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What are some Knowledge Graph Inference Algorithms?



Introduction

- Knowledge Graph Retrieval
 - Query languages
 - SPARQL and Cypher
- Knowledge Graph Inference
 - Drawing conclusions that are not explicit in the knowledge graph
 - E.g., shortest path, concluding new connections



Outline

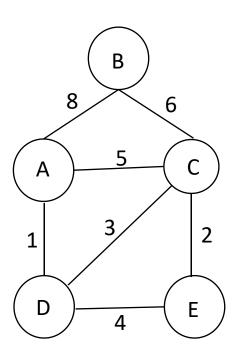
- Knowledge Graph Inference
 - Graph-based inference algorithms
 - Ontology-based inference algorithms



Graph-based Inference Algorithms

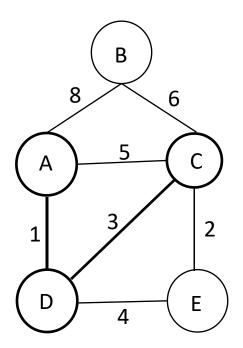
- Path finding
- Centrality Detection
- Community Detection





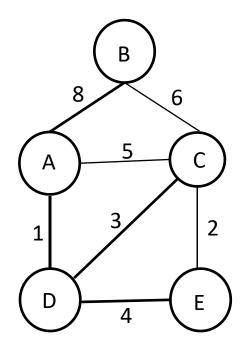


- Shortest path
 - Optimal path in traffic planning



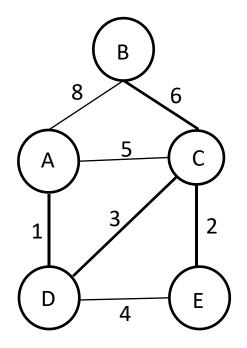


Single Source Shortest path



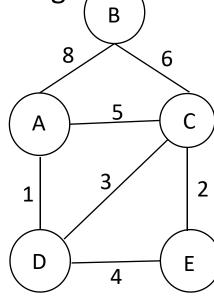


- Minimum Spanning Tree
 - Trip planning

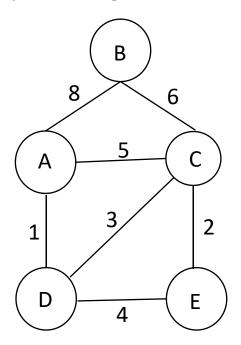




- A* Algorithm
 - Maintain a tree of paths from the start node
 - Extend them until termination criteria is met
 - Extend based on estimated length
 - f(n)=g(n)+h(n)
 - f(n) = cost until now
 - g(n) current cost
 - h(n) estimated cost

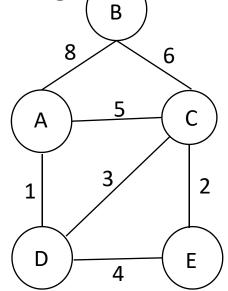


- A* Algorithm
 - Well-known path finding algorithm
 - Originally developed for AI planning





- A* Algorithm
 - Maintain a tree of paths from the start node
 - Extend them until termination criteria is met
 - Extend based on estimated length/
 - f(n)=g(n)+h(n)
 - f(n) = cost until now
 - g(n) current cost
 - h(n) estimated cost

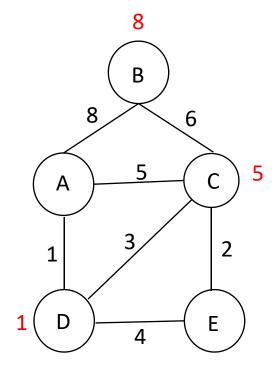


Admissible heuristic

- Never over estimate



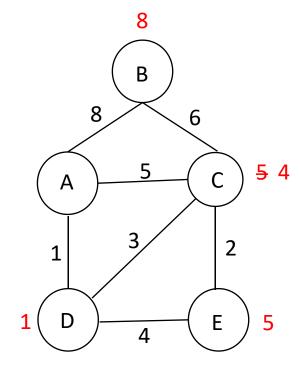
- A* Algorithm
 - Shortest path from A to E
 - h(n)=0
 - Breadth first search
 - Dijkastra's algorithm



