Stanford CS224W: Machine Learning with Graphs Fall 2025/26

CS224W: Machine Learning with Graphs

Jure Leskovec, Stanford University
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http://cs224w.stanford.edu

Stanford CS224W: Course Logistics

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CS224W Course Outline

We are going to explore Machine Learning and Representation Learning for graph data:

- Methods for node embeddings: DeepWalk, Node2Vec
- Graph Neural Networks: GCN, GraphSAGE, GAT…
- Graph Transformers
- Knowledge graphs and reasoning: TransE
- Generative models for graphs: GraphRNN
- Relational Deep Learning: Databases
- GNN + LLMs
- Applications to Biomedicine, Science, Technology

CS224W Course Outline

Date	Topic	Date	Topic
Tue, 9/23	1. Introduction to Machine Learning for Graphs	**Tue, 10/28**	11. GNNs for recommender systems
Thu, 9/25	2. Node Embeddings	**Thu, 10/30**	12. Relational Deep Learning
Tue, 9/30	3. Graph Neural Networks	**Tue, 11/4**	DEMOCRACY DAY – NO CLASS
Thu, 10/2	4. A general perspective on GNNs	**Thu, 11/6**	13. Advanced architectures in RDL
Tue, 10/7	5. GNN augmentation and training	**Tue, 11/11**	14. Advanced topics in GNNs
Thu, 10/9	6. Theory of GNNs	**Thu, 11/13**	15. Towards Foundation Models for Knowledge Graphs
Tue, 10/14	7. Designing Powerful GNNs	**Tue, 11/18**	16. LLM+GNN
Thu, 10/16	8. Graph Transformers	**Thu, 11/20**	17. Agents+Graphs
Tue, 10/21	9. Heterogenous graphs	**Tue, 12/2**	18. Deep Generative Models for Graphs
Thu, 10/23	10. Knowledge graphs	**Thu, 12/4**	19. Conclusion

Prerequisites

- **The course is self-contained.**
- **No single topic is too hard by itself.**
- **But we will cover and touch upon many topics and this is what makes the course hard.**
  - **Some background in:**
    - Machine Learning
    - Algorithms and graph theory
    - Probability and statistics
    - Linear Algebra
  - **Programming:**
    - You should be able to write non-trivial programs (in Python)
    - Familiarity with PyTorch is a plus

Graph Machine Learning Tools

- **We use PyG (PyTorch Geometric):**
  - The ultimate library for Graph Neural Networks
- **We further recommend:**
  - GraphGym: Platform for designing Graph Neural Networks.
    - Modularized GNN implementation, simple hyperparameter tuning, flexible user customization
  - Both platforms are very helpful for the course project (save your time & provide advanced GNN functionalities)
- **Other network analytics tools**: SNAP.PY, NetworkX

CS224W Course Logistics

- **The class meets Tue and Thu 3:00-4:20pm Pacific Time *in person***
  - Videos of the lectures will be recorded and posted on Canvas
- **Structure of lectures:**
  - ~80 minutes of a lecture
    - During this time you can ask questions
  - ~10 minutes of a live Q&A/discussion session

Logistics: Teaching Staff

Instructor

Jure Leskovec

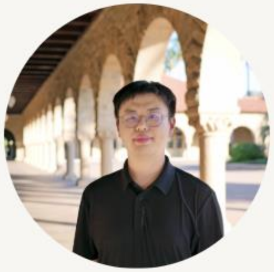
Guest Instructor

Charilaos Kanatsoulis

Course Assistants

Shutong Zhang (Head CA)

Sirui (Ariel) Chen



Tianlang Chen

Havin Hosgur

Harper Hua

Basant Khalil

Poonam Sahoo

Josh Sanyal

Logistics: Website

- http://cs224w.stanford.edu
  - Slides posted before the class
- **Readings:**
  - Graph Representation Learning Book by Will Hamilton
  - Research papers
- **Optional readings:**
  - Papers and pointers to additional literature
  - **This will be very useful for course projects**

Logistics: Communication

- **Ed Discussion:**
  - Access via link on Canvas
  - **Please participate and help each other!**
    - Don't post code, annotate your questions, search for answers before you ask
  - We will post course announcements to Ed (make sure you check it regularly)
- **Please don't communicate with prof/TAs via personal emails, but always use:**
  - cs224w-aut2526-staff@lists.stanford.edu

Logistics: Office Hours

- **OHs will be both in person and virtual**
  - We will have OHs every day, starting from 2nd week of the course
  - See http://web.stanford.edu/class/cs224w/oh.html for Zoom links and link to QueueStatus
  - Schedule to be announced by end of week

Work for Course: Grading

- **Final grade will be composed of:**
  - **Homework: 20%**
    - 3 written homeworks, each worth 6.67%
  - **Coding assignments: 15%**
    - 5 coding assignments using Google Colab, each worth 3%
  - **Exam: 35%**
  - **Course project: 30%**
    - Proposal, Milestone, and Final report
  - **Extra credit: Ed participation, PyG/GraphGym code contribution**
    - Used if you are on the boundary between grades

Work for Course: Submitting

- **How to submit?**
  - **Upload via Gradescope**
    - You will be automatically registered to Gradescope once you officially enroll in CS224W
  - Homeworks, Colabs (numerical answers), and project deliverables are submitted on Gradescope
- **Total of <u>2 Late Periods (LP)</u> per student**
  - Max 1 LP per assignment (no LP for the final report)
    - LP gives **4 extra days**: assignments usually due on Thursday (11:59pm) → with LP, it is due the following Monday (11:59pm)

Work for Course: HWs, Colabs

- **Homeworks (20%, n=3)**
  - **Written assignments take longer and take time (~10-20h) – start early!**
    - A combination of theory, algorithm design, and math
- **Colabs (15%, n=5)**
  - **We have more Colabs but they are shorter (~3-5h); Colab 0 is not graded.**
    - Get hands-on experience coding and training GNNs; good preparation for final projects and industry

Work for Course: Exam

- **Single exam: TBD (35%)**
  - **In-person closed-book, timed**
    - Monday, 11/17 - Friday, 11/21, exact date and time TBD
  - **Content**
    - Will have written questions (similar to Homeworks)
    - More details to come!

Work for Course: Project (30%)

- **Details will be posted soon:**
  - Focus is on real-world applications of GNNs
- **Logistics**
  - **Groups of up to 3 students**
    - Groups of 1 or 2 are allowed (but discouraged); the team size will be taken under consideration when evaluating the scope of the project. But 3 person teams can be more efficient.
  - **Google Cloud credits**
    - We will provide $50 in Google Cloud credits to each student
    - You can also get $300 with Google Free Trial (https://cloud.google.com/free/docs/gcp-free-tier)
- **Read: http://cs224w.stanford.edu/info.html**

Course Schedule

Assignment	Due on (11:59pm PT)
Colab 0	Not graded
Colab 1	Thu, 10/9 (week 3)
Homework 1	Thu, 10/16 (week 4)
Project Proposal	Tue, 10/21 (week 5)
Colab 2	Thu, 10/23 (week 5)
Homework 2	Thu, 10/30 (week 6)
Colab 3	Thu, 11/6 (week 7)
Project Milestone	Thu, 11/6 (week 7)
Homework 3	Thu, 11/13 (week 8)
EXAM	Thu, 11/20 5pm – Sat, 11/23 5am (week 9)
Colab 4	Tues, 12/2 (week 10)
Colab 5	Thu, 12/4 (week 10)
Project Report	Thu, 12/11 **(No Late Periods!)**

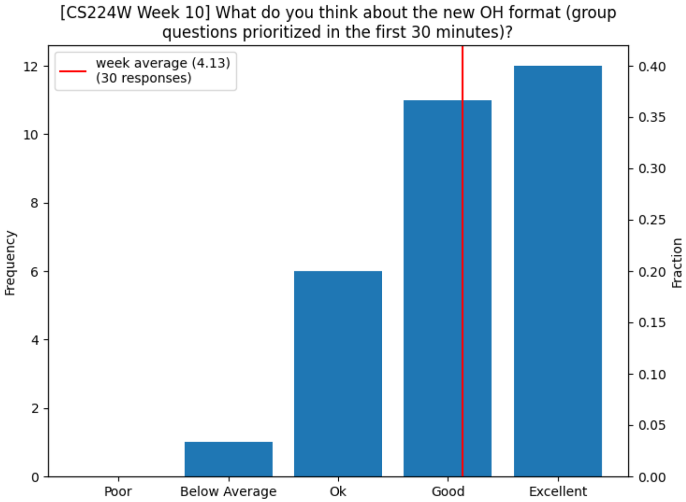
Honor Code

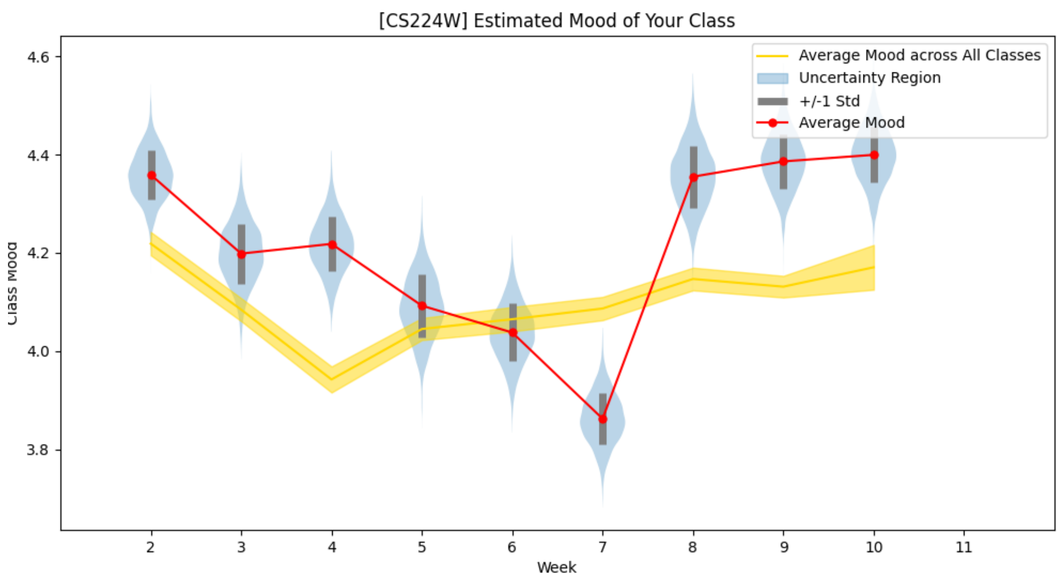
Make sure you read and understand it!

- We strictly enforce the Stanford Honor Code
  - Violations of the Honor Code include:
    - Copying or allowing another to copy from one's own paper
    - Unpermitted collaboration
    - Plagiarism
    - Giving or receiving unpermitted aid on a take-home examination
    - Representing as one's own work the work of another
    - Giving or receiving aid on an assignment under circumstances in which a reasonable person should have known that such aid was not permitted
  - Standard sanction for a first-time offense includes a one-quarter suspension & 40 hours of community service.

High Resolution Course Feedback

- Every week a few students will get a short survey
  - Just 3 questions!
- **Super important that you respond!**
- **Your feedback really helps us improve your class experience**





Course Logistics: Colab 0

- **Colabs 0 and 1 will be released on our course website at 3pm Thursday (9/25)**
- **Colab 0:**
  - Does not need to be handed-in
- **Colab 1:**
  - Due on Thursday 10/9 (2.5 weeks from today)
  - Submit written answers and code on Gradescope
  - Will cover material from Lectures 1-4, but you can get started right away!

Stanford CS224W: Machine Learning with Graphs

CS224W: Machine Learning with Graphs
Jure Leskovec, Stanford University
http://cs224w.stanford.edu

Why Graphs?

Graphs are a general language for describing and analyzing entities with relations/interactions

Many Types of Data are Graphs (1)

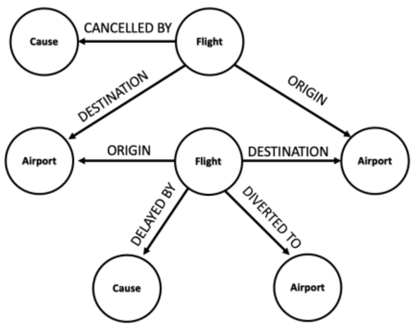
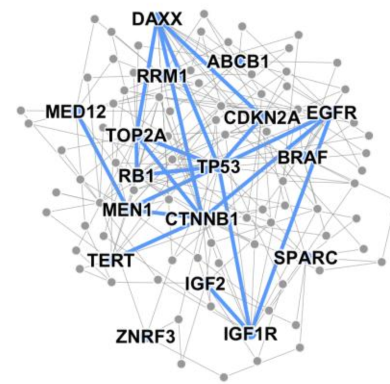


Image credit: SalientNetworks



Event Graphs **Computer Networks** **Disease Pathways**

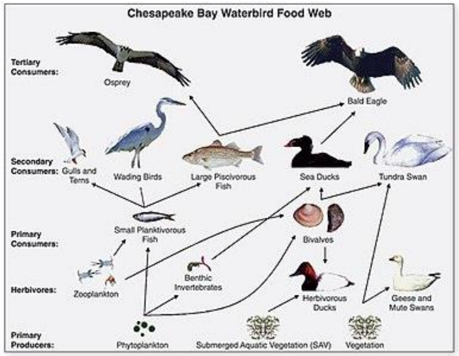


Image credit: Wikipedia

Image credit: Pinterest

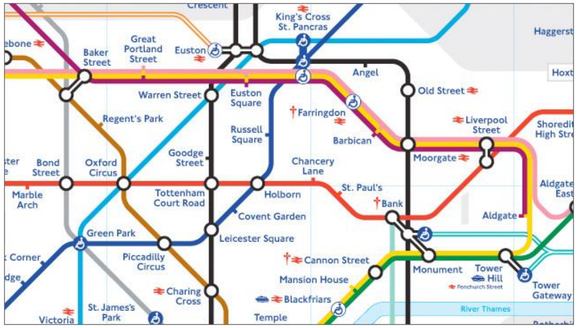


Image credit: visitlondon.com

Food Webs **Particle Networks** **Underground Networks**

Many Types of Data are Graphs (2)

