Model-based Approaches for Independence-Enhanced Recommendation

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Independence-Enhanced Recommender Systems

Providing independent information is useful in recommendation

- Adherence to laws and regulations
- Fair treatment of content providers
- Exclusion of unwanted information

Independence-enhanced Recommender System

The absolutely independent recommendation is intrinsically infeasible, because recommendation always depends on the preference of a specific user

This system makes recommendation so as to enhance independence with respect to a specific sensitive feature

Contributions

Our Previous Work

- We advocated a concept of **independence-enhanced recommendation**
- We developed **a regularization approach** to enhance recommendation independence
- This approach is applied to a probabilistic matrix factorization (PMF) model

This Talk

- We propose another approach to enhance recommendation independence, **a model-based approach**
- **A sensitive feature is embedded into a graphical model** for recommendation, while maintaining independence between recommendation and sensitive information

Outline

- A concept of recommendation independence
- Applications of recommendation independence
- Two approaches to enhance recommendation Independence
  - A regularization approach
    a regularizer to constrain independence is introduced to a probabilistic matrix factorization model
  - A Model-based approach
    a sensitive feature is embedded into a latent class model, while maintaining independence between a recommendation result and a sensitive value
- Experiments
- Related work
- Conclusions

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Sensitive Feature

As in a case of standard recommendation, we use random variables

X: a user, Y: an item, and R: a rating

We adopt an additional variable for recommendation independence

S : sensitive feature

- It is specified by a user depending on his/her purpose
- A recommendation result is independent from this sensitive feature
- Sensitive value is determined depending on a user and an item

Ex. Sensitive feature = movie's popularity / user's gender

A sensitive feature is restricted to a binary type

Recommendation Independence

[Kamishima 12, Kamishima 13]

Recommendation Independence

the statistical independence

between a recommendation result, R, and a sensitive feature, S

$$\Pr[R \mid S] = \Pr[R]$$

$$\equiv$$

$$R \perp\!\!\!\perp S$$

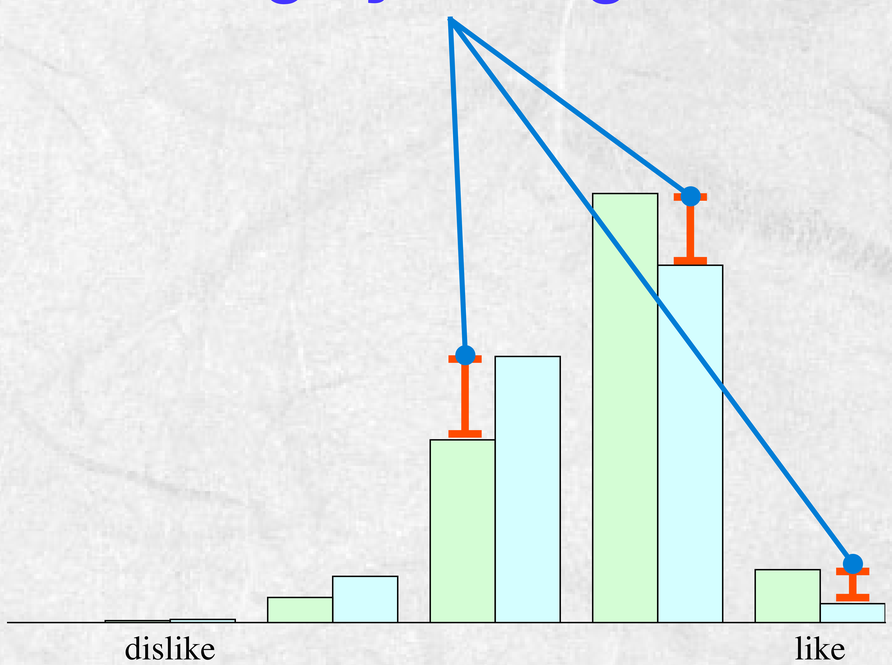
- No information about a sensitive feature influences the result
- The status of the sensitive feature is explicitly excluded from the inference of the recommendation result

Ratings of items are predicted
under this constraint of recommendation independence

