

# Data Mining

## Course Overview and Logistics

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

CS 453/553 – Winter 2026

Yu Wang, Ph.D.

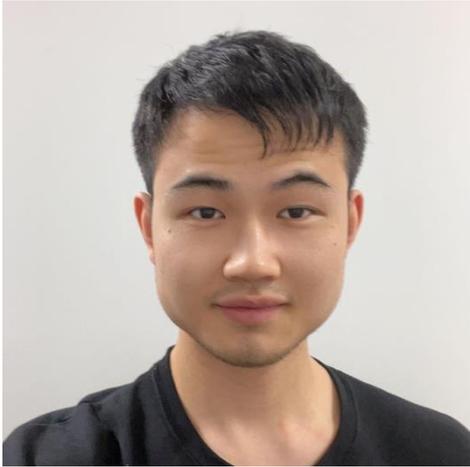
Assistant Professor

Computer Science

University of Oregon



# Self-Introduction



**Yu (Jack) Wang**  
**(You)**

**Contact:**  
[yuwang@uoregon.edu](mailto:yuwang@uoregon.edu)

<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

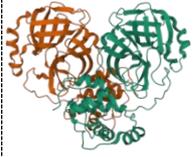


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# What is Data?

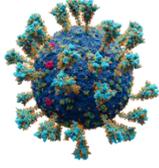
## Science



Protein



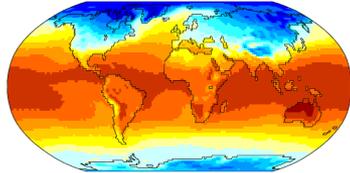
Small Molecule



Virus

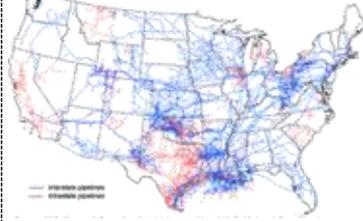


Brain Neural



Surface Temperature of Earth

## Gas Network

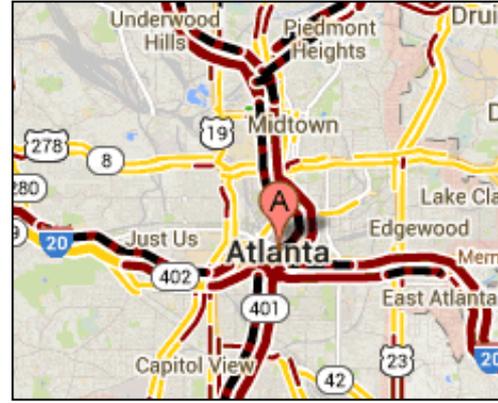


## Power Network

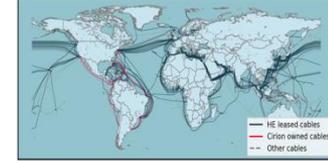


## Infrastructure

### Transportation Network



## Submarine Cable



## Terrestrial Cable



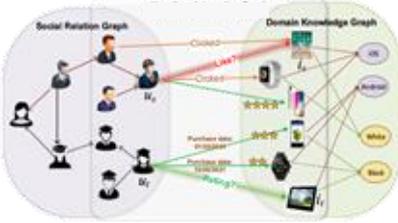
## Social Network



Citation Network



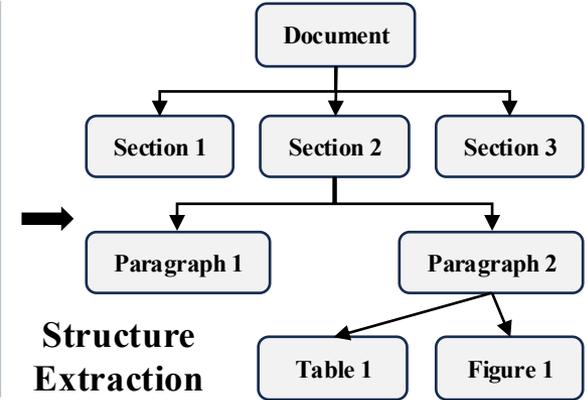
Transaction Network



User-Entity Interaction Graph



## Document



Structure Extraction





# Why Analyze Data? – Paper Management

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## Recommended articles



☆ Analyzing the Properties of Graph Neural Networks with Evolutionary Algorithms ▼  
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☆ Self-Supervised Bipartite Graph Neural Networks with Missing Value Imputation for Small Tabular Data Predictions ▼  
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Mingyang Chen, Tianpeng Li, Haoze Sun, Yijie Zhou, Chenzheng Zhu, Haofen Wang, Jeff Z Pan, Wen Zhang, Huajun Chen, Fan Yang, et al. ReSearch: Learning to reason with search for llms via reinforcement learning. *arXiv preprint arXiv:2503.19470*, 2025. 2, 4, 7, 10, 21

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Guanting Dong, Yifei Chen, Xiaoxi Li, Jiajie Jin, Hongjin Qian, Yutao Zhu, Hangyu Mao, Guorui Zhou, Zhicheng Dou, and Ji-Rong Wen. Tool-star: Empowering llm-brained multi-tool reasoner via reinforcement learning. *arXiv preprint arXiv:2505.16410*, 2025. 2, 10

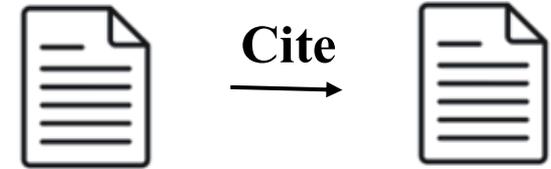
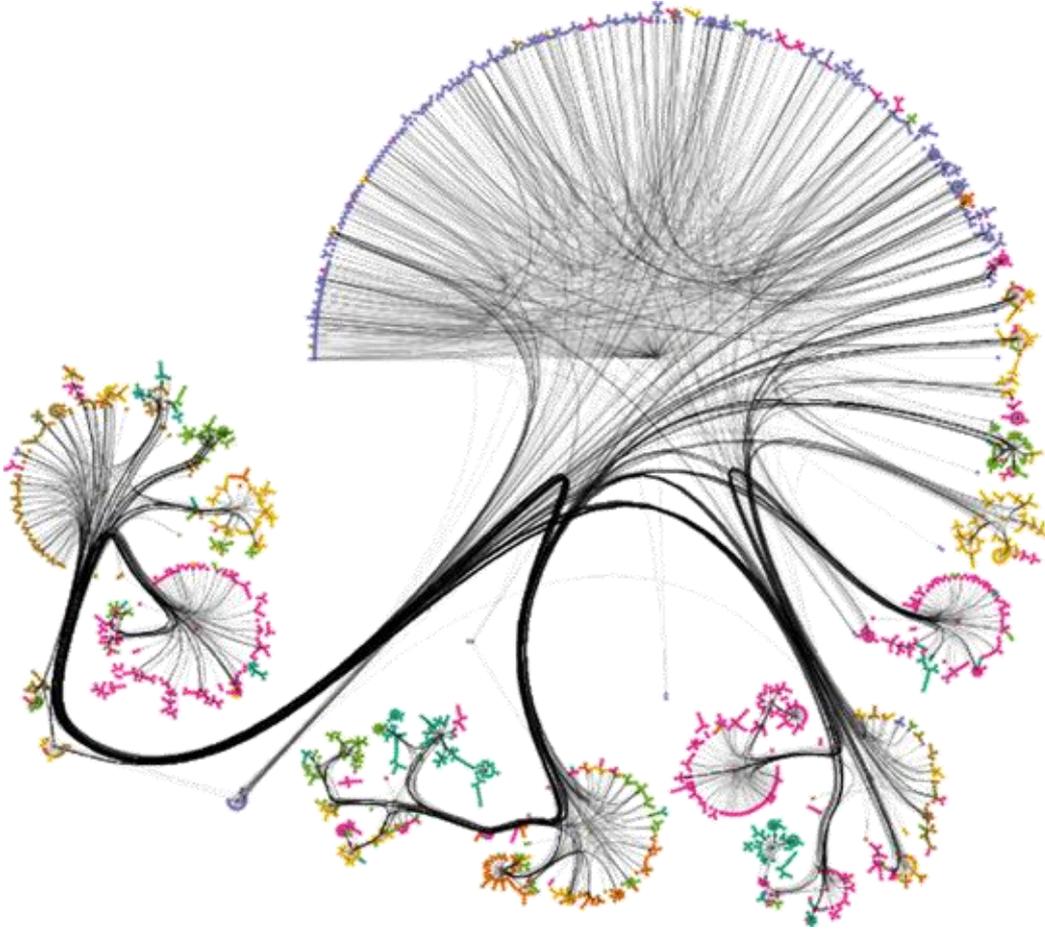


Cite





# Why Analyze Data? – Paper Management



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

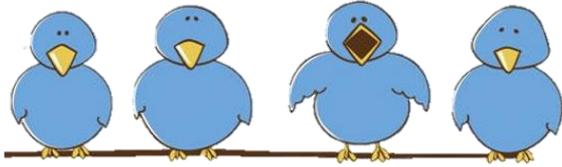
$\mathcal{E}$  - Total Number of Edges

$e_{ij}$  - Edge between node  $i/j$

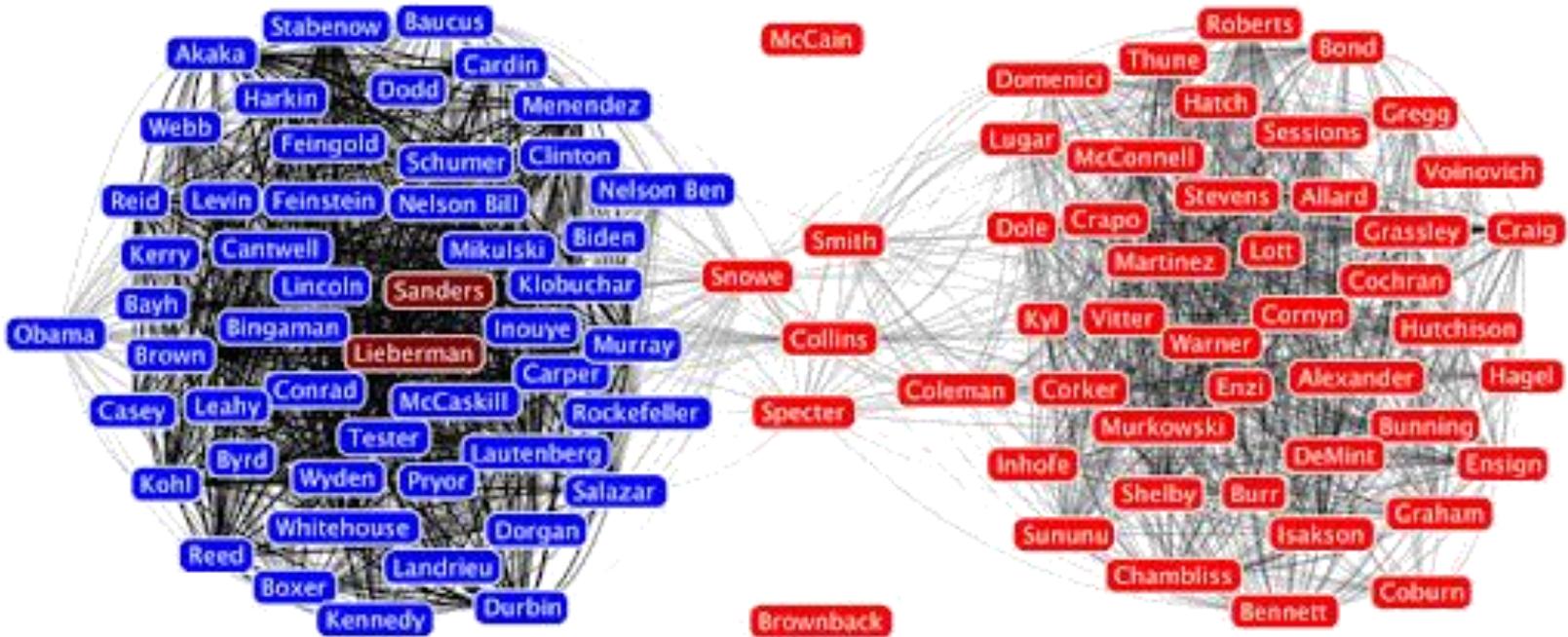
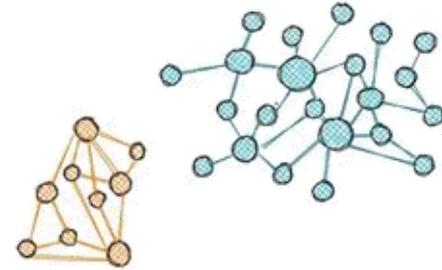
$y_i$  - Label of  $i$



# Why Analyze Data? – Paper Management



Birds of a feather flock together

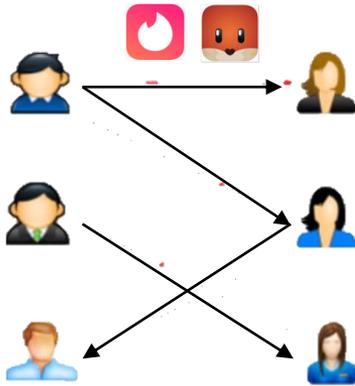


Gun Control Belief Network

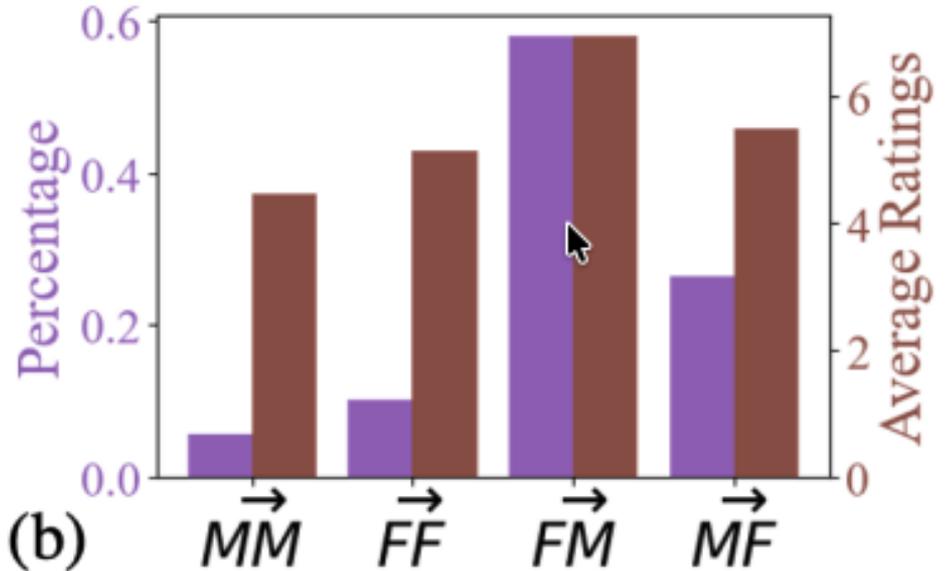
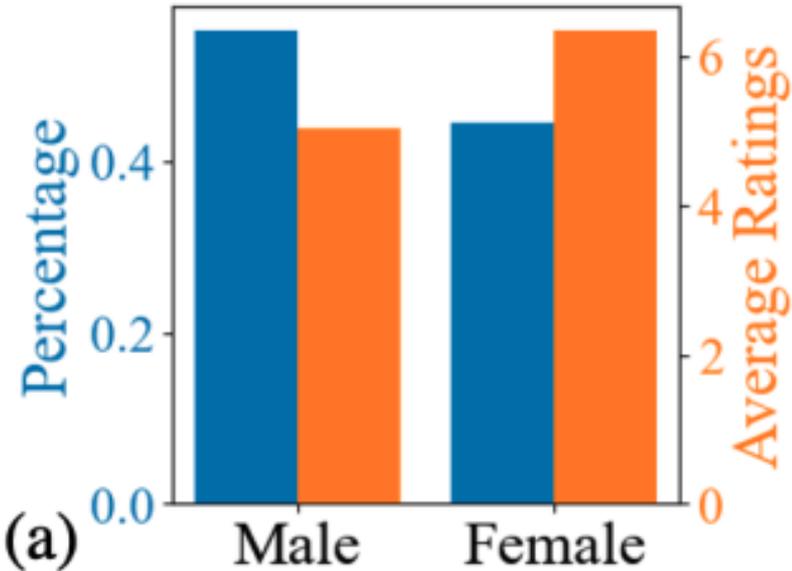
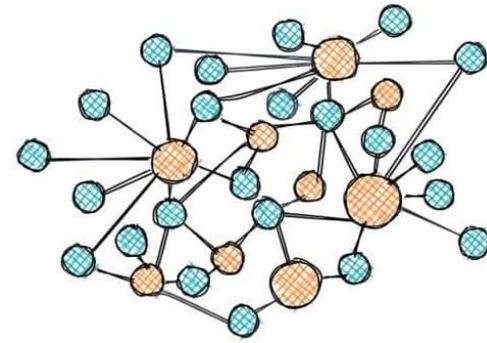




