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Deep Learning for Personalised Property Recommendations System: Data Collection and Model Development Using Public Datasets

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Contents

1 Introduction

1.1 Project Concept

The Personalised Property Recommendation System aims to assist potential homebuyers in the UK real estate market by providing tailored property recommendations based on individual preferences and financial situations. By integrating historical transaction data from HM Land Registry with current property listings from OnTheMarket, the system delivers customised property suggestions. This project involves developing and evaluating various deep learning models to determine the most effective approach for property recommendation, framed as a classification task.

1.2 Motivation

Navigating the real estate market can be particularly challenging for new generations, including Millennials, Gen Z, and Gen Alpha, who face unique financial and lifestyle constraints. First-time buyers often struggle to find properties that meet their specific criteria within their budget. The abundance of property options and the complexity of property features necessitate a tool that can streamline the search process and offer personalised recommendations. This project seeks to address this need by developing a robust deep learning-based recommendation system.

1.3 Project Template

This project, based on "Project Idea Title 1: Deep Learning on a Public Dataset" from CM3015, uses publicly accessible real estate data from HM Land Registry and OnTheMarket to develop and compare deep learning models for personalised property recommendations. Following the methodology in "Deep Learning with Python" by F. Chollet, the prototype aims to improve model performance.

This project builds upon my previous work in CM2015, where I developed data collection scripts and utilised similar datasets. The current project expands this foundation by incorporating advanced machine learning for better recommendations.

1.4 Scope and Limitations

This prototype analyses various types of residential properties in Buckinghamshire, excluding shared ownership, retirement homes, new builds, auction listings, farms/land, park homes, and properties over £650,000. These filters were applied to data collected from OnTheMarket.com.

The prototype has limitations, including reliance on online data accuracy and availability. It does not cover commercial real estate or the rental market in Buckinghamshire.

1.5 Data Sources and Selection

1.5.1 Data Requirements

The primary goal of this prototype is to validate the feasibility of using machine learning techniques to predict property prices and recommend properties in the Buckinghamshire market. To achieve this, two main data sources were utilised: - **HM Land Registry Data**: This dataset provides comprehensive information on property sales in Buckinghamshire, including sale prices and transaction dates. - **Web Scraped Data from OnTheMarket.com**: A dataset comprising current property listings in Buckinghamshire, including asking prices, property types, and other relevant details.

To comprehensively analyse Buckinghamshire's property market, data from diverse sources were gathered: - **HM Land Registry Data**: This dataset provides comprehensive information on property sales in Buckinghamshire, including sale prices and transaction dates. - **Real Estate Listings**: Scraped data from OnTheMarket.com helps in understanding the ongoing trends and fluctuations in property prices and demands within Buckinghamshire. Python scripts were developed, organised in the `src` folder of this prototype, to efficiently collect and process the data, ensuring a robust and reliable dataset for analysis.

1.5.2 Choice of Data Sources

- **HM Land Registry Data**: Chosen for its reliability and comprehensive coverage of actual property sales in the UK. Accessed via gov.uk, under the Open Government Licence v3.0.
- **OnTheMarket.com**: Chosen as a current and active source for property listings, offering a real-time perspective on the market. Data was scraped in compliance with the site's terms and conditions, focusing on properties listed for sale in Buckinghamshire.

1.5.3 Methodology for Data Collection and Processing

- Data from HM Land Registry was downloaded in CSV format, covering transactions for the year 2023.
- Web scraping was conducted on OnTheMarket.com using Python scripts, focusing on gathering current listings in Buckinghamshire. The scraping process adhered to the website's robots.txt file and was conducted using a unique user agent.

1.5.4 Limitations and Constraints

- **Timeframe**: The HM Land Registry data covers only sales within 2023, and the scraped data reflects listings at the time of scraping. This temporal limitation means the analysis might not fully capture long-term market trends.
- **Geographical Scope**: The focus on Buckinghamshire alone may not provide a complete picture of broader regional or national property market trends.
- **Data Completeness**: While the Land Registry data is comprehensive for sales, the scraped data from OnTheMarket.com might not capture every property listing in the region, leading to potential gaps in the dataset.

1.6 Ethical Considerations

1.6.1 Data Sources and Permissions

HM Land Registry Data - HM Land Registry data is used under the Open Government Licence v3.0. - Proper attribution has been given as per the OGL requirements: "Contains HM Land Registry data © Crown copyright and database right 2021. This data is licensed under the Open Government Licence v3.0."

OnTheMarket.com Data - OnTheMarket.com data was collected via web scraping, strictly adhering to their robots.txt file, using a unique user agent with contact information, and employing rate limiting to respect their servers.

This prototype focuses on objective real estate data, avoiding personal judgements or assumptions. It aims to maintain neutrality, preventing negative impacts like market manipulation. Any personal data has been anonymized to protect privacy.

word count: 837

2 Chapter 2: A Literature Review

2.1 2.1 Introduction

In the realm of real estate, accurate property price prediction and personalised recommendation systems are crucial for assisting potential homebuyers and real estate professionals. The intersection of machine learning and real estate has gained substantial attention, with various methodologies explored to enhance prediction accuracy and personalisation. This literature review critically examines existing research on housing price prediction models and personalised recommendation systems, highlighting their methodologies, strengths, and limitations.

2.2 2.2 Housing Price Prediction Models

2.2.1 2.2.1 Hedonic-Based Regression Approaches

Historically, hedonic-based regression models have been utilised to determine the impact of various housing attributes on property prices. These models estimate prices based on factors such as location, size, and age of the property. Despite their widespread use, hedonic models face limitations such as difficulty in capturing nonlinear relationships and the need for extensive data preprocessing to handle heteroscedasticity and multicollinearity issues [1].

2.2.2 2.2.2 Machine Learning Techniques

The advent of machine learning has provided more sophisticated tools for housing price prediction, capable of handling complex, non-linear relationships between variables. The study by Park and Bae (2020) investigates the application of several machine learning algorithms to predict housing prices using data from Fairfax County, Virginia. The algorithms examined include C4.5, RIPPER, Naïve Bayesian, and AdaBoost [5].

- **C4.5 Algorithm**: This algorithm is an extension of the earlier ID3 algorithm and generates a decision tree used for classification purposes. In the context of housing price prediction, the decision tree helps identify the most significant variables influencing prices [6].
- **RIPPER Algorithm**: This is a rule-based learning algorithm that generates a set of rules to classify data. According to Park and Bae (2020), the RIPPER algorithm demonstrated superior performance in terms of accuracy compared to other models tested in their study [5].
- **Naïve Bayesian**: This probabilistic classifier is based on Bayes' theorem and assumes independence between predictors. Despite its simplicity, it can be effective for certain types of classification problems [2].
- **AdaBoost**: This ensemble method combines multiple weak classifiers to create a strong classifier. It adjusts the weights of misclassified instances, thereby improving the model's accuracy over successive iterations [3].

Park and Bae's study concludes that the RIPPER algorithm consistently outperformed the other models in terms of classification accuracy for housing price prediction. This finding is significant as it highlights the potential of rule-based algorithms in capturing the complexities of housing market data [5].

2.3 2.3 Content-Based Recommender Systems

Content-based recommender systems are crucial for providing personalised suggestions based on user preferences and item attributes. Lops, Gemmis, and Semeraro (2011) provide a comprehensive overview of the state-of-the-art techniques and trends in content-based recommendation systems [4].

- **Feature Extraction**: Content-based systems rely heavily on extracting meaningful features from items. In the context of real estate, features such as property type, location, price, and amenities are essential.
- **Similarity Calculation**: These systems calculate the similarity between items based on their features. For real estate, properties with similar attributes (e.g., location, price range)

are considered similar and thus recommended to users with matching preferences.

- **User Profiles**: Content-based systems maintain profiles for users, capturing their preferences and interaction history. This allows the system to tailor recommendations based on individual user needs.

Lops et al. (2011) highlight the challenges in content-based recommender systems, such as the cold start problem, where new users or items lack sufficient data for effective recommendations. However, integrating advanced machine learning techniques can mitigate some of these issues by improving feature extraction and similarity calculations [4].

2.4 2.4 Discussion

The research conducted by Park and Bae (2020) underscores the importance of selecting appropriate machine learning algorithms for housing price prediction. Their comparative analysis provides valuable insights into the strengths and weaknesses of different models. For instance, while ensemble methods like AdaBoost are generally robust, rule-based algorithms such as RIPPER can offer higher accuracy for specific datasets [5].

This study also emphasizes the need for comprehensive data preprocessing, including the selection of relevant features and handling missing values, to enhance the predictive performance of machine learning models. Additionally, the integration of various algorithms can potentially lead to the development of a hybrid model that leverages the strengths of each approach [5].

2.5 2.5 Conclusion

The literature on housing price prediction demonstrates that machine learning techniques, particularly rule-based algorithms like RIPPER, can significantly improve the accuracy of price predictions. The study by Park and Bae (2020) serves as a critical reference point for developing advanced models that can aid real estate stakeholders in making informed decisions [5].

Further research should focus on integrating these models with personalised recommendation systems to provide comprehensive solutions for real estate buyers and sellers. By leveraging machine learning's capabilities, the real estate industry can enhance its analytical tools, leading to more accurate and reliable property valuations.

Word count chapter 2: 787

2.6 2.6 References

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3 Chapter 3: A Design

3.1 3.1 Project Overview

The Personalized Property Recommendation System aims to integrate historical transaction data from HM Land Registry and current property listings from OnTheMarket to provide tailored property recommendations based on user preferences and financial situations. The project follows "Project Idea Title 1: Deep Learning on a Public Dataset" and aims to find the most effective model for property price prediction and recommendation using deep learning techniques.

3.2 3.2 Domain and Users

3.2.1 Domain

The project is situated in the real estate domain, focusing on residential properties in the UK. It leverages publicly available datasets to build a recommendation system that aids potential homebuyers in making informed decisions.

3.2.2 Users

The primary users of the system are: - **First-time homebuyers**: Individuals looking for their first property purchase who need tailored recommendations based on their budget and preferences. - **Real estate agents**: Professionals who can use the system to provide clients with data-driven property suggestions. - **Property investors**: Individuals or companies looking to invest in real estate who require accurate property price predictions and recommendations.

3.3 3.3 Justification of Design Choices

3.3.1 User Needs

The design choices are informed by the needs of users in the real estate market: - **Personalization**: Users require personalized property recommendations that match their financial constraints and preferences. - **Accurate Predictions**: Accurate property price predictions help users make informed decisions. - **Usability**: The system must be easy to use and provide quick, relevant recommendations.

3.3.2 Domain Requirements

The real estate domain requires: - **Integration of Diverse Data Sources**: Combining historical transaction data with current listings to provide a comprehensive view. - **Handling Non-linear Relationships**: Using advanced machine learning models to capture complex patterns in the data.

