

# Stanford CS224W: Machine Learning with Graphs

CS224W: Machine Learning with Graphs

Jure Leskovec, Stanford University

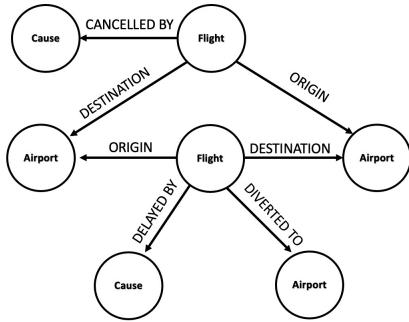
<http://cs224w.stanford.edu>



# Why Graphs?

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

# Many Types of Data are Graphs (1)

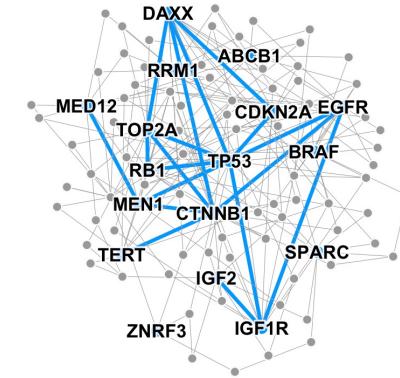


## Event Graphs



Image credit: [SalientNetworks](#)

## Computer Networks



## Disease Pathways

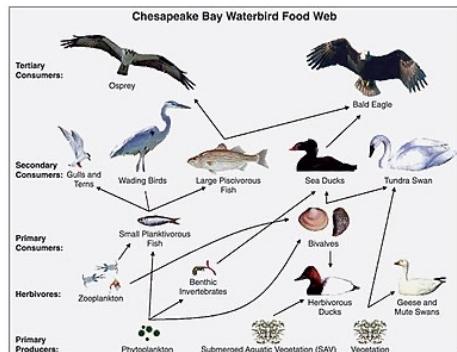


Image credit: [Wikipedia](#)

## Food Webs

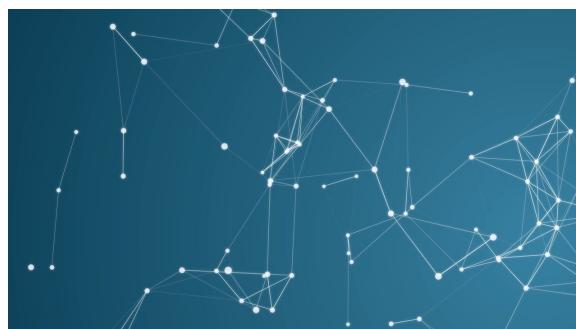


Image credit: [Pinterest](#)

## Particle Networks



Image credit: [visitlondon.com](#)

## Underground Networks

# Many Types of Data are Graphs (2)



Image credit: [Medium](#)

## Social Networks

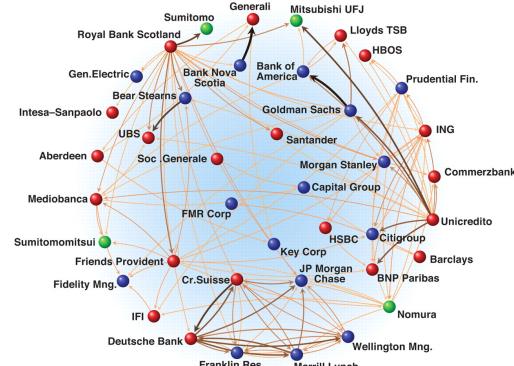


Image credit: [Science](#)

## Economic Networks

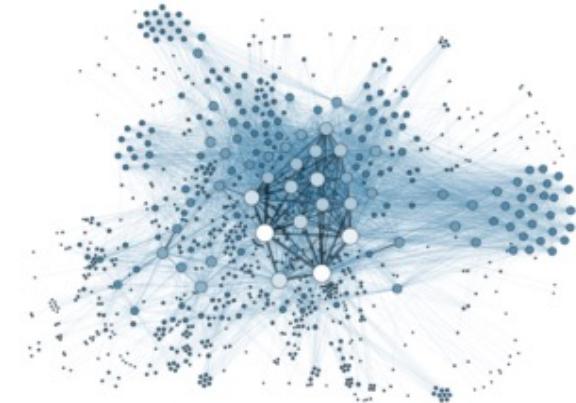


Image credit: [Lumen Learning](#)

## Communication Networks

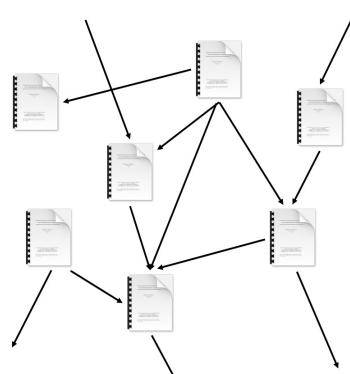


Image credit: [Missoula Current News](#)

## Citation Networks

## Internet

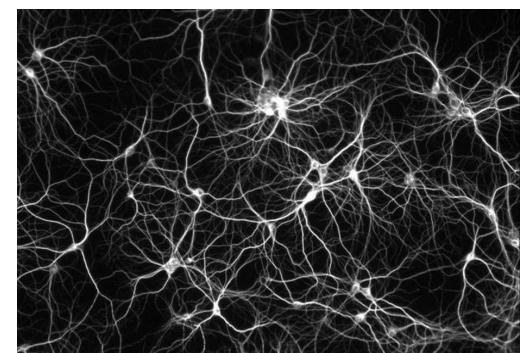


Image credit: [The Conversation](#)

## Networks of Neurons

# Many Types of Data are Graphs (3)

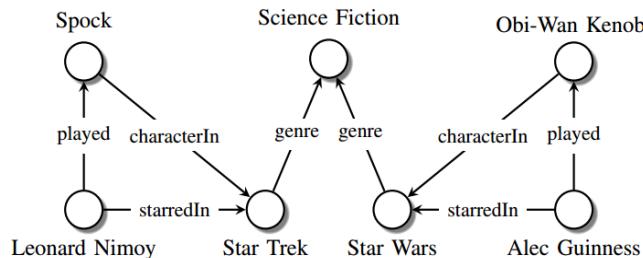


Image credit: [Maximilian Nickel et al.](#)

# Knowledge Graphs

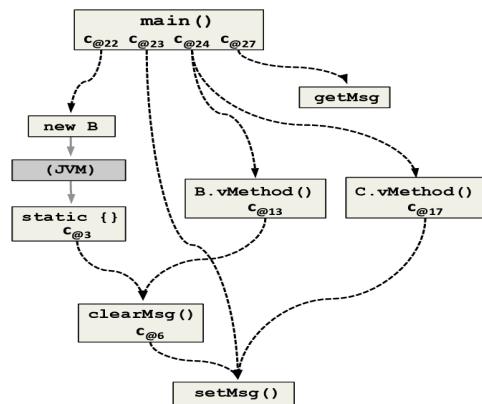


Image credit: [ResearchGate](#)

# Code Graphs

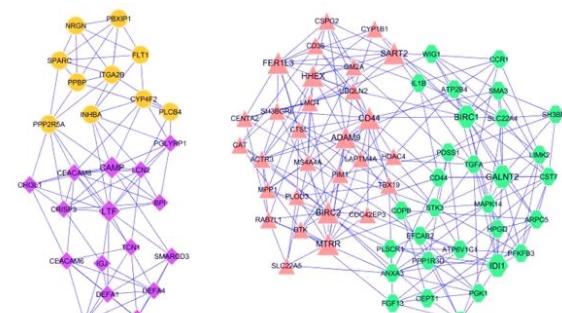


Image credit: [ese.wustl.edu](http://ese.wustl.edu)

# Regulatory Networks

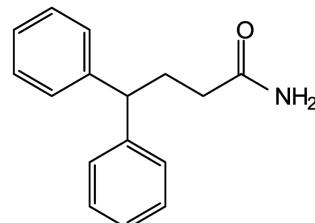


Image credit: [MDPI](#)

## Molecules

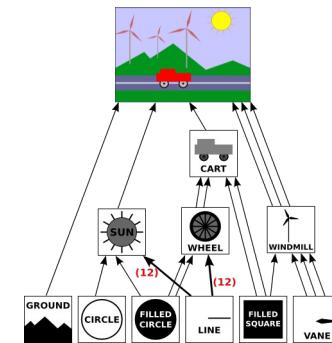


Image credit: [math.hws.edu](http://math.hws.edu)

