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A generalized taxonomy of explanations styles for traditional and social recommender systems

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Abstract Recommender systems usually provide explanations of their recommendations to better help users to choose products, activities or even friends. Up until now, the type of an explanation style was considered in accordance to the recommender system that employed it. This relation was one-to-one, meaning that for each different recommender systems category, there was a different explanation style category. However, this kind of one-to-one correspondence can be considered as over-simplistic and non generalizable. In contrast, we consider three fundamental resources that can be used in an explanation: users, items and features and any combination of them. In this survey, we define (i) the Human style of explanation, which provides explanations based on similar users, (ii) the Item style of explanation, which is based on choices made by a user on similar items and (iii) the Feature style of explanation, which explains the recommendation based on item features rated by the user beforehand. By using any combination of the aforementioned styles we can also define the Hybrid style of explanation. We demonstrate how these styles are put into practice, by presenting recommender systems that employ them. Moreover, since there is inadequate research in the impact of social web in contemporary recommender systems and their explanation styles, we study new emerged social recommender systems i.e. Facebook Connect explanations (HuffPo, Netflix, etc.) and geo-social explanations

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that combine geographical with social data (Gowalla, Facebook Places, etc.). Finally, we summarize the results of three different user studies, to support that Hybrid is the most effective explanation style, since it incorporates all other styles.

Keywords Recommender systems · Explanations · Social justification

1 Introduction

Explanation in intelligent systems has its origins in the area of Expert Systems (Andersen et al. 1989; Buchanan and Shortliffe 1984; Hunt and Price 1988; Lopez-Suarez and Kamel 1994; Wick and Thompson 1992; Lacave and Diez 2004). This research has largely been focused on what kind of explanations can be generated and how these have been implemented in real world systems (Andersen et al. 1989; Hunt and Price 1988; Lopez-Suarez and Kamel 1994; Wick and Thompson 1992). When a user receives an explanation, he can accept a recommendation more easily because the system provides transparency to its recommendation. Due to this virtue, explanations have been studied in many different research areas, such as Human Computer Interaction (Nielsen and Molich 1990; Pu and Chen 2006), User Modelling (O'Sullivan et al. 2004; Paramythis et al. 2001; Sinha and Swearingen 2002), E-Learning systems (McCarthy et al. 2004) and Knowledge-Engineering (Lacave and Diez 2002). Most of the aforementioned explanation styles can also be found in the recommender systems research field.

Recommender systems are gaining widespread acceptance in e-commerce applications as a way of tackling the "information overload" problem. The acceptance of a recommender system is increased when users can understand the strengths and limitations of the recommendations (Herlocker et al. 2000; Adomavicius and Tuzhilin 2005; Tintarev and Masthoff 2007). This can be attained when users receive, along with a recommendation, the reasoning behind it. Such a combination is called an *explained recommendation*. For instance, in e-commerce, justified recommendations help improve customer attraction/retention and boost sales, because customers can evaluate the provided recommendations more easily and accept them if satisfactory (Herlocker et al. 2000). In other words, the ability to request an explanation provides us with a mechanism for handling the possible error that comes with a recommendation. Consider how we as humans handle suggestions as they are given to us by other humans. We recognize that other humans are imperfect recommenders. In the process of deciding whether to accept their suggestions, we might consider the previous performance of the recommender or we may compare the recommender's general interests to our own. However, if there is any doubt, we will ask "Why?", and let the recommender explain his reasoning behind the suggestion. Then we can analyze the logic of the suggestion and decide if the evidence is strong enough. The need for justification is nowadays even more crucial, due to *shilling attacks* by malicious web robots, which favor or disfavor a given item. In a recommender system that is under a shilling attack and does not provide justifications, users cannot understand why they receive incorrect recommendations (possibly with offensive material) resulting from such an attack.

As the need for justified recommendations has started to gain attention, several collaborative filtering recommender systems, like that of Amazon, adopted the following style of justification: "Customers who bought item X also bought items $Y, Z, \ldots$", or "Customer U rated items Y, Z highly". This is the so called "Human" style (Bilgic and Mooney 2005) of justification, which is based on humans performing similar actions (buying/rating items, etc). In contrast, with the so called "Item" style, justifications are of the form: "Item/activity Y is recommended because you rated/bought item/activity X".[1] Thus, the system isolates the item X, that influenced the recommendation of item Y the most. Bilgic and Mooney (2005) claimed that the Item style is better than the Human style, because it allows users to accurately formulate their true opinion of an item.

Pure Content-based filtering systems (Mooney and Roy 2000; Pazzani and Billsus 2002; Burke 2002) assume that each user operates independently and they recommend an item/activity to a user based upon a description of the item/activity which matches an explicitly given user profile of user's interests. There are also other Content-based filtering systems which extract features from the items the user already bought/liked/etc. This could be termed an implicitly given user profile. The description of each item/activity comprises certain relevant features and is recommended to the user if one or more of these features match the user's interests. For example, a restaurant may have features such as location, cuisine and cost. If a user, in his profile, has set his preferable cuisine to be Chinese, then the Chinese restaurants will be presented to him. The explanation behind the recommendation will be based upon the corresponding features, i.e. in this case Chinese cuisine. This kind of explanation is called "Feature style". Other recommender systems that adopt this style of explanation are the Conversational and the Critiquing-based Recommender Systems (CRS). The former try to capture user preferences based on an on-going natural language dialogue. The latter ask the user to provide his preferences and recommend specific items/activities, and then elicit user's feedback in the form of critiques such as "I would like something cheaper". Of course, the limitation of these systems lies upon the fact that other people's preferences are not considered.

To overcome this limitation, several recommender systems have proposed the combination of content data with rating data (Balabanovic and Shoham 1997; Jin 2005; Melville et al. 2002; Salter and Antonopoulos 2006). The combination of content with rating data helps capture more effective correlations between users or items, which yields more accurate recommendations. However, besides the improvement of accuracy of recommendations, the consideration of content can provide high quality justifications as well. Thus, by exploiting Content-Based techniques, many CF systems (Billsus and Pazzani 1999; Mooney and Roy 2000) were able to provide robust explanations for their recommendations. To further understand the merit of a "Hybrid" justification style, consider the following example:

Example 1 Assume an internet newspaper (e.g. Huffington Post) that recommends news articles. Users may express interest about an article based on particular features

[1] Amazon also offers influence style justification through a link named "Why was I recommended this?" next to the recommended items (accessed: 9 Nov 2010).

in it, like its category (politics, athletics etc.), author, or specific terms that it contains. A user has highly rated several articles about scientific news referring to global warming. If the system decides to recommend another such article X, then a Hybrid style justification can be like: "Article X is recommended because its category is Scientific News and contains the terms {global, warming}, which are features contained in articles you rated highly". In contrast, an Item style of explanations will be: "Article X is recommended because you rated article Y". The latter justification burdens the user to make the connection between articles X and Y and understand, e.g., that both refer to global warming. In a system containing thousands articles, such an effort can be rather discouraging for the users. Thus, the Hybrid style of explanations can be very convenient and more effective because users receive explanations with multi-modal information. Notice that since the mentioned hybrid style is based on two types of data (i.e. content and rating data) is called 2-D hybrid explanation style.

