CoBaFi — Collaborative Bayesian Filtering

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ABSTRACT
Given a large dataset of users’ ratings of movies, what is the best model to accurately predict which movies a person will like? And how can we prevent spammers from tricking our algorithms into suggesting a bad movie? Is it possible to infer structure between movies simultaneously?

In this paper we describe a unified Bayesian approach to Collaborative Filtering that accomplishes all of these goals. It models the discrete structure of ratings and is flexible to the often non-Gaussian shape of the distribution. Additionally, our method finds a co-clustering of the users and items, which improves the model’s accuracy and makes the model robust to fraud. We offer three main contributions: (1) We provide a novel model and Gibbs sampling algorithm that accurately models the quirks of real world ratings, such as convex ratings distributions. (2) We provide proof of our model’s robustness to spam and anomalous behavior. (3) We use several real world datasets to demonstrate the model’s effectiveness in accurately predicting user’s ratings, avoiding prediction skew in the face of injected spam, and finding interesting patterns in real world ratings data.

Categories and Subject Descriptors
H.2.8 [Database Management]: Data mining; H.3.m [Information Storage and Retrieval]: Miscellaneous; J.4 [Social and Behavioral Sciences]: Miscellaneous

Keywords
Collaborative Filtering; Sampling; Clustering

1. INTRODUCTION
Collaborative filtering is one of the key tools for providing relevant content and for driving successful electronic commerce. Unsurprisingly, it has attracted a substantial amount of research. Of late, Bayesian approaches have demonstrated good performance, when applied to collaborative filtering [33, 30]. This paper makes the following contributions to the recommender problem:

Rating Model: Many collaborative filtering models simply minimize the squared error between prediction and observed rating. Alternatively, others make the assumption of a Gaussian noise model, assuming that the observed rating is given by the latent rating plus a small perturbation. Unfortunately this assumption is not realistic since the observed ratings are discrete, typically ranging from 1 to 5. Moreover, they need not be unimodal — some products are quite polarizing, attracting a significant number of 1 and 5 ratings with very little in between. We address this by modeling such dependencies explicitly. This builds on [37], the key difference being that the present paper provides an efficient inference algorithm for such a rating distribution.

Profile Distribution: A common approach to modeling user and item profiles is to draw them iid from a distribution that is essentially normal around a common mean [33, 35]. However, often the objects we would like to recommend form clear clusters (e.g. romantic comedies, summer action movies). Hence, sharing of statistical strength even within the same object category is likely to improve accuracy. This extends work of [1, 3, 29] on dyadic factorization models.

Our motivation is that we have rather different amounts of information for different movies (and users). That is, some movies are very popular and using only a small number of latent factors amounts to considerable underfitting; as a result, using a larger number of parameters would be greatly beneficial. On the other hand, many movies have few ratings and it would be good if we could aggregate similar ones into a larger cluster for estimation purposes.

Inference: We propose an efficient sampling algorithm that can be parallelized with relative ease. It combines collapsed inference for discrete variables, uncollapsed inference for cluster parameters, and a Metropolis-Hastings iteration for nonconjugate terms arising from the recommender distribution.\(^1\)

\(^1\) It is over two orders of magnitude faster than the sampling algorithms carried out in Stan mc-stan.org using Hamiltonian Monte-Carlo [14].
Spam Detection: A useful side-effect of the clustering approach is that similar users and items are grouped into the same cluster. This means that users who exhibit consistently abnormal behavior are likely to aggregate into the same clusters, thus limiting their impact on other recommendations and making it easier to detect and remove them.

Outline: We begin discussing our model for addressing the discrete nature of the rating distribution in Section 3. This is followed in Section 4 by a description of a nonparametric mixture of Gaussians akin to [26]. We then give an overview of the statistical model used for collaborative filtering in Section 5, and we subsequently give an in-depth description of statistical inference techniques in Section 6. We then in Section 7 analyze the model’s ability to limit the impact of fraud. Last, we do an in depth analysis of our model on a variety of datasets in Section 8.

2. RELATED WORK

Collaborative filtering algorithms have been some of the best performing methods for recommendation systems. Koren [20] presents an overview of various methods for collaborative filtering. One of the simplest and most effective methods for collaborative filtering is low-rank matrix approximations. The intuition behind factor-based approaches is that preferences for users are determined by small numbers of unobserved factors [33]. Linear factor models make use of two factor vectors — a user factor vector and an item factor vector — with the inner product representing a user’s rating for an item. These vectors can be appended to form User Factor and Item Factor Matrices [33, 36]. Much work has been done on efficient algorithms such as stochastic gradient descent [20, 39] and SVD++ [19].

Several works consider alternative distributions over attribute vectors, e.g. sparse nonnegative factors [21], jointly sparse factorizations [15], cluster aggregation [1], or discrete factorizations [29]. Closest to our work are co-clustering models, such as [5]. Our work uses a Gaussian mixture model to capture information in users and attributes.

The least means squares loss is a mainstay in collaborative filtering, not the least due to the Netflix contest. Nonetheless, there are many other and better objectives that one could strive to optimize for. For instance, [41, 39] study preference ranking instead of estimating scores directly. In fact, research on ranking teems with alternative formulations of preferences [7, 38]. There are variants using distance similarity [40]. However, there is only scarce research in attempting to model the skewed nature of ratings directly. [37] introduce the ranking distribution and show some first strategies for inference by optimization. A full Bayesian treatment of these cases is missing, though. We address this in the present paper by proposing a computationally efficient Metropolis-Hastings sampler for a unified Bayesian treatment. The advantage of our approach is that we only need to build one model to perform recommendation, spam detection, to model the distribution and confidence of a rating distribution explicitly, and to group users and movies.

3. RATING DISTRIBUTION

One of the key components of our approach is to provide a model which captures the bimodality in many of the reviews found on rating sites. For instance, consider the example of a WD15EZRX hard disk (newegg.com, April 27, 2013). It clearly shows a very polarized view of the product, with significant numbers of users rating it very poorly whereas others rate it as excellent.

