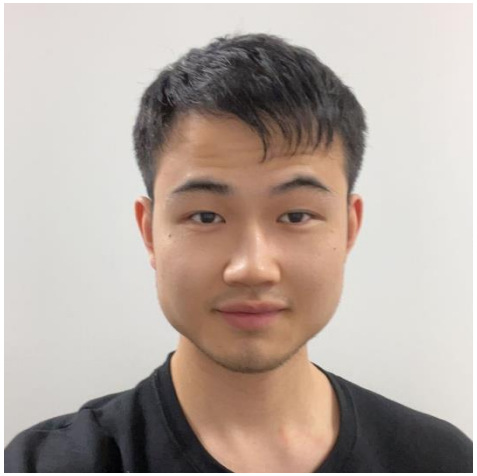
Data Mining

Course Overview and Logistics

https://data-mining.github.io/winter-2026/

CS 453/553 – Winter 2026
Yu Wang, Ph.D.
Assistant Professor
Computer Science
University of Oregon

Self-Introduction



Yu (Jack) Wang (You)

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https://yuwang0103.github.io/

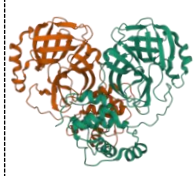
Research Interests:

- Data Mining and Machine Learning
- Neural-Symbolic Learning
- Graph and Network
- LLM + Structured Knowledge
- AI/ML/DM Applications
  - Document Intelligence
  - Social Computing
  - Networking Physical Infrastructure

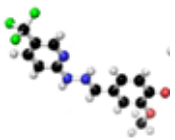
📣📣📣 **Recruiting Ph.D. students and interns!** I am actively seeking highly motivated students for Ph.D. or Research intern positions. Please feel free to email me your CV, transcripts, and brief descriptions about why you want to work with me if you are interested!

What is Data?

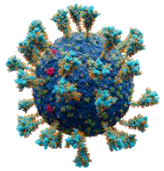
Science



Protein

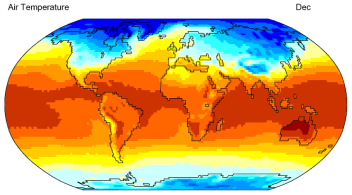


Small Molecule



Virus

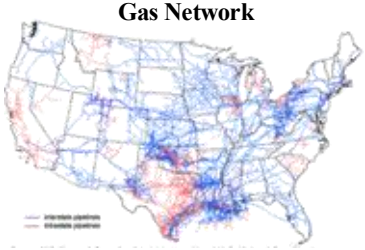
Brain Neural



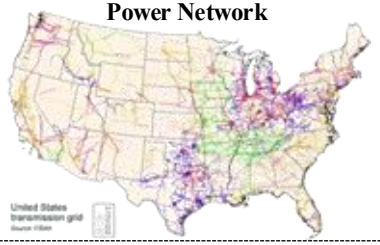
Surface Temperature of Earth

Infrastructure

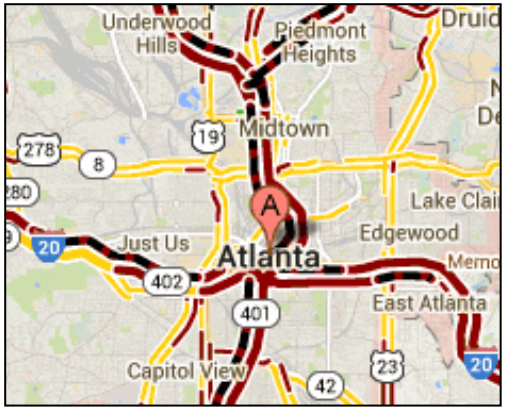
Gas Network



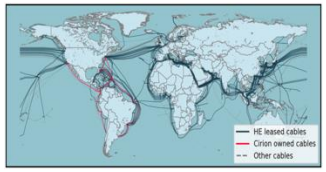
Power Network



Transportation Network

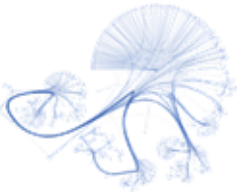


Submarine Cable



Terrestial Cable

Social Network

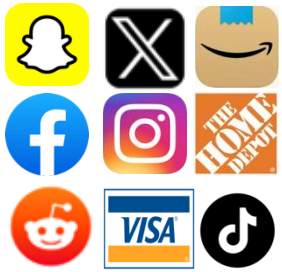


Citation Network

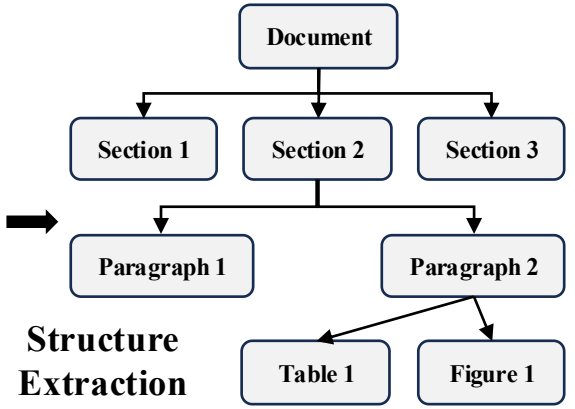
Transaction Network

User-Entity Interaction Graph

Virtual Village with AI Agents

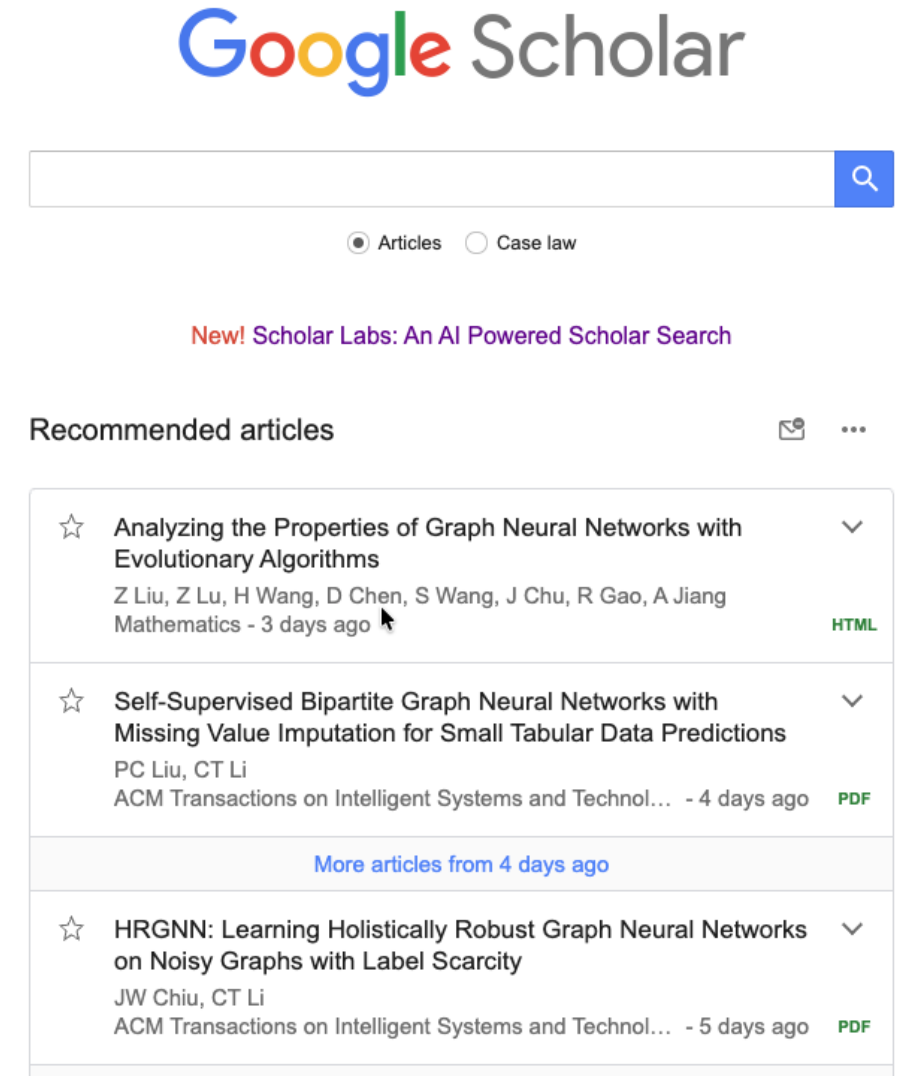


Document



Structure Extraction

Why Analyze Data? – Paper Management



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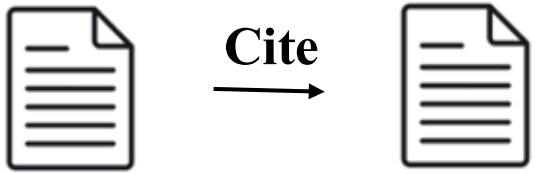

