Identifying characteristics of passers-by to provide dynamic advertising in public spaces using Computer Vision

By

Daniel Hodge

HOD15589698



A dissertation submitted in partial fulfilment of the requirements for the degree of

MSc (Hons) Computer Science

School of Computer Science

University of Lincoln

2019

# Abstract

Targeted advertising has been dominant in recent years, vastly overtaking traditional marketing in cost effectiveness. This is due to it allowing advertisers to pay each time an advert is shown to a potential customer with some kind of interest in the product, instead of paying a flat fee for everybody to see it, regardless of whether it’s relevant. Previously, these enhancements have been exclusive to online advertising, however state of the art techniques are enabling them to be applied to public advertisement spaces as well, such as airports, shopping centres and high streets.

This project implements targeted advertisements in public spaces using a variety of techniques including machine learning and computer vision to improve the cost effectiveness of physical advertising. An increase in cost effectiveness is achieved by advertising to a passer-by only when it specifically applies to them, as opposed to traditional methods which would show an advertisement to all passers-by, increasing the amount of waste.

The results are promising, demonstrating that the combined accuracy of all the identified characteristics averages out at 93.5%. Furthermore, the project features a successfully implemented advertisement recommendation engine which chooses an advert based on its similarity to the identified passer-by, choosing a viable option 100% of the time, assuming the acquired characteristics are correct. It even goes as far evaluating the context of a group, such as friends or family, and creating more personal advertisements for them.

# Table of contents

[Abstract 2](#_Toc17825303)

[Table of contents 3](#_Toc17825304)

[Introduction 5](#_Toc17825305)

[Rationale and Benefits 5](#_Toc17825306)

[Aims and Objectives 6](#_Toc17825307)

[Background 6](#_Toc17825308)

[Report Structure 8](#_Toc17825309)

[Literature Review 9](#_Toc17825310)

[Methodology 13](#_Toc17825311)

[Project Management 13](#_Toc17825312)

[Gantt chart 13](#_Toc17825313)

[Risk Matrix 16](#_Toc17825314)

[Software Development 18](#_Toc17825315)

[Toolsets and Machine Environments 20](#_Toc17825316)

[Dataset 21](#_Toc17825317)

[Research methods 21](#_Toc17825318)

[Design, Development and Evaluation 22](#_Toc17825319)

[Requirements 22](#_Toc17825320)

[Design 22](#_Toc17825321)

[Development 23](#_Toc17825322)

[Evaluation 27](#_Toc17825323)

[Findings and Conclusion 33](#_Toc17825324)

[Results 33](#_Toc17825325)

[Ethics 35](#_Toc17825326)

[Future work 36](#_Toc17825327)

[Reflective analysis 38](#_Toc17825328)

[References 40](#_Toc17825329)

[Appendix 45](#_Toc17825330)

[Appendix 1 45](#_Toc17825331)

[Image 1 45](#_Toc17825332)

[Image 2 46](#_Toc17825333)

[Image 3 47](#_Toc17825334)

[Image 4 48](#_Toc17825335)

[Image 5 49](#_Toc17825336)

[Appendix 2 50](#_Toc17825337)

[Image 1 50](#_Toc17825338)

[Image 2 51](#_Toc17825339)

[Image 3 52](#_Toc17825340)

[Image 4 53](#_Toc17825341)

[Image 5 53](#_Toc17825342)

# Introduction

## Rationale and Benefits

This has been undertaken for two distinct reasons. The first is improving and assessing the implementation of state-of-the-art Computer Vision techniques, such as how well the physical attributes of a passer-by can be identified and determining the context of a situation, such as the type of people in an area as well as the relationship they have to others in their group. Furthermore, the quality of these techniques when applied to a public space will also be considered.

The second reason is to illustrate and assess the applications of these Computer Vision techniques, by using the example of targeted advertising. This is an ambitious goal and solves a real problem that already exists within advertising, which is how to convert all the success of targeted online advertisements to those that can be found in public places such as shopping centres, airports and high streets.

One benefit of this project would be to reduce waste for businesses, by allowing them to advertise straight towards their target market, instead of wasting time, space and money advertising to people that are significantly less likely to buy their products or services. While large companies like fast food chains can afford to advertise in public areas that are seen by everyone, due to their products being universal, there will always be benefits from targeting ads more specifically. For example, these companies could use the technology to advertise children’s meals to their younger market, increasing the effectiveness of their ads without having to reduce their widespread campaign.

If this project were implemented, one of the largest benefits would be for niche businesses. While it would significantly improve cost effectiveness for all companies, the ones who would benefit the most are the ones who can’t justify paying for marketing spaces when their product may only apply to one in every 100 people who walk past. One such example could be electric razors for elderly men, which would only apply to 3% of people (around 9% of the UK population are elderly males, and 34% of those have facial hair (YouGov, 2016)), however not being able to easily publicly advertise this could be harmful to both the company and the individual, as it may be a product that the individual was looking for. While it’s easy to dismiss advertising as only beneficial to the business, it can also help the customer find a product that they need or weren’t aware of previously.

## Aims and Objectives

The aim of this project is to develop a system which integrates tailored advertisements with digital signage to increase the return on investment for advertisements in public spaces. To achieve this aim, the following objectives have been laid out:

Objective 1: Develop a system which can find faces in a photo.

Objective 2: Identify the individuals’ features, such as age, gender and hair.

Objective 3: Infer the context of groups, such as family, friends or couple.

Objective 4: Use the gathered information to recommend an advert.

Objective 5: Gather secondary data, such as location and time.

Objective 6: Run this system in real time.

## Background

Online advertising has seen exponential increases in effectiveness over recent years as a result of advertising services creating profiles of each individual’s online identity, such as their basic details (gender, age etc) and their interests, for example if they watch sports or search for cooking recipes. This information is based on their search history, as well as accounts they create for different websites, where they will likely enter their basic details. Advertisers are then encouraged to use this information to scope into their specific demographic, such as beer companies advertising to young males interested in sports around the time of major sporting events such as the football World Cup. This is a much more efficient approach than the old method, which consisted of placing advertisements on a site for a fixed period of time (or until a certain budget was hit), and just hoping that the correct audience would see it. Small amounts of targeting could still be achieved by doing this however, such as choosing a website which matched potential user interests.

Advertising on digital screens in public spaces is still a static system, which shows the same advertisements to everyone, or at best has a rotation of adverts to display one by one, as these devices have no means of discerning the characteristics of passers-by, and therefore wouldn’t be able to change the advertisement for each individual as a result. The primary issue is that, unless the user can be persuaded to stop and sign into an online account (such as social media), there is no easy way of collecting the users’ data. Therefore, more complicated means are required, such as using Bluetooth to scrape data from the phone or using Computer Vision to analyse the passer-by. This can’t provide the wealth of data that online advertising can, however it is not unreasonable to expect it to be able to build a basic profile, such as age, gender and facial features. This minimal amount of information would allow ads to be tailored to the profile of the person in front of them, meaning adverts could be significantly more cost effective.

The opportunity to begin targeted advertising in public spaces has recently surfaced due to two factors. The first is the increased number of digital screens used for advertising. While they aren’t completely widespread yet, they have seen a large increase, potentially due to the fact that they require less human involvement than the typical paper advertisements, which must be replaced manually, as opposed to digital, internet connected screens, which can simply have the adverts be updated on a server. These provide the opportunity to be more interactive with adverts in many different ways, which can have a large array of positive impacts, such as getting user responses, and providing a more interesting experience for the user, which could increase the chance of them actually buying the product. The second factor is the improvement in methods to gather and analyse a large amount of user data in a short period of time, due to recent advancements made in fields like Big Data and Internet of Things, which provide the framework for these more connected public spaces.

In fact, targeted advertising in public spaces has already seen some early adoption. Westfield shopping centre has implemented an early version of this technology, detecting factors such as age and gender, and advertising based on this (The Guardian, 2019). The system goes further, detecting mood, and sending feedback to advertisers, so they can understand how their marketing affects potential customers. While not much is known about this system yet, or it’s accuracy, it has been revealed that it has a 90% accuracy when detecting gender, and 80% with mood.

Similarly, facial recognition is being used for security in a several cases, with a large amount of discussion around its ethics. One such usage has been at Taylor Swifts concerts, which use the technology to identify stalkers, or other potential threats (The Guardian, 2018b). While some are happy about the increased level of safety, the threat of being misidentified as a criminal has caused many to fear the technology. However, the important thing to take away is that facial recognition technology is now advanced enough to be used on a security and a commercial level.

## Report Structure

There are 5 distinct sections used to explain this project. The first is a literature review, which is used to survey the field of research being targeting. This can be used to highlight areas which require more research, or perhaps to find the current state of the art techniques being used in the field. Ultimately, completing this process allows the project to place itself within its relevant area of research, by finding where it currently sits, and where it can push the boundaries of what is currently being done.

The second section is methodology. This refers to the general approaches and tools used to tackle the predefined problem. This section is split into 4 subsections. The first of which is Project Management, which consists of a Gantt Chart and Risk Matrix in order to plan the scale and timeline of the project, as well as mitigate as much risk as possible in relation to this. The second is Software Development, referring primarily to the framework that was used to produce the artefact, such as Waterfall or Agile. Third is toolsets; describing the tools, software, programming languages, libraries and datasets used in the development of the entire project, whether they be for producing the artefact, or for managing the project as a whole. The last subsection that forms Methodologies is Research Methods, which focuses on the way in which the projects aims and objectives would be evaluated.

The third section is Design, Development and Evaluation. This encompasses the development of the artefact, from start (such as requirement gathering and design) to finish (such as development and evaluation). This will include any methods or documents of particular interest, such as algorithms used, design documents, and a series of ways to evaluate the results of the project.

Following on from the evaluation of the project is the Findings and Conclusion section. This will analyse the results of the project, such as accuracy ratings, and attempt to provide a consensus on the entire project, such as the validity of the initial hypothesis, and how well the aims and objectives have been met. This section will also explore the ethics of the project, as well as exploring some further work that could be done.

Finally, a reflective analysis will be provided to give a retrospective on the project, such as what could have been done differently, as well as some insight into what went well for the project, and what held it back. This will be followed by the references and appendices.

# Literature Review

Targeted advertising has significantly improved the cost effectiveness of online advertisements, as discussed in (Farahat and Bailey, 2012), with adverts targeting users based on browsing history, demographics, user profile and more. This paper goes on to analyse the impact of targeted advertising, finding that targeted ads have the ability to generate 4.5 times more clicks, and discussing the cost of targeting to the advertiser. They also analyse the fact that targeted adverts are significantly more cost effective (a third) for niche companies, due to the ease of accessing their customer base. However, as this paper was released in 2012, the results may have changed dramatically, especially as a result of more awareness of online tracking and privacy, with people using tools such as AdBlock to remove advertisements, and VPNs to remain anonymous online.

When considering targeted advertising, it’s important to consider the methods that are used to achieve it. One of these is collaborative filtering, which is the algorithm that solves the problem of making personalised recommendations. Collaborative filtering is more of an umbrella term, and while the k nearest neighbour approach is the most common, the item-based approach is seeing increase levels of success (Sarwar et al., 2001), especially when used with larger data sets. This replaces the traditional approach of comparing customers, and instead compares the items themselves. Another study analysed the item-based collaborative filter being used at Amazon (Linden, 2003), again stating its ability to perform despite large datasets and short time frames, going as far to say, “Unlike other algorithms, item-to-item collaborative filtering is able to meet this challenge.” While this paper was written when Amazon was significantly smaller, there were still 29 million users, and millions of items to choose from, meaning the algorithm was able to solve a particularly complex problem.

However, there’s an entire field of research dedicated to choosing the right collaborative filtering algorithm, with one study providing the means to decide which to use (Ekstrand et al., 2010), arguing the case for both by stating that the user-based algorithm is better suited to a system in which there are more items than users, with the opposite being true for item-based. It also found that the user-based model reported an increased level of customer satisfaction. Due to a competition by Netflix, there has been an increased amount of modifications and improvements to these different techniques, each surveyed by (Koren and Bell, 2015), summarising the benefits of each, such as fusing the item-item and user-user approach, which saw an increase in accuracy to achieve a RMSE of 0.8966, improving on the base algorithms.

