

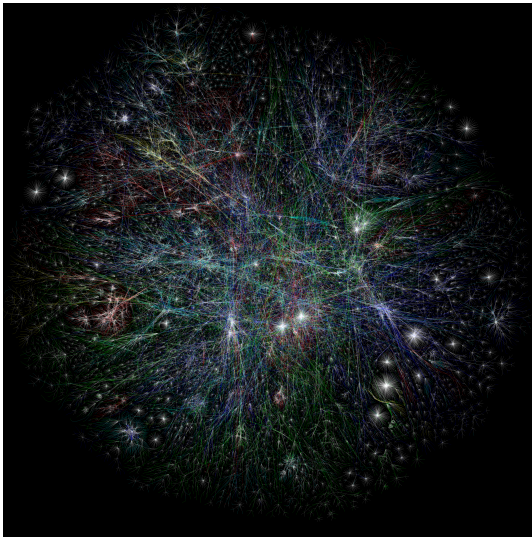
Learning and Reasoning with Graph Data: Neural and Statistical-Relational Approaches

Graph Data: Representation and Reasoning

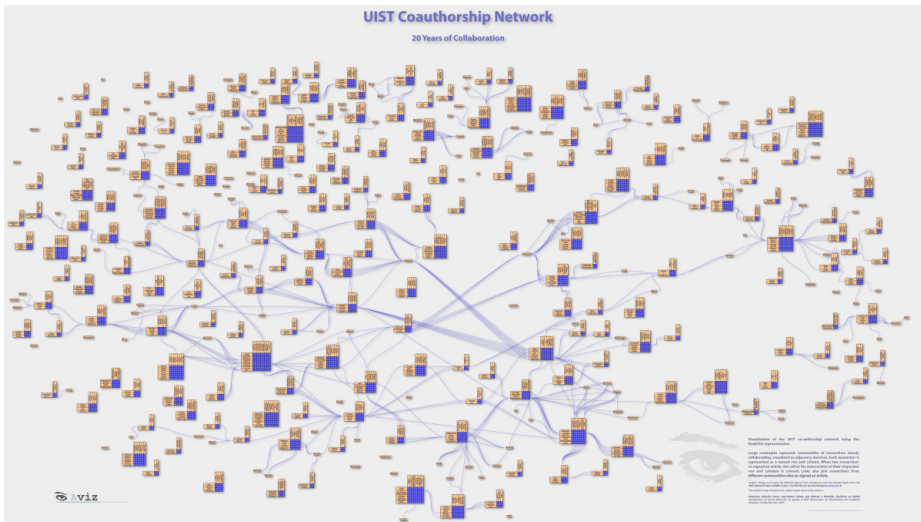
Manfred Jaeger

Aalborg University

Networks!

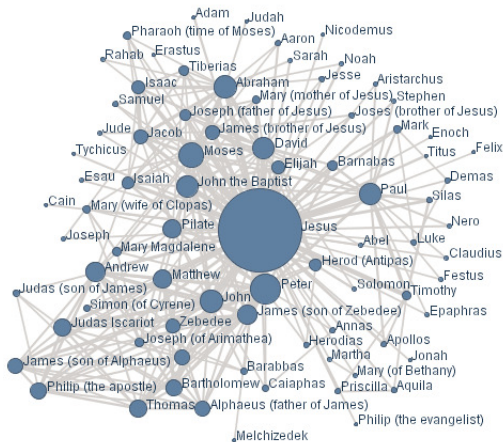


[<https://www.opte.org/the-internet>]



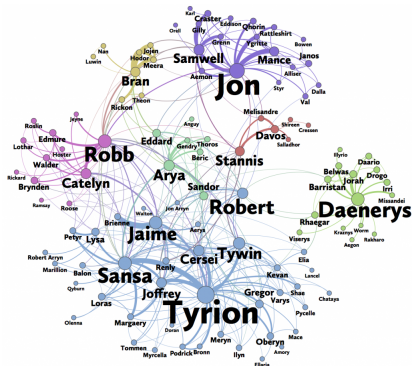
[www.aviz.fr/old/gallery/]

The New Testament social network:



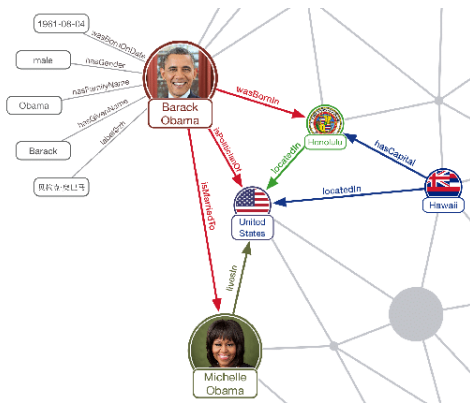
[www.laurentbrouat.com/the-social-network-of-jesus/]