<table>
<thead>
<tr>
<th>score</th>
<th>*</th>
<th>**</th>
<th>***</th>
<th>****</th>
<th>*****</th>
<th>******</th>
</tr>
</thead>
<tbody>
<tr>
<td>ratings</td>
<td>349</td>
<td>114</td>
<td>55</td>
<td>50</td>
<td>201</td>
<td></td>
</tr>
</tbody>
</table>

This type of rating distribution has been commonly ignored in collaborative filtering. In fact, when aiming for a least mean squares fit the optimal rating would be 2.5319 stars, the mean of the reviews. Such a score would be very misleading since only a small minority of reviews, namely only 7% of them actually assume such a value. Moreover, while an RMSE of 2.85 would indicate that the data is a poor fit, it would tell us precious little about the actual distribution. The distribution itself in many cases is just as important as the predicted rating: suggesting an item with a bimodal review distribution, be it an unreliable hard drive or a polarizing film, may be undesirable for a risk-avoiding user.

Note that this is not an isolated case. We have observed many such examples in both product reviews and movies. However, not all items are equally polarizing and, in fact, the majority of reviews follow a more conventional unimodal treatment of these cases is missing, though. We address this in the present paper by proposing a computationally efficient Metropolis-Hastings sampler for a unified Bayesian treatment. The advantage of our approach is that we only need to build one model to perform recommendation, spam detection, to model the distribution and confidence of a rating distribution explicitly, and to group users and movies.

For this purpose we employ an exponential families model of a discrete distribution over the set $X = \{1, \ldots, R\}$, where typically we have $R = 5$. In the following we will refer to this distribution as the recommender distribution. Define

$$
\phi(x) = \left(\frac{1}{2}, \ldots, \frac{1}{2}\right)
$$

(1)

to be the sufficient statistic of the data on $X$. In this case we have $\theta \in \mathbb{R}^2$ the model

$$
p(x|\theta) = e^{\langle \phi(x), \theta \rangle} - g(\theta)
$$

(2)

where $g(\theta) = \log \sum_{j=1}^{R} e^{\langle \phi(j), \theta \rangle}$.

The above generalizes normal distributions to a discrete finite domain. Like the Gaussian, we can adjust mean and variance by modifying the first and second coordinate of
\( \theta \) accordingly. However, quite unlike in a Gaussian, we can also choose coefficients \( \theta_2 \geq 0 \). Such a choice would amount to no variance or negative variance respectively, which is clearly impossible (with correspondingly diverging integrals). On a finite countable domain, however, normalization is easy. As common in exponential families, we have

\[
-\partial_\theta \log p(x|\theta) = \sum_{x'} \phi(x') p(x'|\theta) - \phi(x) \tag{3}
\]

\[
-\partial_\theta^2 \log p(x|\theta) = \text{Cov}_{x' \sim p(x'|\theta)}[\phi(x')] \tag{4}
\]

Note that the covariance is independent of \( x \) since it depends only on the log-partition function \( g(\theta) \). We will exploit this property in the context of a Metropolis-Hastings sampler to infer user and movie dependent parameters.

To illustrate the model we fitted the recommender distribution to the data above. This yielded \( \theta = (-0.157, 0.391) \). The associated distribution can be seen below. For comparison we also display the fit obtained by a Gaussian distribution when discretized over the domain \( \{1, \ldots, 5\} \) and using the mean and variances inherent in the data. It is clear that the Gaussian thoroughly misrepresents the data whereas the recommender distribution is an excellent fit.

In our model we will assume that the amount of polarization, i.e. the value of \( \theta_2 \), is determined in an additive fashion between users and items. That is, the distribution is bimodal if the item encourages such ratings (e.g. an unreliable hard disk) and if the user is prone to praise and condemnation. For the linear term we use an inner product model.

To assess this new rating model we need to evaluate its predictive log-likelihood, since a least mean squares fit clearly obscures the properties of the data. Hence, in our experiments we will compute \( \sum_{i} -\log p(x|\theta) \). By basic facts from information theory \cite{8}, this is bounded from above by the entropy of the uniform distribution, i.e. \( \log 5 \) for 5 different outcomes. The lower bound is naturally the conditional entropy \( H(R|U,M) \), where we conditioned on the user and item pairs. By definition, it is impossible to compute this lower bound explicitly, short of solving the recommendation problem optimally.

4. BI-CLUSTERING

Collaborative filtering is nontrivial whenever the number of ratings is nonuniform over items and users. Like much other natural data, the number of ratings often follows a power-law distribution on a per row and per column basis. For instance, blockbuster big-budget Hollywood movies will attract many more ratings than independent productions, regardless of their quality. Likewise, a small number of enthusiasts can generate an enormous amount of ratings when compared to more casual users.

Conventional collaborative filtering models assume that all users (and items respectively) are parametrized by a fixed dimensional model. In fact, many experiments show that the accuracy of the models plateaus (or even decreases) once a fairly modest number of parameters has been reached. Part of this effect is due to the fact that we have comparatively little data per row (or column) of the recommendation matrix. Furthermore, data scarcity is different, when viewed on a per-column or per-row basis. For instance, we might have millions of users but only thousands of movies.

This suggests that it would be very much desirable to have a mechanism for assigning capacity dynamically. That is, users who generate significant amounts of ratings are sufficiently well-specified to afford a ‘personal’ parameter vector for them. On the other hand, users who generate very little data are probably best modeled as unspecific members of a much larger pool of similar participants. Such a model can be obtained by clustering users, e.g. as mixture of Gaussians.

To accomplish this, we use bi-clustering of the rows and columns of the recommendation matrix to allow for dynamic allocation of statistical capacity between sets of users. This allows us to increase dimensionality beyond what is optimal when treating all users/items equally. Hence we need to introduce a statistical model for partitioning. We resort to the Dirichlet Process for this purpose. This yields a nonparametric mixture of Gaussians. To keep the presentation self-contained we give a brief overview of the model below.

