Neural Nonnegative Matrix Factorization for Hierarchical Multilayer Topic Modeling

Jamie Haddock

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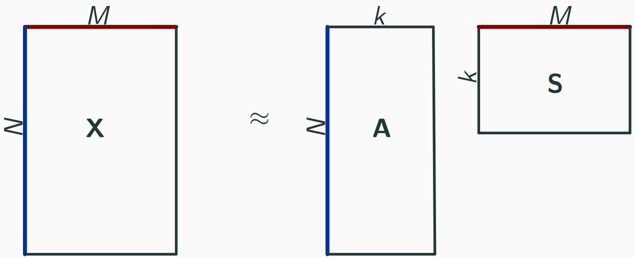
Computational and Applied Mathematics
UCLA

joint with Mengdi Gao, Denali Molitor, Deanna Needell, Eli Sadovnik, Tyler Will, Runyu Zhang

Nonnegative Matrix Factorization (NMF)



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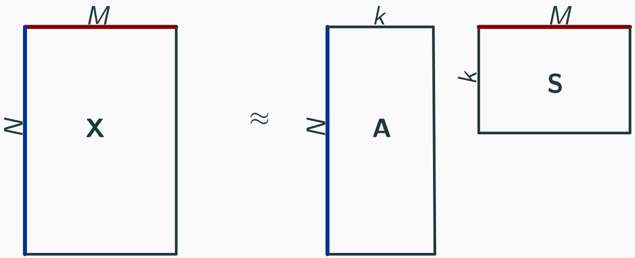

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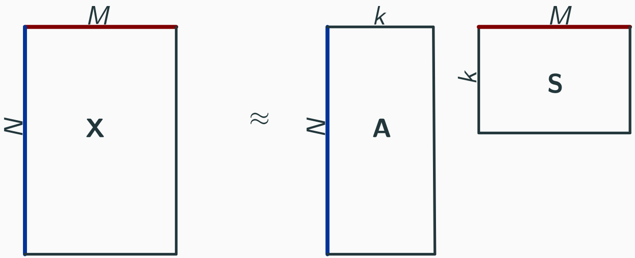

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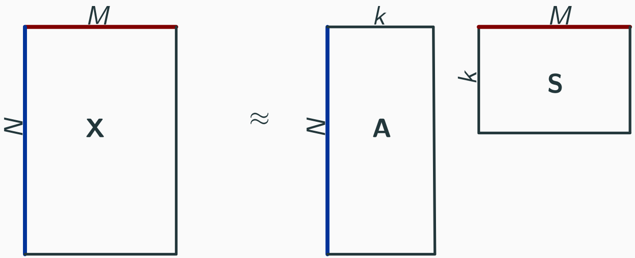

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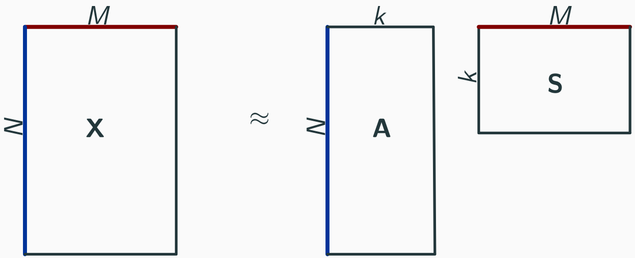

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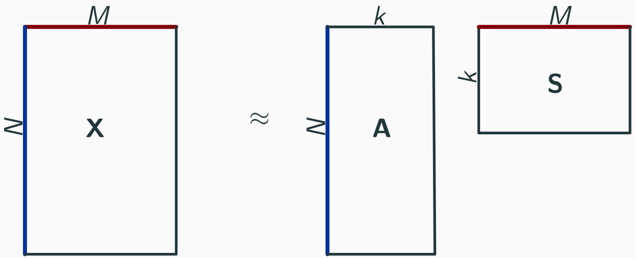

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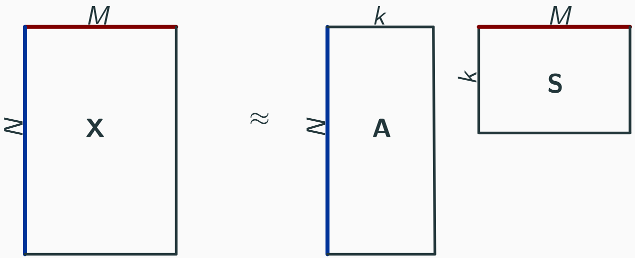

