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Resale HDB Price Prediction Considering Covid-19 through Sentiment Analysis

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Abstract: Twitter sentiment has been used as a predictor to predict price values or trends in both the stock market and housing market. The pioneering works in this stream of research drew upon works in behavioural economics to show that sentiment or emotions impact economic decisions. Latest works in this stream focus on the algorithm used as opposed to the data used. A literature review of works in this stream through the lens of data used shows that there is a paucity of work that considers the impact of sentiments caused due to an external factor on either the stock or the housing market. This is despite an abundance of works in behavioural economics that show that sentiment or emotions caused due to an external factor impact economic decisions. To address this gap, this research studies the impact of Twitter sentiment pertaining to the Covid-19 pandemic on resale Housing Development Board (HDB) apartment prices in Singapore. It leverages SNSCRAPE to collect tweets pertaining to Covid-19 for sentiment analysis, lexicon-based tool, VADER, is used for sentiment analysis, Granger Causality is used to examine the relationship between Covid-19 cases and the sentiment score, and neural networks are leveraged as prediction models. Twitter sentiment pertaining to Covid-19 as a predictor of HDB price in Singapore is studied in comparison with the traditional predictors of housing prices i.e., the structural and neighbourhood characteristics. The results indicate that using Twitter sentiment pertaining to Covid-19 leads to better prediction than using only the traditional predictors and performs better as a predictor compared to two of the traditional predictors. Hence, Twitter sentiment pertaining to an external factor should be considered as important as traditional predictors. In a micro sense, this paper demonstrates the use of sentiment analysis of Twitter data in urban economics. In a macro sense, the paper demonstrates the extent to which social media is able to capture the behavioral economic cues of a population.

Keywords: Sentiment Analysis, Covid-19, Housing Price Prediction, Tweets, Social Media, Singapore HDB, Economics, Neural Networks

1. Introduction

Homeownership is a very important aspect of economic well-being (Seiler et al. 2020). As over 80% of Singaporeans live in Housing Development Board (HDB) apartments (Joo & Wong 2008), their prices are a matter of national importance. The prices of new HDB apartments are determined by the government and the prices of resale HDB apartments are determined by the market (Phang & Wong 1997).

The Covid-19 virus was first detected in December 2019, and by September 2020, all the major economies of the world had hit a recession (Ryan 2020). Singapore was not an exception, and by April 2020, life had changed significantly for all its residents (Lim et al. 2021).

Sentiment analysis is a process of identifying subjective information in a text using the techniques of natural language processing (Wang et al. 2020). Tools such as VADER (Hutto & Gilbert 2014) can be used to identify the sentiment in social media text data resulting in a sentiment score.

Twitter, according to Wojcik & Hughes (2019), is the “modern public square where many voices discuss, debate and share their views”. Since Covid-19 affects not only daily life but also a country’s economy, it is possible to quantify the sentiment of the public during Covid-19 and study its impact on public economic decisions.

A plethora of literature has used Twitter sentiment to predict price values or study price trends both in the stock market (Bollen & Mao 2011) and in the housing market (Velthorst & Güven 2019). However, very little work considers the influence of Twitter sentiment pertaining to an external factor such as Covid-19 on housing prices. Therefore, this research examines the influence of Covid-19 on HDB apartment resale prices in Singapore.

The focus of the studies that used Twitter sentiments to predict price values or study price trends was on the algorithm used as opposed to the data that was collected. However, the results of a model are highly dependent on the data that is given to it (Redman 2018). Therefore, an examination of the data gathering methods used is important.

This research leverages tweets collected during Covid-19 for sentiment analysis to compare the performance of sentiment of Covid-19 of HDB apartment resale prices in Singapore vis-à-vis other traditional factors.

The following are the contributions of this paper:

1. This paper has performed a survey on literature that used social media data to predict price values or study price trends through the lens of the data used and has made a classification of such literature.
2. It has discovered that there has been little work that considered the influence of sentiments pertaining to an external factor such as Covid-19 on housing prices.
3. To address this gap, it has examined the influence of Covid-19 on HDB apartment resale prices in Singapore through Twitter sentiment, compared with that of other predictors: the structural and neighborhood characteristics of the apartments.
4. The result of this research demonstrates that Twitter sentiments pertaining to Covid- 19 is an important source of information for prediction of housing prices compared with the other traditional predictors during the pandemic.
5. To the best of our knowledge, this paper is the first research pertaining to housing prices and Covid-19 in Singapore.