# Why Analyze Data? – Paper Management



Dating Network



Dating Network



# Why Analyze Data? – Paper Management

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

Zhuofeng Li<sup>\*1,2</sup>, Haoxiang Zhang<sup>\*1,3</sup>, Seungju Han<sup>1</sup>, Sheng Liu<sup>1</sup>, Jianwen Xie<sup>4</sup>, Yu Zhang<sup>2</sup>, Yejin Choi<sup>1</sup>, James Zou<sup>1†</sup>, Pan Lu<sup>1†</sup>

<sup>1</sup>Stanford University, <sup>2</sup>Texas A&M University, <sup>3</sup>UC San Diego, <sup>4</sup>Lambda

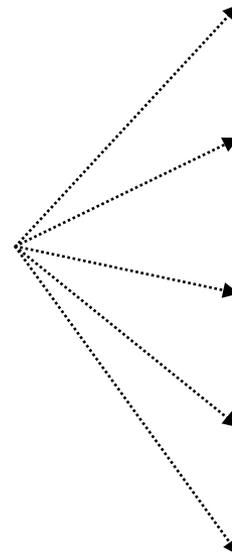


Website: <https://agentflow.stanford.edu>

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.



In-the-flow agentic system optimization for effective planning and tool use

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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

Zhaofeng Li<sup>1,2</sup>, Haosiang Zhang<sup>1,2</sup>, Seungja Han<sup>1</sup>, Sheng Liu<sup>1</sup>, Sheng Liu<sup>1</sup>, Jianwen Xie<sup>1</sup>, Yu Zhang<sup>1</sup>, Yujin Choi<sup>1</sup>, James Zou<sup>1</sup>, Pan Lu<sup>1</sup>  
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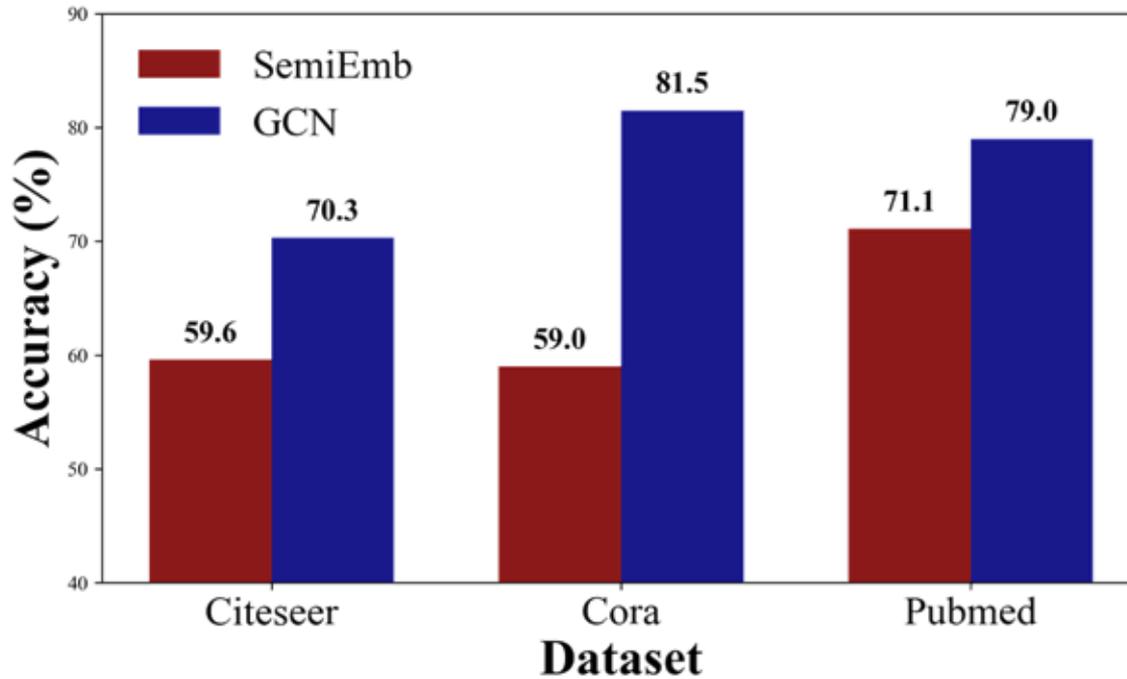
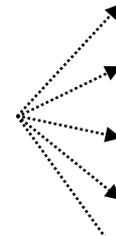
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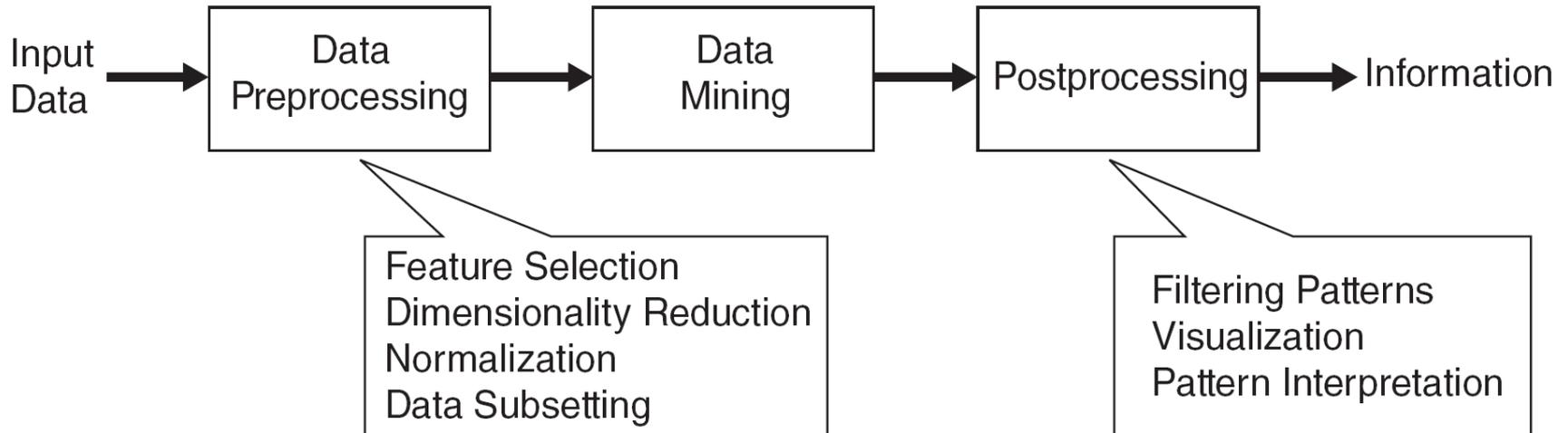
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# What is Data Mining?

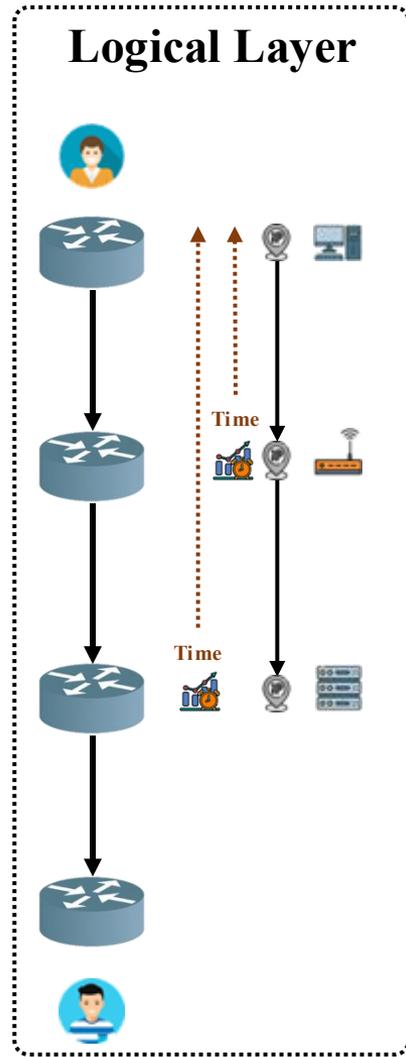
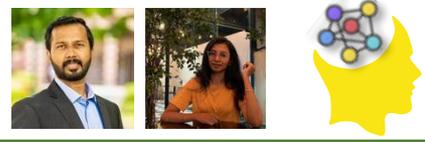


## Many Definitions

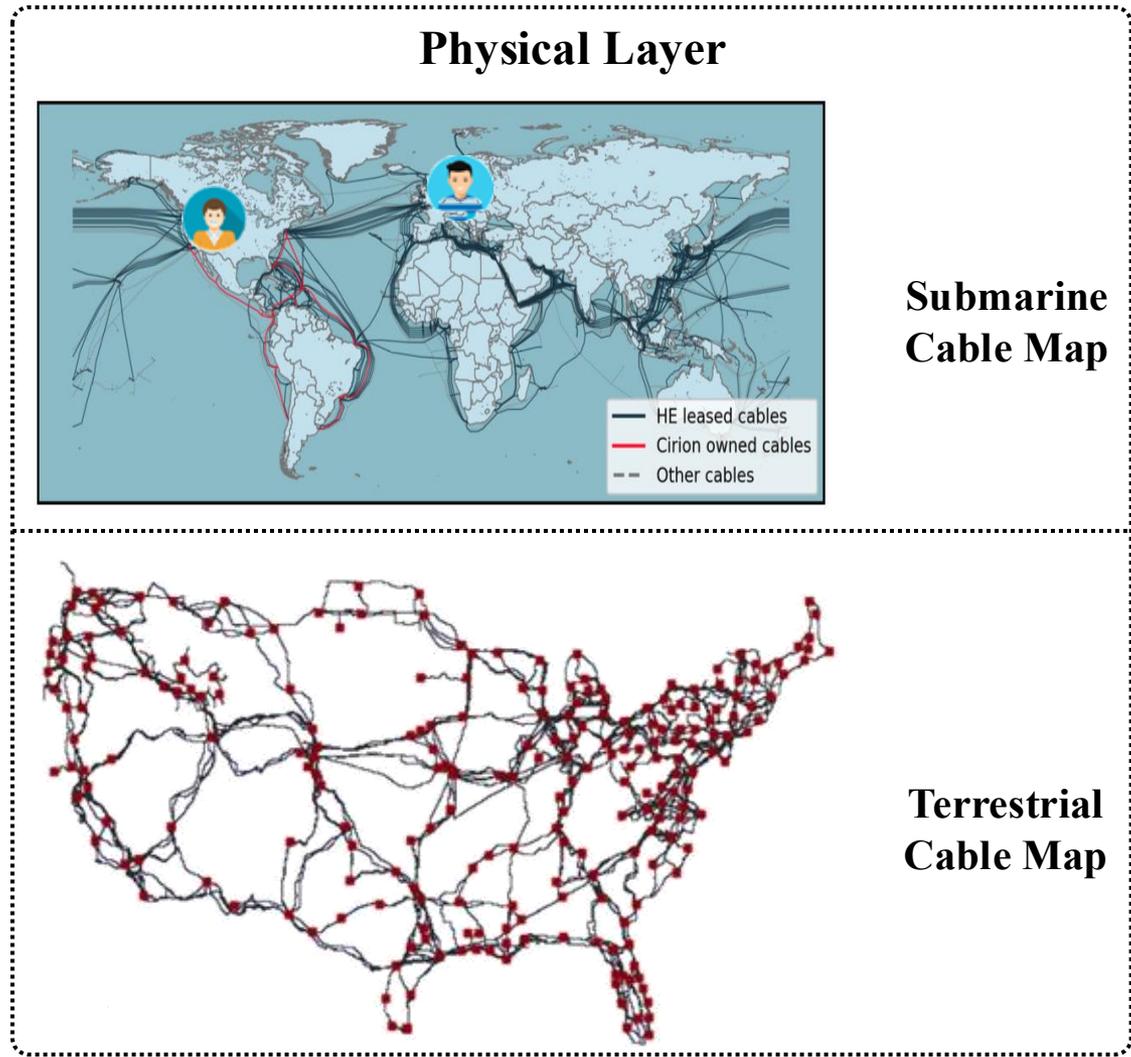
Non-trivial extraction of implicit, previously unknown and potentially useful information from data

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**



Mapping

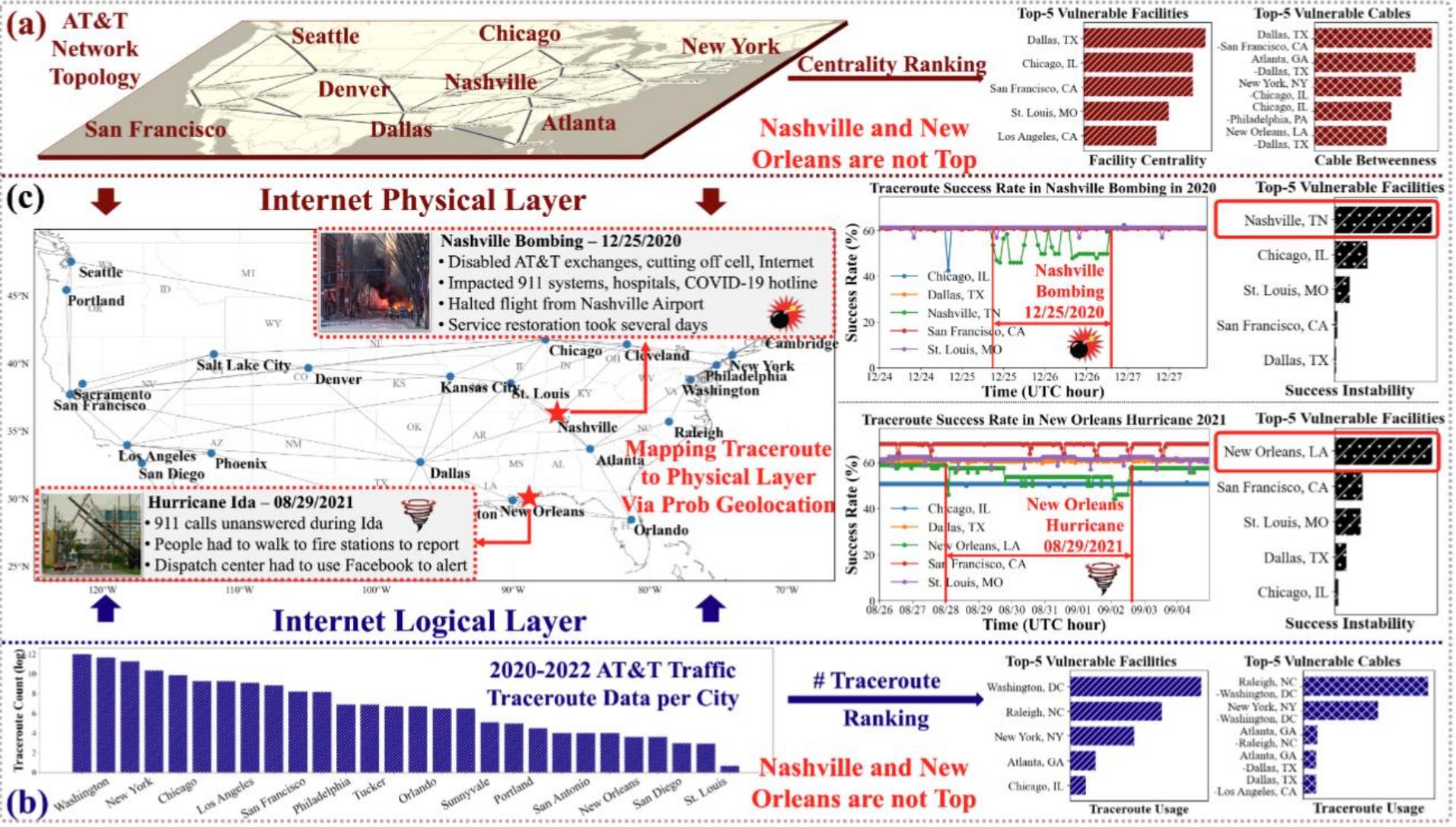


Submarine Cable Map

Terrestrial Cable Map

Which physical cable path does this logic signal traverse?

