Identifiability and Learning of Topic Models: Tensor Decompositions under Structural Constraints

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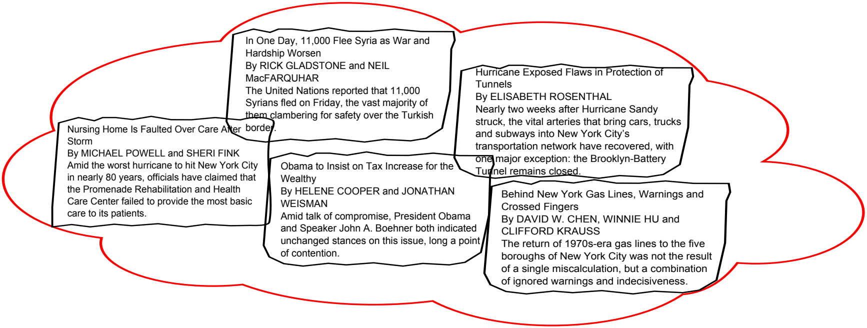
Joint work with Daniel Hsu, Majid Janzamin
Adel Javanmard and Sham Kakade.

Latent Variable Modeling

Goal: Discover hidden effects from observed measurements

Topic Models

- Observations: words. Hidden: topics.



Modeling communities in social networks, modeling gene regulation ...

Challenges in Learning Topic Models

Learning Topic Models Using Word Observations

Challenges in Identifiability

- When can topics be identified?
- Conditions on the model parameter, e.g. on topic-word matrix Φ and on topic proportions distributions (h)?
- Does identifiability also lead to tractable algorithms?

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Challenges in Design of Learning Algorithms

- Maximum likelihood learning of topic models NP-hard (Arora et. al.)
- In practice, heuristics such as Gibbs sampling, variation Bayes etc.
- Guaranteed learning with minimal assumptions? Efficient methods? Low sample and computational complexities?

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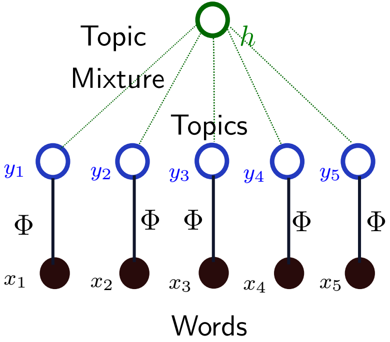
Moment-based approach: learning using low order observed moments

Probabilistic Topic Models

- Useful abstraction for automatic categorization of documents
- Observed: words. Hidden: topics.
- Bag of words: order of words does not matter

Graphical model representation

- l words in a document $x_1, \ldots, x_l$.
- h: proportions of topics in a document.
- Word x_i generated from topic y_i.
- Exchangeability: $\boxed{x_1 \perp\!\!\!\perp x_2 \perp\!\!\!\perp \ldots | h}$
- $\boxed{\Phi(i,j) := \mathbb{P}[x_m = i | y_m = j]}$: topic-word matrix.



Formulation as Linear Models

Distribution of the topic proportions vector h

If there are k topics, distribution over the simplex Δ^{k-1}

$$\boxed{\Delta^{k-1} := \{h \in \mathbb{R}^k, h_i \in [0,1], \sum_i h_i = 1\}.}$$

Distribution of the words $x_1, x_2, \ldots$

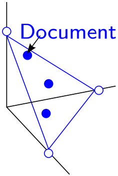
- Order n words in vocabulary. If x_1 is j^{th} word, assign $e_j \in \mathbb{R}^n$
- Distribution of each x_i: supported on vertices of Δ^{n-1}.

Properties

- Linear Model: $\boxed{\mathbb{E}[x_i|h] = \Phi h}$.
- Multiview model: h is fixed and multiple words (x_i) are generated.

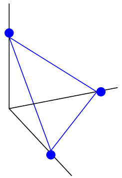
Geometric Picture for Topic Models

Topic proportions vector (h)



Geometric Picture for Topic Models

Single topic (h)



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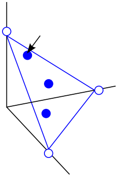

