MWEs: Theoretical Background & Motivation MWEs: Computational Methods Resources, tasks and applications Future challenges and open problems

Robust Semantic Analysis of Multiword Expressions with FrameNet

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Road Map I

- MWEs: Theoretical Background & Motivation
 - Linguistic and CL Theories
- MWEs: Computational Methods
 - "Discovering" MWEs
 - Syntax-based Extraction
 - MWE Identification in Context
 - Interpretation
 - Detecting a Continuum of compositionality in PVs
 - Interpreting Nominal Expressions
 - NLP Tasks and Applications
- Resources, tasks and applications
 - Tools
 - Resources

MWEs: Theoretical Background & Motivation MWEs: Computational Methods Resources, tasks and applications Future challenges and open problems

Road Map II

- Tasks and applications
- Evaluation

Future challenges and open problems

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The study of MWEs

- is almost as old as linguistics itself
- in the traditional generative grammatical framework, the representation of idioms poses a challenge, e.g., the idiom first off is an adverbial locution synonym to firstly
- in Construction Grammar, [Fillmore et al., 1988b]
 - suggest that there must be an appendix to the set of lexical units and syntactic rules of a language model for idiomatic entries and their specific syntactic, semantic and pragmatic charecteristics
 - this way, idioms can become part of the core of the grammar: that is, a language can be fully described by its idioms and their properties

In meaning-text theory (MTT)

- [Mel'čuk and Polguère, 1987] suggest that a dictionary entry contains three zones: (i) the semantic zone, (ii) the syntactic zone, and (iii) the lexical combinatorics zone
- MWEs are present at two points of the computational MTT model: as phrasemes and as lexico-semantic functions (LSF) in the so called lexical combinatorics zone

In psycholinguistics and cognitive linguistics, there has been work on learning

- verb-particle constructions [Villavicencio et al., 2012]
- noun compounds [Devereux and Costello, 2007]
- light verb constructions and
- multiword terms [Lavagnino and Park, 2010] based on corpora evidence and sophisticated cognitive models; these models try to validate computational models for MWE acquisition by checking their correlation with experiments that use similar models for human language acquisition [Joyce and Srdanović, 2008, Rapp, 2008]

In computational linguistics

- the study of MWEs arose from the availability of very large corpora and of computers capable of analysing them by the end of the 80's and beginning of the 90's
- the aim was to build systems for computer-assisted lexicography and terminography of multiword units [Choueka, 1988]
- [Smadja, 1993] proposed Xtract, a tool for collocation extraction based on some simple POS filters and on mean and standard deviation of word distance
- [Church and Hanks, 1990] suggested a more sophisticated association measure based on mutual information

In computational linguistics

- later, [Dagan and Church, 1994] proposed a terminographic environment called Termight, which uses this association score, performs bilingual extraction, and provides tools to easily classify candidate terms, find bilingual correspondences, define nested terms and investigate occurrences through a concordancer
- [Justeson and Katz, 1995] proposed a simple approach based on a small set of POS patterns and frequency thresholds

In computational linguistics

[Dunning, 1993] proposed a 2-gram measure called likelihood ratio. It estimates directly how more likely a 2-gram is than expected by chance. In addition to being theoretically sound, Dunning's score is also easily interpretable. Nowadays, measures based on likelihood ratio (e.g., the log-likelihood score) are still largely employed in several MWE extraction contexts

In computational linguistics

• At the beginning of the 2000's, the Stanford MWE project (http://mwe.stanford.edu/) has revived interest of the NLP community in this topic. One of the most cited publications of the MWE project is the famous "pain-in-the-neck" paper by [Sag et al., 2002b]. It provided an overview of MWE characteristics and types and then presented some methods for dealing with them in the context of grammar engineering. The Stanford MWE project is also at the origin of the MWE workshop series

MWEs: their semantics

MWEs and the Notion of Compositionality: Definition

 degree to which the features of the parts of an MWE combine to predict the features of the whole