Image credit: Medium

Social Networks

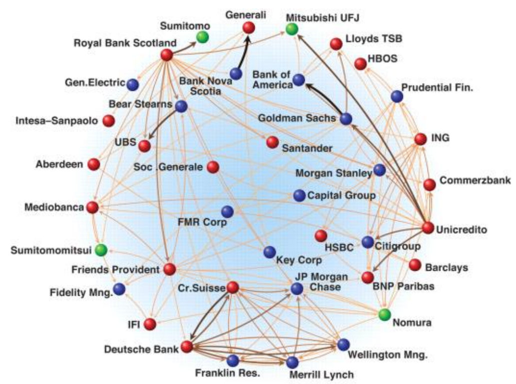
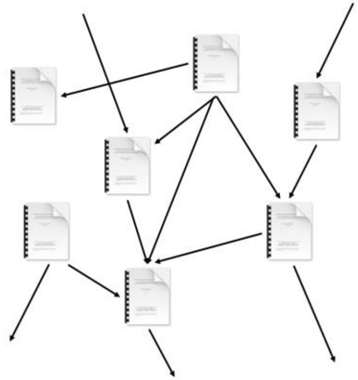


Image credit: Science

Economic Networks

Image credit: Lumen Learning

Communication Networks



Citation Networks

Image credit: Missoula Current News

Internet

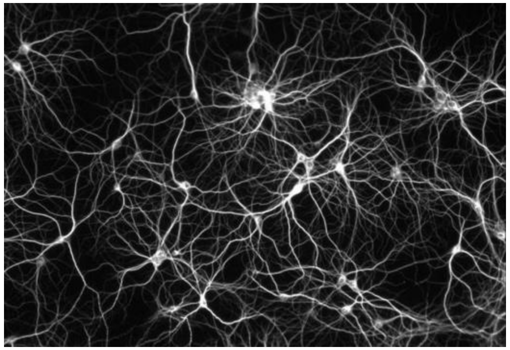


Image credit: The Conversation

Networks of Neurons

Many Types of Data are Graphs (3)

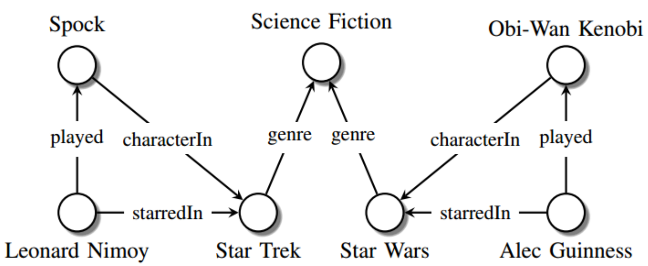


Image credit: Maximilian Nickel et al

Knowledge Graphs

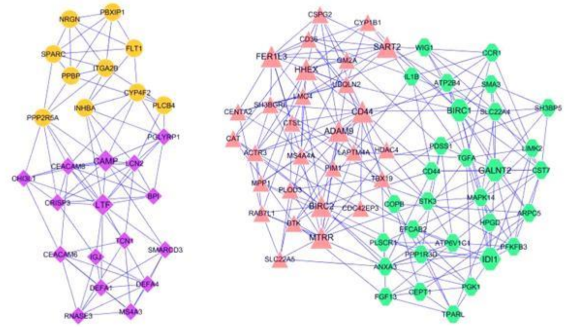


Image credit: ese.wustl.edu

Regulatory Networks

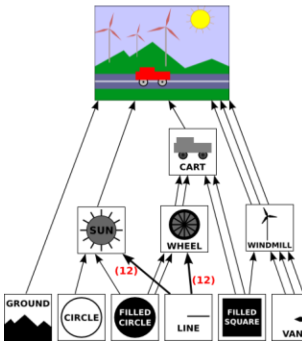


Image credit: math.hws.edu

Scene Graphs

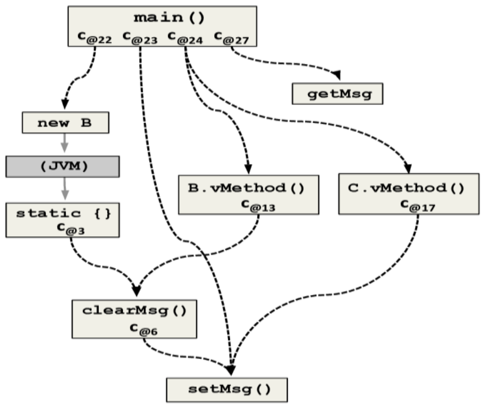


Image credit: ResearchGate

Code Graphs

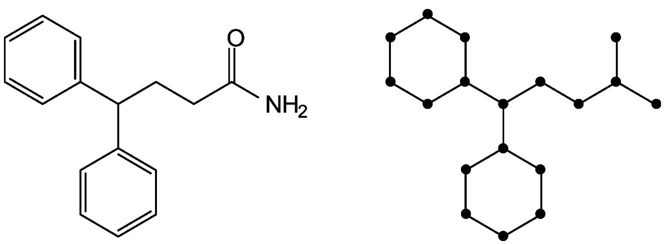


Image credit: MDPI

Molecules

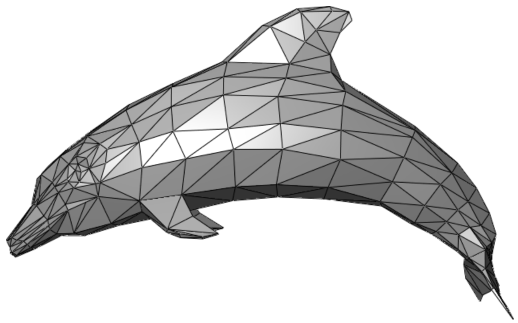
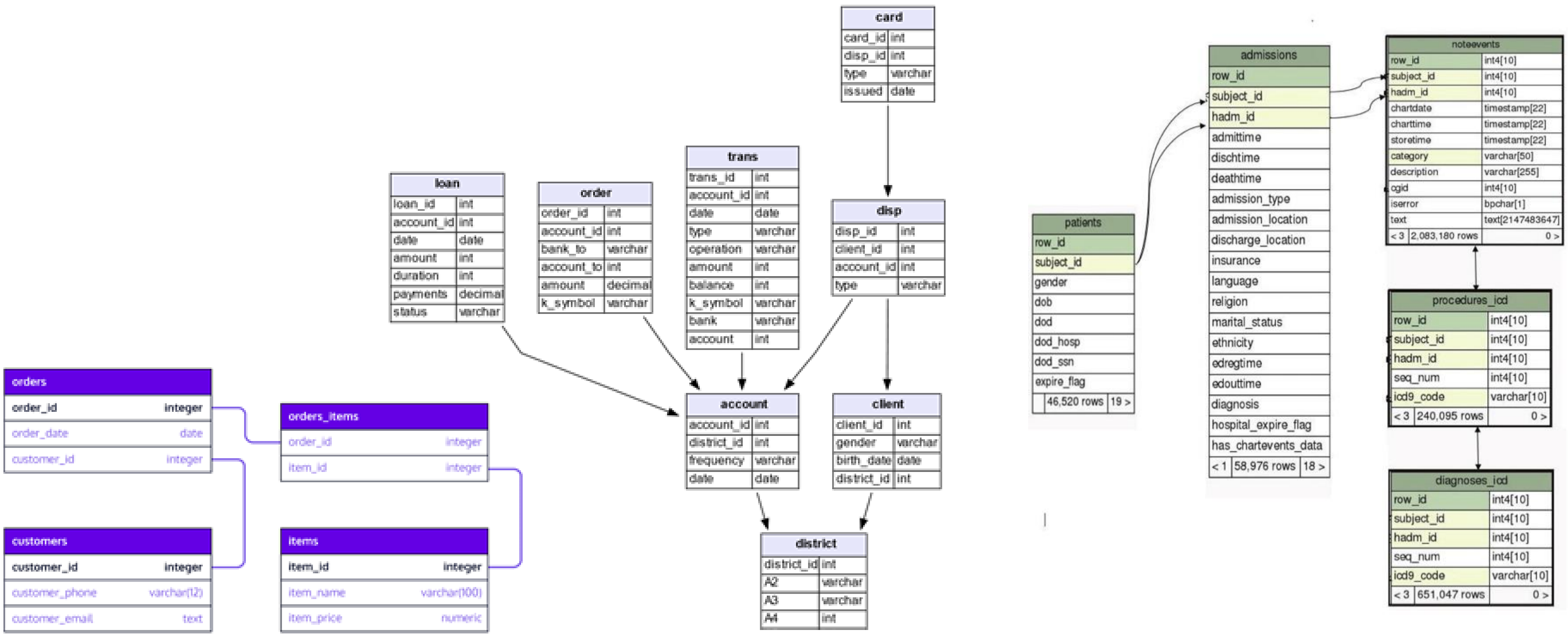


Image credit: Wikipedia

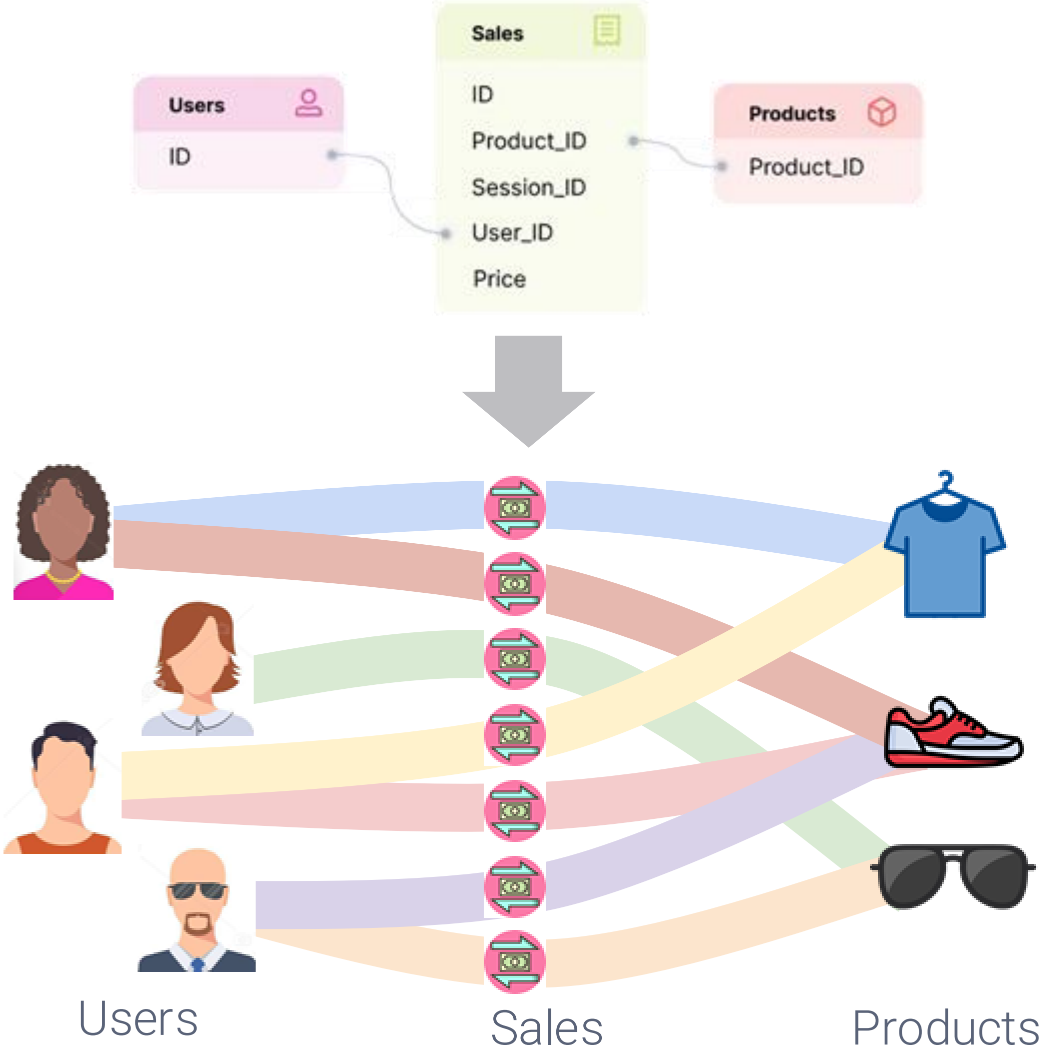
3D Shapes

Databases are Graphs!



Commerce Finance Clinical Trial

Relational Deep Learning



http://relbench.stanford.edu

Graphs: Machine Learning

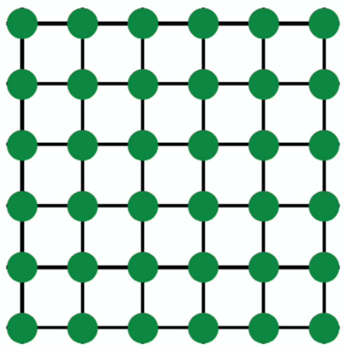
Complex domains have a rich relational structure, which can be represented as a **relational graph**

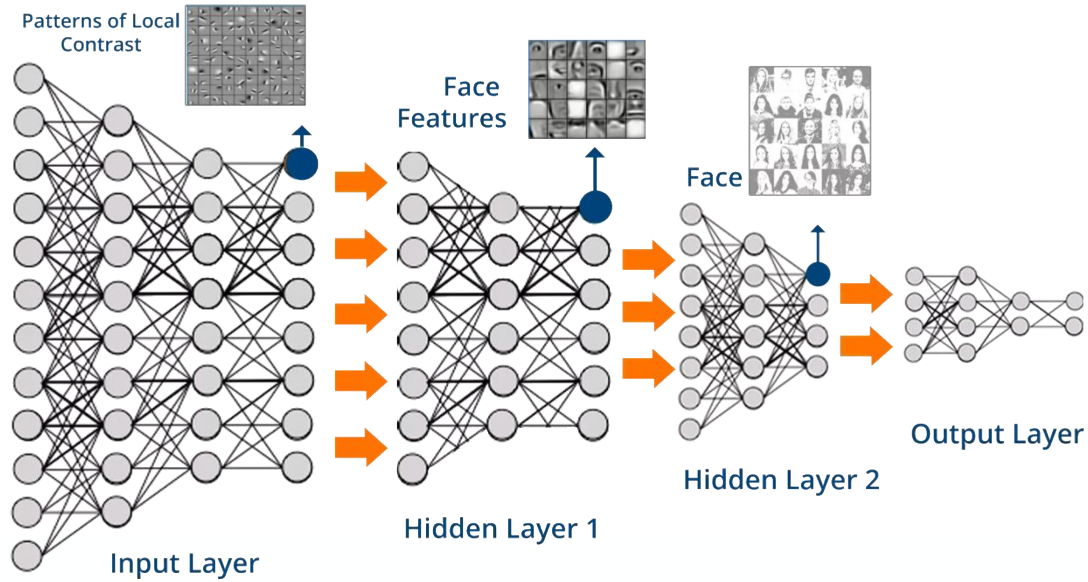
By explicitly modeling relationships we achieve better performance!

