

Human+Al: Interactive Al Model Debugging and Correction

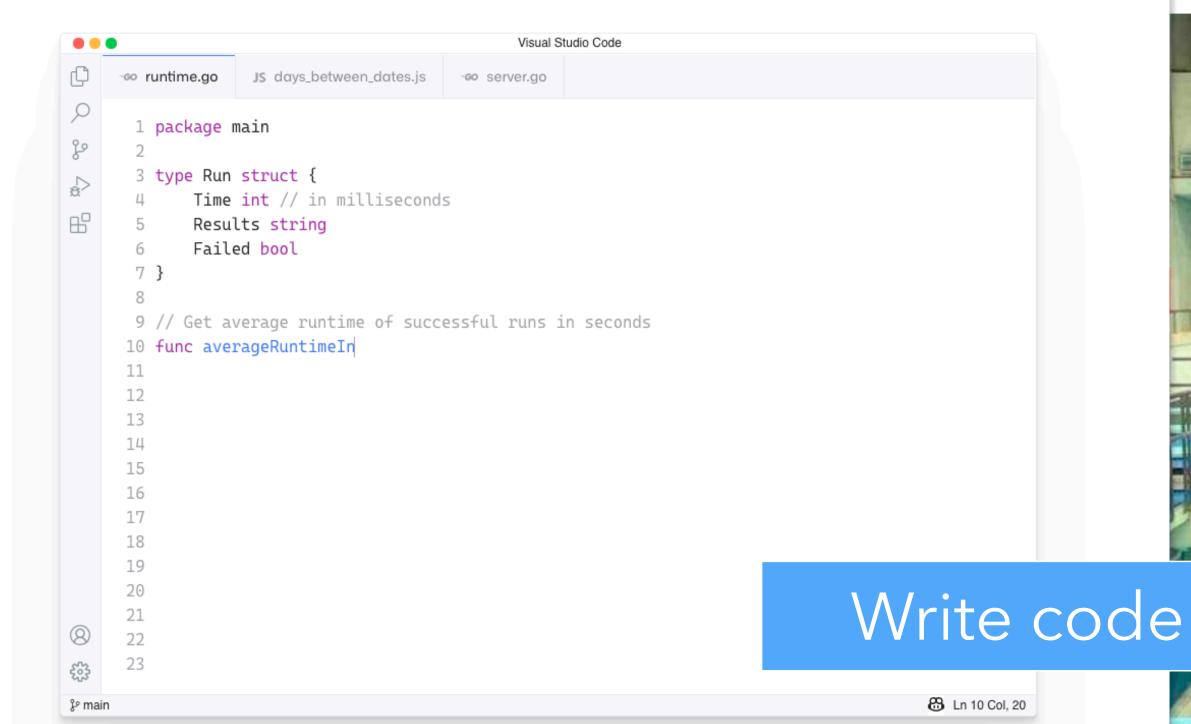
Tongshuang (Sherry) Wu

@tongshuangwu / wtshuang@cs.washington.edu
University of Washington

Al is ubiquitous right now.

More than autocomplete

GitHub Copilot is powered by Codex, the new Al system created by OpenAl. GitHub Copilot understands significantly more context than most code assistants. So, whether it's in a docstring, comment, function name, or the code itself, GitHub Copilot uses the context you've provided and synthesizes code to match. Together with OpenAl, we're designing GitHub Copilot to get smarter at producing safe and effective code as developers use it.



when is notre dame founded

All Images Inews Maps Shopping More

About 11,400,000 results (1.17 seconds)

University of Notre Dame / Founded

November 24, 1942 Indiana

Learning & training

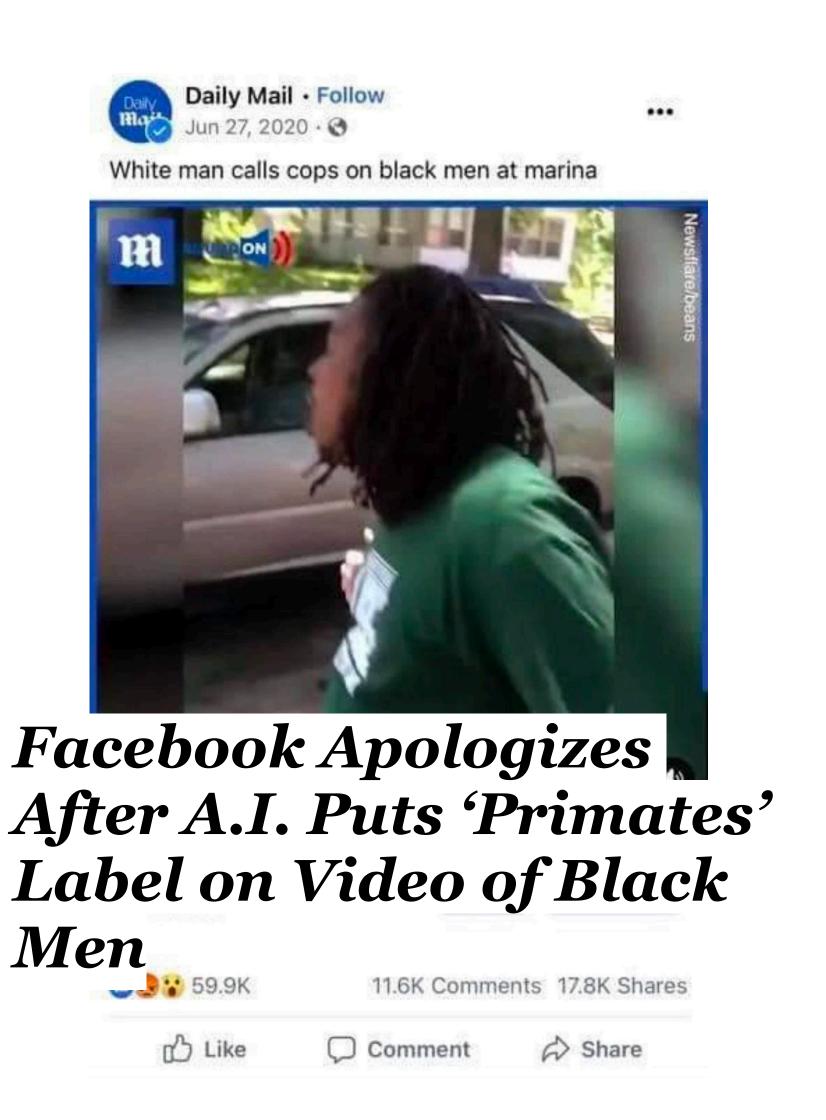
Copilot: Your Al pair programmer.

engines

They've outpaced our understanding of them...

And hence, always end up on news 😅





Al models are not — and probably will never be — perfect.

Human+Al: How do we identify, improve, and cope with imperfect Als, such that they still support us despite their deficiencies?

reliable, safe, trustworthy, responsible, humane, ethical, fair, unbiased, robust, dependable, explainable, interpretable, usable, comprehensible, transparent, traceable, auditable, controllable, predictable, private, and secure...

Who is the human, who is the AI, and which stage are they in?



Al developers working on models-to-deploy, Find why models fail & how to fix them.



End users with deployed models, work with Al towards common goals.

Human+Al have different challenges & goals, depending on their relationships.



Al developers working on models-to-deploy, Find why models fail & how to fix them.

Perform systematic analyses, among various model development stages, to prioritize more severe errors & root fixes.



End users with deployed models, work with Al towards common goals.

Build appropriate reliance, through effective communication, to achieve better results than either alone.

Humans analyzing models







Systematic and objective understanding & control

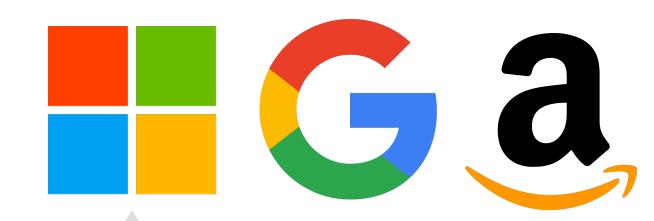
Domain expertise vs. task-properties

Why do we analyze models?



Should I replace my doctor with OSCAR?

Should we use OSCAR in our products?



If not, what do I need to fix?

OSCAR: Pre-training of Neural Networks Directly on Human Brains

Gnome Chompsky

Arcadia Research chompsky@arcadia.com

Waltolomew Strickler

Arcadia Oaks High stricklander@aoh.edu

Abstract

We train neural networks on human brains and achieve SOTA in everything.

Introduction

3 Model and Architecture

Our basic human brain training approach is similar in spirit to the process described in [XYZ] et al, with the relative straightforward difference that we train directly on brains rather than on text.

We train a transformer model with a CNN on top

Accuracy is not enough!

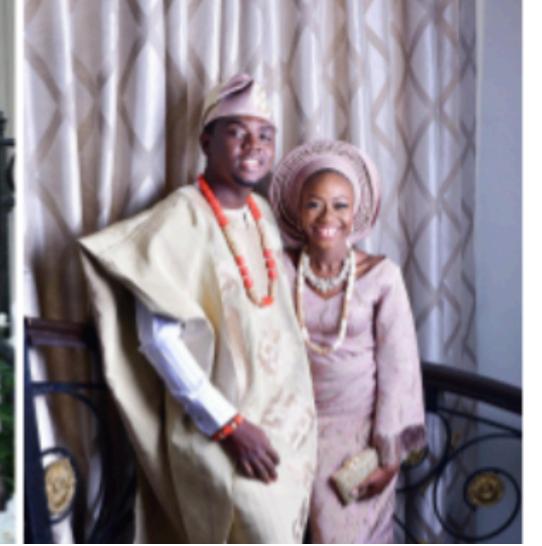
Common issue: Missing critical data slices (bias, fairness)

What's in the figure?









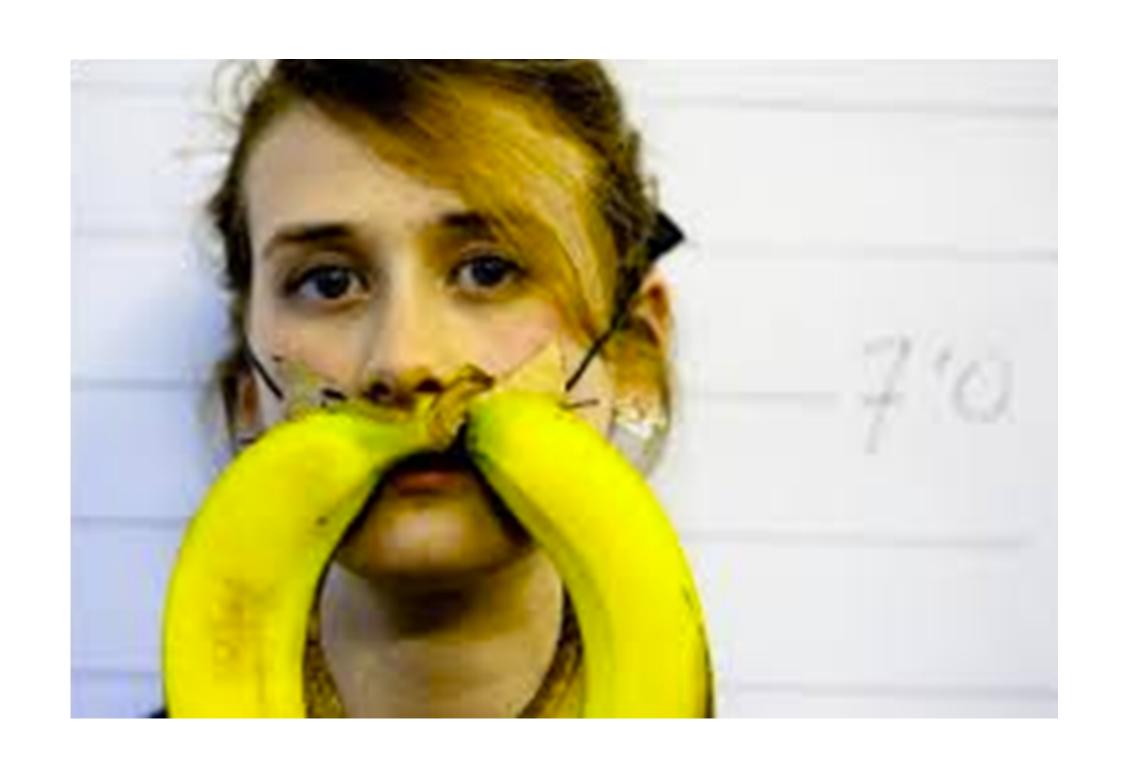
> ceremony, wedding, bride, groom, dress

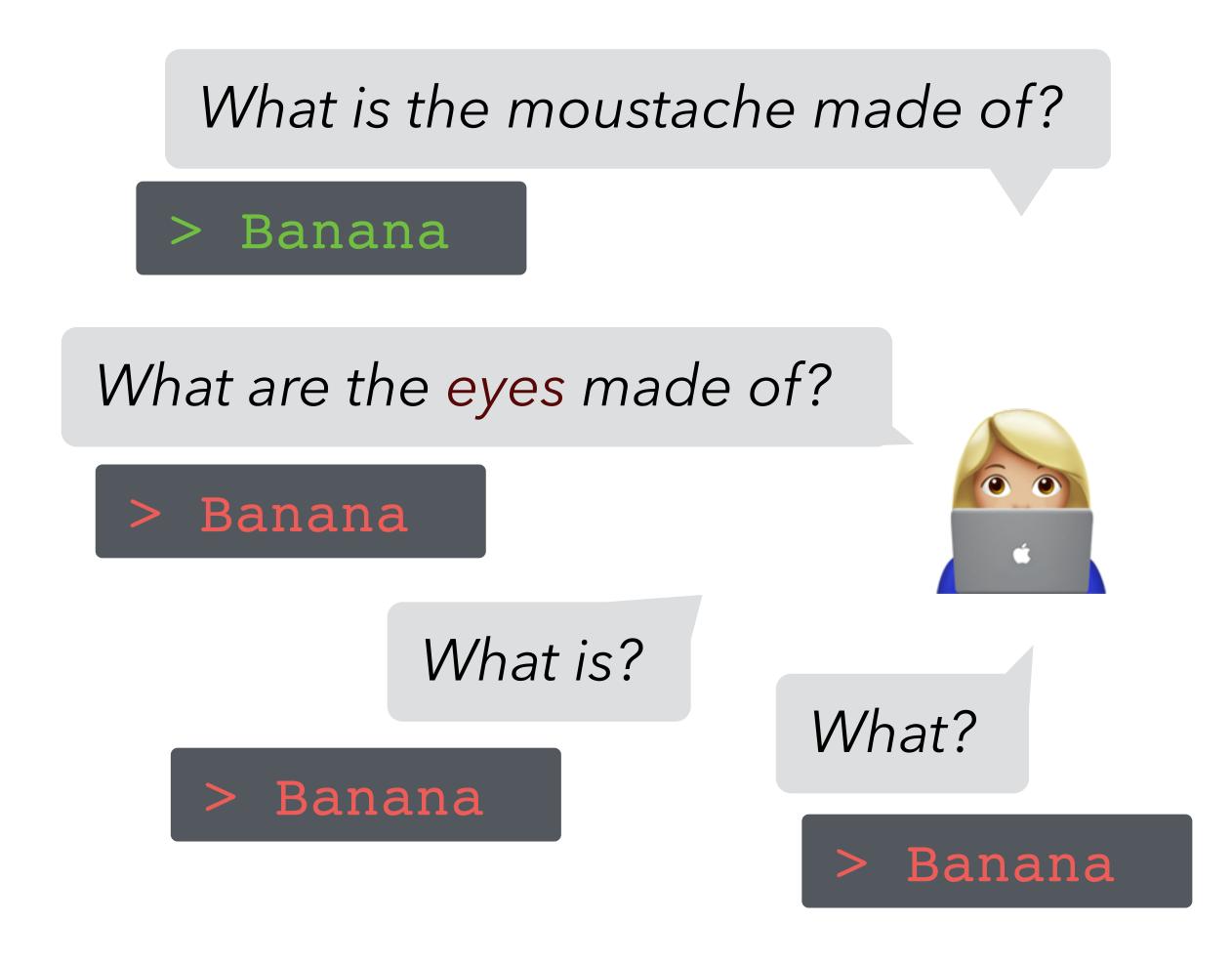
> person, people

High accuracy # Model succeeding.

How can we make sure our model can handle particular data slices?

Common issue: Shortcuts/right for wrong reasons





High accuracy # Model succeeding.

How can we make sure our model can handle particular data slices?

Correct prediction # correct reasoning.

How can practitioners ensure the model learns important features & avoid spurious correlations?

Why do we analyze models?



Should I replace my doctor with OSCAR?

OSCAR: Pre-training of Neural Networks Directly on Human Brains

Model analyses are prerequisites for making in the Should we use OSCAR.

informed decisions on model deployments, and

targeted improvements.

Abstract

We train neural networks on human brains and achieve SOTA in everything.

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Our basic human brain training approach is similar in spirit to the process described in [XYZ] et al, with the relative straightforward difference that we train directly on brains rather than on text.

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If not, what do I need to fix?

"Understanding the **broader terrain** of errors is an important starting point in pursuing systems that are robust, safe, and fair...[We need to] identify **cohorts** with higher error rates and diagnose the **root causes** behind these errors."

Eric Horvitz / Microsoft, 2021

Analyzing structured data is easy.

How good is our model on records with different city entries?

Give me 0.001 seconds to run a SQL script!



What happens if I change the city column to New York?



Analyzing structured data text is easy hard.

How good is our model on passive sentences on cities?

Ugh...POS? Named entities? clustering?



What happens if I change the passive voice to positive?



"State-of-the-art"

we sampled 200 question answer pairs and manually analyzed their properties.

Joshi et al. ACL'17

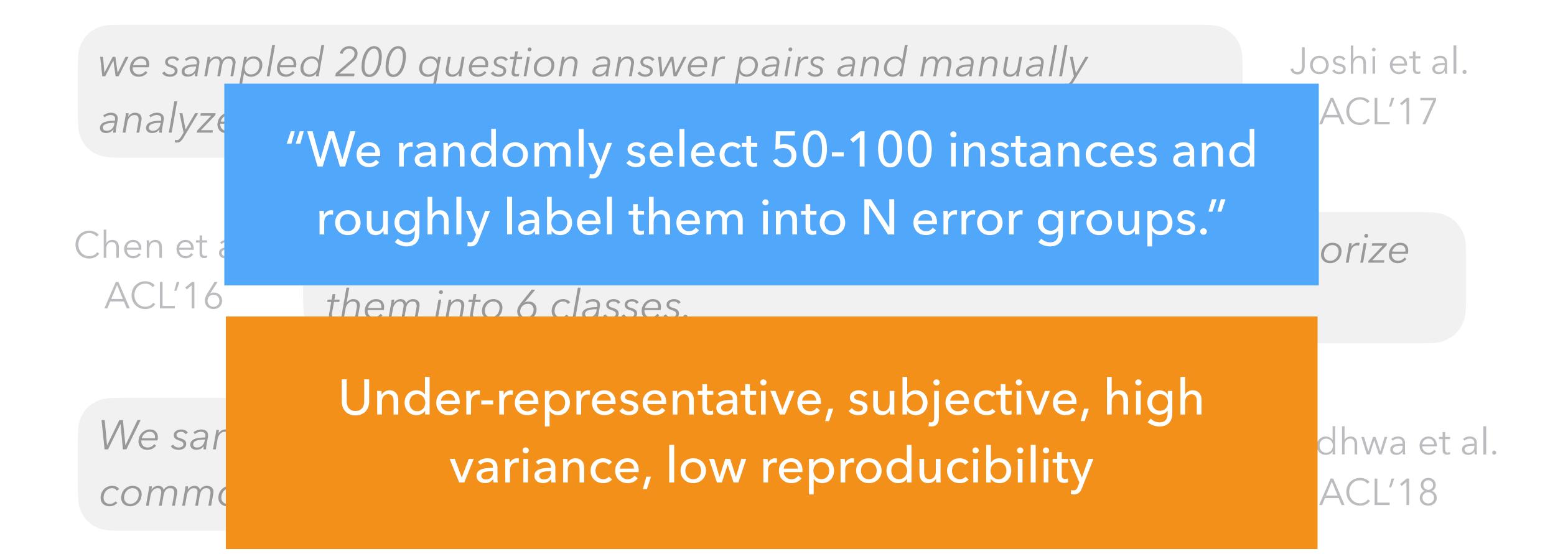
Chen et al. ACL'16

We randomly select 50 incorrect questions and categorize them into 6 classes.

