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Discovering Graph Patterns for Fact Checking in Knowledge Graphs

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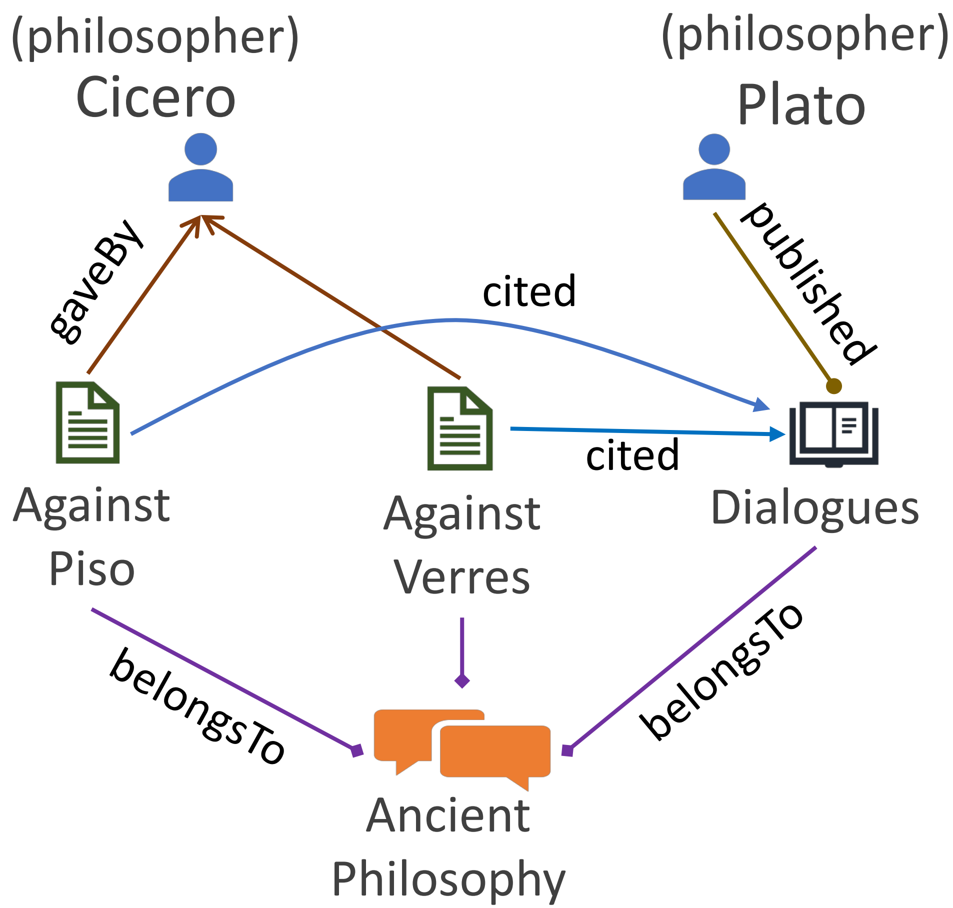
What is fact checking?

Knowledge Graph (KG): G=(V, E, L)



Fact: a triple predicate

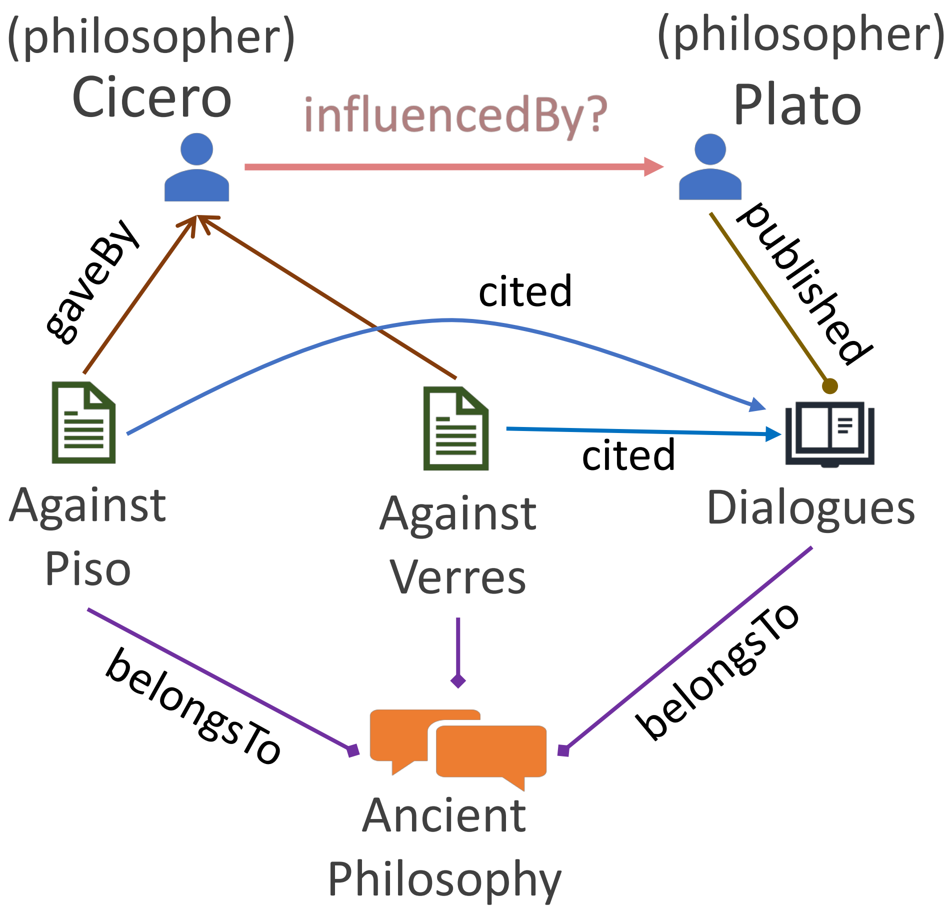
Triple $< v_x, r, v_y >$
- v_x and v_y are two nodes;
- x and y are node labels;
- r is a relationship;

