

Evaluating In-Context Learning for Computational Literary Studies:

A Case Study Based on the Automatic Recognition of Knowledge Transfer in German Drama

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Sommersemester 2024

Based on [Janis Pagel, Axel Pichler, Nils Reiter, Evaluating In-Context Learning for Computational Literary Studies: A Case Study Based on the Automatic Recognition of Knowledge Transfer in German Drama, In Proceedings of the 8th Joint SIGHUM Workshop on Computational Linguistics for Cultural Heritage, Social Sciences, Humanities and Literature \(LaTeCH-CLIL 2024\), pp. 1-10, St. Julians, Malta, March 2024, URL](#)

<https://aclanthology.org/2024.latechclil-1.1>

Observations

- Large language models (LLMs) are said to have “emergent abilities” (Wei et al. 2022)
 - i.e. abilities that are not there in smaller models but suddenly appear in larger models without a change in training data/method
- So called “In-Context Learning” can be used to provide LLMs with a few examples/the desired output with a prompt and get results (Wei et al. 2023)

What is ICL?

In-Context Learning: A frozen LLM learns to solve a specific new task at inference time (without any change to its weights) only by conditioning on a prompt

- **Few-shot in-context learning:** (1) The prompt includes examples of the intended behavior, and (2) *no examples of the intended behavior were seen in training.*

```
Q: What is (2 * 4) * 6?           A: 48
Q: What is 17 minus 14?          A: 3
Q: What is 98 plus 45?           A:
```

From Brown et al. (2020), supplementary material

- **Zero-shot in-context learning:** (1) The prompt includes no examples of the intended behavior (but it can contain other instructions), and (2) *no examples of the intended behavior were seen in training.*

```
Q: What is the German translation of "In no case may they be used for commercial
purposes."
A:
```

From Brown et al. (2020), supplementary material

Advantages / Risks of ICL

General advantages of ICL (Dong et al. 2023):

- Prompts written in natural language
- Training-free (no gradient updates)
- Learning from analogy

Advantages for Computational Literary Studies (CLS):

- No in-depth knowledge of LLMs and NLP
- Corresponds to the low-resource settings and highly individuated character of CLS-questions

Risks for CLS:

- Unreflected usage of ICL can lead to results that do not represent what the prompt/research questions was intending
- Difficult to interpret how the results come about

Research Questions

Primary:

- How adequately do large language models capture the transfer of knowledge about **family relations** in **German drama texts** using **in-context learning (ICL)**?

Adjacent:

- What is necessary to make the models understand the task and get results that can be evaluated automatically?
- What can ICL potentially become for the computational literary studies
 - as a subject of study?
 - as a tool/method for downstream tasks?

Transfer of Family Relations



Transfer of Family Relations

Luke. I'll never join you!

Darth Vader. If you only knew the power of the Dark Side. Obi-Wan never told you what happened to your father.

Luke. He told me enough! It was you who killed him!

Darth Vader. No. I am your father.



- Knowledge: Darth Vader is father of Luke
- Source of knowledge: Darth Vader
- Target of knowledge: Luke

Data

- Dataset described in Andresen et al. (2022)
- 30 German theatre plays from DraCor (Fischer et al., 2019)
- Annotated for knowledge transfer of family relations (parent-of, siblings, spouses, uncle-of, aunt-of, etc.), source and target of knowledge
- 736,808 tokens
- 1,277 annotated passages

Task: Recognition of Family Relations in Dramatic Texts

Classification Task:

- Identify family relationship between two literary characters, given text snippet

Entailment Task:

- Re-formulation of classification task
- Does the text snippet entail that a certain family relationship exists between two characters?

Classification Task Example

Iphigenia.

The eldest,—he whom madness lately seiz'd,
And who is now recover'd,—is Orestes,
My brother, and the other Pylades,
His early friend and faithful confidant.

From: Goethe's *Iphigenia in Tauris* (transl. by Anna Swanwick)

Variation 1: given character names

_____ (Iphigenia, Orestes)

-> Siblings(Iphigenia, Orestes)

Variation 2: character names not given

_____ (_____, _____)

-> Siblings(Iphigenia, Orestes)

Experiments

3 Models:

- Llama 2 (Touvron et al. 2023)
- Platypus 2 (Lee et al. 2023)
- GPT-4 (OpenAi 2023)

- Specific prompt templates per model

Experimental Setups:

- Different model sizes (7B + 13B)
- Different context window size
- w/ + w/o character names
- Zero- and few-shot setups

- Annotations filtered for most frequent categories:

Category	Count
parent-of	29
child-of	26
siblings	23
spouses	11
Total	89

Prompt Examples

Classification Experiment: Llama 2 (zero shot w/o character)

```
<s>[INST]
What kind of family relationship is conveyed in the following German
text {drama_snippet}?

Choose one of "parent_of", "child_of", "siblings", "spouses".
JUST name the label and nothing else!
Family relation:
[/INST]
```

