— 1 —
Theory

This chapter will introduce some basic theory needed to develop our approach to user modeling. We will first describe our stated enemy, the information overload problem, before delving into how user modeling and, more specifically, recommender systems, is currently used to solve this problem.

This chapter will also introduce the notion of personalized search, a field where our user modeling method will be especially applicable. The next chapter will use these theories to build an *even more personalized approach* to user modeling.

1.1 Information Overload

Information overload conveys the act of receiving *too much information*. The problem is apparent in situations where decisional accuracy turns from improving with more information, to being hindered by too much irrelevant data (Bjorkoy, 2010, p13). Needness to say, this is a widespread phenomenon, with as many definitions as there are fields experiencing the problem. Examples include *sensory overload*, *cognitive overload* and *information anxiety* (Eppler and Mengis, 2004).

Two common tasks quickly become difficult in this situation: Consuming content that is known by the user to be relevant can be drowned out by irrelevant noise. Orthogonally, discovering new, interesting yet unknown content also becomes difficult because of the sheer amount of available content. Finding contemporary examples is not difficult:

- Missing important news articles that get drowned out by irrelevant content.
- Forgetting to reply to an email as new messages keep arriving.
- Discovering sub-par movies because those most relevant are never discovered.

The overload is often likened to a *paradox of choice*, as there may be no problem acquiring the relevant information, but rather identifying this information once acquired. As put by Edmunds and Morris (2000): "The paradox — a surfeit of information and a paucity of useful information." While normal cases of such overload typically result in feelings of being overwhelmed and out of control, Bawden and Robinson (2009) points to studies linking extreme cases to various psychological conditions related to stressful situations, lost attention span, increased distractibility and general impatience.

Kirsh (2000) argues that "the psychological effort of making hard decisions about *pushed* information is the first cause of cognitive overload." According to Kirsh, there will never be a fully satisfiable solution to the problem of overabundant information, but that optimal environments can be designed to increase productivity and reduce the level of stress through careful consideration of the user's needs. In other words, to solve the problems of information overload and content discovery, applications must be able to individually adapt to each user.

An insightful perspective on information overload comes from the study of attention economy. In this context human attention is seen a scarce commodity, offset by how much irrelevant noise is present at any given time. Attention can then be defined as "... focused mental engagement on a particular item of information. Items come into our awareness, we attend to a particular item, and then we decide whether to act" (Davenport and Beck, 2001). To evade information overload is then to maximize available attention, allowing more focus on the most important items of an interface.

Conceptual models used in interaction design can help us see when and where information overload interferes with the user experience. Norman (1988) advocates a model called the seven stages of action, describing how each user goes through several states while using a system (see Figure 1.1, adapted from Norman). First, the user forms a goal and an intention to act. The user then performs a sequence of actions on the world (the interface) meant to align the perceived world and the goals. After performing a set of actions, the new world state is evaluated and perceived. At last, the user evaluates the perception and interpretation of the world in accordance with the original goal.

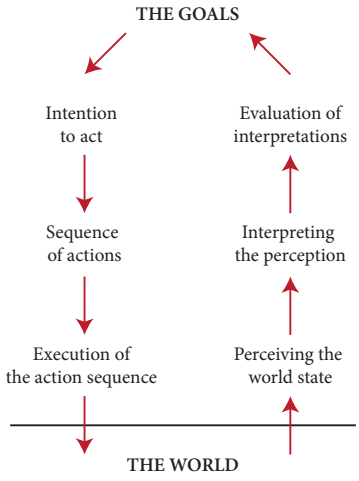


Figure 1.1

As apparent from this model, information overload can interfere both before and after any action is taken. For example, if the application presents too much content, or presents content in a confusing manner, it can be difficult for the user to identify which actions that would help achieve the current goal. Likewise, after actions are taken, the new world state can suffer the same shortcomings of overwhelming scope or lack of presentations, leading to information overload. This precludes the user from properly evaluating the resulting application state.

In short, an application interface can fail both before and after a user tries to interact with it. Information overload happens throughout the interaction process, which is important to know when considering possible solutions.

Online Overload

The Web is a common source of information overload. As we will use the web as an example throughout this paper, this section describes why the Web is so conducive to information overload.

Online information overload is especially pervasive when considering *content aggregating websites*, i.e. sites that collate information from multiple other sites and sources. Online information retrieval (i.e. search engines), fall into this category, as does online newspapers, feed readers and portal websites. As mentioned, the wealth and scope of data are natural culprits of online overload, as well as the varying qualities of websites publishing the information. However, lessons from graph theory can also help us see why information overload occurs on the Web.

Graph theory presents applicable models of the Web that characterize how people navigate between websites, and show how content aggregators form important hubs in the network. These models also show a theoretical foundation for why information overload occurs. In the Web graph, nodes correspond to websites and directed edges between nodes are links from one page to another. The *degree* of a node is defined as its number of edges.

The Internet has the properties of a *small-world network* (Newman and Moore, 2000), a type of random graph, where most nodes are not neighbors, but most nodes are reachable through a small number of edges (See Figure 1.2). This is because of important random shortcuts differentiating the graph from a regular lattice. The graph is not random, but neither is it completely regular. As described by Barabási (2003, p37), the average number of outbound links from a webpage is around 7. From the first page, we can reach 7 other pages. From the second, 49 documents can be reached. After 19 links have been traversed, about 10^{16} pages can be reached (which is more than the actual number of existing web pages, since loops will form in the graph).

