Entity Extraction via Ensemble Semantics

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Abstract

Combining information extraction systems yields significantly higher quality resources than each system in isolation. In this paper, we generalize such a mixing of sources and features in a framework called Ensemble Semantics. We show very large gains in entity extraction by combining state-of-the-art distributional and pattern-based systems with a large set of features from a webcrawl, query logs, and Wikipedia. Experimental results on a web-scale extraction of actors, athletes and musicians show significantly higher mean average precision scores (29% gain) compared with the current state of the art.

1 Introduction

Mounting evidence shows that combining information sources and information extraction algorithms leads to improvements in several tasks such as fact extraction (Paşca et al., 2006), open-domain IE (Talukdar et al., 2008), and entailment rule acquisition (Mirkin et al., 2006). In this paper, we show large gains in entity extraction by combining state-of-the-art distributional and pattern-based systems with a large set of features from a 600 million document webcrawl, one year of query logs, and a snapshot of Wikipedia. Further, we generalize such a mixing of sources and features in a framework called Ensemble Semantics.

Distributional and pattern-based extraction algorithms capture aspects of paradigmatic and syntagmatic dimensions of semantics, respectively, and are believed to be quite complementary. Paşca et al. (2006) showed that filtering facts, extracted by a pattern-based system, according to their arguments’ distributional similarity with seed facts yielded large precision gains. Mirkin et al. (2006) showed similar gains on the task of acquiring lexical entailment rules by exploring a supervised combination of distributional and pattern-based algorithms using an ML-based SVM classifier.

This paper builds on the above work, by studying the impact of various sources of features external to distributional and pattern-based algorithms, on the task of entity extraction. Mirkin et al.’s results are corroborated on this task and large and significant gains over this baseline are obtained by incorporating 402 features from a webcrawl, query logs and Wikipedia. We extracted candidate entities for the classes Actors, Athletes and Musicians from a webcrawl using a variant of Paşca et al.’s (2006) pattern-based engine and Pantel et al.’s (2009) distributional extraction system. A gradient boosted decision tree is used to learn a regression function over the feature space for ranking the candidate entities. Experimental results show 29% gains (19% nominal) in mean average precision over Mirkin et al.’s method and 34% gains (22% nominal) in mean average precision over an unsupervised baseline similar to Paşca et al.’s method. Below we summarize the contributions of this paper:

- We explore the hypothesis that although distributional and pattern-based algorithms are complementary, they do not exhaust the semantic space; other sources of evidence can be leveraged to better combine them;
- We model the mixing of knowledge sources and features in a novel and general information extraction framework called Ensemble Semantics; and
- Experiments over an entity extraction task show that our model achieves large and significant gains over state-of-the-art extractors.

A detailed analysis of feature correlations and interactions shows that query log and webcrawl features yield the highest gains, but easily accessible Wikipedia features also improve over current state-of-the-art systems.
Figure 1: The Ensemble Semantics framework for information extraction.

The remainder of this paper is organized as follows. In the next section, we present our Ensemble Semantics framework and outline how various information extraction systems can be cast into the framework. Section 3 then presents our entity extraction system as an instance of Ensemble Semantics, comparing and contrasting it with previous information extraction systems. Our experimental methodology and analysis is described in Section 4 and shows empirical evidence that our extractor significantly outperforms prior art. Finally, Section 5 concludes with a discussion and future work.

2 Ensemble Semantics

Ensemble Semantics (ES) is a general framework for modeling information extraction algorithms that combine multiple sources of information and multiple extractors. The ES framework allows to:

- Represent multiple sources of knowledge and multiple extractors of that knowledge;
- Represent multiple sources of features;
- Integrate both rule-based and ML-based knowledge ranking algorithms; and
- Model previous information extraction systems (i.e., backwards compatibility).

2.1 ES Framework

ES can be instantiated to extract various types of knowledge such as entities, facts, and lexical entailment rules. It can also be used to better understand the commonalities and differences between existing information extraction systems.

After presenting the framework in the next section, Section 2.2 shows how previous information extraction algorithms can be cast into ES. In Section 3 we describe our novel entity extraction algorithm based on ES.

