COMPUTER SCIENCE & ENGINEERING
TEXAS A&M UNIVERSITY

Arizona State University

Accelerated Attributed Network Embedding

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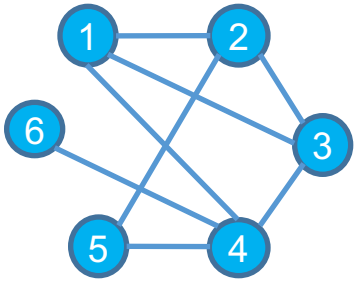
What is Network Embedding

Network



n-dimensional

Embedding Representation

$$\mathbf{H} = \begin{bmatrix} 0.54 & 0.27 \\ 0.22 & 0.91 \\ 0.55 & 0.28 \\ 0.98 & 0.11 \\ 0.32 & 0.87 \\ 0.26 & 0.11 \end{bmatrix} \begin{matrix} n_1 \\ n_2 \\ n_3 \\ n_4 \\ n_5 \\ n_6 \end{matrix}$$

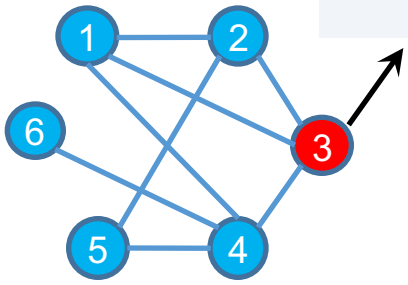
$\mathrm{d} \ll n$

Application

- Classification
- Clustering
- Link Prediction
- Visualization
- …

- Learn a low-dimensional vector representation for each node, such that all the geometrical structure information is preserved.
- Similar nodes have similar representations, and the informative latent space benefits real-world applications.

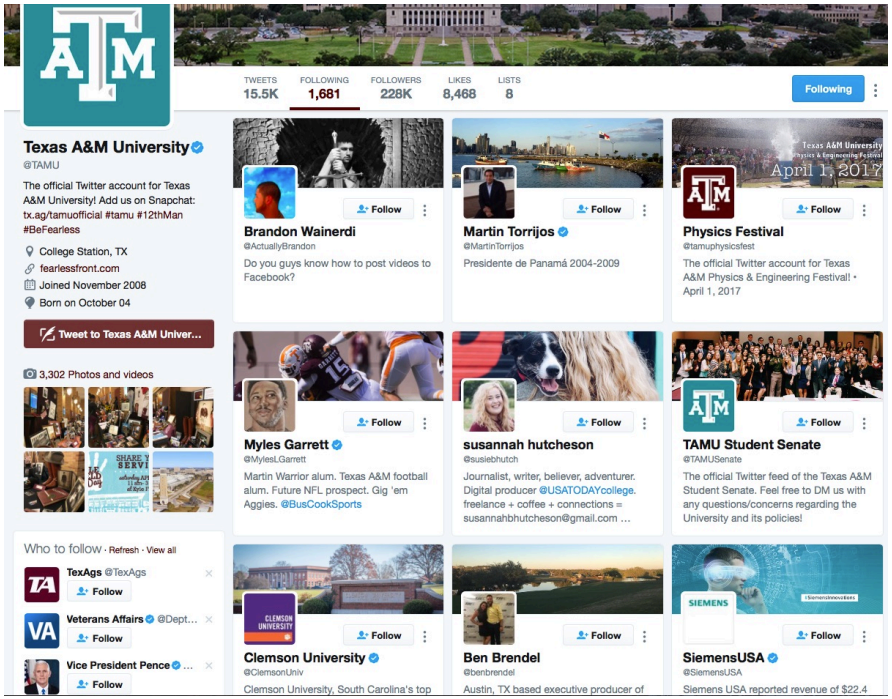
What is Attributed Network



- In real-world information systems, nodes are not just vertices.
- Both node-to-node dependencies & node attribute information are available.

Why Attributes Benefit Embedding

- Node attributes are rich and informative.
- Homophily & social influence: network and node attributes influence each other and are inherently correlated.



