



diaNED: Time-Aware Named Entity Disambiguation for Diachronic Corpora

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Bush to Stress Domestic Issues in Speech.

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George W. Bush

Bush to Stress Domestic Issues in Speech. (*Year 1989*)



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Introduction

Problem Description

Given:

Set of entity mentions \mathcal{M} in a document.

Entities: entries in a Knowledge Base (KB).

Task:

Link each m , where $m \in \mathcal{M}$, to its correct entry in KB , if available.

Predict as an *OOKBE*, otherwise.

Named Entity Disambiguation

In 1959, David Pearson exhibited as part of the Young Contemporaries exhibition in **London**.

In 1981, with a small number of **BNR** colleagues, David Pearson left to found **Orcatech Inc.**

David Pearson raced for **Hoss Ellington** during the 1980 season.

Named Entity Disambiguation

(en.wiki.pedia.org/wiki/Dave_Pearson_(painter))

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(en.wiki.pedia.org/wiki/David_Pearson_(racing_driver))

● Popularity-based Models

Mihalcea and Csomai, 2007 [7]

Entity popularity and mention-entity prior probabilities.

Leverages anchor links structure.

<i>David Pearson</i>	Dave Pearson (painter)	0.1
<i>David Pearson</i>	David Pearson (computer scientist)	0.03

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Local Models

Bunescu and Pasca, 2006[2]; Cucerzan, 2007[3]; Milne and Witten, 2008[8]

Similarity with immediate context words.

Independent disambiguation.

<i>David Pearson</i>	Dave Pearson (painter)	1959, exhibited, young, exhibition, london
<i>David Pearson</i>	David Pearson (computer scientist)	1981, bnr, colleagues, found, orcatech

● Global Models

Kulkarni et al., 2007[6], Houtart et al., 2011[4]

Entities mentioned in a document are related.

Collectively disambiguate entities.

David Pearson

Dave Pearson (painter)

| *London*

David Pearson

David Pearson (computer
scientist)

| *BNR, Orcatech_Inc.*

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Representation Learning and Context Attention

Blanco et al., 2015[1], Hu et al.[5], 2015, Yamada et al, 2016[10]

Use of distributed vector representations.

Trained using the anchor links structure of KB.

Remove noisy words from the context.

David Pearson	Dave Pearson (painter)	$V_{\text{London}}; V_{\text{exhibition}}$
David Pearson	David Pearson (computer scientist)	$V_{\text{BNR}}; V_{\text{Orcatech}}$



Temporal Context

Motivation for Temporal Modeling

Deductions

Previous works fail to factor-in temporal semantics.

Single value for entity popularity.

Bias towards frequently occurring entities in KB and recent news.

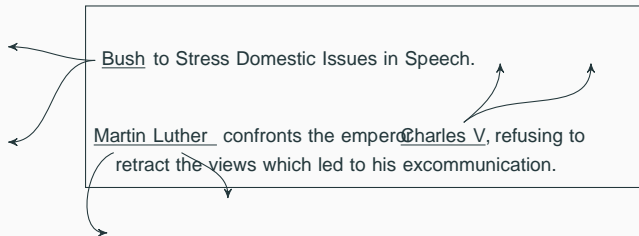


Figure 1: Entity Annotated Sample Texts¹. (Image source: Wikipedia)

¹The values in the brackets indicate the entity popularity.

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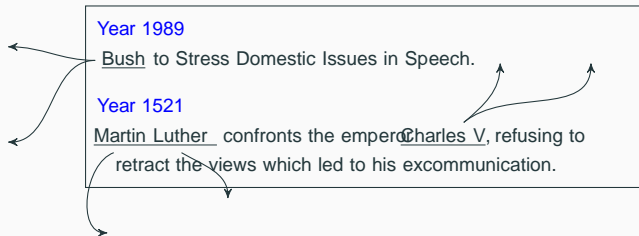


