MIE524 Data Mining

Graph Representation Learning

Slides Credits:
Slides from Leskovec, Rajaraman, Ullman (http://www.mmds.org), Leskovec & Ghashami

Announcements

- Support lab today 4-6pm

- Next Thursday Nov 21:
  - The last assignment will be provided and explained
  - We will have the <u>last</u> quiz (last assignment will not have a quiz)

- Next week:
  - Focus on recommended systems
  - We will cover a popular neural-based recommender system from the literature: **Neural Collaborative Filtering**
  - Reading: Sections 1-3 from the paper: https://arxiv.org/pdf/1708.05031

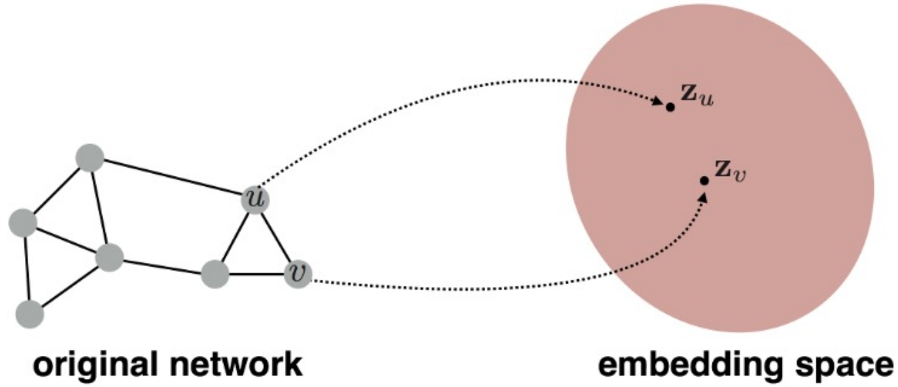
MIE524: Course Topics (Tentative)

Large-scale Machine Learning	High-dimensional Data	Graph Data	Applications
Learning Embedding (NN / AE)	Locality sensitive hashing	Processing Massive Graphs	Recommender systems
Decision Trees	Clustering	PageRank, SimRank	Association Rules
Ensemble Models (GBTs)	Dimensionality reduction	Graph Representation Learning	Neural Language Models

Computational Models:	Single Machine	MapReduce/Spark	GPU

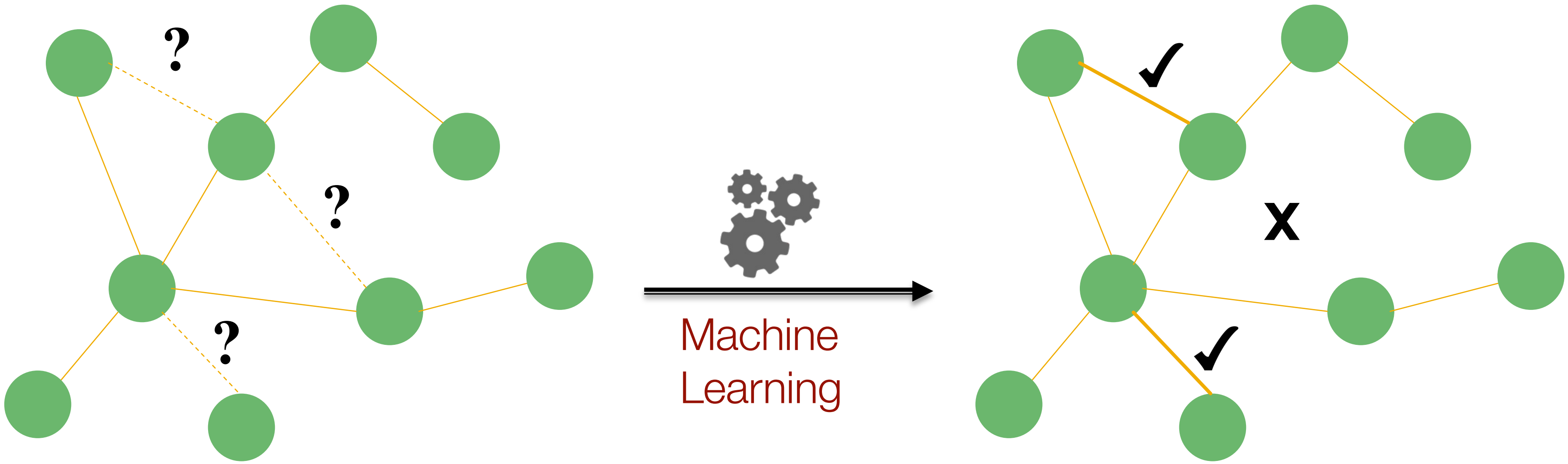
Representation Learning in Graphs

It is to learn a mapping that embeds nodes, subgraphs, or the entire graphs, as points in a low-dimensional vector space.



Such that geometric relationships in the learned space reflect the structure of the original graph.

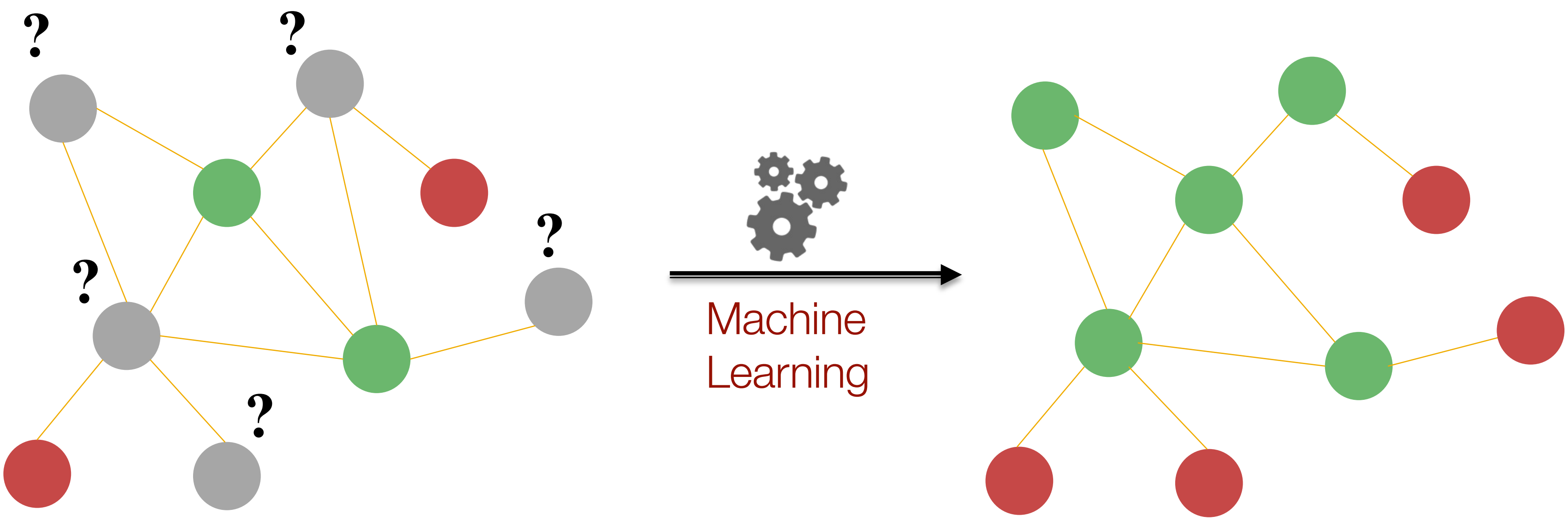
Example: Link Prediction



Examples of link prediction task:

- Identifying real-world friends in social network
- Discovering novel interactions between genes in genomics
- Recommender systems