Main question:

How do we take advantage of relational structure for better prediction?

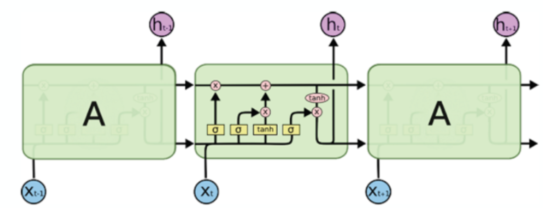
Today: Modern ML Toolbox





Images

Text/Speech



Modern deep learning toolbox is designed for simple sequences & grids

Doubt thou the stars are fire;
Doubt that the sun doth move;
Doubt truth to be a liar;
But never doubt I love...

Text

Audio signals

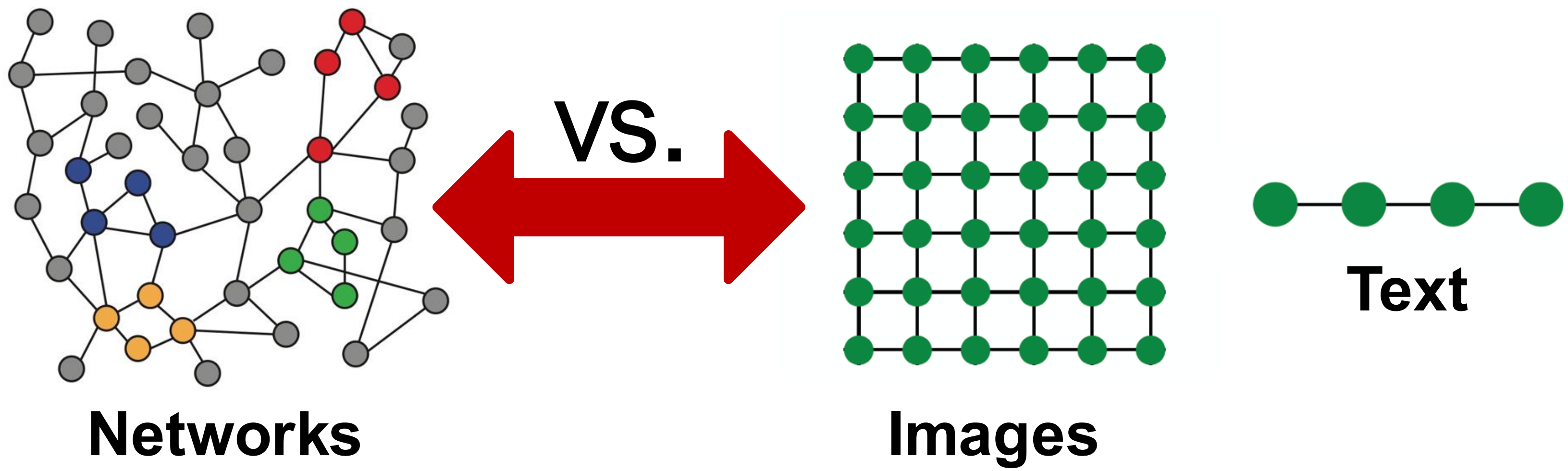
Images

Modern
deep learning toolbox
is designed for
sequences & grids

Why is Graph Deep Learning Hard?

Networks are complex.

- Arbitrary size and complex topological structure (*i.e.*, no spatial locality like grids)



- No fixed node ordering or reference point
- Often dynamic and have multimodal features

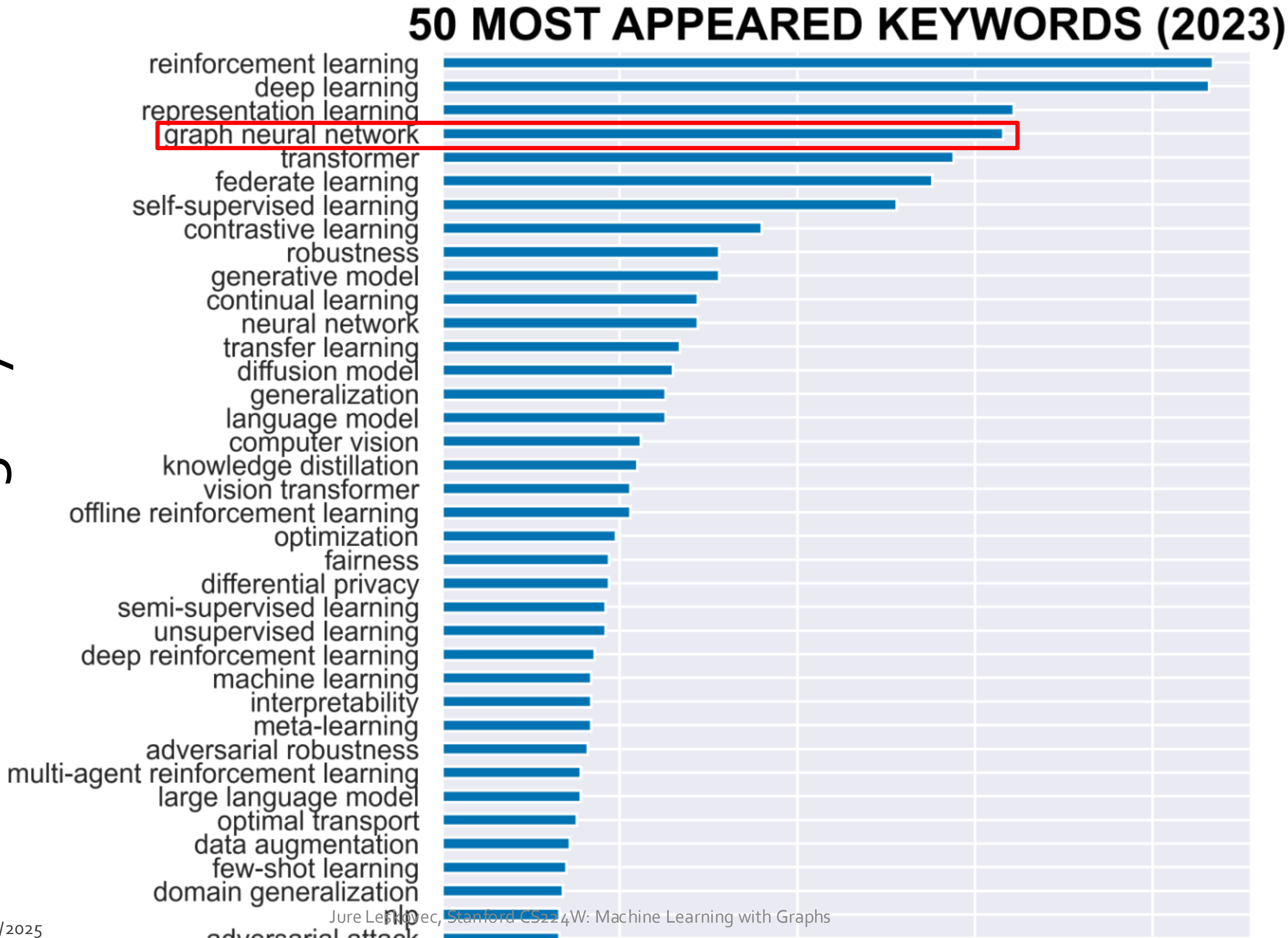
This Course: CS224W

How can we develop neural networks that are much more broadly applicable?

Graphs are the new frontier of deep learning

Hot subfield in ML

ICLR 2023 keywords



Stanford CS224W: Choice of Graph Representation

CS224W: Machine Learning with Graphs

Jure Leskovec, Stanford University

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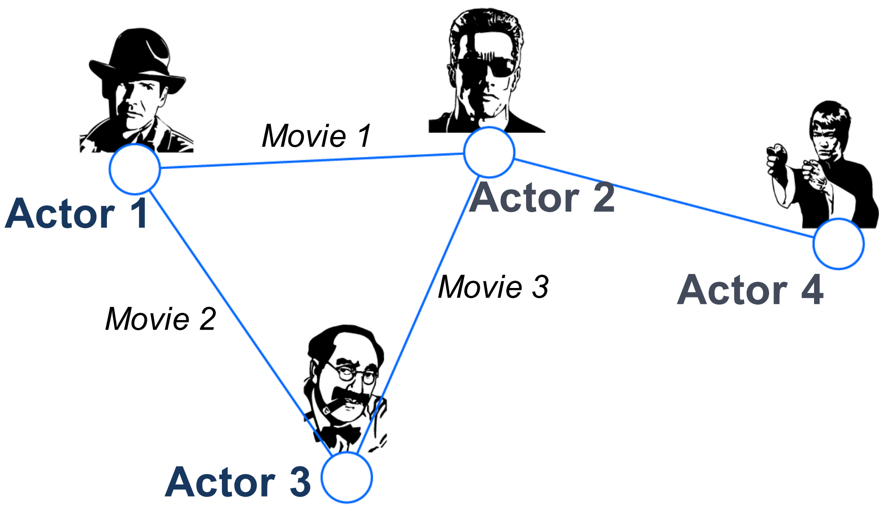
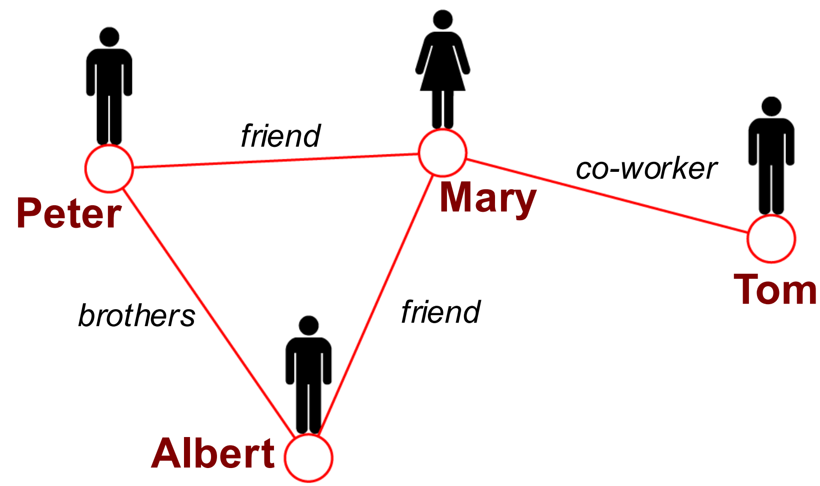
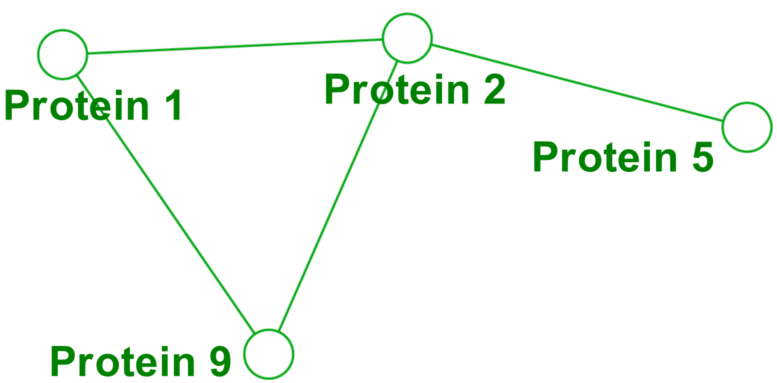
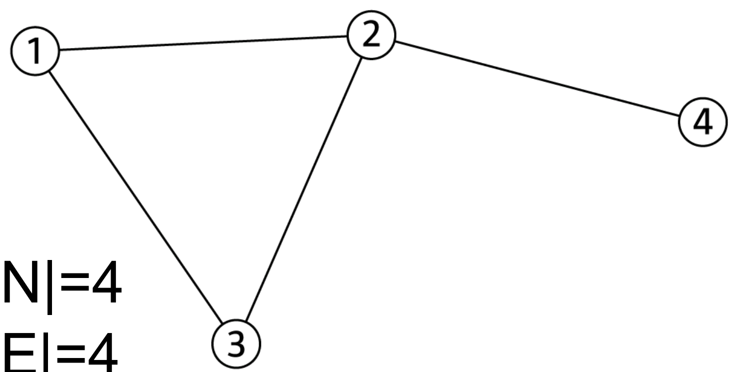
Graphs: A Common Language









$|N|=4$

$|E|=4$

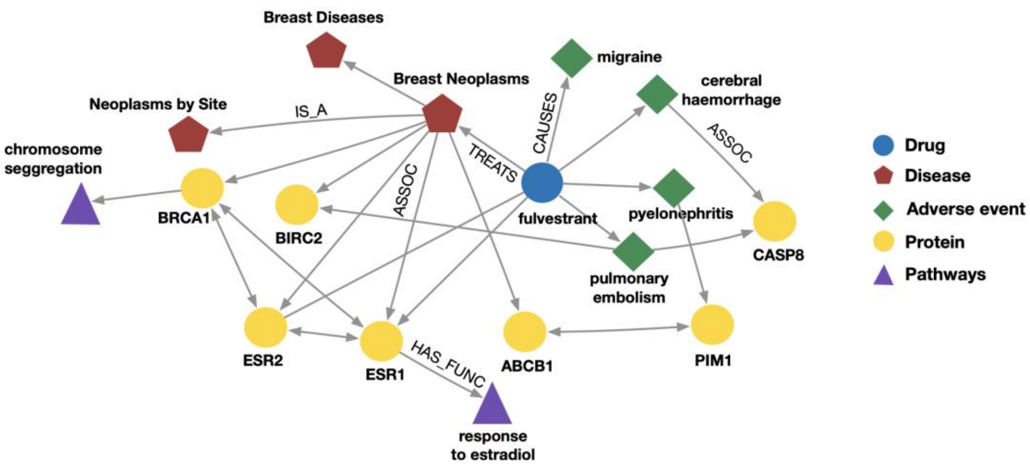
Heterogeneous Graphs

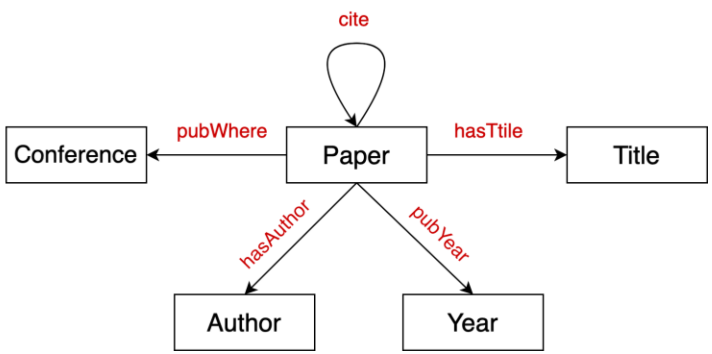
- **A heterogeneous graph is defined as**

$$\boldsymbol{G = (V, E, R, T)}$$

  - Nodes with node types $v_i \in V$
  - Edges with relation types $(v_i, r, v_j) \in E$
  - Node type $T(v_i)$
  - Relation type $r \in R$
  - Nodes and edges have **attributes/features**

