

LinkTransformer: A Unified Package for Record Linkage with Transformer Language Models

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Abstract

Linking information across sources is fundamental to a variety of analyses in social science, business, and government. While large language models (LLMs) offer enormous promise for improving record linkage in noisy datasets, in many domains approximate string matching packages in popular softwares such as R and Stata remain predominant. These packages have clean, simple interfaces and can be easily extended to a diversity of languages. Our open-source package LinkTransformer aims to extend the familiarity and ease-of-use of popular string matching methods to deep learning. It is a general purpose package for record linkage with transformer LLMs that treats record linkage as a text retrieval problem. At its core is an off-the-shelf toolkit for applying transformer models to record linkage with four lines of code. LinkTransformer contains a rich repository of pre-trained transformer semantic similarity models for multiple languages and supports easy integration of any transformer language model from Hugging Face or OpenAI. It supports standard functionality such as blocking and linking on multiple noisy fields. LinkTransformer APIs also perform other common text data processing tasks, *e.g.*, aggregation, noisy de-duplication, and translation-free cross-lingual linkage. Importantly, LinkTransformer also contains comprehensive tools for efficient model tuning, to facilitate different levels of customization when off-the-shelf models do not provide the required accuracy. Finally, to promote reusability, reproducibility, and extensibility, LinkTransformer makes it easy for users to contribute their custom-trained models to its model hub. By combining transformer language models with intuitive APIs that will be familiar to many users of popular string matching packages, LinkTransformer aims to democratize the benefits of LLMs among those who may be less familiar with deep learning frameworks.

1 Introduction

Linking information across sources is fundamental to a variety of analyses in social science, business, and government. A recent literature, focused on matching across e-commerce datasets, shows the promise of transformer large language models (LLMs) for improving record linkage (alternatively termed entity resolution or approximate dictionary matching). Yet these methods have not yet made widespread inroads, with rule-based methods continuing to overwhelmingly predominate in social science and government applications (*e.g.*, see reviews by [Binette and Steorts \(2022\)](#); [Abramitzky et al. \(2021\)](#)). In particular, users commonly employ string-based matching tools available in statistical software packages such as R or Stata.

We suspect that record linkage with large language models has not made further inroads at least in part due to the lack of packages that match the ease of the popular string matching packages, which are intuitive, extensible, and easy-to-use. They require little coding expertise and can easily be applied across different languages and settings. In contrast, existing tools for large language model matching require considerable technical expertise to implement. This makes sense in the context for which these models were developed - classifying and linking products for e-commerce firms, which employ data scientists - but it is a significant impediment for broader use.

To bridge the gap between the ease-of-use of widely employed string matching packages and the power of modern LLMs, we developed LinkTransformer, a general purpose, user friendly package for record linkage with transformer LLMs. LinkTransformer treats record linkage as a text retrieval problem (See Figure 1). The API can be thought of as a drop-in replacement to popular dataframe manipulation frameworks like pandas or tools like R and Stata, catering to those

who lack extensive exposure to coding.

To achieve its objective of democratizing access to the benefits of deep learning amongst those who may lack familiarity with deep learning frameworks, LinkTransformer integrates the following features:

1. An off-the-shelf toolkit for applying transformer models to record linkage and de-duplication with 4 lines of code
2. A rich repository of pre-trained semantic similarity models, supporting multiple languages, that underlies off-the-shelf usage
3. Easy integration of any language transformer model on Hugging Face or OpenAI
4. APIs to support related data processing tasks, *e.g.*, aggregation, de-duplication, and translation-free cross-lingual linkage
5. Comprehensive tools for efficient model tuning to facilitate different levels of customization
6. Easy sharing of models, to promote reusability, reproducibility, and extensibility

The LinkTransformer model zoo currently contains English, Chinese, French, German, Japanese, Spanish, and multilingual pre-trained models. We initialize with semantic similarity models, *e.g.*, Reimers and Gurevych (2019), which have desirable properties relative to using off-the-shelf embeddings from models like RoBERTa or GPT (see Section 2). We further tuned these models on a variety of linked datasets.

