

Stanford CS224W: Node Embeddings

CS224W: Machine Learning with Graphs

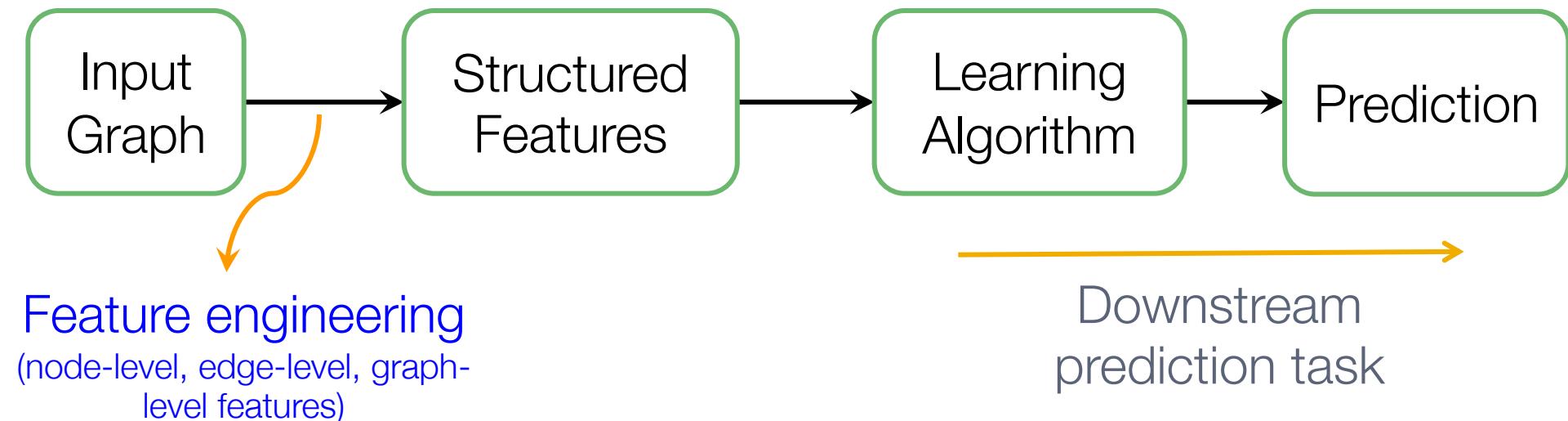
Jure Leskovec, Stanford University

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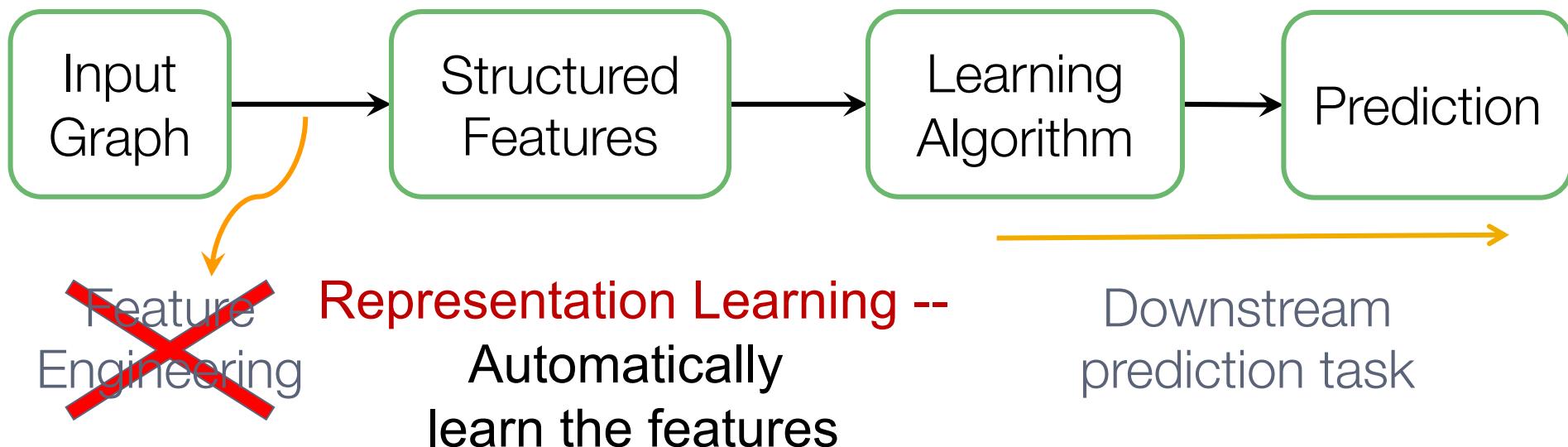
Recap: Traditional ML for Graphs

Given an input graph, extract node, link and graph-level features, learn a model (SVM, neural network, etc.) that maps features to labels.



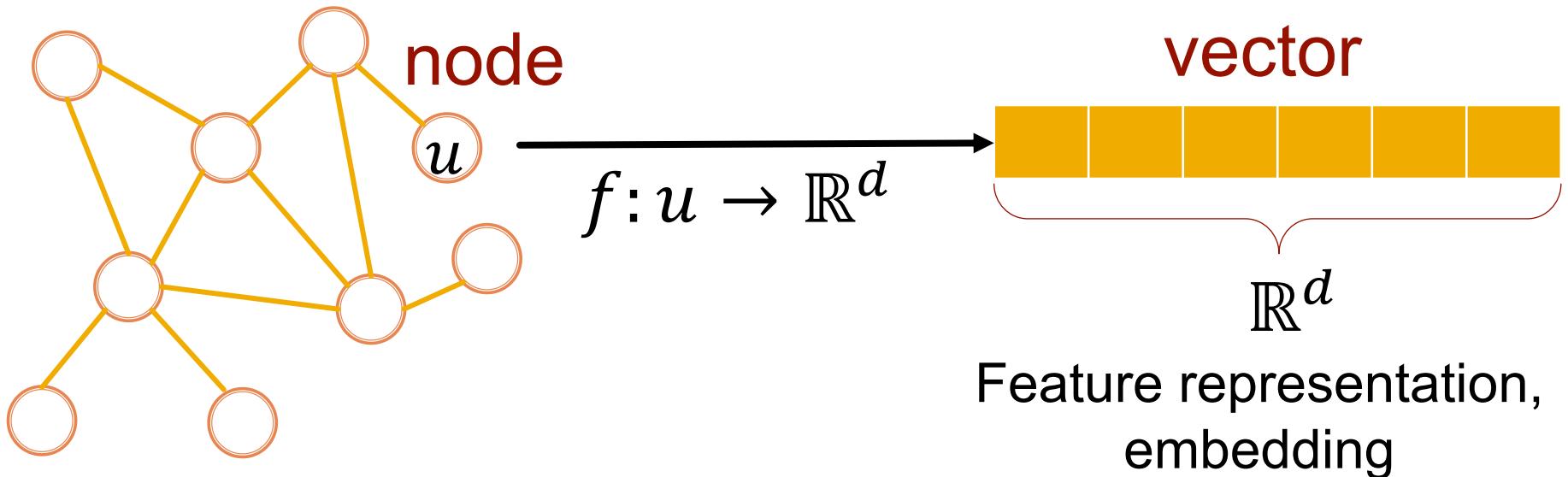
Graph Representation Learning

Graph Representation Learning alleviates the need to do feature engineering **every single time.**



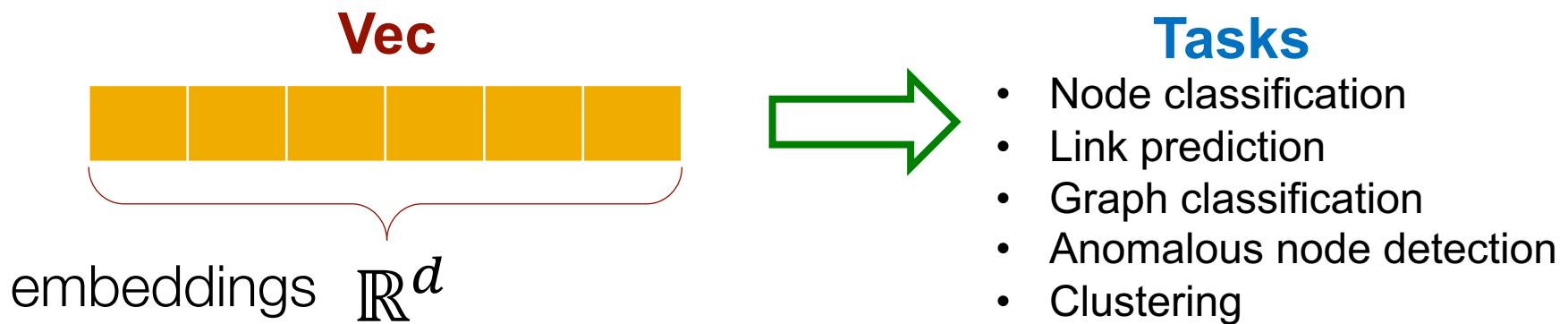
Graph Representation Learning

Goal: Efficient task-independent feature learning for machine learning with graphs!



