Evaluating the word-expert approach for Named-Entity Disambiguation

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Abstract

Named Entity Disambiguation (NED) is the task of linking a named-entity mention to an instance in a knowledge-base, typically Wikipedia. This task is closely related to word-sense disambiguation (WSD), where the supervised word-expert approach has prevailed. In this work we present, for the first time, the results of the word-expert approach to NED, where one classifier is built for each target entity mention string. The resources necessary to build the system, a dictionary and a set of training instances, have been automatically derived from Wikipedia. We provide empirical evidence of the value of this approach, as well as a study of the differences between WSD and NED, including ambiguity and synonymy statistics.

1 Introduction

Construction of formal representations from snippets of free-form text is a long-sought-after goal in natural language processing (NLP). Grounding written language with respect to background knowledge about real-life entities and world events is important for building such representations. It also has many applications in its own right: text mining, information retrieval and the semantic web [Weikum and Theobald, 2010]. Wikipedia and related repositories of structured data (e.g. WikiData or DBpedia) already provide extensive inventories of named entities, including people, organizations and geo-political entities.

An individual named-entity string may refer to multiple entities and the process of resolving the appropriate meaning in context is called entity linking (EL) or named entity disambiguation (NED). The former terminology (EL) stresses the importance of linking a mention to an actual instance in the given knowledge-base [McNamee and Dang, 2009]. We prefer the latter term (NED), which focuses on the potential ambiguity among several possible instances. It highlights the connection to the closely
Edward may refer to several people — Wikipedia lists more than ten,
including the intended athlete — as well as a residential college at Yale and a music
record. Figure 1 shows a disambiguation page for the string, and Figure 2 an excerpt
from the athlete’s Wikipedia article.

In addition to disambiguation pages that list possible entities to which a canonical
string like “Jonathan Edwards” may refer, many naturally-occurring entity mentions
in regular Wikipedia articles are also cross-referenced. For instance, the first sentence
of the entry for Jonathan Edwards (the athlete) includes hyperlinks (shown in blue) to
“CBE,” “British” and “triple jumper.” The first link references an article on the Order of
the British Empire[^3]. Anchor-text (words in blue) often exposes alternate ways of referring to entities: e.g., a member of the Order of the British Empire can be called “CBE.” Figure 3 shows five sentences that link to Jonathan Edwards (the athlete), and Figure 4 shows three sentences with hyperlinks to other people called Jonathan Edwards. Anchors present a rich source of disambiguation information. Aggregating over all occurrences of hyper-text “Jonathan Edwards,” we can compute that, most of the time, it refers to the theologian. Yet by analyzing the context of each named entity’s occurrence, we could conclude that a span like “...triple jumper Jonathan Edwards...” is more similar to mentions of the athlete. These linked spans from Wikipedia can also be

[^1]: http://en.wikipedia.org/wiki/Jonathan_Edwards_(disambiguation)
[^2]: http://en.wikipedia.org/wiki/Jonathan_Edwards_(athlete)
[^3]: http://en.wikipedia.org/wiki/Order_of_the_British_Empire
used to obtain alternative terms that refer to the same entity. Figure 5 shows a variety of ways in which Wikipedia refers to Bill Clinton.

As online encyclopedias grow in size, entities and ideas that are of interest to even small communities of users may get their own Wikipedia pages with relevant descriptions. Thanks to the hyper-linked nature of the web, many online mentions have already been annotated with pointers to corresponding articles, both within Wikipedia and from external sites. As a result, large quantities of freely available information — suitable for supervised machine learning algorithms — already exist, obviating the need for costly manual annotations that are typically associated with the training of traditional NLP systems in general and WSD in particular.

NED is a disambiguation task that is closely related to WSD, where the goal is to disambiguate open-class words (i.e., common nouns, adjectives, verbs and adverbs) with respect to a sense inventory, such as WordNet [Fellbaum 1998]. The extensive WSD literature [Agirre and Edmonds 2006, Navigli 2009] has shown that building a supervised classifier for each target lemma — the so-called word-expert approach — outperforms other techniques [Zhong and Ng 2010].

In this work we propose an architecture for NED following the word-expert approach, where we build a classifier for each named-entity mention, with two main modules: (1) A candidate generation module which, given a string, lists all potentially relevant entities. This module is based on a static dictionary, which also lists the popularity of each of the entities, and can thus serve as a standalone context-independent
The current male and female world record holders are Jonathan Edwards of Great Britain, with a jump of 18.29 meters, and Inessa Kravets of Ukraine, with a jump of 15.50 meters.

During the lead up to the 2012 Olympics a number of people carried the torch through Ilfracombe, amongst these was Jonathan Edwards, the triple jump world record holder, who had the privilege to carry the torch past his former home.

Athlete Jonathan Edwards is the patron of the ‘Be Part of It’ campaign.

Olsson first became interested in triple jump after watching Jonathan Edwards set the world record at the World Championships in his hometown Gothenburg.

They were pitted against a group of 10 celebrities including EastEnders star Adam Woodyatt, pop music presenter Fearne Cotton, Olympic athlete Jonathan Edwards and former Sunday Times editor and broadcaster Andrew Neil.

In North America, missionaries to the native Americans included Jonathan Edwards, the well known preacher of the Great Awakening, who in his later years retired from the very public life of his early career.

One Day Closer is the ninth studio album (eleventh total album) released by singer songwriter Jonathan Edwards and features many ballads and love songs.

Jonathan Edwards (principal from 1686 to 1712) is reported to have spent £1,000 during his lifetime on the interior of the chapel.

Our system is based on two main resources: (i) a dictionary listing all candidate entities for each surface string, together with their frequencies, and (ii) a set of training instances for each target mention. The bulk of the information comes from Wikipedia but we have further complemented the dictionary with web counts from a subset of a 2011 Google crawl. The dictionary’s release was documented in a short conference paper [Spitkovsky and Chang 2012], which we extend with additional explanations and analyses here.

http://www-nlp.stanford.edu/pubs/crosswikis-data.tar.bz2
Arthur Levitt

Levitt was appointed to his first five-year term as Chairman of the SEC by President Clinton in July 1993 and reappointed in May 1998.

Asa Hutchinson

Hutchinson, who had at first decided to run for an open seat in the Arkansas House of Representatives from Sebastian County, defeated Ann Henry, a long-time friend of Bill and Hillary Clinton.

William Jefferson Blythe, Jr.

Three months later, Virginia gave birth to their son, William Jefferson Blythe III, the future President.

HMMT-164

In February 1996, HMMT-164 was called upon to support the President of the United States as he visited the flood-ravaged areas around Portland, Oregon.

Joan Jett Blakk

Smith also ran for president in 1996 with the slogan “Lick Slick Willie in ’96”

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Figure 5: Example sentences from Wikipedia that use different names to refer to the same entity (Bill Clinton).

We present a detailed analysis of the performance of the components and variations of our NED system, as applied to the entity linking task of the NIST Text Analysis Conference’s (TAC) knowledge-base population (KBP) track [Ji and Grishman, 2011]. The task focuses on several target entity mentions, which makes it well suited for our word-expert approach. In the future we would like to explore other datasets which include all mentions in full documents [Hoffart et al., 2011]. Our final results are quite strong despite the simplicity of the techniques used, with the dictionary’s raw frequencies already performing extremely well. We focus on the candidate generation and disambiguation modules, leaving aside mention detection and the task of NIL detection, where mentions which refer to entities not listed in the knowledge-base have to be detected [Durrett and Klein, 2014].

In addition, we will study differences between the closely related worlds of WSD and NED. In WSD, an exhaustive dictionary is provided, while in NED, one has to generate all candidate entities for a target string — a step that has been shown to be critical to success [Hachey et al., 2012]. In WSD very few occurrences correspond to senses missing in the dictionary, but in NED this problem is quite prevalent. We will also show that ambiguity is larger for NED. On the bright side, there is a lot of potential training data for NED, for instance, in the form of human-generated anchor texts. This article shows that an architecture based on WSD methods can work well for NED, and that it is feasible to model candidate generation with a static dictionary. We will also compare ambiguity, synonymy and inter-annotator agreement statistics of both problems.

Note that the authors participated in the TAC-KBP Entity Linking tracks with preliminary versions of the system reported in this article. Those systems, alongside all participant systems [Agirre et al., 2009, Chang et al., 2010, 2011], were reported in publicly available proceedings [Agirre et al., 2009, Chang et al., 2010, 2011].

The paper is organized as follows: we first present related work, followed by the architecture of our system (Section 5). The dictionary for candidate generation is pre-

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6 http://www.nist.gov/tac/
7 There was no peer-review, and all papers were accepted.
sented next (Section 4), followed by methods that produce the training data and build the supervised classifier (Section 5). Section 6 introduces the TAC-KBP dataset used for evaluation, followed by the adaptation of our system (Section 7). Section 8 explores several alternatives to our approach and analyzes their performance on development data, as well as the final results and discussion. We then compare our system to related work, draw conclusions and propose future directions.

2 Related Work

We will now review several NLP problems that are closely related to NED, including wikification and WSD, as well as previous work on NED. For clearer exposition, we group the previous work into three sections: first, the earlier and more influential contributions, followed by work on wikification, and finally NED systems. We briefly touch on state-of-the-art techniques used in NED, specifically, handling of candidate generation (i.e., our dictionary), and disambiguation. A full comparison of our results to those of the latest state-of-the-art systems can be found in Section 8.7.