MWEs: their semantics

MWEs and the Notion of Compositionality

- Generally considered in the context of semantic compositionality, but we can equally talk about:
 - lexical compositionality
 - syntactic compositionality
 - pragmatic compositionality

MWEs: their syntax

Example: Syntactic Compositionality

- Definition: Degree to which the <u>syntactic</u> features of the parts of an MWE combine to predict the <u>syntax</u> of the whole
 - Fixed expression: by and large, San Francisco
 - Verb particles: eat up vs. chicken out
- Syntactic compositionality binary effect: non-compositional MWEs lexicalised

MWEs: their semantics and syntax

Question

Given that compositionality extends over all aspects of markedness that affect MWEs, is it all we need to take into consideration?

Almost, but there are subtleties due to:

- statistical markedness
- decomposability

MWEs: their semantics and syntax

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Almost, but there are subtleties due to:

- statistical markedness
- decomposability

MWEs: back to statistics

Statistical Markedness (Revisited)

- Statistical markedness is not a lack of compositionality:
 - $p(\text{impeccable N}) \times p(\text{Adj eye}) \approx p(\text{impeccable eye})$

BUT

- 2 $p(\text{unblemished N}) \times p(\text{Adj eye}) \gg p(\text{unblemished eye})$
- **3** $p(\text{spotless N}) \times p(\text{Adj eye}) \gg p(\text{spotless eye})$
- 4 $p(\text{flawless N}) \times p(\text{Adj eye}) \gg p(\text{flawless eye})$

MWEs: their semantics revisited

Decomposability: Definition

 degree to which the features of an MWE can be ascribed to those of its parts

MWEs: their semantics revisited

Decomposability: Three Classes of MWEs

Classification of MWEs into 3 classes:

- non-decomposable MWEs: kick the bucket, hot dog
- idiosyncratically decomposable MWEs: spill the beans, let the cat out of the bag
- simple decomposable MWEs: kindle excitement

MWEs: their semantics and syntax

Decomposability and Syntactic Flexibility

- Consider:
 - *the bucket was kicked by Kim Strings were pulled to get Sandy the job.
 - The FBI kept closer tabs on Kim than they kept on Sandy.
 - ... the considerable **advantage** that was **taken of** the situation
- The syntactic flexibility of an idiom can generally be explained in terms of its decomposability

- simple compositionality is adequate for describing many instances of lexical, syntactic, semantic and pragmatic markedness
- BUT the notion of compositionality is significantly different for statistically marked MWEs
- AND decomposability diffuses the markedness boundary

MWEs: their importance for Linguistics and CL

And why is it that we care about MWEs?

- Because of the role of MWEs in:
 - Lexicography/dictionary making
 - Idiomaticity (coherent semantics)
 - Overgeneration
 - Undergeneration
 - Relevance in NLP and LT applications, including MT, IR, QA, ...

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MWEs: Computational Methods

Overview

Adapted from [Anastasiou et al., 2009]

- Acquisition
 - Extraction
 How can we build a list of MWE types from corpora?
 - Identification
 How can we locate the tokens that correspond to MWEs in context?

MWEs: Computational Methods

Overview (contd.)

Adapted from [Anastasiou et al., 2009]

- Classification
 - Interpretation
 How can we discover the syntactic and semantic relations between the units that compose a MWE type?
 - Disambiguation
 How can we disambiguate the syntactic and semantic properties of a MWE token in context?

MWEs: Computational Methods

Overview (contd.)

Adapted from [Anastasiou et al., 2009]

- Representation
 - How can we represent complex MWEs in computational lexicons?
- Tasks and applications
 How can we integrate MWEs in NLP tasks (parsing, WSD) and applications (IR, MT)?

