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| Course name | Web data scraping and text analysis (capstone design) [MGT4208] | | | | | | | | | | | | |
| Project Title | Comparative Analysis of Real Estate Apps for Beginners Based on Review Data​ | | | | | | | | | | | | |
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| 위와 같이 팀 보고서를 제출합니다.  2024년 12월 13일  팀 장 (team leader): 최윤서 (Signature)  담당교수 : 김명석 (인)  **서강대학교 LINC 3.0 사업단장 귀하** | | | | | | | | | | | | | |

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| Executive Summary (1 page) |

**■ Project contents**

The analysis identified the strengths and weaknesses of major real estate apps through user reviews. **다방** excels in filtering features, **직방** is strong in information management, and **피터팬** offers direct transactions without brokerage fees. In contrast, **네이버부동산** faces challenges with functionality and UX issues. Topic and sentiment analysis highlighted areas for improvement, including enhancing management systems for **다방** and strengthening fraud reporting for **피터팬**. A positioning map revealed that **다방** leads in user experience, while **네이버부동산** requires significant improvements in functionality and information management.

**■ Project objectives**

This study aims to analyze user review data from major real estate platforms in the Prop-Tech market to identify unique differentiating features of each platform. It will use text analysis techniques such as frequency analysis, word clouds, and network analysis, and explore the relationship between reviews and ratings through regression analysis. The study will also propose a personalized recommendation system for real estate apps based on platform characteristics and user data, with the goal of reducing the use of multiple apps and enhancing platform loyalty.

**■ Methods used**

The study analyzed user reviews of real estate apps to identify strengths and weaknesses and conducted topic modeling and sentiment analysis. It calculates sentiment scores by applying keyword weights and normalizing them. For rating prediction, TF-IDF vectorization and a Random Forest Regressor are used to predict review scores, with evaluation metrics like MSE and R² to assess model performance.

**■ Expectation and contribution**

This study offers practical real estate app recommendations for beginners using user review data, introduces a text-based sentiment analysis and rating prediction method, and provides insights on platform differentiation and service improvements. It also addresses the issue of false sales in the Prop-Tech market, which is frequently mentioned in user reviews, urging improvements in this area.

**■ Mentor’s opinions**

The mentor suggests providing more detailed explanations, especially in network analysis; refining the weighted calculation method for strength-weakness analysis; conducting further statistical analysis for sentiment score calculations; and ensuring that vectorized word scores are continuous for accurate prediction.

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| Project Summary (more than 15 pages) |

**■ Problem motivation**

1. The Rapid Growth of the Prop-Tech Market

텍스트, 스크린샷, 도표, 폰트이(가) 표시된 사진

자동 생성된 설명The Prop-Tech market is rapidly growing, replacing traditional offline real estate brokerage methods. Prop-Tech platforms leverage mobile and online technologies to provide users with the convenience of searching and comparing properties anytime, anywhere. This transformation meets the demands of the increasing single-person households and the younger generation with a digital-friendly lifestyle, driving changes in the way real estate transactions are conducted.

1. Simultaneous Usage Driven by Intensifying Competition

텍스트, 스크린샷, 번호, 폰트이(가) 표시된 사진

자동 생성된 설명텍스트, 스크린샷, 소프트웨어, 번호이(가) 표시된 사진

자동 생성된 설명In the Prop-Tech market, platforms like **직방**, **다방**, and **네이버 부동산** are competing, each striving to secure a user base through differentiated services. However, many users tend to use multiple platforms simultaneously rather than maintaining consistent brand loyalty to a specific app.

To address this issue, we aim to analyze user review data to identify the strengths and weaknesses of each platform and build a system that **recommends the most suitable app for each individual**. This approach can reduce the problem of overlapping platform usage, enhance user satisfaction, and strengthen loyalty to the platform.

텍스트, 스크린샷, 폰트, 문서이(가) 표시된 사진

자동 생성된 설명**■ Literature review**

Existing real estate research tends to be overly detailed and complex, making it difficult for beginners to understand and increasing entry barriers. One key limitation is that app analysis often relies on features defined by researchers, which may not accurately reflect real user experiences. Additionally, because researchers typically evaluate apps over short periods, their findings may lack the depth and reliability needed to capture long-term user insights.

