Hansel: A Chinese Few-Shot and Zero-Shot Entity Linking Benchmark

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ABSTRACT
Modern Entity Linking (EL) systems entrench a popularity bias, yet there is no dataset focusing on tail and emerging entities in languages other than English. We present Hansel, a new benchmark in Chinese that fills the vacancy of non-English few-shot and zero-shot EL challenges. The test set of Hansel is human annotated and reviewed, created with a novel method for collecting zero-shot EL datasets. It covers 10K diverse documents in news, social media posts and other web articles, with Wikidata as its target Knowledge Base. We demonstrate that the existing state-of-the-art EL system performs poorly on Hansel (R@1 of 36.6% on Few-Shot). We then establish a strong baseline that scores a R@1 of 46.2% on Few-Shot and 76.6% on Zero-Shot on our dataset. We also show that our baseline achieves competitive results on TAC-KBP2015 Chinese Entity Linking task. Datasets and codes are released at https://github.com/HITsz-TMG/Hansel.

CCS CONCEPTS
• Information systems → Information extraction.

KEYWORDS
Entity Linking; Zero-shot Learning; Few-shot Learning; Datasets

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1 INTRODUCTION
Entity Linking (EL) is the task of grounding a textual mention in context to a corresponding entity in a Knowledge Base (KB). It is a fundamental component in applications such as Question Answering [5, 9, 12], KB Completion [28, 36] and Dialogue [4].

An unresolved challenge in EL is to accurately link against emerging and less popular entities. The Zero-Shot Entity Linking problem was presented by Logeswaran et al. [23], aiming at linking mentions to entities unseen during training. On the other hand, Chen et al. [3] raised a common popularity bias in EL, i.e. EL systems significantly under-perform on tail entities that share names with popular entities. Intuitively, we name the challenge to resolve tail entities as Few-Shot Entity Linking, as most of them have only a few number of training examples. Despite the aforementioned studies, non-English resources for zero-shot and few-shot EL are seldom available, hindering progress for these challenges across languages.

Moreover, existing zero-shot and few-shot EL datasets have a limited diversity, because their collection methods rely on hyperlinks or manual templates. Logeswaran et al. [23] extracted mentions from Wikia articles hyperlinked to the Wikia KB, and Botha et al. [2] used links from Wikinews to Wikipedia. Chen et al. [3] generated AmbER sets by filling pre-defined templates with KB attributes. These collection approaches are limited, as mentions are biased towards hyperlink editing conventions or syntactic templates.

To address the language bias and lack of syntactic diversity in few-shot and zero-shot EL datasets, we present Hansel, a human-calibrated and challenging EL benchmark in simplified Chinese. Hansel consists of few-shot and zero-shot test sets, with a Wikipedia-based training set. The few-shot slice is collected from a multi-stage matching and annotation process. A core property of this slice is that all mentions are ambiguous and “hard” [30], where the ground-truth entity is not the most popular by the mention. The zero-shot slice is collected from a searching-based process: given a new entity’s description, annotators find corresponding mentions and adversarial examples with Web search engines over diverse domains. We demonstrate that both slices are challenging for state-of-the-art EL models. We further design a type system based on rich Wikidata structure, and propose a novel architecture utilizing the type system that improves over dual-encoder based models.

The main contributions of this work are:

- Publish Hansel, a challenging multi-domain benchmark for Chinese EL with Wikidata as KB, featuring a zero-shot slice.
with emerging entities, a few-shot slice with hard mentions, and a large training set with 1M documents.

- Propose a novel and feasible zero-shot entity linking dataset collection method, applicable for any language.
- Achieve strong results on TAC-KBP2015 Chinese EL task with a monolingual model, on a par with state-of-the-art multilingual models on this task.

### 2 RELATED WORK

For years, the primary focus of entity linking studies were constrained to English-only and fixed-KB [6, 10, 21, 22]. Cross-lingual entity linking was introduced to link non-English mentions to English KBs [17, 24]. Recently, Botha et al. [2] introduced **Multilingual Entity Linking**, a more general formulation to link mentions from any language to a language-agnostic KB. Their Mewsli-9 multilingual benchmark alleviates the language bias in general EL to some extent, but many languages including Chinese are not covered.