Another important area to explore is the challenges of collaborative filtering, with (Su and Khoshgoftaar, 2009) highlighting and finding solutions for the most common examples, such as data sparsity, scalability, synonymy and grey sheep. They then provide insights into how to tackle these issues by using the different variations of the algorithm, such as stating that “Clustering CF algorithms make recommendations within small clusters rather than the whole dataset and achieve better scalability.”

These advancements in online advertising have led to more research being conducted on how to advertise in a more highly connected world, with (Aksu et al., 2018) giving a smart car as an example of how this could be done, advancing targeted advertisements to a ubiquitous level that follows us wherever we go, due to the 'digital signature' that is created about us, and the fact that connected technology is all around us, such as wearable technology and smart screens in public areas. However, this brings up a myriad of privacy and security concerns, which is why (Alt et al., 2012) proposes the use of interactive public displays, which provide useful information such as maps or weather to entice a passer-by, and then show ads once they have started using the system. This doesn't personalise the ads straight away, although it provides the opportunity to do so in several ways, such as requiring the user to sign into an account (and using data from social media for example) or providing more time for a computer vision algorithm to come to an accurate conclusion on the profile of the user. This could even be verified by the user, as they are already most likely using the system, so can answer some simple questions to verify estimates. However, as with many pervasive technologies like this, transparency is key, as people will start to distrust public systems if they aren't sure what is being tracked and stored, and the ways in which that data is used.

Another approach to bringing new technology to advertising uses the camera not only draw attention, but then to enhance the advertising experience, such as placing the image of the product onto the targeted customer to show how it would look (Lyons et al, 1998). This approach has two appeals; the first is that it allows the user to 'try before you buy', without actually going through the effort of going to the changing rooms, or even having to find the product. Furthermore, this system could be expanded on to target adverts to their specific audience. For example, makeup companies may be interesting in showing their makeup applied to passers-by but may want to specifically target skin tones in which the product is aimed at. The second appeal is that this is a fun gimmick, which is likely to draw a lot of attention to the product. This may only be short term, but it provides the opportunity for people to become comfortable with the technology, which is an important part of tracking user habits, especially when it is making it as obvious as returning an edited image of the passer-by.

Contrary to this, one study considered the ways in which public displays could attract attention whilst remaining non-intrusive (Exeler et al, 2009), an important step to consider when looking at using vision systems to watch individuals. The system has a scanned face on a screen, which reacts to the emotions of a passer-by, and attempts to emulate them. This is successful, and encourages further interaction with the screen, especially when done by people with similar characteristics. The downside to this is that some were deterred from the system as a result of distrust, which again brings in privacy concerns to the conversation. These concerns are further explored in another study, with findings suggesting that giving users control over how their data is used can have a positive impact on the success of personalised adverts as a whole (Tucker, 2014), most likely a result of the transparency of the system, as users understandably want to be informed about how information about them will be used.

Following this trend, a system was developed to change advertisements based on demographic data (Tian et al, 2012), by using Anonymous Viewer Analytics and Data Mining to collect data, which showed an increase in accuracy over context-based targeting, specifically when using Decision trees. Furthermore, this was a paper released by Intel in 2012, showing that this field has been receiving commercial interest for a long time. The system developed in this paper could be expanded upon to provide further improvements in accuracy, using newer technologies such as recent advancements in Machine Learning, and provides useful information on the evaluation of such a system.

The remainder of this literature review will be focused on the different studies and systems attempting to improve the way we gather specific demographics from images of faces. The first example of this is (Huerta et al, 2014), which fused texture and local appearance-based descriptors to achieve fast and accurate results when estimating age, producing a Mean Average Error of 4.25 years, which is sufficient when trying to recommend products or advertisements to potential customers based on age, as it would usually be age groups targeted instead of specific ages anyway. Another benefit of this approach is that it is a robust technique, requiring no additional cues. An early implementation of automatic age estimation completed in 2007 used aging patterns as samples, instead of individual facial images, by first modelling the aging pattern, and consequently estimating the age of the face by finding its position in the pattern (Geng et al, 2007). This has become more of an industry standard, with a significant number of other implementations doing this too.

In another study, the age of participants is gauged by comparing between two people, and choosing who is older, as a way of training the model to make more accurate age estimations (Zhang et al, 2017). The results of this are used in a deep convolutional network to produce estimations of overall age. This more modern paper (2017) used these advanced techniques to achieve a MAE of 2.87 on the MORPH dataset, and 2.52 on MORPH2, which places it amongst the top performers, due to the benefits of deep convolutional networks. Finally, (Guo et al, 2009b) takes advantage of Biologically Inspired Features to train a Kernel Partial Least Squares regression model to estimate age, due to its ability to reduce feature dimensionality and learn the aging function simultaneously in a single learning framework, a factor that places this algorithm above traditional SVM algorithms in accuracy. Being an early study (2009), this was another trendsetter, with many future studies and implementations using Biologically Inspired Features to train more complex models, increasing overall accuracy.

When trying to recognise gender, (Ng et al, 2012) identified the primary challenges as a combination of human factors (such as age, ethnicity and accessories) and the image capture process, e.g. camera angle, lighting or image quality. This paper also helps classify gender classification problems into two groups; geometric based and appearance-based methods. Geometric based methods of feature extraction use the information about the distance between facial features, such as the distance between eyes, or the distance from the nose to the lips. This method was used in multiple papers, such as (Shakhnarovich et al, 2002), which was an early paper that explored geometric based methods based on the now popular Viola Jones algorithm (Viola and Jones, 2004). An interesting technique used in the paper was to combine estimates from many facial detections in order to reduce error rate as a result of noise.

Local Binary Pattern histograms, as presented by (Ojala et al, 2002) are used in (Lian and Lu, 2006) to generate a single vector which represents the face. This LBPH is found by dividing the face into small regions and taking both shape and texture information. Support Vector Machines are then used as the classification model, which outputs an average accuracy of 94%. Although this appears to be a high accuracy, incorrectly identifying gender by 6% could cause significant issues, due to people potentially being insulted by the insinuations. An alternate approach is taken by (Li et al, 2012), which uses both facial features (forehead, eyes, nose, mouth and chin) and external information such as hair and clothing, to classify the image into a given gender, in order to overcome the issues of occlusion (hair, glasses etc. covering the face). This model was slightly different to others, as it classified the images separately based on each type of feature, then combined them afterwards using various strategies, such as Fuzzy integral. As this was an early approach to something like this, being published in 2012, the accuracy of 95% is a significant point, as this wasn't able to use more recent advancements in Machine Learning. Similarly, (Kalam and Guttikonda, 2014) uses facial distance measures as a progenitor for gender classification, such as the distance between the midpoint of the right eye and the midpoint of left eye, and the distance between the lips and the nose. Classification is then applied using this data. The paper also explores the types of pre-processing used, such as converting the RGB image into a two-dimensional grey scale image instead. Another step was to perform noise reduction, with this paper weighing up the benefits of different filters, ultimately choosing the median filter due to its ability to preserve image quality. This paper returns the highest accuracy seen yet, at 95.6%.

Many studies have observed the benefits of gathering groups of demographics at the same time, due to the way they each impact each other, as explored by (Guo et al, 2009a), who states that gender recognition accuracies can be 10% higher on adult faces than young or old. This paper also used Biologically Inspired Features, showing that this method is in fact widespread, and can produce high accuracies on different data sets, and alongside different classifiers. As a result of this paper, the following studies gather more than one demographic feature, to improve accuracy as a whole. One way to improve this accuracy is done by using Biologically Inspired Features (Han et al, 2014), which is explored further in (Guo et al, 2009b), by extracting these features to aid the hierarchical approach consisting of between-group classification, and within-group regression, to estimate age, race and gender. An interesting part of this study is that it compares results against human observers and finds that the system is more accurate. Another method of demographic classification for age, race and gender is explored by (Yang and Ai, 2007), who extract Local Binary Pattern Histogram features for texture description, in order to generate a more accurate classifier. This implementation also used AdaBoost, providing a more unique take on the problem.

Sometimes data sets aren’t perfect, which is why (Moghaddam and Yang, 2000) explored gender classification on thumbnail images (21 x 12 pixels), using SVM’s, and tested the performance against other classification algorithms, and human participants, to show its superior accuracy. This paper actually produces incredibly high accuracies, with the SVM model outputting an error rate of 3.4% using low resolution images, whilst humans produce an error rate of 6.7% on high resolution images.

# Methodology

## Project Management

### Gantt chart

The aim and objectives have been broken down into a series of tasks, that make it significantly easier to plan a project with the use of a Gantt chart. This provides more milestones to aim towards and keeps the project on track, which is very important given its magnitude. If it turns out it’s not on track, actions can be taken to ensure the project as a whole won’t suffer, such as reducing the scale of some of the tasks. These are the tasks I have laid out:

1. Identify faces in an image

2. Get features of the face

3. Get other features, such as hair

4. Recommend an appropriate advertisement

5. Evaluate performance

6. Infer context of the group

7. Improve recommendations

8. Compare task 4 and 7

9. Implement system in a real time environment

10. Retrieve time and location data

Task 1, 2 and 3 were all about using the Microsoft Cognitive Services API to acquire the demographic information about passers-by. These tasks were the most likely to be finished relatively quickly, due to their reliance on third party libraries, which were deeply intertwined with this part of the project. Therefore, they were only given a week each.

Task 4 was about using the information gained from the previous tasks and utilising it in a way that would produce an advertisement fitting for that individual. This task was given a week, as the research showed that it would be a generic algorithm, which wouldn’t need to be altered much for the purposes of this project.

Task 5 was planned to take two weeks, due to the amount of testing needing to be done, as well as the important placed on its correct completion. This task would include testing that the system worked as intended as well as evaluating the accuracy level of the algorithms for tasks 1 to 3.

Task 6 was predicted to be a difficult task, taking 2 weeks to complete, as a result of the more unique approach that it would be taking towards the problem, with little research on the subject to base its development on.

Building on this, task 7 would use the algorithm from task 4 and update it with the information from task 6 to create more in-depth insights, such as recommending different restaurants based on the context of a group, for example choosing a romantic spot for a couple, and a more informal location for a family. The idea behind this is that companies advertising based on the context of the group gives them the ability to make more impactful insights.

Task 8, therefore, would compare this new system to the one from task 4, to see how its recommendations compare, and hopefully identifying the list of improvements made. As this would be more like a list of new recommendations, and not a numerical improvement on the accuracy of the old recommendations, this would only be comparable qualitatively.

Task 9 is to implement the system in an actual physical, functioning way, that would see results to the algorithm in real time. This wouldn’t change much of the system but would instead highlight its features in a more practical way.

Finally, task 10 requires the system to retrieve the locational and temporal data of the site it is based and use this in the advertising process. While the gathering of this data wouldn’t be difficult, it’s implementation into the advertising system would be, with applications including advertising local businesses, not advertising for stores that aren’t nearby or advertising for the breakfast menu of a café before noon. As tasks 9 and 10 are very time consuming, and not necessary to the completion of the project (i.e. meeting its aim), they are considered extension tasks, that should only be prioritised once the rest of the project is complete.

Plotting these tasks provided the Gantt chart shown in Figure 1, predicting the amount of time the project would take to complete. However, the project did change slightly throughout development due to unforeseen circumstances. Therefore, the Gantt chart in Figure 2 shows the actual development time for the project.

The reason for the discrepancy at the start is that it took significantly longer to set up the API and receive a key. However, once this was done, the first three tasks were relatively simple and didn’t take too long, as there is a large amount of documentation available for Azure API services. Task 4, which was to create a system which recommended the advertisement based on the information it received, took an extra week, and in hindsight only timetabling one week may have been an oversight, as this was a large part of the project which required a larger time frame to get right.

Evaluating the performance of the artefact so far by using accuracy metrics took a week less than expected, in part due to how easily the Cognitive API integrated with the labels of the dataset.