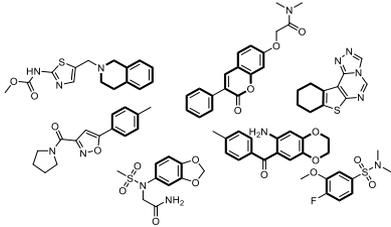
# Why Data Mining? – Networking Infra Risk ONRG





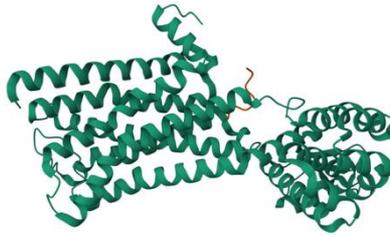
# Why Data Mining? – Drug Design

## Chemical Libraries

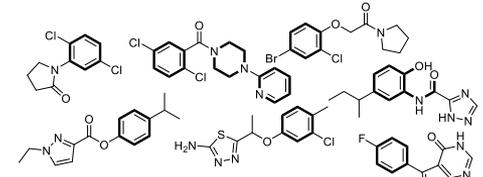


Number of Molecules: 103-106

## Protein Target



## Virtual Libraries



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



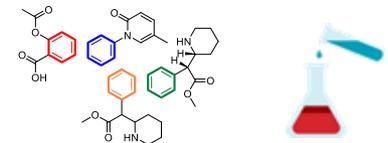
High Throughput Screening (HTS)

Training



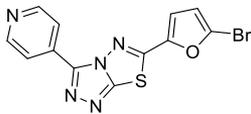
Deep Learning Models

## Predicted Actives



Number of Molecules: 500-1000

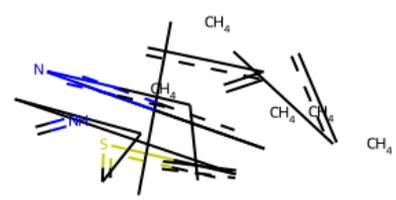
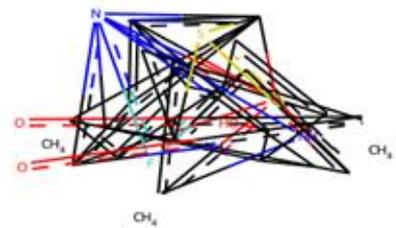
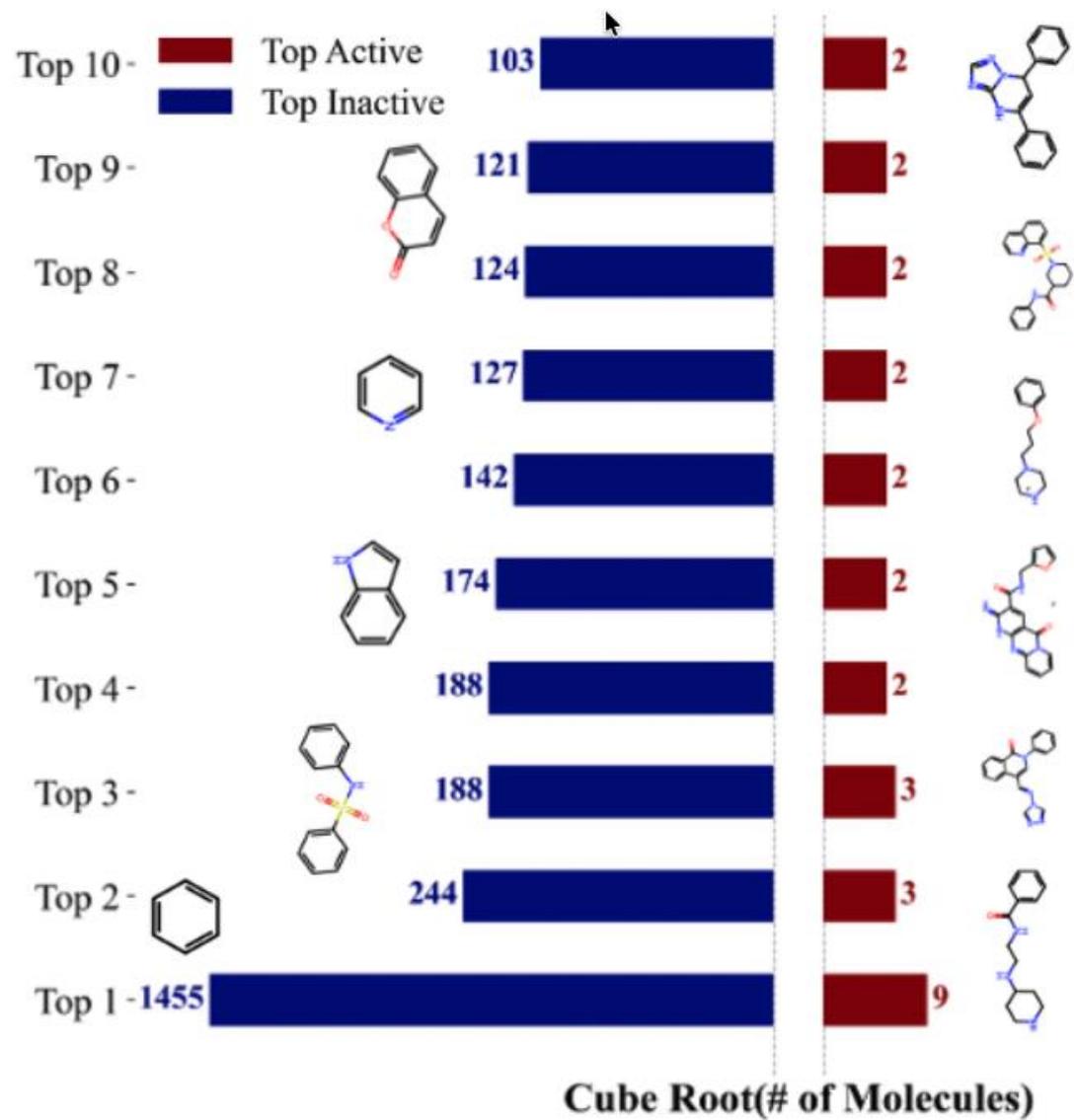
Evaluating



Hit Rate: 0.05%-0.5%



# Why Data Mining? – Drug Design





# Why Data Mining? – Commercial Perspective

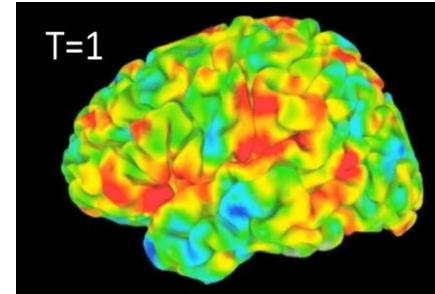
- Lots of data is being collected and warehoused
  - Web data **1,000 terabytes,**  
**1,000,000,000,000,000= bytes**
    - Google has Peta Bytes of web data
    - Facebook has billions of active users
  - purchases at department/  
grocery stores, e-commerce
    - Amazon handles millions of visits/day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

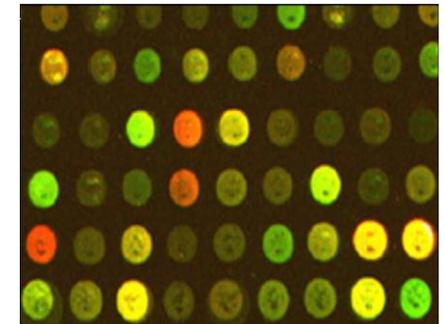
- Data collected and stored at enormous speeds
  - Remote sensors on a satellite
    - NASA EOSDIS archives over petabytes of earth science data / year
  - Telescopes scanning the skies
    - Sky survey data
  - High-throughput biological data
  - Scientific simulations
    - terabytes of data generated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



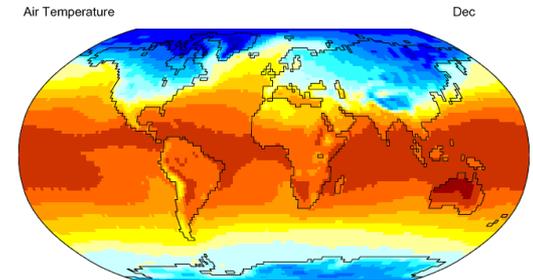
fMRI Data from Brain



Sky Survey Data



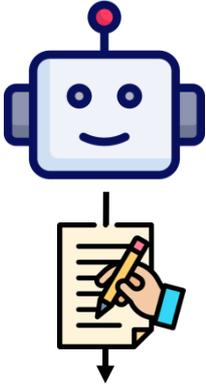
Gene Expression Data



Surface Temperature of Earth

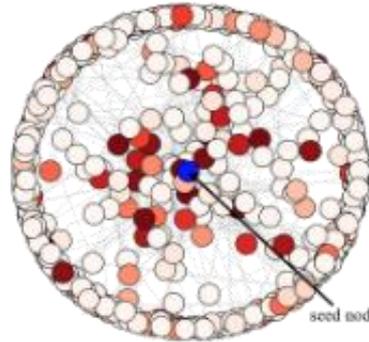


# Why Data Mining? – Social Good

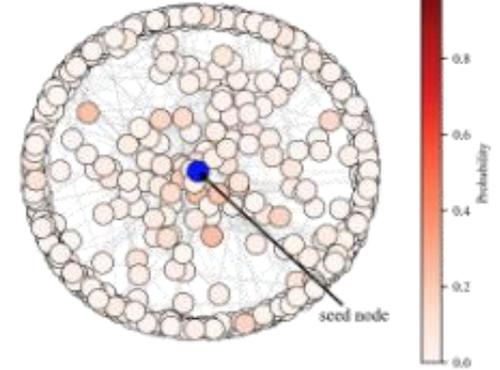


Text: "Breaking: NASA confirms first-ever human colony on Mars will begin next year — tickets for civilians already being sold out in minutes!"

Ours  
Influence Spread=2768.06



IC Model  
Influence Spread=534.50



Recipients

Subject

Hey Casey,

I noticed you and I are b LinkedIn, and that you ju

Since you're an Austin b technology and sustaine, attending our Q&A M

One of the keynote spe fellow green energy shi lth in San Francisco. Sh

Warm regards,

Jane Doe

Email Generation

**CyCLIP: Cyclic Contrastive Language-Image Pretraining**

**Nishant Gup†** UCCLA, nishantg@uccla.edu  
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**Saurabh Mittal†** MSR LA, saurabh.mittal@msr.com

**Yuan A. Bai†** Adobe Research, ybai@adobe.com  
**Vishay Vinyu†** Adobe Research, vinyu@adobe.com  
**Ashley Crow†** UCCLA, ashcrow@uccla.edu

**Abstract**

Recent advances in contrastive representation learning over paired image-text data have led to state-of-the-art (SOTA) text-to-image retrieval performance for non-text classification and distributional coherence. Such models require region proposal networks to extract region proposals from the image and use representations learned by the standard contrastive objective on text embeddings and can be hard to reconfigure for downstream problems. To mitigate this issue, we build a contrastive text-image pretraining framework, named **CyCLIP**, that encourages the model to learn representations that explicitly separate the learned representations in the generatively constructed image-text pairs (cross-modal consistency) and (the contrastive learning objective) and the non-image-text pairs (intra-modal consistency). Experiments show that the proposed consistency in CyCLIP outperforms region proposal networks in text-to-image retrieval (SOTA) and text-to-image distributional coherence on standard benchmarks (SOTA) on CIFAR-100.

Abstract Generation

**Customer Reviews**

★★★★★ These work!

By Amazon on August 28, 2017  
Color: white

When we lost the original cables, we tried several pairs and finally the other for another lighting point (the "shop" brand). They do not work and just headache pain. This means to think any other one will have a good chance of quality. They reach the original apple way for at least a very good price and work like the original. I bought 2, both are great. Back to sleep!

★★★★★ This had they will give you all the space for your activities...

By Jay on November 8, 2017  
Color: white

Will never get old of this. Makes my life easier. I do not have to hold my body anymore, and my back on my bed or couch. Trying to use my old cable and changing with one of the number phones. This had they will give you all the space for your activities and finally for anyone you want it might be easy to bring my laptop to the party. A lot of people think you want my phone is changing, someone will be talking, but also in perspective is okay. I like this change more than most things in life, it keeps cables clean and prevents anything. I love this change.

★★★★★ Good product

By Amazon on November 16, 2017  
Color: white

My rabbit like my four headphones changing the cable as they expect me to buy this new... and they are his favorite and will really spend a cable changing cable. I wanted one that does the same thing as the original. I bought 2, both are great. Back to sleep!

Because they are so cheap!

Review Generation

📄 **Future of LLMs**

📄 **Future of LLMs**

**📄 Future of LLMs**

There have been plenty of articles written about Retrieval Augmented Generation (RAG) pipelines, which as a technology is quite cool. But what's next for the technology of RAG.

**📄 Future of LLMs**

What if we can create models with trainable retrievers, or in short, the entire RAG pipeline is customizable like fine-tuning an LLM?

The problem with current RAGs is that they are not fully in tune with it's submodules, it's like a Frankenstein monster, it somehow works, but the parts are not in harmony and perform quite suboptimally together. So, to tackle all the issues with Frankenstein RAG, let's take a deep dive into RAG 2.0.

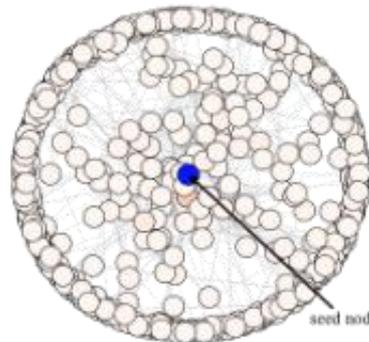
But why does this solve the issues?

Read more »

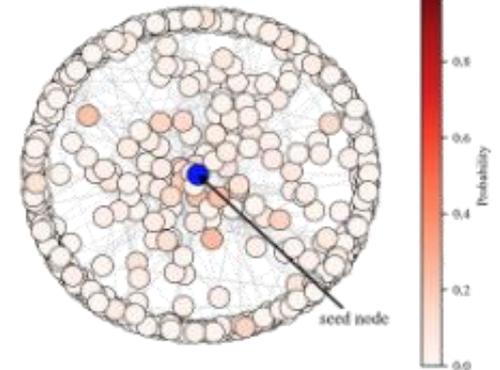
Topic Writing

Text: " Today I bought a new pencil."