A, B 8 A, C 5 A, D 1



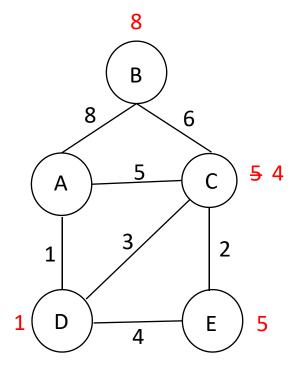
- A* Algorithm
 - Shortest path from A to E
 - h(n)=0
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 - Dijkastra's algorithm



A, B	8
A, C	5
A,D	1
A, D, C	4
A, D, E	5



- A* Algorithm
 - Shortest path from A to E
 - h(n)=0
 - Breadth first search
 - Dijkastra's algorithm



A, B	8
A, C	5
A,D	1
A, D, C	4
A, D, C, E	6
A, D, E	5



Graph-based Inference Algorithms

- Path finding
- Centrality Detection
- Community Detection

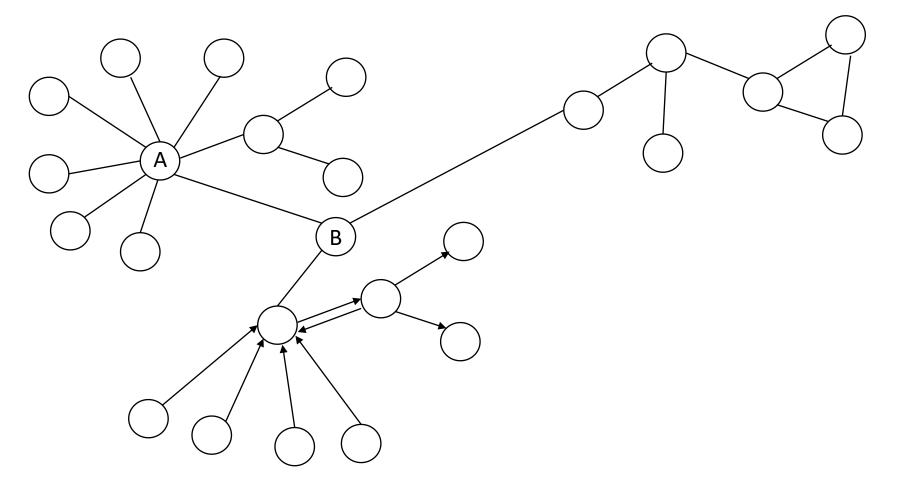


- Helps in understanding the importance of a node in a network
 - Most important nodes
 - Bridges in a network



Helps in understanding the importance of a node in a network

Degree Centrality A has the highest degree

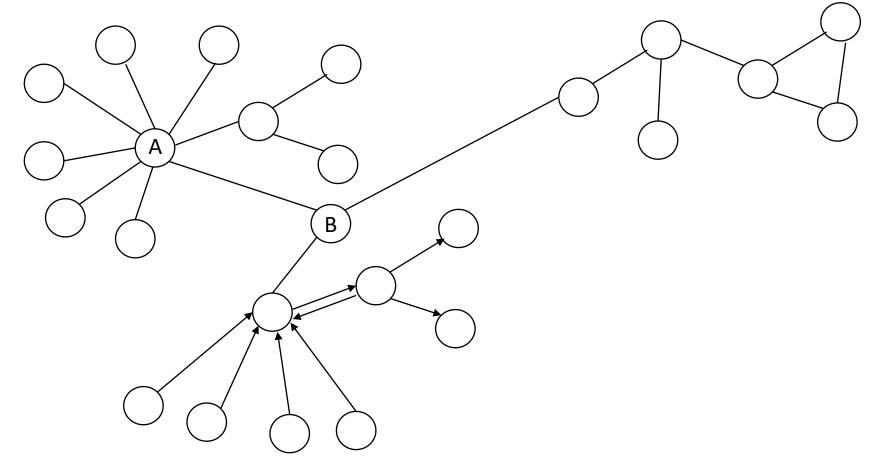




Helps in understanding the importance of a node in a network

Degree Centrality A has the highest degree

Betweenness
Centrality
B has the largest
number of
shortest paths
passing through it

