

Real-Time Visual Analytics for User-Driven Machine Learning

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Two Approaches for Data Analysis

Machine
Learning

Visualization

Automated

Interactive (human in the loop)

Clearly defined tasks

Exploratory analysis

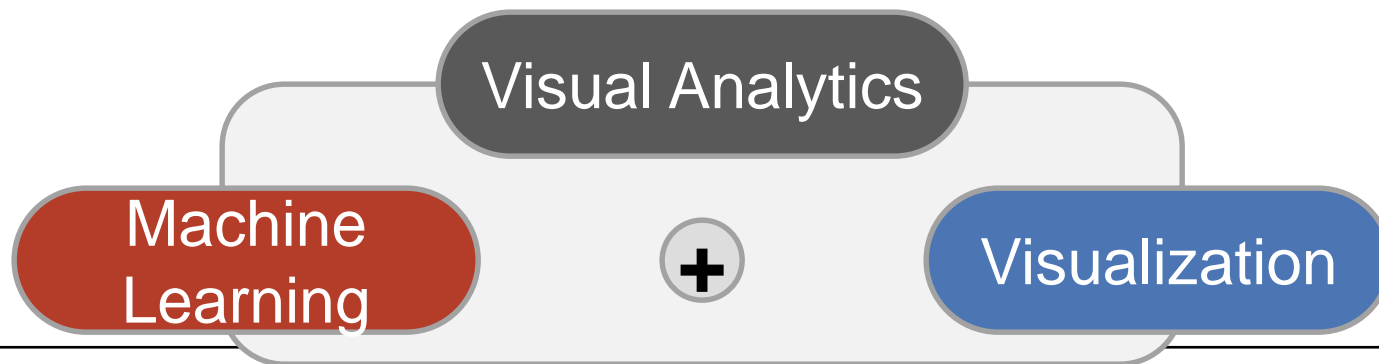
Fast computation

Deeper understanding

>Millions of data items

Thousands of data items

Visual Analytics



Automated

Interactive (human in the loop)

