# Reconnaissance and Recommendation: Wayfinding Through Data With Visualization

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*Visualization in Data Science 2023 keynote*
*23 Oct 2023, Melbourne Australia*

http://www.cs.ubc.ca/~tmm/talks.html#vds23

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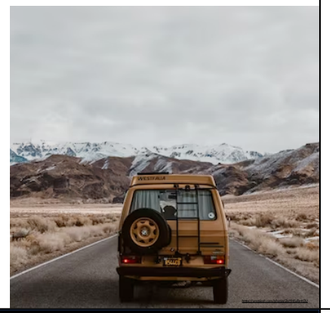
## Extended analogy

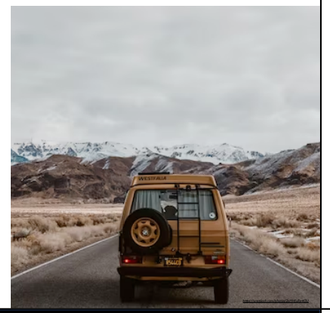
- wayfinding through the world with road trips
- wayfinding through data with visualization



http://www.cs.ubc.ca/~tmm/talks.html#vds23

## Questions in road trips

- where are we?
- what's here?
- are we there yet? are we lost?



http://www.cs.ubc.ca/~tmm/talks.html#vds23

## Questions in road trips - and visualization in data science!

- with each VDS project, addressing more questions
- where are we?
  - Data Reconnaissance & Task Wrangling
- what's here?
  - Automatic Encodings through Recommendation
- are we there yet? are we lost?
  - Visual Assessment of ML Training Completion & Quality

http://www.cs.ubc.ca/~tmm/talks.html#vds23

*Uncovering Data Landscapes through*

# Data Reconnaissance & Task Wrangling

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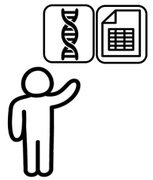
https://amcrisan.github.io/assets/files/papers/Data_Recon_and_Task_Wrangling.pdf

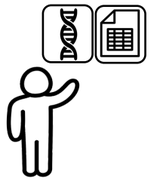
Uncovering Data Landscapes through Data Reconnaissance and Task Wrangling
*Crisan, Munzner. Proc. IEEE VIS 2019, pp. 46-50.*





**Where are we?**

Domain experts need help uncovering and reasoning about heterogeneous data landscapes



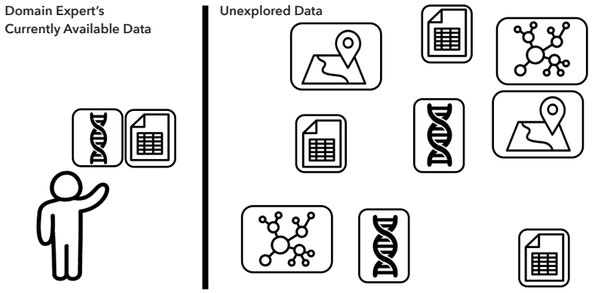
**Data landscape**

the very large space of existing heterogeneous and multidimensional datasets that are not yet understood by a specific person

## Data landscape : collection of heterogeneous datasets

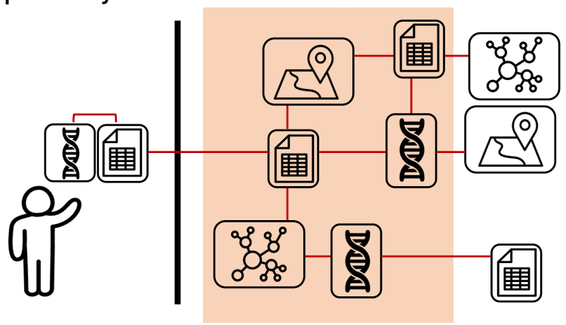
Domain Expert's Currently Available Data

Unexplored Data



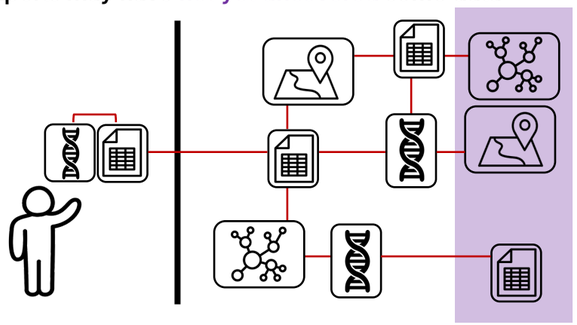


## Experts may not have access to all of data





## Experts may have not yet uncovered some data





**New idea :**
Operational definitions for data reconnaissance and task wrangling

## Two interrelated processes uncover data landscapes:

### Data Reconnaissance

the process of uncovering an unfamiliar data landscape, including datasets that are known, available, unavailable, & unknown

