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DEPARTMENT OF COMPUTING

Analysing property sales data using Data Science

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Abstract

Your abstract.

Acknowledgments

Comment this out if not needed.

Contents

Chapter 1

Introduction

Nowadays, there is a substantial amount of data generated every second. The daily lives of humans are producing it, and some other fields, such as research, health care, economic activities, and environmental information from various sensors, also generate a vast amount of data. Obtaining the relationship between some features or the patterns underlying these massive amounts of data might benefit the entire world. For instance, new causes of diseases might be identified, and technological advancement could be accelerated.

However, this extensive data can be one of the main obstacles for analysis as it is approximately impossible for humans to obtain insights into the data manually. Under this circumstance, artificial intelligence (AI), a technique that empowers the computer to imitate human intelligence and manner, could be one of the methods to mitigate this issue. It can extract patterns from large datasets and use them to make predictions based on future data and even identify which data components are responsible for the results.

In this project, some AI techniques will be applied to property and demographic data to gain insights and understand the factors influencing a homeowner's likelihood to sell. The factors might include the proximity to schools, hospitals, or supermarkets, the accessibility to public transportation, and the property types (flats or houses). It could be highly advantageous to estate agents who would discover homeowners with more potential to become clients and provide them with business.

1.1 Aim & Objective

1.2 Layout of the Report

Chapter 2

Literal Review

Python is one of the most popular programming languages in the world since it is simple to develop, and there are extensive packages for various functionalities. In this project, Python and its packages would be used for loading data, preprocessing data, and constructing and evaluating machine learning models.

2.1 Machine Learning

Machine Learning (ML), a subset of AI, is a technique that the computer can learn and improve from data without explicit programming. The reason for utilizing ML is that its performance is sometimes better than the conventional approach. For example, ML techniques would simplify the solution to a problem that comprises a long list of rules (spam mail detection).

ML can be divided into three categories, one of which is supervised learning. In supervised learning, the dataset contains features (input to the model) and targets (ground truth of the output), and the model's parameters are randomly initialized. Then the features are passed to the model, and the differences between the current output and the ground truth are used to update the parameters until the differences are acceptable.

In this project, a supervised learning model will be implemented for data analysis, and the steps are listed below.

1. Data Preprocessing: Some data from the dataset may be missing, and these values must be handled appropriately before being passed to the model.

2. Standardization: In real life, different features usually have different ranges, and this will cause a problem in ML, which is that high magnitude features would have more weight than low magnitude features (Fandango, 2017). One of the solutions is standardization, which could scale all the features to the same magnitude.

3. Feature encoding: ML models require numerical values, whereas the categorical features in the dataset do not satisfy this requirement. Therefore, these features should be converted into numerical values.

4. Training & Testing: The parameters of the model are updated, and it is expected that the loss will converge during training. The performance of the model is validated when testing.

2.2 Handle Text Information

The format of texts in this project could be classified as HTML and plaintext. Although Python standard libraries provide some string processing capabilities, they are insufficient for this situation.

2.2.1 Beautiful Soup

Beautiful Soup is a Python library for extracting data from markup languages, such as HTML and XML. It can accomplish this with a user-specified parser, for example, ***html.parser***, to navigate, search and modify the parse tree, which would save considerable time (Richardson, 2007).

2.2.2 parse

The ***format*** function in the Python standard library formats a string, whereas the ***parse*** module provides functions with an oppositse effect, i.e., extract information from formatted strings.

2.2.3 Regular Expression

A regular expression is a sequence of ordinary and special characters representing textual patterns. The ordinary characters are identical throughout the expressions and texts, while the special characters specify the pattern, including number, location, and type of characters (Stubblebine, 2007). One of the primary disadvantages of the regular expression is its obscure syntax, which results in difficulty specifying a pattern.

2.2.4 Library Usage

In this project, HTML texts are used extensively in the raw dataset to describe property summaries, property layouts, and council tax. This is the optimal scenario for *Beautiful Soup* which is employed to extract plaintext by specifying tags. Then, *parse* is applied to obtain the information, such as room names, from the plaintexts since they are in the same format. In addition, due to its limitations, the regular expression is only used to acquire numerical values in this project.

2.3 Data Manipulation

2.3.1 NumPy

Numerical Python (***NumPy***) is a scientific computing package designed to support large multidimensional matrices. It uses an optimized *C/C++* API to reduce computation time compared to pure Python computations (McKinney, 2012). A substantial number of complex tasks of data analytics can be simplified by numerous *numpy* features. For example, it provides robust matrix operations, facilitates the construction of multidimensional objects, and serves as the foundation of other packages, including *matplotlib* and *seaborn*.

2.3.2 Pandas

The ***pandas*** is an open-source and compelling package that was developed primarily for data analysis and data manipulation and is built on *numpy*. It is capable of handling data of various types (numerical values, strings, and time) and from a variety of sources (CSV, Excel, and MqSQL database). ***DataFrame*** is one of the *pandas* data structures that is appropriate for handling tabular data with columns of different types. Additionally, it could manage various operations, such as manipulating missing values, creating pivot tables, and grouping data from different columns (Fandango, 2017).

2.3.3 Library Usage

In this project, the dataset provided is in CSV format hence it could be loaded by ***Pandas*** since it is suitable for tabular data. Then the package is utilized for preprocessing, such as handling missing values and grouping columns of data.

Numpy is appropriate for manipulating numerical data and acts as an intermediary between various packages. Therefore, it could be employed to evaluate the performance of ML models and transmit data to plotting packages.

2.4 ML Frameworks

2.4.1 Scikit-learn

Scikit-learn is a popular open-source ML framework that employs *Numpy*. It contains traditional ML algorithms, including clustering, classification, and regression, as well as a variety of utilities that can be applied to preprocess data and evaluate the performance (Géron, 2019). The drawback of this library is that it does not natively support GPU acceleration and is not a neural network framework.