e.g.,
<Cicero, influencedBy, Plato>

- v_x = "Cicero", v_y = "Plato"
- x, y = "philosopher"
- r = "influencedBy"

Fact checking answers if a fact belongs to the missing part of KG.

Fact Checking in Graphs

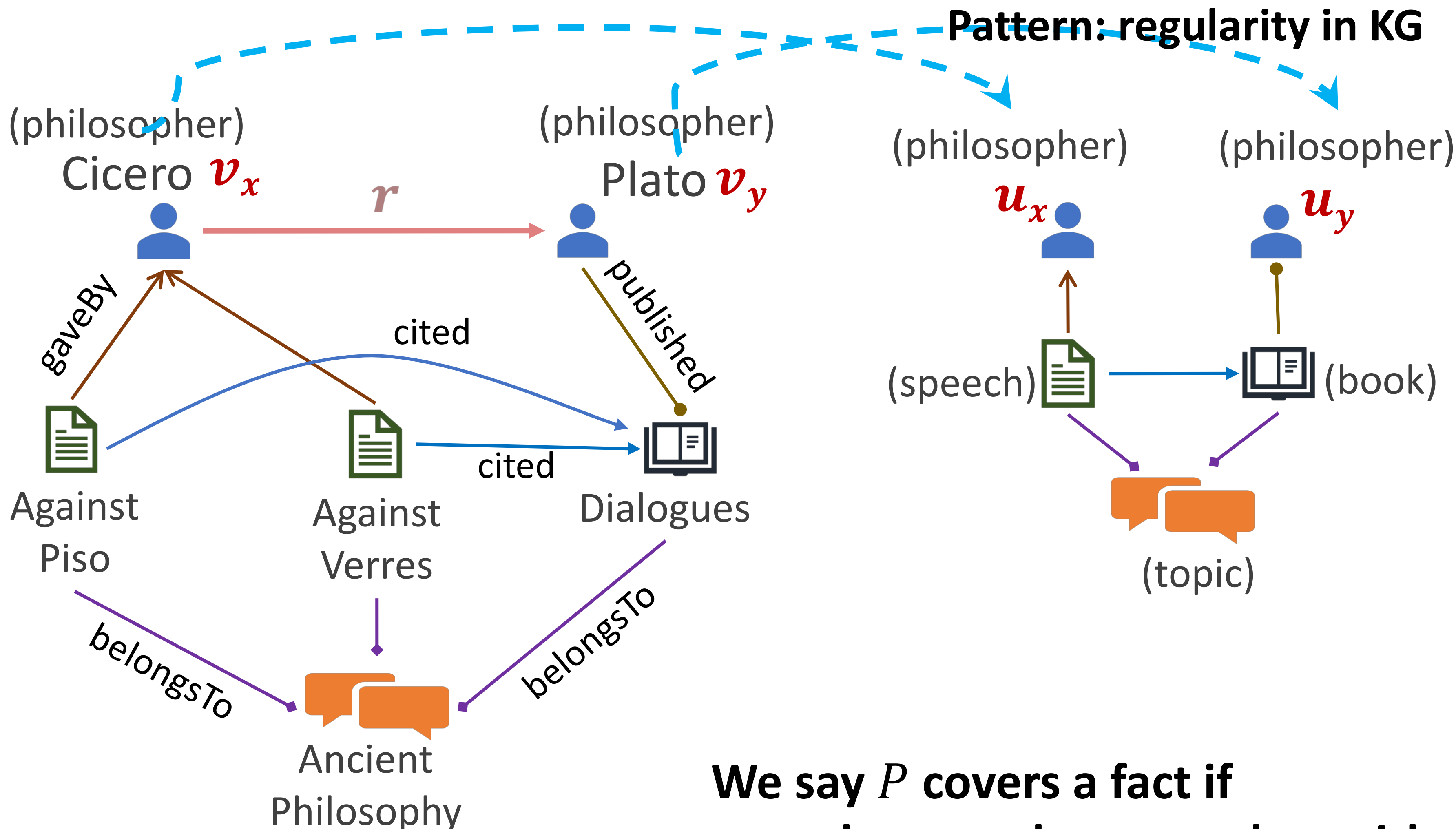


"If a philosopher **X** gave one or more speeches, which cited a book of another philosopher **Y** with the same topic, then the philosopher **X** is likely to be InfluencedBy **Y**."

A fact can be supported by its surrounded substructures!

Graph structure can be evidence for fact checking.

Fact Checking via Graph Patterns



