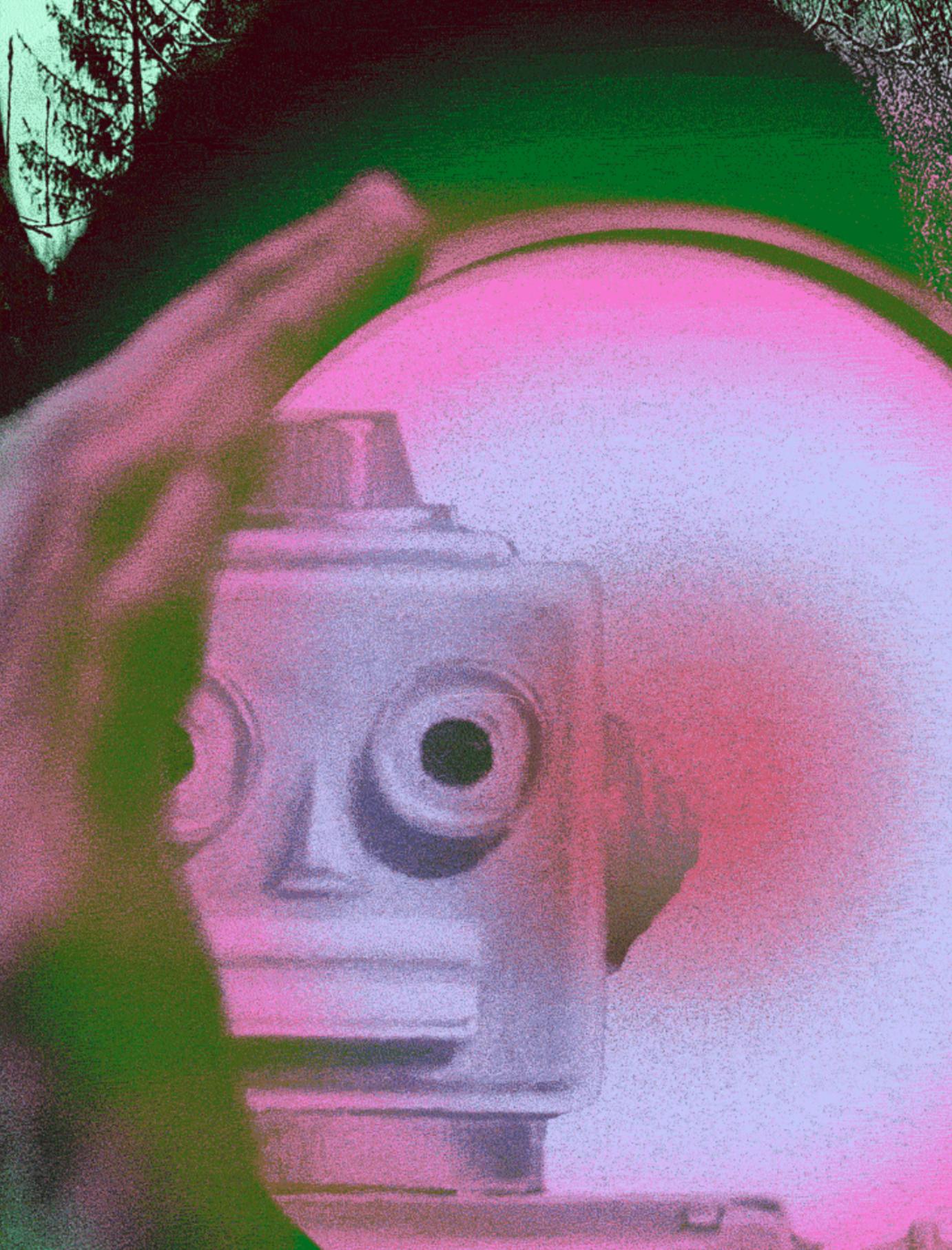


Teaching Machines Language Understanding

Ana Marasović

Allen Institute for Artificial Intelligence (AI2)



Finally, a Machine That Can Finish Your Sentence

Completing someone else's thought is not an easy trick for A.I. But new systems are starting to crack the code of natural language.

Microsoft | The AI Blog The Official Microsoft Blog Microsoft On the Issues Transform

January 15, 2018 | Allison Linn

f | t | in

The animated guide to machine reading (Explanimators: Episode 4)

≡ 🔎 Microsoft

Research ▾

Achieving Human Parity on Automatic Chinese to English News Translation

Hany Hassan Awadalla, Anthony Aue, Chang Chen, Vishal Chowdhary, Jonathan Clark, Christian Federmann, Xuedong Huang, Marcin Junczys-Dowmunt, Will Lewis, Mu Li, Shujie Liu, Tie-Yan Liu, Renqian Luo, Arul Menezes, Tao Qin, Frank Seide, Xu Tan, Fei Tian, Lijun Wu, Shuangzhi Wu, Yingce Xia, Dongdong Zhang, Zhirui Zhang, Ming Zhou

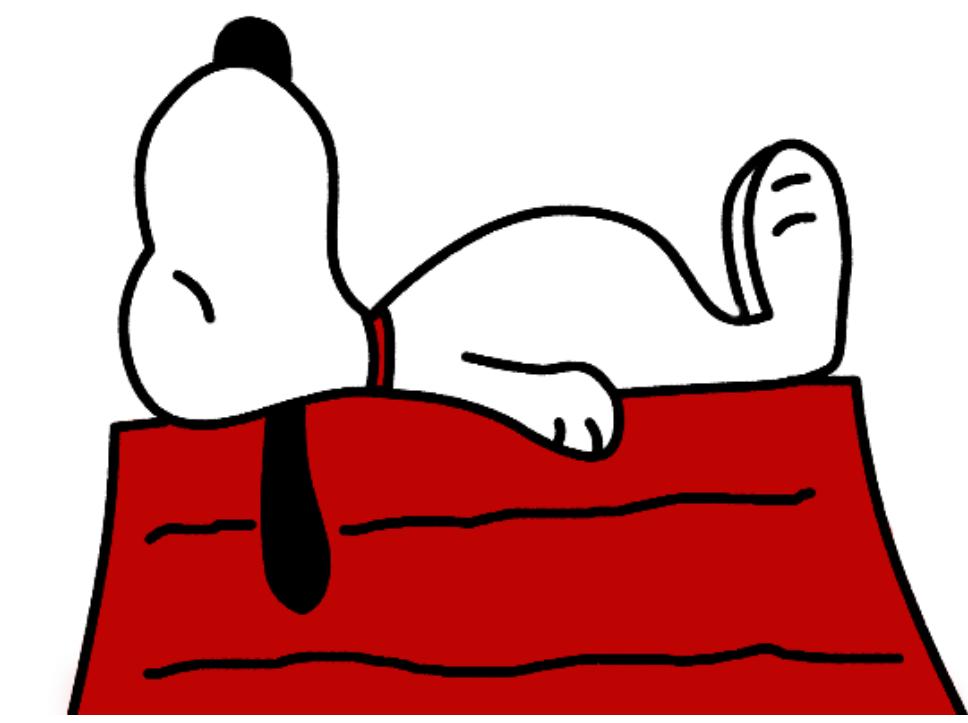
March 2018
arXiv:1803.05567
[View Publication](#)
[Download BibTeX](#)

