

Modeling Polypharmacy with Graph Convolutional Networks

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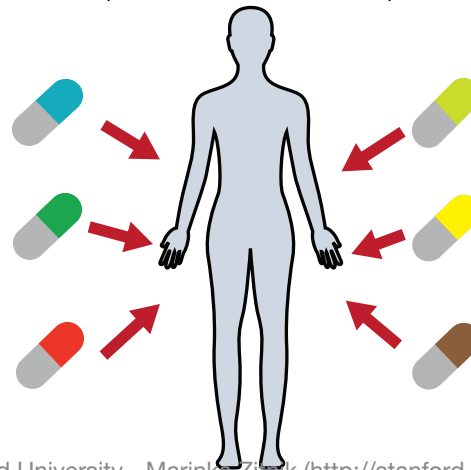
Stanford University



Why polypharmacy?

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

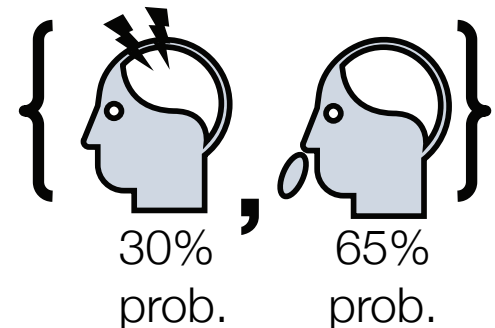
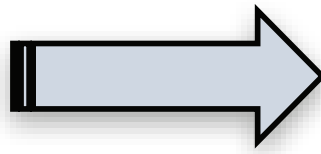
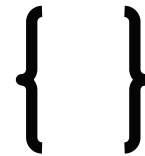
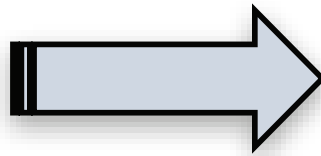
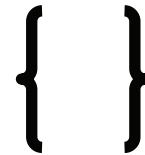
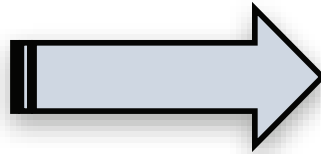
- 25% of people ages 65-69 take more than 5 drugs
- 46% of people ages 70-79 take more than 5 drugs
- Many patients take more than 20 drugs to treat heart disease, depression, insomnia, etc.



Unwanted Side Effects

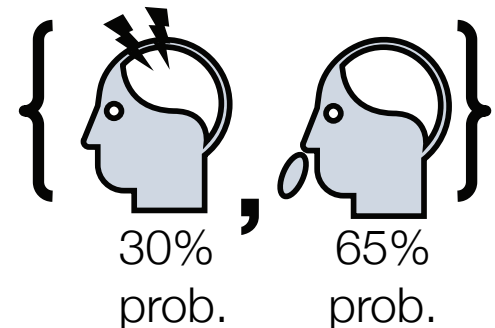
**Prescribed
drugs**

**Drug
side effect**



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**



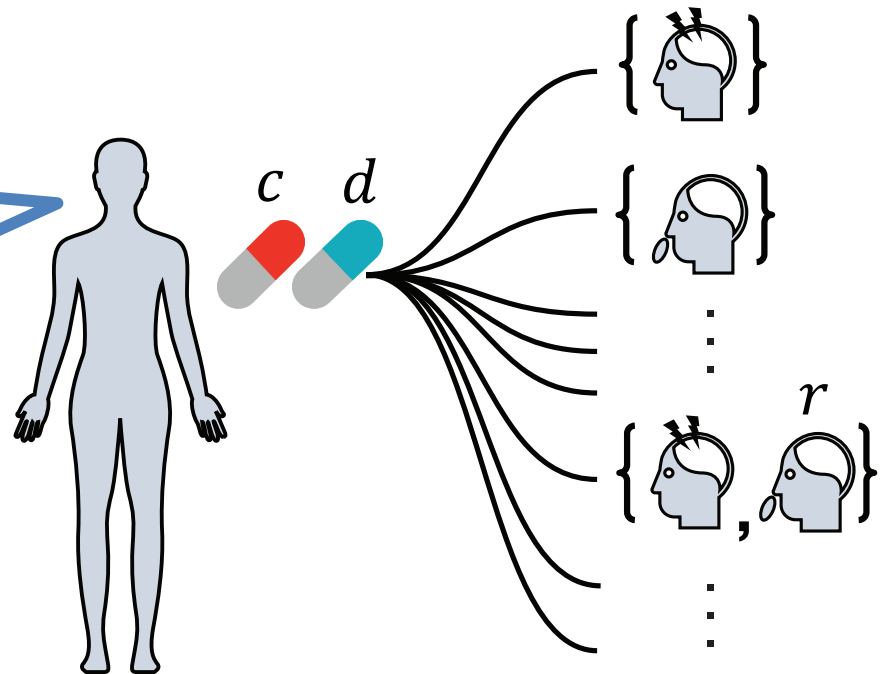
Existing Research

- Experimental screening of drug combs:
 - Expensive, combinatorial explosion
- Computational methods:
 - Supervised methods: Predict probability of a drug-drug interaction [Chen *et al.*, 2016; Shi *et al.*, 2017]
 - Similarity-based methods: Similar drugs have similar interactions [Gottlieb *et al.*, 2012; Ferdousi *et al.*, 2017; Zhang *et al.*, 2017]

