Instructed Language Models with Retriever Are Powerful Entity Linkers

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Abstract

Generative approaches powered by large language models (LLMs) have demonstrated emergent abilities in tasks that require complex reasoning abilities. Yet the generative nature still makes the generated content suffer from hallucinations, thus unsuitable for entity-centric tasks like entity linking (EL) requiring precise entity predictions over a large knowledge base. We present Instructed Generative Entity Linker (INSGENEL), the first approach that enables casual language models to perform entity linking over knowledge bases. Several methods to equip language models with EL capability were proposed in this work, including (i) a sequence-to-sequence training EL objective with instruction-tuning, (ii) a novel generative EL framework based on a light-weight potential mention retriever that frees the model from heavy and non-parallelizable decoding, achieving 4× speedup without compromise on linking metrics. INSGENEL outperforms previous generative alternatives with +6.8 F1 points gain on average , also with a huge advantage in training data efficiency and training compute consumption. In addition, our skillfully engineered in-context learning (ICL) framework for EL still lags behind INSGENEL significantly, reaffirming that the EL task remains a persistent hurdle for general LLMs.

1 Introduction

Entity linking (EL) has emerged as a critical research problem in the intersection of Natural Language Processing (NLP) and Information Retrieval (IR), and it serves as a fundamental task in various NLP applications, including text understanding (Févry et al., 2020), question answering (Asai et al., 2020), to name a few.

Previous EL approaches typically divided EL into two steps: Mention Detection (MD) and Entity Disambiguation (ED). Once the MD model produces mention span proposals over the input document, dense ED models attempt to encode mention context and entity candidates into representations. Then a simple maximum inner product search (MIPS) is utilized to capture mention-entity correspondence, resulting in final entity predictions over the entire knowledge base (KB).

A more recent trend in EL research focuses on building an end-to-end pipeline that intertwines MD and ED and formulates them into different tasks, such as question-answering (Zhang et al., 2022b), multi-task learning (Ayoola et al., 2022) and language generation (Cao et al., 2021b).

While generative large language models (LLMs) have shown dominant abilities in a multitude of NLP tasks (Wang et al., 2022; Ouyang et al., 2022; Xu et al., 2023), their abilities are under-explored in the realm of entity-centric NLP tasks, especially EL. Unlike numerous knowledge language grounding tasks that can be readily unified to text-to-text frameworks (Xie et al., 2022), thanks to their close adherence to a unified surface form (*i.e.*, text), EL presents distinctive challenges. The foremost difficulty lies in the fact that unconstrained generation frequently fails to yield precise entity identifiers, because of the notorious hallucination issue of LLMs. Even though the pre-defined prefix trie proposed in Cao et al. (2021b) can ensure a legal generation sequence, the non-parallel beam search process makes it unsuitable for real-time usage, not to mention its performance lags behind later discriminative alternative. In this work, we revisit generative EL by proposing three variants: INSGENEL, INSGENEL-R and INSGENEL-ICL.

INSGENEL solves EL by leveraging a methodology which constrains the next possible tokens, and eliminates invalid options during generation, thus ensuring the generated text can be successfully parsed into EL results. In contrast to Cao et al. (2021b), the baseline model in INSGENEL diverges by incorporating the input document as part of the prompt and optimizes the casual language modeling (CLM) objective on decoder-only transformer models through instruction fine-tining approach, as opposed to employing a sequence-to-sequence objective based on an encoder-decoder neural architecture. We observe that by instruction fine-tuning decoder-only LMs such as OPT-series (Zhang et al., 2022a) and LLaMA-series (Touvron et al., 2023) , InsGenEL yields superior EL performance compared to previous work that finetunes a generative alternative on BART (Lewis et al., 2020a) with +6.8 F1 points on average. This suggests that instruction fine-tuning may unlock specific entity-related knowledge within pretrained language models. Additionally, this approach exhibits significant improvements in both training compute efficiency and data efficiency, indicating that foundation language models can effectively reduce the learning difficulty of task-specific objectives.

However, directly generating sequences incurs significant computational overhead during inference, as both memory footprint and computation increase with sequence length, not to mention the non-parallelizable nature of auto-regressive decoding. To address these challenges, we propose offloading the Mention Detection (MD) responsibility to an external retriever. For each document, the external retriever selects top-K entities that possibly exist in the document and constructs a possible mention set. Then the surface form matching process dynamically determines the range where decisions are needed during the generation. Finally, greedy decoding is employed only when a choice is necessary (within a decision range), *i.e.*, whether to start a mention, end an entity identifier, or choose among dynamic candidates.

Named InsGenEL-R, this novel EL generation framework offers several key advantages: a) Compared to constrained beam search, InsGenEL-R significantly reduces the number of heavy generation forwards at the cost of a simple vector retrieval. b) It does not fall into beam failure, *i.e.*, getting stuck with improbable mentions during the process of generating mention spans, thereby wasting valuable inference compute. c) It is less likely to miss obvious mentions, while traditional generative EL tends to make mistakes when generating mention boundaries. InsGenEL-R achieves 4× reduction in terms of the number of LM calls, reduces runtime by a similar ratio at the minor cost of performance decline. Moreover, we extend the usage of the same retriever in an in-context learning (ICL) manner on LLMs such as GPT-3 (Brown et al., 2020), GPT-3.5 and Codex, named InsGenEL-ICL. Side-by-side comparative results indicate that while generic LLMs can correctly adhere to the format of exemplars by learning in context, they are unable to match the same accuracy exhibited by InsGenEL-R.

In summary, this paper pushes the generative EL paradigm to new limits, both in terms of evaluation metrics and runtime performance. The novel retrieval-augmented generative EL emulates an agent interacting with the dynamic environment, and sheds light on real-time generative EL without incurring a substantial metric drop. The new in-context learning paradigm for EL also indicates that current LLMs can not support an optimal ICL solution for EL. We release our code and checkpoints at https://github.com/MrZilinXiao/InsGenEntityLinking.

2 Related Works

Entity Linking (EL) is a task of locating mentions and disambiguating these surface forms into entities in some knowledge base. Each EL mention-entity prediction should be in the format of $\langle m_s, m_e, ent\rangle$, where m_s, m_e, ent indicate the start, end position of a mention and the entity identifier in the knowledge base respectively.

While early EL methods (Hoffmann et al., 2011; Daiber et al., 2013) treat EL as decomposed subtasks, such as Mention Detection (MD) and Entity Disambiguation (ED), a more recent trend is considering EL an end-to-end task. Kolitsas et al. (2018) first propose to use a neural-based model to conduct MD and ED jointly. Broscheit (2019) transform the EL into a BIO tagging problem by training a token-classification model with an external entity classification head. Zhang et al. (2022b) formulate EL into a question-answering (QA) problem and borrowed the popular retrieve-then-read pipeline in QA. Ayoola et al. (2022) leverage the type and description of entities and employs aggregation of discriminative scores to obtain the final result.

For the generative EL paradigm, Cao et al. (2021b) first turn EL into sequence-to-sequence constrained generation with an encoder-decoder transformer model, fully exploiting the flexibility of sequence generation. Cao et al. (2022) extend the same paradigm into multilingual EL. De Cao et al. (2021) propose an efficient generative EL model that relies on a shallow LSTM-based decoder, at the cost of generalization over general EL benchmarks. Mrini et al. (2022a) add an entity-matching prediction module over generated sequence and train EL using the MD objective, autoregressive objective and entity-matching objective jointly.

Our methods fall within the generative EL category as well, but they stand out in several distinctive features. First, putting the input document in the instruction enables EL generation on decoder-only casual language models rather than using an encoder to capture the global context. This approach enables us to benefit from the advancements in recent foundation models. Moreover, the mention detection offloading alleviates the burden of non-parallel generation. The practice of invoking the generative model only within the decision range drastically enhances computation efficiency, also presenting an intriguing parallel with interactive agents in knowledge base question answering (KBQA) (Gu et al., 2022) and the principle of Interactive NLP (Wang et al., 2023).

Instruction-tuning (Wei et al., 2022a) usually refers to finetuning language models with a collection of tasks that are formulated as plain-text instructions. Recent LLM pre-training (Brown et al., 2020; Chowdhery et al., 2022) show that emergent abilities (Wei et al., 2022b) exhibit when model size, data and training compute scale. Specifically, one of such abilities is that large models can leverage natural language instructions to solve language problems in a zero-shot fashion. When instructions alone can not guide satisfactory generation, **In-Context Learning (ICL)** can guide LLM to learn from in-context exemplars to perform complex reasoning, such as solving mathematical problems (Wei et al., 2022c).