Effect of Independence Enhancement

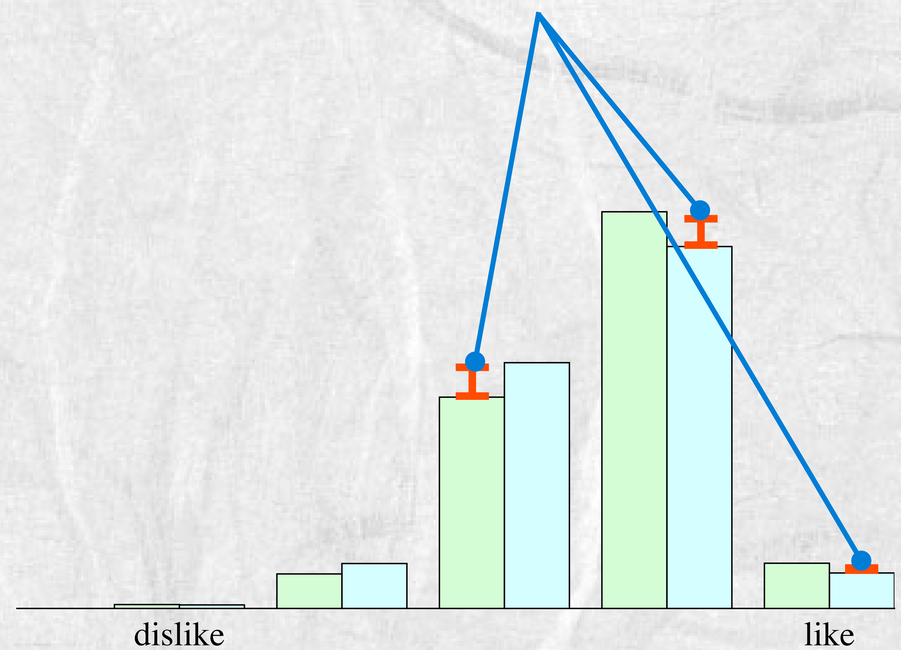
Standard recommendation

two distributions are largely diverged



Independence-enhanced r.

distributions become close by enhancing independence



* each bin of histograms of predicted ratings for older and newer movies

The bias that older movies were rated higher could be successfully canceled by enhancing independence

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Application
Adherence to Laws and Regulations

[Sweeney 13]

A recommendation service must be managed while adhering to laws and regulations

suspicious placement keyword-matching advertisement

Advertisements indicating arrest records were more frequently displayed for names that are more popular among individuals of African descent than those of European descent

⬇

Socially discriminative treatments must be avoided

sensitive feature = users' demographic information

⬇

Legally or socially sensitive information
can be excluded from the inference process of recommendation

Application
Fair Treatment of Content Providers

System managers should fairly treat their content providers

Fair treatment in search engines

[Bloomberg]

The US FTC has investigated Google to determine whether the search engine ranks its own services higher than those of competitors

Fair treatment in recommendation

Marketplace sites should not abuse their position to recommend their own items more frequently than tenants' items

sensitive feature = a content provider of a candidate item

⬇

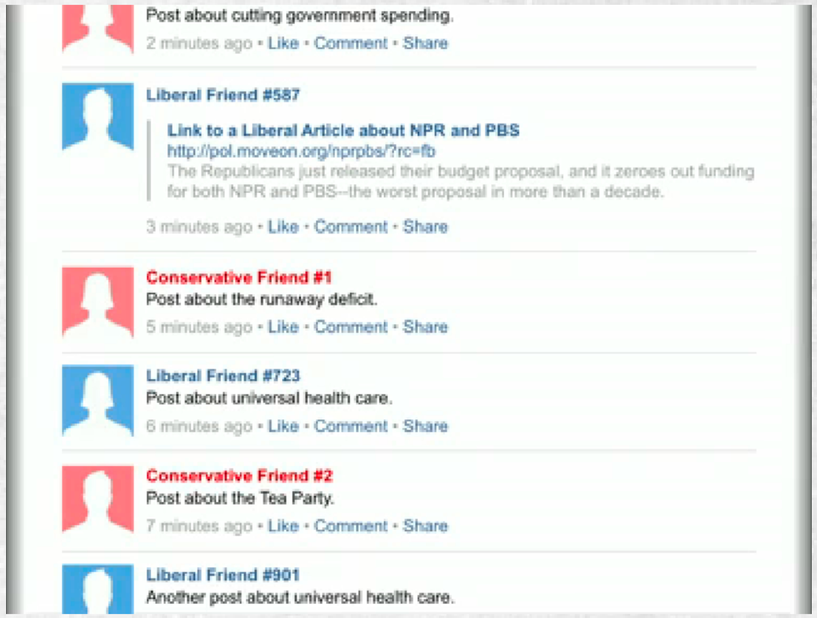
Information about who provides a candidate item can be ignored, and providers are treated fairly