**Zero-Shot Entity Linking** was proposed by Logeswaran et al. [23], with an English zero-shot EL dataset. Mewsli-9 has a zero-shot slice of 3,198 multilingual mentions, but only contains Wikinews hyperlinks. Zero-shot EL on temporally evolving KBs is less discussed. To this end, Hoffart et al. [14] proposed EL on emerging entities, but the dataset is English-only. In this work, we present the first non-English zero-shot EL dataset on emerging entities.

**Few-Shot Entity Linking** was frequently studied in recent years. Provatorova et al. [26] suggested that high accuracy on previous EL datasets can be obtained by merely learning the prior, and released ShadowLink test set whose “Shadow” subset is similar to our few-shot setting, but only available in English. Chen et al. [3] discovered that current EL systems significantly underperform on tail entities, and released AmbER test sets. Their dataset is English-only and generated by filling pre-defined templates with KB attributes. Tsai and Roth [30] has a cross-lingual “hard” subset similar to our setting, but only contains Wikipedia hyperlinks. In this work, we present the first non-English, human-calibrated few-shot EL dataset with better syntactic diversity.

In Chinese language, existing EL datasets are very limited. An established dataset is TAC-KBP2015 [17]. DuEL [13] is an EL dataset annotated to an incomplete subset of Baidu’s knowledge base (390K entities) and thus cannot serve as a comprehensive EL benchmark. None of the above datasets focus on zero-shot or few-shot EL. More comparison of these datasets and their limitations are discussed in Section 6.1. Our proposed benchmark enriches Chinese EL resources and alleviates their popularity bias, providing basis for Chinese and multilingual few-shot and zero-shot EL studies.

### 3 HANSEL DATASET

Define entries in a Knowledge Base (KB) as a set of entities $E$. Given an input document $D = \{s_1, \ldots, s_d\}$ and entity mentions that are spans with known boundaries: $M_D = \{m_1, \ldots, m_n\}$, an entity linking (EL) system outputs mention-entity pairs: $\{(m_i, e_i)\}_{i=1}^n$, where each entity is either a known KB entity or NIL (i.e., an entity outside KB): $e \in E \cup \{\text{NIL}\}$. Another setting of EL where mention spans are not given [6] is out of scope for this work.

We publish an EL dataset for simplified Chinese (zh-hans), named Hansel. The training set is processed from Wikipedia. The test set of Hansel contains Few-Shot (FS) and Zero-Shot (ZS) slices, focusing respectively on tail entities and emerging entities. Both test sets contain mentions from diverse documents, with the ground truth entity ID annotated. Dataset statistics are shown in Table 1.

#### 3.1 Knowledge Base

To reflect temporal evolution of the knowledge base, we split Wiki-data entities into Known and New sets using two historical dumps:

**Known Entities** ($E_{\text{known}}$) refer to WikiData entities in 2018-08-13 dump. All our models are trained with $E_{\text{known}}$ as KB.

**New Entities** ($E_{\text{new}}$) refer to WikiData entities in 2021-03-15 dump that do not exist in $E_{\text{known}}$. Intuitively, entities in $E_{\text{new}}$ were newly added to Wikidata between 2018 and 2021 thus never seen when training on 2018 data, thus considered as a zero-shot setting.

**Entity filtering.** We filter Wikidata entities to get a clean KB: we remove all instances of disambiguation pages, templates, categories, modules, list pages, project pages, Wikidata properties, as well as their subclasses. For the scope of our work, we further constrain to entities with Chinese Wikipedia pages. After filtering, there are roughly 1M entities in $E_{\text{known}}$ and 37K entities in $E_{\text{new}}$.