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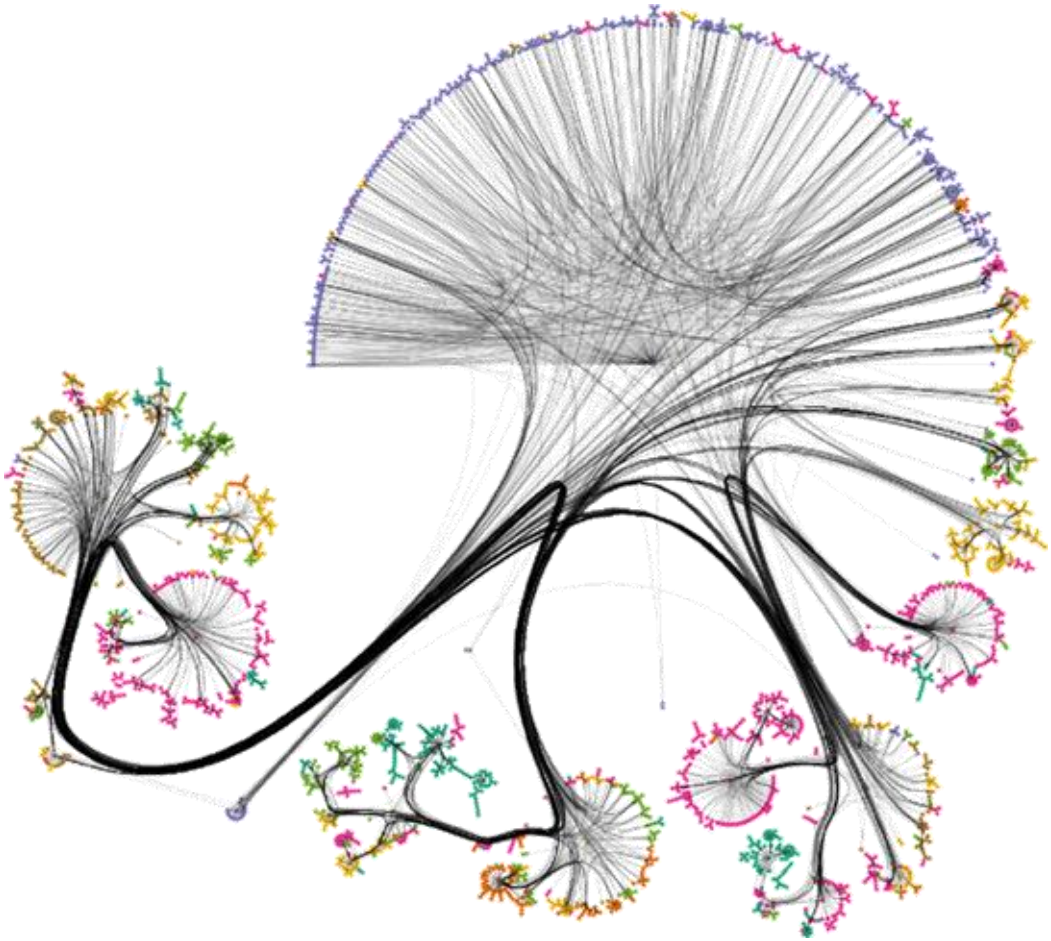

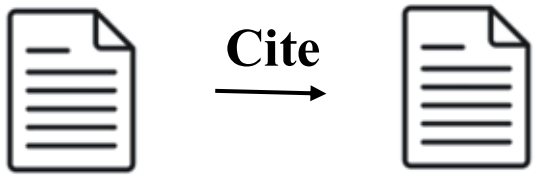

$$\frac{\sum_{e_{ij} \in \mathcal{E}} 1[y_i == y_j]}{|\mathcal{E}|}$$

$\mathcal{E}$ - Total Number of Edges

e_{ij} - Edge between node i/j

y_i - Label of i

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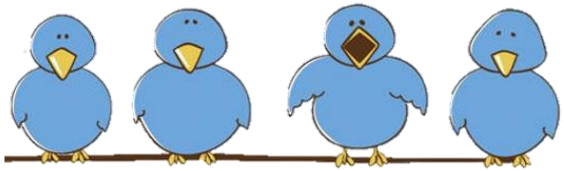
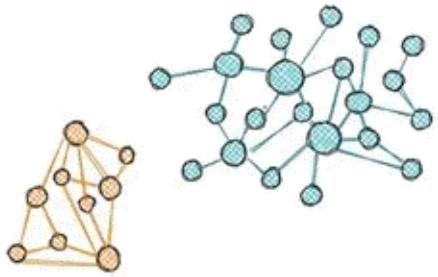
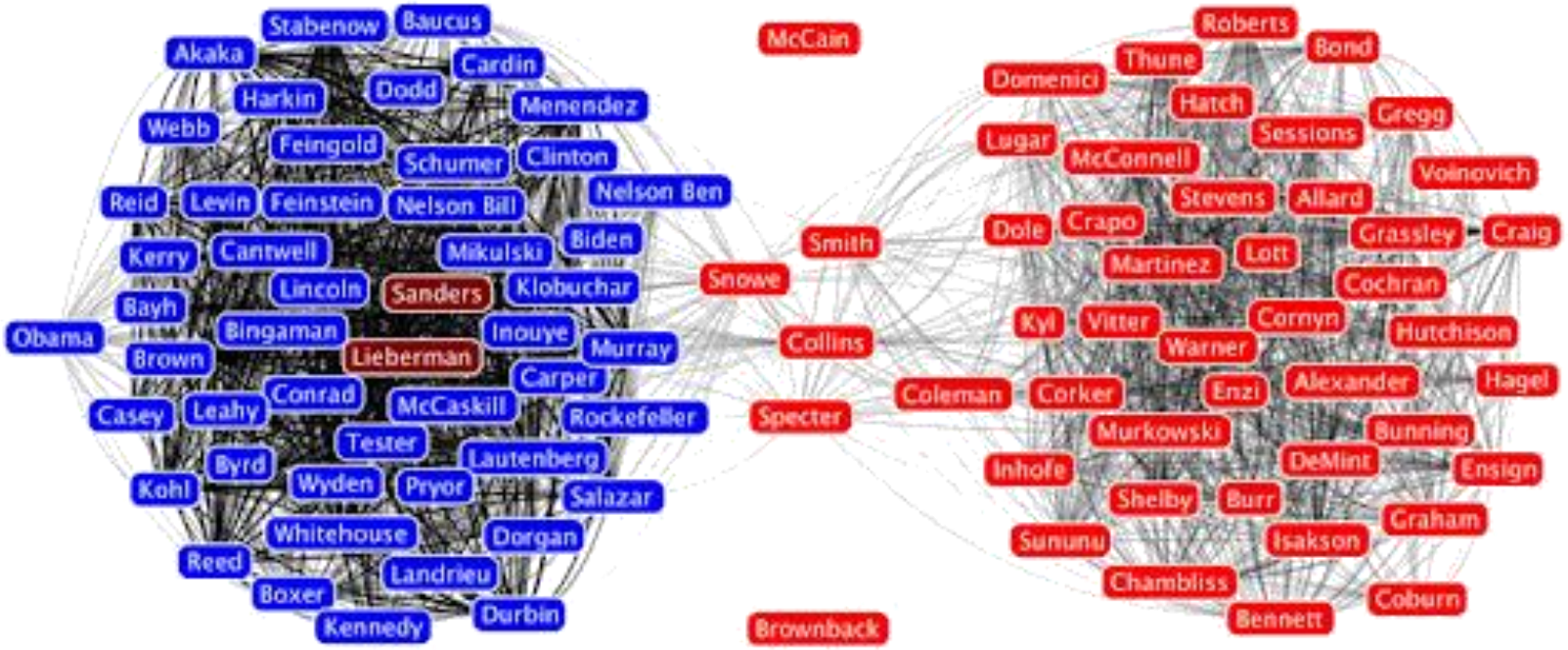


