A Theoretical Model of Explanations in Recommender Systems *

Marta Caro-Martinez, Guillermo Jimenez-Diaz, and Juan A. Recio-Garcia

Department of Software Engineering and Artificial Intelligence
Universidad Complutense de Madrid, Spain
email: martcaro@ucm.es, gjimenez@ucm.es, jareciog@ucm.es

Abstract. Explanations in recommender systems are essential to improve user confidence in recommender systems. In this work, we propose a theoretical model to categorize explanations in recommender systems. Although this work is sustained by previous explanation taxonomies, our model includes concepts not considered in current literature. Moreover, we make a novel contribution regarding the formalization of this model, as our long-term goal is to build an ontology that will be integrated into a development methodology to guide the implementation of explanations in recommendation systems.

1 Introduction

Nowadays, people can find a huge amount of information on the Internet. With the appearance of online shops, like Amazon or eBay, and platforms of entertainment consumption, like Spotify or Youtube, internet users are able to get products in an easy and fast way. However, the amount of products offered by these platforms is immense and it can hinder the task of finding the product that the user really wants. Recommender systems alleviate this problem. They help users to find products that can be interesting to them. Thus, the users make better decisions thanks to the recommendations provided by the system.

Many times, users do not trust recommender systems as they do not know how the recommendation has been carried out and the reasons why a product has been recommended. This problem causes a bad user experience and the system is not used as we would expect. Therefore, explanations for justifying recommendations are necessary for helping the user to understand the system behaviour.

The goal of our work is to introduce a new categorization model for explanation systems in order to help to design successful explanations. Our approach provides a refinement with respect to previous models studied during our work. We enhance those models with some concepts not considered in previous works and we include specifications of novel concepts. The ideas and weaknesses found in current literature are specified in Section 2.

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Additionally, our current work follows our group research line [25, 15] presenting a first attempt to formalize a model that includes the semantic description of explanations in recommender systems. The resulting ontology, together with the RecoLibry framework will be the basic buildings blocks of a future platform for the generation of recommender systems analogous to COLIBRI Studio.

The paper is structured as follows. Section 2 reviews state-of-the art literature about explanations in recommender systems. Next, Section 3 describes our model. Finally, Section 4 describes the way the model will be validated and Section 5 concludes the paper.

2 Background

In this work, we have studied several publications where we can find different ways of explaining recommendations. Some of them are studies that propose ways of classifying explanations [14, 21, 12, 30, 22, 29, 6, 10].

First, we studied the survey by [30], where we found an analysis of the different purposes of explanations in recommender systems. The survey describes the criteria that *good* explanations should have, different ways of presenting recommendations and how users interact with recommender systems. In [12], we also found the properties described by Tintarev *et al.* but applying this knowledge on different ways of presenting the explanations for recommendations. Thanks to this study and the proposal in [14], that describes several explanation approaches for a movie recommender system, we found new ways of visualizing explanations, a facet that we will consider in our model. The work in [6], compares two models of explanation: a normative model and a pragmatic model. The normative model is focused on transparency and user understanding, while the pragmatic model is designed for usability. This approach helps us to refine features that our model should have. Finally, we studied several explanation taxonomies, proposed in [21, 22, 10]. The most detailed one is the systematic review detailed in Nunes *et al.* It presents detailed descriptions of different explanation types according to many aspects. [22] present new concerns about explanations in social recommender systems and [10] introduce new facets about the recommendation types and the importance of knowing these types for explaining recommendations. In [29], that provides a study about the effectiveness of explanatory information and how it is evaluated, we can also find some interesting details about recommender systems and types of knowledge sources for explaining recommendations.