### Task Wrangling

the process of progressively forming a crisper notion of tasks and assessing whether available and known datasets are suitable



## Two interrelated processes uncover data landscapes:

### Data Reconnaissance

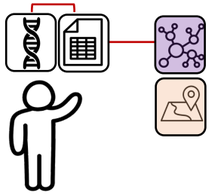
Some Data



## Two interrelated processes uncover data landscapes:

### Data Reconnaissance

Acquire additional data sources



Analysis & visualization of **available** data sources supports acquisition of **new** data:

Acquire new dataset

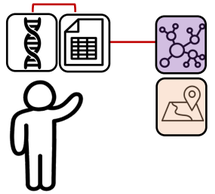
Acquire available, but previously restricted, dataset



## Two interrelated processes uncover data landscapes:

### Data Reconnaissance

Acquire additional data sources



Analysis & visualization of **available** data sources supports acquisition of **new** data:

Acquire new dataset

Acquire available, but previously restricted, dataset

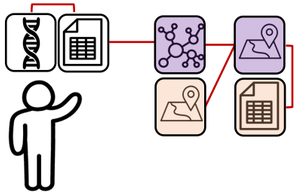
Crisan & Munzner.
*On Regulatory and Organizational Constraints in Visualization Design and Evaluation.*
*Proc BELIV* 2016.



## Two interrelated processes uncover data landscapes:

### Data Reconnaissance

Arrive at a finalized data set



Finalized dataset can be analyzed & visualized in depth

## Two interrelated processes uncover data landscapes:

Data Reconnaissance → Task Wrangling

Low Task Clarity

*"What is this data?"*

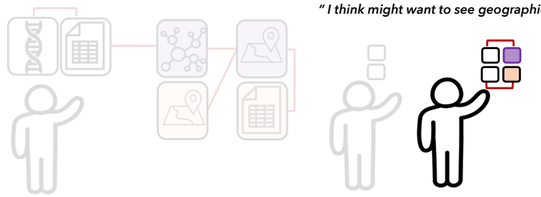


## Two interrelated processes uncover data landscapes:

Data Reconnaissance → Task Wrangling

Evolving Task Clarity

*" I think might want to see geographic patterns"*



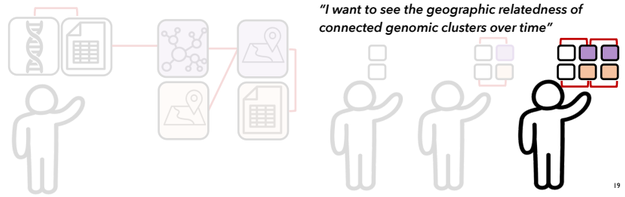


## Two interrelated processes uncover data landscapes:

Data Reconnaissance → Task Wrangling

Refined Task Clarity

*"I want to see the geographic relatedness of connected genomic clusters over time"*

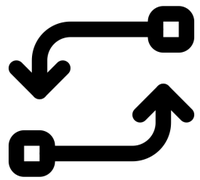




## Processes influence each other over time

**Data Reconnaissance**
Data access inspires & refines tasks

**Task Wrangling**
Refined tasks guide the pursuit of data

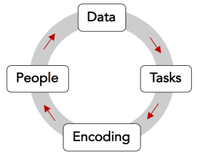




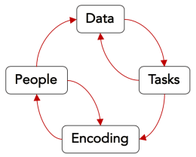
**New idea :**
A conceptual framework for data reconnaissance and task wrangling