While transfer learning can facilitate strong off-the-shelf performance in many scenarios, supporting customization is important. Record linkage applications are extremely diverse in their languages, time periods, and domains, which vary significantly in how out-of-domain they are from the web corpora that underlying LLMs are trained on. Considerable heterogeneity - combined with settings that demand extremely high accuracy - create many scenarios where custom training is useful.

We show that LinkTransformer performs well on challenging record linkage tasks. It is equally applicable to record linkage tasks with a single field - *e.g.*, linking 1940s Mexican tariff product classes across time - and applications that require concatenating an array of noisily measured fields

- *e.g.*, linking 1950s Japanese firms across different large-scale, noisy databases using firm name, location, products, shareholders, and banks. This type of linkage problem would be highly convoluted with traditional string matching methods, as there are many noisily measured fields of relevance (*e.g.*, products can be described in different ways, different subsets of managers and shareholders are listed, etc). Using LinkTransformer to automatically concatenate the information and feed it to a LLM handles these challenges with ease. A demo is available at <https://www.youtube.com/watch?v=Sn47nmCvV9M>.

LinkTransformer has a GNU General Public License. It is being actively maintained, and in the next release we will add support for vision-free and multimodal linkage models, including support to import and customize any timm model (Wightman, 2019). When OCR errors are rampant, vision-only or aligned vision-language transformer models can improve record linkage, relative to string matching or language-only transformer linking *e.g.*, (Yang et al., 2023; Arora et al., 2023).

The rest of the paper is organized as follows. Section 2 provides an overview of related work. The core LinkTransformer library, Model Zoo, customized model training, and model sharing are described in Section 3. Section 4 discusses various use cases. Section 5 discusses limitations.

2 Relation to the Existing Literature

There is a large literature on record linkage spanning social science, statistics, and computer science. Record linkage serves as a prerequisite for many empirical analyses, which often require combining text data from multiple noisy sources. In social science, statistics, and government applications, large language models have made few inroads. A 2022 review of the record linkage literature in *Science Advances* (Binette and Steorts, 2022), entitled “(Almost) All of Entity Resolution”, concludes that deep neural models are unlikely to be applicable to record linkage using structured data, arguing that training datasets are small and there is unlikely to be much gained from large language models since text fields are often short.

While there are undoubtedly linking tasks for which LLMs will not be of much use (discussed further in Section 5 on limitations), an extensive literature on e-commerce applications underscores their utility for linking structured datasets. Bench-

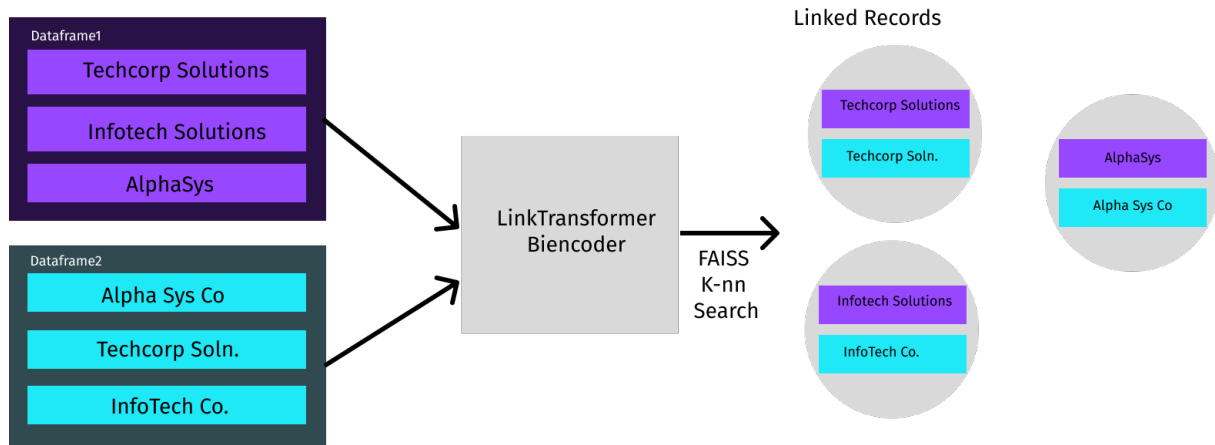


Figure 1: **Visualization.** This figure shows the LinkTransformer architecture.

