CS6784
Advanced Topics in Machine Learning

Spring 2014

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Cornell University

Outline of Today

- Introduction
  - Thorsten Joachims + Joshua Moore
- Overview of Class Topics
  - Structured Prediction
  - Machine Learning with Humans in the Loop
  - Learning Representations
- Administrivia
  - Goals for the Class
  - Pre-Requisites
  - Credit Options and Format
  - Project and Assignments
  - Course Material
  - Warm-up Assignment
  - Contact Info

Topic 1

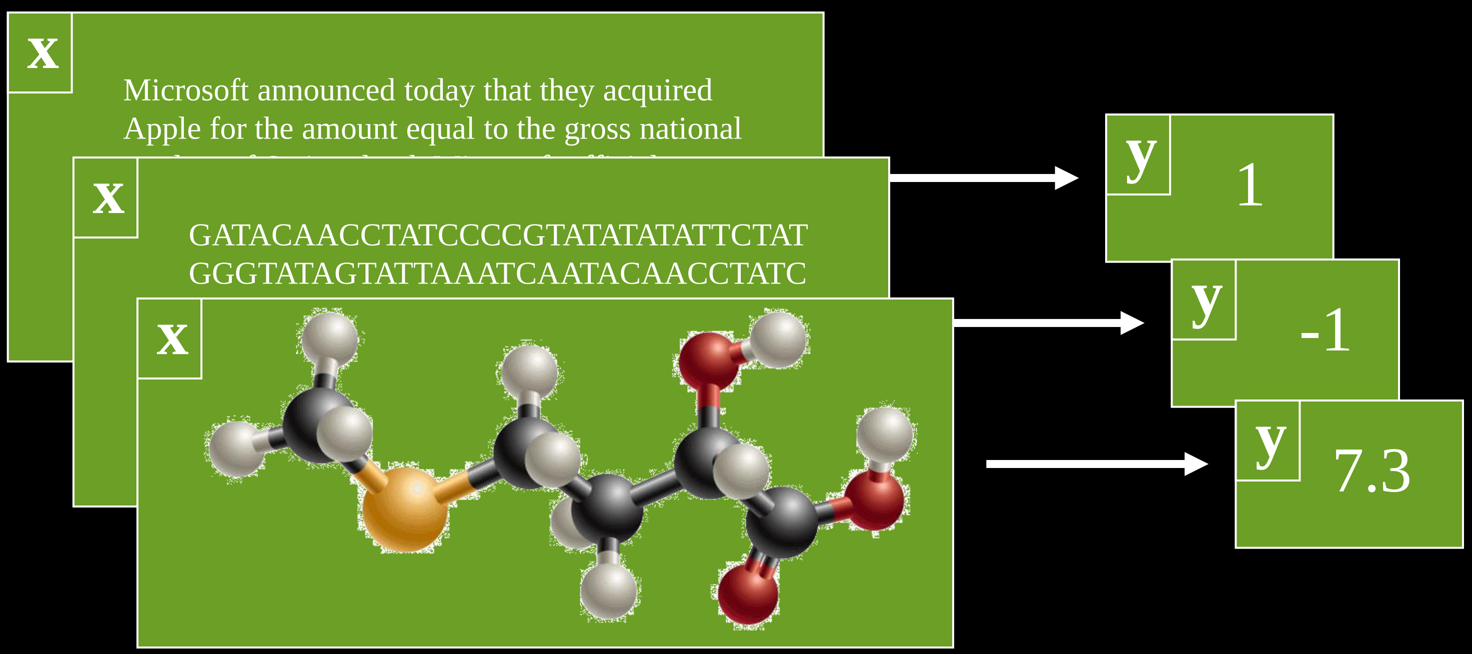
Structured Output Prediction

Conventional Supervised Learning

- Find function from input space *X* to output space *Y*

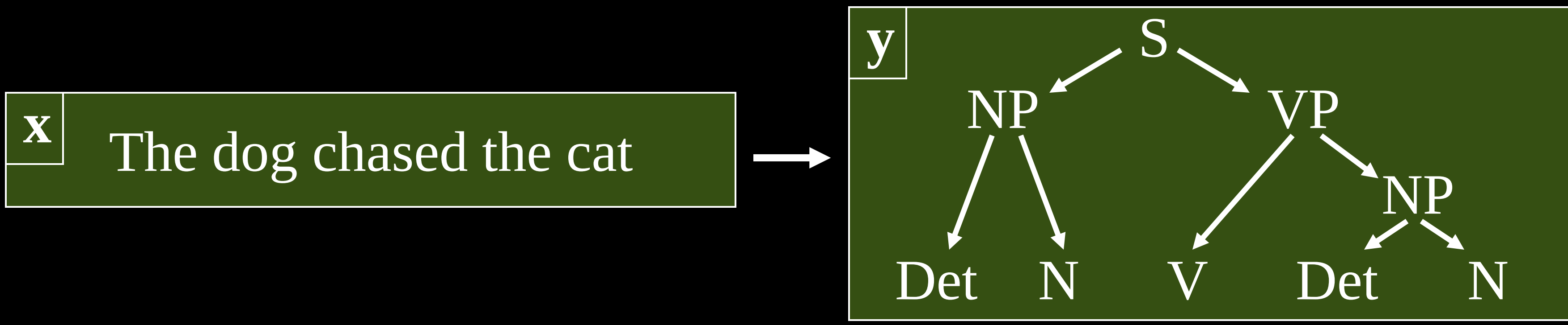
$$h: X \rightarrow Y$$

such that the prediction error is low.



Examples of Complex Output Spaces

- Natural Language Parsing
  - Given a sequence of words *x*, predict the parse tree *y*.
  - Dependencies from structural constraints, since *y* has to be a tree.



Examples of Complex Output Spaces

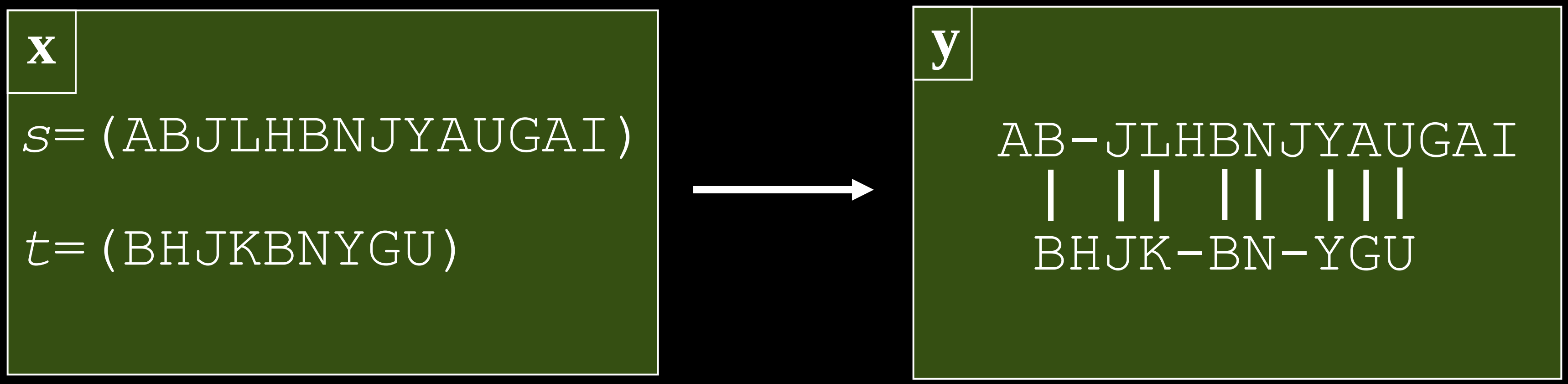
- **Part-of-Speech Tagging**
  - Given a sequence of words *x*, predict sequence of tags *y*.
  - Dependencies from tag-tag transitions in Markov model.

x The rain wet the cat → **y** Det → N → V → Det → N

→ Similarly Named-Entity Recognition, Protein Intron Tagging, etc.

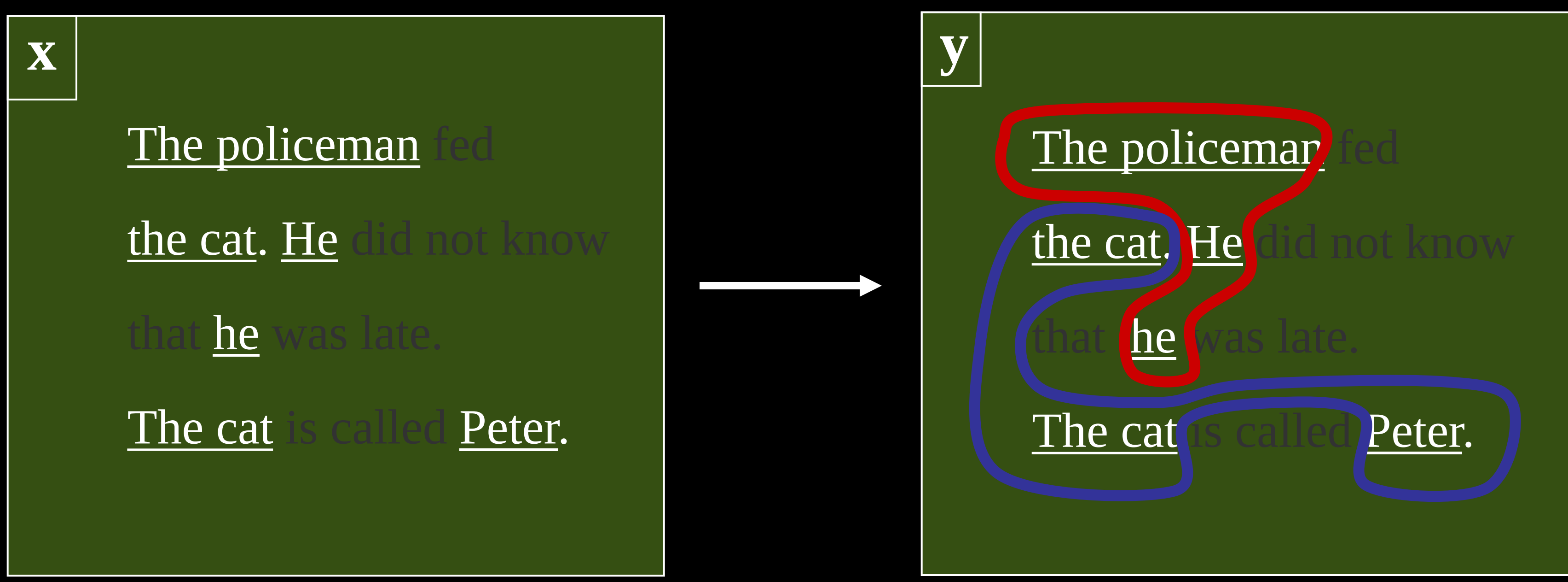
Examples of Complex Output Spaces

- Protein Sequence Alignment
  - Given two sequences $x=(s,t)$, predict an alignment y.
  - Structural dependencies, since prediction has to be a valid global/local alignment.