Machine translation has made rapid advances in recent years. Millions of people are using it today in online translation systems and mobile applications in order to communicate across language barriers. The question naturally arises whether such systems can approach or achieve parity with human translations. In this paper, we first address the problem of how to define and accurately measure human parity in translation. We then describe Microsoft's machine translation system and measure the quality of its translations on the widely used WMT 2017 news translation task from Chinese to English. We find that our latest neural machine translation system has reached a new state-of-the-art, and that the translation quality is at human parity when compared to professional human translations. We also find that it significantly exceeds the quality of crowd-sourced non-professional translations.

[View Publication](#)

Groups
[Machine Translation](#)

Research Areas
[Artificial intelligence](#)



A bit
about me

BA and MA in Zagreb



♥ math ♥



high school in Split



poslovna
inteligencija

Poslovna means Business

Croatia



research or not?
living and working outside Croatia?
mathematics or machine learning?
language or vision?

born in Omiš (population of 14,936)



♥ math

Germany



research

still research?
industry or academia?
teaching?
grants?

Heidelberg



UNIVERSITÄT
HEIDELBERG
ZUKUNFT
SEIT 1386

- Founded in 1386 (Germany's oldest university)
- 56 Nobel Prize winners have been affiliated with the university
- Approximately 1,000 doctorates are completed every year

Croatia



Berlin



amazon



Allen AI Young Investigators

Duration: 1-3 years

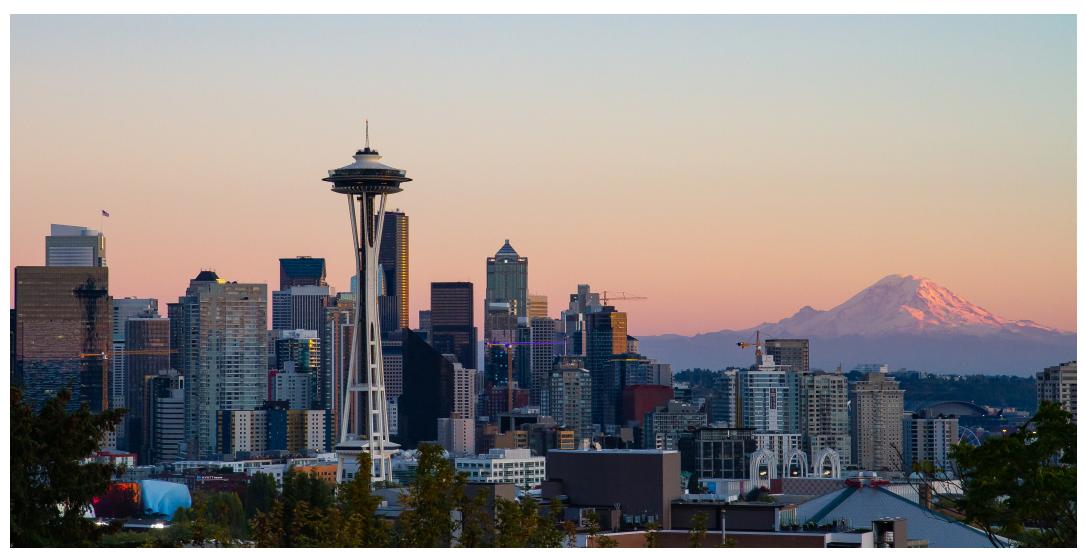
Start date: Flexible (rolling application with no deadline)

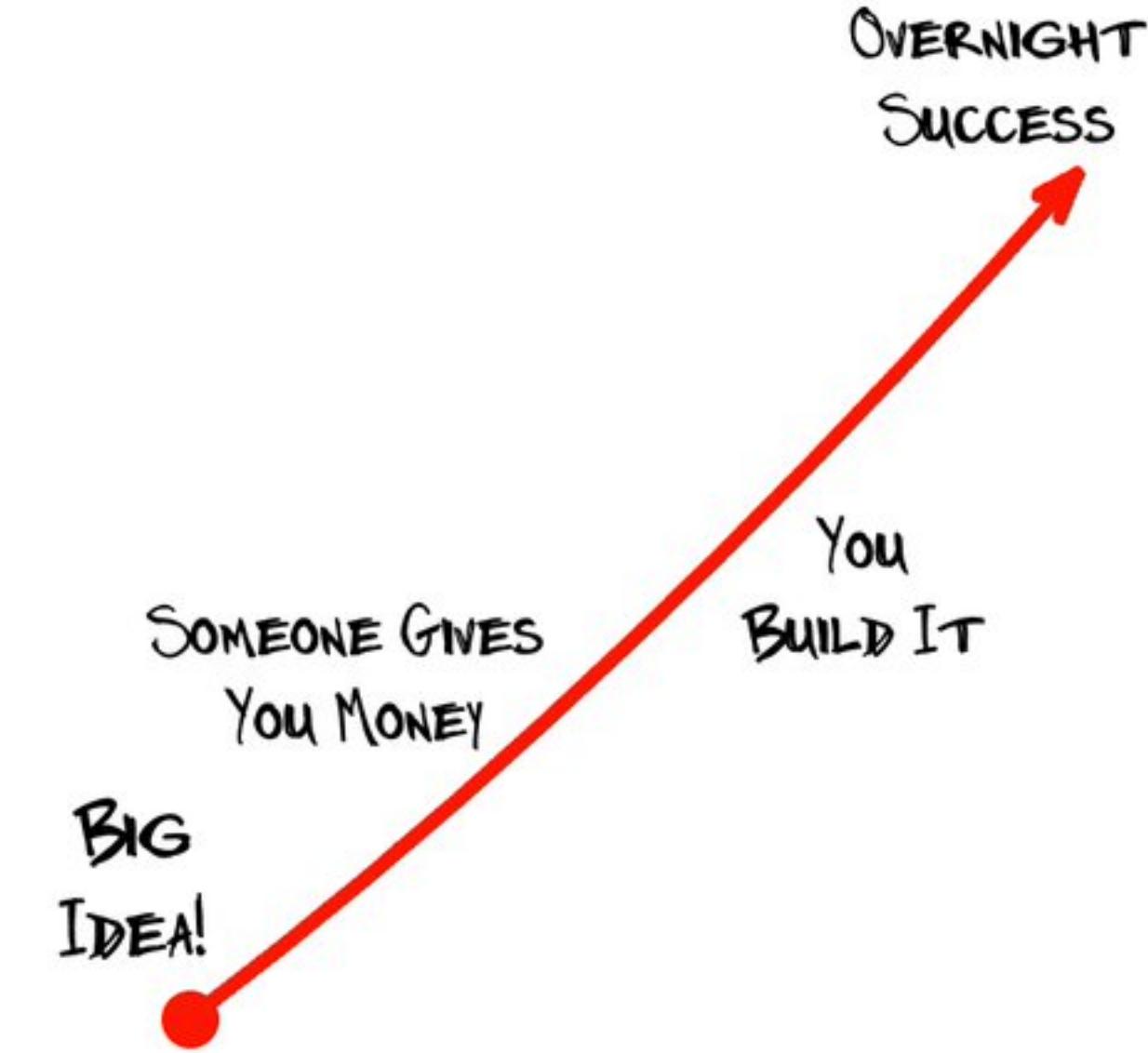
Candidates: Are within one year of completing their PhD, or already have a PhD

