



Machine Learning with Graphs (MLG)

# GNN Applications

Represent the relationships of any things as Graphs

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# References

- GNN for **Tabular** Data
  - “Handling Missing Data with Graph Representation Learning” @ **NeurIPS 2020**
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- GNN for **Biomedical** Data
  - “Modeling polypharmacy side effects with graph convolutional networks” @ **ISMB 2018**

# GRAPE: Bipartite GNN

Data Matrix  
with Missing Values

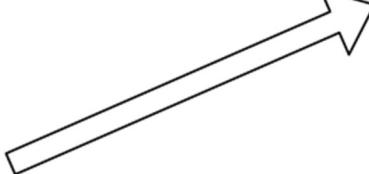
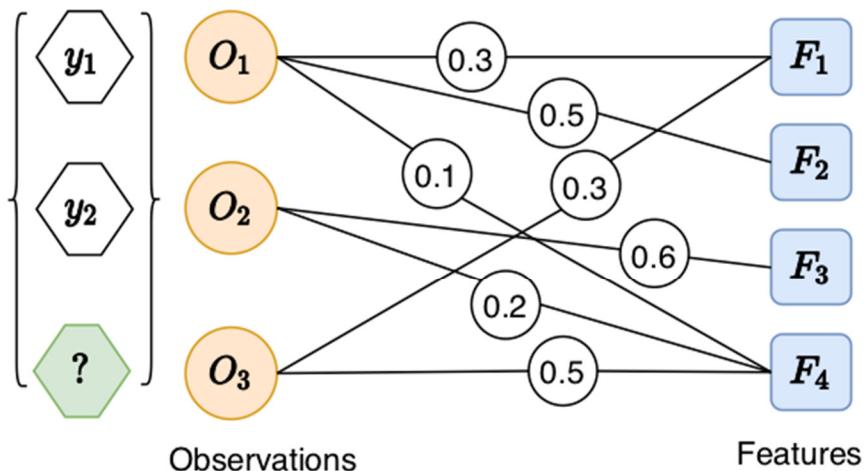
	$F_1$	$F_2$	$F_3$	$F_4$
$O_1$	0.3	0.5	NA	0.1
$O_2$	NA	NA	0.6	0.2
$O_3$	0.3	NA	NA	0.5

Labels

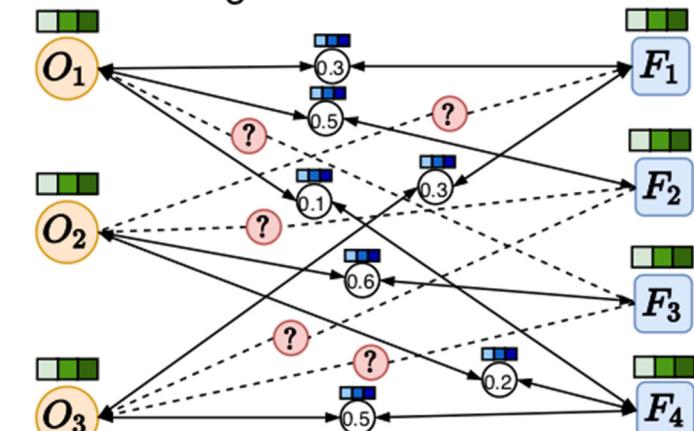
$Y$
$y_1$
$y_2$
?

- [Node Embeddings] Node Embeddings
- [Edge Embeddings] Edge Embeddings
- [↔] Message Passing
- [?] Missing Feature Values
- [?] Downstream Labels

Bipartite Graph

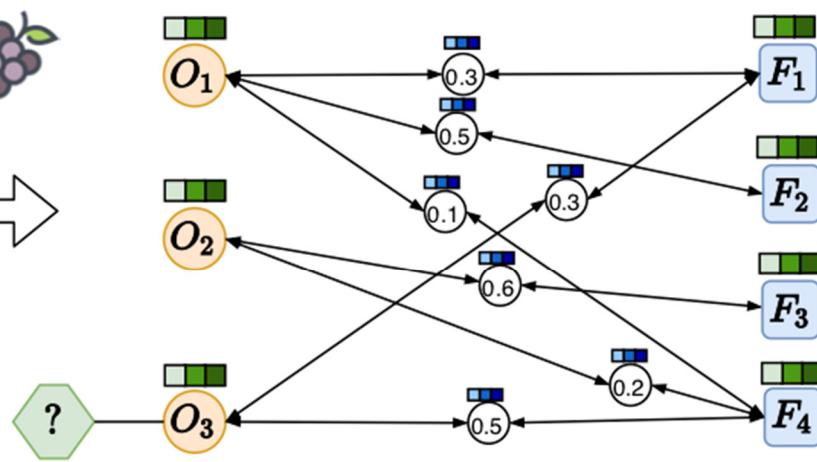


Feature Imputation as  
Edge-level Prediction



Self-supervised Learning

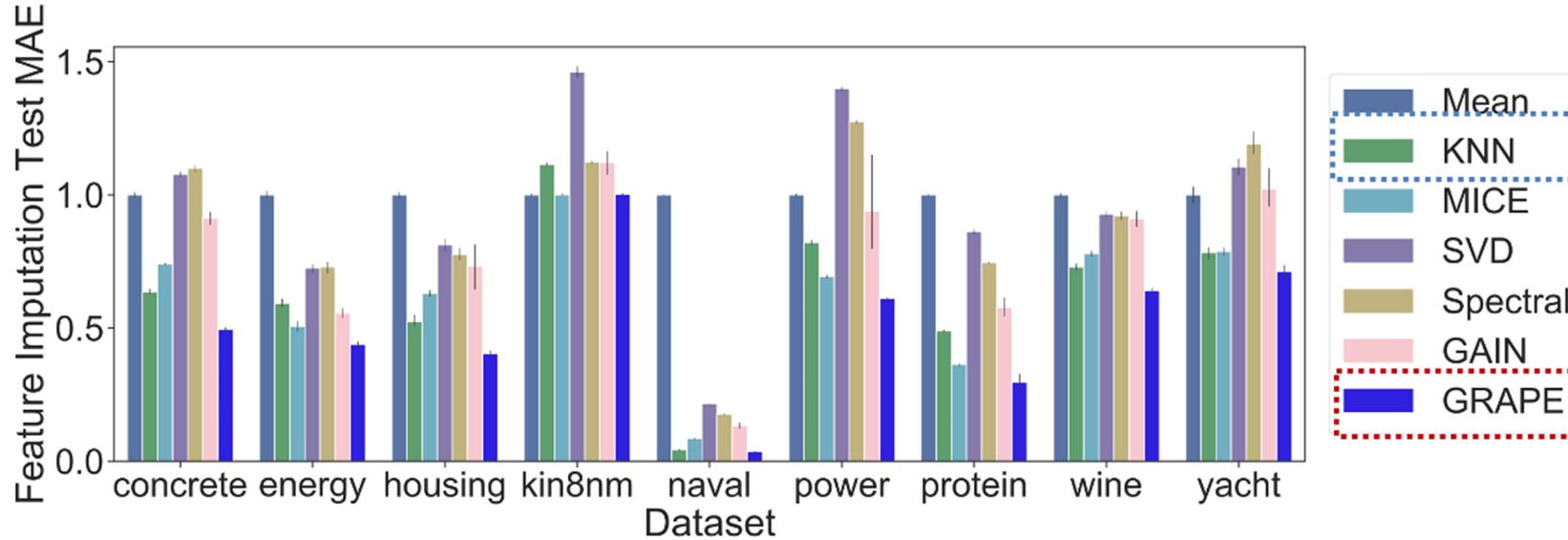
Label Prediction as  
Node-level Prediction



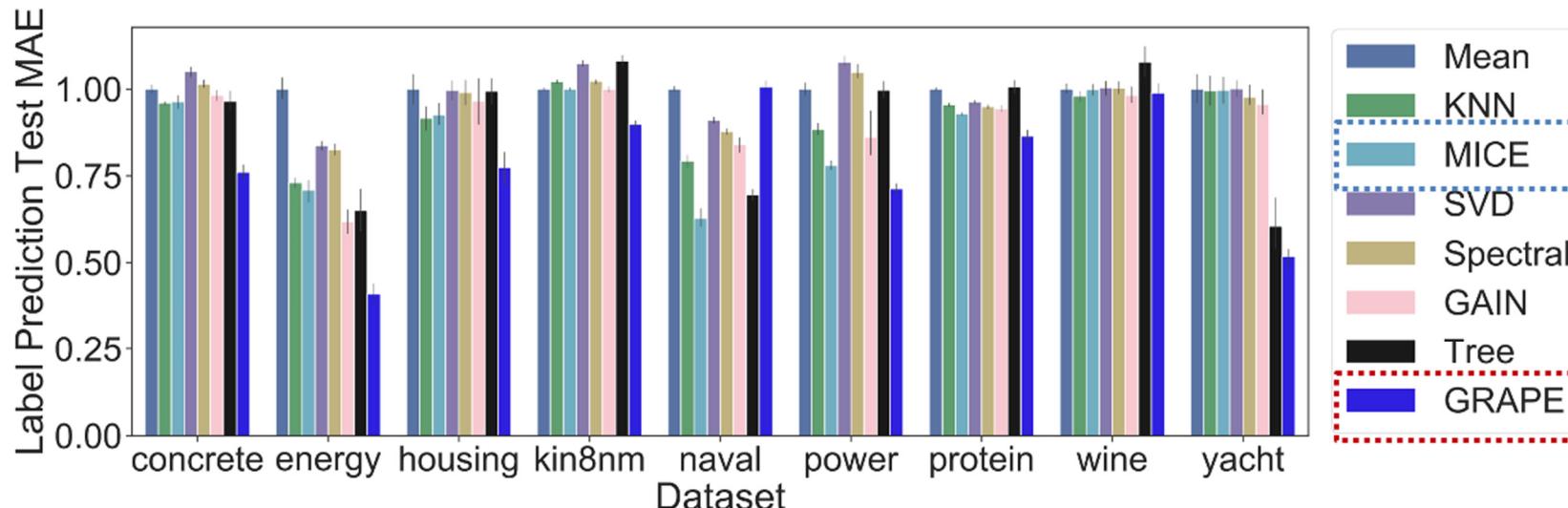
Semi-supervised Learning

# Overall Performance

Experiments on 9 UCI datasets from different domains



Feature imputation:  
20% lower  
MAE than best  
baseline (KNN)

