HEINZ NIXDORF INSTITUT
UNIVERSITÄT PADERBORN

No Need to Be a Know-It-All: Fact Checking with Shallow Knowledge

Umair Qudus, Neha Pokharel, Michael Röder, and Axel-Cyrille Ngonga Ngomo

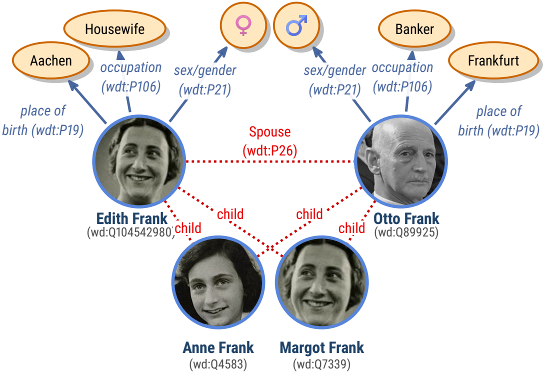
DICE

Data Science Group
Paderborn University

May 13, 2026

Introduction

Motivation



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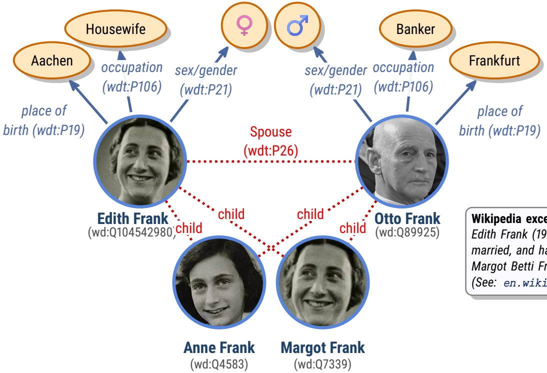

Wikipedia excerpt:
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(See: `en.wikipedia.org/wiki/Edith_Frank`)

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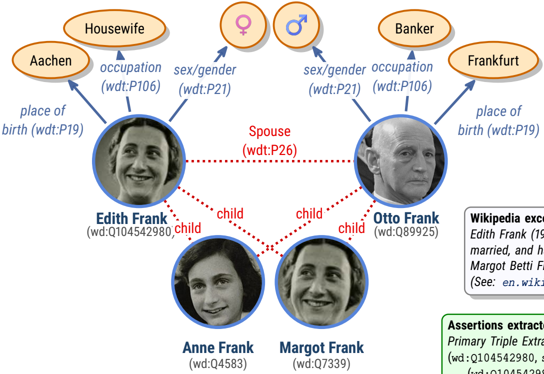

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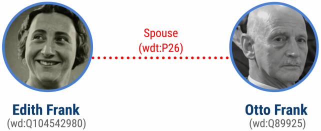
Assertions extracted by ShallKnow:
Primary Triple Extraction:
(wd:Q104542980, spouse (wdt:P26), wd:Q89925)
(wd:Q104542980, child (wdt:P40), wd:Q4583)
(wd:Q104542980, child (wdt:P40), wd:Q7339)
(wd:Q89925, child (wdt:P40), wd:Q4583)
(wd:Q89925, child (wdt:P40), wd:Q7339)

Secondary Triple Extraction:
(only triggered if the previous step extracted less than θ assertions)
(wd:Q4583, :P-born-in, wd:Q1794)
(wd:Q104542980, :P-married-to, wd:Q89925)...

Introduction

Families of approaches & limitations



- Given: Knowledge graph $\mathbb{G}$ and assertion $t = (s, p, o)$
- Goal: Compute $P(t)$

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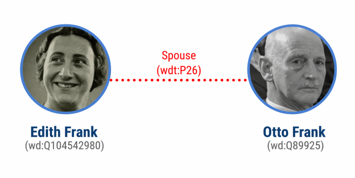

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Families	Key Limitation

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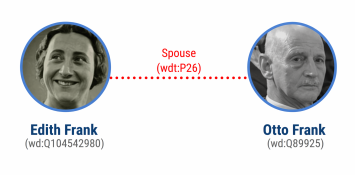

