Tackling The Challenges of Big Data

Big Data Analytics

Machine Learning Tools

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Introduction

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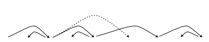
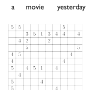
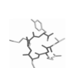
Our Research Group

- **Our research focuses on machine learning, from theory, algorithms, to applications**
- **There are several problems that drive our machine learning research**
  - natural language processing (e.g., parsing)
  - recommender systems (e.g., sparsity, scaling, privacy)
  - predictive user modeling (e.g., mobile)
  - uncovering how biological systems work (e.g., reconstructing transcriptional control)
  - large scale inverse problems (e.g., reservoir modeling)







Machine Learning

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- **Machine learning methods are computer programs that learn to predict based on data**

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CC transaction	Fraudulent?
description 1	yes
description 2	no
. . .	. . .

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CC transaction	Fraudulent?
description 1	yes
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. . .	. . .

  - machine learning methods learn to map descriptions to predictions based on such example data

Machine Learning

- **The mapping from examples (e.g., descriptions of transactions) to labels (e.g., fraudulent or not) is known as a classifier**

transaction as features $\begin{bmatrix} \text{time} \\ \text{location} \\ \text{customer} \\ \text{company} \\ \text{history} \\ \cdots \end{bmatrix} \xrightarrow[\text{parameterized classifier}]{}$ prediction (+1/-1)

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- **Simple classification problems are everywhere**
  - classifying news articles, images, reviews, etc.
  - classifying biomedical samples, measurements, etc.
  - mapping genotype (SNP) signatures to phenotypes
  - predicting the success of financial strategies, etc.

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- **Lots of scalable on-line algorithms are available for learning classifiers from data**

Beyond (simple) Classification

- **We can extend classifiers to predict more complex objects, not just labels**
  - e.g., annotate genomes (genes, their control)
  - e.g., transcribe speech
  - e.g., map natural language sentences to their syntactic parses
- **How do such methods scale?**

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Beyond (simple) Classification

- **We may have lots of data, much of it incomplete, fragmented, potentially erroneous**
- **How do we share, distill such data to obtain more accurate predictions?**

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Beyond (simple) Classification

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- **How do we share, distill such data to obtain more accurate predictions?**
  - e.g., in recommender problems, little data may be available about any particular user (e.g., amazon.com visitor) but there are lots of such users
  - the question is how we can leverage other users' experiences to better predict the behavior of any particular user?

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Example: Scaling Structured Prediction

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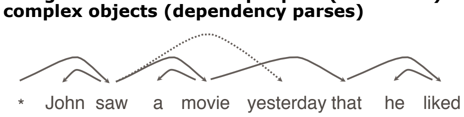
Structured Prediction

- **Natural language processing**
  - e.g., tagging, morphological segmentation, parsing
- **Computer vision**
  - e.g., segmentation, stereo reconstruction, object recognition
- **Computational biology**
  - e.g., annotation, molecular structures, pathway reconstruction
- **Robotics**
  - e.g., imitation learning, inverse kinematics
- **Human computer interaction**
  - e.g., interface alignment, example based design

Structured Prediction: Example

- **The goal is to learn to map inputs (sentences) to complex objects (dependency parses)**



  - in dependency parsing, we draw an arc from the head word of each phrase to words that modify it
  - the parse is a directed tree over the words. In many languages, the tree is non-projective (crossing arcs)
  - each sentence is mapped to arc scores; the parse is obtained as the highest scoring directed tree

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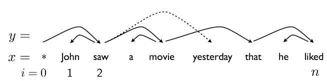
Scaling Structured Prediction

- **Accurate predictions of complex structures (e.g., dependency trees) require rich scoring functions**
- **Refined predictions, on the other hand, consume resources**
- **Three scaling problems we must address:**
  - Prediction (inference): finding a single highest scoring tree (a single prediction) can be already provably hard
  - Estimation: learning requires inference making it challenging to estimate models from large corpuses
  - Uncertainty: modeling uncertainty is substantially harder than solving for the highest scoring tree

The Prediction Problem

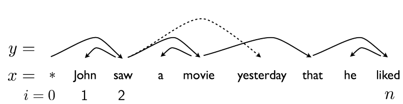
- **The goal is to learn to map sentences (x) to dependency parses (y)**



- **The mapping from x to y is typically decomposed into two parts:**
  - modeling: using sentence x to specify scores for candidate trees and/or their parts
  - computation: the predicted parse is obtained as the highest scoring tree
- **A simple way to score trees is by summing scores for individual arcs ("arc factored scoring")**

Prediction, Challenges

- **The goal is to learn to map sentences (x) to dependency parses (y)**



- **From the point of view of modeling, we would like to include scores for bundles of outgoing arcs ("siblings") instead of just individual arcs**

Prediction, Challenges

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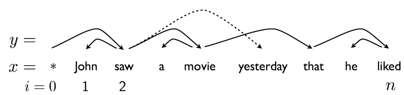

- From the point of view of modeling, we would like to include scores for bundles of outgoing arcs ("siblings") instead of just individual arcs
- But now the prediction problem -- parsing a single sentence -- is computationally hard!

Scaling Prediction (inference)

- We have to find an appropriate balance between accuracy (modeling power) and computation
- Using only the simplest models that scale without effort is limiting… can we do more?

