Word Sense Discrimination on Tweets: A Graph-based Approach

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Abstract: In this paper we are going to detail an unsupervised, graph-based approach for word sense discrimination on tweets. We deal with this problem by constructing a word graph of co-occurrences. By defining a distance on this graph, we obtain a word metric space, on which we can apply an aggregative algorithm for word clustering. As a result, we will get word clusters representing contexts that discriminate the possible senses of a term. We present some experimental results both on a data set consisting of tweets we collected and on the data set of task 14 at SemEval-2010.

1 INTRODUCTION

In the wide research field of Natural Language Processing, the task of Word Sense Disambiguation (WSD) is that of unravelling the intrinsic arbitrariness of human language to provide a better understanding of text or speech. In particular, the case of proper nouns can be very challenging, since the correlation between a name and the object, person, location or the like it denotes is often more obscure and unpredictable than e.g. the continuous shift in meaning of common nouns. This task is even more complex when dealing with text on social networks (e.g. tweets), where shortness and informal writing styles represent an additional challenge. Many approaches in Word Sense Disambiguation are supervised, that is, they resolve to use some kind of external knowledge about the world to discern the possible senses that a given term can assume in the discourse. Concerning the state of the art, several approaches have been proposed for well-formed, i.e. grammatically and orthographically correct text. Three main research directions have been investigated (Navigli, 2009), (Navigli, 2012): 1) supervised (Zhong and Ng, 2010), (Mihalcea and Faruque, 2004), 2) knowledge-based (Navigli and Ponzetto, 2012), (Schmitz et al., 2012) and 3) unsupervised Word Sense Disambiguation (Dorow and Widdows, 2003), (Véronis, 2004), (Biemann, 2006), (Hope and Keller, 2013) where the last approach is better defined as “induction” or “discrimination”. These approaches try to cluster a generic word graph: in (Biemann, 2006) a simplified variant of Markov clustering (*Chinese Whispers*) is used to reproduce the propagation of a sense from one word to the others; in (Véronis, 2004), the concept of density and hub words is used, and the more recent proposal by (Hope and Keller, 2013) permits soft clustering in linear time. To the best of our knowledge, many of these works apply a quite selective choice of words on an underlying corpus when building a graph, and make thereby more or less implicit assumptions on the domain or format of the text, like the frequency of certain syntactical constructions.

In this paper we focus on the automatic discovery of senses from raw text, by pursuing an unsupervised Word Sense Discrimination paradigm. We are interested in the development of a method that can be generally independent from the register or the linguistic well-formedness of a text document, and, given an adequate pre-processing step, from language. Among the many unsupervised research directions, i.e. context clustering (Schütze, 1998), word clustering (Lin, 1998), probabilistic clustering (Brody and Lapata, 2009) and co-occurrence graph clustering (Widdows and Dorow, 2002), we committed to the last one, based on the assumption that word co-occurrence graphs can reveal local structural properties tied to the different senses a word might assume in different contexts.

The structure of the paper is as follows. In Section 2 we present the framework of our approach and explain all passages and constructions in detail; in Section 3 we describe the clustering algorithm; and finally, in Section 4 we show the results obtained both on our custom tweet data set and on SemEval-2010, Task 14’s data set. Section 5 concludes the paper.

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2 OVERVIEW AND DEFINITIONS

2.1 Overview

In the approach that we are going to propose for word sense disambiguation, or better discrimination, we go through four main steps:

- word filtering of the text documents;
- construction of a co-occurrence word graph;
- derivation of metric word spaces from the graph;
- and finally the clustering algorithm.

Word filtering is a necessary step to remove all the words that are of no interest to our goal and that would otherwise just generate noise; it is a fact that only a few words are truly relevant to the conveyance of the general sense of a discourse, and word filtering helps us restrict our attention to those few selected words. The co-occurence graph (and its subgraphs) will serve us as a representation of the underlying structure of the text documents (tweets) we are considering. From there, it is possible to extract contexts[1] of a word v we want to disambiguate. By comparing the contexts of two words, we can define a graph-based distance between words and derive a word metric space from it. Even if it is not possible to visualize this space as some canonical $\mathbb{R}^n$, we can still run clustering algorithms on it, like e.g. k-medoids or similar ones. Our basic assumption is that the word space that arises from the context of a term v we want to disambiguate will present denser areas that we want to identify through clustering. Each one of these agglomerates will then implicitly define a different sense of term v. Our assumptions imply that, even if the possible senses that a word can assume are not predictable *a priori* and could vary from tweet to tweet[2], in every single sentence that word will not display any ambiguity; that is, every word can be ambiguous *a priori*, but the context it is used together defines its sense there unequivocally. We show a high-level overview of our proposed approach in Figure 1.

