

Leveraging Open Large Language Models for Historical Named Entity Recognition

Carlos-Emiliano González-Gallardo¹, Hanh Thi Hong Tran^{2,3,4},
Ahmed Hamdi² & Antoine Doucet²

¹ Université de Tours, France

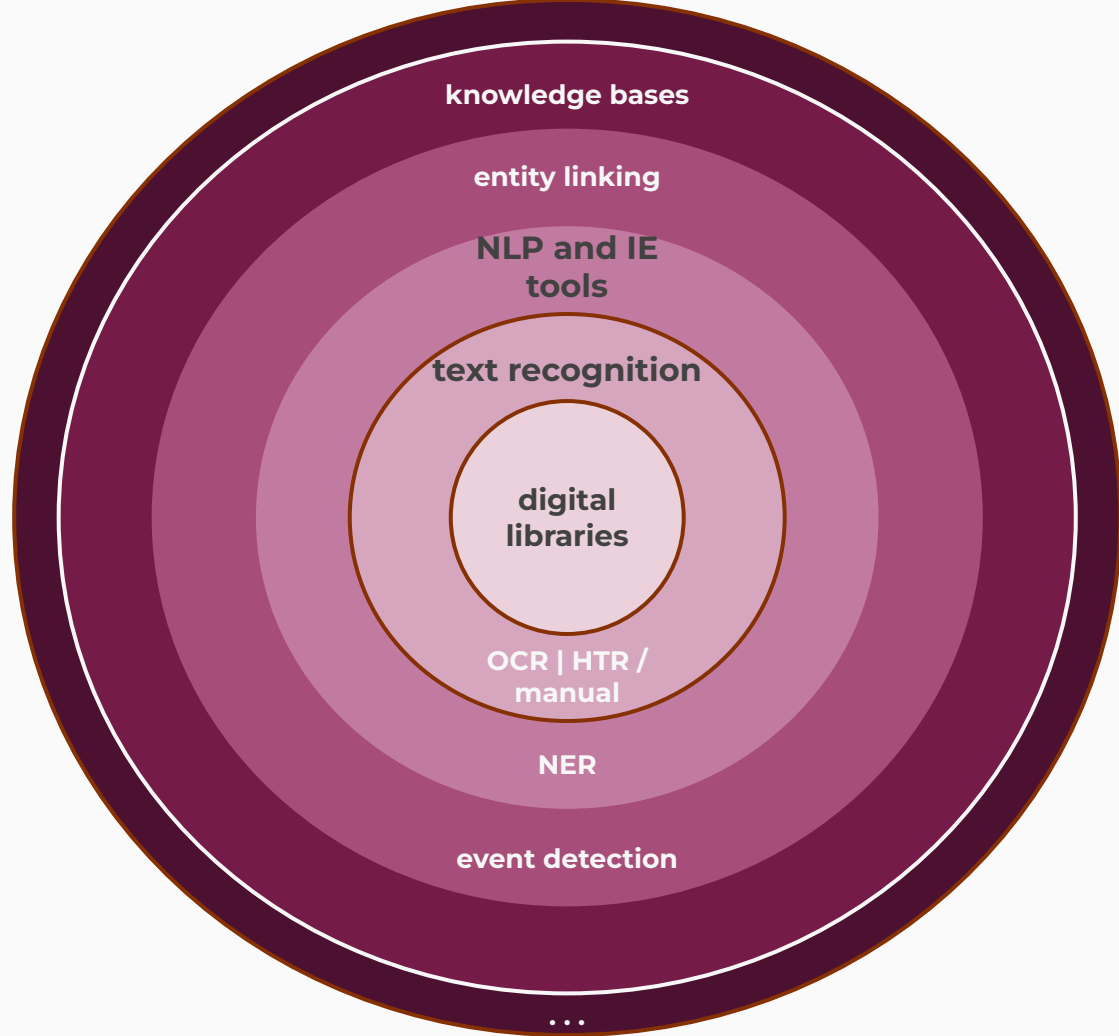
² Université de la Rochelle, France

³ Jožef Stefan International Postgraduate School, Slovenia

⁴ Jožef Stefan Institute, Slovenia



Enriching digital repositories



However... problems and challenges



Document related

- Documents deteriorated by **time**
- Poor **quality** of printing materials & digitization
- Inaccurate **scanning** processes
- **Language** change & evolution