## Existing methods can be slow

Human Centered Design



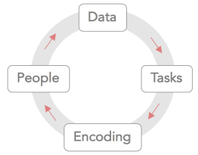

Design Study Methodology



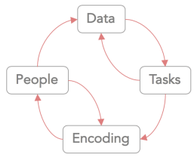



## Uncover data & tasks faster with shortcuts

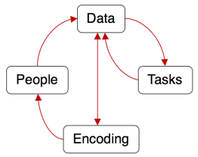
Human Centered Design




Design Study Methodology



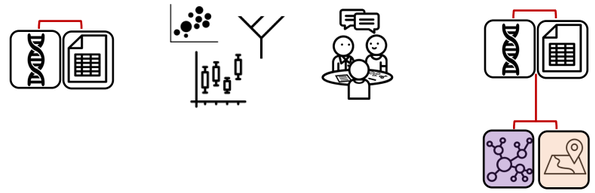

Our speedup





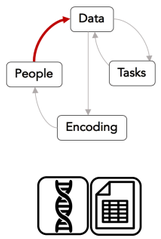

## Steps in our conceptual framework

Acquire → View → Assess → Pursue



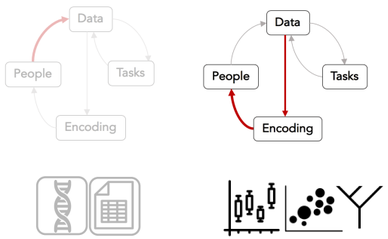


Acquire






Acquire → View






Acquire → View → Assess

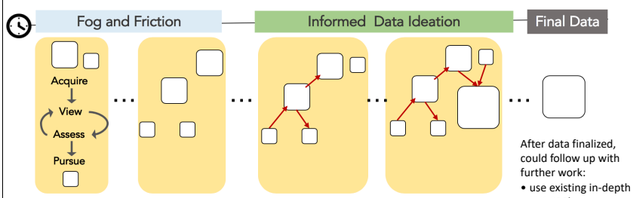



Pursue

Acquire → View → Assess




## From unknown landscape to the final dataset



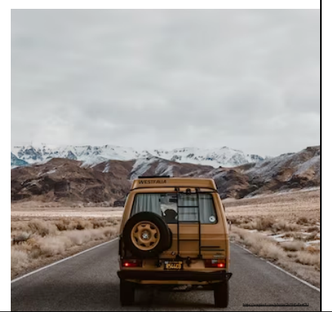

After data finalized, could follow up with further work:
- use existing in-depth EVA tool
- create bespoke system through design study



**Where do we go from here?**
Building systems suitable for data reconnaissance and task wrangling

## Questions in road trips - and visualization in data science!

- where are we?
  - Uncovering Data Landscapes through Data Reconnaissance & Task Wrangling
- what's here?
  - Automatic Encodings through Recommendation



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## GEViTRec:

*Data Reconnaissance Through Recommendation Using a Domain-Specific Visualization Prevalence Design Space*

https://www.cs.ubc.ca/group/infovis/pubs/2021/gevitrec/

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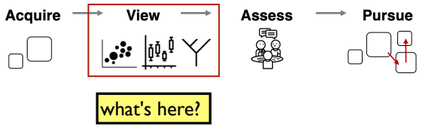
GEViTRec: Data Reconnaissance Through Recommendation Using a Domain-Specific Visualization Prevalence Design Space.
*Crisan, Fisher, Gardy, Munzner. IEEE TVCG 28(12):4855-4872, 2022.*

## Data Reconnaissance

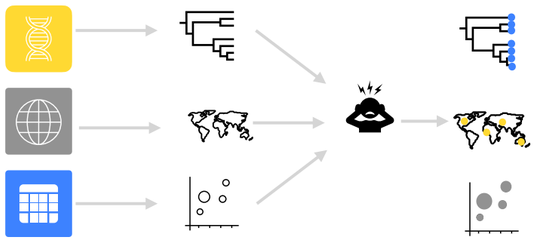
the process of exploring an unfamiliar data landscape; the very large space of existing heterogeneous and multidimensional datasets that are not yet understood by a specific person