Many Graphs are Heterogeneous





Biomedical Knowledge Graphs

Example node: Migraine
Example edge: (fulvestrant, Treats, Breast Neoplasms)
Example node type: Protein
Example edge type (relation): Causes

Academic Graphs

Example node: ICML
Example edge: (GraphSAGE, NeurIPS)
Example node type: Author
Example edge type (relation): pubYear

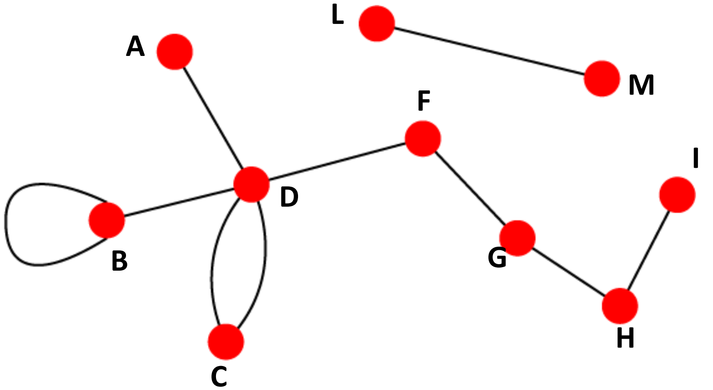
Choosing a Proper Representation

- **How to build a graph:**
  - **What are nodes?**
  - **What are edges?**
- **Choice of the proper network representation of a given domain/problem determines our ability to use networks successfully:**
  - In some cases, there is a unique, unambiguous representation
  - In other cases, the representation is by no means unique
  - The way you assign links will determine the nature of the question you can study

Directed vs. Undirected Graphs

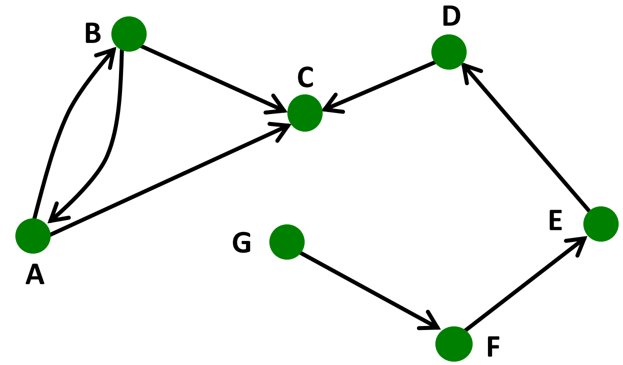
Undirected

- **Links:** undirected (symmetrical, reciprocal)



Directed

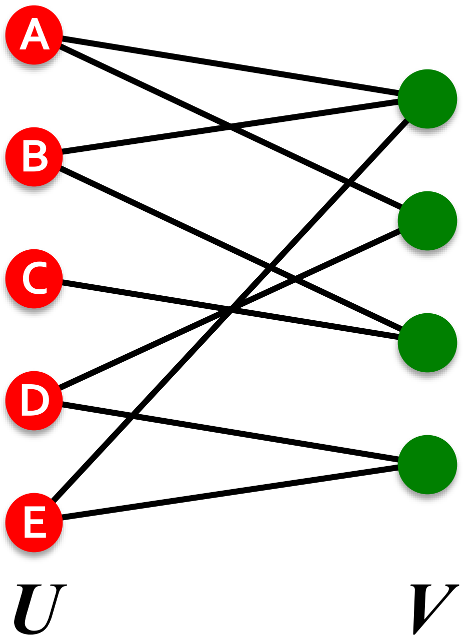
- **Links:** directed



- **Other considerations:**
  - Weights
  - Properties
  - Types
  - Attributes

Bipartite Graph

- **Bipartite graph** is a graph whose nodes can be divided into two disjoint sets ***U*** and ***V*** such that every link connects a node in ***U*** to one in ***V***; that is, ***U*** and ***V*** are **independent sets**
- **Examples:**
  - Authors-to-Papers (they authored)
  - Actors-to-Movies (they appeared in)
  - Users-to-Movies (they rated)
  - Recipes-to-Ingredients (they contain)
- **"Folded" networks:**
  - Author collaboration networks
  - Movie co-rating networks



Stanford CS224W: Applications of Graph ML

CS224W: Machine Learning with Graphs

Jure Leskovec, Stanford University

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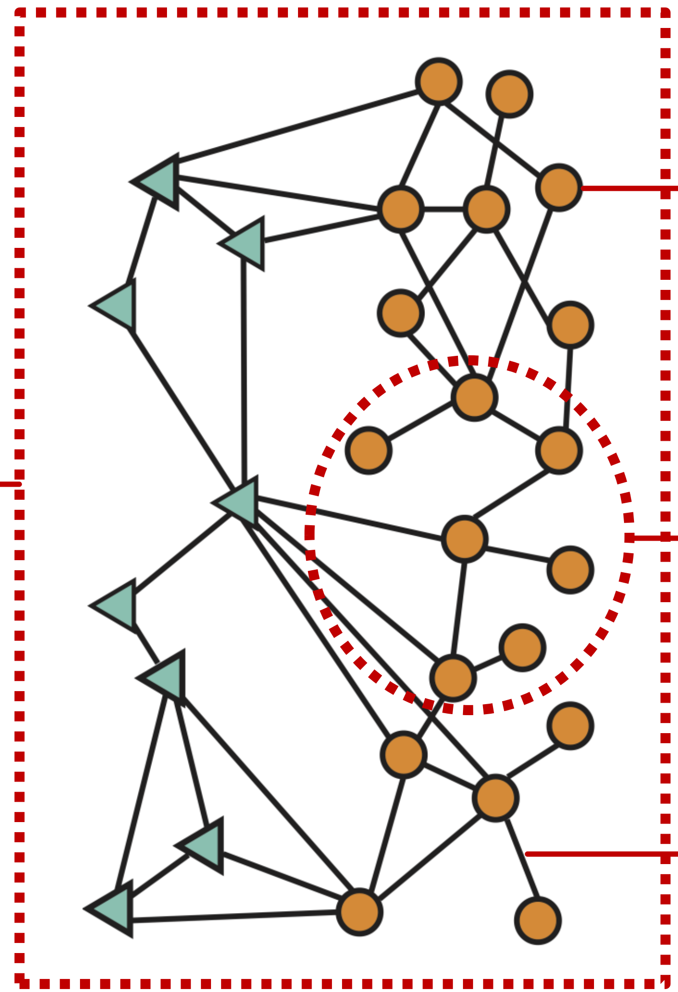
Different Types of Tasks