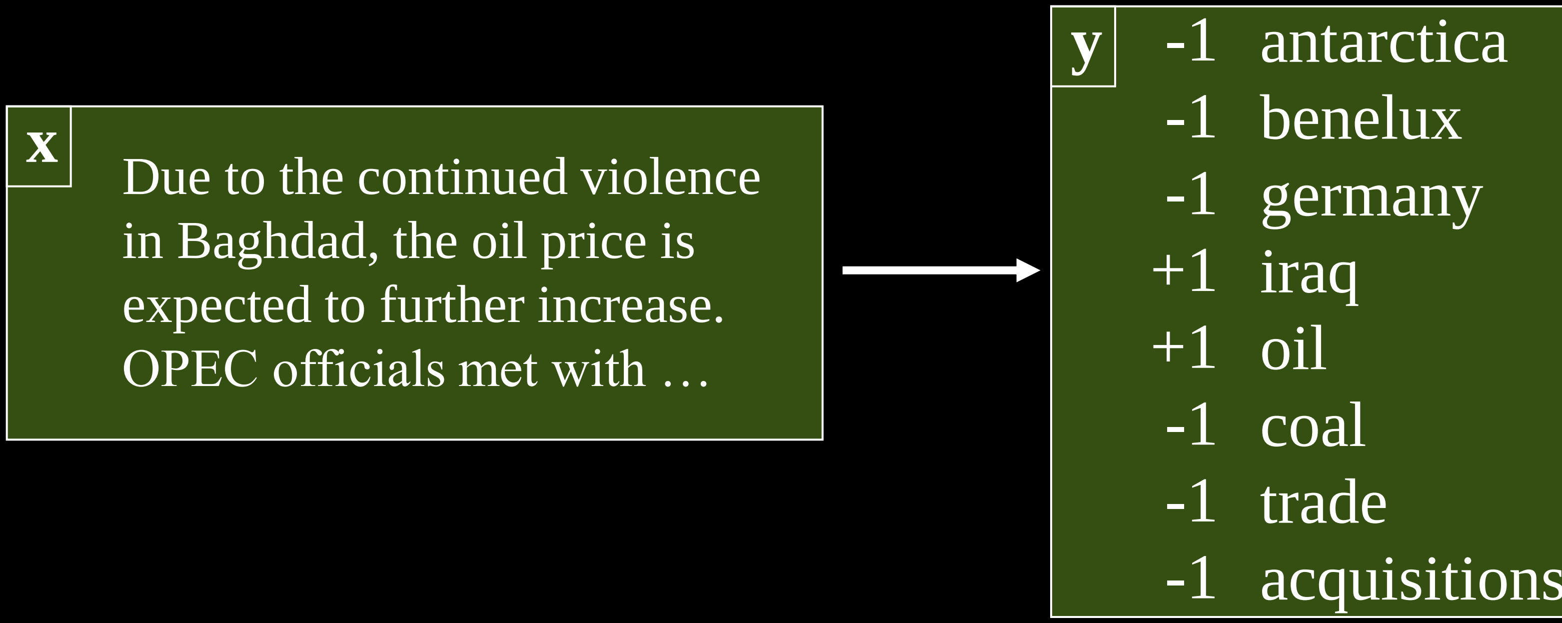
Examples of Complex Output Spaces

- Noun-Phrase Co-reference
  - Given a set of noun phrases *x*, predict a clustering *y*.
  - Structural dependencies, since prediction has to be an equivalence relation.
  - Correlation dependencies from interactions.



Examples of Complex Output Spaces

- Multi-Label Classification
  - Given a (bag-of-words) document x, predict a set of labels *y*.
  - Dependencies between labels from correlations between labels (“iraq” and “oil” in newswire corpus)



Examples of Complex Output Spaces

- Information Retrieval
  - Given a query x, predict a ranking *y*.
  - Dependencies between results (e.g. avoid redundant hits)
  - Loss function over rankings (e.g. AvgPrec)

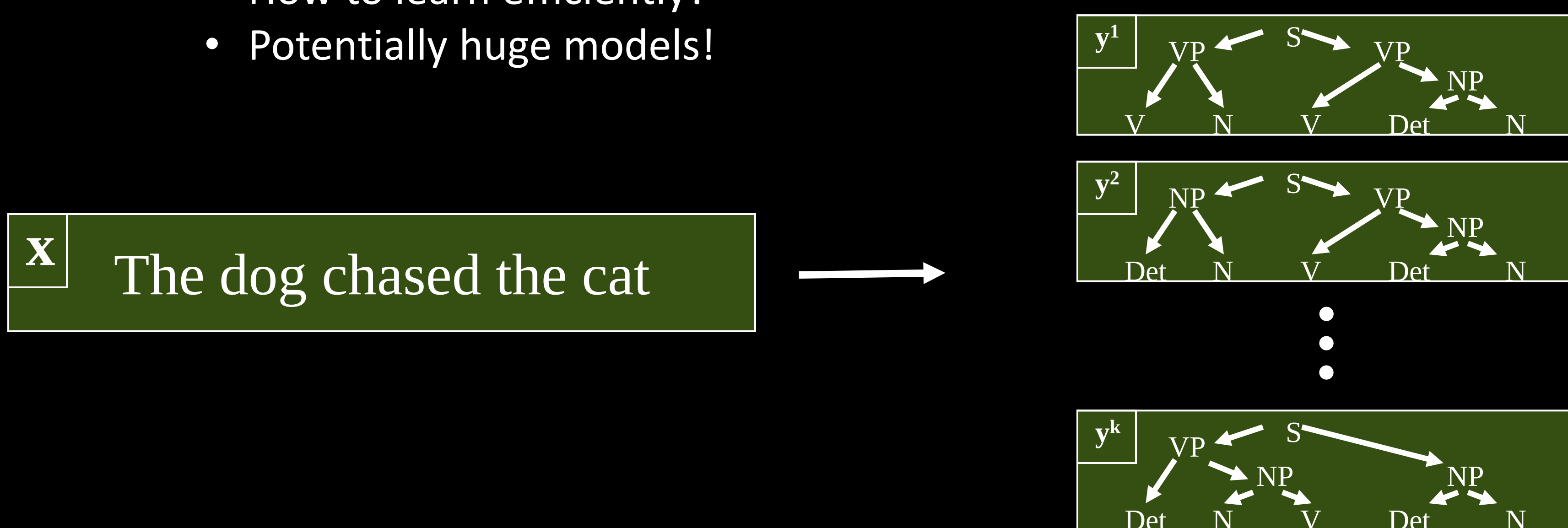
x SVM → **y**

1. Kernel-Machines
2. SVM-Light
3. Learning with Kernels
4. SV Meppen Fan Club
5. Service Master & Co.
6. School of Volunteer Management
7. SV Mattersburg Online

…

Why is Structured Output Prediction Interesting?

- Application Perspective
  - Many interesting real-world problems have structure in outputs
- Research Perspective
  - Like a multi-class problem with exponentially many classes!
    - How to predict efficiently?
    - How to learn efficiently?
    - Potentially huge models!



Overview: Structured Output Prediction

- Existing methods and their properties / limitations
  - Generative models
  - Structural SVMs and other maximum margin methods
  - Conditional Random Fields
  - Search-based methods
  - Gaussian Processes
  - Kernel Dependency Estimation
- Applications
  - Search engines
  - Natural language processing
  - Reinforcement learning
  - Probabilistic reasoning
  - Computational biology