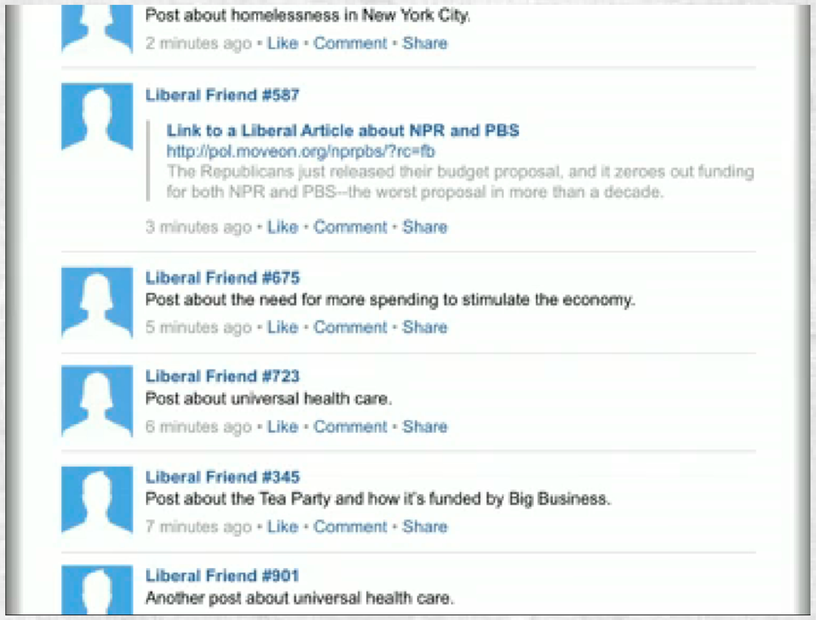
Application
Exclusion of Unwanted Information

[TED Talk by Eli Pariser, http://www.filterbubble.com/]

Information unwanted by a user is excluded from recommendation

Filter Bubble: To fit for Pariser's preference, conservative people are eliminated from his friend recommendation list in FaceBook





sensitive feature = a political conviction of a friend candidate

Information about whether a candidate is conservative or progressive can be ignored in a recommendation process

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Formalizing Task

Predicting Ratings: a task to predict a rating value that a user would provide to an item

Random variables: user X, item Y, rating R, sensitive feature S

Standard Recommendation

Dataset

$$\mathcal{D} = \{(x_i, y_i, r_i)\}$$

Prediction Function

$$\hat{r}(x, y)$$

Independence-Enhanced Rec.

Dataset

$$\mathcal{D} = \{(x_i, y_i, r_i, s_i)\}$$

Prediction Function

$$\hat{r}(x, y, s)$$

Probabilistic Matrix Factorization

[Salakhutdinov 08, Koren 08]

Probabilistic Matrix Factorization Model

predict a preference rating of an item y rated by a user x

well-performed and widely used

Prediction Function

$$\hat{r}(x, y) = \underbrace{\mu}_{\text{global bias}} + \underbrace{b_x}_{\text{user-dependent bias}} + \underbrace{c_y}_{\text{item-dependent bias}} + \underbrace{\mathbf{p}_x \mathbf{q}_y^\top}_{\text{cross effect of users and items}}$$

Objective Function

$$\underbrace{\sum_D (r_i - \hat{r}(x_i, y_i))^2}_{\text{squared loss function}} + \underbrace{\lambda}_{\text{regularization parameter}} \underbrace{\|\mathbf{\Theta}\|^2}_{L_2 \text{ regularizer}}$$

For a given training dataset, model parameters are learned by minimizing the squared loss function with an L_2 regularizer.

