



By  
Dr. Hussein Hazimeh

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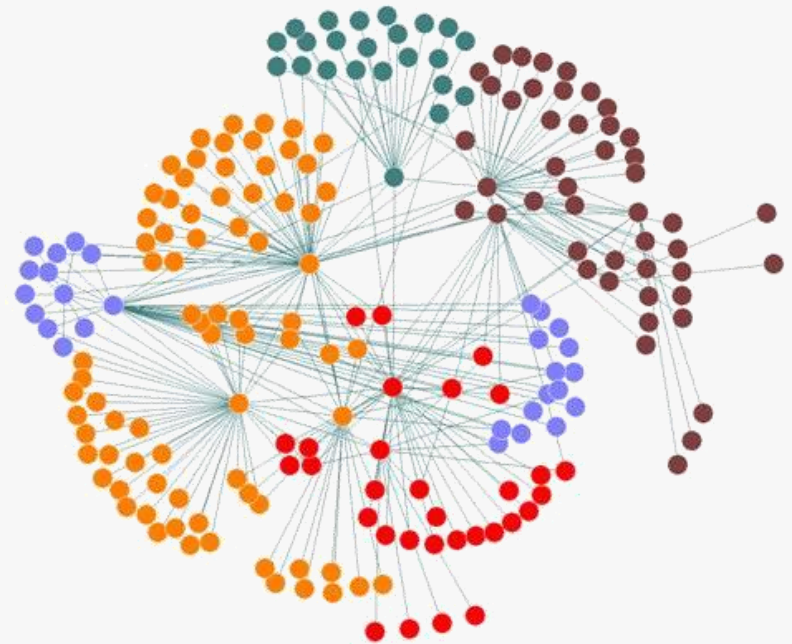
# Lebanese University

## Faculty of Information 1

Data Science Departement

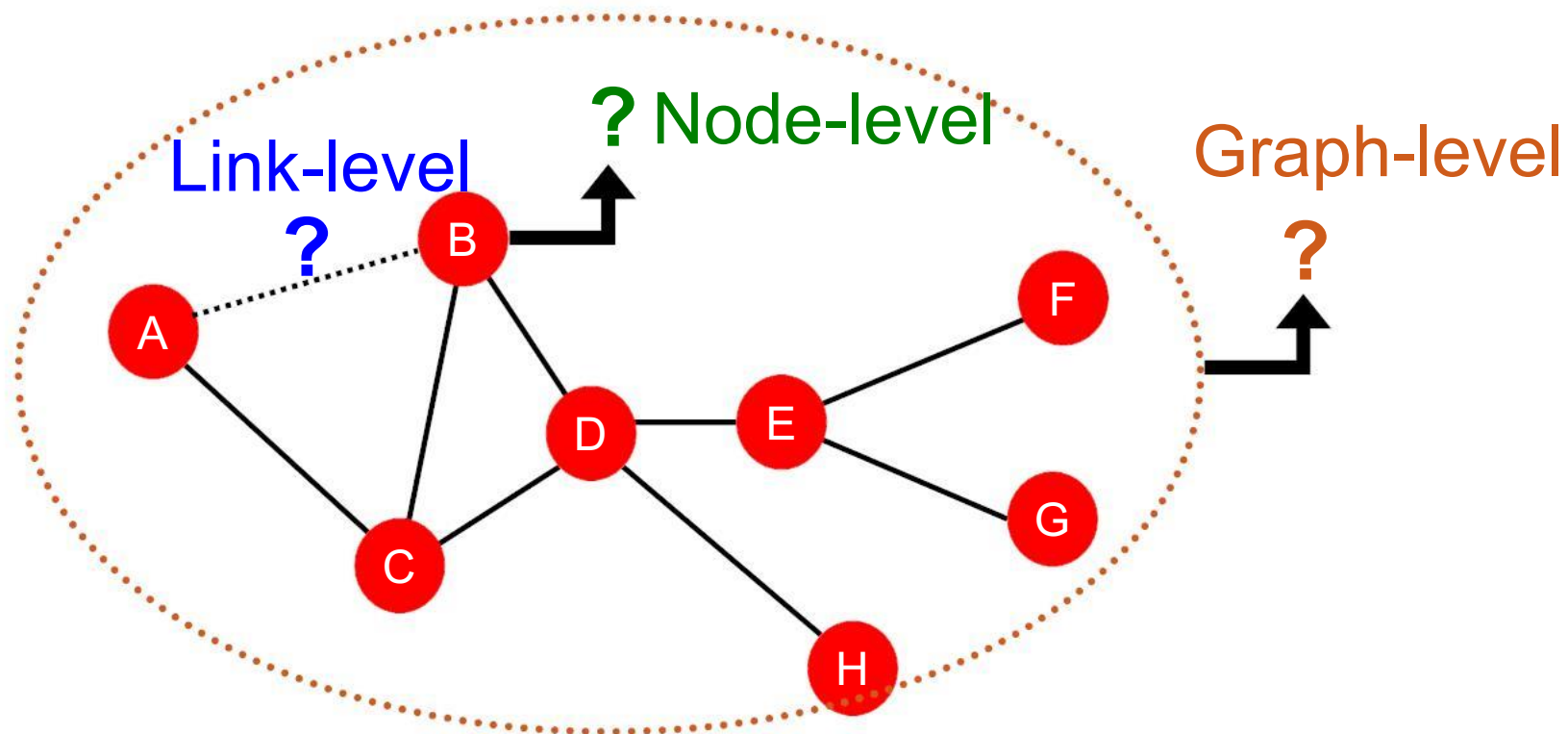
3<sup>rd</sup> year – Social Network Analysis