Prompt Examples

Classification Experiment: Llama 2 (few shot w/ character)

```
<s>[INST]
What kind of family relationship between {person_1} and {person_2} is conveyed in the following
German text {drama_snippet}?

Choose one of the following labels:
A: "child_of"
B: "parent_of"
C: "siblings"
D: "spouses".
JUST name the label and nothing else!
Family relation:
[/INST]
```

Results

Model	Context	Learning method	Prompt	F1	Prec.	Rec.	Acc.
Majority Baseline	–	–	–	0.16	0.10	0.33	0.33
Llama-2-13b	1	zero shot	v2 w/ character	0.66	0.69	0.68	0.68
Llama-2-13b	2	few shot	w/ character	0.68	0.74	0.66	0.66
Platypus2-13b	2	zero shot	w/o character	0.53	0.60	0.54	0.54
GPT-4	2	zero shot	w/ character	0.52	0.55	0.51	0.55

Table 1: Results of Experiment 1: Classification.

Discussion

Striking features of our hands-on experience:

- The major influence that prompt design has on output (even at punctuation level)

Our Hypothesis:

- Llama 2 not able to make connection between implicit knowledge of family relations and propositions
 - Prompt: “Does ‘Peter is taller than John’ imply that ‘John is smaller than Peter’?”
Llama 2: “To entail the latter proposition, the text would need to explicitly state that John is smaller than Peter”

Consequences

Key takeaways:

- An unreflected and generic out-of-the-box use of ICL in CLS not recommended
- Natural language output of LLMs can be seen as regression compared to structured, symbolic output
- Recommendation:
 - Carry out small experiments to check whether the concepts relevant to a particular CLS question are latently represented in the label space of the selected LLM!
 - If not so: use a pretrained PLM and fine tune it!
 - Find way to map output of LLM to structured output

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Appendix

Model	Context window	Learning method	Prompt	F1	Precision	Recall	Accuracy
Majority Baseline	–	–	–	0.16	0.10	0.33	0.33
Llama-2-7b	1	zero shot	w/o character	0.46	0.49	0.45	0.45
Llama-2-7b	1	zero shot	v2 w/o character	0.37	0.57	0.36	0.36
Llama-2-7b	1	few shot	w/o character	0.28	0.35	0.32	0.32
Llama-2-7b	1	zero shot	v2 w/ character	0.58	0.74	0.49	0.49
Llama-2-7b	1	few shot	w/ character	0.29	0.41	0.32	0.32
Llama-2-13b	1	zero shot	w/o character	0.48	0.60	0.51	0.50
Llama-2-13b	1	zero shot	v2 w/o character	0.56	0.56	0.56	0.56
Llama-2-13b	1	few shot	w/o character	0.41	0.41	0.44	0.44
Llama-2-13b	1	zero shot	v2 w/ character	0.66	0.69	0.68	0.68
Llama-2-13b	1	few shot	w/ character	0.63	0.71	0.63	0.63
Llama-2-7b	2	zero shot	w/o character	0.47	0.48	0.47	0.47
Llama-2-7b	2	zero shot	v2 w/o character	0.35	0.65	0.33	0.33
Llama-2-7b	2	few shot	w/o character	0.19	0.27	0.24	0.24
Llama-2-7b	2	zero shot	v2 w/ character	0.51	0.52	0.49	0.49
Llama-2-7b	2	few shot	w/ character	0.20	0.28	0.25	0.25
Llama-2-13b	2	zero shot	w/o character	0.44	0.51	0.47	0.47
Llama-2-13b	2	zero shot	v2 w/o character	0.51	0.50	0.53	0.53
Llama-2-13b	2	few shot	w/o character	0.38	0.36	0.4	0.4
Llama-2-13b	2	zero shot	v2 w/ character	0.67	0.70	0.65	0.65
Llama-2-13b	2	few shot	w/ character	0.68	0.74	0.66	0.66
Platypus2-7b	1	zero shot	w/ character	0.26	0.51	0.19	0.19
Platypus2-7b	1	zero shot	w/o character	0.37	0.47	0.37	0.37
Platypus2-7b	2	zero shot	w/ character	0.29	0.31	0.33	0.33
Platypus2-7b	2	zero shot	w/o character	0.26	0.46	0.25	0.25
Platypus2-13b	1	zero shot	w/ character	0.41	0.50	0.46	0.46
Platypus2-13b	1	zero shot	w/o character	0.44	0.50	0.51	0.50
Platypus2-13b	2	zero shot	w/ character	0.42	0.49	0.46	0.46
Platypus2-13b	2	zero shot	w/o character	0.53	0.60	0.54	0.54
GPT-4	2	zero shot	w/ character	0.52	0.51	0.55	0.55
GPT-4	2	zero shot	w/o character	0.52	0.50	0.55	0.55