Example: Node Classification



Example: Node Classification

Classifying the function of proteins in the interactome

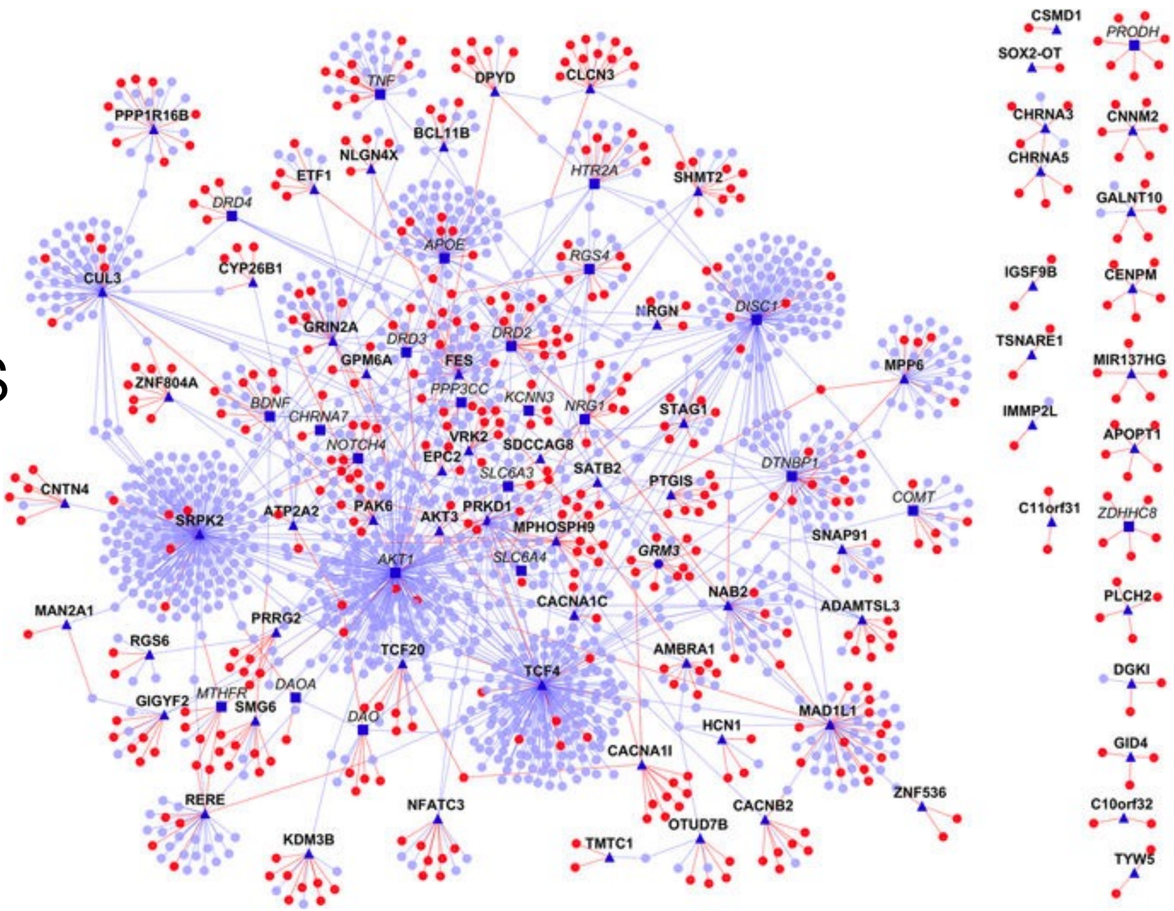
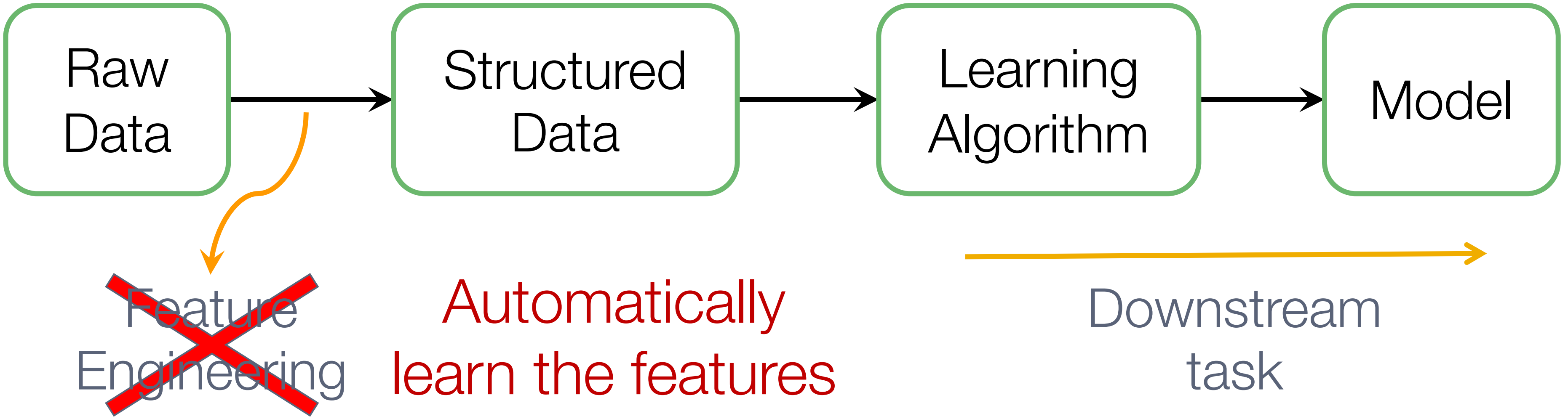


Image from: Ganapathiraju et al. 2016. [Schizophrenia interactome with 504 novel protein–protein interactions](). *Nature*.

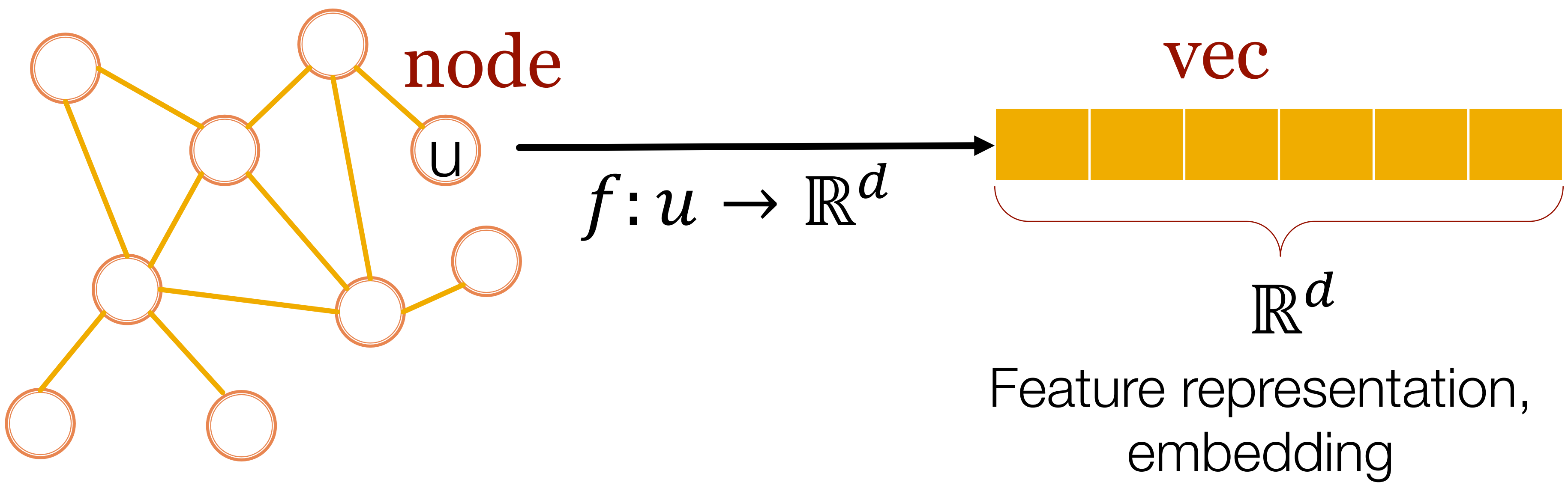
Machine Learning Lifecycle

- **(Supervised) Machine Learning Lifecycle requires feature engineering every single time!**



Feature Learning in Graphs

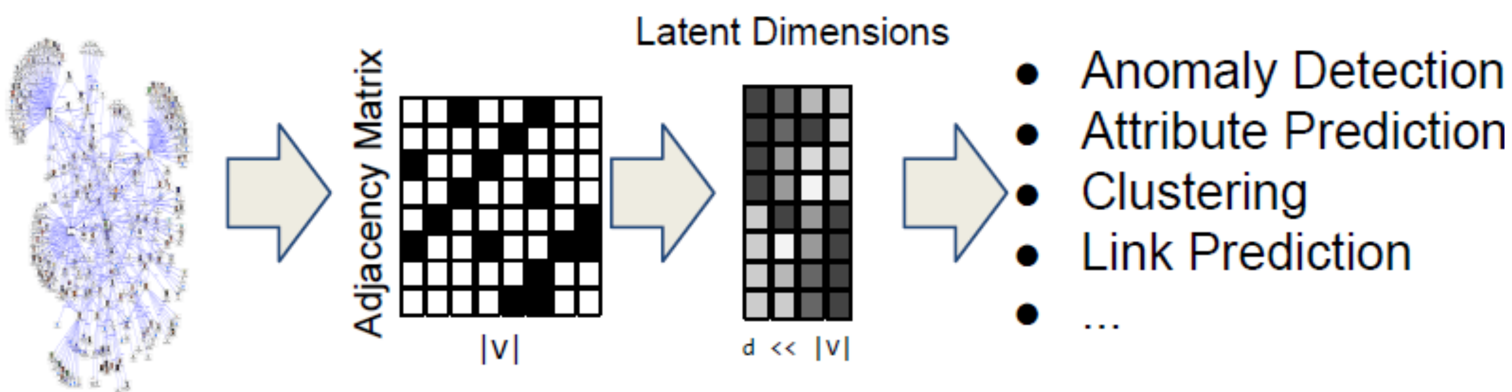
Goal: Efficient task-independent feature learning for machine learning in networks!



