Data in Cognitive Science

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Cognitive Science

The aim of cognitive science is to figure out how the mind works.

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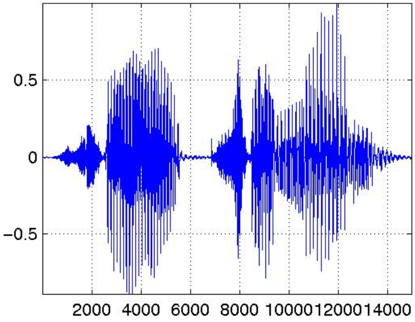

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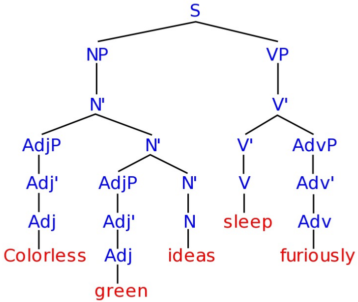

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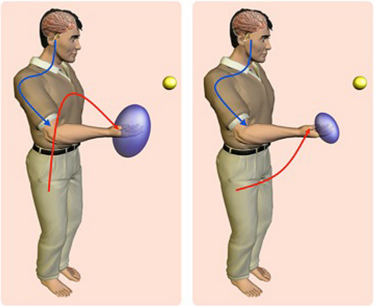

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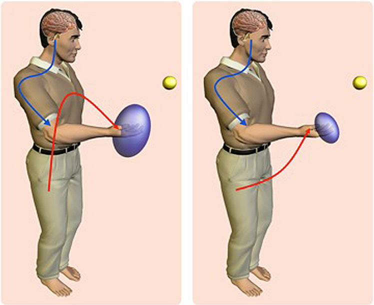
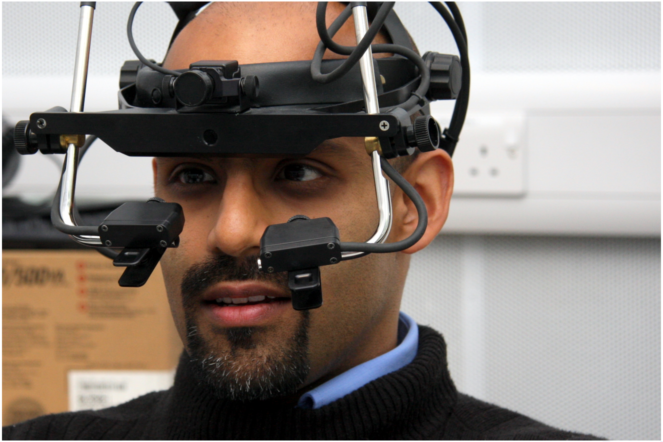


Here, we will focus on vision and language.

Eye-tracking

By recording their eye-movements, we can study how humans process linguistic or visual information.



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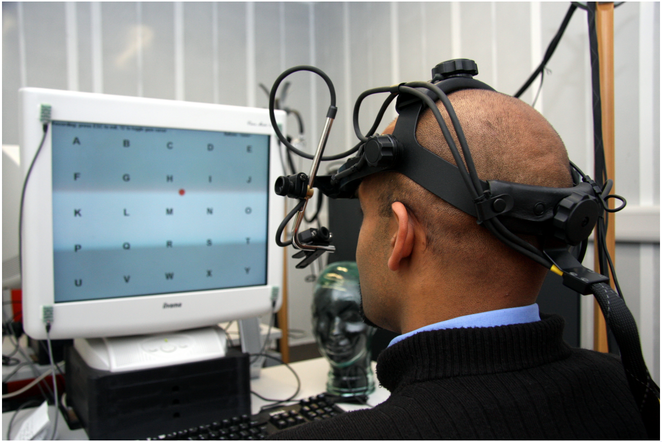

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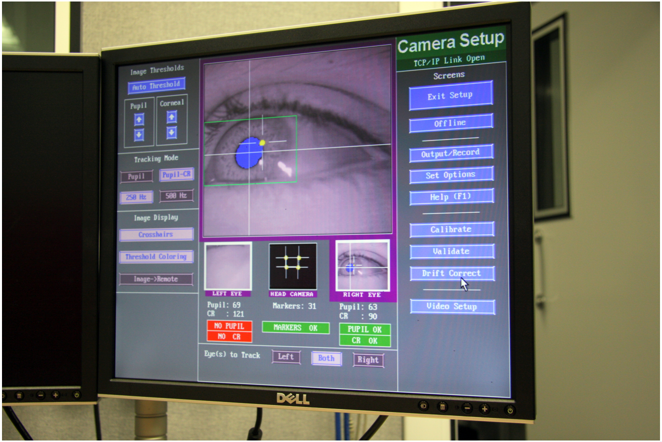