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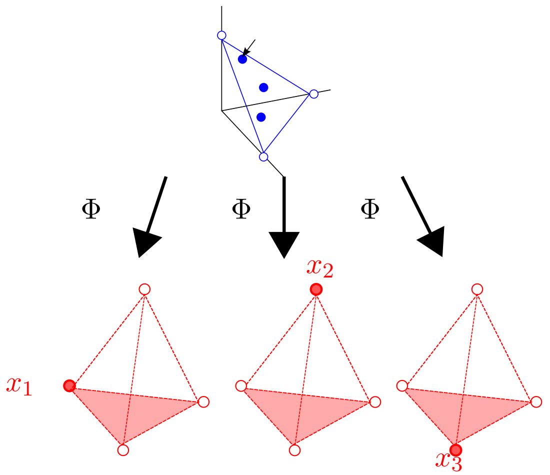

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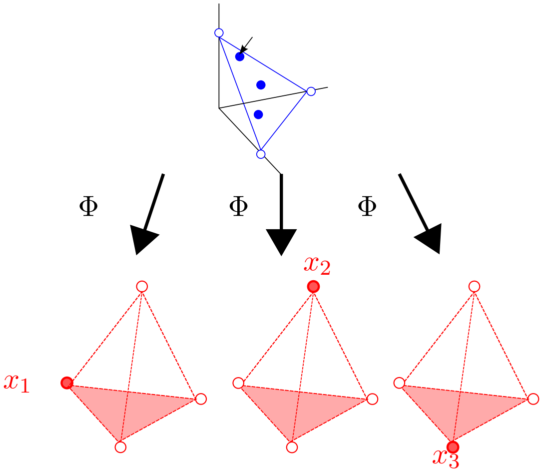


Word generation $(x_1, x_2, \ldots)$

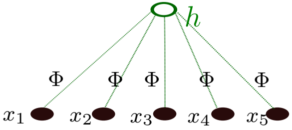
Moment-based estimation: co-occurrences of words in documents

Outline

Recap of CP Decomposition

Recall form of moments for single topic/Dirichlet model.

- $\boxed{\mathbb{E}[x_i|h] = \Phi h.}$ $\boxed{\vec{\lambda} := [\mathbb{E}[h]]_i.}$
- Learn topic-word matrix Φ, vector $\vec{\lambda}$



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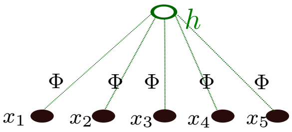

Pairs Matrix M_2

$$M_2 := \mathbb{E}[x_1 x_2^\top] = \mathbb{E}[\mathbb{E}[x_1 x_2^\top|h]] = \Phi \mathbb{E}[hh^\top]\Phi^\top = \sum_{r=1}^{k} \lambda_r \phi_r \phi_r^\top$$

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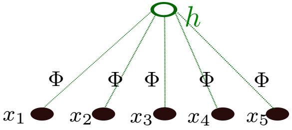

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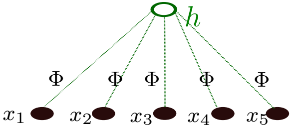

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Matrix and Tensor Forms: $\phi_r := r^{\text{th}}$ column of Φ.

$$\boxed{M_2 = \sum_{r=1}^{k} \lambda_r \phi_r \otimes \phi_r. \qquad M_3 = \sum_{r=1}^{k} \lambda_r \phi_r \otimes \phi_r \otimes \phi_r}$$

Multi-linear Transformation

- For a tensor T, define (for matrices V_i of appropriate dimensions)

$$\boxed{[T(V_1, V_2, V_3)]_{i_1,i_2,i_3} := \sum_{j_1,j_2,j_3} (T)_{j_1,j_2,j_3} \prod_{m\in[3]} V_1(j_m, i_m)}$$

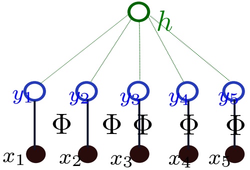
- For a matrix M_2, $\boxed{M(V_1, V_2) := V_1^\top M_2 V_2}$.

$$\boxed{T = \sum_{r=1}^{k} \lambda_r \phi_r \otimes \phi_r \otimes \phi_r}$$

$$\boxed{\begin{aligned} T(W,W,W) &= \sum_{r\in[k]} \lambda_r (W^\top \phi_r)^{\otimes 3} \\ T(I,v,v) &= \sum_{r\in[k]} \lambda_r \langle v, \phi_r\rangle^2 \phi_r. \\ T(I,I,v) &= \sum_{r\in[k]} \lambda_r \langle v, \phi_r\rangle \phi_r \phi_r^\top. \end{aligned}}$$

Form of Moments for a general Topic Model

- $\boxed{\mathbb{E}[x_i|h] = \Phi h.}$
- Learn Φ, distribution of h
- Form of moments?