To overcome these challenges, a text-based approach that incorporates real user experiences is necessary. By analyzing user reviews, research can provide more intuitive and practical insights into the real estate market. This method not only aligns with actual user needs but also helps beginners access and understand real estate information more easily, allowing them to navigate the field with greater clarity and confidence.

**■ Statement of research objectives**

This study aims to conduct an in-depth analysis of user review data from major real estate platforms in the Prop-Tech market to identify specific differentiating features for each platform. To achieve this, text analysis techniques such as frequency analysis, word clouds, and network analysis will be utilized.

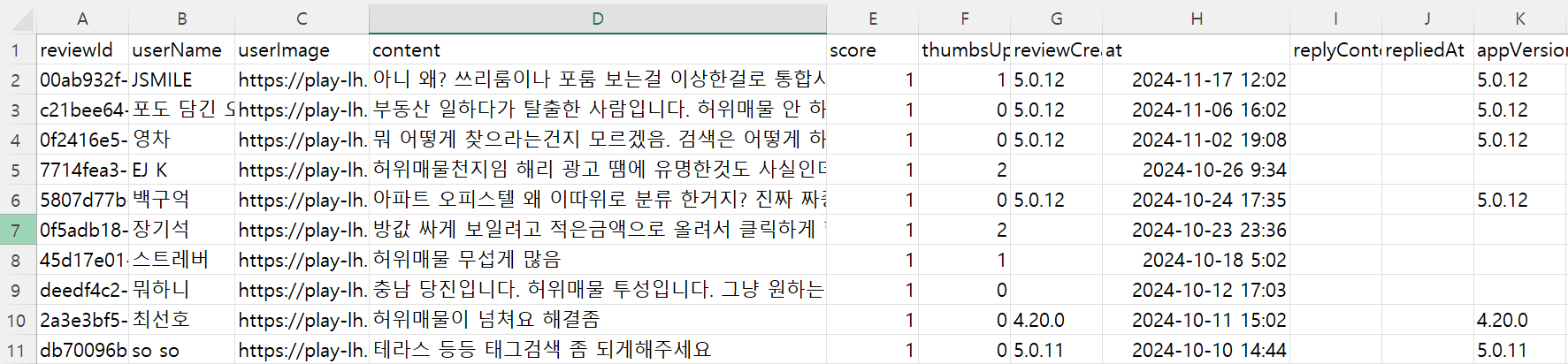
Additionally, the relationship between reviews and ratings will be explored to uncover the impact of user feedback on platform ratings, using regression analysis.

Finally, based on the characteristics and data of each platform, a personalized recommendation system for real estate apps tailored to user needs will be proposed. This system seeks to reduce simultaneous usage of multiple apps and enhance platform loyalty.

**■ Data (tables (descriptive statistics) and graphs)**

1. Data Scrapping

The purpose of this analysis was to collect and systematically analyze the latest reviews of a specific app from the Google Play Store, establishing a foundation for leveraging user feedback effectively. To achieve this, the google-play-scraper library was used for efficient data extraction, and pandas was utilized for data processing and storage.

The analysis process consisted of four stages: **review collection**, **data transformation**, **data integration**, and **CSV storage**. During the review collection stage, data was filtered based on ratings (1–5 stars), language (Korean), and region (South Korea) to gather metadata such as review content, user names, ratings, and submission dates. The collected data was then converted into DataFrames using pandas, organized systematically according to ratings. The organized data was integrated into a unified dataset, including review content, ratings, user names, and submission dates, ready for further analysis.  


This dataset, excluding the file reviews\_data\_다방\_ratings.csv, serves as critical groundwork for various purposes, such as sentiment analysis, feature enhancement, and market analysis.

1. Date Preprocessing

The data preprocessing process consisted of four key stages.

First, **Handling NaN and float values** involved converting missing values (NaN) and floating-point numbers into string format to facilitate text processing. Then, in the **Text Cleaning** stage, regular expressions were applied to extract Korean text and remove unnecessary whitespace. **Spacing Correction** was done using the PyKoSpacing package, which utilizes deep learning to correct spacing errors.