MWEs: Computational Methods

"Discovering" MWEs: Co-occurrences

- If a word is characterized by the company it keeps [Firth, 1957] then we can try to find MWEs using information about how often words co-occur together
- Hypothesis: the more frequently some words occur together, the more likely it is that they form a MWE

"Discovering" MWEs: Filtering with Association Measures

Statistical association measures (AMs)

- can give indication of strength of the association between words (or n-grams)
 - based on frequency of words individually and as a group

"Discovering" MWEs - Filtering with Association Measures

AMs for Ranking MWE Candidates

- Hypothesis: If the words are dependent then the candidate is a MWE
 - Determine the probability given by the Null Hypothesis (that they are independent)
 - Compare with the probability given by a statistical measure
 - t-test, Pearson's X^2 , Pointwise Mutual Information, Mutual Information, ...
 - If Null Hypothesis is rejected then they are dependent (MWEs)



"Discovering" MWEs: Alternative Measures: Entropy-based

Permutation Entropy

Hypothesis: MWEs prefer a certain word order (give a demo vs a demo give)

- If a candidate is result of random combination of words then word order in n-gram is not important: of alcohol and, and of alcohol, alcohol and of, etc
- Entropy: $S = -\frac{1}{\log N} \sum P(abc) \log P(abc)$: $S \to 0$ (prevalent order) \longrightarrow possible MWE

MWE	Pages	S
IVIVV		3
the burden of	36,600,000	0.366
but also in	27,100,000	0.038
to bring together	25,700,000	0.086
points of view	24,500,000	0.017
and the more	23,700,000	0.512
taking into account the	22,100,000	0.009

Evaluation of the Extraction of MWEs

Factors in MWE Extraction [Evert and Krenn, 2005]

- corpus size and type
- MWE type and language
- AMs

Comparison of AMs

- 84 measures among which some are rank-equivalent to one another [Pecina, 2008]
- comparison of their combination [Ramisch et al., 2008]



More on Evaluation of the Extraction of MWEs

For statistical approaches there are two important questions

- Q1 How reliable/generalizable are the results for a given corpus?
- Q2 How precise an association measure is to distinguish MWEs from noise?

Evaluation of the Extraction of MWEs - Comparing corpora

Q1: How reliable/generalizable are the results for a given corpus?

- Hypothesis: relative candidate rankings are preserved across similar corpora
 - If not, different conclusions may be drawn from different corpora
- Evaluation
 - list of MWE candidates
 - 4 corpora
 - standard: BNC vs fragment of the BNC (BNC_f)
 - WACs: Google vs Yahoo



Evaluation of the Extraction of MWEs - Comparing corpora

Relative Frequency Rank for the Trigrams

- Kendall's τ scores between corpora show significant correlation (p \leq 0.000001)
- A higher correlation was observed between Yahoo and Google: as corpora sizes increase, so do the correlations between them

	BNC	Google	Yahoo
BNC_f	0.81	0.73	0.78
BNC		0.73	0.77
Google			0.86



Evaluation of the Extraction of MWEs - Comparing AMs

Q2: How precise an association measure is to distinguish MWEs from noise?

- Using a single corpus (BNC_f), comparing MI, χ^2 and Permutation Entropy (PE)
- Kendall's \(\tau \) for assessing the correlation of the rankings for these AMs and Q is the probability of finding the same ordering in them

	$MI \times \chi^2$	$MI \times PE$	$\chi^2 \times PE$
Q	0.71	0.55	0.45

- The correlations found are statistically significant
- The measures order the trigrams differently
 - 70% chance of getting the same order from MI and χ^2



Verb-particle Constructions (VPCs) [Baldwin, 2005]

- VPC = verb + obligatory particle(s) (e.g.hand in, battle on)
 - intransitive: e.g. the team battled on
 - transitive: e.g. Kim handed the paper in
- Variable word order for transitive VPCs:
 - joined: hand in the paper
 - split: <u>hand</u> the paper <u>in</u>
- Structural/analytical ambiguity:
 - hand [the paper] [in] [here] vs. hand [the paper] [in here] vs. hand [the paper in here]
 - hand [in] [the paper] vs. hand [in the paper]



Token Identification

MWE or not?

- The cook/journalist spilled the beans
- [Kim and Baldwin, 2010] identify token instances of VPCs from output of parser
 - head nouns can help distinguish if V and P in a given sentential context are
 - VPC: Kim handed in the paper or
 - verb-PP: Kim walked in the room
 - post-processing VPC identification
 - combine syntactic and semantic features
 - using sentential context of instances of VPCs and verb-PPs



Token Identification

MWE or not?

