Search Engine Architecture

13. Recommender Systems

Agenda

- Recommender systems
  - Content filtering
  - Collaborative filtering
    - Nearest neighbors
    - Matrix factorization
- Semester in review

Recommender Systems

Motivation

- Contrast:
  - Hit-driven economics
    - Not enough shelf space for all CDs, DVDs
    - Not enough screens to show all movies
    - Not enough channels to show all TV programs
    - Not enough spectrum to play all music
  - Cf. online distribution
    - None of these issues!
    - We can capture the long tail of options
- From scarcity of choices to abundance...
  - A solution: recommendation engines!

Types of Recommender Systems

- Hand-curated
  - Editorial lists
- Aggregates
  - Top 10
  - Recent Uploads
- Tailored to users (another long tail)
  - Amazon
  - Pandora
  - Netflix

Via Jure Leskovec, Stanford C246: Mining Massive Datasets

Two Approaches

- Content filtering – e.g., Pandora
  - Find items with content similar to other items user already likes
- Collaborative filtering – e.g., Netflix
  - Nearest neighbors
    - Find items rated highly by similar users
    - Find items rated similarly to those user already likes
  - Matrix factorization
    - Decompose ratings matrix R into PQ
    - P, Q are skinny factor loadings

Content Filtering

Content Filtering

- Create feature vector for each item
  - E.g., bag of words document-term matrix
- Create user profile vector
  - E.g., weighted average of rated items
- Score candidate items
  - E.g., cosine similarity between item and user vectors

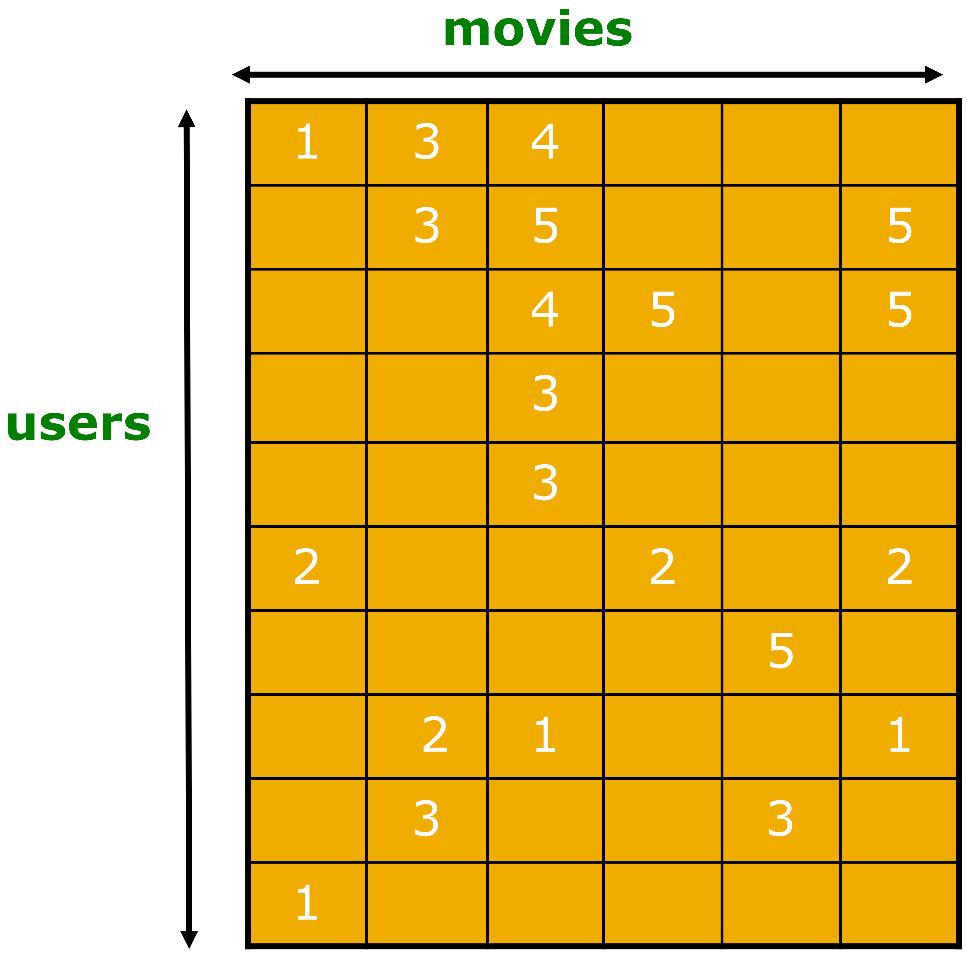
Content Filtering

- Pros
  - No need for data on other users
  - No cold start problem for new items
  - Model is transparent – can look at features to find out why a recommendation was made
- Cons
  - Feature design requires domain expertise
  - Unable to use quality judgments from other users