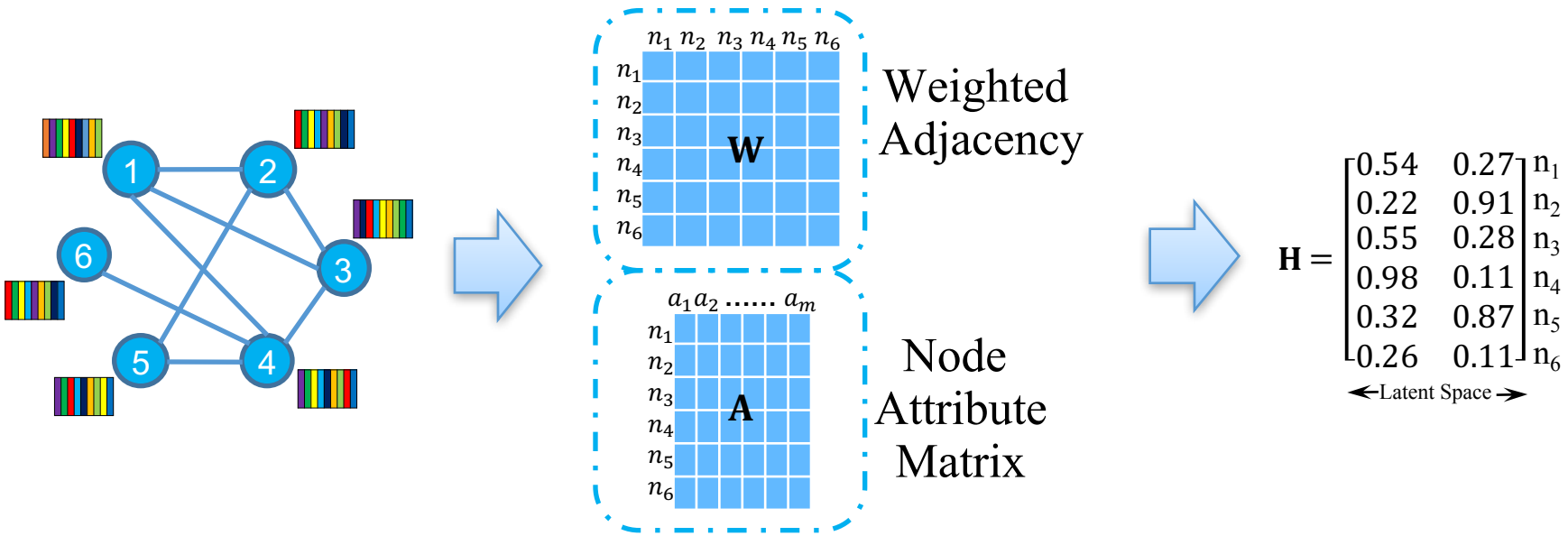
- High correlation of user posts and following relationships.
- Strong association between paper topics and citations.

Major Challenges

- Hard to jointly assessing node proximity from heterogeneous information.
  - Node attribute information such as text is distinct from network topological structure.

- Number of nodes and dimension of attributes could be large.
  - Classical algorithms such as eigen-decomposition and gradient descent cannot be applied.
  - It might be expensive to store or manipulate the high-dimensional matrices such as node attribute similarity.

Define Attributed Network Embedding



- Given **W** and **A**, we aim to represent each node as a d-dimensional row $\mathbf{h}_i$, such that **H** can preserve node proximity both in network and node attributes.
- Nodes with similar topology or attributes would have similar representations.