NER related

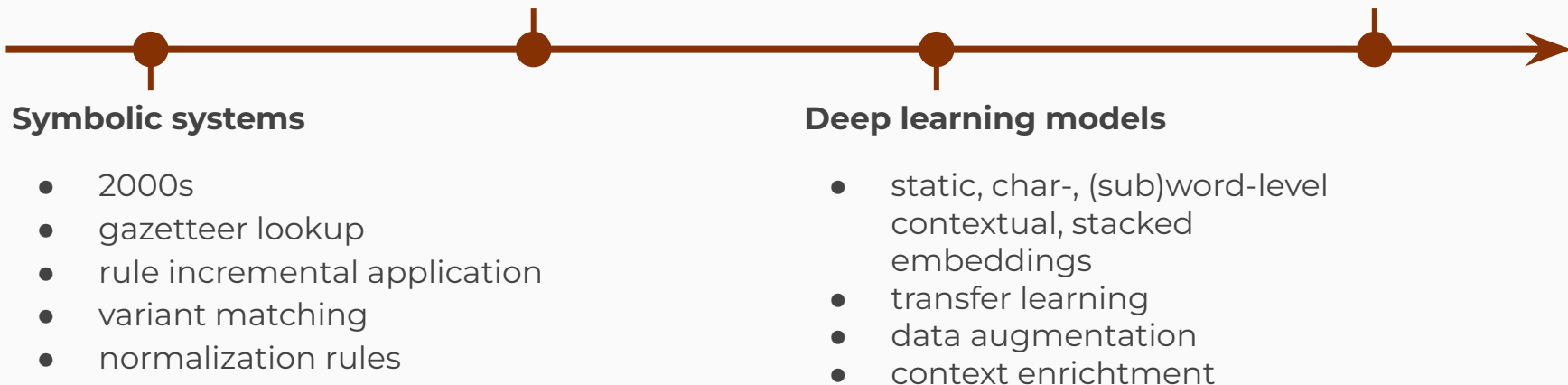
- Inconsistency of annotation **guidelines**
- Entity **complexity**
- **Multilingualism**
- code-switching