Allen AI Young Investigators is a postdoctoral program offering unique benefits. The program will enable you to balance working collaboratively on an AI2 project while pursuing an independent research agenda.

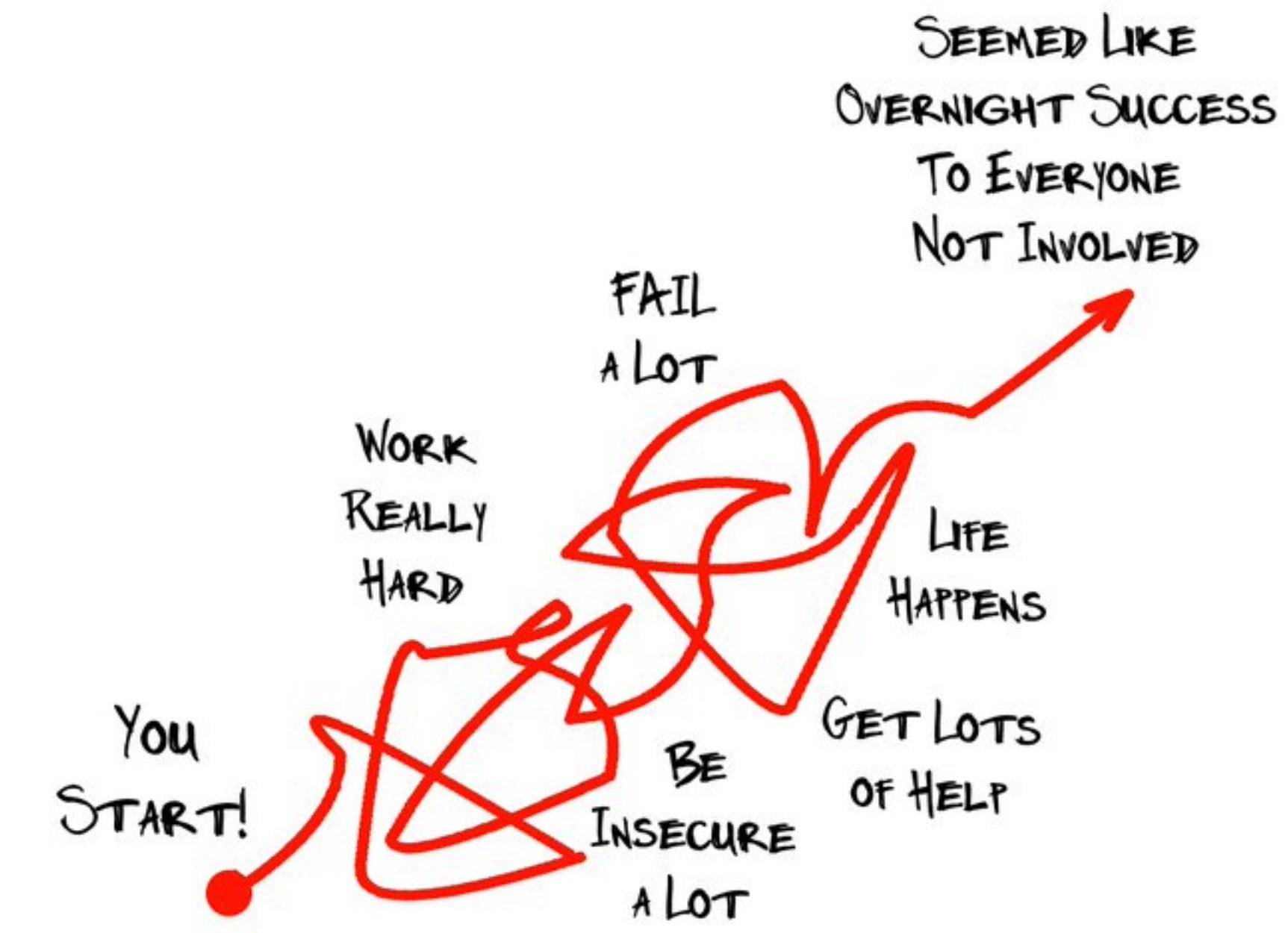
Benefits

- Dedicated AI2 mentor: Mentorship in research, grant writing, and more
- 50% collaborative work on an AI2 project
- 50% work on your own projects
- Generous travel budget
- AI2 provides support for obtaining a visa through its immigration attorney, and pays the necessary expenses
- Access to AI2's data, AWS infrastructure, and other resources as needed
- No grant writing, teaching, or administrative responsibilities
- \$100K research funding from AI2 after completion (based on proposal)





WHAT PEOPLE THINK
IT LOOKS LIKE...



WHAT IT REALLY
LOOKS LIKE...