Independence-Enhaned PMF

Prediction Function

a prediction function is selected according to a sensitive value

$$\hat{r}(x, y, s) = \mu^{(s)} + b_x^{(s)} + c_y^{(s)} + \mathbf{p}_x^{(s)} \mathbf{q}_y^{(s)\top}$$

sensitive feature

Objective Function

independence parameter: control the balance between the independence and accuracy

$$\sum_D (r_i - \hat{r}(x_i, y_i))^2 - \eta \, \mathrm{indep}(R, S) + \lambda \, \|\mathbf{\Theta}\|^2$$

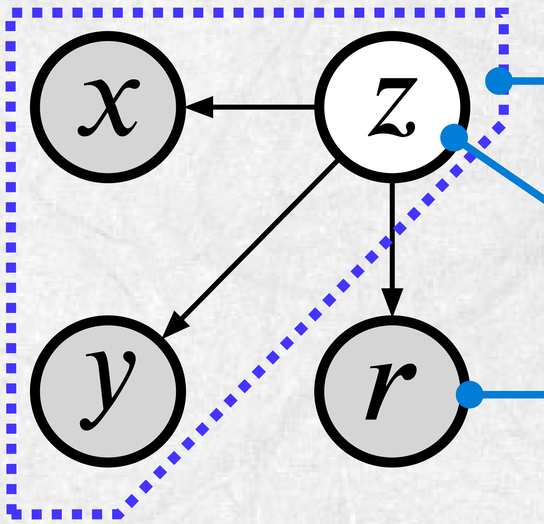
independence term: a regularizer to constrain independence

- The larger value indicates that ratings and sensitive values are more independent
- Matching means of predicted ratings for two sensitive values

Latent Class Model

[Hofmann 99]

Latent Class Model: A probabilistic model for collaborative filtering



A basic topic model, pLSA

latent topic variable

extended so as to be able to deal with ratings r given by users x to items y

Model parameters can be learned by an EM algorithm

Prediction:

$$\hat{r}(x, y) = \mathrm{E}_{\Pr[r|x,y]}[\mathrm{level}(r)] = \sum_r \Pr[r|x, y]\,\mathrm{level}(r)$$

the r-th rating value

A rating value can be predicted by the expectation of ratings

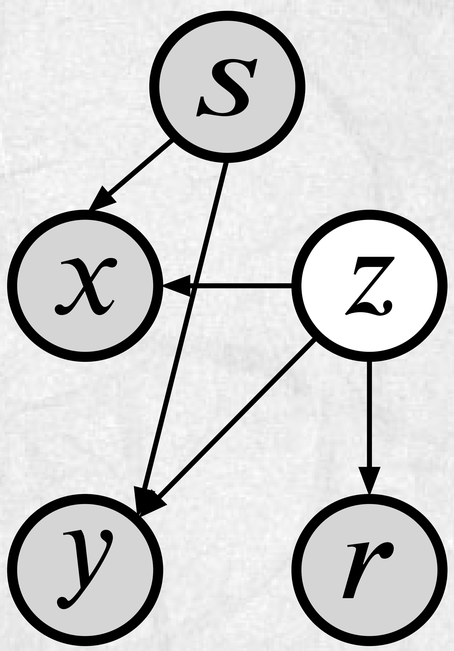
Independence-Enhanced LCM

Independence-Enhancement by a Model-based Approach

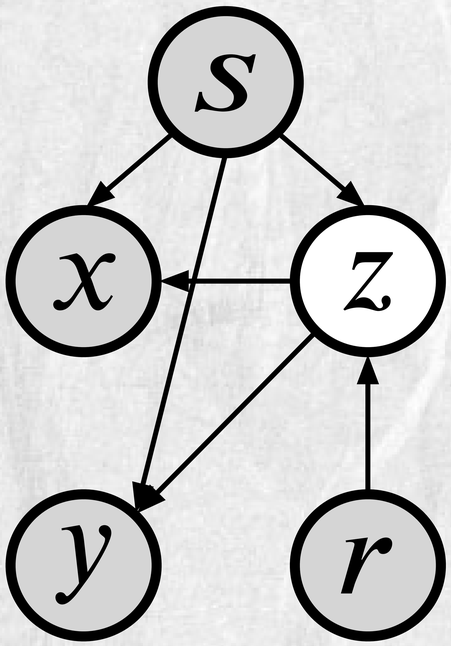
A sensitive variable is embedded into the original LCM