The rest of the paper is organized as follows: Section II is the literature survey, Section III describes the data collection, Section IV examines the relationship between Covid-19 cases and sentiment pertaining to Covid-19, Section V examines the performance of the sentiment as a predictor of HDB resale prices and Section VI provides the conclusion, limitations, and future works.

2. Literature Survey

Humans are not entirely rational in their decision making and emotions, during the time of decision making, play an important part in economic decisions (Nofsinger 2005). Literature shows that stock market prices are impacted by sentiments caused by various external factors such as temperature on the day of trading (Cao & Wei 2005) and results in sports (Edmans et al. 2007). However, these works were unable to quantify public sentiment pertaining to the respective phenomenon or event and had to use a proxy known as a "mood variable" (Edmans et al. 2007). For example, Hirshleifer & Shumway (2003) had to use cloud cover on the day of trading at the location of the stock exchange as the mood variable. However, this method cannot be used universally because while more sunshine may have a positive effect on sentiment in New York, the reverse may be true in Singapore. Using sentiment analysis on Twitter data, the quantification of the sentiment of the public toward an event or phenomenon and the subsequent study of their impact on public economic decisions is possible. Bollen & Mao (2011) was the first to do so, in which Twitter sentiment was used to predict stock prices, drawing upon Hirshleifer & Shumway (2003) and Nofsinger (2005) and thus building a bridge between behavioral economics and natural language processing. Since then, there has been no shortage of similar research.

Literature that follows this trend can be classified into three categories based on the criteria used to collect tweets for sentiment analysis:

1. Generic collection
2. Topic-based collection
3. Object-based collection

In generic tweet collection, tweets are collected with no specific criteria except that the tweets express emotions. An example is Bollen & Mao (2011), in which tweets that "contain explicit statements of their author's mood states" were collected, i.e, the following expressions: "i feel", "i am feeling", "i'm feeling", "i don't feel", "I'm", "Im", "I am" and "makes me". In topic-based tweet collection, keywords pertaining to the topic are used for tweet collection. An example is Ozturk & Ciftci (2014), in which tweets that contain the following were collected: "USD/TRY", "#USD/TRY", "Dollar" and "#Dollar." In object-based tweet collection, keywords pertaining to the object (companies) are used for tweet collection. An example is Ruan et al. (2018), in which tweets were collected that contain the following: "$AAPL", "$FB", "$GOOG", "$NFLX", "$AMZN", "$GE", "$MSFT" and "$GILD".

However, research such as Hirshleifer & Shumway (2003) and Edmans et al. (2007) demonstrate that sentiment caused by external factors impact stock market prices. The works mentioned above do not study the impact of sentiment pertaining to an external factor on the stock market. Ilyas et al. (2020), which used Twitter sentiment pertaining to Brexit to study the impact of Brexit on the FTSE 100 Index, and Kinyua et al. (2021), which used the sentiment of President Trump's tweets to study their impact on the S&P 100 and DJIA indices, are examples of works that do so.

Literature shows that emotions impact house purchasing decisions as well (Jørgensen 2016). Although this was not drawn upon, the same tweet collection methods have been used to predict price values or study price trends in the housing market as well. Tan & Guan (2021), in which tweets were collected within the geographic location of the United States to study their impact on housing prices within the United States and within the geographic location of Manhattan to study their impact on housing prices within Manhattan, is an example of generic tweet collection. Velthorst & Güven (2019), in which tweets containing the Dutch words: "woningmarkt" and "huizenmarkt" (which both mean "housing market") and "huizenprijzen" (which means "housing prices") were collected to predict the market trends in the Dutch housing market, is an example of topic-based tweet collection. Hannum et al. (2019), in which tweets were collected that contain the name of at least one of the 39 districts of Istanbul to study their impact on housing prices within those 39 districts, is an example of object-based tweet collection.