The Game of Thrones social network:

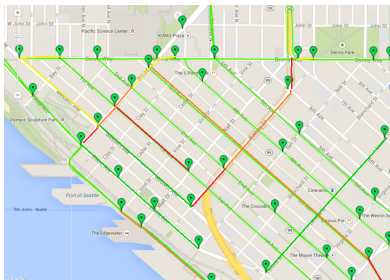


[Andrew Beveridge & Jie Shan (2016) Network of Thrones, Math Horizons

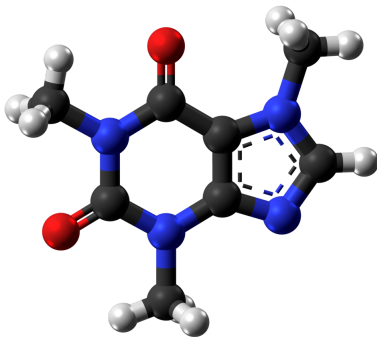
<https://www.tandfonline.com/doi/abs/10.4169/mathhorizons.23.4.18>]



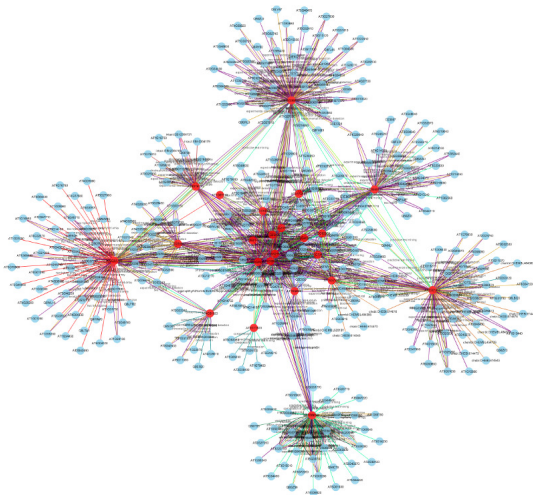
[Zhou, Zhixuan, et al. "Fake news detection via NLP is vulnerable to adversarial attacks." arXiv preprint 1901.09657 (2019).]



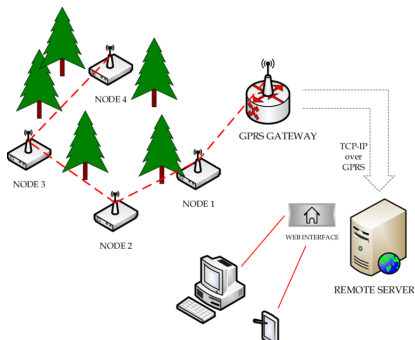
[<https://www.flir.eu/discover/traffic/urban/real-time-traffic-information/>]



[<https://en.wikipedia.org/wiki/Caffeine>]



[gmdd.shgmo.org/Computational-Biology/ANAP/ANAP_V1.1/help/anap-userguide/manual.html]



[L. Bencini et al. Wireless sensor networks for on-field agricultural management process. Wireless Sensor Networks: application-centric design (pp. 1-21). InTech.]

IMDb

The Godfather (1972) - Mozilla Firefox

http://uk.imdb.com/title/tt0068646/

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search

The Godfather (1972)

Directed by [Francis Ford Coppola](#)

Writing credits
[Mario Puzo](#) (novel)
[Mario Puzo](#) (screenplay) ... [more](#)

Photo Gallery [\(see all 52 photos\)](#)

Release Date: 24 March 1972 (USA) [more](#)

Genre: [Crime / Drama](#) [more](#)

Plot Outline: The aging patriarch of an organized crime dynasty transfers control of his clandestine empire to his reluctant son. [more](#)

Plot Keywords: [No Opening Credits](#) / [Greed](#) / [Trilogy](#) / [Blood](#) / [Bloody Violence](#) [more](#)

Awards: Won 3 Oscars. Another 19 wins & 17 nominations [more](#)

User Comments: The Godfather [more](#)

Cast (Cast overview, first billed only)

	Marlon Brando	...	Don Vito Corleone
	Al Pacino	...	Michael Corleone
	James Caan	...	Santino "Sonny" Corleone
	Richard S. Castellano	...	Pete Clemenza (as Richard Castellano)

