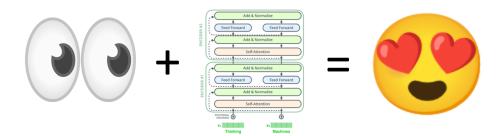






ACL 2025 Tutorial

Eye Tracking and NLP

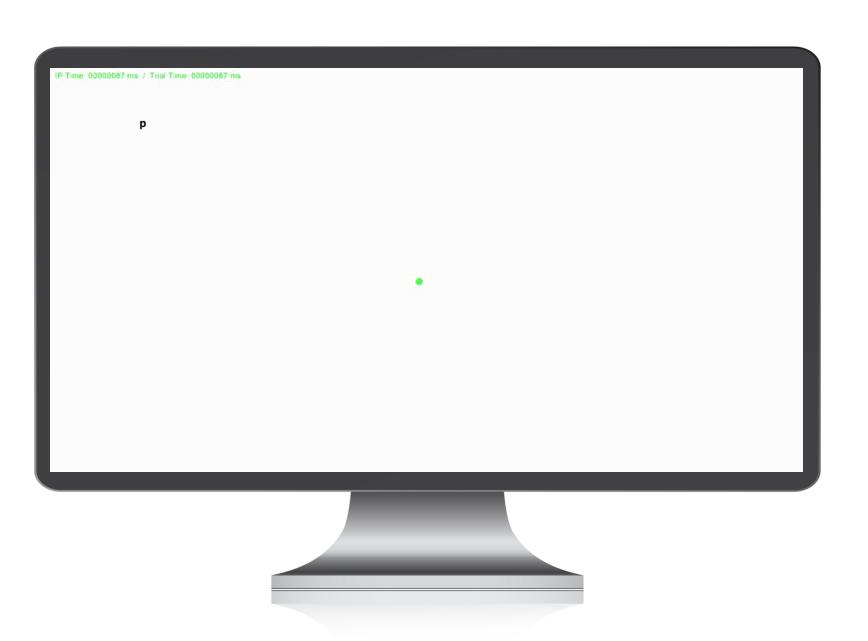


David Reich^{1,2}, Omer Shubi³, Lena Jäger¹ and Yevgeni Berzak³

¹University of Zurich ²University of Potsdam ³Technion

Read the Following Paragraph

Over the next 30 years, the planet's human population will increase to nine billion. Already one billion people do not get enough food. The increase will mean more pressure on agricultural land, water, forests, fisheries and biodiversity resources, as well as nutrients and energy supplies. There is also the issue of methane excreted by cows. The livestock farming contribution, in terms of greenhouse gas emissions, is enormous – 35% of the planet's methane, 65% of its nitrous oxide and 9% of the carbon dioxide.







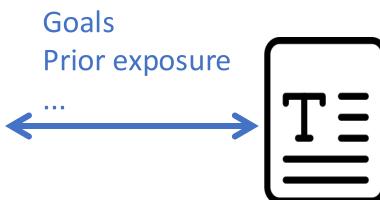




Eye Movements in Reading: Rich Information







Comprehension

Relevance

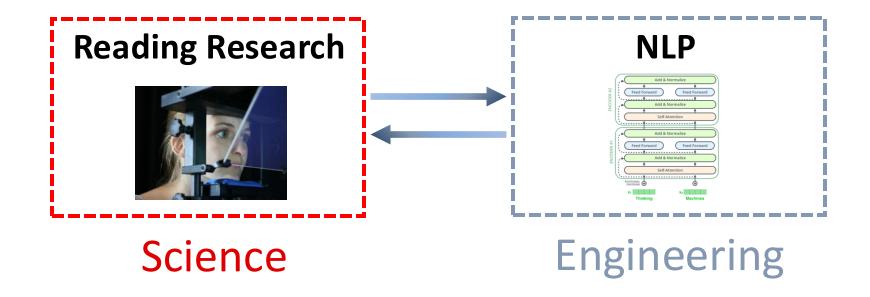
Linguistic knowledge Reading skill Cognitive state

•

Ling. characteristics
Information structure
Difficulty level

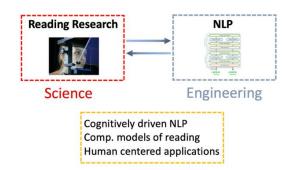
. . .

This Tutorial



Cognitively driven NLP Comp. models of reading Human centered applications

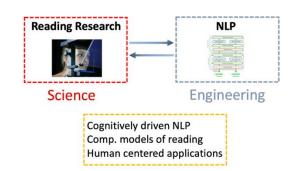
Huge untapped potential for NLP research



- A unique multimodal modeling challenge
- Expanding the role of NLP in cognitive modeling and science
- Opportunities for innovative high-impact applications
 - Education
 - Language learning and assessment
 - Content personalization
 - Content accessibility

• ...

The domain is ripe enough



- Builds on a long tradition in the psychology of reading
- Amount and diversity of eye tracking data has reached a critical mass
- Recent NLP and ML modelling approaches demonstrate feasibility

Tutorial Outline



1. Introduction to eye tracking



2. Uses of eye tracking in NLP + QA 30 minutes break



→ 3. NLP for eye movement and cognitive modeling



 $+ \odot \odot = 255$ 4. New human centered applications



+ •• = ? 5. Outlook and future directions + QA

Introduction to Eye Movements in Reading and Eye Tracking



Introduction to Eye Movements in Reading and Eye Tracking



How do People Read?



Data Representation



Reading Measures





Eye Tracking



Introduction to Eye Movements in Reading and Eye Tracking



How do People Read?



Data Representation



Reading Measures





Eye Tracking



Read the Following Paragraph

Over the next 30 years, the planet's human population will increase to nine billion. Already one billion people do not get enough food. The increase will mean more pressure on agricultural land, water, forests, fisheries and biodiversity resources, as well as nutrients and energy supplies. There is also the issue of methane excreted by cows. The livestock farming contribution, in terms of greenhouse gas emissions, is enormous – 35% of the planet's methane, 65% of its nitrous oxide and 9% of the carbon dioxide.

IP Time 00000087 ms / Trial Time 00000087 ms

р

Online Version





Fixations



Saccades

CNN wants to change its viewers' habits.

CNN wants to change its viewers? habits.

CNN wants to change its viewers' habits.

CNN wants to change its viewers' habits.

Con wants to change its viewers' habits.



CNN wants to change its viewers' habits.

What do you see during a **fixation**?

CNN wants to change its viewers' habits.

Perceptual
Span

What do you see during a **fixation**?

CNN wants to change its viewers' habits.

What do you see during a saccade?

.....**>**

What do you see during a **saccade**?

Nothing!



CNN wants to change its wiewers' habits.

Forward

Saccade

CNN wants to change its viewers' habits.

Forward

Saccade

CNN wants to change its viewers' habits.

Backward Saccade (Regression)











Eye Mind Assumption: "... there is no appreciable lag between what is fixated and what is processed." Just & Carpenter, 1980

Tight correspondence between eye movements and linguistic processing

- Eye movements capture online processing difficulty:
 - e.g. longer, less frequent and less predictable words
 - → longer fixation times, less skipping

Introduction to Eye Movements in Reading and Eye Tracking





How do People Read? Data Representation





Reading Measures





Eye Tracking

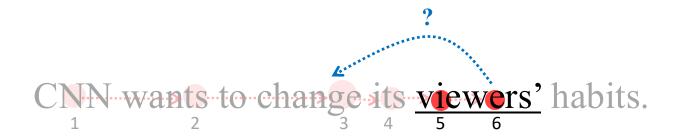




- Skips (also skip rate / fixation probability)
- First fixation duration
- Gaze duration
- Regression rate
- Go-past duration
- Total fixation duration

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- First fixation duration
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Introduction to Eye Movements in Reading and Eye Tracking



How do People Read? Data Representation





Reading Measures

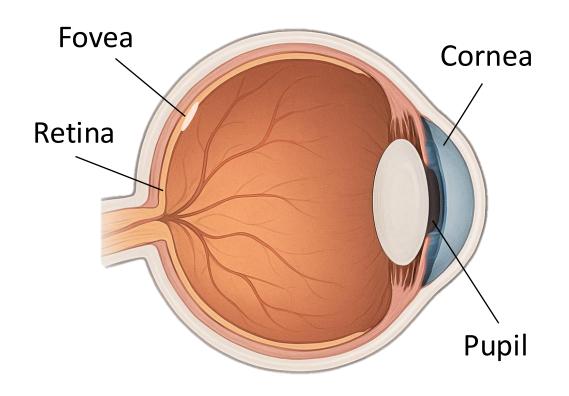




Eye Tracking



Eye Physiology



Photoreceptor Cells on the Retina

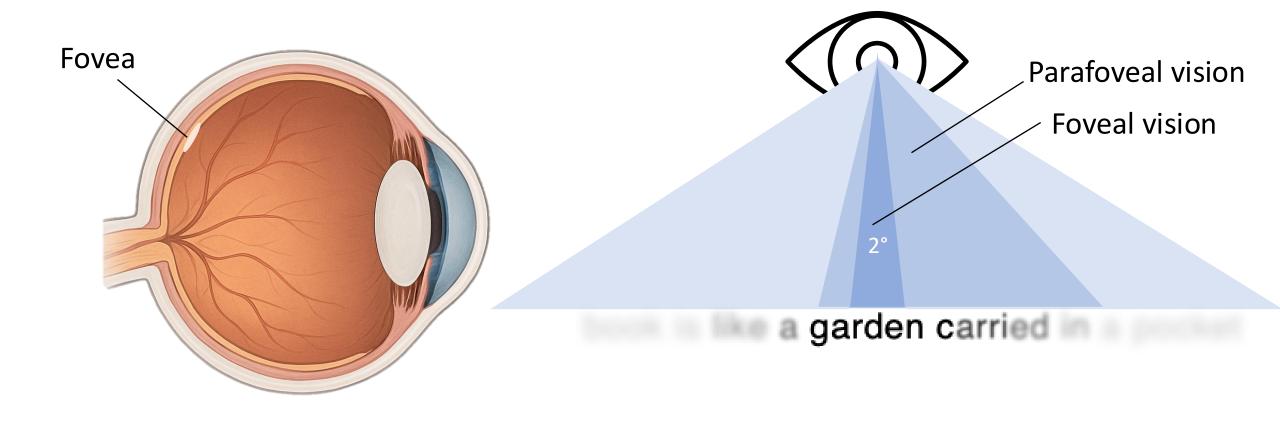
Cones

- Sensitive to "visual detail" (spatial frequency and color)
- High density in the fovea
- Low density in the peripheria

Rods

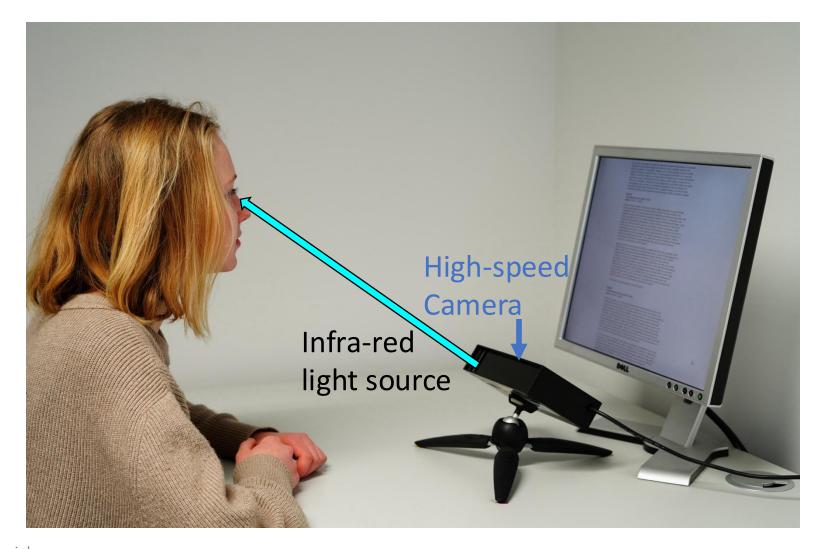
- Sensitive to light
- Low density in the fovea
- High density in the peripheria

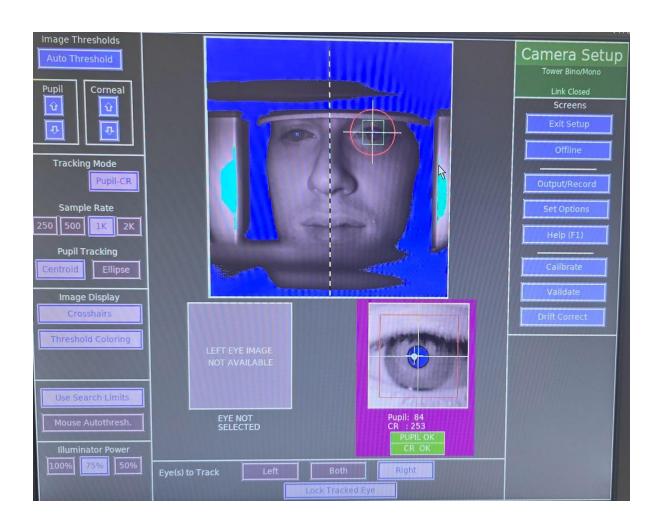
The Perceptual Span in Reading



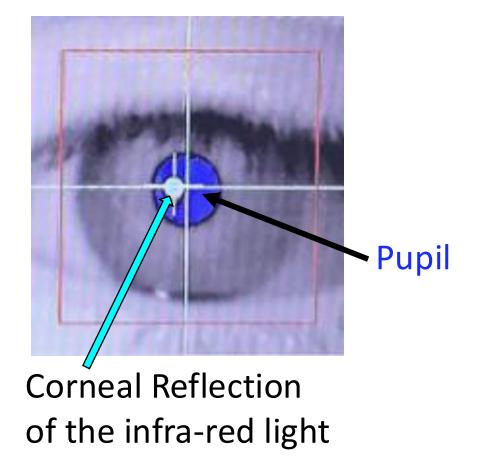
The Perceptual Span in Reading







Two targets



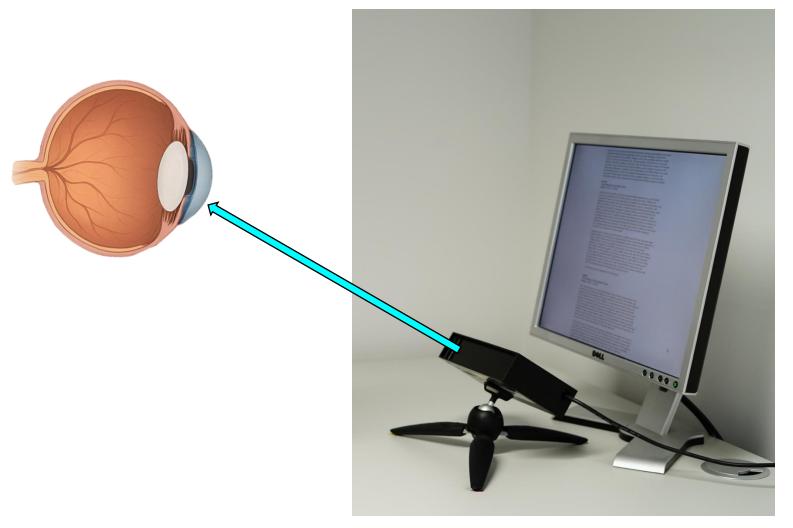
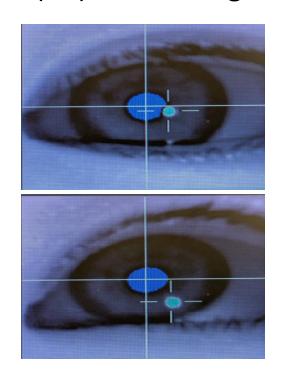


Image detection of the

- pupil
- corneal reflection
 (CR) of the IR light



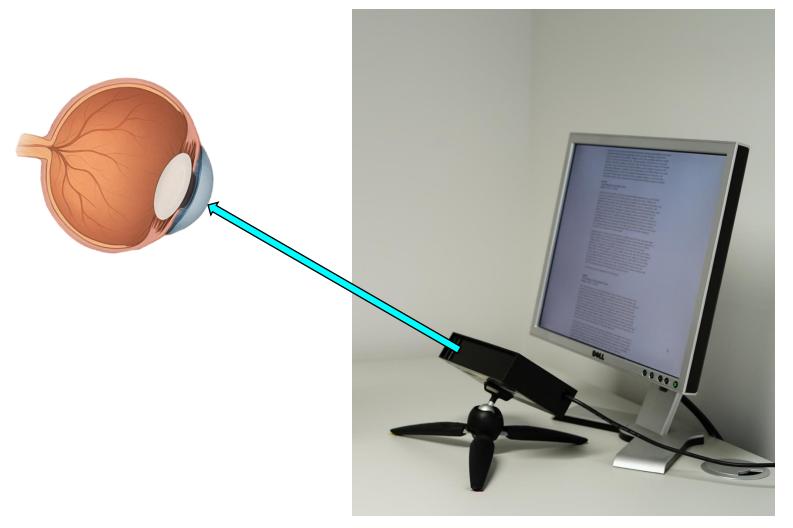
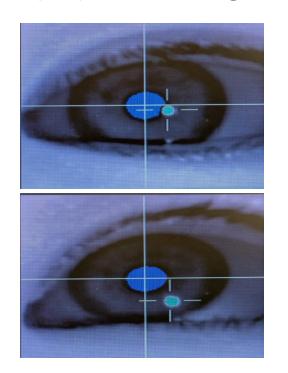


Image detection of the

- pupil
- corneal reflection (CR) of the IR light

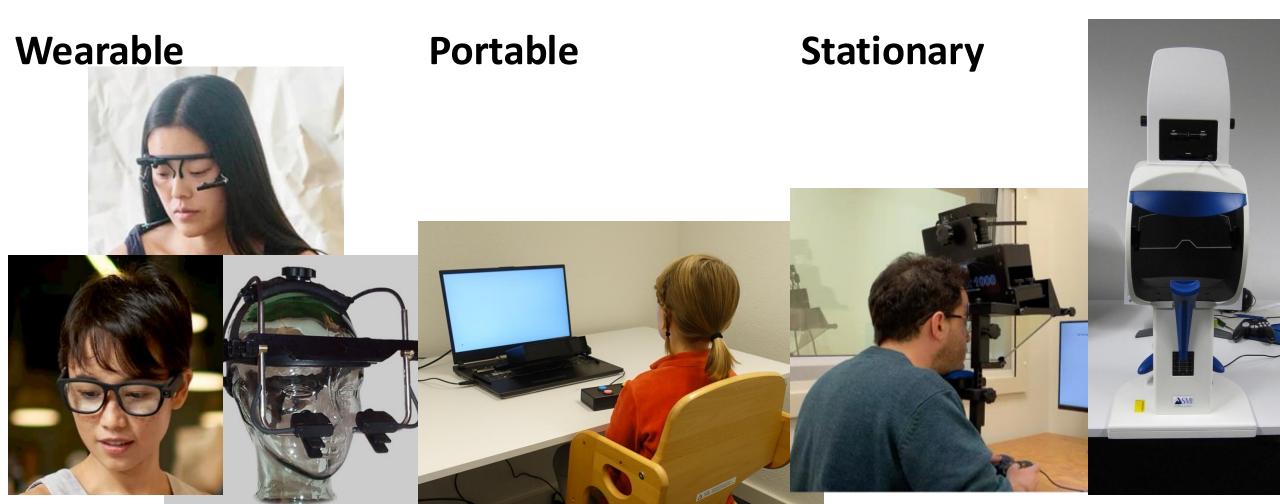


Calibration



Very high calibration quality needed for reading research

Video-Based Eye Tracking Devices



Video-Based Eye Tracking Devices

For eye tracking-while-reading data sets we typically want

- character-level spatial resolution
 - > very high accuracy (calibration quality) needed
 - head-stabilization (chin-rest) recommended
 - > stationary or portable devices typically achieve better calibration than wearables
- precise fixation onset/offset times
 - sampling frequency of at least 200 Hz needed

Data Collection Considerations

Many additional things to take care of

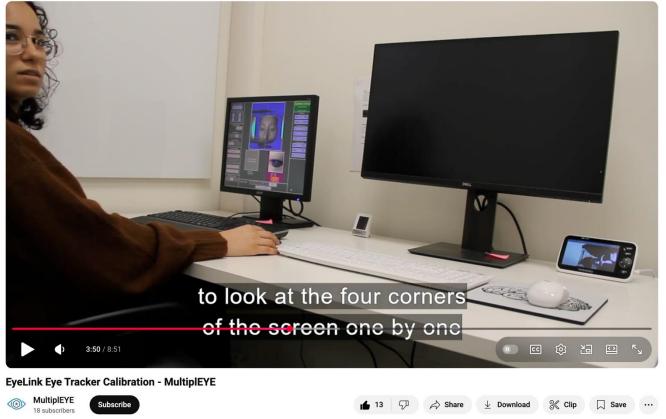
- Experimental design, counter balancing and randomization
- Attention checks / reading comprehension questions
- Monitoring drift and recalibration during the experiment
- Blocking accidental clickthrough's
- Text presentation:
 - Font (often monospace) and font size
 - Line spacing
- IRB (ethics approval, data protection etc.)