These methods **do not predict side effects** of drug combinations

This Work

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



Our study: Model and predict side effects of drug pairs

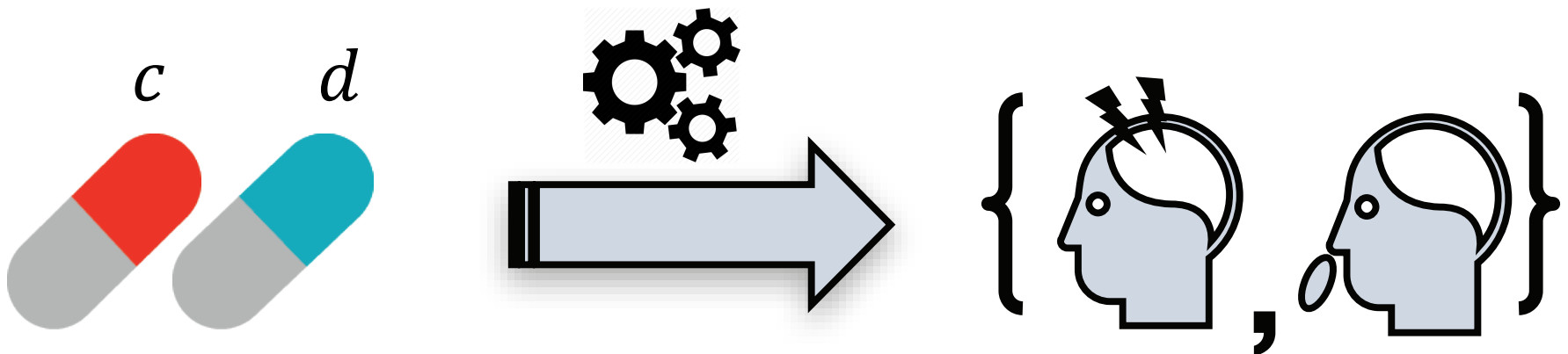
Challenges

- Large number of types of side effects:
 - Each occurs in a small subset of patients
 - Side effects are interdependent
- No information about drug pairs that are not yet used in patients
- Molecular, drug, and patient data:
 - Heterogeneous and multi-relational