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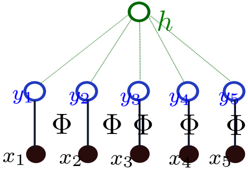

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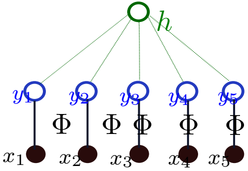

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Tucker Tensor Decomposition

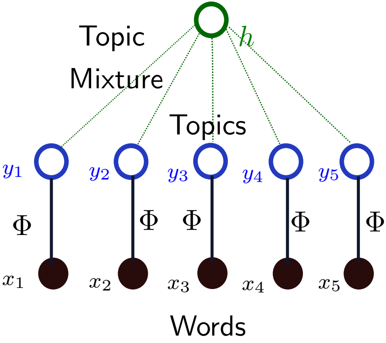
- Find decomposition $M_3 = \mathbb{E}[h^{\otimes 3}](\Phi, \Phi, \Phi)$
- Key difference from CP: $\mathbb{E}[h^{\otimes 3}]$ NOT a diagonal tensor
- Lot more parameters to estimate

Guaranteed Learning of Topic Models

Two Learning approaches

- CP Tensor decomposition: Parametric topic distributions (constraints on h) but general topic-word matrix Φ

- Tucker Tensor decomposition: Constrain topic-word matrix Φ but general (non-degenerate) distributions on h



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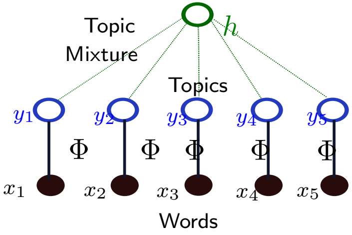
1. Introduction
2. Form of Moments
3. Matrix Case: Learning using Pairwise Moments
   - Identifiability and Learning of Topic-Word Matrix
   - Learning Latent Space Parameters of the Topic Model
4. Tensor Case: Learning From Higher Order Moments
   - Overcomplete Representations
5. Conclusion

Pairwise moments for learning

Learning using pairwise moments: minimal information.

Exchangeable Topic Model



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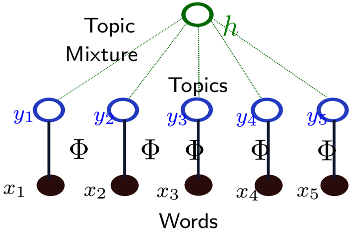

So far..

- Parametric h: Dirichlet, single topic, independent components, ...
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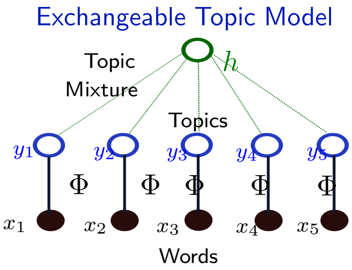

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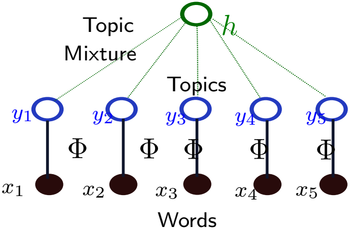

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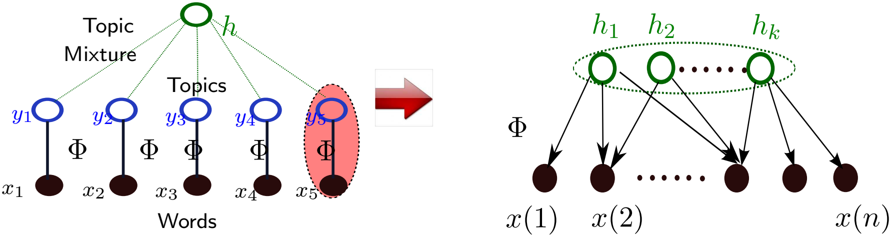
Exchangeable Topic Model | Topic-word matrix



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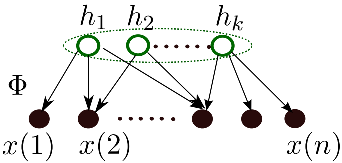

Learning using second-order moments

- Linear model: $\boxed{\mathbb{E}[x_i|h] = \Phi\, h.}$ and $\boxed{\mathbb{E}[x_1 x_2^\top] = \Phi \mathbb{E}[hh^\top]\Phi^\top}$
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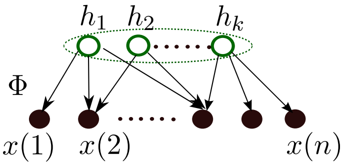