Collaborative Filtering

Collaborative Filtering

- Start with ratings (a.k.a. utility) matrix:


movies
users

1	3	4			
	3	5			5
		4	5		5
		3			
		3			
2			2		2
				5	
	2	1			1
	3			3	
1					

Source: Stanford C246 Mining Massive Datasets

Collaborative Filtering

- Nearest neighbors
  - Find items rated highly by similar users
  - Find items rated similarly to those user already likes
- Matrix factorization
  - Latent factor model
  - Decompose ratings matrix R into PQ
    - P, Q are skinny factor loadings

Collaborative Filtering: Nearest Neighbors

Nearest Neighbors

- User-user
  - Find items rated highly by similar users
  - Compute user similarity with, e.g., Pearson correlation over users' common item ratings
  - Define a user's neighborhood N of similar users
  - Then predicted rating for an item is the weighted average of ratings over user's neighborhood

Nearest Neighbors

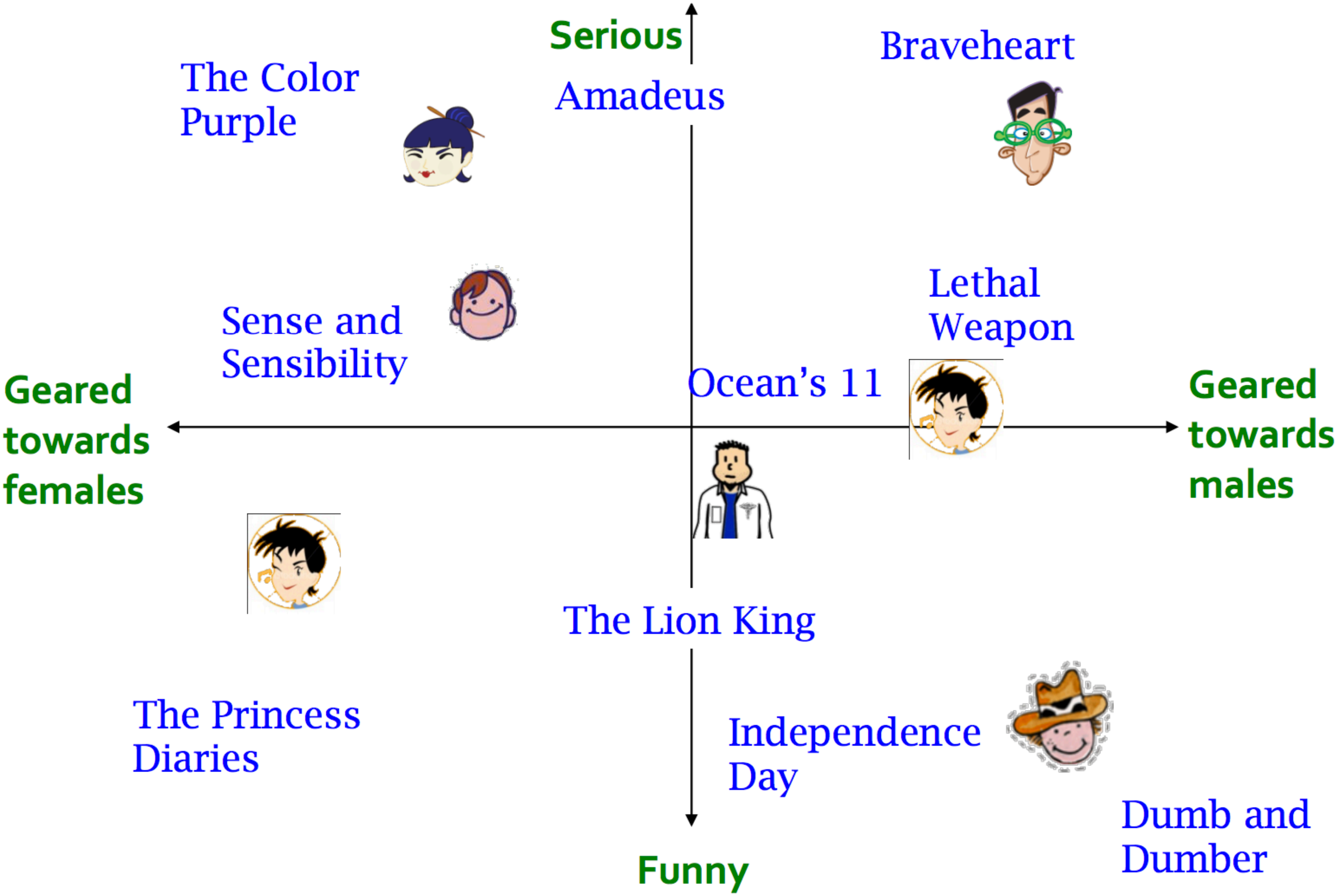
- Item-item
  - Find items similar to those rated highly
  - Compute item similarity with, e.g., Pearson correlation over common users' ratings
    - Cf. content filtering which uses item feature vector
  - Define item's neighborhood N of similar items
  - Predicted rating for an item is weighted average over item's neighborhood