Spring – 2022 – Chapter 4



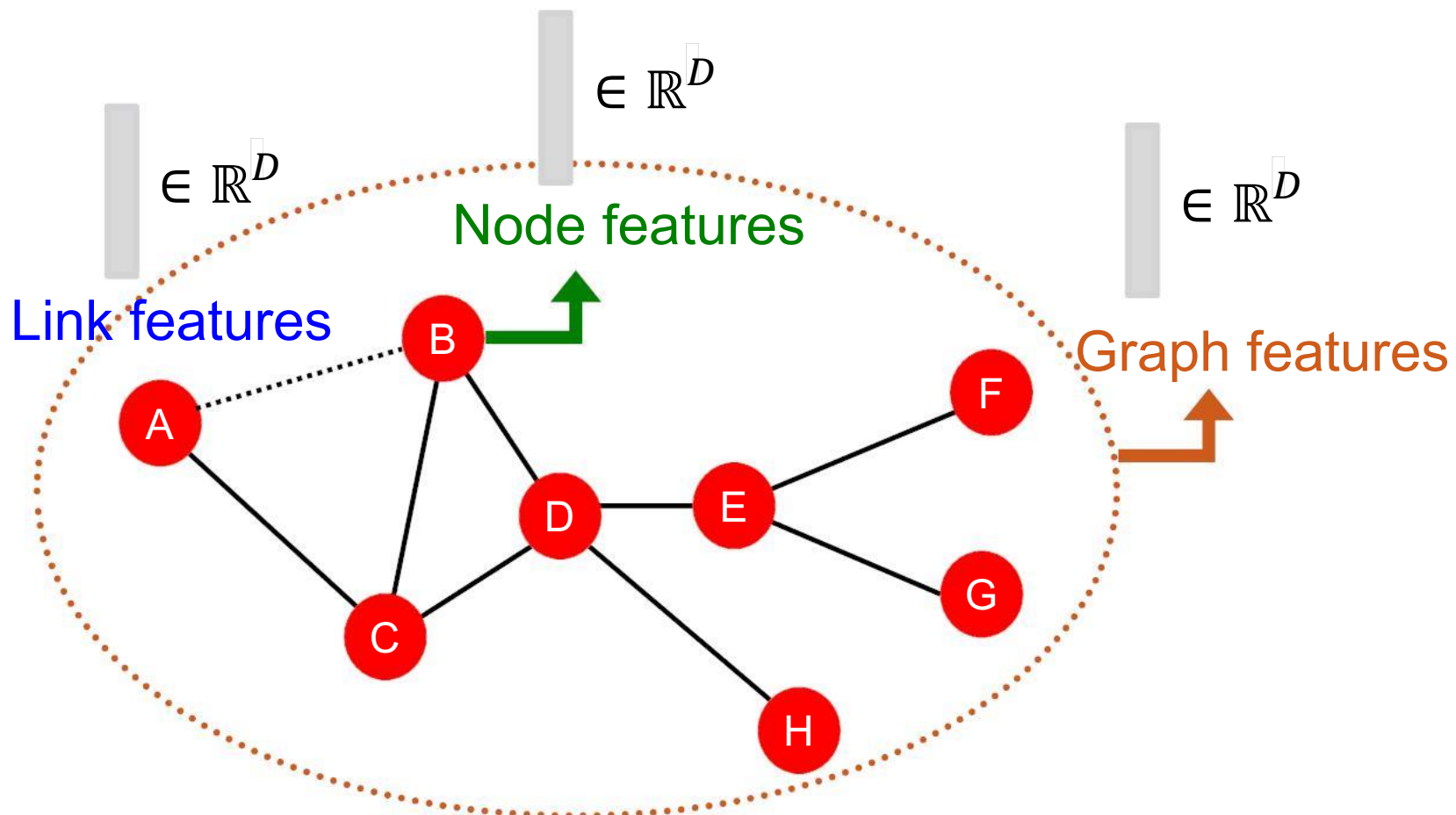
# Machine Learning Tasks: Review

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



# Traditional ML Pipeline

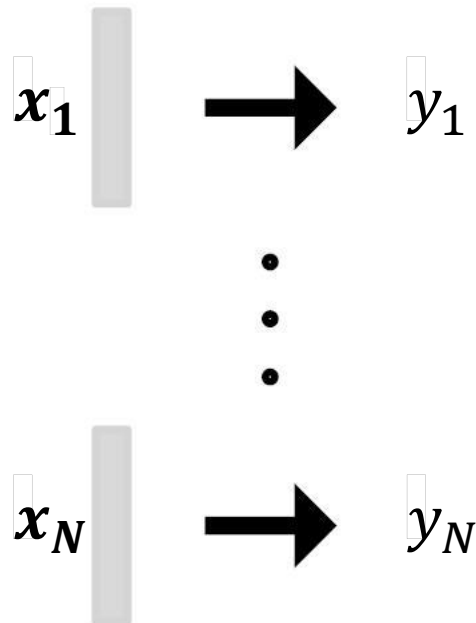
- Design features for nodes/links/graphs
- Obtain features for all training data



# Traditional ML Pipeline

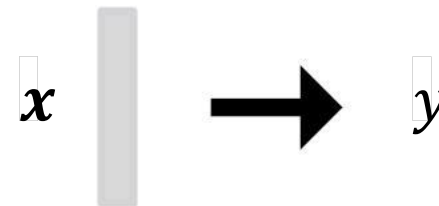
- **Train an ML model:**

- 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 test 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**.

# Machine Learning in Graphs

**Goal:** Make predictions for a set of objects

**Design choices:**

- **Features:**  $d$ -dimensional vectors
- **Objects:** Nodes, edges, sets of nodes, entire graphs
- **Objective function:**
  - What task are we aiming to solve?

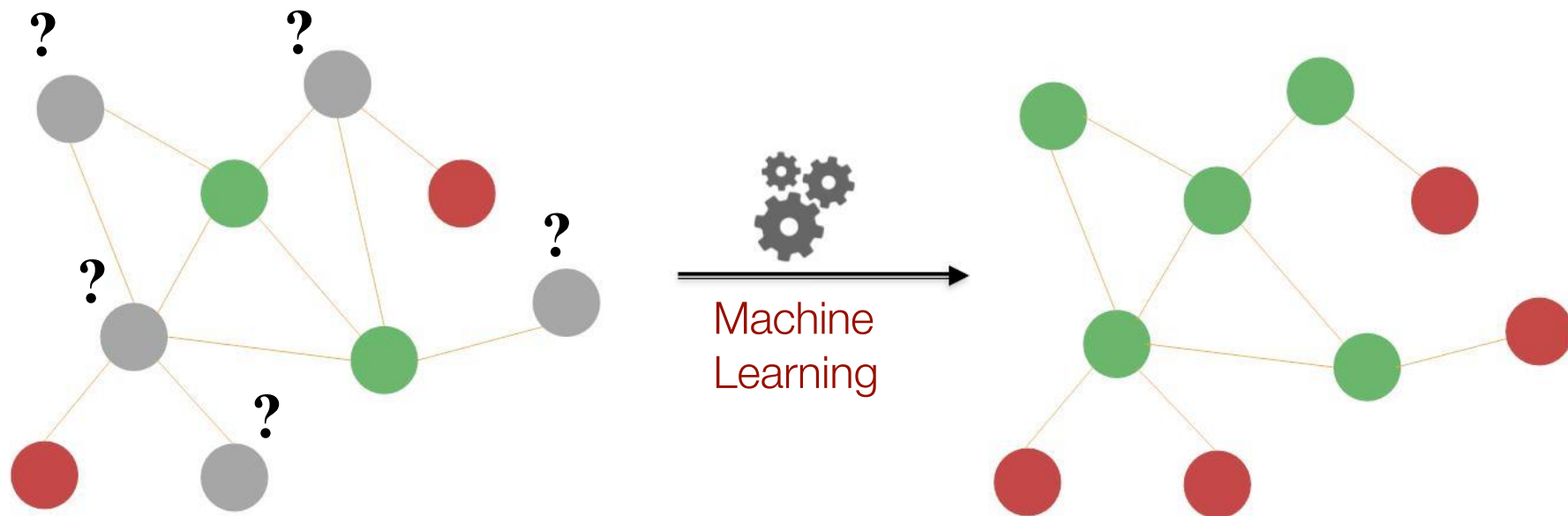
# Machine Learning in Graphs

## Machine learning in graphs:

- Given:  $G = (V, E)$
- Learn a function:  $f : V \rightarrow \mathbb{R}$

How do we learn the function?

