PETUUM

Carnegie Mellon University
School of Computer Science

Probabilistic Graphical Models

Spectral Learning for Graphical Models

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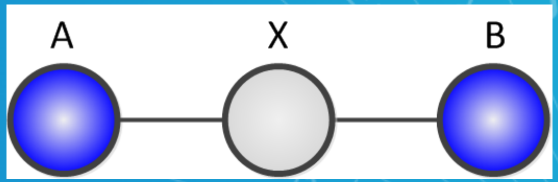
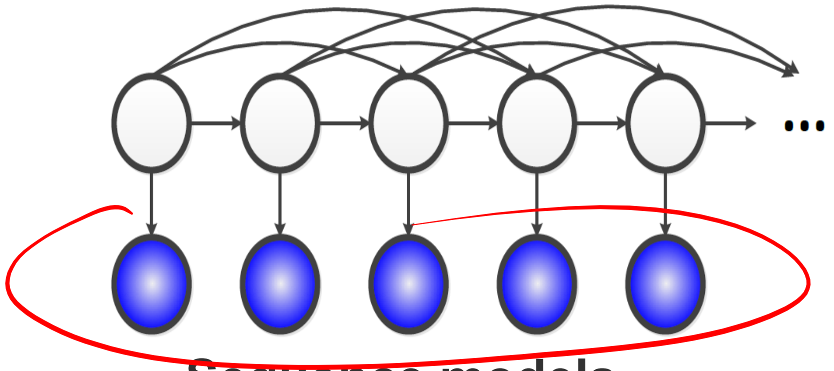
Lecture 25, April 17, 2019



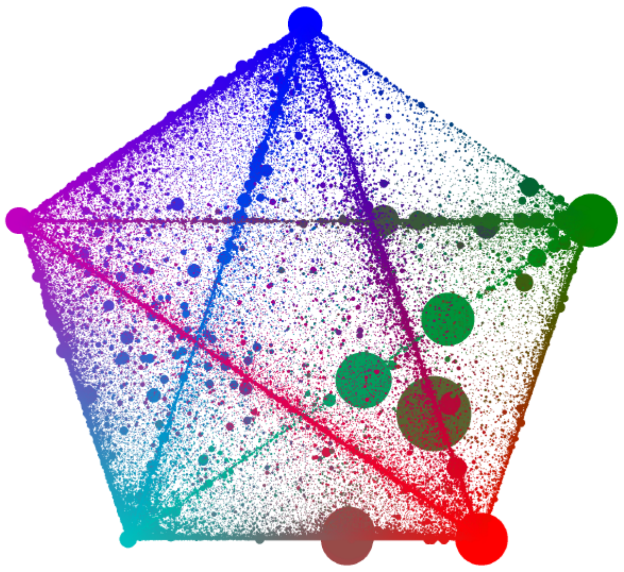
Reading: see class homepage

Acknowledgement: slides drafted by Ankur Parikh

Latent Variable Models



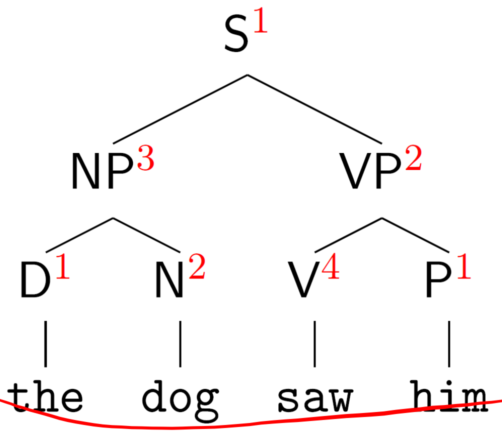
Sequence models



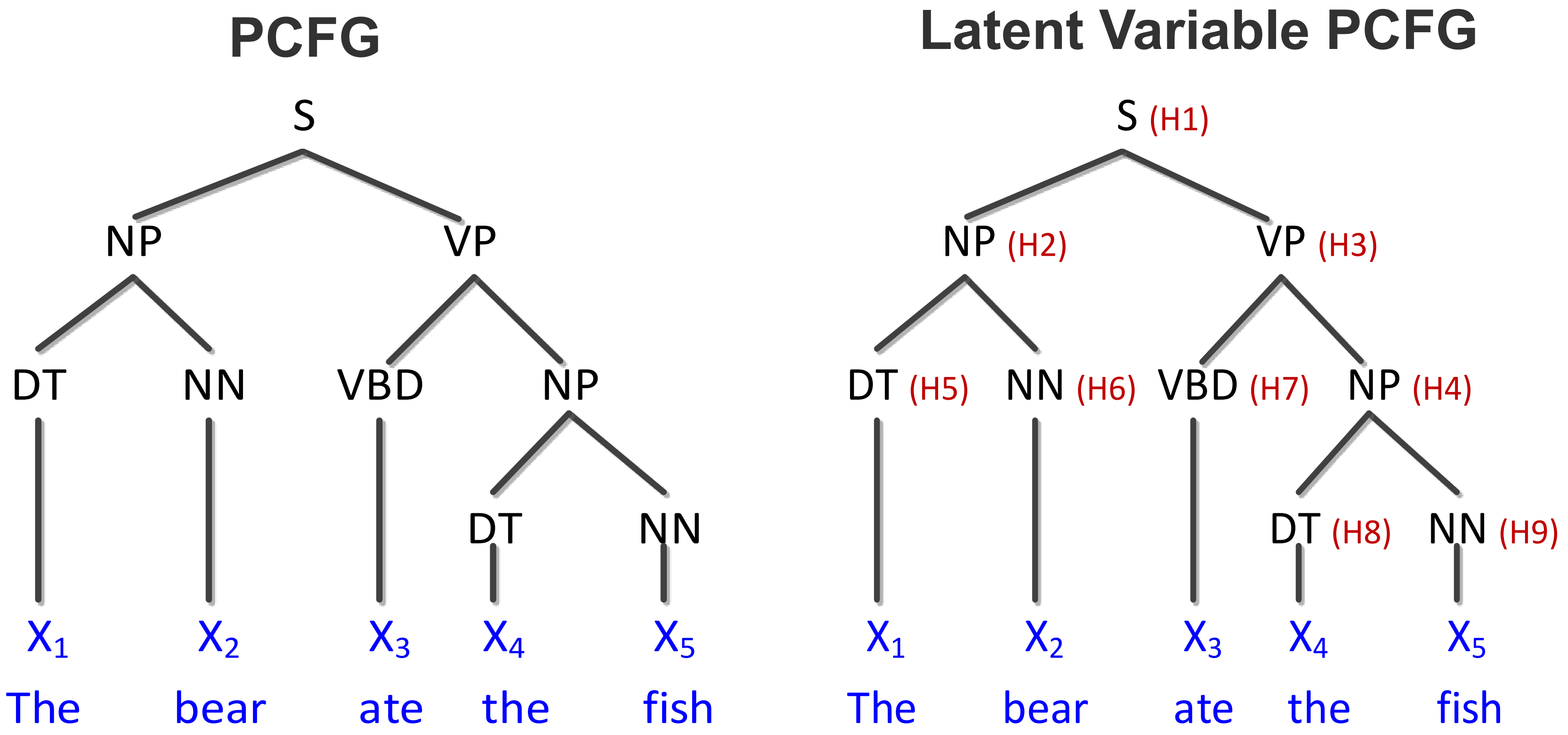
Ho. et al. 2012

Mixed membership models

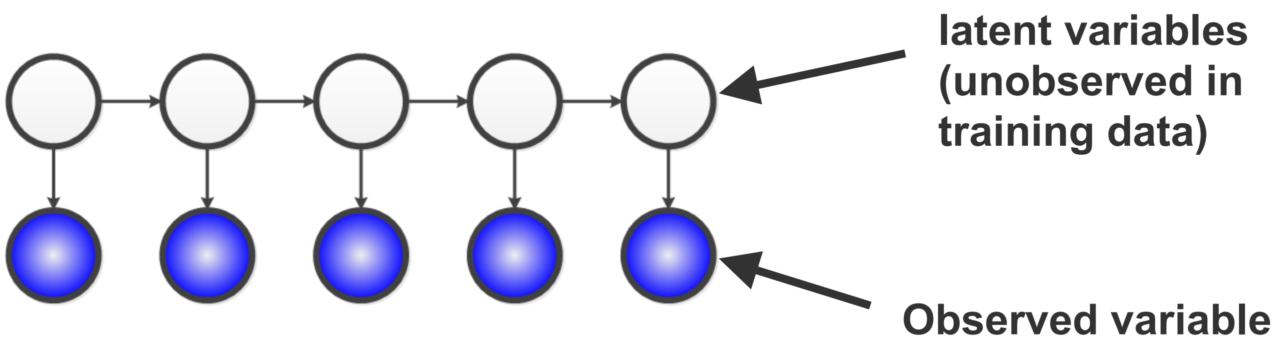
Parsing



Latent Variable PCFG [Matsuzaki et al., 2005, Petrov et al. 2006]



Learning Parameters (EM)



$$\mathbb{P}[X_1, ..., X_5, H_1, ..., H_5] = \mathbb{P}[H_1] \prod_{i=2}^{5} \mathbb{P}[H_i | H_{i-1}] \prod_{i=1}^{5} \mathbb{P}[X_i | H_i]$$

Since latent variables are not observed in the data, we have to use Expectation Maximization (EM) to learn parameters

- Slow
- Local Minima

Spectral Learning

- Different paradigm of learning in latent variable models based on linear algebra

- Theoretically,
  - Provably consistent
  - Can offer deeper insight into the identifiability

- Practically,
  - Local minima free
  - As of now, performs comparably to EM with 10-100x speed-up
  - Can also model non-Gaussian continuous data using kernels (usually performs much better than EM in this case)

