The ACM Conference Series on Recommender Systems

The Recommender Problem *Revisited*

Xavier Amatriain
Research/Engineering Director @ Netflix

@xamat

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1. The Recommender Problem

Everything is a recommendation

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The “Recommender problem”

- *Traditional* definition: Estimate a utility function that automatically predicts how a user will like an item.
- Based on:
  - Past behavior
  - Relations to other users
  - Item similarity
  - Context
  - …

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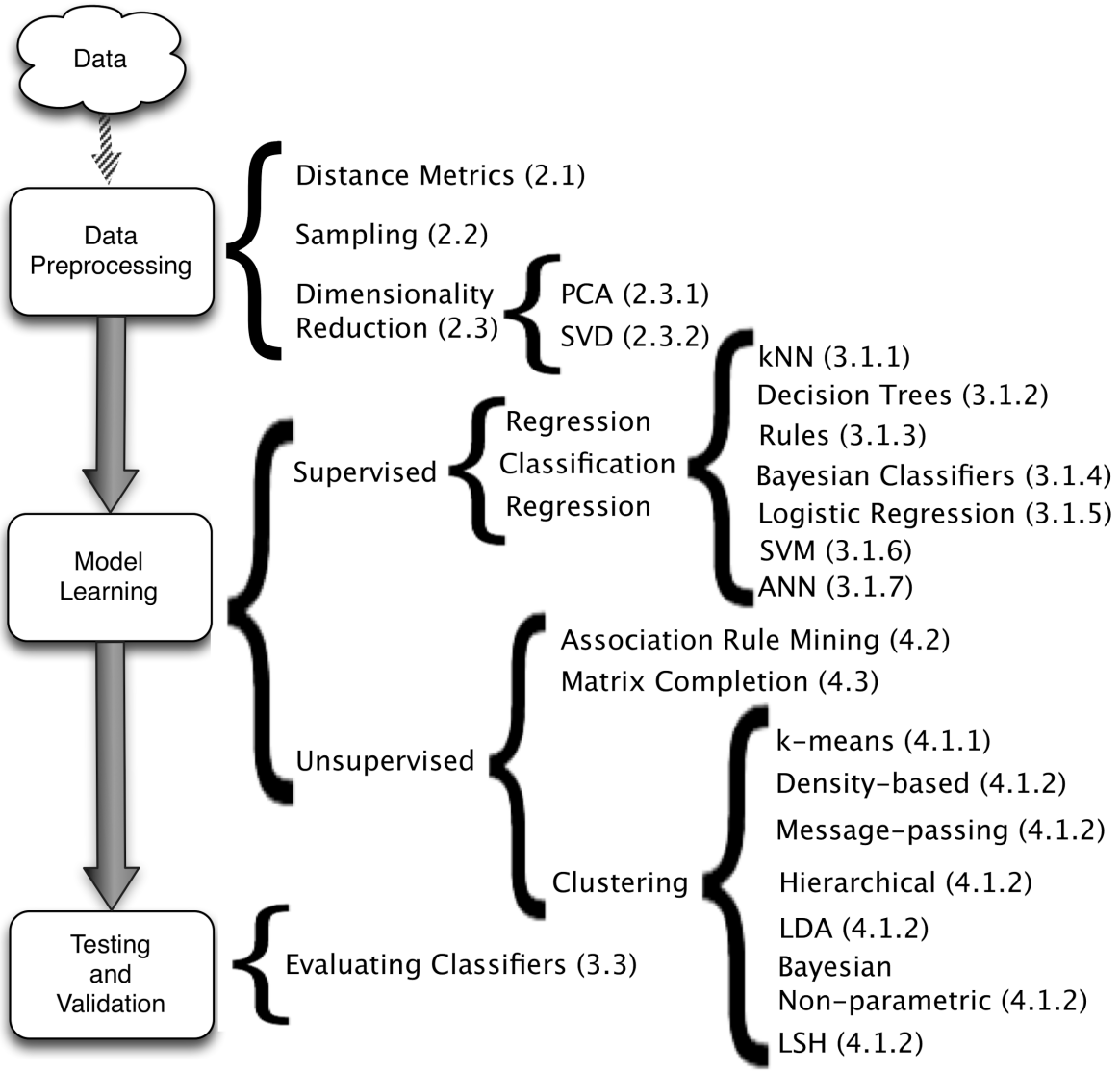
Recommendation as data mining

The core of the Recommendation Engine can be assimilated to a general data mining problem

(Amatriain et al. Data Mining Methods for Recommender Systems in Recommender Systems Handbook)



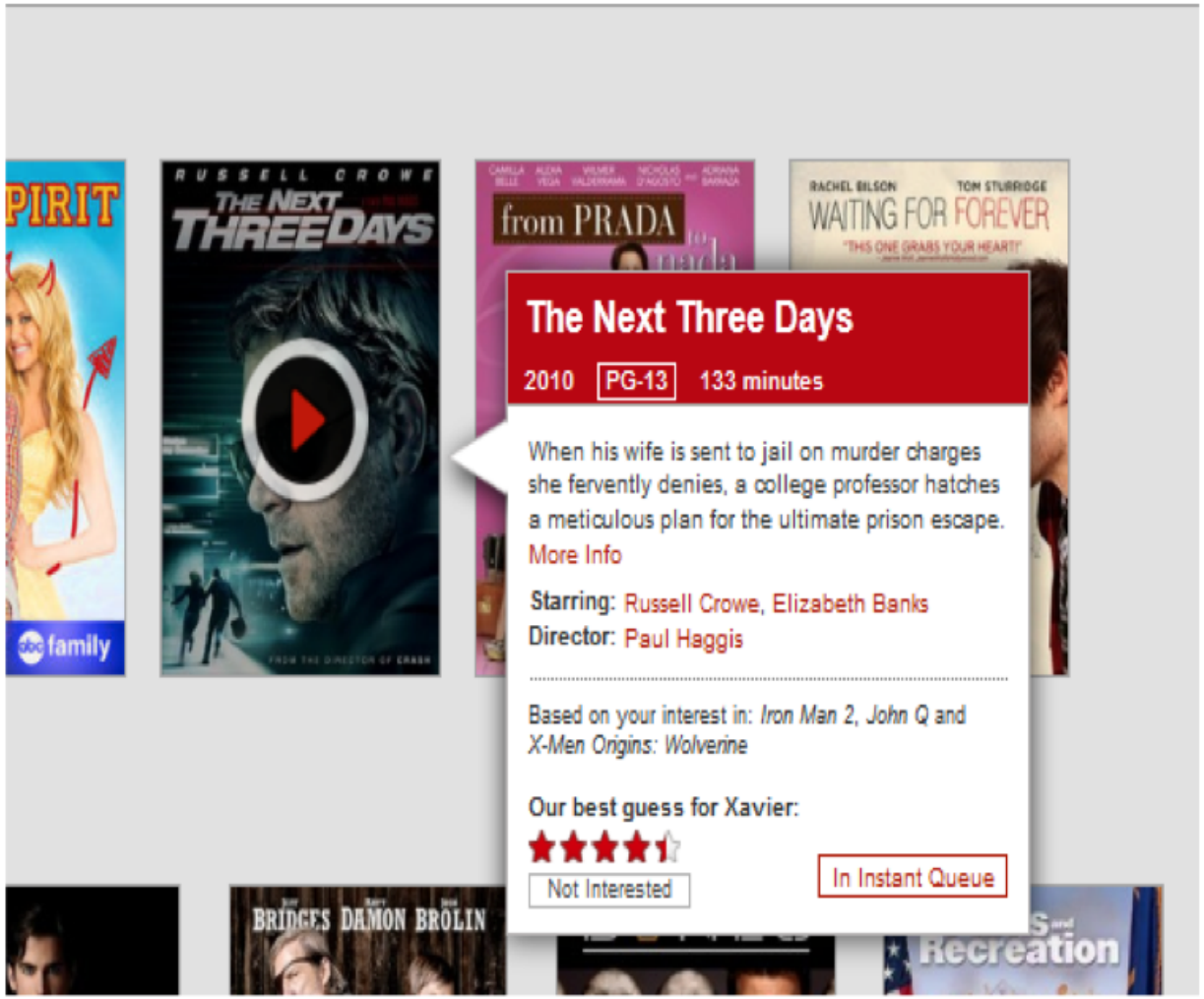
Machine Learning + all those other things

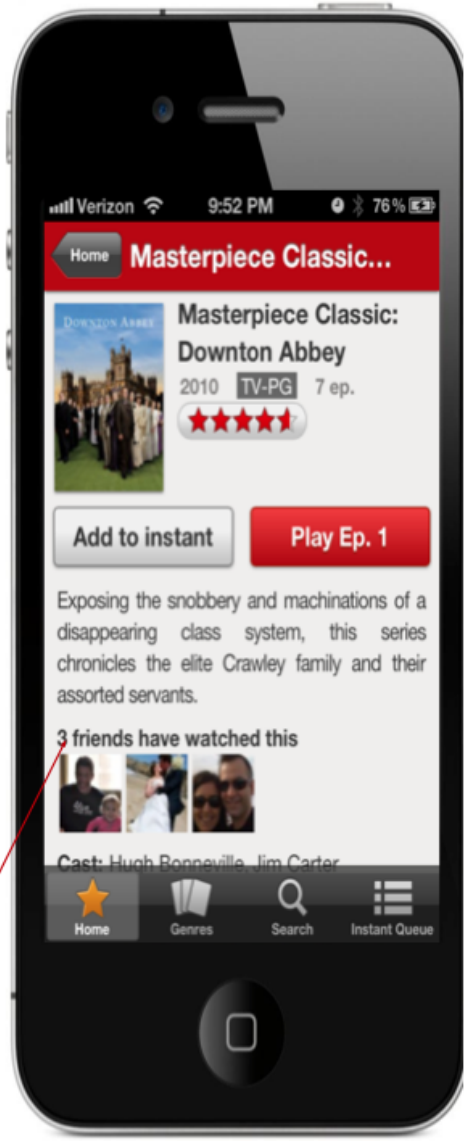
- User Interface
- System requirements (efficiency, scalability, privacy....)
- Serendipity
- Diversity
- Awareness
- Explanations
- …

Serendipity

- Unsought finding
- Don't recommend items the user already knows or **would have found anyway**.
- Expand the user's taste into neighboring areas by improving the obvious
- Collaborative filtering can offer controllable serendipity (e.g. controlling how many neighbors to use in the recommendation)