# Node-level Tasks



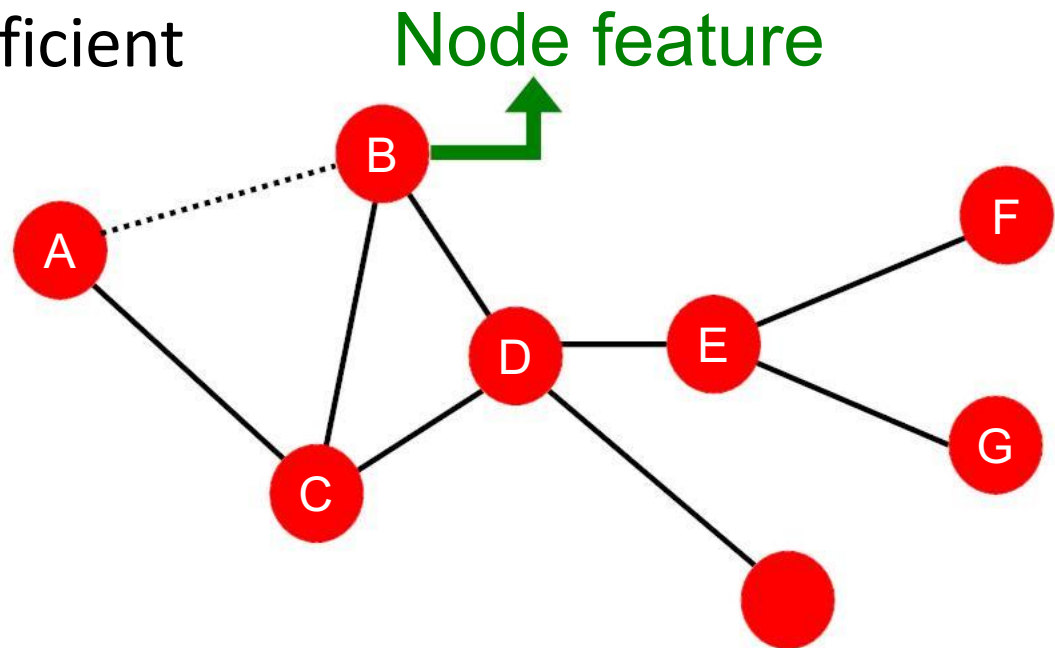
Node classification

**ML needs features.**

# Node-Level Features: Overview

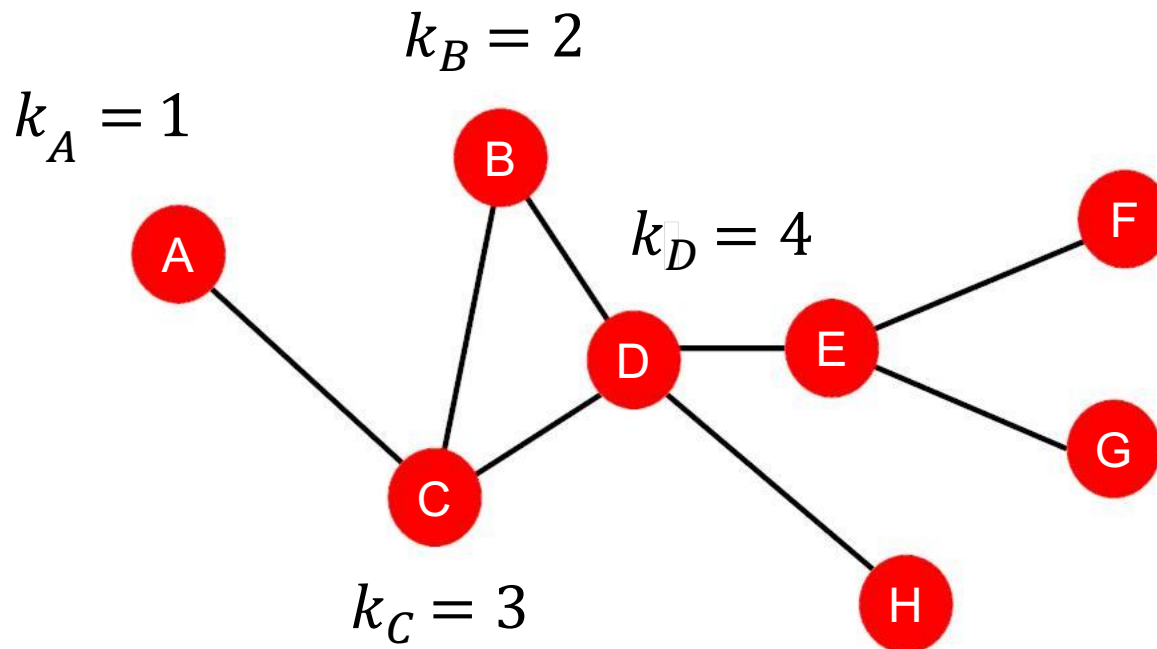
**Goal:** Characterize the structure and position of a node in the network:

- 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 some positive constant

- 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 some positive constant

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

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

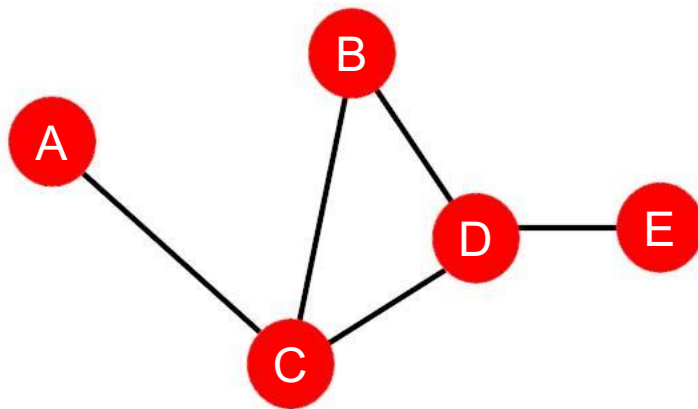
# Node Centrality (2)

## ■ 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:



$$\begin{aligned} c_A &= c_B = c_E = 0 \\ c_C &= 3 \\ &(\text{A-C-B, A-C-D, A-C-D-E}) \\ c_D &= 3 \\ &(\text{A-C-D-E, B-D-E, C-D-E}) \end{aligned}$$

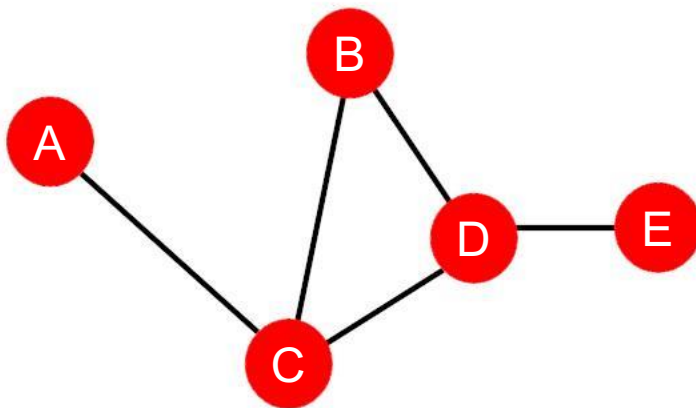
# Node Centrality (3)

- **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)

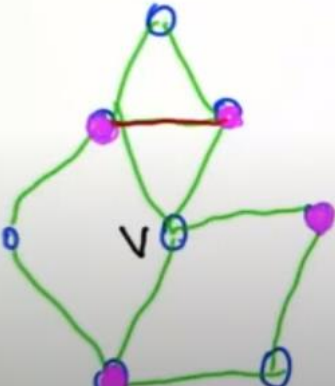
$$c_D = 1/(2 + 1 + 1 + 1) = 1/5$$

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

# Node Features: Clustering Coefficient

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

$CC(v)$ :  $v$ : a node  
 $k_v$ : its degree  
 $N_v$ : number of links between neighbors of  $v$