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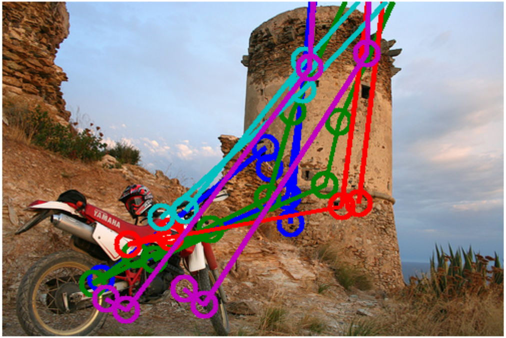

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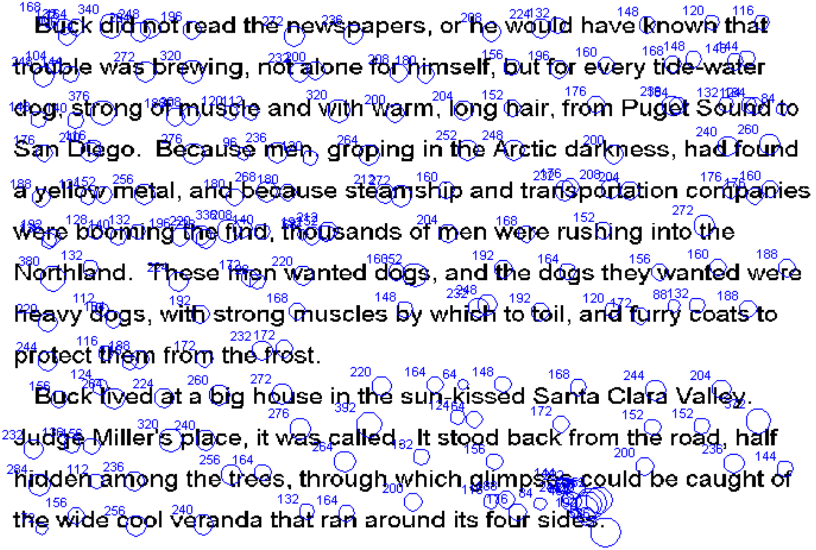
More fixations on salient regions, out-of-context objects, animate objects, task-relevant areas.

Language Processing

Buck did not read the newspapers, or he would have known that trouble was brewing, not alone for himself, but for every tide-water dog, strong of muscle and with warm, long hair, from Puget Sound to San Diego. Because men, groping in the Arctic darkness, had found a yellow metal, and because steamship and transportation companies were booming the find, thousands of men were rushing into the Northland. These men wanted dogs, and the dogs they wanted were heavy dogs, with strong muscles by which to toil, and furry coats to protect them from the frost.

Buck lived at a big house in the sun-kissed Santa Clara Valley. Judge Miller's place, it was called. It stood back from the road, half hidden among the trees, through which glimpses could be caught of the wide cool veranda that ran around its four sides.

Language Processing



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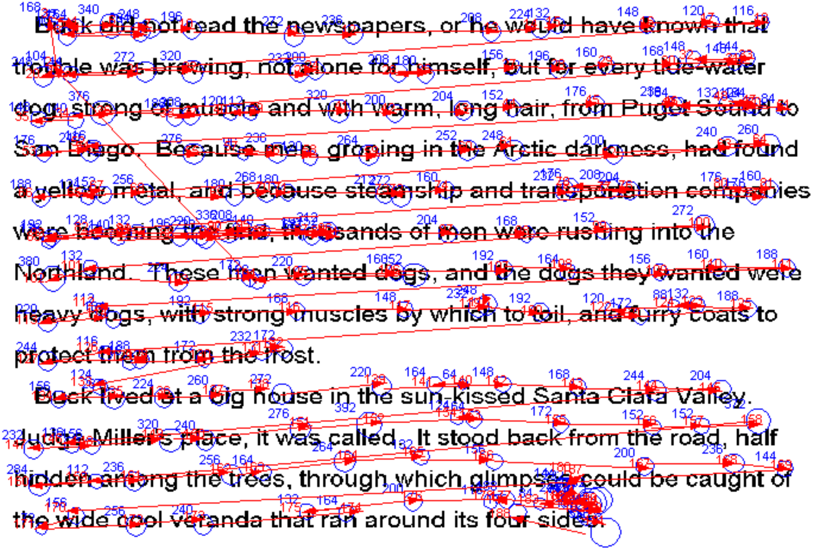

Language Processing

When people read text, they also make fixations and saccades:

- words that are longer or more frequent are fixated for longer;
- syntactic ambiguity leads to re-reading (reverse saccades);
- fixation duration also varies with semantic plausibility, sentence and discourse context, reading task.