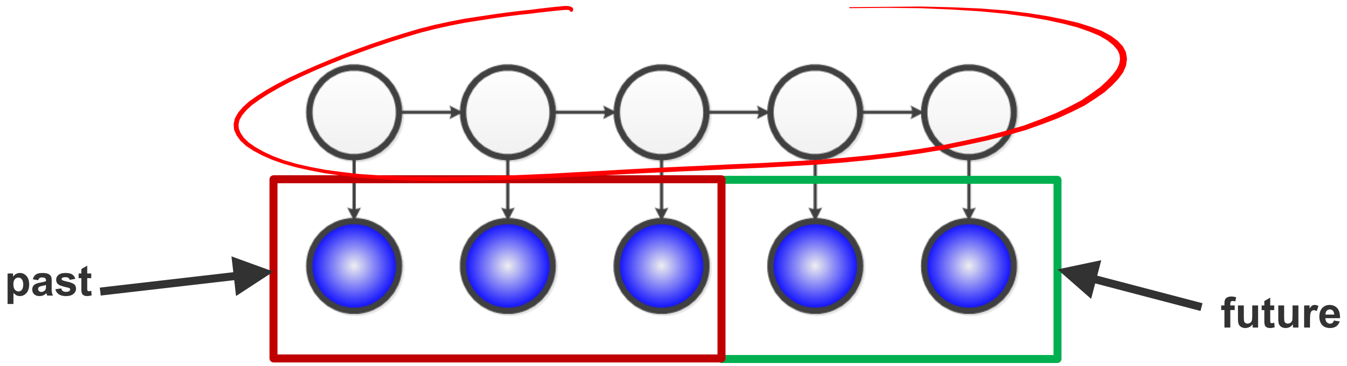
Related References

- Relevant works
  - Hsu et al. 2009 – Spectral HMMs (also Bailly 2009)
  - Siddiqi et al. 2009 – Features in Spectral Learning
  - Parikh et al. 2011/2012 –Tensors to Generalize to Trees/Low Treewidth Graphs
  - Cohen et al. 2012 / 2013 – Spectral Learning of latent PCFGs

- Will present it from "matrix factorization" view:
  - Balle et al. 2012 – Connection between Spectral Learning / Hankel Matrix Factorization
  - Song et al. 2013 – Spectral Learning as Hierarchical Tensor Decomposition

Focusing on Prediction

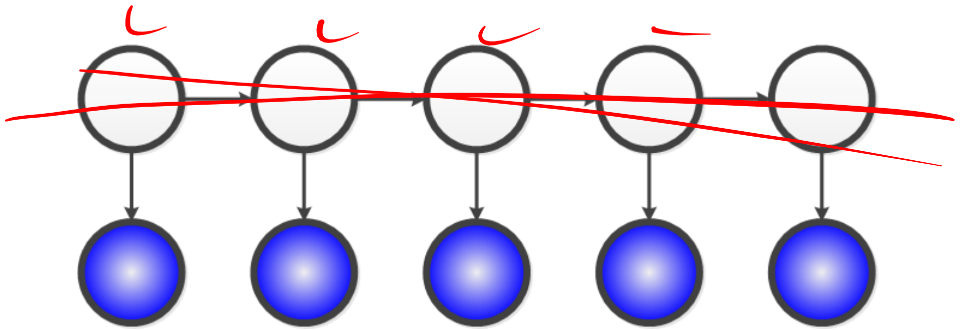
- In many applications that use latent variable models, the end task is not to recover the latent states, but rather to use the model for prediction among observed variables.
- Dynamical Systems – Predict future given past



Focusing on Prediction

- We will only be concerned with quantities related to the observed variables: $$\mathbb{P}[X_1, X_2, X_3, X_4, X_5]$$

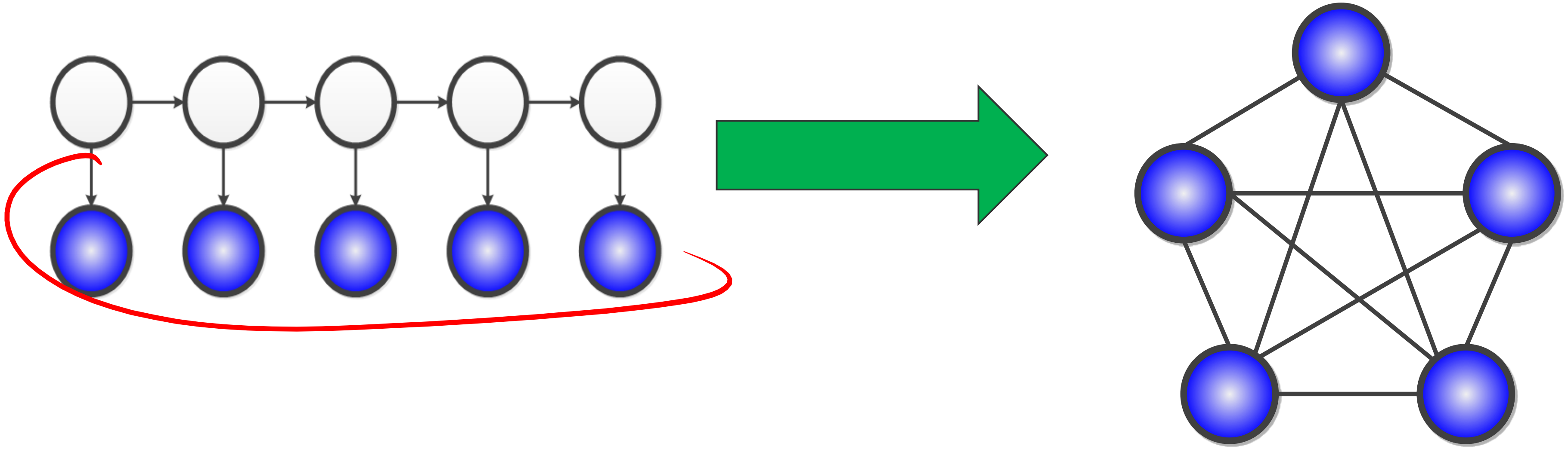
- We do not care about the latent variables explicitly.



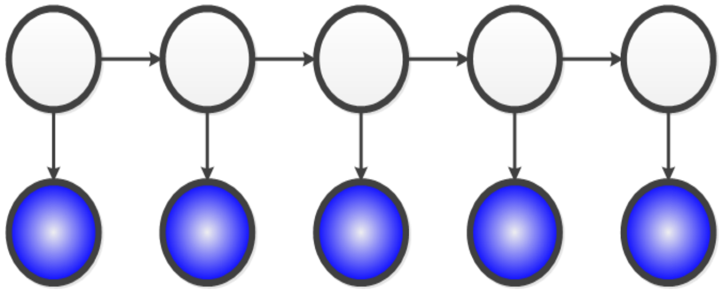
- Do we still need EM to learn the parameters?

But if we don't care about the latent variables....

- Why don't we just integrate them out?
- Because integrating them out results in a clique ☹



Marginal Does Not Factorize



$$\mathbb{P}[X_1, X_2, X_3, X_4, X_5] = \sum_{H_1,\ldots,H_5} \mathbb{P}[H_1]\mathbb{P}[H_1] \prod_{i=2}^{5} \mathbb{P}[H_i|H_{i-1}] \prod_{i=1}^{5} \mathbb{P}[X_i|H_i]$$

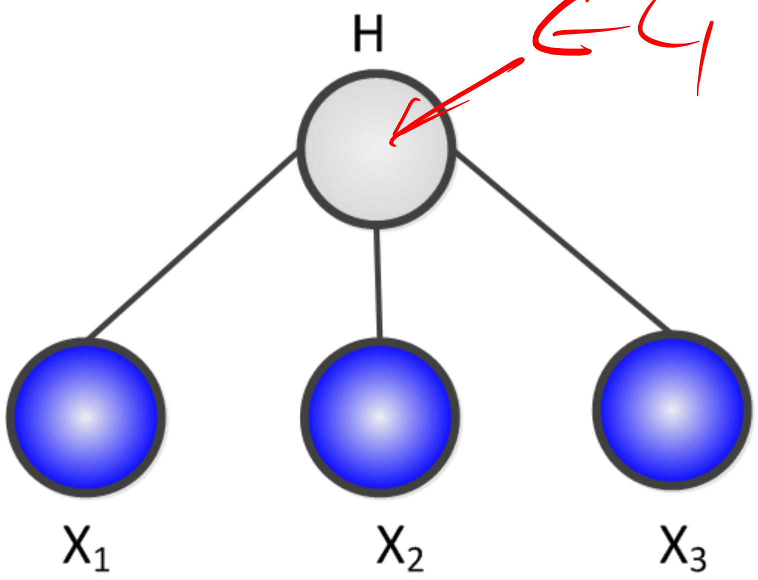
Does not factorize due to the outer sum (Can somewhat distribute the sum, but doesn't solve problem)

But isn't an HMM different from a clique?

- It depends on the number of latent states.

- Consider the following model.

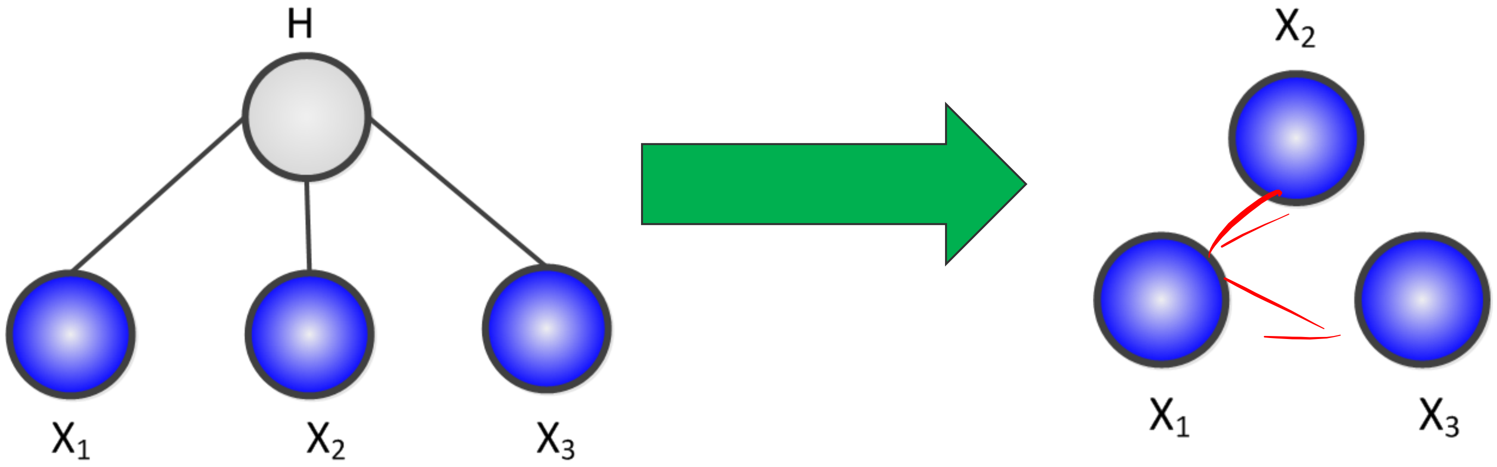
$\in [4]$



$P(X_1 X_2 X_3)$

If H has only one state.....