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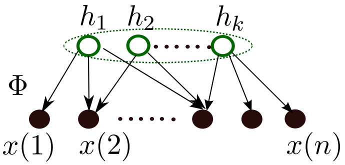

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Sparsity constraints on topic-word matrix Φ

- Main constraint: $\boxed{\text{columns of } \Phi \text{ are sparsest vectors in } \mathrm{Col}(\Phi)}$

Sufficient Conditions for Identifiability

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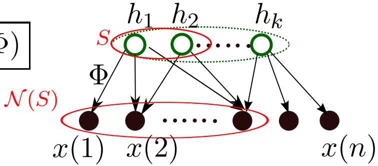

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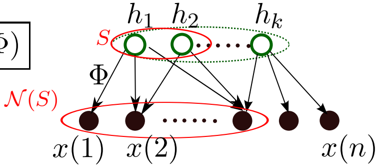

Structural Condition: (Additive) Graph Expansion

$$\boxed{|\mathcal{N}(S)| > |S| + d_{\max}, \text{ for all } S \subset [k]}$$

Parametric Conditions: Generic Parameters

$$\boxed{\|\Phi v\|_0 > |\mathcal{N}_\Phi(\mathrm{supp}(v))| - |\,\mathrm{supp}(v)|}$$

A. Anandkumar, D. Hsu, A. Javanmard, and, S. M. Kakade. Learning Bayesian Networks with Latent Variables. In Proc. of Intl. Conf. on Machine Learning, June 2013.

Brief Proof Sketch

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Structural and Parametric Conditions Imply:

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Claim: Parametric conditions are satisfied for generic parameters

Tractable Learning Algorithm

Learning Task

Recover topic-word matrix Φ from $\boxed{M_2 = \Phi \mathbb{E}[hh^\top]\Phi^\top}$.

Exhaustive search

$$\boxed{\min_{z \neq 0} \|\Phi z\|_0}$$

Convex relaxation

$$\boxed{\min_z \|\Phi z\|_1, \quad b^\top z = 1,}$$

where b is a row in Φ.

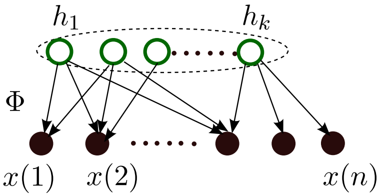
Change of Variables

$$\boxed{\min_w \|M_2^{1/2} w\|_1, \quad e_i^\top M_2^{1/2} w = 1.}$$

Under "reasonable" conditions, the above program exactly recovers Φ

Outline

Latent General Topic Models



So far: recover topic-word matrix Φ from $\boxed{\Phi\mathbb{E}[hh^\top]\Phi^\top}$.

Learning topic proportion distribution

- $\mathbb{E}[hh^\top]$ not enough to recover general distributions
- Need higher order moments to learn distribution of h
- Any models where low order moments suffice? e.g. Dirichlet/single topic require only third order moments. What about any other distributions?

Are there other topic distributions which can be learned efficiently?

Learning Latent Bayesian Networks

BN: Markov relationships on DAG

Pa_i: parents of node i. $\mathbb{P}(h) = \prod_{i=1}^{n} \mathbb{P}(h_i | h_{\mathrm{Pa}_i})$

Linear Bayesian Network: $h_j = \sum_{i \in \mathrm{Pa}_j} \lambda_{ji} h_i + \eta_j$

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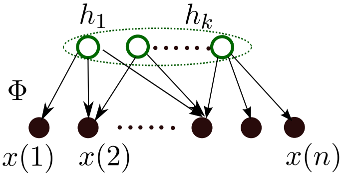

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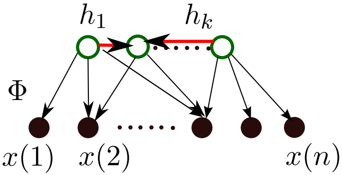

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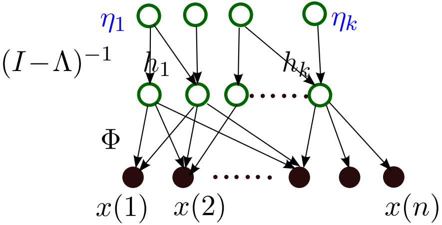

