

Can cognitive neuroscience inform neuro-symbolic architectures?

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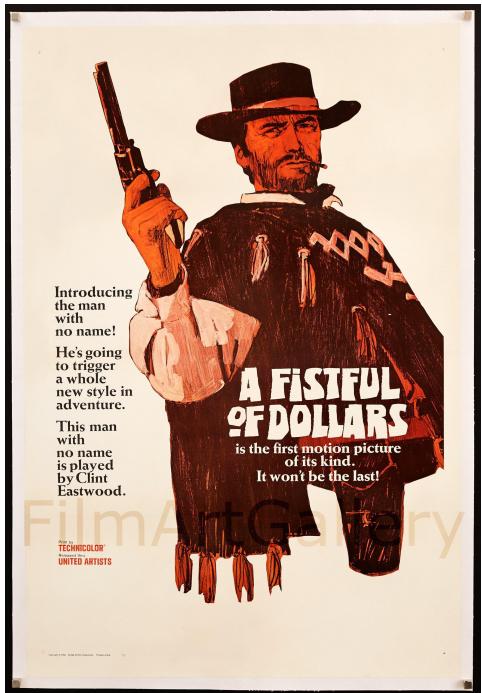
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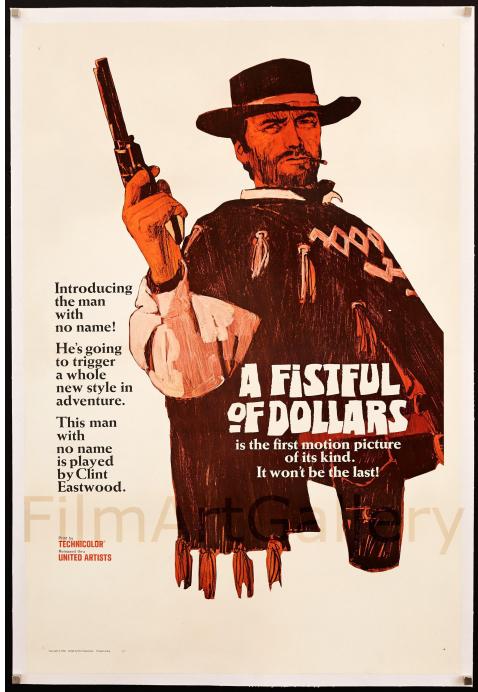
6 May 2021



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A tale of three stories





Human performance on NL inference tasks

Inherent Disagreements in Human Textual Inferences

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Abstract

We analyze human’s disagreements about the validity of natural language inferences. We show that, very often, disagreements are not dismissible as annotation “noise”, but rather persist as we collect more ratings and as we vary the amount of context provided to raters. We further show that the type of uncertainty captured by current state-of-the-art models for natural language inference is not reflective of the type of uncertainty present in human disagreements. We discuss implications of our results in relation to the recognizing textual entailment (RTE)/natural language inference (NLI) task. We argue for a refined evaluation objective that requires models to explicitly capture the full distribution of plausible human judgments.

and then seeking some consensus among them. For example, having raters choose among discrete labels and taking a majority vote (Dagan et al., 2006; Bowman et al., 2015; Williams et al., 2018), or having raters use a continuous Likert scale and taking an average (Pavlick and Callison-Burch, 2016a; Zhang et al., 2017). That is, the prevailing assumption across annotation methods is that there is a single “true” inference about h given p that we should train models to predict, and that this label can be approximated by aggregating multiple (possibly noisy) human ratings as is typical in many other labelling tasks (Snow et al., 2008; Callison-Burch and Dredze, 2010).

