Enhancing Real Estate Market Predictions Through Pre-Trained Language Models: an NLP Approach

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***Abstract*— This capstone project delves into the innovative application of advanced Natural Language Processing (NLP) techniques in the realm of real estate market prediction. Titled "Enhancing Real Estate Market Predictions through Pre-Trained Language Models: An NLP Approach", this study investigates the efficacy of state-of-the-art pre-trained language models, including BERT, DistilBERT, RoBERTa, GPT-2, XLNet, and ELECTRA, in interpreting and predicting real estate market trends.**

Employing a rich dataset encompassing diverse property attributes and descriptions, the project applies these NLP models, typically associated with sophisticated language understanding tasks, to a novel context: analysing and predicting real estate values. The research methodology involves pre-processing real estate data into a structured format that enables the language models to effectively analyse the textual information, thus forging a unique intersection between NLP and real estate analytics.

The experimental phase of the project systematically evaluates the predictive performance of each model, offering comparative insights into their respective strengths and limitations in the context of real estate market analysis. This approach not only showcases the application of NLP in a sector traditionally reliant on numerical and categorical data but also extends the utility of pre-trained language models to a new industry domain.

Initial findings suggest that certain models demonstrate superior accuracy in price prediction (ELECTRA and XLNet), indicating a significant potential for NLP to enhance traditional real estate market analysis methods. This research underscores the versatility of NLP techniques and provides a foundation for further exploration into the synergistic integration of language models and domain-specific datasets. The project's outcomes are expected to offer valuable perspectives to real estate professionals and contribute to the ongoing evolution of data-driven decision-making in the industry.

I. Introduction

The advent of sophisticated natural language processing (NLP) models has revolutionized the analysis of real estate data, a domain traditionally reliant on quantitative data but now increasingly turning to textual content. This study explores the application of various pre-trained NLP models to predict house values based on textual descriptions, reviews, appliances, and addresses.

A. The Challenge of Real Estate Price Prediction

Traditionally, real estate price prediction has emphasized numerical and categorical data like square footage and location. However, this overlooks the rich qualitative information embedded in textual data, which provides deeper insights into a property's appeal and value.

B. Objective of the Study

The primary objective is to identify the most effective NLP model for predicting house prices from textual data. With online platforms like Airbnb and Zillow offering a plethora of textual information, there's a significant opportunity to enhance valuation accuracy and depth.

C. Impact and Significance of the Study

This research integrates advanced NLP techniques into real estate analytics, potentially transforming the industry's approach to market analysis. By utilizing textual data, the study contributes to a more comprehensive understanding of property values and supports more informed investment decisions.

D. Role of Textual Data in Real Estate

Textual data in real estate listings is a rich tapestry of descriptive language, subjective assessments, and nuanced details. It presents both opportunities and challenges: while offering a more complete picture of a property, textual data is inherently unstructured and complex to analyze. Traditional data analysis methods fall short in capturing the subtleties and contextual meanings embedded in natural language. Hence, advanced NLP techniques are essential to extract, interpret, and quantify the valuable information contained within these texts.

E. Leveraging NLP Models for Price Prediction

In this light, sophisticated NLP models, such as BERT, RoBERTa, DistilBERT, GPT-2, XLNet, and ELECTRA, emerge as potent tools for transforming textual data into actionable insights. These models offer varying approaches to understanding and interpreting language, each with its unique strengths and limitations in the context of real estate data. By effectively harnessing these models, it becomes possible to bridge the gap between the qualitative richness of textual descriptions and quantitative accuracy in price prediction.

The subsequent sections delve into each of these models, exploring their technical architectures, benefits, and drawbacks, particularly in the context of real estate price prediction. This examination aims to underscore the transformative potential of NLP in real estate analytics, paving the way for more informed and accurate property valuations.

F. Models Utilized for Real Estate Text Analysis

In evaluating the most suitable NLP model for real estate price prediction from textual data, this study assesses a range of pre-trained models. BERT and its optimized counterpart RoBERTa, introduced by Devlin et al. [1] and Liu et al. [3], employ bidirectional transformer architectures, enabling them to excel in contextually rich text interpretation, a feature indispensable for analyzing real estate descriptions. However, they are computationally demanding [2][4]. DistilBERT, a streamlined version of BERT proposed by Sanh et al. [5], offers a balance between performance and efficiency, suitable for rapid text processing, despite a minor trade-off in handling complex language [6].

GPT-2, crafted by Radford et al. [7], shines in text generation, potentially enhancing real estate narratives for market listings. Yet, its unidirectional approach may not fully capture the contextual depth as bidirectionally trained models do [8]. Yang et al.'s XLNet [9] merges the best of autoregressive and autoencoding methods, providing a powerful tool for detailed textual analysis but with substantial computational requirements [10]. Lastly, ELECTRA, developed by Clark et al. [11], brings forth an efficient pre-training mechanism that classifies token replacements accurately, making it a strong candidate for processing extensive real estate datasets without incurring high computational costs [12].

G. Application to Real Estate Data

This research aims to discern which model best translates real estate textual data into accurate property prices, considering the specific requirements of accuracy, interpretability, and computational efficiency in the real estate context.

II. Literature Review

The domain of real estate price prediction has been extensively explored, with a rich body of research employing various methodologies. Historically, the focus has predominantly been on quantitative models that leverage numerical and categorical data.