Topic 2

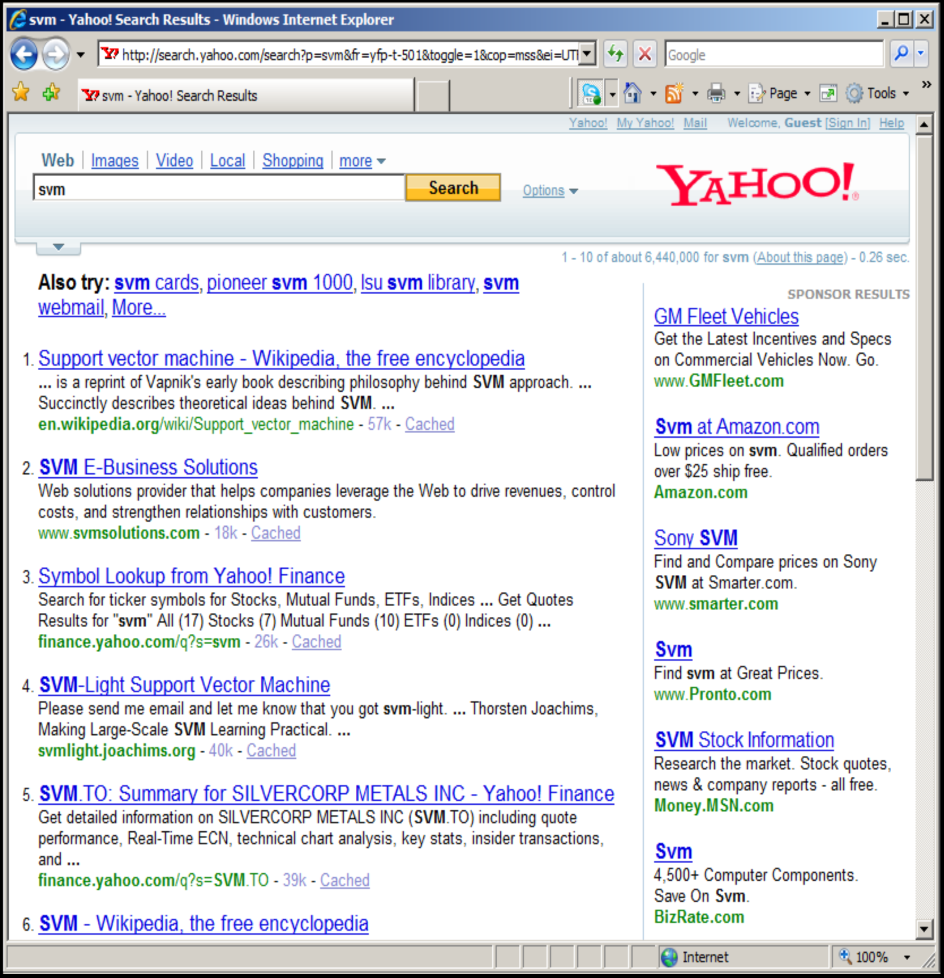
Machine Learning with Humans in the Loop

Interactive Learning Systems

- WHILE(forever)
  - "System" presents options to the user
  - User examines the "Options" and reacts to them
  - "System" observes the selection and learns from it
- "System" / "Options" =
  - Search engine / search results
  - Movie recommender system / recommended movies
  - Online shopping site / products to buy
  - GPS navigation software / route
  - Spelling correction in word processor / word
  - Social network extension / friend
  - Twitter / post

Implicit Feedback in Web Search

- Observable actions
  - Queries / reformulations
  - Clicks
  - Order, dwell time
  - Etc.
- Implicit feedback
  - Personalized
  - Democratic
  - Timely
  - Human intelligence
  - Cheap
  - Abundant



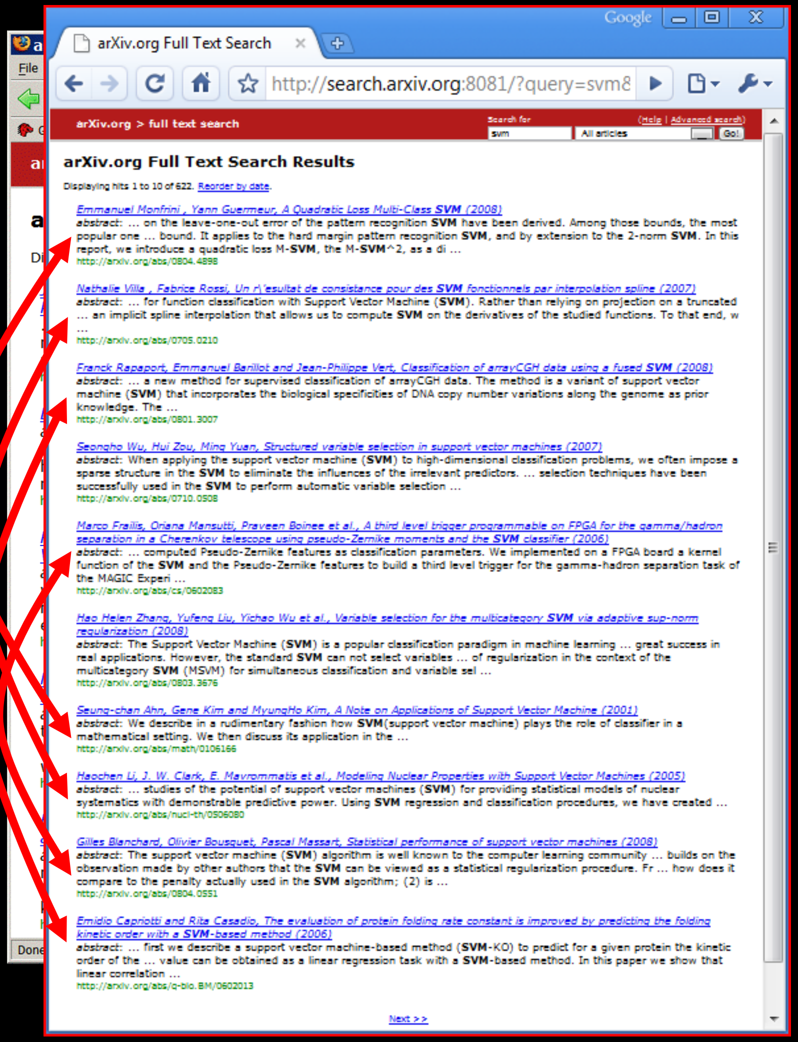
Does User Behavior Reflect Retrieval Quality?

User Study in ArXiv.org

- Natural user and query population.
- User in natural context, not lab.
- Live and operational search engine.
- Ground truth by construction

  Orig $\succ$ Swap2 $\succ$ Swap4
  - Orig: Hand-tuned fielded
  - Swap2: Orig with 2 pairs swapped
  - Swap4: Orig with 4 pairs swapped

  Orig $\succ$ Flat $\succ$ Rand
  - Orig: Hand-tuned fielded
  - Flat: No field weights
  - Rand : Top 10 of Flat shuffled



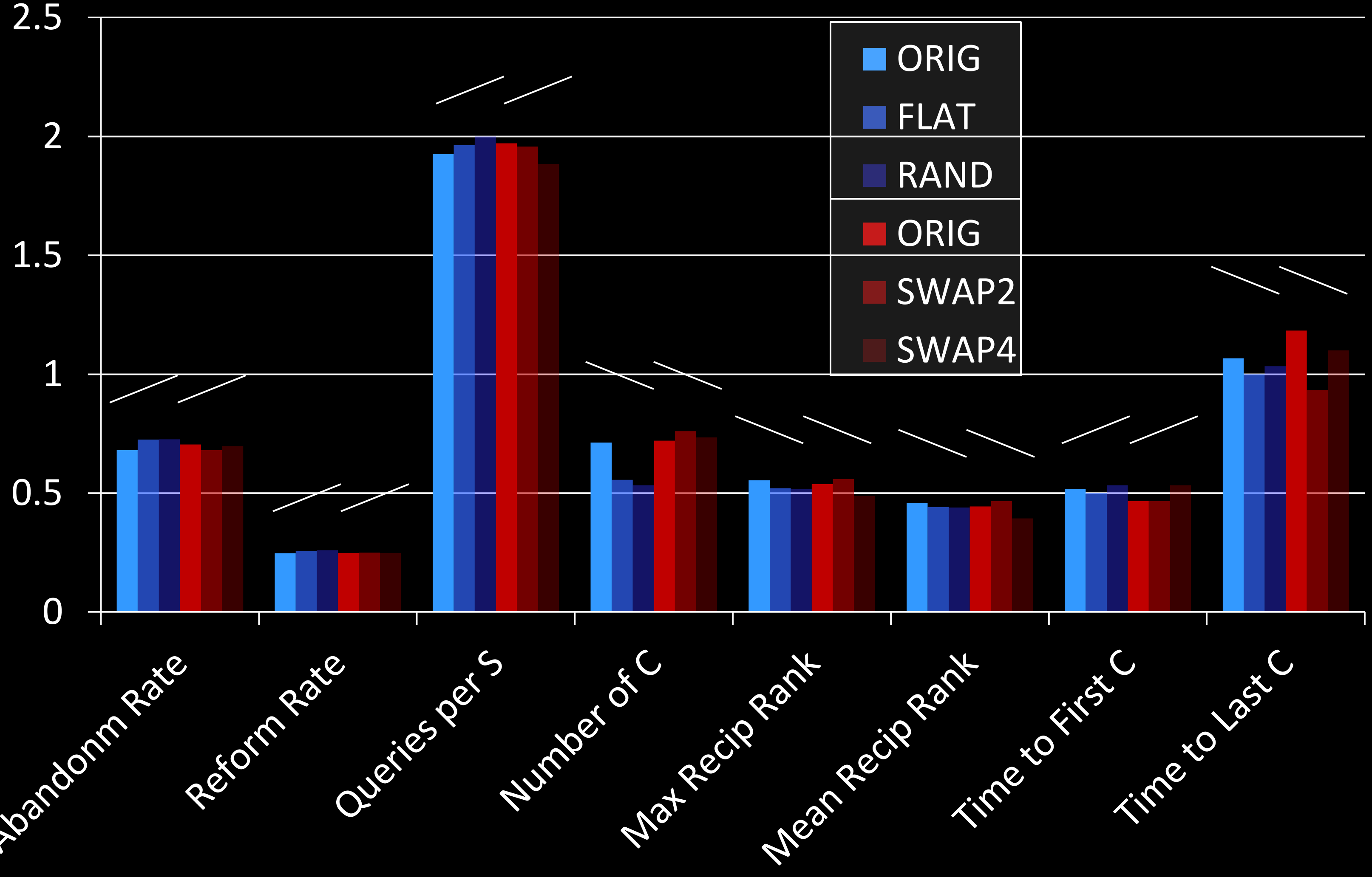
[Radlinski et. al., 2008]

Absolute Metrics: Metrics

Name	Description	Aggre-gation	Hypothesized Change with Decreased Quality
Abandonment Rate	% of queries with no click	N/A	Increase
Reformulation Rate	% of queries that are followed by reformulation	N/A	Increase
Queries per Session	Session = no interruption of more than 30 minutes	Mean	Increase
Clicks per Query	Number of clicks	Mean	Decrease
Max Reciprocal Rank*	1/rank for highest click	Mean	Decrease
Mean Reciprocal Rank*	Mean of 1/rank for all clicks	Mean	Decrease
Time to First Click*	Seconds before first click	Median	Increase
Time to Last Click*	Seconds before final click	Median	Decrease

(*) only queries with at least one click count

Absolute Metrics: Results



Paired Comparisons: What to Measure?