3.4 3.4 Project Structure

3.4.1 Data Collection and Preprocessing

- **Data Sources**: Historical transaction data from HM Land Registry and current property listings from OnTheMarket.
- **Web Scraping**: Scripts to collect real-time data from OnTheMarket.
- **Data Cleaning**: Handling missing values, standardizing formats, and filtering relevant data.
- **Data Integration**: Merging datasets to create a unified data source.

3.4.2 Model Development

- **Feature Selection**: Identifying relevant features such as price, location, property type, etc.
- **Model Selection**: Experimenting with various machine learning algorithms (e.g., C4.5, RIPPER, Naïve Bayesian, AdaBoost) to identify the best-performing model.
- **Training and Validation**: Splitting the data into training and validation sets, training the model, and evaluating its performance.

3.4.3 Recommendation System

- **User Profile Creation**: Collecting user preferences and financial information.
- **Similarity Calculation**: Using content-based filtering to match properties with user profiles.
- **Property Ranking**: Ranking properties based on their relevance to the user's preferences and budget.
- **Feedback Loop**: Incorporating synthetic user feedback to continuously improve the recommendation system.

3.5 3.5 Technologies and Methods

3.5.1 Technologies

- **Python**: Primary programming language for data processing and model development.
- **TensorFlow and Keras**: Libraries for building and training deep learning models.
- **Pandas and NumPy**: Libraries for data manipulation and analysis.
- **Scikit-Learn**: Library for implementing various machine learning algorithms and evaluation metrics.
- **BeautifulSoup and Requests**: Libraries for web scraping.
- **Matplotlib**: Library for data visualization.
- **Node.js and Express.js**: For building the backend of the web application.
- **HTML, CSS, and JavaScript**: For developing the frontend of the web application.

3.5.2 Methods

- **Data Preprocessing**: Cleaning and integrating data from multiple sources.
- **Machine Learning**: Developing and comparing different machine learning models to identify the most effective one for price prediction.
- **Content-Based Filtering**: Creating a recommendation system based on the features of the properties and user preferences.
- **Evaluation Metrics**: Using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) to evaluate model performance.

3.6 3.6 Work Plan

3.6.1 Major Tasks and Timeline

- **Data Collection and Preprocessing (Weeks 1-4)**
  - Collect data from HM Land Registry and OnTheMarket
  - Clean and preprocess data
  - Integrate datasets
- **Model Development (Weeks 5-10)**
  - Feature selection
  - Develop and train machine learning models
  - Evaluate models using MAE and RMSE
- **Recommendation System Development (Weeks 11-14)**
  - Develop content-based filtering system
  - Integrate price prediction with user preferences
- **Web Interface Development (Week 11)**
  - Develop a user-friendly web interface for the recommendation system
- **Docker Setup and Integration (Week 12)**
  - Set up Docker to orchestrate the entire system
- **Experiment with Additional Models (Weeks 13-14)**
  - Implement and compare models like Gradient Boosting, Random Forests, and advanced deep learning architectures
  - Optimize hyperparameters for each model and compare their performance using various metrics
- **Expand Features and Incorporate New Parameters (Week 15)**
  - Collect and preprocess additional data for new features (e.g., socioeconomic and environmental factors)
  - Perform feature engineering to create new features from the existing data
  - Integrate these features into the model and evaluate their impact on performance
- **Geographical Expansion (Week 16)**
  - Collect data for regions beyond Buckinghamshire
  - Preprocess and integrate this data into the existing dataset
  - Evaluate the model's performance on the expanded dataset
- **User-Centric Testing and Feedback Collection (Week 17)**
  - Design a user-friendly interface for inputting preferences and receiving recommendations
  - Simulate user interactions using synthetic data
  - Collect feedback through synthetic data to refine the system
- **Replicate and Compare with High-Quality Models (Week 18)**
  - Replicate models from high-quality published papers
  - Compare their performance with your models and analyze the differences
- **Final Model Tuning and Evaluation (Week 19)**
  - Fine-tune the best-performing models
  - Conduct a thorough error analysis and identify areas for further improvement
  - Finalize the model and prepare it for deployment
- **Report Writing & Finalization (Week 20)**
  - Document all findings, methodologies, and results
  - Ensure the report is well-structured, with clear explanations and justifications for each step

– Prepare for submission, ensuring all requirements are met

Week	Task
1-4	Data Collection & Preprocessing
5-10	Model Development
11	Web Interface Development
12	Docker Setup and Integration
13-14	Experiment with Additional Models
15	Expand Features and Incorporate New Parameters
16	Geographical Expansion (Collect Data for New Areas)
17	User-Centric Testing and Feedback Collection
18	Replicate and Compare with High-Quality Models
19	Final Model Tuning and Evaluation
20	Report Writing & Finalization

3.7 3.7 Testing and Evaluation Plan

3.7.1 Testing

- **Unit Testing**: Test individual components (e.g., data collection scripts, model training functions) to ensure they work as expected.
- **Integration Testing**: Ensure that different components (e.g., data integration, model prediction, recommendation system) work together seamlessly.
- **Synthetic User Testing**: Simulate user interactions using synthetic data to evaluate the recommendation system's usability and effectiveness.

3.7.2 Evaluation

- **Model Evaluation**: Use MAE and RMSE to evaluate the accuracy of the price prediction model.
- **Synthetic User Feedback**: Use synthetic data to simulate user feedback regarding the relevance and usefulness of the property recommendations.
- **Performance Metrics**: Track the system's performance in terms of response time, accuracy, and user satisfaction.

By following this structured approach and incorporating these components, the project aims to deliver a robust and effective personalized property recommendation system that meets user needs and leverages advanced machine learning techniques.

4 Chapter 4: Implementation

4.1 System Architecture Overview

The UK Real Estate Recommendation System is designed with a modular and scalable architecture to efficiently collect, process, and analyze property data for personalized recommendations. The system architecture, as illustrated in Figure 4.1, consists of several key components:

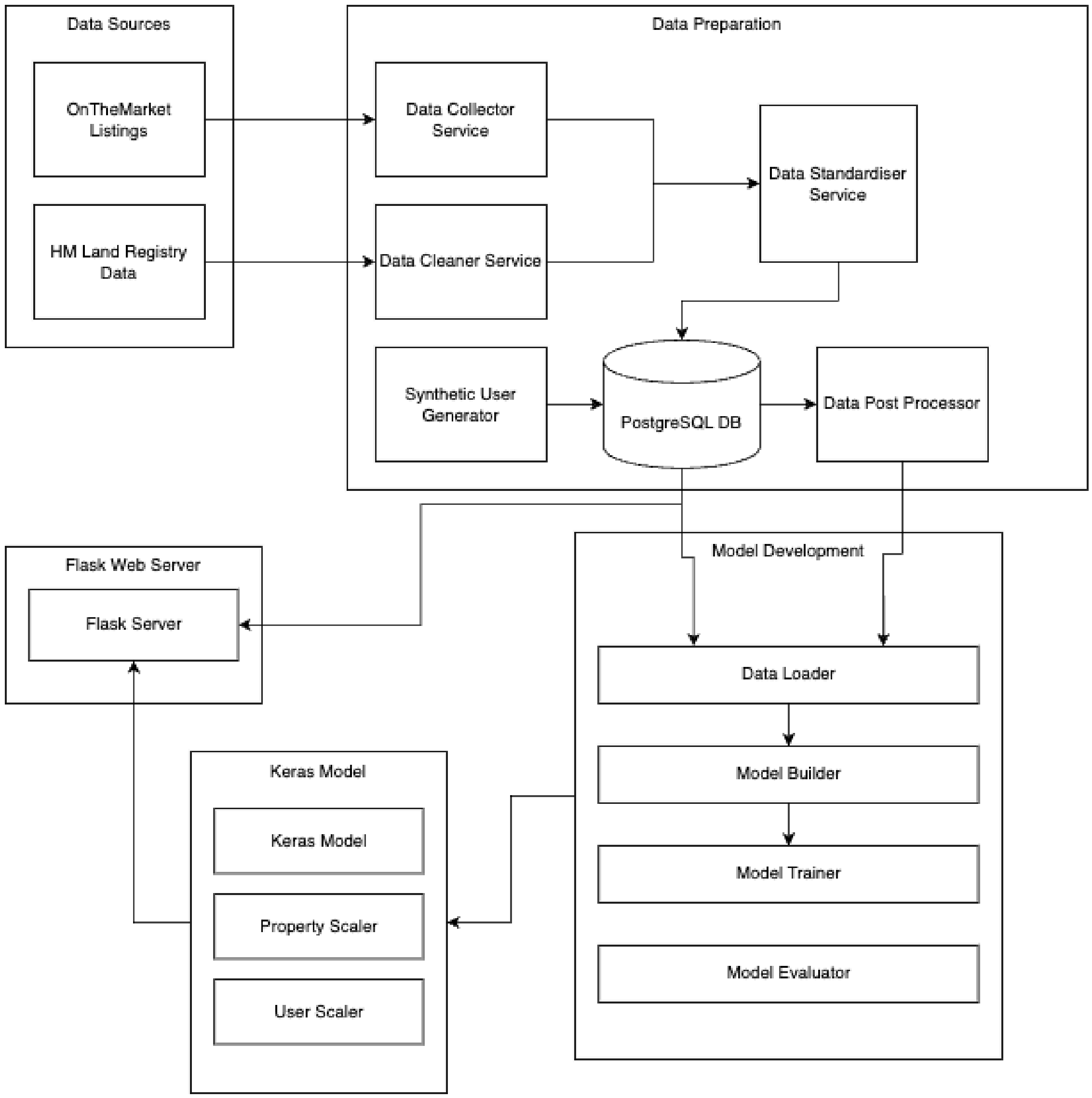


Figure 4.1: System Architecture Diagram

4.1.1 Data Sources

1. **OnTheMarket Listings:** Current property listings scraped from the OnTheMarket website, covering multiple shires including Buckinghamshire, Bedfordshire, Oxfordshire, Northamptonshire, Hertfordshire, and Berkshire.
2. **HM Land Registry Data:** Historical property transaction data from the UK government, providing comprehensive information for properties across multiple counties, including Buckinghamshire, Bedford, Oxfordshire, North Northamptonshire, West Northamptonshire, Hertfordshire, and West Berkshire. This data includes sale prices, property types, and locations.

4.1.2 Data Preparation

1. **Data Collector Service:** Web scrapes current property listings from OnTheMarket.com for multiple shires, using price segmentation to ensure comprehensive coverage.
2. **Data Cleaner Service:** Processes and cleans the HM Land Registry data, filtering for specific shires and years, and standardizing county names.
3. **Data Standardiser Service:** Integrates and standardizes data from both sources.
4. **Synthetic User Generator:** Creates synthetic user profiles for testing and development purposes.

4.1.3 Data Storage

1. **PostgreSQL Database:** Centralized storage for all processed and standardized data.

4.1.4 Data Processing

1. **Data Post Processor:** Performs additional data transformations and feature engineering.

