Towards an Argument-based Music Recommender System

C. E. Briguez M. C. D. Budán C. A. D. Deagustini
A. G. Maguitman M. Capobianco G. R. Simari

Artificial Intelligence Research and Development Laboratory (LIDIA)
Department of Computer Science and Engineering
Universidad Nacional del Sur

Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET)

Presentation outline

1. Usual approaches for recommendation
    - Quantitative vs. Qualitative approaches
    - Content-based vs. Collaborative Filtering
    - Problems

2. Role of argumentation in recommendations
    - Our proposal
    - The use of postulates
    - Preference between postulates
        - Defining how hibrid our recommender will be
        - Expanding aspects: addition of postulates
    - The rol of arguments: an example of a recommendation
    - An additional advantage: supplying explanations for recommendations

3. Conclusions

Motivation

- Nowadays, users interact with large or complex information spaces.
- Within this setting, they need to make their decisions in an efficiently informed way.

Motivation

- Nowadays, users interact with large or complex information spaces.
- Within this setting, they need to make their decisions in an efficiently informed way.
- Recommenders attempt to generate a model of the user or user's task and apply diverse heuristics to anticipate what information may be useful to the user.
- In order to come up with recommendations, conventional recommender systems rely on similarity measures between users or contents, computed on the basis of methods coming either from the information retrieval or the machine learning communities.

Quantitative vs. Qualitative approaches

- In recommendations, there are two main options regarding how the final recommendation is achieved.

Quantitative vs. Qualitative approaches

- In recommendations, there are two main options regarding how the final recommendation is achieved.
- Quantitative approaches are based on numerical measures of similarity between items or users.

Quantitative vs. Qualitative approaches

- In recommendations, there are two main options regarding how the final recommendation is achieved.
- Quantitative approaches are based on numerical measures of similarity between items or users.
- While quantitative approaches establish similarity based on intrinsical properties of items or users

Content-based vs. Collaborative Filtering

- Taking into account while the recommenders rely more heavily in the user for which the recommendation is made or the whole community in which she is in, we can have:

Content-based vs. Collaborative Filtering

- Taking into account while the recommenders rely more heavily in the user for which the recommendation is made or the whole community in which she is in, we can have:
- Content-based recommenders
  - Driven by the premise that users' preferences tend to persist through time.
  - A new item is recommendable if it is similar to another the user has rated as good before.

Content-based vs. Collaborative Filtering

- Taking into account while the recommenders rely more heavily in the user for which the recommendation is made or the whole community in which she is in, we can have:
- Content-based recommenders
  - Driven by the premise that users' preferences tend to persist through time.
  - A new item is recommendable if it is similar to another the user has rated as good before.
- Recommender systems based on collaborative filtering
  - Relies on the assumption that users' preferences are correlated.
  - For a given user, a new item is recommendable if similar user had rated the item as good before.

Content-based vs. Collaborative Filtering

- Taking into account while the recommenders rely more heavily in the user for which the recommendation is made or the whole community in which she is in, we can have:
- Content-based recommenders
  - Driven by the premise that users' preferences tend to persist through time.
  - A new item is recommendable if it is similar to another the user has rated as good before.
- Recommender systems based on collaborative filtering
  - Relies on the assumption that users' preferences are correlated.
  - For a given user, a new item is recommendable if similar user had rated the item as good before.
- A combination of collaborative-filtering and content-based recommendation gives rise to hybrid recommender systems.

Limitation in recommenders

- Existing recommender systems cannot deal formally with the defeasible nature of users preferences in complex environments.

Limitation in recommenders

- Existing recommender systems cannot deal formally with the defeasible nature of users preferences in complex environments.
- Besides, the quantitative approaches adopted by most existing recommender systems do not have a clean underlying model.
- This makes it hard to provide users with a clear explanation of the factors and procedures that led the system to come up with certain recommendations.

