Imperial College London

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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

2.1 Related Works

2.1.1 Datasets

The datasets are the foundation of AI, and a significant number of real estate datasets have been published, some of which are analyzed at the beginning of the project. The first dataset contains the data for Latvia in 2018, which utilizes the real estate announcements posted by one of the most prominent domestic advertisement websites (Skribans et al., 2020). It includes both sale and rental data by region, along with a variety of property types, such as flats, houses, and offices. One of the distinct advantages of this dataset is that the website for updating estate data is monitored by Latvia authorities and is used to enhance the state policy in the real estate market, thereby the reliability of the dataset can be guaranteed.

Nevertheless, the disadvantages of the dataset are noticeable. It only contains the property data in Latvia, suggesting that the conclusions drawn from it might not be applicable to other countries worldwide. Moreover, the regional factors that can significantly influence the real estate transactions, such as economic growth, medical care, and education, are not included in this dataset, meaning that the conclusions base on it only consider the property itself and do not account for the surrounding environment.

The second dataset

2.2 Related Technologies

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.

2.2.1 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.

2.2.2 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.

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).

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.

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.

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.

2.2.3 Data Manipulation

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*.

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).

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.

2.2.4 ML Frameworks

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.

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.

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).

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.

2.2.5 Data Visualization

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.

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).

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.

2.3 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 *<strong>* 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

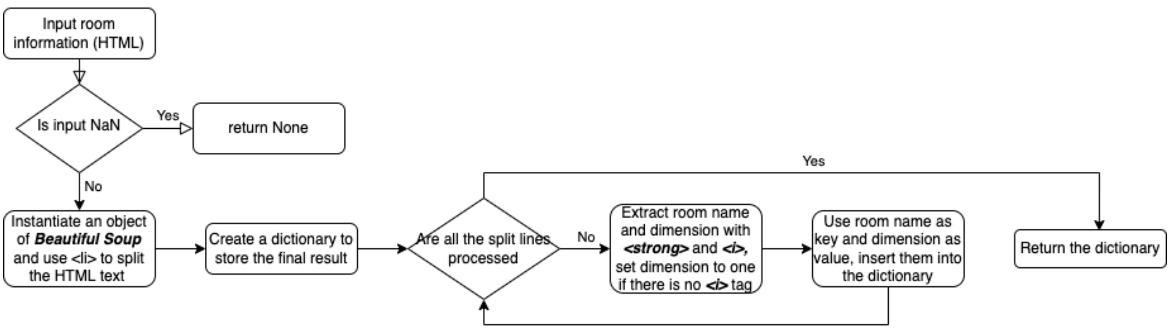


Figure 3.2: Flowchart for extracting room information from HTML

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.

ExtractRooms
- rooms - room_set - current_rooms - extract_area
+ get_rooms(self, *args, operation="split", handle_na="None") + get_rest_rooms(self, *args, handle_na="None") + get_room_statistics(self, room_names) + get_room_areas(self, room_names)

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

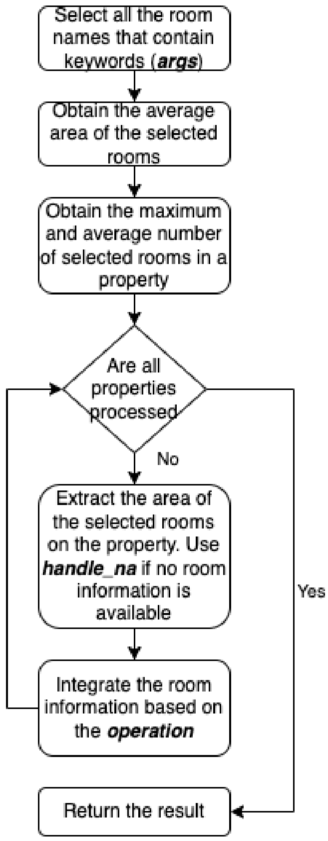


Figure 3.4: Flowchart of *get_rooms*

****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.

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 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.

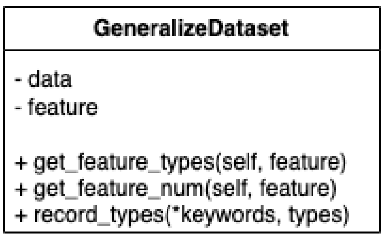


Figure 3.6: The UML diagram of *GeneralizeDataset*

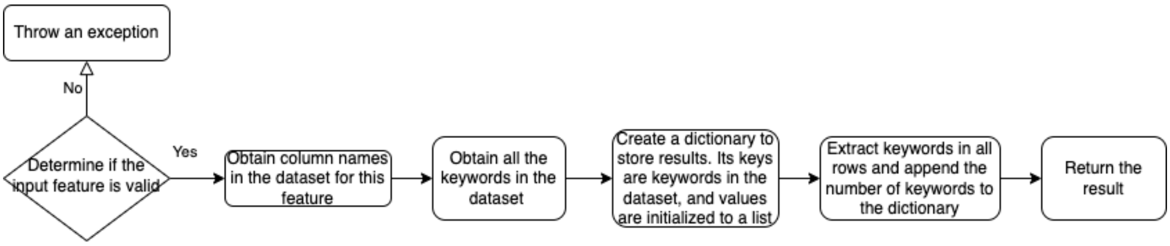


Figure 3.7: Flowchart of *get_feature_types*

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.

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

Figure 3.8: The distribution of prices from raw data

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.

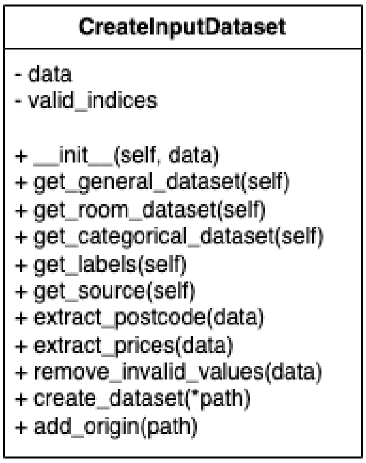


Figure 3.9: The UML diagram of *CreateInputDataset*

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.

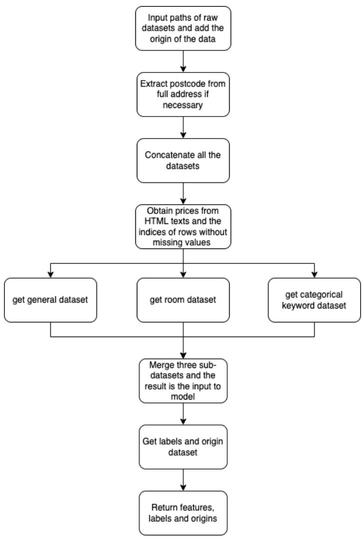


Figure 3.10: The flow diagram of producing input dataset

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.

