

# Presentations

# TASK 2

Paper presentations. 8 -10 minutes

<b>Team</b>	<b>Date</b>	<b>Students</b>	<b>Paper</b>
1	March 15th		
2	March 15th		
3	March 15th		
4	March 15th		
5	March 20th		
6	March 20th		
7	March 20th		
8	March 20th		

# Paper Suggestions I

## Local Item-Item Models for Top-N Recommendation

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### ABSTRACT

Item-based approaches based on SLIM (Sparse LInear Methods) have demonstrated very good performance for top- $N$  recommendation; however they only estimate a single model for all the users. This work is based on the intuition that not all users behave in the same way – instead there exist subsets of like-minded users. By using different item-item models for these user subsets, we can capture differences in their prefer-

based methods, which include item k-NN [8] and Sparse LInear Methods (SLIM) [16] have been shown to outperform the user-based schemes for the top- $N$  recommendation task.

However, item-based methods have the drawback of estimating only a single model for all users. In many cases, there are differences in users' behavior, which cannot be captured by a single model. For example, there could be a pair of items that are extremely similar for a specific user subset,

# Paper Suggestions I

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## Restricted Boltzmann Machines for Collaborative Filtering

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### Abstract

Most of the existing approaches to collaborative filtering cannot handle very large data sets. In this paper we show how a class of two-layer undirected graphical models, called Restricted Boltzmann Machines (RBM's), can be used to model tabular data, such as user's ratings of movies. We present efficient learning and inference procedures for this class of models and demonstrate that RBM's can be successfully applied to the Netflix data set, containing over 100 million user/movie ratings. We also show that RBM's slightly outperform carefully-tuned SVD models. When the predictions of multiple RBM models and multiple SVD models are linearly combined, we achieve an error rate that is well over 6% better than the score of Netflix's own system.

Low-rank approximations based on minimizing the sum-squared distance can be found using Singular Value Decomposition (SVD). In the collaborative filtering domain, however, most of the data sets are sparse, and as shown by Srebro and Jaakkola (2003), this creates a difficult non-convex problem, so a naive solution is not going work.<sup>1</sup>

In this paper we describe a class of two-layer undirected graphical models that generalize Restricted Boltzmann Machines to modeling tabular or count data (Welling et al., 2005). Maximum likelihood learning is intractable in these models, but we show that learning can be performed efficiently by following an approximation to the gradient of a different objective function called "Contrastive Divergence" (Hinton, 2002).

### 2. Restricted Boltzmann Machines (RBM's)

# Paper Suggestions I

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## Restricted Boltzmann Machines for Collaborative Filtering

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### 2. Restricted Boltzmann Machines (RBM's)

# Paper Suggestions II



## Recommending music on Spotify with deep learning

AUGUST 05, 2014

This summer, I'm interning at Spotify in New York City, where I'm working on content-based music recommendation using convolutional neural networks. In this post, I'll explain my approach and show some preliminary results.

### Overview

This is going to be a long post, so here's an overview of the different sections. If you want to skip ahead, just click the section title to go there.

<http://benanne.github.io/2014/08/05/spotify-cnns.html>

# Paper Suggestions III

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## Deep content-based music recommendation

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### Abstract

Automatic music recommendation has become an increasingly relevant problem in recent years, since a lot of music is now sold and consumed digitally. Most recommender systems rely on collaborative filtering. However, this approach suffers from the cold start problem: it fails when no usage data is available, so it is not effective for recommending new and unpopular songs. In this paper, we propose to use a latent factor model for recommendation, and predict the latent factors from music audio when they cannot be obtained from usage data. We compare a traditional approach using a bag-of-words representation of the audio signals with deep convolutional neural networks, and evaluate the predictions quantitatively and qualitatively on the Million Song Dataset. We show that using predicted latent factors produces sensible recommendations, despite the fact that there is a large semantic gap between the characteristics of a song that affect user preference and the corresponding audio signal. We also show that recent advances in deep learning translate very well to the music recommendation setting, with deep convolutional neural networks significantly outperforming the traditional approach.