Apart from the blending of content with rating data, Social web has allowed the emergence of new data combinations that can provide even more robust "Hybrid Explanations". For instance, social networks such as Facebook, Hi5, etc., include information about the connections (link data) between humans. These link data can be combined with rating/feature data of the user/item profile, i.e. Facebook data can be joined with rating/content data from other sites such as HuffPost, Netflix, etc. to provide multi-modal hybrid explanations. To support this claim, consider again our previous example with the Huffington Post internet newspaper.

Example 2 By combining content/rating data with social graph data a multi-modal Hybrid style can be like: "Article X is recommended because its category is Scientific News and contains the terms {global, warming}, which are features contained in articles you and 10 of your friends rated highly". Thus, the combination of social graph data with content/rating data can even more leverage the robustness of hybrid explanations by providing 3-D hybrid explanations that use ratings, features and humans.

Notice that there are also other new emerged social recommender systems which combine social graph data with other resources such as tags. For instance, Vig et al. (2009) introduced "tagsplanations", which are explanations based on community tags. Moreover, the social graph data can be combined with geographical data to enhance location-based services, i.e. geo-social recommendations (Backstrom et al. 2010; Zheng et al. 2010). Geo-social explanations will either be location-based or activity-based. To the best of our knowledge, there is inadequate research in the impact of social graph web in contemporary recommender systems and their explanation styles. In Sect. 2.4, we will discuss about the impact of social web in details.

Up until now there has been a lot of research on evaluation of explanations (Tintarev and Masthoff 2011, 2007; Vig et al. 2009; Symeonidis et al. 2009; Bilgic and Mooney 2005; Herlocker et al. 2000). However, many of these works conducted user studies that have been designed to show different conclusions and targeted on specific explanation styles. In this paper, we summarize the results of different user studies (by integrating their results) to support our basic claim, that Hybrid is the most effective explanation style since it can incorporate all other styles. Notice that the above claim could not be easily extracted if we looked at each user study separately. In Sect. 3, we will analyze and comment on the integrated user studies in details.

The contribution of our work is fourfold. First, we define a generalized taxonomy of explanation styles by categorizing the existing explanation styles into four categories: Human, Item, Feature and Hybrid. Secondly, for each category, we demonstrate how these styles are put into practice, by presenting recommendation systems employing these styles. Thirdly, we study the impact of social graph in contemporary social recommender systems and their explanation styles, i.e. Facebook Connect recommendations with HuffPost, Netflix etc. and geo-social recommendations (Backstrom et al. 2010; Zheng et al. 2010). Finally, we summarize the results of three different user studies, which measure the user satisfaction for each explanation style, to support that Hybrid is the most effective explanation style, since it incorporates all other styles.

The rest of this paper is organized as follows. In Sect. 1.1 we define a generalized taxonomy of explanation styles. Section 2 presents the aforementioned explanation styles by demonstrating their usage in various recommender systems. Section 3 deals with case studies that were conducted to measure user satisfaction against these explanation STYLES and finally Sect. 4 concludes this paper.

1.1 Motivation and definition of a generalized taxonomy of explanations

The motivation of our survey is based on the fact that up until now, the type of an explanation style was considered in accordance to the recommender algorithm that employed it (Tintarev and Masthoff 2011, 2007). For example, in Tintarev and Masthoff (2007) works, each recommender system category, (i.e. collaborative, content-based, conversational, demographic, knowledge/utility-based, etc.) corresponds to the same explanation style category, (i.e collaborative, content-based, conversational, demographic, knowledge/utility-based, etc.). However, we strongly believe that this kind of one-to-one correspondence is simplistic, inefficient and cannot be generalized.

In contrast to this kind of categorization, we consider three fundamental resources that can be used in an explanation: users, items/activities, features and any combination of them. In other words, we define (i) the Human style of explanation (Human), which provides explanations based on similar users, (ii) the Item style of explanation (Item), which is based on choices made by a user on similar items and (iii) the Feature style of explanation (Feature), which explains the recommendation based on features of an item that were rated by the user beforehand. By using any combination of the aforementioned styles we can also define the Hybrid style of explanation (Hybrid). Figure 1, demonstrates the various explanation style combinations that can exist.

As shown in Fig. 1, the explanation style of a recommender system at the first level (1-D explanations) can solely depend either on a user (human), or on an item feature (feature), or on an item (item). This is because the main information that is stored in the heart of a recommender system's database refers to users, items, or item features. Therefore it is logical to produce explanations based on these resources. The second level in Fig. 1, represents the explanation styles which adopt any combination of two of the above styles (2-D hybrid explanations). The third level in Fig. 1, comprises of explanation styles which adopt all three explanation styles (3-D hybrid explanations). Notice that our model can be easily expanded to express higher order

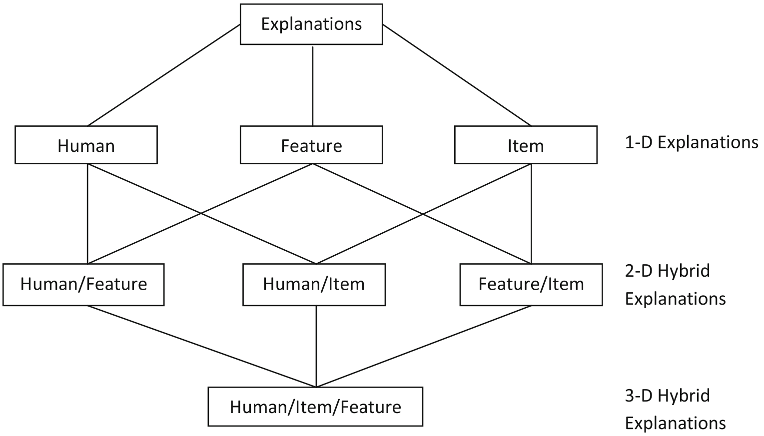


Fig. 1 Possible explanation style combinations

Table 1 A list of selected recommender systems and their respective explanation style

Explanation style	Example
Human	Recommended this book because customers who bought it also bought books Y, Z, …
Item	Recommended this book because you rated/bought book X
Feature	Recommended this book because it contains the terms (global, warming),which are features you are interested in
Human/Item (2-D Hybrid)	Recommended this book because you rated it highly and three other similar users have bought it
Human/Feature (2-D Hybrid)	Recommended this book because three of your Facebook friends have rated it highly and it contains features that you are interested in
Feature/Item (2-D Hybrid)	Recommended this book because it contains the terms (global, warming) which are features you are interested in and you have also rated similar books highly
Human/Feature/Item (3-D Hybrid)	Recommended this Cuban restaurant because you rated similar restaurants highly, many of your friends have eaten there and you like spicy and crispy food

dimensions by incorporating other resources such as time dimension. However, for paper readability purposes we focus only on the aforementioned three resources since the majority (Tintarev and Masthoff 2007, 2011) of real recommender systems are based on them. Table 1 presents an example for each one of the seven different explanation styles that are derived by our three-dimensional model.

