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Introduction

Outline









Introduction

Preliminaries I

- Large-scale Semantic Processing dealing with concepts (senses) rather than words
- Two complementary and interdependent problems:
 - Acquisition bottleneck
 - Autonomous large-scale knowledge acquisition systems
 - Ambiguity
 - Highly accurate and robust semantic systems

Preliminaries II

Acquire Large-scale Semantic Resources for NLP

- Manually-> Hard and expensive task.
 - Small coverage.
 - Dozens of persons developing those resources.
 - for example, WordNet 250.000 relations.
- Automatically-> Difficult but cheap.
 - Wide coverage.
 - Major Challenge of NLP.
 - for example, Multilingual Central Repository [Atserias et al., 2004] 1.600.000 relations

Motivation: Improve the Knowledge Bases I

- Given the noun party, which has 5 senses in WordNet 1.6, the first 2 senses:
 - Sense 1:<party, political party> (an organization to gain political power;)
 - Sense 2: <party> (an occasion on which people can assemble for social interaction and entertainment;)
- The number of semantic relations existing actually:

	sense 1	sense 2
Manually	29	7
spSemCor	20	7
spBNC	226	181
XWN	111	15
MCR	386	210

Motivation: Improve the Knowledge Bases II

Our main goal is:

- Increase the connectivity between the word-senses of the Knowledge Resources.
 - Acquire Large-scale Topic Signatures (TS [Agirre et al., 2000]) for each WordNet sense.
 - For each noun-sense:

party#n#2 an occasion on which people can assemble for social interaction and entertainment;

• We construct a query:

party#n#2: (house_party or record_hop or bunfight or photo_op or barn_dance or cocktail_party or ceremonial_occasion or photo_opportunity or tea_party or birthday_party or ceilidh)

Motivation: Improve the Knowledge Bases III

• Find a set of examples in a corpus

 $2 \rightarrow$ And it was, I mean, right, things like House **Party** and all that lot white man Malcolm X, they 're all black films. $2 \rightarrow$ These two ladies decided to form a social club, and organised a tea **party** which took place at the Ladies Park Club, where the Spurs Club was launched.

 $2 \rightarrow$ He was dissatisfied, as always, with his previous work, and he had detected flaws in The Cocktail **Party** which he wished to remove from the new play.

Motivation: Improve the Knowledge Bases IV

• Calculate the set of related words to a topic using an specific metric or Topic Signatures:

birthday 1.8875; party 1.8677; tea 0.9478; cocktail 0.9162; house 0.4577; dance 0.4030; ceilidh 0.3996; barn 0.3797; photo 0.3067; teaparty 0.2759; night 0.2732;

• Disambiguate establish relation between synset-word

∣ cocktail#n	
terrace#n	?1
baby#n	
flagstaff#n	
potter#n	
birth#n	

Motivation: Improve the Knowledge Bases V

- Characterize discovered relations Which is the relation between party#n#2 and <u>terrace#n#1</u>?? Using ontological properties appearing in MCR [Alvez et al.,2008] ¹.
 - the relation is **LOCATION**.

¹http://adimen.si.ehu.es/drupal/WordNet2TCO

Topic Signatures

- Topic Signatures(TS):
 - Word vectors related to a particular topic (synset)

• Built by retrieving context words of a target word Utilization

- Summarization Tasks [Lin & Hovy, 2000]
- Ontology population [Alfonseca et al., 2004]
- Word sense disambiguation [Agirre et al., 2000], [Agirre et al., 2001b]
- Knowledge Adquisition

There are publicly available Topic Signatures for all WordNet 1.6 [Fellbaum 98] nominal senses [Agirre & Lopez de Lacalle, 2004] http://ixa.si.ehu.es/lxa/resources/sensecorpus.

Example of TS

Related to the noun church, sense 1.