Task 6 was to infer the context of a group relationship, such as friends, family or unrelated. This task took a significantly larger time than planned, due to the increased level of complexity, such as the difficulty in figuring out whether people are in a group, or just separate people walking close together. However, instead of simplifying this to keep the project on track, it was seen as more important to potentially not complete the extension tasks, and complete this to a high level, as it was potentially the most important part of the project.

After this, task 7 wasn’t particularly challenging, and took as long as planned, as this had already partially been done in task 4 and was just being updated to take in new information.

The final task completed was task 8, which was to compare the old system to the new in terms of accuracy and the level of depth. Again, this took as long as planned, as the framework for evaluating the system was already prepared, so there were no surprises.

Tasks 9 and 10 were considered extension tasks, and therefore while they weren’t completed, this isn’t seen as a failure in any way, as effort was taken to ensure the prior tasks were completed to a high standard.

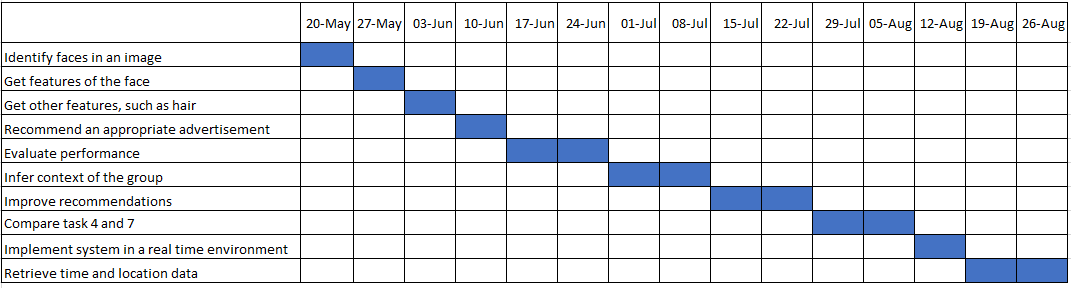
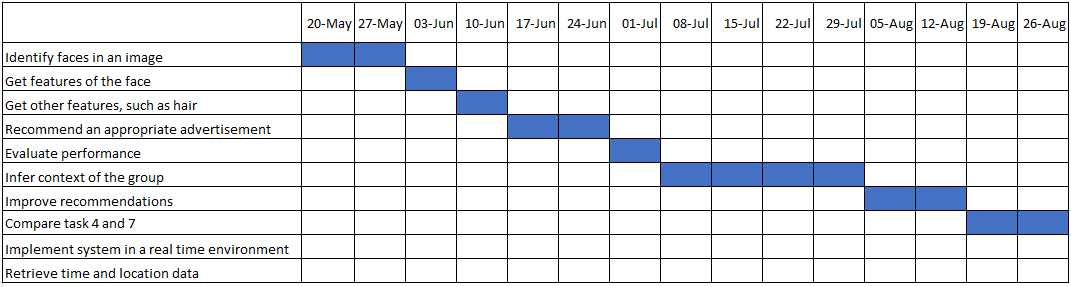


Figure 2: Actual Gantt Chart

Figure 1: Predicted Gantt Chart

### Risk Matrix

|  |  |  |  |
| --- | --- | --- | --- |
| Risk | Likelihood | Impact | Mitigation |
| Microsoft facial recognition API is taken down. | Low | High | Research potential replacements for the chosen Microsoft option, such as the Google Vision API, or the Amazon Rekognition API. |
| Estimations of characteristics in public spaces are low in accuracy. | Medium | Low | Use another API or implement a different solution to the problem based on current research. Alternatively, change the scope of the project to only internal environments, such as airports, to reduce variables such as weather obscuring image quality. |
| No suitable dataset exists for faces in the wild (e.g. data is unlabelled, or from wrong angles). | High | Medium | Try to find a dataset which includes the correct type of images, then self-label data to ensure it can still be evaluated for accuracy. |
| Groups are too difficult to distinguish from random clusters of people. | Medium | Medium | Asses the context of every group, based on the assumption that they are together, and not just happening to walk side by side. |
| Legislation prevents the identification of certain characteristics using computer vision. | Low | Medium | Ensure that the system isn’t reliant on any single feature, such as age, but a combination, in case one is considered too private. Don’t use any ethically questionable data, such as weight or race. Don’t store or use data in any way other than for the purpose of this project. |
| The system can’t process all the incoming information in time to display results to the passer-by. | Low | High | Reduce the scale of the project, to ensure that everything can be calculated and displayed with enough time for the user to see it. Also, improve hardware, such as getting a better cloud system. |
| Advertisers misuse the system in an unethical way, such as targeting children for fast food. | Low | Medium | Write a list of guidelines to be followed, mirroring those created for online advertising (e.g. no drugs) to restrict usage and protect children. Also, not allowing too many things to be identified, such as weight or mood. |

Fortunately, many of these risks didn’t occur during the process of this project. The API remained live, and was sufficient for its purpose, allowing enough calls per minute for the artefact to function exactly as intended. Had it gone down, the alternatives wouldn’t have changed the project in any impactful way but would’ve likely caused many delays as the different formatting was being worked into the project.

The accuracy in public spaces proved to be better than expected, most likely due to the use of industry best practice as part of the API, as will be explored in the evaluation of the results. However, accuracy was lower than it would’ve been had the scope of the project been reduced to indoor environments.

Unfortunately, finding a suitable dataset for this project was a challenge, due to the need for it to contain candid photos from public spaces, or an angle that emulated a camera in a public space, and needing to be labelled, including data from gender and age to makeup and hair. This large set of requirements meant that certain aspects had to be prioritised, which in this case was the angle and candid nature of the photos, with the labels being placed at the bottom of the list. This meant that the mitigation was followed, resulting in a self-labelled dataset. Although this brought new issues into the project regarding the accuracy of the labels, it fixed a significantly larger issue, which would’ve been the inability to quantitively evaluate the accuracy of the solution.

The fourth risk wasn’t completed due to time restraints, however once again the mitigation was used. The reason the mitigation was to go through with the naïve assumption of everyone being together was to show how the system would work, instead of completely ignoring this section. In a real implementation of this system, not knowing whether people were part of a group, especially in busy areas like shopping centres, would cause a large amount of recommendations to be wrong. Therefore, it’s usage here should only be seen as illustrative.

No new legislation came into place during the process of completing this project, and it kept well within current legislation regarding privacy and data usage. However, even if it had, no data was stored or reused in any way that would’ve been targeted by these types of changes.

As the system wasn’t developed in real time, it’s tough to say whether or not the system has enough time to react to an individual passer-by, however the execution time results explored in the evaluation should give backing to the idea that it would give more than enough time for a passer-by to acknowledge the advertisement, as the average amount of time to acquire the advertisement was 0.62 seconds.

The last risk is hard to evaluate, however the system not allowing any ethically ambiguous factors such as race, weight or mood to be captured and used will undoubtedly avoid a large amount of companies misusing this system. Unfortunately, only so much can be mitigated before the risk appears, as companies could use the data available to still do things that aren’t considered ethical, such as recommending unhealthy fast food to children that don’t know better.

## Software Development

For the purposes of this project, the Scrum methodology was used, for a variety of reasons that will be explored. Several different methodologies were considered, such as Waterfall, Spiral or Extreme Programming (XP), to ensure there was a large amount of variety to weigh up.

Scrum is an agile methodology, which is based on frequent ‘Sprints’, which are small chunks of time between 2 weeks and a month that are made up of an entire development cycle, such as requirements analysis, development and testing. These sprints will start and end with client interaction, to ensure the work completed in that sprint is as the client expected. The work done within the sprint will usually be a self-contained piece/unit of work, so that the client can see it working.

In general, Agile development aims to be more responsive and client oriented (Beck et al., 2001), guidelines which Extreme Programming also abides by, making it very similar to Scrum. Extreme Programming is generally seen as an even more fast paced, responsive version of Scrum, as a result of shorter sprints, and the ability to change the plan for the sprints midway through. Besides this, XP’s only other noticeable difference is that XP teams work in priority order for all tasks, as opposed to Scrum which allows the team to work through the backlog in their own order.

Waterfall is an older methodology, that tends to be better suited to more rigid projects that have little client interaction, such as military or healthcare projects. This is because where Agile focuses on speed, Waterfall focuses on quality, preferring to go over deadlines in order to complete the project as it was first intended. This had the added benefit of being more predictable, with the developer being able to give the client a deadline in order to make them feel more comfortable about the contract, which an agile methodology wouldn’t be able to achieve.

Finally, the Spiral methodology stands between Waterfall and Agile methodologies. Spiral can be seen as a series of Waterfalls, with each lasting a large amount of time (usually 6 months to 2 years). This ends with a product that could just be a prototype or could be working software. Although this structure is similar to agile methodologies, agile always aims to end the iteration with something that will add towards the project, and iterations tend to be significantly shorter (generally around a month). This means that it solves some of the problems of both, however also falls short of the collective issues with both as well.

The decision to choose Scrum was made based on three equally important factors: the ability to break the artefact down, the flexibility of the project requirements and the choice between speed and quality/security of the project. In most scenarios, the developer should also consider the skills, preferences and location (on site or dispersed) of the team, however as there is only one developer in this project, this does not need considering.

When it comes to being able to break down a project into tasks, the important consideration to make is whether different milestones in the project can function (and potentially be evaluated) alone. For example, this project has been broken down into several bitesize chunks, such as using the Microsoft Facial Recognition API to return characteristics of a passer-by, creating an advertisement recommendation algorithm, and inferring the context of a group. Each of these tasks can also be seen as its own self-sufficient unit, showing that this project can be broken down into tasks. However, some projects, such as a video encoding algorithm, can’t be effectively tested until the entire artefact is complete. That kind of project would lend itself well to linear methodologies, such as Waterfall or Spiral, where the project doesn’t need to be seen as anything other than one large task, and seeing that task as one single part to be designed, developed and evaluated as a whole is of a great importance, whereas this project fits the agile methodologies such as Scrum and XP (Beck et al., 2001), as these tend to split large tasks into smaller chunks, which can be completed in a single iteration or sprint (a predefined length of time, usually between a week and a month).

Whether a project has flexible requirements has a large impact on the approach taken to complete that project. However, every project has some level of flexibility, whether that’s due to temperamental clients, uncertainty in planning or a reliance on third party tools. Therefore, it is sometimes worth accepting that there is a small amount of flexibility, and still choosing a more rigid methodology, but instead trying to mitigate that flexibility, for example trying to lock in an initial set of requirements from a client that can’t be altered, so that the project can be better planned. With that in mind, it is difficult to know where to place this project, as it has a relatively fixed set of requirements due to an uninvolved client (who in this case is seen as the supervisor of the project), and a well-planned timescale, although it does rely largely on a third-party application. Overall, while the third party requirement is only one small part of the project, the repercussions of its incompatibility in any way could be quite large, and would require a rapid intervention and change in direction, which points towards an Agile methodology. Essentially, if the Waterfall or Spiral methodologies were chosen, commitments would have to be made at an early stage (Sommerville, 2011, 32), which isn’t a viable decision in a project such as this, which is relatively reliant on several moving parts.

Finally, a project must choose whether to focus more heavily on speed or quality/security. Quality and security are placed together as both relate to the same idea of meeting the requirements of a project to the highest possible standard, perhaps going past deadlines in the process. While it would be ideal to have both speed and quality/security, it is in the nature of large projects to have to choose one over the other at some point in the lifecycle. This project is a perfect example of a project that has to focus speed over quality, due to the fact that the deadline is non-negotiable, and therefore won’t allow for any extensions if improving the quality or security of the artefact is prioritised over reaching the deadline. Projects that rely on speed such as this lend themselves well to Agile methodologies, as Agile was largely developed to overcome the issue of projects surpassing deadlines on a regular basis before its inception in the early 2000s (TechBeacon, 2017). Therefore, this project can once again be considered better suited to an Agile methodology than traditional in this way.