Why network embedding?

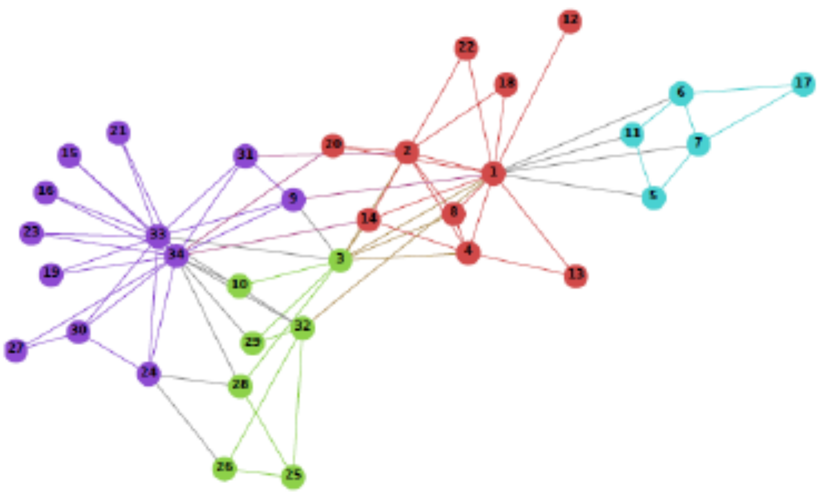
Task: We map each node in a network to a point in a low-dimensional space

- Distributed representation for nodes
- Similarity of embedding between nodes indicates their network similarity
- Encode network information and generate node representation

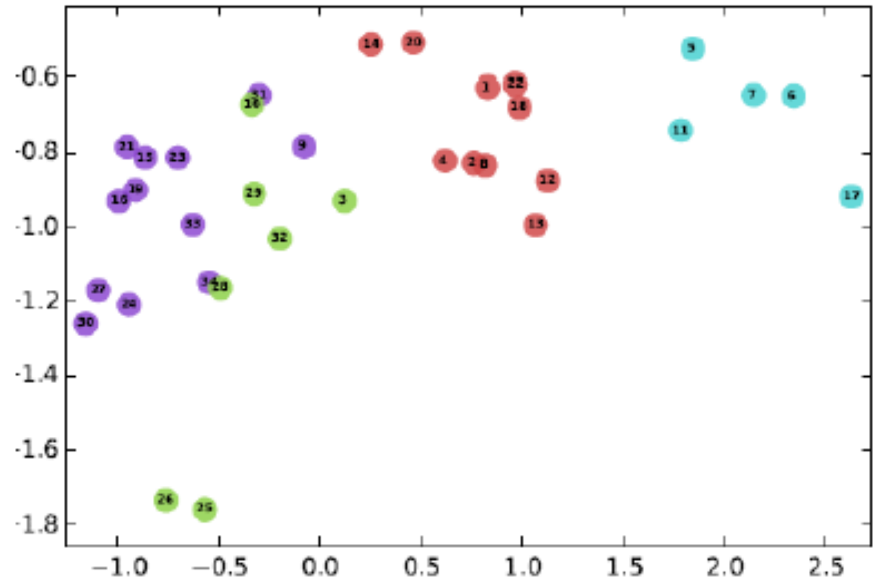


Example Node Embedding

2D embedding of nodes of the Zachary's Karate Club network:



Input



Output

Image from: [Perozzi et al](). DeepWalk: Online Learning of Social Representations. *KDD 2014.*

Embedding Nodes

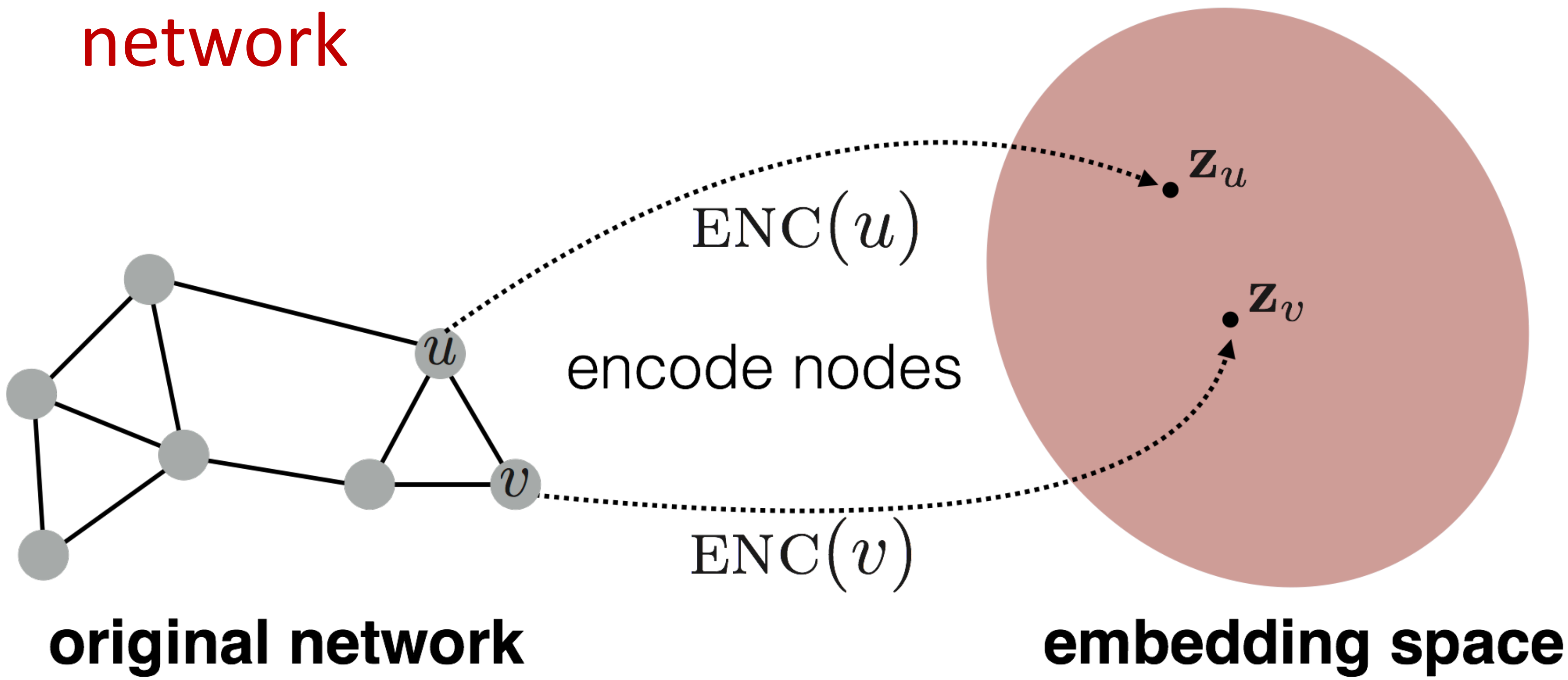
Setup

Assume we have a graph G:

- V is the vertex set
- $\mathbf{A}$ is the adjacency matrix (assume binary)
- **No node features or extra information is used!**

Embedding Nodes

- Goal is to encode nodes so that similarity in the embedding space (e.g., dot product) approximates similarity in the original network



Dot product similarity

- Dot product between vectors A and B: $\mathbf{A} \cdot \mathbf{B} = \sum_{i=1}^{N} a_i b_i.$

- Dot product equals to the product of vector lengths and the cosine of the angle between them: $\mathbf{A} \cdot \mathbf{B} = |\mathbf{A}||\mathbf{B}| \cos(\theta).$
  - If vectors are normalized,
    the dot product is equal to cosine similarity