Training models

Due to the limited training data for this project, cross validation was employed to train the model with different portions of training data. There are two model outputs, including prices and the status of transactions. The loss function for prices is mean squared error (MSE) as they are positive values. However, the status of transactions is either one or zero, hence its loss function is binary cross entropy (BCE).

The optimizer used for training is Adam, which could compute a learning rate for each parameter and has a low computing time. The learning rate is initially set to 1×10^{-3} and would be updated if necessary.

The performance was illustrated after cross validation by plotting training and validation losses against epoch. Based on these graphs, the model with the best performance was selected for the evaluation phase.

Evaluation

The model performance should be evaluated on unseen data. Otherwise, it would be useless. Various metrics are used to quantify the performance of the model in this project.

As the measurements for predicted prices, MSE, mean absolute error (MAE), and coefficient of determination (R^2) are applied. The lower the MAE and MSE, 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.

The confusion matrix is initially obtained to access the predictions regarding the status of transactions. A confusion matrix summarizes the classification problems, indicating where the model outputs wrong predictions and the types of errors. Based on the confusion matrix, various metrics are calculated, and they are shown as follows,

- **Accuracy**: It is the number of correct predictions divided by the total number of predictions. The best accuracy is one and zero is the worst.
- **Precision**: It is the number of correct positive predictions divided by the total number of positive predictions. High precision suggests that predictions on positive can be guaranteed.
- **Recall**: The ratio of correct positive predictions to the total number of positive examples, and the high recall indicates that the positive class is correctly identified.
- **F1 Score**: This is a harmonic mean of both recall and precision. Hence this value can be used to evaluate performance independently.

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.

3.3.3 Basic Model: Output Sale Status and Price

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

The status should be converted into 0 or 1 to, 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.

3.3.4 Basic Model: Predicting Prices

The structure of this model is demonstrated in figure 3.12. Its hidden layers are identical to the model for predicting completeness and prices, whereas the completeness output is removed.

3.3.5 Complex Model: Predicting Prices

The layout of a more complex model is similar to that of figure 3.12, with additional linear layers, and neurons in each layer. The model was constructed for an obvious reason. Intuitively, more complex models are more capable to learn from the input dataset, resulting in enhanced performance.

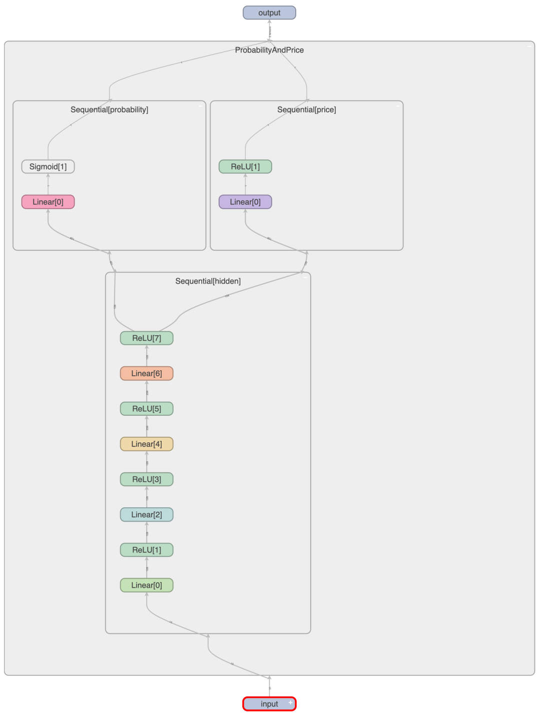


Figure 3.11: The architecture of the basic model

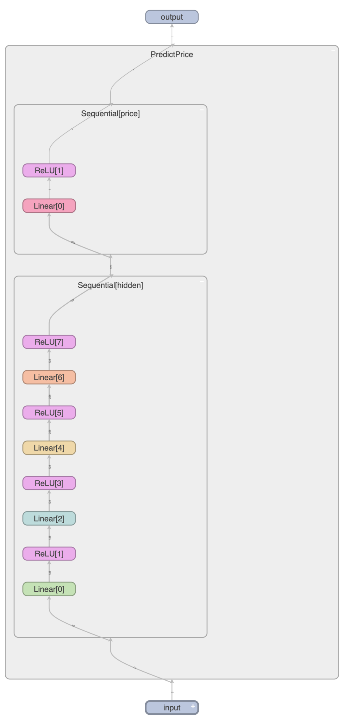


Figure 3.12: The structure of the basic model for predicting prices

3.3.6 Residual Network: Predicting Prices

The second complex model was developed which utilized residual connections. The architecture of the residual blocks and the network are illustrated in figures 3.13 and 3.14, respectively. This model was developed because the performance of the first complex model was not significantly enhanced despite having more layers and neurons. In addition, tuning the hyperparameters of this model was time consuming and the improvement of the accuracy was limited.

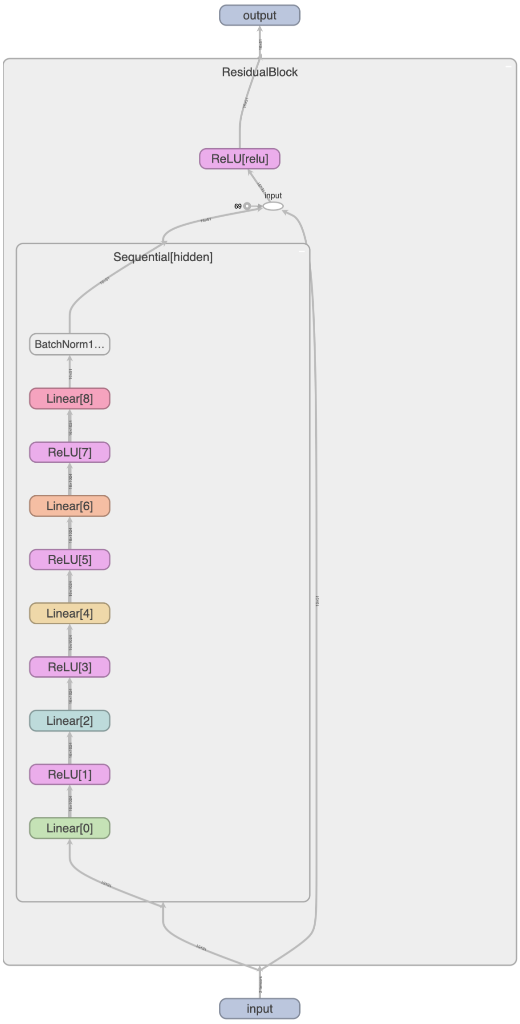


Figure 3.13: The layout of a single residual block

3.3.7 Linear Regression: Predict Status of Transactions

For the same reason as predicting prices, another linear regression model was developed to determine whether a single linear layer is sufficient for the prediction. Figure 3.15 depicts the correlation between the status and other attributes that was