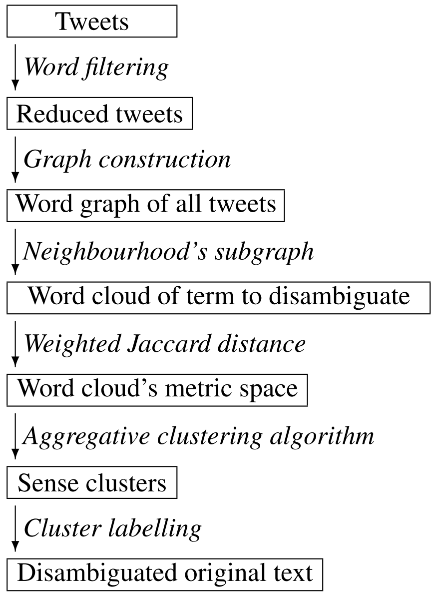


Figure 1: Framework of the proposed disambiguation process.

2.2 Word Filtering

Before building the co-occurrence graph, we want to filter out functional words that do not carry a meaning by themselves (so-called stop words) or that are not significant enough to our ends. We therefore apply a first filtering step based on stop word lists and part-of-speech tagging. First, we remove easily identifiable common stop words, mostly closed-class[3] words like articles (*the*, *a*, ...), prepositions (*of*, *to*, ...), conjunctions (*and*, *but*, ...) and so on, but also modal verbs (*can*, *will*, ...). A difficulty encountered dealing with tweets is the often irregular or idiosyncratic spelling of words, a fact whose consequence is that many closed word classes graphically assume the traits of open classes. Therefore, the preposition *for* could appear as *fir*, *fr*, *fo*, *4*, and be hardly recognizable as such. To overcome this complication, we used the ARK POS tagger for Twitter (Owoputi et al., 2013), based on word clusters. Only what is classified as a noun, a proper noun, a verb or a hashtag (later the # symbol will be removed) is kept, thus excluding all closed-class words (prepositions, conjunctions, articles, ...), adverbs and adjectives (since we are not interested in the "sentiment" of the tweets), mentions of other users (through the @ symbol), emoticons (in some sense a graphical equivalent of adverbs), URLs, numerals, punctuation and other generic noise. We also want to remove clitics like in *Dana'll*, *John's*, and so on.

It has to be remarked that word filtering is a

[1]The context of a word will mostly consist of all the words that co-occur with it in the same tweet, sentence, or whichever textual unit is chosen.

[2]Since we are using a data set consisting of tweets, we consider a tweet the basic textual unit where a word has to be disambiguated. With other types of documents, we could instead consider sentences, paragraphs, or what is deemed as the most adequate choice.

[3]Closed word classes are those whose elements are fixed and of which no new one is produced by the language, at least from a synchronic point of view. They are often function words.

highly language-dependent step, and its implementation heavily depends on many *ad hoc* solutions and decisions.

Principal Component Analysis

The greatly reduced tweets we obtain this way still contain many terms that do not carry a useful enough meaning for our disambiguation task: most of the context is actually irrelevant. To this end, we further reduce our vocabulary by means of principal component analysis. Given a term we want to disambiguate, we want to refine the vocabulary of all the documents, in our case tweets, where it appears. We build a TF-IDF matrix where each row represents one of the selected tweets, each column a word in those tweets' vocabulary V_T, and each entry the TF-IDF score of the corresponding word w in the tweet, possibly 0 if it doesn't appear there. The more the score of a single word (seen as a random variable) varies across the tweets, the more we deem it to be relevant for disambiguation. The first principal component $Y = \sum_{w \in V_T} \alpha_w \cdot w$ obtained from the covariance matrix is by definition the linear combination of word random variables with maximum variance between all possible linear combinations of word random variables. We want to retain only the words which contribute the most to the first principal component: that is, we will retain a word w if and only if $|\alpha_w| > \mu$, where μ is the mean of the absolute values of Y's linear coefficients.