biggest need: accelerate this part



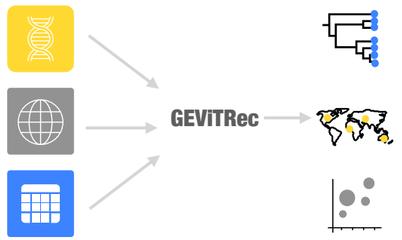



## **Manually** Constructing Chart Combinations



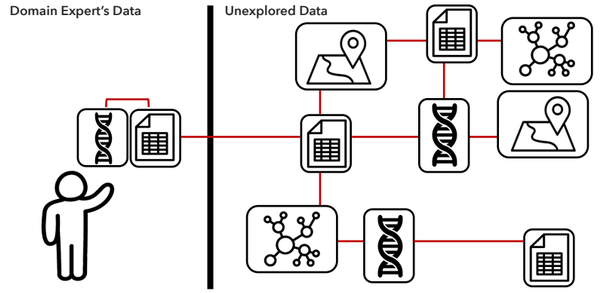


## **Automatically** Constructing Visually Coherent Chart Combinations






## How to connect datasets? Identify shared attributes!






## How to show connections for data recon?

### Visually Coherent Chart Combinations

that prioritize visual coordination of **shared information** between charts with respect to **layout and consistency among visual channels** (position, color)

Static charts avoid interactive view coordination complexities and costs

Fast to view
Easy to disseminate



### New Idea: Visually Coherent Chart Combinations Through Gradual Binding

- Automatically coordinating static charts is not trivial
  - Cannot change encoding after chart rendered into box of pixels!
- **Declarative approach of gradual binding**
  - Initially generate partial specification using template
  - Modify specification in discrete stages, to enforce consistency of channels (color, position) according to desired combination
  - Pass final specification to rendering library
  - Simply concatenate resulting boxes of pixels to display

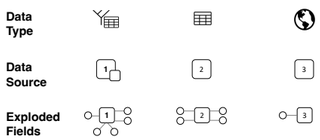


## GEViTRec algorithm: Overview


- **Example: three analysis datasets**
  - 1 : Tree data w/ associated tabular data
  - 2 : Tabular Data
  - 3: Spatial Data



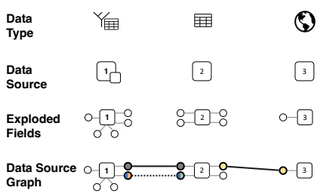
## GEViTRec algorithm: Overview




- **'Explode' attribute fields extracted from data sources**
  - = data source
  - = attribute field



## GEViTRec algorithm: Overview



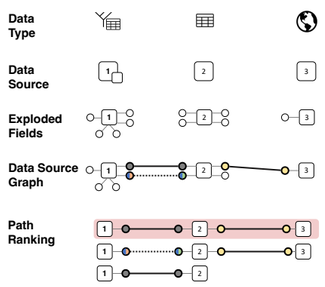

- **Analyze to identify commonalities and create dataset linkages through categorical attribute fields**

| Fields A | Fields B | Jaccard Index | Linkage Type |
|---|---|---|---|
| ● | ● | 1 | Exact |
| ◐ | ◐ | 0<j<1 | Partial |
| ○ | ○ | 0 | None |

- **Input data is now modelled as a graph!**



## GEViTRec algorithm: Overview



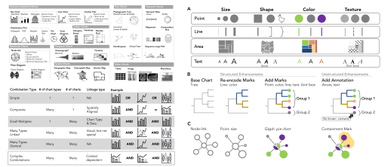

- **Traverse graph: enumerate & rank paths** linking all pairs of data, using three metrics
  - **Strength** of linkages
  - **Diversity** of data types
  - **Relevance** to domain
    - **New idea:** using **domain prevalence design space** in visualization recommendation



Domain Prevalence Design Space:

Captures full scope of visual encodings used by defineable set of experts, includes quantitative estimate for prevalence of each strategy within that domain

Domain-level answer to question of what's here?

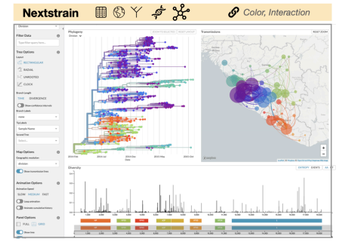


A Crisan, JL Gardy, T Munzner.
*A systematic method for surveying data visualizations and a resulting genomic epidemiology visualization typology: GEVIT.*
Bioinformatics 35(10):1668–1676, 2019.