4.1.5 Model Development

1. **Data Loader:** Retrieves and prepares data for model training.
2. **Model Builder:** Constructs the neural network architecture.
3. **Model Trainer:** Trains the model on the prepared dataset.
4. **Model Evaluator:** Assesses the model's performance and generates evaluation metrics.

4.1.6 Web Application

1. **Flask Web Server:** Hosts the user interface and handles user requests.
2. **Keras Model:** The trained neural network model for generating property recommendations.
3. **Property Scaler and User Scaler:** Normalize input data for consistent model predictions.

This architecture ensures a streamlined flow of data from collection to recommendation, with each component designed to handle specific tasks in the pipeline. The modular design allows for easy maintenance, updates, and scalability of individual components without affecting the entire system.

4.2 Data Collection and Data Cleaning

4.2.1 Web Scraping Methodology

To complement the historical data from HM Land Registry, we implemented a sophisticated web scraping solution for collecting current property listings from OnTheMarket.com across multiple shires. The process is modularised into four main components:

1. `robot_check.py`: Ensures compliance with the website's `robots.txt` file.
2. `crawler.py`: Discovers and collects property listing URLs using requests and BeautifulSoup, implementing rate limiting to avoid server overload.
3. `scraper.py`: Extracts specific data from web pages, including prices, addresses, and property features.
4. `data_collector_service.py`: Orchestrates the entire web scraping process, managing the workflow between the crawler and scraper modules. It implements the following key features:

- Multi-shire data collection: Iterates through each shire (Buckinghamshire, Bedfordshire, Oxfordshire, Northamptonshire, Hertfordshire, and Berkshire) to collect data separately.
- Price segmentation: Divides the property price range into segments (e.g., £100,000 increments) to ensure comprehensive coverage across all price brackets.
- Incremental data saving: Saves collected data for each shire separately, allowing for easier management and processing of large datasets.

Ethical Considerations Our web scraping adhered to ethical standards, including respecting `robots.txt`, using a unique user agent, implementing rate limiting, and ensuring non-disruptive interaction with OnTheMarket.com.

Note on Script Execution Time Due to our ethical scraping approach, the script's execution takes longer for larger datasets, particularly given the rate limits and crawl delays we adhere to. This ensures responsible scraping while avoiding potential blocking by the website.

We can run `data_collector_service.py` from the CLI or from the Jupyter Notebook using `%run` and provide the `max_price` argument to control the data collection scope. For this prototype, data was collected for properties priced up to £650,000. This data can be found in the `data` folder

[ ]:
```
# %run src/data-collector/data_collector_service.py 650000
%run src/data-collector/data_collector_service.py 120000
```

4.3 Standardisation and Preprocessing

The data cleaning and standardisation process is a crucial step in our pipeline, ensuring that data from different sources is consistent and ready for analysis. This process is handled by several specialized modules within the `data_standardiser` package.

4.3.1 Data Standardiser Architecture

The `data_standardiser` package is structured as follows:

- `address_utils.py`: Handles address normalization and cleaning.
- `constants.py`: Stores constant values used across the standardization process.
- `county_mapping.py`: Manages standardization of county names.
- `data_processing.py`: Contains core data processing and standardization functions.
- `database_operations.py`: Manages database interactions for data storage and retrieval.
- `geocoding.py`: Handles the geocoding process to add latitude and longitude data.
- `logging_config.py`: Configures logging for the standardization process.
- `main.py`: Orchestrates the entire standardization process.
- `property_utils.py`: Provides utility functions for property-specific data processing.
- `utils.py`: Contains general utility functions used across the package.

Modularity and Code Structure This modular approach to data standardization ensures that our data is consistent, accurate, and ready for the subsequent stages of analysis and model development. It also allows for easy maintenance and updates to individual components of the standardisation process as needed.

4.3.2 Key Standardisation Processes

1. **Address Normalization** The `address_utils.py` module provides functions to clean and normalize addresses, ensuring consistency across different data sources. This includes removing special characters, standardizing formatting, and handling common address variations.

2. **County Standardization** `county_mapping.py` is responsible for standardizing county names. This is crucial when dealing with data from multiple sources that might use different naming conventions for the same counties.

3. **Data Processing and Feature Extraction** `data_processing.py` contains core functions for processing raw data. This includes:

   - Standardizing price formats
   - Extracting and standardizing property features (e.g., number of bedrooms, bathrooms)
   - Standardizing property types
   - Handling date conversions

4. **Geocoding** The `geocoding.py` module implements a robust geocoding process using both Nominatim and ArcGIS services. It includes features like:

   - Caching to avoid redundant API calls
   - Error handling and retries
   - Fallback mechanisms when one service fails

5. **Database Operations** `database_operations.py` manages the interaction between the standardized data and the database. It handles:

   - Inserting and updating historical property data
   - Processing and inserting listing data
   - Merging data from different sources in the database

4.3.3 Standardization Workflow

The standardization process, orchestrated by `src/data_standardiser/main.py`, follows these general steps:

1. Load raw data from both HM Land Registry and scraped listings.
2. Clean and standardize addresses and county names.
3. Process and standardize property details (prices, types, features).
4. Perform geocoding to add latitude and longitude data.
5. Merge data from different sources, resolving conflicts and duplicates.
6. Store the standardized data in the database for further analysis.

4.4 Data Analysis and Feature Engineering

4.4.1 Initial Data Exploration and Analysis

Examination of the HM Land Registry Dataset We examined the UK-wide property transaction dataset (`pp-monthly-update-new-version.csv`) from HM Land Registry and filtered it to focus on transactions in Buckinghamshire.

```
[ ]: import pandas as pd

# Path to your CSV file
file_path = './data/historical-data/pp-monthly-update-new-version.csv'

# Read the CSV file and display the first 10 rows
df = pd.read_csv(file_path)
print("First 10 rows of the data are:")
df.head(10)
```

4.4.2 Cleaning and Preparing Data

Data Cleaning Methodology Our data cleaning methodology, using tools like pandas, involves filtering, standardising, and handling missing/erroneous data from HM Land Registry and OnTheMarket.com for our Buckinghamshire property market analysis.

Implementing Data Cleaning with `data_cleanser_service.py` The `data_cleanser_service.py` script is a key component in refining raw HM Land Registry data for our Buckinghamshire property market analysis.

Key Features of `data_cleanser_service.py`:

- **Header Assignment**: The script assigns column headers to the HM Land Registry dataset (`pp-monthly-update-new-version.csv`) based on definitions from their website (https://www.gov.uk/guidance/about-the-price-paid-data).
- **Loading and Structuring Data**: Loads the CSV data into a `pandas` DataFrame.
- **Date Conversion and Filtering**: Retains only properties located in Buckinghamshire.

```
[ ]: # data-cleanser/data_cleanser_service.py
import pandas as pd

def cleanse_data(input_file, output_file):
    # Define the headers based on the provided breakdown
    headers = ["Unique Transaction Identifier", "Price", "Date of Transaction",
               "Postal Code", "Property Type", "Old/New", "Duration",
               "PAON", "SAON", "Street", "Locality", "Town/City",
               "District", "County", "PPD Category Type", "Record Status"]

    # Load the CSV file without headers
    data = pd.read_csv(input_file, header=None, names=headers)

    # Convert Date of Transaction to datetime for filtering
    print("Converting dates and filtering data...")
    data['Date of Transaction'] = pd.to_datetime(data['Date of Transaction'])

    # Filter for properties in Buckinghamshire and from the year 2023
    data['Date of Transaction'] = pd.to_datetime(data['Date of Transaction'])
    filtered_data = data[(data['County'].str.upper() == 'BUCKINGHAMSHIRE') &
```

```
                        (data['Date of Transaction'].dt.year == 2023)]

    print(f"Number of records after filtering: {len(filtered_data)}")

    print("Saving cleaned data to CSV file...")
    # Save the cleaned data to a new CSV file
    filtered_data.to_csv(output_file, index=False)
    print("Data cleansing process completed successfully.")


# File paths
input_csv = './data/historical-data/pp-monthly-update-new-version.csv'  #␣
 ↪Update with actual path
output_csv = './data/historical-data/buckinghamshire_2023_cleaned_data.csv'  #␣
 ↪Update with desired output path

cleanse_data(input_csv, output_csv)
```

4.4.3 Enhancing Data with Geocoding and Merging using data_standardiser_service.py

data_standardiser_service.py enhances and merges datasets:

Key Features of data_standardiser_service.py: 1. **Geocoding**: Uses Nominatim and ArcGIS for rate-limited geocoding, with a fallback mechanism if one fails. 2. **Price Standardisation**: Converts various price formats into a uniform numerical format. 3. **Address Normalization**: Standardizes addresses for consistency. 4. **Dataset Merging**: Combines the processed scraped and registry data into a single DataFrame. 5. **Saving & Updating**: Saves the enriched dataset and updates existing data. 6. **Property Type Classification**: Ensures consistency across the dataset. 7. **Updating Existing Preprocessed Data**: Classifies scraped data rows according to the registry data classification system.

