

Summary of the lecture
„MA INF 4316 - Graph Representation
Learning“
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Chapter 0

Motivations - Learning Tasks on Graphs

In this chapter we discuss different learning tasks on graph structured data.

A graph is a type of data structure which describes relationships (edges) between objects (vertices). For more formal definitions see definitions [0.2](#) and [0.1](#). Family trees, social network connections and molecules are examples for graphs.

Graphs may incorporate much information in form of attributes. Vertices for example may correspond to persons and may be attributed by name, age or gender. In this example edges may additionally contain information about relationship properties. Another example are molecular graphs, which have atom types as vertex labels and their edges indicate the type of covalent bond.

The three main learning paradigms of machine learning are:

- **Supervised Learning:** Find a data-consistent function that maps input to output values. In other words, given a set of training data $X = \{(x, f(x))\}$, find a hypothesis function $h \in \mathcal{H}$ such that $h \approx f$.
(E.g. Linear Regression, Logistic Regression, Support Vector Machines, Nearest Neighbor, Naive Bayes Classifier, Decision Trees & Random Forests, (Deep) Neural Networks, ...)
- **Unsupervised Learning:** Find structures by identifying data correlations without explicit knowledge of memberships.
(E.g. clustering, auto-encoders, (frequent) pattern mining, ...)

- **Reinforcement Learning:** Learn a function which maximizes the cumulative output rewards by choosing appropriate actions in an unknown environment.
(Search space exploration to reason about the environment.)

Common supervised learning tasks on graphs are:

- Assign a color to unknown vertices
- Predict likely new edges
- Predict unknown graph class

Common unsupervised learning tasks on graphs are:

- Vertex clustering, Community detection
- Graph clustering
- Link prediction without supervision

The central problem of learning on graphs is how traditional machine learning approaches can be applied to graphs.

Linear Regression, Logistic Regression, Naive Bayes Classifiers, Decision trees and Random Forests expect *tabular data*, i.e. a set of example with a known, fixed set of features.

One may consider to use features of vertices to learn on them. But several non-trivial questions arise, for example:

- How to deal with connections between vertices?
- How to deal with vertices without features?
- What if the objects we want to learn from are graphs themselves? (Possibly with different numbers of vertices or edges.)

Note that the usage of a graph's adjacency matrix as vector representation is not desirable, since isomorphic graphs can be represented in different adjacency matrices.

Another approach to make traditional machine learning approaches applicable to graphs is to use **graph representations**. These vectorize data with respect to task specific properties. Generally, we seek approaches that incorporate aspects of the graph's structure.

It is highly non-trivial to determine which information crucial for a specific learning task shall be represented in which way in the graph representation.

Example - Vertex classification: Consider the graph depicted in Figure 1 and the task to reason about the color of unknown vertices by looking at training data.

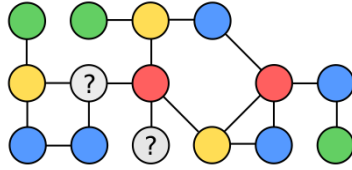


Figure 1 – Example of a graph with colors as vertex features.

A closer look reveals that, in this example, the color of a vertex corresponds to its degree. Thus $\deg(v)$ may be a simple representation of each vertex v .

Example - Graph classification: Consider the graph depicted in Figure 2 and the task to predict the class of an unclassified graph (e.g. the gray one in the figure).

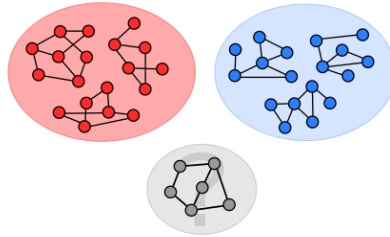


Figure 2 – Example of graph classification (clustering).

A common approach is to use sets of subgraphs to describe (similarity between) graphs. In this example it appears that graphs of the red class contain cycles of length four whereas graphs of the blue class contain triangles. Thus, a graph G may be represented by a vector $\phi(G)$ containing cycle counts of length three and four.

Example - Link prediction: Consider the graph depicted in Figure 3 and the task to predict the likelihood of a not yet existing edge (e.g. the gray one in the figure).

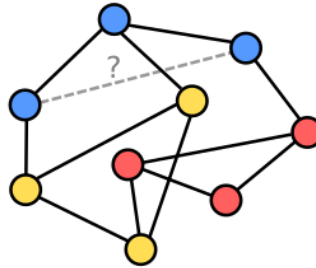


Figure 3 – Example of graph classification (clustering).

A common approach is to consider the shortest path distance and similarity in terms of neighborhoods or vertex attributes. In this example the vertices of same color are more likely to be connected by an edge. Thus one may represent edges using the adjacent vertex colors.

As the given examples indicate, it can be tedious to analyze graph data and choose a suitable graph representation. As it turns out, Machine Learning can be used for learning the graph representations themselves. In the following chapter we will cover two aspects of graph representation learning:

- **Learning with representations** of graphs and
- **learning representations** of graphs.

Chapter 1

Vertex classifications and local features

Definition 0.1: Directed graph

A **directed graph (digraph)** $G = (V, E)$ consists of a set of vertices $V(G)$ and a set of edges $E(G) \subseteq V \times V$.

Definition 0.2: Undirected Graph

A **undirected graph** $G = (V, E)$ consists of a set of vertices $V(G)$ and a set of edges $E(G) \subseteq 2^V$ such that

$$\forall e \in E(G) : |e| = 2$$

As variable naming conventions, we say that graphs have $n = |V(G)|$ vertices and $m = |E(G)|$ edges.

Definition 0.3: Simple graphs

A simple graph is a graph, where edges cannot appear multiple times.

(That is, in the respective definitions of directed and undirected graphs, the set of edges is not a multiset.)

Definition 0.4: Graph attributes and labels

Given an undirected or directed graph G , one can define additional data associated with the graph, vertices or edges. Such data is called **attributes** (if the value domain is continuous) or **labels** (if the value domain is discrete/categorical).

This association can be formalized using **feature spaces** \mathcal{X}^G , \mathcal{X}^V and \mathcal{X}^E :

$$f_G(G) \rightarrow \mathcal{X}^G, \quad f_V(V(G)) \rightarrow \mathcal{X}^V, \quad f_E(E(G)) \rightarrow \mathcal{X}^E$$

(A feature space is some product space $\mathcal{X} = (X_1, X_2, \dots, X_d)$ where the X_i are some appropriately chosen sets.)

Example - Graph labels Typical examples of graph vertex labels are atom names (chemical graphs).

Definition 0.5: Graph isomorphism

Let G and H be two graphs. G and H are **isomorphic**, if and only if there exists a bijective function between the vertices $\varphi : V(G) \rightarrow V(H)$ such that

- edges are preserved:
 $\{v, w\} \in E(G) \iff \{\varphi(v), \varphi(w)\} \in E(H)$
- vertex attributes are preserved:
 $\forall v \in V(G) : f_V(v) = f_V(\varphi(v))$
- edge attributes are preserved:
 $\forall \{v, w\} \in E(G) : f_E(\{v, w\}) = f_E(\{\varphi(v), \varphi(w)\})$

1.1 Property prediction for vertices

Learning functions (properties) on vertices is done under the assumption that there is a multiset of objects $X \subseteq \mathcal{X}$ and there exists an (partially) unknown function $y : X \rightarrow \mathcal{Y}$ and some pairs of objects are associated. This setting is formalized in definition 1.1.