	0.776187	a se sell'a a se	0.651000
service	0.770187	anglican	0.651298
church	0.776186	services	0.651127
clergy	0.718070	tower	0.651071
hymns	0.695500	st	0.650787
peterś	0.695215	congregational	0.648595
episcopal	0.689341	congregation	0.647037
presbyterian	0.685548	priest	0.644656
cathedral	0.685220	memorial	0.644652
churches	0.683878	charters	0.642540
royal	0.673297	worship	0.637472
parish	0.671534	bishop	0.634107
pastoral	0.670789	volunteer	0.629541
maryś	0.666601		

Acquisition of TS

Methods to automatically acquire Large-scale Knowledge Resources (Topic Signatures), using several parameters:

- Corpus: British Nacional Corpus (BNC), SEMCOR vs the WEB.
- Measures: TFIDF, MI and AR.
- Knowledge Resources: WordNet.
- Query Construction: QueryW vs QueryA.
 - **QueryA:** Union set of synonyms, hyponyms and hyperonyms.
 - **QueryW:** Union set of synonyms, direct hyponyms, hypernyms, indirect hyponyms (distance 2 and 3) and siblings. Words are Monosemous Total.

Systems I

TSWEB: Topic Signatures [Agirre & Lopez de Lacalle, 2004].

- size: all nominal senses of WordNet 1.6
- corpus: WEB (1000 snipets per concept)
- measure: TFIDF
- query: queryW

EXRET: Topic Signatures using ExRetriever [Cuadros et al., 2004].

- size: Senseval-3 20 nouns senses
- corpus: BNC (100 milion words)
- measure: TFIDF, MI, AR
- query: queryW and queryA

Systems II

TSSEM: Topic Signatures using SemCor [Cuadros et al., 2007].

- **size:** all SemCor tagged words by pos, lemma and sense (WN 1.6)
- corpus: SEMCOR (192,639)
- measure: TFIDF
- **query:** Building a set of words-senses with an specified weight for each synset with TFIDF using all word-sense coocuring in sentences with contain an specific synset.



Example of the first word-senses we calculate from party#n#1 from TSSEM (SemCor)

political_party $\#$ n $\#1$	2.3219
party $\#$ n $\#1$	2.3219
election $\#$ n $\#1$	1.0926
nominee $\#$ n $\#1$	0.4780
candidate $\#$ n $\#1$	0.4780
campaigner $\#$ n $\#1$	0.4780

KnowNet



2 KnowNet

- Description
- SSI-Dijkstra Algorithm
- Preliminay Overview

3 Evaluation

- Main Goals
- Framework
- Procedure
- Results



KnowNet

Description

What's KnowNet?²

- Extensible, large and accurate knowledge base.
- Derived by semantically disambiguating the TS acquired from the web [Agirre & Lopez de Lacalle, 2004].
 - Knowledge-based WSD algorithm (SSI) to assign the most apropiate sense.
 - Knowlege Base (WN+XWN) [Fellbaum 98], [Mihalcea & Moldovan, 2001]

²http://adimen.si.ehu.es

KnowNet

SSI-Dijkstra Algorithm

SSI-Dijkstra description

Based on Structural Semantic Interconnections algorithm (SSI) [Navigli & Velardi, 2005].

- A knowledge-based iterative approach to Word Sense Disambiguation.
 - Initialization step (All monosemous are included in I (interpreted words)), polysemous in P (pending words))
 - Iterative loop, while no more pending words...
 - Selects a word W from P
 - Selects the sense S of W closer to I (disambiguate W using I as context)
 - Adds S to I and removes W from P

KnowNet

SSI-Dijkstra Algorithm

SSI-Dijkstra graph

- Proximity of one synset to the rest of synsets of I:
 - Build a very large connected graph with 99,635 nodes (synsets) and 636,077 edges. (Boost C++ Library³)
 - Containing direct relations between synsets gathered from WordNet and eXtended WordNet.
 - Compute Dijkstra algorithm. The Dijkstra algorithm is a greedy algorithm for computing the shortest path distance between one node and the rest of nodes of a graph.

