

# Traditional Methods for Machine Learning in Graphs

# Agenda

## Today's Topics:

- Traditional ML pipeline
- The `networkx` package
- Node-level features
- Link-level features
- Graph-level features

# Agenda

## Today's Theme:

- Graph representation learning
  - Many other problems in graph theory, such as graph coloring, Hamiltonian path, max flow, etc.
- How to encode the topological information
  - Local versus global
- Don't focus on the algorithm details, but rather the kinds of structural information captured

# Stanford CS224W: Traditional Methods for Machine Learning in Graphs

CS224W: Machine Learning with Graphs

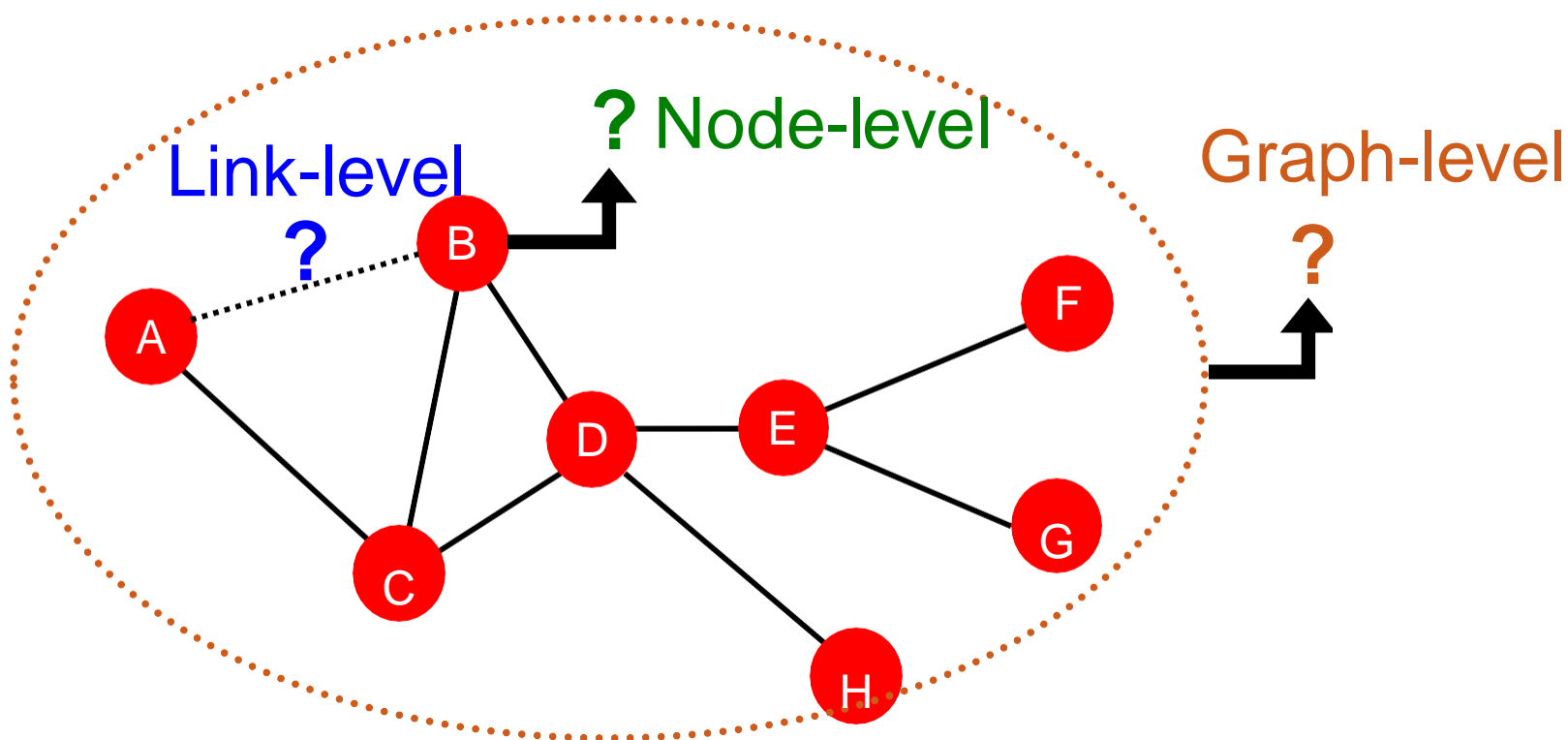
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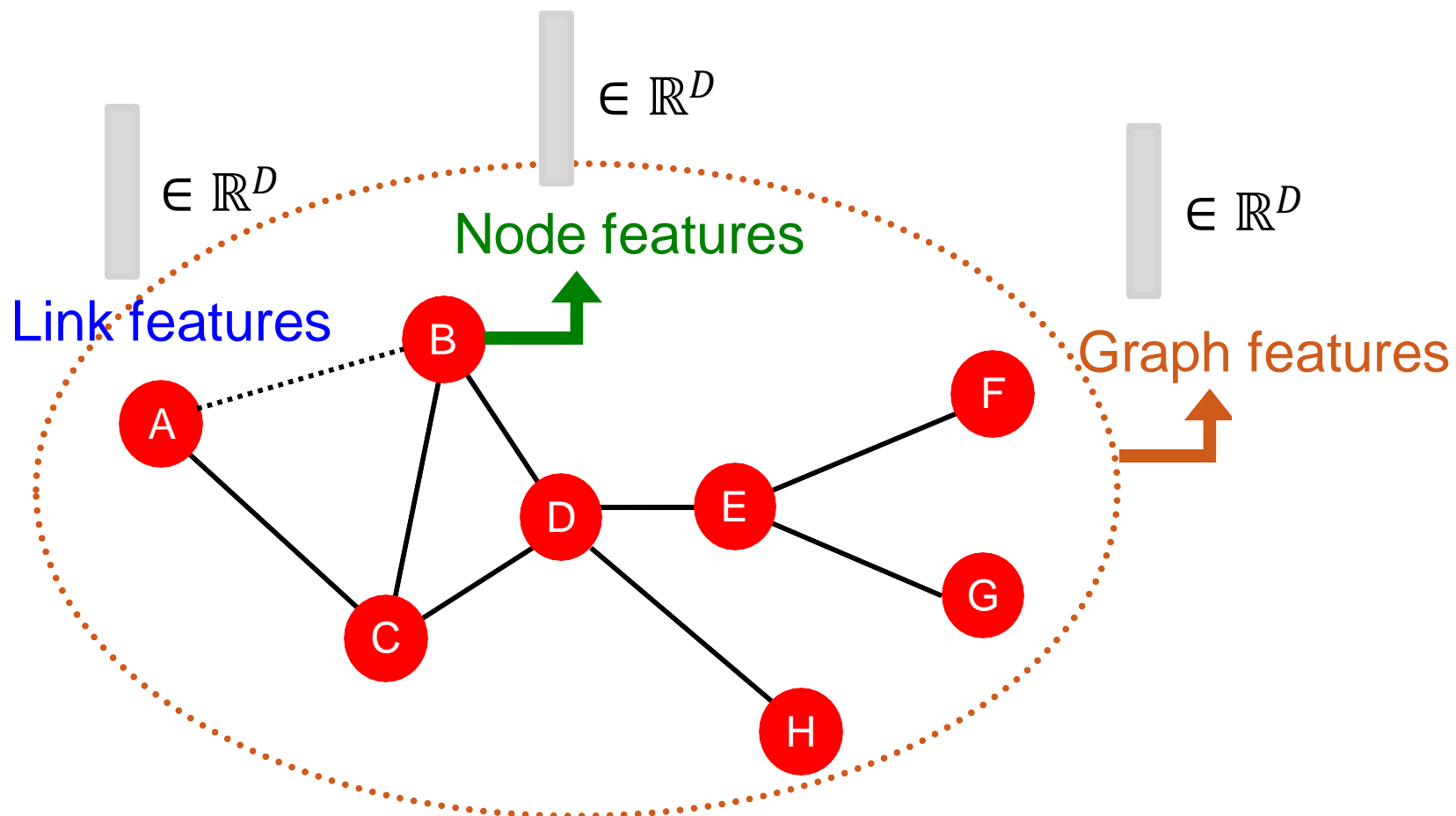
# Machine Learning Tasks: Review

- Node-level prediction
- Link-level prediction
- Graph-level prediction



# Traditional ML Pipeline

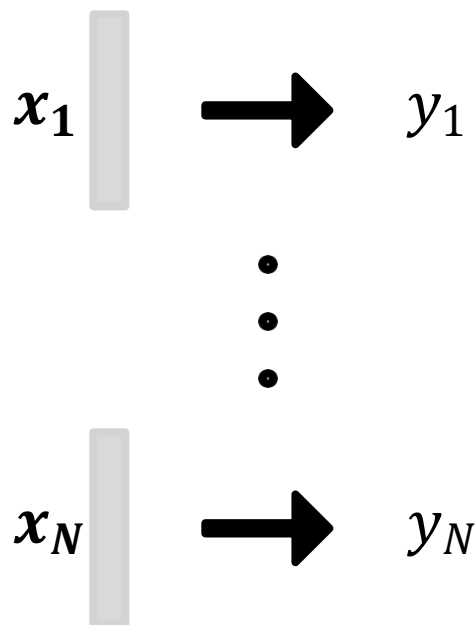
- Design features for nodes/links/graphs
- Obtain features for all training data



# Traditional ML Pipeline

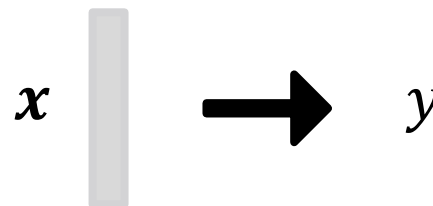
- **Train an ML model:**

- Random forest
- SVM
- Neural network, etc.



- **Apply the model:**

- Given a new node/link/graph, obtain its features and make a prediction



# This Lecture: Feature Design

- Using effective features over graphs is the key to achieving good model performance.
- Traditional ML pipeline uses hand-designed features.
- In this lecture, we overview the traditional features for:
  - Node-level prediction
  - Link-level prediction
  - Graph-level prediction
- For simplicity, we focus on undirected graphs.