- Then the observed variables are independent!

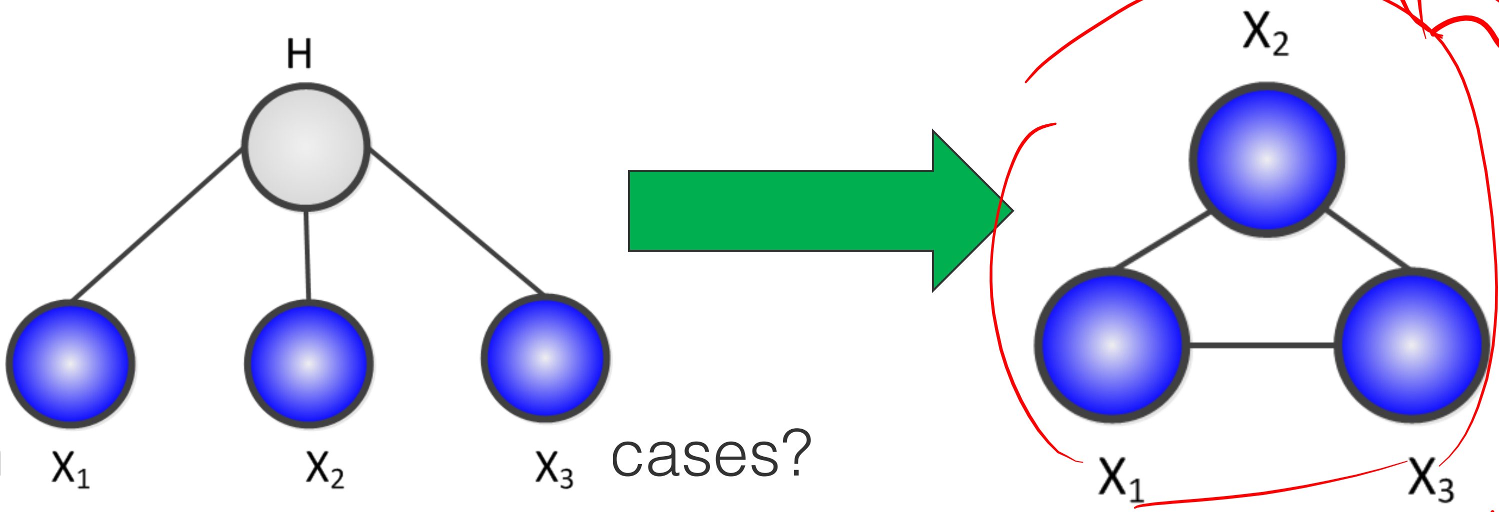


m^3

$P(X_1 X_2 X_3 | H_1)$

What if H has many states?

- Let us say the observed variables each have *m* states.
- Then if H has m^3 states then the latent model can be exactly equivalent to a clique (depending on how parameters are set).



- But wh... cases?

$|H| = m^3$

$p(x_1, x_2, x_3) = \phi \quad \psi$

The Question

- Under existing methods, latent models all require EM to learn regardless of the number of hidden states.

- However, is there a formulation of latent variable models where the difficulty of learning is a function of the number of latent states?

- This is the question that the *spectral view* will answer.

Sum Rule (Matrix Form)

- Sum Rule

$$\mathbb{P}[X] = \sum_Y \mathbb{P}[X|Y]\mathbb{P}[Y]$$

- Equivalent view using Matrix Algebra

$$\mathcal{P}[X] = \mathcal{P}[X|Y] \times \mathcal{P}[Y]$$

$$\begin{pmatrix} \mathbb{P}[X=0] \\ \mathbb{P}[X=1] \end{pmatrix} = \begin{pmatrix} \mathbb{P}[X=0|Y=0] & \mathbb{P}[X=0|Y=1] \\ \mathbb{P}[X=1|Y=0] & \mathbb{P}[X=1|Y=1] \end{pmatrix} \times \begin{pmatrix} \mathbb{P}[Y=0] \\ \mathbb{P}[Y=1] \end{pmatrix}$$

Chain Rule (Matrix Form)

- Chain Rule

$$\mathbb{P}[X,Y] = \mathbb{P}[X|Y]\mathbb{P}[Y] = \mathbb{P}[Y|X]\mathbb{P}[Y]$$

Means on diagonal

- Equivalent view using Matrix Algebra

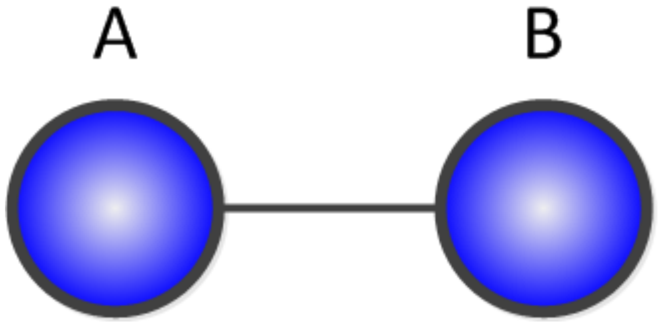
$$\mathcal{P}[X,Y] = \mathcal{P}[X|Y] \times \mathcal{P}[\oslash Y]$$

$$\begin{pmatrix} \mathbb{P}[X=0,Y=0] & \mathbb{P}[X=0,Y=1] \\ \mathbb{P}[X=1,Y=0] & \mathbb{P}[X=1,Y=1] \end{pmatrix} = \begin{pmatrix} \mathbb{P}[X=0|Y=0] & \mathbb{P}[X=0|Y=1] \\ \mathbb{P}[X=1|Y=0] & \mathbb{P}[X=1|Y=1] \end{pmatrix} \times \begin{pmatrix} \mathbb{P}[Y=0] & 0 \\ 0 & \mathbb{P}[Y=1] \end{pmatrix}$$

- Note how diagonal is used to keep Y from being marginalized out.

Graphical Models: The Linear Algebra View

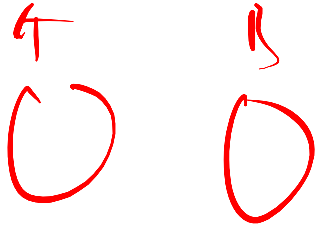
- In general, nothing we can say about the nature of this matrix.



$$\mathcal{P}[A, B]$$

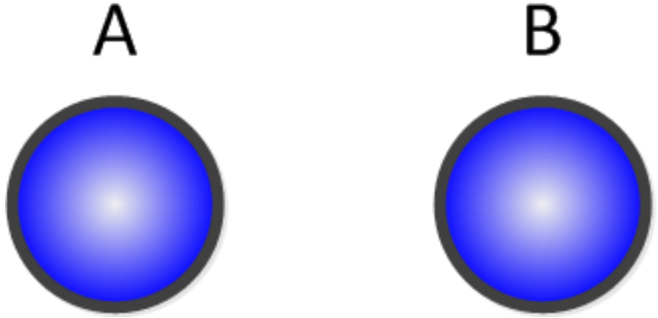
A and B have m states each.

Independence: The Linear Algebra View

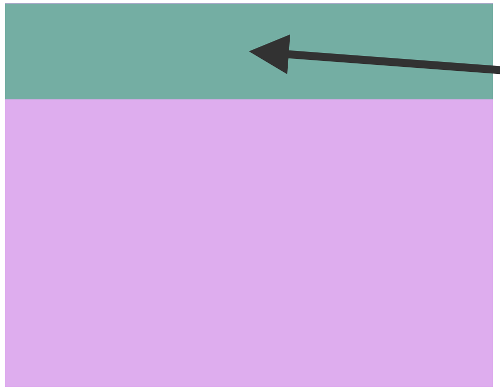


P(A, B)

- What if we know A and B are independent?



$$\mathcal{P}[A, B]$$



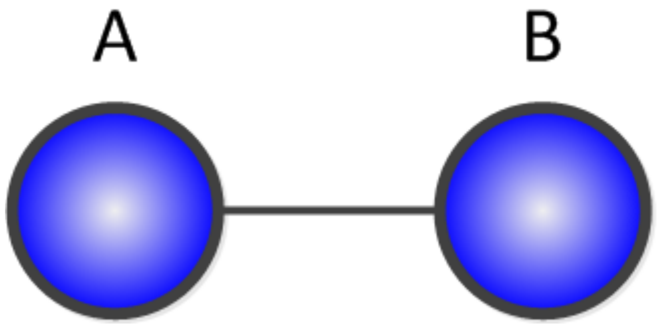
$$\left(\mathbb{P}[A = 1, B = 1], \ldots, \mathbb{P}[A = 1, B = m]\right)$$

$$= \left(\mathbb{P}[A = 1](\mathbb{P}[B = 1], \ldots, \mathbb{P}[B = m])\right)$$

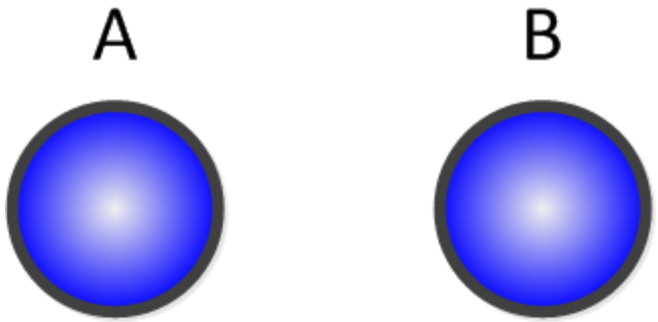
- Joint probability matrix is rank one, since all rows are multiples of one another!!