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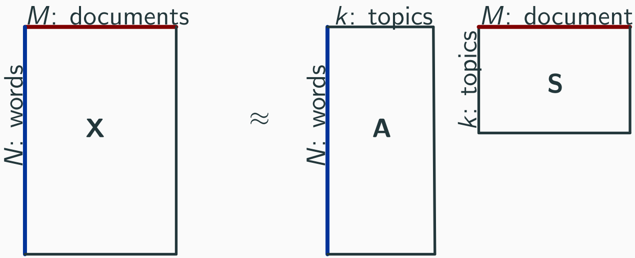

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NMF

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Methods:

- multiplicative updates
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- many others

(Semi)supervised NMF

Goal: Incorporate known label information into problem.

$$\min_{\mathbf{A}\in\mathbb{R}_{\geq 0}^{N\times k},\mathbf{S}\in\mathbb{R}_{\geq 0}^{k\times M},\mathbf{B}\in\mathbb{R}_{\geq 0}^{P\times k}} \|\mathbf{W}\odot(\mathbf{X}-\mathbf{AS})\|_F^2+\lambda\|\mathbf{L}\odot(\mathbf{Y}-\mathbf{BS})\|_F^2$$

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Problem Advantages:

- use of label information
- can extend multiplicative updates method to SSNMF

Hierarchical NMF

Goal: Discover hierarchical topic structure within $\mathbf{X}$.

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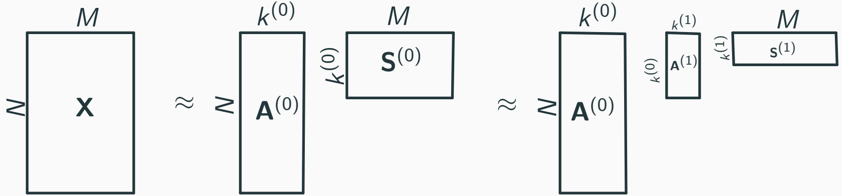

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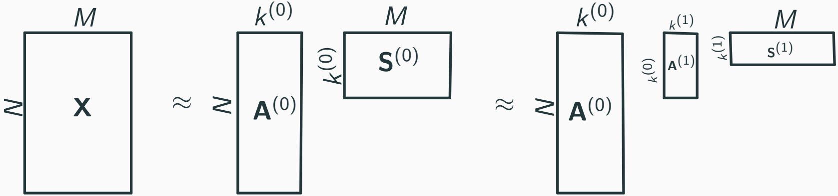

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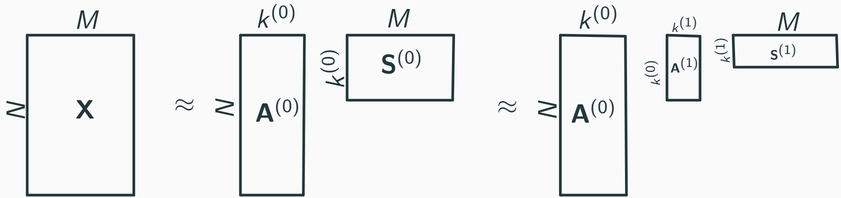

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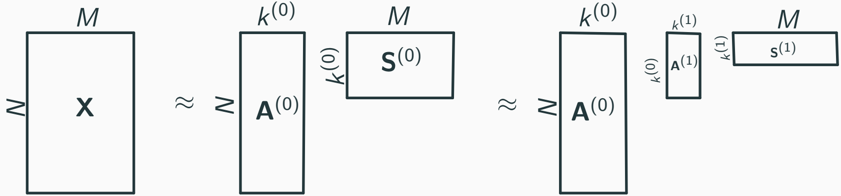