• ...

Data Collection Considerations

Data collection video tutorials (for EyeLink Eye Trackers)

- Dominant eye test
- Calibration





Introduction to Eye Movements in Reading and Eye Tracking





How do People Read?



Data Representation



Reading Measures





Eye Tracking



Eye Tracking: Recorded data

CNN wants to change its viewers' habits.

Raw Data

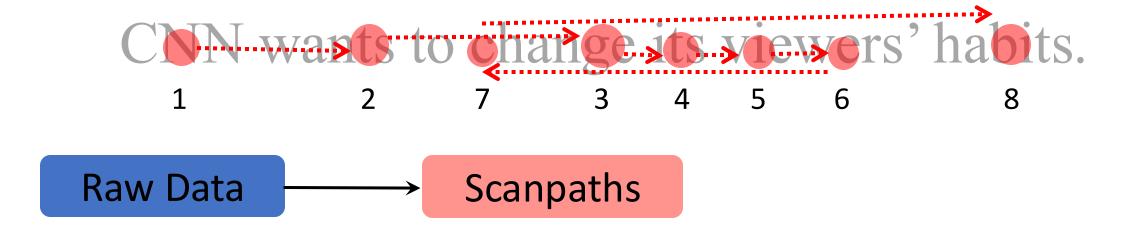
Binocular or monocular





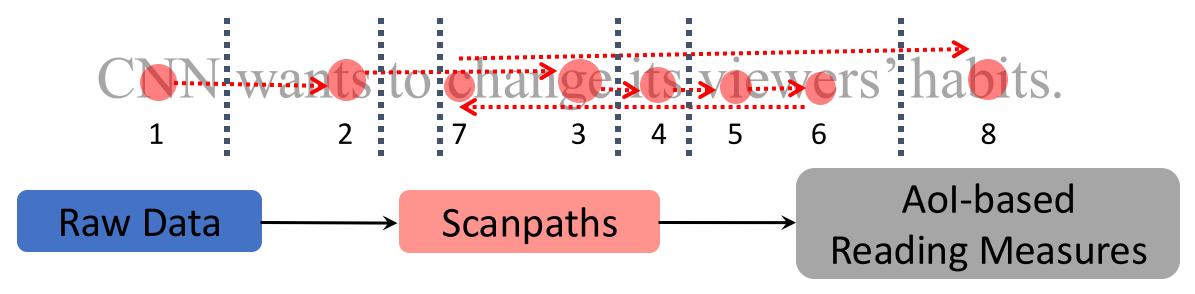
Screen coordinates or visual angle

Eye Tracking: Preprocessing



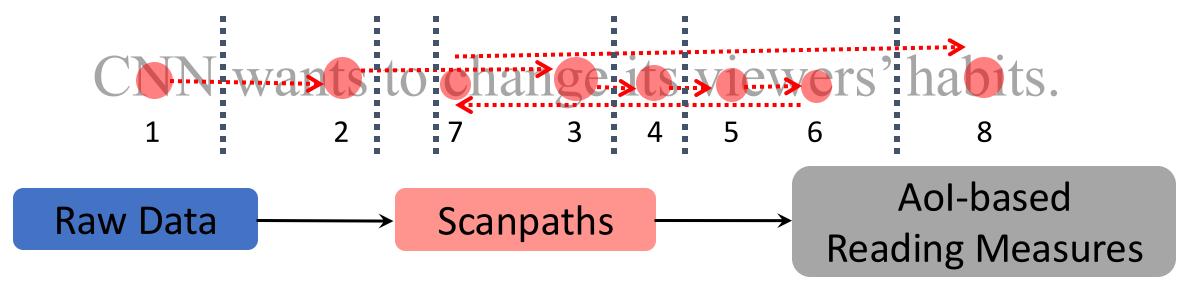
1. Extract fixations from raw samples

Eye Tracking: Preprocessing



- 1. Extract fixations from raw samples
- 2. Map fixations to *Areas of Interest:* Pre-defined screen areas (in pixels)

Eye Tracking: Preprocessing



- 1. Extract fixations from raw samples
- 2. Map fixations to *Areas of Interest:* Pre-defined screen areas (in pixels)



Python package with preprocessing algorithms

pymovements.readthedocs.io

Eye Tracking Data Structure

Raw Data

- > Time series
- Each row contains one raw sample
- N depends on sampling frequency

Time (ms)	x (pixels)	y (pixels)
1	151	372
2	150	371
3	152	374
4	151	370
•••	•••	

Scanpaths

- > Discrete chronological sequence
- > Each row contains one fixation

idx	x (mean, pixels)	y (mean, pixels)	word	aoi	dur
1	151	371	CNN	1	380
2	175	376	wants	2	180
3	198	378	change	4	224
4	227	370	viewers	6	299
5	251	369	habits	7	230
6	192	374	change	4	229
•••	•••	•••	•••	•••	

Aol-based Reading Measures

- ➤ Discrete sequence in aoi-order
- ➤ Each row contains RMs of one aoi read by one subj

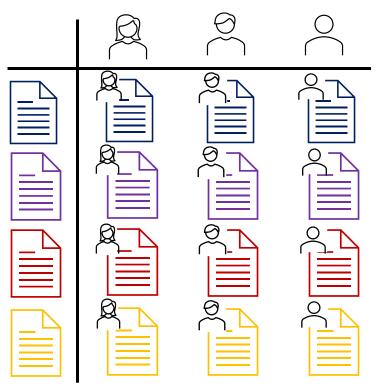
subj	item	word	aoi	FFD
1	1	CNN	1	380
1	1	wants	2	180
1	1	to	3	NA
1	1	change	4	224
1	1	its	5	NA
1	1	viewers	6	299
1	1	habits	7	230
		•••	•••	

Data is **not** iid — it has **structure**

Implications for:

- Statistical modeling
- Training and evaluations
- Applications





Texts

Introduction to Eye Movements in Reading and Eye Tracking



How do People Read? Data Representation





Reading Measures





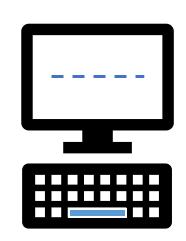
Eye Tracking



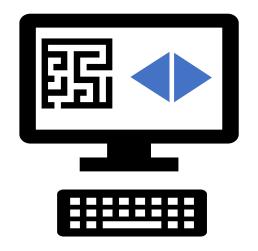
Eye Tracking vs Cheaper Low Tech Methods

Do we really need eye tracking?

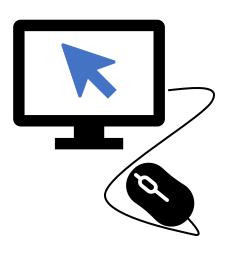
Popular alternatives in psycholinguistics:



Self-Paced Reading



Maze

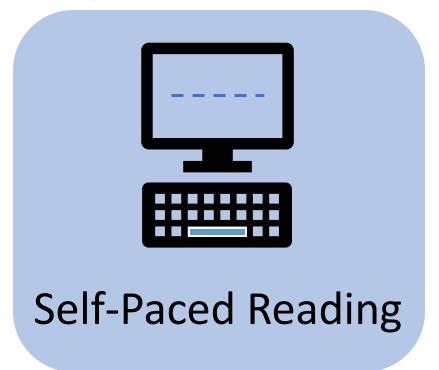


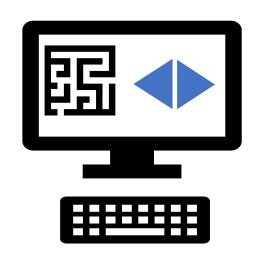
Mouse tracking

Eye Tracking vs Cheaper Low Tech Methods

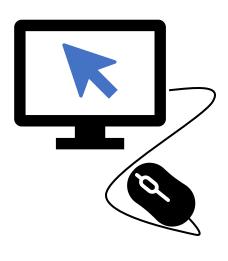
Do we really need eye tracking?

Popular alternatives in psycholinguistics:









Mouse tracking

Self Paced Reading (SPR)

Reveal each consecutive word with a button press

Reveal each consecutive word with a button press

Many-----

Reveal each consecutive word with a button press

----years------

Reveal each consecutive word with a button press

-----later-----

Reveal each consecutive word with a button press

----as-----

Reveal each consecutive word with a button press

-------------he------

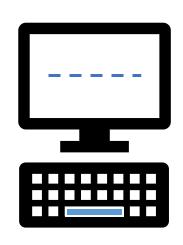
- Reveal each consecutive word with a button press
- Time between button presses as a proxy for incremental processing difficulty

-----faced------

Eye Tracking vs Cheaper Low Tech Methods

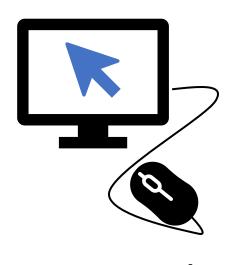
Do we really need eye tracking?

Popular alternatives in psycholinguistics:



Self Paced Reading



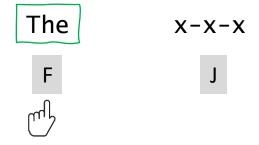


Mouse tracking

Choose a word that fits given the preceding context

F J

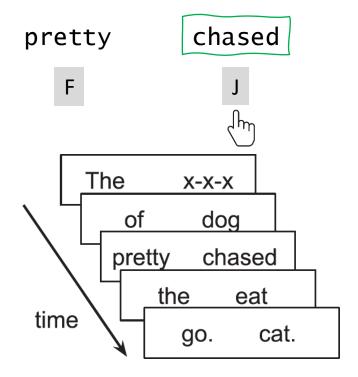
Choose a word that fits given the preceding context



Choose a word that fits given the preceding context



Choose a word that fits given the preceding context

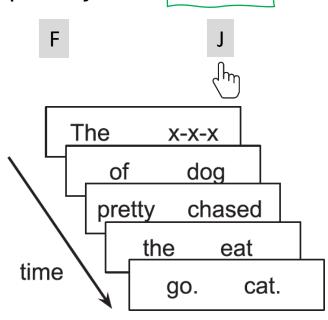


Forster et al. (2009), Boyce et al. (2020)

Choose a word that fits given the preceding context

Time between button presses as a proxy for incremental

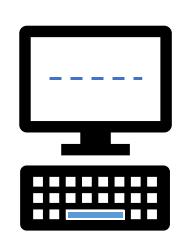
processing difficulty pretty chased



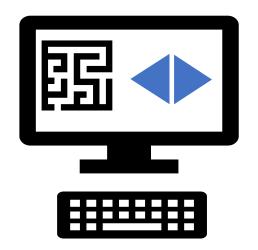
Eye Tracking vs Cheaper Low Tech Methods

Do we really need eye tracking?

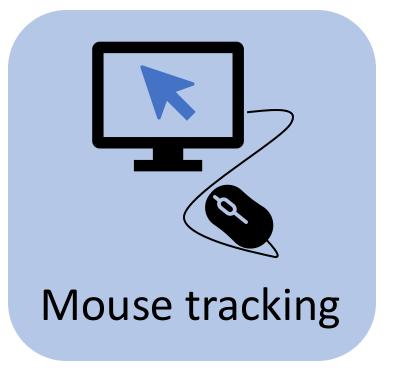
Popular alternatives in psycholinguistics:



Self Paced Reading



Maze



Mouse Tracking

DONE

Synthetic Eye Tracking Data



Over the next 30 years, the planet's human population will increase to nine billion. Already one billion people do not get enough food. The increase will mean more pressure on agricultural land, water, forests, fisheries and biodiversity resources, as well as nutrients and energy supplies. There is also the issue of methane excreted by cows. The livestock farming contribution, in terms of greenhouse gas emissions, is enormous – 35% of the planet's methane, 65% of its nitrous oxide and 9% of the carbon dioxide.



- 1. Cognitive models
- 2. NLP / ML Models

Eye Tracking vs Cheaper Methods

- More naturalistic
- More fine-grained information (multiple measures, not just RTs)
- Doesn't include time to execute button presses and mouse movements
- Higher quality than synthetic data
- Currently cannot be collected at scale (on the web)
- In most use cases, no eye tracking data is available at application time

Introduction to Eye Movements in Reading and Eye Tracking



How do People Read? Data Representation





Reading Measures





Eye Tracking



Datasets

Types of Reading Datasets

Minimal-pairs vs naturalistic reading

1a) The horse

raced past the barn fell.

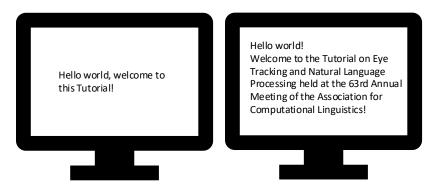
1b) The horse that was raced past the barn fell.

Eye tracking hardware quality





Single sentences vs parags/texts



Reading task

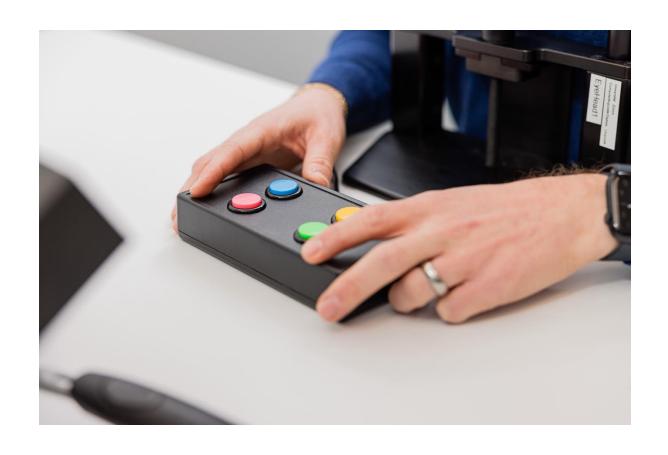
- Natural reading
- Question answering
- Repeated reading

•

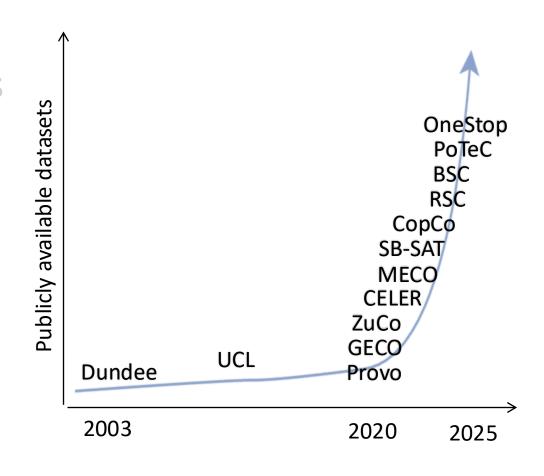


Additional Information Accompanying Eye Tracking Datasets

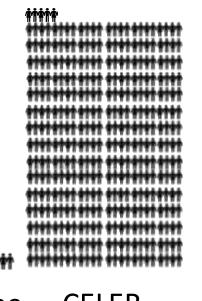
- Behavioral data
 - Response accuracies
 - Judgements/labels
- Psychometric test scores
- Demographic information
- Linguistic background



- Increasing number of data sets
- Increasing number of participants
- Increasing diversity of data sets:
 - Languages & Scripts
 - Populations
 - Tasks
- Multilingual data sets



- Increasing number of data sets
- Increasing number of participants
- Increasing diversity of data sets:
 - Languages & Scripts
 - Populations
 - Tasks
- Multilingual data sets



Dundee CELER (2003) (2022)

N = 20 N = 365

MECO (2022–2025) N=1,202

- Increasing number of data sets
- Increasing number of participants
- Increasing diversity of data sets:
 - Languages & Scripts
 - Populations
 - Tasks
- Multilingual data sets



Chinese: BSC

Danish: CopCo

Dutch: GECO

German: PoTeC

Russian: RSC

• • •

- Increasing number of data sets
- Increasing number of participants
- Increasing diversity of data sets:
 - Languages & Scripts
 - Populations
 - Tasks
- Multilingual data sets



Dyslexia: CopCo

L2: GECO, MECO, CELER, ...

Wide age range: CELER

Domain-expertise: PoTeC

- Increasing number of data sets
- Increasing number of participants
- Increasing diversity of data sets:
 - Languages & Scripts
 - Populations
 - Tasks
- Multilingual data sets



Reading comprehension: SB-SAT,

OneStop, Multipleye

Sentiment classification: ETSA

Relation extraction: ZuCo

Repeated reading: OneStop

Information seeking: OneStop

96

. . .

- Increasing number of data sets
- Increasing number of participants
- Increasing diversity of data sets:
 - Languages & Scripts
 - Populations
 - Tasks
- Multilingual data sets





Large-scale multi-lab multilingual data collection initiatives

MECO: https://meco-read.com

MultipleYE: https://multipleye.eu

Overview of Publicly Available Data Sets









60+
Datasets

4.5K+
Participants
Total

15K+ Text screens 30+
languages

How to Access the Datasets?



Python package to download 24+ datasets with 4.5K+ participants

pymovements.readthedocs.io

Or from:

- Open science repositories
- Direct links from papers
- From authors' websites



Introduction to Eye Movements in Reading and Eye Tracking



How do People Read?