Although instruction-tuning was originally proposed for zero-shot language tasks, we find that tuning models using document instructions also leads to improved prediction and disambiguation of uncommon entities in generative EL. Taking inspiration from ICL, we have extended our approaches to encapsulate EL with the ICL paradigm, facilitating an equitable comparison between INSGENEL-R and general-purpose LLMs.

Retrieval-augmented Language Models are an emerging class of models in the field of NLP. They offer innovative solutions to knowledge-related tasks by combining the power of language models with the ability to retrieve relevant information from a large corpus of external knowledge. Most works augment the input context with retrieved external documents, thus the encoded representation or generated sequence will be conditioned on external knowledge. Guu et al. (2020) firstly train an end-to-end language encoder with a dense retrieval system. Lewis et al. (2020b) finetune a general sequence-to-sequence model with an external retriever.

Our INSGENEL-R utilizes a lightweight encoder for each document to retrieve the most relevant entities, then uses a generative agent to eliminate impossible solutions dynamically. For similar entity-related retrieval scenarios, Févry et al. (2020) is the first to integrate entity supervision on language understanding tasks. Zhang et al. (2022c) constructs an entity memory bank and allows dynamic aggregation of entity representations, boosting the performance of entity-intensive question-answering and generation tasks. However, none of them use retrieved entities to explicitly guide text generation.

3 Methodology

3.1 Vanilla Generative EL

Vanilla generative EL addresses entity linking as an autoregressive sequence generation task, that is, given the document, the generated sequence should both indicate the mentions and their associated KB entities. Special boundary tokens are used to mark up mentioned plain string and entity identifiers. The training setup generally follows a standard sequence-to-sequence neural machine translation task (Wu et al., 2016) , where Cao et al. (2021b) maximize $p_\theta(y \mid x)$ with respect to the model's parameters θ. We refer to Appendix B for inherent problems of vanilla generative EL.

3.2 Instruction-tuned INSGENEL Baseline

Our baseline focuses on instruction-tuning a decoder-only casual language model. The prompt part consists of an optional natural language task instruction plus the document to be linked. The target sequence comprises the linked document in its plain-text form, but with special boundary symbols indicating mentions and corresponding entity identifiers[1].

[1] Following Cao et al. (2021b), we use parentheses as mention boundaries and brackets as entity identifier boundaries.

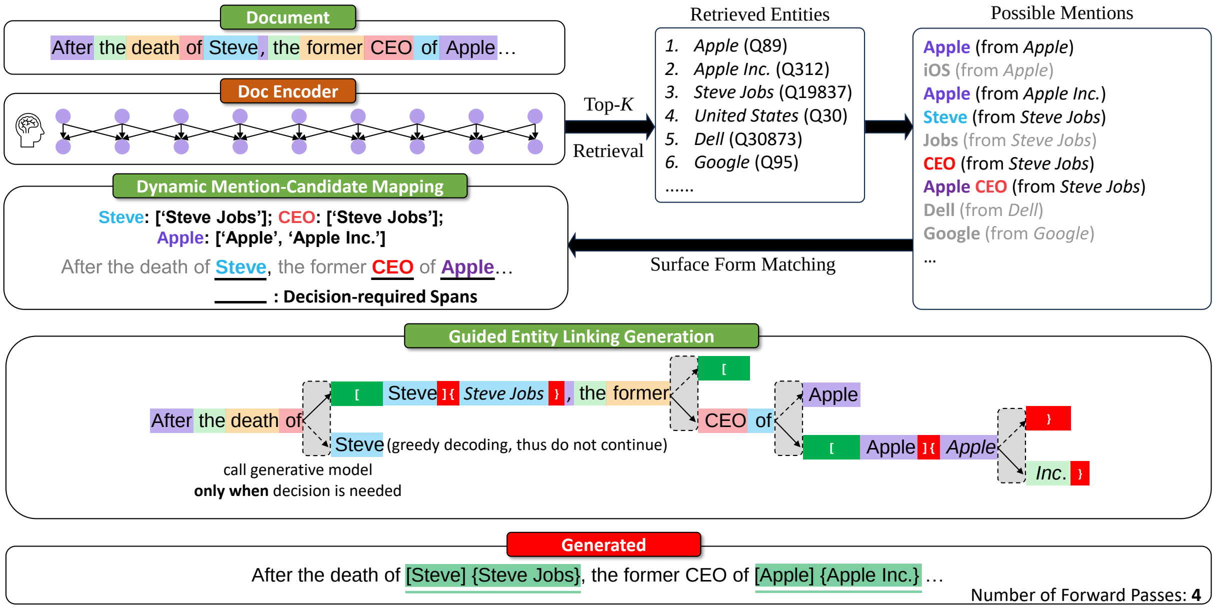

Document
After the death of Steve, the former CEO of Apple…
Doc Encoder
Top-K
Retrieval
Retrieved Entities
1. Apple (Q89)
2. Apple Inc. (Q312)
3. Steve Jobs (Q19837)
4. United States (Q30)
5. Dell (Q30873)
6. Google (Q95)
……
Possible Mentions
Apple (from Apple)
iOS (from Apple)
Apple (from Apple Inc.)
Steve (from Steve Jobs)
Jobs (from Steve Jobs)
CEO (from Steve Jobs)
Apple CEO (from Steve Jobs)
Dell (from Dell)
Google (from Google)
…
Surface Form Matching
Dynamic Mention-Candidate Mapping
Steve: ['Steve Jobs']; CEO: ['Steve Jobs'];
Apple: ['Apple', 'Apple Inc.']
After the death of Steve, the former CEO of Apple…
: Decision-required Spans
Guided Entity Linking Generation
After the death of
[Steve][Steve Jobs], the former
Steve (greedy decoding, thus do not continue)
call generative model
only when decision is needed
[
CEO of
Apple
[Apple][Apple
}
Inc. }
Generated
After the death of [Steve] {Steve Jobs}, the former CEO of [Apple] {Apple Inc.} …
Number of Forward Passes: 4

Figure 1: Overview of INSGENEL-R with greedy decoding strategy. Each box with grey background indicates a generative agent decision, and the dotted arrow denotes an abandoned decoding path. Best viewed in color and be in comparison with Appendix B and Figure 4.

We optimize the following cross-entropy loss, which is known as the next token prediction loss in casual language modeling:

$$\mathcal{L}_{\text{EL}} = -\sum_{i=n}^{N} \log P\left(y_i \mid y_1, \ldots, y_{i-1}\right), \qquad (1)$$

where $\mathbf{y} = [y_1, \ldots, y_n, \ldots, y_N]$ is the concatenation of the prompt and target sequence, and n denotes the length of the prompt sequence. Note that we do not backward the next token prediction loss on the prompt sequence. The fine-tuned model will serve as the generative backbone of all experiments in this paper.

3.3 INSGENEL-R: Retrieval-augmented Generative EL

Given a document chunk $x \in \mathcal{X}$, we would like to build a dual encoder that retrieves top-K candidate entities $\{e_1, e_2, e_3, \ldots, e_k\}$ which might be mentioned in x. The retriever computes document representations X^p and entity representations E^e as follows,

$$X = \mathbf{BERT}_P\left(\texttt{[CLS]}; x; \texttt{[SEP]}\right),$$
$$E^e = \mathbf{BERT}_E\left([\texttt{[CLS]}; \phi_{\text{title}}(e); \phi_{\text{desc}}\left(e\right); \texttt{[SEP]}\right),$$

where $\mathbf{BERT}_P$ and $\mathbf{BERT}_E$ are two BERT (Devlin et al., 2019) text encoders that do not share weights, [CLS] and [SEP] are BERT special tokens. $\phi_{\text{title}}(e)$ and $\phi_{\text{desc}}(e)$ are text identifier and text description of an entity e, respectively.

Specifically, we use a multi-label variant of noise contrastive estimation (NCE) (Gutmann and Hyvärinen, 2010) objective to train an entity retriever conditioned on document input, following the setup in Zhang et al. (2022b).

During training, we prepare a document chunk x and a set of oracle entities $\mathcal{E}(x) \in \mathcal{E}$ that are mentioned in x. We train the retriever with maximizing the following objective:

$$\sum_{e \in \mathcal{E}(x)} \log \left(\frac{\exp\left(S(e)\right)}{\exp\left(S(e)\right) + \sum_{e' \in \mathbf{N}(\mathcal{E},x)} \exp\left(S(e')\right)} \right)$$

where $S(e) = X_1^\top E_1^e$ stands for the matching score between document chunk x and entity e, $\mathbf{N}(\mathcal{E}, x)$ is a set of negative entities that do not overlap with gold entity set $\mathcal{E}(x)$. This objective constructs NCE instances on the fly, treating one gold entity as the only correct answer in each training sample, while excluding other gold entities out of negative examples. 90% negative samples are selected randomly and 10% are chosen by hard negative mining, *i.e.*, selecting the highest-scoring incorrect entity.

