Results of FLAN-T5 and GPT-3.5 LLMs over Four RE Datasets

Vanilla RE

Given a sentence, and two entities within the sentence, classify the relationship between the two entities based on the provided sentence. All possible relationships are listed below:
- per:city_of_birth
- per:city_of_death
- per:cities_of_residence
- no_relation

Sentence: **Wearing jeans and a white blouse, Amanda Knox of Seattle is being cross-examined by prosecutors.**
Entity 1 : **Amanda Knox**
Entity 2 : **Seattle**
Relationship: **per:city_of_birth** ✗

QA4RE

Determine which option can be inferred from the given sentence.

Sentence: **Wearing jeans and a white blouse, Amanda Knox of Seattle is being cross-examined by prosecutors.**

Options:
A. Amanda Knox was born in the city Seattle
B. Amanda Knox died in the city Seattle
C. Amanda Knox lives in the city Seattle
D. Amanda Knox has no known relations to Seattle

Which option can be inferred from the given sentence?
Option: **C.** ✓

Methods		TACRED P	TACRED R	TACRED F1	RETACRED P	RETACRED R	RETACRED F1	TACREV P	TACREV R	TACREV F1	SemEval P	SemEval R	SemEval F1	Avg. F1
Baselines														
NLI$_{BART}$		42.6	65.0	51.4	59.5	34.9	44.0	44.0	74.6	55.3	21.6	23.7	22.6	43.3
NLI$_{RoBERTa}$		37.1	76.9	50.1	52.3	67.0	58.7	37.1	83.6	51.4	17.6	20.9	19.1	44.8
NLI$_{DeBERTa}$		42.9	76.9	<u>55.1</u>	71.7	58.3	64.3	43.3	84.6	57.2	22.0	25.7	23.7	50.1
SuRE$_{BART}$		13.1	45.7	20.4	17.9	34.6	23.6	14.1	52.3	22.2	0.0	0.0	0.0	16.5
SuRE$_{PEGASUS}$		13.8	51.7	21.8	16.6	34.6	22.4	13.5	54.1	21.6	0.0	0.0	0.0	16.4
GPT-3.5 Series														
ChatGPT	Vanilla	32.1	74.8	44.9	45.4	61.3	52.1	30.3	79.6	43.9	18.2	20.8	19.4	40.1
	QA4RE	32.8	68.0	44.2 (−0.7)	48.3	76.8	59.3 (+7.2)	34.7	79.1	48.2 (+4.3)	29.9	35.2	32.3 (+12.9)	46.0 (+5.9)
code-002	Vanilla	27.2	70.1	39.2	42.7	70.4	53.1	27.5	77.7	40.6	27.2	25.6	26.4	39.8
	QA4RE	37.7	65.4	47.8 (+8.6)	48.0	74.0	58.2 (+5.1)	31.7	65.5	42.7 (+2.1)	25.2	29.2	27.0 (+0.6)	43.9 (+4.1)
text-002	Vanilla	31.2	73.1	43.7	44.1	76.3	55.9	30.2	76.8	43.3	31.4	28.8	30.1	43.2
	QA4RE	35.6	68.4	46.8 (+3.1)	46.4	72.4	56.5 (+0.6)	35.7	76.8	48.8 (+5.4)	29.4	34.3	31.6 (+1.5)	45.9 (+2.7)
text-003	Vanilla	36.9	68.8	48.1	49.7	62.2	55.3	38.2	76.8	51.0	33.2	39.3	36.0	47.6
	QA4RE	47.7	78.6	**59.4** (+11.3)	56.2	67.2	61.2 (+5.9)	46.0	83.6	**59.4** (+8.4)	41.7	45.0	<u>43.3</u> (+7.3)	**55.8** (+8.2)
FLAN-T5 Series														
XLarge	Vanilla	51.6	49.1	50.3	54.3	40.3	46.3	56.0	59.1	<u>57.5</u>	35.6	29.8	32.4	46.6
	QA4RE	40.0	78.2	53.0 (+2.7)	57.1	79.7	<u>66.5</u> (+20.2)	40.7	85.9	55.3 (−2.2)	45.1	40.1	42.5 (+10.1)	54.3 (+7.7)
XXLarge	Vanilla	52.1	47.9	49.9	56.6	54.0	55.2	52.6	50.9	51.7	29.6	28.8	29.2	46.5
	QA4RE	40.6	82.9	54.5 (+4.6)	56.6	82.9	**67.3** (+12.1)	39.6	86.4	54.3 (+2.6)	41.0	47.8	**44.1** (+14.9)	<u>55.1</u> (+8.6)