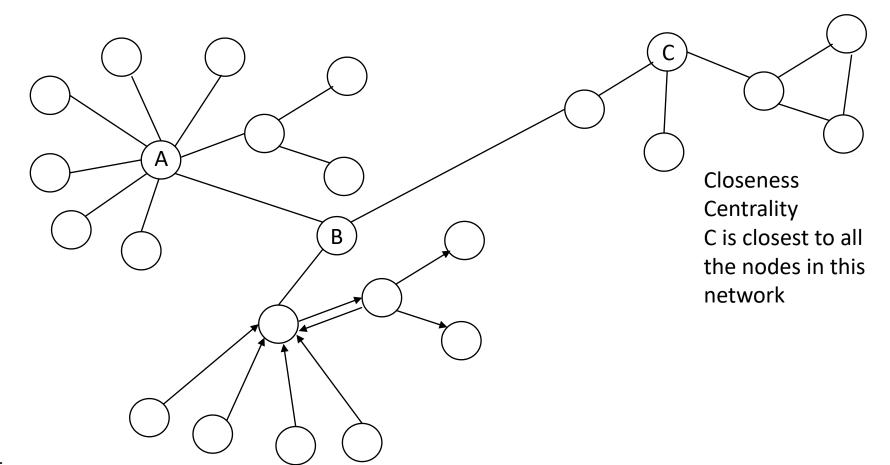




Helps in understanding the importance of a node in a network

Degree Centrality A has the highest degree

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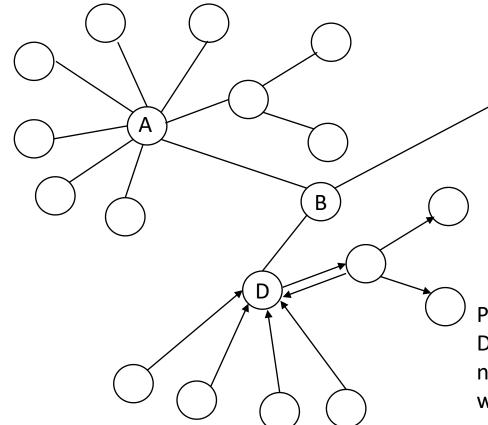




• Helps in understanding the importance of a node in a network

Degree Centrality A has the highest degree

Betweenness
Centrality
B has the largest
number of
shortest paths
passing through it



Closeness
Centrality
C is closest to all
the nodes in this
network

Page Rank
D has the highest
number of
weighted edges
coming into it



Page Rank

- Measure the transitive influence of nodes
 - A node connected to a few influential nodes could be more important than a node connected to lots of unimportant nodes

$$PR(u) = (1 - d) + d * (\frac{PR(T1)}{C(T1)} + ... + \frac{PR(Tn)}{C(Tn)})$$

d – damping factor is usually set to 0.85 Set the values of PR for all nodes to same value, and iteratively improve it

Graph-based Inference Algorithms

- Path finding
- Centrality Detection
- Community Detection



Community Detection

- Identify nodes in the graph that are closely connected to each other
 - More relationships between nodes within the community
- Could be the first step in understanding a graph
 - More in-depth analysis of nodes within the community

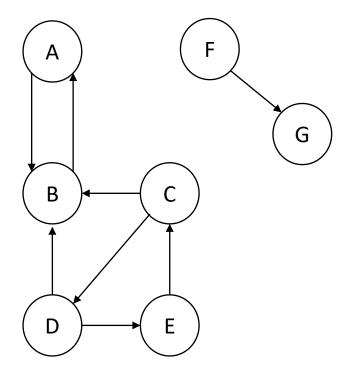


Community Detection

- Two families of algorithms
 - Standard graph algorithms
 - Bottom up algorithms

