One size doesn't fit all: towards adaptive and personalized text simplification

Joachim Bingel

University of Copenhagen

Apr 3, 2018

TEXT SIMPLIFICATION

Our mission: translate difficult text to easier text

What makes text difficult?

- Vocabulary
- Complex grammar
- Long sentences
- Word recognition
- ...

SIMPLIFICATION THEN AND NOW

1990s: simplify for downstream NLP tasks

Steven made an attempt to stop playing Hearts.

Steven attempted to stop playing Hearts.

His willingness to leave made Gillian upset.

He was willing to leave. This made Gillian upset.

It was his best suit that John wore to the ball.

John wore his best suit to the ball.

SIMPLIFICATION THEN AND NOW

2000s: more focus on human readers

Lexical complexity

Zuckerberg announced an ambitious effort to…

Zuckerberg announced a big plan to…

Text cohesion

Mia helped Anna wash the car, but got tired soon.

Mia helped Anna wash the car. But soon, Mia got tired.

TARGET AUDIENCES AND THEIR NEEDS

Language learners

- Unknown vocabulary, complex syntax

Beginner readers

- Infrequent words, high-register language

People with reading impairments (e.g. dyslexia)

- Certain orthography, long words/sentences

People with autism

- Figurative language

TARGET AUDIENCES AND THEIR NEEDS

There can be no one-size-fits-all solution

USER-ADAPTIVE SIMPLIFICATION

Identify possible simplifications

↓

Simplify according to user model

↓

Receive user feedback

↓

Update user model

```
User#512
========
Long words: 0.214
Long sentences: 0.728
Passive voice: 0.015
Foreign words: 0.543
...
```

From black box MT-based models to adjustable, interpretable simplification

BLACK BOX SIMPLIFICATION

Hershey left no heirs when he died in 1945, giving most of his fortune to charity.

MT-style simplification

Hershey died in 1945 and gave most of his fortune to charity.

ADJUSTABLE SIMPLIFICATION

Hershey left no heirs when he died in 1945, giving most of his fortune to charity.

Explicit operation prediction:

Hershey left no heirs when he died in 1945,
giving most of his fortune to charity.

Hershey died in 1945, giving most of his wealth to charity.

Alonso-Manchego, Bingel et al. (2017)

ADJUSTABLE SIMPLIFICATION

Training data generation

Hershey left no heirs when he died in 1945 , giving most of his fortune to charity.

Hershey died in 1945 and gave most of his wealth to charity.

Delete

Replace

Rewrite

Add

Move

Combinations

Algorithm achieves 92% accuracy vs. gold labels

Alonso-Manchego, Bingel et al. (2017)

ADJUSTABLE SIMPLIFICATION

Operation prediction and application

Bi-LSTM to predict operations, achieves 47% acc.