Although all these factors point towards choosing an Agile methodology, that decision is no easy task either, with the number of alternatives growing ever larger. However, here the choices will be limited to XP or Scrum, as these are reflective of most Agile methodologies, and could be interchanged with most. They are also two of the most common choices. Scrum was chosen because of two reasons; however, these are minor, and XP could’ve also been chosen with little change to the project. The first reason is that Scrum allows for slightly longer Sprints, whereas XP tend to keep them under two weeks. Having Sprints take over two weeks worked well to match the frequency of interactions with the client. The second reason is that Scrum allows the choice of what to work on in what order, whereas XP has a stricter priority order. A more lenient policy worked better for this project, due to the lack of experience in being able to plan priority in advance.

Overall, Scrum worked very well for this specific project, and allowed for significant changes to plans when it started to deviate, ensuring no time was wasted in the way that it would be under a more linear methodology such as Waterfall. There’s no doubt that choosing Spiral or Waterfall would’ve led to an incomplete project, due to frequent changes and a more rapid solution to early parts of the project.

## Toolsets and Machine Environments

When it came to the process of developing the artefact, choosing a language was an important, difficult decision. As a primarily Computer Vision project, the choices came down to MATLAB, which is an industry standard in Computer Vision due to it being centred around matrices, which is the simplest representation of an image in computing, Python, which has the largest community in terms of creating up to date libraries that assist with a lot of the work, and C++, which also has a strong following, and allows more low level work to be done in order to develop a more efficient end product.

While C++ has access to libraries such as OpenCV, Python has access to that and more. Python has become the scientific programmers’ tool, in part due to its ease of use, but more importantly because the hardest part of most jobs, the Machine Learning algorithms, or rendering and outputting an image, are available as completed packages. Therefore, Python was chosen as the language for developing this artefact.

In the project, the Microsoft Facial Recognition API was used through a library called Cognitive Services, the Rest API call was made using a library called Requests, and the JSON data returned was made easier to interact with using the JSON library. During debugging, to check that faces had been found, circles were drawn around faces and outputted in an image using the PIL set of libraries. It is because of the work done by these libraries that this project could have such a large scope within such a short time scale, showing how impactful the dedicated community of Python developers can be.

To help manage the development of this artefact, a set of tools were used to improve the time efficiency of the project. One such tool was Trello, which feeds into the discussion of choosing Scrum for this project. Trello is a tool which allows the user to create a to-do list, and move items to a ‘doing’ list, and a ‘completed’ list. This is especially helpful when working as a team, however it still provides benefiting to those working in a solo project, as it helps keep track of the progress made so far and can be used to emulate the backlog in Scrum. Furthermore, it’s a more reliable way to create a list of tasks than using a paper-based system.

GitHub is a version control tool, which allows the user to store and update an entire project, with potentially multiple branches to allow for testing different ideas and approaches. Once again, most of the benefits of the tool are from working as a team, however a massive benefit to a solo project is the ability to go back to a previous version of a project if a change is made which breaks it in some way. This saves a lot of time and prevents the loss of work. While no work had to be recovered during this project, it was still a good idea to use it just in case.

In terms of the machine environment, the artefact was completed on a Windows 7 machine with Python 3.7. However, one of the benefits of Python is the ease of making it cross platform, as only minor changes are needed, such as changing the direction of slashes in file directories.

In practice, this machine would most likely be implemented on a cloud-based system, receiving a stream of images from the site, and sending back an advertisement to display. This reduces the computational demand on site and improves the ability to change the entire system across different sites, all at once. Another benefit of running this on cloud would be that it is easy to expand as more sites are added, making it both scalable and versatile to changes. The cloud system would be easy to install, as it could be housed on a Linux distribution, as long as the required Python version and libraries are installed, which would only need doing during the initial development.

Certain considerations would need to be made to account for the display/camera systems being outdoors, however there have been large improvements in outdoor electronics, with most displays now being made using weather proof, durable glass. The system doesn’t acquire height, and shouldn’t need to operate at night, so the only requirement for the camera is a high enough resolution for the images to be clear.

## Dataset

For this project, a dataset (Wong et al., 2011) was used that contained various images of individuals passing under the camera, aiming to look as if they were unaware of its placement. This dataset enabled the project to quantitively evaluate the accuracy of the systems ability to recognise characteristics of a passer-by, as it was taken at a realistic angle, with faces that weren’t posing for an image. The only flaw with this dataset was that it wasn’t labelled. This meant that the data had to be self-labelled, which causes some doubt as to the accuracy of this project. However, the labelling was done very carefully, and most factors are easy for a human to identify, such as glasses and gender.

After this section of evaluation was completed, the rest was done using a mix of qualitative and quantitative methods, by using use cases that are followed to analyse the effectiveness of the advertisement recommendations. Following the set of instructions to see if the system reaches the correct end point is technically quantitative analysis, however the in-depth analysis of the results afterwards resembles a more qualitative approach.

## Research methods

To evaluate how effectively the artefact answers the research question, multiple steps must be taken. This is because the research question is quite broad, and covers a lot of areas, which must be covered separately. For example, the first section of the research question is “Identifying characteristics of passers-by”, which can be answered by evaluating the accuracy of the outputs of the first stage of the artefact when compared with the labels of the dataset. While this is an effective way to qualitatively test performance, the dataset unfortunately wasn’t labelled, making it difficult to compare to the results of the artefact, requiring the labels to be manually entered first.

While this solved the problem, and allowed the accuracy levels to be collected, this brought the issue of human error, as some of the factors being collected, such as age and makeup, were hard to guess. Although this does bring some doubt into the reliability of these results, the fact that these factors still had high levels of accuracy shows that the labels were likely correct, or at the very least that the artefact was producing human levels of characteristic identification.

The next part of the research question is focused on the advertisements that get recommended to the passers-by. This is significantly harder to evaluate, as the success or failure of this algorithm could be seen as subjective, since there is no one correct output for the algorithm. Therefore, a more lenient test will be devised, in which the algorithm passes or fails for each recommendation, with a fail only being awarded if the advert doesn’t apply to the passer-by. This will then be compared to figures regarding the effectiveness of static advertisements, to figure out the level of improvement.

# Design, Development and Evaluation

## Requirements

This project has six requirements, which are the set of conditions that must be completed in order for the project to be considered fully successful. Although there is a lot of crossover, they differ from the tasks laid out earlier, as some requirements may describe a way of doing something, or a certain aspect which should be avoided, as opposed to tasks which are a set of things which must be done. In a way, these requirements should be seen as the guidelines to follow when producing this project. They are as follows:

1. To perceive the basic characteristics of passers-by, most notably age and gender
2. To be able to operate in a public space
3. To advertise to individuals and groups in a way that mirrors online advertising
4. To infer the context of a group
5. To complete the process of recommending an advertisement with enough time for the passer-by to acknowledge it
6. To comply with data privacy laws

## Design

When it comes to design, this system doesn’t have many user requirements, due to its role as a research tool, not as a commercial product, or a tool that would be used by an end consumer where marketability or ease of use would be issues. Here, the system must meet the aim, which is to identify the features of passers-by, and recommend an advertisement for them. Therefore, features such as a GUI, or alternate forms of inputs, don’t need to be implemented, and so all-important information will be outputted using a console-based system. This leaves designing the system architecture, which refers to the fundamental structures of a software system. Planning the architecture of a system reduces the chance that issues will arise, due to the ability to take a more careful, considered approach to the problem.

Zoomed out, the architecture of the system mirrors that of a client-server architecture. Each site would represent a client, capturing the input images of passers-by, and providing the output of the recommended advertisement. However, the algorithms transforming the inputs into the outputs would be performed on the server, to create a centralised system that enables the local sites to require no particularly powerful machines, only needing embedded processors that can send and receive information. In order to do this effectively, cloud computing would be used, due to its ability to scale up and down with the needs of the system, and the fact that it allows for complex processing to be done off site, lending itself well to the client-server architecture.

In terms of the code, the basic design uses object-oriented principles, such as classes and objects, to ensure the code is legible and easy to work on. Only one developer was working on this project, however it was over a long period of time, so it was important that any code written two months ago could still be understood and changed when needed. This was done by creating an object for each face in the current image, and an object for each advertising unit. This made reading in and comparing between the two significantly easier than it would have been using the imperative paradigm, as each advertisement object and face object has the same set of member variables, which can be called against each other in one loop, instead of trying to compare them one by one.

## Development

When beginning the development of the artefact, the first step was to get a rough idea of the sections that would need to be developed. While these overlap with the list of tasks created earlier, they aren’t identical, as these are specifically the steps that needs to be taken in development, that will roughly be transferred into functions in the final artefact. These steps are as follows:

Step 1: Access the Microsoft Cognitive Services API, and use it to return a set of JSON regarding the image sent as a parameter

Step 2: Parse through the JSON, separating the values returned into usable data (which can be compared with labels)

Step 3: Record the gathered information as a user profile

Step 4: Compare the user profile against pre-created advertiser profiles

Step 5: Of all potential adverts, pick one to show the user, and display it

Step 6: Estimate the relationship of the group

Step 7: Incorporate this into the advertisement recommendation

The first step was largely taken up by signing up to use Microsoft’s Cognitive Services API and reading through the documentation to learn how exactly it worked. As Microsoft is a large company, and as such has many different organisations and individuals using their set of APIs, there is an extensive library of documentation and solutions surrounding them. Therefore, this step didn’t take a particularly large time, and most of the code was quite generic. However, work was done at this stage to ensure that best coding practices were upheld during the process of development. For example, setting the foundation for the functions used, and keeping a consistent naming convention with variables, so that the code would be legible and reusable in the future.

By the end of this step, a paragraph of JSON such as the one below in Figure 3 would be outputted, which would need to be parsed in the next stage.

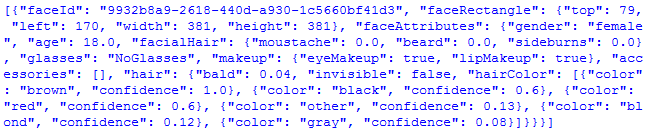


Figure 3: JSON outputted by Microsoft API

The second step was assisted largely by the ‘Json’ library in Python, which did a lot of the work itself. For example, the following screenshot in Figure 4 shows how the gender would be accessed, which is simply done by finding the correct element in the dictionary.



Figure 4: Line of code showing how each data point from JSON is accessed

Using other languages, the JSON would’ve needed to be sifted through, taking up more time, and resulting in less legible code. This solution is perfect for the requirements, and simply outputs “Male” or “Female”, exactly as it is labelled in the dataset.

By the end of this step, the data was ready to be converted into a user profile, which would store the age and gender, as well as detecting the presence of facial hair, baldness, glasses, eye and lip makeup and hats. Age would be stored as either ‘Child’, ‘Adult’ or ‘Elderly’, and the other parameters were all Booleans. Therefore, the third step only consisted of converting the fields such as hair and facial hair from numerical data (between 0 and 1) to Boolean data, which was accomplished by finding a cut off point, and stating that anything below it was false, and anything above it was true. This is shown below in Figure 5:

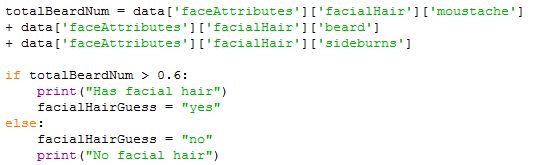


Figure 5: How the value of beard is converted into a binary value

Having the data stored in this way fed into step four, as the data could be compared quite easily once it was in the same format. Figure 6 below shows the format of the user profiles being targeted by an advertising unit, which shows several features. The first line is the name of the advertising unit. Next is each of the characteristics, in the order of age, gender, facial hair, glasses, baldness, eye makeup, lip makeup and hats. If the field is given a response (such as the age range or gender), this means the advertiser wants to target based on that factor. If the field is left null, it means the advertiser isn’t interested in that field, and would like to advertise to them either way. As an example, using Figure 6, Gillette will only advertise to an adult male who is seen to have facial hair. It isn’t concerned with anything else, so will advertise to passers-by regardless of whether they have glasses on, for example. Once an advertising unit is seen as a match to a passer-by, it is added to a list of potential advertisements, so that one can be chosen to display.