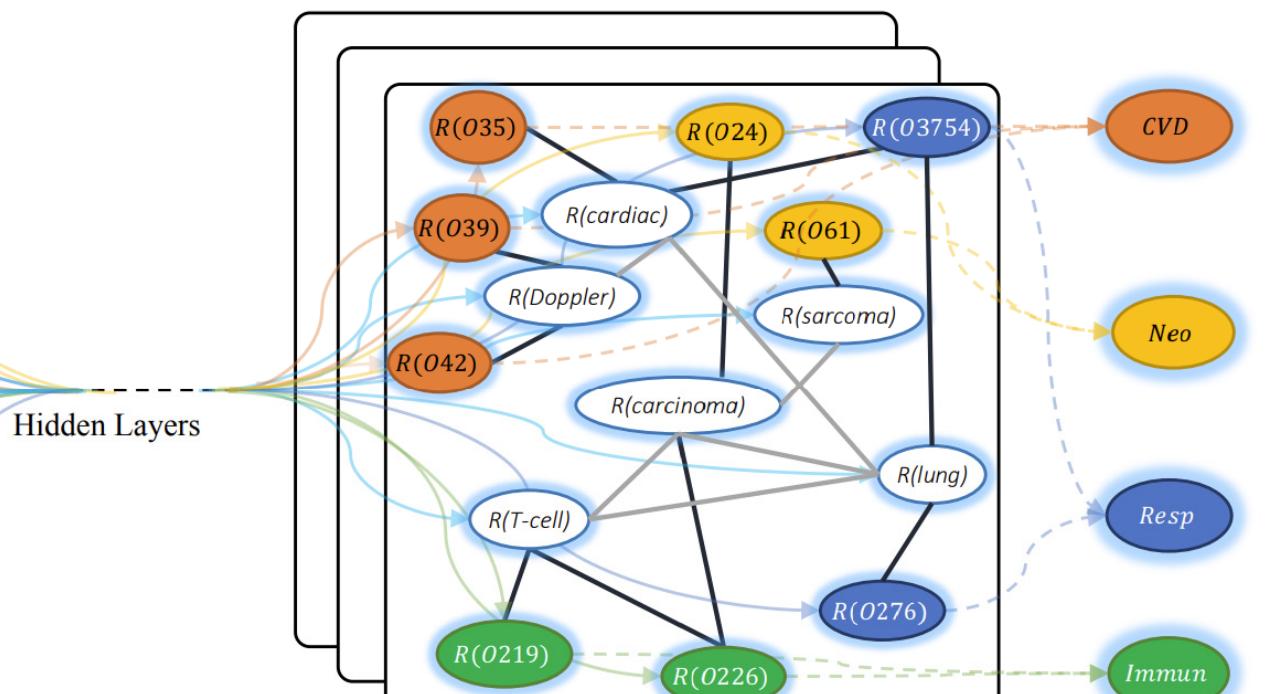
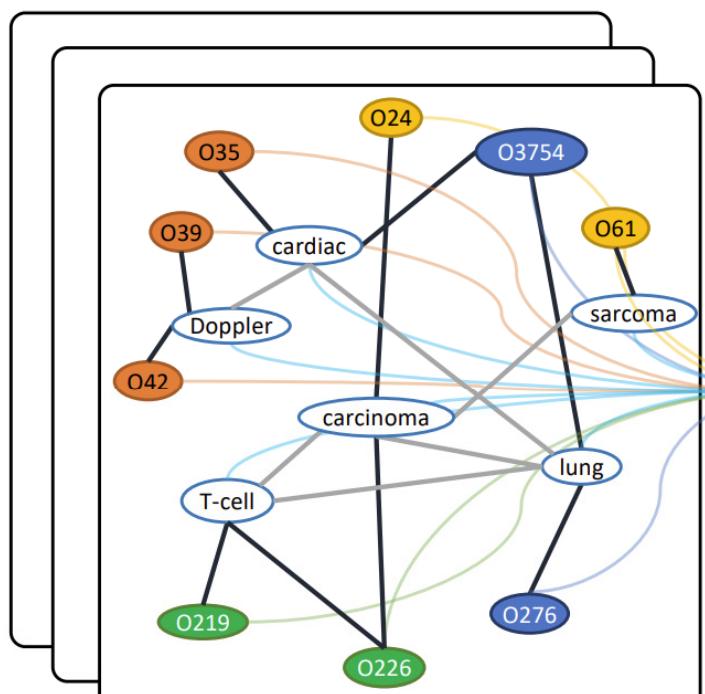


Label prediction:  
10% lower  
MAE than best  
baseline (MICE)

# Text Classification: TextGCN

- Nodes: words and documents
- Edges: co-occurrence (word-word) and TF-IDF (word-doc)
- Model the graph with a Graph Convolutional Network (GCN)
  - Generate document representation
  - Produce the classification outcome

$$A_{ij} = \begin{cases} \text{PMI}(i, j) & i, j \text{ are words, } \text{PMI}(i, j) > 0 \\ \text{TF-IDF}_{ij} & i \text{ is document, } j \text{ is word} \\ 1 & i = j \\ 0 & \text{otherwise} \end{cases}$$



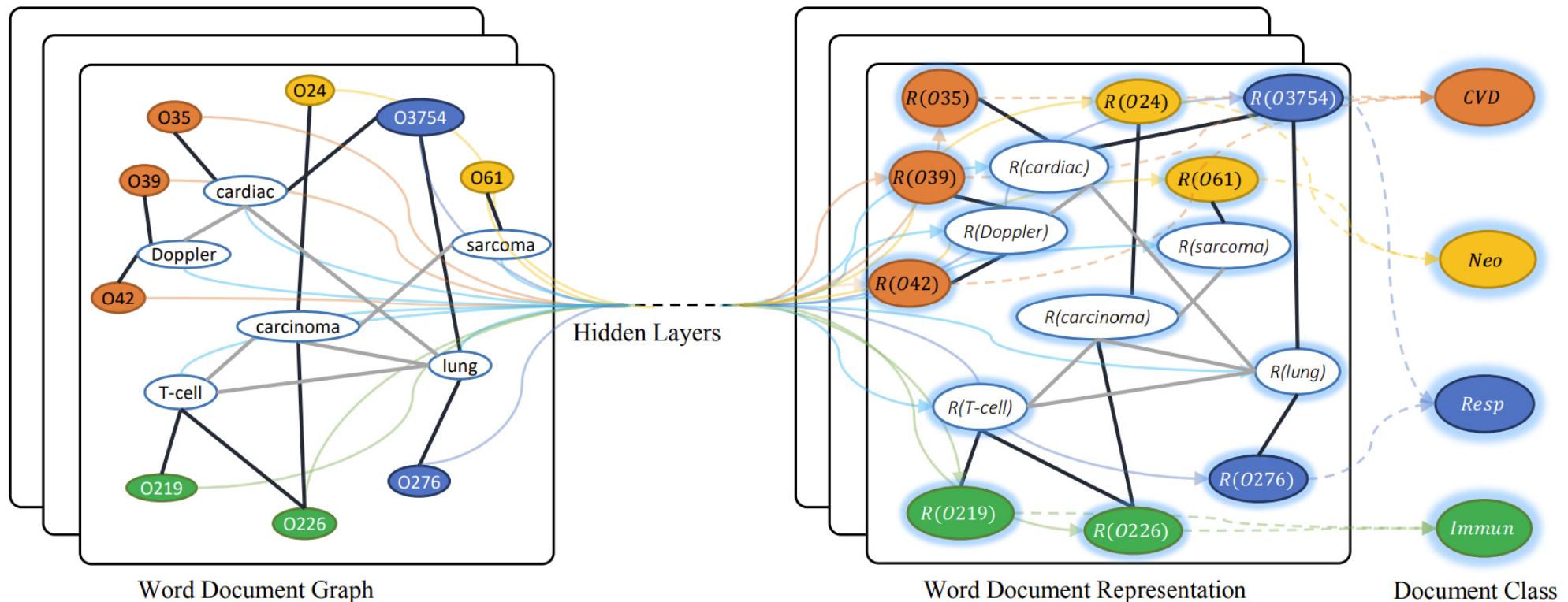
Word Document Graph

Word Document Representation

Document Class

# BERT-GCN: Combining BERT & GCN

- Follow the graph construction in TextGCN
- Initialize document node vectors by BERT document embeddings
- Learning doc embedddings and predictions  
 $Z_{\text{GCN}} = \text{softmax}(g(X, A))$      $Z_{\text{BERT}} = \text{softmax}(WX)$
- Interpolating BERT and GCN predictions  $Z = \lambda Z_{\text{GCN}} + (1 - \lambda)Z_{\text{BERT}}$