2.1 Related Problems

NED is related to several problems in NLP. For instance, it presupposes that mentions of named entities have already been identified in text, building up from the named entity recognition (NER) task [Marsh and Perzanowski, 1998; Tjong Kim Sang and De Meulder, 2003]. Each mention may be further labeled with a broad semantic category — such as names of persons, organizations or locations — via named entity classification (NEC). This last task is often performed by using gazetteers to cover many known entities, in addition to training a single supervised classifier that outputs category types for input mentions given their specific contexts. Overall, we view NED as a specific instantiation of the record linkage problem, in which the task is to find records referring to the same entity across different data sources, such as data files, databases, books or websites.

The term record linkage was first used by Dunn Halbert [1946], in reference to resolving person names across official records held by a government. More recently, Bagga and Baldwin [1998] focused on cross-document coreference of people by first identifying coreference chains within documents and then comparing the found chains’ contexts across documents. Similar problems arise in citation databases, where it is necessary to decide which mentions of authors in bibliographic records refer to the same person [Bhattacharya and Getoor, 2007]. Other typical applications that lack a predefined inventory of entities include resolving names in e-mails and web people search (WePS). In the WePS task, starting from a set of web-pages that mention a name (e.g., John Doe), the goal is to decide how many John Does there are, and who is mentioned where [Artiles et al., 2008; 2009]. The e-mails task can be tackled by assuming that each address corresponds to a distinct person and that people’s identifying information can be deduced from what they write [Elsayed et al., 2008].

Three important aspects differentiate NED from record linkage and other cross-
document entity coreference tasks, such as the exercise studied at ACE 2008 and clustering of documents that mention the same entity [Mann and Yarowsky, 2003; Goel and Allan, 2004]. These differences hinge on the existence of (1) a knowledge-base (e.g., Wikipedia) that lists gold-standard entities; (2) rich textual information describing each entity (i.e., its Wikipedia page); and (3) many explicitly disambiguated mentions of entities (i.e., incoming hyper-links furnished by Wikipedia’s contributors and other, external web publishers). A more closely related task is wikification [Mihalcea and Csomai, 2007; Csomai and Mihalcea, 2008; Milne and Witten, 2008; Kulkarni et al., 2009], which involves first deciding which keywords or concepts are relevant in a given text and then disambiguating them by linking to the correct Wikipedia article. Although the overall thrust of that task is different, since wikification systems target common nouns as well as named entities, its disambiguation techniques are relevant to NED (see Section 2.4).

### 2.2 Word Sense Disambiguation

In WSD, the task is to determine which sense of an open class content word — i.e., an adverb, verb, adjective or noun that isn’t a named entity — applies to a particular occurrence of that word [Agirre and Edmonds, 2006; Navigli, 2009]. Typically, the sense inventory is taken from a dictionary, such as WordNet [Fellbaum, 1998], and fixed in advance. Dictionaries are comprehensive, covering nearly all uses of a word. Consequently, WSD systems tend to return a sense for every occurrence. For instance, the Senseval-3 lexical sample dataset [Mihalcea et al., 2004] contains 2,945 manually annotated occurrences, 98.3% of which have been assigned a dictionary sense: only 1.7% are problematic and have senses not found in the dictionary. By contrast, in NED, a significant portion of mentions are out-of-inventory (around 50% in our dataset). However, in WSD target senses are often open to interpretation, as reflected by low inter-annotator agreement, e.g., 72.5% in the Senseval-3 all-words task [Snyder and Palmer, 2004]. We will show that NED poses a better-defined problem, with less dispute about what constitutes a correct target entity, as indicated by significantly higher inter-annotator agreement.

WSD and NED differ also in two other key properties: (i) polysemy, the expected number of senses a word might have; and (ii) synonymy, the expected number of different words that may be used to lexicalize a given concept. These statistics can be used to characterize the difficulty of an evaluation set. We compared average polysemy and synonymy values for WSD and NED, computed using gold standards (by counting senses listed in dictionaries versus those actually occurring in test data). NED scored substantially higher on both metrics, relative to WSD (see Section 6.4).

The best-performing WSD systems are currently based on supervised machine learning, judging by public evaluation exercises [Snyder and Palmer, 2004; Pradhan et al., 2007]. Typically, the problem is modeled using multi-class classifiers [Marquez et al., 2006], with one classifier trained for each target word (a.k.a. the word expert approach). Training examples are represented by feature vectors (see Section 5) and labeled with gold senses. At test time, inputs are processed and represented in the same...
way, as vectors of features, with appropriate classifiers predicting intended senses. Our proposed system architecture for NED follows this design (see Section [3]).

WSD systems can perform well when training data are plentiful. On the Senseval-3 lexical sample task [Mihalcea et al., 2004], accuracies can reach as high as 72.9% with fine-grained senses and 79.3% with coarser-grained senses. Both performance numbers are well above the most-frequent sense (MFS) baselines (55.2 and 64.5%, respectively). The test set used there comprised 57 target words, each backed by at least 100 manually-annotated examples. But many words found in running text lack sufficient training instances, leading to lower performance in evaluations when all words are considered. The best accuracy reported for the Senseval-3 all words task, testing all open-class words occurring in three texts (editorial, news and fiction), was 65.1%, only slightly higher than the MFS baseline’s 62.4% [Snyder and Palmer, 2004]. Unfortunately, it is expensive to produce thorough hand-tagged training data for WSD and people do not typically annotate their words with the exact sense they meant.

In contrast with WSD, where training data is scarce, the upside for NED is that labeled instances for many mentions are already available in large numbers, annotated by Wikipedia volunteers, since the contexts and targets of hyper-links could be used as supervision. In other respects, we find many similarities between WSD and NED: For each mention that could be used to refer to a named entity, the knowledge base may list all possible targets, as the dictionary does for WSD. E.g., for a string like “John Edwards” a disambiguation page may list all relevant entities (see Figure 1). Naturally, there are also differences: A big downside for NED is that the inventory of meanings is not explicit and, for most strings, will be badly incomplete, unlike dictionaries used in WSD.

In Sections [6] and [8] we will explore the relation between WSD and NED further, showing that (1) ambiguity, synonymy and incidence of dictionary misses are all higher for NED than for WSD; (2) the NED task appears better-defined, as signaled by higher inter-annotator agreement than in WSD; (3) the skew of frequencies is more extreme for NED, with MFS consequently presenting an even stronger baseline there than in WSD; (4) the high number of training instances available to NED enables better supervised training, allowing NED systems to follow the same architecture as WSD systems, using analogous preprocessing, feature sets, and classifiers; and (5) the high ambiguity of mentions encountered by NED makes a typical word expert approach more computationally expensive, but still feasible. Lastly, (6) we will discuss the feasibility of constructing a comprehensive dictionary for NED.

2.3 Early Work on NED

The earliest work on NED using Wikipedia is by [Bunescu and Pasca, 2006], who used article titles, redirects and disambiguation pages to generate candidate entities. Similarity between a mention’s context and article text provided the rankings, according to tf-idf and cosine similarity. Each article’s term vector was further enriched using words from other articles in the same category. Disambiguation of mentions was local, i.e., performed separately for each one.

[Cucerzan, 2007] followed an overall similar design, but using context vectors that consisted of key words and short phrases extracted from Wikipedia. He disambiguated
all named entities in text simultaneously, adding a \textit{global} constraint that required target Wikipedia articles to come from the same category. Candidate lists were augmented with link information whenever a given anchor-text mentioned the same target entity from at least two different Wikipedia pages. His approach was later reimplemented (see Section 8.7) by Hachey et al. [2012], who also reimplemented the earlier system of Bunescu and Pasca [2006].

Fader et al. [2009] also generated candidates as did Cucerzan [2007]. They introduced prior probabilities — estimated from the numbers of anchors that refer to entities — in addition to considering the overlap between the context of a mention and the text of the target articles.

2.4 Wikification

Most research on wikification obviates candidate generation and focuses on disambiguation. In seminal work [Mihalcea and Csomai, 2007, Csomai and Mihalcea, 2008], the authors used mentions in anchors to train a supervised (na"ive Bayes) classifier. This is the work most similar to ours. However, they did not address the problems of building a dictionary or different methods to collect training data (cf. Section 5.2). Wikification work continued with Milne and Witten [2008], who combined popularity and relatedness (computed as the number of inlinks shared between the context and target articles), using several machine learning algorithms. They were the first to use the link structure of Wikipedia. Kulkarni et al. [2009] later proposed a method that collectively wikified an entire document, by solving a global optimization problem, using ideas from both Milne and Witten [2008] and Cucerzan [2007], but now applied in the context of wikification.

Zhou et al. [2010] also built on ideas of Milne and Witten [2008] and included, for the first time, relatedness between entities (based on search engine log analysis). They tested two classifiers (binary and learning-to-rank), with mixed results. Ratinov et al. [2011] utilized link structure — again, following Milne and Witten [2008] — to arrive at coherent sets of disambiguations for input documents. They used a ranker to select best-fitting entities. Although anchor context was used to compute similarity between article texts, it was not tapped for features during classification. Evaluation against their own dataset showed that improvements over local disambiguation were small. Guo et al. [2011] use direct hyperlinks between the target entity and the mentions in the context, using directly the number of such links.