- Semantics of VPC may be
 - derived from semantics of verb and particle: walk off
 - different from them: look up;
- Selectional preferences of VPCs may
 - mirror those of the verbs: clean and clean up
 - diverge: put the book on the table and put on a sweater,

Different selectional preferences for verb in isolation or in VPC



Token Identification

Method

- 1. From parser output identify:
 - verbs and particles and transitive prepositions
 - head nouns of subject and object of each verb
- 2. Obtain lexical semantics of the head nouns
 - based on WordNet 2.1 [Fellbaum, 1998]
 - using the first sense for that word in SemCor (Landes et al., 1998)
- Build a classifier
 - feature vector for VPC and verb-PP: (verb, preposition, subject WN class, object WN class)



Detecting a Continuum of compositionality in PVs

MWE Identification with Distributional Thesaurus

- Compositionality detection [McCarthy et al., 2003] via automatically acquired thesaurus [Lin, 1998]
 - Thesaurus contains 500 neighbors for verb and VPC
 - from subject and object grammatical relations of simplex verb and VPC
- Indicators of VPC Compositionality:
 - overlap of neighbors of simplex and VPC
 - neighbors of VPC include other VPCs with same particle
 - verb neighbor of VPC, etc



Detecting a Continuum of compositionality in PVs

Evaluation: against human judgements

- 116 annotated VPC
- 3 native speakers
 - scale from 0 (non-compositional) to 10 (fully compositional)
- Correlation with
 - frequency of VPC and verb
 - resources
 - Wordnet, Alvey Tools Lexicon
 - AMs
 - χ^2 , log likelihood ratio, PMI



Compound Nominals and Nominalisations

Compounds vs Nominalisations

Compound nominal

- N' made up of two or more nouns
- Largely unrestricted semantically
 - diesel truck/oil/tanker, phone book, cloud bus

Nominalisation:

- subclass of compound nominals in which the head noun is deverbal, e.g.:
 - machine performance, museum construction, family worker, student education, farm agreement
- tend to occur with subject or object interpretation:
 - machine performance, museum construction, student education BUT also soccer competition

Compound Nominals

Characteristics

- Highly productive (≈ 300K NN types in BNC)
- Very frequent (> 1M NN tokens in BNC)
- Very skewed in frequency (\approx 60% of NN types in BNC occur once)

Compound Nominals

Interpretation

- Task: classification of nominalisations as having a subject or object interpretation
- Assumption: the relation of the nominalised head and modifier can be approximated by relation of modified noun and verb from which head is derived
- $P(rel|n_1, n_2) \approx P(rel|v_{n_2}, n_1)$
- **Problem:** getting accurate estimates of $P(rel|v_{n_2}, n_1)$
- Annotator agreement = 89.7%
- Baseline accuracy of 61.5% (OBJ interpretation)

[Lapata, 2002, Kim and Nakov, 2011]

Grammar Engineering and Parsing

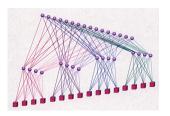
- Lexical coverage is a major barrier to broad-coverage linguistically deep processing
 - 40% parsing failures caused by missing lexical entries [Baldwin et al., 2004]
- MWEs are a significant part of the lexicon
 - Detect potential errors in parsing involving sequences of words
 - Identify MWE candidates
 - Generate new lexical entries based on corpus data

Extension of a hand-crafted linguistic resource with MWEs: English Resource Grammar [Flickinger, 2000]

- A large scale broad coverage precision HPSG grammar
- Lexicon coverage is a major problem
- MWEs comprise a large portion of the missing lexical entries

Lexical hierarchy and atomic lexical types

- The lexical information is encoded in atomic lexical types
- A lexicon is a n: n mapping between lexemes and atomic lexical type

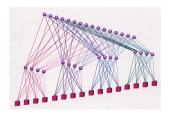




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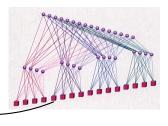




