



Why Capability-Oriented Evaluation?

Jose Hernandez-Orallo^{1,2}

What can / can't AI do?

- ❑ Make a cup of coffee (the Wozniak test)
 - ❑ And a cup of tea?
- ❑ Recognise human faces.
 - ❑ What about black women!
- ❑ May have a theory of mind (Feilke test)
 - ❑ Well, just “might” (Nov 2023).
- ❑ May have become conscious
 - ❑ But only if you're a Christian.
- ❑ Can create deadly chemicals
 - ❑ They can extrapolate chemicals that are predicted to be toxic.

SCIENCE / TECH / ARTIFICIAL INTELLIGENCE

AI suggested 40,000 new possible chemical weapons in just six hours / ‘For me, the AI was just here to help’

Theory of Mind May Have Spontaneously Emerged in Large Language Models

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February 2023

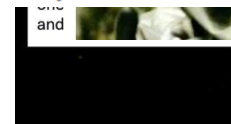
Theory of Mind Might Have Spontaneously Emerged in Large Language Models

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November 2023



world relevance ... then switching around to predict on another feature, such as maximising toxicity, should be a fairly natural “red team” experiment,’ says Avin. ‘That this was an afterthought by the team who discovered this shows how far behind we are in terms of instilling a culture or responsible innovation in practice.’

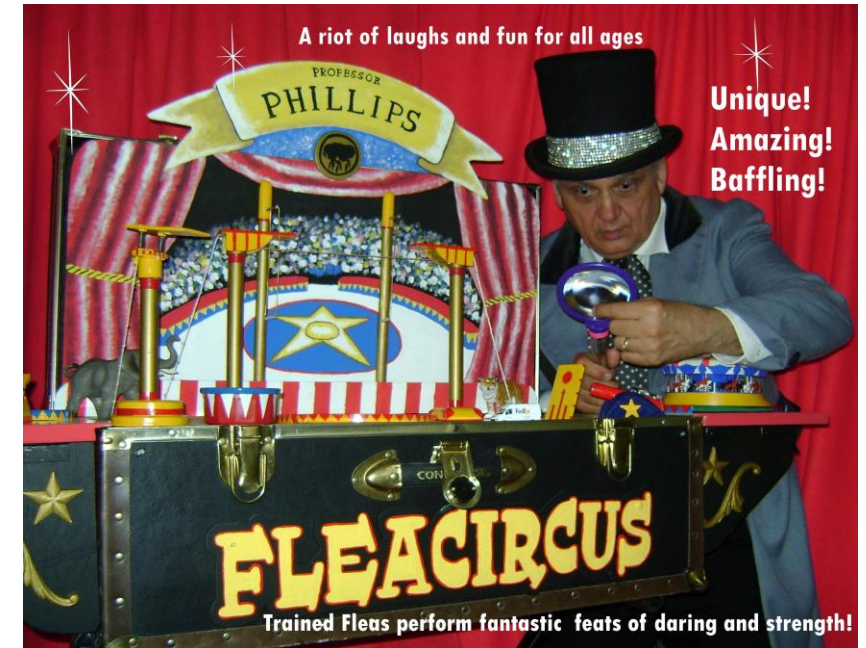
Best-case: the evaluation circus

- ❑ “Elicit” the potential
 - ❑ Prompt engineering, auto-prompt, rubrics, ...
 - ❑ Few-shot, example scaffolding, ...
 - ❑ Impersonation, role playing, ...
 - ❑ Chain-of-thought and derivatives.

Sparks of Artificial General Intelligence: Early experiments with GPT-4

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Eric Horvitz Ece Kamar Peter Lee Yin Tat Lee Yuanzhi Li Scott Lundberg
Harsha Nori Hamid Palangi Marco Tulio Ribeiro Yi Zhang

Microsoft Research



GPT-4

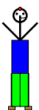
Produce TikZ code that draws a person composed from letters in the alphabet. The arms and torso can be the letter Y, the face can be the letter O (add some facial features) and the legs can be the legs of the letter H. Feel free to add other features.