Our work is focused on building a classification model for explanations in recommender systems. This model should help to design successful explanations for recommender systems. In order to ease the understanding of the model proposed here, it is necessary to define some important concepts related to recommender systems. The main entities involved in recommender systems are *users* and *items*. *Users* are the people who are interested in getting new items and who interact with the system to explore the products of the platform. *Items* are the products available on the recommendation system: food, clothes, hotels, experiences, etc. On one hand, the interactions carried out by users in the recommendation system are one of the most exploited sources of knowledge to recommend new items to these users. One way widely used to identify the user preferences is the *ratings*, a form of feedback of the user about an item. If one user rates an item with a good score, then this item (and its features) will be suitable for this user. On the other hand, another source of knowledge involved in the recommendation process is item descriptions. Every item has its own *content*, an extensive representation of the item, for example, a textual description. Moreover, the content can be represented by a set of *features* that defines the item: its price, colour or size, among others.

Frequently, the recommendation is supported by the *similarities* between users or items. The similarities are the coincidences between two elements, for example, between item features or user ratings. Although, it is common to recommend items similar to the ones that the user interacted with before, some recommendation approaches suggest items on the basis of the user *preferences*. The preferences are the user requirements elicited before interacting with the recommender. Moreover, every user is part of the *community* defined by the recommender system. The behaviour of both every single user and the community can be employed in the recommendation process. Finally, the recommendation can be enhanced using the information extracted from the environment and the circumstances of the user and her interaction with third-party systems. We call this as *contextual information*.

3 Theoretical Model

Thanks to the study that we have carried out, we propose a new model for classifying explanations, which introduces four main classification facets: motivation, knowledge containers, generation and presentation. Figure 1 shows an overview of the classification model developed in our work. We adopt the vocabulary used to define ontologies in order to formalize our classification [7]. With it, we solve the lack of formalization found in the previous studies. Concretely, we use the following ontology relationships:

- *Composition*. Some concepts of our ontology are compositions of other concepts that define them from different points of view. For example, we define the presentation facet as a composition of 4 concepts (format, argumentation, detail and interaction) that describes how an explanation is presented to the user.
- *Subconcept*. A subconcept is an extension of a concept following a *"is-a"* relationship. Subconcepts are not disjoint as explanations can be classified into several concepts. For example, our model shows "Positive" and "Negative" as subclasses of the "Argumentation" aspect.
- *Instance*. An instance is a concrete instantiation of a concept. For example, the "Format" concept, has 4 instances: "Natural language", "Schematic", "Visual" and "Other". An explanation can be characterized by several instances of the same concept.

Next, we detail the main concepts of the model in the following sections.

