Code4Struct: Code Generation for Few-Shot Event Structure Prediction

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Motivation

- Large Language Model (LLM) trained on a mixture of text and code can translate natural language (NL) instructions into structured code.
- Some semantic structures (e.g., output event-entity graph in event argument extraction) can be easily translated into code.

Can we leverage such text-to-code capability of LLM to tackle structured prediction problems?



Ontology Code Representation: We convert the existing event type ontology to Python class definitions. Method Task Prompt: Conditioned on these definitions, we put the input sentence into a docstring to prompt LLM.



Transport. The trigger word(s) of the event is marked fc of honour at Thursday's market debut and , according to Harris , has already -Trigger Marking with **trigger word**. played a key role in attracting worldwide media attention to the event ." Task "Kelly , the US assistant secretary for East Asia and tr Prompt Pacific Affairs , **arrived** in Seoul from Beijing transport_event = Transport(Groundtruth Code artifact=[PER("Heidi Fleiss"),], Friday to brief Yoon , the foreign minister ." destination=[GPE("Melbourne"),], 11 11 11 transport_event = Transport(Arg-Identification F1: Whether LLM can identify an argument correctly (e.g., Kelly, Seoul, Beijing) **Evaluation**

Arg-Classification F1: Whether LLM can match correctly identified argument with a correct role (e.g. agent=Kelly)

Comparison with Supervised Approaches

20-shot Code4Struct rivals fully-supervised approaches trained on >4k training instances. Model Arg-I F1 Arg-C F1 Data DyGIE++ 66.2 60.7 Full **BERT-QA** 65.4 68.2 Full 69.3 OneIE 73.2 Full 61.0 TANL 65.9 Full BART-Gen 69.9 66.7 Full 73.5 DEGREE 76.0 Full $CODE4STRUCT_{text-davinci-003}$ 37.8 0-shot 49.9 Text2Event 19.1 23.1 20-shot* 30.9 DEGREE 33.0 20-shot* $CODE4STRUCT_{\texttt{text-davinci-003}}$ 60.4 65.0 20-shot* Text2Event 30.6 26.0 50-shot* DEGREE 40.8 37.3 50-shot* $CODE4STRUCT_{code-davinci-002}$ 62.3 **58.1** 50-shot*

Code Representation Allows Cross-Sibling Transfer



same-type: using examples from the testing event type itself • **non-sibling type:** using examples from a random non-sibiling

	Arg-I	Arg-C
0-shot	52.8	42.9
1-shot (same type)	54.3	50.2
1-shot (sibling type)	57.2	51.9
1-shot (non-sibling type)	56.3	50.3
10-shot (same type)	58.7	55.2
10-shot (sibling type)	60.8	54.9
10-shot (non-sibling type)	58.5	51.0

Using sibling examples help: they are just as useful as annotated example from the predict event type!

It surpass current SOTA by 29.5% under 20-shot

Is code prompt any better than text prompt?

Translate the following sentence into an instance of Transport event. The trigger word(s) of the event is marked with **trigger word**. "Kelly , the US assistant secretary for East Asia and Pacific Affairs , **arrived** in Seoul from Beijing Friday to brief Yoon , the foreign minister ." 1. agent: () "" 2. artifact: (PER) "Kelly" 3. destination: (GPE) "Seoul" origin: (GPE) "Beijing" 5. vehicle: () ""

(4) Event Instantiation

Text Prompt T1 (code-prompt-style)

Translate the following sentence into an instance of Transport event. The trigger word(s) of the event is marked with **trigger word**. "Kelly , the US assistant secretary for East Asia and Pacific Affairs , **arrived** in Seoul from Beijing Friday to brief Yoon , the foreign minister ." In this event: [] transported ["Kelly"] in [] vehicle from ["Beijing"] place to ["Seoul"] place. (4) Event Instantiation

Text Prompt T2 (BART-Gen-style)

- def __init__(self, artifact: List[FAC | ORG | PER | VEH | WEA] = [],
- Code prompt is generally more effective with sufficient in-context examples.
- Text prompt performance have higher variances: T2 has poor low-shot perf, while being slightly better than code prompt on an LLM finetuned with RLHF.

Model	code-davinci-002							text-davinci-002						text-davinci-003					
k-shot	Arg-I	$\Delta_{C-T}^{(1)}$	$\Delta^{(2)}_{C-T}$	Arg-C	$\Delta^{(1)}_{C-T}$	$\Delta^{(2)}_{C-T}$	Arg-I	$\Delta_{C-T}^{(1)}$	$\Delta^{(2)}_{C-T}$	Arg-C	$\Delta^{(1)}_{C-T}$	$\Delta^{(2)}_{C-T}$	Arg-I	$\Delta_{C-T}^{(1)}$	$\Delta^{(2)}_{C-T}$	Arg-C	$\Delta^{(1)}_{C-T}$	$\Delta^{(2)}_{C-T}$	
0	50.6	0.7	50.6	36.0	-2.2	36.0	48.9	-2.6	20.2	35.0	-2.4	13.1	49.9	-2.1	15.3	37.8	-1.4	12.6	
1	57.3	0.1	4.7	47.8	-1.0	4.7	55.8	1.8	5.3	45.2	3.0	4.9	56.0	-1.5	1.1	44.7	-3.2	1.1	
5	58.0	1.1	1.9	52.5	2.9	1.1	56.0	-2.0	1.0	48.8	3.0	1.4	59.2	-0.9	-0.7	51.7	1.4	-2.1	
10	57.2	-1.4	-0.2	52.8	0.8	0.1	60.6	2.7	2.9	53.9	6.4	5.0	62.8	3.1	0.6	56.3	5.0	-1.2	
20	62.1	1.7	0.2	58.5	3.6	2.4	59.9	0.9	3.7	56.5	8.0	5.8	65.0	3.5	0.7	60.4	7.8	-0.4	