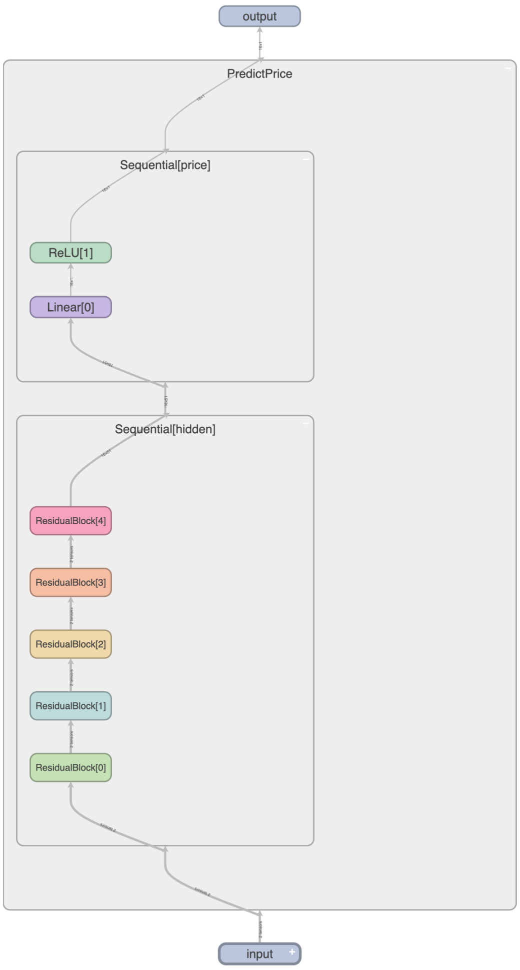


Figure 3.14: The architecture of the residual model

obtained prior to training the model. It is apparent in the bottom right that the actual and predicted prices are not closely related. Therefore, two models were trained in this section, with the actual and predicted prices included in the first but not the second.

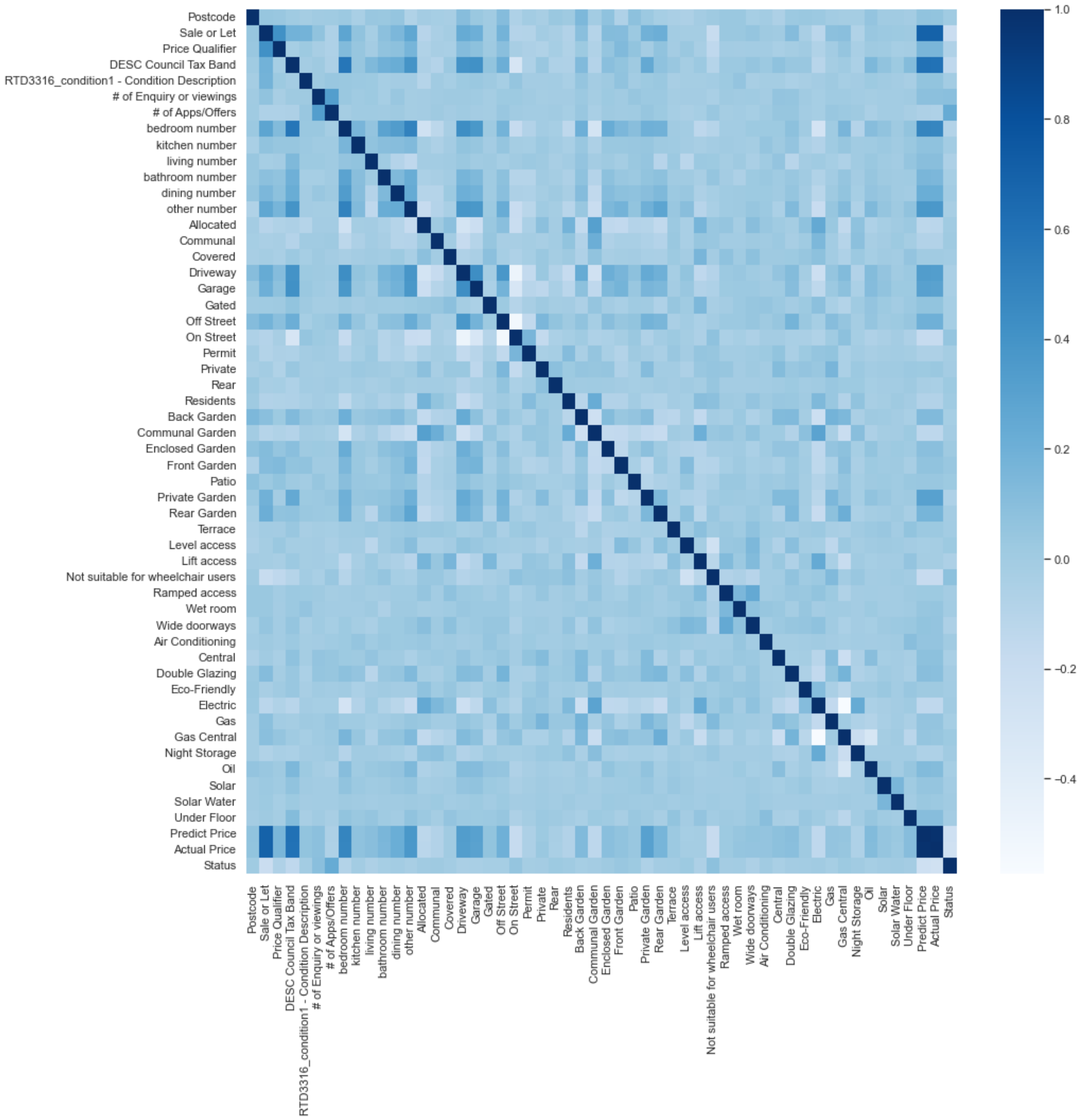


Figure 3.15: The correlation between the status and other attributes

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

```html
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

```html
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*.

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

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 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.

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

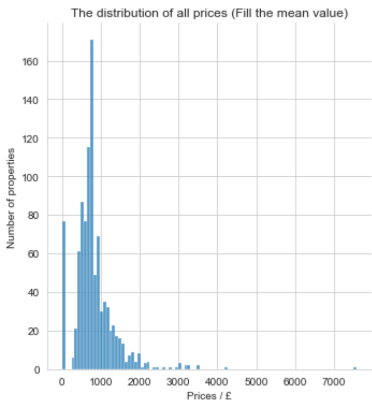
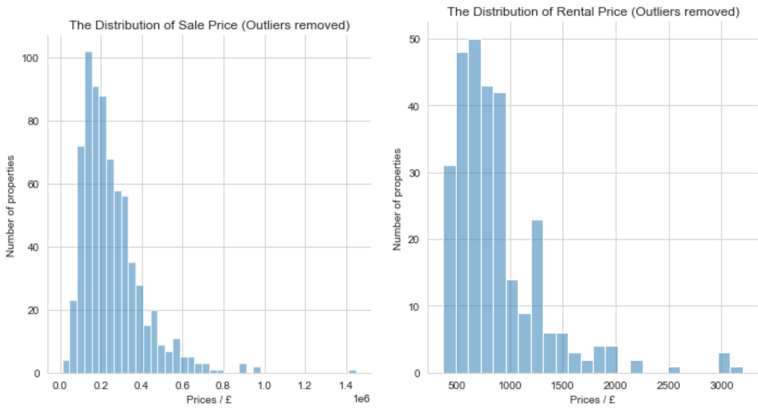


Figure 4.2: The distribution of prices with mean value filled



(a) Sale Prices (b) Rental Prices

Figure 4.3: The distribution of prices with zero prices removed

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.