Table 1: Experimental results on four RE datasets (%). We omit the 'davinci' within the names of GPT-3.5 Series LLMs and ChatGPT refers to gpt-3.5-turbo-0301. We mark the best results in **bold**, the second-best <u>underlined</u>, and F1 improvement of our QA4RE over vanilla RE in green.

1. LLMs with vanilla RE are not strong zero-shot relation extractors.

2. QA4RE consistently improves upon the vanilla RE formulation on GPT-3.5 and FLAN-T5 series LLMs.

3. FLAN-T5 is tuned with <0.5% RE and >12% QA instructions, the consistent improvements by QA4RE strongly verify our hypothesis.

4. QA4RE works effectively on instruction-tuned models with various sizes, ranging from 80M to 175B.

LMs	Model Size	Avg. F1 Vanilla	Avg. F1 QA4RE	Δ
GPT-3.5 Series				
text-001	175B	22.3	14.9	−7.4
code-002	175B	39.8	43.9	+4.1
text-002	175B	43.2	45.9	+2.7
text-003	175B	47.6	55.8	+8.2
FLAN-T5 Series				
Small	80M	19.5	25.0	+5.6
Base	250M	22.3	26.4	+4.2
Large	780M	34.8	41.8	+7.0
XLarge	3B	46.6	54.3	+7.7
XXLarge	11B	46.5	55.1	+8.6

Table 7: Effectiveness of QA4RE on both the GPT-3.5 series and FLAN-T5 with different sizes. The results are averaged over four RE datasets.

Template Robustness

Methods		TEMP1	TEMP2	TEMP3	TEMP4
NLI$_{BART}$		51.4	49.7	4.4	42.0
NLI$_{RoBERTa}$		50.1	47.1	19.6	35.8
NLI$_{DeBERTa}$		55.0	49.4	17.1	36.6
SuRE$_{BART}$		19.9	20.4	2.1	10.1
SuRE$_{PEGASUS}$		20.5	21.8	6.2	19.3
text-003	Vanilla	48.1			
	QA4RE	**56.6**	**59.4**	**48.7**	**50.1**

Table 2: F1 score on TACRED with four templates (%). The best result using each template is marked in bold. text-003 refers to text-davinci-003.

Are Relation Templates All LLMs Need? — No

Vanilla + Template RE

Given a sentence .... All possible relationships with explanations are listed below:
- per:city_of_birth: Entity 1 was born in the city Entity 2
- per:city_of_death: Entity 1 died in the city Entity 2
- per:cities_of_residence: Entity 1 lives in the city Entity 2
- no_relation: Entity 1 has no known relations to Entity 2

Sentence: **Wearing jeans and a white blouse, Amanda Knox of Seattle ...**
Entity 1 : **Amanda Knox**
Entity 2 : **Seattle**
Relationship: **per:city_of_birth**

Methods		P	R	F1	ΔF1
code-002	Vanilla	27.2	70.1	39.2	-
	Vanilla + TEMP	27.5	71.8	39.7	+0.5
	QA4RE	37.7	65.4	47.8	+8.6
text-002	Vanilla	31.2	73.1	43.7	-
	Vanilla + TEMP	26.8	77.8	39.8	−3.9
	QA4RE	35.6	68.4	46.8	+3.1
text-003	Vanilla	36.9	68.8	48.1	-
	Vanilla + TEMP	36.9	76.5	49.8	+1.7
	QA4RE	**47.7**	**78.6**	**59.4**	+11.3

Table 5: Evaluation on TACRED regarding whether incorporating relation explanations based on the same templates into vanilla RE bridges its gap to QA4RE (%).