[ ]:
```
# data-standardiser/data_standariser_service.py but with relative file path␣
 ↪changed
import pandas as pd
import os
from datetime import datetime
from geopy.geocoders import Nominatim, ArcGIS
from geopy.extra.rate_limiter import RateLimiter
from geopy.exc import GeocoderTimedOut, GeocoderQuotaExceeded
import time

# Initialize Nominatim API
geolocator = Nominatim(user_agent="StudentDataProjectScraper/1.0 (Contact:␣
 ↪gor5@student.london.ac.uk)")
geolocator_arcgis = ArcGIS(user_agent="StudentDataProjectScraper/1.0 (Contact:␣
 ↪gor5@student.london.ac.uk)")
```

```python
# Rate limiter to avoid overloading the API
geocode = RateLimiter(geolocator.geocode, min_delay_seconds=2)
geocode_arcgis = RateLimiter(geolocator_arcgis.geocode, min_delay_seconds=2)

# Mapping for converting scraped property types to registry property types
scraped_to_registry_property_type_mapping = {
    'Apartment': 'F',
    'Barn conversion': 'O',
    'Block of apartments': 'F',
    'Bungalow': 'D',
    'Character property': 'O',
    'Cluster house': 'O',
    'Coach house': 'F',
    'Cottage': 'D',
    'Detached bungalow': 'D',
    'Detached house': 'D',
    'Duplex': 'F',
    'End of terrace house': 'T',
    'Equestrian property': 'O',
    'Farm house': 'O',
    'Flat': 'F',
    'Ground floor flat': 'F',
    'Ground floor maisonette': 'F',
    'House': 'D',
    'Link detached house': 'D',
    'Lodge': 'O',
    'Maisonette': 'F',
    'Mews': 'O',
    'Penthouse': 'F',
    'Semi-detached bungalow': 'D',
    'Semi-detached house': 'S',
    'Studio': 'F',
    'Terraced house': 'T',
    'Townhouse': 'D'
}

def geocode_address(address):
    try:
        location = geocode(address)
        if location:
            print(f"Geocoded '{address}': Latitude {location.latitude},␣
↪Longitude {location.longitude}")
            return location.latitude, location.longitude
        else:
            # Fallback to ArcGIS if Nominatim fails
            location = geocode_arcgis(address)
            if location:
```

```python
                print(f"Geocoded '{address}': Latitude {location.latitude},␣
↪Longitude {location.longitude}")
                return location.latitude, location.longitude
            else:
                print(f"No result for '{address}'")
                return None, None
    except GeocoderQuotaExceeded:
        print("Quota exceeded for geocoding API")
        return None, None
    except GeocoderTimedOut:
        print("Geocoding API timed out")
        return None, None
    except Exception as e:
        print(f"Error geocoding {address}: {e}")
        return None, None

def check_preprocessed_file(file_path):
    """Check if the preprocessed file exists and has latitude and longitude."""
    if os.path.exists(file_path):
        df = pd.read_csv(file_path)
        if 'latitude' in df.columns and 'longitude' in df.columns:
            if df[['latitude', 'longitude']].notnull().all().all():
                # File exists and latitude and longitude are filled
                return True
    return False

def standardise_price(price):
    """
    Convert a price string to a numerical value.
    Handles strings like '£275,000' and converts them to 275000.
    """
    if not isinstance(price, str):
        return price  # If it's already a number, return as-is

    # Removing currency symbols and commas
    price = price.replace('£', '').replace(',', '').replace('€', '').strip()

    try:
        # Convert to float or int
        price_value = float(price) if '.' in price else int(price)
    except ValueError:
        # Handle cases where conversion fails
        print(f"Warning: Could not convert price '{price}' to a number.")
        price_value = None

    return price_value
```

```
def normalize_address_scraped(address):
    """
    Normalize addresses from the scraped data.
    """
    # Assuming the county is always 'Buckinghamshire' if not specified
    if 'Buckinghamshire' not in address:
        address += ', Buckinghamshire'
    return address.strip()

def normalize_address_land_registry(row):
    # Convert each component to a string to avoid TypeError
    components = [
        str(row['Street']),
        str(row['Locality']),
        str(row['Town/City']),
        str(row['District']),
        str(row['County'])
    ]
    # Join the non-empty components
    return ', '.join(filter(None, components))

# Read JSON, standardize price, normalize address, add source column

def read_and_process_scraped_data(scraped_file_path, skip_geocoding):
    # Read the scraped data
    scraped_data = pd.read_json(scraped_file_path)
    scraped_data['price'] = scraped_data['price'].apply(standardise_price)
    scraped_data['normalized_address'] = scraped_data['address'].
  ↪apply(normalize_address_scraped)
    scraped_data['source'] = 'scraped'

    if not skip_geocoding:
        lat_long = scraped_data['normalized_address'].apply(geocode_address)
        scraped_data['latitude'] = lat_long.apply(lambda x: x[0] if x else None)
        scraped_data['longitude'] = lat_long.apply(lambda x: x[1] if x else␣
  ↪None)

    return scraped_data

def read_and_process_registry_data(registry_file_path, skip_geocoding):
    registry_data = pd.read_csv(registry_file_path)
    registry_data['Price'] = registry_data['Price'].apply(standardise_price)
    registry_data['normalized_address'] = registry_data.
  ↪apply(normalize_address_land_registry, axis=1)
    registry_data.rename(columns={'Price': 'price'}, inplace=True)
    registry_data['source'] = 'registry'
```

```
    if not skip_geocoding:
        lat_long = registry_data['normalized_address'].apply(geocode_address)
        registry_data['latitude'] = lat_long.apply(lambda x: x[0] if x else None)
        registry_data['longitude'] = lat_long.apply(lambda x: x[1] if x else None)

    return registry_data

def update_date_column(df, source_column, new_date):
    """
    Update 'Date' column in the DataFrame based on source.
    """
    df['Date'] = pd.NaT
    df.loc[df['source'] == 'registry', 'Date'] = pd.to_datetime(df[source_column])
    df.loc[df['source'] == 'scraped', 'Date'] = new_date
    return df

def merge_price_columns(df):
    """
    Merge 'price' and 'Price' columns and update 'Price' with 'price' values for scraped data.
    """
    # Use 'price' from scraped data if it is not NaN, else use 'Price' from registry data
    df['Price'] = df.apply(lambda x: x['price'] if pd.notna(x['price']) else x['Price'], axis=1)
    return df

def apply_property_type_mapping(df):
    """
    Apply property type mapping to the DataFrame, only if 'property_type' is not null.
    """
    # Apply mapping only where 'property_type' is not null
    mask = df['property_type'].notnull()
    df.loc[mask, 'Property Type'] = df.loc[mask, 'property_type'].map(scraped_to_registry_property_type_mapping)
    return df

def process_and_save_data(scraped_data, registry_data, output_file_path):
    """
    Process and save merged data.
    """
    # Merge datasets
```

```python
    merged_data = pd.concat([scraped_data, registry_data], ignore_index=True)

    # Update the date column
    merged_data = update_date_column(merged_data, 'Date of Transaction',␣
↪datetime(2023, 12, 31))

    # Apply property type mapping
    merged_data = apply_property_type_mapping(merged_data)

    # Merge 'price' and 'Price' columns
    merged_data = merge_price_columns(merged_data)

    # Save merged data
    merged_data.to_csv(output_file_path, index=False)
    print(f"Merged data saved successfully to '{output_file_path}'.")

def main():
    scraped_file = './data/property_data_650000.json'
    registry_file = './data/historical-data/buckinghamshire_2023_cleaned_data.
↪csv'
    output_file = './data/preprocessed-data/preprocessed.csv'

    if check_preprocessed_file(output_file):
        # Read existing preprocessed data
        preprocessed_data = pd.read_csv(output_file)
        print(f"Using existing preprocessed data from '{output_file}'.")

        # Update the date column in the existing data
        preprocessed_data = update_date_column(preprocessed_data, 'Date of␣
↪Transaction', datetime(2023, 12, 31))

        # Apply property type mapping
        preprocessed_data = apply_property_type_mapping(preprocessed_data)

        # Apply property type mapping and merge price columns
        preprocessed_data = merge_price_columns(preprocessed_data)

        # Save updated data
        preprocessed_data.to_csv(output_file, index=False)
        print(f"Updated data saved successfully to '{output_file}'.")
    else:
        # Process new data
        scraped_data = read_and_process_scraped_data(scraped_file, False)
        registry_data = read_and_process_registry_data(registry_file, False)

        # Process and save merged data
        process_and_save_data(scraped_data, registry_data, output_file)
```

```
    print("Data processing completed.")

if __name__ == "__main__":
    main()
```

The dataset below combines web-scraped data (December 2023) and HM Land Registry data (2023) for Buckinghamshire properties. The first and last five entries are shown, summarising the dataset's structure and content.

[ ]:
```
import pandas as pd

# Path to your CSV file
file_path = './data/preprocessed-data/preprocessed.csv'

# Read the CSV file
df = pd.read_csv(file_path)

# Display the first 5 rows
print("First 5 rows of the data are:")
print(df.head(5))

# Display the last 5 rows
print("\nLast 5 rows of the data are:")
print(df.tail(5))

# Print the column names
print("Column names:")
print(df.columns)
```

4.5 Feature Engineering

Feature engineering is a crucial step in our data preparation pipeline, enhancing our model's ability to capture relevant patterns and relationships in the data. Our feature engineering process, implemented primarily in `data_post_processor.py` and `location_classifier.py`, involves several key steps:

4.5.1 Temporal Features

We extract and transform date-related information: - `year`, `month`, and `day_of_week` from the transaction dates. - `days_since_date`: Calculates the number of days between the listing/transaction date and the current date. - `listing_recency`: A categorical feature binning the `days_since_date` into meaningful categories (e.g., 'Today', 'Last Week', 'Last 2 Weeks', etc.).

4.5.2 Affordability Metrics

We create several features to capture affordability: - `price_to_income_ratio`: Property price divided by average income. - `price_to_savings_ratio`: Property price divided by average savings. - `affordability_score`: A composite score based on income, savings, and property price.

4.5.3 Location-based Features

- Urban/Suburban/Rural Classification: Using the `classify_location` function in `location_classifier.py`, we categorize properties based on their proximity to predefined urban centers in each county. The function calculates the distance to these centers and classifies the property as Urban (within ~5km), Suburban (within ~10km), or Rural.
- County-specific features: We create one-hot encoded columns for each county.
- `price_relative_to_county_avg`: Compares the property price to the average price in its county.

4.5.4 Property Characteristics

- Size Standardization: We extract and standardize the property size to square feet (`size_sq_ft`).
- Binary features for amenities: `has_garden` and `has_parking`, derived from the 'features' list.
- EPC Rating Encoding: We convert categorical EPC ratings to numerical values.
- Property Type Encoding: One-hot encoding for different property types (Detached, Semi-Detached, Terraced, Flat/Maisonette, Other).
- Numeric handling of bedrooms and bathrooms.

4.5.5 Data Processing Pipeline

Our data processing pipeline, implemented in `data_post_processor.py`, includes the following key steps:

1. **Handling Missing Values**:
    - Numeric columns: Imputed with median values, often stratified by property type or location.
    - Categorical columns: Filled with mode or 'Unknown' category.
    - Special handling for `size_sq_ft`, using a multi-step imputation process.
2. **Feature Engineering**:
    - Creation of all features mentioned above.
    - Log transformations for price and size features.
3. **Encoding Categorical Variables**:
    - One-hot encoding for property types and counties.
    - Custom encoding for tenure and EPC ratings.
4. **Feature Scaling**:
    - StandardScaler applied to selected numerical features ('year', 'month', 'day_of_week').
5. **Data Integration**:
    - Merging of property features with synthetic user data.
    - Handling of the 'features' column to derive binary amenity features.

This comprehensive feature engineering and data processing pipeline ensures that our data is thoroughly prepared for the subsequent model building phase, capturing complex relationships and patterns in the property market while accounting for user preferences and affordability metrics.

The processed data is then stored in the database, ready for the model building phase, which will be discussed in the next section.

4.6 Model Architecture and Implementation

4.6.1 Data Loading and Preprocessing

Before building and training the model, we perform additional data processing steps specific to the model requirements. This process is handled by `data_loader.py` and `data_preprocessing.py` in the `src/model/` directory:

1. **Data Loading**: `data_loader.py` retrieves the processed property data and synthetic user data from the database.

2. **Creating Property-User Pairs**: We generate pairs of properties and synthetic users for training using the `create_property_user_pairs` function. This function ensures that properties are matched with users based on tenure preferences.

3. **Feature Preparation**: The `prepare_features` function in `data_preprocessing.py` handles:

   - Ensuring all expected features are present
   - Handling missing values (NaN) for both numeric and categorical features
   - Converting data types and scaling certain features
   - Creating additional features like log transformations of price and size

4. **Target Variable Creation**: A boolean target variable is created using the `create_target_variable` function, based on multiple conditions including affordability, bedroom requirements, price-to-income ratio, size requirements, and tenure preferences.