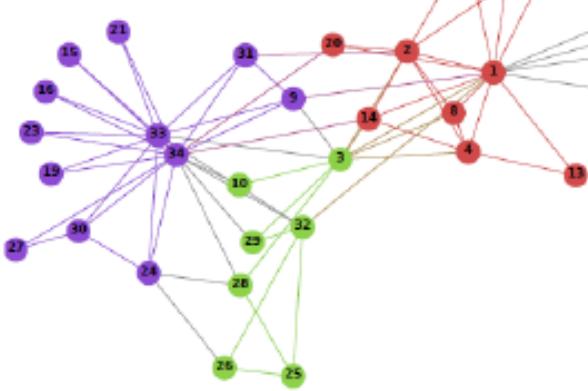
Why Embedding?

- **Task: map nodes into an embedding space**
 - Similarity of embeddings between nodes indicates their similarity in the network. For example:
 - Both nodes are close to each other (connected by an edge)
 - Encode network information
 - Potentially used for many downstream predictions

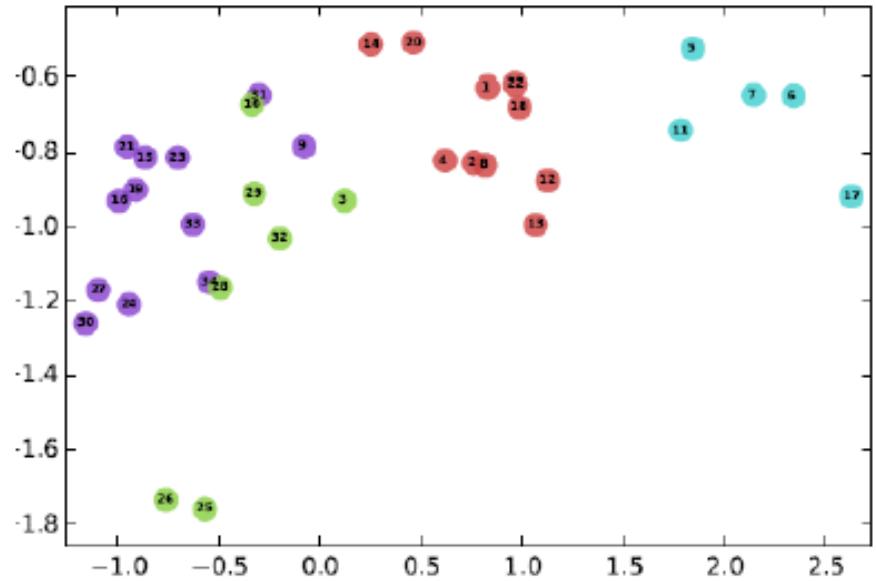


Example Node Embedding

- 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*.

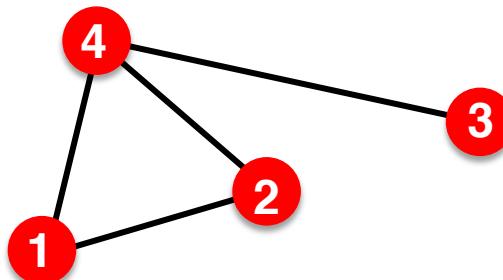
Stanford CS224W: **Node Embeddings:** **Encoder and Decoder**

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Setup

- Assume we have a graph G :
 - V is the vertex set.
 - A is the adjacency matrix (assume binary).
 - **For simplicity: no node features or extra information is used**

