



TAMPEREEN TEKNILLINEN YLIOPISTO  
TAMPERE UNIVERSITY OF TECHNOLOGY

# **JAAKKO PASANEN**

## **NLP FOR CUSTOMER SUPPORT AGENT**

Master of Science thesis

Examiner: Prof. Ari Visa  
Examiner and topic approved by the  
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# ABSTRACT

**JAAKKO PASANEN:** NLP for Customer Support Agent  
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The abstract is a concise 1-page description of the work: what was the problem, what was done, and what are the results. Do not include charts or tables in the abstract.

Put the abstract in the primary language of your thesis first and then the translation (when that is needed).

# TIIVISTELMÄ

**JAAKKO PASANEN:** Luonnollisen kielen ymmärrys asiakapalveluagentilla  
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The abstract in Finnish. Foreign students do not need this page.

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## PREFACE

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Acknowledgements to those who contributed to the thesis are generally presented in the preface. It is not appropriate to criticize anyone in the preface, even though the preface will not affect your grade. The preface must fit on one page. Add the date, after which you have not made any revisions to the text, at the end of the preface.

Tampere, 11.8.2014

On behalf of the working group, Erno Salminen

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## LIST OF ABBREVIATIONS AND SYMBOLS

ANN	Artificial Neural Network
LAS	Labelled Attachment Score
LDA	Latent Dirilecht Allocation
LSA	Latent Semantic Analysis
LSTM	Long short term memory; type of RNN with short term memory.
NER	Named entity recognition
NLP	Natural Language Processing
POS	Part-of-speech; also called lexical category
RNN	Recurrent neural network
S-LSTM	Stack long short term memory
TUT	Tampere University of Technology
UAS	Unlabelled Attachment Score

# NOTES

## 0.1 Terms for Computational Linguistics

**1-of-V Coding** Representing words as sparse binary vectors which have 1 at the word's vocabulary index and 0 all others. With vocabulary {dog, cat, mouse}, dog becomes [1, 0, 0], cat becomes [0, 1, 0] and mouse [0, 0, 1].

**Bag-of-words** Multiset of words appearing in a text with occurrence counts for each word. Used as a tool for feature generation. Does not preserve word order or grammar.

### Clausal Complement

**Constituent** In syntactic analysis, a constituent is a word or a group of words that function(s) as a single unit within a hierarchical structure. Many constituents are phrases. *Yesterday I saw **an orange bird with a white neck***

**Corpus** A collection of texts with linguistic annotations.

**Dimensionality** When discussing word embeddings and word vector spaces the dimensionality refers to definition in linear algebra. Dimensionality of arrays in computing means the number of indices required to specify an element in the array. Word vector in 50 dimensional vector space  $\mathbb{R}^{50}$  would be represented in computing as one dimensional array of length 50 [d1, d2, d3, ..., d50]

**Feature** Data representation that can be effectively exploited in machine learning tasks. E.g. Word occurrence frequencies.

### Feature Vector

**Lemmatisation** Process of finding the base form of a word, e.g. flew -> fly

**Lexeme** A basic lexical unit of a language consisting of one word or several words, the elements of which do not separately convey the meaning of the whole.

**n-gram** Probabilistic language model where probability of current word is the joint probability of previous  $n$  words. Example of a bigram model is  $P(I, \text{ saw, the, red, house}) = P(I \mid \langle s \rangle)P(\text{ saw } \mid I)P(\text{ red } \mid \text{ the})P(\text{ house } \mid \text{ red})P(\langle /s \rangle \mid \text{ house})$ . The words unigram, bigram and trigram language model denote n-gram model language models with  $n = 1$ ,  $n = 2$  and  $n = 3$ , respectively.

**One-hot** Group of bits which the legal combinations of values are only those with a single high (1) and all the others low (0). See also 1-of-V Coding.

**Parsing** Within computational linguistics the term is used to refer to the formal analysis by a computer of a sentence or other string of words into its constituents, resulting in a parse tree showing their syntactic relation to each other, which may also contain semantic and other information.

**POS-tagging** Process of marking up a word to particular part-of-speech (nouns, verbs, etc...) based on both its definition and its context.

**Structured Prediction** Predicting structured objects, rather than scalar discrete or real values. Translating a natural language sentence into a syntactic representation such as a parse tree can be seen as a structured prediction problem in which the structured output domain is the set of all possible parse trees.

**Token** A structure representing a lexeme that explicitly indicates its categorization for the purpose of parsing. In plain words tokens are instances of words in a text. Not to be confused with word type.

**Tree bank** Parsed text corpus that annotates syntactic or semantic sentence structure. Contains trees for sentences where phrases in a sentence are structured in a tree of syntactic or semantic relations. Very useful for training POS-taggers etc...