marks in this literature (e.g., Köpcke et al. (2010); Das et al. (2015); Primpeli et al. (2019)) focus on applications such as matching electronics and software products between Amazon-Google and Walmart-Amazon listings, matching iTunes and Amazon music listings, and matching restaurants between Fodors and Zagats. The focus is on applications in English. Recent studies have used masked language models (e.g., BERT, DistilBERT, RoBERTa) (Li et al., 2020; Joshi et al., 2021; Brunner and Stockinger, 2020), GPT (Peeters and Bizer, 2023; Tang et al., 2022), or both, significantly outperforming static word embedding and other older linkage methods. Zhou et al. (2022), like LinkTransformer, uses Sentence BERT (Reimers and Gurevych, 2019).

The main package in this space to our knowledge, Ditto (Li et al., 2020), implements the methods later published in Li et al. (2023). It requires significant programming expertise to deploy, appropriate for a literature focused on e-commerce - where data scientists predominate - but a hindrance for broader use.

Most of the literature examining record linkage with LLMs poses record linkage as a classification task, which is appropriate for the e-commerce benchmarks. However, this significantly limits extensibility, as in many social science and government applications the number of entities to be linked numbers in the millions, making it computationally infeasible to compute a softmax over all possible classes (entities).

LinkTransformer frames record linkage as a knn-retrieval task, in which the nearest neighbor for each entity in a query embedding dataset is retrieved from a key embedding dataset, using cosine similarity implemented with an FAISS back-

end (Johnson et al., 2019). LinkTransformer includes functionality to tune a no-match threshold - since not all entities in the query need to have a match in the key - and allows for retrieving multiple neighbors, to accommodate many-to-many matches between the query and the key. The LinkTransformer architecture was inspired by a variety of bi-encoder applications for unstructured texts, e.g., passage retrieval (Karpukhin et al., 2020), entity disambiguation (Wu et al., 2019), and entity co-reference resolution (Hsu and Horwood, 2022).

LinkTransformer departs from much of the literature (with the exception of Zhou et al. (2022)) in utilizing LLMs trained for semantic similarity for its pre-trained models.¹ A large literature shows that off-the-shelf LLMs such as BERT or GPT have anisotropic geometries (Ethayarajh, 2019): representations of low frequency words are pushed outwards on the hypersphere, the sparsity of low frequency words violates convexity, and the distance between embeddings is correlated with lexical similarity. This leads to poor performance when individual term representations from the transformer model are pooled to create a representation for longer texts - as is often necessary for record linkage - since pooling assumes convexity, and leads to poor alignment between semantically similar texts. Contrastive training for semantic similarity reduces anisotropy, improving alignment between semantically similar pairs and improving sentence embeddings (Wang and Isola, 2020; Reimers and Gurevych, 2019). LinkTransformer

¹Compare to Zhou et al. (2022), LinkTransformer uses a different loss function, supervised contrastive loss (Khosla et al., 2020). It is well-suited to record linkage as there are multiple positive pairs in the datasets we use for pre-training.

builds closely upon Sentence BERT (Reimers and Gurevych, 2019), whose excellent semantic similarity library inspired many of the features in LinkTransformer.

The knn retrieval structure of LinkTransformer also supports noisy de-duplication, a closely related task that finds noisily duplicated observations within a dataset. LinkTransformer follows the methods developed in Silcock et al. (2023), who show that de-duplication using a contrastively trained bi-encoder significantly outperforms n -gram and locally sensitive hashing methods and is highly scalable.