The high degree of the Web graph would suggest that finding an optimal path to your desired page is quite difficult. Yet, while it is true that finding the *optimal path* is hard, finding *a good path* is not that big a challenge. When people browse the Web, links are not followed blindly — we use numerous different heuristics to evaluate each link, often

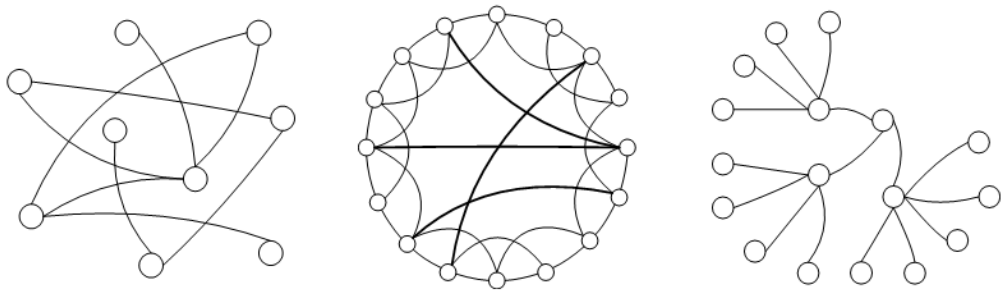


Figure 1.2: Complex Networks, from the left: A random *network, a* small-world *network and a* scale-free *network (which is a type of small-world network). Figure adapted from Huang et al. (2005).*

resulting in a quite good path to where we want to go. So why is the Web still quite challenging to navigate?

As discovered by Albert et al. (1999), the Web also exhibits properties of a *Scale-Free Network* (SFN). They found that in some natural observed networks, there exists a small number of nodes with an extremely high degree. This is also true on the Web — some websites have a huge number of outbound links. For comparison, while a random network is similar to a national highway system, with a regular number of links between major cities, scale-free networks are more like an air traffic system, with central hubs connecting many less active airports (Barabási, 2003, p71).

These highly connected nodes, called *hubs*, are not found in small-world networks or random graphs. As demonstrated by the presence of hubs, the degree distribution of a scale-free network follows a power law, $P(k) \sim k^{-\gamma}$, where $P(k)$ is the probability of a node having k connections and γ is a constant dependent on the type of network, typically in the range $2 < \gamma < 3$. Since the Web has directed edges, we have two power laws: $P_{in}(k) \sim k^{-\gamma_{in}}$ and $P_{out}(k) \sim k^{-\gamma_{out}}$.

Albert et al. (1999) describes a number of studies placing the γ values for the Web in the $[2, 3]$ range, with γ_{out} being slightly higher than γ_{in}. Both these probabilities exhibit power tails (or long tails). In other words, a few important nodes have a huge number of inbound and outbound links — the hubs. Barabási (2003, p86) proposed that hubs emerge in a scale-free networks because of two factors: (1) Growth: Nodes are added to the network one by one, for example when new websites are added to the Internet. (2) Preferential attachment: When new nodes are created, they connect to existing nodes. The probability that the new node will connect to an existing node is proportional to the number of links the existing node has. In other words, older, more established and

central nodes are preferred neighbors.

This is called the Barabási-Albert model (Albert et al., 1999), and the probability for a new node connecting to an existing node is given by $\prod k_i$ in Equation 1.1, where k_i is the number of links pointing to node i.

$$\prod_i k_i = \frac{k_i}{\sum_j^N k_j} \tag{1.1}$$

Another important topological observation of the Web is how fragmented it is. Barabási (2003, p166) describes the Internet as a number of continents:

The first continent is the *central core*, where most important hubs reside. On this continent, most sites are easily reachable through each other. The second is the *in-continent*, and is defined by the group of websites that often link to sites in the central core, but seldom receive reciprocal links from central hubs. The third is the *out-continent*, which are comprised of sites that are often linked to from the central hub, but seldom link back. Finally, the Internet has many *islands*, or dark nets, which are not accessible through links from other continents. The islands of the Web is why search engines allows web masters to manually add their sites to the search engine index — not all sites are discoverable by following simple links. Some of the Web is topographically close, but a lot of it is not.

Returning to our main topic, the *hubs* often represent the previously mentioned *content aggregating websites*. Search engines, social link aggregators, news portals, et cetera are all hubs of the Internet, emerging from the preferential link attachment of newly created nodes. Factor in the existence of multiple sub-graphs, or continents, and we can intuitively see that navigating the Web is not as easy as it might appear from simple models.

What does seem clear is that these content aggregating hubs are prime candidates for overwhelming their users with information. The fundamental observed structure of the Web creates the need for information brokers that link the net together, and the need for techniques to display a lot of data.

So far we have established that information overload is a pervasive problem, especially on the web. The question now becomes how to best solve this issue. This is where user modeling comes in.

1.2 User Modeling

The term *user modeling* (UM) lacks a strict definition. Broadly speaking, when an application is adapted in some way based on what the system knows about its users, we have user modeling. From predictive modeling methods in machine learning and how to implement these methods, to how interface design is influenced by personalization — the field covers a lot of ground.