2.5 Current NED Systems

Given the popularity of NED, we focus this review on systems that evaluate against TAC-KBP 2009 and 2010 data — two of the most cited NED datasets — to which we will compare our own results (see Section 8.7).

In 2009, Varma et al. [2009] obtained the best results, using anchors from Wikipedia to train one classifier per target string, combined with querying of mention contexts against an online search engine. For candidate generation they used a complex mixture of redirect links, disambiguation pages and bold text in leading paragraphs of articles, metaphones to capture possible spelling variations and errors, and a separate module
that tried to find acronym expansions. In addition, they used a dynamic algorithm that returned entities matching some (but not all) tokens of a target string.

In 2010, Lehmann et al. [2010] did best. They used titles, redirects, anchors and disambiguation pages, as well as Google searches, dynamic generation of acronym expansions, longer mentions and inexact matching. Their system pulled in features from both McNamee [2010] and Milne and Witten [2008] to train a binary classifier. McNamee [2010] had the highest-scoring submission among systems that did not use the text in target Wikipedia articles, focusing on the provided KB alone for building the list of candidate entities. A closely related system by Dredze et al. [2010] included finite-state transducers that had been trained to recognize common abbreviations, such as "J Miller" for "Jennifer Miller."

Zheng et al. [2010] also use a number of features that resemble those of McNamee [2010]. They evaluated several learning-to-rank systems, with ListNet yielding best results. Unfortunately their systems were developed, trained and tested on the same corpus, making it unclear whether their results are comparable to those of other systems evaluated in TAC-KBP 2009. A similar system [Zhang et al., 2010] made use of a synthetic corpus, with unambiguous occurrences of strings replaced by ambiguous synonyms. Manufactured training data was then combined with Wikipedia. Unfortunately, since the overall system was developed and evaluated on the same (2009) corpus, it may have been overfitted.

Han and Sun [2011] proposed a generative model with three components: popularities of entities, probabilities of strings lexicalizing an entity, and probabilities of entire documents given a seed entity, estimated from anchor data. They included a translation model, learning string-entity pairs from thousands of training examples. Although their results are highest for TAC-KBP 2009 published to date, they may be overstated, since some parameters were tuned using cross-validation over test data.

Recently, Hachey et al. [2012] reimplemented three well-known NED systems [Bunescu and Pasca, 2006, Cucerzan, 2007, Varma et al., 2009], combined them, and carefully analyzed the performance of candidate generation and disambiguation components for each. They studied contributions from a variety of available candidate sources, including titles (of articles, redirects and disambiguation pages) and link anchors, as well as two additional heuristics: bold in first paragraph and hatnote templates from popular entities to corresponding disambiguation pages.

None of the published NED systems, except Csomai and Mihalcea [2008], uses the context of anchors in Wikipedia to train a classifier for each mention, as we do. In fact, among other relevant systems which have been tested against data sets other than TAC-KBP, all use other kinds of techniques. Given that those other systems have been evaluated on other datasets, we will skip their description here. As mentioned in the introduction, most of the papers on NED describe complex systems with many components and data sources but few ablation studies that might help understand the contribution of each. In contrast, our system relies solely on static dictionary look-ups and supervised classification of mentions.

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9 Again, with the notable exception of work by Hachey et al. [2012], which we will discuss in detail (see Section 8.7).


3 System Architecture

Figure 6 summarizes our approach to NED, which is inspired by the word-expert technique, popular in mainstream WSD systems. We take a surface text form (mention), with the context of its occurrence, and determine an appropriate entity (meaning) to which the input string may refer. In this example, our system disambiguates the mention “Abbott” in the sentence “The voice was provided by Candy Candido, who briefly became Abbott’s partner after Costello had died.” First, a context-independent component (the dictionary) expands the string to a set of potentially-referent candidate entities, ordered by popularity; next, a context-sensitive component (supervised classifier) selects a candidate that seems most appropriate for the context.

The context-independent dictionary maps strings to ordered lists of possible Wikipedia titles; it also provides scores — which are indicative of conditional probabilities of each article given the string — that determine the ranking. This (untuned) component is constructed, primarily, using anchor-texts — of (internal) hyper-links between English Wikipedia articles and (external) web-links into the greater Wikipedia’s pages, covering many languages (see Section 4 for a detailed description of the dictionary and its variants). According to our dictionary, the most probable entity for the mention “Abbott” — ignoring context — is Abbott_Laboratories.

From the set of candidate Wikipedia titles, a classifier can select more appropriate entities, using not only the mention but also surrounding text, in the relevant document. This (optimized) component is trained on contexts around inter-Wikipedia links, i.e., pointers at entities mentioned in Wikipedia articles. We train a separate classifier for
every string: its job is to return the entity which best fits the shared mention’s con-
text (this and other variants of our supervised classifiers are described in Section 5). In
light of context, our system prefers the entity Bud_Abbott.

One could view these two components as performing (i) candidate generation, list-
ing all possible entities for a mention; and (ii) candidate selection [Hachey et al., 2012],
although our generation module also scores and ranks entities (by popularity). Follow-
ing the WSD convention, we will refer to these subsystems as (i) the dictionary; and
(ii) the disambiguation component.

4 The Dictionary

The dictionary is a cornerstone component of our system, serving two objectives. Its
primary goal is to provide a short list of candidate referent Wikipedia articles for any
string that could name an entity. In addition, it provides a score that quantifies the
string’s affinity for each candidate entity.

If the dictionary fails to recognize that a given string could refer to a particular
entity, then our system will not be able to return that entity. Thus, the dictionary intro-
duces a performance bottleneck. We will use this fact to measure an upper bound on
our system’s performance, by means of an oracle whose choices are restricted to just
the entities proposed by the dictionary.

The dictionary represents a set of weighted pairs — an exhaustive enumeration of
all possible string-entity combinations, with corresponding strengths of association.
We constructed this resource from all English Wikipedia pages (as of the March 6th,
2009 data dump) and many references to Wikipedia from the greater web (based on a
subset of a 2011 Google crawl). Individual string-entity co-occurrences were mined
from several sources:

- Article titles that name entities, e.g., “Robert Redford” from http://en.
wikipedia.org/wiki/Robert_Redford[10]. Many title strings had to be
  processed, e.g., separating trailing parentheticals, like “(athlete)” in Figure 2,
  and underscores, from names proper.

- Titles of pages that redirect to other Wikipedia pages, e.g., “Stanford” for the
  article Stanford_University redirected from the page Stanford.

- Titles of disambiguation pages that fan out to many similarly-named articles,
  e.g., linking “Stanford” to Stanford_University, Aaron_Stanford, or
  Stanford,_Bedfordshire among other possibilities, via Stanford_
  (disambiguation).

- Anchor text, e.g., we interpret the fact that Wikipedia editors linked the two
  strings “Charles Robert Redford” and “Robert Redford Jr.” to the article Robert

[10] In the remainder of this article, we will use the following conventions: “string” for a string that can
be used to name an entity (e.g., “Robert Redford”) and suffixes of English Wikipedia URLs, without the
prefix http://en.wikipedia.org/wiki/ as short-hand for corresponding articles (e.g., Robert
Redford).
Figure 7: A connected component of URLs that redirect to [Virginia State Route 758 (Lee County)], which itself does not redirect further and is therefore selected as the canonical article for the entire cluster.

Redford as a strong indication that both could refer to “Robert Redford.” We use the number of links connecting a particular string with a specific entity as a measure of the strength of association.

Note that our dictionary spans not just named entities but also many general topics for which there are Wikipedia articles. Further, it transcends Wikipedia by including anchors (i) from the greater web; and (ii) to Wikipedia pages that may not (yet) exist. For the purposes of NED, it could make sense to discard all but the articles that correspond to named entities. We keep everything, however, since not all articles have a known entity type, and because we would like to construct a resource that is generally useful for disambiguating concepts. Our dictionary can disambiguate mentions directly, simply by returning the highest-scoring entry for a given string. Next, we describe the method used to create several different variants of the dictionary.

4.1 Redirects and Canonical Pages

One of many hassles involved in building a Wikipedia-based dictionary stems from redirects, as it is important to separate articles that are actual entries in Wikipedia from other place-holder pages that redirect to them. We will use the term URL in this context to refer indiscriminately to any article page (redirect or not), e.g., both [http://en.wikipedia.org/wiki/Stanford] and [http://en.wikipedia.org/wiki/Stanford_University], where it is forwarded.

To collect all titles and URLs that refer to the same article, we first map all such strings to URLs using Wikipedia’s canonicalization algorithm.[11] We then connect any two URLs that either appear together as an official redirection (in a Wikipedia dump) or get redirected at crawl-time (via HTTP status codes 3xx). For each title and URL, we then extract a connected component, represented by a single canonical article, with preference given to (1) non-redirect pages from the Wikipedia dump; followed by (2) official redirect pages; and finally (3) pages that did not appear in any official dump.[12] Within each preference category, we resolved ties lexicographically. Figure 7 shows a simple example clustering of URLs, with a canonical article.