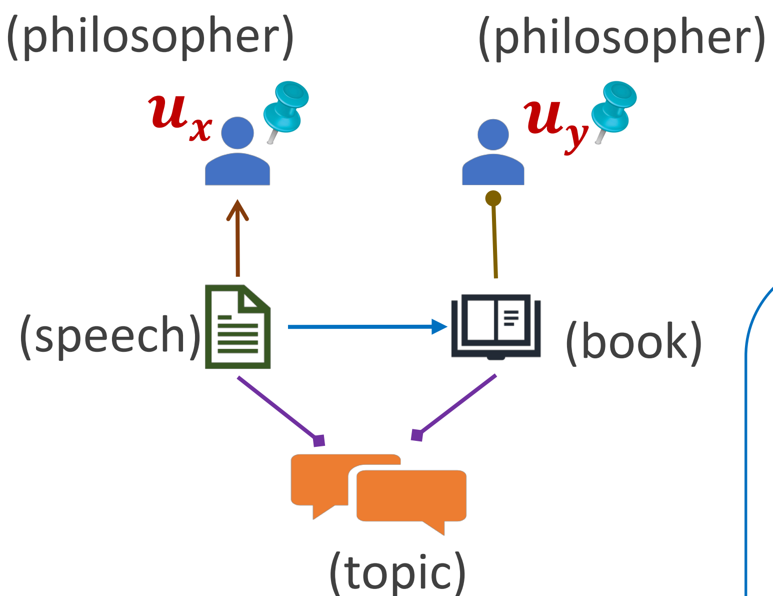
We say P covers a fact if v_x and v_y matches u_x and u_y with r.

Graph structure can be evidence for fact checking.

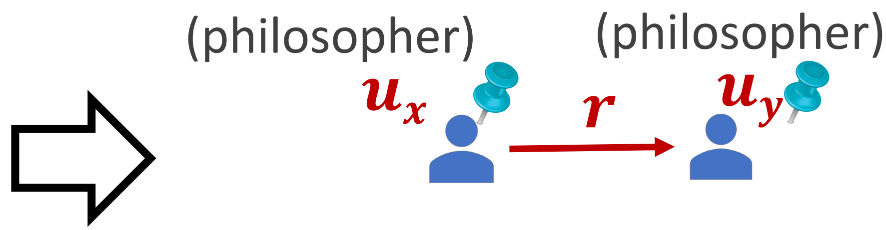
Rule Model: Graph Fact Checking Rules (GFC)

GFC $\varphi : P(x, y) \rightarrow r(x, y)$

LHS



RHS



Rule Semantics:

- GFC φ states that if pattern $P(x, y)$ covers a fact $< v_x, r, v_y >$, then it is true.

Rule matching:

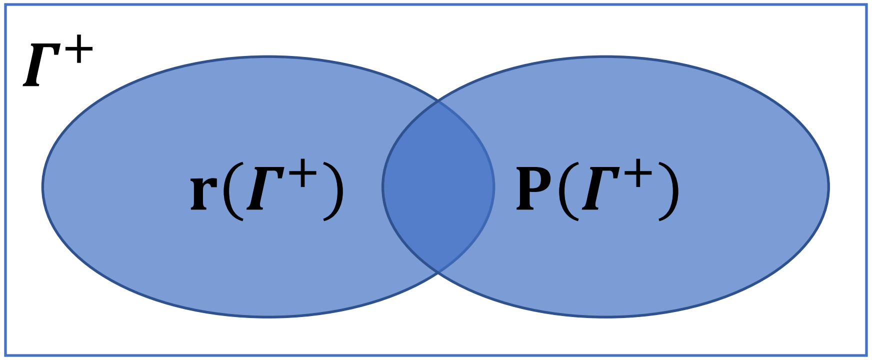
- **Subgraph isomorphism**
  overkill: redundant, too strict, too many
- **Approximate matching**
  (S. Ma, VLDB 2011)

