Clo: an intelligent clothing assistant supporting you with shaping your personal clothing style

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Abstract

Each season, trends in clothing demand renewing and are therefore constantly changing. Consequently, there are more and more clothing styles emerging around you. Accordingly, inexperienced people might question how to shape their own and face this enormous amount of possibilities? There are existing services already out there solving issues such as clothing management and outfit generating. Still, there has not been designed an intelligent system focused on exploring a person's style like the one described in this paper: Clo. Considering the increase in recommendation systems, there is potential in creating this intelligent clothing assistant supporting individuals with shaping their own clothing style. With the integration of a k-nearest neighbor algorithm, it is designed to learn what clothing style a user prefers and which clothing items it eventually might want to purchase. A demonstrator is developed and was able to accentuate the potential of using this algorithm for outfit recommendations. Nevertheless, further research is needed to optimize the effectiveness of Clo in order to get the best outfit matches each day.

Author Keywords

Clothing recommender system; Machine learning; Design; ; K-nn; K-nn algorithm;

ACM Classification Keywords

H.1.2 [Information Systems]: User/machine systems–Human information processing.

Introduction

With the extreme growth in e-commerce [3], people purchase more and more online [4]. However, it remains unclear what decision-making process supports this increased online shopping behavior. A lot of online services are developed to manage their outfits of which a few examples can be found in the section 'Related Work'. The existence of these services could indicate that low-experienced consumers are struggling to figure out what clothing they genuinely like and eventually want to purchase. Regarding the clothing in their wardrobe, it can be challenging to decide on what outfit they wear every day. Moreover, there can be limited time to choose what to wear every single day, especially while also examining the weather conditions and personal agenda. Therefore, the authors of this paper believe there is a potential for investigating in an intelligent system which low-experienced consumers/young adults can use to support their decision making on a daily basis. There is a potential need for an application which can help the target group in exploring/shaping their clothing style.

In this paper, we will first examine some related work to highlight what similar work is currently in the market. After, our final concept and proof of concept(demonstrator) will be described. Those will finally be evaluated regarding four different design aspects: Sensing and Data Collection, Learning, Actuation and Feedback Loop, and Social Aspects and Connectivity.

Related Work

To deal with the problems of choosing daily outfits, we have emerged numerous style management products and applications. The following mentioned, are already slightly supporting the clothing decision-making process. Nonetheless, there are still some unexplored opportunities in each.

Amazon Echo Look (figure 1) aims to comprehend the individual preference and provides a style check based on current trends [1]. It is combined with a physical camera and a mobile application. Echo Look can organize outfits and help users assess their style based on earlier sessions, weather, occasions and more. However, it seems to lack in connecting to similar users ‘through the internet’ that dress up equally in style.

Figure 1: Amazon Echo Look [1]

ClosetSpace (figure 2) can connect to the retailers and many other services - with everything people need to dress better and feel more coordinated [2]. With a machine learning algorithm, ClosetSpace learns people’s preferences based on previous user behavior including saving looks, adding new items, and building outfits while considering temperature, occasion, and weather. Unfortunately, it is not connected to your wardrobe and therefore cannot sufficiently support in recommending what to wear every single day.

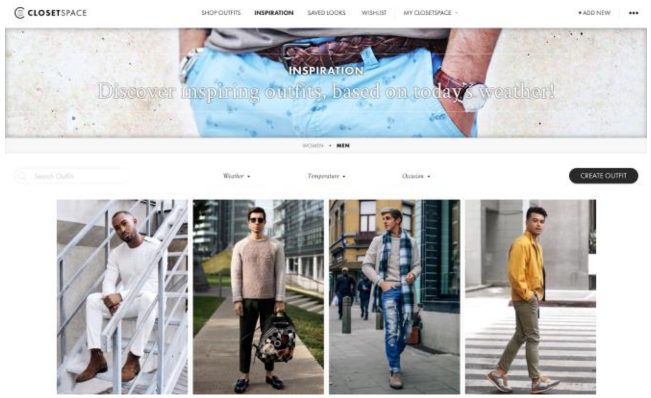

Figure 2: ClosetSpace [2]

StyleBook (figure 3) is an outfit management app, making the most use of what users already have in their closet and integrating with new pieces [6]. Users manually picture all their items to digitalize their wardrobe. This product is not intelligent and cannot recommend and create any outfits.