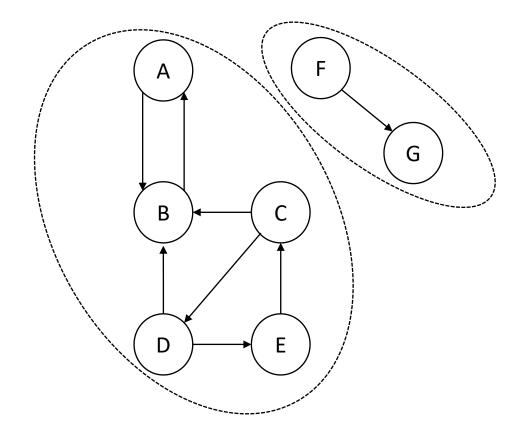


Standard Graph Algorithms



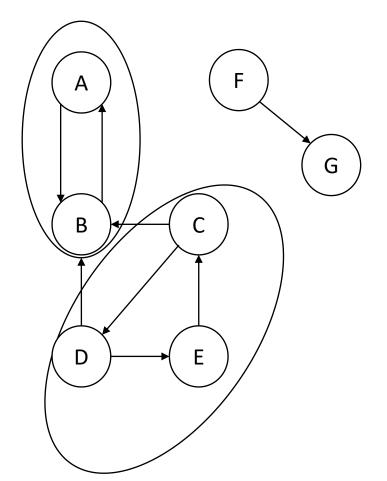


Standard Graph Algorithms – Connected components





Standard Graph Algorithms – Strongly connected components





- Bottom up algorithms
 - Label propagation
 - Unfolding



- Label Propagation
 - Assign each node to be in a different community
 - Examine all nodes in a fixed order
 - Update the community of a node that is shared by most of its neighbors
 - Break Ties in a random order
 - Terminate when each node is in a community shared by most of its neighbors



- Unfolding (Also known as Louvain)
 - Phase I
 - Assign each node into a separate community
 - Examine each node and its neighbors to test if there will be an overall gain in modularity by placing it in the same community as a neighbor
 - Modularity calculated by a formula
 - Phase II
 - Create a new graph in which each node represents a community from Phase I
 - If there are edges between nodes in a community, represent it as a self-loop
 - Repeat Phase I on the Phase II graph



Outline

- Knowledge Graph Inference
 - Graph-based inference algorithms
 - Ontology-based inference algorithms



Ontology-based Inference

- Key differentiator between a general graph and a knowledge graph
 - Associates classes with nodes
 - Defines semantic properties of relationships
 - Two major categories of inference
 - Class-based Inference or Taxonomic Reasoning
 - Rule-based inference



Taxonomic Reasoning

- Applicable when it is useful to organize knowledge into classes
 - Classes are nothing but unary relations or types
 - Membership, specialization, disjointness, value restriction
- Both Property graph and RDF data models support classes
 - In property graphs model, node type is the same as a class
 - RDF has an RDF schema layer
 - More advanced systems use a full-fledged ontology language OWL

Our discussion here will be independent of either of the two models



Example of classes

male(art) male(bob)

male(cal)

male(cam)

female(bea)

female(coe)

female(cory)

class(male)

instance_of(art,male)

instance_of(bob,male)

instance_of(cal,male)

instance_of(cam,male)

class(female)

instance_of(bea,female)

instance_of(coe,female)

instance_of(cory,female)



Class specialization

- We can organize classes into a hierarchy
 - e. g., male and female are subclasses of person subclass-of(female, person) subclass-of(male, person)
 - subclass relationship is transitive
 subclass_of(A,C) :- subclass_of(A,B) & subclass_of(B,C)
 - subclass and instance-of relationships are related instance_of(I,B) :- subclass_of(A,B) & instance_of(I,A)



Disjoint classes

- Classes can be declared to be disjoint
 - e.g, disjoint(male,female)
 - i.e., they do not have any instances in common illegal: disjoint(A,B) & instance_of(I,A) & instance_of(I,B)

or

illegal("Disjoint classes cannot have an instance in common") : disjoint(A,B) & instance_of(I,A) & instance_of(I,B)



Class Definition

- Necessary properties of a class
 - Will have instance-of in the body of the rule has_hair_color(X,brown) :instance_of(X,brown_haired_person)
- Sufficient properties of a class
 - Will have instance-of in the head of the rule instance_of(X,brown_haired_person) :instance_of(X,person) & has_hair_color(X,brown)



Value Restriction

- We can restrict the arguments of a relation to be instances of a specific class
 - domain is the restriction on the first argument

```
illegal :- domain(parent,person) &
     parent(X,Y) &
     ~instance_of(X,person)
```

range is the restriction on the second argument

```
illegal :- range(parent,person) &
    parent(X,Y) &
    ~instance_of(Y,person)
```



Cardinality and Number Restrictions

- We can further restrict the values of relations by specifying cardinality and number restrictions
 - A cardinality restriction limits the number of values of a relation illegal :- instance_of(X,person) & ~countofall(P,parent(P,X),2)
 - A numeric range restriction limits the minimum and maximum value illegal:-instance_of(X,person) & age(X,Y) & min(0,Y,Y) illegal:-instance_of(X,person) & age(X,Y)& min(125,Y,100)



Inheritance

- The relation values are said to inherit to the instances of a class
 - If art is an instance of the class brown-haired-person, we can conclude that art has brown hair



Taxonomic Inference

- Given two classes A and B, whether A is a subclass of B?
- Given a class A and an instance I, whether I is an instance of I?
- Given a ground relation atom determine whether it is true or false?
- Given a relation atom, determine values which values make it true?