It is important to differentiate between adapting the interface of an application and the content of an application. Many user modeling methods strive to personalize the interface itself, e.g. menus, buttons and layout of interface control elements (Jameson, 2009; Fischer, 2001). Adapting the application content, on the other hand, means changing how and what content is displayed For instance, interface adaption might mean changing the order of items in a menu, while content adaption might mean changing the order and emphasis of results in a web search interface.

We are interested in adapting the content of an application since the source of our overload problem often comes down to a mismatch between presented content and desired content. Examples of such user modeling include:

- Translating content based on a user's geographical location.
- Suggesting interesting items based on previous activity.
- Reorganizing or filtering content based on predicted user relevance.
- Changing the presentation of content to match personal preferences or abilities.

The fields of Artificial Intelligence (AI) and Human-Computer Interaction (HCI) share a common goal solving information overload through user modeling. However, as described by Lieberman (2009), they have different approaches and their efforts are seldom combined: while AI researchers often view contributions from HCI as trivial cosmetics, the HCI camp tends to view AI as unreliable and unpredictable — surefire aspects of poor interaction design. Luckily, according to Kobsa (2001), recent research has blurred the lines between the AI and HCI in user modeling.

In AI, user modeling refers to precise algorithms and methods that infer knowledge about a user based on past interaction (e.g. Pazzani and Billsus (2007); Smyth (2007); Alshamri and Bharadwaj (2008); Resnick et al. (1994)). By examining previous actions, predictions can be made of how the user will react to future information. This new knowledge is then embedded in a model of the user, which can predict future actions and reactions. For instance, an individual user model may predict how interesting an

unseen article will be to a user, based on previous feedback on similar articles or the feedback of similar users.

HCI aims to meet user demands for interaction. User modeling plays a crucial role in this task. Unlike the formal user modeling methods of AI, user models in HCI are often cognitive approximations, manually developed by researchers to describe different types of users (e.g. Fischer (2001); Jameson (2009); Cato (2001)). These models are then utilized by interaction designers to properly design the computer interface based on a models predictions of its user's preferences. Totterdell and Rautenbach (1990) describes user modeling in interaction design as a collection of deferred parameters: "The designer defers some of the design parameters such that they can be selected or fixed by features of the environment at the time of interaction [...] Conventional systems are special cases of adaptive systems in which the parameters have been pre-set."

This paper is concerned with the AI approach to user modeling, and in particular, the use of *recommender systems (RS)*. As our goal is to combine different RSs into one coherent user model, we will now describe what an RS entails, and introduce some of the many algorithms they employ.

1.3 Recommender Systems

The name might seem constraining, but recommender systems are incredibly powerful methods in user modeling. Whenever we wish to predict the relevance of an item to a user, recommender systems are the tools to use. Such systems are commonly used on the web to provide a host of predictive functionality, including:

- Recommending products like books or movies based on past purchases.
- Suggesting new social connections based on an existing social graph.
- Recommending items based the activity of similar or like-minded users.
- Ordering news articles by predicted individual relevance.
- Personalizing search results based on the current user.

Common to these examples are a set of users, a set of items, and a sparse set of explicit ratings or preferences. Items can be anything: Documents, movies, music, places, people, or indeed other users. A recommender system is best described by graph and graph operations, even though the underlying algorithms might not use this as the representation. Mirza and Keller (2003) explains how any RS can be expressed as a graph

traversal algorithm. Items and users are nodes, while ratings, social connections et cetera are edges between the nodes. An RS performs predictive reasoning on this graph by estimating the strenghts of hypothetical connections between nodes that are not explicitly connected.

For example, if a user has rated some of the movies in a movie recommendation system, we use these ratings to predict how well the user will like unseen movies, based on a movies ratings from users similar to the one in question. In social networks, recommender systems can be used to infer new social relations based on existing connections. The principle is the same: By evaluating current explicit connections, and the connections of similar users, new connections can be predicted. Recommender systems are then powerful methods for user modeling, personalization and fighting information overload, because of their ability to infer how relevant and item (or another user) will be to the current user.

Formally, a recommender system can be seen as a quintuple, $\mathrm{RS} = (I, U, R, F, M)$, where I is the set of items (e.g. products, articles or movies) and U is the set of users. R is the set of known connections, for example explicit preferences given by users for certain items, or connections in a social graph. F is a framework for representing the items, users and ratings, for example a graph or matrix. M is the actual user modeling method used to infer unknown ratings for predicting a user's preference for an unrated item. This is where AI comes in.

In Adomavicius and Tuzhilin (2005), M is seen as a utility function $f : U \times I \to S$. Here, f is a function that maps the set of users and items into a fully ordered set of items S, ranked by their utility (i.e. rating) to each user. In other words, S is the completely specified version of R, where each user has either an explicit, implicit or predicted preference for each item in I. To predict the best unrated item for each user, we simply find the item with the highest expected utility:

$$\forall u \in U,\ i'_u = \arg\max_{i \in I} f(u, i)$$

The utility function u depends on the modeling method being used, the active user and the item in question. The *reason* for using a recommender system is that the utility u is not defined for the entire $U \times I$ space, i.e. the system does not explicitly know the utility of each item for each user. The point of a recommender system is then to extrapolate u to cover the entire user-item space. In other words, to be able to rank items according to user preferences, the system must be able to predict each user's reaction to items they have not yet explicitly rated themselves. This is where predictive user models come in

handy.