Ours  
Influence Spread=20.45



IC Model  
Influence Spread=534.50



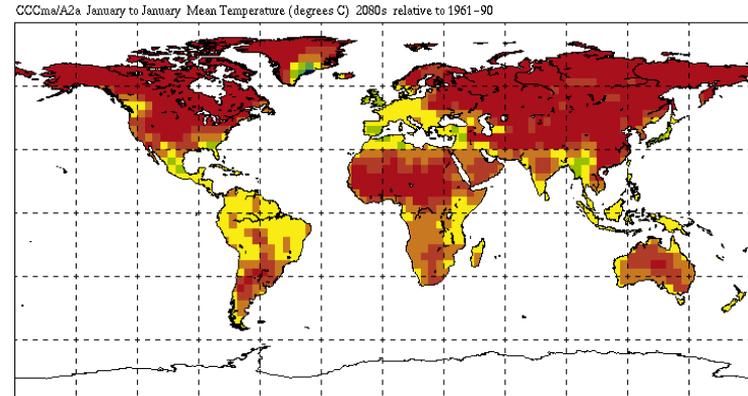


# However, we have challenges – Question

**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



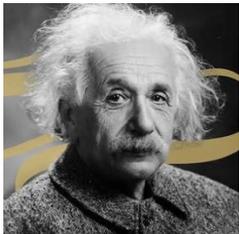
# However, we have challenges – Question

**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

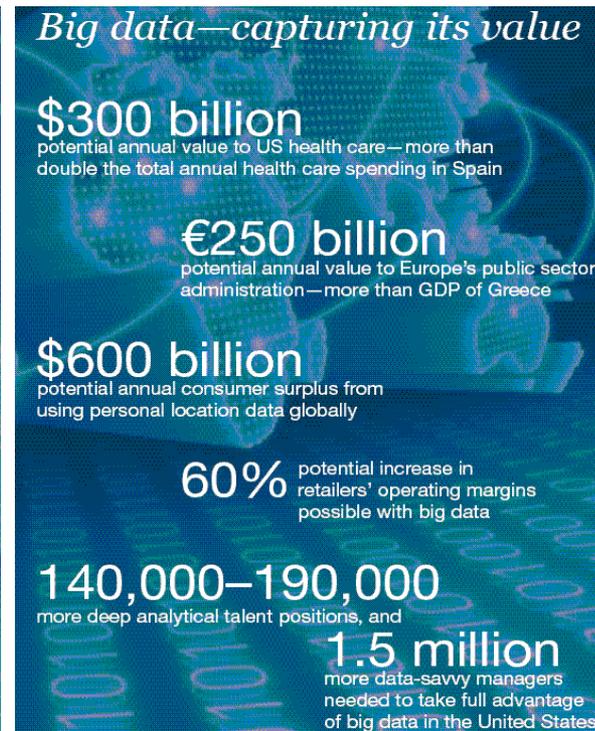
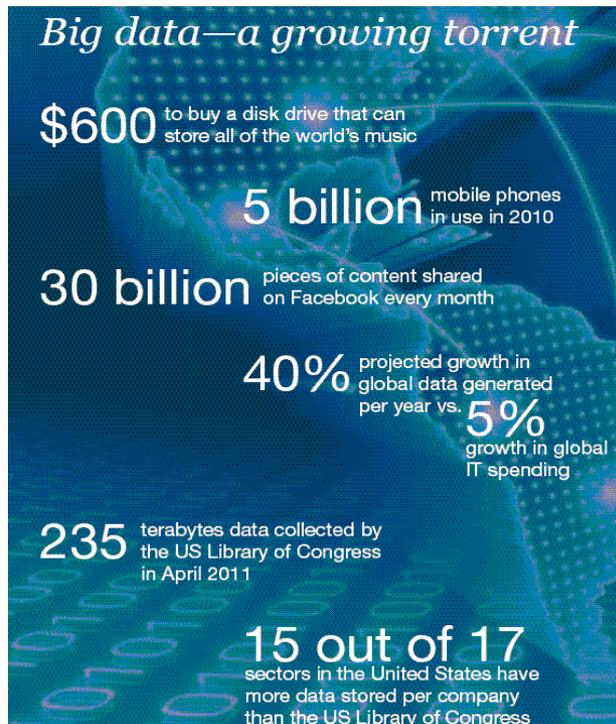


# However, we have challenges – Data

## Data is usually in a very large scale!

McKinsey Global Institute

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

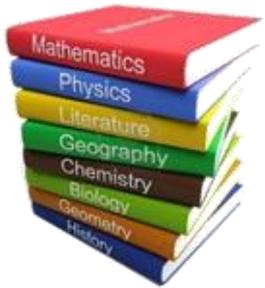




# However, we have challenges – Data

**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](#)



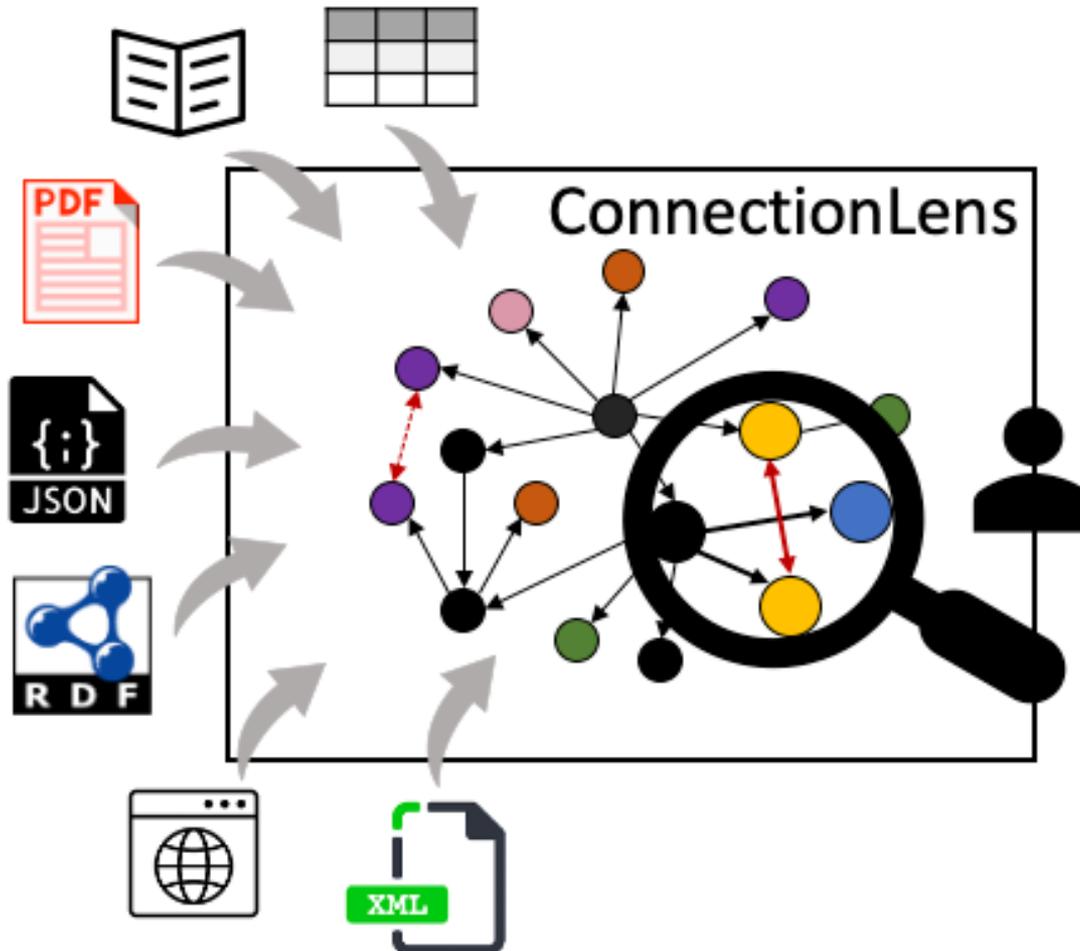
 **2.5 petabytes, 1 billion books**

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



# However, we have challenges – Data

Data is diverse and heterogeneous





- **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 - 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 – Quizz

## 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>

## Components:

### Course Assessment and Grading Scale

Category	CS-453 (%)	CS-553 (%)
Quizz 1	20%	15%
Quizz 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!





# Course Logistics – Quizz

## 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>

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Paper Presentation	15%	20%
Overleaf Bonus	5%	5%

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



# Course Logistics – Project

## 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>

## Components:

### Course Assessment and Grading Scale

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

<https://ml-graph.github.io/winter-2026/project/>



# Course Logistics – Project

## Project

The project may be completed either individually or as a team; both approaches are acceptable. For team-based projects, only one team member should submit the final report and clearly specify all contributing teammates. Bonus Points will apply if you consider doing projects in the following fields with (\*) or any domain beyond the following:

### 1. Background and Problem Formulation - 10%

- **Background - 5%:**
  - What is the general background of the problem you are working on?
    - I want to develop a better paper categorization system
- **Problem Formulation - 5%:**
  - Under the general topic, what specific problem is your project addressing?
    - I want to develop a machine learning model/algorithm to take input of the paper, output the paper topic (machine learning, computer system, human-computer collaboration, etc.)

### 2. Data Mining Stage - 35%

- **Data Collection and Store - 15%:**
  - What data are you looking to kick off your project? How do you collect them? What data structure do you use to represent them?
    - I collect Cora/Citeseer/Pubmed Data from somewhere (e.g., a paper, a GitHub repository, Hugging Face, etc.), and I use an adjacency list to store their connection and a matrix to store their node feature
- **Data Mining - 20%:**
  - What kind of data mining problem do you need to do and why?
    - I need to analyze the network homophily/heterophily since leveraging this property might help me develop a better machine learning model for paper classification.
  - How do you do it?
    - I calculate for every edge, the two ending points, whether they are in the same class or not, and quantify the average ratio as a homophily ratio
  - What kind of pattern do you find? How do you present your findings/analysis?
    - I find that in many paper citation networks, the homophily is pretty high. Using Number/Table/Figure, etc.

### 3. Machine Learning Stage - 35%

- **Machine Learning Model Design:**
  - Based on your targeted problem, what kind of machine learning model do you want to build and why?
    - I want to build a graph neural network to fully exploit the discovered homophily principle.

<https://ml-graph.github.io/winter-2026/project/>



# Course Logistics – Paper Presentation

## 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>

## Components:

### Course Assessment and Grading Scale

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

<https://ml-graph.github.io/winter-2026/presentation/>



# Course Logistics – Paper Presentation

## Presentation

### Paper Presentation Details

You can either collaborate with a team or present individually. The choice of topic is entirely up to you.

- Introduction and Background – What is the general impact and background of the topic?
- Motivation and Problem – What is the core research problem, and why do we study it?
- Related Work and Challenges – How did previous works address this problem, and what are some of the challenges?
- Proposed Solutions/Methods and Rationale – What are the proposed methods/techniques, and why are they proposed? What specific reasons would solving this problem require these proposed(1) methods/techniques?
- Experimental Setting, Results, and Analysis – What experiments are designed to verify the proposed method? How are results being discussed and analyzed? Are there any interesting findings?
- Conclusion and Future Work

Do not use sentences in the slides, but use bullet points and important points that you can logically chain together for your speech I will be very careful taking note of this. Please pardon me for this!

Natural Disaster Modeling

Neural-Biology Analysis

Social Network

Agentic AI

Reasoning/Planning

Knowledge Representation

<https://ml-graph.github.io/winter-2026/presentation/>



# Course Logistics – Paper Presentation – Bad Example

The provided image outlines the logistical and academic requirements for a course at the University of Oregon, likely **CS-453/553**. Classes are held on **Mondays and Wednesdays from 12:00 pm to 1:20 pm PST** in Gerlinger 302, with office hours scheduled for Wednesdays from 1:20 pm to 2:00 pm or by appointment. A specific Zoom link is also provided for virtual access.

The grading structure, labeled "Course Assessment and Grading Scale," distinguishes between undergraduate (**CS-453**) and graduate (**CS-553**) requirements. For undergraduate students, the grade is heavily weighted toward two quizzes at **20% each** (40% total) and a project worth **40%**, followed by a paper presentation at **15%** and participation at **5%**. Graduate students have a slightly different distribution, with quizzes weighted less at **15% each** (30% total), while the project and paper presentation are weighted higher at **45%** and **20%** respectively.

Both groups have the opportunity for a **5% Overleaf Bonus**. Beside the grading chart, a motivational note emphasizes that students will succeed as long as they maintain **active thinking** and **understand the content**.



# Course Logistics – Paper Presentation – Good Example

## 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>

## Components:

### Course Assessment and Grading Scale

Category	CS-453 (%)	CS-553 (%)
Quizz 1	20%	15%
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- As long as you are **active thinking** and **understand the content**, you will be good



# Course Logistics – Timeline

## Basics

EVENT	DATE	DESCRIPTION	COURSE MATERIAL
Lecture	01/05/2026 Monday	Overview Syllabus	Course Materials: • Slides
Assignment	01/05/2026 Monday	Project released!	[Project]
Lecture	01/07/2026 Wednesday	Logistics Basics	Course Materials: • Slides
Lecture	01/12/2026 Monday	Classification KNN/Naive Bayes	Course Materials: • Slides
Lecture	01/14/2026 Wednesday	Classification Decision Tree	Course Materials: • Slides
Martin Luther King, Jr holiday	01/19/2026 04:30 Monday	Enjoy :)	
Lecture	01/21/2026 Wednesday	Clustering K-means, Hierarchical Clustering	Course Materials: • Slides
Lecture	01/26/2026 Monday	Dimension Reduction PCA	Course Materials: • Slides
Lecture	01/28/2026 Wednesday	Linear Regression Gradient Descent	Course Materials: • Slides
Lecture	02/02/2026 Monday	Logistic Classification	Course Materials: • Slides
Lecture	02/04/2026 Wednesday	Neural Network	Course Materials: • Slides
Exam	02/09/2026 16:00 Monday	Quizz 1	Topics: • Lecture 1 - Lecture 8 • Closed Book

### Phase 1 + Quizz 1

## Advanced

Lecture	02/11/2026 Wednesday	Graph Mining	Course Materials: • Slides
	02/11/2026 16:00 Wednesday	Presentation 1	Group • Group 1: 7-7:15 pm • Group 2: 7:15-7:30 pm • Zoom
Lecture	02/16/2026 Monday	Graph Mining	Course Materials: • Slides
	02/16/2026 16:00 Monday	Presentation 2	Group • Group 3: 7-7:15 pm • Group 4: 7:15-7:30 pm • Zoom
Lecture	02/18/2026 Wednesday	Temporal Mining	Course Materials: • Slides
	02/18/2026 16:00 Wednesday	Presentation 3	Group • Group 5: 7-7:15 pm • Group 6: 7:15-7:30 pm • Zoom
Lecture	02/23/2026 Monday	Spatial Cloud Point Mining	Course Materials: • Video Record • Slides • Video
	02/23/2026 16:00 Monday	Presentation 4	Group • Group 7: 7-7:15 pm • Group 8: 7:15-7:30 pm • Zoom
Lecture	02/25/2026 Wednesday	Image Mining	Course Materials: • Video Record • Slides • Video
	02/25/2026 16:00 Wednesday	Presentation 5	Group • Group 9: 7-7:15 pm • Group 10: 7:15-7:30 pm • Zoom
Lecture	03/02/2026 Monday	Language Mining	Course Materials: • Slides
	03/02/2026 16:00 Monday	Presentation 6	Group • Group 11: 7-7:15 pm • Group 12: 7:15-7:30 pm • Zoom
Lecture	03/04/2026 Wednesday	Language Mining	Course Materials: • Slides
	03/04/2026 16:00 Wednesday	Presentation 6	Group • Group 13: 7-7:15 pm • Group 14: 7:15-7:30 pm • Zoom
Lecture	03/09/2026 Monday	Review Future	Course Materials: • Slides
	03/09/2026 16:00 Monday	Presentation 6	Group • Group 15: 7-7:15 pm • Group 16: 7:15-7:30 pm • Zoom
Exam	03/11/2026 16:00 Wednesday	Quizz 2	Topics: • Lecture 9 - Lecture 16 • Closed Book
Due	03/20/2026 23:59 Friday	Project Report Due	

