Evaluation of the algorithm for a personalised dating application to enhance social capital amongst 'social loners'

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Abstract

With the advent of the Fourth Industrial Revolution announcing the beginning of Artificial Intelligence era, the face of many areas of social life has been fundamentally altered, and dating is no different. Mobile dating applications (DA) constitute one of the most dynamically growing branches of the mobile market, generating a revenue reaching 555 million dollars a year as of the time of writing. Despite the multitude of modern DAs available on the market, there is a noticeable dearth of the applications implementing AI-based matchmaking systems, that would utilize the opportunities created recently by Deep Learning to optimize the accuracy of generated matches.

This project aimed to develop an algorithm, which would estimate a matching score between two users of the application and therefore accelerate or even completely replace “swiping” with the automated matchmaking system. In other words, to create a mobile software, that would address the common issues of modern dating applications – lack or low reliability of applied matchmaking algorithms and limited personalisation related to the implementation of the predetermined compatibility policies. To address the issues mentioned above, the prototype application has been developed and enhanced with a Deep Neural Network, which hidden layers were responsible for generating matches and adjusting weight matrix each time new training dataset was provided. The system was evaluated based on the accuracy of produced predictions in comparison to the actual ratings, as well as the participants’ opinions on application UI/UX and the results obtained as a result of performed penetration tests.

The results of the study demonstrated that Deep Neural Networks could be successively adapted as a matchmaking system. However, this process may require careful consideration of parameters extracted for the training purposes from the user dataset. Future work seeks to extend the functionality of the matchmaking system to include reciprocity, as well as the introduction of night mode and offline-first approach.

Abbreviations, Symbols and Notation

• AES	Advanced Encryption Standard
• AI	Artificial Intelligence
• ANN	Artificial Neural Networks
• CB	Content-based
• CBC	Cypher Block Chaining
• CBRS	Content-based Recommender System
• CF	Collaborative filtering
• CFRS	Collaborative filtering Recommender System
• DB	Database
• DL	Deep Learning
• DNN	Deep Neural Network
• FDD	Feature Driven Development
• FN	False Negative
• FP	False Positive
• GDPR	General Data Protection Regulation
• LFRR	Latent Factor Reciprocal Recommender
• ML	Machine learning
• RMSE	Root Mean Square Error
• RS	Recommender System
• SP	Shared Preferences
• TN	True Negative
• TP	True Positive
• U2U	User to User
• UI	User Interface
• UX	User Experience

Keywords

Android, Dating application, Deep Neural Network, Matchmaking algorithm, Recommender System

1. Introduction

1.1 Background

Today, the Internet transforms communities around the world into a global village, and making romantic acquaintances is often perceived as simpler than ever before. According to Pew Research Center statistics, in the US only over 30% of the population use dating applications, while one in eight of them finds love as a consequence (The Virtues and Downsides of Online Dating, 2020). The surge in mobile dating is undeniable; within the last decade, the mobile dating market revenue in the US increased nearly thirteenfold (Fig.1) and is expected to grow at least till 2022 (Business Insider, 2020).

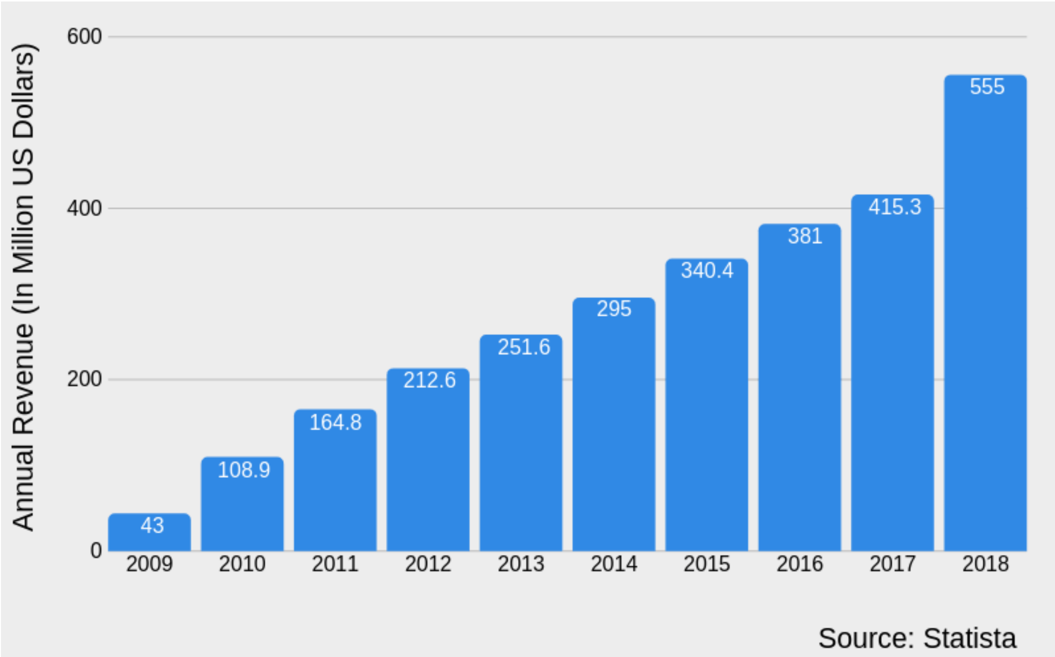


Figure 1 – Mobile Dating Market Revenue in the US from 2009 to 2018

With the ever-growing number of mobile dating users and ubiquity of mobile devices, there is an increasing demand for applications that would provide their users with the ability to meet like-minded individuals. However, those applications often force their users to sift through the vast amount of available profiles to find potential matches, which leads to oversaturation of the system and therefore leaves users overwhelmed with choices. Although modern dating applications implementing

matchmaking systems have indeed been existing in the mobile domain for years, they still constitute a minority on a nearly 2 billion dollar market.
That, in turn, leaves room for new and potentially more innovative systems, which would accelerate the complicated process of finding a match with sophisticated AI solutions.

Various research papers have detailed the ways of implementing matching algorithm through the adaptation of recommendation systems, utilised commonly by significant e-commerce companies and media-services providers. Researchers Nayak et al. approached the issues related to two-way matching nature and created their matchmaking system, tested on a dataset collected from popular dating network (Nayak, Zhang and Chen, 2010). The algorithm designed by Australian scientists combined content-based and collaborative techniques of recommendation, improving the quality of generated matches by utilizing users' past relations and their similarities.
The solution proposed by the authors of the journal, determining the match score as a product of the similarity score and empirically established weights, raised a question on the efficiency of the system in terms of a single individual and therefore the level of personalisation achieved. Analysis of modern approaches to matchmaking in a dating domain, including a widely cited study conducted by Pizatto et al. (2010) inferring user' preferences based on the common attributes of users contacted by a given user, indicated a clear need for a sophisticated algorithm that would outperform contemporary dating applications in terms of achieved match success rate.

1.2 Project focus

The purpose of this project was to design a prototype of a dating application for Android users, which would utilize a matchmaking algorithm to efficiently generate potential matches. Therefore, the overall intention of the project was expressed in the following research question:

> *"Can the personalized dating application utilizing a matching algorithm enhance social capital amongst 'social loners' ?"*

The individual objectives of the project were identified as follows:

- Review current dating applications, especially those inspired on content-based and collaborative filtering recommender systems
- Prototype a robust, functional and visually attractive mobile dating application using relevant techniques and modern technology
- Identify user' attributes inferred by in-app questionnaire and explored by dating platforms to determine future matches
- Review literature into recommender systems and Deep Neural Networks to explore the ways of adapting them to online dating
- Examine fields for improvement
- Suggest future work and opportunities to extend the functionality of the system

1.3 Scope

Chapter 2 provides the reader with an insight into technologies adapted for matchmaking purposes (including AI-based solutions), as well as the rationale behind the adaptation of Deep Neural Networks and development aimed at the Android platform. The project's methodology, justification of applied techniques – including a detailed description of the application structure – and connections between key components are discussed in Chapter 3. Additionally, the measures taken to adhere to the General Data Protection Regulation (GDPR) and the implications this had on the project are also discussed. Chapter 3 is then summarized by the description of the evaluation process. Chapter 4 presents results of the study based on the comparison of predictions generated by the applied matchmaking algorithm with the actual ratings given by participants of the experiment, while Chapter 5 evaluates findings in the light of the solutions discussed in previous chapters. Chapter 6 concludes the study, which enables the identification of future work prospects.

2. Literature review

This chapter provides a brief insight and critical evaluation of techniques utilised in commercial matchmaking systems – the foundation of modern dating applications. The review focuses on the analysis of the differences between the most common approaches, including variables being assessed and forms of data collection. It will also discuss the difficulties faced by researchers developing multi-faceted matching algorithms, and the ways AI technologies can be adopted to address these issues.

2.1. The rationale for matchmaking applications

The technological revolution and recent shifts in social trends have vastly shaped how people connect and whom they connect with. Early online dating services, dating back to late ‘80s, were a response of the digital age to newspapers dedicated to singles, as well as personal advertisements placed in local papers all over the world (Finkel et al., 2012). Despite the slow start caused by the initial stigma, as well as limited resources and simplicity of contemporary technological solutions, those services revolutionised the way of finding love, becoming a solid alternative to conventional dating (Finkel et al., 2012). With the growing popularity of dating services and therefore an increasing user base, the process of selecting the right individuals amongst the vast amount of candidates has become extremely tedious, and available filtering algorithms - ineffective. Arising number of dissatisfied users, overwhelmed by the sheer number of potential candidates, indicated a demand for an effective tool that would eliminate irrelevant matches and increase the chances of finding individuals with a similar worldview, lifestyle, hobbies, and interests.

In 1995, researchers organised an experimental grocery store with two jam displays (Iyengar and Lepper, 2000). The larger display, offering over 24 kinds of jams, enjoyed greater popularity amongst the consumers. Yet, it was the people who picked a jar from a less diverse selection (four times smaller than the main display), that were more likely to make a purchase decision and show greater satisfaction with the chosen product. The scientists concluded that more does not always mean better.

The jar dilemma - also called a paradox of choice – is the concept representing the reason that led thousands of users to delete their dating profiles and to seek professional support in the matchmaking agencies. In response to expressed social demand, eHarmony launched its pioneer matchmaking system, therefore introducing the second generation of online dating services. The company claims the developed algorithm has been based on the research carried out by experienced scientists, studying the factors affecting a couple's satisfaction for over 30 years (Eharmony.co.uk, 2020). According to Chief Scientist at eHarmony, Dr Steve Carter, the success of the company having 10 millions of active users and annual revenue of over 250 millions of dollars (Business Insider, 2020) is closely related to compatibility approach to matchmaking, which aimed at solving the common issue associated with the antagonistic characters or lifestyles of partners in a relationship.

Eharmony's attitude toward matchmaking is visible in the services of its successors, utilizing the empirical research and complex mathematical algorithms to predict which singles should be presented to each other as matches.
Studies performed over 15 years after the matchmaking revolution demonstrate persistent trend on the dating market, proving an unflagging demand for personalised matchmaking applications (Fig.2).

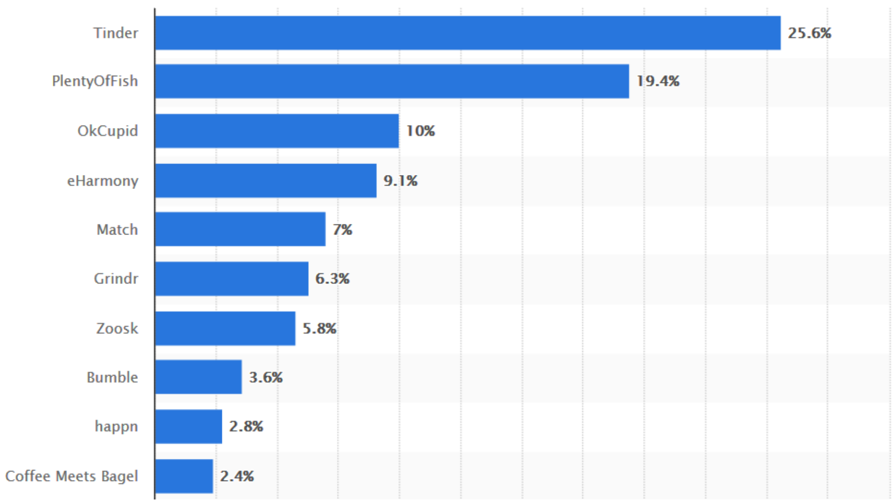


Figure 2- Most popular dating applications in the United States

2.2 Comparison of matching systems present in modern dating applications

The matching systems can be classified in many respects, although this review will primarily focus on the analysis of two aspects deemed crucial for providing sufficient background to understand key differences between modern dating services; variables assessed in the selection process and technological solutions utilised in their implementation.

2.2.1 Variables emphasised in compatibility matching

In 2012 American scientists cooperating with the Psychological Science in the Public Interest Association published a critical analysis of online dating sites from the psychological perspective (Finkel et al., 2012). In the pages of the article, the researchers exhaustively reviewed personal traits inferred from user questionnaires, which in-depth exploration constitutes a quintessence of the matchmaking services. The study based on three dating market leaders (as of 2012) had shown that each of these commercial research centres interpreted compatibility differently, both in terms of variables and a matching principle – similarity or complementarity (Finkel et al., 2012).

Furthermore, some applications such as Gene Partner (Genepartner.com, 2020) prioritise non-self-report data over data provided by the users themselves (Finkel et al., 2012). Apart from data explicitly shared within the application, a broad range of additional information - including location and social media activity - is collected and used to inform users of potential candidates in the vicinity. In terms of common variables measured by dating services, the utilised algorithms primarily focus on assessing emotional temperament, intellect, social style, as well as relationship skills, values, family background and education level. The observed traits are then utilised in comparison of users' data models and creating pairings following chosen matching principles, which may differ for each variable.

2.2.2 Technologies adapted for matchmaking purposes

Majority of the contemporary matchmaking algorithms inherit many of their traits from the recommender systems (RS), which have existed for a long time suggesting products according to the user's browsing history and past product selections

(Nayak, Zhang and Chen, 2010). The published examples of recommendation systems, adapted explicitly to online dating, present two different techniques utilised in the implementation process – content-based (CB) and collaborative filtering (CF). This project will primarily focus on content-based recommender system (CBRS), as an adaptation of collaborative-filtering recommender system (CFRS) would likely associate with an increased demand for the computational power and exert a significant impact on (de)personalisation of the matchmaking system.

CBRS determines the recommendation score based on a comparison between users who received the ratings and those that we have not through analysing the features extracted from their profiles and through psychometric profiling. Using the ratings assigned to candidates, based on certain kind of in-app interaction (e.g. swiping left/right or sending a "wink"), the system selects the candidates whose personality traits are similar to the individuals with highest rating score and then presents them to the user (Fig.3).

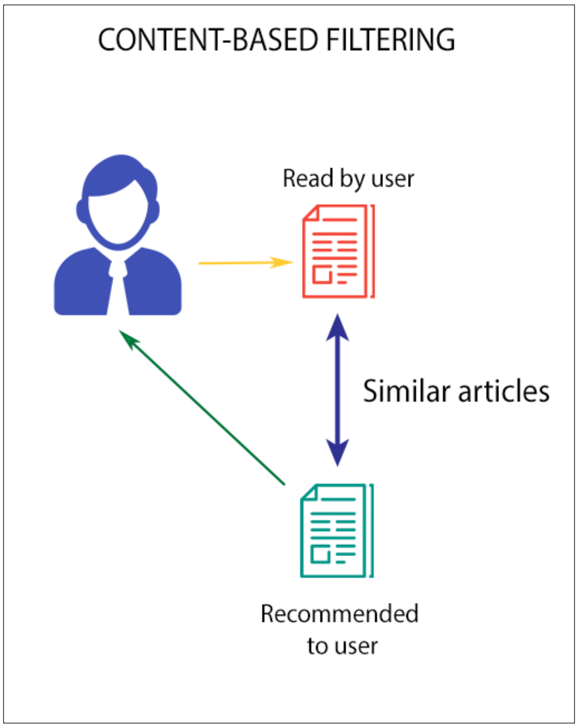


Figure 3 - Comparison between content-based and collaborative filtering

To determine the ways of optimising the efficacy of a recommender system applied to mobile dating, the approaches deemed significant in this field were analysed.
A study carried out by Nayak, Zhang and Chen (2010) linked the social network knowledge with CB and CF techniques of recommendation by utilizing users' past relations and similarities between them to improve recommendation quality. The proposed algorithm determines a match by combining the cosine similarity between user A and group A (set of users which successfully interacted with user A), as well as user B and group B with empirically established weights (sequentially 0.6 and 0.4). The solution presented by Nayak et al. was tested offline on a two million user dataset, which resulted in a success rate of 31% and a recall rate equal to 9%. Due to the low efficacy of the presented solution, the authors emphasized the experiment represents a preliminary study only. The obtained results were utilised in further exploration of the reciprocal recommender systems.