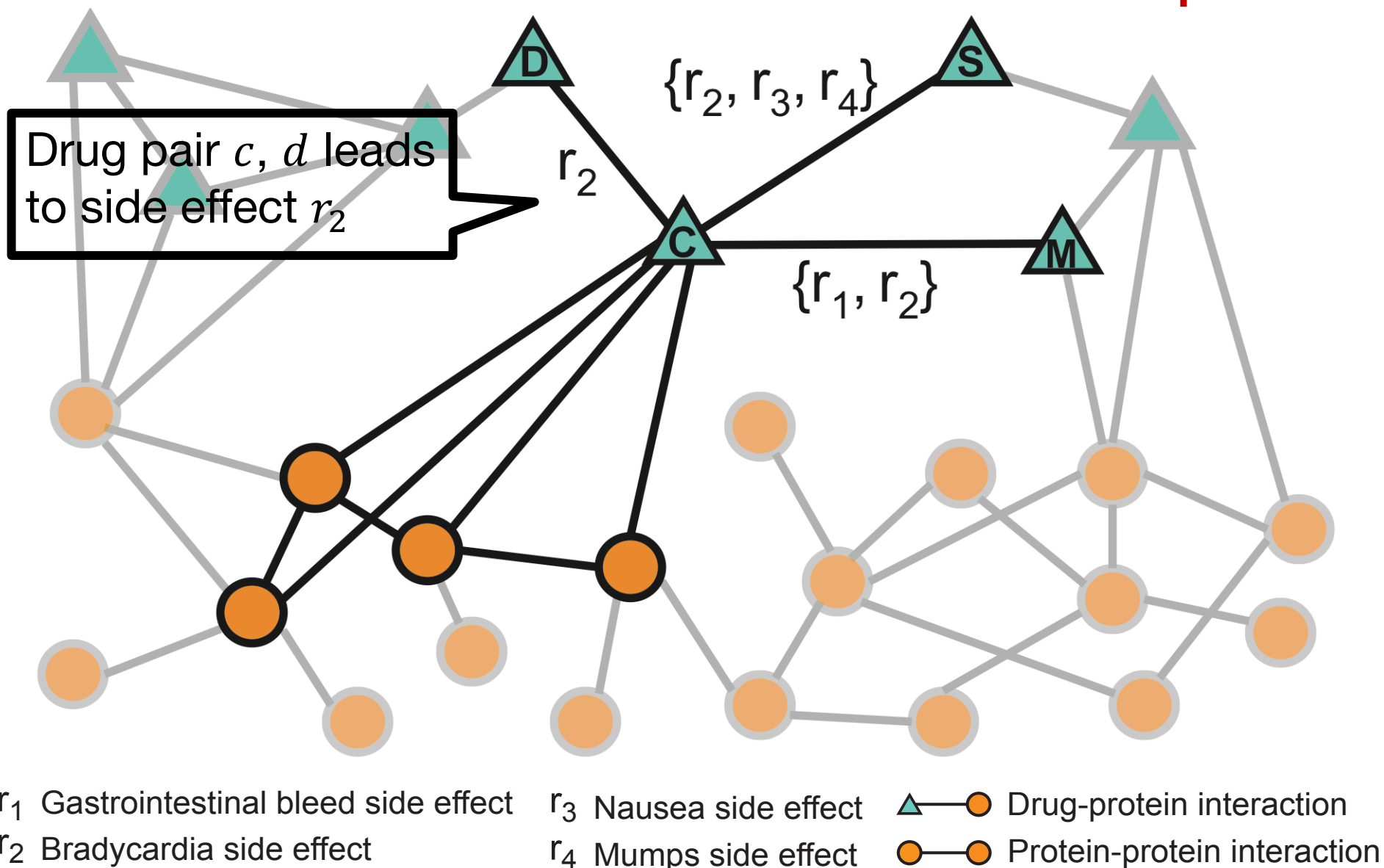
Our Approach

In silico screening of drug combinations

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



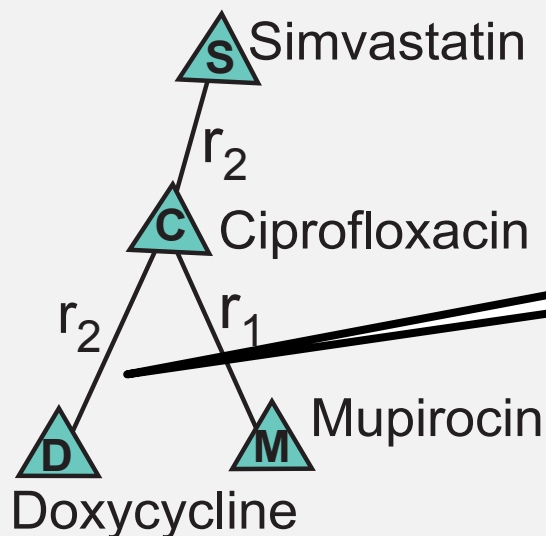
Problem Formulation: Graphs



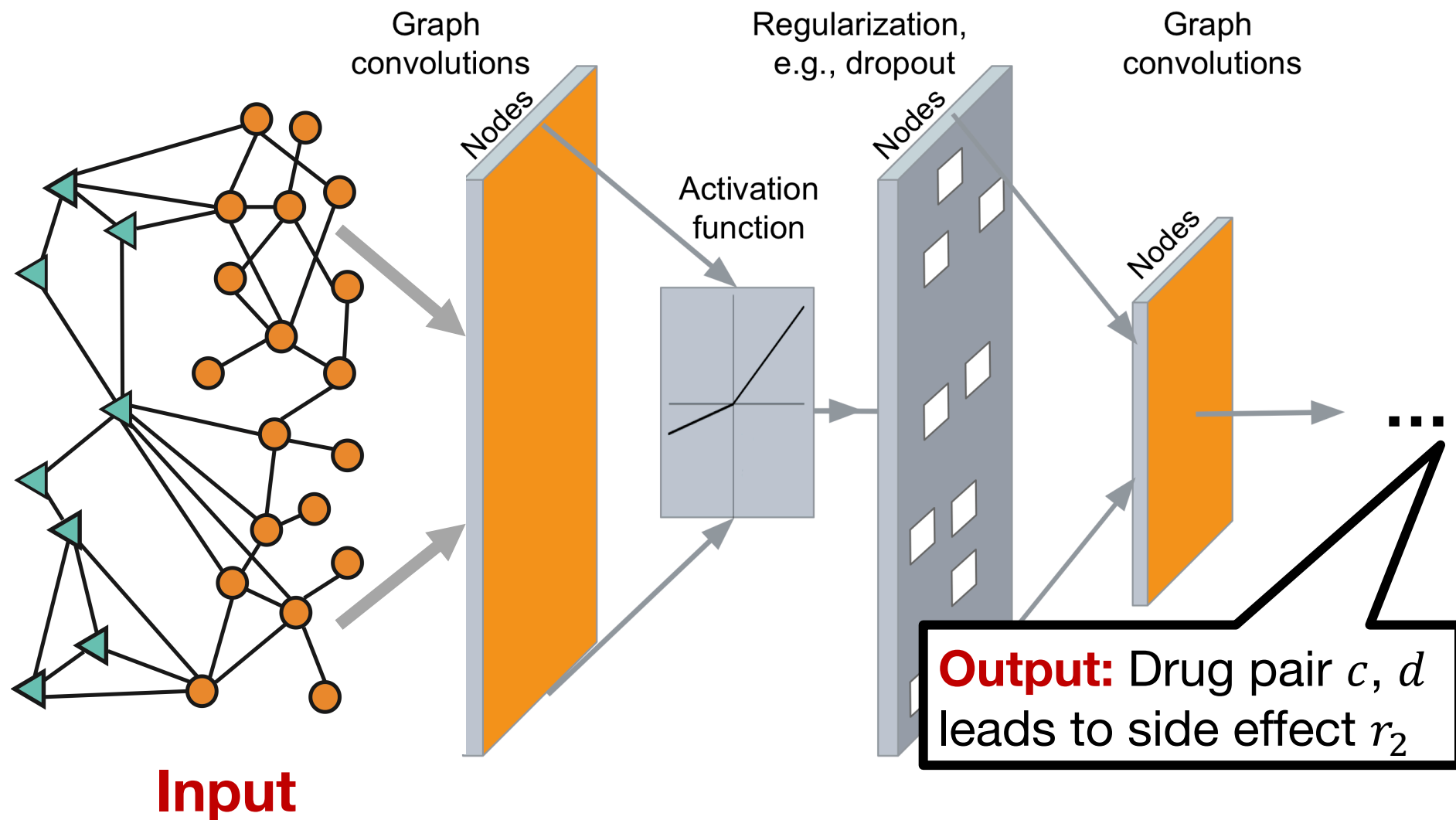
Problem Formulation: Predict

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?

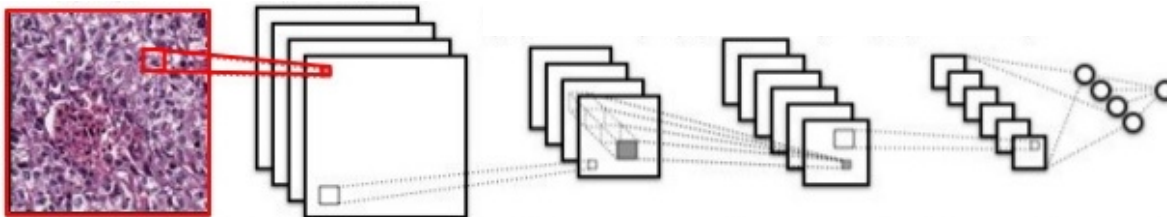
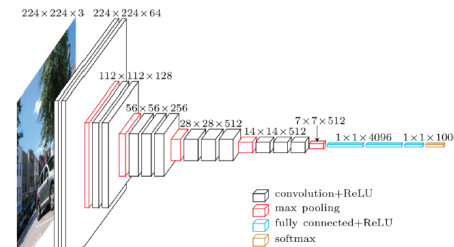
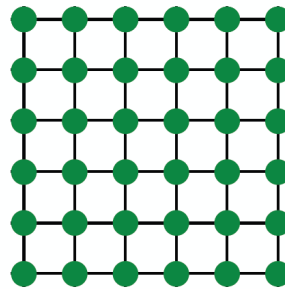
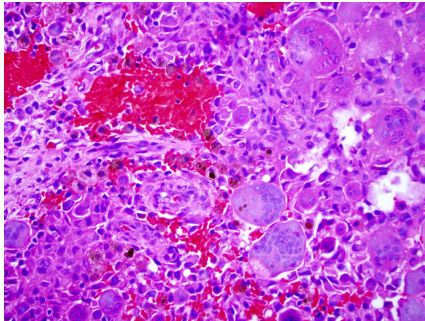


Graph Neural Network



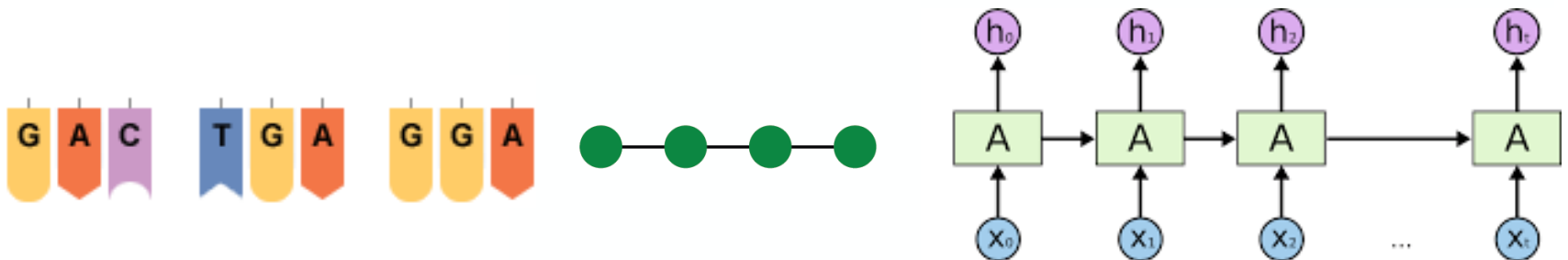
Why Is It Hard?