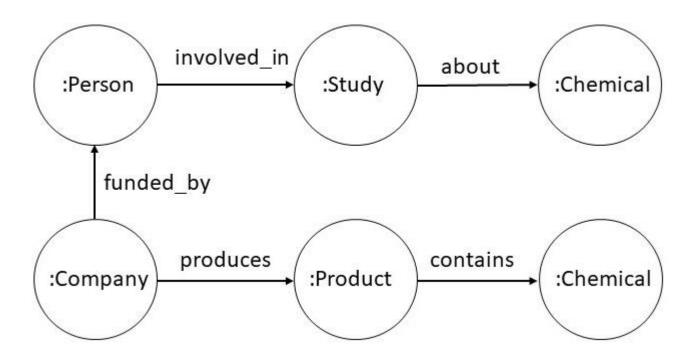
Rule-based Inference

- Boundary between taxonomic inference and rule-based inference is not sharp
 - It is generally a matter of the implementation approach
 - Taxonomic inferences can be usually implemented using rules



Rule-based inference

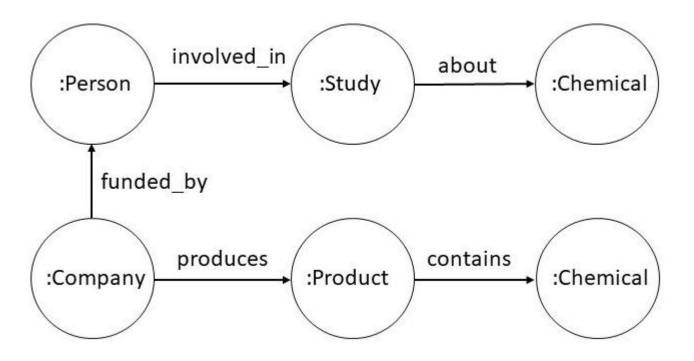
• Example Scenario





Rule-based inference

• Example Scenario



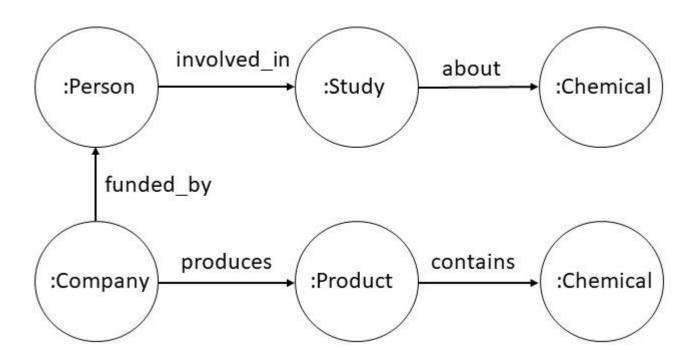
has_interest(X,Z) :- produces(X,Y) & contains(Y,Z)

```
coi(X,Y,Z) :-
involved_in(X,Y) & about(Y,P) &
funded_by(X,Z) & has_interest(Z,P)
```



Rule-based inference

• Example Scenario



```
has_interest(X,Z) :- produces(X,Y) & contains(Y,Z)
```

```
coi(X,Y,Z) :-
involved_in(X,Y) & about(Y,P) &
funded_by(X,Z) & has_interest(Z,P)
```

```
∃ c conflict_of(c,X) & conflict_reason(c,Y) & conflict_with(c,Z) :- involved_in(X,Y) & about(Y,P) & funded_by(X,Z) & has_interest(Z,P)
```



Rule-based Inference

Approaches

- Bottom up strategy (also known as Chase)
 - Apply the rules against the data, and add new facts
 - Ensure termination
 - Process queries as usual
- Top-down strategy
 - Start from the query, and apply rules as needed
 - Requires tighter integration between the rule engine and query evaluation
 - Requires lot less space

Many efficient and scalable rule engines available today



Summary

- Graph inference algorithms fall into two broad categories
 - Traditional Graph Algorithms
 - Path finding, centrality, community detection
 - Ontology-based algorithms
 - Taxonomic reasoning, Rule-based reasoning



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