**Alias table.** An alias table defines the prior probability of a text mention $m$ linking to an entity $e$, i.e. $P(e|m)$, estimated as follows:

$$P(e|m) = \frac{\text{count}(m,e)}{\text{count}(m)}$$  (1)

where $\text{count}(m)$ denotes the number of anchor texts with the surface form $m$ in Wikipedia; $\text{count}(m,e)$ denotes the number of anchor texts with the surface form $m$ pointing to the entity $e$. We extract an alias table AT-base from Wikipedia 2021-03-01 by parsing Wikipedia internal links, redirections and page titles.

Prior work showed that types can benefit EL systems [20, 22, 27]. We present a new formulation for coarse and fine entity typing, utilizing rich structural knowledge in Wikidata:

**Coarse Types.** Define Wikidata entities as $E$, Wikidata property types as $P$, and relation triples as $R(e_1, p, e_2)$. We define a transitive
typing feature denoted as $Type$:

$$R(e_1, P31, e_2) \Rightarrow Type(e_1, e_2)$$

$$Type(e_1, e_2) \wedge R(e_2, P279, e_3) \Rightarrow Type(e_1, e_3)$$

where $P31$ stands for instance of and $P279$ for subclass of.

We define five categories with the above feature in Table 2: person (PER), location (LOC), organization (ORG), event (EVENT), and others (OTHER). Note that our LOC combines GPE, LOC and FAC types as defined in ACE [8] to better fit Wikidata typing guideline\(^1\).

**Fine Types.** Our fine typing system TopSnaks is defined as top 10,000 property-value pairs, i.e. $(p, e_2)$ tuples, sorted by frequency in KB\(^2\). As the 5 examples of Wikidata TopSnaks in Table 3 show, TopSnaks include diverse entity attributes such as types, gender, occupation, country and sport. We verify that the TopSnaks generated from the 2018 Wikidata dump covers about 90% of $E_{new}$, indicating good generalization over emerging entities.

**3.2 Training Data**

Following previous work [2, 6], we use Wikipedia internal links to construct a training set. The alignment of Wikidata and Wikipedia ecosystems enables utility of rich hyperlink structures in Wikipedia.

\(^1\)We refer to [https://www.wikidata.org/wiki/Wikidata:WikiProject_Infoboxes](https://www.wikidata.org/wiki/Wikidata:WikiProject_Infoboxes) when choosing appropriate entities for corresponding types.

\(^2\)"SNAK" is a Wikidata term referring to "some notation about knowledge"; [https://www.wikidata.org/wiki/Q6719099](https://www.wikidata.org/wiki/Q6719099).
All new entities $E_{\text{new}}$ are kept unseen during training. Ideally, one would acquire the 2018 Wikipedia dump as the training corpus. As the full 2018 Wikipedia dump is not publicly available, we use 2021-03-01 Wikipedia dump and hold out all entity pages mapped to $E_{\text{new}}$ as well as all mentions with pagelinks to $E_{\text{new}}$ entities. The training set contains 9.9M mentions from 1.1M documents. We hold out 1K full documents (9.7K mentions) as the validation set.

3.3 Few-Shot Evaluation Slice

For the Few-Shot (FS) test set, we collect human annotations in three Chinese corpora: LCSTS [15], covering short microblogging texts, SohuNews and TenSiteNews [33], covering long news articles.

**Matching.** The FS slice is collected based on a matching-based process as illustrated in Figure 1. We first use AT-base to match against the corpora to generate potential mentions, then randomly sample for human annotation. Note that we only match ambiguous mentions with at least two entity candidates in $E_{\text{known}}$, and keep limited examples per mention word for better diversity.

**Annotation.** Human annotation was performed on more than 15K examples with 15 annotators. For each example, annotators first modify the incorrect mention boundary, or remove the example if it is not an entity mention. Then, they select the referred entity from candidate entities given by AT-base. For each candidate, annotators have access to its description (first paragraph in Wikipedia) and Wikipedia link. If the candidate with the highest prior (AT@1) is correct, then the example is discarded. 75% of examples are dropped if none of the candidates are correct, the annotator finds the correct Wikipedia page for the entity through search engines. If no Wikipedia page can be found, they label a NIL entity with its coarse type from Table 2. Table 4 shows an example of the FS slice.

