

# DELICATE: Diachronic Entity LInking using Classes And Temporal Evidence

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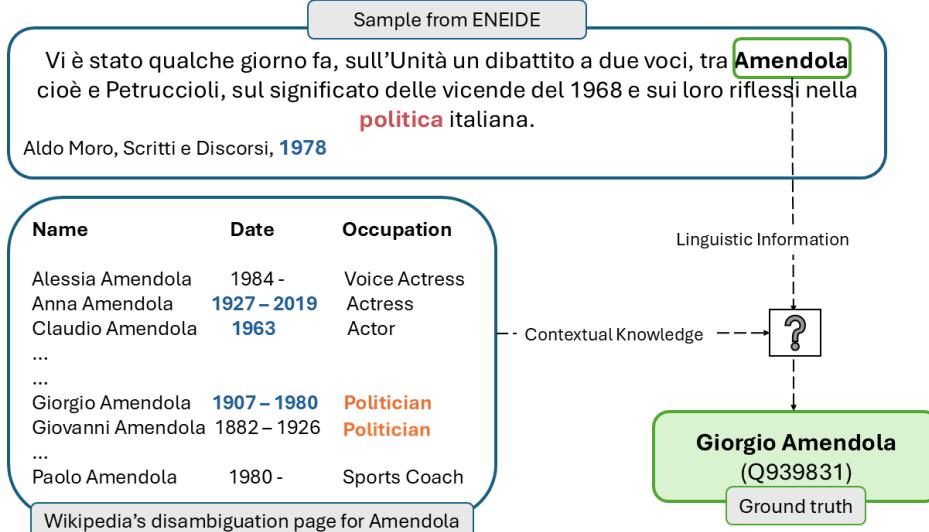
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## Abstract

In spite of the remarkable advancements in the field of Natural Language Processing, the task of Entity Linking (EL) remains challenging in the field of humanities due to complex document typologies, lack of domain-specific datasets and models, and long-tail entities, i.e., entities under-represented in Knowledge Bases (KBs). The goal of this paper is to address these issues with two main contributions. The first contribution is DELICATE, a novel neuro-symbolic method for EL on historical Italian which combines a BERT-based encoder with contextual information from Wikidata to select appropriate KB entities using temporal plausibility and entity type consistency. The second contribution is ENEIDE, a multi-domain EL corpus in historical Italian semi-automatically extracted from two annotated editions spanning from the 19th to the 20th century and including literary and political texts. Results show how DELICATE outperforms other EL models in historical Italian even if compared with larger architectures with billions of parameters. Moreover, further analyses reveal how DELICATE confidence scores and features sensitivity provide results which are more explainable and interpretable than purely neural methods.

**Keywords:** Entity Linking, Historical Italian, Text Corpus, Explainable NLP, Knowledge Bases



**Figure 1** Representation of a sample sentence from the ENEIDE dataset containing a named entity and candidate entities from Wikipedia presented in a disambiguation page. The image shows how contextual information provided in external KBs allows to better determine the correct entity referenced in a historical text.

## 1 Introduction

Entity Linking (EL) is the task of identifying and disambiguating entities mentioned in a text by linking them to their corresponding entries in structured Knowledge Bases (KBs) such as Wikipedia, Wikidata<sup>1</sup> [28], etc. EL is a key component of many Knowledge Extraction (KE) applications in the Digital Humanities (DH), where it enables researchers to trace references to people, locations, organizations, and other named entities across historical sources. Despite the wide application of EL in various domains, general-purpose EL models often perform poorly on historical documents. These texts pose specific challenges, such as linguistic variations over time and the need for accurate chronological context, which are typically overlooked by State-of-The-Art (SoTA) models that rely solely on linguistic information [5, 15, 29]. Figure 1 shows a sentence from a text written by Aldo Moro (Italian politician) in 1978, containing a reference regarding a person mentioned with the surname “Amendola”. As the figure shows, there are multiple politicians in Wikipedia with that surname, therefore the information given only in the text is not enough to find a correct candidate. As this example proves, temporal information given in Wikidata about the entity’s birthdate can guide EL models to a correct decision.

To address this issue, several domain-specific methods have been proposed [9, 14, 16] which incorporate contextual features such as entity types and temporal information derived from KBs for improving disambiguation accuracy. However, a common

<sup>1</sup><https://www.wikidata.org>

limitation of these existing approaches is their reliance on manually crafted rules, which can be rigid and may lack generalizability. In contrast, this paper proposes a method that automatically learns the relevance of contextual information, such as class equivalence and temporal distance, by using them as features in a supervised tree-ensemble model called Gradient Boosted Trees (GBTs). This traditional Machine Learning (ML) approach, compared to more complex Deep Neural Networks (DNNs), has the advantage of efficiently capturing statistical patterns based on numerical features without requiring extensive pre-training, large datasets, and powerful computational resources. Moreover, a further advantage of GBTs is to have a higher level of explainability compared to DNNs since each tree creates explicit if-then rules with clear decision boundaries based on feature thresholds and the relevance of each feature can be measured based on permutation importance or gain-based importance [30].

Moreover, the lack of benchmark datasets for EL in the DH is a pivotal issue that must be addressed for advancing NLP techniques in this field [8]. To the best of our knowledge, currently there are no datasets in Italian which allow to train historical EL models. Due to the increasing amount of data produced in the DH domain including corpora [7], digital editions [4], and KBs [2], it is crucial to understand how to combine these resources to advance the SoTA of EL for under-explored languages such as historical Italian. In this regard, Scholarly Digital Editions (SDEs) [20] are a primary source of annotations for people, places, organizations, bibliographic resources, and other entities, providing a large number of samples of entities referenced in historical texts and disambiguated using Wikidata. As a consequence, this study aims to address the following Research Questions (RQs):

- **RQ1:** How can we address the problem of EL in historical documents by combining approaches based on language models with tree-based methods using background knowledge, i.e. dates and classes, from Wikidata?
- **RQ2:** Can we leverage the information already present in SDEs to build a novel training and evaluation corpus for EL in Italian based on historical documents?
- **RQ3:** Can we analyse the features and scores of GBTs through statistical techniques to provide a clearer explanation of the behaviour of a supervised EL model in the historical domain?

To answer these questions, this study introduces DELICATE, a novel supervised architecture for EL designed specifically for historical texts. DELICATE combines the strengths of neural language models and tree-ensemble methods by integrating a BERT-based [6] bi-encoder model [18] for candidate retrieval with a supervised GBTs classifier for candidate re-ranking. The novel aspect of DELICATE is its ability to incorporate class and temporal information from Wikidata as explicit features in the re-ranking process. In particular, DELICATE uses a GBTs classifier to re-rank the bi-encoder results by computing pairwise similarity scores based on features such as temporal distance, type compatibility, string similarity, and embedding distance. This allows the model to dynamically assess the contextual relevance of each candidate entity, which is important when dealing with diachronic variations in language and meaning. Our tests on historical Italian show how DELICATE achieves better

performances on multiple benchmarks if compared with auto-regressive multilingual models [5] and even when bi-encoders are paired with open-source Large Language Models (LLMs), such as LLaMa3.1 [11].