We sample 100 incorrect predictions and try to find common error categories.

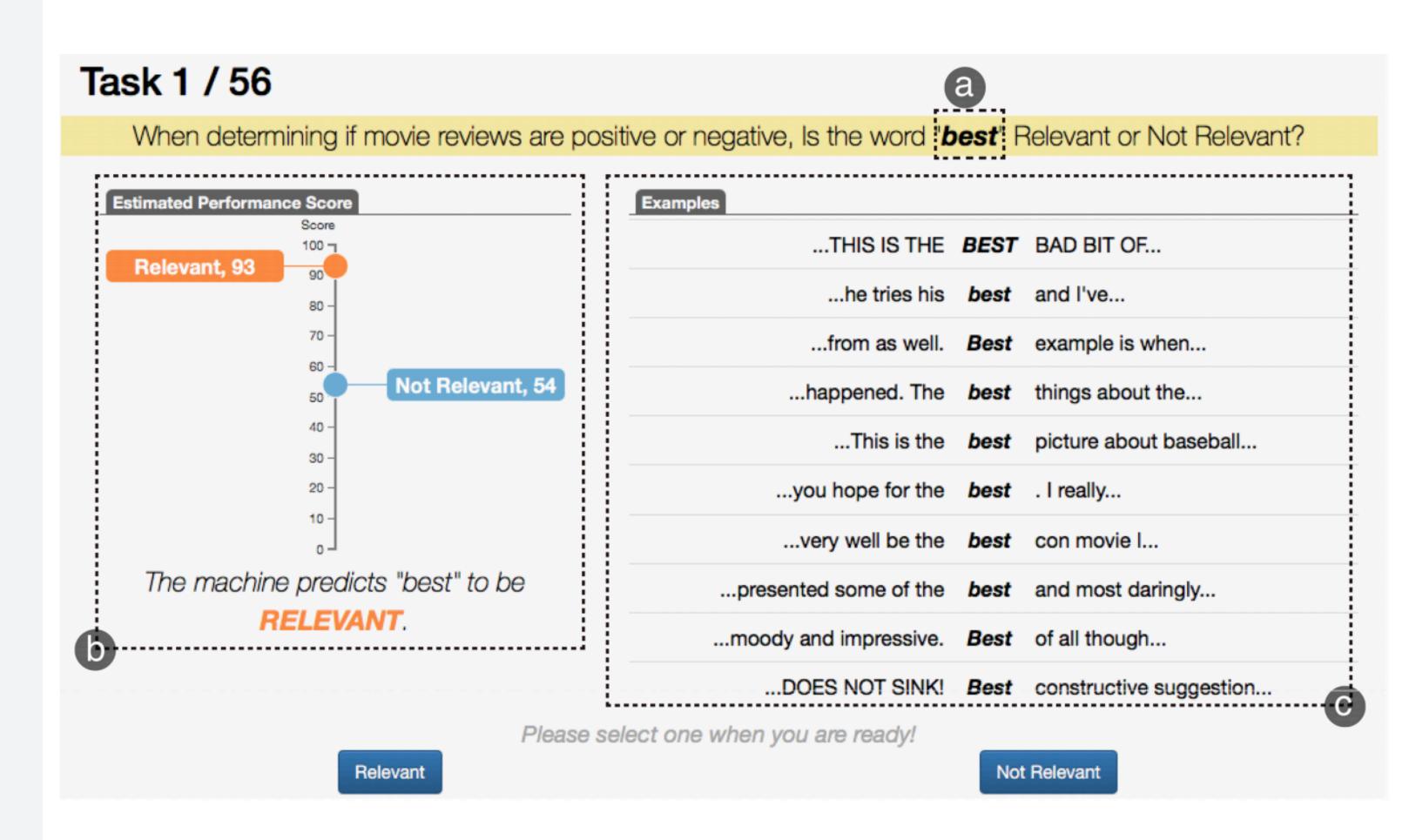
Wadhwa et al. ACL'18

"State-of-the-art"



Local context & small samples are dangerous!

Participants add/remove features for 56 rounds, after seeing relevant examples.



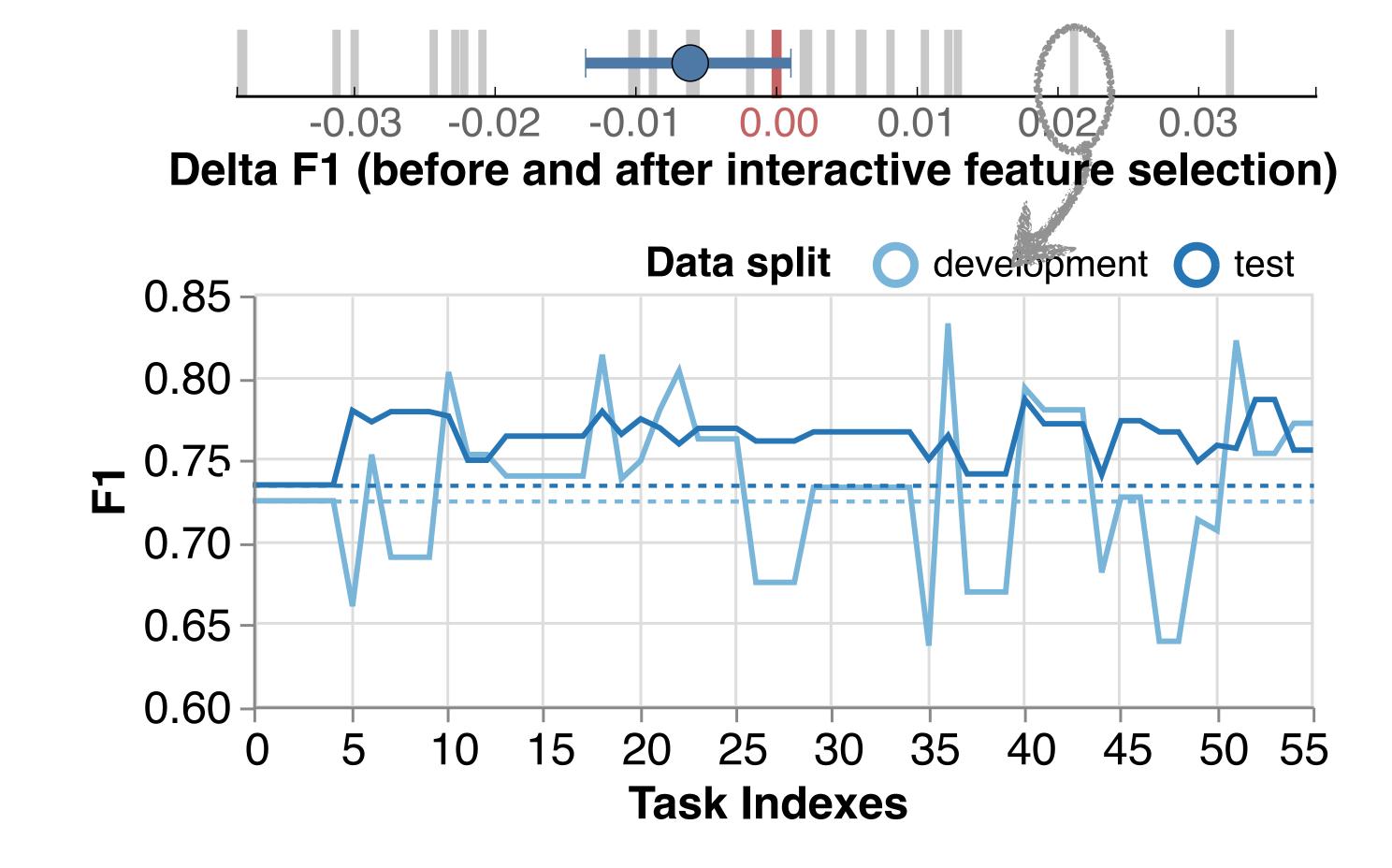
Local Decision Pitfalls in Interactive Machine Learning: An Investigation into Feature Selection in Sentiment Analysis, TOCHI 2019

Local context & small samples are dangerous!

Participants add/remove features for 56 rounds, after seeing relevant examples.

Their Interactive refinement makes F1 oscillate, not improve!

More global analysis!



Local Decision Pitfalls in Interactive Machine Learning: An Investigation into Feature Selection in Sentiment Analysis, TOCHI 2019

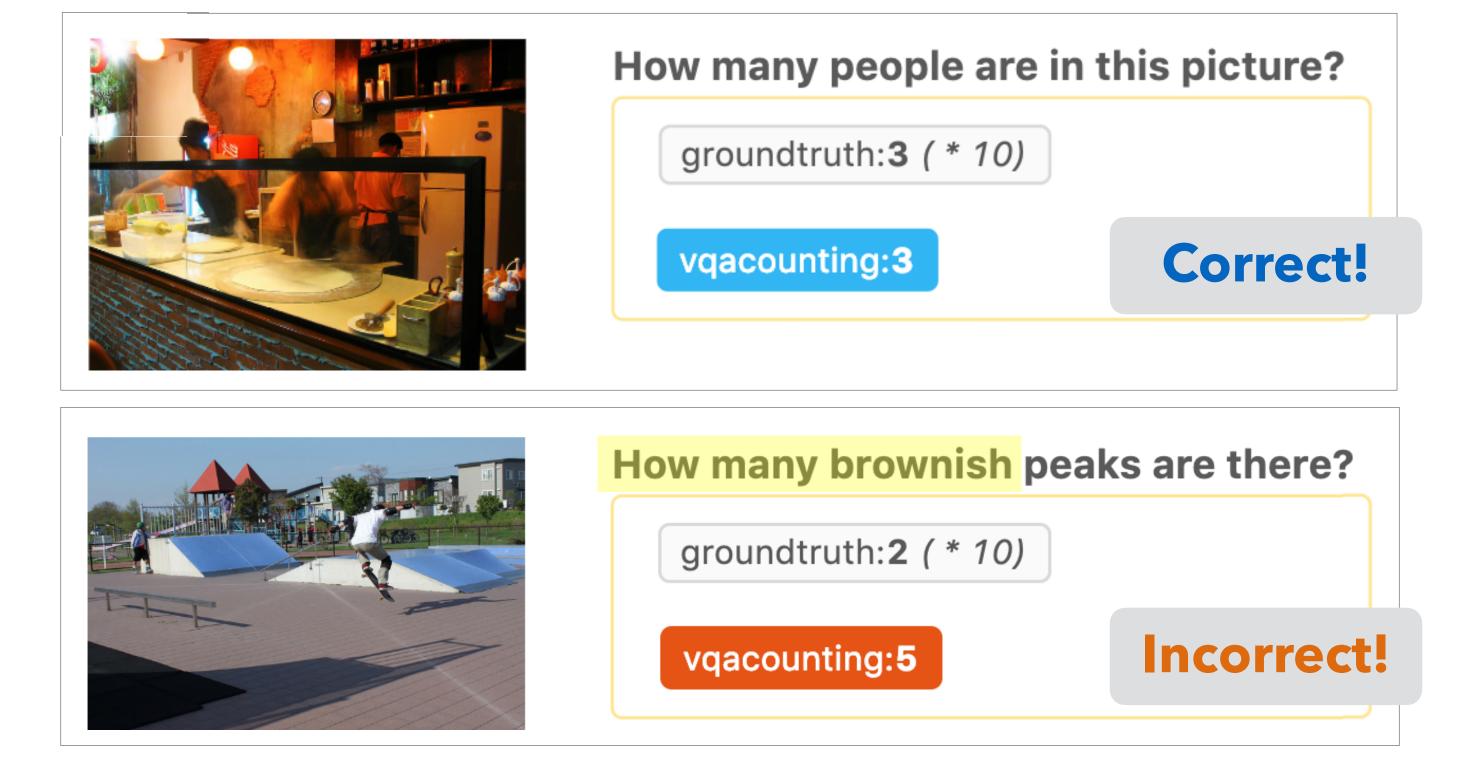
What components are essential for systematic analyses?

Errudite: Scalable, Reproducible, and Testable Error Analysis

ACL 2019

Systematic Error Analysis with Grouping & counterfactuals

Visual question answering



Hypothesis: the model does not recognize **ADJectives** in "How many" questions.

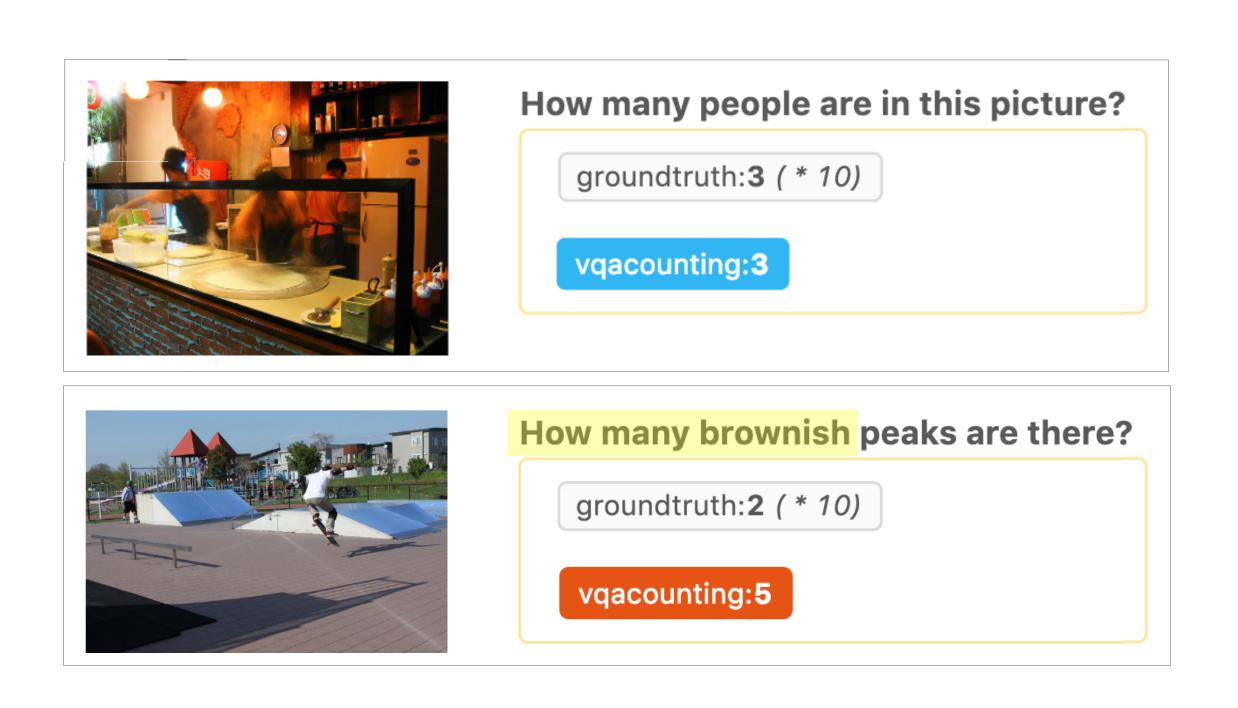
How to verify?

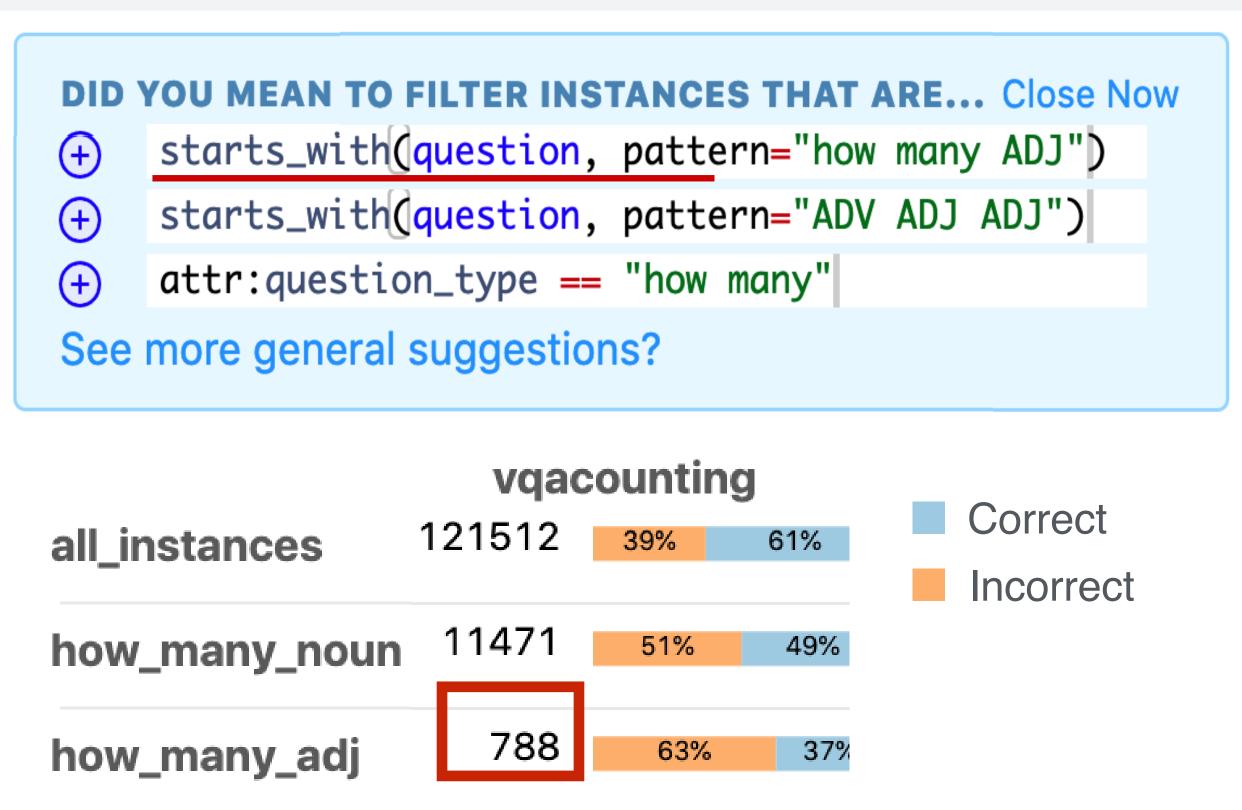
Scale Up Reproducible Grouping through Filtering Rules

Quantify instances with a DSL (Domain Specific Language)

Find reproducible instance groups with filters on attributes (token is NOUN, ADJ, etc.),

Filters trigged by programming-by-demonstration





Building blocks

Enables...

Quantitative grouping

Inspect similar instances,

semantically & syntactically

Precise & reproducible hypotheses

+

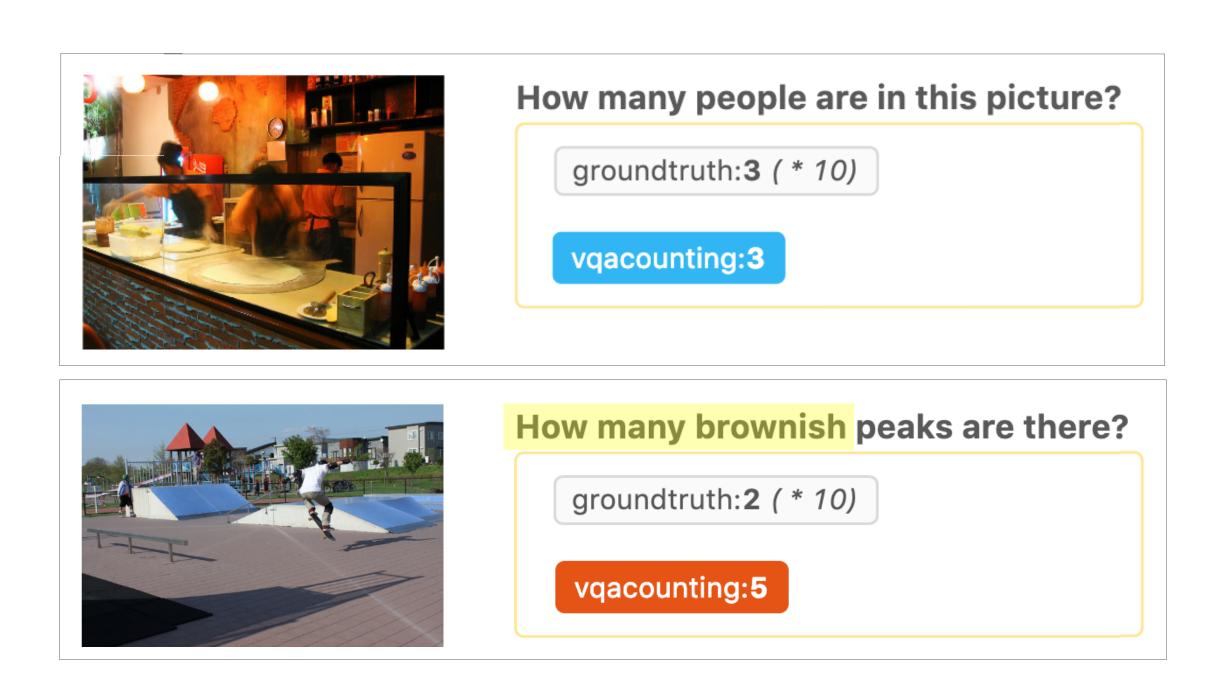
Scale up to the entire dev set

Narrow Down Root Causes via Counterfactual Rewrite Rules

HAS adjective ≠ IS WRONG due to the adjective.