Clearly defined tasks

Exploratory analysis

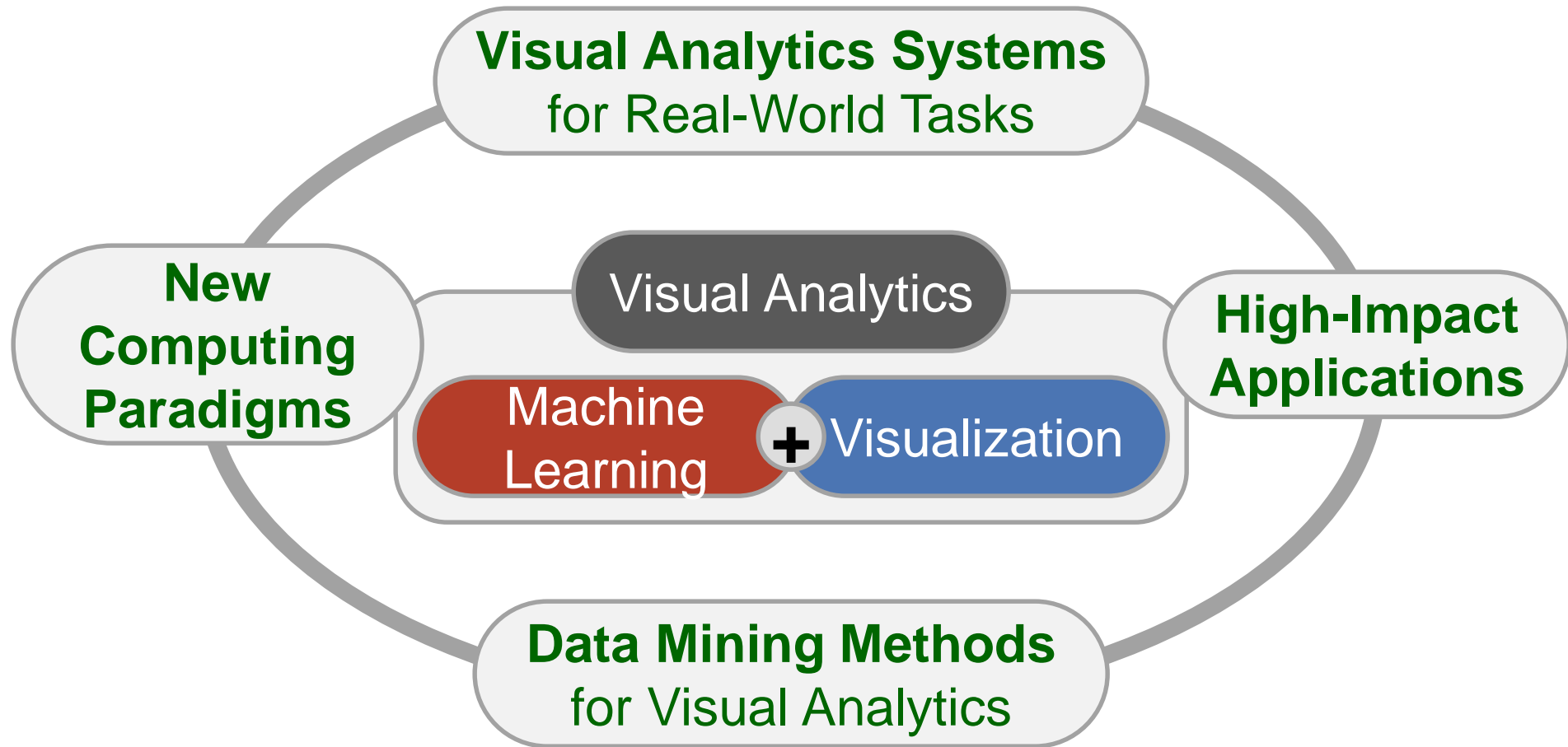
Fast computation

Deeper understanding

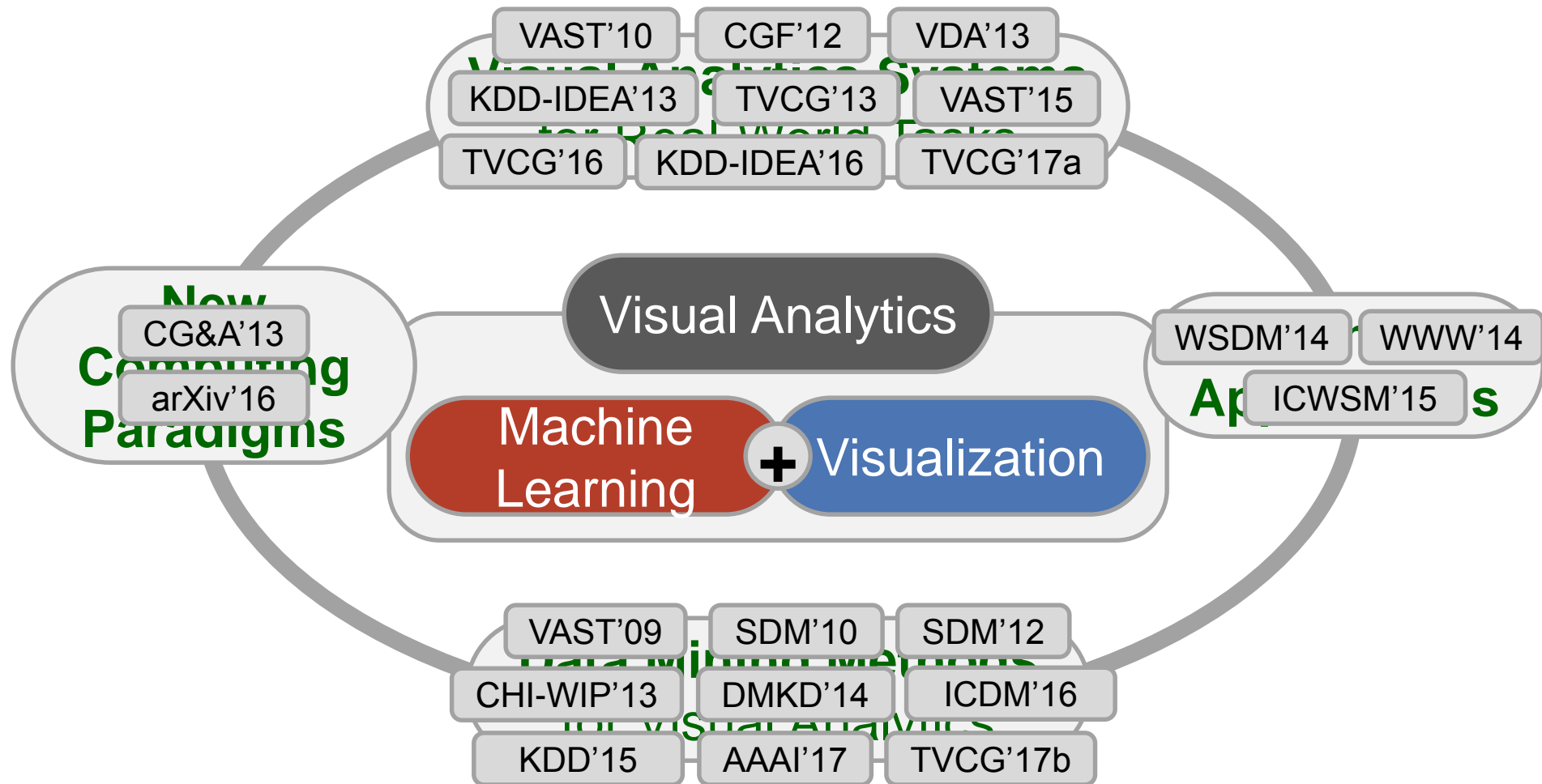
>Millions of data items

Thousands of data items

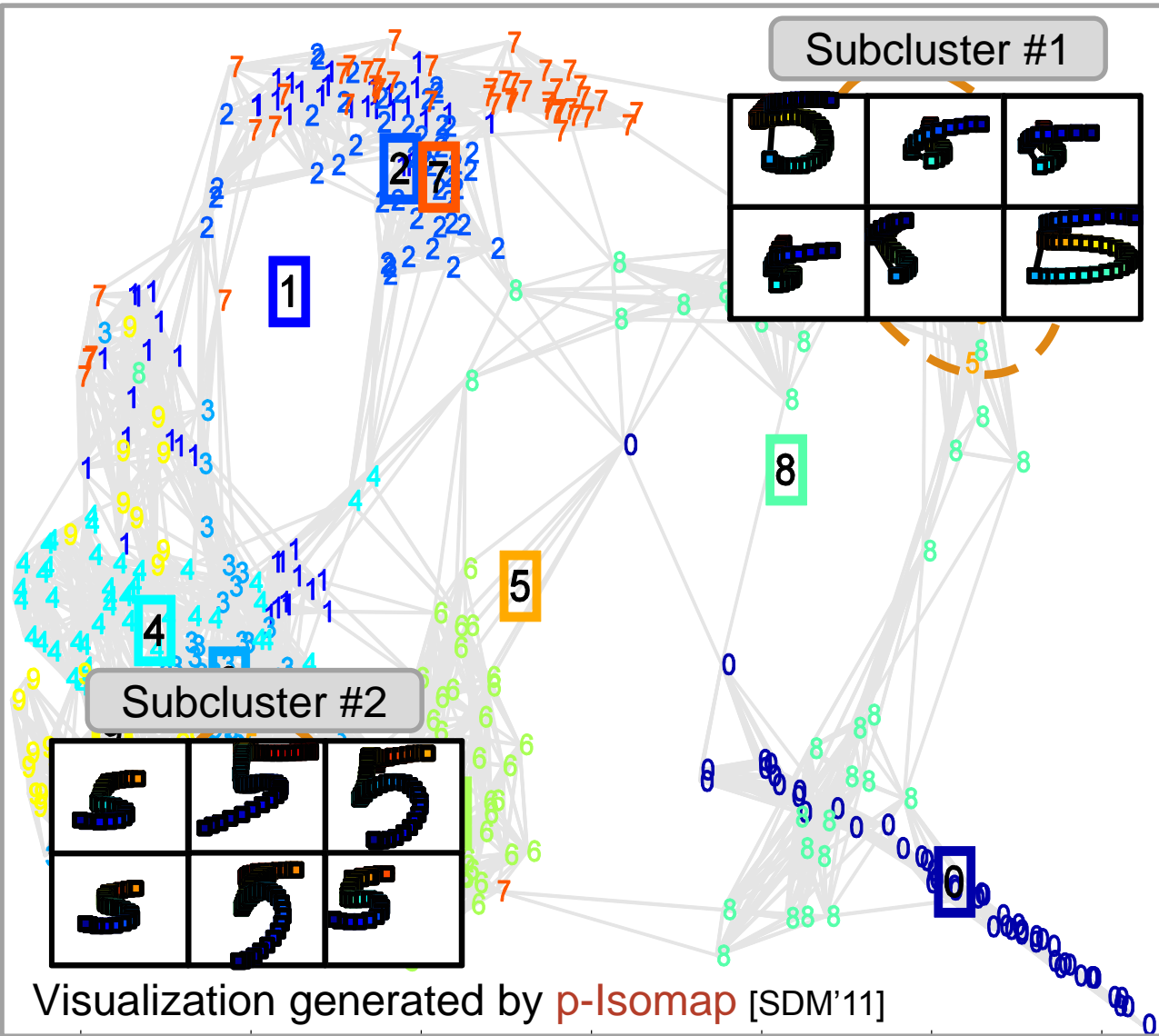
My Research: True Integration of Both Worlds



My Research: True Integration of Both Worlds



Visual Insight to Machine Learning Handwritten Digit Recognition



Visualization generated by **p-Isomap** [SDM'11]

Subclusters in
digit '5'



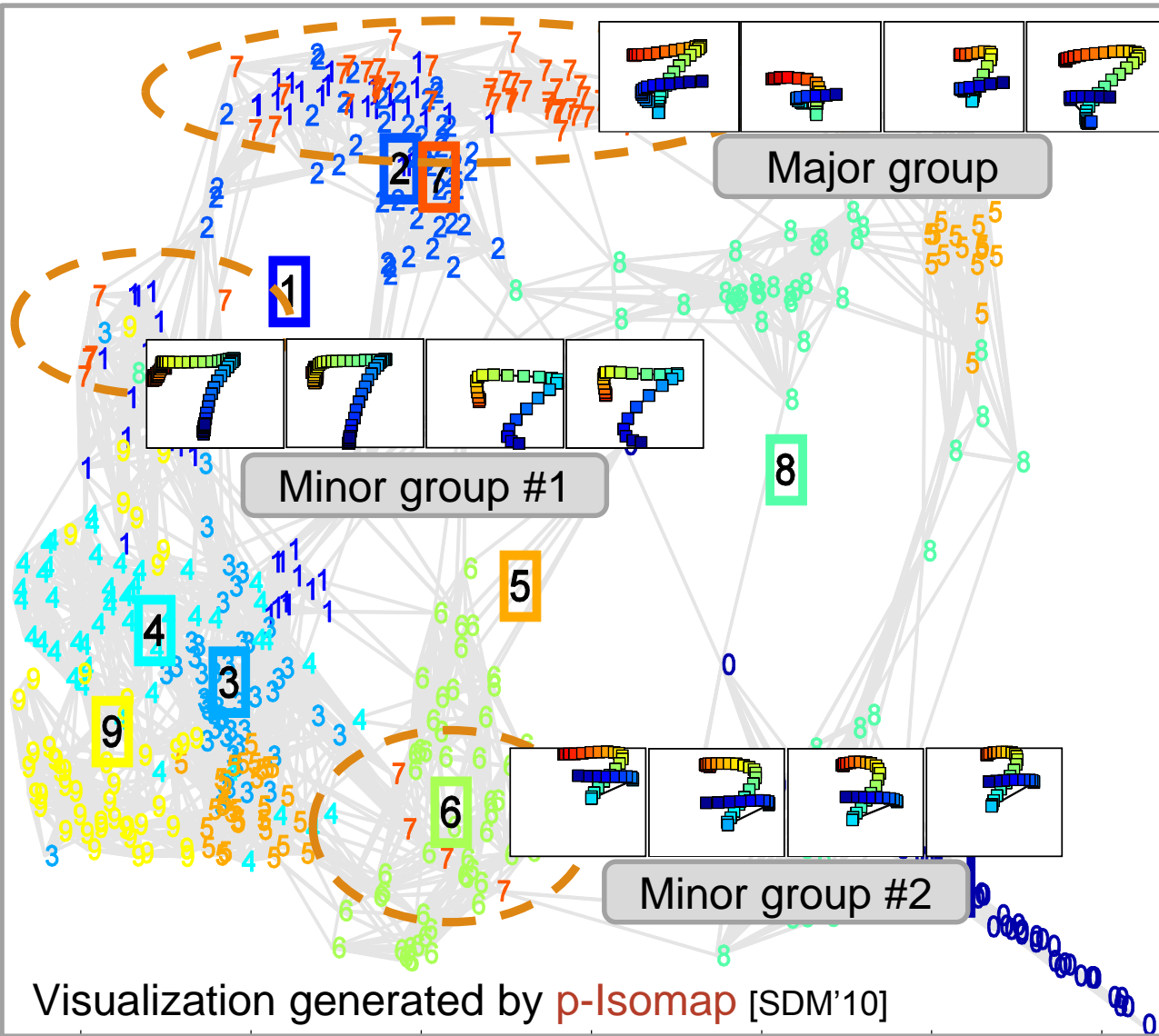
Handling them as
separate clusters



Better prediction
(89% → **93%**)