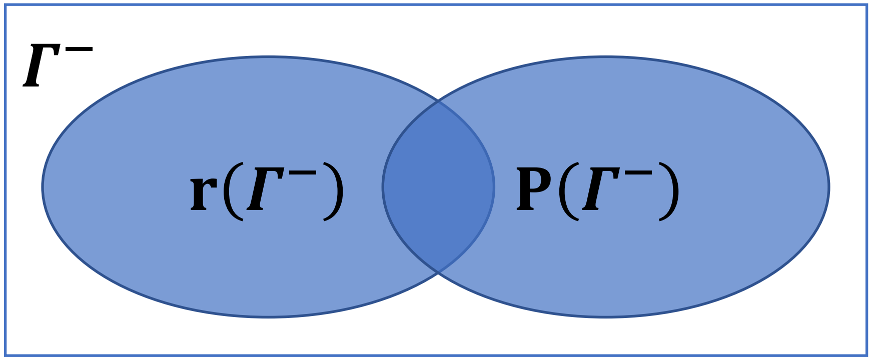
A GFC rule contains two patterns connected by two anchored nodes.

Rule Statistics

- Given: $\mathrm{G} = (\mathrm{V}, \mathrm{E}, \mathrm{L})$
- **GFC** $\varphi : P(x, y) \rightarrow r(x, y)$

- True facts Γ^{+}:
  - sampled from the edges E in G.
- False facts Γ^{-}:
  - sampled from node pairs (v_x, v_y) that have no r between them.
  - following partial closed world assumption (**PCA**)





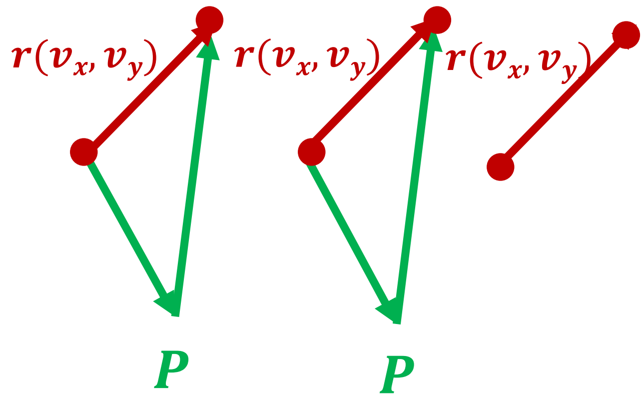
Statistical measures are defined in terms of graph and a set of training facts.

Support and Confidence

GFC: $\varphi : P(x, y) \rightarrow r(x, y)$

- $\text{supp}(\varphi) = \frac{|P(\Gamma^+) \cap r(\Gamma^+)|}{|r(\Gamma^+)|}$

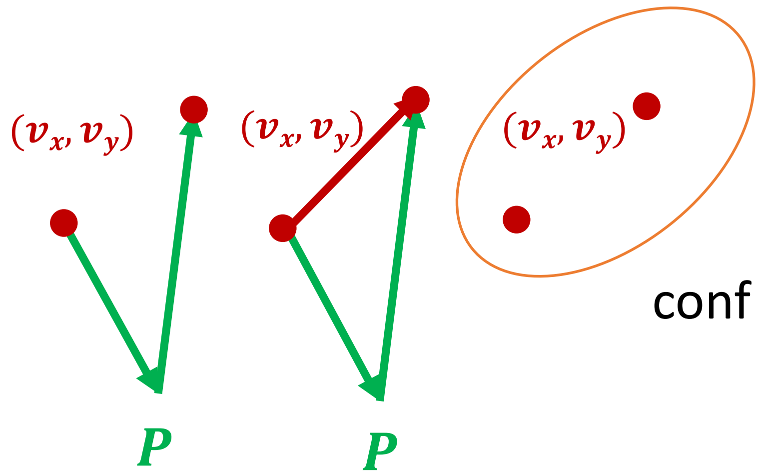
Ratio of facts can be covered out of r(x, y) triples.



supp = 2/3

- $\text{conf}(\varphi) = \frac{|P(\Gamma^+) \cap r(\Gamma^+)|}{|P(\Gamma^+)_N|}$

Ratio of facts can be covered out of (x, y) pairs, under **PCA**.



conf = 1/2

Support and confidence are for pattern mining.

