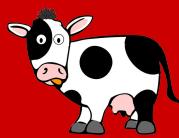




# Reading Time Prediction for Dutch Text Simplification in the PAGINA Project

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**Sijbren van Vaals, Rik van Noord, Malvina Nissim**  
**University of Groningen**  
**CLIN35**



# The PAGINA Team

Our beautiful team and partners:

- RuG: University
- DvhN (Mediahuis): Newspaper
- 8D: Research design and gamification
- AI Hub: Development of AI-applications

[paginaproject.nl](http://paginaproject.nl)





# The PAGINA Project

- Accessibility of Dutch news, with a specific focus on low literacy
- Oct 2024 - Sep 2028
- Main goal: Bringing journalism closer to the public
  
- Text simplification: Difficulty, comprehension, readability
- Perspective and frame: How can we make texts more interesting?



# Motivation

Background of the project:

- 2.5 million Dutch citizens struggle with reading, numeracy, and digital devices (Rijksoverheid, 2019)
- Many citizens feel disconnected from news media, especially young people
- This disconnect threatens democratic participation
- Regional journalism is particularly vulnerable



# Dataset

Dataset from all Mediahuis Noord titles with:

- News articles: Title and body
- Metadata: Topic, newspaper source
- Engagement metrics: Total nb. of views and total reading time (sec)

**DAGBLAD VAN  
HET  
NOORDEN**



# Dataset

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Reading time:

- Captures interest and attention (skimming)
- Approximates complexity and understandability
- Sets the stage for multiple research directions

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# Possibilities

The dataset offers several possibilities, such as:

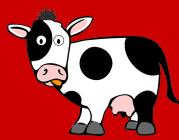
- How do linguistic complexity and length influence reading time?



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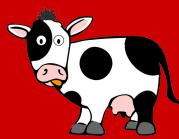
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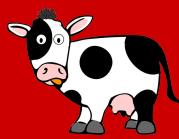
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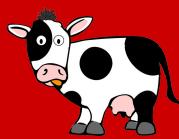
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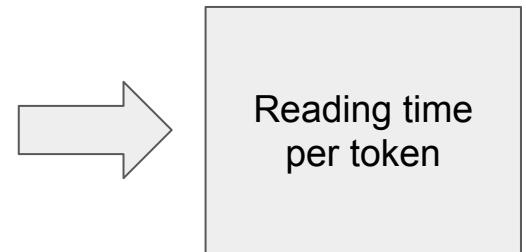
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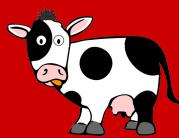
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- Are readability metrics informative in a real-world context?
- What is the extent to which LLMs can effectively predict reading time?
- Can we develop an effective reading time predictor to approximate complexity?



# Experimental Setup

Systematic assessment of blocks of features:





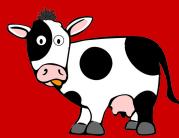
# Experimental Setup

Systematic assessment of blocks of features:

| <b>Text profiling</b> |
|-----------------------|
| Profiling-UD          |
| T-Scan                |
| Lingualyzer           |



Reading time  
per token



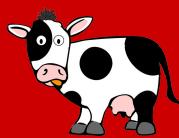
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Systematic assessment of blocks of features:

| Text profiling | Read. metrics   | LLM                                 |
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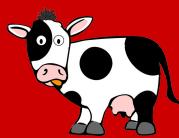
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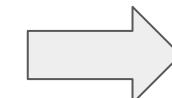
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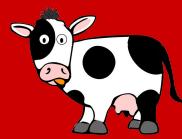
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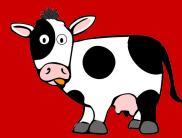
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Reading time  
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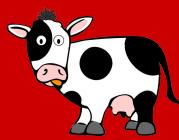
# Our Experiment

## Reading time prediction:

- Assumption: people read faster through simple(r) texts
- Human-centered evaluation, based on actual human data
- Reading time correlates with comprehension (Levy 2008; Wang et al., 2024) and complexity (Singh et al., 2016; Hollenstein et al., 2022)

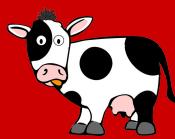
## Idea:

Useful for **evaluating** simplified texts: lower predicted reading time implies a text is easier to read.