Graph-level prediction, Graph generation



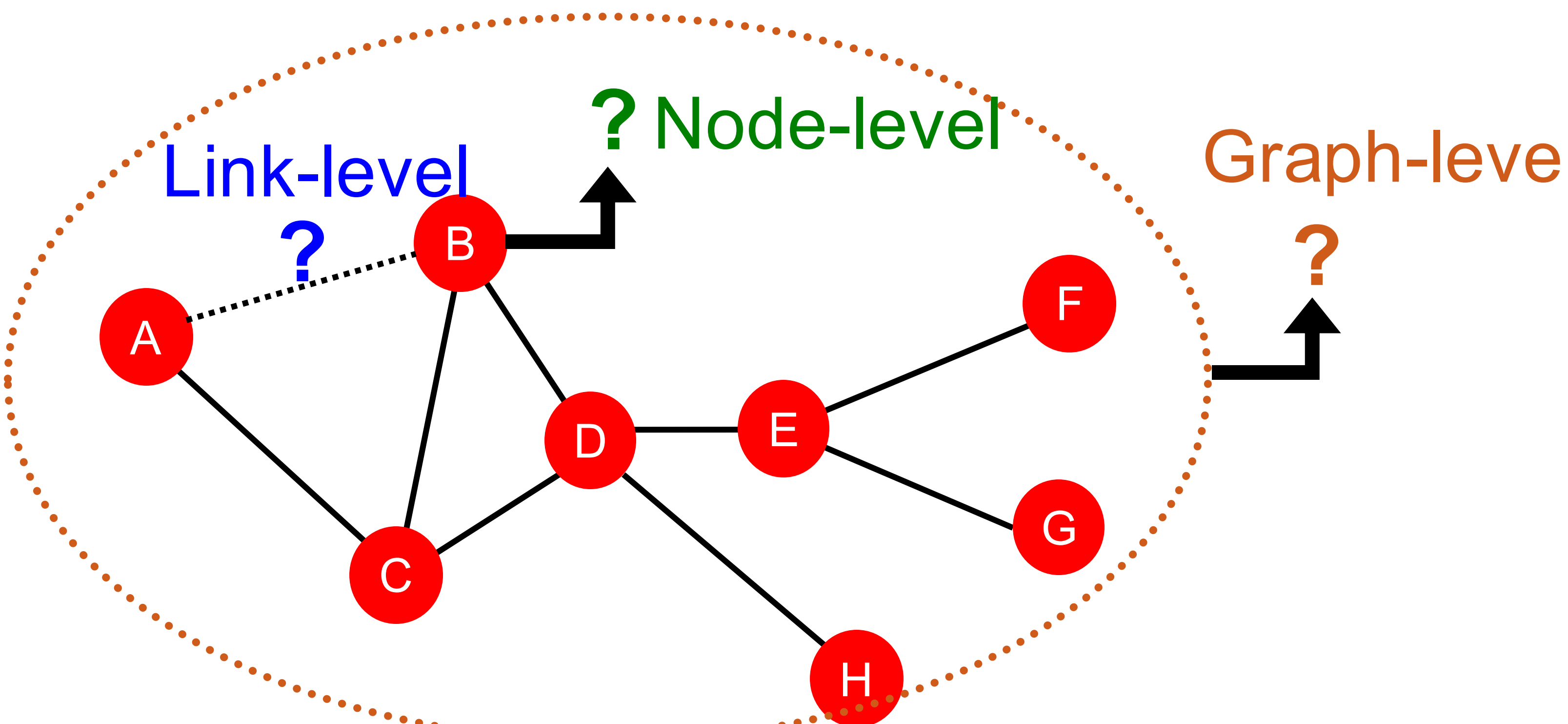
Node level

Community (subgraph) level

Edge-level

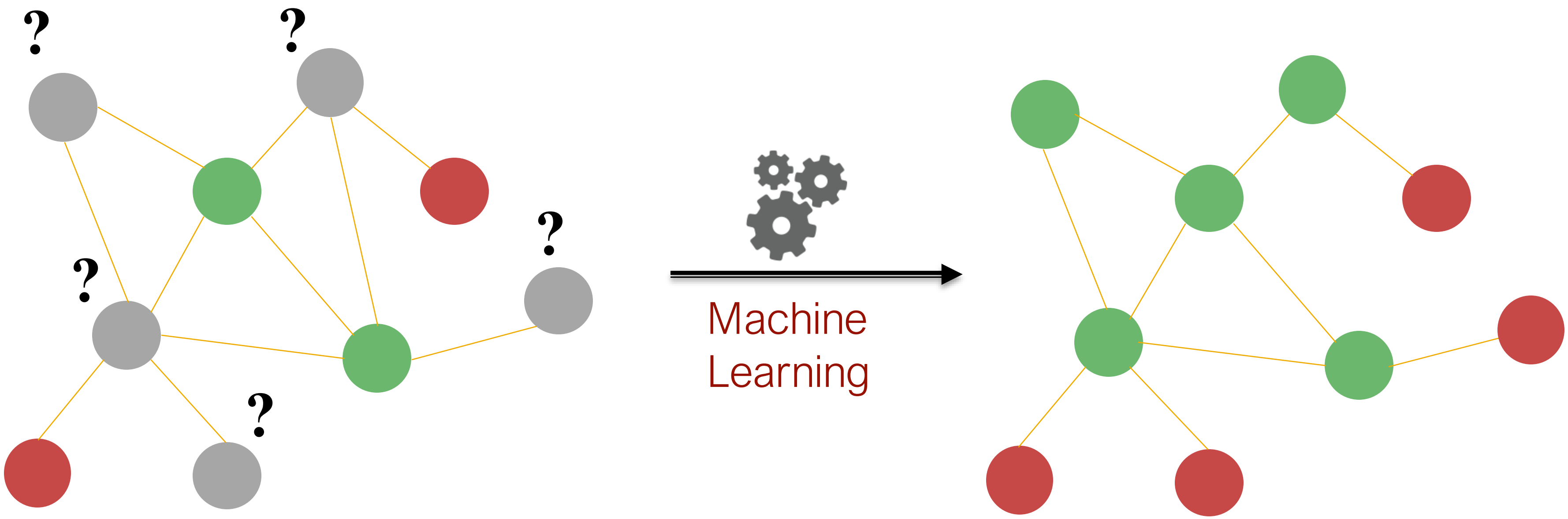
Machine Learning Tasks: Review

- Node-level prediction
- Link-level prediction
- Graph-level prediction



Stanford CS224W:
Node-Level Tasks

Node-Level Tasks

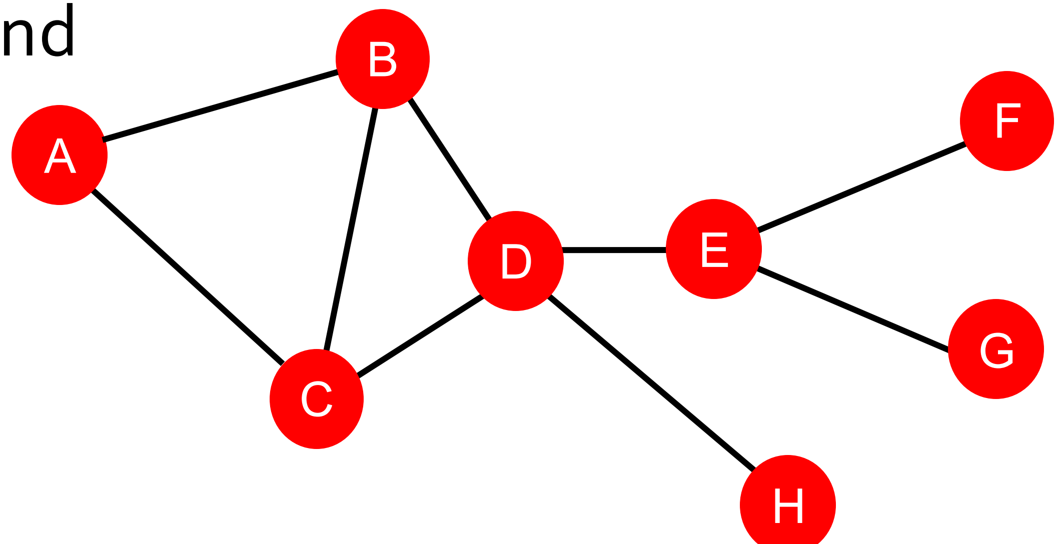


Node classification

Node-Level Network Structure

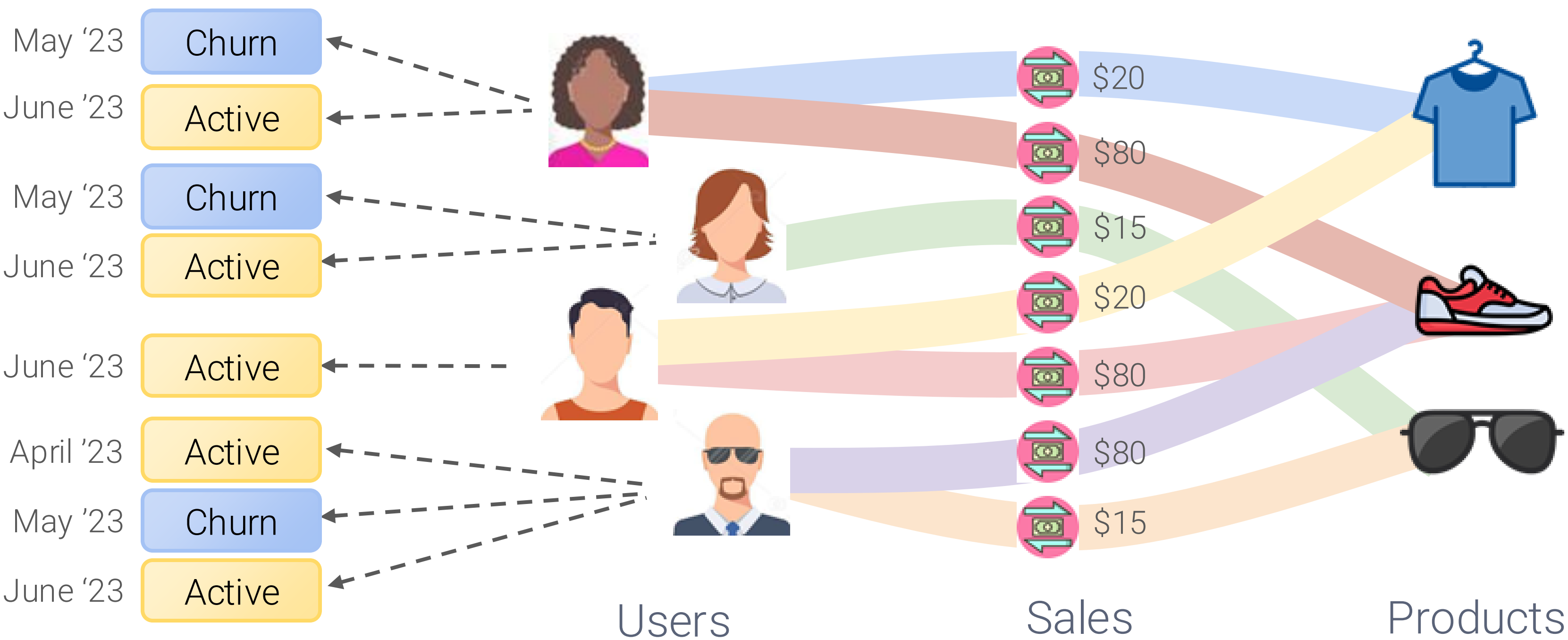
Goal: Characterize the structure and position of a node in the network:

- Node degree
- Node importance & position
  - E.g., Number of shortest paths passing through a node
  - E.g., Avg. shortest path length to other nodes
- Substructures around the node



Example(1): User Churn

Training labels together with timestamps are attached to the graph



Example (2): Protein Folding

Computationally predict a protein's 3D structure based solely on its amino acid sequence:
For each node predict its 3D coordinates

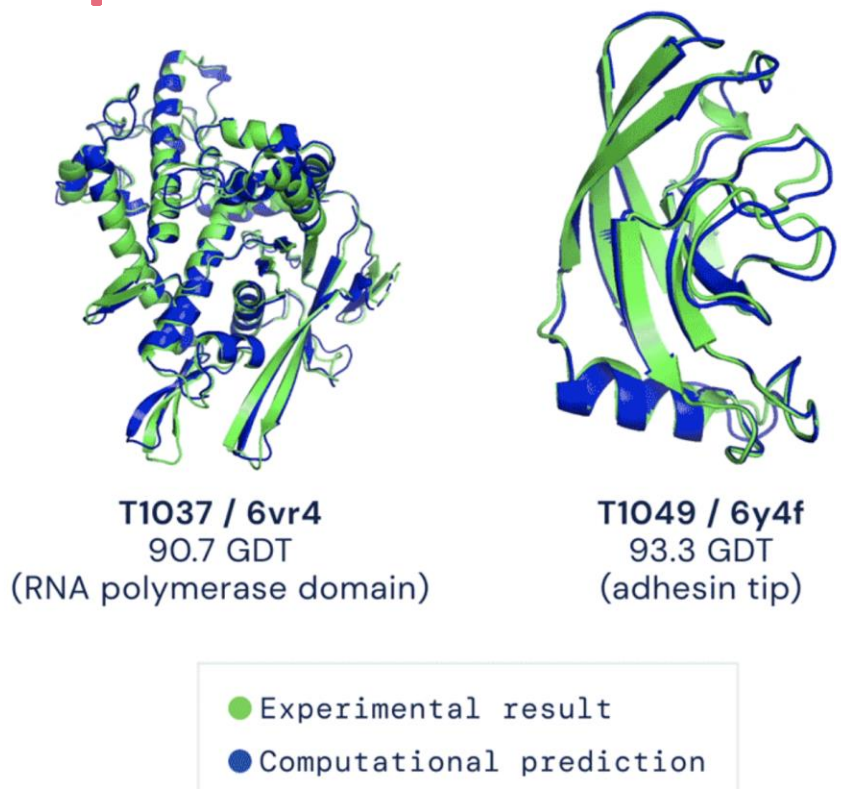


Image credit: DeepMind

AlphaFold: Impact

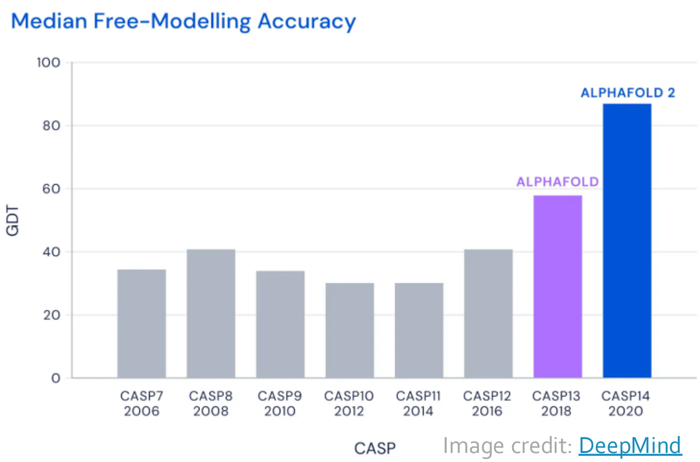


Image credit: DeepMind

Image credit: SingularityHub

AlphaFold's AI could change the world of biological science as we know it

DeepMind's latest AI breakthrough can accurately predict the way proteins fold

Has Artificial Intelligence 'Solved' Biology's Protein-Folding Problem?

12-14-20

DeepMind's latest AI breakthrough could turbocharge drug discovery

AlphaFold: Impact

Oct. 9, 2024

SCIENCE

Nobel Prize in Chemistry Goes to 3 Scientists for Predicting and Creating Proteins

The Nobel, awarded to David Baker of the University of Washington and Demis Hassabis and John M. Jumper of Google DeepMind, is the second this week to involve artificial intelligence.

By Claire Moses, Cade Metz and Teddy Rosenbluth

PRINT EDITION 3 Scientists Used A.I. To Crack Proteins' Code | October 10, 2024, Page A11

AlphaFold: Solving Protein Folding

- **Key idea:** "Spatial graph"
  - **Nodes:** Amino acids in a protein sequence
  - **Edges:** Proximity between amino acids (residues)

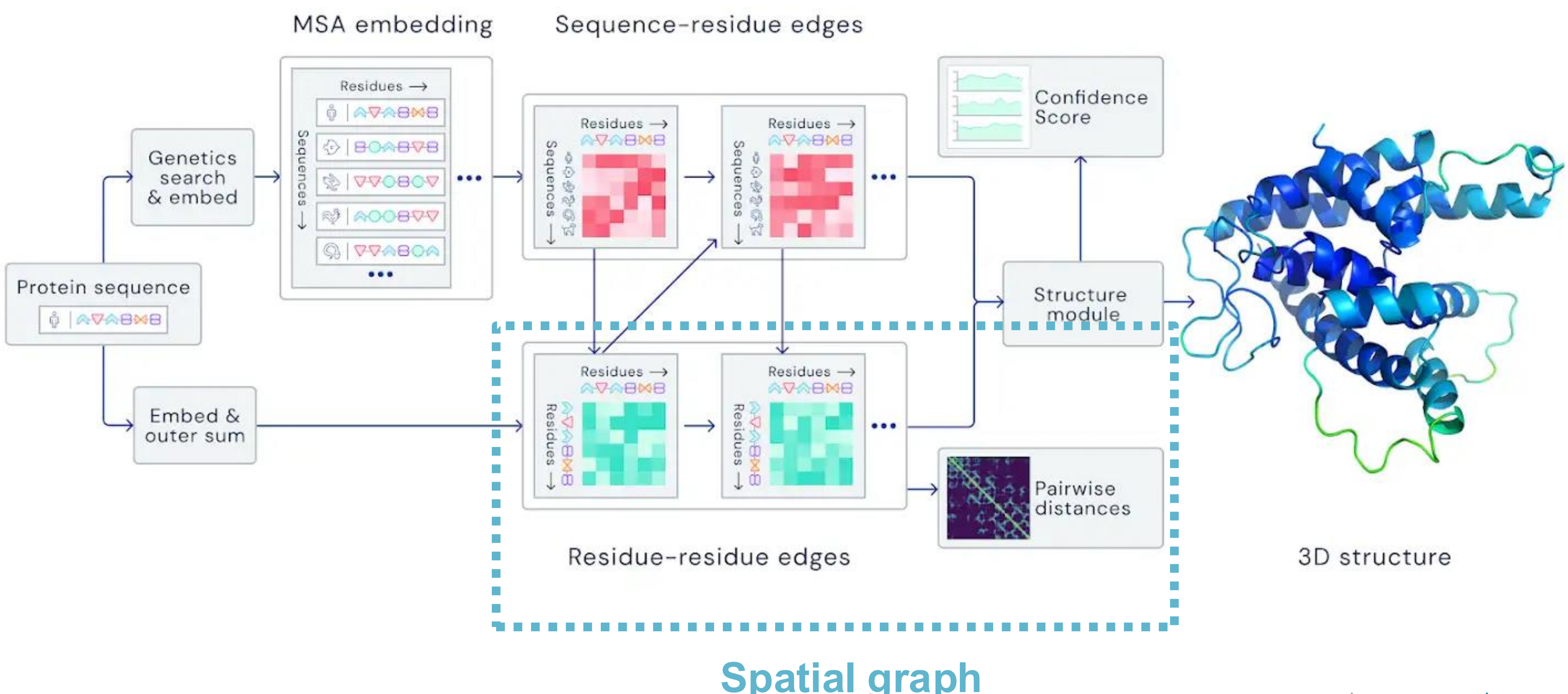


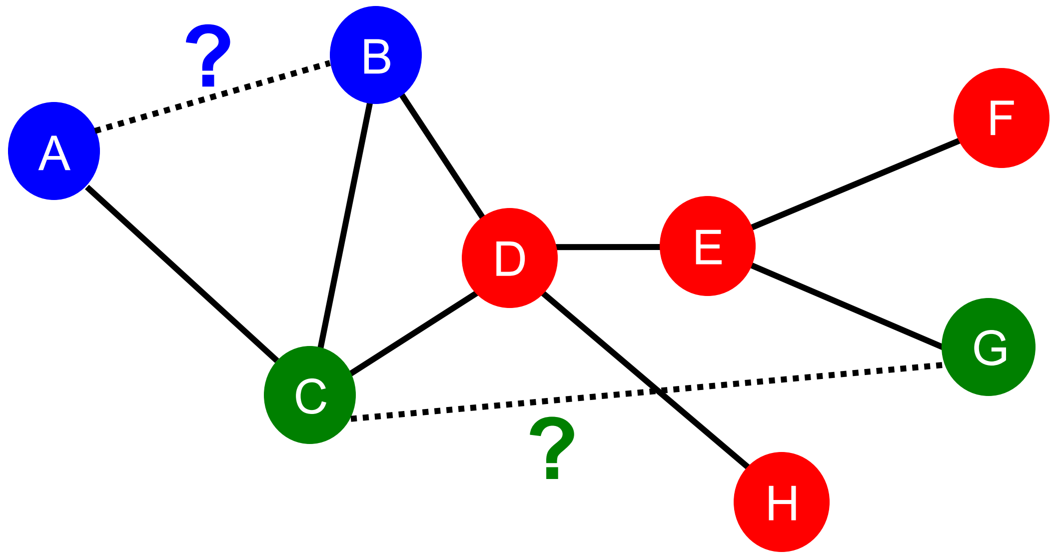
Image credit: [DeepMind]