During inference, entity representations E^e are cached into Faiss (Johnson et al., 2021) index to allow fast top-K retrieval. With retrieved entities, we construct a set of possible mentions by looking up an entity-to-mention dictionary[2]. The top-right corner of Figure 1 illustrates an example set of possible mentions. Each tuple within the possible mention set comprises one of the k entities retrieved and its associated mention string. Be aware that several different entities can correspond to the same mention string.

Then, we run surface form matching between a possible mention set and document text. Any parts of document text that match possible mentions are marked as decision-required[3]. Each decision-required span comprises the start and end indices, and possible mentions that may be within the span.

In the Guided Entity Linking Generation stage, the generative agent will determine the next action based on its current state:

1. Out of a decision-required span: Unlike Vanilla Generative EL in 3.1, which needs to decide whether to initiate a mention prediction at each document token, INSGENEL-R only needs to directly copy the next token when out of a decision-required span.

2. At the beginning of a decision-required span: INSGENEL-R has to decide when to start a mention within a decision-required span. This is achieved by comparing the log probability of next document token and mention start boundary token. A constant score offset is added to the mention start token due to the elevated probability of a mention appearing within a decision-required span. Note that it is also a valid choice for a decision-required span not to generate any mention at all, like the "CEO" span in Figure 1.

3. Within the mention part of a decision-required span: Once a mention has been initiated, if there is only one possible mention with this span, the agent will directly copy this mention (as in the case of "Steve" in sky-blue font in Figure 1). If not, a decision is made on which mention to choose within this span, which is constrained by a dynamically generated prefix tree that covers all mention choices in the span.

4. Within the entity part of a decision-required span: Once a span has completed the decoding of the mention, the agent will continue to decode the entity identifier part. Similar to the decoding of the mention part, if there is only one entity associated with the decoded mention, the agent will directly copy this candidate entity (such as "Steve Jobs" with italic font in Figure 1). Otherwise, the agent will dynamically construct a prefix tree containing associated entities to constrain the generation of the entity identifier (such as "Apple" and "Apple Inc." in italics in Figure 1).

Incurring only the cost of one dense vector retrieval, INSGENEL-R reduces the calls to the generative model by 90% in this sample document and no longer relies on a massive, pre-defined prefix tree. Since the retrieval procedure takes into account the entity description, it mitigates the challenge inherent to the generative EL paradigm, that is to distinguish between entities with similar identifiers.

3.4 INSGENEL-ICL: In-Context Learning Entity Linking Paradigm

In-context learning (ICL) with large language models (LLMs) demonstrates strong zero-shot and few-shot performance in many NLP tasks. However, the direct application of ICL to entity linking (EL) is difficult, primarily due to the limitations on the context window size which prevent the generative model from directly accessing the overwhelming number of candidate entity identifiers. Nonetheless, equipped with a well-trained retriever in INSGENEL-R, we condense the EL task into an advanced machine reading comprehension (MRC) problem: given potential entities and a document, the LLM is required to choose the mention span and the respective entity from a document.

The INSGENEL-ICL paradigm begins with a fixed exemplar and task instruction, both of which are fed to the LLM as an in-context demonstration. The task instruction prompt words have been iteratively refined, integrating well-known engineering techniques for prompting such as bad case demonstrations, and have leveraged automatic prompt optimization tricks. We encourage readers to Figure 5 in the Appendix for the in-context prompt template.

Notably, each prediction will have its final result matched by a regular expression; to prevent failed parsing due to multiple identical surface forms

[2] We refer readers to Appendix C.2 for details of building such a dictionary.

[3] Note that the marked segments may overlap, and will require merging mentions into a unified decision span through the algorithm provided in Appendix C.4.

		In-domain	Out-of-domain							
Category	**Method**	**AIDA**	**MSNBC**	**Der**	**K50**	**R128**	**R500**	**OKE15**	**OKE16**	**Avg**
Discriminative	Hoffart et al. (2011)	72.8*	65.1	32.6	55.4	46.4	42.4	63.1	0.0	47.2
	Kolitsas et al. (2018)	82.4*	72.4	34.1	35.2	50.3	38.2	61.9	52.7	53.4
	van Hulst et al. (2020)	80.5*	72.4	41.1	50.7	49.9	35.0	63.1	58.3	56.4
	Zhang et al. (2022b)	**85.8***	72.1	52.9	64.5	54.1	41.9	61.1	51.3	60.5
	Ayoola et al. (2022)	84.0*	71.8	50.7	64.7	58.1	42.0	64.4	59.1	61.9
Generative	Cao et al. (2021b)	83.7*	73.7	54.1	60.7	46.7	40.3	56.1	50.0	58.2
	Cao et al. (2021a)	85.5*	-	-	-	-	-	-	-	-
	Mrini et al. (2022b)	85.7*	-	-	-	-	-	-	-	-
Ours	InsGenEL	81.5	69.5	**60.9**	**73.8**	**58.6**	**46.8**	**65.7**	62.1	**64.9**
	InsGenEL-R	80.6	**74.2**	59.8	71.9	56.8	45.5	64.1	**63.3**	64.5

Table 1: *InKB* Micro F_1 on the eight popular test sets. For each dataset, **bold** indicates the best model and underline indicates the second best. Metric with * denotes that this model trains on the AIDA-CoNLL train split, while our methods do not utilize any in-domain train set. - indicates the authors neither report the metric on certain test sets nor release their code and checkpoints.

appearing in the same document, we require the model to output not only the mention text in the exemplar, but also the surrounding context for precise span matching.

Considering that the inputs for InsGenEL-R and InsGenEL-ICL are entirely identical, InsGenEL-ICL can serve as a fair comparison point for in-context learning in LLM, which helps examine the distinctions between a generic LLM and a fine-tuned generative model when performing generative EL.

4 Experiment

4.1 Setting

Datasets. We follow the established standard and report *InKB*[4] Micro F1 score on eight entity linking datasets. Specifically, we use eight out-of-domain test sets: the AIDA-CoNLL (Hoffart et al., 2011) test split, MSNBC (Cucerzan, 2007), Derczynski (Der) (Derczynski et al., 2015), KORE 50 (K50) (Hoffart et al., 2012a), N3-Reuters-128 (R128), N3-RSS-500 (R500) (Röder et al., 2014), and OKE challenge 2015 and 2016 (OKE15 and OKE16) (Nuzzolese et al., 2015). Training datasets were built from all article abstracts from English Wikipedia 2023-02-20 dump. Notably, we do not fine-tune our models on domain-specific datasets, but rely solely on Wikipedia, to examine the generalization capability of our method. This means we do not use the train split of the AIDA-CoNLL dataset. We use hyperlinks in Wikipedia as entity labels with a string matching heuristic to solve coreference following Cao et al. (2021a), because when an entity is mentioned multiple times in a Wikipedia article, often only the first mention is correctly linked. Additionally, we construct weak entity labels to increase Wikipedia data quality according to Ayoola et al. (2022).

Training and Evaluation. We utilize two series of decoder-only models as our base models: LLaMA (Touvron et al., 2023) and OPT (Zhang et al., 2022a). The OPT series provide pre-trained models of varying sizes, enabling us to examine the correlation between model size and generative EL performance. The best result is reported on LLaMA 7B version. We do not conduct hyperparameter search; the hyperparameters used during training are detailed in Appendix A. All pieces of training were performed on a node with 8 V100-SXM2-32GB GPUs, utilizing DeepSpeed (Rasley et al., 2020) for distributed training management. We train all models for one epoch. We report training time, size of training data and training compute in Section 4.3. The evaluation was conducted on ELEVANT (Bast et al., 2022) platform with a single V100 GPU. Best-performing InsGenEL-R is with $k = 100$, and we report the impact of k in Section 4.3.

4.2 Main Result

We report the model evaluation results in Table 1. Our model exhibits consistent performance advantages across all test sets, excluding AIDA. This achievement is noteworthy given that, unlike all preceding works, we did not apply domain-

[4] Following common practice in previous works (Ayoola et al., 2022; Zhang et al., 2022b; Kolitsas et al., 2018), only mentions with valid KB entities are used for evaluation.

specific fine-tuning on AIDA. Overall, INSGENEL achieves the state-of-the-art micro F1 score across eight evaluation datasets with +3.0 relative gain compared with the previous best of discriminative peers, with +6.8 compared with the previous best of generative peers.