One of the prototypical tools for nonparametric modeling is the Dirichlet Process \( DP(\varphi, \gamma) \). It allows for a discrete distribution of observations drawn from an arbitrary base measure \( H \) over the domain \( X \) in such a way that the marginals match draws from \( H \), while simultaneously obtaining a countable set of distinct items. Denote by \( X_i \) a partition of \( X \) and let \( c_i := \mu_H(X_i) \) be the measure of \( X_i \) under \( H \). Then the discretization of draws from \( G_0 \) with

![Graph showing distribution comparison](image-url)
\[ G_0 \sim DP(H, \gamma) \] onto the sets \( \mathcal{X} \) behaves as if it had been drawn from a multinomial distribution \( \theta \) with \( \theta \sim \text{Dir}(\gamma) \).

A useful view of the Dirichlet Process is the Chinese Restaurant metaphor. In it, each data point is considered as a customer in a restaurant with an infinite number of tables. Initially all tables are empty. As the tables fill up, customers pick existing tables in proportion to their popularity, resulting in a “rich get richer” scenario. The probability for a customer in a restaurant with an infinite number of tables who have so far occupied tables \( 1, \ldots, k \) and \( a \) respectively, or a new table with probability \( \frac{\gamma_{a+\gamma}}{\gamma_{k+\gamma}} \) for an existing table and \( \frac{\gamma_{a+\gamma}}{\gamma_{k+\gamma}} \) for a new table.

For customer \( i \) to pick table \( j \) is given by

\[
\Pr(z_i = j) = \begin{cases} \frac{N_j}{\sum_k N_k + \gamma} & \text{for an existing table} \\ \frac{\gamma + 1}{\sum_k N_k + \gamma} & \text{for a new table.} \end{cases} \tag{5}
\]

Here \( z_i \) encodes the choice of customer \( i \). \( N_j \) denotes the current number of customers sitting at table \( j \) and \( \sum_k N_k \) is the total number of customers so far. This makes the Chinese Restaurant Process a single parameter distribution over partitions of the integers. Figure 1 provides a pictorial representation of the process. One may show that the distribution over partitions is invariant in the order in which customers arrive, i.e. it is exchangeable.

A benefit of (5) is that it affords for collapsed Gibbs sampling inference by simply drawing

\[
z_i \sim \Pr(z_i | \text{rest}) \text{ where } \Pr(z_i | \text{rest}) \propto \beta(z_i | z_{-i})p(\text{ratings}|z)
\]

Inference proceeds by traversing users (or items) and resampling their cluster assignments in sequence.

## 5. Statistical Model

We describe a model for obtaining collaborative filtering estimates in a pure rating setting rather than a recommendation setting [41]. That is, we assume that for a subset of (user,item) pairs \( (i,j) \) we are given ratings \( r_{ij} \in \{1, \ldots, R\} \). It is our goal to infer user and item specific parameters \( u_i, v_j \) such that we are able to estimate the distribution of \( r_{ij} | i, j \) efficiently. For this purpose we employ a directed graphical model, as depicted in Figure 2.

This model extends existing recommendation algorithms such as [33, 35] by assuming a more complex structure for the latent user and item attributes. We assume that the ratings \( r_{ij} \) are drawn from the recommender distribution. The parameters \( (u_i, v_j) + u_i^{(1)} + v_j^{(1)} + u_i^{(2)} + v_j^{(2)} \), as associated with parts of the user and item specific vectors, account for preference and skew explicitly:

\[
r_{ij} \sim \text{Recommender}
\left( (u_i, v_j) + u_i^{(1)} + v_j^{(1)}, u_i^{(2)} + v_j^{(2)} \right)
\]

From this we have for each user a \( d - 2 \) length vector \( u_i \) and scalars \( u_i^{(1)}, u_i^{(2)} \) giving us \( d \) latent parameters per user (and item). For simplicity, we will often refer to this set of parameters as a single vector \( u_i \).

We assume that the user and item parameter distributions are described by a mixture of Gaussians, where

\[
u_i \sim N(\mu_o, \Sigma_o) \text{ and } v_j \sim N(\mu_b, \Sigma_b).
\]

Here \( \alpha \) and \( \beta \) are the clusters that user \( i \) and item \( j \) belong to respectively. The cluster means and variances \( \mu_o, \Sigma_o \) are drawn from a Gaussian-Wishart distribution with \( \nu_0 \) degrees of freedom and parameters \( \{\mu_o, W_o, \lambda_o\} \) and \( \{\mu_b, W_b, \lambda_b\} \), respectively:

\[
(\mu_o, \Sigma_o) \sim GW(\lambda_o, W_o, \mu_o) \text{ and } (\mu_b, \Sigma_b) \sim GW(\lambda_b, W_b, \mu_b)
\]

This is convenient since in this case the priors are conjugate and we are able to draw from \( \mu_o, \Sigma_o | \alpha, u, a \) exactly without the need for approximation.

The common parameters \( W_o, \mu_o \) (and \( W_b, \mu_b \)) allow us to share information about variance and means between clusters via the conjugate Wishart distribution. Finally, we impose an inverse-Gaussian-Wishart hyperprior on \( W_o, \mu_o, W_b, \mu_b \) respectively. For computational convenience we will maximize the likelihood with regard to those hyperparameters.

Finally, the cluster indicators, \( a_i \) and \( b_j \), allow us to assign users (and items respectively) to particular groups. To sample cluster assignments, we draw

\[
a_i \sim \text{Mult}(\theta) \text{ and } b_j \sim \text{Mult}(\eta) \tag{6}
\]

In turn, we assume that the distribution over clusters follows a Dirichlet distribution conjugate to the multinomials governing cluster membership. Likewise in the nonparametric case (where the number of clusters itself is unbounded), we assume that it is given by a draw from a Dirichlet process.

\[
\theta \sim \text{Dir}(\gamma) \text{ and } \eta \sim \text{Dir}(\delta) \tag{7}
\]

Therefore, in a nutshell, we assume that the interaction between users \( u_i \) and items \( v_j \) can model ratings \( r_{ij} \) similarly to many other collaborative filtering methods. Unlike [33] who assume one common mean and variance for all users (and items respectively), clustering provides the ability to better model what is a similar user.
6. PARAMETER INFERENCE

Inference in the statistical model introduced previously requires sampling and (or) optimization. Matters are simple whenever the distributions are conjugate since the associated parameters can either be integrated out (collapsed) or, alternatively, it is easy to draw from them. The non-conjugate parts do not admit a closed-form treatment. In the following we discuss in detail how to sample the various parameters and variables for the sampler’s Markov chain, subject to these constraints. Since user and item-related parameters are entirely identical, we only discuss users.