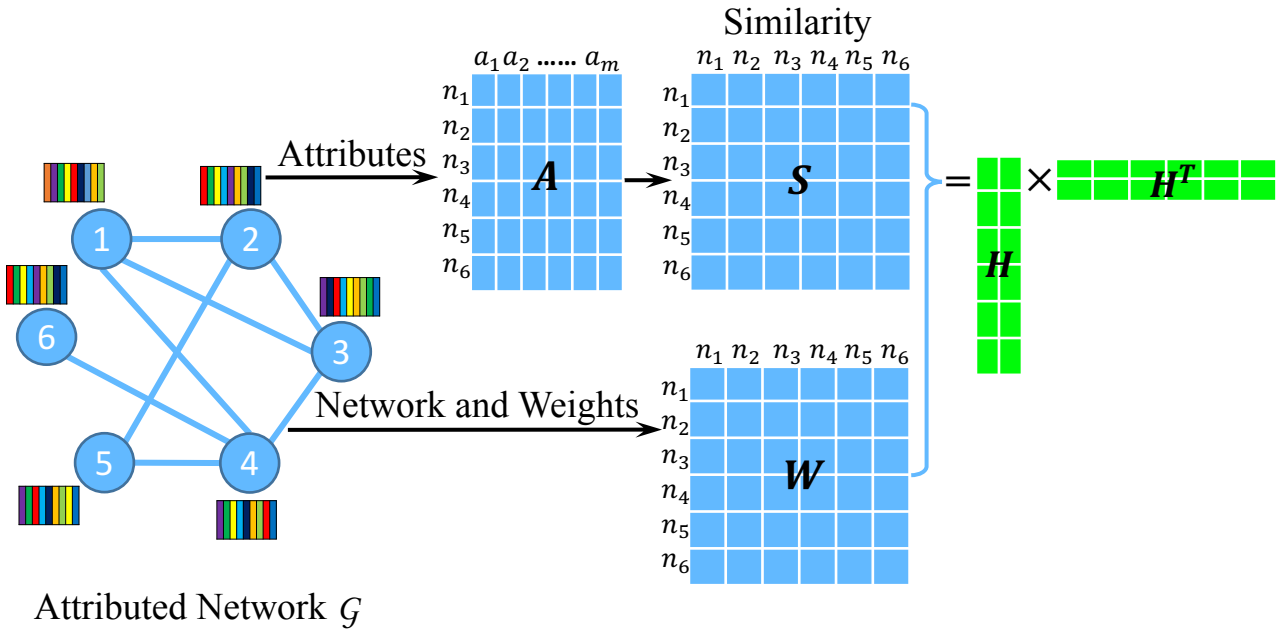
Major Contributions

- Propose a scalable framework AANE to jointly learn node proximity from network and node attributes.

- Present a distributed optimization algorithm to accelerate by decomposing the task into low complexity sub-problems.

- Strategies for filling the gap:
  I. Assimilate the two information in the similarity space to tackle heterogeneity, but without calculating the network similarity matrix.
  II. Avoid high-dimensional matrix manipulation.
  III. Make sub-problems independent to each other to allow parallel computation.

Framework AANE: Strategy I



- Based on the decomposition of attribute similarity and penalty of embedding difference between connected nodes.

$$\min_{\mathbf{H}} \quad \mathcal{J} = \|\mathbf{S} - \mathbf{H}\mathbf{H}^{\top}\|_{\mathrm{F}}^{2} + \lambda \sum_{(i,j)\in\mathcal{E}} w_{ij} \|\mathbf{h}_i - \mathbf{h}_j\|_2$$

  - ℓ_2 norm alleviates the impacts from outliers and missing data.
  - Fused lasso clusters the network without similarity matrix.
  - λ adjusts the size of clustering group.