# Scene Graphs

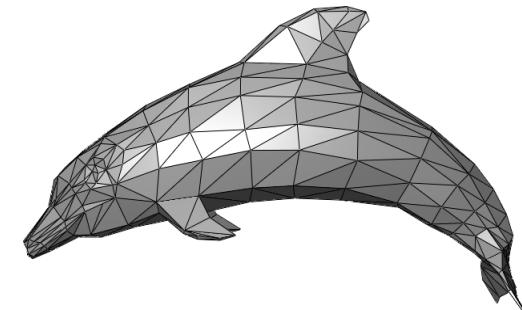
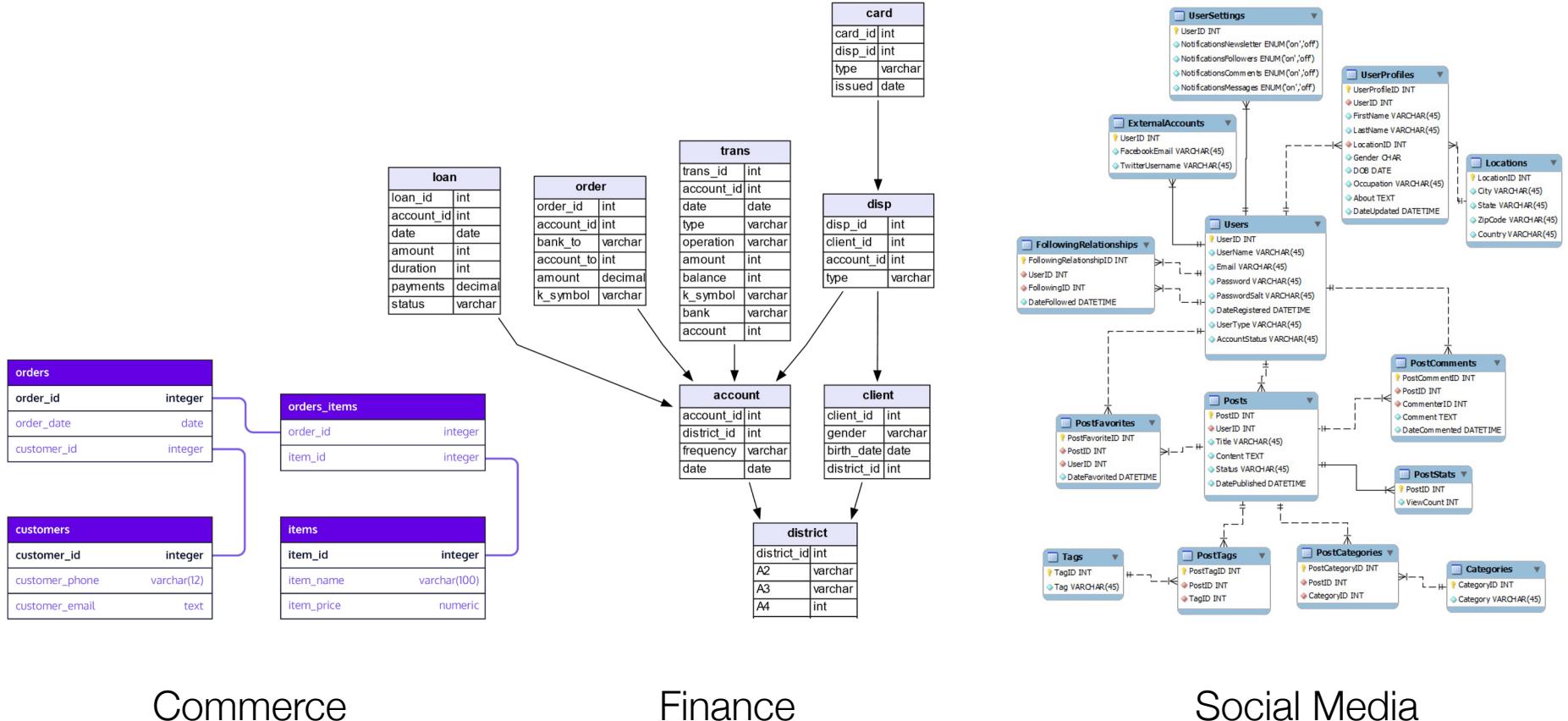


Image credit: [Wikipedia](#)

## 3D Shapes

# Databases are Graphs!

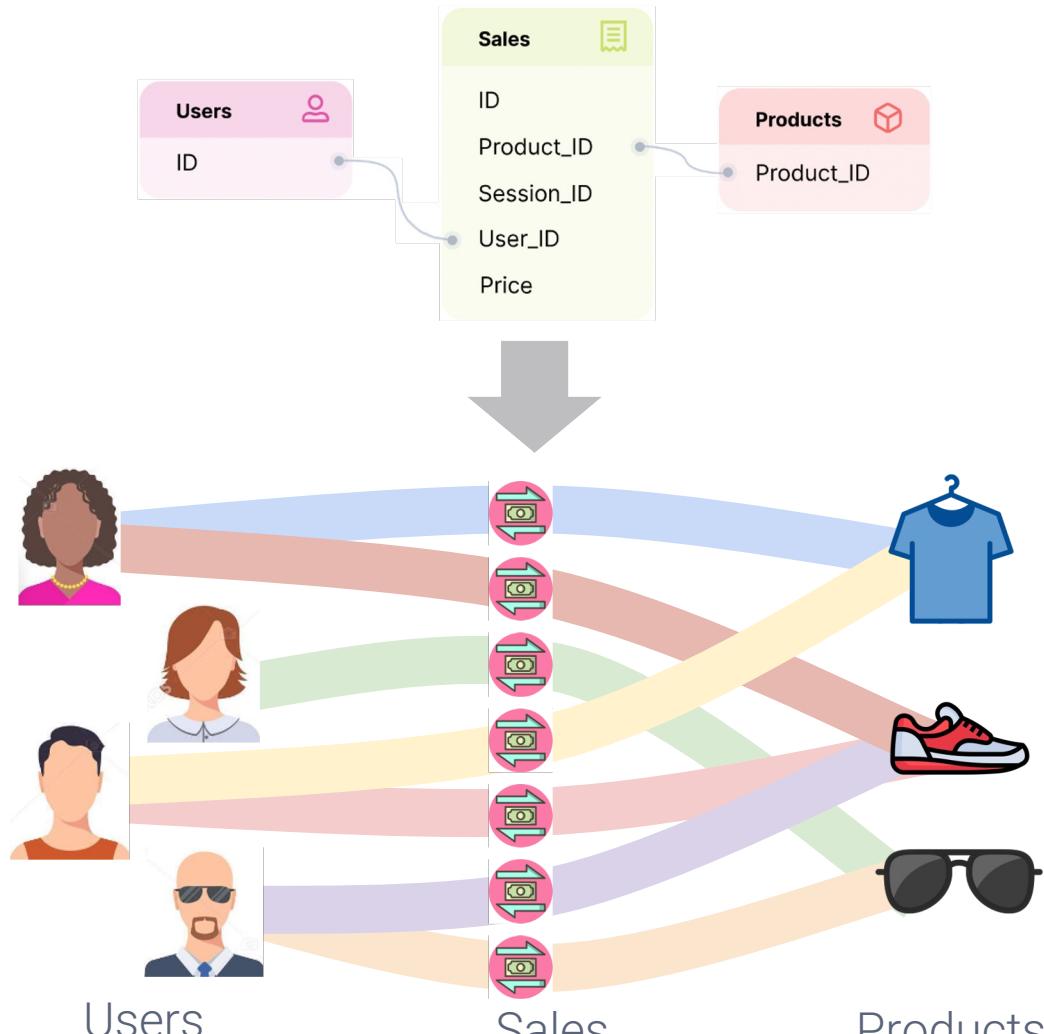


Commerce

Finance

Social Media

# Relational Deep Learning



<http://relbench.stanford.edu>

# Graphs: Machine Learning

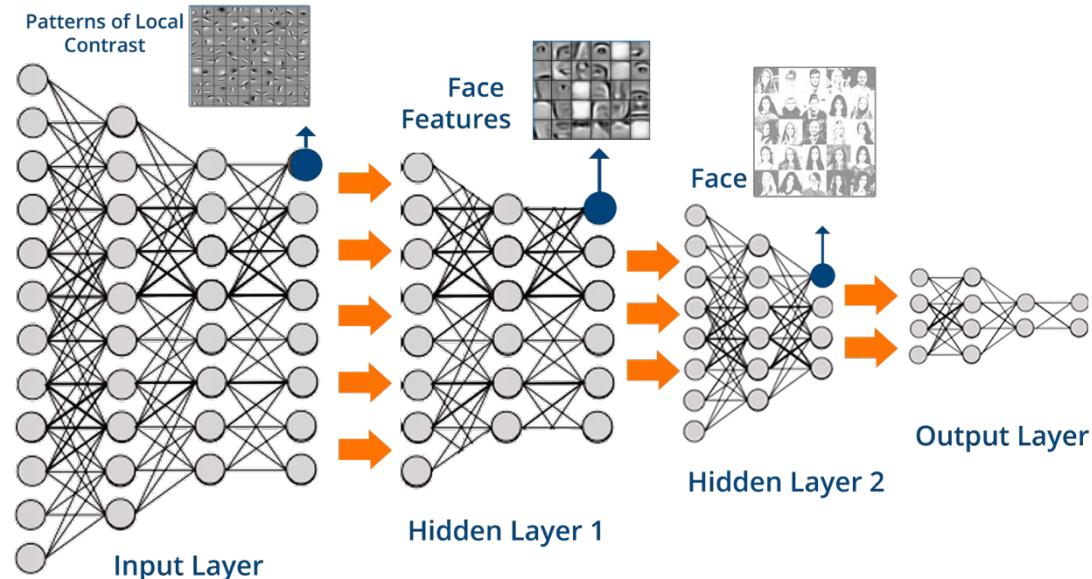
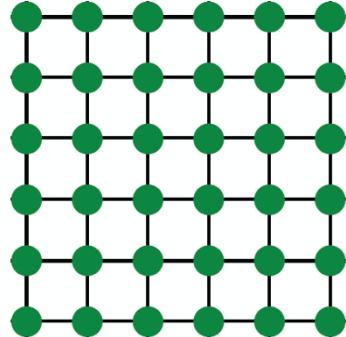
Complex domains have a rich relational structure, which can be represented as a **relational graph**

**By explicitly modeling relationships we achieve better performance!**

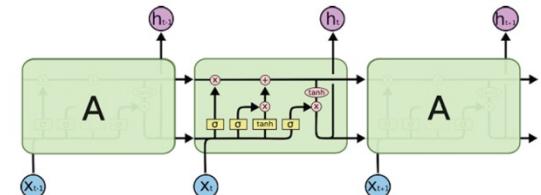
Main question:

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

# Today: Modern ML Toolbox



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



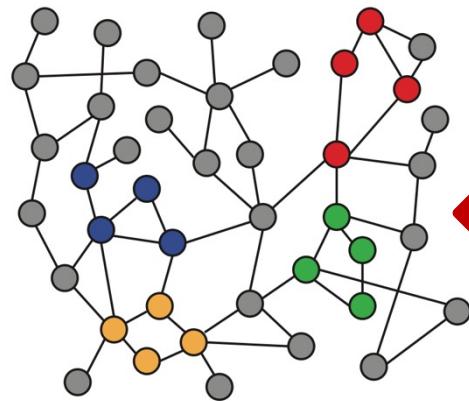
Images

Modern  
deep learning toolbox  
is designed for  
sequences & grids

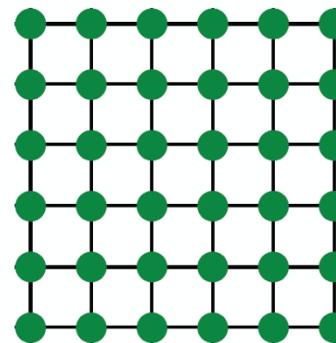
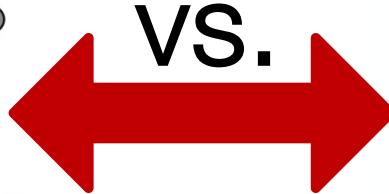
# Why is Graph Deep Learning Hard?