Based on our three-dimensional explanation model, we are now able to distinguish a recommender algorithm from an explanation style that a recommender system provides. In Sect. 1 we have already discussed the Content-based, Collaborative Filtering and Critiquing-based algorithms. However, there are many other categories of algorithms that can provide recommendations. For example, Context-aware algorithms (Adomavicius and Tuzhilin 2008) take into account for a recommendation any

Table 2 Recommender algorithms versus explanation styles

Recommender algorithms	Explanation styles						
	1-D			2-D			3-D
	Human	Feature	Item	Human Feature	Human Item	Feature Item	Human Feature Item
Collaborative Filtering (Herlocker et al. 2000)	X						
Content (Mooney and Roy 2000; Pazzani and Billsus 2002; Burke 2002)		X	X			X	
Critiquing (Pu and Chen 2006)		X	X			X	
Context aware (Adomavicius and Tuzhilin 2008)		X	X			X	
…	…	…	…	…	…	…	…
Multi-criteria (Adomavicius et al. 2010)		X	X			X	
Social tagging (Vig et al. 2009; Marinho et al. 2010)	X	X	X	X	X	X	X
Trust aware (Golbeck 2005; Massa and Avesani 2007)	X	X	X	X	X	X	X

additional contextual information, such as time, location, weather, or the company of other people. Moreover, multi-criteria recommender algorithms (Adomavicius et al. 2010) provide recommendations by modeling a user's utility for an item as a vector of ratings along several criteria. Social tagging recommender algorithms (Vig et al. 2009; Marinho et al. 2010) provide recommendations by combining data from users, their tags, and the tagged resources. Trust-aware recommender algorithms (Golbeck 2005; Massa and Avesani 2007) provide recommendations based on graph (link connections among users which trust each other) and rating (their preferences on items) data. Table 2 presents a list of recommender algorithm categories along with the possible explanation styles that each one can support.

As shown in Table 2, the Human and Feature explanation styles can be provided by Collaborative Filtering/content algorithms respectively. This is obvious since their basic algorithmic elements are the users/features, respectively. However, if an algorithm combines user-based and content-based aspects, depending on which elements it uses, it can support the explanation style that corresponds to these basic elements (e.g. three possible explanation styles: Human, Feature, and 2-D Human/Feature). Notice the fact that human style requires algorithmic processing of data with users and that Feature style requires the algorithmic processing of data with features. Moreover, as shown in Table 2, we have to underline the fact that algorithms that process feature characteristics of items could also provide item explanations, after an appropriate heuristic algorithmic process that transfers the feature ratings to predict a rating for the item.

Finally, a list of real recommender systems that will be presented in this paper along with the explanation style(s) they adopt are shown in Table 3. As shown, in the eighth row of Table 3, Amazon.com can explain a product recommendation to a target user, by providing as explanation other users with similar tastes that also bought it (Human style) or because the target user bought a similar product (Item style). Obviously, Amazon.com can also provide a combination of the above styles (e.g. Human/Item 2-D style). Moreover, in the last row of Table 3, geo-social recommender system, can provide a 3-D explanation style. For example, an activity (e.g. visit in a museum) is recommended to a target user because (i) many of his friends have performed this activity, (ii) he has shown an interest in similar activities and, (iii) he has rated highly some of its features.

2 Explanation styles

In this Section, we demonstrate how the four explanation styles that are defined in the previous Section are put into practice, by presenting recommender systems that employ them. These systems are the following:

Human style	Item style	Feature style	Hybrid style
MovieLens	Amazon	Libra	Tagsplanations
Amazon	Ebay	Organization Interface	MoviExplain
Facebook	Netflix	Top Case	HuffPost, Netflix
Rec. Widget	Geosocial		Gowalla, Foursquare, Facebook Places

We also mention other recommender systems that offer an explanation along with the recommendation.

2.1 Human style of explanation

Explanations which adopt the Human style utilize other users and their preferences to justify their recommendations. Usually the explanation is of type "Customers who bought/rated item X also bought/rated items Y, Z, ...". The Human style relies on the premise that both the target user and the users which were used as an explanation have similar interests.

Herlocker et al. (2000) was among the first to suggest that one of the reasons behind the low acceptance of recommender systems in high-risk domains such as holiday packages or investments portfolios was the black box image of recommender systems. They claimed, as a solution to this problem, that the computational models being used in the development of recommender systems need to be explained to the users in the form of understandable, effective and acceptable recommendations. They present a method for providing explanations based on the user's conceptual model of the recommendation process. To address the reason why recommendations need to

Table 3 Recommender systems versus explanation styles

Recommender systems	Explanation styles						
	1-D			2-D			3-D
	Human	Feature	Item	Human Feature	Human Item	Feature Item	Human Feature Item
Recommender Widget (Guy et al. 2009)	X						
MoviExplain (Symeonidis et al. 2009)						X	
Organization Interface (Pu and Chen 2006)		X					
Top Case (Mcsherry 2005)		X					
Libra (Mooney and Roy 2000)		X					
MovieLens (Herlocker et al. 2000)	X		X		X		
Amazon (www.amazon.com)	X		X		X		
Facebook (www.facebook.com)	X		X		X		
Netflix (www.netflix.com)	X		X		X		
Gowalla (gowalla.com)	X		X		X		
Foursquare (foursquare.com)	X		X		X		
Tagsplanations (Vig et al. 2009)		X	X			X	
Face book + Netflix	X	X	X	X	X	X	X
Geo-social (Zheng et al. 2010)	X	X	X	X	X	X	X

be explained, they present experimental evidence, which shows that providing explanations can improve the acceptance of the recommender systems (Herlocker et al. 2000).

The white box conceptual model of Herlocker et al. (2000) proposes 21 different interfaces of explaining collaborative filtering (CF) recommendations. They demonstrated that the Human style is persuasive in supporting explanations. To prove this,

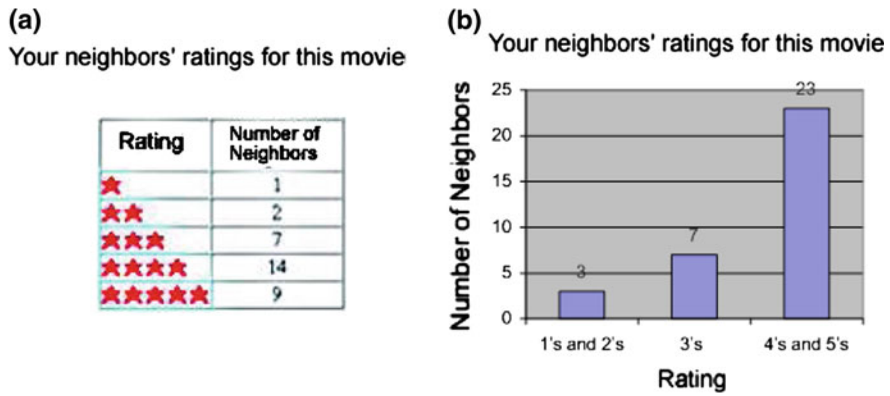


Fig. 2 Two explanation interfaces which where tested to measure the response of the users

Fig. 3 Human explanation style of Amazon.com

they conducted a survey with 210 users of the MovieLens recommender system, demonstrating that explanations can improve the acceptance of CF systems. Most users would like to see them added to CF systems. One can see two of these interfaces in Fig. 2. In Fig. 2a, the user is presented with the exact ratings that his neighbors have entered. In Fig. 2b, the interface displays a histogram of neighbors' ratings for the recommended item. Explanation of Fig. 2b proved to be the best performing explanation.

Even though, Herlocker et al. proved that this approach can improve the acceptance of the recommender systems and consequently persuade users to try an item, it was later proved that this approach is less effective at helping users make accurate decisions (Bilgic and Mooney 2005).

Another recommender system that provides explanations based on the Human style is the online E-Commerce store Amazon.com (http://www.amazon.com). As shown in Fig. 3, the user is presented with similar items that other customers have chosen to buy. This explanation assumes that the user is viewing an item which they are already interested in. The Amazon system then finds similar users, who have already bought that specific item, and recommends the items that they bought to the user.