Independence and Rank

- What about rank in between 1 and m?



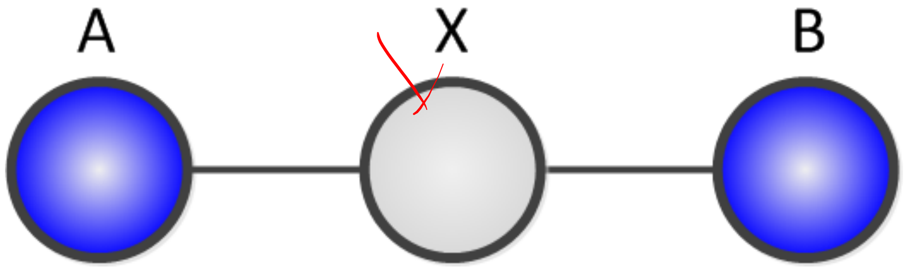
$\mathcal{P}[A, B]$ **has rank m (at most)**



$\mathcal{P}[A, B]$ **has rank 1**

Low Rank Structure

- *A* and *B* are not marginally independent (They are only conditionally independent given *X*).

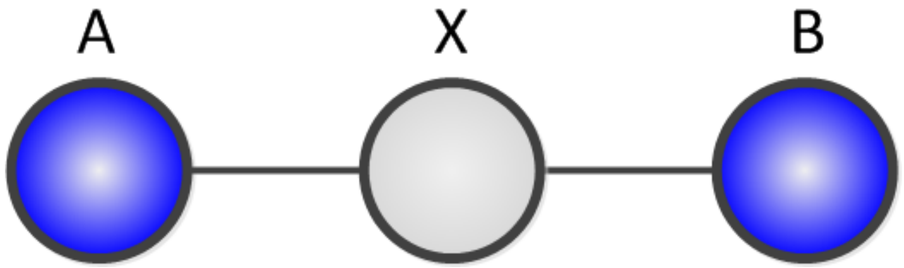


- Assume *X* has *k* states (while *A* and *B* have *m* states).
- Then,

$$rank(\mathcal{P}[A, B]) \leqslant k$$

- Why?

Low Rank Structure



$$\mathcal{P}[A,B] = \mathcal{P}[A|X]\,\mathcal{P}(\oslash X)\,\mathcal{P}[B|X]^\top$$

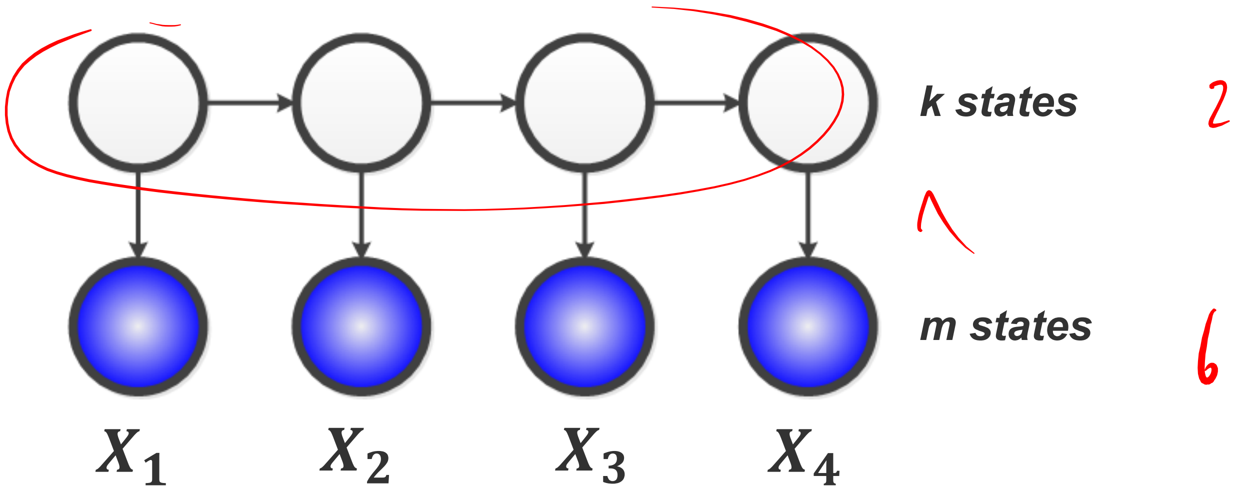
$rank \leq k$ $\quad$ $rank \leq k$ $\quad$ $rank \leq k$ $\quad$ $rank \leq k$

The Spectral View

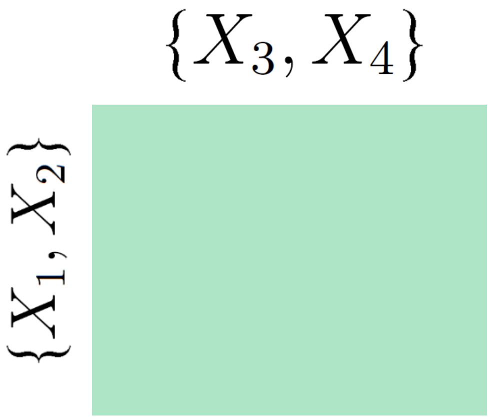
- Latent variable models encode low rank dependencies among variables *(both marginal and conditional)*

- Use tools from linear algebra to exploit this structure.
  - Rank
  - Eigenvalues
  - SVD
  - Tensors

A More Interesting Example



$$\mathcal{P}[X_{\{1,2\}}, X_{\{3,4\}}]$$



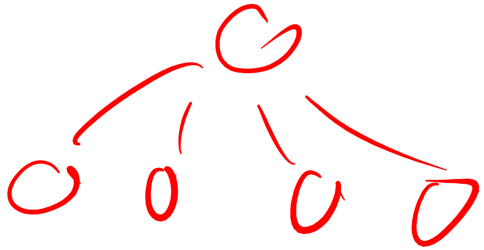
has rank k

Low Rank Matrices "Factorize"

$$M = LR$$

m by n m by k k by n

If M has rank **k**



We already know one factorization!!!

k

$$\mathcal{P}[X_{\{1,2\}}, X_{\{3,4\}}] = \boxed{\mathcal{P}[X_{\{1,2\}}|H_2]}\mathcal{P}[\oslash H_2]\mathcal{P}[X_{\{3,4\}}|H_2]^\top$$

Factor of 4 variables Factor of 3 variables Factor of 3 variables

Factor of 1 variable

Alternate Factorizations

- The key insight is that this factorization is not unique.
- Consider Matrix Factorization. Can add any invertible transformation:

$$M = LR$$
$$M = LSS^{-1}R$$

- The magic of spectral learning is that there exists an alternative factorization that only depends on observed variables!

An Alternate Factorization

- Let us say we only want to factorize this matrix of 4 variables

$$\mathcal{P}[X_{\{1,2\}}, X_{\{3,4\}}]$$

such that it is product of matrices that contain at most three *observed* variables e.g.

$$\mathcal{P}[X_{\{1,2\}}, X_3]$$

$$\mathcal{P}[X_2, X_{\{3,4\}}]$$

An Alternate Factorization

p(x1 x2 x3 x4)

- Note that

$$\mathcal{P}[X_{\{1,2\}}, X_3] = \mathcal{P}[X_{\{1,2\}}|H_2]\mathcal{P}[\oslash H_2]\mathcal{P}[X_3|H_2]^\top$$
$$\mathcal{P}[X_2, X_{\{3,4\}}] = \mathcal{P}[X_2|H_2]\mathcal{P}[\oslash H_2]\mathcal{P}[X_{\{3,4\}}|H_2]^\top$$

p(x2, x3)

- Product of green terms (in some order) is

$$\mathcal{P}[X_{\{1,2\}}, X_{\{3,4\}}]$$

- Product of red terms (in some order) is

$$\mathcal{P}[X_2, X_3]$$

An Alternate Factorization

$$\underbrace{\mathcal{P}[X_{\{1,2\}}, X_{\{3,4\}}]}_{\text{factor of 4 variables}} = \underbrace{\mathcal{P}[X_{\{1,2\}}, X_3]}_{\text{factor of 3 variables}} \underbrace{\mathcal{P}[X_2, X_3]^{-1}\mathcal{P}[X_2, X_{\{3,4\}}]}_{\text{factor of 3 variables}}$$

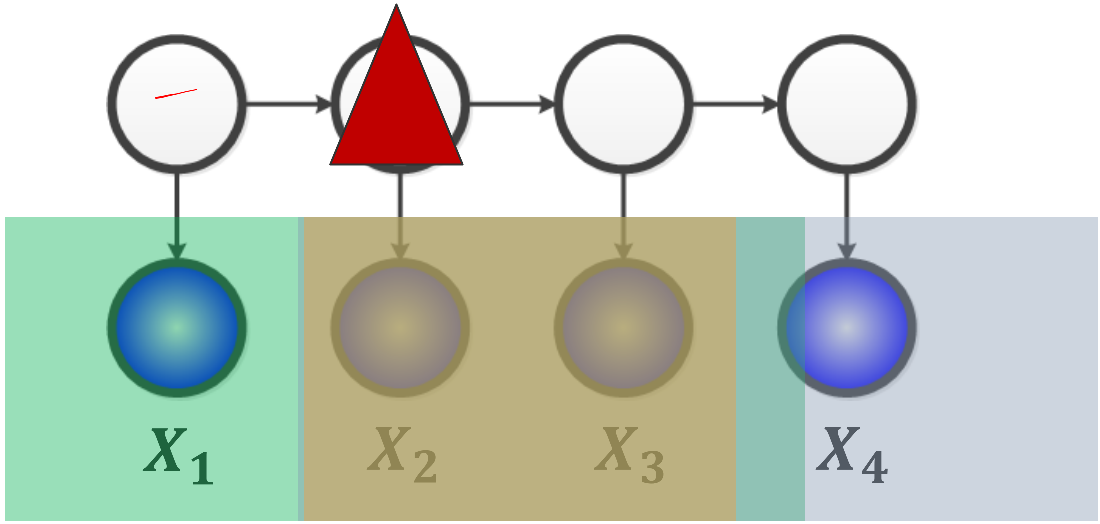
Advantage: Factors are only functions of observed variables! Can be directly computed from data without EM!!!!