In the second stage, **Synonyms and Typos** were addressed. A **custom synonym dictionary** (synonym\_dict) was created to standardize terms like “앱,” “어플,” and “어플리케이션” to “앱.” The **fuzzywuzzy package was used to fix typos** by matching words with a similarity score of 80 or above to corresponding entries in the synonym dictionary, while words with lower similarity scores were left unchanged.

The third stage involved **Tokenization and POS Tagging**. **Tokenization** was performed using the Okt tokenizer from the KoNLPy library, and **POS tagging** was enhanced by augmenting the tokenizing dictionary with additional proper nouns to improve performance, especially for compound words like “호갱노노.”

Finally, in the **Remove Stopwords** stage, a **stopwords dictionary** was defined for both standard stopwords (non-nouns) and meaningless words (identified through iterative preprocessing). These words were filtered out to ensure the analysis focused on the most relevant terms.  
텍스트, 폰트, 스크린샷, 흑백이(가) 표시된 사진

자동 생성된 설명

**■ Methodology**

1. Differentiated Strengths and Weaknesses Analysis

Differentiated strengths and weaknesses analysis began with **extracting the frequency of nouns** from the reviews. Next, we **calculated a weight** for each word based on the number of thumbs-up (likes) it received. The weight was calculated using the formula weight = ln(thumbsUpCount + 1). This logarithmic function was applied because the number of likes indicates the significance of a review, but a single like does not have the same impact as a full review. The use of a logarithmic scale ensures that the weight of likes increases gradually, with 100 likes receiving a weight of approximately 2.0, and 1,000 likes about 3.0. This concept is similar to the log normalization used in the TF-IDF formula, where the inverse document frequency (IDF) is calculated using  to prevent distortion caused by extreme values.

After calculating the weight, we determined the importance of each word by adding its frequency in reviews to its weight, resulting in the formula word importance = word frequency + weight. The nouns were then ranked by their importance, and the top 10 keywords were extracted. Differentiated keywords were identified as those unique to a specific app, meaning they appeared in the top keywords of one app but not in others.

Finally, we categorized strengths and weaknesses based on the review ratings. Keywords that appeared in reviews rated 5 (positive) were considered strengths, while those that appeared in reviews rated 1 (negative) were categorized as weaknesses. This process allowed us to clearly distinguish the unique features of each app and perform a detailed analysis of their strengths and weaknesses.

1. Topic Modeling and Sentiment Analysis
   1. Topic Modeling

In the topic analysis, data from 2020 onward was used. To ensure balance, an equal number of reviews for each app were sampled and combined into a single dataset. For effective topic modeling, high-frequency words were extracted, and words considered irrelevant were treated as stopwords.

텍스트, 라인, 도표, 그래프이(가) 표시된 사진

자동 생성된 설명To determine the optimal number of topics, Perplexity Model was utilized.

The optimal number of topics was determined to be 14, based on the point where the Perplexity exhibited a sharp decline. As a result, the final 5 functional topics used for sentiment analysis are as follows.

텍스트, 스크린샷, 폰트, 번호이(가) 표시된 사진

자동 생성된 설명Topic 11 is about Fake Property Listings. The keyword “허위” represents user complaints and reporting of false listings. “물건,” “금액,” and “인증” refer to property details and the verification process to prevent fraud.

Topic 2 deals with Property Filtering and Advertisement Management. “필터” and “추천,” highlight personalized property recommendations. “운영” and “표기” describe how ads and property listings are managed and displayed.

Topic 4 focuses on Register Property Listings. “매물” refers to the properties listed, and “지역” emphasizes location. “개선” and “관심” represent the process of refining listings based on user interests.

Topic 3 covers Property Management and Map Services. “지도” allows users to view properties on a map, while “문의” and “설정” enable user inquiries and preferences. “수정” and “문제” address updates and issues in property listings.

Topic 10 is about App Feedback. “오류” addresses app issues needing resolution, while “사기” focuses on user protection. “추가” and “클릭” refer to feedback and actions to improve the app.