## Networks are complex.

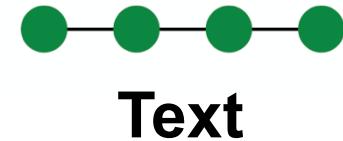
- Arbitrary size and complex topological structure (*i.e.*, no spatial locality like grids)



Networks



Images



Text

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

# This Course: CS224W

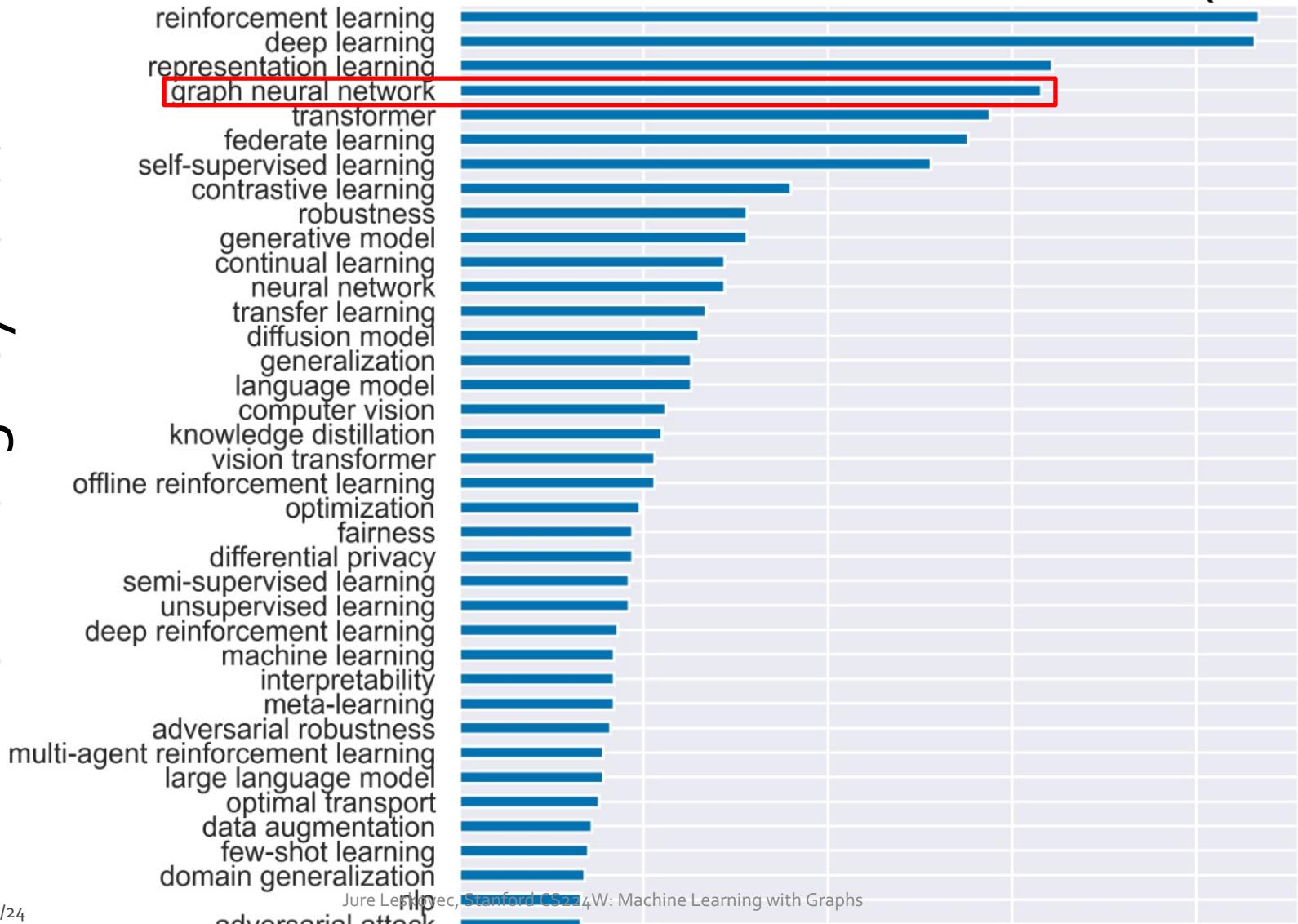
How can we develop neural networks  
that are much more broadly  
applicable?

Graphs are the new frontier  
of deep learning

# Hot subfield in ML

ICLR 2023 keywords

50 MOST APPEARED KEYWORDS (2023)



# Stanford CS224W: Choice of Graph Representation

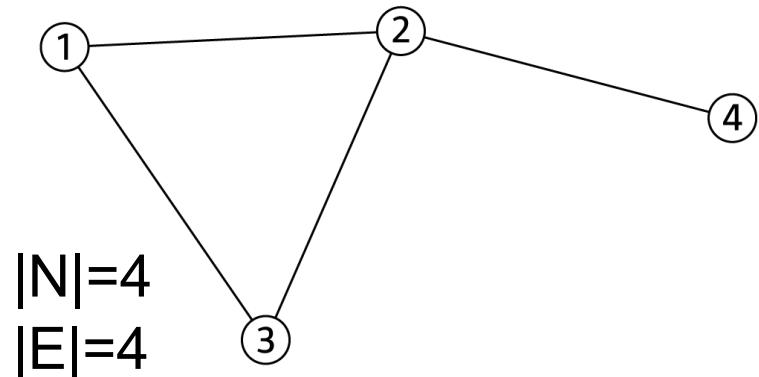
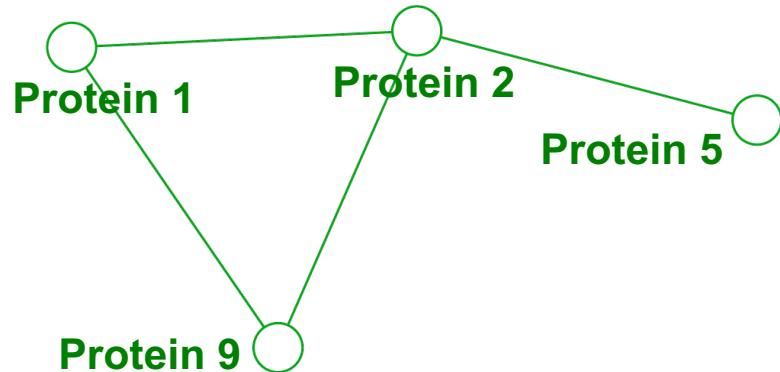
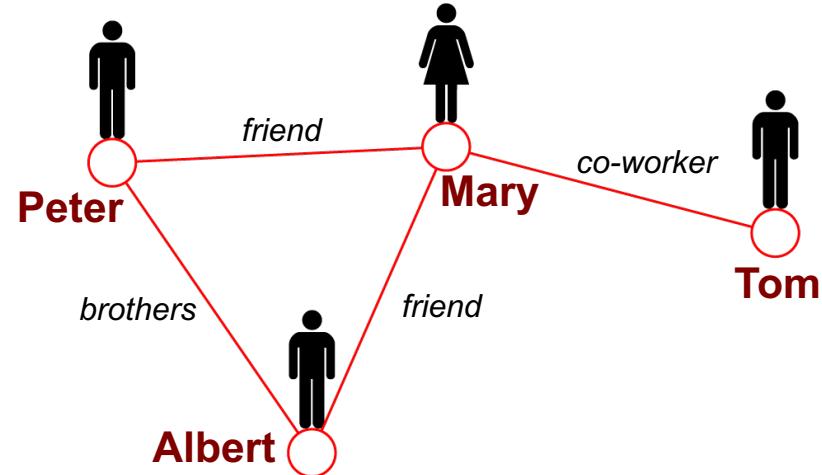
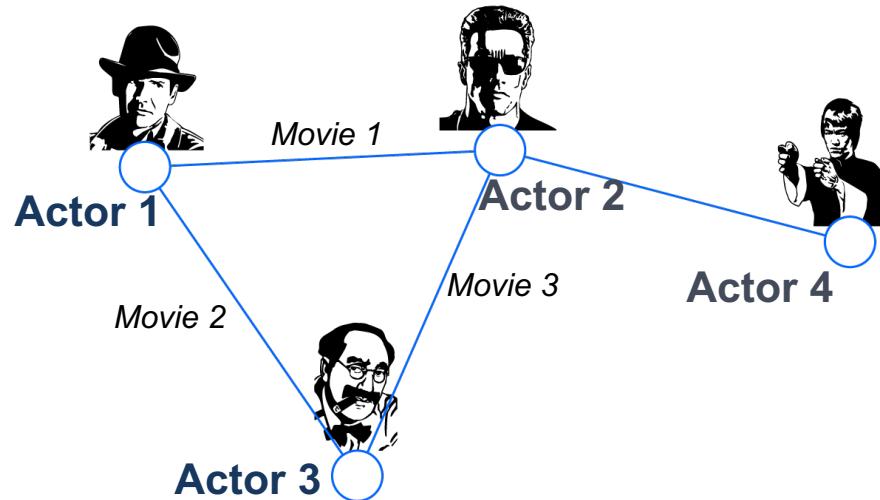
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# Graphs: A Common Language