A. Traditional Approaches to Real Estate Valuation

Traditional real estate valuation methods primarily involve regression models, such as linear regression, to predict property prices based on quantifiable attributes like size, location, age, and amenities [13]. Advanced techniques like machine learning have also been applied, using algorithms such as Random Forests and Support Vector Machines to enhance prediction accuracy [14]. These methods, while effective in capturing the impact of tangible property features, often overlook the nuanced information embedded in textual descriptions.

B. Emergence of Textual Analysis in Real Estate

More recent studies have begun to explore the role of textual data in real estate. Sentiment analysis on user reviews, for instance, has been shown to impact hotel pricing strategies [15]. In the residential real estate sector, preliminary research indicates that the sentiment and quality of textual property descriptions can influence buyer perceptions and, subsequently, property values [16].

C. Use of NLP in Real Estate

The application of NLP in real estate is a relatively new but rapidly evolving area. Research in this field has primarily focused on extracting specific features from property descriptions and correlating them with price variations [17]. However, these studies often employ basic NLP techniques and lack the depth provided by advanced language models like BERT or GPT-2.

D. Gaps in Current Research

While existing research acknowledges the value of textual data in real estate, there remains a significant gap in comprehensively analyzing this data using state-of-the-art NLP models. Most current studies do not fully exploit the advanced capabilities of these models to understand the context and subtleties of language in property descriptions. Moreover, there is limited research comparing the effectiveness of different NLP models in the specific context of real estate price prediction.

E. Potential Contributions of this Study

This study aims to fill these gaps by systematically evaluating several advanced NLP models for their efficacy in predicting real estate prices based on textual data. By comparing models like BERT, RoBERTa, and GPT-2, the research seeks to identify the most suitable model for capturing the intricate relationships between textual descriptions and property values. This approach not only contributes to the field of real estate analytics but also expands the application scope of NLP models, providing valuable insights into their practical utility in diverse domains.

III. Methodology

The methodology of this research is structured into three primary subsections: data collection, the selection of pre-trained models, and data processing and analysis. Each component is crucial to the integrity and success of the study.

A. Data Collection

The real estate data used in this study was sourced from Datafiniti, a comprehensive database offering rich and varied real estate listings. This dataset was chosen due to its extensive coverage and diverse range of property features, including textual descriptions, appliances, architectural styles, and historical price data. The inclusion of these varied data points allows for a holistic analysis of properties and offers a robust foundation for applying advanced NLP techniques.

B. Selection of Pre-trained Models

The study employs several pre-trained NLP models, each chosen for its unique strengths in processing and understanding textual data. The models used are:

1. **RoBERTa**: Known for its robust performance on language understanding tasks, making it ideal for interpreting complex real estate descriptions.
2. **BERT**: Highly effective in understanding context within text, which is crucial for extracting meaningful insights from property descriptions.
3. **DistilBERT**: Offers a balance between performance and efficiency, suitable for scenarios where computational resources might be limited.
4. **GPT-2**: Its generative capabilities allow for innovative approaches to modeling and predicting property values based on descriptive text.
5. **XLNet**: Superior in capturing bidirectional context, which is beneficial for analyzing detailed property listings.
6. **ELECTRA**: Efficient in training and effective in understanding textual nuances, making it a practical choice for large-scale real estate datasets.

These models were selected to explore a range of capabilities, from deep understanding of context to efficient processing of large datasets, thereby catering to different aspects of real estate data.

C. Data Processing and Analysis

The data processing and analysis pipeline consists of several steps:

1. **Preprocessing**: The dataset undergoes initial cleaning and preprocessing. This includes filling missing values, standardizing textual data, and combining relevant features into a singular text representation for each listing.
2. **Feature Engineering**: Key features for the study, including property descriptions and attributes, are extracted, and combined to form a comprehensive textual representation.
3. **Normalization**: The target variable, house price, is normalized to reduce variance and improve model performance.
4. **Model Training and Evaluation**: Each NLP model is trained on the processed dataset. The training involves fine-tuning the models with real estate data, employing techniques like cross-validation to enhance model robustness and accuracy.
5. **Performance Metrics**: Models are evaluated based on metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R2 score). These metrics provide insights into each model's accuracy and predictive capabilities.
6. **Comparative Analysis**: The performance of each model is compared to ascertain the most effective approach for real estate price prediction based on textual data.

This methodology aims to rigorously assess the capability of cutting-edge NLP models in predicting real estate prices and to provide a comprehensive understanding of how textual data can enhance real estate market analyses.

IV. RESULTS

A. Model Performance

The following tables show the model results received:

Model	LR	Batch Size	Epochs	Train Loss	Train RMSE	Train MAE	Train R2	Val Loss	Val RMSE	Val MAE	Val R2	Test Loss	Test RMSE	Test MAE	Test R2	Training Time
roberta	0.01	16	1	1298.7378202676800	6.1801357	5.972852	-35.02360074187740	39.12563959757490	6.2481728	6.2096863	-48.493213526082700	39.49251333872480	6.2776675	6.2205415	-41.81374708999730	
roberta	0.01	16	1	1298.7378202676800	6.1801357	5.972852	-35.02360074187740	39.12563959757490	6.2481728	6.2096863	-48.493213526082700	39.49251333872480	6.2776675	6.2205415	-41.81374708999730	49.99643802642820
roberta	0.01	16	2	1701.055995941160	7.1038494	7.0183215	-46.59689729467560	50.871259689331100	7.1464233	7.0910206	-63.74660896147670	50.72550010681150	7.136418	7.071633	-54.32828391110610	
roberta	0.01	16	2	1701.055995941160	7.1038494	7.0183215	-46.59689729467560	50.871259689331100	7.1464233	7.0910206	-63.74660896147670	50.72550010681150	7.136418	7.071633	-54.32828391110610	91.13442301750180
roberta	0.01	32	1	298.422031402588 0	4.1924214	4.0536437	-15.577577685559000	13.923466046651200	3.7339952	3.7051375	-16.676127008860500	14.173848470052100	3.7703342	3.7446902	-14.443523236164900	
roberta	0.01	32	1	298.4220314025880	4.1924214	4.0536437	-15.577577685559000	13.923466046651200	3.7339952	3.7051375	-16.676127008860500	14.173848470052100	3.7703342	3.7446902	-14.443523236164900	49.99356389045720
roberta	0.01	32	2	658.6245765686040	6.184983	6.0840554	-35.08013332846280	40.07845560709640	6.2835636	6.220481	-49.055479419976600	39.601418813069700	6.274873	6.2010937	-41.775639613374900	
roberta	0.01	32	2	658.6245765686040	6.184983	6.0840554	-35.08013332846280	40.07845560709640	6.2835636	6.220481	-49.055479419976600	39.601418813069700	6.274873	6.2010937	-41.775639613374900	1890.5325791835800
roberta	1E-06	16	1	1318.9089889526400	6.225187	6.1380143	-35.55072081168090	39.289175033569300	6.282553	6.2194605	-49.03937668364180	39.177331606547000	6.2738643	6.200072	-41.7618833353951	
roberta	1E-06	16	1	1318.9089889526400	6.225187	6.1380143	-35.55072081168090	39.289175033569300	6.282553	6.2194605	-49.03937668364180	39.177331606547000	6.2738643	6.200072	-41.7618833353951	51.02522110939030
roberta	1E-06	16	2	1314.2909545898400	6.221478	6.134832	-35.50717852696040	39.2764622370402	6.2815394	6.2184367	-49.02323356546520	39.16465950012210	6.2728524	6.199048	-41.748092918810300	
roberta	1E-06	16	2	1314.2909545898400	6.221478	6.134832	-35.50717852696040	39.2764622370402	6.2815394	6.2184367	-49.02323356546520	39.16465950012210	6.2728524	6.199048	-41.748092918810300	93.09079504013060
roberta	1E-06	32	1	659.1498718261720	6.2264643	6.1380224	-35.56571794081900	40.04010454813640	6.2805266	6.2174125	-49.00710036139340	39.56329472859700	6.271841	6.198025	-41.73431127156530	
roberta	1E-06	32	1	659.1498718261720	6.2264643	6.1380224	-35.56571794081900	40.04010454813640	6.2805266	6.2174125	-49.00710036139340	39.56329472859700	6.271841	6.198025	-41.73431127156530	891.0540671348570
roberta	1E-06	32	2	659.4376602172850	6.2308774	6.1441307	-35.61757190679580	40.02733357747400	6.279515	6.21639	-48.990992815777400	39.55059941609700	6.270831	6.1970034	-41.72055080353550	
roberta	1E-06	32	2	659.4376602172850	6.2308774	6.1441307	-35.61757190679580	40.02733357747400	6.279515	6.21639	-48.990992815777400	39.55059941609700	6.270831	6.1970034	-41.72055080353550	1936.643385887150