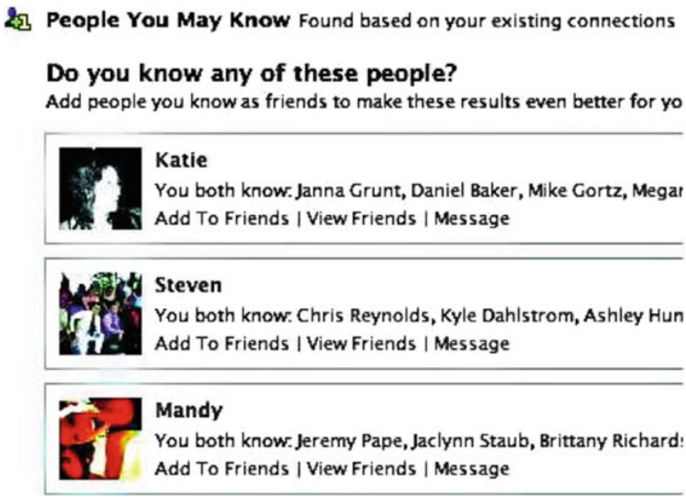


Fig. 4 Human style of explanation provided by Facebook.com

Online social networks (OSNs) such as Facebook.com (http://www.facebook.com), Myspace,[2] Hi5.com,[3] etc. contain gigabytes of data that can be mined to make predictions about who is a friend of whom. OSNs gather information on users' social contacts, construct a large interconnected social network, and recommend other people to users based on their common friends. The reason is that there is a significant possibility that two users are friends, if they share a large number of common friends. The explanation behind the friend recommendation falls under the Human style category since a friend is recommended to a user based on their common friends, i.e. because that friend has selected similar people to be common friends with the user. As shown in Fig. 4, Facebook offers a "People You May Know" list of users which are possible friends of a target user, based on his existing connections with other users.

The reasoning behind the recommendations is also shown, by providing the mutual friends that the two users share. For instance, in Fig. 4, the first possible friend of the target user is Katie because they share 4 friends, Janna Grunt, Daniel Baker, Mike Gortz and Megan. The target user can then add as friend any person he may know, from the proposed list.

Finally, a fourth recommender system that provides Human style is the Recommender Widget in Guy et al. (2009). Figure 5 depicts the widget for providing item recommendations. The user is presented with five items consisting of a mix of bookmarked pages, communities and blog entries. Every item has a title which is a link to the original document and a short description if available. It also includes a list of up to five person names that are related to the item. Each person provides an explanation of why the item is recommended. When hovering over a name, the user is presented with a popup detailing the relationships of that person to the user and to the item.

[2] http://www.myspace.com.

[3] http://www.hi5.com.

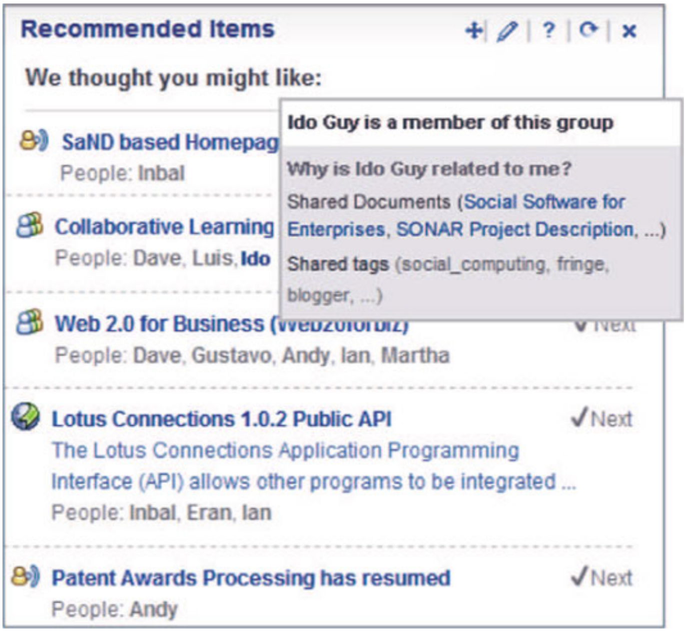


Fig. 5 Human style of Recommender Widget

As shown in Fig. 5, the recommended items are chosen according to the similarity network of the user. The popup indicates that Ido Guy on the one hand is a member of the recommended community and on the other hand is similar to the user as they both share a set of documents and used the same tags. The authors assume that in the case of familiarity the names will mostly suffice as explanations, while in case of similarity, the popup will be used more often to inspect the common activity with a person.

2.2 Item/activity style of explanation

Recommender systems that incorporate the Item style provide recommendations based on the ratings that the user has provided to the system. Usually, the explanation has the following form, ”Item Y is recommended because you rated/bought item X”. The same principle applies when recommending activities. In this case the explanation is of the form “Activity Y is recommended because you were interested in activity X”.

The Amazon.com E-Commerce web site (http://www.amazon.com) supports the Item style in its recommendations. As shown in Fig. 6, Amazon.com displays its book recommendation at the top of the page, followed by the explanation which is based on the items that were previously purchased or rated by the user. Similarly to

Fig. 6 Item style explanation example of the Amazon system

Amazon.com, LibraryThing.com[4] also provides its recommendations based on book ratings/purchases.

Another recommender system that employs the Item style in its recommendations is the eBay.com website.[5] eBay is an online auction site where users bid for items. The highest bidder wins the item. eBay offers two kinds of recommendation features. The first one is through an email containing items similar to the ones the user did not win so that he has the chance to win another similar item. The second one is through recommendations which are displayed at the user's starting page, soon after he has logged in the website. As shown in Fig. 7, the website recommends tennis racquets of different price range based on the items that the user has viewed earlier. Apparently, in this case the user was viewing a tennis racquet before he visited his starting page, which provided other tennis racquets as possible items of interest.

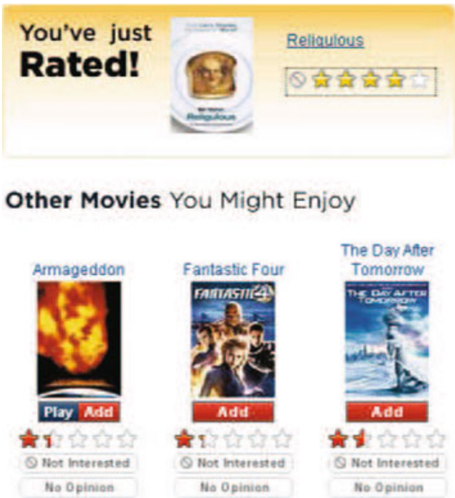
A third recommender system that employs the Item style in its recommendations is the netflix.com website (http://www.netflix.com). This website offers movie streaming and rental services. Users can rate movies beforehand and later get movie recommendations based on these ratings. An example is shown in Fig. 8. A list of recommended movies appears, based on the rating history of the user. In this case, the list contains the movies Armageddon, Fantastic Four and The Day After Tomorrow. The explanation behind the recommendations is that the user rated the movie Reliqulous highly.

[4] http://www.librarything.com.

[5] www.eBay.com.

Fig. 7 Item style explanation example of the eBay system

Fig. 8 Item style explanation example of the Netflix system



Similarly to Netflix.com, LoveFilm.com[6] is a movie rental service that provides movie recommendations based on previously rated/rented movies by the user.