The ES framework is illustrated in Figure 1. It decomposes the process of information extraction into the following components:

Sources (S): textual repositories of information, either structured (e.g., a database such as DBpedia), semi-structured (e.g., Wikipedia Infoboxes or HTML tables) or unstructured (e.g., news articles or a webcrawl).

Knowledge Extractors (KE): algorithms responsible for extracting candidate instances such as entities or facts. Examples include fact extraction systems such as (Cafarella et al., 2005) and entity extraction systems such as (Pašca, 2007).

Feature Generators (FG): methods that extract evidence (features) of knowledge in order to decide which candidate instances extracted from KEs are correct. Examples include capitalization features for named entity extractors, and the distributional similarity matrix used in (Pašca et al., 2006) for filtering facts.

Aggregator (A). A module collecting and assembling the instances coming from the different extractors. This module keeps the footprint of each instance, i.e. the number and the type of the KEs that extracted the instance. This information can be used by the Ranker module to build a ranking strategy, as described below.

Ranker (R): a module for ranking the knowledge instances returned from KEs using the features generated by FGs. Ranking algorithms may be rule-based (e.g., the one using a threshold on distributional similarity in (Pašca et al., 2006)) or ML-based (e.g., the SVM model in (Mirkin et al., 2006) for combining pattern-based and distributional features).
The Ranker is composed of two sub-modules: the Modeler and the Decoder. The Modeler is responsible for creating the model which ranks the candidate instances. The Decoder collects the candidate instances from the Aggregator, and applies the model to produce the final ranking.

In rule-based systems, the Modeler corresponds to a set of manually crafted or automatically induced rules operating on the features (e.g., a combination of thresholds). In ML-based systems, it is an actual machine learning algorithm, that takes as input a set of labeled training instances, and builds the model according to their features. Training instances can be obtained as a subset of those collected by the Aggregator, or from some external resource. In many cases, training instances are manually labeled by human experts, through a long and costly editorial process.

Information sources (S) serve as inputs to the system. Some sources will serve as sources for knowledge extractors to generate candidate instances, some will serve as sources for feature generators to generate features or evidence of knowledge, and some will serve as both.

2.2 Related Work

To date, most information extraction systems rely on a model composed of a single source $S$, a single extractor $KE$ and a single feature generator $FG$. For example, many classic relation extraction systems (Hearst, 1992; Riloff and Jones, 1999; Pantel and Pennacchiotti, 2006; Pasca et al., 2006) are based on a single pattern-based extractor $KE$, which is seeded with a set of patterns or instances for a given relation (e.g., the pattern ‘X starred in Y’ for the act-in relation). The extractor then iteratively extracts new instances until a stop condition is met. The resulting extractor scores are proposed by $FG$ as a feature. The Ranker simply consists of a sorting function on the feature from $FG$.

Systems such as the above that do not consist of multiple sources, knowledge extractors or feature generators are not considered Ensemble Semantics models, even though they can be cast into the framework. Recently, some researchers have explored more complex systems, having multiple sources, extractors and feature generators. Below we show examples and describe how they map as Ensemble Semantics systems. We use this characterization to clearly outline how our proposed entity extraction system, proposed in Section 3, differs from previous work.

Talukdar et al. (2008) present a weakly-supervised system for extracting large sets of class-instance pairs using two knowledge extractors: a pattern-based extractor supported by distributional evidence, which harvests candidate pairs from a Web corpus; and a table extractor that harvests candidates from Web tables. The Ranker uses graph random walks to combine the information of the two extractors and output the final list. The authors show large improvements in coverage with little precision loss.

Mirkin et al. (2006) introduce a machine learning system for extracting lists of lexical entailments (e.g., ‘government’ → ‘organization’). They rely on two knowledge extractors, operating on a same large textual source: a pattern-based extractor, leveraging the Hearst (1992) is-a patterns; and a distributional extractor applied to a set of entailment seeds. Candidate instances are passed to an SVM Ranker, which uses features stemming from the two extractors, to decide which instances are output in the final list. The authors report a +9% increase in F-measure over a rule-based system that takes the union of the instances extracted by the two modules.

Other examples include the system for taxonomic-relation extraction by Cimiano et al. (2005), using a pool of feature generators based on pattern-based, distributional and WordNet techniques; and Pasca and Van Durme’s (2008) system that uses a Web corpus and query logs to extract semantic classes and their attributes.