Given that there are currently no datasets in Italian with chronological information, we also introduce ENEIDE (*Extracted Named Entities from Italian Digital Editions*), a publicly available EL corpus which provides annotated texts in historical Italian spanning multiple domains and years. ENEIDE is semi-automatically constructed using annotations from two SDEs: Digital Zibaldone<sup>2</sup> [26] and Aldo Moro Digitale<sup>3</sup> [1], which comprise both literary and political domains from the 19th to the 20th century. By leveraging existing entity annotations in SDEs and linking them to Wikidata, ENEIDE provides a robust benchmark for training and evaluating EL systems in Italian. Both the source code of DELICATE<sup>4</sup>, the dataset ENEIDE<sup>5</sup> and trained models<sup>6</sup> are publicly available.

The remainder of the paper is structured as follows. Section 2 gives an overview of the current challenges of EL in the domain of cultural heritage and provides a brief analysis of EL corpora and neural models for EL in the humanities. Section 3 contains the description of the architecture of DELICATE. Section 4 discusses how LLMs can be used to refine EL results on historical texts as an alternative to the supervised GBTs. Section 5 presents ENEIDE and discusses the data preprocessing and annotation strategies employed for dataset creation. Section 6 discusses the experimental results of DELICATE for the tasks of Entity Disambiguation (ED) and end-to-end EL on two historical Italian corpus: ENEIDE and MHERCL-ITA [10]. Section 7 gives an overview of the advantages and limitations of the approach herein presented and concludes the work. Source code, dataset and trained models are publicly available.

## 2 Related Work

This section details the related studies. First, Section 2.1 presents the foundations of the field of named entity processing in the historical domain. Then, Section 2.2 discusses the SoTA with respect to neural EL approaches regarding historical corpora. Finally, Section 2.3 lists some of the most important monolingual and multilingual corpora in the field of humanities annotated for the evaluation of EL-related tasks, such as Named Entity Recognition (NER) and Entity Disambiguation (ED).

### 2.1 Historical Named Entity Processing

In the existing literature, named entity processing is divided into two different tasks. The first is NER, in which the entity mentions are identified in text and classified according to different categories such as person, location, organization, or miscellaneous. The subsequent task is ED, in which detected mentions are linked to the respective identifier in a structured KB, such as Wikidata. EL approaches often rely on a separate NER component trained to identify surface forms of named entities within a text [14];

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<sup>2</sup><https://digitalzibaldone.net/>

<sup>3</sup><https://aldomorodigitale.unibo.it/>

<sup>4</sup>source code: <https://github.com/sntcristian/DELICATE>

<sup>5</sup>dataset: <https://github.com/sntcristian/ENEIDE>

<sup>6</sup>trained models: <http://doi.org/10.57967/hf/6984>

however, several approaches have investigated the possibility of training NER and ED jointly within a single end-to-end architecture [13, 15].

Despite the remarkable performances that the NER and ED systems have achieved in contemporary web-crawled data [24], they under-perform when applied to historical documents (such as historical press articles, books, literary texts, or letters), which may be excluded from the training corpora and therefore are not observed in the learning phase. In a recent survey on historical EL [8], the authors highlight four main challenges: (i) the variety of documents (newspapers, letters, memoirs, books); (ii) the presence of noise in the input data due to data processing techniques, such as Optical Character Recognition (OCR); (iii) the problem of linguistic and chronological variations; and (iv) the lack of standardized benchmarks across multiple languages and genres. Furthermore, This study shows that only 2 datasets out of 22 surveyed historical corpora include documents annotated in Italian for NER. To the best of our knowledge, there is a lack of large-scale publicly available datasets annotated in historical Italian for EL.

## 2.2 Neural EL in the Humanities

One of the seminal works on neural end-to-end EL applied to historical documents has been presented in [16]. This system employs several strategies, including an OCR correction mechanism, a probabilistic entity table map, a multilingual KB that contains entity representations obtained from the multilingual Wikipedia and a BiLSTM network which is trained to compute the matching probability between the context in which an entity appears and its representation in the KB. Despite the remarkable performances shown on multilingual historical press articles (excluding Italian), the model makes limited use of contextual knowledge by simply applying rule-based filters on the results using temporal constraints, type-related information, and edit distance between entity labels and surface form. Differently, our approach aims to learn the relevance of contextual information by employing supervised learning techniques.

The ED problem, which is the task of linking already detected mentions, is addressed for historical documents in [14]. This work proposes a multilingual architecture for English, German, and French, based on three components: (a) an entity-candidate lookup; (b) an entity-candidate evaluation; and (c) an entity-candidate ranking. In (a), a word embedding model is used to perform a  $k$ -NN search on a dense index of Wikipedia titles to find the most similar entities with respect to a query mention. In this step, the system also makes use of the date of publication of a document, provided in the metadata, to consider only temporally plausible entities. In the entity-candidate evaluation, a sentence-matching algorithm based on a BERT encoder is used to compare the context of the mention with the Wikipedia text snippets of the candidates returned in (a). In the entity-candidate ranking step, the similarity scores of step (a) and step (b) are fed to a Random Forest algorithm which computes the matching probabilities between the items in the candidate set and the query mention. More recently, [9] proposed the use of rule-based constraints on Wikidata to refine the candidate retrieval step of a bi-encoder architecture to perform ED on historical music periodicals in English. More concretely, they paired BLINK [29] with multiple rule-based constraints in which the entities retrieved are verified for compliance with

respect to the date of publication of a document and the entity type given in the metadata.

One of the main limitations of these approaches is that using filters based on temporal and semantic information in the lookup step may cause the system to incorrectly exclude from linking correct candidates. In contrast, our solution for this problem consists in employing temporal and semantic information in the final re-ranking phase. In DELICATE, information related to dates and types of the *top-k* candidates retrieved is extracted from Wikidata and is used as a feature to train a supervised classifier for the task of learning optimal similarity thresholds between input mentions and attributes of the candidates.

### 2.3 Historical EL Corpora

Due to the need to adapt the NER and EL approaches for documents provided by cultural heritage institutions, several resources have been created in order to provide standardized benchmarks in the field of historical EL. With respect to Italian, a pivotal work has been carried out in [17], where the authors describe *KIND*, a multi-domain dataset for NER extracted from several typologies of texts, including news, literary texts, and political works. Similar to ENEIDE, this dataset includes texts from the political domain, extracted from the De Gasperi Corpus [25] and Aldo Moro Digitale [1]. However, this work does not contain links to a KB for disambiguation.

With respect to the literary domain, one of the first examples of datasets in Italian containing annotated references to literary works (such as citations to books, monographies, and essays), is *LinkedBooks* [3]. In spite of the contribution of this resource for NER with literary entities, the dataset does not include more general entities (such as person, location, or organization) and the references to works are not disambiguated using Wikidata identifiers. More recently, in [19], the authors present a manually annotated dataset of named entity references in classical commentaries of Sophocles' *Ajax*. Similar to the literary texts in ENEIDE, entities are often referenced through abbreviations, as in *Cic.* for *Cicero* (a common practice in philological texts). Another feature that AJMC shares with ENEIDE is the fact that it contains several annotated references to literary works, either disambiguated with Wikidata or labeled as NIL if not present in the KB. A very recent attempt to provide a benchmark for EL in Italian was presented in [10]. In this paper, the authors present MHERCL-ITA<sup>7</sup>, the first gold standard for EL in historical Italian, containing texts extracted from music periodicals published between 1853 to 1943. In total, MHERCL-ITA contains 533 sentences with 2,431 manual annotations of entities linked to Wikidata. In spite of its relevance for historical Italian, the main limitation of MHERCL-ITA is its small scale, since it only comprises a test set and is more suitable to evaluate pre-trained EL models or LLMs in a domain which is distant from the typology of documents with which they are trained.