Explanation/Support for Recommendations

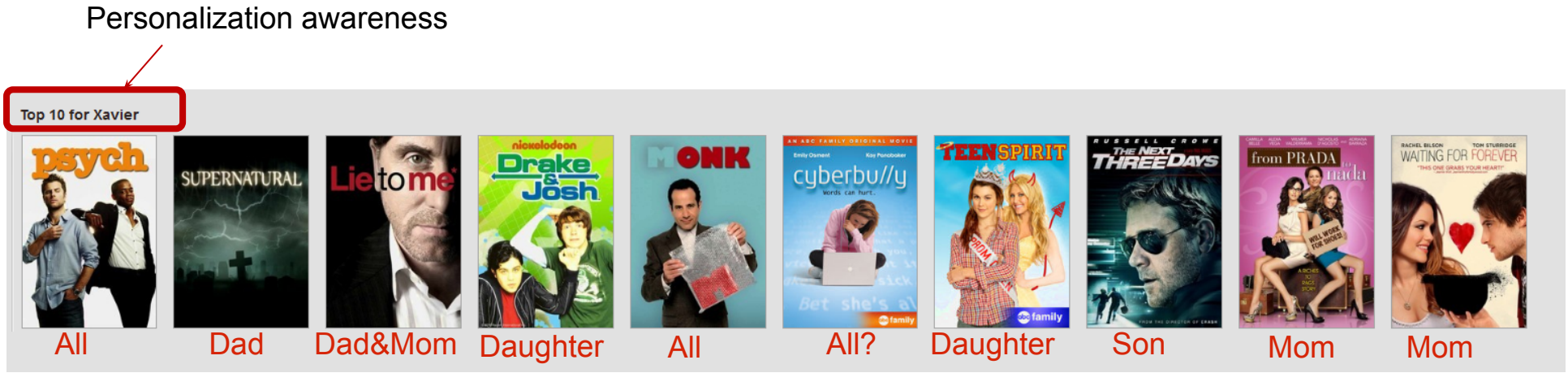




Social Support

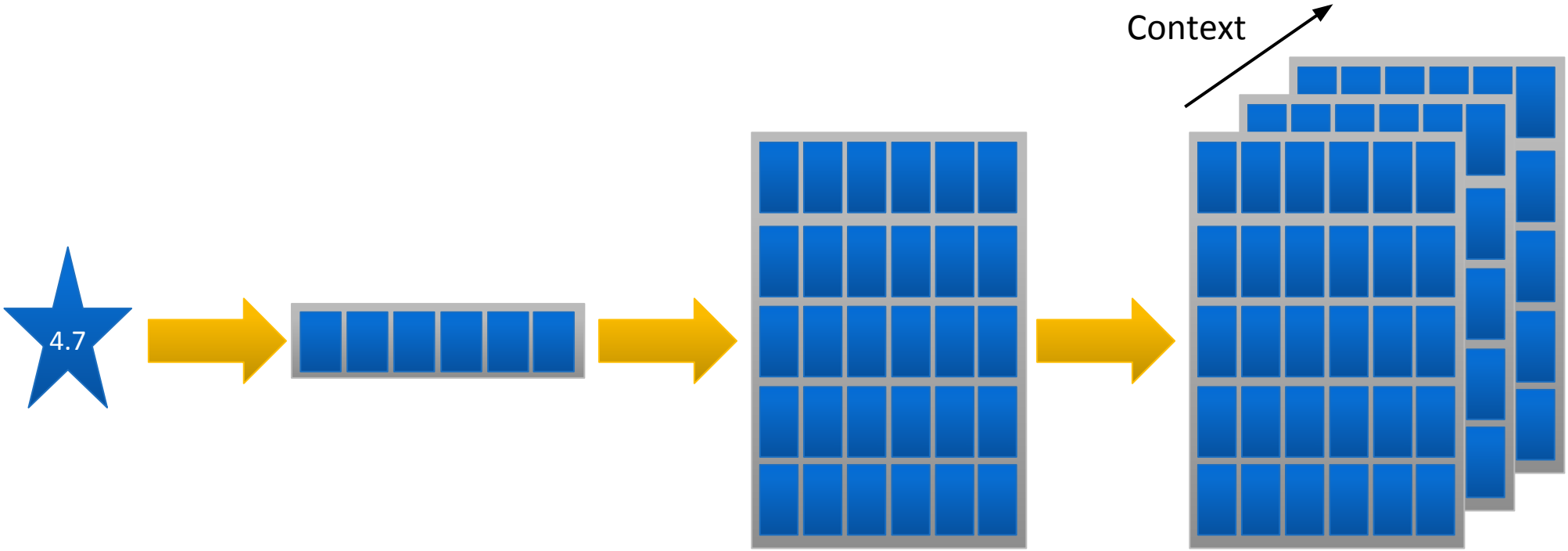
Diversity & Awareness

Personalization awareness



Diversity

Evolution of the Recommender Problem



Rating

Ranking

Page Optimization

Context-aware Recommendations

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2. Traditional Approaches

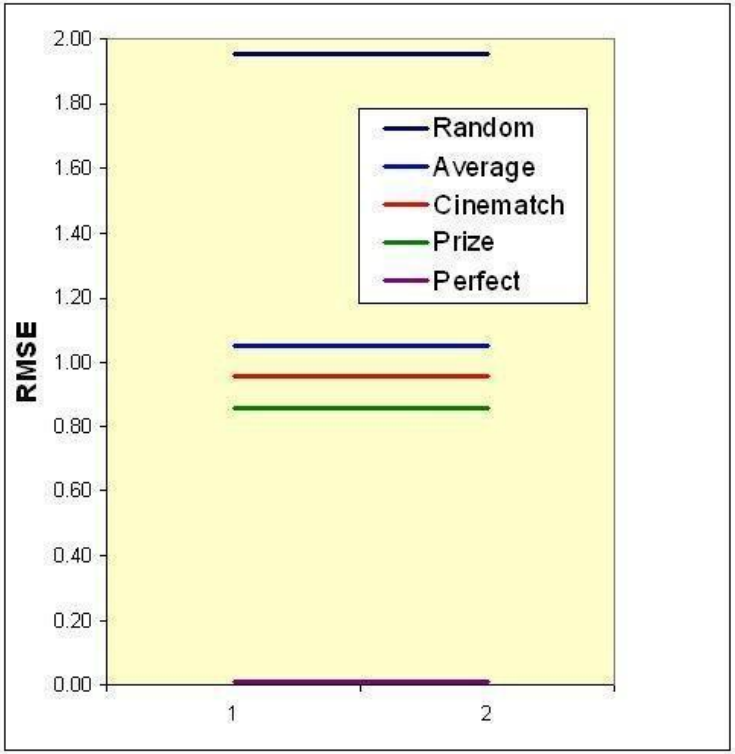
2.1. Collaborative Filtering

Personalized vs Non-Personalised CF

- CF recommendations are **personalized**: prediction based only on **similar users**
- **Non-personalized** collaborative-based recommendation: averagge the recommendations of **ALL** the users
- How would the two approaches compare?

Personalized vs. Not Personalized

- Netflix Prize: it is very simple to produce "reasonable" recommendations and extremely difficult to improve them to become "great"
- But there is a huge difference in business value between reasonable and great



Data Set	users	items	total	density	MAE Non Pers	MAE Pers
Jester	48483	100	3519449	0,725	0,220	0,152
MovieLens	6040	3952	1000209	0,041	0,233	0,179
EachMovie	74424	1649	2811718	0,022	0,223	0,151

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User-based CF

The basic steps:

1. Identify set of ratings for the **target/active user**
2. Identify set of users most similar to the target/active user according to a similarity function (**neighborhood** formation)
3. Identify the products these similar users liked
4. **Generate a prediction** - rating that would be given by the target user to the product - for each one of these products
5. Based on this predicted rating recommend a set of top N products

Item-Based CF

- Look into the items the target user has rated
- Compute how **similar** they are to the target item
  - Similarity **only using** past **ratings** from other users
- Select k most similar items.
- Compute Prediction by taking weighted average on the target user's ratings on the most similar items.

CF: Pros/Cons

- Requires **minimal knowledge**
- Produces good-enough results in most cases

Challenges:

- **Sparsity** – evaluation of large itemsets where user/item interactions are under 1%.
- **Scalability** - Nearest neighbor require computation that grows with both the number of users and the number of items.
- ...

Model-based Collaborative Filtering

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Model Based CF Algorithms

- Memory based
  - Use the entire user-item database to generate a prediction.
  - Usage of statistical techniques to find the neighbors – e.g. nearest-neighbor.
- Model-based
  - First develop a model of user
  - Type of model:
    - Probabilistic (e.g. Bayesian Network)
    - Clustering
    - Rule-based approaches (e.g. Association Rules)
    - Classification
    - Regression
    - LDA
    - ...

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Model-based CF: What we learned from the Netflix Prize

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COMPLETED

What we were interested in:

- High quality *recommendations*

Proxy question:

- Accuracy in predicted rating
- Improve by 10% = $1million!

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2}$$

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2007 Progress Prize

- Top 2 algorithms
  - SVD - Prize RMSE: 0.8914
  - RBM - Prize RMSE: 0.8990
- Linear blend Prize RMSE: 0.88
- Currently in use as part of Netflix' rating prediction component
- Limitations
  - Designed for 100M ratings, we have 5B ratings
  - Not adaptable as users add ratings
  - Performance issues

SVD/MF

$$X\,[n \times m] = U\,[n \times r]\,S\,[r \times r]\,(V\,[m \times r])^T$$

$$\underset{m \times n}{X} = \underset{m \times r}{U} \; \underset{r \times r}{S} \; \underset{r \times n}{V^\top}$$

- **X**: *m x n* matrix (e.g., m users, n videos)
- **U**: *m x r* matrix (m users, r factors)
- **S**: *r x r* diagonal matrix (strength of each 'factor') (r: rank of the matrix)
- **V**: r x n matrix (n videos, r factor)

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Simon Funk's SVD

- One of the most interesting findings during the Netflix Prize came out of a blog post
- Incremental, iterative, and approximate way to compute the SVD using gradient descent

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SVD for Rating Prediction

- User factor vectors $p_u \in \Re^f$ and item-factors vector $q_v \in \Re^f$
- Baseline (bias) $b_{uv} = \mu + b_u + b_v$ (user & item deviation from average)
- Predict rating as $r'_{uv} = b_{uv} + p_u^T q_v$
- Asymmetric SVD (Koren et. Al) asymmetric variation w. implicit feedback

$$r'_{uv} = b_{uv} + q_v^T \left(|R(u)|^{\frac{-1}{2}} \sum_{j \in R(u)} (r_{uj} - b_{uj}) x_j + |N(u)|^{\frac{-1}{2}} \sum_{j \in N(u)} y_j \right)$$

- Where
  - $q_v, x_v, y_v \in \Re^f$ are three item factor vectors
  - Users are not parametrized, but rather represented by:
  - R(u): items rated by user u
  - N(u): items for which the user has given implicit preference (e.g. rated vs. not rated)

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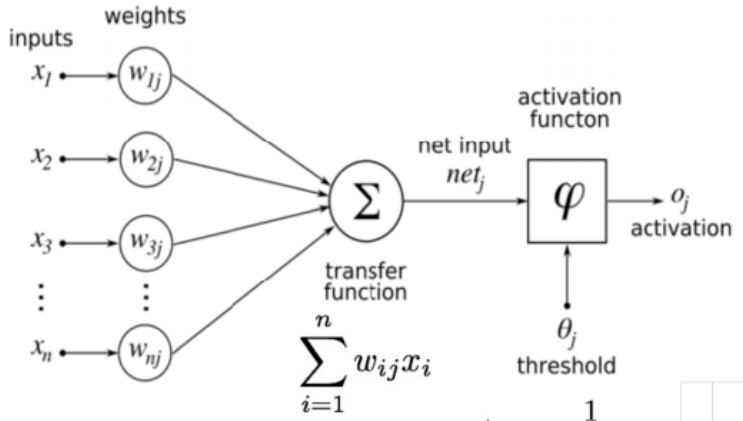
Restricted Boltzmann Machines

- Each unit is a state that can be active or not active
- Each input to a unit is associated to a weight
- The transfer function Σ calculates a score for every unit based on the weighted sum of inputs
- Score is passed to the activation function ϕ that calculates the probability of the unit to be active
- Restrict the connectivity to make learning easier.

  Only one layer of hidden units.

  No connections between hidden units.