Significance

GFC: $\varphi : P(x, y) \rightarrow r(x, y)$

G-Test score

$$\mathrm{sig}(\varphi, p, n) = 2|\Gamma^{+}|(p \ln \frac{p}{n} + (1 - p) \ln \frac{1 - p}{1 - n})$$

p and n are the supports of $P(x, y)$ for positive and negative facts, respectively.

A "rounded up" score $\max\{\mathrm{sig}(\varphi, p, \delta), \mathrm{sig}(\varphi, \delta, n)\}$ is used in practice.
where δ is a small positive to prevent infinities.

In our work, we also normalize it between 0 and 1 by a sigmoid function.

Significance is the ability to distinguish true and false facts.

Diversity

$\boldsymbol{S}$ is a set of GFCs.

$$\mathrm{div}(\boldsymbol{S}) = \frac{1}{|\Gamma^+|}\sum\nolimits_{t\in\Gamma^+}\sqrt{\sum\nolimits_{\varphi\,\in\,\Phi_t(\boldsymbol{S})}\mathrm{supp}(\varphi)}$$

$\Phi_t(S)$ is the GFCs in S that cover a true fact t.

E.g. $\boldsymbol{S}_1 = \{\boldsymbol{P}_1, \boldsymbol{P}_2, \boldsymbol{P}_3\}, \boldsymbol{S}_2 = \{\boldsymbol{P}_4, \boldsymbol{P}_5, \boldsymbol{P}_6\}$

	$\boldsymbol{r(vx,vy)_1}$	$\boldsymbol{r(vx,vy)_2}$	$\boldsymbol{r(vx,vy)}$
$\boldsymbol{P}_1$	✓	✓	
$\boldsymbol{P}_2$		✓	✓
$\boldsymbol{P}_3$	✓		✓

	$\boldsymbol{r(vx,vy)_1}$	$\boldsymbol{r(vx,vy)_2}$	$\boldsymbol{r(vx,vy)}$
$\boldsymbol{P}_4$		✓	✓
$\boldsymbol{P}_5$		✓	✓
$\boldsymbol{P}_6$		✓	✓

$\mathrm{div}(\boldsymbol{S}_1)$ = 2 **>** $\mathrm{div}(\boldsymbol{S}_2)$ = 1.6

Diversity is to measure the redundancy of a set of GFCs

Top-$\boldsymbol{k}$ GFC Discovery Problem

To cope with diversity, the total significance $\mathrm{sig}(\boldsymbol{S}) = \sqrt{\sum_{\varphi \in \boldsymbol{S}} \mathrm{sig}(\varphi)}$.

Coverage function: $\mathrm{cov}(\boldsymbol{S}) = \mathrm{sig}(\boldsymbol{S}) + \mathrm{div}(\boldsymbol{S})$

Problem formulation:
Given graph G, support threshold σ and confidence threshold θ, and a set of true facts Γ^+ and a set of false facts Γ^-, and integer k, identify a size-k set of GFCs $\boldsymbol{S}$,
such that:
(a) For each GFC φ in $\boldsymbol{S}$, $\mathrm{supp}(\varphi) \geq \sigma, \mathrm{conf}(\varphi) \geq \theta$.
(b) $\mathrm{cov}(\boldsymbol{S})$ is maximized.

More significance, less redundancy.

Properties of $\mathrm{cov}(\boldsymbol{S})$

- $\mathrm{cov}(\boldsymbol{S})$ is a set function.

  marginal gain: $\mathrm{mg}(\boldsymbol{S}) = \mathrm{cov}(\boldsymbol{S} \cup \{\varphi\}) - \mathrm{cov}(\boldsymbol{S})$

- $\mathrm{cov}(\boldsymbol{S})$ is monotone.

  Adding elements to $\boldsymbol{S}$ does not decrease $\mathrm{cov}(\boldsymbol{S})$.

- $\mathrm{cov}(\boldsymbol{S})$ is submodular.

  If $\boldsymbol{S}_1 \subseteq \boldsymbol{S}_2$ and $\varphi \notin \boldsymbol{S}_2$, then $\mathrm{mg}(\boldsymbol{S}_2) \leq \mathrm{mg}(\boldsymbol{S}_1)$.

Submodularity is a good property for set optimization problem.

Discovery Algorithms

- OPT = $\max\{\mathrm{cov}(\boldsymbol{S})\}$
  - Cannot afford to enumerate every size-k set of GFCs.
  - $\mathrm{cov}(\boldsymbol{S})$ is a monotone submodular function.
  - A greedy algorithm can have $(1-\frac{1}{e})$ approximation of OPT.

