A Deep Latent Recommender System based on User Ratings and Reviews

Dingge LIANG

(Joint work with M. Corneli, C. Bouveyron and P. Latouche)

Université Côte d'Azur, INRIA MaasAI

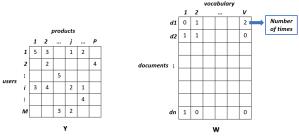




Introduction: towards a topic-aware recommender system

Consider a dataset with M users scoring/reviewing P products, encoded by two matrices:

- Y is an ordinal matrix in $\mathbb{N}^{M\times P}$, with Y_{ij} the rating of the object j by user i.
- W is a document-term matrix (DTM), with $W^{(i,j)}$ encoding a review about object j by user i.



(a) Ordinal matrix

(b) Document-term matrix

Figure: Two encoded matrices.

Dingge LIANG

The generative process and VAE inference

We assume the following generative process for rating and review:

• The rating Y_{ij} is:

$$Y_{ij} = \langle R_i, C_j \rangle + \epsilon_{ij}, \qquad (1)$$

where $R_i \sim \mathcal{N}(0, I_D)$, $C_i \sim \mathcal{N}(0, I_D)$, $\varepsilon_{ij} \sim \mathcal{N}(0, \eta^2)$.

• For the reviews, we assume that:

$$p(W^{(i,j)}|\theta_{ij}) \sim \text{Multinomial}(L_{ij}, \beta \theta_{ij}),$$
 (2)

where

- L_{ij} is the number of words in $W^{(i,j)}$,
- $\beta \in \mathbb{R}^{V \times K}$ is the matrix whose entry β_{vk} is the probability that word v occurs in topic k,
- $\theta_{ij} = \sigma(f_{\gamma}\left(R_{i},C_{j}\right))$ is the topic proportion, where $f_{\gamma}: \mathbb{R}^{2D} \to \mathbb{R}^{K}$ is a continuous function approximated by a neural network parametrized by γ , $\sigma(\cdot)$ denotes the Softmax function.

A Variational auto-encoder is used for the inference: $\log p(Y,W|\eta^2,\gamma,\beta) \geq \mathbb{E}_{q(R,C)}\left[\log \frac{p(Y,W,R,C|\eta^2,\gamma,\beta)}{q(R,C)}\right],$ where

$$q(R_i) = g(\mu_i^R := h_{1,\phi}(Y_i, W^{(i,\cdot)}), S_i^R := h_{2,\phi}(Y_i, W^{(i,\cdot)})),$$

$$(1) \quad q(C_j) = g(\mu_j^C := h_{1,\iota}(Y^j, W^{(\cdot,j)}), S_j^C := h_{2,\iota}(Y^j, W^{(\cdot,j)})).$$

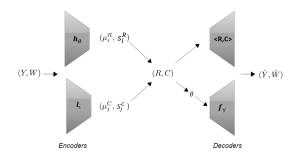


Figure: A deep learning view of deepLTRS.

Numerical experiments

Benchmark on simulated data:

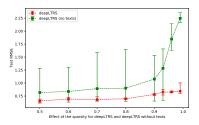


Figure: Comparison of deepLTRS with and without texts.

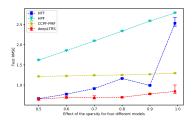


Figure: Test RMSE of models: HFT, HPF, CCPF and deepLTRS with different sparsity level on simulated data.

Amazon Fine Food data:

Table: Test RMSE on Amazon Fine Food data.

Model	Run 1	Run 2	Run 3	Runt 4	Run 5	Average
HFT HPF	1.4241 2.9486	1.5327 2.9682	2.9311	1.4228 2.9428	2.9734	1.4477 (±0.0510) 2.9528 (±0.0158)
CCPF-PMF deepLTRS	1.2695 1.1364	1.2964 1.2595	1.3035 1.2445	1.2923 1.1710		1.2913 (\pm 0.0115) 1.2518 (\pm 0.0489)
uccpring	1.1304	1.2333	1.2443	1.1/10	1.2413	1.2310 (±0.0409)