Nearest Neighbors

- Pros
  - No domain expertise needed for feature design
- Cons
  - Cold start problem for new items
  - Requires users to have rated the same items
    - Problematic for sparse ratings matrix (long tail!)

Collaborative Filtering: Matrix Factorization

Latent Factor Models



Serious

Braveheart

The Color Purple

Amadeus

Lethal Weapon

Sense and Sensibility

Ocean's 11

Geared towards females

Geared towards males

The Lion King

The Princess Diaries

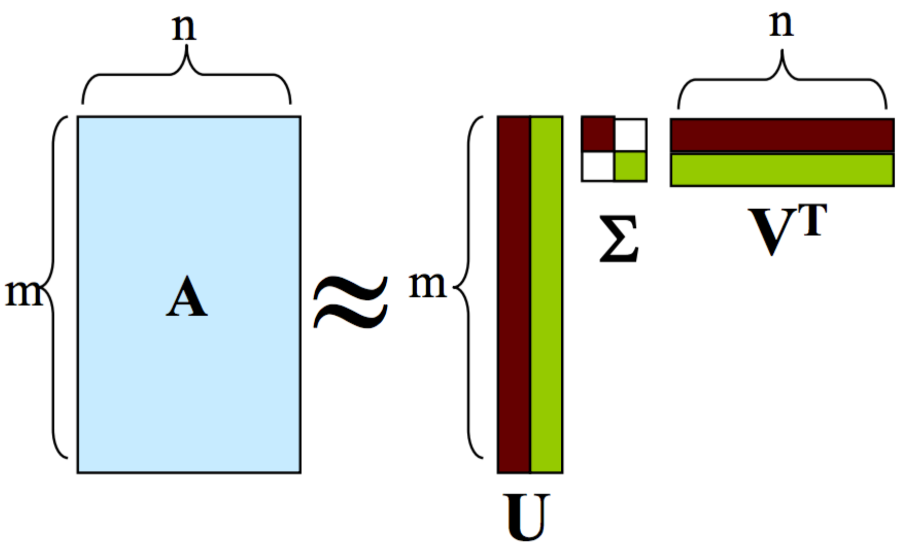
Independence Day

Dumb and Dumber

Funny

SVD Recap

- **Remember SVD:**
  - **A**: Input data matrix
  - **U**: Left singular vecs
  - **V**: Right singular vecs
  - Σ: Singular values

