Learning from Complex and Relational Data

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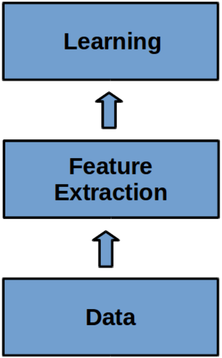
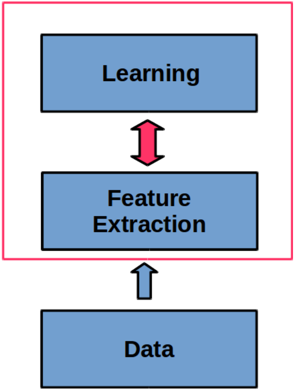
Learning from Data: The Traditional Way



A two-stage process. Stage 1 often hand-crafted.

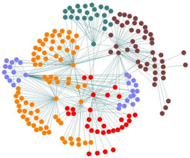
Learning via "Feature Learning"



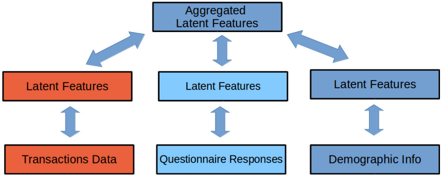
Learning features tuned for specific tasks. Lot of recent buzz (e.g., deep learning).

Why **Learn** Features?

- May not be obvious which features to use (too many, possibly noisy, features)
- Data may not have explicitly defined features (e.g., data is a graph)

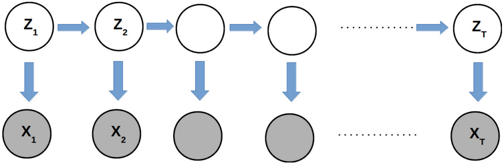


- Data may be heterogeneous and multi-modality



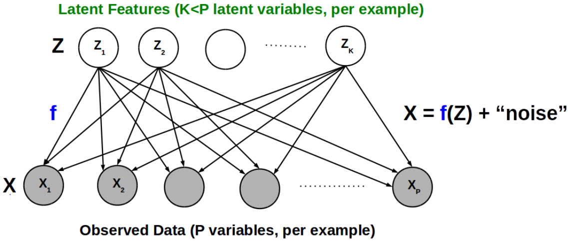
Why Learn Features?

- Data may be temporally evolving ("drifting distribution")



Generative Models for Feature Learning

- Assume that the observations arise from a generative process



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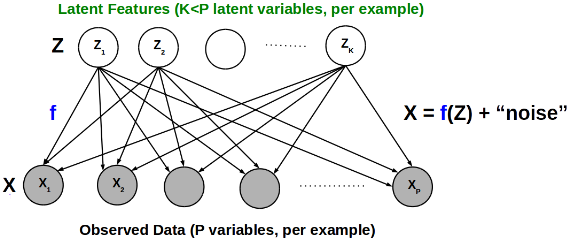
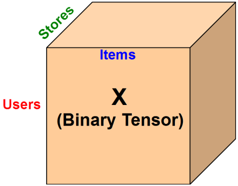


- Can be extended to multiple layers of latent features (Deep Learning)
- Many other advantanges
  - Handling missing/noisy observations
  - Learning the "right" number of latent features

Feature Learning from Tensors

- Tensor: generalization of matrices to more than two dimensions or "ways"
- Assume $\mathbf{X}$ is a binary 3-way tensor of size $N_U \times N_I \times N_S$



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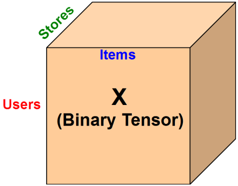

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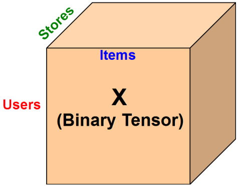

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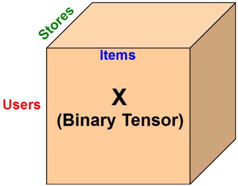

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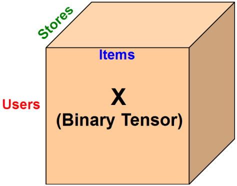