Similarly to these methods, our proposed entity extractor (Section 3) utilizes multiple sources and extractors. A key difference of our method lies in the Feature Generator module. We propose several generators resulting in 402 features extracted from Web pages, query logs and Wikipedia articles. The use of these features results in dramatic performance improvements, reported in Section 4.

3 ES for Entity Extraction

Entity extraction is a fundamental task in NLP responsible for extracting instances of semantic classes (e.g., ‘Brad Pitt’ and ‘Tom Hanks’ are instances of the class Actors). It forms a building block for various NLP tasks such as ontology learning (Cimiano and Staab, 2004) and co-reference resolution (McCarthy and Lehn-
Table 1: Feature space describing each candidate instance (S indicates the set of seeds for a given class).

| Family     | Type       | Features                                                                 |
|------------|------------|--------------------------------------------------------------------------|
| Web (w)    | Frequency  | term frequency; document frequency; term frequency as noun phrase         |
|            | Confidence | confidence score returned by $KE_{pat}$; pmi with the 100 most reliable patterns |
|            | Text       | used by $KE_{pat}$                                                       |
|            | Pattern    | distributional similarity with the centroid in $KE_{dis}$; distributional similarities with each seed in S |
|            | Termness   | ratio between term frequency as noun phrase and term frequency; pmi between internal tokens of the instance; capitalization ratio |
| Query log (q) | Frequency | number of queries matching the instance; number of queries containing the instance |
|            | Co-occurrence | query log pmi with any seed in S |
|            | Pattern    | pmi with a set of trigger words T (i.e., the 10 words in the query logs with highest pmi with S) |
|            | Distribution | distributional similarity with $S$ (vector coordinates consist of the instance’s pmi with the words in T) |
|            | Termness   | ratio between the two frequency features $F$ |
| Web table (t) | Frequency | table frequency |
|            | Co-occurrence | table pmi with $S$; table pmi with any seed in $S$ |
| Wikipedia (k) | Frequency | term frequency |
|            | Co-occurrence | pmi with any seed in $S$ |
|            | Distribution | distributional similarity with $S$ |

3.1 ES Entity Extraction Model

In this section, we propose a novel entity extraction model following the Ensemble Semantics framework presented in Section 2. The sources of our systems can come from any textual corpus. In our experiments (described in Section 4.1), we extracted entities from a large crawl of the Web, and generated features from this crawl as well as query logs and Wikipedia.

3.1.1 Knowledge extractors

Our system relies on two knowledge extractors: one pattern-based and the other distributional.

**Pattern-based extractor ($KE_{pat}$).** We reimplemented Pašca et al.’s (2006) state-of-the-art web-scale fact extractor, which, given seed instances of a binary relation, finds instances of that relation. We extract entities of a class, such as Actors, by instantiating typical relations involving that class such as act-in(Actor, Movie). We instantiate such relations instead of the classical is-a patterns since these have been shown to bring in too many false positives, see (Pantel and Pennacchiotti, 2006) for a discussion of such generic patterns. The extractor’s confidence score for each instance is used by the Ranker to score the entities being extracted. Section 4.1 lists the system parameters we used in our experiments.

**Distributional extractor ($KE_{dis}$).** We use Pantel et al.’s (2009) distributional entity extractor. For each noun in our source corpus, we build a context vector consisting of the noun chunks preceding and following the target noun, scoring pointwise mutual information (pmi). Given a small set of seed entities $S$ of a class, the extractor computes the centroid of the seeds’ context vectors as a geometric mean, and then returns all nouns whose similarity with the centroid exceeds a threshold $\tau$ (using the cosine measure between the context vectors). Full algorithmic details are presented in (Pantel et al., 2009). Section 4.1 lists the threshold and text preprocessing algorithms used in our experiments.

The Aggregator simply takes a union of the entities discovered by the two extractors.

3.1.2 Feature generators

Our model includes four feature generators, which compute a total of 402 features (full set described in Table 1). Each generator extracts from a specific source a feature family, as follows:

- **Web (w):** a body of 600 million documents...
crawled from the Web at Yahoo! in 2008;
• Query logs \( (q) \): one year of web search queries issued to the Yahoo! search engine;
• Web tables: all HTML inner tables extracted from the above Web source; and
• Wikipedia: an official Wikipedia dump from February 2008, consisting of about 2 million articles.