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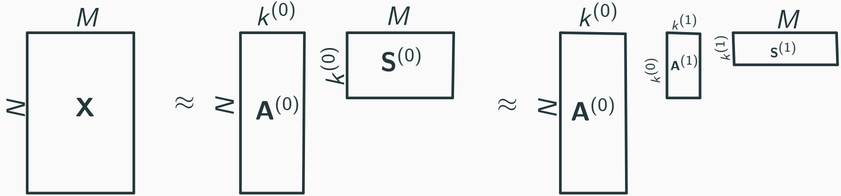

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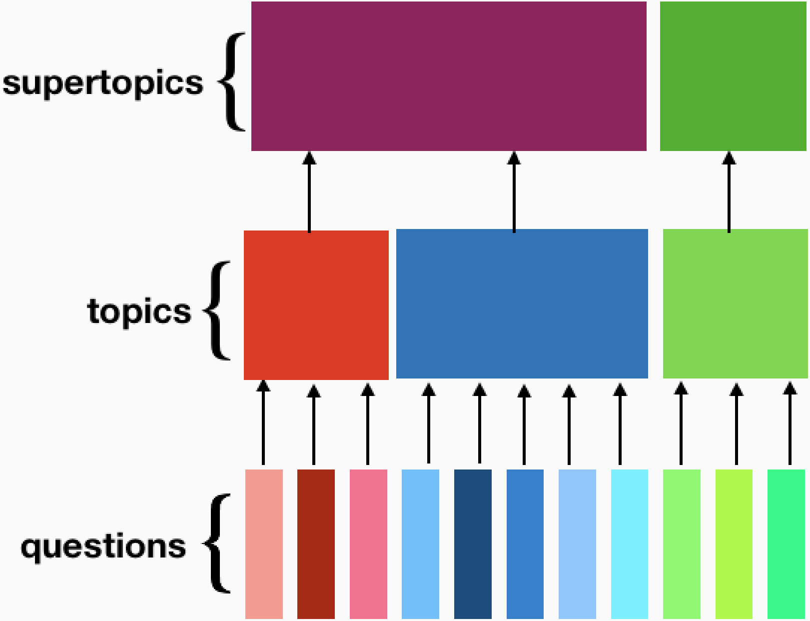

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▷ [Sun, Nasrabadi, Tran '17]

- similar method lacking nonnegativity constraints

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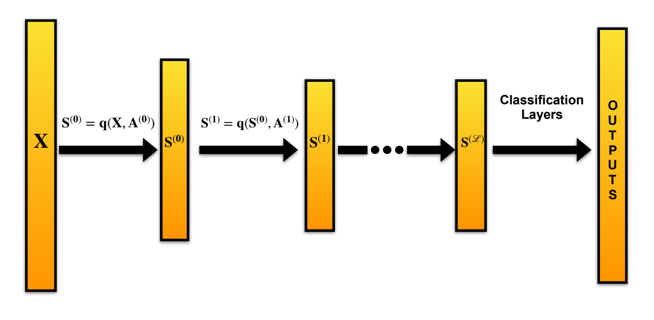

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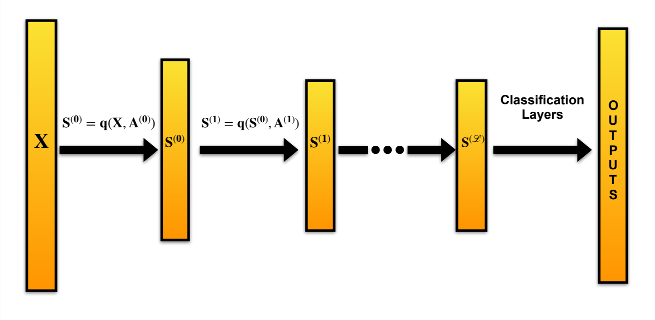

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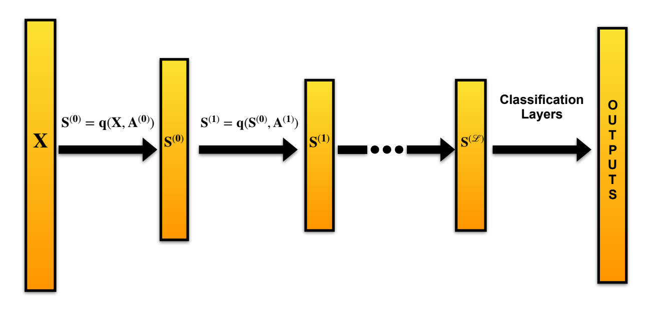

- ▷ Pin the values of **S** to those of **A** by recursively setting $\mathbf{S}^{(\ell)} := q(\mathbf{S}^{(\ell-1)}, \mathbf{A}^{(\ell)})$.
- ▷ Can we compute derivatives and backpropagate?