Definition 1.1: Supervised vertex property prediction on fixed graphs

Input: a graph G with labeling functions f_V, f_E ,
 a hypothesis class $\mathcal{H} \subseteq \{h \mid h : V(G) \rightarrow \mathcal{Y}\}$,
 properties $y(v)$ for a set of vertices $v \in V' \subseteq V(G)$ and
 a loss function $L_{V,y} : \mathcal{H} \rightarrow \mathbb{R}$.
Output: $\operatorname{argmin}_{h \in \mathcal{H}} L_{V,y}(h)$.

Note that one can extend hypothesis classes on graph vertices to their vertex representation. More explicitly, let \mathcal{X} be a feature space and $r : V(G) \rightarrow \mathcal{X}$ some vertex representation on the graph G . Let $\mathcal{H} \subseteq \{h \mid h : \mathcal{X} \rightarrow \mathcal{Y}\}$ be a hypothesis class. Then the *extended hypothesis class*

$$\mathcal{H}' := \{h \circ r \mid h \in \mathcal{H}\} \quad (\text{Eq. 1})$$

is a hypothesis class on $V(G)$, too.

On top of that one can generalize the vertex representation r to a set of several graph representation $\mathcal{R} \subseteq \{r \mid r : V(G) \rightarrow \mathcal{X}\}$ and yield the further extended hypothesis class $\mathcal{H}' := \{h \circ r \mid r \in \mathcal{R}, h \in \mathcal{H}\}$ on $V(G)$.

1.1.1 Loss Functions - MERGE & MOVE WITH THE STATISTIC SCRIPT

To measure the quality of hypothesis, with respect to vertex property predictions, one can use a variety of loss functions. Most of these can be generalized to other applications of hypothesis evaluation.

Definition 1.2: Classification Loss

The **classification loss** of a hypothesis on vertices to predict their properties is defined as the probability of false predictions:

$$L_{V,y}(h) := \mathbb{P}[y(v) \neq h(v)] = 1 - \frac{1}{|V(G)|} \sum_{v \in V(G)} \delta(y(v), h(v)) \quad (\text{Eq. 2})$$

where

$$\delta(a, b) = \begin{cases} 1 & \text{if } a = b \\ 0 & \text{if } a \neq b \end{cases}$$

Definition 1.3: Regression

The **mean squared error** can be used as a loss function of a hypothesis on vertex property prediction. Using it to improve the quality of the found hypothesis is called **regression**:

$$L_{V,y}(h) := \mathbb{E}[(y(x) - h(x))^2] = \frac{1}{|V(G)|} \sum_{v \in V(G)} (y(v), h(v))^2 \quad (\text{Eq. 3})$$

When evaluating a (machine learning) model during training, we test a hypothesis on empirical data and optimize for the best solution. Both the optimization and the empirical data induce a bias on the estimate of the quality of the hypothesis. This bias can be reduced using **cross validation** (TODO - see Figure ??).

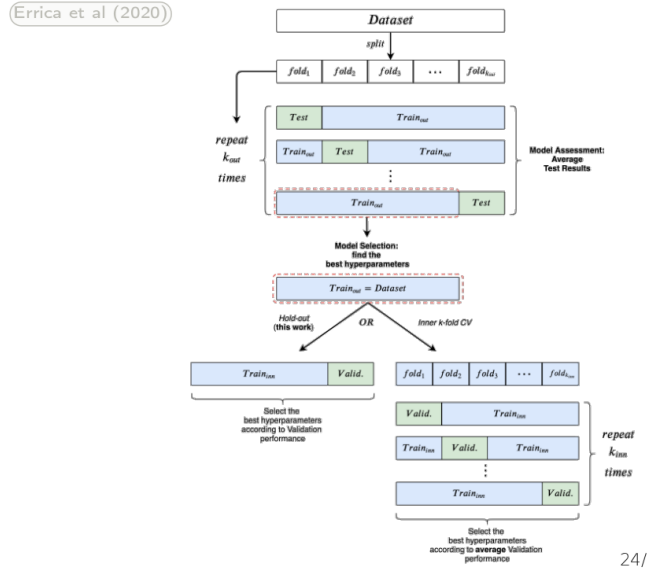


Figure 1.1 – TODO: replace image

Cross validation can be used to compare different hypothesis. If there is a statistically significant difference between their performances, one could be better than the other.

1.1.2 Baselines for graph learning

Interestingly, some baseline methods, which do not include specific graph structures may perform well, even better than GNNs on some graph datasets. In other words, improvements that do not clearly outperform structure-agnostic competitors should be viewed with moderation.

Note that whenever information about individual vertices is available, one should consider using it extensively. In many cases, it is more valuable for the task at hand, than the actual graph structure that combines these.

To conclude, to evaluate a graph representation one should measure its performance against a model which ignores the graph structure. Thus when dealing with an attributed graph G it can be beneficial to start with its vertex attributes $f_V : V(G) \rightarrow \mathcal{X}$ and first consider a hypothesis class over \mathcal{X} , only. Only after that, one may think about including graph representations into the hypothesis class.

1.2 Local Feature Counts

In this subsection we will define various simple vertex representations $f : V(G) \rightarrow \mathbb{R}$ for fixed graphs. Let \mathcal{R}' be the set of all one-dimensional vertex representations. These representations can be grouped in the following way:

$$\mathcal{R} := \{\times_R : V(G) \rightarrow \mathbb{R}^{|R|} \mid R \subseteq \mathcal{R}'\} \quad (\text{Eq. 4})$$

where $\times_R(v) = (r_1(v), r_2(v), \dots, r_{|R|}(v))$ for a vertex v and representations $r_i \in R$.

Definition 2.1: Vertex neighborhood

Let G be a undirected graph and $v \in V(G)$. The **neighborhood** of v is the set

$$N(v) := \{w \mid \{v, w\} \in E(G)\}$$

If G is directed, we define respectively the **outgoing neighborhood** as

$$N_{\text{out}}(v) := \{w \mid (v, w) \in E(G)\}$$

and the **incoming neighborhood** as

$$N_{\text{in}}(v) := \{w \mid (w, v) \in E(G)\}$$

THEOREM 2.1 - Full Neighborhood Representation:

By fixing an order of the vertices $V = \{v_1, \dots, v_n\}$ and defining

$$A(v_j)[i] := \begin{cases} 1 & \text{if } v_i \in N(v_k) \\ 0 & \text{if } v_i \notin N(v_k) \end{cases} \quad (\text{Eq. 5})$$

one can represent a vertex by its neighborhood. This is called **Full Neighborhood Representation**.

The drawbacks of a Full Neighborhood Representation include:

- The space requirements grow quadratically with n .
- Learning algorithms that use this representation will likely overfit.
- It requires additional effort to check, whether a given vertex is already included in the representation.
- It requires additional effort to find neighbors of neighbors.

The first two drawbacks can be reduced, by so called Compressed Neighborhood Representations.

Definition 2.2: Vertex degree

Let G be a undirected graph and $v \in V(G)$ be a vertex. The **degree** is the number of edges incident to v , i.e.

$$\delta(v) := |N(v)|$$

if G is directed, we define respectively the **outdegree neighborhood** as the number of (incident) edges starting in v , i.e.

$$\delta_{\text{out}}(v) := |N_{\text{out}}(v)|$$

and the **indegree neighborhood** as the number of (incident) edges ending

in v , i.e.

$$\delta_{\text{out}}(v) := |N_{\text{out}}(v)|$$

The neighborhood $N(v)$ of a vertex v induces a subgraph $G[N(v)]$ with the vertices in $N(v)$ and all edges between these vertices:

$$G[N(v)] = \left(N(v), \{ \{w, w'\} \mid w, w' \in N(v) \} \right)$$

The generalized definition is given in definition 2.4. This subgraph $G[N(v)]$ can have at most

$$\frac{\delta(v)(\delta(v) - 1)}{2}$$

edges, since every of the $\delta(v)$ neighbors of v can have at most one edge, to all other $\delta(v)$ neighbors in $G[N(v)]$. Notice, not to count every edge twice in this argumentation. If there are exactly this many edges (without loops), the subgraph is *fully connected*.

