What am I gonna wear?: Scenario-Oriented Recommendation

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ABSTRACT

Electronic Commerce on the Web is thriving, but consumers still have trouble finding products that will meet their needs and desires. AI has offered many kinds of Recommender Systems [11], but they are all oriented toward searching based on concrete attributes of the product (e.g. price, color) or the user (as in Collaborative Filtering). We introduce a novel technique, Scenario-Oriented Recommendation, which works even when users don't necessarily know exactly what product characteristics they are looking for.

Users describe a goal for a real-life scenario in which the desired product might be used, e.g. "I want something elegant to wear for my boss's birthday party". We use a Commonsense reasoning system to map between the goals stated by the user, and possible characteristics of the product that might be relevant. For example, the boss's birthday party suggests a higher value for the "formal vs. casual" attribute, than say, a child's birthday party. Reasoning is based on an 800,000-sentence Common Sense knowledge base, and spreading activation inference. Scenario-oriented recommendation breaks down boundaries between products' categories, finds the "first example" for existing techniques like Collaborative Filtering, and helps promote independent brands. We describe our scenario-oriented fashion recommendation system, *What Am I Gonna Wear?*.

ACM Classification:

General terms: Design, Algorithms

Keywords: Scenario-Oriented Recommendation, Commonsense Reasoning

INTRODUCTION

Suppose you are planning to attend your boss's birthday party, at his house. Thinking to yourself, "what am I gonna wear?", you decide to buy something nice, but not too formal, since he is a good friend, and also someone you respect. You are not quite sure, however, exactly what particular outfit or brand you want. So, you go to a department store, and try to find the ideal outfit, browsing through one brand after another, but nothing seems right. Then you see a salesperson and decide to ask him or her. What's the first thing you say?

It's no use just trying to ask for the location of specific brands, styles or sizes – that's what you are trying to figure out! Instead, you describe the situation of the party and ask for suggestions. The salesperson might respond with "If I was going, I'd wear…" or "Our more formal clothing is in this section…". Even if you don't get exact recommendations, it helps you on the road to making a decision.

What's going on here? What you're doing is communicating the *scenario of use* of a product, and the salesperson is helping you by using their common sense to map from a scenario to characteristics of clothing that are appropriate to the scenario. Only then can you begin exploring the search space of what the store has to offer, since it organized by product characteristics, not by scenario.

In this paper, we introduce a novel recommendation technique, *Scenario-Oriented Recommendation*. Unlike other recommender systems that require users to provide specific product attributes, our approach analyzes users' goals, and maps them to possible characteristics of the products that might be relevant. This capability is achieved by using Open Mind Common Sense, a knowledge corpus that contains 800,000 sentences about everyday life, gathered from Web volunteers. Using this resource, we successfully built a fashion recommendation system, *What am I Gonna Wear*?, as a prototype of a new kind of shopping experience.

The contribution of this paper is, to the best of our understanding, that it is the first recommendation system that is based on users' textual description of scenarios over a broad range of everyday situations. While a more sophisticated approach may be required for real-world commercial usage, we believe that this paper shows that it is practical to map between scenarios and products by using current Commonsense Reasoning technology.

The outline of this paper goes as follows. First, it clarifies how scenario-oriented recommendation may benefit people. It then introduces how such a system may be built, and, finally, discusses the implemented system.

Toward a New Shopping Experience

A clearer scenario of the proposed shopping experience is as follows. Each user has his/her own personal webpage that integrates online shopping and management of their personal collection of products (e.g. a wardrobe in the case of clothes). When the user, say, John, logs on to his personal page, he can see the photos of all kinds of merchandise he owns, (e.g. clothes, books, albums, etc.), his personal profile (e.g. "I like rock music and surfing. I care about global warming…"), and the links to his friends' pages. Several input entries are on John's webpage for searching his collected items as well as new products.

He can input descriptions like, "I am going to my boss's birthday party at his place. I want to find something nice, but not too formal...". The system can extract the styles within the text and prompts the suggestion by matching them with a collection of clothes, either items he already owns, or those available for purchase. By leveraging John's personal profile, collected items, and even the browsing/purchasing history of products, it can also make inferences about John's tastes and make better suggestions. Through the system's introduction with others who share similar tastes and interests, John will be able to locate his desired products more easily, because their online collections may provide good guidance.