3 The LinkTransformer Library

3.1 Off-the-shelf Toolkit

At the core of LinkTransformer is an off-the-shelf toolkit that streamlines record linkage with transformer language models. The record linkage models enable using pre-trained or self-trained transformer models with just 4 lines of code. Any Hugging Face or OpenAI model can be used by configuring the `model` and `openai_key` arguments. This future-proofs the package, allowing it to take advantage of the open-source revolution that Hugging Face has pioneered. Here is an example of the core **merge** functionality, based on embeddings sourced from an external language model.

```
1 import linktransformer as lt
2 #Load data frame
3 df1 = pd.read_csv("df1.csv")
4 df2 = pd.read_csv("df2.csv")
5 df_matched = lt.merge(df2, df1,
    merge_type='1:m', on=["Varname"],
    model="sentence-transformers/all-
    MiniLM-L6-v2", openai_key=None)
```

LinkTransformer provides a wealth of pre-trained model weights, covering different languages and domains. It currently supports six languages (English, Chinese, French, German, Japanese, and Spanish) with both multilingual and monolingual models. Training datasets include:

1. A novel dataset of firm aliases that we compiled from Wikidata for 6 languages
2. United Nations economic classification schedules (International Standard Industrial Classification, Standard International Trade Classification, and Central Product Classification), which homogenize industry and product classifications across varying national systems. We include models trained on these for 3 of the 6 official languages of the UN.

3. A variety of e-commerce linking datasets (see Supplemental Materials)

We name these models with a semantic syntax: `{org_name}/lt-{data}-{task}-{lang}`. Each model has a detailed model card, with the appropriate tags for quick model discovery. Additionally, for the tasks we trained our models on, we provide a high-level interface to download the right model by task through a wrapper that retrieves the best model for a task chosen by the user.

LinkTransformer makes no compromise in scalability. All functions are vectorized wherever possible and the vector similarity search underlying knn retrieval is accelerated by an FAISS (Johnson et al., 2019) backend that can easily be extended to perform retrieval on GPUs on massive datasets. We also allow “blocking” - running knn-search only within “blocks” that can be defined by the `blocking_vars` argument.

Record linkage frequently requires matching databases on multiple noisily measured keys. LinkTransformer allows a list of as many variables as needed in the `on` argument. The merge keys specified by the `on` variable are serialized by concatenating them with a `< SEP >` token, which is based on the underlying tokenizer of the selected base language model. This ensures that the serialization takes advantage of a token already introduced in training and the process is agnostic to the choice of the model.

Since we have designed the API around dataframes - due to their familiarity amongst users of R, Stata or Excel - all import/export formats supported.

The accessible LinkTransformer API supports a plethora of other features that are an essential part of routine data analysis pipelines. These include:

Aggregation: Data processing often requires the aggregation of fine descriptions into coarser categories, that are consistent across datasets/time or facilitate interpretation. This problem can be thought of as a merge between finer categories and coarser ones, where LinkTransformer classifies the finer categories by means of finding their nearest coarser neighbor(s). We provide a high-level API for this task, `lt.aggregate_rows`, with a similar syntax to the main record linkage API.

Deduplication: Text datasets can contain noisy duplicates. Popular libraries like dedupe (Gregg and Eder, 2022) only support deduplication using metrics that most closely resemble edit distance.

LinkTransformer allows for semantic deduplication with a single, intuitive function call.

```
1 df=pd.read_csv("df1.csv"))
2 df_dedup=lt.dedup_rows(df,on="
    CompanyName",model="sentence-
    transformers/all-MiniLM-L6-v2",
3     cluster_params= {'threshold': 0.7})
```

LinkTransformer de-duplication clusters embeddings under the hood, with embeddings in the same cluster classified as duplicates. LinkTransformer supports several clustering methods like SLINK, DBSCAN, HDBSCAN, and agglomerative clustering.

Cross-lingual linkage: Analyses spanning multiple countries often require cross-lingual linkage. This task typically requires machine translation followed by a merge. Edit distance metrics tend to do particularly poorly in this scenario, necessitating costly hand linking. LinkTransformer users can bypass translation by using multilingual transformer models.