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- Backpropagate and update all $\mathbf{A}$ matrices simultaneously via GD or SGD.

Neural NMF

Method 1 Neural NMF

Require: data matrix $\mathbf{X} \in \mathbb{R}^{N \times M}$, number of layers $\mathcal{L}$, step size γ, cost function C, initial matrices $\mathbf{A}^{(i)}$ for $i = 0, ..., \mathcal{L}$

procedure $\textsc{ForwardPropagation}(\mathbf{A}^{(0)}, \ldots, \mathbf{A}^{(\mathcal{L})})$

  for $i := 0 ... \mathcal{L}$ **do**

    $\mathbf{S}^{(i)} \leftarrow q(\mathbf{A}^{(i)}, \mathbf{S}^{(i-1)})$

ForwardPropagation$(\mathbf{A}^{(0)}, \ldots, \mathbf{A}^{(\mathcal{L})})$

while not converged **do**

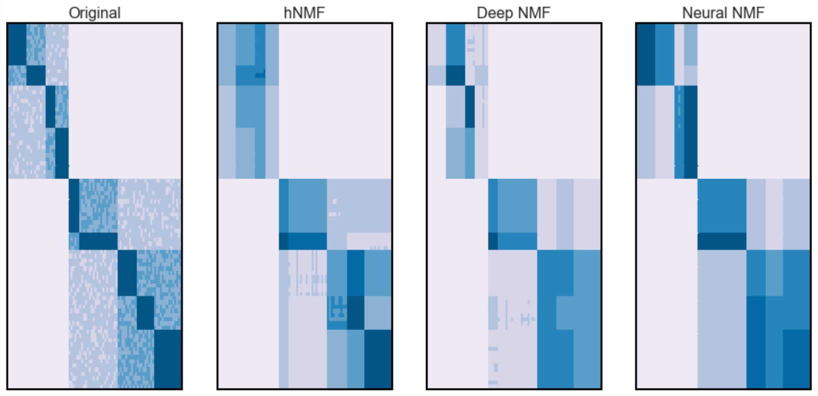
  for $i := 0 ... \mathcal{L}$ **do**

    $\mathbf{A}^{(i)} \leftarrow \mathbf{A}^{(i)} - \gamma * \frac{\partial C}{\partial \mathbf{A}^{(i)}}$ ▷ Gradient descent

    $\mathbf{A}^{(i)} \leftarrow \mathbf{A}^{(i)}_{+}$ ▷ Project onto positive orthant

  ForwardPropagation$(\mathbf{A}^{(0)}, \ldots, \mathbf{A}^{(\mathcal{L})})$

Experimental Results



- unsupervised reconstruction with two-layer structure ($k^{(0)} = 9, k^{(1)} = 4$)

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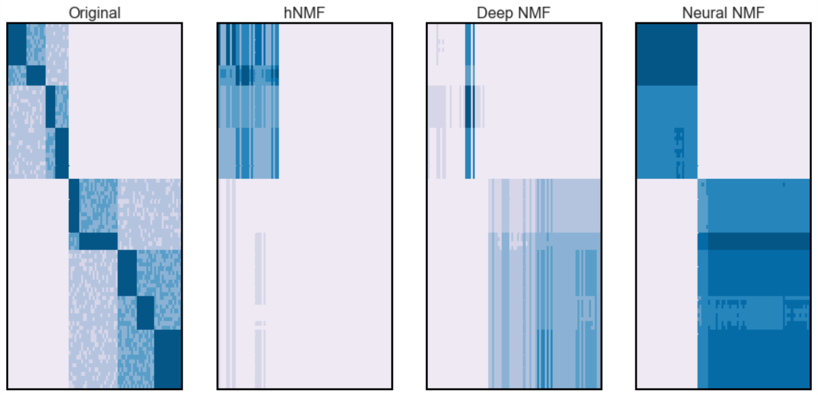