Some studies use sentiment analysis of data from other social media platforms such as Weibo (Deng et al. 2018) and of financial news (Hu et al. 2021) to predict stock market prices and trends. There are also examples of the use of sentiment analysis of Weibo data (Li et al. 2022) and of news articles (Hausler et al. 2018) for predicting housing prices and trends. To the best of our knowledge there has been no study that has used sentiment analysis of social media data pertaining to an external factor such as Covid-19 to predict price values or study price trends in the housing market.

The Covid-19 pandemic has impacted the housing market across the world (Yiu 2021). It is possible to use Twitter data and sentiment analysis to quantify the public sentiment towards Covid-19 (Ridhwan & Hargreaves 2021). Subsequently, it is possible to study the impact of this sentiment on resale HDB prices in Singapore. To the best of our knowledge, there has been no study on the impact of Covid-19 on the housing market in Singapore.

3. Data Collection

3.1 HDB Data

The HDB resale data and the HDB resale price index data are taken from data.gov.sg and are filtered for the following dates: January 2018 to February 2022, which includes the peak period of the Covid-19 pandemic in Singapore. The resale price is deflated to Quarter I of 2018. Block and street names are combined to form the address and age is calculated from the lease commencement date. The list of primary schools is taken from moe.gov.sg; the list of MRT stations is taken from mrtmapsingapore.com; the list of bus interchanges is taken from landtransportguru.net; and the list of hawker centres is taken from sgclean.gov.sg with their addresses being taken from streetdirectory.com. Using the addresses and OneMapAPI (One Map API 2018), the longitude and latitude are calculated. The following are calculated for each apartment: Proximity to the Nearest Primary School, Proximity to the Nearest MRT Station, Proximity to the Nearest Bus Interchange, Proximity to the Central Business District (CBD) and Proximity to the Nearest Hawker Centre, using the GeoPy library (Esmukov 2021). The total number of instances in the dataset is 100,506.

This dataset is further divided into Pre-Covid, dating from January 2018 to December 2019, the period before the Covid-19 pandemic, and Covid, dating from May 2020 to February 2022, which falls within the peak period of the pandemic. The number of instances in the Pre-Covid dataset and in the Covid dataset are 43,743 and 50,830, respectively.

3.2 Twitter Data

Tweets were collected using the Python library SNSCRAPE (Snscrape 2022) for the dates: from 15th February 2020 to 15th February 2021 pertaining to the location: Singapore, language: English and using keywords such as: 'coronavirus', 'nCoV2019','2019nCoV', 'COVID', 'SARS-COV-2', 'circuit breaker', 'Covid-19' as was done in

Ridhwan & Hargreaves (2021). Duplicated tweets were removed based on Tweet ID, @ mentions, retweet symbols, hyperlinks and special characters were removed.

Then sentiment scores were calculated for each tweet using VADER (Hutto & Gilbert 2014). Based on the sentiment scores, daily average sentiment scores were calculated.

3.3 Daily Covid-19 Cases Data

The daily Covid-19 case data from February 15th, 2020, to February 15th, 2022, was collected from moh.gov.sg.

4. Relationship Analysis: Covid-19 Cases and Covid-19 Sentiment

4.1 Adjusted VADER

Covid-19 has been a very negative experience in Singapore and has caused panic among the public (Ho et al. 2020). But the number of positive tweets pertaining to Covid-19 calculated using VADER far exceeds that of negative tweets as shown in Fig.1, which is in line with the results of Ridhwan & Hargreaves (2021). This could be because VADER being a lexicon-based sentiment analysis tool (Hutto & Gilbert 2014), is limited by its lexicon (Kannan et al. 2016) and is unable to handle neologisms.