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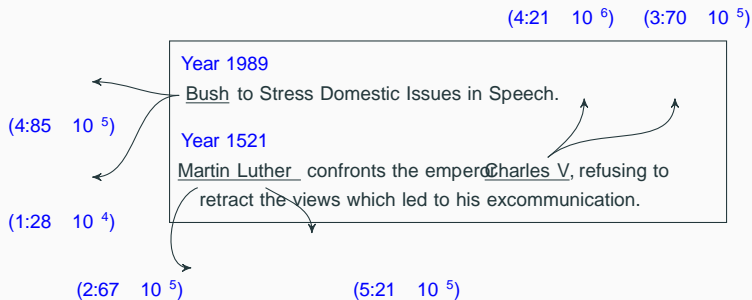


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Temporal Context

Factor-in temporal semantics.

Distributed popularity.

Independent of anchor link structure.

Unbiased towards document creation time.

Temporal NED Model

Figure 2: Temporal Vector Space Modeling²

²Representations: Entity as <entity signature> and mention as (mention, year)

Temporal Signatures of KB Entities

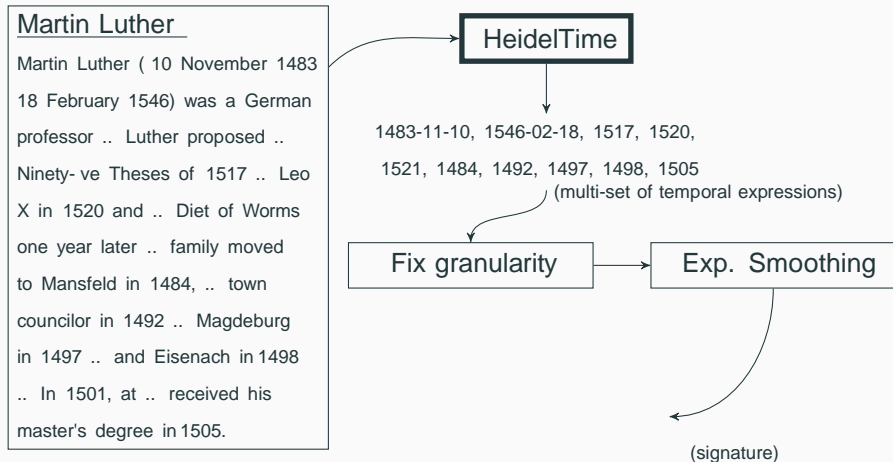


Figure 3: Extraction of Temporal Signatures from Wikipedia Article Content.

Temporal Context for Entity Mentions

1. Document Creation Time (DCT): t_m^{dct}

Mention is represented as a One-Hot Vector.

Applicable for news articles.

All values in the vector are 0, except a single 1 at the index position corresponding to DCT.

2. In-context Temporal Information: $t_m^{content}$

In-context expressions can be extracted using a temporal tagger.

Applicable for narrative documents.

There are 1s at index positions corresponding to the set of date values $T(m)$ extracted by the temporal tagger.

3. Combined Contexts: t_m

The context similarity scores can also be aggregated.

$$t_m = t_m^{dct} + (1 - \alpha) t_m^{content}$$

Disambiguation Example

Figure 4: Temporal signatures of entity candidates for mention (Bush, 1989) and (Martin Luther, 1521).

Time-Aware Start-of-the-Arts

Making NEDs Time-aware

diaNED-1, extension of [Hoffart et al.: Robust Disambiguation of Named Entities in Text, EMNLP 2011]

Document as a graph with mentions and entities as nodes.
Mention-entity priors, mention entity similarity, and entity coherence used as edge weights.
Disambiguation: A one-one mapping between each mention and entity node..

diaNED-2, extension of [Yamada et al.: Joint Learning of the Embedding of Words and Entities for Named Entity Disambiguation, SIGNLL 2016]

Representation of context words and entities in a single vector space using skip gram model.
Disambiguation: A learning-to-rank model using prior stats, string similarity, mention-entity, and coherence similarity as features.

Evaluation

CoNLL-AIDA	1996
TAC 2010	2004-2007
Microposts 2014	2011

Shortcomings

Minimal improvements with Time-aware models.