Besides this major benefit, we also present four other capabilities that improve product searching activities:

It helps users to find the "first example". Some current recommender techniques, such as collaborative filtering, can provide suggestions only if they have users' purchase history. Scenario-oriented recommendation helps provide the "first example" to seed existing recommendation systems, and helps introduce new users to the recommendation activity. Even after the first example, it takes a while for traditional recommenders to build up enough history to provide a high level of confidence in the recommendations. A plausible strategy is to start with scenario-oriented recommendation, and let collaborative filtering "kick in" only after a sufficient history is developed.

It breaks down the boundaries between products' categories. It is almost a trend for a single piece of merchandise to blend different elements or concepts in this digital age, as peoples' life styles and thinking patterns become more and more heterogeneous. For example, Zhan's book, "The Economy of Aesthetics" [14] could be categorized into the following subjects: trends, business, design, popular culture, or sociology. Takashi Murakami's[1] graphics and toys span pop, Japanese comic, and commercial design styles. Porter tankers by Yoshida & Co.[2] can be used as attaché cases, backpacks, and shoulder bags. Scenario-oriented recommendation benefits the market by freeing customers from searching from one category to another, and by saving the sellers from the troublesome process of category development.

It encourages the formation of online communities. As in Liu and Maes's "InterestsMap" [9], a user's personal collection of products can be viewed as a form of identity. This identity captures his/her taste and interests, and serves as a fruitful resource for online social activities. We think that collections of real products, such as the online wardrobe in our example system, will be more authentic and personally meaningful than keyword descriptions used as profiles in today's online shops. If users upload their actual possessions to our recommender website, they will be able more inclined to take advantage of the system's suggestions in real life. Scenario-oriented recommendation allows users to find others sharing similar interests without actively searching for them. Community members will also be more likely to share similar interests than in forums organized around topic keywords.

It supports cross-domain product recommendation. It means that the system can give John suggestions about albums based on his purchase history of clothes or books. The reason is twofold. First, as discussed in InterestMap [9], users' tastes and interests extracted from the purchased products capture their personalities, and can therefore be applied to all kinds of merchandise domains. Second, one can browse all kinds of items in the collections owned by other members in the same community. For instance, while John is looking at the collection of someone in his biking community, he might find some albums very close to what he wants. This is a consequence of the previously mentioned benefit of encouraging the formation of online communities.

In addition to providing users a better shopping experience, scenario-oriented shopping may also lead to two consequences:

It shifts shopping from a store-centered to a customer-and-product-centered activity. In the flow of traditional shopping, customers often start out at a store (either physical or virtual), then figure out the store's organization, select and purchase a product. In scenario-oriented shopping, the starting point will be a personal portal where description of their situation will lead to connection with a store, search engine, group of products, or other resource. The customers and the products will become the centers of e-commerce activity, as they deserve to be.

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1 http://www.takashimurakami.com/

2 http://www.yoshidakaban.com/

It fosters independent brands with low marketing budgets by matching them with their target customers. The acceptance of the Internet as an e-commerce platform can potentially become a boon for independent brands providing products full of originality. Based on the capability of extracting and matching concepts, scenario-oriented recommendation allows these products to be found more easily. Hence, items