- Modern deep learning toolbox is designed **for grids** or simple sequences
 - Images have 2D grid structure
 - Can define convolutions (CNN)



Why Is It Hard?

- Modern deep learning toolbox is designed for grids or **simple sequences**
 - Sequences have linear 1D structure
 - Can define sliding window, RNNs, word2vec, etc.



Why Is It Hard?

- But networks are far more complex!
 - Arbitrary size and complex topological structure (i.e., no spatial locality like grids)

Goal: Generalize convolutions
beyond simple lattices



Networks

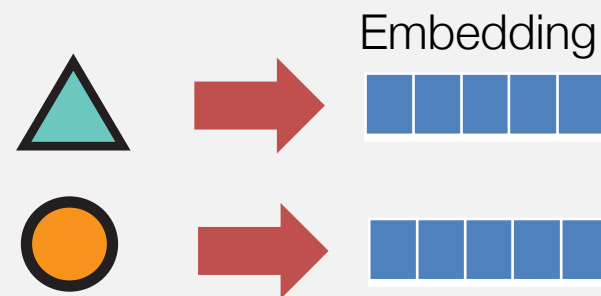


Images

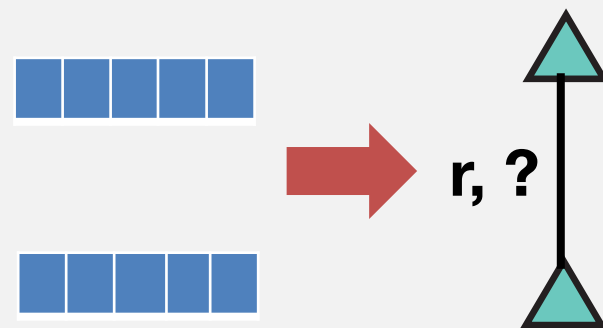
- No fixed node ordering or reference point
- Often dynamic and have multimodal features

Decagon: Graph Neural Net

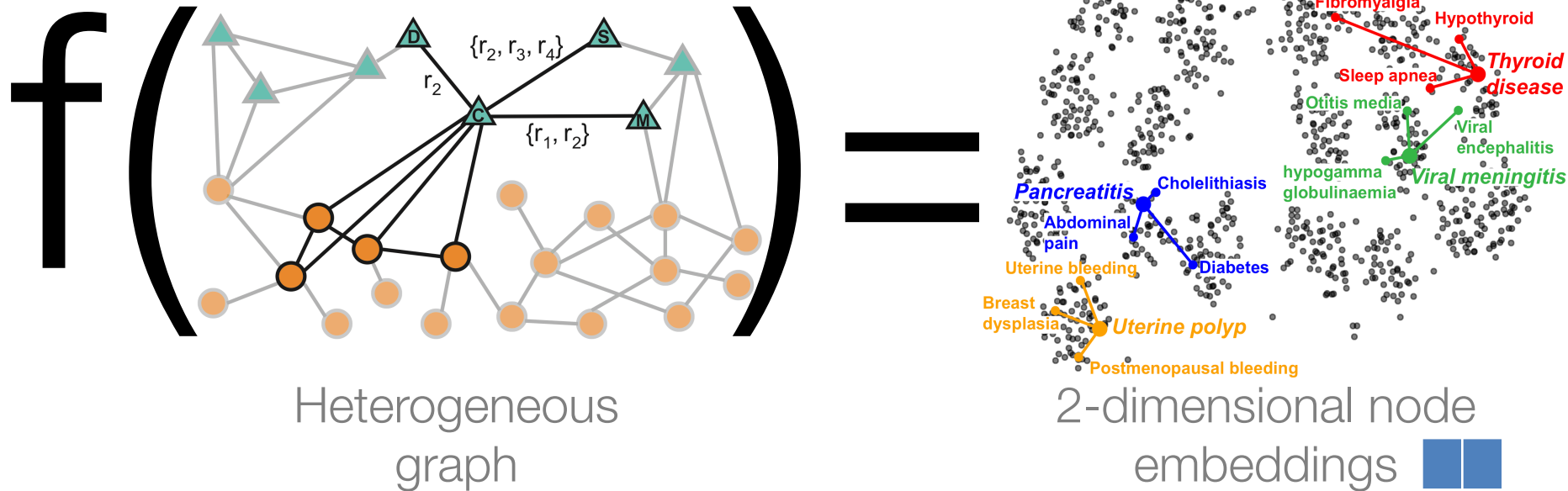
1. Encoder: Take the graph and learn an *embedding* for every node



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



Embedding Nodes



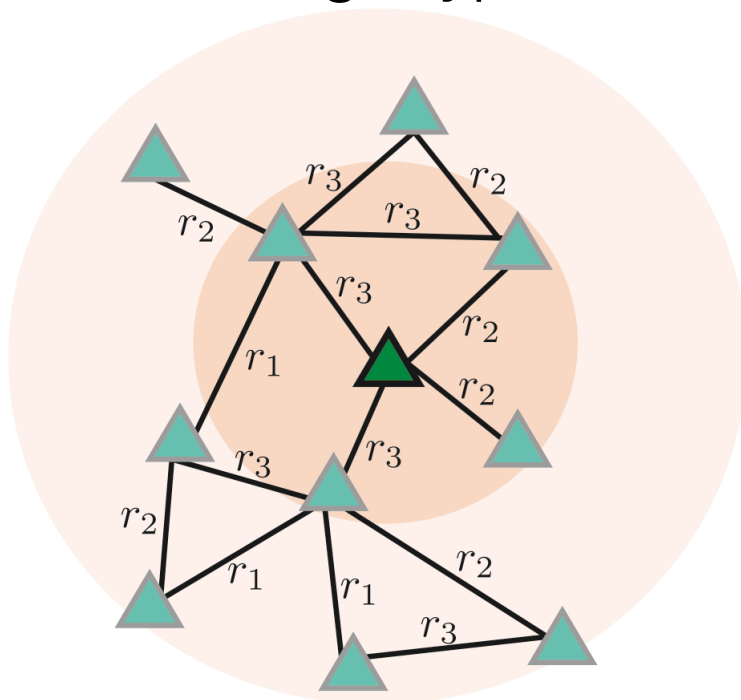
How to learn f ?