2.3 The Co-occurrence Graph

Given a collection of tweets, a co-occurrence word graph can be defined as an undirected, weighted graph $G = (V_G, E_G)$, where the set of vertices V_G corresponds to the vocabulary of the tweets and two nodes, i.e. words or tokens, are connected by an edge if and only if they co-occur in the same tweet. The weight of that edge is the number of such co-occurrences. It is interesting to note how all the words in the same tweet will be connected to each other, so that each tweet with k different words appearing in the documents will be represented by a clique of k nodes in the graph G; this means that G can be considered as arising from gluing many cliques of different sizes along their common nodes[4]. Another property of G, and of word graphs in general (i Cancho and Solé, 2001), is its small-world (Watts and Strogatz, 1998) and probably scale-free structure. By "small world" we mean that the graph has a radically different distribution than what would be expected from a randomly generated graph on the same set of nodes. The small-world structure of G reflects syntactical and lexical rules that underlie the formation of utterances in natural languages. In particular, a small-world graph is defined as having a very short average shortest path (the famous "six degrees of separation"), but a high average clustering coefficient[5]; furthermore, "scale-free" means that node degrees are distributed according to a power law, so that there are just a few nodes with very high degrees that act as "hubs" for the paths in the graph. In other words, the graph is locally very cohesive and globally hinges on few nodes from which nearly every other node can be reached. This fact can be interpreted noting that language itself hinges on some particular words (or better, morphemes) to express grammatical and syntactical dependencies (e.g. *the*, *of*, *that*, in English), or tends to recur to words with a more prototypical or general meaning than others (e.g. *dog* vs. *pitbull*) (Gärdenfors, 2004).

Word Clouds

The set of nodes V_G of the graph G encompasses all the words appearing in our filtered text documents. However, when disambiguating a term v, we will only focus on a specific open neighbourhood of v, i.e. its word cloud, defined as follows:

Definition 1. *The word cloud G_v of v is its n-th degree open neighbourhood graph (or "ego graph"), consisting of the subgraph of G induced by all the nodes no more than n steps away from v, excluding v itself.*

The global graph G will serve us as the underlying structure from which we will extract local subgraphs that represent the contexts of the words we are interested in disambiguating. We are not including v in its neighbourhood, since the resulting word cloud would be warped around it and resemble a star graph: v would have the highest degree and be the most central node in G_v. Since we are interested in investigating the relations between words in the context of v, we are going to remove v from its neighbourhood as an interfering factor. In our work, we will just consider 1 as the neighbourhood's degree, thus taking into account only nodes adjacent to v.

[4]From this point of view, G could be seen as a particular case of CW-complex construction (Fritsch and Piccinini, 1990).

[5]The clustering coefficient for a node v is defined as the ratio of the number of all existing edges between any two nodes in the open neighbourhood of v to the maximum possible number of those edges.

2.4 The Word Metric Space

Given a generic word graph $F = (V_F, E_F)$, in order for the vocabulary V_F to possess the structure of a metric space, we first need a distance on it. We are going to define a *weighted Jaccard distance* based on the Jaccard index. Given a node $v \in V_F$, we define its weighted neighbourhood as the multiset[6]

$$N(v) = \{(w, c_w) | (v, w) \in E_F\} \cup \{(v, c_v)\}, \quad (1)$$

where c_w is the weight of the edge connecting v to w, and c_v, the "automultiplicity" of v, is defined as the greatest weight over all the edges departing from v. Now, we define the intersection of two multisets A and B as the multiset with the least multiplicity for each element in both A and B (possibly 0, so not counting it) and conversely their union as the multiset with the greatest multiplicity for each element in both A and B. The cardinality of a multiset is the sum over the multiplicities of its elements.

Finally, we define the weighted Jaccard distance between two nodes $v, w \in V_F$ as the quantity

$$d_J(v, w) = 1 - \frac{|N(v) \cap N(w)|}{|N(v) \cup N(w)|}. \quad (2)$$

It is easily verifiable that this is a distance which can assume values between 0 (the neighbourhoods of v and w are identical both in terms of nodes and weights) and 1 (the neighbourhoods of v and w are totally disjunct in terms of nodes). A distance of 0 is only possible inside an isolated clique where all weights are equal. This could happen when there is an isolated tweet which is completely disconnected from all the other ones (e.g., a tweet in a different language).