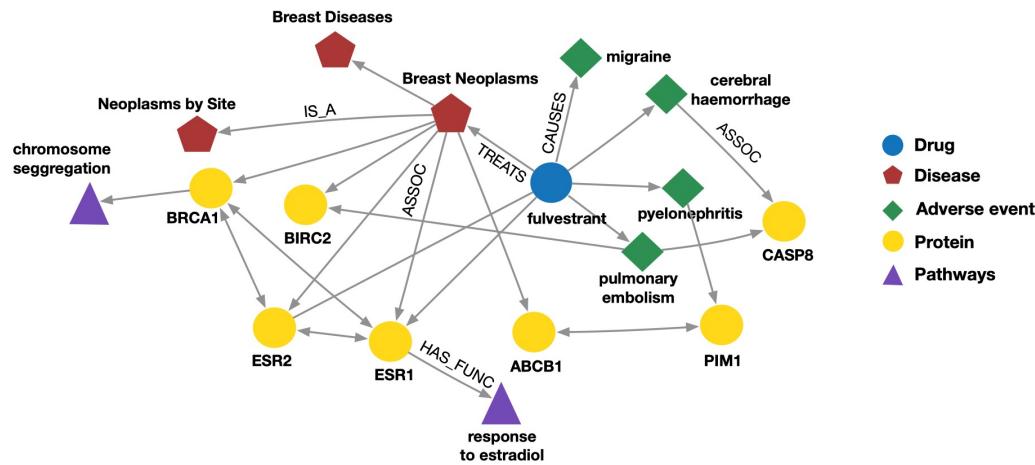
# Heterogeneous Graphs

- A heterogeneous graph is defined as

$$G = (V, E, R, T)$$

- 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



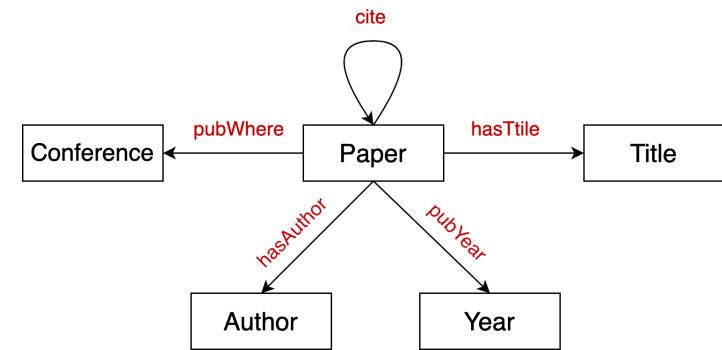
## Biomedical Knowledge Graphs

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

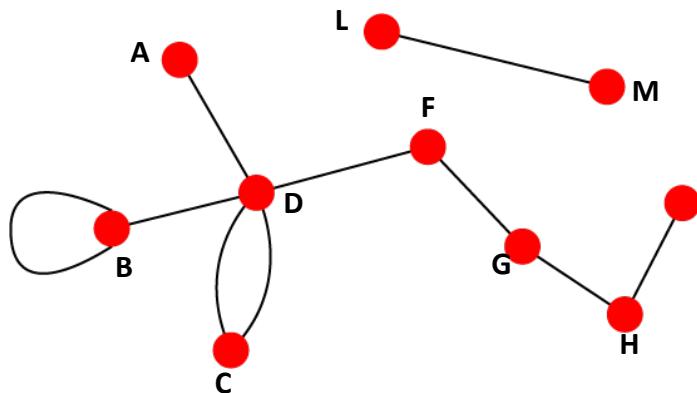
# Choosing a Proper Representation

- **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

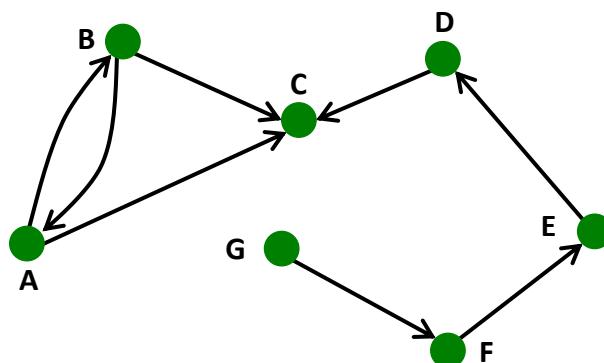
## Undirected

- Links: undirected  
(symmetrical, reciprocal)



## Directed

- Links: directed

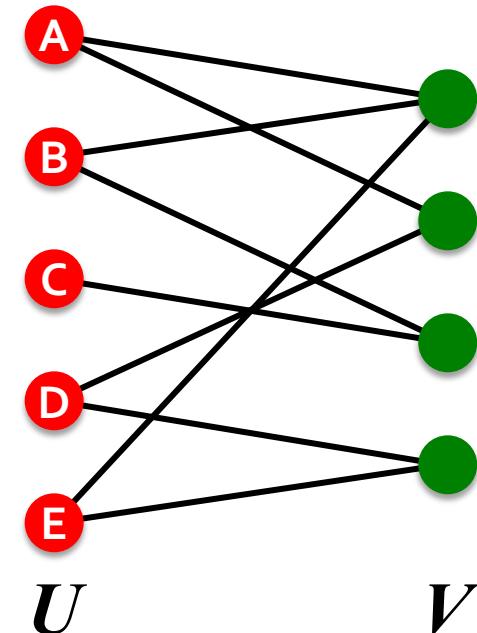


## ■ Other considerations:

- 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

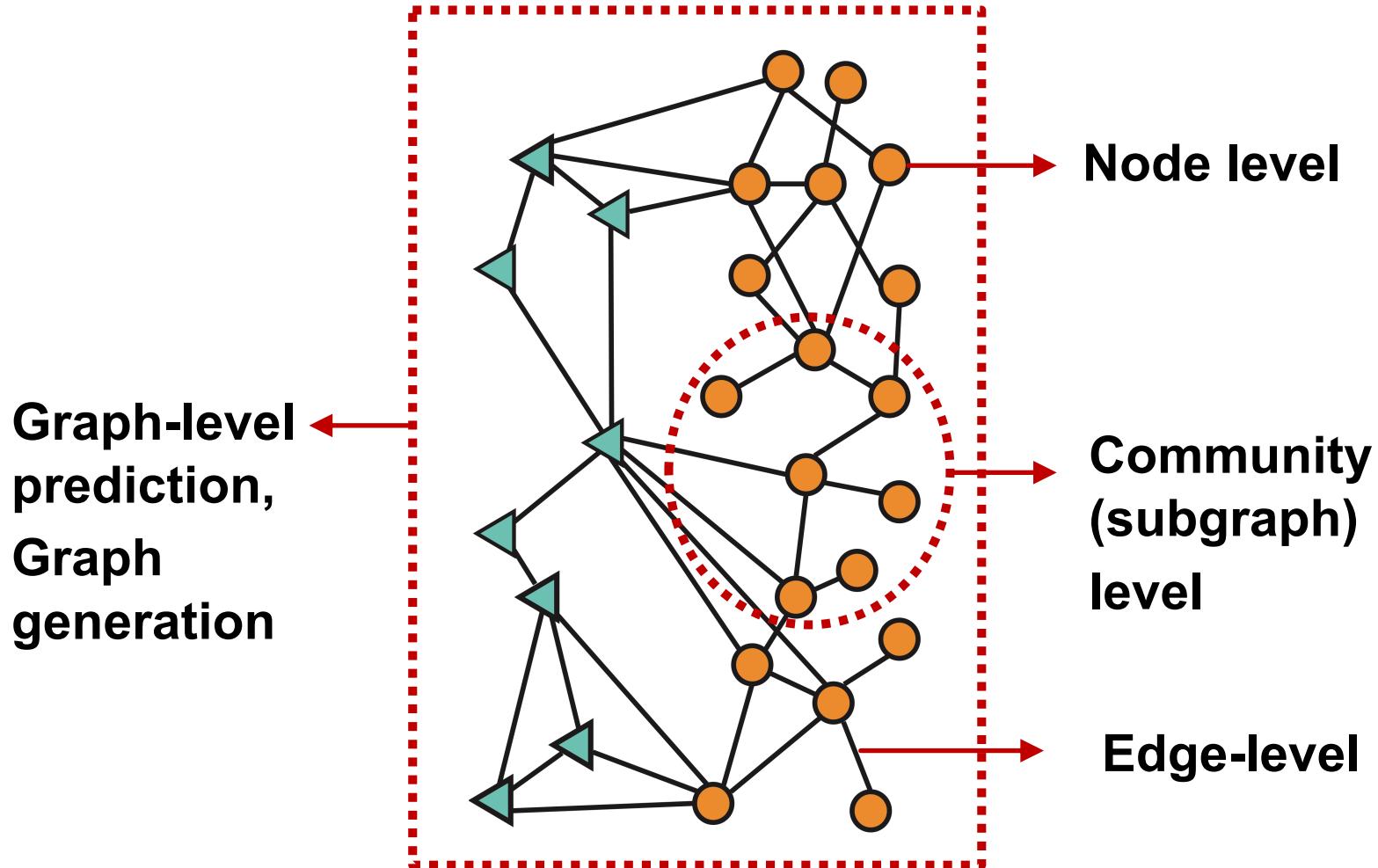
CS224W: Machine Learning with Graphs

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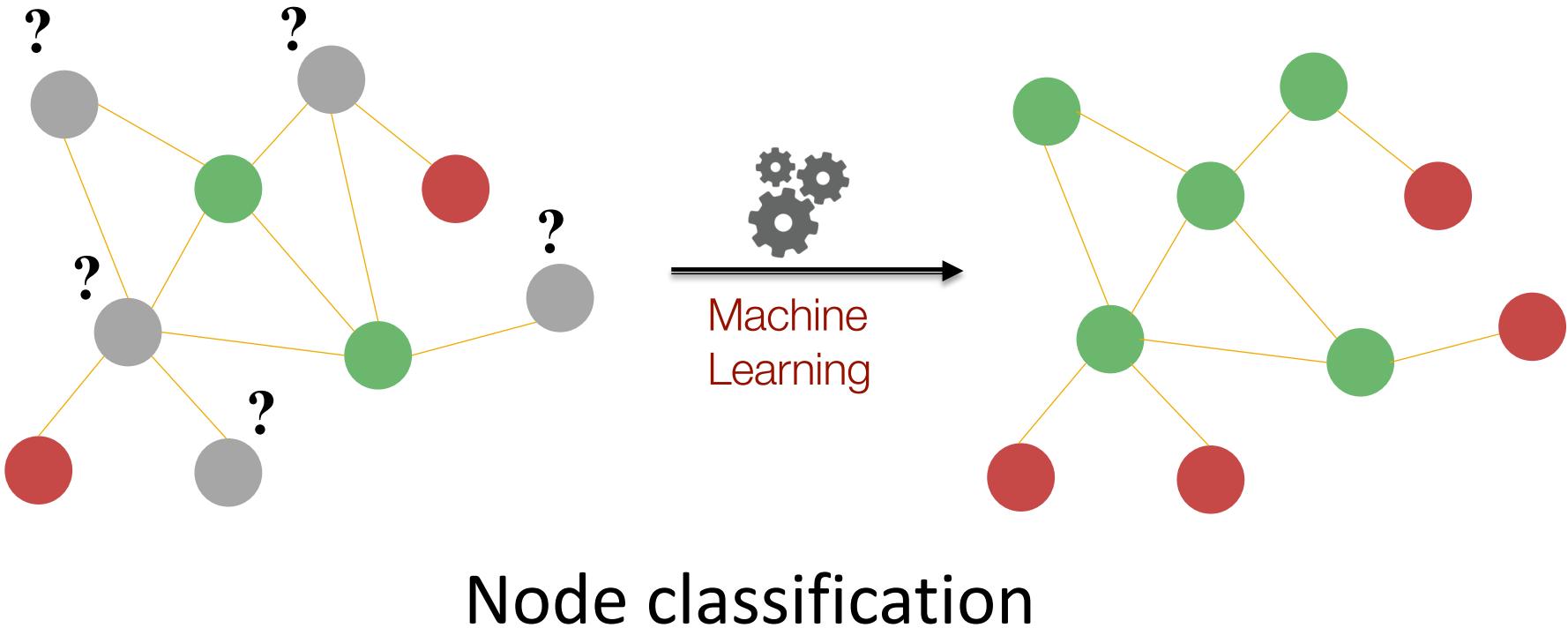
<http://cs224w.stanford.edu>