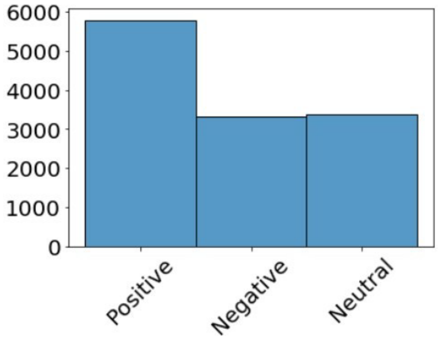

Figure 1: Histogram of Tweets – VADER

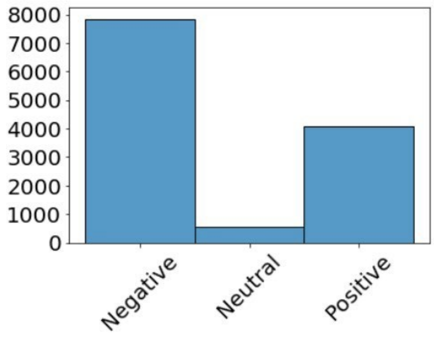

Figure 2: Histogram of Tweets - Adjusted VADER

Based on the keywords used for tweet collection, words and sentiment scores were added to VADER's lexicon. pertaining to Covid-19 such as :'coronavirus','2019nCoV', 'COVID -1', 'SARS-COV-2', 'circuit breaker', 'Covid-19', 'Covid19', 'covid', 'cases', 'circuitbreaker', 'stayhome', 'death and 'deaths' were considered negative, words that ameliorated the situation such as: 'vaccine' and 'vaccines' were considered positive and due to the negative im plications and ubiquity of the phrase 'Covid positive' the word 'positive' was considered neutral. This is called the Adjusted VADER. Then sentiment scores were calculated again for each tweet using this Adjusted VADER. Fig.2 shows that negative tweets exceed positive tweets as it is befitting of tweets pertaining to Covid-19

Table 1: Granger Causality - Cases on Adjusted VADER Sentiment

Lags	SSR based F Test	P - value	SSR based Chi2 Test	P - value
1	42.515	0.0000	42.690	0.0000
2	17.805	0.0000	35.855	0.0000
3	11.244	0.0000	34.060	0.0000
4	6.976	0.0000	28.253	0.0000
5	5.047	0.0001	25.625	0.0001
6	4.335	0.0003	26.487	0.0002

Table 2: Granger Causality - Adjusted VADER Sentiment on Cases

Lags	SSR based F Test	P - value	SSR based Chi2 Test	P - value
1	0.061	0.8056	0.061	0.8052
2	0.198	0.8207	0.398	0.8195
3	0.339	0.7969	1.028	0.7945
4	0.529	0.7143	2.144	0.7094
5	0.899	0.4811	4.565	0.4712
6	0.792	0.5760	4.841	0.5643

Table 3: Results of Model 1

Characteristics	F - statistic	P - value
Flat Type	535.43	0
Storey Range	528.46	0
Flat Model	1056.68	0
Floor Area	530.42	0
Age	13158.179	0
Proximity to Nearest Bus Interchange (Bus Interchange)	779.58	0
Proximity to Nearest MRT Station (MRT)	246.32	0
Proximity to Central Business District (CBD)	142.33	0
Proximity to Nearest Primary School (Primary School)	17.22	0
Proximity to Nearest Hawker Centre (Hawker Centre)	18.70	0

4.2 Granger Causality

Subsequently, daily average sentiment scores were calculated. As indicated by Table 1 and Table 2, at a 5% significance level, the daily Covid-19 case number Granger Causes the daily average Covid-19 sentiment score calculated using the Adjusted VADER, but the reverse is not true.

5. Performance Analysis and Discussion: Covid-19 Sentiment as a Predictor for HDB Resale Prices

5.1 Hedonic Price Model

Using the Hedonic Price Model, the price function of housing can be represented as follows: P = f (S, N) where S is the structural characteristics of the house and N is the neighborhood characteristics (Rosen 1974). According to the Monocentric City Model, most business activity occurs around a single point i.e, the CBD. Therefore, housing prices decrease with distance from the CBD (Alonso 1964). HDB resale apartment prices in Singapore are influenced by the following structural characteristics: Floor Area, Apartment Type, Apartment Model, Apartment Age, Apartment Storey and the following neighborhood characteristics: Proximity to the CBD, Proximity to the Nearest Bus Interchange, Proximity to the Nearest MRT Station, Proximity to the Nearest Hawker Centre and Proximity to the Nearest Primary School (Yuen 2005) (Belcher & Chisholm 2018).

$$Price_{it} = \alpha_i + \beta_1 type_i + \beta_2 storey_i + \beta_3 area_i + \beta_4 apartmentmodel_i + \beta_5 age_{it} + \beta_6 interchange_i$$

$$+ \beta_7 MRT_i + \beta_8 CBD_i + \beta_9 school_i + \beta_{10} hawker_i + \beta_{11} dummy_{quarterly} + \beta_{12} dummy_{town} + \epsilon_{it} \quad (1)$$

To confirm this, Model (1) 1 is fit on the Pre-Covid dataset, whose results are shown in Table 3. At a 5% significance level, all the characteristics listed above influence the resale HDB apartment prices in Singapore (R2 = 0.848).