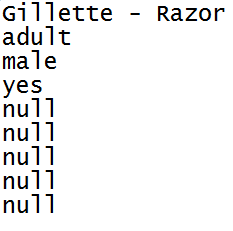


Figure 6: The text file of an advertiser unit

To choose an advertisement to add to the list of potential recommendations, the diagram in Figure 7 shows the logic of the system, and how each option is chosen in the case of the mock-up advertisers. In the live system, this would be more complex, with many more options, and potentially multiple choices at the end of each tree. However, for the purposes of illustrating this system, the green circles represent an advertiser, and black represents a characteristic. If the diagram can be followed to an advertiser, it is added as a viable option.

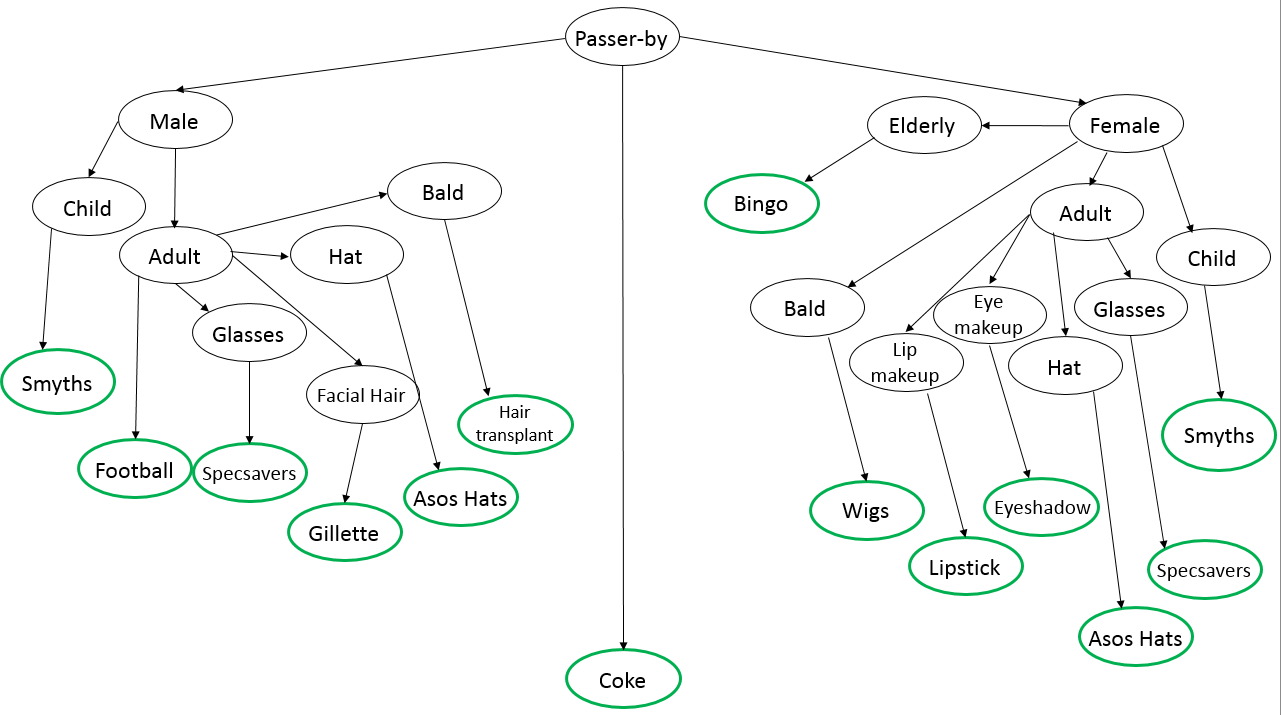


Figure 7: The diagram used to develop the logic for the system, and to test it

The fifth step in developing this part of the system was to take this list of potential advertisers and choose one to display to the user. This was done by simply choosing one at random, to ensure that over time, a fair distribution of advertisers is achieved, however is an area where further work could be explored.

After this was done, step 6 was to estimate the relationship of a group, such as family, friends or a couple. As this was developed during a limited timeframe, this was done in a way that emulated the statistically most likely ways people fitted into these groups, instead of covering every base, meaning this model was not perfect. For example, it would be hard to separate a same sex couple from two friends without incorporating proximity, which is out of the scale of this project, meaning instead this project had to assume these two people were friends. This is an obvious ethical issue and would be a top priority to fix if the system were to be launched.

The system determines what kind of relationship the passers-by are in by comparing their age and gender. This allows the system to put them into a logical group, for example two people in the same age group, and of opposite genders are most likely a couple. Or, two or more people with at least one of them being a different age group to the rest are most likely a family. The way these two groups are advertised to wouldn’t change significantly based on age, however friends are more likely to be. For example, a young couple and an elderly couple are probably going to be advertised romantic films, or gifts for a partner that don’t change significantly with age. However, a group of friends who are children will want to be recommended completely different things to a group of elderly friends, and therefore the friendship group has been split into the three age groups; children, adults and elderly. Therefore, friends are defined as a group of two or more, who are the same gender, and split between young friends, adult friends, and elderly friends, making five groups that can be distinguished from each other.

After this, the final step was to use this information in creating even more advanced recommendations than before. This was done by keeping the system as it was and adding the group inferences to the pool of potential ads that could be chosen, as explained in step four. This meant that these advertisements were incorporated into the same system and had the same chance as any other to appear.

However, this did require the advertising units to be changed. Originally, they were as seen in Figure 6, however an extra line was added to the bottom that corresponded with the type of relationship being targeted, such as elderly friends, couple of family. If this was left null, the advertisement would be left as it was in step five, but if it wasn’t, and other fields were also chosen (such as facial hair), the advert will only be chosen if the group is correct, and at least one person in the frame has facial hair.

## Evaluation

The first part of the project to evaluate is the predicted characteristics of the passers-by. This is done first to ensure that this part of the project doesn’t fail, or it would have large, damaging consequences to the accuracy of the entire project. For example, if a passer-by is thought to have glasses when they don’t, Specsavers would be an incorrect recommendation to make, even though the recommendation system itself may be functioning correctly.

To test this part of the system, the outputted characteristics of the passer-by will be compared with the labelled data, and a percentage of accuracy will be given. As this is a purely quantitative test, an analysis of the figures will be given afterwards, to explain any issues that have been brought up.

The accuracy for the age is measured by checking whether the predicted age is within 10 years of the actual figure. This is quite lenient, however the actual system only checks whether the passer-by is a child, adult or elderly person, and so therefore this provides a good measure of how accurate it can be, by forcing it to pass an even more difficult test than it needs to. The overall accuracy figure for age is 85%, which is a strong figure, especially since outliers are usually only around 2 years off the boundary. Furthermore, some of the images in this dataset are actors and actresses, known for looking younger than the average person their age, and so therefore this is a difficult, and perhaps unrepresentative test for the system.

Gender performs perfectly, achieving a 100% success rate. This is somewhat to be expected, as gender is the easiest of the characteristics to identify most of the time, with only a few rare exceptions. This is because there is a very easy to identify difference in facial features, which the machine learning algorithm can sort effectively.

More surprisingly, facial hair has a success rate of 98%. This figure was expected to be closer to the accuracy of the age, due to the amount of variability in length, colour and shape, and the fact that this system was artificially selecting a number which defined whether or not there was in fact a beard, whereas the Facial Recognition API was returning a value between 0 and 1 for chin, sideburns and moustache. Turning this into a binary value is not what was initially intended for the system, so the fact that this didn’t have a larger impact on overall accuracy is a massive success.

Like gender, glasses performed as expected, with 99% accuracy, and only a single mistake found. This was expected to perform well, again due to the consistency of images with glasses. Machine Learning algorithms perform better when a problem is consistent, as all they are really doing is comparing images (and their labels), so since glasses are always in the exact same place, and follow very similar patterns, it would be hard to misidentify them. The image which wasn’t correctly identified contained glasses with a very small, hard to spot frame, and had the face in a shadow, making it understandable for the system to not pick this up.

The accuracy of the system predicting the presence of hair was 96%, however this could’ve been higher. This is because two of the three errors were a result of men wearing hats. This understandably causes confusion, and should probably have been considered beforehand, as it is a problem which needs a workaround to be created, such as always saying that a passer-by wearing a hat has hair, since this is statistically more likely.

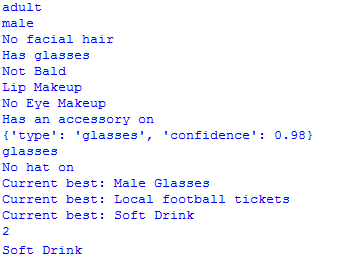
Lip makeup scored a surprisingly high accuracy of 89%, which like age, was expected to be significantly lower. In this case, this is because the natural colour of lips changes on a person to person basis, and therefore it can be hard to say whether they are wearing makeup at all. The same logic applies to eye makeup, which was expected to be similar to lip makeup, but actually dropped to 82%, the lowest of all measured characteristics. This is likely due to the variability of this characteristic, since eye makeup can consist of mascara, eye liner or eye shadow, and these can be in different shades and styles, that look different depending on the who it’s on, especially considering age and skin colour.

Finally, detecting the presence of a hat has an accuracy of 99%. Again, this was as predicted, since hats are usually very easy to distinguish from a face, even from a large distance. In fact, it’s surprising that this isn’t the highest accuracy, however the one instance of the hat being incorrectly located is from an image which recognised the hat as hair. This is likely the result of the image being taken from a strange angle and would be unlikely to appear again.

Overall, the accuracy of the system so far is more than satisfactory, with only a few underperformers. Age underperformed due to reasons that shouldn’t appear in the live system, however makeup could be a point of concern, specifically eye makeup. While 82% would be unlikely to deter advertisers from using a system such as this, moves could be made to increase the effectiveness of the system, such as merging lip and eye makeup to advertise all makeup based on the prevalence of either one of them, based on the assumption that most women that wear one will inevitably wear both.

The next step to take is to measure the effectiveness of the advertisement recommendations. The success of this system is a lot more difficult to measure; is one advertisement better to show than another? What if the passer-by was misidentified? How could the results of the system be shown on a scale of success, or should they at all?

With all these options considered, the choice was made to have a pass or fail system, analysing a set of test cases to ensure that the system was working correctly. It didn’t make sense to have a scale of success, as deciding if one correct advertisement was better than another would be a completely arbitrary task, as their levels of success are subjective. For example, if the system picks up a woman with makeup and glasses, why would a glasses company be a better fit than a makeup company? Either choice would be a suitable fit, and so the system will be evaluated as such.

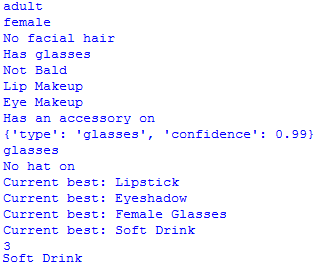
A mix of five faces from the dataset have been chosen to be analysed as part of the system. The images will be provided in Appendix 1. They are people of different ages, genders and features, to see if the system picks up on different things. As the system first finds a list of suitable ads, and then outputs the single one it selects at random from that list, all the ‘suitable’ advertisements will be listed, to identify if anything is incorrectly chosen.

Firstly, Image 1 is identified as an adult male, with no facial hair, eye makeup or hat, but is considered to have glasses, hair and (incorrectly) lip makeup, as shown in the complete console output in Figure 8. The characteristics are now checked against the premade list of advertiser profiles, and the following adverts are collected (shown as current best): Glasses (male), local football tickets and soft drinks.

Figure 8: The systems output regarding image 1

The first thing to do here is to make sure none of the recommended ads are incorrect, by identifying what caused them to be selected. Glasses were identified as a result of his wearing glasses, local football tickets because he is an adult male and a soft drink as this is deemed a universal product, which would want to advertise to everyone, and should appear in each entry. Each of these adverts is justifiable, and therefore has not created any false positives. However, the system could also miss out an advertiser, and therefore the diagram shown earlier in figure 7 should be followed to try and identify more advertisers. In this case, it does not.

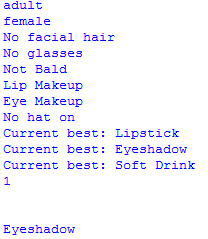
Overall, the system randomly chose to advertise the soft drink.