Definition 2.3: Neighborhood density

The **density** of a vertex's neighborhood v is defined as the ratio of all existing edges and all possible edges (in a fully connected neighborhood):

$$c(v) := \frac{2|E(G[N(v)])|}{\delta(v)(\delta(v) - 1)}$$

Definition 2.4: Induced subgraph

Let G be a graph and $X \subseteq V(G)$ a set of its vertices. The **subgraph** of G **induced by** X is the graph H with

- $V(H) = X$ and
- $E(H) = \{ \{v, w\} \mid \{v, w\} \in E(G) \wedge v, w \in X \}$

A **triangle graph** is a simple graph on three vertices with three edges.

Definition 2.5: Triangle subgraphs

Let $\mathcal{D}(v)$ be the set of all triangle subgraphs of a graph G that contain the vertex v .

Let $\Delta(v) := |\mathcal{D}(v)|$ be its carnality.

THEOREM 2.2 - Upper bound on the adjacent triangle count:

Let G be a graph and $v \in V(G)$. Then

$$\Delta(v) \leq |E(G[N(v)])|$$

Proof: Let $D \in \mathcal{D}(v)$ be an arbitrary triangle adjacent to $v \in V(G)$. Then $V(D) \subseteq N(v) \subseteq G[N(v)]$ since in a triangle all vertices are adjacent and thus all vertices in the triangle are adjacent to v (i.e. contained in its neighborhood). Notice, that there are two kind of edges in $G[N(v)]$, the ones incident to v ($v \in e$, there are $\delta(v)$ many of them) and these which are not ($v \notin e$). The ones incident to v can be part of at most two triangles in $\Delta(v)$, while the edges that are not incident to v can be part in exactly one triangle in $\Delta(v)$. That is because the two vertices that are adjacent to such an edge, together with v , completely define a triangle (if all edges are present). On the other hand, every triangle in $D(v)$ must contain exactly one edge, that is not incident to v (and two which are incident to v).

Therefore the number of triangles $\Delta(v)$ is equal to the number of edges in $G[N(v)]$ that are not incident to v , which is a fraction of all edges in $G[N(v)]$:

$$\begin{aligned} \Delta(v) &= |\{e \in E(G[N(v)]) \mid v \notin e\}| \\ &\leq |\{e \in E(G[N(v)]) \mid v \notin e\}| + \delta(v) \\ &= |E(G[N(v)])| \end{aligned}$$

(Note that in the second equation, the equality is only achieved, if v has no neighbors.) \square

Definition 2.6: Induced Subgraph Isomorphism Problem

Input: two graphs G, H .

Output: the decision if H is isomorphic to an induced subgraph of G .

THEOREM 2.3 - Difficulty of the Ind. Subgraph Iso. Pb.:

The induced subgraph isomorphism problem is **NP-complete**.

Proof: Let K_n be a complete graph on n vertices. Then solving the induced subgraph isomorphism problem for K_n and G solves the k -Clique Problem for G , which is NP-complete itself. \square

Notice, that if one could count the induced subgraphs for two graphs efficiently, one could decide the induced subgraph isomorphism problem. Hence *counting induced subgraphs is NP-hard*.

But if one keeps the size of the induced subgraphs fix, the problem becomes tractable.

1.2.1 Graphlet Counting

Definition 2.7: Graphlet

Small connected induced subgraphs are called **graphlets**.

We would like to count, for each vertex v , the number of graphlets of a certain type, that contain v . Lets call these **v -incident graphlets**.

Definition 2.8: Incident Induced Graphlets Count Problem

Input: a graph G and
a graphlet H of size k .

Output: the number of v -incident induced subgraphs isomorphic to H for all $v \in V(G)$:

$$r_H(v) := |\{X \subseteq V \mid v \in X \wedge G[X] \stackrel{\text{iso.}}{\equiv} H\}|$$

Algorithm 1 Brute Force - Counting Incident Graphlets

Input: a graph G and
a graphlet H of size k .

Output: the number of v -incident induced subgraphs isomorphic to H for all $v \in V(G)$.

- 1: $gc(v) = 0$ for all $v \in V(G)$
- 2: **for all** $X \subseteq V(G)$ with $|X| = k$ **do**
- 3: **if** $G[X]$ is isomorphic to H **then**
- 4: $gc(x) = gc(x) + 1$ for all $x \in X$

Runtime: There are $\binom{n}{k}$ choices for X , and there need $\gamma(k) \in \mathcal{O}(k! k^2)$ graphs to be checked for isomorphism. Thus the total runtime for a constant k is

$$\mathcal{O}(n^k \gamma(k)) = \mathcal{O}(n^k)$$

Since a lot of graph structured data can be considered Big Data (w.r.t. size; not speed), cubic runtime in the number of vertices is not acceptable.

THEOREM 2.4 - Runtime bound on the Incident Induced Graphlets Count

Problem:

Let G be a bounded degree graph and let d denote the maximum degree in G . If all graphlet structures size $k \in \{3, 4, 5\}$ are known (precomputed), then all v -incident graphlets of G with size $k \in \{3, 4, 5\}$ can be enumerated in $\mathcal{O}(nd^{k-1})$ time.

Notice that the maximum degree d of a graph is typically much smaller than the number of its vertices n .

Proof: Graphlets of size k can be divided into two classes:

1. Graphlets that contain a simple path of length $k - 1$ and
2. Graphlets that to not contain such a path.

First, lets consider graphlets with paths of length $k - 1$ and one fixed vertex $v \in V(G)$. We can enumerate all such paths in G starting from v by a depth-first search in $\mathcal{O}(d^{k-1})$.

Each such path P induces a subgraph $G[V(P)]$ containing v , which we can construct in $\mathcal{O}(k^2)$ time using appropriate data structures.

We can find the graphlet that $G[V(P)]$ is isomorphic to in $\gamma(k) \in \mathcal{O}(k! k^2)$ time and increase its count for v :

- Consider all $k!$ permutations of the vertex set of $G[V(P)]$ and
- check if the resulting adjacency matrix is identical to one of our precomputed graphlets ($\mathcal{O}(k^2)$, there are less than 30 of them).

Notice, that this approach has a couple of drawbacks:

1. If a graphlet may contain more than one path of length $k - 1$, it will be counted/found multiple times!
2. If v is only in the middle of a path of length $k - 1$ including graphlet, not graphlets that contain v are found!

There exist a solution for these drawbacks: Let $G[X]$ be a graphlet and $|X| = k$. Each $k - 1$ path inducing $G[X]$ will be found exactly twice, one starting from each endpoint $v \neq v'$. Thus we will find $G[X]$ twice for each $k - 1$ path in it. Thus increasing a counter for each $w \in X$ each time we find $G[X]$ will yield a final count of

$$2\#(k - 1 \text{ paths in } G[X])$$

□

Algorithm 2 Exact Graphlet Counting Algorithm

Input: a graph G and

a graphlet H of size k and $1 \leq p$ paths of length $k - 1$.

Output: the number of v -incident subgraphs isomorphic to H for all $v \in V(G)$.

- 1: $gc(v) = 0$ for all $v \in V(G)$
 - 2: **for all** $v \in V(G)$ **do**
 - 3: **for all** $k - 1$ length paths P in G starting in v **do**
 - 4: **if** $G[V(P)]$ is isomorphic to H **then**
 - 5: $gc(x) = gc(x) + 1$ for all $x \in X$
 - 6: **for all** $v \in V(G)$ **do** $gc(v) = \frac{gc(v)}{2p}$ ▷ B.c. of double counting
-

To understand the runtime complexity, we need to consider how many graphlets without paths of length $k - 1$ here are.