Another popular way of describing, and implementing an RS is using a simple matrix. Here, one dimension represents users, the other dimension represents items, and each cell corresponds to an explicit rating. This matrix then becomes the framework F in our RS quintuple:

$$R_{u,i} = \begin{pmatrix} r_{1,1} & r_{1,2} & \cdots & r_{1,i} \\ r_{2,1} & r_{2,2} & \cdots & r_{2,i} \\ \vdots & \vdots & \ddots & \vdots \\ r_{u,1} & r_{u,2} & \cdots & r_{u,i} \end{pmatrix}$$

Critically, these matrices are usually extremely sparse (i.e. most of the cells are empty). Consider that while there may be a large number of users and items, each individual user only rates or connects to a few number of items. For example, in the seminal Netflix Challenge movie recommender dataset, almost 99% of the potential user/item pairs have no rating (Bell and Koren, 2007a, p1). In other words, the recommender system must be able to produce results from a matrix where only 1% of the cells have meaningful values.

Naturally, this is the defining characteristic of many recommender systems: the ability to extract meaningful patterns from sparse data, through dimensionality reduction, neighborhood estimation and other methods, as we shall see.

Recommender systems face many challenges other than the sparsity problem. A directly related problem is the need for large datasets. Since the data is often sparse, the systems will most often perform well if used on large numbers of items and users. As in many machine learning methods, concept drift, where the characteristics of a user or item changes over time, is also always present.

The performance of RSs is often closely tied to their computational complexity. Real world usage of the most precise methods is often hindered by the computational power needed to actually put them into production.

Finally, the scale of the data in question should be a concern. If the ratings are ordinal data (e.g. 1-5) input directly by users, the RS should take into account the domain specific meaning of these intervals. For example, in a system for rating movies, the jump between ratings 4-5 might not have the same significance as the jump from 2-3. However, this is a fact seldom mentioned in the literature. Most RSs employ metrics that assume a normal distribution, and even the common evaluation techniques such as RMSE or MAE treat

ordinal data as a continous scale.

Prediction

The most interesting and important part of any RS is how it predicts unknown ratings. (Note that altough we use "ratings", "utility", "preference", "relevance" and "connection strength" depending on the context, they all basically mean the same.) Because of this, each method is best categorized based on a few dimensions of its predictive capabilities (see Table 1.1). In our taxonomy, these dimensions are: *data*, *method*, *granularity*, *temporality* and *agents*.

The *data* variable represents what data the RS uses to perform predictions. Content-based methods use only the items, inter-item relations, and an individual user's past history as predictive of future actions (Pazzani and Billsus, 2007). By only considering the individual user in adapting an application, highly personal models can be created. However, such methods often require a lot of interaction before reliable models can be created (Adomavicius and Tuzhilin, 2005). The problem of having to do complex inference from little data, as is often is in content-based predictions, is often called the *sparsity problem* or the *cold start* problem. This is closely related to the problem of *overfitting* data, where the algorithms creates models that match the training data, but not the actual underlying relationships. A lot of research looks at ways to overcome sparse data, i.e. achieving "warmer" cold start. When using content-based predictions, the utility function $f(u, i)$ of user u and item i is extrapolated from $f(u, i_u)$, where i is an item similar to i_u and $f(u, i_u)$ is known.

Collaborative or social recommendations build predictive models for users based on the actions of similar users (Schafer et al., 2007). The observation is that similar users should have similar usage and action patterns. By using data from more than one user, expansive models may be built. These methods are especially useful when considering

Variable	*Values*
Data	Content-based | Collaborative | Hybrid
Method	Heuristic | Model-based
Granularity	Canonical | Typical | Individual
Temporality	Short-term | Long-term
Agents	Implicit | Explicit

Table 1.1: A taxonomy of recommender systems. From Bjorkoy (2010).

new users of a service. A central problem with collaborative methods is that the resulting model is not as individually tailored as one created through content-based prediction. Collaborative models must be careful not to represent the *average* user, but a single individual. When using a collaborative method, the utility $f(u, i)$ of item i for user u is extrapolated from $f(u_j, i)$ where u_j is a user similar to u.

Because of *the new user problem* of content-based prediction and the *average user problem* of collaborative prediction, many systems use a hybrid approach (Burke, 2007). By combining content-based and collaborative methods, systems that properly handle predictions for new users and avoid too much generalization in the models can be achieved.

The *method* variable, is another way to classify recommenders. Orthogonal to what data the method uses, this variable concerns *how* the data is used to produce recommendations. First we have the *model-based* approach, where the recommender system builds predictive models based on the known data. Unseen items can then be fed into this model to compute its estimated utility score. For example, creating a Bayesian networks from past interaction is a model-based approach. The other category is the *heuristic* or *memory-based* approach. These methods use the raw data of items, users and ratings to directly estimate unknown utility values. For example, recommending items similar to the ones already rated by computing the cosine similarity of their feature vectors is a heuristic approach.

The *granularity* variable tells whether this approach creates models for the canonical user, stereotypical users or individual users. Rich (1979) presented one of the first user modeling systems based on stereotypes, used to predict which books in a library each user would most enjoy. Here, a dialogue between the system and the user was performed to place the user into a set of sterotypes. Each stereotype has a set of *facets* which is then used to match books and users.