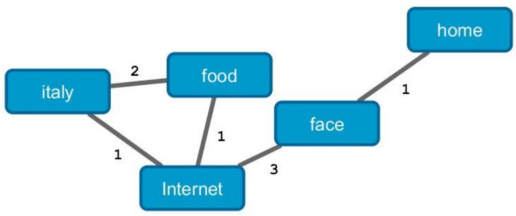


Figure 2: Example of computation of weighted Jaccard distance.

Example 1. *We give a sample of computation of the weighted Jaccard distance referring to Figure 2. Here, the weighted neighbourhood N(Internet) of* Internet *is*

$$\{(italy, 1), (food, 1), (face, 3), (Internet, 3)\},$$

that of home *is*

$$\{(face, 1), (home, 1)\}.$$

Then we will have that $N(Internet) \cup N(home)$ *corresponds to*

$$\{(italy, 1), (food, 1), (face, 3), (Internet, 3), (home, 1)\},$$

with cardinality 9*, and*

$$N(Internet) \cap N(home) = \{(face, 1)\},$$

whose cardinality is 1*. This means that the distance* $d_J(Internet, home)$ *in our sample graph is* $1 - \frac{1}{9} = 0{,}888\ldots$ *We could similarly obtain* $d_J(Internet, food) = 0{,}4$ *and* $d_J(italy, home) = 1$*. The latter result is evident, since there are no common neighbours between the two words.*

The weighted Jaccard distance we defined in Equation 2 just considers all the elements in the neighbourhood of a node v. Of course, it could be expanded to neighbourhoods of depth greater than 1: for increasing depths, we would take into account neighbourhoods of neighbour words of v, neighbourhoods of neighbourhoods, and so on, depending on the chosen depth. This means that, increasing the depth, at some threshold the Jaccard distance will begin losing significance. In this work we decided to consider the case of degree 1.

Now, using the distance defined in Equation 2, we can define the word metric space[7] $W_F = (V_F, d_J)$ derived from graph F. Having a metric space allows us to employ aggregative clustering techniques, like e.g. k-medoids, as will be shown in the following Sections.

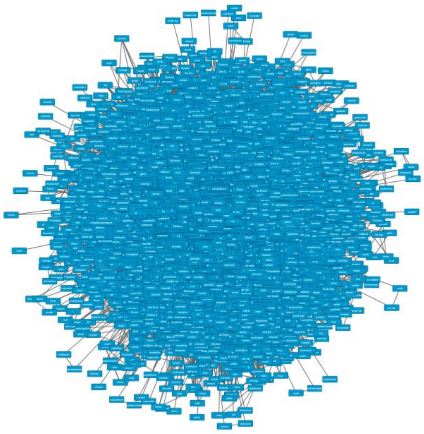
We shall content ourselves by remarking that W_F is a bounded space (the maximum distance between any two points is 1) and that we know that the distance between any two points v and w is less than 1 if and only if there is a path of length at most 2 connecting them in F. Indeed, it is quite difficult, if not outright impossible, to visualize the (discrete) metric space W_F: even if it were of Euclidean nature, the problem of retrieving its underlying structure from its elements and the distance still remains an open area of research in Mathematics, called Distance Geometry (Mucherino et al., 2012).

3 THE CLUSTERING ALGORITHM

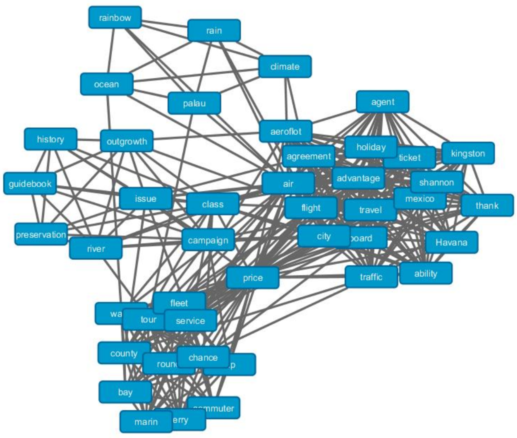
Given a data set of tweets, we construct the global graph G from it, as defined in Section 2.3. We choose

[6] A multiset is a set where an element can recur more than once, and can be defined as a set of couples (element, multiplicity) (Aigner, 2012).