For $k = 2$ There are no such graphlets.

For $k = 3$ There are no such graphlets.

For $k = 4$ There is only the 3-star.

We need to lookup all $\mathcal{O}(\binom{d}{3})$ neighbor triplets of v and check if they induce the 3-star graphlet. This can be done in $\mathcal{O}(d^3\gamma(4))$.

For $k = 5$ All connected graphlets with no 4-paths have the 3-star as subgraph.

Thus enumerate all occurrences of the 3-star and check the neighbors of each node (in the star) to see if they induce one of the graphlets. This takes $\mathcal{O}(d\gamma(5))$ per induced graph.

Thus the overall runtime is $\mathcal{O}(d^4\gamma(5))$.

Now, considering the relevance of the 3-star we notice that since it has only one center, they cannot be found twice. Thus one may think, that the normalization step of the counter can be avoided.

However, the counts for graphlets of size five need to be normalized by the number of subgraphs of the pattern that are isomorphic to the 3-star. Lets use this knowledge in another version of the algorithm.

Algorithm 3 Exact Graphlet Counting Algorithm 2

Input: a graph G and
the 3-star H .

Output: the number of v -incident subgraphs isomorphic to H for all $v \in V(G)$.

```

1:  $gc(v) = 0$  for all  $v \in V(G)$ 
2: for all  $v \in V(G)$  do
3:   for all  $X \subseteq N(v)$  with  $|X| = 3$  do
4:     if  $G[X \cup \{v\}]$  is isomorphic to  $H$  then
5:        $gc(v) = gc(v) + 1$  for all  $x \in X \cup \{v\}$ 

```

Runtime: For pattern H with $|V(H)| = k$ the runtime is $\mathcal{O}(nd^{k-1})$

Repeating this for the set $\mathcal{G}_{3,4,5}$ for all 29 pairwise non-isomorphic graphs of size $k = 3, 4, 5$ is also in $\mathcal{O}(nd^{k-1})$.

Algorithm 4 Exact Graphlet Counting Algorithm 3

Input: a graph G and
the 3-star H of size 5 without simple $k - 1$ length paths and $1 \leq x$ 3-stars.
Output: the number of v -incident subgraphs isomorphic to H for all $v \in V(G)$.

```

1:  $gc(v) = 0$  for all  $v \in V(G)$ 
2: for all  $v \in V(G)$  do
3:   for all  $X \subseteq N(v)$  with  $|X| = 3$  do
4:     if  $G[X \cup \{v\}]$  is isomorphic to  $H$  then
5:       for  $w \in \bigcup_{x \in X \cup \{v\}} N(x)$  do
6:         if  $H$  is isomorphic to  $G[X \cup \{v, w\}]$  then
7:            $gc(x) = gc(x) + 1$  for all  $x \in X \cup \{v, w\}$ 
8: for all  $v \in V(G)$  do  $gc(v) = \frac{gc(v)}{2^p}$  ▷ B.c. of double counting

```

Runtime: For pattern H with $|V(H)| = k$ the runtime is $\mathcal{O}(nd^{k-1})$

Repeating this for the set $\mathcal{G}_{3,4,5}$ for all 29 pairwise non-isomorphic graphs of size $k = 3, 4, 5$ is also in $\mathcal{O}(nd^{k-1})$.

(Note that in practice the order of the loops should be changed.)

With these algorithms at hand, we can proclaim that for all $H \in \mathcal{G}_{3,4,5}$ we can efficiently compute

$$r_H(v) := |\{X \subseteq V \mid v \in X \wedge G[X] \text{ is isomorphic to } H\}|$$

and hence we can efficiently compute the representation of graphs by 2, 3, 4, 5-graphlets:

$$\times_{\{r_H \mid H \in \mathcal{G}_{2,3,4,5}\}} : V(G) \rightarrow \mathbb{R}^{29} \quad (\text{Eq. 6})$$

One may ask, how significant the runtime improvement from $\mathcal{O}(n^k)$ in Algorithm 1 to $\mathcal{O}(nd^{k-1})$ in Algorithm 4 really is. As it turns out this improvement is the change between an impractical and a practical algorithm since in the latter only connected subgraphs considered, which is as desired. In most real world graphs, there are much less such connected sets than there are subsets.

One may also ask, how significant these results are, given that we only considered small graphlets. As it turns out, in many databases these small graphlets can be interpreted more easily than bigger ones. For example in social net-

works, many triangle graphlets may indicate that friends of friends tend to be friends as well. While many 2-paths imply the opposite. Nevertheless, larger graphlets can be useful in practice too.

Keep in mind, that so far we considered unlabeled graphs. Taking labels into account yields much more pairwise non-isomorphic graphs. Note that in practice, graphlet counting (and multiple other pattern based representation methods) tends to *work better with discretely labeled attributes* than with continuous attributes (e.g. $f_V : V(G) \rightarrow \mathbb{R}$). Thus it may be desirable to discretize given continuous labels.

1.3 Distance based node representations

We have seen that graphlet counting (as an example of local feature counting) extends the trivial neighborhood set representation to the immediate neighborhood. But it does not go beyond a few neighbors.

1.3.1 Centrality measures with distances

Definition 3.1: Geodesic graph distance

Let G be a graph and $v, w \in V(G)$. Then the **(geodesic) distance** $d(v, w)$ is the length of the **shortest path** in G with v and w as its endpoints.

More explicitly, the **unweighted (geodesic) distance** is the number of edges in the path. On the other hand the **weighted (geodesic) distance** for some weight function $c : E(G) \rightarrow \mathbb{R}_{\geq 0}$ is the sum of weights of edges in this path.

If such a path between v and w does not exist, set $d(v, w) := \infty$.

A trivial but expensive approach to represent the graph structure is to compute and store all distances to all other vertices in the graph. This has time complexity

- $\mathcal{O}(nm)$ using BFS for *unweighted* graphs and
- $\mathcal{O}(n^2 \log(n) + nm)$ using Johnsons algorithm for *weighted* graphs

and space complexity $\Theta(n^2)$. For many (big) real world graphs this is infeasible.

Definition 3.2: (Vertex) closeness centrality

Let G be a connected graph and $v \in V(G)$. The **closeness centrality** of v is defined as

$$C_c(v) := \begin{cases} \infty & \text{if } G \text{ is disconnected} \\ 0 & \text{if } G \text{ has only one vertex} \\ \frac{n-1}{\sum_{w \in V(G) \setminus \{v\}} d(v,w)} & \text{else} \end{cases} \quad (\text{Eq. 7})$$

That is the ratio of the distance of all vertices to v , if v would be connected to every vertex - and the actual accumulated distances to all vertices.