11 12

1

10

2

9

3

8

4

7

11 12

1

2

3

10

9

8

7

6

5

4

11 12

1

2

3

4

5



The AI Blog

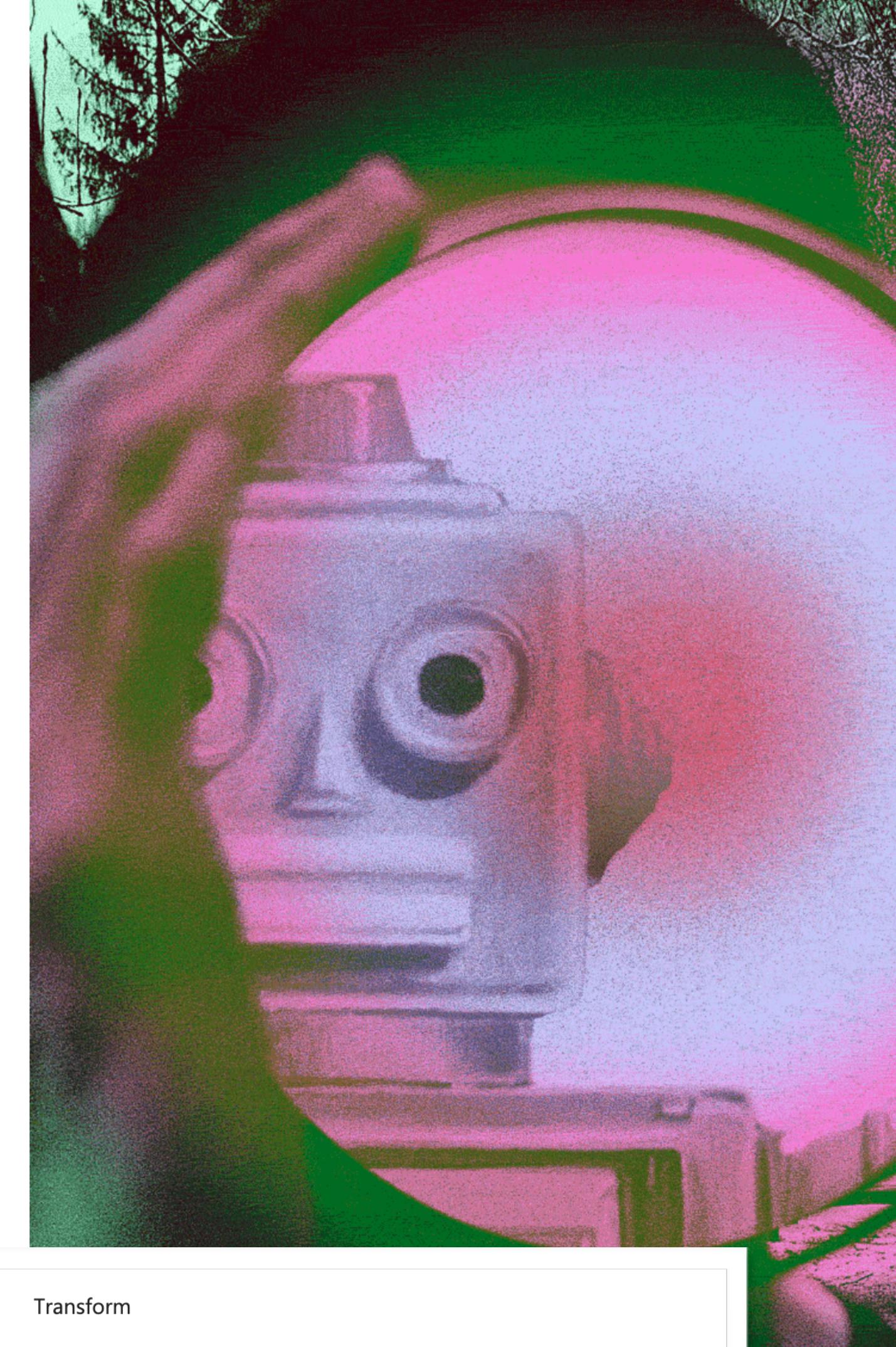
The Official Microsoft Blog

Microsoft On the Issues

Transform

Microsoft creates AI that can read a document and answer questions about it as well as a person

January 15, 2018 | [Allison Linn](#)



Finally, a Machine That Can Finish Your Sentence

Completing someone else's thought is not an easy trick for A.I. But new systems are starting to crack the code of natural language.



Microsoft

Research ▾

Achieving Human Parity on Automatic Chinese to English News Translation

Hany Hassan Awadalla, Anthony Aue, Chang Chen, Vishal Chowdhary, Jonathan Clark, Christian Federmann, Xuedong Huang, Marcin Junczys-Dowmunt, Will Lewis, Mu Li, Shujie Liu, Tie-Yan Liu, Renqian Luo, Arul Menezes, Tao Qin, Frank Seide, Xu Tan, Fei Tian, Lijun Wu, Shuangzhi Wu, Yingce Xia, Dongdong Zhang, Zhirui Zhang, Ming Zhou

March 2018

arXiv:1803.05567

[View Publication](#)

[Download BibTex](#)

Machine translation has made rapid advances in recent years. Millions of people are using it today in online translation systems and mobile applications in order to communicate across language barriers. The question naturally arises whether such systems can approach or achieve parity with human translations. In this paper, we first address the problem of how to define and accurately measure human parity in translation. We then describe Microsoft's machine translation system and measure the quality of its translations on the widely used WMT 2017 news translation task from Chinese to English. We find that our latest neural machine translation system has reached a new state-of-the-art, and that the translation quality is at human parity when compared to professional human translations. We also find that it significantly exceeds the quality of crowd-sourced non-professional translations.

[View Publication](#)

Groups

[Machine Translation](#)

Research Areas

[Artificial intelligence](#)

If **machines** can do all of these tasks,
then they must possess **true language understanding** and
reasoning capabilities?

Question Answering

Paragraph: "In January 1880, two of Tesla's uncles put together enough money to help him leave Gospić for Prague where he was to study. Unfortunately, he arrived too late to enroll at Charles-Ferdinand University; he never studied Greek, a required subject; and he was illiterate in Czech, another required subject. Tesla did, however, attend lectures at the university, although, as an auditor, he did not receive grades for the courses."

Question: "What city did Tesla move to in 1880?"

Answer: Prague

80% accuracy

Paragraph: "In January 1880, two of Tesla's uncles put together enough money to help him leave Gospić for Prague where he was to study. Unfortunately, he arrived too late to enroll at Charles-Ferdinand University; he never studied Greek, a required subject; and he was illiterate in Czech, another required subject. Tesla did, however, attend lectures at the university, although, as an auditor, he did not receive grades for the courses. **Tadakatsu moved to the city of Chicago in 1881.**"

Question: "What city did Tesla move to in 1880?"

Answer: Chicago

34.2% accuracy

Machine Translation

phonetic	
tut	Tud (devoicing of final stops)
sieht	zieht (s = /z/ before vowel)
Trotzdem	Trozdem (tz = /z/)
gekriegkt	gekricht (vowel length)
Natürlich	Naturlich/Näutrlch (diacritics)
omission	
erfahren, Babysitter, selbst, Hausschuhe	erfaren, Babysiter, selbst, Hausschue
morphological	
wohnt, fortsetzt, wünsche	wonnen, forzusetzen, wünchen
key swap	
Eltern, Deine, nichts, Bahn	Eltren, Diene, nichst, Bhan
other	
Agglomerationen	Agromelationen (omission + letter swap)
Hausaufgaben	Hausausgabe
Thema	Temer
Detailhandelsfachfrau	Deitellhandfachfrau
34.79 BLEU	14.02 BLEU

Sentiment Analysis

There is no pleasure in watching a child suffer.