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Families		Key Limitation
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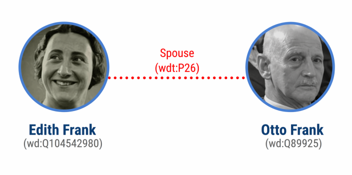

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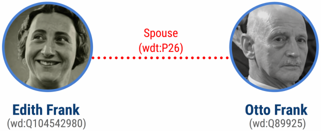

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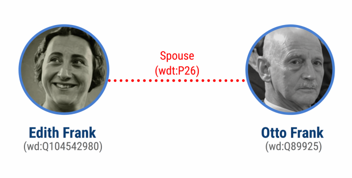

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4. Hybrid	$\longrightarrow$	High system complexity

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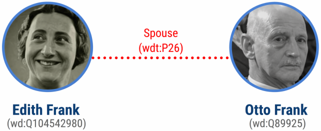

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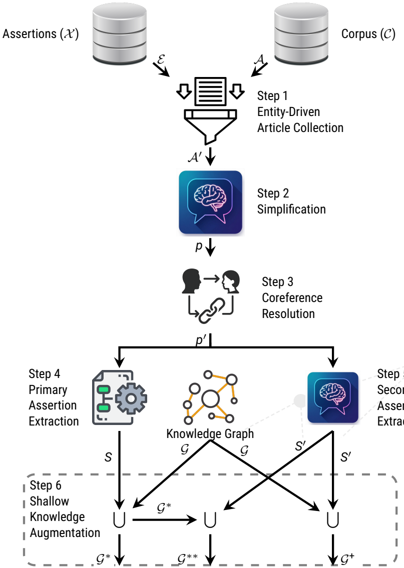
Bridging the Gap

ShallKnowFramework

- **Goal:**
  Fix KG incompleteness for path-based fact-checking



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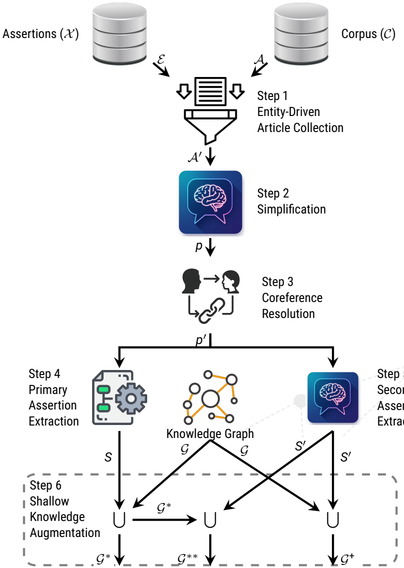
- **The Solution: SHALLKNOW**
  Augments KGs with **Shallow Knowledge**



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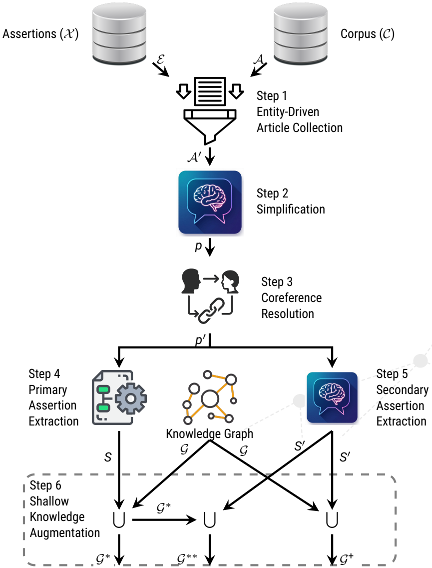
  - RDF assertions mined from raw text.
  - Fills missing paths; no strict ontology needed.