  Hidden units are independent given visible states



RBM for Recommendations

- Each visible unit = an item
- Num. of hidden units a is parameter
- In training phase, for each user:
  - If user rated item, v_i is activated
  - Activation states of v_i = inputs to h_j
  - Based on activation, h_j is computed
  - Activation state of h_j becomes input to v_i
  - Activation state of v_i is recalculated
  - Difference between current and past activation state for v_i used to update weights w_{ij} and thresholds
- In prediction phase:
  - For the items of the user the v_i are activated
  - Based on this the state of the h_j is computed
  - The activation of h_j is used as input to recompute the state of v_i
  - Activation probabilities are used to recommend items

Restricted Boltzmann Machines
for Collaborative Filtering

Ruslan Salakhutdinov RSALAKHU@CS.TORONTO.EDU
Andriy Mnih AMNIH@CS.TORONTO.EDU
Geoffrey Hinton HINTON@CS.TORONTO.EDU
University of Toronto, 6 King's College Rd., Toronto, Ontario M5S 3G4, Canada

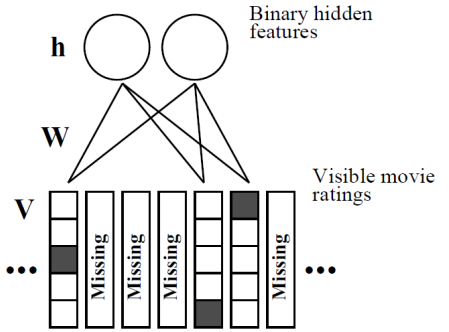
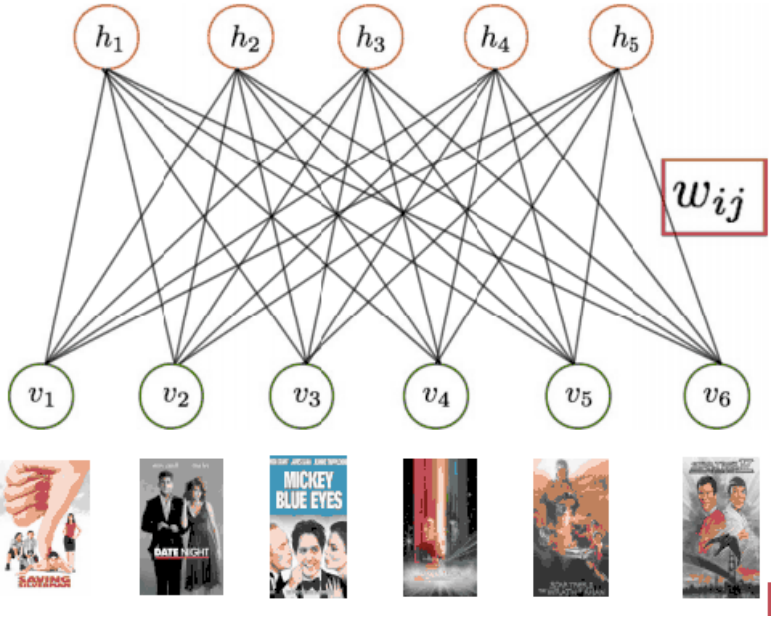


Figure 1. A restricted Boltzmann machine with binary hidden units and softmax visible units. For each user, the RBM only includes softmax units for the movies that user has rated. In addition to the symmetric weights between each hidden unit and each of the $K = 5$ values of a softmax unit, there are 5 biases for each softmax unit and one for each hidden unit. When modeling user ratings with an RBM that has Gaussian hidden units, the top layer is composed of linear units with Gaussian noise.



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What about the final prize ensembles?

- Remember that current production model includes an **ensemble** of both SVD++ and RBMs
- Our offline studies showed final ensembles were too computationally intensive to scale
- Expected improvement not worth the engineering effort
- Plus…. Focus had already shifted to other issues that had more impact than rating prediction.

Clustering

Clustering

- Goal: **cluster** users and compute per-cluster "typical" preferences
- Users receive recommendations computed at the cluster level

Locality-sensitive Hashing (LSH)

- Method for grouping similar items in highly dimensional spaces
- Find a hashing function s.t. similar items are grouped in the same buckets
- Main application is Nearest-neighbors
  - Hashing function is found iteratively by concatenating random hashing functions
  - Addresses one of NN main concerns: performance

Other “interesting” clustering techniques

- k-means and all its variations
- Affinity Propagation
- Spectral Clustering
- LDA
- Non-parametric Bayesian Clustering (e.g. Chinese Restaurant Processes, HDPs)

Association Rules

Association rules

- Past purchases are interpreted as transactions of “associated” items
- If a visitor has some interest in Book 5, she will be recommended to buy Book 3 as well
- Recommendations are constrained to some minimum levels of confidence
- Fast to implement and execute (e.g. A Priori algorithm)

		Also bought...					
		Book1	Book2	Book3	Book4	Book5	Book6
Customers who bought...	Book1				1	1	
	Book2			2		1	1
	Book3		2			2	
	Book4	1					
	Book5	1	1	2			
	Book6		1				

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Classifiers

Classifiers

- **Classifiers** are general computational models trained using positive and negative examples
- They may take in inputs:
  - Vector of item features (action / adventure, Bruce Willis)
  - Preferences of customers (like action / adventure)
  - Relations among item
- E.g. Logistic Regression, Bayesian Networks, Support Vector Machines, Decision Trees, etc...

Classifiers

- Classifiers can be used in CF and CB Recommenders
- Pros:
  - Versatile
  - Can be combined with other methods to improve accuracy of recommendations
- Cons:
  - Need a relevant training set
  - May overfit (Regularization)
- E.g. Logistic Regression, Bayesian Networks, Support Vector Machines, Decision Trees, etc...

Limitations of Collaborative Filtering

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Limitations of Collaborative Filtering

- **Cold Start**: There needs to be enough other users already in the system to find a match. New items need to get enough ratings.
- **Popularity Bias**: Hard to recommend items to someone with unique tastes.
  - Tends to recommend popular items (items from the tail do not get so much data)

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2.2 Content-based Recommenders

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Content-Based Recommendation

- Recommendations based on content of items rather than on other users' opinions/interactions
- Goal: recommend items **similar** to those the user liked
- Common for recommending **text-based products** (web pages, usenet news messages,)
- Items to recommend are "described" by their associated **features** (e.g. keywords)
- **User Model** structured in a "similar" way as the content: features/keywords more likely to occur in the preferred documents (lazy approach)
- The user model can be a **classifier** based on whatever technique (Neural Networks, Naïve Bayes...)

Pros/cons of CB Approach

Pros

- No need for data on other users: No cold-start or sparsity
- Able to recommend to users with unique tastes.
- Able to recommend new and unpopular items
- Can provide explanations by listing content-features

Cons

- Requires content that can be encoded as meaningful features (difficult in some domains/catalogs)
- Users represented as learnable function of content features.
- Difficult to implement serendipity
- Easy to overfit (e.g. for a user with few data points)

A word of caution

Recommending New Movies: Even a Few Ratings Are More Valuable Than Metadata

István Pilászy *
Dept. of Measurement and Information Systems
Budapest University of Technology and Economics
Magyar Tudósok krt. 2.
Budapest, Hungary
pila@mit.bme.hu

Domonkos Tikk *,†
Dept. of Telecom. and Media Informatics
Budapest University of Technology and Economics
Magyar Tudósok krt. 2.
Budapest, Hungary
tikk@tmit.bme.hu

ABSTRACT

The Netflix Prize (NP) competition gave much attention to collaborative filtering (CF) approaches. Matrix factorization (MF) based CF approaches assign low dimensional feature vectors to users and items. We link CF and content-based filtering (CBF) by finding a linear transformation that transforms user or item descriptions so that they are as close as possible to the feature vectors generated by MF for CF.

We propose methods for explicit feedback that are able to handle 140 000 features when feature vectors are very sparse. With movie metadata collected for the NP movies we show that the prediction performance of the methods is comparable to that of CF, and can be used to predict user preferences on new movies.

We also investigate the value of movie metadata compared to movie ratings in regards of predictive power. We compare

1. INTRODUCTION

The goal of recommender systems is to give personalized recommendation on items to users. Typically the recommendation is based on the former and current activity of the users, and metadata about users and items, if available.

There are two basic strategies that can be applied when generating recommendations. Collaborative filtering (CF) methods are based only on the activity of users, while content-based filtering (CBF) methods use only metadata. In this paper we propose hybrid methods, which try to benefit from both information sources.

The two most important families of CF methods are matrix factorization (MF) and neighbor-based approaches. Usually, the goal of MF is to find a low dimensional representation for both users and movies, i.e. each user and movie is associated with a feature vector. Movie metadata (which

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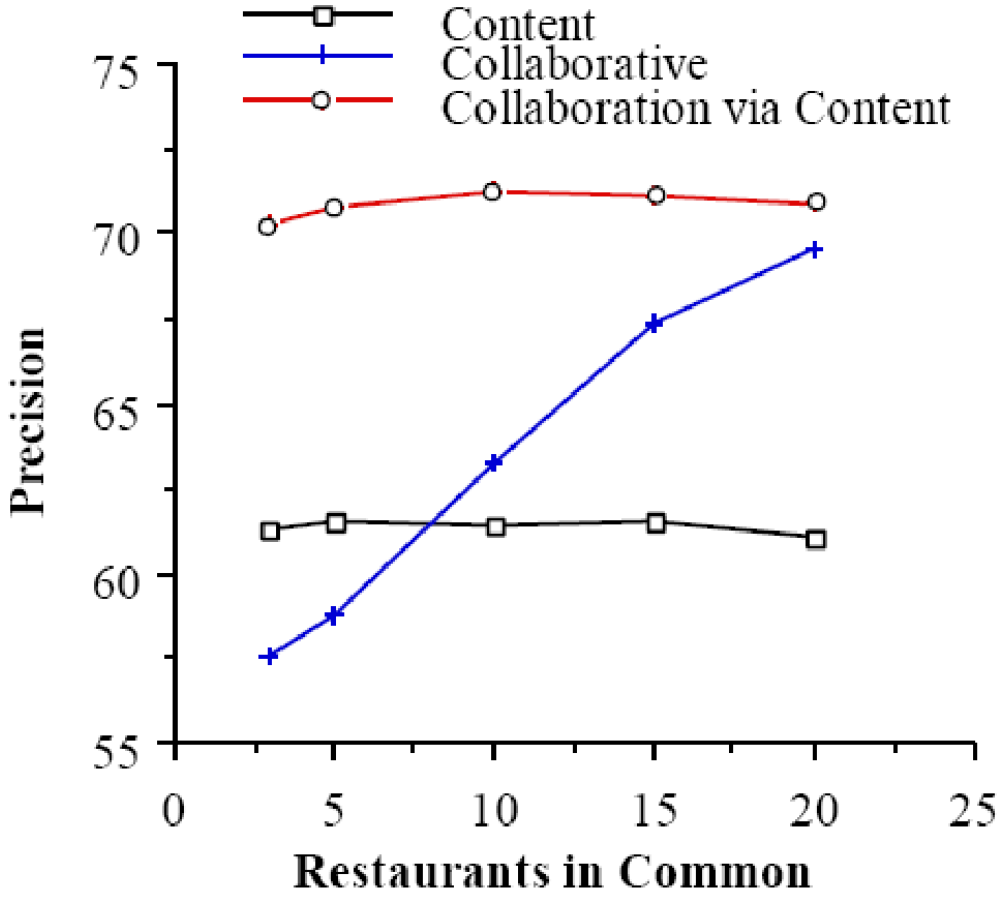
2.3 Hybrid Approaches

Comparison of methods (FAB system)

- Content–based recommendation with Bayesian classifier
- Collaborative is standard using Pearson correlation
- Collaboration via content uses the content-based user profiles



Averaged on 44 users

Precision computed in top 3 recommendations

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Hybridization Methods

Hybridization Method	Description
Weighted	Outputs from several techniques (in the form of scores or votes) are combined with different degrees of importance to offer final recommendations
Switching	Depending on situation, the system changes from one technique to another
Mixed	Recommendations from several techniques are presented at the same time
Feature combination	Features from different recommendation sources are combined as input to a single technique
Cascade	The output from one technique is used as input of another that refines the result
Feature augmentation	The output from one technique is used as input features to another
Meta-level	The model learned by one recommender is used as input to another