* 1. Sentiment Score  
     텍스트, 스크린샷, 폰트, 번호이(가) 표시된 사진

     자동 생성된 설명

The sentiment analysis process begins with the use of the KNU Korean Sentiment Dictionary. Polarity values are extracted by matching words in the target sentences with words in the sentiment dictionary, and the polarity value of each sentence is calculated as the sum of the polarity values of the included words. These calculated sentiment scores are then added to the existing dataset.

Next, topic-specific keyword sets are defined based on the results of topic modeling. For example, for Topic 1 (Fake Property Listings), keywords like “허위,” “물건,” “금액,” and “인증” are identified. Review data containing these keywords is filtered and used for analysis. From this filtered data, only adjectives and adverbs are extracted as sentiment words.

To calculate the sentiment scores, keyword weighting is applied by calculating the frequencies of the keywords. Weighted sentiment scores are then calculated by applying weights to these keywords. The sentiment scores are normalized to a range of 1 to 100 using Min-Max Scaling. The normalized sentiment scores are averaged to produce the final sentiment score, which completes the sentiment analysis process.

텍스트, 스크린샷, 번호, 폰트이(가) 표시된 사진

자동 생성된 설명

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자동 생성된 설명

We apply weights to enhance the accuracy and relevance of sentiment analysis. By applying weights, we ensure that keywords with higher frequencies have a greater impact on the sentiment scores. For example, if a particular keyword appears frequently, its sentiment score will be weighted, resulting in a higher score for data containing that keyword. This strengthens the representation of important keywords and leads to a more precise analysis. Additionally, applying weights enables more accurate sentiment scores that reflect the characteristics of the data. In cases where significant keywords appear frequently within a topic, the sentiment score for that topic will be higher, offering a more detailed sentiment analysis. Without weights, all data would be treated with equal importance, potentially failing to capture the full impact of key keywords.

Comparing sentiment scores with and without weights also provides valuable insights. For instance, in **네이버부동산**, the “Filter and Ads” and “Property Management & Map” categories showed a sharp increase in sentiment scores after applying weights, highlighting the significant influence of these keywords. In contrast, **호갱노노** saw a notable decrease in sentiment scores for “Fake Property Listings” and “App Feedback,” suggesting these keywords had a relatively minor impact or were associated with negative feedback. For **다방** and **피터팬**, the score changes were smaller, but certain keywords, such as “Register Property Listings” in **다방** and “App Feedback” in **피터팬**, saw slight increases, indicating a meaningful impact. On the other hand, in **직방**, sentiment scores decreased across all categories after applying weights, implying that the keywords in these categories either did not significantly affect sentiment or were linked to negative feedback.

In summary, applying weights allows us to more accurately reflect the significance of specific keywords, improving the overall quality and precision of sentiment analysis.

1. Review-Based Rating Prediction

We determined that users might be curious about how keywords not covered in topic modeling are related to ratings. For this reason, we decided to conduct an analysis of rating prediction based on app-specific reviews.

* 1. Random Forest

### TF-IDF vectorization

### The noun list from the review text is transformed into numerical data using TF-IDF vectorization. The max\_features=500 option ensures that only the top 500 most significant words are included in the vector.

### TF-IDF vectorization transforms text into numerical data by emphasizing words that are important in a specific document but rare in the overall corpus. It is a critical step for converting raw text into structured input for machine learning models.

### Model-Training

### The vectorized text data is used as input features (X), and the review scores are set as the target variable (y) to create the training dataset. A Random Forest Regressor is employed to train the model for predicting review scores. The trained model and vectorizer are saved for each app individually using pickle.

* 1. BERT
     1. Tokenization  
         In the BERT-based approach, the review text is tokenized using the BertTokenizer. Each review is converted into a sequence of token IDs, padded to a uniform length of 128, and includes special tokens [CLS] (start of a sequence) and [SEP] (end of a sequence). Additionally, an attention mask is generated to distinguish real tokens from padding. This step prepares the text data for input into the BERT model.

A custom PyTorch dataset is created to handle the tokenized data and the corresponding review scores. Each sample in the dataset consists of the input\_ids, attention\_mask, and the target score. The dataset is split into training and testing sets using an 80-20 ratio to ensure a fair evaluation.