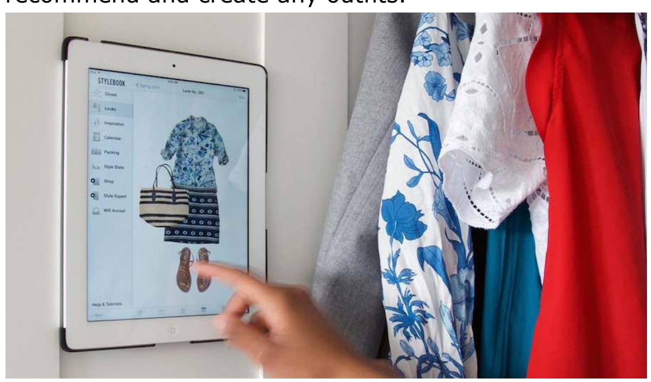

Figure 1: StyleBook

Whether the products mentioned above lack in intelligence or personalization, it becomes clear that there is a potential in designing an outfit recommender system, based upon daily weather conditions and personal agenda. There is no intelligent product found supporting people to choose outfits based upon their present clothing items.

Final Concept

Combining the obtained knowledge gathered a concept was developed to help young adults explore their clothing style. It is an intelligent system using machine

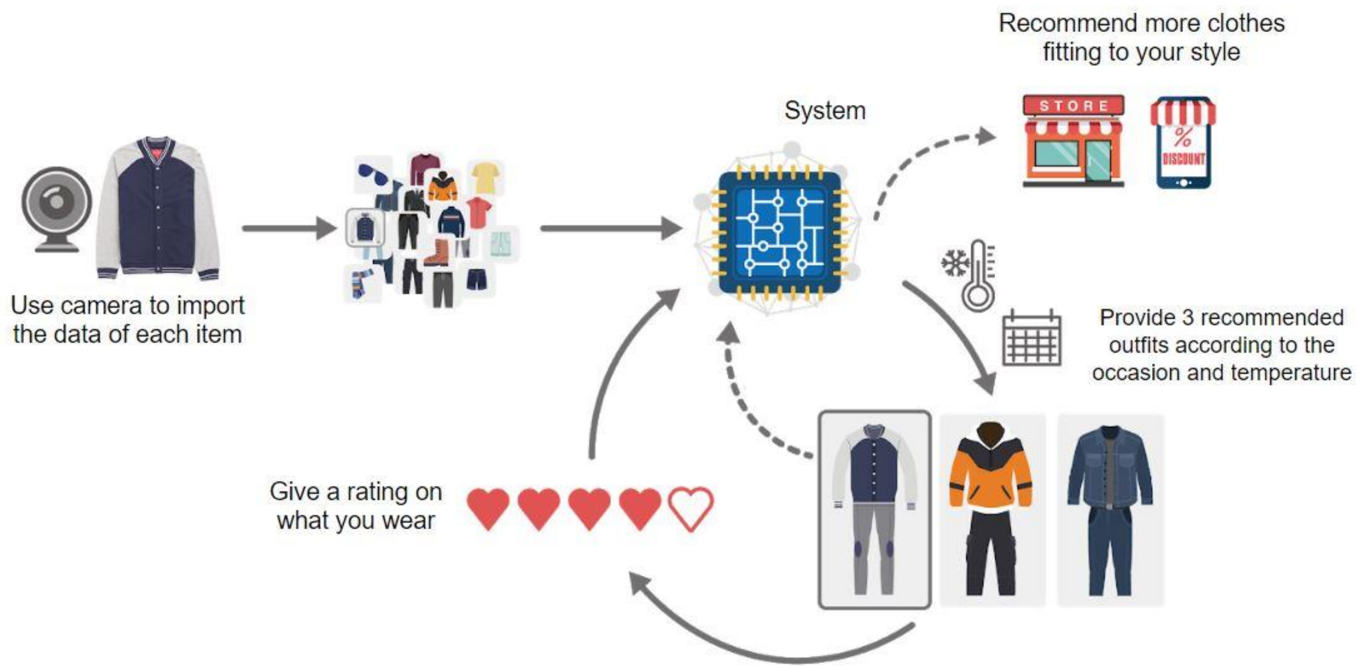

Figure 3: Figure of the final concept

learning to recommend outfits based on numerous variables (figure 4). A camera is used to take pictures of the user's clothing items and to determine its properties. These properties are linked to the photo and stored in a dataset of the user's wardrobe. Furthermore, the user initiates a profile by inserting its gender and occupation. The system completes this profile by adding a prediction of a user's favorite color and style based on the specific clothing items in their wardrobe. Using this information, a user gets matched with similar profiles of other users. Each user has their own database with previous outfits worn which are matched to their profile. Based on the weather forecast, calendar events, a user's style and a ranking, three outfit recommendations are given. These outfits are chosen as recommendations by looking at what kind of outfits similar users had worn during similar conditions and rated high. During the first week outfits with different style certifications are shown to get a better understanding of the user's style. By choosing a specific outfit the user provides the system with feedback on its style allowing the system to give better recommendations next times. After one week, the best recommendations are shown but the choice of an outfit can still influence a user's style as it is determined by the system. At the end of the day each user ranks the recommended outfit on a scale from 1-5 which enforces the feedback loop and helps the system to provide better suiting outfits in the future.