Often, however, we observe large disagreements among humans about whether or not h can be inferred from p (see Figure 1). The goal of this study is to establish whether such disagree-

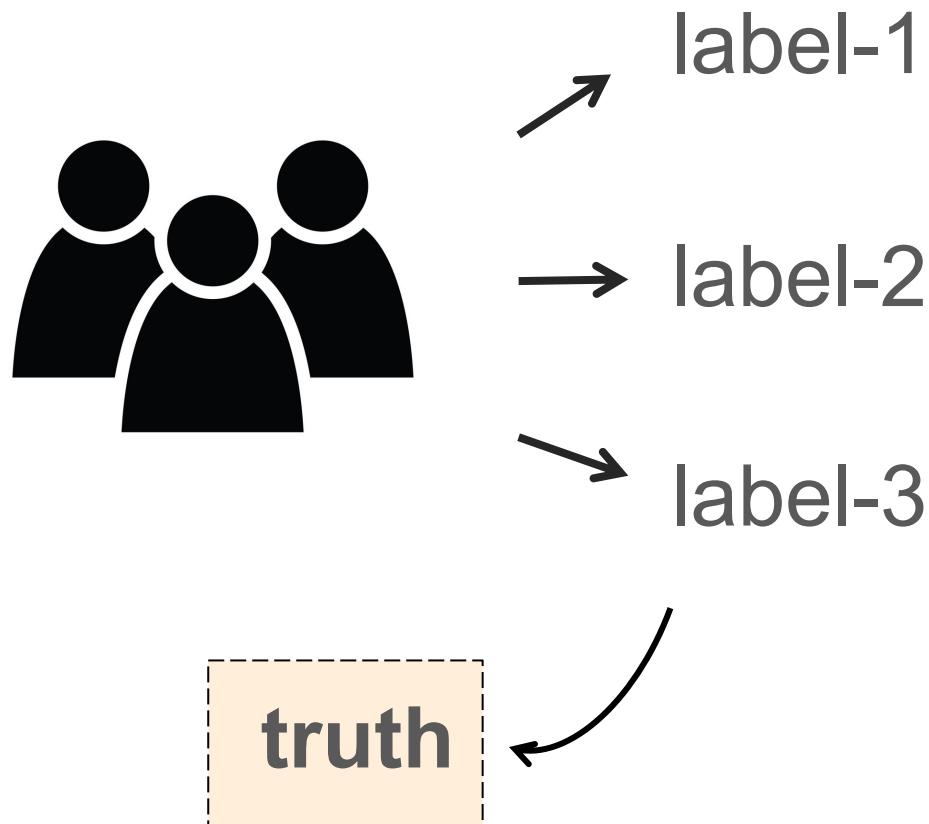
Entailment tasks

Three dogs on a sidewalk. → There are more than one dog here.

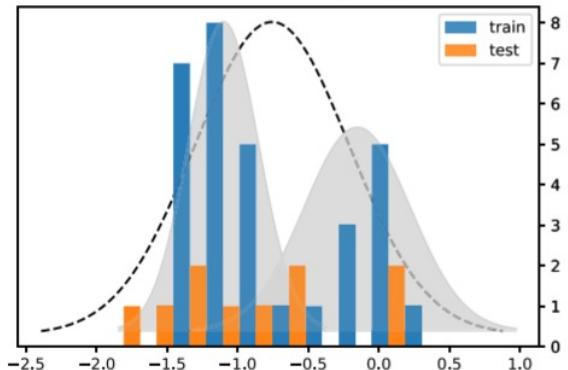
A red rally car taking a slippery turn in a race. → \neg The car is stopped at a traffic light.

