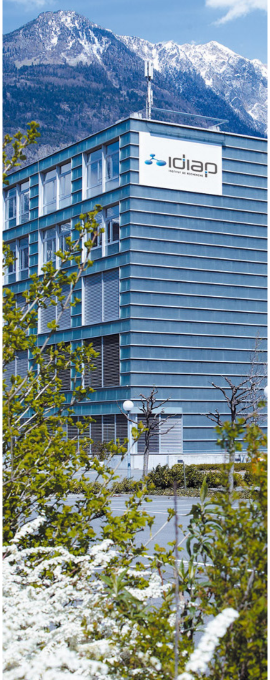

Automatic Diagnosis of Alzheimer's Disease Using Neural Network Language Models

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Outline

1. Problem Statement
2. Language Modeling based Alzheimer's Classification
3. Experimental Methodology
4. Results & Analysis
5. Conclusions

How to Assess a Demented Person's Cognitive State

- Alzheimer's dementia is a neurodegenerative disease

Mini-mental state exam (MMSE)

- executed by a physician
- 30 questions to assess mental capabilities:
  - score < 19: severe dementia
  - score > 29: median of healthy people

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Automatic analysis of spontaneous speech

- **Cookie Theft picture description**

Alzheimer's Classification based on Language Structures

Cookie Theft picture description

- natural approximation to spontaneous discourse

Alzheimer’s Classification based on Language Structures

Cookie Theft picture description

natural approximation to
spontaneous discourse

Alzheimer’s patient:

« There’s a young boy getting a cookie jar.
And it he’s uh in a bad shape because uh the thing is falling over. »

Healthy control:

« A boy is trying to get cookies out of a jar
and he’s about to tip over on a stool. »

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Language Modeling based Alzheimer's Classification

Language modeling

- assigning probabilities $P(w)$ to words given previous words
  - *« the high ... tree/tower/mountain »*

Language Modeling based Alzheimer's Classi cation

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the high ... tree/tower/mountain

Language model evaluation: perplexity (PPL)

$PPL(S) = P(S)^{-\frac{1}{N}}$, $P(S)$:= probability of sequence S, N := # words in S

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Perplexity-based Alzheimer's classification using n-grams [1]

- perplexity difference used for binary Alzheimer's classification
- n-grams have a fixed context length

[1] S. Wankerl, E. Nöth, and S. Evert, "An n-gram based approach to the automatic diagnosis of alzheimer's disease from spoken language," in Proc. Interspeech, 2017.

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Experimental Methodology

Address shortcomings of n-grams: RWTHLM toolkit

- building and evaluating neural network language models (NNLMs)
- designed for using recurrent and long short-term memory (LSTM) layers
- ! allowing variable context length

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Experimental setup

- LMs from Alzheimer's $M_{\text{Alzheimer's}}$ and control transcriptions M_{control}
- leave-one-speaker-out cross-validation
- excluding 10 randomly selected speakers for validation

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Evaluation

- perplexity evaluation of each speaker on 2 LMs giving ppl_{own} and ppl_{other}

$$ppl_{diff} = \begin{cases} ppl_{own} - ppl_{other} & \text{if } s \in \text{Alzheimer's group} \\ ppl_{other} - ppl_{own} & \text{if } s \in \text{control group} \end{cases}$$

Perplexity Di erence for Binary Classi cation

Comparison of perplexity means from both groups

classi cation threshold at equal-error rate (EER)

Data   DementiaBank's Pitt Corpus

English Cookie Theft picture descriptions & MMSE scores

- conducted yearly
- publicly available

Selection for Alzheimer's classi cation:

- 168 Alzheimer's patients, 255 transliterations
- 98 control patients, 244 transliterations

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Performance Evaluation with ROC Curves (1)

Overall accuracy:85.6% at EER, 72 wrongly classi ed transliterations (compared to 77.1% at EER with tri-grams)

Performance Evaluation with ROC Curves (2)

Overall accuracy:85.6% at EER, 72 wrongly classi ed transliterations (compared to 77.1% at EER with tri-grams)

Speakers with an MMSE score from 21 to 30: 79.9% at EER, 66 wrongly classi ed transliterations

Performance Evaluation with ROC Curves (3)

All speakers: 85% true positive rate (TPR), 10% false positive rate (FPR)

Speakers with an MMSE score from 21 to 30: 85% TPR, 33% FPR

Performance Evaluation with ROC Curves (4)

All speakers: 85% true positive rate (TPR), 10% false positive rate (FPR)

Speakers with an MMSE score from 21 to 30: 73% TPR, 10% FPR

Classi cation Results per MMSE (1)

Histogram of all Alzheimer's MMSE scores

Classi cation Results per MMSE (2)

Histogram of all Alzheimer's and control MMSE scores

Classi cation Results per MMSE (3)

Histogram of all Alzheimer's and control MMSE scores and accuracy per MMSE

Using Perplexity Di erence for MMSE Estimation

Pearson's correlation r and Spearman's correlation between MMSE scores and perplexity di erence p_{di} :

	r	
Alzheimer's	0.433	0.547
Control	0.112	0.109
All	0.656	0.771

Conclusions

Neural network-based language models used for Alzheimer's classi cation

- model language structures well (85.6% vs 77.1% with tri-grams)
- perplexity di erence correlates well with MMSE scores
- is a purely statistical approach transferable to other languages

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Neural network-based language models used for Alzheimer's classification

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Acknowledgements

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ROC Curve Comparison to N-grams

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LSTM-NNMLs: **85.6%** at EER, 72 wrongly classified transliterations

Tri-gram LMs: **77.1%** at EER, 114 wrongly classified transliterations