# Feature Extraction

- Get as many features from different linguistic layers as possible
- Profiling-UD pipeline (Brunato et al., 2020)
- Add more uncovered features and readability metrics
- Perform PCA to account for dependent features



# Model Selection

- Random Forest (linear regressor)
- Generative AI models:
  - GPT-4o (ChatGPT)
  - Fietje-2-chat
  - Llama-3-8b-instruct





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# Random Forest

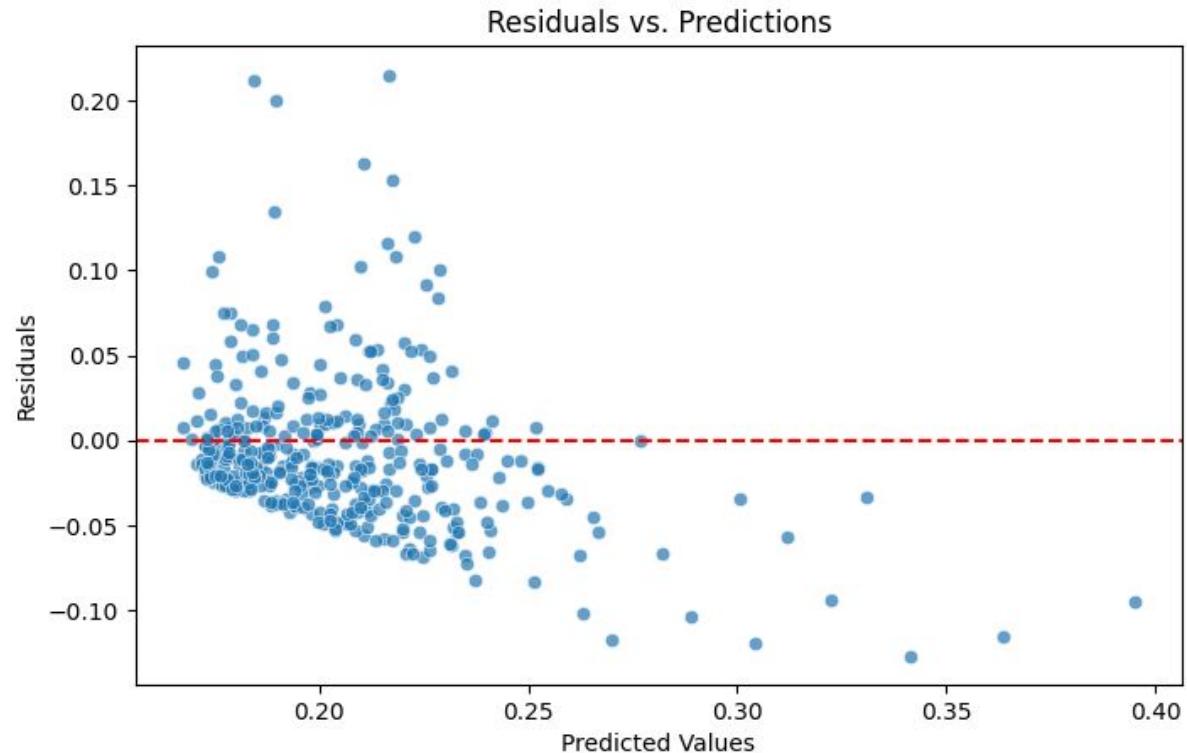


# Prediction Performance

Error plot:

Correlation with gold data:

$\rho=0.35$ ; p-value=1.05e-12

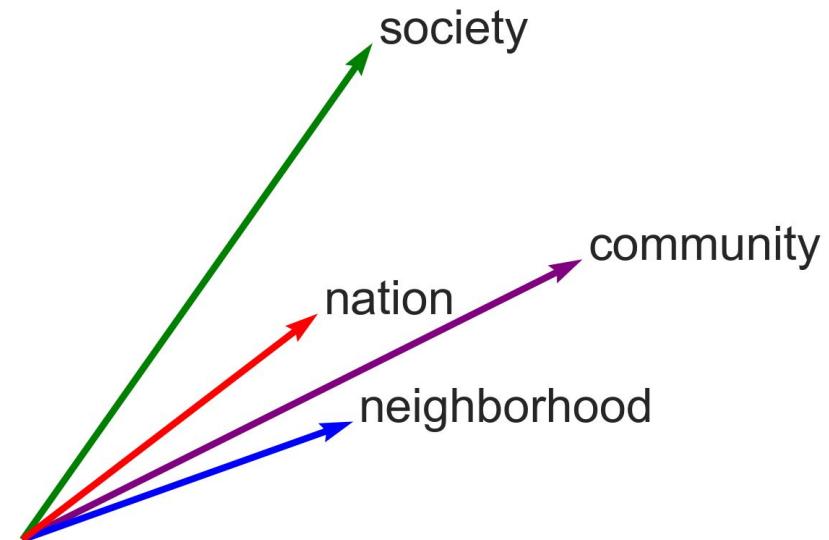


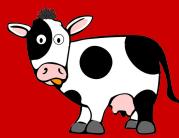


# Feature Importance

From multiple SHAP plots we observe that good features are:

- Noun similarity

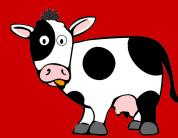




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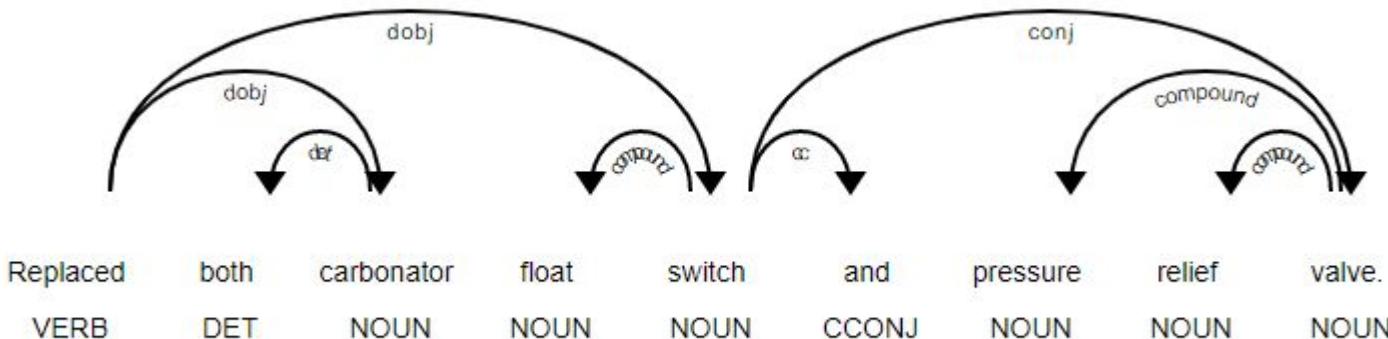
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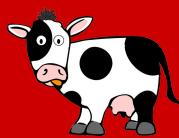


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- Noun similarity
- Hapaxes (lexical density)
- Verb edges
- Distribution of monosyllabic words