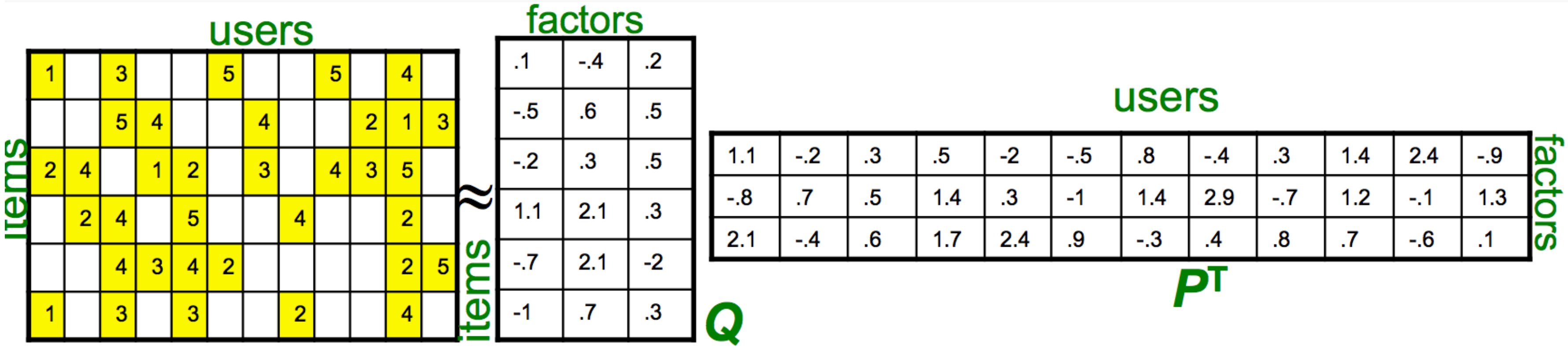


- **So in our case:**
  "SVD" on Netflix data: $R \approx Q \cdot P^T$
  $A = R, \; Q = U, \; P^T = \Sigma V^T$

$$\hat{r}_{xi} = q_i \cdot p_x$$

Source: Stanford C246 Mining Massive Datasets

Latent Factor Models



1		3			5			5		4	
		5	4			4			2	1	3
2	4		1	2		3		4	3	5	
	2	4		5			4			2	
		4	3	4	2					2	5
1		3		3			2			4	

.1	-.4	.2
-.5	.6	.5
-.2	.3	.5
1.1	2.1	.3
-.7	2.1	-2
-1	.7	.3

1.1	-.2	.3	.5	-2	-.5	.8	-.4	.3	1.4	2.4	-.9
-.8	.7	.5	1.4	.3	-1	1.4	2.9	-.7	1.2	-.1	1.3
2.1	-.4	.6	1.7	2.4	.9	-.3	.4	.8	.7	-.6	.1

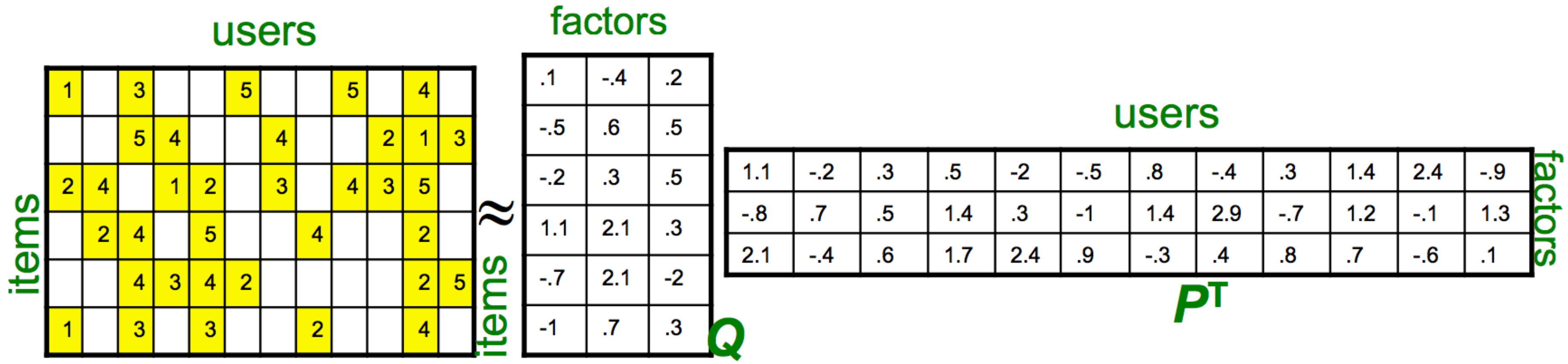
- **SVD isn't defined when entries are missing!**
- **Use specialized methods to find *P, Q***
  - $$\min_{P,Q} \sum_{(i,x)\in \mathrm{R}} \left(r_{xi} - q_i \cdot p_x\right)^2 \qquad \hat{r}_{xi} = q_i \cdot p_x$$
  - **Note:**
    - We don't require cols of ***P, Q*** to be orthogonal/unit length
    - ***P, Q*** map users/movies to a latent space
    - The most popular model among Netflix contestants