6.1 Sampling the user and item parameters \(u_i\)

We omit details for the case where \(r_{ij}\) is Gaussian, as it is almost identical to [33]. Since the recommender distribution does not have conjugacy, sampling the user and item parameters \(u_i\) and \(v_j\) is challenging and we resort to a Metropolis-Hastings procedure [6]. In its simplest form the idea is that rather than sampling from some difficult distribution \(p(x)\) we draw \(\tilde{x}\) from an approximation \(q(x)\) and accept the move \(x \rightarrow \tilde{x}\) with probability \(\min(1, p(\tilde{x})q(x)/p(x)q(\tilde{x}))\).

In our case the distribution \(p\) is given by the log-concave point-generation \(p(u_i|\text{rest})\) and we obtain \(q\) by performing a Laplace approximation of \(p\). In other words, we perform a second order Taylor approximation of \(\log p(\tilde{x})\) and accept the move \(x \rightarrow \tilde{x}\) with probability \(\min(1, p(\tilde{x})q(x)/p(x)q(\tilde{x}))\).

As before \(u_i^{(1)}\), \(u_i^{(2)}\) denote the latent parametrization, the linear biases and the quadratic biases for the user, with corresponding terms for item parameters \(v\). The log-partition function \(g\) is as defined in (2) with appropriate derivatives given by (3) and (4).

Convex minimization of \(-\log p(u_i|\text{rest})\) yields the mode \(\bar{\mu}\). By first order conditions and since the objective is analytic, we know that at \(\bar{\mu}\) the gradient vanishes and we may compute the ‘variance’ of \(q(u_i)\) via

\[\bar{\Sigma}^{-1} = \sigma_u^{-1} + \sum_{j \in \text{ratings}(i)} \partial_u^2 g(u_i^{(1)} + v_j^{(1)} + \langle u_i, v_j \rangle, u_i^{(2)} + v_j^{(2)})\]

Using \(\tilde{u} \sim N(\bar{\mu}, \bar{\Sigma})\) we accept the MH proposal with

\[\min\left(1, \frac{p(\tilde{u}|\text{rest})N(\tilde{u}|t, \mu, \Sigma)}{p(u_i|\text{rest})N(u_i|t, \bar{\mu}, \bar{\Sigma})}\right)\]

(8)

where \(\tilde{u} = u_i(t + 1) \leftarrow u_i(t)\). The advantage of this strategy is that we need to compute \(\bar{\mu}\) and \(\bar{\Sigma}\) only once per resample of \(u_i\). Multiple MH steps ensure proper mixing.

The computational cost of this step is \(O(d^3 + d^2n_{\text{ratings}})\) per user, i.e. for the purpose of the Taylor approximation we need to aggregate all ratings \(n_{\text{ratings}}\) of a given user and subsequently draw from it. Hence the total cost is \(O(d^3|V| + d^2|E|)\), when viewing the set of (user, item) pairs as a graph with \(V\) vertices and \(|E|\) edges.

6.2 Sampling the cluster membership \(a_i\)

Our generative model represents cluster assignments of users and items as draws of indicator variables \(a_i\) and \(a_j\) from multinomial distributions, parametrized by \(\theta\) and \(\eta\). These multinomials are in turn drawn from their conjugate, the Dirichlet distribution. We take advantage of a collapsed Gibbs sampler to deal with the Dirichlet process in \(a\) and \(b\) respectively [26, 10]. More specifically, we may integrate out \(\theta, \eta\) such that we are left with an exchangeable distribution over \(\{a_i\} \gamma\) (and corresponding terms in \(b, \delta\)). This leaves us with (5), i.e.

\[p(a_i = \tilde{a}|\{a_i\}) = \begin{cases} \frac{n_{\tilde{a}i}}{\bar{n}_{\gamma} + \bar{\gamma} - 1} & \text{for existing cluster} \\ \frac{\bar{n}_{\gamma} + 1}{\bar{n}_{\gamma} + \bar{\gamma} - 1} & \text{for new cluster} \end{cases}\]

(9)

Analogous values can be obtained if we want to use the Pitman-Yor process [28]. Secondly, we need to evaluate the likelihood of \(u_i|a_i\), as given by \(N(\mu_{ai}, \Sigma_{ai})\). This governs how well \(u_i\) fits an existing cluster. Whenever we instantiate a new cluster, matters are slightly more involved — the acceptance probability of drawing a new random set of parameters \(\mu, \Sigma\) from the associated Gaussian-Wishart distribution would be very low. Instead, we integrate out \(\mu, \Sigma\) and evaluate directly \(p(u_i|\mu_{ai}, W_{ai}, \lambda_{ai})\). However, to do this we must integrate and collapse out the intermediate cluster parameters, see e.g. [11]. Thus the collapsed probability of \(u_i\) is

\[p(u_i|\mu_{ai}, W_{ai}, \lambda_{ai}) = T \left( \nu_0 + d + \frac{\lambda_{ai}^{\mu}u_i + \bar{\nu}_{ai} \lambda_{ai}}{\lambda_{ai} + 1} \right) \frac{\lambda_{ai} + 2}{\lambda_{ai} + 1} \frac{1}{V_{ai}} \]

where \(V_{ai} = W_{ai}^{-1} + u_i - \mu_{ai} (\mu_{ai} - u_i)^T\). Here \(T\) is the student-t distribution, \(\nu_0\) is a user specified parameter and \(d\) is the rank of the decomposition. Ultimately, this gives us an estimate of the likelihood of a new cluster for \(u_i\):

\[p(a_i = \tilde{a}|\text{rest}) \propto \begin{cases} \frac{n_{\tilde{a}i}}{\bar{n}_{\gamma} + \bar{\gamma}} N(u_i|\mu_{ai}, \Sigma_{ai}) & \text{if cluster exists} \\ \frac{\bar{n}_{\gamma} + 1}{\bar{n}_{\gamma} + \bar{\gamma}} p(u_i|\mu_{ai}, W_{ai}, \lambda_{ai}) & \text{for new cluster} \end{cases}\]

Lastly, if we draw a new cluster, we need to instantiate the values of \(\mu_{ai}, \Sigma_{ai}\). Since this is no different for clusters of size 1 or larger, we describe the general case below.