Prediction: negative

83.1% accuracy

Syntactic paraphrase:

In watching the child suffer, there is no pleasure.

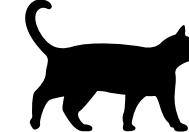
Prediction: positive

41.8% dev instances broken
(correct prediction becomes incorrect)

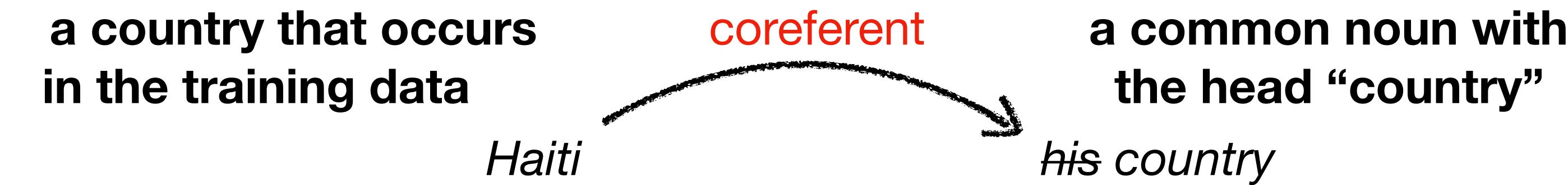
Natural Language Inference

premise	entailment	hypothesis
Some men and boys are playing frisbee in a grassy area.	(generalization)	People are playing frisbee outdoors .
A person in a red shirt is mowing the grass with a green riding mower.	(shortening)	A person in red is cutting the grass on a riding mower.

premise	neutral	hypothesis
A middle-aged man works under the engine of a train on rail tracks.	(modifiers)	A man is doing work on a black Amtrak train.
A group of female athletes are huddled together and excited.	(purpose clauses)	They are huddled together because they are working together .

premise	contradiction	hypothesis
Older man with white hair and a red cap painting the golden gate bridge on the shore with the	(negation)	Nobody wears a cap.
Three dogs racing on racetrack.		Three cats race on a track.

Coreference Resolution



Visual Question Answering



question	answer
How many...?	2
Is/Are...?	Yes
What sport...?	Tennis
What animal...?	Dog

How can we measure how well our systems perform on new, previously unseen inputs? How do we **measure** how well our systems generalize?

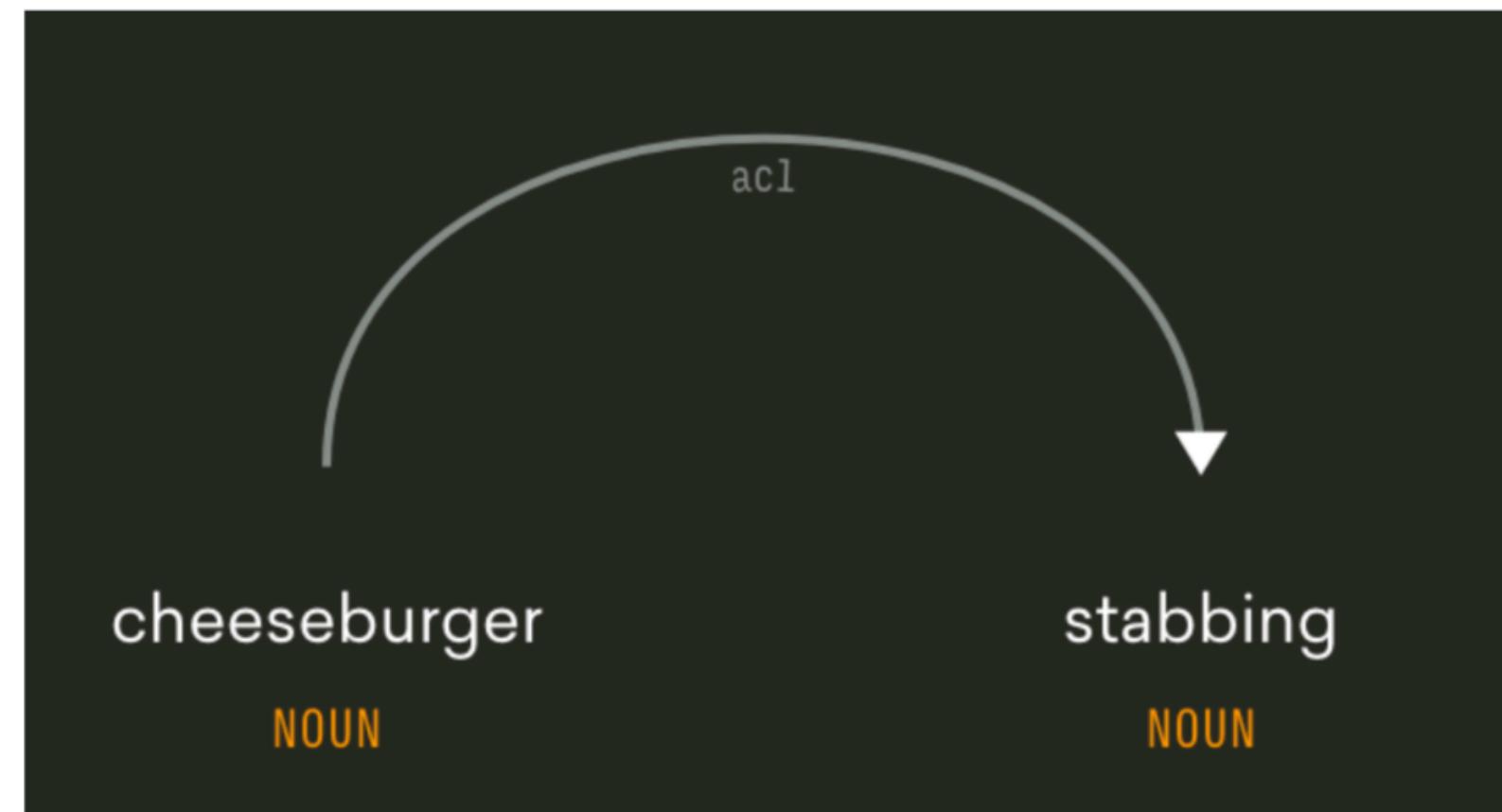
How should we modify our models so that they **generalize better**?