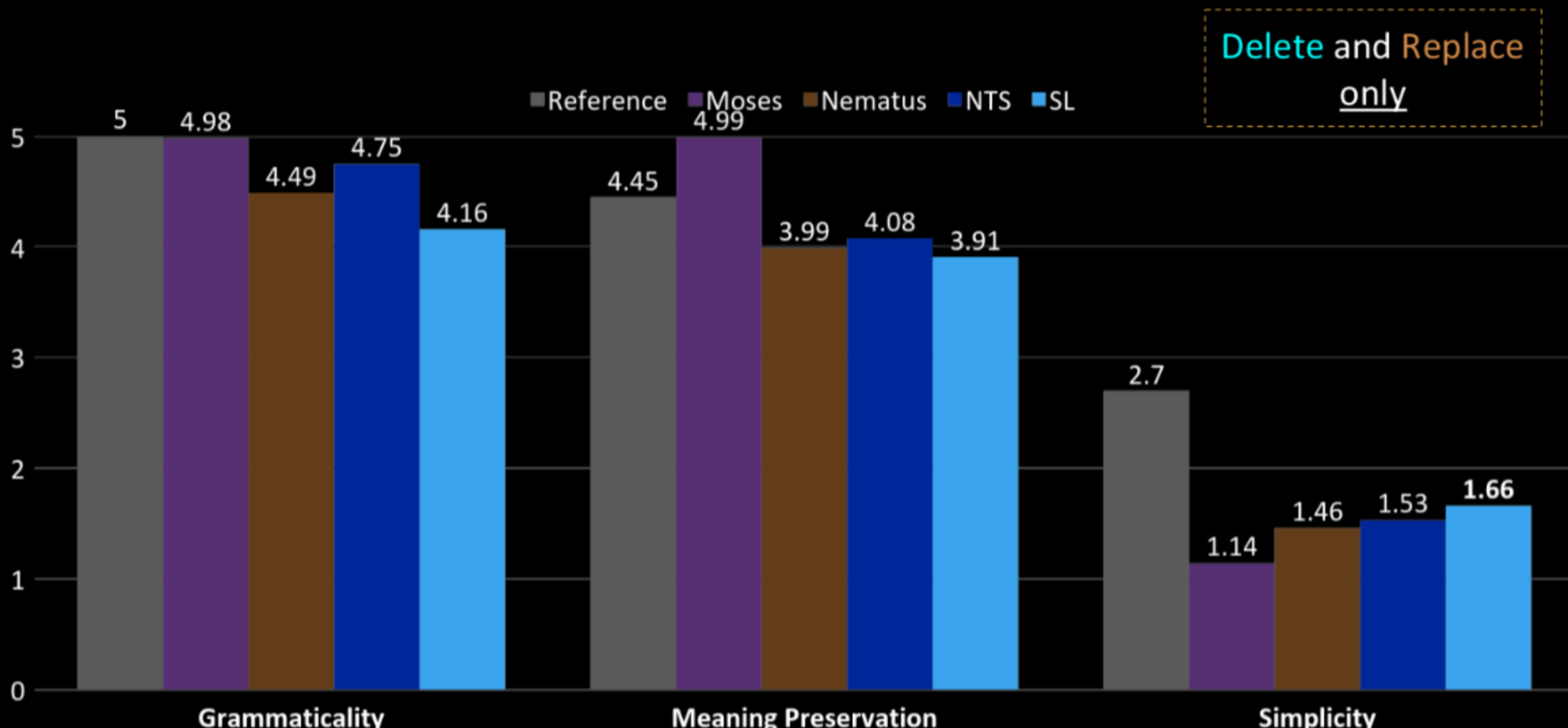
Application of operations:

- Trivial for Delete
- For Replace, lexical simplifier by Paetzold and Specia (2017)

Alonso-Manchego, Bingel et al. (2017)

ADJUSTABLE SIMPLIFICATION

Human evaluation



Alonso-Manchego, Bingel et al. (2017)

ADJUSTABLE SIMPLIFICATION

Hershey left no heirs when he died in 1945, giving most of his fortune to charity.

Explicit operation prediction:

Hershey left no heirs when he died in 1945,
giving most of his fortune to charity.

Hershey died in 1945, giving most of his wealth to charity.

Alonso-Manchego, Bingel et al. (2017)

Adaptive lexical simplification

LEXICAL SIMPLIFICATION PIPELINE

… giving most of his fortune to charity.

1. Target identification (CWI)
2. Synonym generation
3. Selection
4. Substitution Ranking (SR)

luck

wealth

destiny

riches

millions

… giving most of his wealth to charity.

Paetzold and Specia (2015)

USER-ADAPTIVE LEXICAL SIMPLIFICATION

User choices as new training data

… giving most of his fortune / wealth to charity.

Ranking as online learning

Bingel, Paetzold and Søgaard (under review)

LEXI

lexi

Browser extension for adaptive lexical simplification

[demo]

Bingel, Paetzold and Søgaard (under review)

Alpha version (for Danish) available in Chrome webstore

LEXI: HOW IT WORKS

lexi

Backend sends simplifications S and receives index i (index of the word in S that the user finds easiest)

Ranking module is a pairwise logistic regression ranker, which we update with user feedback:
$\{\langle S_i, S_j \rangle \mid j \neq i\}$

Collect overall satisfaction as means of evaluation

Bingel, Paetzold and Søgaard (under review)

LEXI: SINCE THE DEMO VERSION

February 2018: User tests with 4 Danish dyslexics, aged 20-30

Generally excited about the software

Solicit simplifications themselves

Reduced frontend

Bingel, Paetzold and Søgaard (under review)

LEXI: FUTURE WORK

New languages

Sentence-level simplification

Transfer knowledge between users (clustering, multi-task learning)

Bingel, Paetzold and Søgaard (under review)

