# Recommendation for multi-stake holders and through neural review mining

Muthusamy Chelliah
Flipkart
muthusamy.c@flipkart.com

Yong Zheng
Illinois Institute of Technology
yzheng66@iit.edu

Sudeshna Sarkar
IIT Kharagpur
shudeshna@gmail.com

Vishal Kakkar
IIT Kharagpur
vishal.kakkar@flipkart.com

**ABSTRACT**

In multiple scenarios or applications (e.g., advertising, dating, job seeking, education), multiple stakeholders are involved and their perspectives cannot be ignored, e.g., kids may like to watch car Ads, but it may hurt the benefits of car producer, since they expect the watcher to purchase cars. Kids are not the target buyers from the perspective of car producers, while they are the appropriate users in view of the advertisers who just expects users to click the Ads. Tutorial initially will give background and existing techniques in multi-stakeholder recommender systems (MSRS), and finally introduce how to use the multi-objective learning open-source library MOEA to build the methods for MSRS.

Reviews in an e-commerce platform may be mined to address the cold-start problem and to generate explanations. Our earlier tutorial covered text mining methods for feature-specific sentiment analysis of products and topic models/distributed representations that bridge vocabulary gap between user reviews and product descriptions. Focus herein instead is on recent neural methods for review mining - covering hands-on code for review text mining and its use to enhance product recommendation. Each section will introduce the topic from various mechanism (e.g., attention) and task (e.g., review ranking) perspectives, present state of the art methods and a walkthrough of programs executed on Jupyter notebook using real-world datasets.

**AUDIENCE/IMPACT**

This tutorial is expected to catalyse intermediate-level academics and industry practitioners in NLP and data mining community towards further research aligned to business needs and prototype implementations with underlying deep technology respectively.

**A. MULTI-STAKE HOLDER RECOMMENDER SYSTEM (60 min.)**

**1. MOTIVATION [10 minutes]**

- Discussion about specific applications or domains. In particular, we will take Advertising, E-Commerce, Micro Finance (e.g., Kiva), and Reciprocal recommendation (e.g., job seeking) as sample domains, and describe potential stakeholders involved, and how the utility of items varies from the perspective of multiple stakeholders, as well as why a trade-off is required in MSRS. Talk will be extended based on dating/education as our case studies in the next section.

**2: METHODOLOGIES [20 minutes]**

- Utility representations (introduce different possible ways to present the utility of the items from the perspective of multiple stakeholders)
- Balancing the needs of multiple stakeholders and finding appropriate trade-off by using Multi-objective learning
- A mature framework: utility-based multi-stakeholder recommendations o General workflow and algorithms
- Case Study 1: online dating by using dating data on Kaggle.com, https://www.kaggle.com/annavictoria/speed-dating-experiment o Case Study 2: Educations (i.e., project recommendations by using our own data)

**3. DEMO BY USING MOEA FRAMEWORK [20 min.s]**

- Intro to MOEA (an open-source and easy-using framework for multi-objective learning) http://moeaframework.org
- Demo by using the online dating case study mentioned above

**4. CHALLENGES/OPEN DISCUSSION [10 min.s]**

- Any other interesting or useful domains or applications
- Any other methods to represent utilities
- Whether it is necessary to develop special multi-objective learning algorithms to adapt to the research problems in MSRS
- How to deal with conflicting interests
- User-centric evaluations: user studies, A/B test, transparency, explanations, etc

**B. NEURAL REVIEW MINING FOR RECOMMENDATION (120 mi.)**

Reviews help regularize collaborative filtering methods such as matrix factorization (MF) that are typically used for product recommendation. The rating of a user for items that they have not evaluated can be predicted by using not just their historical ratings but also reviews written by them. Most methods discussed in our earlier tutorial [18] integrate topic and latent factor models to learn interpretable user and item factors. Topic models can discover latent semantic structures in a text body. But the use of topic models to identify product aspects limits generalities of extracted features.