Model	LR	Batch Size	Epochs	Train Loss	Train RMSE	Train MAE	Train R2	Val Loss	Val RMSE	Val MAE	Val R2	Test Loss	Test RMSE	Test MAE	Test R2	Training Time
bert	0.01	16	1	110.57659429311800	1.8065695	1.1512983	-2.078225419983270	2.5006083250045800	1.5576451	1.376613	-2.075930561590320	2.569309175014500	1.5900182	1.388406	-1.7465705210036000	
bert	0.01	16	1	110.57659429311800	1.8065695	1.1512983	-2.078225419983270	2.5006083250045800	1.5576451	1.376613	-2.075930561590320	2.569309175014500	1.5900182	1.388406	-1.7465705210036000	56.10219120979310
bert	0.01	16	2	38.74633648991590	1.1632482	0.49835822	-0.2762504845585140	0.7968538155158360	0.9160265	0.5085656	-0.0637892553956960	0.935744668046633 0	0.9898822	0.5536989	-0.0645195231151616	
bert	0.01	16	2	38.74633648991590	1.1632482	0.49835822	-0.2762504845585140	0.7968538155158360	0.9160265	0.5085656	-0.0637892553956960	0.9357446680466330	0.9898822	0.5536989	-0.0645195231151616	96.12300610542300
bert	0.01	32	1	140.3304141163830	2.8814414	1.683706	-6.830882478605010	2.748516400655110	1.6204996	1.5268022	-2.3291813995714900	2.8310807148615500	1.6764892	1.5927197	-2.053431478000770	
bert	0.01	32	1	140.3304141163830	2.8814414	1.683706	-6.830882478605010	2.748516400655110	1.6204996	1.5268022	-2.3291813995714900	2.8310807148615500	1.6764892	1.5927197	-2.053431478000770	1160.930669784550
bert	0.01	32	2	1652.454330444340	9.6413145	9.449053	-86.67254952897000	100.85150909423800	10.001138	9.961624	-125.8055839388800	100.16867701212600	9.9921665	9.945973	-107.46908420214400	
bert	0.01	32	2	1652.454330444340	9.6413145	9.449053	-86.67254952897000	100.85150909423800	10.001138	9.961624	-125.8055839388800	100.16867701212600	9.9921665	9.945973	-107.46908420214400	2429.9720571041100
bert	1E-06	16	1	3298.995445251470	9.85078	9.793189	-90.52344291616140	99.61670112609860	9.993928	9.954387	-125.62282738316900	99.43082364400230	9.985003	9.938775	-107.31362143666200	
bert	1E-06	16	1	3298.995445251470	9.85078	9.793189	-90.52344291616140	99.61670112609860	9.993928	9.954387	-125.62282738316900	99.43082364400230	9.985003	9.938775	-107.31362143666200	58.00340676307680
bert	1E-06	16	2	3295.691566467290	9.844026	9.786455	-90.39796770739680	99.47240193684900	9.986698	9.947128	-125.4396883955640	99.287535349528	9.97782	9.931557	-107.1578331294720	
bert	1E-06	16	2	3295.691566467290	9.844026	9.786455	-90.39796770739680	99.47240193684900	9.986698	9.947128	-125.4396883955640	99.287535349528	9.97782	9.931557	-107.1578331294720	96.56240630149840
bert	1E-06	32	1	1643.3438262939500	9.832062	9.77569	-90.1759529775317	100.41589991251600	9.979404	9.939805	-125.2550632057210	99.736878712972	9.970572	9.9242735	-107.00077759543100	
bert	1E-06	32	1	1643.3438262939500	9.832062	9.77569	-90.1759529775317	100.41589991251600	9.979404	9.939805	-125.2550632057210	99.736878712972	9.970572	9.9242735	-107.00077759543100	1109.239040851590
bert	1E-06	32	2	1643.0171661377000	9.829436	9.772556	-90.12727519092670	100.26933670043900	9.972081	9.932451	-125.06983242258800	99.59159342447920	9.963297	9.916963	-106.8432024493830	
bert	1E-06	32	2	1643.0171661377000	9.829436	9.772556	-90.12727519092670	100.26933670043900	9.972081	9.932451	-125.06983242258800	99.59159342447920	9.963297	9.916963	-106.8432024493830	2444.113608121870

Model	LR	Batch Size	Epochs	Train Loss	Train RMSE	Train MAE	Train R2	Val Loss	Val RMSE	Val MAE	Val R2	Test Loss	Test RMSE	Test MAE	Test R2	Training Time
distilbert	0.01	16	1	61.96952587738630	1.3548375	0.5170141	-0.7312730061902730	0.8822642639279370	0.968316	0.37971714	-0.1887042766561730	0.9949457574014860	1.0258099	0.35884652	-0.1431951616265710	
distilbert	0.01	16	1	61.96952587738630	1.3548375	0.5170141	-0.7312730061902730	0.8822642639279370	0.968316	0.37971714	-0.1887042766561730	0.9949457574014860	1.0258099	0.35884652	-0.1431951616265710	32.7311589717865
distilbert	0.01	16	2	335.49607038497900	3.2295768	2.8684797	-8.837444889577230	8.957903663317360	2.9891171	2.9535353	-10.327274567624300	9.131769816080730	3.017799	2.9971714	-8.89389352862517	
distilbert	0.01	16	2	335.49607038497900	3.2295768	2.8684797	-8.837444889577230	8.957903663317360	2.9891171	2.9535353	-10.327274567624300	9.131769816080730	3.017799	2.9971714	-8.89389352862517	54.41192889213560
distilbert	0.01	32	1	604.3134021759030	5.959168	5.7426267	-32.493644384643300	33.77615451812740	5.824804	5.787667	-42.01324286945090	34.18400637308760	5.855234	5.8006473	-36.24561722297400	
distilbert	0.01	32	1	604.3134021759030	5.959168	5.7426267	-32.493644384643300	33.77615451812740	5.824804	5.787667	-42.01324286945090	34.18400637308760	5.855234	5.8006473	-36.24561722297400	495.62900400161700
distilbert	0.01	32	2	4353.690460205080	15.776985	15.630849	-233.7681240937060	286.5729064941410	16.891214	16.86785	-360.71067938523100	285.3092041015630	16.875751	16.848457	-308.39469143692000	
distilbert	0.01	32	2	4353.690460205080	15.776985	15.630849	-233.7681240937060	286.5729064941410	16.891214	16.86785	-360.71067938523100	285.3092041015630	16.875751	16.848457	-308.39469143692000	1005.2031831741300
distilbert	1E-06	16	1	8709.795944213870	15.984037	15.936715	-239.97060306493000	284.7221934000650	16.885885	16.862514	-360.48250408504100	284.19608815511100	16.870424	16.84312	-308.199382531237	
distilbert	1E-06	16	1	8709.795944213870	15.984037	15.936715	-239.97060306493000	284.7221934000650	16.885885	16.862514	-360.48250408504100	284.19608815511100	16.870424	16.84312	-308.199382531237	32.885764837265000
distilbert	1E-06	16	2	8719.468002319340	15.988322	15.93931	-240.09983797473900	284.5418853759770 0	16.880543	16.857162	-360.2537658571390	284.0159962972010	16.865082	16.837769	-308.00360269139600	
distilbert	1E-06	16	2	8719.468002319340	15.988322	15.93931	-240.09983797473900	284.54188537597700	16.880543	16.857162	-360.2537658571390	284.0159962972010	16.865082	16.837769	-308.00360269139600	54.809365034103400
distilbert	1E-06	32	1	4352.483459472660	16.00218	15.957713	-240.51800288072000	286.0309295654300	16.875193	16.851807	-360.0248408464270	284.7683970133460	16.859734	16.83241	-307.8076493880600	
distilbert	1E-06	32	1	4352.483459472660	16.00218	15.957713	-240.51800288072000	286.0309295654300	16.875193	16.851807	-360.0248408464270	284.7683970133460	16.859734	16.83241	-307.8076493880600	492.8191351890560
distilbert	1E-06	32	2	4330.487289428710	15.962767	15.917137	-239.32972729703400	285.85036214192700	16.869852	16.846457	-359.7963485098210	284.5882212320960	16.854393	16.827065	-307.61207067062500	
distilbert	1E-06	32	2	4330.487289428710	15.962767	15.917137	-239.32972729703400	285.85036214192700	16.869852	16.846457	-359.7963485098210	284.5882212320960	16.854393	16.827065	-307.61207067062500	973.2529797554020