Learning individual word difficulty from gaze

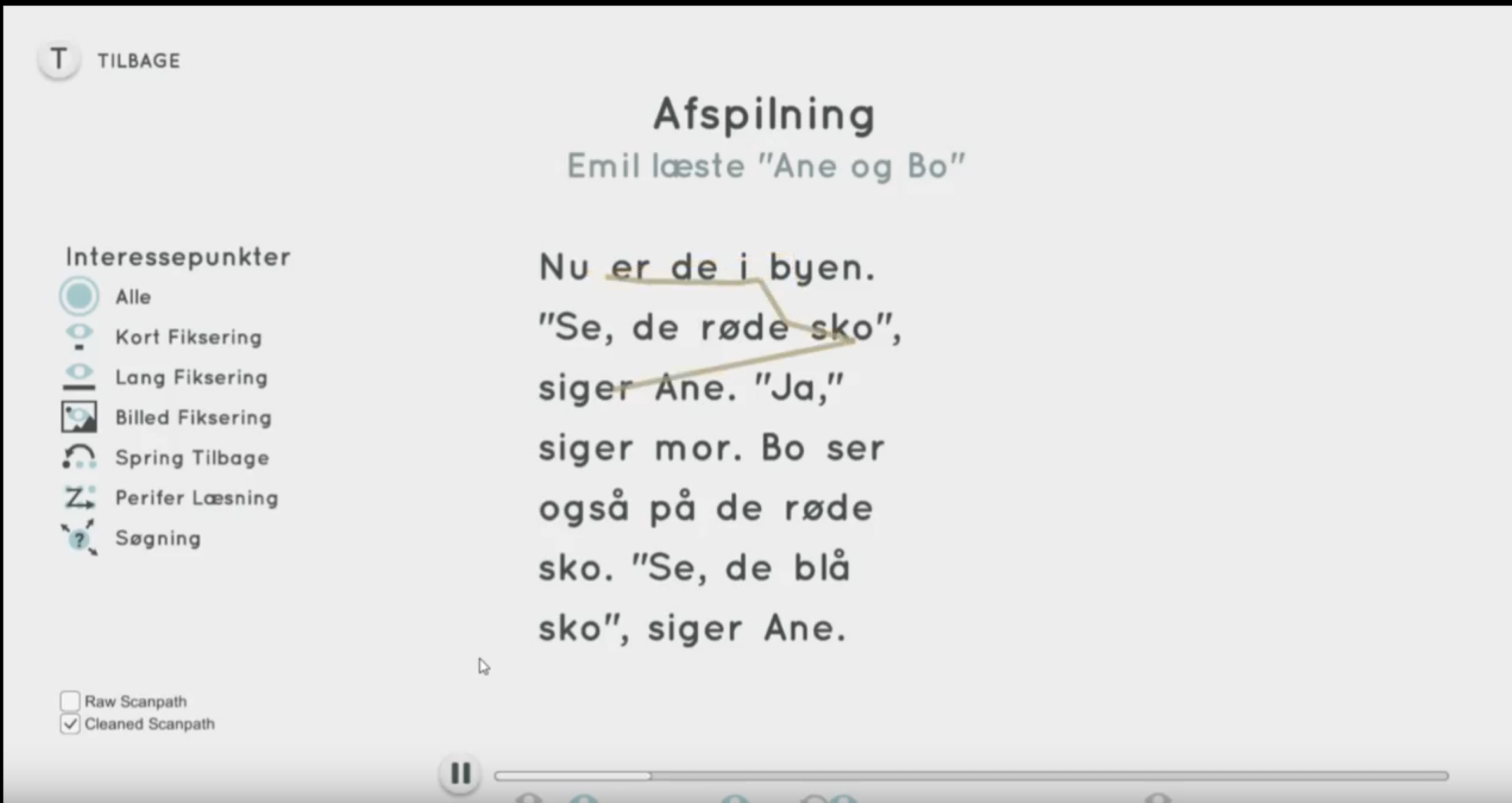
PREDICTING MISREADINGS FROM GAZE

Collaboration with Copenhagen-based startup

EyeJustRead: track and record reader's gaze, used in special-needs schools

Analysis of reading strategies, tracking reading skill progress

PREDICTING MISREADINGS FROM GAZE



PREDICTING MISREADINGS FROM GAZE

PREDICTING MISREADINGS FROM GAZE

40 pupils reading 7,647 words, of which 531 misreadings (2% – 40% per pupil)

Features: linguistic vs. gaze-based

BASIC	word length, sentence length, position in sentence, …
LINGUISTIC	POS tag, frequency, character perplexity, vowel count, …
GAZE-WORD	#fixations, 1st fixation duration, pupil size, fixation positions in word, …
GAZE-CONTEXT	nth pass incoming/outgoing direction, prev/next word fixated, …

Bingel, Barrett and Klerke (under review)