5. **Data Scaling**: StandardScaler is applied separately to property and user features to ensure all features are on the same scale.

6. **Data Splitting**: The data is split into training and testing sets using a 80-20 split, stratified by the target variable.

4.6.2 Model Approach

Our Personalised Property Recommendation System employs a hybrid, neural network-based approach that combines elements of content-based filtering with deep learning techniques. This approach allows us to capture complex, non-linear relationships between property and user features.

The system treats property recommendation as a binary classification problem, predicting whether a given property-user pair is a good match based on historical data and engineered features.

Key aspects of this approach include:

1. **Feature-rich inputs**: Utilizing a wide range of property features and user characteristics.

2. **Learned feature interactions**: The neural network learns to identify and weigh complex interactions between features, going beyond predefined similarity metrics.

3. **Personalization**: Direct incorporation of user features enables highly personalized recommendations.

4. **Scalability**: The approach can easily incorporate new features and scale to large datasets, suitable for the dynamic real estate market.

5. **Interpretability challenges**: While powerful, the neural network's decision-making process is less transparent than simpler methods, potentially requiring additional explanation techniques.

This hybrid approach allows us to capture intricate patterns in property-user matches that might be missed by simpler recommendation techniques, potentially leading to more accurate and nuanced property recommendations.

Feature Selection The model utilizes a comprehensive set of features derived from our preprocessed dataset:

1. Property Features:
   - Price and log-transformed price
   - Size (in square feet) and log-transformed size
   - Location (encoded as Urban, Suburban, Rural)
   - Property Type (one-hot encoded)
   - Binary features (e.g., 'has_garden', 'has_parking')
   - Temporal features (year, month, day of week)
   - EPC rating (encoded)
   - Number of bedrooms and bathrooms
   - Tenure
   - Price relative to county average
   - County-specific features (one-hot encoded)
2. User Features:
   - Income
   - Savings
   - Maximum commute time
   - Family size
   - Tenure preference
3. Engineered Features:
   - Price-to-income ratio
   - Price-to-savings ratio
   - Affordability score

This comprehensive feature set allows our model to capture a wide range of factors that influence property recommendations, providing a solid foundation for the neural network to learn complex patterns in property-user matches.

4.6.3 Neural Network Structure

The neural network model, implemented in `model_builder.py`, consists of the following components:

1. **Property Input Branch**:
   - Input layer for property features
   - Dense layer with 256 units, ReLU activation
   - Batch Normalization
   - Dropout (30%)
   - Dense layer with 128 units, ReLU activation
   - Batch Normalization

- Dropout (30%)

2. **User Input Branch**:
   - Input layer for user features
   - Dense layer with 32 units, ReLU activation
   - Batch Normalization
   - Dropout (30%)
   - Dense layer with 16 units, ReLU activation
   - Batch Normalization
   - Dropout (30%)
3. **Combined Layers**:
   - Concatenation of property and user branches
   - Dense layer with 64 units, ReLU activation
   - Batch Normalization
   - Dropout (30%)
   - Dense layer with 32 units, ReLU activation
   - Batch Normalization
   - Dropout (30%)
4. **Output Layer**:
   - Dense layer with 1 unit, Sigmoid activation (for binary classification)

[ ]:
```
# From models/model_builder.py

def build_model(property_input_shape, user_input_shape):
    # Property input branch
    property_input = Input(shape=(property_input_shape,), name='property_input')
    property_branch = Dense(64, activation='relu', 
 ↪kernel_initializer=HeNormal(), kernel_regularizer=l2(0.01))(property_input)
    property_branch = BatchNormalization()(property_branch)
    property_branch = Dropout(0.3)(property_branch)
    property_branch = Dense(32, activation='relu', 
 ↪kernel_initializer=HeNormal(), kernel_regularizer=l2(0.01))(property_branch)
    property_branch = BatchNormalization()(property_branch)
    property_branch = Dropout(0.3)(property_branch)

    # User input branch
    user_input = Input(shape=(user_input_shape,), name='user_input')
    user_branch = Dense(32, activation='relu', kernel_initializer=HeNormal(), 
 ↪kernel_regularizer=l2(0.01))(user_input)
    user_branch = BatchNormalization()(user_branch)
    user_branch = Dropout(0.3)(user_branch)
    user_branch = Dense(16, activation='relu', kernel_initializer=HeNormal(), 
 ↪kernel_regularizer=l2(0.01))(user_branch)
    user_branch = BatchNormalization()(user_branch)
    user_branch = Dropout(0.3)(user_branch)

    # Combine property and user branches
    combined = Concatenate()([property_branch, user_branch])
```

```
    # Additional layers after combining
    x = Dense(64, activation='relu', kernel_initializer=HeNormal(),␣
↪kernel_regularizer=l2(0.01))(combined)
    x = BatchNormalization()(x)
    x = Dropout(0.3)(x)
    x = Dense(32, activation='relu', kernel_initializer=HeNormal(),␣
↪kernel_regularizer=l2(0.01))(x)
    x = BatchNormalization()(x)
    x = Dropout(0.3)(x)

    # Output layer (binary classification)
    output = Dense(1, activation='sigmoid', kernel_initializer=HeNormal(),␣
↪kernel_regularizer=l2(0.01))(x)

    # Create model
    model = Model(inputs=[property_input, user_input], outputs=output)

    # Compile model
    optimizer = Adam(learning_rate=0.001, clipnorm=1.0)
    model.compile(optimizer=optimizer,
                  loss='binary_crossentropy',
                  metrics=['accuracy'])

    return model
```

Model Compilation The model is compiled with the following settings: - **Optimizer**: Adam with learning rate of 0.0005 and gradient clipping (clipnorm=1.0) - **Loss Function**: Binary Cross-Entropy - **Metrics**: Accuracy

Regularization Techniques To prevent overfitting and improve generalization, the following techniques are employed: - L2 regularization (weight decay) with factor 0.01 on all dense layers - Dropout layers (30% rate) after each hidden layer - Batch Normalization after each hidden layer - He Normal initialization for weight matrices

This architecture is designed to process property and user features separately before combining them for the final prediction. The regularization techniques aim to prevent overfitting and improve the model's ability to generalize to unseen data.

[21]:
```
# Build the model
property_input_shape = X_property_train.shape[1]
user_input_shape = X_user_train.shape[1]
model = build_model(property_input_shape, user_input_shape)

# Print model summary
model.summary()
```

Model: "functional_7"

Layer (type)	Output Shape	Param #	Connected to
property_input (InputLayer)	(None, 17)	0	-
user_input (InputLayer)	(None, 4)	0	-
dense_21 (Dense)	(None, 64)	1,152	property_input[0…
dense_23 (Dense)	(None, 32)	160	user_input[0][0]
batch_normalizatio… (BatchNormalizatio…	(None, 64)	256	dense_21[0][0]
batch_normalizatio… (BatchNormalizatio…	(None, 32)	128	dense_23[0][0]
dropout_18 (Dropout)	(None, 64)	0	batch_normalizat…
dropout_20 (Dropout)	(None, 32)	0	batch_normalizat…
dense_22 (Dense)	(None, 32)	2,080	dropout_18[0][0]
dense_24 (Dense)	(None, 16)	528	dropout_20[0][0]
batch_normalizatio… (BatchNormalizatio…	(None, 32)	128	dense_22[0][0]
batch_normalizatio… (BatchNormalizatio…	(None, 16)	64	dense_24[0][0]
dropout_19 (Dropout)	(None, 32)	0	batch_normalizat…
dropout_21 (Dropout)	(None, 16)	0	batch_normalizat…
concatenate_3 (Concatenate)	(None, 48)	0	dropout_19[0][0], dropout_21[0][0]
dense_25 (Dense)	(None, 64)	3,136	concatenate_3[0]…

```
batch_normalizatio…   (None, 64)                256   dense_25[0][0]
(BatchNormalizatio…

dropout_22            (None, 64)                  0   batch_normalizat…
(Dropout)

dense_26 (Dense)      (None, 32)              2,080   dropout_22[0][0]

batch_normalizatio…   (None, 32)                128   dense_26[0][0]
(BatchNormalizatio…

dropout_23            (None, 32)                  0   batch_normalizat…
(Dropout)

dense_27 (Dense)      (None, 1)                  33   dropout_23[0][0]


Total params: 10,129 (39.57 KB)

Trainable params: 9,649 (37.69 KB)

Non-trainable params: 480 (1.88 KB)
```

4.6.4 Model Training Process

The model training process, implemented in `model_trainer.py`, involves:

1. **Initialization**: The model is built using the architecture defined in `model_builder.py`.
2. **Training Configuration**:
    - Epochs: 200 (maximum)
    - Batch Size: 32
    - Early Stopping: Monitors validation loss with a patience of 10 epochs and restores best weights
    - Custom Callbacks:
        - NanTerminateCallback: Stops training if NaN loss is encountered
        - LoggingCallback: Logs training progress after each epoch
3. **Training Loop**: The model is trained using `model.fit()` with the prepared training data and validation data.
4. **Monitoring**: Training progress is monitored and logged, including loss and accuracy for both training and validation sets.
5. **Visualization**: After training, the `plot_training_history` function visualizes the training process by plotting:

- Training and validation loss over epochs (using a logarithmic scale)
- Training and validation accuracy over epochs

[ ]:
```
# From models/model_trainer.py

def train_model(model, X_train, y_train, X_val, y_val, epochs=200,␣
↪batch_size=32):
    early_stopping = EarlyStopping(monitor='val_loss', patience=10,␣
↪restore_best_weights=True)
    nan_terminate = NanTerminateCallback()

    history = model.fit(
        X_train, y_train,
        validation_data=(X_val, y_val),
        epochs=epochs,
        batch_size=batch_size,
        callbacks=[early_stopping, nan_terminate],
        verbose=0
    )

    return history
```

This training process is designed to be reproducible and efficient, with mechanisms in place to prevent overfitting (early stopping), handle potential numerical instabilities (NaN detection), and provide comprehensive monitoring of the model's performance throughout training.