- **GFC_batch:**

```
1.  Mine all the patterns satisfying support and confidence.
2.  S = ∅
3.  While |S| < k, do
4.    Select the pattern P with the largest marginal gain.
```

GFC_batch: mining in batch and selecting greedily

Discovery Algorithms

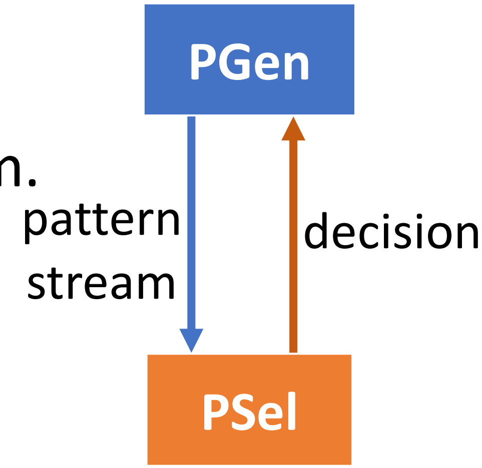
- GFC_batch is infeasible and slow.
  - Still, it requires mine all patterns first.
  - Can we do better?

- **GFC_stream**:
  - Interleave pattern generation and rule selection.
  - Find the top-k GFCs *on-the-fly*.
  - One pass of pattern mining.
  - $(\frac{1}{2} - \epsilon)$ approximation of OPT

GFC_stream: mining and selecting *on-the-fly!*

Discovery Algorithms

- **PGen: pattern generation**
  - Generates patterns *in a **stream** way.*
  - Pass the patterns for selection
  - Can be in any order, e.g., Apriori, DFS, or random.



- **PSel: pattern selection**
  - Selects and constructs GFCs *on-the-fly.*
  - Based on a "sieve" strategy, $\left(\frac{1}{2} - \epsilon\right) \mathrm{OPT}$

Fast compute!

```
1. Estimate the range of OPT by max{cov(P)}
2. Each one is a size-k sieve with an estimation m for OPT.
3. While the sieves are not full
4.      if mg(P,S) ≥ (m/2 − cov(S))/(k − |S|), add P to sieve S.
5. Signal PGen to stop and output the sieve with largest cov.
```

GFC_stream: mining and selecting *on-the-fly!*

GFC-based fact checking

- **GFact$_R$: Using GFCs as rules:**
  - Invokes GFC_stream to find top-k GFCs.
  - "Hit and miss"
    - True if a fact is covered by one GFC.
    - False If no GFC can cover the fact.
  - A typical rule model to compare with: AMIE+

- **GFact: Using GFCs in supervised link prediction:**
  - A feature vector of size k.
  - Each entry encodes the presence of one GFC.
  - Build a classifier, by default, Logistic Regression.
  - A typical rule models to compare with: PRA

Experiment settings

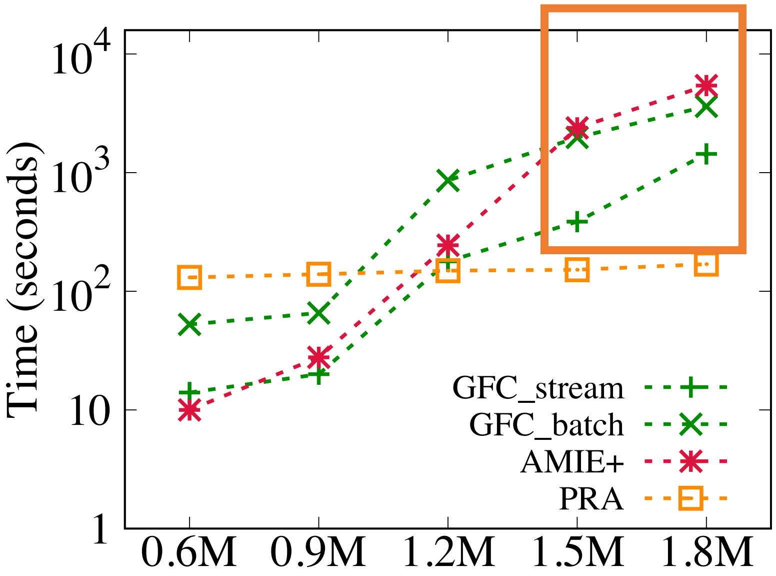
Dataset	category	|V|	|E|	# node labels	# edge labels	# $< x, r, y >$
Yago	Knowledge base	2.1 M	4.0 M	2273	33	15.5 K
DBpedia	Knowledge base	2.2 M	7.4 M	73	584	8240
Wikidata	Knowledge base	10.8 M	41.4 M	18383	693	209 K
MAG	Academic network	0.6 M	1.71 M	8665	6	11742
Offshore	Social network	1.0 M	3.3 M	356	274	633