Feature families are further subclassified into five types: frequency \( (F) \) (frequency-based features); co-occurrence \( (C) \) (features capturing first order co-occurrences between an instance and class seeds); distributional \( (D) \) (features based on the distributional similarity between an instance and class seeds); pattern \( (P) \) (features indicating class-specific lexical pattern matches); and termness \( (T) \) (features used to distinguish well-formed terms such as ‘Brad Pitt’ from ill-formed ones such as ‘with Brad Pitt’). The seeds \( S \) used in many of the feature families are the same seeds used by the KE\(_{pat}\) extractor, described in Section 3.1.1.

The different seed families are designed to capture different semantic aspects: paradigmatic \( (D) \), syntagmatic \( (C \text{ and } P) \), popularity \( (F) \), and term cohesiveness \( (T) \).

3.1.3 ML-based Ranker

Our Modeler adopts a supervised ML regression model. Specifically, we use a Gradient Boosted Decision Tree regression model - GBDT (Friedman, 2001), which consists of an ensemble of decision trees, fitted in a forward step-wise manner to current residuals. Friedman (2001) shows that by drastically easing the problem of overfitting on training data (which is common in boosting algorithms), GBDT competes with state-of-the-art machine learning algorithms such as SVM (Friedman, 2006) with much smaller resulting models and faster decoding time. The model is trained on a manually annotated random sample of entities taken from the Aggregator, using the features generated by the four generators presented in Section 3.1.2. The Decoder then ranks each entity according to the trained model.

3.2 Related Work

Entity extraction systems follow two main approaches: pattern-based and distributional. The pattern-based approach leverages lexico-syntactic patterns to extract instances of a given class. Most commonly used are is-a pattern families such as those first proposed by Hearst (1992) (e.g., ‘Y such as X’ for matching ‘actors such as Brad Pitt’). Minimal supervision is used in the form of small sets of manually provided seed patterns or seed instances. This approach is very common in both the NLP and Semantic Web communities (Cimiano and Staab, 2004; Cafarella et al., 2005; Pantel and Pennacchiotti, 2006; Pašca et al., 2006).

The distributional approach uses contextual evidence to model the instances of a given class, following the distributional hypothesis (Harris, 1964). Weakly supervised, these methods take a small set of seed instances (or the class label) and extract new instances from noun phrases that are most similar to the seeds (i.e., that share similar contexts). Following Lin (1998), example systems include Fleischman and Hovy (2002), Cimiano and Volker (2005), Tanev and Magnini (2006), and Pantel et al. (2009).

4 Experimental Evaluation

This section reports our experiments, showing the effectiveness of our entity extraction system and the importance of our different feature families.

4.1 Experimental Setup

Evaluated classes. We evaluate our system over three classes: Actors (movie, tv and stage actors); Athletes (professional and amateur); Musicians (singers, musicians, composers, bands, and orchestras)

System setup. We instantiated our knowledge extractors, KE\(_{pat}\) and KE\(_{dis}\) from Section 3.1.1, over our Web crawl of 600 million documents (see Section 3.1.2). The documents were preprocessed using Brill’s POS-tagger (Brill, 1995) and the Abney’s chunker (Abney, 1991). For KE\(_{dis}\), context vectors are extracted for noun phrases recognized as NP-chunks with removed modifiers. The vector space includes the 250M most frequent noun chunks in the corpus. KE\(_{dis}\) returns as instances all noun phrases having a similarity with the seeds’ centroid above \( \tau = 0.005 \).\(^1\) The sets of seeds \( S \) for KE\(_{dis}\) include 10, 24 and 10 manually chosen instances for respectively the Actors, Athletes and Musicians classes\(^2\). The sets of seeds \( P \) for KE\(_{pat}\)

\(^{1}\)Experimentally set on an independent development set.
\(^{2}\)The higher number of seeds for Athletes is chosen to cover different sports.
Table 2: Number of extracted instances and the sample sizes (P and N indicate positive and negative annotations).

| Dataset       | Actors | Athletes | Musicians |
|---------------|--------|----------|-----------|
| KE_{pat}      | 58,065 | 40,816   | 123,657   |
| KE_{dis}      | 72,659 | 24,380   | 24,593    |
| KE_{pat} ∪ KE_{dis} | 113,245 | 61,709   | 142,694   |
| KE_{pat} ∩ KE_{dis} | 17,419  | 3,487    | 7,556     |
| R             | 500    | 500      | 500       |

Table 3: Average precision (AP) and coverage (Cov) results for our proposed system ES-all and the baselines. ‡ indicates AP statistical significance at the 0.95 level wrt all baselines.