Apart from product recommendations, there exist other systems that provide activity recommendations. Such a system is the one used in Zheng et al. (2010). Specifically, the system recommends activities to a user at a certain location. Activity recommendation is a relatively new research issue with little research on it so far. Previous work focused on recognizing an activity from sensor data by ubiquitous computing (Liao et al. 2005; Wyatt et al. 2005; Zheng et al. 2005). In contrast, the authors mine over the users' activities history with GPS trajectories and recommend what a user can do at some location. The system's user interface is shown in Fig. 9. As shown, a user has uploaded a GPS trajectory in Beijing. This trajectory can be used as explanations for

[6] http://www.lovefilm.com.

Fig. 9 Item style explanation example of the geo-social system

future activity recommendations to him, when he visits similar places. For example, as shown in Fig. 9, the system recommends a visit to the nearby National Art Museum because the user has visited five times similar Art museums, meaning that the user is interested in such an activity.

Similarly to the system presented in Zheng et al. (2010), there exist online applications that provide activity recommendations based on geographical data. Such systems are gowalla.com (http://gowalla.com) and foursquare.com (http://foursquare.com). Both ask the visiting users to log the places they visit on their profile. At the moment the functionality is limited to users being able to see each other's visited spots but it could be the case where in the near future, people would get an activity recommendation based on the activities they have performed so far in that area. Of course these services are also provided in conjunction with Facebook, Twitter, etc. where users are allowed to use their mobiles to signal where they are to friends who may be nearby.

2.3 Feature style of explanation

Many types of items, such as books or websites, contain textual content that may be mined for features. Certain "Feature-based" approaches use words as features in the explanation. For instance, the Libra book (Mooney and Roy 2000) recommender system extracts keywords from the book text based on their predictive power in a naive Bayesian classifier and uses them to explain the recommendation. Bilgic et al. showed that these explanations helps users make more accurate decisions (Bilgic and Mooney 2005). However, explanations using item content face several challenges. One limitation is that keywords extracted from content represent data rather than metadata, and therefore may be too low-level. Existing feature-style approaches only require that an item has a set of words and corresponding frequencies.

The Fabric of Reality:
The Science of Parallel Universes – And Its Implications
by David Deutsch recommended because:

Word	Strength
Multiverse	75.12
Universes	25.08
Reality	22.96

Fig. 10 List of the words provided as Feature style of explanation in Libra

The word UNIVERSES is positive due to your ratings:

Title	Rating	Count
The Life of the Cosmos	10	15
Before the Beginning: Our Universe and Others	8	7
Unveiling the Edge of Time	10	3

Fig. 11 List of the user's rated books that influenced the recommendations

Many pure content-based (CB) systems have tried to provide explanations to users. For instance, Billsus and Pazzani (1999) proposed a personal, news agent that could talk, learn and explain. In particular, they used pure CB to recommend news articles to users, providing also explanations for reasoning their recommendations. Moreover, they exploited user's feedback to improve the recommendation process. In 2000, Mooney and Roy (2000) proposed a method based also on pure CB for recommending books, known as Libra recommender system. Their content-based book recommender system utilized a machine-learning algorithm for text categorization. Exploiting CB techniques, they provide explanations for their recommendations. The Feature explanation style of Libra is presented in Figs. 10 and 11. As shown in Fig. 10, Libra recommends a book to the user, namely "The Fabric of Reality: The Science of Parallel Universes—And Its Implications". The Feature style of explanation is presented underneath the recommendation by listing the strength of the words that appear in that book. The strength of a word can be further explained by listing the user's previously rated books that most influenced its strength, as shown in Fig. 11 where "Count" gives the number of times a word appears in the rated book.

In 2005, Bilgic and Mooney (2005) claimed that the Item and Feature explanation styles are better than the Human explanation styles, proposed by Herlocker et al. (2000), because they help users to accurately formulate their true opinion of an item. In contrast, neighbor style explanation caused users to overestimate the quality of an item. To prove their claim, they conducted an online survey on their book recommender system LIBRA (Mooney and Roy 2000), which was initially developed as a purely content-based system containing a database of 40,000 books. The current version employs a hybrid algorithmic approach called Content-Boosted Collaborative Filtering (CBCF) (Melville et al. 2002).

Other recommender systems that adopt this style of explanation are the Critiquing-based and Conversational recommender systems. Critiquing-based recommender system can be especially helpful in domains where the user has incomplete knowledge about the details of products, features or services offered.

The most popular product

	Manufacturer	Price	Processor speed	Battery life
◉	-	$2'095.00	1.67 GHz	4.5 hour(s)

We also recommend the following products because they are cheaper and lighter, but have lower processor speed

	Manufacturer	Price	Processor speed	Battery life
○	-	$1'499.00	1.5 GHz	5 hour(s)
○	-	$1'739.99	1.5 GHz	4.5 hour(s)
○	-	$1'625.99	1.5 GHz	5 hour(s)
○	-	$1'426.99	1.5 GHz	5 hour(s)
○	-	$1'929.00	1.2 GHz	4 hour(s)
○	-	$1'595.00	1 GHz	5.5 hour(s)

Fig. 12 Feature explanation style of the organization interface

Pu and Chen (2006) suggested that in order to establish trust with users and convince them that the recommendations they offer, do indeed satisfy their preferences, a trust model needs to be build, based on certain design principles and algorithms. According to their research, the new interface, which they call the "Organization Interface", has shown to be significantly more effective in building user trust than traditional approaches, due to the fact that the results are grouped according to their trade off properties. One can see an example of their organization interface in Fig. 12. As shown, a recommender system for computer processors could propose a top candidate recommendation (i.e. the fastest processor) in addition to other recommendations (i.e. processors that could be cheaper but with lower speed).

The authors have implemented more than 13 prototypes of their organization-based interface, to explore all design dimensions of a recommender system. Based on a users' survey, they concluded that an organization-based explanation interface is likely to be more effective than the simple "why" interface, since most participants felt it would be easier to compare different products and make a quicker decision. They also found that a higher level of perceived competence of a recommender system can significantly lead to users' increased intention to return to the system for more products' information.

Conversational Recommender Systems (CRSs) handle the full recommendation process by supporting a conversation with the user. In 2005, Mcsherry (2005) focused on a conversational case-based reasoning (CCBR) approach to produce recommendations that can be explained and justified. For example, the system can recommend a movie to a user, even if he has issued an incomplete query. This can be explained by the fact that the missing preferences of the user's query, cannot affect the outcome (Mcsherry 2005). Their recommender system, Top Case, can explain the relevance of any question the user has asked by eliminating competing cases. It can justify its recommendations on the grounds that any un-elicited preferences of the user cannot affect the outcome.

Top Case:	Please enter your query
User:	type = wandering, month = aug
Top Case:	The target case is:
	Case 510: 609, aug, tyrol, 5, 7, wandering, flat, car (0.28)
	Other competing cases (972) include:
	Case 702: 1698, aug, giant_mountains, 3, 14, wandering, star2, car (0.28) Case 574: 529, aug, alps, 4, 7, wandering, flat, car (0.28)
	What is the preferred location?
User:	**why**
Top Case:	Because if location = tyrol this will increase the similarity of Case 510 from 0.28 to 0.44 and eliminate 866 cases, including Case 574
	What is the preferred location?
User:	alps
Top Case:	The target case is:
	Case 574: 529, aug, alps, 4, 7, wandering, flat, car (0.44)
	Other competing cases (82) include:
	Case 570: 799, aug, alps, 4, 7, wandering, flat, car (0.44) Case 586: 1958, aug, alps, 6, 14, recreation, flat, car (0.36)

Fig. 13 Recommendation dialogue example of the Top Case system

In CCBR approaches to produce a recommendation, descriptions of the available products are stored in a case library and retrieved in response to a query representing the preferences of the user. Then, a query is incrementally elicited in an interactive dialogue with the user. One can see an example of a recommendation dialogue of the Top Case system, which stores information about the travel domain in its case library and produced the respective explanations with its recommendations. As shown in Fig. 13 each recommended case consists of the following attributes: price, month, location, persons, duration, type, accommodation and transport. For instance, in case 510 the corresponding values are 609, august, tyrol, 5, 7, wandering, flat, car.

