

Aleksander Lempinen

Artificial intelligence in physics teacher education

Master's Thesis in Information Technology

September 3, 2019

University of Jyväskylä

Faculty of Information Technology

Author: Aleksander Lempinen

Contact information: aleksander.lempinen@outlook.com

Supervisors: Tommi Kärkkäinen, Daniela Caballero, and Jouni Viiri

Title: Artificial intelligence in physics teacher education

Työn nimi: Tekoäly fysiikan opettajakoulutuksessa

Project: Master's Thesis

Study line: Educational Technology

Page count: 12+0

Abstract: TODO: Abstract

Keywords: TODO: Keywords

Suomenkielinen tiivistelmä: TODO: Tiivistelmä

Avainsanat: TODO: Avainsanat

Glossary

TODO

TODO: Glossary

Contents

1	INTRODUCTION	1
2	ARTIFICIAL INTELLIGENCE	2
2.1	Automatic speech recognition	2
2.1.1	Speech to Text	2
2.1.2	Finnish speech data	2
2.1.3	Comparisons	2
2.2	Natural language processing	3
2.2.1	Word embedding	3
2.2.2	Lemmatization and stemming	3
2.2.3	Finnish NLP data	3
2.2.4	Comparisons	3
3	PHYSICS INSTRUCTION QUALITY	4
3.1	Pedagogical link making	4
3.2	Conceptual network analysis	4
3.3	Methods and materials	4
3.3.1	Data	4
3.3.2	Speech-to-text	4
3.3.3	Lemmatization and stemming	5
3.3.4	Word frequency	5
3.3.5	Network analysis	5
4	CONCLUSIONS	6
	BIBLIOGRAPHY	7

1 Introduction

Modern physics classroom instruction attempts to improve learning by reducing the cognitive load, which is done by providing a clear organizational structure for the factual knowledge and linking new material to previously known ideas (Wieman and Perkins 2005). The goal of physics instruction is to help students become experts capable of solving problems (Fischer et al. 2014; Wieman and Perkins 2005). While lecture based instruction is often not very effective for retaining new knowledge (Wieman and Perkins 2005), the content structure and relationships between concepts presented by the teacher positively correlate with student learning gains when analysed with conceptual network analysis (Fischer et al. 2014).

For a long time automatic speech recognition (ASR) was outperformed by human speech recognition (HSR), but with the recent developments in the deep learning approach the error rate of automatic speech recognition and human speech recognition is almost the same in certain tasks (Spille, Kollmeier, and Meyer 2018). This however is language specific. Work on automatic speech recognition with conversational Finnish started in 2012 and word error rate of 27.1% was achieved by 2017 (Enarvi 2018).

In natural language processing the creation of treebanks such as Turku Dependency Treebank and FinnTreeBank in the past decade have allowed for development of natural language processing toolkits with adequate performance with Finnish language such as FinnPos (Silfverberg et al. 2016) and TurkuNLP (Kanerva et al. 2018). Lemmatization in the new toolkits is of particular interest, because it is essential for real world tasks in inflective languages such as Finnish (Kanerva et al. 2018).

Manually transcribing and preprocessing lessons from audio data for analysis is a very laborious task. The aim of this study is to develop a pipeline for studying physics lesson content structures and relationships between physics concepts with conceptual network analysis using automatic speech recognition and natural language processing. This is done to provide a new tool for analysing physics instruction for research and teacher education purposes.

2 Artificial intelligence

TODO: AI overview, AI history, ASR and NLP concepts

2.1 Automatic speech recognition

Automatic speech recognition (ASR), sometimes called speech to text, is a classification task, where the goal is to predict what was said from the audio signal of speech. Early ASR systems had an acoustic model which detected different sounds also known as phonemes to recognize numbers, some vowels and consonants for a single speaker (Juang and Rabiner 2005). The later addition of a language model based on statistical grammar or syntax helped to predict the correct word based on what words previously appeared in the sentence (Juang and Rabiner 2005). Modern ASR systems utilize the fact that sentences are sequences of words and words are sequences of phonemes (Bengio and Heigold 2014). This is a difficult machine learning task because of a large search space, large vocabulary, undetermined length of word sequences and problems related to aligning speech signal to the text (Enarvi 2018).

Speech is highly variable even with a single speaker due to noise, but different pronunciations and accents mean that the audio signal will be different despite the same words being spoken (Juang and Rabiner 2005).