(u=tj,q="svm")

$f_1(u,q) \rightarrow r_1$

1. Kernel Machines
   http://svm.first.gmd.de/
2. Support Vector Machine
   http://jbolivar.freeservers.com/
3. An Introduction to Support Vector Machines
   http://www.support-vector.net/
4. Archives of SUPPORT-VECTOR-MACHINES ...
   http://www.jiscmail.ac.uk/lists/SUPPORT...
5. SVM-Light Support Vector Machine
   http://ais.gmd.de/~thorsten/svm light/

$f_2(u,q) \rightarrow r_2$

1. Kernel Machines
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2. SVM-Light Support Vector Machine
   http://ais.gmd.de/~thorsten/svm light/
3. Support Vector Machine and Kernel ... References
   *http://svm.*research.bell-labs.com/SVMrefs.html
4. Lucent Technologies: SVM demo applet
   http://svm.research.bell-labs.com/SVT/SVMsvt.html
5. Royal Holloway Support Vector Machine
   http://svm.dcs.rhbnc.ac.uk

Interpretation: $(r_1 \succ r_2) \leftrightarrow \text{clicks}(r_1) > \text{clicks}(r_2)$

Balanced Interleaving

(u=tj, q="svm")

$f_1(u,q) \rightarrow r_1$

1. Kernel Machines
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$f_2(u,q) \rightarrow r_2$

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5. Royal Holloway Support Vector Machine
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Interleaving(r_1,r_2)

1.	Kernel Machines *http://svm.first.gmd.de/*	1
2.	Support Vector Machine *http://jbolivar.freeservers.com/*	2
3.	SVM-Light Support Vector Machine *http://ais.gmd.de/~thorsten/svm light/*	2
4.	An Introduction to Support Vector Machines *http://www.support-vector.net/*	3
5.	Support Vector Machine and Kernel ... References *http://svm.*research.bell-labs.com/SVMrefs.html	3
6.	Archives of SUPPORT-VECTOR-MACHINES ... *http://www.jiscmail.ac.uk/lists/SUPPORT...*	4
7.	Lucent Technologies: SVM demo applet *http://svm.*research.bell-labs.com/SVT/SVMsvt.html	4

Model of User:
Better retrieval functions is more likely to get more clicks.

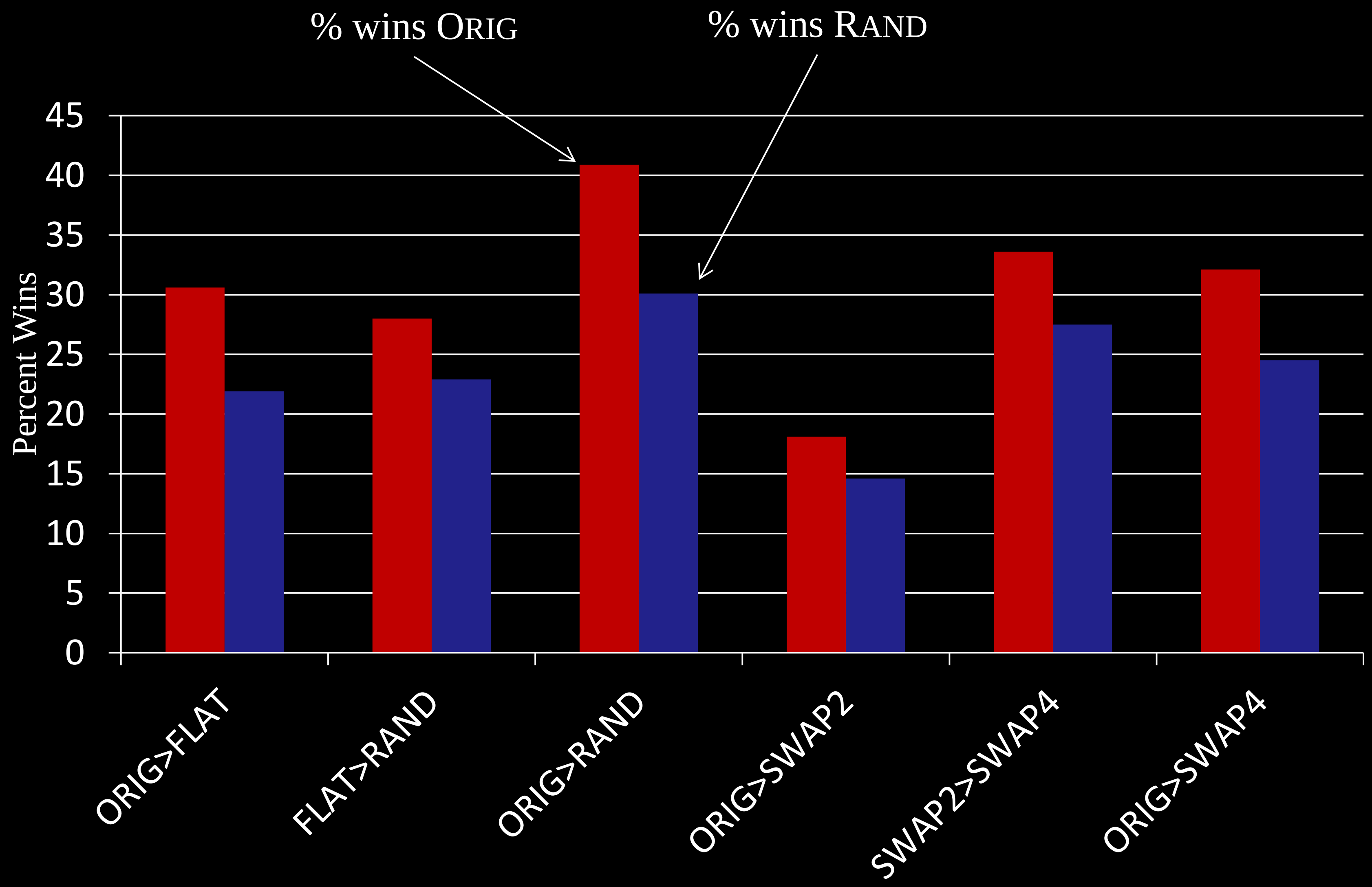
Invariant:
For all k, top k of balanced interleaving is union of top k_1 of r_1 and top k_2 of r_2 with $k_1=k_2 \pm 1$.

Interpretation: $(r_1 \succ r_2) \leftrightarrow$ clicks(topk(r_1)) > clicks(topk(r_2))

→ see also [Radlinski, Craswell, 2012] [Hofmann, 2012]

[Joachims, 2001] [Radlinski et al., 2008]

Arxiv.org: Interleaving Results



Issues in Learning with Humans

- Presentation Bias
  - Get accurate training data out of biased feedback
  - Use randomization to collect unbiased data
  - Experiment design
- Online Learning
  - Exploration/exploitation trade-offs
  - Observational vs. experimental data
  - Ability to run interactive experiments with users
- Measuring User Satisfaction
  - Turning behavior into evaluation measure

Overview: Learning with Humans

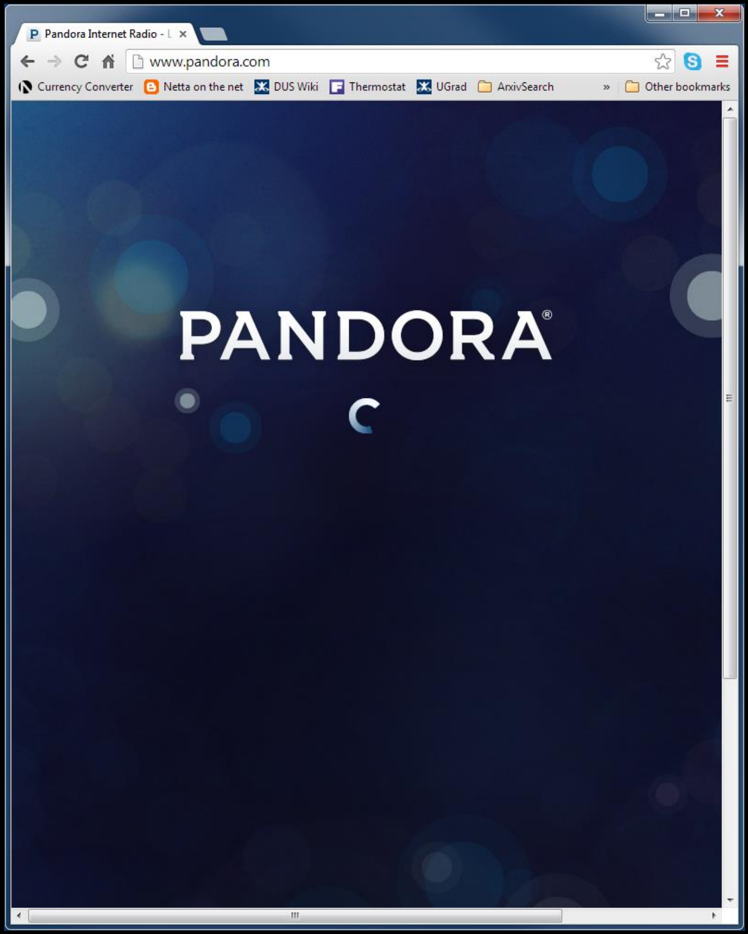
- Methods
  - Online learning and multi-armed bandits
  - Methods for interpreting user behavior
  - Matrix decomposition methods for recommendation
  - Active learning
- Applications
  - Information retrieval
  - Recommender systems
  - Online shopping
  - Mechanical turk
  - Web server usage