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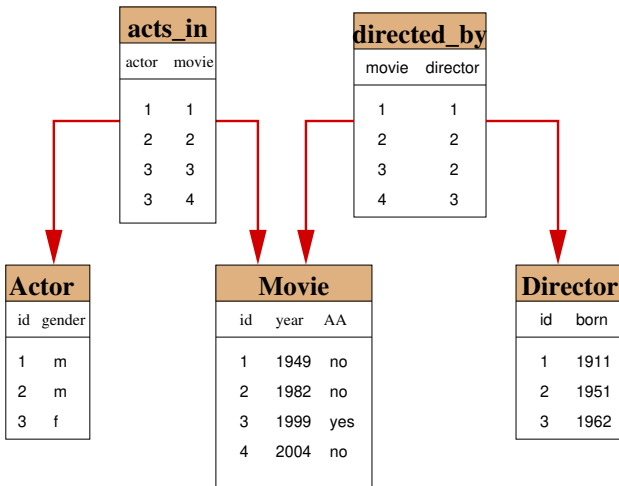
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IMDB Schema (simplified)



Real-world networks

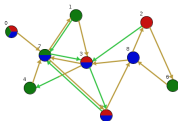
- ▶ Social networks
- ▶ Knowledge graphs
- ▶ Sensor networks
- ▶ Traffic networks
- ▶ ...

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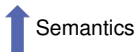
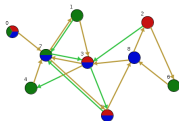


Model

Abstract: graphs

Real-world networks

- ▶ Social networks
- ▶ Knowledge graphs
- ▶ Sensor networks
- ▶ Traffic networks
- ▶ ...

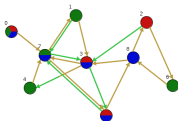
**Abstract: graphs****Predicate logic (relational)**

$\forall x(r(x) \rightarrow \exists y(e(x, y) \wedge b(y)))$
 $\exists z, x, y \neg(e(x, y) \wedge e(x, z) \wedge (e(y, z)))$

...

Real-world networks

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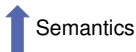
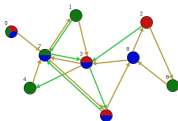
+*uncertainty*

A blue arrow pointing to the right, indicating the transition from abstract graphs to probabilistic models.

- ▶ Probabilistic Logic
- ▶ Statistical (Random) Graph Theory
- ▶ Statistical Relational Learning (Probabilistic Logic Learning)
- ▶ Graph Learning and Mining
- ▶ Graph Neural Networks

Real-world networks

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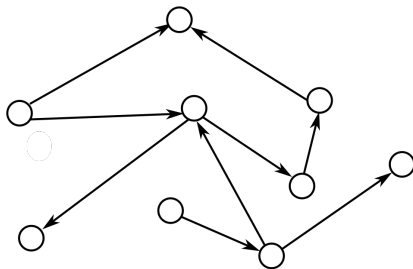
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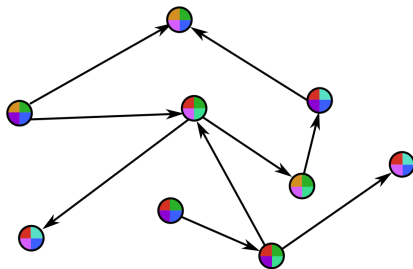
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- ▶ Graph Learning and Mining
- ▶ **Graph Neural Networks**

- ▶ Graph representations
- ▶ Learning and reasoning with graphs
- ▶ GNN approaches
- ▶ SRL approaches
- ▶ Comparisons & Integration

Graph Representations

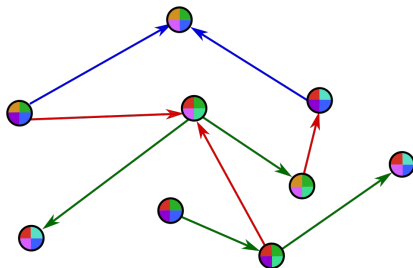


Graph: (V, E)



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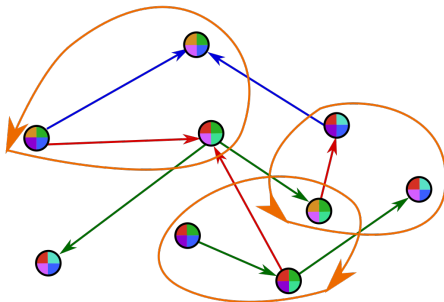
Attributed graph: (V, E, \mathbf{A}) . Node attributes \mathbf{A} : *Boolean, categorical, or numeric*