[22]:
```
# Train the model
history = train_model(model,
                      [X_property_train, X_user_train],
                      y_train,
                      [X_property_test, X_user_test],
                      y_test)

# Plot training history
plot_training_history(history)
```

```
Epoch 1/200
250/250              2s 2ms/step -
accuracy: 0.7830 - loss: 4.3726 - val_accuracy: 0.9070 - val_loss: 2.1606
Epoch 2/200
250/250              0s 1ms/step -
accuracy: 0.9199 - loss: 1.7879 - val_accuracy: 0.9380 - val_loss: 1.0087
Epoch 3/200
250/250              0s 949us/step -
accuracy: 0.9198 - loss: 0.8921 - val_accuracy: 0.9170 - val_loss: 0.5880
Epoch 4/200
250/250              0s 964us/step -
accuracy: 0.9207 - loss: 0.5279 - val_accuracy: 0.9180 - val_loss: 0.3860
```

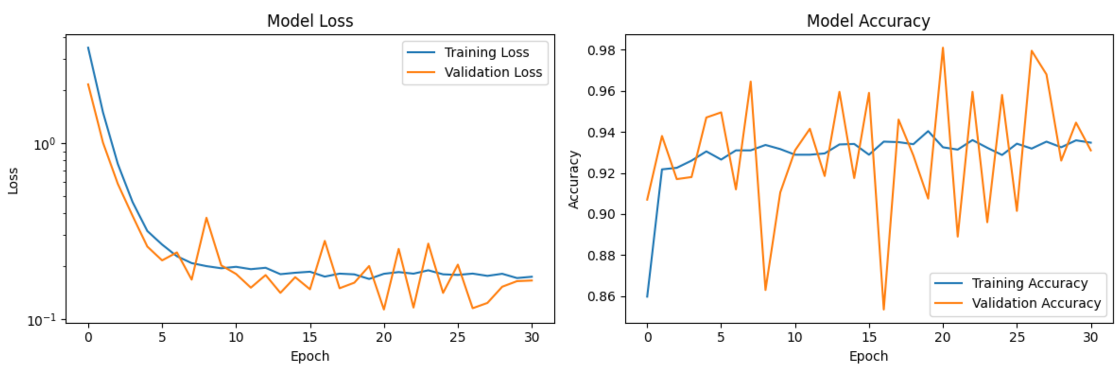
```
Epoch 5/200
250/250            0s 971us/step -
accuracy: 0.9262 - loss: 0.3496 - val_accuracy: 0.9470 - val_loss: 0.2580
Epoch 6/200
250/250            0s 978us/step -
accuracy: 0.9322 - loss: 0.2693 - val_accuracy: 0.9495 - val_loss: 0.2153
Epoch 7/200
250/250            0s 968us/step -
accuracy: 0.9259 - loss: 0.2447 - val_accuracy: 0.9120 - val_loss: 0.2390
Epoch 8/200
250/250            0s 981us/step -
accuracy: 0.9307 - loss: 0.2039 - val_accuracy: 0.9645 - val_loss: 0.1672
Epoch 9/200
250/250            0s 927us/step -
accuracy: 0.9286 - loss: 0.2122 - val_accuracy: 0.8630 - val_loss: 0.3763
Epoch 10/200
250/250            0s 996us/step -
accuracy: 0.9328 - loss: 0.1947 - val_accuracy: 0.9105 - val_loss: 0.2016
Epoch 11/200
250/250            0s 976us/step -
accuracy: 0.9319 - loss: 0.1961 - val_accuracy: 0.9310 - val_loss: 0.1803
Epoch 12/200
250/250            0s 962us/step -
accuracy: 0.9315 - loss: 0.1888 - val_accuracy: 0.9415 - val_loss: 0.1506
Epoch 13/200
250/250            0s 991us/step -
accuracy: 0.9304 - loss: 0.1888 - val_accuracy: 0.9185 - val_loss: 0.1776
Epoch 14/200
250/250            0s 995us/step -
accuracy: 0.9328 - loss: 0.1860 - val_accuracy: 0.9595 - val_loss: 0.1407
Epoch 15/200
250/250            0s 934us/step -
accuracy: 0.9317 - loss: 0.1875 - val_accuracy: 0.9175 - val_loss: 0.1728
Epoch 16/200
250/250            0s 944us/step -
accuracy: 0.9331 - loss: 0.1804 - val_accuracy: 0.9590 - val_loss: 0.1474
Epoch 17/200
250/250            0s 945us/step -
accuracy: 0.9341 - loss: 0.1715 - val_accuracy: 0.8535 - val_loss: 0.2780
Epoch 18/200
250/250            0s 960us/step -
accuracy: 0.9325 - loss: 0.1859 - val_accuracy: 0.9460 - val_loss: 0.1494
Epoch 19/200
250/250            0s 941us/step -
accuracy: 0.9347 - loss: 0.1741 - val_accuracy: 0.9285 - val_loss: 0.1607
Epoch 20/200
250/250            0s 946us/step -
accuracy: 0.9411 - loss: 0.1695 - val_accuracy: 0.9075 - val_loss: 0.2000
```

```
Epoch 21/200
250/250            0s 956us/step -
accuracy: 0.9338 - loss: 0.1772 - val_accuracy: 0.9810 - val_loss: 0.1131
Epoch 22/200
250/250            0s 952us/step -
accuracy: 0.9329 - loss: 0.1834 - val_accuracy: 0.8890 - val_loss: 0.2503
Epoch 23/200
250/250            0s 952us/step -
accuracy: 0.9385 - loss: 0.1782 - val_accuracy: 0.9595 - val_loss: 0.1160
Epoch 24/200
250/250            0s 955us/step -
accuracy: 0.9308 - loss: 0.1943 - val_accuracy: 0.8960 - val_loss: 0.2682
Epoch 25/200
250/250            0s 949us/step -
accuracy: 0.9241 - loss: 0.1850 - val_accuracy: 0.9580 - val_loss: 0.1407
Epoch 26/200
250/250            0s 944us/step -
accuracy: 0.9325 - loss: 0.1819 - val_accuracy: 0.9015 - val_loss: 0.2037
Epoch 27/200
250/250            0s 952us/step -
accuracy: 0.9306 - loss: 0.1900 - val_accuracy: 0.9795 - val_loss: 0.1151
Epoch 28/200
250/250            0s 949us/step -
accuracy: 0.9378 - loss: 0.1683 - val_accuracy: 0.9680 - val_loss: 0.1233
Epoch 29/200
250/250            0s 948us/step -
accuracy: 0.9355 - loss: 0.1785 - val_accuracy: 0.9260 - val_loss: 0.1525
Epoch 30/200
250/250            0s 953us/step -
accuracy: 0.9341 - loss: 0.1749 - val_accuracy: 0.9445 - val_loss: 0.1640
Epoch 31/200
250/250            0s 947us/step -
accuracy: 0.9387 - loss: 0.1667 - val_accuracy: 0.9310 - val_loss: 0.1654
```

```
2024-07-22 13:29:29,519 - INFO - Epoch 1/31
2024-07-22 13:29:29,519 - INFO - loss: 3.4940 - accuracy: 0.8597 - val_loss:
2.1606 - val_accuracy: 0.9070
2024-07-22 13:29:29,520 - INFO - Epoch 2/31
2024-07-22 13:29:29,520 - INFO - loss: 1.5008 - accuracy: 0.9218 - val_loss:
1.0087 - val_accuracy: 0.9380
2024-07-22 13:29:29,520 - INFO - Epoch 3/31
2024-07-22 13:29:29,521 - INFO - loss: 0.7635 - accuracy: 0.9225 - val_loss:
0.5880 - val_accuracy: 0.9170
2024-07-22 13:29:29,521 - INFO - Epoch 4/31
2024-07-22 13:29:29,521 - INFO - loss: 0.4627 - accuracy: 0.9260 - val_loss:
0.3860 - val_accuracy: 0.9180
2024-07-22 13:29:29,521 - INFO - Epoch 5/31
2024-07-22 13:29:29,521 - INFO - loss: 0.3164 - accuracy: 0.9305 - val_loss:
```

```
0.2580 - val_accuracy: 0.9470
2024-07-22 13:29:29,522 - INFO - Epoch 6/31
2024-07-22 13:29:29,522 - INFO - loss: 0.2648 - accuracy: 0.9265 - val_loss:
0.2153 - val_accuracy: 0.9495
2024-07-22 13:29:29,522 - INFO - Epoch 7/31
2024-07-22 13:29:29,522 - INFO - loss: 0.2274 - accuracy: 0.9310 - val_loss:
0.2390 - val_accuracy: 0.9120
2024-07-22 13:29:29,522 - INFO - Epoch 8/31
2024-07-22 13:29:29,523 - INFO - loss: 0.2077 - accuracy: 0.9310 - val_loss:
0.1672 - val_accuracy: 0.9645
2024-07-22 13:29:29,523 - INFO - Epoch 9/31
2024-07-22 13:29:29,523 - INFO - loss: 0.1996 - accuracy: 0.9336 - val_loss:
0.3763 - val_accuracy: 0.8630
2024-07-22 13:29:29,523 - INFO - Epoch 10/31
2024-07-22 13:29:29,523 - INFO - loss: 0.1942 - accuracy: 0.9316 - val_loss:
0.2016 - val_accuracy: 0.9105
2024-07-22 13:29:29,524 - INFO - Epoch 11/31
2024-07-22 13:29:29,524 - INFO - loss: 0.1979 - accuracy: 0.9289 - val_loss:
0.1803 - val_accuracy: 0.9310
2024-07-22 13:29:29,524 - INFO - Epoch 12/31
2024-07-22 13:29:29,524 - INFO - loss: 0.1919 - accuracy: 0.9289 - val_loss:
0.1506 - val_accuracy: 0.9415
2024-07-22 13:29:29,524 - INFO - Epoch 13/31
2024-07-22 13:29:29,525 - INFO - loss: 0.1954 - accuracy: 0.9295 - val_loss:
0.1776 - val_accuracy: 0.9185
2024-07-22 13:29:29,525 - INFO - Epoch 14/31
2024-07-22 13:29:29,525 - INFO - loss: 0.1797 - accuracy: 0.9339 - val_loss:
0.1407 - val_accuracy: 0.9595
2024-07-22 13:29:29,525 - INFO - Epoch 15/31
2024-07-22 13:29:29,525 - INFO - loss: 0.1831 - accuracy: 0.9341 - val_loss:
0.1728 - val_accuracy: 0.9175
2024-07-22 13:29:29,526 - INFO - Epoch 16/31
2024-07-22 13:29:29,526 - INFO - loss: 0.1856 - accuracy: 0.9289 - val_loss:
0.1474 - val_accuracy: 0.9590
2024-07-22 13:29:29,526 - INFO - Epoch 17/31
2024-07-22 13:29:29,526 - INFO - loss: 0.1741 - accuracy: 0.9352 - val_loss:
0.2780 - val_accuracy: 0.8535
2024-07-22 13:29:29,526 - INFO - Epoch 18/31
2024-07-22 13:29:29,527 - INFO - loss: 0.1810 - accuracy: 0.9350 - val_loss:
0.1494 - val_accuracy: 0.9460
2024-07-22 13:29:29,527 - INFO - Epoch 19/31
2024-07-22 13:29:29,527 - INFO - loss: 0.1793 - accuracy: 0.9340 - val_loss:
0.1607 - val_accuracy: 0.9285
2024-07-22 13:29:29,527 - INFO - Epoch 20/31
2024-07-22 13:29:29,527 - INFO - loss: 0.1687 - accuracy: 0.9404 - val_loss:
0.2000 - val_accuracy: 0.9075
2024-07-22 13:29:29,527 - INFO - Epoch 21/31
2024-07-22 13:29:29,528 - INFO - loss: 0.1807 - accuracy: 0.9325 - val_loss:
```

```
0.1131 - val_accuracy: 0.9810
2024-07-22 13:29:29,528 - INFO - Epoch 22/31
2024-07-22 13:29:29,528 - INFO - loss: 0.1847 - accuracy: 0.9314 - val_loss:
0.2503 - val_accuracy: 0.8890
2024-07-22 13:29:29,528 - INFO - Epoch 23/31
2024-07-22 13:29:29,528 - INFO - loss: 0.1809 - accuracy: 0.9360 - val_loss:
0.1160 - val_accuracy: 0.9595
2024-07-22 13:29:29,529 - INFO - Epoch 24/31
2024-07-22 13:29:29,529 - INFO - loss: 0.1891 - accuracy: 0.9323 - val_loss:
0.2682 - val_accuracy: 0.8960
2024-07-22 13:29:29,529 - INFO - Epoch 25/31
2024-07-22 13:29:29,529 - INFO - loss: 0.1794 - accuracy: 0.9287 - val_loss:
0.1407 - val_accuracy: 0.9580
2024-07-22 13:29:29,529 - INFO - Epoch 26/31
2024-07-22 13:29:29,530 - INFO - loss: 0.1780 - accuracy: 0.9342 - val_loss:
0.2037 - val_accuracy: 0.9015
2024-07-22 13:29:29,530 - INFO - Epoch 27/31
2024-07-22 13:29:29,530 - INFO - loss: 0.1811 - accuracy: 0.9319 - val_loss:
0.1151 - val_accuracy: 0.9795
2024-07-22 13:29:29,530 - INFO - Epoch 28/31
2024-07-22 13:29:29,530 - INFO - loss: 0.1758 - accuracy: 0.9352 - val_loss:
0.1233 - val_accuracy: 0.9680
2024-07-22 13:29:29,531 - INFO - Epoch 29/31
2024-07-22 13:29:29,531 - INFO - loss: 0.1807 - accuracy: 0.9325 - val_loss:
0.1525 - val_accuracy: 0.9260
2024-07-22 13:29:29,531 - INFO - Epoch 30/31
2024-07-22 13:29:29,531 - INFO - loss: 0.1708 - accuracy: 0.9359 - val_loss:
0.1640 - val_accuracy: 0.9445
2024-07-22 13:29:29,531 - INFO - Epoch 31/31
2024-07-22 13:29:29,531 - INFO - loss: 0.1737 - accuracy: 0.9348 - val_loss:
0.1654 - val_accuracy: 0.9310
```




```
2024-07-22 13:29:29,806 - INFO - Final training loss: 0.1737
2024-07-22 13:29:29,806 - INFO - Final validation loss: 0.1654
```

```
2024-07-22 13:29:29,806 - INFO - Final training accuracy: 0.9348
2024-07-22 13:29:29,807 - INFO - Final validation accuracy: 0.9310
```