We will provide helpful notebooks and tutorials on the LinkTransformer website to outline the use of these functionalities and also some toy datasets. In the coming weeks, we will release a string of tutorials to help those who are less familiar with language models to select ones that best fit their use case. More detailed information and additional features that we cannot highlight in the interest of brevity can be found in the online LinkTransformer documentation that is available on our public repo.²

3.2 Customized Model Training

Record linkage tasks are highly diverse. Hence, LinkTransformer also supports easy model training. Custom training can be initialized using the weights of any Hugging Face transformer model.

Training data are expected in a *pandas* data frame, removing entry barriers for the typical social science user who is familiar with other programming languages and statistical packages. A data frame can include only positive labeled examples (linked observations) as inputs, in which case the model is evaluated using an information retrieval evaluator that measures top-1 retrieval accuracy. Alternately, it can take a list of both positive and negative pairs, in which case the model is evaluated using a binary classification loss.

²<https://github.com/dell-research-harvard/linktransformer>

Only the most important arguments are exposed and the rest have reasonable defaults which can be tweaked by more advanced users. Additionally, LinkTransformer supports logging of a training run on Weights and Biases (Biewald, 2020).

```
1 best_model_path=lt.train_model(
2     model_path="hf-path-to-base-
    model",
3     data="df1.csv"),
4     left_col_names=["left_var"],
5     right_col_names=["right_var"],
6     left_id_name=["left_id"],
7     right_id_name=["right_id"],
8     label_col_name=None,
9     log_wandb=False,
10    training_args={"num_epochs": 1}
11 )
```

Default training expects positive pairs. A simple argument that specifies `label_col_name` switches the dataset format and model evaluation to adapt to positive and negative labels.

LinkTransformer is sufficiently sample efficient that most models in the model zoo were trained with a student Google Colab account, an integral feature since the vast majority of potential users have constrained compute budgets.

3.3 User Contributions

LinkTransformer aims to promote the reusability and reproducibility of record linkage pipelines. End-users can upload their self-trained models to the LinkTransformer Hugging Face hub with a simple `model.save_to_hub` command. Whenever a model is saved, a model card is automatically generated that follows best practices outlined in Hugging Face’s Model Card Guidebook. This process adds a pipeline-tag, supported language(s) (given the base model), and other tags to the model card’s header that facilitate model discovery by other Hugging Face users. Moreover, the automatically generated card contains instructions on how to use the model for record linkage and model-specific architecture and training details.

4 Applications

The LLMs in the LinkTransformer model zoo outperform non-neural methods by a wide margin. We examine applications from both modern web data and historical datasets that we digitized from hard copy historical firm and government records. These tasks are representative of applications in quantitative social science, industry, and government. The results are reported in the supplementary materials.

First, we evaluate in-domain performance on semantic similarity datasets used to pre-train LinkTransformer models, with the supplementary materials comparing the accuracy of Levenshtein edit distance matching (Levenshtein et al., 1966), semantic similarity models off-the-shelf, and LinkTransformer tuned models. The LinkTransformer models tend to outperform edit distance metrics by a wide margin in matching Wikidata firm aliases, with the top-1 retrieval accuracy tending to be 20-30 points higher for LinkTransformer linkage than for edit distance based matching. Cases that LinkTransformer gets wrong are often impossible even for a skilled human to resolve from the firm names alone, *e.g.*, in cases where a firm is referred to by two completely disparate acronyms. For multilingual linkage, the F1 is a whopping 46 points higher with LinkTransformer than with edit distance matching. In all these cases, off-the-shelf semantic similarity models also tend to outperform string matching methods, albeit not by as much of a margin as tuned models.

Second, we examine historical applications. The first setting is a concordance between products in two 1940s Mexican tariffs schedules, published by the Mexican government and digitized from the hard copy documents (Secretaría de Economía de Mexico, 1948). Tariffs were applied at an extremely disaggregated product level and each of the many thousands of products in the tariff schedule is identified only by a text description, which can change each time the tariff schedule is updated. Around 2,000 products map to different description across the schedules. While there are considerable debates on the role that trade policies have played in long-run development, empirical evidence is limited in part due to the considerable challenges in homogenizing extremely detailed historical tariff schedules across time, as crosswalks do not exist for most tariff schedule changes.