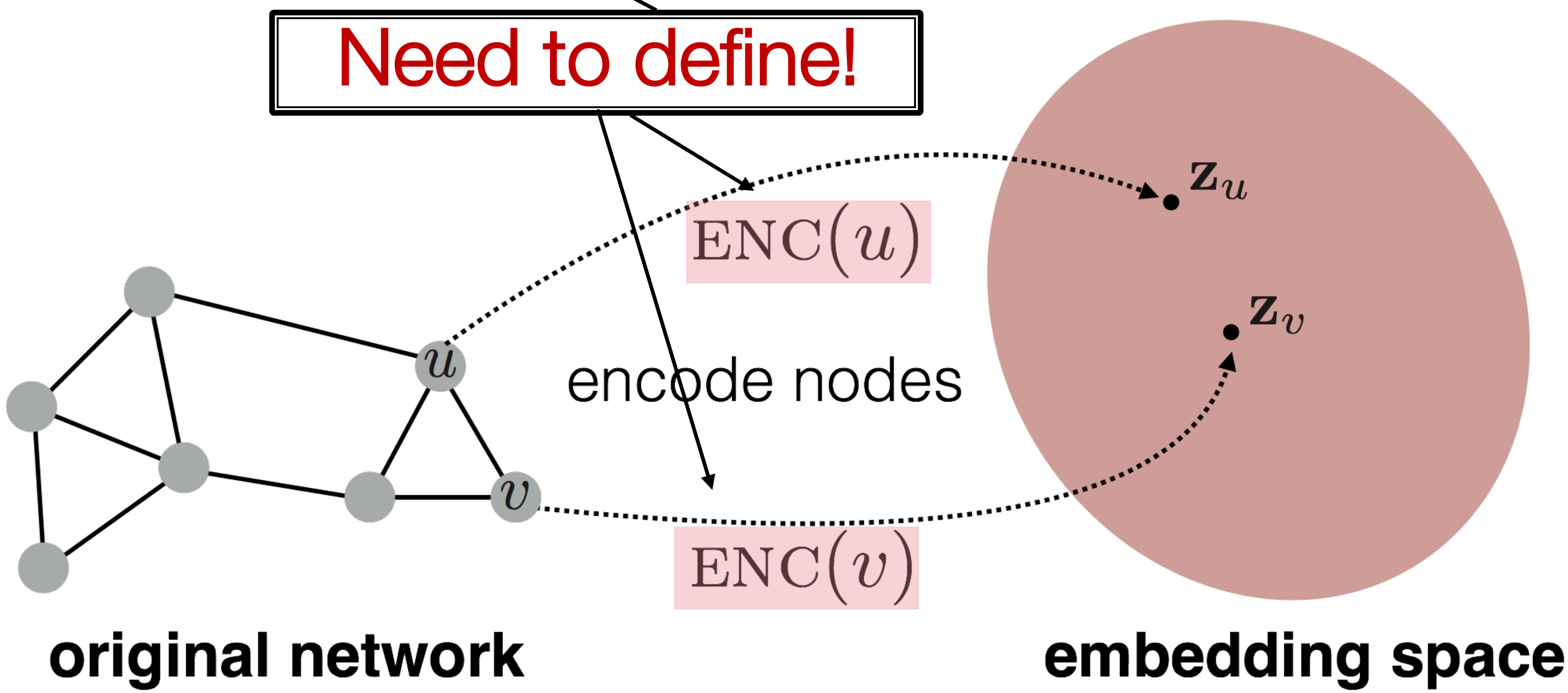
- Often used to measure similarity between embeddings
  - Larger dot product imply higher similarity
  - Orthogonal vectors will have a dot product of zero

Embedding Nodes

Goal: $\text{similarity}(u, v) \approx \mathbf{z}_v^\top \mathbf{z}_u$

in the original network

Similarity of the embedding



Learning Node Embeddings

1. **Define an encoder** (i.e., a mapping from nodes to embeddings)
2. **Define a node similarity function** (i.e., a measure of similarity in the original network)
3. **Optimize the parameters of the encoder so that:**

$$\underbrace{\text{similarity}(u, v)}_{\text{in the original network}} \approx \underbrace{\mathbf{z}_v^\top \mathbf{z}_u}_{\text{Similarity of the embedding}}$$

Two Key Components

- **Encoder** maps each node to a low-dimensional vector

$$\text{ENC}(v) = \mathbf{z}_v$$

d-dimensional embedding

node in the input graph

- **Similarity function** specifies how relationships in vector space map to relationships in the original network

$$\text{similarity}(u, v) \approx \mathbf{z}_v^\top \mathbf{z}_u$$

Similarity of u and v in the original network

dot product between node embeddings

"Shallow" Encoding

- Simplest encoding approach: **encoder is just an embedding-lookup**

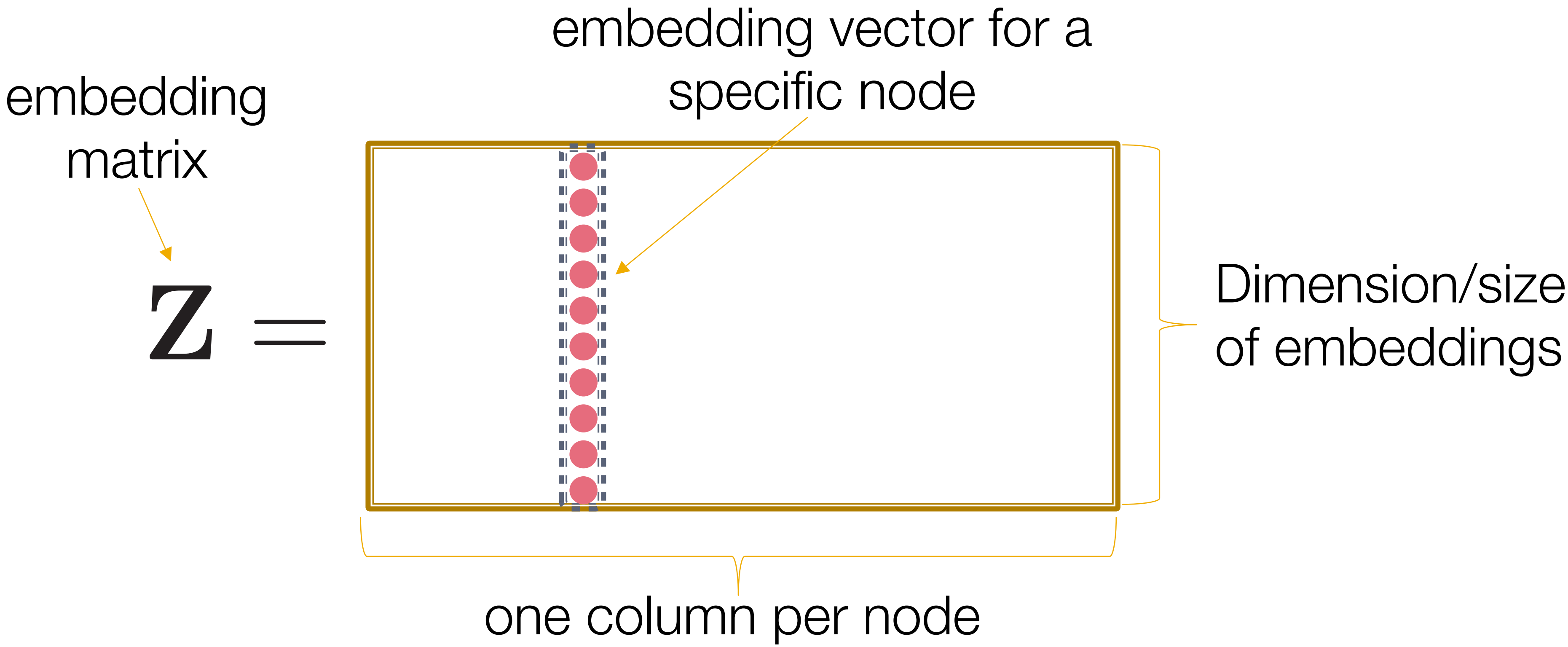
$$\mathrm{ENC}(v) = \mathbf{Z}\mathbf{v}$$

$\mathbf{Z} \in \mathbb{R}^{d \times |\mathcal{V}|}$ Matrix, each column is d-dim node embedding **[what we learn!]**

$\mathbf{v} \in \mathbb{I}^{|\mathcal{V}|}$ Indicator vector, all zeroes except for a "1" at the position that corresponds to node v

"Shallow" Encoding

- Simplest encoding approach: **encoder is just an embedding-lookup**



"Shallow" Encoding

Simplest encoding approach: **encoder is just an embedding-lookup**

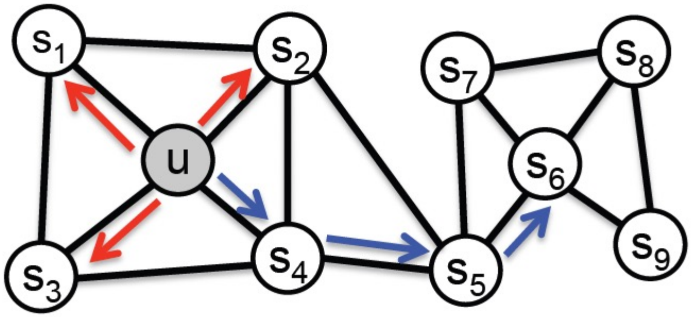
Each node is assigned a unique embedding vector

Many methods: node2vec, DeepWalk, LINE

How to Define Node Similarity?