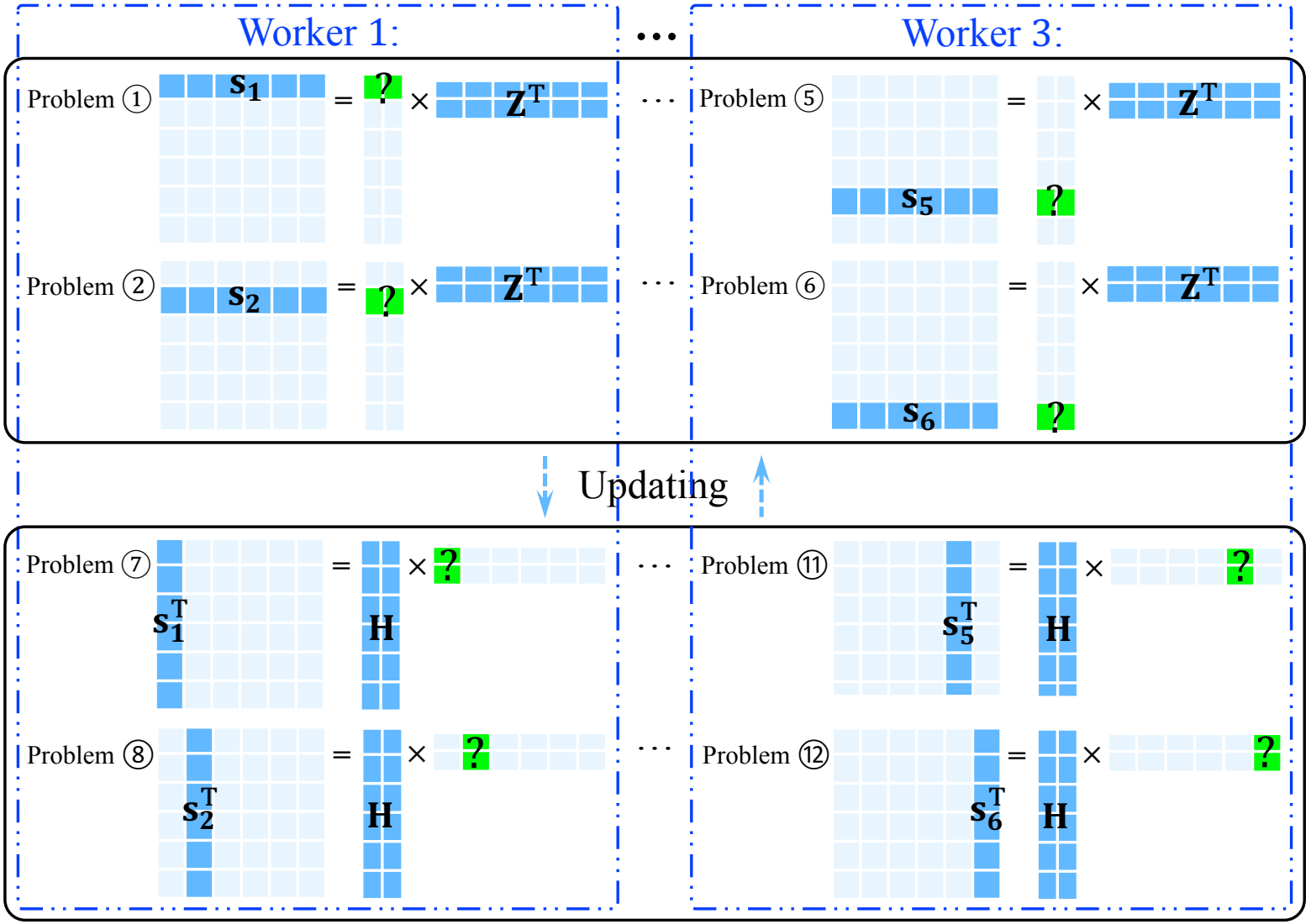
Framework AANE: Strategy II

- Make a copy of **H** and reformulate into a linearly constrained problem.

$$\min_{\mathbf{H}} \quad \sum_{i=1}^{n} \|\mathbf{s}_i - \mathbf{h}_i \mathbf{Z}^\top\|_2^2 + \lambda \sum_{(i,j)\in\mathcal{E}} w_{ij} \|\mathbf{h}_i - \mathbf{z}_j\|_2,$$
$$\text{subject to} \quad \mathbf{h}_i = \mathbf{z}_i,\ i = 1, \ldots, n.$$

- Given fixed **H**, all the row $\mathbf{z}_i$ could be calculated independently.
- Each sub-problem only needs row $\mathbf{s}_i$, not the entire **S**.
- Time complexity of updating $\mathbf{h}_i$ is $\mathcal{O}(d^3 + dn + d|N(i)|)$, with space complexity $\mathcal{O}(n)$.
- Alternating Direction Method of Multipliers (ADMM) converges to a modest accuracy in a few iterations.

