

Task-Oriented Automatic Fact-Checking with Frame-Semantics

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Overview

Problem

- > Misinformation poses serious threats to informed decision-making
- > Most research relies on pre-curated data, e.g., Wikipedia tables
- Previous work focuses on low-volume tables (<100 rows per table)</p>
- LLM-based fact-checking methods often lack interpretability
- > Different claims require varying fact-checking processes

Contributions

- > Novel task-oriented fact-checking paradigm using frame semantics
- Two high-volume structured datasets with annotated real-world claims from reputable fact-checking organizations
- > FE-based retrieval improves performance and interpretability
- > Publicly released demo, code, and datasets

Case Studies

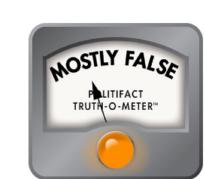
Case Study 1: Voting Records





Datasets (congress.gov):

- > **342,466 Bills** from 1973-2023
- > 7,195,798 Votes since 1989
- While serving in Congress,
 Transportation Secretary Sean
 Duffy "voted against upgrading
 air traffic control systems."



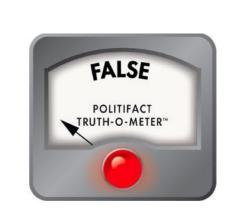
- > 4,230 Avg. votes per member
- > 79 Fact-checks annotated with relevant bills and votes

Case Study 2: Country Statistics (OECD)

Datasets (oecd.gov):

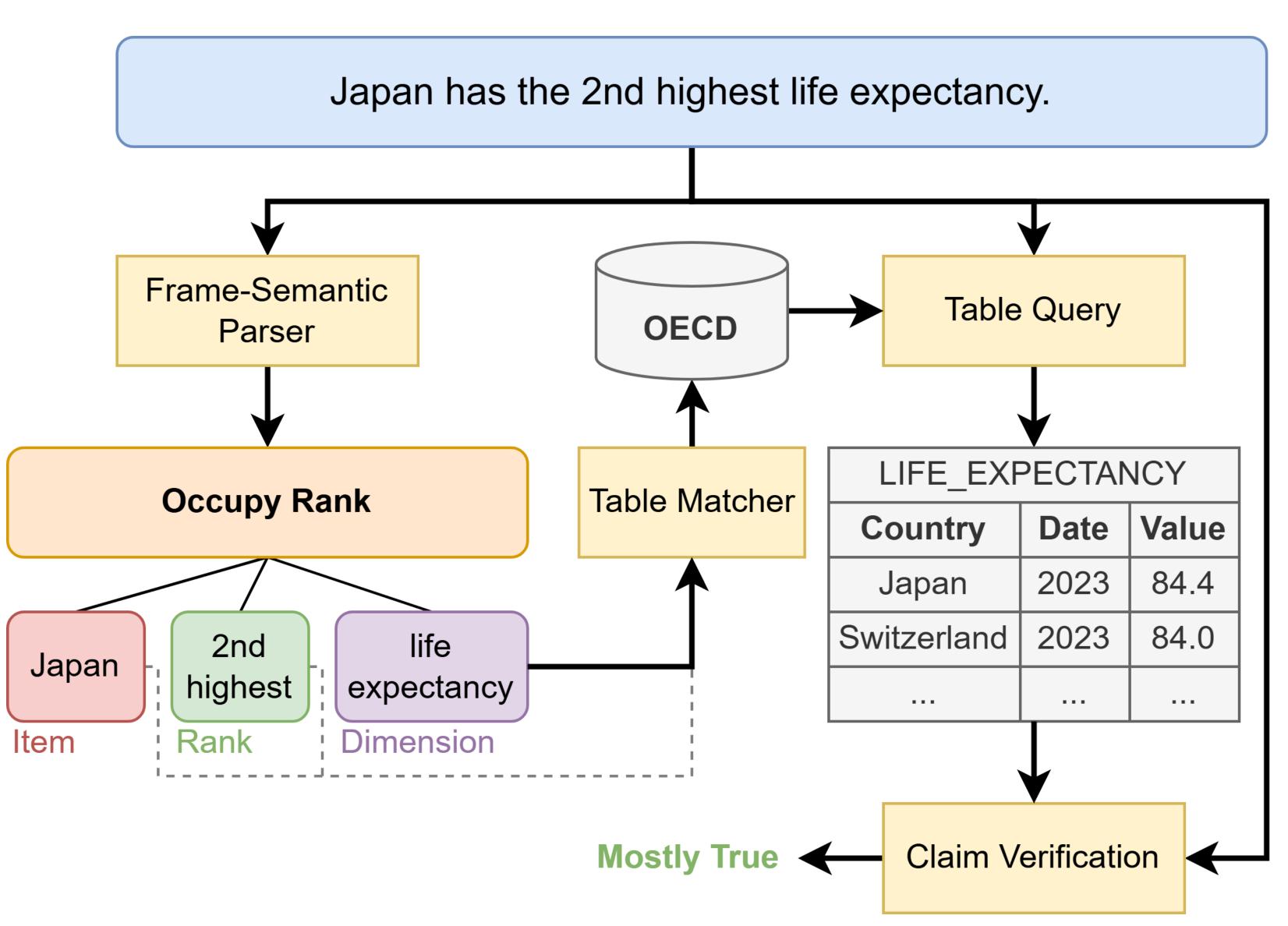
- > 434 Tables of diverse topics
- > **596,552** Avg. rows per table a day in tar