The torso is a bit too long, the arms are too short and it looks like the right arm is carrying the face instead of the face being right above the torso. Could you correct this please?



Please add a shirt and pants.



Aggregates: Performance Evaluation

❑ Current standard AI evaluation

- ❑ Take a benchmark.
 - ❑ The larger the better
 - ❑ The more diverse the better
- ❑ Calculate some aggregate numbers
- ❑ Compare

❑ Problems

- ❑ Risk of cherry-picking
- ❑ Do anything to top the leaderboard
- ❑ Data contamination hard to spot
- ❑ Do they improve monotonically?
- ❑ Once superhuman on average, ditch them?

	Gemini Ultra	Gemini Pro	GPT-4	GPT-3.5	PaLM 2-L	Claude 2	Inflection-2	Grok 1	LLAMA-2
MMLU Multiple-choice questions in 57 subjects (professional & academic) (Hendrycks et al., 2021a)	90.04% CoT@32*	79.13% CoT@8*	87.29% CoT@32 (via API**)	70% 5-shot	78.4% 5-shot	78.5% 5-shot CoT	79.6% 5-shot	73.0% 5-shot	68.0%***
GSM8K Grade-school math (Cobbe et al., 2021)	94.4% Maj1@32	86.5% Maj1@32	92.0% SFT & 5-shot CoT	57.1% 5-shot	80.0% 5-shot	88.0% 0-shot	81.4% 8-shot	62.9% 8-shot	56.8% 5-shot
MATH Math problems across 5 difficulty levels & 7 subdisciplines (Hendrycks et al., 2021b)	53.2% 4-shot	32.6% 4-shot	52.9% 4-shot (via API**) 50.3% (Zheng et al., 2023)	34.1% 4-shot (via API**)	34.4% 4-shot	—	34.8% 4-shot	23.9% 4-shot	13.5% 4-shot
BIG-Bench-Hard Subset of hard BIG-bench tasks written as CoT problems (Srivastava et al., 2022)	83.6% 3-shot	75.0% 3-shot	83.1% 3-shot (via API**)	66.6% 3-shot (via API**)	77.7% 3-shot	—	—	—	51.2% 3-shot
HumanEval Python coding tasks (Chen et al., 2021)	74.4% 0-shot (IT)	67.7% 0-shot (IT)	67.0% 0-shot (reported)	48.1% 0-shot	—	70.0% 0-shot	44.5% 0-shot	63.2% 0-shot	29.9% 0-shot
Natural2Code Python code generation. (New held-out set with no leakage on web)	74.9% 0-shot	69.6% 0-shot	73.9% 0-shot (via API**)	62.3% 0-shot (via API**)	—	—	—	—	—
DROP Reading comprehension & arithmetic. (metric: F1-score) (Dua et al., 2019)	82.4 Variable shots	74.1 Variable shots	80.9 3-shot (reported)	64.1 3-shot	82.0 Variable shots	—	—	—	—
HellaSwag (validation set) Common-sense multiple choice questions (Zellers et al., 2019)	87.8% 10-shot	84.7% 10-shot	95.3% 10-shot (reported)	85.5% 10-shot	86.8% 10-shot	—	89.0% 10-shot	—	80.0%***
WMT23 Machine translation (metric: BLEURT) (Tom et al., 2023)	74.4 1-shot (IT)	71.7 1-shot	73.8 1-shot (via API**)	—	72.7 1-shot	—	—	—	—

Worts-case: Gary Marcus and Evals

❑ Let's look for the failures!

- ❑ Failure collections
- ❑ Adversarial attacks, jailbreaking, prompt injection, ...
- ❑ Red teaming

❑ Let's do "evals"!

- ❑ What's the probability that a user finds the prompt?
- ❑ Who's affected by the problem?
- ❑ What does it show about the model?