# The networkx package

## Code Examples



# Stanford CS224W: Node-Level Tasks and Features

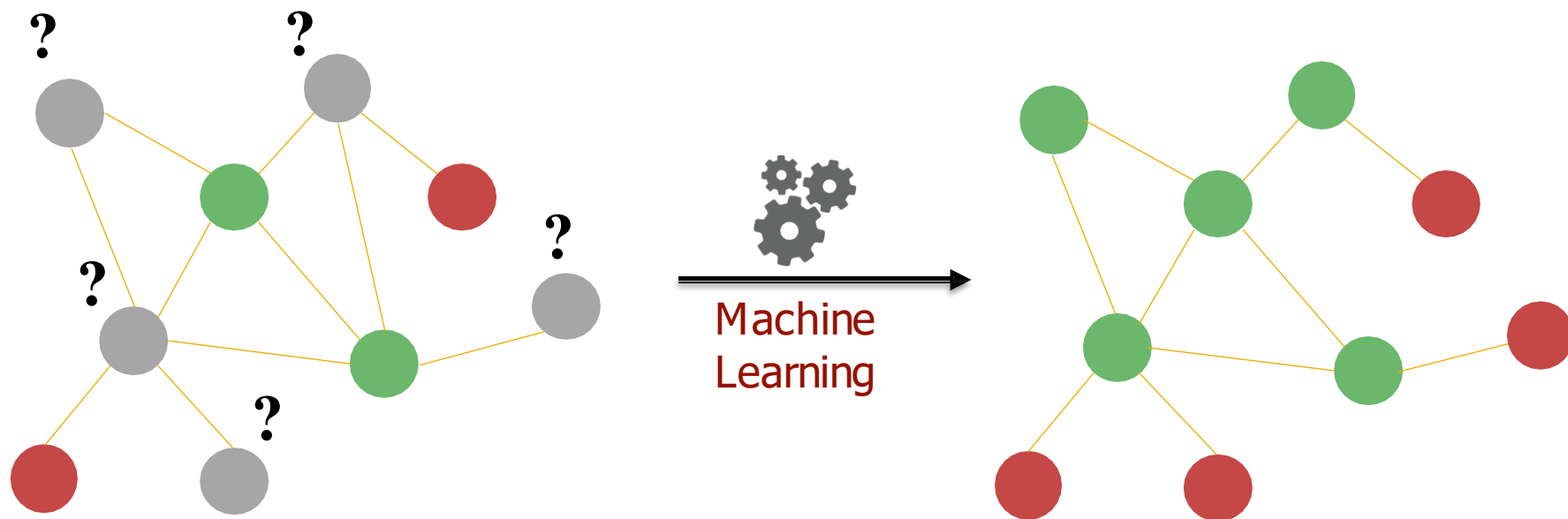
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# Node-Level Tasks



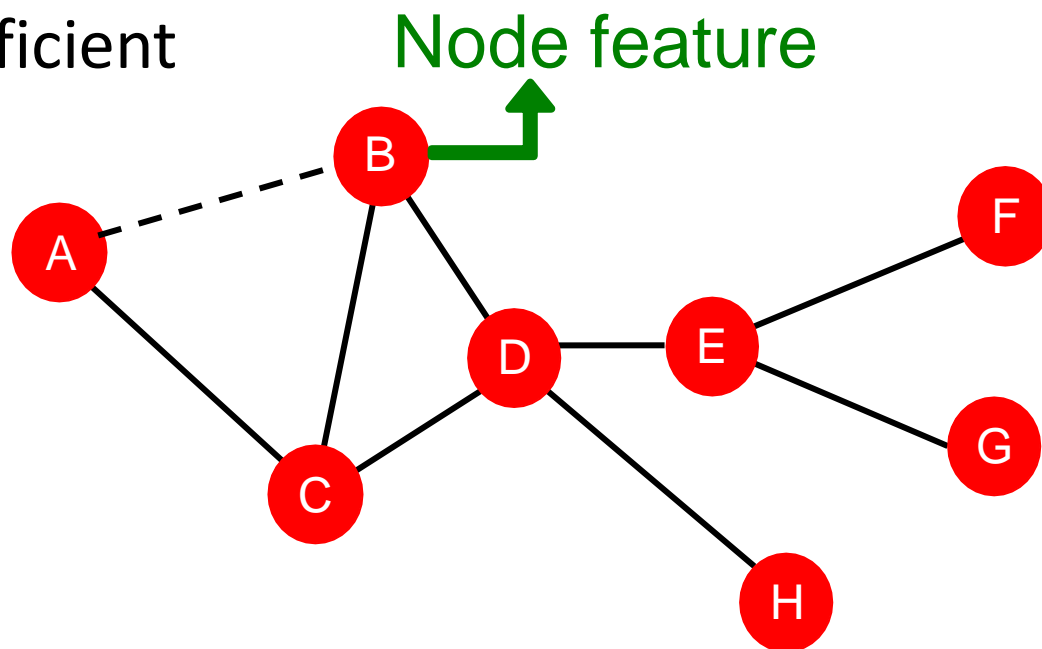
Node classification

ML needs features.

# Node-Level Features: Overview

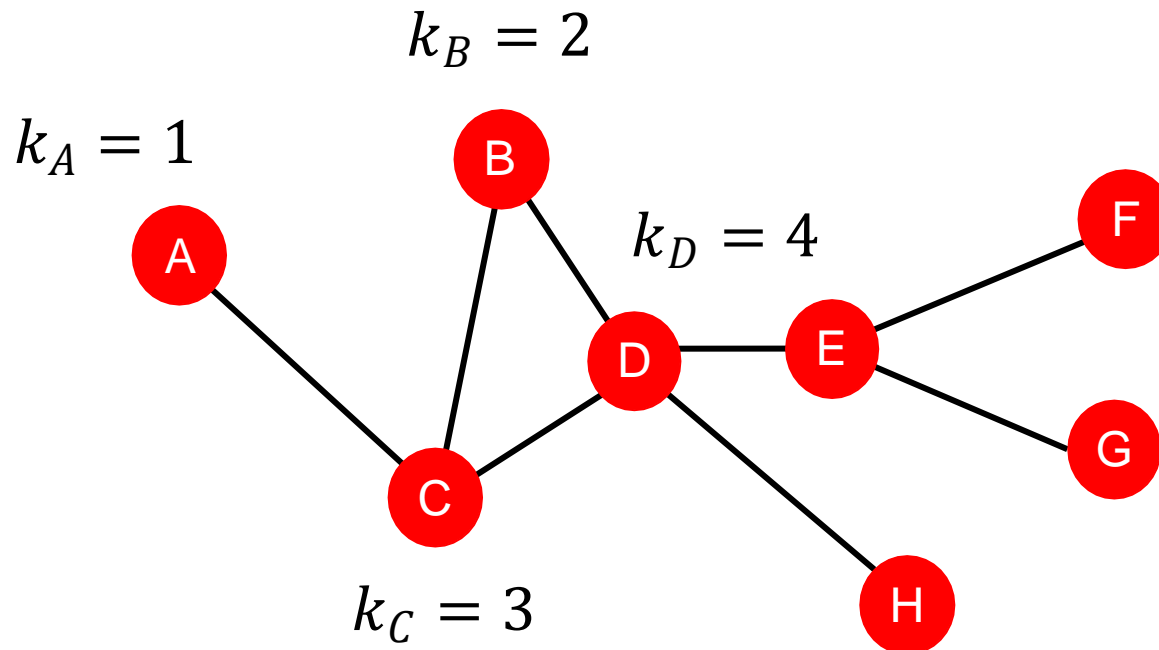
**Goal:** Characterize the structure and position of a node in the network:

- Node degree
- Node centrality
- Clustering coefficient
- Graphlets



# Node Features: Node Degree

- The degree  $k_v$  of node  $v$  is the number of edges (neighboring nodes) the node has.
- Treats all neighboring nodes equally.



# Node Features: Node Centrality

- Node degree counts the neighboring nodes without capturing their importance.
- Node centrality  $c_v$  takes the node importance in a graph into account
- **Different ways to model importance:**
  - Eigenvector centrality
  - Betweenness centrality
  - Closeness centrality
  - and many others...

# Node Centrality (1)

- **Eigenvector centrality:**

- A node  $v$  is important if **surrounded by important neighboring nodes**  $u \in N(v)$ .
- We model the centrality of node  $v$  as **the sum of the centrality of neighboring nodes**:

$$c_v = \frac{1}{\lambda} \sum_{u \in N(v)} c_u$$

$\lambda$  is normalization constant (it will turn out to be the largest eigenvalue of  $A$ )

- Notice that the above equation models centrality in a **recursive manner**. **How do we solve it?**

# Node Centrality (1)

## ■ Eigenvector centrality:

- Rewrite the recursive equation in the matrix form.

$$c_v = \frac{1}{\lambda} \sum_{u \in N(v)} c_u \quad \longleftrightarrow \quad \lambda \mathbf{c} = \mathbf{A} \mathbf{c}$$

$\lambda$  is normalization const  
(largest eigenvalue of  $\mathbf{A}$ )

- $\mathbf{A}$ : Adjacency matrix  
 $A_{uv} = 1$  if  $u \in N(v)$
- $\mathbf{c}$ : Centrality vector
- $\lambda$ : Eigenvalue

- We see that centrality  $\mathbf{c}$  is the **eigenvector of  $\mathbf{A}$ !**
- The largest eigenvalue  $\lambda_{max}$  is always positive and unique (by Perron-Frobenius Theorem).
- The eigenvector  $\mathbf{c}_{max}$  corresponding to  $\lambda_{max}$  is used for centrality.