A year later, the authors of the social matchmaking system resumed the research, introducing a model altering past relation-based groups with male and female user clusters according to their explicit information, i.e. profile and preference attributes. The similarity between users in each cluster is determined by the nearest neighbour algorithm based on SimRank score – a measure of similarity of the structural context based on their relationships with other objects. Using the computed SimRank score and collaborative filtering technique, the system recommends Top-n potential partners (matches).
Although the second approach increased the accuracy (success rate) of the matchmaking system by nearly 5%, it negatively affected the sensitivity rate (recall), which dropped to 3.4% as a result. Moreover, the proposed method did not include the capability for handling new users, therefore raising a question on the effect the cold-start phenomenon would exert on the results of the experiment, provided it was conducted in an online mode.

Another example of the reciprocal recommendation system was detailed in a widely cited work by Pizatto et al. The algorithm proposed by the authors of the paper extracts implicit preferences by looking at common attributes amongst the users messaged by a given participant of the experiment (Pizzato et al., 2010). RECON calculates the preference scores from a given user A to another user B and viceversa using the aforementioned implicit preferences as a base. The preference scores are then combined into a match score with the use of harmonic mean. The evaluation of the algorithm demonstrated that it performed better than an explicit search in creating satisfactory matches for the two end-users involved.

A study carried out by British scientists Neve and Palomares (2020) aimed to present a method of reciprocal recommendation based on latent factor models, which efficiency in a user-to-user domain has not been investigated as of the time of writing. The proposed algorithm attempts to solve the issues related to a limited amount of interactions between users and the common limitations of conventional recommender systems. To account for the bidirectional nature of reciprocal recommendation, the authors introduced the Latent Factor Reciprocal Recommender (LFRR). Machine learning-driven LFRR utilizes matrix factorisation (depicted in Figure 4) to infer two latent factor models; one to indicate male users' preferences for female users, and one to indicate female users' preferences for male users. The latent factor vectors are initialised to random values, which are then adjusted by error minimisation with the use of Stochastic Gradient Descent (SGD) in each iteration. SGD, a method for finding the optimal parameter configuration for a machine learning algorithm, is utilised to calculate the error for each individual data point and then to modify the relevant feature vectors in the negative direction of the gradient, proportional to the learning rate.

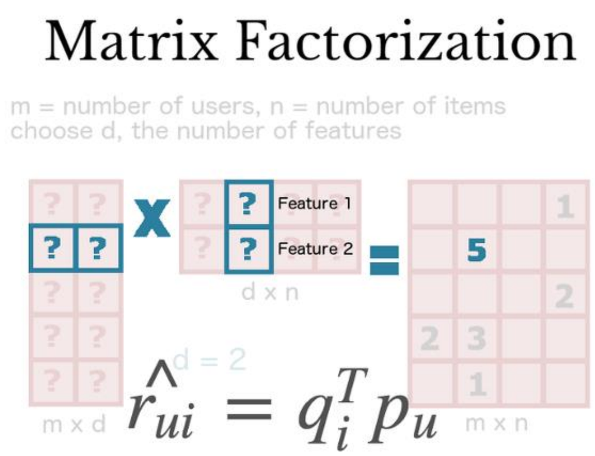
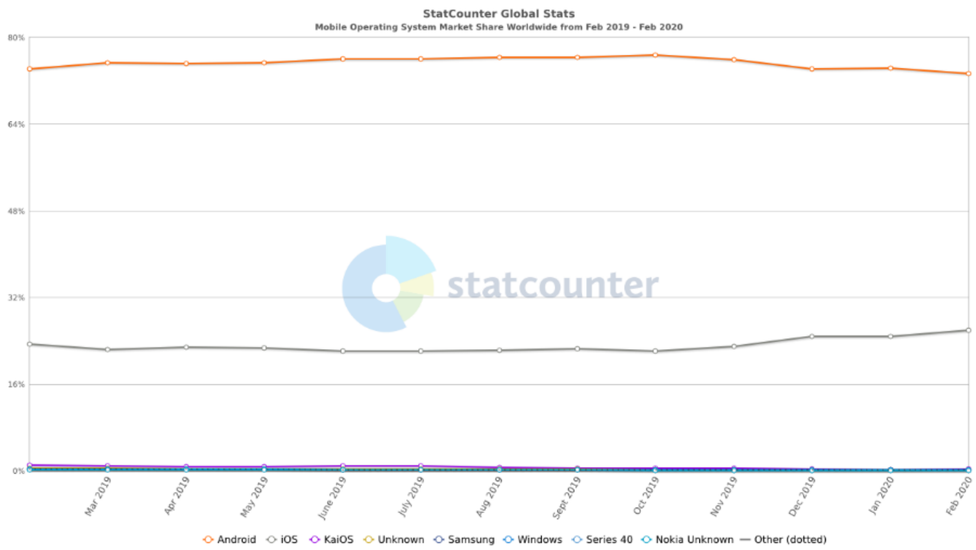


Figure 4- Illustration of the Matrix Factorization

Obtained preference metrics are merged using aggregation operators to indicate users that are likely to be a positive match, and therefore which recommendations to display. Based on the evaluation of the study described on the pages of the journal and methodology applied it was concluded, that LFRR represents the most efficient and potentially the most sophisticated approach to matchmaking in user-to-user environment out of four scientific implementations presented in this chapter.

2.3 Android OS

Out of multiple operating systems powering mobile devices, dominant on the mobile OS market for almost 20 years, Android OS can boast of over 73% of Mobile OS share worldwide (Fig.5). In the UK only, every other mobile user in 2019 was an Android phone holder (Android vs iOS market share 2019, 2019).



Key: Android - 73.3%, iOS - 25.89%, KaiOS - 0.23%, Samsung - 0.18%, Unknown - 0.13%, Windows - 0.12%

Figure 5- Mobile OS Market Share Worldwide (Feb 2019 - Feb 2020)

Adoption of Android development generates several benefits; aside from audience size and high profitability, Android-based applications can be written with the use of Java – a powerful object-oriented programming language - and run in Android Runtime environment, which replaced standard Java Virtual Machine. Android applications can be easily ported to some of the niche OS, including Blackberry and Ubuntu Touch, as well as placed on Google Store as alpha/beta release, which makes it available only to a selected group of testers.

2.4 Role of AI in modern dating applications

From compatibility estimation, based on personality traits and determination of the attractiveness of a chosen profile picture, to an evaluation of conversation flow - sophisticated AI techniques accompany the user along each stage of the online dating process, improving UX and increasing the chances of finding a match.

Connectionist systems (also called Artificial Neural Networks, ANN) demonstrated high potential in many fields they were applied, including Lung Cancer Detection (Sasikala, Bharathi and Sowmiya, 2018), as well as Medical and Analytical Chemistry (Maltarollo, Honório and da Silva, 2013). Although ANN has proved to be successful in the area of classification tasks (Zhang, 2000) and is perceived a promising AI technology, little research has been conducted on their adaptation to social and dating domains. Connectionist systems are computational models, that consist of several processing elements receiving inputs and delivering outputs based on their predefined activation functions. The predecessor of the Dueling Neural Network, which was announced a breakthrough technology for 2018 by Massachusetts Institute of Technology (MIT Technology Review, 2018), was inspired by a biological neural network and the way the electrical signal is being transmitted. Neurons (Fig.6), the building blocks of the nervous system, constitute information-processing units in the connectionist systems, passing the signal received from dendrites (input of the layer) down to axon (output).

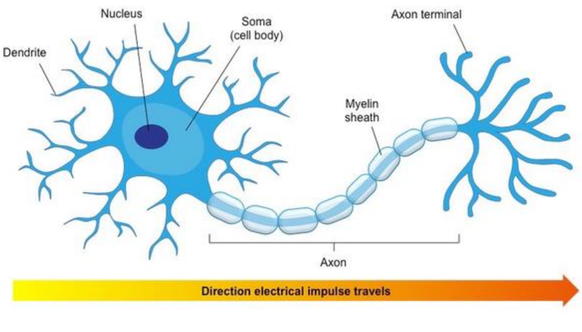


Figure 6 - Neuron anatomy

In a simplified model, each of the artificial neurons (represented graphically as circular nodes, Fig.7) is assigned a weight, that represents its relative importance and bias, as well as additional parameter adjusting the output to fit best the given data. The computed result of the above is then subjected to an activation function (e.g. sigmoid or ReLu) and passed as an output of currently processed layer. The neural networks learn through the backpropagation; they compare the output obtained as a result of ANN calculations with the expected output and then modify the weights of connections between the neurons in the network. Repeating the process *x* times (where x corresponds to the defined number of iterations), the connectionist system is able to minimize the gap between both numbers and infer the optimal set of weights.

Due to their remarkable abilities of data mining and therefore high level of adaptiveness, the Artificial Neural Networks has been chosen as a lead technique in the design and implementation of the application matchmaking algorithm.

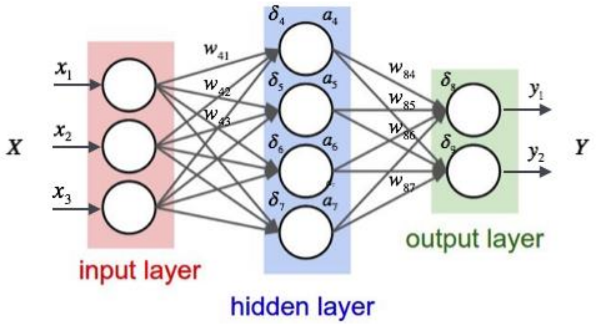


Figure 7- Artificial neural network structure

2.5 Proposed solution

The aim of the project was to review existing dating applications, and then develop an algorithm producing the optimal matches based on the explicit user profile inferred from the responses to in-app questionnaire and ratings assigned for each new conversation. The application will utilise the rating system inherited from U2U (user to user) content-based recommender systems as the output in the training of the Deep Neural Network. Similarly to LFRR, applied ANN will adjust the weight and bias matrices through backpropagation (Stochastic Gradient Descent), inferring the importance of each feature based on previous data, and then select the candidates with the highest scores. The reader will gain a better insight into the methodology behind the project in the following chapter.

3. Methodology

This chapter outlines the methods utilised in the implementation of the personalised mobile dating application, as well as the details of the development phases of the matchmaking algorithm as a key functionality of the system. The reasons for adopting a Feature Driven Development and testing approach are highlighted, and the structure of the application along with external components is presented. Project objectives are discussed at the beginning of the chapter, and the actions taken to satisfy them are detailed. The extensive description of the project methodology is finally concluded with an evaluation of the implemented solution, as well as the description of conducted tests.

3.1 Analysis of the Project

Careful consideration of the project aims, objectives, as well as target audience allowed to identify steps required to design and implement of the personalised dating application, which were classified as presented in Table 1.

#	Description of the actions taken
1	Designing user interface following Android Material Design guidelines
2	Incorporating the Firebase Realtime Database into the application
3	Implementing social application functionality including authorization, change of user settings, as well as browsing users and messaging system.
4	Devising a draft of the matching algorithm in Jupyter Notebook
5	Integration of the algorithm within the core application
6	Conducting White-box and penetration tests
7	Beta tests conducted with a group of participants
8	Drawing conclusions and critical analysis of the system in terms of efficiency and performance

Table 1 - Steps required to design and implement Ahavoo DA

3.2 Development Methodology

Each stage of development of the project, from planning and prototyping to implementation, tests and deployment utilised iterative techniques being the domain of the agile approach. The application of Agile Methodology allowed to account for changes emerging from investigating new ideas and eliminate redundant information from the documentation, therefore amplifying the efforts to enhance the application in terms of security, usability and design. Regarding the clarity of aims and objectives, Feature Driven Development (FDD) was deemed the most suitable for project dynamics. Utilizing FDD contributed to increasing the efficiency of production with the progress measured by comparison between features implemented based on the listed requirements and detailed Gantt's chart. Referencing to the Gantt's chart on a regular basis improved time management and boosted flexibility of development.

3.3 Project Management

The professional organization of the project in each applicable aspect was deemed vital for the improvement of the workflow and avoiding delays, as any major time-lapses could directly affect the scheduling of Beta tests. A Kanban board was utilised to assign activities according to the Gantt's chart and supervise the execution of tasks running simultaneously. Source control was implemented through GitHub, simple web interface supporting Git - distributed version control system. Using version control facilitated storing back-ups and compare changes made between each version cloned in the GitHub repository.

3.4 User Interface

The process of designing the application began with preparing a sketch in Adobe Xd (design tool dedicated for web and mobile systems) based on the list of project requirements and Principles of Mobile App Design (Think with Google, 2020). Each of the features specified on the list of objectives has been reflected in the prototype, which graphic layout was inspired by modern social and dating applications such as Tinder (Tinder | Match. Chat. Date., 2020) and Match.com (Online Dating Site - Register For Free on Match UK, 2020) (Fig.8).

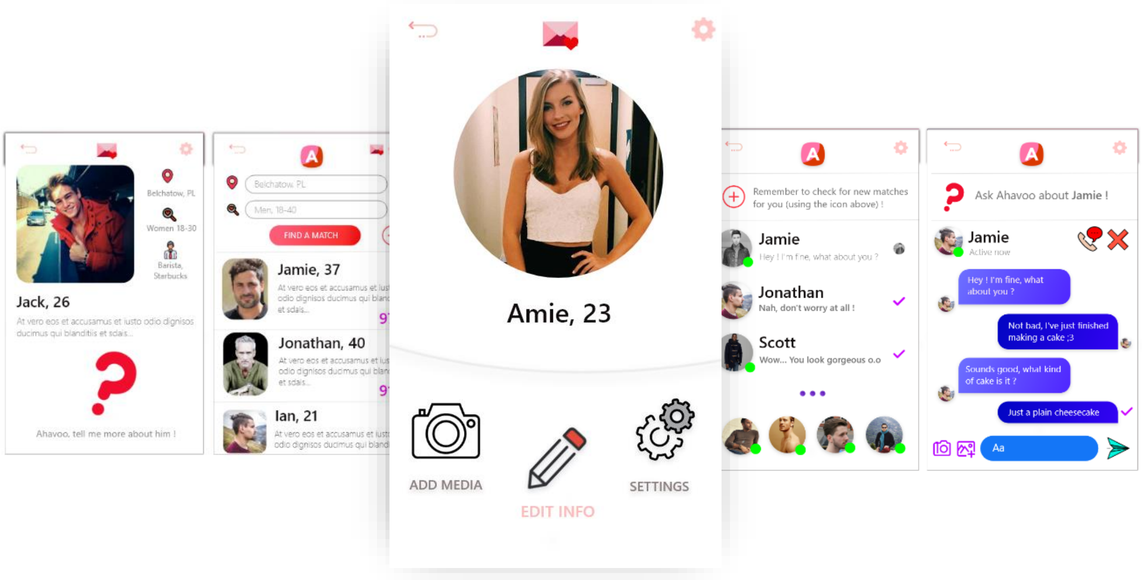


Figure 8- UI prototype presenting the main components of the application

Development of the wireframe significantly expedited implementation of User Interface and ensured consistency between the original concept and the final product. Due to the project dynamics, some of the additional features included in the sketch has been removed, while other has become a subject to refactoring. Prioritizing features and defining milestones based on the Gantt's chart prevented the increase of system complexity where considered features would not significantly influence User Experience.

3.5 Database choice

The database choice was made based on the analysis of the project characteristics, as well as strengths and limitations of common database types. As a result of the conducted comparison, targeted at rapid development No-SQL database was identified as an optimal solution. Adoption of No-SQL database (DB) enabled flexible handling of large volumes of semi-structured data, as well as provided the ability to horizontally scale the system (*database sharding*) if required. Further research on available No-SQL DB distributions, which could be easily adapted for the mobile development led to the conclusion that Firebase Realtime DB (Firebase Realtime Database | Store and sync data in real-time, 2020) is one of the best suited for Android development.

Among many arguments for Firebase in terms of its adaptation to the mobile development environment, the decisive were identified as follows:

- Detailed documentation on the integration of Firebase services within chosen technologies
- Compatibility with Android
- Storing data as key-value pairs
- Efficient serialization of application states (in real-time)
- Initial setup process limited to a minimum
- Secured data access - internal API and reverse proxy is not required
- Support provided by Google and users contributing to improving Firebase open-source platform

3.6 Android lifecycle

Amidst many dimensions defining mobile development, the application lifecycle is a key element differentiating it from other types of software development. Each of the activities, formed by a group of methods associated with certain graphic layout, was designed to provide functionality while responding to user gestures and reacting to state transitions by system callbacks. By declaring actions required to take in a certain case, the application has been protected against interruptions caused by unexpected events, such as phone call or received notification (Fig.9).

