

Fact-Checking Complex Claims with Program-Guided Reasoning

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What is Fact Checking?

• The proliferation of disinformation in various forms, including propaganda, news, and social media, has made automated fact-checking a crucial application of natural language processing (NLP).

In the language of NLP:

• The goal of fact-checking is, given a claim made by a claimant, to find a collection of evidence and provide a verdict about the claim's veracity based on the evidence. (Glockner et al., 2022)

Verifying Deep Claims

• To verify a real-world claim, we often cannot find a "direct evidence" to support / refute the claim. Instead, it often requires complex, multi-step reasoning.



Claim: Both James Cameron and the director of the film Interstellar were born in Canada.



Idea: We formulate the above process as Program Execution

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We decouple the program generation and program execution for flexibility and easy debugging.

Reasoning Program Generation

Claim: Both James Cameron and the director of the film Interstellar were born in Canada.



We use in-context learning for data efficiency.

Sub-Functions: QA

Functions QA Model Fact Checker Logical Reasoner

We base the sub-functions on the FLAN-T5 model, which finetunes T5 with 1.8k finetuning tasks, including chain-of-thought data.

Instruction finetuning



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Sub-Functions: QA



Evaluation Datasets

- HOVER (Jiang et al., 2020)
 - 1,126 two-hop claims
 - 1,835 three-hop claims
 - 1,039 four-hop claims

Claim: Patrick Carpentier currently drives a Ford Fusion, introduced for model year 2006, in the NASCAR Sprint Cup Series.

Evidence:

Doc A: Ford Fusion is manufactured and marketed by Ford. Introduced for the 2006 model year, ...

Doc B: Patrick Carpentier competed in the NASCAR Sprint Cup Series, driving the Ford Fusion. ...

Verdict: Supported

- FEVEROUS (<u>Aly et al., 2021</u>)
 - We only selected 2,962 claims that require exclusively textual evidence.

Claim: Red Sundown screenplay was written by Martin Berkeley; based on a story by Lewis B. Patten, who often published under the names Lewis Ford, Lee Leighton and Joseph Wayne.

Evidence:

Page: wiki/Red_Sundown e₁(Introduction):

Red Sundown

Directed by Jack Arnold Produced by Albert Zugsmith Screenplay by Based on Lewis B. Patten

Page: wiki/Lewis_B._Patten
e2(Introduction): He often published under the names
Lewis Ford, Lee Leighton and Joseph Wayne.

Verdict: Supported

Baseline Models

- Pretrained Transformer models
 - BERT-FC (Soleimani et al., 2020)
 - LisT5 (Jiang et al., 2021)
- FC/NLI fine-tuned models
 - RoBERTa-NLI (Nie et al., 2020)
 - DeBERTaV3-NLI (He et al., 2021)
 - MULTIVERS (Wadden et al., 2022)
- In-context learning models
 - FLAN-T5
 - GPT3-Codex

Main Results

Few-shot learning models		HOVER (2-hop)		HOVER (3-hop)		HOVER (4-hop)		FEVEROUS-S	
		Gold	Open	Gold	Open	Gold	Open	Gold	Open
Ι	BERT-FC (Soleimani et al., 2020)	53.40	50.68	50.90	49.86	50.86	48.57	74.71	51.67
	LisT5 (Jiang et al., 2021)	56.15	52.56	53.76	51.89	51.67	50.46	77.88	54.15
II	RoBERTa-NLI (Nie et al., 2020)	74.62	63.62	62.23	53.99	57.98	52.40	88.28	57.80
	DeBERTaV3-NLI (He et al., 2021)	<u>77.22</u>	68.72	65.98	60.76	60.49	56.00	91.98	58.81
	MULTIVERS (Wadden et al., 2022b)	68.86	60.17	59.87	52.55	55.67	51.86	86.03	56.61
III	GPT3-Codex (Chen et al., 2021)	70.63	65.07	66.46	56.63	63.49	57.27	89.77	62.58
	FLAN-T5 (Chung et al., 2022)	73.69	69.02	65.66	60.23	58.08	55.42	90.81	63.73
IV	ProgramFC (N=1)	74.10	69.36	66.13	60.63	65.69	59.16	91.77	67.80
	ProgramFC (N=5)	75.65	<u>70.30</u>	<u>68.48</u>	<u>63.43</u>	<u>66.75</u>	57.74	<u>92.69</u>	<u>68.06</u>