The performance of INSGENEL-R is marginally affected since the top-K retrieved entities may not always cover the gold entity. The influence of k on INSGENEL-R's performance is discussed comprehensively in Section 4.3.

Owing to the API quota budget, we only present the INSGENEL-ICL performance of selected four test sets under two OpenAI endpoints in Table 2. The evaluation on `code-davinci-002` and `text-davinci-003` are similar on average, despite varying metrics across different datasets. While our In-Context Learning approach for EL has undergone considerable prompt optimization, it still falls significantly short when compared to our INSGENEL-R which also takes the document and top-K entities as inputs. This may suggest that In-Context Learning for EL needs further investigation and we leave it as future work and list possible solutions in the Limitation Section.

Method	AIDA	MSNBC	K50	R500	Avg
INSGENEL-ICL	-	-	-	-	-
- `text-davinci-003`	50.0	53.3	39.2	34.9	44.4
- `code-davinci-002`	60.7	47.4	39.0	25.4	43.1
INSGENEL-R	80.6	74.2	71.9	45.5	68.1

Table 2: *InKB* Micro F_1 reported on selected four test sets . Metrics for INSGENEL-R are listed in the last row for direct comparison.

4.3 Ablation Study

We discuss ablation studies on INSGENEL, mainly focusing on the training data efficiency and model size. Additionally, we will evaluate INSGENEL-R retriever top-k gold entity coverage and its influence on the performance of our retrieval-augmented generative EL system.

Data Efficiency. Our ablations commence with data efficiency to highlight the superiority of our approach in terms of training data utilization. As depicted in Figure 2, we illustrate the correlation among training data relative size, training compute and EL evaluation performance. The legends indicate that colors of data points represent different EL methods, while the size of data points denotes GPU hours used for training. INSGENEL, the generative state-of-the-art peer GENRE (Cao et al., 2021b), and the discriminative best model ReFinED (Ayoola et al., 2022) were all trained using V100 GPUs, thus, their training GPU hours are comparable.

We set the training of GENRE using all Wikipedia abstracts as a data size reference point (*i.e.*, a training data ratio of 1) and sequentially downsample all Wikipedia abstract data using coefficients of 0.01, 0.05, 0.1, 0.2, and 0.5 as our comparative data splits. Meanwhile, ReFinED trained on the full volume of Wikipedia, approximately ten times the volume of Wikipedia abstracts. Our best-performing model, trained for around 2.5 days on an 8-V100 node using half of the Wikipedia abstracts, corresponds to 480 GPU hours in the legend. For comparison, GENRE was trained for 30 hours on 64 V100s, and ReFinED for 24 hours on 8 V100s, corresponding to 1,920 and 192 GPU hours in the legend, respectively.

Compared to the previous Generative EL method GENRE, our method exceeded the evaluation performance of GENRE (60.16 vs. 58.2) using just a tenth of the data and a twentieth of the training compute (96 GPU hours vs. 1920). This gap further increased to +6.8 F1 points with the increase of training data and computation.

Likewise, against the earlier Discriminative EL method ReFinED, our method accomplished superior performance (63.72 vs. 61.90) using the same training compute but only 2% of the data volume. Similarly, this lead widened to +3.0 F1 points as training resources increased.

Model Size. We seek to explore the potential correlation between model size, type and EL performance by training on different scales of decoder-only generative models. As shown in Figure 3, the five data points correspond to the models of the OPT series 350m, 1.3b, 2.7b, 6.7b, and LLaMA 7b, and their evaluation results after training on the same split of data. We observed a certain emergent ability in the models, with `opt-2.7b` surpassing the previous Generative EL method. Also, despite a similar number of parameters, `opt-6.7b` and `llama-7b` exhibit a noticeable performance gap. This further highlights the ability of our instruction-tuning method to exploit the excellent pre-training quality of LLaMA, as well as to stimulate the latent knowledge transfer capability.

Retriever Coverage. Although INSGENEL-R delivers exceptional results in both runtime perfor-

Method	k	Recall@k (%)	Micro F1 Score (%)
InsGenEL-R	5	42.57	37.70
	10	54.05	49.33
	20	62.16	60.58
	50	75.00	67.71
	100	89.20	71.90

Table 3: Retriever coverage and performance impact of InsGenEL-R's k on K50 test set.

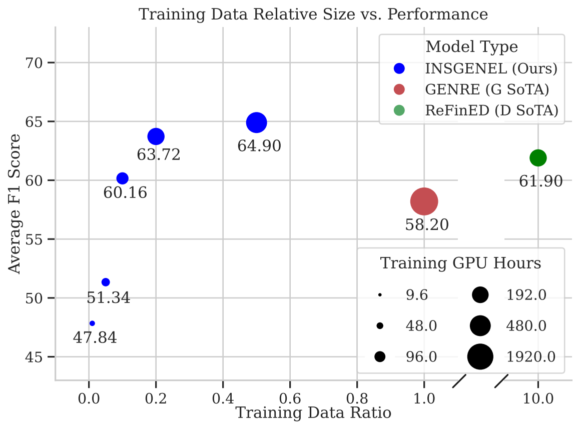


Figure 2: Comparison among training data relative size, training compute and EL performance. Selected works are all trained with V100, thus their training GPU hours are comparable. Letters "G" and "D" in the legend represent generative and discriminative respectively.

mance and linking metrics compared with previous generative EL works, one might be curious about how the coverage of entity retriever might impact the EL evaluation results of InsGenEL-R. After all, if the gold entity is not retrieved, InsGenEL-R would be impossible to link any mention to the correct entity. Table 3 reveals the relationship among the number of top retrieved entities k, the corresponding gold entity recall@k within the document chunk of length $L = 32$, and the Micro F1 score evaluated on the K50 dataset when completing retrieval-augmented generative EL using the corresponding k entities.

We notice that InsGenEL-R performance generally improves as k increases, which aligns with our intuition since as k increases, candidates cover more gold entities so the chance for InsGenEL-R to link the correct entity also increases. Unfortunately, as the EL checkpoint in Cao et al. (2021b) is not publicly available, we are unable to test whether our retriever-augmented EL scheme would work in other sequence-to-sequence EL frameworks.

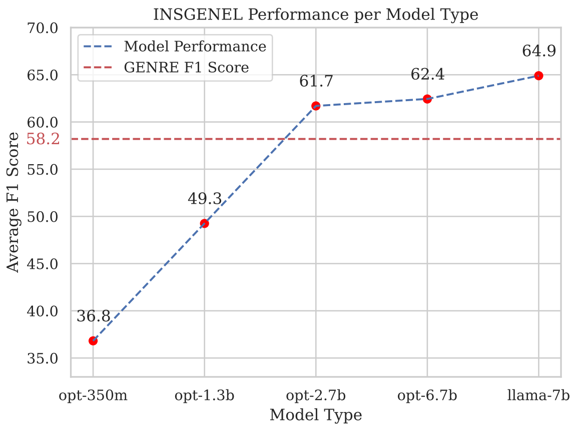


Figure 3: InsGenEL performance with different base models.

Method	# of Forwards	Runtime (s)	K50 F1
Ayoola et al. (2022)	50	2.97	64.7
van Hulst et al. (2020)	-	7.32	50.7
Zhang et al. (2022b)	-	$131.32^{\dagger}$	64.5
Cao et al. (2021b)	-	196.30	60.7
InsGenEL	2221	$160.86_{\pm 0.52}$	73.8
InsGenEL-R	594	$44.92_{\pm 0.28}$	71.9
- w/ FA	594	$23.76^{\ddagger}$	71.9
- w/ FA + KV	594	$16.32^{\ddagger}$	71.9

Table 4: Runtime performance benchmark on K50 test set. † denotes that the runtime is estimated based on the maximum throughput of the base model, and the actual runtime should be higher. ‡ denotes the runtime is estimated based on the typical speedup ratio reported here, and the real runtime may vary. "FA" and "KV" mean FlashAttention and KV caching, respectively.

4.4 Runtime Performance Benchmark

One major barrier to the application of generative EL is its autoregressive nature, which hinders real-time use. In Table 4 we report the runtime of leading and competitive EL systems on the K50 test set covering 50 documents. Among these, our InsGenEL and InsGenEL-R were run 10 times using different random seeds and reported the mean and standard deviation of runtime. Evidently, our model substantially curtails nearly three-quarters of the generative model calls, albeit at a minor sacrifice in accuracy.

Admittedly, there is still nearly 15× the runtime difference compared to the efficiency-centric peer, but we recognize an abundant scope for runtime improvement. For instance, by simply hot-patching attention layers with FlashAttention (Dao et al., 2022), we gain a doubling of inference speed. Also, the decoder-only property of our model enables the convenience of caching previously generated hidden states, known as KV caching. Furthermore, our retrieval-augmented framework can benefit from parallel decoding with reference (Yang et al., 2023) since many tokens are copied rather than generated – a convenience other discriminative models can not avail. We leave further inference optimization of generative EL as future work.