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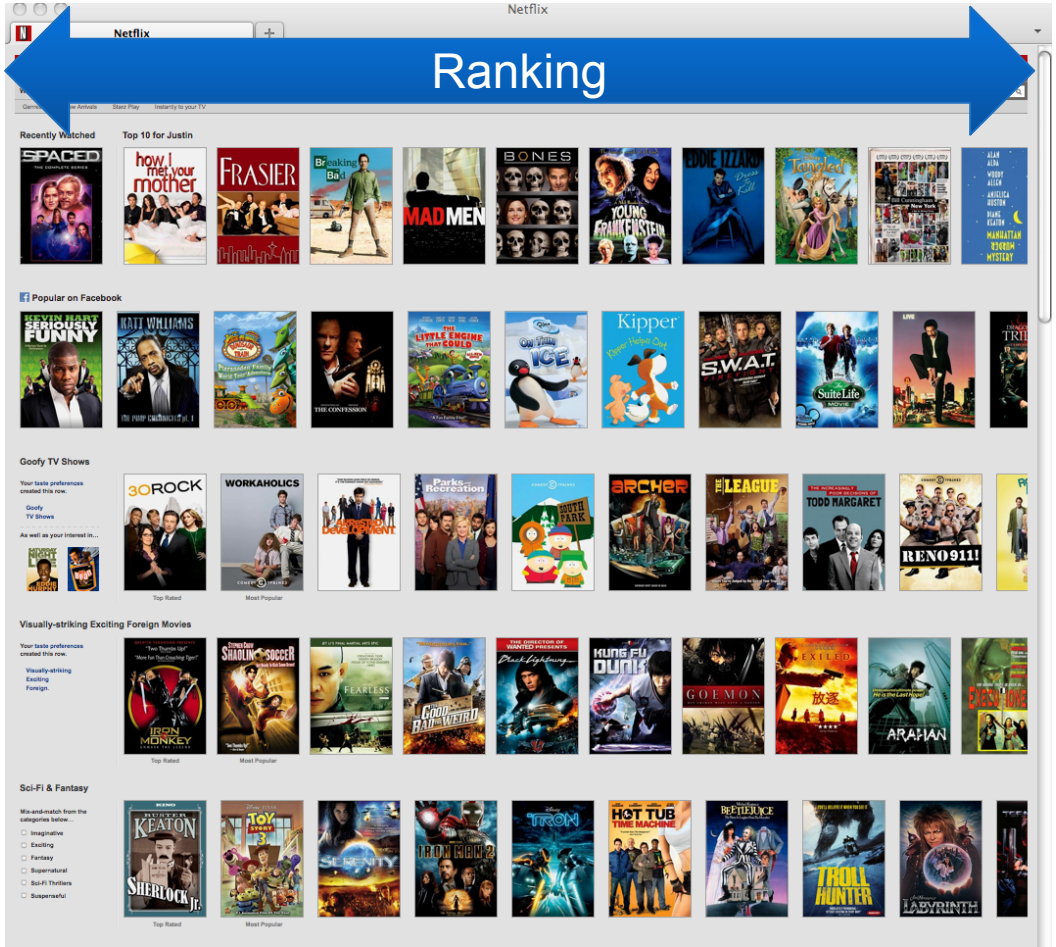
3. Beyond traditional approaches to Recommendation

3.1 Ranking

Ranking

Key algorithm, sorts titles in most contexts



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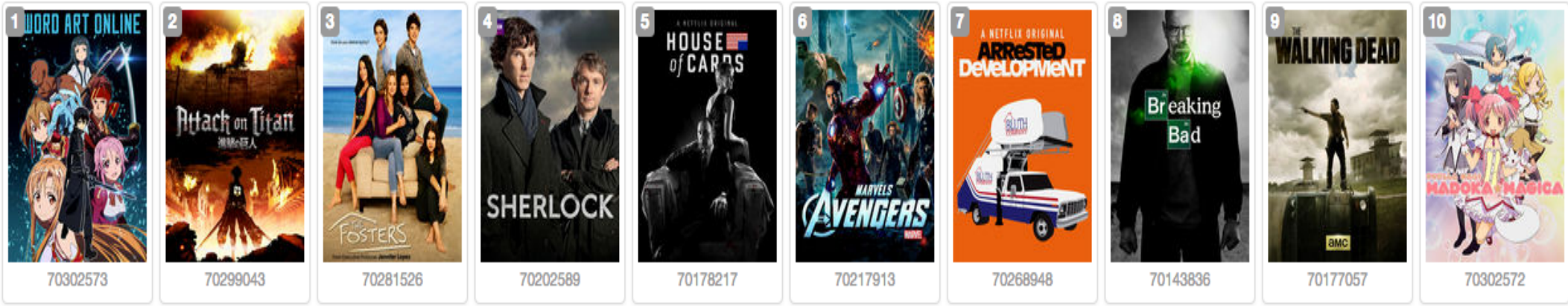
Ranking

- Most recommendations are presented in a sorted list
- Recommendation can be understood as a ranking problem
- Popularity is the obvious baseline
- Ratings prediction is a clear secondary data input that allows for personalization
- Many other features can be added

Ranking by ratings



4.7 4.6 4.5 4.5 4.5 4.5 4.5 4.5 4.5 4.5

Niche titles

High average ratings… by those who would watch it

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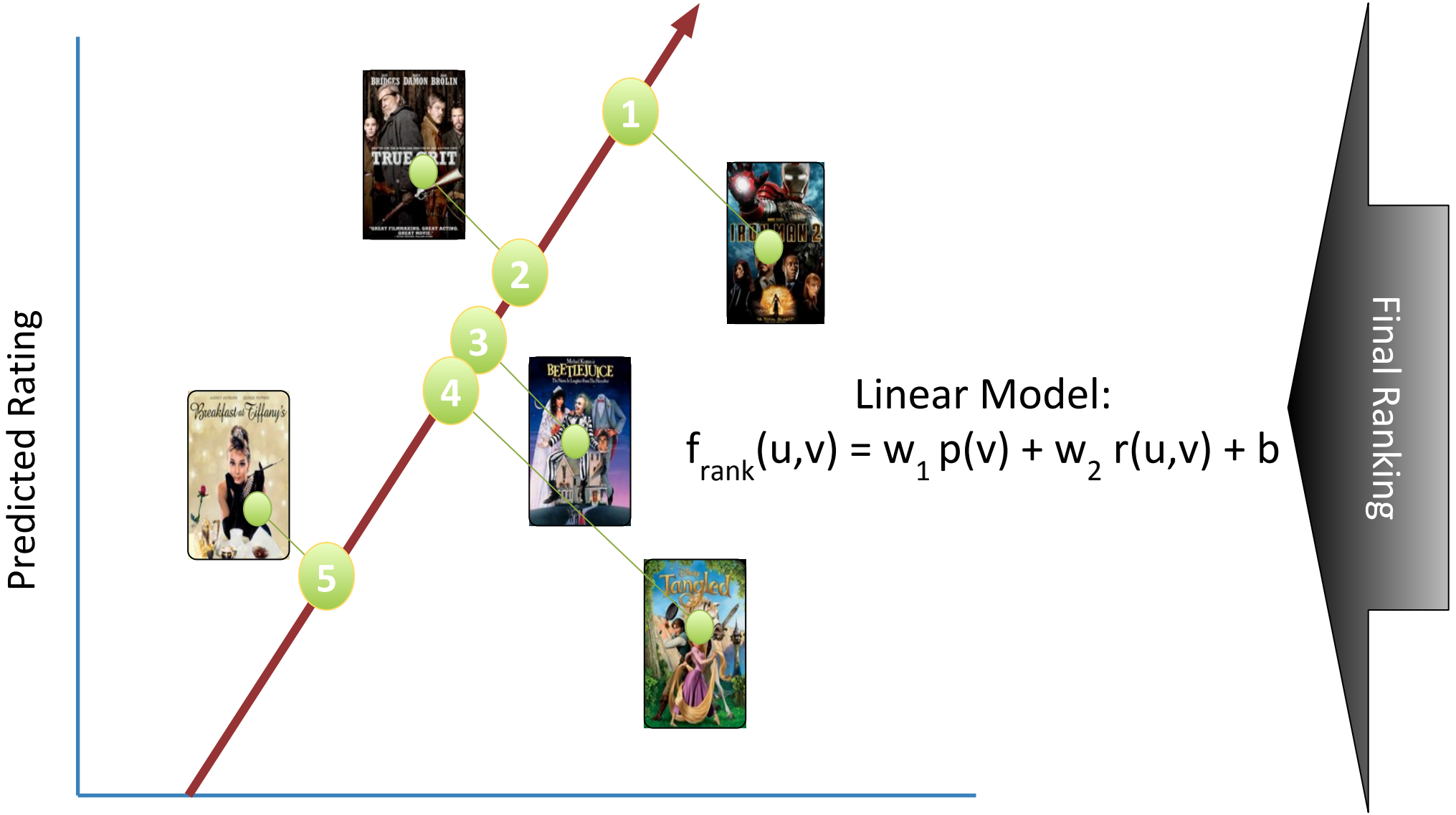
Example: Two features, linear model



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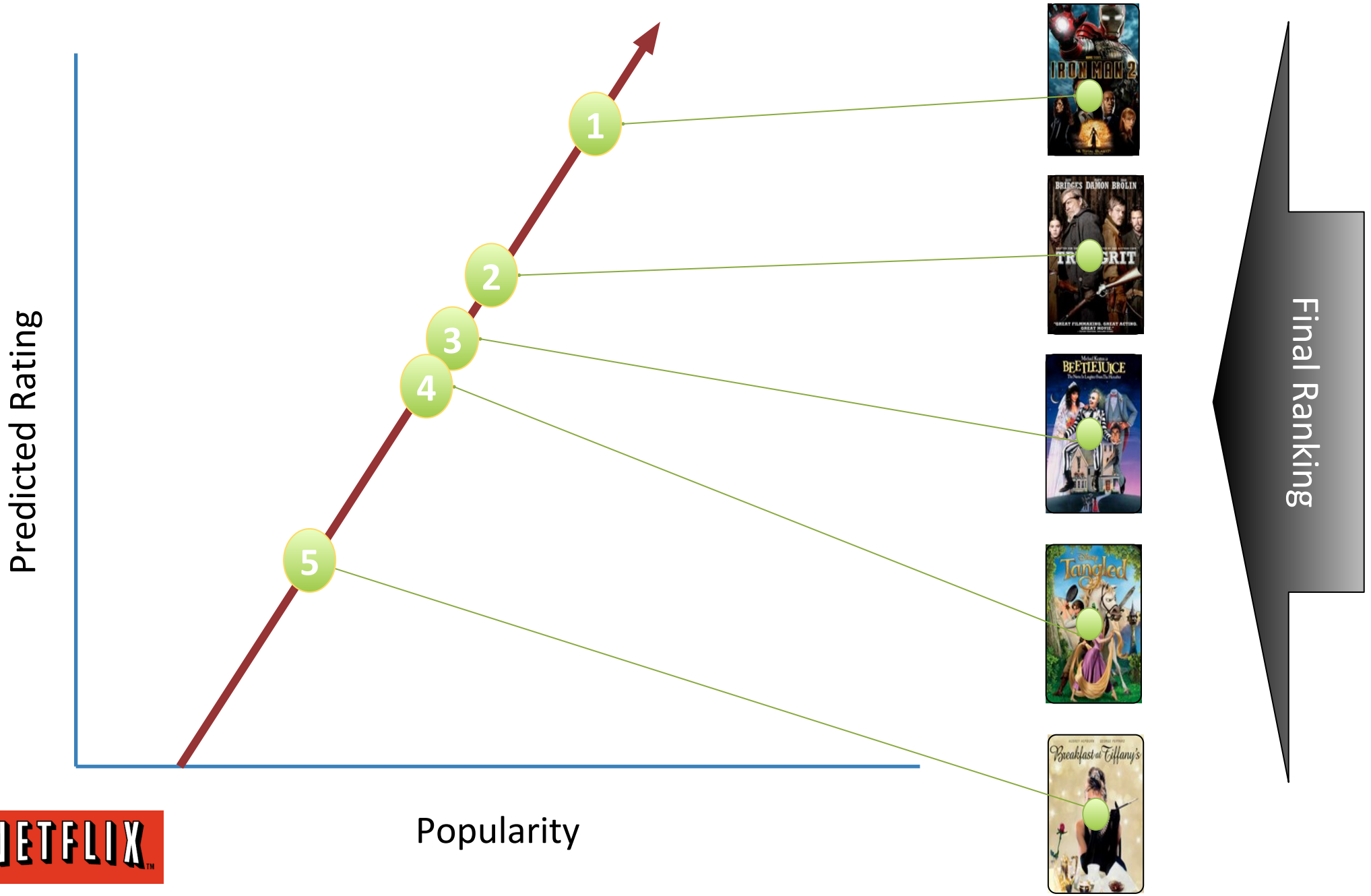
Example: Two features, linear model