Stanford CS224W: Link Prediction

CS224W: Machine Learning with Graphs
Jure Leskovec, Stanford University
http://cs224w.stanford.edu

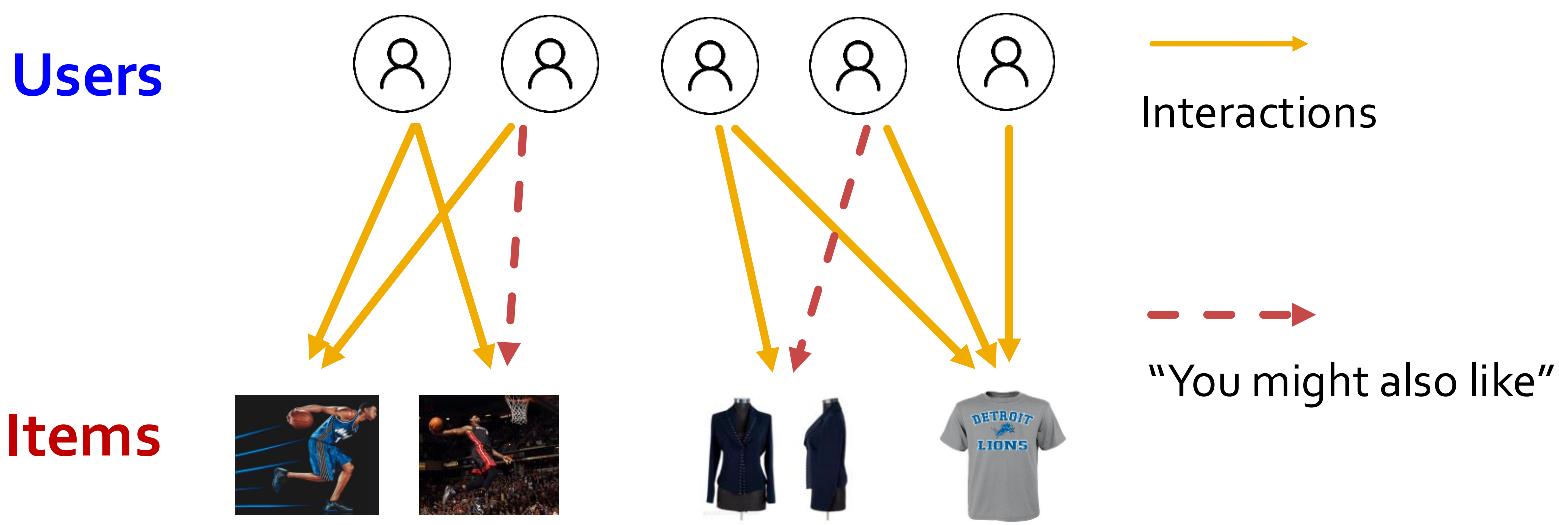
Link-Level Prediction Task

- The task is to predict **new/missing/unknown links** based on the existing links.
- At test time, node pairs (with no existing links) are ranked, and top K node pairs are predicted.
- Task: Make a prediction for **a pair of nodes**.



Example (1): Recommender Systems

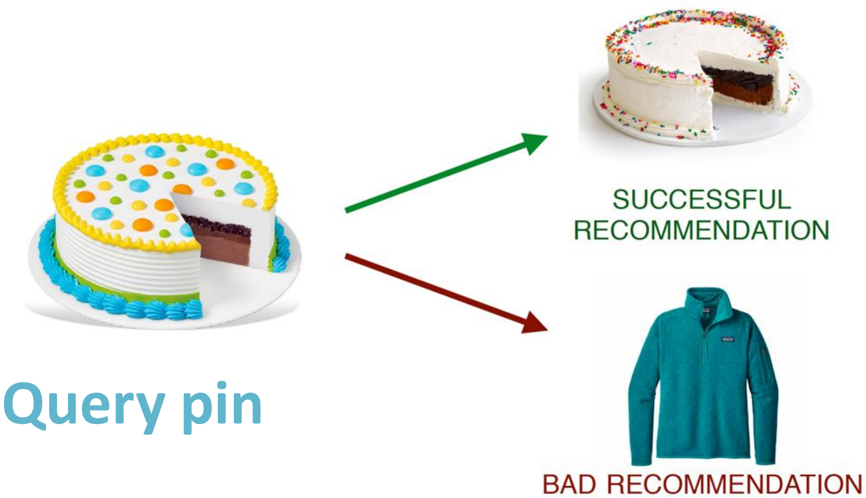
- **Users interacts with items**
  - Watch movies, buy merchandise, listen to music
  - **Nodes:** Users and items
  - **Edges:** User-item interactions
- **Goal: Recommend items users might like**



Ying et al., [Graph Convolutional Neural Networks for Web-Scale Recommender Systems](), KDD 2018

PinSage: Graph-based Recommender

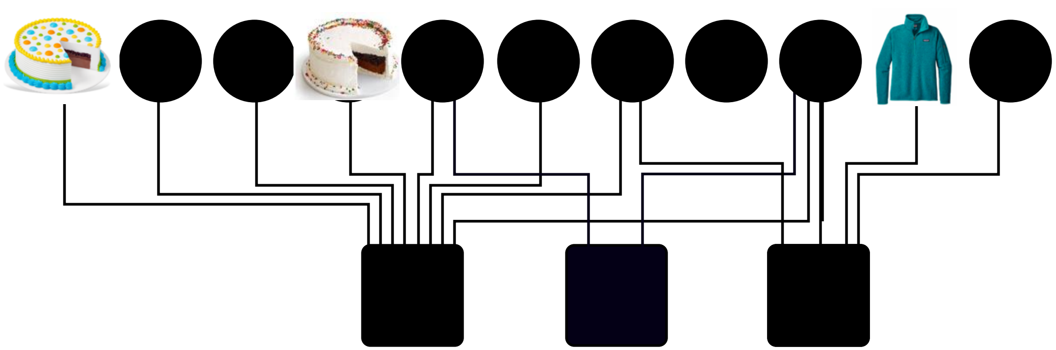
Task: **Recommend related pins to users**

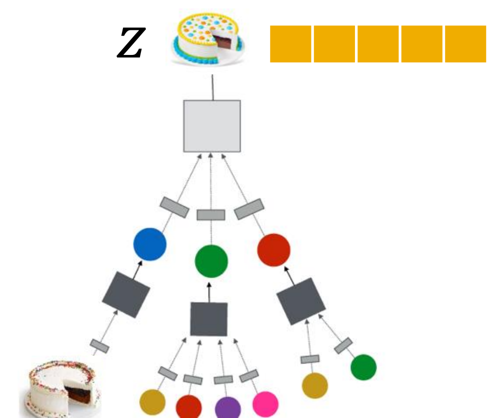


Task: Learn node embeddings z_i such that

$$d(z_{cake1}, z_{cake2}) < d(z_{cake1}, z_{sweater})$$

Predict whether two nodes in a graph are related



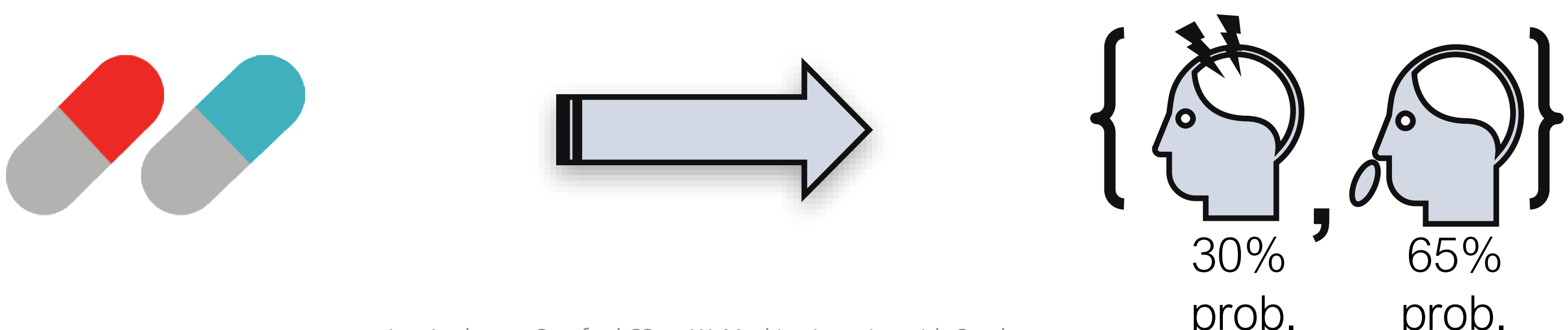


Example (2): Drug Side Effects

Many patients take multiple drugs to treat complex or co-existing diseases:

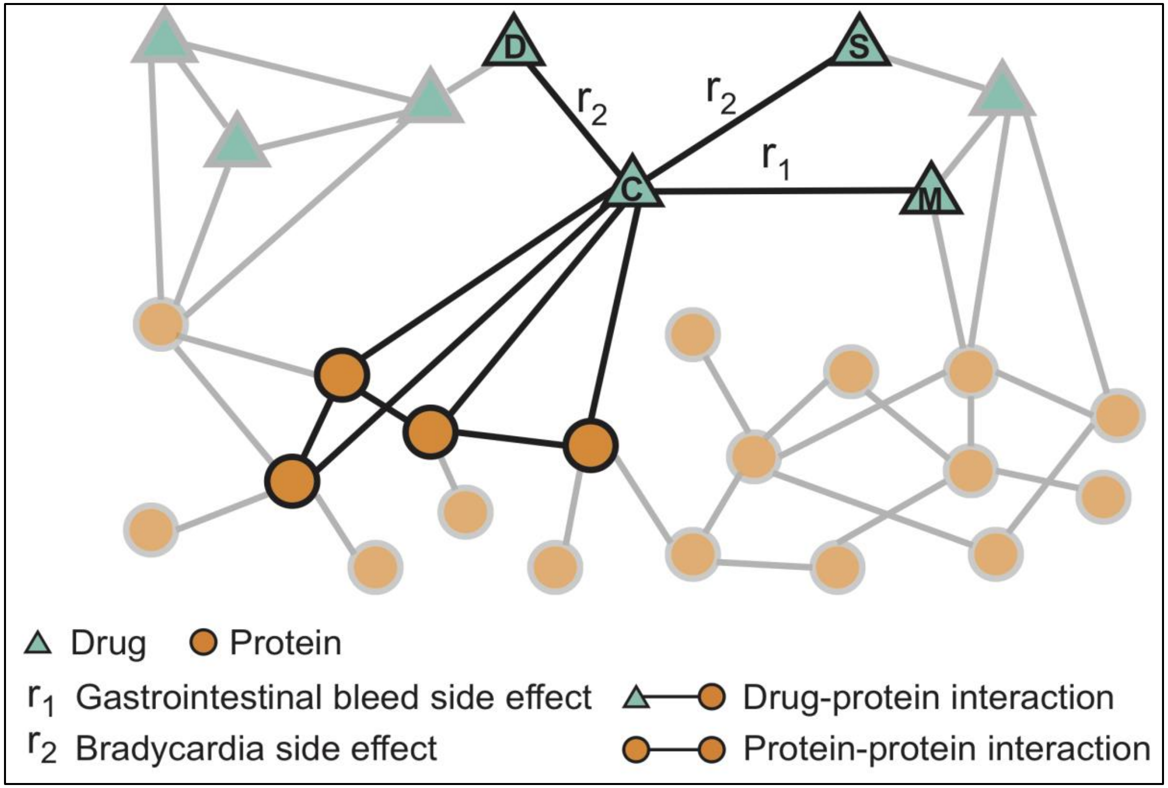
- 46% of people ages 70-79 take more than 5 drugs
- Many patients take more than 20 drugs to treat heart disease, depression, insomnia, etc.

Task: Given a pair of drugs predict adverse side effects

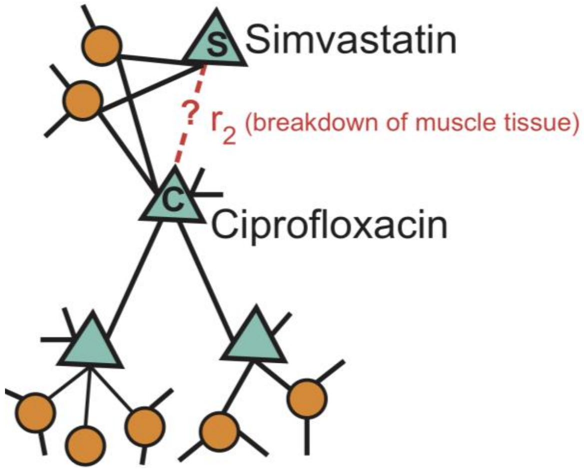


Biomedical Graph Link Prediction

- **Nodes**: Drugs & Proteins
- **Edges**: Interactions



Query: How likely will Simvastatin and Ciprofloxacin, when taken together, break down muscle tissue?