Temporality refers to how volatile the gathered knowledge will be. While most RSs produce long term, relatively stable knowledge based on lasting user preference and taste, some systems use fluctuating parameters such as the time of day, exact location and the current context to produce recommendations. For example, Horvitz et al. (2003) used clues from a user's calendar, camera and other sensors to determine the attentional state of the user before delivering personalized and contextual notifications.

The *agents* variable signifies whether the knowledge gathering and presentation is implicit and opaque, or explicit and requires dedicated user interaction. Explicit feedback through ratings is common in movie, product or music rating services (e.g. Bell et al. (2007); Basu et al. (1998); Hotho et al. (2006)). However, for other services such as person-

alized search, implicit mining of query logs and user interaction is often used to build user models (e.g. Shen et al. (2005); Agichtein et al. (2006); Speretta and Gauch (2000); Teevan et al. (2005))

Approaches

Because our solution will combine different recommender systems, we need a short introduction to some of the approaches we will combine. Let us take a closer look at (1) *baseline ratings*, (2) *neighborhood estimation*, (3) *dimensionality reduction*, and (4) *network traversal*. This is by no means an exhaustive list, but rather a quick rundown of common approaches in recommender systems, that we will use in the next chapter. See Adomavicius and Tuzhilin (2005), Pazzani and Billsus (2007), Schafer et al. (2007) or Bjorkoy (2010) for a more comprehensive exploration of different types of recommenders.

(1) *Baseline ratings* are the simplest family of recommender systems, based on item and user rating averages. The data is content-based, and used to compute heuristic predictions. This is done on a per-user, individual basis and collects long term knowledge so far as the user is rational in most of his or her ratings. While simple in nature, they are often helpful as starting points for more complex systems, or as benchmarks for exploring new approaches. (Koren, 2008, p2) computes the baselines for items and users, and use more involved methods to move this starting point in some direction. The baseline for a user/item pair is given by

$$b_{ui} = \mu + b_u + b_i$$

where μ is the average system rating, b_u is the user baseline and b_i is the item baseline. The user and item baselines correspond to how the user's and item's ratings deviate from the norm. This makes sense as some items may be consistently rated higher than the average, some users may be highly critical in their assesments, and so on. Koren computes these baselines by solving the least squares problem

$$\min_{b*} = \sum_{(u,i)\in R} (r_{ui} - \mu - b_u - b_i)^2 + \lambda(\sum_u b_u^2 + \sum_i b_i^2)$$

which finds baselines that fit the given ratings while trying to reduce overfitting (by punishing greater values, as weighted by the λ parameter). By using baselines instead of

simple averages, more complex predictors gain a better starting point, or in other words, a better average.

Another approach based on simple averages is the *Slope One* family of collaborative filtering algorithms. As introduced by Lemire and Maclachlan (2005), these algorithms predict unknown ratings based on the average difference in ratings between two items. For example, if item i is on average rated δ points above item j, and the user u has rated item j, that is, we know r_{uj}, the predicted rating of i is simply $r_{uj} + \delta$, for all ratings that match this pattern. In other words,

$$\hat{r}_{ui} = \frac{\sum_{j \in K_u} \text{ratings}(j) \times (r_{uj} + \text{diff}(i,j))}{\sum_{j \in K_u} \text{ratings}(j)},$$

where $\hat{r}_{ui}$ is the estimated rating, K_u is the items rated by user u, $\text{ratings}(i)$ is the number of ratings for item i, and $\text{diff}(i,j)$ is the average difference in ratings for items i and j. While simplistic, Slope One is computationally effective and produces results comparable to more complex methods (Lemire and Maclachlan, 2005, p5).

(2) *Neighborhood estimation* is part of many recommendation systems. It is the core principle behind most collaborative filtering algorithms, that estimate an unknown rating by averaging the ratings of similar users, weighted by this similarity. The principal method for computing user similarity is the *pearson correlation coefficient* (PCC) (Segaran, 2007, p11). While simple, the PCC compares favorably to more complex approaches, and is often used as a benchmark for testing new ideas (e.g. in Lemire and Maclachlan (2005); Ujjin and Bentley (2002); Konstas et al. (2009)).

The PCC is a statistical measure of the correlation between two variables. In our domain, the variables are two users, and their measurements are the ratings of co-rated items. The coefficient produces a value in the range $[-1, 1]$ where 1 signifies perfect correlation (equal ratings), 0 for no correlation and -1 for a negative correlation. The negative correlation can for example signify two users that have diametrically opposing tastes in movies. We compute PCC by dividing the covariances of the user ratings with their standard deviations:

$$\text{pcc}(u,v) = \frac{cov(R_u, R_v)}{\sigma_{R_u} \sigma_{R_v}}.$$

When expanding the terms for covariance and standard deviations, and using a limited neighborhood size n, we get

$$\text{pcc}_n(u,v) = \frac{\sum_{i \in K}^{n}(R_{ui} - \bar{R}_u)(R_{vi} - \bar{R}_v)}{\sqrt{\sum_{i \in K}^{n}(R_{ui} - \bar{R}_u)^2}\sqrt{\sum_{i \in K}^{n}(R_{vi} - \bar{R}_v)^2}}.$$

The limited neighborhood size becomes the statistical sampling size, and is a useful way of placing an upper bound on the complexity of computing a neighborhood. n does not have to be a raondom sampling — it can also be limited by the number of ratings the two compared users have in common, the number of ratings each user have, or something similar, as denoted by K in our the formula.