# References

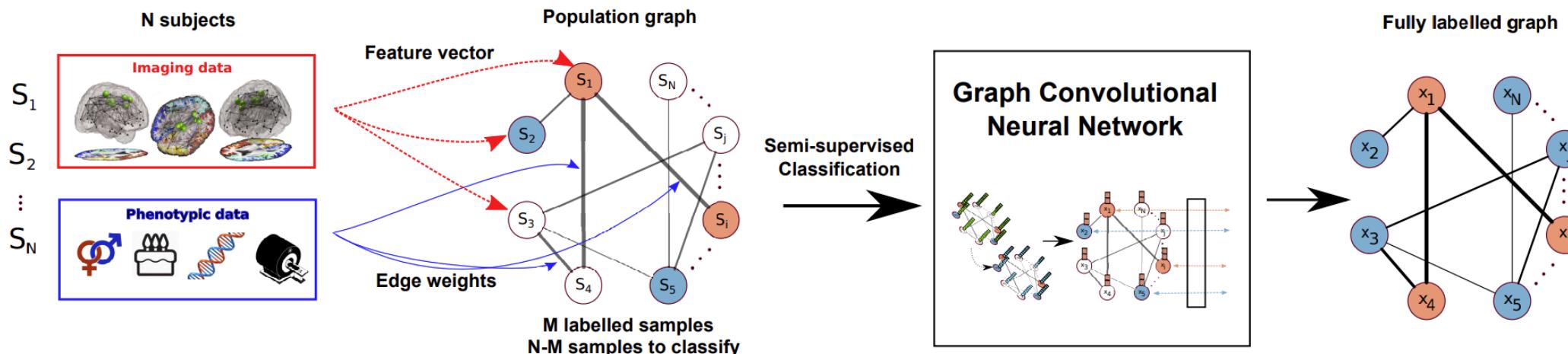
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# GCN for Autism Spectrum Disorder

## Prediction (Medical Images)

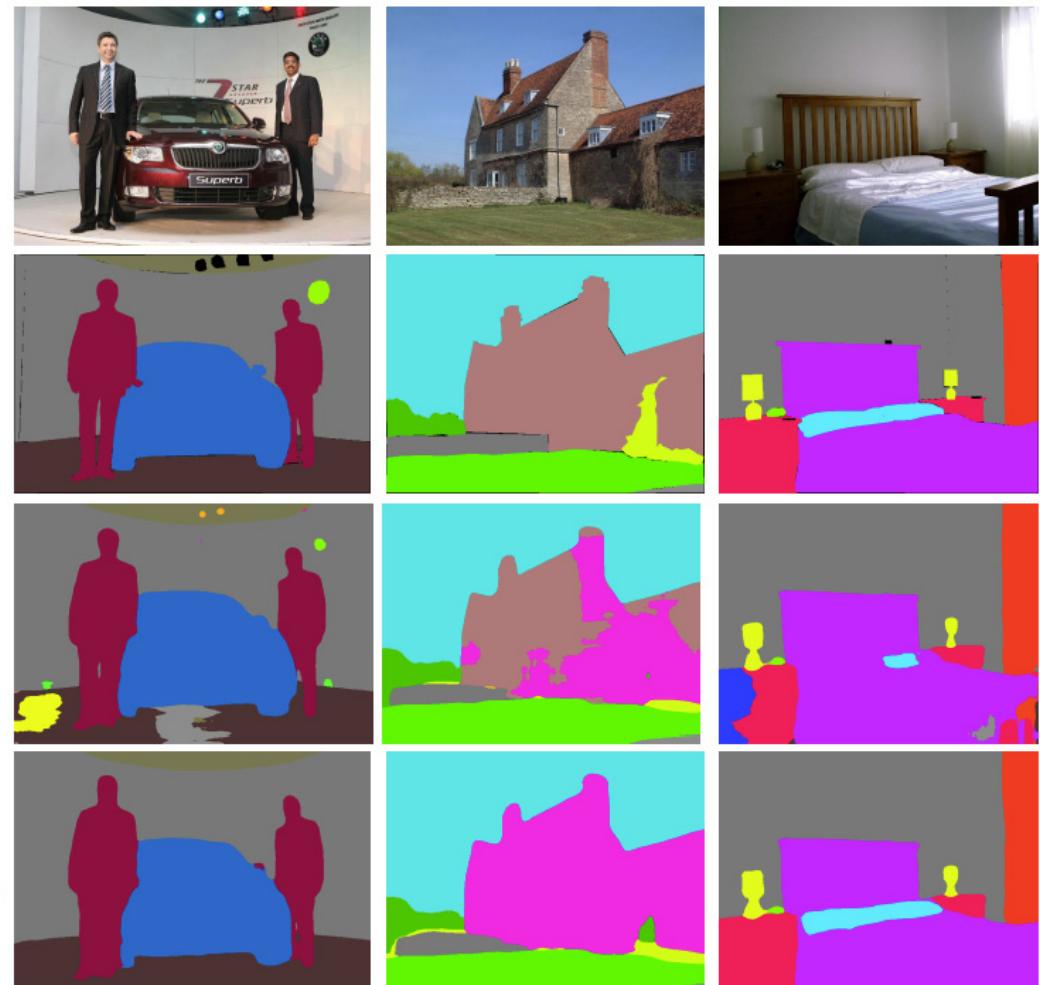
自閉症類群障礙

- Task: Disease prediction (binary classification)
- Nodes: patients (initial vectors: CNN image features)
- Edges: similarity based on clinical data
  - E.g., k-nearest neighbors
  - E.g., fully-connected weighted graph



# GNN for Computer Vision

## Semantic Segmentation

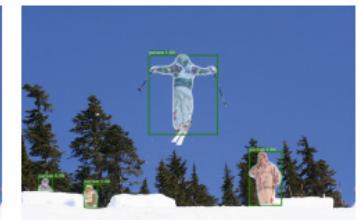
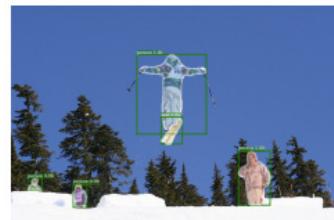
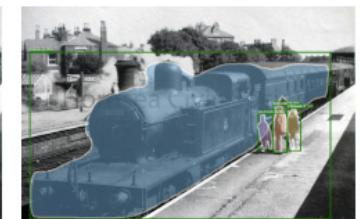
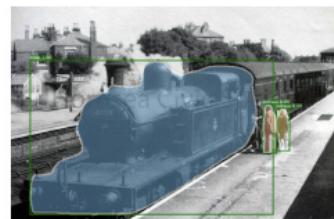


## Object Instance Segmentation

Mask RCNN

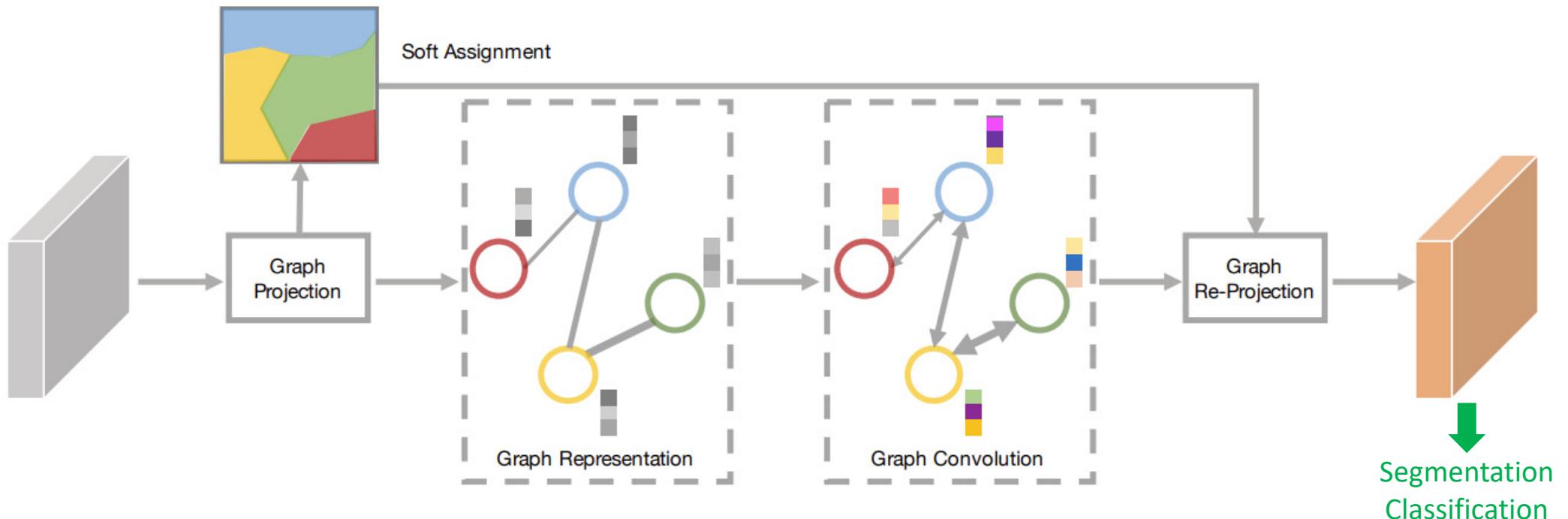


GNN

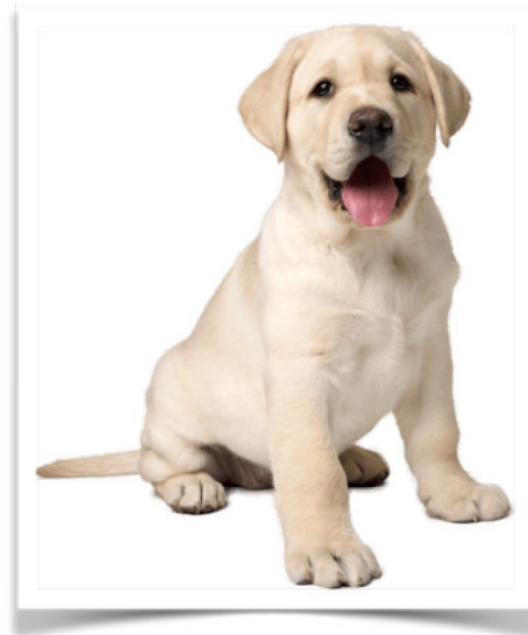


# GNN for Computer Vision

- Learning graph representation from 2D feature maps
  - Capture long range dependencies among regions
  - Facilitate reasoning beyond regular grids
- Nodes: clusters of pixels (e.g., regions)
- Edges: similarity between clusters in feature space