# Different Types of Tasks



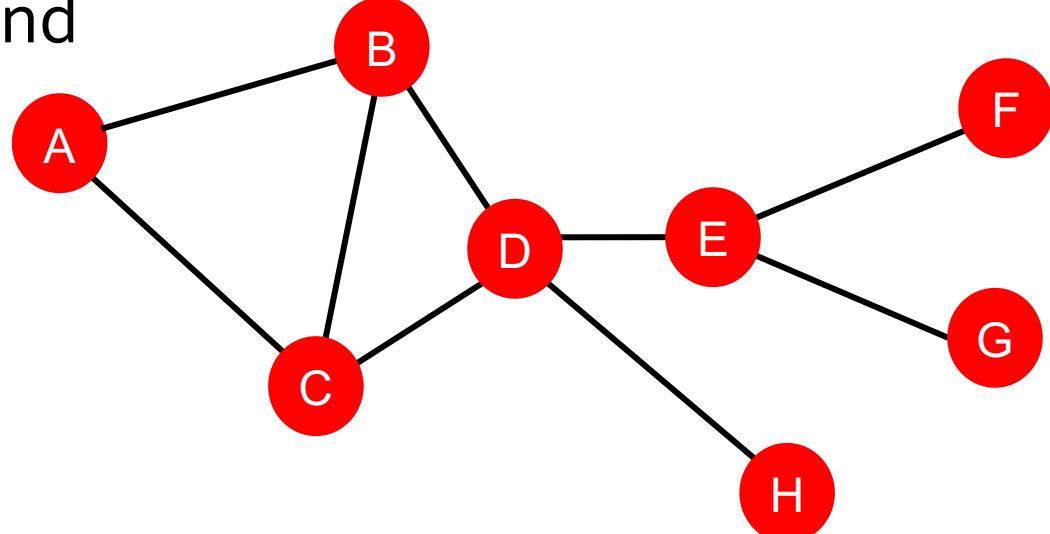
# Node-Level Tasks



# Node-Level Network Structure

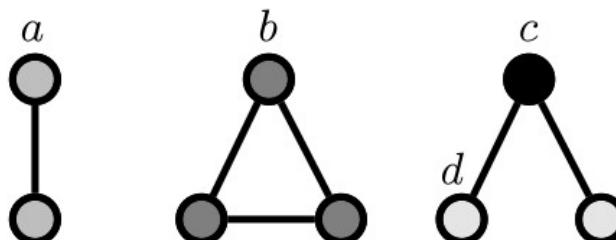
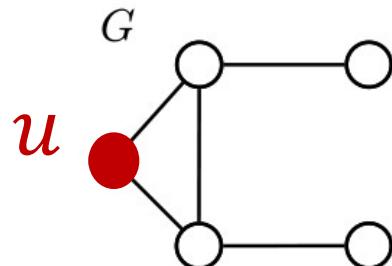
**Goal:** Characterize the structure and position of a node in the network:

- 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

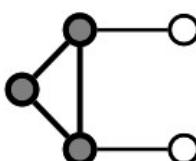
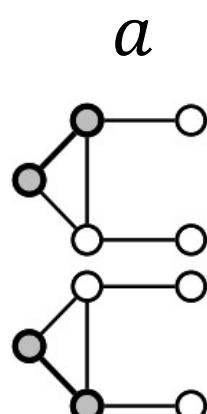


# Node's Subgraphs: Graphlets

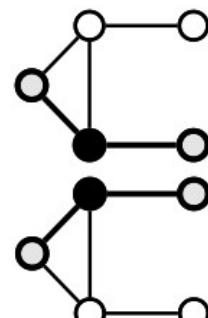
- **Graphlets:** A count vector of rooted subgraphs at a given node.
- **Example:** All possible graphlets on up to 3 nodes



Graphlet instances of node  $u$ :



$c$

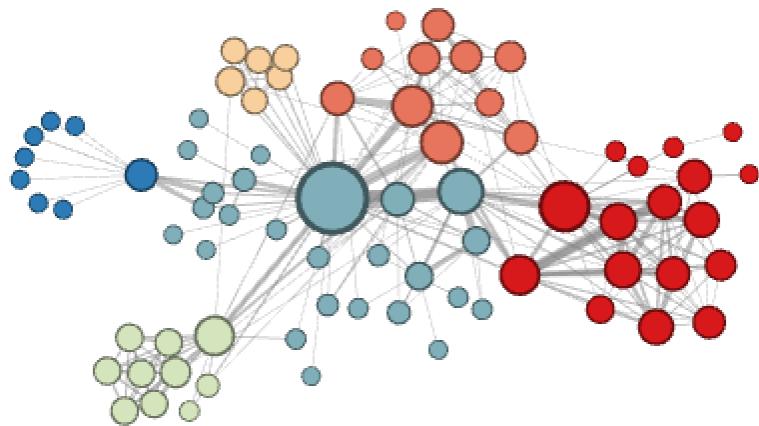
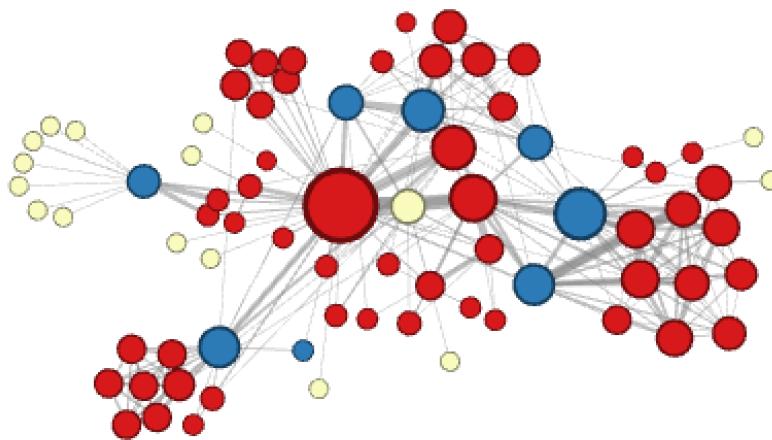


$d$

Graphlets of node  $u$ :  
 $a, b, c, d$   
[2,1,0,2]

# Discussion

Different ways to label nodes of the network:

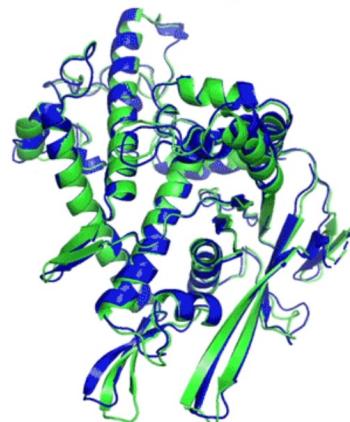


Node features defined so far would allow to distinguish nodes in the above example

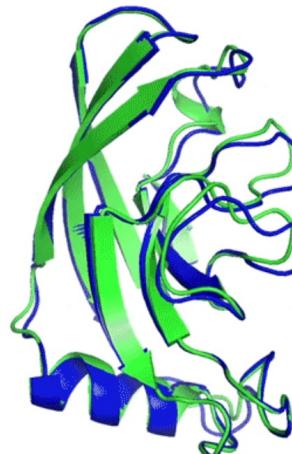
However, the features defines so far would not allow for distinguishing the above node labelling

# Example (1): Protein Folding

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



T1037 / 6vr4  
90.7 GDT  
(RNA polymerase domain)

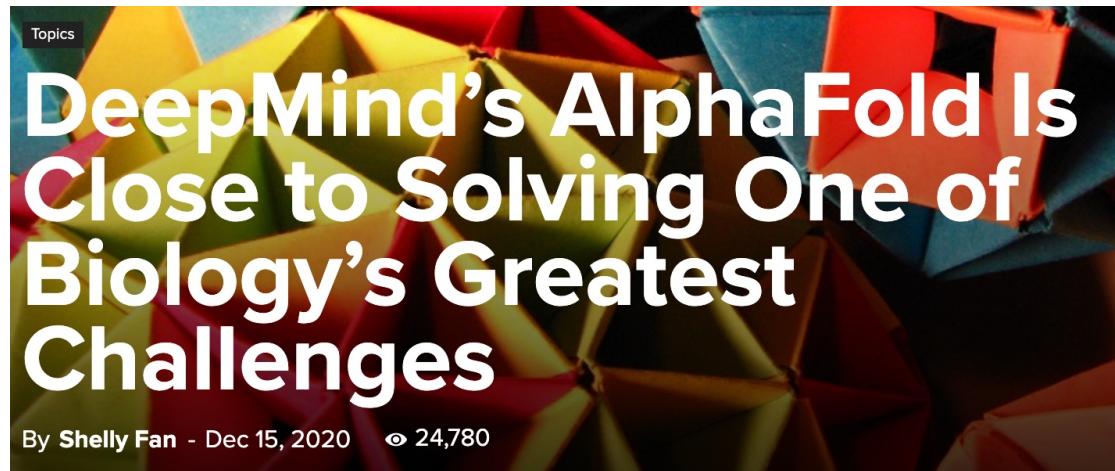
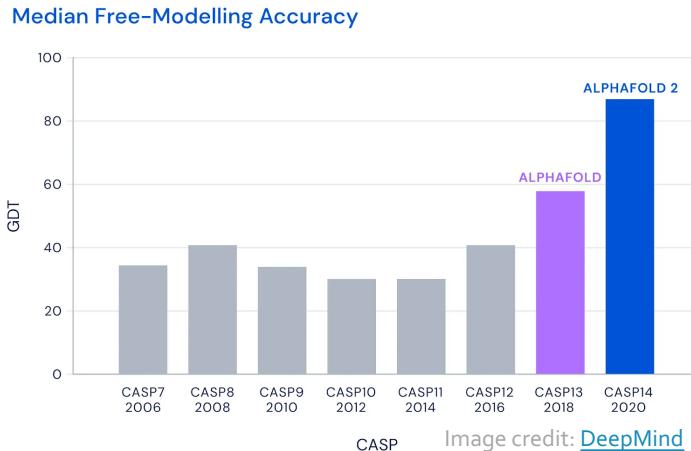