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Attributed multirelational graph: $(V, \mathbf{E}, \mathbf{A})$. \mathbf{E} : set of different edge relations

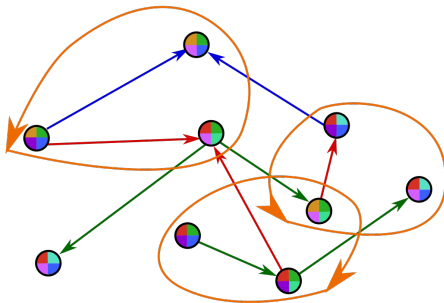


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Attributed multirelational hyper-graph: (V, \mathbf{R}) . \mathbf{R} : set of 1,2,3,...-ary relations (subsumes \mathbf{A}, \mathbf{E})



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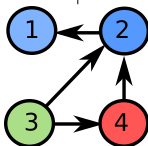
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Examples for higher arity relations:

3-ary traffic network relation: *on_shortest_path*(location,location,location)

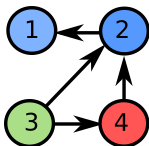
3-ary movie data: *made_contract*(agent,actor,movie)

Node	color
1	blue
2	blue
3	green
4	red

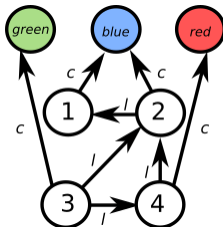


(a)

Node	c_blue	c_green	c_red
1	1	0	0
2	1	0	0
3	0	1	0
4	0	0	1



(b)

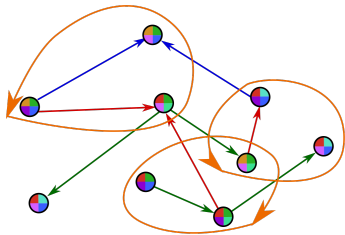


(c)

(a): unary, categorical values

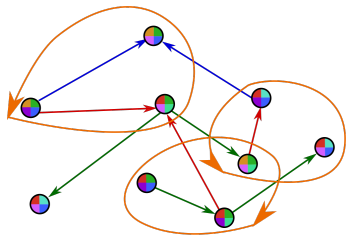
(b): unary, Boolean/binary values (one-hot encoding)

(c): binary relation between objects and attribute values materialized as nodes

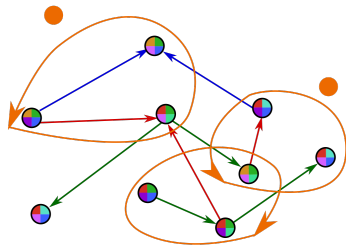


(a)

(a): as tuples of nodes



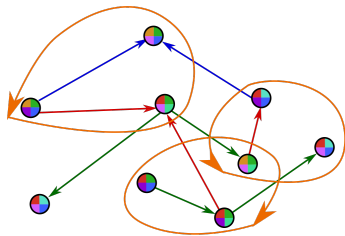
(a)



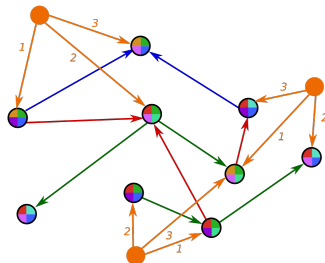
(b)

(a): as tuples of nodes

(b): materialize tuples of nodes;



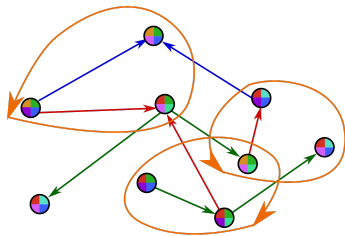
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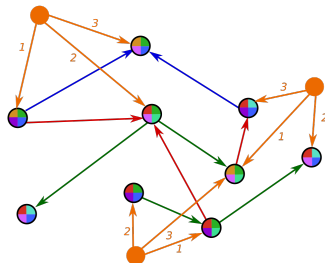
(b)

(a): as tuples of nodes

(b): materialize tuples of nodes;
connect tuple-nodes with entity-nodes by binary relations



(a)



(b)

(a): as tuples of nodes

(b): materialize tuples of nodes;
connect tuple-nodes with entity-nodes by binary relations

➡ Boolean values and binary relations are enough in principle (but can be user-unfriendly).