3.2.3 Model Training

The BERT model used is BertForSequenceClassification, pre-trained and fine-tuned for regression tasks. The model architecture is configured with a single output node (num\_labels=1) to predict continuous values, making it suitable for review score prediction. The training process involves feeding batches of tokenized inputs (input\_ids and attention\_mask) and their associated scores into the model. The training process involves feeding batches of tokenized inputs and their associated scores into the model. This process is repeated for multiple epochs.

### Model-Evaluation Model evaluation metrics include **Mean Squared Error (MSE)**, **Root Mean Squared Error (RMSE)**, and **R-squared (R²)**. **MSE** represents the average squared difference between predicted and actual scores, where lower values indicate better model accuracy. **RMSE**, the square root of MSE, provides a more interpretable measure on the same scale as the target variable, with lower values also signifying better accuracy. **R²** measures the explanatory power of the model, with values closer to 1 indicating stronger predictive performance.

### Model-Evaluation Result

BERT outperforms the Random Forest model in all metrics. Its ability to achieve lower error values (MSE and RMSE) and a higher R² score indicates its superior capability in capturing the underlying patterns in the data. This aligns with the expectation that transformer-based models like BERT excel in tasks requiring a deeper understanding of complex relationships within the data. Therefore, we decided to proceed with using the BERT model for predictions instead of the Random Forest model.

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| |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | |  | **다방** | **직방** | **피터팬** | **네이버부동산** | **호갱노노** | | **MSE** | 1.07 | 1.55 | 1.12 | 1.66 | 1.88 | | **RMSE** | 1.03 | 1.24 | 1.06 | 1.29 | 1.37 | | **R²** | 1.57 | 0.41 | 0.52 | 0.21 | 0.36 | | |  |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | --- | |  | | **다방** | **직방** | **피터팬** | **네이버부동산** | **호갱**  **노노** | | **Loss** | **Epoch 1/3** | 2.0171 | 1.9626 | 2.9208 | 2.2488 | 4.3334 | | **Epoch 2/3** | 1.1876 | 1.5530 | 1.1889 | 1.9019 | 2.2638 | | **Epoch 3/3** | 0.0308 | 1.4258 | 1.0785 | 1.7964 | 2.0583 | | **MSE** | | **0.87** | 1.23 | 0.96 | 1.62 | **1.82** | | **RMSE** | | **0.93** | 1.11 | 0.98 | 1.27 | **1.35** | | **R²** | | **0.65** | 0.53 | 0.56 | **0.21** | 0.37 | |
| Random Forest Model | BERT Model |

### Mean Squared Error (MSE), Root Mean Squared Error (RMSE)

**다방**’s MSE is 0.87, which is **the lowest** **MSE**, meaning this model has the best prediction accuracy among the apps. **호갱노노**’s MSE is 1.82, which is **the highest MSE**, indicating higher prediction error.

* 1. R-squared (R²)

**다방** has **the highest R²** = 0.65, meaning this model explains the data better than the others. **네이버부동산** has **the lowest R²** = 0.21, indicating bad explanatory power, but meaningful a little.

**■ Analysis result**

1. Basic Analysis

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Word Cloud** | **Top 30 Nouns** | **Two-gram** |
| **다방** |  |  |  |
| **직방** |  |  |  |
| **피터팬** |  |  |  |
| **네이버부동산** |  |  |  |
| **호갱노노** |  |  |  |

The analysis process was carried out step-by-step, starting from data collection to in-depth text analysis. Using Google Play Scraper, the latest review data from major applications was collected, and the data was preprocessed by removing unnecessary words and extracting nouns for analysis. Based on the preprocessed data, **word clouds** were generated to visually identify frequently mentioned keywords in each app review, and the **top 30 most frequently used nouns** were analyzed and graphically represented. Furthermore, co-occurring words with frequently mentioned nouns were analyzed to create **bigrams**, providing deeper insights into the specific topics emphasized by users.

As a result of the analysis, **다방** prominently featured keywords related to property listings and false listings, such as “허위매물”, “정보”, “원룸,” and “추천.” **직방** reviews frequently mentioned topics like photos and property searches, such as “사진,” “정보,” and “검색.” **피터팬** highlighted keywords related to direct transactions, such as “직거래,” “수수료,” and “최고.” **네이버부동산** stood out for feedback on app updates, with keywords like “업데이트,” “버전,” “뒤로가기,” and “검색.” **호갱노노** focused on apartment-related information, with terms like “아파트,” “정보,” and “실거래.”