The second image is identified as an adult female with hair, no facial hair or hat and wearing glasses, lip makeup and eye makeup. When compared against the advertiser profiles, the following are outputted: Lipstick, Eyeshadow, glasses (female) and soft drinks. The complete output is shown below, in Figure 9.

Each of these adverts is based on a correct assumption, such as lipstick, eye shadow and glasses being based on their identification in the image, and the soft drink being an option for everyone.

After searching through the diagram, no advertiser has been missed, so the system has correctly identified every potential option, and has passed again. As can be seen in Figure 9, the system once again randomly chose the soft drink to advertise to the passer-by.

Figure 9: The systems output regarding image 2



The third image provided a similar set of characteristics as the second image, but without the glasses. This provided the console output shown in Figure 10. Predictably, this meant that it selected the exact same advertisements as Image 2, except for the glasses, which are not identified in Image 3. This means that this is also a correct output of potential advertisers.

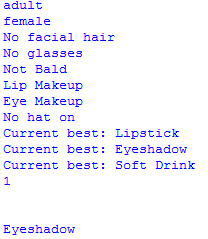
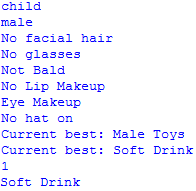
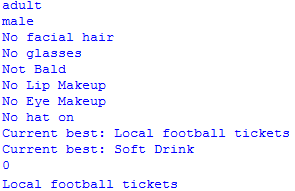
Similarly, searching through the diagram proves that no advert is missing, meaning that this image is also a success. The advert chosen to be displayed was for eyeshadow.

Figure 10: The systems output regarding image 3

For the fourth image, a male child was identified, with no facial hair, balding, glasses, lip makeup or hat, however eye makeup was mistakenly identified. This set of characteristics led to two adverts being correctly recommended, Toys (male) and soft drinks. This output is shown in Figure 11.

To ensure that no advertisement is missed, the diagram can again be followed, which shows that these are indeed the two correct outputs for the system. Overall, the system chose to advertise soft drinks out of the two.

Figure 11: The systems output regarding image 4

For the final image, a male adult with no facial hair, balding, glasses, makeup or hat was identified., as seen in Figure 12. This limited number of features led to two adverts being recommended; local football tickets and soft drinks. Both these adverts are acceptable given the characteristics.

Due to the lack of any features other than age and gender, the diagram clearly illustrates that there are no other potential options that could’ve been explored, making this example also correct. The advert that was chosen to be displayed was local football tickets.

Figure 12: The systems output regarding image 5

To test the group relationship inferences, as similar test was performed, as this is another area that would be unlikely to find as a data set. Therefore, five images were found, one for each group, and the system was tested to see if it would identify them correctly. In this test, a good result is if the system correctly identifies the group, an acceptable result is if it doesn’t give any group recommendations at all, and a bad result is if it gets the group wrong. The reason it’s acceptable to not give any at all is that the system will always have other options anyway, so it’s better to use one of them than to recommend something that doesn’t apply.

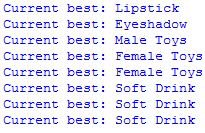
As shown in Appendix 2, Image 1 is of a group of young children, who are expected to be identified as friends. When the system runs, however, it doesn’t identify a group. The reason for this is that the systems logic only determines a group as friends if they are all the same gender, which in this case is a mistake. The advertisement recommendations are shown in Figure 13, which contain more than usual, due to the fact that adverts are being generated for each face in the image, so that one of the people is being targeted.

Figure 13: The systems output regarding Appendix 2, image 1

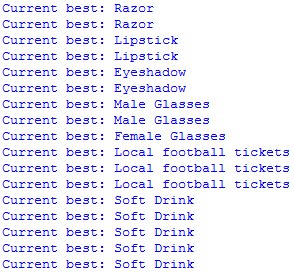
Image 2 of the same set shows a group of adult friends. This image runs into the same issue as the first, as there is a mix of genders in the image. While this is common in stock photos online, groups of friends are less likely to be mixed genders in real life, especially as adults. The advertisement recommendations are shown in Figure 14. The list is so long due to the prevalence of five faces in the image.

Figure 14: The systems output regarding Appendix 2, image 2

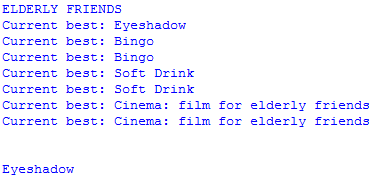
For the third image in Appendix 2, the correct result is achieved, as shown in Figure 15. The system correctly identifies the two elderly women as elderly friends and considers advertising a film to them based on this. However, as shown in the results, this doesn’t necessarily mean it will be the advertisement recommended to them, and in this case, it was eye makeup, which was identified in the image.



Figure 15: The systems output regarding Appendix 2, image 3



The fourth image also correctly identifies the relationship of the group, which in this case is a family. As a result, it considers recommending a family film to them, as seen in Figure 16, which would be an accurate recommendation.

Once again, however, the system doesn’t actually recommend this, and recommends a soft drink instead, which was identified as a potential advert for each of the family members.

Figure 16: The systems output regarding Appendix 2, image 4

Finally, Image 5 is correctly identified as a couple, which means they have the potential to be recommended a film for a couple. In this case, this was shown to them as the advertisement, as shown in Figure 17.

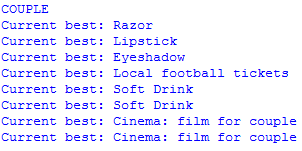


Figure 17: The systems output regarding Appendix 2, image 5

Finally, the time taken for the system to load in the frame and make the recommendation must be evaluated, in order to ensure that the system can make these inferences in enough time to present the user with the advert before they walk out of range. The test used was incredibly simple, timing the script from start to finish within the script itself. Figure 18 shows the results of this being done 10 times to make up for any outliers, with the average time being 0.619 seconds, which is a perfectly acceptable amount of time, with the advertisement recommendation algorithm having a complexity of O(N), meaning it will scale linearly with the amount of advertising units added. However, a lot of the time taken here is most likely fixed, such as the script being launched, faces being analysed, and most importantly, waiting for the API call to be made, which after being run in a script on its own, takes an average of 0.6 seconds, showing that a tiny amount of the 0.619 seconds will actually grow linearly.

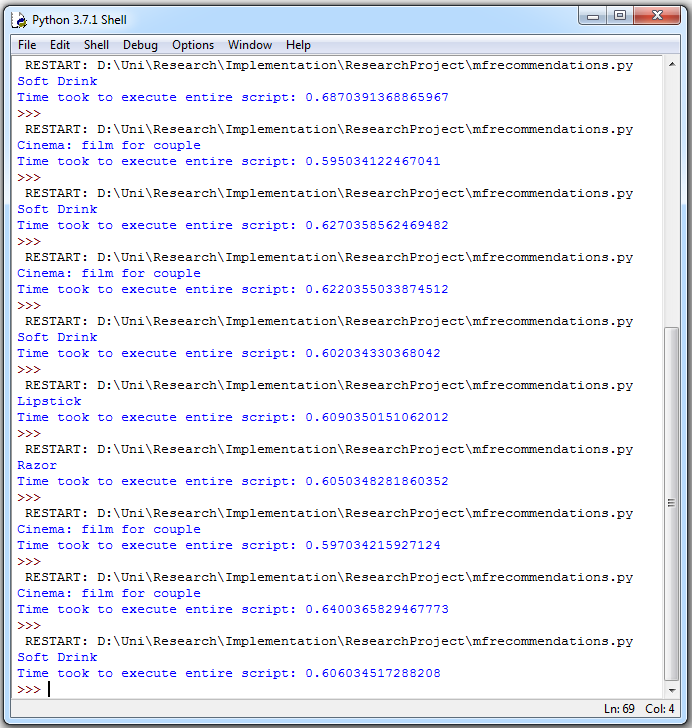


Figure 18: The results of timing the scripts performance

# Findings and Conclusion

## Results

Firstly, a deeper insight into the results of the evaluation should be made, to consider the effectiveness of the artefact in meeting the aim and objectives of this project. One such way of doing this is analysing the accuracy of the algorithm which gathers passer-by characteristics. For example, products which advertise only to men or women in static advertisements (i.e. adverts that aren’t targeted) will inevitably be a waste half of the time, as they only relate to 50% of people. However, since gender was accurate 100% of the time, this makes the advertisement twice as cost effective as it was before, as there is less time wasted showing it to people who won’t be interested in it, and in that case advertisers are paying the for space taken by the advert, not the time it is shown.

In the United Kingdom, the percentage of people wearing glasses is around 68% (Statista, 2018a) so static advertisements are actually quite cost effective as it is in this case, however when it comes to targeting more carefully, such as by gender or age, the effectiveness plummets. For example, 24% of the population in the UK is under 18 (Howden and Meyer, 2011), so if around 68% of these people wear glasses, that leaves 16% of the entire population being under 18 and wearing glasses. So, a static advertisement targeting this group would only apply to one in every 6 people that saw it, as opposed to the system outlined in this project, which would essentially be 6 times more cost effective.

While most of the characteristics are similar to this example (with higher levels of targeting providing better results), it is important to analyse the worst as well. Eye makeup only had an accuracy of 82%, meaning around 1 in 5 people shown eye makeup marketing material would be seen as a waste of money. Comparatively, although there are no statistics on the amount of women wearing makeup in public at any one time, it can be assumed from (Statista, 2018b) that this figure is around 50%, which would mean a static advertisement for women’s makeup would target around 25% of people, which translates to being cost ineffective 3 out of 4 times, a much larger figure than the targeted system. This means that even at it’s worst, this system still helps companies save a significant amount of their marketing budget, by reducing waste and helping them show the adverts to those who are more likely to go out and buy the product or service being shown.

Another way this system can improve physical marketing is through inferring the context of a group, and advertising to them. While the results of the evaluation highlighted one problem in the logic, overall this system provides insights that can be used in many interesting ways, and the rest of the results back that up. This adds more value to the system than perhaps online advertising ever could, due to the wealth of information that this provides. To give an example of this, a sports equipment company will be used, to show how one company could benefit. Just using the basic information, the company could advertise sports trainers to men, women and children separately. They could also advertise school sports bags to children, or golf clubs to elderly men. There are many examples of this but moving on to group relationships makes this even more substantial. For example, a couple could have tennis rackets marketed towards them, or a family could have bikes shown to them, or perhaps a table tennis set. Overall, where the company would be forced to simply advertise a few products to everyone walking past, and pay for that full space, they can advertise their entire range of products, targeting them to the people who may actually want to buy them.

And while this is an obvious improvement over physical, static advertisements, this could even be seen as improving on online, tailored advertising. The main issue with online ads is that they tailor to the user based on their search history, so for example if they’ve looked for bikes recently, they’ll be more likely to see bikes. However, this doesn’t consider that they’ve most likely already found what they wanted and bought it. Or even if they haven’t, this isn’t a very insightful recommendation, as the user is already interested in the product being advertised, and so probably made their mind up before regarding whether or not to buy it. However, this proposed system could be advertising a product that the customer hasn’t considered before. The example of a family being advertised a table tennis set perfectly encompasses this, as the parents may have been considering what to buy for Christmas, or what to buy for the entire family to enjoy, and this recommendation could be a new idea. As well as displaying the value this adds for the company, this further shows that the advertisements could be in the interest customers as well.

Therefore, based on these results, the artefact should be considered successful at meeting the aim of the project, as this project could have a considerably large impact on the return of investment for companies hoping to advertise in public spaces, by tailoring these adverts in a meaningful, insightful way.

## Ethics

Another important consideration to make when analysing the success of this project is ethics. There has been a growing concern over the last few years of surveillance, in particular the growing use of facial recognition techniques in public places. While this primarily applies to its use in security, this crosses over to commercial use as well, due to an increased level of care regarding personal privacy from the general public. Seeing how data is being used without consent, such as during the Cambridge Analytica scandal (The Guardian, 2018a) and Googles collection of open Wi-Fi data when collecting street view data (BBC News, 2013) has caused a knee jerk response to any technology that can potentially misuse personal information. This means that, if this system were to be implemented, several steps would need to be made in order to maintain a level of trust. The most important step would to be transparent with the public about what is collected, and how it is used, in as simple terms as possible. Everything done in the scope of this project is done as ethically as possible, and so a project of a similar nature should trust this, and be as open as possible, since the most common source of failure is when it is found out that something is being identified which people weren’t made aware of beforehand.

