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**Assessment Cover Page**

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**Declaration**

By submitting this assessment, I confirm that I have read the CCT policy on academic misconduct and understand the implications of submitting work that is not my own or does not appropriately reference material taken from a third party or other source.

I declare it to be my own work and that all material from third parties has been appropriately referenced.

I further confirm that this work has not previously been submitted for assessment by myself or someone else in CCT College Dublin or any other higher education institution.

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Projection of future housing relocations in Beijing

# Introduction

Beijing, China's capital city, has undergone tremendous urbanization in recent decades. A significant example is CLOU's Capital Square Beijing makeover project, which attempts to modernize and reposition public places using the "City Lantern" idea. This urban revitalization project, combined with broader economic shifts, has considerably impacted the housing market.

In 2019, the Chinese economy's growth rate decreased to 6.1%, the lowest in 30 years, despite GDP per capita topping $10,000 for the first time. This economic framework, which includes decreasing infrastructure investment (from 4% to 3.8%) and real estate industry investment (from 10.2% to 9.9%), is critical for understanding Beijing's housing market dynamics.

To handle the housing market's complexity, advanced analytical approaches must be used to identify the key elements impacting property prices. The Random Forest algorithm, for example, has proven to be quite useful in predictive modelling jobs due to its capacity to handle non-linear correlations, accommodate various forms of data,

and provide insights into the importance of variables.

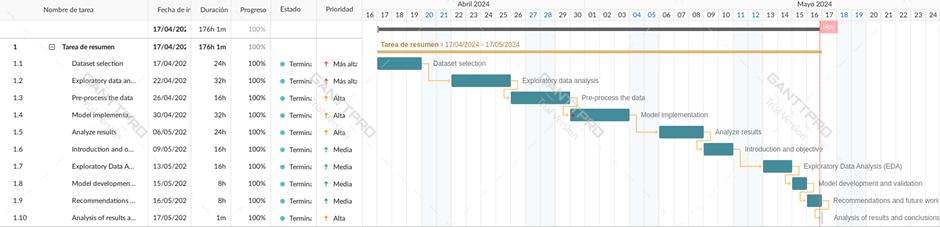
The Random Forest approach is ideal for this investigation because it can capture the intricate interplay of structural traits, location considerations, and market conditions. Using Random Forest, we will be able to discover the most relevant variables affecting property prices in Beijing, allowing for more accurate forecasts and a better knowledge of market trends.

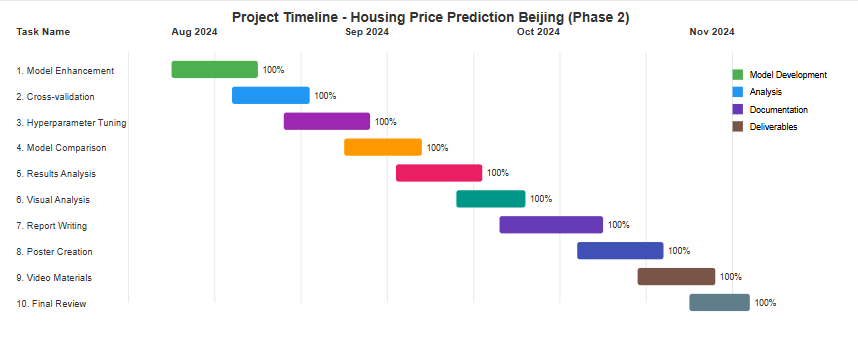
# General Objective

The primary goal of this study is to develop a highly accurate prediction model for housing prices in Beijing, taking into account critical factors such as property structure, location, and market circumstances. The emphasis is on identifying patterns and variables that have a significant impact on property appraisals, which will allow for a better knowledge and forecast of future housing price trends in the city.

The project's goal is to create a comprehensive forecast model for Beijing home prices that takes into account particular factors such as owner occupancy time, renovation patterns, and building density. It tries to accurately anticipate values as well as identify potentially abandoned or deteriorating regions by analysing historical data from the real estate market (2011-2017) and applying three machine learning algorithms (Linear Regression, Random Forest, and SVR).