5 Conclusion

We present three variations of generative entity linking (EL) solutions, where INSGENEL realizes an improvement of +3.0 F1 points on popular EL test sets (+6.8 increase compared to previous generative methods). Built upon this model, we propose a novel retrieval-augmented generative EL framework INSGENEL-R that determines when to invoke the large language decoder on the fly. Moreover, our pioneering INSGENEL-ICL marks the inception of in-context learning in EL, despite necessitating additional follow-up research to achieve competitive results.

Limitations

Although our work pushes the generative EL paradigm to its limit and uses fewer computational resources and training time than most peers, its runtime performance still lags behind that of discriminative EL models, even with a novel retrieval-augmented EL framework in place. This may render our approach suitable for scenarios prioritizing higher linking accuracy over real-time performance. Also, we do not investigate numerous works that improve LM training efficiency, such as low-rank adaption (Hu et al., 2022). These possibilities remain as future work as they could potentially accelerate the training further. In addition, due to budget limitations and inaccessibility to the `gpt-4-32k` endpoint, our INSGENEL-ICL paradigm has not been tested on the GPT-4 series. We may observe a significant performance improvement on the `gpt-4` or `gpt-4-32k`, especially with the latter one's expanded context window that will allow more diverse in-context demonstrations. Last, how to properly organize, select and format exemplars for EL could be an interesting future work of our INSGENEL-ICL paradigm.

Ethics Statement

Large foundation models carry inherent risks and potential harms, such as the generation of harmful, offensive, or biased content. Even though our work involves controlled generation, we can not guarantee that the fine-tuned model will strictly adhere to ethical requirements in an unconstrained generation setting. As such, we do not recommend a direct conversion from our work to downstream applications without further investigation and mitigation of risks.

References

Akari Asai, Kazuma Hashimoto, Hannaneh Hajishirzi, Richard Socher, and Caiming Xiong. 2020. Learning to retrieve reasoning paths over wikipedia graph for question answering. In *8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020*. OpenReview.net.

Tom Ayoola, Shubhi Tyagi, Joseph Fisher, Christos Christodoulopoulos, and Andrea Pierleoni. 2022. ReFinED: An efficient zero-shot-capable approach to end-to-end entity linking. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies: Industry Track*, pages 209–220, Hybrid: Seattle, Washington + Online. Association for Computational Linguistics.

Hannah Bast, Matthias Hertel, and Natalie Prange. 2022. ELEVANT: A fully automatic fine-grained entity linking evaluation and analysis tool. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 72–79, Abu Dhabi, UAE. Association for Computational Linguistics.

Samuel Broscheit. 2019. Investigating entity knowledge in BERT with simple neural end-to-end entity linking. In *Proceedings of the 23rd Conference on Computational Natural Language Learning (CoNLL)*, pages 677–685, Hong Kong, China. Association for Computational Linguistics.

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners. In *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual*.

Nicola De Cao, Wilker Aziz, and Ivan Titov. 2021a. Highly parallel autoregressive entity linking with discriminative correction. In *Proceedings of the 2021*

Conference on Empirical Methods in Natural Language Processing, EMNLP 2021, Virtual Event / Punta Cana, Dominican Republic, 7-11 November, 2021, pages 7662–7669. Association for Computational Linguistics.

Nicola De Cao, Gautier Izacard, Sebastian Riedel, and Fabio Petroni. 2021b. Autoregressive entity retrieval. In *9th International Conference on Learning Representations, ICLR 2021, Virtual Event, Austria, May 3-7, 2021*. OpenReview.net.

Nicola De Cao, Ledell Wu, Kashyap Popat, Mikel Artetxe, Naman Goyal, Mikhail Plekhanov, Luke Zettlemoyer, Nicola Cancedda, Sebastian Riedel, and Fabio Petroni. 2022. Multilingual autoregressive entity linking. *Trans. Assoc. Comput. Linguistics*, 10:274–290.

Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, Parker Schuh, Kensen Shi, Sasha Tsvyashchenko, Joshua Maynez, Abhishek Rao, Parker Barnes, Yi Tay, Noam Shazeer, Vinodkumar Prabhakaran, Emily Reif, Nan Du, Ben Hutchinson, Reiner Pope, James Bradbury, Jacob Austin, Michael Isard, Guy Gur-Ari, Pengcheng Yin, Toju Duke, Anselm Levskaya, Sanjay Ghemawat, Sunipa Dev, Henryk Michalewski, Xavier Garcia, Vedant Misra, Kevin Robinson, Liam Fedus, Denny Zhou, Daphne Ippolito, David Luan, Hyeontaek Lim, Barret Zoph, Alexander Spiridonov, Ryan Sepassi, David Dohan, Shivani Agrawal, Mark Omernick, Andrew M. Dai, Thanumalayan Sankaranarayana Pillai, Marie Pellat, Aitor Lewkowycz, Erica Moreira, Rewon Child, Oleksandr Polozov, Katherine Lee, Zongwei Zhou, Xuezhi Wang, Brennan Saeta, Mark Diaz, Orhan Firat, Michele Catasta, Jason Wei, Kathy Meier-Hellstern, Douglas Eck, Jeff Dean, Slav Petrov, and Noah Fiedel. 2022. Palm: Scaling language modeling with pathways. *CoRR*, abs/2204.02311.

Silviu Cucerzan. 2007. Large-scale named entity disambiguation based on Wikipedia data. In *Proceedings of the 2007 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning (EMNLP-CoNLL)*, pages 708–716, Prague, Czech Republic. Association for Computational Linguistics.

Joachim Daiber, Max Jakob, Chris Hokamp, and Pablo N. Mendes. 2013. Improving efficiency and accuracy in multilingual entity extraction. In *I-SEMANTICS 2013 - 9th International Conference on Semantic Systems, I-SEMANTICS '13, Graz, Austria, September 4-6, 2013*, pages 121–124. ACM.

Tri Dao, Daniel Y. Fu, Stefano Ermon, Atri Rudra, and Christopher Ré. 2022. FlashAttention: Fast and memory-efficient exact attention with IO-awareness. In *Advances in Neural Information Processing Systems*.

Nicola De Cao, Wilker Aziz, and Ivan Titov. 2021. Highly parallel autoregressive entity linking with discriminative correction. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 7662–7669, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Leon Derczynski, Diana Maynard, Giuseppe Rizzo, Marieke van Erp, Niraj Aswani, Raphaël Troncy, and Kalina Bontcheva. 2015. Analysis of named entity recognition and linking for tweets. *Information Processing and Management, Volume 51, N°2, March 2015, Elsevier*. © Elsevier. Personal use of this material is permitted. The definitive version of this paper was published in Information Processing and Management, Volume 51, N°2, March 2015, Elsevier and is available at : http://dx.doi.org/10.1016/j.ipm.2014.10.006.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Thibault Févry, Livio Baldini Soares, Nicholas FitzGerald, Eunsol Choi, and Tom Kwiatkowski. 2020. Entities as experts: Sparse memory access with entity supervision. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 4937–4951, Online. Association for Computational Linguistics.

Yu Gu, Xiang Deng, and Yu Su. 2022. Don't generate, discriminate: A proposal for grounding language models to real-world environments. *CoRR*, abs/2212.09736.

Michael Gutmann and Aapo Hyvärinen. 2010. Noise-contrastive estimation: A new estimation principle for unnormalized statistical models. In *Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics, AISTATS 2010, Chia Laguna Resort, Sardinia, Italy, May 13-15, 2010*, volume 9 of *JMLR Proceedings*, pages 297–304. JMLR.org.

Kelvin Guu, Kenton Lee, Zora Tung, Panupong Pasupat, and Ming-Wei Chang. 2020. Retrieval augmented language model pre-training. In *Proceedings of the 37th International Conference on Machine Learning, ICML 2020, 13-18 July 2020, Virtual Event*, volume 119 of *Proceedings of Machine Learning Research*, pages 3929–3938. PMLR.

Johannes Hoffart, Stephan Seufert, Dat Ba Nguyen, Martin Theobald, and Gerhard Weikum. 2012a. Kore: Keyphrase overlap relatedness for entity disambiguation. In *Proceedings of the 21st ACM International*

Conference on Information and Knowledge Management, CIKM '12, page 545–554, New York, NY, USA. Association for Computing Machinery.