Results: *De novo* Predictions

Rank	Drug c	Drug d	Side effect r	Evidence found
1	Pyrimethamine	Aliskiren	Sarcoma	Stage *et al.* 2015
2	Tigecycline	Bimatoprost	Autonomic neuropathy	
3	Omeprazole	Dacarbazine	Telangiectases	
4	Tolcapone	Pyrimethamine	Breast disorder	Bicker *et al.* 2017
5	Minoxidil	Paricalcitol	Cluster headache	
6	Omeprazole	Amoxicillin	Renal tubular acidosis	Russo *et al.* 2016
7	Anagrelide	Azelaic acid	Cerebral thrombosis	
8	Atorvastatin	Amlodipine	Muscle inflammation	Banakh *et al.* 2017
9	Aliskiren	Tioconazole	Breast inflammation	Parving *et al.* 2012
10	Estradiol	Nadolol	Endometriosis	

Case Report

Severe Rhabdomyolysis due to Presumed Drug Interactions between Atorvastatin with Amlodipine and Ticagrelor

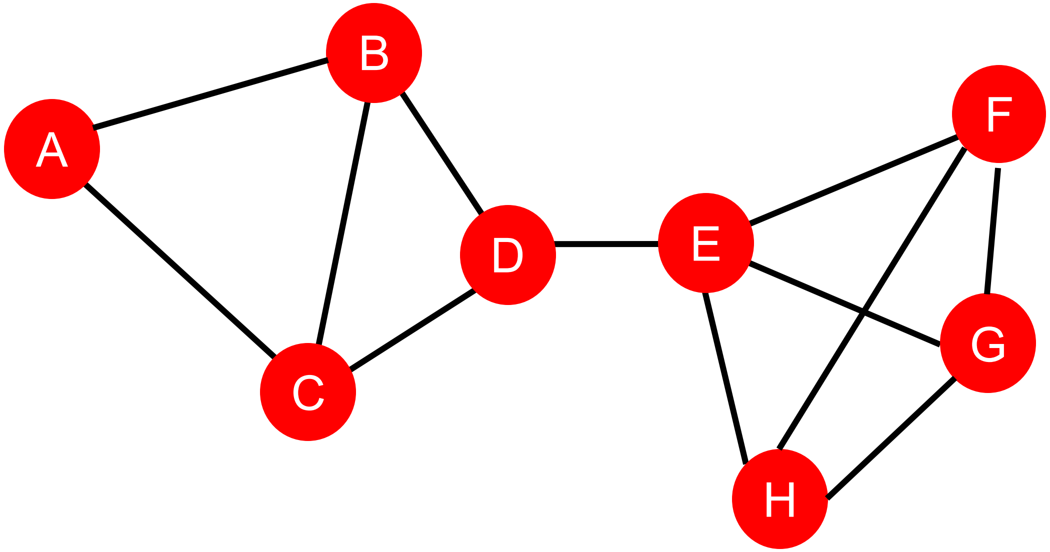
Stanford CS224W: Graph-Level Tasks

CS224W: Machine Learning with Graphs
Jure Leskovec, Stanford University
http://cs224w.stanford.edu

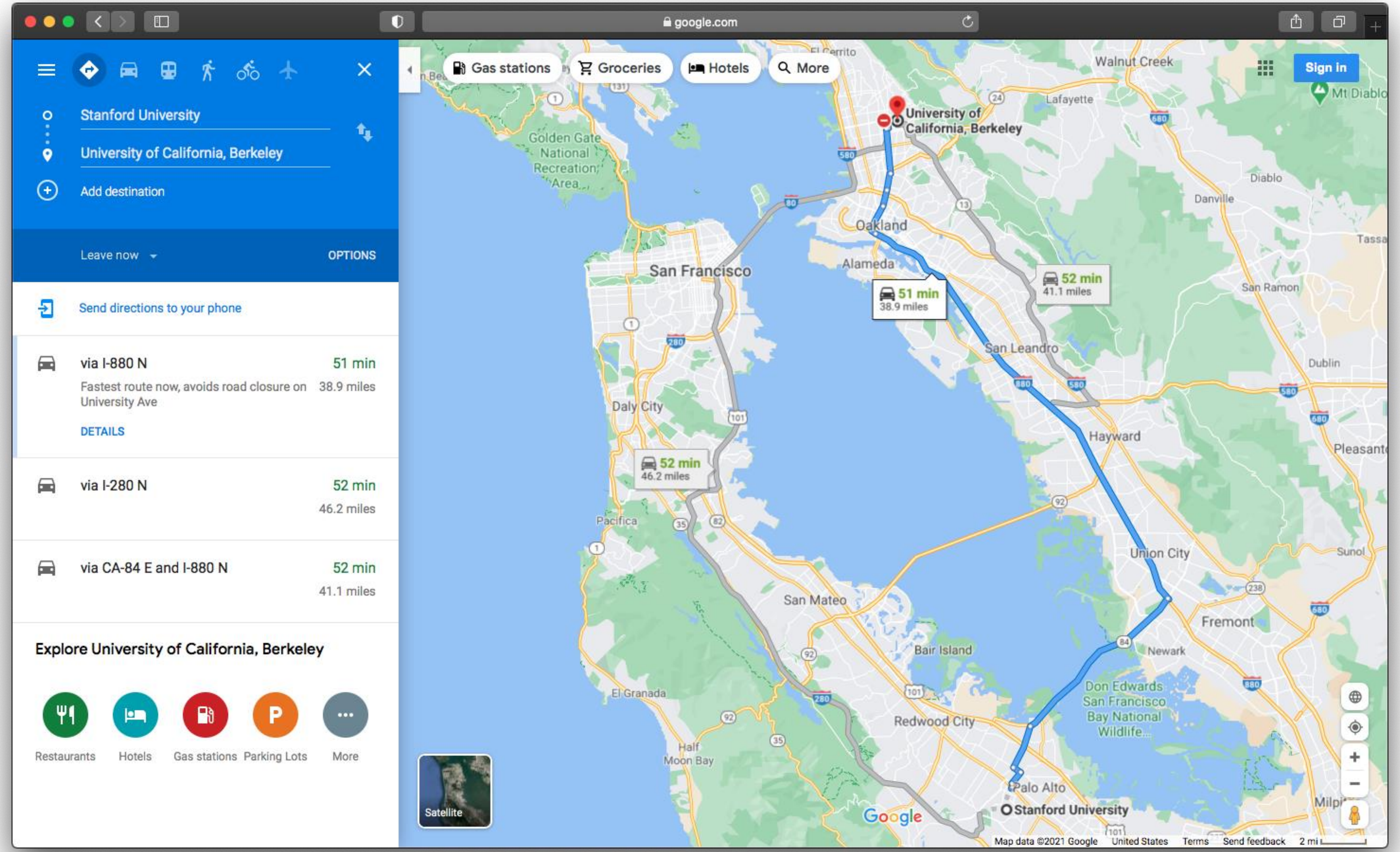
Graph-Level Prediction

- **Goal:** We want make a prediction for an entire graph or a subgraph of the graph.

- **For example:**



Example (1): Traffic Prediction



Road Network as a Graph

- **Nodes:** Road segments
- **Edges:** Connectivity between road segments
- **Prediction:** Time of Arrival (ETA)

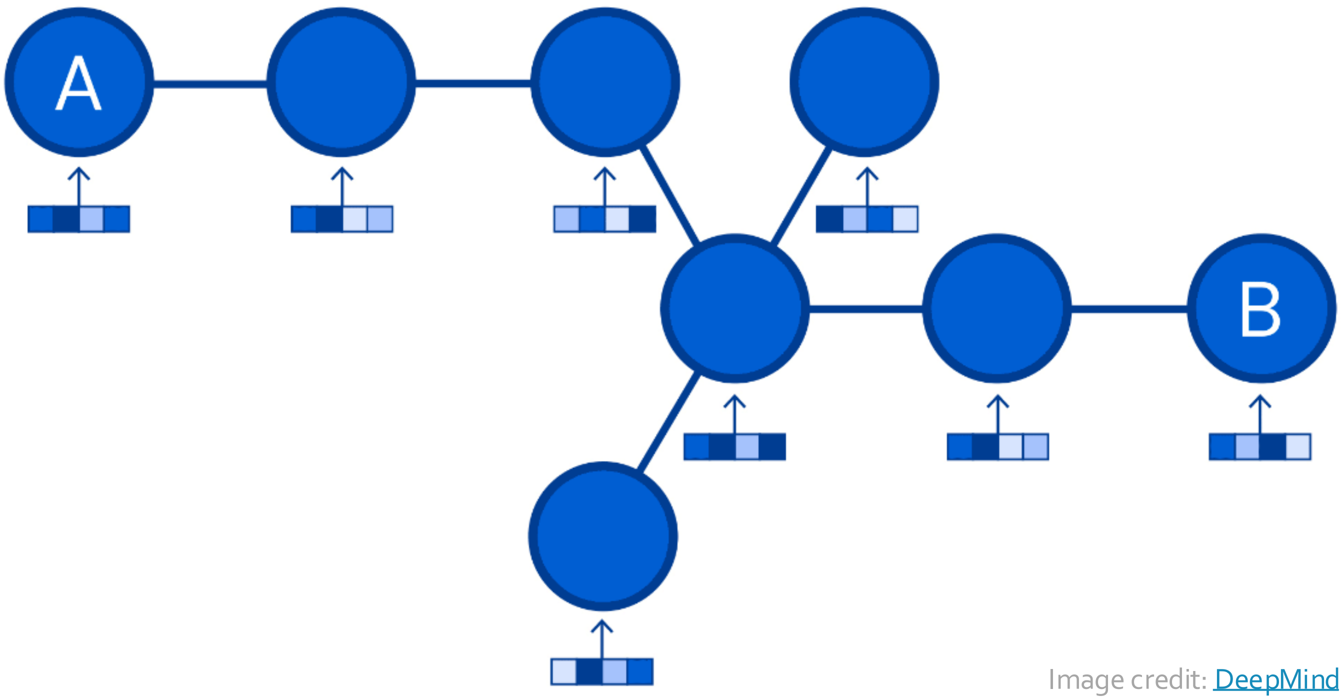
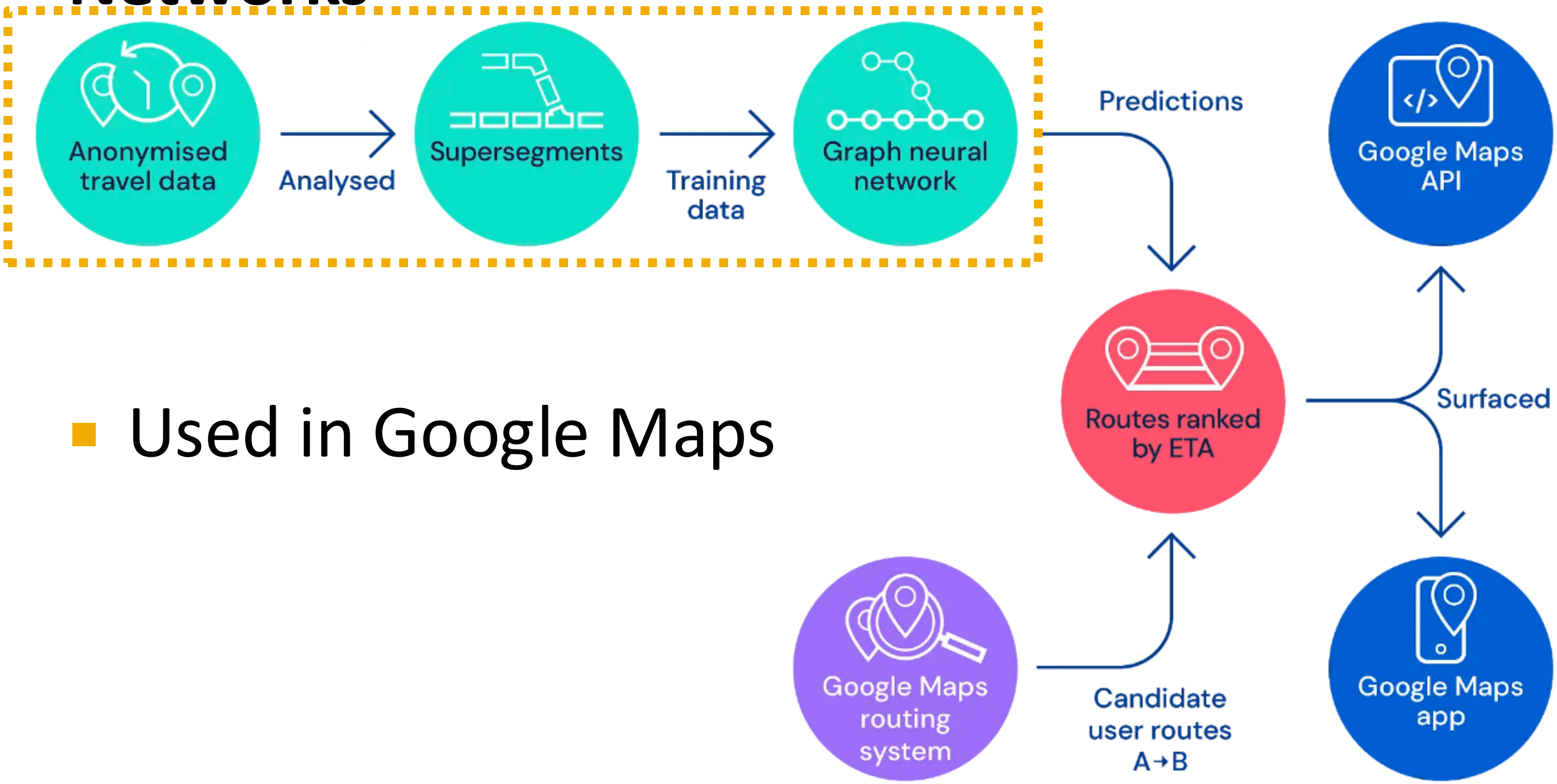


Image credit: DeepMind

Traffic Prediction via GNN

Predicting Time of Arrival with Graph Neural Networks



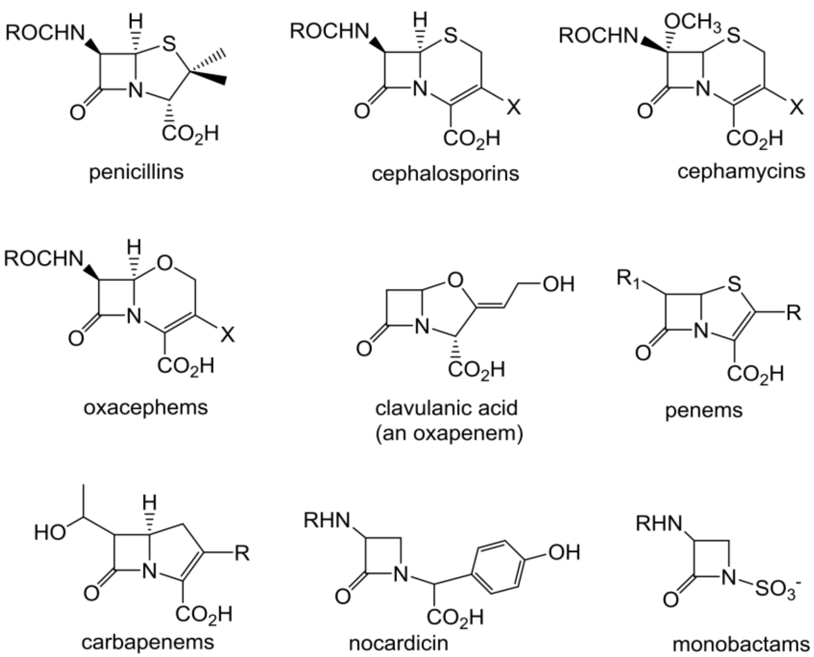
- Used in Google Maps

THE MODEL ARCHITECTURE FOR DETERMINING OPTIMAL ROUTES AND THEIR TRAVEL TIME.