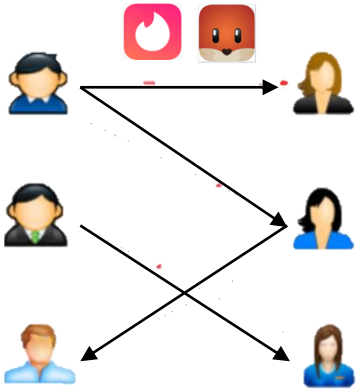
Birds of a feather flock together



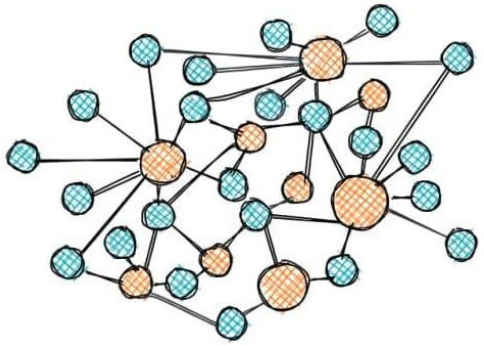


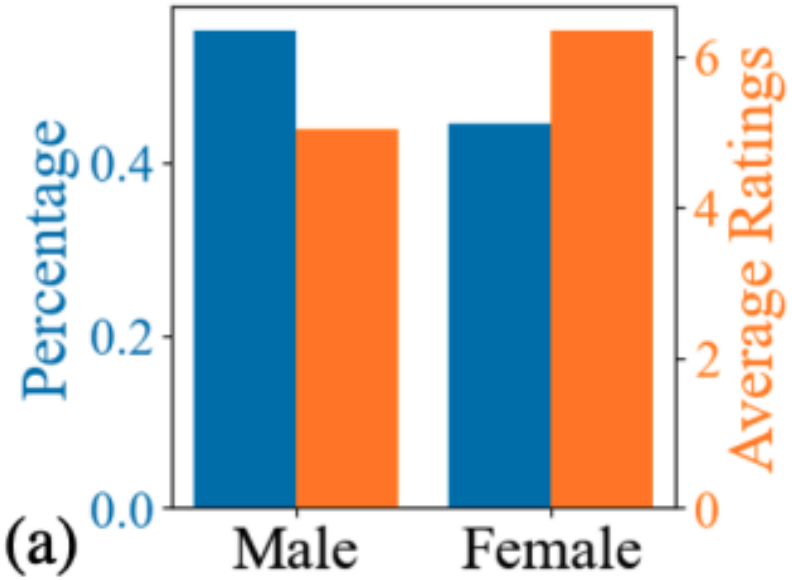
Gun Control Belief Network

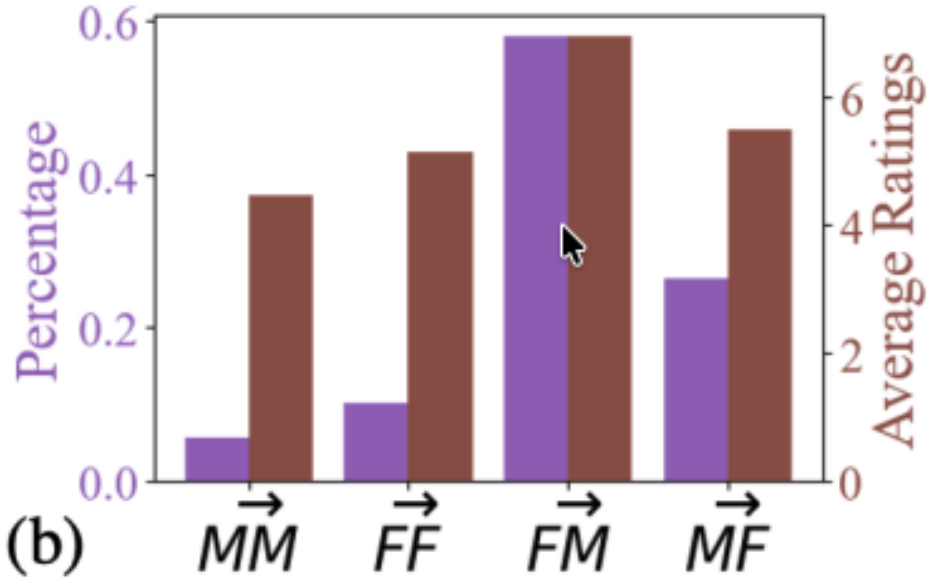
Why Analyze Data? – Paper Management



Dating Network







Dating Network

Why Analyze Data? – Paper Management

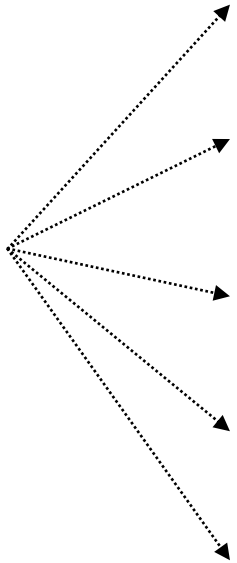
In-the-Flow Agentic System Optimization for Effective Planning and Tool Use

Zhuofeng Li[*1,2], **Haoxiang Zhang**[*1,3], **Seungju Han**[1], **Sheng Liu**[1], **Jianwen Xie**[4], **Yu Zhang**[2], **Yejin Choi**[1], **James Zou**[†1], **Pan Lu**[†1]
[1]Stanford University, [2]Texas A&M University, [3]UC San Diego, [4]Lambda

Website: https://agentflow.stanford.edu
Code Model Demo Visualize

Abstract

Outcome-driven reinforcement learning has advanced reasoning in large language models (LLMs), but prevailing tool-augmented approaches train a single, monolithic policy that interleaves thoughts and tool calls under full context; this scales poorly with long horizons and diverse tools and generalizes weakly to new scenarios. Agentic systems offer a promising alternative by decomposing work across specialized modules, yet most remain training-free or rely on offline training decoupled from the live dynamics of multi-turn interaction. We introduce AGENTFLOW, a trainable, *in-the-flow* agentic framework that coordinates four modules (planner, executor, verifier, generator) through an evolving memory and directly optimizes its planner inside the multi-turn loop. To train on-policy in live environments, we propose *Flow-based Group Refined Policy Optimization* (Flow-GRPO), which tackles long-horizon, sparse-reward credit assignment by converting multi-turn optimization into a sequence of tractable single-turn policy updates. It broadcasts a single, verifiable trajectory-level outcome to every turn to align local planner decisions with global success and stabilizes learning with group-normalized advantages. Across ten benchmarks, AGENTFLOW with a 7B-scale backbone outperforms top-performing baselines with average accuracy gains of 14.9% on search, 14.0% on agentic, 14.5% on mathematical, and 4.1% on scientific tasks, even surpassing larger proprietary models like GPT-4o. Further analyses confirm the benefits of in-the-flow optimization, showing improved planning, enhanced tool-calling reliability, and positive scaling with model size and reasoning turns.



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Which category does this paper belong to?