Learning Latent Bayesian Networks

BN: Markov relationships on DAG

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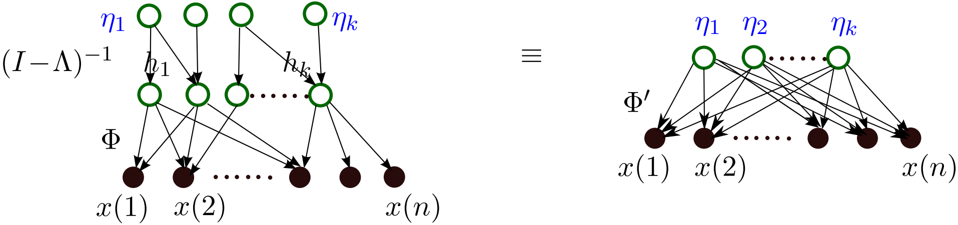

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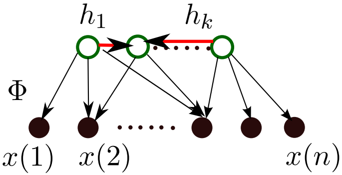

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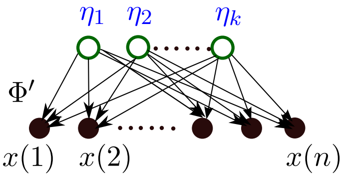

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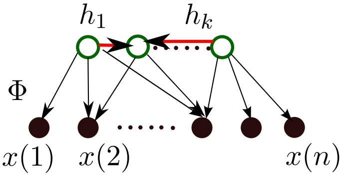

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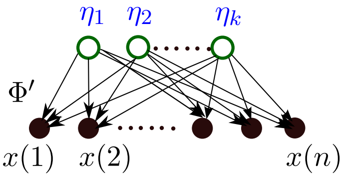

- Φ: structured and sparse while Φ' is dense
- h: correlated topics while η are uncorrelated

Learning Latent Bayesian Networks

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Solving CP decomposition through Tensor Power Method

- Recall η_i are uncorrelated: $\mathbb{E}[\eta^{\otimes}]$ is diagonal.
- Reduction to CP decomposition: can be efficient solved via tensor power method

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Un-mix Φ from $\Phi' = \Phi(I-\Lambda)^{-1}$ through ℓ_1 optimization.

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Learning both structure and parameters of Φ and distribution of h
Combine non-convex and convex methods for learning!

Outline

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Extension to learning overcomplete representations

So far..

- Pairwise moments for learning structured topic-word matrices
- Third order moments for learning latent Bayesian network models
- Number of topics k, n is vocabulary size and $k < n$.

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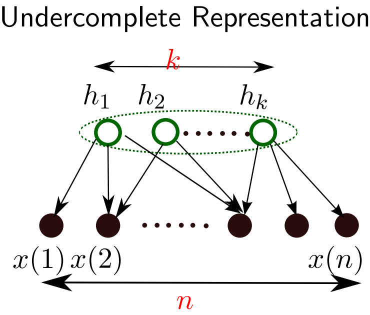

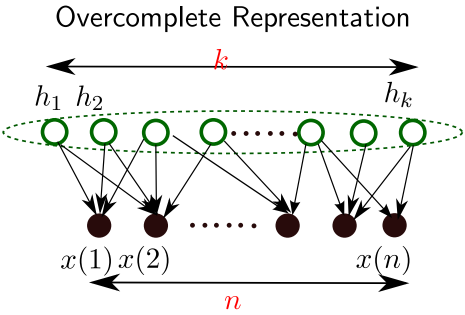

What about overcomplete models: $k > n$? Do higher-order moments help?

Learning Overcomplete Representations

Why Overcomplete Representations?

- Flexible modeling, robust to noise
- Huge gains in many applications, e.g. speech and computer vision.

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- $k > n$: Tucker decomposition not unique: model non-identifiable.

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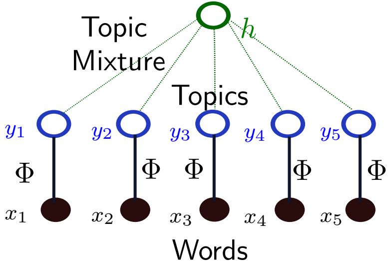
Identifiability of Overcomplete Models

- Possible under the notion of topic persistence
- Includes single topic model as a special case.

