Pocket Knowledge Base Population

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Abstract
Existing Knowledge Base Population methods extract relations from a closed relational schema with limited coverage, leading to sparse KBs. We propose Pocket Knowledge Base Population (PKBP), the task of dynamically constructing a KB of entities related to a query and finding the best characterization of relationships between entities. We describe novel Open Information Extraction methods which leverage the PKB to find informative trigger words. We evaluate using existing KBP shared-task data as well as new annotations collected for this work. Our methods produce high quality KBs from just text with many more entities and relationships than existing KBP systems.

1 Introduction
Much of human knowledge is contained in text in books, encyclopedias, the internet, and written communications. Building knowledge bases to store, search, and reason over this information is an important problem in natural language understanding. A lot of work in knowledge base population (KBP) has focused on the NIST Text Analysis Conference track of the same name, and specifically the slot filling task. Slot Filling (SF) defines a relational schema similar to Wikipedia infoboxes. SF KBP systems extract facts from text corresponding to an entity called the query.

This work addresses two issues concerning SF KBP. First, the SF schema has strict semantics for the relations which can be extracted, and thus no SF relation can be extracted for most related entities, leading to sparse KBs. Second, because SF has a small static schema, most research has focused on batch processing for a single schema, limiting downstream usefulness. This means KBs built by slot filling have limited applicability in some real world settings of interest.

We address these issues by proposing Pocket Knowledge Base Population. Pocket KBs (PKBs) are dense entity-centric KBs dynamically constructed for a query. In both SF and pocket KBP, a query is an entity of interest and a document mentioning that entity. However, in PKB the primary goal is to populate the KB with nodes for all entities related to the query, irrespective of any prior beliefs about relations. PKB edges store representations of mentions referring to the entities connected by that edge, and thus may better serve downstream tasks which don’t perfectly align to a particular schema.

We describe a PKBP system which builds KBs from text corpora. This includes unsupervised methods for finding related entities and mentions of them and the query with accuracies of 89.5 and 93.1 respectively when evaluated on SF queries. We also propose novel entity-centric Open IE (Banko et al., 2007) methods for characterizing the relationship between entities which perform twice as well as a syntactically-informed baseline. Our contributions also include a comparison between pocket and SF KBs constructed on SF queries, showing our KBs are multiple times larger while remaining high quality. We make our system publicly available.¹

2 Pocket Knowledge Base Population
The defining characteristic of pocket KBs is they are small, entity-centric, and dynamically generated according to a query. Most work in KBP is centered around batch processing with a relation extractor, whereas PKBP is based on entity men-

¹https://hub.docker.com/r/hltcoe/pocket-knowledge-base-population
tion search and ad-hoc trigger extraction. PKBs resemble a hub and spoke graph where the hub is the query and nodes on the outside are related entities. The spokes represent mentions proving that an entity is related to the query. Traversing this graph by crossing a spoke is akin to building a new PKB with that related entity as the new hub.

PKBs are aids for “knowledge-based” search over a document collection. KBs are useful for question answering (Yao, 2014) and PKBs serve this goal because related entities are good answer candidates for questions about a query. SF KBs are specialized to the case where you know the questions ahead of time, like “Where does Mary work?” and “Who is ACME’s parent company?”. PKBs are aids for “knowledge-based” search over a document collection. KBs are useful for question answering (Yao, 2014) and PKBs serve this goal because related entities are good answer candidates for questions about a query.

Next, we use context features: a word unigram tf-idf vector. We implement a compromise between Cucerzan (2007) (used sentences before, after, and containing a mention) and Bagga and Baldwin (1998) (used any sentence in a coreference chain). Instead of running a coreference resolver, we use the high-precision heuristic of linking mentions with the same headword and NER type. Terms are weighted as \(\frac{2}{1+d}\) where \(d\) is the distance in sentences to the nearest mention.

Our attribute features are a generalization of Mann and Yarowsky (2003). They train a few ad-hoc relation extractors like birth year and occupation from seed facts. Their extractions provide high-precision signal for merging entity mentions. We found extracting all NNP stars or capitalized JJ stars within 4 edges in a dependency tree was less sparse, requires no seeds, and produced similar quality attributes. We union these attributes across mentions found by the headword and NER type coreference heuristic to build a fine-grain tf-idf vector. We use the same \(\frac{2}{1+d}\) re-weighting for attributes, except where \(d\) is the distance in dependency edges to the entity mention head. The closest attributes are descriptors within a noun phrase like HEAD-nn-Dr... We include the NER type of the headword to distinguish between attributes like PERSON-nn-American and ORGANIZATION-nn-American.

Given the triage features \(t(m)\), context features \(c(m)\), and attribute features \(a(m)\), we search for mentions \(m\) which maximize

\[
(1 + \alpha_t \cos \theta_t)(1 + \alpha_c \cos \theta_c)(1 + \alpha_a \theta_a)
\]

where \(\cos \theta_t\) is the cosine similarity between
We only consider the subset of mentions that have \( \cos \theta_t > 0 \), which can be efficiently retrieved via an inverted index.