Machine learning models

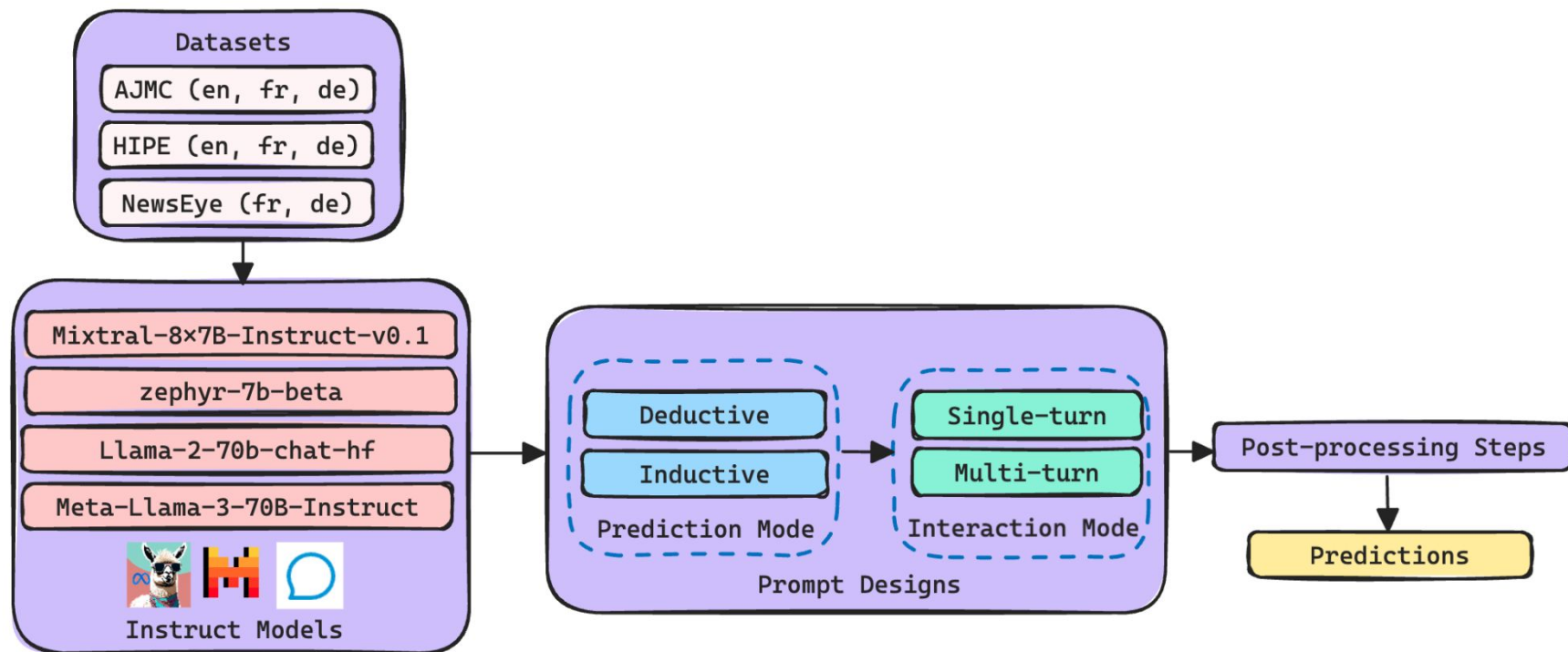
- annotated training data
- manually selected features
- CRF
- CRF + gazetteer

LLMs models

- in-context learning
- API-accessible
- Computer-assisted NER
- Digital libraries processing ad-hoc pipelines



Few-shot Prompting for Historical NER



Historical document datasets

Greek tragedy written in the 5th century BCE by Sophocles

CLEF-HIPE-2022 evaluation lab corpora

Classic commentaries (19C)

- AJMC (en, fr, de)

Historical newspapers (19C-20C)

- HIPE-2020 (en, fr, de)
- NewsEye (fr, de)

NER annotations

Universal (person, location, organization, time, human production)

Domain-specific (bibliographic references)

HIPE 2022
A CLEF Evaluation Lab.

About Tasks & Data Evaluation Results Timeline Workshop References

HIPE – Identifying Historical People, Places and other Entities

Shared Task on Named Entity Recognition and Linking in Multilingual Historical Documents



REPORT 200 LOST IN ISLAIRE WRECK OFF STORMWAY

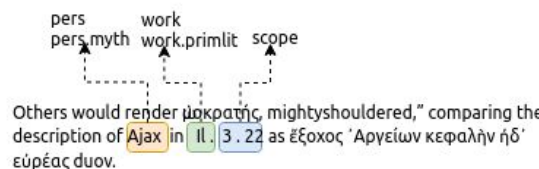
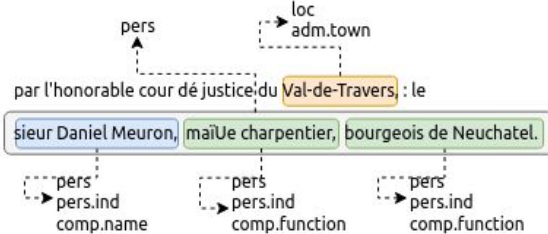
NORTHERN PACIFIC, TRANSPORT STRANDED OFF FIRE ISLAND, IS NOW BEING SUCCORED BY A FLEET OF CRUISERS AND LIFEBOATS

ΑΘΗΝΑ.