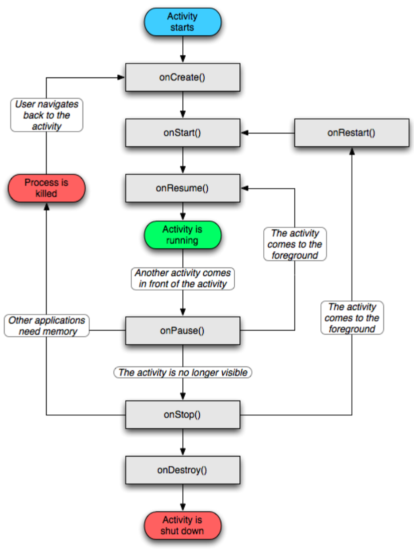


Figure 9- Android activity lifecycle

3.7 System architecture

3.7.1 Database design

The data collected within the application are stored in the No-SQL database, split into six logical branches (depicted in Fig.10). Following denormalization rules and Firebase node nestling policy, the database was designed to achieve the balance between a single table, posing a risk of triggering a series of unnecessary layout updates, and creating a separate table for each logical group of data. Therefore, it was decided that the questionnaire responses will be secluded from the survey setup, as well as *Predictions*, *Test credentials* and *Access codes* will be separated from the *Users* table, which will restrict to storing participant's credentials, chats and list of blocked users.

Following the practices recommended by Firebase on structuring the database, node nestling was restricted to three levels deep. This way, the access to data is limited strictly to the nodes operating within provided services.

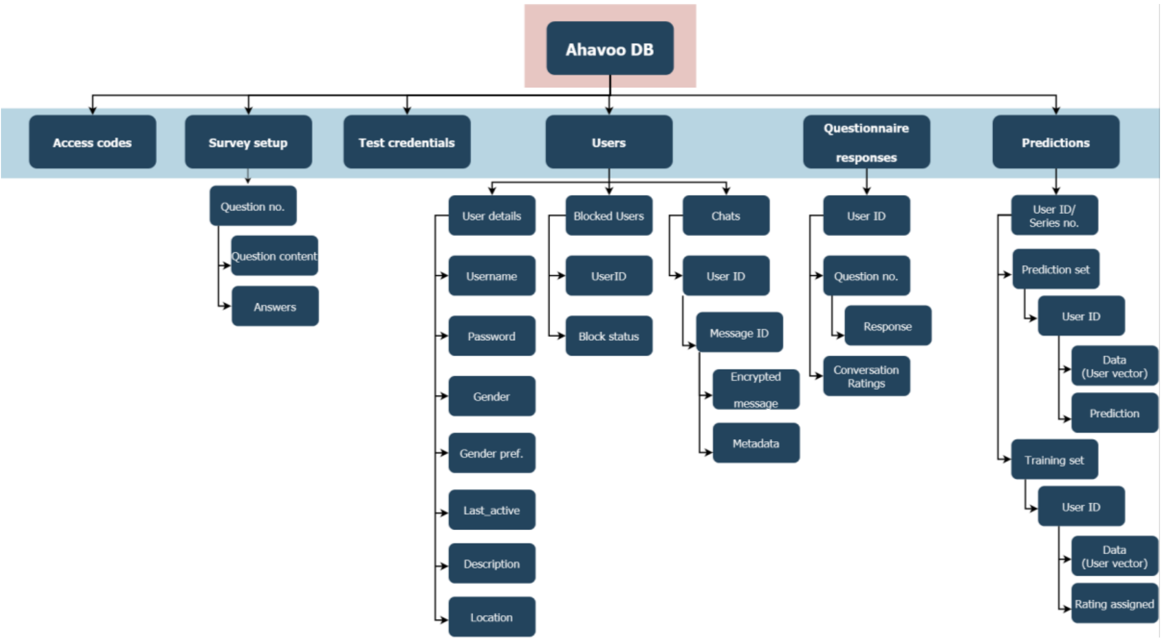


Figure 10 - Database structure

3.7.2 Application structure

Like many Android applications, Ahavoo is a combination of activities, layout files, database unit, as well as classes, responsible for performing calculations and forming data structure required to retrieve the data from the DB. In combination with Gradle files, supporting automatic configuration of project dependencies and utilised libraries, as well as Android Manifest file, responsible for declaring required permissions and providing other essential information about the application and hardware/software settings, these elements created application framework expanded during further development. Major changes were related with the implementation of a Tab Layout - providing a horizon layout reacting to swipe gestures, that required expending application structure with fragments and adapters, utilised to populate the recyclers with chosen content. The full application structure was presented in Appendix B.

Since the quality of cooperation between the application units may significantly affect its performance and data safety, each transformation between activities was additionally inspected to ensure the application runs smoothly. Ahavoo utilised two ways of passing the data between the activities – intents, providing operational data explicitly to designated activity and Shared Preferences (described in Chapter 3.12). The Workflow of the application considering various decision paths is depicted in Appendix C.

3.8 In-app questionnaire

As a subject matter of the model training and predictions generation, the questionnaire included in the application was identified as a crucial component of the matchmaking system. Regarding a limited experience of the author of the dissertation in the Psychology field, set of questions utilised in the application has been based on reliable scientific resources - compatibility tests existing in eHarmony dating service and 16 Myers-Briggs personality test (Free personality test | 16Personalities, 2020), popular personality type indicator.

To address the ethical concerns related to the nature of the questionnaire, any questions deemed confidential or intimate were excluded from the survey. The questionnaire, consisting of 38 questions based on a 1-5 Likert scale, explores 10 different aspects corresponding to an individual's personality, lifestyle and worldview. The score obtained in each section is an arithmetic average of given responses, that indicates the direction of the bias and therefore expresses user's affiliation to a certain group (i.e. introverts vs extraverts, minimalists vs extravagates). Following the policy of eharmony, the questionnaire excludes questions regarding user's expectations regarding a potential candidate, as it often leads to the phenomenon of 'a universe of one.' (Carter, 2017). Moreover, such data would not improve the efficiency of the prototype aimed at a small group of testers, as its diversity may be quite limited due to natural causes.

3.9 Solving the cold-start problem

One of the most common issues associated with matchmaking process is the limited ability to produce reliable matches for a freshly registered user, that has not yet provided the sufficient amount of information essential for further analysis of compatibility between candidates and current user (Fig.11). Systems suffering from initial data sparsity may mitigate these issues by implementing methods determining the correlation between given sets of data.

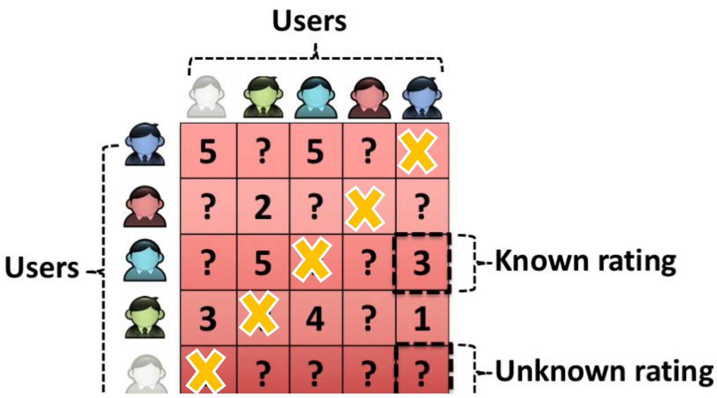


Figure 11- Rating Matrix

Amongst the most popularised techniques of measuring similarity – including Pearson's correlation, Euclidean distance and Jaccard similarity – the cosine similarity (Fig.12) was chosen due to the effectiveness in handling complex, multidimensional data entries consisting of dozens of features determining unique characteristics of each user. The cosine measure of similarity was utilised in a solution proposed by Nayak et al. (2010) to determine the matching score, as well as in the continuation of the study (2011) supporting the SimRank method in generating potential matches.

$$s(\mathbf{x}, \mathbf{y}) = \frac{\mathbf{x} \cdot \mathbf{y}}{\|\mathbf{x}\|\|\mathbf{y}\|} = \frac{\sum_{i=0}^{n-1} x_i y_i}{\sqrt{\sum_{i=0}^{n-1} (x_i)^2} \times \sqrt{\sum_{i=0}^{n-1} (y_i)^2}}$$

Figure 12 - Cosine similarity formula

3.10 Neural Network

The unique aspect of the Ahavoo dating application is the ability to generate potential matches based on the conversation rating. This was achieved by the implementation of the Artificial Neural Network, that constitutes a complex data structure subjected to various logical and mathematical operations. The results produced by the network depend on factors such as the quality of data sets normalisation, type of activation function applied, amount of implemented hidden layers and efficiency of backpropagation process.

The neural network created within the application is based on two hidden layers and therefore constitutes a Deep Neural Network. Contrary to simple, single hidden layer NN, which is taught processing and learning from data (representing Machine Learning), DNN possesses the ability of self-teaching by filtering the information from multiple layers, which translates into increased accuracy of predictions.

3.10.1 Artificial neuron

As an elementary unit of the ANN, artificial neurons perform mathematical operation calculating the value of its input through applying weights and adding bias – a constant utilised to adjust the output – to the weighted sum (Figure 13). NN incorporated in the matchmaking algorithm was built with ten input neurons, which value was the average score corresponding to each of ten sections of the questionnaire.

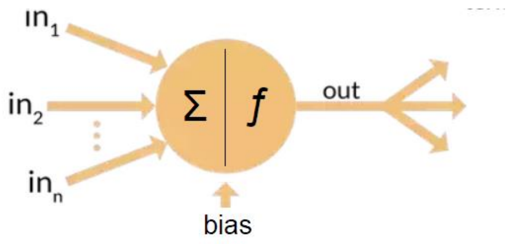


Figure 13- Artificial neuron

(where ∑ is a sum of input multiplied by weights

and f is an activation function based on given ∑)

3.10.2 Bias neutron

The hidden layer has been augmented with an additional neuron, which allowed to shift the activation function in the right direction. Similar to a set of weights adjusted throughout the training process, bias neurons were initially assigned random values generated by the system and then modified to decrease the difference between the model output and target with each iteration. Implementation of biases enabled optimization of the learning model and therefore increased the prediction accuracy.

3.10.3 Activation function

To achieve nonlinearity of the model, amplifying complexity to each hidden layer and increasing the accuracy of predictions, an activation function was introduced (Fig.14). Out of three most popular non-linear activation functions utilised by ANN – ReLU, tanh and sigmoid (logistic), the differentiable logistic function was deemed the most suitable given the nature of the project. The sigmoid function output ranges in the scale between 0 and 1, which facilitates generating percentage predictions of a match.

```java
public class NeuronLayer
{

    public Function <Double, Double> activationFunction, activationFunctionDerivative;

    double[][] weights;

    public NeuronLayer(int numberOfNeurons, int numberOfInputsPerNeuron) {
        weights = new double[numberOfInputsPerNeuron][numberOfNeurons];

        for (int i = 0; i < numberOfInputsPerNeuron; ++i) {
            for (int j = 0; j < numberOfNeurons; ++j)
            {
                weights[i][j] = ((2 * Math.random()) - 1); //
            }
        }

        NNMath nnmath = new NNMath();

        activationFunction = NNMath::sigmoid;
        activationFunctionDerivative = NNMath::sigmoidDerivative;
```

```java
public class NNMath
{

    public static double sigmoid(double x) {
        return 1 / (1 + Math.exp(-x));
    }
```

Figure 14 - Implementation of the activation function

3.11 Implementation & optimisation of the matchmaking algorithm

The matchmaking algorithm was split into three logical classes – *NNMath*, performing matrix calculations (such as multiplication of neuron value by assigned weight) and sigmoid derivation, *NeuronLayer,* responsible for generation of initial weight matrix in the range of -1 to 1, and finally *NeuralNetwork,* utilizing the methods of the aforementioned classes in training and prediction process (Fig.15). Whenever the user signs in the application (provided they completed the in-app questionnaire and rated conversations with a minimum of three individuals), the system retrieves the data on answers provided in the questionnaire, as well as a rating assigned to each of users as a result of their in-app interaction. The data are then split into training and testing groups and converted into the right format. It is a vital step in data pre-processing, as Neural Network will not be able to train the model with the input number of neurons different than expected. On the normalisation stage, 38 answers given to the questionnaire by each of the users (considered in the training process) are transformed into ten parameters, representing the arithmetic mean of the answers for each of ten corresponding questionnaire sections, which will become neurons in the input layer of NN. Finally, the application calls *NeuralNetwork* to update the model and therefore future prediction accuracy.

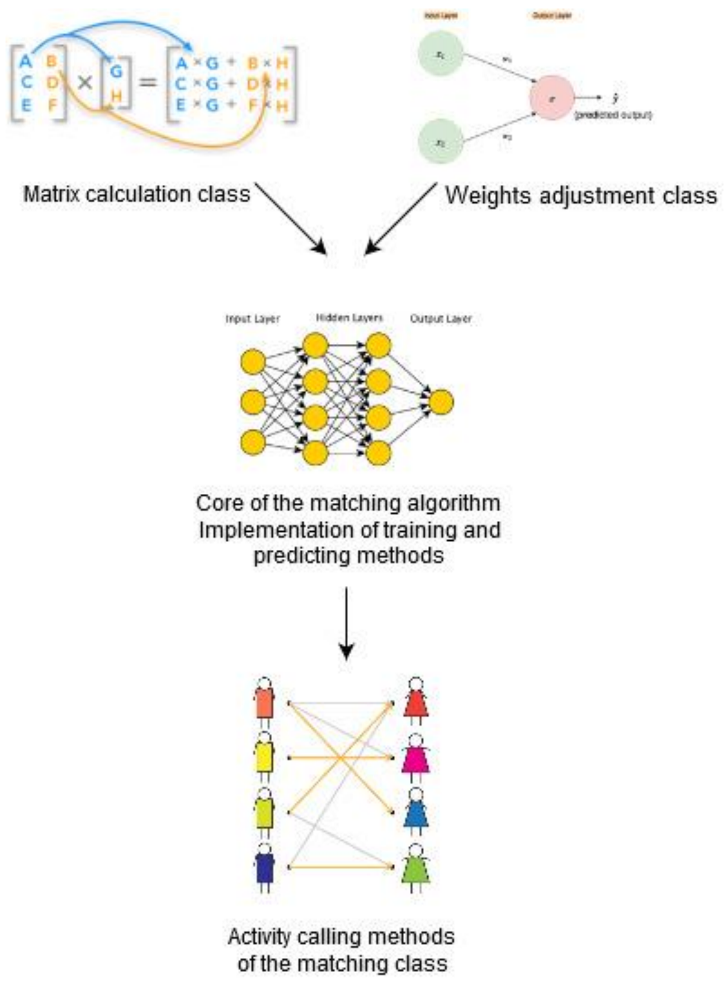


Figure 15 - Matching algorithm implementation (key components)

Neural Network class, providing methods vital for matchmaking system, is a core of the matchmaking algorithm. T*rain()* function it provides runs the training loop *X* times (where x is a number of iterations) through adjusting weights controlled by the given learning rate. The learning rate configures the network by controlling the degree to which the estimated error affects the model, and thus its value was inferred through the empiric analysis. Predictions are generated through the execution of *think()* method for each hidden layer, as presented in Figure 16.

```
public void think(double[][] inputs)
{
    outputLayer1 = apply(matrixMultiply(inputs, layer1.weights), layer1.activationFunction);
    outputLayer2 = apply(matrixMultiply(outputLayer1, layer2.weights), layer2.activationFunction);
}
```

Figure 16 - Prediction function (NeuralNet.java)

3.12 Application security

3.12.1 AES-128 message encryption

The messaging system implemented within the application was secured with the Advanced Encryption Standard – modern symmetric block cypher.

AES consists of three vital components: initialization vector *IV,* being a four-byte arbitrary number, 128-bit secret key and *Ciphertext* – encrypted output from the Cipher, that has passed through a specified number of rounds (10 in case of AES-128). AES is considered an efficient and secure encryption standard, that provides higher performance and percentage efficiency comparing to its 64-bit predecessor DES, as well as other common encryption algorithms – IDEA, Blowfish and asymmetric RSA (Fig.17, Ullah et al., n.d.). The encrypted message is stored in a database, as depicted in Figure 18.

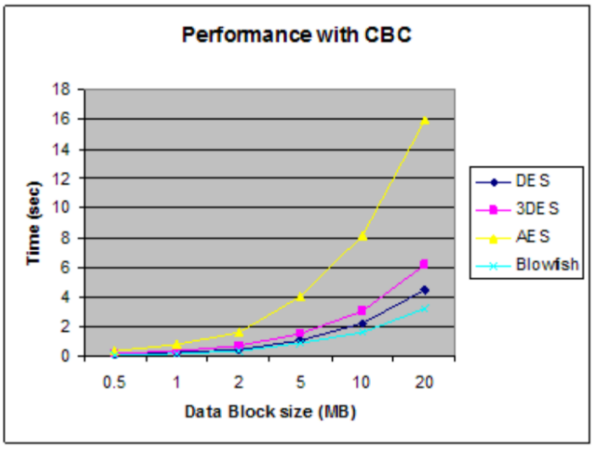


Figure 17 - Comparison of encryption times for common encryption algorithms

Figure 18 - AES-encrypted message stored in Firebase DB

3.12.2 Session management

Introduced to enhance the user's comfort, the user sessions required a way of storing basic profile information, such as username and identification number, which could be verified by each of the triggered activities.

Following the best practices of Android development, Shared Preferences (SP) - an interface designed for the temporary storage of preference data - was deemed the most efficient and secure solution. SP was implemented in a private mode to prevent an external application from accessing the SP file and was designed to clear the collected data at logout.