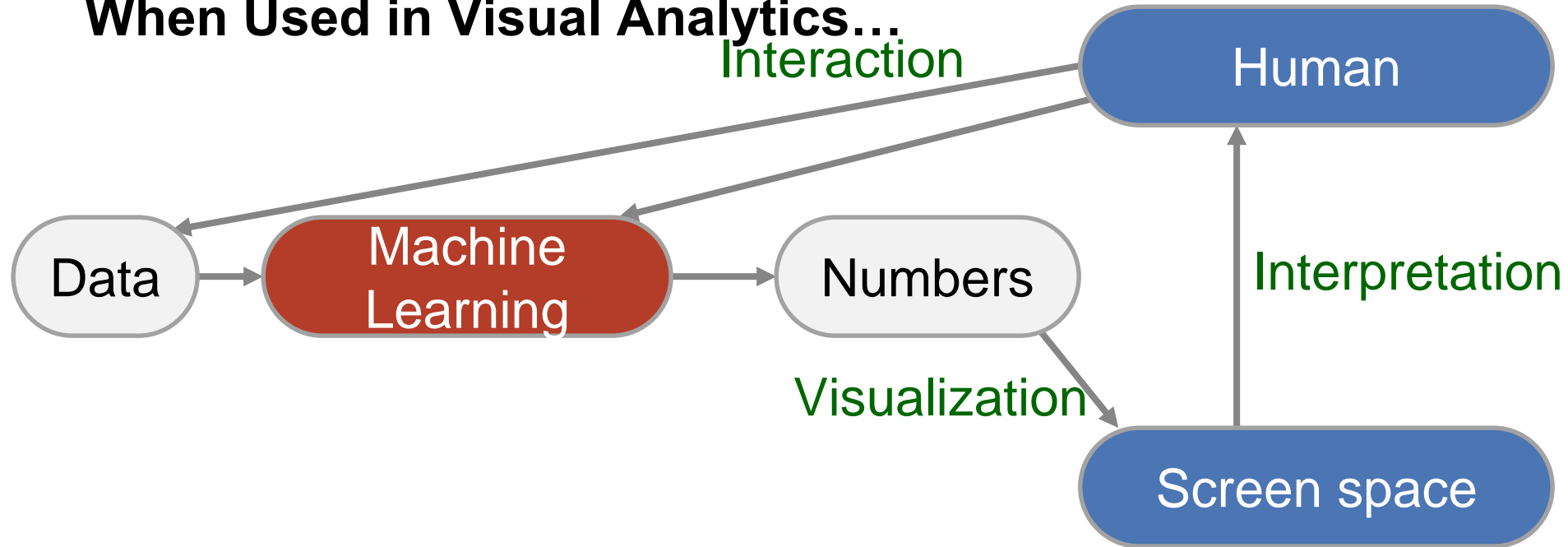
Visual Insight to Machine Learning

Handwritten Digit Recognition



Challenges in Machine Learning + Visualization

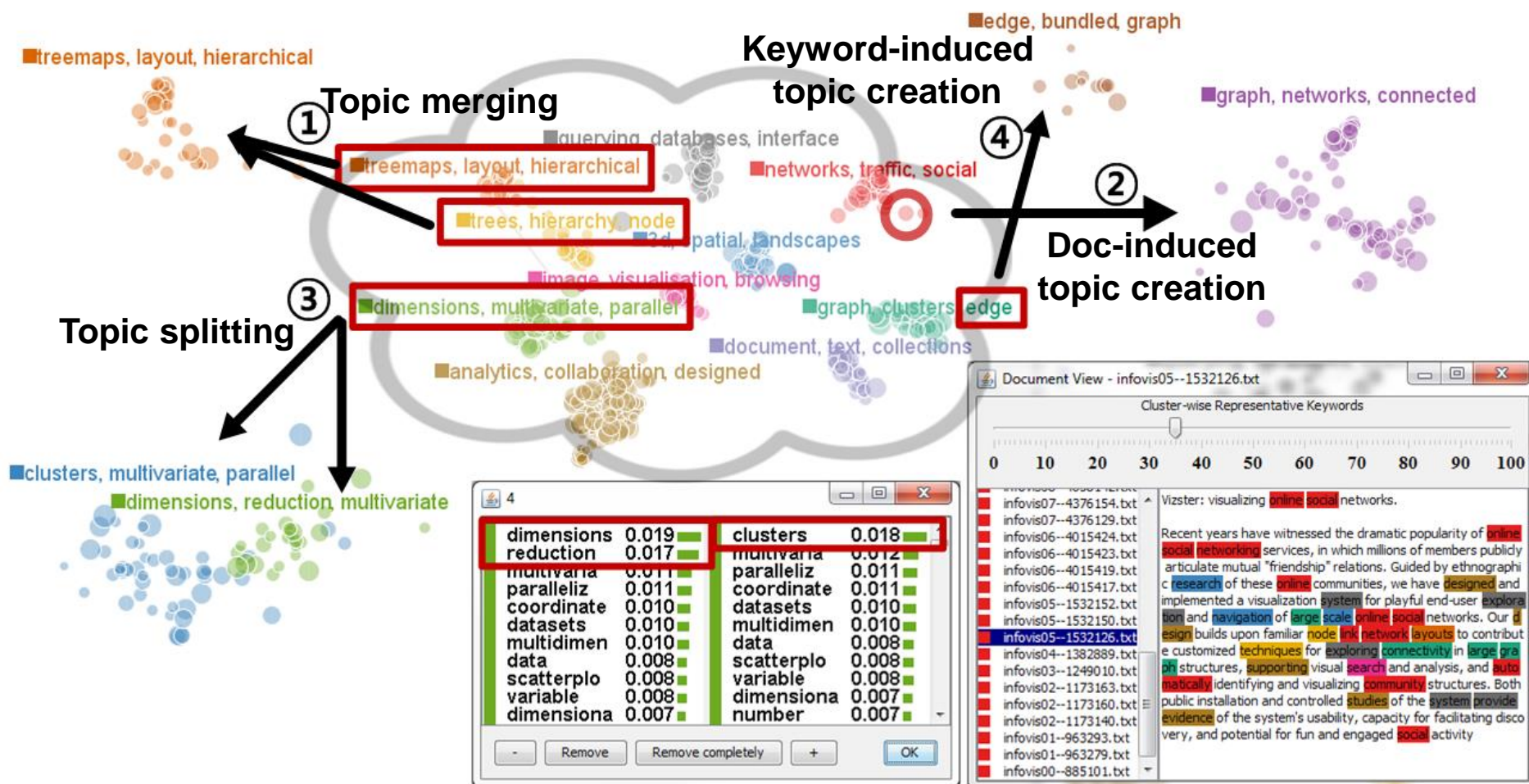
When Used in Visual Analytics...



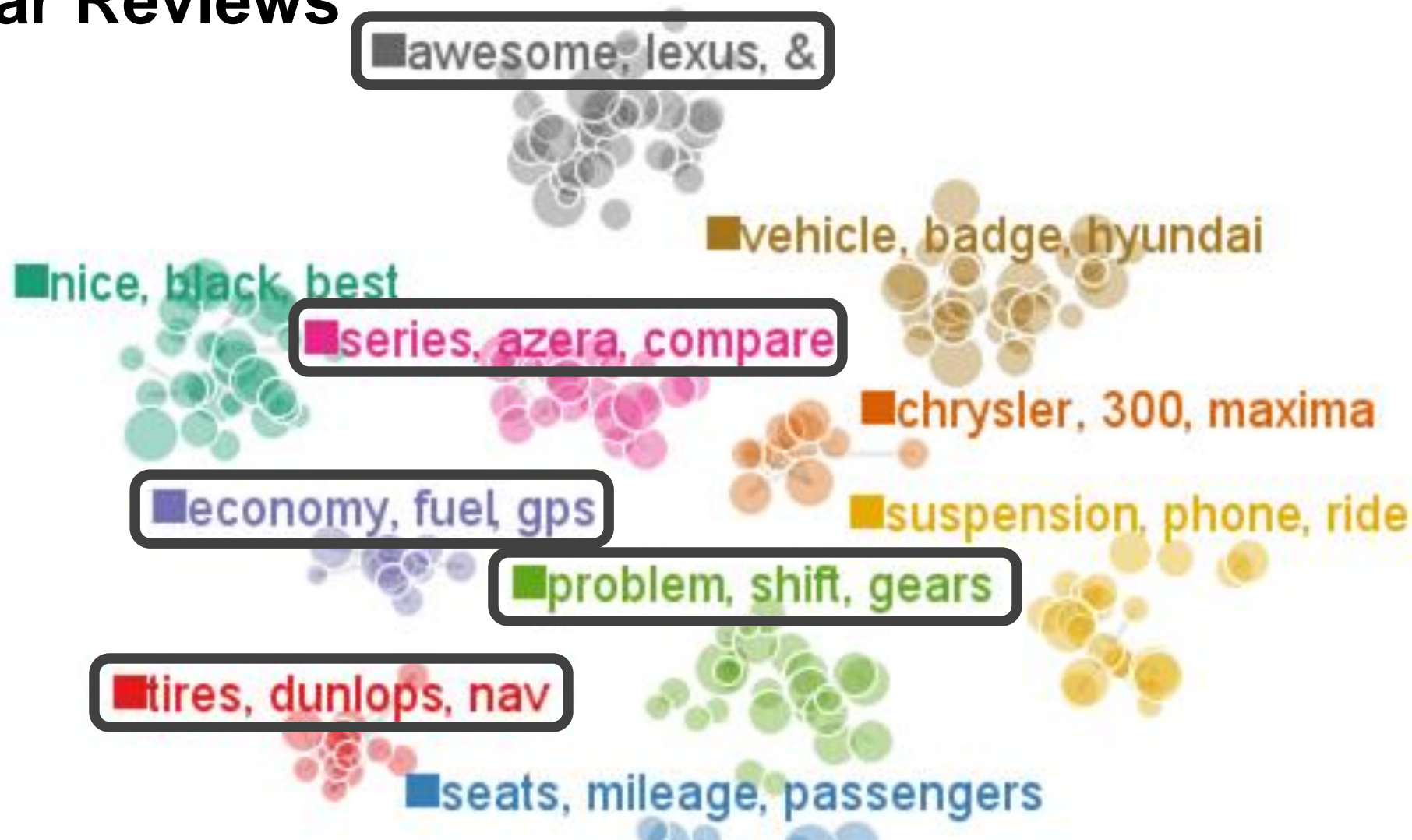
Machine learning methods should be

- More interpretable
- More user-interactive
- Real-time responsive, i.e., faster

UTOPIAN: User-Driven Topic Modeling Based on Interactive NMF



Visualization Example: Car Reviews



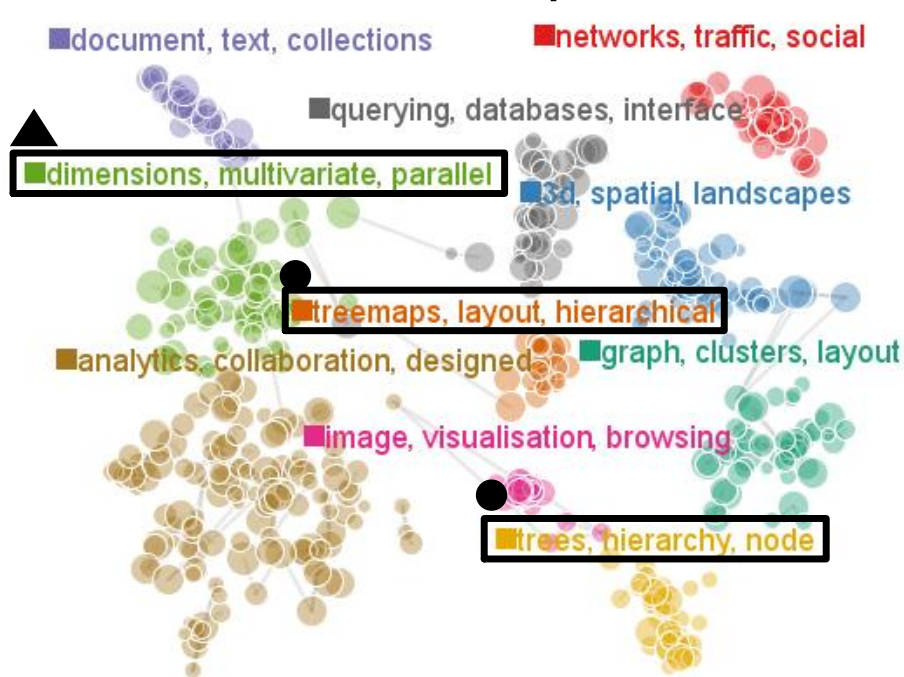
Topic summaries are **NOT** perfect.

➔ UTOPIAN allows **user interactions** for improving them.