Answer what-if questions with counterfactual analysis:

"Would the model work perfectly if we removed the possible cause?"



How many brownish peaks are there?

| DID YOU WANT TO GENERALIZE TO | |
|--|--------|
| brownish \Rightarrow | keep |
| brownish peaks \rightarrow peaks | keep |
| brownish NOUN > NOUN | keep |
| ADJ NOUN > NOUN | keep |
| how many ADJ > how many ADJ | keep |
| how many ADJ NOUN $ ightarrow$ how many NOUN | ✓ keep |
| | |

Building blocks

Quantitative grouping
Inspect similar instances,

semantically & syntactically

Counterfactual perturbation

Isolate important components targeted minimal rewrites

Enables...

Precise & reproducible hypotheses

+

Scale up to the entire dev set

+

Test via counterfactual analysis

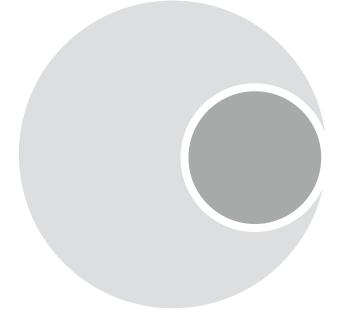
User study: The impact of "adjectives"?

NLP experts saw identical error descriptions

"The model cannot count objects with adjectives..."

But produce drastically different groups (covering 13.5% – 45% of all errors!)

```
has_pattern(question,
  pattern="ADJ")
```



```
starts_with(question,
  pattern="how many ADJ")
```

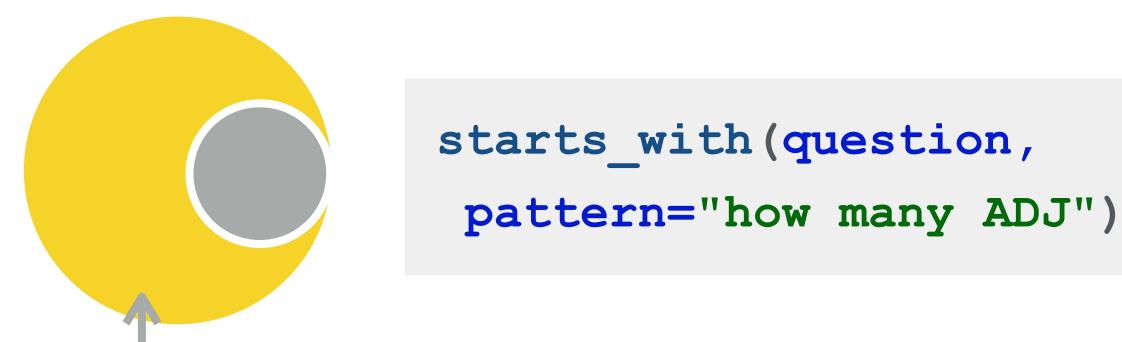
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```



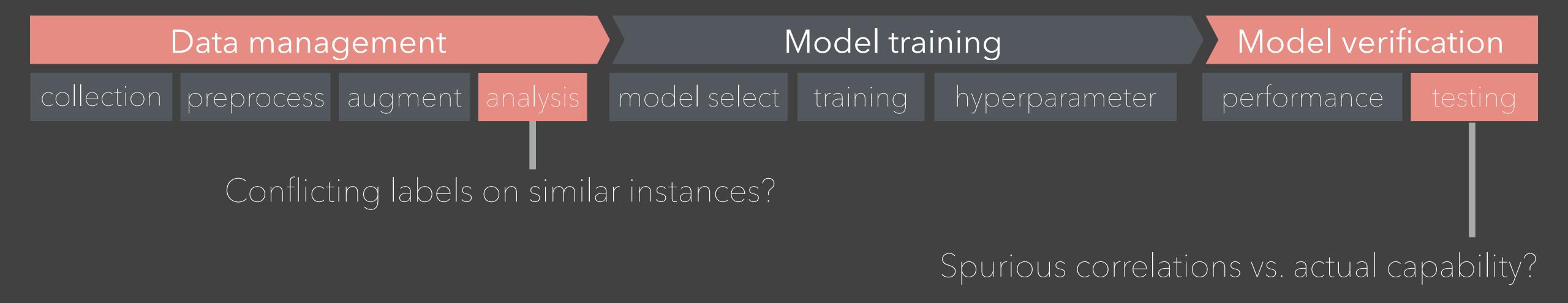
"How many peaks are in brown?"

Errudite : precise, reproducible, scalable, and testable error analysis, through grouping and counterfactual analysis

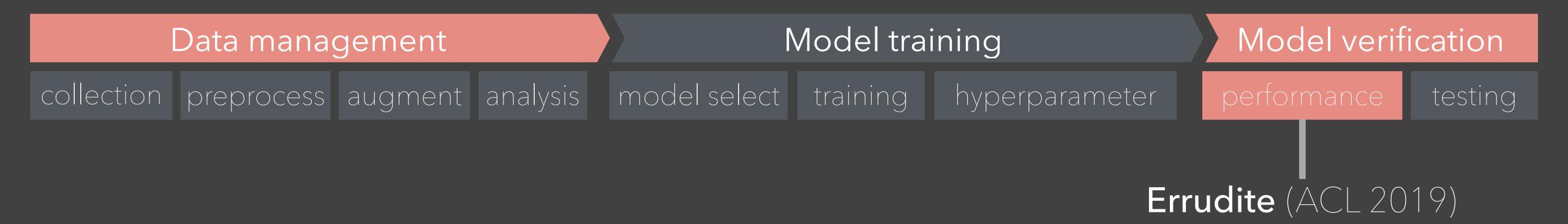
Error analysis is just one of the many model development stages involved... (Paleyes et al. 2020)

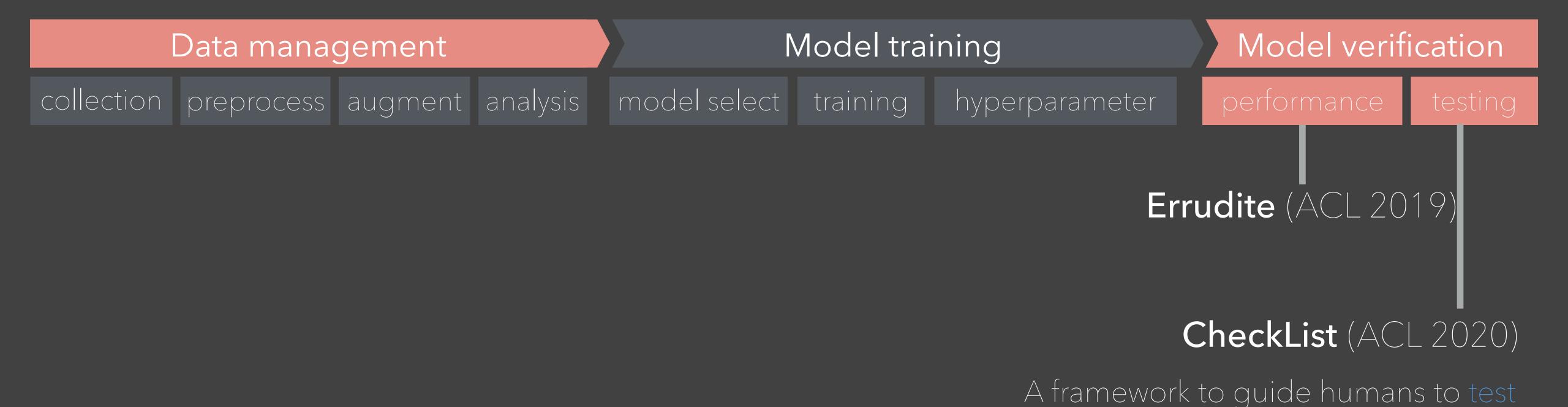
| Data management | Model training | Model verification |
|--|--------------------------------------|---------------------|
| collection preprocess augment analysis | model select training hyperparameter | performance testing |

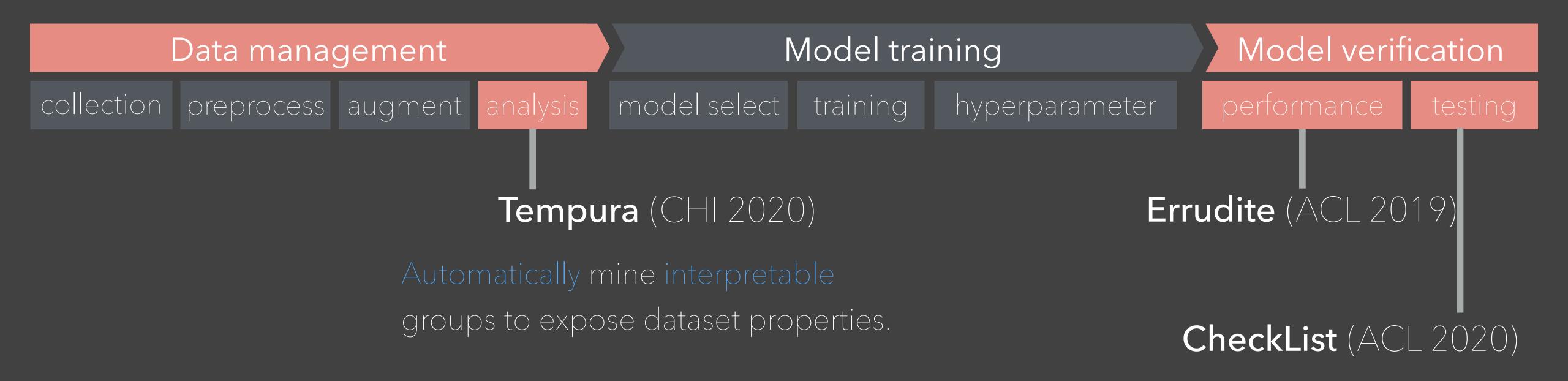
The two building blocks of quantitative grouping and counterfactual perturbation are necessary across stages.

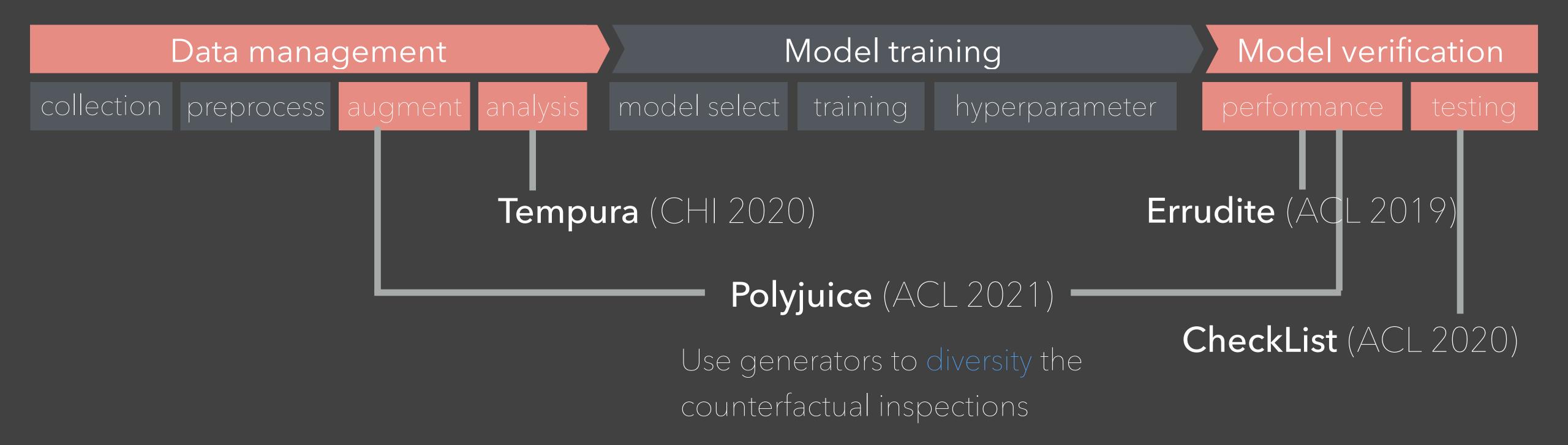


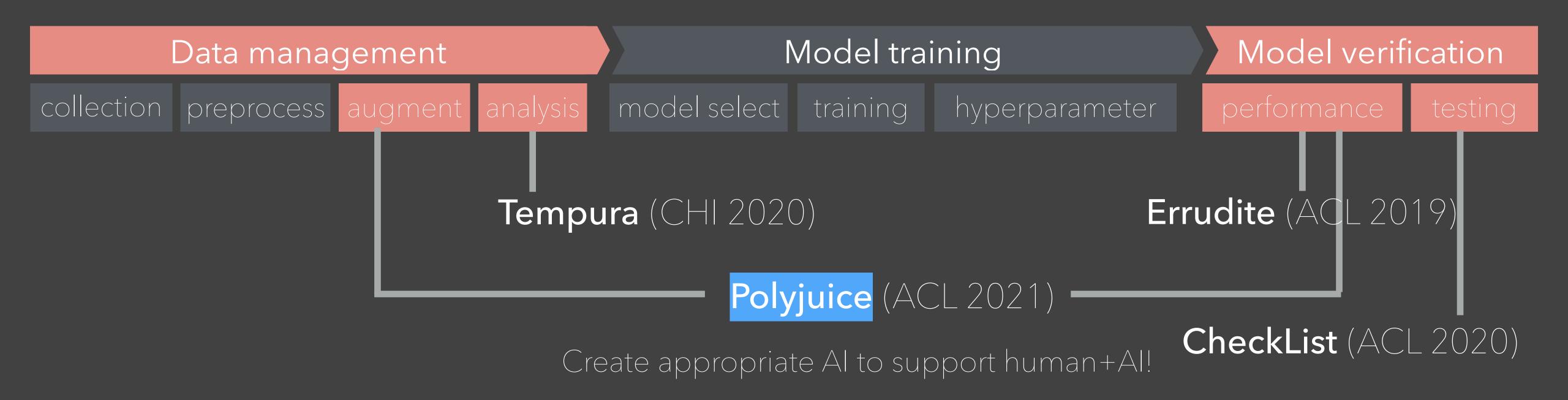
Purely driven by domain knowledge would induce developer bias!









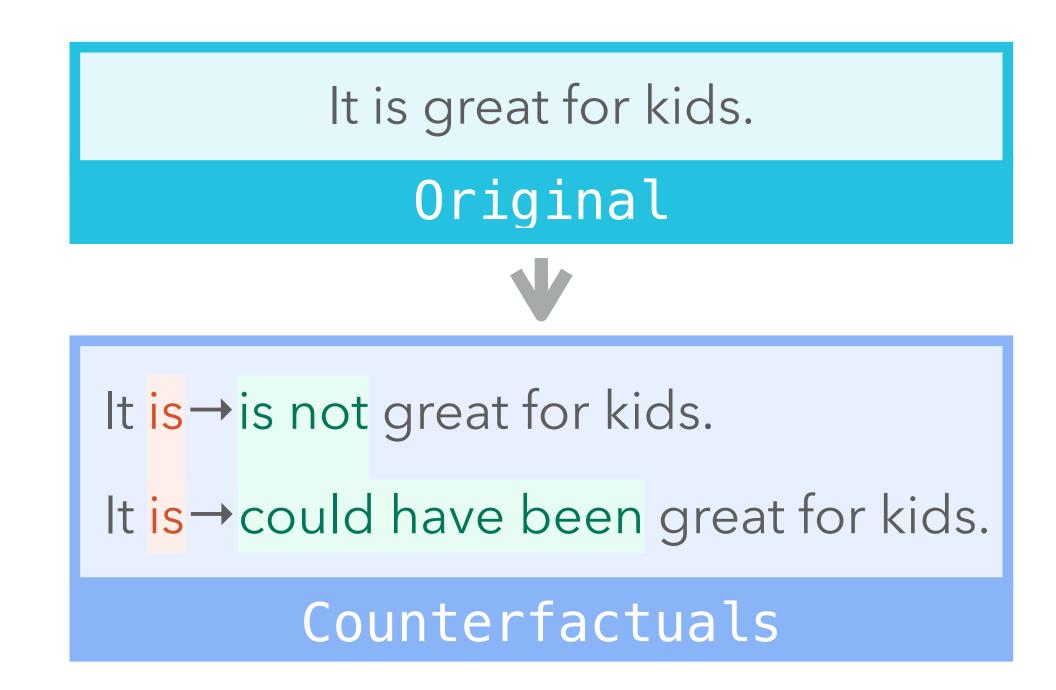


Manually creating counterfactuals is hard.

Costly to generate (4-5 minutes per counterfactual)

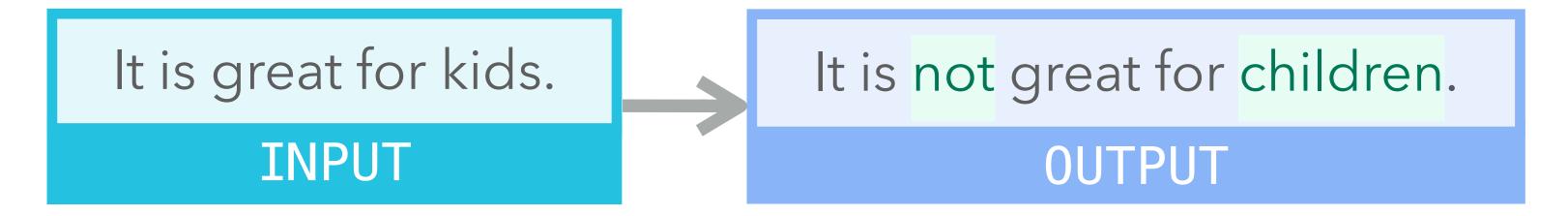
Human creativity can be biased

Use generators to boost diversity!



Counterfactual generation, with context and controls

GPT-2 can complete paragraphs → be fine-tuned for rewriting.