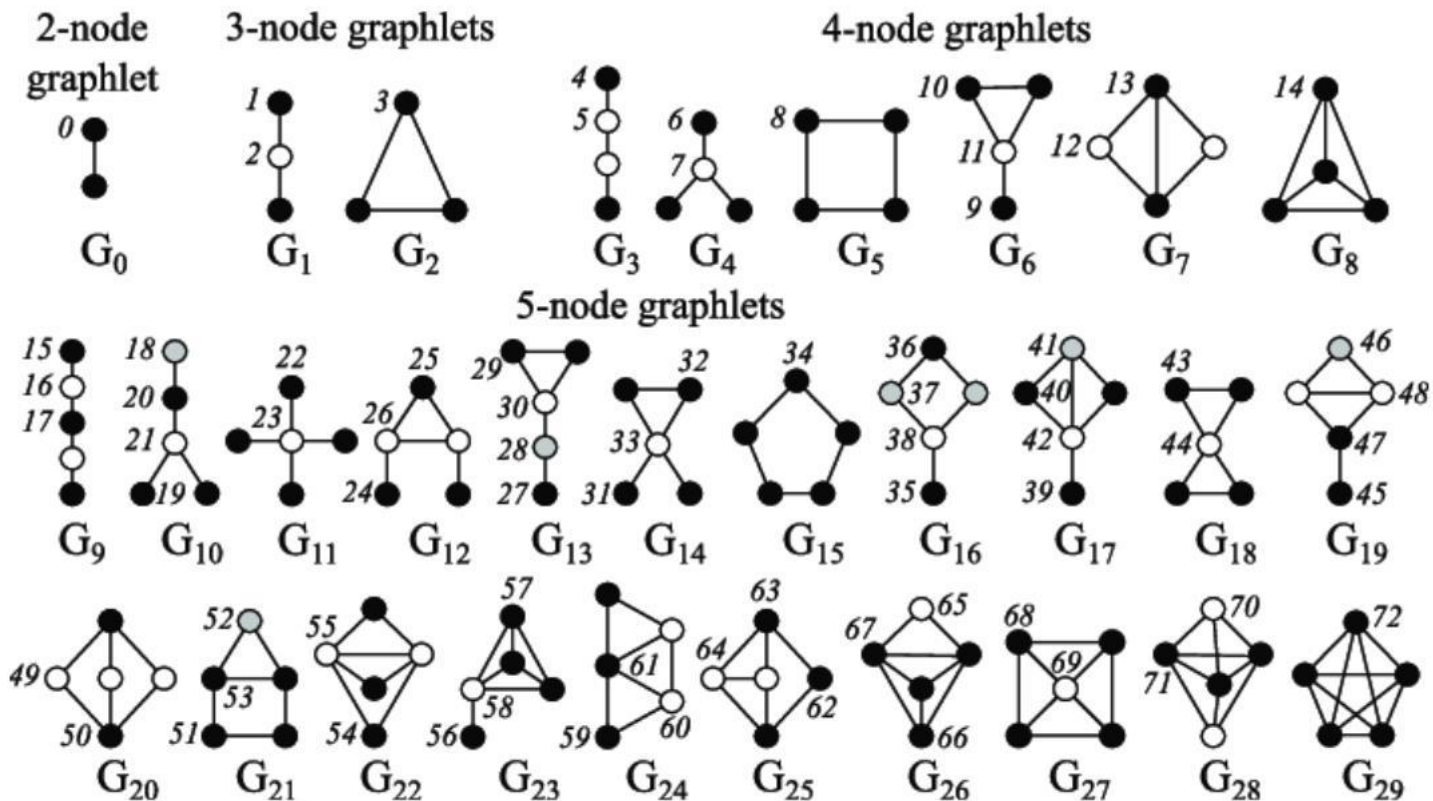


$k_v = 4$   
 $N_v = 1$

$$CC(v) = \frac{2N_v}{k_v(k_v - 1)} = \frac{2 \cdot 1}{4 \cdot 3} = \frac{1}{6}$$

# Node Features: Graphlets

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



# Node Features: Graphlets

## Graphlets: calculation

In a particular problem,  $m = 20$ ,  $n = 180$

Attempt at solution:

1. Find the total possible number of edges (so that every vertex is connected to every other one)  
 $k = n(n - 1)/2 = 20 \cdot 19/2 = 190$
2. Find the number of all possible graphs:  $s = C(n, k) = C(190, 180) = 13278694407181203$

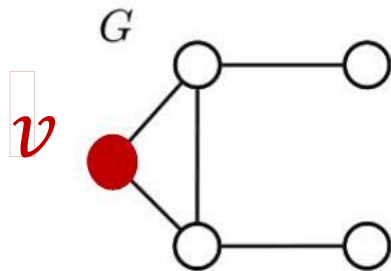
[https://www.calculatorsoup.com/calculators/d  
iscretemathematics/combinations.php](https://www.calculatorsoup.com/calculators/discretemathematics/combinations.php)

# Node Features: Graphlets

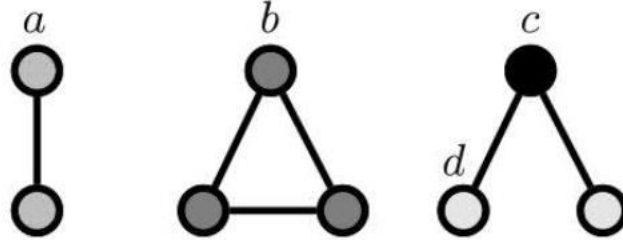
- **Graphlet Degree Vector (GDV)**: Graphlet-base features for nodes
- **GDV** counts **#(graphlets)** that a node touches

# Node Features: Graphlets

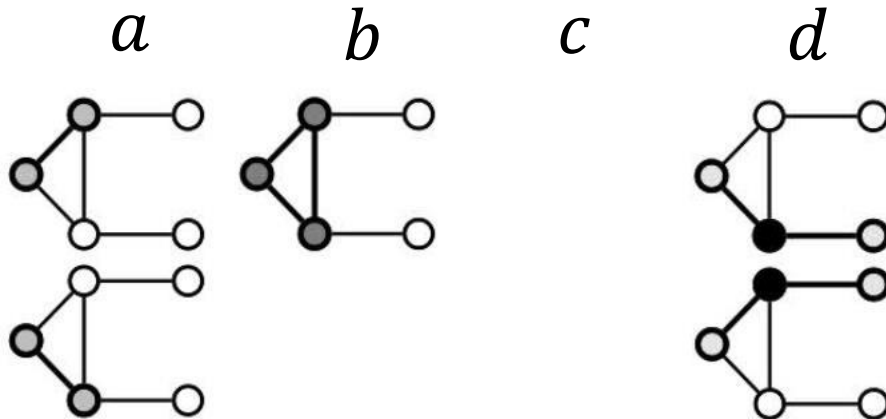
- **Graphlet Degree Vector (GDV):** A count vector of graphlets rooted at a given node.
- **Example:**



List of graphlets



Graphlet instances:



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

# Node-Level Feature: Summary

- We have introduced different ways to obtain node features.
- They can be categorized as:
  - Importance-based features:
    - Node degree
    - Different node centrality measures
  - Structure-based features:
    - Node degree
    - Clustering coefficient
    - Graphlet count vector

# Node-Level Feature: Summary

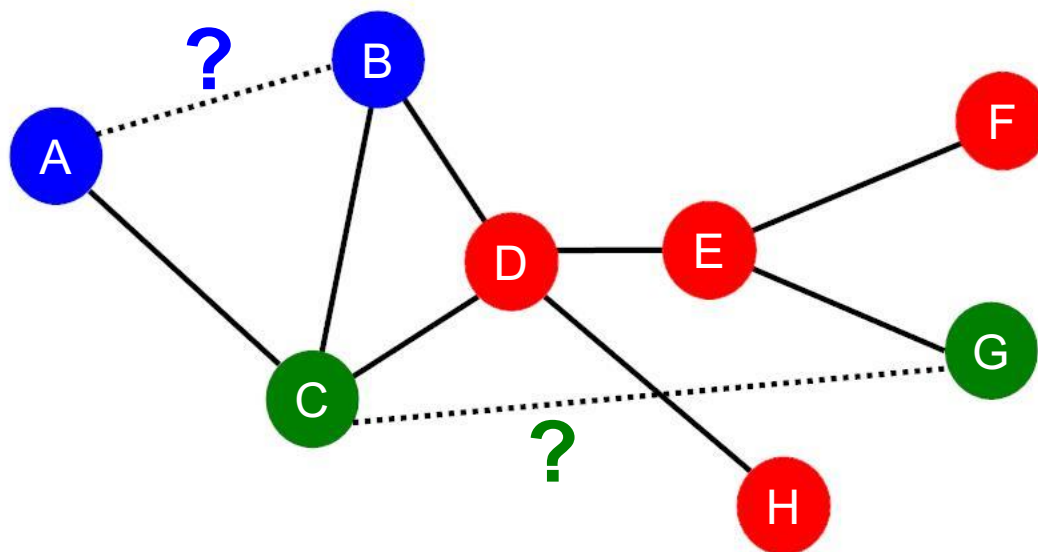
- **Importance-based features:** capture the importance of a node in a graph
  - Node degree:
    - Simply counts the number of neighboring nodes
  - Node centrality:
    - Models **importance of neighboring nodes** in a graph
    - Different modeling choices: eigenvector centrality, betweenness centrality, 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.