Topic 3

Learning Representations

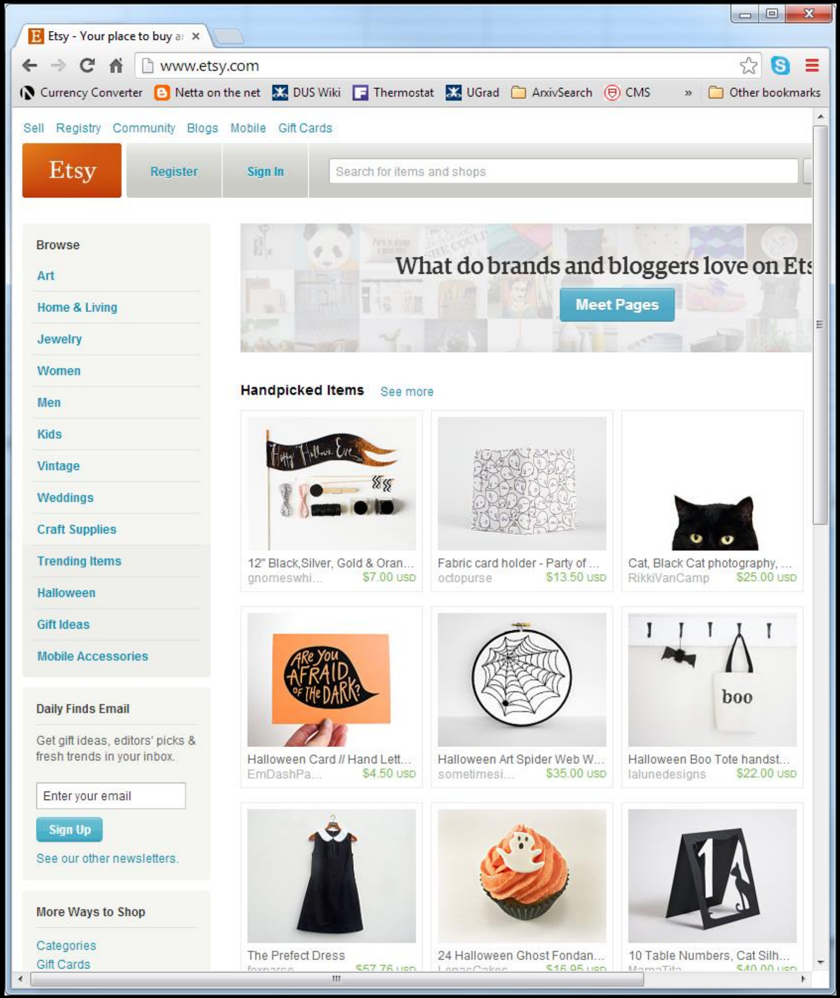
Learning about Music

- Collection of songs
  - $S = \{s_1, s_2, s_3, \ldots, s_N\}$
- Example playlists
  - $p_1 = [s_9, s_{527}, s_{12}, \ldots]$
  - $p_2 = [s_{7192}, s_{67}, s_{726}, \ldots]$
- Goals
  - Automatically generate new playlists
  - Understand semantic space of songs
    - Query by tag, similar song
  - Visualization



Learning about Products

- Collection of products
  - $P = \{p_1, p_2, p_3, \ldots, p_N\}$
- Example browsing sequences
  - $s_1 = [p_9, p_{527}, p_{12}, \ldots]$
  - $s_2 = [p_{7192}, p_{67}, p_{726}, \ldots]$
- Goals
  - Automatically recommend other items based on session prefix
  - Understand semantic space of products
    - Query by keyword, similar product
  - Visualization



Challenges and Approach

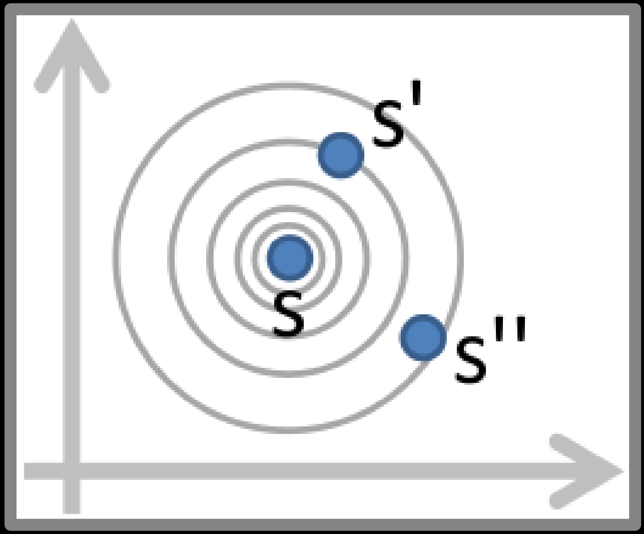
- Challenges
  - Items (i.e. songs, products) don't have good features
    → We would like to generate "style" features
  - Number of items is large
    → Traditional sequence models (e.g., NLP) do not scale
- Approach
  - Model sequences as (k-th order) Markov model
    - $P(s_1, \ldots, s_k) = \prod P(s_i \mid s_{i-1})$
  - Find model for transitions $P(s_i \mid s_{i-1})$ that
    - does not require N^2 storage.
    - generalizes well beyond the observed data.

Logistic Markov Embedding

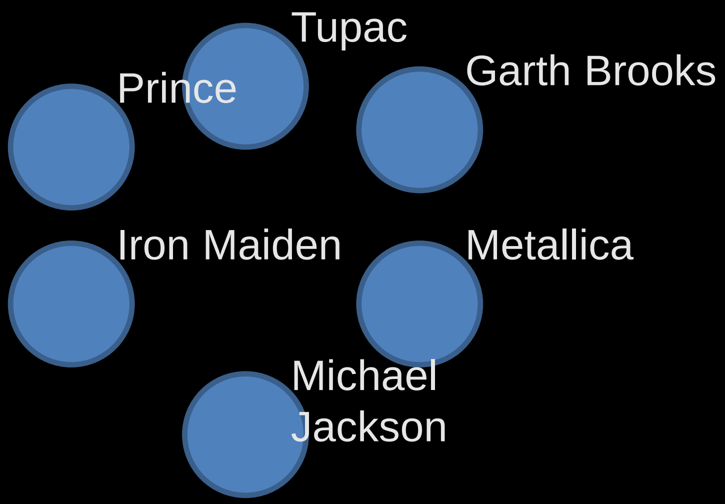
- Model
  - Distance in space ~ transition probability

$$\Pr(p^{[i]}|p^{[i-1]}) = \frac{e^{-||X(p^{[i]})-X(p^{[i-1]})||_2^2}}{\sum_j e^{-||X(p^{[j]})-X(p^{[i-1]})||_2^2}}$$

- Training
  - Maximum likelihood
  - Stochastic gradient
  - O(n) iteration complextiy
    → O(1) iteration complextiy



Learning Song Positions



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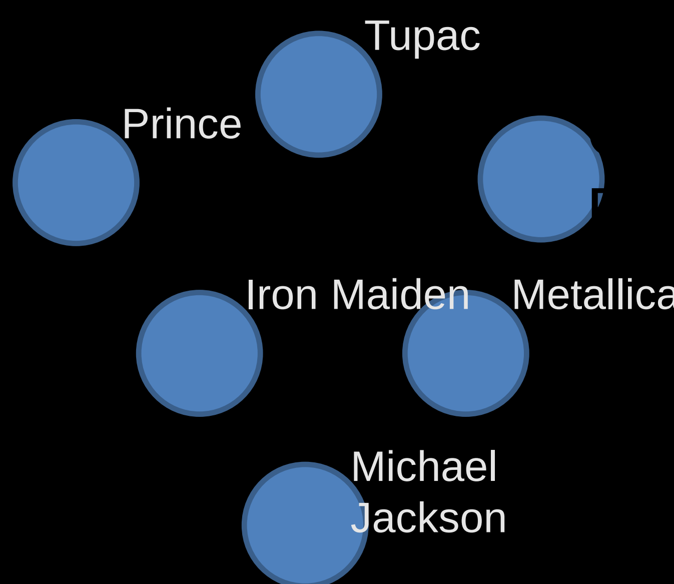

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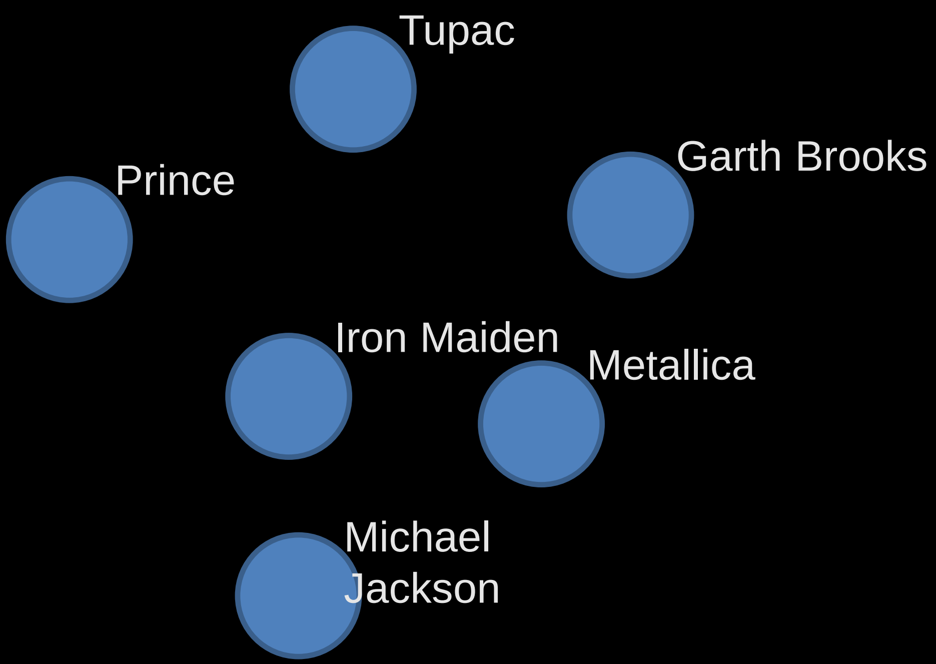