3.12.3 Access code

The potential risk of exceeding the tier of allocated database calls and storage capacity available within Spark Plan (Free Firebase plan dedicated to start-ups and prototype development) was addressed by assigning one-time access code for each participant. This way, combined with pre-generation of username and password, only the users who officially declared participation in the experiment could get access to application functionality.

3.13 Testing

Due to the diversity of services and elements incorporated within the application, each of the tests analysed the system in a different dimension. Three categories of tests were distinguished – manual unit tests, integration tests and penetration tests, executed by an automated online tool.

3.13.1 Unit tests

The manual unit tests were performed to determine whether implemented components correspond to the project specifications. By conducting unit tests, defects and malfunctions were identified in the early development stage, which reduced the cost of code refactorization. The results of test cases utilised in the unit validation process were detailed in the table below (Table 2).

Test nr	Test scenario	Expected result	Actual result	Pass/ Fail
1	User A blocks User B	User B loses the ability to contact User A with immediate effect	As expected	PASS
2	The application moves to background (onPause())	The application retrieves saved state and comes back to last activity	As expected	PASS
3	The application moves to background (onStop(), onDestroy())	The application returns to Main Activity, retrieving shared references data	As expected	PASS
4	New user leaves the applications without filling in the in-app questionnaire	The application retrieves the first of not yet answered questions of the survey	As expected	PASS
5	The application loses connection with the internet	The error message is being displayed, none of the services (excluding logout) is available	As expected	PASS
6	More than one user attempts to register using the same access code	User is notified this access code is no longer valid	As expected	PASS
7	User rates the conversation more than once	Rating is being updated in the database; predictions are regenerated after session expiry	As expected	PASS
8	User's device runs on Android OS below version 7.0.0 (Nougat, API level 24)	The application provides all standard services except matchmaking system, that requires API level 24+	As expected	PASS

Table 2 - Unit Test cases

3.13.2 Integration testing

On successful completion of the Unit tests, further examination of the application in terms of cooperation between modules was commenced. Integration tests were aimed at evaluation of the system's coherency, as well as identification of potential malfunctions caused by lack or inaccurate communication between components. Due to the nature of the project, all integration tests were performed by the developer, and not by the separate testing team as recommended.

3.13.3 Penetration testing

The penetration tests were conducted by Mobile App Scanner (Mobile App Security Test by ImmuniWeb, 2020) – a proven tool created to detect the most common vulnerabilities in tested mobile applications. The security test identified two medium risks. The first risk was related to documentation of common image loading library (Glide). On the other hand, the second alerted of medium level of MD5 password encryption. While the first of abovementioned hazards was independent to the developer and therefore could not be mitigated in a way different than replacement by one of less efficient alternative, the later was considered as a mild risk due to random generation of test passwords.

Low- level risks listed in the further part of the report, excluding the debug mode disabled immediately after white-box tests completion, were deemed unthreatening to the experiment. According to the report obtained on scan completion (presented in Fig.19), the application has been marked as secure and listed in the ranking of applications with top security scores (Fig.20).

Figure 19- The result of security analysis performed by Mobile App Scanner

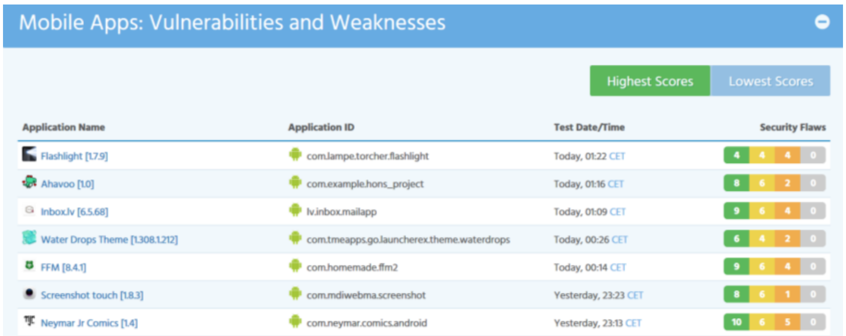


Figure 20 - Ranking of applications with high security scores

3.14 Evaluation

The evaluation of the application has been divided into two stages. Firstly, Ahavoo was assessed in terms of security and integrity, while white and black-box tests were being conducted on the testing stage. Secondly, human participants were invited to take part in Beta testing, which aimed at evaluation of matching algorithm and UI while following clearly defined rules.

3.14.1 Ethical considerations

Due to participants engagement in the project – both in terms of questionnaire and application test – the ethical implications of their involvement had to be considered. There was a significant amount of effort put into ensuring the participants fully understood the aims and objectives of the project, as well as Ahavoo's terms of use and provided instructions. From the very beginning of the experiment, it was clearly emphasized that any anti-social behaviour will not be tolerated and will result in immediate exclusion from the experiment.

The testers were instructed they can withdraw from evaluation at any time and without providing any reason. Users were also advised that while Ahavoo constitutes a prototype of a dating application, some of the users may treat it as a social application and therefore may not wish to make or pursue aquaintances established online. In case any of the participants did not feel comfortable being messaged by another user, they could immediately block them or notify the experimenter, who would exclude the individual from the experiment if deemed necessary. The participants were informed that the project does not recommend any kind of interactions outside the application environment, as it may deprive the user of maintained anonymity.

3.14.2 General Data Protection Regulation

The participants of beta tests were provided with test username and passwords, which were then utilised to register without the use of personal or university email address. Date of birth required in most commercial dating applications was deemed as sensitive data and therefore has been excluded from the data set hold within the application. The measures taken ensured no private data were recorded in the system, and the user profiles were fully anonymous throughout the experiment.

3.14.3 Participants

The participants that volunteered in the tests represented a group of 19 men and women in the age over 18, studying at the University of Abertay Dundee. Each of them was provided with a detailed experiment description and submitted the Research Consent form (Appendix D), therefore giving informed consent to participate in the experiment under the agreed conditions.

3.14.4 Method of evaluation

The volunteers involved in the experiment were asked to download the application using a link to the application source file uploaded to experimenter's Google Drive account. The participants were then requested to sign up with provided username, generated password and one-time access code. Once registered, users were instructed on how to use the application and asked to fulfil the in-app questionnaire. Incomplete set of survey responses was automatically disqualifying the user from accessing the main functionality of the application, as the responses to the questionnaire were essential to training the AI model and generating predictions.

The participants were encouraged to establish interactions with other users (respecting granted anonymity and following the Terms of Use) through chat and then rate the conversation whenever they felt ready (the ratings could be updated more than once). The evaluation of the application was split into two parts; evaluation in terms of the UI/UX, as well as the efficiency of implemented matchmaking algorithm – both based on performed calculations and participant's feedback, obtained through a post-experimental questionnaire. The results of the evaluation were presented in Chapter 4.

4. Results

This chapter illustrates the results obtained through the conducted experiment, as well as a post-experimental survey presenting participants' feedback on the study and the application tested.

The male to female user ratio achieved in the experiment was relatively balanced and equalled 58% (male users) to 42% (female users), outperforming Tinder with highly asymmetric 9:1 ratio and dating platforms in the UK with 85% of male users (Online dating trends - Netimperative, 2019). Out of 19 volunteers that decided to take an active part in a week-long study, 8 of them directly contributed towards the evaluation of the matchmaking algorithm through the generation of three or more conversation ratings. Those were analysed through the comparison of the percentage matching predictions produced by DNN and the actual scores submitted by a participant.

Figures 21, 23, 25-26 depict the matchmaking process for each case with a minimum of three prediction stages. For the analysis sake, data such as given ratings and generated predictions - stored in the database in the range between 0 to 1 - were converted into a percentage scale to simplify the observation of variations between the following series. Each of the aforementioned figures consists of several blocks presenting data divided into training and testing sets. The training set is represented as a top part of the block, separated from the prediction set with a horizontal line. The final state summarises the prediction process for a given participant, comparing the rating of the user (translated into a percentage score given the maximum rating of 5) to the latest prediction (highlighted in yellow). For the sake of the experiment, a match was considered when a minimum of 75% of conversation satisfaction has been observed (or predicted), translating into a minimum of 4-star rating.

Participant A (Fig.21) constitutes the most successful case out of 4 participants analysed in this chapter. With no variations within the core training set and high consistency in the rating policy, the matchmaking algorithm achieved 100% accuracy in three registered test cases.

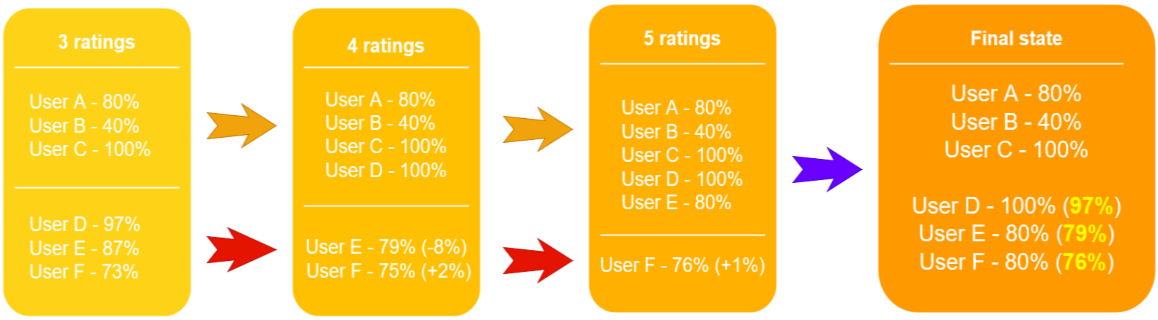


Figure 21- Results of Participant A

Based on the given data, Root Mean Square Error (RMSE, Fig.22) - an indicator of the absolute fit of the model, were calculated. The RMSE score of 0.029 demonstrated a high concentration of data around the line of best fit.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}$$

Figure 22- RMSE formula (standard deviation of the residuals)

Case of Participant B (Fig.23) contrasts with a highly accurate model trained by Participant A. Although the gradual training increased system accuracy by nearly 13% (based on comparison of RMSE scores of initial predictions and predictions from the last series), it returned a success rate of only 33% and RMSE of 0.468, indicating low accuracy of generated predictions related to a significant diffuseness of predictions against the line of best fit. The further investigation, performed to identify the potential cause of such low accuracy, led the experimenter to the identification of a positive correlation between the number of messages exchanged and ratings given to a particular user. That, in turn, led to the conclusion, that some of the ratings would be altered if the conversation revived. Figure 24 represents a scatterplot of correlation between those parameters.

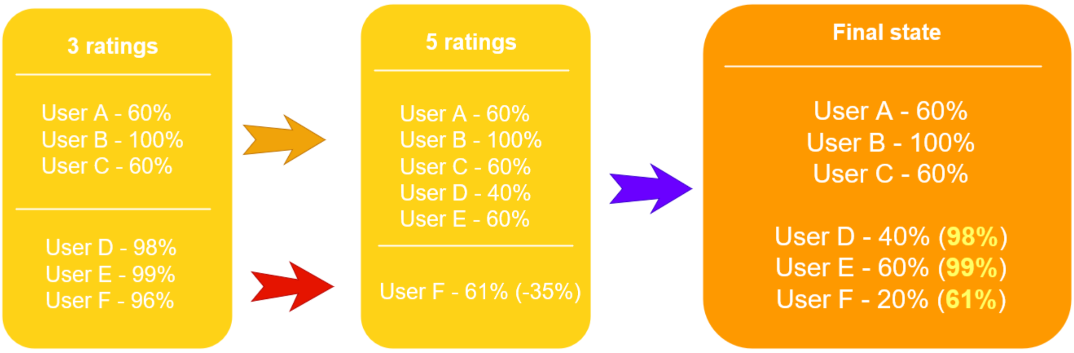


Figure 23 - Results of Participant B

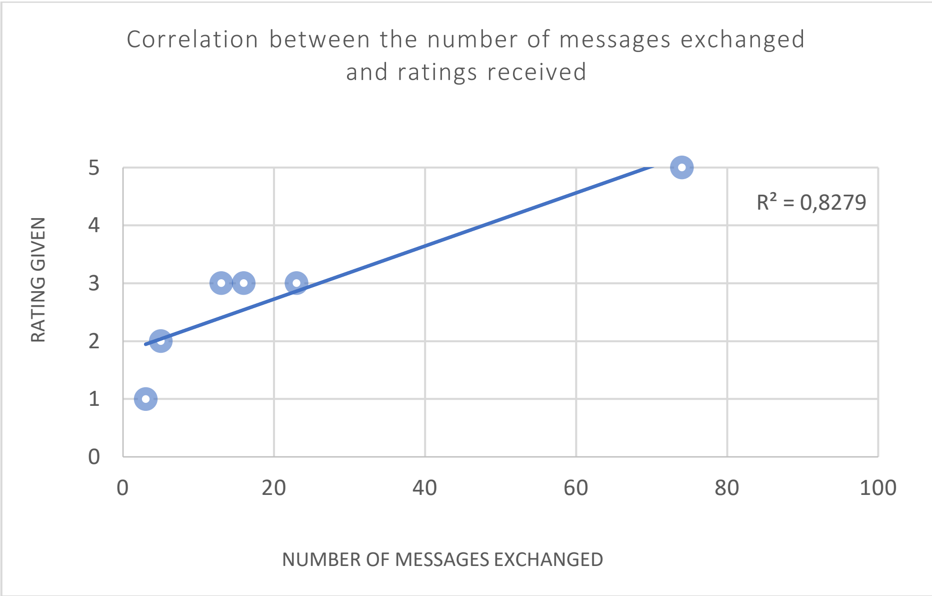


Figure 24 - Correlation between the number of messages exchanged

Participant C, whose prediction generation process was depicted in Figure 25, was recognised as one of the most active application users, which translated into as much as eight conversation ratings. The model adopted to newly introduced ratings, reaching an 80% accuracy in a match and 40% in rating prediction. With RMSE of 0.2 and 63% of accuracy in applying corrections (through identification and adjustment to rating trends), the model proved its high efficiency when dealing with unpredictable behaviours, specific to social studies.

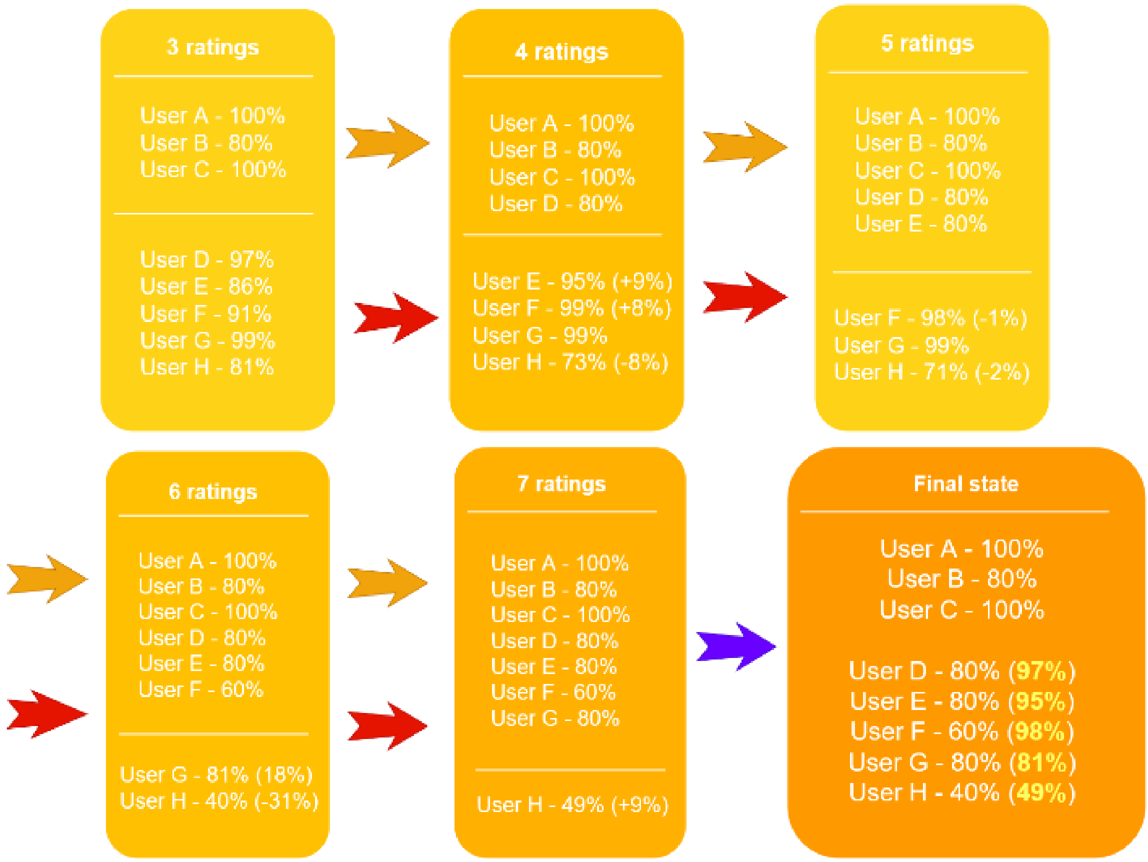


Figure 25 - Results of Participant C

The last of the presented cases, consisting of six generated predictions, was identified with a negative value of correlation coefficient, which indicated an inverse correlation between generated predictions and conversation ratings. The calculations performed to support the analysis shown exceptionally high RMSE score equal to 0.557. Regarding low consistency of given ratings (RMSE of corrections equal to 0.37), a match accuracy of 33% and RMSE exceeding the mean value by 1.5 of standard deviation, the case has been classified as an outlier. That, in turn, led to the exclusion of the Participant D from further evaluation of the overall accuracy of the matchmaking algorithm due to the negative impact of the extreme values on the accuracy of the small dataset submitted to analysis.