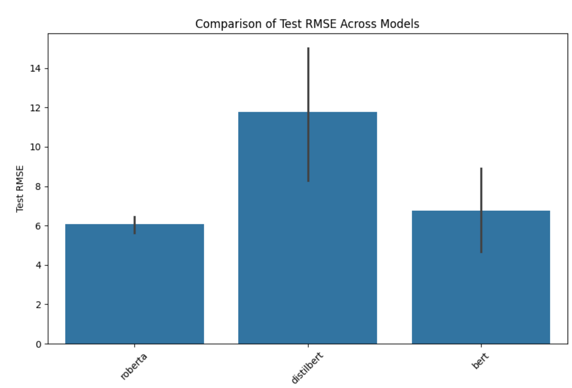
Model	LR	Batch Size	Epochs	Train Loss	Train RMSE	Train MAE	Train R2	Val Loss	Val RMSE	Val MAE	Val R2	Test Loss	Test RMSE	Test MAE	Test R2	Training Time
xlnet	0.01	16	1	473.023146212101	3.736286	2.6574292	-12.16653077561990	3.892769237359370	1.9752946	1.9100174	-3.946561053622060	4.091598093509670	2.0254076	1.9790596	-3.456679732882350	
xlnet	0.01	16	1	473.023146212101	3.736286	2.6574292	-12.16653077561990	3.892769237359370	1.9752946	1.9100174	-3.946561053622060	4.091598093509670	2.0254076	1.9790596	-3.456679732882350	89.0032708644867
xlnet	0.01	16	2	984.5781154632570	5.3964176	5.317327	-26.46642967775910	27.136863390604700	5.2032027	5.171812	-33.32266482979090	27.466521898905400	5.2349005	5.187878	-28.77168730404670	
xlnet	0.01	16	2	984.5781154632570	5.3964176	5.317327	-26.46642967775910	27.136863390604700	5.2032027	5.171812	-33.32266482979090	27.466521898905400	5.2349005	5.187878	-28.77168730404670	169.99778199195900
xlnet	0.01	32	1	204.7184739112850	3.4743686	3.13951	-10.38525995248310	8.602225144704180	2.9273221	2.8885477	-9.863771335856960	8.790741602579750	2.9680703	2.9474	-8.570507615413290	
xlnet	0.01	32	1	204.7184739112850	3.4743686	3.13951	-10.38525995248310	8.602225144704180	2.9273221	2.8885477	-9.863771335856960	8.790741602579750	2.9680703	2.9474	-8.570507615413290	375.6898527145390
xlnet	0.01	32	2	166.58821392059300	3.2657857	3.0400498	-9.059270298522370	10.677594820658400	3.2059739	3.0805	-12.03045262229650	10.432507197062200	3.2079406	3.0611117	-10.17993441745620	
xlnet	0.01	32	2	166.58821392059300	3.2657857	3.0400498	-9.059270298522370	10.677594820658400	3.2059739	3.0805	-12.03045262229650	10.432507197062200	3.2079406	3.0611117	-10.17993441745620	1265.2853922843900
xlnet	1E-06	16	1	322.76727867126500	3.0831409	2.8892956	-7.965568592165950	10.132081906000800	3.2008636	3.075181	-11.98894542879130	10.14258631070460	3.2028656	3.0557928	-10.14458932411050	
xlnet	1E-06	16	1	322.76727867126500	3.0831409	2.8892956	-7.965568592165950	10.132081906000800	3.2008636	3.075181	-11.98894542879130	10.14258631070460	3.2028656	3.0557928	-10.14458932411050	150.44208908081100
xlnet	1E-06	16	2	332.8230333328250	3.1324098	2.9398804	-8.254401171766980	10.100510279337600	3.1959105	3.0700257	-11.94877929261040	10.111215829849200	3.197947	3.0506375	-10.11038690665890	
xlnet	1E-06	16	2	332.8230333328250	3.1324098	2.9398804	-8.254401171766980	10.100510279337600	3.1959105	3.0700257	-11.94877929261040	10.111215829849200	3.197947	3.0506375	-10.11038690665890	427.68637204170200
xlnet	1E-06	32	1	161.39128160476700	3.0830333	2.899476	-7.96494401325196	10.579944133758500	3.1908617	3.0647693	-11.90789894794070	10.336018085479700	3.1929336	3.045381	-10.07557648545970	
xlnet	1E-06	32	1	161.39128160476700	3.0830333	2.899476	-7.96494401325196	10.579944133758500	3.1908617	3.0647693	-11.90789894794070	10.336018085479700	3.1929336	3.045381	-10.07557648545970	606.2479128837590
xlnet	1E-06	32	2	162.847421169281	3.0984142	2.90427	-8.054616992714220	10.54744036992390	3.1858158	3.059515	-11.86710724920550	10.303902626037600	3.1879227	3.0401275	-10.04084231802090	
xlnet	1E-06	32	2	162.847421169281	3.0984142	2.90427	-8.054616992714220	10.54744036992390	3.1858158	3.059515	-11.86710724920550	10.303902626037600	3.1879227	3.0401275	-10.04084231802090	1204.2874600887300