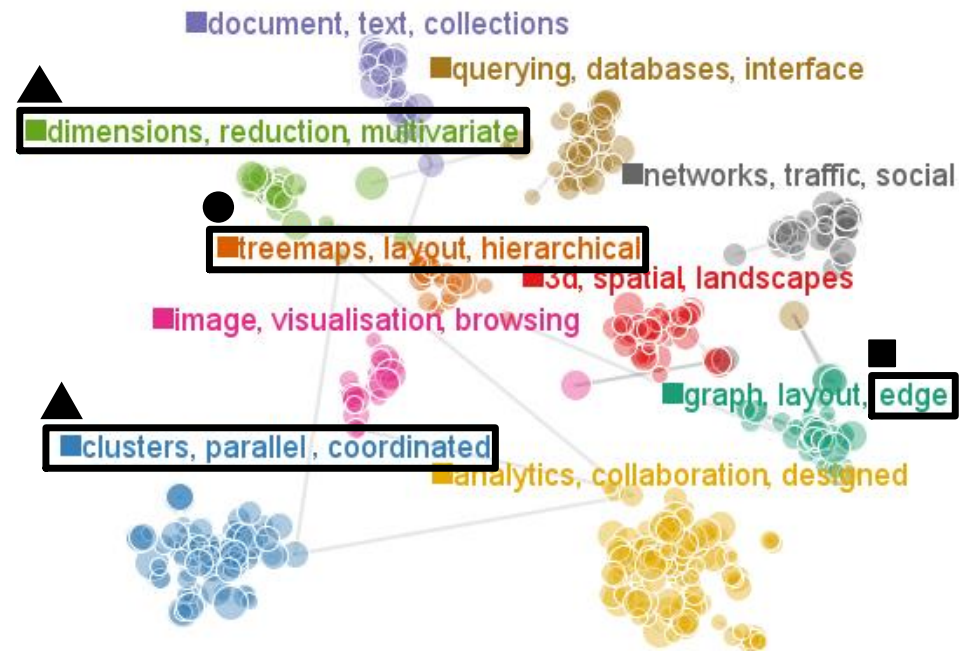
UTOPIAN Demo

<http://tinyurl.com/UTOPIAN2013>

InfoVis-VAST Paper Data



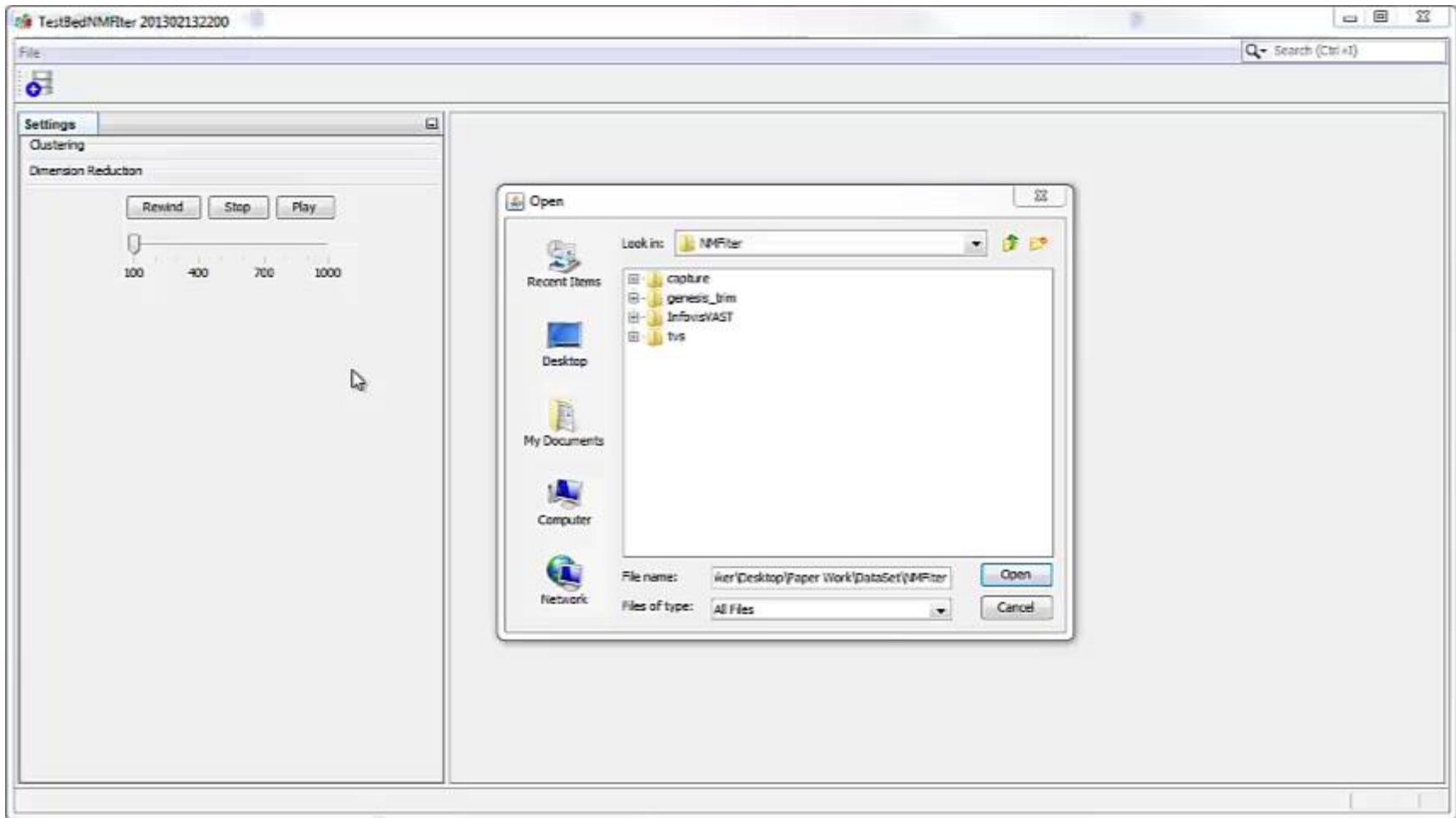
Before interaction



After topic splitting (triangle)
and topic merging (circle)

UTOPIAN Demo

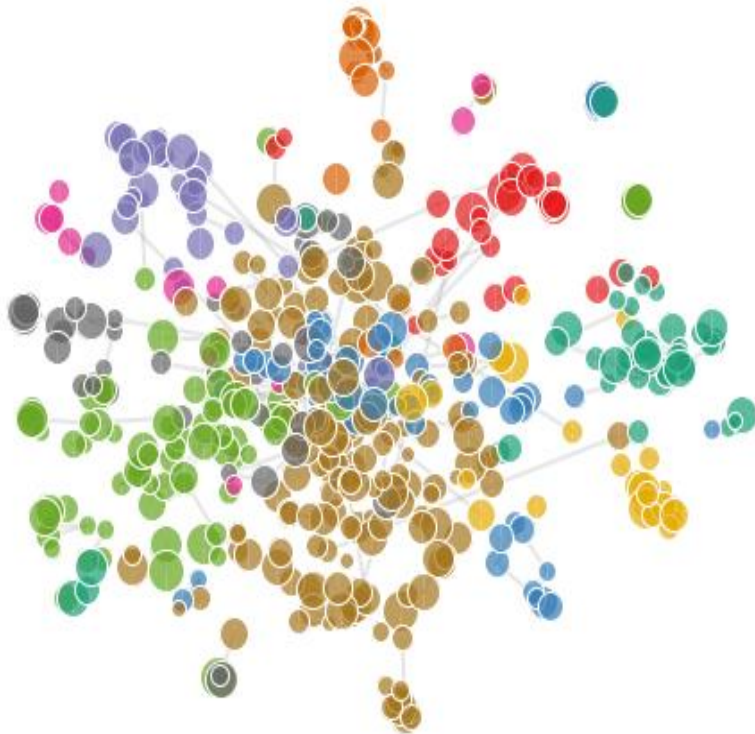
<http://tinyurl.com/UTOPIAN2013>



Supervised t-SNE: Visualizing documents

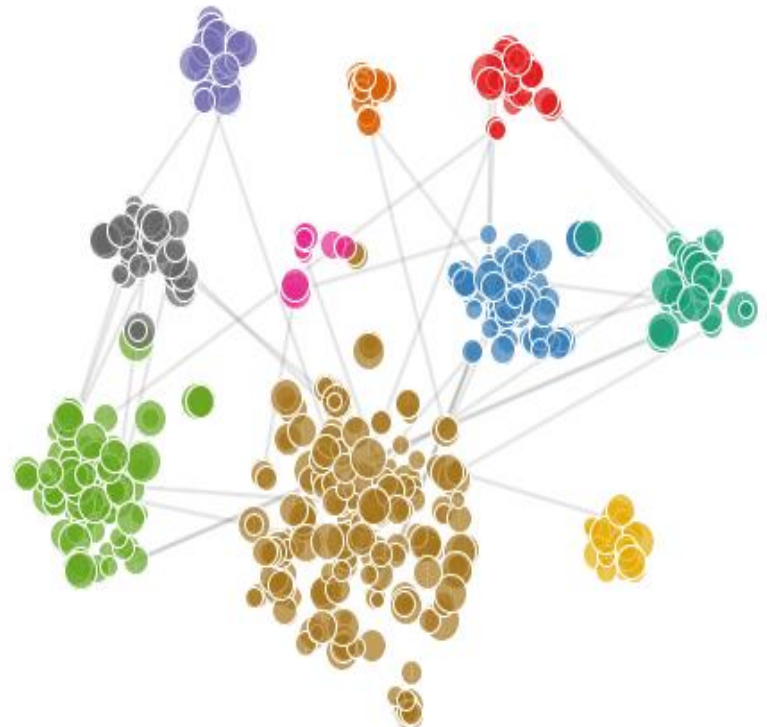
Original t-SNE

- Documents do not have clear topic clusters.



Supervised t-SNE

- $d(x_i, x_j) \leftarrow \alpha \cdot d(x_i, x_j)$ if x_i and x_j belong to the same topic.
(e.g., $\alpha = 0.3$)



Weakly Supervised NMF: Supporting user interactions

Weakly supervised NMF

$$\min_{W \geq 0, H \geq 0} \|A - WH\|_F^2 + \alpha \|(W - W_r)M_W\|_F^2 + \beta \|M_H(H - D_H H_r)\|_F^2$$

W_r, H_r : **reference** matrices for W and H (user-input)

M_W, M_H : diagonal matrices for **weighting/masking** columns and rows of W and H

► Algorithm: block-coordinate descent framework

PIVE: (Per-Iteration Visualization Environment)

https://youtu.be/zURFA9P5E_s

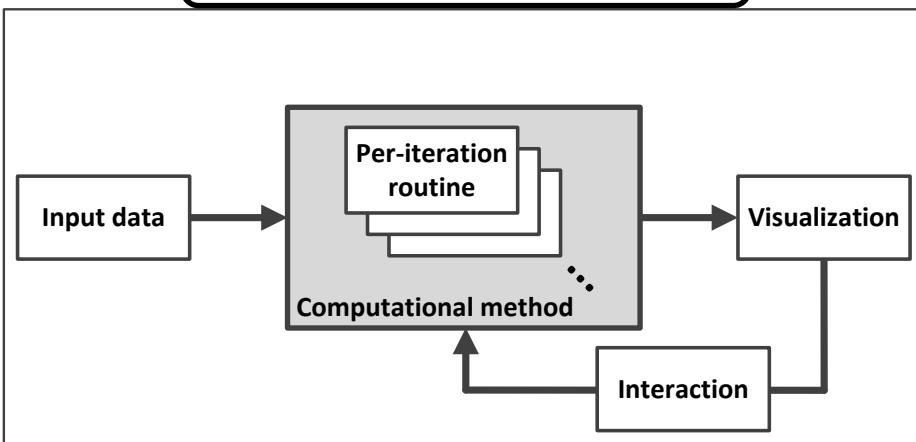
Motivation

- ▶ Many algorithms are iterative methods.

