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MultiRank: Reputation Ranking for Generic Semantic Social Networks

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Outline

- motivation
- the Actor-Concept-Instance model
- multi-way relationships
- propagation of ranking
- mapping to a binary-relational network
- applying PageRank
- incentive from reputation

Motivation

- success of collaborative tagging systems
- relative complexity of Web 3.0 community applications
    - need for effective incentive mechanisms
- implicit “reputation” of ranking systems
    - identify the “best” or most important users or resources

What is reputation?

- reputation is a collective measure of trustworthiness in the estimation of the community
- value of reputation:
  - prescriptive -- defines good behavior
  - descriptive -- enables ranking and classification
    - provides candidates for reuse
- implicit reputation of PageRank
  - based on the network of relationships within the community

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The Actor-Concept-Instance model

- minimal framework for semantic social networks
- tripartite model of:
  - instances -- photos, videos, web pages, etc.
  - concepts -- tags, keywords, classes, etc.
    - semantic annotation
  - actors -- human users, robots, etc.
    - add a social dimension

Multi-way relationships

- Actor-Concept-Instance model demands support for multi-way relationships
  - involves two or more elements
- e.g. annotation of an instance with a class by an actor
- no “right” way to map multi-way relations into the binary-relational domain
  - depends upon implicit qualities of the social network

Propagation of ranking

- PageRank: based on propagation of ranking in a binary-relation network

$$PR(p) = \frac{1-d}{N} + \sum_{q \in B(p)} \frac{PR(q)}{N_q}$$

- MultiRank: construct a “virtual” binary-relational network G_{prop}
  - nodes: actors, concepts, and instances
  - edges: propagate ranking from node to node
  - apply PageRank to the virtual network