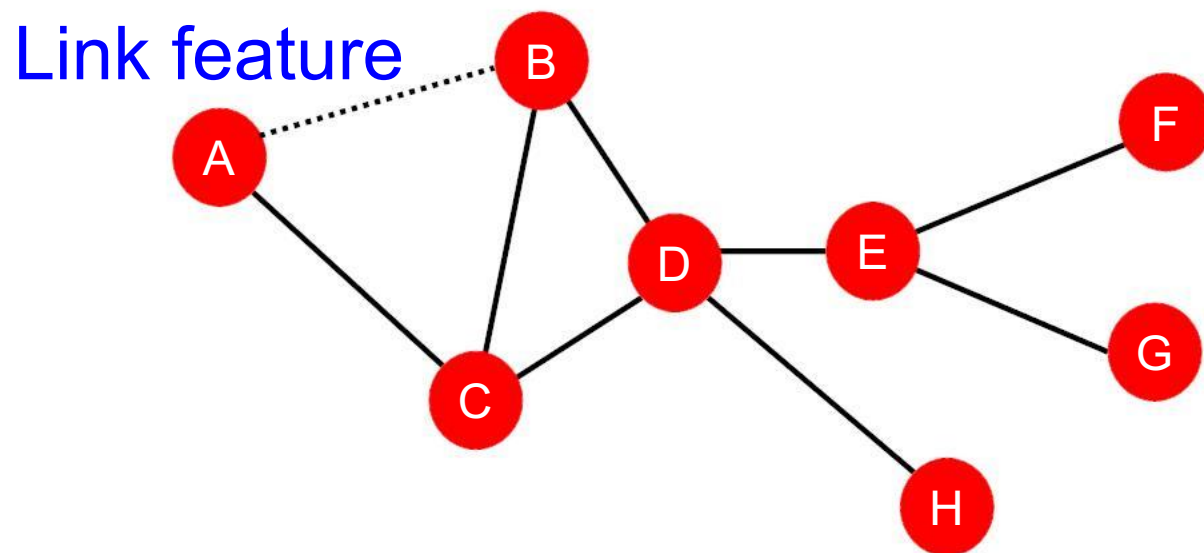
# Link-Level Prediction Task: Recap

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



# Link-Level Features: Overview

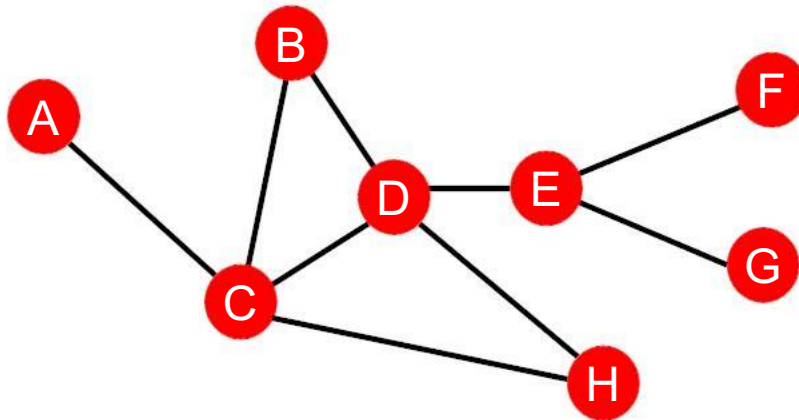
- Distance-based feature
- Local neighborhood overlap
- Global neighborhood overlap



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

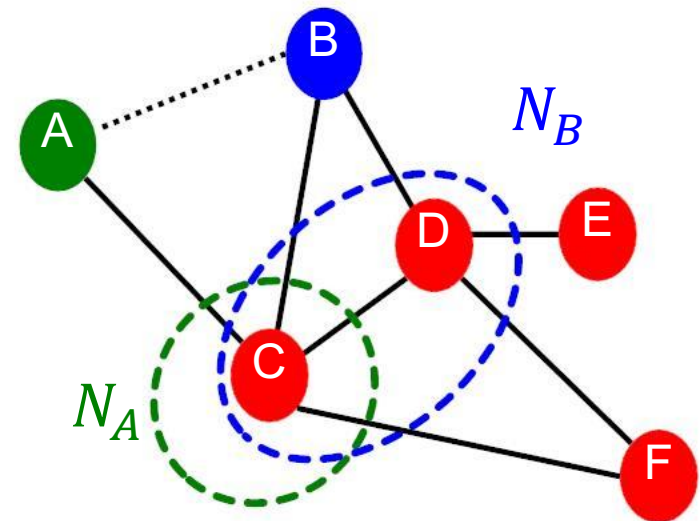
- **Jaccard's coefficient:**  $\frac{|N(v_1) \cap N(v_2)|}{|N(v_1) \cup N(v_2)|}$

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

- **Adamic-Adar index:**

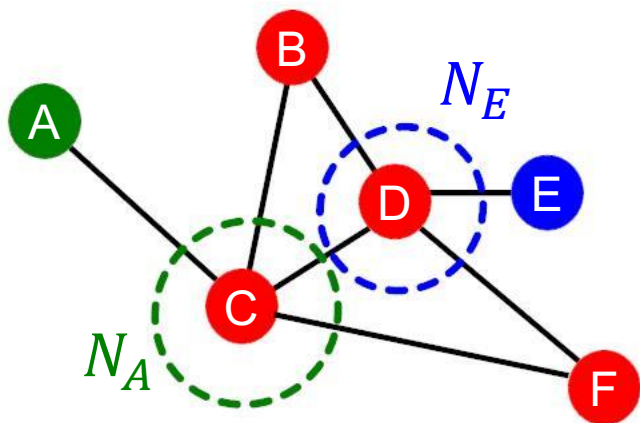
$$\sum_{u \in N(v_1) \cap N(v_2)} \frac{1}{\log(k_u)}$$

- 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 paths of all lengths between a given pair of nodes.
- **Q:** How to compute #paths between two nodes?

# Intuition: Powers of Adj Matrices

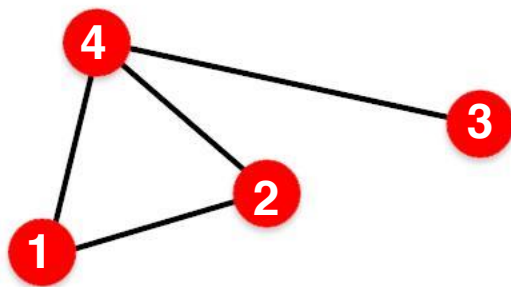
- Computing #paths between two nodes

- Recall:  $A_{uv} = 1$  if  $u \in N(v)$

- Let  $P_{uv}^{(K)}$  = #paths of length  $K$  between  $u$  and  $v$

- We will show  $P^{(K)} = A^k$

- $P_{uv}^{(1)}$  = #paths of length 1 (direct neighborhood) between  $u$  and  $v$  =  $A_{uv}$



$$P_{12}^{(1)} = A_{12}$$

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

# Global Neighborhood Overlap

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

# 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 #paths of all lengths between two nodes.

# 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  $\mathbf{K} = (K(G, G'))_{G, G'}$
  - There exists a feature representation  $\phi(\cdot)$  such that

$$K(G, G') = \phi(G)^T \phi(G')$$

# Graph-Level Features: Overview

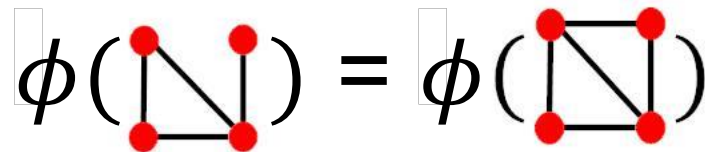
- **Graph Kernels:** Measure similarity between two graphs:
  - Graphlet Kernel [1]
  - Weisfeiler-Lehman Kernel [2]
  - Other kernels are also proposed in the literature (beyond the scope of this lecture)
    - Random-walk kernel
    - Shortest-path graph kernel
    - And many more...