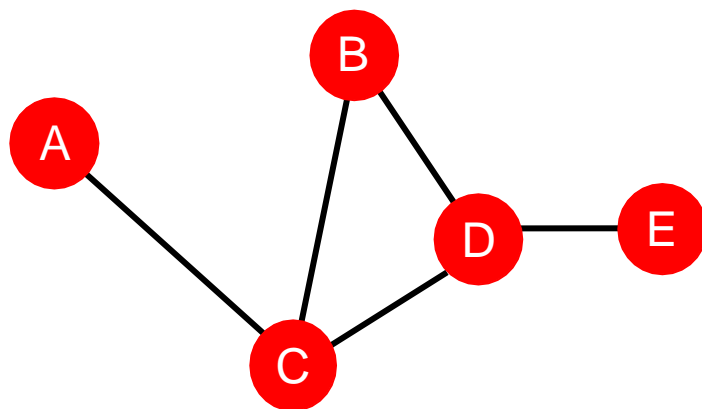
# Node Centrality (2)

## ■ Betweenness centrality:

- A node is important if it lies on many shortest paths between other nodes.

$$c_v = \sum_{s \neq v \neq t} \frac{\#(\text{shortest paths between } s \text{ and } t \text{ that contain } v)}{\#(\text{shortest paths between } s \text{ and } t)}$$

## ■ Example:



$$c_A = c_B = c_E = 0$$

$$c_C = 3$$

(A-C-B, A-C-D, A-C-D-E)

$$c_D = 3$$

(A-C-D-E, B-D-E, C-D-E)

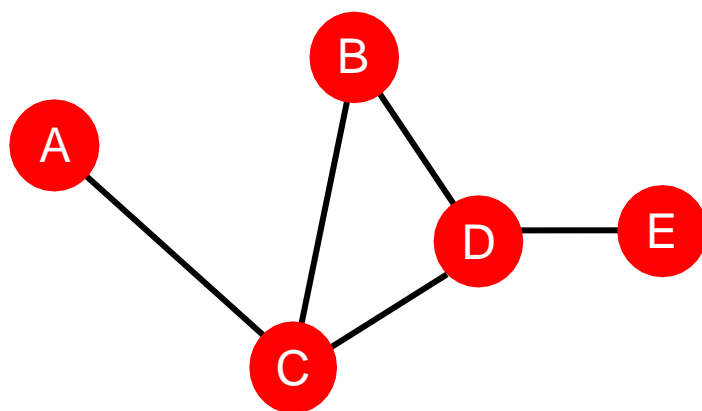
# Node Centrality (3)

## ■ Closeness centrality:

- A node is important if it has small shortest path lengths to all other nodes.

$$c_v = \frac{1}{\sum_{u \neq v} \text{shortest path length between } u \text{ and } v}$$

## ■ Example:



$$c_A = 1/(2 + 1 + 2 + 3) = 1/8$$

(A-C-B, A-C, A-C-D, A-C-D-E)

$$c_D = 1/(2 + 1 + 1 + 1) = 1/5$$

(D-C-A, D-B, D-C, D-E)

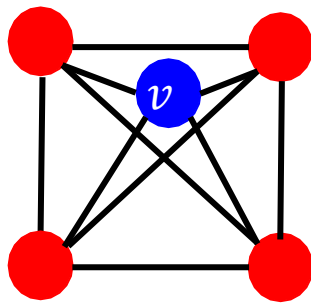
# Node Features: Clustering Coefficient

- Measures how connected  $v$ 's neighboring nodes are:

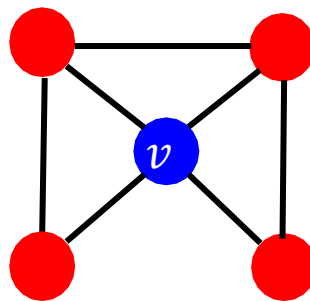
$$e_v = \frac{\#(\text{edges among neighboring nodes})}{\binom{k_v}{2}} \in [0,1]$$

#(node pairs among  $k_v$  neighboring nodes)  
In our examples below the denominator is 6 (4 choose 2).

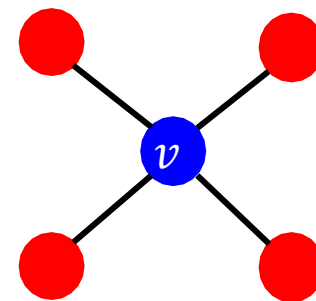
- Examples:**



$$e_v = 1$$



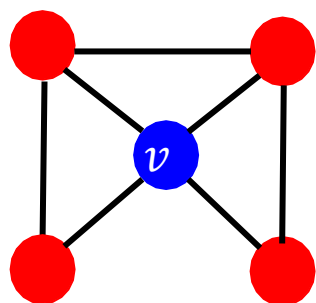
$$e_v = 0.5$$



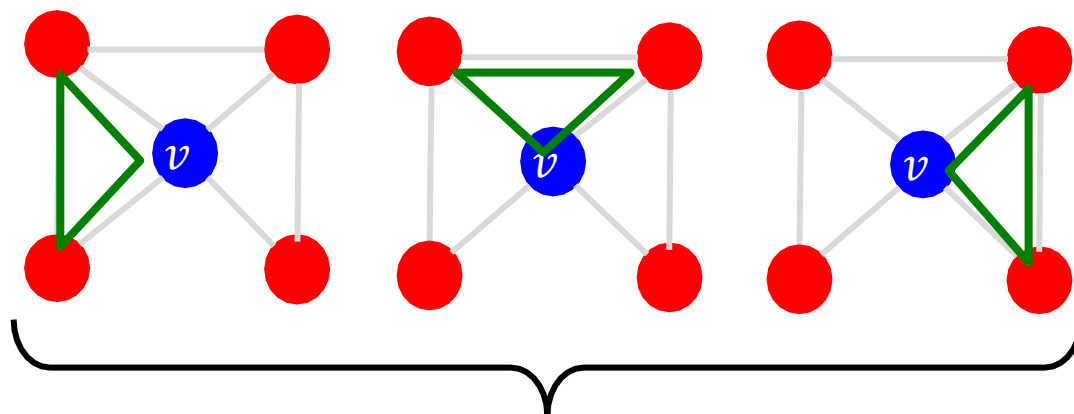
$$e_v = 0$$

# Node Features: Graphlets

- **Observation:** Clustering coefficient counts the #(triangles) in the ego-network



$$e_v = 0.5$$

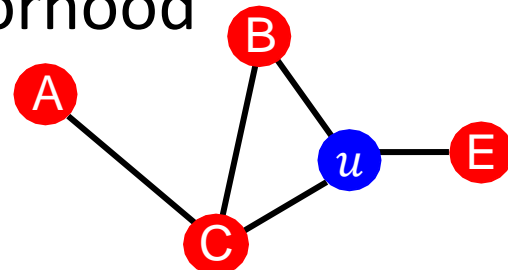


3 triangles (out of 6 node triplets)

- We can generalize the above by counting #(pre-specified subgraphs, i.e., **graphlets**).

# Node Features: Graphlets

- **Goal:** Describe network structure around node  $u$ 
  - **Graphlets** are small subgraphs that describe the structure of node  $u$ 's network neighborhood

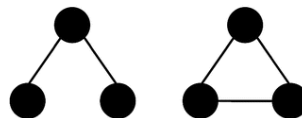
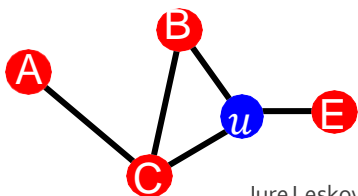


## Analogy:

- **Degree** counts **#(edges)** that a node touches
- **Clustering coefficient** counts **#(triangles)** that a node touches.
- **Graphlet Degree Vector (GDV)**: Graphlet-base features for nodes
  - **GDV** counts **#(graphlets)** that a node touches

# Node Features: Graphlets

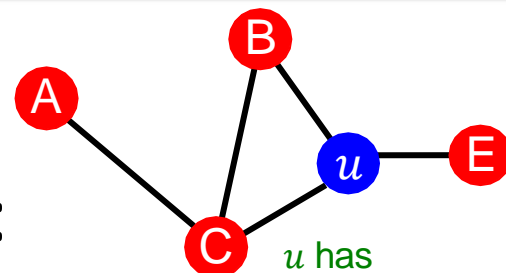
- Considering graphlets of size 2-5 nodes we get:
  - **Vector of 73 coordinates** is a signature of a node that describes the topology of node's neighborhood
- Graphlet degree vector provides a measure of a **node's local network topology**:
  - Comparing vectors of two nodes provides a more detailed measure of local topological similarity than node degrees or clustering coefficient.



# Node Features: Graphlets

**Graphlets:** Rooted connected induced non-isomorphic subgraphs:

Take some nodes and all the edges between them.

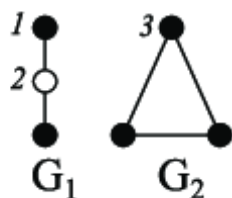


$u$  has graphlets: 0, 1, 2, 3, 5, 10, 11, ...

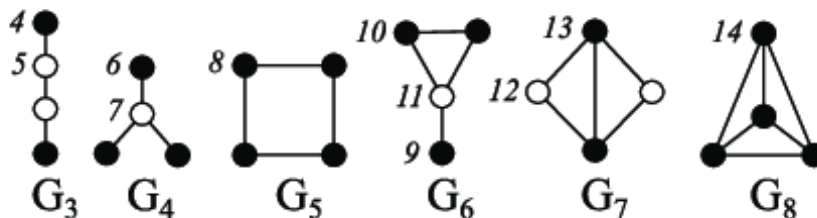
2-node graphlet



3-node graphlets

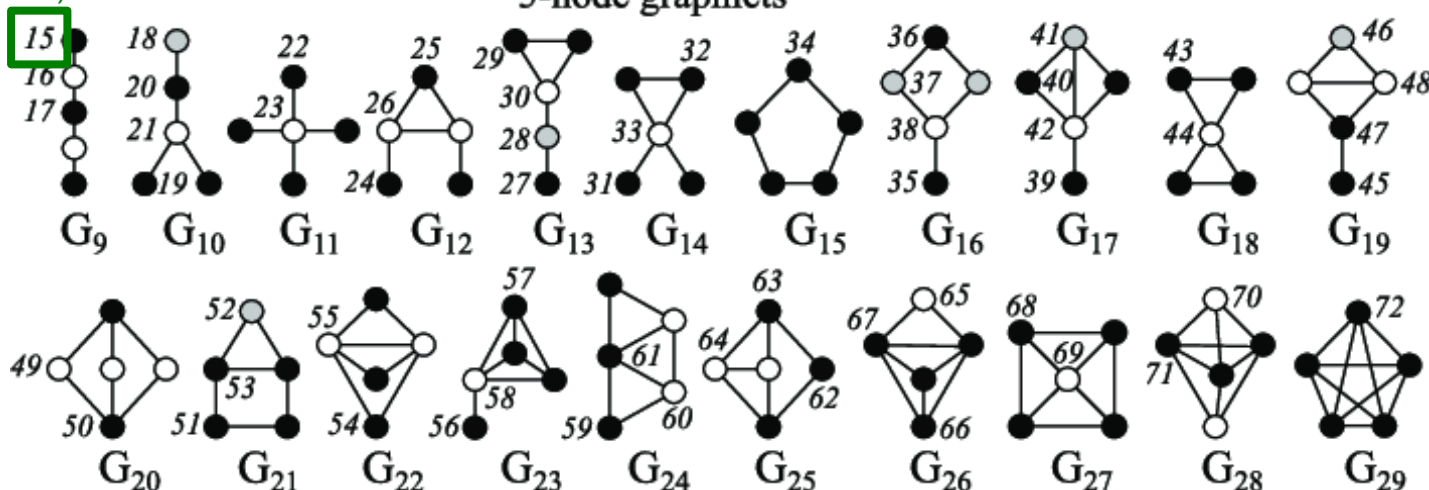


4-node graphlets



Graphlet id (Root/ "position" of node  $u$ )