Design Process

In a timespan of eight weeks the final concept was shaped and prototyped. In this section we explain the design decisions made regarding the four design aspects; Sensing and Data Collection, Learning, Actuation and Feedback Loop, and Social Aspects and Connectivity.

Sensing and Data Collection

For our final concept, it was carefully considered which data regarding clothing should be considered. Finding ways to gather this data and sensing the aspects of the clothing caused a lot of internal discussions. At first gender, age, profession and style were thought to be the most critical variables. However, through testing, it was found out that specifically age was not as crucial as we initially expected. A 50-year old man can like to wear the same outfits as young adults aged 20 or the other way around. Hence, we neglected age. Furthermore, the concept has been adapted a bit over time, and therefore the target group also changed to 'young adults': These young adults are more likely studying instead of working. For that reason, 'profession' was replaced by 'occupation'.

The clothing attributes which were included, were (1) Pattern [checkered, striped, floral, graphic, solid], (2) Fabric [cotton, chiffon, lace, wool, silk], (3) Style [casual, formal, party, winter, summer] and (4) Shape [full-sleeve, half-sleeve, sleeveless]. The users are asked to picture their own clothing to let the system recognize and label the different attributes in a wardrobe Comma Separated Value (CSV) file (table 1). It was not ascertained whether one of the attributes was less effective than the others.

Classification				
Image				...
Label	sweater	T-shirt	trousers	...
Color	blue	gray	black	...
Pattern	graphic	solid	solid	...
Fabric	wool	cotton	cotton	...
Style	casual	casual	formal	...

Table 1: An example how the data was classified

Learning

Personal agenda and weather conditions vary continuously, and people try to find suitable outfits every day. Accordingly, it was argued that including machine learning to make our system intelligent would be significant. Considering that clothing outfits are sensitive for trends it was best to have a recommender system showing optional outfits appreciated by other people. To have quick learning behavior of the system, it was found that k-nearest neighbor (k-nn), a supervised machine learning algorithm [8], was the best fitting. Earlier, Q-learning [9] was assumed to be the best match. However, Q-learning would require the user to train the system for probably several years to get accurate (i.e. useful) recommendations.

For the algorithm, once three (gender, occupation and style) and once four dimensions (temperature, occasion, style and ranking) were used. Consequently, a suitable k-value had to be chosen. To give reasonable recommendations, it was tested and found that a k-value of 3 was showing best recommendations given the size of our dataset (see figure 5 for visualizations of the algorithm).

Figure 4: Two-dimensional plots in which the algorithms are visualized (nearest profiles above and nearest outfits below).

Actuation and Feedback Loop

During the design process of the concept, a lot of thought went into how we can provide the system with meaningful feedback to improve the recommendations. Looking at the user and determining what was needed to give them the best recommendations possible resulted in two feedback loops. It was decided that since clothing preference would be relevant for the user, the system should be able to learn these things. By providing the user with three optional outfits, the selected outfit can say something about their preference. By feeding this choice back into the system, a feedback loop is established. The second feedback loop is implemented in the form of a ranking system. This ranking is provided as a way to improve the recommendations. By providing a ranking, you not only enhance the recommendation for yourself but also for other users. By giving a low ranking to a certain outfit, similar outfits will not be recommended to you and not to others next time(more weight on the first).

The actuation of the recommendations is envisioned in the form of a mobile phone application. This causes a low threshold to start using the application since almost everybody has a smartphone nowadays. Pop-up notifications can be provided to involve users throughout the day.

