# Implementation

The components proposed in the previous chapter shall be further discussed in detail. The implementations used where done using the following applications and libraries: Vuforia [14], Unity Engine [14] and Python 3.7. Vuforia was mainly used to train image and model targets, Unity is a game engine/editor used in our case for building the augmented reality application architecture, and Python 3.7 was used for image sharpening as well as for training and testing the recommendation system. This chapter highlights all the necessary details about the data handling, feature extraction, user-query recommendation as well as the user interface and system architecture built accordingly. Vuforia was used for augmented reality, mainly because it is the “most popular SDK for developing ARapplications on a wide selection of devices” [14]. Similar to ARCore and ARKit, Vuforia can be used on multiple devices to recognise images, objects and text.

## Data Handling

### Images

Initially the project started by gathering a numerous number of images of the workplace’s ﬁrst ﬂoor. A good number of images were taken of all the corridors, objects inside the corridors and doors. Images of the interior of the oﬃce rooms within the ﬁrst ﬂoor were excluded, as it is not within the project’s interest to capture them within the augmented reality application. Diﬀerent variations of the same image were captured, capturing as possible diﬀerent lighting and time scenarios. The reason behind this was mainly because GPS signals are weak indoors and Vuforia does not support location-based tracking. Therefore, the Augmented Reality had to be marker-based through image and model targets. The challenge in this case, was capturing the same images in diﬀerent scenarios. For example, if in one image a door was open, another image had to be captured where the door was closed, that way the system would be trained in the various settings and contexts.

### Markers

The next step was choosing the markers, which Vuforia could use to recognise and overlay the augmentation on. Choosing the best markers is important, as that can entirely aﬀect the user’s experience within the augmented reality. Initially, it was thought to use images of the corridors themselves were going to be used as markers. However, this meant that for one corridor, one needed to take several images capturing an inﬁnitely amount of variations which could occur in that image. For example, as shown in Figure 4 and in Figure 5, one can see several clear sight variations of the same corridor. By ﬁnding diﬀerences in edges and contours computed in Figure 6, a structured similarity index of 0.62 was found which is a very low similarity, hence making it diﬃcult to augment corridors. Therefore, it was decided to use door signs as markers. The ﬂoor used for the application, had a good amount of doors, each had their own unique sign placed at the centre. Therefore, the signs were used as markers for their static looks, meaning, it was very unlikely for the marker to diﬀer in diﬀerent images taken at diﬀerent times and angles and for their unique attributes as shown in Figure 7.

### 3D Models

To build the model targets one must provide a 3D object within the Vuforia Model Target Generator as explained in [14]. The 3D models generated were those of the door markers placed around the whole ﬂoor areas and of the coﬀee machine as shown in ﬁgure 8 and in ﬁgure 9. The 3D models for the door markers were generated using an online library Selva3d which generates a 3D model from a given picture.

### Recommendation Data Set

The recommendation system was made up of a combination of item-based similarity and collaborative ﬁltering techniques. For the collaborative ﬁltering techniques, there was no existing dataset which one could make use of, since there were not any previous similar applications where users could rate the system. Therefore, a prototype recommendation system was built through generated data, simply to analyse how the system works along with the augmented reality application. As previously mentioned, three tasks were picked for a visitor proﬁle, for which the collaborative techniques would be applied to. The tasks were an interview, a delivery and a site-visitation. For each task a dataset containing the user-tasks along with the rating of that task was created. Every entry had the following attributes: user id, task id, locations of interest, user-task id, and the rating. The task id represents the id of either an interview, a delivery or a visit. Locations of interest is a 7-bit binary code representing the accountant’s oﬃce, the human resource’s oﬃce, the manager’s oﬃce, the secretary’s oﬃce, the kitchen, the toilet rooms and the games room respectively. Each dataset has a respective smaller dataset containing several locations of interest which were activated by previous users. The primary key of the tasks’ dataset is the foreign key within the user-task dataset which was called “user-task id”.

## Feature Extraction

### Image Targets

The ﬁrst step in the feature extraction process was feeding the images within the Vuforia library, for it to extract features from them as shown in [14]. The library applies natural feature extraction to identify contours and edges from within the image and as a result display a 5-star rating according to how augmentable the image is. Initially when corridors where tried as markers the library had a problem with identifying key features from plain white painted corridors, as they appeared to show no distinct edges and contours and due to lighting the images had a glossy texture which was harder for Vuforia to track. However, then the door signs were used as markers, the images representing the markers were sharpened using OpenCV, taken in proper lighting scenes and fed into the library. The result is as shown in ﬁgure 10. The sharpening enhances the strength of certain edges and corners making the marker more detectable for the library.