‘ΑΕΙ μὲν, ὦ παῖ Λατρίου, δέδορκα σε πείραν τιν’ ἐχθρὸν ἀρπάσαι θηρόμενον· καὶ νῦν ἐπὶ σκηναῖς σε ναυτικάς ὁρᾷ Αἴαντος, ἐνθα τάξιν ἐσχάτην ἔχει, πάλαι κυνηγετούδα καὶ μετρούμενον ἔχον τὰ κείνου νεοχαραχθ’, ὅπως ἴδῃς εἰτ’ ἐνδον εἰτ’ οὐκ ἐνδον. εὐ δέ σ’ ἐκφέρει

1. Λατρίου ΛΑ. Λατρίου C' Vat. ac. Λατρίου L'. 6. τὰ 'είσον Λ. τείνειον Pal. νεοχαραχθ' νεοχαραχθ' L. νεοχαραχθ' C' L' Vat. ac.

1-3. Athena's eye is ever on Odysseus, and she is now come from Olympus to succour him. *Infra* l. 36.
4. δέ μιν καὶ νῦν The structure is periphrastic; i.e. 'As I have ever seen thee... so now I see thee.' *Essay on Language*, § 36, p. 68.
5. (1) 'In quest to snatch some exploit on a foe, i.e. seeking to effect some surprise against a foe. Or, (2) 'Seeking to foil (or detect) some enemy's attempt. The latter (2) is simpler, and *πείρα* is used of the attempt of Ajax, *infra*, 299, 303; but the former (1) is on the whole more probable. For Athena does not profess to know the circumstances until l. 36. She asks for information, and only assumes, what is evident, that Odysseus is engaged in some hostile adventure. This aspect of his character appears in the tenth Iliad. Cp. *infra*, 18, *ἐνέχοναι* εἰ μ' ἐν' ἀσπίδι θηρόμεναι I believe evading'.
6. νεοχαραχθ' Ajax has but recently returned, dragging the cattle with him, *infra*, 296. Odysseus has tracked him so far, but the confused struggle at the tent-door has made it uncertain whether he is not gone forth again.
7, 8. εὐ δέ σ' ἐκφέρει, *εξ ἧς* λ.) Odysseus is like a huntsman who is led to the right point by the scent of a keen Spartan hound. The dog is introduced to complete the image. Cp. *infra*, 19, 22. Is *ἐνέχοναι* (1) *accom.* or (2) *gen.*? *ἐνέχοναι* occurs in Aesch. *Ag.* 1092, and the authorities for *ἐνέχοναι* are late. But the sentence is more balanced if the epithet is taken by *hypoallage* with *πείρα*, and the object *θεῖον* is somewhat abrupt by itself. Cp. the forms *ἐνέχοναι*, *ἐνέχοναι*, *ἐνέχοναι*.



Prompt Designs

Inductive

Next are the annotation guidelines for each named entity type.

- + PERSON (pers):
<specify the guidelines here>
...
- + ORGANISATION (org):
<specify the guidelines here>
...
- + LOCATION (loc):
<specify the guidelines here>
...
- + HUMAN PRODUCTION (HumanProd):
<specify the guidelines here>
...
- + TIME (time):
<specify the guidelines here>
...
- + Non-annotated entities:
<specify the guidelines here>
...

The output should be SAME sentence respecting casing and white spaces with the identified named entities delimited by <TYPE>named entity</TYPE>.
Do not add or remove white spaces from the input sentence.
Do not any note or explanation to the output.

Task Description

You are an excellent automatic named entity recognition (NER) system.
I will provide you the sentence delimited by double quotes from which
you need to identify and classify the named entities into the
following types: PERSON, ORGANISATION, PRODUCTION, TIME and LOCATION.