Limitation in recommenders

- Existing recommender systems cannot deal formally with the defeasible nature of users preferences in complex environments.
- Besides, the quantitative approaches adopted by most existing recommender systems do not have a clean underlying model.
- This makes it hard to provide users with a clear explanation of the factors and procedures that led the system to come up with certain recommendations.
- Another problem faced by recommender systems is that modeling the users' preference criterion is not an easy task, since it generally involves incomplete and potentially inconsistent knowledge about the search domain.

Our proposal

- We introduce a novel hybrid approach to refine recommendations achieved by quantitative methods with a qualitative approach based on argumentation, where suggestions are given after considering several arguments in favor or against the recommendations.

Our proposal

- We introduce a novel hybrid approach to refine recommendations achieved by quantitative methods with a qualitative approach based on argumentation, where suggestions are given after considering several arguments in favor or against the recommendations.
- In order to accomplish this, we use *Defeasible Logic Programming* (DeLP) as the underlying formalism for obtaining recommendations. This approach has a number of advantages over other existing recommendation techniques.

Our proposal

- We introduce a novel hybrid approach to refine recommendations achieved by quantitative methods with a qualitative approach based on argumentation, where suggestions are given after considering several arguments in favor or against the recommendations.
- In order to accomplish this, we use *Defeasible Logic Programming* (DeLP) as the underlying formalism for obtaining recommendations. This approach has a number of advantages over other existing recommendation techniques.
- In particular, recommendations can be refined at any time by adding new polished rules, and explanations may be provided supporting each recommendation in a way that can be easily understood by the user, by means of the computed arguments.

Our proposal

- We introduce a novel hybrid approach to refine recommendations achieved by quantitative methods with a qualitative approach based on argumentation, where suggestions are given after considering several arguments in favor or against the recommendations.
- In order to accomplish this, we use *Defeasible Logic Programming* (DeLP) as the underlying formalism for obtaining recommendations. This approach has a number of advantages over other existing recommendation techniques.
- In particular, recommendations can be refined at any time by adding new polished rules, and explanations may be provided supporting each recommendation in a way that can be easily understood by the user, by means of the computed arguments.
- Also, DeLP helps to model the users' preference criterion incompleteness and inconsistency.

Identifying recommendations: the use of postulates

- The process of obtaining recommendations in an argument-based system is very different from the usual approach applied by quantitative systems.
  - Quantitative-approaches: similarity established by numerical methods.
  - Argumentation-based qualitative approaches: similarity established using postulates that state which characteristics have to be shared between objects or users to be considered similar.

Identifying recommendations: the use of postulates

- The process of obtaining recommendations in an argument-based system is very different from the usual approach applied by quantitative systems.
  - Quantitative-approaches: similarity established by numerical methods.
  - Argumentation-based qualitative approaches: similarity established using postulates that state which characteristics have to be shared between objects or users to be considered similar.
- These postulates are used to express aspects based on the principles of both the collaborative filtering and the content-based approaches.

Proposed postulates

Postulate	Description
1	A user may like a song if he likes another song by the same artist.
2	A user may dislike a song if he dislikes another song by the same artist.
3	A user may like a song if he likes another song performed by an artist related to this song.
4	A user may dislike a song if he dislikes another song performed by an artist related to this song.
5	A user may like a song if he likes another song with the same musical genre.
6	A user may dislike a song if he dislikes another song with the same musical genre.
7	A user may like a song if the song is liked by a similar user.
8	A user may dislike a song if the song is disliked by a similar user.
9	A user may like a song if the song is liked by a group of similar users.
10	A user may dislike a song if the song is disliked by a group of similar users.
11	A user may like a song if the song is often listened by the rest of the system's users.
12	A user may dislike a song if the song is not often listened by the rest of the system's users.

Preference between postulates

- With the presented postulates it is possible to obtain arguments in favor or against the potential recommendations.
- A problem arising from this situation is how to decide whether to finally recommend the track or not.