Model	LR	Batch Size	Epochs	Train Loss	Train RMSE	Train MAE	Train R2	Val Loss	Val RMSE	Val MAE	Val R2	Test Loss	Test RMSE	Test MAE	Test R2	Training Time
electra	0.01	16	1	38.33446381986140	1.0652548	0.4320352	-0.0702817872511397	0.7680253411332770	0.90104824	0.45563576	-0.0292850512314140	0.9040619824081660	0.97458285	0.49788177	-0.0318679773783834	
electra	0.01	16	1	38.33446381986140	1.0652548	0.4320352	-0.0702817872511397	0.7680253411332770	0.90104824	0.45563576	-0.0292850512314140	0.9040619824081660	0.97458285	0.49788177	-0.0318679773783834	20.182512760162400
electra	0.01	16	2	36.52598222345110	1.0834352	0.33446813	-0.1071258164889570	0.7788178748063120	0.91120785	0.30221856	-0.0526269081335689	0.9010549878391130	0.9769672	0.2990484	-0.0369232570685900	
electra	0.01	16	2	36.52598222345110	1.0834352	0.33446813	-0.1071258164889570	0.7788178748063120	0.91120785	0.30221856	-0.0526269081335689	0.9010549878391130	0.9769672	0.2990484	-0.0369232570685900	32.57154607772830
electra	0.01	32	1	105.3798890709880	2.4905818	2.2940714	-4.850496424510480	6.067662318547570	2.450119	2.405172	-6.6105133160957400	6.218811591466270	2.4947333	2.4694896	-5.761372629803730	
electra	0.01	32	1	105.3798890709880	2.4905818	2.2940714	-4.850496424510480	6.067662318547570	2.450119	2.405172	-6.6105133160957400	6.218811591466270	2.4947333	2.4694896	-5.761372629803730	26.645070791244500
electra	0.01	32	2	26.49004492163660	1.3226254	0.7770499	-0.6499273194994300	1.6875171562035900	1.1960117	0.8010341	-0.8134702097648810	1.6108131855726200	1.2375169	0.7816459	-0.6637533282855820	
electra	0.01	32	2	26.49004492163660	1.3226254	0.7770499	-0.6499273194994300	1.6875171562035900	1.1960117	0.8010341	-0.8134702097648810	1.6108131855726200	1.2375169	0.7816459	-0.6637533282855820	31.96080994606020
electra	1E-06	16	1	53.19749566912650	1.2536762	0.7013515	-0.4823880751541590	1.3649863104025500	1.195551	0.8003463	-0.8120737159867360	1.4640085498491900	1.2370827	0.7809581	-0.662585797938553	
electra	1E-06	16	1	53.19749566912650	1.2536762	0.7013515	-0.4823880751541590	1.3649863104025500	1.195551	0.8003463	-0.8120737159867360	1.4640085498491900	1.2370827	0.7809581	-0.662585797938553	20.02436923980710
electra	1E-06	16	2	53.28360438346860	1.246272	0.69857055	-0.4649297222056990	1.3638980289300300	1.1950896	0.79965687	-0.8106751815385440	1.4629470854997600	1.2366475	0.7802686	-0.661416349119551 0	
electra	1E-06	16	2	53.28360438346860	1.246272	0.69857055	-0.4649297222056990	1.3638980289300300	1.1950896	0.79965687	-0.8106751815385440	1.4629470854997600	1.2366475	0.7802686	-0.6614163491195510	32.680584192276
electra	1E-06	32	1	26.46658581495290	1.250956	0.7010383	-0.4759621519924910	1.6840792099634800	1.1946276	0.7989661	-0.8092754166431370	1.607528194785120	1.2362119	0.77957803	-0.6602459334622250	
electra	1E-06	32	1	26.46658581495290	1.250956	0.7010383	-0.4759621519924910	1.6840792099634800	1.1946276	0.7989661	-0.8092754166431370	1.607528194785120	1.2362119	0.77957803	-0.6602459334622250	20.567044019699100
electra	1E-06	32	2	26.29951211810110	1.2458451	0.69570494	-0.463926324620374	1.6829301367203400	1.1941648	0.7982738	-0.8078733766168270	1.6064302672942500	1.2357754	0.77888554	-0.6590736476301230	
electra	1E-06	32	2	26.29951211810110	1.2458451	0.69570494	-0.463926324620374	1.6829301367203400	1.1941648	0.7982738	-0.8078733766168270	1.6064302672942500	1.2357754	0.77888554	-0.6590736476301230	32.03794288635250