Setup

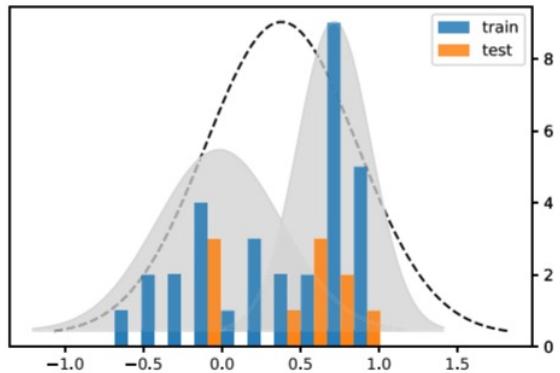
inference
task



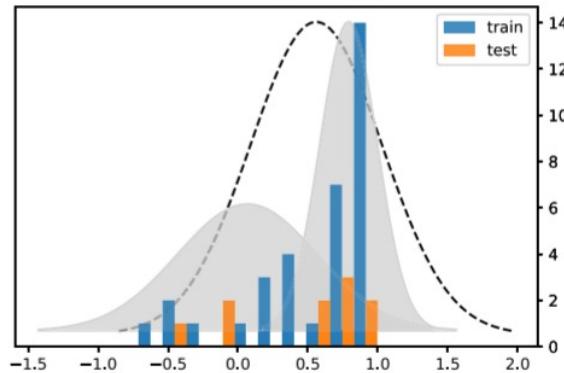
p: A homeless man being observed
by a man in business attire.
h: Two men are sleeping in a hotel.



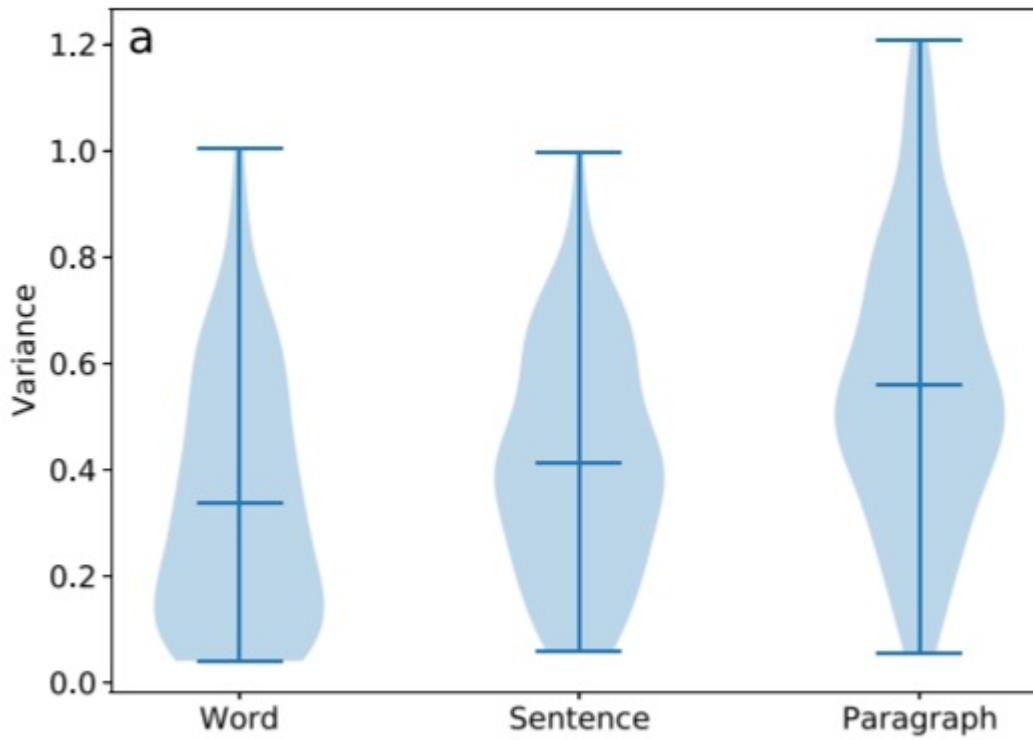
p: Paula swatted the fly.
h: The swatting happened in a
forceful manner.



p: Someone confessed that a
particular thing happened.
h: That thing happened.



Does context play a role then?



Do NL models display similar ambiguity?

- softmax, cross-entropy heads naturally provide a distribution, and not a point estimate
- Perhaps then human judgment mimics these heads?

Do NL models display similar ambiguity?