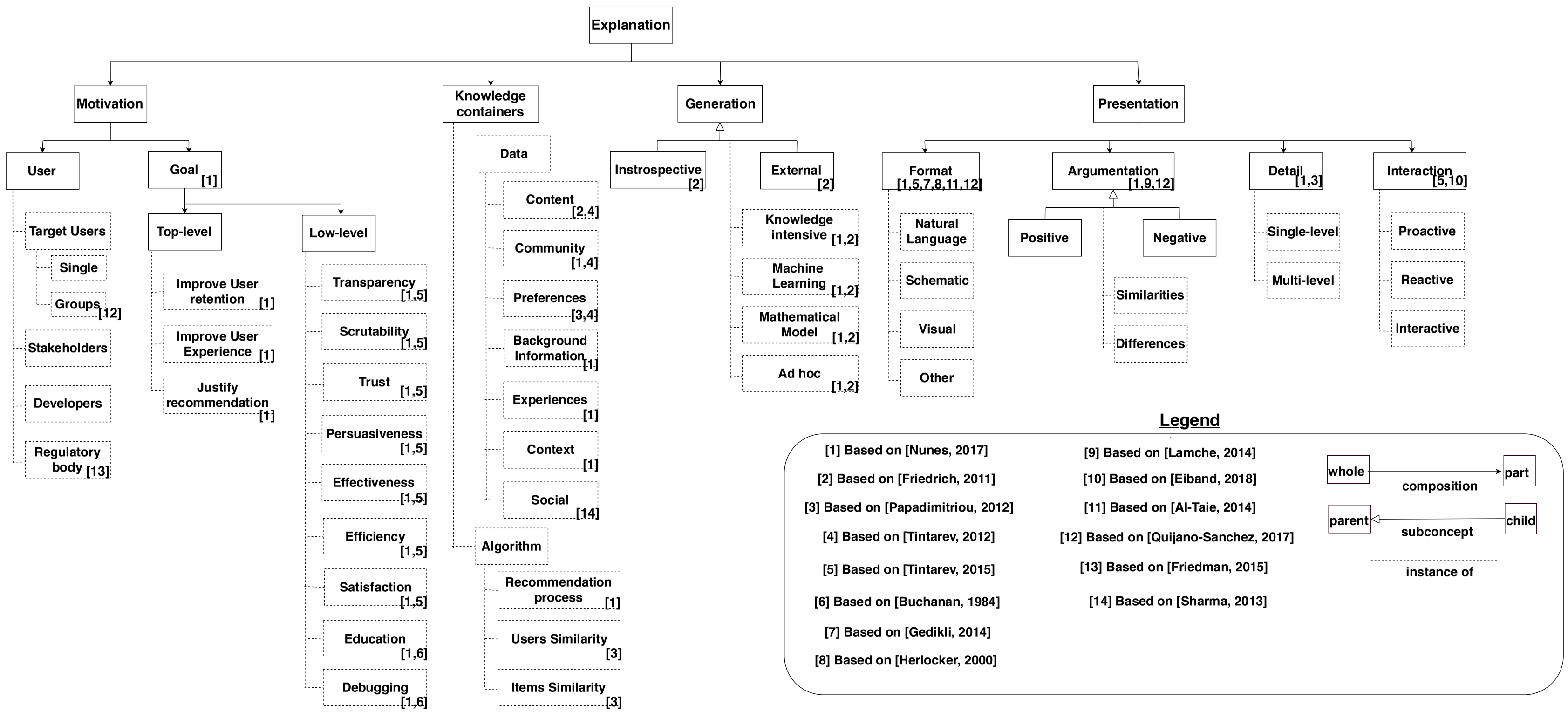

Fig. 1: Classification Model for explanations in recommender systems.

3.1 Motivation

Motivation refers to the goal of the explanation according to the target user. Both ideas, goal and user, are the two major subconcepts that characterize explanations according to the motivation.

3.1.1 User.

Recommender systems are supposed to satisfy user needs. However, explanations do not have to be aimed exclusively at the **Target User**, the people who receive the recommendations made by the system. Our model also classifies users as **Stakeholders** (the people interested in the success of the recommender system), **Developers** (the people who need to know how the recommender is working in order to debug it) and **Regulatory body** (which represents the legislative and government organizations that need to know how recommender systems work in order to regulate their transparency and their correct use [9]).

3.1.2 Goal.

The goal of an explanation is closely related to the user to whom the explanation is targeted. The goals can be divided into two subconcepts: top-level goals and low-level goals. The top-level goals are focused on the user, while the low-level ones help to achieve the top-level goals.

Top-level goals distinguish three groups, inspired by Nunes and Jannach's proposal [21]: **Improve user retention** (to increase the probabilities of a user to return to the recommendation system), **Improve user experience** (to help users to make good decisions and to enjoy the recommendation activity) and **Justify recommendation** (to support the recommendation provided, helping the user to understand why an item was recommended).

Our low-level goals match with the criteria for designing good explanations defined in [30] and [3]. We have included the following low-level goals for the explanations: **Effectiveness** [30] (the explanation helps the user to find the items that she needs), **Efficiency** (it helps the user to make decisions faster), **Trust** [30, 3] (it increases the user confidence in the system), **Scrutability** [30] (the user will be able to provide feedback when the system provides a wrong recommendation), **Persuasiveness** [30, 3] (it convinces the user that the recommendation is appropriate), **Transparency** [30, 3] (it specifies how and why a recommendation is made), **Education** [3] (users can learn something about the recommender system using the explanation) and **Debugging** [3] (it allow users to identify bugs in the recommendation system).