³http://www.boost.org

KnowNet

SSI-Dijkstra Algorithm

SSI-Dijkstra vs. original SSI

- SSI-Dijkstra uses the available knowledge from WN and XWN.
- SSI-Dijkstra always provides the minimum distance between a synset and the set of already interpreted words.
- Original SSI uses an in-house knowledge base.
- Original SSI not always provide a path distance because it depends on a grammar.

KnowNet

SSI-Dijkstra Algorithm

Example of Use (party#n#1)

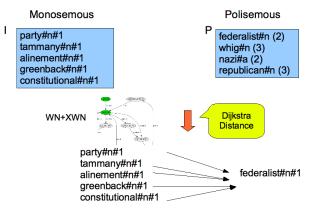
Query

KnowNet

SSI-Dijkstra Algorithm

Example of Use (party#n#1)

Query

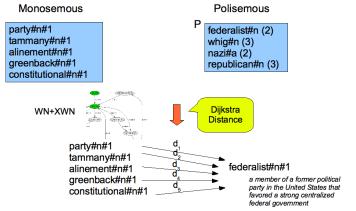


KnowNet

SSI-Dijkstra Algorithm

Example of Use (party#n#1)

Query

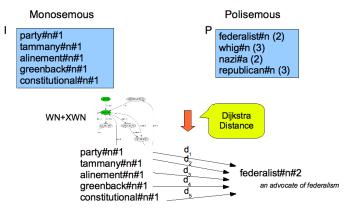


KnowNet

SSI-Dijkstra Algorithm

Example of Use (party#n#1)

Query



KnowNet

SSI-Dijkstra Algorithm

Example of Use (party#n#1)

Query

party#n alinement#n federalist#n whig#n greenback#n nazi#a republican#n constitutional#n

Monosemous

party#n#1
tammany#n#1
alinement#n#1
greenback#n#1
constitutional#n#1

Polisemous

P federalist#n (2) whig#n (3) nazi#a (2) republican#n (3)

federalist#n#1 ?? federalist#n#2

KnowNet

SSI-Dijkstra Algorithm

Example of Use (party#n#1)

Query

party#n alinement#n federalist#n whig#n greenback#n nazi#a republican#n constitutional#n

Monosemous

party#n#1 tammany#n#1 alinement#n#1 greenback#n#1 constitutional#n#1

federalist#n#1 ??

Polisemous

P federalist#n (2) whig#n (3) nazi#a (2) republican#n (3)

federalist#n#2

KnowNet

SSI-Dijkstra Algorithm

Example of Use (party#n#1)

Query

party#n alinement#n federalist#n whig#n greenback#n nazi#a republican#n constitutional#n

Monosemous

party#n#1 tammany#n#1 alinement#n#1 greenback#n#1 constitutional#n#1 federalist#n#1

Polisemous

P

whig#n (3) nazi#a (2) republican#n (3)

KnowNet

SSI-Dijkstra Algorithm

1

Example of Use (party#n#1)

Query

party#n alinement#n federalist#n whig#n greenback#n nazi#a republican#n constitutional#n

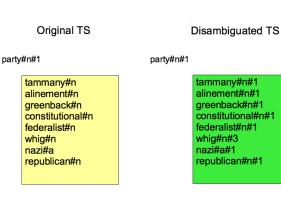
Final Disambiguation

party#n#1 tammany#n#1 alinement#n#1 greenback#n#1 constitutional#n#1 federalist#n#1 whig#n#3 nazi#a#1 republican#n#1

KnowNet

SSI-Dijkstra Algorithm

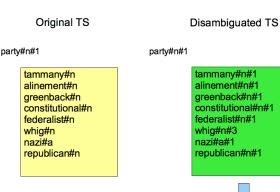
KnowNet Construction



KnowNet

SSI-Dijkstra Algorithm

KnowNet Construction



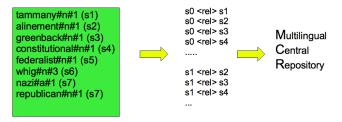


KnowNet

SSI-Dijkstra Algorithm

KnowNet Construction

party#n#1 (s0)