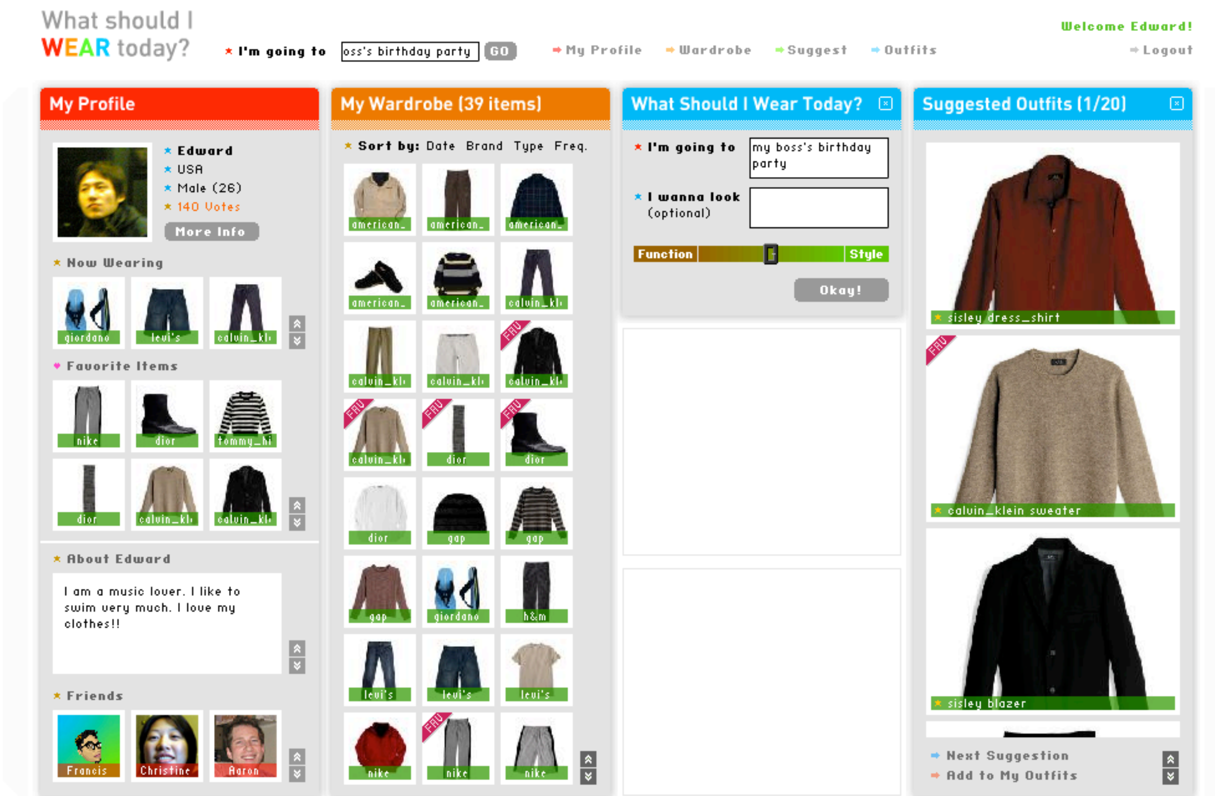


Figure 1: The fashion recommendation website with partial result for "I'm going to my boss's birthday party"

with high quality will not be overlooked because of insufficient marketing budget, and talented designers or creators will not be submerged. Product seekers need expend less effort to find idiosyncratic products expressive of their personal style.

What am I Gonna Wear

We implemented a fashion recommendation system, "What am I Gonna Wear?" (Figure 1), as an example for our theory. Each user has an online wardrobe that contains all his/her own clothing items. The clothes are labeled with brands (e.g. Nike), types (e.g. jeans), and can be annotated with English sentences to describe their styles (e.g. "This suit makes me look sexy"). There are two input entries for users to find items for particular occasions or moods, i.e., "I am going to …" and "I want to look more…". Based on commonsense reasoning, the system matches the clothes' styles and functions with the concepts needed for the context, and gives suggestion accordingly. It also relates the users to others sharing similar tastes, and allows them to browse each others' items, if they have permission to do so.

Currently, this system is not linked to any commercial websites, so it oriented around a user's personal wardrobe and does not provide any shopping functionality. However, as the reader can see below, we believe the approach can be easily extended to collections of products available for purchase at a store in addition to selection from the user's personal collection.

COMMONSENSE REASONING TECHNOLOGY

We now introduce our Commonsense Reasoning approach, and will describe how this technique can be applied to our example, the fashion recommendation system.

OMCS & ConceptNet

The knowledge used in our scenario-oriented fashion recommendation system is all derived from the Open Mind Common Sense (OMCS) website [13]. This is a project that aims to collect common sense such as, "You may use umbrella when it is raining", "A dog is an animal", etc. Currently, OMCS contains over 800,000 English sentences about commonsense, collectively contributed by over 20,000 users from the Web community. With projects collecting commonsense in other languages such as Portuguese, Korean, Japanese, Chinese, etc. based on the approach of OMCS [13], we believe that scenario-oriented recommendation may benefit more users in the future. On the other hand, the CYC Knowledge Base [6], which is also a huge commonsense corpus, contains more than 1,000,000 hand-entered data entries. CYC differs from OMCS that it uses a formal logic representation to minimize the ambiguity, as opposed to OMCS' natural language representation.