Resampling the cluster membership for a user requires us to evaluate the cluster likelihood for each existing (and one new) cluster. Each of these steps cost \(O(d^2)\) computation. Given \(k\) clusters this amounts to \(O(kd^2|V|)\) CPU cost for one sampling pass.

6.3 Sampling cluster parameters \(\mu_{ai}, \Sigma_{ai}\)

Since the Gauss-Wishart distribution is conjugate to the Gaussian, it follows that the conditional posterior \(p(\mu_{ai}, \Sigma_{ai}|\text{rest})\) is also a Gauss-Wishart. Moreover, the update equations for a cluster are particularly simple: draw \(\mu_{ai}, \Sigma_{ai}\) from a Gauss-Wishart distribution with parameters

\[
\begin{align*}
\bar{\lambda}_a &= \lambda_a + N_a \\
\lambda_a \bar{\mu}_a &= \lambda_a \mu_a + \sum_{t:a_i = a} u_{ti} \\
\bar{\lambda}_a \bar{W}_a^{-1} &= \lambda_a \Sigma_a^{-1} + \lambda_a \mu_a \mu_a^T + \sum_{t:a_i = a} u_{ti} u_{ti}^T \\
\bar{\nu} &= \nu_0 + N_a 
\end{align*}
\]

(10a-d)
The Gauss-Wishart distribution is given by

\[ p(\mu, \Sigma | \mu_0, \lambda, W, \nu) = \mathcal{N}(\mu | \mu_0, \lambda^{-1}\Sigma) \mathcal{W}(\Sigma^{-1} | W, \nu) \]  

where \( \mathcal{W}(\Sigma^{-1} | W, \nu) = 2^{-\frac{d+\nu}{2}} | \Sigma |^{\frac{\nu}{2}} \Gamma_d^{-1}(\nu/2) |W|^{-\frac{\nu+d-1}{2}} e^{-\frac{1}{2} \text{tr} W \Sigma^{-1} \nu} \).

This distribution is used to model the covariance matrices of Gaussian distributions and is particularly useful when we have a prior distribution on the parameters that we are trying to estimate. The parameters \( \mu_0, \lambda, W, \nu \) correspond to the prior mean, the precision matrix, the Wishart scale matrix, and the degrees of freedom, respectively.

### 6.4 Inference for hyperparameters \( \mu_0, W, \lambda \)

The last remaining step for inference is to estimate a suitable value for the parameters of the Gauss-Wishart distribution. Choosing these terms appropriately is important since they provide the default (prior) for the cluster specific factors. We resort to maximization rather than sampling, since the number of clusters is large relative to the number of parameters involved in determining \( \mu_0, W, \lambda \), hence we expect the posterior to be rather peaked. For the sake of completeness, we give the full derivation below. In a nutshell, we compute the parameters using a conjugate to the Wishart distribution. While this is not available in closed form, it is easily constructed implicitly by adding an additional spurious normal distribution. We choose one with unit variance and zero mean. For notational convenience, we will include such a ‘prior’ in the set of \( (\mu_0, \Sigma_0, \lambda_0) \) terms.

The Gauss-Wishart distribution is given by

\[ p(\mu, \Sigma | \mu_0, \lambda, W, \nu) = \mathcal{N}(\mu | \mu_0, \lambda^{-1}\Sigma) \mathcal{W}(\Sigma^{-1} | W, \nu) \]  

Computing \( W, \mu_0 \) and \( \lambda \) costs \( O(kd^3) \) work since we need to aggregate over all cluster centers. In summary, we have the following runtime properties:

### Remark 1

Per iteration the algorithm requires \( O(kd^3 + |V|d^3 + |V|d^2k + |E|d^2) \) computation. That is, it is cubic in the number of latent parameters, linear in the number of clusters, and linear in the amount of data given.

Furthermore, if needed, these steps could be parallelized efficiently, since most work is specific per user (or per item) with communication required only once for each round of sampling and optimization.

### 7. ROBUSTNESS TO SPAM

Fraud detection is a persistent challenge and requires a multi-tiered approach. By default, most recommender systems are not very resilient, allowing any spam that is not caught ahead of time to skew recommendations significantly. To illustrate this, consider Bayesian matrix factorization [35]. In this case the influence of a malicious user cannot be bounded: the sufficient statistic governing the normal distribution over users is a linear combination of the statistics of all constituents. Hence it follows that each individual contribution can assume arbitrary amounts, provided that the associated statistic is also unbounded. Moreover, even for bounded sufficient statistics, the aggregate influence can be arbitrarily high, provided that a sufficiently large number of malicious users contributes. In other words, if a sufficiently high number of fraudulent likes for an objectionable movie is received, this will lead to the movie being rated very highly.

The example below quantifies this effect.