n	number of nodes/vertices
\mathcal{R}	a <i>signature</i> of 1,2,3,...-ary relation symbols
\mathbf{R}	specific values of the relations in \mathcal{R} in a graph $G = (V, \mathbf{R})$.
$G = (V, \mathbf{R})$	a graph with node set V , and relations \mathbf{R}
$\mathcal{G}(V, \mathcal{R})$	set of all graphs with node set V , and relations in the signature \mathcal{R}
$\Delta\mathcal{G}(V, \mathcal{R})$	set of all probability distributions over $\mathcal{G}(V, \mathcal{R})$

Generally assume that $V = \{1, \dots, n\}$, and $i, j, \dots \in \mathbb{N}$ denote nodes.

Arrays, Matrices, Tensors

Attributes:

n -dimensional array (entries categorical);

Color:

(blue, green, ..., red, blue)

k different attributes collected in $n \times k$ -dimensional matrix

Binary relations:

$(n \times n)$ -dimensional *adjacency matrix*;

Friends:

$$\begin{pmatrix} 0 & 1 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & 0 & 1 \end{pmatrix}$$

l different relations may be collected in a $(n \times n \times l)$ -dimensional *adjacency tensor*

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Logic

(Boolean) relations of all arities:

List positive and negative facts as a *knowledge base* of (negated) *ground atoms* :

$c_blue(17)$
 $\neg c_red(21)$
 $friends(2,53)$
 $\neg friends(53,8)$
 \vdots

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Knowledge Graphs

Triplet notation

$(Barack\ Obama, was_born_in, Honolulu)$

can be seen as “infix” notation for ground atoms:

$was_born_in(Barack\ Obama, Honolulu)$

Pros and Cons

- Tensors:**
- + compact, computationally efficient
 - + support for categorical (attribute) values
 - incomplete data requires '?' or 'NaN' values
- Logic:**
- + coherent treatment of relations of all arities
 - + uniform treatment of positive and negative facts
 - + natural support for incomplete knowledge
 - non binary relations require special treatment
 - non-compact

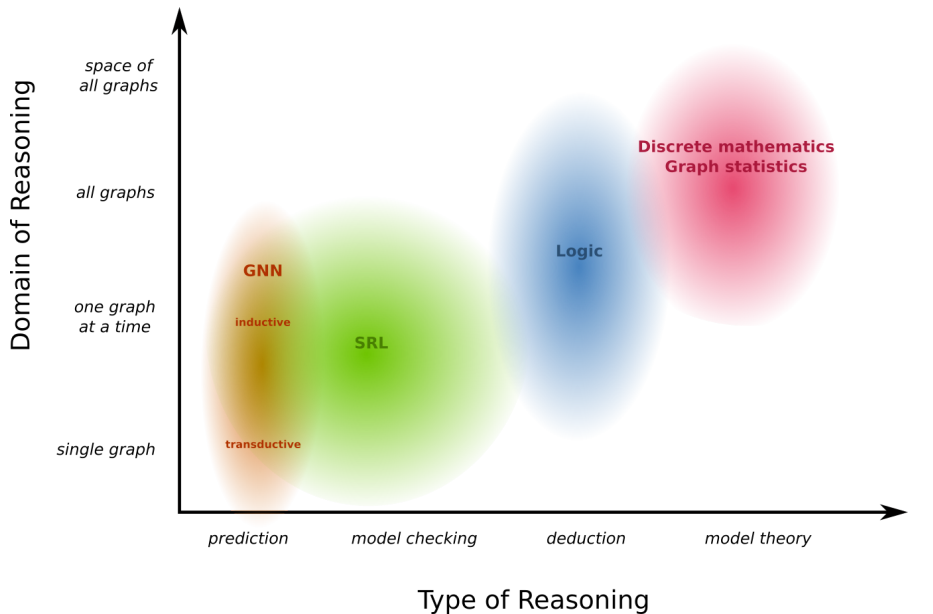
Missing information

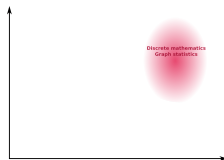
Tensors: '0' in adjacency matrix can mean: "there is no edge", or "there is no confirmed edge"

Logic: Positive and negative information are equally definitive. Missing information visible as incomplete knowledge base

To handle semantic asymmetry: *closed-world assumption* used to postulate that all facts not contained in the knowledge base are assumed to be *false* by default.