PREDICTING MISREADINGS FROM GAZE

Ensemble of 10 random forests and 10 feed-forward neural nets

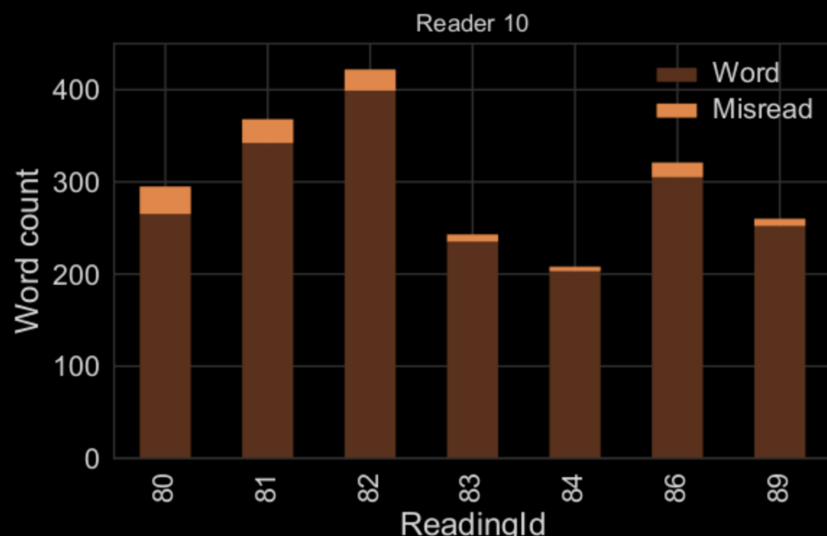
Results are based on 10-fold cross validation across entire dataset

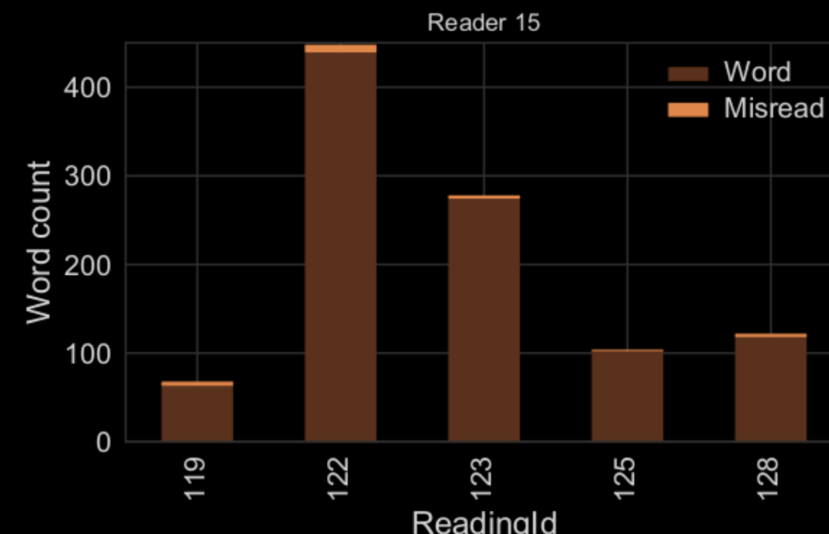
Feature Group	F_1
BASIC	18.56
+ GAZE (W)	39.00
+ GAZE (C)	25.13
+ LINGUISTIC	23.45
+ GAZE (W) + GAZE (C)	40.31
+ GAZE (W) + LINGUISTIC	41.25
+ GAZE (C) + LINGUISTIC	25.12
All features	40.12

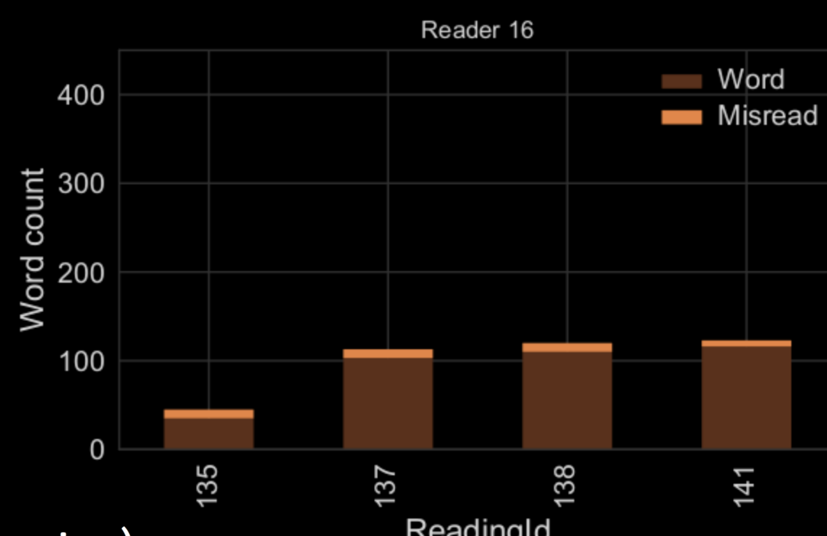
Bingel, Barrett and Klerke (under review)