Data Representation



Reading Measures





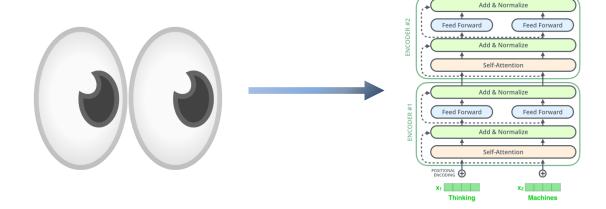
Eye Tracking



Tutorial Outline

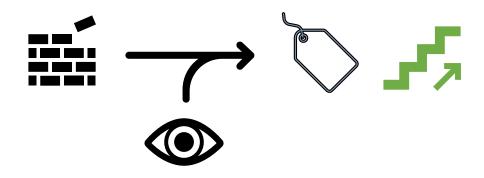
- 1. Introduction to eye tracking
- 2. Uses of Eye Tracking in NLP
- - → 3. NLP for eye movement and cognitive modeling
- - + 4. New human centered applications
- - + = ? 5. Outlook and future directions

Uses of Eye Tracking in NLP



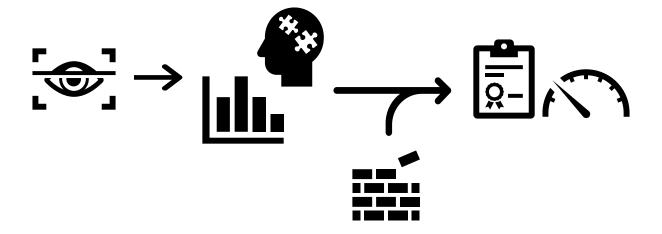
Uses of Eye Tracking in NLP

Modeling



Eye movements can enhance the performance of NLP models

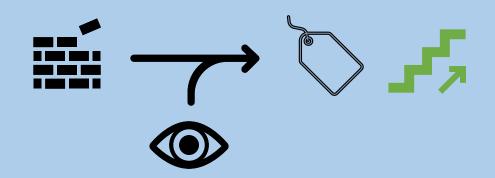
Evaluation



Eye movements as behavioral benchmarks for evaluating NLP models

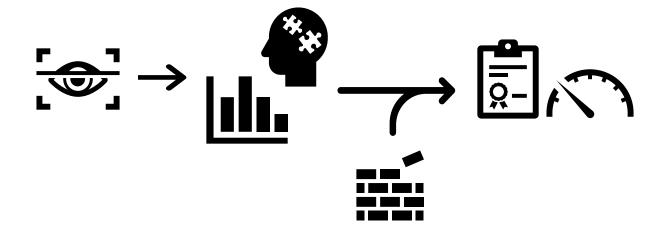
Uses of Eye Tracking in NLP

Modeling



Eye movements can enhance the performance of NLP models

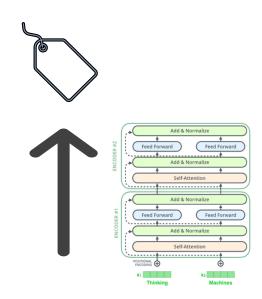
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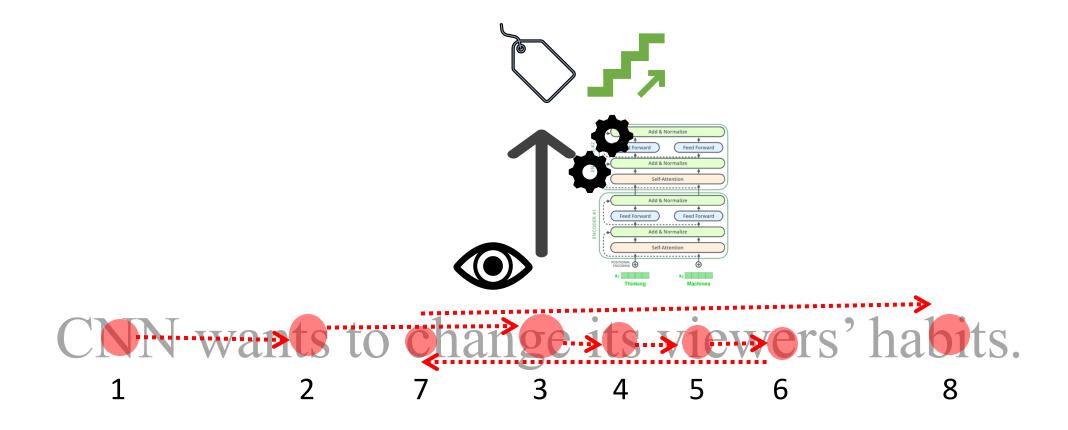
Language modeling





CNN wants to change its viewers' habits.

Language modeling and eye movements ••---



Improving NLP with Gaze

Tasks



- NER Hollenstein and Zhang (2019)
- Paraphrase generation, sentence compression <u>Sood et al. (2020)</u>, Klerke et al. (2016)
- Relation extraction, sentiment analysis, NER Ren and Xiong (2021)
- GLUE <u>Deng et al. (2023)</u>, <u>Deng et al. (2024)</u>
- Readability assessment <u>González-Garduño and Søgaard (2017)</u>
- Dependency parsing <u>Strzyz et al. (2019)</u>
- QA <u>Malmaud et al. (2020)</u>





Why eye movements?

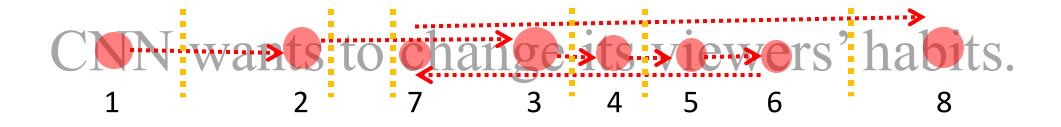
- Eye movement in reading are influenced by
 - the **difficulty** of the text
 - the individual
 - cognitive demands
 - •



Static text: linguistic axis

? Alignment

• Dynamic eye movements: temporal axis

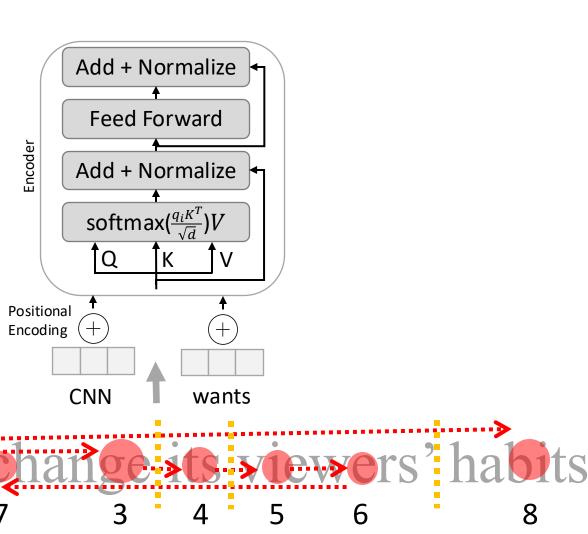


- Word-level alignment
 - E.g. total fixation duration



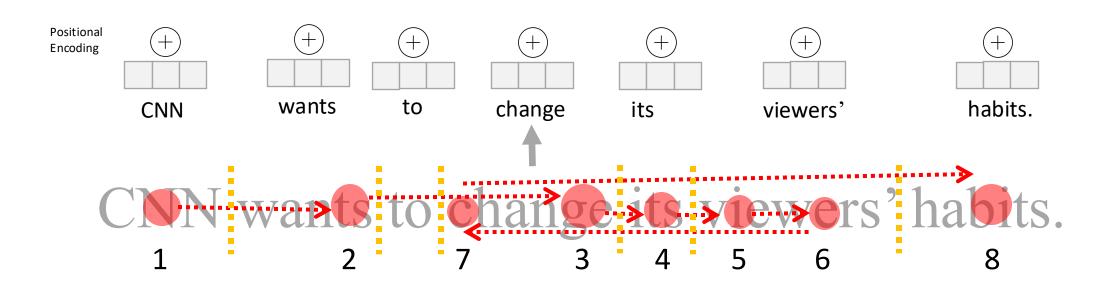
text?

Word-level alignment

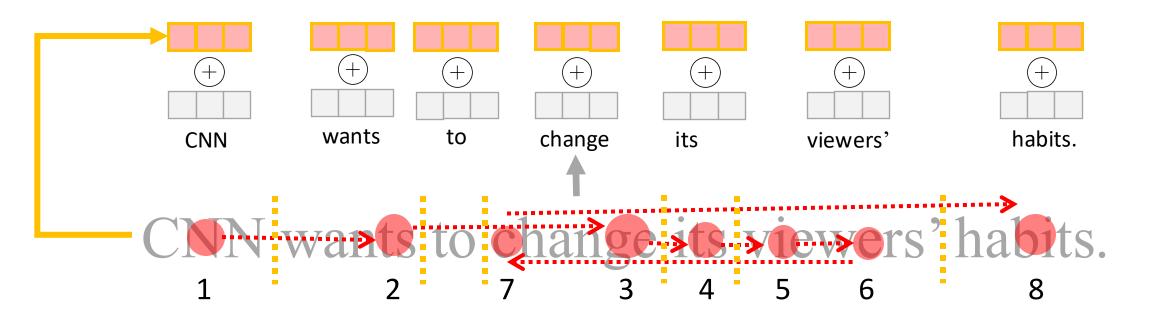


1 2 7 3 4 5 6 8

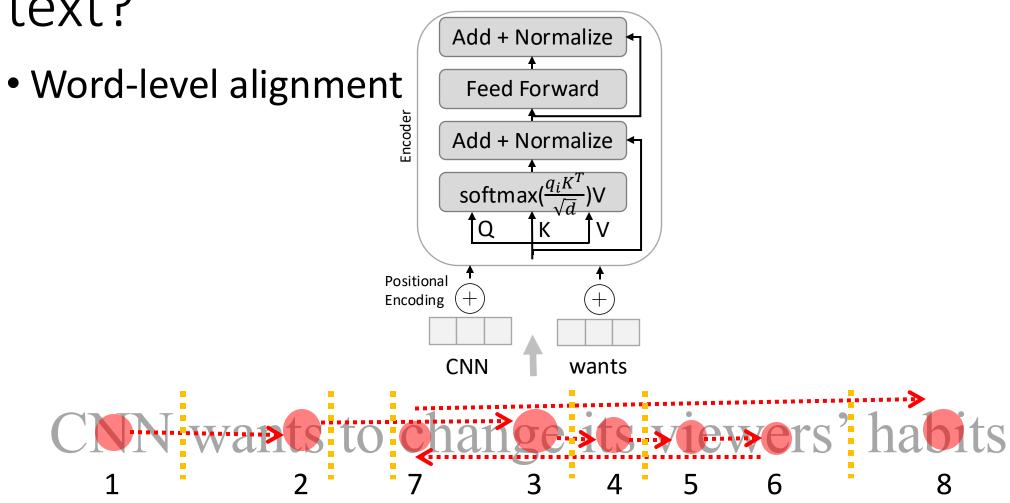
Word-level alignment



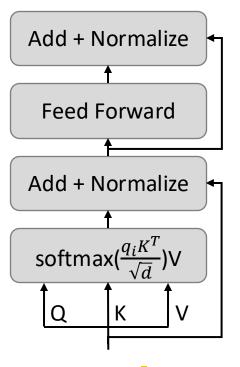
Word-level eye movement embedding

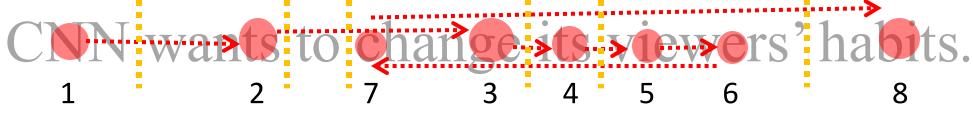


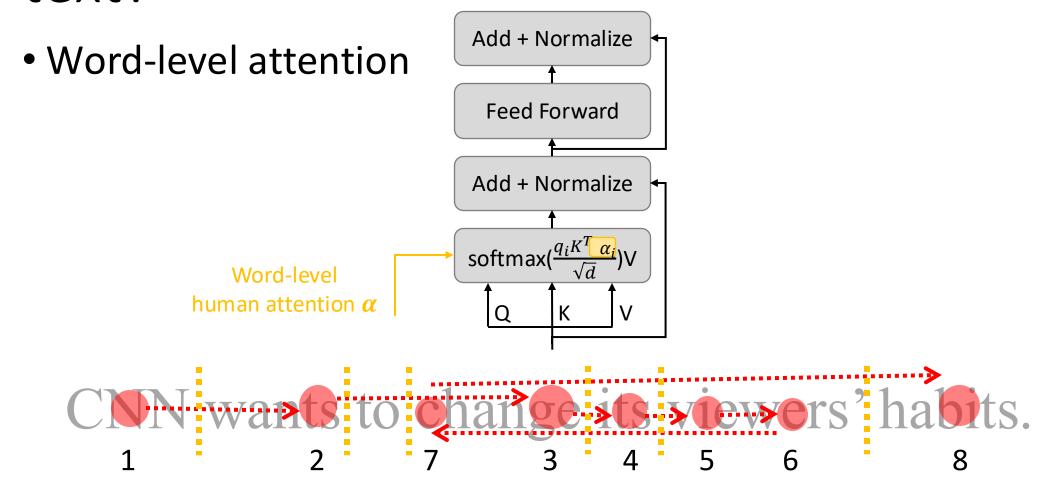
text?



• Word-level alignment





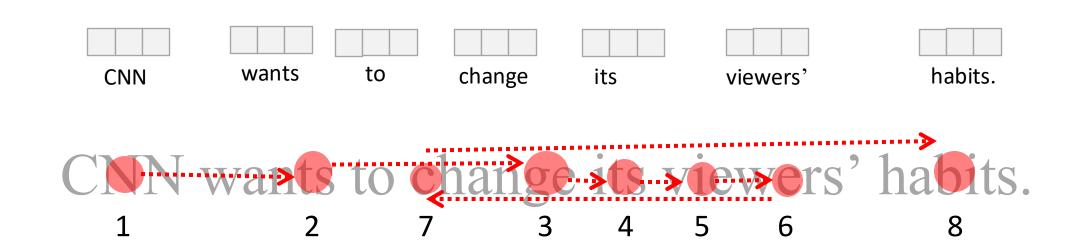


ACL2025 - Eye Tracking and NLP Tutorial Sood et al. (2022)

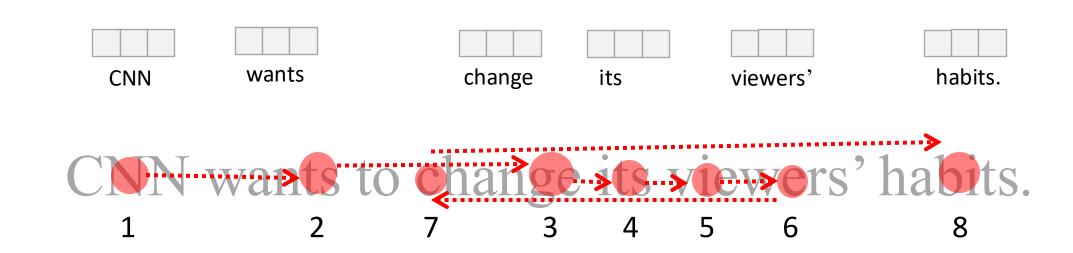
- Word-level alignment
 - E.g. total fixation duration



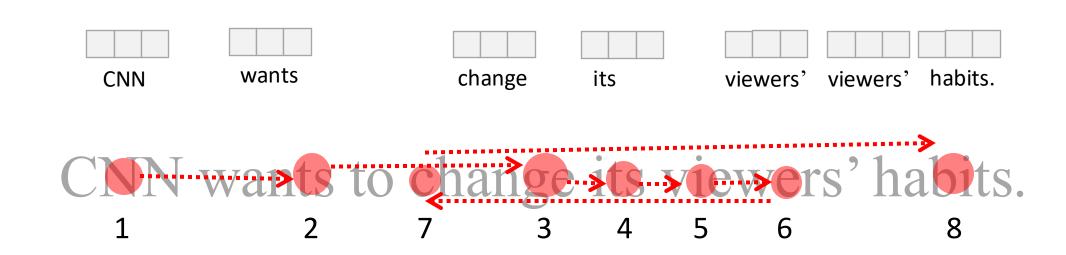
Word reordering



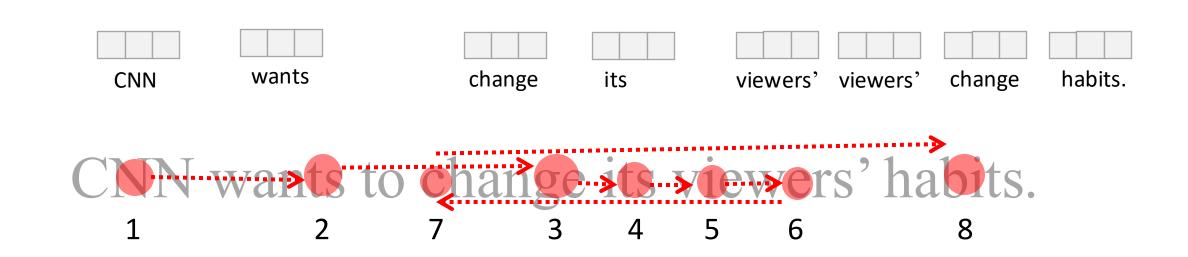
Word reordering



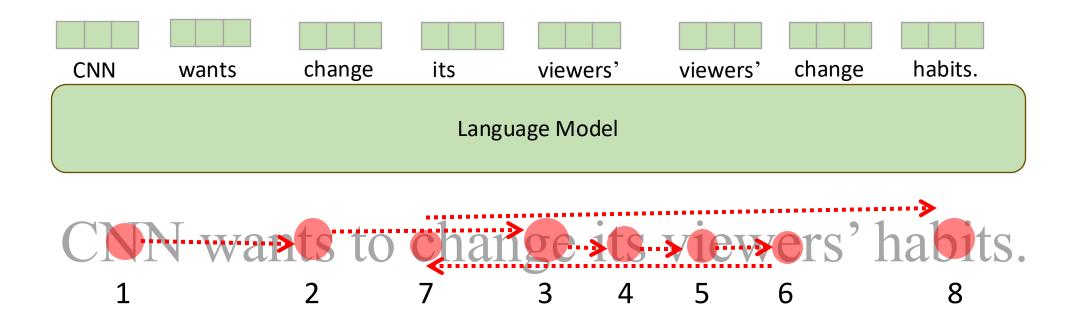
Word reordering



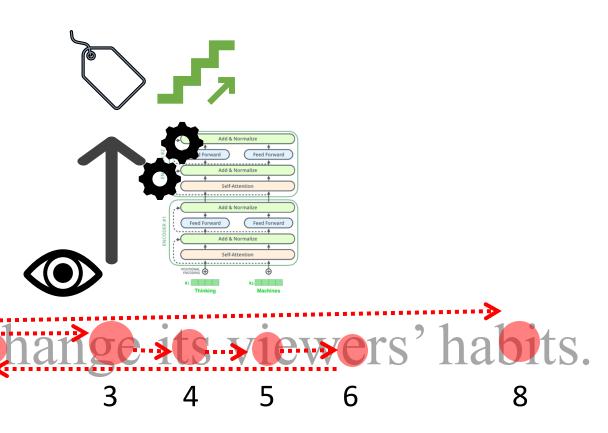
Word reordering

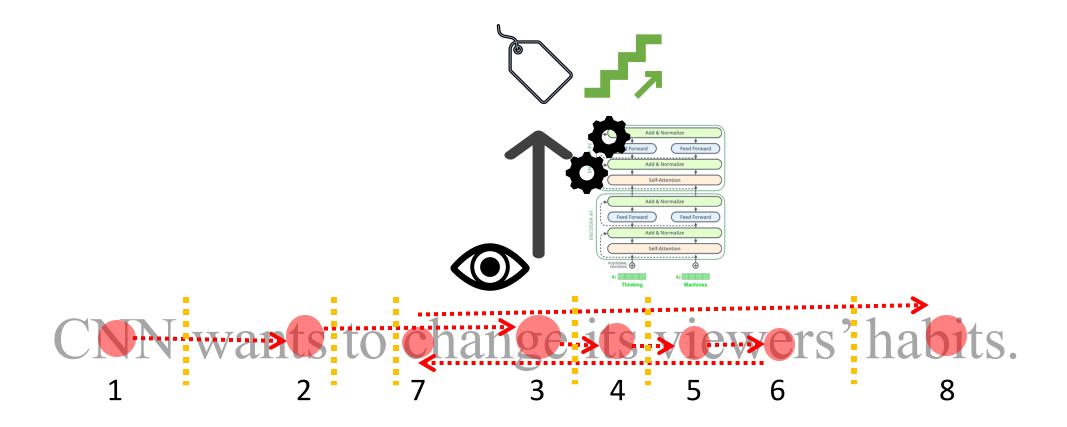


Word reordering

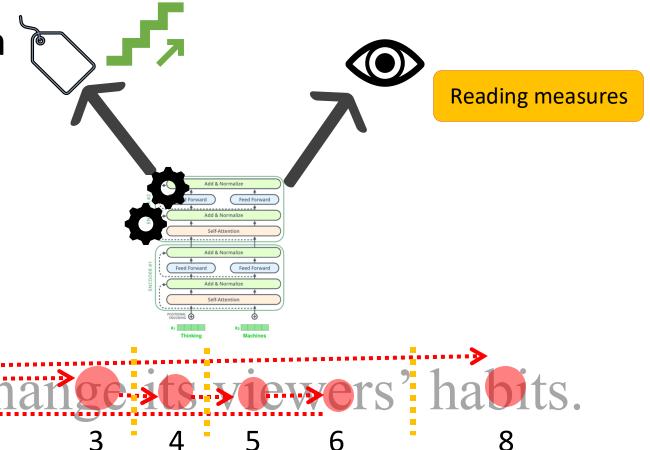


- Input:
 - Positional encoding
 - Attention
 - Reordering





 Multi-task learning with ordinary reading data



Klerke et al. (2016), González-Garduño and Søgaard (2017), Barrett et al. (2018), Strzyz et al. (2019) 125