### Phase 2 + Quizz 2 + Project Report



# Course Logistics – Timeline

## Basics

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Lecture	02/04/2026 Wednesday	Neural Network	Course Materials: • Slides
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Phase 1 + Quizz 1

## Advanced

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	02/18/2026 16:00 Wednesday	Presentation 3	Group • Group 5: 7-7:15 pm • Group 6: 7:15-7:30 pm • Zoom
Lecture	02/23/2026 Monday	Spatial Cloud Point Mining	Course Materials: • Video Record • Slides • Video
	02/23/2026 16:00 Monday	Presentation 4	Group • Group 7: 7-7:15 pm • Group 8: 7:15-7:30 pm • Zoom
Lecture	02/25/2026 Wednesday	Image Mining	Course Materials: • Video Record • Slides • Video
	02/25/2026 16:00 Wednesday	Presentation 5	Group • Group 9: 7-7:15 pm • Group 10: 7:15-7:30 pm • Zoom
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	03/02/2026 16:00 Monday	Presentation 6	Group • Group 11: 7-7:15 pm • Group 12: 7:15-7:30 pm • Zoom
Lecture	03/04/2026 Wednesday	Language Mining	Course Materials: • Slides
	03/04/2026 16:00 Wednesday	Presentation 6	Group • Group 13: 7-7:15 pm • Group 14: 7:15-7:30 pm • Zoom
Lecture	03/09/2026 Monday	Review Future	Course Materials: • Slides
	03/09/2026 16:00 Monday	Presentation 6	Group • Group 15: 7-7:15 pm • Group 16: 7:15-7:30 pm • Zoom
Exam	03/11/2026 16:00 Wednesday	Quzz 2	Topics: • Lecture 9 - Lecture 16 • Closed Book
Due	03/20/2026 23:59 Friday	Project Report Due	

Phase 2 + Quizz 2 + Project Report

Paper Presentation



# Course Logistics – Timeline

## Basics

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Phase 1 + Quizz 1

## Advanced

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Due	03/20/2026 23:59 Friday	Project Report Due	

Out of Town, Video Record

Phase 2 + Quizz 2 + Project Report

# Question Time!





- **Linear Algebra**
- **Calculus**
- **Statistics/Probability**



# Basics – Linear Algebra – Scalar/Vector/Matrix

## Scalar

$$\mathbf{v} = 3$$

## Vector

$$\mathbf{v} = [1 \quad 2 \quad 5]$$

$$\mathbf{u} = \begin{bmatrix} 1 \\ 2 \\ 5 \end{bmatrix}$$

**Please note that we will use  
this one by default**

## Matrix

$$\mathbf{A} = \underbrace{\begin{bmatrix} 1 & 2 & 3 \\ 0 & 5 & 1 \\ 2 & 3 & 7 \\ 3 & 9 & 8 \end{bmatrix}}_{3 \text{ columns}} \left. \vphantom{\begin{bmatrix} 1 & 2 & 3 \\ 0 & 5 & 1 \\ 2 & 3 & 7 \\ 3 & 9 & 8 \end{bmatrix}} \right\} 4 \text{ rows}$$

$$\mathbf{v} \in \mathbb{R}^{1 \times 3}$$

$$\mathbf{u} \in \mathbb{R}^{3 \times 1}$$

$$\mathbf{A} \in \mathbb{R}^{4 \times 3}$$



# Basics – Linear Algebra – Scalar/Vector/Matrix

## Scalar

$$v = 3$$

## Vector

$$v = [1 \quad 2 \quad 5]$$

## Matrix

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 0 & 5 & 1 \\ 2 & 3 & 7 \\ 3 & 9 & 8 \end{bmatrix} \left. \vphantom{\begin{bmatrix} 1 & 2 & 3 \\ 0 & 5 & 1 \\ 2 & 3 & 7 \\ 3 & 9 & 8 \end{bmatrix}} \right\} \begin{array}{l} 4 \text{ rows} \\ 3 \text{ columns} \end{array}$$

## Scalar Operation

```
a = 1
b = 2
print('a:', a)
print('b:', b)
print('a+b:', a+b)
print('a*b:', a*b)
print('a/b:', a/b)
print('a-b:', a-b)
```

✓ 0.0s

```
a: 1
b: 2
a+b: 3
a*b: 2
a/b: 0.5
a-b: -1
```



# Basics – Linear Algebra – Scalar/Vector/Matrix

## Scalar

$$v = 3$$

## Vector

$$v = [1 \quad 2 \quad 5]$$

## Matrix

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 0 & 5 & 1 \\ 2 & 3 & 7 \\ 3 & 9 & 8 \end{bmatrix} \left. \vphantom{\begin{bmatrix} 1 & 2 & 3 \\ 0 & 5 & 1 \\ 2 & 3 & 7 \\ 3 & 9 & 8 \end{bmatrix}} \right\} 4 \text{ rows}$$

3 columns

## Scalar Operation with Vector

```
✓ def scalar_vector_ops_list(s: float, v: List[float]) -> None:
    add = [s + x for x in v]      # scalar + vector (element-wise)
    sub = [x - s for x in v]     # vector - scalar
    mul = [s * x for x in v]    # scalar * vector
    div = [x / s for x in v]    # vector / scalar

    print("== Pure Python lists ==")
    print(f"scalar s = {s}")
    print(f"vector v = {v}")
    print(f"s + v = {add}")
    print(f"v - s = {sub}")
    print(f"s * v = {mul}")
    print(f"v / s = {div}")
    print()
```

```
if __name__ == "__main__":
    s = 2.0
    v_list = [1.0, -2.0, 3.5, 0.0]

    scalar_vector_ops_list(s, v_list)
    scalar_vector_ops_numpy(s)

✓ 0.0s

== Pure Python lists ==
scalar s = 2.0
vector v = [1.0, -2.0, 3.5, 0.0]
s + v = [3.0, 0.0, 5.5, 2.0]
v - s = [-1.0, -4.0, 1.5, -2.0]
s * v = [2.0, -4.0, 7.0, 0.0]
v / s = [0.5, -1.0, 1.75, 0.0]
```



# Basics – Linear Algebra – Scalar/Vector/Matrix

## Scalar

$$v = 3$$

## Vector

$$v = [1 \quad 2 \quad 5]$$

## Matrix

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 0 & 5 & 1 \\ 2 & 3 & 7 \\ 3 & 9 & 8 \end{bmatrix} \left. \vphantom{\begin{bmatrix} 1 & 2 & 3 \\ 0 & 5 & 1 \\ 2 & 3 & 7 \\ 3 & 9 & 8 \end{bmatrix}} \right\} 4 \text{ rows}$$

3 columns

## Scalar Operation with Vector

```
def scalar_vector_ops_numpy(s: float) -> None:
    import numpy as np

    v = np.array([1.0, -2.0, 3.5, 0.0], dtype=float)

    add = s + v          # broadcasting
    sub = v - s
    mul = s * v
    div = v / s

    # Useful extras
    dot = np.dot(v, v)  # dot product (v · v)
    norm = np.linalg.norm(v)

    print("== NumPy arrays ==")
    print(f"scalar s = {s}")
    print(f"vector v = {v}")
    print(f"s + v = {add}")
    print(f"v - s = {sub}")
    print(f"s * v = {mul}")
    print(f"v / s = {div}")
    print(f"v · v = {dot}")
    print(f"||v|| = {norm:.6f}")
    print()
```

```
== NumPy arrays ==
scalar s = 2.0
vector v = [ 1. -2.  3.5  0. ]
s + v = [3.  0.  5.5  2. ]
v - s = [-1. -4.  1.5 -2. ]
s * v = [ 2. -4.  7.  0. ]
v / s = [ 0.5 -1.  1.75  0. ]
v · v = 17.25
||v|| = 4.153312
```



# Basics – Linear Algebra – Scalar/Vector/Matrix

## Scalar

$$v = 3$$

## Vector

$$v = [1 \quad 2 \quad 5]$$

## Matrix

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 0 & 5 & 1 \\ 2 & 3 & 7 \\ 3 & 9 & 8 \end{bmatrix} \left. \vphantom{\begin{bmatrix} 1 & 2 & 3 \\ 0 & 5 & 1 \\ 2 & 3 & 7 \\ 3 & 9 & 8 \end{bmatrix}} \right\} 4 \text{ rows}$$

3 columns

## Scalar Operation with Matrix

```
# -----  
# 1) Pure Python (list of lists)  
# -----  
def scalar_matrix_ops_list(s: float, M: List[List[float]]) -> None:  
    add = [[s + x for x in row] for row in M] # scalar + matrix  
    sub = [[x - s for x in row] for row in M] # matrix - scalar  
    mul = [[s * x for x in row] for row in M] # scalar * matrix  
    div = [[x / s for x in row] for row in M] # matrix / scalar
```

```
scalar s = 2.0  
matrix M =  
[1.0, -2.0, 3.0]  
[4.5, 0.0, -1.5]  
s + M =  
[3.0, 0.0, 5.0]  
[6.5, 2.0, 0.5]  
M - s =  
[-1.0, -4.0, 1.0]  
[2.5, -2.0, -3.5]  
s * M =  
[2.0, -4.0, 6.0]  
[9.0, 0.0, -3.0]  
M / s =  
[0.5, -1.0, 1.5]  
[2.25, 0.0, -0.75]
```



# Basics – Linear Algebra – Scalar/Vector/Matrix

## Scalar

$$v = 3$$

## Vector

$$v = [1 \quad 2 \quad 5]$$

## Matrix

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 0 & 5 & 1 \\ 2 & 3 & 7 \\ 3 & 9 & 8 \end{bmatrix} \left. \vphantom{\begin{bmatrix} 1 & 2 & 3 \\ 0 & 5 & 1 \\ 2 & 3 & 7 \\ 3 & 9 & 8 \end{bmatrix}} \right\} \begin{array}{l} 4 \text{ rows} \\ 3 \text{ columns} \end{array}$$

## Scalar Operation with Matrix

```
# -----  
# 2) NumPy (array-based)  
# -----  
def scalar_matrix_ops_numpy(s: float) -> None:  
    import numpy as np  
  
    M = np.array([[1.0, -2.0, 3.0],  
                 [4.5, 0.0, -1.5]], dtype=float)  
  
    add = s + M          # broadcasting  
    sub = M - s  
    mul = s * M  
    div = M / s
```

```
== NumPy arrays ==  
scalar s = 2.0  
matrix M =  
[[ 1. -2.  3.]  
 [ 4.5  0. -1.5]]  
s + M =  
[[3.  0.  5.]  
 [6.5  2.  0.5]]  
M - s =  
[[-1. -4.  1.]  
 [ 2.5 -2. -3.5]]  
s * M =  
[[ 2. -4.  6.]  
 [ 9.  0. -3.]]  
M / s =  
[[ 0.5 -1.  1.5 ]  
 [ 2.25 0. -0.75]]
```



## Matrix Multiplication

$$\mathbf{A} = \begin{bmatrix} 1 & 2 & 3 \\ 0 & 5 & 1 \\ 2 & 3 & 7 \\ 3 & 9 & 8 \end{bmatrix} \times \mathbf{B} = \begin{bmatrix} 1 & 2 \\ 2 & 3 \\ 5 & 7 \end{bmatrix} \longrightarrow \mathbf{C} = [ \quad ] \quad ?$$

$4 \times 3$                        $3 \times 2$

**Dimensions much match!**

**What is the dimension of C?  $(4 \times 3)(3 \times 2) \rightarrow 4 \times 2$**



# Basics – Linear Algebra – Scalar/Vector/Matrix

## Matrix Multiplication

$$\begin{matrix} \mathbf{A} = \begin{bmatrix} \underline{1} & \underline{2} & \underline{3} \\ 0 & 5 & 1 \\ 2 & 3 & 7 \\ 3 & 9 & 8 \end{bmatrix} & \times & \mathbf{B} = \begin{bmatrix} \underline{1} & 2 \\ \underline{2} & 3 \\ \underline{5} & 7 \end{bmatrix} & \longrightarrow & \mathbf{C} = \begin{bmatrix} 1 \times 1 + 2 \times 2 + 3 \times 5 \\ \phantom{1 \times 1 + 2 \times 2 + 3 \times 5} \\ \phantom{1 \times 1 + 2 \times 2 + 3 \times 5} \\ \phantom{1 \times 1 + 2 \times 2 + 3 \times 5} \end{bmatrix} \\ 4 \times 3 & & 3 \times 2 & & \end{matrix}$$

$$\begin{matrix} \mathbf{A} = \begin{bmatrix} \underline{1} & \underline{2} & \underline{3} \\ 0 & 5 & 1 \\ 2 & 3 & 7 \\ 3 & 9 & 8 \end{bmatrix} & \times & \mathbf{B} = \begin{bmatrix} 1 & \underline{2} \\ 2 & \underline{3} \\ 5 & \underline{7} \end{bmatrix} & \longrightarrow & \mathbf{C} = \begin{bmatrix} 1 \times 2 + 2 \times 3 + 3 \times 7 \\ 20 & \underline{29} \\ \phantom{20} & \phantom{29} \\ \phantom{20} & \phantom{29} \end{bmatrix} \\ 4 \times 3 & & 3 \times 2 & & \end{matrix}$$



# Basics – Linear Algebra – Scalar/Vector/Matrix

## Matrix Multiplication

$$\mathbf{A} = \begin{bmatrix} 1 & 2 & 3 \\ 0 & 5 & 1 \\ 2 & 3 & 7 \\ 3 & 9 & 8 \end{bmatrix} \times \mathbf{B} = \begin{bmatrix} 1 & 2 \\ 2 & 3 \\ 5 & 7 \end{bmatrix} \longrightarrow \mathbf{C} = \begin{bmatrix} 20 & 29 \\ 15 & \end{bmatrix}$$

$4 \times 3 \qquad 3 \times 2$

$0 \times 1 + 5 \times 2 + 1 \times 5$

*(Note: In the original image, a red horizontal line is drawn under the second row of matrix A, and a red vertical line is drawn under the first column of matrix B. An arrow points from the calculation above to the element 15 in the second row, first column of matrix C.)*

$$\mathbf{A} = \begin{bmatrix} 1 & 2 & 3 \\ 0 & 5 & 1 \\ 2 & 3 & 7 \\ 3 & 9 & 8 \end{bmatrix} \times \mathbf{B} = \begin{bmatrix} 1 & 2 \\ 2 & 3 \\ 5 & 7 \end{bmatrix} \longrightarrow \mathbf{C} = \begin{bmatrix} 20 & 29 \\ 15 & 22 \end{bmatrix}$$

$4 \times 3 \qquad 3 \times 2$

$0 \times 2 + 5 \times 3 + 1 \times 7$

*(Note: In the original image, a red horizontal line is drawn under the second row of matrix A, and a red vertical line is drawn under the second column of matrix B. An arrow points from the calculation above to the element 22 in the second row, second column of matrix C.)*



# Basics – Linear Algebra – Scalar/Vector/Matrix

## Matrix Multiplication

$$\mathbf{A} = \begin{bmatrix} 1 & 2 & 3 \\ 0 & 5 & 1 \\ 2 & 3 & 7 \\ 3 & 9 & 8 \end{bmatrix} \times \mathbf{B} = \begin{bmatrix} 1 & 2 \\ 2 & 3 \\ 5 & 7 \end{bmatrix} \longrightarrow \mathbf{C} = \begin{bmatrix} 20 & 29 \\ 15 & 22 \\ 43 & \end{bmatrix}$$