**Example 1 (Spam and sufficient statistics)**

Denote by \( \phi(x) \) the sufficient statistic of \( x \in X \). Moreover, let \( X := \{x_1, \ldots, x_m\} \) and \( X' := \{x_1', \ldots, x_{m'}\} \) be regular and malicious observations respectively. Let \( m_0, \mu_0 \) be sufficient statistics arising from a conjugate prior. Then the posterior mean yields

\[ \hat{\mu} := \frac{1}{m_0 + m + m'} \left[ m_0 \mu_0 + \sum_{i=1}^{m} \phi(x_i) + \sum_{i=1}^{m'} \phi(x'_i) \right] \]

That is, the mean posterior is given by what amounts to Gaussian posterior averaging; the prior on covariances \( W \) is given by the average covariance, suitably normalized by dimensions and degrees of freedom; the variance scale \( \lambda \) is given by an average over clusters and dimensions. The degrees of freedom \( \nu > d - 1 \) control the effective dimensionality of the space. Large values of \( \nu \) encourage a larger volume of the associated covariance matrices, whereas a values emphasize low-dimensional per-cluster distributions. We set \( \nu = \frac{d}{2} \).

Several researchers, such as [32], have attempted to address this problem. However, [32] deals primarily with robustness in the nearest neighbor case, and the extension to other estimators is highly nontrivial. Our approach borrows from [34] which investigates mixture models for outlier-resistant density estimation. The key difference is that we perform biclustering of pairs of conditioning attributes. Moreover, we use clustering as latent information in an estimation problem.

Our analysis relies on the idea that when generating multiple clusters, malicious users can typically only affect a real users very little. Whenever spammers are very different from regular users they will be aggregated into clusters of their
own. Alternatively, whenever they are very similar to regular users, they cannot do much damage. It exploits the fact that whenever a user is rather different, (9) suggests that it should be assigned to a new cluster.

Denote by $X$ and $X'$ two sets of $m$ and $m'$ observations respectively. In a Dirichlet process, the probability of two vs. one cluster is given by \( \frac{m m'}{(n + \alpha)^2} \) vs. \( \frac{m + m'}{n + \alpha} \). Hence, if the data likelihood for two separate clusters exceeds that of a single joint cluster via

\[
p_{\text{cluster}}(X) p_{\text{cluster}}(X') \frac{m m'}{(n + \alpha)^2} > p_{\text{cluster}}(X \cup X') \frac{m + m'}{n + \alpha}
\]

then there is benefit in splitting observations. From this we see that a split is likely whenever $m'$ is large, i.e. whenever we have a large number of spammers, or alternatively, whenever their behavior deviates substantially from regular users.

On the other hand, if the spammers try being subtle (to avoid detection), then their presence will improve overall parameter estimates. As a result, egregious spammers are clustered together, limiting their impact on others’ recommendations and making them easier to directly spot, through analyzing the clusters or testing users within the clusters.

8. EXPERIMENTS

The model described above is particularly interesting because of the insight it gives into the many common datasets used throughout data mining. Here we demonstrate its effectiveness accurately modeling real world data, both matching some expectations of reviews and breaking others.

<table>
<thead>
<tr>
<th></th>
<th>Users</th>
<th>Items</th>
<th>Ratings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Netflix-48k</td>
<td>48,090</td>
<td>17,770</td>
<td>10,015,137</td>
</tr>
<tr>
<td>Netflix-24k</td>
<td>24,047</td>
<td>17,770</td>
<td>5,038,411</td>
</tr>
<tr>
<td>BeerAdvocate</td>
<td>12,652</td>
<td>5000</td>
<td>51,438</td>
</tr>
<tr>
<td>Amazon Electronics</td>
<td>29,294</td>
<td>2000</td>
<td>30,378</td>
</tr>
<tr>
<td>Amazon Clothing</td>
<td>16,017</td>
<td>5000</td>
<td>51,438</td>
</tr>
</tbody>
</table>

Table 1: Review datasets used in our experiments

8.1 Datasets and Set up

Various ratings systems and datasets have very different characteristics. We look at a few real-world datasets with varying distributional properties. As some domains may be more polarizing than others, the simple assumption that ratings will look the same across domains does not hold. We looked at four different sets of review data comprising movies, beer, clothing, and electronics. A summary of the datasets can be found in Table 1.

In analyzing movies data, we used the Netflix Prize dataset. We create two subsets of the data by randomly sampling users but keeping all movies. This creates one dataset of 48,090 users and 17,770 movies, which we will refer to as Netflix-48k, and one dataset of 24,047 users and 17,770 movies, which we will refer to as Netflix-24k. The Netflix-48k dataset has a total of 10,015,137 ratings and the Netflix-24k dataset has 5,038,411 ratings.

Second, we use user reviews of beers from BeerAdvocate.com, as was scraped in [24]. Here we again take a subset of the data, comprising 5000 beers and their associated reviews from 12,652 users. This makes for a total of 112,981 reviews.

We also use two datasets of Amazon reviews [23]. We first use reviews of a subset of products from Amazon’s Electronics category. This includes 2000 products and all of their associated from 29,294 users. The total number of reviews in the dataset is 30,378. We note that this is just over 1 review per user on average, making this dataset much sparser than the rest. Last, we use the reviews from a subset of the products in Amazon’s Clothing & Accessories category. This is 51,348 reviews on 5000 products from 16,017 users.

Implementation: We implement our model and Gibbs sampling procedure in Matlab along with its parallel toolbox for speed. For simplicity and efficiency purposes we set a maximum number of clusters for users and items in each run, which we will specify for the experiments below. In all cases we use the PMF solution from [33] as our starting point. For all experiments below we set the rank (the length of $u_i$ and $v_j$) $d = 30$ and $\nu_0 = \frac{1}{d}$. Comparing on predictive probability: To measure our model’s fit, we use the predictive probability (PP):

\[
PP = \frac{1}{N} \sum_{r_{ij}} - \log p(r_{ij}|u_i, v_j)
\]

In order to make this a fair comparison with non-discrete distributions such as the typical Gaussian distribution, we discretize it first before any comparison. Because our recommender model can also act like a Gaussian, we can convert a Gaussian model $\mathcal{N}(\langle u_i, v_j \rangle, \sigma^2)$ to a recommender model $\text{Recommender}(\langle \hat{u}_i, \hat{v}_j \rangle, \sigma^2)$ as follows:

\[
\tilde{u}_i = \sigma \cdot u_i
\]

\[
\tilde{v}_j = \sigma \cdot v_j
\]

As a result, no weight of the distribution is wasted on regions for which there couldn’t be a rating. We tested many different values of $\sigma^2$ that gave the best predictive probability for a Gaussian and ultimately chose to use $\sigma^2 = 1.0$ because it generally produced the best results. Additionally, to compare against BPMF we run our code with a maximum of 1 cluster and fitting a normal as was done in their model.