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.

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

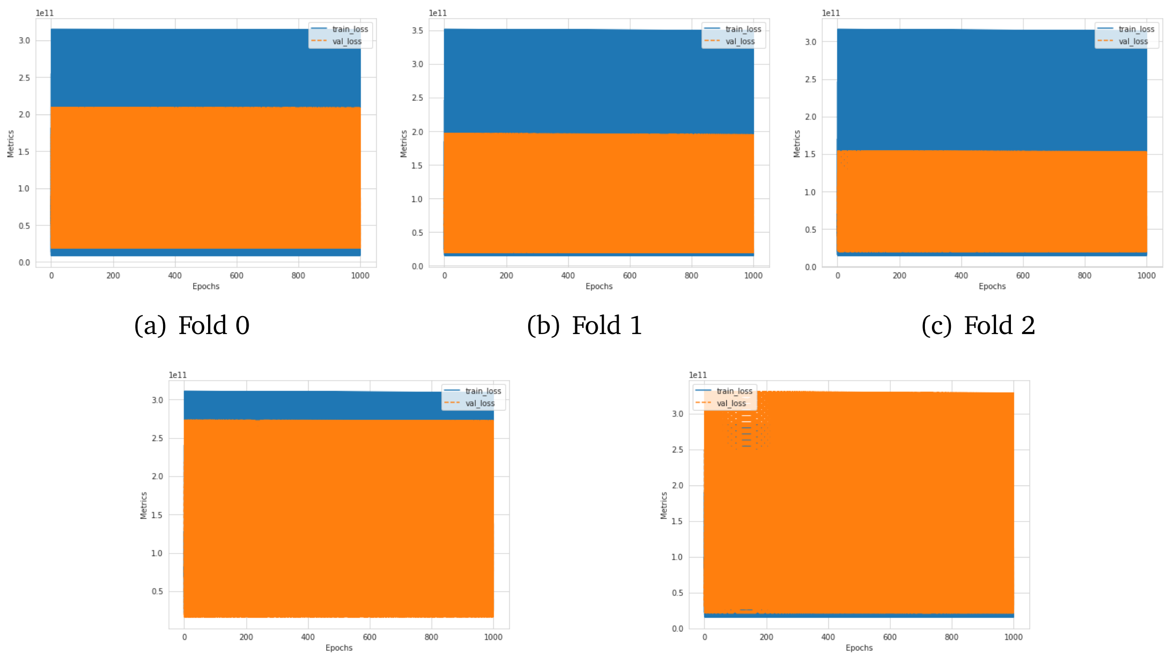
	Postcode	Sale or Let	Price Qualifier	DESC Council Tax Band	RTD3316_condition1	# of Enquiry or viewings	# of Apps/Offers
0	LU7 4WN	Sale	Offers In Excess Of	Band B	Good	32	12
2	DA17 5PJ	Sale	Guide Price	Band D	Good	14	4
6	RG26 5PX	Sale	Guide Price	Band E	Good	10	2
7	BD8 0HT	Sale	Offers in Region Of	Band 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



(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)

Table 4.6: Comparison 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

extract patterns from the dataset and that neural networks with multiple layers are compulsory.

4.2.2 Basic Model: Output Sale Status and Price

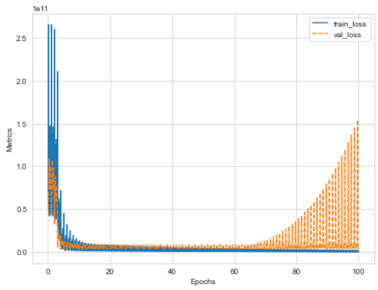
The training and validation losses against epochs for each fold is displayed in figure 4.6. For fold zero, the model was overfitting as the training loss was approximately the same after 60 epochs, whereas the validation loss was increasing. If the training stops elrly, then the performance of this model 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.

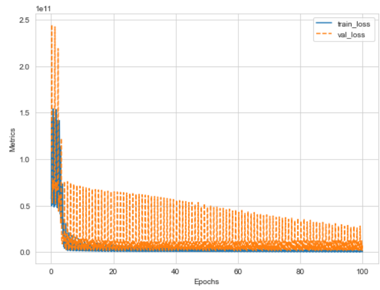
The metrics for price prediction are as follows, $MAE = 57527$, $MSE = 7559964776$ and $R^2 = 0.54$. Comparing this model to the linear regression model demonstrates that the neural network is able to extract patterns from the dataset, resulting in superior performance.

Figure 4.7 illustrates the confusion matrix of predicting completeness, from which the accuracy, precision, recall, and F1 score are calculated to be 0.638, 0.638, 1, and 0.78, respectively.

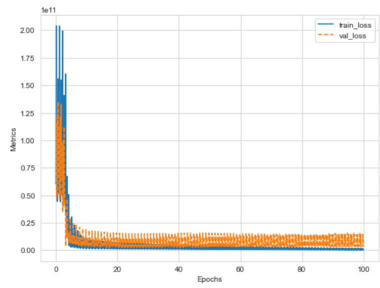
The error results could be caused by loss functions. The completeness is either zero or one, hence the BCE loss was used. For the prices which is greater than zero, the