ConceptNet, developed by Liu and Singh [10], is an open-source tool for using the Commonsense knowledge collected in OMCS. It is a semantic network with 20 link types that describe different relations among things, events, characters, etc, and is the major technology used in our fashion system. Example relations in ConceptNet include:

- IsA(A, B) (e.g., "A [dog] is an [animal]")
- LocationOf(A, B) (e.g., "[Books] are in the [library]")
- UsedFor(A, B) (e.g., "[Forks] are used for [eating]")

In the example above, the "IsA" link, connects the two nodes, "dog" and "animal". Both of these nodes can be in turn connected with other nodes in various links as well. Depending on the inference goals, the links in ConceptNet can be used in different ways. For example, by applying spreading activation inferences can be made by propagating concepts (e.g., styles, functions, moods, etc) through the connected network, as will be discussed under "finding the styles" in the later section.

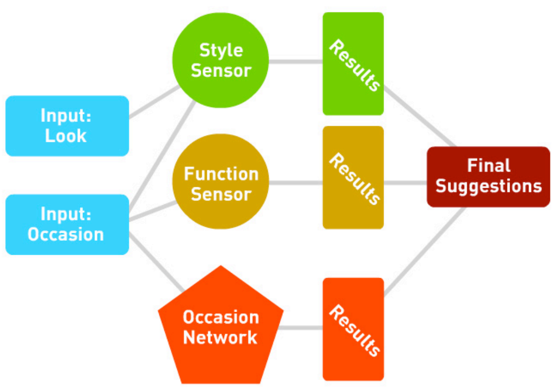


Figure 2: The architecture of the fashion system

SCENARIO-ORIENTED FASHION RECOMMENDATION

We now introduce the detailed design of the fashion recommendation system in Figure 1. Again, the system gives suggestions about what the users might want to put on according to a natural language description about the occasion and the desired style, their personal profile, and their online wardrobe. Each user has his/her clothing "items" (e.g., a cab or a pair of shorts) in the wardrobe, and also "outfits" that are combinations of several items including upper wear, lower wear, shoes, accessories, etc (e.g., a sports outfit for playing tennis). The system prompts outfits as its suggestions, and users can keep the suggestions for later use if they are satisfied. The selected outfits will be recorded as users' feedback to the system's recommendation for these particular occasions. Users can also make up the outfits by selecting the items themselves, or by asking their friends to make selections.

Concepts in Different Domains

Recommendation generation is the process of searching existing options that best suit the user's goal. If we can find descriptions that capture the characteristics in both the options and users' goals, then the problem will become matching the descriptions until the most similar pair is found. Therefore, the first step in scenario-oriented recommendation becomes determining the suitable descriptions, or, "concepts", for the two domains.

Consider the problem of looking for the appropriate outfit for a party or a meeting. What we wear may reflect our manner, taste, or how we regard the events and whom we interact with. Hence, one can define the domains in this matching problem as: a) how the clothes function and express our character, and b) what the occasions, and people we are to meet, mean to us. Accordingly, two types of concepts may be suitable for bridging these domains, namely, style and function, which we believe to be directly related the characteristics in both domains.

Thus, the recommendation problem is reformulated as matching the styles and functions in both users' clothing items and their input description. As will be introduced below, the input text of the scenario will be processed by a *style sensor*, a *function sensor*, and an *occasion network*. The input description of the look, on the other hand, will be processed by the style sensor only.

Style Sensing and Spreading Activation

Both the styles in users' input text and clothes will be sensed before they are matched. The styles are extracted according to four types of information, including the clothing items' brands, types, and materials, and words that are related to the occasions. All these types of information are processed with a uniform computational representation. We use a six-tuple to represent the dimensions of the concept "style", including luxurious, formal, funky, elegant, trendy, and sporty. Using this mathematical form, we are able to express the style for any pieces of clothing, and for any English sentences or phrases.