Prediction mode

Interaction mode

INPUT:

OUTPUT:

Input Query

Prompt Designs : HIPE-2020 dataset

Single-turn

Multi-turn

Deductive process → from general to particular (annotation guidelines)

NewsEye Named Entity and Stance Annotation Guidelines

Version: 31 - March 2020

Initially based on version 2.0 of the Impresso NE annotation guidelines¹

1. Preamble

2. General instructions

2.1 Entity types and subtypes

2.2 Named entity mention lexical characteristics

2.3 Nesting and special constructions

2.4 Ambiguities

3. Entities

3.1 Person

3.2 Organisations

3.3 Locations

3.4 Human production

3.5 Non-annotated entities

4. Quick guide and concrete considerations

4.1 Heuristics

4.2 Overview of types, subtypes and components

5. Stance annotation guidelines

6. Named entity linking guidelines

6.1 How Specific Should Linked Entities Be?

6.2 Metonymy

6.3 Can Mention Boundaries Overlap?

ANNEX A Main changes w.r.t. Quareso v1

ANNEX B Main changes w.r.t. Impresso v1

ANNEX C Main changes w.r.t. NewsEye v1

¹ By Maud Ehrmann, Camille Watter, Matteo Romanello and Impresso adjustments, Maud Ehrmann for the Matteo Romanello for Impresso adjustments.

These guidelines were primarily written to support corpus. They are however also useful for system development. In this case, instructions regarding manual annotation

¹ Camille Watter for initial Quareso translation and Impresso adjustments, Simon Clematide and Matteo Romanello



Impresso Named Entity Annotation Guidelines

Version: 2.1 - December 2019

Maud Ehrmann, Camille Watter, Matteo Romanello, Simon Clematide¹

Guidelines for the Annotation of Named Entities in the Domain of Classics

Matteo Romanello (Université de Lausanne)
Sven Najem-Meyer (Ecole Polytechnique Fédérale de Lausanne)

Table of Contents

Guidelines for the Annotation of Named Entities in the Domain of Classics

1. Introduction

2. Annotation of Named Entity Recognition (NER)

2.1 General annotation rules

2.2 Generic entities

Person

Location

Organisation

Date

Work

Source

Object

2.3 Bibliographic entities

Primary sources

Primary-secondary

Secondary sources

Secondary-full

Secondary-met

Secondary-variant

3. Annotation of Entity Linking (EL)

4. Text corrections (segmentation, orthography, OCR)

References



Creative Commons CC BY 4.0

Version 18.03.2022

Post-processing Steps

" My Lord , • ' 1 received yesterday , at eleven o ' clock at night , the note and the counter projet which your excellency did me the honour to address to roe .

- HIPE (en)
- Zephyr 7b
- Inductive
- Single-turn

#####

Estimated length: 222

OUTPUT: "<SENTENCE>'My Lord ', at eleven o' clock at night yesterday, I received the note and the counter proposal which your excellency did me the honour to address to roe. '</SENTENCE>"

Named entities:

- 'My Lord' is not annotated as it does not contain a proper name.
- 'yesterday' is annotated as a <time>entity.
- 'eleven o' clock at night' is annotated as a <time>entity.
- 'note' and 'counter proposal' are annotated as <humanprod>entities.
- 'your excellency' and 'roe' are annotated as <pers>entities.

Note: The output does not include any explanations or notes. The entities are delimited by <TYPE> and the sentence is preserved with the same casing and white spaces as the input.

FINAL Estimated length: 222

#####

Parsing & alignment process

- Remove text that is not part of the original sentence
- Insert the text that has been removed
- Replace the characters that have been modified

Results and Final Thoughts

Evaluation metrics

- Precision, recall & F1-score
- Micro level
- Strict & fuzzy boundary matching

General results

- Unbalance precision vs recall
- F1-score below 40%
- Inductive prediction shows better performance
- Single-turn mode better but noisy recall
- Multi-turn mode reduces output noise

In a nutshell

- Fined-tuned neural models on historical corpora are still a better option
- Language capacities of LLMs can play against you

NewsEye dataset (fr, de)

- Better with single-turn mode with and without guidelines

HIPE dataset (en, fr, de)

- Better with single-turn mode without guidelines

AJMC dataset (en, fr, de)

- Better with multi-turn mode with deductive prediction (with guidelines)



Merci !