2.4.2 PyTorch

PyTorch is one of the popular ML frameworks developed by Facebook, which is designed to implement neural networks with flexibility and speed (Godoy, 2021). It provides various components for model construction and training. For instance, there are numerous types of modules that comprise a model, such as linear layers, dropout, and activation functions, as well as a variety of loss functions and optimizers that can be employed in model training.

Furthermore, it can be beneficial to construct and train a model with *Pytorch*. It has a Pythonic nature which means that its syntax is similar to Python, making it more straightforward for Python programmers to develop neural networks than other ML frameworks. Moreover, it is a rapidly expanding framework for developing neural networks with a vast ecosystem, meaning that a substantial number of utilities have been developed on top of it (Godoy, 2021). Additionally, *PyTorch* supports automatic differentiation and GPU acceleration which can be advantageous for model training.

2.4.3 TensorFlow

TensorFlow is another ML framework produced by Google that specializes in deep learning and neural networks. It provides approximately the same components as *PyTorch* and also supports automatic differentiation and GPU acceleration. One of the appealing characteristics of *TensorFlow* is called ***TensorBoard***, which is an interactive visualization system that can display the flowchart of the data manipulation and plot the tendency of the performance (Shukla and Fricklas, 2018).

2.4.4 Library Usage

This project aims to construct a neural network which means *scikit-learn* is not applicable at this stage. Although *TensorFlow* provides the same capabilities as *PyTorch* and is superior in visualization, the model construction and training will use *PyTorch* due to its Pythonic syntax and compatibility with *TensorBoard*.

However, *scikit-learn* can be used to preprocess datasets and evaluate performance. It provides various utilities that can be helpful before training, for example, encoding categorical features and splitting the dataset into training and validation. In addition, it offers features for model evaluation, such as confusion matrix, accuracy, and recall.

2.5 Data Visualization

2.5.1 Matplotlib

Matplotlib is a Python package for 2D plotting that produces high-quality figures. It supports interactive and non-interactive plotting and can save images in multiple

formats, including PNG and JPEG. It can also generate numerous types of graphs, such as line plots, scatter plots, and pie plots.

2.5.2 Seaborn

Seaborn is a Python library for creating statistical graphs that integrates with *pandas* to offer a high-level interface to *matploblib*. If a dataset is provided, *seaborn* can automatically generate the figure with appropriate plotting attributes, such as color and legend. Additionally, it is capable of generating comprehensive graphics with a single function call and a minimum number of arguments (Waskom, 2021).

2.5.3 Library Usage

In this project, data visualization would be beneficial during preprocessing data and performance evaluation. For preprocessing, the distribution of the raw data should be inspected, hence *seaborn* could be an optimal choice since the input is a *DataFrame* and its syntax is concise. During evaluation, the model output will be converted to *Numpy* arrays. Therefore, *matplotlib* can be used in this case, as it is interactive and the figure can be further adjusted to illustrate the performance.

2.6 Methodology

Chapter 3

Implementation

3.1 Data Source and Collection

The datasets used in this project are provided by EweMove, and transactions from 2018 to 2022 are included. There are 34591 records with 36 parameters describing each property after merging these datasets. Some parameters, such as postcodes, and room information, are independent variables that would be the model input. In contrast, the price and status of the transaction are dependent variables that serve as labels of supervised learning. The features that are used to train the model are listed in table 3.1.

Table 3.1: The features used to train the model

Feature	**Description**	**Type**
Postcode	The location of the property	Categorical
Sale or Let	Whether the property is for sale or rent	Categorical
EweMove Description S3 Rooms	The room names and dimensions	HTML texts
RTD3308_outside_space	Keywords describing outside spaces	Categorical
RTD3307_parking	Keywords describing parking	Categorical
RTD3316_condition	The condition of the property	Categorical
RTD3318_heating	Keywords describing heating	Categorical
RTD3317_accessibility	Keywords describing accessibility	Categorical
Price / Rent	The price of the property	HTML texts
Price Qualifier		Categorical
DESC Council Tax Band	Type of the council tax	Categorical
# of Enquiry or viewings	Number of viewing inqueries	Numerical
# of Apps/Offers	Number of offers	Numerical

3.2 Data Preprocessing

3.2.1 Handle Room Descriptions (HTML)

Acquire room name and dimension

The structure of the HTML texts containing the room information in a property is shown in figure 3.1. The rooms are separated by tag *<li>*, and the room name and its dimension is denoted by ** and *<i>* tags, respectively. Therefore, a function (***EweMove_Description_S3_Rooms***) was implemented to split the HTML texts by utilizing *Beautiful soup*, and its flowchart is shown in figure 3.2.

```
This home includes:
<ul>
    <li>
        <strong>01 - Living Room</strong><br><br>
        <i>4.34m x 4.11m (17.8 sqm) - 14' 3" x 13' 5" (192 sqft)</i><br><br>
    </li>
    <li>
        <strong>02 - Dining Room</strong><br><br>
    </li>
</ul>
```

Figure 3.1: The layout of HTML texts

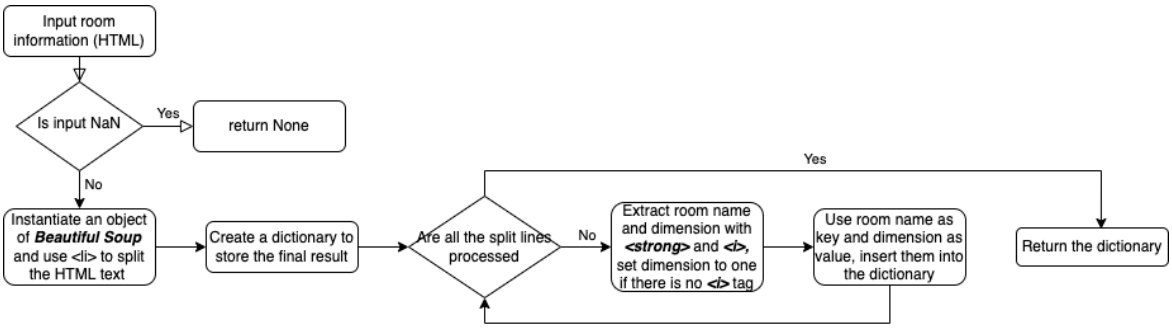


Figure 3.2: Flowchart for extracting room information from HTML

The names of rooms are analyzed after the room descriptions in the dataset have been processed. As a consequence, there are over 200 unique room names for approximately 36000 records, some of which are exceptionally uncommon across the entire dataset. For instance, only two properties have cinema rooms, and one has a lift, which is less than 0.1% of all entries.