- softmax, cross-entropy heads naturally provide a distribution, and not a point estimate
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NO

Well then?

- How humans infer – not straightforward
- Making NL models infer like humans – not straightforward

Something more that we're missing?



Understanding the human brain

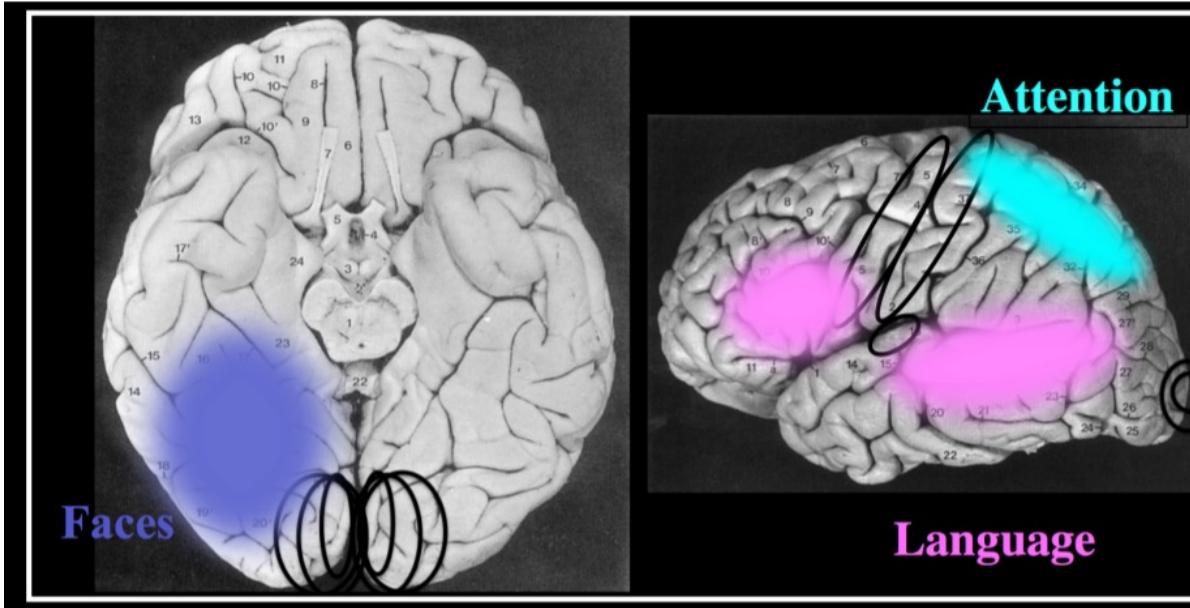
Understanding the human brain

Broad functions

- Vision
- Audio
- Motor control and dexterity
- Emotions
- Language

Understanding the human brain

Early 90s



Understanding the human brain

Broad functions

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Understanding the human brain

Broad functions

- **Vision**
- Audio
- Motor control and dexterity
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- Language

Faces

Color

Places

Words/letters

Bodies

Motion

Shape

Understanding the human brain

Broad functions

- Vision
- Audio
- Motor control and dexterity
- Emotions
- **Language**
 - Responds to both comprehension and production
 - Across modalities (speech, written, ASL)
 - Responds to typologically diverse languages
 - Causally important for language

Understanding the human brain

Broad functions

- Vision
- Audio
- Motor control and dexterity
- Emotions
- Language
- **Multiple Demand system**

Broadly recruited in math, logic, reasoning, learning like tasks

Research Report: Regular Manuscript

The domain-general multiple demand (MD) network does not support core aspects of language comprehension: a large-scale fMRI investigation

