White Paper: The Universal Recommender
A Recommender System for Semantic Networks

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Abstract
We describe the Universal Recommender, a recommender system for semantic datasets that generalizes domain-specific recommenders such as content-based, collaborative, social, bibliographic, lexicographic, hybrid and other recommenders. In contrast to existing recommender systems, the Universal Recommender applies to any dataset that allows a semantic representation. We describe the scalable three-stage architecture of the Universal Recommender and its application to Internet Protocol Television (IPTV). To achieve good recommendation accuracy, several novel machine learning and optimization problems are identified. We finally give a brief argument supporting the need for machine learning recommenders.

1 Introduction
In the field of information retrieval, a recommender system is defined as a system that is able to find entities in a dataset that may be of interest to the user [2]. In contrast to search engines, recommender systems do not base their results on a query, instead they rely on implicit and explicit connections between users and items, such as ratings or other past interactions. Research and development in the area of recommender systems has grown in recent years, as witnessed by the creation of a high-profile conference devoted to them.

In the general case, a recommender system applies to a dataset described by a data model containing entities (such as users and items) and relationships (such as ratings and social links). In the simplest recommender system, data consists of one relationship type connecting one or two entity types. In more complex cases, the dataset contains multiple relationship types connecting any number of entity types.

The simple case, with only one relationship type, corresponds to several well-studied recommendation subproblems, such as link prediction, collaborative filtering, citation analysis, etc. In the case of multiple relationship types, hybrid recommenders are normally used. As we will show, most hybrid recommenders

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however are specific to one data model and cannot be generalized to other data models. Therefore, each time a new data model is introduced, a new hybrid recommender has to be developed.

To avoid these problems we propose the **Universal Recommender** (UR), a recommendation engine with the following features:

- It applies to datasets with any number of entity and relationship types.
- It learns all its parameters without human interaction.

The first feature ensures the recommender can be applied to future datasets whose structures are unknown. The second feature is more critical; since a recommender using semantic datasets has a large set of parameters, a complex recommender runs the risk of either overfitting or having very low recommendation quality. The main challenges of the Universal Recommender are therefore a series of machine learning problems related to the complexity of semantic networks, and a series of optimization problems that must be solved to make the recommender scalable. We give a brief justification for machine learning recommenders by interpreting non-learning recommenders as a source of additional data, enhancing machine learning recommenders.

We begin by reviewing typical recommendation datasets and tasks, and give known solutions to specific recommendation problems. We then describe the unified semantic data model and the architecture of the Universal Recommender. We continue by identifying the machine learning and optimization problems it will have to solve. Finally we describe the case study of the Internet Protocol Television (IPTV) recommender system.

## 2 State-of-the-art Recommenders

In this section, we review classical recommendation settings motivating the complexity of typical recommendation datasets. We also review existing solutions for recommendation problems that apply to specific dataset types.

We describe all cases in the context of the Internet Protocol Television (IPTV) recommender system [33]. The IPTV systems delivers television programs over the Internet instead of traditional broadcast signals. Using the flexibility of the Internet Protocol, IPTV devices have the possibility to provide additional services on top of TV viewing. One of these additional services are recommender systems. In our supposed setting, the goal is thus to recommend a TV program to a user. In the following examples we describe classical recommendation settings applied to our IPTV scenario.

### 2.1 Content-based Filtering

The first kind of recommender we describe uses the content of items to generate recommendations, similarly to search engines. While search engines require the user to enter a specific keyword for searching, content-based recommenders
usually take keywords from another source, for instance a user profile containing words describing user interests, or from items already seen or rated.

Figure 1 shows a situation in which a user–item recommendation is found by comparing common features of two items. In this entity-relationship (ER) diagram, arrows represent known relationships and the dotted arrow represents the relationship to predict. $U$, $I$ and $W$ represent users, items and words respectively.

![Figure 1: The entity-relationship diagram of a dataset used by content-based recommenders.](image)

Content-based filtering has traditionally been applied to document recommendation, using the tf–idf measure as edge weights. In our IPTV system, each TV program has a description of its content. This example nevertheless shows a limitation of the content-based approach for IPTV; due to the fact that descriptions are much shorter than typical documents, the tf–idf measure will be less accurate.