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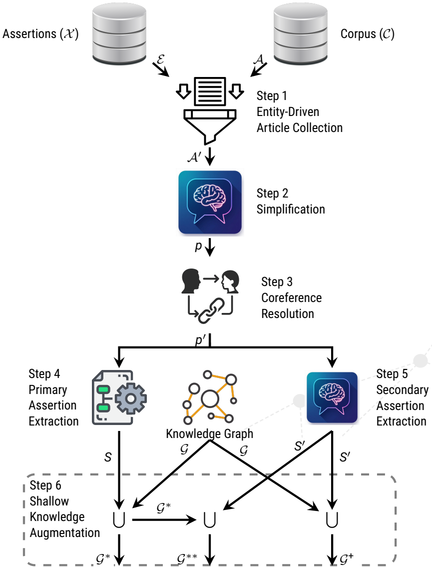
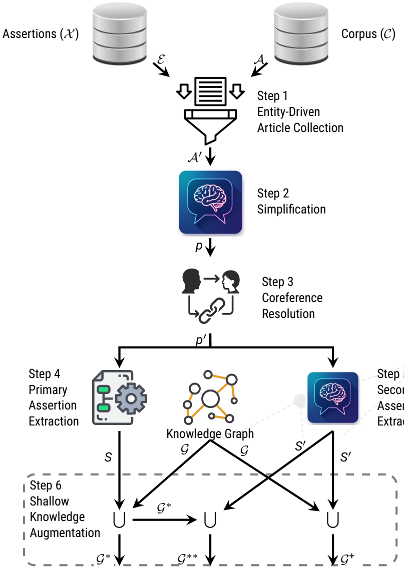
- **Outcome**
  Boost in graph completeness



Methodology

Contextualizing Entities (Steps 1–3)

- Step 1: Article Collection
  - Retrieve reference corpus articles ($\mathcal{A}$)
  - Add 1-hop linked articles ($\mathcal{A}'$)



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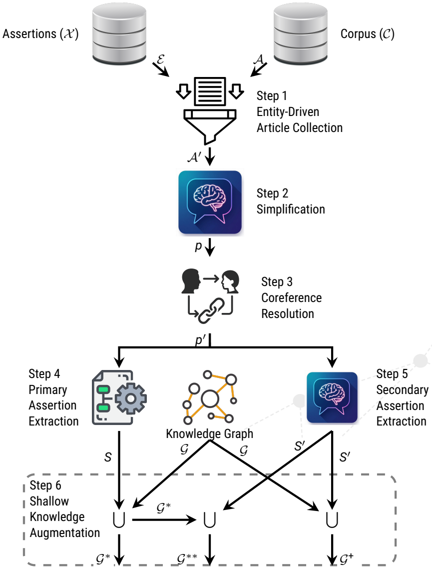
  - LLM removes markups and noise
  - Generates summary paragraph (p)



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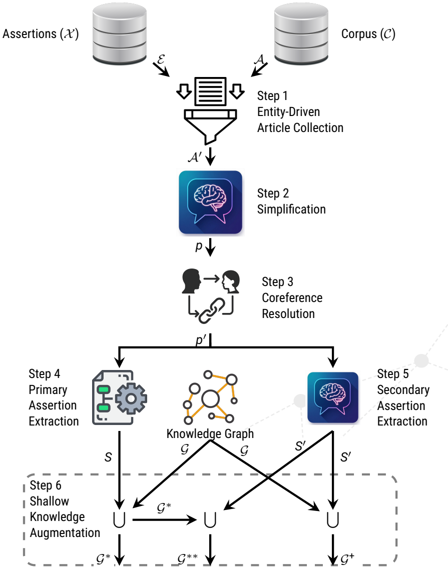
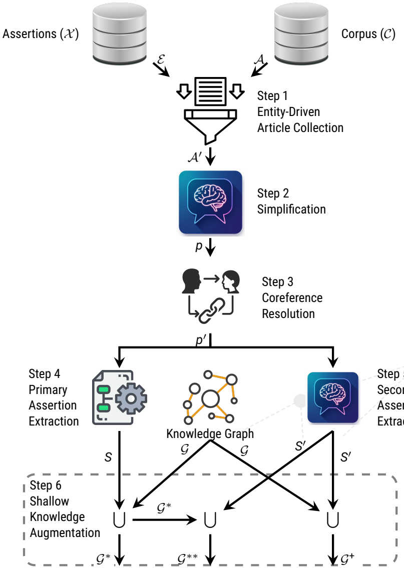
- Step 3: Coreference Resolution
  - Replace pronouns with entity names
  - **Result:** clean snippet (p')



Methodology

The Two-Tier Extraction Engine

- Step 4: Primary Extraction
  - RE tools extraction
  - KG properties ($P_{\mathcal{G}}$)
  - Default execution
  - Fast, structured, schema-aligned extraction