ES-all. Our ES system, using KE_{pat} and KE_{dis}, the full set of feature families described in Section 3.1.2, and the GBDT ranker.

B1. KE_{pat} alone, a state-of-the-art pattern-based extractor reimplementing (Paşca et al., 2006), where the Ranker assigns scores to instances using the confidence score returned by KE_{pat}.

B2. KE_{dis} alone, a state-of-the-art distributional system implementing (Pantel et al., 2009), where the Ranker assigns scores to instances using the similarity score returned by KE_{dis} alone.

B3. A rule-based ES system, combining B1 and B2. This system uses both KE_{pat} and KE_{dis} as extractors, and a Ranker that assigns scores to instances according to the sum of their normalized confidence scores.

B4. A state-of-the-art machine learning system based on (Mirkin et al., 2006). This ES system uses KE_{pat} and KE_{dis} as extractors. The Ranker is a GBDT regression model, using the full sets of features derived from the two extractors, i.e., wP and wD (see Table 1). GBDT parameters are set as for our proposed ES-all system.

4.2 Experimental Results

Table 3 summarizes the average-precision (AP) and coverage results for our ES-all system and the baselines. Figure 2 reports the precision at each rank for the Athletes class (the other two classes follow similar trends). Table 6 lists the top-10 entitics discovered for each class on one test fold. ES-all outperforms all baselines in AP (all results are statistically significant at the 0.95 level), offering at the same time full coverage.

B1: KE_{pat} alone, a state-of-the-art pattern-based extractor reimplimenting (Paşca et al., 2006), where the Ranker assigns scores to instances using the confidence score returned by KE_{pat}.

B2: KE_{dis} alone, a state-of-the-art distributional system implementing (Pantel et al., 2009), where the Ranker assigns scores to instances using the similarity score returned by KE_{dis} alone.

B3: A rule-based ES system, combining B1 and B2. This system uses both KE_{pat} and KE_{dis} as extractors, and a Ranker that assigns scores to instances according to the sum of their normalized confidence scores.

B4: A state-of-the-art machine learning system based on (Mirkin et al., 2006). This ES system uses KE_{pat} and KE_{dis} as extractors. The Ranker is a GBDT regression model, using the full sets of features derived from the two extractors, i.e., wP and wD (see Table 1). GBDT parameters are set as for our proposed ES-all system.

Table 3: Average precision (AP) and coverage (Cov) results for our proposed system ES-all and the baselines. ‡ indicates AP statistical significance at the 0.95 level wrt all baselines.

ES-all. Our ES system, using KE_{pat} and KE_{dis}, the full set of feature families described in Section 3.1.2, and the GBDT ranker.

B1. KE_{pat} alone, a state-of-the-art pattern-based extractor reimplementing (Paşca et al., 2006), where the Ranker assigns scores to instances using the confidence score returned by KE_{pat}.

B2. KE_{dis} alone, a state-of-the-art distributional system implementing (Pantel et al., 2009), where the Ranker assigns scores to instances using the similarity score returned by KE_{dis} alone.

B3. A rule-based ES system, combining B1 and B2. This system uses both KE_{pat} and KE_{dis} as extractors, and a Ranker that assigns scores to instances according to the sum of their normalized confidence scores.

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Table 3: Average precision (AP) and coverage (Cov) results for our proposed system ES-all and the baselines. ‡ indicates AP statistical significance at the 0.95 level wrt all baselines.

ES-all. Our ES system, using KE_{pat} and KE_{dis}, the full set of feature families described in Section 3.1.2, and the GBDT ranker.

B1. KE_{pat} alone, a state-of-the-art pattern-based extractor reimplementing (Paşca et al., 2006), where the Ranker assigns scores to instances using the confidence score returned by KE_{pat}.