3.2 Knowledge containers

Explanations for recommender systems can be created based on different types of knowledge sources or containers [26, 33]. We have observed that explanations can use information extracted from two types of sources: from the data available in the recommender system or from the algorithm used in the recommendation.

3.2.1 Data. These explanations are based on the information available at the recommender system. We have found different types of data used in explanations: **Content** (the explanation refers to the item description, like "This shirt is white and its price is 8.99 €."), **Preferences** (it refers to the item features, considering the known user preferences [22, 29], like 'This shirt is white, a colour that you like, and its price is 8.99 €, less than 10 €, your limit price."), **Community** (it refers to the information extracted from the behaviour of the community of users interacting with the recommender system [21, 29], like "This shirt is one of the shop's top-sellers"), **Background Information** (The data is extracted from the domain [21], like information from reviews or external interactions), **Experiences** (explanations that refer to user past experiences and system history [21], like "This shirt is white and you bought white shirts yesterday"), **Context** (it refers to the dynamic features that describe the requirements of target users, like weather restrictions) and **Social** (the explanation refers to user's relationships [27, 24], like "Your brother also bought this shirt").

3.2.2 Algorithm. The explanations are based on the information that the system collects from the recommendation algorithm. The classes proposed for this knowledge container are: **Recommendation Process** (the explanation shows how the algorithm performs a recommendation [21, 6]), **User Similarity** (it justifies the recommendation through the interactions that similar users have carried out with the recommended items [22]) and **Item Similarity** (it is based on the similarity that exists among recommended items and the items that the user previously interacted with [22]).

3.3 Generation

Explanations for recommender systems can be implemented using different processes and techniques. During the analysis of these techniques, we observed that recommender systems commonly act in two different ways: as a black box system, when it does not show how it works to the user to whom recommends the items, or as a white box system, which is transparent to the users and it allows them to know the way the recommender algorithm operates [10].

We can classify explanations as **Introspective**, when the explanations are generated by the recommendation algorithm itself because it acts as a white box system [10], or **External**, if the recommender system acts as a black box system, so the explanation system has to implement a new technique for creating justifications, different from the underlying recommendation algorithm [10].

No matter whether the system operates as black box or as white box, different techniques can be used to generate the explanations. Therefore, explanation systems can be also classified by the method that they use for generating explanations. The types of explanation according to their explanation algorithms are [21]: **Knowledge-based Explanation** (based on techniques that use a knowledge source for solving problems), **Machine Learning Explanation** (explanation uses information about past experiences to explain recommendations),

Mathematical model Explanation (based on mathematical models to justifying recommendations) and **Ad-hoc Explanation** (the explanation algorithm provides the explanations required by the recommender system).

3.4 Presentation

The presentation aspect represents the way the system displays the explanation to the user. Among all of the publications studied, we have identified four different subconcepts related with the presentation: the display format, the argumentation, the level of detail and the way of interaction.

3.4.1 Display Format. The explanations can be shown in different ways, more or less simple. The following ones are the main formats that we have found in literature [14, 12, 21, 30, 1, 24]: **Natural Language** (the justification for a recommendation is displayed as a text, commonly based on templates), **Schematic** (explanations are shown in a simplified text format, like tables, logs or ratings), **Visual** (explanations use a more graphic way as charts or histograms) and **Other** (which employ more innovative display formats, like audio, video or even augmented reality[11]).

3.4.2 Argumentation. Explanations can show different outlooks for a recommended item. They can be **Positive** (they justify why a recommended item is suitable for the user with positive arguments) or **Negative** (explanations show features that do not fit user preferences and tastes using negative argumentation) [16, 21, 24]. Additionally, these arguments can be supported using **Similarities** or **Differences** between item features and user preferences and tastes.