Further, each of the characteristics is individually used as a predictor of resale HDB apartment prices. The training set and test set (test-train split = 0.25: 0.75), which are both taken from the Pre Covid dataset, are kept the same across the predictors. The prediction is carried out using neural networks of four hidden layers, using two different activation functions: Rectified Linear Unit (ReLU) and Scaled Exponential Linear Unit (SELU). The neural networks are built using the library Keras (Chollet 2015), and each network is trained across 1000 epochs with early stoppage whose results are shown in Fig.3 and Fig.4. The results show that the structural characteristics are better predictors of resale HDB apartment prices than the neighborhood characteristics.

1dummyquarterly captures the time variant effects on apartment prices and dummytown captures the effect on apartment prices that varies from one residential town in Singapore to as was done in Belcher & Chisholm (2018).

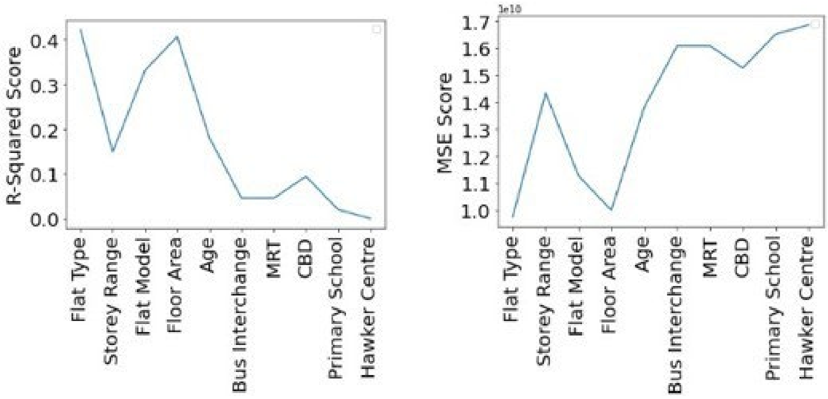

Figure 3: Prediction of Pre Covid HDB Prices using SELU Activation

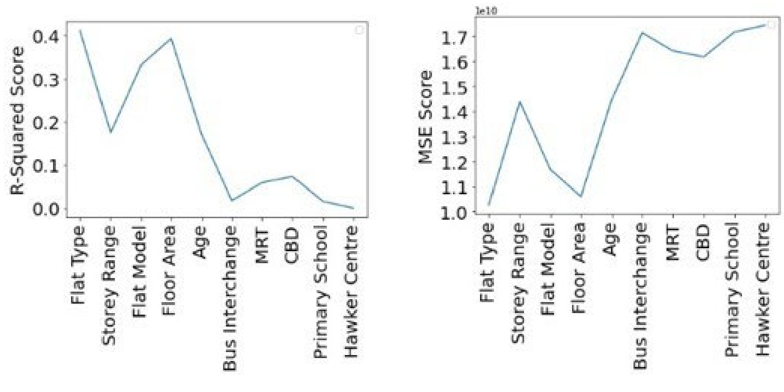

Figure 4: Prediction of Pre Covid HDB Prices using ReLU Activation

5.2 Covid-19 Sentiment as a predictor of HDB resale Prices

As the statistical significance of the traditional characteristics of housing that determine housing prices i.e., the structural and neighbourhood characteristics has been confirmed, their performance as predictors of HDB resale prices can be compared to that of Twitter sentiment pertaining to Covid-19.