B2. KE_{dis} alone, a state-of-the-art distributional system implementing (Pantel et al., 2009), where the Ranker assigns scores to instances using the similarity score returned by KE_{dis} alone.

B3. A rule-based ES system, combining B1 and B2. This system uses both KE_{pat} and KE_{dis} as extractors, and a Ranker that assigns scores to instances according to the sum of their normalized confidence scores.

B4. A state-of-the-art machine learning system based on (Mirkin et al., 2006). This ES system uses KE_{pat} and KE_{dis} as extractors. The Ranker is a GBDT regression model, using the full sets of features derived from the two extractors, i.e., wP and wD (see Table 1). GBDT parameters are set as for our proposed ES-all system.
Our simple rule-based combination baseline, B3, leads to a large increase in coverage wrt the individual extractors alone (B1 and B2) without significant impact on precision. The supervised ML-based combination baseline (B4) consistently improves AP across classes wrt the rule-based combination (B3), but without statistical significance. These results corroborate those found in (Mirkin et al., 2006), where this ML-based combination was reported to be significantly better than a rule-based one on the task of lexical entailment acquisition.

The large set of features adopted in ES-all accounts for a dramatic improvement in AP, indicating that existing state-of-the-art systems for entity extraction (reflected by our baselines strategies) are not making use of enough semantic cues. The adoption of evidence other than distributional and pattern-based, such as features coming from web documents, HTML tables and query logs, is here demonstrated to be highly valuable.

The above empirical claim can be grounded and corroborated by a deeper semantic analysis. From a semantic perspective, the above results translate in the observation that distributional and pattern-based evidence do not completely capture all semantic aspects of entities. Other evidence, such as popularity, term cohesiveness and co-occurrences capture other aspects. For instance, in one of our Actors folds, the B3 system ranks the incorrect instance ‘Tom Sellek’ (a misspelling of ‘Tom Selleck’) in 9th position (out of 142), while ES-all lowers it to the 33rd position, by relying on table-based features (intuitively, tables contain much fewer misspelling than running text). Other than misspellings, ES-all fixes errors that are either typical of distributional approaches, such as the inclusion of instances of other classes (e.g. the movie ‘Someone Like You’ often appears in contexts similar to those of actors); errors typical of pattern-based approaches, such as incorrect instances highly-associated with an ambiguous pattern (e.g., the pattern ‘X of the rock band Y’ for finding Musicians matched an incorrect instance ‘song submission’); or errors typical of both, such as the inclusion of common nouns (e.g. ‘country music hall’) or too generic last names (e.g. ‘Johnson’). ES-all successfully recovers all these error by using termness, co-occurrence and frequency features.

We also compare ES-all with a state-of-the-art random walk system (RW) presented by Talukdar et al. (2008) (see Section 2.2 for a description). As we could not reimplement the system, we report the following indirect comparison. RW was evaluated on five entity classes, one of which, NFL players, overlaps with our Athletes class. On this class, they report 0.95 precision on the top-100 ranked entities. Unfortunately, they do not report coverage or recall statistics, making the interpretation of this analysis difficult. In an attempt to compare RW with ES-all, we evaluated the precision of our top-100 Athletes, obtaining 0.99. Using a random sample of our extracted Athletes, we approximate the precision of the top-22,000 Athletes to be 0.97 ± 0.01 (at the 0.95 level).

### 4.3 Feature Analysis

**Feature family analysis:** Table 4 reports the average precision (AP) for our system using different feature family combinations (see Table 1). Column 1 reports the family combinations; columns