Tool Learning **Agentic Learning**

Why Analyze Data? – Paper Management

IN-THE-FLOW AGENTIC SYSTEM OPTIMIZATION FOR EFFECTIVE PLANNING AND TOOL USE

Zhuofeng Li[*1,2], Haoxiang Zhang[*1,3], Seungju Han[1], Sheng Liu[1], Jianwen Xie[4], Yu Zhang[2], Yejin Choi[1], James Zou[†1], Pan Lu[†1]
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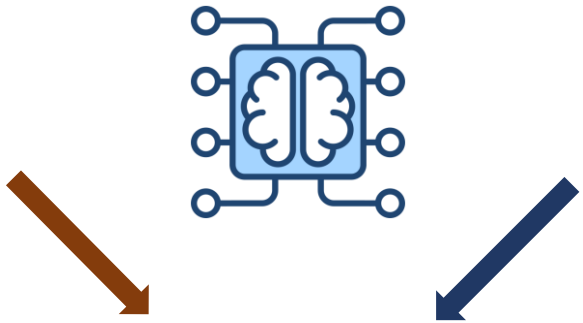

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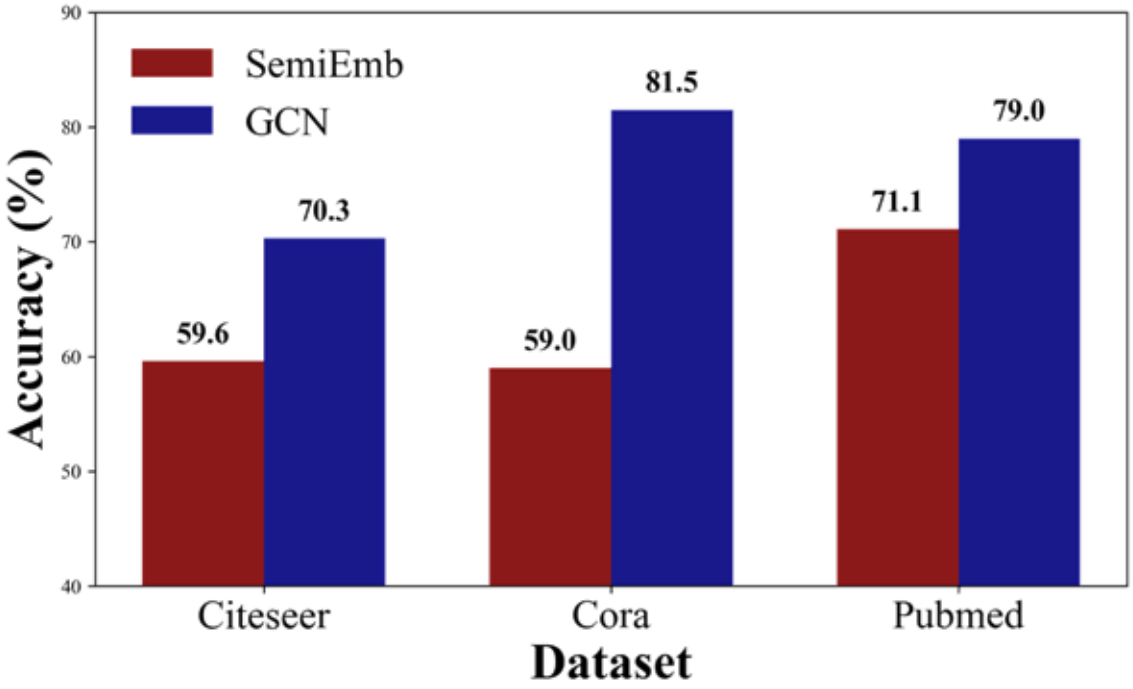
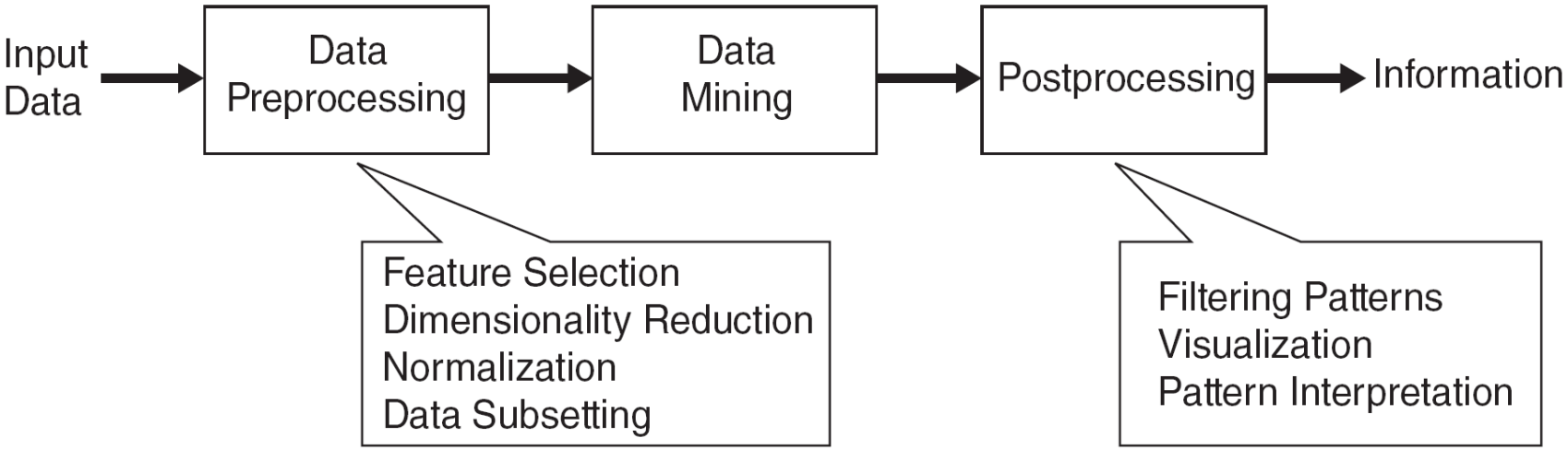


What is Data Mining?



Many Definitions

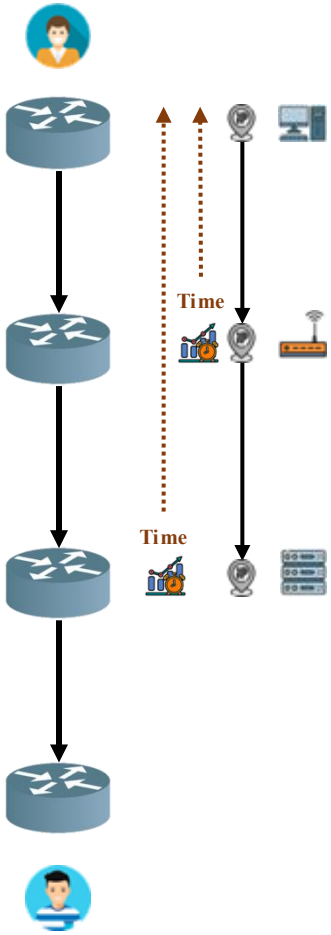
Non-trivial extraction of implicit, previously unknown and potentially useful information from data

Exploration & analysis, by automatic or semi-automatic means, of large quantities of data in order to discover meaningful patterns