The results obtained in the study were summarised in Table 3.

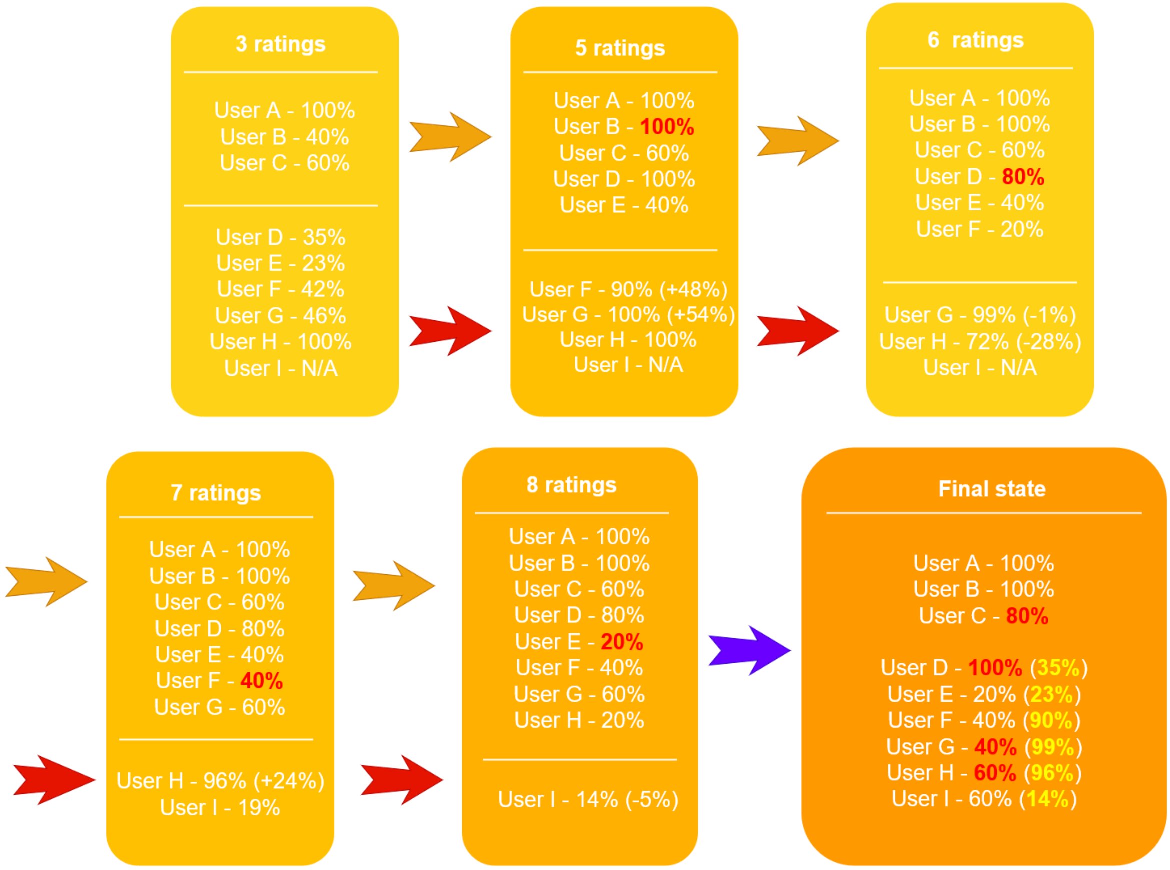


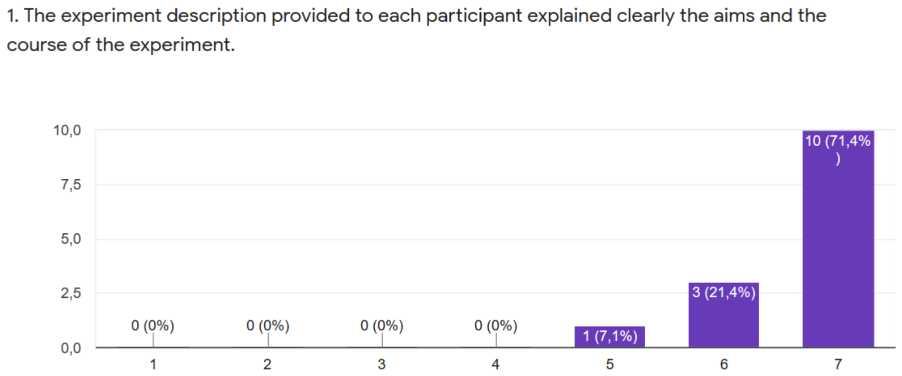
Figure 26 - Results of Participant D

User #	Predictions generated	Correct match predictions	Success rate	RMSE	R-squared	TP	TN	FP	FN
1	1	1	100%	0.0036	N/A	1	0	0	0
2	1	0	0%	0.378	N/A	0	0	1	0
3	1	0	0%	0.16	N/A	0	0	0	1
4	2	2	100%	0.127	N/A	2	0	0	0
5	3	1	33%	0.468	0.77	0	1	2	0
6	3	3	100%	0.029	0.98	3	0	0	0
7	5	4	80%	0.203	0.57	3	1	1	0
8	6	2	33%	0.557	0.029	0	2	3	1

(where TP – True Positives, TN – True Negatives, FP – False Positives and FN – False Negatives)

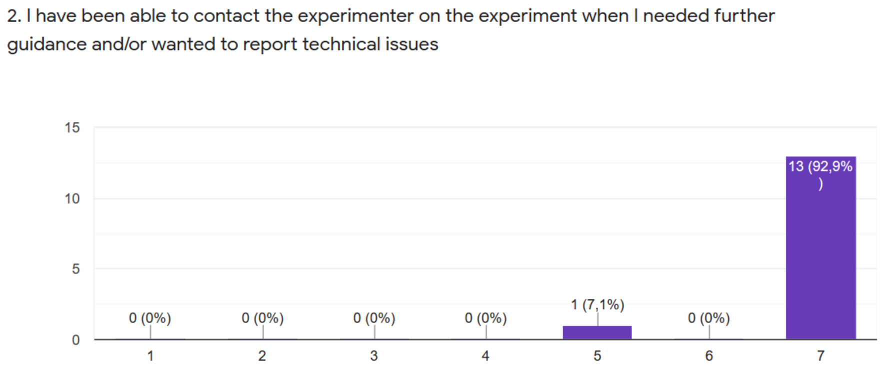
Table 3 - Individual results obtained by participants of the experiment

Following the completion of the experiment, the participants were asked to fill out a short questionnaire aimed at obtaining the feedback on general satisfaction from the experiment, opinion on application UI/UX, efficiency of the matchmaking algorithm and suggestions for improvement. The answers given to questions 1 to 3 (presented in Fig.27-29), formed as statements based on a seven-point Likert scale, proved that the study has been conducted professionally and went according to the plan.



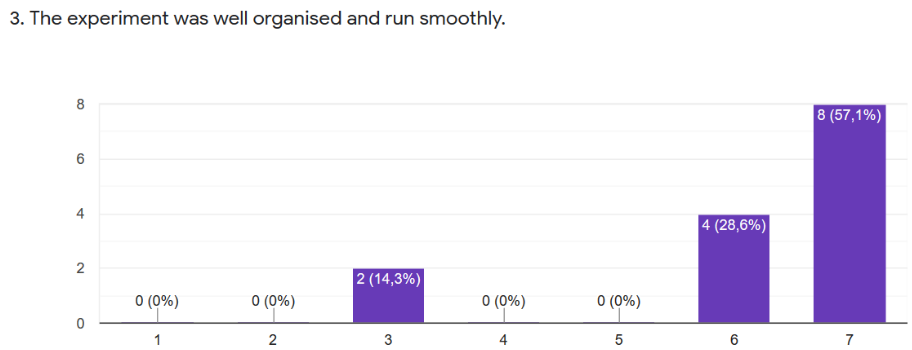
In a scale from 1 (Strongly disagree) to 7 (Strongly agree)

Figure 27 - The evaluation of materials provided by the experimenter



In a scale from 1 (Strongly disagree) to 7 (Strongly agree)

Figure 28 - The evaluation of the support offered by the experimenter



In a scale from 1 (Strongly disagree) to 7 (Strongly agree)

Figure 29 - The evaluation of the experiment and support provided by the experimenter

The survey indicated that the vast majority of beta test participants found the application very simple in use (79% of interviewees, Q4), assigning Ahavoo an average rating of 7.7 out of 10 in UI/UX terms (Q9, Fig.30 - 31).

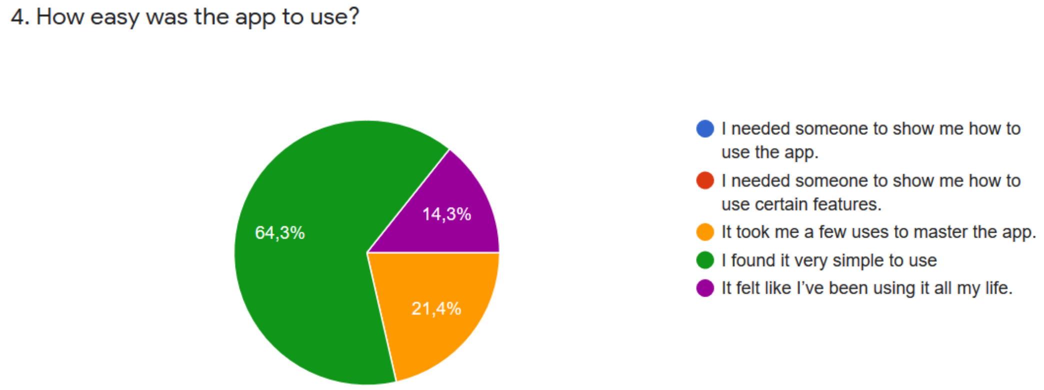


Figure 30 - Participants' feedback on application ease of use

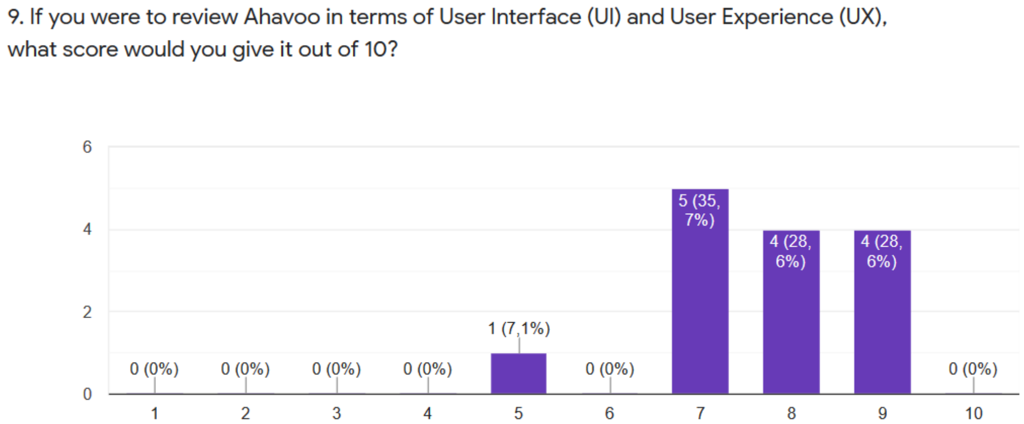
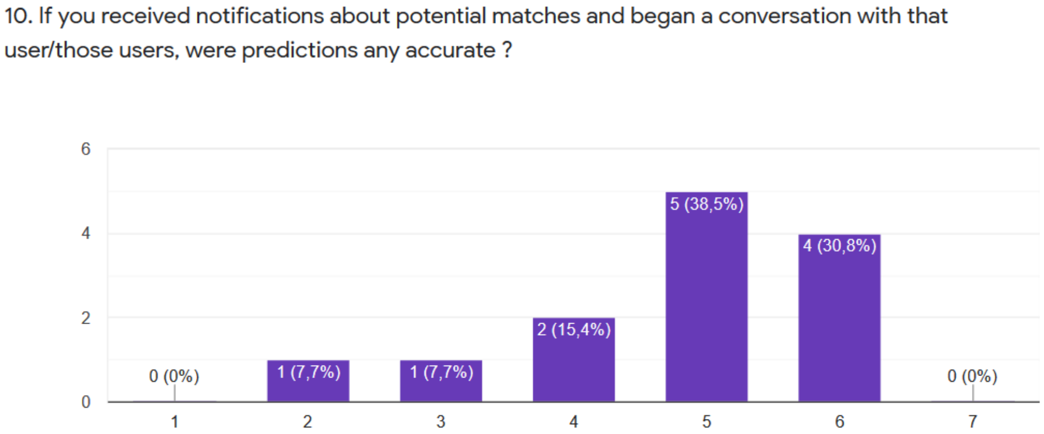


Figure 31 - Participants' feedback on UI/UX

To find out how the matchmaking system performed in practice, the experimenter asked students to review its accuracy based on the satisfaction from conversations initiated by produced matches. Regarding the complexity of the algorithm and the limited size of a training dataset, the views were anticipated to vary between participants depending on individual experiences.

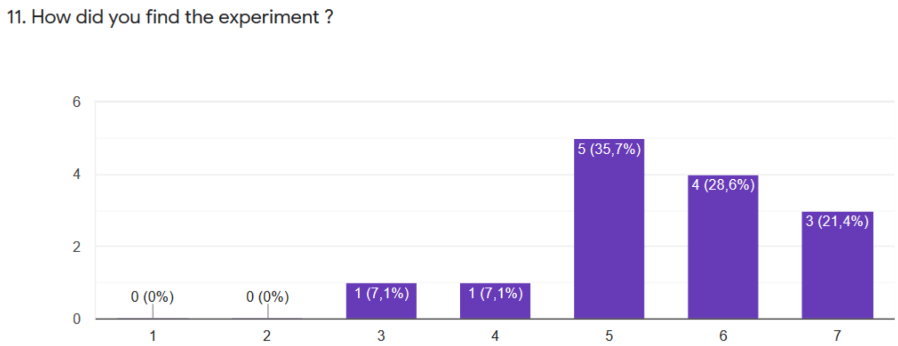
Nonetheless, obtained results showed 9 out of 13 interviewees veered towards a positive assessment, indicating the majority of participants were satisfied with the matchmaking service (Fig.32).



In a scale from 1 (Very inaccurate) to 7 (Very accurate)

Figure 32 - Participants' feedback on the efficiency of the matchmaking algorithm

The smooth organisation of the experiment reflected in general satisfaction from the experiment, as 86% of interviewees confirmed they found the experiment absorbing (Figure 33).



In a scale from 1 (Strongly disagree) to 7 (Strongly agree)

Figure 33 - Evaluation of the application entertainment aspects

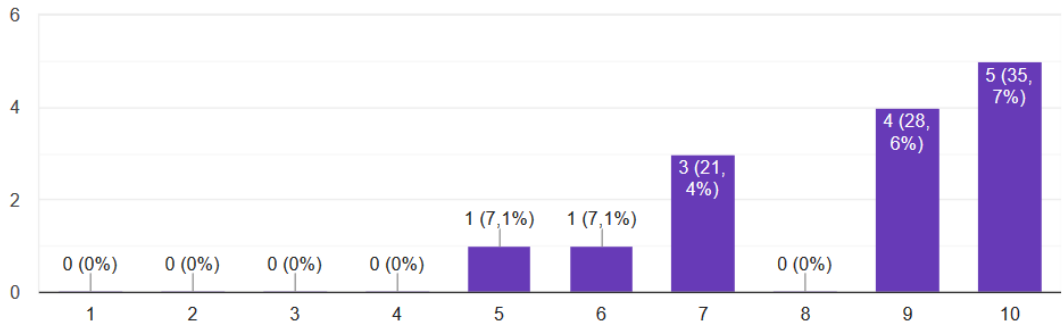
In the further part of the survey participants were given the ability to express their opinions on their favourite and then least liked aspect of Ahavoo, as well as suggesting a single thing they would like to change in Ahavoo. Obtained feedback was presented in Table 4.

What do you like best about Ahavoo?	What do you like least in Ahavoo?	If you could change one thing about Ahavoo, what would it be and why?
~ "*The percentage system.*" ~ "*The fact you see matching with other participants.*" ~ "*Interface and ease of use.*" ~ "*It is simple to use and good fun.*" ~ "*I like the idea that matches are based on how alike your questionnaire responses are to the other person's. That means we will truly have things in common to talk about.*" ~ "*The possible match idea is great! It is a very smart thing to add to an app!*"	~ "*Lack of notifications*" (x2) ~ "*Colour scheme.*"	~ "*Ability to change profile picture.*" ~ "*Notifications. Without them conversations were harder to form properly, as each person would have to remember to check the app every so often.*" ~ "*The messages to be saved in the app in a way that they could not disappear without an internet connection.*" ~ "*I would like most recent messages to be prioritized and be shown on top.*"

Table 4 - Unstructured user feedback

In the conclusion of the experiment, the participants were asked how likely they would recommend the application. According to the results, over half of interviewees would definitely recommend Ahavoo to their friends (Fig.34). The results obtained by each of the presented participants and responses recorded in the questionnaire are discussed in Chapter 5.