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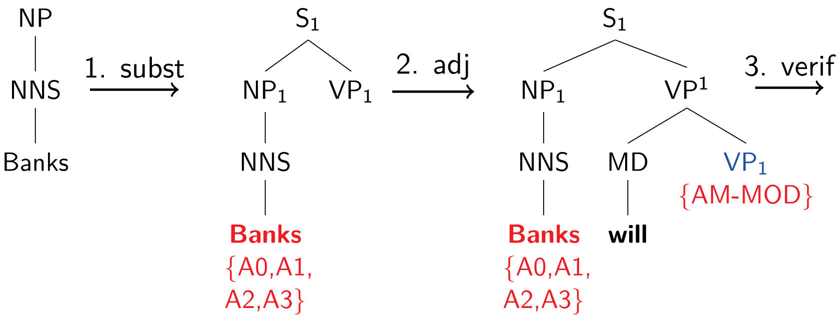
Human Parsing

Incremental TAG model proposed by Demberg et al. (2013):



1. NP $\rightarrow \langle$\{A0,A1,A2,A3\},Banks,nil$\rangle$

2. VP $\rightarrow \langle$AM-MOD,will,nil$\rangle$

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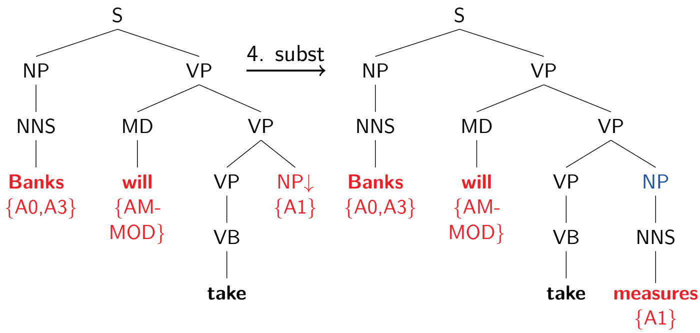
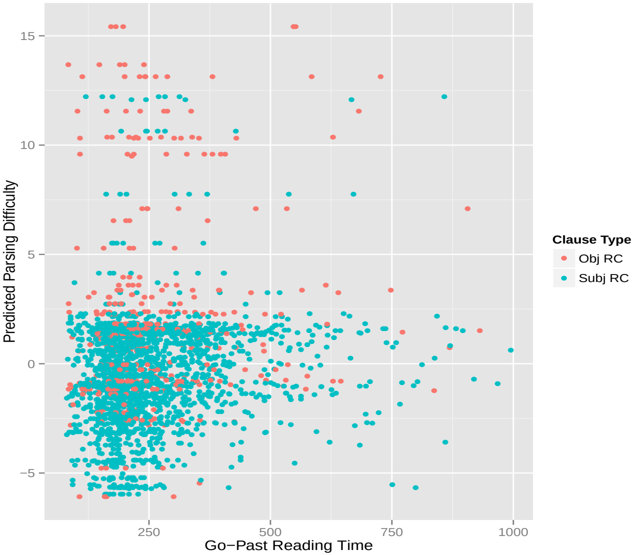


3. NP $\rightarrow$ $\langle$\{A0,A3\},Banks,take$\rangle$
   VP $\rightarrow$ $\langle$AM-MOD,will,take$\rangle$

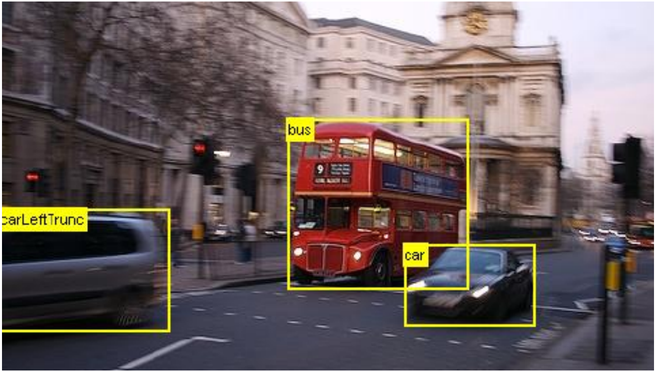
4. NP $\rightarrow$ $\langle$A1,measures,take$\rangle$

Predicting Reading Times



Object Detection

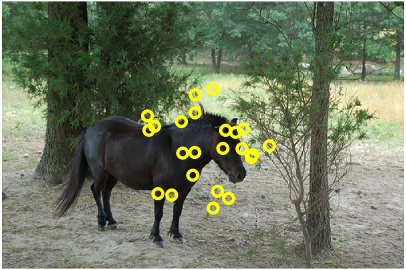
We can use eye-tracking data for a classic computer vision task: object class detection.