T1049 / 6y4f  
93.3 GDT  
(adhesin tip)

- Experimental result
- Computational prediction

Image credit: [DeepMind](#)

# AlphaFold: Impact



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

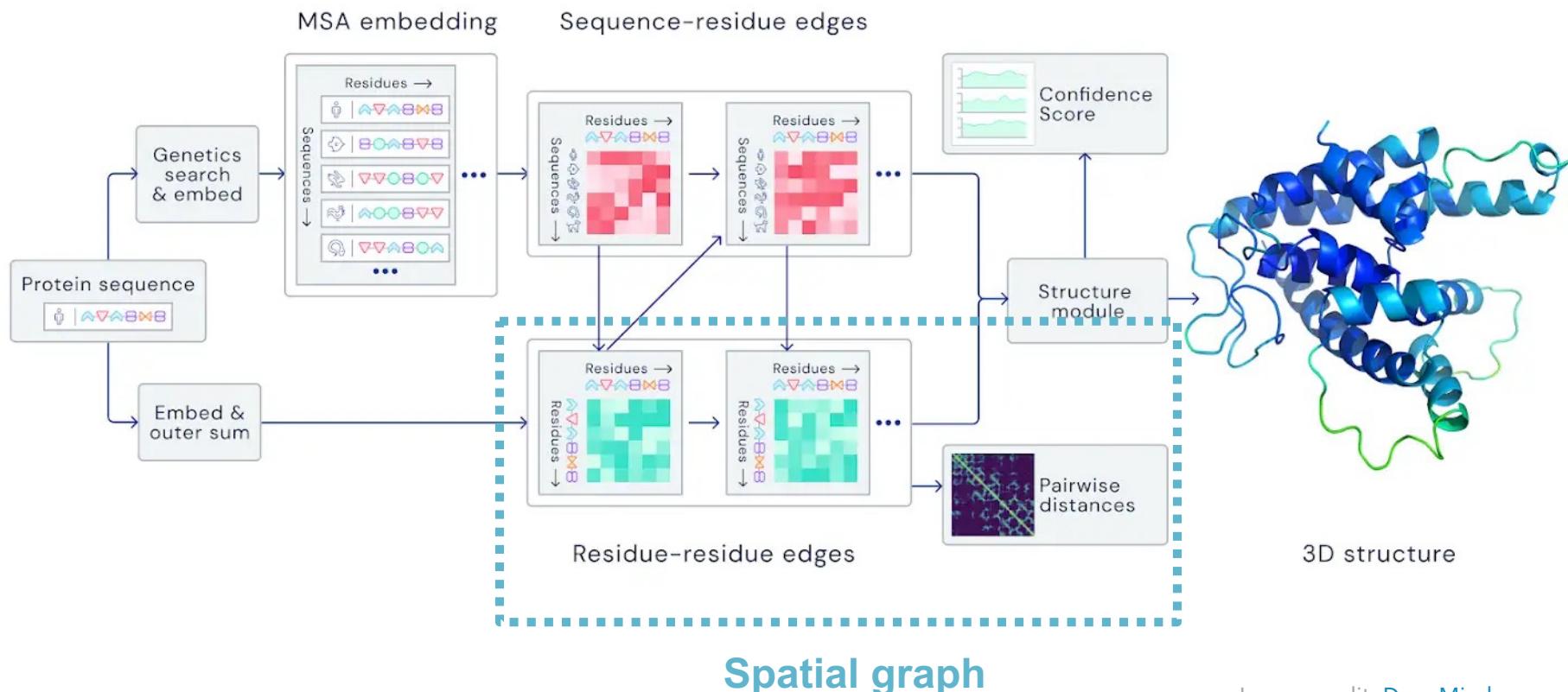
**DeepMind's latest AI breakthrough can accurately predict the way proteins fold**

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

12-14-20  
**DeepMind's latest AI breakthrough could turbocharge drug discovery**

# AlphaFold: Solving Protein Folding

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



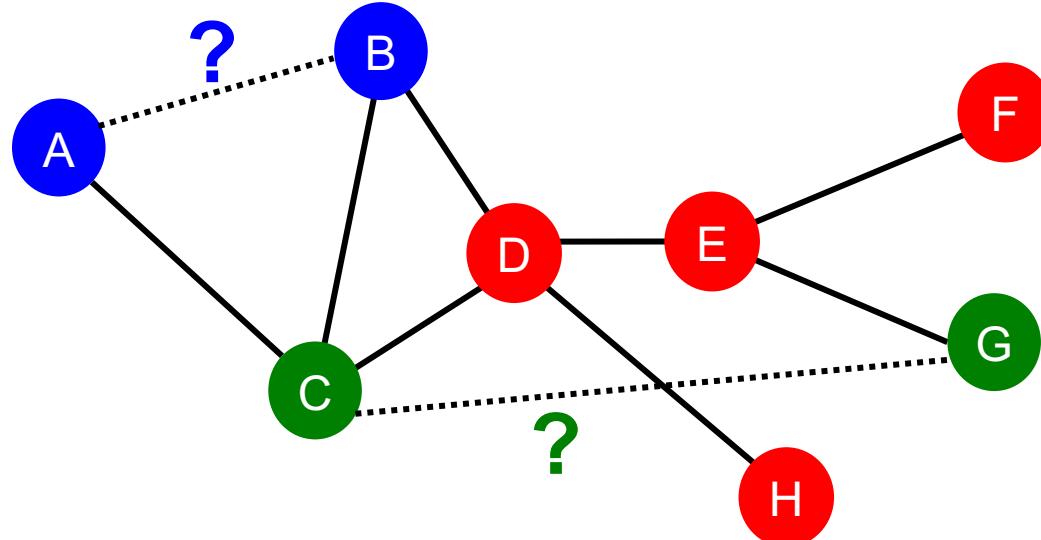
# Stanford CS224W: Link Prediction

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<http://cs224w.stanford.edu>



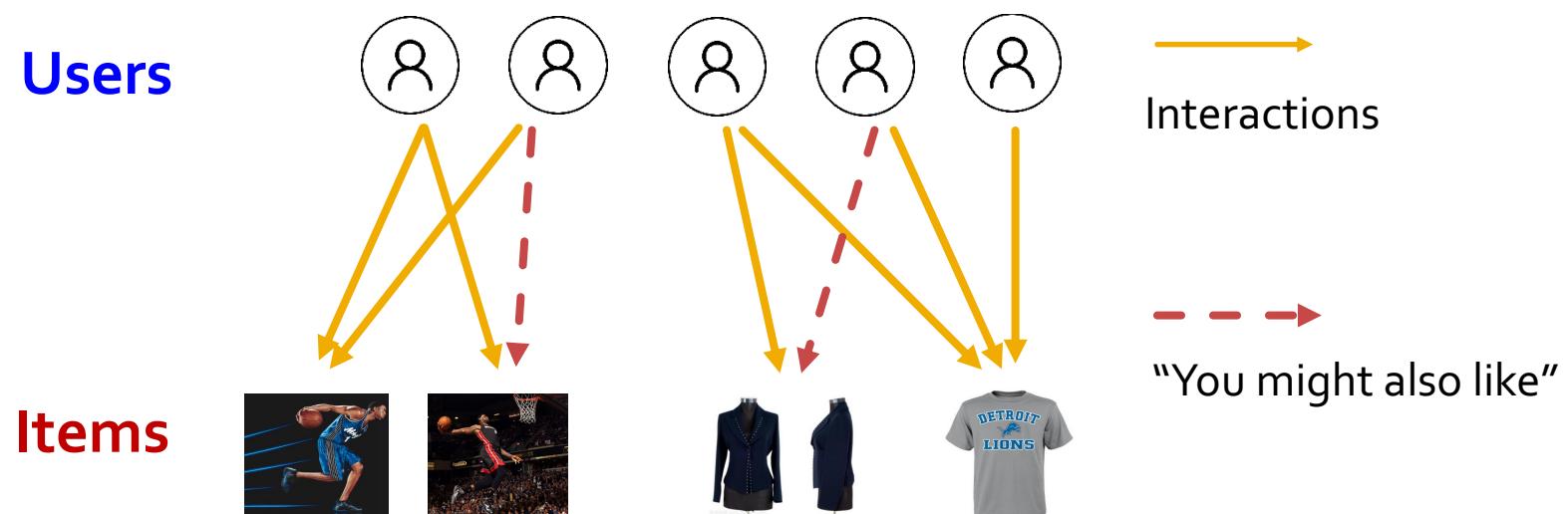
# Link-Level Prediction Task

- 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.