Why Data Mining? – Networking Infra Risk

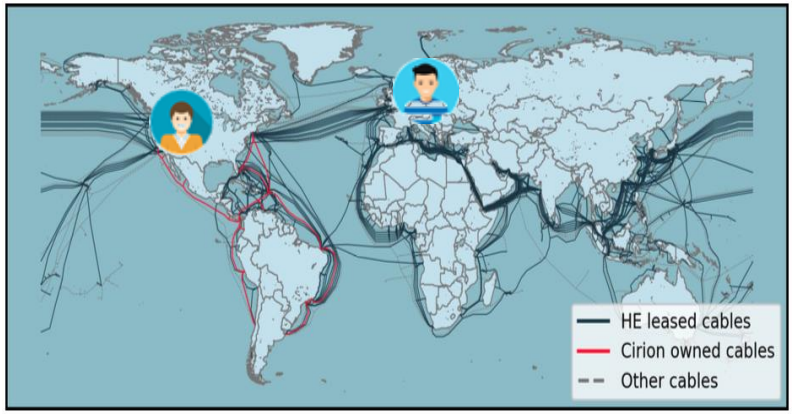
ONRG

Logical Layer

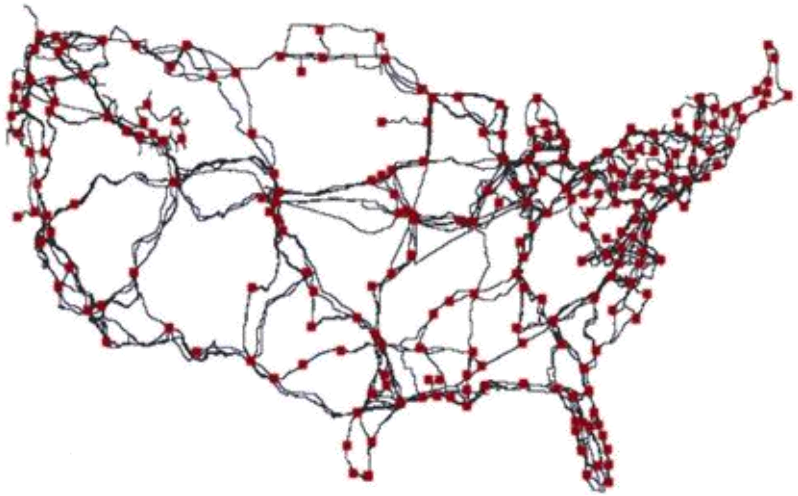


Mapping

Physical Layer



Submarine Cable Map

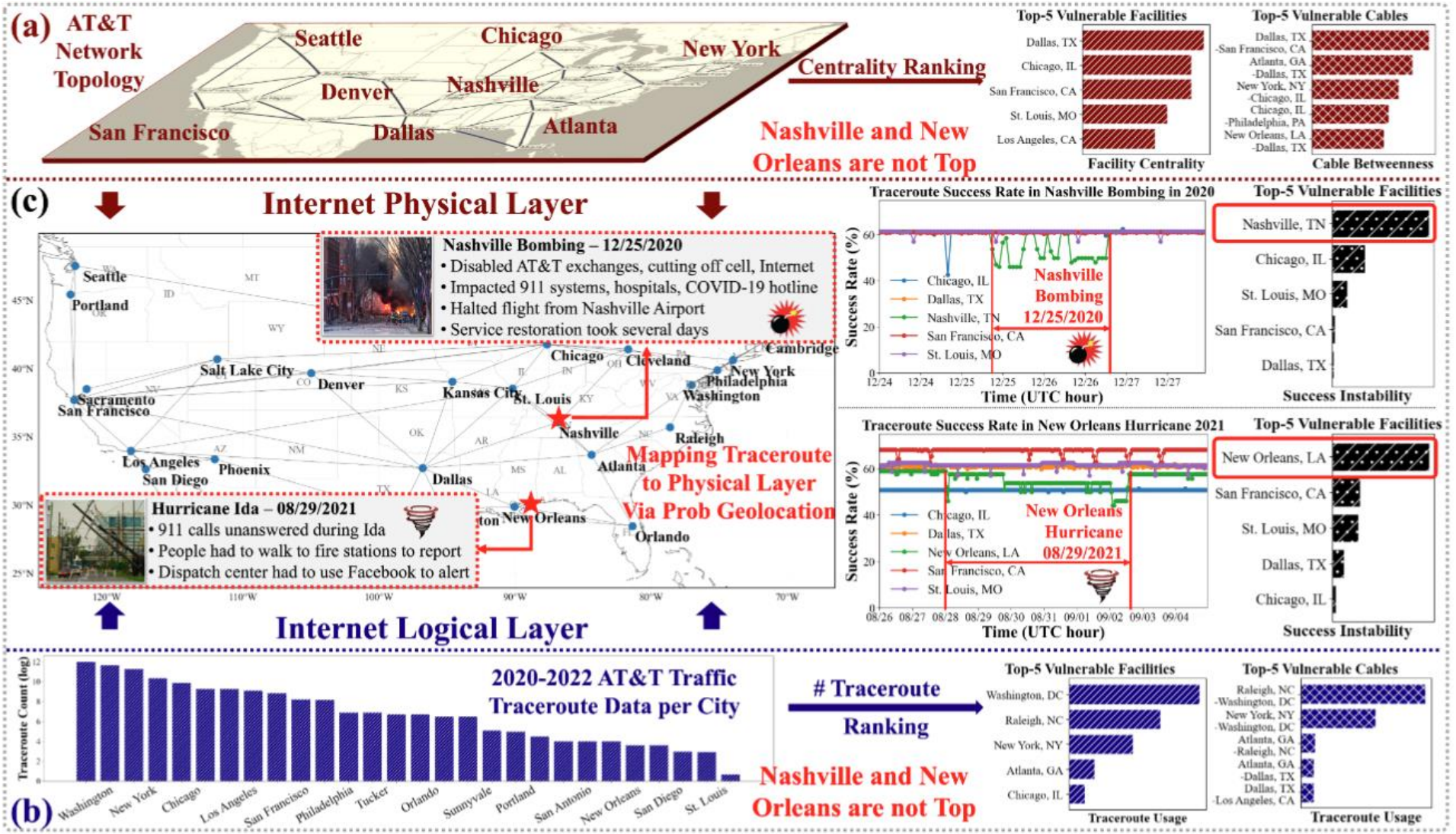


Terrestrial Cable Map

Which physical cable path does this logic signal traverse?

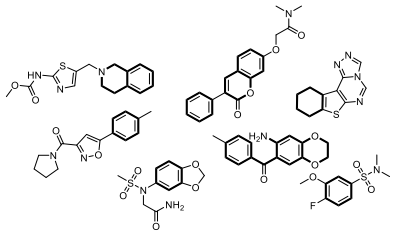
Why Data Mining? – Networking Infra Risk

ONRG



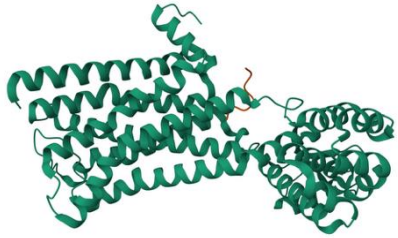
Why Data Mining? – Drug Design

Chemical Libraries

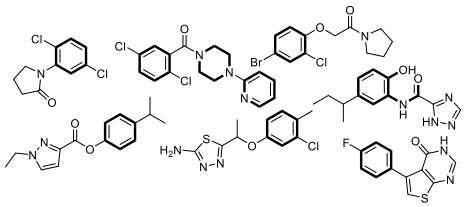


Number of Molecules: 103-106

Protein Target



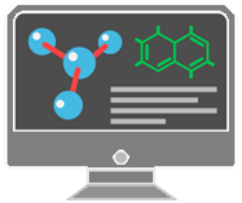
Virtual Libraries



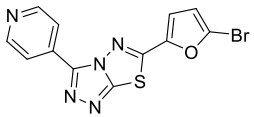
e.g., 10^9 Virtual Molecules on the REAL database in Enamine Ltd.