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<sup>7</sup>[https://github.com/polifonia-project/KE-MHISTO/blob/main/Datasets/MHERCL\\_ITA.json](https://github.com/polifonia-project/KE-MHISTO/blob/main/Datasets/MHERCL_ITA.json)

### 3 DELICATE

**Preliminaries:** The ED task aims to resolve the ambiguity of a given mention  $m$  appearing in a context of words  $c$  by linking it to the most appropriate entity  $e_i$  from a predefined finite set  $E = \{e_1, \dots, e_i, \dots, e_n\}$ , where  $E$  is a collection of entities extracted from a KB and  $e_i \in E$ .

Each mention  $m$  is characterized by a set of attributes  $A_m = \{s_m, t_m, d_m\}$ , where:

- $s_m$  is the surface form with which an entity is referred in the text,
- $t_m$  denotes the entity type associated with  $m$ , given in the ground-truth annotation or by a NER model,
- $d_m$  represents the timestamp of the mention, inferred from the document date.

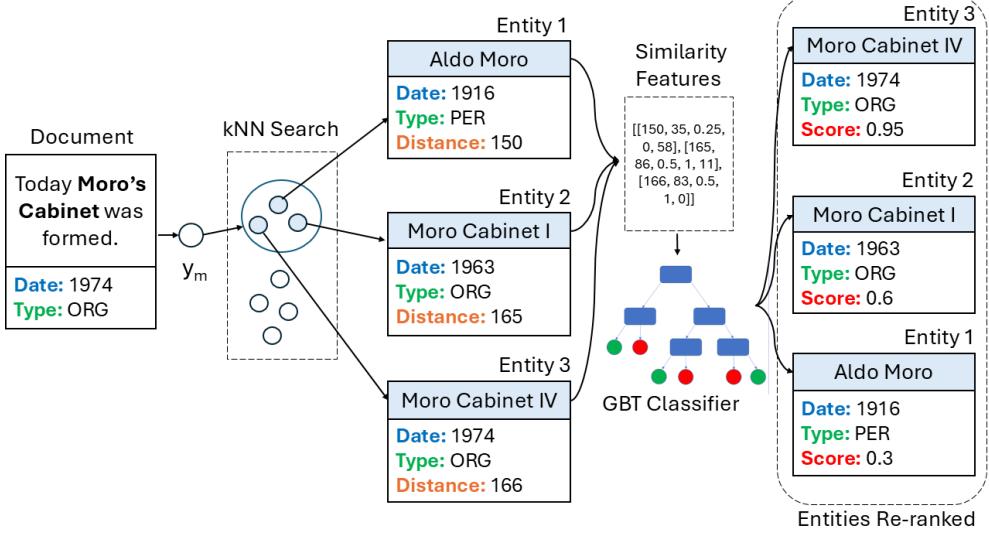
Similarly, each entity  $e_i$  is described by a set of attributes  $A_{e_i} = \{s_{e_i}, t_{e_i}, d_{e_i}\}$ , where:

- $s_{e_i}$  is the surface form of an entity in the KB, e.g., the Wikidata label in Italian,
- $t_{e_i}$  denotes the entity type as defined in the KB,
- $d_{e_i}$  is a date associated with  $e_i$  in the KB.

**Architecture:** *DELICATE* is a novel architecture to perform ED on digitized historical and humanistic texts which makes use of entity types and temporal information from Wikidata to disambiguate entities in diachronic and historical texts. Figure 2 shows the overall architecture of *DELICATE*, which relies on the following components:

- a **bi-encoder** based on the BLINK architecture [29] which encodes a mention and its surrounding context in a latent representations to be used for k-NN search,
- a **dense vector index**, implemented with FAISS [12], which contains embeddings for each entity in the Italian Wikipedia encoded from the first Wikipedia paragraph using the bi-encoder,
- a **lookup table**, which contains structured information about the entities in Wikipedia, such as entity types and dates extracted from Wikidata,
- a **GBTs classifier**, which makes a pairwise comparison between the mention and each Wikipedia entity retrieved with k-NN search and computes a probability score for each candidate entity to predict the most plausible match.

While the use of a bi-encoder for candidate retrieval has already been explored in [29] for English and in [18] for Italian, the novelty of this work consists in refining the results of the bi-encoder in an additional re-ranking step. In this step, a supervised classifier trained on labelled data takes as input a set of similarity features between the entity mention and the Wikipedia candidates, such as temporal distance, type equivalence, string similarity, and  $L^2$  embeddings distance, and returns a set of probability scores which are used to filter and re-rank candidates. The hypothesis of this work is that the use of carefully selected features to model  $(m, e_i)$  similarity based on



**Figure 2** High-level representation of DELICATE. At first, similar entities with respect to a given mention are retrieved from a dense index of Wikipedia entities by performing k-NN search using the BLINK bi-encoder. In the second step, entities are re-ranked by a GBTs model which takes as input pairwise similarity features computed for each mention-entity pair.

the respective set of attributes  $A_m$  and  $A_{e_i}$  allows to improve the performance of ED systems on historical datasets.

### 3.1 Bi-encoder and Dense Vector Index

For performing candidate retrieval, DELICATE adopts a BLINK model originally proposed in [29]. BLINK is a ED model which adopts a Transformer-based model to encode representations of entity references and Wikipedia candidates in the same latent space. In order to do so, BLINK encodes each mention and its surrounding context (i.e., words preceding and following) into a vector using a BERT-based model [6]. The same model is used to encode representations of each entity inside Wikipedia by modelling the concatenation of the Wikipedia page title and its first 10 sentences into an embedding. While the mention representations are computed at inference time, the entity representations are precomputed and stored into a dense vector index implemented with FAISS. In BLINK, the scoring function is simply the dot product between the mention vector  $y_m$  and the entity vector  $y_{e_i}$ , and is computed as follows:

$$s(m, e_i) = y_m \cdot y_{e_i} \quad (1)$$

The loss function used to train the bi-encoder aims to maximize the dot product of the correct entity, while minimizing the scores of the incorrect ones, and is specified as follows:

$$L(m, e_i) = -s(m, e_i) + \log \sum_{j=1}^B \exp(s(m, e_j)) \quad (2)$$

DELICATE stores embeddings of entities in a FAISS index comprising  $\approx 1.5M$  entities from the Italian Wikipedia. To perform candidate retrieval, the embedding of the text mention is used to perform k-NN search on the index which returns *top-k* candidates sorted by Euclidean distance (or  $L^2$  distance). The implementation of DELICATE relies on the frozen weights of BLINK<sub>ITA</sub> presented in [18].

### 3.2 Lookup Table

To obtain additional information about the candidates retrieved using the bi-encoder, DELICATE uses a lookup table stored in a SQLITE database to associate each entity in Wikipedia with structured information. First, each entity in the index is linked to its Wikidata identifier. Then, each Wikipedia entity is classified according to one of the four entity types in our dataset (person, location, organization, and work), based on its Wikidata class. In order to map Wikidata classes into the entity types in ENEIDE, a set of parent classes was identified for each entity type in Wikidata. Once these classes were defined, their subclasses were queried from Wikidata using the `subclass` property (P279). This step was performed recursively for each subclass to obtain the full hierarchy. Moreover, classes belonging to multiple entity types (e.g., person and organization) were removed. The complete list of parent classes for each type in our dataset is available in Appendix A.