# Multi-Label Image Classification



• Dog •

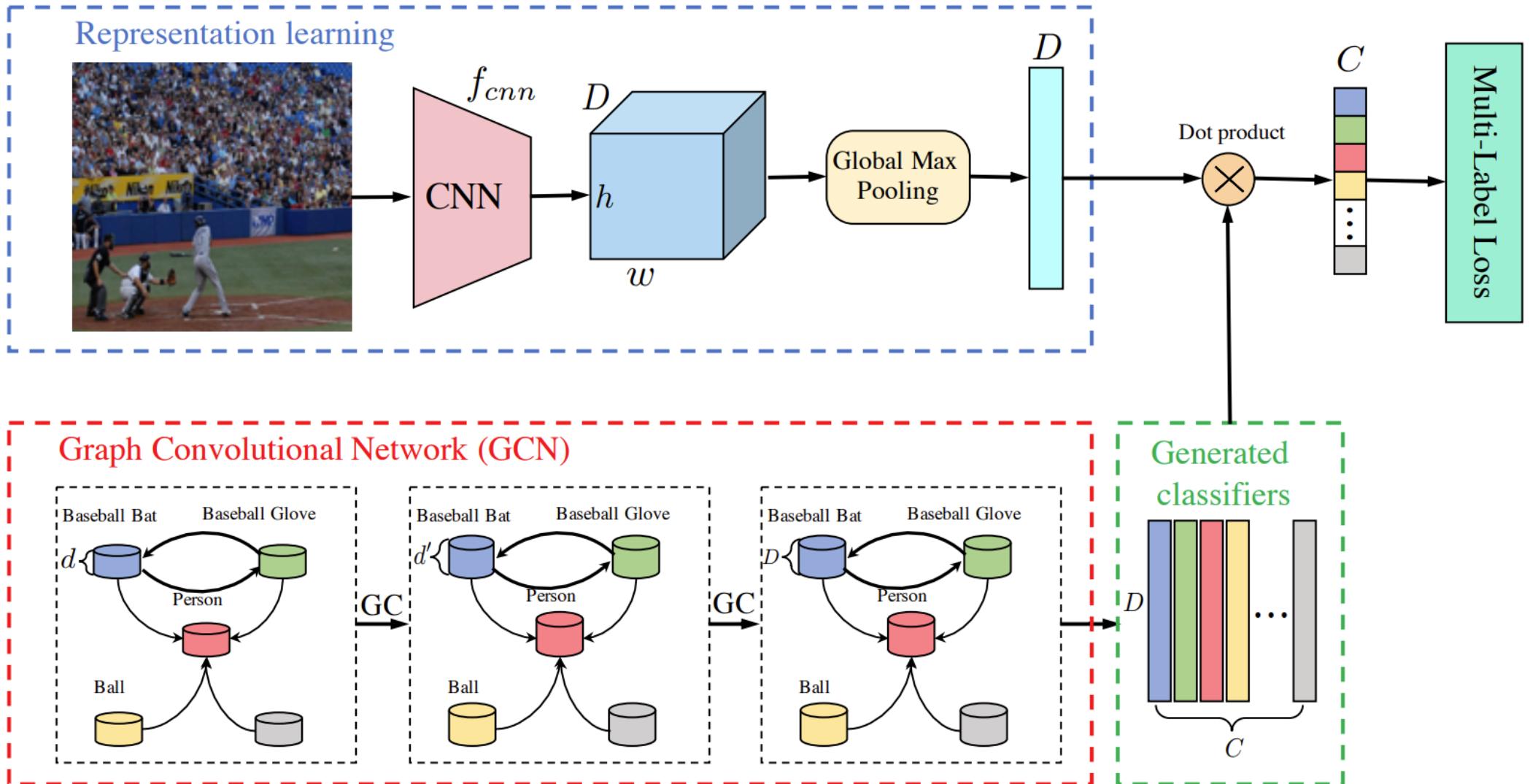


• Cloud • Rainbow • Sky •

Traditional image recognition  
(Single-label recognition)

Multi-Label image recognition

# Multi-Label GCN (ML-GCN)



# Directed Graph for ML-GCN



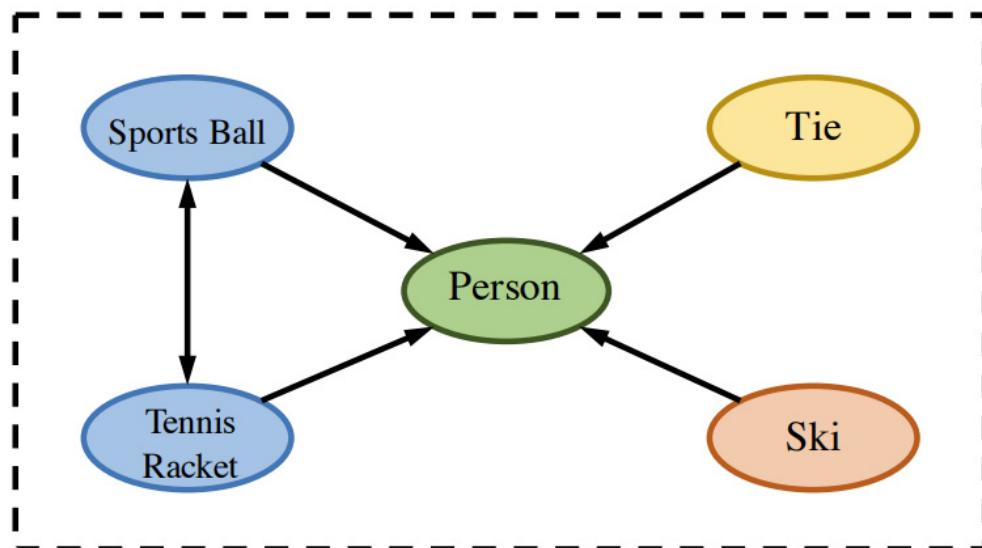
Person, Sports Ball,  
Tennis Racket



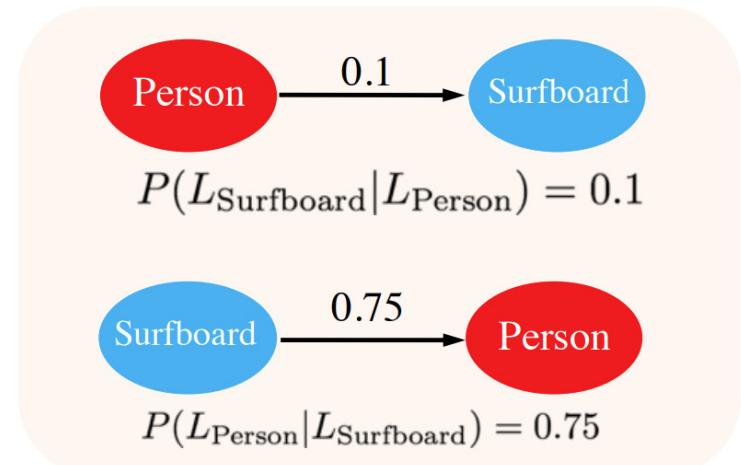
Person, Tie



Person, Ski



Conditional Prob.



# References

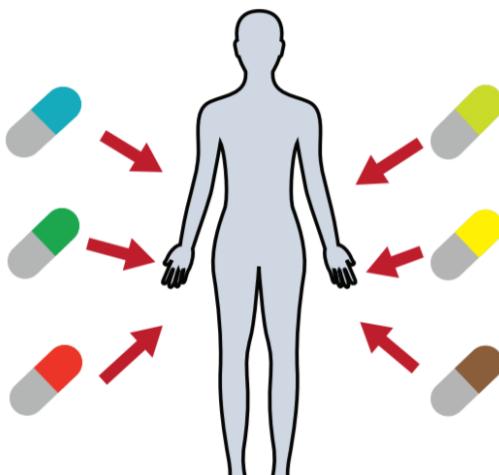
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# Modeling Polypharmacy with GCN

## Why polypharmacy?

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

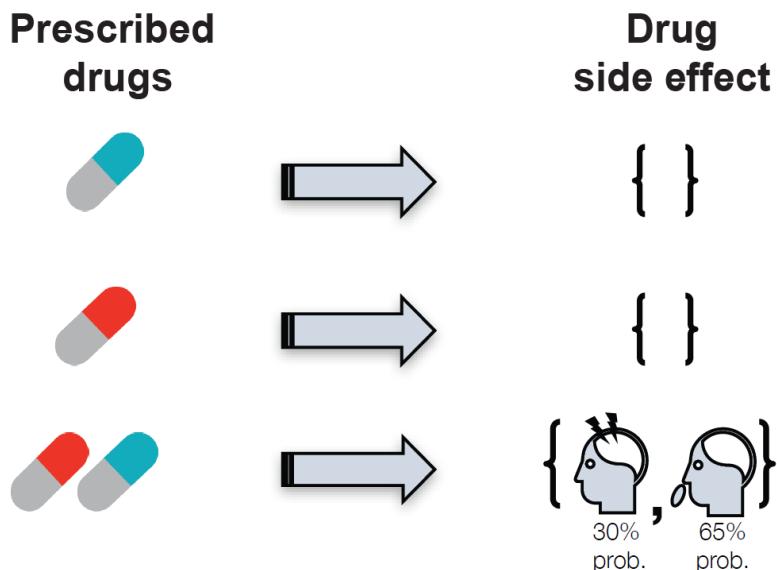
- 25% of people ages 65-69 take more than 5 drugs
- 46% of people ages 70-79 take more than 5 drugs
- Many patients take more than 20 drugs to treat heart disease, depression, insomnia, etc.