Due to the large number of room names, it is impossible to use it as the input of the model. Therefore, the rooms are divided into six categories: bedrooms, bathrooms, kitchens, living/reception rooms, dining rooms, and other rooms so that the data

can be generalized.

Generalize room information

A class, ***ExtractRooms***, was developed to acquire and integrate the room information, especially the area in square meters, and its UML diagram is shown in figure 3.3. The member variable *rooms* is a list containing the result of invoking *EweMove_Description_S3_Rooms*, *room_set* comprises all the room names, *current_rooms* consists of the room names that have been processed, and *extract_area* is a formatted string for acquiring room area.

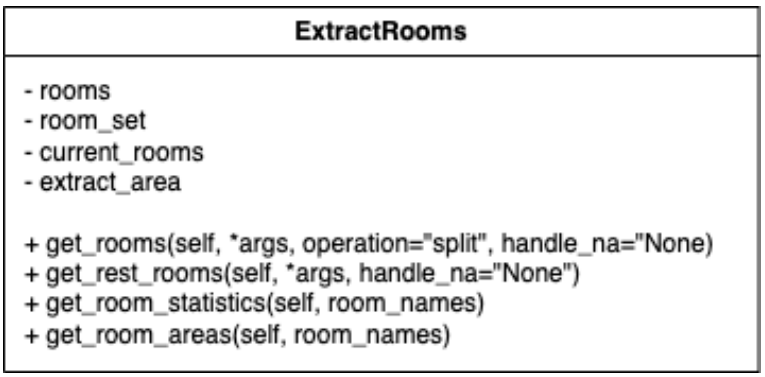


Figure 3.3: The UML diagram of the class (*ExtractRooms*)

Key member functions

- get_rooms
  The flow diagram of this method is shown in figure 3.4 and the arguments are listed below.

  1. args: It should be noted that this is a variable-length argument, which means that it can accept as many arguments as possible, and it is used to select room names from *room_set*. For instance, **args = [living, reception]* will select all names containing *living* or *reception*.
  2. operation: The argumen determines the types of the final result and the valid inputs include *sum*, *mean*, *split*, and *number*. For example, if args is *bedroom*, then the function can return the sum of bedroom areas, the average bedroom area, the area of each bedroom and the number of bedrooms.
  3. handle_na: This parameter specifies how to manage missing values, either by ignoring them or by filling the mean value if the input is *None* or *mean*, respectively.

- get_rest_room:
  This method is identical to ***get_room*** with two exceptions. The parameter

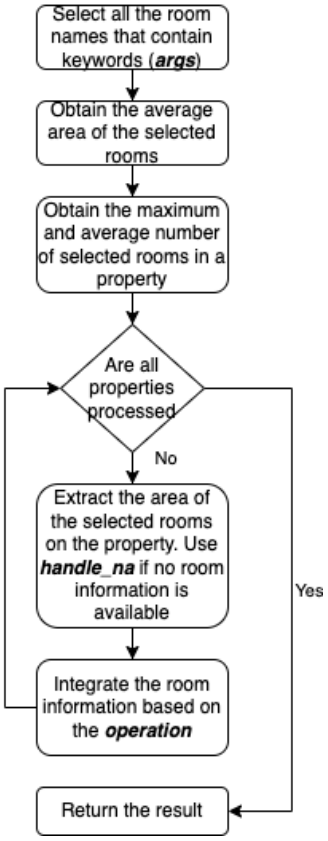


Figure 3.4: Flowchart of *get_rooms*

***args** is used to disgard the room names containing the keywords, and only the number and the total areas of other rooms are returned.

3.2.2 Manipulate Categorical Keywords

In the dataset, four features are characterized by categorical keywords, including parking, heating, accessibility, and outdoor spaces. Figure 3.5 is a snippet of the parking dataset that is used as an example to illustrate the manipulation of the keywords. The first three rows indicate that there is a parking space for the first property, which is **allocated off-street** parking for **residents**, the second has none, and the third property has one **on-street** parking space. In this situation, feature encoding cannot be applied since there are multiple columns of keywords describing a feature, and the order and quantity of the keywords have no effect.

Figure 3.6 illustrates the UML diagram of the class ***GeneralizeDataset***, which was developed to determine how these features of each property are described and the number of keywords within the description. The core of this class is member function ***get_feature_types***, and its flowchart is displayed in figure 3.7. In addition, function ***get_feature_num*** can be used to determine the number of keywords for each property.

RTD3307_parking1 - Parking Description	RTD3307_parking2 - Parking Description	RTD3307_parking3 - Parking Description
Allocated	Off Street	Residents
On Street		
Driveway	Garage	Off Street
Driveway	Garage	Off Street
Driveway		
Driveway	Garage	
Garage	Driveway	

Figure 3.5: The parking spaces in the first five properties

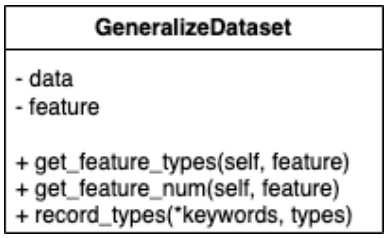


Figure 3.6: The UML diagram of *GeneralizeDataset*

3.2.3 Manage Outliers

The price is crucial to the project, and the distribution of the raw data was inspected, as shown in figure 3.8. The spike on the left side of the figure indicates that numerous properties have zero prices, which is illogical. Therefore, these abnormal values should be addressed as they could significantly impact the performance of the model.