KnowNet

SSI-Dijkstra Algorithm

Few Examples I

00003095-n 04197156-n 00003095-n cell#n#2

the basic structural and functional unit of all organisms; cells may exist as independent units of life (as in monads) or may form colonies or tissues as in higher plants and animals 04197156-n blood#n#1

the fluid (red in vertebrates) that is pumped by the heart

KnowNet

SSI-Dijkstra Algorithm

Few Examples II

00003095-n 10785027-n 00003095-n cell#n#2

the basic structural and functional unit of all organisms; cells may exist as independent units of life (as in monads) or may form colonies or tissues as in higher plants and animals 10785027-n antibody#n#1

any of a large variety of immunoglobulins normally present in the body or produced in response to an antigen which it neutralizes, thus producing an immune response

KnowNet

SSI-Dijkstra Algorithm

Few Examples III

00013700-n 04955371-n

00013700-n motivation#n#1 motive#n#1 need#n#3

the psychological feature that arouses an organism to action; the reason for the action 04955371-n lesson#n#3 moral#n#1

the significance of a story or event

KnowNet

SSI-Dijkstra Algorithm

Few Examples IV

00013700-n 05085310-n 00013700-n motivation#n#1 motive#n#1 need#n#3 the psychological feature that arouses an organism to action; the reason for the action 05085310-n belief#n#2 dogma#n#1 tenet#n#1 a religious doctrine that is proclaimed as true without proof

KnowNet

SSI-Dijkstra Algorithm

Few Examples V

00014045-n 05349662-n

00014045-n feeling#n#1

the psychological feature of experiencing affective and emotional states

05349662-n expression#n#4 locution#n#1 saying#n#1

a word or phrase that particular people use in particular situations

KnowNet

SSI-Dijkstra Algorithm

Few Examples VI

00014045-n 06661163-n

00014045-n feeling#n#1

the psychological feature of experiencing affective and emotional states

06661163-n impulse#n#1 urge#n#1

an instinctive motive

KnowNet

SSI-Dijkstra Algorithm

Few Examples VII

00262937-n 00870386-v

00262937-n operation#n#4

a planned activity involving many people performing various actions

00870386-v puncture#v#1

pierce with a pointed object; make a hole into

KnowNet

Preliminay Overview

Overlapping and Size

Setting a window of 5, 10, 15 since 20 words of the Topic Signature

KB	WN+XWN	#relations	#synsets
KN-5	3,1%	231163	39,864
KN-10	5,0%	689610	45,817
KN-15	6,9%	1378286	48,521
KN-20	8,5%	2358927	50,789

Table: Size and percentage of overlapping relations between KnowNet versions and WN+XWN

KnowNet

Preliminay Overview

Comparing number of relations

Source	#relations		
Princeton WN3.0	235,402		
Selectional Preferences from SemCor	203,546		
eXtended WN	550,922		
Co-occurring relations from SemCor	932,008		
New KnowNet-5	231,163		
New KnowNet-10	689,610		
New KnowNet-15	1,378,286		
New KnowNet-20	2,358,927		

Table: Number of synset relations

Evaluation		
Main Goals		

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Evaluation

Main Goals

Evaluating Knowledge Resources

Main Goals:

- Establishment of a relative quality of KnowNet in a neutral environment.
- Compare the performance of KnowNet with other Knowledge Resources.

Evaluation

Framework

Framework: Senseval-3/SemEval-07

- Senseval covers a wide number of tasks and languages.
- We focus our Evaluation on a WSD task, the Lexical Sample Task for English and Spanish:
 - Determines the sense of a tagged word in a sentence
 - Uses the context words of the sentence for the Disambiguation Algorithms.
- We expect better resources will obtain higher accuracy figures on the task

Evaluation

Procedure

Evaluation Procedure

- For each noun-test example, between the Test and all the Topic Signatures related to the possible senses of the noun:
 - A simple word overlapping (by occurrence or weight) is defined for each sense example as:
 - **occurrence** evaluation measure: counts the words occurring from the TS.

The synset having higher overlapping for a chosen method is selected for a particular test example.