8.2 Model fit

We run our model on the Netflix-24k and BeerAdvocate datasets to verify that it better models the data. We compare the results of running BPMF [33] to that from our model with a maximum of 50 clusters. As explained before, we want to measure the fit of our model so we use average predictive probability. As seen in Table 2 (where smaller predictive probability is better), CoBaFi fits the data much better than BPMF for both Netflix-24k and BeerAdvocate.

<table>
<thead>
<tr>
<th></th>
<th>Uniform</th>
<th>BPMF</th>
<th>CoBaFi</th>
</tr>
</thead>
<tbody>
<tr>
<td>Netflix-24k</td>
<td>1.6904</td>
<td>1.2525</td>
<td>1.1827</td>
</tr>
<tr>
<td>BeerAdvocate</td>
<td>2.1972</td>
<td>1.9855</td>
<td>1.6741</td>
</tr>
</tbody>
</table>

Table 2: Comparison of predictive log-likelihood on Netflix-24k and BeerAdvocate data.
8.3 Robustness to spam

One of the benefits of incorporating clusters into a model is that similar users will get clustered together, whether it be users who have similar tastes, or anomalous users who may try to manipulate ratings for their own gain. Spammers are an issue in any large, community-driven rating system as there is frequently a financial incentive for positive ratings and an incentive for negative ratings for competitors. By modeling the latent clusters of users, we are able to group similar users together. This means that anomalous users, such as spammers, may get grouped together, and thus have a smaller impact overall on ratings outside of their collective group or groups. To do this we ran two experiments. In each we take one of the datasets above and inject spammers who are trying to manipulate the ratings for a subset of items. We then measure how much these spammers effect the fit of our model on these items.

<table>
<thead>
<tr>
<th></th>
<th>PP Before</th>
<th>PP After</th>
</tr>
</thead>
<tbody>
<tr>
<td>BPMF</td>
<td>1.7047</td>
<td>1.8146</td>
</tr>
<tr>
<td>CoBaFi</td>
<td>1.0549</td>
<td>1.7042</td>
</tr>
</tbody>
</table>

Table 3: Predictive probability on “attacked items” in the Amazon Electronics dataset before and after adding spammers.

<table>
<thead>
<tr>
<th></th>
<th>PP Before</th>
<th>PP After</th>
</tr>
</thead>
<tbody>
<tr>
<td>BPMF</td>
<td>1.2375</td>
<td>1.3057</td>
</tr>
<tr>
<td>CoBaFi</td>
<td>0.9670</td>
<td>1.2935</td>
</tr>
</tbody>
</table>

Table 4: Predictive probability on “attacked movies” in the Netflix-24k dataset before and after add spam from hijacked accounts.

Dumb spammers: For the first experiment we model spammers who are quite flagrant in how they try to manipulate certain reviews and do not camouflage their behavior by also providing typical ratings. To do this we use the Amazon Electronics dataset and see if we can take generally well-liked products and bring their ratings down (as a competitor would want). We select 31 products with a high average rating and at least 100 reviews. These products include Logitech speakers, an HDMI cable, a TiVo USB Network Adapter, and an HP LaserJet Printer, among many others. For these products we randomly select 100 ratings for each project to be included in the training dataset and the rest to be held out for the test dataset. We subsequently create 100 new accounts, and for all of these products our spam accounts give a rating of 1.0. As such, each product being manipulated now has half real reviews and half fake. As can be seen in Table 3, the predictive probability of our model is better than that for BPMF before and after we add the spam. Additionally, while the model is clearly affected by the spammers as it shifts to cover both the 1 star and 5 star reviews, it does an even better job of clustering spammers and the products they attack. As can be seen in Figure 4(a), most of the spammers (83%) are placed in the same cluster. Additionally, not graphed due to its simplicity, the attacked products are all placed into the same cluster. In an industry setting, this sort of interpretability and ability to understand group behavior would be valuable for investigating suspicious behavior.

Spammers with hijacked accounts: Second we test the model’s robustness to more clever spammers - those who hijack real accounts. In this case we take real users and assume their account has been hijacked and begin providing misleading dubious reviews. This is a common issue in online systems and is the worst-case form of spammers who add realistic-looking reviews to try to camouflage their fraudulent behavior. To test our model in this setting we use the Netflix-24k dataset. Here we choose 85 movies with an average rating over 4.3 and with at least 200 reviews. Additionally we select 99 users at random (their average number of ratings is approximately 209). As before, for each of the movies selected to be attacked we include 100 of their ratings at random in the training set and use the rest for the test set. For the hijacked accounts we merely add 1 star reviews to all of the movies attacked. Again, we see in Table 4 that our model has a better predictive probability than BPMF both before and after we add the spam. More impressively, CoBaFi is still successful in clustering together the hijacked users and the attacked movies, as seen in Figures 4(b-c). Note, this is particularly surprising for the hijacked users since they may have hundreds or thousands of legitimate reviews along with the only 85 fake reviews that contribute to their profile. From this we see that CoBaFi naturally handles spammers in a way that minimizes their impact on collaborative filtering and groups them together.

8.4 Natural clusters in real world

As mentioned earlier, being able to understand your data and interpret your latent parameters is useful in many applications and industry settings. Besides clustering anomalous behavior, our model provides interesting insight into the natural clusters of items based on their latent preferences in $v_j$.