The average time taken for housing purchase decisions in Israel was about 8.2 weeks in 2010 (Genesove & Han 2012), its local population in 2010 was 7.6236 million (Population,Total-Israel 2021), and that of Singapore in 2018 was 3.9942 million (Population trends 2018 2018). As the number of houses in a country is a function of the population of the country (Mulder 2006), it can be said that the time taken for housing purchase decisions depends on the population. Therefore, the estimated average time taken for housing purchase decisions in Singapore is about 4.3 weeks, or approximately a month. Hence, the monthly average Covid-19 sentiment score calculated using the Adjusted VADER is chosen as a predictor.

Before prediction, Model (2) is fit on the Covid dataset, whose results are shown in Table 4. At a 5% significance level, the monthly average Covid-19 sentiment score calculated using the Adjusted VADER is statistically significant even though two traditional neighbourhood characteristics: Proximity to Nearest Primary School and Proximity to Nearest Hawker Centre are not (R2 = 0.902).

$$Price_{it} = \alpha_i + \beta_1 type_i + \beta_2 storey_i + \beta_3 area_i + \beta_4 apartmentmodel_i + \beta_5 age_{it} + \beta_6 interchange_i$$

$$+\beta_7 MRT_i + \beta_8 CBD_i + \beta_9 school_i + \beta_{10} hawker_i + \beta_{11} sentiment_t + \beta_{12} dummy_{quarterly} + \beta_{13} dummy_{town} + \epsilon_{it} \quad (2)$$

The monthly average Covid-19 sentiment score's performance as a predictor of resale HDB apartment prices is compared with that of the structural and neighborhood characteristics listed above. This was done on Covid dataset using the same approach as was done for the Pre Covid dataset, using the same test-train split (0.25−0.75), whose results are shown in Fig.5 and Fig.6.

Furthermore, using the same training and test set, the R-squared of a combined predictor which uses the traditional structural and neighbourhood characteristics, and the monthly average Covid-19 sentiment score is

Table 4: Results of Model 2

Characteristics	F - statistic	P - value
Flat Type	67.073	0
Storey Range	582.523	0
Flat Model	461.486	0
Floor Area	4806.183	0
Age	24522.495	0
Bus Interchange	712.039	0
MRT	237.220	0
CBD	150.860	0
Primary School	1.436	0.231
Hawker Centre	0.027	0.870
Monthly Average Covid-19 Sentiment Score (Sentiment)	57.275	0