[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...

$$\phi(\text{Graph 1}) = \phi(\text{Graph 2})$$


# Graph Kernel: Key Idea

What if we use Bag of node degrees?

Deg1: ● Deg2: ● Deg3: ●

$$\phi(\text{Graph 1}) = \text{count}(\text{Graph 2}) = [1, 2, 1]$$

$$\phi(\text{Graph 3}) = \text{count}(\text{Graph 4}) = [0, 2, 2]$$



Obtains different features for different graphs!

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

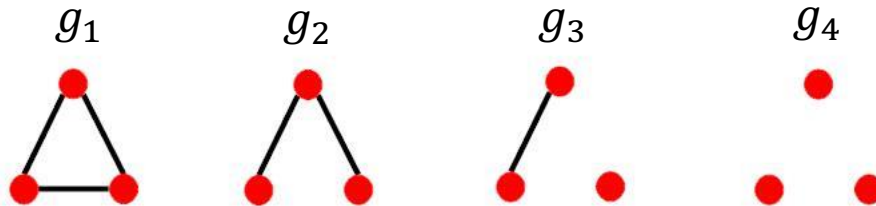
# Graphlet Features

- **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.

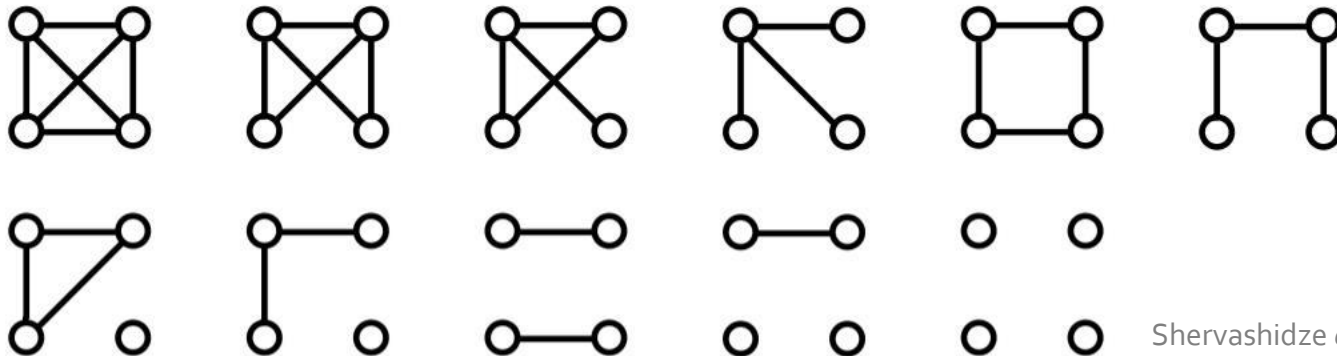
# Graphlet Features

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

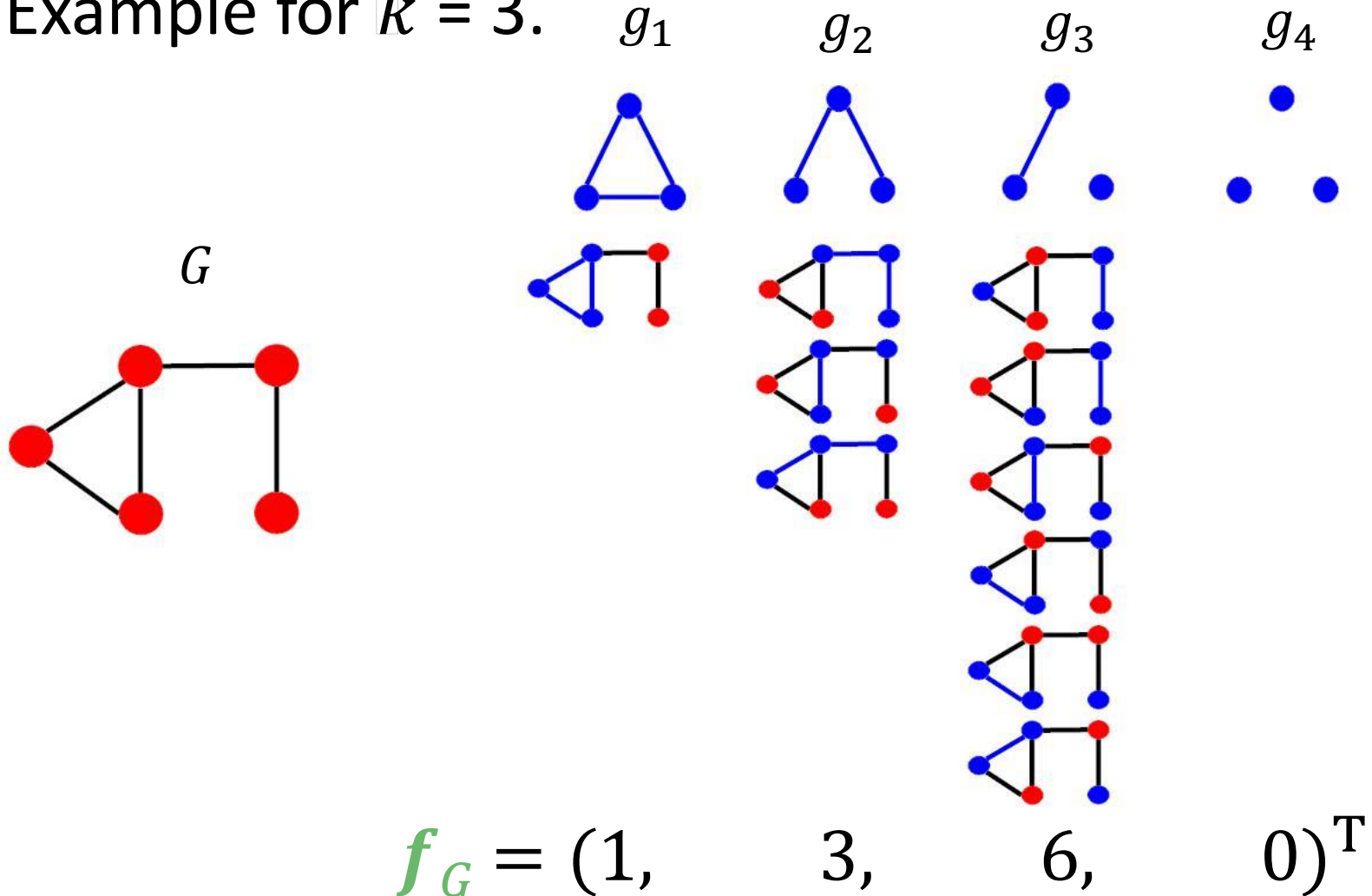
# Graphlet Features

- 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  $n^k$ .
- 

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

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

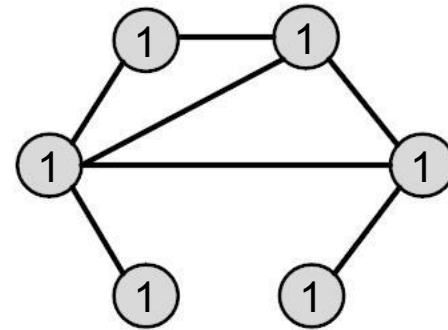
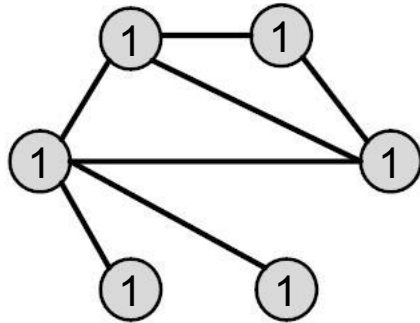
where **HASH** maps different inputs to different colors.