Additionally, to enrich our lookup table with temporal information from Wikidata, a set of time-related properties has been identified in the KB following the approach of [9]. These properties, reported in Appendix B, have been used to find relevant dates for the candidates in the Italian Wikipedia to use them as discriminative features during the candidate re-ranking step. To associate each candidate inside our KB with only one date, only the earliest date is selected if multiple time-related properties are found for one entity. The function of the lookup table is to convert each candidate retrieved from the index during the candidate retrieval step into a tuple of the following form:  $T_{e_i} = (e_i, s_{e_i}, t_{e_i}, d_{e_i}, L_{e_i}^2)$  where  $s_{e_i}$  is the label in Italian associated to  $e_i$  in Wikidata,  $t_{e_i}$  is the entity type associated to that entity in the lookup table,  $d_{e_i}$  is the date retrieved from the table, and  $L_{e_i}^2$  is the Euclidean distance between  $y_i$  and  $y_{e_i}$  computed in the k-NN search.

### 3.3 Gradient-Boosted Trees Classifier

In the candidate re-ranking step, each Wikipedia entity retrieved by the bi-encoder is evaluated by a GBTs classifier in order to predict the match probability for a given  $(m, e_i)$  pair. The classifier is trained to distinguish correct entities from incorrect ones based on a set of pairwise similarity features  $F_{m, e_i}$ . This similarity is computed both at the candidate-level and at the set-level (i.e., including every entity retrieved by the bi-encoder). These features are carefully crafted in order to represent similarity across 4 dimensions: vector similarity, string similarity, type similarity, and time interval. While vector and string similarity scores are based on information coming from the

Similarity Type	Feature Name	Description
Vector Similarity	$L^2_{e_i}$	$L^2$ distance between the entity and mention embeddings
	min	minimum $L^2$ distance in the candidates set
	max	maximum $L^2$ distance in the candidates set
	mean	mean of the $L^2$ distances in the candidates set
String Similarity	Jaccard	median $L^2$ distance in the candidates set
	Levenshtein	Jaccard distance between the token sets in $s_m$ and $s_{e_i}$
Type Similarity	Type match	1 if $t_m = t_{e_i}$ , 0 otherwise
Time Interval	$\Delta_{time}$	Time delta computed as $d_m - d_{e_i}$

**Table 1** Pairwise similarity features used to train the GBTs classifier.

retrieval step, type similarity and time interval are computed based on information coming from the dataset, such as the annotated entity type ( $t_m$ ) and the date of the mention ( $d_m$ ). The complete list of features used to train the GBTs classifier is available in Table 1. If an entity has no date in the lookup table, the interval between the date of the document and that of the entity is set to 0.

Given a candidate set of Wikipedia entities, the GBTs classifier is trained to predict the probability of a given  $(m, e_i)$  pair to refer to the same entity based on the similarity features  $F_{m, e_i}$ . The output of the GBTs classifier is a probability score  $p_{m, e_i}$  which estimates the correctness of each entity for disambiguating  $m$ . Moreover, the probability score is used to filter candidates by specifying a threshold  $\Delta_{NIL}$  and candidates are returned only if  $p_{m, e_i} \geq \Delta_{NIL}$ . If no candidate is returned, a mention is labelled as NIL.

## 4 Historical EL using LLMs

In addition to our supervised re-ranking approach, we explore an unsupervised alternative, i.e., prompting an LLM. We use BLINK<sub>ITA</sub>-LLM, which leverages an LLM as a heuristic to select among bi-encoder candidates without any further supervised training. BLINK<sub>ITA</sub>-LLM couples the same bi-encoder, FAISS index and lookup table used by DELICATE for candidate retrieval, but replaces the GBTs re-ranking step with a disambiguation task performed by an open-source LLM. More Precisely, as first step, a bi-encoder (BLINK<sub>ITA</sub> [18]) performs k-NN search in the FAISS index of the Italian Wikipedia, returning the *top-k* candidates ranked by Euclidean distance. In the second step, a multilingual instruction-tuned open-source LLM is prompted to choose the correct entity from the candidate list, based on entity type, and temporal cues. In our experiments we used LLaMa-3.1-8B-Instruct<sup>8</sup> [11].

The prompt comprises four components:

<sup>8</sup><https://huggingface.co/meta-llama/Llama-3.1-8B-Instruct>

1. A concise system instruction frames the LLM as an “*information extraction system specialized in disambiguating entities within humanities texts*”,
2. A user instruction describes the candidate selection task, provides the document publication date and asks for a JSON response containing the chosen Wikipedia title and Wikidata ID,
3. The annotated text is presented with the target mention marked by [ENT] tags,
4. The list of  $top-k$  candidates is provided as a JSON array, where each entry includes the Wikipedia title, Wikidata ID, type (person, location, organization, or work), associated date from Wikidata, and the bi-encoder’s similarity score.

The complete prompt used in the experiments is given in Appendix C.

Compared to DELICATE, no further fine-tuning or supervised learning is applied: the LLM relies solely on the information provided in the prompt to resolve ambiguity. While DELICATE’s supervised GBTs classifier is explicitly trained to exploit vector, string, type, and temporal features to optimize ED performance, BLINK<sub>ITA</sub>-LLM relies on the LLM’s prompt to interpret the same cues. This unsupervised variant allows for rapid deployment without annotated training data, but may exhibit variability depending on prompt sensitivity and LLM’s response stochasticity. We evaluate both approaches on different Italian historical benchmarks to quantify the trade-off between DELICATE’s efficiency and the potential of zero-shot LLMs.

## 5 ENEIDE Dataset

To train and test DELICATE, we collected ENEIDE, a diachronic, multi-domain corpus for EL in Italian, semi-automatically extracted from two SDEs: *Digital Zibaldone* (DZ) and *Aldo Moro Digitale* (AMD). These sources span two centuries (19th to 20th) and offer heterogeneous textual genres, enabling the evaluation of EL systems on humanistic documents rich in contextual and diachronic challenges.

DZ is a TEI/XML-encoded digital edition of Giacomo Leopardi’s *Zibaldone di pensieri*, a collection of over 4,500 pages of reflections on diverse intellectual domains, such as literature, history and philosophy, written between 1817 and 1832. The edition is encoded in HTML, with internal and external references including named entities linked to Wikidata when available. AMD, on the other hand, presents the complete works of the Italian politician Aldo Moro (1916–1978), including political, legal, and journalistic texts spanning from the 1930s to 1978. Encoded in RDFa, AMD uses semantic web annotations embedded in HTML to reference people, organizations, and places, aligning with Wikidata.

Together, these corpora offer a broad typology of entity references. DZ annotations cover “person” (PER), “location” (LOC), and “literary work” (WORK) types, while AMD includes “person”, “location”, and “organization” (ORG). In both, indirect references and historical variations in entity surface forms pose a challenge for EL systems. Additionally, both datasets contain entities not covered by Wikidata, introducing the task of NIL prediction, i.e., identifying entities that do not correspond to any known entry in a target KB.

