Unsupervised Discovery of Corroborative Paths for Fact Validation

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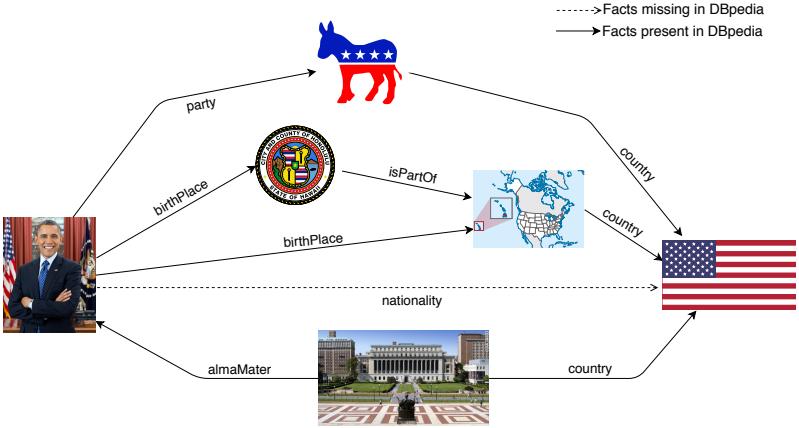
Facts missing in DBpedia
Facts present in DBpedia
party
birthPlace
isPartOf
country
country
birthPlace
nationality
almaMater
country

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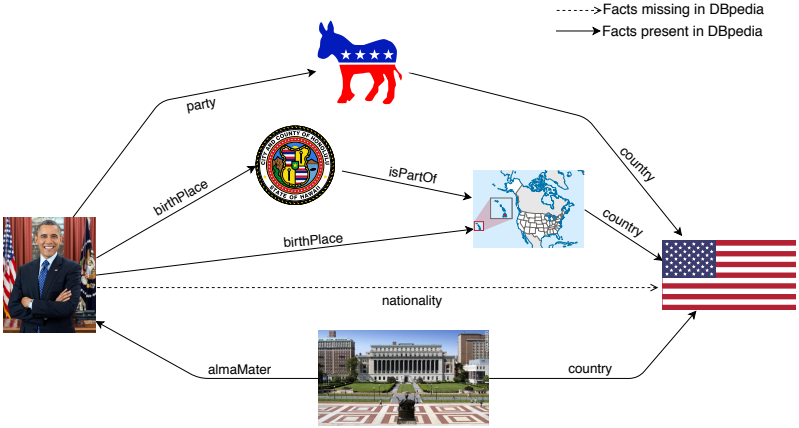

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- **Knowledge graph:** An RDF knowledge graph $\mathcal{G}$ is a set of RDF triples, i.e.,

$$\mathcal{G} = \{(s, p, o) | s \in \mathbb{E} \cup \mathbb{B}, p \in \mathbb{P}, o \in \mathbb{E} \cup \mathbb{B} \cup \mathbb{L}\}$$

Directed path: $\pi^k(v_0, v_k) \rightarrow (v_0, p_1, v_1), (v_1, p_2, v_2), ..., (v_{k-1}, p_k, v_k)$

- $\forall i \in [0, k-1]\ (v_i, p_{i+1}, v_{i+1}) \in \mathcal{G}$
- $\forall i, j \in [0, k], i \neq j \rightarrow v_i \neq v_j$

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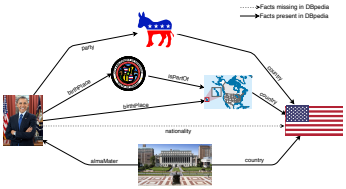
Undirected path: $\mu^k(v_0, v_k) \rightarrow (v_0, p_1, v_1), (v_1, p_2, v_2), ..., (v_{k-1}, p_k, v_k)$

- $\forall i \in [0, k-1]\ (v_i, p_{i+1}, v_{i+1}) \in \mathcal{G} \vee (v_{i+1}, p_{i+1}, v_i) \in \mathcal{G}$
- $\forall i, j \in [0, k], i \neq j \rightarrow v_i \neq v_j$



Example (Directed path)