We analyze the clusters produced from the Netflix-48k dataset. In fitting our model, we set the maximum number of clusters to 50, which given the number of movies/beers being rated leaves a still fairly coarse clustering. In order to isolate the effects of the clustering mechanism and not the flexible distribution, we use a Normal as our recommender distribution so that clusters are based only on $v_j$. In the Netflix-48k dataset we analyzed the clustering in two different ways. In Figure 3, we look at the distribution of different series across different clusters. We see that for most of the series nearly all of the seasons or films in that series are clustered together. Additionally, we see in Table 5 that clusters often contain movies within the same genre, with Cluster 28 containing generally comedies, Cluster 30 containing material for children, and Cluster 48 including science fiction. This sort of interpretable model is of course useful in practice to understand your data and user preferences.

<table>
<thead>
<tr>
<th>Cluster 28</th>
<th>Cluster 30</th>
<th>Cluster 48</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simpsons</td>
<td>Scooby Doo</td>
<td>Star Trek</td>
</tr>
<tr>
<td>Family Guy</td>
<td>Spy Kids</td>
<td>Back to the Future</td>
</tr>
<tr>
<td>Monty Python</td>
<td>Stuart Little</td>
<td>Southpark</td>
</tr>
<tr>
<td>Curb your Enthusiasm</td>
<td>Dr. Dolittle</td>
<td>Lord of the Rings</td>
</tr>
<tr>
<td>The Twilight Zone</td>
<td>Lion King</td>
<td>Harry Potter</td>
</tr>
<tr>
<td>Arrested Development</td>
<td>Agent Cody Banks</td>
<td>The X-Files</td>
</tr>
<tr>
<td>Chappelle Show</td>
<td>Monty Python</td>
<td></td>
</tr>
<tr>
<td>Seinfeld</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 5: Clusters of movies and shows from Netflix. Series are only included if there are at least 2 items from that show or series in the cluster.
Figure 3: Distribution of movies from TV series over clusters. Movies from the same series are highly concentrated. Viewing series as ground truth, we see that the accuracy is fairly high. Note that movies within the same series are not necessarily uniform (different seasons, directors, script writers).

Figure 4: Distribution of spammers over clusters; Left: Dumb spammers on the electronics dataset; Middle: Hijacked users on the electronics dataset; Right: Spammed movies on the Netflix-24k spam dataset. In all three cases the spammers congregate tightly in a very small number of clusters.

Figure 5: Rating distributions from the data and as estimated by CoBaFi. From left to right: Sony 50CDQ80RS 80 Minute 700 MB 48x CD-R 50 Pack Spindle on Amazon Electronics (the most skewed distribution); The Rookie on Netflix (the most Gaussian distribution); Vanity Fair Women’s My Favorite Illumination String Bikini Panty on Amazon Clothing; Ovila Abbey Saison - Sierra Nevada Brewing Co. on BeerAdvocate.

8.5 Shape of real world data

The most interesting interpretable parameter of our model is understanding the wide range of distributions. In analyzing our results, we quickly see the world is not so normal. For each of our datasets we calculate the convexity of each item, \( \hat{\theta}_j^{(2)} \):

\[
\hat{\theta}_j^{(2)} = v_j^{(2)} + \frac{1}{|\text{ratings}(j)|} \sum_{i \in \text{ratings}(j)} u_i^{(2)}
\]

With this term, we can generally see how convex (“U”-shaped) or concave (Gaussian) our item ratings actually are.

Beer Ratings: The simplest of the results, though surprising given the others, was with the BeerAdvocate ratings. For all beers we found \( \hat{\theta}_j^{(2)} < 0 \), meaning that the distribution was always Gaussian. Additionally, the distributions were not overly skewed as in other datasets; the items with the smallest values of \( \hat{\theta}_j^{(2)} \) and thus the least variance were typically centered at 4.0 or less as seen in Figure 5(d).

Looking at the distribution of variances \( \hat{\theta}_j^{(2)} \) we see a fairly wide range of variances across the beers. This explains why our model has such an improved predictive probability than BPMF as shown above and demonstrates the importance of fitting the variance as well as the mean.

Netflix Ratings: Within the Netflix dataset, the results were not nearly as simple. Here we found that, possibly to the surprise of many data-miners, for most items on Netflix, \( \hat{\theta}_j^{(2)} < 0 \) and thus the distribution is Gaussian. Taking a closer look at the skews, we find some interesting patterns. In particular, as seen in Table 7, television shows were the most convex. For nearly all of these cases, we see that the shows produce highly polarized results that are usually heavily skewed in one direction. Alternatively, the items that were fitted to be the most Gaussian were mediocre movies such as “The Rookie.” A comparison of the distributions can be seen in Figure 5(b). Intuitively, this makes sense. Watch-
season of TV,” or (c) “This was a good/bad piece of video entertainment?” Similarly, the selection bias arising from the additional effort to watch a full season of a show may also arise in the additional effort to go online and rate a product on Amazon. Additionally, we may only be able to compare quality against highly similar items as has been found in pricing studies in behavioral economics. From this we see polarized views from items that are difficult to evaluate or we have fewer instances to compare against, e.g. printers, seasons of a TV show, jeans, and more Gaussian ratings from items that we can compare against a wide variety of past experiences, e.g. comedy movies, action movies, beers.

While there is no definitive explanation for why these patterns emerge, it is clear that ratings have complex meaning. While our model is effective at fitting the wide range of distributions generated from such varied motives, we believe these discovered discrepancies demonstrate the need to further understand online ratings and better understand the latent factors that contribute to rating decision.

9. SUMMARY

In this paper we demonstrated that a single model suffices to provide both good recommendation performance, the ability to capture nontrivial bimodal and skewed distributions, the ability to analyze and group users and movies, and a mechanism for detecting spammers. Often these four problems are addressed by separate tools, often even by separate teams in commercial contexts. Our research shows that this is not needed. Instead, it is likely better to jointly model all these effects in a moderately detailed statistical generative process. While this may be costlier than each individual specialized solution, the overall engineering cost of a joint model is considerably less than maintaining these specialized methods. Furthermore, additional data can help improve all aspects simultaneously. We anticipate that large integrated data modeling will become a pervasive trend for recommendation, ranking and content analysis.

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10. REFERENCES