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[11] http://en.wikipedia.org/wiki/Wikipedia:Canonicalization
[12] This process can be particularly complicated when reconciling snapshots of Wikipedia taken at different times (i.e., an official dump and a web crawl), since sources and targets of redirects can switch roles over time, yielding cycles.
4.2 The Core and Other Dictionaries

We created a core dictionary by extracting strings from titles of canonical articles, redirects and disambiguation pages, as well as the referring anchor text encountered in both Wikipedia and the Google crawl. In all cases, we paired a string with the canonical article of the respective cluster.

Our core dictionary maps strings to sorted lists of Wikipedia articles, with associated scores. These scores are computed from the occurrence frequencies of the anchor texts. For a given string-article pair, where the string has been observed as the anchor-text of a total of $y$ inter-Wikipedia — and $v$ external — links, of which $x$ (and, respectively, $u$) pointed to a page that is represented by the canonical article in the pair, we set the pair’s score to be $\frac{x+u}{y+v}$.

We call this dictionary exact (EXCT), as it matches precisely the raw strings found using the methods outlined above. For example, Figure 8 shows all eight articles that have been referred to by the string “Hank Williams.” Note that this dictionary does no filtering: removal of undesired target Wikipedia pages (such as disambiguations) will be done at a later stage (see Section 4.3).

4.2.1 Aggregating String Variants

In addition to exact string lookups, we also adopt two less strict views of the core dictionary. They capture string variants whose lower-cased normalized forms are either the same (the LNRM dictionary) or close (the FUZZ dictionary) by Levenshtein edit-distance to that of the string being queried. In both cases, an incoming string now matches a set of keys (strings) in the dictionary, whose lists of scored articles are then merged, as follows: given $n$ articles, with scores $a_i/b_i$, their aggregate score is also a ratio, $\frac{\sum_{i=1}^{n} a_i}{\sum_{i=1}^{n} b_i}$.

We form the lower-cased normalized variant $l(s)$ of a string $s$ by canonicalizing Unicode characters, eliminating diacritics, lower-casing and discarding any resulting ASCII-range characters that are not alpha-numeric. If what remains is the empty string, then $s$ maps to no keys; otherwise, $s$ matches all keys $k$ such that $l(s) = l(k)$, with the exception of $k = s$, to exclude the original key (which is already covered by EXCT). Figure 9 shows a subset of the LNRM dictionary, with combined contributions from
strings $k$ that are similar to (but different from) $s$.

We define the FUZZ dictionary via a metric, $d(s, s')$: the byte-level UTF-8 Levenshtein edit-distance between strings $s$ and $s'$. If $l(s)$ is empty, then $s$ maps to no keys once again; otherwise, $s$ matches all keys $k$, whose $l(k)$ is also not empty, that minimize $d(l(s), l(k)) > 0$. This approach excludes not only $k = s$ but also $l(k) = l(s)$, already covered by LNRM. For example, for the string Hank Williams, there exist keys whose signature is exactly one byte away, including Tank Williams, Hanks Williams, hankwilliam, and so forth. Figure 10 shows the three articles — two of them already discovered by both EXCT and LNRM dictionaries — found via this fuzzy match.

4.2.2 Querying Search Engines

In addition to constructing our own custom dictionaries, we also experimented with emulating a lookup by (twice) querying the Google search engine, which we call the GOOG dictionary, on the fly. Our query pairs consisted of the raw target string, `<str>` — and also a separately-issued phrase-query, `<str>` — combined with a restriction, site:en.wikipedia.org. We kept only the returned URLs that begin with http://en.wikipedia.org/wiki/ using their (sums of) inverse ranks as scores. Although this method cannot be used effectively to find all strings that may name an entity, given any string, the dictionary portion for that specific string can be filled in dynamically, on demand.

4.3 Disambiguating with Dictionaries

For any input string, one could simply use a dictionary to select a highest-scoring entity. Our core dictionary’s scores already capture the popularity of each entity given a string, approximated by the frequency of their pairing in anchor texts. The Google dictionary may, in addition, reflect relatedness to the text of the corresponding Wikipedia
article, according to more sophisticated ranking algorithms. Such approaches would be closely related to the MFS heuristic in WSD and could also be viewed as context-free disambiguation, since they do not take into account the context of the mention, always returning the same article, regardless of the surrounding text.

A set of dictionaries, like ours, can be abstracted away behind a single dictionary interface, to be used by downstream components. Internally, dictionaries could be combined using a variety of strategies. We suggest a backoff approach that checks the dictionaries in order of precision, and also a heuristic that discards very unlikely candidates. Other strategies, such as using decision trees or a weighted combination of the dictionaries, are also possible. But many of these strategies would involve parameter tuning (e.g., learning the weights). A thorough exploration of more optimal techniques for combining dictionaries lies outside of the present paper’s scope.

Our first strategy is a cascade of dictionaries: for a given string, it provides a ranked list of entities by consulting the dictionaries in order of their precision. It starts from EXCT, which is most precise, backing off to the rest. We consider two specific cascades (in remaining sections, all references to the LNRM dictionary correspond to the LNRM cascade, and similarly for FUZZ):

- the LNRM cascade first checks the EXCT dictionary, returning its associated entities and scores if the string has an entry there, and defaulting to LNRM dictionary’s results if not;
- the FUZZ cascade also first checks the EXCT dictionary, backs off to the LNRM dictionary in case of a miss, but then finally defaults to the contents from the FUZZ dictionary.

Our second strategy is a heuristic combination (HEUR): it combines suggestions from the original (EXCT, LNRM, and FUZZ) dictionaries while also filtering out some of the noise. Its goal is to retain good suggestions without drowning in obviously bad choices: since many titles suggested by the FUZZ dictionary are noisy, we only include those for which there is additional evidence of relevance (for instance, if the suggestion is an acronym for the string). Similarly, if a string has been used to link to an article only a few times, the connection between them may not be reliable, calling for more evidence before the entity could be accepted as a possible referent for the string. Naturally, we also discard articles that are clearly not real entities — such as disambiguation pages, “list of” pages, and pages of dates — using additional features collected with the core dictionary. Table 1 summarizes our complete list of heuristics, which was finalized by consulting the news subset of the 2010 TAC-KBP development dataset (see Section 6.1).

Heuristic combinations can yield dictionaries that are considerably smaller than full cascades. For example, for the string ABC, the EXCT dictionary offers 191 options, the LNRM cascade 253, and the FUZZ cascade 3,527. But with the above-mentioned filters, the number of candidate Wikipedia titles can be reduced to just 110. Although our heuristics could be applied to any dictionary or cascade, in the remainder of the paper we will use the short-hand HEUR to refer to the larger FUZZ cascade, followed by the application of these heuristic filtering rules.

Inevitably, HEUR will sometimes discard a correct mapping in favor of inferior choices. For instance, the feasible suggestion Angela Dorothea Kasner → Angela_Merkel gets dropped, but the undesirable association Angela Merkel → German_
1. Discard disambiguation pages.
   Example: Discard: * → Hank_Williams_(disambiguation)

2. Discard date pages.
   Example: Discard: * → 2000

3. Discard list-of pages.
   Example: Discard: * → List_of_cheeses

4. Discard pages only suggested by FUZZ, unless:
   - string and title could be an acronym pair; Keep: NDMC → National_Defense_Medical_Center
   - string is a substring of the title; Keep: DeLorean_Motor → DeLorean_Motor_Company
   - string is very similar to the title. Keep: Chunghua_Telecom → Chunghwa_Telecom

5. Discard articles supported by few links, unless:
   - article may disambiguate the string; Keep: CNS → Szekler_National_Council
   - string is the title of the page. Keep: Chunghwa_Telecom → Chunghwa_Telecom

Table 1: Rules of the heuristic combination dictionary (HEUR).

[federal_election,_2005] is kept. Nevertheless, with a reduced set of candidates, it will be easier for supervised classifiers to narrow down remaining options based on a document’s context, down the road (see Section 5).

5 Supervised Disambiguation

The large number of naturally-occurring links pointing at entities in Wikipedia makes it possible to gather richly-annotated data automatically, to augment context-free disambiguation provided by the raw frequency information the dictionaries. In this respect, NED differs from many other applications in natural language processing and information retrieval, where most available input data is not already pre-labeled, and substantial resources are devoted to manual annotation efforts.

5.1 Core Method

We followed a mainstream WSD approach (word-expert), training supervised classifiers for all target strings, as follows: For every string in the dictionary, we first identify the entities to which it may refer. We then gather all example spans from Wikipedia articles that contain links to any of these entities. To ensure that our training data is natural language (and not, e.g., lists or tables), we only include text marked as paragraphs (i.e., enclosed between HTML tags <P> and </P>). The relevant training subset for a target string then consists of example contexts with anchor texts containing the string.

14I.e., either (a) the string is an acronym for the title; or (b) the title is an acronym for the string.
15I.e., either (a) the strings are the same; or (b) both strings have length less than or equal to six, with an edit distance exactly equal to one; or (c) the ratio between edit distance and string length is less than or equal to 0.1.
16I.e., if (a) the number of total links to the page (both inside Wikipedia and from the external web) is no more than ten; or (b) the number of times the string links to the page is no more than one; or (c) the score is no more than 0.001.
17The target string is a substring of the anchor text after case normalization.
On February 27, 2004, SuperFerry 14 was bombed by the Abu Sayyaf terrorists killing 116 people. It was considered as the worst terrorist attack...