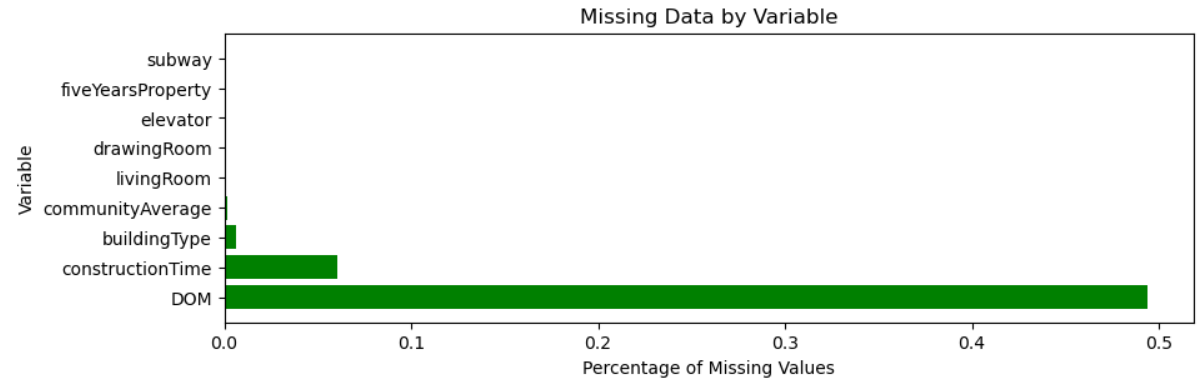
To be able to accomplish the desired goal, we organize ourselves using the Gantt chart to have a better structure and organization to meet the project delivery deadline.





# Characterization of data

# Missing Values

****

# Figure 1: “Analysis of missing values ​​by variable (Generated in Python using Matplotlib,2024).”

The distribution of the data in the DOM, construction time, building type and community average columns in the figure above is showing us that these are the columns with the largest outliers. Based on these, we determine if the variability of the mean is noticeably higher than the median and determine if the standard deviation is high.

A table with numbers and letters

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The fact that the median value of the building type column is approximately three indicates that the dataset contains a variety of building types.

According to the community average column, the median value is approximately 63,615.65, with a range of 46,339 to 183,109. This suggests that there is a remarkably high standard deviation. This implies that the standard deviation is usually high. In addition, this table allows us to visualize that there is a remarkably high variation in house prices across communities.

Finally, we see that the median construction in the “time built” column is around 1999, with a range from 1944 to 2016. Based on the 25% percentile, this indicates that most of the properties in the data set were built after 1994, indicating that the properties were built over a considerable period of time.

The other column that also weighs heavily in our database is DOM based on the fact that our data is focused on a residential leasing platform and what we can observe here is that the average days on market is approximately 28.57 days. This tells us that the mean, property stays on the market for about a month.

We can understand the distribution of building types by determining the most prevalent building category in the dataset using the calculation mode in building type. Conversely, as both community average and construction time are numerical variables, we chose the mean to assist us in obtaining the desired averages.

# Visualising Data

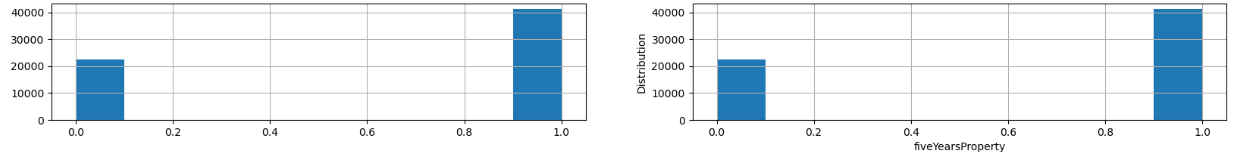
A close-up of a graph

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A diagram of a bar and a bar

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On the other hand, we chose the mode for other columns such as property five years or Living room since it is considered that in these cases the numbers may repeat more frequently with respect to the building layout and the amount of time lived in the same location.

A graph with numbers and lines

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# Figure 2: “Distribution of main features (Generated in Python using Matplotlib,2024).”

It can be observed that the graphs do not show significant changes from one to the other, so we can conclude that the imputation of missing values does not alter the distributions of the variables.