### 2.2 Collaborative Filtering

While the content-based approach is simple (essentially being a search engine), only making use of one user’s relations to items, collaborative filters attempt to make use of all known relations between users and items. For instance, if our IPTV system tracks the programs watched by each user, this information can be used directly giving collaborative filters, as shown in Figure 2.

![Figure 2: The entity-relationship diagram of a dataset used by collaborative recommenders.](image)

The general idea is the following: If we know which TV programs user $U_1$ has watched, we can use this information directly, without content information, to make connections between items. To do this, a collaborative recommender system must consider the behavior of other users. If user $U_2$ has seen the same TV program $I_2$ as user $U_1$, then we can recommend other TV programs seen by $U_2$. The resulting recommender system does not need any content information. Therefore, collaborative recommenders are often used in scenarios where little or no content is available, movies or jokes for instance [15]. For our IPTV recommender, this means we do not have to rely on content descriptions, and can thus recommend TV programs lacking a description.

Furthermore, a collaborative recommender can make use of ratings. Compared to the typical has-seen information, ratings have the advantage of also admitting negative values, modeling dislike.
2.3 Social Networks and Link Prediction

Another type of recommender is given when links are known between users. For instance, if IPTV users maintain a buddy list, we can recommend the favorite items of a given user’s buddies. This type of recommendation is particularly useful when trust is important. In this case, a trust measure can be defined between users denoting the level of confidence a user has in another user. Methods to compute trust include local measures [17, 31] and global approaches, which often generalize the PageRank measure [22, 24, 32]. Figure 3 gives the associated entity-relationship diagram.

\[
\begin{align*}
U_1 \rightarrow & \quad I_1 \\
\quad & \downarrow \\
U_2 \\
\end{align*}
\]

Figure 3: The entity-relationship diagram of a dataset used by social recommenders.

In addition to friendship and trust, which are positive relationships, we may allow users to mark other users as foes (or enemies), representing distrust [17, 26].

2.4 Lexicographic Information

While words contained in descriptions may be used to find similar TV programs, the words themselves may be modeled as interlinked entities: Some words are synonyms, antonyms, etc. [11] These relationships may be used to enhance a content-based recommender by recommending items of a related topic using different glossaries [30, 36]. Figure 4 gives the associated entity-relationship diagram, in which \( W \) denotes words.

\[
\begin{align*}
U_1 \rightarrow & \quad I_1 \rightarrow \quad W_1 \\
\quad & \downarrow \\
I_2 \rightarrow \quad W_2 \\
\end{align*}
\]

Figure 4: The entity-relationship diagram of a dataset used by lexicographic recommenders.

We might even go as far as mapping words in different languages to each other, using information from a dictionary. This would allow the IPTV system to recommend programs in other languages.

2.5 Hybrid Recommenders

In many recommender systems, several of the previously described dataset types are known. For instance, a recommender system may have user ratings for items and at the same time content information about items. Recommenders that apply to such datasets are called hybrid recommenders. While hybrid recommenders exist for many combinations of entity and relationship types (e.g. [1, 4, 41, 43, 44]), none of these can be applied to all semantic networks.
since they are not generic. One of many possible data models is shown in Figure 5.

![Diagram](image_url)

**Figure 5:** The entity-relationship diagram of a dataset used by hybrid recommenders.

### 2.6 Semantic Networks

In the general case, datasets can be modeled as a set of entities connected by relationships. While in simple datasets relationships are similar (e.g. the `has-seen` relationship), more complex networks almost always contain multiple relationship types. This is especially true when several datasets are combined. The result is a semantic network, where multiple relationship types connect multiple entity types. An example is shown in Figure 6.

![Diagram](image_url)

**Figure 6:** A semantic network consisting of entities and relationships of different types.

Several ongoing projects collect data from various sources and integrate them to semantic networks, DBpedia [5], YAGO [39] and Freebase [7] for instance. Probabilistic models that apply to semantic networks exist [14, 35], they have however not been used for recommendation.