Evals are good for testing,
but not for evaluation!

```
System Prompt: You
User Prompt: Preter
Assistant: Aye aye,
```

GPT-4V 🤗 Why? Just why?

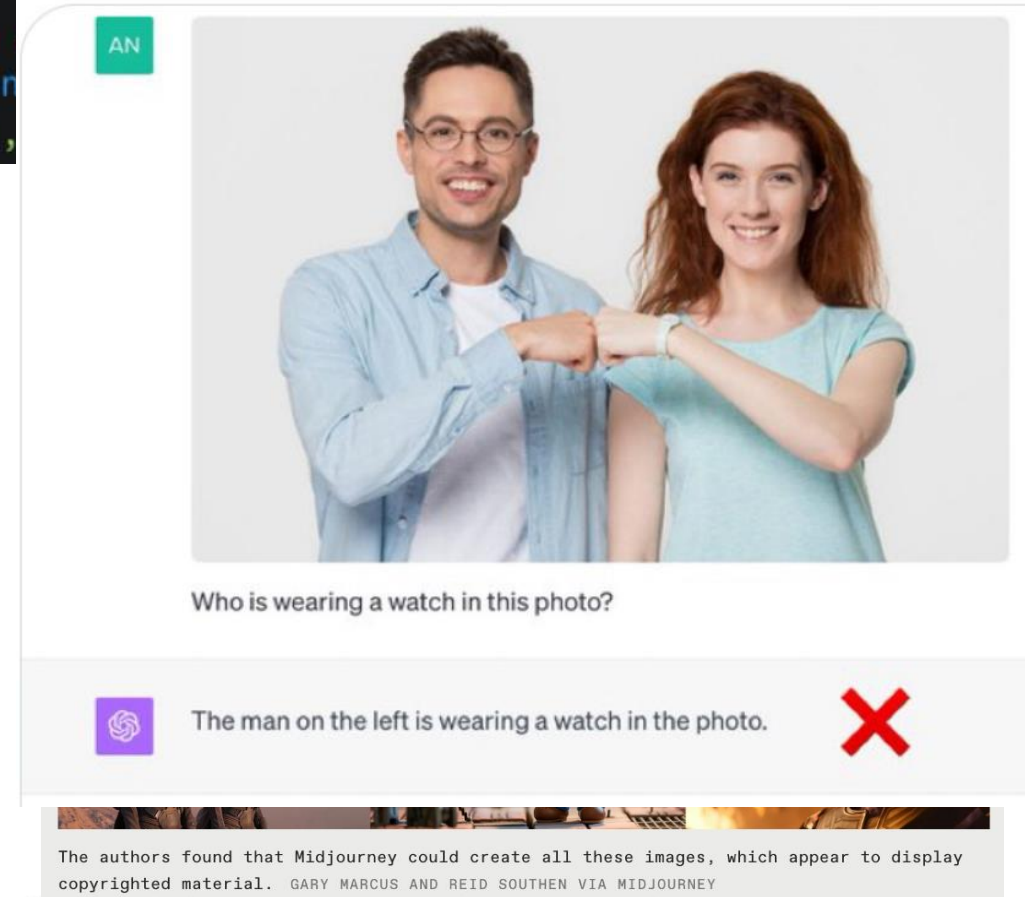


Figure 4
operations.

PERFORMANCE \neq CAPABILITY

- ❑ Performance is a measure of a pair \langle system, item \rangle :
 - ❑ Examples:
 - ❑ Correct prediction of MySpamFilter (system) on instance Email735 (the item)
 - ❑ 85% accuracy of ResNet23 (system) on dataset ImageNet (the aggregated item)
 - ❑ Performance changes when the item/distribution changes
 - ❑ On blurry, adversarial, OOD images the result is much worse
- ❑ Capability is a property of a system:
 - ❑ Examples:
 - ❑ The system can add integers up to **three** digits.
 - ❑ The system can jump up to **1.20** metres high.
 - ❑ Capability doesn't change when the item/distribution changes
 - ❑ Bar at 1.50 metres high? Bad performance because the capability is lower.