Framework AANE: Strategy III



Experimental Setup

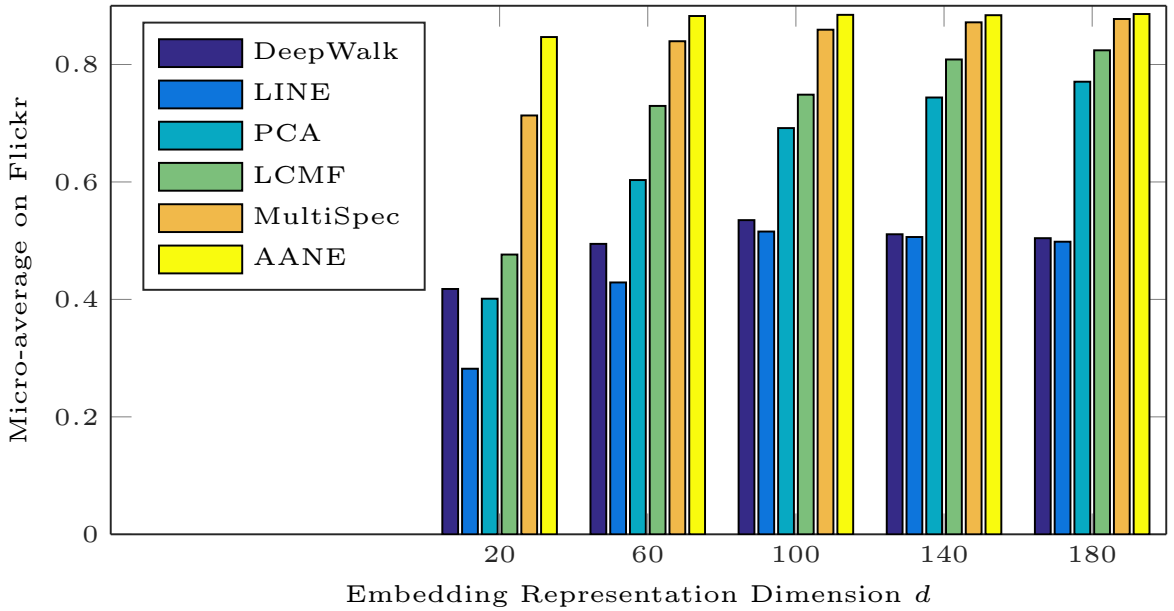
- Classification on three real-world network:
  - BlogCatalog
  - Flickr
  - Yelp

- Three types of baselines:
  - Scalable network embedding, DeepWalk & LINE.
  - Node attribute modeling based on PCA.
  - Attributed network representation learning, multispec & LCMF.