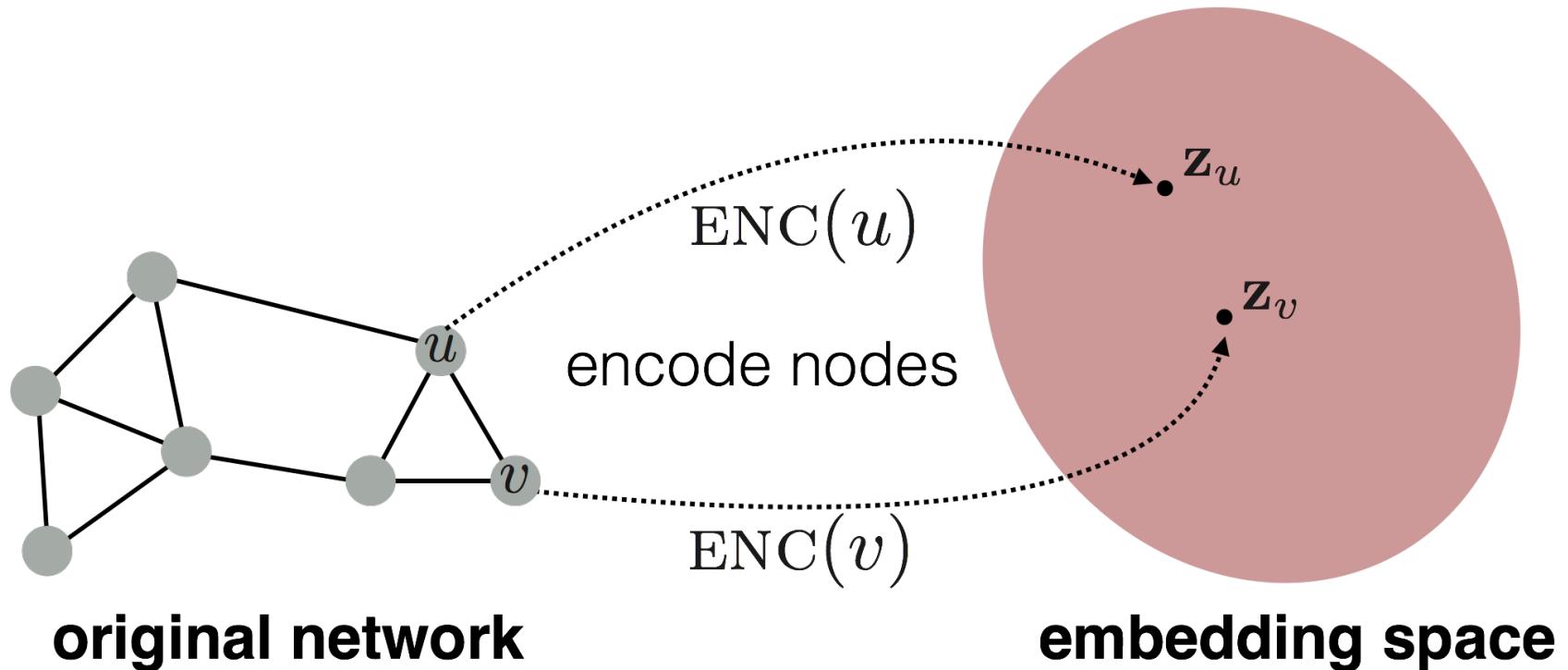


$V: \{1, 2, 3, 4\}$

$$A = \begin{pmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{pmatrix}$$

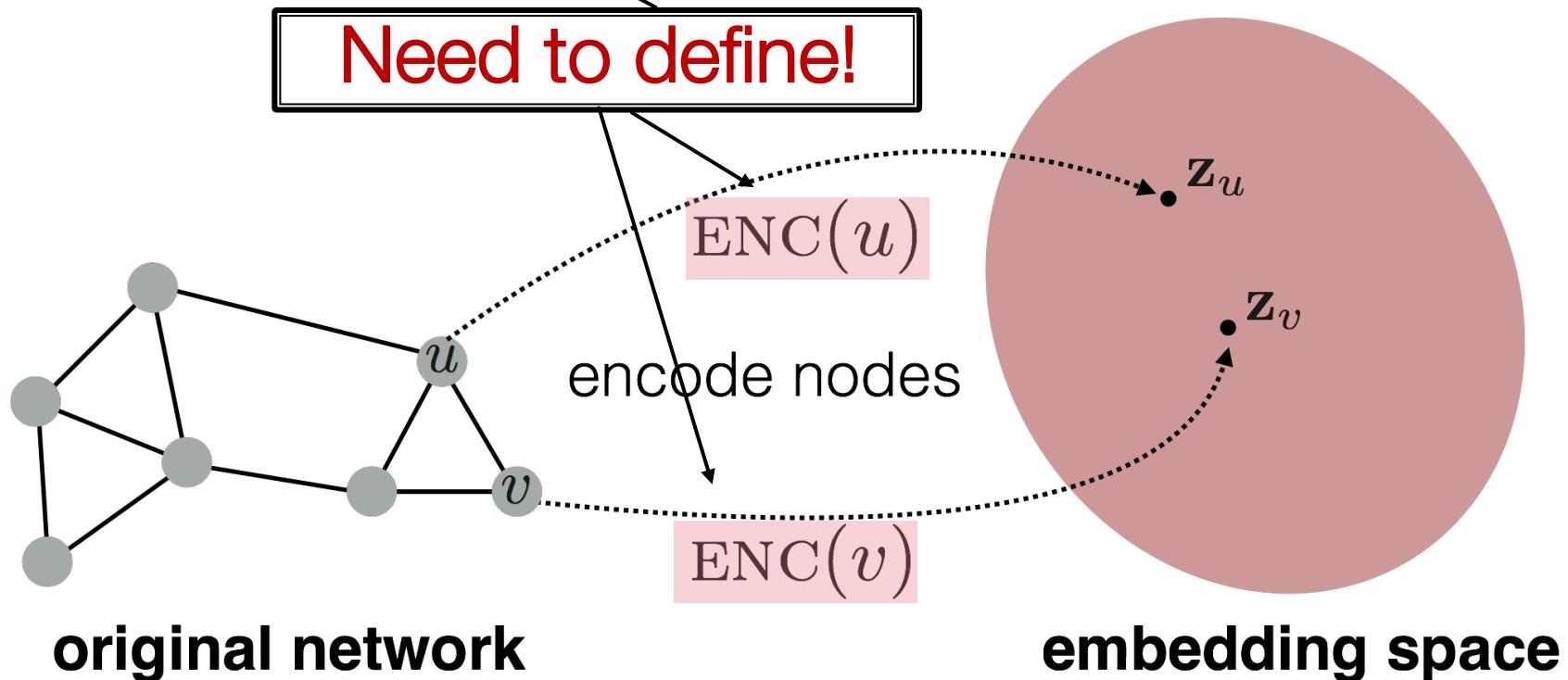
Embedding Nodes

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



Embedding Nodes

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



Learning Node Embeddings

1. **Encoder** maps from nodes to embeddings
2. Define a node similarity function (i.e., a measure of similarity in the original network)
3. **Decoder DEC** maps from embeddings to the similarity score
4. Optimize the parameters of the encoder so that:

DEC($\mathbf{z}_v^T \mathbf{z}_u$)

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

in the original network

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 the relationships in vector space map to the relationships in the original network

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

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**

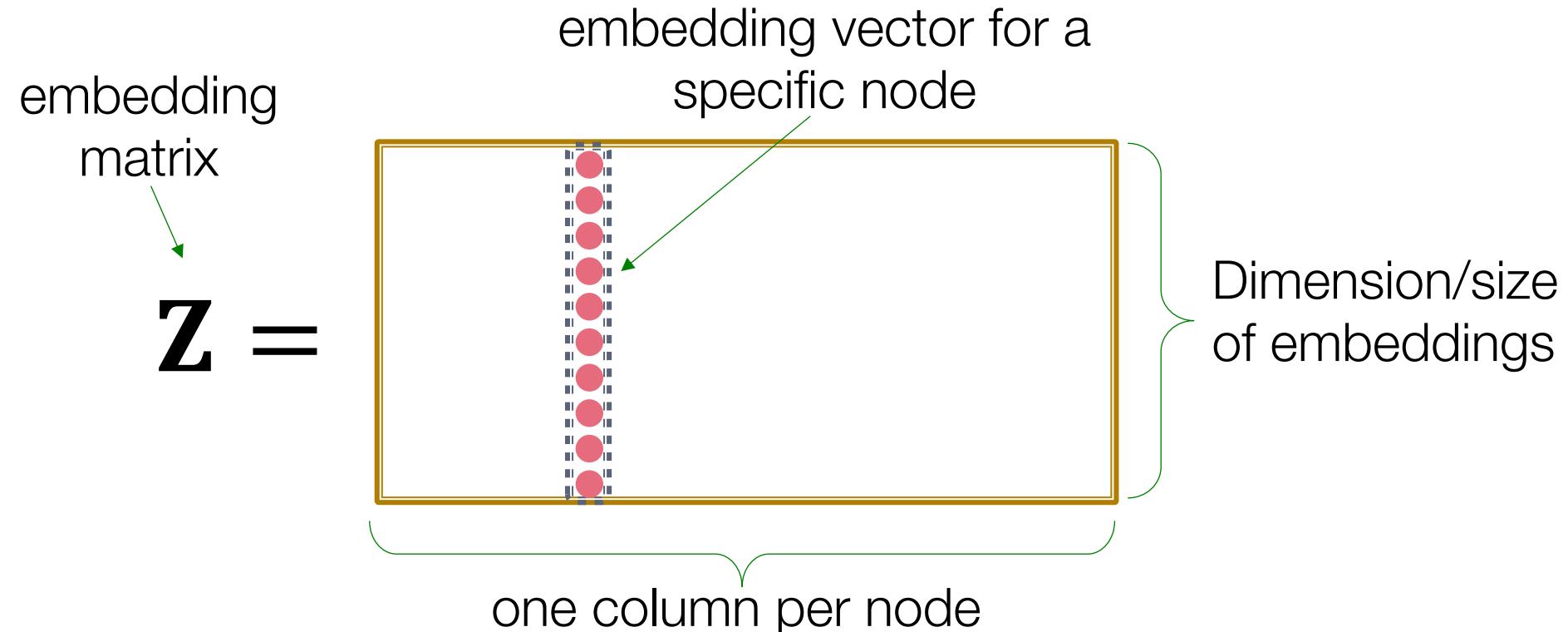
$$\text{ENC}(v) = z_v = Z \cdot v$$

$Z \in \mathbb{R}^{d \times |\mathcal{V}|}$ matrix, each column is a node embedding [what we learn / optimize]

$v \in \mathbb{I}^{|\mathcal{V}|}$ indicator vector, all zeroes except a one in column indicating 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**

(i.e., we directly optimize
the embedding of each node)

Many methods: DeepWalk, node2vec

Framework Summary

- **Encoder + Decoder Framework**
 - Shallow encoder: embedding lookup
 - Parameters to optimize: \mathbf{Z} which contains node embeddings \mathbf{z}_u for all nodes $u \in V$
 - We will cover deep encoders (GNNs) in Lecture 6
- **Decoder:** based on node similarity.
- **Objective:** maximize $\mathbf{z}_v^T \mathbf{z}_u$ for node pairs (u, v) that are **similar**

How to Define Node Similarity?

- Key choice of methods is **how they define node similarity**.
- Should two nodes have a similar embedding if they...
 - are linked?
 - share neighbors?
 - have similar “structural roles”?
- We will now learn node similarity definition that uses **random walks**, and how to optimize embeddings for such a similarity measure.

Note on Node Embeddings

- This is **unsupervised/self-supervised** way of learning node embeddings
 - We are **not** utilizing node labels
 - We are **not** utilizing node features
 - The goal is to directly estimate a set of coordinates (i.e., the embedding) of a node so that some aspect of the network structure (captured by DEC) is preserved
- These embeddings are **task independent**
 - They are not trained for a specific task but can be used for any task.

Stanford CS224W: Random Walk Approaches for Node Embeddings

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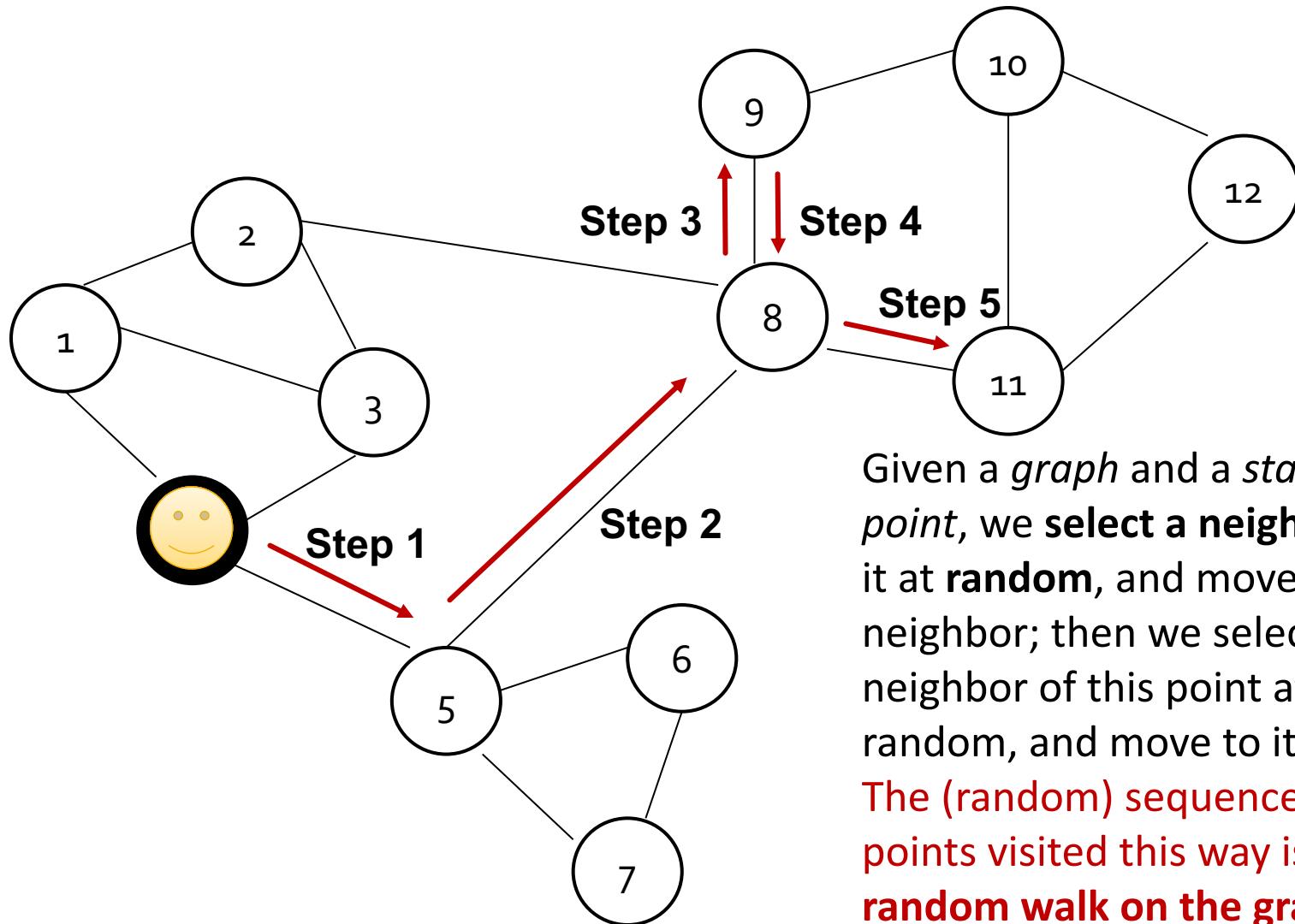
Notation