Image credit: [DeepMind]

Example (2): Drug Discovery

- **Antibiotics are small molecular graphs**
  - **Nodes:** Atoms
  - **Edges:** Chemical bonds



Konaklieva, Monika I. "Molecular targets of β-lactam-based antimicrobials: beyond the usual suspects." Antibiotics 3.2 (2014): 128-142.

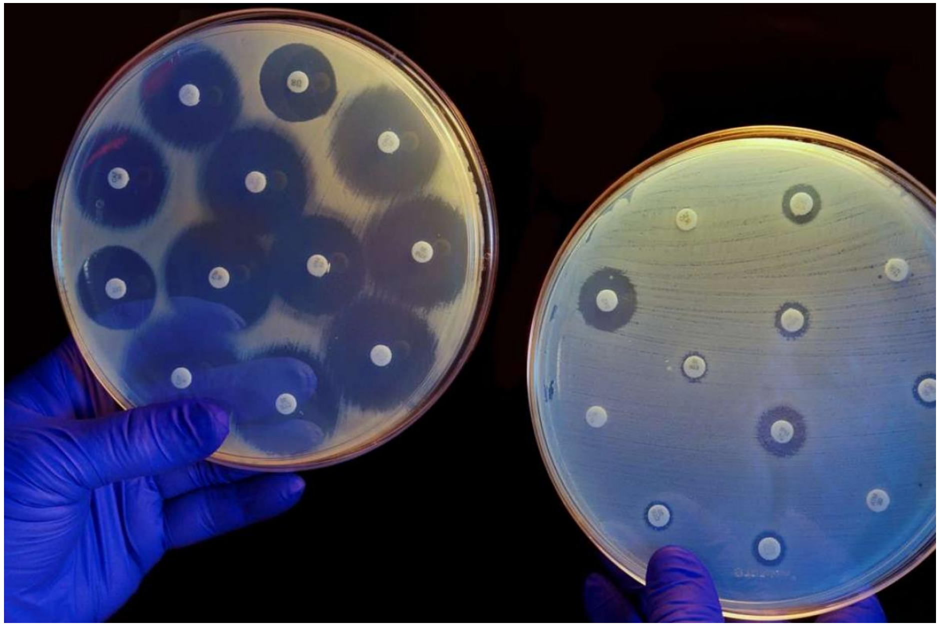
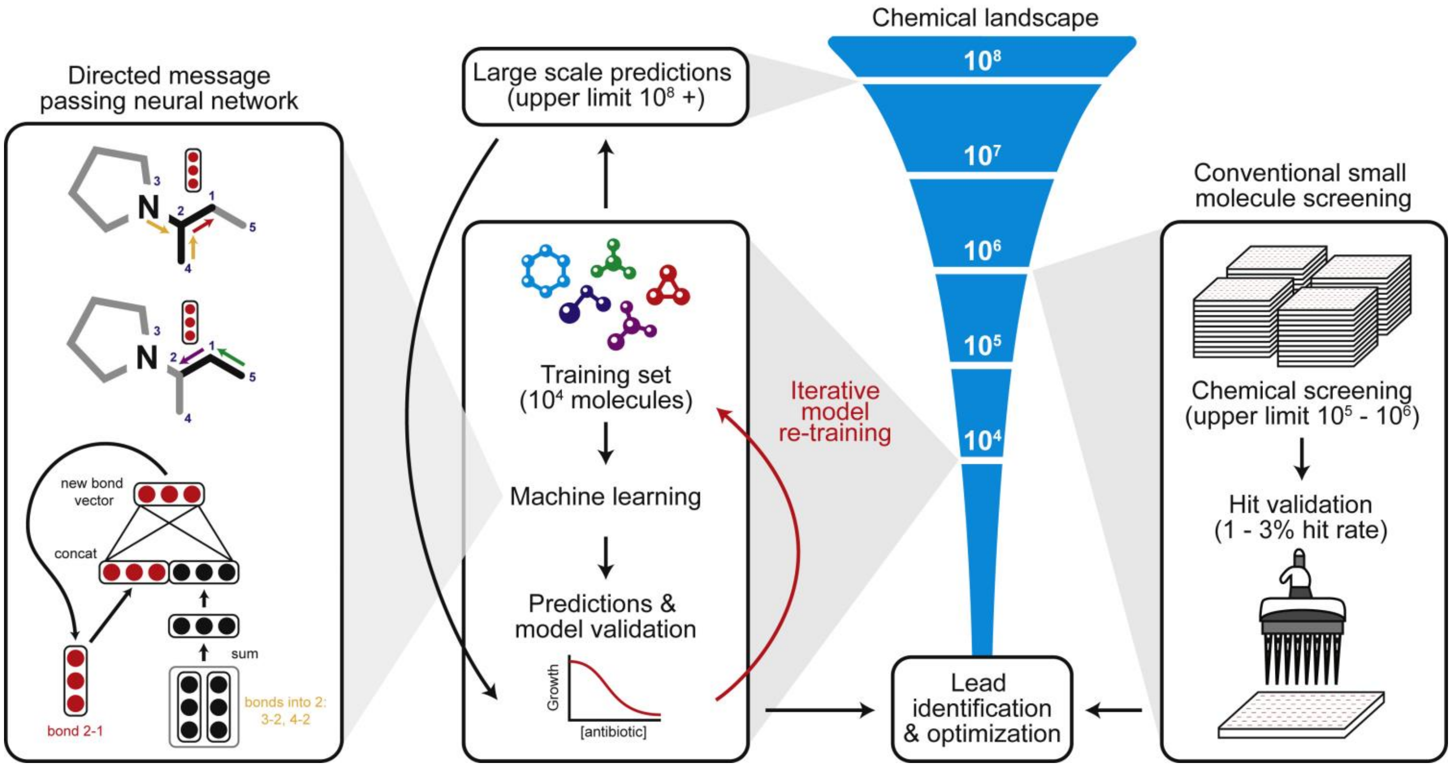


Image credit: [CNN]

Deep Learning for Antibiotic Discovery

- A Graph Neural Network **graph classification model**
- Predict promising molecules from a pool of candidates



Stokes, Jonathan M., et al. "A deep learning approach to antibiotic discovery." Cell 180.4 (2020): 688-702.

Sanchez-Gonzalez et al., Learning to simulate complex physics with graph networks, ICML 2020

Example (3): Physics Simulation

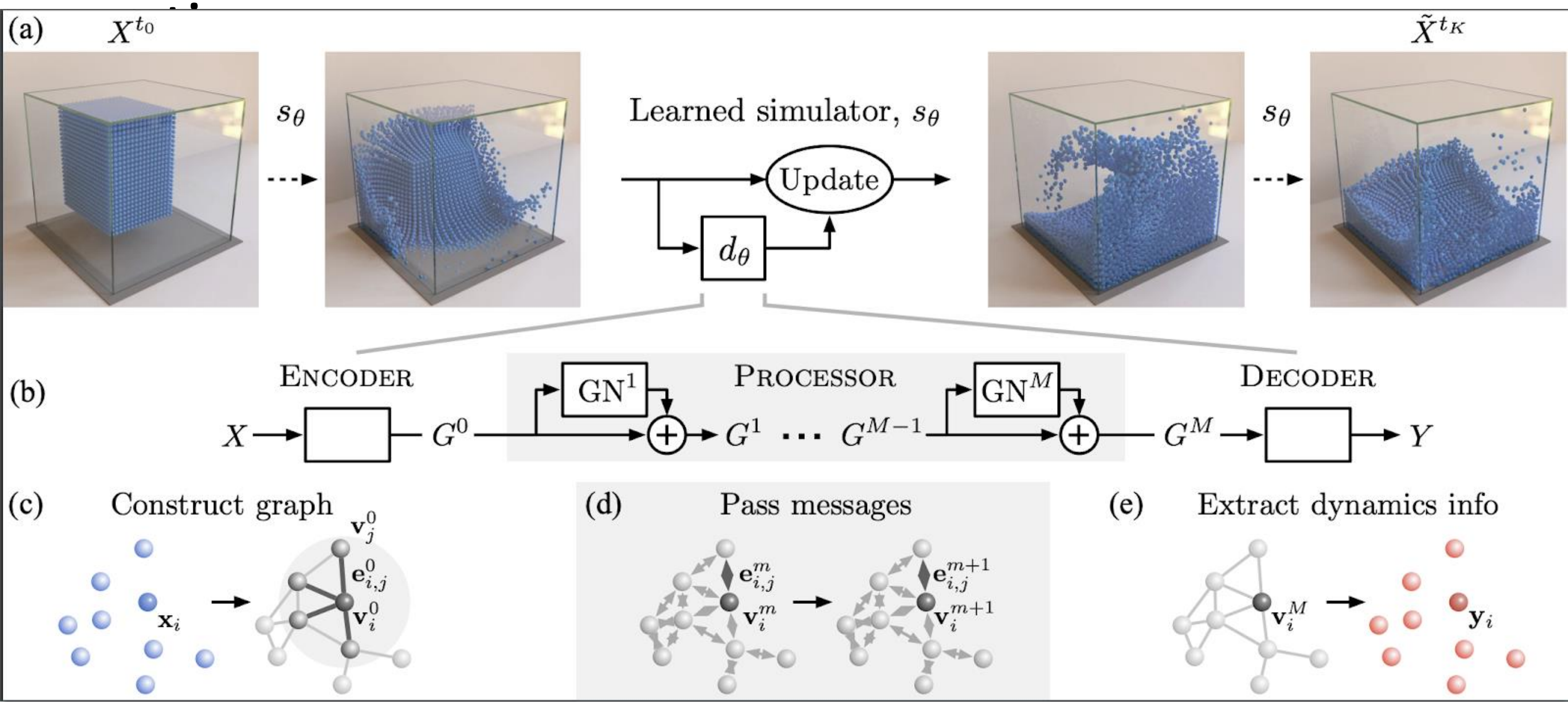
Physical simulation as a graph:

- **Nodes**: Particles
- **Edges**: Interaction between particles

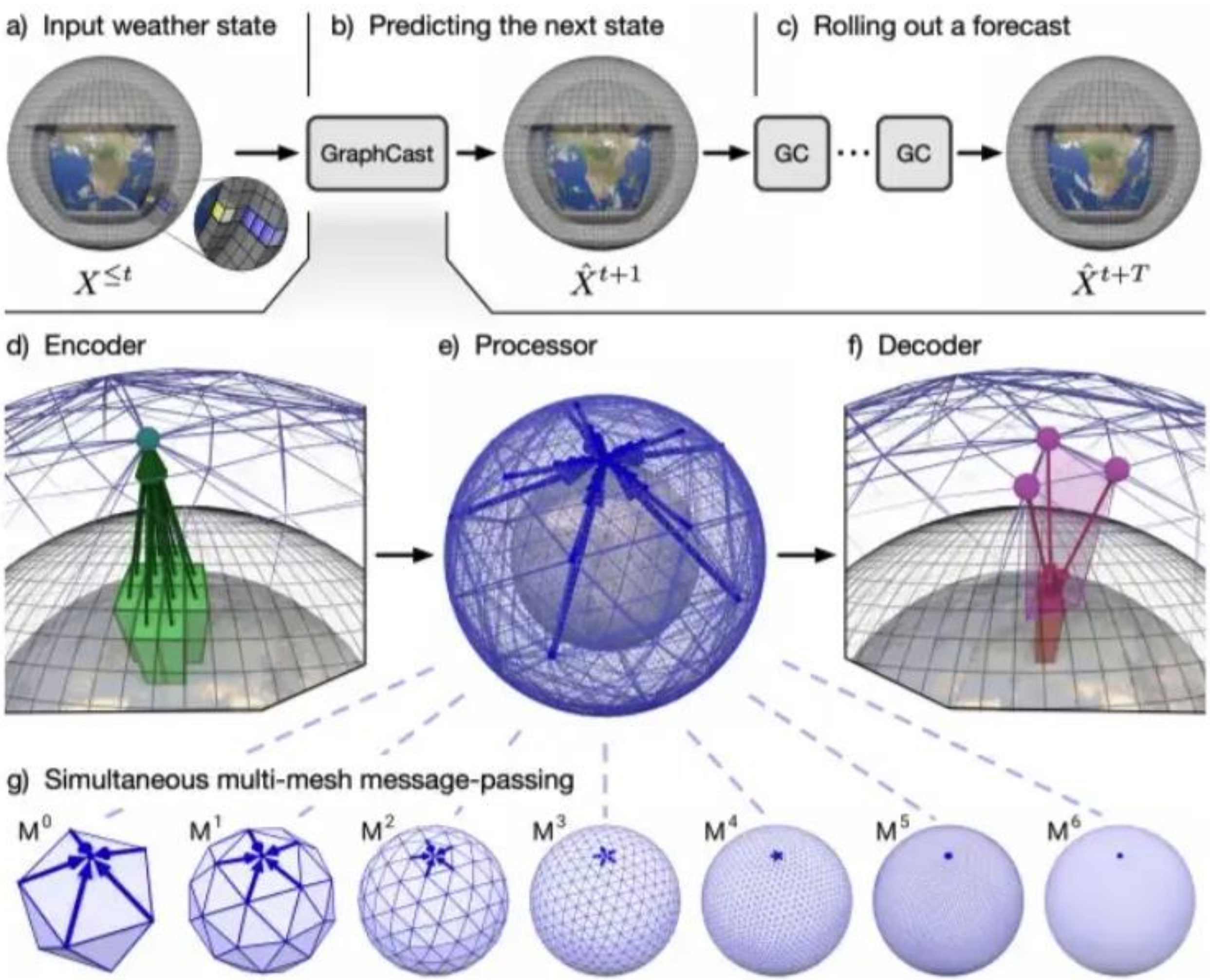
Simulation Learning Framework

A graph evolution task:

- **Goal**: Predict how a graph will evolve over



Application: Weather forecasting



https://medium.com/syncedreview/deepmind-googles-ml-based-graphcast-outperforms-the-world-s-best-medium-range-weather-9d114460aa0c

Summary

ML in the language of graphs:

- Node-level:
  - Churn
  - Life-time value
  - Next best action
- Link-level:
  - Product affinity
  - Recommendations
- Graph-level:
  - Fraud, money laundering