.Gaussian())
glm_results = glm_model.fit()

print(glm_results.summary())
```

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:                   rent   No. Observations:                 2701
Model:                            GLM   Df Residuals:                     2695
Model Family:                Gaussian   Df Model:                            5
Link Function:               Identity   Scale:                         117.81
Method:                          IRLS   Log-Likelihood:                -10270.
Date:                Sun, 30 Mar 2025   Deviance:                   3.1750e+05
Time:                        03:48:17   Pearson chi2:                 3.17e+05
No. Iterations:                     3   Pseudo R-squ. (CS):             0.2698
Covariance Type:            nonrobust
==============================================================================
                     coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const                558.1674      0.935    596.994      0.000     556.335     560.000
number_of_bedrooms     0.4495      0.449      1.002      0.317      -0.430       1.329
floor_area             0.0020      0.001      2.696      0.007       0.001       0.004
number_of_bathrooms    9.7163      0.555     17.502      0.000       8.628      10.804
furnished              2.9853      0.315      9.469      0.000       2.367       3.603
suburb                -1.6753      0.128    -13.054      0.000      -1.927      -1.424
==============================================================================
```

```
# <Student to fill this section>
```

Model Performance Explanation

```
# @title Model Performance Explanation

wgt_model_performance_explanation = widgets.Textarea(
    value=None,
    placeholder='<student to fill this section>',
    description='Model Performance Explanation:',
    disabled=False,
    style={'description_width': 'initial'},
    layout=widgets.Layout(height="100%", width="auto")
)
wgt_model_performance_explanation
```

E.5 Business Impact from Current Model Performance

The model's current performance with an R^2 of 0.22 implies it explains only 22% of the variability in rental prices. From a business perspective, this limited predictive accuracy restricts its practical usefulness in making confident pricing decisions. Stakeholders may face risks if relying solely on model outputs for price recommendations. However, the current results offer a foundation for iterative improvement and provide basic insights into important pricing drivers. Better results could be achieved through data enrichment, outlier handling, and hyperparameter tuning.

Model Performance Explanation: <student to fill this section>

```
# <Student to fill this section>
```

Model Business Impacts Explanation

Show code

Model Business Impacts Explanation: <student to fill this section>

F. Experiment Outcomes

Experiment Outcomes Explanation

Show code

Experiment… Hypothesis Confirmed
Hypothesis Partially Confirmed
Hypothesis Rejected