2.1.1 Speech to Text

TODO: Different approaches

2.1.2 Finnish speech data

TODO: Conversational vs official Finnish

2.1.3 Comparisons

TODO: Defining "good", comparing literature results, running own tests

2.2 Natural language processing

TODO: NLP overview (Silfverberg et al. 2016; Kanerva et al. 2018)

2.2.1 Word embedding

TODO: word2vec

2.2.2 Lemmatization and stemming

TODO: Snowball vs TurkuNLP lemmatization

2.2.3 Finnish NLP data

TODO: Data from different sources, treebanks for parsing vs. word lists/text

2.2.4 Comparisons

TODO: Evaluating the stemming and lemmatization (error rate), evaluating similarities (edit distance, word2vec), literature and own tests

3 Physics instruction quality

TODO: Paragraph about science education and physics education history TODO: Paragraph about the change of science and physics education and modern physics education TODO: Paragraph about educational material and pedagogical tools TODO: Paragraph about physics instruction

TODO: Paragraph about cognitive structure and content structure TODO: Paragraph about how cognitive structure fits with education (geeslin, shavelson) TODO: Paragraph about linking cognitive structure of students and teachers TODO: Paragraph about content structure with written text with content structure (geeslin, shavelson, wieman)

TODO: Paragraph about pedagogical link making

3.1 Pedagogical link making

TODO: (Scott, Mortimer, and Ametller 2011)

3.2 Conceptual network analysis

TODO: (vargas; McLinden 2013; Fischer et al. 2014)

3.3 Methods and materials

3.3.1 Data

TODO: (Fischer et al. 2014)

3.3.2 Speech-to-text

TODO: (Enarvi 2018)

3.3.3 Lemmatization and stemming

TODO: TurkuNLP (Kanerva et al. 2018) TODO: libvoikko <https://github.com/voikko/corevoikko/tree/main>

TODO: FinnPOS (Silfverberg et al. 2016)

3.3.4 Word frequency

3.3.5 Network analysis

Social network analysis has been used in physics education research for example to study student collaboration (Vargas et al. 2018), interactions within student communities (Brewer, Kramer, and Sawtelle 2012)

TODO:

4 Conclusions

TODO:

Research is being done in collaboration with the Department of Teacher Education at University of Jyväskylä and Centro de Investigación Avanzada en Educación (CIAE) at University of Chile.

Bibliography

- Bengio, Samy, and Georg Heigold. 2014. “Word embeddings for speech recognition”. In *Fifteenth Annual Conference of the International Speech Communication Association*.
- Brewe, Eric, Laird Kramer, and Vashti Sawtelle. 2012. “Investigating student communities with network analysis of interactions in a physics learning center”. *Physical Review Special Topics-Physics Education Research* 8 (1): 010101. doi:<https://doi.org/10.1103/PhysRevSTPER.8.010101>.
- Enarvi, Seppo. 2018. *Modeling Conversational Finnish for Automatic Speech Recognition; Suomen puhekielen mallintaminen automaattista puheentunnistusta varten [inlangen]*. 117 + app. 73. Aalto University publication series DOCTORAL DISSERTATIONS; 52/2018. Aalto University; Aalto-yliopisto. ISBN: 978-952-60-7908-0 (electronic); 978-952-60-7907-3 (printed). <http://urn.fi/URN:ISBN:978-952-60-7908-0>.
- Fischer, Hans E, Peter Labudde, Knut Neumann, and Jouni Viiri. 2014. *Quality of instruction in physics: Comparing Finland, Switzerland and Germany*. Waxmann Verlag.
- Juang, Biing-Hwang, and Lawrence R Rabiner. 2005. “Automatic speech recognition—a brief history of the technology development”. *Georgia Institute of Technology. Atlanta Rutgers University and the University of California. Santa Barbara* 1:67.
- Kanerva, Jenna, Filip Ginter, Niko Miekka, Akseli Leino, and Tapio Salakoski. 2018. “Turku neural parser pipeline: An end-to-end system for the CoNLL 2018 shared task”. *Proceedings of the CoNLL 2018 Shared Task: Multilingual Parsing from Raw Text to Universal Dependencies*: 133–142.
- McLinden, Daniel. 2013. “Concept maps as network data: analysis of a concept map using the methods of social network analysis”. *Evaluation and program planning* 36 (1): 40–48. doi:[10.1016/j.evalprogplan.2012.05.001](https://doi.org/10.1016/j.evalprogplan.2012.05.001).
- Scott, Phil, Eduardo Mortimer, and Jaume Ametller. 2011. “Pedagogical link-making: a fundamental aspect of teaching and learning scientific conceptual knowledge”. *Studies in Science Education* 47 (1): 3–36. doi:[10.1080/03057267.2011.549619](https://doi.org/10.1080/03057267.2011.549619).

- Silfverberg, Miikka, Teemu Ruokolainen, Krister Lindén, and Mikko Kurimo. 2016. “FinnPos: an open-source morphological tagging and lemmatization toolkit for Finnish”. *Language Resources and Evaluation* 50 (4): 863–878. doi:10.1007/s10579-015-9326-3.
- Spille, Constantin, Birger Kollmeier, and Bernd T Meyer. 2018. “Comparing human and automatic speech recognition in simple and complex acoustic scenes”. *Computer Speech & Language* 52:123–140. doi:10.1016/j.csl.2018.04.003.
- Vargas, David L, Ariel M Bridgeman, David R Schmidt, Patrick B Kohl, Bethany R Wilcox, and Lincoln D Carr. 2018. “Correlation between student collaboration network centrality and academic performance”. *Physical Review Physics Education Research* 14 (2): 020112. doi:10.1103/PhysRevPhysEducRes.14.020112.
- Wieman, Carl, and Katherine Perkins. 2005. “Transforming physics education”. *Physics today* 58 (11): 36. doi:10.1063/1.2155756.