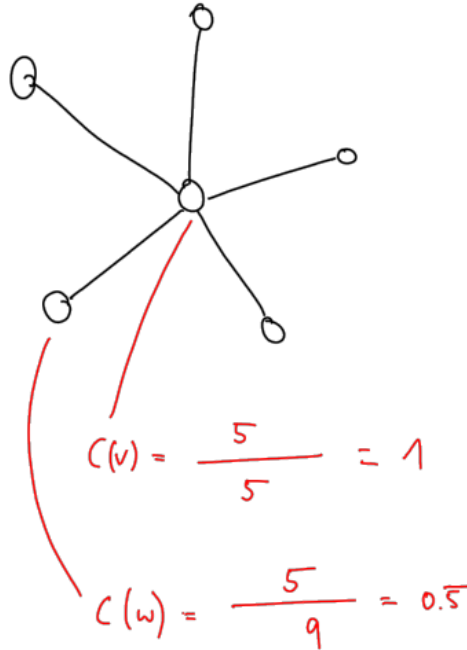


Figure 1.2

Note that this closeness centrality is a well-known centrality measure. A scaled version of it is used for example in the k-means cluster reassignment step. There one is optimizing with respect to the accumulated pairwise Euclidean

distance:

$$\operatorname{argmin}_{x \in \mathbb{R}^2} \sum_{y \in C_i} L_2^2(x, y) = \operatorname{argmax}_{x \in \mathbb{R}^2} \frac{1}{\sum_{y \in C_i} L_2^2(x, y)} = \operatorname{argmax}_{x \in \mathbb{R}^2} \frac{n-1}{\sum_{y \in C_i} L_2^2(x, y)}$$

Definition 3.3: Harmonic closeness centrality

Let G be a graph and $v \in V(G)$. The **harmonic closeness centrality** of v is

$$C_{hc}(v) := \frac{1}{n-1} \sum_{w \in V(G) \setminus \{v\}} \frac{1}{d(v, w)} \quad (\text{Eq. 8})$$

while defining $\frac{n-1}{\infty} := 0$.

Thus C_{hc} is well defined on disconnected graphs and again zero if there is only one vertex in G .

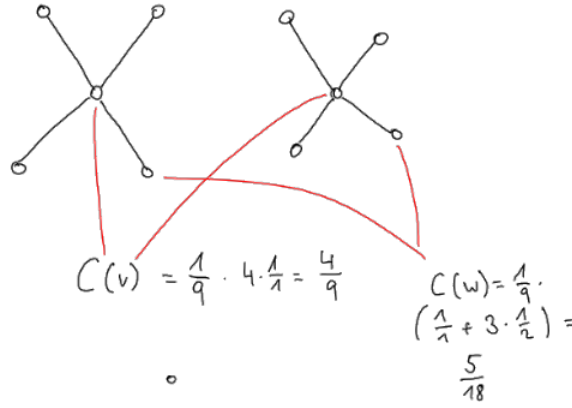


Figure 1.3

Unfortunately, no algorithm is known to compute the closeness centrality for all vertices faster than by trivially computing all-pairs-shortest paths. This is possible in $\mathcal{O}(n^2 \log(n) + nm)$ in the weighted case.

Definition 3.4: Sampled harmonic closeness centrality

Let G be a graph, $v \in V(G)$ and $L \subseteq V(G)$. The **sampled harmonic**

closeness centrality of v with respect to L is

$$C_{\text{hc},L}(v) := \frac{1}{|L \setminus \{v\}|} \sum_{w \in L \setminus \{v\}} \frac{1}{d(v,w)} \quad (\text{Eq. 9})$$

while defining $\frac{|L|}{\infty} := 0$.

This is the harmonic closeness centrality, limited to a subset L of vertices of the graph.

The sampled harmonic closeness centrality for all vertices can be computed in $\mathcal{O}(|L|(m + n \log(n)))$ by running Dijkstra's algorithm starting from each vertex $l \in L$, which we call **landmarks**. This approach can be implemented to have $\mathcal{O}(n)$ space complexity (in addition to storing the graph itself).

Similar to the graphlet graph representation equation Eq. 6 we can express the representation in terms of these landmarks:

$$\times_{\{d_l \mid l \in L\}} : V(G) \rightarrow \mathbb{R}^{|L|} \quad (\text{Eq. 10})$$

A real life interpretation of this sampled harmonic closeness would be to define one's position by saying: "I am 1 km away from the university and 500 m away from the church." The usefulness of this description depends on the selected landmarks L of course. There is no generally optimal strategy to select them. Some example approaches are:

- random initialization
- high-degree graph vertices
- in 2D-embedded (planar) graphs, use vertices on the convex hull
- vertices with high (or low) closeness centrality
- informed choice: cover the graph such that most vertices have at least one landmark close by

1.3.2 Centrality measures without distances

The sampled closeness centrality proposed in the last subsection might not be good enough. On the other hand, more exact closeness computations are easily to expensive. On top of that, in some graphs, all vertices might be almost

equally central (curse of dimensionality). Thus in this subsection we will explore alternatives to distances.

Degeneracy

Another way of defining centrality is via *density*. Intuitively, it would make sense for a graph to have a dense core and a sparse shell. To be efficient, one has to be careful to not solve the Clique problem along the way.

Definition 3.5: Vertex degree

Let G be a graph and H be a subgraph of G . For $v \in V(H) \subseteq V(G)$ we denote the degree of v in H by $\delta_H(v)$.

Definition 3.6: k -core component of a graph

A **k -core component** X of a graph G is an inclusion-wise maximal connected induced subgraph $G[X]$ such that each vertex $x \in X$ has at least degree k in the induced subgraph

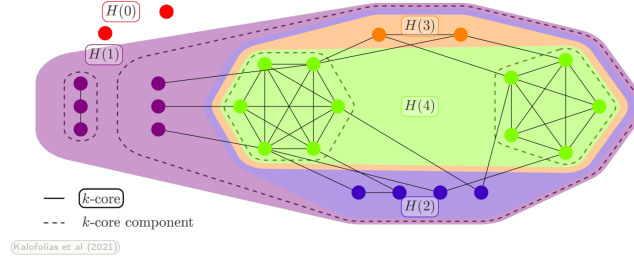
$$\delta_{G[X]}(x) \geq k$$

Definition 3.7: k -core of a graph

The subgraph $H(k)$ of G consisting of all k -core components is called the **k -core of G** .

Definition 3.8: Degeneracy

The **degeneracy** $\deg(v)$ of $v \in V(G)$ is the largest k such that v is contained in the k -core of G .

Figure 1.4 – Example graph with all k -cores and thus degeneracies visualized.**Definition 3.9: Smallest first vertex ordering**

The vertices v_1, \dots, v_n of G are in **smallest first ordering** if for all $i \in \{1, \dots, n\}$ holds:

$$v_i \text{ is the vertex with smallest degree in } G[\{v_i, \dots, v_n\}]$$

Algorithm 5 Degeneracy sweep

Input: a graph G .

Output: the degeneracies \deg of all vertices $v \in V(G)$.

- 1: $k = 0$
- 2: **for** $i \in \{1, \dots, n\}$ **do**
- 3: Remove $v = \operatorname{argmin}_{v \in V} d_{\min}$ and all incident edges from G
- 4: $k = \max(d_{\min}, k)$
- 5: $\deg(v) = k$

Runtime: $\mathcal{O}(n)$.

Special property: The algorithm processes the vertices in smallest first vertex order.

THEOREM 3.1 - Complexity of degeneracy:

Let G be a graph. The degeneracy of all vertices $v \in V(G)$ can be computed in linear time.

Proof: We have proven the claim if algorithm 5 runs in linear time. Therefore we need to show that $\deg(v) = k$ in line 5 correctly computes the degeneracy

of v in each iteration, since every vertex is touched exactly once in the for loop. Let v_1, \dots, v_n be the smallest first vertex order used by the algorithm. Let $d_i := \delta_G[\{v_i, \dots, v_n\}](v_i)$. Then

$$\forall i \in \{1, \dots, n\} : \quad \delta_G[\{v_i, \dots, v_n\}](v) \geq d_i \quad (\text{Eq. 11})$$

That is, $G[\{v_i, \dots, v_n\}]$ is a subgraph of the d_i -core of G .

This also implies that $G[\{v_i, \dots, v_n\}]$ is a subgraph of the d_j -core for all $1 \leq j \leq i$.

Hence, line 4 of the algorithm sets a lower bound on the degeneracy of each vertex coming after the current one in the smallest first ordering.