 Multi-task learning with task specific (QA) data Malmaud et al. (2020)

Ordinary reading (no question preview)

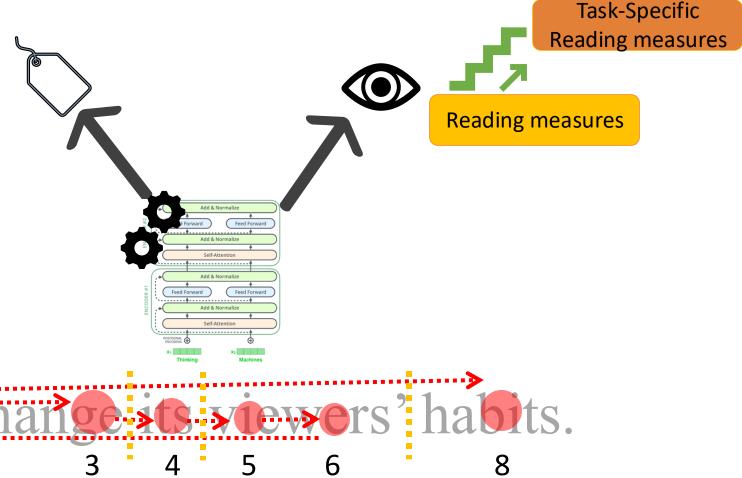


Information seeking (with question preview)

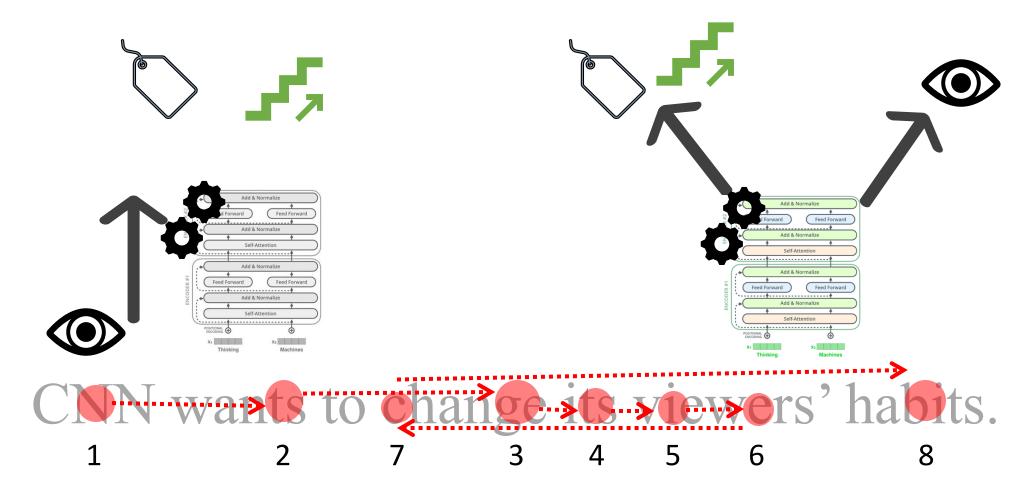
Q: What will result from an increase in human population in the future?



 Multi-task learning with task-specific reading data

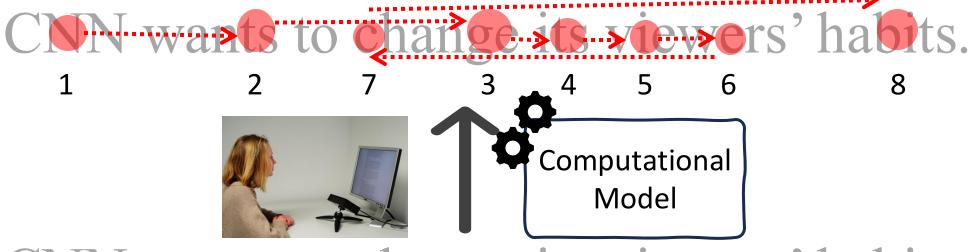


Malmaud et al. (2020)



Additional challenges

- Human data is scarce
 - ➤ Scale with synthetic eye movements



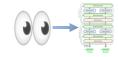
CNN wants to change its viewers' habits.

Additional challenges

- Human data is scarce
 - ➤ Scale with synthetic eye movements
- In reality, subwordtokens instead of words
 - ➤ Need to decide how to match representations



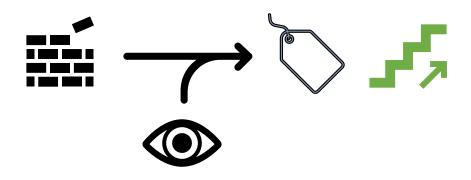
Discussion



- Performance improvements are typically modest
- Hard to beat scale!
 - Currently no convincing example of large and robust improvements for a state-of-the-art LLM
- Possible directions forward
 - Better modeling
 - More human data
 - Higher quality synthetic eye movements
 - Low resource scenarios
 - Multilingual approaches

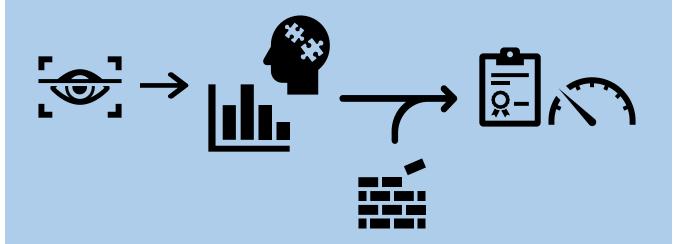
Uses of Eye Tracking in NLP ••--

Modeling



Eye movements can enhance the performance of NLP models

Evaluation



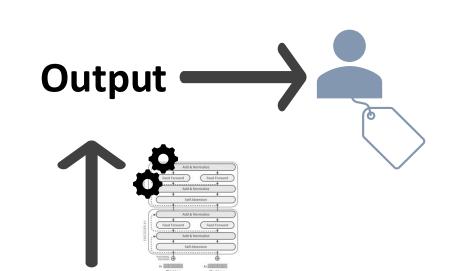
Eye movements for evaluating the performance of NLP models

Evaluating Task Performance



Offline Human Reference

Captures a behavioral end product of linguistic processing

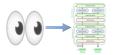


Annotation Summary Translation Preference

• •

CNN wants to change its viewers' habits.

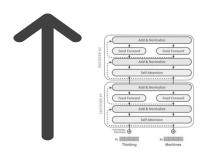
Evaluating Task Performance



Online Human Behavior

Captures language processing in **real time**

Output





CNN wants to change its viewers' habits.

How do people read?



Eye Mind Assumption: "... there is no appreciable lag between what is fixated and what is processed." Just & Carpenter, 1980



Tight correspondence between eye movements and linguistic processing

Evaluating Task Performance



Online Human Behavior

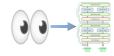
Captures language processing in real time

Machine translation <u>Doherty et al. (2010)</u> Sajjad et al. (2016)

Summarization <u>Ikhwantri et al. (2024)</u>

Readability Gruteke Klein et al. (2025)

Example Task - ARA



Automatic Readability Assessment (ARA):

Scoring the difficulty level of a text

- Popular task in NLP
- Over 100 years of research
- Hundreds of papers, dozens of measures and systems
- Many real-world applications

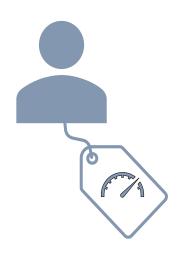


Standard evaluation methods:

Reading Comprehension Performance



Human Labeling







Reader's Comprehension

 Traditional readability measures fitted to reading comprehension data

Harder to answer reading comprehension questions ->
 the less readable the text.





Reader's Comprehension ≠ Text's Readability

- Possible, but not necessary a byproduct of readability
- Depends on the difficulty of the questions
- Hard to estimate reliably





Human labeling \rightarrow very challenging task

Text 1

A domain name is an identification string that defines a realm of administrative autonomy, authority or control within the Internet. Domain names are formed by the rules and procedures of the Domain Name System (DNS). Any name registered in the DNS is a domain name. Domain names are used in various networking contexts and application-specific naming and addressing purposes. In general, a domain name represents an Internet Protocol (IP) resource, such as a personal computer used to access the Internet, a server computer hosting a web site, or the web site itself or any other service communicated via the Internet. In 2015, 294 million domain names had been registered.

Domain names are organized in subordinate levels (subdomains) of the DNS root domain, which is nameless. The first-level set of domain names are the top-level domains (TLDs), including the generic top-level domains (gTLDs), such as the prominent domains com, info, net, edu, and org, and the country code top-level domains (cCTLDs).

Text 2

An organism is any living thing. It is easy to recognise a living thing, but not so easy to define it. Animals and plants are organisms, obviously. Organisms are a biotic, or living, part of the environment. Rocks and sunshine are parts of the non-living environment.

Organisms usually have five basic needs. They need air, water, nutrients (food), energy and a place to live. However, not all living things need all these at the same time. Many organisms do not need access to air at all.

A little thought is needed about viruses. There is no agreement as to whether they should be regarded as living. They are made of protein and nucleic acid, and they evolve, which is a really important fact. However, they exist in two quite different phases. One phase is dormant, not active. The other is inside a living cell of some other organism. Then the virus is very active reproducing littelf

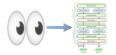
(1) Read both texts. (2) Answer the questions. (3) Click "Rate Next Set."

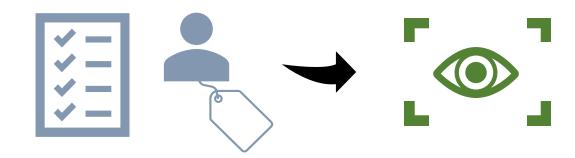
5/10 comparisons completed.

Text 1 mentions subdomains. True False

Text 2 mentions vaccines. True False

Which text is easier to understand? Text 1 Text 2





From reading comprehension performance and human

labeling of text difficulty to

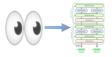
cognitive evaluation of reading ease using eye tracking



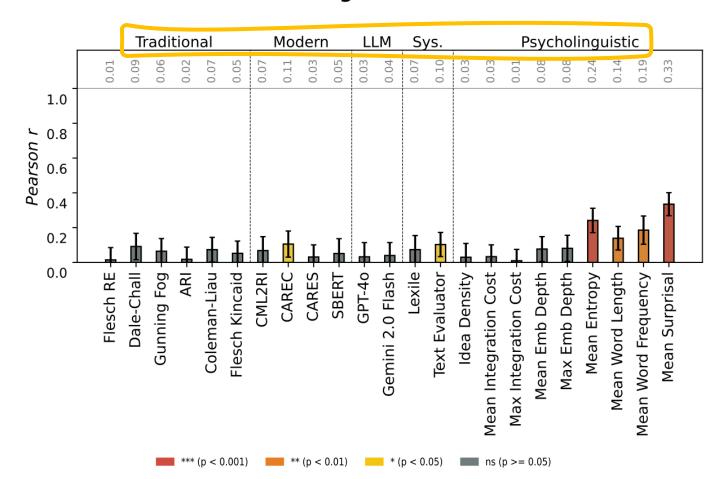


Evaluation of readability measure M is the Pearson r of:

 $RT \sim Score_M$



△ Regression Rate



Low correlation between existing measures and reading ease

Evaluating Task Performance



Online Human Behavior

Captures language processing in real time

Machine translation <u>Doherty et al. (2010)</u>
<u>Sajjad et al. (2016)</u>

Summarization <u>Ikhwantri et al. (2024)</u>

Readability Gruteke Klein et al. (2025)

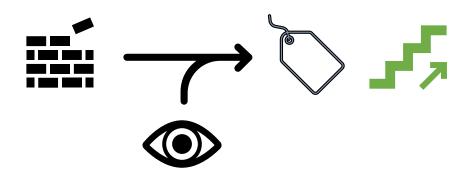
Discussion: Eye Movements for Evaluating NLP Models

Current uses are limited

- ➤ Better use of existing eye tracking data
- ➤ Collect more eye tracking data for specific NLP tasks
- > Large scale evaluations with synthetic eye movements

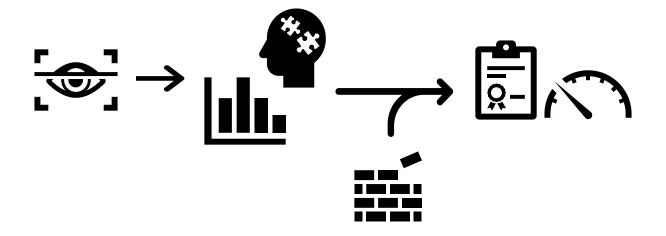
Uses of Eye Tracking in NLP

Modeling



Eye movements can enhance the performance of NLP models

Evaluation



Eye movements for evaluating the performance of NLP models

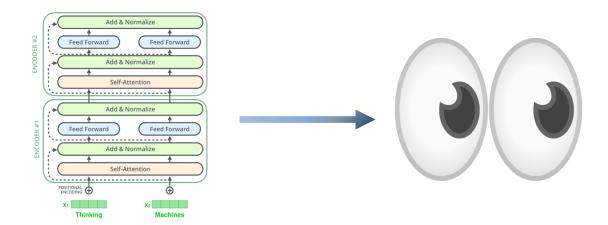
Tutorial Outline

- 1. Introduction to eye tracking
- 2. Uses of eye tracking in NLP
- - → 3. NLP for eye movement and cognitive modeling

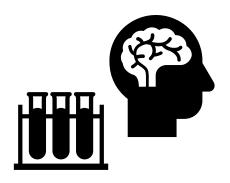


- + • 4. New human centered applications
- $+ \cdot \cdot \cdot = ?$ 5. Outlook and future directions

Uses of NLP in Modeling Human Language Processing and Eye Movements



Uses of NLP in Modeling Eye Movements and Human Language Processing



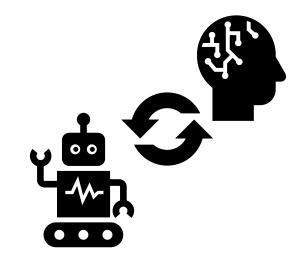
Testing Psycholinguistic
Theories



Representations

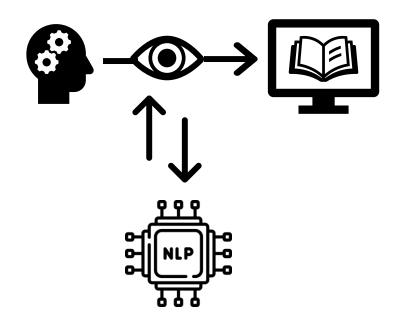


Linguistic quantities

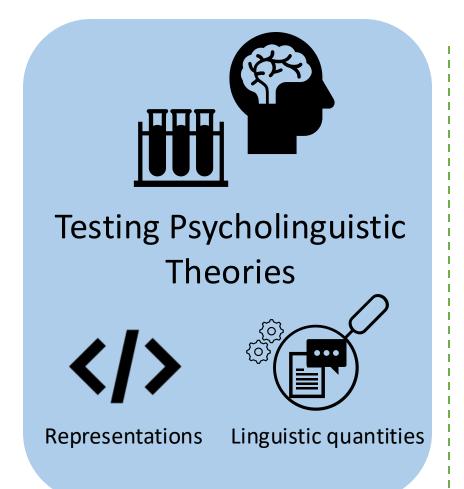


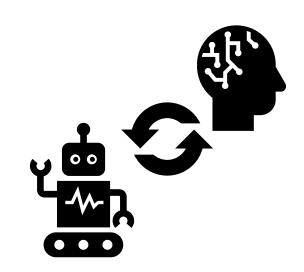
Testing LLM alignment with human language processing

NLP for modeling eye movements in reading



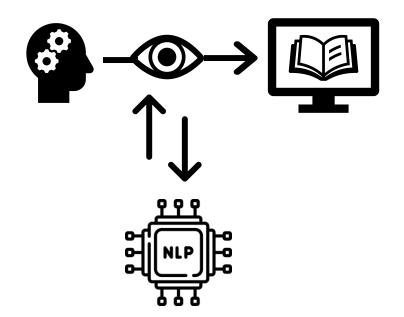
Uses of NLP in Modeling Eye Movements and Human Language Processing → •••