Caveat: some factors are no longer probability tables (do not have to be non-negative)

We will call this factorization the observable factorization.

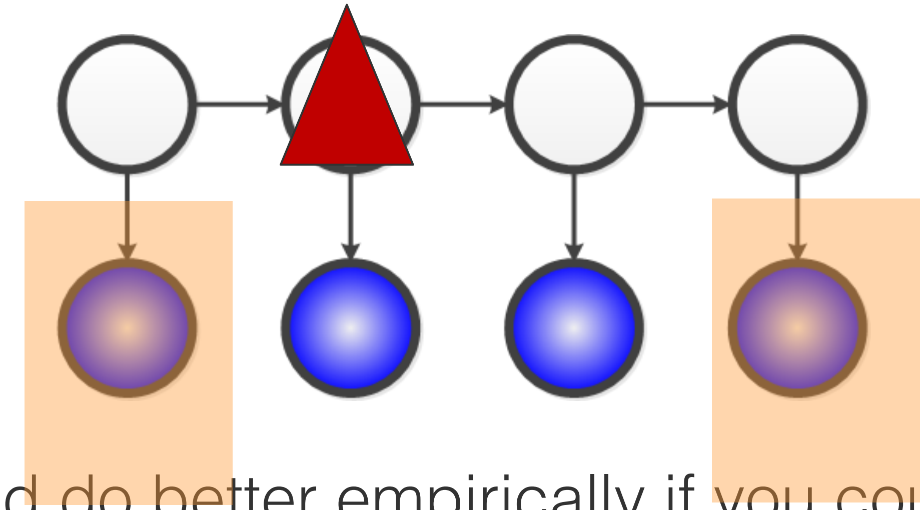
Graphical Relationship

$$\mathcal{P}[X_{\{1,2\}}, X_{\{3,4\}}] = \underline{\mathcal{P}[X_{\{1,2\}}, X_3]}\,\underline{\mathcal{P}[X_2, X_3]^{-1}}\,\underline{\mathcal{P}[X_2, X_{\{3,4\}}]}$$



Another Factorization

$$\mathcal{P}[X_{\{1,2\}}, X_{\{3,4\}}] = \mathcal{P}[X_{\{1,2\}}, X_4]\mathcal{P}[X_1, X_4]^{-1}\mathcal{P}[X_1, X_{\{3,4\}}]$$



- Seems we would do better empirically if you could "combine" both factorizations. Will come back to this later.

Relationship to Original Factorization

- What is the relationship between the original factorization and the new factorization?

$$\underbrace{\mathcal{P}[X_{\{1,2\}}, X_{\{3,4\}}]}_{\boldsymbol{M}} = \underbrace{\mathcal{P}[X_{\{1,2\}}|H_2]\mathcal{P}[\oslash H_2]}_{\boldsymbol{L}}\underbrace{\mathcal{P}[X_{\{3,4\}}|H_2]^\top}_{\boldsymbol{R}}$$

$$\boldsymbol{M} = \boldsymbol{L}\boldsymbol{R}$$

$$\boldsymbol{M} = \boldsymbol{L}\boldsymbol{S}\boldsymbol{S}^{-1}\boldsymbol{R}$$

Can I choose S to get the observable factorization?

Relationship to Original Factorization

- Let

$$\boldsymbol{S} := \mathcal{P}[X_3|H_2]$$

$$\mathcal{P}[X_{\{1,2\}}, X_{\{3,4\}}] = \underbrace{\mathcal{P}[X_{\{1,2\}}, X_3]}_{= \boldsymbol{LS}} \underbrace{\mathcal{P}[X_2, X_3]^{-1}\mathcal{P}[X_2, X_{\{3,4\}}]}_{= \boldsymbol{S}^{-1}\boldsymbol{R}}$$

$$\mathcal{P}[X_{\{1,2\}}, X_{\{3,4\}}] = \mathcal{P}[X_{\{1,2\}}|H_2]\mathcal{P}[\oslash H_2]\mathcal{P}[X_{\{3,4\}}|H_2]^\top$$

Our Alternative Factorization

$$\underbrace{\mathcal{P}[X_{\{1,2\}}, X_{\{3,4\}}]}_{\text{factor of 4 variables}} = \underbrace{\mathcal{P}[X_{\{1,2\}}, X_3]}_{\text{factor of 3 variables}} \mathcal{P}[X_2, X_3]^{-1} \underbrace{\mathcal{P}[X_2, X_{\{3,4\}}]}_{\text{factor of 3 variables}}$$

- It may not seem very amazing at the moment (we have only reduced the size of the factor by 1)
- What is cool is that every latent tree of V variables has such a factorization where:
  - All factors are of size 3
  - All factors are only functions of observed variables

Generalizing To More Variables

- Consider HMM with 5 observations. Using similar arguments as before we will get that:

$$\mathcal{P}[X_{\{1,2\}}, X_{\{3,4,5\}}] = \mathcal{P}[X_{\{1,2\}}, X_3]\mathcal{P}[X_2, X_3]^{-1}\mathcal{P}[X_2, X_{\{3,4,5\}}]$$

reshape and decompose recursively

$$\mathcal{P}[X_{\{2,3\}}, X_{\{4,5\}}] = \mathcal{P}[X_{\{2,3\}}, X_4]\mathcal{P}[X_3, X_4]^{-1}\mathcal{P}[X_3, X_{\{4,5\}}]$$

Training / Testing with Spectral Learning

- We have that

$$\mathcal{P}[X_{\{1,2\}}, X_{\{3,4\}}] = \mathcal{P}[X_{\{1,2\}}, X_3]\mathcal{P}[X_2, X_3]^{-1}\mathcal{P}[X_2, X_{\{3,4\}}]$$

- In training, we compute estimates:

$$\mathcal{P}_{MLE}[X_{\{1,2\}}, X_3] \quad \mathcal{P}_{MLE}[X_2, X_3]^{-1} \quad \mathcal{P}_{MLE}[X_2, X_{\{3,4\}}]$$

- In test time, we can compute probability estimates (let lowercase letters denote fixed evidence values):

$$\widehat{\mathbb{P}}_{spec}[x_1, x_2, x_3, x_4] = \mathcal{P}_{MLE}[x_{\{1,2\}}, X_3]\mathcal{P}_{MLE}[X_2, X_3]^{-1}\mathcal{P}_{MLE}[X_2, x_{\{3,4\}}]^{\top}$$

Consistency

- A trivial consistent estimator is to simply attempt to estimate the "big" probability table from the data without making any conditional independence assumptions

$$\mathcal{P}_{MLE}[X_1, X_2; X_3, X_4] \rightarrow \mathcal{P}[X_1, X_2; X_3, X_4]$$

as number of samples increases

- While this is consistent, it is not very statistically efficient

Unsupervised Parsing

Training Set – Given sentences and part-of-speech tags

DT NN VB NN
The bear likes fish

DT NN VB DT NN
The llama eats the grass

Test Set – Find (unlabeled) parse tree for each sentence

NN ADV VB NN CONJ NN
Lions quickly chase deer and antelope

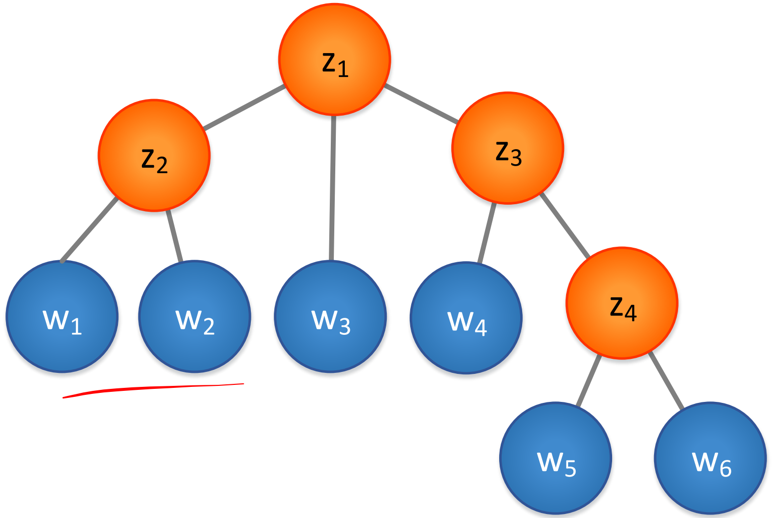
Parse tree structure is a *latent* variable

Conditional Latent Tree Model

- Each tag sequence $\boldsymbol{x}$ associated with a latent tree

$$p(\boldsymbol{w}, \boldsymbol{z} \mid \boldsymbol{x}) = \prod_{i=1}^{H} p(z_i \mid \pi_{\boldsymbol{x}}(z_i)) \times \prod_{i=1}^{\ell(x)} p(w_i \mid \pi_{\boldsymbol{x}}(w_i))$$

$\boldsymbol{x}_2 = (DT, NN, VBD, DT, ADJ, NN)$



The bear ate the big fish

The moose ran the tiring race

- Traditional Approach

Training

(Given the latent tree) Estimate parameters using *nonconvex optimization*:

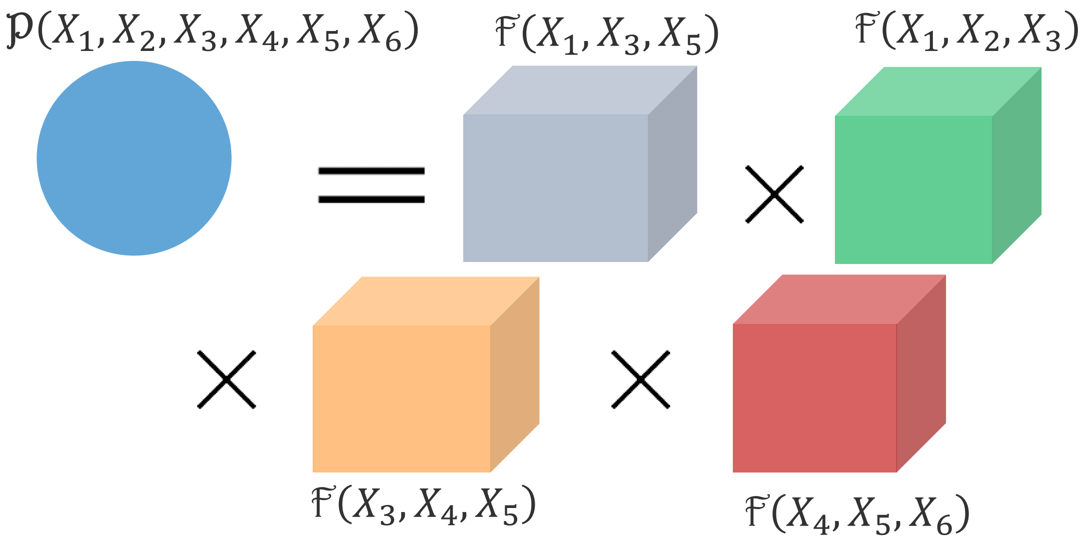
$\hat{P}(H_1)$ $\hat{P}(X_1|H_2)$ $\hat{P}(X_5|H_4)$ .....