Johannes Hoffart, Stephan Seufert, Dat Ba Nguyen, Martin Theobald, and Gerhard Weikum. 2012b. KORE: keyphrase overlap relatedness for entity disambiguation. In *21st ACM International Conference on Information and Knowledge Management, CIKM'12, Maui, HI, USA, October 29 - November 02, 2012*, pages 545–554. ACM.

Johannes Hoffart, Mohamed Amir Yosef, Ilaria Bordino, Hagen Fürstenau, Manfred Pinkal, Marc Spaniol, Bilyana Taneva, Stefan Thater, and Gerhard Weikum. 2011. Robust disambiguation of named entities in text. In *Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing*, pages 782–792, Edinburgh, Scotland, UK. Association for Computational Linguistics.

Raphael Hoffmann, Congle Zhang, Xiao Ling, Luke Zettlemoyer, and Daniel S. Weld. 2011. Knowledge-based weak supervision for information extraction of overlapping relations. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, pages 541–550, Portland, Oregon, USA. Association for Computational Linguistics.

Edward J. Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. 2022. Lora: Low-rank adaptation of large language models. In *The Tenth International Conference on Learning Representations, ICLR 2022, Virtual Event, April 25-29, 2022*. OpenReview.net.

Jeff Johnson, Matthijs Douze, and Hervé Jégou. 2021. Billion-scale similarity search with gpus. *IEEE Trans. Big Data*, 7(3):535–547.

Nikolaos Kolitsas, Octavian-Eugen Ganea, and Thomas Hofmann. 2018. End-to-end neural entity linking. In *Proceedings of the 22nd Conference on Computational Natural Language Learning*, pages 519–529, Brussels, Belgium. Association for Computational Linguistics.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020a. BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7871–7880, Online. Association for Computational Linguistics.

Patrick S. H. Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, Sebastian Riedel, and Douwe Kiela. 2020b. Retrieval-augmented generation for knowledge-intensive NLP tasks. In *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual*.

Khalil Mrini, Shaoliang Nie, Jiatao Gu, Sinong Wang, Maziar Sanjabi, and Hamed Firooz. 2022a. Detection, disambiguation, re-ranking: Autoregressive entity linking as a multi-task problem. In *Findings of the Association for Computational Linguistics: ACL 2022*, pages 1972–1983, Dublin, Ireland. Association for Computational Linguistics.

Khalil Mrini, Shaoliang Nie, Jiatao Gu, Sinong Wang, Maziar Sanjabi, and Hamed Firooz. 2022b. Detection, disambiguation, re-ranking: Autoregressive entity linking as a multi-task problem. In *Findings of the Association for Computational Linguistics: ACL 2022, Dublin, Ireland, May 22-27, 2022*, pages 1972–1983. Association for Computational Linguistics.

Andrea Giovanni Nuzzolese, Anna Lisa Gentile, Valentina Presutti, Aldo Gangemi, Darío Garigliotti, and Roberto Navigli. 2015. Open knowledge extraction challenge. In *Semantic Web Evaluation Challenges*, pages 3–15, Cham. Springer International Publishing.

Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. 2022. Training language models to follow instructions with human feedback. *Advances in Neural Information Processing Systems*, 35:27730–27744.

Jeff Rasley, Samyam Rajbhandari, Olatunji Ruwase, and Yuxiong He. 2020. Deepspeed: System optimizations enable training deep learning models with over 100 billion parameters. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery &amp; Data Mining*, KDD '20, page 3505–3506, New York, NY, USA. Association for Computing Machinery.

Michael Röder, Ricardo Usbeck, Sebastian Hellmann, Daniel Gerber, and Andreas Both. 2014. N^3 - a collection of datasets for named entity recognition and disambiguation in the NLP interchange format. In *Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC'14)*, pages 3529–3533, Reykjavik, Iceland. European Language Resources Association (ELRA).

Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, Aurélien Rodriguez, Armand Joulin, Edouard Grave, and Guillaume Lample. 2023. Llama: Open and efficient foundation language models. *CoRR*, abs/2302.13971.

Johannes M. van Hulst, Faegheh Hasibi, Koen Dercksen, Krisztian Balog, and Arjen P. de Vries. 2020. REL: an entity linker standing on the shoulders of giants. In *Proceedings of the 43rd International ACM SIGIR* *conference on research and development in Information Retrieval, SIGIR 2020, Virtual Event, China, July 25-30, 2020*, pages 2197–2200. ACM.

Yizhong Wang, Swaroop Mishra, Pegah Alipoormolabashi, Yeganeh Kordi, Amirreza Mirzaei, Atharva Naik, Arjun Ashok, Arut Selvan Dhanasekaran, Anjana Arunkumar, David Stap, Eshaan Pathak, Giannis Karamanolakis, Haizhi Lai, Ishan Purohit, Ishani Mondal, Jacob Anderson, Kirby Kuznia, Krima Doshi, Kuntal Kumar Pal, Maitreya Patel, Mehrad Moradshahi, Mihir Parmar, Mirali Purohit, Neeraj Varshney, Phani Rohitha Kaza, Pulkit Verma, Ravsehaj Singh Puri, Rushang Karia, Savan Doshi, Shailaja Keyur Sampat, Siddhartha Mishra, Sujan Reddy A, Sumanta Patro, Tanay Dixit, and Xudong Shen. 2022. Super-NaturalInstructions: Generalization via declarative instructions on 1600+ NLP tasks. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 5085–5109, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

Zekun Wang, Ge Zhang, Kexin Yang, Ning Shi, Wangchunshu Zhou, Shaochun Hao, Guangzheng Xiong, Yizhi Li, Mong Yuan Sim, Xiuying Chen, Qingqing Zhu, Zhenzhu Yang, Adam Nik, Qi Liu, Chenghua Lin, Shi Wang, Ruibo Liu, Wenhu Chen, Ke Xu, Dayiheng Liu, Yike Guo, and Jie Fu. 2023. Interactive natural language processing. *CoRR*, abs/2305.13246.

Jason Wei, Maarten Bosma, Vincent Y. Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M. Dai, and Quoc V. Le. 2022a. Finetuned language models are zero-shot learners. In *The Tenth International Conference on Learning Representations, ICLR 2022, Virtual Event, April 25-29, 2022*. OpenReview.net.

Jason Wei, Yi Tay, Rishi Bommasani, Colin Raffel, Barret Zoph, Sebastian Borgeaud, Dani Yogatama, Maarten Bosma, Denny Zhou, Donald Metzler, Ed H. Chi, Tatsunori Hashimoto, Oriol Vinyals, Percy Liang, Jeff Dean, and William Fedus. 2022b. Emergent abilities of large language models. *Trans. Mach. Learn. Res.*, 2022.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed H. Chi, Quoc V. Le, and Denny Zhou. 2022c. Chain-of-thought prompting elicits reasoning in large language models. In *NeurIPS*.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. 2020. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45, Online. Association for Computational Linguistics.

Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V. Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, Jeff Klingner, Apurva Shah, Melvin Johnson, Xiaobing Liu, Lukasz Kaiser, Stephan Gouws, Yoshikiyo Kato, Taku Kudo, Hideto Kazawa, Keith Stevens, George Kurian, Nishant Patil, Wei Wang, Cliff Young, Jason Smith, Jason Riesa, Alex Rudnick, Oriol Vinyals, Greg Corrado, Macduff Hughes, and Jeffrey Dean. 2016. Google's neural machine translation system: Bridging the gap between human and machine translation. *CoRR*, abs/1609.08144.

Tianbao Xie, Chen Henry Wu, Peng Shi, Ruiqi Zhong, Torsten Scholak, Michihiro Yasunaga, Chien-Sheng Wu, Ming Zhong, Pengcheng Yin, Sida I. Wang, Victor Zhong, Bailin Wang, Chengzu Li, Connor Boyle, Ansong Ni, Ziyu Yao, Dragomir Radev, Caiming Xiong, Lingpeng Kong, Rui Zhang, Noah A. Smith, Luke Zettlemoyer, and Tao Yu. 2022. Unifiedskg: Unifying and multi-tasking structured knowledge grounding with text-to-text language models. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing, EMNLP 2022, Abu Dhabi, United Arab Emirates, December 7-11, 2022*, pages 602–631. Association for Computational Linguistics.

Can Xu, Qingfeng Sun, Kai Zheng, Xiubo Geng, Pu Zhao, Jiazhan Feng, Chongyang Tao, and Daxin Jiang. 2023. Wizardlm: Empowering large language models to follow complex instructions. *CoRR*, abs/2304.12244.

Nan Yang, Tao Ge, Liang Wang, Binxing Jiao, Daxin Jiang, Linjun Yang, Rangan Majumder, and Furu Wei. 2023. Inference with reference: Lossless acceleration of large language models. *CoRR*, abs/2304.04487.

Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Moya Chen, Shuohui Chen, Christopher Dewan, Mona T. Diab, Xian Li, Xi Victoria Lin, Todor Mihaylov, Myle Ott, Sam Shleifer, Kurt Shuster, Daniel Simig, Punit Singh Koura, Anjali Sridhar, Tianlu Wang, and Luke Zettlemoyer. 2022a. OPT: open pre-trained transformer language models. *CoRR*, abs/2205.01068.

Wenzheng Zhang, Wenyue Hua, and Karl Stratos. 2022b. Entqa: Entity linking as question answering. In *The Tenth International Conference on Learning Representations, ICLR 2022, Virtual Event, April 25-29, 2022*. OpenReview.net.

Zhihan Zhang, Wenhao Yu, Chenguang Zhu, and Meng Jiang. 2022c. A unified encoder-decoder framework with entity memory. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 689–705, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

A Experimental Details

Hyperparameter	OPT	LLaMA
learning rate	9.65e-6	2e-5
weight_decay	0	
batch size per device	4	3
effective batch size	128	96
learning rate strategy	WarmupLinearDecay	
optimizer	AdamW	
dropout	0.1	
gradient clipping	1.0	Disabled

Table 5: Hyperparameter settings for OPT and LLaMA training of InsGenEL.

We implemented all of our neural models using the `transformers` (Wolf et al., 2020) library. As decision spans in InsGenEL-R are not lengthy, we do not notice significant performance improvement in beam search, thus we employ greedy decoding in all InsGenEL-R experiments. We use beam_size=2 in InsGenEL experiments. If out-of-memory is triggered during training for some model types, optimizer partitioning, gradient state partitioning, and parameter partitioning will be sequentially enabled to ensure successful training completion.

Due to the license attached to LLaMA (Touvron et al., 2023) models, we are not able to directly distribute LLaMA-based weights. Instead, we provide delta weights of our pre-trained checkpoint, and interested readers should fill this form to get base model from Meta AI, then apply delta weights on it to get a functional generative EL model. Hyperparameters for training neural models are listed in Table 5.

Experiments with online OpenAI[5] models were conducted earlier in March 2023 with `openai-python` library. We set `temperature=0` in OpenAI generation to ensure maximum reproducibility, but generation results may differ as OpenAI backend models keep evolving. `gpt-3.5-turbo` endpoint which supports ChatGPT can not correctly adhere to our instruction. For `code-davinci-002` and `text-davinci-003`, we apply generation configuration of max_token=300, top_p=1, frequency_penalty=0.0 and presence_penalty=0.0. We do not run experiments on `text-ada-001`, `text-babbage-001` and `text-curie-001` as they are with 2,048 tokens of context window, which can hardly satisfy our requirements since a typical length of our input prompt is around 3,000 tokens.

B Inherent Problems of Vanilla Generative EL

To ensure the legality of generated sequence, *i.e.*, the generated entities are within the KB, vanilla generative EL employs a constrained beam search strategy for inference. At each generation time step, the vanilla approach either chooses to generate the input document verbatim, or start a new mention. Note that this mention start decision is mandatory for each possible token in the document, thus resulting in massive inference overhead as a considerable number of document tokens are unlikely mentioned. See case (a) with grey background in Figure 4, where each arrow or group of arrows represents a forward pass of the generative model.

Once it chooses to start a mention, the vanilla approach seeks advice from a pre-generated prefix tree (a.k.a. trie) to constrain the tokens that are allowed in the next time step and eliminate other options. The same strategy is also used to guide entity identifier generation to remove impossible entities from candidate sequences. Vanilla generative EL relies solely on unique entity title identifiers to distinguish between different entities. This might lead to potential confusion among entities with closely related names when finer-grained information, such as entity descriptions, is not taken into account.

Considering the local optimality of greedy decoding and the potential for it to get stuck in infeasible options during generation, the vanilla approach uses beam search to maintain top-k sequences, falls back to previous states when walking into unreasonable paths, and ultimately parses the top-1 sequence into EL result. As the generative model decides only ONE next step in each beam, some generated sequence in a beam may be illegal to form a valid mention, resulting in wasted inference compute. See case (b) in Figure 4 for details.

Last, the large generative model pre-trained on web-scale text data sometimes suffers from missing important mentions in the generative EL setting even after fine-tuning, which leads to a low recall score during evaluation. See case (c) in Figure 4.

[5] https://platform.openai.com/

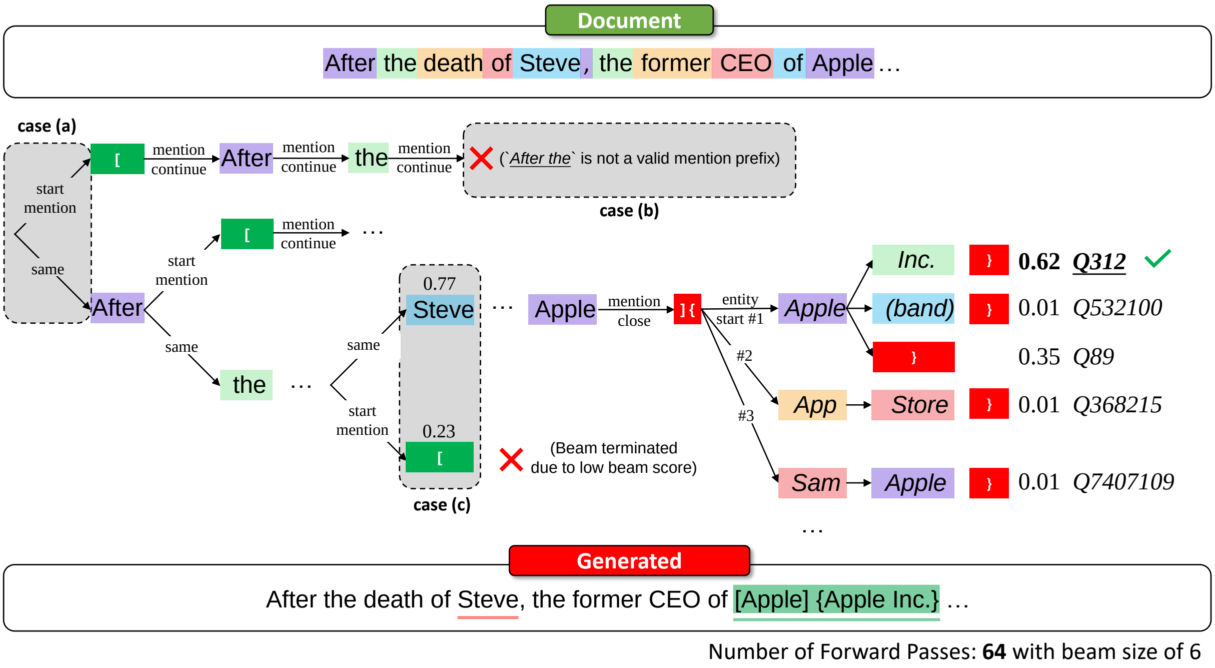


Figure 4: Overview of vanilla generative EL proposed in Cao et al. (2021b) with constrained beam search. Each path is a possible beam during beam search, and the decimal number at the end of each path is the normalized beam score. The decimal numbers in case (c) indicate generative models sometimes make mistakes when initiating mention boundaries. The color scheme for text tokens is adopted from the OpenAI Tokenization webpage and for idea depiction only, and the real tokenization depends on the base model. Best viewed in color.

C Entity Linking Setting

C.1 Candidate Set Construction

Previous neural entity linking systems pre-selects a reasonable number of candidate entities for each mention based on empirical probabilistic $p(e|m)$ scores. We build such a mention candidate dictionary with the combination of Kolitsas et al. (2018) and Hoffart et al. (2011) for INSGENEL, following these systems. Given the generative character of our work, as opposed to a discriminative one, the size of the candidate set does not affect the inference speed. Thus in line with Cao et al. (2021a), we place no restrictions on the candidate set size during inference.

C.2 Candidate-to-Mention Mapping Construction

Differing from all previous entity linking works, we need an empirical candidate-to-mention mapping for determining the decision range of INSGENEL-R. We reverse the key-value pairs in the mention candidate dictionary in Appendix C.1, remove duplicates of mentions under the same entity entry, and eliminate stop words. The candidate-to-mention mapping, developed from a known dictionary that is utilized by peer works, without the addition of other knowledge or data, provides a fair point of comparison.

C.3 Evaluation Dataset Statitics

Following Ayoola et al. (2022), we present the topic, number of documents and number of mentions for each dataset used for evaluation. The datasets cover a variety of sources including Wikipedia text, news articles, web text, and tweets. Note that the performance of the model outside these domains may be significantly different.