[Charlesworth *et al.*, 2015]

# Unwanted Side Effects

- Side effects due to drug-drug interactions
- Extremely difficult to identify:
  - Impossible to test all combinations of drugs
  - Side effects not observed in controlled trials
- 15% of the U.S. population affected
- Annual costs exceed \$177 billion

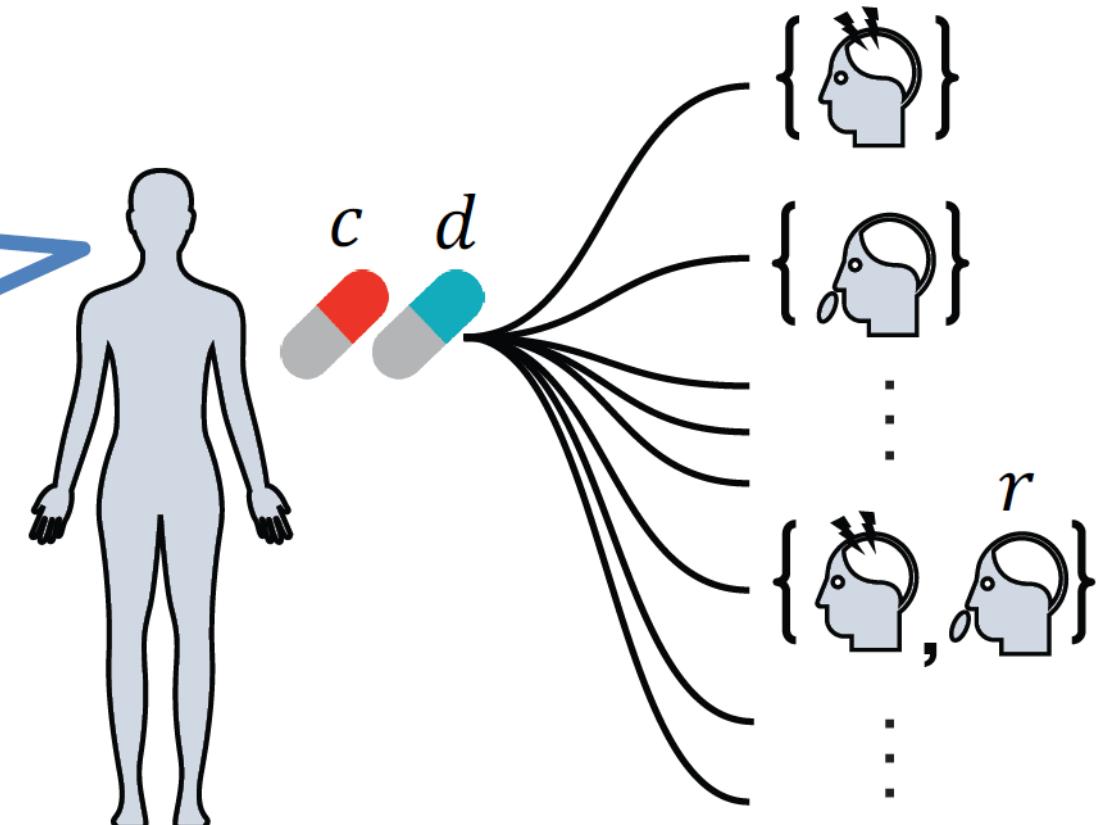


[Kantor et al., 2015]

# The Task

Goal: Modeling and predicting  
side effects of drug pairs

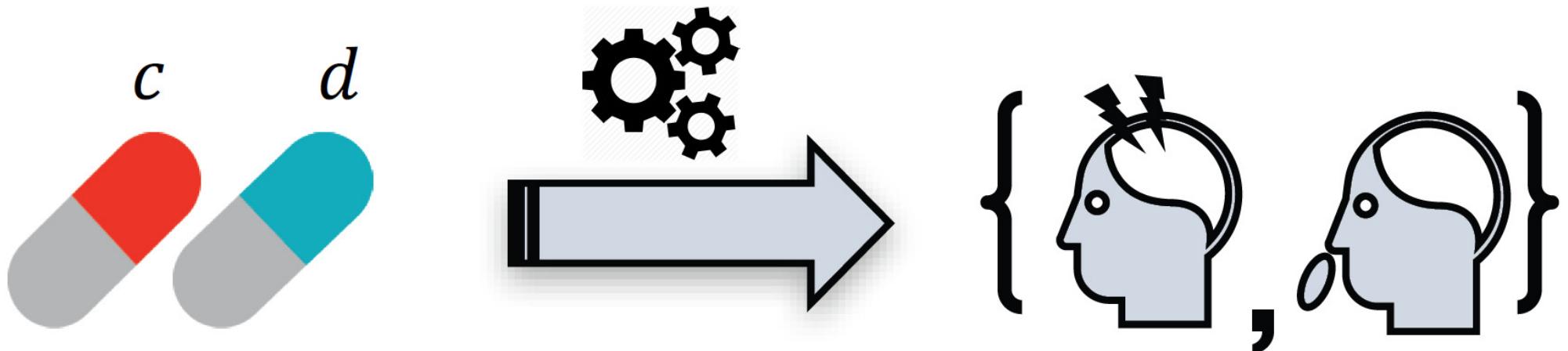
How likely with a  
pair of drugs  $c, d$   
lead to side effect  $r$ ?



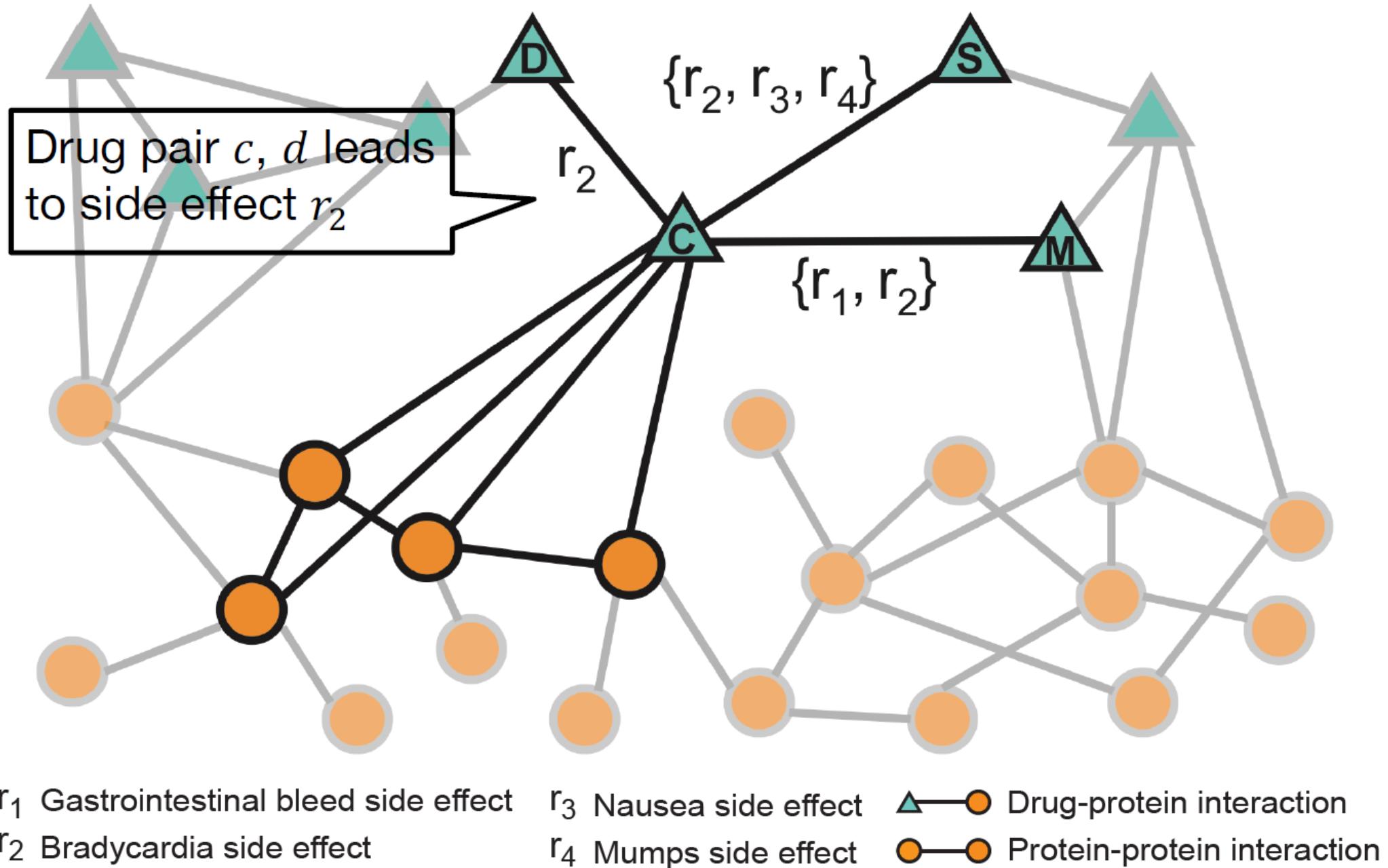
# The Approach

## *In silico* screening of drug combinations

- Use molecular, drug, and patient data
- Task: Given a drug pair  $c, d$ ,
- Goal: predict side effects of that drug pair