| System | Actors | AP | Musicians | MAP |
|--------|--------|----|-----------|-----|
| B3     | 0.676  | 0.664 | 0.576 | 0.639 |
| B4     | 0.715  | 0.697 | 0.579 | 0.664 |
| B4+w   | 0.813  | 0.908 | 0.724 | 0.815 |
| B4+q   | 0.815  | 0.905 | 0.743 | 0.821 |
| B4+t   | 0.784  | 0.825 | 0.727 | 0.779 |
| B4+k   | 0.776  | 0.825 | 0.624 | 0.741 |
| B4+w+q | 0.835  | 0.915 | 0.758 | 0.836 |
| B4+w+t | 0.840  | 0.906 | 0.774 | 0.840 |
| B4+w+k | 0.814  | 0.903 | 0.725 | 0.814 |
| B4+q+t | 0.847  | 0.910 | 0.774 | 0.844 |
| B4+q+k | 0.832  | 0.906 | 0.748 | 0.829 |
| B4+t+k | 0.817  | 0.861 | 0.743 | 0.807 |
| B4+w+q+t | 0.846 | 0.917 | 0.782 | 0.849 |
| B4+w+q+k | 0.841 | 0.916 | 0.756 | 0.838 |
| B4+w+t+k | 0.835 | 0.906 | 0.783 | 0.841 |
| **ES-all** | **0.860** | **0.915** | **0.788** | **0.854** |

Table 4: Overall AP results of the different feature configurations, compared to two baselines. † indicates statistical significance at the 0.95 level wrt B3. ‡ indicates statistical significance at 0.95 level wrt both B3 and B4.
2-4 report AP for each class; and column 5 reports the mean-average-precision (MAP) across classes. In all configurations, except the $k$ family alone, and along all classes, our system significantly outperforms (at the 0.95 level) the baselines.

Rows 3-6 report the performance of each feature family alone. $w$ and $t$ are consistently better than $q$ and $k$, across all classes. $k$ is shown to be the least useful family. This is mostly due to data sparseness, e.g., in our experiments almost 40% of the text instances in the Actors sample do not have any occurrence in Wikipedia. However, without access to richer resources such as a webcrawl or query logs, the features from $k$ do indeed provide large gains over current baselines (on average +10.2% and +7.7% over $B3$ and $B4$).

Rows 7-12 report results for combinations of two feature families. All combinations (except those with $k$) appear valuable, substantially increasing the single-family results in rows 3-6, indicating that combining different feature families (as suggested by the ES paradigm) is helpful. Second, it indicates that $q$, $w$ and $t$ convey complementary information, thus boosting the regression model when combined together. It is interesting to notice that $q+t$ tends to be the best combination, surprising given that $t$ alone did not show high performance (row 5). One would expect the combination $q+w$ to outperform $q+t$, but the good performance of $q+t$ is mainly due to the fact that these two families are more complementary than $q+w$. To verify this intuition, we compute the Spearman correlation coefficient $r$ among the rankings produced by the different combinations. As expected, $q$ and $w$ have a higher correlation ($r = 0.82$) than $q$ and $t$ ($r = 0.67$) and $w$ and $t$ ($r = 0.66$), suggesting that $q$ and $w$ tend to subsume each other (i.e. no added information for the regression model).

Rows 13-15 report results for combinations of three feature families. As expected, the best combination is $q+w+t$ with an average precision nearly identical to the full ES-all system. If one has access to Web or query log sources, then the value of the Wikipedia features tends to be subsumed by our web and query log features.

**Feature by feature analysis:** The feature families analyzed in the previous section consist of 402 features. For each trained GBDT model, one can inspect the resulting most important features (Friedman, 2001). Consistently, the two most important features for ES-all are, as expected, the confidence scores of $KE_{pat}$ and $KE_{dis}$. This suggests that syntagmatic and paradigmatic information are most important in defining the semantics of entities. Also very important, in third position, is a feature from $qT$, namely the ratio between the number of queries matching the instance and the number of queries containing it as a substring. This feature is a strong indicator of termness.

Webcrawl term frequencies and document frequencies (from the $wF$ set) are also important. Very frequent and infrequent instances were found to be often incorrect (e.g., respectively ‘song’ and ‘Brad Pitt’). Table PMI (a feature in the $qC$ family) also ranked high in importance: instances that co-occur very frequently in the same column/row with seeds $S$ are often found to be correct (e.g., a column containing the seeds ‘Brad Pitt’ and ‘Tom Hanks’ will likely contains other actors). Other termness ($T$), frequency-based ($F$) and co-occurrence ($C$) features also play some role in the model.

