

GRAPH THEORY

Basic properties of graph:

1. Distance b/w 2 vertices
- shortest path b/w $x \& y$ [no. of edges]
2. Eccentricity
- maximum distance b/w 2 vertices.
3. Radius
- minimum eccentricity
4. Diameter
- maximum eccentricity
5. Centre, central points
- vertex w/ eccentricity = radius
6. Circumference
- longest cycle.
7. Girth
- shortest cycle.

No. of edges in a complete graph: $n(n-1)/2$

Determine the order $|V|$ of the graph (V, E) in the following -

(i) G is a cubic graph (degree 3) w/ 9 edges.

$$\Rightarrow 3n = 2 \times e$$

$$n = \frac{2 \times 9}{3} = 6.$$

(ii) G is regular w/ 15 edges.

$$k \cdot n = 2 \times e$$

$$k \cdot n = 2 \times 15.$$

$$n = 30/k$$

(iii) G has 10 edges w/ 2 vertices of degree 4 and all others of deg. 3.

$$= (2 \times 4) + (3 \times n) = 2 \times e.$$

$$3n = 20 - 8$$

$$n = 4.$$

Binary Relations

Equivalence relation

1. Reflexive
2. Symmetric
3. Transitive

TREES

Let T be a full m -ary tree with $|V| = n$.

$$n = m^i + 1$$

$$l = \frac{(m-1)n+1}{m}$$

CUTSETS

Theorem:

Please that every cutset in connected graph G must contain at least one branch of every spanning tree.

Proof by contradiction

Let G be a connected graph

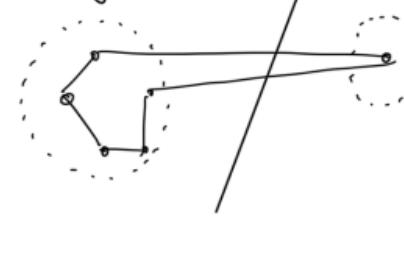
$S \rightarrow$ cutset of G .

$T \rightarrow$ spanning tree

\hookrightarrow T is completely contained in $G-S$
 $\hookrightarrow G$ must be connected

Theorem:

Every circuit has an even number of edges in common with any cut set.



Fundamental Cutset

Consider a spanning tree T of a connected graph G . Let b be a branch in T .

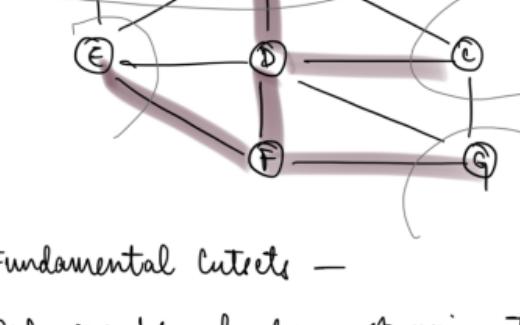
Fundamental Cutset S will contain only 1 branch - Basic cutset

Ring sum of 2 graphs

Graph consisting of $V(G) \cup V(H)$ & of edges that are either in G or in H but not in both.

$$\{d, e, f\} \Delta \{f, g, h\}$$

$$\hookrightarrow \{d, e, g, h\}$$



\therefore Fundamental Cutsets -

only one branch from spanning tree

Fleury's & Hierholzer's algorithms.

GRAPH COLOURING

A graph G is k -colourable if it has a k -colouring.

The smallest integer k for which the graph is k -colourable is called the chromatic number, $\chi(G)$

$$\chi(K_n) = n \text{ for all } n \geq 1$$

$$\chi(C_n)_{\text{even}} = 2$$

$$\chi(C_n)_{\text{odd}} = 3$$

$$\chi(\text{Bipartite}) = 2$$

$$\chi(\text{Tree}) = 2$$

Graph colouring is an NP complete problem

Welch-Powell Algorithm

Kuratowski's Theorem

A graph G is said to be planar iff

- G does not contain K_5 or $K_{3,3}$ as subgraph

Petersen graph \rightarrow contains $K_{3,3}$

Elementary tests for planarity -

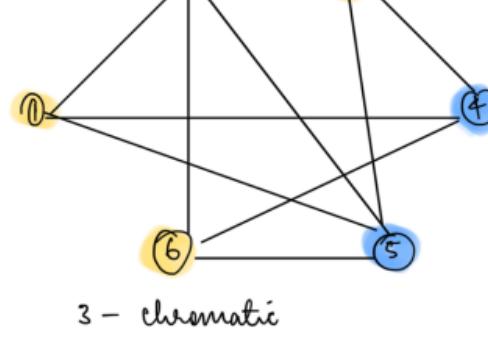
$$\text{Planar} \rightarrow \begin{cases} e \leq \frac{9}{5} \\ n < 5 \end{cases} \quad \left\{ \begin{array}{l} n-e+r=2 \\ \dots \end{array} \right.$$

$$\text{Non planar} \rightarrow 3n-6 < e$$

GRAPH ISOMORPHISM

Two graphs are said to be isomorphic to each other if

- There's a one to one correspondence b/w their vertices and edges such that
- the incidence relationship is preserved.