**1. MOTIVATION/BACKGROUND (10 min.s)**

Latent Dirichlet Analysis (LDA) used for topic modeling is not able to retain word order and local context information, which is a prominent issue for sentiment analysis, as only document-level co-occurrence information is used to model words in review text. Further, users and items cannot be fully represented by reviews due to fixed size of the representation. Not all words and topics in each review are relevant to its rating score as well. Direct equivalence in addition may bring irrelevant information to some dimensions of embeddings and harm accuracy of rating prediction. Performance of review-based recommendation also degrades when reviews are sparse.

**2. BASIC NEURAL METHODS (30 min.s)**

Conditional distribution of words in review text given a product puts most of its probability mass on only a few product-specific words, while leaving most other words with nearly zero probabilities. Product of experts (PoE) (e.g., recurrent neural networks - RNNs) are thus naturally better suited to modelling peaky distributions rather than mixture models (e.g., LDA), because an element of the product representation could exercise a strong influence suppressing the expression of a given set of words. Chain of PoE in addition helps take into account word order in reviews - item-specific or as language feature.

**2.1 COLD-START RECOMMENDATION (15 min.s)**

Embeddings (vectors) offer a mechanism for negative correlation between words to be explicitly expressed by elements of item representation. Complex user/item features are extracted building their vector representations with aggregated review text using attention-based convolutional neural networks (CNN). RNN models likelihood of review using item's latent factors; it is combined with matrix factorisation via a trade-off term as regularisation to tame curse of data sparsity.

- Neural-network-based document model - bag-of-words (boW) paragraph vector - outperform LDA based approaches [1]
- Collaborative, multi-level embedding (CMLE) [2] relaxes strict equivalence requirement by projecting review embedding to user and item embeddings.

**2.2 PERSONALIZATION (15 min.s)**

Word embeddings more powerful than BoW however ignore intrinsic characteristics of user rating behavior. Two parallel neural networks coupled in the last layer of a deep network can address this issue: one focuses on learning user behaviours exploiting reviews written by user, and the other learns item properties from reviews written for item.

- Deep  Cooperative Neural Networks(DeepCoNN) [3] consists of a shared layer on top that enables latent factors learned for users/items to interact with each other in a manner similar to factorization machine
- TransNets [4] extends DeepCoNN model by introducing an additional latent layer representing target user-target item pair which is then regularized, at training time, to be similar to yet another latent representation of the pair.
- User-item **p**air-dependent features (e.g., super-hero fans may like Ant man movie) from **a**uxiliary **r**eviews (e.g., Marvel movie Avengers) by **l**ike-minded users (PARL) [5] can be plugged into various deep learning systems to improve recommendations provided by them.

**3. ATTENTION-BASED APPROACHES (40 min.s)**

Aggregated review text of items cannot cover same sentimental expression for each individual user (e.g., rating linked to *nice* can be 4 or 5). Also, users consider preference over different item aspects while giving evaluations; unknown items ratings can then be obtained by weighted summation over different aspects. Not all words are equally important in a review; choice of words (e.g., long) reflect different meanings based on context (e.g., battery life vs. startup time). Attention before convolution layer but after embedding learns importance of local/global windows of words through their weights. It's thus possible to select informative keywords and ignore noisy/irrelevant words in long reviews.

**3.1 REVIEW USEFULNESS (20 min.s)**

Soft attention helps assign weight to reviews according to their usefulness. This enables use of most informative (i.e., unbiased, detailed, relevant) reviews for rating prediction. Attentive weights are consistent with users' perception so such crowd-sourced utility scores are used as ground truth.

- Review-by-review pointer-based learning scheme [6] which extracts important user/item reviews and subsequently matches them with a co-attention mechanism in a word-by-word fashion
- Weight function (multi-layer neural network) incorporating user/item characteristics with review content in a distant, supervised fashion [7].