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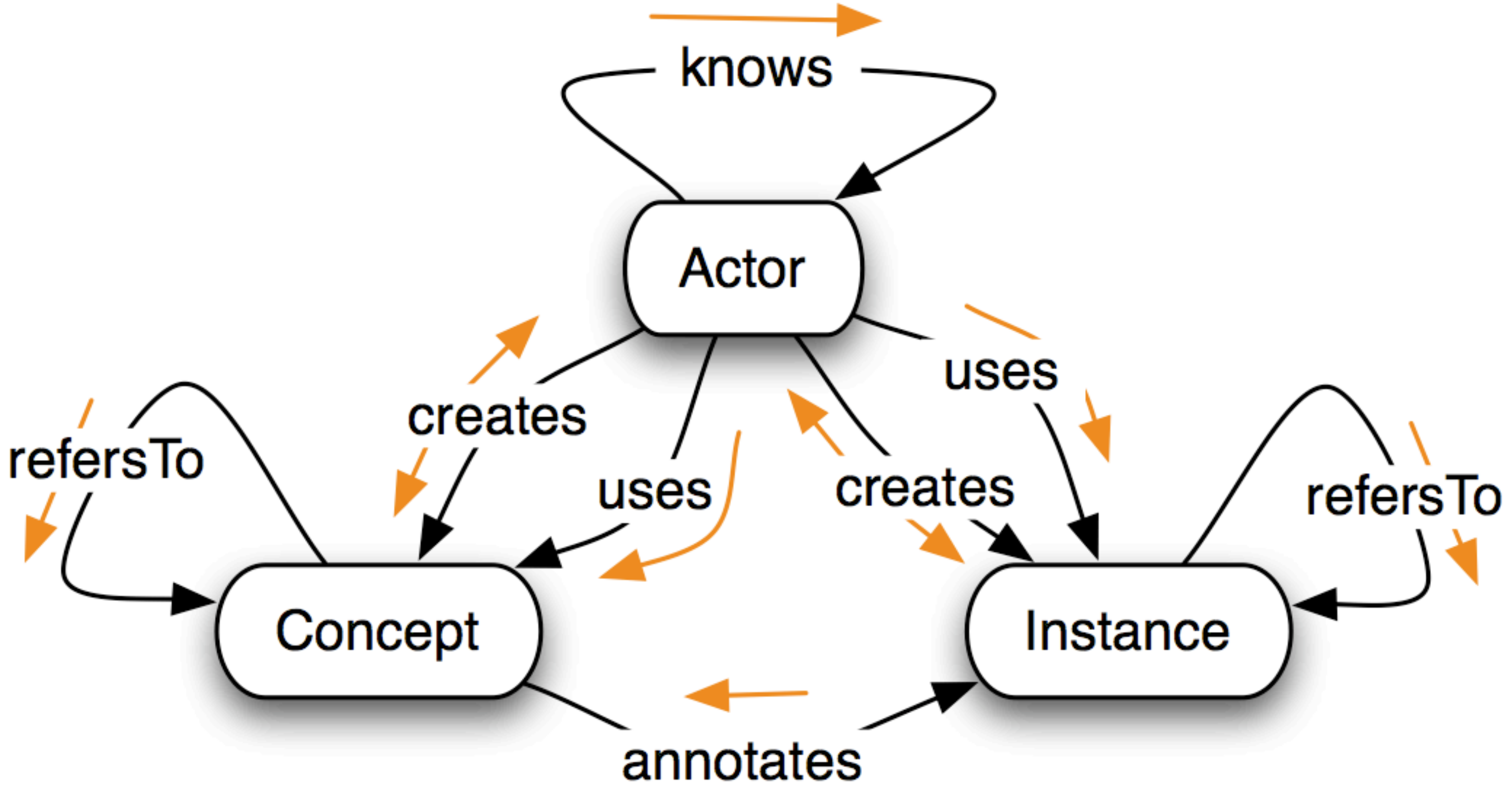
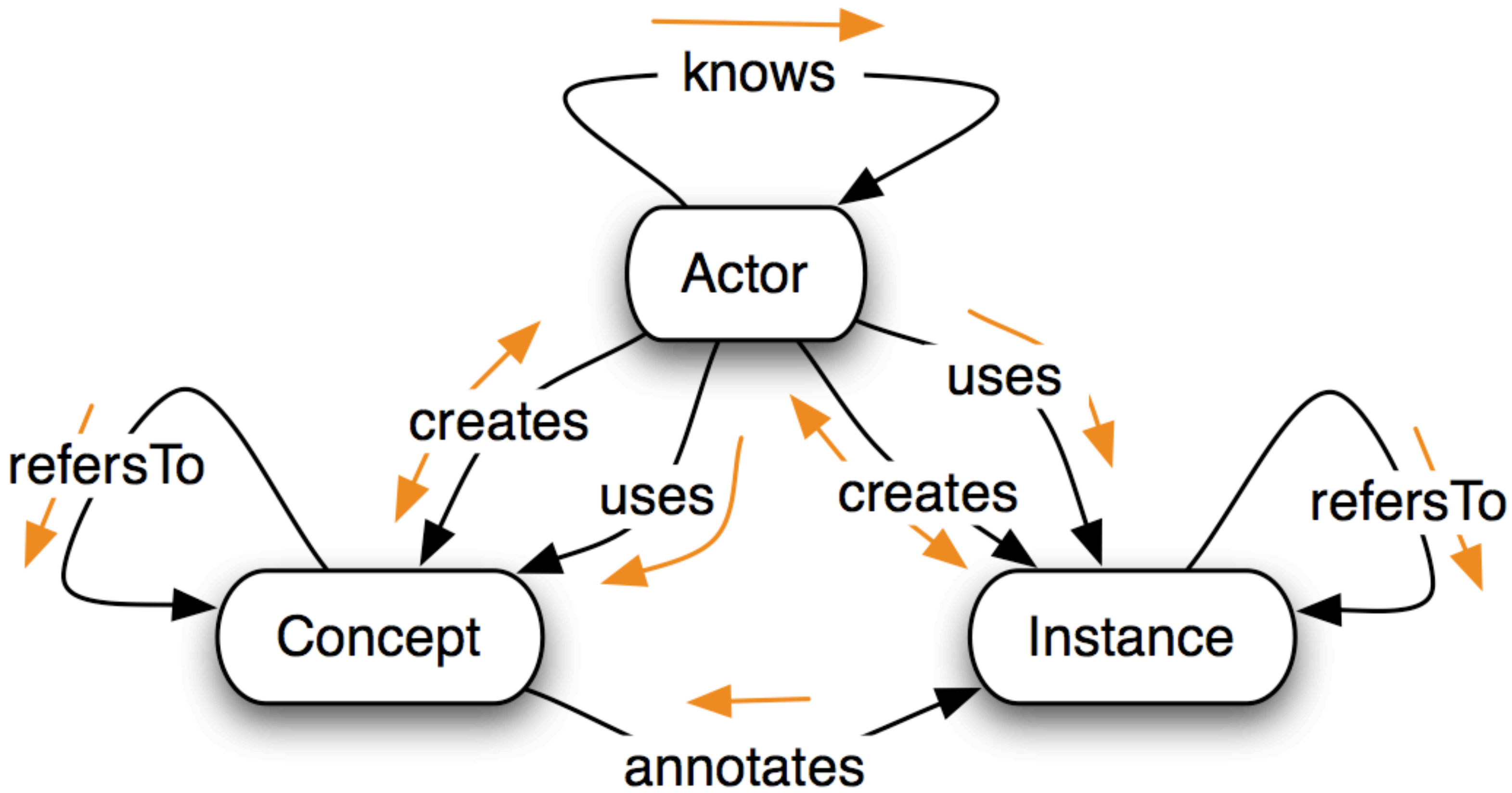
Propagation example