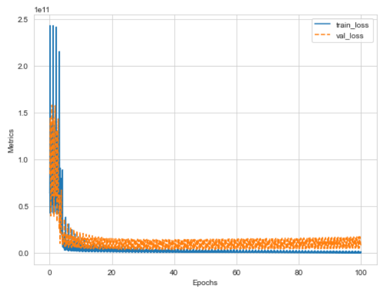
(a) Fold 0



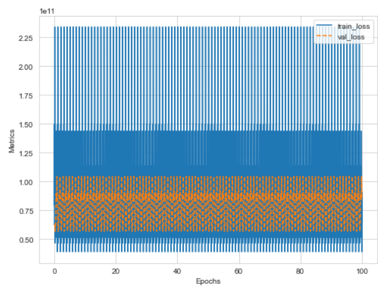
(b) Fold 1



(c) Fold 2



(d) Fold 3



(e) Fold 4

Figure 4.6: The training & validation loss for different folds

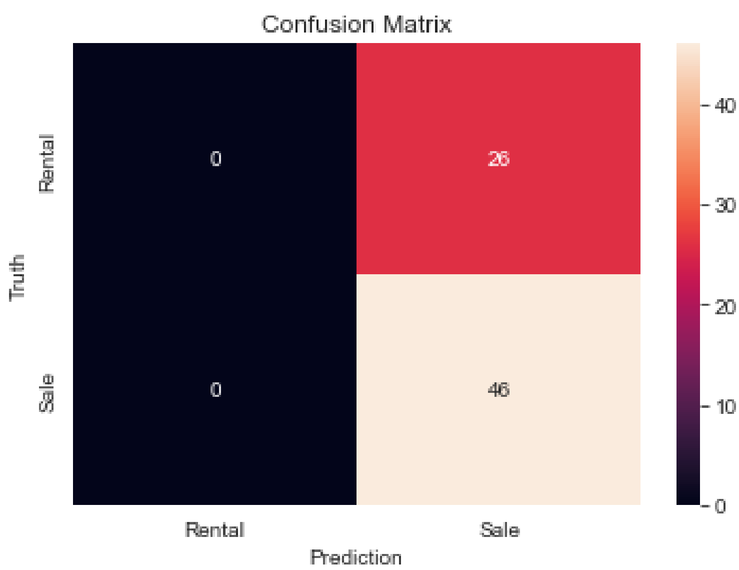


Figure 4.7: The confusion matrix of the basic model

MSE loss was applied. As the model outputs both completeness and prices, the BCE and MSE loss were added to produce a total loss which was then used for backpropagation. However, the BCE loss is 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: Comparison between truth and model predictions

Completed	Price	Predicted Status	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

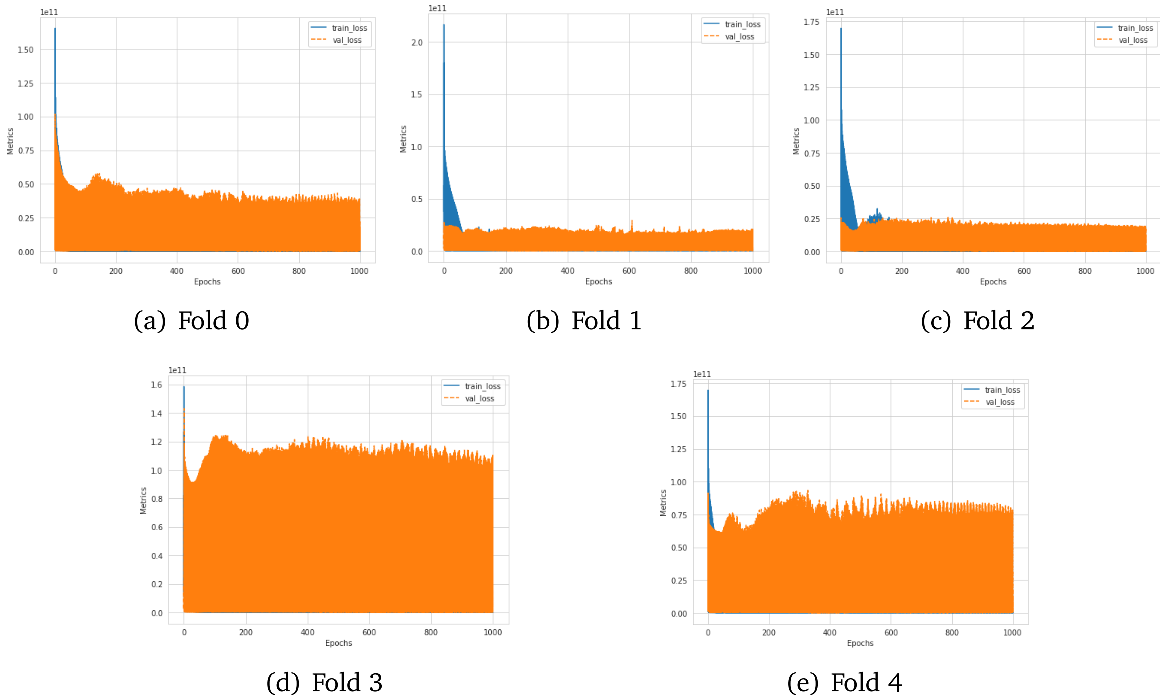
4.2.3 Basic Model: Predicting Prices

Initially, the training & validation losses of this model is displayed in figure 4.8, and the model from fold one was selected for the evaluation because of its performance. The first ten predictions are shown in table 4.7, and the metrics of this model are as follows, $MAE = 36538$, $MSE = 4918700785$, and $R^2 = 0.85$.

Table 4.8: True and predicted prices for basic model

Predictions	Actual Price	Price Error %
0	695	100
593571	350000	69.59
177140	130000	36.26
0	475	100
156217	105000	48.77
509198	450000	13.15
0	460	100
389259	325000	19.77
571157	585000	2.36
0	900	100

It is evident from table 4.8 that the rental prices which are around few hundreds are all predicted to be zero, whereas the error for some sale prices can be acceptable.



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

(d) Fold 3 (e) Fold 4

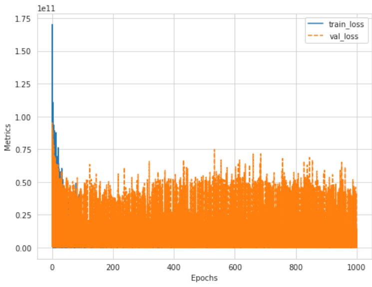
Figure 4.8: Training & validation loss (Model for predicting prices)

This could be caused by the imbalanced dataset, which contains twice as many sale data as rental data. Therefore, the weighted random sampler (WRS), which can ensure that the number of distinct classes in a mini-batch are approximately the same, was utilized to address the issue caused by imbalanced dataset.

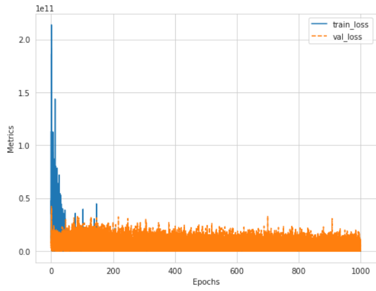
Figure 4.9 illustrates the training & validation losses after applying WRS. Base on these figures, the model trained in fold two was selected for the evaluation, and the first ten predicted prices are displayed in table 4.9. The metrics of this model are $MAE = 34099$, $MSE = 4635616774$, and $R^2 = 0.86$.