[7] For detailed definitions, see (Rudin, 1964).



(a) First we build the global word graph.



(b) Then, we take the subgraph induced by the open neighbourhood of a given term, e.g. *tourist*.

(c) Finally, we obtain a metric space of words, where we know the distance between any two terms.

Figure 3: Progression from word graph to word metric space.

a term v whose senses we want to discriminate and the corresponding metric space $W_{G_v} = (V_{G_v}, d_J)$ derived from its word cloud G_v (see Sections 2.3 and 2.4). Our goal is to find a partition $\mathcal{C}_v = \{C_1, \ldots, C_{k_v}\}$ of W_{G_v}, with the assumption that each C_i will implicitly define one of the k_v senses that v assumes in the tweets we are considering.

The number k_v of clusters is not pre-determined. However, we expect every term we want to disambiguate to give rise to one or two bigger clusters and a host of smaller ones: it is a common pattern for an ambiguous word to have a more used sense and many rarer ones. The clustering process starts by selecting the word $u \in V_{G_v}$ with highest degree in G_v as the representative of the first cluster. According to this choice, u can be viewed as a possible "sense hub", i.e. a central word around which many others tend to gravitate and which could possibly be the most important representant of one of v's senses. We set u as the medoid of the cluster. We then check the distance between u and each other word w in W_{G_v}. If u and w are close enough, i.e. the distance is less than or equal to a previously set threshold $\sigma \in [0,1)$, we add w to u's cluster. Otherwise, if w is more distant than σ, w will originate a new cluster. This iterative process will be applied to all words $w \in W_{G_v}$. Once all the words have been processed, at the end of the first iteration we will have obtained k_v clusters, each represented by a medoid. Now, for each cluster the corresponding medoid, i.e. the element with lowest mean distance from all the other elements in the cluster, will be updated. Then, we will start the next iteration, again (re)assigning every word to the cluster whose medoid it is closest to. We repeat the whole process until convergence is reached, i.e. until either the medoids do not change between consecutive iterations, or a maximum number of iterations are performed. At the end of the clustering process, the partitioning $\mathcal{C}_v = \{C_1, \ldots, C_{k_v}\}$ will be identified with all the possible senses that can be associated to the word v in the tweets.

Given a threshold σ and a maximum number of iterations $maxiter$, the proposed algorithm works as displayed in Algorithm 1. By C_x we will denote the cluster represented by its medoid x.

Labelling

Finally, after having obtained the clustering $\mathcal{C}_v = \{C_1, \ldots, C_{k_v}\}$ relative to the chosen term v, we want to use the C_i's to label each of v's occurrences in the tweets. We adopt a sort of majority voting system: for each reduced tweet where v appears, we compute the Jaccard distance between that tweet's set of words $T = \{t_1, \ldots, t_n\}$ and each cluster C_i. Then, we assign to the term the label referring to the cluster

Algorithm 1: Aggregative algorithm (σ, *maxiter*).

$\mathcal{C} = \{\}$ ▷ The set of clusters
$\mathcal{M} = \mathcal{M}' = \{\}$ ▷ The sets of new and old of medoids
$u = \arg\max_{w \in G_v} \deg(w)$
$\mathcal{M} = \mathcal{M} \cup u$
$C_u = \{\}$
$\mathcal{C} = \mathcal{C} \cup C_u$
$numiter = 0$
do
  $\mathcal{M} = \mathcal{M}'$
  for $w \in W_{G_v}$ **do**
    if $\exists m \in \mathcal{M} \mid d_J(w,m) < \sigma$ **then**
      $x = \arg\min_{m \in \mathcal{M}} d_J(w,m)$
      $C_x = C_x \cup w$
    else
      $\mathcal{M} = \mathcal{M} \cup w$
      $C_w = \{w\}$ ▷ w originates a new cluster
      $\mathcal{C} = \mathcal{C} \cup C_w$
    end if
  end for
  $\mathcal{M}' = \{\}$
  for $m \in \mathcal{M}$ **do** ▷ Medoid recalculation
    $m' = \arg\min_{\mu \in C_m} \sum_{w \in C_m} d_J(\mu,w)$
    $\mathcal{M}' = \mathcal{M}' \cup m'$
  end for
  $numiter = numiter + 1$
while $\mathcal{M} \neq \mathcal{M}'$ and $numiter \leq maxiter$
return $\mathcal{C}$