We hand-crafted a key file for each of the four information types. Each of the six numbers for a key ranges from 0 to 10. Example keys are:

- Levi's: [4, 2, 7, 3, 6, 6]
- Shirt: [7, 8, 4, 6, 5, 1]

As the reader can see, the formal and elegant values are high for shirts, the funky value for the brand Levi's is higher than all its other dimensions, and so on. Based on the handcrafted keys, the default style value for any clothing item can be derived by averaging its brand, type, and material, (and natural language description, if provided) when it is uploaded. Users can also adjust the values by dragging the scrollbars on our graphical user interface, if they do not agree with the default style.

All the possible brands, types, and materials need to be listed in the style key files, but not all the occasions. This is because it is difficult for the system to infer the style for an unknown brand, but, using commonsense reasoning our system can guess the style for any English word, even if it does not appear in the occasion key file.

Following the affect sensing approach by Liu et al [8], we achieve style inferencing by performing spreading activation in ConceptNet. For each procedure during spreading activation, the style value of a node in ConceptNet is propagated outwards to its neighboring nodes with a discount factor *d* (0.25 in our system). So, suppose the word "wedding" is in the occasion key file, but "church" and "chapel" are not. Then, because of the two existing relations, LocationOf(wedding, church)and IsA(chapel, church), in ConceptNet, after the first iteration, the word "church" will have the style [1.25, 2.25, 1.25, 2.25, 1.25, 0.25], and word "chapel" will in turn become [0.3125, 0.5625, 0.3125, 0.5625, 0.3125, 0.0625]. Based on this approach, our system successfully provides plausible style sensing outcome for any usual English words, with only several tens of words in the occasion key file.

Function Sensing

Unlike style sensing, when finding the function for clothes and occasions, only three relations in ConceptNet are employed, namely, "used for", "location of", and "capable of receiving action". We use these relations to find the possible occasions for the clothes according to their types, and match them with the input description during the online interaction. For the example input, "I am going to swim", swimsuit will be prompted as an suggestion, because swimming is a possible occasion for wearing a swimsuit according to the UsedFor(swimsuit, swim) relation appearing in ConceptNet.

It is a different approach from the style-sensing algorithm. The reason is, since function is a one-to-one relationship, it is unsuitable for spreading activation. To give an example, using spreading activation for function sensing will match "raincoat" for "going to the beach", because they are both related to the concept "water".

Personalization and Social Recommendation

In the above subsections, we discussed how we apply commonsense to the decision making process. Users' own personal wearing style, however, is extremely important too. Our system gradually learns individuals' tastes and wearing habits along the interaction, which makes it a real personalized recommendation tool. While the textual network derived from OMCS provides linkage information between conceptually-related words or phrases [10], items in our system are also linked if they share similar styles. We call this the *occasion network,* as shown in Figure 3. When a user presses the "Wear it now" button, the system attaches the input occasions to the selected items, and the occasions will be spreading activated through the links between items. Therefore, if, say, I wear a T-shirt for going bowling today, the system will not only learn that I'd like to wear this T-shirt for bowling next time, but also some pair of shoes, jeans, or another T-shirt, if similar with this T-shirt.

We also detect users' personal styles within resources such as their textual personal profiles, their wardrobes' average styles and so on. The detected styles are used as another approach toward personalized recommendation. (For example, if the user is fond of sports, i.e., having a profile with a high sporty value, the items with higher sporty values will be preferred.) Meanwhile, they are also used to relate different users, as mentioned in the previous section of scenario-oriented recommendation's benefits.

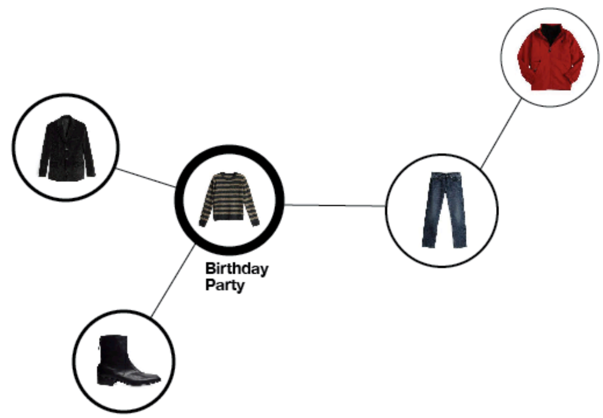


Figure 3: A partial example of the occasion network

Using the Fashion Recommendation System

We now show some results of the fashion recommendation system. Table 1 provides the system's recommendation for several different scenarios. Each row has a natural language description in its left-most column, and its other columns show the suggestions based on this description. We try to make the recommendations complete outfits, but, say, if the styles of all the possible shoes' scores are below our specified threshold, the system will not recommend any shoes, and will let the users make their own decision.