$4 \times 3 \qquad 3 \times 2$

$2 \times 1 + 3 \times 2 + 7 \times 5$

*Note: In the original image, the second row of matrix A and the first column of matrix B are highlighted in red. An arrow points from the calculation  $2 \times 1 + 3 \times 2 + 7 \times 5$  to the value 43 in the resulting matrix C.*

$$\mathbf{A} = \begin{bmatrix} 1 & 2 & 3 \\ 0 & 5 & 1 \\ 2 & 3 & 7 \\ 3 & 9 & 8 \end{bmatrix} \times \mathbf{B} = \begin{bmatrix} 1 & 2 \\ 2 & 3 \\ 5 & 7 \end{bmatrix} \longrightarrow \mathbf{C} = \begin{bmatrix} 20 & 29 \\ 15 & 22 \\ 43 & 62 \end{bmatrix}$$

$4 \times 3 \qquad 3 \times 2$

$2 \times 2 + 3 \times 3 + 7 \times 7$

*Note: In the original image, the third row of matrix A and the second column of matrix B are highlighted in red. An arrow points from the calculation  $2 \times 2 + 3 \times 3 + 7 \times 7$  to the value 62 in the resulting matrix C.*



# Basics – Linear Algebra – Scalar/Vector/Matrix

## Matrix Multiplication

$$\mathbf{A} = \begin{bmatrix} 1 & 2 & 3 \\ 0 & 5 & 1 \\ 2 & 3 & 7 \\ 3 & 9 & 8 \end{bmatrix} \times \mathbf{B} = \begin{bmatrix} 1 & 2 \\ 2 & 3 \\ 5 & 7 \end{bmatrix} \longrightarrow \mathbf{C} = \begin{bmatrix} 20 & 29 \\ 15 & 22 \\ 43 & 62 \\ 61 & \end{bmatrix}$$

$3 \times 1 + 2 \times 9 + 5 \times 8$

$4 \times 3$                        $3 \times 2$

$$\mathbf{A} = \begin{bmatrix} 1 & 2 & 3 \\ 0 & 5 & 1 \\ 2 & 3 & 7 \\ 3 & 9 & 8 \end{bmatrix} \times \mathbf{B} = \begin{bmatrix} 1 & 2 \\ 2 & 3 \\ 5 & 7 \end{bmatrix} \longrightarrow \mathbf{C} = \begin{bmatrix} 20 & 29 \\ 15 & 22 \\ 43 & 62 \\ 61 & 89 \end{bmatrix}$$

$3 \times 2 + 3 \times 9 + 7 \times 8$

$4 \times 3$                        $3 \times 2$



# Basics – Linear Algebra – Scalar/Vector/Matrix

```
def matmul_list(A: List[List[float]], B: List[List[float]]) -> List[List[float]]:
    """
    Compute C = A @ B using pure Python.
    A: m x n
    B: n x p
    C: m x p
    """
    m, n = len(A), len(A[0])
    n2, p = len(B), len(B[0])
    assert n == n2, "Inner dimensions must match"

    C = [[0.0 for _ in range(p)] for _ in range(m)]

    for i in range(m):
        for j in range(p):
            for k in range(n):
                C[i][j] += A[i][k] * B[k][j]
    return C
```

```
def demo_numpy():
    import numpy as np

    A = np.array([
        [1, 2, 3],
        [4, 5, 6]
    ], dtype=float)

    B = np.array([
        [7, 8],
        [9, 10],
        [11, 12]
    ], dtype=float)

    C1 = A @ B          # preferred operator
    C2 = np.matmul(A, B)
    C3 = np.dot(A, B)  # works for 2D matrices
```



# Basics – Physical Meaning of Matrix Multiplication in ML



**House 1**  
**Size – 1000 sqft**  
**2 bed, 2 bath**  
**Location: 3**



**House 2**  
**Size – 2000 sqft**  
**3 bed, 2 bath**  
**Location: 2**



**House 3**  
**Size – 1500 sqft**  
**2 bed, 3 bath**  
**Location: 4**

**HOUSE PRICE PREDICTION**  
USING MACHINE LEARNING TECHNIQUES





# Basics – Physical Meaning of Matrix Multiplication in ML



**House 1**  
Size – 1000 sqft  
2 bed, 2 bath  
Location: 3

**Contribution Coefficient** 0.002, 1, 0.5, 1.2

$$1000*0.002 + 2*1 + 2*0.5 + 3*1.2 = 8.6$$



**House 2**  
Size – 2000 sqft  
3 bed, 2 bath  
Location: 2

$$2000*0.002 + 3*1 + 2*0.5 + 2*1.2 = 10.4$$



**House 3**  
Size – 1500 sqft  
2 bed, 3 bath  
Location: 4

$$1500*0.002 + 2*1 + 3*0.5 + 4*1.2 = 11.3$$



# Basics – Physical Meaning of Matrix Multiplication in ML



**House 1**  
**Size – 1000 sqft**  
**2 bed, 2 bath**  
**Location: 3**

**Contribution Coefficient** 0.002, 1, 0.5, 1.2

$$\mathbf{X} = \begin{bmatrix} 1k & 2k & 1.5k \\ 2 & 3 & 2 \\ 2 & 2 & 3 \\ 3 & 2 & 4 \end{bmatrix}$$



**House 2**  
**Size – 2000 sqft**  
**3 bed, 2 bath**  
**Location: 2**

$$\mathbf{A} = \begin{bmatrix} 0.002 \\ 1 \\ 0.5 \\ 1.2 \end{bmatrix}$$



**House 3**  
**Size – 1500 sqft**  
**2 bed, 3 bath**  
**Location: 4**

$$\mathbf{Y} = \mathbf{A}^T \mathbf{X}$$



# Basics – Linear Algebra

## 1 Basics

$$\begin{aligned}(AB)^{-1} &= B^{-1}A^{-1} & (1) \\(ABC\dots)^{-1} &= \dots C^{-1}B^{-1}A^{-1} & (2) \\(A^T)^{-1} &= (A^{-1})^T & (3) \\(A+B)^T &= A^T+B^T & (4) \\(AB)^T &= B^T A^T & (5) \\(ABC\dots)^T &= \dots C^T B^T A^T & (6) \\(A^H)^{-1} &= (A^{-1})^H & (7) \\(A+B)^H &= A^H+B^H & (8) \\(AB)^H &= B^H A^H & (9) \\(ABC\dots)^H &= \dots C^H B^H A^H & (10)\end{aligned}$$



## Matrix Codebook

<https://www.math.uwaterloo.ca/~hwolkowi/matrixcookbook.pdf>

## The Matrix Cookbook

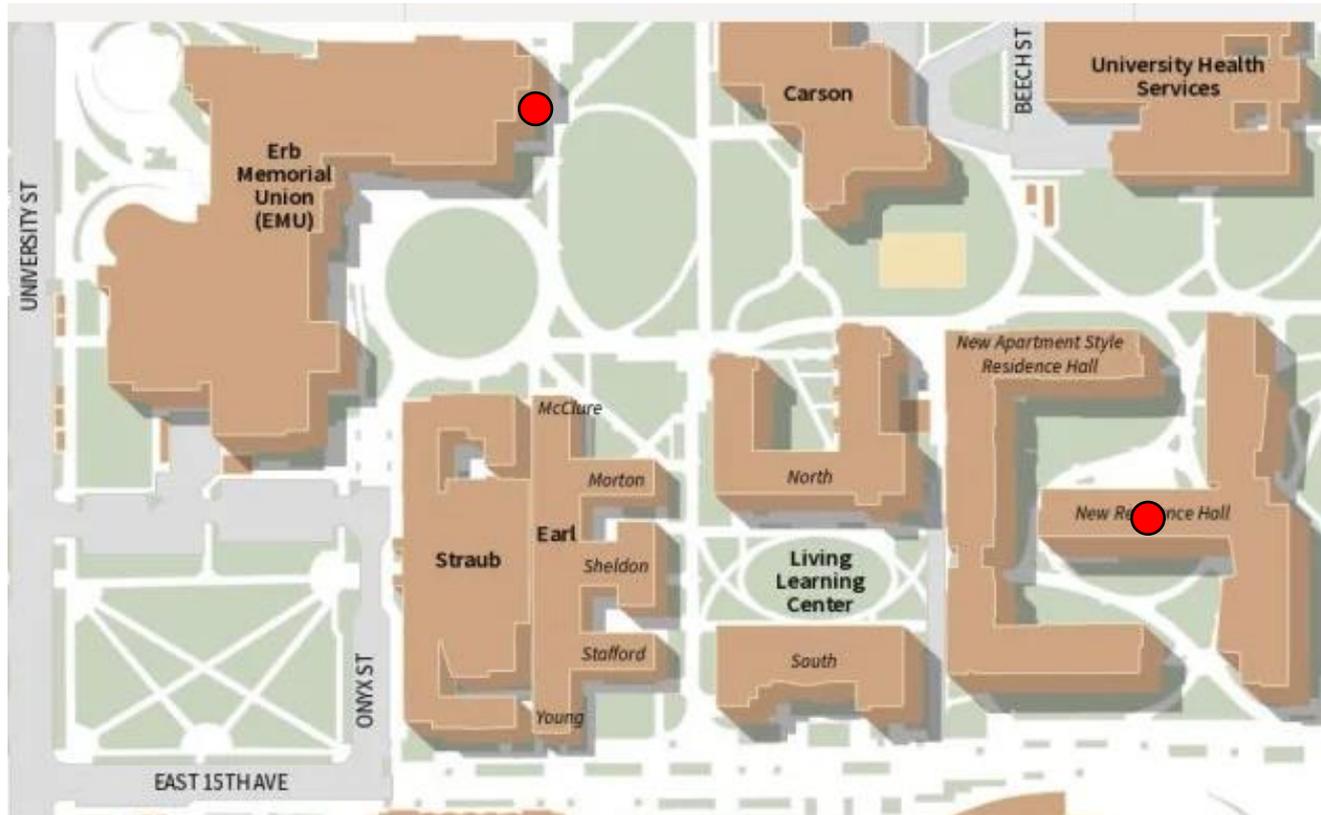
[ <http://matrixcookbook.com> ]

Kaare Brandt Petersen  
Michael Syskind Pedersen

VERSION: NOVEMBER 15, 2012

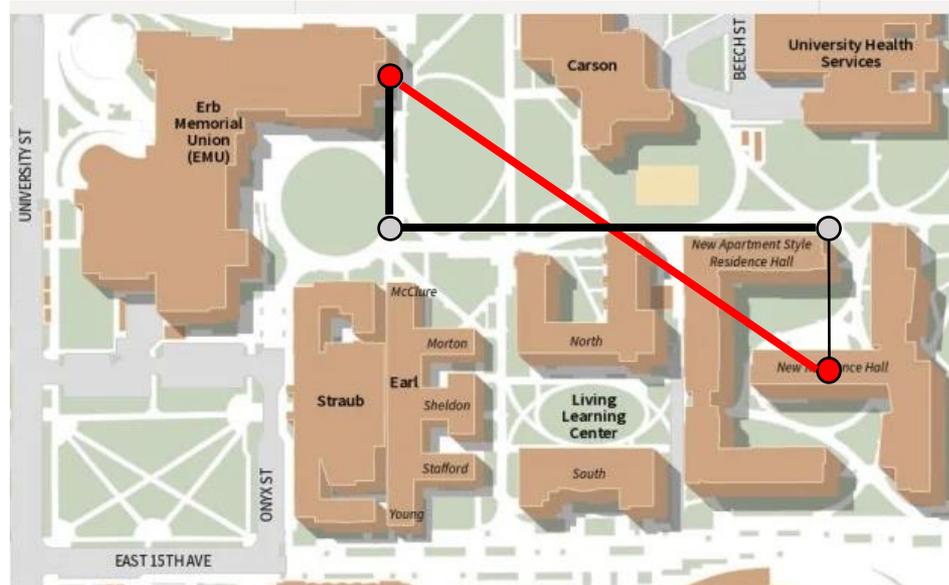


# Basics – Linear Algebra - Distance





# Basics – Linear Algebra - Distance



$$D(a, b) = \left[ (a_x - b_x)^2 + (a_y - b_y)^2 \right]^{-0.5}$$

$$D(a, b) = |a_x - b_x| + |a_y - b_y|$$



# Basics – Linear Algebra - Distance

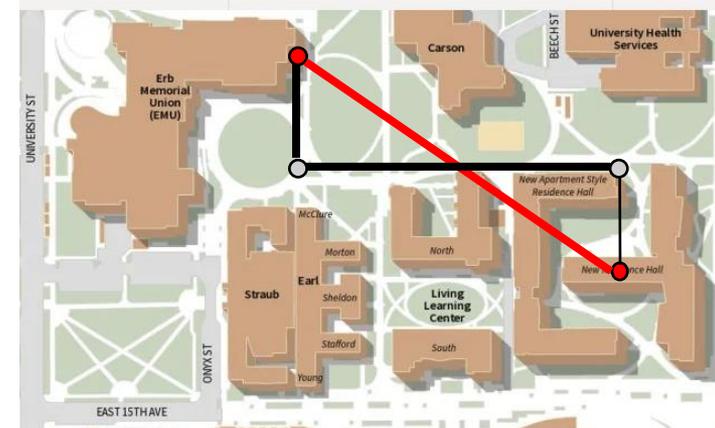
- $\|\mathbf{u} - \mathbf{v}\|^p$
- Function from a vector space to a single positive real value:  $f: \mathbb{R}^d \rightarrow \mathbb{R}$
- Distance between  $\mathbf{u}$  and  $\mathbf{v}$

$$\|\mathbf{u} - \mathbf{v}\|^p = \left( \sum_{i=1}^d |\mathbf{u}_i - \mathbf{v}_i|^p \right)^{\frac{1}{p}}$$

- Examples:

(1) Manhattan distance ( $L_1$ ):  $\|\mathbf{u} - \mathbf{v}\|^1 = \left( \sum_{i=1}^d |\mathbf{u}_i - \mathbf{v}_i| \right)$

(2) Euclidean distance ( $L_2$ ):  $\|\mathbf{v}\|^2 = \left( \sum_{i=1}^d |\mathbf{u}_i - \mathbf{v}_i|^2 \right)^{\frac{1}{2}}$





- **Linear Algebra**
- **Calculus**
- **Statistics/Probability**

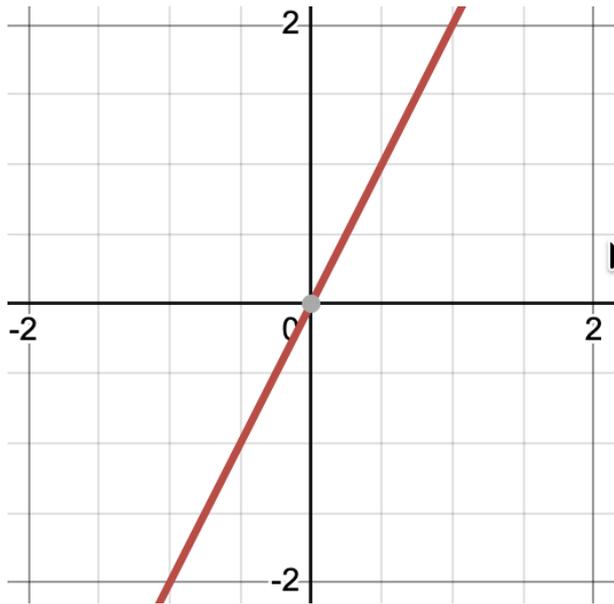


# Basics – Derivative and Gradient

$$y = 2x, \quad \frac{dy}{dx} = 2$$

## Scalar Input vs Scalar Output

How much change does the single unit change of  $x$  would cause on  $y$ ?



```
import torch

# Define input tensor with gradient tracking enabled
x = torch.tensor(3.0, requires_grad=True)

# Define function y = 2x
y = 2 * x

# Compute derivative dy/dx
y.backward()

# Access gradient
print("x =", x.item())
print("y =", y.item())
print("dy/dx =", x.grad.item())
```