- **Vector \mathbf{z}_u :**
 - The embedding of node u (what we aim to find).
 - **Probability $P(v | \mathbf{z}_u)$** :  Our model prediction based on \mathbf{z}_u
 - The **(predicted) probability** of visiting node v on random walks starting from node u .
-

Non-linear functions used to produce predicted **probabilities**

- **Softmax** function
 - Turns vector of K real values (model predictions) into K probabilities that sum to 1: $\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}}$.
- **Sigmoid** function:
 - S-shaped function that turns real values into the range of $(0, 1)$. Written as $S(x) = \frac{1}{1+e^{-x}}$.

Random Walk



Given a *graph* and a *starting point*, we **select a neighbor** of it at **random**, and move to this neighbor; then we select a neighbor of this point at random, and move to it, etc. The (random) sequence of points visited this way is a **random walk on the graph**.

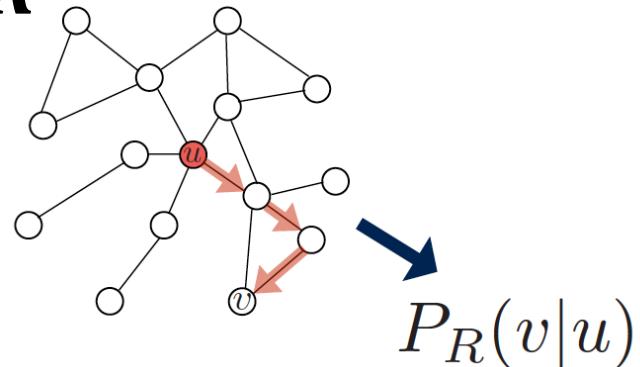
Random-Walk Embeddings

$$\mathbf{z}_u^T \mathbf{z}_v \approx$$

probability that u and v co-occur on a random walk over the graph

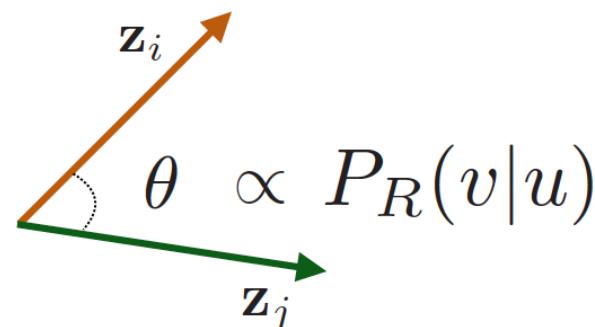
Random-Walk Embeddings

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



2. Optimize embeddings to encode these random walk statistics:

Similarity in embedding space (Here: dot product= $\cos(\theta)$) encodes random walk “similarity”



Why Random Walks?

1. **Expressivity:** Flexible stochastic definition of node similarity that incorporates both local and higher-order neighborhood information
Idea: if random walk starting from node u visits v with high probability, u and v are similar (high-order multi-hop 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 that preserves similarity
- **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 random walk strategy R

Feature Learning as Optimization

- Given $G = (V, E)$,
- Our goal is to learn a mapping $f: u \rightarrow \mathbb{R}^d$:
$$f(u) = \mathbf{z}_u$$
- Log-likelihood objective:

$$\max_f \sum_{u \in V} \log P(N_R(u) | \mathbf{z}_u)$$

- $N_R(u)$ is the neighborhood of node u by strategy R
- Given node u , we want to learn feature representations that are predictive of the nodes in its random walk neighborhood $N_R(u)$

Random Walk Optimization

1. Run **short fixed-length random walks** starting from each node u in the graph using some random walk 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 $N_R(u)$**

$$\max_f \sum_{u \in V} \log P(N_R(u) | \mathbf{z}_u) \implies \text{Maximum likelihood objective}$$

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

Random Walk Optimization

Equivalently,

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

- **Intuition:** Optimize embeddings z_u to maximize the likelihood of random walk co-occurrences
- **Parameterize $P(v|z_u)$ using softmax:**

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

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:

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

sum over all nodes u

sum over nodes v seen on random walks starting from u

predicted probability of u and v co-occurring on random walk

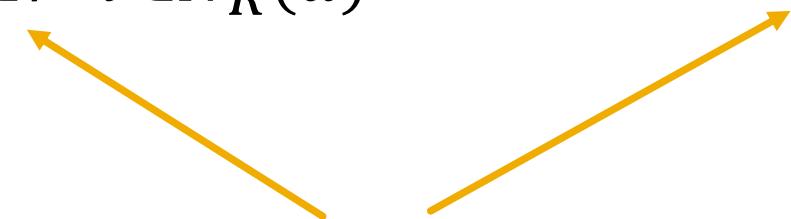
Optimizing random walk embeddings =

Finding embeddings \mathbf{z}_u that minimize \mathcal{L}

Random Walk Optimization

But doing this naively is too expensive!

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



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

Random Walk Optimization

But doing this naively is too expensive!

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

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

Negative Sampling

■ Solution: Negative sampling

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

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

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

random distribution over nodes

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

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>

Negative Sampling

$$\log\left(\frac{\exp(\mathbf{z}_u^\top \mathbf{z}_v)}{\sum_{n \in V} \exp(\mathbf{z}_u^\top \mathbf{z}_n)}\right) \approx \log\left(\sigma(\mathbf{z}_u^\top \mathbf{z}_v)\right) - \sum_{i=1}^k \log\left(\sigma(\mathbf{z}_u^\top \mathbf{z}_{n_i})\right), n_i \sim P_V$$

random distribution
over nodes



- Sample k negative nodes each with prob. proportional to its degree
 - Two considerations for k (# negative samples):
 1. Higher k gives more robust estimates
 2. Higher k corresponds to higher bias on negative events
- In practice $k = 5-20$

Stochastic Gradient Descent

- After we obtained the objective function, how do we optimize (minimize) it?

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

- Gradient Descent:** a simple way to minimize \mathcal{L} :

- Initialize z_i at some randomized value for all i .
- Iterate until convergence.

- For all i , compute the derivative $\frac{\partial \mathcal{L}}{\partial z_i}$.

η : learning rate

- For all i , make a step towards the direction of derivative: $z_i \leftarrow z_i - \eta \frac{\partial \mathcal{L}}{\partial z_i}$.

Stochastic Gradient Descent

- **Stochastic Gradient Descent:** Instead of evaluating gradients over all examples, evaluate it for each **individual** training example.
 - Initialize z_i at some randomized value for all i .
 - Iterate until convergence:
$$\mathcal{L}^{(u)} = \sum_{v \in N_R(u)} -\log(P(v|\mathbf{z}_u))$$
 - Sample a node i , for all j calculate the derivative $\frac{\partial \mathcal{L}^{(i)}}{\partial z_j}$.
 - For all j , update: $z_j \leftarrow z_j - \eta \frac{\partial \mathcal{L}^{(i)}}{\partial z_j}$.

Random Walks: Summary

1. Run **short fixed-length** random walks starting from each node on the graph
2. For each node u collect $N_R(u)$, 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!

How should we randomly walk?