Source: Stanford C246 Mining Massive Datasets

Latent Factor Models

- **Our goal is to find P and Q such tat:**

$$\min_{P,Q} \sum_{(i,x)\in R} \left(r_{xi} - q_i \cdot p_x\right)^2$$

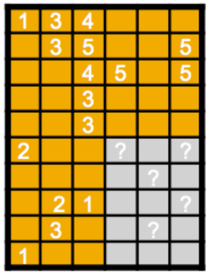


$$\begin{bmatrix} 1 & & 3 & & & 5 & & & 5 & & 4 & \\ & & 5 & 4 & & & 4 & & & 2 & 1 & 3 \\ 2 & 4 & & 1 & 2 & & 3 & & 4 & 3 & 5 & \\ & 2 & 4 & & 5 & & & 4 & & & 2 & \\ & & 4 & 3 & 4 & 2 & & & & & 2 & 5 \\ 1 & & 3 & & 3 & & & 2 & & & 4 & \end{bmatrix} \approx \begin{bmatrix} .1 & -.4 & .2 \\ -.5 & .6 & .5 \\ -.2 & .3 & .5 \\ 1.1 & 2.1 & .3 \\ -.7 & 2.1 & -2 \\ -1 & .7 & .3 \end{bmatrix} \begin{bmatrix} 1.1 & -.2 & .3 & .5 & -2 & -.5 & .8 & -.4 & .3 & 1.4 & 2.4 & -.9 \\ -.8 & .7 & .5 & 1.4 & .3 & -1 & 1.4 & 2.9 & -.7 & 1.2 & -.1 & 1.3 \\ 2.1 & -.4 & .6 & 1.7 & 2.4 & .9 & -.3 & .4 & .8 & .7 & -.6 & .1 \end{bmatrix}$$

Source: Stanford C246 Mining Massive Datasets

Overfitting

- **Want to minimize SSE for unseen test data**
- **Idea: Minimize SSE on training data**
  - Want large ***k*** (# of factors) to capture all the signals
  - But, **SSE** on **test data** begins to rise for ***k*** > 2
- This is a classical example of **overfitting:**
  - With too much freedom (too many free parameters) the model starts fitting noise
    - That is, it fits too well the training data and thus **not generalizing** well to unseen test data

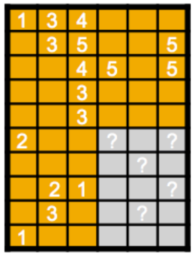


1	3	4			
	3	5			5
		4	5		5
		3			
		3			
2			?		?
				?	
	2	1			?
	3			?	
1					

Source: Stanford C246 Mining Massive Datasets

Regularization

- **To solve overfitting we introduce regularization:**
  - Allow rich model where there are sufficient data
  - Shrink aggressively where data are scarce