$$C_{min} = \arg\min_{C \in \mathcal{C}_v}, \tag{3}$$

i.e. the cluster closest to T in terms of Jaccard distance. It is possible that not every cluster will be assigned to a term's occurrence; these are "weak" clusters that are maybe either too insignificant or too fine-grained. In any case, we have thus defined a mapping $\mathfrak{I}$ that goes from the set $\mathcal{T}_v$ of tweets in which v occurs to the clusters in $\mathcal{C}_v$.

4 RESULTS AND EVALUATIONS

In order to evaluate the performances of our proposed approach from a quantitative point of view, we have created a benchmark data set consisting of tweets. We are going to present, evaluate and discuss the results obtained on it by our algorithm. We are also going to compare it with another clustering algorithm called *Chinese Whispers* (Biemann, 2006). Finally, we are going to evaluate our algorithm also on an officially recognized data set such as that of Task 14 at SemEval-2010 (Manandhar et al., 2010), noting that its nature is quite different from our tweet data set.

4.1 The Tweet Data Set

The data set we decided to examine consisted of 5291 tweets in English, downloaded from Twitter on a single day using eleven different keywords, averaging about 500 tweets per keyword. Keywords were chosen to be common words that may possess many different senses (see Table 1). We are taking into account only nouns and not verbs, to avoid complicating issues related to the many conjugated and sometimes irregular forms verbs can assume. Every tweet contains one of our keywords as a free-standing term (e.g. a hashtag like *#milanfashion* would not count as an instance of *milan*).

The terms that we want to disambiguate correspond to the keywords used in the creation of our benchmark. To this purpose, we have manually disambiguated them. To briefly illustrate our criteria, let us consider e.g. the keyword *mcdonald*: we made a distinction between each single individual bearing this name, the fast food restaurants as a whole, and the company. Of course, many other possible senses exist for *mcdonald*. A problem arises with complex expressions we might call collocations[8]: there, we decided to give a term the sense of the entire collocation if it appears as the head of its noun phrase (as in "*Mars* Hill", a place name) or if it is part of a fixed proper name (as in "Thirty seconds to *Mars*", a band name). If the term is a complement, we assign to it its "basic" sense (in "Inter *Milan*", the football team, *milan* will be tagged as the city).

To run our algorithm on the tweets, we first have to pre-process them. Tweets are lowercased, tokenized and their parts of speech tagged using the ARK POS tagger for Twitter. Then, we proceed with word filtering, as explained in Section 2.2.

After pre-processing, we can build the global co-occurrence word graph G, as detailed in Section 2.3. In this specific case, G will consist of 12439 nodes or distinct words and 145256 edges. Its average shortest path has a length of 2,738 and its average clustering coefficient is 0,78. Clearly, G is warped by construction around our eleven keywords, which are the elements with the highest degrees. This serves our purpose to test our algorithm in a controlled environment where we know at which "most ambiguous" terms we have to direct our attention. Even so, this is not far from the realistic assumption that the terms whose disambiguation is most relevant are the most preeminent ones in a co-occurrence graph in terms of degree and other coefficients.

4.2 Evaluation Methods

We used two evaluation methods: the first one was defined by us as a way to assess the quality and co-

[8]See chapter 5 of (Manning and Schütze, 1999)

Table 1: Keywords and entities.

Keywords	Tagged tweets	No. of senses	Most common senses ($\geq$ 10%)
blizzard	463	23	snowstorm 43%, video game company 37%
caterpillar	467	23	CAT machines 30%, animal 24%, The Very Hungry Caterpillar 17%, CAT company 16%
england	474	11	country (UK) 65%, national football team 10%, New England (USA) 10%
ford	558	12	Harrison Ford 40%, Ford vehicles 30%, Tom Ford (fashion designer) 25%
india	474	5	country 50%, national cricket team 48%
jfk	474	13	New York airport 61%, John Fitzgerald Kennedy 33%
mcdonald	425	47	McDonald's (restaurants) 38% , McDonald's (company) 31%
mars	440	24	planet 66%, Bruno Mars 17%
milan	594	41	Milano (Italy) 58%, A.C. Milan football team 24%
pitbull	440	7	rapper 49%, dog breed 48%
venice	482	9	Venezia (Italy) 55%, Venice beach (California) 42%

herence of our clusters, while the second one is the Adjusted Mutual Information score (AMI).