- So far we have described how to optimize embeddings given a random walk strategy R
- **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?**

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

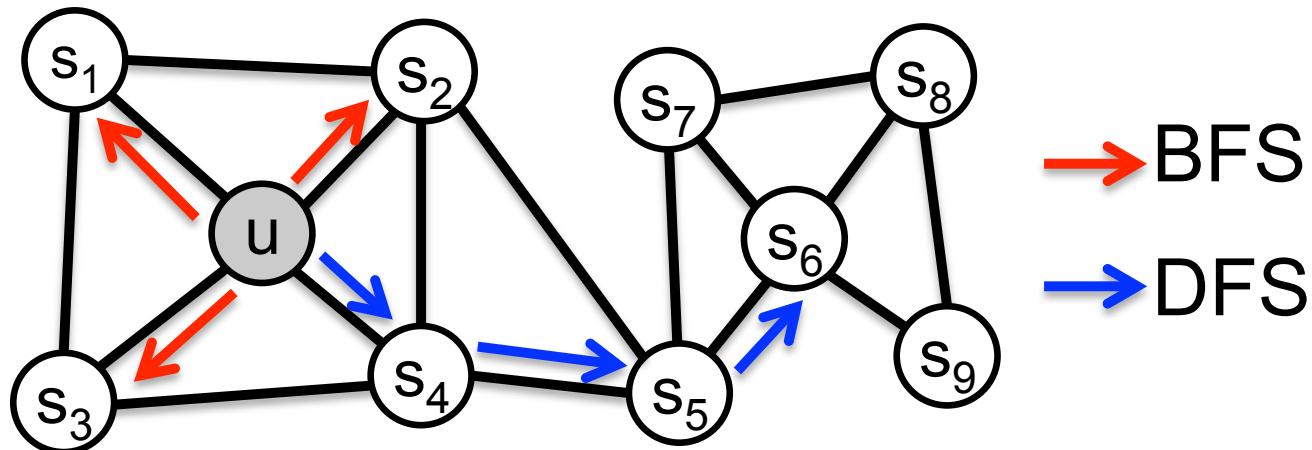
Overview of node2vec

- **Goal:** Embed nodes with similar network neighborhoods close in the feature space.
- We frame this goal as a maximum likelihood optimization problem, independent to the downstream prediction task.
- **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

Reference: Grover et al. 2016. [node2vec: Scalable Feature Learning for Networks](#). KDD.

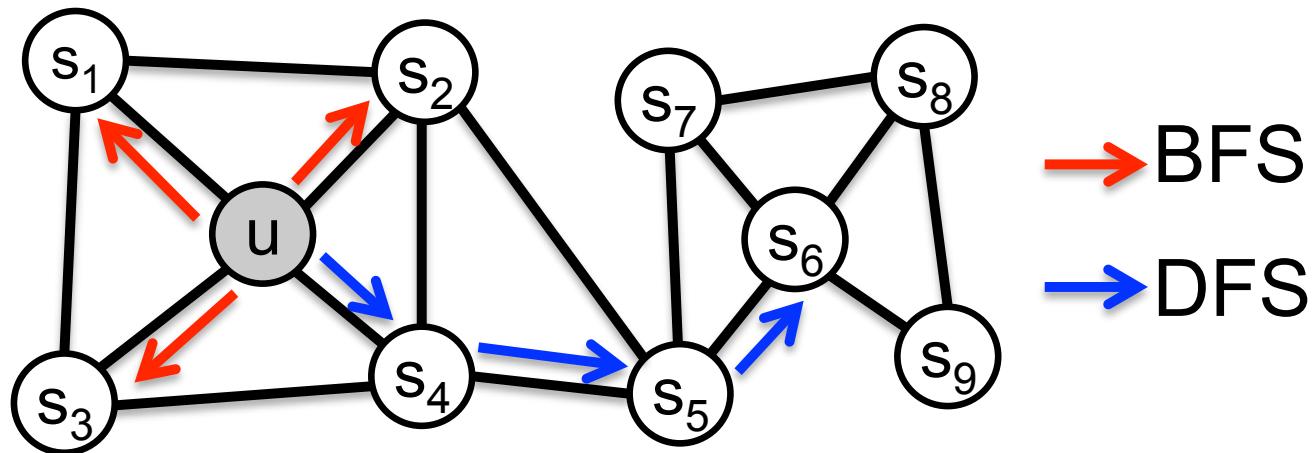
node2vec: Biased Walks

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 :

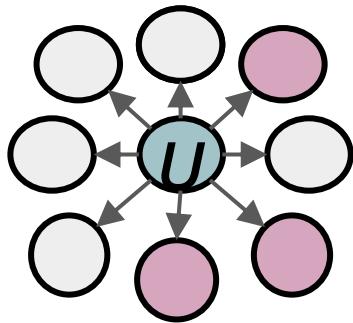


Walk of length 3 ($N_R(u)$ of size 3):

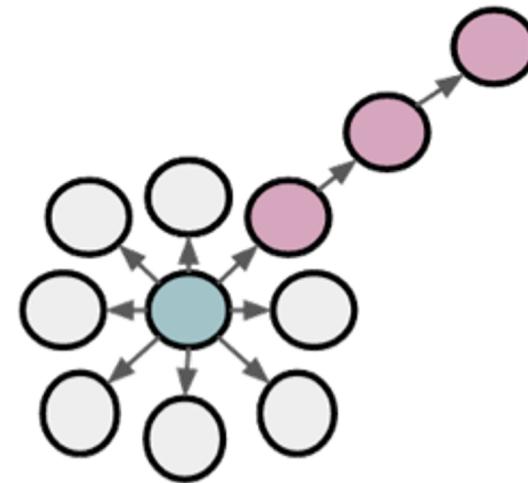
$$N_{BFS}(u) = \{s_1, s_2, s_3\} \quad \text{Local microscopic view}$$

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

BFS vs. DFS



BFS:
Micro-view of
neighbourhood



DFS:
Macro-view of
neighbourhood

Interpolating BFS and DFS

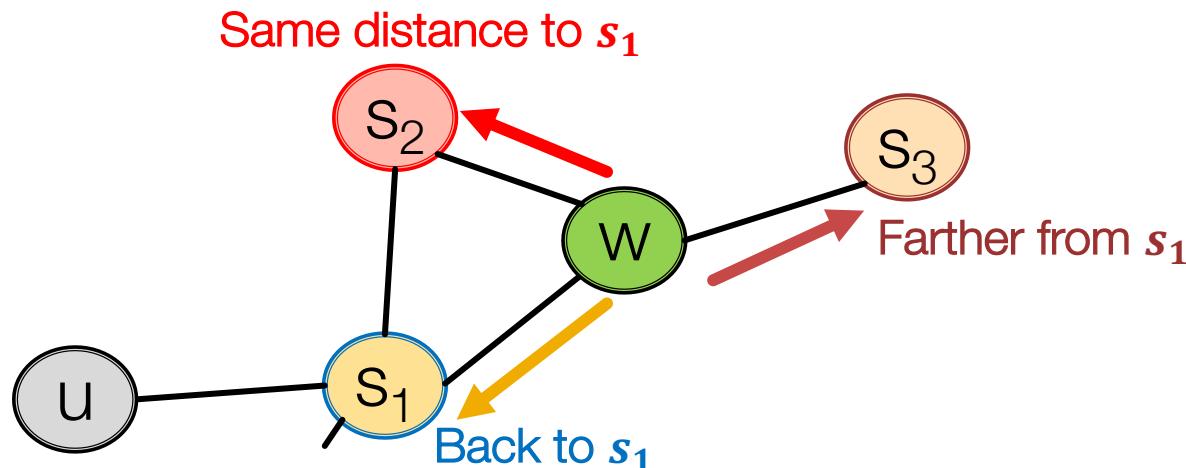
Biased fixed-length random walk R that given a node u generates neighborhood $N_R(u)$

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

Biased Random Walks

Biased 2nd-order random walks explore network neighborhoods:

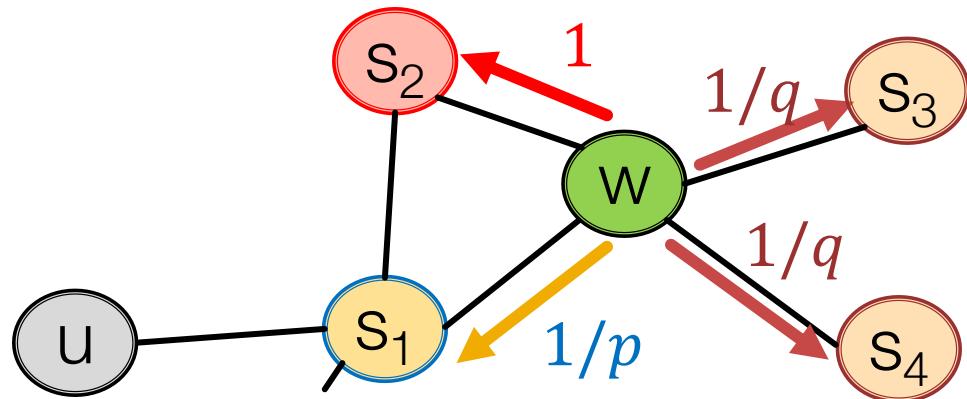
- Rnd. walk just traversed edge (s_1, w) and is now at w
- **Insight:** Neighbors of w can only be:



Idea: Remember where the walk came from

Biased Random Walks

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

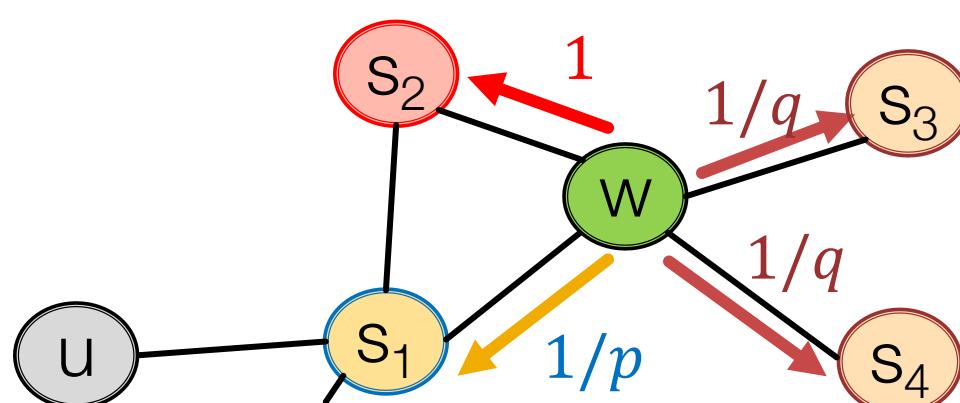


$1/p, 1/q, 1$ are unnormalized probabilities

- 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?