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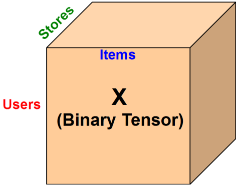

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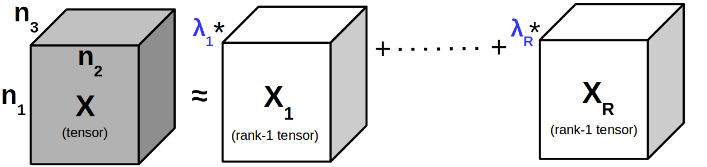
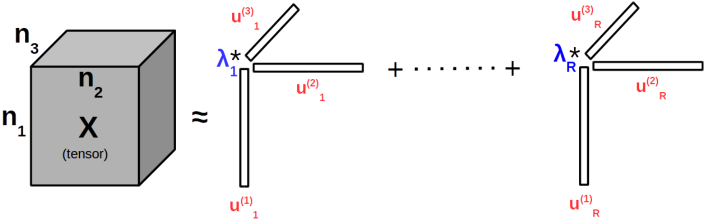
- Learning features for users/items/stores is the key

Tensor Decomposition

Low-Rank approximation: Express a tensor as a weighted sum of rank-1 tensors



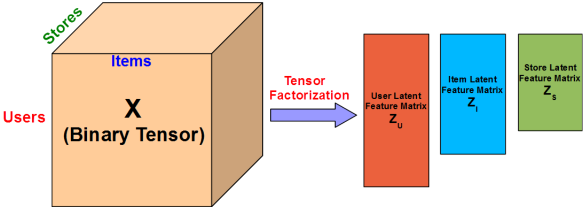
Each rank-1 tensor is an outer product of a set of column vectors (factors)



Akin to **Singular Value Decomposition** (SVD) used for matrix factorization

Feature Learning via Tensor Decomposition

Original tensor decomposed into factor matrices (one for each tensor dimension)



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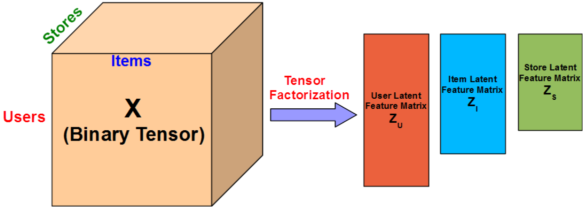
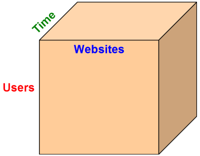


Some of our recent work on generative models for tensor decomposition:

- Interpretability: non-negativity & sparsity of the eigenvectors (latent factors)
- Simultaneous ranking/clustering of entities along with tensor decomposition
- Scalability for massive-sized tensors (computations scale w.r.t. nonzeros)
- Loss functions that model "rareness" in the data
- Online Learning

[ICML 2014, AAAI 2014, IJCAI 2015, ECML 2015, UAI 2015]

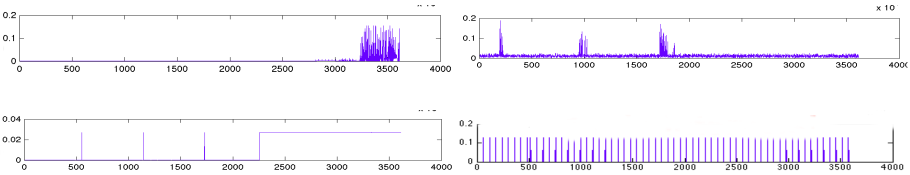
Example: Anomaly Detection



A look at what time-dimension eigenvectors might reveal

Top row: two eigenvectors capturing normal behaviors

Bottom row: two eigenvectors capturing bot-like behaviors



Can detect anomalous users by looking at the corresponding eigenvectors of users

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- Predicting the arrival times (e.g., on an e-commerce portal)
  - When will the next visit happen?
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- Learning from mislabeled data (adversary might label some frauds as legit)
- How to leverage knowledge from other (related) data sources
  - Especially useful if we have a new learning problem with no training data
  - Algorithms: Transfer or Multitask Learning, Domain Adaptation

Thanks! Questions?