In the bigram analysis, **다방** showed strong associations between keywords related to studio apartments, such as “원룸 허위매물” and “원룸 매물.” **직방** emphasized photo quality-related keywords, such as “사진 방,” “허위매물 사진,” and “실매물 사진.” **피터팬** prominently featured keywords related to direct transactions and cost savings, such as “안심 직거래,” “중개 수수료,” and “수수료 직거래.” **네이버부동산** frequently mentioned issues related to app updates, such as “업데이트 오류”“ and “최악 업데이트.” **호갱노노** highlighted a strong demand for detailed apartment information, such as “아파트 정보,” “아파트 평수,” and “아파트 이야기.”

From the analysis results, common insights were derived. Feedback on false listings was repeatedly raised across most apps, indicating a major issue in the real estate app market that needs resolution. Additionally, user feedback on update issues in **네이버부동산** and the demand for improved photo quality and reviews in **직방** suggest the need for UX improvements. Moreover, distinct strengths of each app were identified. **피터팬** is specialized in direct transactions and cost-saving features, while **호갱노노** excels in providing reliable, apartment-centric information.

In conclusion, this analysis provides foundational data for proposing strategic improvement directions to enhance user experience and service quality based on key insights derived from user feedback. This type of review analysis will play a crucial role in continuously monitoring and improving services.

1. 예술이(가) 표시된 사진

   자동 생성된 설명Network Analysis

**[다방]**

Users have provided significant feedback on 다방 regarding usability, navigation and information provision, and service quality. The connections between key keywords (“사용,” “기능,” “검색,” “정보,” “시간,” “사진,” etc.) highlight navigation functionality and user experience as crucial areas for improvement. Additionally, peripheral keywords (“서비스,” “비교,” “광고”) help identify specific needs perceived by certain users.

**예술이(가) 표시된 사진

자동 생성된 설명[직방]**

At the center of the graph, keywords such as “사용,” “검색,” “정보,” “계약,” “매물,” and “사진” are identified. These are the most frequently mentioned terms in reviews, indicating that users often leave feedback about navigation functionality, information accuracy, ease of use, as well as contract and property management.

**원, 예술이(가) 표시된 사진

자동 생성된 설명[피터팬]**

At the center of the graph, keywords such as “사용,” “기능,” “정보,” “계약,” and “사진” are identified. These are the most frequently mentioned terms in reviews, indicating that users often leave feedback on navigation functionality, information provision, and contract and property management.

**몰드, 시각화이(가) 표시된 사진

중간 신뢰도로 자동 생성된 설명[네이버부동산]**

Users mainly leave reviews about “usability,” “functionality,” “navigation,” and “information-providing features.” Key terms such as “사용,” “기능,” “검색,” “정보,” and “지도” were identified. This highlights the need for improvements in app UI/UX, optimization of map and search functions, and customized services to address specific user requirements, as suggested by keywords like “참고” and “아파트”.

**예술이(가) 표시된 사진

낮은 신뢰도로 자동 생성된 설명[호갱노노]**

At the center of the graph, keywords such as “사용,” “기능,” “정보,” “매물,” “신고,” “삭제,” and “거래” are identified. These are the most frequently mentioned terms in reviews, indicating that users often leave feedback regarding navigation, information reliability, and issue resolution processes.

1. Differentiated Strengths and Weaknesses Analysis
   1. Differentiated Keywords, Strength Keywords, Weakness Keywords  
      텍스트, 폰트, 스크린샷, 번호이(가) 표시된 사진

      자동 생성된 설명  
       The analysis of differentiated keywords revealed the following:

For **다방**, key terms included “Filter” and “One-Room.” **직방** focused on “Real Listings” and “Photo.” **피터팬** was associated with “Direct Transaction” and “Contact.” **네이버부동산** showed concerns with “Usage,” “Back Button,” “Screen,” “Version,” and “Map.” **호갱노노** featured “Apartment,” “Price,” “Real Transactions,” and “Area.”