Key choice of methods is **how they define node similarity.**

E.g., should two nodes have similar embeddings if they…
- are connected?
- share neighbors?
- similar "structural roles"?
- …?



Random Walk Approaches to Node Embeddings

Material based on:

- Perozzi et al. 2014. DeepWalk: Online Learning of Social Representations. *KDD.*
- Grover et al. 2016. node2vec: Scalable Feature Learning for Networks. *KDD.*

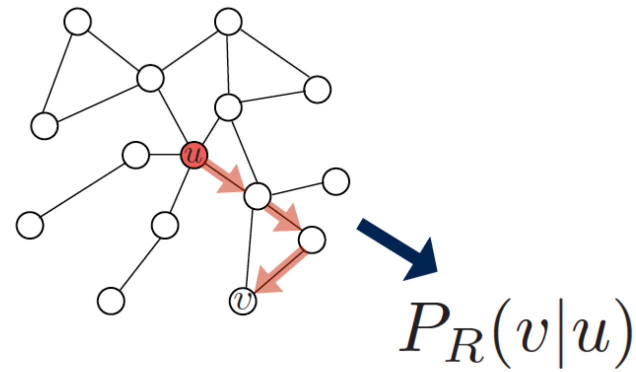
Random-walk Embeddings

$$\mathbf{z}_u^\top \mathbf{z}_v \approx$$ Probability that u and v co-occur on a random walk over the network

z_u … embedding of node u

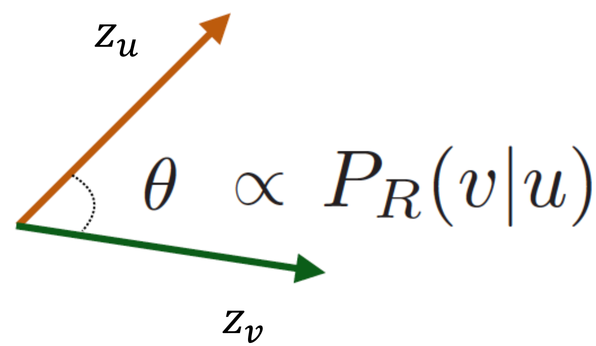
Random-walk Embeddings

The probability of visiting node v on a random walk starting from node u using some random walk strategy R



$$\mathbf{z}_u^\top \mathbf{z}_v \approx P_R(v|u)$$

Optimize the embeddings to capture node similarity



Why Random Walks?

1. **Expressivity:** Flexible stochastic definition of node similarity that incorporates both local and higher-order neighborhood information

2. **Efficiency:** Do not need to consider all node pairs when training; only need to consider pairs that co-occur on random walks

Unsupervised Feature Learning

- **Intuition:** Find embedding of nodes in d-dimensional space so that node similarity is preserved
- **Idea:** Learn node embedding such that nearby nodes are close together in the network
- **Given a node u, how do we define nearby nodes?**
  - $N_R(u)$ … neighbourhood of u obtained by some strategy R

Feature Learning as Optimization

- Given $G = (V, E)$. Our goal is to learn a mapping $z: u \to \mathbb{R}^d$
- Given node u, we want to learn feature representations predictive of nodes in its neighborhood $N_{\mathrm{R}}(u)$
- Maximum likelihood optimization problem:
  - Maximize Log-probability of observing neighborhood:

$$\max_{z} \sum_{u \in V} \log \mathrm{P}(N_{\mathrm{R}}(u) | z_u)$$

  - where $N_R(u)$ is neighborhood of node u

Random Walk Optimization

1. Run **short fixed-length random walks** starting from each node on the graph using some strategy R
2. For each node u collect $N_R(u)$, the multiset* of nodes visited on random walks starting from u
3. Optimize embeddings according to: Given node u, predict its neighbors $N_{\mathrm{R}}(u)$

$$\max_{z} \sum_{u \in V} \log \mathrm{P}(N_{\mathrm{R}}(u) |\, z_u)$$

*$N_R(u)$ can have repeat elements since nodes can be visited multiple times on random walks

Random Walk Optimization

$$\max_{z} \sum_{u \in V} \log P(N_R(u) | z_u)$$

- **Conditional independence**
  - Likelihood of observing a neighborhood node is independent of observing any other neighborhood node

$$P(N_R(u)|z_u) = \prod_{v \in N_R(u)} P(z_v \mid z_u)$$

  - **Softmax parametrization:**

$$P(z_v|z_u) = \frac{\exp(z_v \cdot z_u)}{\sum_{n \in V} \exp(z_n \cdot z_u)}$$

Why softmax?
We want node v to be most similar to node u (out of all nodes n).
Intuition: $\sum_i \exp(x_i) \approx \max_i \exp(x_i)$

Random Walk Optimization

Putting it all together:

$$\mathcal{L} = \underbrace{\sum_{u \in V}}_{\text{sum over all nodes } u} \underbrace{\sum_{v \in N_R(u)}}_{\text{sum over nodes } v \text{ seen on random walks starting from } u} - \log \Bigg(\underbrace{\frac{\exp(\mathbf{z}_u^\top \mathbf{z}_v)}{\sum_{n \in V} \exp(\mathbf{z}_u^\top \mathbf{z}_n)}}_{\text{predicted probability of } v \text{ appearing in random walk starting from } u} \Bigg)$$

Optimizing random walk embeddings =

Finding node embeddings z that minimize $\mathcal{L}$

Random Walk Optimization

But doing this naively is too expensive!!

$$\mathcal{L} = \sum_{u \in V} \sum_{v \in N_R(u)} -\log\left(\frac{\exp(\mathbf{z}_u^\top \mathbf{z}_v)}{\sum_{n \in V} \exp(\mathbf{z}_u^\top \mathbf{z}_n)}\right)$$

Nested sum over nodes gives
$O(|V|^2)$ complexity!

Random Walk Optimization

But doing this naively is too expensive!!

$$\mathcal{L} = \sum_{u \in V} \sum_{v \in N_R(u)} -\log\left(\frac{\exp(\mathbf{z}_u^\top \mathbf{z}_v)}{\sum_{n \in V} \exp(\mathbf{z}_u^\top \mathbf{z}_n)}\right)$$

The normalization term from the softmax is the culprit... can we approximate it?

Negative Sampling

- **Solution:** Negative sampling

Why is the approximation valid?
Technically, this is a different objective. But Negative Sampling is a form of Noise Contrastive Estimation (NCE) which approx. maximizes the log probability of softmax.

New formulation corresponds to using a logistic regression (sigmoid func.) to distinguish the target node v from nodes n_i sampled from background distribution P_v.

More at https://arxiv.org/pdf/1402.3722.pdf

$$\log\left(\frac{\exp(\mathbf{z}_u^\top \mathbf{z}_v)}{\sum_{n \in V} \exp(\mathbf{z}_u^\top \mathbf{z}_n)}\right)$$

$$\approx \log(\sigma(\mathbf{z}_u^\top \mathbf{z}_v)) - \sum_{i=1}^{k} \log(\sigma(\mathbf{z}_u^\top \mathbf{z}_{n_i})), n_i \sim P_V$$

sigmoid function
(makes each term a "probability" between 0 and 1)

random distribution over all nodes

Instead of normalizing w.r.t. all nodes, just normalize against k random "**negative samples**" n_i