3.2.4 Create Input Dataset

Feature Encoding

This technique is applicable to categorical features in the dataset, including price qualifier, council tax band, and property condition. The label encoding was employed, which is capable of converting the feature into numeric values between 0 and N - 1, where N is the number of distinct classes in a column.

Manage Missing Values

The datasets used in this project contain a significant number of missing values. For example, approximately 30% of the room layout and more than 40% of the council tax band are missing. Under this situation, it is impossible to replace them with the mean value since it causes the model to focus on the average and result in low performance. Therefore, another approach was applied, which was removing the missing values in the datasets.

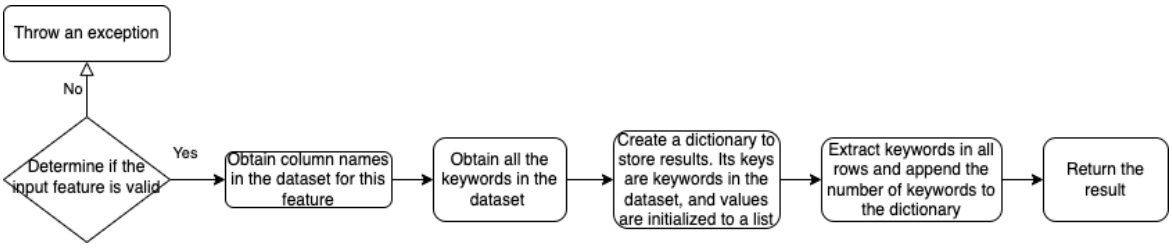
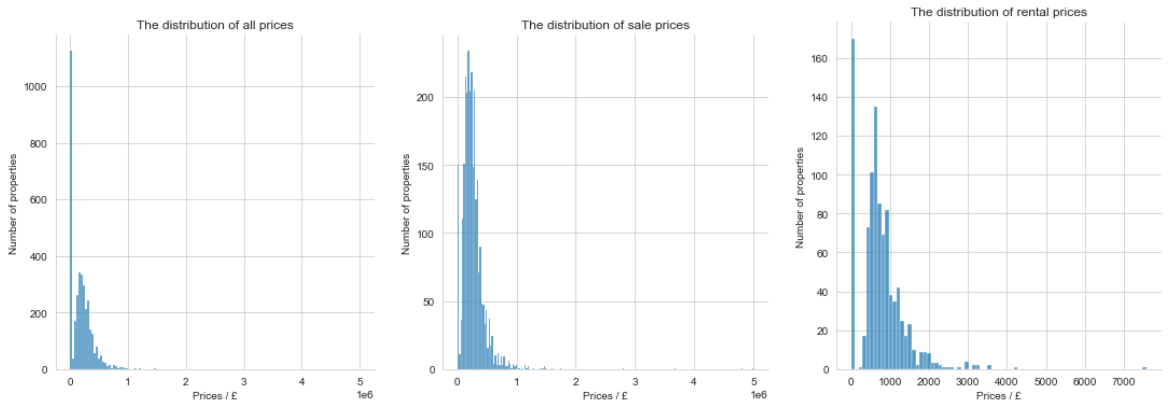


Figure 3.7: Flowchart of *get_feature_types*



(a) All Prices (b) Sale Prices (c) Rental Prices

Figure 3.8: The distribution of prices from raw data

Classy Approach

After extracting the information from HTML texts and categorical keywords, it is combined with other columns in the dataset to produce a clean dataset for the model input. Figure 3.9 is the UML diagram of ***CreateInputDataset***, which is a class developed for this objective, and the flow diagram of producing an input dataset is displayed in figure 3.10.

3.3 Model Construction

3.3.1 Development Steps

Data Preparation

The datasets created during preprocessing are initially loaded. Then they are split into training and testing sets, which represent 80% and 20% of the total dataset, respectively. In the meantime, the datasets are also shuffled as some datasets might contain intrinsic patterns.

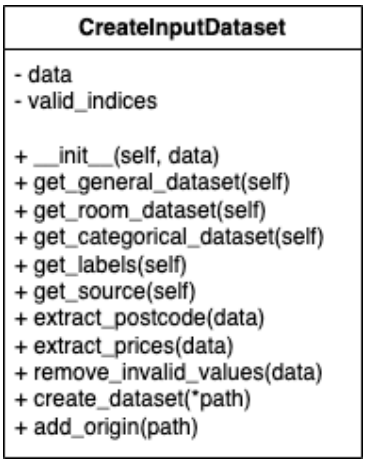


Figure 3.9: The UML diagram of *CreateInputDataset*

Training models

Due to the limited amount of training data for this project, cross validation was employed to train the model with different portions of training data. The performance was then illustrated by plotting training and validation loss against epoch, and the model with the best performance was selected for the evaluation phase based on these figures.

Evaluation

The model performance should be evaluated on unseen data. Otherwise, it would be useless. In this project, various metrics are used to quantify the model performance, including mean absolute error (MAE), mean squared error (MSE), and coefficient of determination (R^2). The lower the MAE and MSE errors, the better the performance. R^2 values range from 0 to 1. A model with $R^2 = 0$ means the model cannot make accurate predictions, while $R^2 = 1$ indicates that the model can precisely predict the results. In rare instances, the R^2 can be negative, indicating that the model does not match the trend of the data, which is the worst performance.

3.3.2 Linear Regression: Predict Price

Prior to the construction of any neural networks, a linear regression model with a single linear layer was developed. Its input size is the same as the number of features, and the output is the price. If this model can accurately predict the price, it eliminates the need to build more complex neural networks with multiple layers, which is the motivation for its creation. To train this model, Mean squared error (MSE) is applied as prices can be any positive values. The optimizer is Adam, and the learning rate is 0.001.