<https://doi.org/10.1523/JNEUROSCI.2036-19.2020>

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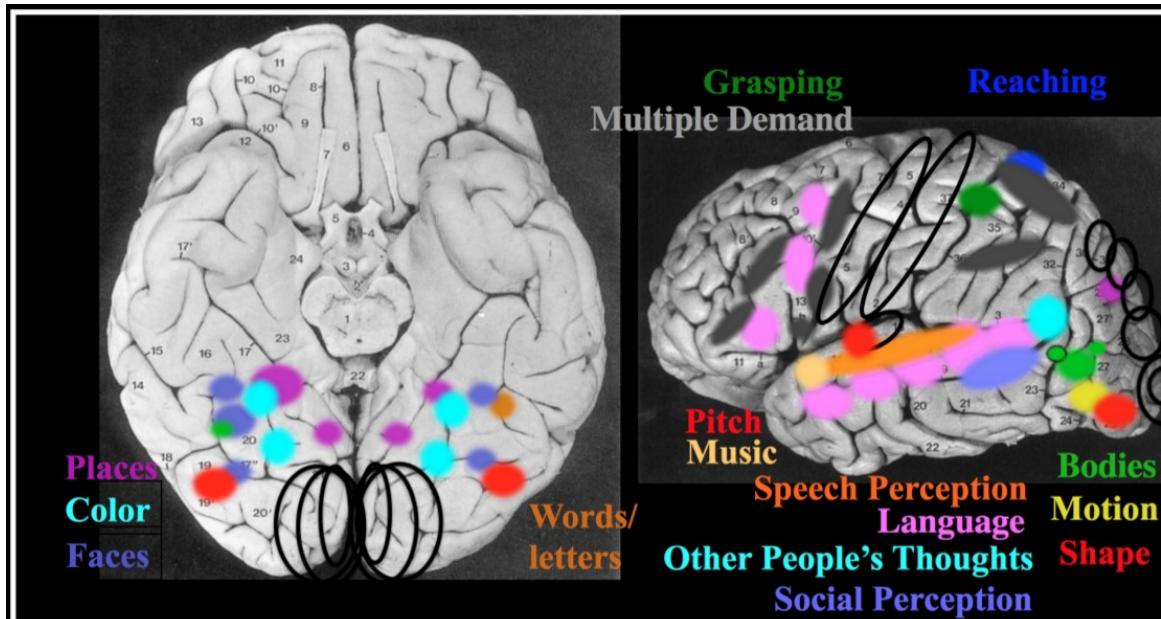
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Understanding the human brain