Table 4.9: True & predicted prices for basic model (WRS applied)

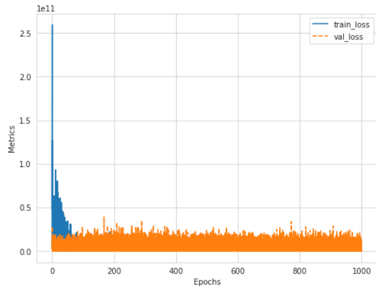
Prediction	True Price	Error %
764	695	10.06
0	1	100
233418	130000	79.55
619	475	30.37
91812	105000	12.55
575859	450000	27.96
595	460	29.38
360867	325000	11.03
655685	585000	12.08
1149	900	27.66



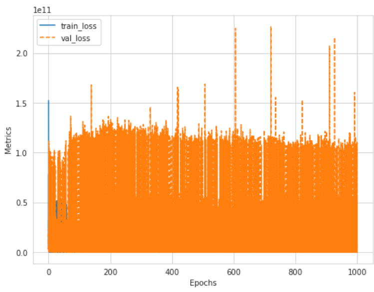
(a) Fold 0



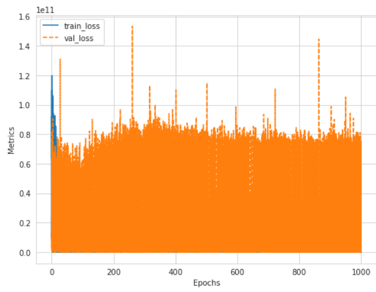
(b) Fold 1



(c) Fold 2



(d) Fold 3



(e) Fold 4

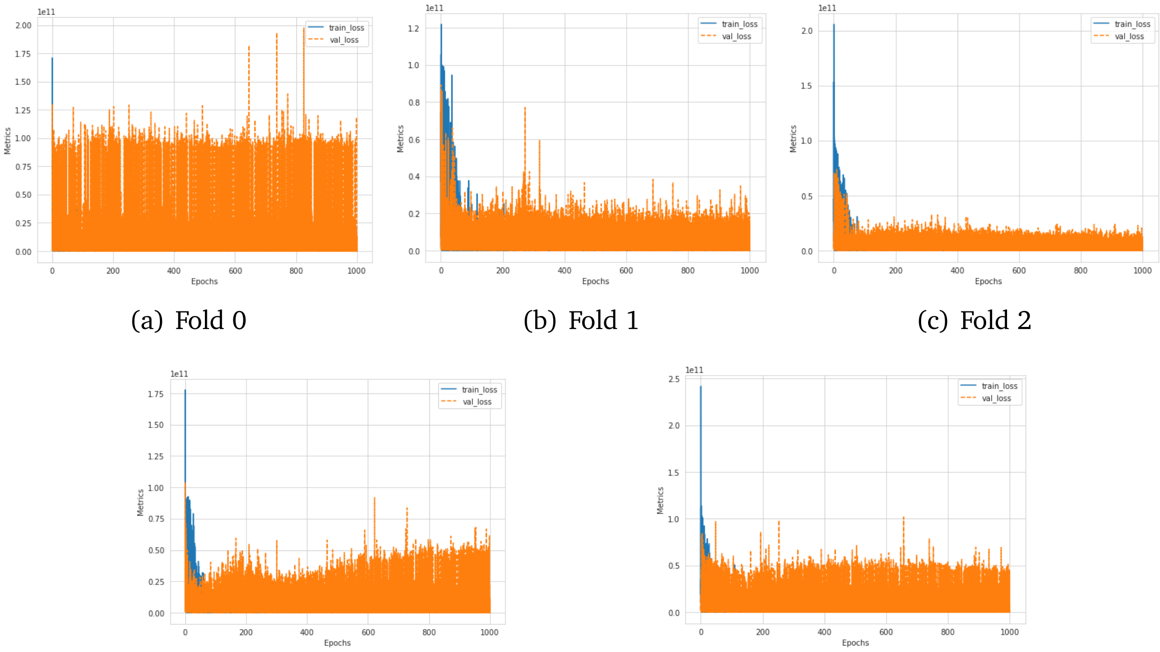
Figure 4.9: Training & validation loss for basic model (WRS applied)

The predicted rental prices in table 4.9 are not zero, but it should be noted that one of the actual prices is an outlier which has the potential to impact the performance significantly. Therefore, all the outliers (actual prices less than 100) were removed from the dataset, and the model was retrained.

Figure 4.10 depicts the training and validation losses after removing the outliers, and the model trained on fold one was chosen for evaluation based on its performance. Some actual and predicted prices are displayed in table 4.10. This model has following metrics, $MAE = 35391$, $MSE = 4580892828$, and $R^2 = 0.87$.

Table 4.10: True & predicted prices for basic model (outlier removed)

Predicted Price	Actual Price	Error %
92743	105000	11.67
527	475	10.96
183196	180000	1.77
802	1250	35.77
522	395	32.27
159249	230000	30.76
1119	950	17.88
74438	60000	24.06
345296	285000	21.15
115000	127500	9.80



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

(d) Fold 3 (e) Fold 4

Figure 4.10: Training & validation loss for basic model (outliers removed)

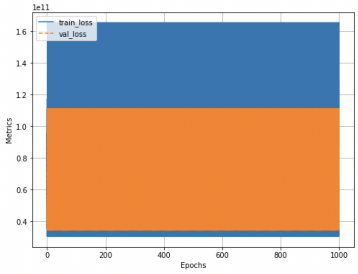
4.2.4 Complex Model: Predicting Prices

The training and validation losses of this model are depicted in figure 4.11. The predictions made by the model in fold two are displayed in table 4.11, along with its metrics, $MAE = 193166$, $MSE = 70788722849$, and $R^2 = -1.11$. Clearly, the complex model was not learning, and this might be caused by error hyperparameters. Therefore, the model was tuned so that its performance could be improved.

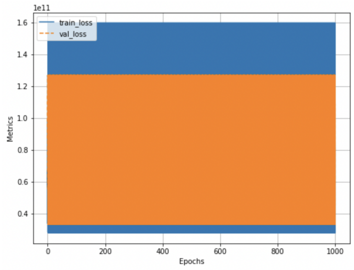
Table 4.11: True and predicted prices for basic model

Predictions	True Price	Error %
0	1300	100
0	425000	100
0	800000	100
0	265000	100
0	140000	100
0	525	100
0	460	100
0	650000	100
0	200000	100
0	650	100

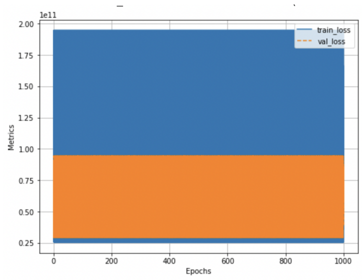
The hyperparameters tuned to enhance the performance are number of epochs, learning rate, number of layers and neurons in each layer.