We link the tariff schedules using an off-the-shelf semantic similarity model, as well as a model tuned on the in-domain historical data and GPT. All transformer widely outperform edit distance, with the fine-tuned LinkTransformer model performing (at no charge) and purchased GPT hidden states producing similar, near perfect results.

We also link firms across two different 1950s publications created by different Japanese credit bureaus (Jinji Koshinjo, 1954; Teikoku Koshinjo,

1957). One has around 7,000 firms and the other around 70,000, including many small firms. Firm names can be written differently across publications and there are many duplicated or similar firm names. To make this task feasible, we concatenate information on the firm’s name, prefecture, major products, shareholders, and banks. These variables contain OCR noise and the information included in each publication varies somewhat, *e.g.* in terms of which products are described, which shareholders are included, etc. This makes rule-based methods quite brittle. Again, an LinkTransformer fine-tuned model significantly outperforms string matching methods.

Finally, we examine the various e-commerce and industry benchmarks that prevail in this literature. We used exactly the same training procedure for each benchmark, to avoid overfitting, which is often not the case in the literature. We have generally comparable performance, sometimes outperformed by other models (that could be integrated into LinkTransformer as well if on Hugging Face) and sometimes outperforming other models.

5 Limitations

LinkTransformer is built upon transformer language models, and hence will not be suitable for lower resource languages that lack pre-trained LLMs. LinkTransformer will also be less useful in contexts where little language understanding enters record linkage, *e.g.*, when linking records solely using individual names. For these contexts, the next release of LinkTransformer will integrate vision-only transformer models, which the authors have reported on extensively elsewhere (Arora et al., 2023; Yang et al., 2023).

Furthermore, in settings where OCR errors are considerable, too much information may have been destroyed to successfully link entities using garbled texts. In this case, a multimodal framework (*e.g.*, Arora et al. (2023)) that uses aligned language and vision models to incorporate the original image crops or a matching framework that incorporates character visual similarity (Yang et al., 2023) - as OCR errors tend to confuse visually similar characters - may be required. This again will be incorporated into LinkTransformer.

LinkTransformer relies on backends that many end users - accustomed primarily to working with statistical packages like Stata or R - will not be familiar with. We recommend that users new to

LLMs deploy the package using a cloud service optimized for deep learning, such as Colab, to avoid the need to resolve dependencies. To reduce startup costs, we will provide detailed tutorials for LinkTransformer instillation, inference, and training on Colab.

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Supplementary Materials

S-1 Datasets and Results

Table S-1 describes the datasets used for training the LinkTransformer model zoo. They are drawn from multilingual UN product and industry concordances, Wikidata company aliases, a 1948 Mexican government concordance between tariff schedules ([Secretaría de Economía de Mexico, 1948](#)), and a hand-linked dataset between two 1950s Japanese firm level datasets collected by credit bureaus, one containing around 7,000 firms and the other around 70,000 ([Teikoku Koshinjo, 1957](#); [Jinji Koshinjo, 1954](#)).

Model	Training Data
lt-products-en-es-fr	UN product data in English, French, and Spanish.
lt-wikidata-comp-en	Wikidata English-language company names.
lt-wikidata-comp-fr	Wikidata French-language company names.
lt-wikidata-comp-de	Wikidata German-language company names.
lt-wikidata-comp-ja	Wikidata Japanese-language company names.
lt-wikidata-comp-zh	Wikidata Chinese-language company names.
lt-wikidata-comp-es	Wikidata Spanish-language company names.
mexicantrade4748	Mexican tariff schedule concordance.
historicjapanesecompanies	Historical Japanese firm records.

Table S-1: Model names and training data sources for various models in the LinkTransformer model zoo.

Next, Table S-2 describes the train-val-test splits for each of these datasets.