Variable importance is only an intrinsic indicator of feature relevance. In order to better assess the actual impact of the single features on AP, we ran our system on each feature type: results for the web ($w$), query log ($q$) and table ($t$) features are reported in Table 5. For reason of space constraints, we here only focus on some high level observations. The set of web termness features ($wT$) and frequency features ($wF$) are alone able to provide a large improvement over $B4$ (row 1), while their combination (row 2) does not improve much over the features taken individually.

| System     | Actors | Athletes | Musicians | MAP  |
|------------|--------|----------|-----------|------|
| $B4$       | 0.715  | 0.697    | 0.579     | 0.664|
| $B4+w$     | 0.813  | 0.908    | 0.724     | 0.815|
| $B4+wF$    | 0.798  | 0.865    | 0.679     | 0.781|
| $B4+wT$    | 0.806  | 0.891    | 0.717     | 0.805|
| $B4+t$     | 0.784  | 0.825    | 0.727     | 0.779|
| $B4+q$     | 0.815  | 0.905    | 0.743     | 0.821|
| $B4+qF$    | 0.786  | 0.890    | 0.693     | 0.790|
| $B4+qC$    | 0.715  | 0.738    | 0.581     | 0.678|
| $B4+qD$    | 0.735  | 0.709    | 0.644     | 0.696|
| $B4+qP$    | 0.779  | 0.796    | 0.648     | 0.741|
| $B4+qT$    | 0.780  | 0.868    | 0.725     | 0.791|
| $B4+qF+qW+qT$ | 0.816 | 0.906 | 0.743 | 0.822|
| ES-all     | 0.860  | 0.915    | 0.788     | 0.854|

Table 5: Ablation study of the web ($w$), query-log ($q$) and table ($t$) features (bold letters indicate whole feature families).
Table 6: Listing of all seeds used for $K_{E_{dis}}$ and $K_{E_{pat}}$, as well as the top-10 entities discovered by ES-all on one of our test folds.

| Actors | Athletics | Musicians |
|--------|-----------|-----------|
| Jodie Foster | Bob Gibson | Randy Moss |
| Humphrey Bogart | Don Drysdale | Peyton Manning |
| Anthony Hopkins | Albert Pujols | Kenny Perry |
| Katharine Hepburn | Yogi Berra | Martin Kaymer |
| Christopher Walken | Dejan Bodiroga | Alexander Ovechkin |
| Gene Hackman | Allen Iverson | Shea Weber |
| Diane Keaton | Yao Ming | Patrick Roy |
| Edward Norton | Tim Duncan | Alexei Kovalev |
| Robert Duvall | Hilary Swank | Roberto Baggio |

This suggests that $wT$ and $wF$ capture very similar information: they are indeed highly correlated ($r = 0.80$). Rows 5-7 refer to web table features: the features $tC$ outperform and subsume the frequency features $tF$ ($r = 0.92$). For query log features (rows 8-14), only $qF$, $qP$ and $qT$ significantly increase performance. Distributional and co-occurrence features ($qD$ and $qC$) have very low effect, as they are mostly subsumed by the others. The combination of $qF$, $qP$ and $qT$ (row 14) performs as well as the whole $q$ (row 8).

**Experiment conclusions:** From our experiments, we can draw the following conclusions:

1. Wikipedia features taken alone outperform the baselines, however, web and query log features, if available, subsume Wikipedia features;

2. $q$, $t$ and $w$ are all important, and should be used in combination, as they drive mostly independent information;

3. the syntagmatic and paradigmatic information conveyed by the two extractors are most relevant, and can be significantly boosted by adding frequency- and termness-based features from other sources.

5 **Conclusions and Future Work**

In this paper, we presented a general information extraction framework, called Ensemble Semantics, for combining multiple sources of knowledge, and we instantiated the framework to build a novel ML-based entity extraction system. The system significantly outperforms state-of-the-art ones by up to 22% in mean average precision. We provided an in-depth analysis of the impact of our proposed 402 features, their feature families (Web documents, HTML tables, query logs, and Wikipedia), and feature types.

There is ample directions for future work. On entity extraction, exploring more knowledge extractors from different sources (such as the HTML tables and query log sources used for our features) is promising. Other feature types may potentially capture other aspects of the semantics of entities, such as WordNet and search engine click logs. For the ranking system, semi- or weakly-supervised algorithms may provide competing performance to our model with reduced manual labor. Finally, there are many opportunities for applying the general Ensemble Semantics framework to other information extraction tasks such as fact extraction and event extraction.
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