PREDICTING MISREADINGS FROM GAZE

How does this work for individual users?



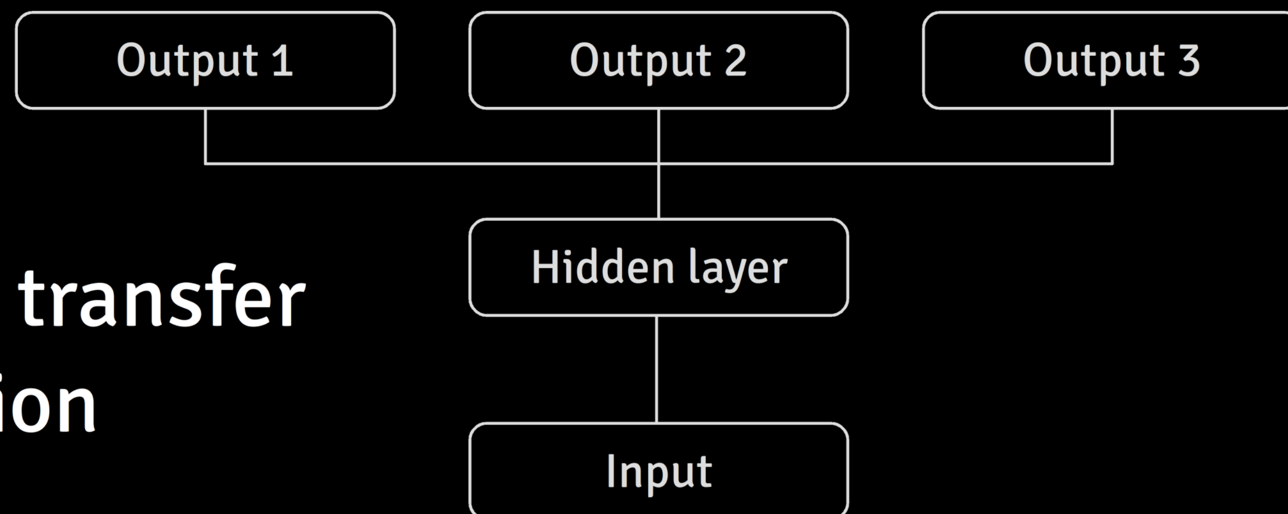




Bingel, Barrett and Klerke (under review)