✓ 0.0s

```
x = 3.0
y = 6.0
dy/dx = 2.0
```



# Basics – Derivative and Gradient

$$y = 2x_1 + 3x_2, \quad \frac{\partial y}{\partial x_1} = 2, \frac{\partial y}{\partial x_2} = 3$$

$$y = \mathbf{a}^T \mathbf{x}$$

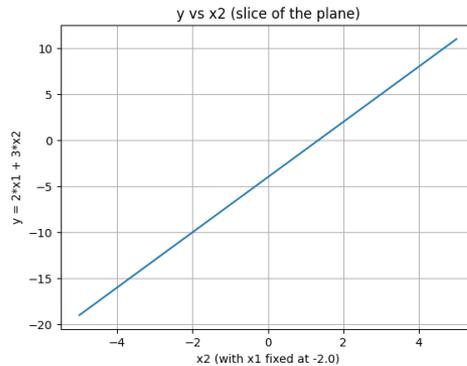
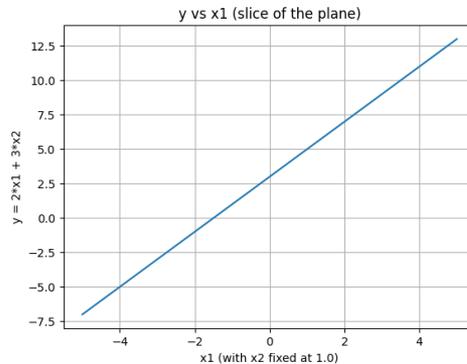
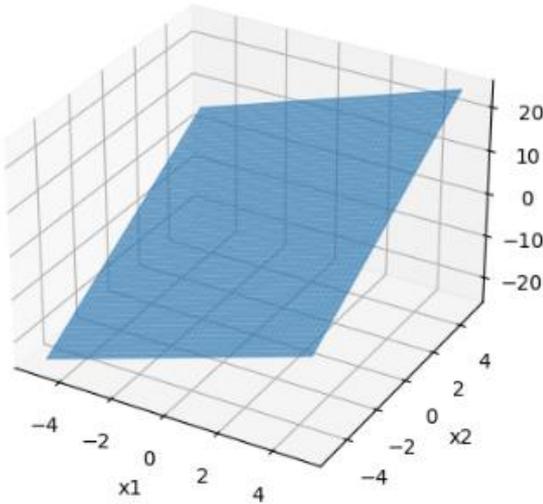
$$\mathbf{a} = \begin{bmatrix} 2 \\ 3 \end{bmatrix} \quad \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$\nabla_x y = \mathbf{a}$$

Scalar Input  
vs  
Vector Output

How much change does the single unit change of x would cause on y?

Plane:  $y = 2x_1 + 3x_2$



```
import torch

# x[0] = x1, x[1] = x2
x = torch.tensor([1.5, -0.5], requires_grad=True)

y = 2 * x[0] + 3 * x[1]
y.backward()

print("x1 =", x[0].item(), "x2 =", x[1].item())
print("y =", y.item())
print("∂y/∂x1 =", x.grad[0].item())
print("∂y/∂x2 =", x.grad[1].item())
```

✓ 0.0s

```
x1 = 1.5 x2 = -0.5
y = 1.5
∂y/∂x1 = 2.0
∂y/∂x2 = 3.0
```



# Basics – Derivative and Gradient

$$y_1 = 2x_1 + 3x_2, \quad \frac{\partial y_1}{\partial x_1} = 2, \frac{\partial y_1}{\partial x_2} = 3 \quad \mathbf{a} = \begin{bmatrix} 2 & 4 \\ 3 & 3 \end{bmatrix} \quad \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$y_2 = 4x_1 + 5x_2, \quad \frac{\partial y_2}{\partial x_1} = 4, \frac{\partial y_2}{\partial x_2} = 5$$
$$\frac{\partial \mathbf{y}}{\partial \mathbf{x}} = \mathbf{a}$$
$$\mathbf{y} = \mathbf{a}^T \mathbf{x}$$

**Vector Input**  
vs  
**Vector Output**

```
import torch

def f(x):
    """
    x: tensor of shape (2,) -> [x1, x2]
    returns: tensor of shape (2,) -> [y1, y2]
    """
    y1 = 2 * x[0] + 3 * x[1]
    y2 = 4 * x[0] + 5 * x[1]
    return torch.stack([y1, y2])

# Input
x = torch.tensor([1.0, 2.0], requires_grad=True)

# Compute Jacobian
J = torch.autograd.functional.jacobian(f, x)

print("Jacobian dy/dx:")
print(J)

✓ 0.0s

Jacobian dy/dx:
tensor([[2., 3.],
        [4., 5.]])
```

**How much change does the single unit change of x would cause on y?**



# Basics – Example

```
import numpy as np
import matplotlib.pyplot as plt
import torch
import torch.nn as nn
import torch.optim as optim
from sklearn.feature_extraction.text import CountVectorizer

# Dataset with overlapping vocabulary
ml_abstracts = [
    "We use a learning algorithm to model inflation based on training data.",
    "Neural network models predict inflation trends from economic data.",
    "Machine learning improves inflation forecasting with training-based models.",
    "This study applies a predictive learning algorithm to inflation modeling.",
    "Our model learns to predict inflation using neural networks and structured data.",
    "We evaluate algorithmic models that learn inflation patterns from data.",
    "Learning-based inflation models are trained on macroeconomic time series.",
    "The prediction model uses training data and machine learning techniques.",
    "Inflation is modeled using data-driven algorithms with predictive learning.",
    "Our learning system models inflation trends using economic indicators."
]

non_ml_abstracts = [
    "We analyze inflation using an economic theory-driven model and historical data.",
    "Inflation modeling relies on classical economic indicators and structured data.",
    "This study examines inflation dynamics using theoretical models and analysis.",
    "Inflation is analyzed through traditional models and economic frameworks.",
    "Economic data supports a theory-based approach to modeling inflation.",
    "The model explains inflation trends through historical economic data.",
    "A theory-driven framework models inflation based on macroeconomic variables.",
    "We use economic assumptions to analyze inflation using structured models.",
    "Historical data is used to model inflation without predictive algorithms.",
    "Inflation analysis is grounded in economic theory and empirical modeling."
]

texts = ml_abstracts + non_ml_abstracts
labels = [1] * len(ml_abstracts) + [0] * len(non_ml_abstracts)
```



# Basics – Example

```
vectorizer = CountVectorizer(stop_words='english', binary=True)
X = vectorizer.fit_transform(texts)
feature_names = vectorizer.get_feature_names_out()
print(f"Number of keyword features: {len(feature_names)}")
print("Sample keywords:", feature_names[:10])
```

[130] ✓ 0.0s

```
... Number of keyword features: 61
Sample keywords: ['algorithm' 'algorithmic' 'algorithms' 'analysis' 'analyze' 'analy
'applies' 'approach' 'assumptions' 'based']
```



```
import torch
import torch.nn as nn

num_features = X.shape[1]          # vocabulary size (e.g. 80)
num_classes = len(set(labels))     # e.g. 2 for binary classification

model = nn.Linear(num_features, num_classes)
print(model)
# Linear(in_features=80, out_features=2, bias=True)
```

[122] ✓ 0.0s

```
... Linear(in_features=61, out_features=2, bias=True)
```



# Basics – Example

```
from torch.utils.data import TensorDataset, DataLoader
import torch.optim as optim

# Convert feature matrix and labels to tensors
X_tensor = torch.tensor(X.toarray(), dtype=torch.float32)
y_tensor = torch.tensor(labels, dtype=torch.long)

# Group based on Y and for each group get 5 to get total 10
unique_labels = torch.unique(y_tensor)
train_indices = []
test_indices = []
for lbl in unique_labels:
    ... lbl_indices = (y_tensor == lbl).nonzero(as_tuple=True)[0]
    ... train_indices.extend(lbl_indices[:5].tolist())
    ... test_indices.extend(lbl_indices[5:].tolist())

X_train, X_test = X_tensor[train_indices], X_tensor[test_indices]
y_train, y_test = y_tensor[train_indices], y_tensor[test_indices]

# Define optimizer and loss function
optimizer = optim.SGD(model.parameters(), lr=0.01)
criterion = nn.CrossEntropyLoss()

# Training loop
epochs = 120
for epoch in range(epochs):
    ... model.train()
    ... optimizer.zero_grad()
    ... outputs = model(X_train)
    ... loss = criterion(outputs, y_train)
    ... loss.backward()
    ... optimizer.step()
```

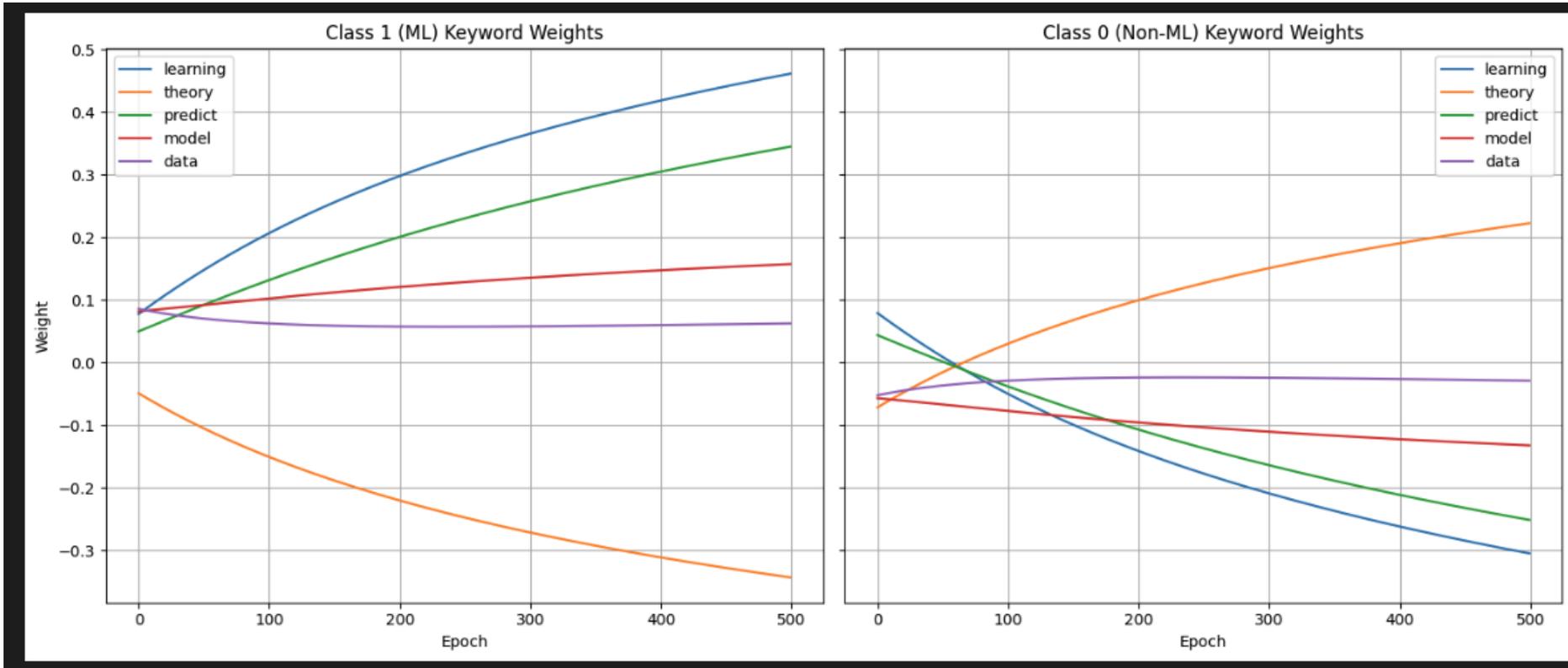
```
model.eval()
with torch.no_grad():
    logits = model(X_test)
    predictions = torch.argmax(logits, dim=1)
accuracy = (predictions == y_test).float().mean().item()
print(f"Test accuracy: {accuracy:.2f}")
```

✓ 0.0s

Test accuracy: 0.80



# Basics – Example





- **Linear Algebra**
- **Calculus**
- **Statistics/Probability**



- **Probability** → *from model to data*



A fair coin  
 $P(\text{Head}) = 0.5$

**What is the probability of observing 7 heads in 10 tosses?**

- **Statistics** → *from data to model (machine learning as well)*

**Data:** 10 tosses → 7 heads



**Question:** Is the coin fair? What is  $p$ ?



# Basics – Probability

- **Sample Space:** The set of all possible outcomes
- **Event:** A subset of the sample space
- **Probability:** under certain situation, how much likelihood of event



Space  $\{1, 2, 3, 4, 5, 6\}$

“Rolling an even number” =  $\{2, 4, 6\}$



# Basics – Probability

Event	Details	Formula (from English to mathematical operations)
A	Probability of A, $P(A)$	<b>P(A) is at or between zero and one: <math>0 \leq P(A) \leq 1</math></b>
not A, $A^c$	$A^c$ is the complement of A	<b>Probability of not A = <math>P(A^c) = 1 - P(A)</math></b>
A and B	A and B are <b>independent</b> events	<b><math>P(A \text{ and } B) = P(A) \cdot P(B)</math></b>
	A and B are <b>dependent</b> events	<b><math>P(A \text{ and } B) = P(A) \cdot P(B   A) = P(B) \cdot P(A   B)</math> as 2 forms</b>
	A and B are <b>mutually exclusive</b> events	<b><math>P(A \text{ and } B) = 0</math></b>
A or B	A and B are <b>independent</b> events	<b><math>P(A \text{ or } B) = P(A) + P(B) - P(A) \cdot P(B)</math> conveniently expands to <math>= 1 - [1 - P(A)] \cdot [1 - P(B)]</math> or is obtained from De Morgan's Rule</b>
	A and B are <b>dependent</b> events	<b><math>P(A \text{ or } B) = P(A) + P(B) - P(A) \cdot P(B   A)</math> as 1 of 2 forms</b>
	A and B are <b>mutually exclusive</b> events	<b><math>P(A \text{ or } B) = P(A) + P(B)</math></b>
A given B, $A   B$	<u>Conditional</u> : outcome of A given B has occurred	<b><math>P(A \text{ given } B) = P(A   B) = P(A) \cdot P(B   A) / P(B)</math> [Bayes' Thm] To make this formula, solve the 2 forms in "A and B" for <math>P(A   B)</math></b>

<https://www.nasa.gov/wp-content/uploads/2023/11/210624-probability-formulas.pdf>



# Basics – Probability



$$P(B=W) = 0.3$$

$$P(ND|W) = 0.6$$



$$P(B=G) = 0.5$$



$$P(ND|G) = 0.2$$



$$P(B=S) = 0.2$$

$$P(ND|S) = 0.05$$



# Basics – Probability

$$P(B=W) = 0.3$$

$$P(ND|W) = 0.4$$

$$P(B=G) = 0.5$$

$$P(ND|G) = 0.8$$

$$P(B=S) = 0.2$$

$$P(ND|S) = 0.95$$



**After one earthquake, the building is not collapsed**

$$P(G|ND) = \frac{0.8 * 0.5}{0.71} = 0.56 \quad P(S|ND) = \frac{0.95 * 0.2}{0.71} = 0.27$$

$$P(T|ND) = \frac{P(ND|T)P(T)}{P(ND)}$$

$$P(W|ND) = \frac{P(ND|W)P(W)}{P(ND)} = \frac{0.4 * 0.3}{0.71} = 0.17$$

$$P(ND) = \sum_T P(ND|T)P(T)$$

$$\begin{aligned} P(ND) &= \sum_T P(ND|T)P(T) \\ &= 0.3 * 0.4 + 0.5 * 0.8 + 0.2 * 0.95 = 0.71 \end{aligned}$$