Figure 11: Example training context and features extracted from Wikipedia’s article for SuperFerry.
We take spans of up to 100 tokens to the left — and another 100 to the right — of a link to be the contexts. Figure 11 shows one such sample training instance in detail.

Since the EXCT dictionary often provides too few examples, we used the LNRM cascade as our source dictionary (with remapped canonical articles — see Section 4.1). Given this training data, we applied standard machine learning techniques to perform supervised disambiguation of entities. We trained a multi-class classifier for each target string. Then, given a mention of the target string in the test data, we applied its classifier to the context of the mention, and returned the corresponding article. We did not construct classifiers for strings whose training data maps to a unique entity. Instead, in those cases, a default classifier falls back to LNRM cascade’s output.

From each context, we extracted features (see Figure 11) commonly used for supervised classification in the WSD setting [Agirre and Lopez de Lacalle, 2007, Zhong and Ng, 2010]:

- the anchor text;
- the unordered set of lemmas in the span;
- lemma for noun/verb/adjective in a four-token window around the anchor text;
- lemma/word for noun/verb/adjective before and after the anchor text;
- word/lemma/part-of-speech bigram and trigrams including the anchor text.

5.2 Variations

Over the course of developing our system, we tested several variations of the core algorithm:

**Classifier**: We tried maximum entropy models (MAXENT) and support vector machines (SVM).

**Dictionary**: A dictionary influences supervised classification in two places. First, when building the training data, to filter example spans selected for training. And second, as a backup ranker, for cases when a classifier is not trained, due to a lack of examples. In both the filtering stage and the back-off stage, we compared using the HEUR dictionary in place of the LNRM cascade.

**Span**: In addition to training with contexts of (up to) 100 tokens to the left and right of a string, we also tried single-sentence and full-paragraph spans (the 100, SENT and PARA variants).

**Match**: When gathering examples for a target string, we made sure that the anchor text contains this string (the LEX default). Alternatively, we could allow additional examples, ignoring anchor text mismatch (the SENSE variant): given the entities that a dictionary lists for the target string, we include as training examples all contexts that apply to these entities, regardless of their anchor text. In this variant, the target string is simply treated as another feature by the classifier. If a test example’s string does not match any of the anchor text seen in training, then features that include the target string (i.e., its unigram, bigram, and trigram features) will not fire. Classification will then depend on features describing the rest of the context: a classifier could still give a high score, but only if surrounding words of a span carry a strong enough signal for an entity. This approach may allow us to classify aliases for which there isn’t exact training data, provided that our filtering dictionary yields a precise list of potential entities corresponding to a target string.
Figure 12: Example of a KB person entity from the TAC-KBP dataset.

6 Datasets for NED

Evaluation of NED systems requires manually annotated data. Although many corpora have been introduced in various papers, we decided to focus on the earlier datasets developed for the entity linking task of the knowledge-base population (KBP) track at Text Analysis Conferences (TAC) which have been running annually each year since 2009 [McNamee and Dang, 2009, Ji et al., 2010, Ji and Grishman, 2011].

The TAC-KBP evaluation focuses on three main types of named entities: persons (PER), organizations (ORG) and geo-political entities (GPE). Given a set of hand-selected mentions of entities — and documents containing these strings — the task is to determine which knowledge-base instance, if any, corresponds to each named entity string. The knowledge-base (KB) is derived from a subset of Wikipedia. Mentions are chosen among occurrences in a collection of 1,286,609 newswire documents and 490,596 web-pages. The tasks’ organizers have released substantial amounts of development and test data, as well as standardized evaluation software.

There are several reasons why we chose to evaluate against TAC-KBP data: (i) it consists of named entity mentions from two genres (news articles and pages crawled off the web); (ii) it focuses on several taget entity mentions, making it well suited to our word-expert approach; and (iii) its high number of participating systems — and subsequent publications — provide an informative setting for comparing state-of-the-art techniques. Among TAC-KBP datasets, those from 2009 and 2010 attract the largest number of papers [Varma et al., 2009, McNamee, 2010, Lehmann et al., 2010, Zheng et al., 2010, Dredze et al., 2010, Zhang et al., 2010, Han and Sun, 2011, Ploch, 2011, Chen and Ji, 2011, Gottipati and Jiang, 2011, Hachey et al., 2012, Han and Sun, 2012]. In the future we would like to extend our work to other datasets which include all mentions in full documents [Hoffart et al., 2011].
6.1 The TAC-KBP Dataset

The TAC-KBP exercise provides an inventory of target named entities, based on a subset of Wikipedia articles that had info-boxes in October of 2008. This KB contains 818,741 entities (a.k.a. KB instances), each marked with (i) its name (a string); (ii) the assigned entity type (one of PER, ORG or GPE); (iii) a KB instance ID (a unique identifier, such as E001); (iv) the set of info-box slot names and values from the corresponding Wikipedia page; and (v) the text of that Wikipedia page. Figure 12 shows a sample KB entry for a person, whose entity derives from the Wikipedia article identified by the URL [Mike Quigley (footballer)].

Given a query that consists of a string and a document ID (see Figure 13), the task is to determine the knowledge-base entity to which that document’s string refers (or to establish that the entity is not present in the reference KB). The document provides context which may be useful in disambiguating the string. A referent entity will generally occur in multiple TAC-KBP queries, under different surface name variants and in different documents. Because of possible auto-correlations, official rules stipulate that queries must be processed independently of one another. As expected, some entities share confusable names (e.g., the string Stanford refers to a university, its town and founder, among many other possibilities). For each query, a system must return a KB ID (or NIL when there is no corresponding KB-instance). All of the queries had been tagged by a team of annotators. Inter-annotator agreement is high for organizations (ORG: 92.98%) and people (PER: 91.53%), and somewhat lower for remaining entities (GPE: 87.5%).

TAC-KBP has been running and releasing development and test data each year since 2009. It attracted 13 teams in the first year and 16 teams in 2010. We use the same data split as in the 2010 task. For the dev-set, all news examples come from the 2009 test-set, and web examples are exclusively from the 2010 training set; the 2010 test-set contains both types. Table 2 gives a break-down of our development and evaluation sets by the three entity types (PER, ORG, GPE). Note that news samples in the dev-set are especially skewed toward ORG, with approximately five times as many examples as either PER or GPE; the rest of the data is perfectly balanced.

Since the inventory of entities used in TAC-KBP is incomplete, it is possible for queries to refer to unlisted entities. In such cases, human annotators tagged the mentions as NILs. Note that the development and test datasets a large number of NIL mentions, 49% and 55%, respectively. We evaluate on non-NIL mentions.

18 http://www.nist.gov/tac/
Table 2: Number of examples in the development and evaluation datasets, broken down by genre and entity type. We explicitly mention the relation to the 2009 and 2010 TAC KBP datasets.

|                | Total | PER | ORG | GPE |
|----------------|-------|-----|-----|-----|
| Development    | 5,404 |     |     |     |
|                | 3,904 | 627 | 2,710 | 567 |
| Evaluation     | 2,250 | 1,127 | 3,210 | 1,067 |
|                | 1,500 | 500  | 500  | 500  |
|                | 1,500 |     |     |     |

Table 3: Ambiguity of target strings in the development and evaluation datasets, according to the gold standard.

|                | Unique Strings | No Entities (NILs) | Single Entity (Monosemous) | Multiple Entities (Polysemous) | Ambiguity |
|----------------|-----------------|--------------------|-----------------------------|-------------------------------|-----------|
| Development    | 1,162           | 462                | 488                         | 112                           | 2.34      |
| Evaluation     | 752             | 366                | 317                         | 69                            | 2.17      |

### 6.2 Ambiguity

Some simple measurements can give an idea as to the difficulty of a problem or dataset. In our case, one such quantity is a mention’s ambiguity: a lower bound on the number of different KB-instances to which its string can refer. In WSD, an equivalent notion would be the concept of polysemy. In our dictionary, for example, the string ICNC covers four distinct entities in Wikipedia.

We estimated ambiguity as follows: For each target string in a dataset, we counted the number of different KB-instances associated to it by human annotators. Table 3 reports ambiguities in both development and evaluation sets. The section of the development set, for instance, comprises 1,162 unique target strings (types). Of those, 462 were tagged with NIL, as no referent entity was deemed appropriate in the KB; 488 strings had all their mentions tagged with the same entity; and only 112 had been tagged with multiple KB-instances — an average of 2.34 entities per ambiguous string. Of course, this calculation grossly underestimates actual polysemy, as the number of potential articles to which a string could refer may far exceed those found in our collection by annotators. As mentioned in the previous section, populating a complete list of entities that could have been invoked is part of the task, and as such, still an open question. However, many target strings tend to be highly skewed, in the sense that they usually refer to one specific entity. This fact is reflected by the large number of strings which refer to a single entity in the gold standard sample.