Persistent Topic Models

Bag of Words Model



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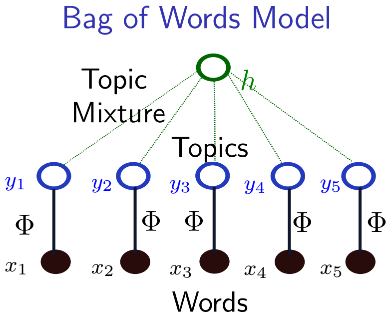

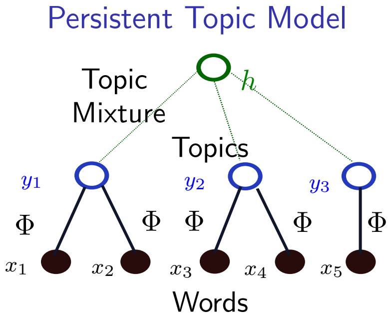

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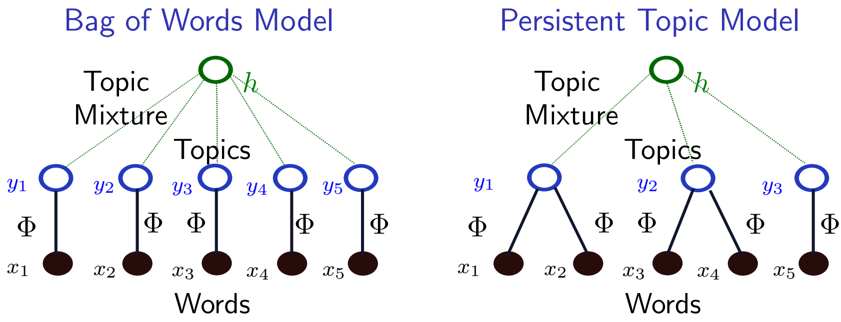

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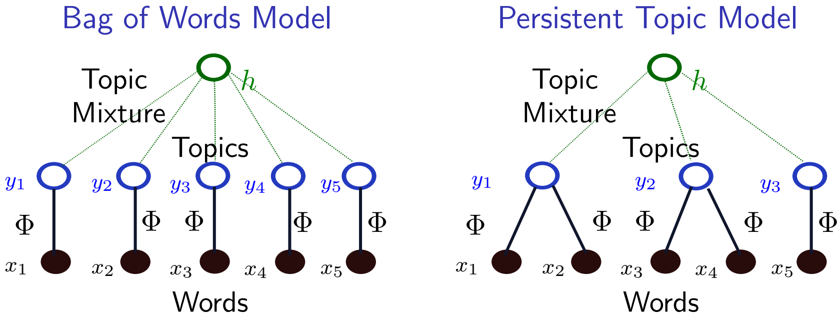

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Identifiability conditions for overcomplete models?

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- Tensor form: $\mathbb{E}(x_1 \otimes x_2 \otimes x_3 \otimes x_4) = \mathbb{E}[h^{\otimes 4}](\Phi, \Phi, \Phi, \Phi)$
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Kronecker vs. Khatri-Rao Products

- Φ: Topic-word matrix, is $n \times k$.
- $(\Phi \otimes \Phi)$: Kronecker product, is $n^2 \times k^2$ matrix.
- $(\Phi \odot \Phi)$: Khatri-Rao product, is $n^2 \times k$ matrix.

Some Intuitions

- Bag-of-words Model:

$$\boxed{(\Phi \otimes \Phi)\mathbb{E}[(h \otimes h)(h \otimes h)^\top](\Phi \otimes \Phi)^\top}$$

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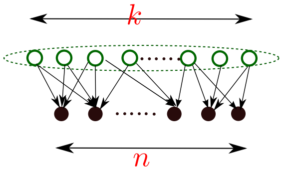
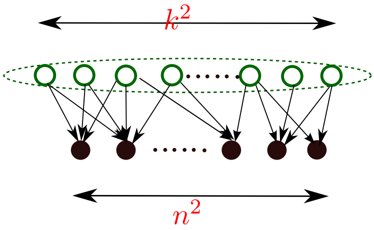
Topic-Word Matrix Φ



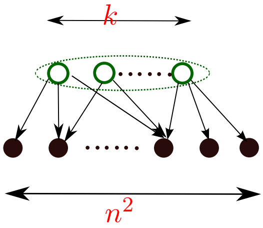
Effective Topic-Word Matrix Given Fourth-Order Moments:

Bag of Words Model:
Kronecker Product $\Phi \otimes \Phi$



Not Identifiable

Persistent Model:
Khatri-Rao Product $\Phi \odot \Phi$



Identifiable

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Conclusion

Moment-based Estimation of Latent Variable Models

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Practical Considerations for Tensor Methods

- Not covered in detail in this tutorial.
- Matrix algebra and iterative methods.
- Scalable: Parallel implementation on GPUs