For example, "This shirt is yellow, that is not your favourite colour, but it might also like it" is a negative explanation based on differences that can also be suitable for the user when the explanation needs to justify the diversity or the serendipity. However, "This shirt is green, the colour that you are looking for" is positive when the explanation highlights the similarities between user likes and item features.

3.4.3 Level of detail. It is the degree of specification about a recommendation included in its explanation. The level of detail can vary in different explanations, depending on what the user needs to know or what the developer wants to show. Due to the level of detail is a subjective aspect, we take into account the knowledge base, the number of visualization types and the length of the explanation for modelling this concept.

As the authors in [21, 22] state, we have considered **Single-level** (explanations that use a single knowledge base, have a single way to display it and/or are a short explanation with few details) and **Multi-level** (explanations that use several knowledge containers, have different visualization formats and/or they are a long explanation with many details, like Tag cloud by [12]) detailed explanations.

3.4.4 Interaction The different ways of interaction depend on how the user obtains explanations through the system [30, 6]. The main ways of interaction are: **Proactive** (when the explanation is shown with the recommendation, like Amazon, eBay or Netflix), **Reactive** (when the user asks for the explanation of the recommendation received, like the conversational system in [19]) or **Interactive** (when the explanation is already available to the user and she can interact with the explanation for getting more information, like Shopr [16])

4 Model validation

To validate the proposed model, we have studied and classified 23 different explanation approaches collected from the literature. Some of them are explanation approaches for classification methods or machine learning techniques since we also wanted to validate the extensibility of our model in other fields. In some cases, we do not have enough information in order to complete every aspect within our model.

- "Explainable Movie Recommendation Systems by using Story-based Similarity" [17] (A).
- "Explaining Recommendations by Means of User Reviews" [4] (B).
- "Explaining Complex Scheduling Decisions" [18] (C).
- "Explaining Contrasting Categories" [23] (D).
- "Explaining smart heating systems to discourage fiddling with optimized behaviour" [28] (E).
- "The design and validation of an intuitive confidence measure" [31] (F).
- "Interactive Explanations in Mobile Shopping Recommender Systems" [16] (G).
- "A Review of Explanation and Explanation in Case-Based Reasoning" [5]. We have studied the following CBR systems mentioned in this publication: CARES (H), DIRAS (I) and MOCAS (J).
- "How should I explain? A comparison of different explanation types for recommender systems" [12] (K).
- "Explaining Collaborative Filtering Recommendations" [14]. We have studied seven explanations methods proposed in this work: Histogram with grouping (L), Neighbour ratings histogram (M), Table of neighbours rating (N), MovieLens Percent confidence in prediction (O), Number of neighbours (P), Overall percent 4+ (Q), and Overall average rating (R).
- "Tagsplanations: Explaining Recommendations Using Tags" [32] (S).
- "A case-based reasoning system for aiding detection and classification of nosocomial infections" [13] (T).
- "A framework for Explanation of Machine Learning Decisions" [2] (U).
- "Great Explanations: Opinionated Explanations for Recommendations" [20] (V).
- "Knowledge-based systems, viewpoints and the world wide web" [8] (W).