Target t	Prob.	Dist. (s_1, t)
S_1	$1/p$	0
S_2	1	1
S_3	$1/q$	2
S_4	$1/q$	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**

Other Random Walk Ideas

- **Different kinds of biased random walks:**
 - Based on node attributes ([Dong et al., 2017](#)).
 - Based on learned weights ([Abu-El-Haija et al., 2017](#))
- **Alternative optimization schemes:**
 - Directly optimize based on 1-hop and 2-hop random walk probabilities (as in [LINE from Tang et al. 2015](#)).
- **Network preprocessing techniques:**
 - Run random walks on modified versions of the original network (e.g., [Ribeiro et al. 2017's struct2vec](#), [Chen et al. 2016's HARP](#)).

Summary so far

- **Core idea:** Embed nodes so that distances in embedding space reflect node similarities in the original network.
- **Different notions of node similarity:**
 - Naïve: similar if 2 nodes are connected
 - Neighborhood overlap (covered in Lecture 2)
 - Random walk approaches (**covered today**)

Summary so far

- **So what method should I use..?**
- No one method wins in all cases....
 - E.g., node2vec performs better on node classification while alternative methods perform better on link prediction ([Goyal and Ferrara, 2017 survey](#))
- Random walk approaches are generally more efficient
- **In general:** Must choose definition of node similarity that matches your application!

Stanford CS224W: Embedding Entire Graphs

CS224W: Machine Learning with Graphs

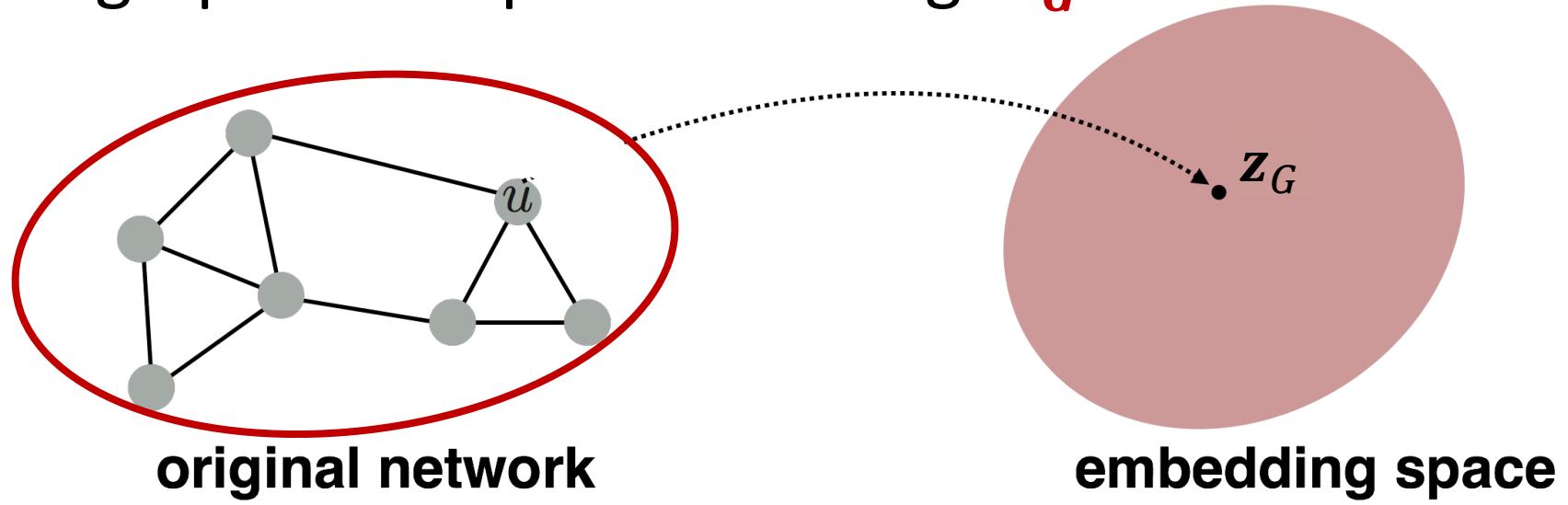
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Embedding Entire Graphs

- **Goal:** Want to embed a subgraph or an entire graph G . Graph embedding: \mathbf{z}_G .



- **Tasks:**
 - Classifying toxic vs. non-toxic molecules
 - Identifying anomalous graphs

Approach 1

Simple idea 1:

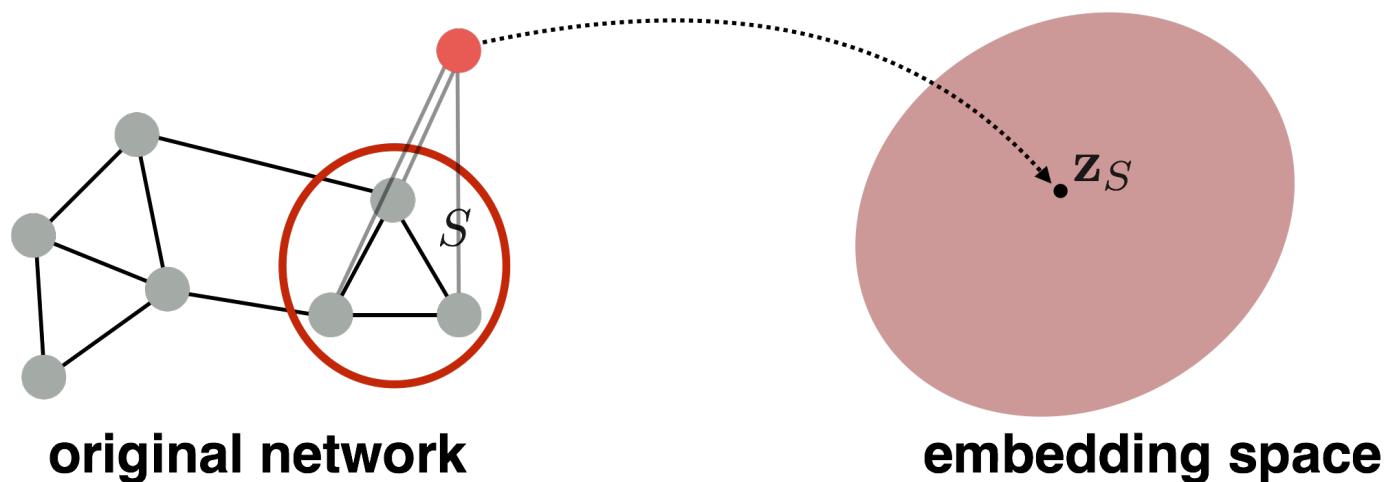
- Run a standard graph embedding technique *on* the (sub)graph G
- Then just sum (or average) the node embeddings in the (sub)graph G