https://doi.org/10.1093/bioinformatics/bty832



**Domain Context:**
Genomic Epidemiology



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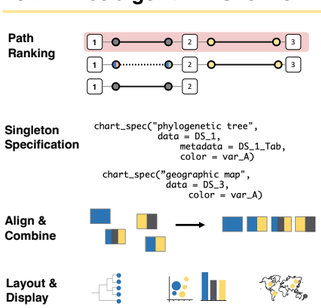
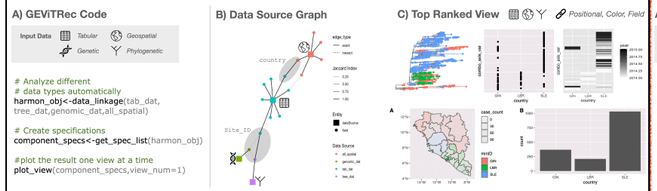



- **For each high-ranked path, automatically generate initial partial specifications for each singleton chart**
- **Align & combine specifications into multi-chart combination**
- **Use existing packages for layout**
- **Combine rendered boxes of pixels into final display**



## **Automatically** Constructing Visually Coherent Chart Combinations

- **GEViTRec runs in R Markdown notebooks**
- **Example: 2013-2016 Ebola outbreak data**



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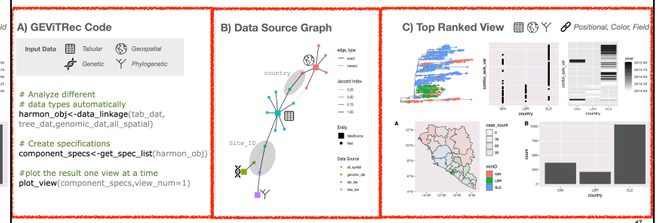




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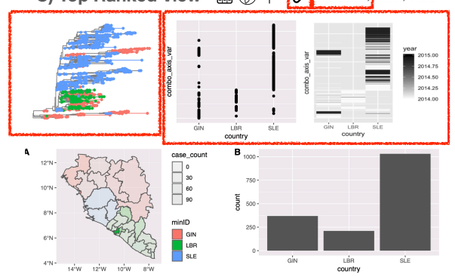
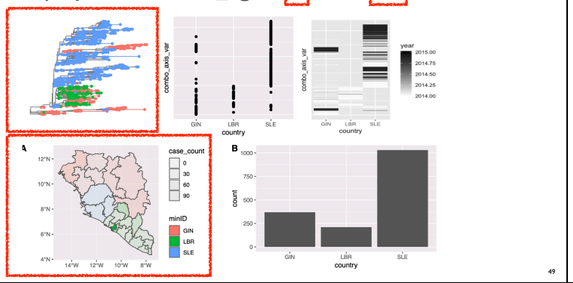


## **Automatically** Constructing Visually Coherent Chart Combinations

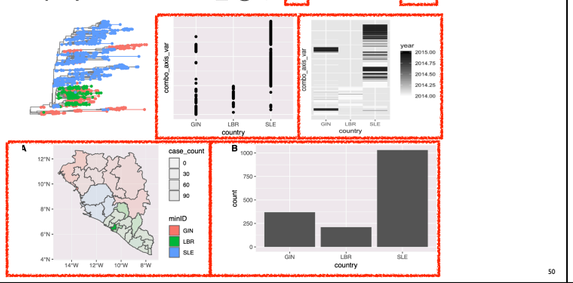
C) Top Ranked View — Positional, Color, Field



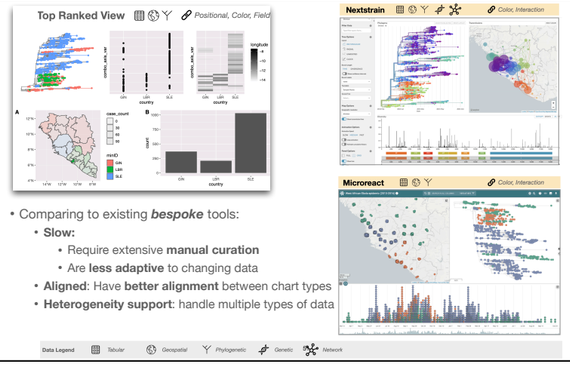


## **Automatically** Constructing Visually Coherent Chart Combinations

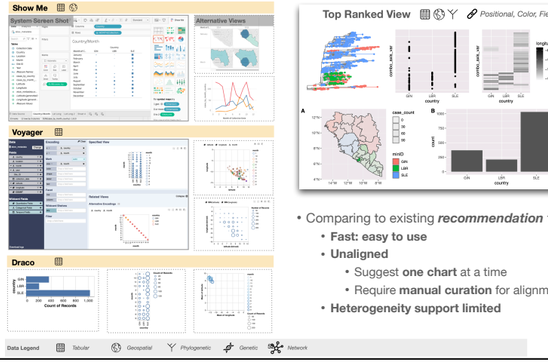
C) Top Ranked View — Positional, Color, Field