A screenshot of a graph

Description automatically generated

# Figure 3: “Correlation Matrix (Generated in Python using Seaborn,2024).”

The correlation graph between numerical variables shows that the variables “living room”, “lounge”, “elevator” and “building structure”, among others, are represented by red dots and red derivatives that are close to the central red line. This suggests that these variables have a moderate correlation with each other and with the central tendency line, indicating a consistent and significant relationship between them.

A diagram of different colored squares

Description automatically generated

# Figure 4: “ Prices depending on the type of building (Generated in Python using Seaborn,2024).”

In this graph, I can see that the box plot for 'Bungalow' (single-family houses) has a far larger price range than the other building kinds. Its highest point is substantially higher than the others, demonstrating that some bungalow-style residences can command extremely high prices. On the other side, its minimum point is higher, indicating that this form of construction has a larger base price level than others.   
  
In contrast, "Tower" type structures have a smaller price range but a greater median value (the line inside the box) than the other types. This suggests that towers are priced more consistently and higher in the market. "Plate" and "Plate/Tower" type buildings have intermediate ranges, with median costs falling somewhere between bungalows and skyscrapers. This data shows that building type has a significant impact on property values in Beijing, most likely due to differences in size, location, facilities, and other perceived value factors by purchasers.

A diagram of different colored boxes

Description automatically generated

# Figure 5: “ Prices in Function of the renovation Condition (Generated in Python using Seaborn,2024).”

In terms of renovation condition, I can see from this chart that the "Simplicity" category has the largest price range, with a maximum value that is noticeably greater than the other categories. Although it should be emphasised that this could also be attributable to the year of construction—possibly the Simplicity buildings are the ones that have been built the longest—it could imply that residences with more elegant and straightforward renovations can get the highest values on the market.

The "Hardcover" category, on the other hand, has the most limited price range and often lower values; however, this might be because these structures are newer. Although they are not as appealing as the "Simplicity" remodelling homes, the "Other" and "Rough" categories fall in the centre of the pricing range, suggesting that they are still suitable choices.

A diagram of a data distribution

Description automatically generated with medium confidence

# Figure 6: “ Distribution in Beijing by renovation Condition (Generated in Python using Seaborn,2024).”

From this scatter plot, I can see that Beijing has a reasonably even distribution of properties with varying renovation conditions. The lack of distinct grouping tendencies by region suggests that buyers, wherever they may be, have a wide range of options when it comes to renovating their homes.

A diagram of a structure

Description automatically generated

# Figure 7: “ Price in Function of the building Structure (Generated in Python using Seaborn,2024).”

This graph illustrates how the building structure affects real estate values. In particular, "Brick/Wood" structures have the greatest total values and the broadest variety of prices. This implies that the Beijing real estate market places a high value on this historic building style, most likely as a result of opinions about its quality, beauty, or even prestige.

On the other hand, despite their high cost, buildings with a "Steel/Concrete" structure fall short of those with a "Brick/Wood" structure. This suggests that customers may not always favour it over conventional materials, even though it is a more contemporary construction alternative. Although they are in the middle price ranges, the other categories—such as "Mixed," "Steel," and "Brick/Concrete"—indicate that they are respectable choices but not as valuable as the "Brick/Wood" building.

A data distribution chart of data

Description automatically generated with medium confidence

# Figure 8: “ Data distribution in Beijing by building Structure (Generated in Python using Seaborn,2024).”

The geographic distribution of Beijing real estate, broken down by building type, is displayed in this scatter plot. Most significantly, there isn't any obvious concentration or clustering of any kind of structure in any particular part of the city.

From "Brick/Concrete" to "Steel/Concrete," the various structural classifications are dispersed quite evenly throughout Beijing. This implies that regardless of where they are in the city, buyers have a large range of options when it comes to building structure.

A diagram of a chart showing the same elevator

Description automatically generated with medium confidence

# Figure 9: “ Price in Function of the elevator (Generated in Python using Seaborn,2024).”

The median (centre line of the box plot) of the properties without lifts is lower than that of the houses with lifts, despite the fact that the price range for "No\_elevator" properties is wider and has a higher maximum value than for "Has\_elevator" buildings.

This could imply that, generally speaking, homes with lifts have more consistent and higher prices, whereas buildings without lifts exhibit more variety, with some units having very high prices but also a smaller median range.