$$\mathbf{z}_G = \sum_{v \in G} z_v$$

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

Approach 2

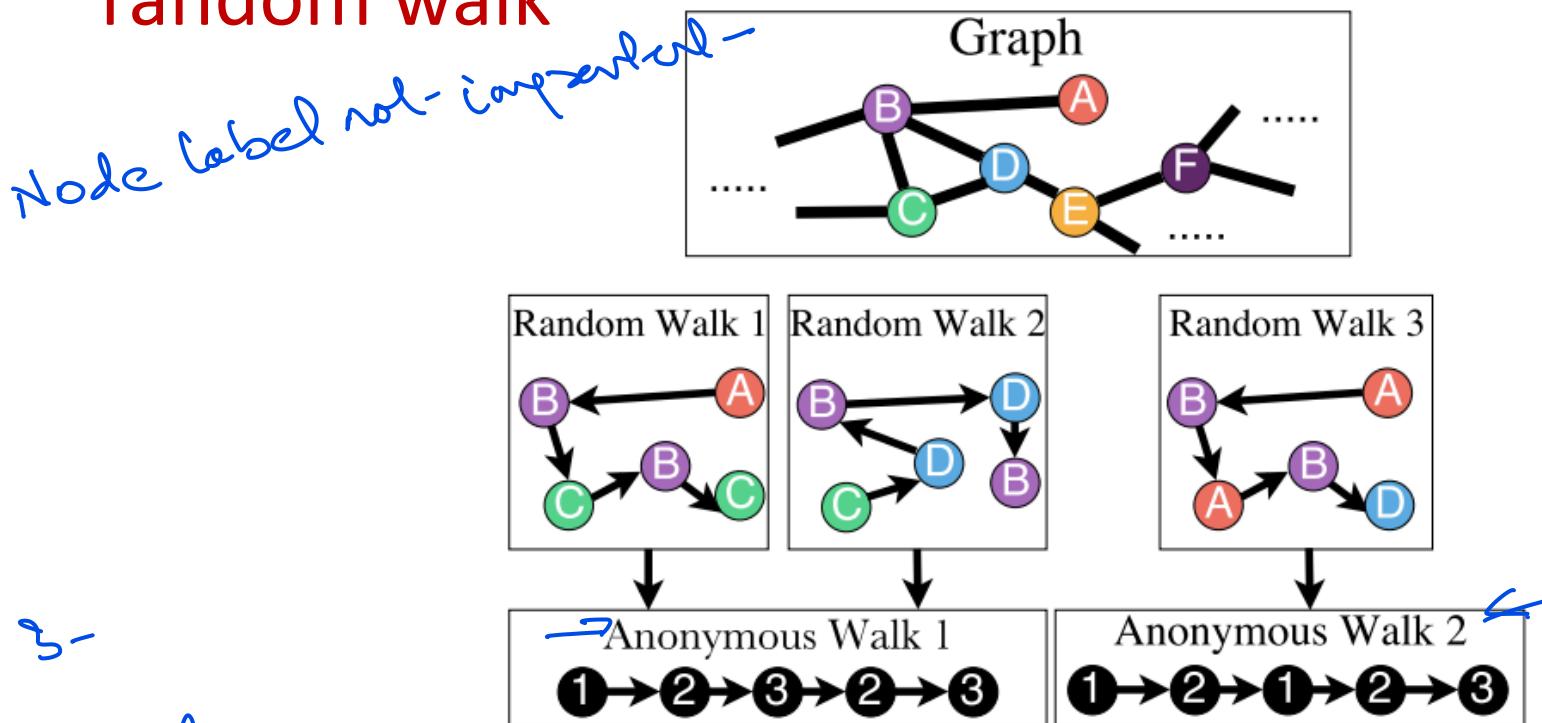
- Idea 2: Introduce a “**virtual node**” to represent the (sub)graph and run a standard graph embedding technique



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

Approach 3: Anonymous Walk Embeddings

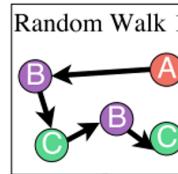
States in **anonymous walks** correspond to the index of the **first time** we visited the node in a random walk



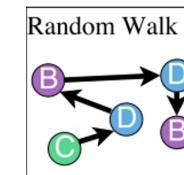
Anonymous Walk Embeddings, ICML 2018 <https://arxiv.org/pdf/1805.11921.pdf>

Approach 3: Anonymous Walk Embeddings

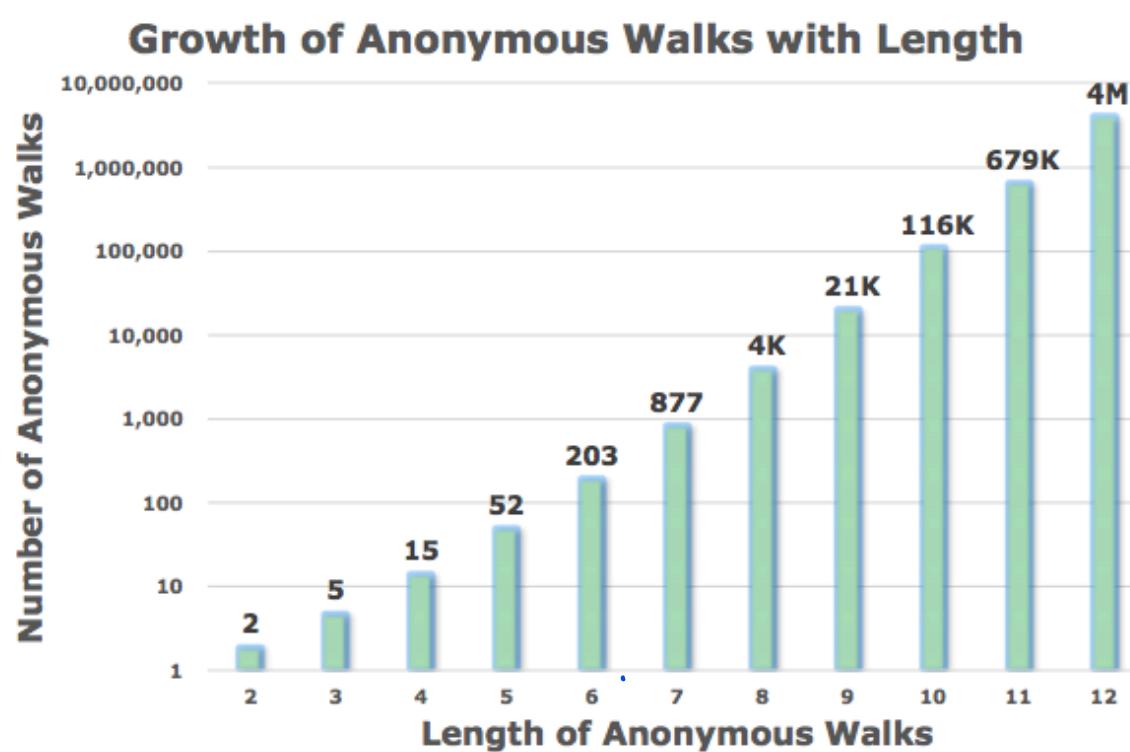
- Agnostic to the identity of the nodes visited (hence anonymous)
- Example RW1:



- Step 1: node A → node 1
- Step 2: node B → node 2 (different from node 1)
- Step 3: node C → node 3 (different from node 1, 2)
- Step 4: node B → node 2 (same as the node in step 2)
- Step 5: node C → node 3 (same as the node in step 3)
- Note: RW2 gives the same anonymous walk



Number of Walks Grows



Number of anonymous walks grows exponentially:

- There are 5 anon. walks w_i of length 3:

$$w_1 = 111, w_2 = 112, w_3 = 121, w_4 = 122, w_5 = 123$$

Simple Use of Anonymous Walks

- Simulate anonymous walks w_i of l steps and record their counts
- Represent the graph as a probability distribution over these walks
- For example:
 - Set $l = 3$
 - Then we can represent the graph as a 5-dim vector
 - Since there are 5 anonymous walks w_i of length 3: 111, 112, 121, 122, 123
 - $Z_G[i] = \text{probability of anonymous walk } w_i \text{ in } G$

Sampling Anonymous Walks

- **Sampling anonymous walks:** Generate independently a set of m random walks
- Represent the graph as a probability distribution over these walks
- How many random walks m do we need?
 - We want the distribution to have error of more than ε with prob. less than δ :

$$m = \left\lceil \frac{2}{\varepsilon^2} (\log(2^\eta - 2) - \log(\delta)) \right\rceil$$

where: η is the total number of anon. walks of length l .

For example:
There are $\eta = 877$ anonymous walks of length $l = 7$. If we set $\varepsilon = 0.1$ and $\delta = 0.01$ then we need to generate $m=122,500$ random walks

New idea: Learn Walk Embeddings

Rather than simply represent each walk by the fraction of times it occurs, we **learn embedding z_i of anonymous walk w_i**

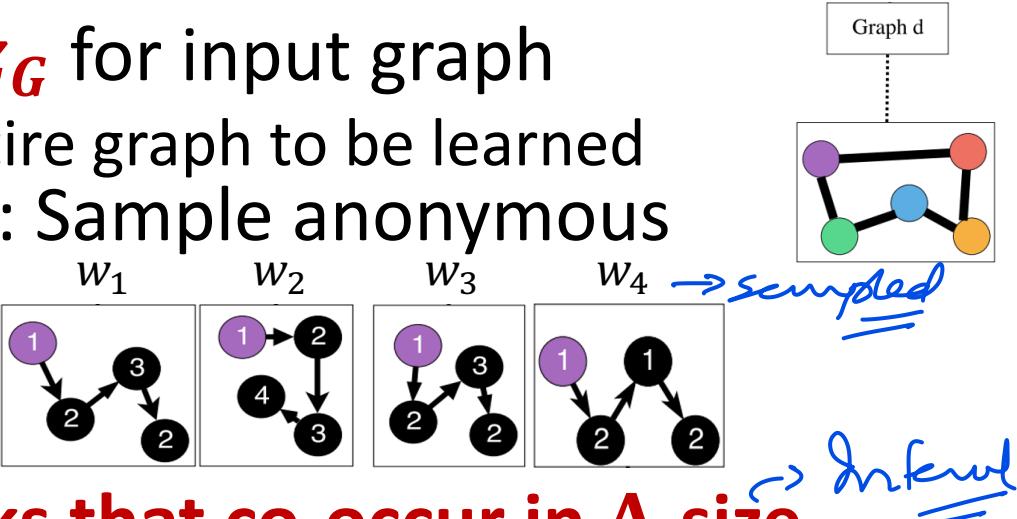
- Learn a graph embedding Z_G together with all the anonymous walk embeddings z_i
 $Z = \{z_i : i = 1 \dots \eta\}$, where η is the number of sampled anonymous walks.