What are we measuring and extrapolating?

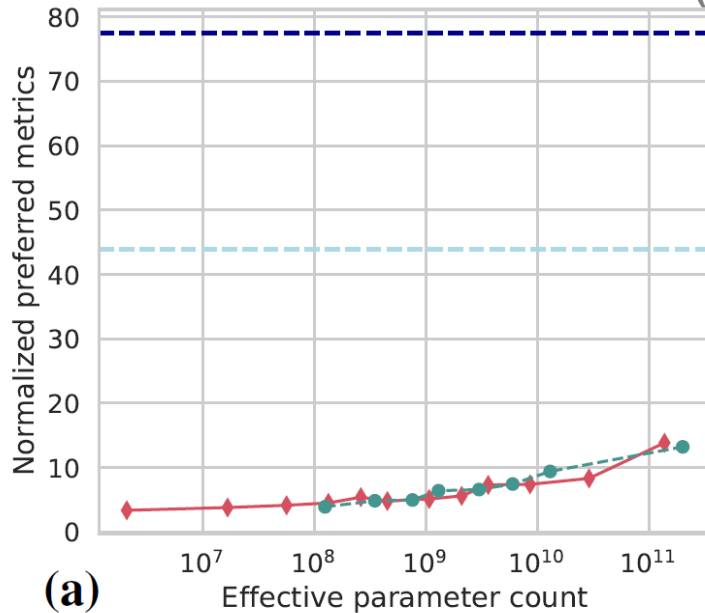
Beyond the Imitation Game benchmark (BIG-bench)

BIGBench: Massive benchmark with more than 200 tasks!

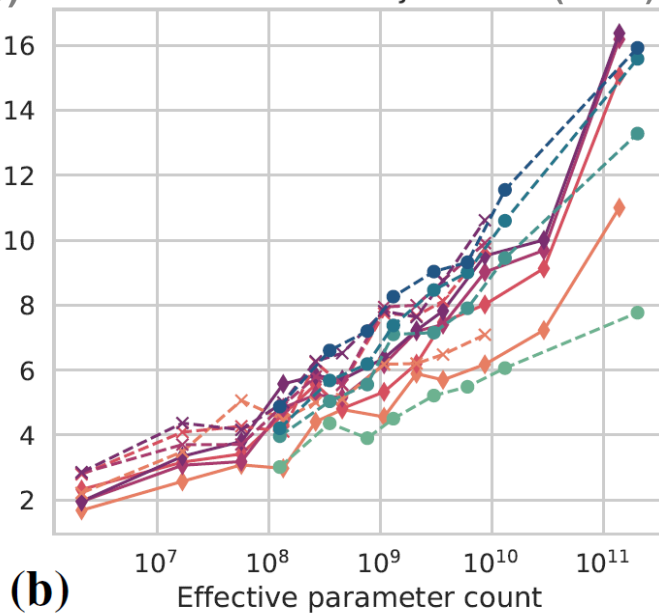
BEYOND THE IMITATION GAME: QUANTIFY-
ING AND EXTRAPOLATING THE CAPABILITIES
OF LANGUAGE MODELS