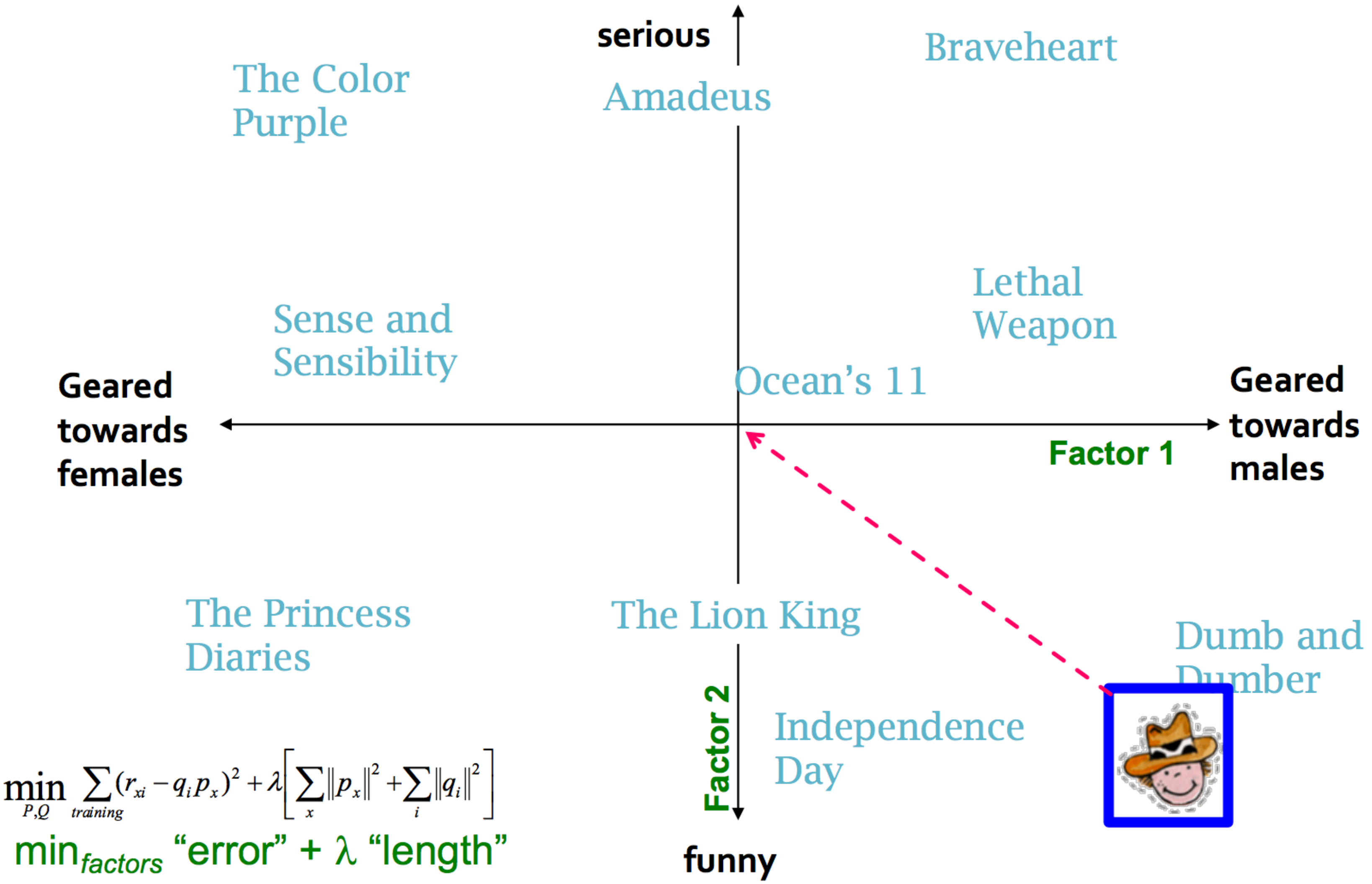
$$\min_{P,Q} \sum_{training} \underbrace{(r_{xi} - q_i p_x)^2}_{\text{“error”}} + \left[\lambda_1 \underbrace{\sum_x \|p_x\|^2 + \lambda_2 \sum_i \|q_i\|^2}_{\text{“length”}} \right]$$

λ_1, λ_2 … user set regularization parameters

Note: We do not care about the “raw” value of the objective function, but we care in P,Q that achieve the minimum of the objective

Source: Stanford C246 Mining Massive Datasets

Effect of Regularization



serious

funny

Geared towards females

Geared towards males

Factor 1

Factor 2

The Color Purple

Amadeus

Braveheart

Lethal Weapon

Sense and Sensibility

Ocean's 11

The Princess Diaries

The Lion King

Dumb and Dumber

Independence Day

$$\min_{P,Q} \sum_{training} (r_{xi} - q_i p_x)^2 + \lambda \left[\sum_x \|p_x\|^2 + \sum_i \|q_i\|^2 \right]$$

$\min_{factors}$ “error” + λ “length”

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Review: Recommender Systems

- Content filtering
  - Find content similar to that user already likes
- Collaborative filtering
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    - Latent factor model
    - Decompose ratings matrix R into PQ
      - P, Q are skinny factor loadings
    - Item2vec? User2vec?