Direction 1: More inductive biases (but cleverly)

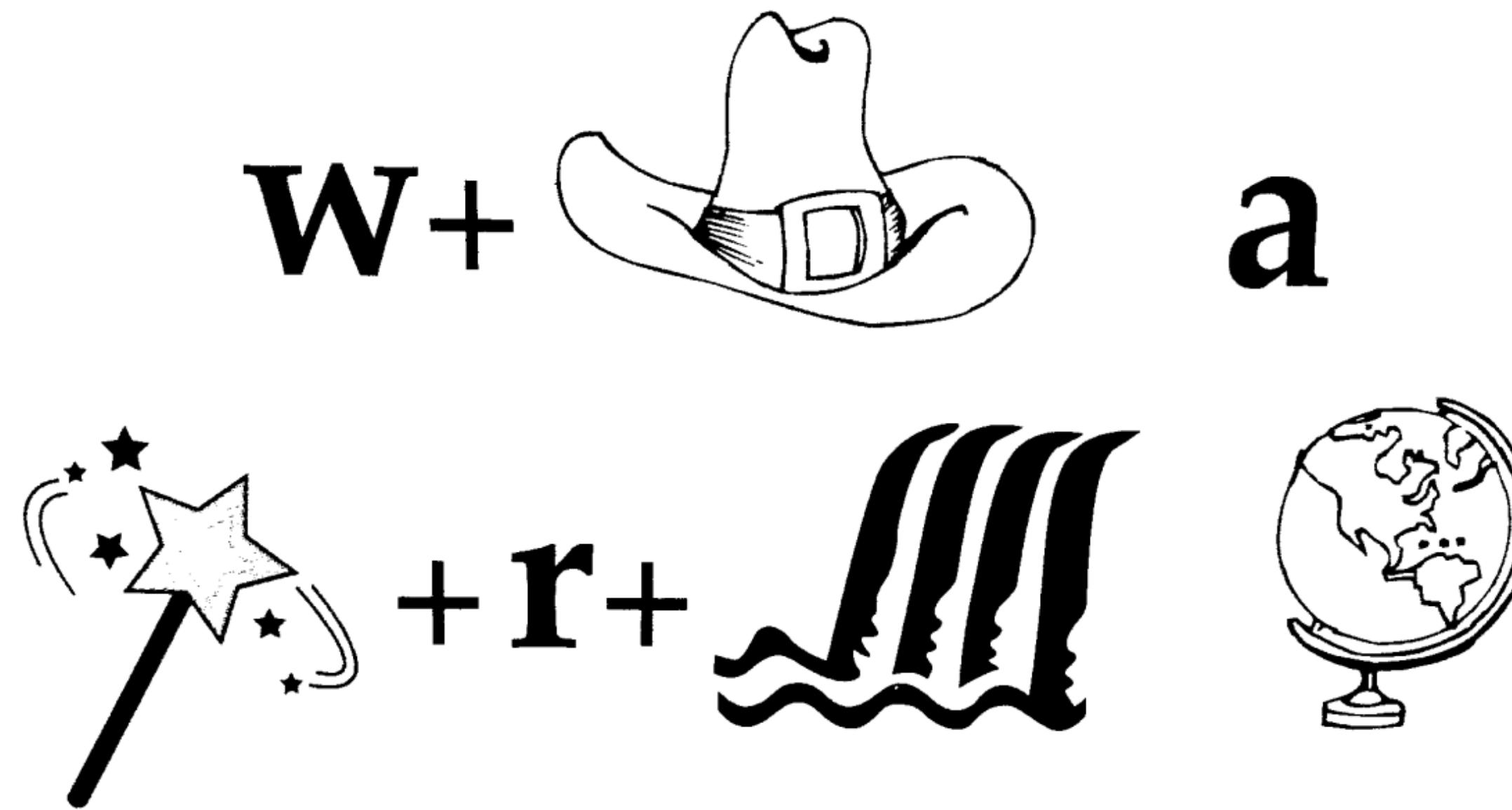
All in all, I would highly recommend this hotel to anyone who wants to be in the heart of the action.

All in all, I would highly recommend this hotel to anyone who wants to be in the heart of the action, and want to be in the heart of the action. If you want to be in the heart of the action, this is not the place for you. However, if you want to be in the middle of the action, this is the place to be.

Direction 2: Common sense



Direction 3: Evaluate unseen distributions and unseen tasks



Direction 3: Evaluate unseen distributions and unseen tasks

But what about...

Commonsense knowledge

Logical reasoning

Linguistic phenomena

Intuitive physics

...

MACHINE LEARNING DOESN'T CARE





Linguistic Knowledge and Transferability of Contextual Representations

Nelson F. Liu♦♡* Matt Gardner♦ Yonatan Belinkov◊

Matthew E. Peters♦ Noah A. Smith♦♣

*Paul G. Allen School of Computer Science & Engineering,
University of Washington, Seattle, WA, USA

♡Department of Linguistics, University of Washington, Seattle, WA, USA

♣Allen Institute for Artificial Intelligence, Seattle, WA, USA

◊Harvard John A. Paulson School of Engineering and Applied Sciences and
MIT Computer Science and Artificial Intelligence Laboratory, Cambridge, MA, U