# Paper Suggestions IV

## Deep Neural Networks for YouTube Recommendations

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### ABSTRACT

YouTube represents one of the largest scale and most sophisticated industrial recommendation systems in existence. In this paper, we describe the system at a high level and focus on the dramatic performance improvements brought by deep learning. The paper is split according to the classic two-stage information retrieval dichotomy: first, we detail a deep candidate generation model and then describe a separate deep ranking model. We also provide practical lessons and insights derived from designing, iterating and maintaining a massive recommendation system with enormous user-facing impact.

### Keywords

recommender system; deep learning; scalability

### 1. INTRODUCTION

YouTube is the world's largest platform for creating, sharing and discovering video content. YouTube recommendations are responsible for helping more than a billion users discover personalized content from an ever-growing corpus of videos. In this paper we will focus on the immense impact deep learning has recently had on the YouTube video recommendations system. Figure 1 illustrates the recommendations on the YouTube mobile app home.

Recommending YouTube videos is extremely challenging

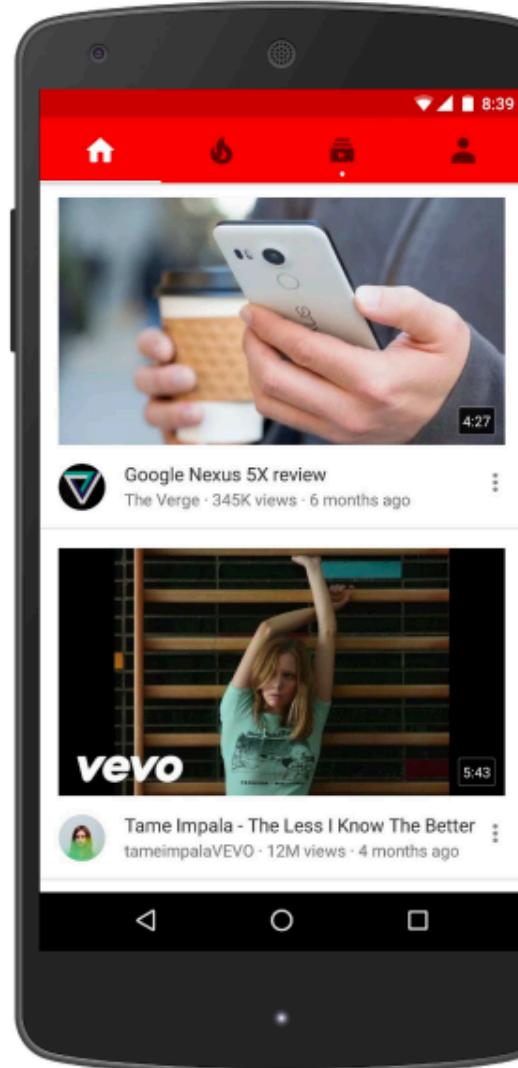


Figure 1: Recommendations displayed on YouTube mobile app home.

with well-established videos can be understood from an exploration/exploitation perspective.

# Paper Suggestions V

## **Wide & Deep Learning for Recommender Systems**

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Hrishi Aradhye, Glen Anderson, Greg Corrado, Wei Chai, Mustafa Ispir, Rohan Anil,  
Zakaria Haque, Lichan Hong, Vihan Jain, Xiaobing Liu, Hemal Shah

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# Paper Suggestions VI

## Collaborative Knowledge Base Embedding for Recommender Systems

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### ABSTRACT

Among different recommendation techniques, collaborative filtering usually suffer from limited performance due to the sparsity of user-item interactions. To address the issues, auxiliary information is usually used to boost the performance. Due to the rapid collection of information on the web, the knowledge base provides heterogeneous information including both structured and unstructured data with different semantics, which can be consumed by various applications. In this paper, we investigate how to leverage the heterogeneous information in a knowledge base to improve the quality of recommender systems. First, by exploiting the knowledge base, we design three components to extract items' semantic representations from structural content, textual content and visual content, respectively. To be specific, we adopt a heterogeneous network embedding method, termed as TransR, to extract items' structural representations by considering the heterogeneity of both nodes and relationships. We apply stacked denoising auto-encoders and stacked convolutional auto-encoders, which are two types of deep learning based embedding techniques, to extract items' textual representations and visual representations, respectively. Finally, we propose our final integrated framework, which is termed as Collaborative Knowledge Base Embedding (CKE), to jointly learn the latent representations in collaborative filtering as well as items' semantic representations from the knowledge base. To evaluate the performance of each embedding component as well as the whole system, we conduct extensive experiments with two real-

filtering (CF) based methods, which make use of historical interactions or preferences, have made significant success [23]. However, CF methods usually suffer from limited performance when user-item interactions are very sparse, which is very common for scenarios such as online shopping where the item set is extremely large. In addition, CF methods can not recommend new items since these items have never received any feedbacks from users in the past. To tackle these problems, hybrid recommender systems, which combine collaborative filtering and auxiliary information such as item content, can usually achieve better recommendation results and have gained increasing popularity in recent years [2].