Now let H be a k -core component in G and let v_1, \dots, v_n be any smallest first ordering. Let i be the smallest index with $v_i \in V(H)$. We claim that it is $d_i \geq k$. To see this note that as $V(H) \subseteq \{v_i, \dots, v_n\}$, H is a subgraph of $G[\{v_i, \dots, v_n\}]$. This implies

$$d_i = \delta_G[\{v_i, \dots, v_n\}](v_i) \geq \delta_H(v_i) = k$$

Thus line 4 of the algorithm also sets an upper bound on the degeneracy of each vertex. Thus the equality $d_i = k$ is proven. \square

With respect to the space complexity of Algorithm 5 we note that in each iteration we have to find the remaining vertex with the smallest degree, remove it, and update the degrees of the (ex-)neighbors. We can do this in linear time using lists and arrays:

- Store G in a standard adjacency list format.
- In an array A , for each $\delta \in \{1, \dots, n\}$ store a **double linked list**, initialized with all vertices that have degree i .
- On an array B , for each vertex, store its current degree and a pointer to its unique list entry maintained in B .
- Start with the first non-empty list in A , popping the first element v , decreasing the degrees of its neighbors by one in B , and moving them from their current list in A to the list of their new degree (using the pointer in B for constant time access to the list entries).
- Continue looking for the first non-empty list in A , starting with the previous list in A , checking if there is now a vertex with that degree.

Keep in mind that as A contains double linked lists, removing and adding list items takes constant time.

1.4 Message passing

Note that the power set of a set X can be denoted as 2^X . Since multisets contain objects a non-negative number of times, the set of all multisets of objects from X can be denoted as \mathbb{N}^X .

We will now introduce a very flexible framework. Assume that we have some feature representation $r_0 : V(G) \rightarrow \mathbb{R}^d$ for the vertices in our graph. It is reasonable that in many situations neighboring vertices influence each other. Consider a social network where users spread their content along connections to their affiliates. In turn, neighbors might be influenced by that and hence spread (a variant of) that information (aka. “retweet”).

Message passing models this kind of behavior as a *simultaneous round based process*:

Definition 4.1: Message passing

Message passing models a simultaneous round based process. Let $v \in V(G)$ be a vertex, $k \geq 0$ and $r_0 : V(G) \rightarrow \mathcal{X}_0$ a feature representation. $\{\{r_k(w) \mid w \in N(v)\}\}$ is the multiset of (old) representations of the neighbors of $v \in V(G)$. Define the following two functions:

- $\text{agg}_k : \mathbb{N}^{\mathcal{X}_k} \rightarrow \mathcal{X}'_k$ **aggregates** a set of (old) representations to some value.
- $\text{upd}_k : \mathcal{X}_k \times \mathcal{X}'_k \rightarrow \mathcal{X}_{k+1}$ **updates** the representation of v given its old representation and the aggregate of the neighbors.

Omit k in the notation of upd_k and agg_k when the functions are iteration independent ($\text{upd}_0 = \text{upd}_1 = \dots$).

With these notations message passing can be described as the following representation update:

$$r_{k+1}(v) = \text{upd}_k\left(r_k(v), \text{agg}_k(r_k(w) \mid w \in N(v))\right) \quad (\text{Eq. 12})$$

In practice, message passing is often used with $\mathcal{X}_0 = \mathcal{X}'_0 = \mathcal{X}_1 = \mathcal{X}'_1 = \dots = \mathbb{R}^d$ for some fixed d . Then the aggregation function $\text{agg} : \mathbb{N}^{\mathbb{R}^d} \rightarrow \mathbb{R}^d$ a set of

(old) representations to some value from the same domain. The update function is then of the form $\text{upd} : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{R}^d$.

Note that the definition of message passing depends on the multiset of neighbors of a vertex. Thus the order in which those neighbors are (practically) processed does not influence the resulting representation of the central vertex. More general, the method is **invariant under isomorphism**:

THEOREM 4.1 - Message passing is invariant under isomorphism:

Let G and H be two graphs and r_0^G and r_0^H two vertex representations with fixed aggregator and update functions:

$$r_1^G(v) = \text{upd}\left(r_0^G(v), \text{agg}(\{r_0^G(w) \mid w \in N(v)\})\right)$$

$$r_1^H(v) = \text{upd}\left(r_0^H(v), \text{agg}(\{r_0^H(w) \mid w \in N(v)\})\right)$$

Let $\varphi : V(G) \rightarrow V(H)$ be an isomorphism that respects r_0^G and r_0^H :

$$r_0^G(v) = r_0^H(\varphi(v)) \quad (\text{Eq. 13})$$

Then message passing (the next iteration of the vertex representation) is invariant under isomorphism:

$$\forall k \geq 0 : \quad r_k^G(v) = r_k^H(\varphi(v))$$

Proof: The case $k = 0$ is true by definition of φ (equation Eq. 13). First let's prove $k = 1$. Let $v \in V(G)$. We will use the preserved neighborhoods under isomorphism

$$w \in N(v) \iff \varphi(w) \in N(\varphi(v)) \quad (\text{Eq. 14})$$

and the following equality of multisets (using again equation Eq. 13):

$$\begin{aligned} \{r_0^G(w) \mid w \in N(v)\} &= \{r_0^H(\varphi(w)) \mid \varphi(w) \in N(\varphi(v))\} \\ &= \{r_0^G(w') \mid w' \in N(\varphi(v))\} \end{aligned} \quad (\text{Eq. 15})$$

Now it is:

$$\begin{aligned}
r_1^G(v) &= \text{upd}\left(r_0^G(v), \text{agg}(\{r_0^G(w) \mid w \in N(v)\})\right) && \text{by definition} \\
&= \text{upd}\left(r_0^H(\varphi(v)), \text{agg}(\{r_0^G(w) \mid w \in N(v)\})\right) && \text{using Eq. 15} \\
&= \text{upd}\left(r_0^H(\varphi(v)), \text{agg}(\{r_0^H(w') \mid w' \in N(\varphi(v))\})\right) && \text{using Eq. 14} \\
&= r_1^H(\varphi(v)) && \text{by definition}
\end{aligned}$$

Now lets prove the statement for $k > 1$. □

We have just shown that the vertex representations computed by message passing do not depend on the order of the vertices. Note that instead of a multiset of neighbor representations, a set would work to.

Also note, that in iteration k the representation of v is determined by the (intermediate) representations of all vertices of distance at most k from v , since more the neighborhood of the next iteration depends on its neighbors of the previous one.

1.4.1 Aggregator functions

Common choices for aggregator functions are:

- counts,
- means, sums, products,
- histograms,
- hashes and
- neural networks.

Lets consider these aggregator functions one by one.

Neighbor count aggregator

Consider the **neighbor count aggregator**. Since the graph structure does not change, the multiset of neighbor representations of any vertex v has constant size in each iteration. Thus the aggregator will, for each vertex, produce a **constant value** over all iterations of message passing. This is rather trivial.

Means, sums and products aggregator

One can also generalize the **means**, **sums** and **products aggregator** by defining a binary operation that is commutative and associative $\circ : \mathcal{X} \times \mathcal{X} \rightarrow \mathcal{X}$. For $X = \{x_1, x_2, \dots, x_{|X|}\}$

$$\bigcirc_{x \in X} x = x_1 \circ x_2 \circ \dots \circ x_{|X|}$$

is a well defined aggregator.