	Motivation		Knowledge Container	Generation		Presentation				
System	User	Low-level Goal				Display Format	Perspective		Detail Level	Interaction
A	-	-	-	Knowledge-intensive	External	-	-	-	-	-
B	-	Transparency	Background information	Machine Learning	External	-	-	-	-	-
C	Target User: Single	-	Content	Knowledge-intensive	Introspective	Natural Language / Visual	Similarities	Positive	Multi-level	Proactive / Reactive
D	Target User: Single	-	Content	Machine Learning	Introspective	Natural Language / Visual	Similarities	Positive	Multi-level	Proactive
E	Target User: Single	Trust	Preferences	Knowledge-intensive	Introspective	Natural Language / Schematic / Visual	Similarities	Positive	Multi-level	Proactive / Reactive
F	Target User: Single	Debugging (validation)	Experiences	Knowledge-intensive	External	Schematic	-	-	Single-level	-
G	Target User: Single	Transparency / Scrutability	Preferences	Ad hoc	External	Natural Language / Visual	Similarities / Differences	Positive / Negative	Multi-level	Proactive / Reactive / Interactive
H	Target User: Single	-	Experiences	Knowledge-intensive	Introspective	Natural Language	Similarities	Positive	Multi-level	Proactive
I	Target User: Single	-	Experiences	Knowledge-intensive	Introspective	Schematic	Similarities	Positive	-	Proactive
J	-	-	Experiences	Knowledge-intensive	Introspective	-	-	-	-	-
K	Target User: Single	-	Content / Preferences	Machine Learning	External	Visual	Similarities / Differences	Positive / Negative	Multi-level	-
L	Target User: Single	Effectiveness, Satisfaction, Transparency	Users similarity	Machine Learning	Introspective / External	Visual	Similarities	Positive	Single-level	-
M	Target User: Single	Effectiveness, Satisfaction, Transparency	Users similarity	Machine Learning	Introspective	Visual	Similarities	Positive	Single-level	-
N	Target User: Single	Effectiveness, Satisfaction, Transparency	Users similarity	Machine Learning	Introspective	Schematic	Similarities	Positive	Single-level	-
O	Target User: Single	Effectiveness, Satisfaction, Transparency	-	Machine Learning	Introspective	Schematic	Similarities	Positive	Single-level	-
P	Target User: Single	Effectiveness, Satisfaction, Transparency	Users similarity	Machine Learning	Introspective	Schematic	Similarities	Positive	Single-level	-
Q	Target User: Single	Effectiveness, Satisfaction, Transparency	Community	Machine Learning	Introspective	Schematic	Similarities	Positive	Single-level	-
R	Target User: Single	Effectiveness, Satisfaction, Transparency	Community	Machine Learning	Introspective	Schematic	Similarities	Positive	Single-level	-
S	Target User: Single	Transparency, Effectiveness, Efficiency	Content / Preferences	Ad hoc	External	Visual	Similarities	Positive	Multi-level	-
T	Target User: Single	-	Experiences	Knowledge-intensive	Introspective	-	-	-	-	-
U	-	-	Content	Ad hoc	External	Natural Language	Similarities	Positive	Single-level	-
V	Target User: Single	Efficiency, Persuasiveness	Background information / Experiences / Preferences	Knowledge-intensive	Introspective	Schematic	Similarities / Differences	Positive / Negative	Multi-level	Proactive / Interactive
W	Target User: Single / Stakeholders	-	Recommendation Process	Knowledge-intensive	Introspective	Schematic	Similarities / Differences	Positive / Negative	Single-level	-

Table 1: Classification of approaches studied according to our model. Dash values ("-") represents that we do not have enough information to define this concept.

According to the motivation aspect, in most of the approaches studied the user who receives the explanation is a single target user. We have found only an approach whose user is a stakeholder (W), although it also explains decisions to a single target user. Only a few studies just describe the main goal of the explanations using low-level goals. The most usual goal is "Transparency".

From the publications studied, the knowledge containers based on data are more used than the algorithm-based ones. "Content" type seems to be one of the most used knowledge containers and it is commonly used in combination with "Preferences". We have found only an explanation approach based on "Recommendation Process" as knowledge container.

According to the "Generation" facet, we can see that the classification is equally distributed between the "Introspective" and the "External" values. Regarding the explanation algorithm, the most used is "Knowledge-intensive". There are some systems whose algorithms are "Ad-hoc", but we have not found systems using a "Mathematical model".

In reference to the "Display format" concept, several studies combine "Natural language" (used to explain by default) with "Visual" (to explain with more details when users ask for it, using a reactive explanation). Regarding the argumentation facet, we can observe that "Similarities" are commonly used with a "Positive" argumentation, while "Differences" are used in "Negative" argumentations. The "Level of detail" is also distributed between high detailed and low detailed explanation methods. Finally, we have not found too much information according to the way of interaction facet.