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Maximum Entropy Model-based Lexical Type Predictor

- A statistical classifier that predicts for each occurrence of an unknown word or a missing lexical entry
- Input: features from the context
- Output: atomic lexical types

$$p(t,c) = \frac{exp(\sum_{i} \theta_{i} f_{i}(t,c))}{\sum_{t' \in T} exp(\sum_{i} \theta_{i} f_{i}(t',c))}$$

"Words-with-spaces" vs. compositional approaches

Words-with-spaces approach [Zhang et al., 2006]

- Assign lexical types for the entire MWE
- Grammar coverage significantly improves
- Loss in generality for productive MWEs

Compositional approach

- Assign new lexical entries for the head word to treat the MWE as compositional
- Hopefully the grammar coverage improves without drop in accuracy



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Experiment

- Rank all the MWE candidates according to the three statistical measures: MI, χ^2 , PE, and select the top 30 MWE with highest average ranking
- Extract sub-corpus from BNC_f which contains at least one of the MWE for evaluation (674 sentences)
- Use heuristics to extract head words (20 head words)
- Run lexical acquisition for head words on the sub-corpus (21 new entries)

Grammar Coverage

	item #	parsed #	avg. analysis #	coverage %
ERG	674	48	335.08	7.1%
ERG + MWE	674	153	285.01	22.7%

- The coverage improvement is largely compatible with the results of "words-with-spaces" approach reported in [Zhang et al., 2006] (about 15%)
- Great reduction in lexical entries added

Grammar Accuracy

- 153 parsed sentences are analyzed by hand
- 124 (81.0%) of them receive at least one correct/acceptable analysis (comparable to the accuracy reported by [Baldwin et al., 2004])
- Parse selection model finds best analysis in top-5 for 66% of the cases, and top-10 for 75%

Outlook

- Hand-crafted precision grammars usually face coverage/robustness challenges when applied to unseen data with unknown words/MWEs, unknown constructions, etc., all over the place
- [Baldwin et al., 2004] reported parsing coverage of 18% on unseen BNC data parsed with the ERG, with the majority of parsing failures related to missing lexical entries
- The Lexical Type Prediction model presented as an example above is used to handle unknown words (simplex and MWE) on-the-fly
- With the use of this model the ERG achieves around 84% parsing coverage on unseen WSJ data



Outlook

Other "Deep" Parsing Systems

- LFG
 - XLE 79.6% F-Score [Kaplan et al., 2004]
- CCG
 - C&C 81.86% F-Score [Clark and Curran, 2007]
- HPSG
 - Enju 82.64% F-Score [Sagae et al., 2008]
- The aforementioned systems are evaluated on 700 sentences selected from WSJ data (PARC 700), using Grammatical Relations (GR)

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Tools Resources Tasks and applications Evaluation

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Future challenges and open problems

Text::NSP

- N-gram statistics in text files
- Set of Perl scripts for counting and calculating AMs
- Mostly 2-grams, some measures for 3- and 4-grams
- Customization: sub-n-gram counts and non-tokens

http://search.cpan.org/dist/Text-NSP

[Pedersen et al., 2011, Banerjee and Pedersen, 2003]

UCS

- Large set of sophisticated AMs
- Input: list of bigrams and their counts (proper extraction must be performed externally, e.g. with NSP)
- Perl and R scripts, includes advanced statistical tools for evaluation

```
http://www.collocations.de/software.html
```

[Evert, 2004]



LocalMaxs

- Extracts MWEs based on the local maxima of the distribution of a customisable AM
- Relaxed and strict versions
- Non-contiguous variation
- Scalability

http://hlt.di.fct.unl.pt/luis/multiwords/

[Silva and Lopes, 1999, da Silva et al., 1999]

Varro

- Find regularities in treebanks
- Rank regular subtrees by description length

http://sourceforge.net/projects/varro/

[Martens, 2010, Martens and Vandeghinste, 2010]

mwetoolkit

- Multi-level patterns for candidate generation
- Several filtering methods
- Focused on genericity and flexibility

http://mwetoolkit.sourceforge.net

[Ramisch et al., 2010a, Ramisch et al., 2010b]