As also shown in Fig. 13, the current similarity of each retrieved case, normalized by the sum of all the importance weights, is shown in brackets. In response to the user's initial query for getting recommendations of travel places in August, the Top Case presents to the user, the three most probable answers. The first one is case 510 with a similarity of 0.28. The system then asks for the travel location, as it would increase the likelihood of the case 510 being the right answer and also eliminate other possible answers. The user also has the chance to ask for the reasoning behind this question and therefore to increase his trust in the recommender system since a reasonable answer is presented to him. Finally, the system concludes that the recommended case is case 574 even though, as explained to the user, it differs from his query only in price.

Another three recommender systems that explain their recommendations based on item features are NewsDude (Billsus and Pazzani 1999), Pandora.com[7] and SASY (Czarkowski 2006). NewsDude provides news stories recommendations. The explanations are provided in various templates. The Feature explanation style template is of the form "This story received a [high/low] relevance score, because it contains the words f1, f2 and f3". Pandora.com distinguishes between music tracks based on

[7] http://www.pandora.com.

features such as the tempo of the track. For example, a user who has requested tracks with a slow tempo will be presented with the corresponding tracks. An explanation example would be "We are playing this track because it features a subtle use of vocal harmony, major key tonality, a vocal-centric aesthetic, slow tempo, acoustic rhythm guitars". Finally, SASY (Czarkowski 2006) provides holiday recommendations based on personal details provided by the user. Being single for example will play a role in the recommendation process and have a different outcome than the case where the user is not single. An explanation example would be " we recommended Ibiza as your holiday destination because you are single, your age is between 20 and 30 years old and you like swimming and clubbing".

2.4 Hybrid style of explanation

In recent years, there are new emerged social recommender systems that combine explanation styles. The combination of (i) content with rating data, (ii) social with content/rating data, and (iii) social with geographical data, is becoming a way of handling shortcomings when only one type of data is taken under consideration. For example, the social graph (i.e. trust/friend connections) is not dealing with item analysis, whereas collaborative filtering maintains a user profile mainly based on rating data. The idea of a hybrid approach suggests that by using both data (i.e. social and rating data) it is possible to overcome each other's shortcomings and make the recommendation result to be more accurate. The same idea stands for the explanations.

In the following, we present two main categories of hybrid explanations, which are provided by new emerged social recommender systems and combine either (i) rating with content data, (ii) the social graph with content/rating data (i.e. Social tagging/rating recommender systems), or (iii) the social graph with geographical data (i.e. geo-social recommender systems). These recommender systems can provide Hybrid Explanations, since they handle multi-modal data.

2.4.1 Social tagging/rating recommender systems

One example of the combination of content with rating data is the Symeonidis and coworkers (Symeonidis et al. 2008a; Symeonidis 2008b) work. They combine the rating user profile and the feature item profile to reveal the favorite features of users. Their justification style combines the Feature and the Item explanation styles, having the following form: "Item X is recommended, because it contains features $a, b, \ldots$, which are included in items $Z, W, \ldots$ that you have already rated". They have evaluated the quality of their justifications with an objective metric in two real data sets (Reuters and Movielens) showing the superiority of the proposed approach.

For the Movielens data set, they selected a user at random (among the 943 users of the set), and recommended two movies. Table 4 depicts these recommended movies along with their justifications. Notice that the second column of Table 4 concerns the Feature explanation style, whereas the third column of Table 4 concerns the Item explanation style. The combination of those two columns is their proposed explanation

Table 4 Justification example for the Movielens data set

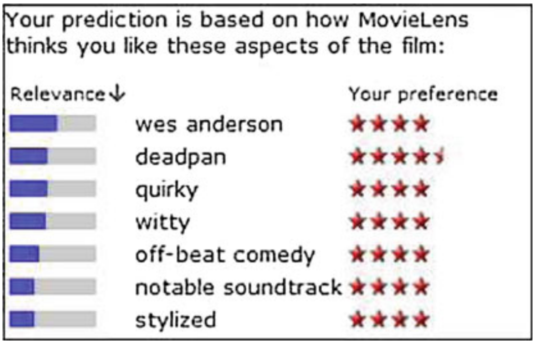
Recommended Movie title	The reason is the participant	Who appears in
Indiana Jones and the Last Crusade (1989)	Ford, Harrison	5 movies you have rated
Die Hard 2 (1990)	Willis, Bruce	2 movies you have rated

Table 5 Justification for the Reuters data set

Recommended Article title	The reason is terms	because "Coffee" contains
ICO Council ends in failure to agree quotas	Brazil, ICO, coffee	3 articles with these terms
Coffee traders expect sell off after ICO talks fail	ICO, coffee, dollars	2 articles with these terms

ICO stands for International Coffee Organization

Fig. 14 The MovieLens interface with tag explanations



style. Therefore the explanation style that is adopted in this case is the 2-D Hybrid (Feature Item) explanation style.

For the Reuters data set, they recommend articles for a given news category. They selected a random category, called "Coffee" and recommended two articles for this category. Table 5 presents the two recommended articles and their justifications.

Apart from the combination of rating with content data, Vig et al. (2009) introduced "tagsplanations", which are explanations based on user's tags preference and the user's item preferences. The basic two components in this case are tag relevance, i.e. the degree to which a tag describes an item, and item preference, which indicates the user's opinion of the item. Figure 14, presents the explanation interface, which shows both tag relevance (the left two columns) and item preference (the column on the right). Results are sorted by tag relevance. This explanation style falls under the 2-D Hybrid (Human Item) explanation style category.

According to the authors there are two possible measures of relevance. The first one, tag popularity, refers to the number of users that have applied a specific tag to a given item. A tag applied by many users is probably more relevant to the given item. The second measure is the correlation between item preference and tag preference. A strong correlation may suggest that the tag is highly relevant. As far as tag preference is concerned, it can be computed in two possible ways. Preference may be

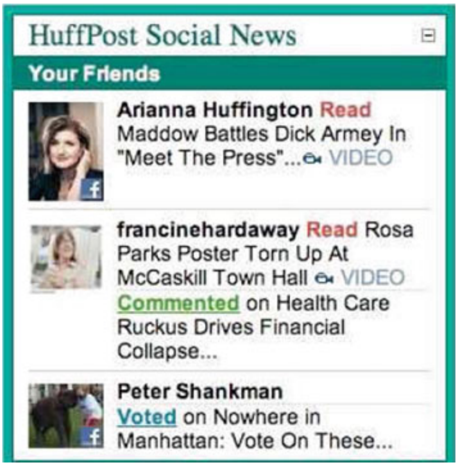


Fig. 15 The HuffPo Social News interface combined with Facebook

assessed directly, by asking a user his/her opinion of a tag, or it may be inferred based on a user's actions. Giving high ratings to an item that has a particular tag, may mean that the user has a positive preference toward that tag. The advantage of inferring tag preference over asking users directly is that no additional work is needed from the users.