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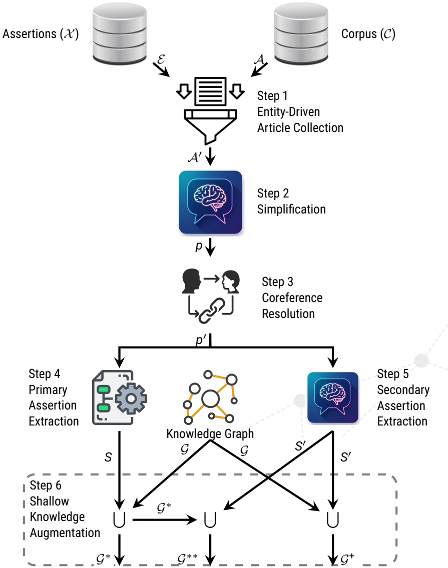
  - Novel properties ($P_{\mathcal{C}}$)
  - Trigger if: $|\mathcal{S}| < \theta$
  - Improves recall and fill missing gaps



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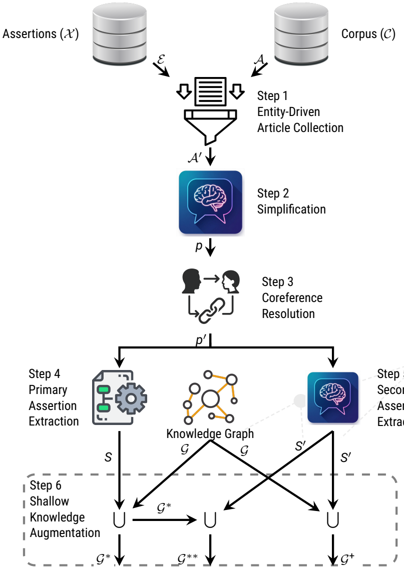
This threshold-based mechanism (θ) balances extraction depth with computational efficiency.



Methodology

Shallow Knowledge Augmentation Strategies

- **Given:**
  - $\mathcal{G}$: Original KG
  - $\mathcal{S}$: Primary Assertions *(existing schema)*
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$\mathcal{S}$	$\mathcal{G}$	$\mathcal{S}'$

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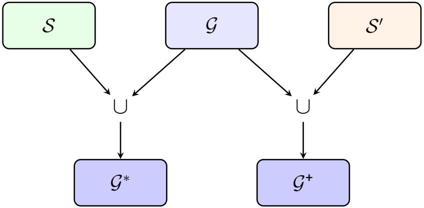

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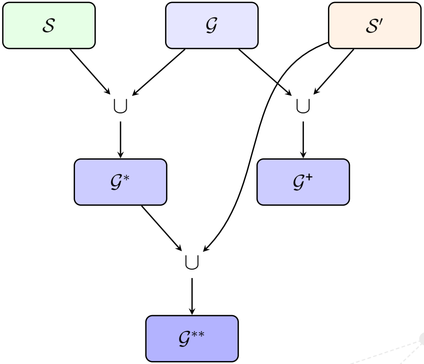

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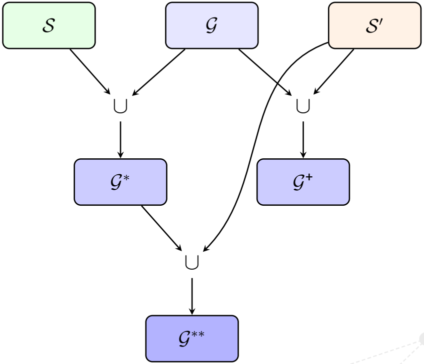
- **Outcome:** Enriched graphs for downstream path-based fact-checking task.