We will show that actual polysemy is much higher (e.g., according to our dictionaries — see Section 6.4), since many of the possible entities do not appear in standard datasets. This fact further differentiates NED from typical WSD settings, where most senses can be found in a gold standard. Table 4 shows polysemy as average number...
Table 4: Ambiguity for Senseval-3 lexical sample (a popular WSD dataset), including all senses covered in the gold standard (GS), as well as any senses attested by the dictionary; note that all of the words are polysemous.

| Words (Polysemous) | Ambiguity GS | Ambiguity Dictionary |
|--------------------|-------------|----------------------|
| Nouns              | 20          | 5.05                 | 5.80                 |
| Verbs              | 32          | 4.56                 | 6.31                 |
| Adjectives         | 5           | 6.20                 | 10.20                |
| **Total**          | **57**      | **4.88**             | **6.47**             |

Table 5: Synonymy of target entities in the development and evaluation datasets, according to the gold standard.

| Development | Unique Entities | Single String (85%) | Multiple Strings (15%) | Average Synonymy |
|-------------|-----------------|----------------------|------------------------|------------------|
|             | 1,239           | 1,053                | 186                    | 2.49             |

| Evaluation  | Unique Entities | Single String (98%) | Multiple Strings (2%)  | Average Synonymy |
|-------------|-----------------|----------------------|------------------------|------------------|
|             | 871             | 853                  | 18                     | 2.06             |

6.3 Synonymy

Another quantity that sheds light on the complexity of a disambiguation task, in a manner that is complementary to ambiguity, is the number of different strings that can be used to name a particular entity: its synonymy, in WSD terms. As before, tallying all unique strings that may refer to a given entity is an open problem. Table 5 tabulates the gold standard’s synonymy (i.e., the number of strings found in the document collection by the annotators) for each entity in the KB. Most entities are associated with only a single string, especially in the evaluation sets. This could be an artifact of how the organizers constructed the test data, since their procedure was to first choose ambiguous strings and then find documents containing different meanings (entities) for these mentions — as opposed to first choosing entities and then querying string variants of names. The annotators thus did not search for alternative lexicalizations (synonyms) to be used as query strings. As was the case with ambiguity, actual synonymy is much higher (see Section 6.4, in which we compute similar figures to analyze some of the dictionaries used by our systems).

Table 6 shows average synonymy for a WSD dataset (Senseval-3 lexical sample). The gold standard contains 278 senses (for 57 target words), of which 85 have a unique lexicalization (and 193 have multiple), with 3.66 synonyms on average. Average synonymy in this WSD setting is slightly higher than that of TAC-KBP’s gold standard, similarly to polysemy (though Section 6.4 will show that, in practice, synonymy for
Table 6: Synonymy for Senseval-3 *lexical sample*, as attested by the gold standard.

| Unique Synsets | Single string | Multiple Strings | Average Synonymy |
|----------------|--------------|------------------|------------------|
| Nouns          | 101          | 30               | 71               | 3.34             |
| Verbs          | 146          | 39               | 107              | 3.84             |
| Adjectives     | 31           | 16               | 15               | 3.87             |
| Total          | 278          | 85               | 193              | 3.66             |

Table 7: Ambiguity, according to dictionaries, of target strings in the development dataset: top six rows show figures for the LNRM and HEUR dictionaries; last two rows focus on HEUR only, after discarding entities that lack training examples, according to the LEX and SENSE methods (see Section 5).

| Unique Strings | No Entities | Single Entity | Multiple Entities |
|----------------|-------------|---------------|-------------------|
| LNRM           | 1,162       | 111           | 331               | 765               | 86.14           |
| HEUR           | 1,162       | 94            | 331               | 737               | 22.26           |
| LEX + HEUR     | 1,162       | 193           | 372               | 597               | 15.44           |
| SENSE + HEUR   | 1,162       | 136           | 344               | 682               | 19.01           |

NED can be much higher, according to a dictionary.

To summarize, the number of cases where annotators could not assign an entity (NILs) is significantly higher in NED than in WSD (around 50% compared to just 1.7%). And ambiguity and synonymy, according to gold standards, are substantially lower than in WSD (with average ambiguities of around 2 vs. 5, and average polysemies of 2 vs. 4). These statistics are misleading, however, since TAC-KBP's actual ambiguity and synonymy are more extreme, according to our dictionaries (discussed in Section 6.4). Finally, inter-annotator agreement for TAC-KBP is higher — ranging between 87% and 93%, depending on the entity type — compared to 72% in WSD.

### 6.4 Ambiguity and Synonymy in Dictionaries

We now consider polysemy and synonymy in our dictionaries. Table 7 reports ambiguities for the LNRM and HEUR dictionaries on development data. For instance, the dev-set comprises 1,162 target strings, of which LNRM has no suggestions for 111 (94 with HEUR). Among the remaining strings, 331 yield a unique suggestion from Wikipedia (331 with HEUR). The average ambiguity for the 765 strings with multiple candidates is 86.14 (only 22.26 with HEUR). The distribution of the ambiguity between news and web datasets is distinct, 50.90 and 103.24, respectively. Thus, HEUR covers more strings and has fewer monosemous entries yet lower polysemy than LNRM. Thus, HEUR retains more references from Wikipedia and simultaneously substantially reduces ambiguity. Although we don’t tabulate figures for other dictionaries, we note here that FUZZ has even higher polysemy than LNRM. The two lower rows in the the table also shows ambiguities faced by our supervised classifiers,
Table 8: Synonymy of target entities in the development dataset for the EXCT dictionary, with and without filtering heuristics; since some of these entities are not in Wikipedia, they cannot be suggested by our dictionaries.

|        | Unique Entities | No Strings | Single String | Multiple Strings | Average Synonymy |
|--------|-----------------|------------|---------------|------------------|------------------|
| EXCT   | 1,239           | 279 (23%)  | 0             | 960 (77%)        | 210.38           |
| EXCT-HEUR | 1,239       | 296 (24%)  | 0             | 943 (76%)        | 46.37            |

Table 9: Synonymy for Senseval-3 lexical sample, as attested by the dictionary.

|         | Unique Synsets | Single String | Multiple Strings | Average Synonymy |
|---------|----------------|---------------|------------------|------------------|
| Nouns   | 114            | 34            | 80               | 3.35             |
| Verbs   | 202            | 58            | 144              | 3.76             |
| Adjectives | 53         | 30            | 23               | 4.04             |
| Total   | 369            | 122           | 247              | 3.66             |

which discard dictionary suggestions for which there is no training data (e.g., entities that do not occur as targets of an anchor link — see Section 5). The lower half of the table focuses on the HEUR dictionary in combination with the LEX and SENSE strategies for gathering training instances. As expected, resulting ambiguities are lower than for full dictionaries, with more cases of zero or one candidates and fewer strings mapping to multiple entities (also with lower ambiguities); the decrease is smaller for the more conservative filtering strategy (SENSE), which is again consistent with our expectations.

Ambiguity in dictionaries is much higher than according to the gold standard (compare to Table 3). This comes as no surprise, since the gold standard severely underestimates true ambiguity by focusing exclusively on entities that are mentioned in a target dataset. Since many target strings can, in fact, refer to dozens of possible external entities, our estimates of ambiguity are also much higher than in WSD settings (see Table 4). In contrast to WSD, NED’s true ambiguity usually remains unknown, as its determination would require a laborious inspection of all strings and entities, and an exhaustive search for examples of usage in actual text. Although our dictionaries have good quality and come close to covering all entities in the gold standard (see Section 8.6), a manual inspection showed that they also contain incorrect entries. Therefore, we suspect that actual ambiguity maybe be slightly lower than our estimate obtained with the HEUR dictionary.

Table 8 shows synonymy figures for both the raw EXCT dictionary and also after applying heuristic rules (EXCT-HEUR). Entities corresponding to NILs were not covered by the dictionary (tallied under the No Strings heading), and all of the remaining entities were lexicalized by a large number of strings (none by just one). The EXCT dictionary had, on average, 210 strings, which is reduced to 46 with heuristics. Although high estimates reflect the comprehensive coverage afforded by our dictionaries, they do not reveal true levels of synonymy, which would require hand-checking all en-
tries, as before. Nevertheless, these figures illustrate, at a high level, another important difference between NED and WSD, where synonymy tends to be much lower (e.g., around 3.5, according to one popular dictionary — see Table 9). Extending the table to include LNRM and FUZZ dictionaries would require performing more complicated calculations, but the resulting synonymy estimates would only be higher for these omitted cascades.

7 A NED System for TAC-KBP

Evaluating our system on the TAC-KBP exercise required several adaptations. Figure 14 shows the updated architecture. In it, a new module looks up top-ranked articles in the KB. If a top-scorer has a corresponding entry in the KB, the module returns its KB ID. Since all KB-instances came from Wikipedia, there is a direct mapping from titles to KB IDs. To guarantee matches, we altered our dictionary construction process slightly, making sure to include all Wikipedia titles explicitly referenced by the official KB (see Figure 12). When deciding which pages are canonical (see Section 4.1), we preferred entries listed in the KB over all others (from a superset of Wikipedia data that included the TAC-KBP dump of October 2008).
Table 10: Performance of dictionaries on the news subset of the development dataset — as micro-averages — for two individual dictionaries (EXCT and GOOG), the two dictionary cascades (LNRM and FUZZ) and our heuristic dictionary (HEUR). For LNRM, we show also results with partitions of counts (i.e., just the popularity within Wikipedia versus on the rest of the web).

|          | Wikipedia counts only | web counts only |
|----------|-----------------------|-----------------|
| EXCT     | 0.6937                |                 |
| LNRM     | 0.6949                | 0.6513          |
| FUZZ     | 0.7134                | 0.6758          |
| HEUR     | 0.7212                |                 |
| GOOG     | 0.6955                |                 |

8 Experimental Results and Performance Analyses

We now evaluate different variants of dictionaries and supervised classifiers on development data. These experiments allow us to tune settings, to be used with the blind test set (see Section 8.7).