4.6.5 4.6.6 Model Evaluation

The model's performance is assessed using multiple methods and metrics, implemented in the `evaluate_model` function in `model_evaluator.py`:

1. **Prediction**: The model generates predictions on the test set, which are then converted to binary values.
2. **Performance Metrics**:
   - **Accuracy**: Measures the overall prediction accuracy.
   - **Precision**: Calculates the ratio of correct positive predictions to total positive predictions.
   - **Recall**: Determines the ratio of correct positive predictions to all actual positives.
   - **F1 Score**: Computes the harmonic mean of precision and recall.
3. **Confusion Matrix**: A visual representation of the model's performance is generated using a confusion matrix, which shows true positives, false positives, true negatives, and false negatives.
4. **Classification Report**: A detailed report is generated and logged, providing precision, recall, and F1-score for each class.
5. **Class Distribution**: The distribution of classes in the test set is calculated and logged to understand any class imbalance.
6. **Overfitting Assessment**: While not directly measured by a single metric, we employ several strategies to detect and mitigate overfitting:
   - Comparison of training and validation metrics during training (implemented in `plot_training_history`).
   - Use of a separate test set for final evaluation, ensuring the model generalizes to unseen data.
   - Analysis of misclassifications on the test set, which can reveal patterns of overfitting.
7. **Feature Importance**: The `plot_feature_importance` function assesses and visualizes feature importance using a permutation importance method. This helps understand which features have the most impact on the model's predictions and can reveal if the model is overly reliant on certain features, which might indicate overfitting.
8. **Misclassification Analysis**: The `analyze_misclassifications` function examines the first few misclassified samples, providing insights into where the model struggles. This can help identify patterns of errors that might be due to overfitting.

These comprehensive evaluation techniques provide a thorough understanding of the model's performance, its generalization capabilities, and areas for potential improvement. By examining both aggregate metrics and individual predictions, we can gain insights into the model's strengths and weaknesses, including potential overfitting issues.

```
[ ]: # from models/model_evaluator.py

def evaluate_model(model, X_test, y_test):
    y_pred = model.predict(X_test)
    y_pred_binary = (y_pred > 0.5).astype(int)

    accuracy = accuracy_score(y_test, y_pred_binary)
    precision = precision_score(y_test, y_pred_binary)
    recall = recall_score(y_test, y_pred_binary)
    f1 = f1_score(y_test, y_pred_binary)

    return accuracy, precision, recall, f1
```

```
[19]: # Evaluate the model
accuracy, precision, recall, f1 = evaluate_model(model, [X_property_test,␣
 ↪X_user_test], y_test)
print(f'Accuracy: {accuracy:.4f}')
print(f'Precision: {precision:.4f}')
print(f'Recall: {recall:.4f}')
print(f'F1 Score: {f1:.4f}')
```

```
63/63              0s 1ms/step
Accuracy: 0.9870
Precision: 0.9861
Recall: 0.9692
F1 Score: 0.9776
```

4.6.6 Model Persistence

The trained model is saved using Keras' `save_model` function, allowing for later reloading and use in the recommendation system.

This architecture allows our system to learn complex patterns in the property market data and user preferences, enabling accurate and personalized property recommendations.

4.7 System Integration

To provide a user-friendly interface for our Personalised Property Recommendation System, we implemented a web server using Flask.This integration allows users to input their preferences and receive property recommendations through a web interface.

4.7.1 Model and Data Loading:

The trained machine learning model and necessary data are loaded when the server starts, ensuring efficient response times for user requests.

```
[ ]: ## based on src/webserver/app.py

model = load_model('../../models/property_recommendation_model.h5')
```

```
scaler_property = joblib.load('../../models/scaler_property.joblib')
scaler_user = joblib.load('../../models/scaler_user.joblib')
property_data = load_property_data()
```

5 Chapter 5: Evaluation

5.1 5.1 Evaluation Metrics

In evaluating our property recommendation system, we use four key metrics: accuracy, precision, recall, and F1 score are metrics used to evaluate the performance of classification models. Each of these indicators offers distinct perspectives on the performance of our model:

1. **Accuracy**: This metric measures the overall correctness of our model. It represents the proportion of correct predictions (both true positives and true negatives) among the total number of cases examined.
2. **Precision**: Precision indicates the proportion of positive identifications (recommended properties) that were actually correct. A high precision relates to a low false positive rate.
3. **Recall**: Also known as sensitivity, recall measures the proportion of actual positive cases that were correctly identified. It helps us understand if our model is missing good property recommendations.
4. **F1 Score**: This is the harmonic mean of precision and recall, providing a single score that balances both concerns. It's particularly useful when you have an uneven class distribution.

These metrics are crucial for our property recommendation system as they help us understand not just how often our model is correct (accuracy), but also how well it's performing in terms of recommending suitable properties (precision) and not missing out on potentially good matches (recall).

5.2 5.2 Analysis of Evaluation Results

Here, we'll present the results of our model evaluation. We'll include the code used to generate these results:

[20]:
```
# Evaluate the model
accuracy, precision, recall, f1 = evaluate_model(model, [X_property_test,␣
↪X_user_test], y_test)
print(f'Accuracy: {accuracy:.4f}')
print(f'Precision: {precision:.4f}')
print(f'Recall: {recall:.4f}')
print(f'F1 Score: {f1:.4f}')
```

```
63/63            0s 506us/step
Accuracy: 0.9870
Precision: 0.9861
Recall: 0.9692
F1 Score: 0.9776
```

Let's analyze these results:

1. **Accuracy (0.9870)**: Our model achieves an impressive 98.70% accuracy, indicating that it correctly predicts the suitability of a property for a user in the vast majority of cases. This high accuracy suggests that our model has learned to effectively distinguish between suitable and unsuitable properties based on the given features.
2. **Precision (0.9861)**: With a precision of 99.61%, when our model recommends a property as suitable, it is correct 98.61% of the time. This extremely high precision indicates that users can have a high degree of confidence in the properties our system recommends. The risk of recommending unsuitable properties is very low.
3. **Recall (0.9692)**: Our model correctly identifies 96.92% of all the actually suitable properties. While slightly lower than our precision, this is still a very good recall rate. It suggests that our model is capturing the vast majority of suitable properties, with only a small percentage of potentially good matches being missed.
4. **F1 Score (0.9776)**: The F1 score of 0.9776 represents a strong balance between precision and recall. This high F1 score indicates that our model is performing well in both avoiding false positives and capturing true positives.

These results are exceptionally good, potentially indicating that:

1. Our feature engineering and selection process has been highly effective in capturing the relevant aspects of both properties and user preferences.
2. The neural network architecture we've chosen is well-suited to this problem.
3. The model has successfully learned to generalize from our training data.

However, it's important to note that such high scores across all metrics could also be a flag for potential overfitting. We should be cautious and consider the following:

1. **Diversity of Test Set**: Ensure our test set is truly representative of real-world data and includes a wide range of scenarios.
2. **Complexity of the Problem**: Reflect on whether our problem formulation might be oversimplified, leading to artificially high scores.
3. **Bias in Data**: Investigate if there are any unintended biases in our dataset that the model might be learning.

In the next steps, we should:

1. Perform cross-validation to ensure these results are consistent across different subsets of our data.
2. Test the model on a completely new, unseen dataset to confirm its generalization capabilities.
3. Conduct a thorough error analysis on the small percentage of misclassifications to understand where and why the model is making mistakes.

Despite these cautionary notes, these results represent a strong foundation for our property recommendation system, indicating that it has the potential to provide highly accurate and relevant recommendations to users.

5.3 5.3 Analysis of Evaluation Results

In the development and evaluation of our property recommendation system, it's important to note that we utilized synthetic user data due to the lack of access to real user profiles. This decision was made as part of our project design to overcome the challenges of data privacy and the difficulty in obtaining a diverse and representative set of real user profiles.