High Throughput Screening (HTS)

Training



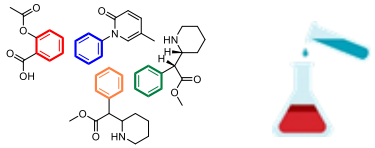
Deep Learning Models



Hit Rate: 0.05%-0.5%

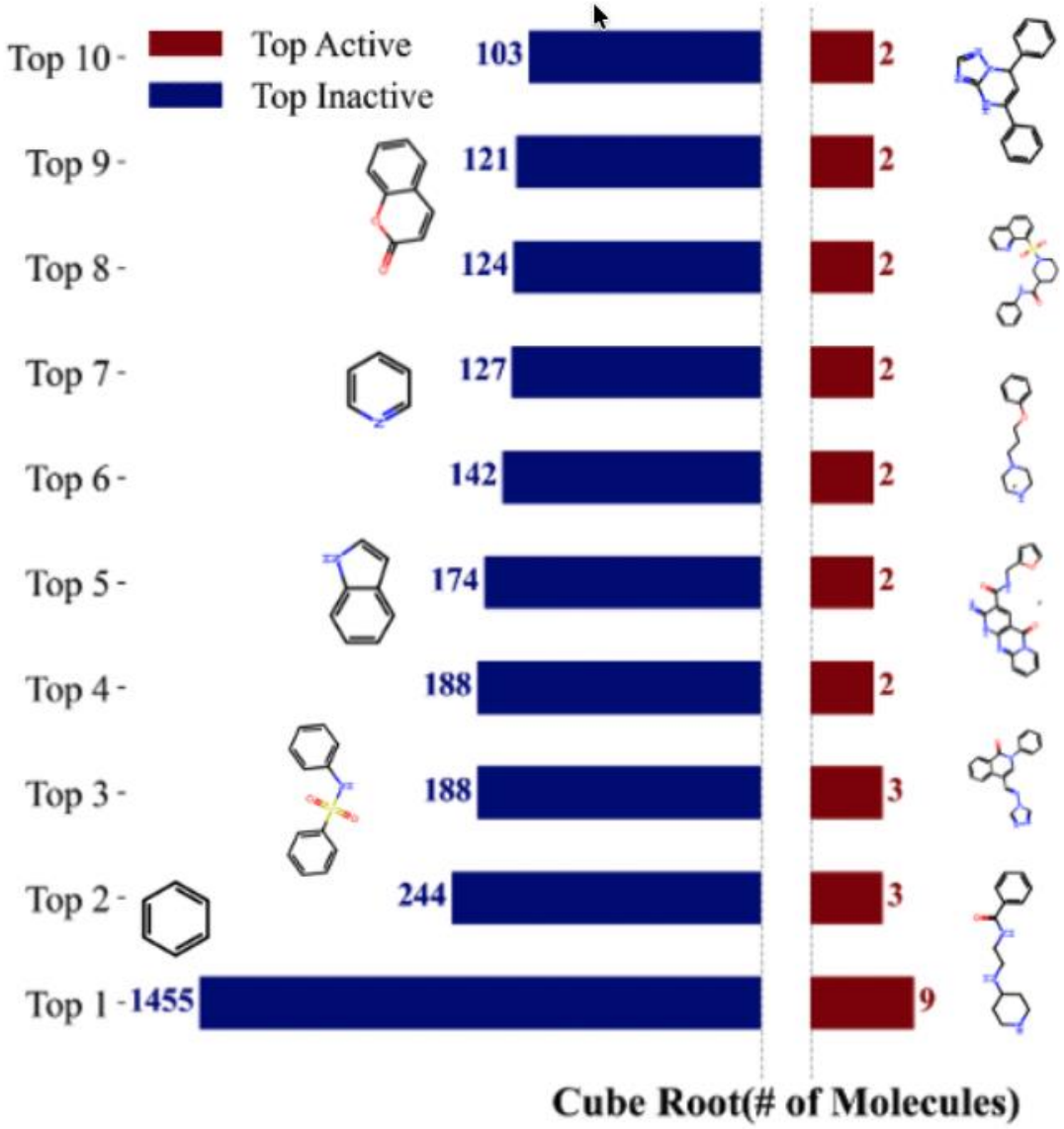
Evaluating

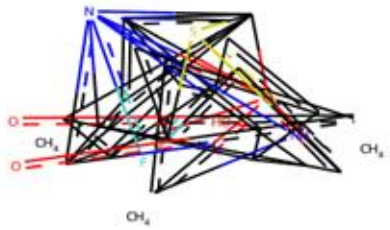
Predicted Actives

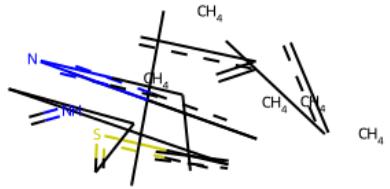


Number of Molecules: 500-1000

Why Data Mining? – Drug Design







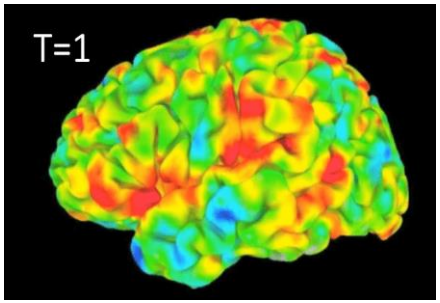
Why Data Mining? – Commercial Perspective

- Lots of data is being collected and warehoused
  - Web data 1,000 terabytes, 1,000,000,000,000,000= bytes
    - Google has Peta Bytes of web data
    - Facebook has billions of active users
  - purchases at department/ grocery stores, e-commerce
    - Amazon handles millions of visits/day
  - Bank/Credit Card transactions

- Computers have become cheaper and more powerful
- Competitive Pressure is Strong
  - Provide better, customized services for an edge (e.g. in Customer Relationship Management)

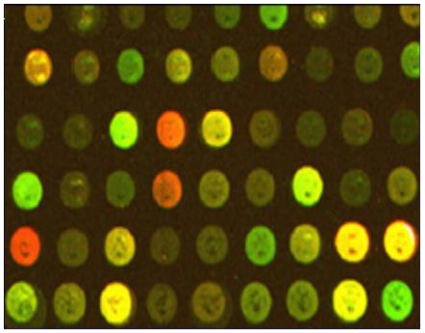
Why Data Mining? – Scientific Perspective

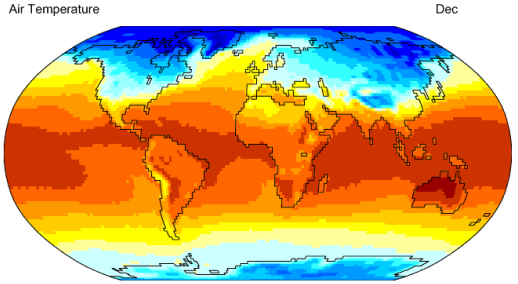
- Data collected and stored at enormous speeds
  - Remote sensors on a satellite
    - NASA EOSDIS archives over petabytes of earth science data / year
  - Telescopes scanning the skies
    - Sky survey data
  - High-throughput biological data
  - Scientific simulations
    - terabytes of data generated in a few hours
- Data mining helps scientists
  - in automated analysis of massive datasets
  - In hypothesis formation