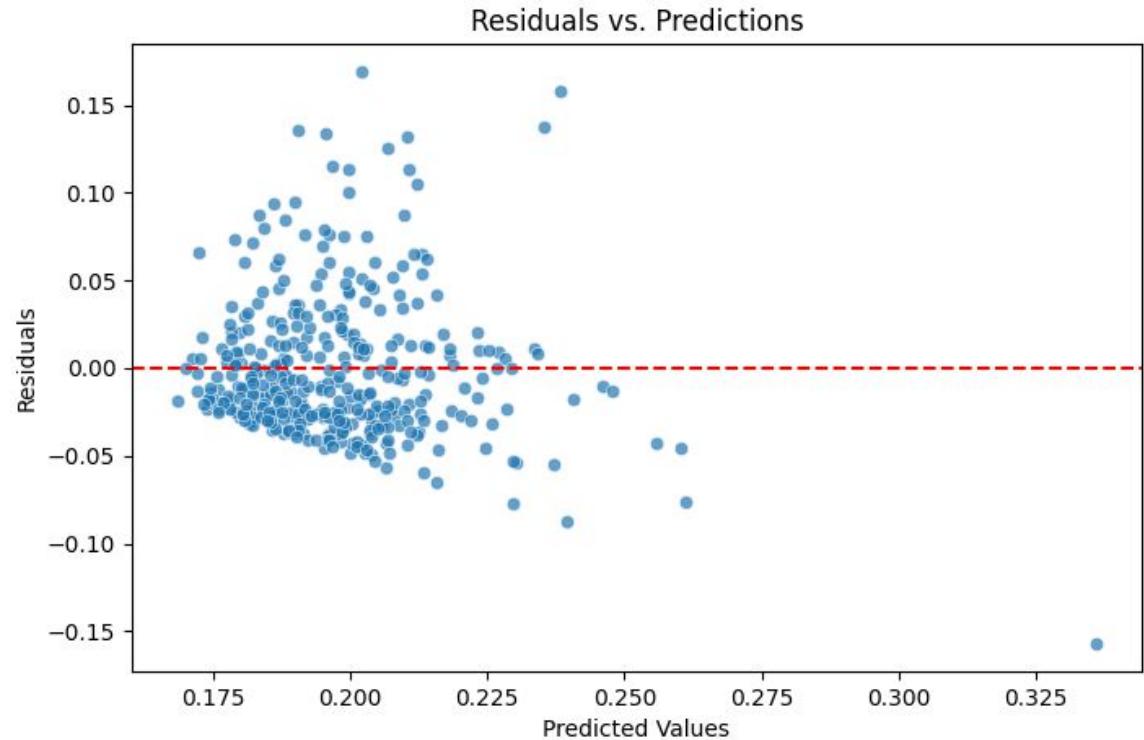


# Baseline Performance

Random forest with n-grams:

Correlation with gold data:

$\rho=0.3$ ;  $p\text{-value}=3.3\text{e-}09$





# Baseline Importance

The baseline's most important n-grams were by far:

**Snein**

**Sneon**



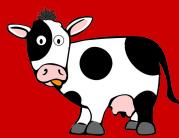
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The Frisian words for Sunday and Saturday, respectively



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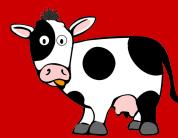
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What if we make a distinction between weekend and weekdays?





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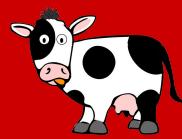
- Weekdays: **p=0.22**; p-value=9.1e-05
- Weekend: **p=0.36**; p-value=0.005

→ New angle of disentangling text complexity from reader interest

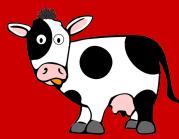


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# Generative AI models



# Model Evaluation

## GPT-4o and Llama-3-8b-instruct:

- Provide valid explanations
- Look at: structure, tone, information layers, and comprehension
- Corr. with gold reading time:  $\rho=0.87$ ; p-value=0.001



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## Fietje-2-chat:

- Confuses input with the provided example
- Can only take two or three examples



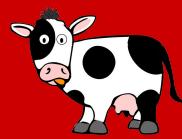
# What we will do next

## In the upcoming months we will:

- Finalise the systematic assessment
- Disentangle text complexity from reader interest
- Train LLMs for text simplification
- Field test the simplification with a target group

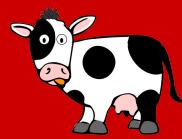
## What do we need?

- Parallel data with original and simplified pairs (by humans)
- Human judgements of the simplified text to validate performance

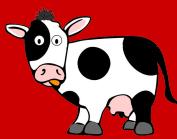


# Takeaways

- Focus on readers first
- Good features emerge at different linguistic levels (lexical, semantic, syntax)
- LLMs can look into more subtle features: style, tone, and comprehension
- Weekday news reading is different from weekend news reading



**Feel free to ask  
questions!**



# Contact Information

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Project website: [paginaproject.nl](http://paginaproject.nl)