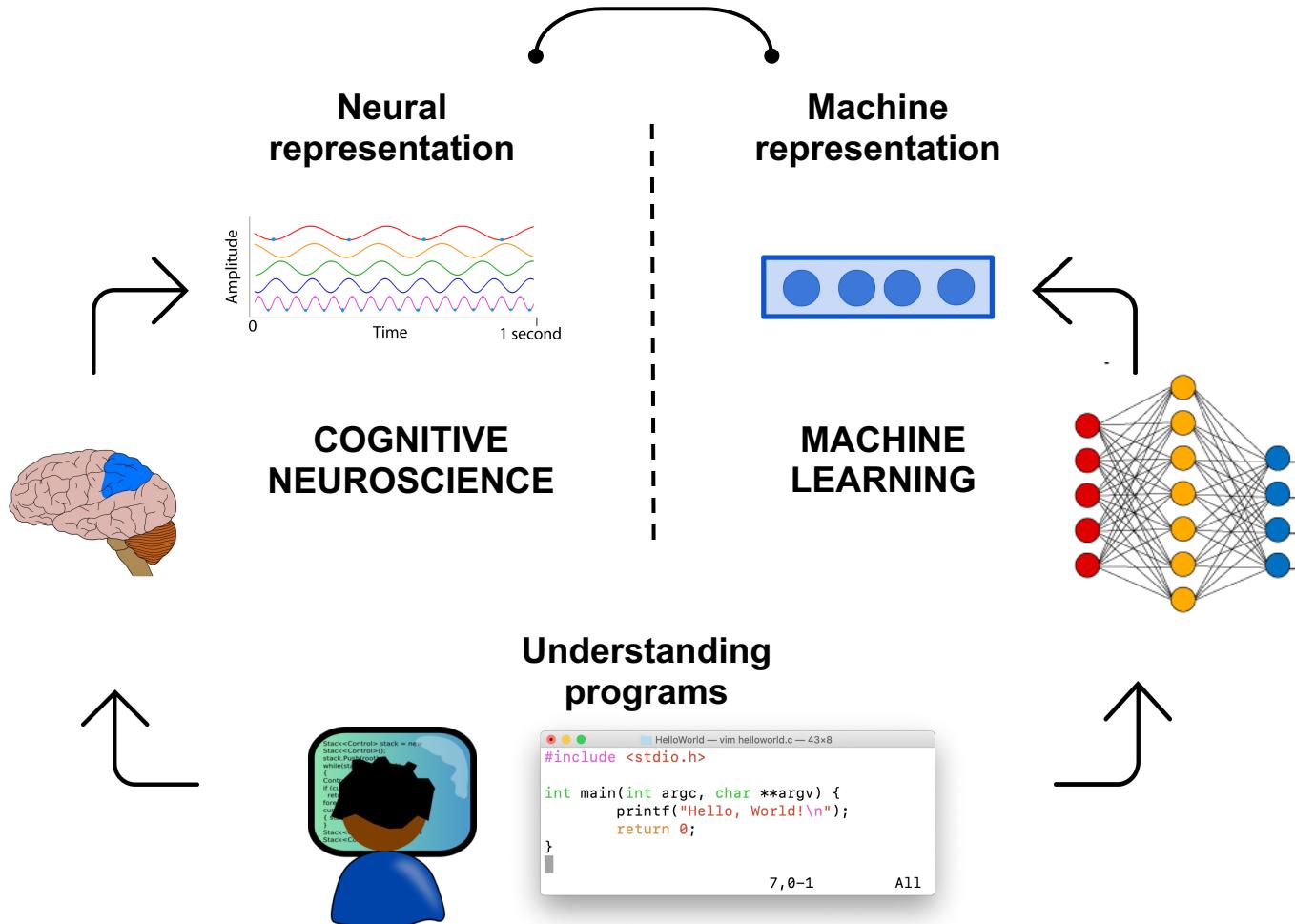
Current understanding



SERGIO LEONE

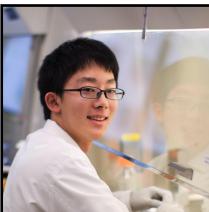


Computer programs and the human brain

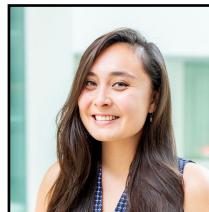




Anna Ivanova



Yotaro Sueoka



Hope Kean



Riva Dhamala



Ev Fedorenko



Una-May O'Reilly



Marina Bers



Some slides adapted from Nancy Kanwisher's course on The Human Brain (9.17, 2019)

Where to look?

Broad functions

- Vision
- Audio
- Motor control and dexterity
- Emotions
- Language
- Multiple Demand system

Understanding code?

Where to look?

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Understanding code

1. Vision system activated

Where to look?

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Understanding code

1. Vision system activated
2. Recognize characters, tokens to form statements and blocks.

Where to look?

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Understanding code

1. Vision system activated
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3. Understand what the code does

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1. Vision system activated
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4. Mentally trace it/debug it and calculate output.

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Where to look?

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Code simulation

1. Vision system activated
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Where to look?

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Code reading

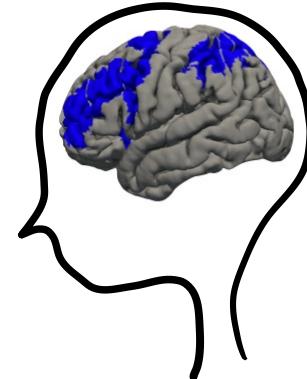
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Where to look?