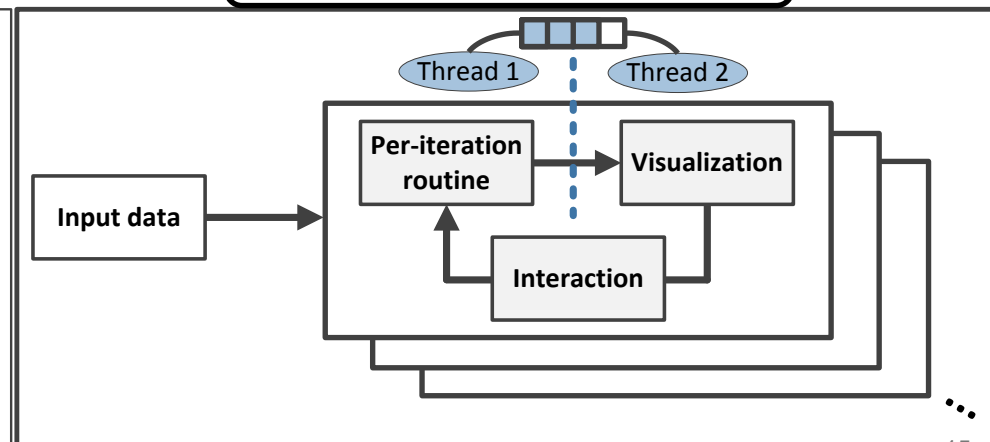
PIVE

- ▶ Integration methodology of iterative methods for **Real-Time** interactive visualization

Standard approach

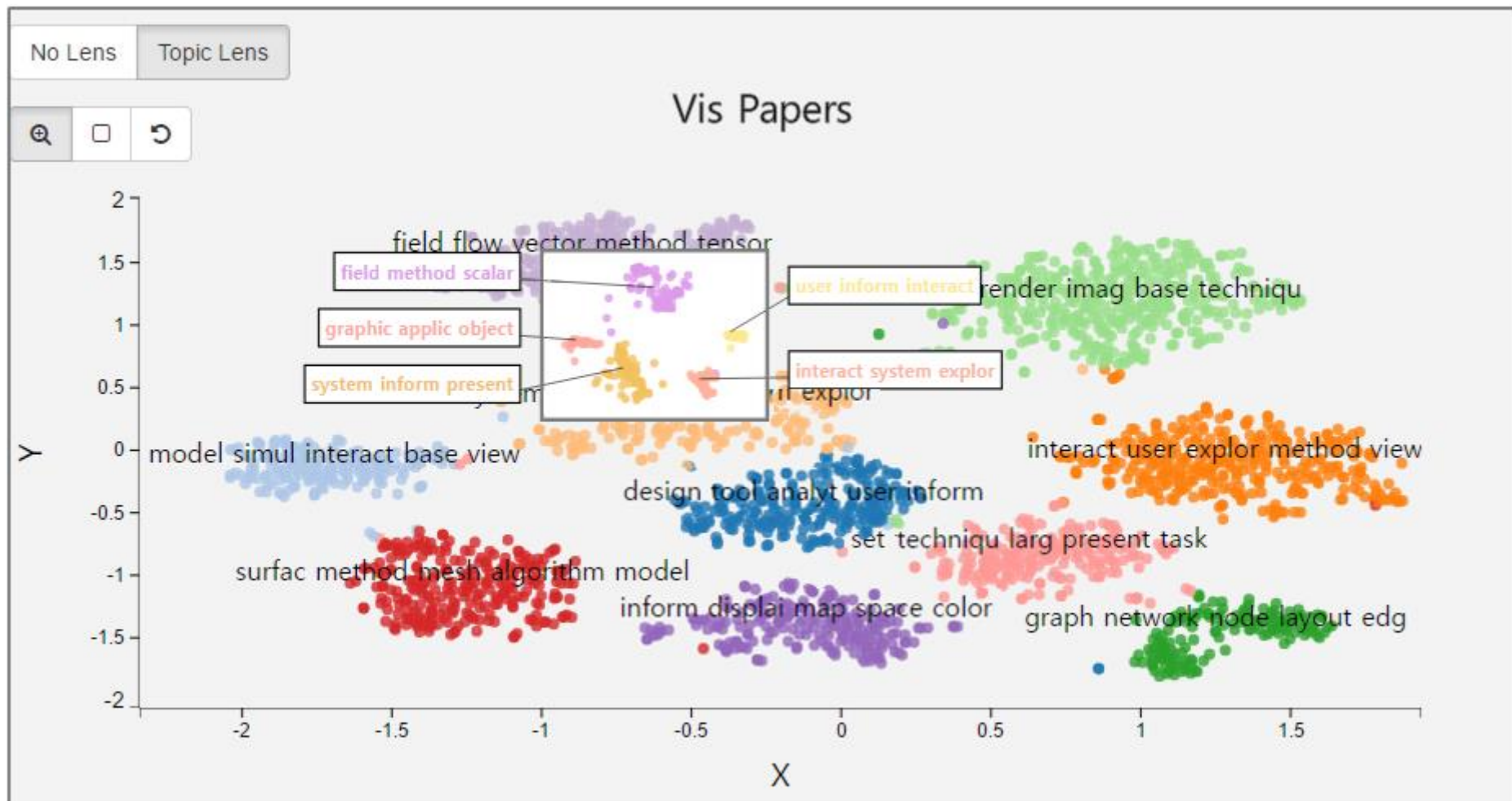


PIVE approach



PIVE Demo

TopicLens: Efficient Multi-Level Visual Topic Exploration



TopicLens: Efficient Multi-Level Visual Topic Exploration

Key aspects of backend topic modeling and dimension reduction methods

- ▶ Real-time response

- How can we ensure real-time response against highly-dynamic user interactions such as lens?

- ▶ Continuity and consistency with previous results

- How can we allow users to maintain the continuity and consistency between the previous and the new results?

TopicLens Demo

Compare and Contrast: Joint Topic Discovery

Formulation

$$\min_{W \geq 0, H \geq 0} \quad 1/n_1 \|A_1 - W_1 H_1\|_F^2 + 1/n_2 \|A_2 - W_2 H_2\|_F^2 +$$

$$\alpha \|W_{1,c} - W_{2,c}\|_F^2 + \beta \|W_{1,d}^T W_{2,d}\|_F^2$$

where $W_i = [W_{i,c} \ W_{i,d}]$

2000-2005

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Common
topics in DM

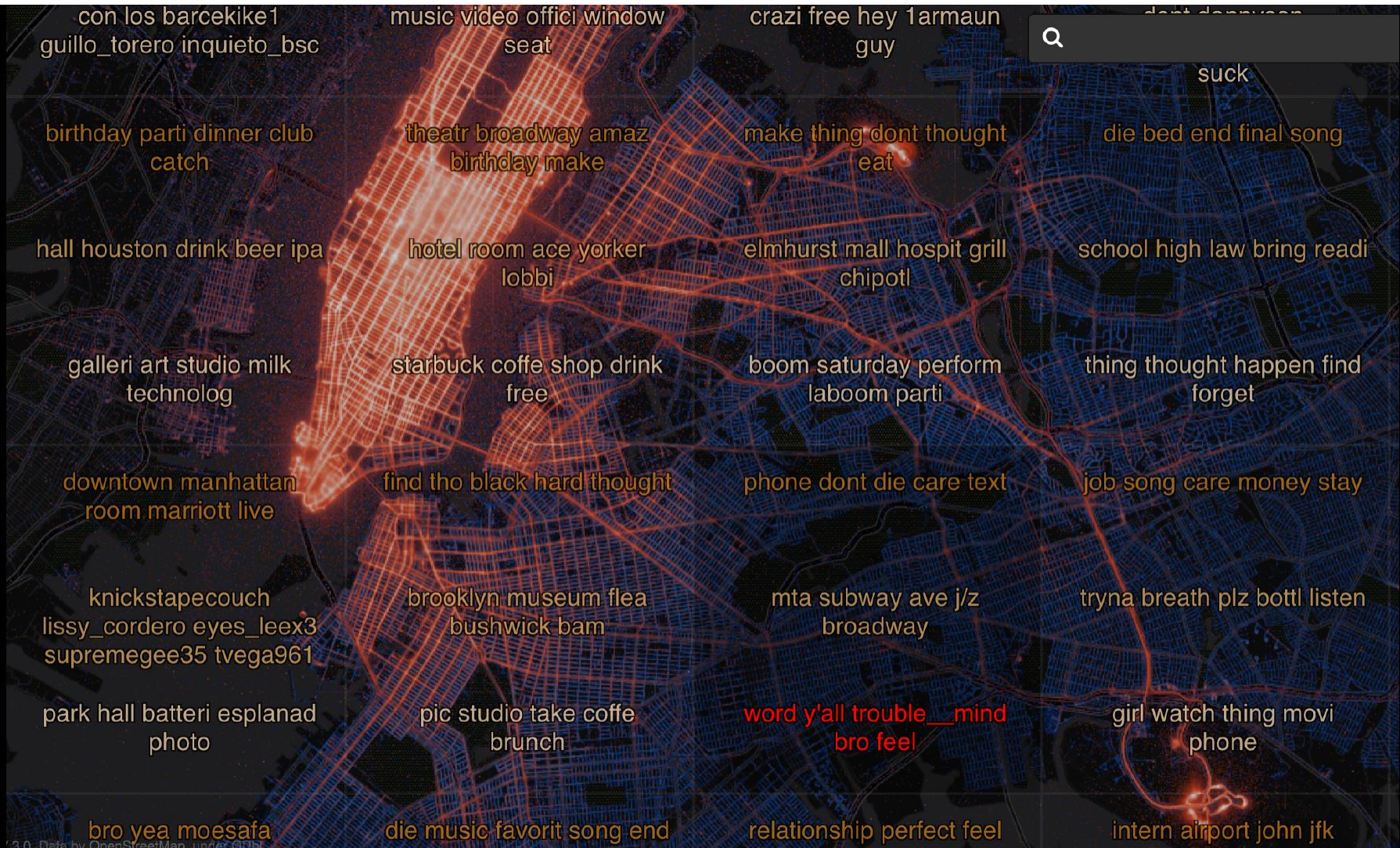
outlier sequenc dataset motif mino
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weight seri chang inform point anomali
event system spam intrus vidio
non attribut geograph robust
measur subspac geo relationship optim spatial
distanc hierarchi cluster
region