3 - chromatic

If F is a forest with k components (trees), prove that $n = m + k$

Total number of vertices in the forest = n .

In a tree of order n , no. of edges, $m = n-1$

* forest is a group of k -disconnected components where each one is a tree.

$$n - k = m \Rightarrow n = m + k.$$

CHROMATIC PARTITIONING

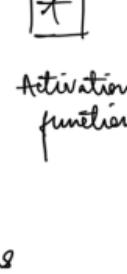
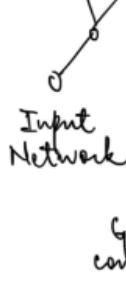
Independent set - no two adjacent edges.

Maximal independence set / Maximal internally stable set - no other vertex added to the set.

Independence no : Max number of vertices in ind. set.

Uniquely colorable graph - graph w/ only one chromatic partitioning.

^{V4} ML w/ GRAPHS



Regularization Dropout

Graph convolutions

Nodes in a graph are not independent & identically distributed (i.i.d)
↳ semi supervised

community detection → unsupervised clustering

e.g: functional modules in genetic networks

fraudulent user in financial transaction network

Traditional ML with Graphs

Given: $G(V, E)$

Let $\pi: V \rightarrow \mathbb{R}^D$

mean a function, $f: V \rightarrow \mathbb{R}$

characterise the structure & position of a node in network

1. Node degree - no. of edges incident on a node.
2. Node centrality _____
3. Clustering coefficient
4. Graphlets

Closeness centrality
Betweenness centrality
Eigenvector centrality

(i) Eigenvector centrality:

A node v is important if it is surrounded by important neighbouring nodes.

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

$\lambda \rightarrow$ normalization constant
largest eigenvalue of A .

$$\lambda e = Ae$$

(ii) Betweenness centrality

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

$$c_v = \frac{\#(\text{shortest paths b/w } s \text{ & } t \text{ w/ } v)}{\#(\text{total # of shortest paths b/w } s \text{ & } t)}$$

(iii) Closeness centrality

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

$$c_v = \frac{1}{\sum \text{shortest path length b/w } u \text{ & } v}$$

3. Clustering coefficient

Measures how connected v 's neighbouring nodes are.

$$c_v = \frac{\#(\text{edges among neighbouring nodes})}{k c_2}$$

GDV \rightarrow Graphlet Degree Vector provides a measure of a node's local network topology.

Graphlets \rightarrow nested, connected induced non-isomorphic subgraphs.

Kernel Methods for graph level prediction

Design kernels instead of feature vector.

Kernel SVM used to make predictions

Graph kernels - measure similarity b/w kernels.

(i) Graphlet kernel

(ii) Weisfeiler - Lehman kernel

Bag of \Rightarrow representation of graph (instead of node degrees)

(i) Graphlet Kernel:

Given two graphs $G \circ G'$, the graphlet kernel is computed as -

$$K(G, G') = f_G^T f_{G'}$$

Normalize each feature vector.

$$f_G = \frac{f_G}{\sqrt{\sum (f_G)^2}}$$

-11-

$$K(g, g') = h_g^T h_{g'}$$

→ NP hard problem, computationally expensive, n^k

↳ Goal: Define an efficient graph feature descriptor.
Use coarse refinement algorithm.

(ii) Weisfeiler Lehman kernel

Assign an initial color $c^0(v)$ to every node v .

Iteratively refine node colors.

$$c^{k+1}(v) = \text{Hash}(\{c^k(v), \{c^k(u)\}_{u \sim v}\})$$

→ Computationally efficient

Linear time, linear in #edges

Input Graph → Feature engineering → Structured feature
(node level, edge level, graph level)

learning model (SVM, NN) that maps
features to labels.

Map nodes into an embedding space

Encode network information

Used for many downstream predictions

Encoder-Decoder framework

1. Encoder maps from nodes to embeddings

2. Define a node similarity function

3. Decoder maps from embeddings to
similarity score.

4. Optimize parameters of the encoder.

Nodes $\xrightarrow{\text{Encoder}}$ Embeddings $\xrightarrow{\text{Decoder}}$ Similarity score

$$\text{similarity}(u, v) \approx z_v^T z_u$$

(original)

→ optimize similarity function

$$\text{ENC}(v) = z_v \rightarrow \text{DEC}(z_v^T z_u)$$

embedding lookup

Random walk → Expressivity & efficiency

flexible stochastic def. of node similarity

Limitations of shallow embeddings

1. Does not share parameters b/w nodes

Statistically & computationally inefficient

2. Do not leverage node features in encoder

3. Inherently transductive

Only generate embeddings for nodes present
during training phase.