4.2.1 Our Method

In Section 3 we defined the labelling mapping $\mathfrak{l}$ that labels a term with the cluster representing one of its found senses. We want to compare this labelling with the ground truths arising from our manual annotations, as explained in Section 4.1. Similarly to the construction of $\mathfrak{l}$, we define a mapping $\mathfrak{m}$ that goes from the clustering $\mathcal{C}_v$ to all the h true senses $\mathcal{G}_v = \{g_1, \ldots, g_h\}$ of a chosen word v in the following way: given a cluster C_i, we compute the Jaccard distance between the set of all the words appearing in all the tweets labelled with C_i (i.e. the contexts of C_i) and the set of all the words appearing in all the tweets labelled with a true sense g_j (i.e. the contexts of g_j), for each $j = 1, \ldots, h$. We then assign to C_i the sense g_j to which it is closest. The mapping $\mathfrak{m}$ is almost always not bijective, even if this would be the ideal case. We therefore define the local labelling accuracy score of v as the ratio of correctly labelled tweets according to $\mathfrak{m}$ to the number of tweets where v occurs. Analogously, a global accuracy score can be computed.

4.2.2 Adjusted Mutual Information

Adjusted Mutual Information was introduced after the more classical measures of F-score and V-measure, used for the evaluation of task 14 at SemEval-2010, detailed in (Manandhar et al., 2010), were found to be biased, depending too much just on the number of clusters: the more clusters, the higher the F-score and the lower the V-measure (to a minimum of 0 if just one cluster was detected for a specific term), and viceversa for a low number of clusters, apparently regardless of their quality. It was probably for this reason that the best results were achieved by the baseline algorithm that assigns to a word its most frequent sense. Adjusted Mutual Information was introduced to circumvent this problem, taking into account the fact that two big clusterings tend to have a higher mutual information score, even if they do not truly share more information (Vinh et al., 2009).

4.3 Results

In Table 2 local accuracy scores relative to our keywords for our aggregative clustering algorithm with different σ thresholds and the *Chinese Whispers* algorithm are shown. Only values greater than 0,9 are shown for σ, since this is where the overall most significant scores were achieved.

Looking at Table 2, we see that the keywords with more dispersed senses (i.e. *caterpillar*, *mcdonald*) tend to have the lowest accuracies, whereas more polarized (i.e. *pitbull*, *venice*) words give better results. By "polarized" and "dispersed" we denote a word whose two main senses, as from Table 1, cover respectively more or less than 90% of the tweets where it occurs. Interestingly, this behaviour is not exactly mirrored by the number of found clusters. Of course, the number of clusters tends to diminish as the threshold increases, since a greater σ means that the algorithm is more permissive, in the sense that clusters have a bigger radius and contain more words. On the contrary, the *Chinese Whispers* algorithm finds a very low number of clusters, probably because of the small-world nature of the underlying graph: since this algorithm assigns to a node a sense based on the senses of its neighbours, a couple of hub nodes (as mentioned in Section 2.3) will tend to influence most of the other nodes in the graph. In the light of this, *Chinese Whispers* will closely resemble the "most frequent sense" baseline algorithm. This behaviour im-

Table 2: Local accuracies (in percentages, first row) and number of clusters for each keyword.