Statistic	DZ	AMD
Annotations in samples	403	215
Wrong annotations	13	18
Missing annotations	10	64
Precision	96.8	91.6
Recall	94.4	70.6
F1	95.6	79.8

**Table 2** Quality assessment statistics for samples in DZ and AMD

Dataset	Docs			Annotations			% Overlap (train+dev vs test)
	train	dev	test	train	dev	test	
DZ	735	157	158	2935	727	617	93.19
AMD	743	159	160	2766	604	657	75.38

**Table 3** Statistics about number of documents, number of annotations and number of overlapping annotations in ENEIDE.

Annotations were extracted using `Beautiful Soup`, identifying entities through HTML links. To construct the corpus, different sampling strategies were applied to each digital edition. For DZ, two subsections of the Zibaldone were extracted: one from pages 1000 to 2001 and another from pages 2700 to 4000. These sections are sampled respectively from 1821 and 1823, the most productive years of the author. For AMD, the first paragraph of each document in the collection was sampled. To ensure quality and a balanced distribution throughout the corpus, texts with anomalous word counts relative to a normal distribution were excluded. Moreover, only documents containing at least one named entity were retained. This process resulted in a corpus of 1050 items from DZ and 1061 items from AMD. For both datasets, train, validation, and test splits were created by dividing the dataset with a 70/15/15 ratio using stratified sampling for maintaining a similar chronological distribution in all splits. Annotation quality was evaluated by domain experts using 100 samples per dataset. As shown in Table 2, DZ annotations scored highest with an F1 of 95.6, while AMD scored lower due to missing annotations (Recall: 70.6).

To improve AMD coverage, a semi-automatic enhancement pipeline was developed. It included (i) extraction and expert validation of frequent surface forms with Wikidata IDs; (ii) tagging of missing mentions in the text; (iii) application of the Italian StanzaNLP NER model to identify unannotated entities; and (iv) final expert validation. This multi-step process increased annotation completeness without employing a fully manual annotation process.

Tables 3 and 4 provide detailed statistics for both datasets across all splits, including annotation counts, unique entity identifiers, NIL entities, and the percentage of annotation overlap between training and test. The high overlap in DZ (93.19%) contrasts with AMD (75.38%), reflecting the different natures of the two corpora.

Split	DZ					AMD				
	PER	LOC	WORK	NIL	IDs	PER	LOC	ORG	NIL	IDs
train	1661	488	786	182	623	759	940	1067	64	583
dev	375	149	203	74	276	158	226	206	13	203
test	318	130	169	42	241	194	190	205	9	238

**Table 4** Fine-grained statistics about number of annotations per class, number of NIL entities and unique entities (i.e. Wikidata identifiers) in each dataset split.

## 6 Experimental Results

### 6.1 Experimental Setup

We evaluated DELICATE against other SoTA models on two EL datasets, ENEIDE and MHERCL-ITA, focusing on both ED and end-to-end EL tasks. While ENEIDE is described in Section 5, MHERCL-ITA was recently introduced [10] as an Italian expansion of an English EL dataset [9] extracted from a corpus of music periodicals. Differently from ENEIDE, MHERCL-ITA annotates named entities based on 34 fine-grained types. This dataset was used to test the generalizability of our approach on a different domain. In order to apply DELICATE’s entity type heuristic, a manual mapping was done between the classes in ENEIDE and those in MHERCL-ITA (see Appendix D).

In the experiments, DELICATE was compared with general and specialized baselines:

- BLINK<sub>ITA</sub><sup>9</sup> [18]: a transformer-based ED model for Italian, which performs dense candidate retrieval using embedding similarity. This model is also used in the candidate retrieval step of DELICATE.
- BLINK<sub>ITA</sub>-LLM: a specialized version of BLINK presented in Section 4 where the bi-encoder is combined with an LLM used as a heuristic tool to select the most appropriate candidate from the bi-encoder’s output.
- C-BLINK<sub>ITA</sub>: a customized BLINK variant for historical texts introduced in [9], which filters candidates retrieved by the bi-encoder using boolean rules based on entity type matching and temporal consistency.
- mGENRE<sup>10</sup> [5]: a multilingual ED system based on BERT which is trained to generate Wikipedia entities from in-text mentions in an auto-regressive way.

Three distinct variants of the DELICATE architecture were tested, (i) DELICATE<sub>DZ</sub> and (ii) DELICATE<sub>AMD</sub>, which were respectively fine-tuned on the two partitions of ENEIDE, and (iii) DELICATE<sub>ALL</sub>, which was fine-tuned on the whole ENEIDE corpus. One of the advantages of DELICATE is the small computational cost of fine-tuning, since the weights of the pre-trained BERT bi-encoder are frozen and the only component which is trained is the supervised GBTs classifier. For

<sup>9</sup>[https://github.com/rpo19/pozzi\\_aixia\\_2023](https://github.com/rpo19/pozzi_aixia_2023)

<sup>10</sup><https://github.com/facebookresearch/GENRE>

<b>Hyper-parameter</b>	<b>DZ</b>	<b>AMD</b>	<b>ALL</b>
Learning rate	0.115	0.185	0.135
Maximum depth	11	14	8
Minimum samples leaf	0.0155	0.08	0.01
Minimum samples split	0.015	0.02	0.037
Number of estimators	350	300	500
Block size	50	20	50
$C_{neg}$ size	10	6	8

**Table 5** Best hyper-parameters of the GBTs model for each dataset partition.

training the classifier, we retrieved the  $top-k$  candidates for each mention in the training data using the BLINK bi-encoder and from each block of candidates we sampled a positive candidate  $c_{pos}$ , if present, and a set of negatives  $C_{neg}$  containing wrong entities with  $L^2$  distances evenly distributed along the median. Hyper-parameter search was carried out for 100 iterations to find the best parameters of the GBTs model for each dataset partition. The best hyper-parameters over which the results are reported are shown in Table 5. The  $\Delta_{NIL}$  parameter was selected empirically by finding the best threshold on the development set of each dataset partition. For DZ,  $\Delta_{NIL}$  was set to 0.4 and for AMD it was set to 0.2.

On ENEIDE all models were tested in two tasks: ED and end-to-end EL. In the ED task, a model should predict the correct identifier for a sequence of tokens containing an entity mention. In the end-to-end EL task, each ED model is paired with a NER model and is evaluated on the task of identifying entity mentions within a sentence and correctly linking them. Since all the architectures tested only perform ED, for the end-to-end EL experiments we paired all models with a GLiNER model [31] fine-tuned independently on the whole ENEIDE corpus for four epochs, given the good performances of this architecture for historical Italian reported in [10, 23]. With respect to MHERCL-ITA, we evaluated the generalizability of DELICATE models on a different domain by evaluating only the ED task.

With respect to the evaluation metrics, the ED task was assessed using accuracy, both micro and macro-averaged across all entity types. However, end-to-end EL is evaluated with micro-averaged precision, recall, and F1. For end-to-end EL, metrics are computed in two settings: *exact* and *fuzzy*. Both approaches require that the predicted entity identifier matches the entity in the ground truth, but they differ in how they handle mention detection. The exact matching criterion considers a detected mention as correct only when the detected tokens perfectly align with the ground truth, while the fuzzy matching criterion allows for partial overlaps between the predicted and ground truth tokens.