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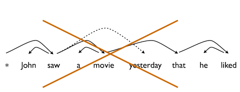
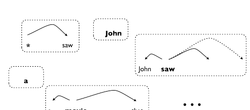
- We can adaptively break (decompose) refined models into smaller loosely coupled pieces





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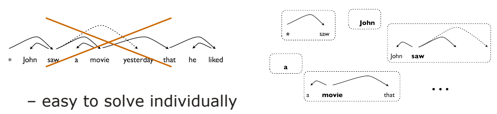

  - easy to solve individually
  - pieces encouraged to agree (adaptively)
  - typically results in the same prediction as the original model

Scaling Prediction (inference)

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Dan	99.07
Dut	98.19
Por	99.65
Slo	90.55
Swe	98.71
Tur	98.72
Eng^1	98.65
Eng^2	98.96
Dan	98.50
Dut	98.00

Scaling Structured Prediction

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Example: Scaling Structured Prediction

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Example: Collaborative Filtering

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Learning to Recommend

- **Many prediction problems can be viewed as matrix completion problems**
- **Co-occurrence data**
  - e.g., ratings, viewing, purchasing, actions
  - arranged into a large incomplete matrix

Movies, books (items)

Users

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

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Learning to Recommend

- **Many prediction problems can be viewed as matrix completion problems**
- **Scaling issues**
  - huge matrices (millions x tens of thousands)
- **Statistical issues**
  - largely unobserved (e.g., 1%), diverse
- **Modeling issues**
  - many interpretations for missing entries
- **Privacy issues**
  - how much info to release?

Movies, books (items)

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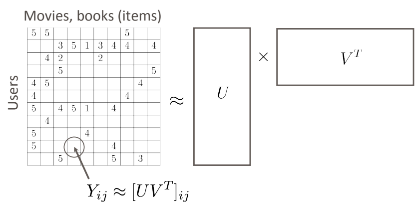
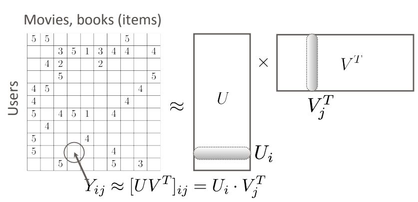
Typical Approach: Factorization

- **We reconstruct the data matrix by finding the "simplest" matrix (nearly) consistent with the limited observations**



Typical Approach: Factorization

- **We reconstruct the data matrix by finding the "simplest" matrix (nearly) consistent with the limited observations**
- **In doing so, we identify "user features" and "item features", and predict by comparing the two**



Typical Approach: Factorization

- **We identify "user features" and "item features", and predict responses by comparing the two**
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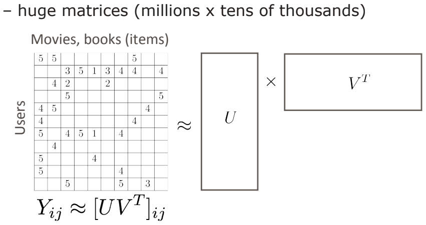
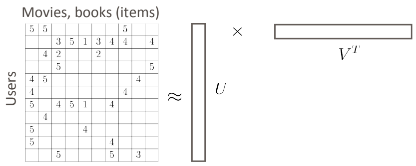


Typical Approach: Factorization

- **We identify "user features" and "item features", and predict responses by comparing the two**
- **Scaling issues**
  - huge matrices (millions x tens of thousands)
  - we can estimate each feature coordinate pair at a time



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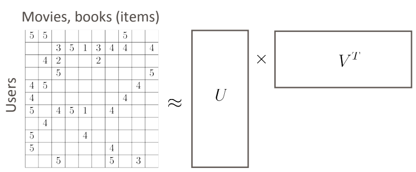

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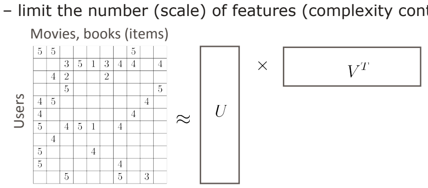
Typical Approach: Factorization

- **We identify "user features" and "item features", and predict responses by comparing the two**
- **Statistical issues**
  - largely unobserved (e.g., 1%), diverse
  - limit the number (scale) of features (complexity control)



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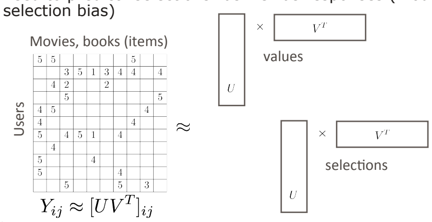
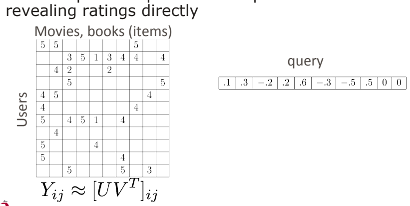
Approach: factorization

- **We identify "user features" and "item features", and predict responses by comparing the two**
- **Modeling issues**
  - many interpretations for missing entries
  - need to predict "selections" as well as responses (model selection bias)



Approach: Factorization

- **We identify "user features" and "item features", and predict responses by comparing the two**
- **Privacy issues**
  - how much info (each user needs) to release?
  - need to trade privacy for accuracy
  - users respond to queries about preferences rather than revealing ratings directly



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