- > 38 different countries (and sometimes more)
- > 68 Fact-checks annotated with relevant table and frame elements

System Architecture



Claim Understanding

- > Identifies semantic frames and frame elements
- > Fine-tuned RoBERTa-based joint frame-semantic parsing model

Evidence Retrieval

- > Frame elements used to find relevant database tables
 - > Voting: matches Agent and Issue FEs to senators and bills
 - > OECD: matches frame-specific FEs to tables

Claim Verification

- > Retrieved evidence and claim are given to LLM to predict veracity
- > Outputs one of: True, Mostly True, Half-True, Mostly False, False
- > LLM is prompted to consider the *spirit of the claim* in prediction

Experiments

Semantic Frame Survey

Predicted distribution of frames across 21K fact-check articles

Vote, Occupy Rank, andComparing Entities among the most common frames

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Evidence Retrieval

Evaluated **similarity models** and **querying strategies**

Voting: DistilBERT-TAS-B

> **OECD:** RoBERTa v2

Model	Query	Data	R@K
distilbert-tas-b	Full claim	Vote	0.143
distilbert-tas-b	Issue FE	Vote	0.165
Max Possible	-	Vote	0.568
RoBERTa (v2)	Full claim	OECD	0.653
RoBERTa (v2)	FE	OECD	0.726
Max Possible	-	OECD	0.910

Frame Element semantic search query outperforms full claim query

Frame-Semantic Parsing

RoBERTa joint frame-semantic
 parsing model drastically
 outperforms in-context learning
 baseline on FE identification

•	Similar	performance	on frame s

Model	Frames	Frame Acc	FE Acc
Random	Vote	0.488	0.254
GPT-40-mini	Vote	0.974	0.618
Vote FSP	Vote	0.990	0.889
Random	OECD	0.602	0.000
GPT-40-mini	OECD	0.537	0.372
GPT-40-mini*	OECD	0.713	0.461
OECD FSP	OECD	0.742	0.873

End-to-End Fact Verification

Benchmarked end-to-end system against PolitiFact verdicts

> Naïve - No evidence

Irrelevant – Samples where no useful evidence is found

Model	Dataset	Accuracy
GPT-40 Naive	Vote	0.044
Ours w/ Irrelevant	Vote	0.076
Ours w/o Irrelevant	Vote	0.207
GPT-40 Naive	OECD	0.073
Ours w/ Irrelevant	OECD	0.214
Ours w/o Irrelevant	OECD	0.429