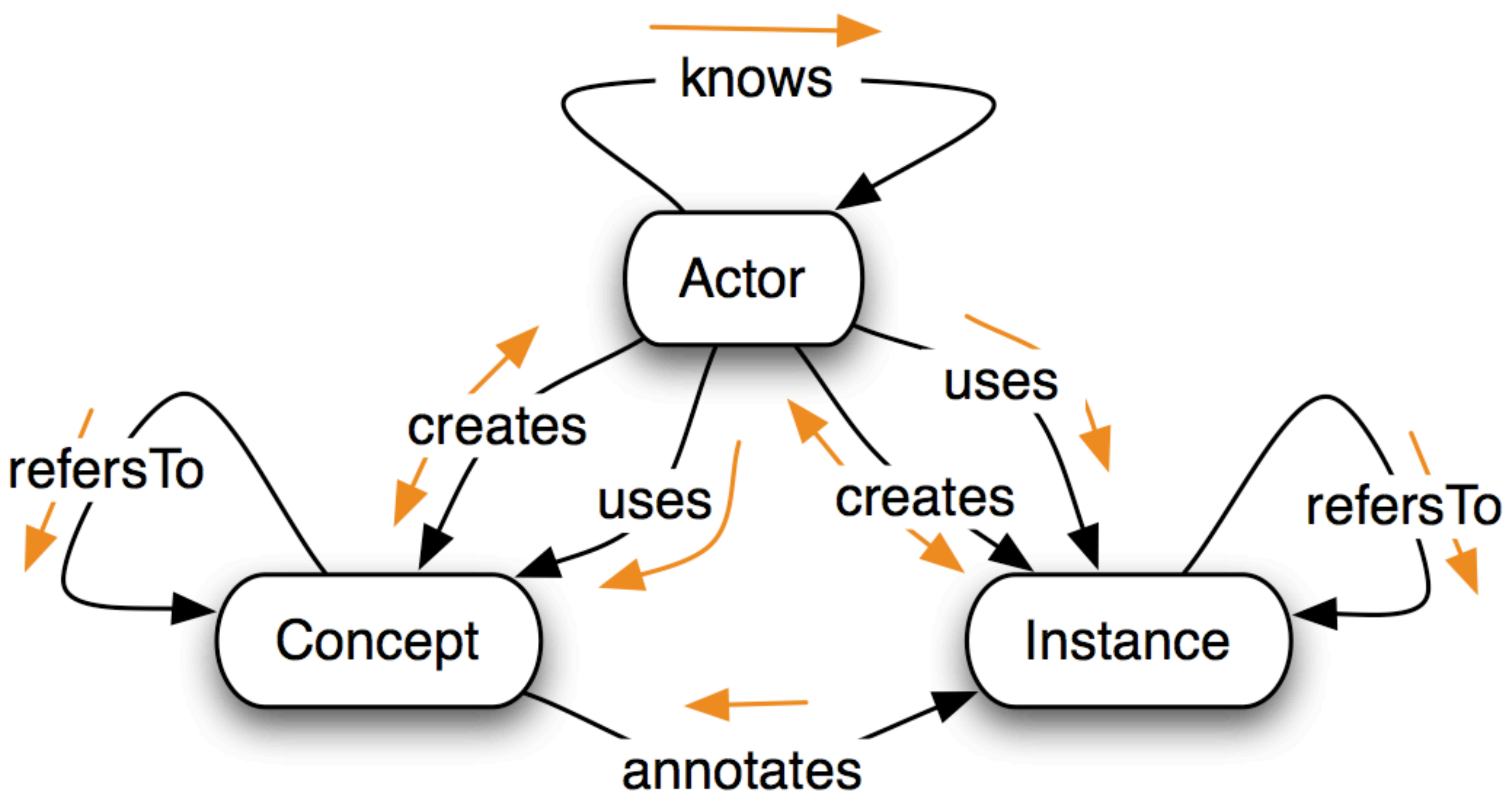
- rule #1:
  - actor a_1 knows actor a_2
  - $\Rightarrow$ a_1's reputation should propagate to a_2