Model	Total	Train	Val	Test
lt-products-en-es-fr	3589	2871	359	359
lt-wikidata-comp-en	35914	2873	3591	3591
lt-wikidata-comp-fr	8410	6728	841	841
lt-wikidata-comp-de	12664	10131	1266	1266
lt-wikidata-comp-ja	12651	10120	1265	1265
lt-wikidata-comp-zh	6966	5572	697	697
lt-wikidata-comp-es	2816	2253	281	281
mexicantrade4748	2992	2393	299	299
historicjapanesecompanies	2151	1721	215	215

Table S-2: Data Splits: the table shows train-val-test splits for various models in the LinkTransformer model zoo.

Table S-3 shows results of fine-tuned models: when the models are evaluated on the test set of the

dataset they were training on.

Model	Accuracy		
	Edit Distance	Semantic Sim	Fine Tuned
<i>Cross-lingual linkage</i>			
lt-products-en-es-fr	0.38	0.49	0.84
<i>Firm name linkage</i>			
lt-wikidata-comp-en	0.34	0.42	0.65
lt-wikidata-comp-fr	0.45	0.43	0.73
lt-wikidata-comp-de	0.41	0.35	0.64
lt-wikidata-comp-ja	0.38	0.26	0.61
lt-wikidata-comp-zh	0.45	0.25	0.53

Table S-3: Training Dataset Linking: The table examines linking WikiData firm aliases and UN trade product datasets using Levenshten edit distance, the base semantic similarity model off-the-shelf, and LinkTransformer models fine-tuned on the dataset under evaluation. The evaluation metric is top-1 retrieval accuracy.

Table S-4 examines performance on two historical linkage tasks: linking historical Mexican tariff schedules and linking historical Japanese firms across large, noisy databases.

Dataset	Semantic Sim	Fine Tuned	Edit Distance	OpenAI ChatGPT
mexicantrade4748	0.79	0.97	0.78	0.97
historicjapanesecompanies	0.24	0.65	0.42	-

Table S-4: Historical Linking. We examine the base semantic similarity model off-the-shelf, a fine-tuned LinkTransformer version, Levenshtein edit distance on the tariff description or company name, and ChatGPT. The table reports top-1 accuracy.

Table S-5 reports results on standard industry and e-commerce benchmarks for record linkage.

Type	Dataset	Domain	Size	# Pos.	# Attr.	Ours (ZS)	Ours (FT)	Magellan	Deep matcher	Ditto	REMS
Structured	BeerAdvo-RateBeer	beer	450	68	4	82.35	87.5	78.8	72.7	84.59	96.65
	iTunes-Amazon1	music	539	132	8	70	80	91.2	88.5	92.28	98.18
	Fodors-Zagats	restaurant	946	110	6	88	93	100	100	98.14	100
	DBLP-ACM1	citation	12,363	2,220	4	90	97.5	98.4	98.4	98.96	98.18
	DBLP-Scholar1	citation	28,707	5,347	4	76	91.4	92.3	94.7	95.6	91.74
	Amazon-Google	software	11,460	1,167	3	39.4	68	49.1	69.3	74.1	65.3
	Walmart-Amazon1	electronics	10,242	962	5	28	69	71.9	67.6	85.81	71.34
Textual	Abt-Buy	product	9,575	1,028	3	33.6	78.4	33	55	88.85	67.4
	iTunes-Amazon2	music	539	132	8	74	81.3	46.8	79.4	92.92	94.74
Dirty	DBLP-ACM2	citation	12,363	2,220	4	79.6	97.2	91.9	98.1	98.92	98.19
	DBLP-Scholar2	citation	28,707	5,347	4	75	91.2	82.5	93.8	95.44	91.76
	Walmart-Amazon2	electronics	10,242	962	5	25	65	37.4	53.8	82.56	65.74

Table S-5: Benchmarks. ZS is LinkTransformer models zero-shot and FT is LinkTransformer models fine-tuned on the benchmark. The remaining columns report comparisons. The metric is F1, as these datasets frame linkage as a binary classification problem.

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