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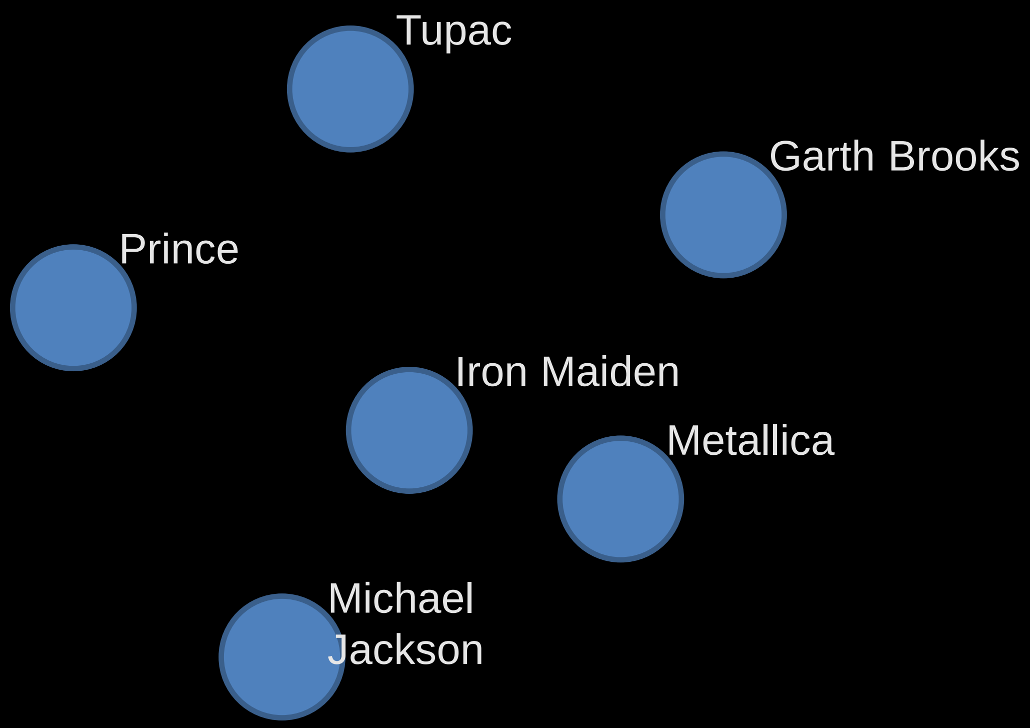

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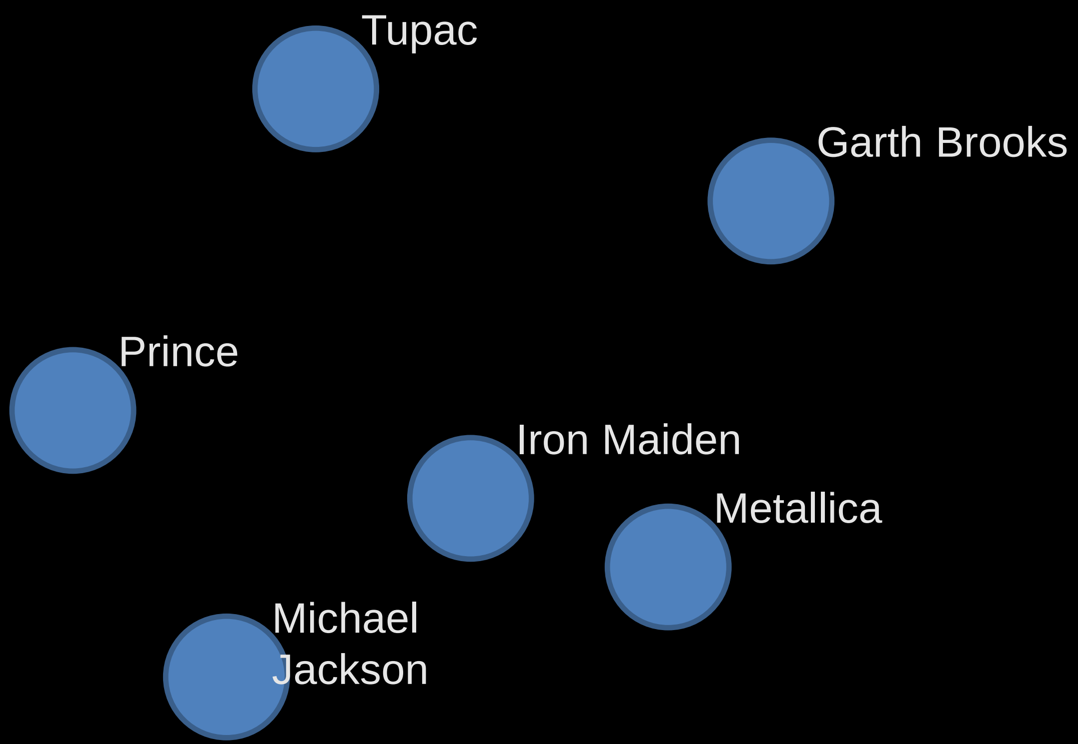
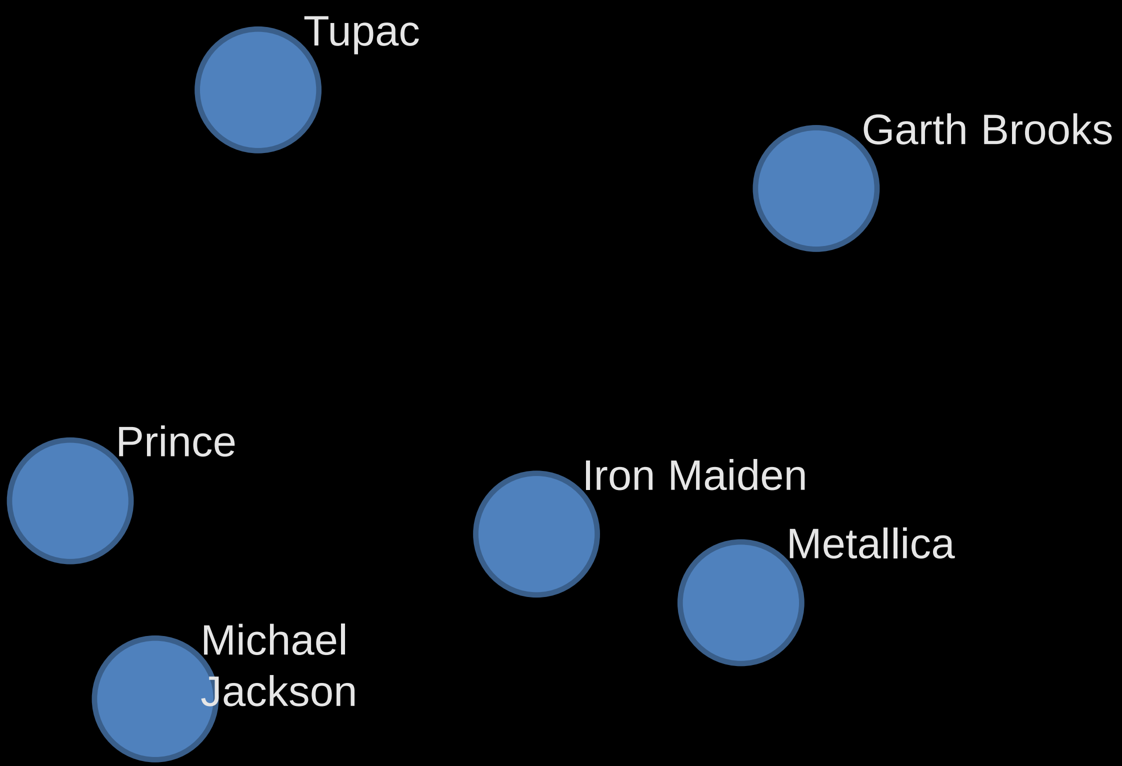
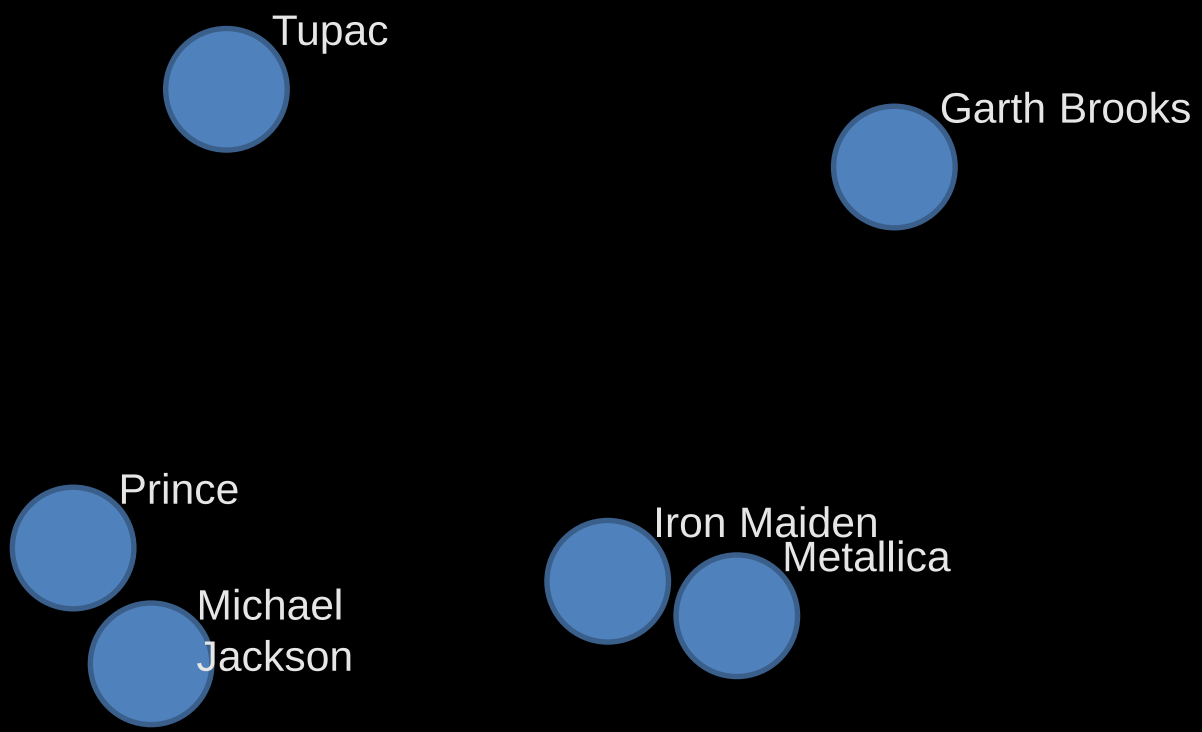