### Model Targets

The second step was feeding the 3D models within the model target generator. Vuforia’s object recognition utilizes natural feature tracking by analysing the object at 3 diﬀerent axis. Vuforia does not speciﬁcally say what deep learning techniques they make use of. However, according to [14] they are most likely making use of Interest Point Detection, which makes use of a set of images of the same object at diﬀerent scenarios, angles and lighting. The model target generator takes a maximum of 20 model targets. Their CNN is then trained on that one 3D object and meta data is outputted which can later be fed into Unity. The model target generator trained a total of 10 3D objects which consist of the coﬀee machine and the door markers. As shown in Figure 11 the model’s distance, angle and orientation were adjusted for training hence making the object easy to track.

### User-Query

The ﬁnal step was extracting features from the tasks’ dataset for the recommendation feature. The features extracted where the user id, the user-task id and the rating. This was done the same way for the three tasks (Interview, Visit, and Delivery) separately, since there is no connection between each task and therefore the recommendation system is best trained on each one individually. In the next section the recommendation system shall be further explained in detail.

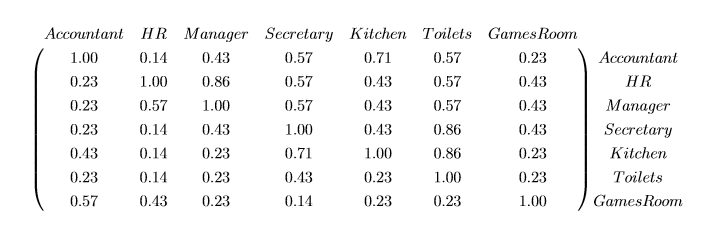
## User-Query Recommendation

### Overview

As previously explained in Chapter 4, along with the Augmented Reality it was thought to implement a recommender system depending on the proﬁle of the user (Visitor or Intern). The system would incorporate functionalities of an item-item similarity-based recommender system and functionalities of a collaborative ﬁltering system.

### Similarity Based

The item to item similarity-based recommendation consists of two main components. A user to item matrix which in our case is the user query, this changes depending on the user’s preference and the item-item matrix. The latter matrix stays constant and represents the similarity one location has with another based on whether the user passes right in front of it, when trying to ﬁnd an oﬃce. The locations chosen were the accountant’s oﬃce, the human resource’s oﬃce, the manager’s oﬃce, the secretary’s oﬃce, the kitchen, the toilet rooms and the games room. Each row was computed using the term frequency approach. TF was chosen to enhance the relevant importance of a sought query, in this case the oﬃce one wants to go to, TF-IDF was not used as matrix scaling was done using one-fold normalization due to having a term (a location within the oﬃce) appearing in every task (a task is equivalent to a document). Below one can see the ﬁnal normalized item-item similarity matrix.



### Collaborative-Based Filtering Techniques

The collaborative ﬁltering approach is a model built based on user’s past experiences of the decisions, locations of interest picked and task they had in completing their own task. However, initially there were not any similar systems, where users could rate their experience. Therefore, the data was not gathered but was created solely to provide a prototype of the system and evaluate its performance. For building the collaborative ﬁltering techniques the following python packages were used; pandas, NumPy and sklearn. Each dataset contains 101 user ratings. Following a similar procedure as used in [35], the system uses a truncated Single Value Decomposition to generate a utility matrix. To avoid having empty ﬁelds within the utility matrix, add-k smoothing is applied where k is of 0.01. The matrix is then transposed and decomposed using TruncatedSVD. The decision to apply SVD based algorithms instead of PCA or CA-CF was to achieve a higher accuracy [35]. Finally a correlation matrix is generated and the ﬁnal recommendation is based of it, where the results are then all stored in separate CSV ﬁles and fed into Unity Editor.

The three top recommendations are then presented within the AR application and whichever one the user chooses, the system then multiplies its item to item similarity matrix with that of the user’s query matrix using dot product and the result matrix is ﬁnally obtained. The result matrix’s elements represent the size of a location’s gameobject within the 3D augmented map sketched. By applying a threshold value of 0.4 to a gameobject’s size, if its size is below it, it simply does not appear within the 3D holographic map. The larger the size of an oﬃce pinpoint location is, the higher it is being recommended to the user. Therefore, that oﬃce, has a higher relevance than the rest.