12. How likely are you to recommend this app to a friend (provided all technical issues have been solved) ?



In a scale from 1 (Very unlikely) to 10 (Very likely)

Figure 34 - General participants' feedback

5. Discussion

This chapter discusses the results presented in the previous section, as well as the findings of implementing Ahavoo Dating Application. The success of the project is measured by the extent the aims and objectives identified in the introduction chapter were fulfilled. Using the results from the two-tier evaluation of the application, conclusions can be drawn in regards to the efficiency of the Matchmaking algorithm, based on Deep Neural Network.

5.1 Evaluation of the matchmaking algorithm efficiency

As described in Chapter 2, the solution proposed in this document has been primarily inspired by recommender systems, in particular content-based RECON algorithm (Pizzato et al., 2020) and Latent Factor Models in Reciprocal Recommender Systems (Neve and Palomares, 2020), and as such has several common features. The similarities between Ahavoo and the aforementioned systems include consideration of the significance of conversation satisfaction and introducing personalisation by learning the individual preferences of the users. Although the implemented algorithm, being a simplified concept of a user-user recommender system by definition, did not fully take into account bidirectional nature of matchmaking systems, it achieved the results satisfactory comparable to those obtained by the aforementioned reciprocal recommender systems.

The evaluation process began with the exclusion of the identified outliers, which extreme values would exert a negative impact on the rest of the results. Based on a comparison of generated predictions with conversation ratings assigned to corresponding users, the accuracy of matches was calculated according to the following formula (Fig. 35):

$$\textbf{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$

(where TP – True Positives, TN – True Negatives, FP – False Positives and FN – False Negatives)

Figure 35 - Formula of Model Accuracy

Given a sum of true positives (TP) and true negatives (TN) constituted 11 out of 16 of the obtained scores, the accuracy of the algorithm was estimated to 69%. Considering that numerous studies have shown the accuracy is not a representative metric for the evaluation of recommender systems, the evaluation focused on more sophisticated indicators of AI technology effectiveness.

The following factors utilised commonly in the studies on ANN efficiency were considered: recall (also referred as sensitivity, Fig.36), defining the fraction of matches detected, and precision (Fig.37), evaluating the relevance of identified matches.

$$\text{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

$$= \frac{True\ Positive}{Total\ Actual\ Positive}$$

Figure 36 - Recall formula

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

$$= \frac{True\ Positive}{Total\ Predicted\ Positive}$$

Figure 37 - Precision formula

Precision rate is considered particularly important for dating applications, as a large quantity of matches that do not meet criteria may discourage users and make them lose trust in the quality of the application services. Taking 75% prediction score a potential match, the algorithm precision amounted to 69%. Compared to the results obtained by the LFFR system (precisely the mean of the results for each aggregation function applied to compute prediction scores of a pair of users) obtained during a week-long study with 4000 user dataset, the precision rate of matches generated by Ahavoo turned out to be lower by 13%.

Although 69% precision rate was deemed sufficient to prove the relevance of the majority of the identified matches, it raised a question on the culprit of the False

Positives (FP) prevalence. Exploration of data representing participants' engagement in the experiment - such as a number of established conversations and average of sent messages - led to the conclusion that some of the negative ratings (considered as 3 stars or below) might have been assigned significantly too soon. Therefore, many of the ratings did not reflect the actual satisfaction of the conversation commenced, but rather the dissatisfaction with correspondent's "radio silence". A linear regression analysis, illustrating the correlation between the number of messages exchanged and the assigned ratings, is presented in Figure 38.

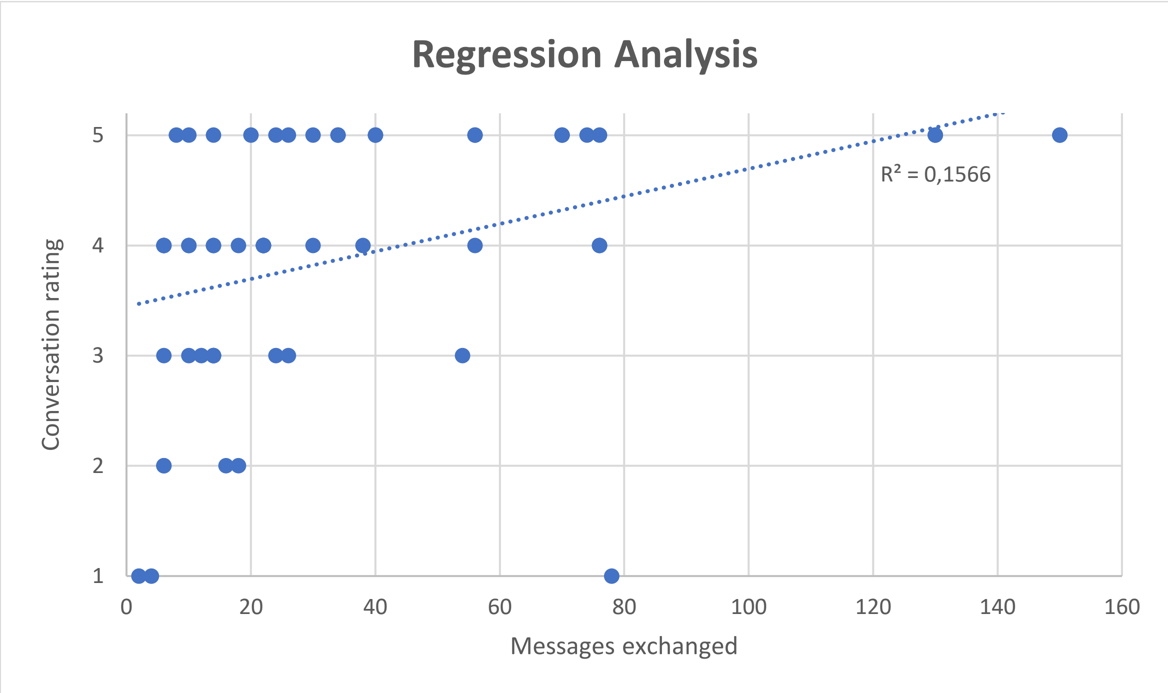


Figure 38 - Regression analysis

Interpretation of the above figure indicated that nearly 70% of conversations rated on a scale from 1-3 stars were limited to less than 20 exchanged messages. This, in turn, demonstrated many of them might not have provided the opportunity to meet the correspondent closer. Lack of such opportunity precluded participants from expressing an honest opinion about other users, leading to noticeable disparity in deliberate and inconsiderate ratings. The analysis of the correlation between the level of engagement in the chat and the ratings assigned was based on the examination of the correlation of determination (R-squared value).

To determine the meaningfulness of the obtained correlation rate, the existing studies on the interpretation of the variance in statistical analysis have been investigated. A study carried out by Abelson (1985), presenting the variance explanation paradox with the use of the baseball players example, shed new light on R-squared interpretation. The paradox indicated by Abelson referred to the analysis of the correlation between batting skills of the basketball player and single batting performance, which yielded an extremely small value of variance explanation (0.3%) significantly different from the expected rate. The researcher concluded that even a marginal R^2 can be meaningful.

Given that some of the credible resources of statistical analysis consider R-squared equal to 0.10 acceptable in social studies (Ozili, 2016), and other confirm values between 0 (exclusive) and 0.35 represent small positive association (Kalin, n.d.), the R-squared amounted to 0.157 was deemed as a proof of a weak, yet positive correlation between analysed variables. The above analysis shows that the precision of Ahavoo's matchmaking algorithm could be significantly enhanced if the instructions on rating the conversation were more accurate, and the experiment itself was extended by another week to account for participant's limited time availability.

Having interpreted the potential reason behind a high rate of FP occurrences, the analysis focused on another factor vital for measuring the system's efficiency – recall. Using the recall measure, the exactness of a given prediction algorithm has been determined. While the precision of the proposed solution showed the room for improvement when compared to a latent factor recommender system, its sensitivity rate equal to 90% outperformed by 1% the score achieved by LFRR system and by 45% the sensitivity achieved by RECON. The recall (sensitivity rate) obtained in this study indicated a high efficacy of Ahavoo in detecting matches, which outperformed each of four dating recommender/matchmaking systems presented in Chapter 2. The first phase of statistical analysis was summarised with the determination of F1 score (Fig.39), defined as the weighted harmonic mean of the aforementioned measures of efficiency – precision and recall.

Although F-score and accuracy measure have a common aim, which is an estimation of the general system effectiveness, each of them realises it differently. Unlike the accuracy metric, F1 score accounts for unbalanced data distributions. It, therefore, constitutes the preferred efficiency estimation method for studies, in which FPs and FNs are deemed more critical than TPs and TNs (crucial for accuracy measure). F1 score obtained by Ahavoo equalled to 78% and was comparable to the mean of the best F1 score for each corresponding aggregation function in LFRR, which was estimated to 82%.

$$F1 = 2 \times \frac{Precision * Recall}{Precision + Recall}$$

Figure 39 - F-score formula

5.2 Analysis of questionnaire responses

The responses collected through the post-experimental survey, reflecting participants' views on crucial aspects of Ahavoo as a dating platform, constituted a second phase of the evaluation process. Conducting a questionnaire at the end of the week-long study aimed to provide a better understanding of the application performance from the user perspective and identification of the room for improvement.

Taking into account the complexity of the project, as well as the differences regarding the age and technology-related experience possessed by participants, 3 initial questions referred to the reflections on the organisation of the experiment and the clarity of provided description of the study. The role of this section was to ascertain if the volunteers gained a comprehensive understanding of the application structure and the grounds for implementing the project.

Out of 14 respondents, 93% agreed they could extensively acquaint with the experiment aims and course, as well as confirmed the experimenter stayed in touch throughout the experiment duration, responding to any study-related questions. Section *zero* concluded with a statement of "*The experiment was well organised and run smoothly*", which was confirmed 86% interviewees. The above data show that the experiment was conducted in a professional manner, providing its participants with solid knowledge of the background and course of the study.

Section *one*, incorporating questions 4-9, constituted the main body of the survey.

Its role was to identify Ahavoo's strength and weaknesses, as well as the technical issues the participants struggled with and general ease of use. The following breakdown presents the results for each individual question of Section *one*, as well as justifies their significance in the context of this project.

Question 4: *"How easy was the application to use?"*
Question 9: *"If you were to review Ahavoo in terms of User Interface (UI) and User Experience (UX), what score would you give it out of 10?"*
The popularity of mobile applications is vastly shaped by the first impression it makes on its users. Overwhelming the audience with intricated functionality, redundant features and lack of consistency in the design may adversely affect User Experience (UX); a crucial aspect of a digital product. That, in turn, may irrevocably destroy the reputation of a brand, which – considering the importance of brand loyalty in the online dating industry – may permanently exclude the application from the market. Although Ahavoo constitutes a prototype of a dating application, it is a high-quality software package and as such represents the best practices of mobile and dating application development, which was confirmed by 93% of participants who positively reviewed Ahavoo in UI/UX terms. Given the median of UI/UX ratings equal to 8 out of 10 and the ease of use rated as *Simple/ Extremely Simple in use* by 86% of the participants it can be concluded, that the application adapted to the target audience and realised the assumptions of the Android Material Design. Due to lack of official results of polls that would allow to explicitly review top DAs in terms of UI/UX, the comparison between proposed prototype and existing mobile dating platforms was based on the average rating provided by users in Google Play - a distribution service for android applications (Google Play, 2020). The average rating for UI/UX of the implemented application (equal to 7.7/10, see Chapter 4) was converted into the 5-point scale and contrasted with the results of other dating brands (as depicted in Fig.40).

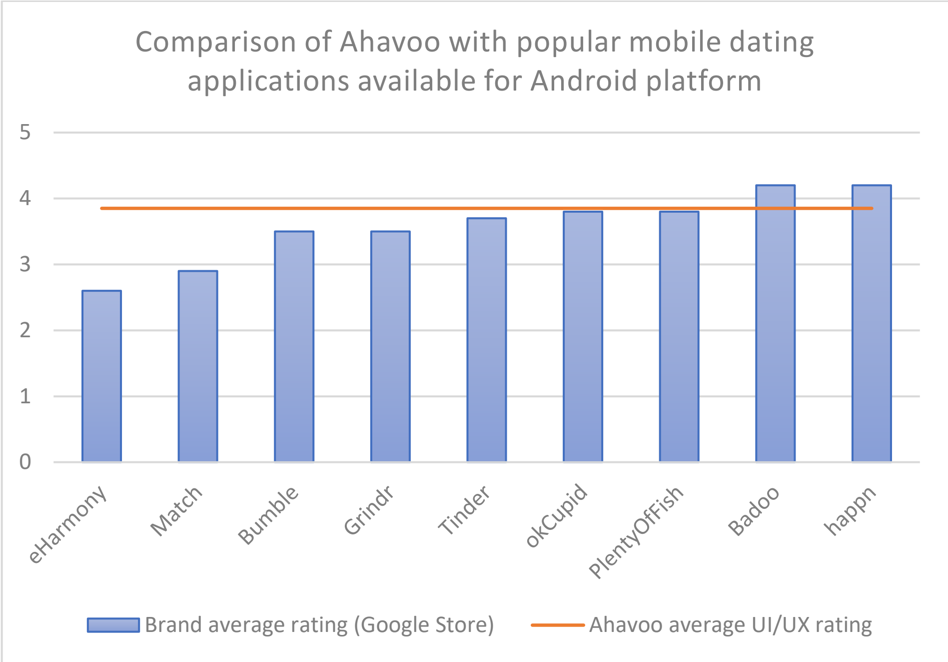


Figure 40 - Comparison of Ahavoo with popular commercial

The sample size utilised in the analysis, corresponding to the number of UI/UX ratings given in the post-experimental questionnaire, reflected the limitations of the project and therefore significantly differed from the sample size representing other subjects of the analysis. The disproportions recorded in the distribution was related to long-term existence in the public sector of mobile dating applications, which facilitated obtaining extensive feedback on their functionality and user experiences. The distribution of ratings for each analysed brand was depicted in Fig.41.

The conducted comparison indicated that Ahavoo outperformed the majority of leading mobile application brands, achieving a score higher than 78% of presented products. The results of the analysis were deemed more than satisfactory, as the prototype developed without financial contributions and technical support of cooperating team achieved a rating no less than the majority of presented commercial alternatives.

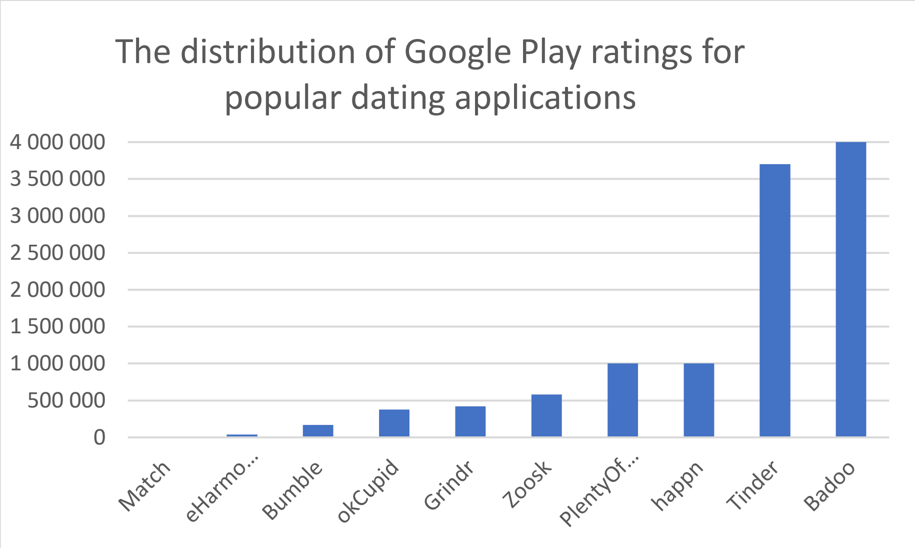


Figure 41 - The distribution of Google Play ratings for popular dating applications

Question 5: *"Have you experienced any technical issues while testing the application? If answered yes, please describe briefly experienced technical issues."* Awareness of the application shortcomings is vital in delivering safe and reliable services. Based on the information provided in the comments about 60% of users experienced technical issues, while every third of them confirms the situation took place more than twice. Further description of those faults indicated that they all concerned lack of system notifications when the message could not be sent due to lack of the internet connection, which forced some of the users to resend the message. As the technical issues recorded in the experiment were limited to a single defect, they did not exert a significant effect on the quality of the application, which maintained its credibility status throughout the experiment. The feedback on the technical issues recorded by the participants of the experiment became a starting point in an analysis of the room for improvement, discussed in broad detail in Chapter 7 - *Suggestions for improvement*.