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

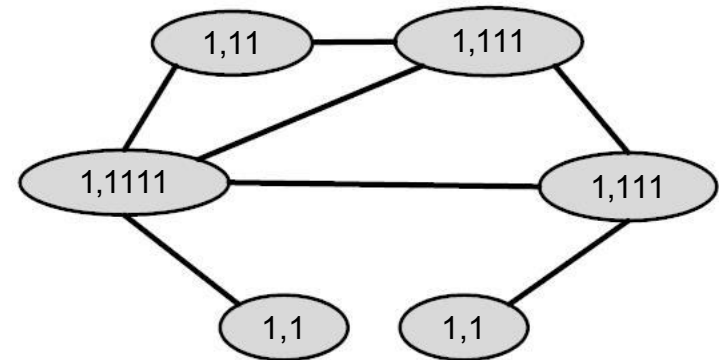
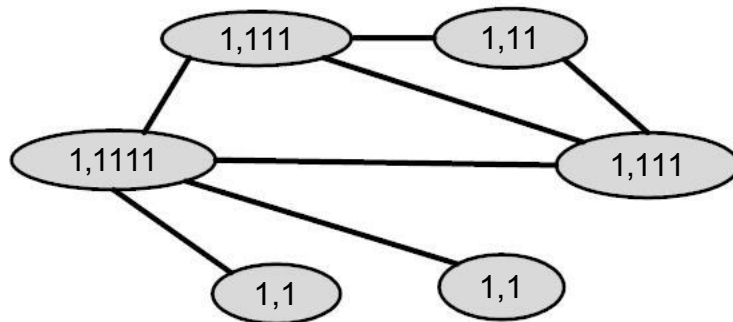
# Color Refinement (1)

## Example of color refinement given two graphs

- Assign initial colors



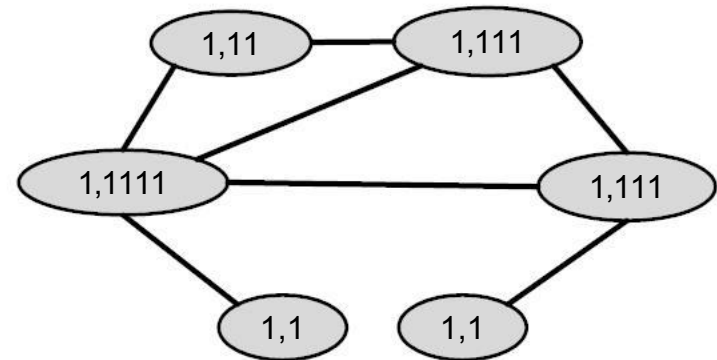
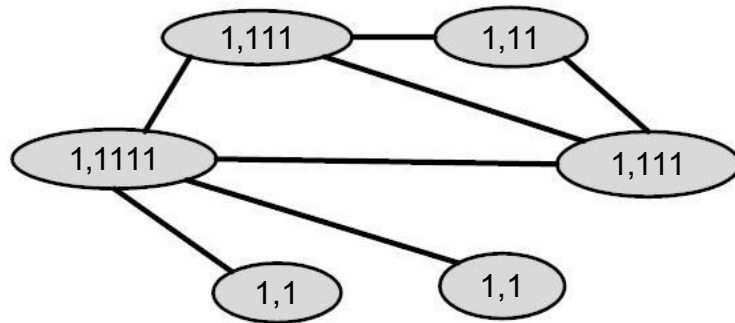
- Aggregate neighboring colors



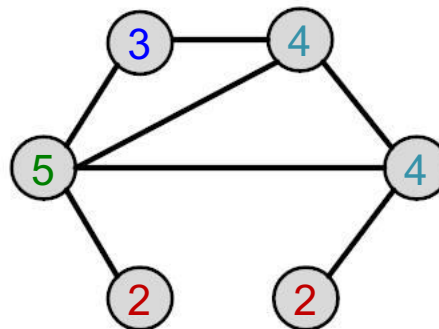
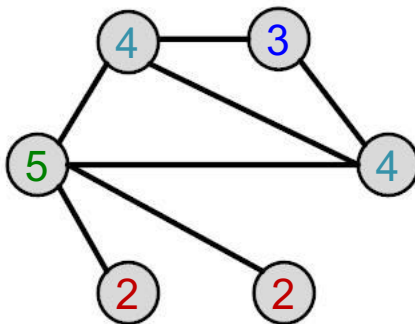
# Color Refinement (2)

## Example of color refinement given two graphs

- Aggregated colors



- Hash aggregated colors



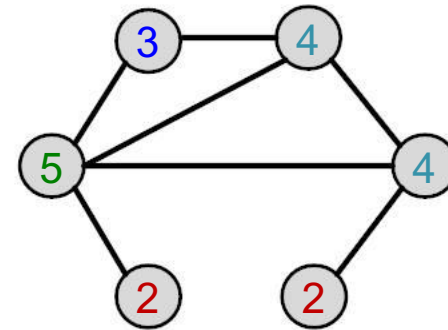
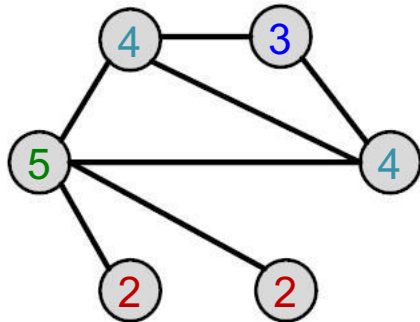
Hash table

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

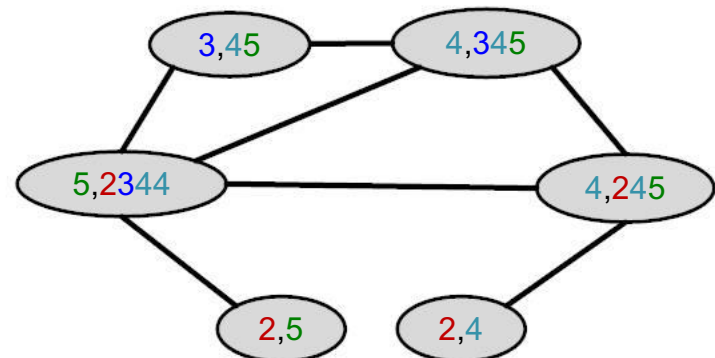
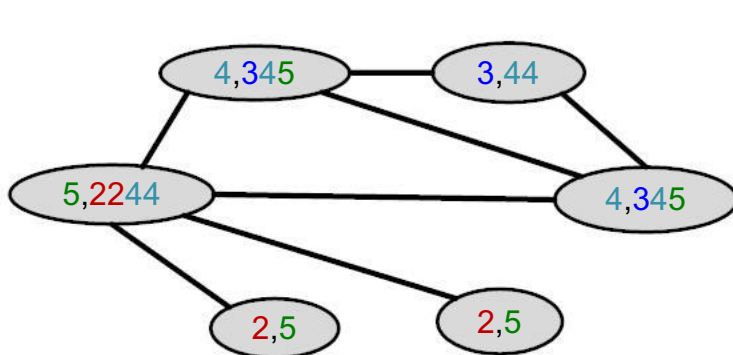
# Color Refinement (3)