2006-2008

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larg scale graph databas
design corre represent
bipartit paramet compact adapt
short strategi duplic recommend veri dynam
rank commun neural
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research propag predict behavior latent group
onlin network
traffic

Geospatio-Temporal Topic Modeling

<http://aperture.xdataonline.com/#/>



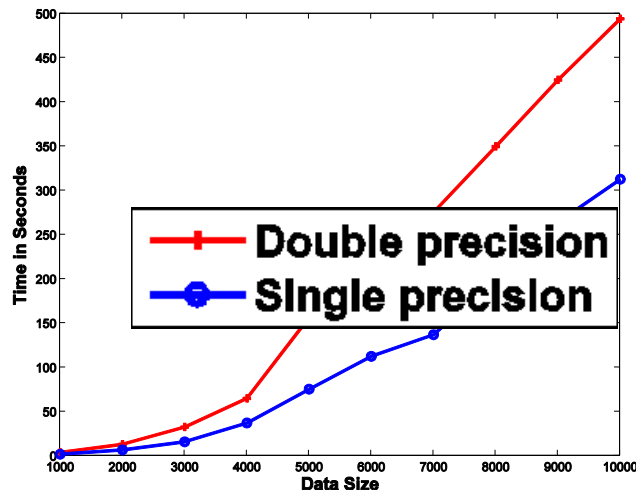
Perception- and Screen Space-Driven Integration Framework

Motivation

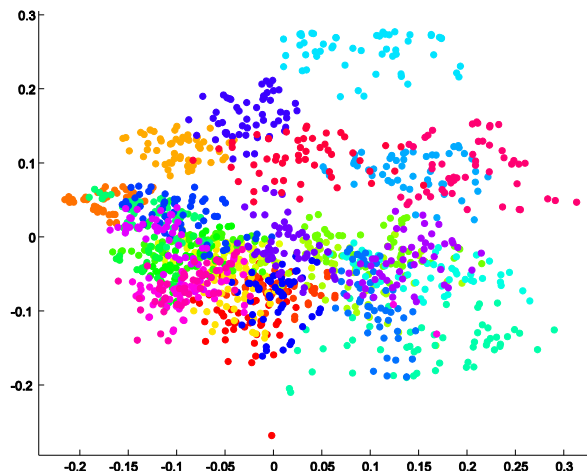
- ▶ Humans and computer screens **do not** require **high precision**.

Approach

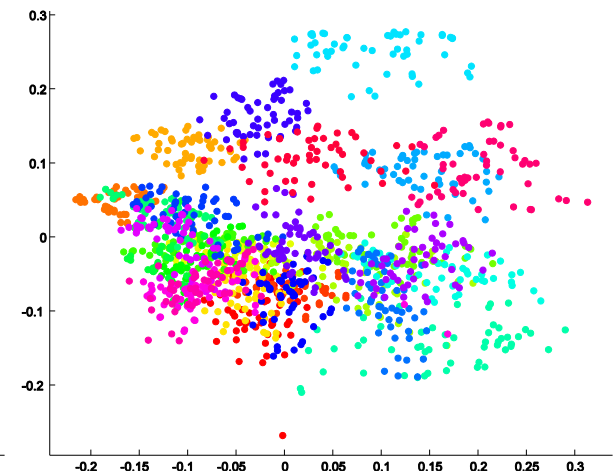
- ▶ **Approximate computing**



Computing time
vs. data size



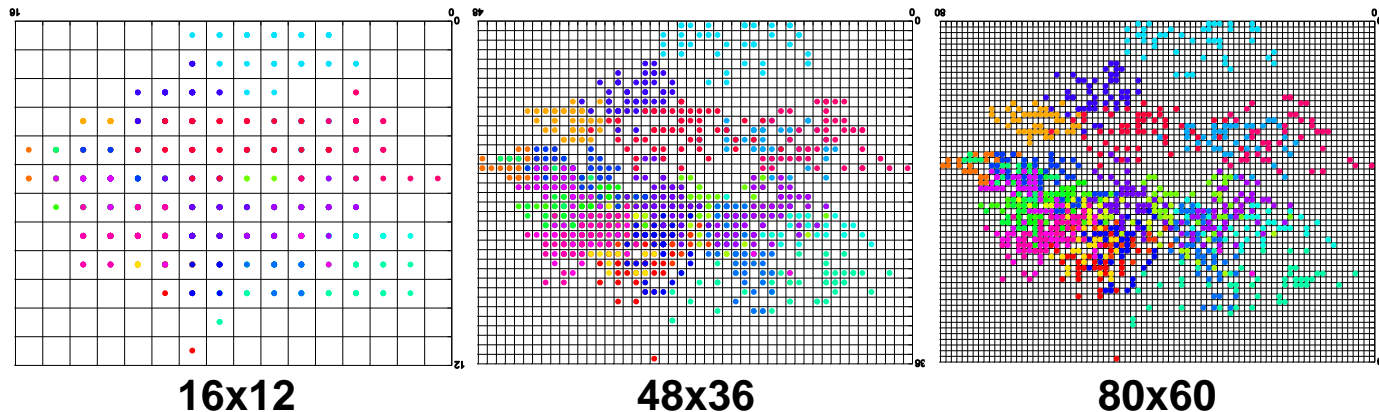
Double-precision PCA



Single-precision PCA

New Computing Paradigms for Visual Analytics

Adaptive hierarchical refinement

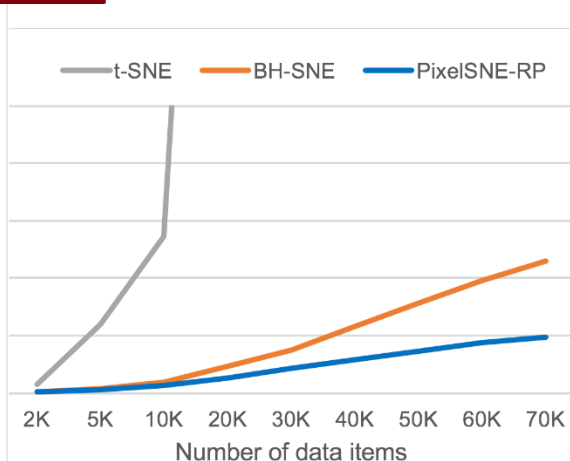
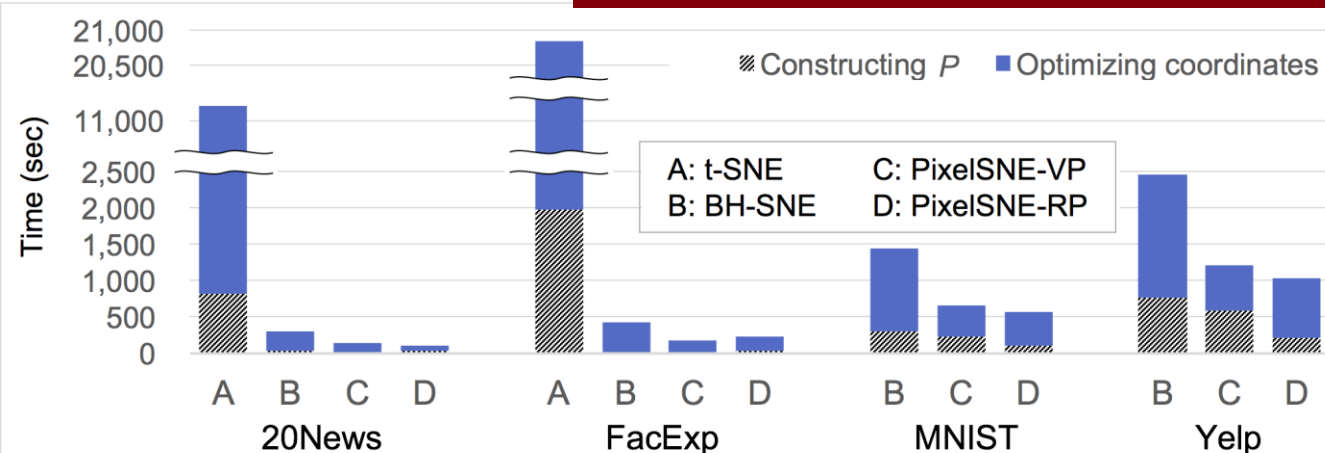
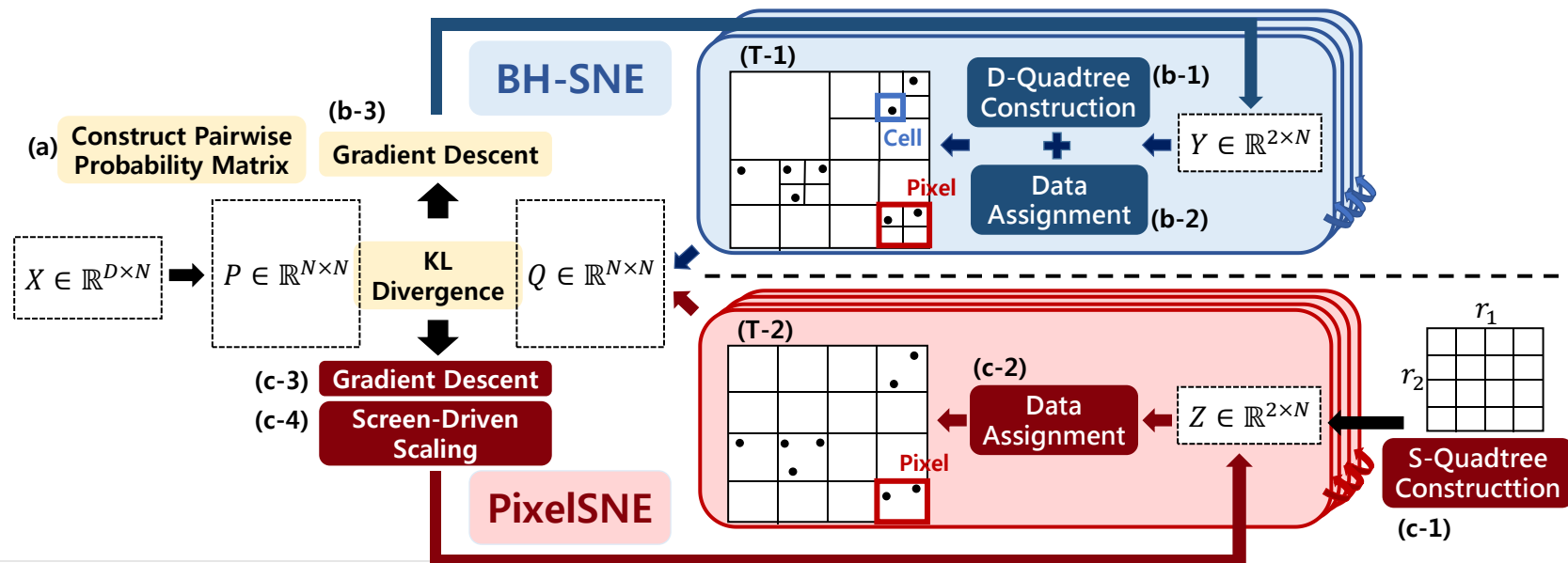