Carlos-Emiliano
González-Gallardo

gonzalezgallardo@univ-tours.fr

EUROPEAN EDITION—PARIS, FRIDAY

CIFIC, TRANSPORT STRANDED ISLAND, IS NOW BEING SUCCORED A FLEET OF CRUISERS AND LIFEBOATS

Many
Goes
ing

RAID.)
Northern
which
ing off
efloated,
neasures
bsolutely

ft Brest
2,451 re-
m, were
headles



CHART SHOWING SPOT WHERE TRANSPORT GROUNDED.

Table 1. NER strict and fuzzy micro results in NewsEye dataset. For each evaluation metric, bold represents the highest score for each setting, and underline represents the highest score above all four settings.

		strict						fuzzy					
		fr			de			fr			de		
		P	R	F1	P	R	F1	P	R	F1	P	R	F1
G + R	Llama-3	<u>42.9</u>	16.0	23.3	18.1	15.2	16.5	<u>55.5</u>	20.7	30.2	24.5	20.5	22.3
	Llama-2	16.7	21.1	18.6	9.0	21.2	12.6	27.7	35.1	31.0	13.2	31.3	18.6
	Mistral	24.3	21.9	23.0	12.7	20.1	15.6	40.0	36.1	38.0	21.0	33.3	25.7
	Zephyr	31.5	17.9	22.8	12.9	11.0	11.9	49.7	28.2	36.0	21.7	18.5	20.0
G + nR	Llama-3	40.7	15.4	22.4	<u>18.3</u>	14.7	16.3	24.9	20.0	22.2	<u>50.2</u>	27.6	35.7
	Llama-2	31.7	29.6	30.6	12.6	29.6	17.7	44.7	41.7	43.1	17.7	<u>41.6</u>	24.9
	Mistral	21.8	13.2	16.4	10.5	13.9	12.0	38.9	23.4	29.2	19.1	25.2	21.7
	Zephyr	30.0	13.1	18.2	11.4	7.5	9.1	22.2	14.6	17.6	33.0	19.1	24.2
nG + R	Llama-3	37.9	16.6	23.0	16.0	15.1	15.5	50.4	22.0	30.7	22.1	20.9	21.5
	Llama-2	21.1	22.8	22.0	8.5	13.2	10.3	33.6	36.3	34.9	12.3	19.2	15.0
	Mistral	19.3	14.9	16.8	9.4	12.1	10.6	33.8	26.0	29.4	19.5	25.1	21.9
	Zephyr	35.9	19.7	25.4	14.0	10.1	11.7	53.3	29.2	37.7	21.5	15.6	18.1
nG + nR	Llama-3	42.3	10.4	16.7	16.6	14.9	15.7	53.3	13.1	21.0	23.3	20.9	22.0
	Llama-2	28.7	36.3	32.1	11.4	29.0	16.3	40.8	<u>51.6</u>	<u>45.6</u>	16.1	41.0	23.1
	Mistral	19.6	13.5	16.0	9.5	14.0	11.3	33.5	23.0	27.3	18.0	26.4	21.4
	Zephyr	28.5	11.1	16.0	10.9	4.7	6.6	43.2	16.8	24.2	23.3	10.1	14.1
SOTA	Stacked NER [5]	75.0	70.6	72.7	64.9	50.2	56.6	85.4	80.5	82.9	82.3	66.4	73.5
	ChatGPT [20]	70.9	72.3	71.6	-	-	-	77.8	79.4	78.6	-	-	-

Table 2. NER strict and fuzzy micro results on HIPE dataset. For each evaluation metric, bold represents the highest score for each setting, and underline represents the highest score above all four settings.