Directed path: BarackObama $\xrightarrow{\texttt{birthPlace}}$ Hawaii $\xrightarrow{\texttt{country}}$ USA

Example (Undirected path)

Undirected path: BarackObama $\xleftarrow{\texttt{alumni}}$ GreenwichHighSchool $\xrightarrow{\texttt{country}}$ USA

- **Typed path:** Given set of types t_x and t_y, typed paths are given by

$$\Pi^k_{(t_x,t_y)} = \{\pi^k(v_0, v_k) \mid \gamma(v_0) \sqsubseteq t_x \wedge \gamma(v_k) \sqsubseteq t_y\}$$

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Example (Typed path)

$t_x = \{\texttt{Person}\}$, $t_y = \{\texttt{Place}\}$

$$\Pi^2_{(t_x,t_y)} : \texttt{BarackObama} \xrightarrow{\texttt{party}} \texttt{DemocraticParty} \xrightarrow{\texttt{country}} \texttt{USA}$$

- **$\vec{q}$-restricted typed path:** $\vec{q} = q_1, \ldots, q_k$

$$\Pi^k_{(t_x,t_y),\vec{q}} = \{\pi^k(v_0, v_k) \mid \pi^k(v_0, v_k) \in \Pi^k_{(t_x,t_y)}, \\ \forall i \in [0, k-1] : (v_i, p_{i+1}, v_{i+1}) \in \pi^k(v_0, v_k) \rightarrow p_{i+1} = q_{i+1}\}$$

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Example ($\vec{q}$-restricted typed path)

$t_x = \{\texttt{Person}\}$ and $t_y = \{\texttt{Place}\}$ and $\vec{q} = (\ \texttt{birthPlace}, \texttt{country})$,

$$\Pi^2_{(t_x,t_y)} : \texttt{BarackObama} \xrightarrow{\texttt{birthPlace}} \texttt{Hawaii} \xrightarrow{\texttt{country}} \texttt{USA}$$

- Given $t = (s, p, o)$: *Only typed paths in* $\Pi^k_{(D(p),R(p)),\vec{q}}$ *can corroborate facts with the predicate* p

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- *Corroborative paths* for a predicate p

$$\Pi^k(p) = \bigcup_{j=1}^{k} \Pi^j_{(D(p),R(p)),\vec{q}}$$

- Association strength: NPMI [3]

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$$\text{NPMI}(\Pi^{j}_{(t_x,t_y),\vec{q}}, p) = \frac{\log\left(\frac{\mathcal{P}\left(\Pi^{j}_{(t_x,t_y),\vec{q}},p\right)}{\mathcal{P}\left(\Pi^{j}_{(t_x,t_y)}\right)\cdot\mathcal{P}(p)}\right)}{-\log\left(\mathcal{P}\left(\Pi^{j}_{(t_x,t_y),\vec{q}},p\right)\right)}$$

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- Approximation to NPMI

$$\widehat{\text{NPMI}}(\Pi^j_{(t_x,t_y),\vec{q}}, p) = \frac{\log\left(\frac{\widehat{\mathcal{P}}\left(\Pi^j_{(t_x,t_y),\vec{q}},p\right)}{\widehat{\mathcal{P}}\left(\Pi^j_{(t_x,t_y)}\right)\cdot\mathcal{P}(p)}\right)}{-\log\left(\widehat{\mathcal{P}}\left(\Pi^j_{(t_x,t_y),\vec{q}}, p\right)\right)}$$

$$\widehat{\mathcal{P}}(\Pi^j_{(t_x,t_y),\vec{q}}) = \frac{|\Pi^j_{(t_x,t_y),\vec{q}}|}{|\lambda(t_x)|\cdot|\lambda(t_y)|}$$

$$\widehat{\mathcal{P}}(\Pi^j_{(t_x,t_y),\vec{q}}, p) = \frac{|\{\pi^j(a,b) \in \Pi^j_{(t_x,t_y),\vec{q}} : (a,p,b) \in \mathcal{G}\}|}{|\lambda(t_x)|\cdot|\lambda(t_y)|}$$

$$\mathcal{P}(p) = \frac{|\{(a,p,b) : \gamma(x) \sqsubseteq t_x \wedge \gamma(y) \sqsubseteq t_y \wedge (a,p,b) \in \mathcal{G}\}|}{|\lambda(t_x)|\cdot|\lambda(t_y)|}$$