The first row and the second row are used to show our system's capability of recognizing the styles in different occasions, i.e., "going to the beach" is a sportier and more casual event, whereas going to a dinner is relatively more formal and elegant. Also, the system detects the needed function of clothing for going to the beach, and gives the recommendation of a swimsuit. The remaining two rows can be compared with the second one. They both share the same content with the second one, but more information is provided to contribute to the overall style. That is, "look more casual" and "with my boss" made the result more casual and formal, respectively. (Note that in the case of the third row, the text in both input entries are utilized, while only one of the entries are used in the forth one.)

EVALUATION

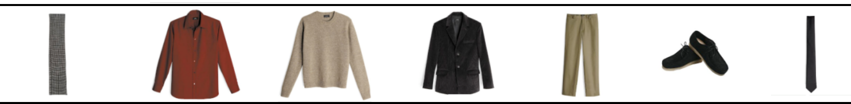
In order to examine the usability of our fashion recommendation system as well as our theory of Scenario-Oriented

Recommendation), we conducted a pilot study of this system, described in the following subsections.

The Experiment Setting

There are 7 subjects in this study, all of which are either graduate or undergraduate students at MIT. All these subjects are male, since all the clothing items in our testing database are for men, and there are 3 nationalities among

Table 1: Example results of the fashion recommendation system

I am going to the beach	
I am going to have dinner	
I am going to have dinner. I want to look more casual.	
I am going to have dinner with my boss	

these subjects. There are totally 87 items in the database, categorized as 23 upper-inner wear, 7 upper- middle wear, 15 upper-outer wear, 16 lower-outer wear, 16 foot wear, 6 head wear, 3 neck wear, and 1 swimming suit. Each of these major categories contains several item types. For example, upper-inner wear contains dress-shirt, tank-top, short-sleeved-Tee, etc.; lower-outer wear contains jeans, dress-pants, cargo-shorts, etc.; and neck wear contains tie, and scarf. Totally there are 82 types and 21 brands, all of which are assigned with style values, varying from 0 to 10. All the types are assigned with function values as well. We rate these values according to our understanding of how these brands or types are generally considered by the public, and, as the reader can see from the experiment result, the users still found the system helpful even though these values are not rated according to any formal statistical experiment.

The main part of the study comes in two stages. In both stages, the subject is asked to find clothing items that he would want to put on the most, according to the given scenarios, the weather of the day that the test takes place, and conditions freely assigned by the subjects if unspecified. A traditional online catalog, where the items are grouped in categories, is provided in the first stage; whereas in the second stage, the subject is free to switch between the traditional interface and our recommendation system (which is the default interface) at all time. Our system generates, for each category, a list of items sorted by the recommendation score in the second stage. Links to the corresponding categories on the traditional catalog are provided too. Finally, they were asked to fill a 3-page questionnaire.

The subjects are asked to complete the item-searching task for 7 scenarios in both stages. Specifically, there are two blanks to fill for each scenario, namely, "I want to look more___" and "The id numbers of what I want to put on are__ ". The scenarios may include places, social relationships, goals, and so on, such as, "I am going to the bookstore to find something interesting to read". There are two scenario sets, A and B, each containing 5 specified and 2 unspecified scenarios. For the first three subjects, set A is used in the first stage and set B in the second stage, and for the rest four subjects A, B are interchanged.

The goal of this study is to investigate, given real-life scenarios, whether the following claims hold true: 1) the system provides useful item recommendation, 2) the recommendation makes the subjects' item-searching and outfit-making process easier, and 3) the recommendation service is desirable in fashion stores. The items are shown in categories because the test is not designed for answering whether it recommends useful outfits, since more criteria need to be satisfied (e.g. aesthetics). And, we choose the traditional catalog in the control group as opposed to our system in the experiment group. This is because, as we claimed that this is the first scenario-oriented recommendation tool, it is difficult to find another system that functions under the same experiment setting.