Preference between postulates

- With the presented postulates it is possible to obtain arguments in favor or against the potential recommendations.
- A problem arising from this situation is how to decide whether to finally recommend the track or not.
- In this work we use two argument preference criteria that will help to solve this problem.
  - Priority among rules is used as the preponderating criterion.
  - Generalized specificity is used to solve clashes in arguments that use rules with the same priority.

Preference between postulates

- This combined preference criteria is formalized in the following manner (Def. 2 of the paper)

Definition

Defeat
Let $\mathcal{P} = (\Pi, \Delta)$ be a de.l.p. Let $\langle A_1, h_1 \rangle$ and $\langle A_2, h_2 \rangle$ be two arguments in $\mathcal{P}$. We say that $\langle A_2, h_2 \rangle$ defeats $\langle A_1, h_1 \rangle$ if and only if there exists a sub-argument $\langle A, h \rangle$ of $\langle A_1, h_1 \rangle$ such that $\langle A_2, h_2 \rangle$ counter-argues $\langle A_1, h_1 \rangle$ at literal h and it holds that:

1. *$\langle A_2, h_2 \rangle$ is preferred by priority to $\langle A, h \rangle$ (proper defeater), or*
2. *$\langle A, h \rangle$ is not preferred by priority to $\langle A_2, h_2 \rangle$ and $\langle A_2, h_2 \rangle$ is strictly more specific that $\langle A, h \rangle$ (proper defeater), or*
3. *$\langle A_2, h_2 \rangle$ is unrelated to $\langle A, h \rangle$ (blocking defeater)*

Defining how hibrid our recommender will be

- The use of the priority among rules criterion gives us the opportunity to easily find the best combination of postulates by empirical trials.

Defining how hibrid our recommender will be

- The use of the priority among rules criterion gives us the opportunity to easily find the best combination of postulates by empirical trials.
  - We can use a content-based approach and then refine the answer using collaborative-filtering postulates, or the other way around.

Defining how hibrid our recommender will be

- The use of the priority among rules criterion gives us the opportunity to easily find the best combination of postulates by empirical trials.
  - We can use a content-based approach and then refine the answer using collaborative-filtering postulates, or the other way around.
  - Moreover, we can mix the postulates (and by extension the approaches used) in any arbitrary way we want. For instance, we can state a content-based postulate as the top priority postulate, then two collaborative-filtering postulates as second and third, and so on.

Expanding aspects: the addition of postulates

- The postulates represent the cases they model in a very clear, colloquial and independent way that is easy to understand and discuss.
- This leads to another advantage of our approach: we can model new cases by adding rules to the system at any time, without the need of examining the effects on other rules.

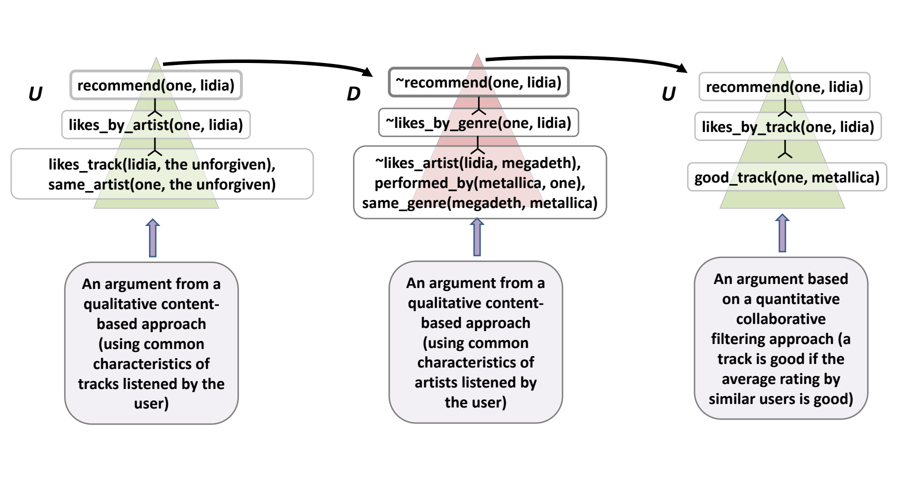
Expanding aspects: the addition of postulates