Propagation example



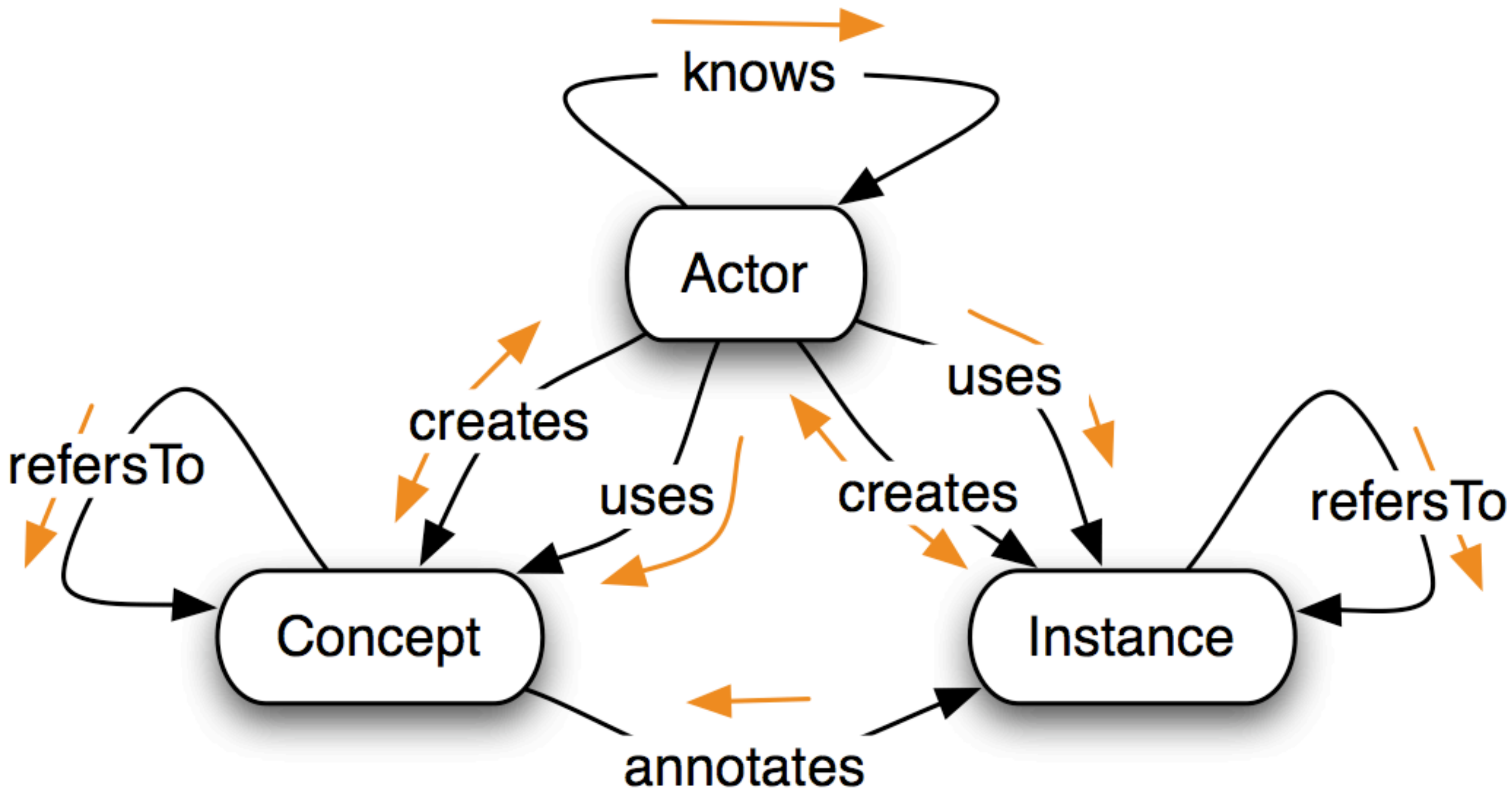
- rule #2:
  - actor a creates artifact t
  - ⇒ a's reputation should propagate to t, and vice versa