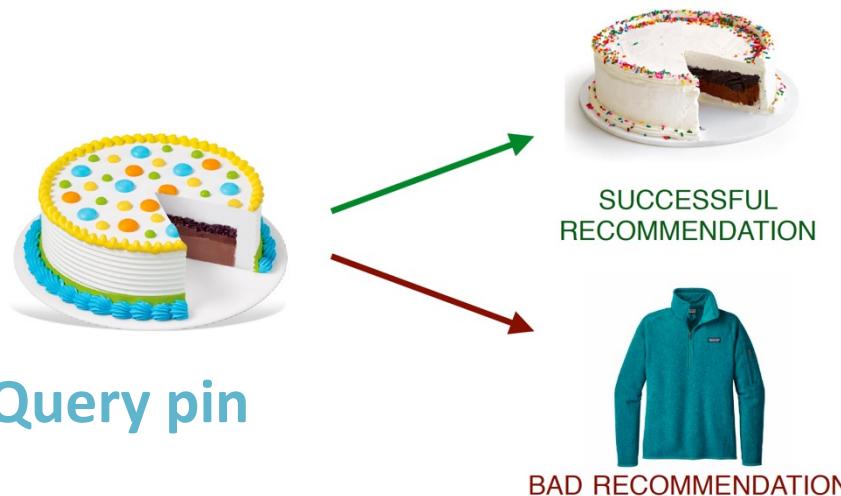
# Example (1): Recommender Systems

- **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**



# PinSage: Graph-based Recommender

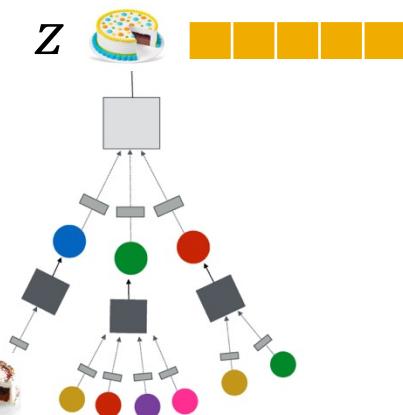
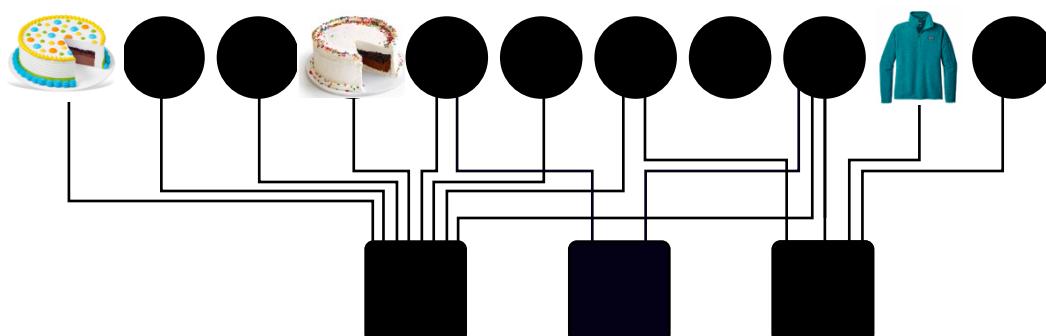
**Task: Recommend related pins to users**



**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**



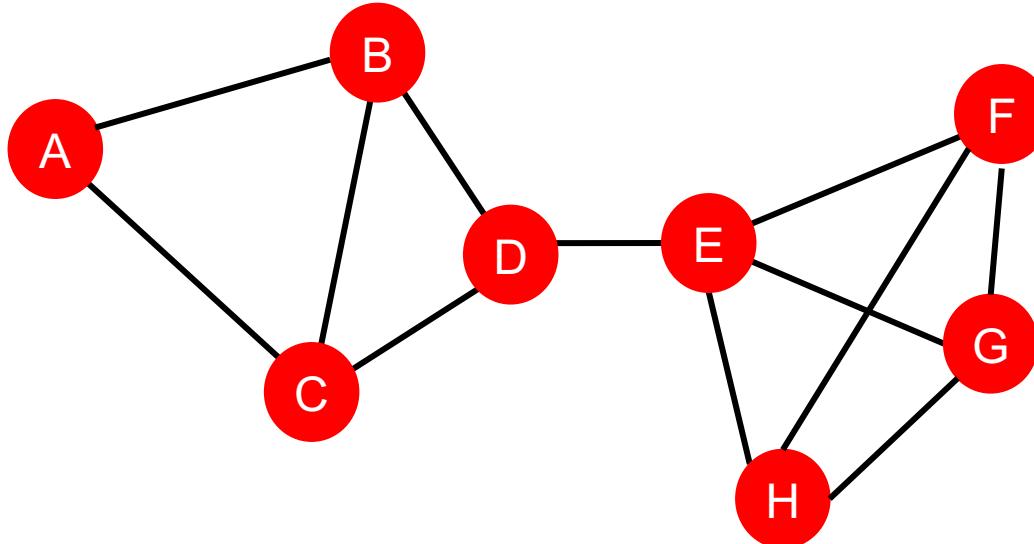
# Stanford CS224W: Graph-Level Tasks

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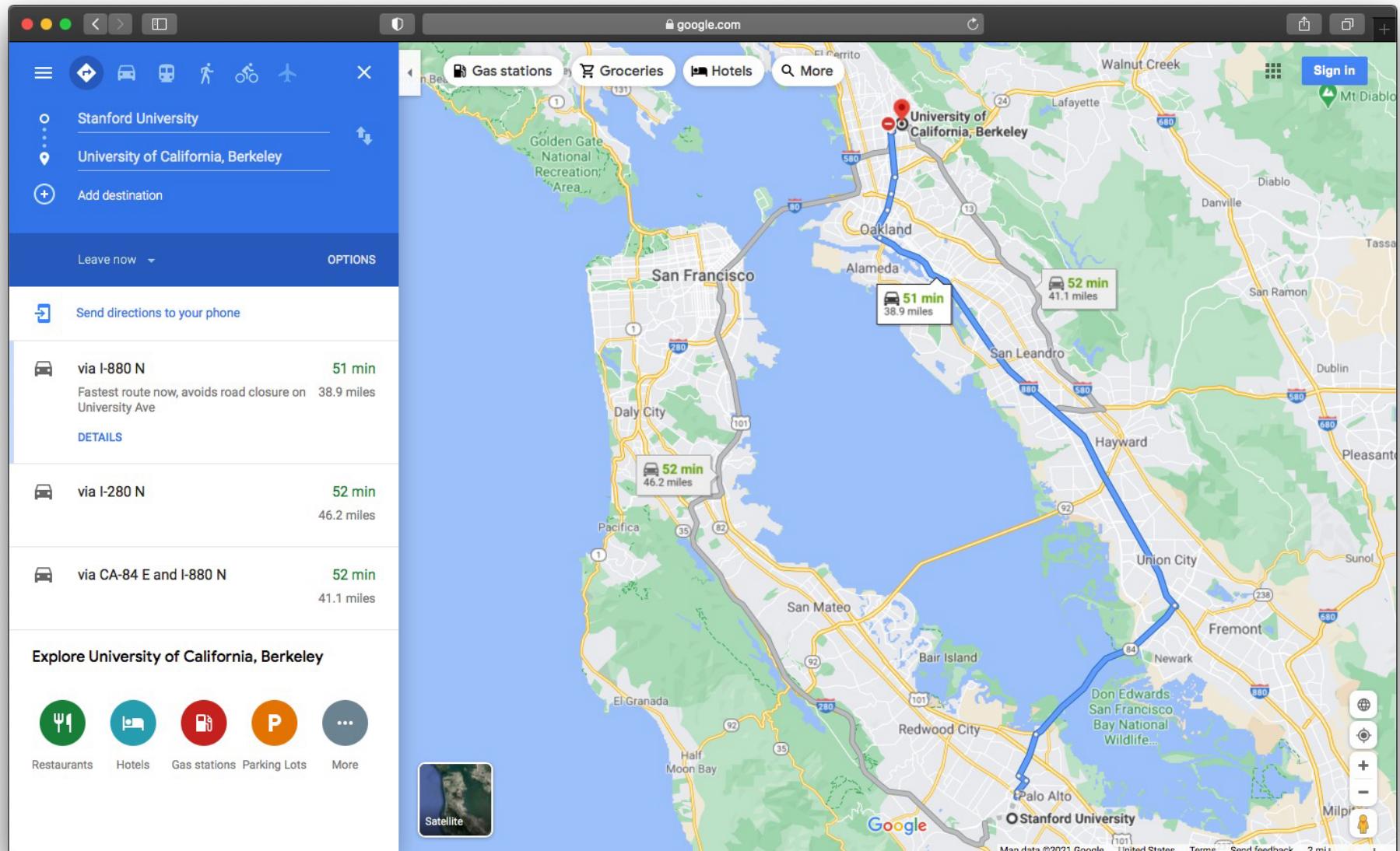


# Graph-Level Prediction

- **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)