Model	LR	Batch Size	Epochs	Train Loss	Train RMSE	Train MAE	Train R2	Val Loss	Val RMSE	Val MAE	Val R2	Test Loss	Test RMSE	Test MAE	Test R2	Training Time
gpt2	0.01	1	1	853.7451867313540	1.2573822	0.505757	-0.4911647744269070	1.1766580057294900	1.0847386	0.5779107	-0.49172862669880200	1.2125515904513700	1.1011592	0.5359809	-0.31730654688887200	
gpt2	0.01	1	1	853.7451867313540	1.2573822	0.505757	-0.4911647744269070	1.1766580057294900	1.0847386	0.5779107	-0.49172862669880200	1.2125515904513700	1.1011592	0.5359809	-0.31730654688887200	119.65372109413100
gpt2	0.01	1	2	104450.78143310500	13.803007	12.896139	-178.6960555266230	395.3787306043840	19.884132	19.859467	-500.2482539178740	392.5929381649800	19.813957	19.78822	-425.509891850913	
gpt2	0.01	1	2	104450.78143310500	13.803007	12.896139	-178.6960555266230	395.3787306043840	19.884132	19.859467	-500.2482539178740	392.5929381649800	19.813957	19.78822	-425.509891850913	193.00622582435600
gpt2	1E-06	1	1	104425.18715286300	13.906113	12.990334	-181.3906747181280	395.26605597602000	19.8813	19.85663	-500.1054087004750	392.48029424340700	19.811115	19.785372	-425.38751637714000	
gpt2	1E-06	1	1	104425.18715286300	13.906113	12.990334	-181.3906747181280	395.26605597602000	19.8813	19.85663	-500.1054087004750	392.48029424340700	19.811115	19.785372	-425.38751637714000	119.97450065612800
gpt2	1E-06	1	2	107560.89487838700	14.222375	13.263481	-189.78110706352900	395.1289916992190	19.877851	19.85318	-499.9316430825930	392.3439632858360	19.807674	19.781929	-425.23940749306000	
gpt2	1E-06	1	2	107560.89487838700	14.222375	13.263481	-189.78110706352900	395.1289916992190	19.877851	19.85318	-499.9316430825930	392.3439632858360	19.807674	19.781929	-425.23940749306000	204.77244210243200

Fig. 1. Model Results

The following graphs show the key performances of the models results tabulated above:



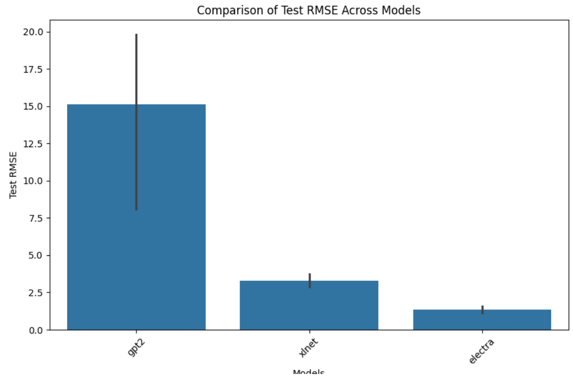
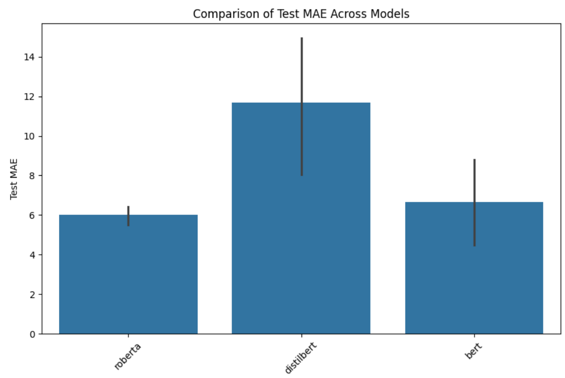


Fig. 2. Comparison of Test RMSE Across Models



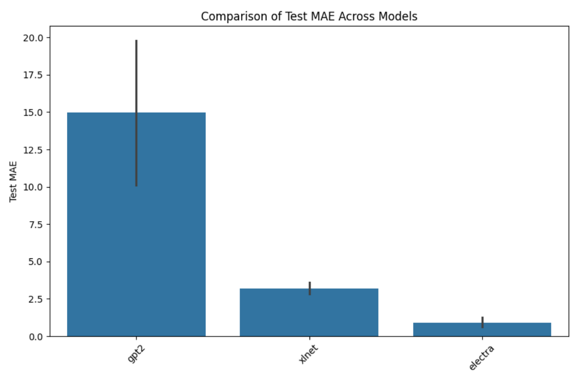


Fig. 3. Comparison of Test MAE Across Models

Some test RMSE and test MAE graphs were also produced:

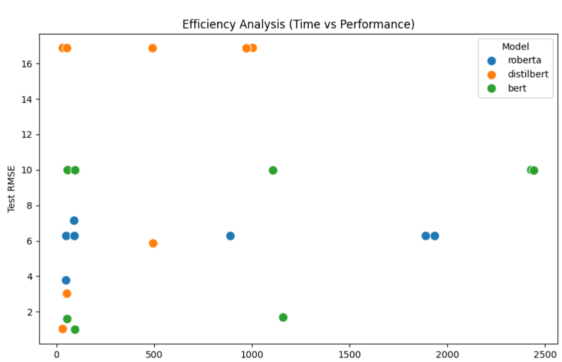


Fig. 4. Efficiency Analysis of RoBERTa, DistilBERT, and BERT

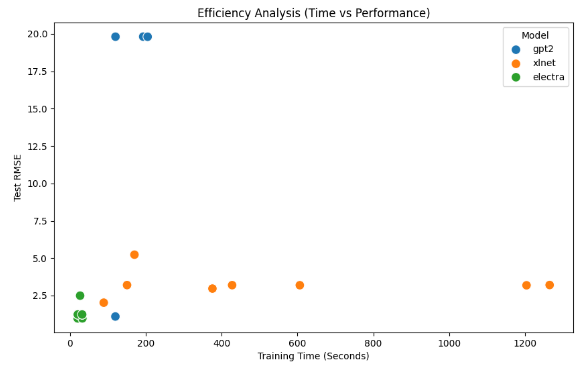


Fig. 5. Efficiency Analysis of GPT2, XLNet, and ELECTRA

The results revealed that ELECTRA outperformed other models significantly, demonstrating superior efficiency and accuracy. It achieved a training, validation, and test Root Mean Squared Error (RMSE) of approximately 1.2 and a Mean Absolute Error (MAE) of around 0.7, coupled with a relatively short training duration. Notably, ELECTRA's loss metric stood at 30, which is considerably lower compared to other models in the study.

XLNet also exhibited commendable performance, although its training duration was substantially longer than that of ELECTRA. This extended training time, however, did not diminish its effectiveness in real estate price prediction, as evidenced by its competitive RMSE and MAE scores.

Conversely, DistilBERT and GPT-2 were the least effective models in this study. DistilBERT recorded a training and validation RMSE of approximately 15.9 and a test RMSE of around 16.8. GPT-2 showed a similar trend with a training and validation RMSE of about 14.2 and a test RMSE of roughly 19.8. The MAE values for both models mirrored this underperformance.

The following are also some sample loss trends that were observed for the best case (ELECTRA) and worst case (DistilBERT). The losses followed the same trend across the models as the accuracy measurements did where ELECTRA and XLNet performed the best and DistilBERT and GPT2 performed the worst.

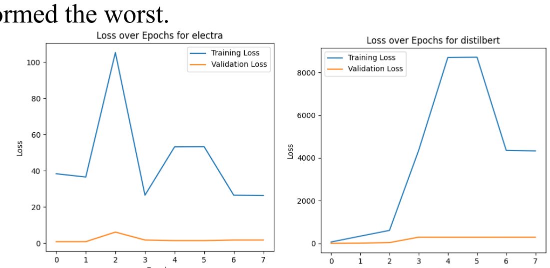


Fig. 6. Loss Over Epochs for ELECTRA and DistilBERT

V. Discussions

The underperformance of BERT, RoBERTa, DistilBERT, and GPT-2 in comparison to XLNet and ELECTRA can be attributed to several factors:

1. **BERT and RoBERTa**: While these models are renowned for their deep understanding of language context, their architecture might not be ideally suited for the specific task of price prediction based on real estate textual data. Their bidirectional nature, though advantageous for context comprehension, may not directly translate to effective numerical prediction from varied and nuanced textual descriptions in real estate listings.
2. **DistilBERT**: As a distilled version of BERT, DistilBERT aims to maintain much of BERT's effectiveness but at a reduced computational cost. This efficiency, however, comes at the price of reduced complexity and depth, which likely contributed to its subpar performance in capturing the intricate relationships within real estate data necessary for accurate price prediction.
3. **GPT-2**: GPT-2's design is more aligned with generative tasks rather than the regression-based task of price prediction. Its unidirectional architecture, focusing on generating coherent text, may not be as effective in the analytical processing required for this specific application.
4. **Model-Specific Nuances**: Each of these models has inherent characteristics that cater to certain types of data processing tasks. The real estate dataset, with its unique blend of descriptive text and implicit value indicators, might be better suited to the more efficient and focused processing capabilities of models like XLNet and ELECTRA.

VI. Conclusions

A. Summary of Findings

In summary, while models like BERT and RoBERTa offer profound contextual understanding and DistilBERT and GPT-2 provide efficiency and generative capabilities, they may not be as adept as XLNet and ELECTRA in directly correlating the nuances of real estate textual data with property values.

B. Contribution to the Field

This research makes a significant contribution to the field of real estate analytics by integrating advanced NLP techniques, traditionally applied in linguistic and textual analysis, into the valuation of real estate properties. By employing sophisticated models like BERT, RoBERTa, XLNet, and ELECTRA, the study provides new insights into how the subtleties and nuances of language in real estate listings can quantitatively influence property valuations. This interdisciplinary approach opens novel pathways for automated, accurate, and nuanced property appraisal methods that go beyond traditional numerical data analysis.

From an NLP perspective, the work extends the application of language models to a sector where qualitative data is abundant but not fully leveraged. The research demonstrates the untapped potential of textual analysis in real estate, providing a blueprint for future studies to explore NLP's applicability in other domains where qualitative attributes significantly impact value assessment. Moreover, the comparative analysis of different NLP models' effectiveness in this context enriches the understanding of each model's operational strengths and limitations, paving the way for optimized, context-specific applications of NLP in industry.

C. Final Thoughts

The potential of NLP models in real estate represents a paradigm shift in how industry professionals approach property valuation, offering a method to integrate qualitative analysis into quantitative frameworks. This study not only reinforces the viability of NLP in real estate but also sets a precedent for its application across similar domains where the qualitative nuances of textual information play a crucial role in value assessment, such as art, antiques, and collectibles markets.

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