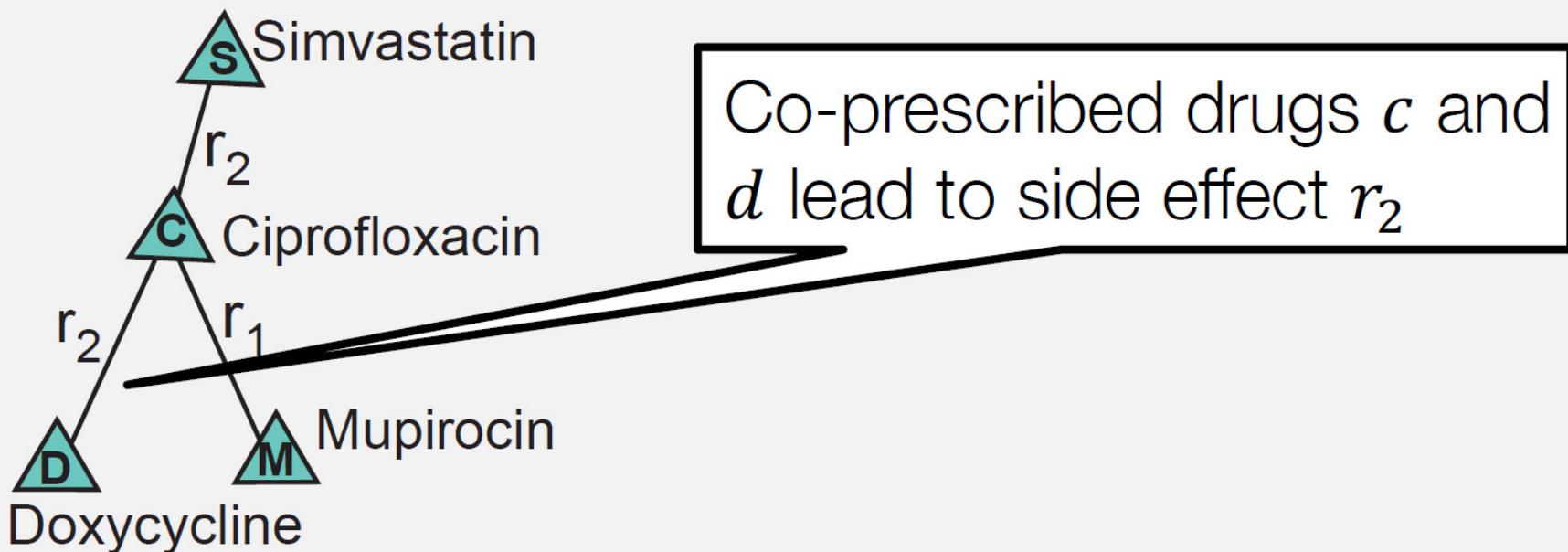
# Problem Formulation: Graphs



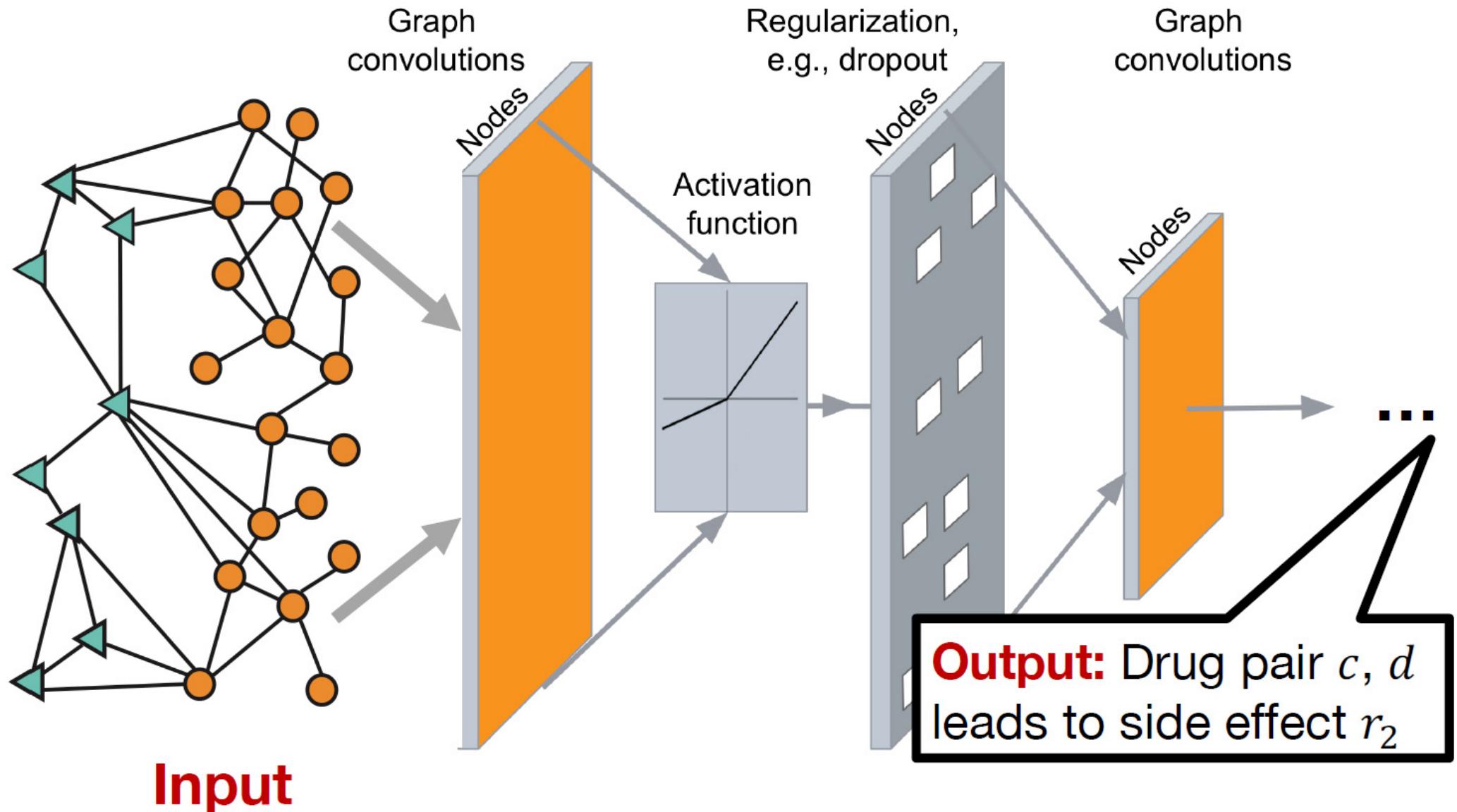
# Problem Formulation: Predict

Goal: Given a partially observed graph,  
predict labeled edges between drug nodes