Finally, in order to gain insight on the explainability of DELICATE and the interpretability of its results with respect to other ED models, we carried an explainability analysis on models’ features and a correlation test between entity scores and ground truth annotations. More specifically, we carried a permutation test to investigate feature relevance for classifying positive and negative candidates during re-ranking. For

	<b>Model</b>	<b>Acc<sub>Micro</sub></b>	<b>Acc<sub>PER</sub></b>	<b>Acc<sub>LOC</sub></b>	<b>Acc<sub>{WORK,ORG}</sub></b>	<b>Acc<sub>Macro</sub></b>
DZ	BLINK <sub>ITA</sub>	50.24	56.92	82.30	13.02	50.75
	BLINK <sub>ITA</sub> -LLM	56.24	66.35	74.62	23.08	54.68
	C-BLINK <sub>ITA</sub>	38.41	54.40	29.23	15.38	33.00
	mGENRE	57.86	67.92	<u>84.62</u>	18.34	56.96
	DELICATE <sub>DZ</sub>	<b>62.88</b>	<b>68.87</b>	<b>86.92</b>	<b>33.14</b>	<b>62.98</b>
	DELICATE <sub>ALL</sub>	<u>61.75</u>	<u>68.24</u>	83.85	<u>32.54</u>	<u>61.54</u>
AMD	BLINK <sub>ITA</sub>	64.35	59.28	84.74	50.24	64.75
	BLINK <sub>ITA</sub> -LLM	70.63	<u>69.59</u>	78.95	<b>63.90</b>	70.81
	C-BLINK <sub>ITA</sub>	49.24	60.82	36.32	50.24	49.13
	mGENRE	68.93	59.79	85.79	<u>61.95</u>	69.18
	DELICATE <sub>AMD</sub>	<u>71.47</u>	66.49	<b>87.37</b>	61.46	<u>71.78</u>
	DELICATE <sub>ALL</sub>	<b>72.67</b>	<b>71.65</b>	<u>86.84</u>	60.49	<b>72.99</b>

**Table 6** ED results computed in micro and macro-averaged accuracy, as well as separately for all classes. For each evaluation metric, bold and underlined represent best and second best performance respectively.

	<b>Model</b>	<i>Exact</i>			<i>Fuzzy</i>		
		Precision	Recall	F-1	Precision	Recall	F-1
DZ	BLINK <sub>ITA</sub>	47.12	39.71	43.10	47.50	40.03	43.45
	BLINK <sub>ITA</sub> -LLM	54.00	45.87	49.60	54.96	46.70	50.48
	C-BLINK <sub>ITA</sub>	37.21	31.60	34.18	37.40	37.77	34.36
	mGENRE	54.62	46.02	49.96	55.20	46.50	50.48
	DELICATE <sub>DZ</sub>	<b>56.49</b>	<b>47.97</b>	<b>51.88</b>	<b>57.44</b>	<b>48.78</b>	<b>52.76</b>
	DELICATE <sub>ALL</sub>	<u>54.96</u>	<u>46.67</u>	<u>50.48</u>	<u>55.92</u>	<u>47.48</u>	<u>51.36</u>
AMD	BLINK <sub>ITA</sub>	61.21	60.27	60.74	61.21	60.27	60.74
	BLINK <sub>ITA</sub> -LLM	67.30	65.70	66.50	67.48	65.87	66.67
	C-BLINK <sub>ITA</sub>	47.65	46.52	47.08	47.83	46.69	47.25
	mGENRE	64.83	63.84	64.33	64.83	63.84	64.33
	DELICATE <sub>AMD</sub>	<u>68.87</u>	<u>67.23</u>	<u>68.04</u>	<u>69.04</u>	<u>67.40</u>	<u>68.21</u>
	DELICATE <sub>ALL</sub>	<b>69.91</b>	<b>68.25</b>	<b>69.07</b>	<b>70.08</b>	<b>68.42</b>	<b>69.24</b>

**Table 7** End-to-end Entity Linking results.

analysing the interpretability of DELICATE’s scores, we carried a point-biserial correlation test to analyse the relation between predictions’ scores of each candidate entity and their correctness. All the experiments were conducted on a Dell7920 machine equipped with an Nvidia RTX A6000 GPU.

## 6.2 Evaluation on ENEIDE

Table 6 shows the results of all models performing ED on ENEIDE. For DZ, the best-performing model is DELICATE<sub>DZ</sub>, with a micro-average accuracy of 62.88, reporting also the best results in a per-class analysis. The second best-performing model in terms

of micro-average accuracy is  $\text{DELICATE}_{\text{ALL}}$ , which achieves a score of 61.75, closely followed by mGENRE.

Overall, the most difficult class to disambiguate remains the “work” class, with the best-performing model,  $\text{DELICATE}_{\text{DZ}}$ , reaching an accuracy of 33.14. This result aligns with previous findings on similar datasets containing references to literary works [7], primarily due to the high prevalence of NIL entities in this category (96.43% of NIL entities in the test set are literary works). In the AMD dataset, a similar trend is observed:  $\text{DELICATE}_{\text{ALL}}$  achieves the best performance, with a micro-averaged accuracy of 72.67, followed by  $\text{DELICATE}_{\text{AMD}}$ , which scores 71.47.  $\text{DELICATE}_{\text{DZ}}$  also attains the highest macro-averaged accuracy and performs particularly well in the disambiguation of person entities, surpassing all other models. The remarkable improvement in the disambiguation of people is likely due to the relevance of temporal information in resolving these entities. For instance, entities referenced by their social role (e.g., “the Pope”), which frequently appear in AMD, can easily lead to false positives if temporal information is not used in the disambiguation process.

Our experiments further reveal significant insights regarding the application of LLMs for ED across different textual domains. When utilizing LLMs for entity selection in  $\text{BLINK}_{\text{ITA}}\text{-LLM}$ , we observe competitive performance on contemporary political texts (AMD), yielding results comparable to supervised approaches. However, this effectiveness diminishes considerably when applied to older texts (DZ), where the inherent complexity and linguistic heterogeneity of 19th-century literary works present substantial challenges for contemporary language models. This performance variation prompted an investigation of candidate filtering strategies, revealing a clear disparity between methods. The rule-based constraint methodology employed in C-BLINK for filtering bi-encoder outputs proves markedly less effective than supervised re-ranking techniques. Systematic error analysis indicates that many misclassification errors originate from the inappropriate inclusion of temporally irrelevant information. For example, the Wikidata entity *Italy* (Q38) records June 18, 1946, as its inception date in the KB; a historically accurate marker for the Italian Republic, yet misleading when disambiguating references to Italy in earlier historical texts.

Table 7 reports the performance of the evaluated models in an end-to-end EL setting, pairing all models with GliNER. In both DZ and AMD datasets, DELICATE variants outperform the baseline systems. For DZ,  $\text{DELICATE}_{\text{DZ}}$  achieves an F-1 score of 51.88 under exact matching and 52.76 under fuzzy matching. The second-best performing model is  $\text{DELICATE}_{\text{ALL}}$ , which achieves 50.48 and 51.36 in the exact and fuzzy settings, respectively. For AMD,  $\text{DELICATE}_{\text{ALL}}$  achieves the best results, with an F-1 score of 69.07 under exact matching and 69.24 under fuzzy matching, while  $\text{DELICATE}_{\text{AMD}}$  follows closely with 68.04 and 68.21, respectively. The improvement in F-1 against the baseline systems is particularly significant, with  $\text{DELICATE}_{\text{ALL}}$  outperforming even architectures with a higher number of parameters. These gains illustrate that DELICATE is not only effective at disambiguation but also robust to potential errors when integrated with a NER component, such as boundary misdetection and entity type misclassification.

