# CSE258 Assignment 1

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## 1 Cook prediction

For this task I tried a lot of different approaches, as I was not quite sure what would be the best approach. My baseline solution was a simple "predict true if recipe is popular enough", which actually worked quite well. I tried combining this with Jaccard similarity, both between recipes and users, without any great success.

After that I started implementing a One-Class model, more specifically a Bayesian Personalized Ranking model using Tensorflow. After trying out a wide range of parameters with regards to learning rate, K, lambda and iterations, I found a model which performed reasonably good on my validation set. I then started improving the model by taking cold start problems into account, and predicting these through a popularity-based and Jaccard-based measure, like the extended baseline implementation. After getting an accuracy I was relatively satisfied with on the validation set, I re-trained the model on the whole dataset, before predicting the test set.

### 1.1 Kaggle performance

|          | Public leaderboard | Private leaderboard |
|----------|--------------------|---------------------|
| Accuracy | 70.3 %             | 70.4 %              |
| Ranking  | 566/1121           | 586/1121            |

### $\mathbf{2}$ Rating prediction

For this task I also tried out a lot of different approaches. I started out using the "Surprise" library to implement a Latent Factor Model. I did not quite get the MSE I was hoping for using this library, so I went on to try implement another Latent Factor Model using Tensorflow. I unfortunately did not manage to get the MSE I was hoping for with this approach either.

I then went on to a Latent Factor Model with only the bias terms on the form

$$rating(user, item) \simeq \alpha + \beta_{user} + \beta_{item}$$
 (1)

$$\underset{\alpha,\beta}{\operatorname{arg\,min}}_{\alpha,\beta} \sum_{u,i} (\alpha + \beta_u + \beta_i - R_{u,i})^2 + \lambda \left[ \sum_{u,j} \beta_u^2 + \sum_{i} \beta_i^2 \right] (2)$$

where the optimization problem then becomes  $\arg\min_{\alpha,\beta} \sum_{u,i} \left(\alpha + \beta_u + \beta_i - R_{u,i}\right)^2 + \lambda \left[\sum_u \beta_u^2 + \sum_i \beta_i^2\right](2)$  By solving the following equations iteratively until they converge, I got the basis for my predictor

$$\alpha = \frac{\sum_{u,i \in train} (R_{u,i} - (\beta_u + \beta_i))}{N_{train}} \beta_u = \frac{\sum_{i \in I_u} R_{u,i} - (\alpha + \beta_i)}{\lambda + |I_u|} \beta_i = \frac{\sum_{u \in U_i} R_{u,i} - (\alpha + \beta_u)}{\lambda + |U_i|}$$
(3)

I then used some time to tune my predictor, starting with a very coarse-grained search with different lambdas, before narrowing the search down to find a good lambda on the validation set. I then did some small adjustments, like making sure the predicted rating was saturated from above at 5 and from below at 0. since exceeding this range only can lead to a greater MSE. Then the model was re-trained on the whole dataset, before predicting the test set. I then uploaded my predictions to Kaggle, with a result I am very satisfed with.

#### 2.1 Kaggle performance

|         | Public leaderboard | Private leaderboard |
|---------|--------------------|---------------------|
| MSE     | 0.82151            | 0.79289             |
| Ranking | 88/552             | 33/552              |