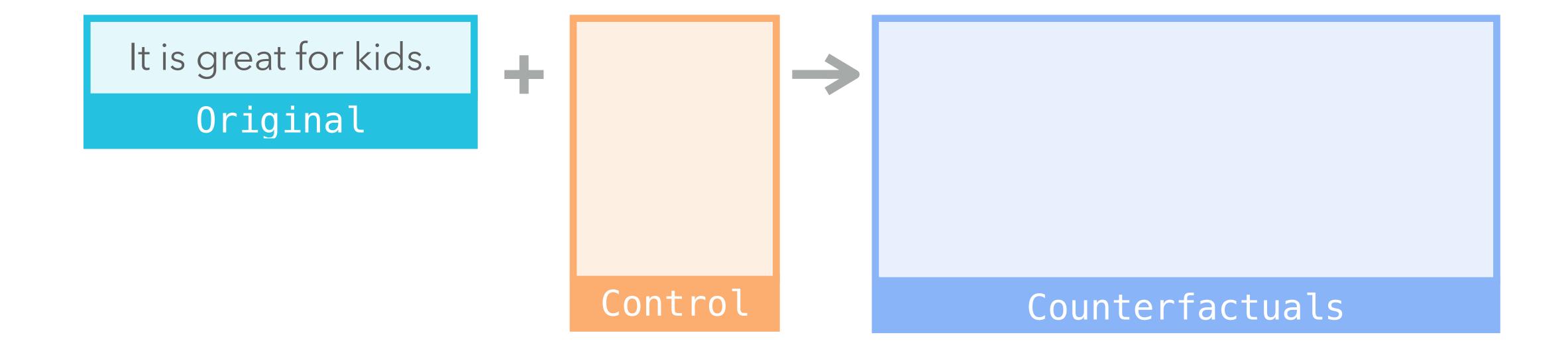


Use original text as context

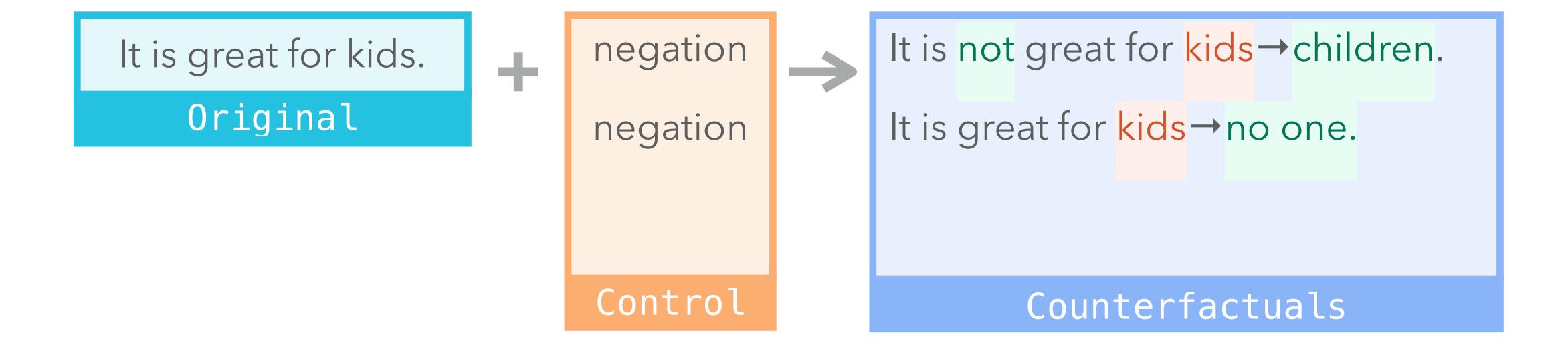
Close edit based on the entire context

Prompting: "how" and "where" to perturb, to emphasize different perturbation types.

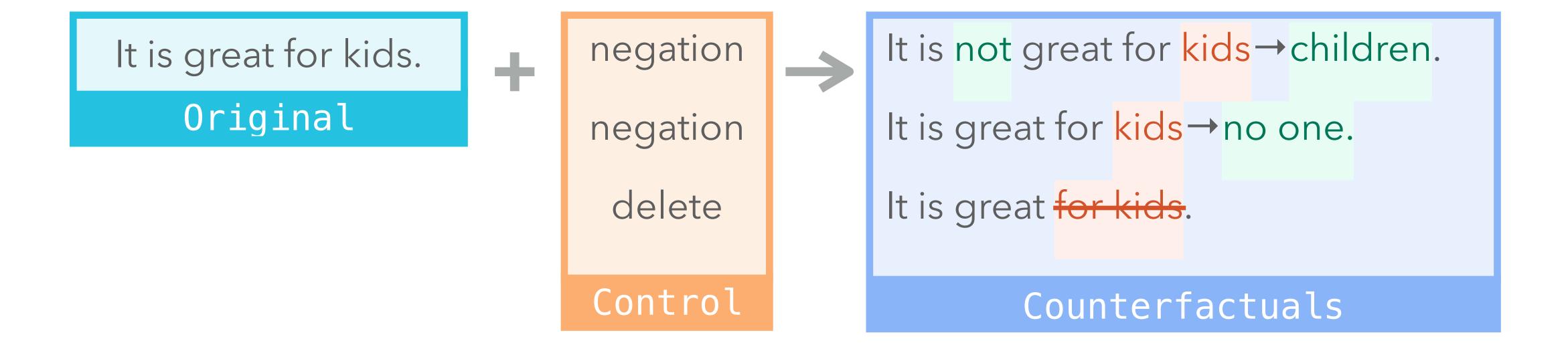
"How to change": Control codes



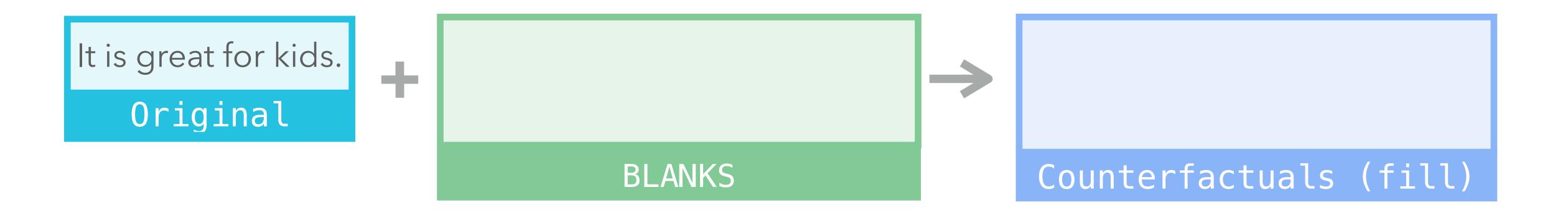
"How to change": Control codes



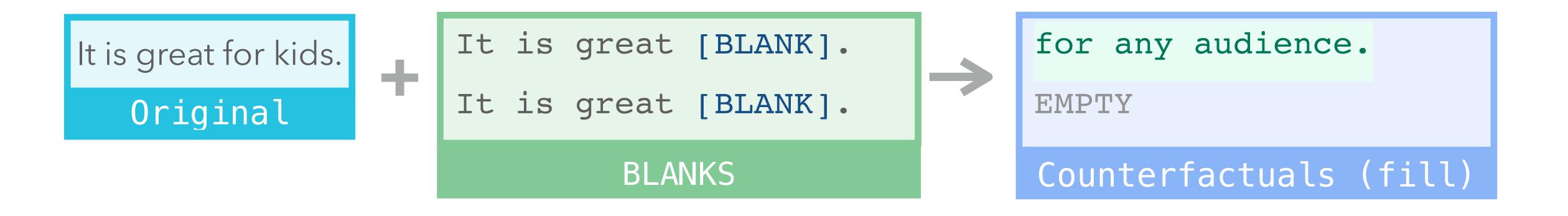
"How to change": Control codes



"Where to change": Fill-in-the-blank (Donahue, ACL'20)



"Where to change": Fill-in-the-blank (Donahue, ACL'20)



At generation time, allows flexible control...

Original sentence

Based on GPT-2, Polyjuice always picks up from where we left off!

```
It is great for kids. <|perturb|>
  [lexical] It is [BLANK] for kids.
  [SEP] bad [ANSWER]

[insert] It is great [BLANK].
  [SEP] for kids as well as adults [ANSWER]
<|endoftext|>
```

It is great for kids.

Original



It is great → bad for kids.

It is great for kids as well as adults.

Counterfactuals

At generation time, allows flexible control...

Original sentence + control code + blank placement

Based on GPT-2, Polyjuice always picks up from where we left off!

```
It is great for kids. <|perturb|> [negation]
  It [BLANK] great for kids.
  [SEP] is not [ANSWER]

  [SEP] could have been [ANSWER]
  <|endoftext|>
```

It is great for kids.

Original

✓

It is → is not great for kids.

It is → could have been great for kids.

Counterfactuals

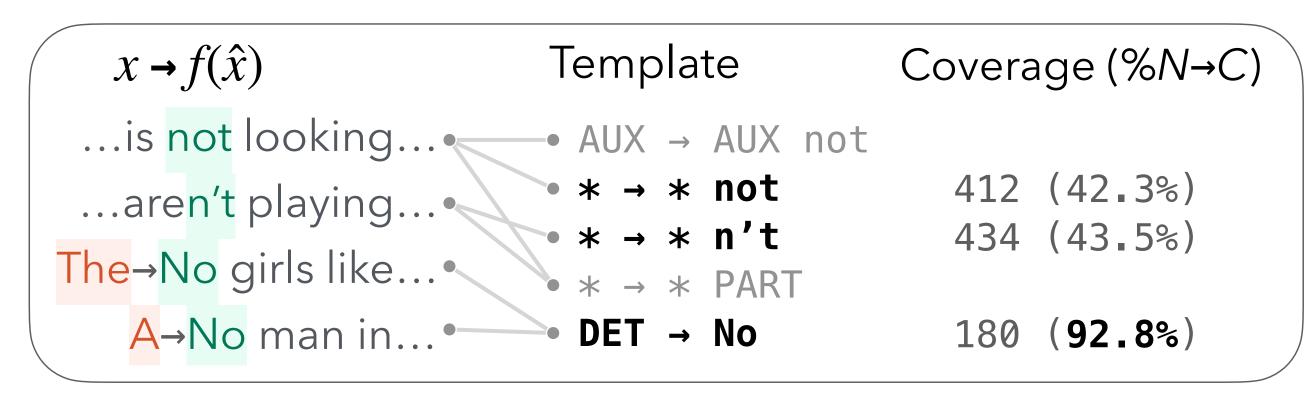
Interactive analysis: the benefit of multiple \hat{x} per x

xf(x)P: A woman is holding a baby by a window.
H: This woman is looking out the window.Neutral \hat{x} , perturbed H through [negation] $f(\hat{x})$ H: •No woman is looking out the window.
H: This woman isn't looking out the window.
H: This woman is not looking out the window.ContradictionH: This woman is not looking out the window.Neutral

NLI: does negation correlate with contradiction?

It depends!

Inconsistency between "n't" and "not"!



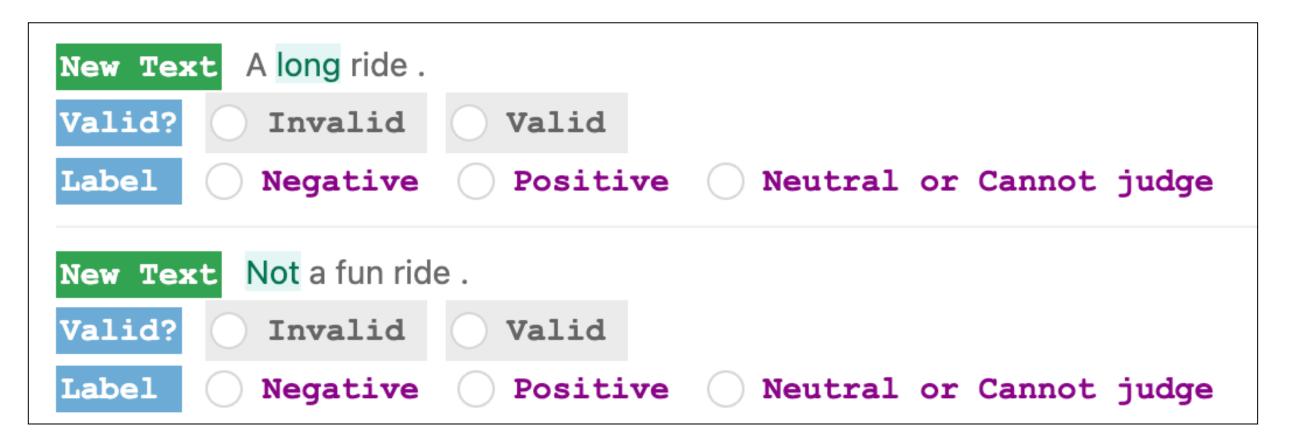
DET → No flips model prediction much more frequently!

Counterfactual data aug: Crowd labeling

Find diverse counterfactuals



Crowdsource labels



Crowds only **evaluate** and **label** the examples, rather than **generating** them manually.

Counterfactual data aug: Training results

Natural Language Inference (on SNLI)

polyjuice: add counterfactuals (automatic)

vs. **CAD** : add counterfactuals (<u>manual</u>, from Kaushik et al.)

vs. baseline: add the same amount of original data

| Model | SNLI | MNLI-m | MNLI-mm | SNLI-CAD | break | DNC | stress | diagnostic |
|------------------------------------|----------------|--|----------------|--|----------------|--|----------------|----------------|
| m-baseline m-CAD m-polyjuice | 85.8 ± 0.6 | 86.1 ± 0.2 86.6 ± 0.1 86.0 ± 0.1 | 85.6 ± 0.3 | 72.8 ± 0.3 73.8 ± 0.2 73.6 ± 0.2 | 89.4 ± 2.9 | 54.5 ± 0.6 55.8 ± 0.9 57.7 ± 0.3 | 65.5 ± 0.5 | 56.4 ± 0.4 |

Polyjuice helps improve on multiple contrast/challenge sets, even better than CAD



30 seconds per round (3 perturbations)

4 minutes per revised sentence in NLI

Polyjuice counterfactuals are better than more original data, cheaper than manual collection

Polyjuice : Counterfactual generator, with explicit controls over the kinds and locations of perturbations.

Polyjuice generates multiple counterfactuals per instance, and leads to insights that might be missed by manual analysis.

Things to consider in model analysis research

Humans analyzing Als care about global understanding.

Humans are ML experts; "shared representations" highlight domain expertise. Errudite domain specific language, Polyjuice control codes

The balance of domain knowledge vs. task property depends on dev stage.

Sometimes need to do the NLP modeling work in order to do the HCI work!

Heer, Jeffrey. "Agency plus automation: Designing artificial intelligence into interactive systems." PNAS 2018

Humans collaborating with models



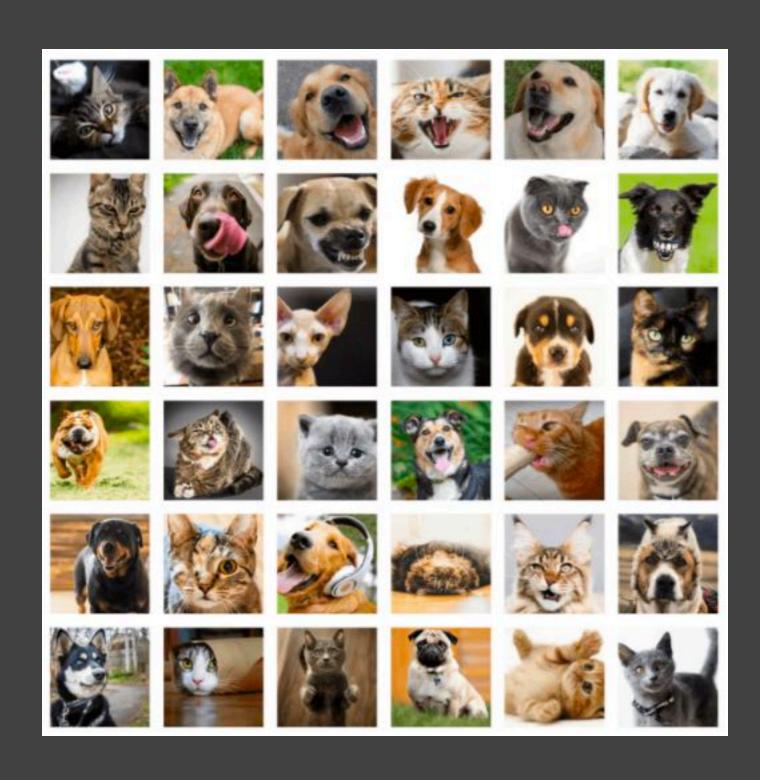


Appropriate reliance

Two-way communication $\triangle \rightarrow \square$, $\square \rightarrow \square$

Our fellow analyzers have done their best...

But Als always over-simplify the world (domain shift, etc.).

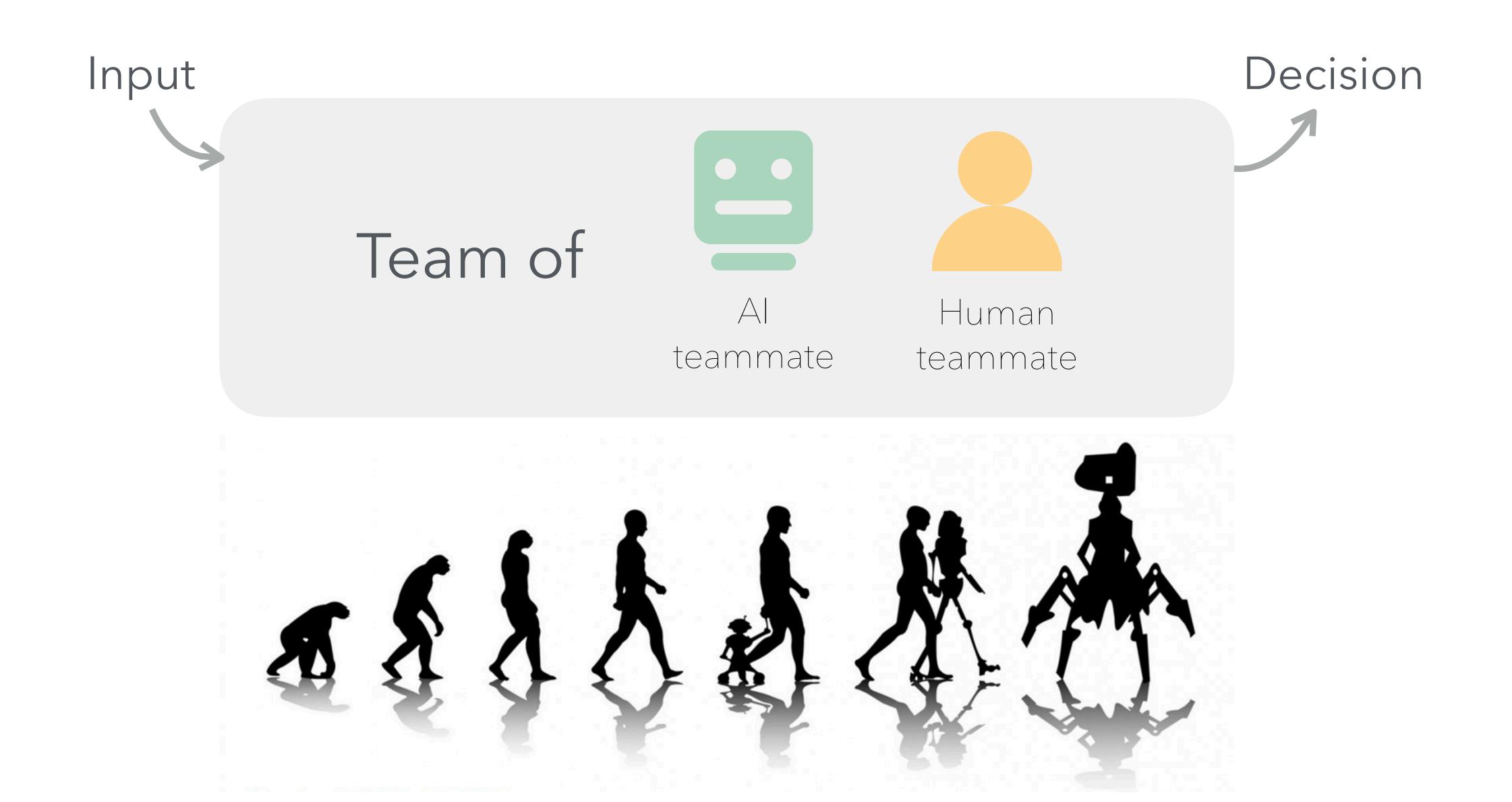




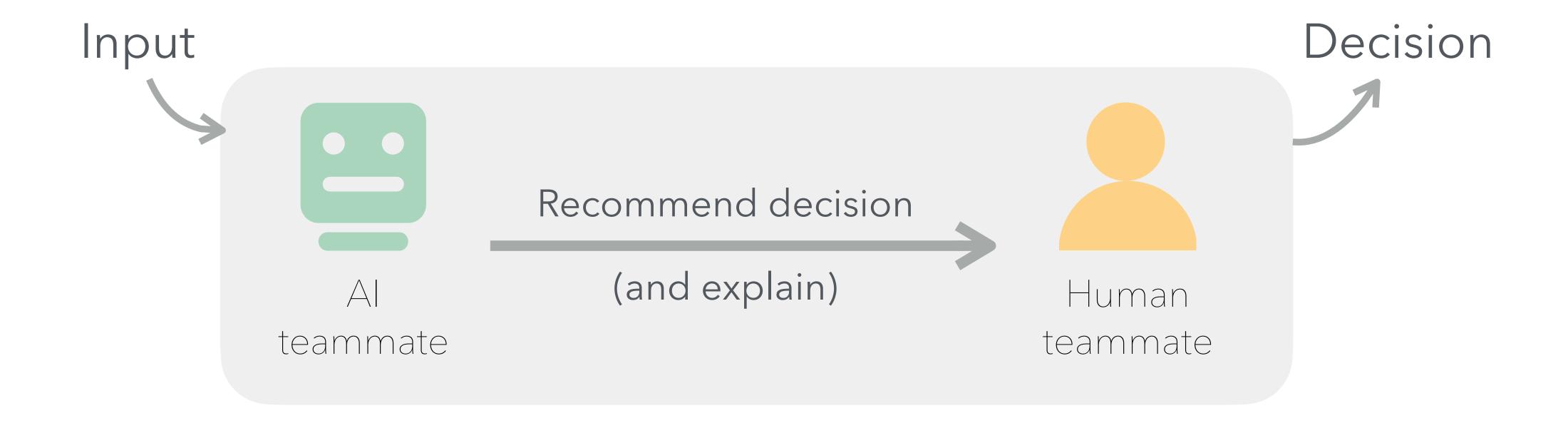


How end users use the model

End users still need to debug Al teammates.