Embedded

- FIPS parser [Seretan and Wehrli, 2009, Seretan and Wehrli, 2011]
- Stanford parser [Green et al., 2011]
- Phrasal verbs in RASP
- Most parsers include (minimal) MWE processing

Related tools

- Complex corpus searches: CQP [Christ, 1994] and Manatee [Rychlý and Smrz, 2004]
- Terminology extraction
 - TermoStat

```
http://olst.ling.umontreal.ca/~drouinp/termostat_web/
```

AntConc

```
http://www.antlab.sci.waseda.ac.jp/software.html
```

TerMine

```
http://www.nactem.ac.uk/software/termine/
```

Named entity recognition



Tools
Resources
Tasks and application
Evaluation

Tools for acquisition

Which one to chose? [Ramisch et al., 2012]

LocMax	mwetk	NSP	UCS
+	+	+	_
+	+	+	_
_	+	+	
_	+	_	_
_	_	+	+
Partly	+	+	_
+	Partly	+	+
_	_	_	_
Free	Free	Free	Free
	+ + - - - Partly + -	+ + + + + + + + + + + + + Partly + Partly	+ + + + + + + + + + + + + + + + + + +

Tools
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Resources

Why do we need MWE acquisition?

- MWEs are very frequent in human languages
 [Jackendoff, 1997b]
- Computational resources (corpora, grammars, lexicons) do not reflect this

Tools
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Resources

Corpora

- At least 17% of Europarl sentences contain a phrasal verb
- 70% of terms in Genia are multiwords
- Flat annotation of noun compounds in treebanks (PTB, French treebank, etc)

Resources

Wordnet			
		Non-MWE	MWE
	Nouns	57535	60292
	Verbs	8729	2829
	Adverbs	3796	714
	Adjectives	21012	496

- Other languages?
- Missing MWE types (e.g. support verb constructions)?
- New expressions?



Resources

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- Parsing
- Information retrieval
- Word sense disambiguation
- Machine translation
- Educational testing
- Sentiment analysis

Parsing

- Small set of fixed MWEs (e.g. conjunctions) in most parsers, chunkers and POS taggers
- Joining contiguous nominal expressions with an underscore prior to parsing [Korkontzelos and Manandhar, 2010]
- Extend HPSG lexicon with MWEs as words with spaces
 [Zhang and Kordoni, 2006, Villavicencio et al., 2007]
- Named entities replaced by placeholders [Hogan et al., 2011]

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Tasks and applications

Parsing (contd.)

- Feature for disambiguation [Wehrli et al., 2010]
- Tree substitution grammars [Green et al., 2011]
- Joint MWE identification and POS tagging with CRF [Constant and Sigogne, 2011]

Overgeneration vs undergeneration



Word sense disambiguation

- An MWE is less polysemous than its words, one sense per collocation
 - voice = 11 senses
 - mail = 5 senses
 - voice mail = 1 sense
- Wordnet average polysemy: MWEs = 1.07 synsets, words
 = 1.53 synsets
- Use of jMWE to join words, then perform WSD → improvement of 5 F-measure points [Finlayson and Kulkarni, 2011]

Information retrieval

- Joining the words before indexation [Acosta et al., 2011]
- Tightness of 4-character sequences in Chinese for segmentation [Xu et al., 2010]
- Document representation in topic modelling [Baldwin, 2011]

Machine translation (rule-based)

- Morphological and syntactic analysis in ITS-2 [Wehrli, 1998, Wehrli et al., 2010]
- MWE-specific rules in semantic transfer system Jaen [Haugereid and Bond, 2011]
- French-japanese terms [Morin and Daille, 2010]
- Web as corpus for disambiguating traslation [Grefenstette, 1999]
- Japanese compounds through compositional translation + SVM ranker [Tanaka and Baldwin, 2003, Baldwin and Tanaka, 2004]

Machine translation (statistical)