Results

The questionnaire has 17 questions in 5 point Likert scale. Figure 4 shows the statistical results with regard to the first and second study goals. The numbers on the x-axis are corresponded with the numbered questions in Table 2. The numbers in the y-axis, on the other hand, are the subject's agreements to the questions (strongly disagree:1, strongly agree:5). As the readers can see, the reactions of the subjects are generally supportive with regard to the first and second claims. Having no questionnaires filled prior to our pilot study, if we use "neutral" as users' answers to all the questions before participating the test, we will get $p<0.05$ in the pooled variance t test for all the questions, showing the test result statistically significant. The time that subjects took was also measured. On average, the subjects took 11 minutes 0 seconds to complete the first stage and 11 minutes 5 seconds (0.76% bigger) for the second one. That is, the times that the two stages take are virtually identical. Nevertheless, there were occasions where non-native English speakers had misspelling or wording problems. Therefore, from subjects' agreement in the questionnaire, we claim that finding clothes under the help of the recommendation system is either equally or more efficient than using traditional catalog. To

Table 2: The questions listed in the questionnaire

1. Generally speaking, you like the recommendation that the system provides.
2. Generally speaking, you find the recommendation useful.
3. The recommended clothing items are appropriate for the scenarios.
4. You have never seen or heard of any systems that can give recommendation based on the real-life scenario
5. In terms of style of the clothing items, the recommendation makes sense
6. In terms of function of the clothing items, the recommendation makes sense.
7. The recommendation system makes the decision making process more efficient.
8. The recommendation helps you to understand more about the scenario and to realize the styles that the scenario can possibly have
9. It is easier to decide on the clothing items with the recommendation
10. It is easier to decide on an outfit with the recommendation
11. It is fun to use the recommendation system
12. When containing no exactly desired clothing items, the recommendation still gives you inspiration for items for the scenario
13. All in all, you would like to use this system when you need to find clothes or outfits for certain scenarios

discuss the result with regard to the third claim, we plot the statistical result for four of the questions in Figure 5. The four respective questions for the four bars are, from left to right, whether the subject, as a customer, think this service should be provided in online fashion stores, in physical stores as a customer, in online stores as the owner of the store, and in physical stores as the owner. From this chart we can see that more than 80% of the subjects agree or strongly agree the recommendation system to be used in online stores, whether from customers' or owners' points of view. For physical stores, on the other hand, subjects are relatively conservative about the necessity of this system, even though the results are still positive (>50%). We think this is very likely to match our first claim that online shopping needs to be assisted with scenario-oriented recommendation because there is no salesperson that you can ask. Even though this statistical result may possibly be reflecting other problems such as the potential difficulty of interacting with the system in a physical shopping situation, at least up to this stage, the result is supportive to our claim.

One other interesting thing in this figure is that, our subjects tend to agree to have this recommendation system in the stores if they are standing from the owners' point of view. After looking at the comments and talking to them, we suspect that this might come from the fact that some subjects do not like the item database, either because they dislike the brands that we chose, or they have to choose something less appropriate in terms of style and/ or function because they do not like the most appropriate ones. As the owner of a fashion store, we suspect that they would feel more comfortable and controllable of all the items in the database.

In summary, this study shows that the this system provides useful clothing item recommendation under specified scenarios, makes the decision-making process easier, and is desirable in either online and physical stores (to different degrees). Nevertheless, it is only a pilot study, meaning that the subjects of more diversity (e.g., gender, age, nationality, race, etc.) and more complicated experiment setting need to be involved in order to investigate more into the problem.