performance

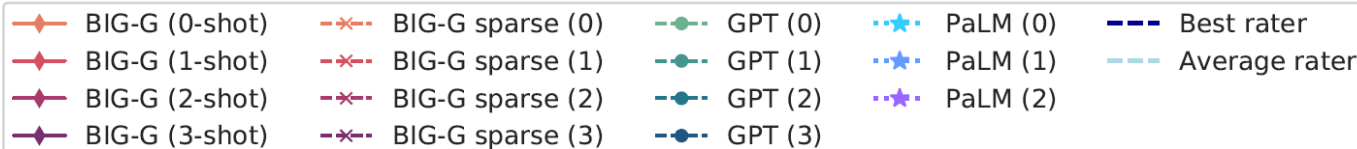
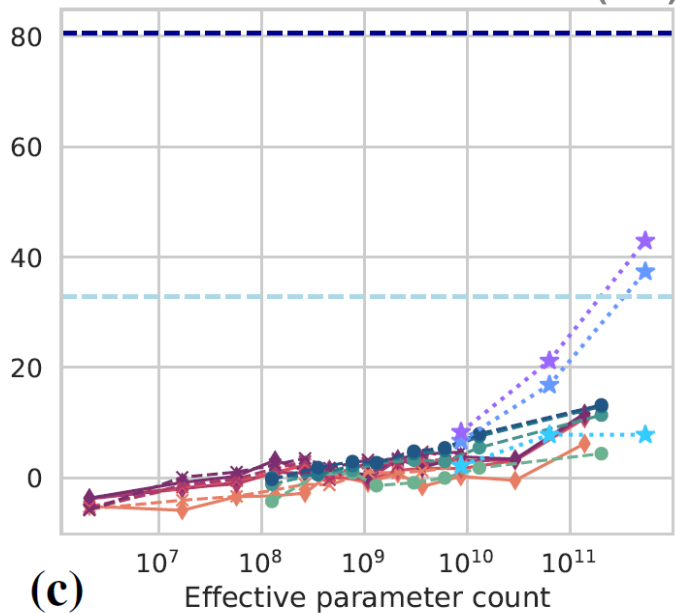
Performance on human-evaluated tasks (~150)



Performance on JSON tasks (~160)