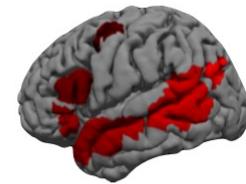
Broad functions

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- Language
 - Multiple Demand system

Multiple demand
(MD)



Language



Disambiguate reading and simulation

code

```
big_num, small_num = 64, 16  
  
if big_num % small_num == 0:  
    print(1)  
else:  
    print(0)
```

sent

You are given two numbers 64 and 16. If the remainder when the first number is divided by the second number is 0, you perform one good deed. Otherwise, you perform no good deeds. How many good deeds will you perform?

```
filename = "alphabet.java"  
modified = filename.split(".")  
  
print(modified[-1])
```

A file is named "alphabet.java". You split the name at the dot character. What is the last part of the resulting split?





MD system

Language system

PYTHON



Strong,
generalizable
responses to
code



Moderate,
task/language
dependent (?)
responses to
code

Understanding code

1. Vision system activated
2. Recognize characters, tokens to form statements and blocks.
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4. Mentally trace it/debug it and calculate output.

SCRATCH
JR

So..

Modeling the distinction between MD and language system
may be worth exploring in computational models

What's the human baseline in NL tasks? Are we as good as
we want our models to be? Worth exploring, and perhaps
NS systems may help model that uncertainty.



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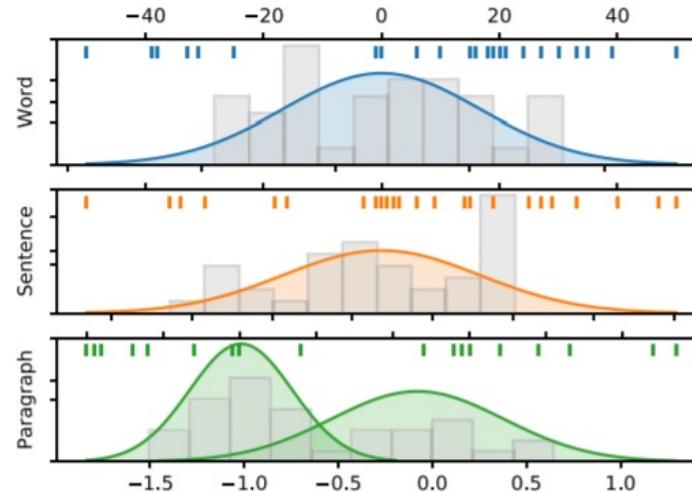


@ShashankSrikant

<https://shashank-srikant.github.io/>

A watercolor painting celebrating that event hangs today in the Chenango Museum in Norwich. The canal itself was also utilized for recreation. In the summer months it supported swimming, **boating** and fishing. In the winter months, after the surface froze over, ice skating and even horse racing became favorite pastimes. Before the Chenango Canal was built, much of the Southern Tier and Central New York was still considered to be frontier.

In the summer months it supported swimming , **picnicking** and fishing .



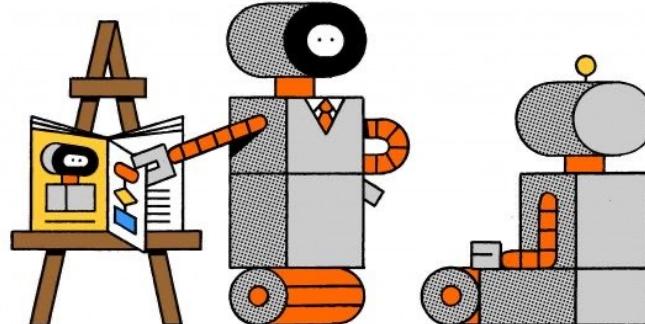
Programming language



```
#include <stdio.h>

int main(int argc, char **argv) {
    printf("Hello, World!\n");
    return 0;
}
```

7,0-1 All



Teaching machines to read code