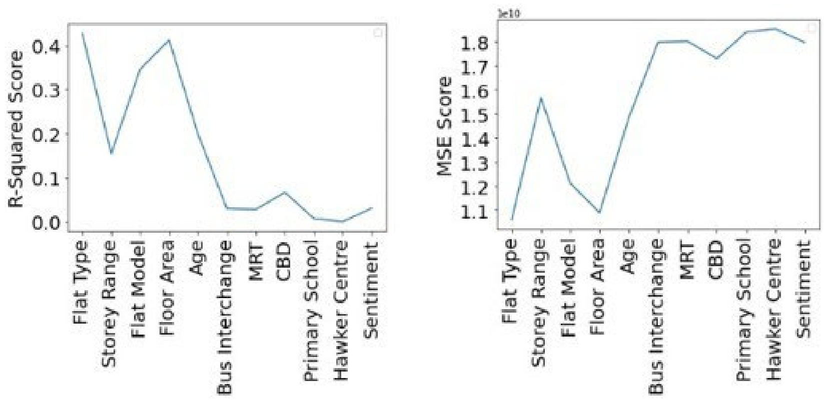

Figure 5: Prediction of Covid HDB Prices using SELU Activation

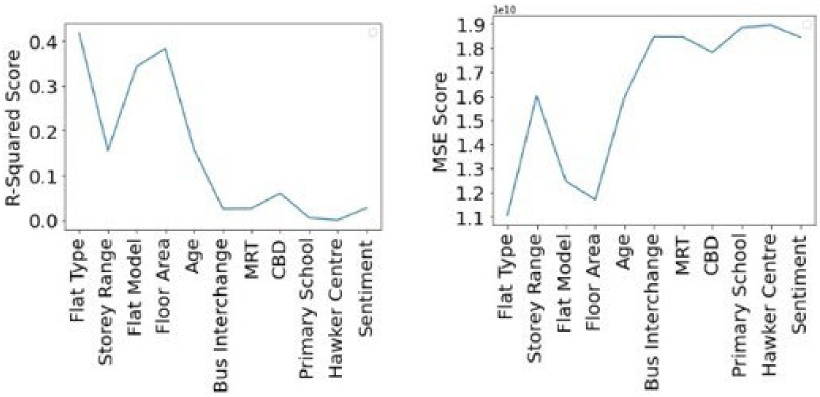

Figure 6: Prediction of Covid HDB Prices using ReLU Activation

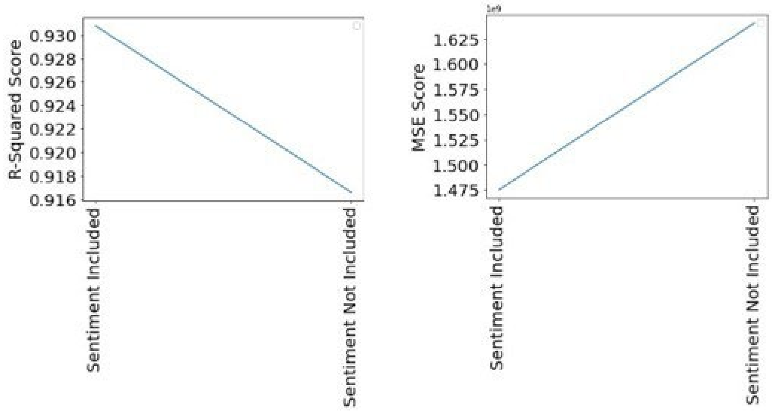

Figure 7: Prediction of Covid HDB Prices using SELU Activation with and without Sentiment

compared to a combined predictor which uses only the traditional structural and neighbourhood characteristics. The results of this comparison are shown in Fig.7 and Fig.8. The results indicate the following:

1. The monthly average Covid-19 sentiment score is a better predictor than the neighbourhood characteristics: Proximity to the Nearest Primary School and Proximity to the Nearest Hawker Centre i.e., higher R- Squared score and lower Mean Squared Error.
2. The combined predictor that uses the monthly average Covid-19 sentiment score performs better than the one that does not i.e., higher R- Squared score and lower Mean Squared Error.

The results indicate that sentiment pertaining to Covid-19 leads to better prediction of housing prices in Singapore during the Covid-19 pandemic than only using traditional predictors. This is notable because it is well established in literature that structural characteristics and neighborhood characteristics influence housing prices (Belcher & Chisholm 2018) (Yuen 2005), but there is no literature precedent for an external factor such as Covid-19 influencing housing prices.

6. Conclusion, Limitations and Future Works

6.1 Conclusion

An examination of the literature that uses sentiment analysis of social media data to either predict price values or study price trends showed that sentiment pertaining to an external factor such as Covid-19 has never been used to predict housing prices. This research addressed this gap and proposed to study the resale HDB apartment price considering Twitter sentiment during the Covid-19 pandemic. It examines the influence of Covid-19 on HDB resale prices in Singapore through Twitter sentiment analysis in comparison with other traditional predictors of housing price: the structural and neighbourhood characteristics. The results show that Twitter sentiment pertaining to Covid- 19 can be an important predictor of HDB resale prices vis-à-vis other traditional predictors. In a micro sense, this paper demonstrates the use of sentiment analysis of Twitter data in urban economics. In a macro sense, the paper demonstrates the extent to which social media is able to capture the behavioral economic cues of a population. This research draws on works in natural language processing, behavioral economics and urban economics and opens opportunities for future interdisciplinary research.

6.2 Limitations

Although this research provides useful insights and practical insights about the application of twitter sentiment analysis during the Covid-19 pandemic to resale HDB apartment price prediction, it has its limitation in that it has only considered HDB resale prices in Singapore and not private property prices.

6.3 Future Works

Future work could include private property data and compare the impact of the two through the lens of property rights theory. Future works could also examine what exactly does Twitter sentiment pertaining to Covid-19 represents from an economic perspective. Future works could examine how social media sentiment fits into the area of urban economics. Future works could also examine how the impact of this sentiment on housing prices varies through the different phases of the pandemic.

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