**Query:** Given a drug pair  $c, d$ , how likely does an edge  $(c, r_2, d)$  exist?

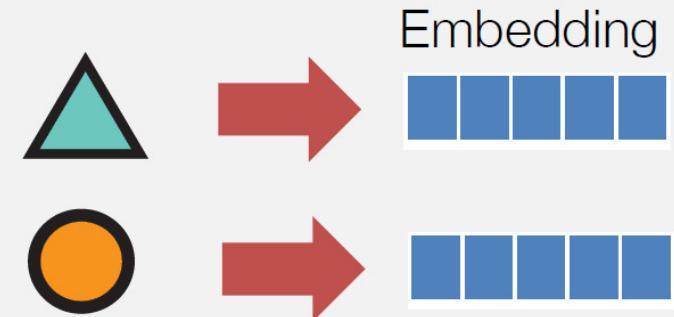


# Graph Neural Network

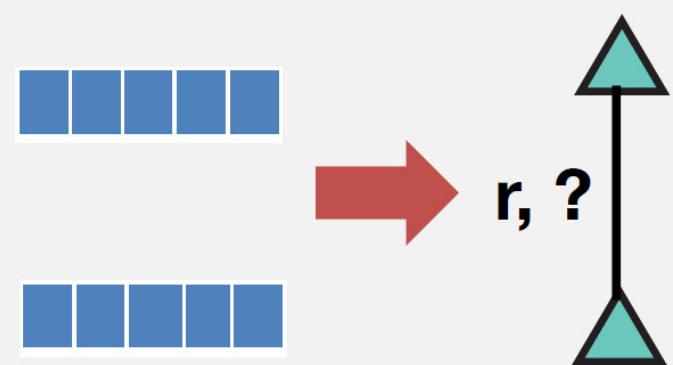


# Graph Neural Network

**1. Encoder:** Take the graph and learn an *embedding* for every node

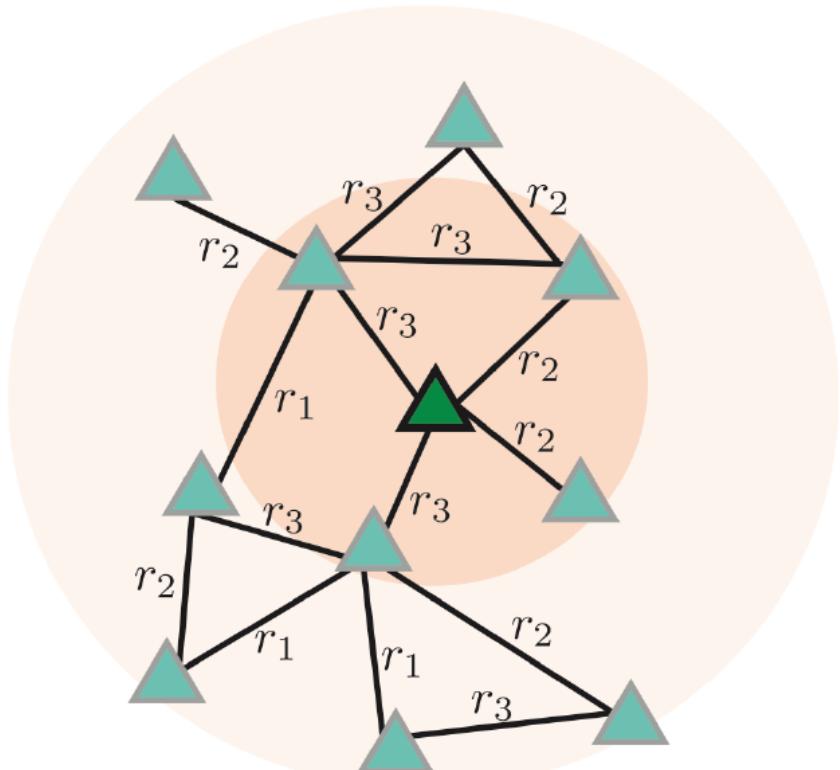


**2. Decoder:** Use the learned embeddings to predict side effects

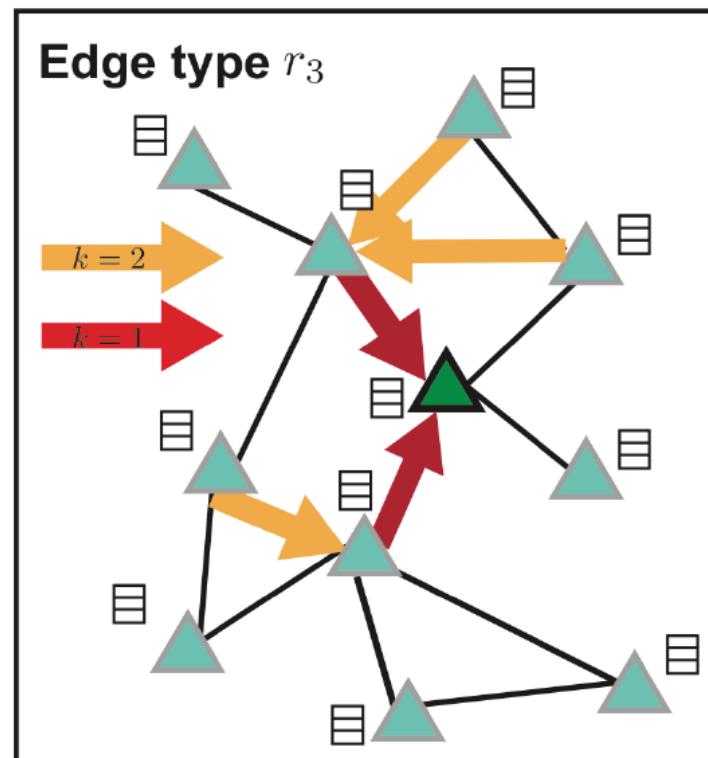


# Encoder: Principle

- **Key idea:** Generate node embeddings based on **local network neighborhoods**
- Each edge type is modeled separately