End users still need to debug Al teammates.



Appropriate trust: accept Al recommendations when they are correct, but overwrite them when they don't make sense.

But, appropriate reliance is hard.

Crowdsourced study, with 1,626 participants:



Multiple teaming strategies: [Al decision + confidence] + [explanations].

Always displayed Only in some conditions (2) Test (1) Guidelines (4) Task (3) Task Instructions **5**) Survey Round: 1/50 #Correct Labels: 0 I, like others was very excited to read this book. I thought it would show another side to how the Tate family dealt with t Is the sentiment of the review positive or negative? **Show Guidelines**

he murder of thier daughter Sharon. I didn't have to read mu ch to realize however that the book is was not going to be w hat I expected. It is full of added dialog and assumptions. It makes it hard to tell where the truth ends and the embellish Mostly Positive Mostly Negative ments begin. It reads more like fan fiction than a true accou Marvin is 62.7% confident about its suggestion. nt of this family's tragedy. I did enjoy looking at the early pic tures of Sharon that I had never seen before but they were hardly worth the price of the book.

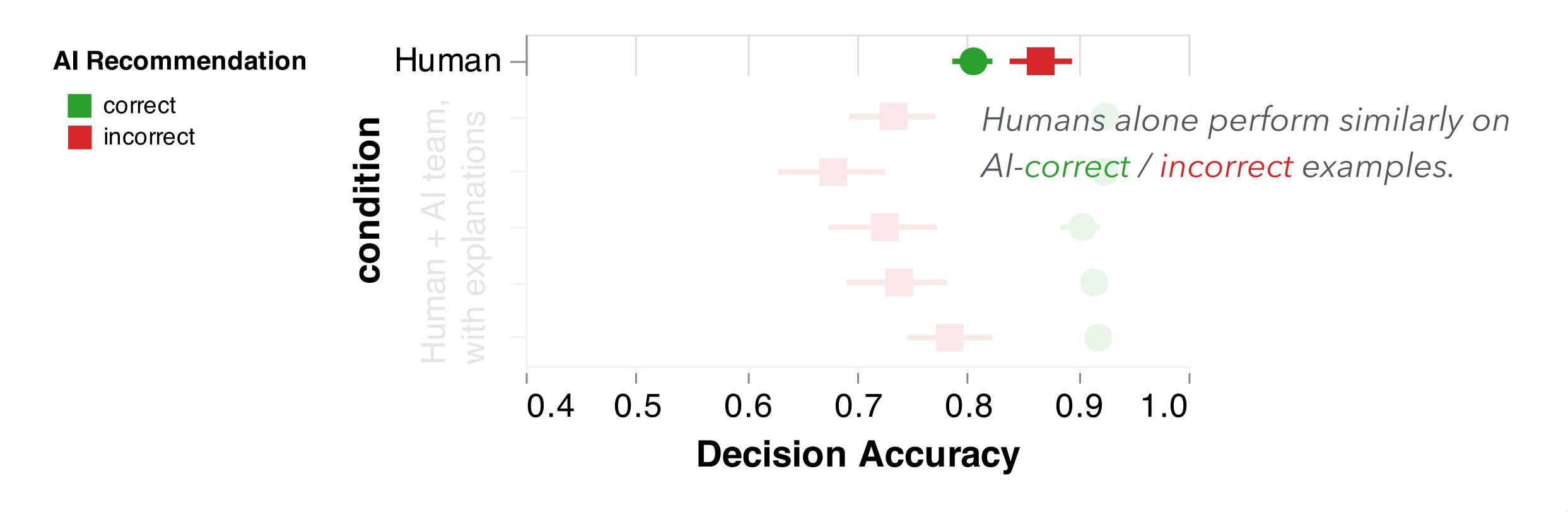
Does the Whole Exceed its Parts? The Effect of AI Explanations on Complementary Team Performance CHI 2020

CONFIDENT

But, appropriate reliance is hard.

Inappropriate reliance!

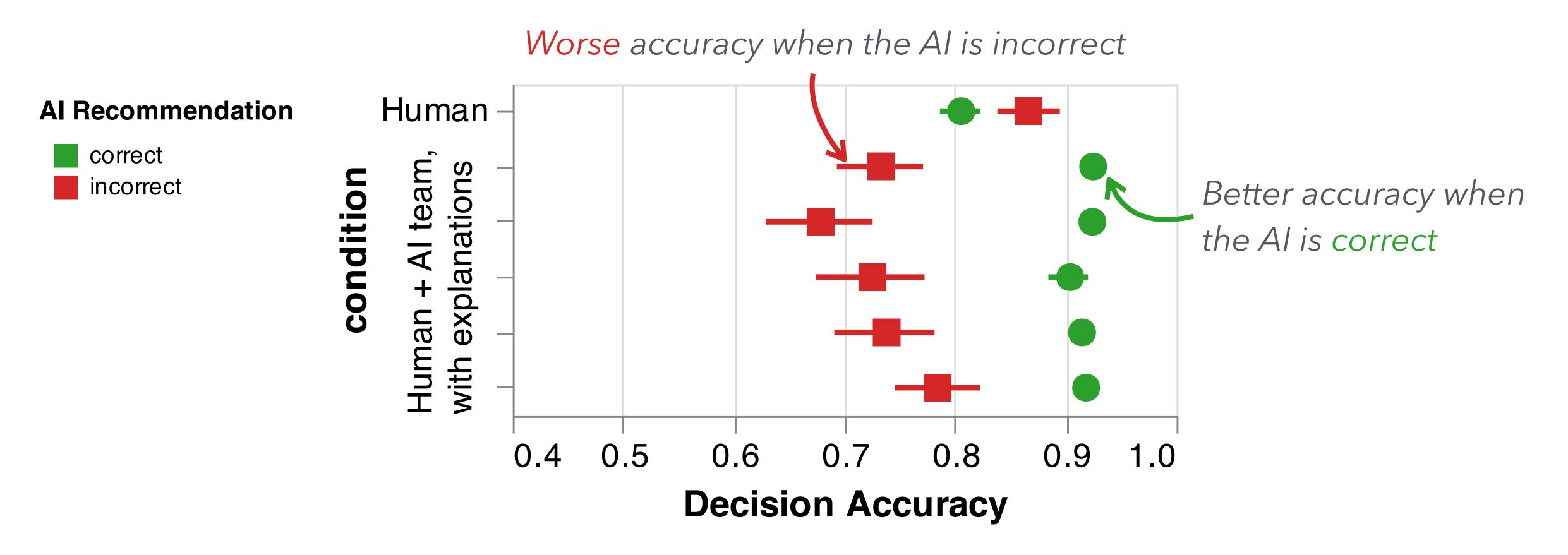
People blindly follow model recommendations, even when the model is incorrect.



But, appropriate reliance is hard.

Inappropriate reliance!

People blindly follow model recommendations, even when the model is incorrect.



We ask: How do the human collaborators use information from the Al collaborator?

We performed qualitative categorization on users' survey replies...

```
Mostly Follow AI "I went with the AI most times."

AI as Prior Guide "I looked at his prediction and then I read the passage."

AI as Post Check "I didn't. I figured out the paragraph for myself."

Mostly Ignore AI "I ignored it until I made my decision and then verified what it said."
```

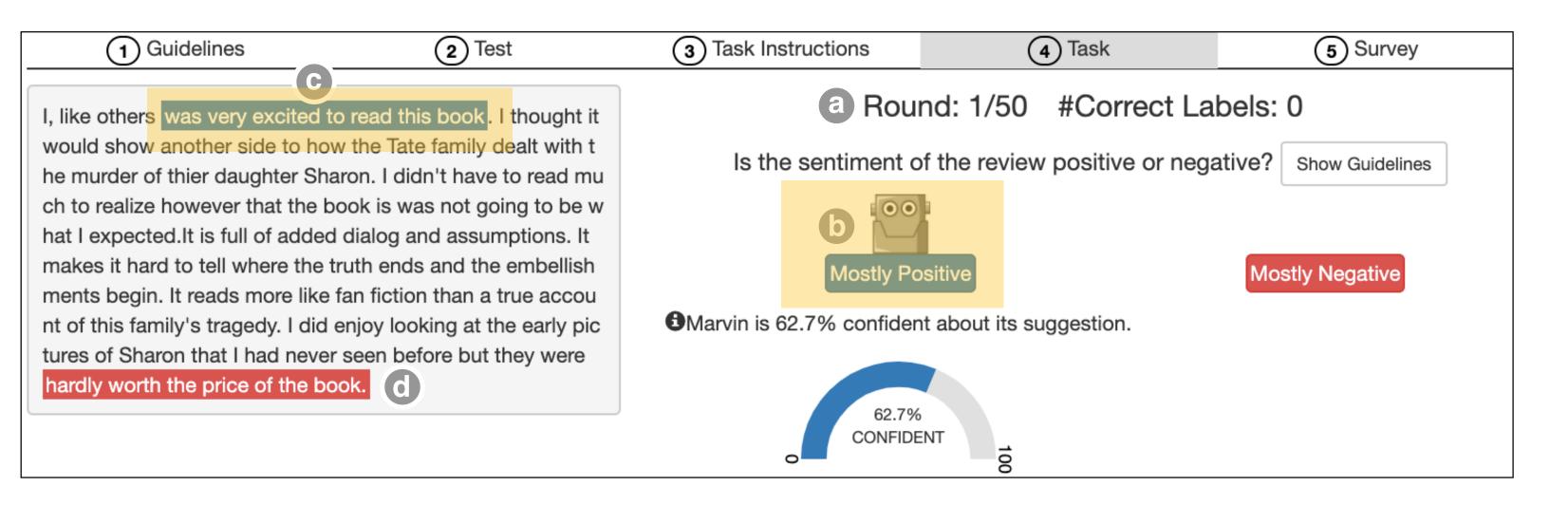
Multiple factors would affect these...

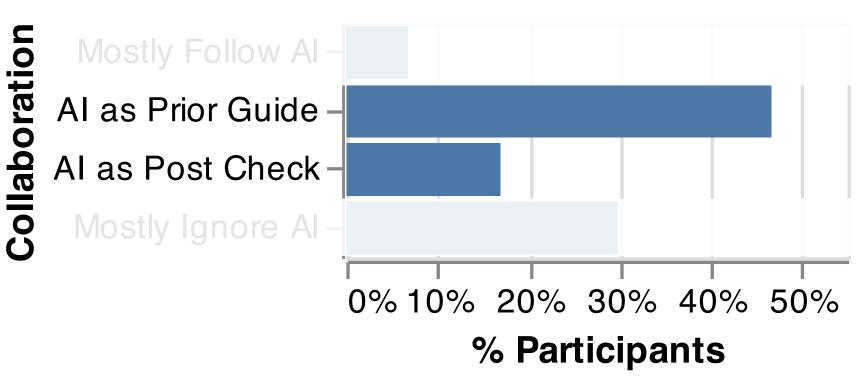
One example: When & how to display the AI recommendation matters.

inline highlight → confirmation bias ("this sentence seems reasonable enough")

See Al decision first → anchoring effect ("I will agree with Al's decision")

Classification task



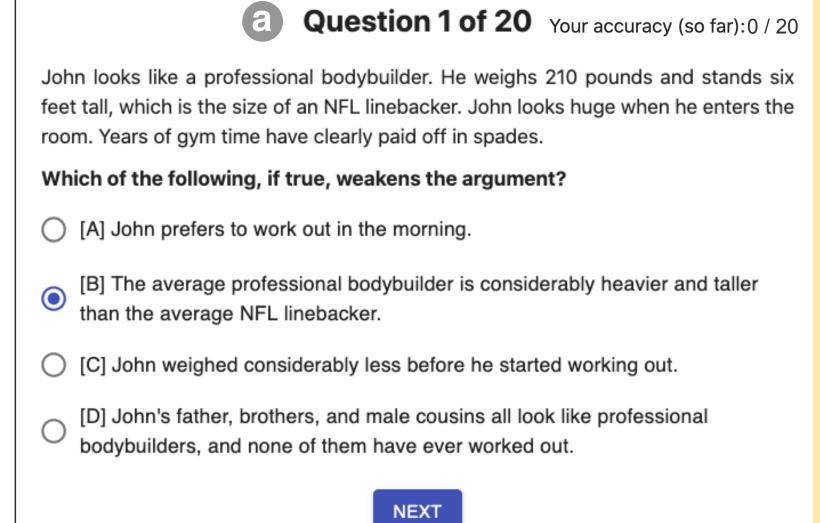


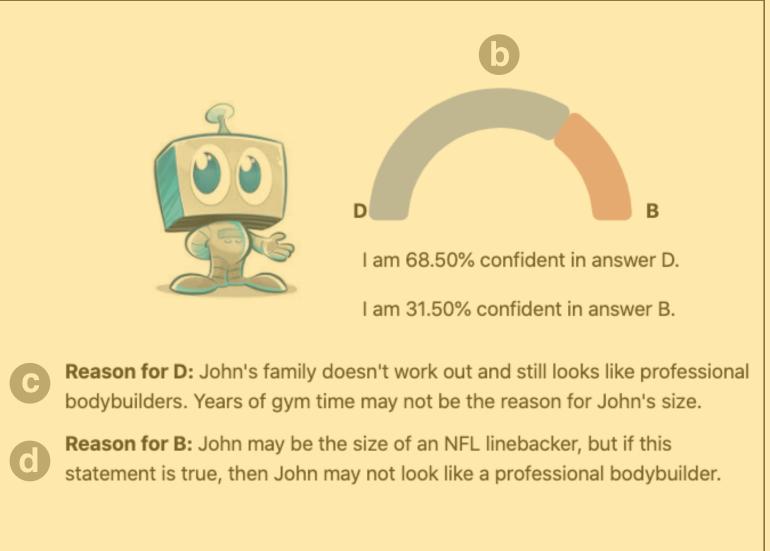
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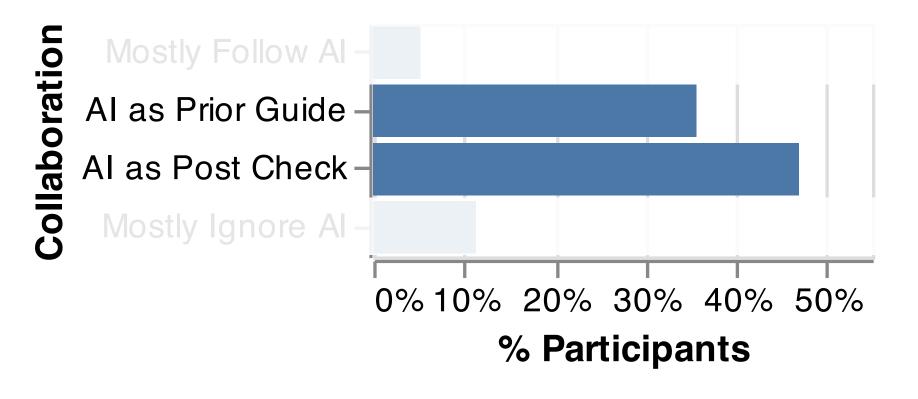
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Multi-choice question answering task







One example: When & how to display the AI recommendation matters.

inline highlight → confirmation bias ("this sentence seems reasonable enough")

See Al decision first → anchoring effect ("I will agree with Al's decision")

HCI solution

Display of Al recommendation

Present evidence, but not final decision

Timing of Al decision

Asynchronous display, increase independence

As the Al/NLP communities iterate on models, the HCl community works on thoughtful visual and interaction designs.

CASE STUDY

Concretely, how does HCI research help improve human-AI collaboration quality?

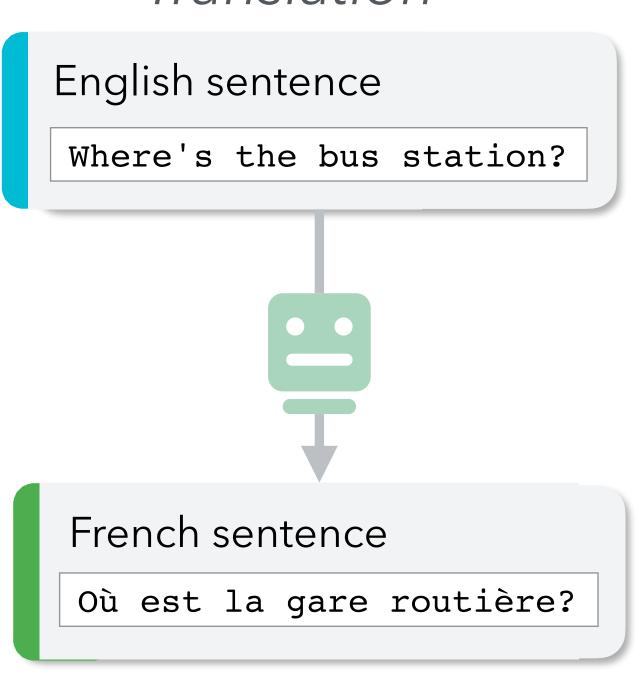
Al Chains: Transparent and Controllable Human-Al Interaction by Chaining Large Language Model (LLM) Prompts

Submitted to CHI 2022, in collaboration with Google PAIR

Large Language Models (LLMs) are helpful in many

"In-context learning": adapt to a wide range of tasks, without re-training the model.

Translation



Given the English sentence, translate to French.

English: Where's the bus station?

French: Où est la gare routière?