Over the past years, more and more semantic data are published following the Linked Data principles<sup>1</sup>, by connecting various information from different topic domains such as people, books, musics, movies and geographical locations in a unified global data space. These heterogeneous data, interlinked with each other, forms a huge information resource repository called knowledge base. Several typical knowledge bases have been constructed, including academic projects such as YAGO<sup>2</sup>, NELL<sup>3</sup>, DBpedia<sup>4</sup>, and DeepDive<sup>5</sup>, as well as commercial projects, such as Microsoft's Satori<sup>6</sup> and Google's Knowledge Graph<sup>7</sup>. Using the heterogeneous connected information from the knowledge base can help to develop insights on problems which are difficult to uncover with data from a single domain [6]. To date, information retrieval [9], community detection [25], sentiment analysis [4] - to name a few - are the noteworthy applications that successfully leverage the knowledge base.

# Paper Suggestions VII

## SESSION-BASED RECOMMENDATIONS WITH RECURRENT NEURAL NETWORKS

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### ABSTRACT

We apply recurrent neural networks (RNN) on a new domain, namely recommender systems. Real-life recommender systems often face the problem of having to base recommendations only on short session-based data (e.g. a small sportswear website) instead of long user histories (as in the case of Netflix). In this situation the frequently praised matrix factorization approaches are not accurate. This problem is usually overcome in practice by resorting to item-to-item recommendations, i.e. recommending similar items. We argue that by modeling the whole session, more accurate recommendations can be provided. We therefore propose an RNN-based approach for session-based recommendations. Our approach also considers practical aspects of the task and introduces several modifications to classic RNNs such as a ranking loss function that make it more viable for this specific problem. Experimental results on two data-sets show marked improvements over widely used approaches.

# Paper Suggestions VIII

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## Graph Convolutional Matrix Completion

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University of Amsterdam

**Max Welling**  
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### Abstract

We consider matrix completion for recommender systems from the point of view of link prediction on graphs. Interaction data such as movie ratings can be represented by a bipartite user-item graph with labeled edges denoting observed ratings. Building on recent progress in deep learning on graph-structured data, we propose a graph auto-encoder framework based on differentiable message passing on the bipartite interaction graph. Our model shows competitive performance on standard

in the form of node features. Predicting ratings then reduces to predicting labeled links in the bipartite user-item graph.

We propose graph convolutional matrix completion (GC-MC): a graph-based auto-encoder framework for matrix completion, which builds on recent progress in deep learning on graphs [2, 6, 19, 5, 15, 30, 14]. The auto-encoder produces latent features of user and item nodes through a form of message passing on the bipartite interaction graph. These latent user and item representations are used to reconstruct the rating links through a bilinear decoder.

# Paper Suggestions IX

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## Deep Models of Interactions Across Sets

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### Abstract

We use deep learning to model interactions across two or more sets of objects, such as user–movie ratings or protein–drug bindings. The canonical representation of such interactions is a matrix (or tensor) with an exchangeability property: the encoding’s meaning is not changed by permuting rows or columns. We argue that

$\langle n, m, x \rangle \in \mathbb{X}$ . Learning our function corresponds to *matrix completion*: using patterns in  $\mathbb{X}$  to predict values for the remaining elements of  $X$ .

$X$  is what we will call an *exchangeable matrix*: any row- and column-wise permutation of  $X$  represents the same set of ratings and hence the same matrix completion problem. Exchangeability has a long history in machine learning and statistics. For example, the common iid assumption implies

huge list here:

**[https://github.com/  
hongleizhang/RSPapers](https://github.com/hongleizhang/RSPapers)**