For strengths, **다방** excelled in “Filter” and “One-Room.” **직방** was strong in “Photo.” **피터팬** showed strength in “Brokerage” and “Direct Transaction.” **네이버부동산** was noted for “View,” “Update,” and “Lease.” **호갱노노** excelled in “Real Listings,” “Apartment,” and “Search.”

For weaknesses, **다방** had issues with “Management,” **직방** with “Real Listings” and “Photo,” **피터팬** had no major weaknesses, **네이버부동산** struggled with “Usage,” “Back Button,” and “Map,” and **호갱노노** showed weaknesses in “Information,” “People,” and “Post.”

* 1. Insights

From the Problem Motivation, it was observed that users frequently utilize multiple real estate apps. However, upon analyzing review text data, it became evident that each app has carved out its own niche, targeting specific segments of the market.

**직방**, a pioneer among mobile real estate apps, lacked noticeable differentiation. On the other hand, **다방**, a later entrant, attracted users with its filtering options, particularly appealing to single-person household seeking one-room accommodations, as evidenced by the keyword “One-Room”. **피터팬** demonstrated a unique value proposition by facilitating direct transactions between tenants without brokerage fees. **호갱노노** was specialized in apartment-related searches and information. **네이버부동산**, available on both PC and mobile platforms, showed a focus on app functionality, with keywords like “Update” and “Back Button” indication technical aspects of its UX.

The analysis of differentiated weakness keywords highlighted several areas for improvement. **다방** needs to enhance its management systems. **직방** should implement robust mechanisms to filter out false listings, addressing its weakness regarding “Real Listings”. **피터팬** showed no significant weaknesses compared to other apps. **네이버부동산** requires consistent updates to resolve technical issues and improvement UX design. **호갱노노**, with its community features focused on apartments, must ensure the reliability of posts and information to address weaknesses in this area.

This analysis provided a clear understanding of each app’s differentiated strengths and weaknesses. It also offered actionable insights to target specific markets and improve areas requiring attention, contributing to a strategic direction for app development and market positioning.

1. Positioning Map

This report aims to analyze the positioning of housing-related applications based on user satisfaction and identify the strengths and weaknesses of each application, providing strategic directions for improvement. The analysis focuses on five key topics: Fake Property Listings, Filter and Ads, Register Property Listings, Property Management & Map, and App Feedback.

Sentiment analysis data extracted from user reviews was used to calculate the average user satisfaction scores for each topic, and these scores were visualized in a 3D positioning map using PCA (Principal Component Analysis). Each topic is defined as follows:

1. **Fake Property Listings:** User feedback related to reporting and preventing fraudulent property listings.
2. **Filter and Ads:** Evaluations of property filtering options and ad management features.
3. **Register Property Listings:** User experience in registering properties and setting conditions for property listings.
4. **Property Management & Map:** Reviews related to property management services, including map and inquiry features.
5. **App Feedback:** User evaluations on handling app errors and incorporating user feedback.

This topic-based analysis provides a multi-dimensional evaluation of each application's performance, with a focus on identifying specific areas for improvement to enhance user satisfaction and competitiveness in the market.

도표, 텍스트, 스크린샷, 라인이(가) 표시된 사진

자동 생성된 설명The PCA analysis identified three principal components that explain the variance in the data. The first principal component (PC1) accounts for 64.13% of the variance and reflects user experiences related to **filter and ad management**, **app feedback handling**, and **property management & map services**. High PC1 scores indicate positive user evaluations in these areas, while low scores suggest areas needing improvement. The second principal component (PC2) explains 26.53% of the variance and represents performance in **fake property listings reporting** and **ad management**, which are crucial for building user trust. High PC2 scores indicate strong performance in trust-building and ad quality, while low scores reveal weaknesses. The third principal component (PC3) explains 8.32% of the variance and reflects user evaluations related to **property registration** and **transaction management**. High PC3 scores signify strengths in these functionalities, whereas low scores highlight functional weaknesses.