Semester In Review

1. Big Ideas

- Scale out, not up
- Assume failures will happen
- Good APIs hide system details
- Aim for ideal scalability
- Move code to the data
- Avoid random disk access

2. NoSQL

- Key ideas:
  - Partition – for scalability, latency
  - Replicate – for availability, throughput
  - Caching – for latency
- Key-value stores
  - Consistent hashing, hash rings
- Bigtable / LSM trees
- CAP theorem

3. Modeling and Evaluation

- Language models
- Preprocessing
  - Case folding, tokenization, stopwords, stemming
- Boolean retrieval
- Ranked retrieval
  - Vector space model, TF-IDF, cosine similarity
- Model evaluation
  - Unranked – precision, recall, F-measure
  - Ranked – MAP, nDCG

4. Indexing and Retrieval

- Inverted index
  - TF-IDF
  - Positional
- Retrieval
  - Document-at-a-time vs. term-at-a-time
- Postings list encoding (d-gaps)
- Partitioning
  - Term vs. document partitioning

5. MapReduce

- Constrained API helps with synchronization problems
- Map, combine, partition, shuffle and sort, reduce
- Data locality – pairs and stripes
- Inverted index construction
- Value-to-key conversion
- The datacenter *is* the computer!

6. Link Analysis

- Graph representation
- Shortest path
  - MapReduce – parallel BFS
- PageRank
  - Time on page under random surfer model
  - Static prior for ranking
  - Computed iteratively
- PageRank in MapReduce
  - Iterative algorithms are hard in MapReduce

7. Classification

- Supervised classification in sklearn
- Logistic regression
- Gradient descent
  - MapReduce – M partial gradients, 1 model update
- Stochastic gradient descent
- Ensemble methods
  - MapReduce implementation – mappers only
- Case study: GoogLeNet 2014

8. Clustering

- For exploratory analysis, recommender systems, preprocessing, …
- Hierarchical agglomerative clustering
  - Start with N clusters, merge until one
- K-means
  - Iteratively recompute centroids and reassign points
  - MapReduce – map: assign, reduce: new centroids
- Gaussian mixture models
  - Soft assignment of points to clusters
  - MapReduce – similar to K-means

9. Distributed Word Representations

- Distributed representations
  / distributional hypothesis
- Dimensionality reduction
- Artificial neural networks
- Representation learning
- Word2vec
  - Skip-gram
  - CBOW
- Doc2vec
- SVD reduction

10. Learning to Rank

- ML vs. IR
- Classification
  - Predict class of query-document pair
- Pointwise learning
  - Learn thresholds to separate ranks
- Pairwise learning
  - Turns ordinal regression into binary classification
- Issues
  - Cost sensitivity for high-ranked documents
  - Query normalization

11. Beyond MapReduce

- Addressing MapReduce criticisms
  - Schemas with Thrift
  - High-level languages – Hive, Pig
- Dataflow – DAG of transformations
- Spark
  - RDD – store transforms needed to reproduce data
- Pregel
  - Graph-centric, express graph algorithms naturally
  - Each vertex passes messages to neighbors
  - Synchronization via supersteps

12. Streams

- Sampling
- Hashing
  - Set cardinality – HyperLogLog counter
  - Set membership – Bloom filter
  - Frequency estimation – Count-min sketch
- Storm
  - Spouts, bolts, and clever tracking
- Spark Streaming
  - Small, deterministic batch jobs
- Dataflow
  - Windows, triggers, and incremental processing

13. Finding Similar Items

- Represent documents with short signatures
  - Minhash
    - Given hash function, find term with smallest hash value
    - $P[h1(D_1) = h2(D_2)] = \text{Jaccard}(D_1, D_2)$
- Find candidates that are likely similar
  - Compute *k* minhashes per document (“band”)
  - Documents that match in a band are candidates
    - Evaluate candidates thoroughly
  - Repeat for *n* bands

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Thank you!