Evaluation

Procedure

Ev. Process: Test Example of Party sense 1 in Senseval-3

<instance id="party.n.bnc.00008131" docsrc="BNC"> <context> Up to the late 1960s, catholic nationalists were split between two main political groupings. There was the Nationalist Party, a weak organization for which local priests had to provide some kind of legitimation. As a <head>party</head>, it really only exercised a modicum of **power** in relation to the Stormont administration . Then there were the republican parties who focused their attention on Westminster elections . The disorganized nature of catholic nationalist **politics** was only turned round with the emergence of the civil rights movement of 1968 and the subsequent forming of the SDLP in 1970. </context> </instance>

Evaluation

Procedure

Studied Resources I

Wide range of large-scale Knowledge Resources integrated into **Multilingual Central Repository** (MCR):

- WordNet (WN) [Fellbaum 98]
 - tree#n#1-hyponym->teak#n#2
- eXtended WordNet [Mihalcea & Moldovan, 2001]
 - teak#n#2-gloss->wood#n#1
- large collections of semantic preferences:
 - Acquired from SemCor
 - [Agirre & Martinez, 2001, Agirre & Martinez, 2002].
 - Acquired from the BNC [McCarthy, 2001]
 - read#v#1-tobj->book#n#1

Evaluation

Procedure

Studied Resources II

Large-Scale Automatically Acquired Topic Signatures:

- TSWEB Acquired from the web [Agirre & Lopez de Lacalle, 2004].
 - querying google for each wordNet 1.6 synset.
 - building a set of words with an specified weight for each synset with TFIDF using all the snippets obtained.
- TSSEM Acquired from Semcor [Cuadros et al., 2007].
 - constructed using all Semcor tagged words by pos, lemma and sense (WN 1.6)
 - Building a set of words-senses with an specified weight for each synset with TFIDF using all word-sense coocuring in sentences with contain an specific synset.

Evaluation

Procedure

English Baselines

- **RANDOM**: A random sense lower-bound.
- WordNet MFS (WN-MFS): The first sense in WordNet.
- **TRAIN-MFS**: The most frequent sense in the training corpus.
- Train Topic Signatures (TRAIN): Using the training corpus to directly build a Topic Signature upper-bound of our evaluation framework.

Evaluation

Results

KnowNet Results: Senseval-3 in English

КВ	Р	R	F1	Av. Size
TRAIN	65.2	65.1	65.1	450
TRAIN-MFS	54.5	54.5	54.5	-
WN-MFS	53.0	53.0	53.0	-
TSSEM	52.5	52.4	52.4	103
SEMCOR-MFS	49.0	49.1	49.0	
MCR^2	45.1	45.1	45.1	26,429
WN+XWN+KN-20	44.8	44.8	44.8	671
MCR	45.3	43.7	44.5	129
KnowNet-20	44.1	44.1	44.1	610
KnowNet-15	43.9	43.9	43.9	339
spSemCor	43.1	38.7	40.8	56
KnowNet-10	40.1	40.0	40.0	154
(WN+XWN) ²	38.5	38.0	38.3	5,730
WN+XWN	40.0	34.2	36.8	74
TSWEB	36.1	35.9	36.0	1,721
XWN	38.8	32.5	35.4	69
KnowNet-5	35.0	35.0	35.0	44
WN ³	35.0	34.7	34.8	503
WN ⁴	33.2	33.1	33.2	2,346
WN ²	33.1	27.5	30.0	105
spBNC	36.3	25.4	29.9	128
WN	44.9	18.4	26.1	14
RANDOM	19.1	19.1	19.1	-

Table: P, R and F1 fine-grained results for the resources evaluated at Senseval-3, English Lexical Sample Task.