3.4 Zero-shot Evaluation Slice

Collecting a Zero-Shot (ZS) slice is challenging, due to the difficulty to find occurrences of new entities on a fixed text corpus, especially when the corpus has no hyperlink structure. To address this challenge, we design a novel data collection scheme by searching entity mentions across the Web given an entity description.

**Type balancing.** We first sample from $E_{\text{new}}$ to get a subset with diversified coarse types, as the original type distribution of $E_{\text{new}}$ is heavily biased towards OTHER (52%) and PER (38%). We sample from $E_{\text{new}}$ by 50% random sampling and 50% uniform sampling.

**Searching-based Annotation.** Given the title, description and aliases of an entity in $E_{\text{new}}$, annotators search the Internet$^3$ for a corresponding mention and collect the mention context. They further seek 1 or 2 adversarial examples by searching for a same or similar mention referring to a different entity. The process is shown in Figure 2 with an annotation example. Such ambiguous mentions introduce more diversity on this dataset. Table 5 shows another example and its adversarial mention in the ZS slice.

3.5 Dataset Quality and Statistics

**Expert checking.** For both FS and ZS slices, after the first pass of annotation, there is an expert-checking phase, where 5 human experts manually examine and correct all annotated examples. “Experts” are well-trained annotators who made fewest mistakes in the trial annotation and learned basic knowledge of entity linking. Each example is labeled by one annotator and reviewed by one expert (i.e. tie-breaking by choosing the expert’s result). The expert-reviewed results are used as the ground truth (GT) of this dataset.

**Dataset statistics.** As Table 1 shows, the FS slice has 5,260 mentions from 5,234 documents, covering 2,720 diverse entities. The ZS slice has 4,715 mentions across 4,707 documents, covering 4,046 distinct entities. Domains are news (51.9%) and social media (48.1%) for FS slice, and news (38.6%), social media (14.9%), and other articles such as E-books and commerce (46.5%) for ZS slice.

**Dataset Quality.** To measure dataset quality, we first calculate the percentage agreement between the annotator and the expert. The percentage agreement of Hansel-FS and Hansel-ZS are 87.3% and 95.9% respectively, i.e. modification rate is 12.7% and 4.1% during expert checking. Both imperfect mention boundaries and wrong entities count as disagreements. Boundary changes account for 40.1% for FS disagreements and 53% for ZS.

We further take a random sample from the final dataset, 100 examples from FS and 100 from ZS. Two annotators independently label whether the GT entity is correct. In this step, two annotators agree on 88% of the cases in FS slice and 94% of the cases in ZS slice. We use Cohen’s Kappa coefficient to evaluate the inter-annotator agreement. The coefficient is 0.622 for FS and 0.651 for ZS, indicative of substantial agreement between annotators [11]. Average human accuracy (evaluating on GT) is 88% for FS and 95.5% for ZS.

4 MODELS

We establish baselines on Hansel with a Dual Encoder (DE) model and a Cross-Attention encoder (CA) model for entity disambiguation. We also present a novel architecture that exploit our coarse and fine typing system to add typing-based supervision on DE.

4.1 Dual Encoder Model

Following previous work [2, 34], we train a Dual Encoder (DE) model to project entity and mention contextual representations into a same vector space. Such models are scalable in that the entity embeddings can be pre-computed and stored, enabling fast retrieval or dot-product based similarity scoring.

The dual encoder takes a mention-entity pair $(m, e)$ and outputs their cosine similarity score:

$$sim(m,e) = \frac{\langle \phi(m)^T, \psi(e) \rangle}{\|\phi(m)\|\|\psi(e)\|}$$

where both $\phi$ and $\psi$ are learned transformer encoders projecting mention and entity input sequences into $d$-dimensional vectors ($d=256$), i.e. mapping the [CLS] token with a dense layer to the output embedding. We use boundary tokens (denoted as $[E1]$ and $[E1]$) to wrap mentions for the input of $\phi$. We concatenate the title and the description as an entity’s description for the input of $\psi$. The DE model is optimized with in-batch sampled softmax loss.