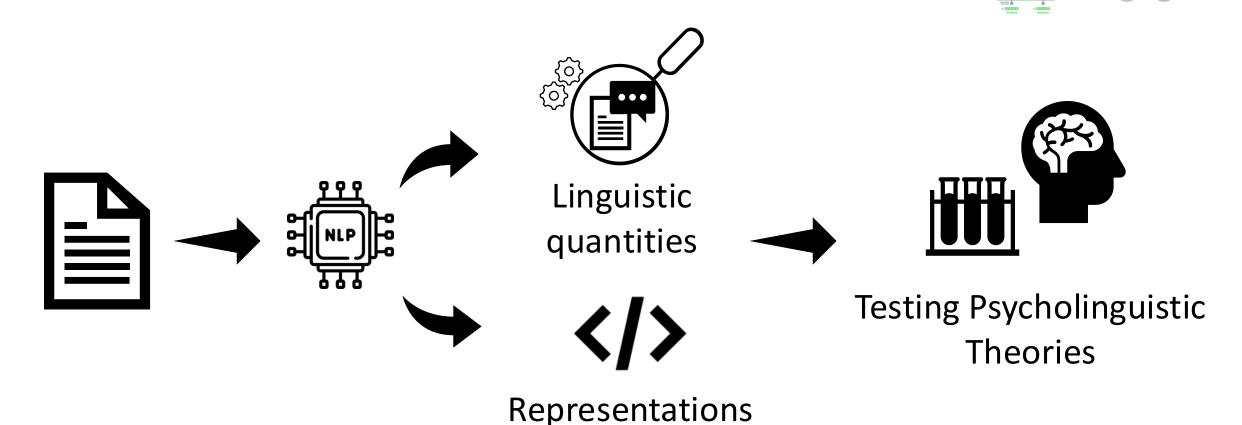




Testing LLM alignment with human language processing

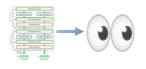
NLP for modeling eye movements in reading





ACL2025 - Eye Tracking and NLP Tutorial

Mechanisms

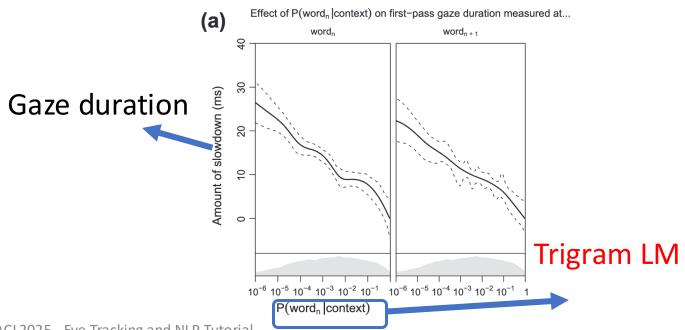


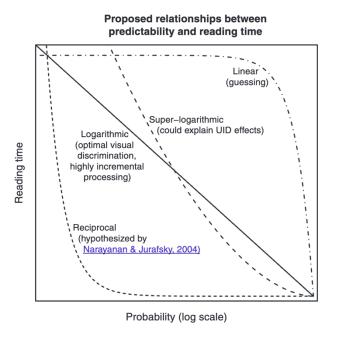
- NLP for broad coverage stimulus annotations
 - Surprisal, entropy
 - Syntactic structure
 - Semantic relations
 - Word embeddings
- Annotations (or derived quantities) are central for testing psycholinguistic theories of language processing
 - Surprisal theory <u>Hale (2001)</u>, <u>Levy (2008)</u>
 - Dependency locality theory (DLT) Gibson (1998), Gibson (2000)
 - Uniform information density (UID) <u>Levy & Jaeger (2007)</u>
 - Cue-based retrieval (ACT-R) <u>Lewis & Vasishth (2005)</u>, <u>Engelmann et al.</u>
 (2019)



Smith and Levy (2013) testing predictions of Surprisal Theory

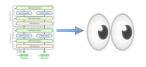
- Reading times (Dundee) as proxy for processing difficulty
- LM based surprisal as proxy for word predictability



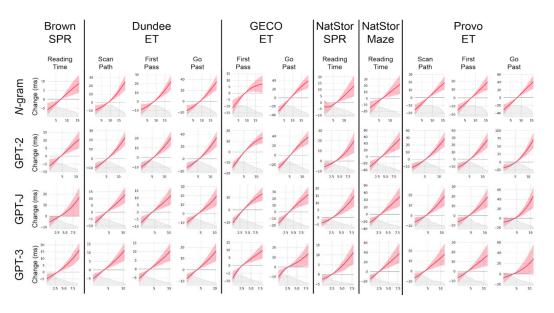


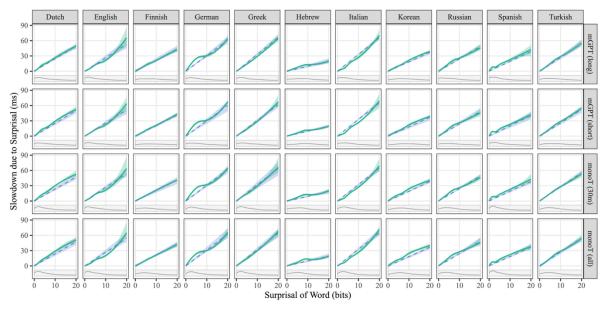
ACL2025 - Eye Tracking and NLP Tutorial

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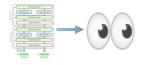
Linearity holds for different LLMs Shain et al. (2023) and across languages Wilcox et al (2023)





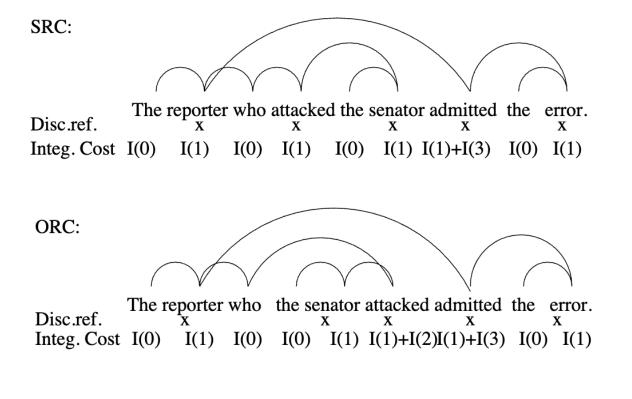
Shain et al. (2023)

MECO data, Wilcox et al (2023)



Testing predictions of DLT and Surprisal Theory <u>Demberg and Keller (2008)</u>

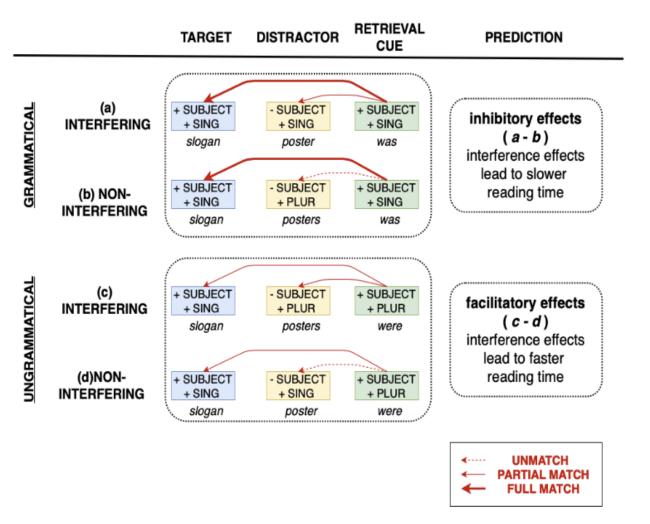
- Reading times (Dundee) as proxy for processing difficulty
- LM based surprisal as proxy for word predictability
- Dependency parsing for obtaining sentence structure





Controlled experiments with GPT2 surprisal for testing surprisal and interference based explanations to agreement phenomena

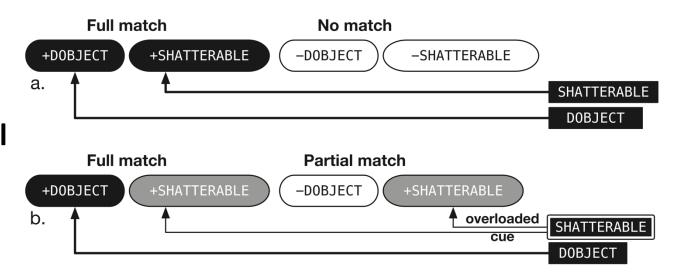
Ryu and Lewis (2021)



a) ... the plate that the butler with the tie accidentally shattered ...
b) ... the plate that the butler with the cup accidentally shattered ...

Cue-based Retrieval (ACT-R) assumes a content-addressable memory.

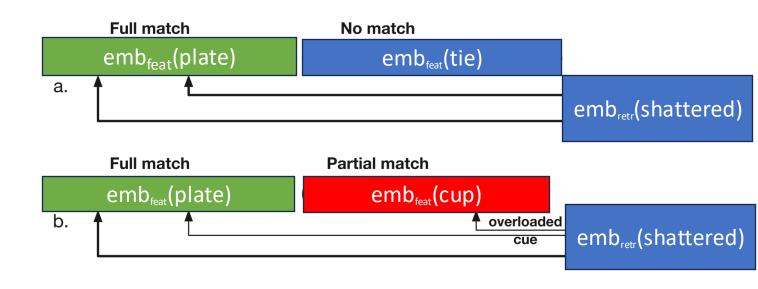
Dependency formation: Retrieval cues serve to access relevant chunks (e.g., words) from memory.



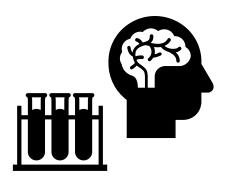
a) ... the plate that the butler with the tie accidentally shattered ...
b) ... the plate that the butler with the cup accidentally shattered ...

Replacing hand-crafted feature vectors with word embeddings as cognitive representations for lexical items in memory.

Smith and Vasishth (2020)



Uses of NLP in Modeling Eye Movements and Human Language Processing → →

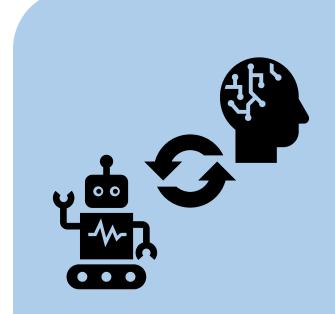


Testing Psycholinguistic
Theories



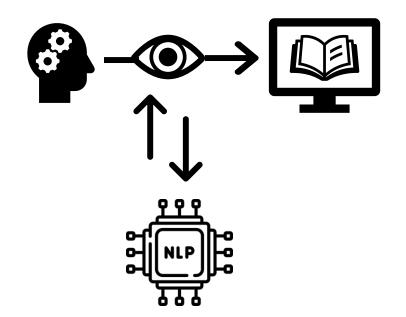


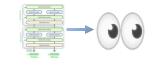
Representations Linguistic quantities



Testing LLM alignment with human language processing

NLP for modeling eye movements in reading





- Are LLMs good models of human linguistic processing?
 If not, how can we make them relevant?
- Big and open area where eye tracking data could play a larger role
- Current directions:
 - Testing alignment of LLMs with reading data
 - Improving alignment with more cognitively plausible architectures

Predictive power of LLM-extracted **surprisal** (or other metrics) for human reading times (RTs)

Step 1:

Fit two regression models predicting reading times, with and without surprisal as predictor

Step 2:

Compute Log-Likelihood (LL) of each model

Step 3:

Predictive Power (PP) of surprisal is the ΔLL of the two models

$$\mathcal{M}_{baseline}: RT \sim baseline_variables \longrightarrow LL(\mathcal{M}_{baseline})$$
 \longrightarrow
 $\mathcal{M}_{surprisal}: RT \sim baseline_variables \longrightarrow LL(\mathcal{M}_{surprisal})$
 $\oplus surprisal$

PP(surprisal)

 $\coloneqq \Delta LL(\mathcal{M}_{surprisal}, \mathcal{M}_{baseline})$

 $\coloneqq LL\big(\mathcal{M}_{surprisal}\big) - LL(\mathcal{M}_{baseline})$



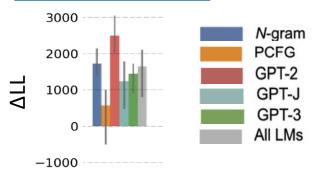
Older Models

Better LM --> surprisal predicts RTs better

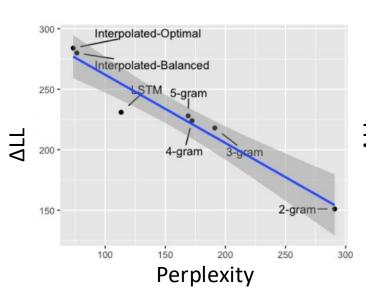
LLMs

Better LM --> surprisal predicts RTs worse

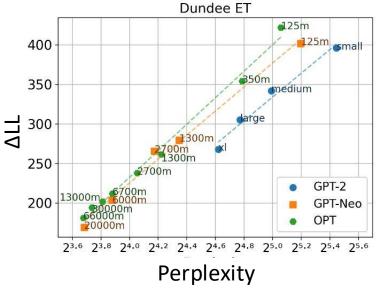
Shain et al. (2023)



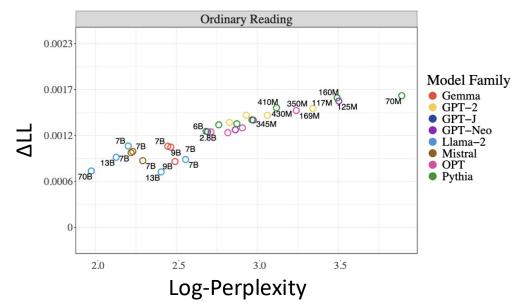
Goodkind and Bicknell (2018)



Oh and Schuler (2023)

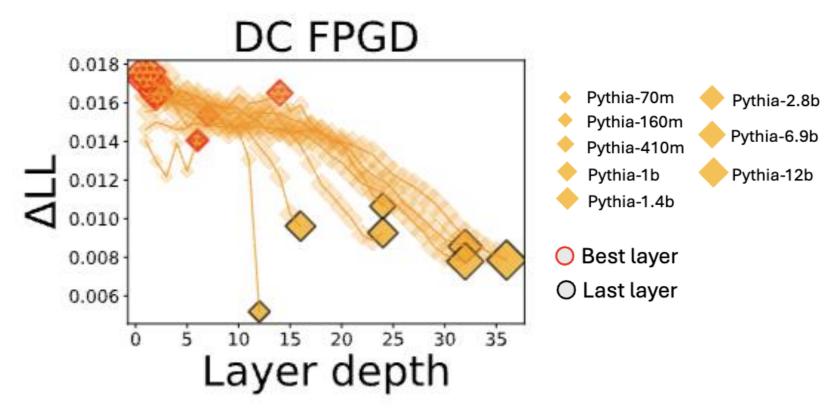


Gruteke Klein et al. (2024)





<u>Kuribayashi et al. (2025)</u> opposite conclusion for intermediate layers



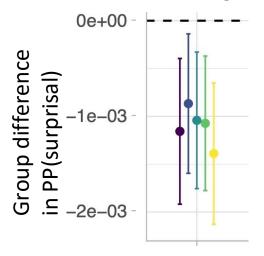


Haller et al. (2024) compare the PP on first-pass reading time of LM surprisal and LM entropy for different cognitive groups of readers.

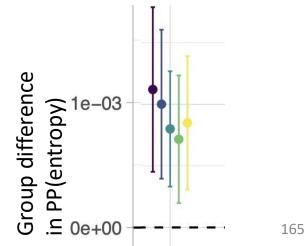
- PP of surprisal is higher for readers with lower verbal intelligence.
- PP of entropy is higher for readers with higher working memory capacity.



Verbal Intelligence



Working Memory Capacity





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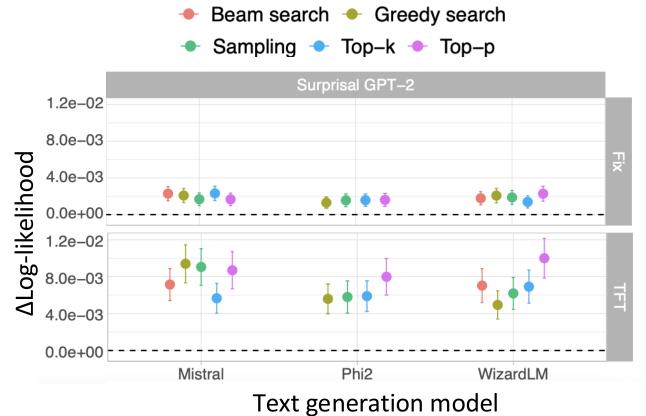
LLM Alignment with Human Reading

Bolliger et al. (2024) Predictive power for reading times varies between texts generated by different

- models
- decoding strategies

And across different

reading measures



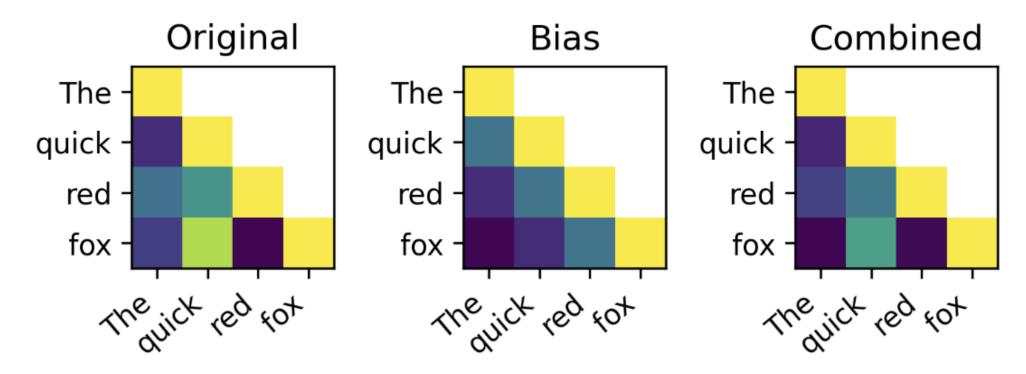


- Rich literature that focuses on
 - Models trained on human scale data
 - Controlled evaluations of targeted linguistic phenomena
- LLMs as a lower bound of what can be learned from the input without postulating innate linguistic knowledge ("poverty of the stimulus")
- Current online evals are primarily on SPR and Maze. E.g. van Schijndel & Linzen (2018), Wilcox et al. (2021)
- Open area for future work with eye tracking data!