Test

To query probabilities: $\mathbb{P}(X_1 = 0, \ldots X_6 = 1)$
multiply learned parameters

The Spectral Approach

Latent Tree ***Observable*** Factorization



Training

Estimate alternate parameters:

$\mathcal{F}(X_1, X_2, X_3)$ $\mathcal{F}(X_1, X_3, X_5)$ $\mathcal{F}(X_3, X_4, X_5)$ $\mathcal{F}(X_4, X_5, X_6)$

Test

To query probabilities: $\mathcal{P}(X_1 = 0, \ldots X_6 = 1)$
tensor multiply parameters

Consistency

- A better estimate is to compute likelihood estimates of the factorization:

$$\mathcal{P}_{MLE}[X_{\{1,2\}}|H_2]\mathcal{P}_{MLE}[\oslash H_2]\mathcal{P}_{MLE}[X_{\{3,4\}}|H_2]^\top$$
$$\rightarrow \mathcal{P}[X_1, X_2; X_3, X_4]$$

- But this requires running EM, which will get stuck in local optima and is not guaranteed to obtain the MLE of the factorized model

Consistency

- In spectral learning, we estimate the alternate factorization from the data

$$\mathcal{P}_{MLE}[X_{\{1,2\}}, X_3]\mathcal{P}_{MLE}[X_2, X_3]^{-1}\mathcal{P}_{MLE}[X_2, X_{\{3,4\}}]$$
$$\rightarrow \mathcal{P}[X_1, X_2; X_3, X_4]$$

- This is consistent and computationally tractable (at some loss of statistical efficiency due to the dependence on the inverse)

Where's the Catch?

- Before we said that if the number of latent states was very large then the model was equivalent to a clique.

- Where does that scenario enter in our factorization?

$$\mathcal{P}[X_{\{1,2\}}, X_{\{3,4\}}] = \mathcal{P}[X_{\{1,2\}}, X_3]\mathcal{P}[X_2, X_3]^{-1}\mathcal{P}[X_2, X_{\{3,4\}}]$$

When does this inverse exist?

When Does the Inverse Exist

$$\mathcal{P}[X_2, X_3] = \mathcal{P}[X_2|H_2]\mathcal{P}[\oslash H_2]\mathcal{P}[X_3|H_2]^\top$$

- All the matrices on the right hand side must have full rank. (This is in general a requirement of spectral learning, although it can be somewhat relaxed)

When m > k

- The inverse cannot exist, but this situation is easily fixable (project onto lower dimensional space)

$$\mathcal{P}[X_{\{1,2\}}, X_{\{3,4\}}] =$$
$$\mathcal{P}[X_{\{1,2\}}, X_3]\boldsymbol{V}(\boldsymbol{U}^\top \mathcal{P}[X_2, X_3]\boldsymbol{V})^{-1}\boldsymbol{U}^\top \mathcal{P}[X_2, X_{\{3,4\}}]$$

- Where U, V are the top left/right **k** singular vectors of $\mathcal{P}[X_2, X_3]$

When k > m

- The inverse does exist. But it no longer satisfies the following property, which we used to derive the factorization

$$\mathcal{P}[X_2, X_3]^{-1} = \left(\mathcal{P}[X_3|H_2]^{\top}\right)^{-1}\mathcal{P}[\oslash H_2]^{-1}\mathcal{P}[X_2|H_2]^{-1}$$

$\times\, \mathbb{P}(X_2\ X_3)^{-2}$

- This is much more difficult to fix, and intuitively corresponds to how the problem becomes intractable if *k >> m*.

What does k>m mean?

- Intuitively, large *k*, small *m* means long range dependencies

- Consider following generative process:
  (1) With probability 0.5, let *S= X*, and with probability 0.5 let *S=Y*.
  (2) Print *A n* times.
  (3) ~~Print *S*~~
  (4) ~~Go back~~ to step (2)

H(

With *n=1* we either generate:
AXAXAXA…… or AYAYAYA…..

With *n=2* we either generate:
AAXAAXAA….. or AAYAAYAA…….

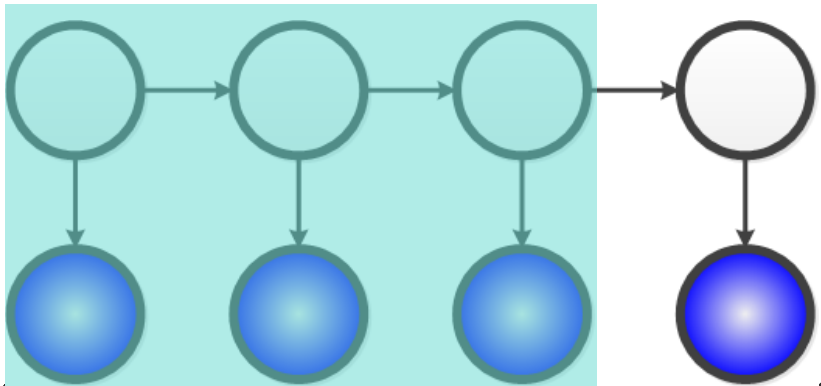
How many hidden states does HMM need?

- HMM needs 2n states.
- Needs to remember count as well as whether we picked $S=X$ or $S=Y$
- However, number of observed states m does not change, so our previous spectral algorithm will break for $n > 2$.
- How to deal with this in spectral framework?

Making Spectral Learning Work In Practice

- We are only using marginals of pairs/triples of variables to construct the full marginal among the observed variables.

- Only works when $k < m$.

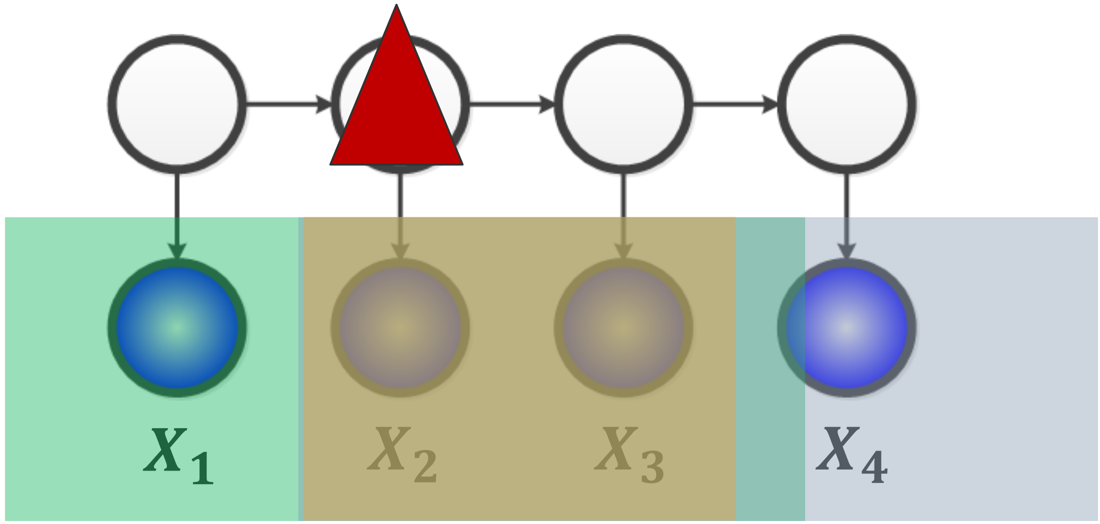


$P(X_1\ X_2\ X_3)$

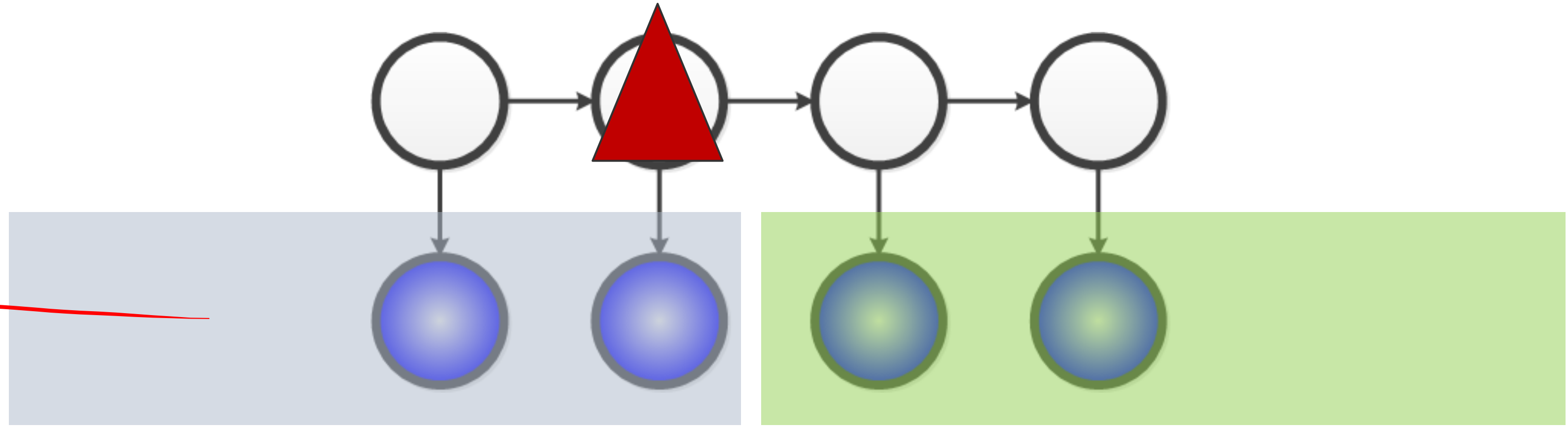
- However, in real problems we need to capture longer range dependencies.