## Example of color refinement given two graphs

- Aggregated colors



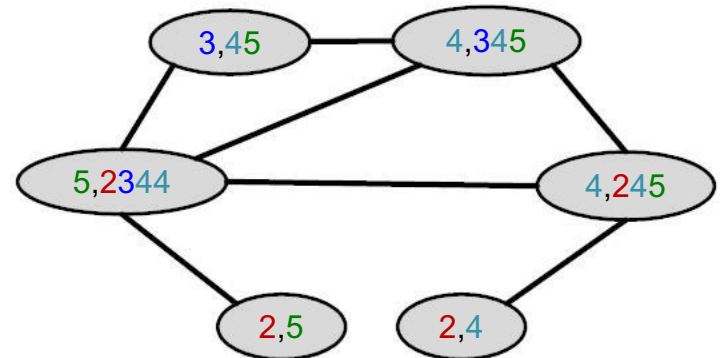
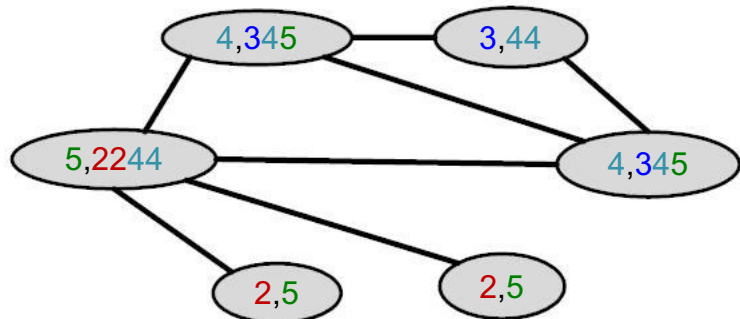
- Hash aggregated colors



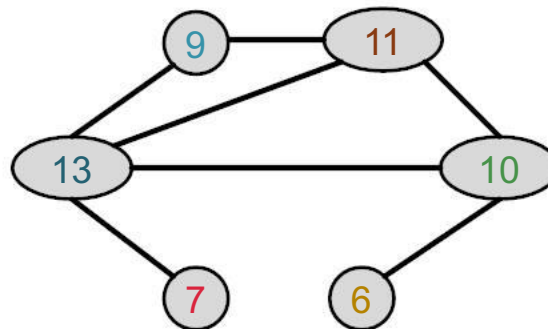
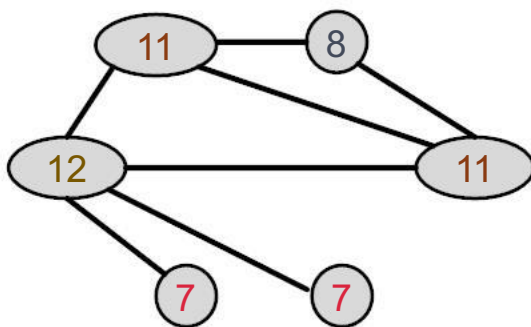
# Color Refinement (4)

## Example of color refinement given two graphs

- Aggregated colors



- Hash aggregated colors

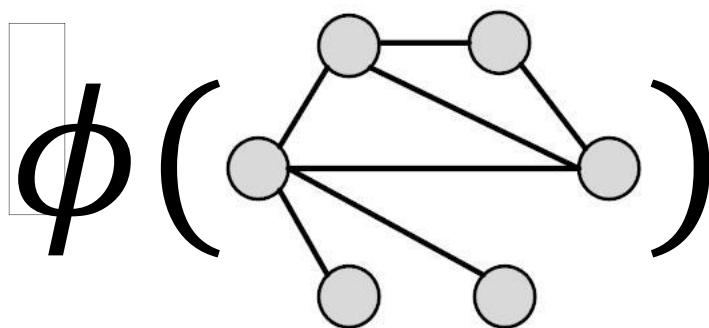


Hash table

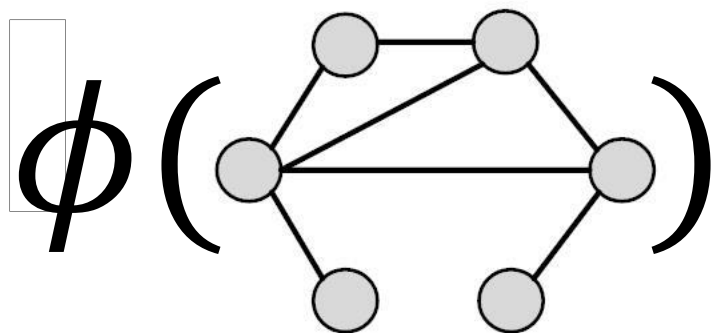
2,4	-->	6
2,5	-->	7
3,44	-->	8
3,45	-->	9
4,245	-->	10
4,345	-->	11
5,2244	-->	12
5,2344	-->	13

# Weisfeiler-Lehman Graph Features

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



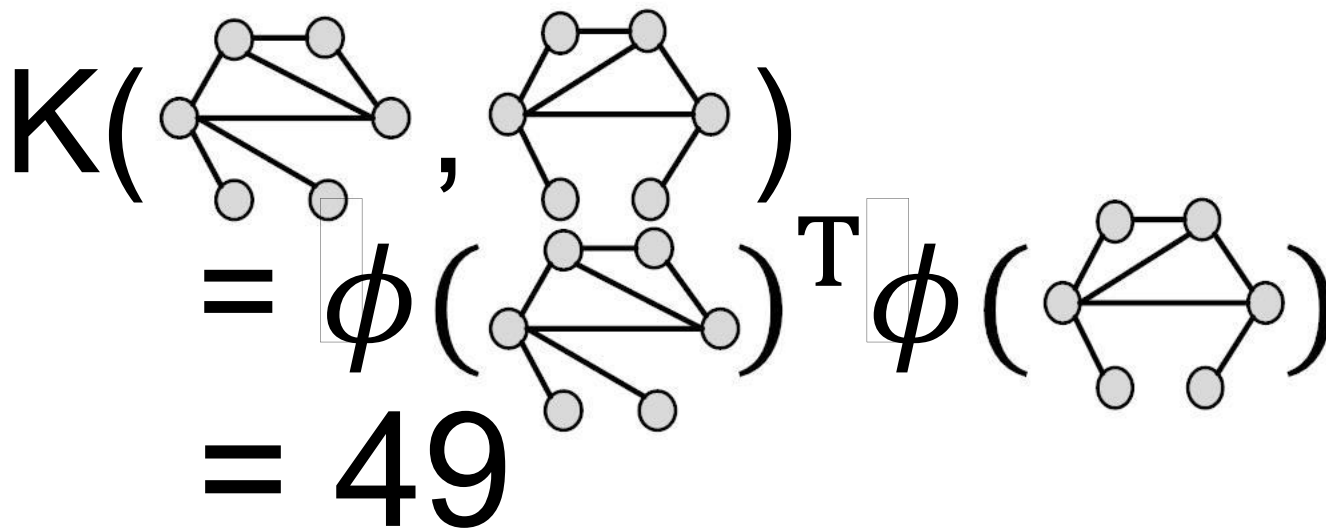
Colors  
 $1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13$   
 $= [6, 2, 1, 2, 1, 0, 2, 1, 0, 0, 0, 2, 1]$   
 Counts



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

# Weisfeiler-Lehman Kernel

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

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


$$\mathbf{a} \cdot \mathbf{b} = \sum_{i=1}^n a_i b_i = a_1 b_1 + a_2 b_2 + \cdots + a_n b_n,$$

# 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!)

# 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