		strict									fuzzy								
		en			fr			de			en			fr			de		
		P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1
G + R	Llama-3	25.5	23.8	24.6	36.9	22.1	27.6	32.6	30.1	31.3	39.1	36.5	37.7	47.2	28.3	35.4	42.6	39.3	40.9
	Llama-2	20.0	21.2	20.6	25.7	25.6	25.6	20.4	26.5	23.0	32.0	33.9	32.9	36.5	36.3	36.4	28.3	36.8	32.0
	Mistral	19.5	18.0	18.8	25.8	34.8	29.6	20.6	21.4	21.0	34.2	31.6	32.9	38.1	<u>51.4</u>	43.8	32.1	33.3	32.7
	Zephyr	25.4	3.3	5.9	24.8	20.8	22.6	20.1	10.6	13.8	<u>45.8</u>	6.0	10.6	34.8	29.1	31.7	29.4	15.4	20.2
G + nR	Llama-3	25.6	22.9	24.2	38.6	21.3	27.4	34.6	29.6	31.9	40.9	36.8	38.7	50.2	27.6	35.7	46.2	39.6	42.7
	Llama-2	21.2	32.7	25.7	31.3	37.2	34.0	21.3	36.2	26.9	32.1	<u>49.7</u>	39.0	41.9	49.9	45.6	28.5	48.3	35.8
	Mistral	15.6	13.1	14.3	25.6	17.6	20.8	19.1	19.7	19.4	31.2	26.3	28.5	39.9	27.4	32.5	30.7	31.7	31.2
	Zephyr	21.2	6.2	9.6	23.4	13.5	17.1	18.8	10.7	13.7	34.1	10.0	15.5	33.0	19.1	24.2	28.4	16.2	20.7
nG + R	Llama-3	24.5	25.2	24.8	34.6	22.2	27.1	29.2	30.1	29.6	37.7	38.8	38.2	44.9	28.8	35.1	39.9	41.1	40.5
	Llama-2	21.1	22.1	21.6	26.5	28.2	27.3	21.6	29.0	24.7	33.0	34.5	33.7	38.0	40.4	39.2	30.0	40.4	34.4
	Mistral	17.1	19.2	18.1	26.8	26.9	26.9	19.5	21.0	20.2	30.8	34.5	32.6	39.2	39.4	39.3	29.8	32.3	31.0
	Zephyr	20.6	5.8	9.0	28.2	20.4	23.7	22.8	12.1	15.8	34.1	9.6	15.0	37.9	27.4	31.8	34.8	18.5	24.1
nG + nR	Llama-3	<u>28.3</u>	24.1	26.0	<u>41.1</u>	21.1	27.9	<u>35.6</u>	30.0	32.5	44.0	37.4	40.4	<u>54.0</u>	27.8	36.7	<u>47.7</u>	40.2	<u>43.6</u>
	Llama-2	23.8	28.3	25.9	31.7	35.4	33.5	24.6	<u>36.4</u>	29.4	39.0	46.3	<u>42.4</u>	43.8	48.8	<u>46.2</u>	33.3	<u>49.3</u>	39.8
	Mistral	16.9	14.0	15.3	30.7	23.6	26.7	20.2	18.7	19.5	34.6	28.7	31.4	45.2	34.7	39.3	33.2	30.7	31.9
	Zephyr	26.2	3.6	6.3	30.4	9.7	14.7	26.0	6.4	10.2	39.3	5.4	9.4	40.0	12.8	19.4	40.2	9.9	15.8
SOTA	Stacked NER [5]	-	-	-	83.5	84.9	84.2	78.6	78.7	78.7	-	-	-	91.3	92.9	92.1	91.3	92.9	92.1
	Temporal NER [18]	64.3	61.7	63.0	76.5	76.5	76.5	75.9	76.7	76.3	78.7	80.0	79.3	86.7	86.7	86.7	85.2	85.7	85.4
	ChatGPT [20]	-	-	-	32.5	50.0	39.4	-	-	-	-	-	-	49.0	75.4	59.4	-	-	-