Histogram aggregator

Lets take a closer look at **histogram aggregators**. Let \mathcal{X} be a set and $B_1, B_2, \dots, B_k \subseteq \mathcal{X}$ be bins. Then for $X \in \mathbb{N}^{\mathcal{X}}$ and B_i we can define

$$\text{count}_{B_i}(X) := |\{x \in X \mid x \in B_i\}|$$

and $\text{hist}_{B_1, \dots, B_k} : \mathcal{X} \rightarrow \mathbb{N}^k$ as

$$\text{hist}_{B_1, \dots, B_k}(X) := (\text{count}_{B_1}(X), \dots, \text{count}_{B_k}(X))$$

Note that the histograms generalize multisets, since a multiset is a histogram where each bin contains a single object. One can also define **weighted versions** where one sums over weights of objects in a bin.

While histograms are very useful, they are not straightforwardly applicable to message passing.

Hash aggregator

We can define an aggregator that assigns each multiset an (ideally unique) identifier (hash). Abstractly, we only require that $\# : \mathbb{N}^{\mathcal{X}} \rightarrow \mathcal{X}'$ is a function, i.e. that the same multiset will always be mapped to the same value. If such a function is injective it is called a **perfect hash function**. There are multiple ways of implementing this in practice.

Neural network aggregator

We can use any neural network $f_\phi : \mathbb{N}^{\mathbb{R}^d} \rightarrow \mathbb{R}^{d'}$ that accepts a set of representations as input and produces an output. In the simplest case, one can use a

Perceptron with indegree equal to the maximum degree of the graph times d . One has to be careful to have a permutation invariant function, though.

1.4.2 Update functions

The update function $\text{upd} : \mathcal{X}_k \times \mathcal{X}'_k \rightarrow \mathcal{X}_{k+1}$ updates the representation of v given its old representation and the aggregate of the neighbors.

Again, in principle, one can use any function. It does not have to be commutative, and in fact it will likely lose information if it is, since it then no longer distinguishes between the representation of the current vertex and its neighborhood.

Standard update functions are:

- weighted sums and products of the results (for numerical data)
 $(+_{\alpha,\beta} : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{R}^d \text{ like } +_{\alpha,\beta}(x, y) := \alpha \cdot x + \beta \cdot y \text{ or } \cdot_{\alpha} : \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{R}^d \text{ like } \cdot_{\alpha}(x, y) := \alpha \cdot x \cdot y),$
- neural networks (trainable functions),
- hash functions,
- ...

1.4.3 Weisfeiler Lehman Relabeling Algorithm

Definition 4.2: Weisfeiler Lehman Label Propagation Scheme

The **Weisfeiler Lehman Label Propagation Scheme** is defined as

$$r_{k+1}^{\text{WL}}(v) = \#_k \left(r_k^{\text{WL}}(v), \text{id}_k(\{r_k^{\text{WL}}(w) \mid w \in N(v)\}) \right) \quad (\text{Eq. 16})$$

Where

$r_0^{\text{WL}} : V(G) \rightarrow \mathcal{X}_0$ maps to a discrete space,

$\text{id}_k : \mathbb{N}^{X_k} \rightarrow \mathbb{N}^{X_k}$ is the identity function and

$\#_k : \mathcal{X}_k \times \mathbb{N}^{X_k} \rightarrow \mathcal{X}_{k+1}$ is a perfect hash function.

Recall, that by definition the hash values in iteration k encode the k -hop neighborhood of the vertex it has been assigned to.

THEOREM 4.2 - Isomorphism invariance of Weisfeiler and Lehman's vertex representation:

Let G, H be two graphs with vertex label functions $r_0^{\text{WL},G}, r_0^{\text{WL},H}$. If G and H are isomorphic (respecting $r_0^{\text{WL},G}, r_0^{\text{WL},H}$) then

$$\forall k \geq 0 : \quad \{\{r_k^{\text{WL},G}(v) \mid v \in V(G)\}\} = \{\{r_k^{\text{WL},H}(v) \mid v \in V(H)\}\}$$

This means the vertex representation can reduce the graph isomorphism to multiset equality.

Proof: The proof follows directly from the invariance theorem (theorem 4.1) for the message passing framework: For an isomorphism $\varphi : V(G) \rightarrow V(H)$ we have

$$\forall v \in V(G) : \quad r_{k+1}^{\text{WL},G}(v) = r_{k+1}^{\text{WL},H}(\varphi(v))$$

Hence, the multisets of vertex representations must be equal, as well, as φ is a bijective function. \square

Note however that the other direction is true. There are non-isomorphic graphs which can have identical label histograms, see Figure 1.5 for example.

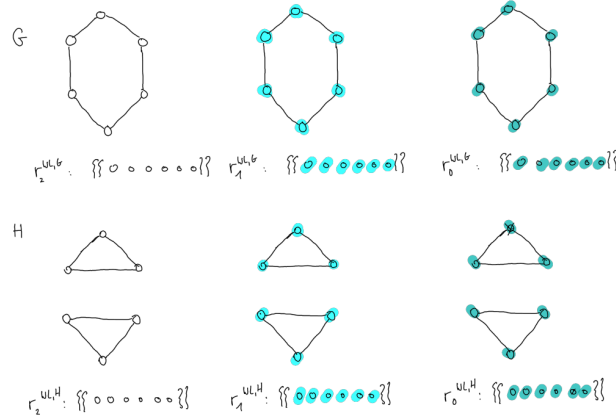


Figure 1.5 – Example of non-isomorphic graphs with identical label histograms.

This result allows us to test if two graphs G and H are not isomorphic. Therefore simply compute the multisets $\{\{r_k^{\text{WL},G}(v) \mid v \in V(G)\}\}$ and $\{\{r_k^{\text{WL},H}(v) \mid v \in V(H)\}\}$.

$V(H)\}$. If these multisets differ for any $0 \leq k \leq \max(|V(G)|, |V(H)|)$ the graphs G and H are not isomorphic.

Note that if the two multisets are identical, the graphs might be isomorphic or not!

Efficient computation of the WL labels

Recall the Weisfeiler Lehman labeling scheme presented in equation Eq. 16:

$$r_{k+1}^{\text{WL}}(v) = \#_k \left(r_k^{\text{WL}}(v), \text{id}_k(\{\{r_k^{\text{WL}}(w) \mid w \in N(v)\}\}) \right)$$

To compute it efficiently, we need a fast way to hash multisets X from \mathcal{X} . Let $<$ be a total order on \mathcal{X} , then sorting all elements in X according to $<$ returns a unique results. Thus we can compute a canonical string of symbols for each multiset. This would already be a perfect hash function.

With a canonical string of a neighbor label multiset, we can now build a lookup table (on the fly) that assigns each pair (central vertex label and canonical string of neighbor labels) a unique (integer) id.

1.4.4 Message passing on GNNs

We would like to train a graph neural network to implement the message passing, i.a. compute the update and aggregation function, which we have seen already in equation Eq. 12

$$r_{k+1}(v) = \text{upd}_k \left(r_k(v), \text{agg}_k(r_k(w) \mid w \in N(v)) \right)$$

In its oldest form, a graph neural network layer is defined for all $v \in V(G)$ as

$$r_{k+1}(v) = \sigma \left(W_k^{\text{self}} r_k(v) + W_k^{\text{neigh}} \sum_{w \in N(v)} r_k(w) + b_k \right) \quad (\text{Eq. 17})$$

where

- $W_k^{\text{self}}, W_k^{\text{neigh}} \in \mathbb{R}^{d_k \times d_{k+1}}$ are trainable parameter matrices,
- $\sigma : \mathbb{R}^{d_{k+1}} \rightarrow \mathbb{R}^{d_{k+1}}$ is an element-wise non-linear function (e.g. tanh, ReLU or sigmoid) and
- $b \in \mathbb{R}^{d_{k+1}}$ denotes trainable bias parameters.