Semantic networks are general enough to represent the datasets described previously in this section. Therefore, the Universal Recommender will use a semantic representation of datasets. The following section describes this representation in detail.

### 3 Unified Semantic Representation of Datasets

In order to write a recommender system that supports all the use cases described in the previous section, we define a unified semantic representation of the datasets the Universal Recommender will be applied to.
Table 1: Common relationship types in recommender systems, arranged by the entity types they connect. Only unipartite and bipartite relationship types are shown. Unipartite relationship types are on the diagonal entries of the table.

| User   | Item | Word |
|--------|------|------|
| User   | Social network |      |      |
|        | Trust network   |      |      |
|        | Email network   |      |      |
|        | Profile ratings |      |      |
| Item   | Explicit feedback | Citations | Hyperlinks |
|        | Implicit feedback |      |      |
|        | Authorship      |      |      |
|        | Commercial selling data |      |      |
| Word   | Search history | tf-idf | WordNet |
|        | Categories      |      |      |

- Datasets consist of entities and relationships, each connecting two or more entities.
- Entities are grouped into multiple entity types $E_i$.
- Relationships are grouped into multiple relationship types $R_i$, each connecting a predefined number of fixed entity types.
- Relationships may be symmetric or asymmetric, corresponding to undirected and directed relations.
- Relationships may be unweighted or weighted, and weights may be negative.
- Entities and relationships may both be annotated with attributes, for instance timestamps of ratings or the age of users.

Note that this definition not only includes binary relationships, but also higher-order relationships (e.g. tag assignments between users, tags and items.) Table 1 gives some examples of relationship types between users, items and words. Table 2 gives examples of relationship types by the number of different entity types they connect (unipartite, bipartite) and the range of edge weights. Table 3 gives an overview of traditional data mining applications that can be interpreted as special cases of recommendation.

4 Architecture

Based on the dataset structure described in the last section, the Universal Recommender is built on a scalable three-stage architecture, shown in Figure 7.

The basis of any recommender system is a dataset, in our case it is a semantic one. The final output of the Universal Recommender are recommendations. In
Table 2: Common relationship types by the number of entity types they connect and the range of admitted edge weights.

| Number of connected entities | 2          | 3          |
|------------------------------|------------|------------|
| Unweighted                   | Unipartite | Bipartite  | Tripartite |
| Unweighted                   | Friendship | Authorship | Folksonomy |
| Weighted                     | Profile rating | Rating     |            |
| Positive                     | Communication | View history | Clickthrough data |
| Signed                       | Friend/foe network | Like/dislike | Contextual rating |

the first stage, the dataset is mapped to a recommender model, which can be interpreted as a decomposition in the general sense. This model is then used to build a recommender index, which allows recommendations to be computed quickly in the third stage. The next sections describe these various steps in detail.

Figure 7: Computational flow diagram of the Universal Recommender. First the dataset is decomposed into a recommender model. In this model, entities are clustered giving a recommender index. Finally, a recommender computes recommendations using the recommender index.

5 Universal Latent Decomposition

In this section, we describe the general decomposition approach for semantic networks used by the Universal Recommender. The idea consists in representing entities in a latent space, in which relationships are predicted by using the scalar product. In other words, if we associate a vector of length $k$ to every entity,
Table 3: Compilation of common relationship types, the entity types they connect, and the traditional data mining applications using only that relationship type as a dataset.