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Learning to rank

- Machine learning problem: goal is to construct ranking model from training data
- Training data can be a partial order or binary judgments (relevant/not relevant).
- Resulting order of the items typically induced from a numerical score
- Learning to rank is a key element for personalization
- You can treat the problem as a standard supervised classification problem

Learning to rank - Metrics

- Quality of ranking measured using metrics as
  - Normalized Discounted Cumulative Gain
  - Mean Reciprocal Rank (MRR)
  - Fraction of Concordant Pairs (FCP)
  - Others…
- But, it is hard to optimize machine-learned models directly on these measures (e.g. non-differentiable)
- Recent research on models that directly optimize ranking measures

Learning to rank - Approaches

1. Pointwise
   - Ranking function minimizes loss function defined on individual relevance judgment
   - Ranking score based on regression or classification
   - Ordinal regression, Logistic regression, SVM, GBDT, …
2. Pairwise
   - Loss function is defined on pair-wise preferences
   - Goal: minimize number of inversions in ranking
   - Ranking problem is then transformed into the binary classification problem
   - RankSVM, RankBoost, RankNet, FRank…

Learning to rank - Approaches

3. Listwise
   - Indirect Loss Function
     - RankCosine: similarity between ranking list and ground truth as loss function
     - ListNet: KL-divergence as loss function by defining a probability distribution
     - Problem: optimization of listwise loss function may not optimize IR metrics
   - Directly optimizing IR metric (difficult since they are not differentiable)
     - Genetic Programming or Simulated Annealing
     - LambdaMart weights pairwise errors in RankNet by IR metric
     - Gradient descent on smoothed version of objective function (e. g. CLiMF or TFMAP)
     - SVM-MAP relaxes MAP metric by adding to SVM constraints
     - AdaRank uses boosting to optimize NDCG

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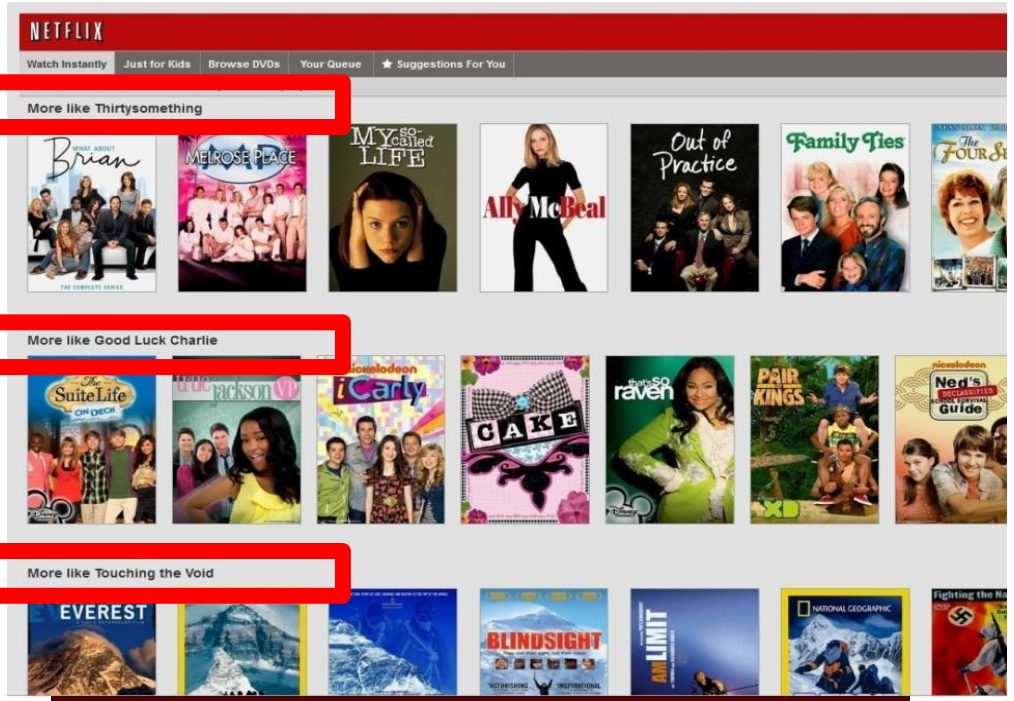
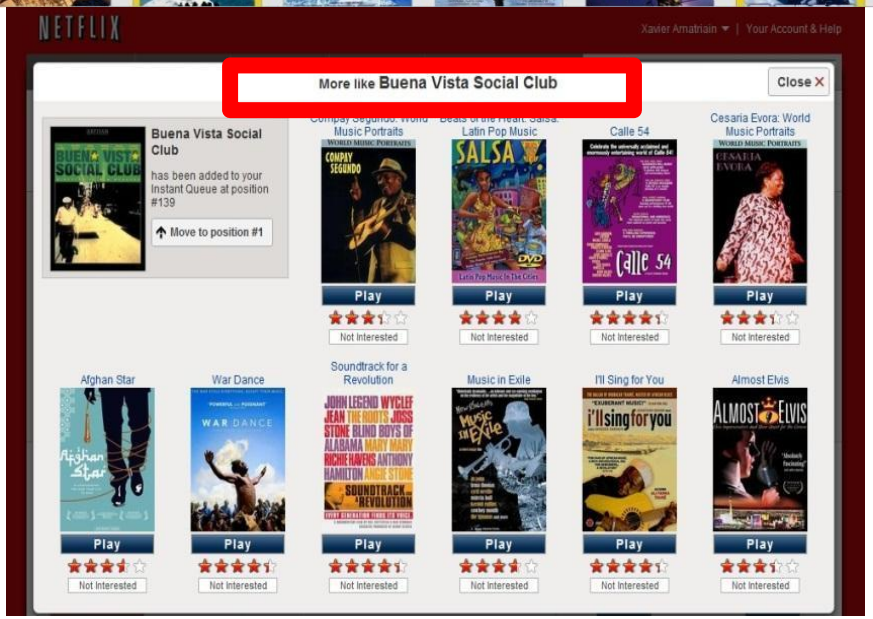
3.2 Similarity as Recommendation

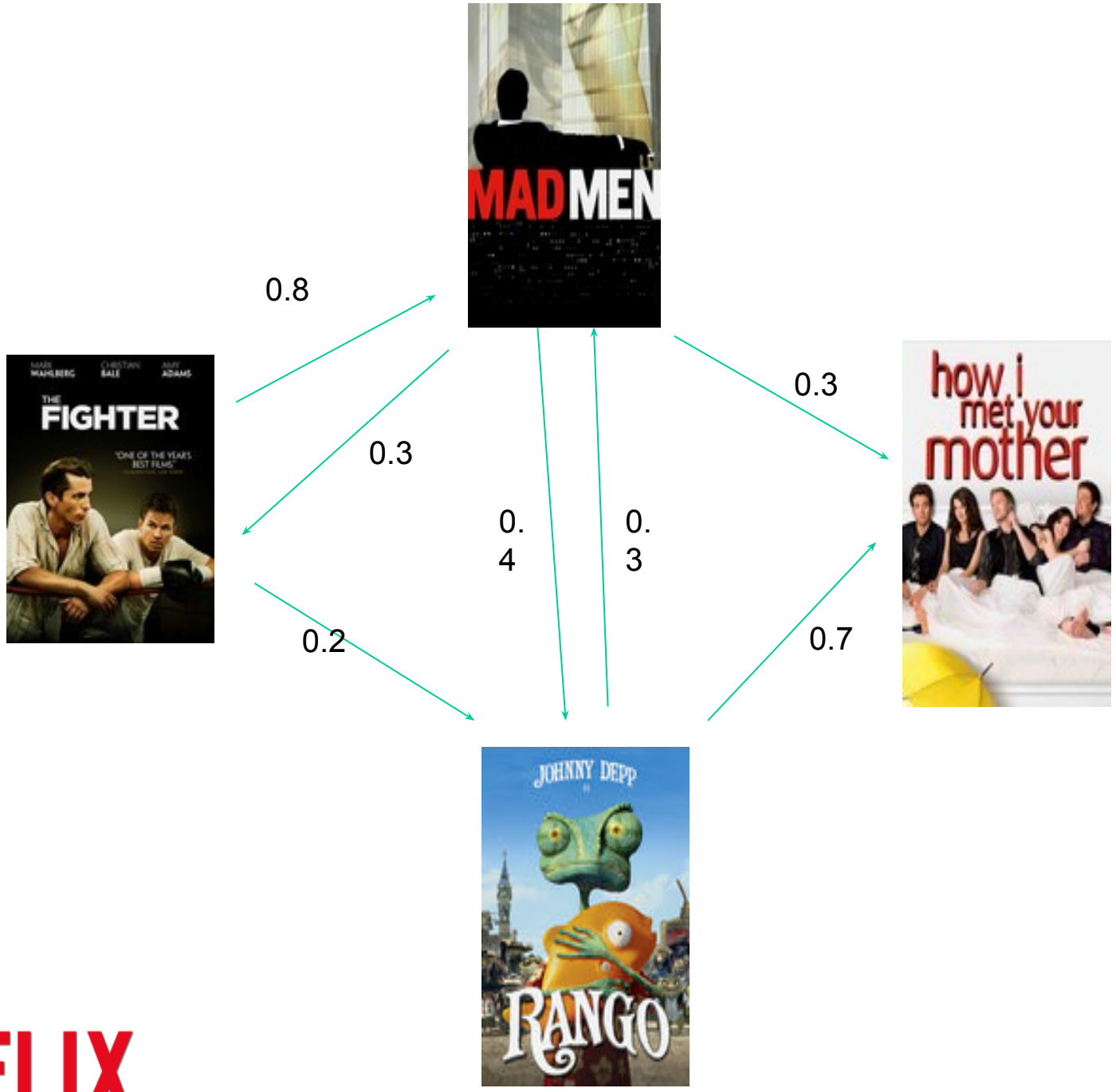
Similars

- Displayed in many different contexts
  - In response to user actions/context (search, queue add…)
  - More like… rows





Graph-based similarities



Example of graph-based similarity: SimRank

- SimRank (Jeh & Widom, 02): “two objects are similar if they are referenced by similar objects.”

$$s(a,b) = \frac{C}{|I(a)||I(b)|} \sum_{i=1}^{|I(a)|} \sum_{j=1}^{|I(b)|} s(I_i(a), I_j(b))$$

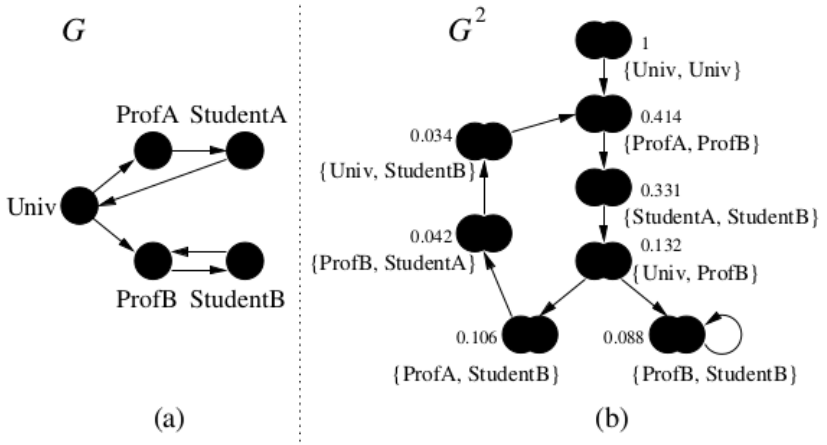


Figure 1: A small Web graph G and simplified node-pairs graph G^2. SimRank scores using parameter $C = 0.8$ are shown for nodes in G^2.