Graph embedding $\rightarrow z_g = \sum_v z_v$

- Simple
- Virtual
- Anonymous walk embedding

Graph Neural Network

Map nodes to d -dimensional embeddings such that similar nodes in the graph are embedded close to each other.

Link level features - local neighbourhood overlap.

$$1. \text{ common neighbours} = |N(v_1) \cap N(v_2)|$$

$$2. \text{ Jaccard coefficient} = \frac{|N(v_1) \cap N(v_2)|}{|N(v_1) \cup N(v_2)|}$$

$$3. \text{ Adamic Adar index} = |N(v_1) \cap N(v_2)| \frac{1}{\log(|C|)}$$

$$\text{Normalization, Resonson: } \frac{2 |N(u) \cap N(v)|}{d_u + d_v}$$

$$\text{Salton index} = \frac{2 |N(u) \cap N(v)|}{\sqrt{d_u d_v}}$$

Global neighbourhood - Katz index

$$s = \sum_{i=1}^{\infty} p^i A^i = (1 - pA)^{-1} - I$$

V4 Social Network Analysis

Network level measures - size & Density

Path level measures - Length & Distance

Standard clustering models

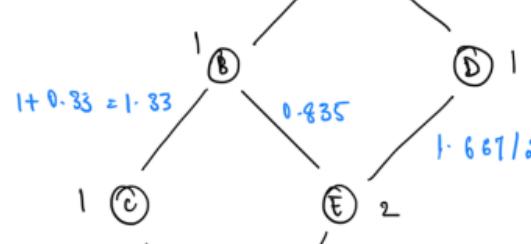
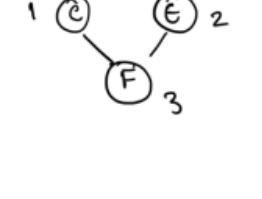
1. Hierarchical (Agglomerative)
2. Point assignment

Community detection algorithms

1. Girvan Newman
2. Fluid communities
3. Label propagation
4. Clique percolation
5. Kernighan Lin

Girvan Newman -

1. convert to BFS tree



$$\frac{1}{3} = 0.33 \quad \frac{2}{3} = 0.66$$

F

3

GRAPH DATABASES

Graph database models -

- RDF [Resource description framework graphs]
- Labelled property graphs

HUNGARIAN METHOD

	J1	J2	J3	J4
C1	4	2	5	7
C2	8	3	10	9
C3	12	5	4	5
C4	6	3	7	14

① Subtract minimum value from each row.

2	0	3	5
5	0	7	5
8	1	0	1
3	0	4	11

② Subtract minimum value from each column.

0	0	3	4
3	0	7	4
6	1	0	0
1	0	4	10

Subtract the smallest element from the uncovered elements and add it to the intersection.

0	1	3	4
2	0	6	3
6	2	0	0
0	0	3	9

0 1 3 4

2 0 6 3

6 2 0 0

0 0 3 9

C1 C2 C3 C4

C1 0 1 0 1

C2 2 0 3 0

C3 9 5 0 0

C4 0 0 0 6

Brunn's Rule

If the degree of every non-leaf vertex is 3,
the number of vertices is an even number.

No. of leaf vertices $\rightarrow n$

$$2e = 3(n-n) + n$$

$$2e = 3n - 3n + n$$

$$2e = 3n - 2n$$

$$2e + 2n = 3n$$

$$= \frac{2 \left[e + x \right]}{3} = n$$

$$\begin{array}{rcl} 2v & \longrightarrow & 2 \\ 4v & \longrightarrow & 3 \\ 3v & \longrightarrow & 4 \\ ? & \longrightarrow & 1 \end{array}$$

$$n = 2e - 28$$

$$e = n - 1$$

$$n = 2 + 4 + 3 + x = 9 + n$$

$$e = 8 + x$$

$$e = 2e - 28 + 8$$

Chromatic Polynomial $P_n(x)$ of a graph w/ n vertices

$$P(G, x) = \sum c_i x^i$$

$$P(G, x) = \frac{c_1 x}{1!} + \frac{c_2 [x(x-1)]}{2!} + \dots$$

for a graph with $n = 3$



$$\begin{aligned} c_1 &= 0 \\ c_2 &= 0 \\ c_3 &= 3! = 6 \end{aligned}$$

$$P(G, x) = c_3 \frac{x(x-1)(x-2)}{3!}$$

$$= x(x-1)(x-2)$$

For a graph w/ $n = 5$

$$c_3 = 3! = 6$$

$$c_4 = 4P_3 \times 2 = 48$$

$$c_5 = 5! = 120$$