8.1 Evaluation Setup for TAC-KBP

We follow a standard evaluation procedure, using scripts from the 2009–10 TAC-KBP exercise. The metric is (micro-averaged) accuracy: given a reference set with $N$ queries — and a corresponding set of guesses, where $C$ are correctly disambiguated (i.e., a system’s output label equals the gold standard’s entity ID string) — the score is simply $C/N$. Since our main goal is to disambiguate among entities, we will focus on evaluation of the dictionaries and supervised classifiers restricted to entities present in the KB (i.e., ignoring gold standard examples tagged with NILs).

8.2 Performance of Top Dictionary Entries

Table 10 shows performance on the news subset of development data for the EXCT and GOOG dictionaries (69.4 and 69.6%), the LNMR and FUZZ cascades (69.5 and 71.3%), and the heuristic combination, HEUR (72.1%). It confirms our intuition (see Section 4): HEUR improves over the FUZZ cascade, offering cleaner suggestions (since it yields many fewer candidates). Results from GOOG are competitive with cascades and may be a good alternative in situations when full dictionaries are unavailable. The table also shows that using counts from Wikipedia alone is worse than relying on counts from the rest of the web — and that merging the two sets of counts (see Section 4) works best — for the LNRM cascade; we use merged counts in all remaining experiments. Hovering at 70%, MFS heuristics have higher accuracies here than even in typical WSD settings, where they are known to be strong (e.g., around 19%)

19However, this may require querying the search engine just-in-time, using Google’s API, with consequent limitations.
Figure 15: Precision and recall @k curves for a random subset of the news development dataset (without NILs).

55% — see Section 2.2, which shows that choosing most popular entries makes for powerful methods in NED as well.

### 8.3 Precision/Recall Curves for Dictionaries

Although performance of top candidates is indicative of a dictionary’s overall quality, it tells us little about the less popular choices. We use dictionaries to expand queries into pools of possible candidates, to be disambiguated by a supervised system. Therefore, it is important to understand how close a dictionary might come to capturing all — even low-ranking — entities that may be relevant to a gold standard. Figure 15 shows precision/recall curves that evaluate our dictionaries beyond just top-ranking entries (the left-most points of each curve, corresponding to Table 10).

These curves show that the FUZZ cascade generates more entities than other dictionaries, with higher recall at similar levels of precision; unfortunately it draws on far too many candidates. The LNRM and EXCT dictionaries perform similarly at all recall levels; HEUR performs better at high precision, slightly better at high recall, and worse in-between. The GOOG dictionary performs worse everywhere except at the highest recall, where it dominates (at close to 99%); its generally-low performance indicates that although GOOG manages to generate candidates for nearly all strings, its ranking function is less-well suited to the NED task than are our methods.

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20 Precision is the number of correct entities divided by the total number of entities returned; recall is the number of correct entities divided by the total number of gold standard entities. The P/R curve is obtained taking the top K candidates with highest probability.
Table 11: Performance of the supervised classifier on the *news* subset of development data, as micro-averages, for our default supervised classifier (top row) and several variants, each of which differs from the default in exactly one parameter setting, with the rest indicated by dashes (-).

### 8.4 Performance of Supervised Classifiers

Table 11 shows performance on the *news* subset of development data for several variants of our supervised classifier (described in Section 5). The first row corresponds to default parameters; the rest represent a greedy exploration of the space of alternatives. Each additional row specifies a setting that differs from the first row; dashes (-) indicate that all other parameters are the same.

**Classifier**: The second and third rows correspond to the accuracies of a multi-class classifier, based on SVMmulticlass [Tsochantaridis et al., 2004], and a one-versus-all approach, using SVMlight binary classifiers [Joachims, 1999]. Both alternatives perform worse than our default classification algorithm (maximum entropy with $\ell_2$-regularization), MAXENT [Manning and Klein, 2003]. We did not tune any of the available parameters, since we were interested in out-of-the-box performance of all methods (for SVMs, we used a linear kernel with a cost of 0.01).

**Dictionary**: The fourth row shows that the LNRM cascade generates worse training examples than our default dictionary combination, HEUR. We do not show results for other dictionaries, which yield too many candidates (without improving precision). The fifth row shows that HEUR also performs better than LNRM when used as a back-off dictionary, improving over the default.

**Span**: Rows six and seven show that supervised classification performs equally well using either sentences or paragraphs (but that the best results are obtained using left and right 100 tokens). One reason for similar performance is that most paragraphs are not marked correctly, in Wikipedia, often comprising a single sentence. A fixed span of tokens to each side of a mention may extend beyond sentence boundaries, providing more context to help with disambiguation.

**Match**: The last row shows that using all examples that refer to an entity (SENSE) improves over the default approach, which uses only a subset of examples that contain the target string (LEX).
8.5 Extending Analyses to Web Data

The best results for the news portion of the development data were obtained with the MAXENT classifier, the HEUR dictionary for both filtering training examples and backing off, 100-token spans, and the SENSE match strategy. On web data, our dictionary and supervised components yield somewhat different results, most of them congruent with conclusions based on news data.

Table 12 shows a subset of the variants with qualitatively different outcomes. For instance, the LNRM dictionary, our default for back-off, is the better option with web data. As for plain dictionary look-ups, HEUR is still the best overall choice, although GOOG performs slightly better on web data. This disparity may stem from search engines being developed primarily with web-pages in mind, whereas our heuristics came about from analyzing examples of news articles in the development set: LNRM may be the more robust back-off dictionary for similar reasons. Furthermore, our classifiers fall through to a back-off dictionary only when there aren’t enough training instances, which tends to be the case for rare entities. Since LNRM has higher recall than HEUR, it may be generally more useful for obscure references. Overall, performance differences between dictionaries are smaller for web data, and average accuracies are substantially higher than with the news portion. Evaluated against the combined news+web development data, ranks of dictionaries remain the same as for news alone.

All variations of the supervised system with good performance on news worked better still for web data, scoring well above the dictionaries. The reduction in error going from news to web is remarkable, with accuracies well over 90%. Manual inspection showed that mentions in web data are more heavily skewed towards most popular entities, compared to news data, which may explain the much higher accuracies of both supervised classifiers and the underlying dictionaries. In fact, web data referenced, for the most part, extremely well-known entities (e.g., European Union), along with some that are relatively unknown (e.g., CCC — the Cincinnati Cycle Club). Entities in news data, on the other hand, tended to be of substantially more ambiguous nature.

The second (and final) variant that does better on news but did not pan out with web data is the SENSE strategy for gathering training instances. Although it has higher coverage (see Section 6.4), additional matches tend to be less precise, as these examples aren’t required to contain the target string. Since preliminary results indicate that relative performance is sensitive to the type of data, we decided to stick with the simpler, more conservative strategy, LEX. We conclude that our default settings may already be optimal for unseen data, and will thus evaluate this set-up against the TAC-KBP 2010 test data, to compare our system with the state-of-the-art.

8.6 Upper Bounds for Supervised Classification with Our Dictionaries

An important function of the filtering dictionary is to provide sets of plausible entities, which determine construction of (distantly) supervised training data. Given an ideal...
classifier, we would prefer to use comprehensive dictionaries that might contain the correct entity for all strings in the evaluation set, even if that meant dragging in many incorrect candidates too. Table 14 shows the skyline results that could be attained by an oracle, choosing the best possible entity available to each system. For LNRM and HEUR cascades, gold standard entities are among the dictionaries’ suggestions about 92% of the time (98% for web data). Supervised classification with the LEX strategy lowers these bounds slightly, because in some cases there are no training examples available for the gold entity, which precludes our classifiers from returning the correct result; by expanding the pool of training instances, the SENSE strategy restores this bound to nearly what it was for HEUR. Naturally, higher bounds aren’t necessarily superior: for example, FUZZ yields the overall largest number of possibilities, but has lower realized performance than HEUR.
Table 14: Performance on the 2010 test data, for our best dictionary and supervised classifier, broken down also for the news and web subsets.

| System                      | news   | web   | full  |
|-----------------------------|--------|-------|-------|
| HEUR dictionary             | 0.6984 | 0.8149| 0.7490|
| SUPERVISED (LEX+HEUR)       | 0.8125 | 0.8668| 0.8448|

Table 15: The state-of-the-art for 2009/2010 TAC-KBP test data, including performance of our dictionary (HEUR) and classifier (SUPERVISED); results from non-blind evaluation set-ups (see Section 2.5) are starred (*).

| System                      | KB-only |
|-----------------------------|---------|
| [Dredze et al., 2010]       | 0.7063  |
| [Hachey et al., 2012]       | *0.723  |
| [Varma et al., 2009]        | 0.7654  |
| [Zhang et al., 2010]        | *0.792  |
| [Han and Sun, 2011]         | *0.79   |
| [Guo et al., 2011]          | 0.74    |
| [Varma et al., 2009]        | Best submission to TAC 2009. |
| [Zhang et al., 2010]        | *0.792  |
| [Han and Sun, 2011]         | *0.79   |
| [Guo et al., 2011]          | 0.74    |
| [Varma et al., 2009]        | Best system at TAC 2010. |
| [Hachey et al., 2012]       | *0.784  |
| [Lehmann et al., 2010]      | 0.8059  |
| [Lehmann et al., 2010]      | *0.7490 |
| SUPERVISED (LEX+HEUR)       | 0.8448  |

8.7 Final Results and Comparison to the State-of-the-Art

Following the development phase, we tested our best dictionary and supervised classifier on the hidden (2010 test) dataset. Table [14] shows both results, also broken down by data type. This final evaluation confirmed that the heuristic dictionary already performs quite well (at 75%) overall, and that trained classifiers can tap into further improvements (scoring close to 85%). The improvement is larger on news, which is again more challenging than the web dataset. The results are similar to those of development, except for web, where results have dropped around 5 points.