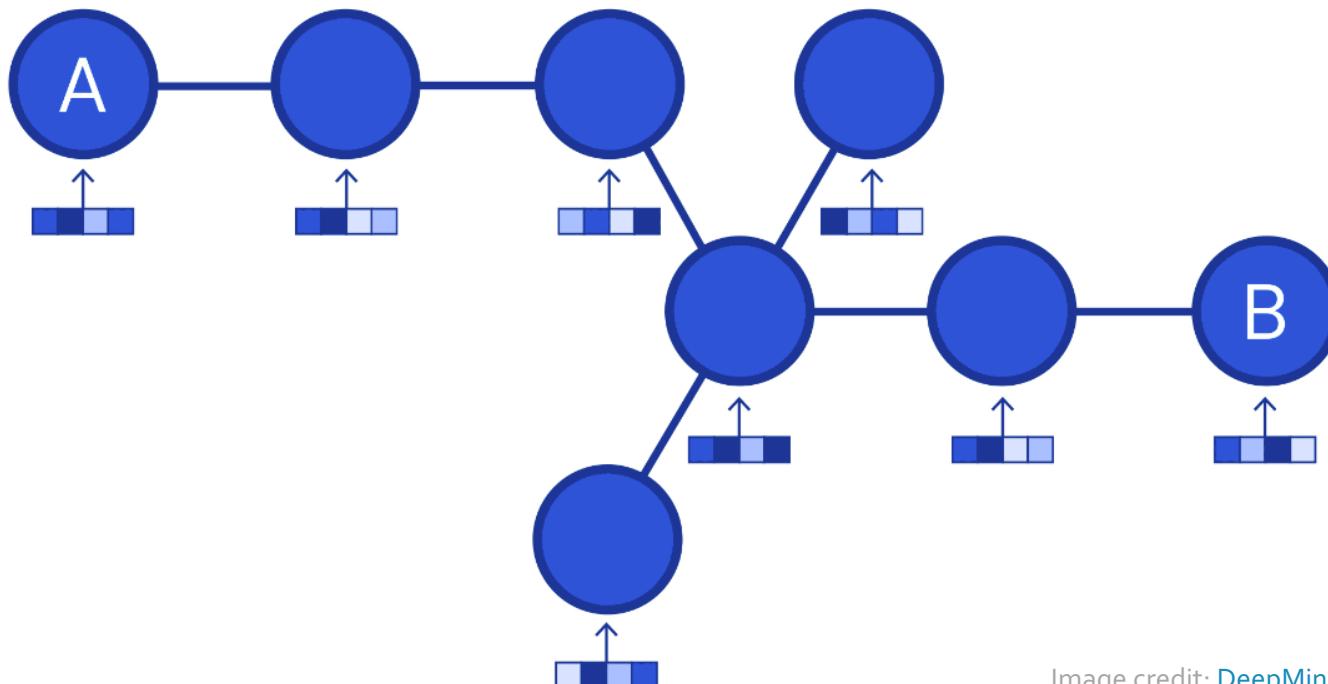
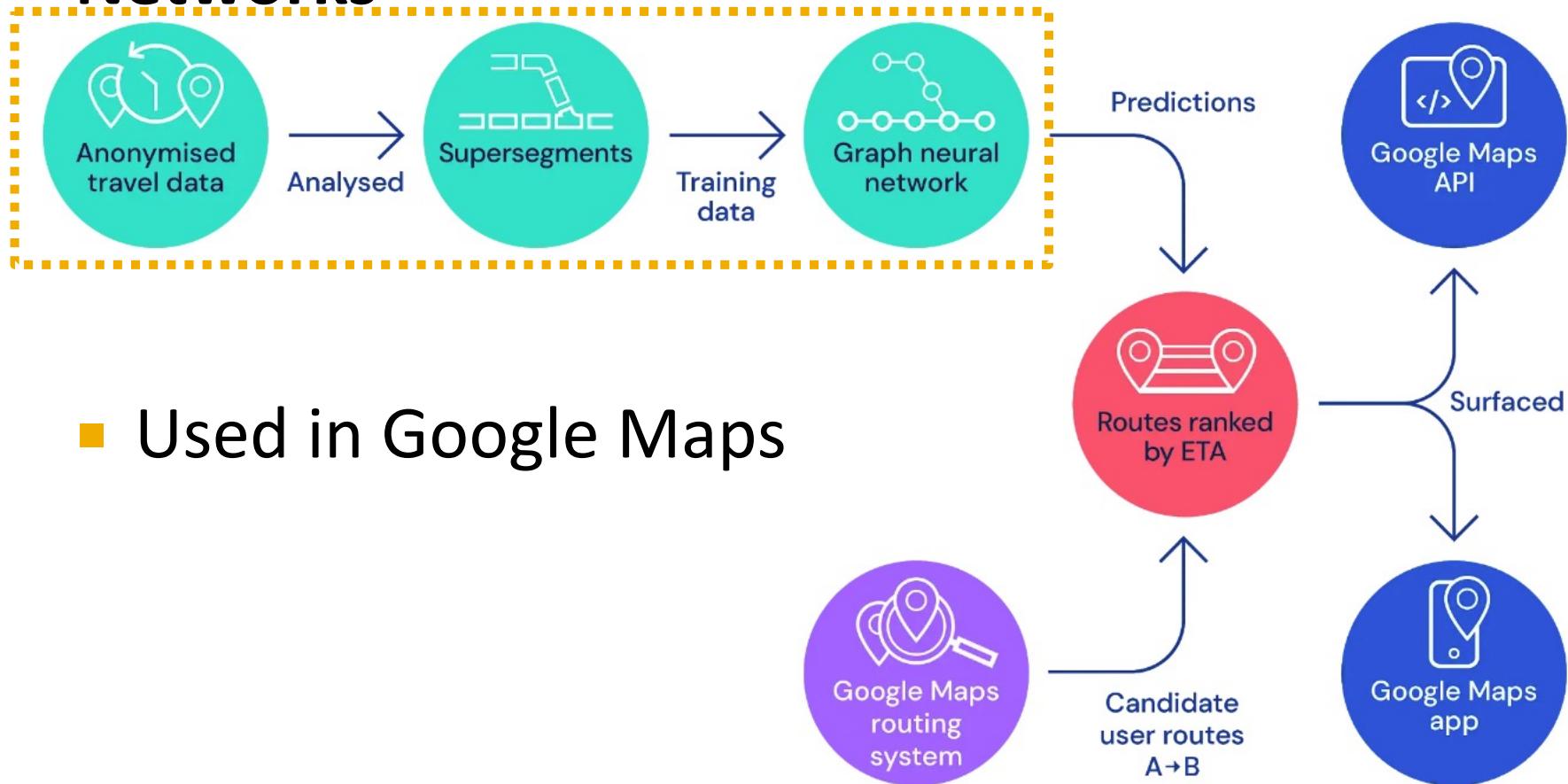


Image credit: [DeepMind](#)

# Traffic Prediction via GNN

## Predicting Time of Arrival with Graph Neural Networks

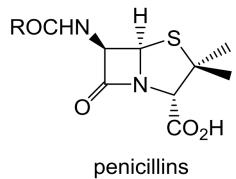


- Used in Google Maps

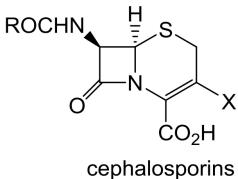
# Example (2): Drug Discovery

## ■ Antibiotics are small molecular graphs

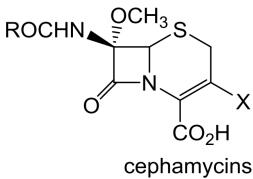
- **Nodes:** Atoms
- **Edges:** Chemical bonds



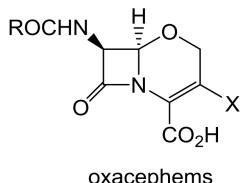
penicillins



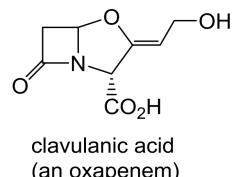
cephalosporins



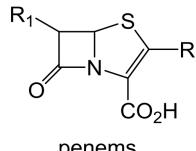
cephamycins



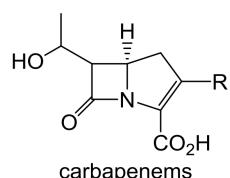
oxacephems



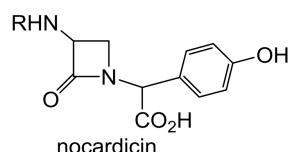
clavulanic acid  
(an oxapenem)



penems



carbapenems



nocardicin



monobactams

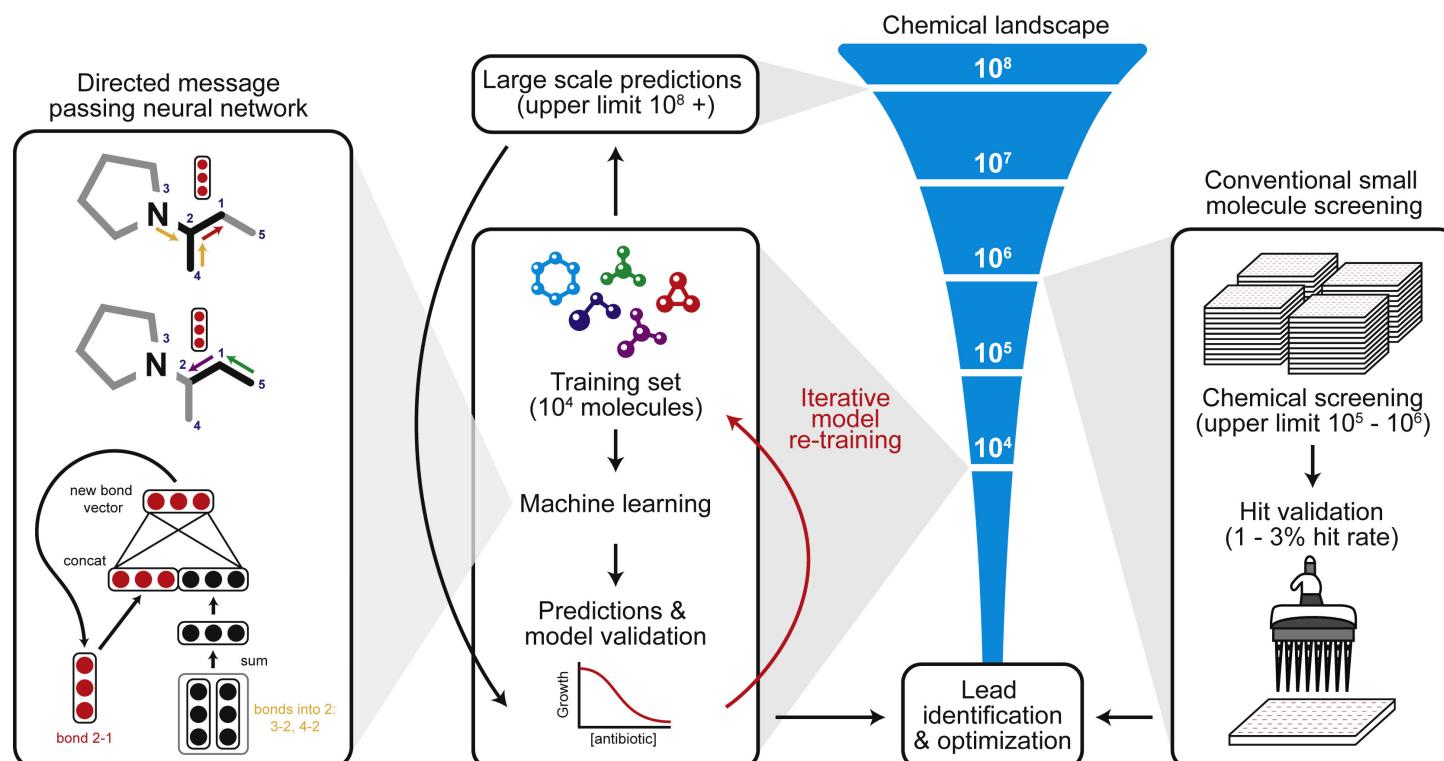


Konaklieva, Monika I. "Molecular targets of β-lactam-based antimicrobials: beyond the usual suspects." *Antibiotics* 3.2 (2014): 128-142.

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.

# 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