Social Aspects and Connectivity

A lot of connections are possible between our system and existing applications. Getting recommendations for clothing available in online stores could help users purchase better suiting clothes as well as give online shops more revenue. Being able to connect it to a smart laundry machine or laundry bucket could help with determining which items are not available for the

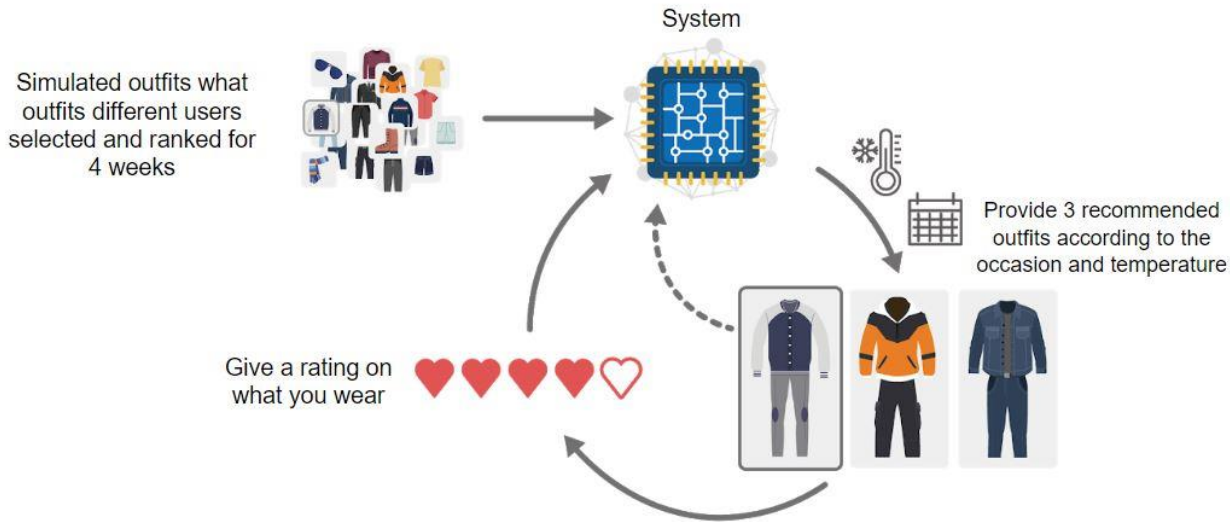

Figure 5: A scheme of the prototyped demonstrator

recommendation or based on the upcoming recommendation which items you should wash first the day before.

Social media could also play an interesting role in connecting with your friends' wardrobes and seeing their outfits and clothing styles to influence yours. Sharing your chosen outfit online or having people vote which recommendation to pick would also be interesting. It is then possible to determine your style and share your fashion with the world to keep up to date on today's trends. Connecting with products such as the Amazon look (figure 1) could help in clothing recognition and provide an easy way to get a dataset of a user's wardrobe.

Demonstrator

A working demonstrator was developed to validate the feasibility and desirability of the concept. Due to the time frame of approximately eight weeks appointed to this project, it was decided to exclusively focus on the part of the concept as illustrated in (figure 6). The demonstrator was developed as a 'proof of concept', to examine whether the use of a k-nn algorithm in a clothing recommendation system was legitimate. To do so, it was decided to instead only focus on the recommendation and feedback loop and exclude the data collection of the clothing items.

Using a dataset of roughly 200 male and 200 female clothing items from Zara [10], 25 independent CSV files of male and female wardrobes were constructed. Each featured a set of roughly 15 clothing items reasonably chosen according to their persona. With these wardrobe files, 25 new user files were made storing each user's favorite color, style and occupation. These user files were consisting of a dataset of four weeks full of outfits changing each day (figure 6).

	A	B	C	D	E	F	G	H	I	J	
1	day	Temperatu	Occasion	Style	Ranking	item id 1	item mode	item color	item style	item path	it
2	1	15	1	1	4	142	trousers	grey	casual/for	data/items	
3	2	13	0	2	4	121	trousers	black	casual	data/items	
4	3	10	0	2	5	121	trousers	black	casual	data/items	
5	4	10	0	2	4	142	trousers	grey	casual/for	data/items	
6	5	12	0	2	5	142	trousers	grey	casual/for	data/items	
7	6	16	1	1	3	82	skirts	black	casual/for	data/items	
8	7	16	0	2	4	121	trousers	black	casual	data/items	

Figure 6: All outfits collected in a CSV file

Each outfit was labelled with the outside temperature (-10°C to 40°C) and calendar events (occasion or no occasion) of the day as well as the corresponding style of the outfit (numbered from 1 till 5) (figure 8). Furthermore, a path to the picture of each clothing item was added to this CSV file. This database of different CSV files was developed alongside the developed prototype to support the algorithm as good as possible.

Figure 8: An example of style 1(left) and style 5(right) used for the demonstrator.