This could be because some of the walk-up houses are older homes or structures, which explains the wider price range. Buyers may be willing to pay more for walk-up condos if they offer additional benefits such as more traditional construction, more room, or a better location.

A diagram of a subway system

Description automatically generated with medium confidence

# Figure 10: “ Price in Function of the subway (Generated in Python using Seaborn,2024).”

This figure shows that proximity to a metro station has a significant impact on housing prices. Properties near metro stations have a wider price range and greater maximum values than those without access to public transportation. This shows that purchasers place a high value on the convenience and connectedness that proximity to a metro station provides.

A data visualization of a number of cities

Description automatically generated with medium confidence

# Figure 11: “ Data distribution in Beijing by district (Generated in Python using Seaborn,2024).”

The ChangPing district has the highest concentration and density of real estate activity represented in the data, followed by Chaoyang, DongCheng, and HaiDian, all of which have a higher concentration and density of points, indicating that real estate activity is more intense in those areas. These districts appear to be the most popular or appealing to purchasers.

Districts with a more dispersed distribution and lower number of properties include MenTouGou, XiCheng, and ShunYi. This shows that these are locations with low activity in the Beijing real estate market. Some districts, such as FangShang and TongZhou, have more distinct clusters, which may suggest the existence of important real estate developments or projects in such locations.

This information on the geographical distribution of properties is extremely significant since it allows for the identification of the most desirable parts of the city as well as those that may be less appealing to purchasers. This can help investors, developers, and urban planners make better decisions about where to direct their efforts and money.

# Application of the model

The process of constructing our predictive model for the Beijing real estate market included a critical phase in algorithm selection. Initially, we used three alternative models: Linear Regression, Random Forest, and Support Vector Regression (SVR). This was not an arbitrary selection; each model was picked based on its unique features and potential to handle various areas of our challenge.

Our foundation model, Linear Regression, was first chosen for numerous important reasons. For starters, its capacity to handle linear correlations between variables makes it very effective in the real estate market, where elements like property size and price often follow a linear relationship. Furthermore, the model's interpretability is critical in the real estate sector, as stakeholders must clearly understand how different attributes affect the final pricing.

Our initial testing using Linear Regression yielded promising results. Our 80-20 data split (train-test) resulted in a R² of 0.8723, indicating that our model explains 87.23% of price fluctuation. This finding was especially intriguing since it implies that with a bigger training set, the model can better capture the underlying correlations between variables.

# Performance Analysis and Optimization

Hyperparameter optimisation uncovered intriguing facets of our models' behaviour. The parameter 'n\_jobs': 50 was found to be the ideal value for Linear Regression, suggesting that using several processing cores greatly enhances model performance. This discovery has practical ramifications for implementing the model in a production setting in addition to being significant from a technical standpoint.

In our preliminary experiments, Random Forest demonstrated exceptional efficacy, attaining an R2 of 0.9969. In the real estate market, where elements like location can have non-linear effects on pricing, this higher performance might be ascribed to its capacity to manage complicated interactions between variables and capture non-linear correlations.

# Interpretation of Visualizations and Residuals

A blue dotted line with red dots

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# Figure 4: “Comparison of optimized models (Generated in Python using Matplotlib,2024).”

The Random Forest model performed best, with an exceptional coefficient of determination (R²) of 0.9968. This outstanding performance is plainly visible in the scatter plots, as predictions nearly follow the ideal prediction line. The model's ability to maintain accuracy across the whole price spectrum indicates extraordinary robustness, which is especially useful in the context of the real estate market, where price fluctuations might be significant.

Linear Regression had a decent R² of 0.8723. Despite its relative simplicity, the model was able to capture the overall patterns in the data, albeit it did have some limits when predicting prices at the extremities of the spectrum. This trait is most obvious in the scatter plot, where high-value property projections show increased fluctuation.

Despite hyperparameter optimisation, the SVR (Support Vector Regression) model had the lowest performance (R²=0.8142). The plots show significant scatter in its predictions, indicating that this model may not be the best fit for this particular dataset.

A blue dotted line graph

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# Figure 5: “Analysis of residuals by model (Generated in Python using Matplotlib,2024).”