Pathologies of Neural Models Make Interpretations Difficult

Shi Feng¹ Eric Wallace¹ Alvin

Pedro Rodriguez¹ Jo

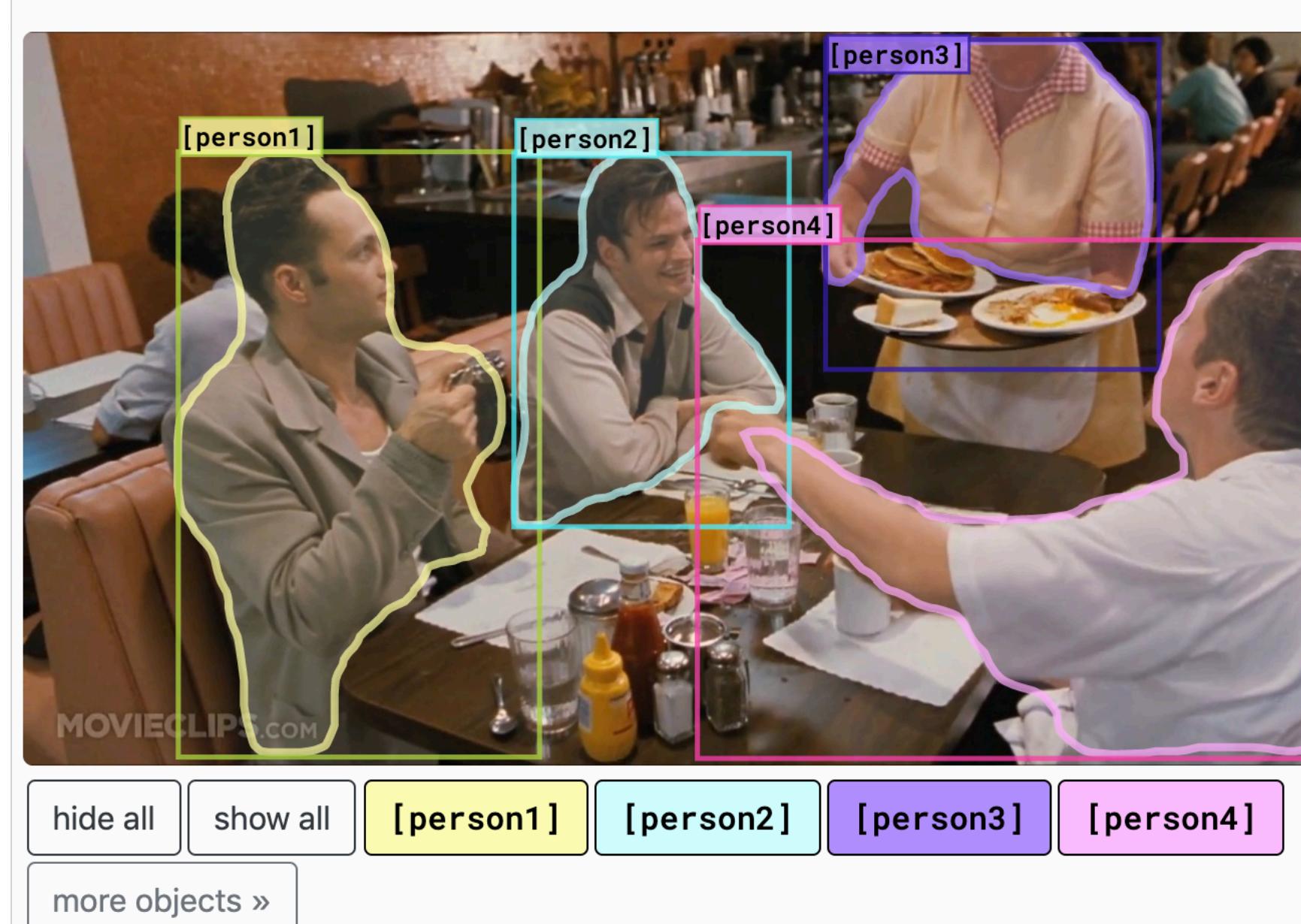
¹University of Maryland

³UMass Amherst ⁴Allen Insti

{shifeng, ewallac2, entil:
agrissom@ursinus.edu}

Abstract

One way to interpret neural model predictions is to highlight the most important input features—for example, a heatmap visualization over the words in an input sentence. In existing interpretation methods for NLP, a word’s importance is determined by either input perturbation—measuring the decrease in model confidence when that word is removed—or by the gradient with respect to that word. To understand the limitations of these methods, we use input reduction, which iteratively removes the least important word from the input. This exposes pathological behaviors of neural models: the remaining words



on the Reduced question as the original, with even higher confidence. For humans, the reduced question, “did”, is nonsensical.

On Measuring Social Biases in Sentence Encoders

Chandler May¹ Alex Wang² Shikha Bordia²

Samuel R. Bowman² Rachel Rudinger¹

¹Johns Hopkins University ²New York University

[chandler.may, ruderger}@jhu.edu {alexwang, sb6416, bowman}@nyu.edu

Why is [person4] pointing at [person1]?

- a) He is telling [person3] that [person1] ordered the pancakes.
- b) He just told a joke.
- c) He is feeling accusatory towards [person1].
- d) He is giving [person1] directions.

Rationale: I think so because...

- a) [person1] has the pancakes in front of him.
- b) [person4] is taking everyone's order and asked for clarification.
- c) [person3] is looking at the pancakes both she and [person2] are smiling slightly.
- d) [person3] is delivering food to the table, and she might not know whose order is whose.



Make a difference.

CURRENT OPENINGS

AI2 is a non-profit focused on contributing to AI research and engineering efforts intended to **benefit the common good**.



Our Beliefs

These days, I'm disinclined to invest in completely open-ended research. I've learned that creativity needs tangible goals and hard choices to have a chance to flourish.

— Paul Allen



YOUR
TURN!





*"But enough about me—
now let's talk about my work."*

Deep Learning With Sentiment Inference For
Discourse-Oriented Opinion Analysis



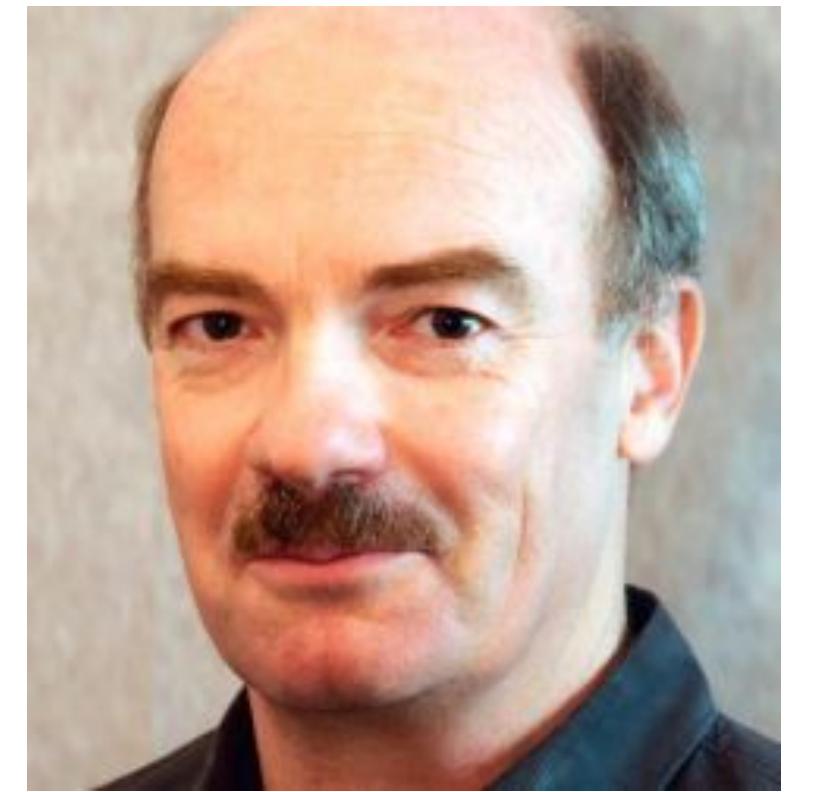
Ana Marasović

Department of Computational Linguistics
Heidelberg University

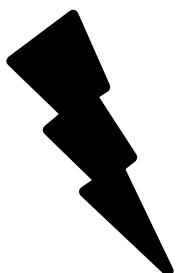
This dissertation is submitted for the degree of
Doctor of Philosophy

What Is an Opinion?