**3.2 ASPECT-BASED RECOMMENDATION (20 min.s)**

Different users (e.g., expensive vs. cheap) of an item (e.g., cellphone) place varying importance to many aspects (e.g., high-res camera vs. connection/call quality). Each review part of an item (e.g., restaurant) thus focuses on an aspect (e.g., seafood) or facet of user experience (e.g., outdoor seating).

- Neural, Gaussian mixture model [8] for every rating where each component has zero variance and mean/weight described by the corresponding component are user and item latent vectors respectively
- Local attention [9] for insight on words about a user's preferences or an item's properties and Global attention to focus on whole review text
- co-attention mechanism toward aspect-level user/item importance [10]
- Network/weight vector to capture a user's special attention/preference on each aspect of the targeted item [11]

**5 GENERATIVE APPROACHES (40 min.s)**

User review documents are indicative of user preferences (e.g., price) wheres item reviews describe features (e.g., quality). Review generation requires model to maintain quality over longer sequences. Single-topic nuggets of information in contrast can save time of reading long reviews. Some users prefer short sentences and direct wordings (e.g., great, easy) whereas others talk about facts with longer sentences indirectly.

**5.1 REVIEWS (20 min.s)**

A multi-tasking framework can help reveal underlying factors which determine user's opinion towards an item even if they were never implied by the user. Overlap between latent vectors learned by matrix factorisation and textual features by sequential auto encoder can be leveraged for generation of reviews given a recommendation, user pair.

- Recurrent user review generator for creating reviews likely to be written by users and convolutional discriminator to distinguish adversarial samples from authentic reviews [12]
- [13] focuses on generating reviews as an output of recommendation model stacking 2 LSTMs combining latent factors with text input
- Fusion gate as soft attention to weigh contribution of sentiment features based on users/items for review generation [14]
- Deep memory network to generate reviews for a user towards an unreviewed product [15]

**5.2 TIPS (20 min.s)**

Unlike explanations, simple extraction of words/phrases from text suggest quick insights. User and item latent representations can be translated into concise sentences that predict user experience/feelings.

Despite abstractive generation process, linguistic quality is maintained as well. Persona is represented using latent embeddings and memory stores persona related words - retrieved by a pointer network for tips generation.

- Sequence decoder based on Gated recurrent neural networks (GRU) with hidden variable from rating prediction as sentiment context [15]
- Adversarial, variational auto encoder for intrinsic style [16]

**NAME, EMAIL AND BIO OF PRESENTERS:**

**Muthusamy Chelliah** heads external research collaboration for Flipkart -engaging academia on solving problems relevant to industry leveraging research in ML, IR, NLP and data mining. He holds a PhD degree in Computer Science from Georgia Tech., Atlanta He's passionate about catalyzing industry−relevant data science in global universities.

He has published articles in conferences like IEEE SRDS as well as journals like TKDE. Chelliah presented following tutorials:

- Chelliah M, Sarkar S. : Product Recommendations Enhanced with Reviews. RecSys-2017.
- Concept to Code: Neural Network for Sequence Learning. ECIR 2019.
- Concept to Code: Deep Learning for Fashion Recommendation. The Web Conference 2019

**Yong Zheng** is currently an assistant professor at the department of information technology and management, Illinois Institute of Technology, Chicago. His research in recommender systems includes algorithmic development and human factors in personalization. He served in the organization committees of ACM IUI (2018, 2019), UMAP (2018, 2019), and RecSys (2018). Long had delivered the following tutorials already:

- Yong Zheng. "Multi-Stakeholder Recommendations: Case Studies, Methods and Challenges", RecSys 2019
- Yong Zheng. "Context-awareness In Information Retrieval and Recommender Systems", IEEE/WIC/ACM Web Intelligence 2016

**Sudeshna Sarkar** is a professor of the department of computer science and engineering at Indian Institute of Technology Kharagpur - from where she receive da PhD degree as well. Her broad research interests are in text mining, NLP and recommender systems. She worked on various algorithms for collaborative filtering, rating prediction and information retrieval as principal scientist of Minekey, a company incubated at IIT Kharagpur that provided personalization services for content discovery. Sudeshna has following tutorials presented:

- Chelliah M, Sarkar S. : Product Recommendations Enhanced with Reviews. RecSys-2017.
- Concept to Code:  Learning Distributed Representation of Heterogenous sources for Recommendation. RecSys-2018.