We use the DE model as a scoring step on candidates generated by the alias table AT-base, combining the model’s prediction $sim(m,e)$ with the prior $P(e|m)$ to produce a score $s(m,e)$:

$$s(m,e) = P(e|m)sim(m,e).$$
4.2 Cross-Attention Encoder Model

Following Wu et al. [34], Cross-Attention encoder (CA) takes concatenated mention and entity as input and outputs their similarity (in the range 0 to 1), optimized with a binary cross-entropy loss.

Since the training set only comes with positive examples, we collect incorrect entities retrieved by the alias table as negative examples, and randomly keep 20% of them to reduce label imbalance.

4.3 TyDE: Typing-enhanced Dual Encoder

Previous work [22, 27] suggested that type coherence can benefit EL systems. However, models like DE or CA only implicitly learn type coherence with pretrained contextualized representations. Moreover, types for new entities in KB can be incomplete.

We propose a novel typing-enhanced dual encoder (TyDE), using type prediction as an auxiliary supervision task to improve the dual encoder. As Figure 3 shows, on top of mention and entity encodings output by ϕ and ψ, we add classification layers for coarse and fine typing. On each side, we use a softmax classifier for coarse types and a binary classifier for each of 10K fine types. The TyDE model is optimized with type classification losses in addition to in-batch sampled softmax loss. The supervision approach does not rely on types as encoder input, thus less affected by KB incompleteness.
During inference, we use the similarity score as defined in DE, $P(e|m) \cdot \text{sim}(m,e)$, and combine it with the predicted coarse and fine typing scores. Note that we do not require entity types for inference. Coarse typing score $S_c$ and fine typing score $S_f$ are defined as:

$$
S_c(m,e) = \sigma_c(m)^T \rho_c(e),
$$
$$
S_f(m,e) = \sigma_f(m)^T \rho_f(e)
$$

where $\sigma_c$, $\rho_c$, $\sigma_f$ and $\rho_f$ are single linear dense layers, projecting $\phi$ and $\psi$ outputs to corresponding type dimensions. $\sigma_c$ and $\rho_c$ project to 5 coarse types, and $\sigma_f$ and $\rho_f$ project to 10,000 fine types.

There are 2 different scoring settings for TyDE: (1) similarity only, i.e. $P(e|m) \cdot \text{sim}(m,e)$, so typing information is only used implicitly via co-training; (2) multiply similarity with coarse, fine, or both typing scores, i.e. $P(e|m) \cdot \text{sim}(m,e) \cdot \sigma_c(m,e)$, $P(e|m) \cdot \text{sim}(m,e) \cdot \sigma_f(m,e)$, $P(e|m) \cdot \text{sim}(m,e) \cdot \sigma_c(m,e) \cdot \sigma_f(m,e)$ respectively. Note that the combination requires trivial additional computation for scoring. Evaluation of these settings is detailed in Section 5.2.

5 EXPERIMENTS

In this section, we first describe implementation details (Section 5.1). Then we evaluate our baseline models on TAC-KBP2015, an established Chinese dataset with the most reported results, to show our model’s competitive result with the state-of-the-art mGENRE [7] (Section 5.2). Next, we set baselines on Hansel with our models and mGENRE (Section 5.3), showing the huge performance difference between TAC-KBP2015 and Hansel (discussed in Section 6.3).

5.1 Experiment Details

DE, TyDE and CA models are implemented with Tensorflow [1]. The DE, TyDE and CA encoders all use 12 transformer encoder layers, initialized with Chinese BERT-base parameters. The number of parameters for DE, TyDE and CA are roughly 204M, 210M, 102M. The models are trained on a single NVIDIA V100 GPU. We use Adam optimizer [19] with linear weight decay and use 10% steps for a linear warmup schedule. All general models are trained for 100K steps. Training of DE and TyDE models takes approximately 30 hours. Training CA on Wikipedia takes 16 hours, and finetuning CA on TAC-KBP2015 takes 4 hours.