- Calculate association strength for each path
  - $\forall \Pi^j_{(t_x,t_y),\vec{q}} \in \Pi^k(p)$, calculate $\widehat{\mathcal{P}}(\Pi^j_{(t_x,t_y),\vec{q}})$, $\widehat{\mathcal{P}}(\Pi^j_{(t_x,t_y),\vec{q}}, p)$ and $\mathcal{P}(p)$
  - $\forall \Pi^j_{(t_x,t_y),\vec{q}} \in \Pi^k(p)$ calculate $\widehat{\mathrm{NPMI}}(\Pi^j_{(t_x,t_y),\vec{q}}, p)$

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  - $\forall \Pi^j_{(t_x,t_y),\vec{q}} \in \Pi^k(p)$ calculate $\widehat{\text{NPMI}}(\Pi^j_{(t_x,t_y),\vec{q}}, p)$
- Veracity calculation

$$Ver(p) = 1 - \prod_{\Pi^j_{(t_x,t_y),\vec{q}} \in \Pi^k(p)} \left(1 - \widehat{\text{NPMI}}(\Pi^j_{(t_x,t_y),\vec{q}}, p)\right).$$

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Competing approaches

- **Knowledge Stream (KS):** Maximum information flow between paths [1]
- **Relational Knowledge Linker (KL-REL):** Information flow via single best path [1]
- **PredPath:** Supervised approach for learning discriminative paths [4]

- **Real-World:** Extracted from GREC and WSDM'17 challenge
- **Synthetic:** Facts from the domains of entertainment, sports etc.
- **FactBench-DBpedia:** Facts pertaining to DBpedia extracted from **FactBench** [5]

Dataset	*FactBench-DBpedia*						*Real-World*				*Synthetic*						
Subset	Domain	Domain-Range	Range	Mix	Property	Random	Birth-Place	Death-Place	Education	Nationality	US-CAP	NBA-Team	Oscars	CEO	US-WAR	US-VP	FLOTUS
Positive	1,124	1,124	1,124	1,124	1,124	1,124	273	126	466	50	50	41	78	201	126	47	16
Negative	1,119	1,006	1,123	1,014	1,153	511	819	378	1,395	150	250	123	4,602	1,007	584	227	240
Total	2,243	2,130	2,247	2,138	2,277	1,635	1,092	504	1,861	200	300	164	4,680	1,208	710	274	256

- Results of COPAAL using directed and undirected paths

	Domain	**Domain-Range**	**Range**	**Mix**	**Random**	**Property**
Undirected Paths	**0.9348**	**0.9389**	**0.8937**	**0.8561**	**0.9411**	**0.7307**
Directed Paths	0.7741	0.7824	0.7416	0.5914	0.6411	0.4713

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- Directed paths limit the evidences

- Results comparison of COPAAL against other approaches

	Birth Place	**Death Place**	**Education**	**Nationality**
COPAAL	**0.9441**	0.8997	**0.8731**	**0.9831**
PredPath	0.8997	0.8054	0.8644	0.9520
KL-REL	0.9254	**0.9095**	0.8547	0.9692
KS	0.7197	0.8002	0.8651	0.9789

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- PredPath is limited to handle specificity of path w.r.t predicate in question
- KL-REL is limited to single best path

- Comparison of all approaches on the balanced dataset

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COPAAL	**0.9348**	0.9389	**0.8561**	**0.7307**	**0.9411**	0.8937
PredPath	0.9301	**0.9447**	0.8408	0.7154	0.9354	**0.8992**
KL-REL	0.8453	0.8619	0.7721	0.6154	0.8547	0.8219
KS	0.8019	0.8124	0.7215	0.6047	0.7911	0.8047

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- Ontological information is important indeed

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Limitations:

- Existence of ontological information
- Limited to evidences found in one RDF graph

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References

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