Question 6: "*If you could change one thing about Ahavoo, what would it be and why ?".* The role of this question was to provide the users with the opportunity to express their opinion on features, which adaptation (from the participant perceptive) would enhance the value of the application in visual, functional and entertainment terms. Interviewees responses focused primarily on push notifications, which received a low priority rating on an iteration feature list and therefore were not implemented as other features were deemed more significant for the sake of the experiment. Other comments assumed extending the application with the ability to add a profile picture, which idea was rejected in the early development stage due to anonymisation of the experiment, as well as prioritisation of messages based on their timestamp and introduction of cache to increase the quality and performance of the chat.

Question 7 & 8: *"What do you like least/best about Ahavoo ?"*

The feedback regarding the least liked features of Ahavoo noticeably covered the responses to Q5-6, excluding the additional comment on the colour scheme - which (in the interviewee's opinion) "could be slightly changed", and as such will not be discussed further. On the other hand, the comments concerning the other half of the question were considered highly valuable for the experiment, providing the ability to look at the application from an entirely different perspective. Asked about the favourite features of Ahavoo, the participants pointed out the cosine similarity measure - a solution to the cold-start problem - as a source of information on the compatibility matching, suggesting the users most similar to themselves. Further comments referred to the implementation of the matchmaking system, as well as the interface, ease of use and adaptation to the needs of individuals of different orientations. The responses provided in Q7 shown a high potential of Ahavoo as a dating application and proved it conforms to the standards represented by its commercial equivalents.

Question 10: *"If you received notifications about potential matches and began a conversation with that user/those users, were predictions any accurate ?"*

Given that the project aimed to develop an efficient matchmaking algorithm, gathering feedback on the accuracy of the produced dating environment was imperative to determine whether the system proved its efficacy in practice. The survey outcomes demonstrate that no unequivocal answer was given to this question. Although the responses varied, it was registered that the majority of them tilted towards an affirmative answer, as 69% of interviewees answered *Agree/Rather agree* on a seven-point Likert scale.

Considering the extreme disproportions between the number of parameters subjected to the training process, as well as a highly limited dataset linked with relatively few interactions established, the algorithm's ability to produce accurate matches was considered significantly lower compared to other algorithms discussed in 6.1. Therefore, constructive evaluation of Ahavoo’s matchmaking algorithm required an individual approach, that would take into account the character of a testing environment. Considering the lack of any official statistics on the efficiency of matchmaking algorithm incorporated in popular dating applications, the evaluation of match accuracy limited to comparison with scientific, offline tested dating recommender systems (discussed in Chapter 5.1).

Section *two* focused on the summation of the experiment.

Question 11: *“How did you find the experiment ?”*

Aside from the functional features distinguishing the product from the competition, it is the entertainment value which constitutes a crucial aspect of a dating application. The role of this question was to explore whether the experiment met the entertainment objectives from the participants perspective and whether the participants enjoyed the dating application in this formula. The analysis of the outcomes showed that 86% of interviewees found the experiment absorbing, while every fourth of them claimed they found it extremely interesting. The response to Q11 demonstrated that the application met the participants’ expectations and proved the need for this project.

Question 12: *“How likely are you to recommend this app to a friend (provided all technical issues have been solved)?”*

The emotional connection the application builds with their users establishes the foundation of loyalty needed to stay on a competitive market of mobile dating platforms. The role of the last question of the survey was to determine how likely the participants, familiarised with the idea of the project and its implementation in practice, would be to recommend Ahavoo to their friends. Given that 64% of the interviewees express it would be extremely likely, it was concluded that Ahavoo presents a high potential as a modern dating application.

5.3 Ecological validity of the proposed solution

The ecological validity constitutes an important aspect of any application prototype, as it indicates the extent to which the environment experienced by the subjects in a scientific investigation (participants of the experiment) has the properties it is assumed to have by the experimenter (Schmuckler, 2001). In other words, it raises the question of whether the behaviours observed in the experiment conditions reflect natural reactions in a given situation. To estimate environmental credibility of the study, two main guidelines of establishing ecological validity were utilised; *veridicality*, referring to the extent to which test scores correlate with measures of real-world functioning, and *verisimilitude*, determining whether tasks performed during testing resemble those performed in daily life.

To address the first of the ecological validity concepts, the experiment and conducted post-experimental questionnaire was contrasted with the test methods utilised by commercial equivalents of the proposed application. Although little information on the UI/UX studies of leading dating applications is publicly accessible, it can be assumed that surveys utilised in the process are likely based on standard UI/UX survey structure recommended by specialists in UX design. User opinions of the application were explored once the Beta tests concluded. Such opinions included most and least liked features of the research subject, UI rating, accuracy of matches and elements which may enhance user experience once implemented. The *veridicality* of the proposed solution was also reflected during the evaluation of the matchmaking algorithm utilising standard measures for determining the accuracy of predictions and other aspects of the system, used by authors of LFRR and RECON (see Chapter 2).

The other half of ecological validity verification was related to the exploration of experimental realism and addressed the question regarding the accuracy in the simulation of real-life conditions. Given the limitations of the study, including a limited number of participants who expressed a will to involve in the research, the situation where some of the volunteers who declared as involved in a relationship imitated their needs of finding a partner was deemed an inevitable consequence of project constraints. To ensure the credibility of the results of the study, each participant was requested to use the application in the same way as other dating applications. The participants of the study expressed their views on functionality and

UI/UX aspects according to the generally accepted standards of both mobile applications and dating platforms.

The prototype differed from classic dating applications in two crucial aspects; namely, it granted absolute anonymity for each individual participating in the study and altered profile pictures with a selection of user icons. Despite the anonymisation applied, the vast majority of participants endorsed the application in implemented form. In the opinion of Participants, the presented approach allowed users to focus on the personality of individuals over physical beauty. The above analysis on the realism of the study and the credibility of test methods led to the conclusion that the experiment represents a moderate level of ecological validity. Therefore, the findings of the study can mostly be generalised in real-life situations.

5.4 Research Question

The evaluation of the experiment, conducted based on both quantitive and qualitative study, allowed to affirmatively answer the research question of "*Can the personalized dating application utilizing matching algorithm enhance a social capital amongst 'social loners'?".* The responses to the post-experimental questionnaire, aiming to extensively explore the feedback given by the participants, allowed to take advantage of their hands-on experience in determining to what extent the project met the proposed aims and objectives. The proposed solution allowed to avoid clustering users (Nayak et al., 2011) and utilizing environmental data such as past relationships (Nayak et al., 2010), reaching nearly twice the success rate and almost 10 times higher sensitivity compared to aforementioned systems. Ahavoo matchmaking algorithm outperformed RECON system proposed by Pizatto et al. (2010) in any applicable terms (those include success rate, recall and precision), as well as achieved marginally higher sensitivity compared to LFRR. Based on the analysis conducted in Chapter 5.2 it can be concluded, that introduction of an unprecedented approach to matchmaking in the dating domain resulted in a promising foundation for a modern, AI-based mobile dating application.

5.5 Limitations

The level of the matchmaking algorithm sophistication and functionality of user interface was limited due to the time and resource constraints of the project. Although the algorithm represents the recommender system adapted to a user-to-user domain, it does not take into account the bidirectional nature of matching in a dating environment. Therefore, if the dating application was to be developed further, it would require carrying out an additional study to address reciprocity and determine an optimal aggregation function based on the studies with RECON and LFRR reciprocal recommender systems (discussed in Chapter 2).

Ahavoo provides the user with freedom of updating the ratings unlimited times throughout the conversation. Although the algorithm adapts to changes in a smooth manner, in marginal cases unstableness in assigning the rating may lead to low accuracy of the matchmaking system. Therefore, additional countermeasure needs to be applied to ensure that the matchmaking system operates correctly.

5.6 Significance of the Study and the Results

Through the adaptation of a recommender system to social science, the project contributed to the landscape of already existing studies on matchmaking systems. Considering the issues (lack of personalisation, low accuracy of generated matches) and suggestions (cold-start problem, consideration of reciprocity in a match) included in the literature, the dating application addressing some of the points raised by the researchers has been designed and implemented. The project aimed to develop easy in use and visually attractive dating application, which could enhance UX with an efficient matchmaking system. This was achieved through the implementation of a Deep Neural Network-based recommender system, which utilised implicit user profile based on in-app questionnaire answers (called user vector) and assigned conversation ratings to determine feature matches. Given that the applied algorithm outperformed three out of four alternative systems in the aspects of a success rate, precision and sensitivity (presented in Chapter 2) it was concluded that the project offers a valuable insight into what tools and approaches could be used to apply Deep Neural Networks into matchmaking systems.

6. Conclusions

Over the past decade, there have been a significant number of studies on the adaptation of sorting/filtering algorithms and recommender systems, used as matchmaking algorithms (see Chapter 2). While the vast majority of the aforementioned algorithms indeed broach the issues related to a two-way matching dilemma and the cold start problem, many of the proposed solutions noticeably lack personalisation of the process or require a significant dataset to initiate the recommendation process. Through the completion of this project, a prototype Android-based dating application has been developed (see Chapter 3). The aim of this system was achieved by following the project schedule along with the identified milestones and scrupulous realisation of determined objectives. Those included reviewing current dating applications, as well as designing and finally building a robust, functional and visually attractive mobile application using relevant techniques and technology.

The promising results obtained through a weeklong experiment with a group of 19 participants exhibit acutely high accuracy of the matchmaking algorithm in regards to the training dataset limited singular input (see Chapter 4). Therefore, the matchmaking system fulfilled its purpose, which was creating an application that would enhance social capital among ‘social loners’ - individuals that find themselves between two extremes of being part of social networking and isolating themselves from others simultaneously (Urban Dictionary: social loner, 2020). Through the implementation of the project, a robust and visually attractive prototype of an AI-based dating application was developed and tested by a group of participants; the majority of which claimed they would likely recommend the application to their friends.

Moreover, the experiment revealed some of the system weaknesses, both in terms of User Interface and the matching algorithm itself (see section 6.1).

The project concludes that Ahavoo dating application constitutes an effective tool for meeting other singles (those not romantically involved with another person) and like-minded individuals - referred as potential matches. However, some functionality may require further refactoring to adapt its services for commercial use.

6.1 Suggestions for improvement

Even though the post-experiment survey shown high satisfaction in terms of conforming to UI/UX standard, the shortages of the system registered during the experiment could adversely affect the application in case of further adaptation. The constraints of the developed system were analysed in terms of algorithm constituting the core of Ahavoo, User Interface and functionality provided within, as well as system performance in terms of database usage. Given the number of parameters in the training/prediction process, as well as the quantitive data obtained as a result of the experiment it was concluded, that the volume of the average training dataset is disproportionate to the number of features being a subject of the prediction process. Therefore, the parameters of DNN require further adjustment with the training limitations taken into account. That, in turn, may involve restructuring the in-app questionnaire and its in-depth evaluation from the sociological perspective.

The application implemented in this project focused primarily on operational goals and customisation of the UI to enhance the UX of the target audience, which led to shortages related to lack of database calls limitations. The introduction of caching in combination with internal storage (e.g. in the form of self-contained SQLite database) could not only significantly reduce the Firebase DB usage and therefore decrease the costs, but also optimise the battery life. Moreover, the chat activity could be restructured to load only a set amount of newest messages, requesting for more “on-demand” of the *OnScroll* listener. This way, the system could significantly reduce the number of database calls triggered to retrieve older conversations, which may become costly in the long run.

6.2 Future work

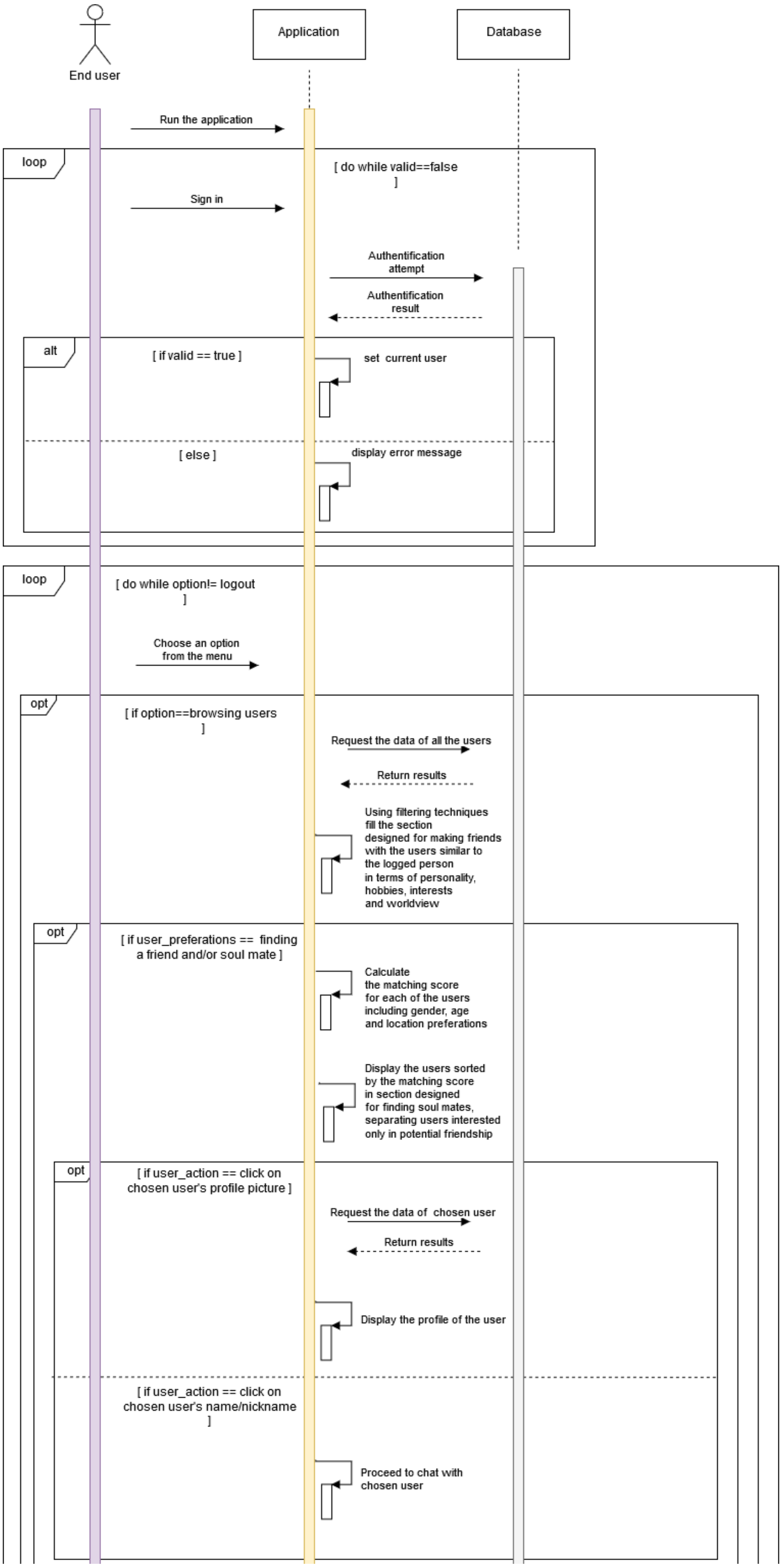
Given that the prototype application and matchmaking algorithm based on DNN developed in this project was introduced as a proof of the concept, there is a broad range of improvements which can be implemented. An offline-first architecture could be considered to address the issue of unstable internet connection, as only 43% of mobile users have access to the 4G network (Peakin, 2017). Following the offline-first architecture would enable the application to provide basic services, even despite having no internet access.