Similarity ensembles

- Similarity can refer to different dimensions
  - Similar in metadata/tags
  - Similar in user play behavior
  - Similar in user rating behavior
  - …
- Combine them using an ensemble
  - Weights are learned using regression over existing response
  - Or… some MAB explore/exploit approach
- The final concept of “similarity” responds to what users vote as similar

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3.3 Deep Learning for Recommendation

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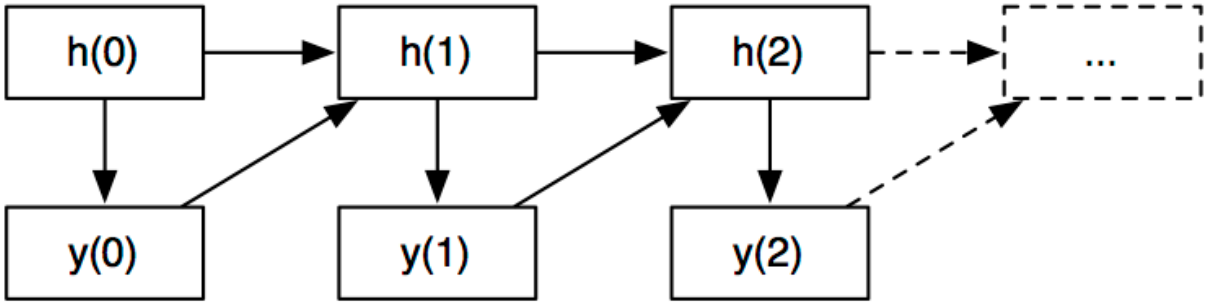
Deep Learning for Collaborative Filtering

- Spotify uses Recurrent Network (http://erikbern.com/?p=589)



- In order to predict the next track or movie a user is going to watch, we need to define a distribution $P(y_i|h_i)$
  - If we choose Softmax as it is common practice, we get:

$$P(y_i|h_i) = \frac{\exp(h_i^T a_j)}{\sum_k \exp(h_i^T a_k)}$$

    - Problem: denominator is very expensive to compute
    - Solution: build tree that implements hierarchical softmax
- More details on the blogpost

Deep Learning for Content-based Recommendations

- Another application of Deep Learning to recommendations also from Spotify
  - http://benanne.github.io/2014/08/05/spotify-cnns.html also *Deep content-based music recommendation, Aäron van den Oord, Sander Dieleman and Benjamin Schrauwen, NIPS 2013*
- Application to coldstart new titles when very little CF information is available
- Using mel-spectrograms from the audio signal as input
- Training the deep neural network to predict 40 latent factors coming from Spotify's CF solution

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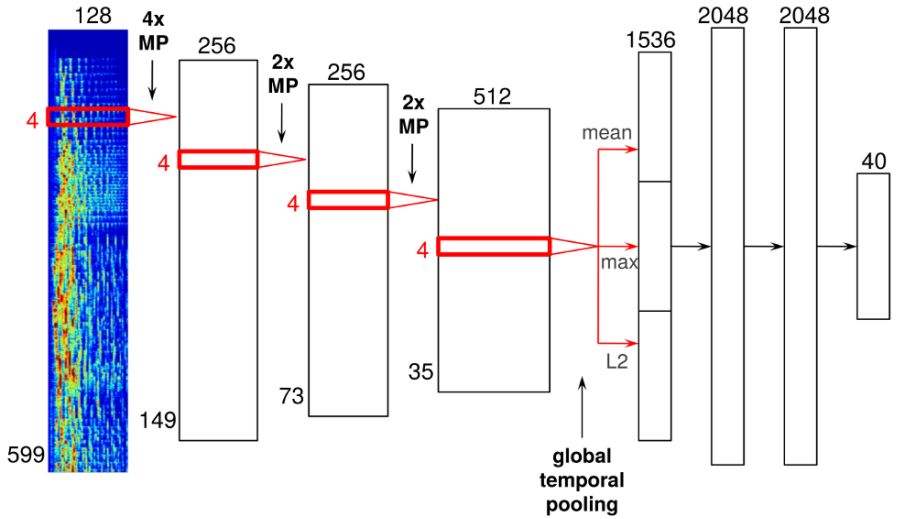
Deep Learning for Content-based Recommendations

- Network architecture made of 4 convolutional layers + 4 fully connected dense layers



- One dimensional convolutional layers using RELUs (Rectified Linear Units) with activation max(0,x)
- **Max-pooling operations** between convolutional layers to downsample intermediate representations in time, and add time invariance
- **Global temporal pooling layer** after last convolutional layer: pools across entire time axis, computing statistics of the learned features across time:: mean, maximum and L2-norm
- Globally pooled features are fed into a series of **fully-connected layers** with 2048 RELUs

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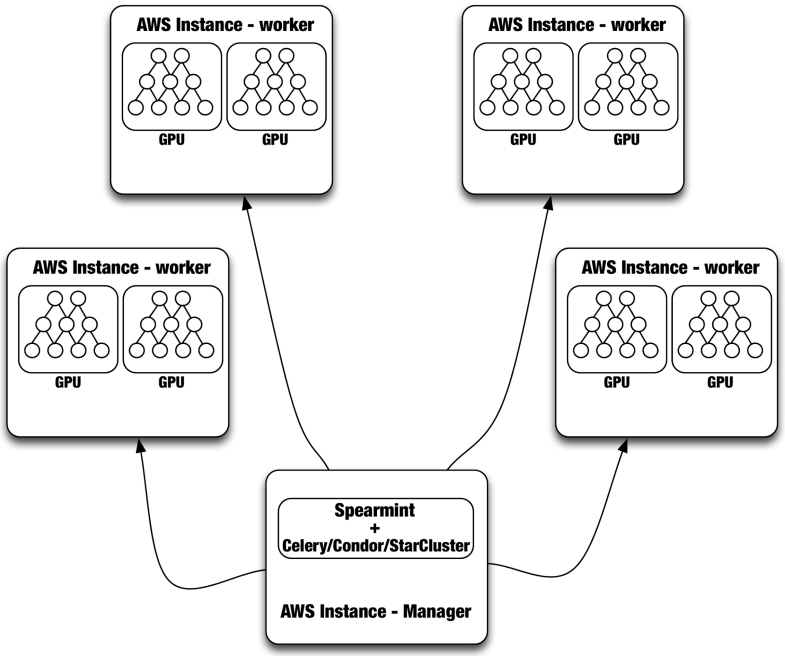
ANN Training over GPUS and AWS

- How did we implement our ANN solution at Netflix?
  - Level 1 distribution: machines over different AWS regions
  - Level 2 distribution: machines in AWS and same AWS region
    - Use coordination tools
      - Spearmint or similar for parameter optimization
      - Condor, StarCluster, Mesos… for distributed cluster coordination
  - Level 3 parallelization: highly optimized parallel CUDA code on GPUs



http://techblog.netflix.com/2014/02/distributed-neural-networks-with-gpus.html

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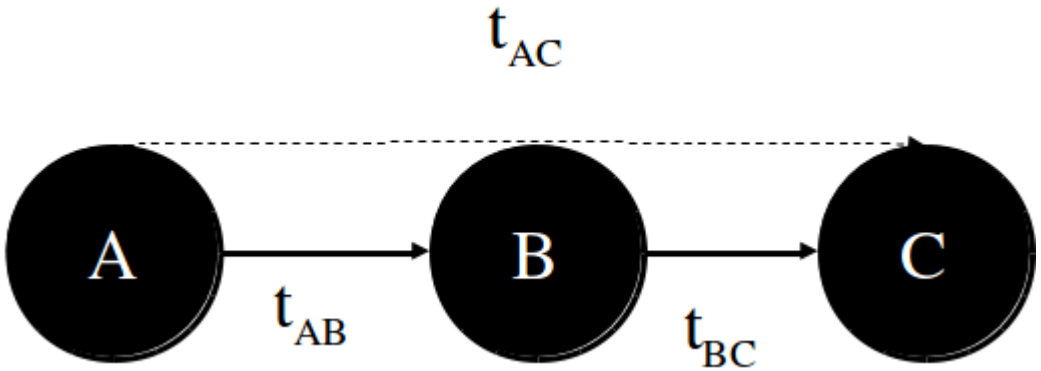
3.4 Social Recommendations

Social and Trust-based recommenders

- A social recommender system recommends items that are “popular” in the social proximity of the user.
- Social proximity = trust (can also be topic-specific)
- Given two individuals - the *source* (node A) and *sink* (node C) - derive how much the source should trust the sink.
- Algorithms
  - Advogato (Levien)
  - Appleseed (Ziegler and Lausen)
  - MoleTrust (Massa and Avesani)
  - TidalTrust (Golbeck)



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Other ways to use Social

- Social connections can be used in combination with other approaches
- In particular, “friendships” can be fed into collaborative filtering methods in different ways
  - replace or modify user-user “similarity” by using social network information
  - use social connection as a part of the ML objective function as regularizer
  - …

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Demographic Methods

- Aim to categorize the user based on personal attributes and make recommendation based on demographic classes
- Demographic groups can come from marketing research – hence experts decided how to model the users
- Demographic techniques form people-to-people correlations

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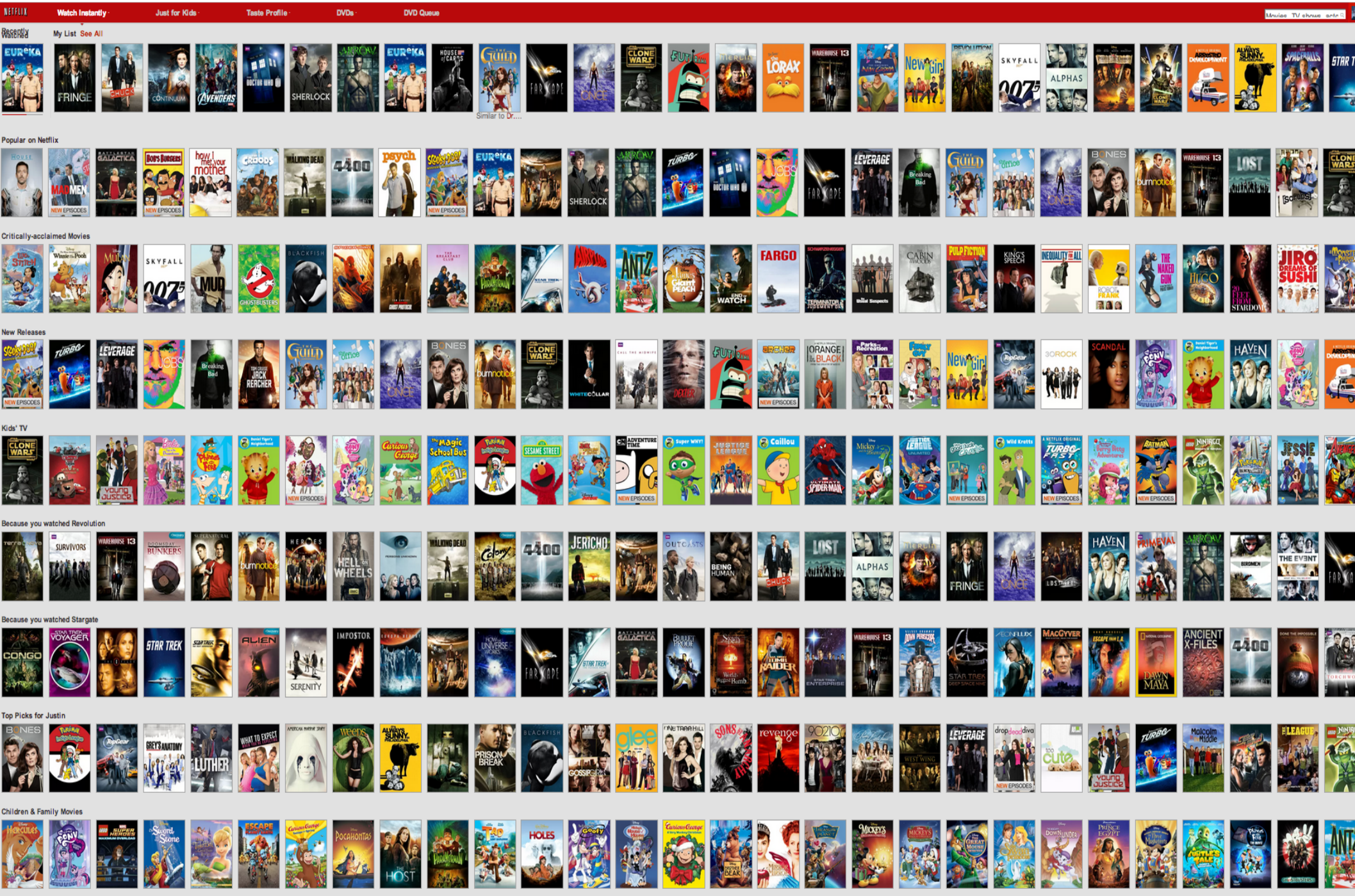
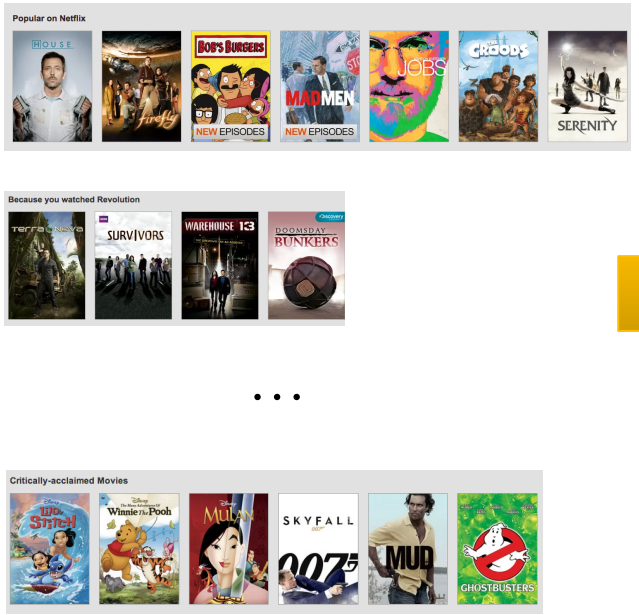
3.5. Page Optimization