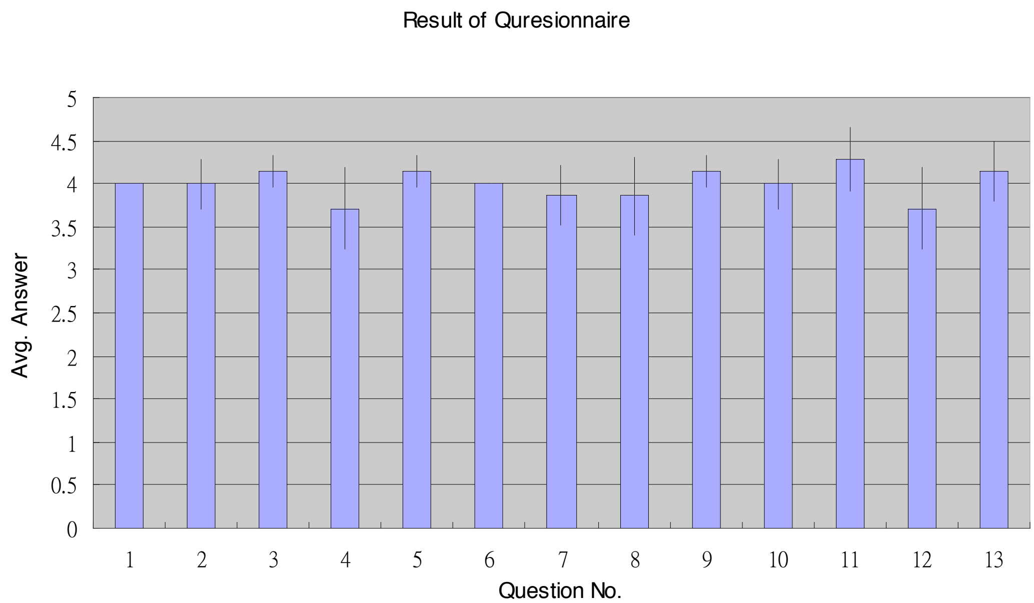


Figure 4: The average and standard deviation of the answers to questions in the questionnaire

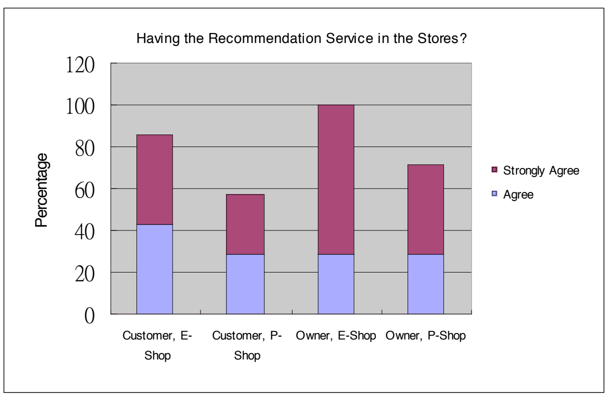


Figure 5: The willingness chart of having the recommendation service in online/physical stores

RELATED WORK

The term "recommender systems" typically refers to systems that suggest books, music albums, from a set of input parameters, possibly including user profiles, purchase history, product attributes, etc. In recent years, a popular technique has been Collaborative Filtering [11], which works by clustering users' purchase history. While capturing the "word- of-mouth" concept, many of these systems do not consider users' goals in the search activity. More advanced systems take into account users' goals such as preferences or even lifestyles [1, 3, 5, 12]. These systems try to capture users' goals by applying critiquing interaction, complex user models, and other techniques, but they either require users to provide specific descriptions in terms of product attributes, or require that the correspondence between scenarios and product attributes be explicitly coded. Our approach differs from all the above techniques in that, thanks to the commonsense reasoning technique, a broad range of scenarios and user goals can be covered without explicitly programming them, and implicit goals can often be recognized.

As for the input modality, most systems use check boxes and forms that are by nature suitable for narrowing down the search domains. There are also approaches enabling natural language descriptions [4], or even face-to-face interaction [2], but discourse is limited in a specific domain as well. In short, none of these systems allows users to input scenarios using a broad range of natural language descriptions.

CONCLUSION

In this paper, we introduce a novel recommender technique, *Scenario-Oriented Recommendation*. Based on OMCS, a knowledge corpus containing common sense about people's everyday life, it is the first technique providing product suggestions based on real-world user scenarios across a broad range of topics. It helps users by matching the characteristics of the circumstances and the possible products, and helps people to determine the ideal products more easily, even if they don't know what exactly that might be. We list six other benefits enabled by scenario-oriented recommendation, and describe design details of our prototype system, *What am I Gonna Wear?*. Not everybody is rich enough to have a personal shopping assistant, but with scenario-oriented recommendation, maybe we can give them the next best thing.

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