Prompt
Natural Language instruction

Model output

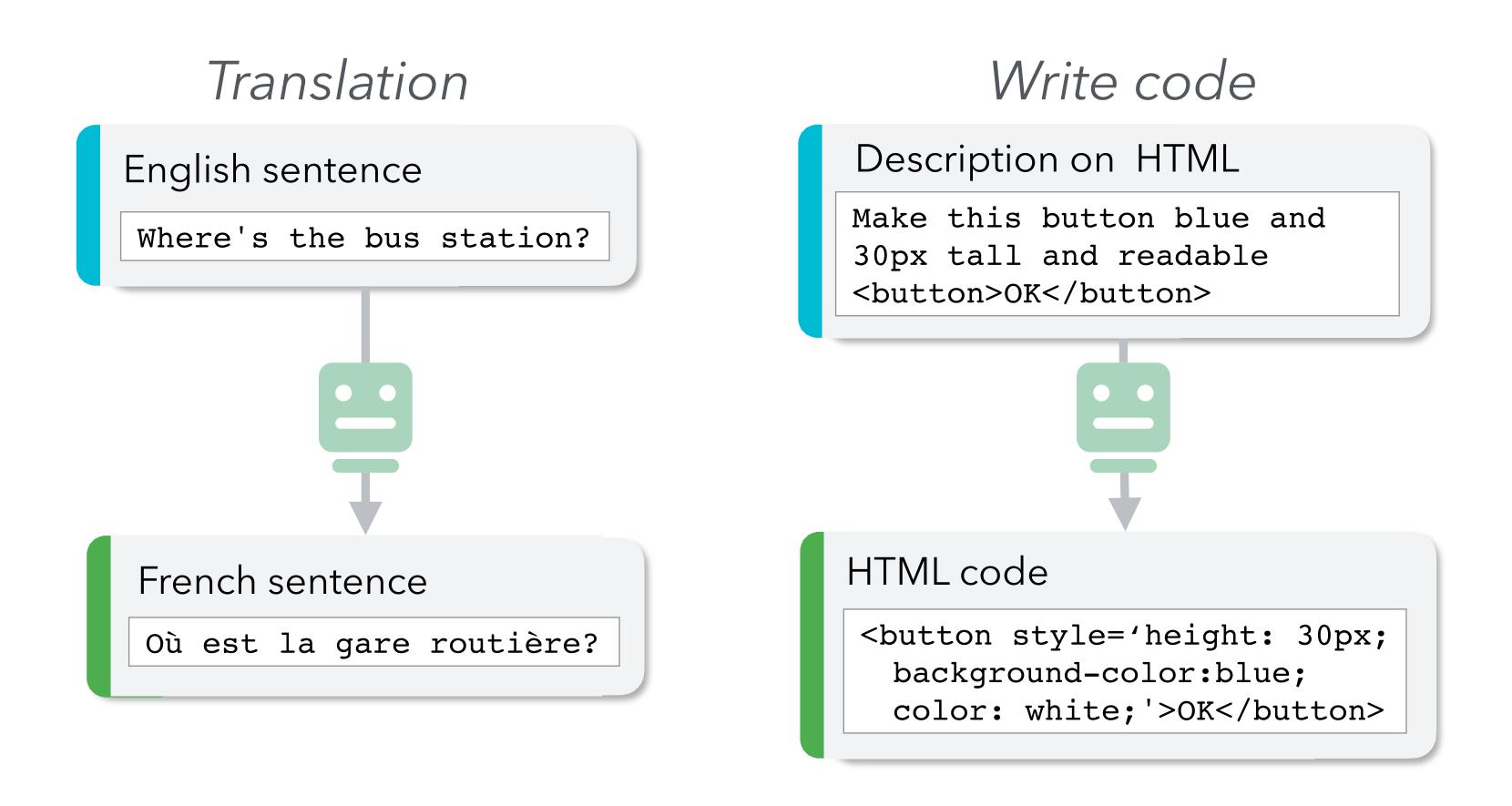
FURTHER READ!
Large Language Model 101

Bommasani, Rishi, et al. "On the Opportunities and Risks of Foundation Models." arXiv 2021 Brown, Tom B., et al. "Language models are few-shot learners." arXiv 2020

Prompt Engineering 101

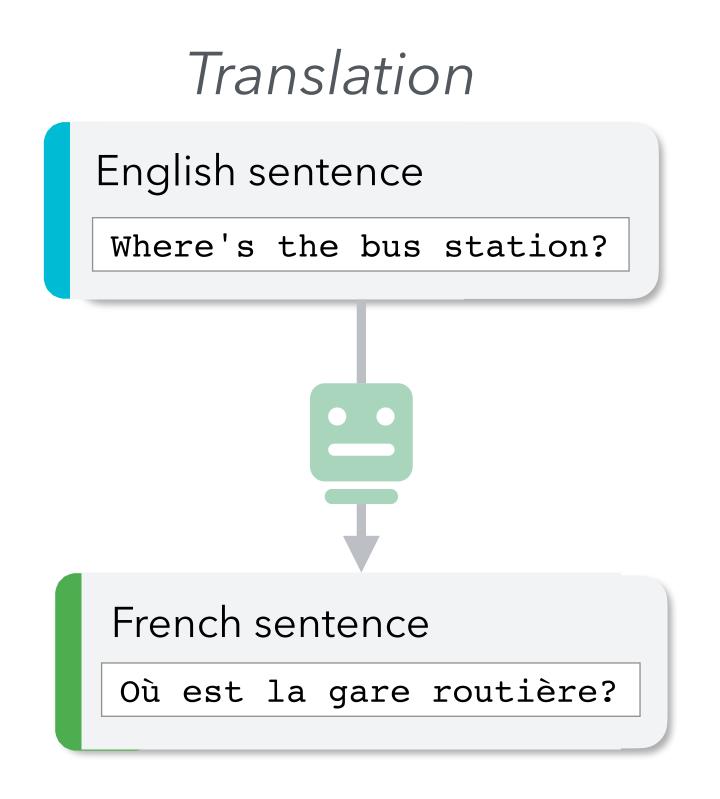
Large Language Models (LLMs) are helpful in many ways.

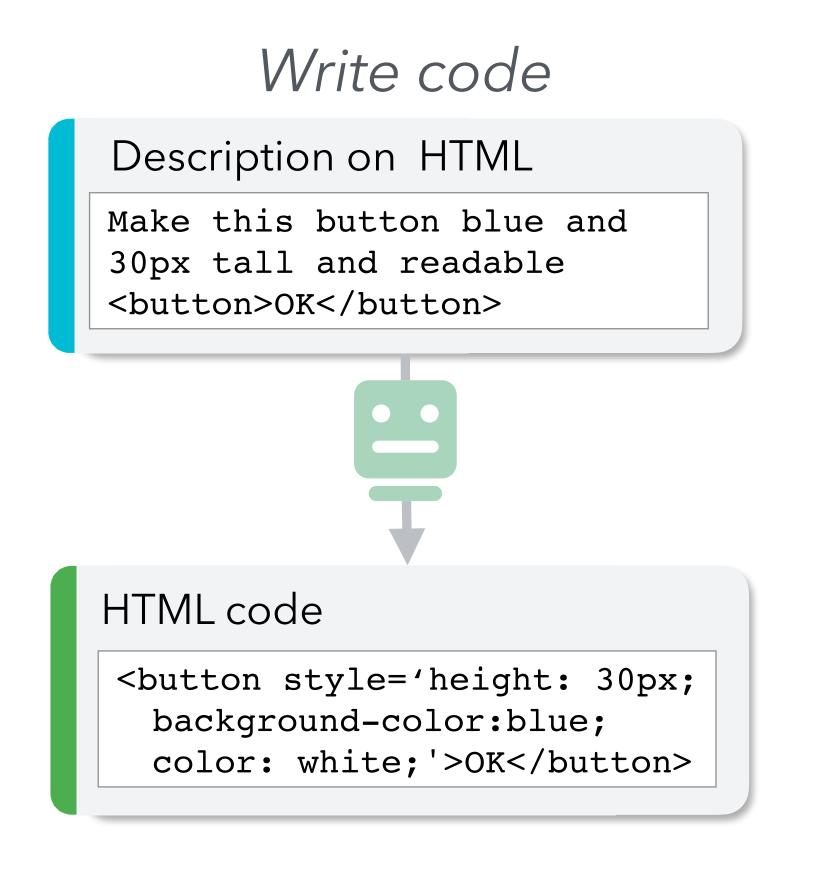
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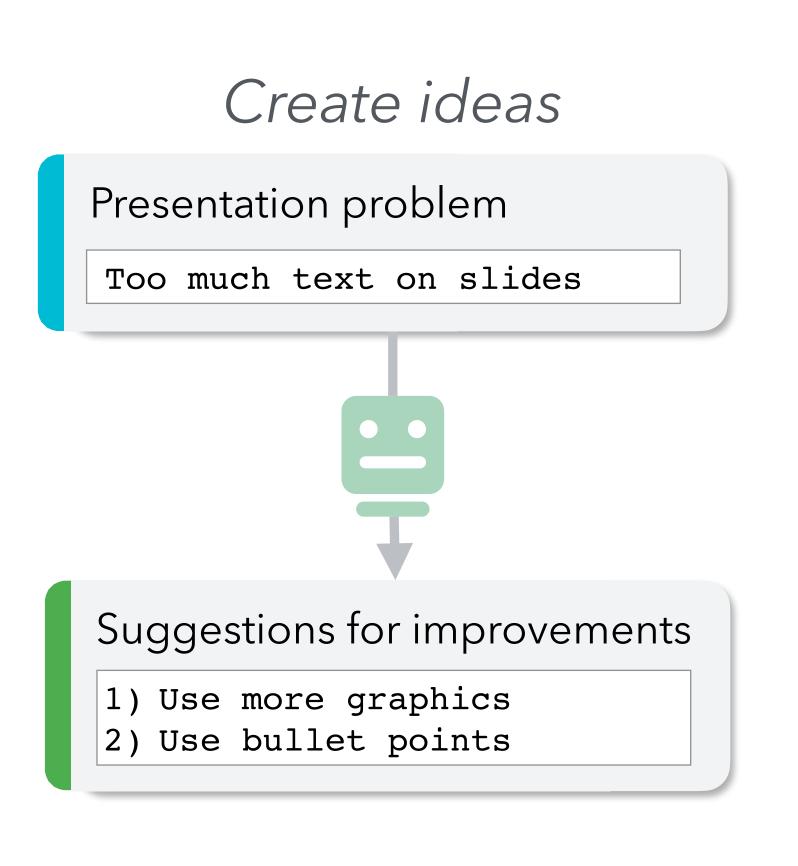


Large Language Models (LLMs) are helpful in many ways.

"In-context learning": adapt to a wide range of tasks, without re-training the model.







LLM may get lost on complex (real world!) tasks.

Example: Peer review rewriting

Given the following feedback, rewrite it into a friendly paragraph with concrete suggestions for each of Alex's presentation problems.

Original feedback:

Alex could improve his presentation skills. He has too much text on his slides. His presentation meanders from topic to topic without a clear structure. He also does not engage with his audience when he presents.

More friendly feedback:

Alex, you have too many words on your slides. You should use images and bullet points to help get your message across. You should have a clear structure for the presentation. You should also engage with your audience.

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× Inherently multi-step

- 1 Identify all presentation problems
- 2 Ideate suggestions per problem
- Compose them into a paragraph

× Too much freedom to debug!

Need more suggestion on "engagement"

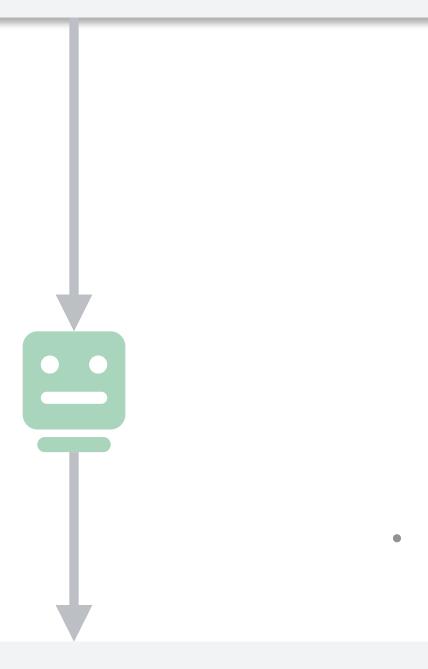
– How to change the prompt?

Al Chain :: Raise the ceiling of collaborating with LLMs, by using multiple LLM calls to solve distinct sub-tasks.

Instead of solving the task in one run...

Original feedback

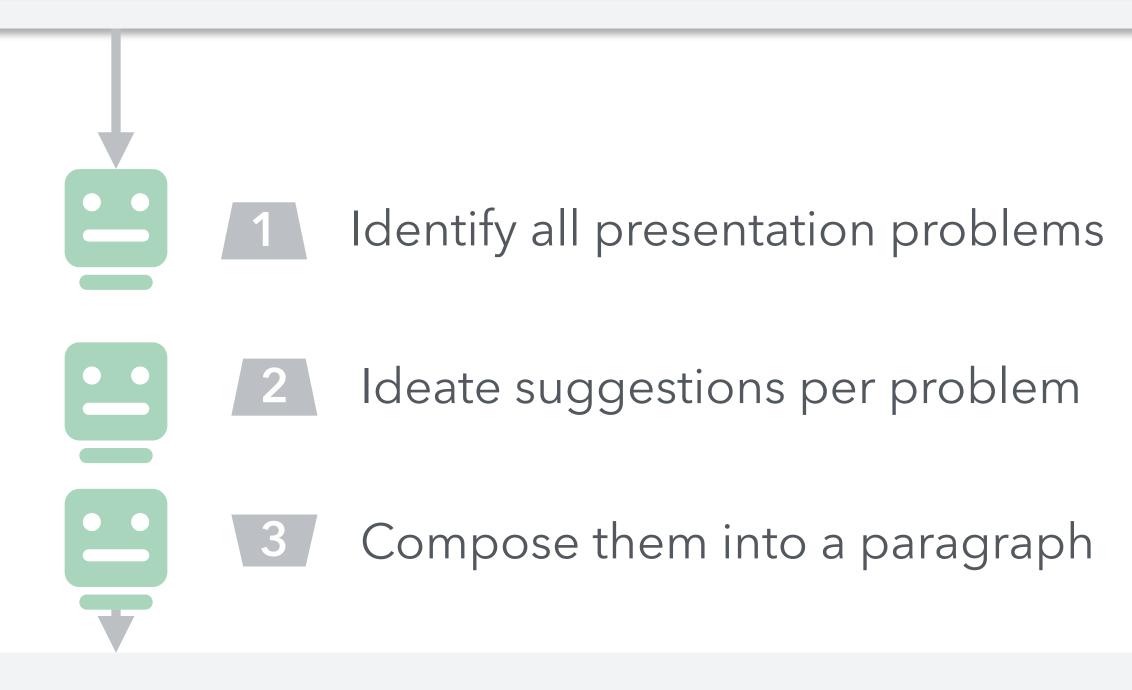
Alex could improve his presentation skills. He has too much text on his slides. His presentation meanders from topic to topic without a clear structure. He also does not engage with his audience when he presents.



A three-step LLM Chain for peer review rewriting

Original feedback

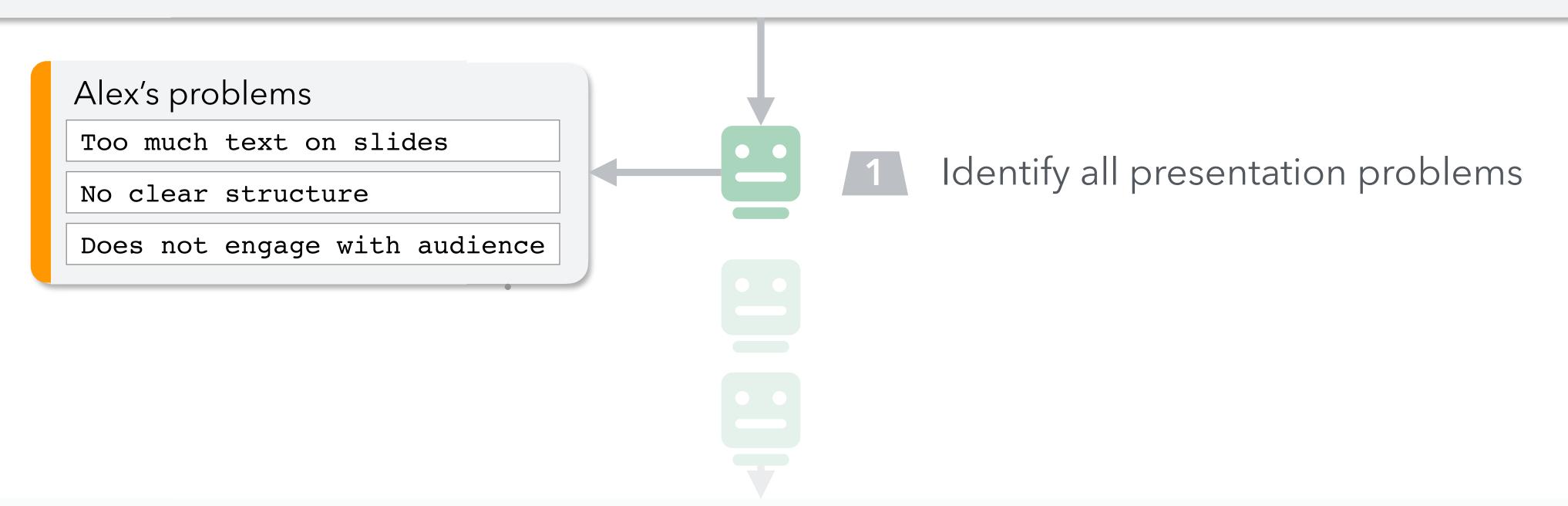
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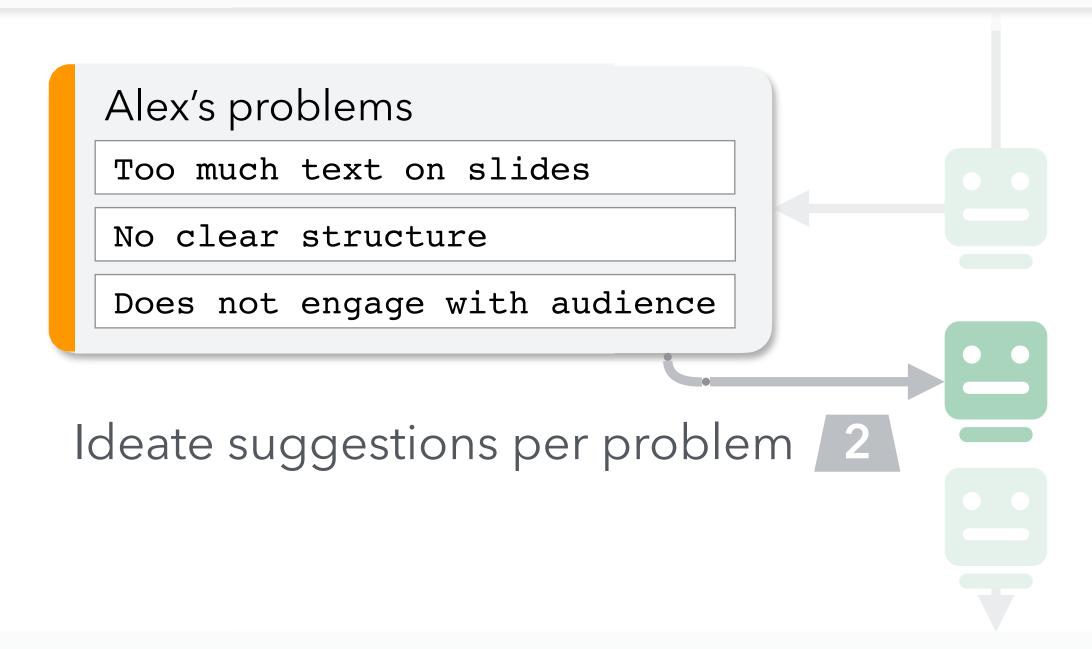
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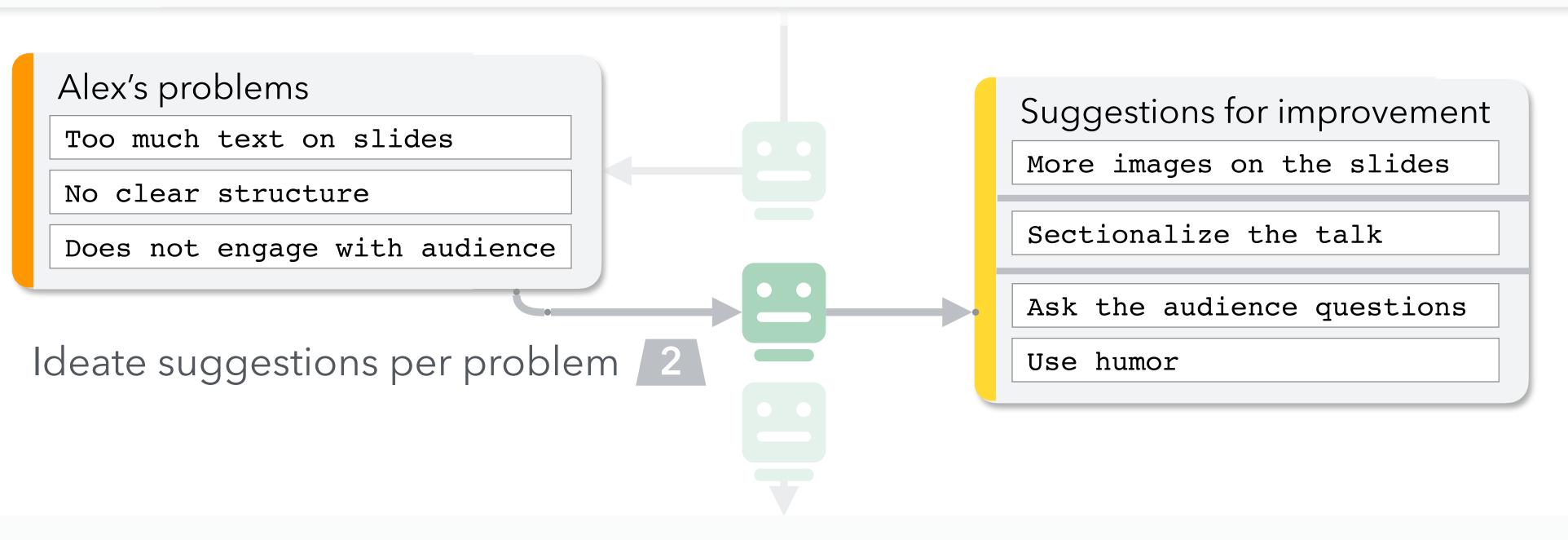
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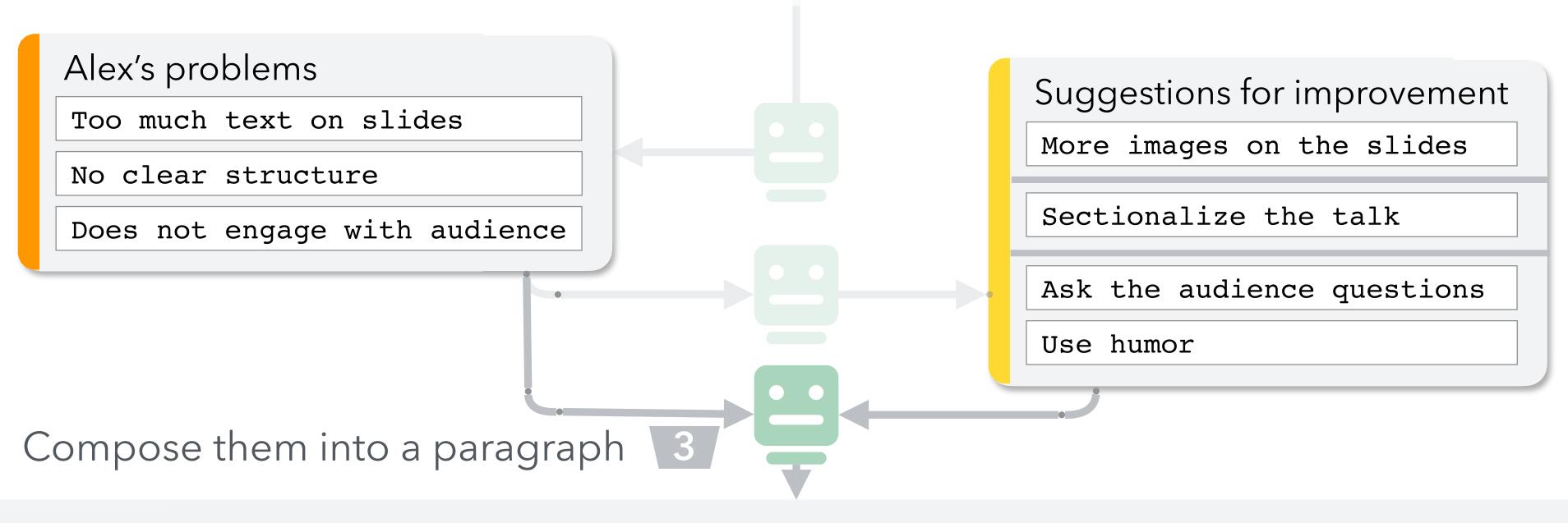