fMRI Data from Brain

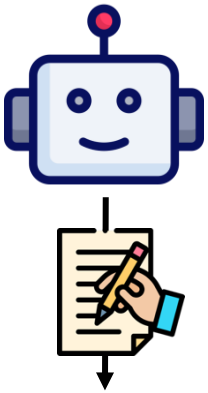

Sky Survey Data

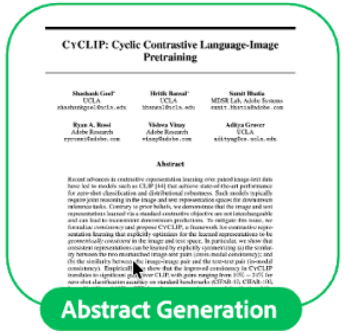

Gene Expression Data

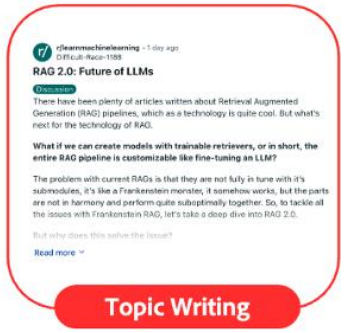


Surface Temperature of Earth

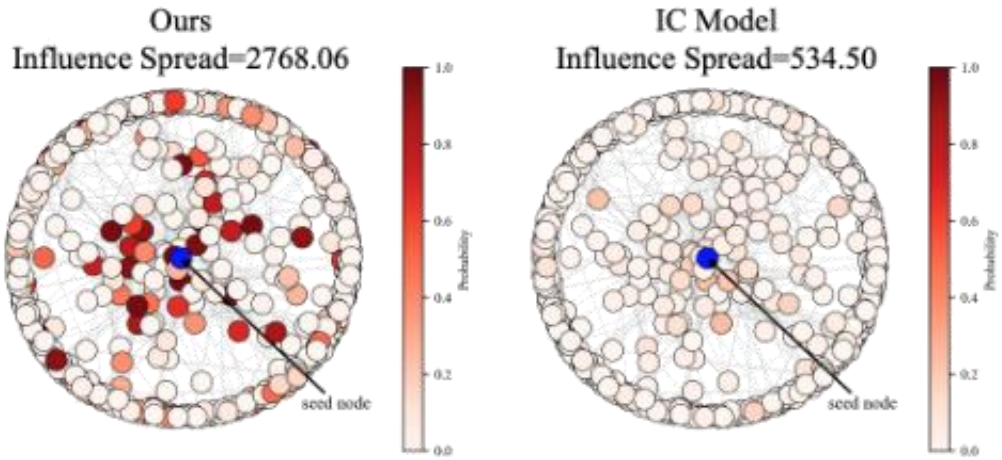
Why Data Mining? – Social Good



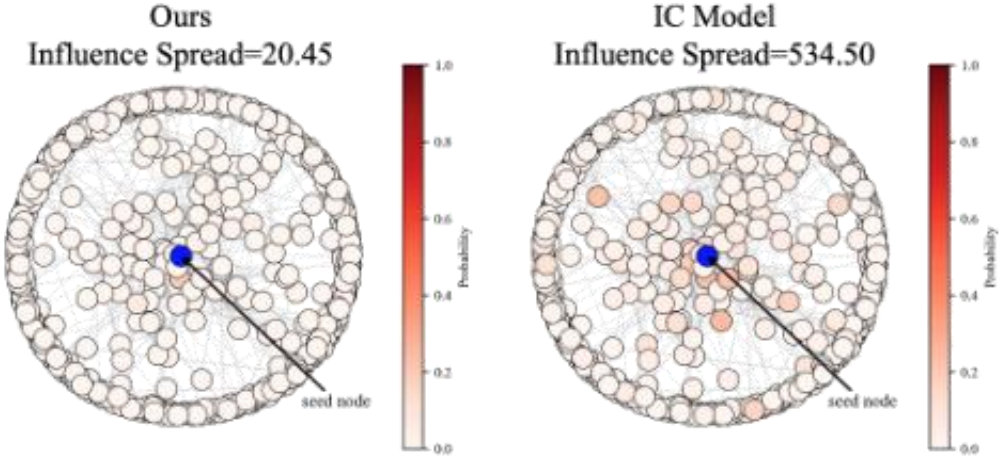




Text: "Breaking: NASA confirms first-ever human colony on Mars will begin next year — tickets for civilians already being sold out in minutes!"



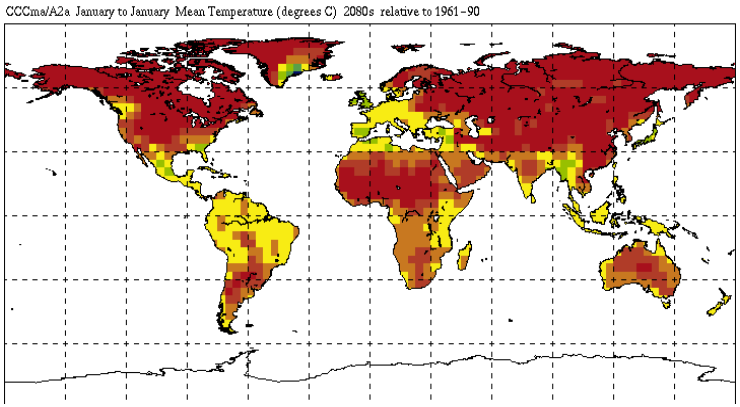
Text: " Today I bought a new pencil."



However, we have challenges – Question

What kind of data mining question you want to answer?

Improving health care and reducing costs



Predicting the impact of climate change

Finding alternative/ green energy sources

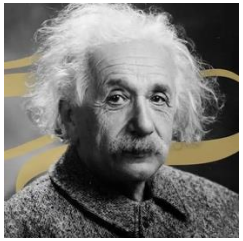
Reducing hunger and poverty by increasing agriculture production

However, we have challenges – Question

What kind of data mining question you want to answer?

Judge a man by his questions rather than his answers.

------ Voltaire



The important thing is not to stop questioning.

------ Albert Einstein

He who asks a question is a fool for five minutes; he who does not ask a question remains a fool forever.

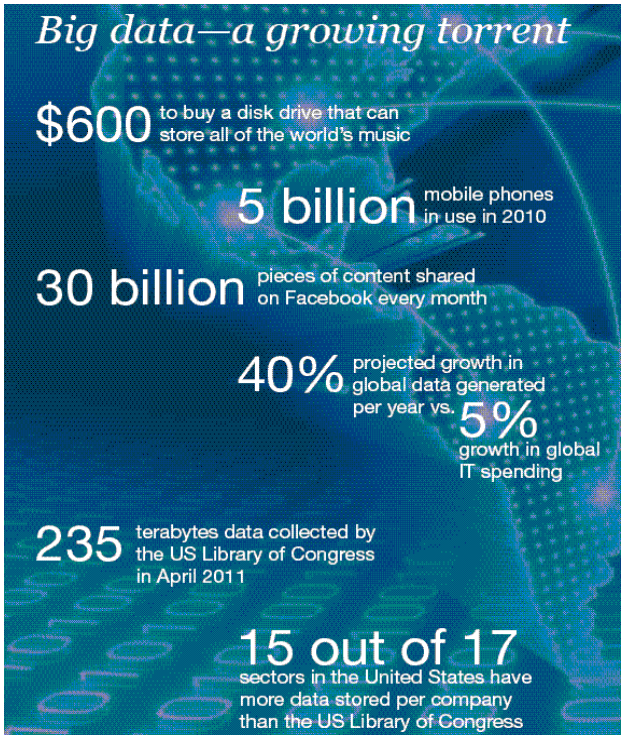
------ Confucius

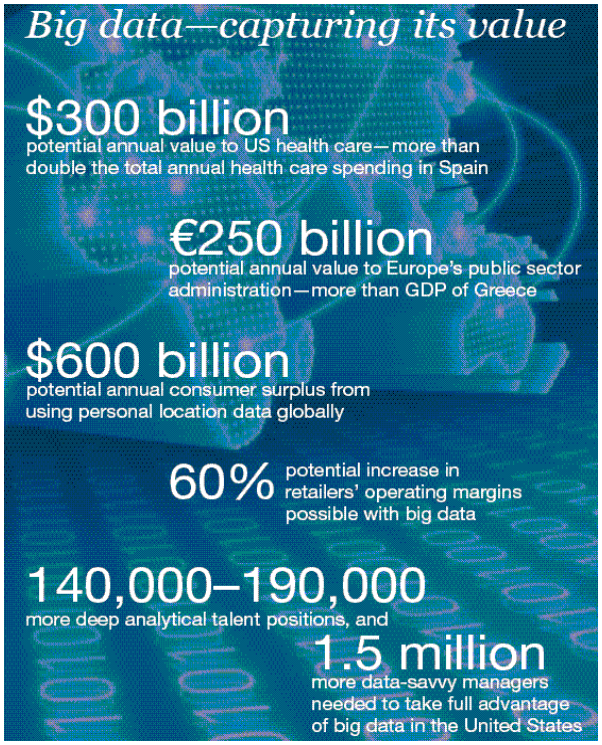
However, we have challenges – Data

Data is usually in a very large scale!