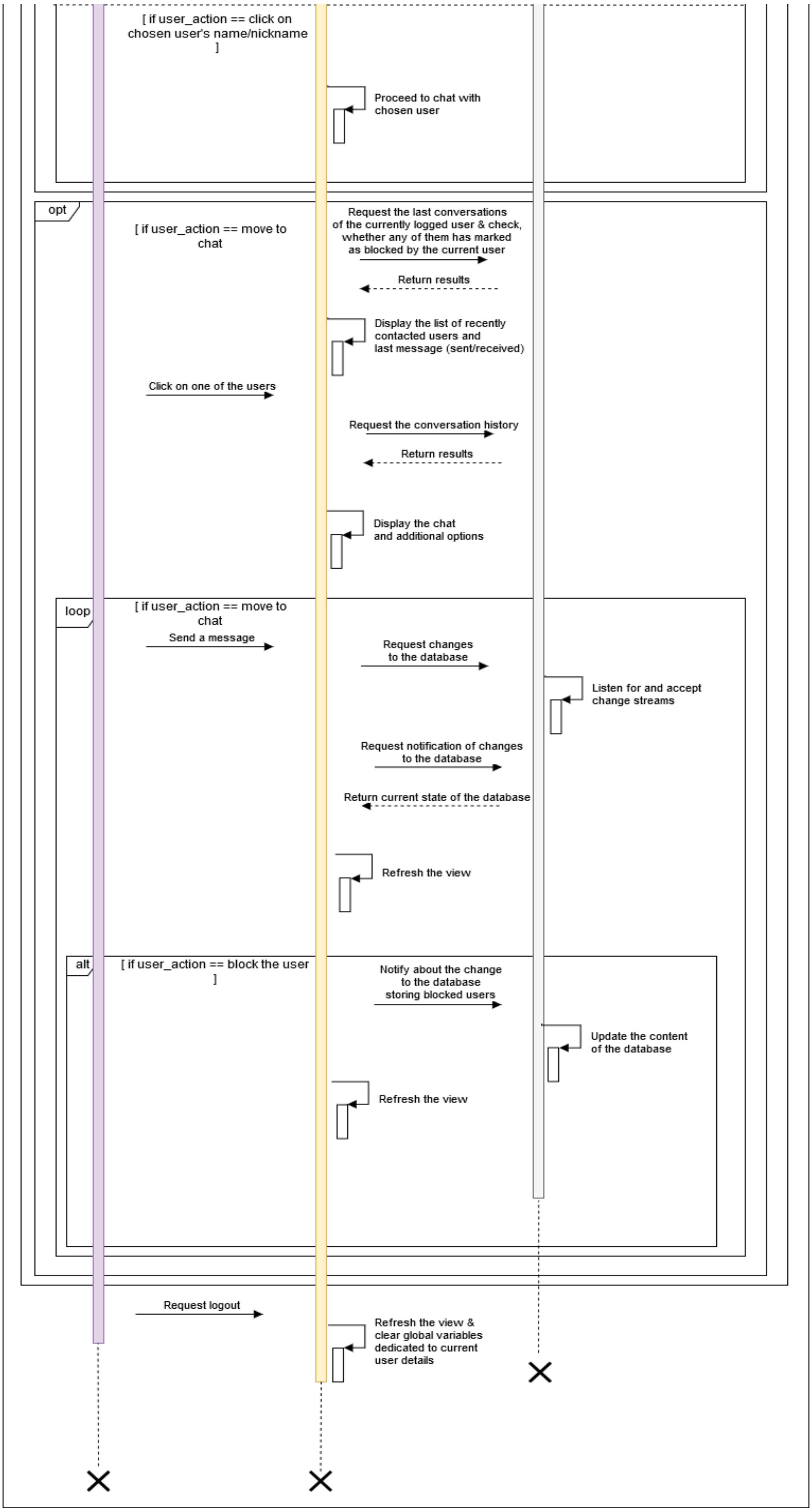
Observing the effectiveness of Ahavoo in generating potential matches, further research could be conducted to examine the alternative methods for increasing the success rate and precision of the aforementioned algorithm, as well as the implementation of reciprocity concept with the use of the aggregation function or empirically established weights.

Participants expressed that night mode is one of the key features the system lacks. The functionality of the application may be extended by enabling group chats and photo messaging, which would require a sophisticated encryption mechanism. Further enhancement of UI could be achieved by taking advantage of existing android libraries which support material design, such as Ionic (Ionic - Cross-Platform Mobile App Development, 2020) and Flutter (Flutter - Beautiful native apps in record time, 2020).

Appendices

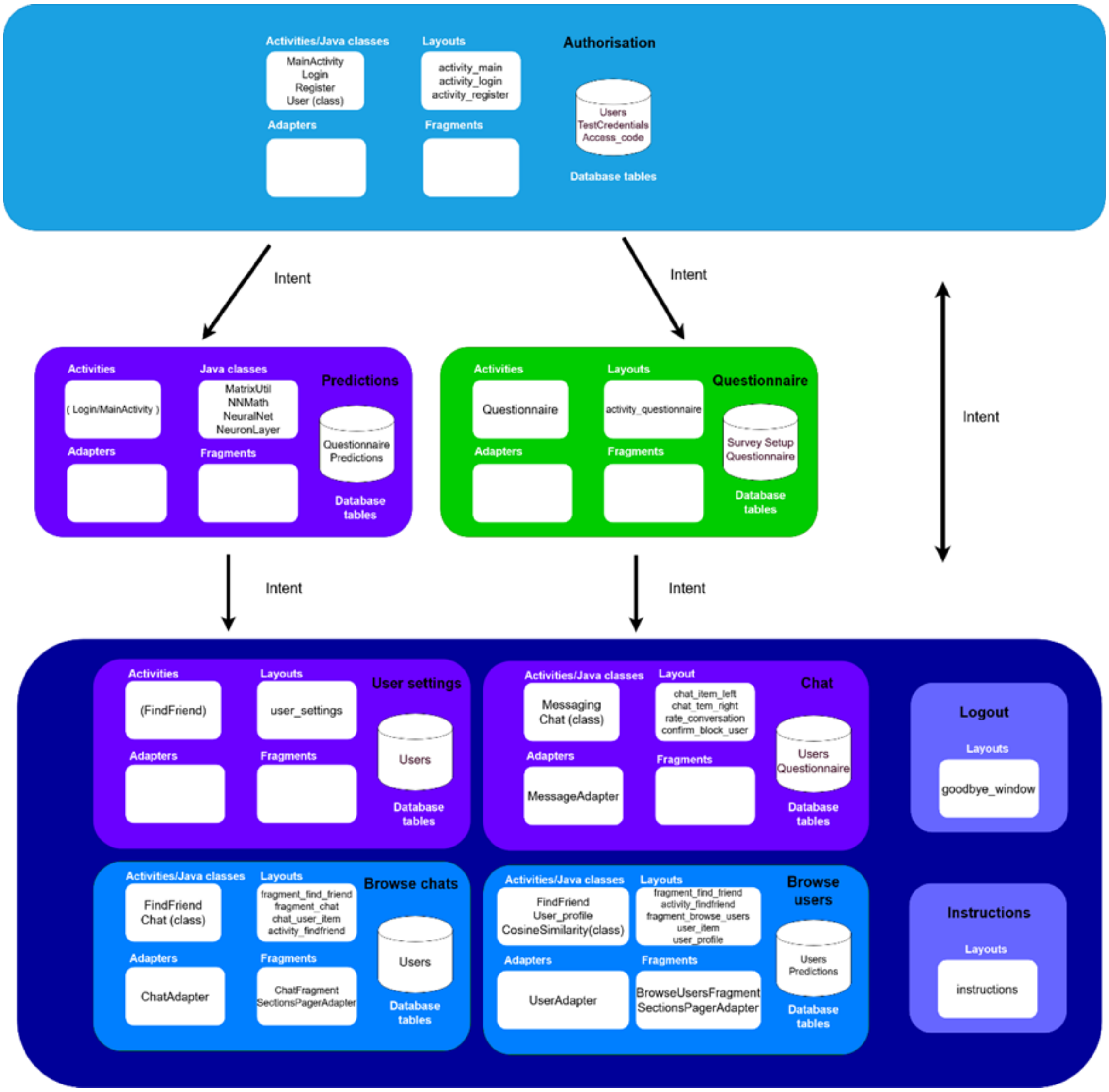
Appendix A - Sequence Diagram



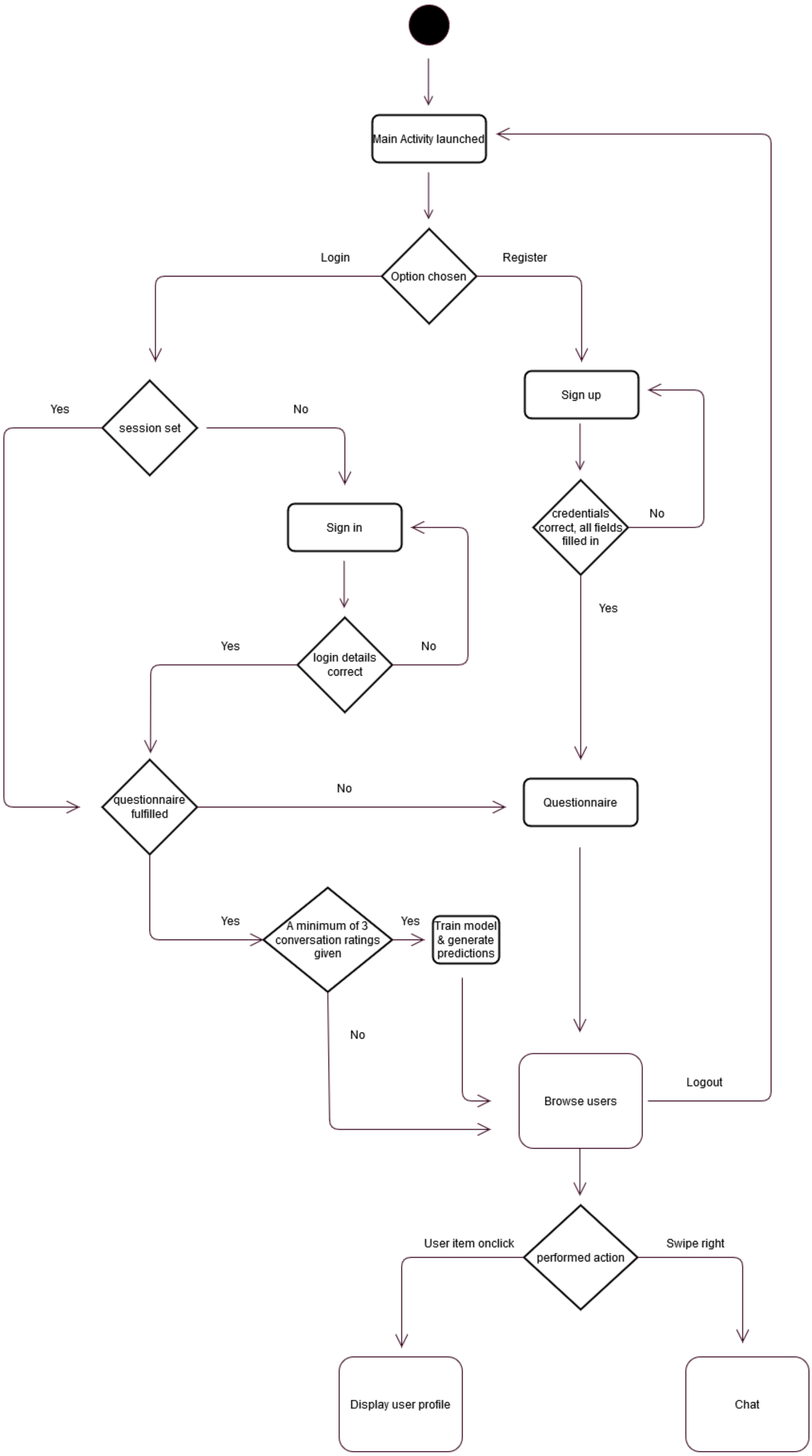


[if user_action == click on chosen user's name/nickname]
Proceed to chat with chosen user
opt
[if user_action == move to chat
Request the last conversations of the currently logged user & check, whether any of them has marked as blocked by the current user
Return results
Display the list of recently contacted users and last message (sent/received)
Click on one of the users
Request the conversation history
Return results
Display the chat and additional options
loop
[if user_action == move to chat
Send a message
Request changes to the database
Listen for and accept change streams
Request notification of changes to the database
Return current state of the database
Refresh the view
alt
[if user_action == block the user]
Notify about the change to the database storing blocked users
Update the content of the database
Refresh the view
Request logout
Refresh the view & clear global variables dedicated to current user details

Appendix B - Application components



Appendix C - Activity Diagram



Appendix D – Research Consent form

Research Consent Form

Who is the researcher?
My name is Dorota Marczak and I am a 4th year Computing student at Abertay University.
I am interested in modern dating applications and I would like to invite you to take part in my experiment.
If you have further queries in relation to this study or how the data are processed you can contact me at 1604779@abertay.ac.uk or our Data Protection Officer at DataProtectionOfficer@abertay.ac.uk

What is the research about?
The experiment is aimed at examining the level of effectiveness of the matchmaking algorithm constituting a core element of Ahavoo dating application (the subject matter of the research), as well as assessing the application in terms of User Experience.

What will I be required to do?
Individuals participating in the research will be asked to download the application with the link attached in the information email, sign up with provided details and then to fill in a short in-app questionnaire on their personality, lifestyle and worldviews.
For the duration of experiment (7 days) the participants will be asked to initiate a number of (anonymous) interactions with other users through provided chat facility, rating the satisfaction from the conversation whenever considered appropriate (rating may be updated more than once). By providing the rating for each of established conversation, Ahavoo will gain the data required to train AI model and then generate match predictions (on the evaluation stage generated predictions will be compared to actual rating scores in order to evaluate algorithm efficiency)
The participants get the ability to block the users they do not wish to stay in contact and report any anti-social behaviour to the experimenter, who will then decide on excluding the participant from the experiment.

Do I have to take part?
This form has been written to help you decide if you would like to take part. It is up to you and you alone whether you wish to take part. If you do decide to take part you will be free to withdraw at any time without providing a reason and without penalty.

How will you handle my data?
Your data will be stored in an anonymised form and will only be accessible to the experimenter (see contact details below). This means that nobody including the researchers could reasonably identify you within the data/a key stored separately will link your research data to your real identity/your data will be fully identifiable as yours.
Your data will be stored in a secure database with data fully anonymised at the earliest opportunity (i.e. when data that could identify you is no longer necessary for the purposes of the research).
The messages exchanged between users are additionally encrypted to ensure participants' privacy and data safety.
Your data collected within the application are treated in the strictest confidence - it will be impossible to identify individuals within a dataset when any of the research is disseminated (e.g. in publications/presentations).

Privacy notice and legal basis for processing:
Abertay University (the "University"/"we") is committed to protecting the privacy and security of your personal data in accordance with the Data Protection Act 2018 (or any successor legislation) and (EU) 2016/679 the General Data Protection Regulation ("GDPR") (and any other directly applicable EU regulation relating to privacy) (together "Data Protection Law"). This research has been approved by the Ethics Committee of Abertay University (and XXXX if additional Ethical Approval is required). The research team adhere to the Ethical guidelines of [their professional body] (and/or the principles of the Declaration of Helsinki, 2013) and the principles of the General Data Protection Regulations (GDPR). The Abertay University Privacy Notice for Research Participants is available at https://www.abertay.ac.uk/legal/ . General information on Data Protection law is available from the Information Commissioner's Office. For research involving living humans, the Data Controller adheres to, and collects, processes and handles/archives data in compliance with: Article 6 (1) e: processing is necessary for the performance of a task carried out in the public interest or in the exercise of official authority vested in the controller. Article 9 (2) j: processing is necessary for archiving purposes in the public interest, scientific or historical research purposes or statistical purposes in accordance with Article 89(1) based on Union or Member State law which shall be proportionate to the aim pursued, respect the essence of the right to data protection and provide for suitable and specific measures to safeguard the fundamental rights

and the interests of the data subject. Where applicable, this form is prepared in consultation with Article 13 of EU GDPR legislation, detailing the information to be provided where personal data are collected from the data subject. If you have concerns about this research, please contact researchethics@abertay.ac.uk for enquiries (stage 1), or for more formal concerns (stage 2), please contact complaints@abertay.ac.uk. If you are not happy with the way your information is being handled, in the first instance, you should contact the University's Data Protection Officer (DataProtectionOfficer@abertay.ac.uk). If you remain unhappy with the response received from us, you have the right to lodge a complaint with the Information Commissioner's Office at Wycliffe House, Water Lane, Wilmslow, SK9 5AF (https://ico.org.uk/).

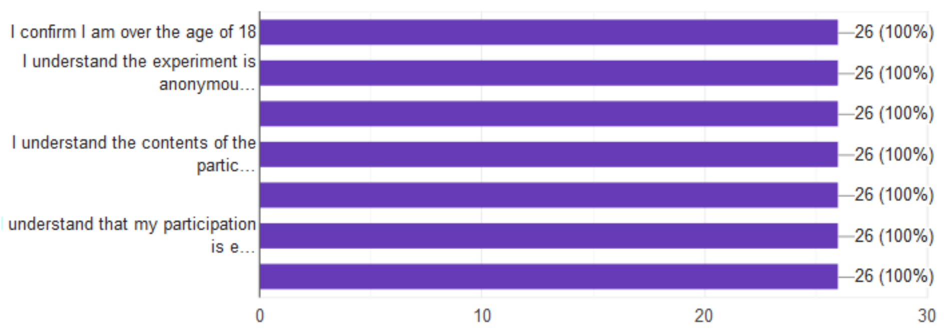
Abertay University acts as Data Controller (DataProtectionOfficer@abertay.ac.uk).

Experimenter contact details: Dorota Marczak, 1604779@abertay.ac.uk

You are indicating consent under the following assumptions : *

- [ ] I confirm I am over the age of 18
- [ ] I understand the experiment is anonymous and it is recommended not to share any private or sensitive data.
- [ ] I understand that anti-social behaviour will NOT be tolerated and will result in immediate exclusion from th ...
- [ ] I understand the contents of the participant information sheet and consent form.
- [ ] I have been given the opportunity to ask questions about the research and have had them answered satisf ...
- [ ] I understand that my participation is entirely voluntary and that I can withdraw from the research(parts of t ...
- [ ] I understand who has access to my data and how it will be handled at all stages of the research project.

You are indicating consent under the following assumptions :



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