Tasks	Rule Mining	Fact Checking
Our methods	**GFC_batch**, **GFC_stream**	**GFact**, **GFact$_R$**
Baselines	AMIE+, PRA	AMIE+, PRA, KGMiner
Evaluation Metrics	running time vs. $\|E\|, \|\Gamma^+\|$	prediction rate, precision, recall, F1

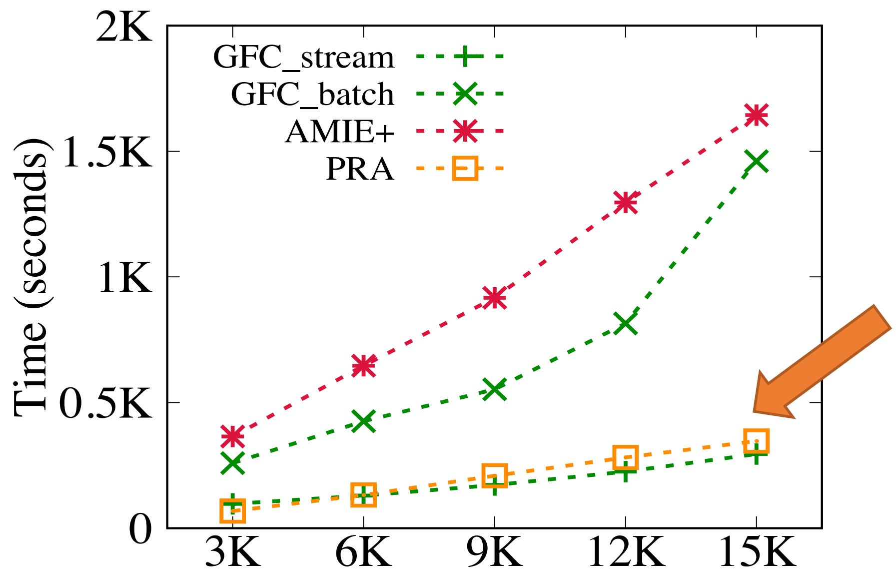
Experiment: efficiency

Overview

- GFC_stream takes 25.7 seconds to discover 200 GFCs over Wikidata with 41.4 million edges and 6000 training facts.
- On average, GFC_stream is 3.2 times faster than AMIE+ over DBpedia.



Varying $|E|$ (DBPedia)

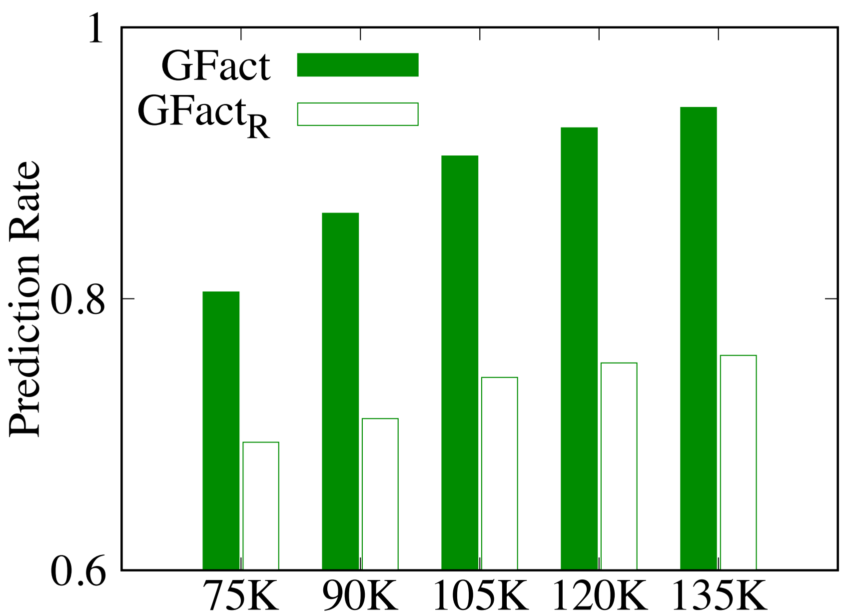


Varying $|\Gamma^+|$ (DBpedia)