For now, let's assume that the weights and biases are chosen appropriately and focus on the forward pass.

Let us use θ_k to denote *trainable weights in iteration k* of the GNN. We will interpret this as a flattened vector, i.e. $\theta_k \in \mathbb{R}^{2d_k d_{k+1} + d_{k+1}}$.

Let's identify the update and aggregator function. The latter is trivial (and ensures permutation invariance):

$$\text{agg}_k(\{r_k(w) \mid w \in N(v)\}) = \sum_{w \in N(v)} r_k(w)$$

$$\text{upd}_k = W_k^{\text{self}} r_k(v) + W_k^{\text{neigh}} \text{agg}_k(\cdot) + b_{k+1}$$

Example - Message Passing on a GNN Let's compute the next representation for this example graph with a simple GNN:

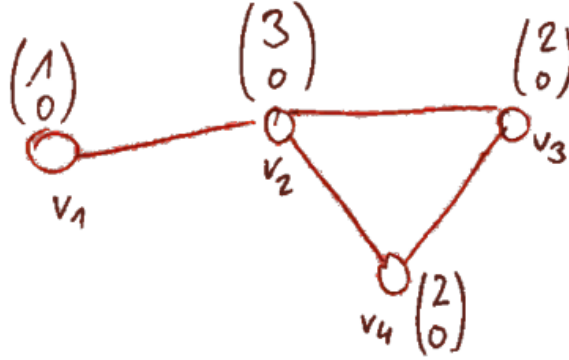


Figure 1.6

Initialize the GNN with

- $\sigma = \text{id}$
- $b_i = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$
- $W_i^{\text{self}} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}$
- $W_i^{\text{neigh}} = \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix}$

We compute:

$$\begin{aligned}
r_1(v_1) &= W_0^{\text{self}} r_0(v_1) + W_0^{\text{neigh}} (r_0(v_2)) + b_i \\
&= \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 3 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \end{bmatrix} \\
&= \begin{bmatrix} 1 \\ 0 \end{bmatrix} + \begin{bmatrix} 3 \\ 3 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \end{bmatrix} &= \begin{bmatrix} 4 \\ 3 \end{bmatrix} \\
r_1(v_2) &= W_0^{\text{self}} r_0(v_2) + W_0^{\text{neigh}} (r_0(v_1) + r_0(v_3) + r_0(v_4)) + b_i \\
&= \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 3 \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} \left(\begin{bmatrix} 1 \\ 0 \end{bmatrix} + \begin{bmatrix} 2 \\ 0 \end{bmatrix} + \begin{bmatrix} 2 \\ 0 \end{bmatrix} \right) + \begin{bmatrix} 0 \\ 0 \end{bmatrix} \\
&= \begin{bmatrix} 3 \\ 0 \end{bmatrix} + \begin{bmatrix} 5 \\ 5 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \end{bmatrix} &= \begin{bmatrix} 8 \\ 5 \end{bmatrix} \\
r_1(v_3) &= W_0^{\text{self}} r_0(v_3) + W_0^{\text{neigh}} (r_0(v_2) + r_0(v_4)) + b_i \\
&= \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} \left(\begin{bmatrix} 3 \\ 0 \end{bmatrix} + \begin{bmatrix} 2 \\ 0 \end{bmatrix} \right) + \begin{bmatrix} 0 \\ 0 \end{bmatrix} \\
&= \begin{bmatrix} 2 \\ 0 \end{bmatrix} + \begin{bmatrix} 5 \\ 5 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \end{bmatrix} &= \begin{bmatrix} 7 \\ 5 \end{bmatrix} \\
r_1(v_4) &= r_1(v_3) &= \begin{bmatrix} 7 \\ 5 \end{bmatrix}
\end{aligned}$$

Chapter 2

END »» FURTHER ANNOUNCED TOPICS

2.1 Link prediction

2.2 Graph classification, regression and clustering in transactional graph databases

Chapter 3

Feature Extraction and Graph Mining

In this chapter we focus on extracting graph representations following a fixed process. Therefore we discuss several pattern (or feature) classes and focus on the following questions:

- What kind of features are there (e.g. local and global)?
- How viable are these features?
- How expressive is their extraction?
- How powerful are graph representations in terms of distinguishing inputs?
- How do we evaluate their quality?

Chapter 4

Learning on Graphs and Graph Kernels

In this chapter we discuss learning with (implicit) graph representations. Therefore we introduce machine learning models specific to the task of classifying graphs.

4.1 Support Vector Machine (SVM)

4.2 Expressive power of machine learning models

4.3 Kernel of special interest: Weisfeiler-Lehman kernel

Chapter 5

Graph Neural Networks (GNNs)

In this chapter we will introduce the learning of representations of graphs. We discuss how neural networks can be used to learn graph representations and to subsequently perform machine learning tasks.

5.1 Relationship to Weisfeiler-Lehman method

5.2 Structure of GNNs

5.3 Expressive power of GNNs

Chapter 6

Exercises

6.1 Sheet 0 - Python

6.2 Sheet 1

6.2.1 Assignment 1a - Bias of an estimator

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Solution:

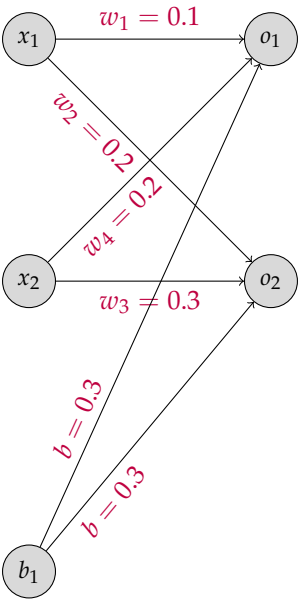


Figure 6.1 – Multi-Layer Perceptron

n	x_1	x_2	p_1	p_2
1	0.1	0.4	0.1	0.9
2	0.8	0.2	0.95	0.05
3	0.6	0.5	0.4	0.6
4	0.3	0.9	0.75	0.25
5	0.3	0.5	0.9	0.1

Table 6.1 – Training batch

Algorithm 6 Generative Adversarial Networks (GAN)

Input: a discriminator function D ,
 a generator function G ,
 noise samples Z ,
 true samples X (with an underlying data generation distribution $\mathbb{P}_{\text{data}}[X]$),
 desired size of mini-batches m ,
 a number k of improvement iterations for the discriminator,
 stopping criterion $T_{\text{condition}}$

Output: a generator G that is able to fool the trained discriminator D

- 1: **while** not $T_{\text{condition}}(f, \theta)$ **do**
- 2: **for** k steps **do**
- 3: Sample a minibatch of noise samples $\{z^{(1)}, \dots, z^{(m)}\}$
- 4: Sample a minibatch of true samples $\{x^{(1)}, \dots, x^{(m)}\}$
- 5: Perform stochastic gradient ascend for the discriminator:

$$\nabla_{\theta^{(d)}} \frac{1}{m} \sum_{i=1}^m \left(\log(d(x^{(i)}; \theta^{(d)})) + \log(1 - d(g(z^{(i)}; \theta^{(g)}), \theta^{(d)})) \right)$$

- 6: Sample a minibatch of noise samples $\{z^{(1)}, \dots, z^{(m)}\}$
- 7: Perform stochastic gradient descending for the generator:

$$\nabla_{\theta^{(g)}} \frac{1}{m} \sum_{i=1}^m \left(\log(1 - d(g(z^{(i)}; \theta^{(g)}), \theta^{(d)})) \right)$$

Bibliography

- [1] „EXAMPLE: Finite Elemente - Theorie, schnelle Löser und Anwendungen in der Elastizitätstheorie “von Dietrich Braess, 5. Auflage, Springer, 2013