We fix sequence length to be 128 tokens for both mention and entity encoder for DE and TyDE, and 256 tokens for CA. The batch size is 64 for DE and TyDE, and 32 for CA. We search learning rate among [1e-5, 2e-5, 1e-4] for DE and TyDE. Following Botha et al. [2], we fix 1e-5 as the learning rate for CA. We search learning rate among [1e-6, 5e-6] for CA-tuned. We search mention and entity embedding dimension $d$ within [128, 256] for DE and TyDE. We use accuracy in validation set to make hyper-parameter choices. Best-performing hyper-parameters are: embedding dimension $d$ is 256, learning rate is 2e-5 for DE and TyDE, and 5e-6 for CA-tuned.

mGENRE. For mGENRE’s performance on Hansel, We use the mGENRE model in the publicly available GENRE repository. We do not perform any fine-tuning to its parameters. Since mGENRE uses both Wikipedia and Wikidata dumps from 2019-10-01, and Hansel-ZS include entities from Wikidata 2021-03-15, we extend mGENRE’s catalog of entity names with all languages for every entity in $E_{new}$ for Hansel-ZS evaluation.

5.2 Evaluation on TAC-KBP2015

To compare our models with prior work, we benchmark on the established TAC-KBP2015 Chinese EL task. Note that TAC-KBP2015 was originally designed for cross-lingual EL, but still suitable as a monolingual benchmark. Following De Cao et al. [7], we do not consider the annotated NIL entities in the dataset. We use full Chinese Wikipedia ($E_{known}$ and $E_{new}$) as our target KB. The evaluation metric is Recall@K, where $K=1$ is equivalent to accuracy.

Following De Cao et al. [7], we use the TAC-KBP2015 train set to extend AT-base, denoted as AT-ext. Models are trained with $E_{known}$ examples only, as described in Section 3.2, where only AT-base was used for generating negatives. We further fine-tune CA on TAC-KBP2015’s training set for 1 epoch, using AT-ext to generate negatives. The finetuned model is denoted as CA-tuned.

We evaluate DE, TyDE and CA models, based on AT-ext’s top-10 candidates. Table 6 shows evaluation results. Despite using a monolingual approach, our CA-tuned is on a par with the state-of-the-art model using multilingual data for training. In particular, CA-tuned outperforms all previous cross-lingual models [29, 31, 37].

Inference strategy of TyDE. We experiment with TyDE’s different typing score combinations for inference in Table 7. Combining only fine typing score, i.e. $P(e|m) \cdot \text{sim}(m,e) \cdot \psi(m,e)$, performs the best among different settings. We will adopt this setting for TyDE’s inference on Hansel. TyDE improves over a standard DE with minimal added complexity. In addition, we find that combining coarse typing score leads to performance degradation. A possible reason is that five coarse types are not enough for entity disambiguation.

Table 6: Results on TAC-KBP2015 Chinese EL task. Our monolingual CA-tuned is on a par with the multi-lingual SOTA. We also report recall of our base and extended aliases tables.

| Metric | Value |
|--------|-------|
| Tsai and Roth [30] | R@1 85.1 |
| Sil et al. [29] | R@1 85.9 |
| Upadhyay et al. [31] | R@1 86.0 |
| Zhou et al. [37] | R@1 85.9 |
| De Cao et al. [7] | R@1 88.4 |
| DE | R@1 75.2 |
| TyDE | R@1 76.2 |
| CA | R@1 81.7 |
| CA-tuned | R@1 88.1 |
| AT-base | R@1 73.1 |
| AT-base | R@10 89.1 |
| AT-base | R@100 89.4 |
| AT-ext | R@1 75.3 |
| AT-ext | R@10 91.1 |
| AT-ext | R@100 91.5 |

We use a Freebase API to resolve predictions to a Freebase MID, to be consistent with the dataset. When our system cannot resolve the link, it counts as a prediction error.
We evaluate on Hansel, we do not use dataset-specific tuning. We set up baselines on Hansel-FS and Hansel-ZS with our models. While the base version can recover some alias table misses. On Hansel-ZS, although mGENRE was trained on a Wikidata dump that overlaps with $E_{\text{new}}$, partially violating the zero-shot constraint, the best variant of mGENRE still under-performs CA (-8.7).