## User Interface and System Architecture

### System Architecture

There are three main components which make up the system architecture. The ﬁrst most essential component is the user. The user is important as the system must serve as an essential tool for assisting them around the workplace. Their decision-making process drives the Augmented Reality application capabilities to its extent. The second component is the recommendation system which as previously explained provides collaborative and similarity based ﬁltering techniques depending on the user’s proﬁle. The third component is the Augmented Reality provided by Vuforia. This component can be further subdivided into two other sub-components: the SDK library and the built architecture within unity tailor made for this project.

As explained in [17] the Vuforia AR SDK consists of the smartphone’s camera and the target resources (the targets’ database) communicating with the tracker. The tracker then detects the real-world objects, converting each frame and snapshot to render augmented logic back on the user’s smartphone. Figure 12 shows graphically how the Vuforia AR SDK works.

The built architecture within unity consists of three features. The ﬁrst feature is called “Oﬃces”. This feature allows the user to wander around the workplace and view augmented information from the oﬃces’ marker. The second feature is “Locate” this oﬀers oﬃce information and oﬄine directions to the user, depending on their preferred recommendation. The third feature is “coﬀee machine”, which provides employees and visitors with information of how to make use of the coﬀee machine. This information is provided via text, images and video instructions.

The main challenge encountered, was in the ﬁrst two features. Vuforia can detect multiple image targets yet can only detect one model target for every scene within unity. However, using model targets in certain scenarios can provide a more eﬃcient user experience as the real-world object is more recognizable due to deep learning techniques being utilised for recognition, rather than just traditional computer vision techniques. Therefore, a combination of image targets and model targets were used. The object is ﬁrst detected using traditional computer vision methods, then once it is recognized the user is interested, the users prompts to view relevant information according to the marker being recognized by clicking the open button. Once the user prompts to view the respective augmented information the model target is activated. Once the user exits from the augmented information, the respective model target is deactivated. Therefore, through a combination of traditional computer vision and deep learning a more accurate system is provided, which as a result can oﬀer eﬃciency and an immersive experience. Even more so a solution was found to one of Vuforia’s lacking feature which still does not enable the users to use multiple model targets in one. Therefore, the aforementioned technique served as a workaround to make use of multiple model targets.

### User Interface

When the application starts, the user is presented with three options: ‘Oﬃces’, ‘Location’, and ‘Coﬀee Machine’ as shown in Figure 13. The ‘Oﬃces’ directs the user to the augmented reality system, where the user can wander around the workplace and view augmented information about the oﬃces. ‘Location’ directs the user to selecting a proﬁle between an intern and a visitor. For the Visitor’s proﬁle the user chooses a task from the following options: visit, interview, and delivery via a dropdown button. As shown in Figure 16 the user is provided with three recommendations. Each recommendation contains features which are recommended via an approval green sign, whilst the ones which are not recommended are represented by a X-sign in red. The approved signs for accountant, human resources, manager and secretary are clickable. Once any one of them is clicked, it will direct the user to the augmented reality system, where they can view augmented information about the oﬃces via the door markers and locate the respective oﬃce which was previously clicked. Each oﬃce augments its own respective main menu as shown in Figure 17.

The details panel provides details of the room and the ‘Locate’ button augments a 3D hologram of the workplace and provides the user with hard-coded directions towards the oﬃce they are interested in as shown in ﬁgure 19 and in ﬁgure 20. As one can observe the oﬃces in the hologram are colour coded and are represented as a sphere. They are scale-wise recommended, this means that the larger the oﬃce’s marker appears the more important and relevant it is to the user. The oﬃces which do appear in the hologram, are the result of the collaborative and similarity based ﬁltering techniques provided by the recommendation system.

The coﬀee machine functionality allows the user’s phone camera to recognize the DeLonghi Esam2600 Coﬀee machine. The user can view text and video instructions on how to make a cappuccino, view a diagram of the machine’s functionalities, and a view a 3D model of the machine.

## Conclusion

In this chapter we have seen in the detail how the workplace assistant AR application was implemented, and the decisions taken behind every feature which were provided. In the next chapter, tests and evaluations shall be provided to highlight the system’s performance.

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