# Basics – Probability

$$P(B=W) = 0.17$$

$$P(ND|W) = 0.4$$

$$P(B=G) = 0.56$$

$$P(ND|G) = 0.8$$

$$P(B=S) = 0.27$$

$$P(ND|S) = 0.95$$



**After two earthquake, the building is not collapsed**

$$P(G|ND) = \frac{0.8 * 0.17}{0.77} = 0.177 \quad P(S|ND) = \frac{0.95 * 0.27}{0.77} = 0.33$$

$$P(T|ND) = \frac{P(ND|T)P(T)}{P(ND)}$$

$$P(W|ND) = \frac{P(ND|W)P(W)}{P(ND)} = \frac{0.4 * 0.17}{0.77} = 0.09$$

$$P(ND) = \sum_T P(ND|T)P(T)$$

$$\begin{aligned} P(ND) &= \sum_T P(ND|T)P(T) \\ &= 0.17 * 0.4 + 0.56 * 0.8 + 0.27 * 0.95 = 0.77 \end{aligned}$$



# Basics – Probability



$$P(B=W) = 0.3$$



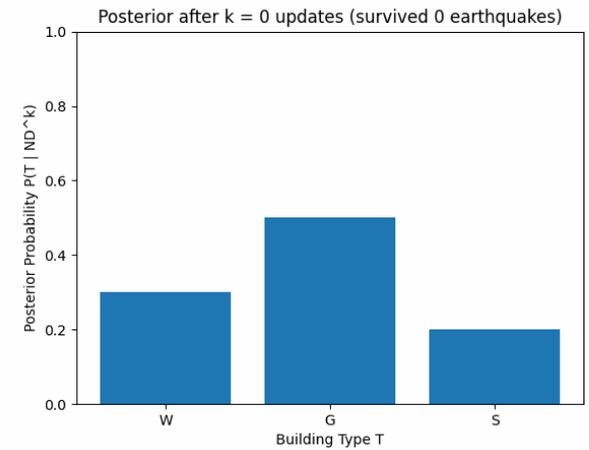
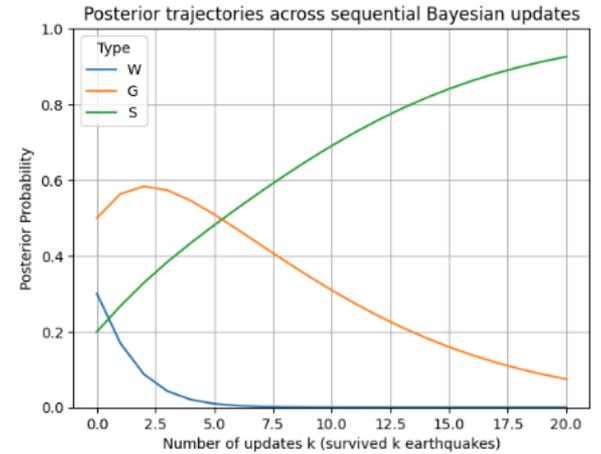
$$P(B=G) = 0.5$$



$$P(B=S) = 0.2$$



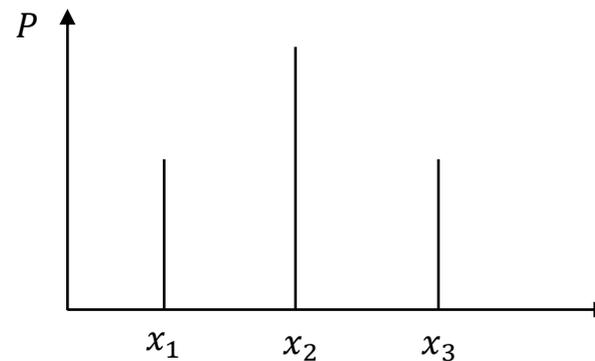
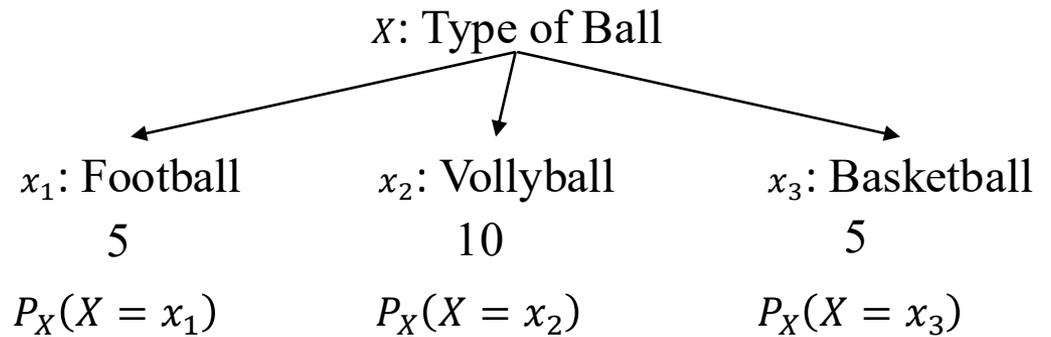
....





# Basics – Probability

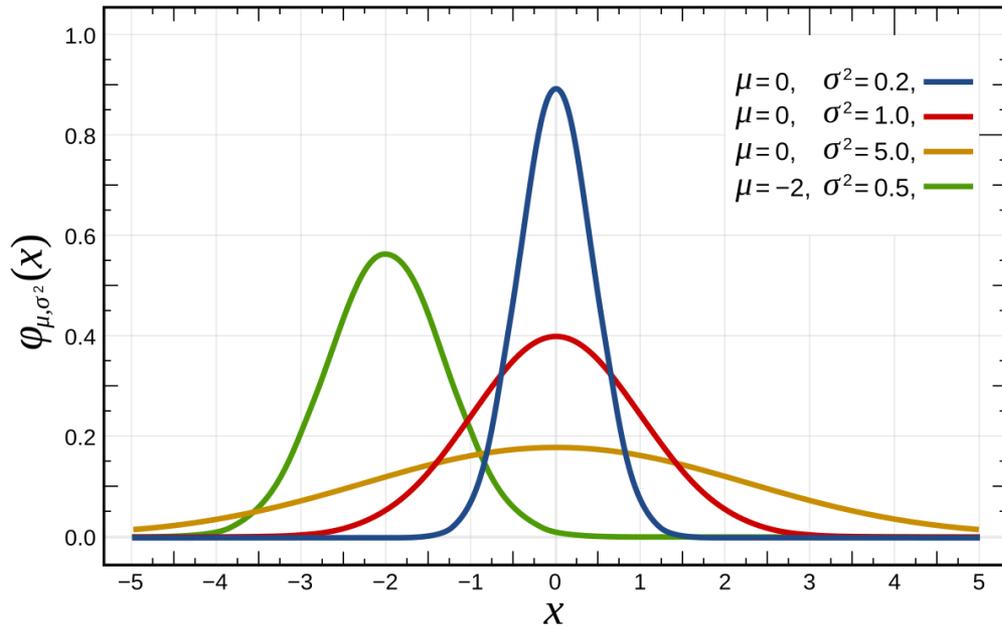
Probability of the random variable  $X$  taking the value  $x$   $P_X(X = x)$



$P_X$   
 $P(X)$   
Probability  
Distribution



# Basics – Probability Density Function – Distribution



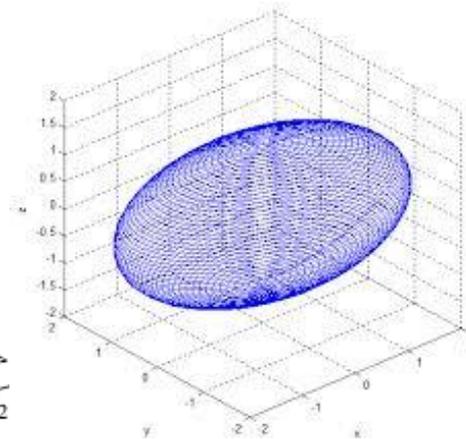
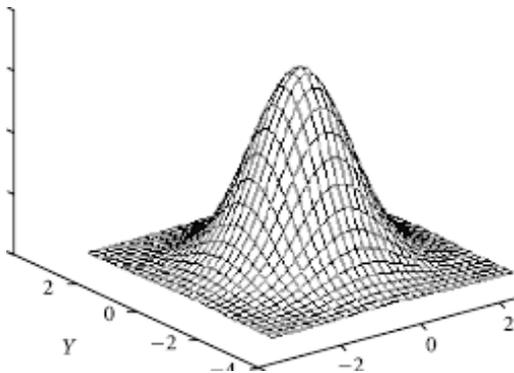
**1-D Probability Density Function**

**2-D Probability Density Function**

**3-D Probability Density Function**



**N-D Probability Density Function**



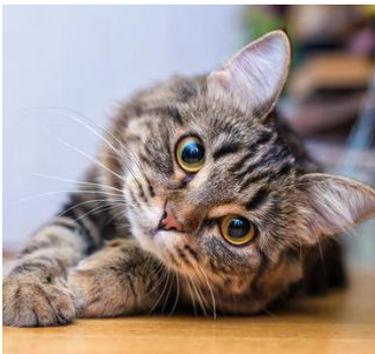


# Basics – High Dimensional Random Variable

## Dog



## Cat





# Basics – High Dimensional Random Variable

## Dog – P(Dog)

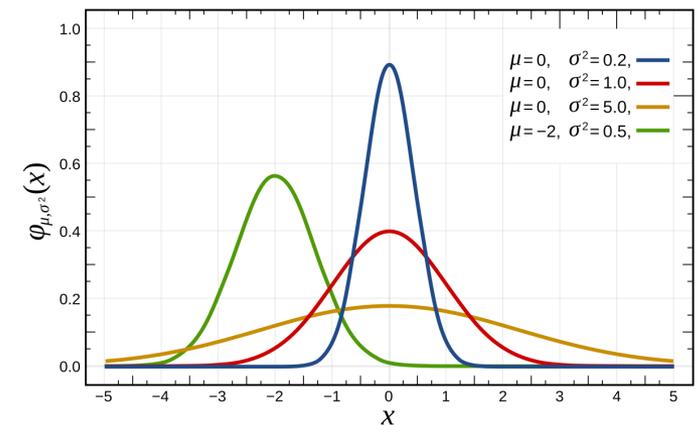


## Cat – P(Cat)



1. There is no concrete image/shape of the dog, everyone can come up with one of your own choice
2. But somehow dog and cat image distributions are different

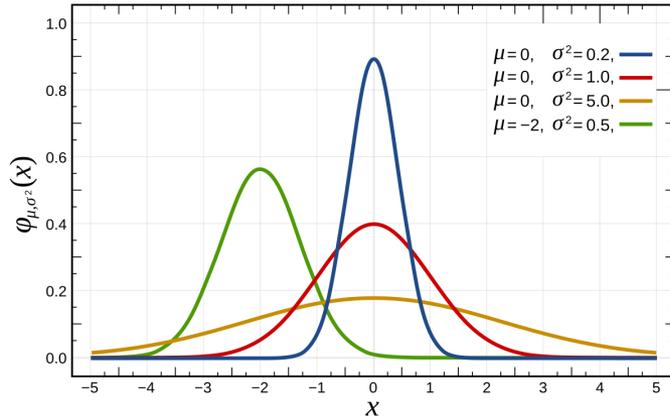
**When you draw an image, you are actually sampling from a probability distribution!**





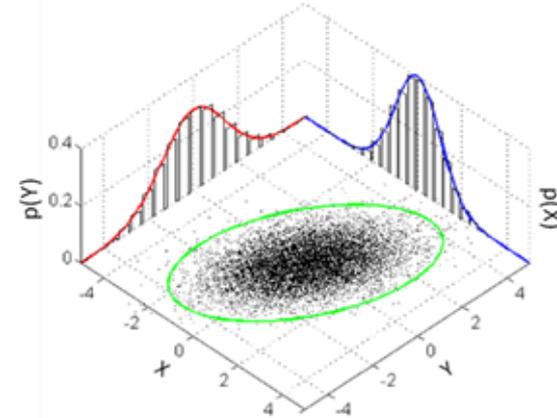
# Basics – Data Distribution

## 1D Gaussian Distribution



$\mathbb{R}$

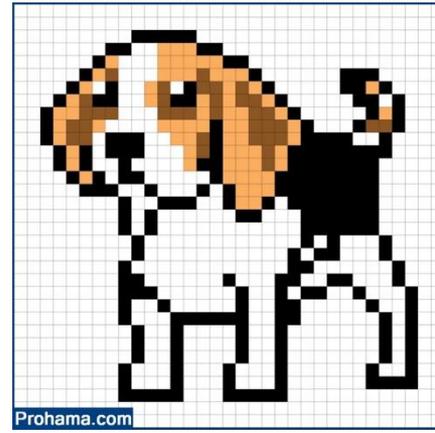
## 2D Gaussian Distribution



$\mathbb{R}^2$



$\mathbb{R}^{256 \times 256}$



$\mathbb{R}^{256 \times 256}$



# Basics – High Dimensional Random Variable

Probability of the random variable  $X$  taking the value  $x$   $P_X(X = x)$



$X \in \mathbb{R}^{256 \times 256} : \text{Image}$

$x_1: \text{Image1}$

5

$P_X(X = x_1)$



$x_2: \text{Image2}$

10

$P_X(X = x_2)$



$x_3: \text{Image3}$

5

$P_X(X = x_3)$



$P_X$

$P(X)$

Probability  
Density  
Distribution





# Basics – High Dimensional Random Variable

Probability of the random variable  $X, Y$  taking the value  $x, y$   $P_{X,Y}(X = x, Y = y)$

Sampling something about  
Cat

Sampling something about  
dog



$P_{\text{Image,Category}}(\text{Image} = \text{Image}, \text{Category} = \text{Category})$

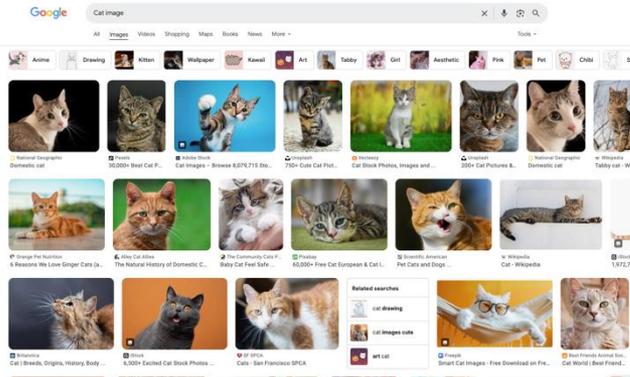


# Basics – High Dimensional Random Variable

Probability of the random variable  $X = x$  given  $Y = y$

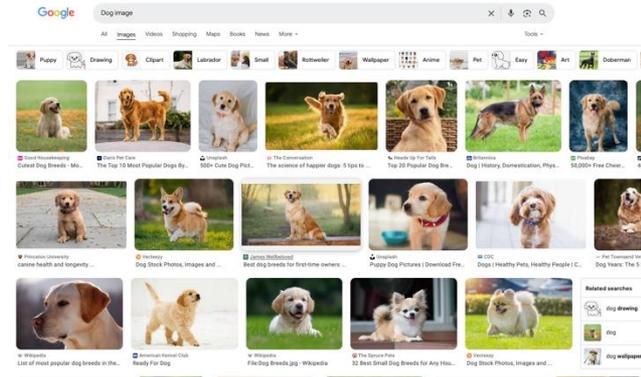
$$P_{X|Y}(X = x|Y = y)$$

Sampling something about



$$P(X|Y=\text{Cat})$$

Sampling something about



$$P(X|Y=\text{Dog})$$