- Comparing to existing ***bespoke*** tools:
  - **Slow:**
    - Require extensive **manual curation**
    - Are **less adaptive** to changing data
  - **Aligned**: Have **better alignment** between chart types
  - **Heterogeneity support**: handle multiple types of data




- Comparing to existing ***recommendation*** tools:
  - **Fast: easy to use**
  - **Unaligned**
    - Suggest **one chart** at a time
    - Require **manual curation** for alignment
  - **Heterogeneity support limited**

## GEViTRec lowers burden to quickly visualize data

- **Speeds up** the process of data reconnaissance - **where are we?**
- Automatically shows us **what's here?**
  - Identifies connections among datasets
  - Exploits domain prevalence design space
  - Constructs visually coherent chart combinations through gradual binding

what's here?
for workbook repos

# VizCommender:

*Computing Text-Based Similarity in Visualization Repositories for Content-Based Recommendations*

Michael Oppermann
UBC/
Virtual Identity

Robert Kincaid
Tableau

Tamara Munzner
UBC

https://www.cs.ubc.ca/group/infovis/pubs/2020/vizcommender/

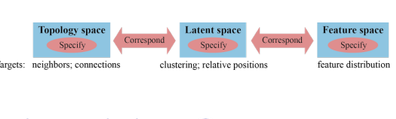
VizCommender: Computing Text-Based Similarity in Visualization Repositories for Content-Based Recommendations
*Oppermann, Kincaid Munzner. IEEE TVCG 27(2): 495-505, 2021 (Proc. VIS 2020).*



## Questions in road trips - and visualization in data science!

- where are we?
  - Data Reconnaissance & Task Wrangling
- what's here?
  - Automatic Encodings through Recommendation to shed light on data landscapes
- are we there yet? are we lost?
  - Visual Assessment of ML Training Completion & Quality

http://www.cs.ubc.ca/~tmm/talks.html#vds23




# Visualizing Graph Neural Networks with CorGIE:

*Corresponding a Graph to Its Embedding*

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Tamara Munzner
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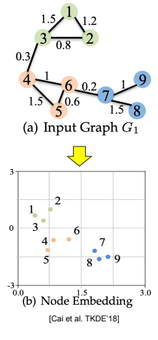
https://arxiv.org/abs/2106.12839

Visualizing Graph Neural Networks with CorGIE: Corresponding a Graph to Its Embedding.
*Liu, Wang, Bernard, Munzner. IEEE TVCG 28(6):2500-2516, 2022.*



## Graph neural network (GNN)

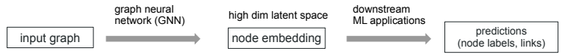
- machine learning (ML) models for graphs
  - like CNN for images
  - like Transformer for text
- many real-world graph-related applications
  - node classification
    - examples: fraud detection, disease classification
  - link prediction
    - examples: product recommendation, protein interactions



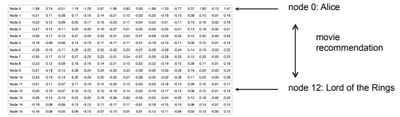

[Cai et al. TKDE'18]



## Graph neural network (GNN)



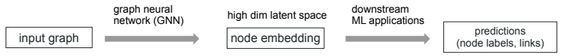

movie – user graph



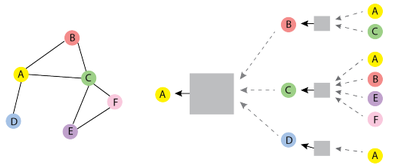

a vector for each node



## Graph neural network (GNN)




**node features** are aggregated / passed through **topological neighborhood**



Remake from https://snap-stanford.github.io/cs224w-notes/machine-learning-with-networks/graph-neural-networks



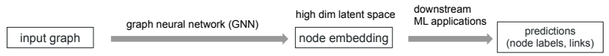
## Evaluating GNN quality

Two big-picture questions

- Are we there yet? *Should we train / tune more?*
- Are we lost? *Does it behave as we expect?*



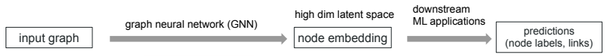
## Evaluate GNN: CorGIE idea




where are we?
what's here?