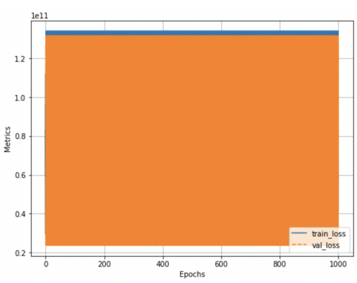
(a) Fold 0



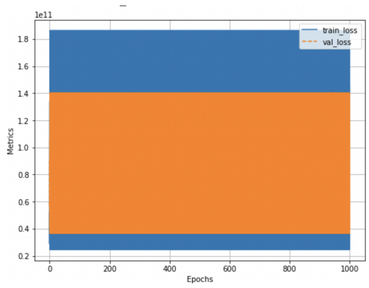
(b) Fold 1



(c) Fold 2



(d) Fold 3



(e) Fold 4

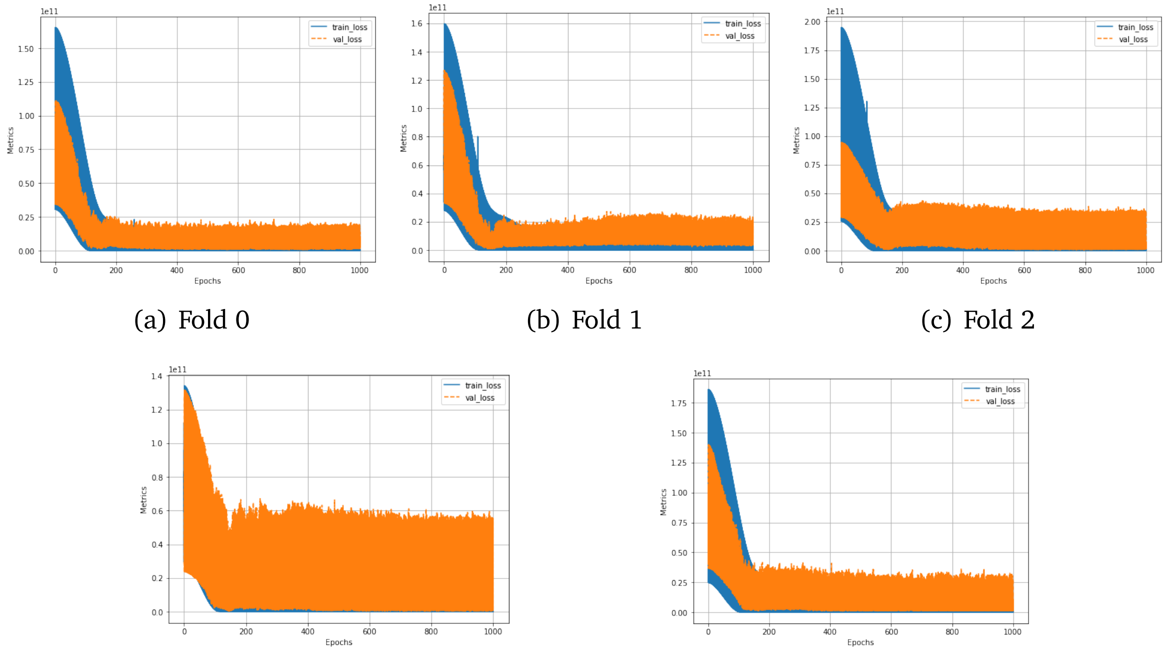
Figure 4.11: Training & validation loss (Model for predicting prices)

4.2.5 Residual Network: Predicting Prices

Figure 4.12 illustrates the training and validation losses for residual networks, and the model from fold one was selected for evaluation due to its low loss. Some predicted prices are displayed in table 4.12; its metrics are $MAE = 35607$, $MSE = 4515004136$, and $R^2 = 0.87$.

Table 4.12: True and predicted prices for basic model

Predictions	Actual Price	Error %
146653	200000	26.67
434	475	8.44
117730	105000	12.12
1840	1250	47.26
177246	180000	1.52
123018	140000	12.12
325667	300000	8.55
122508	150000	18.32
747	525	42.38
255869	200000	27.93



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

(d) Fold 3 (e) Fold 4

Figure 4.12: Training & validation loss (Model for predicting prices)

4.2.6 Comparing models for predicting prices

Table 4.13 summarizes the metrics of all the models for predicting prices. It is evident that the linear regression model has the worst performance since its simple architecture is incapable of extracting insight from datasets. For the basic models, their performance becomes better when WRS is applied and outliers are removed. Moreover, although the remaining two complex models have more layers and neurons, they cannot improve the accuracy of their predictions significantly. Therefore, the basic model was chosen for predicting prices because of its acceptable performance and simple architecture, which results in smaller model size and less prediction time.

Table 4.13: Metrics for various models

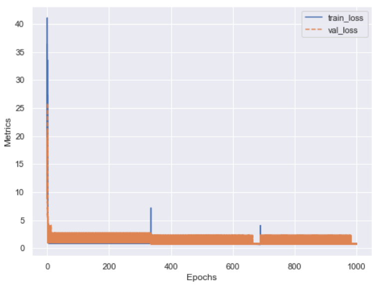
	MAE	MSE	R^2
Linear Regression Model	179836	66601086343	-0.91
Basic Model (Price and Status)	57527	7559964776	0.54
Basic Model (Price only)	36538	4918700785	0.85
Basic Model (WRS applied)	34099	4635616774	0.86
Basic Model (Outliers removed)	35391	4580892828	0.87
Complex Model			
Residual Network	35607	4515004136	0.87

4.2.7 Linear Regression: Predict Status of Transactions

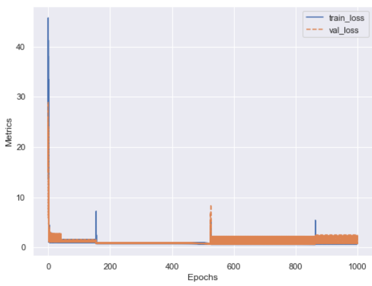
Actual and Predicted Prices Included

The training and validation losses of the model are depicted in figure 4.13, and all the models can converge and the losses of the last three models are comparable. Therefore, they were utilized for evaluation, and the threshold for converting numerical values into status has been set to 0.5. Figure 4.14 displays the confusion matrics of three models, and their metrics are listed in table 4.14.

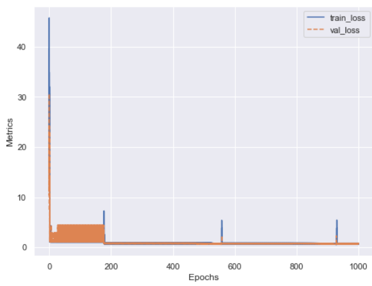
From table 4.14, the recall has the highest values, indicating that the model can predict the completed transactions with greater confidence. However, the precision and F1 score are around 0.3, which means that the performance of these models is unacceptable.