Random Walks: Stepping Back

1. Run **short fixed-length** random walks starting from each node on the graph using some strategy R.

2. For each node u collect $\mathrm{N}_R(u)$, the multiset of nodes visited on random walks starting from u

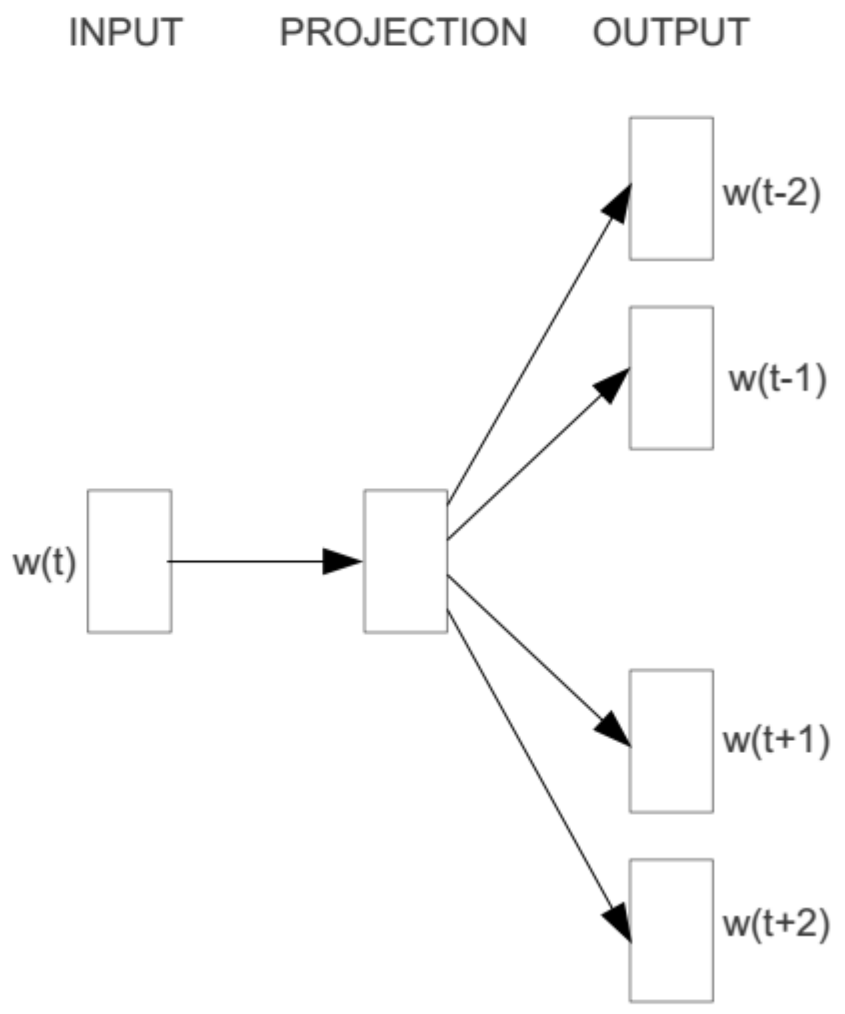
3. Optimize embeddings using Stochastic Gradient Descent:

$$\mathcal{L} = \sum_{u \in V} \sum_{v \in N_R(u)} -\log(P(v|\mathbf{z}_u))$$

We can efficiently approximate this using negative sampling!

Reminder: Word2Vec

Key idea: Predict surrounding words of every word



Skip-gram

How should we randomly walk?

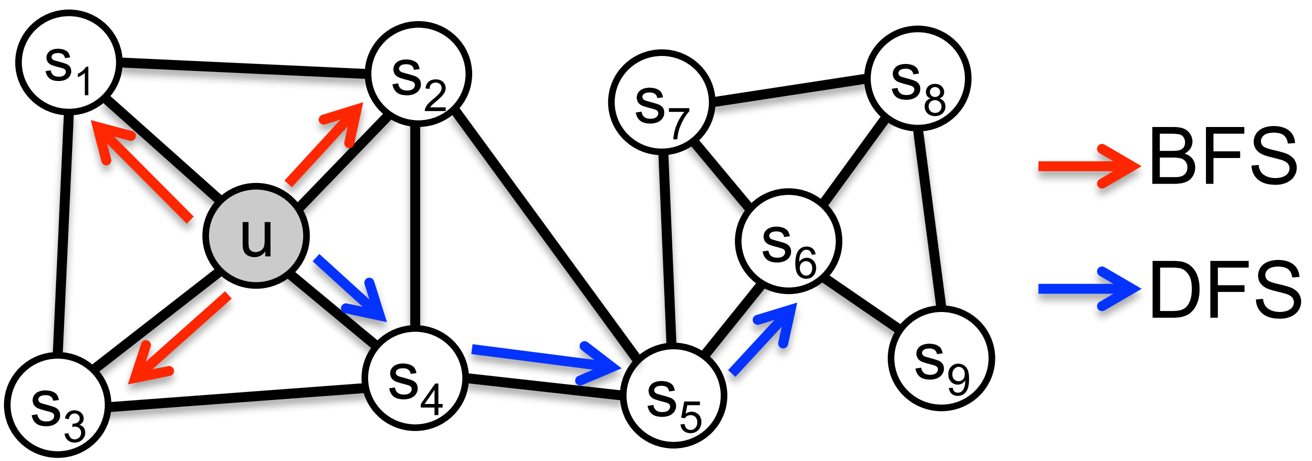
- So far we have described how to optimize embeddings given random walk statistics
- **What strategies should we use to run these random walks?**
  - Simplest idea: **Just run fixed-length, unbiased random walks starting from each node** (i.e., DeepWalk from Perozzi et al., 2013).
    - The issue is that such notion of similarity is too constrained
  - How can we generalize this?

Overview of node2vec

- **Goal:** Embed nodes with similar network neighborhoods close in the feature space
- We frame this goal as prediction-task independent maximum likelihood optimization problem
- **Key observation:** Flexible notion of network neighborhood $N_R(u)$ of node u leads to rich node embeddings
- Develop biased 2nd order random walk R to generate network neighborhood $N_R(u)$ of node u

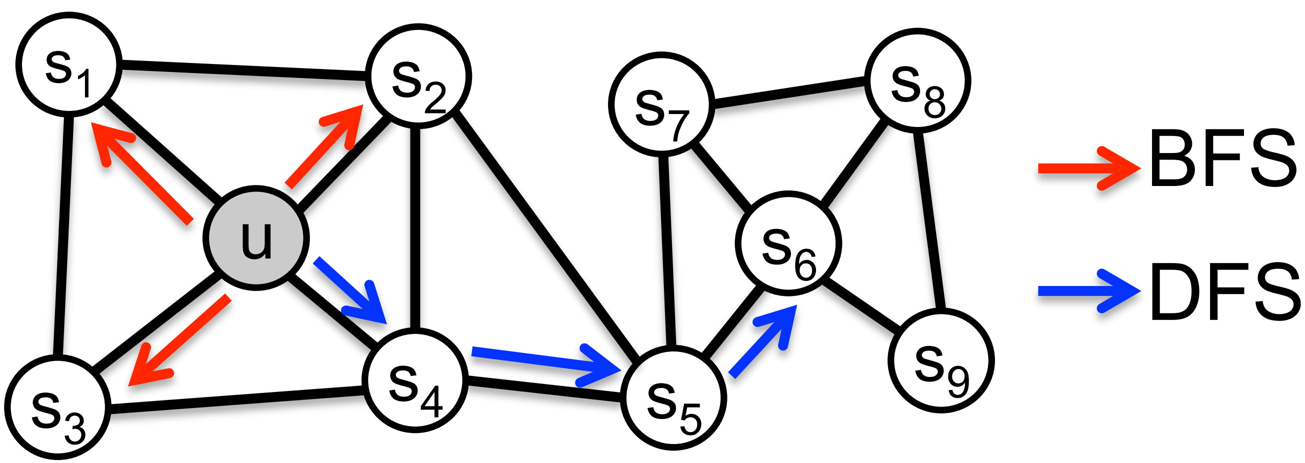
node2vec: Biased Walks

Idea: use flexible, biased random walks that can trade off between **local** and **global** views of the network (Grover and Leskovec, 2016).



node2vec: Biased Walks

Two classic strategies to define a neighborhood $N_R(u)$ of a given node u:



Walk of length 3 ($N_R(u)$ of size 3):

