

Natural language processing: state of the art, prospects for the next few years

Alistair Knott

Types of structure found in language

- Speech / orthography
- Lexical semantics
- Syntax
- Compositional semantics
- Dialogue

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- Dialogue (utterance → next utterance)

Speech / orthography

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Almost a solved problem.

Lexical semantics

How to represent the meaning of the word *crinkly*?

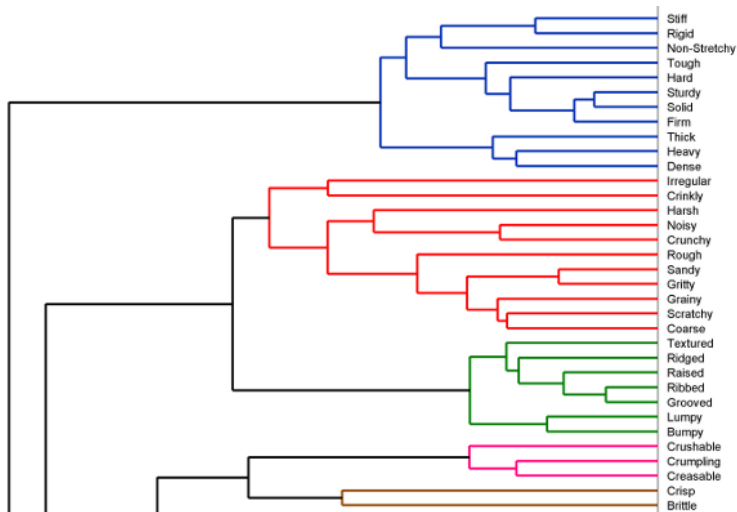
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Illustrating the statistical modelling approach



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SEMEVAL/SENSEVAL competitions:
Coarse-grained word-sense disambiguation: over 90%.

Syntax

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PARSEVAL competition

Over 90% (metric involves precision, recall, tree-similarity)

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- Some linguists think that syntactic structures are *nothing but* learned conventions.
- Others think that syntactic structures also reflect an *innate* capacity for language.

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- Caveat 1: we don't know what syntax is.
- Caveat 2: we don't know what word meanings are.

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- Performance: see Google translate.

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There are two basic methods:

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QA systems are evaluated in the TREC competition.

- Circa 2013: The best systems can successfully answer 70% of 'factoid' questions.
- '90% of nurses follow Watson's guidance' in a specialised healthcare application.

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- Surface-based methods (e.g. Microsoft's Tay): basically like text-based machine translation.
- Knowledge-based methods: the best ones use dialogue managers, and often planning systems. These systems are clever, but fragile.

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Some parts of the pipeline already work very well.

- Speech, writing
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- Compositional semantics


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- Those aspects of syntax that reflect conventions
- Compositional semantics

Other parts still need big theoretical advances.

- Grounding lexical semantics in the world
- Answering foundational questions about ‘what syntax is’
- Building dialogue systems that are robust *and* deep.



I WISH I WAS
DEEP INSTEAD
OF JUST MACHO!