Intuition: Map nodes to d -dimensional **embeddings** such that **similar nodes in the graph** are **embedded close together**

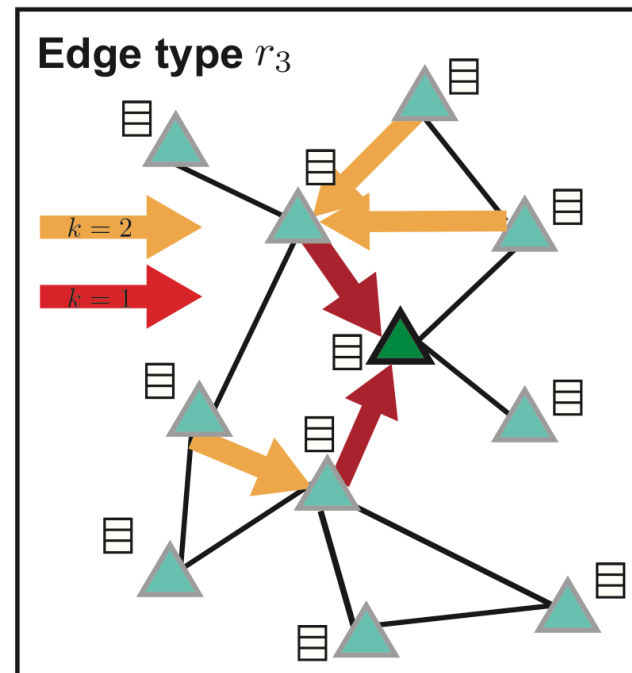
Encoder: Principle

Key idea: Generate node embeddings based on **local network neighborhoods**

Each edge type is modeled separately

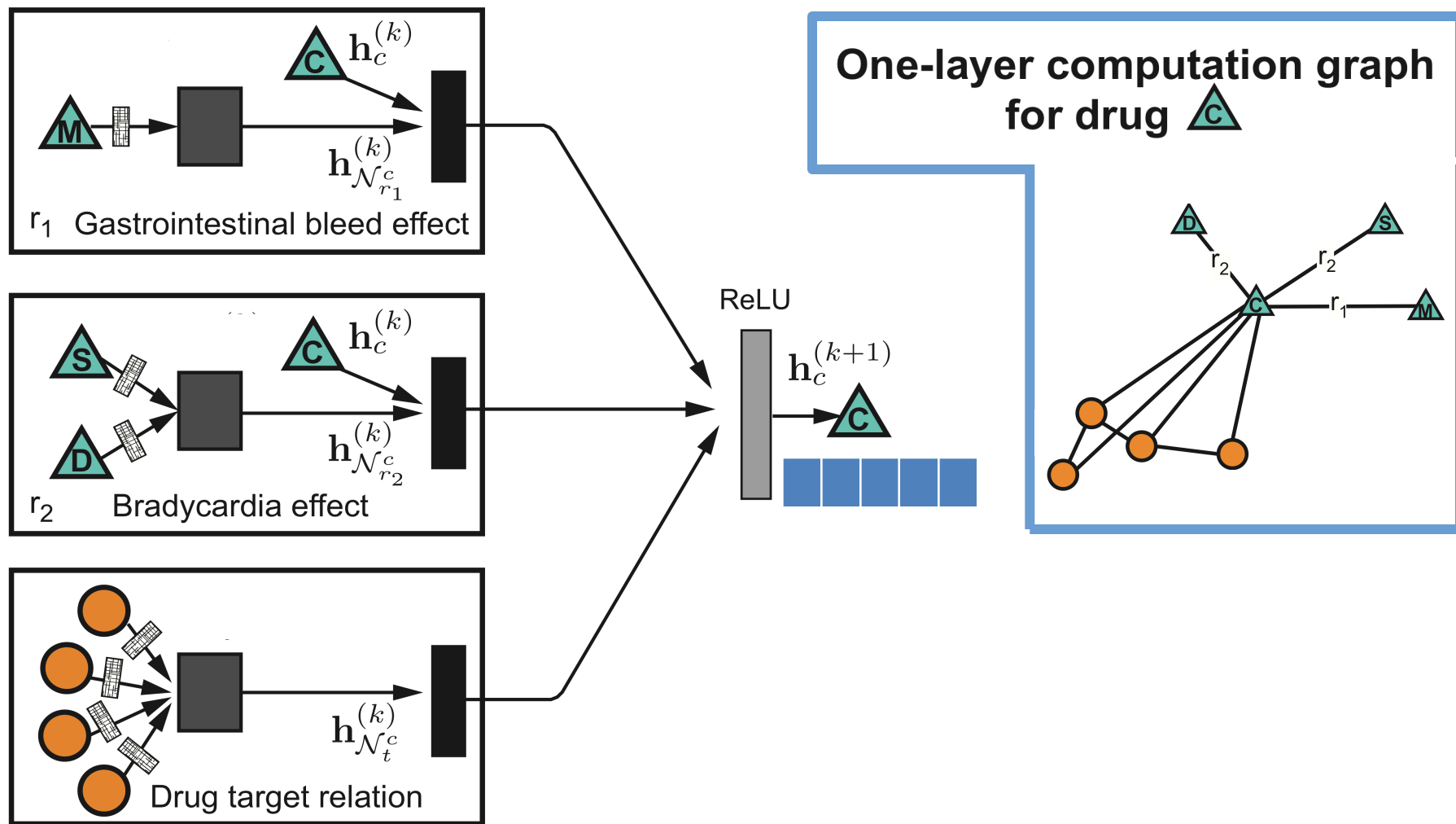


**Determine a node's
computation graph**

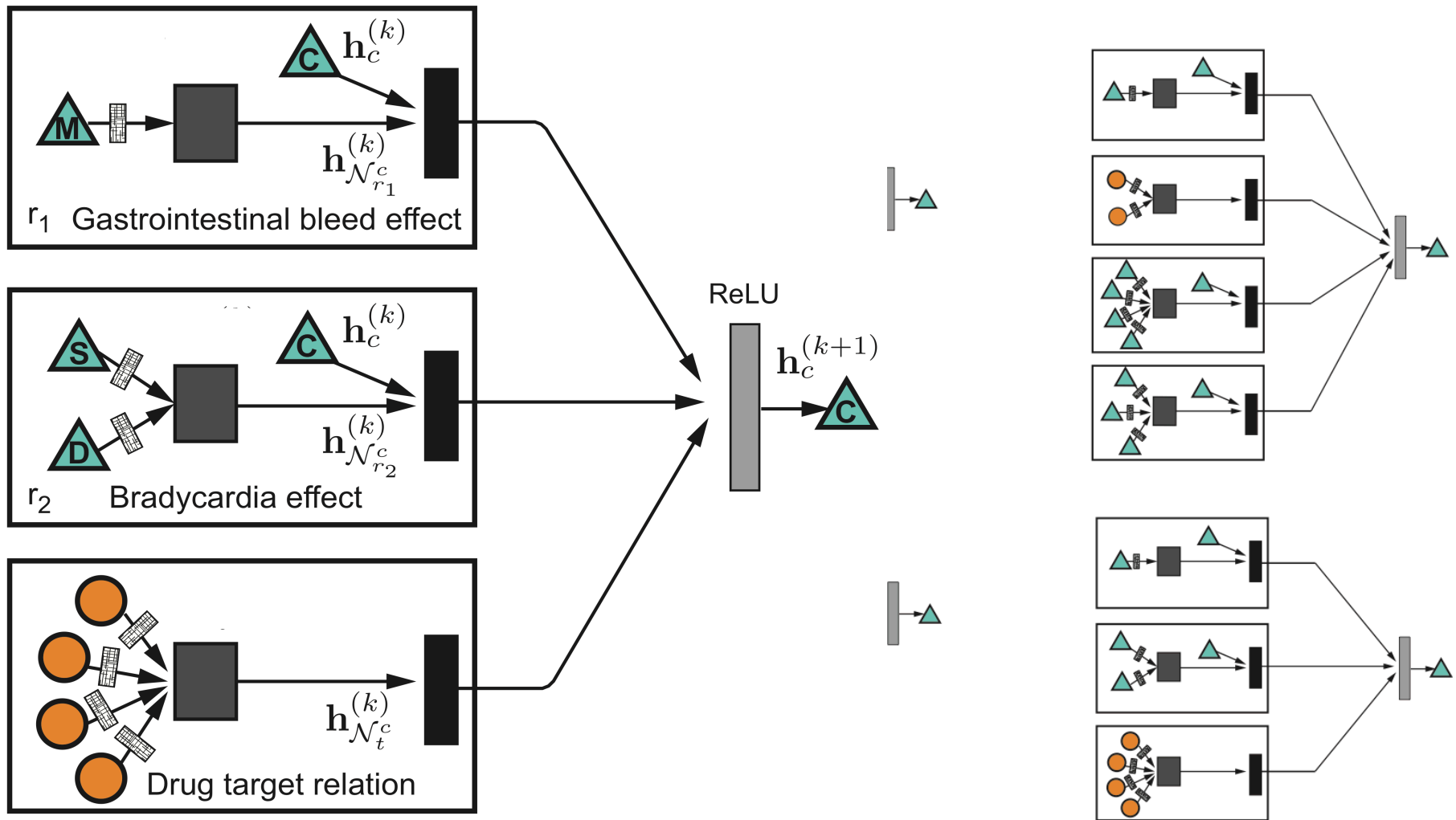