Few-shot Effectiveness

Methods	K=0	K=4	K=8	K=16	K=32
Fine-Tuning	-	9.0	21.2	29.3	33.9
PTR	-	26.8	30.0	32.9	36.8
KnowPrompt	-	30.2	33.7	34.9	35.0
NLI$_{DeBERTa}$-TEMP1	55.0	**64.2**	**64.7**	**58.7**	**65.7**
NLI$_{DeBERTa}$-TEMP2	49.4	**51.2**	47.3	**50.5**	48.1
Vanilla	48.1	46.2		-	
QA4RE	59.4	**62.0**		-	

Table 4: Few-shot F1 on TACRED (%). All results are averaged over 3 different training subsets for each K. We use text-davinci-003 for vanilla RE and QA4RE. For the best-performing baseline (NLI) as well as vanilla RE and QA4RE, we mark the results in **bold** when they are improved over their zero-shot alternatives.

Takeaways

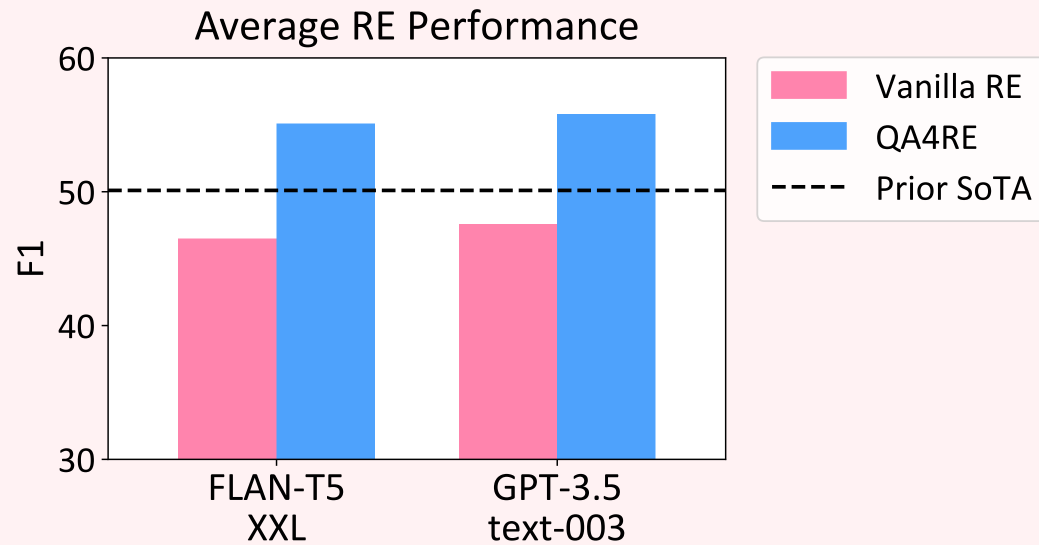
1. Reformulating tasks (RE) that are not well covered in the instruction datasets to popular tasks (QA) unlocks LLMs' abilities.

2. QA4RE makes LLMs strong and robust zero-shot relation extractors.

Do all tasks benefit equally from LLM instruction tuning? Relation extraction: Not at all!

RE is underrepresented in all instruction tuning datasets (< 0.5%).

By reformulating RE as a popular instruction tuning task (QA, ~12%), we improve up to **8.6%** absolute F1 on **9** models over **4** datasets.



Aligning Instruction Tasks Unlocks Large Language Models as Zero-Shot Relation Extractors

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