5 Conclusions

In this work, we have defined a classification model for explanations in recommender systems. Our model includes features and concepts considered in previous works and it is improved with additional aspects and some formalization knowledge that other models lack. The main goal of this formalization is to set the foundations of an ontology to complement our frameworks jCOLIBRI and RecoLibry with explanations. This way, we expect that our model will be an useful tool to guide the design and development of explanations for recommender systems.

Our model includes the main aspects that explanations should have. In this work, we detail what these aspects are and we define the types of explanations according to them. We have also classified different approaches found in the literature in order to prove the validity of our model. We have found that most of the approaches studied do not describe information about all of our model concepts. Moreover, we have not found approaches for a few categories proposed. As future work, we will research in depth to achieve examples for all the types defined here.

References

1. Mohammed Z Al-Taie and Seifedine Kadry. Visualization of explanations in recommender systems. *Journal of Advanced Management Science Vol*, 2(2):140 – 144, 2014.
2. Chris Brinton. A framework for explanation of machine learning decisions. In *IJCAI-17 Workshop on Explainable AI (XAI)*, page 14.
3. Bruce G Buchanan and Edward H Shortliffe. Explanation as a topic of AI research. *Rule-based expert systems: the MYCIN experiments of the Stanford Heuristic Programming Project*, page 331, 1984.
4. Tim Donkers, Benedikt Loepp, and Jürgen Ziegler. Explaining recommendations by means of user reviews. In *Workshop On Explainable Smart Systems (EXSS)*, 2018.
5. Dónal Doyle, Alexey Tsymbal, and Pádraig Cunningham. A review of explanation and explanation in case-based reasoning. Technical report, Trinity College Dublin, Department of Computer Science, 2003.
6. Malin Eiband, Hanna Schneider, and Daniel Buschek. Normative vs pragmatic: Two perspectives on the design of explanations in intelligent systems. In *Workshop On Explainable Smart Systems (EXSS)*, 2018.
7. Jérôme Euzenat, Pavel Shvaiko, et al. *Ontology matching*, volume 18. Springer, 2007.
8. Ian Finch. Knowledge-based systems, viewpoints and the world wide web. In *IEE Colloquium on Web-Based Knowledge Servers (Digest No. 1998/307)*, pages 8/1–8/4, Jun 1998.
9. Arik Friedman, Bart P. Knijnenburg, Kris Vanhecke, Luc Martens, and Shlomo Berkovsky. *Privacy Aspects of Recommender Systems*, pages 649–688. Springer US, Boston, MA, 2015.
10. Gerhard Friedrich and Markus Zanker. A taxonomy for generating explanations in recommender systems. *AI Magazine*, 32(3):90–98, 2011.
11. Damianos Gavalas, Charalampos Konstantopoulos, Konstantinos Mastakas, and Grammati Pantziou. Mobile recommender systems in tourism. *Journal of network and computer applications*, 39:319–333, 2014.
12. Fatih Gedikli, Dietmar Jannach, and Mouzhi Ge. How should I explain? a comparison of different explanation types for recommender systems. *International Journal of Human-Computer Studies*, 72(4):367–382, 2014.
13. HJ Gómez-Vallejo, B Uriel-Latorre, M Sande-Meijide, B Villamarín-Bello, Reyes Pavón, F Fdez-Riverola, and Daniel Glez-Peña. A case-based reasoning system for aiding detection and classification of nosocomial infections. *Decision Support Systems*, 84:104–116, 2016.
14. Jonathan L Herlocker, Joseph A Konstan, and John Riedl. Explaining collaborative filtering recommendations. In *Proceedings of the 2000 ACM conference on Computer supported cooperative work*, pages 241–250. ACM, 2000.
15. Jose L. Jorro-Aragoneses, Belén Díaz-Agudo, Juan A. Recio-García, Diego M. López-Gutierrez, and Gineth M. Ceron-Rios. RecOnto: An ontology to model recommender systems and its components. In *2017 International Conference on Tools with Artificial Intelligence*, pages 815–821. IEEE, 2017.
16. Béatrice Lamche, Ugur Adıgüzel, and Wolfgang Wörndl. Interactive explanations in mobile shopping recommender systems. In *Joint Workshop on Interfaces and Human Decision Making in Recommender Systems*, page 14, 2014.