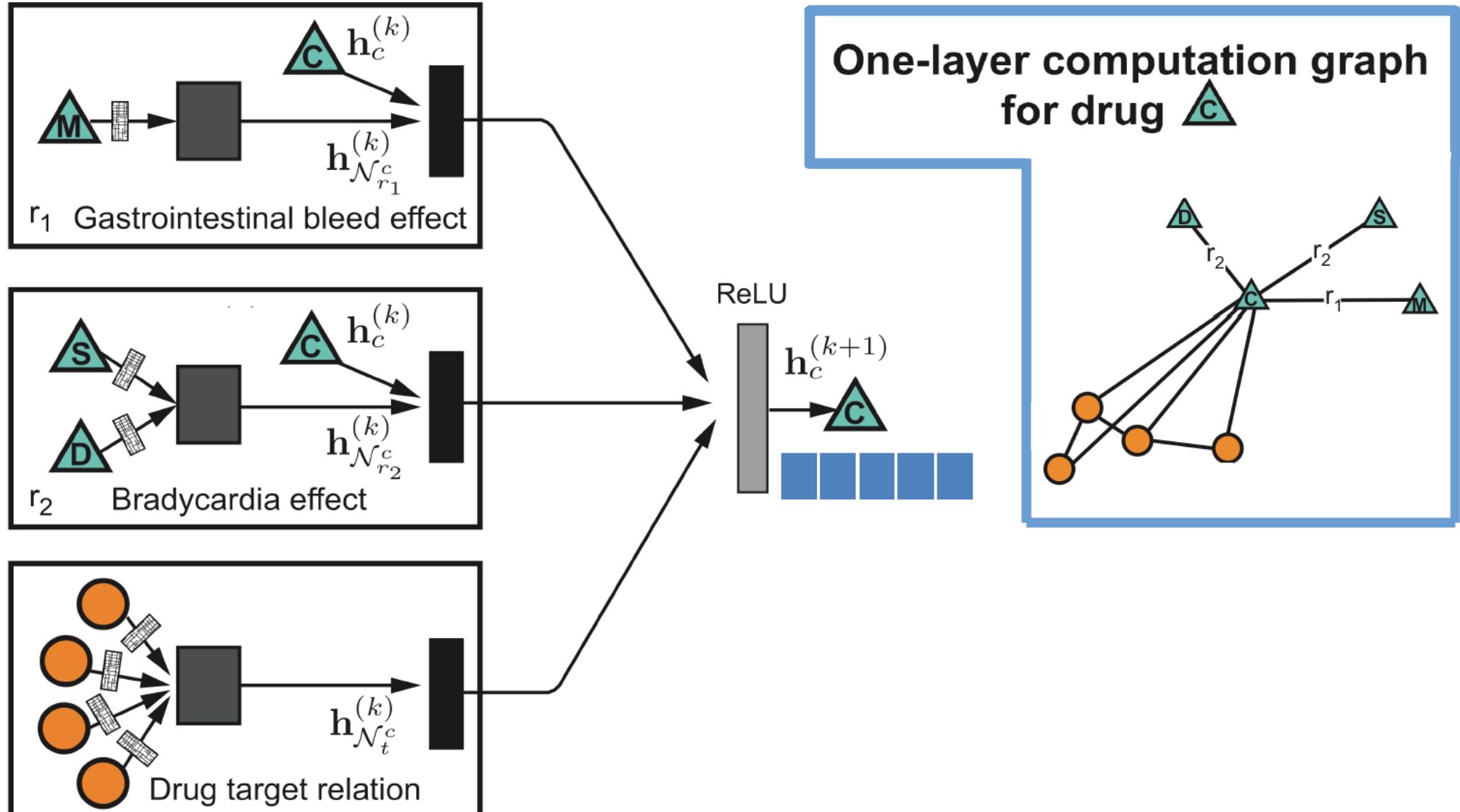


Determine a node's computation graph

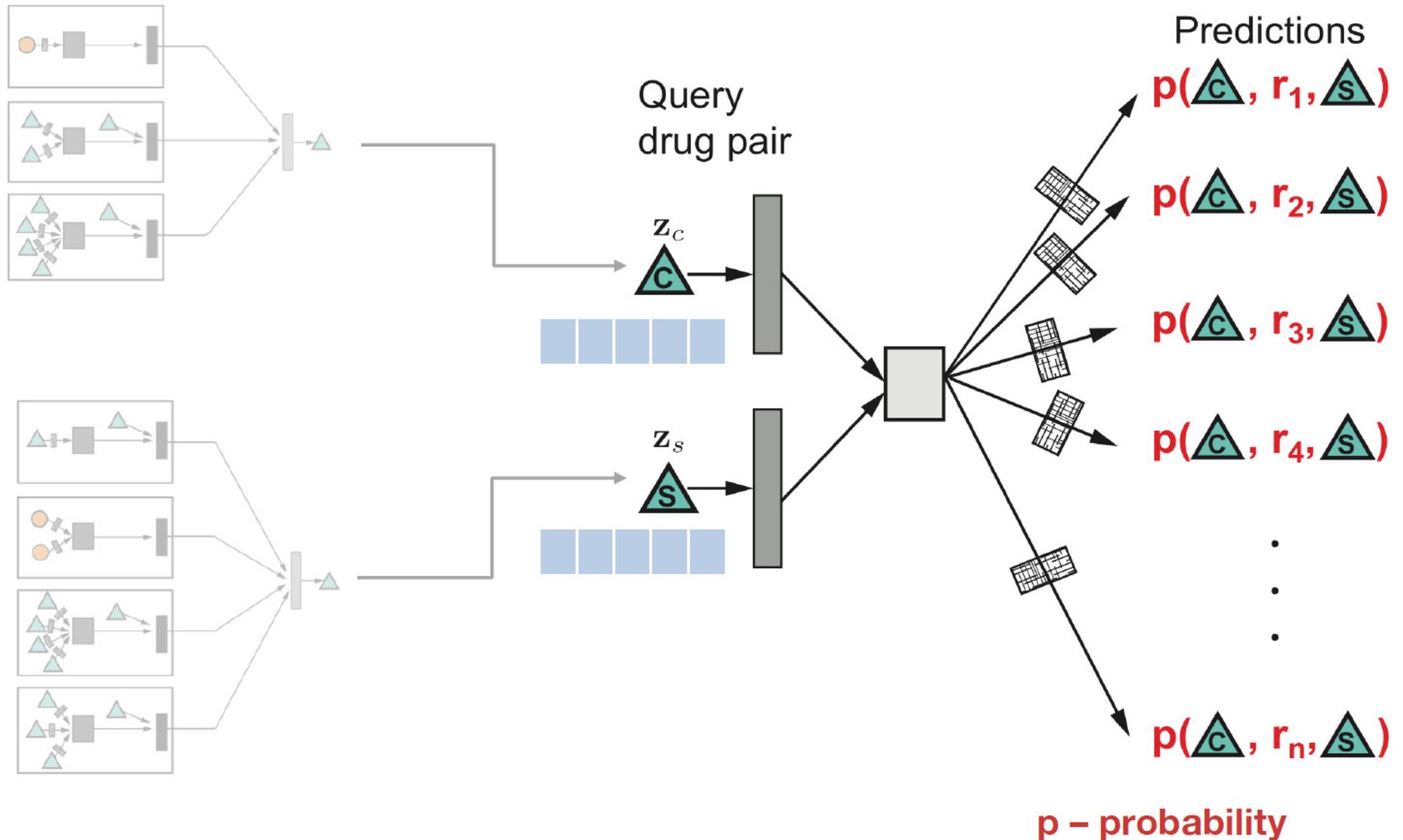


Learn how to transform and propagate information across the graph

# Encoder: Embeddings

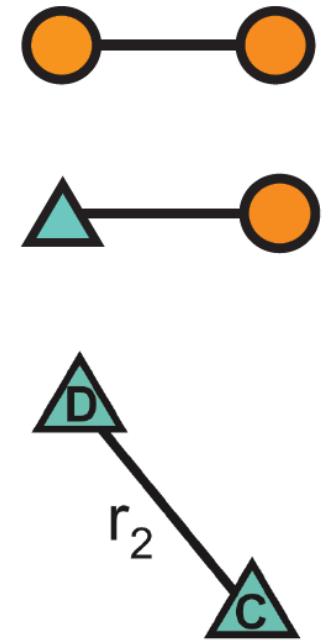


# Decoder: Link Prediction



# Data: Molecular, Drug & Patient

- Protein-protein interactions: Physical interactions in humans [720K edges]
- Drug-target relationships [19K edges]
- Side effects of drug pairs:  
National adverse event reporting system [4.6M edges]
- Additional side information



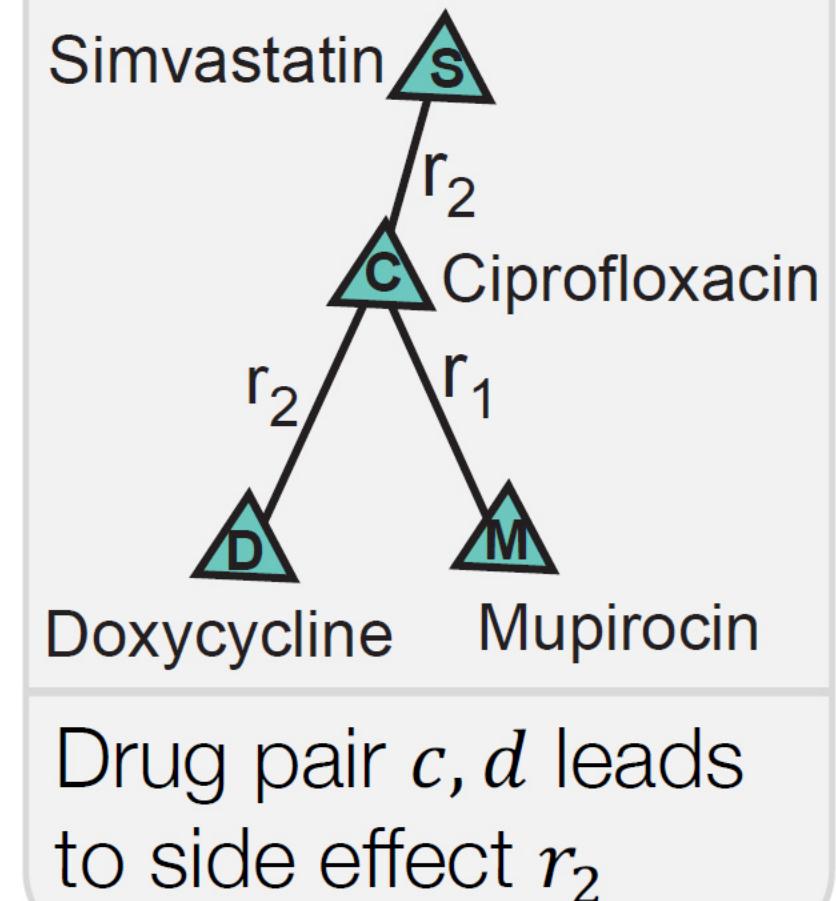
Final graph has 966 different edge types

# Experimental Setup

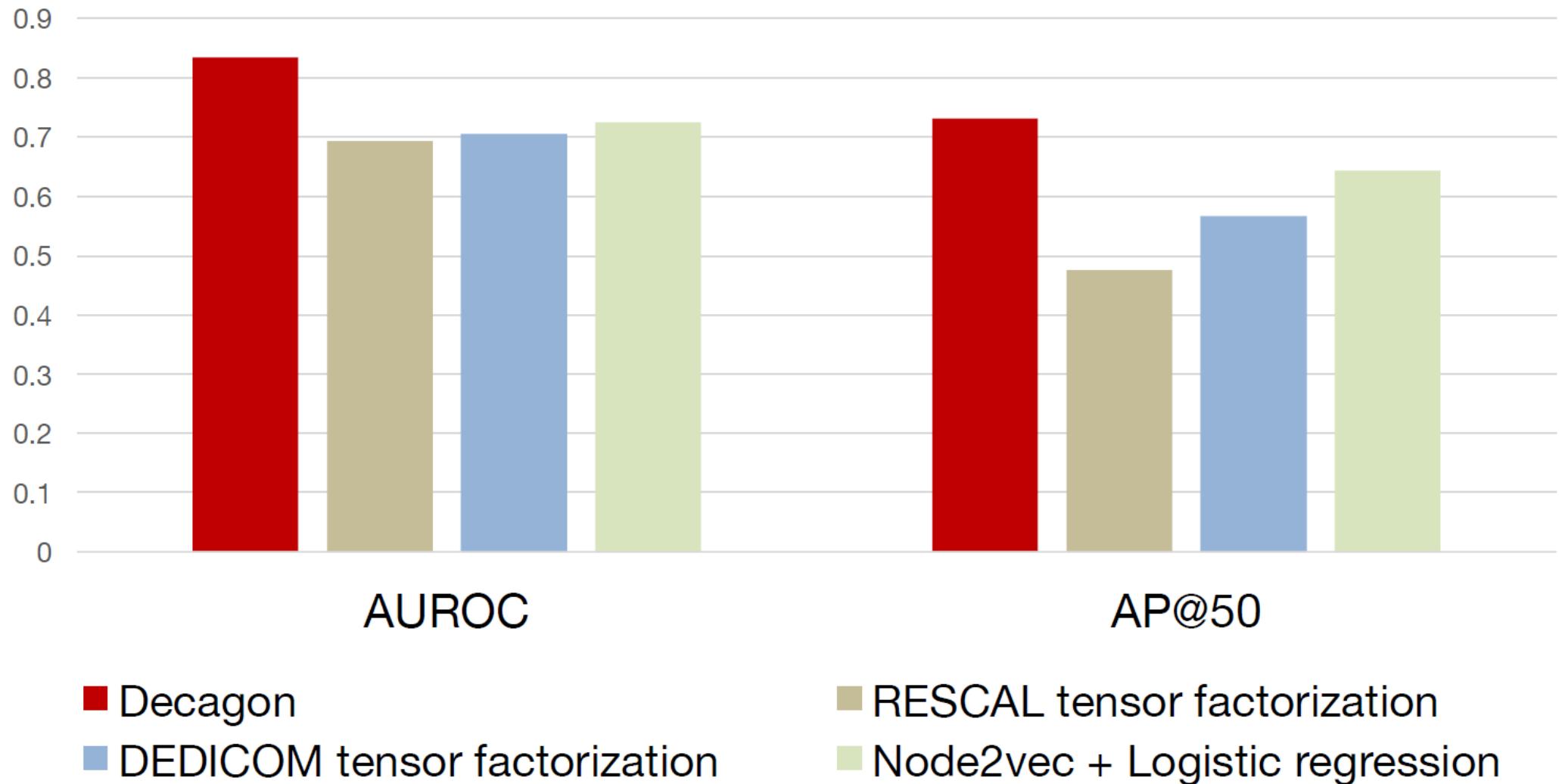
Construct a heterogeneous graph of all the data

Side-effect centric evaluation:

- **Train:** Fit a model on known side effects of drug pairs
- **Test:** Given a query drug pair, predict all types of side effects



# Results: Side Effect Prediction



36% average in AP@50 improvement over baselines

# *De novo* Predictions

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

*Case Report*

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

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