Table 3. NER strict and fuzzy micro results on AJMC dataset. For each evaluation metric, bold represents the highest score for each setting, and underline represents the highest score above all four settings.

		strict									fuzzy								
		en			fr			de			en			fr			de		
		P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1
G + R	Llama-3	27.4	9.2	13.8	24.3	5.0	8.3	35.2	11.8	17.7	37.6	12.6	18.9	31.1	6.4	10.6	40.6	13.6	20.4
	Llama-2	16.8	8.1	10.9	41.6	17.8	24.9	29.6	12.6	17.7	44.3	21.3	28.7	52.6	22.5	31.5	46.9	19.9	27.9
	Mistral	26.0	33.1	29.1	25.4	30.8	27.9	27.9	41.6	33.4	40.1	50.9	44.8	33.2	40.3	36.4	38.7	57.9	46.4
	Zephyr	36.8	16.4	22.7	41.1	17.2	24.3	42.5	18.6	25.9	47.7	21.3	29.4	51.7	21.7	30.5	48.5	21.2	29.5
G + nR	Llama-3	26.5	8.9	13.3	27.6	6.7	10.7	40.2	10.7	16.9	35.9	12.1	18.1	32.2	7.8	12.5	48.0	12.8	20.3
	Llama-2	21.8	10.6	14.3	48.7	21.1	29.5	29.2	13.1	18.1	51.8	25.3	34.0	62.2	27.0	37.6	48.0	21.5	29.7
	Mistral	23.6	14.4	17.9	27.3	14.7	19.1	21.3	20.4	20.8	36.3	22.1	27.5	30.9	16.7	21.7	30.0	28.8	29.4
	Zephyr	32.6	8.9	14.0	36.5	8.6	13.9	41.3	10.0	16.0	43.2	11.8	18.5	45.9	10.8	17.5	46.7	11.3	18.1
nG + R	Llama-3	21.3	9.2	12.9	19.5	6.1	9.3	23.6	10.0	14.0	28.7	12.4	17.3	25.7	8.1	12.3	26.7	11.3	15.8
	Llama-2	18.6	10.1	13.1	36.2	21.1	26.7	28.7	15.7	20.3	43.6	23.6	30.6	48.6	28.3	35.8	42.6	23.3	30.1
	Mistral	18.9	21.6	20.2	20.8	16.9	18.7	21.7	21.5	21.6	28.5	32.5	30.4	27.0	21.9	24.2	30.2	29.8	30.0
	Zephyr	30.0	15.5	20.5	38.0	15.0	21.5	34.0	13.6	19.4	37.8	19.5	25.8	47.9	18.9	27.1	41.8	16.8	23.9
nG + nR	Llama-3	22.4	9.2	13.0	22.6	6.4	10.0	24.3	8.9	13.0	30.8	12.6	17.9	27.5	7.8	12.1	28.6	10.5	15.3
	Llama-2	22.3	14.1	17.3	47.0	21.7	29.7	34.4	17.5	23.2	50.9	32.2	39.4	56.0	25.8	35.4	50.3	25.7	34.0
	Mistral	13.8	15.8	14.7	15.0	16.1	15.5	25.9	18.1	21.3	21.6	24.7	23.0	18.6	20.0	19.3	32.3	22.5	26.5
	Zephyr	29.4	5.8	9.6	29.5	6.4	10.5	25.0	6.0	9.7	39.7	7.8	13.0	42.3	9.2	15.1	31.5	7.6	12.2
SOTA	Temporal NER	18			86.6	88.8	87.7	84.8	83.9	84.4	92.1	91.1	91.6	92.2	94.5	93.3	90.2	89.2	89.7
	ChatGPT	20			-	-	-	21.8	26.1	23.8	-	-	-	-	-	-	25.5	30.6	27.8