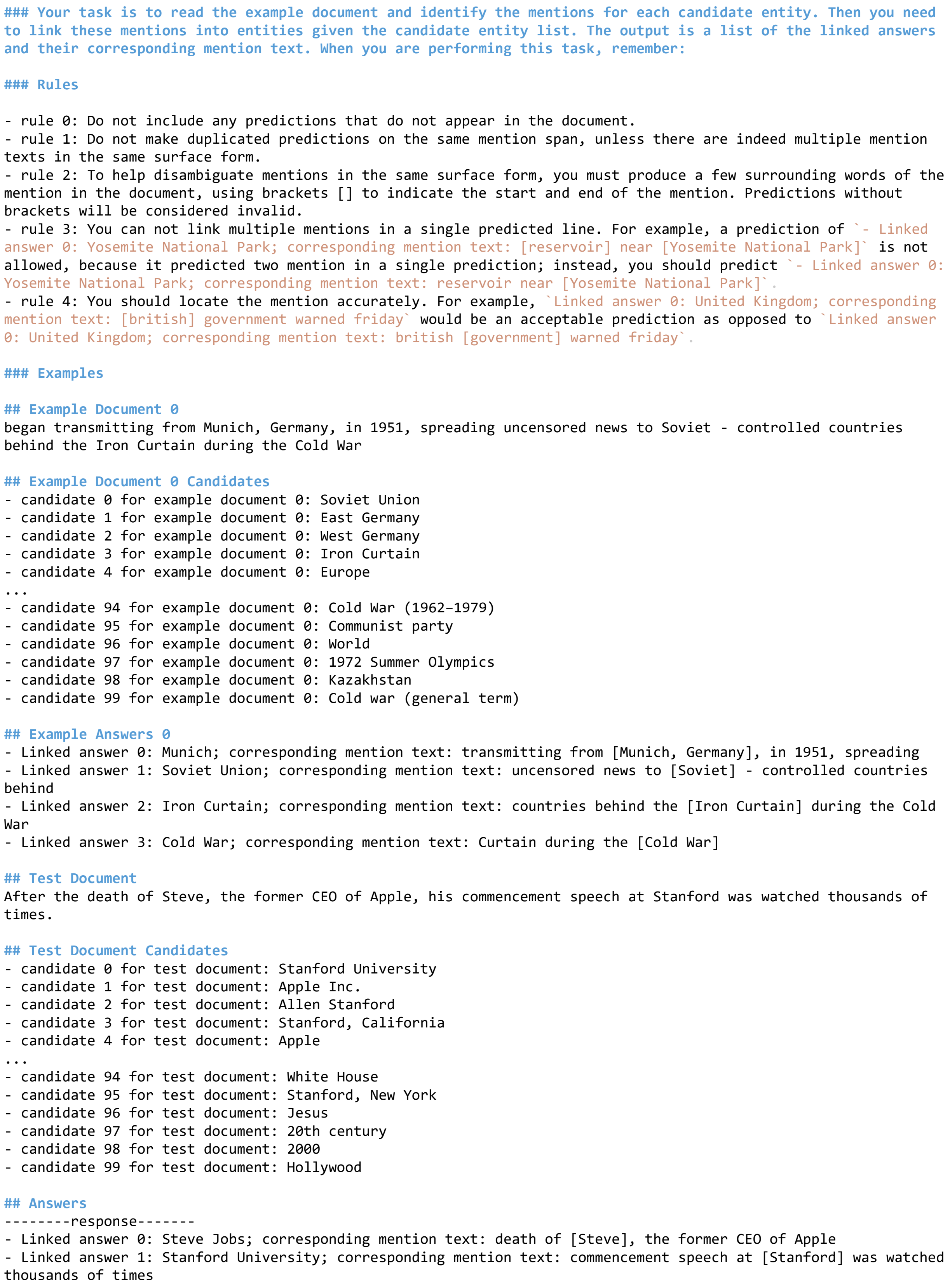
	Topic	Num docs	Num Mentions
AIDA	news	231	4464
MSNBC	news	20	656
DER	tweets	182	242
K50	mixed	50	145
R128	news	128	638
R500	news	500	530
OKE15	wikipedia	199	1017
OKE16	wikipedia	254	1402

Table 6: Dataset statistics for EL datasets

C.4 Algorithm for Merging Overlapping Decision Spans for Different Mentions

Algorithm 1 Merging Overlapping Decision Span

```
procedure MERGE(decision_span_lst)
    Sort decision_span_lst in ascending order by start
    merged_mentions $\leftarrow$ []
    for each tuple (start, end, mention) in decision_span_lst do
        if merged_mentions is not empty and merged_mentions[-1][0] $\leq$ start $\leq$ merged_mentions[-1][1] then
            merged_mentions[-1][1] $\leftarrow$ max(merged_mentions[-1][1], end)
            append mention to merged_mentions[-1][2]
        else
            append (start, end, [mention]) to merged_mentions
    return merged_mentions
```



```
### Your task is to read the example document and identify the mentions for each candidate entity. Then you need
to link these mentions into entities given the candidate entity list. The output is a list of the linked answers
and their corresponding mention text. When you are performing this task, remember:

### Rules

- rule 0: Do not include any predictions that do not appear in the document.
- rule 1: Do not make duplicated predictions on the same mention span, unless there are indeed multiple mention
texts in the same surface form.
- rule 2: To help disambiguate mentions in the same surface form, you must produce a few surrounding words of the
mention in the document, using brackets [] to indicate the start and end of the mention. Predictions without
brackets will be considered invalid.
- rule 3: You can not link multiple mentions in a single predicted line. For example, a prediction of `- Linked
answer 0: Yosemite National Park; corresponding mention text: [reservoir] near [Yosemite National Park]` is not
allowed, because it predicted two mention in a single prediction; instead, you should predict `- Linked answer 0:
Yosemite National Park; corresponding mention text: reservoir near [Yosemite National Park]`.
- rule 4: You should locate the mention accurately. For example, `Linked answer 0: United Kingdom; corresponding
mention text: [british] government warned friday` would be an acceptable prediction as opposed to `Linked answer
0: United Kingdom; corresponding mention text: british [government] warned friday`.

### Examples

## Example Document 0
began transmitting from Munich, Germany, in 1951, spreading uncensored news to Soviet - controlled countries
behind the Iron Curtain during the Cold War

## Example Document 0 Candidates
- candidate 0 for example document 0: Soviet Union
- candidate 1 for example document 0: East Germany
- candidate 2 for example document 0: West Germany
- candidate 3 for example document 0: Iron Curtain
- candidate 4 for example document 0: Europe
...
- candidate 94 for example document 0: Cold War (1962–1979)
- candidate 95 for example document 0: Communist party
- candidate 96 for example document 0: World
- candidate 97 for example document 0: 1972 Summer Olympics
- candidate 98 for example document 0: Kazakhstan
- candidate 99 for example document 0: Cold war (general term)

## Example Answers 0
- Linked answer 0: Munich; corresponding mention text: transmitting from [Munich, Germany], in 1951, spreading
- Linked answer 1: Soviet Union; corresponding mention text: uncensored news to [Soviet] - controlled countries
behind
- Linked answer 2: Iron Curtain; corresponding mention text: countries behind the [Iron Curtain] during the Cold
War
- Linked answer 3: Cold War; corresponding mention text: Curtain during the [Cold War]

## Test Document
After the death of Steve, the former CEO of Apple, his commencement speech at Stanford was watched thousands of
times.

## Test Document Candidates
- candidate 0 for test document: Stanford University
- candidate 1 for test document: Apple Inc.
- candidate 2 for test document: Allen Stanford
- candidate 3 for test document: Stanford, California
- candidate 4 for test document: Apple
...
- candidate 94 for test document: White House
- candidate 95 for test document: Stanford, New York
- candidate 96 for test document: Jesus
- candidate 97 for test document: 20th century
- candidate 98 for test document: 2000
- candidate 99 for test document: Hollywood

## Answers
--------response-------
- Linked answer 0: Steve Jobs; corresponding mention text: death of [Steve], the former CEO of Apple
- Linked answer 1: Stanford University; corresponding mention text: commencement speech at [Stanford] was watched
thousands of times
```

Figure 5: Example prompt input and `text-davinci-003`'s response for an example document from kore50 dataset (Hoffart et al., 2012b). The ellipsis omits the majority of top-100 potential entities for clear depiction. Markdown format highlight is enabled. INSGENEL-ICL with `text-davinci-003` made two predictions in this document, and both were correct. However, it missed an obvious mention "Apple". Best viewed in color.