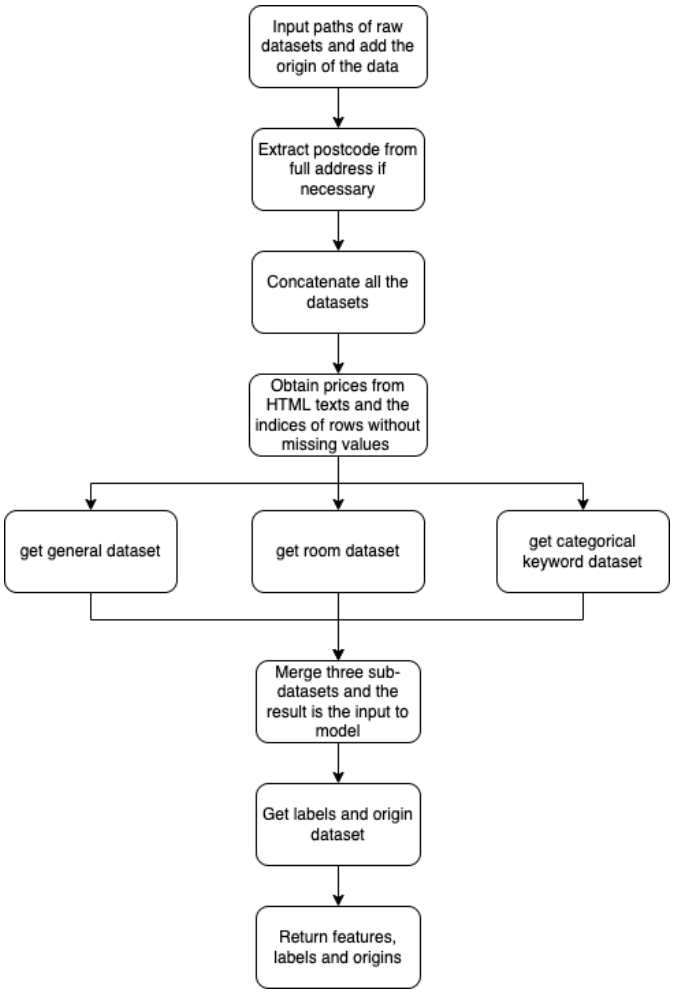


Figure 3.10: The flow diagram of producing input dataset

3.3.3 Basic Model: Output Sale Status and Price

The architecture of this model only consists of linear layers and activation functions, as depicted in figure 3.11. There are two outputs of the model, which are prices and probabilities of selling. Therefore, the activation functions of the output layers are ReLU and sigmoid, respectively.

The predicted probability should be converted into 0 or 1 to indicate the status of the transaction, given that it is either completed or not in the datasets. Therefore, a threshold of 0.5 is established. If the probability exceeds the threshold, then it is converted to 1. Otherwise, it is set to 0.

The loss function for the status of the transaction is binary cross entropy (BCE), as it has only two possible outcomes. For the same reason as the linear regression model, MSE loss is applied to prices. Therefore, the total loss for this model is the sum of the BCE and MSE. In addition, the optimizer used for training is Adam, and the learning rate is 0.001.

```
==========================================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================================
ProbabilityAndPrice                      [1, 1]                    --
├─Sequential: 1-1                        [1, 128]                  --
│    └─Linear: 2-1                       [1, 128]                  6,656
│    └─ReLU: 2-2                         [1, 128]                  --
│    └─Linear: 2-3                       [1, 128]                  16,512
│    └─ReLU: 2-4                         [1, 128]                  --
│    └─Linear: 2-5                       [1, 256]                  33,024
│    └─ReLU: 2-6                         [1, 256]                  --
│    └─Linear: 2-7                       [1, 128]                  32,896
│    └─ReLU: 2-8                         [1, 128]                  --
├─Sequential: 1-2                        [1, 1]                    --
│    └─Linear: 2-9                       [1, 1]                    129
│    └─Sigmoid: 2-10                     [1, 1]                    --
├─Sequential: 1-3                        [1, 1]                    --
│    └─Linear: 2-11                      [1, 1]                    129
│    └─ReLU: 2-12                        [1, 1]                    --
==========================================================================================
```

Figure 3.11: The architecture of the basic model

Chapter 4

Testing & Experimental Results

Comprehensive testing and analyzing were conducted throughout the implementation but it is documented in this separate chapter for the sake of illuatration.

4.1 Data Preprocessing

4.1.1 Handle Room Descriptions (HTML)

There were two tests for this objective, the first test examing if the room name and its dimension can be acquiare from HTML texts and the second test focuses on whether the room areas can be obtained and integrated correctly.

Acquire room name and dimension

This test utilized two HTML texts, which are illustrated in figure 4.1. By invoking the function *EweMove_Description_S3_Rooms* with two snippets and retrieving the results (shown in tables 4.1 & 4.2), it is evident that the room names in two HTML snippets could be obtained, and the dimensions were acquired if available otherwise, the value was set to one. Therefore, this function can pass the test.

Table 4.1: Information from HTML snippet in figure 4.1(a)