When a neighborhood is determined, it is time to predict our desired rating. Basically, this means averaging the neighborhood ratings weighted by similarity (Segaran, 2007, p16):

$$\bar{r}_{ui} = \frac{\sum_{v \in K(u,i)} \text{sim}(u,v) \times R_{vi}}{\sum_{v \in K(u,i)} \text{sim}(u,v)},$$

where $\text{sim}(u,v)$ is the similarity between two users, $K(u,i)$ is the set of users in the neighborhood of u that have rated item i. This is possible the simplest way of computing a neighborhood-based prediction. Most systems use more complex estimations. For instance, Koren (2008) uses the baseline ratings discussed above instead of plain user and item ratings, to remove what they call global effects where some users are generous or strict in their explicit preferences, and some items are consistently rated differently than the average.

There are many other methods than the PCC used to compute neighborhoods. Other simple measures include the *euclidean distance* (Segaran, 2007, p10) or matching metrics from information retrieval, as used in the *vector space model* (VSM) (as explained in section 1.4). Bell and Koren (2007b) shows a more sophisticated approach by computing global interpolation weights as an optimization problem. Combinations are also possible. Ujjin and Bentley (2002) first use a simple metric to gather a larger neighborhood, which is then refined by a *genetic algorithm*. Another way of computing neighborhoods is by reducing the dimensions of the ratings matrix, as we will now introduce.

(3) *Dimensionaliy reduction* is an oft-used technique when creating recommender systems. The ratings matrix is factored into a set of lower dimension matrixes, that can be used to approximate the original matrix. Since this has the added effect of trying to approximate unknown cells, the lower dimension matrices can be used to predict unknown ratings (a type of least squares data fitting).

Singular Value Decomposition (SVD) is a common method for such matrix factorization (e.g. Billsus and Pazzani (1998, p5), Sun et al. (2005), Bell et al. (2007)). This is the same underlying technique used by *latent semantic indexing* (LSI) in information retrieval (Baeza-Yates and Ribeiro-Neto, 1999, p44). Formally, SVD is the factorization $M = U\Sigma V^*$. M is an $m \times n$ matrix, in our case the ratings matrix, with m users and n items. U is an $m \times m$ factor (sometimes called the "hanger"), V^* (the conjugate transpose of V) is an $n \times n$ factor ("stretcher"). Σ is a $m \times n$ diagonal matrix ("aligner").

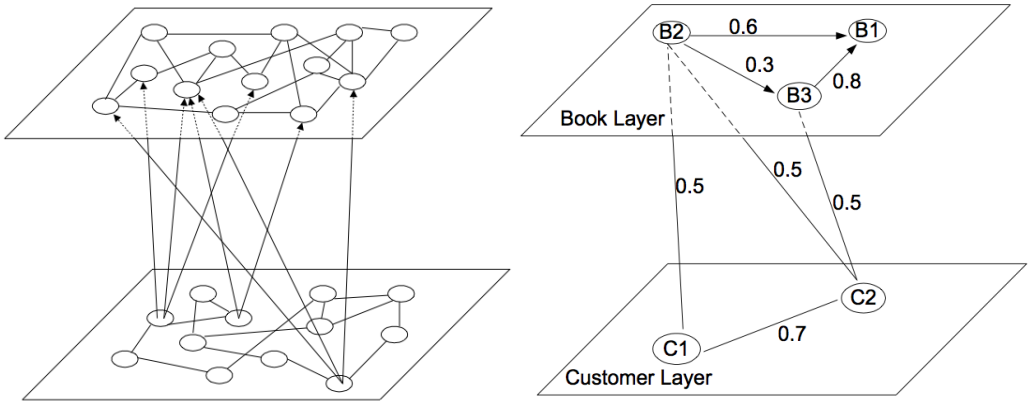
The dimensionalty of the ratings space is performed by truncating the factor matrices each to a number of rows or columns, where the number is a paramenter depending on the current domain and data. By truncating the factors, we in essence create a higher-level approximation of the original matrix that can identify latent features in the data. With the factors reduced to k dimensions, the result looks like this:

$$\begin{bmatrix} \\ R_{m,n} \\ \\ \end{bmatrix} \Rightarrow \begin{bmatrix} \\ U_{m,k} \\ \\ \end{bmatrix} \begin{bmatrix} \Sigma_{k,k} \end{bmatrix} \begin{bmatrix} \quad V^*_{k,n} \quad \end{bmatrix}$$

Two important transformations happen in this reduction. First, ratings that do not contribute to any greater pattern are removed as "noise". Second, ratings that in some way correlate to each other are enhanced, giving more weight to the actual predictive parts of the data. This means that the reduced factors can for instance identify features that correspond to correlations between items or users. These features are comparable to the mapping of terms to concepts in LSI.

There are many ways of using the reduced factors. We can for instance use the resulting reduced factors to find similar users by their cosine similarity (explained below). SVD is then an ingenious way of dealing with the commonly sparse ratings data, by identifying latent correlations and patterns in the data, which is exactly what we need to predict unknown ratings or connections.

(4) *Network traversal* refers to estimating predictions by traversing a graph of users and items to provide recommendations. The connections between nodes can be any type of relation that makes sense to the RS. Examples include linking item and user nodes based on purchases or explicit ratings, linking user nodes from asymetrical (directed edges) symetrical (undirected edges) relations, or linking items based on some similarity metric.