**Learn how to transform and
propagate information across the graph**

Encoder: Embeddings

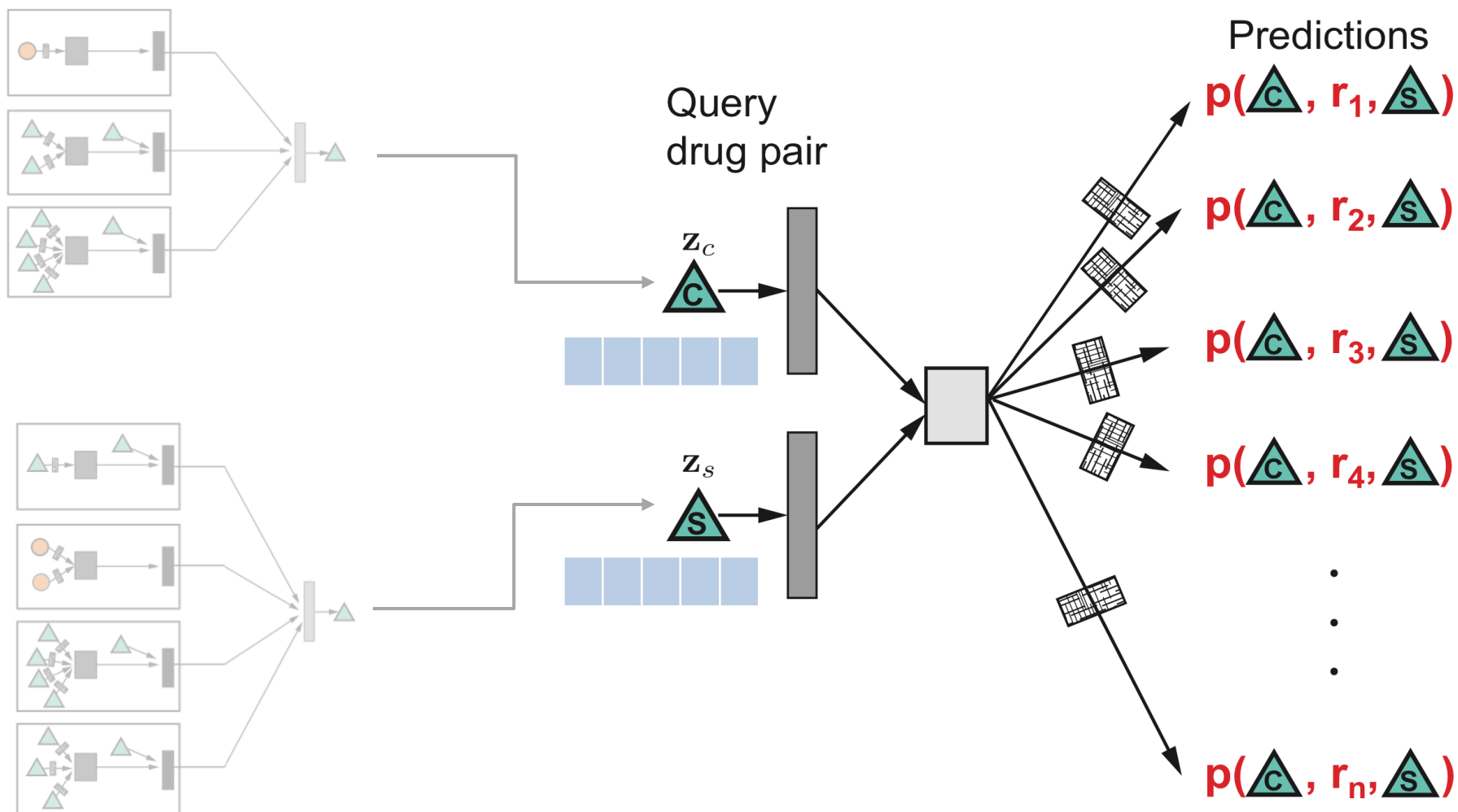


Encoder: Embeddings



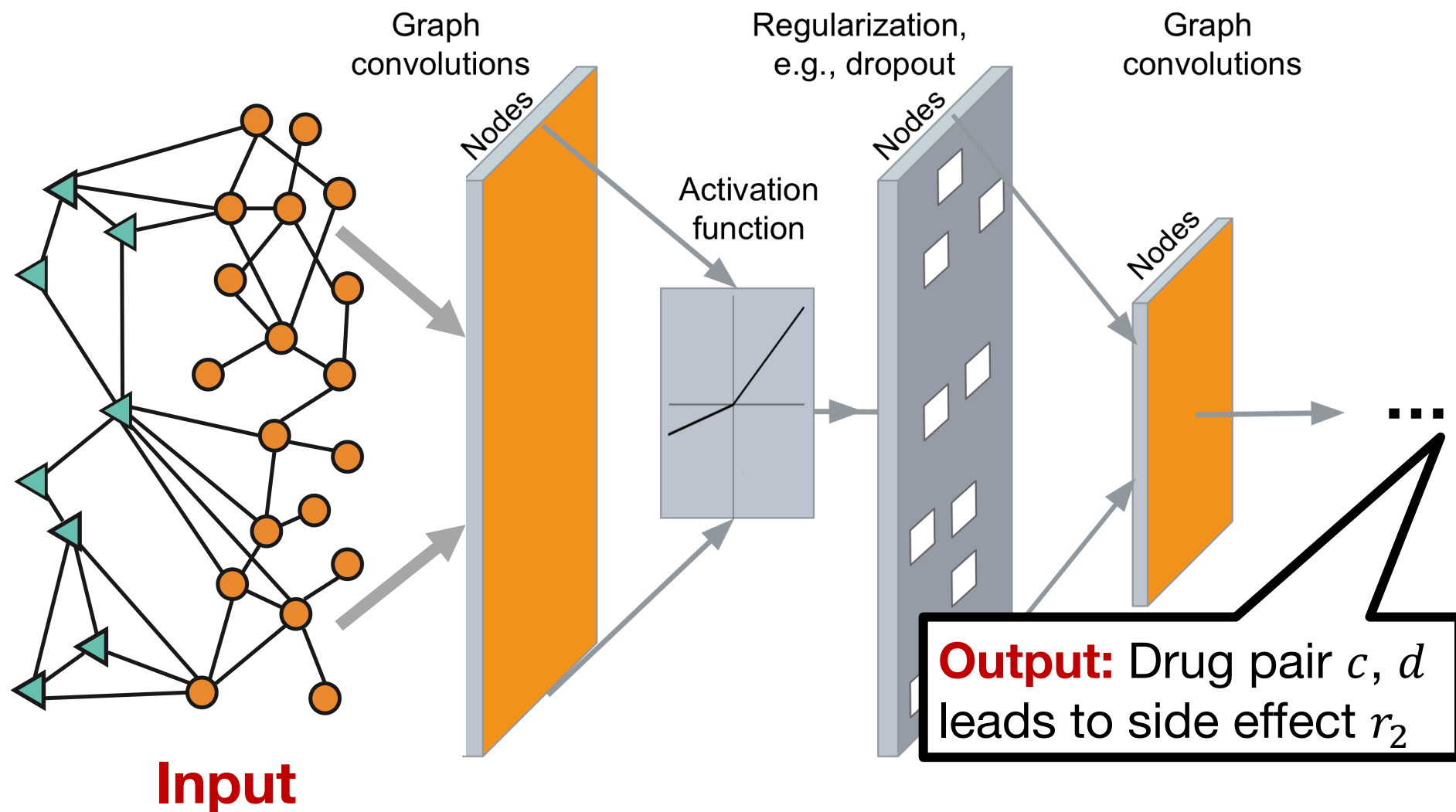
A batch of computation graphs

Decoder: Link Prediction



p – probability

Graph Neural Network



Deep Learning for Network Biology

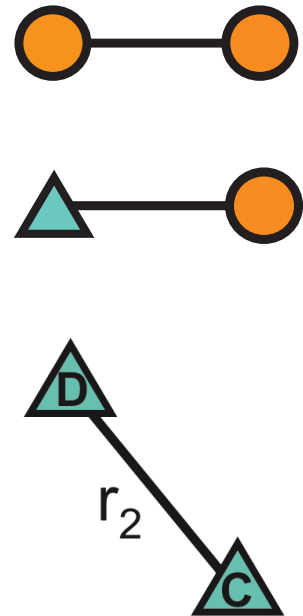
snap.stanford.edu/deepnetbio-ismb

Tutorial at ISMB 2018:

- From basics to state-of-the-art in graph neural nets
- Deep learning **code bases**:
 - End-to-end examples in Tensorflow/PyTorch
 - Popular code bases for graph neural nets
 - Easy to adapt and extend for your application
- Network **analytics tools** and biological **network data**

Data: Molecular, Drug & Patient

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



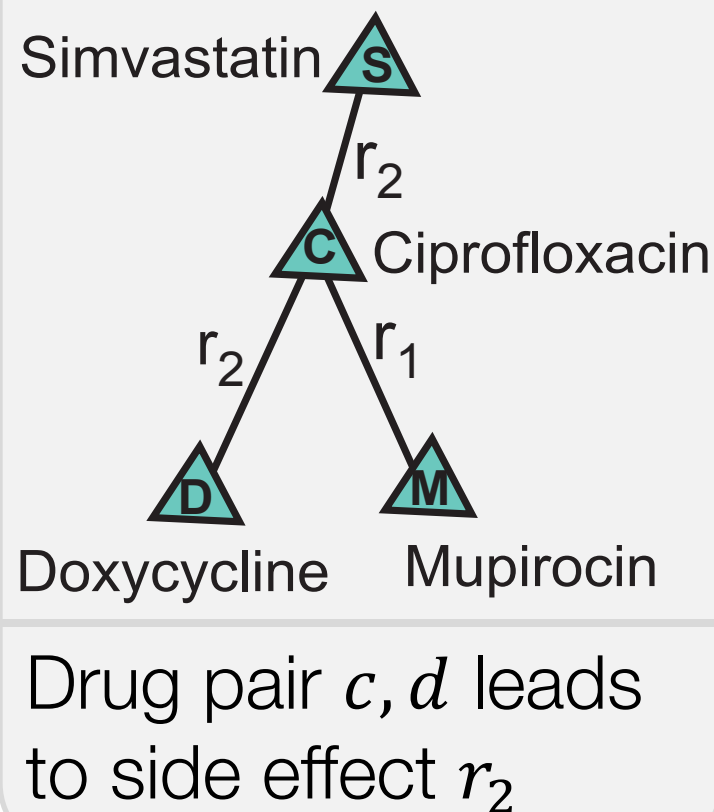
Final graph has **966 different edge types**