Any mention with a score higher than \( \tau \) is considered coreferent with the query. We extract mentions in the same sentences as the query as candidate related entities if they have an NER type of PER, ORG, or LOC. We link candidate mentions against entities in the PKB using the same coreference score used to retrieve query mentions. If a candidate’s best link has a score \( s < \tau \), we promote it to an entity and add it to the PKB with probability \( 1 - \frac{s}{\tau} \). \(^2\)

### 3.2 Joint Linking of Related Entities

At this point, there are on the order of 100 mentions of the query and 20 to 50 related entities.\(^3\) For each entity, we perform a joint search for it and the query. These entity co-occurrences will form the spokes in the PKB and be used to characterize the relationship between and relatedness to the query.

Joint entity searches are similar to single-mention searches in §3.1 with two differences. First, instead of having a single mention to compute feature vectors from, there are multiple. Feature vectors for entities are built up from mentions, where the weight of a mention \( w(m) = \rho^b \) for \( \rho \in (0, 1) \) and \( b \) is how many mentions were linked before \( m \). Second, we are scoring mention pairs (with both mentions in the same sentence) as the geometric mean of the coreference scores of both links. The coreference score function does not need to change, but the triage step does: we only consider sentences which have \( \cos \theta_t > 0 \) for both the query and the related entity and use the same \( \tau \). Entity relatedness is a function of how often entities are mentioned together. We modeled it as the sum of the joint entity linking probabilities, where the probability of a link is \( \log^{-1}(\frac{z}{\tau}) \).

### 3.3 Trigger Word Analysis

At this stage, we have found on the order of 2 to 20 sentences which mention the query and a related entity which will be used to determine the relationship between them. There is work on rule-based (Banko et al., 2007; Fader et al., 2011; Angeli et al., 2015), supervised (Mausam et al., 2012), and distantly-supervised (Mintz et al., 2009) methods for characterizing relations in text. Our method is similar to distant supervision, where a KB of known facts is used to infer how relations are expressed, but we use supervision from the KB being constructed. We cast the problem of characterizing a relation as a search for trigger words. We state our priors on trigger words and condition on the data to find likely triggers.

**Predicate (triggers) and arguments are syntactically close together.** Assuming the related entity mention heads are arguments, we compute the probability that these two random walks in a dependency tree end up at the same token. This serves as a weak syntactically informed prior.

**Information is conveyed as a surprisal under a background distribution (codebook).** We compute a unigram distribution over words which are likely under our syntactic prior for triggers (conditioned on the NER type of the two arguments). We use this marginal distribution as a codebook. We divide out this codebook probability in every pair of related entity mentions in the PKB giving a cost in bits (log probability ratio) of each trigger word.

**Repetition indicates importance.** We sum the costs for each trigger across sentences. We weaken this assumption by averaging the max and the sum for each trigger for the final score.

This process yields a score for every trigger word, and we use the top \( k \) triggers to characterize the relationship between entities. For each trigger we keep, we also maintain provenance information for mentions using a given trigger.

### 4 Experiments

We use the TAC SF13 query entities to evaluate our methods; 50 person and 50 organization entities are used as queries to construct 100 PKBs. 70 of the 100 query entities were NIL (26/60 PER and 44/50 ORG), meaning that they do not appear in the TAC KB, though our methods aren’t in principle sensitive to this because they create entities on the fly. We use annotated versions of Gigaword 5 (Parker et al., 2011; Ferraro et al., 2014) and English Wikipedia (February 24, 2016 dump) to construct our PKBs.\(^4\) We use Amazon Mechanical Turk workers as annotators. We generated our PKBs with \( \tau = 15, \rho = 0.5, \alpha_t = 40, \alpha_c = 20, \) and \( \alpha_a = 10 \). These constants were tuned by hand.

\(^{2}\)Mentions with a score near \( \tau \) may be coreferent, so we prefer low scoring mentions to avoid over-splitting entities.

\(^{3}\)These values depend on the query (which are more or less rare in a corpus) and pruning thresholds (for our experiments we stop at 100 query mentions).

\(^{4}\)We do not use the coreference annotations provided by Annotated Gigaword, only the features described in §3.1.
and are not sensitive to small changes. We take a subset of the PKB which covers the 15 most related entities and the one-best trigger for each. We call these “explanations” where each is a sentence with three labels: a) a mention of the query \( m_q \), b) a mention of the a related entity \( m_r \), and c) a trigger word \( t \).

**Entity Linking and Relatedness** For each explanation, we ask: COREF: Does the query mention refer to the same entity as \( m_q \)? RELATED: Is the query entity meaningfully related to the referent of \( m_r \)? These annotations are not done by the same annotators to avoid confirmation bias. Worried annotators might be lulled into thinking all COREF instances were true, we made the task ternary by adding an intruder entity (randomly drawn from SF13 queries). Annotators were shown \( m_q \) and could choose coreference with the query, the intruder, or neither.\(^5\) We drop annotations from annotators who chose an intruder\(^6\) because we know these to be incorrect, and compute accuracy as proportion of the remaining annotations which chose the query.