Recall our factorization

$$\mathcal{P}[X_{\{1,2\}}, X_{\{3,4\}}] = \underline{\mathcal{P}[X_{\{1,2\}}, X_3]}\,\underline{\mathcal{P}[X_2, X_3]^{-1}}\,\underline{\mathcal{P}[X_2, X_{\{3,4\}}]}$$



Key Idea: Use Long-Range Features



Construct feature vector of left side

ϕ_L

Construct feature vector of right side

ϕ_R

Spectral Learning With Features

$$\mathcal{P}[X_2, X_3] = \mathbb{E}[\boldsymbol{\delta}_2 \otimes \boldsymbol{\delta}_3] := \mathbb{E}[\boldsymbol{\delta}_2 \boldsymbol{\delta}_3^\top]$$

Use more complex feature instead:

$$\mathbb{E}[\phi_L \otimes \phi_R]$$

$$\begin{aligned}\mathcal{P}[X_{\{1,2\}}, X_{\{3,4\}}] &= \mathbb{E}[\boldsymbol{\delta}_{1\otimes 2}, \boldsymbol{\delta}_{3\otimes 4}] \\ &= \mathbb{E}[\boldsymbol{\delta}_{1\otimes 2}, \phi_R]\boldsymbol{V}(\boldsymbol{U}^\top \mathbb{E}[\phi_L \otimes \phi_R]\boldsymbol{V})^{-1}\boldsymbol{U}^\top \mathcal{P}[\phi_L, X_{\{3,4\}}]\end{aligned}$$

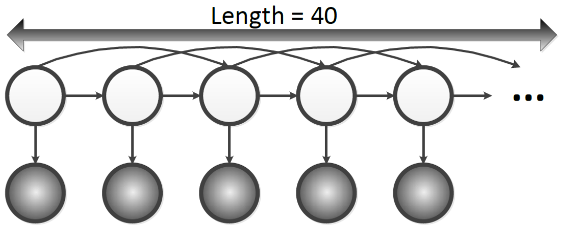
Experimentally,

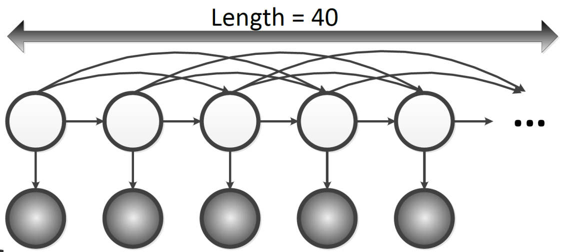
- Has been shown by many authors that (with some work) spectral methods achieve comparable results to EM but are 10-50x faster
  - Parikh et al. 2011 / 2012
  - Balle et al. 2012
  - Cohen et al. 2012 / 2013

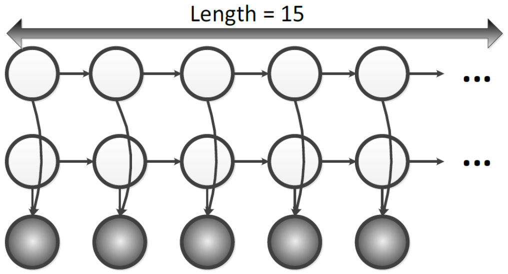
- The following are some synthetic and real data results demonstrating the comparison between EM and spectral methods.

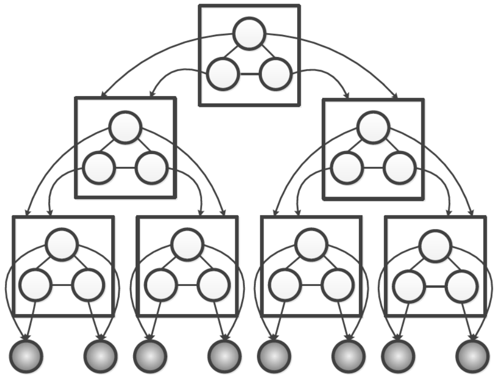
Synthetic Data [Parikh et al. 2012]

- Different latent variable models





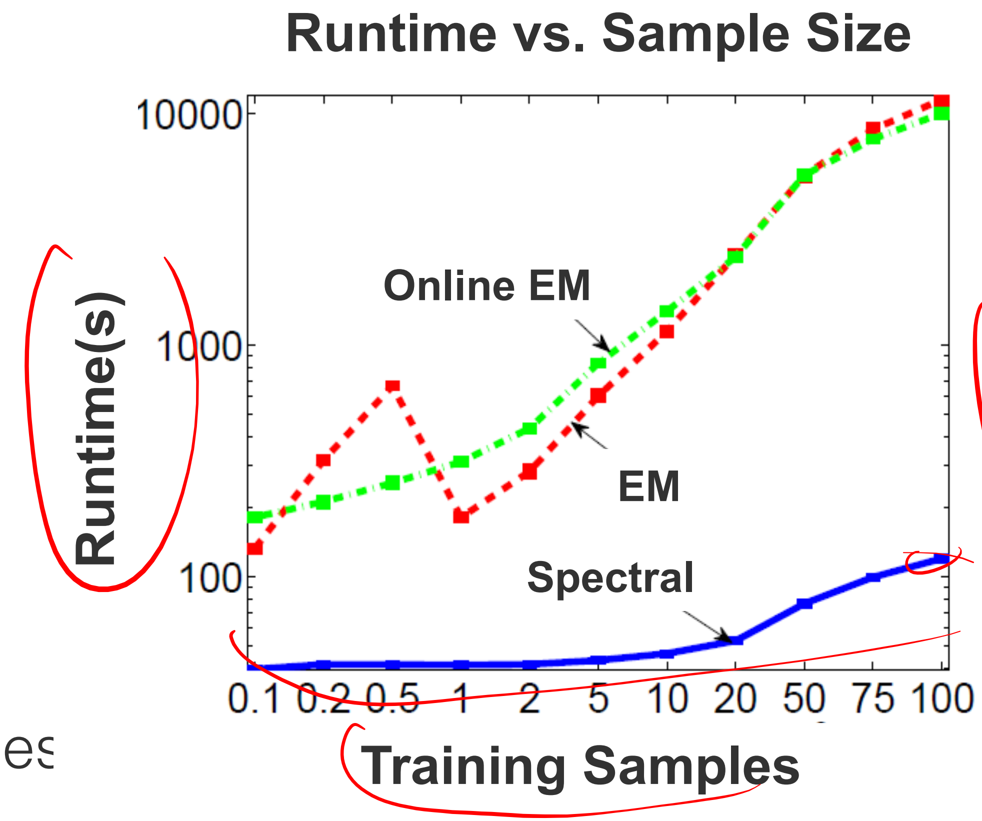


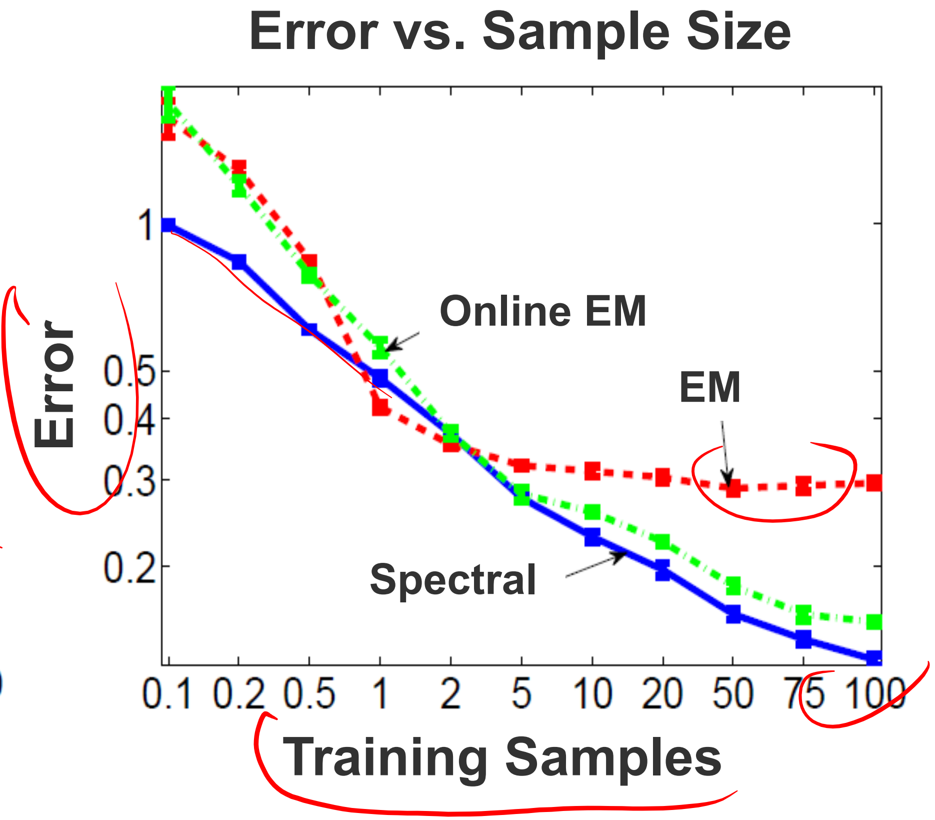


- Train: Learn parameters for a given model given samples of observed variables
- Test: Evaluate likelihood of random samples drawn from model and compare to the true likelihood

Synthetic Data [Parikh et al. 2012]

- Synthetic 3rd order HMM Example (Spectral/EM/Online EM):