(a) (b)

Figure 1.3: Network Traversal: (a) A graph with two kinds of nodes, e.g. items and users. (b) A graph with books and customers, where recommendations can be made by traversing the weighted connections. Connections between nodes of the same type represent similarity, while connections between books and customers represent purchases. Figures from Huang et al. (2002).

Huang et al. (2002) used network traversal to create a simple system for recommending books to customers. Here, edges between items and users correspond to ratings, and edges connecting nodes of the same type are created by connecting elements that have similarity above a certain threshold. Predictions are generated by traversing the graph a preset number of steps starting at the current user, and multiplying the weights of paths leading to the target item (see Figure 1.3).

The complexity of recommender systems based on networks are only limited by the kinds of relations we can produce. For example, recommending other users in social networks can easily utilize friend or friend-of-a-friend relations to find others the current user might be interested in connecting to. Indeed, any relevant similarity metric can be used to connect nodes of the same type, or nodes of different types.

One variation comes from Walter et al. (2008), who create a network of *transitive trust* to produce recommendations. Here, the neighborhood of users is determined by traversing through users connected by a level of trust. The trust can for example be a function of how many agreeable results the connection to a user has produced. In other words, users trust each others recommendations based on previous experience.

Konstas et al. (2009) takes yet another approach that measures the similarity between two nodes through their *random walks with restarts* (RWR) technique.

Starting from a node x, the RWR algorithm randomly follows a link to a neighboring node. In every step, there is a probability α that the algorithm will restart its random walk from the same node, x. A user-specific column vector $\mathbf{p}^{(t)}$ stores the long term probability rates of each node, where $\mathbf{p}_i^{(t)}$ represents the probability that the random walk at step t is at node i. $\mathbf{S}$ is the column-normalized adjacency-matrix of the graph, i.e. the transition probability table. $\mathbf{q}$ is a column vector of zeroes with a value of 1 at the starting node (that is, $\mathbf{q}_i$ is 1 when the RWR algorithm starts at node x). The stationary probabilities of each node, signifying their long term visiting rate, is then given by

$$\mathbf{p}^{(t+1)} = (1 - \alpha)\mathbf{S}\mathbf{p}^{(t)} + \alpha\mathbf{q}$$

when it is run to convergence (within a small delta). Then, the *relatedness* of nodes x and y is given by $\mathbf{p}_y$ where p is the user model for the user represented by node x. Konstas et al. found that this approach outperformed the PCC, as long as the social networks were an explicit part of the system in question. In other words, the connections between users had to be one actively created by the users to be of such quality and precision that accurate predictions could be made.

After this whirlwind tour of recommender systems, it is time to look at some closely related topics: information retrieval and personalized search. This will form the basis for the case study performed in the next chapter.

1.4 Personalized Search

Information retrieval (+ information overload)

An Information Retrieval Model is a quadruple (Baeza-Yates and Ribeiro-Neto, 1999, p23):

$$\text{IR} = (Documents, Queries, Framework, ranking(q_i, d_i)) \tag{1.2}$$

Common metrics

(x) *IR methods* vector space, page rank

Personalized metrics

Relation to recommender systems

1.5 Aggregate Modeling

Current methods (non-personal)

Use cases (netflix, ...)

For personalized search (speculation)

Explain next chapter

— 2 —

Methods

Getting past 80%

Power of data

Hypotheses

2.1 Modeling Phase

$$\text{AM} = (Items, Users, Framework, Methods, Aggregation) \tag{2.1}$$

2.2 Prediction Phase

2.3 Implementation

2.4 Evaluation

Datasets

Metrics

Experiments

References

Adomavicius, G. and Tuzhilin, A. (2005). Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions. *IEEE Transactions on Knowledge and Data Engineering*, 17(6):734–749.

Agichtein, E., Brill, E., Dumais, S., and Ragno, R. (2006). Learning user interaction models for predicting web search result preferences. *Proceedings of the 29th annual international ACM SIGIR conference on Research and development in information retrieval - SIGIR '06*, page 3.

Albert, R., Jeong, H., and Barabási, A. (1999). The diameter of the world wide web. *Arxiv preprint cond-mat/9907038*, pages 1–5.

Alshamri, M. and Bharadwaj, K. (2008). Fuzzy-genetic approach to recommender systems based on a novel hybrid user model. *Expert Systems with Applications*, 35(3):1386–1399.

Baeza-Yates, R. and Ribeiro-Neto, B. (1999). *Modern information retrieval*, volume 463. ACM press New York.

Barabási, A. (2003). Linked: The new science of networks. *American journal of Physics*.

Basu, C., Hirsh, H., and Cohen, W. (1998). Recommendation as Classification: Using Social and Content-Based Information in Recommendation. In *Proceedings of the National Conference on Artificial Intelligence*, pages 714–720. JOHN WILEY & SONS LTD.

Bawden, D. and Robinson, L. (2009). The dark side of information: overload, anxiety and other paradoxes and pathologies. *Journal of Information Science*, 35(2):180–191.

Bell, R., Koren, Y., and Volinsky, C. (2007). The BellKor solution to the Netflix prize. *KorBell Team's Report to Netflix*.