5-node graphlets



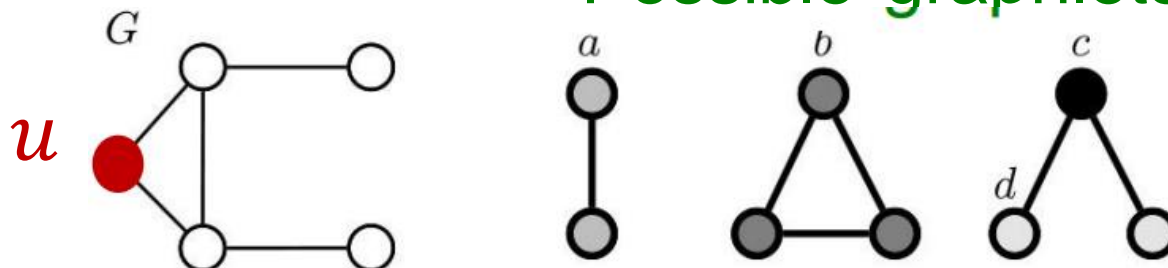
There are 73 different graphlets on up to 5 nodes

# Node Features: Graphlets

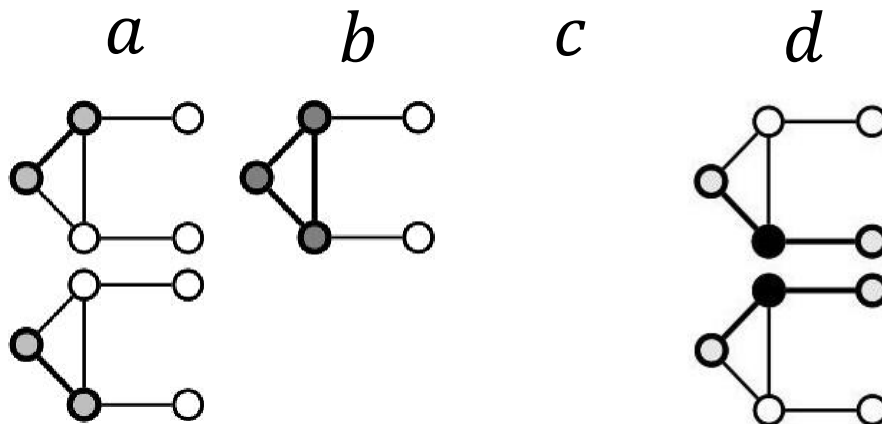
- **Graphlet Degree Vector (GDV):** A count vector of graphlets rooted at a given node.

- **Example:**

Possible graphlets up to size 3



Graphlet instances of node  $u$ :



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



# Node-Level Feature: Summary

- **Importance-based features:** capture the importance of a node in a graph
  - Node degree:
    - Simply counts the number of neighboring nodes
  - Node centrality:
    - Models **importance of neighboring nodes** in a graph
    - Different modeling choices: eigenvector centrality, betweenness centrality, closeness centrality
- Useful for predicting influential nodes in a graph
  - **Example:** predicting celebrity users in a social network

# Node-Level Feature: Summary

- **Structure-based features:** Capture topological properties of local neighborhood around a node.
  - **Node degree:**
    - Counts the number of neighboring nodes
  - **Clustering coefficient:**
    - Measures how connected neighboring nodes are
  - **Graphlet degree vector:**
    - Counts the occurrences of different graphlets
- **Useful for predicting a particular role a node plays in a graph:**
  - **Example:** Predicting protein functionality in a protein-protein interaction network.

# Discussion and Coding

Questions?



Code Examples



# Stanford CS224W: Link Prediction Task and Features

CS224W: Machine Learning with Graphs

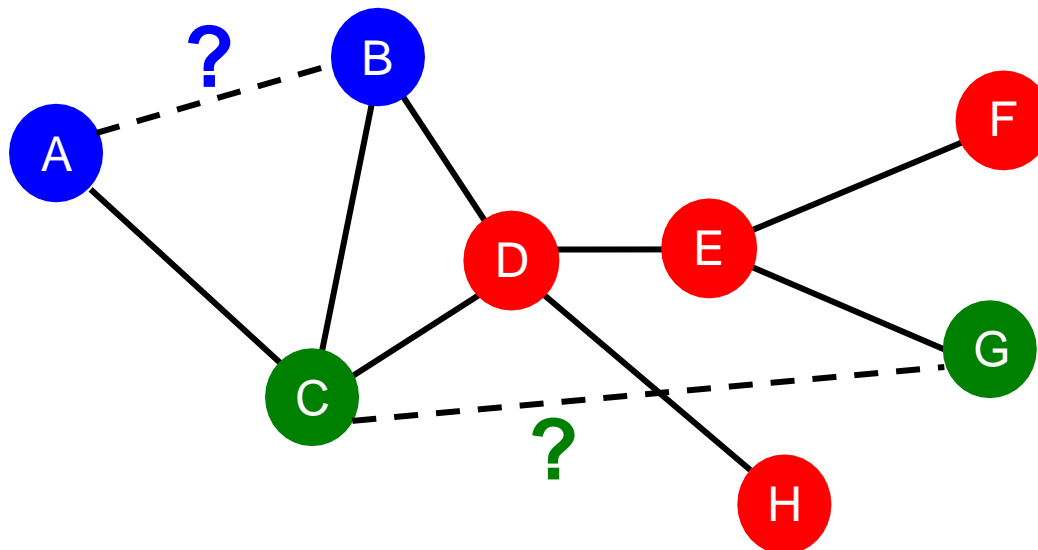
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# Link-Level Prediction Task: Recap

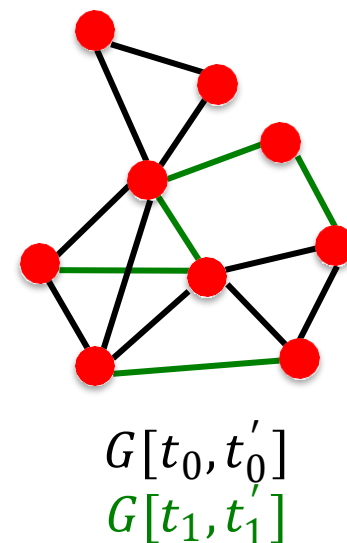
- The task is to predict **new links** based on the existing links.
- At test time, node pairs (with no existing links) are ranked, and top  $K$  node pairs are predicted.
- The key is to design features for a **pair of nodes**.



# Link Prediction as a Task

## Two formulations of the link prediction task:

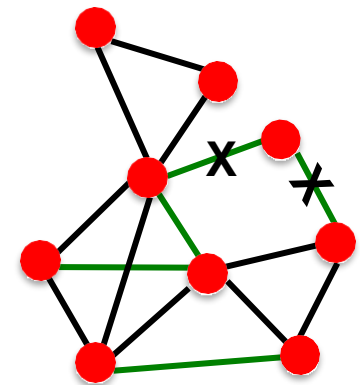
- **1) Links missing at random:**
  - Remove a random set of links and then aim to predict them
- **2) Links over time:**
  - Given  $G[t_0, t'_0]$  a graph defined by edges up to time  $t'_0$ , **output a ranked list  $L$**  of edges (not in  $G[t_0, t'_0]$ ) that are predicted to appear in time  $G[t_1, t'_1]$
  - **Evaluation:**
    - $n = |E_{new}|$ : # new edges that appear during the test period  $[t_1, t'_1]$
    - Take top  $n$  elements of  $L$  and count correct edges



# Link Prediction via Proximity

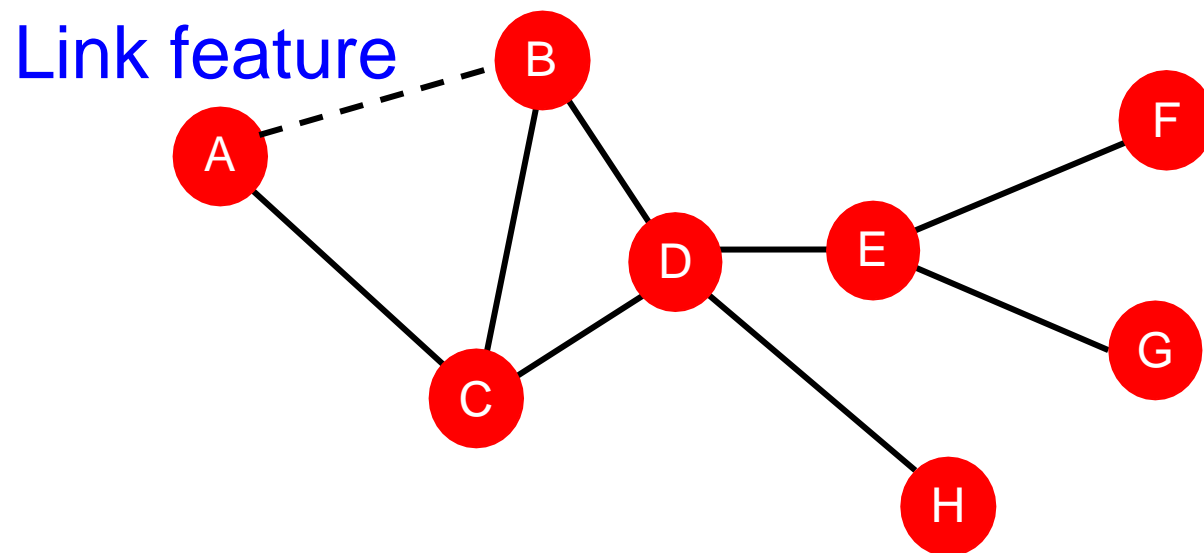
## ■ Methodology:

- For each pair of nodes  $(x,y)$  compute score  $c(x,y)$ 
  - For example,  $c(x,y)$  could be the # of common neighbors of  $x$  and  $y$
- Sort pairs  $(x,y)$  by the decreasing score  $c(x,y)$
- **Predict top  $n$  pairs as new links**
- **See which of these links actually appear in  $G[t_1, t'_1]$**



# Link-Level Features: Overview

- Distance-based feature
- Local neighborhood overlap
- Global neighborhood overlap

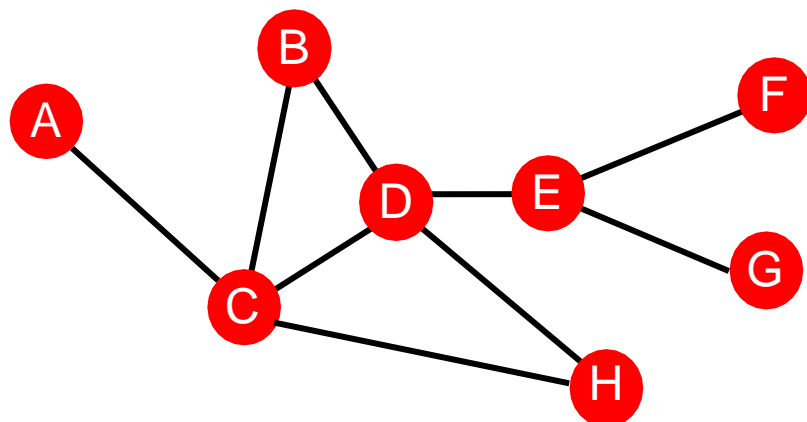




# Distance-Based Features

## Shortest-path distance between two nodes

- Example:



$$S_{BH} = S_{BE} = S_{AB} = 2$$

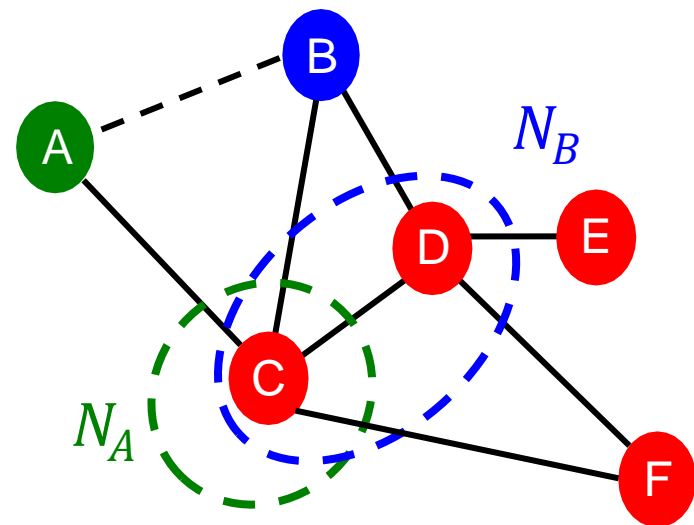
$$S_{BG} = S_{BF} = 3$$

- However, this does not capture the degree of neighborhood overlap:
  - Node pair  $(B, H)$  has 2 shared neighboring nodes, while pairs  $(B, E)$  and  $(A, B)$  only have 1 such node.

# Local Neighborhood Overlap

Captures # neighboring nodes shared between two nodes  $v_1$  and  $v_2$ :

- **Common neighbors:**  $|N(v_1) \cap N(v_2)|$ 
  - Example:  $|N(A) \cap N(B)| = |\{C\}| = 1$
  - This does not take into account if the nodes have low or high degree
  - Several approaches to normalizing



# Local Neighborhood Overlap

Captures # neighboring nodes shared between two nodes  $v_1$  and  $v_2$ :

- **Common neighbors:**  $|N(v_1) \cap N(v_2)|$

- Example:  $|N(A) \cap N(B)| = |\{C\}| = 1$

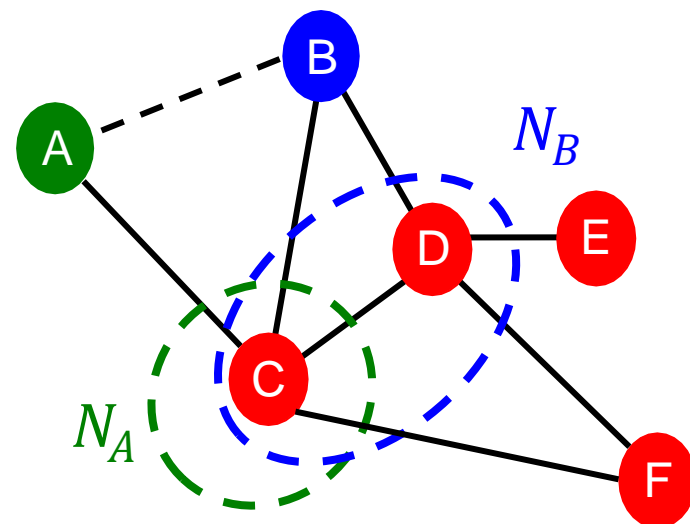
- **Jaccard's coefficient:**  $\frac{|N(v_1) \cap N(v_2)|}{|N(v_1) \cup N(v_2)|}$

- Example:  $\frac{|N(A) \cap N(B)|}{|N(A) \cup N(B)|} = \frac{|\{C\}|}{|\{C, D\}|} = \frac{1}{2}$

- **Adamic-Adar index:**

$$\sum_{u \in N(v_1) \cap N(v_2)} \frac{1}{\log(k_u)}$$

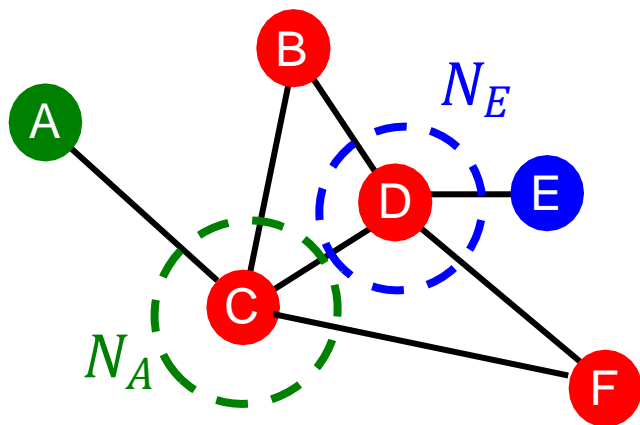
- Example:  $\frac{1}{\log(k_C)} = \frac{1}{\log 4}$



# Global Neighborhood Overlap

- **Limitation of local neighborhood features:**

- Metric is always zero if the two nodes do not have any neighbors in common.



$$N_A \cap N_E = \phi$$
$$|N_A \cap N_E| = 0$$

- However, the two nodes may still potentially be connected in the future.
- **Global neighborhood overlap** metrics resolve the limitation by considering the entire graph.

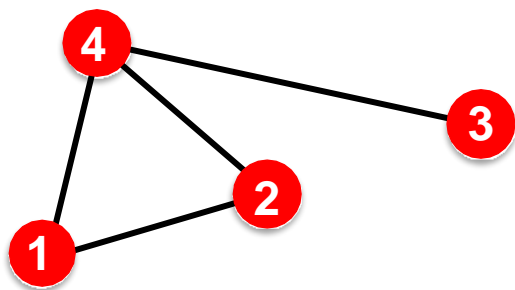
# Global Neighborhood Overlap

- **Katz index:** count the number of walks of all lengths between a given pair of nodes.
- **Q: How to compute #walks between two nodes?**
- Use **powers of the graph adjacency matrix!**

# Intuition: Powers of Adj Matrices

## ■ Computing #walks between two nodes

- Recall:  $A_{uv} = 1$  if  $u \in N(v)$
- Let  $P_{uv}^{(K)} = \text{\#walks of length } K \text{ between } u \text{ and } v$
- We will show  $P^{(K)} = A^k$
- $P_{uv}^{(1)} = \text{\#walks of length 1 (direct neighborhood) between } u \text{ and } v = A_{uv}$



$$P_{12}^{(1)} = A_{12}$$
$$A = \begin{pmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{pmatrix}$$

# Intuition: Powers of Adj Matrices

- How to compute  $P_{uv}^{(2)}$  ?
  - Step 1: Compute **#walks** of length 1 **between each of  $u$ 's neighbor and  $v$**
  - Step 2: **Sum up** these #walks across  $u$ 's neighbors
  - $P_{uv}^{(2)} = \sum_i A_{ui} * P_{iv}^{(1)} = \sum_i A_{ui} * A_{iv} = A_{uv}^2$

Node 1's neighbors

#walks of length 1 between  
Node 1's neighbors and Node 2

$$P_{12}^{(2)} = A_{12}^2$$

$$A^2 = \begin{pmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{pmatrix} \times \begin{pmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{pmatrix} = \begin{pmatrix} 2 & 1 & 1 & 1 \\ 1 & 2 & 1 & 1 \\ 1 & 1 & 1 & 0 \\ 1 & 1 & 0 & 3 \end{pmatrix}$$

Power of adjacency

# Global Neighborhood Overlap

- **Katz index:** count the number of walks of all lengths between a pair of nodes.
- How to compute #walks between two nodes?
- Use **adjacency matrix powers!**
  - $A_{uv}$  specifies #walks of length 1 (direct neighborhood) between  $u$  and  $v$ .
  - $A_{uv}^2$  specifies #walks of **length 2** (neighbor of neighbor) between  $u$  and  $v$ .
  - And,  $A_{uv}^l$  specifies #walks of **length  $l$** .