$N_{BFS}(u) = \{ s_1, s_2, s_3 \}$ Local microscopic view

$N_{DFS}(u) = \{ s_4, s_5, s_6 \}$ Global macroscopic view

Interpolating BFS and DFS

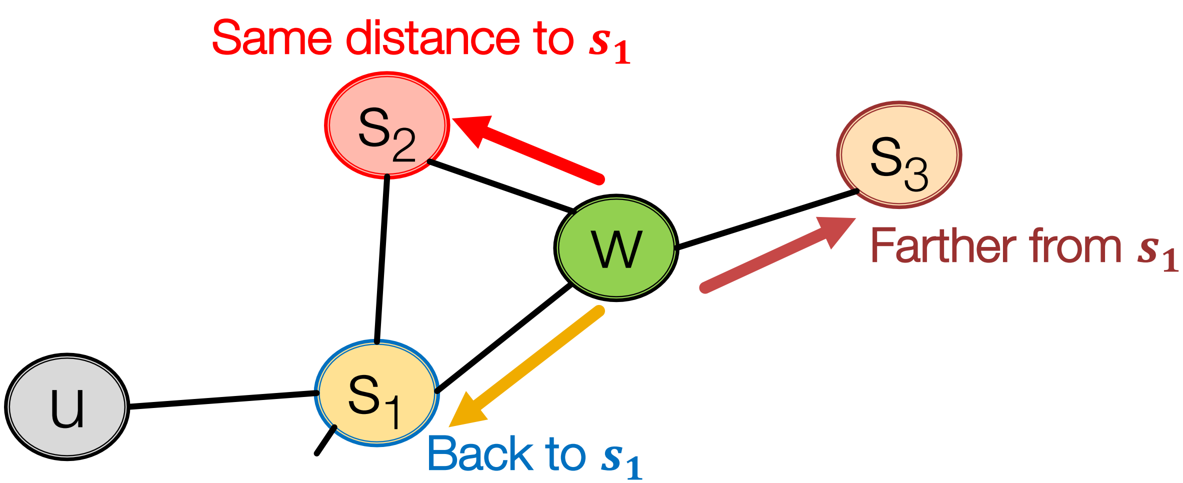
Biased fixed-length random walk R that given a node u generates neighborhood $N_R(u)$

- Two parameters:
  - **Return parameter p:**
    - Return back to the previous node
  - **In-out parameter q:**
    - Moving outwards (DFS) vs. spreading (BFS)
    - Intuitively, q is the "ratio" of BFS vs. DFS

Biased Random Walks

Biased 2nd-order random walks explore network neighborhoods:

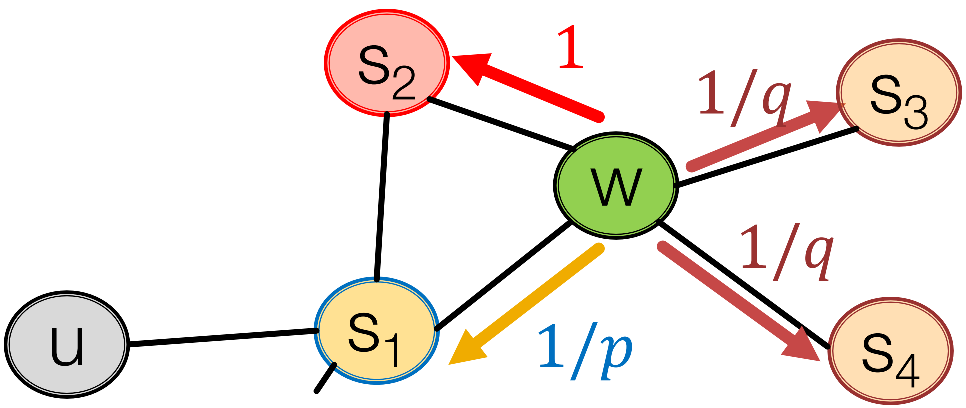
- Rnd. walk just traversed edge (s_1, w) and is now at w
- **Insight:** Neighbors of w can only be:



Idea: Remember where that walk came from

Biased Random Walks

- Walker came over edge (s_1, w) and is at w. Where to go next?

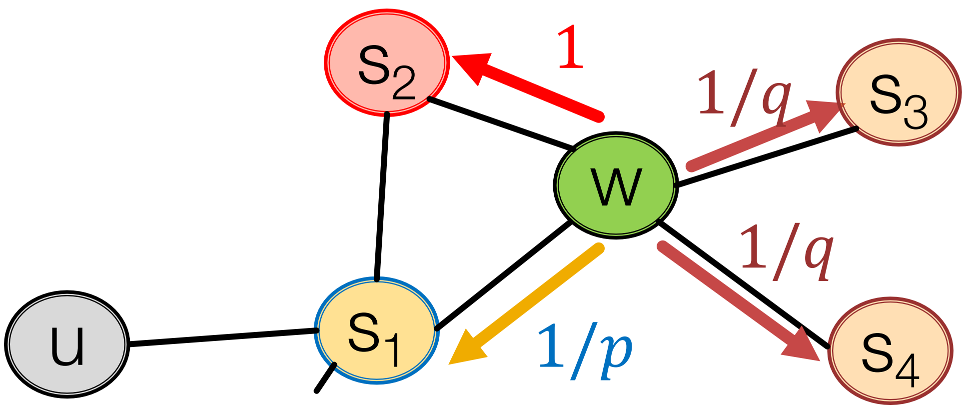


$1/p, 1/q, 1$ are unnormalized probabilities

- p, q model transition probabilities
  - p … return parameter
  - q … "walk away" parameter

Biased Random Walks

- Walker came over edge (s_1, w) and is at w. Where to go next?



w →

Target t	Prob.	Dist. (s_1, t)
s1	$1/p$	0
s2	1	1
s3	$1/q$	2
s4	$1/q$	2

Unnormalized transition prob. segmented based on distance from s_1

- **BFS-like** walk: Low value of p
- **DFS-like** walk: Low value of q

$N_R(u)$ are the nodes visited by the biased walk

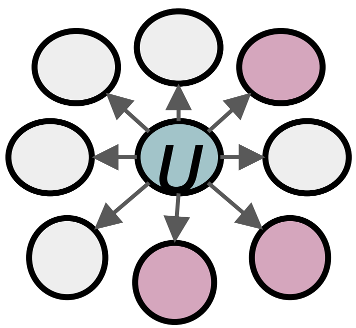
node2vec algorithm

- 1) Compute random walk probabilities
- 2) Simulate r random walks of length l starting from each node u
- 3) Optimize the node2vec objective using Stochastic Gradient Descent

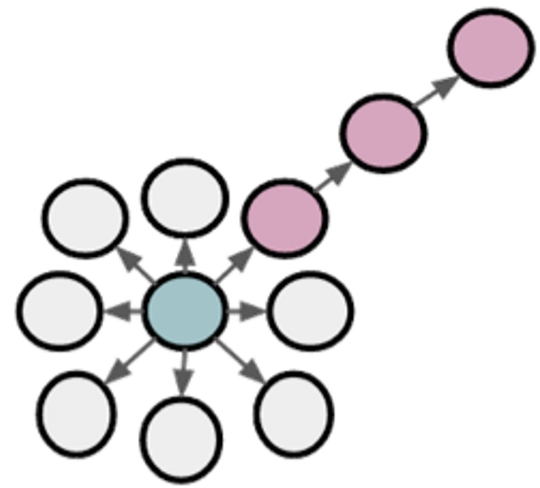
Linear-time complexity.

All 3 steps are individually parallelizable

BFS vs. DFS



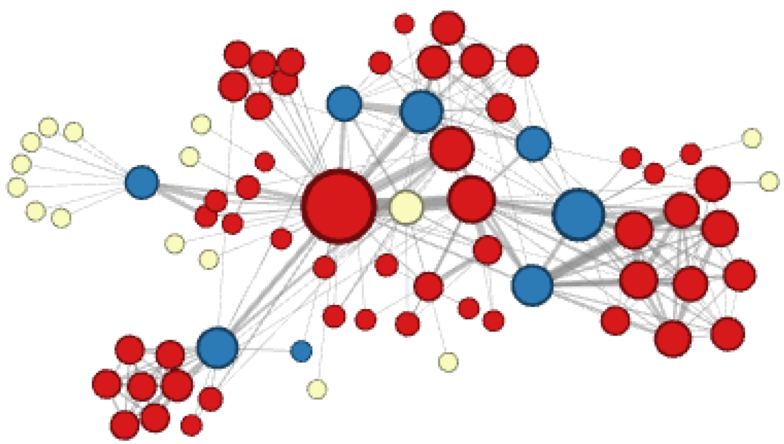
BFS:
Micro-view of neighbourhood



DFS:
Macro-view of neighbourhood

Experiments: Micro vs. Macro

Small network of interactions of characters in a novel:



p=1, q=2

Microscopic view of the network neighbourhood

p=1, q=0.5

Macroscopic view of the network neighbourhood

How to Use Embeddings

- **How to use embeddings z_i of nodes:**
  - **Clustering/community detection:** Cluster nodes/points based on z_i
  - **Node classification:** Predict label $f(z_i)$ of node i based on z_i
  - **Link prediction:** Predict edge (i, j) based on $f(z_i, z_j)$
    - Where we can: concatenate, avg, product, or take a difference between the embeddings:
      - Concatenate: $f(z_i, z_j)$= $g([z_i, z_j])$
      - Hadamard: $f(z_i, z_j)$= $g(z_i * z_j)$ (per coordinate product)
      - Sum/Avg: $f(z_i, z_j)$= $g(z_i + z_j)$
      - Distance: $f(z_i, z_j)$= $g(||z_i - z_j||_2)$

Summary so far

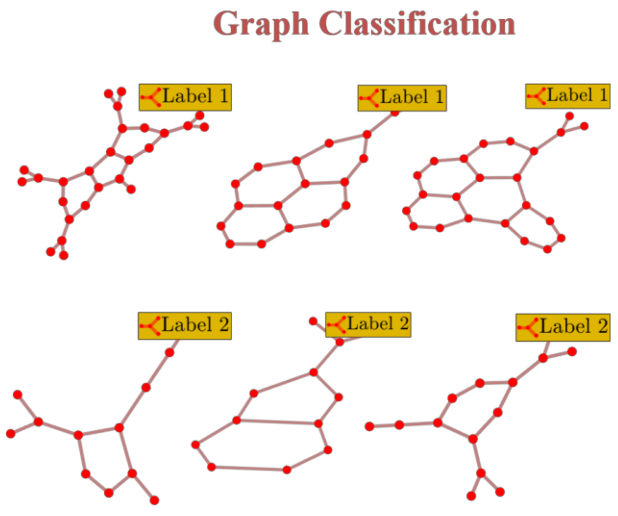
- **Basic idea:** Embed nodes so that similarities in embedding space reflect node similarities in the original network.