Page Composition



Page Composition

10,000s of possible rows



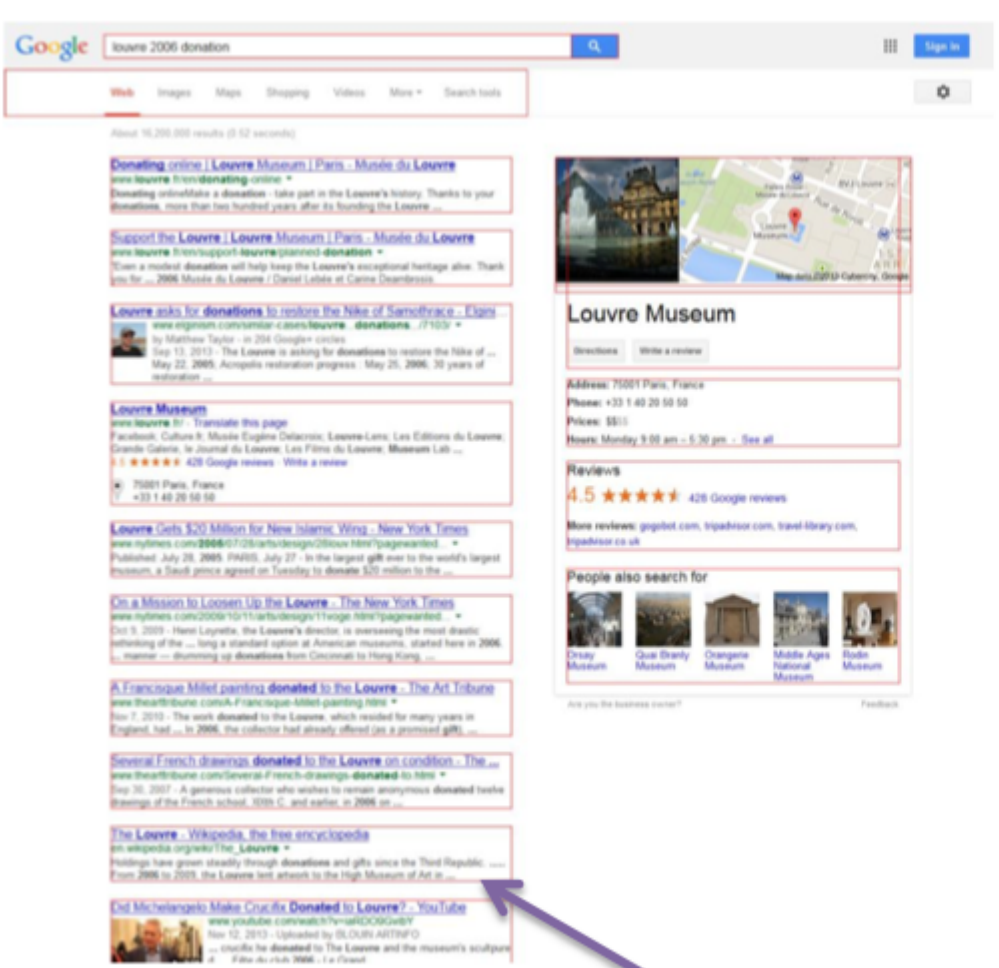
Variable number of possible videos per row (up to thousands)

1 personalized page

10-40 rows

per device

Page Composition



From “Modeling User Attention and Interaction on the Web” 2014 - PhD Thesis by Dmitry Lagun (Emory U.)

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User Attention Modeling

More likely to see

Less likely

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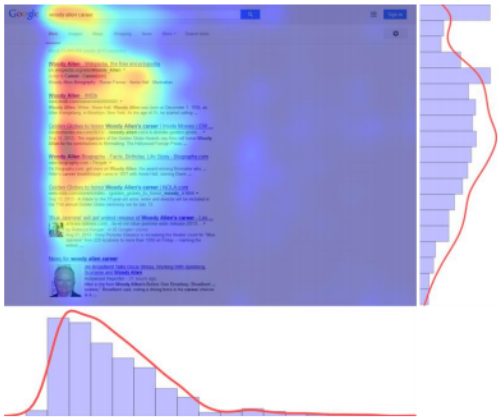
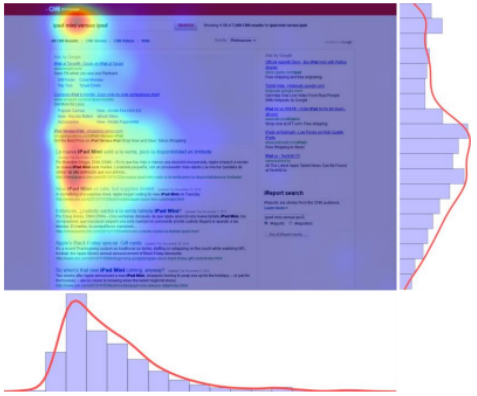
User Attention Modeling

Web Search (Google)



Social Network (Twitter)

News (CNN)



Shopping (Amazon)

From “Modeling User Attention and Interaction on the Web” 2014 - PhD Thesis by Dmitry Lagun (Emory U.)

Page Composition

Accurate vs. Diverse
Discovery vs. Continuation
Depth vs. Coverage
Freshness vs. Stability
Recommendations vs. Tasks

- To put things together we need to combine different elements
  - Navigational/Attention Model
  - Personalized Relevance Model
  - Diversity Model

Fair and Balanced: Learning to Present News Stories

Amr Ahmed*[1], Choon Hui Teo*[1], S.V. N. Vishwanathan[2], Alex Smola[1]
* Co-first authors.
[1]Yahoo! Research, Santa Clara, CA 95053, USA
[2]Purdue University, West Lafayette, IN 47907, USA
{amahmed,choonhui,smola}@yahoo-inc.com, vishy@stat.purdue.edu

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3.6 Tensor Factorization & Factorization Machines

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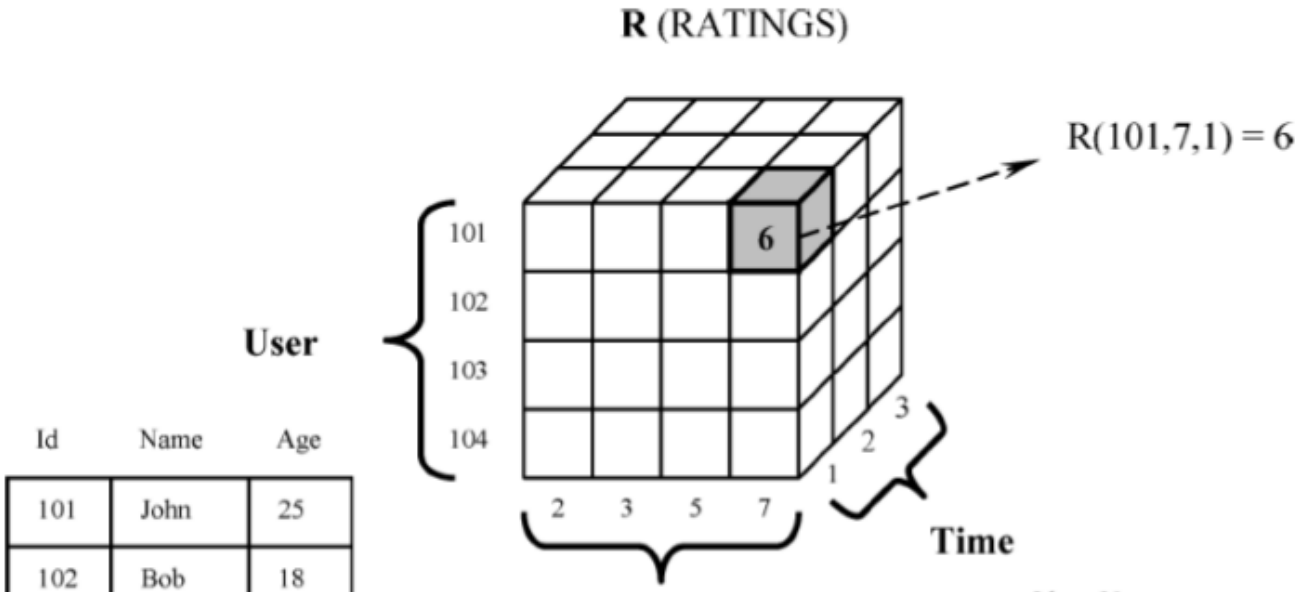
N-dimensional model