Propagation example



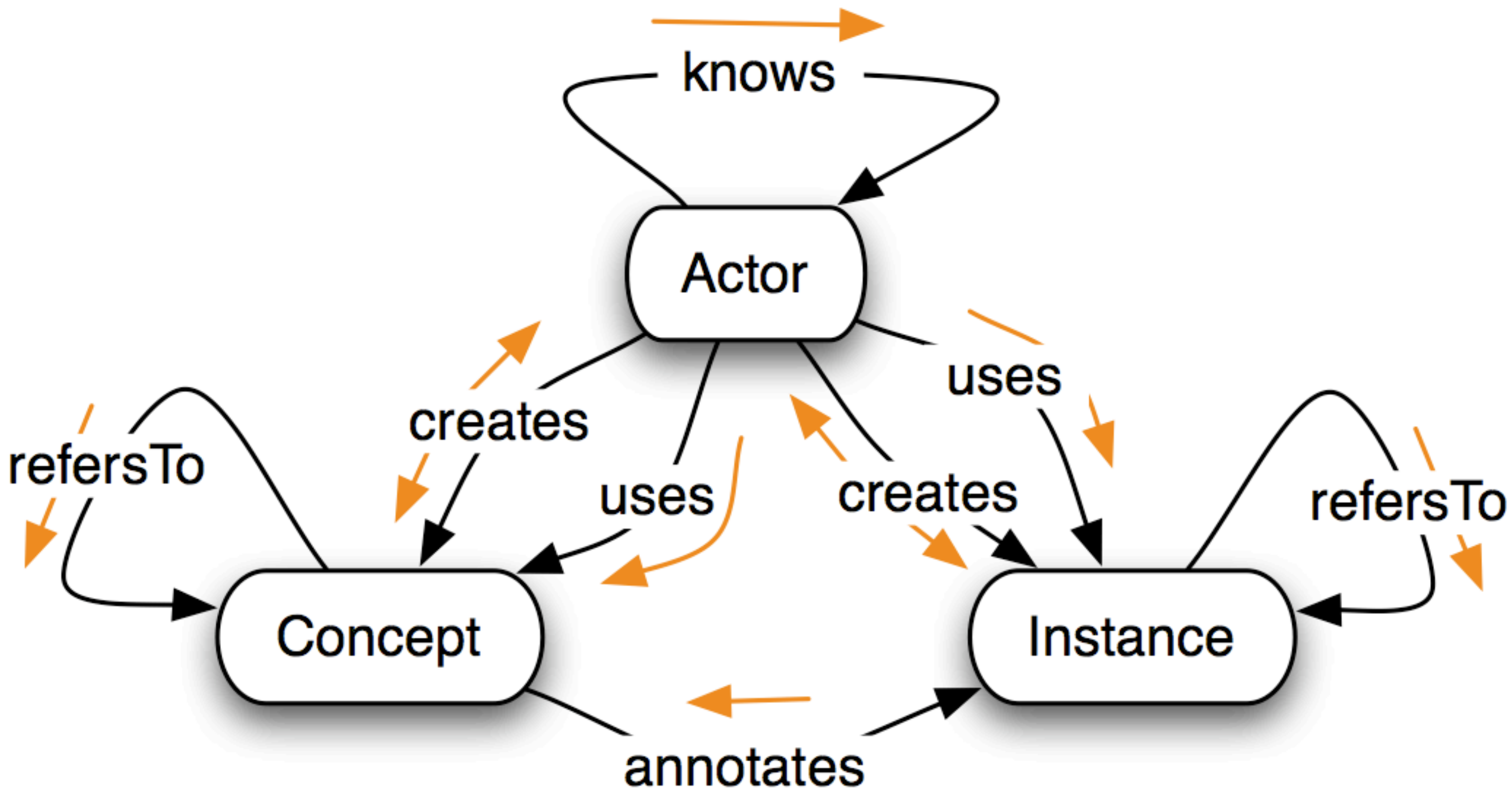
- rule #3:
  - actor a uses artifact (concept or instance) t
  - ⇒ a's reputation should propagate to t