- Phrases in Moses [Koehn et al., 2007]
- Static and dynamic strategies for English MWEs from Wordnet [Carpuat and Diab, 2010]
- Monolingual paraphrases for increasing training data [Nakov, 2008a]
- Pre- and post-processing for German compounds [Stymne, 2011, Stymne, 2009]
- Named entities and compound verbs tokenisation [Pal et al., 2010]
- Corpus and phrase-table artificial extensions [Ren et al., 2009]

Evaluation context

- What are the acquisition goals (that is, the target applications) of the resulting MWEs?
- What is the nature of the evaluation measures that we intend to use?
- What is the cost of the resources (dictionaries, reference lists, human experts) required for the desired evaluation?
- 4 How ambiguous are the target MWE types?

Tools
Resources
Tasks and application
Evaluation

Evaluation context

Acquisition goals

- Intrinsic: Evaluate the MWEs per se, using human annotation or gold standard dictionaries.
- Extrinsic: Evaluate an application output which includes MWE acquisition.

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Evaluation context

Nature of evaluation measures

- Quantitative: Objective measures (precision, recall, P@100, MAP)
- Qualitative: More fine-grained characterisation of errors.

Evaluation context

Availability of resources

- Manual annotation. Sample annotated by group of (expert) native speakers. Realiability depends on quality of quidelines, agreement, sample size, etc.
- Automatic annotation. Compare extracted MWEs with existing gold standard (dictionary, thesaurus). Assumes the gold standard is complete.
- A mixture of both is commonly employed.

Tools Resources Tasks and applications Evaluation

Evaluation context

Type of target MWEs

- Type-based evaluation. Non-ambiguous expressions, can be evaluated out of context. Several resources available on MWE website [Laporte and Voyatzi, 2008, Krenn, 2008, Nicholson and Baldwin, 2008, Nakov, 2008b]
- Token-based evaluation. Target MWEs are ambiguous (e.g. phrasal verbs, idioms). Fewer resources available [Cook et al., 2007, Cook et al., 2008, Baldwin, 2008, Fritzinger et al., 2010].

Acquisition context

Generalisation of evaluation results depends on parameters of acquisition context:

- Characteristics of target MWEs
 - Type
 - Language
 - Domain
- Characteristics of corpora
 - Size
 - Nature
 - Level of analysis
- Existing resources



Road Map I

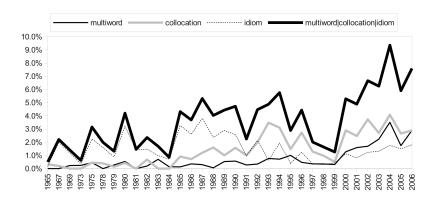
- MWEs: Theoretical Background & Motivation
 - Linguistic and CL Theories
- 2 MWEs: Computational Methods
 - "Discovering" MWEs
 - Syntax-based Extraction
 - MWE Identification in Context
 - Interpretation
 - Detecting a Continuum of compositionality in PVs
 - Interpreting Nominal Expressions
 - NLP Tasks and Applications
- Resources, tasks and applications
 - Tools
 - Resources



Road Map II

- Tasks and applications
- Evaluation

Future challenges and open problems



Trending topics

- Semantics
- Multilingualism
- Applications
- Evaluation
- Machine learning

Current and future activities

- MWE workshop series (11th edition at NAACL HLT 2015: http://www.aclweb.org/anthology/W15-09; 12th edition planned in conjunction to ACL 2016 in Berlin http://acl2016.org)
- ACM TSLP Special Issue on MWEs in 2 parts (http://dl.acm.org/citation.cfm?id=2483691&picked=prox)
- SIGLEX-MWE Section (http://multiword.sourceforge.net/)
- Forthcoming Book: Valia Kordoni. 2016. Multiword Expressions
 From Linguistic Analysis to Language Technology
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Future challenges

- Identification is not a solved problem
- Integration and representation in applications
- Robust methods for new MWEs in web texts

MWEs: Theoretical Background & Motivation MWEs: Computational Methods Resources, tasks and applications Future challenges and open problems

Further reading

Please refer to complete list of references :-)

Further reading

Thank you!

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