$\sigma =$	0,9	0,91	0,92	0,93	0,94	0,95	0,96	0,97	0,98	0,99	*Chinese Whispers*
blizzard	**59,8**	55,1	57,5	50,8	53,1	53,3	54,4	47,3	47,3	45,1	43,0
	47	43	38	35	27	24	16	12	12	6	1
caterpillar	42,4	41,3	42,6	42,8	42,4	**43,7**	30,6	42,8	**43,7**	39,0	**43,7**
	31	29	26	21	20	14	10	9	7	6	6
england	40,5	40,5	41,8	53,6	60,5	63,3	63,5	**65,4**	**65,4**	65,2	**65,4**
	57	49	48	36	30	25	21	15	14	9	1
ford	74,2	**82,3**	71,3	78,3	63,3	72,2	74,7	81,9	39,6	39,6	80,1
	22	18	19	15	13	10	6	6	4	3	3
india	70,3	67,1	77	71,1	76,8	79,5	82,1	**82,9**	70,3	77,0	63,1
	61	53	44	43	35	30	24	20	18	16	2
jfk	64,8	72,6	63,5	67,3	68,4	69,4	70,7	67,1	69,8	**78,1**	61,2
	30	30	28	24	22	17	14	11	10	8	2
mcdonald	44,7	40,2	41,9	40,5	44,2	44,7	40,2	**46,4**	44,9	37,9	40,7
	36	35	30	26	23	20	18	13	11	10	3
mars	74,1	65,5	64,8	74,5	73,4	78,9	68,0	**80**	66,0	68,0	66,4
	17	13	11	8	8	6	6	4	4	3	2
milan	53,7	54,0	51,0	57,2	**62,8**	58,2	56,7	58,8	56,2	50,2	58,2
	45	42	40	34	27	21	23	16	15	14	1
pitbull	70	64,8	65,9	59,8	76,3	75,7	52,5	76,6	75	51,6	**81,1**
	46	37	36	33	26	23	15	11	10	7	3
venice	72,6	69,9	67,8	78,0	76,8	63,5	79,5	71,6	64,3	**82,4**	55,0
	38	31	28	25	24	20	16	14	10	8	1

plies too simplistic results that are in contrast with the variety of possible and actual senses for each term, as highlighted in Table 1. In this sense, the *Chinese Whispers* algorithm fails to capture all the facets of a term.

The algorithm we proposed generally has better performances than *Chinese Whispers*, especially for the threshold 0,97. In that case, the respective global accuracies are 69,6% and 60,1%. The same trend can be observed in Table 3 when applying the Adjusted Mutual Information score, both on our data set and on SemEval-2010's task 14's data set for nouns. It is to be noticed that the scores are much lower on SemEval's data set, probably due to the fact that it is much sparser than ours. In fact, disambiguation is done for 50 terms, whose number of text samples can vary between few dozens and nearly one thousand, and the samples themselves come from very different media and sources. As a consequence, a method like the one we proposed will have to work on much less significant contexts and word graphs, leading to a more fragmented clustering. Nonetheless, our algorithm still outperforms *Chinese Whispers* and is not far from the best results achieved during SemEval 2010's competition.

Table 3: Compared overall AMI scores for the aggregative clustering algorithm and for *Chinese Whispers* on our tweet data set and on SemEval-2010's task 14 data set.

	Tweet data set	SemEval-2010
$\sigma = 0{,}91$	0,162	**0,048**
$\sigma = 0{,}92$	0,161	0,046
$\sigma = 0{,}93$	0,178	0,043
$\sigma = 0{,}94$	0,175	0,045
$\sigma = 0{,}95$	0,188	0,040
$\sigma = 0{,}96$	0,193	0,037
$\sigma = 0{,}97$	**0,209**	0,037
$\sigma = 0{,}98$	0,192	0,036
$\sigma = 0{,}99$	0,196	0,032
Chinese Whispers	0,116	0,013

5 CONCLUSION

In this paper we presented an unsupervised, graph-based approach to Word Sense Discrimination. Our aim was to discriminate terms in spontaneous and uncontrolled texts, so that we chose to focus on tweets. The main challenge we encountered was the difficulty of handling a large graph of the small-world type: even after word filtering, the graph structure that arises from a text could be still considered very noisy. In the end, defining a distance on the graph, we resolved to "loosen" the graph into a metric space, where it is possible to apply well known methods such as the aggregative clustering algorithm we proposed, which yields good results.

Apart from the design of the algorithm itself, we have to underline that word clustering represents just the last step of a procedure that starts with pre-processing and tokenization of a text, which are both mostly supervised in nature and have a fundamental influence on the outcomes of the algorithm. Furthermore, text pre-processing poses many challenges for languages of a different typology and with richer morphology than English. For these reasons, we envision as our possible future goals to further investigate relations between text pre-processing and clustering results and how to make the whole process as unsupervised and language-independent as possible.

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