Model	$\text{Acc}_{\text{Micro}}$
BLINK <sub>ITA</sub>	41.69
BLINK <sub>ITA</sub> -LLM	49.79
C-BLINK <sub>ITA</sub>	31.70
mGENRE	45.84
LLAMA 3.3 70B	48
GPT-4o mini	51
DELICATE <sub>DZ</sub>	55.48
DELICATE <sub>AMD</sub>	<u>58.27</u>
DELICATE <sub>ALL</sub>	<b>58.78</b>

**Table 8** ED results of DELICATE and baseline models on MHERCL-ITA.

### 6.3 Evaluation on MHERCL-ITA

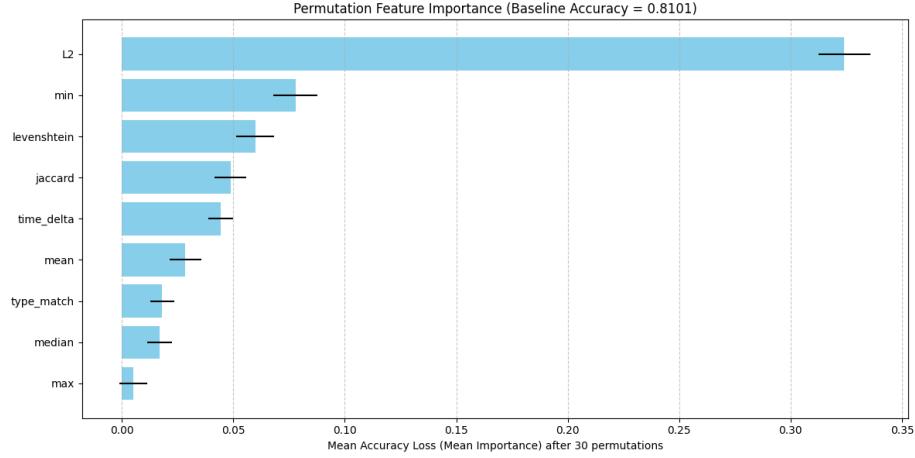
To assess the generalizability of DELICATE to other domains, we evaluate architectures trained on ENEIDE on MHERCL-ITA, a publicly available EL dataset extracted from Italian music periodicals published in the 19th century. This dataset presents three key challenges for historical EL systems: (i) pervasive OCR errors that can mislead models trained on web-crawled text, (ii) a high concentration of long-tail entities with limited representation in Wikipedia/Wikidata, and (iii) a substantially higher proportion of NIL entities compared to ENEIDE (28.67% vs 7%). For these experiments, we apply DELICATE models without additional fine-tuning, using the hyper-parameters optimized for DZ (block size = 50,  $\Delta_{\text{NIL}} = 0.4$ ).

Table 8 reports micro-averaged accuracy for all models on the ED task, including results for large-scale LLMs in zero-shot settings as reported in Graciotti et al. [10]. DELICATE variants substantially outperform all baselines, with DELICATE<sub>ALL</sub> achieving the best performance at 58.78% accuracy, followed closely by DELICATE<sub>AMD</sub> at 58.27%. These results demonstrate strong cross-domain generalization despite being trained solely on ENEIDE’s literary and political texts.

Among the baselines, standard approaches struggle considerably with this challenging dataset. BLINK<sub>ITA</sub> achieves only 41.69% accuracy, while mGENRE reaches 45.84%, highlighting the difficulty of disambiguating 19th-century musical references with methods that cannot handle NIL entities. The rule-based C-BLINK<sub>ITA</sub> performs worst at 31.70%, indicating that handcrafted temporal and type constraints fail to scale when confronted with noisy OCR-ed texts and long-tail entity distributions.

Incorporating LLMs yields mixed results. BLINK<sub>ITA</sub>-LLM improves substantially over the base bi-encoder (49.79%), suggesting that LLMs can leverage contextual cues to recover from retrieval errors. However, even large-scale models like LLAMA 3.3 70B (48%) and GPT-4o mini (51%) in zero-shot settings remain far below DELICATE’s performance, demonstrating the limitations of current LLMs for specialized historical information extraction tasks.

The superior performance of DELICATE variants, particularly DELICATE<sub>ALL</sub>, trained on the complete ENEIDE corpus, reveals several important advantages of the



**Figure 3** Plot of mean importance of each feature of the GBTs model after 30 Permutation Tests on the full ENEIDE test set.

proposed approach. First, the supervised GBTs re-ranker effectively handles the combination of OCR noise, long-tail entities, and high NIL rates without domain-specific fine-tuning. Second, the model’s ability to generalize across distinct historical domains (from literary and political texts to music periodicals) validates the robustness of learning similarity features from temporal and type information. Finally, the computational efficiency of DELICATE makes it a practical solution for rapidly deploying EL systems across different languages and historical corpora.

#### 6.4 Explainability Analysis

Due to the importance of explainability and interpretability in NLP applications for the humanities, we further analysed the performance of DELICATE by adopting two standard statistical tests. More specifically, a permutation test was carried out on feature relevance in order to estimate the importance of each feature in leading the GBTs component to classify positive and negative candidates. Moreover, the point-biserial coefficient was used to analyse the degree of correlation between prediction scores of each model and the rate of true and false positives predicted in the ED task.

The plots of the mean accuracy losses obtained after 30 permutation tests for DELICATE<sub>ALL</sub> are shown in Figure 3. As shown, vector-based similarity distances are the most important for the GBTs model, closely followed by string similarity ones, i.e., Levenshtein and Jaccard distances. Moreover, permutation tests show how time intervals have high relevance, being the fifth most important feature with a mean importance of  $\approx 0.05$ . This suggests the relevance of temporal constraints in reducing the rate of false positives in historical texts.

Table 9 presents the point-biserial correlation between prediction scores and correct predictions for all ED models on ENEIDE. The higher correlation observed for DELICATE indicates that its confidence scores are strongly associated with correct

	Model	Point-biserial Corr.	p-value
DZ	BLINK <sub>ITA</sub>	0.5986	2.97e-61
	BLINK <sub>ITA</sub> -LLM	0.5358	3.92e-47
	C-BLINK <sub>ITA</sub>	0.4270	9.28e-29
	mGENRE	0.5969	7.84e-61
	DELICATE <sub>DZ</sub>	<b>0.7973</b>	5.47e-137
	DELICATE <sub>ALL</sub>	0.6383	6.54e-72
AMD	BLINK <sub>ITA</sub>	0.1490	2.86e-04
	BLINK <sub>ITA</sub> -LLM	0.2826	2.80e-12
	C-BLINK <sub>ITA</sub>	0.1413	5.84e-04
	mGENRE	0.4287	1.00e-27
	DELICATE <sub>AMD</sub>	<b>0.6848</b>	9.83e-83
	DELICATE <sub>ALL</sub>	0.6465	5.07e-71

**Table 9** Point-biserial Correlation between prediction scores and correct predictions for all ED models. High scores are an index of a strong correlation between prediction scores and correctness of the result.

disambiguation decisions. This suggests that supervised methods, such as GBTs, despite having the disadvantage of requiring training data, produce more interpretable scores than the approaches based on language models, such as BLINK and mGENRE. This is interesting also with respect to the black box issue that language models usually have, since it demonstrates how it can be tackled by employing more traditional ML methods in downstream tasks. Moreover, this degree of interpretability in the prediction scores is particularly valuable for applications that require reliable confidence measures and suggests the importance of integrating DELICATE in human-in-the-loop systems, where it could be paired with a domain expert for verifying and consolidating the results. However, investigating this application of DELICATE goes beyond the scope of this study.

## 7 Discussion and Conclusion

### *Discussion.*

The experimental results indicate that the proposed DELICATE architecture offers several notable advantages while also revealing challenges that require further investigation. First of all, DELICATE achieves significant efficiency gains by fine-tuning only the supervised GBTs and keeping the BERT bi-encoder weights frozen. This design choice allows for rapid adaptation even on CPU-based systems, which is especially beneficial for settings with limited computational resources or when training samples are few.