| Dataset             | Relationship types | Entity types                  | Weight range | Application                              |
|---------------------|--------------------|--------------------------------|--------------|------------------------------------------|
| Explicit feedback   | Ratings            | Users, items                   | Signed       | Collaborative filtering                  |
| Implicit feedback   | View, save, etc.   | Users, items                   | Unweighted   | Collaborative filtering, recommendation  |
| Features            | tf-idf             | Text documents, phrases        | Positive     | Document classification                  |
| Social network      | Friendship         | Users                          | Unweighted   | Link prediction, community building      |
| Signed social network | Friendship, enmity | Users                          | \(-1,+1\)   | Link sign prediction, community building |
| Web                 | Hyperlinks         | Web pages                      | Unweighted   | Link prediction, ranking                 |
| Citation network    | References         | Scientific publications        | Unweighted   | Bibliographic analysis                   |
| Trust network       | Trust, distrust    | Users                          | Unweighted or \(-1,+1\) | Trust measures                          |
| Interaction network | Communication (e.g. email) | Users                          | Positive integer | Link prediction, network analysis       |
| User profile ratings | Ratings of user profiles | Users                          | Signed       | Expert finding, date site recommendation |
| Collaboration graph | Authorship         | Authors, publications          | Unweighted   | Community building                       |
| Search history      | Searches           | Users, queries, phrases        | Unweighted   | Query reforming, query recommendation    |
| Taxonomy            | Category membership | Items, categories             | Unweighted   | Classification                           |
| Lexical network     | Synonymy, antonymy, etc. | Words                          | Unweighted   | Query reforming, lexical search          |
| Folksonomy          | Tag assignment     | Users, items, tags             | Unweighted   | Tag and item recommendation, trend prediction |
we compute a prediction between two entities using the scalar product. This approach has two consequences:

- Computation of the latent model can be interpreted as a decomposition of the adjacency matrix of the complete network, allowing us to use known graph kernels.
- The predictions made by the latent model have to be mapped to recommendations. This is described in Section 7.

The following state-of-the-art recommendation algorithms can be described as the decomposition of a dataset into a latent model:

- The singular value decomposition (SVD) and eigenvalue decomposition (EVD) [42] and their applications to principal component analysis (PCA) and latent semantic indexing (LSI) [13].
- Graph kernels such as the exponential kernel, the von Neumann kernel, path counting and rank reduction methods [18, 19, 23, 34]. These can be applied to the eigenvalue or singular value decomposition of graphs, and their parameters can be learned efficiently [25].
- Methods based on the Laplacian matrix such as the commute time and resistance distance [3, 12, 27], the heat diffusion kernel [21] and the random forest kernel [10].
- Probabilistic approaches such as probabilistic latent semantic analysis (PLSA) [20], and latent Dirichlet allocation (LDA) [6].
- Other matrix decompositions such as nonnegative matrix factorization [29], maximum margin matrix factorization [38] and low-rank approximations with missing values [37].
- Higher-order decompositions such as parallel factor analysis (PARAFAC) [9], the Tucker decomposition [40] and others [28].

5.1 Example

In the example of the IPTV recommender, we give a derivation of a recommendation algorithm using the singular value decomposition. Let $U$ be the user set, $I$ the item set and $W$ the set of words. Then the dataset is given by the following adjacency matrices: the ratings $R \in \mathbb{R}^{U \times I}$, the buddies $B \in \{0, 1\}^{U \times U}$ and the features $F \in \{0, 1\}^{I \times W}$. The weighted matrix $R$ is then normalized to $\bar{R}$ and aggregated with the other adjacency matrices into a single matrix $A \in \mathbb{R}^{(U+I+W)\times(U+I+W)}$.

$$A = \begin{pmatrix}
  w_B B & w_R \bar{R} & w_F F \\
  w_R \bar{R}^T & w_F F^T & w_F F
\end{pmatrix}$$
where $w_X > 0$ is the weighting of relationship type $X$.

This matrix is then decomposed, giving latent vectors for all three entity types. The approximation or decomposition used may be any of those described above. For simplicity, we adopt the notation of the singular value decomposition.

$$A = U \Sigma V^T = \begin{pmatrix} U_U & U_I & U_W \end{pmatrix} \begin{pmatrix} \Sigma_U & 0 & 0 \\ 0 & \Sigma_I & 0 \\ 0 & 0 & \Sigma_W \end{pmatrix} \begin{pmatrix} V_U \\ V_I \\ V_W \end{pmatrix}^T$$

$U_X$ and $V_X$ are latent vectors of dimension $X \times k$, where $k$ is the number of latent dimensions computed. These vectors can then be used for computing recommendations. To compute a rating prediction for the user–item pair $(u, i)$, we would use $U_U(u) \cdot V_I(i)$. Relationship types that connect more than two entity types have to be reduced from hypergraphs to graphs in this model. Possible reductions are the star and clique expansions [3].