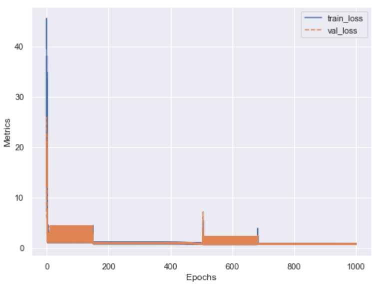
(a) Fold 0



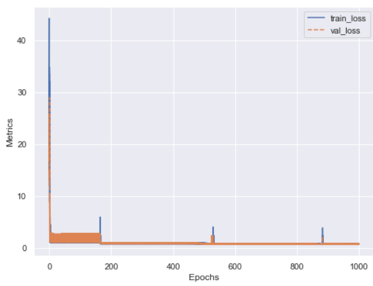
(b) Fold 1



(c) Fold 2



(d) Fold 3

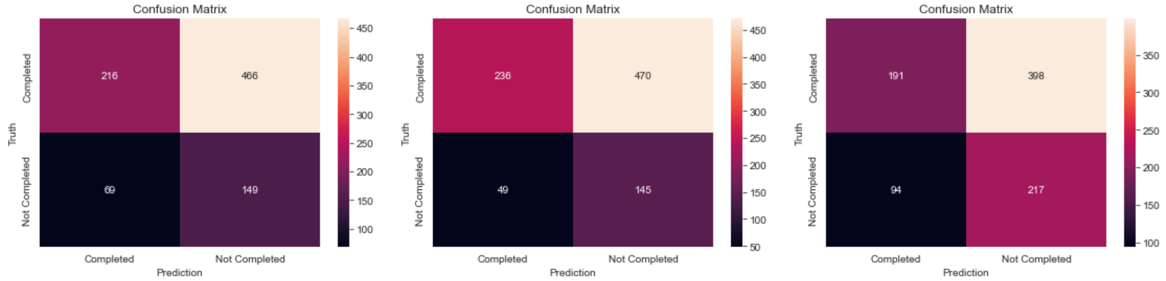


(e) Fold 4

Figure 4.13: Training & validation loss (Model for predicting status)

Table 4.14: Metrics of linear regression models (prices included)

Fold	Accuracy	Precision	Recall	F1 Score
2	0.405	0.242	0.683	0.357
3	0.423	0.235	0.747	0.358
4	0.453	0.352	0.697	0.468



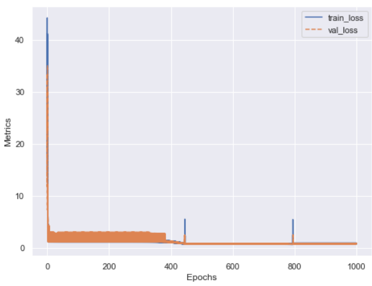
(a) Fold 2 (b) Fold 3 (c) Fold 4

Figure 4.14: Confusion matrices for linear regression models (prices included)

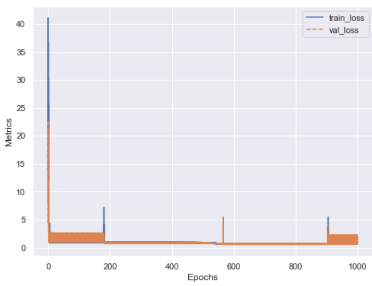
Actual and Predicted Prices Excluded

Figure 4.15 illustrates the training and validation losses of the models that were trained without prices. It is evident that all the models can converge, and the models from folds zero, two and four were utilized for evaluation since they have superior performance. The confusion matrices and metrics are illustrated in figure 4.16 and table 4.15, respectively.

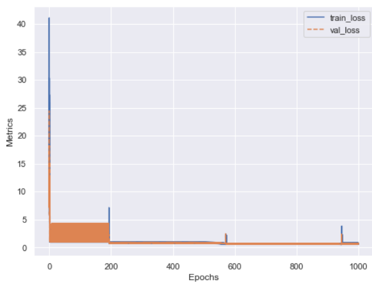
In table 4.15, the recall is the highest, while the precision and F1 score are low, suggesting that although the loss can converge, the performance of models is unreliable. Therefore, more complex neural networks are essential for robust performance regardless of price.



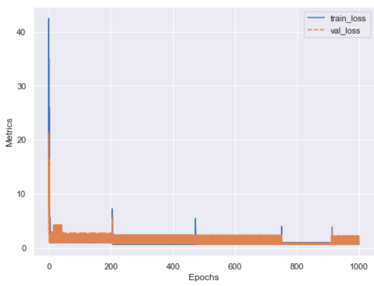
(a) Fold 0



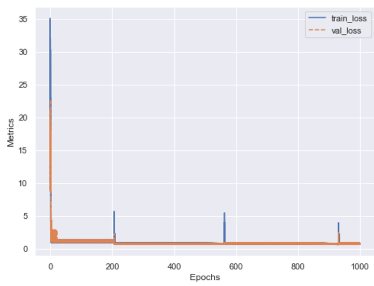
(b) Fold 1



(c) Fold 2

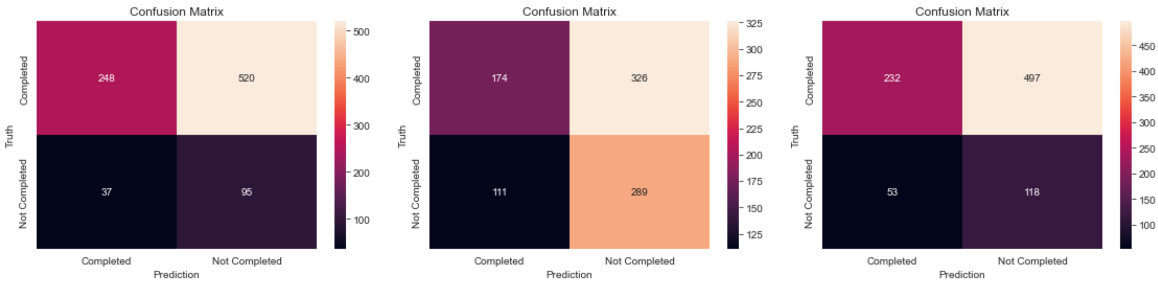


(d) Fold 3



(e) Fold 4

Figure 4.15: Training & validation loss of model for status(without prices))



(a) Fold 0 (b) Fold 2 (c) Fold 4

Figure 4.16: Confusion matrices for linear regression models (prices excluded)

Table 4.15: Metrics of linear regression models (prices excluded)

Fold	Accuracy	Precision	Recall	F1 Score
0	0.381	0.154	0.719	0.254
2	0.514	0.469	0.722	0.569
4	0.388	0.191	0.690	0.300

Chapter 5

Conclusion

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