McKinsey Global Institute

Big data: The next frontier for innovation, competition, and productivity

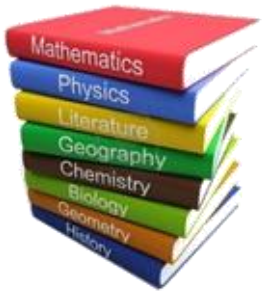




However, we have challenges – Data

Data is usually in a very large scale!

Textbook Knowledge Base



158 million books

ISBN DB 2023

Internet Knowledge Base

1.1 billion websites

Musemind 2024

Neural Knowledge Base

405 billion parameters

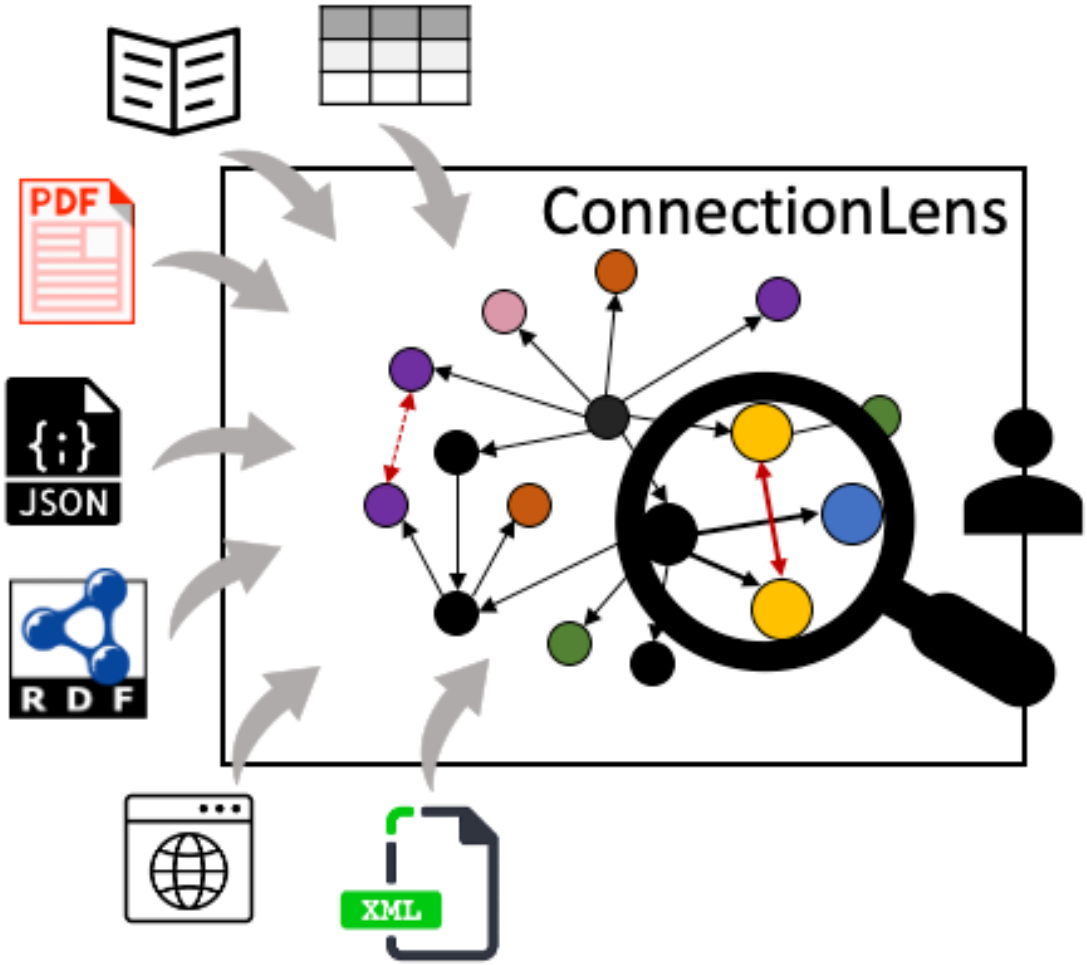
Hugging Face 2024

- **We remember meanings, not details.**
- **We forget on purpose.**
- **Tiny active memory, Larger long-term memory.**

2.5 petabytes, 1 billion books

However, we have challenges – Data

Data is diverse and heterogeneous



Summary

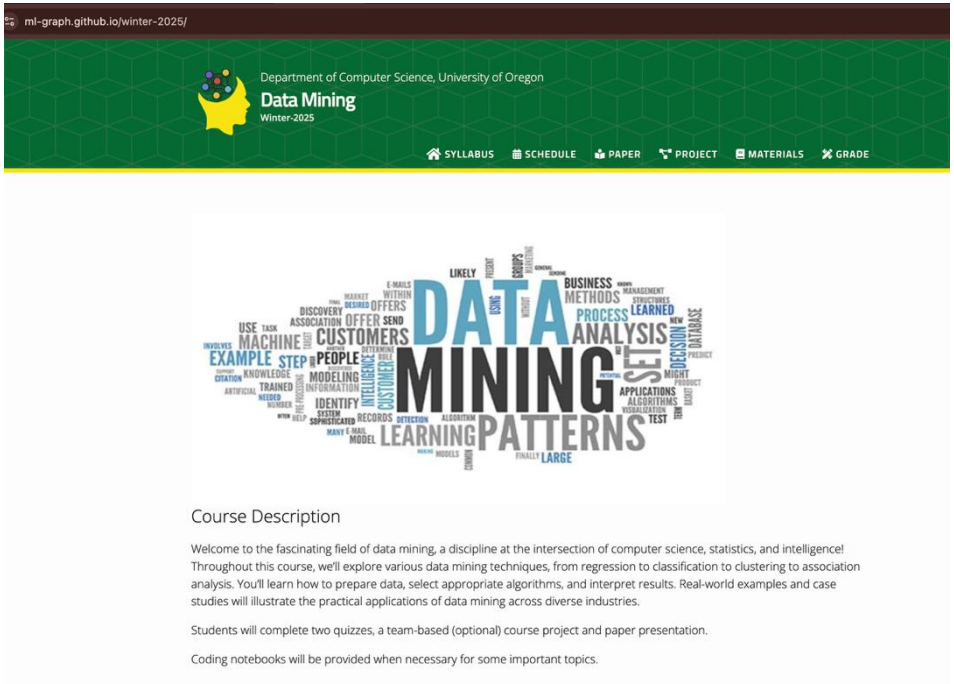
- **Data is everywhere**
- **Data Mining brings scientific advancement and social wellness**
- **However, there are challenges**

(1) What are good questions to ask?
(2) Data is scattered around the world, how to find them?
(3) Data is very large-scale, how to analyze them efficiently, space/time?
(4) Data is very heterogeneous and specialized

This is the reason for taking data mining!

Question Time!

Course Logistics



https://ml-graph.github.io/winter-2025/

All information will be available on the website!

Goals

- Broad overview of Data Mining
- Data Mining Skills – Knowledge and Code
- Machine Learning Skills – Knowledge and Code
- Real-world GML/DM applications

Prerequisite

- Linear Algebra, Probability /Statistics, Calculus
- Programming – Python, PyTorch
- Curiosity – Critical Thinking
- Diligence – Hard Working

Course Logistics - Time

Times:

- **Classes:** Monday/Wednesday 12:00-1:20 pm PST, Gerlinger 302
- **Office hours:** Wednesday 1:20-2:00 pm PST, other time by appointment
- **Zoom:** https://uoregon.zoom.us/j/4052006678

Course Logistics – Quzz

Times:

- **Classes:** Monday/Wednesday 12:00-1:20 pm PST, Gerlinger 302
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Components:

Course Assessment and Grading Scale

Category	CS-453 (%)	CS-553 (%)
Quzz 1	20%	15%
Quzz 2	20%	15%
Project	40%	45%
Participation	5%	5%
Paper Presentation	15%	20%
Overleaf Bonus	5%	5%

- As long as you are **active thinking** and **understand the content**, you will be good

Question Time!