- A rating and a sensitive variable are mutually independent
- A user, an item, and a rating are conditionally independent given Z

Type 1 model



Type 2 model



A type 2 model can more strictly enhance recommendation independence, because in addition to X and Y, Z depends on a sensitive variable

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Experimental Conditions

Data Sets

- **ML1M-Year**: Movie preference data. A sensitive feature is whether movies' release year is old or new.
- **ML1M-Gender**: Movie preference data. A sensitive feature is a gender of a user.
- **Flixster**: Movie preference data. A sensitive feature is whether a movie is popular or not.
- **Sushi** (not presented here)

Evaluation measures

- **MAE (Mean Absolute Error)**
  - Precision measure. The smaller is the better.
- **KS (Statistic of the two-sample Kolmogorov-Smirnov test)**
  - Independence measure. The smaller is the better.
  - The area between two empirical cumulative distributions of predicted ratings for $S = 0$ and $S = 1$.

Experimental Results

	ML1M-Year		ML1M-Gender		Flixster	
	MAE	KS	MAE	KS	MAE	KS
PMF	0.685	0.1687	0.685	0.0389	0.655	0.1523
PMF-r	0.697	0.0271	0.694	0.0050	0.653	0.0165
LCM	0.729	0.1984	0.729	0.0487	0.671	0.1787
LCM-mb1	0.717	0.0752	0.719	0.0243	0.672	0.0656
LCM-mb2	0.720	0.1030	0.720	0.0364	0.672	0.0656

PMF: original PMF, **PMF-r**: independence-enhanced PMF,
LCM: original LCM, **LCM-mb1**: Type1 LCM, **LCM-mb2**: Type 2 LCM

- Independence indexes were improved compared to their original method, but their precisions were slightly sacrificed
- Contrary to our expectation, no clear differences between Type 1 and Type 2 models
- Independence seemed to be less strictly enhanced by a model based approach

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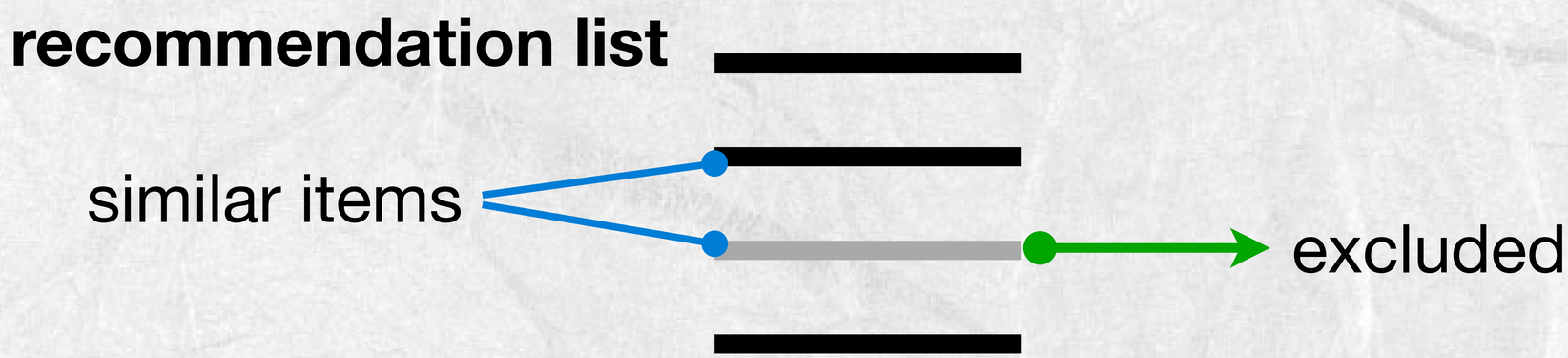
Recommendation Diversity

[Ziegler+ 05, Zhang+ 08, Latha+ 09, Adomavicius+ 12]