**Tri-Training** Parsing unlabeled data with two different parsers and selecting only the sentences for which the two parsers produce the same trees Weiss et al. 2015

**Word Lookup Table** Matrix  $\mathbf{P} \in \mathbb{R}^{d \times |V|}$  of  $d$  rows and  $|V|$  columns, where  $d$  is the word vector dimensionality and  $|V|$  is the size of vocabulary. Word lookup tables are unable to generate representations for previously unseen words, as is required for morphology. Ling et al. 2015

**Word Type** Unique words in a text. *Good wine is good* has 4 tokens but only 3 word types.

**Word vector** N-dimensional vector representation of a word with interesting properties such as:  $\text{vector}(\text{'Paris'}) - \text{vector}(\text{'France'}) + \text{Vector}(\text{'Italy'}) \rightarrow \text{vector}(\text{'Rome'})$



## 0.2 Universal Dependencies

### 0.2.1 CoNNL-U format

Universal dependencies use CoNNL-U format for treebanks, CoNNL-U is revised version of CoNNL-X. Annotations are encoded in text files with word lines, blank lines for sentence boundaries and comments starting with hash (#).

Word lines consist of following columns:

ID	Word ID in sentence
FORM	Word form or punctuation symbol
LEMMA	Lemma or stem of word form
UPOSTAG	Universal part-of-speech tag
XPOSTAG	Language specific part-of-speech tag
FEATS	List of morphological features
HEAD	Head of the current token, value of ID or zero (0)
DEPREL	Universal dependency relation to the HEAD
DEPS	List of secondary dependencies
MISC	Any other annotation

Example in Finnish: Jäällä kävely avaa aina hauskoja ja erikoisia näkökulmia kaupunkiin

ID	FORM	LEMMA	UPOSTAG	XPOSTAG
1	Jäällä	jää	NOUN	N
2	kävely	kävely	NOUN	N
3	avaa	avata	VERB	V
4	aina	aina	ADV	Adv
5	hauskoja	hauska	ADJ	A
6	ja	ja	CONJ	C
7	erikoisia	erikoinen	ADJ	A
8	näkökulmia	näkö#kulma	NOUN	N
9	kaupunkiin	kaupunki	NOUN	N
10	.	.	PUNCT	Punct

## FEATS

---

Case=Ade|Number=Sing  
 Case=Nom|Number=Sing  
 Mood=Ind|Number=Sing|Person=3|Tense=Pres|VerbForm=Fin|Voice=Act

—

Case=Par|Degree=Pos|Number=Plur

—

Case=Par|Degree=Pos|Number=Plur

Case=Par|Number=Plur

Case=Ill|Number=Sing

—

HEAD	DEPREL	DEPS	MISC
2	nmod	—	—
3	nsubj	—	—
0	root	—	—
3	advmod	—	—
8	amod	—	—
5	cc	—	—
5	conj	8:amod	—
3	dobj	—	—
8	nmod	—	SpaceAfter=No

## 0.2.2 Universal POS tags

ADJ	Adjective. Describing word qualifying noun or noun phrase. <b>deep</b> , <b>intelligent</b>
ADP	Adposition. Word expressing spatial or temporal relations <b>under</b> , <b>around</b> , <b>before</b> or mark various semantic roles <b>of</b> , <b>for</b>
ADV	Adverb. Modifies another word. Typically express manner, place, time, frequency etc. She sang <b>loudly</b> . You are <b>quite</b> right.
AUX	Auxiliary verb. A verb used in forming the tenses, moods, and voices of other verbs. <b>Do</b> you want tea?. He <b>has</b> given his all.
CONJ	Coordinating conjunction. Conjunction placed between words, phrases, clauses or sentences of equal rank. <b>and</b> , <b>but</b> , <b>or</b> .
DET	Determiner. Expresses reference of a noun (group). <b>The</b> girl is a student. <b>Which</b> book is that?
INTJ	Interjection. Shows emotion or feeling of the author, includes exclamations, curses, greetings and such. <b>Ouch!</b> , <b>hey</b> , <b>huh?</b> .

NOUN	Noun. Denotes a person, animal, place thing or idea. The <b>cat</b> sat on a <b>mat</b> .
NUM	Numeral. Number, written with digits or letters. <b>12</b> , <b>eleven</b> .
PART	Particle. Cannot be inflected. Interjections and conjunctions. In finnish also <b>että</b> , <b>jotta</b> , <b>koska</b> , <b>kun</b> etc...
PRON	Pronoun. Replaces (often previously introduced) noun. Joe saw Jill, and <b>he</b> waved at <b>her</b> .
PUNCT	Punctuation. Full stop, comma, bracket etc.
SCONJ	Subordinating conjunction. A conjunction that introduces a subordinating clause, e.g. <b>although</b> , <b>because</b> , <b>whenever</b> .
SYM	Symbol.
VERB	Verb. Conveys an action <b>bring</b> , <b>read</b> , an occurrence <b>happen</b> , <b>become</b> , or a state of being <b>be</b> , <b>exist</b> .
X	Other