## Evaluate GNN: CorGIE idea



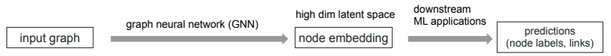

Examples of correspondences:

Check [similar topology? Similar node features?] ← Pick [a cluster]

where are we?
what's here?



## Evaluate GNN: CorGIE idea




Examples of correspondences:

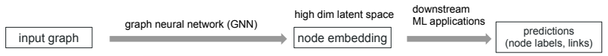
Check [similar topology? Similar node features?] ← Pick [a cluster]

Check [different topology? Different node features?] ← Pick [two far-away clusters]

where are we?
what's here?



## Evaluate GNN: CorGIE idea




Examples of correspondences:

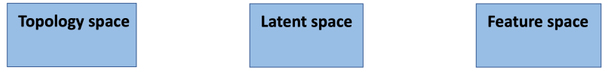
Check [similar topology? Similar node features?] ← Pick [a cluster]

Check [different topology? Different node features?] ← Pick [two far-away clusters]

Pick [two nodes sharing many topo neighbors] → Check [how close the nodes are compared to others?]

where are we?
what's here?

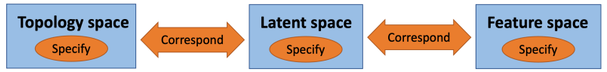
## Data and tasks




- three data spaces



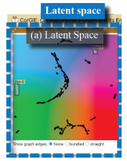
## Data and tasks




- three data spaces
- tasks
  - specify
  - correspond

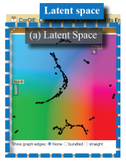


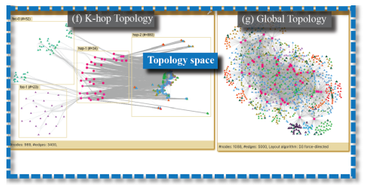
## CorGIE multi-view interactive interface






## CorGIE multi-view interactive interface



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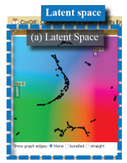
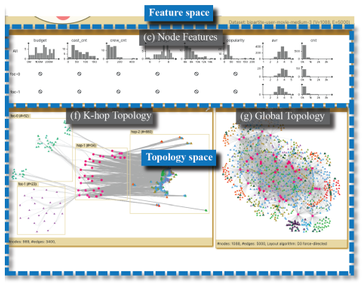
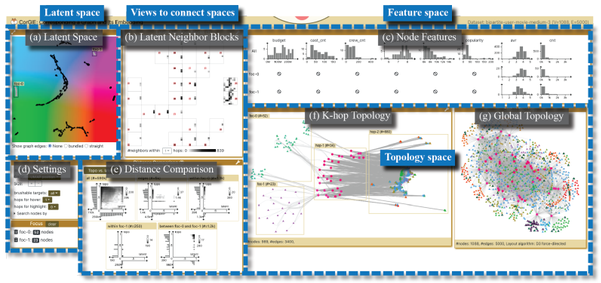





## CorGIE multi-view interactive interface






## CorGIE: Visual Assessment of ML Training Completion & Quality

- Addresses **where are we?**
  - Visually explore correspondences between input graph and node embedding to show **what's here?**
- Addresses are **we there yet?**
  - Has the GNN training process captured all expected data about k-hop neighborhoods in the input graph, or should we keep going with train/tune?
- Addresses **are we lost?**
  - Are the GNN predictions high quality or low quality?

## Questions in road trips - and visualization in data science!

- one VDS project for each question

- where are we?
  - Data Reconnaissance & Task Wrangling
- what's here?
  - Automatic Encodings through Recommendation
- are we there yet? are we lost?
  - Visual Assessment of ML Training Completion

**http://www.cs.ubc.ca/~tmm/talks.html#vds23**

## More information

- this talk
  http://www.cs.ubc.ca/~tmm/talks.html#vds23

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  http://www.cs.ubc.ca/~tmm
- book
  http://www.cs.ubc.ca/~tmm/vadbook

- VIS23 book table from CRC/Routledge
  - physical table
  - virtual bookshop: https://bit.ly/IEEEVIS23


Visualization Analysis and Design. Munzner.
*CRC Press, AK Peters Visualization Series, 2014.*

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