Moreover, the system shows a reduced bias towards under-represented entities, as highlighted by improved performance on long-tail entities in ENEIDE and MHERCL-ITA. This improvement suggests that DELICATE’s candidate re-ranking mechanism is more resilient to domain shifts and chronological variations. Additionally, by integrating type and time information from Wikidata, the model enhances its disambiguation capabilities in historical documents where contextual information is often necessary.

A further evidence of DELICATE’s generalizability is its strong performance on the out-of-domain MHERCL-ITA dataset. Despite being fine-tuned solely on ENEIDE,  $\text{DELICATE}_{\text{ALL}}$  and  $\text{DELICATE}_{\text{AMD}}$  achieve micro-averaged accuracies above 58% (and macro above 56%), substantially outperforming both generic baselines and more complex architectures employing bi-encoders paired with LLMs.

Another noteworthy strength is the adoption of GBTs in the final classification stage, which contributes to the explainability and interpretability of system’s results. This tree-based approach not only facilitates insight into the relevance of different similarity dimensions but also yields confidence scores that correlate strongly with linking accuracy. Such characteristics are particularly valuable in historical EL pipelines, where manual verification of uncertain links is often required.

#### ***Limitations.***

Despite these strengths, the experiments also revealed some limitations. DELICATE relies on annotated training data to fine-tune the GBTs classifier effectively, which poses a challenge when labelled resources are scarce. In addition, inaccuracies in the initial candidate retrieval step (e.g., due to OCR errors) can propagate through to the final ranking, potentially reducing overall accuracy. Finally, the need to tune hyper-parameters (e.g., learning rate, tree depth,  $\Delta_{\text{NIL}}$ ) for each dataset partition introduces additional complexity which however seems to not impact scalability and generalizability.

#### ***Summary & Conclusion.***

To summarise, this paper presented DELICATE, a novel supervised method that combines a BERT-based bi-encoder and structured information from KBs to perform ED on historical documents from multiple domains and written across different chronological periods. Experimental results show that DELICATE not only outperforms general-purpose ED systems when trained with domain-specific data, but also demonstrates strong cross-domain adaptability by achieving good performances on new datasets without further fine-tuning. A further contribution of this study is the release of a novel Italian corpus for training and evaluating EL systems, called ENEIDE, which is semi-automatically extracted from two digital editions. All resources produced in this work, including datasets, source code, trained models and results, are released on open-source to enhance the reproducibility of the study. Future work may extend DELICATE to multilingual historical EL by refining its KB using more structured taxonomies such as YAGO-4.5 [27]. The ENEIDE corpus could also be expanded with multilingual resources to serve as a benchmark for multilingual EL systems in the humanities. Another promising direction involves the integration of DELICATE into KE pipelines for different historical documents, such as letters [21] and books [22].

Entity Type	Parent Wikidata Classes
Person	person (Q215627), fictional character (Q95074), fictional person (Q97498056)
Organization	governing body (Q895526), group of humans (Q16334295), fictional organization (Q14623646)
Location	fictional location (Q3895768), geographic entity (Q27096213), spatial object (Q58416391)
Work	creative work (Q17537576), intellectual work (Q15621286)

**Table 10** Root Wikidata classes for different entity types in our dataset

## A Entity Type Mapping with Wikidata Classes

To categorize entities in the Italian Wikipedia according to the four entity types used in the ENEIDE benchmark — person, organization, location, and work — a mapping between Wikidata classes and ENEIDE types was constructed. This mapping relies on a manually curated list of root Wikidata classes, chosen for each ENEIDE entity type based on their semantic alignment.

For each of these root classes, the entire subclass hierarchy was obtained using the `subclass of` property (P279). This ensures comprehensive coverage of Wikidata’s ontological structure. Classes that appeared under more than one ENEIDE category were excluded to maintain mutually exclusive type assignments.

The resulting class-to-type mappings were used to annotate each entity in the dense index by checking whether its Wikidata class belonged to the subtree of a parent class. The root classes for each entity type used in our mapping are shown in Table 10.

## B Wikidata time-related properties used for candidate re-ranking

To enrich the knowledge base with temporal information, a curated list of time-related properties from Wikidata was created. These properties provide semantically relevant dates linked to entities, such as their inception, publication, or debut. The inclusion of temporal information allows DELICATE system to prioritize or disambiguate candidates during re-ranking, especially when the context includes temporal cues.

The list of used properties presented in Table 11 based on the taxonomy presented in [9], and each property was selected for its relevance across the four ENEIDE entity types.

Property	Name
P569	Date of Birth
P571	Inception
P1619	Date of Official Opening
P1191	Date of First Performance
P10135	Recording Date
P577	Publication Date
P575	Time of Discovery or Invention
P1317	Floruit
P7124	Date of the First One
P10673	Debut Date
P9448	Introduced On
P6949	Announcement Date
P729	Service Entry
P2031	Work Period (Start)
P585	Point in Time

**Table 11** Time-related Wikidata properties used in the lookup table.

## C BLINK<sub>ITA</sub>-LLM Prompt Template

This appendix presents the full prompt used in BLINK<sub>ITA</sub>-LLM to perform entity disambiguation, translated in English for increased readability. The prompt includes a task instruction, the input text with the target mention marked by [ENT] tags, and a JSON block listing candidate entities with associated type and temporal information.

**System Prompt:** You are an effective information extraction system specialized in disambiguating entities within texts from the humanities. Your task is to analyse the text provided by the user and disambiguate the reference marked by [ENT] tags by selecting a Wikidata entity from a given list of candidates. Always respond by returning a JSON-formatted answer; do not generate Python code.

**User Prompt:** Read the input text published in {document\_date}.

Disambiguate the entity mentioned between the [ENT] tags by selecting the most appropriate Wikidata entity from the list of candidates.

Return the corresponding Wikipedia title and Wikidata ID of the selected entity in a JSON object formatted as follows: { "wikipedia\_title": "", "wikidata\_id": "" }

Make sure to select both the Wikipedia title and the Wikidata ID from the provided list of candidates.

If none of the candidates match the entity tagged with [ENT], return an empty JSON object.

Input Text: {annotated\_text}

List of Candidates: {candidates\_in\_json}

## D Entity Type Mapping from MHERCL-ITA to ENEIDE

To enable the application of DELICATE’s entity type heuristic on MHERCL-ITA, we manually mapped the 34 fine-grained entity types defined in MHERCL-ITA to the

ENEIDE Type	MHERCL-ITA Fine-Grained Types
Person	person
Organization	family, organization, school, government-organization, university, newspaper, magazine
Location	city, country, country region, continent, location, mountain, road, lake, island, building, worship-place, facility, theater
Work	book, work-of-art, publication, music, music key, award, event, festival, court decision, war, conference, law

**Table 12** Manual mapping of MHERCL-ITA fine-grained types to ENEIDE’s coarse-grained types used by DELICATE.

four coarse-grained categories used in ENEIDE: PER (person), ORG (organization), LOC (location), and WORK (work). Table 12 summarizes this mapping.

## Data Availability

Source code, dataset and trained models produced in this research are publicly available:

- DELICATE (source code): <https://github.com/sntcristian/DELICATE>
- DELICATE (trained models): <http://doi.org/10.57967/hf/6984>
- ENEIDE (dataset): <https://github.com/sntcristian/ENEIDE>

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