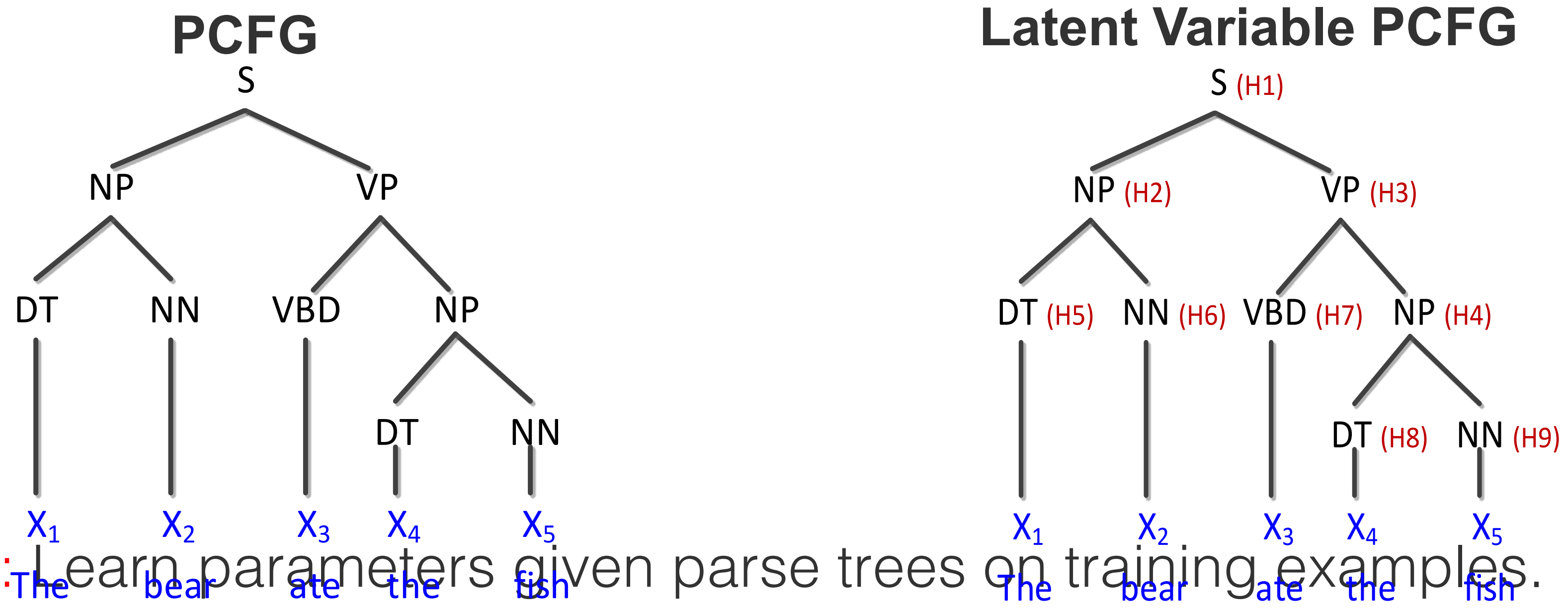




- Res

Supervised Parsing [Cohen et al. 2012/2013]

- Learn a latent variable Probabilistic Context Free Grammar model (latent PCFG) which is a PCFG augmented with additional latent states



- Train: Learn parameters given parse trees on training examples.
- Test: Estimate most likely parse structure on test sentences

Empirical Results for Latent PCFGs [Cohen et al. 2013]

	section 22		section 23	
	EM	spectral	EM	spectral
$m = 8$	86.87	85.60	—	—
$m = 16$	88.32	87.77	—	—
$m = 24$	88.35	88.53	—	—
$m = 32$	88.56	88.82	87.76	88.05

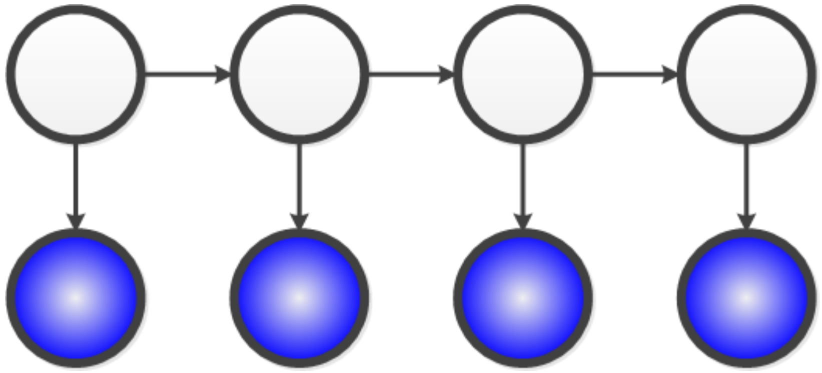
Evaluation Measure: *F1 bracketing score*

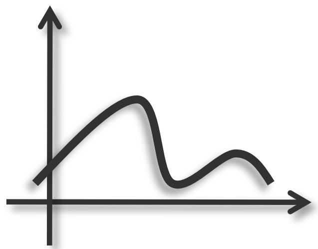
Timing Results on Latent PCFGs [Cohen et al. 2013]

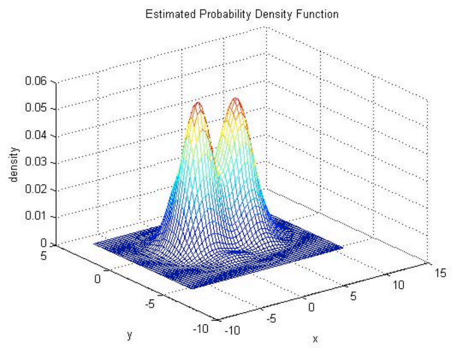
	single EM iter.	EM best model	spectral algorithm total	feature	transfer + scaling	SVD	$a \rightarrow b\ c$	$a \rightarrow x$
$m = 8$	6m	3h	3h32m	22m	49m	36m	1h34m	10m
$m = 16$	52m	26h6m	5h19m			34m	3h13m	19m
$m = 24$	3h7m	93h36m	7h15m			36m	4h54m	28m
$m = 32$	9h21m	187h12m	9h52m			35m	7h16m	41m

Dealing with Nonparametric, Continuous Variables

- It is difficult to run EM if the conditional/marginal distributions are continuous and do not easily fit into a parametric family.







- However, we will see that Hilbert Space Embeddings can easily be combined with spectral methods for learning nonparametric latent models.

Connection to Hilbert Space Embeddings

- Recall that we could substitute features for variables

$$\mathcal{P}[X_2, X_3] = \mathbb{E}[\boldsymbol{\delta}_2 \otimes \boldsymbol{\delta}_3] := \mathbb{E}[\boldsymbol{\delta}_2 \boldsymbol{\delta}_3^\top]$$

Use more complex feature instead:

$$\mathbb{E}[\phi_L \otimes \phi_R]$$

Can Also Use Infinite Dimensional Features

- Replace

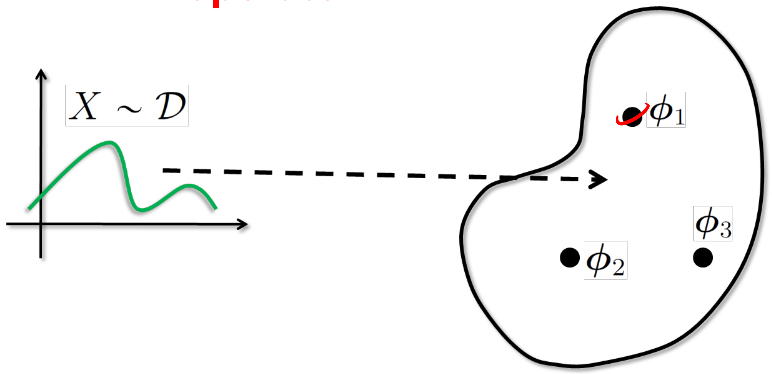
$$\mathcal{P}[X_2, X_3] = \mathbb{E}[\boldsymbol{\delta}_2 \otimes \boldsymbol{\delta}_3] := \mathbb{E}[\boldsymbol{\delta}_2 \boldsymbol{\delta}_3^\top]$$

- with

$$\mathcal{C}[X_2, X_3] = \mathbb{E}[\phi_{X_2} \otimes \phi_{X_3}]$$

covariance operator

- (and similarly for other quantities)



Connection to Hilbert Space Embeddings

Discrete case:

$$\mathcal{P}[X_{\{1,2\}}, X_{\{3,4\}}] =$$
$$\mathcal{P}[X_{\{1,2\}}, X_3]\boldsymbol{V}(\boldsymbol{U}^\top \mathcal{P}[X_2, X_3]\boldsymbol{V})^{-1}\boldsymbol{U}^\top \mathcal{P}[X_2, X_{\{3,4\}}]$$

Continuous case:

$$\mathcal{C}[X_{\{1,2\}}; X_{\{3,4\}}] =$$
$$\mathcal{C}[X_{\{1,2\}}; X_3]\boldsymbol{V}(\boldsymbol{U}^\top \mathcal{C}[X_2, X_3]\boldsymbol{V})^{-1}\boldsymbol{U}^\top \mathcal{C}[X_2; X_{\{3,4\}}]$$

Summary - EM & Spectral (Part I)

EM

- Aims to Find MLE so more "statistically" efficient
- Can get stuck in local-optima
- Lack of theoretical guarantees
- Slow
- Easy to derive for new models

Spectral

- Does not aim to find MLE so less statistically efficient.
- Local-optima-free
- Provably consistent
- Very fast
- Challenging to derive for new models (Unknown whether it can generalize to arbitrary loopy models)

Summary - EM & Spectral (Part II)

EM

- No issues with negative numbers
- Allows for easy modelling with conditional distributions
- Difficult to incorporate long-range features (since it increases treewidth).
- Generalizes poorly to non-Gaussian continuous variables.

Spectral

- Problems with negative numbers. Requires explicit normalization to compute likelihood.
- Allows for easy modelling with marginal distributions
- Easy to incorporate long-range features.
- Easy to generalize to non-Gaussian continuous variables via Hilbert Space Embeddings