Entrance Hall	1
Living/Dining Room	6.58m x 3.78m (24.8 sqm) - 21’ 7” x 12’ 4” (267 sqft)
Kitchen	2.68m x 2.14m (5.7 sqm) - 8’ 9” x 7’ (61 sqft)
Bedroom 1	3.37m x 2.45m (8.2 sqm) - 11’ x 8’ (88 sqft)
Bedroom 2	2.54m x 2.45m (6.2 sqm) - 8’ 4” x 8’ (67 sqft)
Bathroom	2.14m x 2.04m (4.3 sqm) - 7’ x 6’ 8” (46 sqft)
Garden	1
Parking	1

```
This home includes:
<ul>
    <li>
        <strong>01 - Entrance Hall</strong><br><br>
    </li>
    <li>
        <strong>02 - Living/Dining Room</strong><br><br>
        <i>6.58m x 3.78m (24.8 sqm) - 21' 7" x 12' 4" (267 sqft)</i><br><br>
    </li>
    <li>
        <strong>03 - Kitchen</strong><br><br>
        <i>2.68m x 2.14m (5.7 sqm) - 8' 9" x 7' (61 sqft)</i><br><br>
    </li>
    <li>
        <strong>04 - Bedroom 1</strong><br><br>
        <i>3.37m x 2.45m (8.2 sqm) - 11' x 8' (88 sqft)</i><br><br>
    </li>
    <li>
        <strong>05 - Bedroom 2</strong><br><br>
        <i>2.54m x 2.45m (6.2 sqm) - 8' 4" x 8' (67 sqft)</i><br><br>
        The second double bedroom is bright and well-sized, with room for all required furniture.<br><br>
    </li>
    <li>
        <strong>06 - Bathroom</strong><br><br>
        <i>2.14m x 2.04m (4.3 sqm) - 7' x 6' 8" (46 sqft)</i><br><br>
    </li>
    <li>
        <strong>07 - Garden</strong><br><br>
        Communal Gardens.<br><br>
    </li>
    <li>
        <strong>08 - Parking</strong><br><br>
        2 allocated parking spaces.<br><br>
    </li>
</ul>
```

(a) Snippte 1

```
This home includes:
<ul>
    <li>
        <strong>01 - Entrance Porch</strong><br><br>
    </li>
    <li>
        <strong>02 - Lounge Diner</strong><br><br>
        <i>6.76m x 4.04m (27.3 sqm) - 22' 2" x 13' 3" (293 sqft)</i><br><br>
    </li>
    <li>
        <strong>03 - Kitchen</strong><br><br>
        <i>2.97m x 2.36m (7 sqm) - 9' 8" x 7' 8" (75 sqft)</i><br><br>
    </li>
    <li>
        <strong>05 - Bathroom</strong><br><br>
    </li>
    <li>
        <strong>07 - Bedroom (Double)</strong><br><br>
        <i>4.05m x 3.25m (13.1 sqm) - 13' 3" x 10' 7" (142 sqft)</i><br><br>
    </li>
    <li>
        <strong>08 - Bedroom (Double)</strong><br><br>
        <i>3.28m x 2.36m (7.7 sqm) - 10' 9" x 7' 8" (83 sqft)</i><br><br>
    </li>
    <li>
        <strong>09 - Bedroom (Double)</strong><br><br>
        <i>4.3m x 2.44m (10.4 sqm) - 14' 1" x 8' (112 sqft)</i><br><br>
    </li>
    <li>
        <strong>10 - Bathroom</strong><br><br>
    </li>
</ul>
```

(b) Snippet 2

Figure 4.1: The HTML snippets for testing

Table 4.2: Information from HTML snippet in figure 4.1(b)

Entrance Porch	1
Lounge Diner	6.76m x 4.04m (27.3 sqm) - 22’ 2” x 13’ 3” (293 sqft)
Kitchen	2.97m x 2.36m (7 sqm) - 9’ 8” x 7’ 8” (75 sqft)
Bathroom	1
Bedroom (Double)	4.05m x 3.25m (13.1 sqm) - 13’ 3” x 10’ 7” (142 sqft)
Badroom (Double)	3.28m x 2.36m (7.7 sqm) - 10’ 9” x 7’ 8” (83 sqft)
Bedroom (Double)	4.3m x 2.44m (10.4 sqm) - 14’ 1” x 8’ (112 sqft)
Bathroom	1

Generalize room information

The data obtained from HTML texts (figure 4.1) was used to access the behavior of *ExtractRooms*, particularly its member function *get_rooms*. During testing, the selected type is the bedroom, and all the operations of *get_room* were inspected. Additionally, the other rooms were used to test function *get_rest_rooms*.

The results of calling *get_rooms* are displayed in tables 4.3 and 4.4. It is obvious that all the bedrooms and their respective areas in tables 4.1 and 4.2 were successfully extracted. Moreover, the numerical values could also be obtained without error if the operations were appropriately configured. These behaviors demonstrated that the functionality and design are identical. In addition, the result of invoking *get_rest_rooms* is displayed in table 4.4(d). It is clear that there is no statistical inconsistency using the information from tables 4.1 and 4.2, hence this function can pass the test.

Table 4.3: Room information (*split*)

	Bedroom 1	Bedroom 2	Bedroom 3
0	8.2	6.2	0.0
1	13.1	7.7	10.4

Table 4.4: Bedroom information integrated by different operations

(a) Mean

	Average area
0	7.2
1	10.4

(b) Sum

	Total area
0	14.4
1	31.2

(c) Number

	Number of rooms
0	2
1	3

(d) Other rooms

	Number	Area
0	6	34.8
1	5	34.3

4.1.2 Manipulate Categorical Keywords

The data utilized for this test is displayed in figure 3.5. Initially, an invalid feature, *Distance to School*, was input into the function *get_feature_types*, and the feature was then set to *parking*. With the same data, the member function *get_feature_num* was evaluated.

In the initial test, an exception was thrown if an invalid feature was entered, in this case, *Distance to School*. Next, the result of calling function *get_feature_types* is shown in table 4.5. Since there are ten properties in the snippets and six keywords in total, this table has ten rows and six columns which is correct, and its elements are consistent with the dataset snippet. For the first property with an **allocated off-street** parking space for **residents**, the three keywords in the first row are set to one while the others are zero, and this conclusion holds true for the remaining properties. In addition, the number of keywords associated with each property can be obtained accurately by calling *get_feature_num*.

4.1.3 Manage Outliers

During preprocessing, both filling the mean value and removing outliers were attempted. The distributions of the prices after applying two methods are demonstrated in figures 4.2 and 4.3. For filling the average value, it is apparent that the left-hand spike is diminished, meaning that there is no price of zero. A new peak in the middle suggests that the original distribution has been modified. If zero prices were removed, the peak on the left would also be reduced, and the distribution would remain unchanged.