Propagation example



- rule #4:
  - concept c annotates instance i
  - c's reputation should propagate "backwards" to i

Propagation example



- rule #5:
  - artifact t_1 refers to artifact t_2
  - $\Rightarrow$ t_1's reputation should propagate to t_2

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Mapping to a binary-relational network

- term $t \in T$
  - any object in the social network
- variable $v \in V$
  - to be replaced by a term
- binding $b \in V \times T$
  - connects a variable to a term

Propagation patterns

- relation $R \subseteq V \times V \times \mathbf{R}$
- pattern of ranking propagation in G_{prop}
- abstract weighted edges between variables
    - edge is a type of path for ranking propagation
    - weight determines extent of flow
- patterns are pre-defined by the developer for each relation

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Example propagation patterns

Relation	Variables	Propagation	Rules
actor knows actor	$\{a_1, a_2\}$	$(a_1, a_2, 0.6)$	1
actor creates concept	$\{a, c\}$	$(a, c, 0.4)$ $(c, a, 1.0)$	2
actor creates instance	$\{a, i\}$	$(a, i, 0.4)$ $(i, a, 1.0)$	2
actor uses concept to annotate instance	$\{a, c, i\}$	$(a, c, 0.2)$ $(a, i, 0.2)$ $(i, c, 0.8)$	3, 4
concept refers to concept	$\{c_1, c_2\}$	$(c_1, c_2, 0.6)$	5
instance refers to instance	$\{i_1, i_2\}$	$(i_1, i_2, 0.6)$	5

Solving for propagation patterns

- combine a relation R with a set B of bindings:

$$
\begin{aligned}
PropEdges(R, B) = \{(t_1, t_2, w) \quad : \quad & (\exists v_1, v_2 \in V, w \in \mathbb{R}) \\
& ((v_1, t_1) \in B) \\
& ((v_2, t_2) \in B) \\
& ((v_1, v_2, w) \in R)\}
\end{aligned}
$$

- replace variables in R with terms in T according to variable-to-term pairs in B
- produces a multi-set of weighted edges
  - propagates ranking among specific terms in T
- analogous to solutions to SPARQL, relational database queries

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Generating the propagation graph

- solving all relation-binding pairs yields the propagation graph:

$$G_{prop} = (T, \biguplus_{(R,B)\in S} PropEdges(R, B))$$

- G_{prop} is a weighted multigraph over the set T of terms
- set of relation-binding pairs may be drawn from:
  - a SPARQL query
  - a SQL database
  - any other source of tabular, relational data

Applying PageRank

- apply PageRank to G_{prop} by solving for $\pi \in \mathbf{R}^{|T|}$ in:

$$\pi = (1-d)E + dG'_{prop}\pi$$

- merge parallel edges by adding their weights together
- ranking result π contains the computed reputation of each term
- rank source $E \in \mathbf{R}^{|T|}$ allows personalization of ranking
  - e.g. for trust-based reputation

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Incentive from reputation

- prescriptive value of reputation as a basis for incentive mechanisms
- use ranking results in application-specific ways, e.g.
  - “top X” list of actors
  - “best of” lists of artifacts
- ranking as incentive helps to insure that:
  - top actors get the attention they deserve
  - top artifacts are re-discovered and re-used

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Related work

- Swoogle's OntoRank
  - PageRank for ontologies
- SWSE's ReConRank
  - extends semantic network with provenance information
- mapping of semantic networks to single-relational networks
- MultiRank adds support for multi-way relations

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Conclusion

- reputation ranking as incentive
- adapt PageRank for multi-way relationships
    - e.g. in Actor-Concept-Instance model of semantic social networks
- MultiRank algorithm
    - loading stage: apply patterns
    - computational stage: apply PageRank
- flow of reputation reflects a human's understanding of the network

Future work

- Java-based implementation is under development
  - uses JUNG for graph representation
- test data sets
  - Freebase event logs
- evaluation of MultiRank in a live environment

Questions?