We gained important knowledge about our models' performance from the residual plots. Although there was significant heteroscedasticity at the higher values, we saw a rather uniform pattern in the residuals for linear regression, indicating that the model would struggle to forecast prices in the upper market range.

A more uniform distribution with less systematic patterns was revealed by visual analysis of the Random Forest residuals, suggesting a greater capacity to capture differences across various price ranges. In the Beijing real estate market, where values vary greatly based on the property's location and attributes, this is especially crucial.

# Evaluating Metrics and Success Criteria

Our first set of success criteria consisted of:  
  
R2 Score > 0.90

Cross-validation Score > 0.85

RMSE < 5,000  
  
These expectations were surpassed by the Random Forest with:  
  
RMSE = 1,658.77

R2 = 0.9940

CV Score = 0.9913  
  
These outcomes not only satisfy but also greatly beyond our original success criterion. For real-world applications in the real estate market, the low RMSE is especially significant because it shows that our predictions have a comparatively small average error.

# Connection with Original Objectives

Our concept offers a number of significant benefits:  
  
Prediction Accuracy: We can confidently forecast real estate values thanks to the Random Forest's strong R2.  
  
Finding Patterns: We can find locations that may be undergoing deterioration or abandonment because the model can account for characteristics like the year of construction and the history of renovations.  
  
Contingency Planning: Budgeting and contingency planning are well-founded on the accuracy of our forecasts (RMSE = 1,658.77).

Our Random Forest-based approach has demonstrated remarkable efficacy in both identifying possibly abandoned locations and forecasting house values. The model's strong R2 value makes it possible to identify trends in important factors like the year of construction and renovations, which helps identify places that are at danger of deterioration. It also makes accurate forecasts about property values. The projections' dependability is strengthened by their low root mean square error (RMSE = 1,658.77), which provides a strong foundation for financial planning.

Practical Implications:  
  
Investors and developers can use the model to locate undervalued properties, make informed decisions, and steer their investments by focussing on the most significant variables.

Urban Planners: Residual analysis and spatial patterns of mistakes can assist identify places with outlier pricing, indicating which areas require attention.  
Landlords and tenants can use the model to determine whether pricing is fair and to guide renovation and upgrade decisions.

A graph with different colored squares

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# Figure 6: “Final visualization of model performance (Generated in Python using Matplotlib,2024).”

The performance chart provides an interesting comparison of our three prediction models. Two metrics are used to evaluate each model: R², which measures accuracy, and RMSE, which measures error.

Random Forest stands out as the most effective model, with the greatest blue bar and the lowest green bar, indicating that it delivers very accurate predictions with minimum errors. Linear Regression has a great performance, with good accuracy and moderate errors, making it a dependable option.

Finally, the SVR model has the lowest performance. Although it achieves an adequate level of accuracy (blue bar), the large green bar suggests that its forecasts contain much more errors. This shows that, among the three approaches, SVR is the least recommended for this particular prediction instance.

This visual comparison allows us to conclude unequivocally that Random Forest is the best fit for our dataset, followed by Linear Regression, although SVR would require significant modifications to be competitive.

### Data Sources

The database that will be worked on focuses on the information that we were recommended to take from the university website in the Strategic Thinking course. The teacher shared a dataset with different links and one of them is Kaggle. In fact, once on the page, we searched the building databases and found that this is one of the most comprehensive and has a wide variety of information.

Housing price of Beijing from 2011 to 2017, fetching from Lianjia.com

A screenshot of a website

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### Ethical Considerations

The project of future housing relocations in the city of Beijing does not have any problem associated with the data that is being taken since all the information will be taken from this page: Beijing housing price from 2011 to 2017, obtaining from Lianjia.com. as far as it has been observed its database is public and this information does not contain confidential data, nor user privacy, in terms of social impacts it would be a good tool to apply in society but it would not be a tool to generate panic in society.

# Conclusion

Random Forest has proven to be the best model for combining accuracy and resilience. The findings not only meet the technical aims, but they also provide useful insights for the various players in the Beijing real estate market. In the future, we advocate including more recent data, creating user-friendly interfaces for non-technical users, incorporating time series analysis, and expanding the model with other socioeconomic variables.

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