Friendly paragraph

A three-step LLM Chain for peer review rewriting

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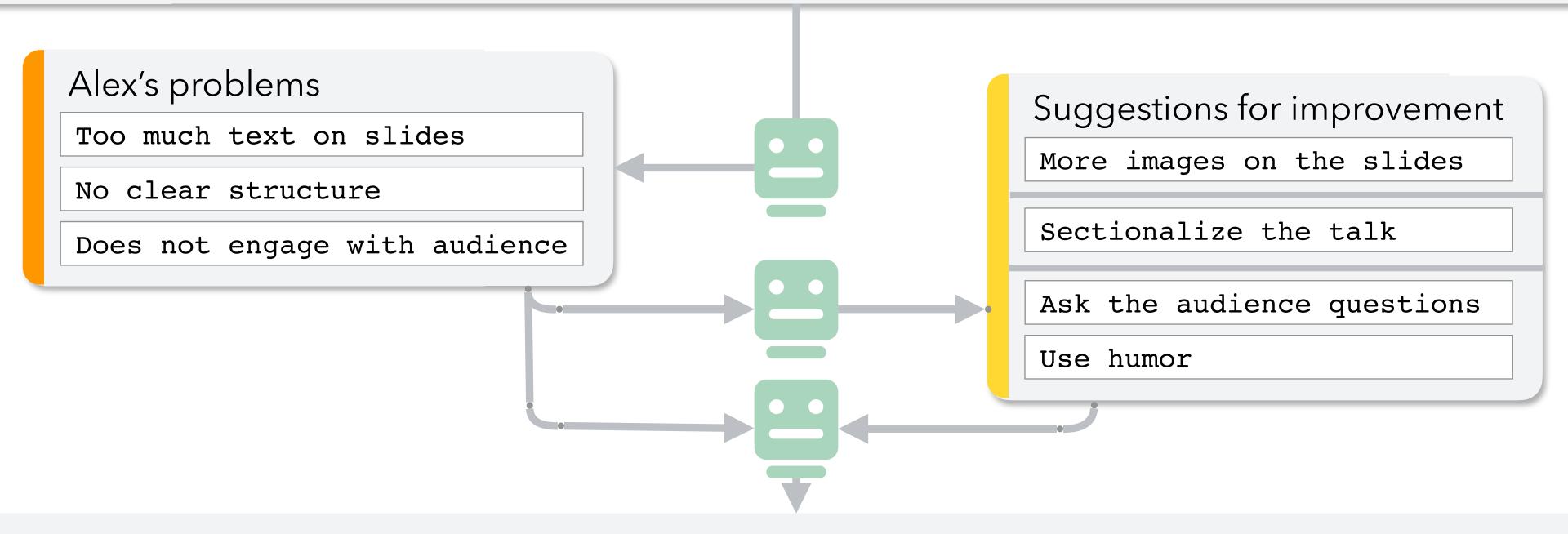


Original feedback

A three-step LLM Chain for peer review rewriting

Original feedback

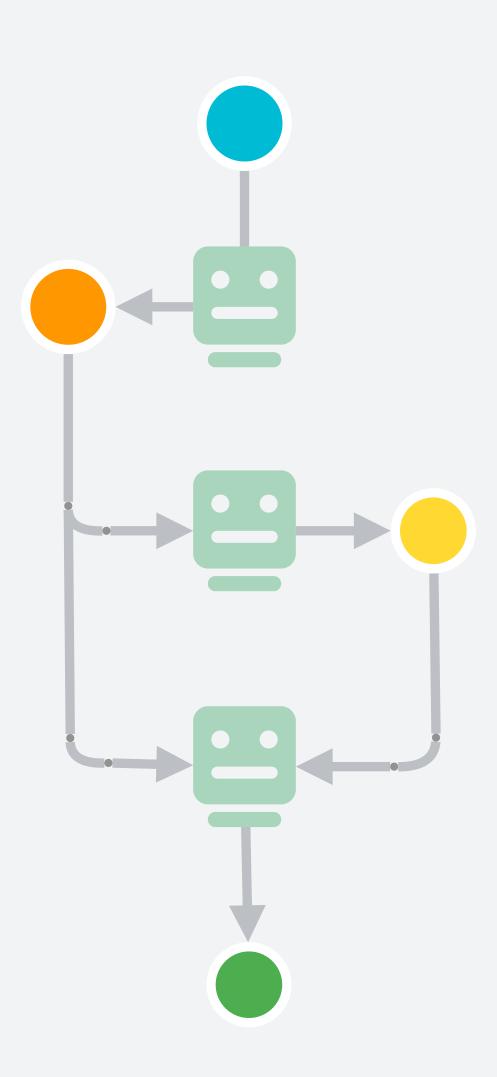
Alex could improve his presentation skills. He has too much text on his slides. His presentation meanders from topic to topic without a clear structure. He also does not engage with his audience when he presents.



Friendly paragraph

Alex, your presentation was interesting! However, I noticed that you have a lot of information on your slides. It might be helpful to vary pictures with text so that it is easier to follow. Also, you might consider the flow of your theme. If it were me, I would have divided it into three sections and then used your conclusion. You may also want to add some humor, and ask more questions to engage the audience.

LLM Chain improves task outcome.



vs. solving the entire task in one go...

Run the same model on multiple sub-tasks.

Each sub-task is more likely to succeed.

The aggregated final outcome is also improved.

How does Chaining impact collaboration?

User study

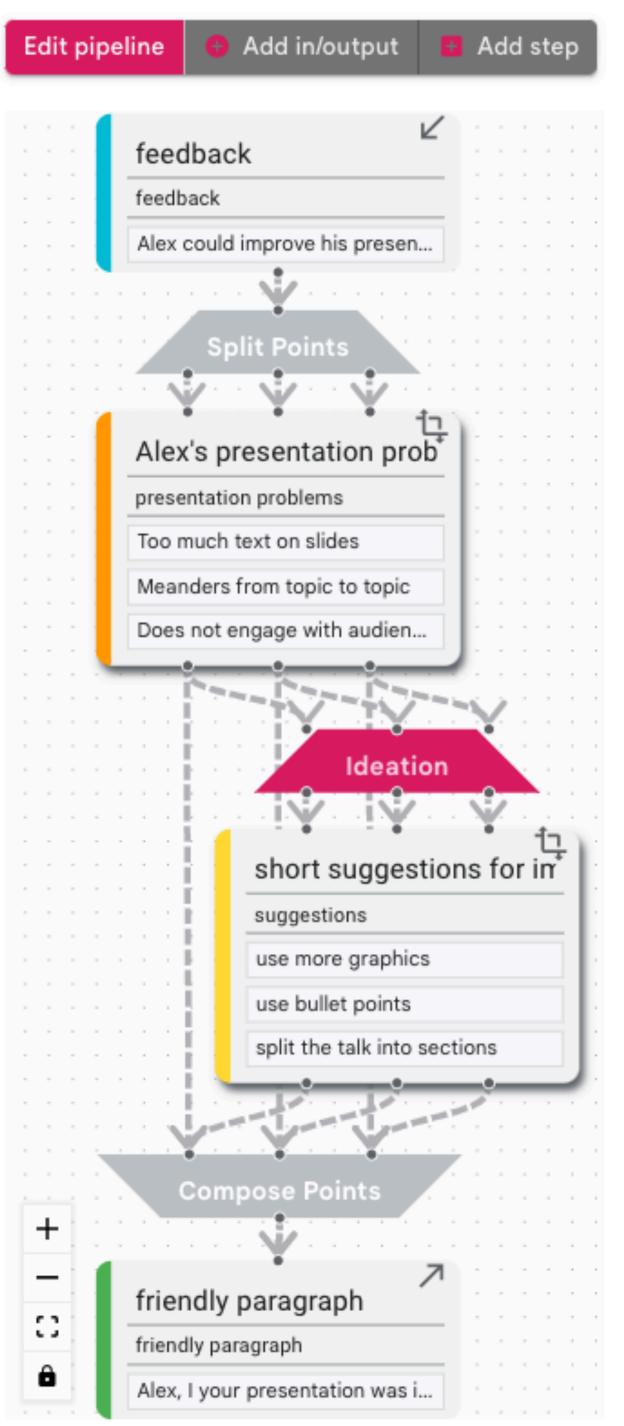
Two UI: Chaining vs. single run

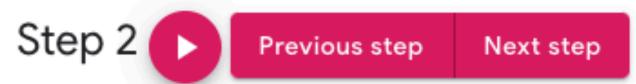
20 lay users of models

Within-subject

Complete the same task in two Uls

We find...



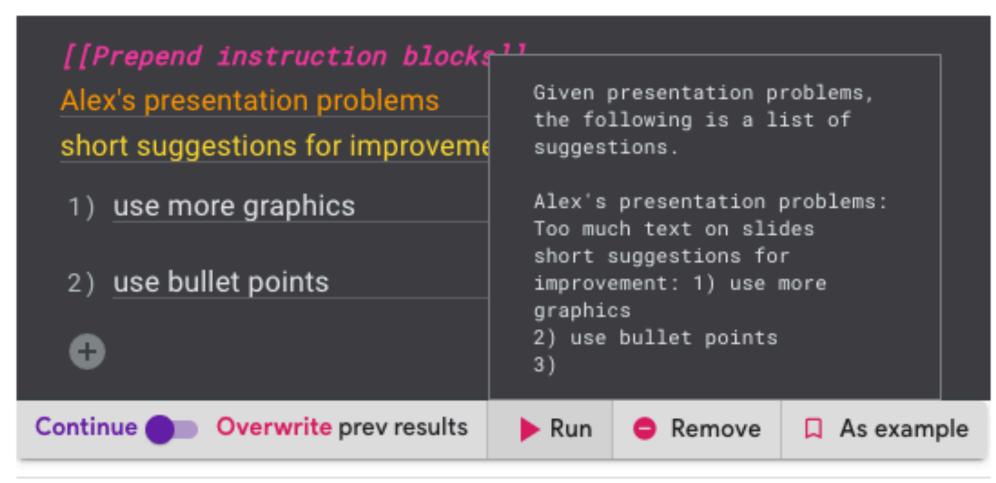


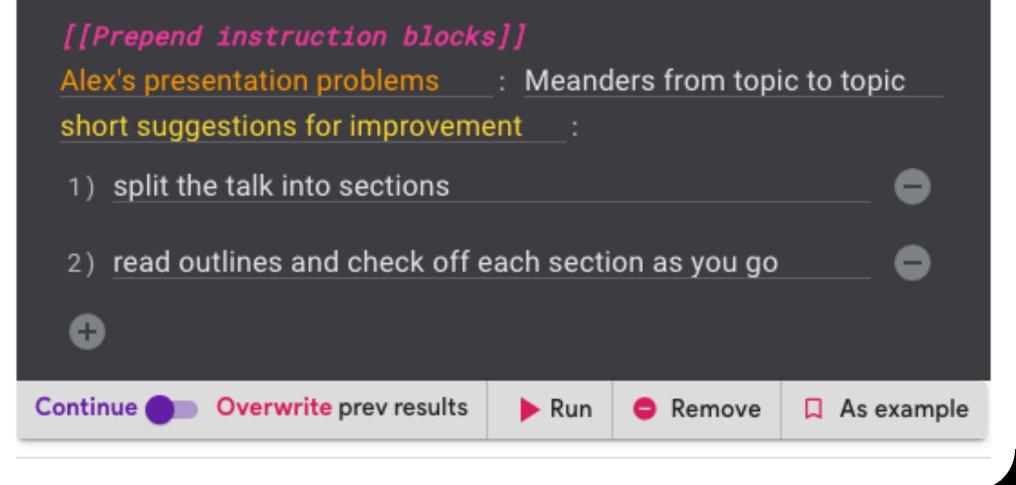
[[Instruction block]]

Given presentation problems, the following is a list of suggestions.
[[Append running blocks]]

Temperature:

[[Running blocks]]

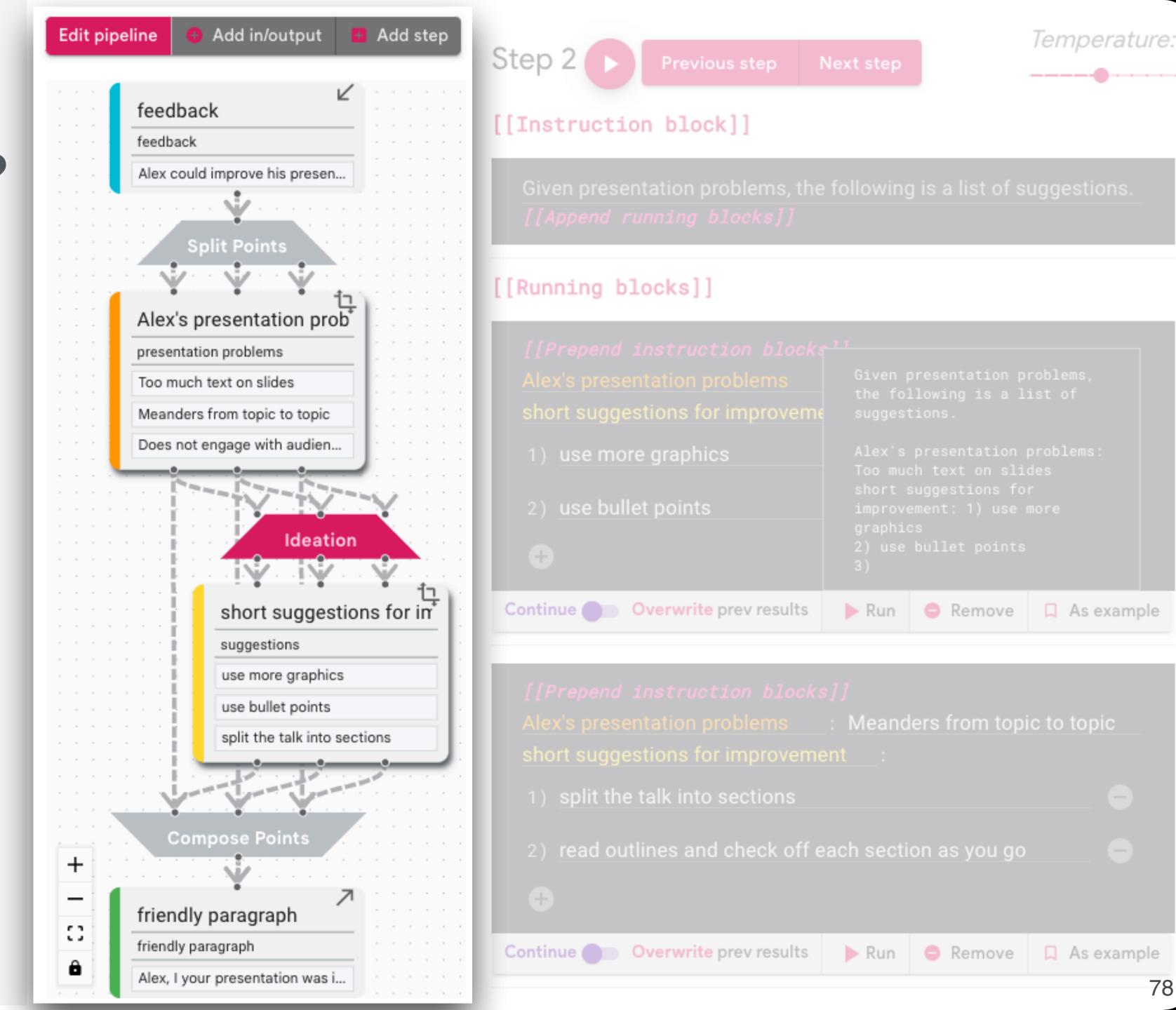




How does Chaining impact collaboration?

Think through the task by tracking the progress

"if I want to do the task with precision, I prefer the Chaining structure."