PREDICTING MISREADINGS FROM GAZE

Transfer knowledge across readers with MTL

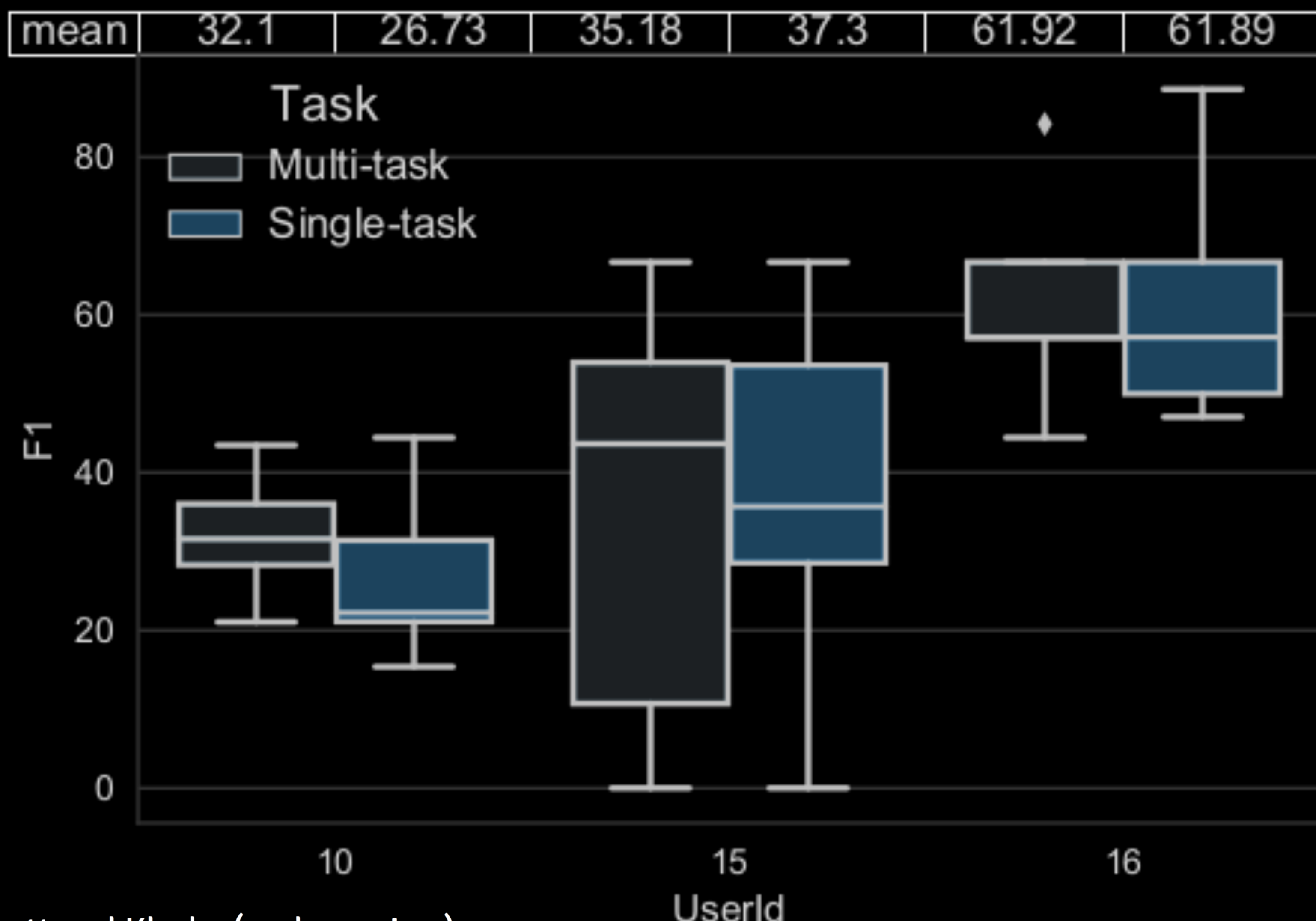


- MTL for domain transfer and regularization
- Users are tasks
- Train MTL model by iteratively optimizing for individual users

Bingel, Barrett and Klerke (under review)

PREDICTING MISREADINGS FROM GAZE

Transfer knowledge across readers with MTL



Bingel, Barrett and Klerke (under review)

REAL-LIFE APPLICABILITY

"But eye-tracking hardware is expensive and clunky!"

High-quality eye-trackers are now under $100

Integration into phone/tablet cameras and webcams likely to happen soon (Skovgaard et al., 2013; Xu et al., 2015)

Conclusions

CONCLUSIONS

Very diverse target populations require personalised simplification models

Most existing work in simplification is too generic

We can build adaptive, personalised systems from user feedback and cognitive input

Gràcies!

bingel@di.ku.dk

REFERENCES

Alva Manchego, F.; Bingel, J.; Scarton, C.; Paetzold, G. H.; Specia, L. (2017): Learning How to Simplify From Explicit Labeling of Complex-Simplified Text Pairs. In IJCNLP 2017, Taipei.

Bingel, J.; Paetzold, G. H.; Søgaard, A. (2018): Lexi: a tool for adaptive, personalized text simplification. Under review.

Bingel, J.; Barrett, M.; Klerke, S. (2018): Predicting misreadings from gaze in children with reading difficulties. Under review.

Paetzold, G., & Specia, L. (2015). LEXenstein: A Framework for Lexical Simplification. In ACL (System Demonstrations) (pp. 85-90).

Paetzold, G., & Specia, L. (2017). Lexical Simplification with Neural Ranking. EACL 2017.

Skovsgaard, H.; Hansen, J.P.; Møllenbach, E. (2013). Gaze tracking through smartphones. In Gaze Interaction in the Post-WIMP World CHI 2013 One-day Workshop.

Xu, P.; K. A. Ehinger, Y. Zhang, A. Finkelstein, S. R. Kulkarni, , and J. Xiao. (2015). TurkerGaze: Crowdsourcing saliency with webcam based eye tracking. arXiv:1504.06755.