- The postulates represent the cases they model in a very clear, colloquial and independent way that is easy to understand and discuss.
- This leads to another advantage of our approach: we can model new cases by adding rules to the system at any time, without the need of examining the effects on other rules.
  - Add a rule that refines an existing one, if we discover that certain rule has marked counter-examples, and we know the characteristics that those counter-examples share.

Expanding aspects: the addition of postulates

- The postulates represent the cases they model in a very clear, colloquial and independent way that is easy to understand and discuss.
- This leads to another advantage of our approach: we can model new cases by adding rules to the system at any time, without the need of examining the effects on other rules.
  - Add a rule that refines an existing one, if we discover that certain rule has marked counter-examples, and we know the characteristics that those counter-examples share.
  - Add an entirely new postulate modeling a relation between data that we have not been taking into account, or if we suddenly have access to data that was previously absent.

The rol of arguments: an example of a recommendation



An additional advantage: supplying explanations for recommendations

- Another advantage of using an argumentative approach for recommenders is that giving explanations to recommendations is almost straightforward, as arguments can be seen as self-explanatory set of reasons.

An additional advantage: supplying explanations for recommendations

- Another advantage of using an argumentative approach for recommenders is that giving explanations to recommendations is almost straightforward, as arguments can be seen as self-explanatory set of reasons.
- For instance, take the case of the recently introduced example. We can express in a slightly more colloquial way the structure of the argument that has prevailed in the dialectical procedure using the functors of predicates in the rule, and offer that to the user as the reason behind the recommendation.
- In this case, we state that the track One by Metallica is recommended as we know that the user has listened (and liked) another Metallica song, which is a more powerful reason than the one founded against the recommendation (the user dislike for a band similar to Metallica).

Conclusions

- We have introduced an argumentation-based approach with the capability to improve recommendation technologies.
- Argumentation can be used to perform a qualitative analysis on users and items.
- This allows us to go a step forward with respect to the classical purely quantitative approach to recommendation.

Conclusions: main advantages of the approach

- Several aspects can be taken into account at the same time before giving the recommendation.

Conclusions: main advantages of the approach

- Several aspects can be taken into account at the same time before giving the recommendation.
- Aspects can be applied to model some useful features that are hard to take into account in quantitative approaches (*e.g.*, the defeasible nature of users' preferences).

Conclusions: main advantages of the approach

- Several aspects can be taken into account at the same time before giving the recommendation.
- Aspects can be applied to model some useful features that are hard to take into account in quantitative approaches (*e.g.*, the defeasible nature of users' preferences).
- The rule-based modeling of aspects allows us to make recommendations based on quantitative or qualitative criteria, or even mix them in any way.

Conclusions: main advantages of the approach

- Several aspects can be taken into account at the same time before giving the recommendation.
- Aspects can be applied to model some useful features that are hard to take into account in quantitative approaches (*e.g.*, the defeasible nature of users' preferences).
- The rule-based modeling of aspects allows us to make recommendations based on quantitative or qualitative criteria, or even mix them in any way.
- It makes easier to model restrictions to recommendations based on contextual information (*e.g.*, users' moods).

Conclusions: main advantages of the approach

- Several aspects can be taken into account at the same time before giving the recommendation.
- Aspects can be applied to model some useful features that are hard to take into account in quantitative approaches (*e.g.*, the defeasible nature of users' preferences).
- The rule-based modeling of aspects allows us to make recommendations based on quantitative or qualitative criteria, or even mix them in any way.
- It makes easier to model restrictions to recommendations based on contextual information (*e.g.*, users' moods).
- The use of coherent structures of reasons (arguments) makes giving explanations to recommendations an almost straightforward process.