“An opinion is a decision made by someone (the holder) about a topic. This decision assigns the topic to one of a small number of classes (the valences) that affect the role that the topic will play in the holder’s future goals and planning decisions.” Hovy (2011)



Who expressed what kind of attitude toward what or who?



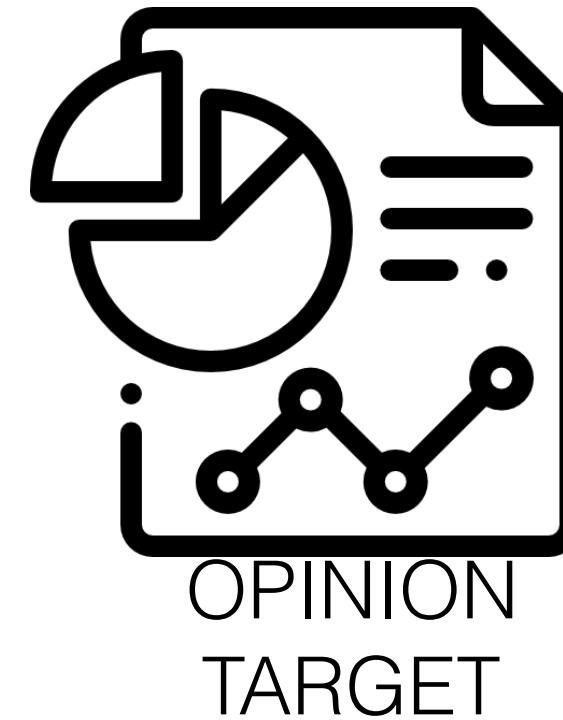
What is the overall polarity of a given text?

Fine-Grained Opinion Analysis

“We therefore as the MDC (Movement for Democratic Change) *do not accept* this result.”



OPINION HOLDER

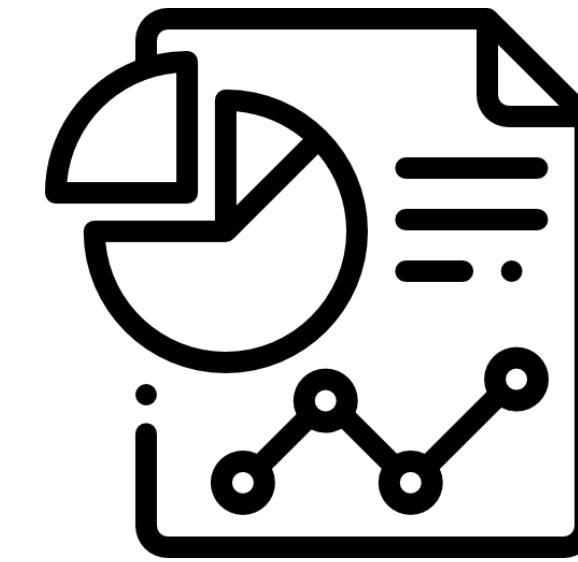


Resolve Anaphors to Analyze Opinions in Discourse

Registrar General Tobaiwa Mudede announced on state television that **Mugabe was re-elected with 1,685,212 votes against 1,258,758 votes for Tsvangirai**, leader of the Movement for Democratic Change (MDC). "I ... therefore declare Robert Mugabe the winner for the office of the presidency of Zimbabwe", Mudede said. Observers had warned that should the outcome be seen to have been rigged, violence could explode across the volatile southern African nation. As the results were being announced, about 100 heavily armed soldiers moved into Zimbabwe's second city Bulawayao and surrounded the MDC offices, where opposition officials had gathered. Defence Minister Sydney Sekeramayi has put security forces on the highest level of alert, according to state media. Police roadblocks were seen on the main roads leading to central Harare, security forces were patrolling the city and six police officers were stationed outside MDC headquarters. Tsvangirai rejected Mugabe's election victory out of hand. "The election was massively rigged," he told a packed press conference. "We therefore as MDC *do not accept this result.*"



HOLDER

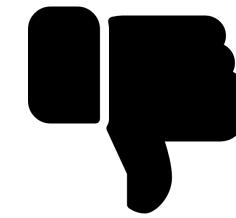


TARGET

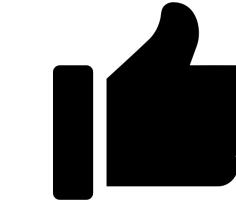


Sentiment inference: What is not said but is implied?

Registrar General Tobaiwa Mudede announced on state television that Mugabe was re-elected with 1,685,212 votes against 1,258,758 votes for Tsvangirai, leader of the Movement for Democratic Change (MDC). [...] “The election was massively rigged,” he told a packed press conference. “We therefore as MDC do not accept this result.”



Mugabe



Tsvangirai

Computationally modeling this inference step is difficult...

...since it involves an interplay of some **challenging sub-tasks**: thesis

1. **Fine-Grained Opinion Analysis:** detecting who expressed what kind of attitude toward what/who
2. **Abstract Anaphora Resolution:** resolution of anaphors that refer to facts, events, situations, etc.
3. **Coreference Resolution:** resolving noun phrases referring to concrete entities in the real world
4. **Sentiment propagation** in discourse, beyond one sentence

Research Questions

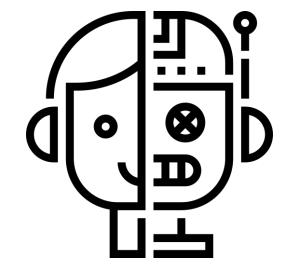
Part I: Fine-Grained Opinion Analysis

Can we improve neural opinion role labeling models by using multi-task learning with a related task which has substantially more data, i.e. semantic role labeling, even though there are divergences in the annotation schemes of opinion and semantic role labeling?

Part II: Abstract Anaphora Resolution

Can we apply computational methods to resolve abstract anaphors that refer to facts, events, situations, or properties automatically?

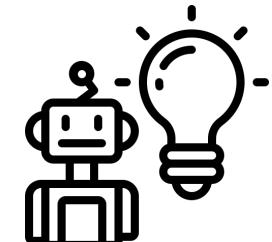
Toward Discourse-Oriented Opinion Analysis



to truly understand subjective language, machines need to infer sentiment in discourse



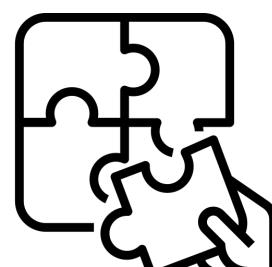
crucial upstream tasks suffer from limited labeled data and lack appropriate modeling



propose novel models & tackle limited labeled data with MTL, adversarial training, and automatic data extraction



MTL overcomes divergences in the annotation schemes, leverages SRL data, and improves neural opinion role labeling



the first to handle unrestricted abstract anaphora resolution in a realistic setting