Therefore, removing zero prices was applied to create input datasets for models as

Table 4.5: The keywords for each property

	Allocated	Driveway	Garage	Off Street	On Street	Residents
0	1	0	0	1	0	1
1	0	0	0	0	0	0
2	0	0	0	0	1	0
3	0	0	0	0	0	0
4	0	1	1	1	0	0
5	0	0	0	0	0	0
6	0	1	1	1	0	0
7	0	1	0	0	0	0
8	0	1	1	0	0	0
9	0	1	1	0	0	0

it retains the original distribution, whereas filling the mean value causes the data alternation. Consequently, the model will learn more from average, which results in poor performance.

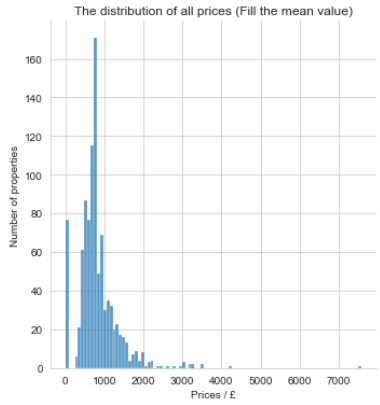
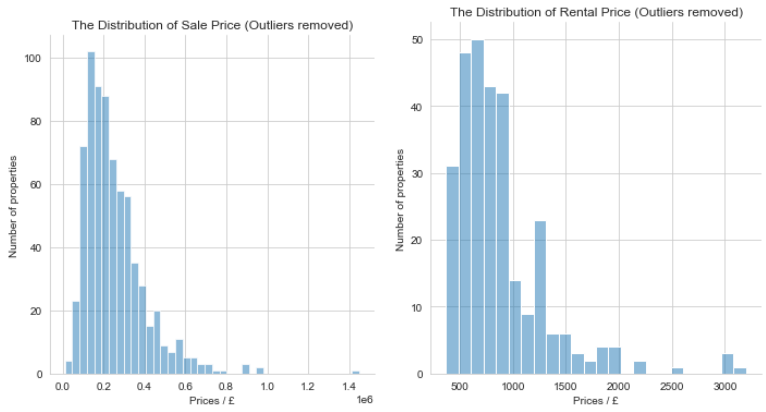


Figure 4.2: The distribution of prices with mean value filled

4.1.4 Create Input Dataset

The first step in evaluating the behavior of this class is to determine if the categorical features are encoded, and the second test is to inspect whether the missing values are eliminated.

For general information, the first ten rows after preprocessing and their corresponding rows in the original dataset are displayed in figure 4.4. The categorical features, such as postcode and council tax band, are encoded as numerical values allowing the first test to be passed. In addition, it is evident that the indices in the new dataset are not continuous, indicating that the rows with missing values have been removed. Hence it can pass the second test.



(a) Sale Prices (b) Rental Prices

Figure 4.3: The distribution of prices with zero prices removed

4.2 Model Construction

4.2.1 Linear Regression: Predict Price

The training & validation losses of this model are depicted in figure 4.5, and the model trained in fold two has been chosen for evaluation since it has the best performance.

Table 4.6: Comparsion between truth and model predictions

Predicted Price	price	price error / %
940	695	35.37
4150	350000	98.81
1790	130000	98.62
-2101	475	542.46
1829	105000	98.25
3058	450000	99.32
-4289	460	1032.47
855	325000	99.74
3255	585000	99.44
1071	900	19.10

The first ten predictions and the actual prices are displayed in table 4.6, and it is evident that there are significant differences between the predictions and the truth. Moreover, the model's metrics are as follows, $MAE = 179836$, $MSE = 66601086343$ and $R^2 = -0.9136$. These results demonstrate that a linear regression model cannot extract patterns from the dataset and that neural networks with multiple layers are compulsory.

	Postcode	Sale or Let	Price Qualifier	DESC Council Tax Band	RTD3316_condition1	# of Enquiry or viewings	# of Apps/Offers
0	LU7 4WN	Sale	Offers In Excess Of	Band B	Good	32	12
2	DA17 5PJ	Sale	Guide Price	Band D	Good	14	4
6	RG26 5PX	Sale	Guide Price	Band E	Good	10	2
7	BD8 0HT	Sale	Offers in Region Of	Band B	Good	9	1
15	HU17 7AB	Sale	Offers Over	Band B	Good	1	2
19	PR9 7PN	Rental	Monthly	Band E	Good	0	4
28	PR8 5AW	Rental	Monthly	Band A	Good	0	5
118	PR8 6XQ	Rental	Monthly	Band B	Good	0	2
121	PR9 7SN	Rental	Monthly	Band A	Good	0	0
127	PR9 7SN	Rental	Monthly	Band A	Good	0	0

(a) Original dataset

	Postcode	Sale or Let	Price Qualifier	DESC Council Tax Band	RTD3316_condition1	# of Enquiry or viewings	# of Apps/Offers
0	1595	1	4	1	0	32	12
2	389	1	2	3	0	14	4
6	2185	1	2	4	0	10	2
7	196	1	7	1	0	9	1
15	998	1	6	1	0	1	2
19	2028	0	3	4	0	0	4
28	2021	0	3	0	0	0	5
118	2023	0	3	1	0	0	2
121	2030	0	3	0	0	0	0
127	2030	0	3	0	0	0	0

(b) Preprocessed dataset

Figure 4.4: Comparsion between original and preprocessed dataset

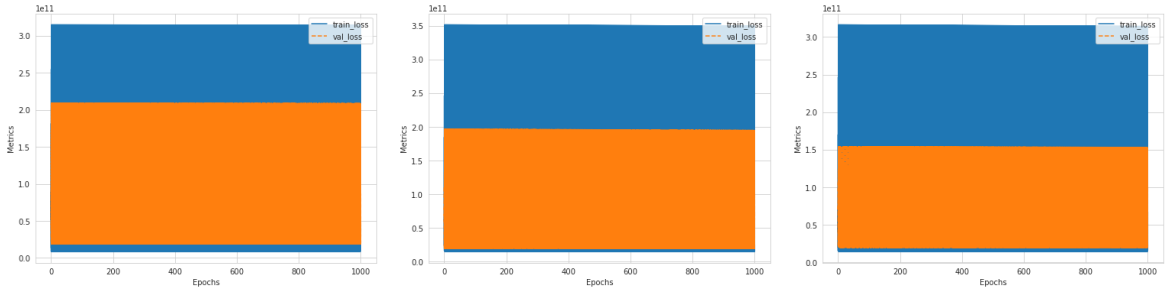
4.2.2 Basic Model: Output Sale Status and Price

The model with best performance was selected based on the figures for training and validation losses. Then the testing data were input to the model and the output are compared with the labels.