Table [15] shows performance of recent NED systems that report results for either of the 2009/2010 TAC-KBP test sets (see Section 2 for their descriptions), including our dictionary and classifier.

The dictionary performs well on the KB-only subset of the 2009 test set, beating some of the more complex systems. Since we used the 2009 data to choose bests of several system variants, evaluation on this test set is not blind and may overstate our results, as well as those of many other published systems that did the same. [Zhang]
et al., 2010; Han and Sun, 2011; Hachey et al., 2012; our supervised classifier scores 77% on the KB-only subset, behind two systems [Zhang et al., 2010; Han and Sun, 2011] scoring 79%, both of which were also developed using 2009 test data.

For the 2010 test data, our evaluation was completely blind. Here the dictionary performs better than the next best “no context” system [McNamee, 2010] by a large margin: 75% vs. 65%. The supervised classifier also scores highest — 85% vs. 81% for the next best system [Lehmann et al., 2010]. The entry for [Hachey et al., 2012] represents the best of several systems chosen on the test set; their best variant according to development data was, in fact, the system of [Varma et al., 2009], which scores 7% lower.\(^2\)

9 Discussion

We have shown that it is possible to construct an effective dictionary for NED, covering between 92% and 98% of the manually annotated string-entity pairs (for development data). Although the ambiguity in such dictionaries varies, it tends to be higher than for the gold standard in NED and also for a typical WSD dataset. Since a similar phenomenon is also observed with synonymy, one might expect NED to pose a more difficult problem than WSD; nevertheless, we observed the opposite effect in practice. Our popularity-based dictionary heuristic performs even more strongly than the MFS baseline in WSD (75% in our blind NED evaluation, compared to 55%); supervised system variants also score much higher (84% vs. 73%). Of course, comparing evaluation numbers across tasks requires extreme caution. Nonetheless, we suspect that qualitatively large differences in performance here indicate that NED has larger numbers of training data, compared to WSD.

High ambiguity and synonymy, together with the large volumes of text data, make NED computationally more demanding than WSD, both in the scope of regular memory and disk storage capacities, as well as speed and efficient processing requirements. Our approach in particular could invoke training of potentially millions of classifiers, requiring significant engineering effort. But since each classifier can be trained independently, parallelization is simple and easy.

We found that more comprehensive dictionaries that provide better coverage aren’t always optimal when it comes to training supervised classifiers, since it is also important to have enough examples for each candidate entity being suggested. Instead, a dictionary that contains the most precise and common choices may work better, as demonstrated by our cascades of dictionaries.

All in all, our systems fare well, compared to the state-of-the-art. The dictionary beats all systems not using context in the 2010 TAC-KBP task by a large margin. And the supervised system, despite its simplicity, outperforms other systems as well. More detailed comparisons are difficult, because many recent papers lack ablative analyses: even when performance of individual components is reported, interactions with NILs

\(^2\)Note that, since [Hachey et al., 2012] reimplemented three well-known systems [Bunescu and Pasca, 2006; Cucerzan, 2007; Varma et al., 2009], our results also compare favorably to the other two.
As mentioned previously, our dictionaries could be expanded by drawing on additional sources of data. This fact should not be overlooked, since Hachey et al. [2012] found that candidate generation accounted for most of the performance variation in the systems that they reimplemented; in particular, acronym handling, using coreference resolution to find longer mentions, led to substantial improvements. We could augment our dictionaries via various techniques for mining acronyms [Varma et al. 2009, McNamee 2010, Lehmann et al. 2010], metaphones [Varma et al. 2009], as well as bolded words in first paragraphs and hatnote templates [Hachey et al. 2012]. Moving beyond the static dictionary model, it is also possible to exploit dynamic methods for proposing candidates. Online techniques can make use of partial matches between tokens in query strings and entities [Varma et al. 2009, McNamee 2010, Lehmann et al. 2010], finite-state transducers [Dredze et al. 2010], matches with longer mentions [Lehmann et al. 2010], automatic spelling correction [Zheng et al. 2010], Wikipedia search engines and the “Did you mean...” functionality [Zhang et al. 2010]. Storing as much information as possible in static dictionaries will make it easier to debug, replicate and share resources. But some dynamic lookups could also be batched to enrich a dictionary just-in-time. A thorough study of the overlap and contribution of various enhanced candidate generation methods may make for a fruitful research direction.

With respect to disambiguation, our approach closely followed that of typical supervised WSD systems, which train a classifier for each target string. We used anchor texts in Wikipedia articles to train logistic regressions, showing that this method is also appropriate and computationally feasible for NED. Given their popularity in WSD research, we expected straightforward classification techniques to be more prevalent in NED, at least as baselines. Methods such as ours may also prove to be useful in combination with other disambiguation systems which tap on different knowledge sources, e.g., those using the hyperlink structure [Milne and Witten 2008, Moro et al. 2014].

In summary, our NED system can be easily replicated because it uses an offline dictionary. Its simplicity allows for a clearer understanding and ablative analyses, compared with systems that rely on dynamic candidate generation methods. As a result, it may make a good platform for testing and incorporating various modular extensions to NED, such as NIL classifiers, candidate generators, similarity-based techniques, global coherence or coreference resolution. We designed the system to work with the entire space of Wikipedia articles and strings: no thresholds or other kinds of parameters were fine-tuned to the test data. Given the limited number, scope and complexity of decisions made even in development, we expect our system to be robust. Naturally,

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23 E.g., Han and Sun [2011] report end-to-end performance of their popularity and name model (roughly equivalent to our dictionary), combined with a NIL detection system, excluding KB- or NIL-only results. Their score on the 2009 test set is far below ours (50% vs. 72%), but it is not possible to identify the main reason behind this discrepancy.

24 An exception, Hachey et al. [2012] provide precision and recall of their candidate generation component for KB queries (56.3 and 87.8, respectively) on the 2009 test data (the news subset of our development set), which can be compared to oracle and realized performance of HEUR (91.88 and 72.12); they also report an ambiguity of 7.2, obtained by dividing the number of candidate entities by the total number of query strings (our corresponding figure for HEUR would be 9.08, if calculated in the same fashion, i.e., differently from the numbers listed in Table 3).
performance could be further optimized to fit a target corpus or genre, if desired.

10 Conclusions and Future Work

We presented a system for NED based on word-experts, which is a well-understood technique from the WSD literature. Our system comprises two components: (1) a context-independent module, based on frequencies of entities, which returns most popular candidates; and (2) a context-sensitive classifier for each named-entity string that selects entities that are best suited to a mention’s surrounding text. We show that such a word-expert provides results which are competitive to the state-of-the-art, as measured on the 2009 and 2010 TAC datasets.

In the future we would like to extend our work to other datasets, which will provide further points of comparison to the state of the art. We would also like to include our classifiers in more complex NED systems, where complementary information like link structure [Moro et al., 2014], similarities between article texts and mention contexts [Hoffart et al., 2012], as well as global optimization techniques [Ratinov et al., 2011] could further improve the results.

We highlighted many connections between WSD and NED. In WSD settings, dictionaries are provided, but NED involves constructing possible mappings from strings to entities — a step that Hachey et al. [2012] showed to be key to success, which we also confirmed experimentally. The resulting dictionaries exhibit very high synonymy and ambiguity (polysemy) yet still do not cover many occurrences that ought to be tagged by a NED system, making the task appear more difficult, in theory, compared to WSD. But in practice, the opposite seems to be the case, due to actual mentions being more heavily skewed towards popular entities than in WSD, a plethora of available training data in the form of human-entered anchor-texts of hyperlinks on the web, and higher inter-annotator agreement, which indicates more crisp differences between possible shades of meanings than in WSD. As a result, both popularity-based dictionary lookups (MFS heuristics) and supervised classifiers, which are traditional WSD architectures, perform better for NED than for WSD. In the future, we would like to extend our study using datasets which include all mentions in full documents [Hoffart et al., 2011].

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