- semisupervised reconstruction (40% labels) with three-layer structure ($k^{(0)} = 9, k^{(1)} = 4, k^{(2)} = 2$)

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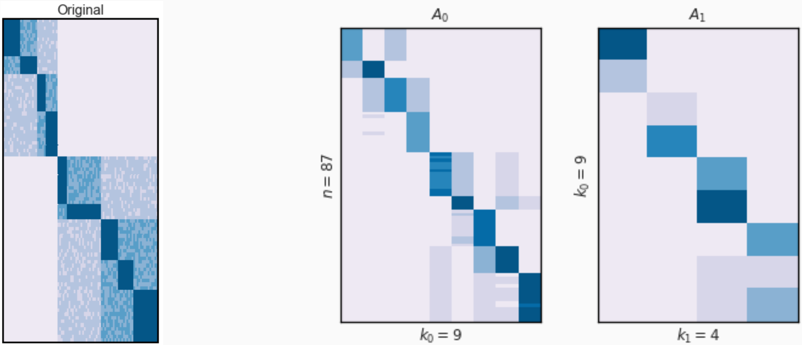
Note that despite reconstruction error increasing as layers increase (since the final rank decreases), the topic structure can be resolved from the intermediate factorizations.



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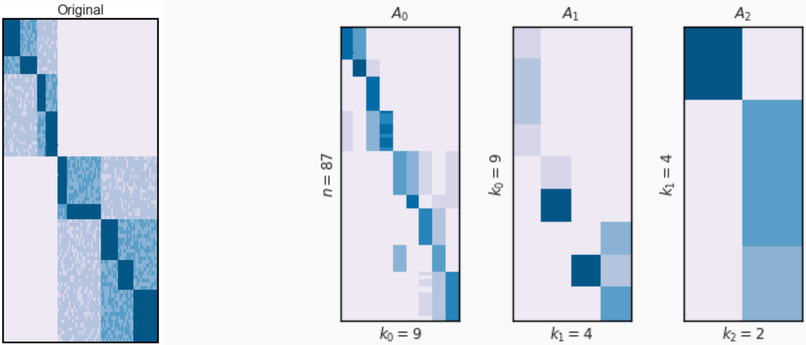

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Table 1: Reconstruction error / classification accuracy

	Layers	Hier. NMF	Deep NMF	Neural NMF
Unsuper.	1	0.053	0.031	0.029
	2	0.399	0.414	**0.310**
	3	0.860	0.838	**0.492**
Semisuper.	1	0.049 / 0.933	0.031 / 0.947	0.042 / **1**
	2	0.374 / 0.926	0.394 / 0.911	**0.305** / **1**
	3	0.676 / 0.930	0.733 / 0.930	**0.496** / **0.990**
Supervised	1	0.052 / 0.960	0.042 / 0.962	0.042 / **1**
	2	0.311 / 0.984	0.310 / 0.984	0.307 / 1
	3	0.495 / 1	0.494 / 1	0.498 / 1

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- extend to method for hierarchical nonnegative tensor factorization

Thanks for listening!

Questions?

[1] Jennifer Flenner and Blake Hunter. **A deep non-negative matrix factorization neural network, 2018.** Unpublished.

[2] Jonathan Le Roux, John R Hershey, and Felix Weninger. **Deep nmf for speech separation.** In Int. Conf. Acoust. Spee., pages 66–70. IEEE, 2015.

[3] Daniel D. Lee and H. Sebastian Seung. **Learning the parts of objects by non-negative matrix factorization.** Nature, 401:788–791, 1999.

[4] H. Lee, J. Yoo, and S. Choi. **Semi-supervised nonnegative matrix factorization.** IEEE Signal Proc. Let., 17(1):4–7, Jan 2010.

[5] Xiaoxia Sun, Nasser M. Nasrabadi, and Trac D. Tran. **Supervised multilayer sparse coding networks for image classification.** CoRR, abs/1701.08349, 2017.

[6] George Trigeorgis, Konstantinos Bousmalis, Stefanos Zafeiriou, and Björn W Schuller. **A deep matrix factorization method for learning attribute representations.** IEEE T. Pattern Anal., 39(3):417–429, 2016.