- Leveraging ideas from other literatures, e.g., wavelet



Images src: http://www.cse.lehigh.edu/~spletzer/rip_f06/lectures/lec013_Pyramids.pdf

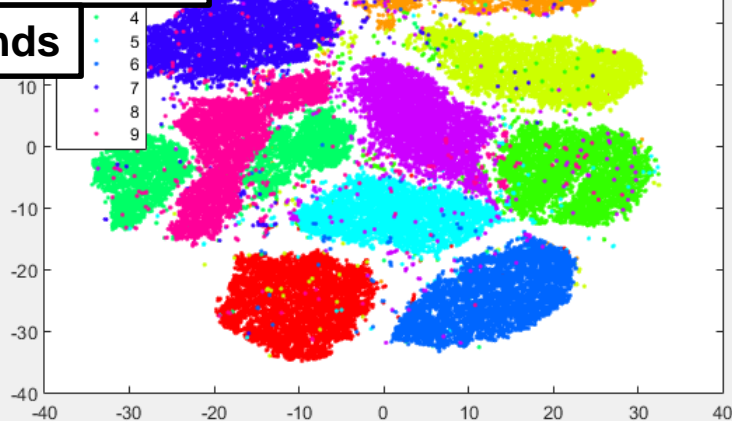
PixelSNE: Pixel-Aligned t-SNE



PixelSNE: Pixel-Aligned t-SNE

Original BH t-SNE
(full resolution)

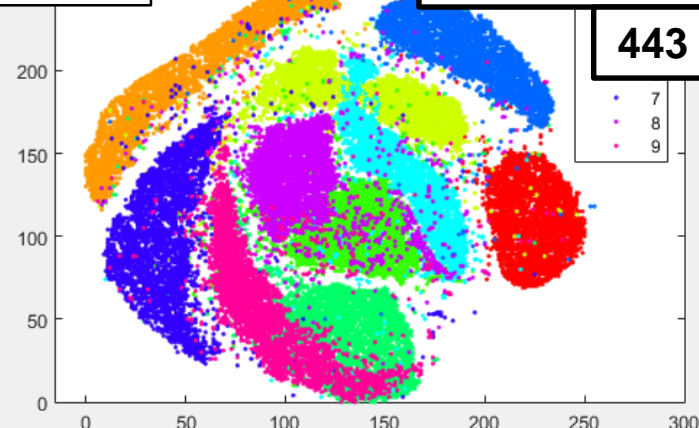
1406 seconds



MNIST data
(50k items)

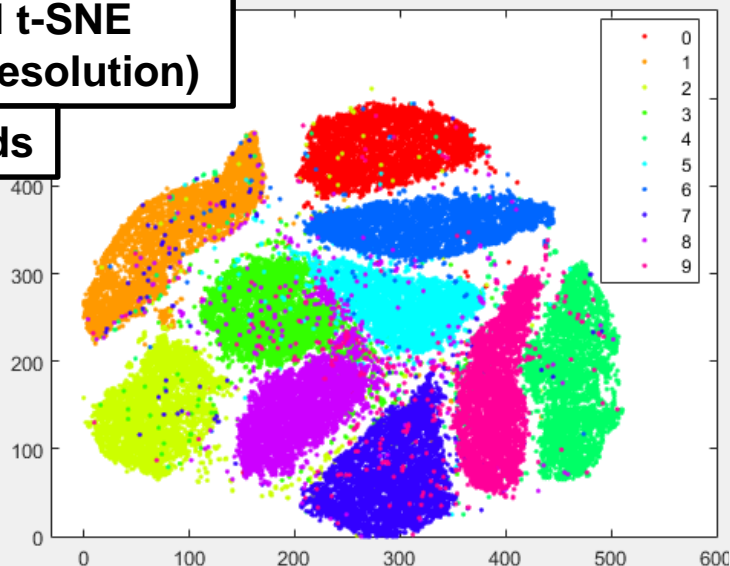
Our BH t-SNE
(256x256 resolution)

443 seconds



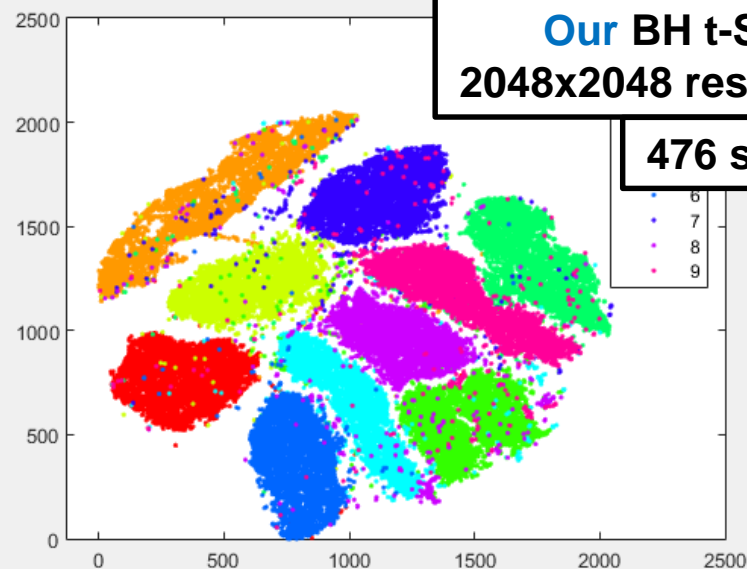
Our BH t-SNE
(512x512 resolution)

452 seconds



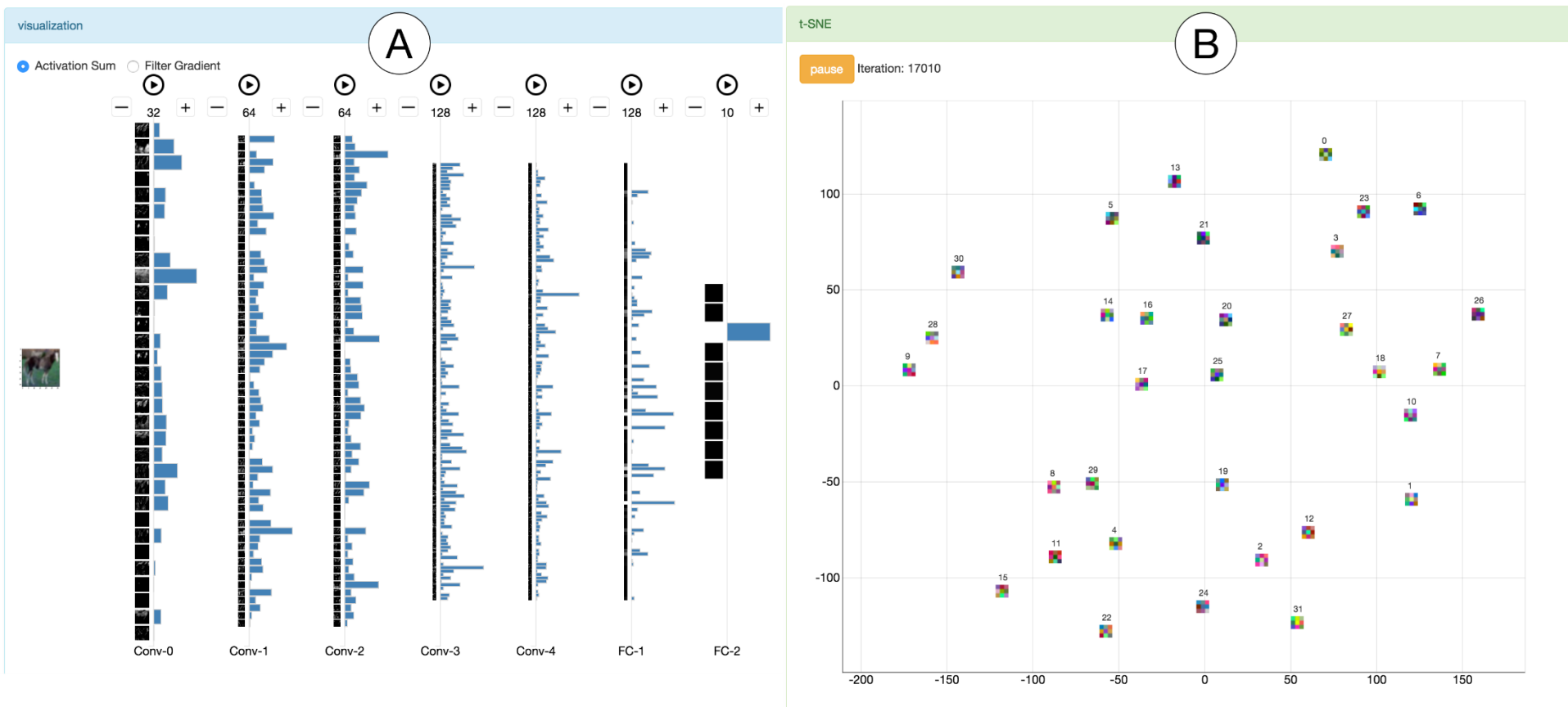
Our BH t-SNE
(2048x2048 resolution)