The positioning map analysis shows that **다방** recorded low scores on PC1 and PC2, indicating negative user evaluations in critical areas such as filtering, ad management, and app feedback. It also achieved moderate scores on PC3, showing no significant strengths in property management or registration. Therefore, **다방** needs to enhance its filtering and feedback management systems to improve the overall user experience. **직방** scored high on PC2, demonstrating strengths in ad management and fake property listings reporting. However, its low PC1 score suggests the need for improvements in feedback management and filtering functionalities. **네이버부동산** scored high on both PC1 and PC2, reflecting strengths in filtering, ad management, and fake property listings reporting. However, its relatively low PC3 score indicates the need to improve property registration and transaction management. **호갱노노** scored moderately on PC3, showing stability in ad management and property registration. However, its low PC1 and PC2 scores indicate deficiencies in filtering and feedback management. Finally, **피터팬** achieved the highest score on PC3, demonstrating strengths in property registration and transaction management. However, its low PC1 and PC2 scores reveal weaknesses in ad quality and feedback management.

This analysis provides strategic recommendations based on the strengths and weaknesses of each application, offering concrete steps to maximize user satisfaction and enhance market competitiveness.

1. Review-Based Rating Prediction

텍스트, 폰트, 스크린샷, 영수증이(가) 표시된 사진

자동 생성된 설명When a review containing specific words is given, those words are transformed into embeddings using BERT's pre-trained language model. These embeddings capture contextual and semantic meanings of the words. The embeddings are then passed through the fine-tuned BERT model to predict the review's score. For example, the model predicts individual scores for words like “scam,” “good,” “worst,” and “kind” by analyzing their contextual representations and associations within the review text.

The predicted ratings vary for each app depending on specific keywords included in the reviews (“사기,” “좋아요,” “최악,” “친절”). For instance, keywords like “좋아요” and “친절” generally result in high ratings (above 4) across most apps, whereas “사기” and “최악” show significant differences in ratings depending on the app. This demonstrates how the BERT model leverages the contextual sentiment of user reviews to influence ratings differently for each app.

**■ Expected original contribution**

1. Practical Real Estate App Recommendations for Beginners  
    While previous studies have focused on expert-centered analyses that are difficult for beginners to understand, this study utilizes actual user review data to provide real estate app recommendations that beginners can easily comprehend and choose from.
2. Introduction of Text-Based Sentiment Analysis and Rating Prediction  
    By leveraging text analysis techniques on review data, this study overcomes the limitations of previous research and offers practical insights based on user experiences. In particular, it develops a new analytical methodology by analyzing the relationship between reviews and ratings to predict user satisfaction. This not only suggests directions for app improvement but also expands future research and industrial application possibilities.
3. Derivation of platform differentiation  
    By quantitatively evaluating the platform differentiation between major real estate apps through review data, it is possible to clearly define the strengths and weaknesses of each platform and provide customized recommendations.
4. Provides direction for service improvement  
    Based on user complaints (e.g., false offerings) and positive feedback, we can present improvements to app developers and suggest specific strategies to increase their competitiveness.
5. Need to solve the problem of false sales across the Prop-Tech market  
    Consumers have so many complaints about false sales that the “false” keyword is counted at the top of the top of the top four apps and is also derived from topic modeling, so it is necessary to recognize and improve the problem situation.

**■ Mentor’s direction (Date and opinions of mentor)**

1. More detailed explanations are needed overall, particularly in the network analysis section for each application.
2. The weighted calculation method used in the strength-weakness analysis requires further refinement based on Professor Myung Suk Kim's feedback. This could involve referencing prior studies or providing additional, clearer explanations.
3. In the section on calculating sentiment scores by topic, the values derived range between 0 and 1. Instead of simply presenting these values, it is recommended to perform further statistical analysis. For example, if these are relative scores, using statistical methods such as one-way ANOVA can help demonstrate the significance of a score like 0.39 in comparison to others.
4. When vectorizing words and calculating expected scores for specific words, ensure that the scores are continuous. If they are not, this approach may lead to inaccuracies.
5. Using a Random Forest model with only one variable is inappropriate. Machine learning typically requires more complex models with multiple variables. If you wish to use Random Forest, ensure there are sufficient variables-for instance, treating 500 words as separate variables would be suitable.