In recent years, new innovations in online Social Networks have encouraged more sharing between users even of different networks. The recommendations are made based on the common network that two users belong to. The most striking of these innovations is Facebook Login (formerly Facebook Connect). The way it works is that partner firms install Login buttons and plugins on their websites and devices, which give Facebook users automatic access to information about their friends' activities. Facebook says there are now some 80,000 Connect-enabled websites and devices, such as Microsoft's Xbox console. Two such examples are HuffPost Social News and Netflix.

HuffPost is a site run by the Huffington Post, a well known American blog, where Facebook users can see what their friends have been reading and exchange stories and comments about them. The personalized HuffPost Social News pages create a forum for users to converse about news stories they have read, and in some cases add their relevant information for Facebook friends to read. The Huffington Post creates a social news experience with the "Recommendations" plugin on its home page, showing users personalized recommendations along with explanations. The system's user interface is shown in Fig. 15. The post recommendations (i.e. blog stories) are explained based on both the preferences of a user's friends and the ratings that these items have received.

Moreover, Netflix is a company that hires out DVDs by post or via internet. Netflix accesses a user's Facebook profile as shown in Fig. 16, and provides him with the opportunity to see which films their friends have watched, their film ratings and their comments. To generate recommendations to users along with explanations, Netflix considers all the social interactions from Facebook. For a logged in Facebook user,

Fig. 16 The Netflix interface combined with Facebook

the Facebook Connect plugin will give preference to and highlight films her friends have interacted with.

Furthermore, there exist other recommender systems that could provide the hybrid style of explanation, which are based on social and rating data. TidalTrust (Golbeck 2005) for example is a breadth first search-based algorithm that finds paths between two users and makes predictions based on both trust values that are found on these paths and ratings provided by the users. MoleTrust (Massa and Avesani 2007) is basically the same algorithm. The difference is that MoleTrust only considers users up to a maximum depth, i.e. path length, between them.

2.4.2 Geo-social recommender systems

With the increasing popularity of location-based social networks (Gowalla.com, Foursquare.com, Facebook Places etc.), new geo-social systems that provide activity or location recommendation have emerged. These systems are considered to be the next big thing on the web (The Economist Editorial Team 2010). One such system that provides location and activity recommendations along with explanations is the Gowalla.com web site. The system's user interface is shown in Fig. 17. As shown, a target user can provide to the system the activity he wants to do and the place he is (e.g. coffee in New York). Then, the system provides a map with coffee places which are nearby the user's location (i.e. EuroPan Cafe in location A) and were visited many times (i.e. 15 times) from people he knows (i.e. 2-D Hybrid Explanation style).

Another system that can provide hybrid explanation style recommendations is the one mentioned in Zheng et al. (2010), where geographical data is combined with social data to provide location and activity recommendations. The authors in Zheng et al. (2010) use GPS location data, user ratings and user activities to propose recommendations to interested users and explain them accordingly. Therefore, the explanation style that is adopted is based both on humans, i.e. Human style, and items/activities, i.e. Item style. The system's user interface is shown in Fig. 18. To use this system, for example in activity recommendation, a user who is situated in Beijing, can input a location, as a location query; then the system can show the queried location on the map and suggest a ranking list of activities (top 3 here). These recommendations are then

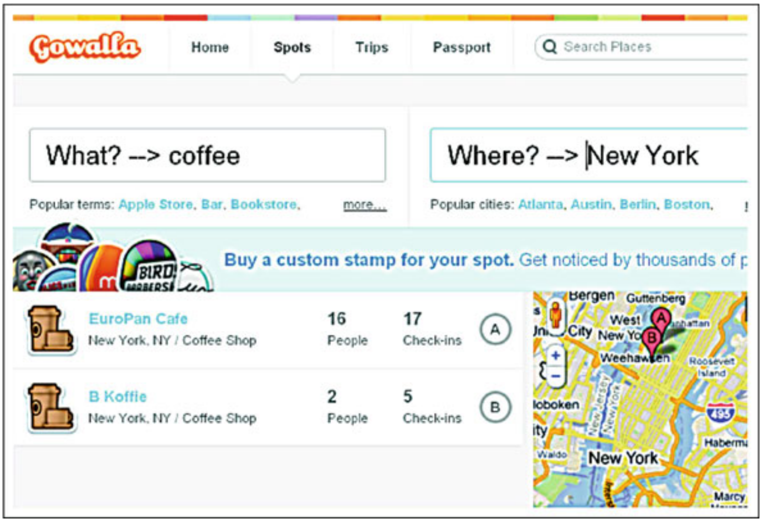


Fig. 17 Hybrid style of the Gowalla system

Fig. 18 Hybrid style of the geo-social system

explained both by the previous visits of similar users at that location and the activity ratings, i.e. Art in our example, that the user has entered beforehand. Therefore a 2-D Hybrid explanation style (Human / Item) is created. Notice that the difference between this system and the system shown in Fig. 9 is that the former offers a Hybrid style of explanation while the latter one offers an Item style of explanations.

A third system that provides geo-social recommendations along with explanations is Facebook Places (http://www.facebook.com). Places is a Facebook feature that allows users to see where their friends are and share their location in the real world. Places uses the last place a user visited to determine which of his friends are nearby. Then, it sends to the user a number of location recommendations that are likely to be the most interesting to her. Finally, the authors in Backstrom et al. (2010) use user-supplied address data and the network of associations between members of the Facebook social network to measure the relationship between geography and friendship. Using these measurements, they can predict the location of an individual.

3 Qualitative analysis of explanations

In this section we aim to gather an in-depth understanding of human perception of explanation styles and the reasons that govern such behavior. Many of previously reported works on evaluation of explanations (Vig et al. 2009; Symeonidis et al. 2009; Bilgic and Mooney 2005; Herlocker et al. 2000) conducted user studies that have been designed to show different conclusions and targeted on specific explanation styles. In this section, we generalize the results of three user studies (by integrating their results) to support our basic claim, that Hybrid is the most effective explanation style, since it can incorporate all other styles. In particular, the first user study (Bilgic and Mooney 2005) concludes that Item and Feature styles dominate the human style. The second user study (Symeonidis et al. 2009) concludes that the combination of Item and Feature styles (i.e. hybrid style) dominates the Item and Feature style. Finally, the third user study (Vig et al. 2009) confirms the same results reported in Symeonidis et al. (2009) even if it refers to tags. Notice that the above conclusion could not be easily extracted if we looked at each user study separately.

3.1 Measuring promotion versus satisfaction

In this section, we integrate the results of two user studies to answer two questions: (i) Which explanation style only convince users to adopt recommendations (i.e. just promote products)? and, (ii) Which explanation styles really help users make more accurate decisions (i.e. promote user satisfaction)? The explanation styles that are used in the comparison are the following: Item style, Feature style, Human style, and Hybrid style.

In Bilgic's (Bilgic and Mooney 2005) user study people filled out an online survey. The methodology that they used to measure satisfaction versus promotion is the following:

1. Get sample ratings on random books from the user.
2. Compute a book recommendation r.
3. For each explanation system e
   (a) Present book r to the user with e's explanation.
   (b) Ask the user to rate book r.
4. Ask the user to read book r and then rate it again.