Experimental Setup

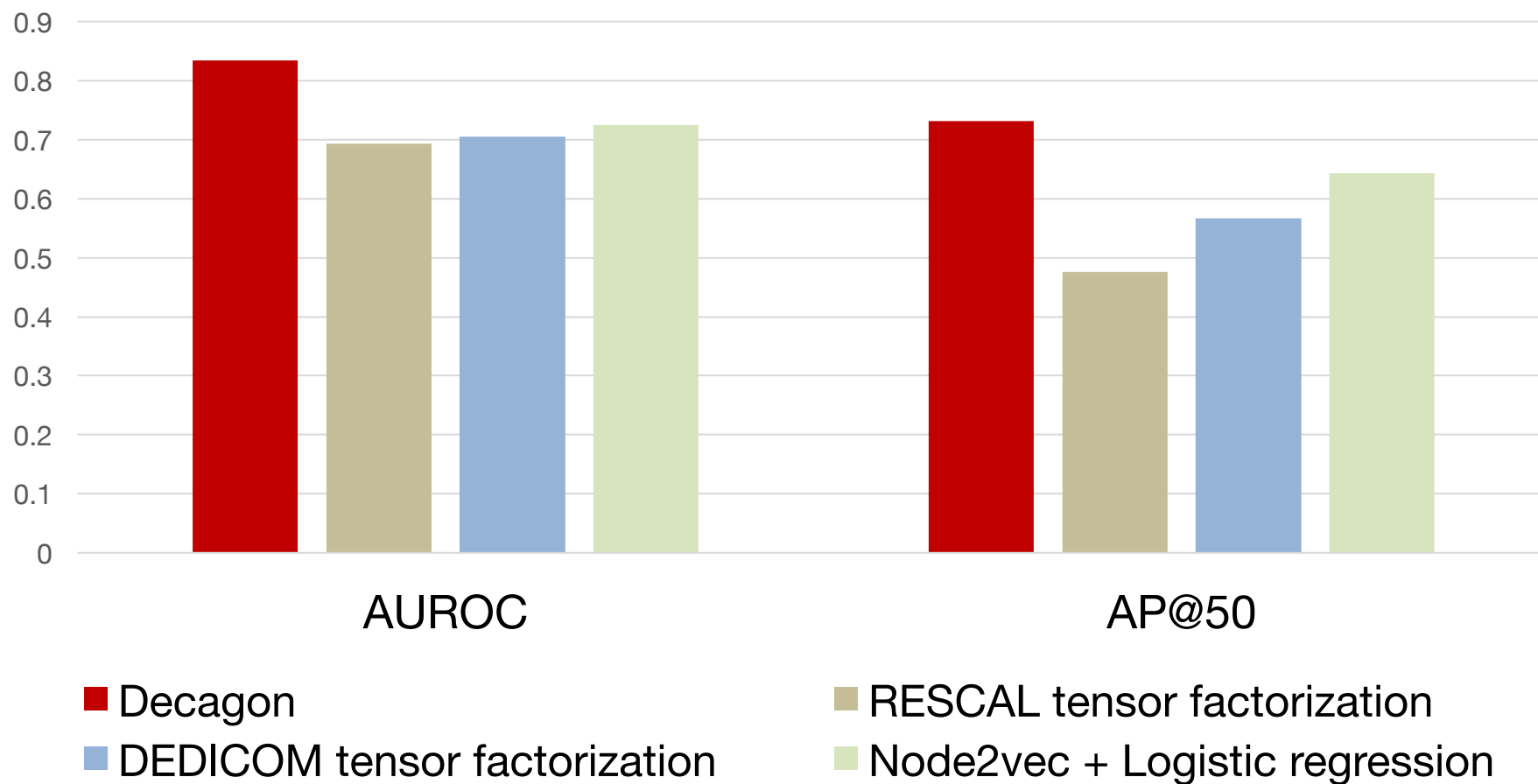
Construct a heterogeneous graph of all the data

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



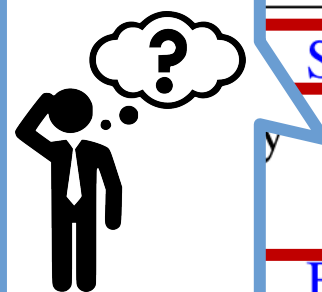
36% average in AP@50 improvement over baselines

De novo Predictions

| Rank | Drug c | Drug d | Side effect r |
|------|---------------|---------------|------------------------|
| 1 | Pyrimethamine | Aliskiren | Sarcoma |
| 2 | Tigecycline | Bimatoprost | Autonomic neuropathy |
| 3 | Omeprazole | Dacarbazine | Telangiectases |
| 4 | Tolcapone | Pyrimethamine | Breast disorder |
| 5 | Minoxidil | Paricalcitol | Cluster headache |
| 6 | Omeprazole | Amoxicillin | Renal tubular acidosis |
| 7 | Anagrelide | Azelaic acid | Cerebral thrombosis |
| 8 | Atorvastatin | Amlodipine | Muscle inflammation |
| 9 | Aliskiren | Tioconazole | Breast inflammation |
| 10 | Estradiol | Nadolol | Endometriosis |

De novo Predictions

| Rank | Drug c | Drug d | Side effect r | Evidence found |
|------|---------------|---------------|------------------------|-------------------------------------|
| 1 | Pyrimethamine | Aliskiren | Sarcoma | Stage et al. 2015 |
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| 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

Conclusions

Decagon predicts side effects of any drug pair:

- The first method to do that
- Even for drug combinations not yet used in patients

Project website with data & code:

snap.stanford.edu/decagon

Deep learning for network biology:

snap.stanford.edu/deepnetbio-ismb