Experiments

Setup details

- Benchmark Datasets (size in #assertions)

Dataset	Train (T/F/Total)	Test (T/F/Total)	DP
BPDP 22 [3]	100/100/200	103/103/206	2
FactBench Mix 22 [9]	633/486/1119	637/492/1129	9
FAVEL-DS [7]	380/385/765	163/164/327	11

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- Evaluation Metric: AUC-ROC

Results (Part 1): BPDP & FactBench

DS	Approach	w/o	$\mathcal{G}^*$	Δ	$\mathcal{G}^+$	Δ	$\mathcal{G}^{**}$	Δ
BPDP 22	FAVEL [7]	0.6701	0.6822	†+0.0121	0.7091	†**+0.0390**	0.7232	†+0.0410
	COPAAL [10]	0.5314	0.5497	†+0.0183	0.5370	†+0.0190	0.5515	†+0.0201
	PredPath [8]	0.6311	0.6522	†**+0.0211**	0.6680	†+0.0369	0.6748	†**+0.0437**
	Pathent [11]	0.4985	0.4985	0.0000	0.4988	†+0.0005	0.4990	†+0.0005
	DP [2]	0.5000	0.5000	0.0000	0.5000	0.0000	0.5000	0.0000
	PRA [5]	0.5801	0.5905	†+0.0104	0.6155	†+0.0354	0.6212	†+0.0411
	Jaccard [6]	0.5009	0.5011	†+0.0002	0.5015	†+0.0006	0.5016	†+0.0007
	Adamic [1]	0.4983	0.4983	0.0000	0.4983	0.0000	0.4983	0.0000
	SimRank [4]	0.4817	0.4856	†+0.0039	0.4920	†+0.0087	0.4945	†+0.0100
FactBench Mix 22	FAVEL [7]	0.8133	0.8656	†+0.0223	0.9052	†+0.0919	0.9121	†+0.0988
	COPAAL [10]	0.7903	0.8404	†**+0.0501**	0.8960	†**+0.1057**	0.9011	†**+0.1108**
	PredPath [8]	0.7355	0.7425	+0.0070	0.7766	†+0.0411	0.7895	†+0.0540
	Pathent	0.7054	0.7035	†+0.0019	0.7130	†+0.0076	0.7218	†+0.0164
	DP	0.4467	0.4569	†+0.0102	0.4575	†+0.0108	0.4607	†+0.0140
	PRA	0.5704	0.6033	†+0.0329	0.6170	†+0.0466	0.6221	†+0.0517
	Jaccard	0.6271	0.6344	†+0.0073	0.6537	†+0.0266	0.6621	†+0.0350
	Adamic Adar	0.6591	0.6793	†+0.0202	0.6980	†+0.0389	0.7328	†+0.0737
	SimRank	0.5881	0.6104	†+0.0223	0.6525	†+0.0644	0.6622	†+0.0741

†We use a Wilcoxon signed rank test with a significance threshold α = 0.05.

Results (Part 2): FAVEL-DS

DS	Approach	w/o	$\mathcal{G}^*$	Δ	$\mathcal{G}^+$	Δ	$\mathcal{G}^{**}$	Δ
FAVEL-DS	FAVEL	0.7231	0.7532	†+0.0301	0.7831	†+0.0600	0.7921	†+0.0690
	COPAAL	0.5102	0.7222	†**+0.2120**	0.7400	†**+0.2298**	0.7493	†**+0.2391**
	PredPath	0.7189	0.7233	+0.0044	0.7482	†+0.0293	0.7623	†+0.0434
	Pathent	0.5733	0.6221	†+0.0588	0.7400	†+0.1667	0.7533	†+0.1800
	DP	0.5247	0.5247	0.0000	0.5350	†+0.0103	0.5379	†+0.0132
	PRA	0.5322	0.5466	†+0.0144	0.5530	†+0.0208	0.5567	†+0.0245
	Jaccard	0.5398	0.5554	†+0.0156	0.5840	†+0.0442	0.5958	†+0.0560
	Adamic	0.5467	0.5865	†+0.0398	0.6380	†+0.0913	0.6747	†+0.1280
	SimRank	0.5603	0.5778	+0.0175	0.6023	†+0.0420	0.6085	†+0.0428

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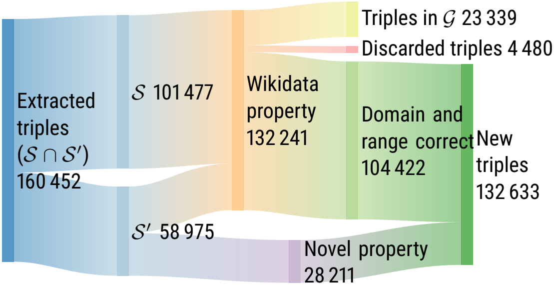
Quality Control: Can We Trust Shallow Assertions?