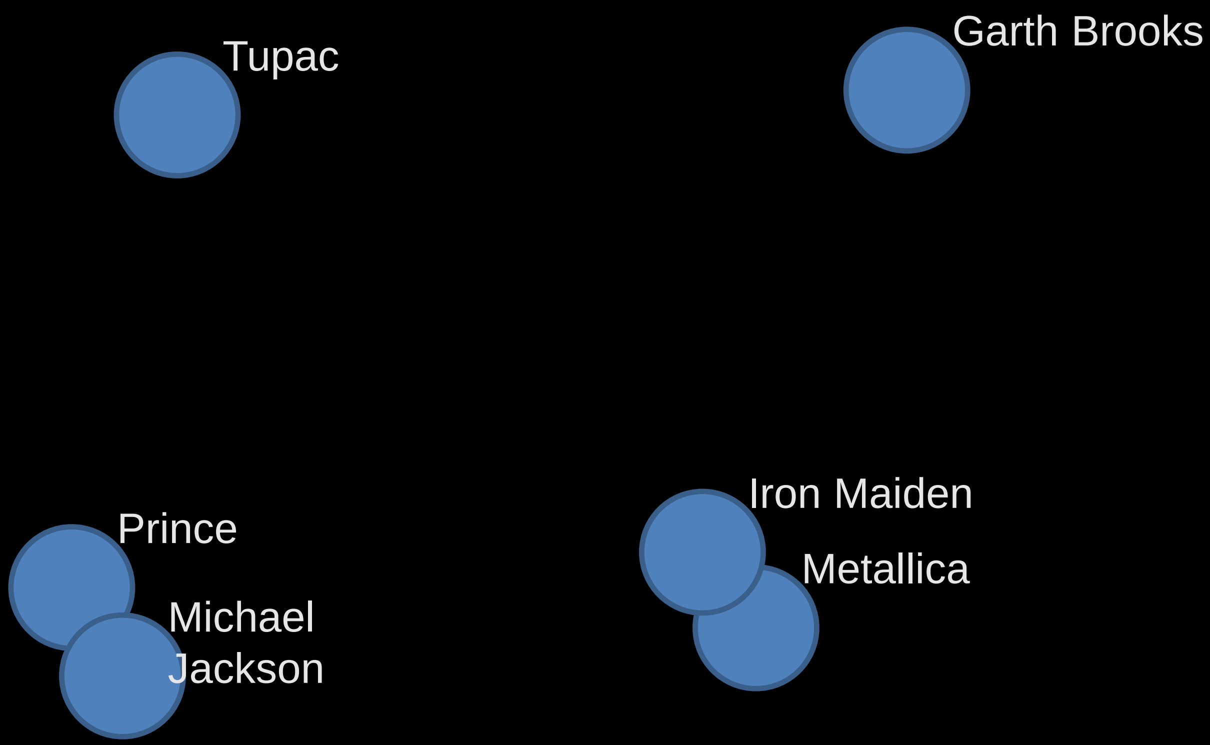
Learning Song Positions



Learning Song Positions

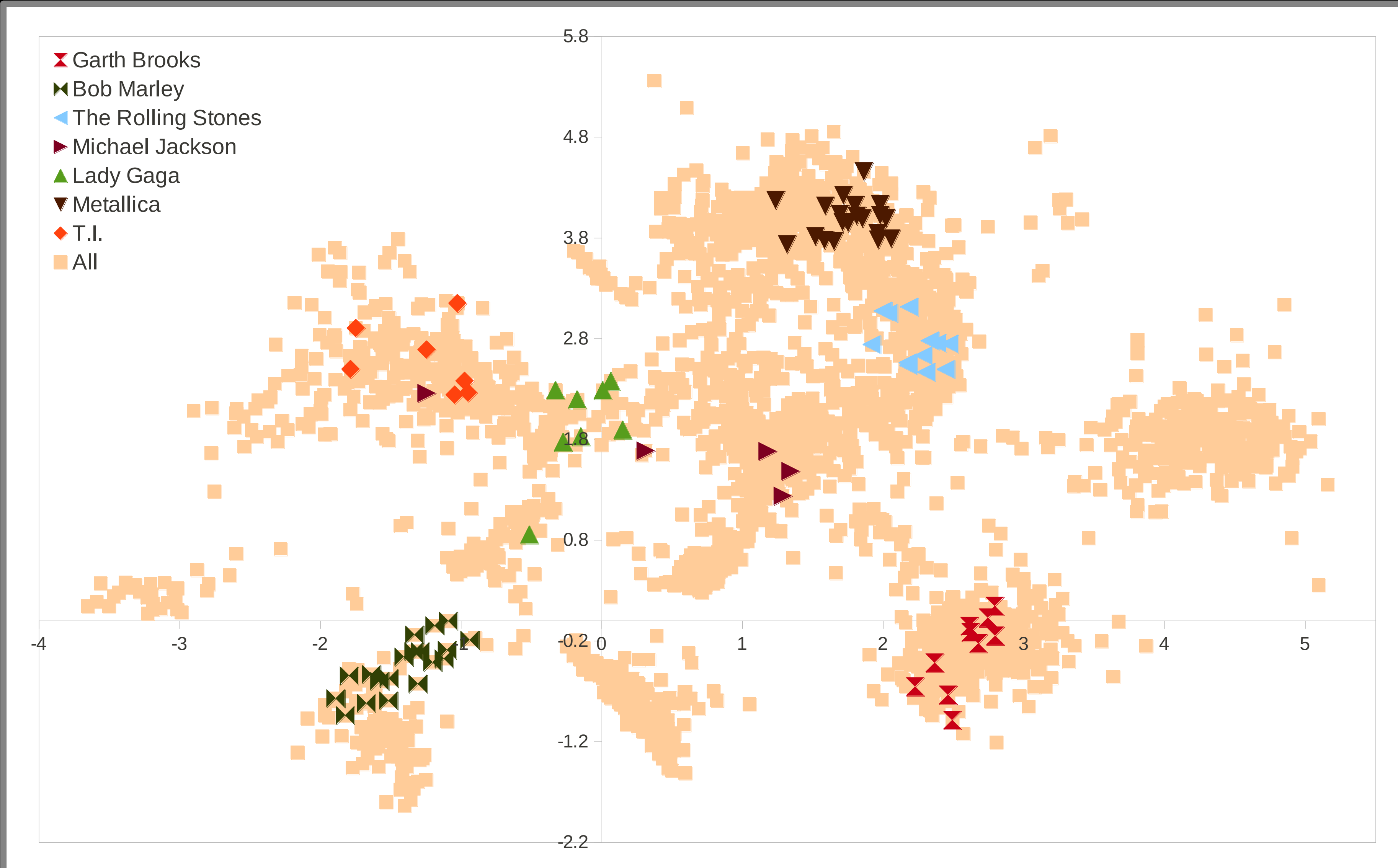


Learning Song Positions

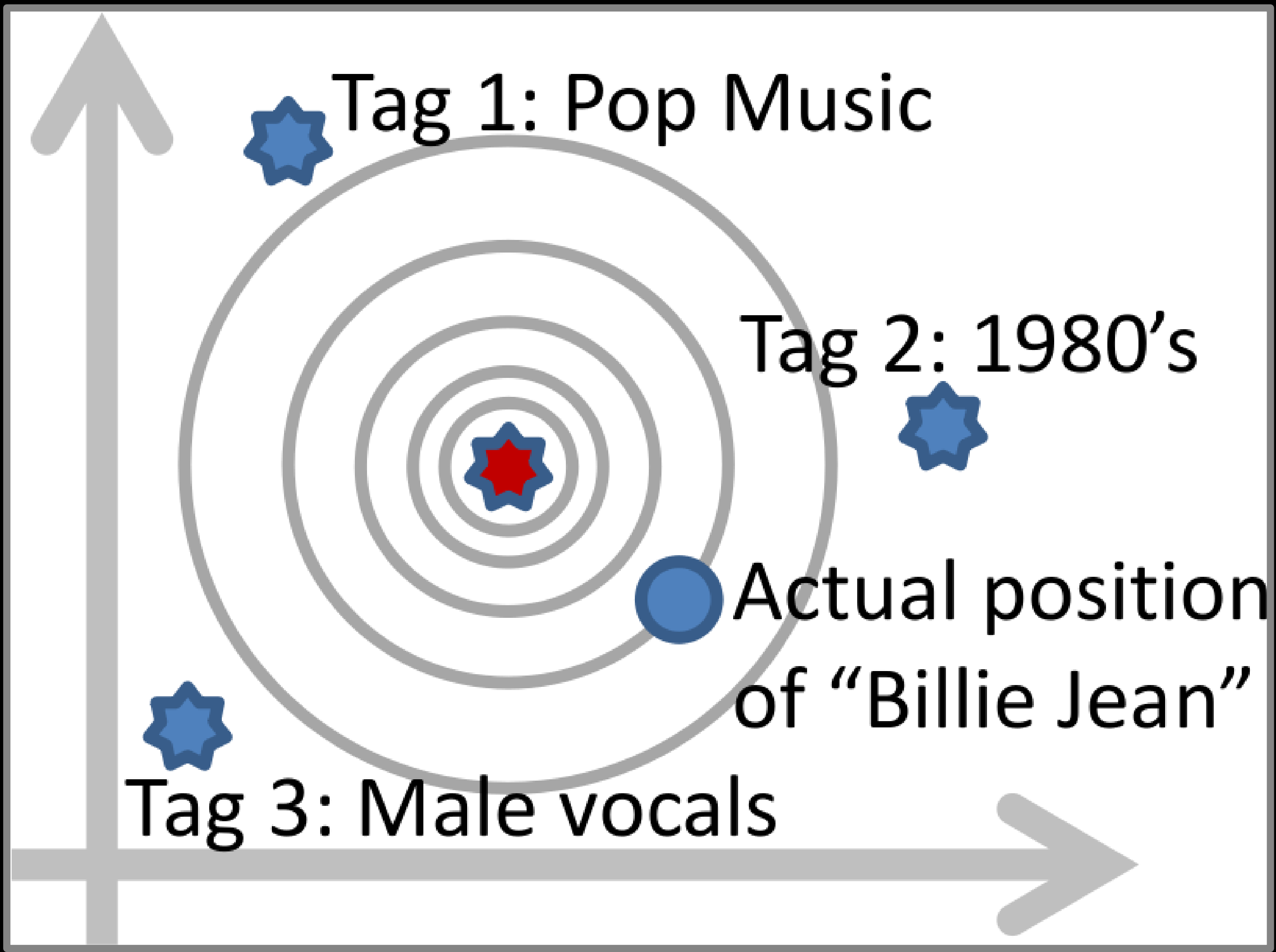


Converged

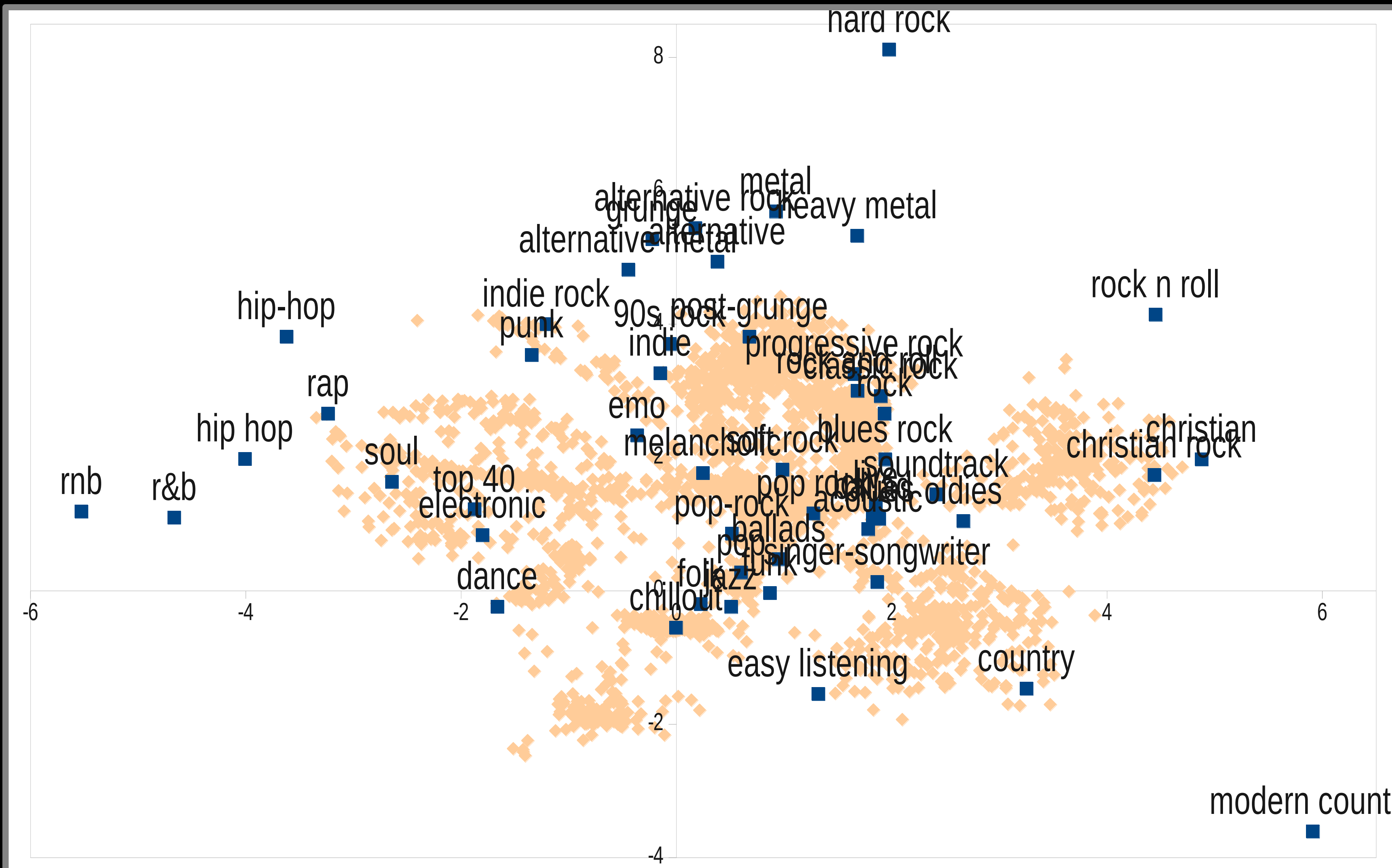
Result: Song Embedding



Extension: Tag Model



Result: Genre Tag Embedding



Overview: Learning Representations

- Methods
  - Embeddings based on sequence data
  - Embeddings based on co-occurrence data
  - Embeddings for bipartite graphs
  - Matrix factorization for rating data
  - Modeling structured objects
  - Modeling compositionality
- Applications
  - Playlist modeling
  - Natural language processing
  - Image search
  - Modeling human behavior

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Goals for this Class

- Deepen your knowledge in three active research areas of ML
- Enable and improve your thesis research
- Practice being a successful academic

→ Class targeted towards current (or soon to be) PhD students!

Pre-Requisites

- This is not an introductory Machine Learning class!
- You need to satisfy one of the following ML pre-reqs:
  - Successfully taken CS4780 "Machine Learning"
  - Successfully taken CS6780 "Advanced Machine Learning"
  - Successfully taken a comparable "Intro to ML" class (*)
  - Acquired the equivalent ML knowledge in some other way (e.g. strong background in Statistics + ML textbook) (*)
- Basic probability and linear algebra
- Programming skills required for many projects

- (*) means talk to me

Format of Class

- Lectures (by TJ)
  - Background material on general ML and 3 topics
- Research paper presentations (by students)
  - Reach current state of the art in each of 3 topics
- Project
  - Semester long, original research project
- Mock funding proposals
  - Develop your own research ideas for the 3 topics
- Peer reviewing

Research Paper Presentations

- Pair of students present the paper in class
  - Slide presentation
  - Create critique, extended bibliography, examples, demo software, experiments etc. that help understand the paper
  - Prepare discussion topics / group activity
  - Prepare quiz
  - Do dry-run of presentation in my office before class (30% of the grade).
- Everybody reads the paper in preparation for class
  - Quiz about each paper
- All students give feedback afterwards.

Mock Funding Proposals

- Write short funding proposal
  - Practice to develop your own research ideas and research plan
  - Practice to justify your research
  - Practice to convince others of your ideas