5.3 Evaluation on Hansel

We set up baselines on Hansel-FS and Hansel-ZS with our models. When evaluating on Hansel, we do not use dataset-specific tuning. We use AT-base as the alias table and evaluate DE and CA based on AT-base’s top-10 candidates. Table 8 shows the results on Hansel.

Comparison with mGENRE. We evaluate the state-of-the-art mGENRE for comparison. From Table 8, the base version of mGENRE outperforms its variants with candidates and marginalization. This may be due to the low recall of AT-base on Hansel-FS, while the base version can recover some alias table misses. On Hansel-FS, our CA model outperforms mGENRE by 9.6 points. On Hansel-ZS, although mGENRE was trained on a Wikidata dump that overlaps with $E_{\text{new}}$, partially violating the zero-shot constraint, the best variant of mGENRE still under-performs CA (-8.7).

In short, CA currently achieves the best result for both zero-shot (76.6%) and few-shot (46.2%) slices, outperforming mGENRE by a large margin on both scenarios. This suggests that CA is less prone to popularity bias and generalizes better to tail and emerging entities. Large room of improvement remains on both datasets.

Error analysis. Among all R@1 errors of CA-tuned, in 211 (20%) cases, the gold entities do not have a Chinese Wikipedia page and do not exist in either $E_{\text{known}}$ or $E_{\text{new}}$, so our model misses these examples, whereas cross-lingual and multilingual models [7, 31] are inherently better at such examples. 545 (53%) errors do not have the mention-entity pair in alias table’s top-10 candidates, suggesting major headroom of overcoming the restriction of alias tables. In 256 (25%) cases, the model does not choose the correct candidate. In 20 (2%) cases, the freebase MIDs are not resolved to Wikidata.

Table 7: Evaluations of TyDE inference strategy on TAC-KBP2015. We compare multiplying similarity with coarse, fine or both typing scores.

| Strategy                  | R@1 |
|--------------------------|-----|
| DE                       | 75.2|
| TyDE (sim only)          | 75.9|
| TyDE (sim+coarse)        | 74.9|
| TyDE (sim+fine)          | 76.2|
| TyDE (sim+coarse+fine)   | 75.1|

6 DISCUSSION

In this section, with regard to each contribution listed in Section 1, we discuss about the necessity of Hansel (Section 6.1), exporting annotation methods to other languages (Section 6.2), and the performance difference on TAC-KBP2015 and Hansel (Section 6.3).

6.1 Comparison of Hansel and Existing Chinese EL Datasets

The only 2 series of Chinese EL datasets that link to Wikidata are TAC-KBP series [16–18] and CLEEK [35]. Table 9 summarizes the datasets’ statistics and domains. Hansel sets itself apart by filling the vacancy of non-English few-shot and zero-shot datasets.

To obtain a few-shot slice, it is intuitive to subsample existing datasets, i.e. removing correct AT@1 examples as the human annotation stage does. Although subsampling is feasible, the major disadvantage still exists, i.e. the lack of mention and entity diversity. As Table 9 shows, the few-shot subsets of TAC-KBP and CLEEK lack diversity due to their intrinsic features. Take TAC-KBP2017 for example, its subset has 3,883 mentions, covering only 877 different surface forms, 167 documents and 350 entities, suggesting lots of lexical repetitions across examples. In contrast, Hansel-FS has 5,260 (1.4x) mentions, covering 4,097 (5x) different surface forms, 5,234 (30x) documents and 2,720 (8x) entities. The diversity of Hansel-FS is rooted from our collection method, as we sample mentions from a large set of documents and avoid repetitive mentions and entities, making the dataset challenging and syntactically diverse.