Improving Alignment: Adding Cognitive Constraints



 Recency bias for transformer attention <u>de Varda and Marelli</u> (2024), <u>Clark et al (2025)</u>



Discussion: Alignment



- Most studies focus on a single reading measure (e.g., Gaze Duration, Total Fixation Duration)
- No clear advantage of eye tracking over other methods
- Similar evaluations are done with cheaper methods that can be (and are) deployed on the web at scale (SPR, Maze)
- Possible directions forward
 - More fine-grained analyses of reading measures to reveal dynamics over time, scanpath prediction
 - Populations with different linguistic knowledge (e.g. L1 vs L2)

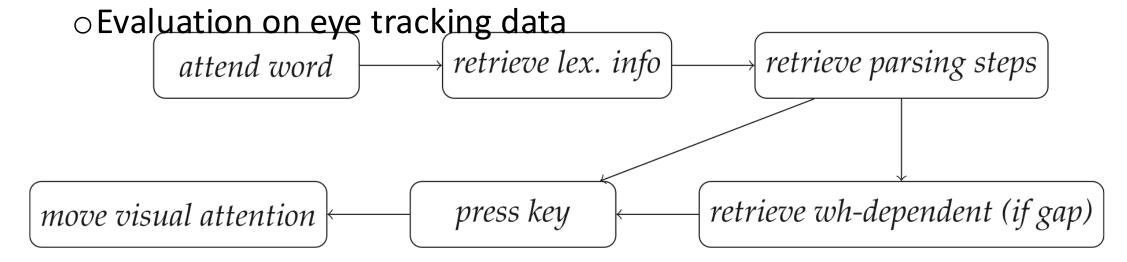


Addendum: Parsers as Cognitive Models

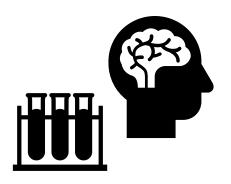
Long Tradition in computational linguistics (e.g., <u>Jurafsky</u>, <u>1996</u>)

Example: Dotlačil (2021)

Transition based parser combined with cue-based retrieval (ACT-R)



Uses of NLP in Modeling Eye Movements and Human Language Processing → •

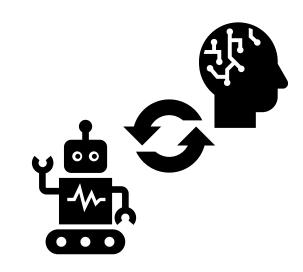


Testing Psycholinguistic Theories

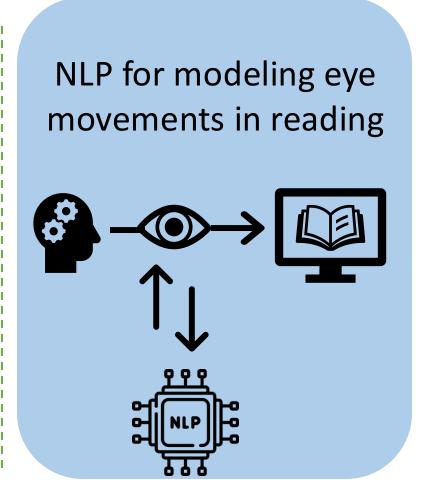


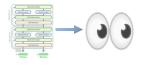


Representations Mechanisms Linguistic quantities

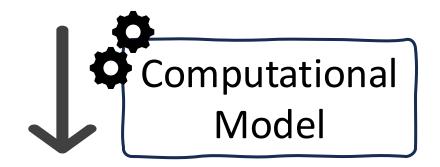


Testing LLM alignment with human language processing

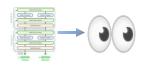


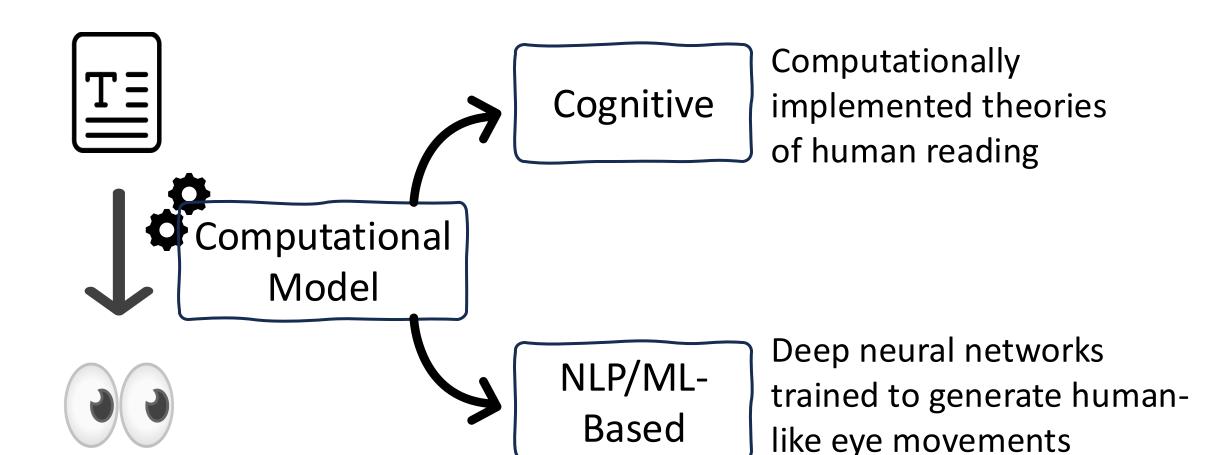


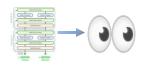
CNN wants to change its viewers' habits.











Cognitive

Computationally implemented theories of human reading

Parameters

<u>Interpretable?</u>

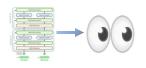
Few

Most parameters have direct cognitive interpretation

NLP/ML-Based Deep neural networks trained to generate humanlike eye movements

Many

Typically not interpretable



Cognitive

Computationally implemented theories of human reading

NLP/ML-Based Deep neural networks trained to generate humanlike eye movements

Examples

E-Z Reader <u>Reichle et al. (1998, 2009)</u>

SWIFT Engbert et al. (2005)

SEAM Rabe et al. (2024)

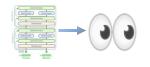
OB1-Reader Snell et al. (2018)

NEAT Hahn and Keller (2023)

Eyettention Deng, Reich et al. (2023)

ScanDL Bolliger et al. (2023, 2025)

SP-EyeGan Prasse, Reich et al. (2023)



Examples

Model

Cognitive

E-Z Reader Reichle et al. (1998, 2009) SWIFT Engbert et al. (2005) SEAM Rabe et al. (2024) OB1-Reader Snell et al. (2018) Serial attention
Parallel attention
Activation-coupled

Bayesian inference

NLP/ML-Based NEAT <u>Hahn and Keller (2023)</u>
Eyettention <u>Deng, Reich et al. (2023)</u>
ScanDL <u>Bolliger et al. (2023, 2025)</u>
SP-EyeGan <u>Prasse, Reich et al. (2023)</u>

RNN
Cross-attention
Diffusion
GAN



Examples

<u>Output</u>

Cognitive

E-Z Reader Reichle et al. (1998, 2009) SWIFT Engbert et al. (2005) SEAM Rabe et al. (2024) OB1-Reader Snell et al. (2018) Fixation

Fixation, transition probability Fixation, transition probability Fixation, transition probability

NLP/ML-Based NEAT <u>Hahn and Keller (2023)</u>
Eyettention <u>Deng, Reich et al. (2023)</u>
ScanDL <u>Bolliger et al. (2023, 2025)</u>
SP-EyeGan <u>Prasse, Reich et al. (2023)</u>

Fixation

Transition probability

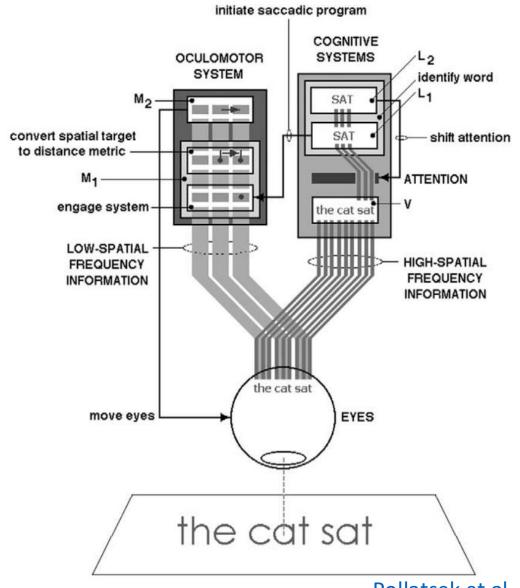
Fixation

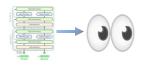
Raw samples

NLP for Modeling Eye Movements in

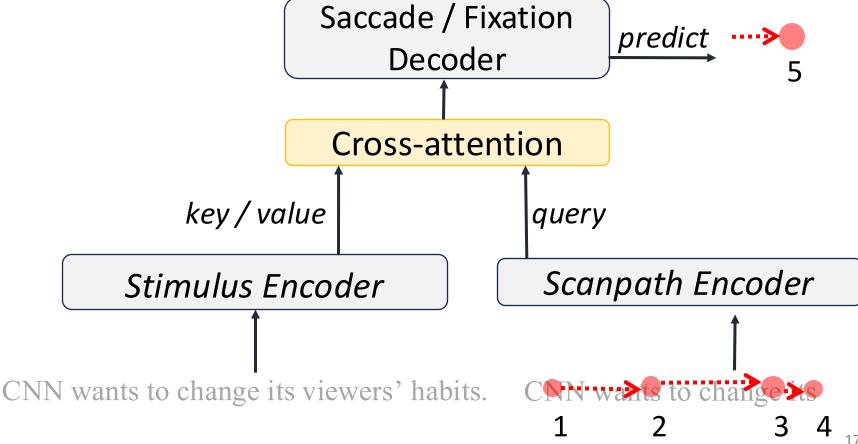
Reading

• E-Z Reader





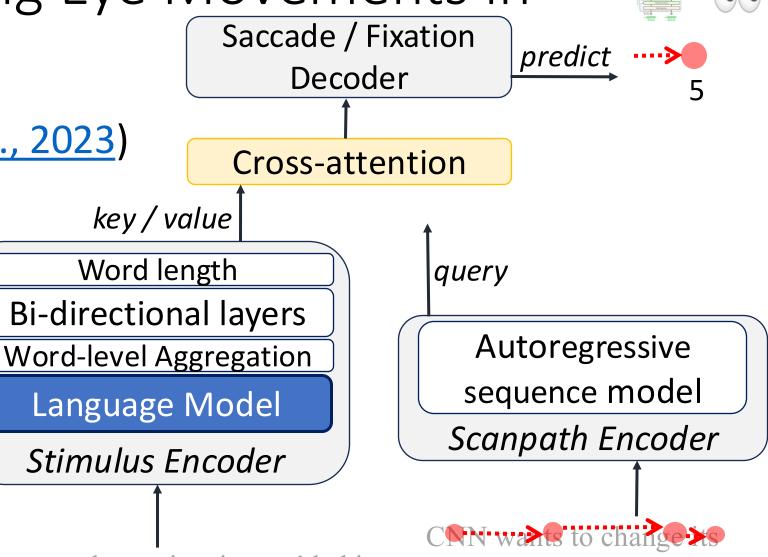
Eyettention (Deng et al., 2023)



NLP for Modeling Eye Movements in

Reading

Eyettention (Deng et al., 2023)



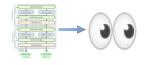
180

Extensions:

Reader- and populationspecific models

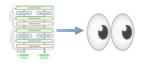
CNN wants to change its viewers' habits.

NLP for Modeling Eye Movements in Reading



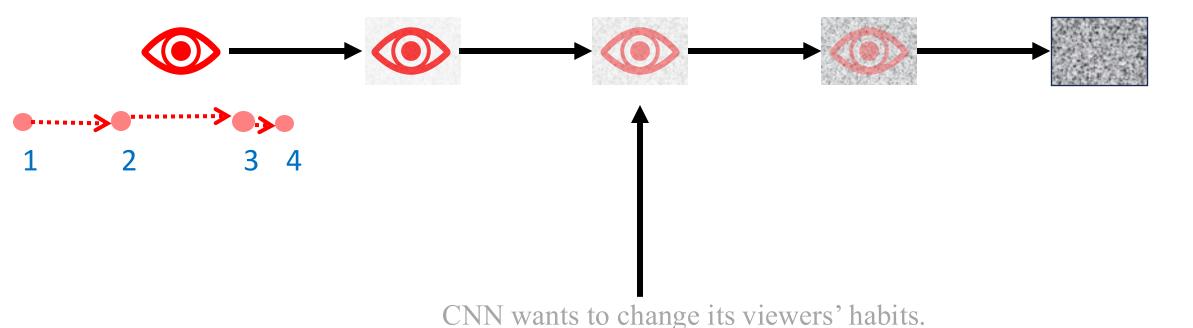
ScanDL, ScanDL 2.0 (<u>Bolliger et al., 2023</u>, 2025)

NLP for Modeling Eye Movements in Reading

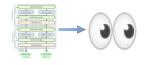


ScanDL, ScanDL 2.0 (<u>Bolliger et al., 2023</u>, <u>2025</u>)

• How? Discrete input into continuous space

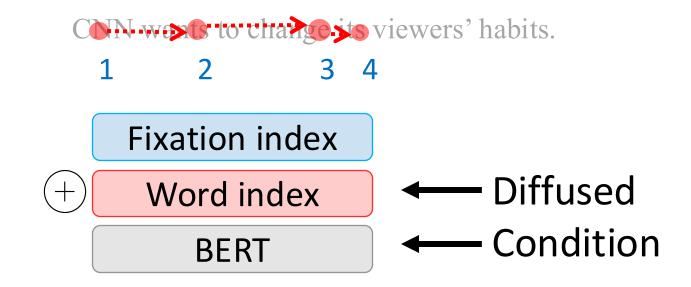


NLP for Modeling Eye Movements in Reading

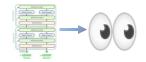


ScanDL, ScanDL 2.0 (<u>Bolliger et al., 2023</u>, <u>2025</u>)

How? Discrete input into continuous space

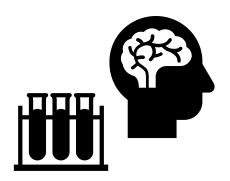


Discussion: NLP for Modeling Eye Movements in Reading



- NLP/ML based models outperform cognitive models
 - But metrics for scanpath generation nontrivial!
- Making NLP/ML models more cognitively plausible and interpretable

Uses of NLP in Modeling Eye Movements and Human Language Processing → •••

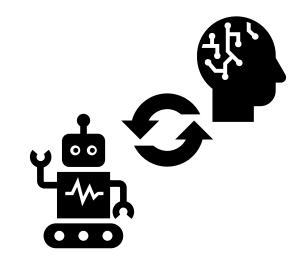


Testing Psycholinguistic
Theories



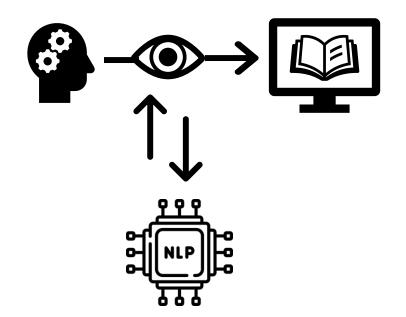


Representations Linguistic quantities



Testing LLM alignment with human language processing

NLP for modeling eye movements in reading



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Tutorial Outline

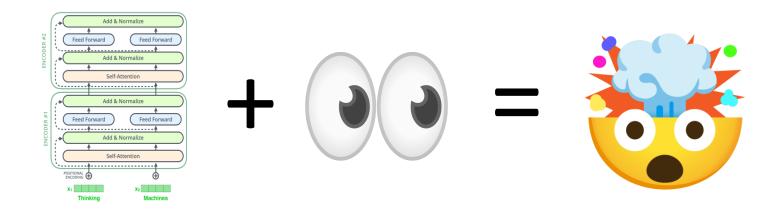
- 1. Introduction to eye tracking
- 2. Uses of eye tracking in NLP
- - → 3. NLP for eye movement and cognitive modeling



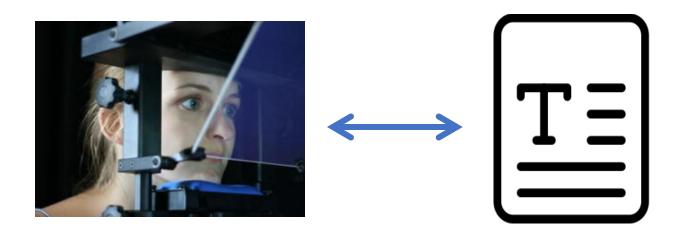
- + • 4. New human centered applications
- - + = ? 5. Outlook and future directions

New Human Centered

Applications



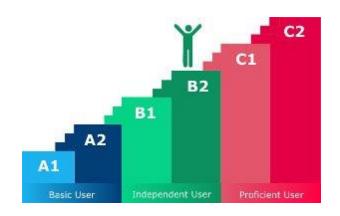
- Rethinking the future of NLP
- Enabling a wide range of new human centered tasks
- Real-time predictions about reader and their interactions with the text



Language assessment

Reading impairment screening and monitoring

Assessment of Reading Comprehension



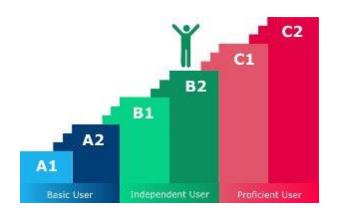




Language assessment

Reading impairment screening and monitoring

Assessment of Reading Comprehension







Language Proficiency Assessment 📶



- Over 2 billion English learners worldwide
- Grammar & vocabulary quizzes
- Reading comprehension
- Listening comprehension
- Essay writing







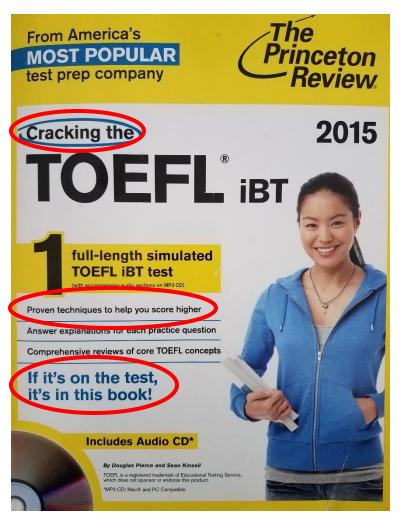






Language Proficiency Assessment 41





Language Proficiency Assessment 41

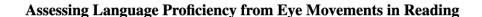


- Expensive
- Require test specific preparation
- Cheating
- Manually crafted ad-hoc tasks
- No ability to track language processing online

Language Proficiency Assessment 41



Eye movements are informative of L2 language proficiency



Yevgeni Berzak MIT BCS berzak@mit.edu

Boris Katz MIT CSAIL boris@mit.edu

Roger Levy MIT BCS rplevv@mit.edu

Berzak et al. (2018)



Demareva et al. (2022)

Inferring Search User Language Proficiency from Eye Gaze Data

Ben Steichen California State Polytechnic University, Pomona bsteichen@cpp.edu

Wilsen Kosasih California State Polytechnic University, Pomona wkosasih@cpp.edu

Christian Becerra California State Polytechnic University, Pomona ceb@cpp.edu

Steichen et al. (2024)

Predicting First-Language and Second-Language Proficiency Using Eye Fixation Data and Demographic Information: Assumptions, Data Representations, and Methods

Publisher: IEEE | Cite This ß PDF

Soroosh Shalileh (10); Matvey Kairov (10); Ranga Baminiwatte (10); Olga Parshina; Olga Dragoy All Authors

Shalileh et al. (2024)

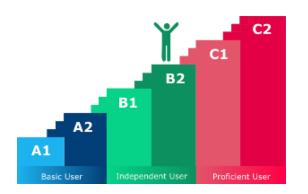
CNN wants to change its viewers' habits.



