Questions to answer about other papers (recommendations systems)

1. Problem trying to solve
2. Deficiency in their solution
3. Similar to our work
4. Different to our work
5. Have we done what they haven’t addressed

PAPER 1 - 1406.2431 - Budget-Constrained Item Cold-Start Handling in Collaborative Filtering Recommenders via Optimal Design.

1. Item cold start problems. When you have lack of item rating. Their question: given a new item, a pool of available users, and a budget constraint, select which users to assign with the task of rating the new item in order to minimize the prediction error of our model.
2. Deficiency?
3. Just as ours, they are asking new users to rate several carefully selected items of a seed set during a short interview.
4. They are considering cost and we are looking at performance. When we have no rating in an item, that item still can be recommended because we consider similar jobs to those that were done by that user. On their solution, they used the optimal design approach, and it relies on the assumption that the ratings are generated via an Equation. They calculated the prediction accuracy that was measured using the RMSE metric over all predictions, we did not.
5. We have used the mean normalization in order to fill out ratings for a new user when there are no ratings.

PAPER 2 - collab-ranking - Collaborative Ranking with a Push at the Top

1. It introduces a novel family of collaborative ranking algorithms which focus on accuracy at the top of the list for each user while learning the ranking functions collaboratively.
2. Deficiency?
3. Just as ours, they care about the top recommendations for a user (by pushing down non-relevant items and/or pulling up relevant items), and also about the learning with the collaborative filtering (the use of a low rank representation for collaborative scoring).
4. They are considering three specific formulations, based on collaborative p-norm push, that we don’t use it (three collaborative approaches). They are considering Loss function and square loss. They found out that using high rank representation, it resulted in numerical instability issues.
5. ?

PAPER 3 - jzhouWWW15 - Who, What, When, and Where: Multi-Dimensional Collaborative Recommendations Using Tensor Factorization on Sparse User-Generated Data

1. Users would benefit from recommendations for activities in which to participate at those locations along with suitable times and days. They presented a system and an approach for performing multidimensional collaborative recommendations for Who (User), What (Activity), When (Time) and Where (Location), using tensor factorization on sparse user-generated data.