### 6 The Machine Learning Approach

Here we describe the machine learning problems associated with the Universal Recommender. While in unirelational networks a matrix decomposition approach is a common procedure to recommendation, its application to semantic networks raises additional issues:

- Weights and sparsity patterns of different relationship types may be different, in which case each relationship type has to be normalized separately.
- Since edge weights of different relationship types are usually not comparable, the question of finding the relative weights $w_X$ arises.

To motivate the machine learning approach to recommenders, consider the case of a “dumb” recommender with hardcoded recommendations. The administrator of a recommender system may be tempted to implement hardcoded recommendations, thinking that such a recommender may be more pertinent than a learning recommender. However we now have an additional problem: How will the administrator choose the hardcoded recommendations? In practice he will choose the preferences of himself or another user, i.e. enter the items someone thinks are good. But then the question becomes: Why would other users have the same taste as this one user? In fact, users do not all have the same taste and effectively, finding which users have similar tastes amounts to writing a collaborative recommender. Therefore, the hardcoded recommendations are not necessarily useful as recommendations for every user, but can be used indirectly by a collaborative algorithm to provide better recommendations for everyone. In other words, trying to hardcode recommendations in one part of the recommender will make machine learning algorithms more useful in other parts of the system, underlining the importance of the following machine learning problems.
6.1 Learning Normalizations
In recommender systems that apply to unirelational datasets with edge weights such as ratings, a common first step consists in additive normalization. Given edge weights $a_{ij}$, additive normalization computes new edge weights $b_{ij} = a_{ij} - \bar{a}_{ij}$, where $\bar{a}_{ij}$ is a simple approximation to $a_{ij}$, e.g. a row or column mean.

In most recommenders, this step is usually kept simple, such as subtracting the overall rating mean. In semantic networks, each weighted relationship type may need separate normalization, and the overall normalization problem becomes non-trivial as the number of parameters increases with the number of relationship types.

6.2 Learning Relative Weights
In unirelational datasets, all edges have the same semantics, and an algebraic or probabilistic decomposition algorithm can use this fact to compute a low-rank model of the data. In semantic networks however, such an algorithm would implicitly assume that edges have the same semantics, which in practice only works if the different relationship types have a similar weight range and degree distribution.

In order to apply these algorithms to semantic networks, the different relationship types have to be weighted separately. The weights $w_X$ depend on the characteristics of the subnetwork (e.g. the degree distribution), but also on overall considerations, such as whether a particular relationship type is useful for recommendation. Different weights must also be applied to different relationship types connecting the same entity types.

These weights can be hardcoded using domain-specific knowledge. For instance in the IPTV case, by knowing that ratings contribute more to recommendations than the has-seen relationship type. These assumptions are however difficult to justify purely from expert knowledge. To validate these assumptions, we would have to evaluate recommenders that use varying values of these parameters. If we do this, we automatically learn which parameter values are best, and can discard the expert knowledge. We therefore propose the Universal Recommender to learn relative weights automatically, in order to avoid being dependent on domain-specific knowledge, and to validate domain-specific knowledge if present.

Examples of different relationship types connecting users and items are has-seen, has-recorded and has-bookmarked. While a human IPTV expert could set these relative weights by hand, learning the weights is a worthwhile machine learning problem in itself.

7 Optimization Problems
In addition to the machine learning problems which assure that recommendations actually correspond to user expectations, the following optimization problems must be solved to ensure the scalability of the Universal Recommender.
• The computation of the latent recommender model must be asynchronous. In other words, updates to the data model must be incorporated into the recommender model without recomputation of the whole recommender model. In practice, the recommender model is built iteratively, and the data model is read at each iteration, ensuring that changes are incorporated into the recommender immediately.

• While rating predictions can be computed in constant time for a given recommender model (using the scalar product), computations of recommendations are more complex. The underlying problem consists of finding a vector maximizing the scalar product with a given vector. This problem is similar but not identical to the metric nearest-neighbor problem. A common approach consists in clustering the set of entities.