Id	Name	Age
101	John	25
102	Bob	18
103	Alice	27
104	Mary	21

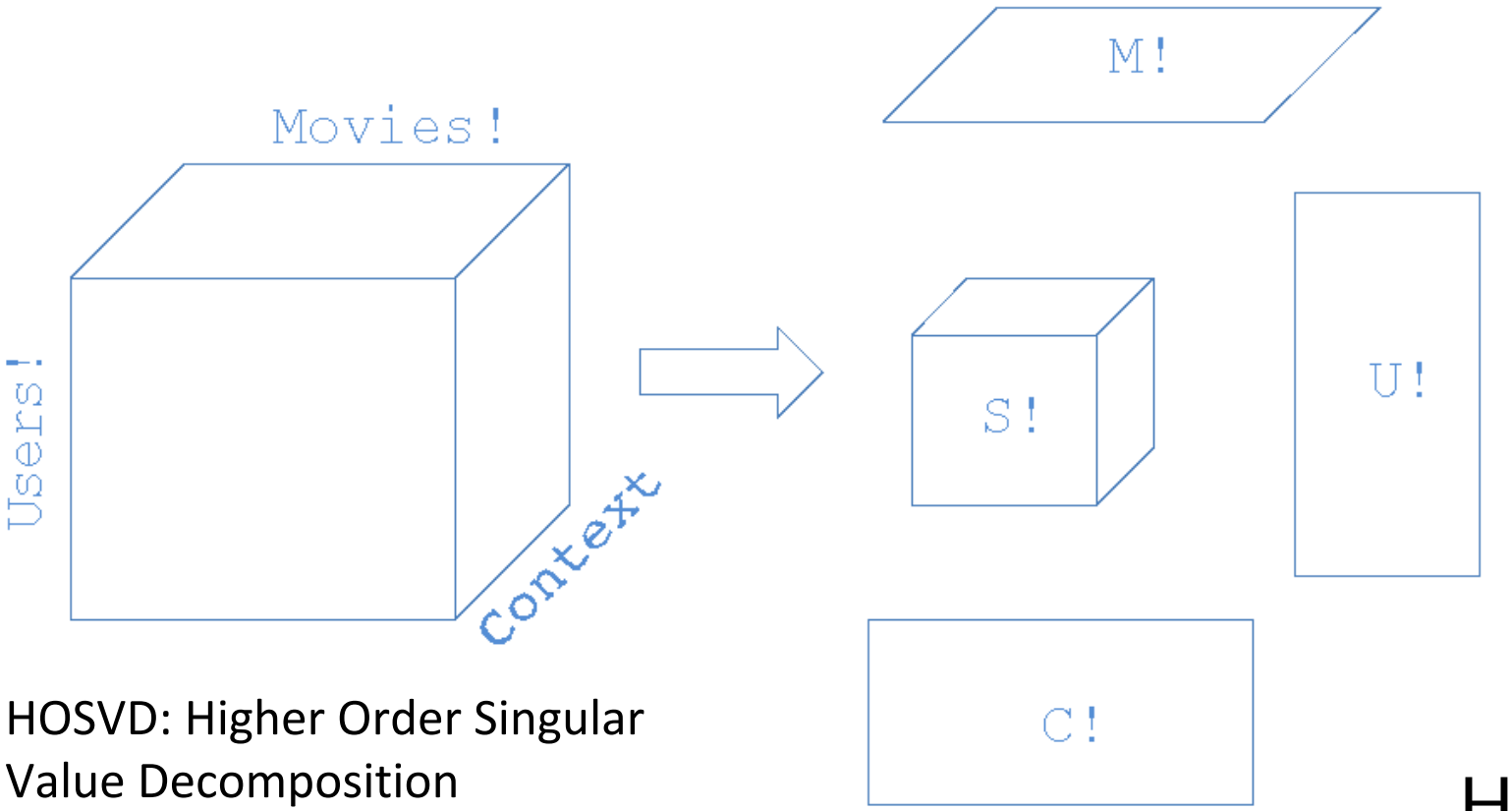
Item

Id	Name	Cost
2	AB17	250.00
3	AB23	299.95
5	XY70	150.00
7	ZZ55	115.50

Id	Name
1	Weekday
2	Weekend
3	Holiday

[Adomavicius et al., 2005]

Tensor Factorization



HOSVD: Higher Order Singular Value Decomposition

$U \in \mathbb{R}^{n \times d_U}$. $M \in \mathbb{R}^{m \times d_M}$ and $C \in \mathbb{R}^{c \times d_C}$

$S \in \mathbb{R}^{d_U \times d_M \times d_C}$

HOSVD Model

$$R[U, M, C, S] := L(F, Y) + \Omega[U, M, C] + \Omega[S]$$

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Factorization Machines

- Generalization of regularized matrix (and tensor) factorization approaches combined with linear (or logistic) regression
- Problem: Each new adaptation of matrix or tensor factorization requires deriving new learning algorithms
- Combines “generality of machine learning/regression with quality of factorization models”

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Factorization Machines

- Each feature gets a weight value and a factor vector
  - O(*dk*) parameters

$$b \in \mathbb{R}, \mathbf{w} \in \mathbb{R}^d, \mathbf{V} \in \mathbb{R}^{d \times k}$$

- Model equation:

$$f(\mathbf{x}) = b + \sum_{i=1}^{d} w_i x_i + \sum_{i=1}^{d} \sum_{j=i+1}^{d} x_i x_j \mathbf{v}_i^T \mathbf{v}_j \qquad O(d^2)$$

$$= b + \sum_{i=1}^{d} w_i x_i + \frac{1}{2} \sum_{f=1}^{k} \left(\left(\sum_{i=1}^{d} x_i v_{i,f} \right)^2 - \sum_{i=1}^{d} x_i^2 v_{i,f}^2 \right) \qquad O(kd)$$

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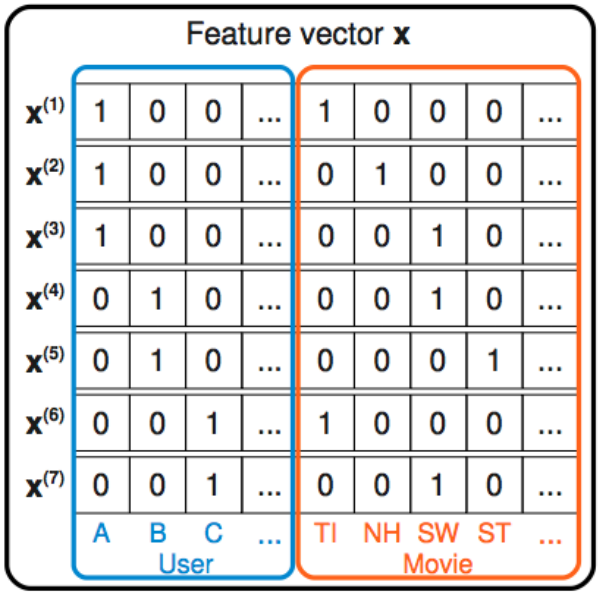
Factorization Machines

- Two categorical variables (*u*, *i*) encoded as real values:



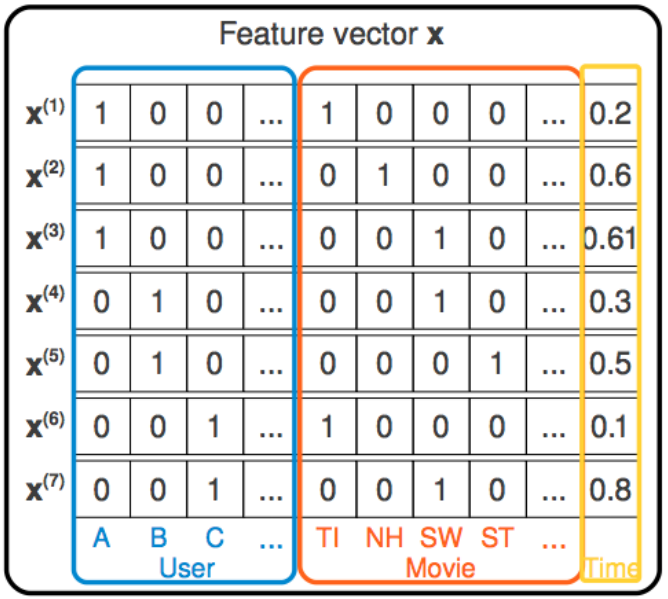
- FM becomes identical to MF with biases:

$$f(\mathbf{x}) = b + w_u + w_i + \mathbf{v}_u^T \mathbf{v}_i$$

From Rendle (2012) KDD Tutorial

Factorization Machines

- Makes it easy to add a time signal



- Equivalent equation:

$$f(\mathbf{x}) = b + w_u + w_i + x_t w_t + \mathbf{v}_u^T \mathbf{v}_i + x_t \mathbf{v}_u^T \mathbf{v}_t + x_t \mathbf{v}_i^T \mathbf{v}_t$$

From Rendle (2012) KDD Tutorial

Factorization Machines

- L2 regularized
  - Regression: Optimize RMSE
  - Classification: Optimize logistic log-likelihood
  - Ranking: Optimize scores
- Can be trained using:
  - SGD
  - Adaptive SGD
  - ALS
  - MCMC

Gradient:

$$\frac{\partial}{\partial\theta} f(\mathbf{x}) = \begin{cases} 1 & \text{if } \theta \text{ is } b \\ x_i & \text{if } \theta \text{ is } w_i \\ x_i \sum_{j=1}^{d} v_{j,f} x_j - v_{i,f} x_i^2 & \text{if } \theta \text{ is } v_{i,f} \end{cases}$$

Least squares SGD:

$$\theta' = \theta - \eta \left((f(\mathbf{x}) - y) \frac{\partial}{\partial\theta} f(\mathbf{x}) + \lambda_\theta \theta \right)$$

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3.7 MAB Explore/Exploit

Explore/Exploit

- One of the key issues when building any kind of personalization algorithm is how to trade off:
  - **Exploitation**: Cashing in on what we know about the user right now
  - **Exploration**: Using the interaction as an opportunity to learn more about the user
- We need to have informed and optimal strategies to drive that tradeoff
  - **Solution**: pick a reasonable set of candidates and show users only "enough" to gather information on them

Multi-armed Bandits

- Given possible strategies/candidates (slot machines) pick the arm that has the maximum potential of *being good* (minimize **regret**)

- Naive strategy: $\varepsilon - greedy$
  - Explore with a small probability ε (e.g. 5%) -> choose an arm at random
  - Exploit with a high probability (1- ε) (e.g. 95%) -> choose the best-known arm so far
- Translation to recommender systems
  - Choose an arm = choose an item/choose an algorithm (MAB testing)

Multi-armed Bandits

- Better strategies not only take into account the mean of the posterior, but also the variance
- Upper Confidence Bound (UCB)
  - Show item with maximum score
  - Score = Posterior mean + Δ
  - Where Δ can be computed differently depending on the variant of UCB (e.g. $\propto$ to the number of trials or the measured variance)
- Thompson Sampling
  - Given a posterior distribution $P(\theta|\mathcal{D}) \propto P(\mathcal{D}|\theta)P(\theta)$
  - Sample on each iteration and choose the action that maximizes the expected reward

Multi-armed Bandits

A Contextual-Bandit Approach to Personalized News Article Recommendation

Lihong Li†, Wei Chu†, †Yahoo! Labs lihong,chuwei@yahoo-inc.com

John Langford‡ ‡Yahoo! Labs jl@yahoo-inc.com

Robert E. Schapire+* +Dept of Computer Science Princeton University schapire@cs.princeton.edu

Explore-Exploit in Top-N Recommender Systems via Gaussian Processes

Hastagiri P Vanchinathan ETH Zürich hastagiri@inf.ethz.ch

Isidor Nikolic * Microsoft, Zürich inikolic@microsoft.com

Andreas Krause ETH Zürich krausea@ethz.ch

Fabio De Bona Google, Zürich fdb@google.com

Context Adaptation in Interactive Recommender Systems

Negar Hariri DePaul University Chicago, IL 60604, USA nhariri@cs.depaul.edu

Bamshad Mobasher DePaul University Chicago, IL 60604, USA mobasher@cs.depaul.edu

Robin Burke DePaul University Chicago, IL 60604, USA rburke@cs.depaul.edu

LinkedIn

Recommending Items to Users: An Explore Exploit Perspective

Deepak Agarwal, Director Machine Learning and Relevance Science, LinkedIn, USA

CIKM, 2013

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- Amr Ahmed et al. "*Fair and balanced".* In Proc. WSDM 2013
- Deepak Agarwal. 2013. *Recommending Items to Users: An Explore Exploit Perspective*. CIKM '13

Online resources

- Recsys Wiki: http://recsyswiki.com/
- Recsys conference Webpage: http://recsys.acm.org/
- Recommender Systems Books Webpage: http://www.recommenderbook.net/
- Mahout Project: http://mahout.apache.org/
- MyMediaLite Project: http://www.mymedialite.net/

Thanks!

Questions?

Xavier Amatriain

xavier@netflix.com

@xamat

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