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PROGRAMFC achieves the best performance on 7 out of 8 evaluations.

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		0 70/		4 0 0 (4.4.004			

+2.7%

+4.3%

+14.9%

ProgramFC is more effective on deeper claims.

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Aggregating reasoning programs is helpful.

How Reasoning Program Helps?



- **PROGRAMFC v.s. FLAN-T5** using different language model sizes.
- The performance of the end-to-end FLAN-T5 model decreases significantly with decreasing model size. However, this trend is less obvious for PROGRAMFC.

The high-level planning offered by reasoning programs alleviates the demand on strong, large-scale models.

How Reasoning Program Helps?

• In the open-book setting, ProgramFC significantly outperforms one-step retrieval.



Intuition: Some information may not be present in the original claim, but is only revealed during the reasoning process (e.g., "Christopher Nolan" in the previous example).

Figure 5: Retrieval recall@10 for the one-step retrieval and the iterative retrieval in PROGRAMFC.

Iteratively retrieving information guided by the reasoning program leads to better results.

Reasoning Program Evaluation

Correct Examples

Claim: Tritonia and Phyteuma are both names for a plant genus.

Predicted Program: fact_1 = Verify("Tritonia is a name for a plant genus.") fact_2 = Verify("Phyteuma is a name for a plant genus.") label = Predict(fact_1 and fact_2)

Claim:

The country that Fujairah College is located in had a 2013 population of 9.2 million until it was hit by the plague in 1483 when the population was halved.

```
Predicted Program:
answer_1 = Question("Which country is Fujairah College located in?")
fact_1 = Verify("{answer_1} had a 2013 population of 9.2 million.")
fact_2 = Verify("{answer_1} was hit by the plague in 1483.")
fact_3 = Verify("The population of {answer_1} was halved in 1483.")
label = Predict(fact 1 and fact 2 and fact 3)
```

Reasoning Program Evaluation

• Wrong Examples

Semantic Error — Token: incorrect or missing arguments/variables

Example 1: Bitter Jester and The Future of Food are not both documentaries about food.

Semantic Error — Structure: incorrect program structure

Example 3: Richard Strauss, German composer of Die Nacht, composed another well-established opera called Der Rosenkavalier.

Reasoning Program Evaluation

• Wrong Examples

Semantic Error — Subtask: missing / redundant / incorrect sub-task calls
Example 5:
The musician, who founded Morningwood with Max Green, is older than Max Green.
Predicted Program:
answer_1 = Question("Who founded Morningwood with Max Green?")
answer_2 = Question("When was Max Green born?")
answer_3 = Question("When was the musician born?")
fact_1 = Verify("{answer_3} is older than {answer_2}.") → {answer_1} is older than {answer_2}.

Free Type	Proportion (%)						
LITOI Type	2-hop	3-hop	4-hop				
Syntax error	0%	0%	0%				
Semantic error	29%	38%	77%				
Token	8%	20%	18%				
Structure	19%	13%	57%				
Subtask	2%	5%	2%				
Incorrect execution	71%	62%	23%				

Summary

We talked about how to build a fact-checking system that are:

- Data Efficiency
 - Build a model with minimal or no training data.
- Explanablility
 - Provide a clear explanation of its reasoning process.
- Deep Reasoning
 - Collect multiple pieces of evidence and applying complex reasoning.

Our solution: Program-guided Reasoning.





Thanks!

Any questions?

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