Bell, R. M. and Koren, Y. (2007a). Lessons from the Netflix prize challenge. *ACM SIGKDD Explorations Newsletter*, 9(2):75.

Bell, R. M. and Koren, Y. (2007b). Scalable Collaborative Filtering with Jointly Derived Neighborhood Interpolation Weights. *Seventh IEEE International Conference on Data Mining (ICDM 2007)*, pages 43–52.

Billsus, D. and Pazzani, M. (1998). Learning collaborative information filters. In *Proceedings of the Fifteenth International Conference on Machine Learning*, volume 54, page 48.

Bjorkoy, O. (2010). User Modeling on The Web: An Exploratory Review.

Burke, R. (2007). Hybrid Web Recommender Systems.

Cato, J. (2001). *User-centered web design*. Pearson Education.

Davenport, T. and Beck, J. (2001). *The attention economy: Understanding the new currency of business*. Harvard Business Press.

Edmunds, A. and Morris, A. (2000). The problem of information overload in business organisations: a review of the literature. *International Journal of Information Management*, 20(1):17–28.

Eppler, M. and Mengis, J. (2004). The concept of information overload: A review of literature from organization science, accounting, marketing, MIS, and related disciplines. *The Information Society*, 20(5):325–344.

Fischer, G. (2001). User modeling in human–computer interaction. *User modeling and user-adapted interaction*, 11(1):65–86.

Horvitz, E., Kadie, C., Paek, T., and Hovel, D. (2003). Models of attention in computing and communication: from principles to applications. *Communications of the ACM*, 46(3):52–59.

Hotho, A., J, R., Schmitz, C., and Stumme, G. (2006). Information Retrieval in Folksonomies: Search and Ranking.

Huang, C., Sun, C., and Lin, H. (2005). Influence of local information on social simulations in small-world network models. *Journal of Artificial Societies and Social Simulation*, 8(4):8.

Huang, Z., Chung, W., Ong, T.-H., and Chen, H. (2002). A graph-based recommender system for digital library. *Proceedings of the second ACM/IEEE-CS joint conference on Digital libraries - JCDL '02*, page 65.

Jameson, A. (2009). Adaptive interfaces and agents. *Human-Computer Interaction: Design Issues, Solutions, and Applications*, page 105.

Kirsh, D. (2000). A few thoughts on cognitive overload. *Intellectica*, 1(30):19–51.

Kobsa, A. (2001). Generic User Modeling Systems.

Konstas, I., Stathopoulos, V., and Jose, J. (2009). On social networks and collaborative recommendation. In *Proceedings of the 32nd international ACM SIGIR conference on Research and development in information retrieval*, pages 195–202. ACM.

Koren, Y. (2008). Factorization meets the neighborhood: a multifaceted collaborative filtering model. In *Proceeding of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 426–434. ACM.

Lemire, D. and Maclachlan, A. (2005). Slope one predictors for online rating-based collaborative filtering. *Society for Industrial Mathematics*.

Lieberman, H. (2009). User interface goals, AI opportunities. *AI Magazine*, 30(2).

Mirza, B. and Keller, B. (2003). Studying recommendation algorithms by graph analysis. *Journal of Intelligent Information*.

Newman, M. and Moore, C. (2000). Mean-field solution of the small-world network model. *Physical Review Letters*.

Norman, D. (1988). The design of everyday things. *Basic Book Inc./New York*.

Pazzani, M. and Billsus, D. (2007). Content-based recommendation systems. In *The adaptive web*, pages 325–341. Springer-Verlag.

Resnick, P., Iacovou, N., Suchak, M., Bergstrom, P., and Riedl, J. (1994). GroupLens : An Open Architecture for Collaborative Filtering of Netnews.

Rich, E. (1979). User modeling via stereotypes. *Cognitive science*, 3(4):329–354.

Schafer, J., Frankowski, D., Herlocker, J., and Sen, S. (2007). Collaborative filtering recommender systems. *The adaptive web*, pages 291–324.

Segaran, T. (2007). Programming collective intelligence.

Shen, X., Tan, B., and Zhai, C. (2005). Implicit user modeling for personalized search. *Proceedings of the 14th ACM international conference on Information and knowledge management - CIKM '05*, page 824.

Smyth, B. (2007). Case-Based Recommendation.

Speretta, M. and Gauch, S. (2000). Personalized Search Based on User Search Histories. *The 2005 IEEE/WIC/ACM International Conference on Web Intelligence (WI'05)*, pages 622–628.

Sun, J., Zeng, H., Liu, H., and Lu, Y. (2005). CubeSVD: a novel approach to personalized Web search. *on World Wide Web*, pages 382–390.

Teevan, J., Dumais, S. T., and Horvitz, E. (2005). Personalizing search via automated analysis of interests and activities. *Proceedings of the 28th annual international ACM SIGIR conference on Research and development in information retrieval - SIGIR '05*, page 449.

Totterdell, P. and Rautenbach, P. (1990). *Adaption as a Problem of Design*, pages 59—-84.

Ujjin, S. and Bentley, P. J. (2002). Learning user preferences using evolution.

Walter, F., Battiston, S., and Schweitzer, F. (2008). A model of a trust-based recommendation system on a social network. *Autonomous Agents and Multi-Agent Systems*, 16(1):57–74.

Appendix

Sourcecode, tables, et cetera.