Effectiveness Evaluation

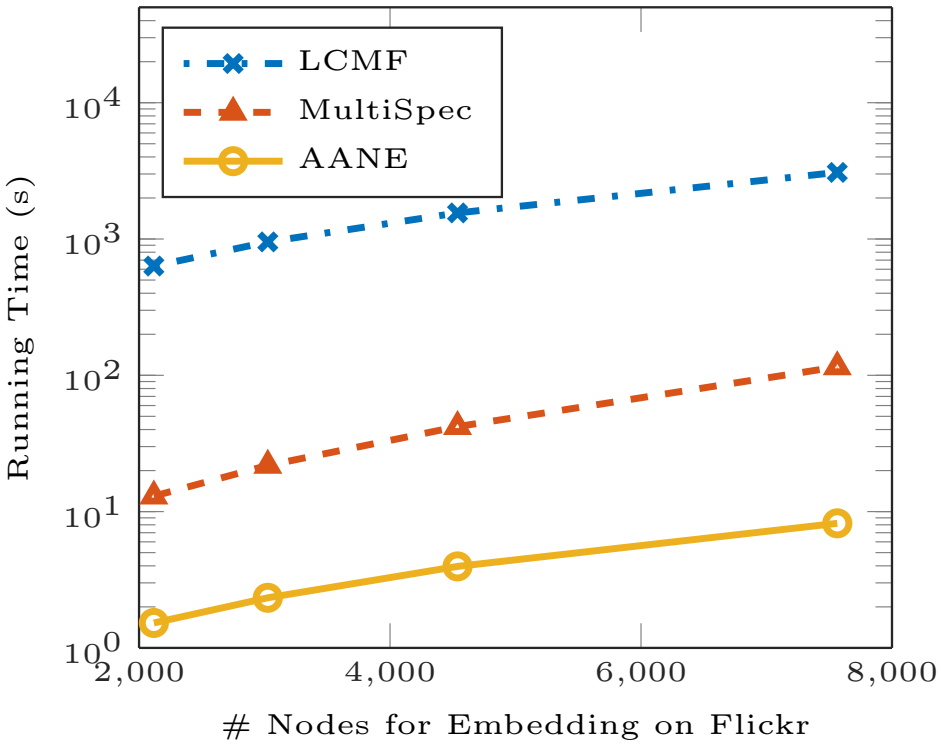
- AANE achieves higher performance than the state-of-the-art embedding algorithms with different training percentage and latent dimension d.

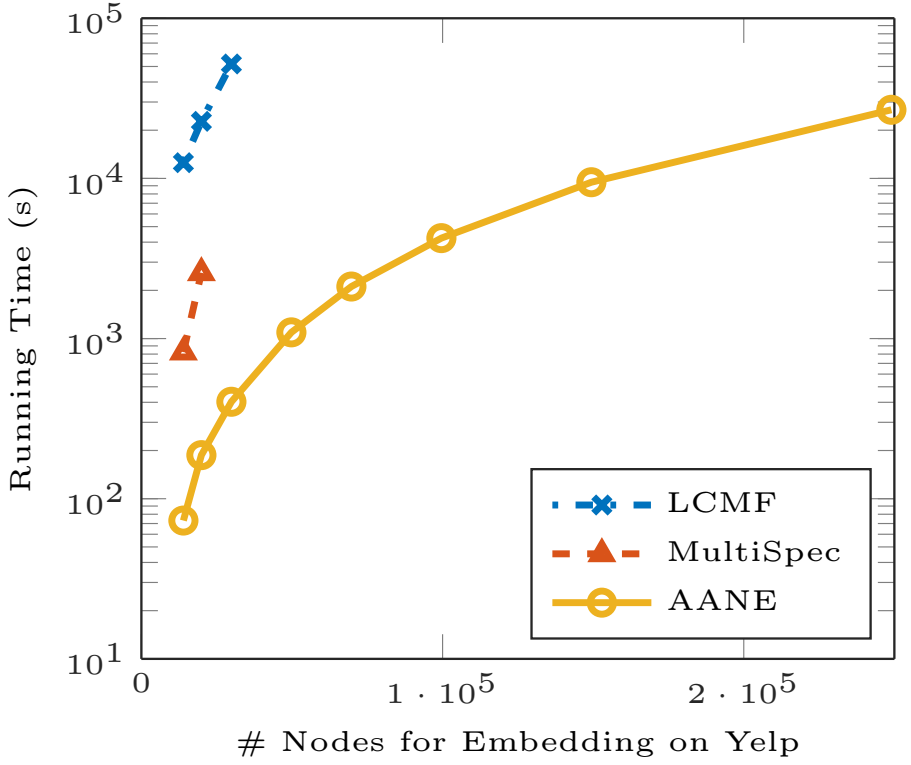
		BlogCatalog			
Training Percentage		10%	25%	50%	100%
# nodes for embedding		1,455	2,079	3,118	5,196
Macro-average	DeepWalk	0.489	0.548	0.606	0.665
	LINE	0.425	0.542	0.620	0.681
	PCA	0.691	0.780	0.821	0.855
	LCMF	0.776	0.847	0.886	0.900
	MultiSpec	0.677	0.787	0.847	0.895
	AANE	**0.836**	**0.875**	**0.912**	**0.930**