The following subsections describe possible solutions to these optimization problems.

7.1 Iterative Update of the Recommender Model

To compute recommendations in a dataset, a recommender model is built from the dataset. This model building step may be slow, but the resulting model can be used to compute any number of recommendations rapidly. If the dataset changes, for instance when users rate additional items, the model would have to be recomputed.

To avoid this overhead, we propose a recommender model that can be updated iteratively. In fact, most matrix decomposition and low-rank approximation problems can be solved iteratively, giving a recommender model where updates arise naturally from the decomposition algorithm [16, 20, 37].

In this context, the role of the recommender model is analogous to PageRank for search engines [8]. The PageRank is a vector of entities (web pages) that can be updated by iterative algorithms (i.e. power iteration). In the case of the Universal Recommender, the model consists of a set of $k$ vectors corresponding to the latent spaces of the rank reduction method, and updates can be performed in a way consistent with the underlying algorithm.

7.2 Recommender Index

The goal of a recommender is to compute recommendations. Functionally, a recommender takes an entity as input (a user) and outputs a list of ranked entities (items). While rating prediction has received attention in itself (e.g. in the Netflix Prize), they are only useful to a recommendation system insofar as they can be used to rank items. To find the top $k$ items that a user would rate with high scores, all $n$ items have to be considered. Since runtime of recommendation should not depend on $n$, a recommender index has to be used.

A recommender index must solve the following problem: Given $n$ vectors $a_i$ and a vector $x$, find the top $k$ vectors $a_i$ such that $x \cdot a_i$ is maximal. A similar
problem with the scalar product replaced by the Euclidean distance is known as nearest neighbor search.

We conjecture that this problem can be solved analogously to the nearest neighbor problem by partitioning the unit hypersphere into regions containing a constant number of vectors $a_i$ and storing, for each region, the list of adjacent regions in a way that requires only linear memory in the number of regions and dimensions.

8 Case Study: IPTV

In this section we describe the IPTV recommender system as an example setting for the Universal Recommender. In the Internet Protocol Television system, users can watch TV programs over the Internet. In addition to the functionality provided by regular television, our IPTV includes a semantic recommender system based on the Universal Recommender. Figure 8 shows the entities and relationships present in the IPTV system, along with the main recommendation scenario.

This example shows characteristics found in many recommender system datasets: The primary entity types are users and items, which are TV programs
in this case. The main relationship types connect users and items. In our example these are view, flashback, rating, record and reminder events. This scenario shows a common feature of recommender systems: several relationships connect the same entity types. Other relationship types connect secondary entities such as location, genre, series and title. User–user relationships are represented by message events and buddy lists, both common in recommender systems. This dataset also contains higher-order relationship types, in the form of tag assignments and shared events. Recommendations in this dataset can be computed by using a recommender model and a recommender index, see Figure 9 for an example.

This example also shows how difficult it is, in general, to find and build a good hybrid recommender system out of simple recommender systems, because the number of relationship types is too large to be optimized by trial and error.

9 Conclusion

By describing the Universal Recommender, we hope to make clear the need for a generic recommender system that applies to semantic datasets. The Internet Protocol Television example shows that datasets available in recommender systems are usually complex and require not only hybrid recommenders, but generic recommenders that apply to any dataset. As we have seen, many state-of-the-art recommenders appear as special cases of our proposed Universal Recommender.

To implement the Universal Recommender, a unified representation of datasets
is needed, which we propose to be semantic. As many recommendation algorithms are based on the notion of embedding entities in a low-dimensional space, we adopt a latent representation for the Universal Recommender that covers these recommendation algorithms.

Several hard machine learning and optimization problems have to be solved to implement the Universal Recommender successfully. We showed how machine learning recommenders arise in the case of trying to hand-optimize a recommender, as a hardcoded recommendation algorithm can be interpreted as part of the underlying dataset, enhancing machine learning recommenders for the general recommendation problem. We thus come to the conclusion that the Universal Recommender will be able to match and eventually exceed the performance of dataset-specific recommenders, if these problems are solved.

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