High inter-annotator agreement confirms the reliability of extracted assertions (up to 89% precision and κ = 0.8790).

Conclusion and Future Work

- Summary of Contributions
  - Addressed the core limitation of path-based fact-checking: the reliance on KG completeness.
  - Introduced **SHALLKNOW**, a model-agnostic framework that systematically augments incomplete KGs using shallow knowledge from unstructured text.
  - Demonstrated consistent and significant AUROC improvements across 3 benchmark datasets for state-of-the-art path-based methods.

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  - Introduced **ShallKnow**, a model-agnostic framework that systematically augments incomplete KGs using shallow knowledge from unstructured text.
  - Demonstrated consistent and significant AUROC improvements across 3 benchmark datasets for state-of-the-art path-based methods.

- Future Directions
  - **Scalability:** Improve computational efficiency and scalability of the assertion extraction process.
  - **Refinement:** Normalize semantically equivalent properties and better manage rare relations.

Summary

That's all folks!

SHALLKNOW boosts path-based fact-checking by augmenting incomplete knowledge graphs with shallow knowledge from text.

Web: dice-research.org

Code: github.com/dice-group/shallknow

Twitter: @DiceResearch

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NEBULA
Nutzerzentrierte KI-basierte Erkennung von Fake News und Fehlinformationen

SAIL
SUSTAINABLE LIFE-CYCLE OF INTELLIGENT SOCIO-TECHNICAL SYSTEMS

KI AKADEMIE OWL

LEARN2RAG

GEFÖRDERT VOM
Bundesministerium für Bildung und Forschung

Bundesministerium für Forschung, Technologie und Raumfahrt

Ministry of Culture and Science of the State of North Rhine-Westphalia

References

[1] Adamic, L.A., Adar, E.: Friends and neighbors on the web. Social Networks **25**(3), 211–230 (2003). https://doi.org/https://doi.org/10.1016/S0378-8733(03)00009-1

[2] Ciampaglia, G.L., Shiralkar, P., Rocha, L.M., Bollen, J., Menczer, F., Flammini, A.: Computational fact checking from knowledge networks. PloS one **10**(6), e0128193 (2015)

[3] Gerber, D., Esteves, D., Lehmann, J., Bühmann, L., Usbeck, R., Ngonga Ngomo, A.C., Speck, R.: Defacto-temporal and multilingual deep fact validation. Web Semant. **35**(P2), 85–101 (Dec 2015). https://doi.org/10.1016/j.websem.2015.08.001, https://doi.org/10.1016/j.websem.2015.08.001

[4] Jeh, G., Widom, J.: Simrank: A measure of structural-context similarity. In: Proceedings of the Eighth ACM SIGKDD Intern. Conf. on Knowledge Discovery and Data Mining (2002)

[5] Lao, N., Cohen, W.: Relational retrieval using a combination of path-constrained random walks. Machine Learning **81**, 53–67 (10

Expert Inter-Annotator Agreement verified factual accuracy.

89% Precision

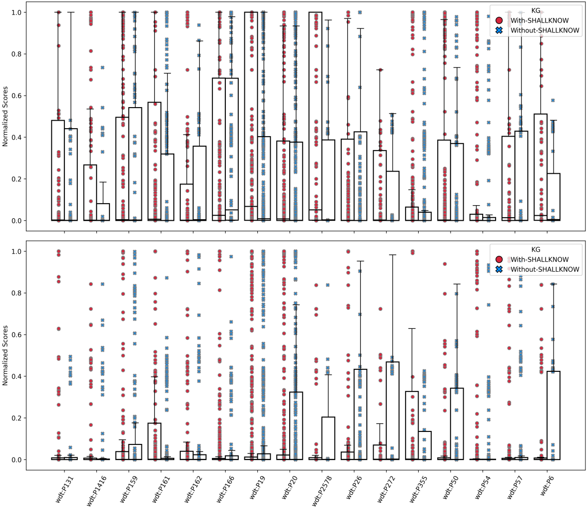
for novel predicates

86% Precision

for schema-aligned predicates

More Results

Predicate-wise Score Distribution



Predicate-wise predicted scores for **true** (top, higher is better) and **false** (bottom, lower is better) assertions with and without SHALLKNOW.