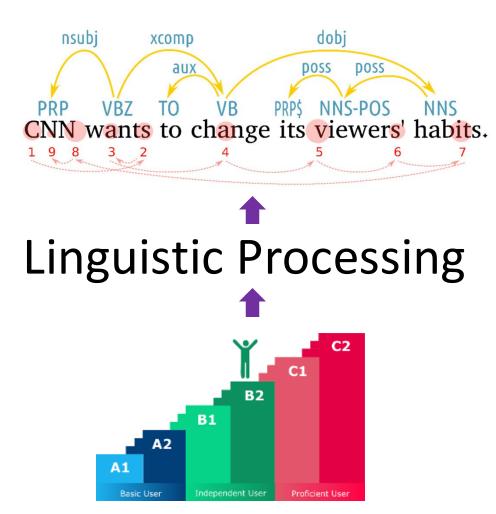


Ordinary Reading

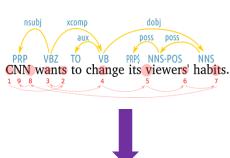




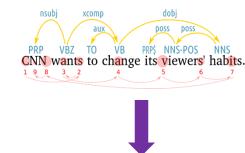


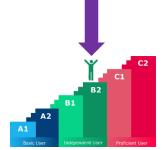


- Expensive
- Require test specific preparation
- Cheating
- Manually crafted ad-hoc tasks
- Ability to track language processing online







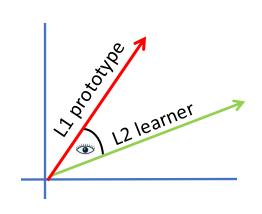


ESL proficiency \approx Similarity of reading patterns to native speakers of English

EyeScore

Berzak et al. (2018)

- Extract eye movement features for each participant
- Compute English L1 "prototype"
- **EyeScore** = cosine similarity to L1 prototype





But

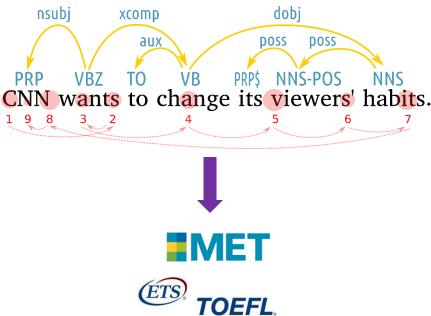




Predicting Scores on Standardized Tests

Berzak et al. (2018)

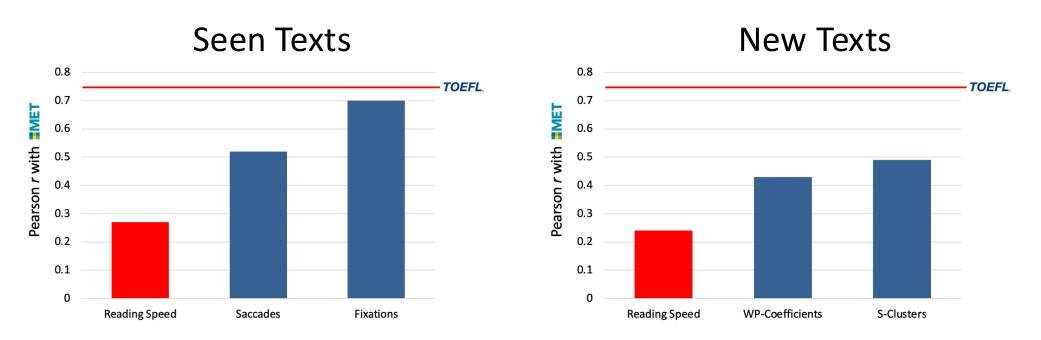
 Eye movement in reading can be used to predict scores of specific external proficiency tests



Predicting Scores on Standardized Tests

Berzak et al. (2018)

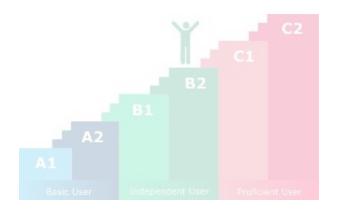
 Eye movement in reading can be used to predict scores of specific external proficiency tests



Language assessment

Reading impairment Screening and monitoring

Assessment of Reading Comprehension







Reading Impairments Developmental Dyslexia



"... impairment in reading [which] is characterised by significant and persistent difficulties in learning academic skills related to reading, ... [and] is not due to a disorder of intellectual development, sensory impairment (vision or hearing)," (WHO, 2025)

- Affects approx. 7-10% of the population (<u>Catts et al., 2005</u>, <u>Peterson & Pennington, 2012</u>; <u>Moll et al., 2014</u>)
- Early detection and intervention is key (<u>Snowling</u>, <u>2012</u>; <u>Torgesen</u>, <u>2002</u>)
- Existing testing batteries must be administered by a trained specialist.





```
Πηγαίνοντας με το λεωφορείο να επίσκεφτώ την
αδερφή μου που είχε κάνει μια εγχείρηση πέρασα
μπροτιά το τετράνωνο που βρισκόταν το
εργουτάσιο στο οποίο δούλευε η μητέρα μόν. Το
εργοσιάσιο κα εξέξεσαζε πλυντήρια Είναι πολύ
χρήσιμο να υπάρχει ένα ελυντήριο στο Εποθει.
```

```
Πηναίνουτα τη ε το λεωφορείο να
    τάσιο, στο γρίο δούλει
         κατας στα πλιτιτήοι γιο Τ
```

Reading Impairments Developmental Dyslexia



Detecting Readers with Dyslexia Using Machine Learning with Eye Tracking Measures

Luz Rello
Human-Computer Interaction Institute
School of Computer Science
Carnegie Mellon University
luzrello@cs.cmu.edu

Miguel Ballesteros Natural Language Processing Group Universitat Pompeu Fabra miguel.ballesteros@upf.edu

Rello and Ballesteros (2014)

Screening for Dyslexia Using Eye Tracking during Reading

Mattias Nilsson Benfatto 🖪, Gustaf Öqvist Seimyr, Jan Ygge, Tony Pansell, Agneta Rydberg, Christer Jacobson

Published: December 9, 2016 • https://doi.org/10.1371/journal.pone.0165508

Nilsson Benfatto et al. (2016)

Predictive Model for Dyslexia from Fixations and Saccadic Eye Movement Events

A Jothi Prabha 🖰 🖾 , R Bhargavi

Jothi Prabha and Bhargava (2020)

Eye-tracking based classification of Mandarin Chinese readers with and without dyslexia using neural sequence models

Patrick Haller¹, Andreas Säuberli¹, Sarah E. Kiener¹ Jinger Pan³, Ming Yan⁴, Lena A. Jäger^{1,2}

Haller et al. (2022)

Dyslexia Prediction from Natural Reading of Danish Texts

Marina Björnsdóttir, Nora Hollenstein, Maria Barrett

Björnsdóttir et al. (2023)

Identifying dyslexia in school pupils from eye movement and demographic data using artificial intelligence

Soroosh Shalileh 61*, Dmitry Ignatov2, Anastasiya Lopukhina3, Olga Dragoy1,4

Shalileh et al. (2023)

Automatic detection of dyslexia based on eye movements during reading in Russian

Anna Laurinavichyute

Anastasiya Lopukhina

David R. Reich

Laurinavichyute et al. (2025)





Björnsdóttir et al. (2023)

 58 L1, L2 or adults with dyslexia reading paragraphs

Shalileh et al. (2023)

- 300+ children with or without dyslexia
- Two different assessments

Reading Impairments Developmental Dyslexia

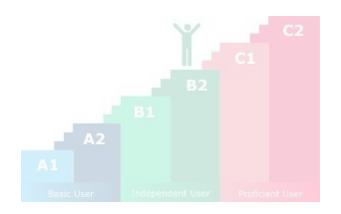
- Scale with few eye trackers
 - Cheaper alternatives possible
- Beyond screening



Language

Reading impairment diagnostics and monitoring

Assessment of Reading Comprehension



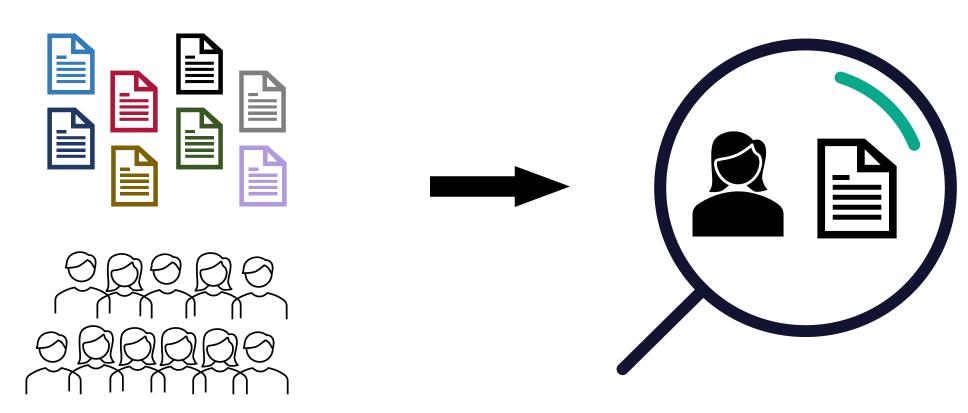






Reading Comprehension

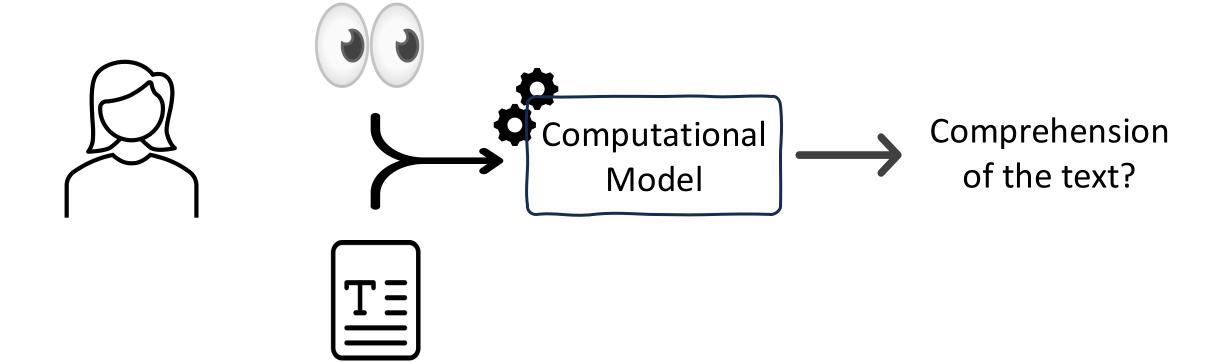
A Holy Grail in psycholinguistics



ACL2025 - Eye Tracking and NLP Tutorial Just and Carpenter (1980); Among others



Reading Comprehension





Reading Comprehension

Towards Predicting Reading Comprehension From Gaze Behavior

Seoyoung Ahn Stony Brook University Stony Brook, New York

Aruna Balasubramanian Stony Brook University Stony Brook, New York Conor Kelton Stony Brook University Stony Brook, New York

Gregory Zelinsky Stony Brook University Stony Brook, New York

Fine-Grained Prediction of Reading Comprehension from Eye Movements

Omer Shubi¹, Yoav Meiri¹, Cfir Avraham Hadar¹, Yevgeni Berzak^{1,2}

Shubi et al. (2024)

Ahn et al. (2020)

Above chance performance but highly challenging task!



Reich et al. (2022)



Zhang et al. (2025)

Human Centered NLP with Eye Movements Open Frontiers



Information accessibility

Education and digital learning



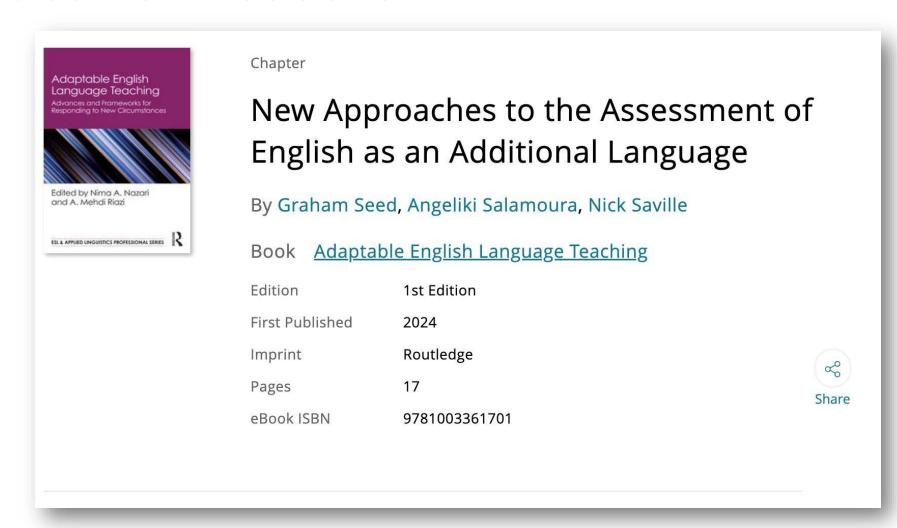
Human-machine communication

Interactive online systems

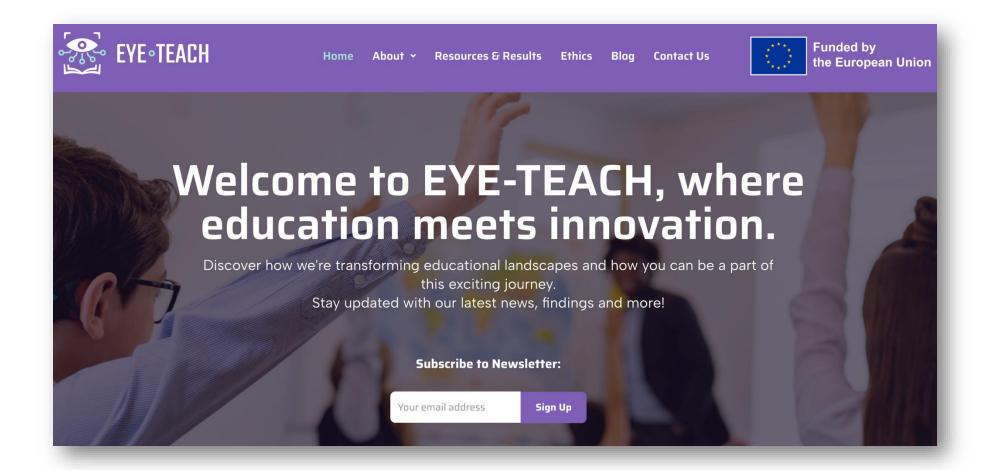


This is happening now!

Eye tracking is starting to gain traction in education research!

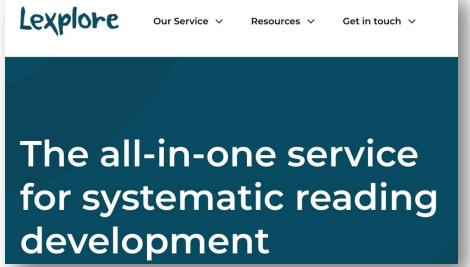


Eye tracking is starting to gain traction in education research!

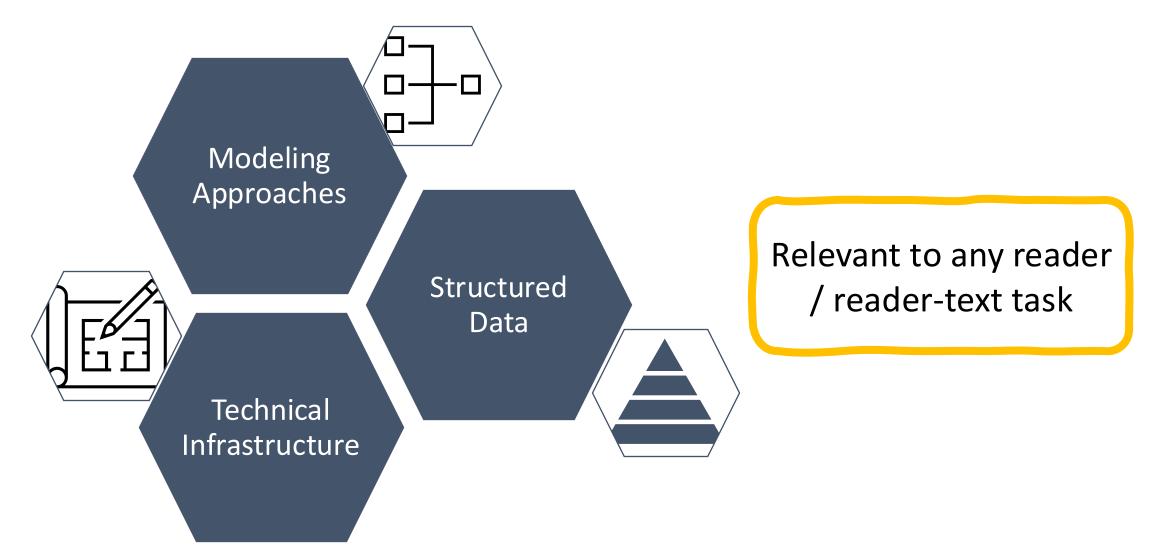


Eye tracking is starting to gain traction in education applications!