Explanation-ratings are the ratings given to an item by the users in step 3.b, while *actual-ratings* are the ones given to an item by the users in step 4. According to the authors, the explanation style that minimizes the difference between *Explanation-ratings* and *actual-ratings* is the best (i.e. help users to make more accurate decisions).

Table 6 Results of the user survey conducted by Bilgic and Mooney

Expl. styles	μ	σ	μ_d	σ_d
Item	3.75	1.07	0.00	1.30
Feature	3.75	0.98	0.00	1.14
Human	4.49	0.64	0.74	1.21

This table shows the means and SDs of ratings collected by LIBRA as well as the means and SDs of differences between explanation and actual ratings. The smallest μ_d value indicates the best explanation style

The authors make two hypotheses. The first one is that Human explanation style will cause the users to overestimate the rating of an item. The second is that the Feature and Item explanation styles will allow users to accurately estimate ratings. For their survey, 34 subjects were recruited to fill out the online survey, most of them being students in various departments at the University of Texas at Austin. The system allowed users to repeat the process so they were able to collect data on 53 recommendations.

The results of the survey are shown in Table 6. As shown in the second column of Table 6, the mean ratings of all explanation styles (μ) are pretty high, which is to be expected as LIBRA tries to compute good recommendations. The authors measured the mean μ_d and standard deviation σ_d of the differences between Explanation ratings and Actual ratings. The best explanation is the one that allows users to best approximate the *actual-rating*, i.e. the mean of the difference between *explanation-ratings* and *actual-ratings* for a good explanation, which should be centered around 0. Notice that in Table 6, the explanation style which has a mean μ_d closest to 0 and the smallest standard deviation σ_d is the Feature explanation style, attaining values of $\mu_d = 0.00$ and $\sigma_d = 1.14$.

Moreover, Symeonidis et al. (2009) conducted a user study to measure in Movi Explain recommender system the user satisfaction versus promotion against the Feature, Item and Hybrid styles of explanations, where the Hybrid style combines the previous two explanation styles. The Human style was not included in the user study as it was previously proved by Bilgic that it is only good for product promoting purposes (Bilgic and Mooney 2005). The participants that took part in the study were 42 pre- and post-graduate students of Aristotle University of Thessaloniki, who filled out an on-line survey, following a procedure that is similar to the one presented in the Bilgic and Mooney (2005) work. Their results are illustrated in Table 7. As earlier described, the best explanation is the one that allows users to best approximate the Actual rating. That is, the distribution of difference between Explanation ratings and Actual ratings should be centered around 0. These values, for each explanation style, are presented in the fourth and fifth columns of Table 7. As expected, Hybrid explanation style has the smallest μ_d value equal to 0.06, because with Hybrid style users receive explanations with richer information.

3.2 Measuring effectiveness, justification, and preference

In this section, we present a third user study and the second part of the user study reported in Symeonidis et al. (2009). In the first user study, users were asked how

Table 7 Results of the user survey conducted by Symeonidis et al

Expl. styles	μ	σ	μ_d	σ_d
Feature	3.70	0.55	0.46	0.13
Item	3.97	0.63	0.73	0.14
Hybrid	3.30	0.56	**0.06**	0.13

This table shows the means and SDs of ratings collected by MoviExplain as well as the means and SDs of differences between explanation and actual ratings. The smallest μ_d value indicates the best explanation style

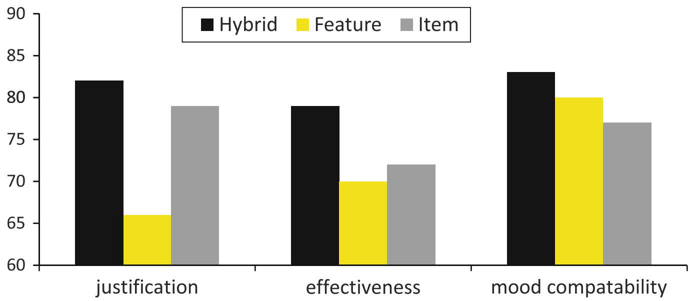


Fig. 19 Percentage of responses that were agree or strongly agree for each explanation style interface

well each explanation interface helped them to: (i) understand why an item was recommended (justification), (ii) decide if they would like the recommended item (effectiveness), and (iii) determine if the recommended item matched their mood (mood compatibility). In the second part of the user study reported in Symeonidis et al. (2009), users answered the following question: (iv) "what is your favorite explanation style?"

As far as the first three questions are concerned, Vig et al. (2009) conducted a survey, in which users evaluated (by an agree or strongly agree response) three explanation styles: Item, Feature, Hybrid. As shown in Fig. 19, the Hybrid explanation style outperforms both other styles explanation interfaces in all three aforementioned categories (i.e. justification, effectiveness, and mood compatibility).

In the second part of the user study reported in Symeonidis et al. (2009), asked target users to rate separately each explanation style to explicitly express their actual preference among the three styles. The mean values of the explicitly expressed user preferences over the explanation styles are shown in Fig. 20. As shown, the hybrid style is the user's favorite.

To sum up, the integration of the results of all three user studies have shown that the hybrid style (Hybrid), which can be constructed by any combination of the basic explanation styles (Item, Feature, Human), is the most effective explanation style and the users' favorite. This is expected because Hybrid style can incorporate all other styles and users receive more robust explanations.

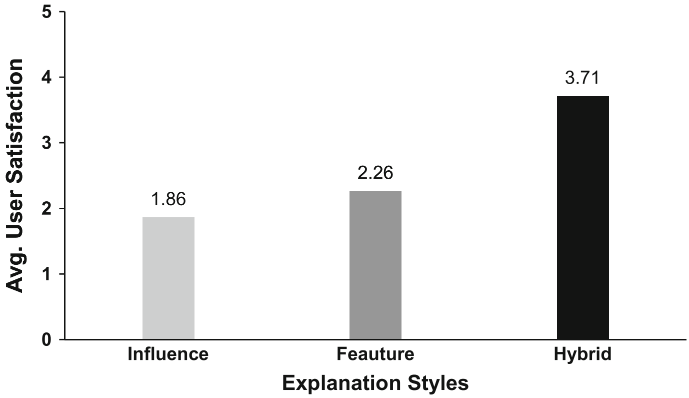


Fig. 20 User satisfaction ratings collected by the user study on explanation styles

4 Conclusions

Recommender systems help users in finding products they like. The need to provide justifiable recommendations has recently attracted significant attention, especially in e-commerce sites (Amazon, eBay, etc.). In this paper, we performed a survey on the basic explanation styles, provided by recommender systems. We categorized the existing explanation styles into four categories, Human, Item, Feature and Hybrid. For each category, we demonstrated how these styles are put into practice, by presenting recommendation systems employing these styles. Then, we studied the impact of social web in contemporary recommender systems and their explanation styles,i.e. Facebook Connect recommendations (HuffPo and Netflix) and geo-social recommendations (Backstrom et al. 2010; Zheng et al. 2010). Finally, we integrated the results of three different user studies. Based on our findings, the hybrid is the most effective and the users' favorite explanation style.

As future work, we intend to extend our three dimensional model of explanation styles to higher order representations, by incorporating other possible justification elements, which are related to the context of a recommendation (e.g. the time of a recommendation, the weather etc.). Moreover, we indent to conduct a user study to measure user satisfaction by comparing 2-D, 3-D, and higher order dimension explanation styles.

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