Reasoning



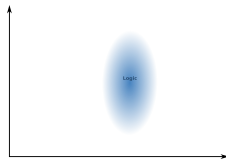


Given: a probabilistic model for the random generation/evolution of graphs.

Question: what is the probability that the graph becomes (stays) connected, as the number of nodes goes to infinity?

➡ Or many other questions about the global properties of a random graph model.

➡ Mostly (human powered) mathematics, rather than algorithmic reasoning



Given: a knowledge base

$$\forall x \exists y \text{ follows}(x, y) \\ \exists y \neg \exists x \text{ follows}(x, y)$$

Question: Does the knowledge base imply a given query statement?

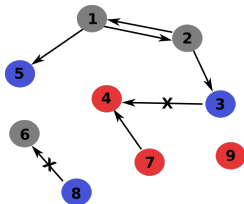
$$(\exists y \exists \geq^2 x \text{ follows}(x, y)) \vee \exists \geq^{10.000} x ?$$

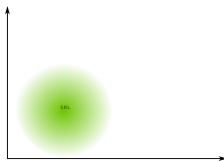
➡ Algorithmic reasoning implemented by *theorem provers*.



Given: a generative probabilistic model for graphs.

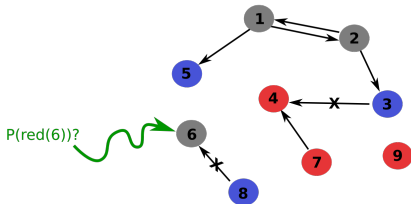
Question: for a single partially observed graph, what are the probabilities of unobserved features?

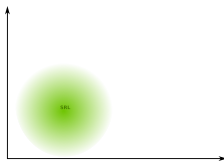




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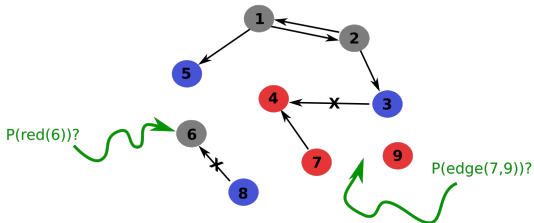
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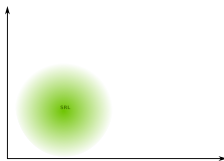




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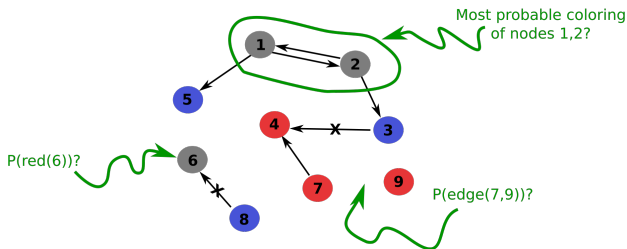
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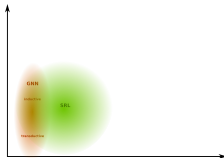




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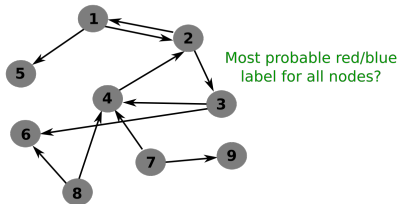
Question: for a single partially observed graph, what are the probabilities of unobserved features?





Given: a discriminative model for specific node label.

Question: for an input graph (edges, node attributes), what are predicted node labels?

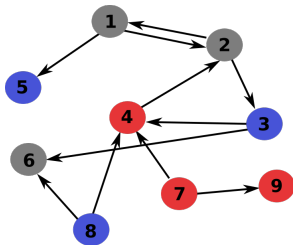


➡ Similarly: link prediction, graph classification.

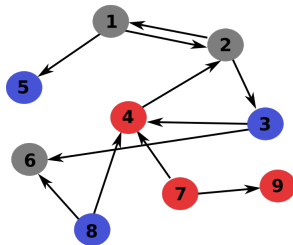
Learning

Learning and Reasoning about a single graph:

Training data

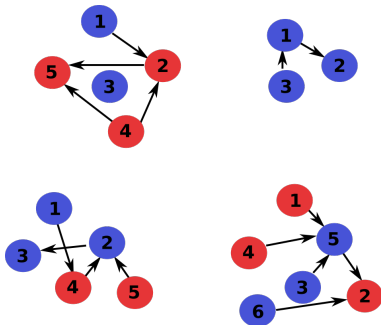


Reasoning domain



Learning and Reasoning about different graphs:

Training data



Reasoning domains (a.k.a. test cases)