Human Centered NLP with Eye Movements



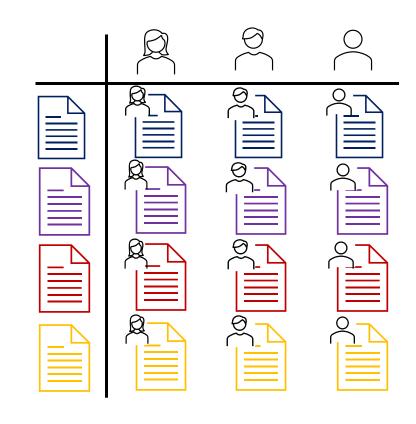
Data is **not** iid — it is **structured**

Implications for:

- Statistical modeling
- Training and Evaluations
- Applications

t-test \rightarrow mixed effects models

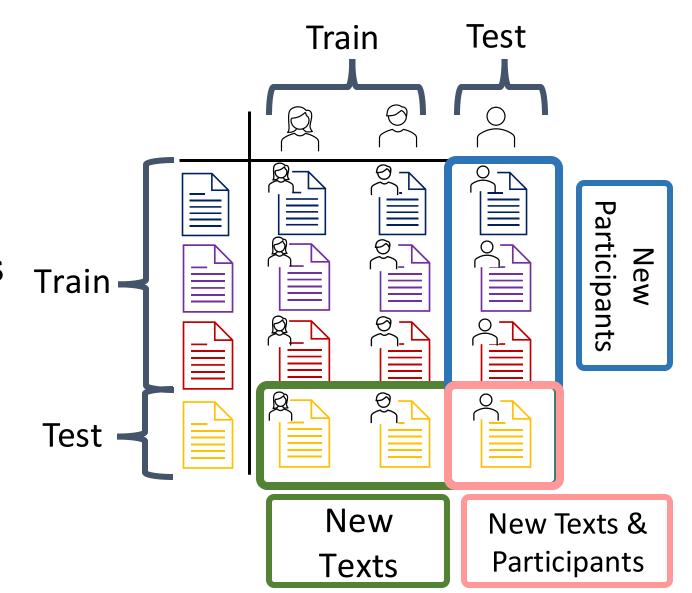
Shravan Vasishth's Intro Stats course



Data is **not** iid — it is **structured**

Implications for:

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- Applications

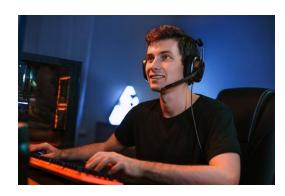


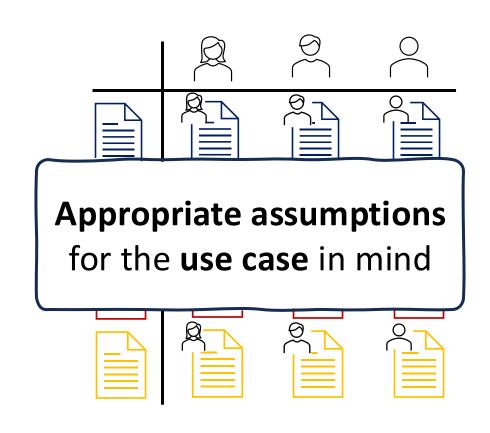
Data is **not** iid — it has **structure**

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Human Centered NLP with Eye Movements Open Frontiers



Information accessibility

Education and digital learning



on and arning

Human-machine communication

Interactive online systems



Tutorial Outline

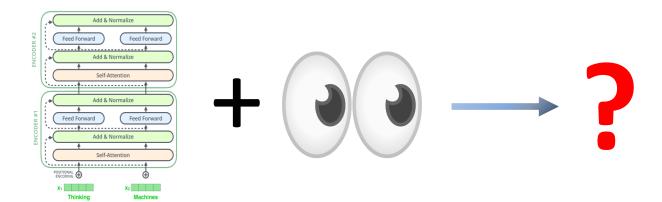
- 1. Introduction to eye tracking
- 2. Uses of eye tracking in NLP
- - → 3. NLP for eye movement and cognitive modeling



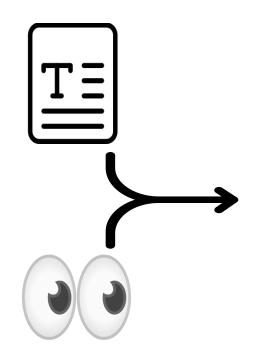
- + • 4. New human centered applications
- - + = ? 5. Outlook and future directions

Directions for Future

Research



The Future: Text + Gaze Multimodal Models



Highly open and challenging problem

Eye movements representation

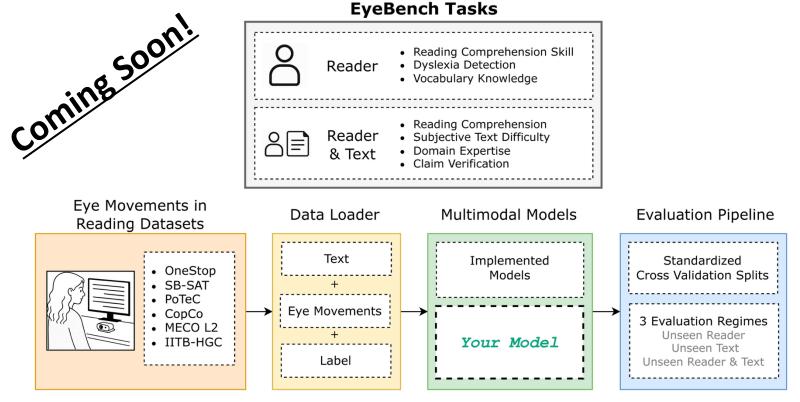
Alignment with text

Low resource settings

First-principles cognitive modeling

How to get involved? EyeBench!

EyeBench: Predictive Modeling from Eye Movements in Reading

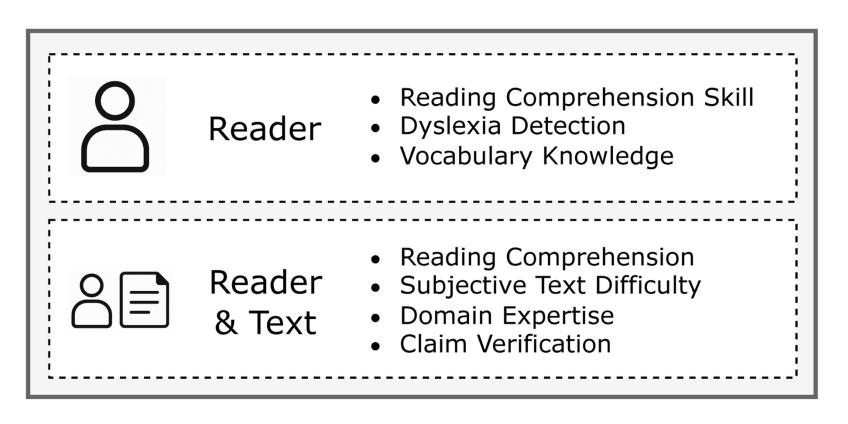


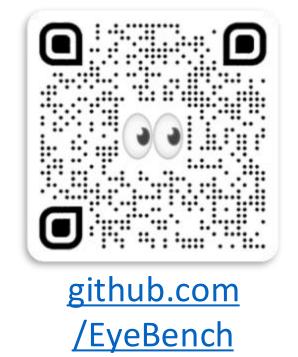


Shubi, Reich et al. (in prep)

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EyeBench: Predictive Modeling from Eye Movements in Reading

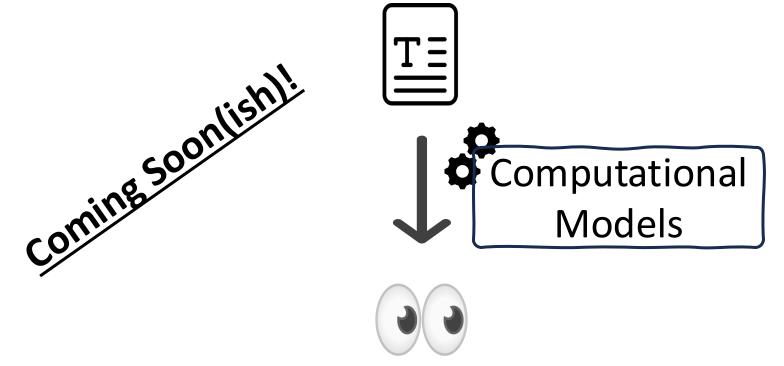




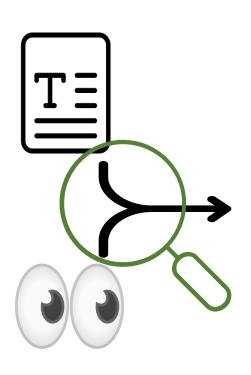
Shubi, Reich et al. (in prep)

Next Up – EyeGenBench!

EyeGenBench: An Evaluation Framework for Models of Eye Movements in Reading



The Future: Interpretability





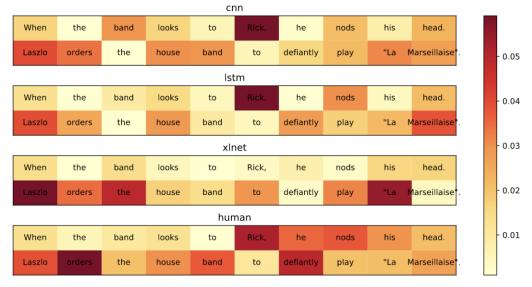
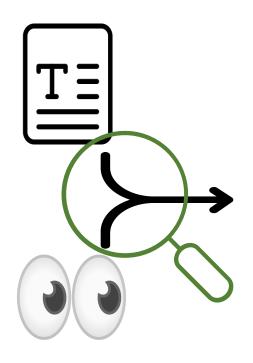


Figure 1: Example attention distributions of neural models (cnn, lstm, xlnet) and humans. Sood et al. (2020)

The Future: Interpretability



Explain and steer models

Identify reading strategies?

Do the models encode reader groups?

What properties are the models sensitive to?

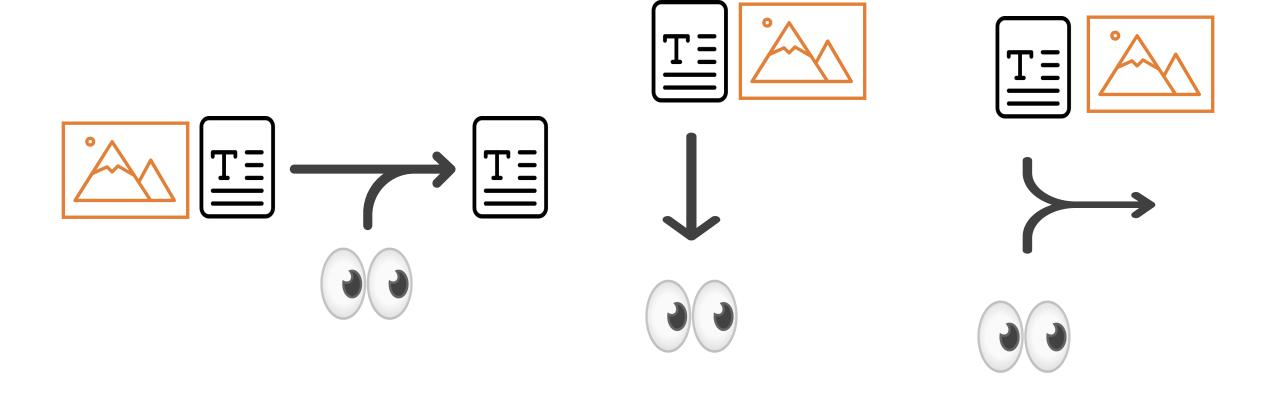
Simulate diverse readers and experiments?

The Future: Cognitive Alignment



Using eye movements to make language models more human-like

- Increasing the relevance of LMs as models of human linguistic processing
- Alignment with different target groups
- Alignment with other cognitive signals (e.g. the brain)
- Practical gains for NLP (e.g. resource efficiency)



Building on foundational work on visual saliency

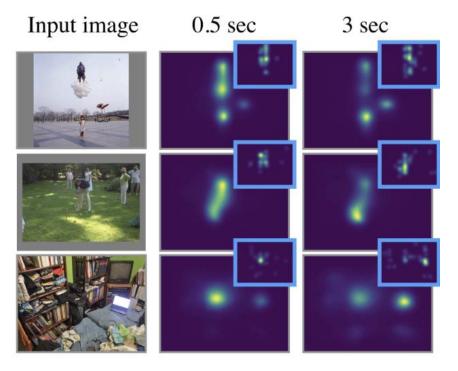
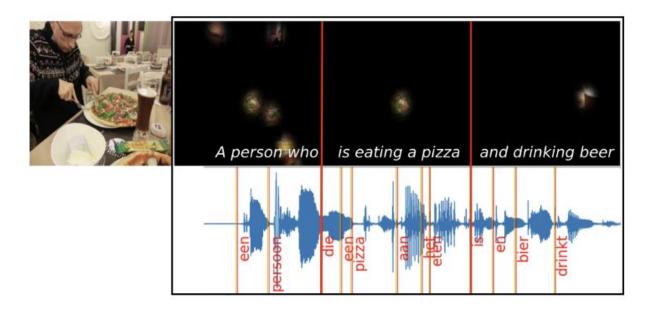


Image from Fosco et al. (2020)

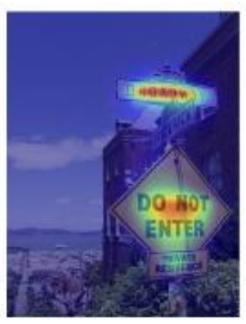
Image captioning

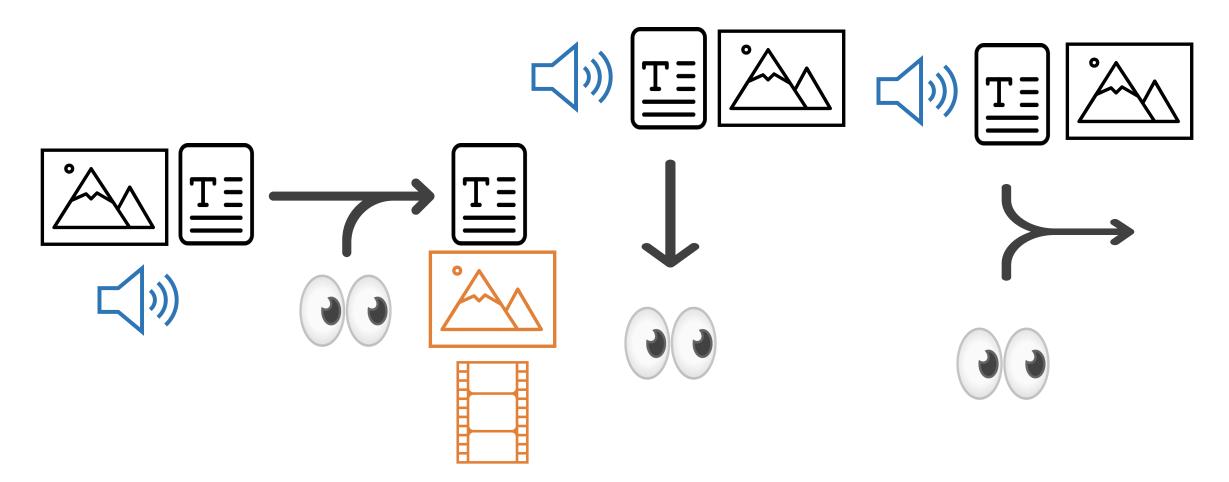
Takmaz et al. (2020)

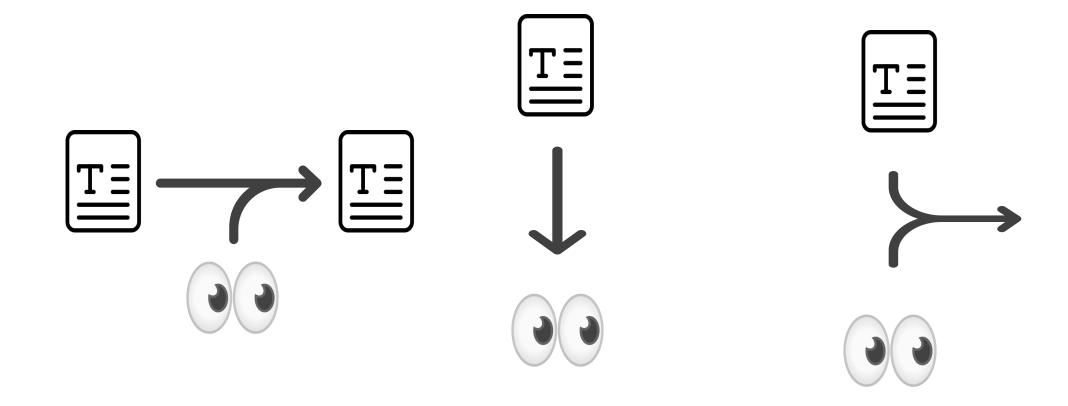


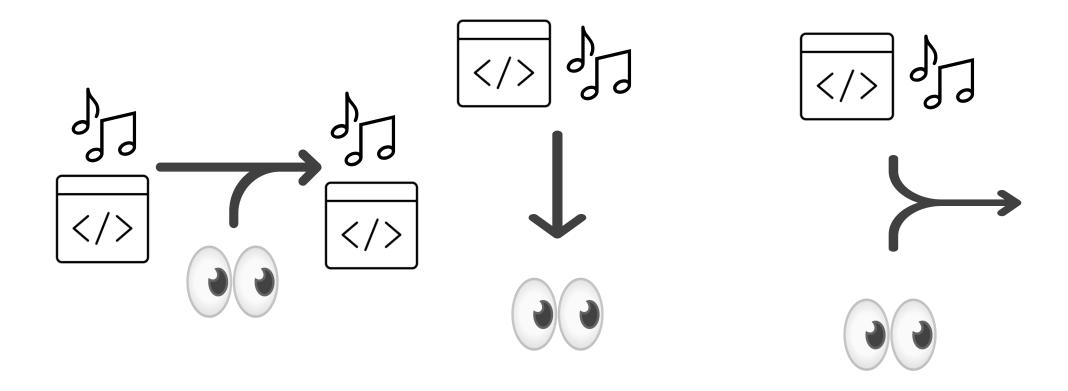
Visual question answering Sood et al. (2023)











The Future: Bias, Robustness and Fairness

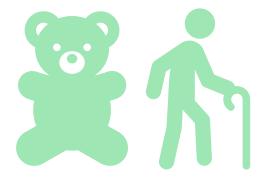
Evaluating and ensuring model performance across groups







Educational Background



Age & Gender



Native Language & Language Skills

Human Centered NLP with Eye Movements Open Frontiers



Information accessibility

Education and digital learning



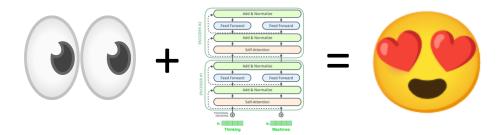


Human-machine communication

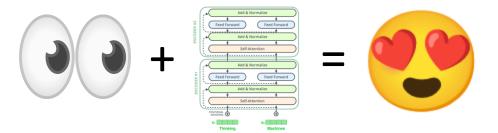
Interactive online systems



Integrate eye tracking data into YOUR research!



What Now?

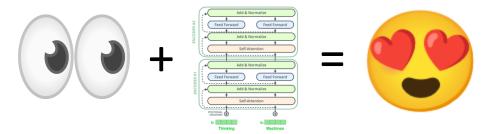


Slides and links to additional resources will be available on the

tutorial website



What Now?



Join a new **Discord channel** on Eye Tracking and NLP



We thank Cui Ding, Jakub Dotlačil, Ece Takmaz and Shachar Frenkel for their support in preparing this tutorial!









Department of Computational Linguistics



Eye Tracking and NLP Papers at ACL 2025

Session Details	Title		
Monday, July 28 – 14:00-15:30 Room 1.61 – Session 3: IP-Orals	Déjà Vu? Decoding Repeated Reading from Eye Movements, Meiri et al.	+00 =	
Monday, July 28 – 18:00-19:30 Hall 4/5 – Session 5: IP-Posters	Beyond the Average Reader: the Reader Embedding Approach, Scozzaro et al.		
Tuesday, July 29 – 10:30-12:00 Hall 4/5 – Session 7: IP-Posters	CogSteer: Cognition-Inspired Selective Layer Intervention for Efficiently Steering Large Language Models, Wang et al.		
	Exploring the Effect of Nominal Compound Structure in Scientific Texts on Reading Times of Experts and Novices, Landwehr et al.		
	Automatic detection of dyslexia based on eye movements during reading in Russian, Laurinavichyute et al.	+00=	
Wednesday, July 30 – 11:00-12:30 Hall 4/5 – Session 12: IP-Posters	Decoding Reading Goals from Eye Movements, Shubi and Hadar et al.	+00 =	
	From Human Reading to NLM Understanding: Evaluating the Role of Eye-Tracking Data in Encoder-Based Models, Dini et al.		
	ScanEZ: Integrating Cognitive Models with Self-Supervised Learning for Spatiotemporal Scanpath Prediction, Sood et al.	• • •	
· Eye Tracking and NLP Tutorial	Fine-Grained Spatio-Temporal Modeling of Reading Behavior, Re et al.	-	

Ethical Considerations

- **Informed Consent** Collect data only with IRB approval and written participant consent.
- **Privacy Protection** Keep data anonymized; avoid storing information enabling user identification.
- Responsible Use Only with explicit consent.
- Bias Awareness Validate models for fairness, especially for L2 learners, cognitive/visual impairments.
- Transparency Clearly communicate risks, limitations, and intended uses of predictive systems.