17. O-Joun Lee and Jason J Jung. Explainable movie recommendation systems by using story-based similarity. In *Workshop On Explainable Smart Systems (EXSS)*, 2018.
18. Jeremy Ludwig, Annaka Kalton, and Richard Stottler. Explaining complex scheduling decisions. In *Workshop On Explainable Smart Systems (EXSS)*, 2018.
19. David McSherry. Explanation in recommender systems. *Artificial Intelligence Review*, 24(2):179–197, 2005.
20. Khalil Muhammad, Aonghus Lawlor, Rachael Rafter, and Barry Smyth. Great explanations: Opinionated explanations for recommendations. In *International Conference on Case-Based Reasoning*, pages 244–258. Springer, 2015.
21. Ingrid Nunes and Dietmar Jannach. A systematic review and taxonomy of explanations in decision support and recommender systems. *User Modeling and User-Adapted Interaction*, 27(3-5):393–444, 2017.
22. Alexis Papadimitriou, Panagiotis Symeonidis, and Yannis Manolopoulos. A generalized taxonomy of explanations styles for traditional and social recommender systems. *Data Mining and Knowledge Discovery*, 24(3):555–583, 2012.
23. Michael Pazzani, Amir Feghahati, Christian Shelton, and Aaron Seitz. Explaining contrasting categories. In *Workshop On Explainable Smart Systems (EXSS)*, 2018.
24. Lara Quijano-Sanchez, Christian Sauer, Juan A Recio-Garcia, and Belen Diaz-Agudo. Make it personal: a social explanation system applied to group recommendations. *Expert Systems with Applications*, 76:36–48, 2017.
25. Juan A. Recio-García, Belén Díaz-Agudo, and Pedro A. González-Calero. *The COLIBRI Platform: Tools, Features and Working Examples*, pages 55–85. Springer Berlin Heidelberg, Berlin, Heidelberg, 2014.
26. Michael M Richter and Rosina O Weber. *Case-based reasoning*. Springer, 2016.
27. Amit Sharma and Dan Cosley. Do social explanations work?: studying and modeling the effects of social explanations in recommender systems. In *Proceedings of the 22nd international conference on World Wide Web*, pages 1133–1144. ACM, 2013.
28. Simone Stumpf, Simonas Skrebe, Graeme Aymer, and Julie Hobson. Explaining smart heating systems to discourage fiddling with optimized behavior. In *Workshop On Explainable Smart Systems (EXSS)*, 2018.
29. Nava Tintarev and Judith Masthoff. Evaluating the effectiveness of explanations for recommender systems. *User Modeling and User-Adapted Interaction*, 22(4-5):399–439, 2012.
30. Nava Tintarev and Judith Masthoff. Explaining recommendations: Design and evaluation. In *Recommender Systems Handbook*, pages 353–382. Springer, 2015.
31. Jasper van der Waa, Jurriaan van Diggelen, and Mark Neerincx. The design and validation of an intuitive confidence measure. In *Workshop On Explainable Smart Systems (EXSS)*, 2018.
32. Jesse Vig, Shilad Sen, and John Riedl. Tagsplanations: explaining recommendations using tags. In *Proceedings of the 14th International Conference on Intelligent User Interfaces*, pages 47–56. ACM, 2009.
33. Markus Zanker and Daniel Ninaus. Knowledgeable explanations for recommender systems. In *Web Intelligence and Intelligent Agent Technology (WI-IAT), 2010 IEEE/WIC/ACM International Conference on*, volume 1, pages 657–660. IEEE, 2010.