For Hansel-ZS, we use the emerging entities in temporally evolving Wikidata to collect data. We apply this zero-shot setting due to its practical use. Since EL is often used in knowledge base construction and population [14, 28], this setting simulates how to link mentions to emerging entities with 2018’s training data.

The TAC-KBP datasets are available for a price, but Hansel is open-source for the convenience of future research.

In conclusion, Hansel provides a comprehensive and open-source EL benchmark and cannot be substituted by simply subsampling.

6.2 Extending to Other Languages

To port our annotation method to a new language, one may re-use our Wikidata entity splits, i.e. $E_{\text{new}}$ and $E_{\text{known}}$. Then, one may obtain an alias table by parsing language-specific Wikipedia. With a large text corpus for the language, one may adopt our matching-based process in Section 3.3 for a few-shot EL dataset. For new entities (also applicable for few-shot entities if no large corpus is available), one may refer to the searching-based method in Section 3.4. The annotators need to have expertise in the target language.

6.3 Performance Difference

Difference between TAC-KBP2015 and Hansel. Compared with overall results on TAC-KBP2015 (see Table 6), results on Hansel...
Table 8: Evaluation of our baselines, mGENRE (denoted as GEN.) and mGENRE’s variants (+margin, +cand, +both) on the Hansel dataset. Both datasets are challenging for the state-of-the-art MEL model, while our CA model generalizes better to few-shot and zero-shot settings. mGENRE numbers on Hansel-ZS*: does not follow zero-shot training constraints, but still lower than CA results.

Table 9: Comparison of existing Chinese EL datasets and the Hansel dataset. We break down the number of mentions, distinct mentions and documents by whether the label is a NIL entity or inside Wikidata (In-KB). We also provide statistics of existing datasets’ few-shot (FS) subsets.

decrease across all models (see Table 8), suggesting the challenge of few-shot and zero-shot setting. For CA and mGENRE comparison, on TAC-KBP2015, CA has a slightly lower performance (88.1%) than mGENRE (88.4%), i.e. mGENRE gets 26 more correct examples than CA. However, the results of CA is higher than mGENRE by a large margin on both slices of Hansel. In conclusion, CA does significantly better on tail and new entities than mGENRE, while keeping a strong performance on general entities. The big performance variance between mGENRE and CA on TAC-KBP2015 and Hansel-FS indicates the popularity bias issue raised by Chen et al. [3]. Hansel will facilitate future research that reduce such biases.

Few-shot setting harder than zero-shot setting? This observation is actually coherent with prior state-of-the-art systems. These EL systems achieve higher scores in zero-shot settings than few-shot settings on English EL datasets: Wu et al. [34] achieve the best performance so far on the zero-shot ZESHEL [23] with an accuracy of 63.0%, but in the few-shot setting, the accuracy is only 49.0% on the “Tail” slice of AmbER-H for fact checking [3].

The reason behind this lies in the intrinsic difficulty of few-shot EL datasets. For each mention in Hansel-FS, although the ground-truth entity has appeared a few times in the training data, it is not the most popular entity that share the same surface form. Previous work sometimes refers to this few-shot setting as "overshadowed" [26], “tail” [3] or “hard” [30]. For example, the correct entity for “Michael Jordan” in “Michael Jordan published a new paper in machine learning” is “Michael Jordan (scientist)”, but as reported in state-of-the-art entity linking systems GENRE [6], REL [32] and WAT [25] all link to the most common entity “Michael Jordan (basketball player)”. On the other hand, for our zero-shot slice, although ground-truth entities are unseen during training, some may still be the most popular by their names, thus easier to resolve.

7 CONCLUSION

To address the popularity and language bias with entity linking (EL) datasets, we present Hansel, a new Chinese EL benchmark consisting of two slices: Hansel-FS where the correct entities are not the most popular, and Hansel-ZS where the entities are not observed in training. We establish strong baselines on Hansel and make the dataset and baseline models publicly available. Along with the dataset, we propose a method to collect human-calibrated few-shot and zero-shot EL datasets, applicable for any language. Future work on Chinese or multilingual EL may use our benchmark to test generalization over tail and emerging entities.

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