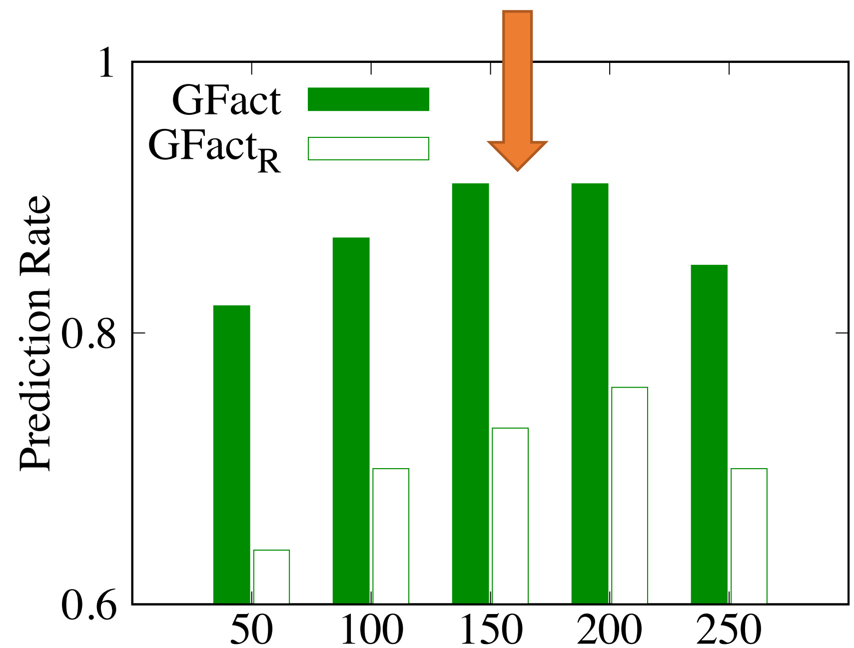
Experiment: effectiveness

Compared with AMIE+, PRA and KGMiner, respectively, on average:

- GFact achieves additional 30%, 20%, and 5% gains of precision over DBpedia.
- GFact achieves additional 20%, 15%, and 16% gains of F1-score over Wikidata.



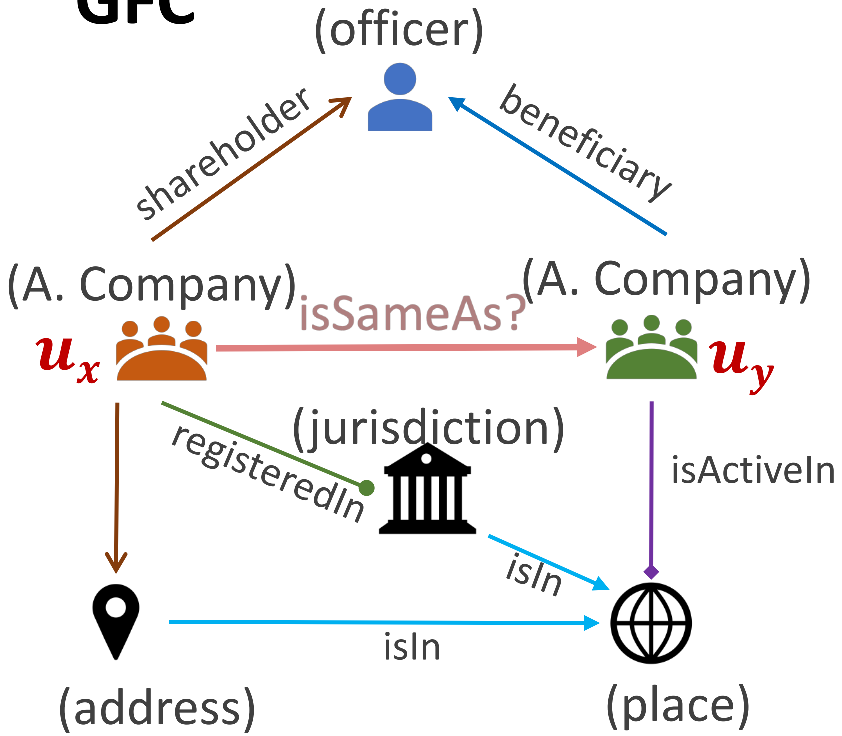
Varying $|\Gamma^+|$ (Wikidata)



Varying k (Wikidata)

Case study: are two anonymous companies same? (Offshore)

GFC



- If an officer is both a shareholder of company u_x and a beneficiary of company u_y, and u_x has an address and is registered through a jurisdiction in a place, and u_y is active in the same place, then they are likely to be the same anonymous company.

AMIE+

- If two anonymous companies are registered in the same place, then they are same.
- Low accuracy.

Conclusions and future work

- *Graph Fact Checking Rules* (GFCs)
- *Top-k GFCs discovery problem*

  Maximize a submodular cov *function.*
- A stream-based rule discovery algorithm
  - One pass, $\left(\frac{1}{2} - \epsilon\right)$ OPT
- Evaluation of GFCs-based techniques
  - Rule models, fact checking (2 methods), efficiency, and case studies.
- Our future work: scalable GFC-based methods
  - Parallel mining, Distributed learning

Sponsored by:

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Thank you!

Related work: Gstream (IEEE BigData 2017)
Event Pattern Discovery by Keywords in Graph Streams
Mohammad Hossein Namaki, Peng Lin, Yinghui Wu
https://ieeexplore.ieee.org/abstract/document/8258019/