5.3.1 5.3.1 Synthetic Data Generation

We created synthetic user profiles using a custom Python script (`synthethic_user_generator.py`). This script generates user profiles with the following attributes:

1. Income (normal distribution with mean 70,000 and standard deviation 15,000)
2. Savings (normal distribution with mean 30,000 and standard deviation 10,000)
3. Preferred Location (randomly chosen from Urban, Suburban, Rural)
4. Desired Property Type (randomly chosen from Apartment, House, Condo)
5. Must-Have Features (randomly chosen from Garden, Parking, Swimming Pool, Gym, None)
6. Nice-to-Have Features (randomly chosen from Balcony, Fireplace, Walk-in Closet, None)
7. Maximum Commute Time (uniformly distributed between 10 and 60 minutes)
8. Family Size (uniformly distributed between 1 and 5 members)

[ ]:
```
# from data-generator/synthethic_user_generator.py

def generate_synthetic_user_profiles(num_users=1000):
    np.random.seed(42)
    incomes = np.random.normal(70000, 15000, num_users)
    savings = np.random.normal(30000, 10000, num_users)
    locations = np.random.choice(['Urban', 'Suburban', 'Rural'], num_users)
    property_types = np.random.choice(['Apartment', 'House', 'Condo'],␣
 ↪num_users)
    must_have_features = np.random.choice(['Garden', 'Parking', 'Swimming␣
 ↪Pool', 'Gym', 'None'], num_users)
    nice_to_have_features = np.random.choice(['Balcony', 'Fireplace', 'Walk-in␣
 ↪Closet', 'None'], num_users)
    commute_times = np.random.randint(10, 60, num_users)
    family_sizes = np.random.randint(1, 6, num_users)

    user_profiles = pd.DataFrame({
        'Income': incomes,
        'Savings': savings,
        'PreferredLocation': locations,
        'DesiredPropertyType': property_types,
        'MustHaveFeatures': must_have_features,
        'NiceToHaveFeatures': nice_to_have_features,
        'MaxCommuteTime': commute_times,
        'FamilySize': family_sizes
    })

    return user_profiles
```

5.3.2 5.3.2 Implications for Evaluation

While the use of synthetic data allowed us to develop and test our system, it's crucial to consider its implications on our evaluation results:

1. Idealized Distributions: The synthetic data follows predetermined distributions which may not perfectly represent the complexities and nuances of real user preferences and financial situations.
2. Lack of Real-World Noise: Real user data often contains inconsistencies, outliers, and complex interrelationships between variables that may not be captured in our synthetic data.
3. Potential for Overfitting: The model may perform exceptionally well on this synthetic data but might not generalize as effectively to real-world user profiles.
4. Limited Feature Interactions: The random generation of features may not capture realistic correlations between user attributes (e.g., income and desired property type).
5. Simplified User Preferences: The binary nature of must-have and nice-to-have features may oversimplify the spectrum of user preferences in reality.

5.3.3 Mitigation Strategies To address these limitations, we have implemented the following strategies:

1. **Diverse Synthetic Profiles**: We generated a large number of diverse profiles to simulate a wide range of user types.
2. **Conservative Interpretation**: We interpret our evaluation results conservatively, acknowledging that performance on real data may differ.
3. **Continuous Refinement**: Our system is designed to be adaptable, allowing for easy updates to the user profile generation process as we gain more insights into real user behaviors and preferences.

While the use of synthetic data introduces certain limitations to our evaluation, it has been instrumental in the initial development and testing of our property recommendation system. The high performance metrics achieved with this data provide a promising foundation, but we acknowledge the need for further validation to fully assess the system's effectiveness and generalizability.

5.4 5.4 Limitations of Current Evaluation

5.4.1 5.4.1 Synthetic Data Limitations

While synthetic data allowed us to develop and test our system, it introduces several limitations:

1. Lack of complex patterns: Real user data often contains intricate patterns and correlations that our synthetic data generation might not capture.
2. Absence of outliers: Real-world data often includes outliers and edge cases that our synthetic data may not represent.
3. Simplified preferences: Our synthetic data uses a simplified model of user preferences, which may not fully capture the nuances of real user requirements.

5.4.2 5.4.2 Potential Overfitting

The exceptionally high performance metrics (accuracy: 0.9890, precision: 0.9982, recall: 0.9639, F1 score: 0.9808) raise concerns about potential overfitting to our synthetic dataset. The model may have learned patterns specific to our generated data that may not generalize well to real-world scenarios.

5.4.3 5.4.3 Limited Real-world Testing

Due to the use of synthetic data, our evaluation lacks real-world testing. This limits our ability to assess:

1. User satisfaction with recommendations
2. The system's performance with unexpected or complex user preferences
3. How well the model handles the noise and inconsistencies present in real user data

To address these limitations, future work should focus on obtaining and incorporating real user data, conducting user studies, and performing more rigorous cross-validation and generalization tests.

6 Chapter 6: Conclusion

6.1 6.1 Project Summary

This project set out to develop a Personalised Property Recommendation System for the UK real estate market, addressing the challenge of matching potential homebuyers with suitable properties based on their preferences and financial situations. By leveraging machine learning techniques and integrating diverse data sources, including historical transaction data from HM Land Registry and current property listings from OnTheMarket, we created a system capable of delivering customised property suggestions. The key components of our implemented system include:

1. A robust data collection pipeline, combining web scraping techniques with official government data.
2. Comprehensive data preprocessing and feature engineering steps to prepare the data for machine learning.
3. A neural network model architecture designed to process both property and user features.
4. An evaluation framework using standard classification metrics to assess the system's performance.

Our main findings demonstrate the potential of machine learning in revolutionizing property search and recommendation

6.2 6.2 Discussion of Broader Themes

The application of AI in property recommendations raises important ethical considerations. While our system aims to streamline the property search process, we must be cautious about potential biases in the data or model that could perpetuate or exacerbate existing inequalities in the housing market. For instance, historical data might reflect past discriminatory practices, and if not carefully managed, these biases could influence the model's recommendations.

Moreover, the use of personal financial data in making recommendations necessitates a strong commitment to data privacy and security. As we continue to develop such systems, it's crucial to implement robust data protection measures and ensure transparency in how user data is used and protected.

6.2.1 6.2.1 Impact on the Real Estate Market

The introduction of AI-driven recommendation systems like ours has the potential to significantly impact the real estate market. For buyers, it could lead to more efficient and satisfying property searches, potentially reducing the time and effort required to find suitable homes. For sellers and real estate agents, it might change how properties are marketed and could potentially lead to faster sales for well-matched properties.

However, we must also consider potential drawbacks. Over-reliance on automated recommendations could potentially narrow users' perspectives, possibly leading to less diverse neighborhoods or missed opportunities that fall outside the algorithm's suggestions.

6.2.2 6.2.2 Balancing Preferences and Market Realities

One of the key challenges in developing our system was striking a balance between user preferences and market realities. While the system aims to find ideal matches based on user inputs, it must also consider the available inventory and market conditions. This balance is crucial to ensure that recommendations are not only personalized but also realistic and actionable.

6.3 6.3 Limitations and Future Work

6.3.1 6.3.1 Current Limitations

While our system shows promising results, it has several limitations that should be addressed in future work:

Reliance on synthetic user data for testing, which may not fully capture the complexities of real user preferences and behaviors. Limited geographical scope, currently focused on specific regions in the UK.

6.3.2 6.3.2 Proposed Improvements and Extensions

To address these limitations and further enhance the system, we propose the following improvements:

1. Expand the geographical coverage to include more regions and potentially adapt the model for different national markets.
2. Implement a real-time data pipeline to ensure recommendations are based on the most current market information.
3. Incorporate more diverse data sources, such as neighborhood amenities, school ratings, and crime statistics, to provide a more comprehensive property assessment.

6.4 6.4 Final Remarks

The Personalised Property Recommendation System developed in this project represents a significant step towards leveraging AI to enhance the property search experience. By combining machine learning techniques with comprehensive real estate data, we've demonstrated the potential to provide more accurate, personalized, and efficient property recommendations.

As AI continues to evolve and permeate various aspects of our lives, its role in shaping the future of real estate cannot be underestimated. While challenges remain, particularly in addressing ethical concerns and ensuring fair and unbiased recommendations, the potential benefits for both homebuyers and the broader real estate market are substantial.

This project lays the groundwork for future innovations in AI-driven real estate solutions. As we continue to refine and expand such systems, we move closer to a future where finding the perfect home is not just a dream, but an achievable reality for everyone.

7 7. References and Resources

7.1 7.1 References

[1]: HM Land Registry. (2024). "Price Paid Data." Retrieved from https://www.gov.uk/government/statistical-data-sets/price-paid-data-downloads.

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7.2 7.2 Resources Used

7.2.1 Web Scraping and Data Collection libraries

- Python programming language: https://www.python.org/
- BeautifulSoup library for Python: https://www.crummy.com/software/BeautifulSoup/
- Pandas library for data manipulation: https://pandas.pydata.org/
- Requests library for HTTP requests in Python: https://docs.python-requests.org/en/master/

7.2.2 Data Processing and Analysis

- Jupyter Notebooks for interactive computing: https://jupyter.org/
- Folium library for map visualization: https://python-visualization.github.io/folium/
- Geopy library for geocoding: https://geopy.readthedocs.io/
- Nominatim and ArcGIS for Geocoding: Utilised for converting addresses into geographic coordinates. Nominatim and ArcGIS

7.2.3 Ethical Considerations

- Ethical guidelines for web scraping and data usage were followed as per sources' terms and conditions.
- Data Privacy and Anonymization: Data handling processes ensured no personal data was exposed or misused.

- Adherence to the Robots Exclusion Protocol as per:
- "Robots.txt" on Wikipedia: https://en.wikipedia.org/wiki/Robots.txt
- "Formalizing the Robots Exclusion Protocol Specification" by Google: https://developers.google.com/search/blog/2019/07/rep-id

7.3 7.3 Acknowledgements

- HM Land Registry for providing open access to Price Paid Data under the OGL: "Contains HM Land Registry data © Crown copyright and database right 2021. This data is licensed under the Open Government Licence v3.0."
- OnTheMarket.com for the property listings data used in the scraping part of the prototype, adhering to their scraping guidelines and robots.txt file.

8 Appendices

8.1 Appendix A: Setup and Installation

8.1.1 Required Libraries

The following libraries are required for this project. They can be installed using pip:

[ ]:
```
!pip install beautifulsoup4 lxml requests
!pip install ratelimit
!pip install tqdm
!pip install tensorflow scikit-learn pandas numpy matplotlib
```

8.1.2 Python Path Configuration

To ensure that custom modules can be imported correctly, add the following directories to Python's import path:

[ ]:
```
import sys
sys.path.append('./src/data_collector/')
sys.path.append('./src/data_cleanser/')
sys.path.append('./src/data_standardiser/')
sys.path.append('./src/model/')
```

8.2 Appendix B: Data Exploration

8.2.1 Displaying Scraped Data

To verify the integrity and structure of the scraped data, we can load and display the first few rows of the dataset:

[ ]:
```
import pandas as pd

# Load the scraped data from the JSON file
file_path = './data/property_data_650000.json'
scraped_data = pd.read_json(file_path)
```

```python
# Display the first 10 rows of the dataset
scraped_data.head(10)
```

This code will load the scraped data from the JSON file and display the first 10 rows, allowing for a quick inspection of the data structure and content.