Recommender Systems: Overview and Package rectools

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December 13, 2016

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- Above referred to as *collaborative filtering*. Various other approaches are popular as well.

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- Etc.

Statistical Issues (Part I)

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  - Discussed in (Breiman, 2001) and (Matloff, 2014).
- ML people in denial. They talk about predicting new cases, overfitting etc. — all implicitly assuming sampling from a population.

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$$M = (Y_{ij}) \approx UV$$

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$$Y_{ij} = \mu + \alpha_i + \beta_j + \epsilon_{ij}$$

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with α_i and β_j being random and latent effects, mean 0. Then apply MLE (e.g. **lme4** package in R) or, better, Method of Moments (MM).

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Hybrid kNN-MF Model

- Find U, V for $M \approx UV$.

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Hybrid kNN-MF Model

- Find U, V for $M \approx UV$.
- The rows of V are (or should be) interpreted as forming a kind of basis, consisting of synthetic reprentative users.
- For each new case C to predict for item j, find the closest row of V to (the known elements of) C, denoted by R. Predict the rating to be element j of R_j.
- Should be much, much faster, and maybe more accurate.

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Multiplicative Model for Binary R

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- MF not designed for binary Y, but still could use them; they are only heuristics anyway.
- For RE, **lme4** package offers GLM analysis for binary Y, but MLE is too slow, especially with large data.
- Desirable: Alternative using MM.

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Multiplicative Model (cont'd.)

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- Instead of independent *additive* model, $Y_{ij} = \mu + \alpha_i + \beta_j + \epsilon_{ij}$, have an independent *multiplicative* model,

$$P(Y_{ij} = 1) = \nu \alpha_i \beta_j$$

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- For identifiability, set $E\alpha_i = E\beta_j = 1$.
- Apply MM, get very simple closed-form expressions.

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- At *https://github.com/Pooja-Rajkumar/rectools*, soon to be submitted to CRAN.
- kNN, MF, RE (MLE/MM)
- Implements (or will implement) the above proposed methods and others.
- Some parallel computational capability, using Software Alchemy (Matloff, 2016).

Statistical Issues (Part II)

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- So, **rectools** does various plots.

Covariate Data

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- But covariate data should be helpful in some settings, e.g. kNN with a new case that has covariate data but not much of a ratings history.
- The **rectools** package does allow covariates in most of its functions.

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Example: Czech Dating Site

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Ratings 1:10.

```
> dat <- read.csv('ratings.dat',header=FALSE)
> idxs <- sample(1:nrow(dat),100000)
> dat100k <- dat[idxs,]
> mmout <- trainMM(dat100k)
> dat100k[1,]
              V1     V2 V3
14857272 115894 14800  4
# how would user 115894 like member 2?
> z <- dat100k[1,]
> z$V2 <- 2
> predict(mmout,z)
[1] 8.45566
```

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Plotting Example

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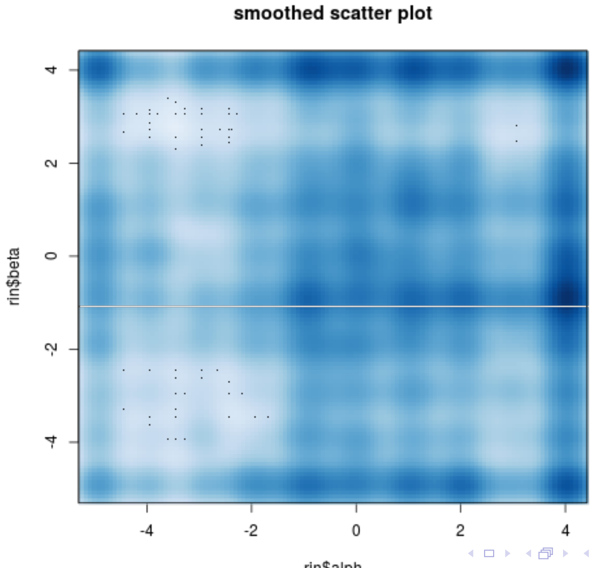
MLE model assumes the α, β independent, normal.



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