476 seconds



ReVACNN: Real-Time Visual Analytics for CNN

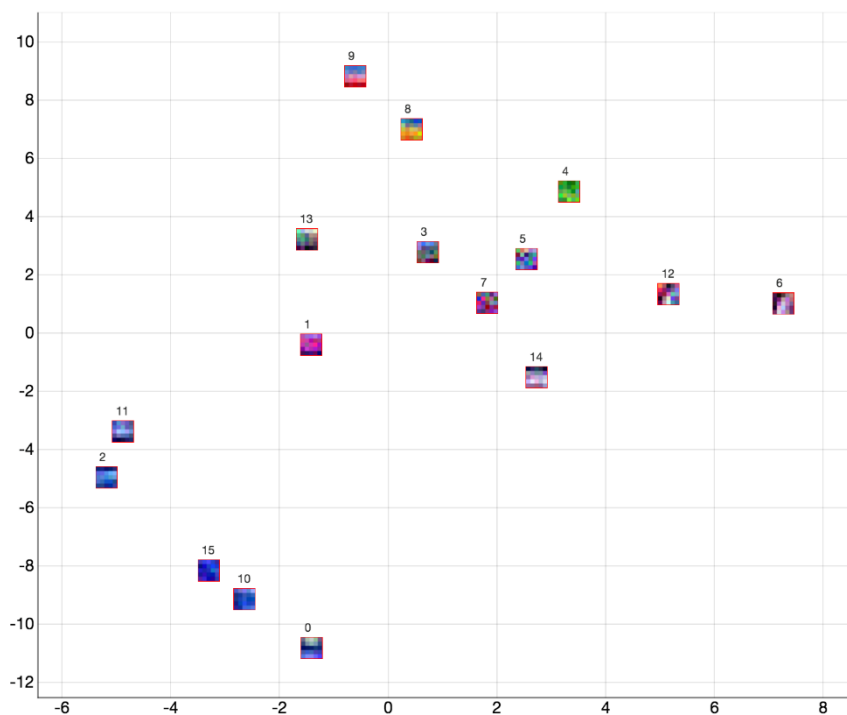
[KDD'16 IDEA Workshop, NIPS'16 FILM Workshop]



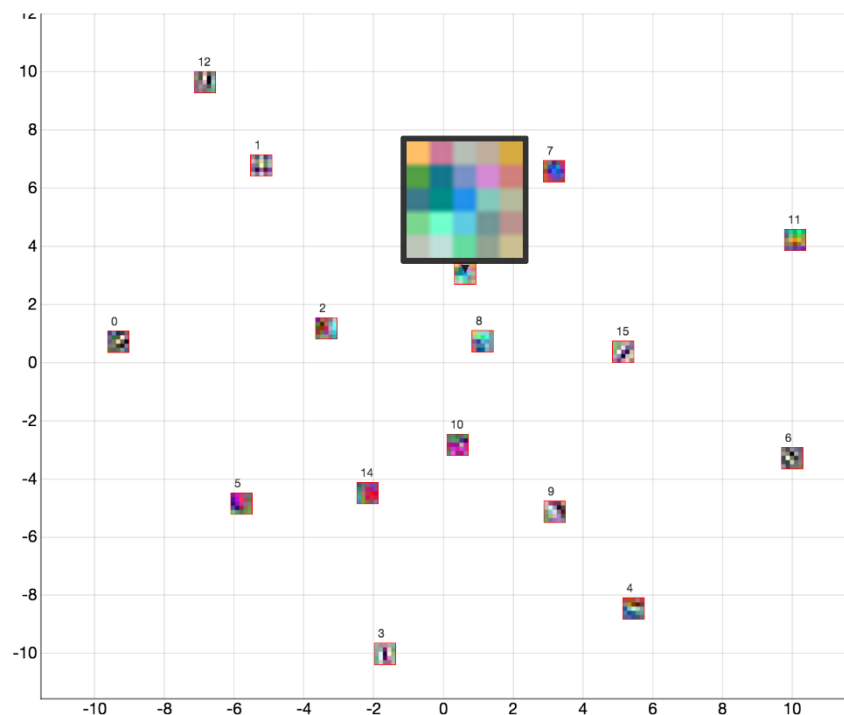
ReVACNN: Real-Time Visual Analytics for CNN

[KDD'16 IDEA Workshop, NIPS'16 FILM Workshop]

2D embedding of first-layer filters



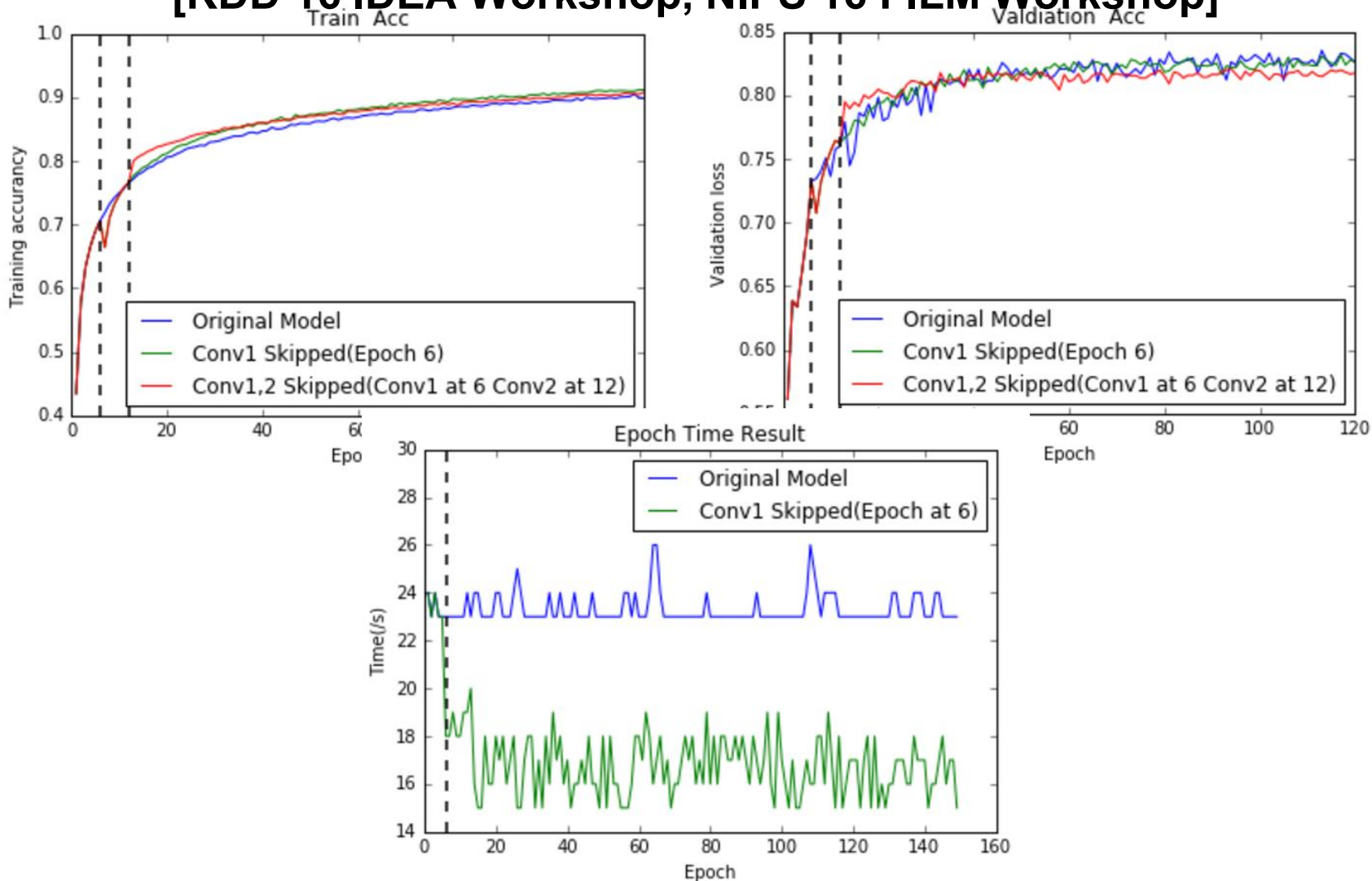
Improperly trained
pattern, showing
clear clusters



Properly trained
pattern, showing
no clusters

ReVACNN: Real-Time Visual Analytics for CNN

[KDD'16 IDEA Workshop, NIPS'16 FILM Workshop]



On-Going and Future Work

- ▶ Scalable visual analytics for deep networks
 - Tracking activations on residual deep network
- ▶ Fast, low-powered deep network on mobile devices
 - Personalized predictive keywords
- ▶ End-to-end learning integrated with handcrafted features
 - Automatic debugging on programs
- ▶ Semantic word embedding
 - Nonnegative matrix factorization + word embedding
- ▶ Direction-agnostic deep networks

Thank you! Jaegul Choo jchoo@korea.ac.kr

Collaborators from academia, industry, and the government

A. Endert, A. Gray, A. White, B. Drake, B. Dilkina, B. Kwon, C. Görg, C. Reddy, C. Lee, C. Stolper, D. Lee, E. Clarkson, E. Fujimoto, F. Li, G. Nakamura, H. Park, H. Pileggi, H. Lee, H. Zha, H. Kim, J. Eisenstein, J. Shim, J. Park, J. Kihm, J. Yi, J. Ye, J. Kang, J. Stasko, J. Turgeson, K. Joo, M. Hu, P. Walteros, P. Chau, R. Sadana, R. Decuir, R. Boyd, S. Yang, S. Bohn, S. Muthiah, T. Liu, W. Zhuo, Y. Han, Z. Liu, ...

Selected Papers

- ▶ PIVE: Per-Iteration Visualization Environment for Real-time Interactive Visualizations, **AAAI**, 2017
- ▶ AxiSketcher: Interactive Nonlinear Axis Mapping through Users' Drawing on Visualization, **TVCG**, 2017
- ▶ TopicLens: Efficient Multi-Level Visual Topic Exploration of Large-Scale Document Collections, **TVCG**, 2017
- ▶ L-EnsNMF: Boosted Local Topic Discovery via Ensemble of Nonnegative Matrix Factorization, **ICDM**, 2016
- ▶ PixelSNE: Visualizing Fast with Just Enough Precision via Pixel-Aligned Stochastic Neighbor Embedding, **arXiv**, 2016
- ▶ InterAxis: Observation-level Interactive Axis Steering for Scatterplots of Multi-Dimensional Data Visualization, **TVCG**, 2015
- ▶ VisOHC: Designing Visual Analytics for Online Health Communities, **TVCG**, 2015
- ▶ Simultaneous Discovery of Common and Discriminative Topics via Joint Nonnegative Matrix Factorization, **KDD**, 2015
- ▶ To Gather Together for a Better World: Understanding and Leveraging Communities in Micro-lending Recommendation, **WWW**, 2014
- ▶ Understanding and Promoting Micro-finance Activities in Kiva.org, **WSDM**, 2014
- ▶ Weakly Supervised Nonnegative Matrix Factorization for User-Driven Clustering, **DMKD**, 2014
- ▶ Document Topic Modeling and Discovery in Visual Analytics via Nonnegative Matrix Factorization, **TVCG**, 2013
- ▶ Screen space- and Perception-based Framework for Efficient Computational Algorithms in Large-scale Visual Analytics, **CG&A**, 2013
- ▶ Heterogeneous Data Fusion via Space Alignment Using Nonmetric Multidimensional Scaling, **SDM**, 2012 30
- ▶ p-ISOMAP: An Efficient Parametric Update for ISOMAP for Visual Analytics, **SDM**, 2010