**Vishal Kakkar** has an MS in Data Mining from Indian Institute of Science, Bangalore. Presently, He works as a Data Scientist in Flipkart with pub.s in Fraud, User Insight and Search**:**

-  Kakkar V, et al.: A Sparse Nonlinear Classifier Design Using AUC Optimization. SDM 2017.
- Saha A, Kakkar V, Ravindra Babu T.: Noise-aware Missing Shipment Return Comment Classification in E-Commerce.

**REFERENCES:**


**A. MULTI-STAKE HOLDER RECOMMENDER SYSTEM**

1. Zheng Y. Multi-Stakeholder Personalized Learning with Preference Corrections, ICALT 2019.
2. Zheng Y., Pu A. Utility-Based Multi-Stakeholder Recommendations By Multi-Objective Optimization, Web Intelligence 2018
3. Himan A, Burke R, and Mobasher B. Recommender systems as multistakeholder environments. UMAP 2017.

**B. NEURAL REVIEW MINING FOR RECOMMENDATION**

1. Almahairi A, Kastner K, Cho K, Courville A. Learning distributed representations from reviews for collaborative filtering. RecSys 2016.
2. Zhang W, Yuan Q, Han J, Wang J. Collaborative multi-Level embedding learning from reviews for rating prediction. IJCAI 2016.
3. Zheng L, Noroozi V, Yu PS. Joint deep modeling of users and items using reviews for recommendation. WSDM 2017
4. Catherine R, Cohen W. Transnets: Learning to transform for recommendation. RecSys 2017.
5. Wu L, Quan C, Li C, Ji D. PARL: Let Strangers Speak Out What You Like. CIKM 2018.
6. Tay Y, Luu AT, Hui SC. Multi-pointer co-attention networks for recommendation. KDD 2018.
7. Chen C, Zhang M, Liu Y, Ma S. Neural attentional rating regression with review-level explanations. WWW 2018.
8. Deng D, Jing L, Yu J, Sun S, Zhou H. Neural gaussian mixture model for review-based rating prediction. RecSys 2018.
9. Seo S, Huang J, Yang H, Liu Y. Interpretable convolutional neural networks with dual local and global attention for review rating prediction. RecSys 2017.
10. Chin JY, Zhao K, Joty S, Cong G. ANR: Aspect-based Neural Recommender. CIKM 2017.
11. Cheng Z, Ding Y, He X, Zhu L, Song X, Kankanhalli MS. A^ 3NCF: An Adaptive Aspect Attention Model for Rating Prediction. IJCAI 2018.
12. Lu Y, Dong R, Smyth B. Why I like it: multi-task learning for recommendation and explanation. RecSys 2018.
13. Ni J, Lipton ZC, Vikram S, McAuley J. Estimating reactions and recommending products with generative models of reviews. IJCNLP 2017.
14. Truong QT, Lauw H. Multimodal Review Generation for Recommender Systems. Webconf 2019.
15. Wang, Z. and Zhang, Y. Opinion recommendation using neural memory model. EMNLP 2017.
16. Li P, Wang Z, Ren Z, Bing L, Lam W. Neural rating regression with abstractive tips generation for recommendation. SIGIR 2017.
17. Li P, Wang Z, Bing L, Lam W. Persona-Aware Tips Generation. Webconf 2019.
18. Chelliah M, Sarkar S. Product Recommendations Enhanced with Reviews. Tutorial. Recsys 2017.