# Global Neighborhood Overlap

- **Katz index** between  $v_1$  and  $v_2$  is calculated as

Sum over *all walk lengths*

$$S_{v_1 v_2} = \sum_{l=1}^{\infty} \boxed{\beta^l} \boxed{A_{v_1 v_2}^l}$$

#walks of length  $l$  between  $v_1$  and  $v_2$

$0 < \beta < 1$ : discount factor

- Katz index matrix is computed in closed-form:

$$S = \sum_{i=1}^{\infty} \beta^i A^i = \underbrace{(I - \beta A)^{-1} - I}_{= \sum_{i=0}^{\infty} \beta^i A^i}$$

by geometric series of matrices

# Link-Level Features: Summary

- **Distance-based features:**
  - Uses the shortest path length between two nodes but does not capture how neighborhood overlaps.
- **Local neighborhood overlap:**
  - Captures how many neighboring nodes are shared by two nodes.
  - Becomes zero when no neighbor nodes are shared.
- **Global neighborhood overlap:**
  - Uses global graph structure to score two nodes.
  - Katz index counts #walks of all lengths between two nodes.

# Discussion and Coding

Questions?



Code Examples



# Stanford CS224W: Graph-Level Features and Graph Kernels

CS224W: Machine Learning with Graphs

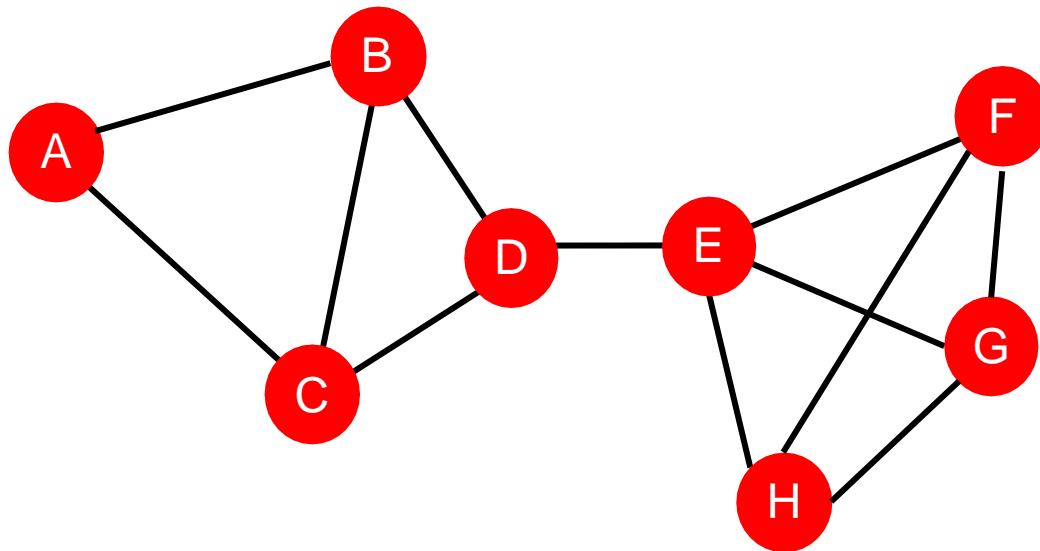
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# Graph-Level Features

- **Goal:** We want features that characterize the structure of an entire graph.
- **For example:**



# Background: Kernel Methods

- **Kernel methods** are widely-used for traditional ML for graph-level prediction.
- **Idea: Design kernels instead of feature vectors.**
- **A quick introduction to Kernels:**
  - Kernel  $K(G, G') \in \mathbb{R}$  measures similarity b/w data
  - Kernel matrix  $\mathbf{K} = (K(G, G'))_{G, G'}$  must always be positive semidefinite (i.e., has positive eigenvalues)
  - There exists a feature representation  $\phi(\cdot)$  such that  $K(G, G') = \phi(G)^T \phi(G')$
  - Once the kernel is defined, off-the-shelf ML model, such as **kernel SVM**, can be used to make predictions.

# Graph-Level Features: Overview

- **Graph Kernels:** Measure similarity between two graphs:
  - Graphlet Kernel [1]
  - Weisfeiler-Lehman Kernel [2]
  - Other kernels are also proposed in the literature (beyond the scope of this lecture)
    - Random-walk kernel
    - Shortest-path graph kernel
    - And many more...

1 Shervashidze, Nino, et al. "Efficient graphlet kernels for large graph comparison." Artificial Intelligence and Statistics. 2009.

2 Shervashidze, Nino, et al. "Weisfeiler-lehman graph kernels." Journal of Machine Learning Research 12.9 (2011).

# Graph Kernel: Key Idea

- **Goal:** Design graph feature vector  $\phi(G)$
- **Key idea:** Bag-of-Words (BoW) for a graph
  - **Recall:** BoW simply uses the word counts as features for documents (no ordering considered).
  - Naïve extension to a graph: **Regard nodes as words.**
  - Since both graphs have **4 red nodes**, we get the same feature vector for two different graphs...

$$\phi(\text{triangle with extra node}) = \phi(\text{square with diagonals})$$



# Graph Kernel: Key Idea

What if we use Bag of node degrees?

Deg1: ● Deg2: ● Deg3: ●

$$\phi(\text{triangle}) = \text{count}(\text{triangle with colored nodes}) = [1, 2, 1]$$



Obtains different features for different graphs!

$$\phi(\text{square}) = \text{count}(\text{square with colored nodes}) = [0, 2, 2]$$

- Both Graphlet Kernel and Weisfeiler-Lehman (WL) Kernel use **Bag-of-\*** representation of graph, where **\*** is more sophisticated than node degrees!

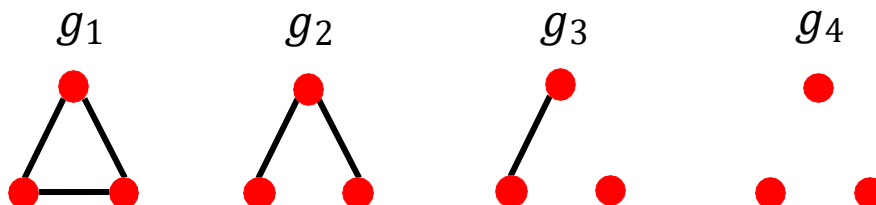
# Graphlet Features

- **Key idea:** Count the number of different graphlets in a graph.
- **Note:** Definition of graphlets here is slightly different from node-level features.
- The two differences are:
  - Nodes in graphlets here do **not need to be connected** (allows for isolated nodes)
  - The graphlets here are not rooted.
  - Examples in the next slide illustrate this.

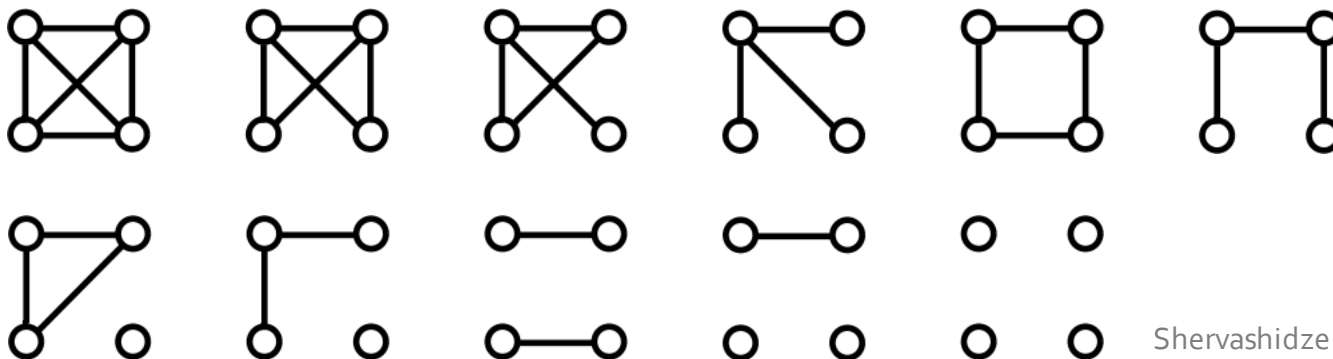
# Graphlet Features

Let  $\mathcal{G}_k = (g_1, g_2, \dots, g_{n_k})$  be a list of graphlets of size  $k$ .

- For  $k = 3$ , there are 4 graphlets.



- For  $k = 4$ , there are 11 graphlets.