RELATED was posed as a binary task of whether \( m_r \) is more related to the query or the intruder (without highlighting \( m_q \)). In positive cases, the annotator should observe that sentence shown contains a mention of the query entity and explains why they are related. The results are in Table 1.

Our system retrieves coreferent and related mentions with high accuracy. For coreference, mistakes usually happen when there is significant lexical overlap but some distinguishing feature that proves too subtle for our system to doubt the match, like Midwest High Speed Rail Association vs U.S. High Speed Rail Association or [English] Nationwide Building Society vs Irish Nationwide Building Society.

For relatedness, the biggest source of errors are news organizations listed as related entities because it is common to see sentences like “Mohammed Sobeih, Moussa’s deputy, told The Associated Press on Monday that...”. Future work might address this problem by using normalized measures of statistical relatedness like PMI rather than raw co-occurrence counts.

**Trigger Words** To evaluate the informativeness of chosen triggers, we present annotators with \( m_q \), \( m_r \), and two potential trigger words highlighted. One trigger is chosen according to §3.3 and the other is an NN* | VB* | JJ* | RB* word in the projection of the dependency node dominating both entities.\(^7\) The annotator may choose either trigger as a good characterization of the situation involving \( m_q \) and \( m_r \), or label neither as sufficient. Note that this baseline is strong: it shares the entity linking (§3.2), trigger sentence selection (§3.3), and dependency parse tree as our system. We report the results in Table 2.

Our method is chosen about twice as often as a syntactically informed baseline, but fails to find a high quality trigger word more than half of the time. Some mistakes are caused by rare but oft-repeated words like “50” in: “Bolland, 50, ... will replace Briton Stuart Rose”. “50” has nothing to do with the relationship between Bolland and Rose, but it’s repeated in 4 sentences about both of them, a stylistic coincidence our system cannot ignore. In other cases there is no word in situ which can explain entities’ relatedness, like “... the day after Wimbledon concludes, Montcourt must serve a five-week ban and ...”. The author and the reader can likely infer that Montcourt competed at Wimbledon, but this fact is not explicitly committed to, limiting our systems ability to extract a trigger.

| Related Entities vs Slot Fillers | Our system retrieved 17.6 relevant entities/query,\(^8\) each having 4.6 trigger words/pair, 2.1 mentions/trigger word, and 9.8 |

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\(^5\)The order of the intruder and the query were randomized. 
\(^6\)This affected 6.1% of COREF annotations. 

### Table 1: PKB entity accuracy.

|          | PER | ORG | All |
|----------|-----|-----|-----|
| COREF    | 94.6| 91.5| 93.1|
| RELATED  | 90.7| 88.2| 89.5|
| COREF and RELATED | 86.6| 80.9| 83.9|

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### Table 2: Related entity trigger identification.

|          | System | Intruder | Neither |
|----------|--------|----------|---------|
| Person   | 29.4   | 12.4     | 58.2    |
| Organization | 29.1  | 17.3     | 53.7    |
| All      | 29.2   | 14.7     | 56.1    |

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\(^7\)If no nodes match this, we walk up the tree until we find a node which has at least one allowed descendant. 
\(^8\)This is given a cap of 20 relevant entities per query to avoid a skewed average and keep construction time down.
Table 3: Examples of slices of PKBs for the three most related entities for six queries and the best triggers for each pair. Supporting sentences for related entities and trigger words are not shown.

5 Related Work

Blanco and Zaragoza (2010) study the information retrieval problem of finding support sentences which explain the relationship between a query and an entity, which is similar to this work. Our work addresses two new aspects of this problem: 1) how to automatically find related entities, which are assumed given in that work and 2) how to find the salient parts of support sentences (trigger words) by aggregating evidence across sentences.

This work shares goals with Dalton and Dietz (2013) and Dietz and Schuhmacher (2015), who create “knowledge sketches”: distributions over documents, entities, and relations related to a query. The primary difference is that our work creates a KB instead of returning results from an existing one. They use Freebase for relations and Wikipedia for anchor text and links. Our approach uses parsed and NER tagged text.

Open vocabulary characterization of entities was investigated by Raghavan et al. (2004). They found intersecting entity language models yields common descriptors. Their notion of similarity (e.g. Ronald Reagan and Richard Nixon are both presidents) is different from our notion of relatedness (e.g. Alexander Haig and Princeton, NJ are related via Meredith – Haig’s sister).

Finally other work has used Open IE for SF KBP. Soderland et al. (2013) and Finin et al. (2015) manually created a mapping between the Ollie (Mausam et al., 2012) and SF schemas. Angel et al. (2015) perform OpenIE and then map between their schema and SF with PMI².

6 Conclusion

We propose Pocket Knowledge Base Population for dynamically building dense entity-centric KBs. We evaluate our methods on SF queries and find high accuracies of related entity discovery and coreference. We propose novel Open Information Extraction methods which leverage the PKB to identify trigger words and show they are effective at explaining related entities. In future work we hope to use PKBs for tasks like QA and IR.

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