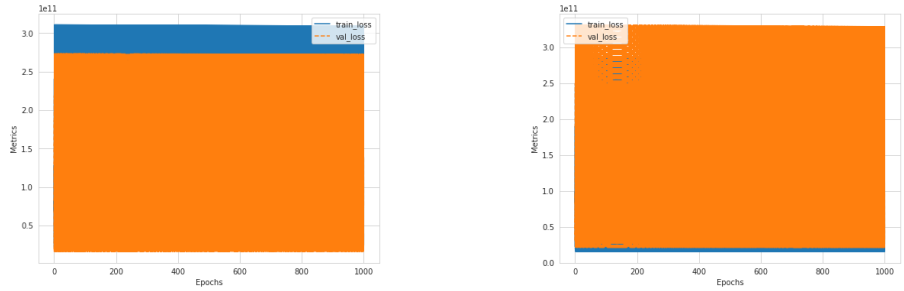
The training and validation losses against epochs for each fold is displayed in figure 4.6. For fold zero, the model was overfitting as the training loss was approximately the same after 60 epochs, whereas the validation loss was increasing. If the training stops elrly, then the performance of this model might be the best. For fold one, the model is underfitting as the validation loss keeps decreasing and its performance might be better if it was trained for more epochs. For the next two folds, the performance of the models are the best and should be selected for testing. The model trained from last fold did not learn anything since both training and validation loss is osciliating.

Based on the performance plot, the model trained in fold 3 was selected. The first ten predictions and true values are shown in table 4.7. It is evident that the model only predict one for completeness regardless of the truth values, whereas the predicted prices were better and the average error for the whole testing test is 26%.

This error result could be caused by loss functions. The completeness is either zero or one, hence the binary cross entroty (BCE) loss was used. For the prices which is greater than zero, the mean squared error (MSE) loss was applied. As the model outputs both completeness and prices, the BCS and MSE loss were added to produce a total loss which was then used for backpropagation. However, the BCE loss is



(a) Fold 0 (b) Fold 1 (c) Fold 2



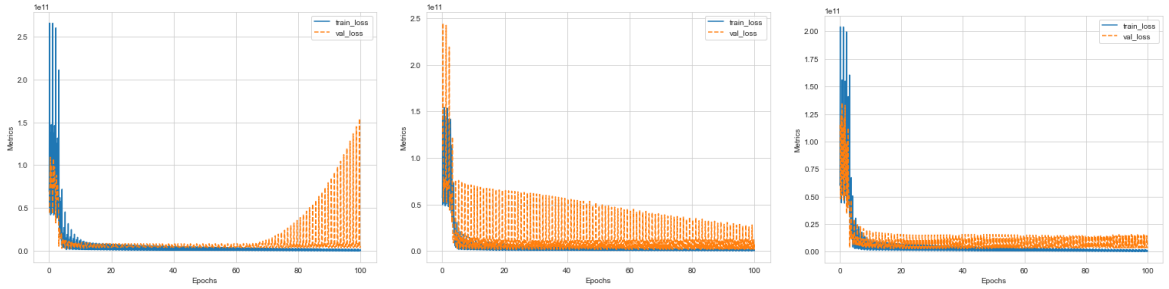
(d) Fold 3 (e) Fold 4

Figure 4.5: The training & validation loss for different folds (linear regression model)

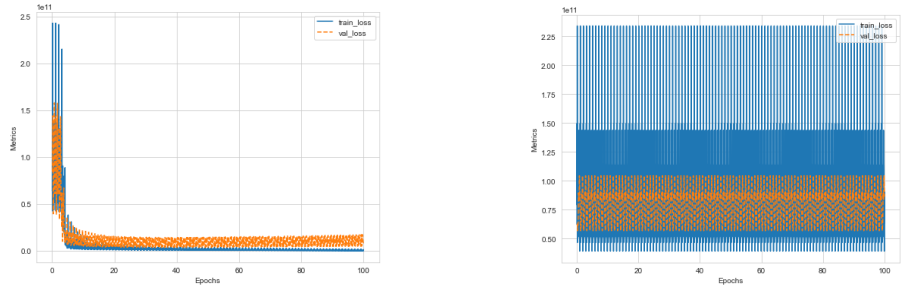
small compared with MSE loss. Therefore, the total loss resulted in the model learning more in predicting prices and completeness was ignored. Additionally, another reason causing the wrong predictions on completness was that the price is not input into the model and it is one of the most important factors in real-life transactions.

Table 4.7: Comparsion between truth and model predictions

Completed	Price	Predicted completed	Predicted price	Price error / %
1	675000	1	600810	10.99
0	80000	1	36130	70.16
0	90000	1	53198	40.89
0	295000	1	253552	14.05
0	105000	1	105753	0.72
1	270000	1	297239	10.09
0	115000	1	124108	7.92
1	600000	1	528918	11.85
1	4000000	1	376152	5.96
0	125000	1	157276	25.82



(a) Fold 0 (b) Fold 1 (c) Fold 2



(d) Fold 3 (e) Fold 4

Figure 4.6: The training & validation loss for different folds

Chapter 5

Conclusion

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