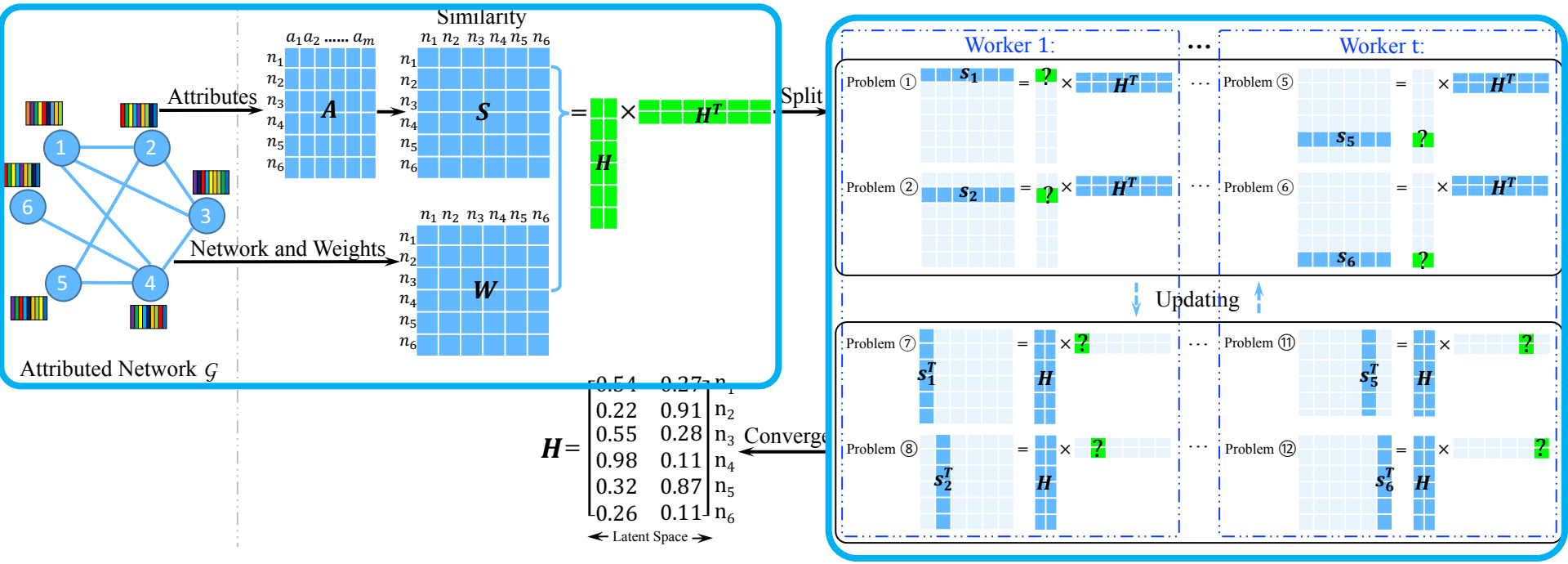
Efficiency Evaluation

- AANE takes much less running time than the attributed network representation learning methods even with single-thread.





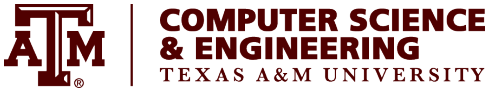
Conclusions



- The proposed accelerated attributed network embedding (AANE) framework is scalable, efficient, and effective.
- Future work:
  - Embedding of large-scale and dynamic attributed networks.
  - Semi-supervised attributed network embedding.

Acknowledgement

- DATA Lab and collaborators



Data Analytics at Texas A&M (DATA Lab)

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