- Individual or group
- Peer reviewed

Project

- Full Semester Project
  - Topic of your choice that relates to CS6784
  - Scoped to be a publishable paper
  - Individual or group
- Timeline
  - 2/9: Proposal (10 %)
  - 3/16: First status report (10 %)
  - 4/20: Second status report (10 %)
  - 5/1-6: Project presentation (20 %)
  - 5/12: Final project report (50 %)
- At each step peer review
  - 5/18: Peer reviews due for project reports

Credit Options and Grades

- Letter grade:
  - project (40%)
  - paper presentation (20%)
  - in-class assignments and participation (15%)
    - three lowest grades dropped
  - funding proposals (12%)
  - peer reviewing (10%)
  - warm-up assignment (3%)
- Pass/Fail:
  - not allowed, unless you have very good arguments
- Audit:
  - not allowed, unless you have very good arguments

Course Material

- Background Reading
  - K. Murphy, "Machine Learning - a Probabilistic Perspective", MIT Press, 2012. (online via Cornell Library)
  - T. Mitchell, "Machine Learning", McGraw Hill, 1997.
  - B. Schoelkopf, A. Smola, "Learning with Kernels", MIT Press, 2001. (online)
  - C. Bishop, “Pattern Recognition and Machine Learning”, Springer, 2006.
  - R. Duda, P. Hart, D. Stork, "Pattern Classification“, Wiley, 2001.
  - T. Hastie, R. Tishirani, and J. Friedman, "The Elements of Statistical Learning“, Springer, 2001.
  - N. Cristianini, J. Shawe-Taylor, "Introduction to Support Vector Machines", Cambridge University Press, 2000. (online via Cornell Library)
- Slides, Notes and Papers
  - Slides available on course homepage
  - Papers on course homepage

Warm-up Assignment

- Read the paper:
  - C. Cortes, V. Vapnik, “Support Vector Networks”, Machine Learning, 20:273-297, 1995. http://link.springer.com/article/10.1023/A:1022627411411
- Write a short paper that
  - is at most 800 words long
  - is submitted by Tuesday Jan 28 at 11:59pm EST

  and that addresses the following questions:
  - What are the main original contributions described in this paper? Briefly describe the top 3 and argue why those are top.
  - For each original contribution, briefly describe in how far related ideas were already present in earlier papers.
- Peer review

How to Get in Touch

- Course Web Page
  - http://www.cs.cornell.edu/Courses/cs6784/2014sp/
- Email
  - Thorsten Joachims: tj@cs.cornell.edu
  - Joshua Moore: jlmo@cs.cornell.edu
- Office Hours
  - Thursdays 3:00pm – 4:00pm, 418 Gates Hall
- Piazza
  - https://piazza.com/cornell/spring2014/cs6784
- Peer reviewing platform
  - TBA