Recommendation Diversity

Similar items are not recommended in a single list, to a single user, to all users, or in a temporally successive lists



Diversity

Items that are similar in a specified metric are excluded from recommendation results

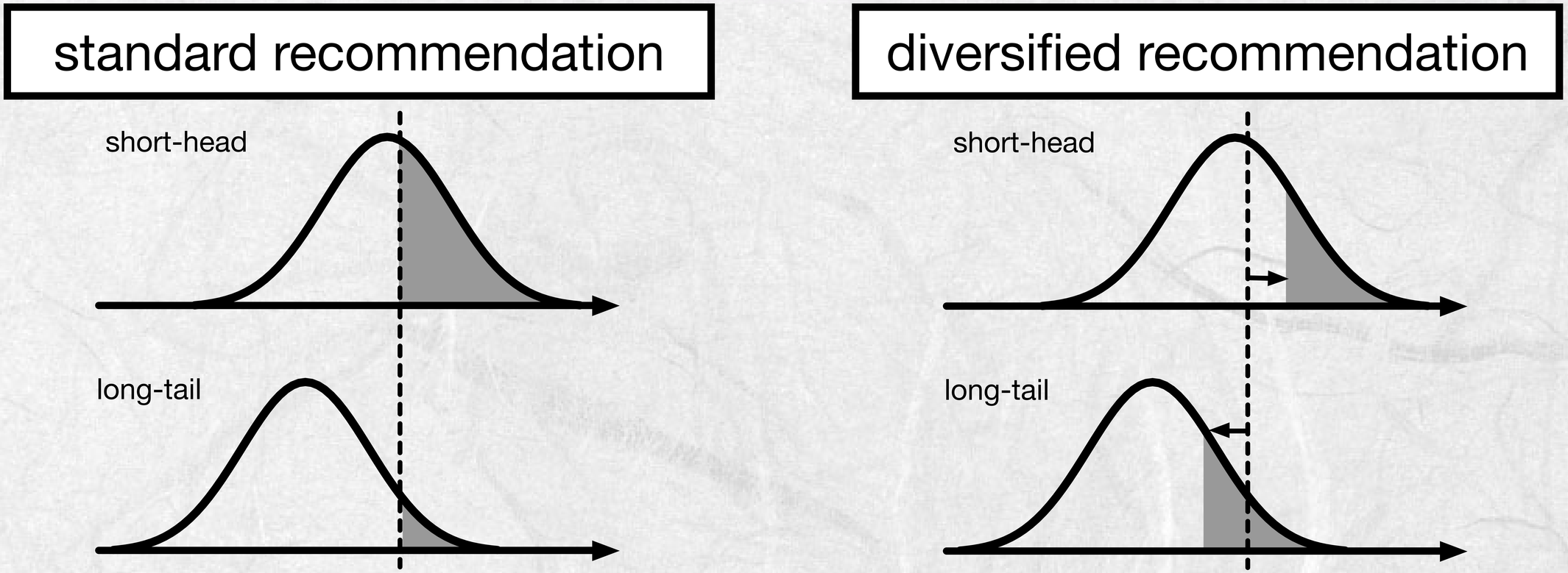
The mutual relations among results

Independence

Information about a sensitive feature is excluded from recommendation results

The relations between results and sensitive values

Independence vs Diversity



Because a set of recommendations are diversified by abandoning short-head items, **predicted ratings are still biased**

Prediction ratings themselves are unbiased by enhancing recommendation independence

Privacy-preserving Data Mining

recommendation results, R, and sensitive features, S,
are statistically independent

mutual information between a recommendation result, R,
and a sensitive feature, S, is zero

$$\mathrm{I}(R; S) = 0$$

In a context of privacy-preservation

Even if the information about R is disclosed,

the information about S will not exposed

In particular, a notion of the *t*-closeness has strong connection

Conclusions

Contributions

- We proposed a new model-based approach to enhance recommendation independence
- This approach was implemented into a latent class model
- Experimental results showed the successful enhancement of recommendation independence by this approach

Future work

- Developing a regularization approach for a latent class model, and comparing the performance with a model-based approach
- Bayesian extension

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