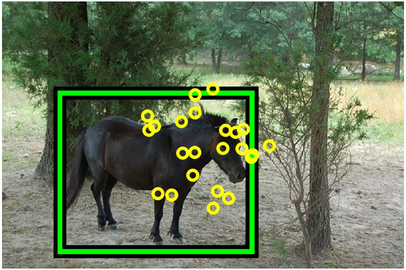
Object detectors are trained on images that are manually annotated with bounding boxed around the objects.

Object Detection

Alternative: infer bounding boxes from eye-tracking data (Papadopoulos et al. 2014):

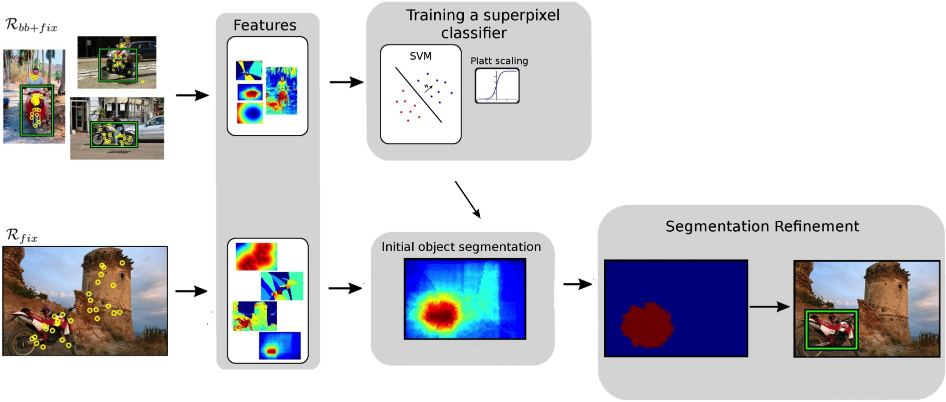


$\Rightarrow$



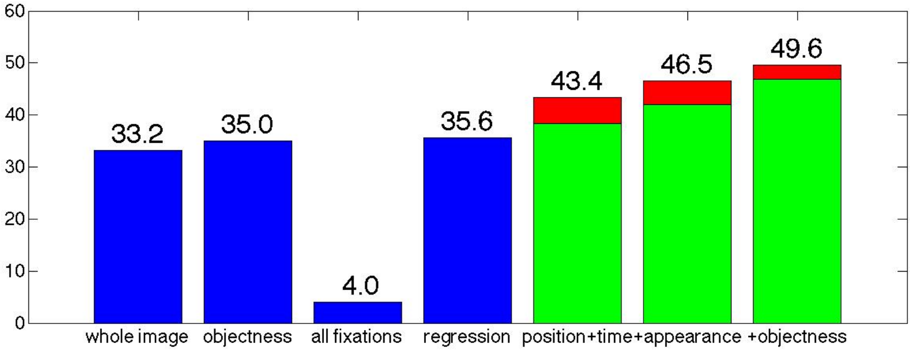
- much faster: 1 s per image vs. 22 s for BB drawing;
- no need for trained annotators, guidelines, etc.

From Fixations to Bounding Boxes



From Fixations to Bounding Boxes

Evaluation using CorLoc (intersection over union > 0.5):



Other Topics in Cognitive Data Science

- Build an incremental semantic role labeler which can be evaluated against eye-tracking data (Konstas et al. 2014);
- use synchronous grammars to align image structure with linguistic structure, e.g., for image description (Elliott & Keller 2013);
- build sequence models (e.g., based on HMMs) that human predict fixation behavior, either for images or for text;
- use eye-tracking data to improve unsupervised PoS tagging or parsing models.

References

Demberg, V., Keller, F., & Koller, A. (2013). Incremental, predictive parsing with psycholinguistically motivated tree-adjoining grammar. *Computational Linguistics*, *39*, 1025–1066.

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