Shervashidze et al., AISTATS 2011

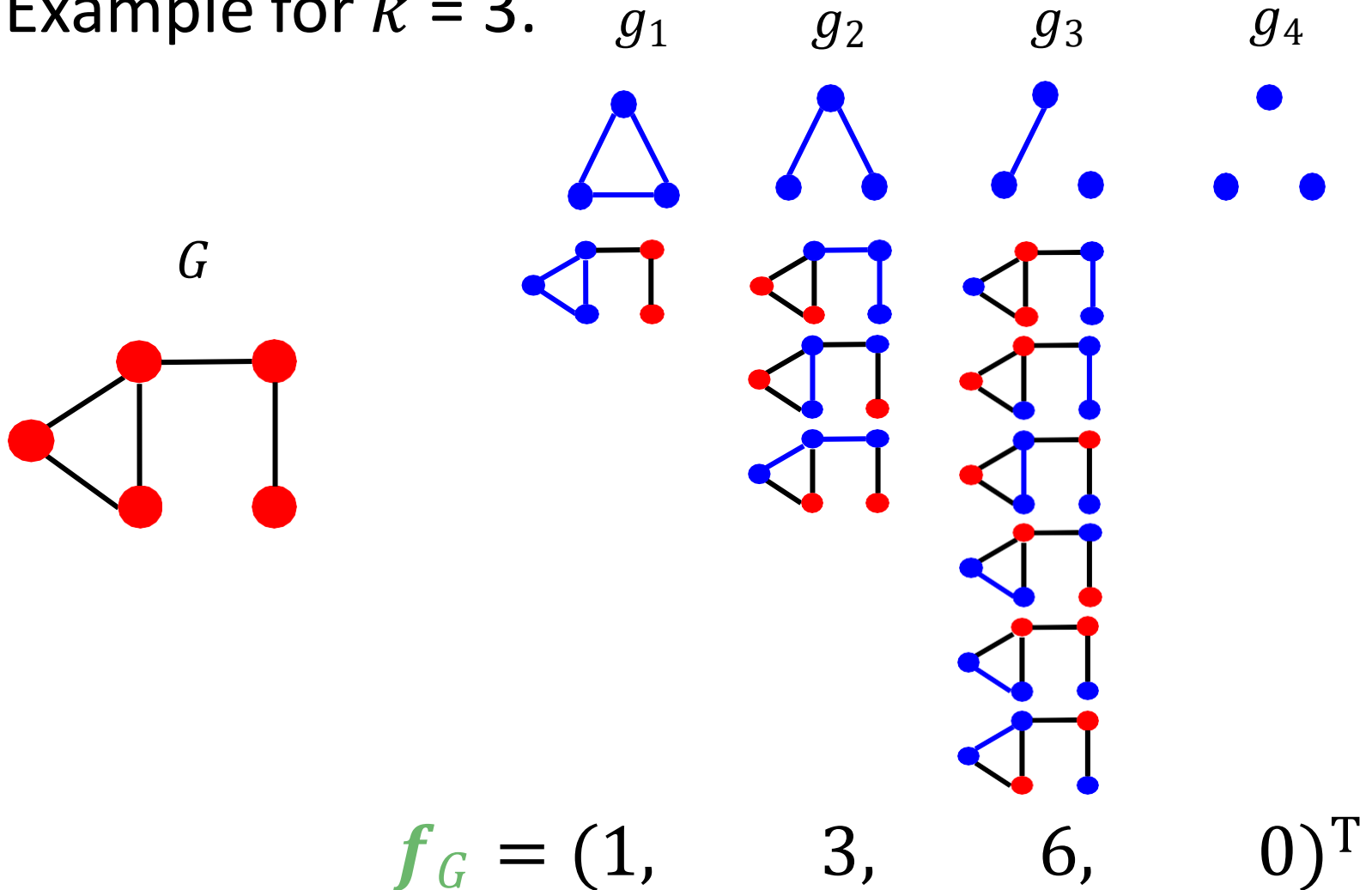
# Graphlet Features

- Given graph  $G$ , and a graphlet list  $\mathcal{G}_k = (g_1, g_2, \dots, g_{n_k})$ , define the graphlet count vector  $f_G \in \mathbb{R}^{n_k}$  as

$$(f_G)_i = \#(g_i \subseteq G) \text{ for } i = 1, 2, \dots, n_k.$$

# Graphlet Features

- Example for  $k = 3$ .



# Graphlet Kernel

- Given two graphs,  $G$  and  $G'$ , graphlet kernel is computed as

$$K(G, G') = \mathbf{f}_G^T \mathbf{f}_{G'}$$

- **Problem:** if  $G$  and  $G'$  have different sizes, that will greatly skew the value.
- **Solution:** normalize each feature vector

$$\mathbf{h}_G = \frac{\mathbf{f}_G}{\text{Sum}(\mathbf{f}_G)} \quad K(G, G') = \mathbf{h}_G^T \mathbf{h}_{G'}$$

# Graphlet Kernel

**Limitations:** Counting graphlets is **expensive!**

- Counting size- $k$  graphlets for a graph with size  $n$  by enumeration takes  $n^k$ .
- This is unavoidable in the worst-case since **subgraph isomorphism test** (judging whether a graph is a subgraph of another graph) is **NP-hard**.
- If a graph's node degree is bounded by  $d$ , an  $O(nd^{k-1})$  algorithm exists to count all the graphlets of size  $k$ .

**Can we design a more efficient graph kernel?**

# Weisfeiler-Lehman Kernel

- **Goal:** Design an efficient graph feature descriptor  $\phi(G)$
- **Idea:** Use neighborhood structure to iteratively enrich node vocabulary.
  - Generalized version of **Bag of node degrees** since node degrees are one-hop neighborhood information.
- **Algorithm to achieve this:**

**Color refinement**



# Color Refinement

- **Given:** A graph  $G$  with a set of nodes  $V$ .
  - Assign an initial color  $c^{(0)}(v)$  to each node  $v$ .
  - Iteratively refine node colors by

$$c^{(k+1)}(v) = \text{HASH} \left( \left\{ c^{(k)}(v), \{c^{(k)}(u)\}_{u \in N(v)} \right\} \right),$$

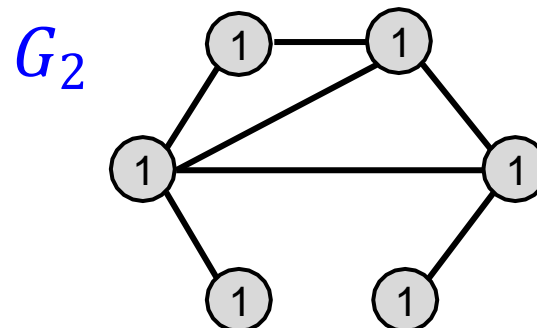
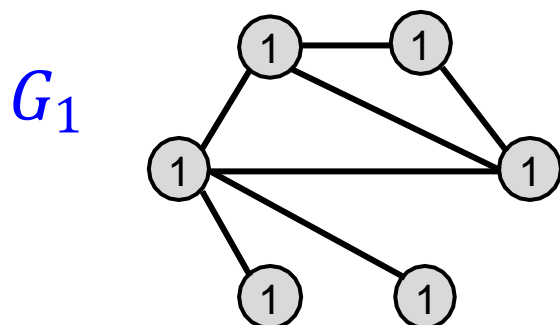
where **HASH** maps different inputs to different colors.

- After  $K$  steps of color refinement,  $c^{(K)}(v)$  summarizes the structure of  $K$ -hop neighborhood

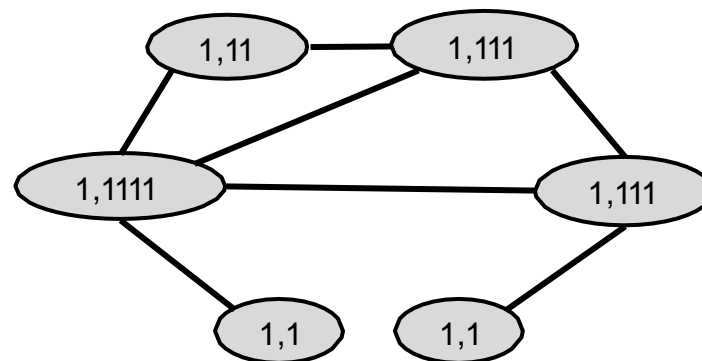
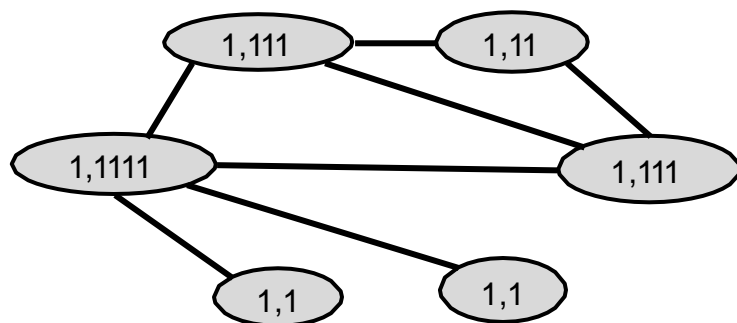
# Color Refinement (1)

## Example of color refinement given two graphs

- Assign initial colors



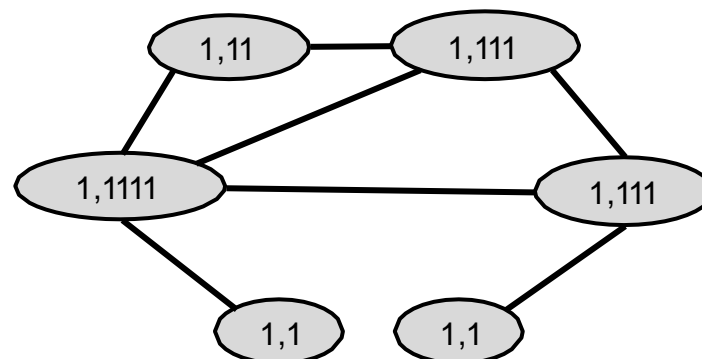
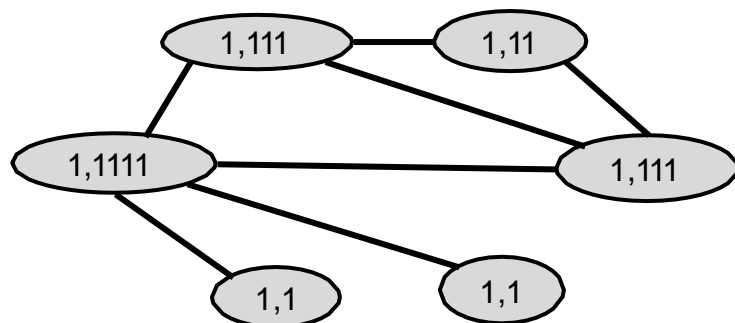
- Aggregate neighboring colors



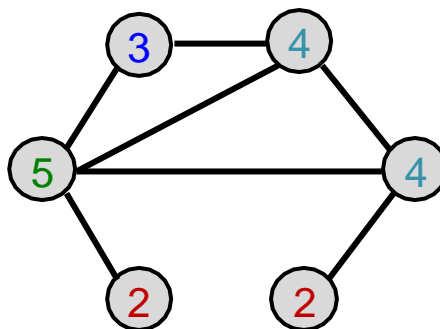
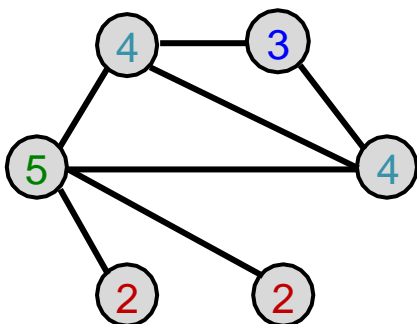
# Color Refinement (2)