How to embed walks?

- Idea: Embed walks s.t. the next walk can be predicted .
So that-

Learn Walk Embeddings

- A vector parameter \mathbf{z}_G for input graph
 - The embedding of entire graph to be learned
- Starting from **node 1**: Sample anonymous random walks, e.g.

Handwritten note: $w_i \rightarrow w_j$
- **Learn to predict walks that co-occur in Δ -size window** (e.g. predict w_2 given w_1, w_3 if $\Delta = 1$)

- Objective:
$$\max \sum_{t=\Delta}^{T-\Delta} \log P(w_t | w_{t-\Delta}, \dots, w_{t+\Delta}, \mathbf{z}_G)$$

→ Condition on Graph G
- Sum the objective over all nodes in the graph

Learn Walk Embeddings

- Run T different random walks from u each of length l :

$$N_R(u) = \{w_1^u, w_2^u \dots w_T^u\}$$

- Learn to predict walks that co-occur in Δ -size window
- Estimate embedding z_i of anonymous walk w_i
Let η be number of all possible walk embeddings

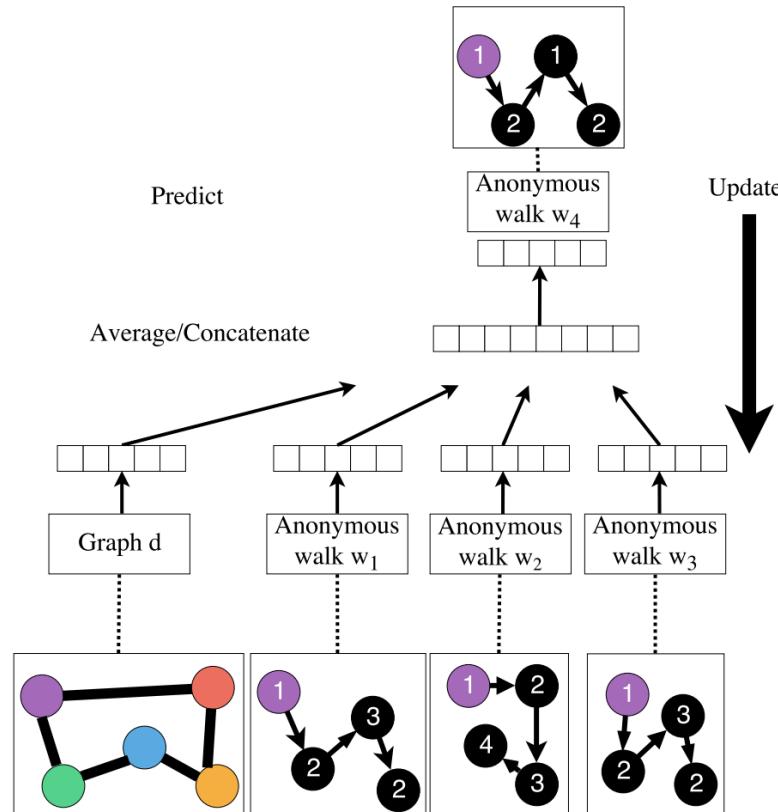
Objective: $\max_{Z,d} \frac{1}{T} \sum_{t=\Delta}^{T-\Delta} \log P(w_t | \{w_{t-\Delta}, \dots, w_{t+\Delta}, z_G\})$

- $P(w_t | \{w_{t-\Delta}, \dots, w_{t+\Delta}, z_G\}) = \frac{\exp(y(w_t))}{\sum_{i=1}^{\eta} \exp(y(w_i))}$ All possible walks
(require negative sampling)
- $y(w_t) = b + U \cdot \left(\text{cat}\left(\frac{1}{2\Delta} \sum_{i=-\Delta}^{\Delta} z_i, z_G\right) \right)$
 - $\text{cat}\left(\frac{1}{2\Delta} \sum_{i=-\Delta}^{\Delta} z_i, z_G\right)$ means an average of anonymous walk embeddings in window, concatenated with the graph embedding z_G
 - $b \in \mathbb{R}, U \in \mathbb{R}^D$ are learnable parameters. This represents a linear layer.

Learn Walk Embeddings

- We obtain the graph embedding \mathbf{z}_G (learnable parameter) after optimization
- Use \mathbf{z}_G to make predictions (e.g. graph classification)
 - **Option1:** Inner product Kernel $\mathbf{z}_{G_1}^T \mathbf{z}_{G_2}$ (Lecture 2)
 - **Option2:** Use a neural network that takes \mathbf{z}_G as input to classify

Overall Architecture



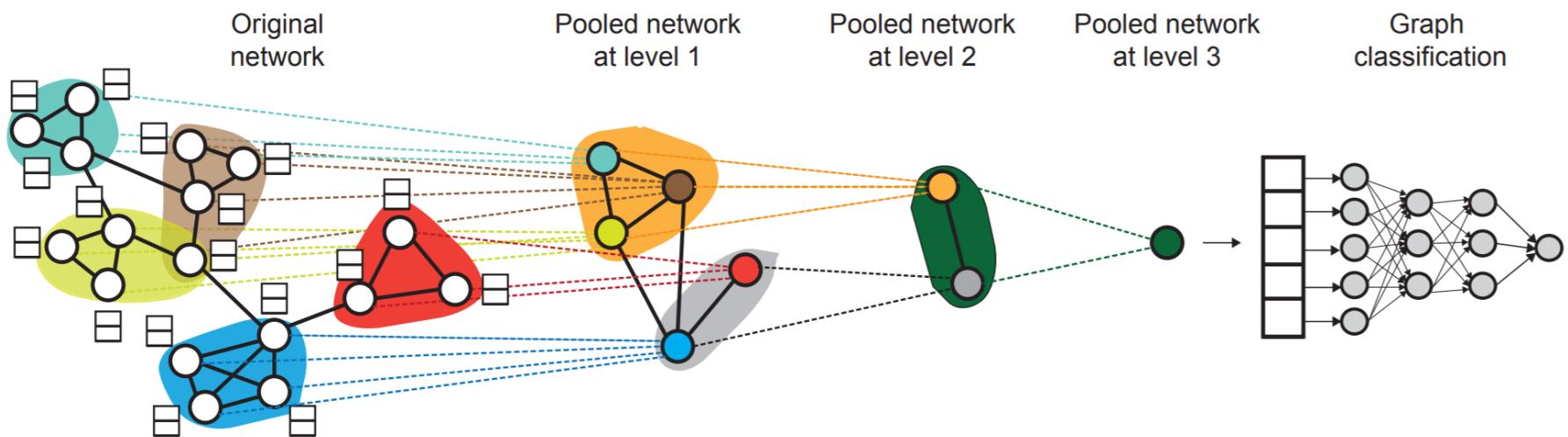
Summary

We discussed 3 ideas to graph embeddings

- **Approach 1:** Embed nodes and sum/avg them
- **Approach 2:** Create super-node that spans the (sub) graph and then embed that node
- **Approach 3: Anonymous Walk Embeddings**
 - Idea 1: Sample the anon. walks and represent the graph as fraction of times each anon walk occurs
 - Idea 2: Embed anonymous walks, concatenate their embeddings to get a graph embedding

Preview: Hierarchical Embeddings

- We will discuss more advanced ways to obtain graph embeddings in Lecture 8.
- We can **hierarchically** cluster nodes in graphs, and **sum/avg** the node embeddings according to these clusters.



How to Use Embeddings

- **How to use embeddings z_i of nodes:**
 - **Clustering/community detection:** Cluster points \mathbf{z}_i
 - **Node classification:** Predict label of node i based on \mathbf{z}_i
 - **Link prediction:** Predict edge (i, j) based on $(\mathbf{z}_i, \mathbf{z}_j)$
 - 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: $f(z_i, z_j) = g(\|z_i - z_j\|_2)$
 - **Graph classification:** graph embedding \mathbf{z}_G via aggregating node embeddings or anonymous random walks.
Predict label based on graph embedding z_G

Today's Summary

We discussed **graph representation learning**, a way to learn **node and graph embeddings** for downstream tasks, **without feature engineering**.

- **Encoder-decoder framework:**
 - Encoder: embedding lookup
 - Decoder: predict score based on embedding to match node similarity
- **Node similarity measure:** (biased) random walk
 - Examples: DeepWalk, Node2Vec
- **Extension to Graph embedding:** Node embedding aggregation and Anonymous Walk Embeddings