The developed prototype was made using a k-nn algorithm and coded in Processing [5] software environment. The way the prototype worked is you can input a user's gender, occupation, clothing style, and wardrobe. Using the user's wardrobe their favorite color is computed by counting how many times every color is mentioned in the wardrobe database. By checking all the profiles for the right gender, profiles with the same gender were added to a new data set of potential profiles. This dataset is used as an input for the k-nn. The algorithm maps out all the values of style, favorite color and occupation of the different profiles in the profiles dataset. Using the Euclidean distance formula [7] which is shown in (figure 9) the distance is calculated between the input datapoint and all the profiles in the dataset.

$$d(\mathbf{p},\mathbf{q}) = d(\mathbf{q},\mathbf{p}) = \sqrt{(q_1-p_1)^2 + (q_2-p_2)^2 + \cdots + (q_n-p_n)^2}$$
$$= \sqrt{\sum_{i=1}^{n} (q_i-p_i)^2}.$$

Figure 9: The Euclidean distance formula [7]

This data is then transferred to a new table and sorted. The three closest profiles (k =3) are then used as input for a second k-nn calculation. A distance is calculated between each outfit and a second datapoint based on the four variables: temperature, occasion, average style and ranking. The three closest outfits of each of the three earlier selected profiles are gathered in a new dataset of nine outfits. If this recommendation is requested in the first week of use, random outfits out of these nine are displayed as recommendations for the user to wear. This in order to learn what specific style the user prefers. If the prototype has been used for more than a week the closest three outfits are recommended from the 9 nearest outfits. Depending on what outfit is chosen the user's average style can adapt. If a user chooses a lot of styles labelled with a higher style rating its average style would increase, resulting in more outfit recommendations in those style segments. The user is also able to rank a chosen outfit throughout the day. This ranking is saved in a CSV file with all the chosen user outfits per profile which is becoming available for other users' their recommendations.

Discussion

Although the demonstrator generally functions as a proof of concept and shows the relevance of a k-nn algorithm it is still coming short in some aspects.

Sensing and Data Collection

Since the data collection was now done manually a more effective way needs to be thought of to generate different profiles. This sensing and data collection is something that has not been completely implemented yet into the demonstrator and therefore not completely defined yet. At the moment of writing there is not a dataset available that matches our needs causing us to create a dataset manually. This also relates to recognizing the style of a specific outfit as well as recognizing clothing items. Therefore, a way to gather this data should be created. An example of this is to develop an application in which people input their clothing choices each day for four weeks and get possibly a reward in return. The calendar data at the moment of writing is only used to distinguish between an occasion and no occasion. By providing more data relevant to these occasions better recommendations could be provided. The same holds for the weather data which is now only manually generated temperature.

Learning

In the current version, the system can learn your preferences by comparing you with similar users and learn from the clothing you choose to give better recommendations every day. The k-nn can recommend suiting outfits depending on your favorite color, style, someone's ranking and the current outside temperature. Although, it could learn more about for example item attributes, the weather forecast and calendar input to provide better recommendations. It can advise you to wear a raincoat when it is going to be rainy and a suit when you have a formal event scheduled. Next to that, it might recommend you to buy a striped sweater, because you like your striped t-shirts a lot.

There was little time spent in examining the effectiveness of the k-value. Whether k=3 the parameter amounts 3 or 4 are most accurate is not determined. Further research on testing the algorithm is needed.

Furthermore, in the demonstrator the clothing recommendation is still based on the clothing the nearest profiles have and not the clothing which is available in the user's wardrobe. A way to recognize and suggest similar clothing that is available in a user's wardrobe needs to be taught to provide a more useful recommendation. This is something that should be developed further before launching this application.

Actuation and Feedback Loop

The feedback loop is an important aspect of the concept however a difficult subject to implement. Sensing what causes the user to choose a certain outfit is a challenging performance and given more time could have been explored better. At the moment the outfit chosen says something about what kind of style a user prefers to the system. This causes a feedback loop in which the k-nn would provide more outfits close to your chosen style. However, more variables are probably considered by the user to choose a certain outfit. Currently, these variables are not fed back into the system because it has no means of sensing that data. Whereas the ranking of each outfit is saved at the end of the day, this data is not yet used as feedback for the system to provide better recommendations for the user itself and for other similar users.

In the same manner as with the outfit choice, difficulty was found designing a way to capture what this ranking really means (i.e. temperature comfort or style liking) and use it as a more sophisticated input for better recommendations.

Social Aspects and Connectivity
Even though there are still a lot of uncertainties in the execution the concept provides a lot of interesting opportunities in connectivity and social settings. There are a lot of interesting systems and services to connect this system to. Unfortunately, these links have not been explored or tested out yet. This makes it difficult to say something about the feasibility of these connections.

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