## Example of color refinement given two graphs

- Aggregated colors



- Hash aggregated colors



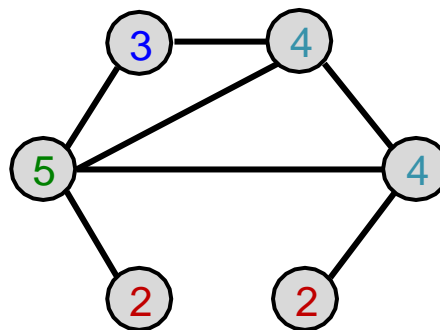
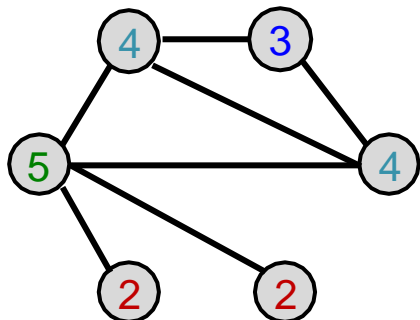
### Hash table

1,1	-->	2
1,11	-->	3
1,111	-->	4
1,1111	-->	5

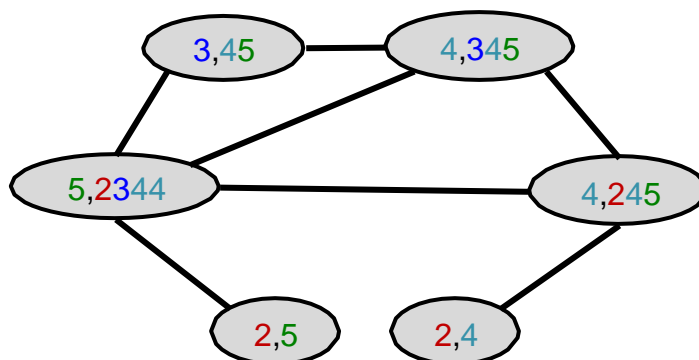
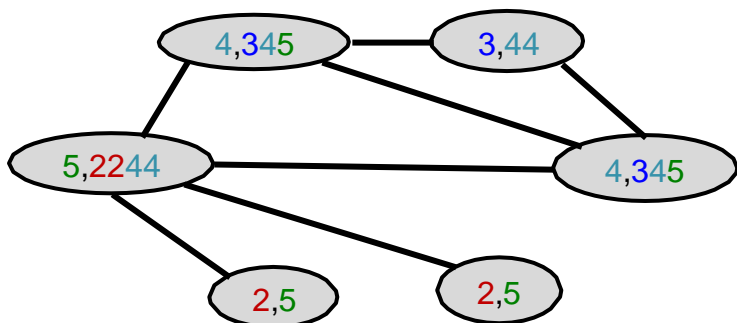
# Color Refinement (3)

## Example of color refinement given two graphs

- Aggregated colors



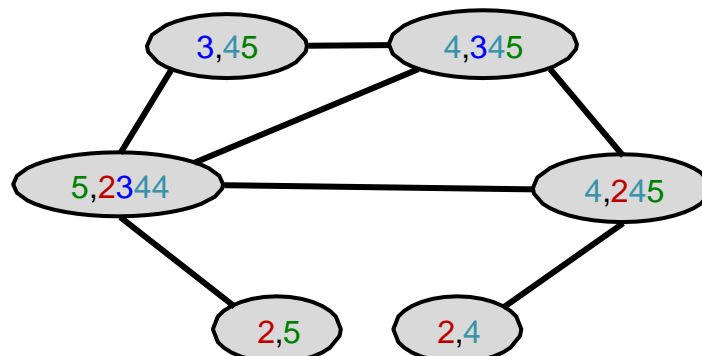
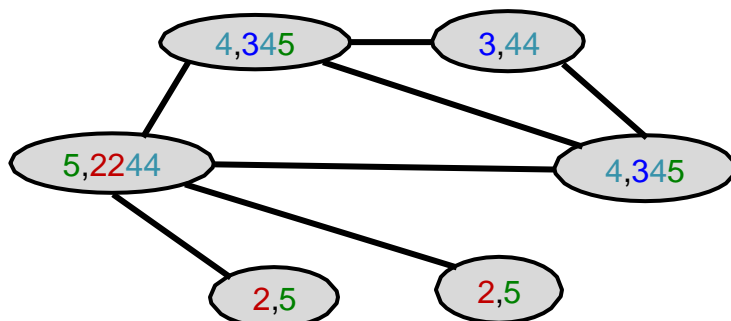
- Hash aggregated colors



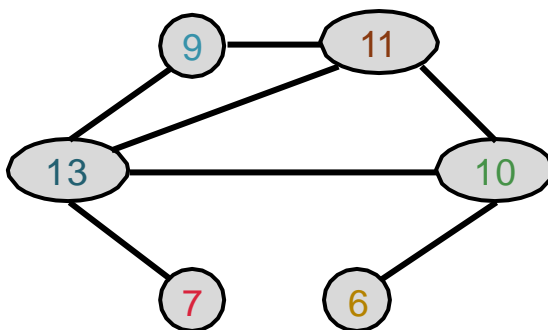
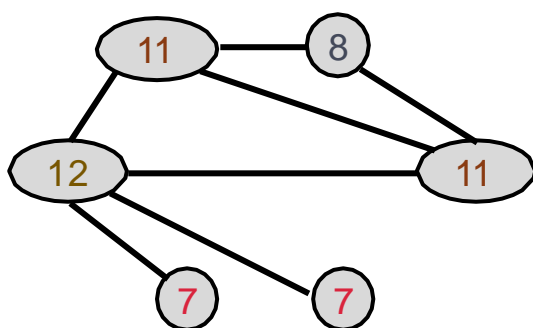
# Color Refinement (4)

## Example of color refinement given two graphs

### ■ Aggregated colors



### ■ Hash aggregated colors

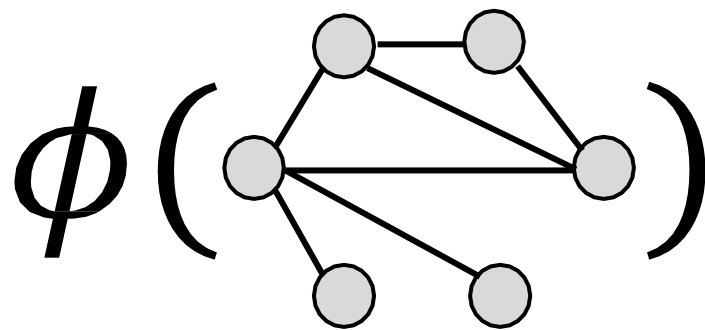


Hash table

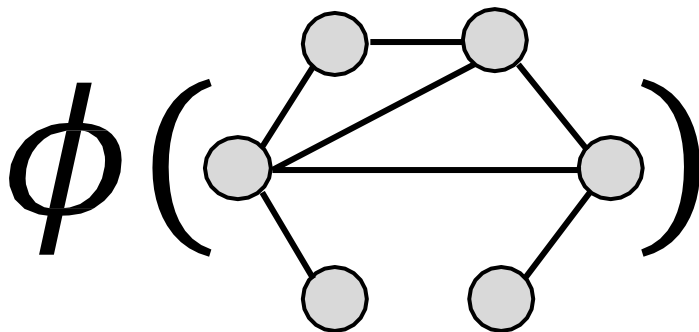
2,4	-->	6
2,5	-->	7
3,44	-->	8
3,45	-->	9
4,245	-->	10
4,345	-->	11
5,2244	-->	12
5,2344	-->	13

# Weisfeiler-Lehman Graph Features

After color refinement, WL kernel counts number of nodes with a given color.



Colors  
1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13  
= [6, 2, 1, 2, 1, 0, 2, 1, 0, 0, 0, 2, 1]  
Counts



1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13  
= [6, 2, 1, 2, 1, 1, 1, 0, 1, 1, 1, 0, 1]

# Weisfeiler-Lehman Kernel

The WL kernel value is computed by the inner product of the color count vectors:

$$\begin{aligned} K(\text{graph}_1, \text{graph}_2) &= \phi(\text{graph}_1)^T \phi(\text{graph}_2) \\ &= 49 \end{aligned}$$

# Weisfeiler-Lehman Kernel

- WL kernel is **computationally efficient**
  - The time complexity for color refinement at each step is linear in  $\#(\text{edges})$ , since it involves aggregating neighboring colors.
- When computing a kernel value, only colors appeared in the two graphs need to be tracked.
  - Thus,  $\#(\text{colors})$  is at most the total number of nodes.
- Counting colors takes linear-time w.r.t.  $\#(\text{nodes})$ .
- In total, time complexity is **linear in  $\#(\text{edges})$** .



# Graph-Level Features: Summary

- **Graphlet Kernel**

- Graph is represented as **Bag-of-graphlets**
- **Computationally expensive**

- **Weisfeiler-Lehman Kernel**

- Apply  $K$ -step color refinement algorithm to enrich node colors
  - Different colors capture different  $K$ -hop neighborhood structures
- Graph is represented as **Bag-of-colors**
- **Computationally efficient**
- Closely related to Graph Neural Networks (as we will see!)

# Discussion and Coding

Questions?



Code Examples



# Today's Summary

- **Traditional ML Pipeline**
  - Hand-crafted feature + ML model
- **Hand-crafted features for graph data**
  - **Node-level:**
    - Node degree, centrality, clustering coefficient, graphlets
  - **Link-level:**
    - Distance-based feature
    - local/global neighborhood overlap
  - **Graph-level:**
    - Graphlet kernel, WL kernel

# Summary

## Hand crafted features:

- Degree and neighborhood only capture local information
- Graphlets, shortest paths, and random walks extend to more global information
- All of these features are permutation invariant or permutation equivariant
- Selected algorithms were mostly computationally efficient, but many prior attempts were not
- Some algorithms have hyperparameters

# What's next

## Session Roadmap:

- **Today:** Traditional Methods
- **Next:** Node Embeddings
  - Generalized graph representation learning
- **Then:** PageRank
  - Treating graph as a matrix & matrix factorization
- **Followed By:** Graph Neural Networks (GNNs)
  - Embedding graph structure & using node features