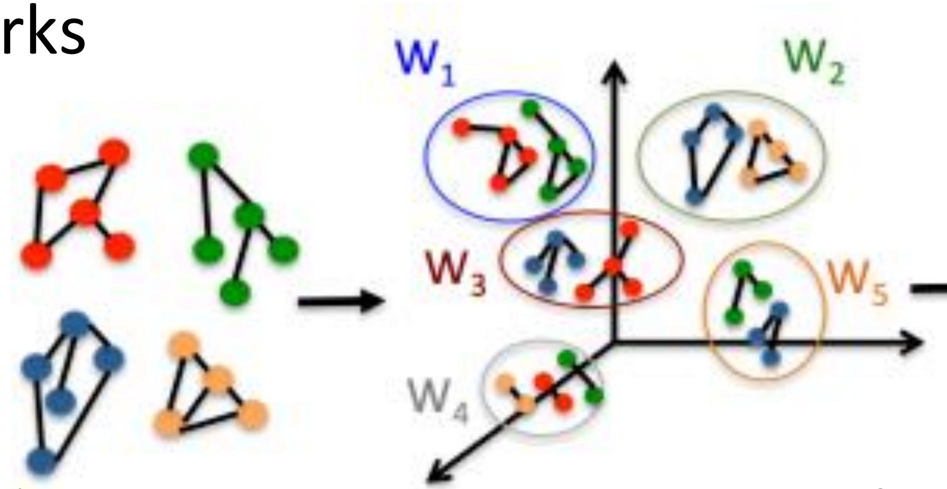
- **Different notions of node similarity:**
  - Adjacency-based (i.e., similar if connected)
  - Multi-hop similarity definitions.
  - Random walk approaches **(covered today)**

Embedding Entire Graphs

Graph Classification

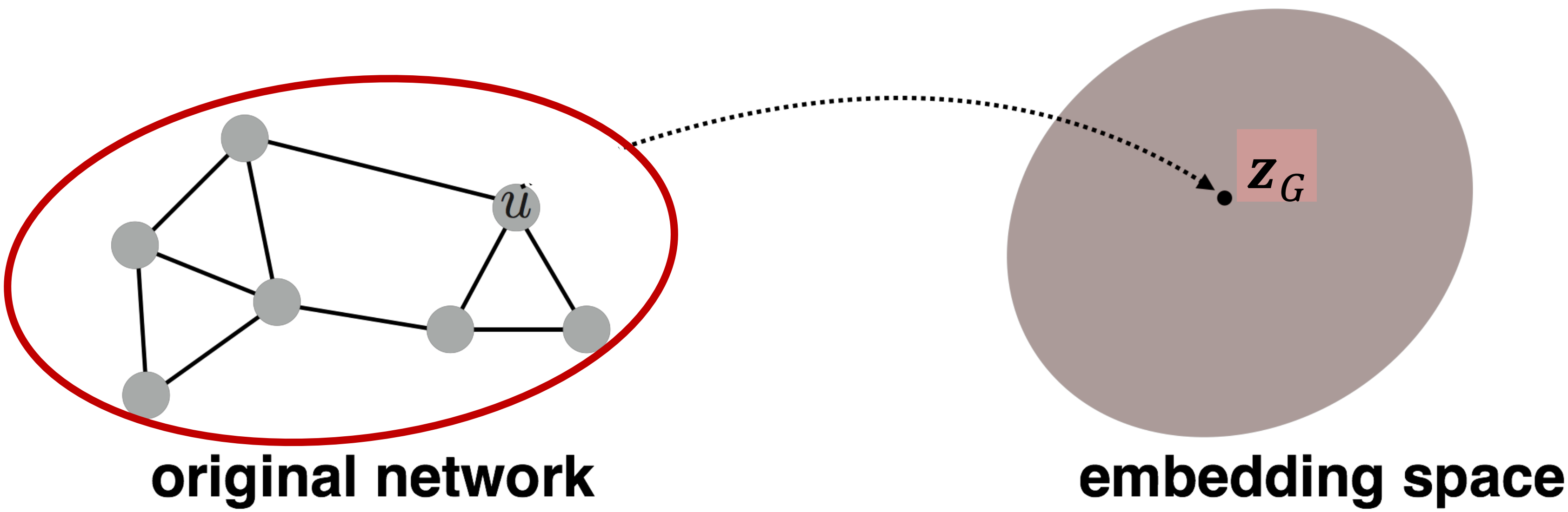
- **Tasks:**
  - Classifying toxic vs. non-toxic molecules
  - Identifying cancerogenic molecules
  - Graph anomaly detection
  - Classifying social networks





Embedding Entire Graphs

- **Goal:** Want to embed an entire graph G



Approach 1

Simple idea:

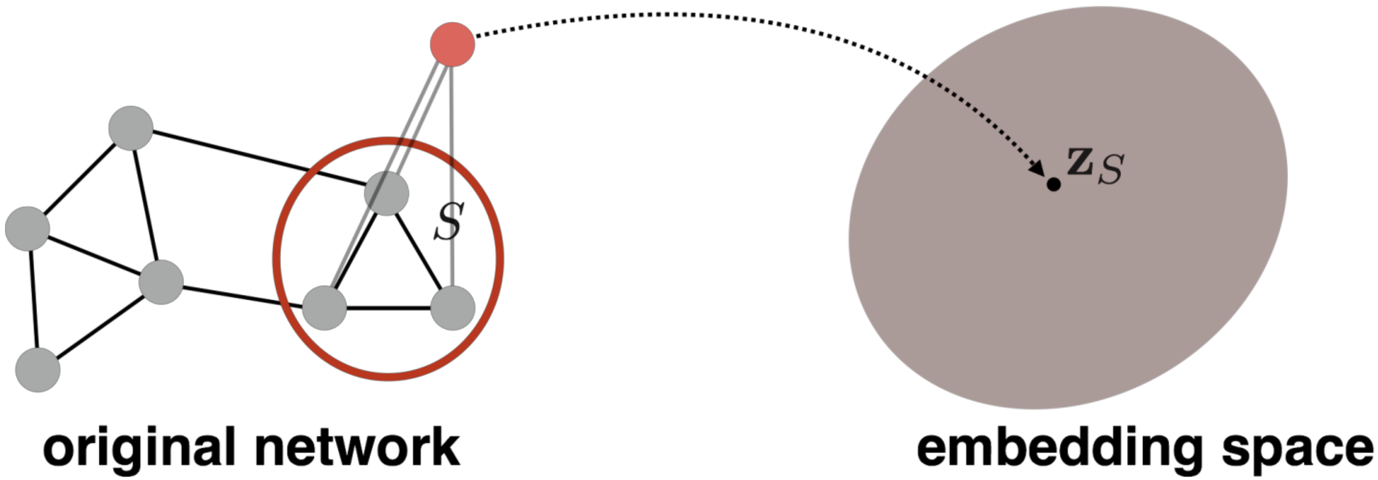
- Run a standard graph embedding technique *on* the (sub)graph G
- Then just sum (or average) the node embeddings in the (sub)graph G

$$z_G = \sum_{v \in G} z_v$$

- Used by Duvenaud et al., 2016 to classify molecules based on their graph structure

Approach 2

- **Idea:** Introduce a **"virtual node"** to represent the (sub)graph and run a standard graph embedding technique



- Proposed by Li et al., 2016 as a general technique for subgraph embedding