Evaluation

Results

KnowNet Results: SemEval-07

КВ	Р	R	F1	Av. Size
TRAIN	87.6	87.6	87.6	450
TRAIN-MFS	81.2	79.6	80.4	
WN-MFS	66.2	59.9	62.9	
WN+XWN+KN-20	53.0	53.0	53.0	627
(WN+XWN) ²	54.9	51.1	52.9	5,153
TSWEB	54.8	47.8	51.0	700
KnowNet-20	49.5	46.1	47.7	561
KnowNet-15	47.0	43.5	45.2	308
XWN	50.1	39.8	44.4	96
KnowNet-10	44.0	39.8	41.8	139
WN+XWN	45.4	36.8	40.7	101
SEMCOR-MFS	42.4	38.4	40.3	
MCR	40.2	35.5	37.7	149
TSSEM	35.1	32.7	33.9	428
KnowNet-5	35.5	26.5	30.3	41
MCR ²	32.4	29.5	30.9	24,896
WN ³	29.3	26.3	27.7	584
RANDOM	27.4	27.4	27.4	
WN ²	25.9	27.4	26.6	72
spSemCor	31.4	23.0	26.5	51
WN ⁴	26.1	23.9	24.9	2,710
WN	36.8	16.1	22.4	13
spBNC	24.4	18.1	20.8	290

Table: P, R and F1 fine-grained results for the resources evaluated at SemEval-2007, English Lexical Sample Task.

Evaluation

Results

Conclusions for English

- Regarding the baselines, all knowledge resources surpass RANDOM, but none achieves neither WN-MFS, TRAIN-MFS nor TRAIN.
- Different versions of KnowNet seem to be more robust and stable across corpora changes.
- The knowledge they contain outperform any other resource when is empirically evaluated in Senseval-3 and SemEval-07.
- KN-20 > KN-15 > KN-10 > KN-5

Evaluation

Results

Spanish Baselines

- **RANDOM**: A random sense lower-bound.
- Minidir MFS (Minidir-MFS): Most Frequent Sense in MiniDir (Minidir-MFS is equal to TRAIN-MFS).
- Train Topic Signatures (TRAIN): Using the training corpus to directly build a Topic Signature upper-bound of our evaluation framework.

Evaluation

Results

KnowNet Results: Senseval-3 in Spanish

КВ	Р	R	F1	Av. S
TRAIN	81.8	68.0	74.3	450
MiniDir-MFS	67.1	52.7	59.2	
KnowNet-15	54.7	48.9	51.6	176
KnowNet-20	51.8	49.6	50.7	319
KnowNet-10	53.5	43.1	47.7	81
MCR	46.1	41.1	43.5	66
WN ²	56.0	29.0	42.5	51
(WN+XWN) ²	41.3	41.2	41.3	1,892
KnowNet-5	58.5	26.9	36.8	22
TSSEM	33.6	33.2	33.4	208
XWN	42.6	27.1	33.1	24
WN	65.5	13.6	22.5	8
RANDOM	21.3	21.3	21.3	

Table: P, R and F1 fine-grained results for the resources evaluated individually on Spanish.

Conclusions for Spanish

- Regarding the baselines, all knowledge resources surpass RANDOM, but none achieves neither Minidir-MFS (equal to TRAIN-MFS) nor TRAIN.
- MCR (F1 of 43.5) almost doubles WN (F1 of 22.5).
- KnowNet-5 performs better than WN, XWN and the TS acquired from SemCor.
- From KnowNet-10 all KnowNet versions perform better than any other knowledge resource on Spanish derived by manual or automatic means (including the MCR).
- KN-15 > KN-20 > KN-10 > KN-5

KnowNet: Building a Large Net of Knowledge from the Web Conclusions and Future Work

Overall Conclusions

- Different versions of KnowNet seem to be more robust and stable across corpora changes and across languages.
- The initial results obtained for the different versions of KnowNet seem to be a major step towards the autonomous acquisition of knowledge from raw corpora.
- They are several times larger than the available knowledge resources which encode relations between synsets.
- The knowledge they contain outperform any other resource when is empirically evaluated in Senseval-3 and SemEval-07.

KnowNet: Building a Large Net of Knowledge from the Web Conclusions and Future Work



- Label the new relations.
- Create new links and relations for the unknown words/concepts (e.g Gatwick#n#0).
- Evaluate KnowNet in another languages like italian, ...

Conclusions and Future Work

Moltes gràcies!

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