# 1. INTRODUCTION

Testing citation Andor et al. 2016

## 2. NATURAL LANGUAGE PROCESSING

«««< HEAD

### 2.1 Pre-processing

=====

### 2.2 Feature Engineering in NLP

#### 2.2.1 Word Embeddings

- Traditionally words have been represented by indices. Mikolov, Corrado, et al. 2013
- Index representation is simple as computationally cheap, making use of huge datasets possible. Simple models with huge data outperform complex models with less data. Mikolov, Corrado, et al. 2013
- Word embeddings represent words as n-dimensional vectors. Mikolov, Corrado, et al. 2013
- see section 1.2 of Mikolov, Corrado, et al. 2013 for previous work and history of word embeddings
- See LSA and LDA for previous systems. Neural networks significantly outperform LSA in preserving linearities. LDA doesn't scale for large datasets. Mikolov, Corrado, et al. 2013
- Word embeddings try to map words with semantic similarities close to each other. Words may have several types of similarities such as France and Italy are countries but dogs and triangles are both in plural form. Mikolov, Yih, et al. 2013

### 2.2.2 Word2vec

- Mikolov, Corrado, et al. 2013
- Can be used with datasets of billions of words
- Has two models: Continuous bag-of-words and continuous skip-gram
- Continuous bag-of-words predicts current word from the context (surrounding words)
- Continuous skip-gram predicts context (surrounding words) from current word.
- Continuous Bag-of-Words is better for small datasets, continuous skip-gram is better for large datasets.
- CBOW is better for syntax, Skip-gram is better for semantics.
- Can be used to find semantic relationships like  $\text{vector('biggest')} - \text{vector('big')} + \text{vector('small')} \Rightarrow \text{vector('smallest')}$
- State of the art (as of 2013)

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## 2.3 POS Tagging

- Started from rule based taggers
- Tagger by Brill 1992 (known as Brill tagger) learns the rules and as such can be considered as a hybrid approach
- Contemporary research is focused on statistical and ANN based taggers
- Rest of this section focuses on statistical parsers
- Ling et al. 2015 introduced S-LSTM based State-of-the-art tagger
- Andor et al. 2016 Improved accuracy with transition based tagger
- Chen and Manning 2014 were first to represent POS-tag and arc labels as embeddings
- Andor et al. 2016 and Weiss et al. 2015 built their solutions based on Chen and Manning 2014
- Nivre 2004 introduced system for transition based taggers known as arc-standard system Chen and Manning 2014

### 2.3.1 Turku Dependency Treebank

- Treebanks are needed in computational linguistics.
- First Finnish treebank.
- Open licence, including for text annotated
- 204339 tokens, 15126 sentences
- Based on Stanford Dependency scheme with minor modifications to exclude phenomena not present in Finnish and to include new annotations not present in English.
- Transposed to CoNNL-U scheme by universal dependencies project
- Connexor Machine Syntax is the only currently available Finnish full dependency parser.
- Texts from 10 different categories ranging from news and legal text to blog entries and fiction.
- Dependency parsing is done manually with full double annotation process.
- Uses Omorfi for morphological analysis. Ambiguous tokens are handled partly manually, partly rule based and partly with machine learning.
- FTB uses 3 different taggers for morphology, check them out!
- FTB is 97% grammar examples, meant for rule based POS tagger development

### 2.3.2 Transition Based Parsers

- Good balance between efficiency and accuracy Weiss et al. 2015
- Parsed left to right; at each position the parser chooses action from a set of possible actions.
- Greedy models are fast but error prone and need hand engineered features Weiss et al. 2015
- Actions can be chosen by ANN to avoid hand engineering Chen and Manning 2014, Weiss et al. 2015

### 2.3.3 Syntaxnet

- Transition based
- Locally and globally normalized
- Backpropagation through entire net
- State-of-the-Art
- Andor et al. 2016

## 2.4 Dependency Parsing

## 2.5 Co-Reference Parsing

## 2.6 Sentence Segmentation

## 2.7 Lemmatisation

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## 2.8 Synonym recognition

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- See OMorFi

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## **APPENDIX A. SOMETHING EXTRA**

Appendices are purely optional. All appendices must be referred to in the body text

## **APPENDIX B. SOMETHING COMPLETELY DIFFERENT**

You can append to your thesis, for example, lengthy mathematical derivations, an important algorithm in a programming language, input and output listings, an extract of a standard relating to your thesis, a user manual, empirical knowledge produced while preparing the thesis, the results of a survey, lists, pictures, drawings, maps, complex charts (conceptual schema, circuit diagrams, structure charts) and so on.