Not suitable to demonstrate/evaluate power of time-awareness.

HistoryNet

Historynet.com: online resource of major historical events.

Manually annotated 865 mentions in 350 randomly selected documents³.

NewYorkTimes

NYT headlines published between 1987 and 2007.

Manually annotated 368 mentions in 300 randomly selected headlines.

³The named entities were identified using the 3 class Stanford NER tagger

Results: diaNED-1

Feature set	HistoryNet		NewYorkTimes	
	w/o time	w/ time	w/o time	w/ time
Prior	72.26	80.48*	38.14	54.24*
Context	63.63	66.10*	48.31	62.71*

Table 1: Micro-accuracy of diaNED-1 with and without time-awareness feature.

* significant over w/o time (Welch's t-test at level of 0.01).

Results: diaNED-2

Feature set	HistoryNet		NewYorkTimes	
	w/o time	w/ time	w/o time	w/ time
Base	89.44	90.23*	85.81	87.36*
String	89.40	90.00*	86.28	87.07*
Context	91.10	91.81*	87.07	88.34*
Coherence	91.16	91.98*	86.83	88.69*

Table 2: Micro-accuracy of diaNED-2 with and without time-awareness feature.

* significant over w/o time (Welch's t-test at level of 0.01).

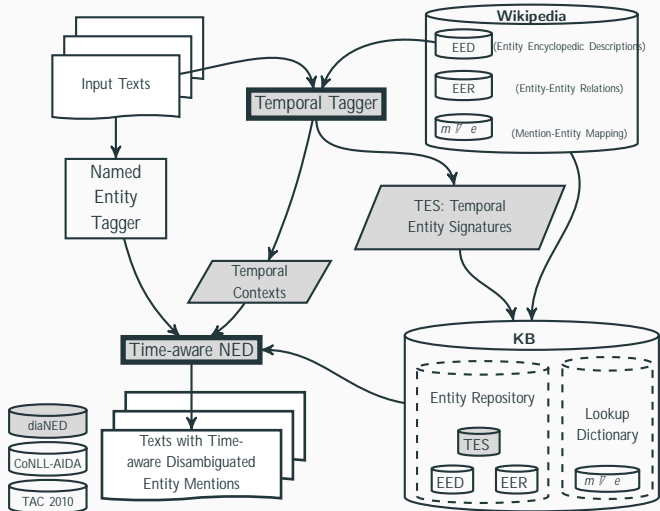
Results: diaNED

system	<i>HistoryNet</i>	<i>NewYorkTimes</i>
xLisa-NGRAM [Zhang and Rettinger, 2014]	87.07	66.30
xLisa-NER [Zhang and Rettinger, 2014]	83.32	60.25
WAT [Ferragina and Scaiella, 2012]	82.26	70.95
PBOH [Ganea et al., 2016]	90.26	71.75
FREME NER [Dojchinovski and Kliegr, 2013]	48.50	45.27
FRED [Consoli and Recupero, 2015]	23.18	15.44
FOX [Speck and Ngomo, 2014]	77.85	54.25
Dexter [Ceccarelli et al., 2013]	69.88	49.12
DBpedia Spotlight [Mendes et al., 2011]	56.92	61.91
AIDA [Hoffart et al, 2011]	82.68	70.14
AGDISTIS [usbeck et al, 2014]	70.77	50.14
Gupta et al., 2017	62.82	43.33
re-impl. of [Yamada et al., 2016]	90.87	72.55
diaNED-2	91.68	76.09

Table 3: Micro-f1 scores on the *HistoryNet* and *NewYorkTimes* datasets of diaNED-2 (trained on CoNLL-AIDA [4]) and other tools available on GERBIL [9].

Summary

Summary



The annotated **diaNED Corpora** and **Entity Temporal Signatures** are available at: <https://www.mpi-inf.mpg.de/yago-naga/di-aned/>

Study how temporal affinity can be used for identifying out-of-KB entities.

Large scale experiments using data-sets generated using semi-supervised methods.

Adding multilingual support for the temporal signatures.

Thank you! Questions?



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