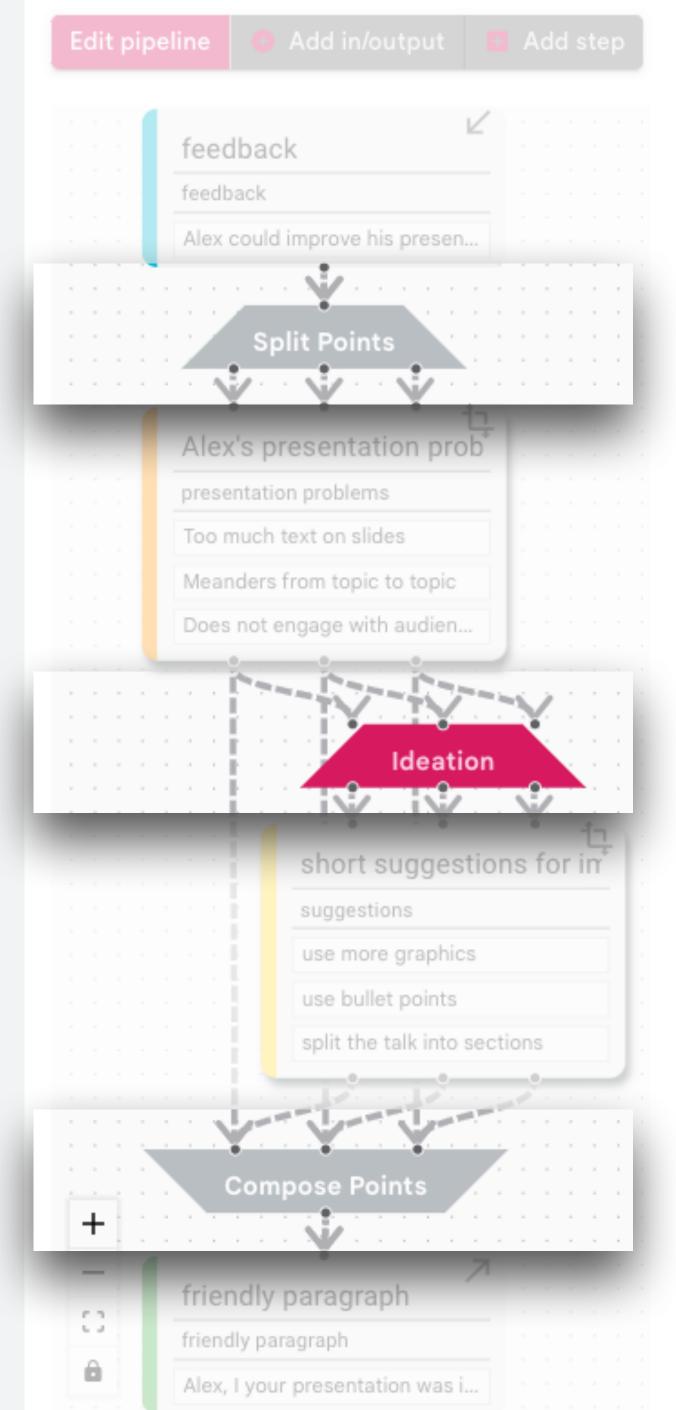


How does Chaining impact collaboration?

Think through the task

Get more help from models with different capabilities highlighted

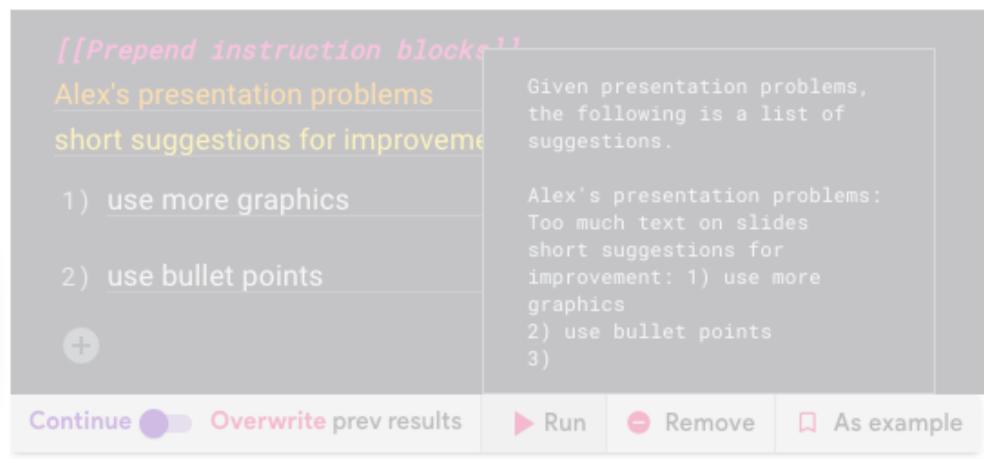
"I didn't need to give it as much, but it was giving me a lot."





[[Instruction block]]

[[Running blocks]]





Temperature:

How does Chaining impact collaboration?

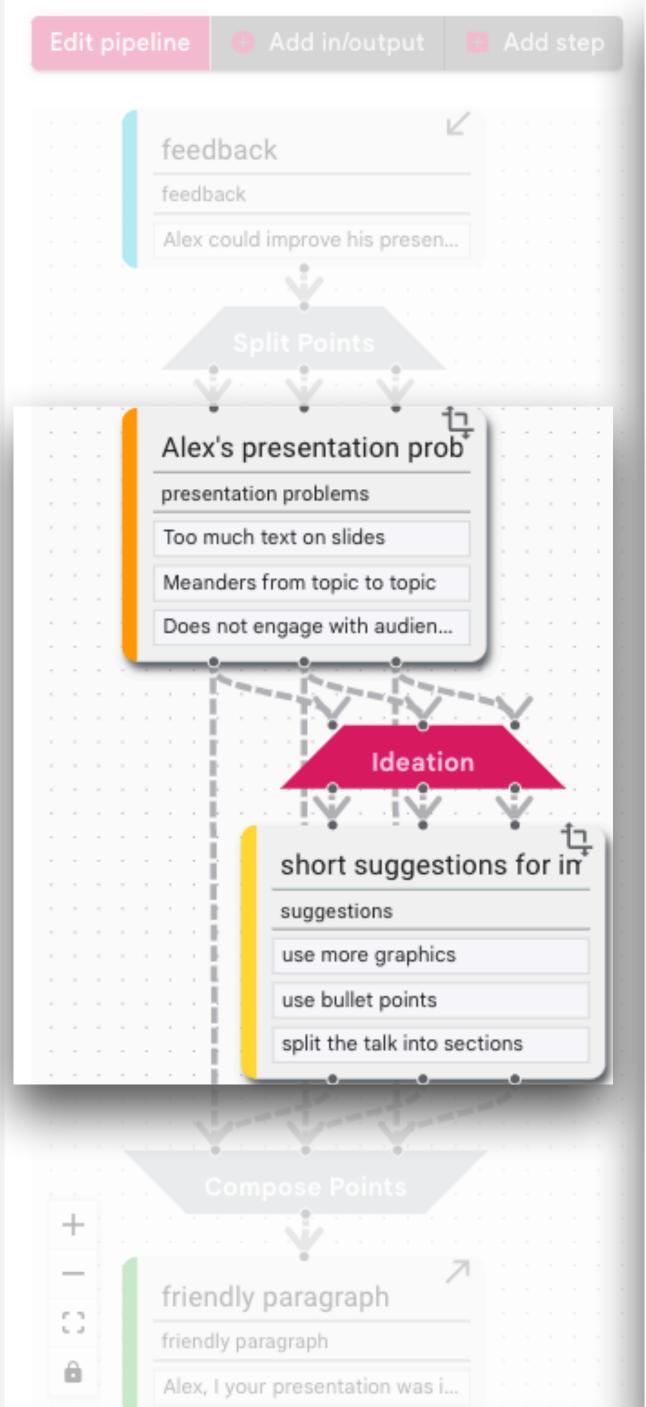
Think through the task

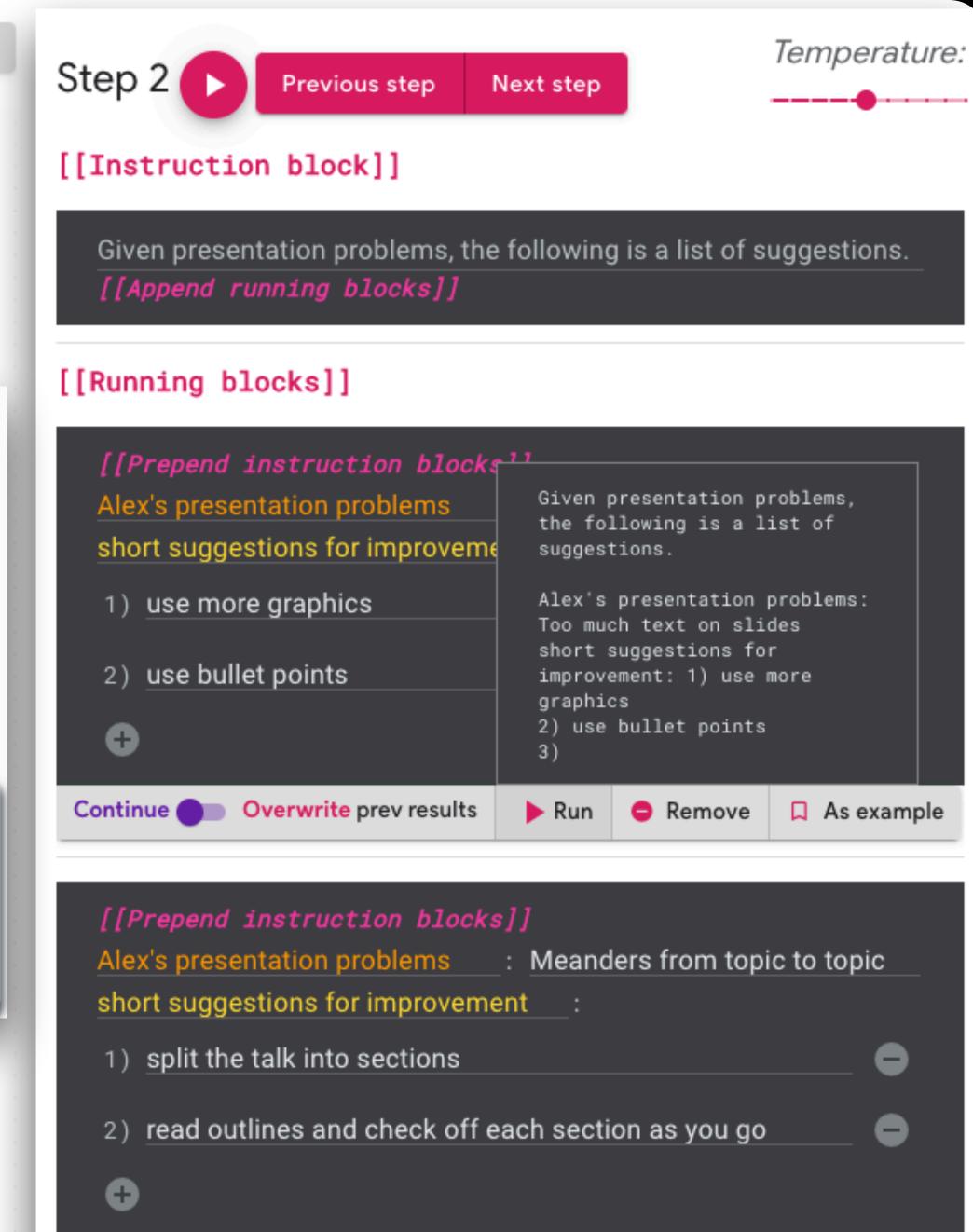
Get more help from models

System more transparent

better convey model's goal per step (vs. all-encompassing)

"Chaining helped you speak the language. It lift[ed] up the hood and showed what's happening at different phrases."





▶ Run 🛑 Remove

As example

Continue Overwrite prev results

How does Chaining impact collaboration?

Think through the task

Get more help from models

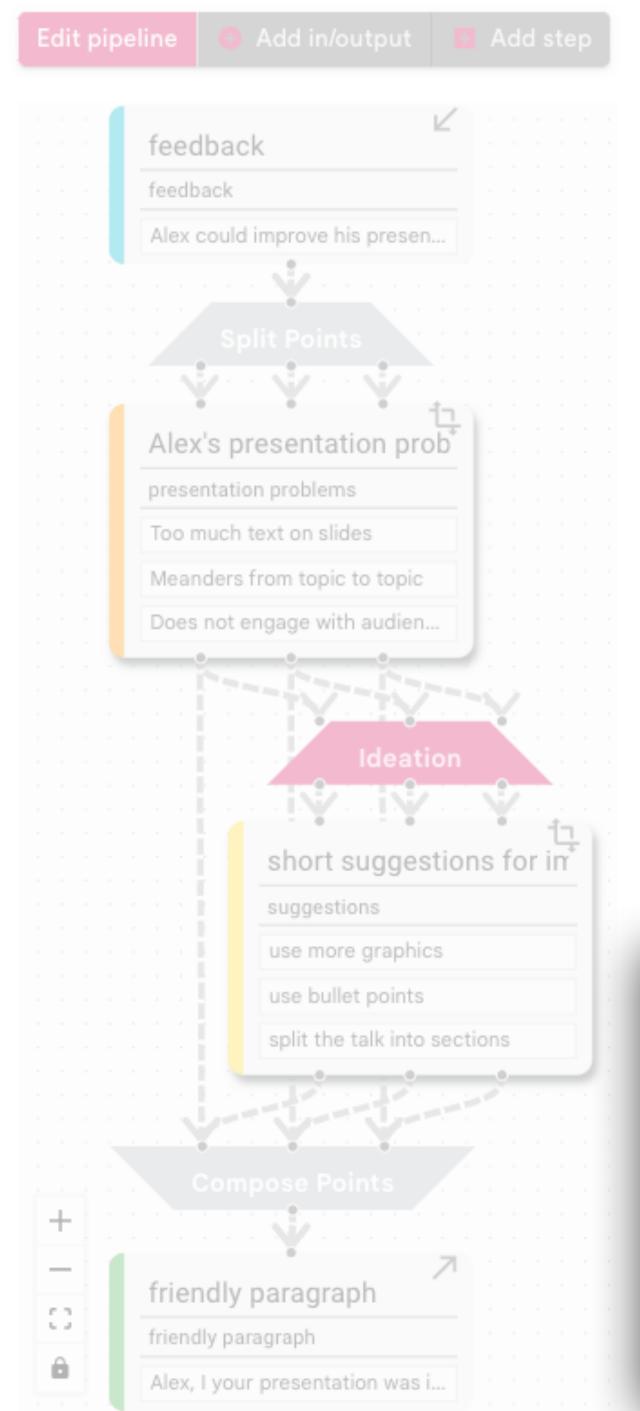
System more transparent

System more controllable

Modular feedback,

Explicit "knobs" on what can change.

"Chaining makes it easier to finetune things...Too much freedom [without Chaining] is a curse."





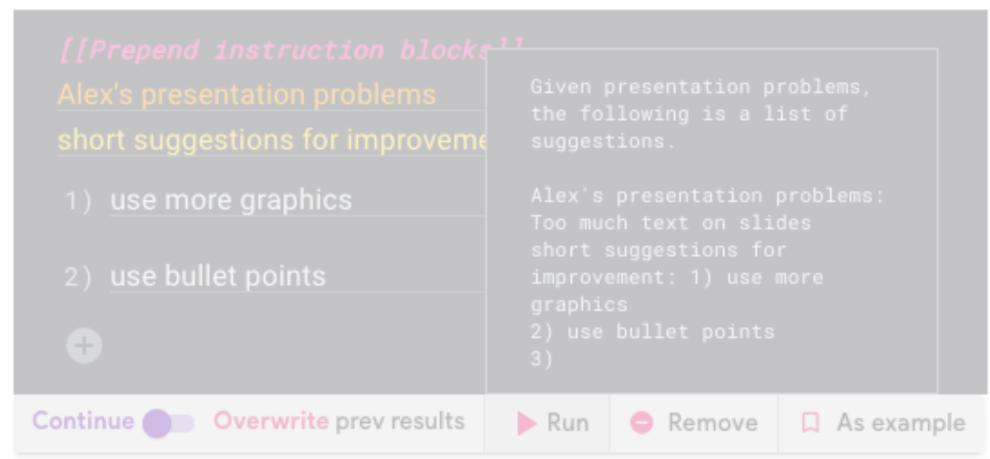
[[Instruction block]]

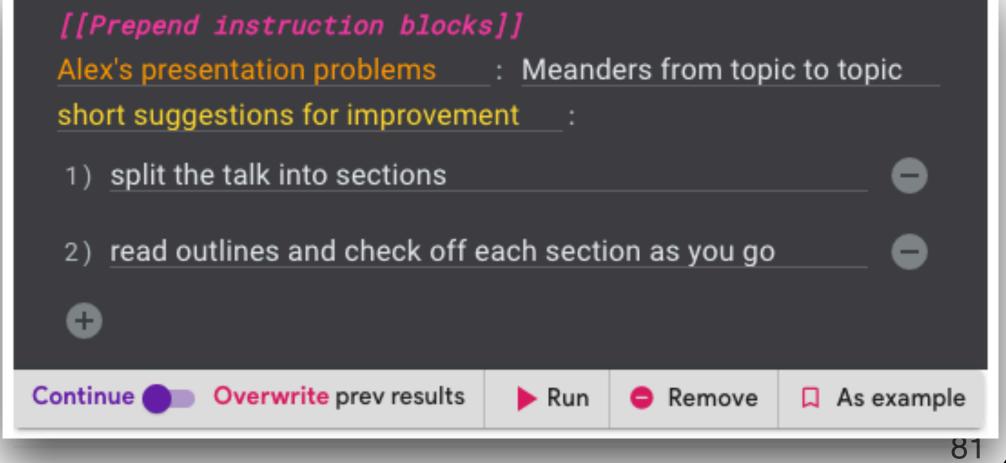
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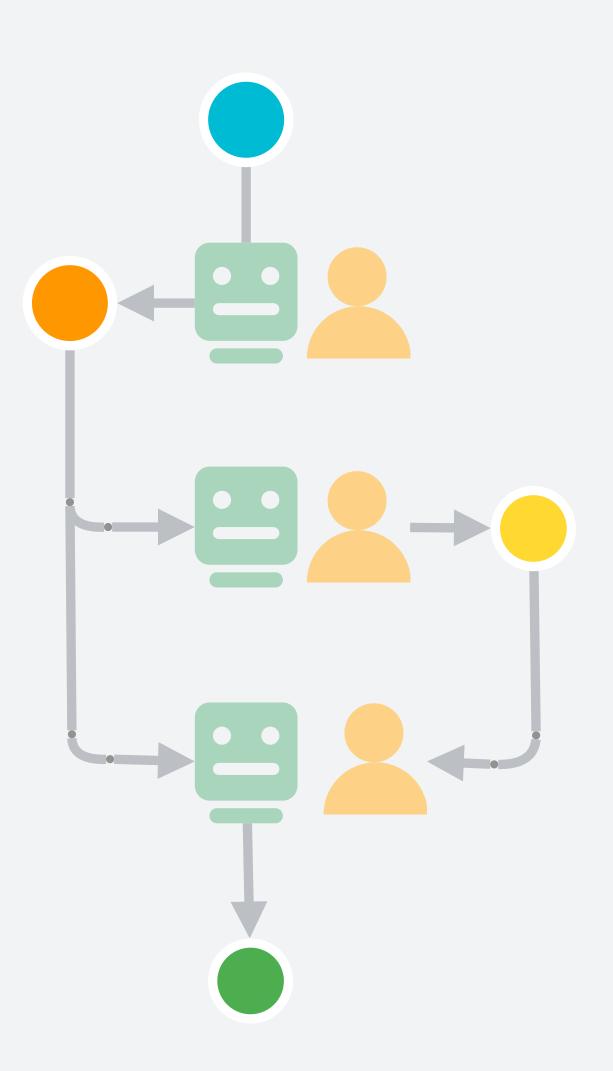
Temperature:

[[Running blocks]]





Al Chain: The Big Picture



Al Chain : Raise the ceiling of collaborating with LLMs, by using multiple LLM calls to solve distinct sub-tasks.

Better task outcome, more controllable, transparent, etc.

Gains purely from novel interaction, no model retraining.

Things to consider in Human-Al collaboration research

Human-Al collaboration cares about appropriate reliance.

Which dimensions are we relying on the Al for?

What's the task?

Close-ended decision making like classification

Open-ended co-creation, in the Chaining case

What's Al's role?

Guardrail on quality (grammar check)

Cognitive off-loader (summarize large amount of data),

Assistant on tedious tasks (e.g. fill out the color)

Leaders asking for human help (active learning)

Things to consider in Human-Al collaboration research

Human-Al collaboration cares about appropriate reliance.

How are we building the reliance?

"Shared representation"

Informative but intuitive explanations on model rationales

Chaining: natural language input-output,

Presenting shared representations

Explanation format, modality, timing

Structuring inputs and outputs



Al developers working on models-to-deploy, Find why models fail & how to fix them.

Perform systematic analyses, among various model development stages, to prioritize more severe errors & root fixes.



End users with deployed models, work with Al towards common goals.

Maximize complementary skills, through effective communication, to achieve better results than either alone.

HCI people can do a lot more!

Consider domain experts.

What unique concerns do people have in domains like medical, education, etc.? How should Al roles change accordingly? (When to lead, when to assist, etc.)

Do more data work.

Can we directly design data collection and evaluation workflows, to combat the root of "garbage-in, garbage-out"?

Clarify under-specified big terms in human-Al interaction.

What do we mean by trust, ethics, etc.? Is human-human interaction a good role model for human-Al interaction?