Another consideration to make is what identified information should be used. For example, the Microsoft Facial Recognition API used in this project can also return emotion, and it wouldn’t be too hard to identify race or weight, all of which could be severely misused and should be avoided at all costs.

Finally, the captured data should not be stored, sold or reused in any way. This is a common practice with online companies, with the phrase “If you’re not paying for it, you’re the product” entering the public conversation from its widespread usage. And although it’s lucrative business, it’s hard to get the targets consent for the reuse of data, and is therefore considered unethical, and a breach of trust.

There are also some ethical issues that this project has had to tackle. One of these is the necessary use of stereotyping when creating advertiser profiles. An example of this is recommending football tickets to adult males only. While statistically this is a logical decision, it encourages the idea that going to football matches is only for men and could enforce these ideas that society has been trying to tackle (McDowell and Schaffner, 2011). This goes further when children are considered, who are considered more impressionable to media, including advertisements (Borzekowski and Robinson, 2001). This is explored further in (Pike and Jennings, 2005), which shows that the toys advertised to children can indeed have an impact on what they deem appropriate for their gender. This can be damaging for the individual, and for society in general (Bem, 1981).

However, as only one of these issues has actually surfaced, the project should still be deemed successful, so long as any company or researcher furthering this work considers these issues and plans ahead to avoid them at all costs. While an improvement in computer vision technology and online advertising is beneficial for many parties, they shouldn’t interfere with the privacy and safety of the general public.

## Future work

While this project has been successful in meeting its aim, there is still more that can be done to improve its effectiveness, or perhaps utilise it in different ways. Although this project is interested in the way data can be captured and used to make a recommendation for an advertisement, it’s also worth looking at the advertisements themselves, and how they can be improved and evaluated using similar methods.

Firstly, the parts of the project that could benefit from improvements will be explored. One of these is simply improving the accuracy of recognising characteristics such as makeup. While this will always be one of the harder tasks to accomplish, more research and larger datasets could certainly go a long way in bridging the discrepancy between these accuracy scores and the rest of the characteristics, such as gender. The more accurate this can be, the more cost effective the system becomes, which would make it more viable as an option for companies to invest in. Similarly, the age accuracy needs to be improved, particularly at younger ages. While an age disparity of 4 may seem inconsequential, the difference between a 12-year-old and a 16-year-old is arguably much larger than the difference between a 40-year-old and a 50-year-old, despite the much shorter disparity. Research on recognising age has already been thorough, and the algorithms that achieve it are already using the best techniques possible, so perhaps the steps that need to be taken next are to acquire more datasets to train these systems to recognise age in different settings, such as in public, where some of these systems may actually be used, and yet have significantly lower accuracy, as seen in this project.

The other improvement that could be made is to the advertisement recommendations. The current system is effective in demonstrating how this technology can be used, however it fails to emulate the state of the art in the way that advertisements are actually chosen to show users online, which is the system that should be used as best practice, with minor alterations. For online advertisements, there may be many ads competing for the same person. For example, if a user searches for “Chairs”, there are around nine advertisements for chairs shown to the user. These aren’t companies, but individual chairs. This means that every company could have a set of chairs they want to advertise, meaning the number of potential advertisements for this could climb to the thousands when considering the number of companies, online and physical, that would want to find a customer. Therefore, the advertising algorithm must use a variety of factors, such as the amount of the advertising budget has been spent (if they paid £1000 for ads to be shown at a regular pace, but only £50 has been spent, then the ads will be more likely to be shown than an ad which has spent 50% of its budget) or the relevancy of the ad, for example recommending the types of chairs that have previously been searched for by the user. If this had been implemented, it would’ve brought the system closer to what a live version of it would look like, however without weeks of work creating advertiser profiles, it couldn’t have been effectively presented.

Aside from small improvements to the project as it stands, other future work could consist of using this technology in a new way. The most exciting potential usage comes from (Lyons et al, 1998), in which interactive displays are used to enhance the advertising experience. While literal interactions such as showing a clothing product being worn by the passer-by could be unrealistic in a fast moving, public setting, the scaled down version, such as changing the advertised product based on the individual could be implemented. For example, makeup companies selling foundation market their different skin tones, which should be matched to the skin tone of the consumer. This expansion to the project would allow the foundation to be advertised at the right skin tone, assisting the customer in finding what they may not have known would exist, especially considering the difficulty that certain skin tones have in finding the correct colour, with (Caisey et al., 2006) stating that African American women feel that “appropriate foundation shades are not available in store.” This idea could also be applied to hair dye colours, and (perhaps more unethically) clothes sizes, although great care and respect would have to be shown if this were to be implemented.

A further extension of the system could be recognising symbols/logos on clothing and hats, and advertising based on those, to help companies find and advertise to those who already like their products. While this would of course be beneficial for clothing companies, it would be ideal for sports teams, for example identifying the team’s logo on a hat or shirt, and advertising tickets for the next game, or displaying the new kit.

Finally, detecting the mood of the passer-by after seeing the advertisement could be beneficial for providing feedback to advertisers, so they could alter their marketing campaigns at a faster rate than waiting to see its impact on sales figures. This is already in use in Westfield shopping centre (The Guardian, 2019), showing that there is a commercial desire for this to be implemented.

# Reflective analysis

After the completion of this project, it became obvious that there were series of successes and failures, that can only be seen with hindsight. While some couldn’t be avoided, due to time constraints or extraneous variables, there were some that could’ve been solved by better planning, whether that be more in-depth risk analysis, or more realistic time management.

The first success I’d like to talk about is that I completed 80% of all tasks, with the last two being considered extension tasks. This is obviously important, as the number of tasks completed is one of the most important ways to measure the success of the project. I attribute this achievement to the time management strategies that were used, as well as the research and planning that was done before development started. Doing this allowed me to find the best methods to solve difficult problems, and to choose the methods that would fit the time frame. For example, developing my own algorithm for recognising characteristics instead of using Microsoft’s Facial Recognition API could’ve increased accuracy as I could’ve based it on the requirements of this project, instead of using their one size fits all approach. However, due to my research, I concluded that an approach like that would’ve been out of scope of this project due to the time constraints, leading me to using the API instead, which turned out to be very accurate anyway.

However, the two tasks that weren’t completed could still be considered a failure. Even if they were considered extension tasks, they would still have contributed to a more complex, effective system. Although running the system in real time could’ve enabled me to better display the systems capabilities, it wouldn’t change the logic behind it, and would therefore be a very time-consuming task that would offer very little to the fulfilment of the original aim. The final task, however, would’ve been more impactful, enabling local businesses to get involved, as well as the ability to introduce time-based logic to the system, such as not advertising to children after 9pm. The reason this task wasn’t implemented was merely due to how long it would take to complete. While acquiring the information would be a simple job, using it to make inferences would not, as each individual inference would have to be individually catered for. Overall, while the failure of this task is partially the loss of what could’ve been a highly effective part of the system, the larger failure was in time management, and its inclusion in the first place. More planning would’ve led me to removing it from the list of objectives and tasks, as it quickly became obvious after starting that neither task was feasible.

The time spent working on the first eight tasks instead could be considered the reason for the project’s biggest success – it’s accuracy, and in-depth inferences that add extra value to advertising. These factors are included as one, as they both feed into each other, and more importantly, both illustrate that the project met it’s aim. Giving a cinema company the ability to only advertise family films to groups that are identified as families reduces waste by a significant margin, and certainly increases effectiveness, as the films/products are being shown to their key demographics. Also, being able to identify characteristics correctly almost every time means that these insights can be made in the first place and prevents any wasted advertising time from misidentification.

Finally, I’d like to talk about another failure, which is the lack of a suitable dataset. While this risk was predicted and mitigated, this is not the same as a complete fix. The self-labelling of the data brought in a new issue to tackle, which was the difficulty in detecting some of the characteristics. One example of this was age, which is known to be difficult to estimate. I tried my best and am confident that the majority of my estimations were correct, however those that were incorrectly labelled could’ve led to false positives or negatives. This would negate some of the accuracy that was just considered a success, leading to some doubts about the specific degree of accuracy in the project. However, as it’s unlikely that more than a couple of images were incorrectly labelled, the project can still be called an overall success either way, although perhaps the accuracy of the identification of characteristics should be considered 91 – 95% on average, as this would cover any misidentification.

# References

Aksu, H., Babun, L., Conti, M., Tolomei, G. and Uluagac, A.S., 2018. Advertising in the iot era: Vision and challenges. *IEEE Communications Magazine*, *56*(11), pp.138-144. Available from <https://arxiv.org/pdf/1802.04102.pdf> [accessed 3 April 2019].

Alt, F., Müller, J. and Schmidt, A., 2012. Advertising on public display networks. *Computer*, *45*(5), pp.50-56. Available from <https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=6193076&tag=1> [accessed 3 April 2019].

BBC News (2013) *Google faces Streetview wi-fi snooping action.* London: BBC. Available from <https://www.bbc.co.uk/news/technology-24047235> [accessed 10 August 2019].

Beck, K., Beedle, M., Van Bennekum, A., Cockburn, A., Cunningham, W., Fowler, M., Grenning, J., Highsmith, J., Hunt, A., Jeffries, R. and Kern, J., 2001. Manifesto for agile software development. Available from <https://pdfs.semanticscholar.org/3eda/bb96a07765704f9c6a1a5542e39ac2df640c.pdf> [accessed 23 June 2019].

Bem, S.L., 1981. Gender schema theory: A cognitive account of sex typing. *Psychological review*, *88*(4), p.354. Available from <https://ahcaf.com/wp-content/uploads/2015/07/gender_schema_theory.pdf> [accessed 3 August 2019].

Borzekowski, D.L. and Robinson, T.N., 2001. The 30-second effect: an experiment revealing the impact of television commercials on food preferences of preschoolers. *Journal of the American Dietetic Association*, *101*(1), pp.42-46. Available from <https://www.researchgate.net/profile/Dina_Borzekowski/publication/246144531_The_30Second_Effect/links/5a4e72690f7e9bbfacfc2da4/The-30Second-Effect.pdf> [accessed 3 August 2019].

Caisey, L., Grangeat, F., Lemasson, A., Talabot, J. and Voirin, A., 2006. Skin color and makeup strategies of women from different ethnic groups. *International journal of cosmetic science*, *28*(6), pp.427-437. Available from <https://www.researchgate.net/profile/Diane_Baras/publication/285588520_Skin_color_and_makeup_strategies_of_women_from_different_ethnic_groups_yinattarenzhonggurupunishusurunuxingnopifunosetomeikuappuzhane/links/5a7d538a0f7e9b9da8d773f1/Skin-color-and-makeup-strategies-of-women-from-different-ethnic-groups-yinattarenzhonggurupunishusurunuxingnopifunosetomeikuappuzhane.pdf> [accessed 4 August 2019].

Cockburn, A. and Highsmith, J., 2001. Agile software development: The people factor. *Computer*, (11), pp.131-133. Available from <https://www.researchgate.net/profile/Alistair_Cockburn/publication/2955526_Agile_software_development_The_people_factor/links/56d434b908ae868628b2453c/Agile-software-development-The-people-factor.pdf> [accessed 23 June 2019].

Ekstrand, M.D., Riedl, J.T. and Konstan, J.A., 2010. Collaborative Filtering Recommender Systems. *Human–Computer Interaction*, *4*(2), pp.81-173. Available from <https://www.researchgate.net/profile/Jon_Herlocker/publication/215470714_Evaluating_collaborative_filtering_recommender_systems/links/563f7c5608ae8d65c0150ddc.pdf> [accessed 7 June 2019].

Exeler, J., Buzeck, M. and Müller, J., 2009, October. eMir: digital signs that react to audience emotion. In *2nd workshop on pervasive advertising* (pp. 38-44). Available from <https://pdfs.semanticscholar.org/4acc/d415ef99e73fb2ecd4534b7fe5f5793761af.pdf?_ga=2.88568219.1018234308.1552315262-1902740231.1552315262> [accessed 3 April 2019].

Farahat, A. and Bailey, M.C., 2012, April. How effective is targeted advertising? In *Proceedings of the 21st international conference on World Wide Web* (pp. 111-120). ACM. Available from <https://www2012.universite-lyon.fr/proceedings/proceedings/p111.pdf> [accessed 3 April 2019].

Geng, X., Zhou, Z.H. and Smith-Miles, K., 2007. Automatic age estimation based on facial aging patterns. *IEEE Transactions on pattern analysis and machine intelligence*, *29*(12), pp.2234-2240. Available from <http://dro.deakin.edu.au/eserv/DU%3A30007652/geng-automaticage-2007.pdf> [accessed 3 April 2019].

The Guardian (2018a) *Revealed: 50 million Facebook profiles harvested for Cambridge Analytica in major data breach.* London: Guardian Media Group. Available from <https://www.theguardian.com/news/2018/mar/17/cambridge-analytica-facebook-influence-us-election> [accessed 10 August 2019].

The Guardian (2018b) *Surveillance fears grow after Taylor Swift uses face recognition tech on fans.* London: Guardian Media Group. Available from <https://www.theguardian.com/music/2018/dec/13/taylor-swift-facial-recognition-technology-surveillance> [accessed 20 June 2019].

The Guardian (2019) *Are you being scanned? How facial recognition technology follows you, even as you shop.* London: Guardian Media Group. Available from <https://www.theguardian.com/technology/2019/feb/24/are-you-being-scanned-how-facial-recognition-technology-follows-you-even-as-you-shop> [accessed 20 June 2019].

Guo, G., Dyer, C.R., Fu, Y. and Huang, T.S., (2009a), September. Is gender recognition affected by age? In *2009 IEEE 12th International Conference on Computer Vision Workshops, ICCV Workshops* (pp. 2032-2039). IEEE. Available from <https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=5457531&tag=1> [accessed 3 April 2019].

Guo, G., Mu, G., Fu, Y. and Huang, T.S., (2009b), June. Human age estimation using bio-inspired features. In *2009 IEEE Conference on Computer Vision and Pattern Recognition* (pp. 112-119). IEEE. Available from <https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=5206681> [accessed 4 April 2019].

Han, H., Otto, C., Liu, X. and Jain, A.K., 2014. Demographic estimation from face images: Human vs. machine performance. *IEEE transactions on pattern analysis and machine intelligence*, *37*(6), pp.1148-1161. Available from <http://vipl.ict.ac.cn/uploadfile/upload/2017020711105957.pdf> [accessed 4 April 2019].

Howden, L. and Meyer, J. (2011) *Age and Sex Composition: 2010.* Washington, DC: U.S. Department of Commerce. Available from <https://www.census.gov/prod/cen2010/briefs/c2010br-03.pdf> [accessed 14 August 2019].

Huerta, I., Fernández, C. and Prati, A., 2014, September. Facial age estimation through the fusion of texture and local appearance descriptors. In *European conference on computer vision* (pp. 667-681). Springer, Cham. Available from <http://hertasecurity.com/sites/default/files/publication/files/ECCVW14_CR_send.pdf> [accessed 4 April 2019].

Kalam, S. and Guttikonda, G., 2014. Gender classification using geometric facial features. *International Journal of Computer Applications*, *85*(7). Available from <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.429.3406&rep=rep1&type=pdf> [accessed 7 April 2019].

Koren, Y. and Bell, R., 2015. Advances in collaborative filtering. In *Recommender systems handbook* (pp. 77-118). Springer, Boston, MA. Available from <https://s3.amazonaws.com/academia.edu.documents/36167999/Collaborative-Filtering-_Koren-and-Bell_.pdf?response-content-disposition=inline%3B%20filename%3DAdvances_in_Collaborative_Filtering.pdf&X-Amz-Algorithm=AWS4-HMAC-SHA256&X-Amz-Credential=AKIAIWOWYYGZ2Y53UL3A%2F20190823%2Fus-east-1%2Fs3%2Faws4_request&X-Amz-Date=20190823T153127Z&X-Amz-Expires=3600&X-Amz-SignedHeaders=host&X-Amz-Signature=10968cb4d73cd3a8dcd0036845174987be5626d731c223827511391c1854c4cf> [accessed 7 June 2019].

Li, B., Lian, X.C. and Lu, B.L., 2012. Gender classification by combining clothing, hair and facial component classifiers. *Neurocomputing*, *76*(1), pp.18-27. Available from <https://www.sciencedirect.com/science/article/pii/S0925231211004589> [accessed 7 April 2019].

Lian, H.C. and Lu, B.L., 2006, May. Multi-view gender classification using local binary patterns and support vector machines. In *International Symposium on Neural Networks*(pp. 202-209). Springer, Berlin, Heidelberg. Available from <https://www.researchgate.net/profile/Bao-Liang_Lu2/publication/5663358_Multi-view_Gender_Classification_Using_Local_Binary_Patterns_and_Support_Vector_Machines/links/540289350cf2c48563af8b7b.pdf> [accessed 7 April 2019].

Linden, G., Smith, B. and York, J., 2003. Amazon. com recommendations: Item-to-item collaborative filtering. *IEEE Internet computing*, (1), pp.76-80. Available from <http://cseweb.ucsd.edu/classes/fa17/cse291-b/reading/Amazon-Recommendations.pdf> [accessed 7 April 2019].

Lyons, D., Pelletier, D. and Knapp, D., 1998, November. Multimodal interactive advertising. In *Proc. Wkshp. Percept. User Interfaces* (pp. 83-86). Available from <https://www.researchgate.net/profile/Damian_Lyons/publication/255564024_Multimodal_Interactive_Advertising/links/53ce6de80cf279d93530a103/Multimodal-Interactive-Advertising.pdf> [accessed 7 April 2019].

McDowell, J. and Schaffner, S., 2011. Football, it’s a man’s game: Insult and gendered discourse in The Gender Bowl. *Discourse & Society*, *22*(5), pp.547-564. Available from <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.839.5846&rep=rep1&type=pdf> [accessed 2 June 2019].

Moghaddam, B. and Yang, M.H., 2000, March. Gender classification with support vector machines. In *Proceedings Fourth IEEE International Conference on Automatic Face and Gesture Recognition (Cat. No. PR00580)* (pp. 306-311). IEEE. Available from <https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=840651> [accessed 7 April 2019].

Ng, C.B., Tay, Y.H. and Goi, B.M., 2012, September. Recognizing human gender in computer vision: a survey. In *Pacific Rim International Conference on Artificial Intelligence*(pp. 335-346). Springer, Berlin, Heidelberg. Available from <https://www.researchgate.net/profile/Yong_Haur_Tay/publication/262152447_Recognizing_Human_Gender_in_Computer_Vision_A_Survey/links/55fe351a08aec948c4e1feec.pdf> [accessed 7 April 2019].

Ojala, T., Pietikäinen, M. and Mäenpää, T., 2002. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. *IEEE Transactions on Pattern Analysis & Machine Intelligence*, (7), pp.971-987. Available from <http://vision.stanford.edu/teaching/cs231b_spring1415/papers/lbp.pdf> [accessed 7 April 2019].

Pike, J.J. and Jennings, N.A., 2005. The effects of commercials on children’s perceptions of gender appropriate toy use. *Sex roles*, *52*(1-2), pp.83-91. Available from <https://www.researchgate.net/profile/Nancy_Jennings/publication/30846400_The_Effects_of_Commercials_on_Children's_Perceptions_of_Gender_Appropriate_Toy_Use/links/53d291fb0cf2a7fbb2e9a76d/The-Effects-of-Commercials-on-Childrens-Perceptions-of-Gender-Appropriate-Toy-Use.pdf> [accessed 3 June 2019].

Sarwar, B.M., Karypis, G., Konstan, J.A. and Riedl, J., 2001. Item-based collaborative filtering recommendation algorithms. *Www*, *1*, pp.285-295. Available from <http://www.ra.ethz.ch/cdstore/www10/papers/pdf/p519.pdf> [accessed 7 April 2019].

Shakhnarovich, G., Viola, P.A. and Moghaddam, B., 2002, May. A unified learning framework for real time face detection and classification. In *Proceedings of Fifth IEEE international conference on automatic face gesture recognition* (pp. 16-23). IEEE. Available from <https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=1004124> [accessed 8 April 2019].

Sommerville, I. (2011) Software Engineering, 9th Edition. Cambridge: Pearson.

Statista (2018a) *Share of individuals who wear spectacles in selected European countries 2017*. Statista. Available from <https://www.statista.com/statistics/711514/individuals-who-wear-spectacles-in-selected-european-countries/> [accessed 2 August 2019].

Statista (2018b) *Frequency of makeup use among consumers in the United States as of May 2017, by consumer group*. Statista. Available from <https://www.statista.com/statistics/713191/makeup-use-frequency-by-consumer-group/> [accessed 2 August 2019].

Su, X. and Khoshgoftaar, T.M., 2009. A survey of collaborative filtering techniques. *Advances in artificial intelligence*, *2009*. Available from <http://downloads.hindawi.com/archive/2009/421425.pdf> [accessed 7 June 2019].

TechBeacon (2017) To agility and beyond: The history—and legacy—of agile development. TechBeacon. Available from <https://techbeacon.com/app-dev-testing/agility-beyond-history-legacy-agile-development> [accessed 23 June 2019].

Tian, P., Sanjay, A.V., Chiranjeevi, K. and Malik, S.M., 2012, August. Intelligent advertising framework for digital signage. In *Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining* (pp. 1532-1535). ACM. Available from <http://wan.poly.edu/KDD2012/docs/p1532.pdf> [accessed 8 April 2019].

Tucker, C.E., 2014. Social networks, personalized advertising, and privacy controls. *Journal of Marketing Research*, *51*(5), pp.546-562. Available from <https://journals.sagepub.com/doi/abs/10.1509/jmr.10.0355> [accessed 8 April 2019].

Wong, Y., Chen, S., Mau, S., Sanderson, C., Lovell, B. 2011, *Patch-based Probabilistic Image Quality Assessment for Face Selection and Improved Video-based Face Recognition*, IEEE. Available from <http://arma.sourceforge.net/chokepoint/> [accessed 20 May 2019].

Yang, Z. and Ai, H., 2007, August. Demographic classification with local binary patterns. In *International Conference on Biometrics* (pp. 464-473). Springer, Berlin, Heidelberg. Available from <https://link.springer.com/content/pdf/10.1007/978-3-540-74549-5_49.pdf> [accessed 13 April 2019].

Viola, P. and Jones, M.J., 2004. Robust real-time face detection. *International journal of computer vision*, *57*(2), pp.137-154. Available from <https://s3.amazonaws.com/academia.edu.documents/30232675/viola-facedetection-ijcv04.pdf?response-content-disposition=inline%3B%20filename%3DRobust_real-time_face_detection.pdf&X-Amz-Algorithm=AWS4-HMAC-SHA256&X-Amz-Credential=AKIAIWOWYYGZ2Y53UL3A%2F20190828%2Fus-east-1%2Fs3%2Faws4_request&X-Amz-Date=20190828T153731Z&X-Amz-Expires=3600&X-Amz-SignedHeaders=host&X-Amz-Signature=304b406b3504526cc53f85ecbcb103a78a09d1c3d437b561faf5bf455d86138b> [accessed 13 April 2019].

YouGov (2016) YouGov Survey Results. YouGov. Available from <https://d25d2506sfb94s.cloudfront.net/cumulus_uploads/document/y8qax35a1p/InternalResults_161109_FacialHair_W.pdf> [accessed 5 August 2019].

Zhang, Y., Liu, L. and Li, C., 2017. Quantifying facial age by posterior of age comparisons. *arXiv preprint arXiv:1708.09687*. Available from <https://arxiv.org/pdf/1708.09687.pdf> [accessed 13 April 2019].

# Appendix

## Appendix 1

### Image 1



### Image 2



### Image 3



### Image 4



### Image 5



## Appendix 2

### Image 1



### Image 2



### Image 3



### Image 4



### Image 5