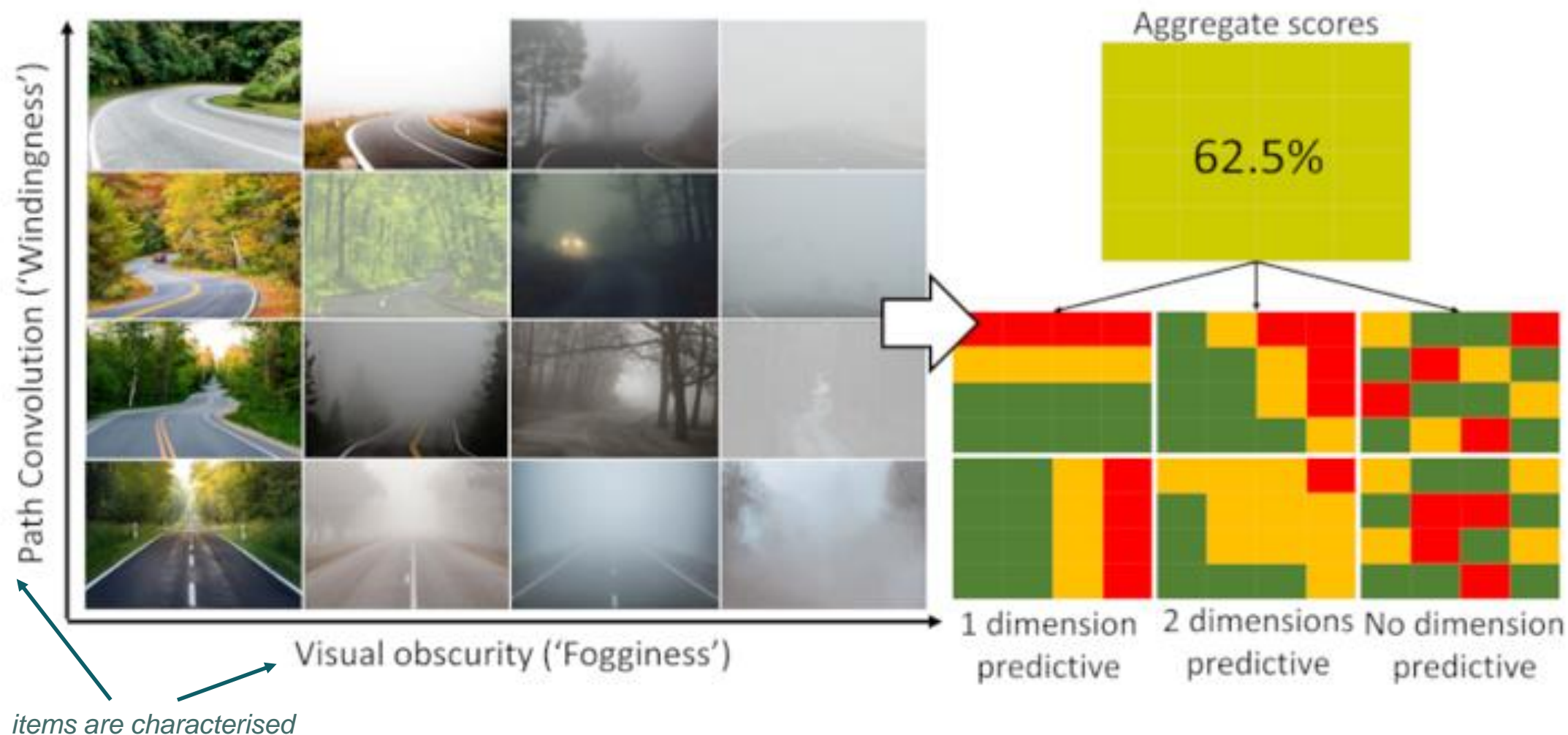


Performance on BIG-bench Lite (~24)



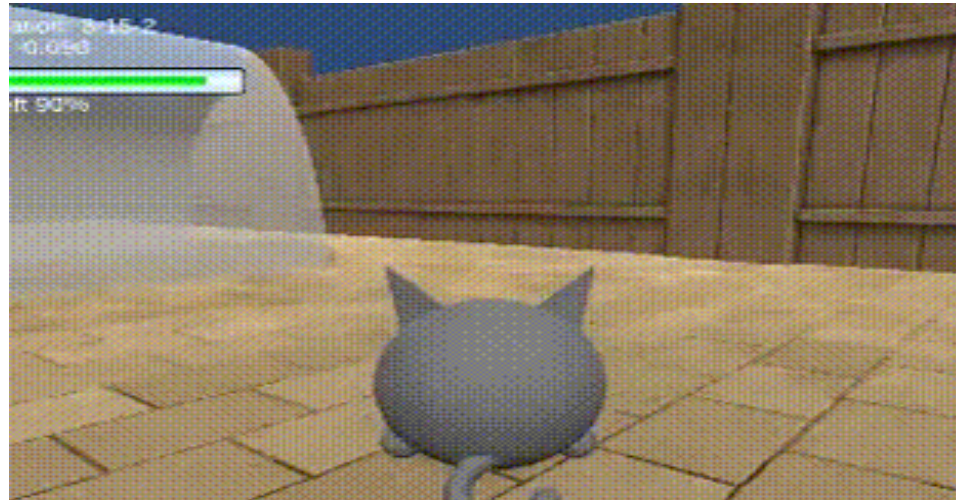
Adam R. Brown, Adam Santoro,
Alex Ray, Alex Warstadt, Alexan-
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Ashish Sabharwal, Austin Herrick,
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ag, Chitta Baral, Chiyu Wu, Chris
Clara E. Rivera, Clemencia Siro,
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Deniz Yuret, Derek Chen, Derek
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Emma Lam, Eric Chu, Eric Tang,
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Vossen, Xiang Ren, Xiaoyu Tong,
ri, Yejin Choi, Yichi Yang, Yiding
Wang, Zijie J. Wang, Zirui Wang,

Aggregate scores limit OOD extrapolation



How can we identify capabilities?

- ❑ Selected subset of AAI0 instances measuring simple goal-directed behaviour
- ❑ Data across 99 instances from 68 agents

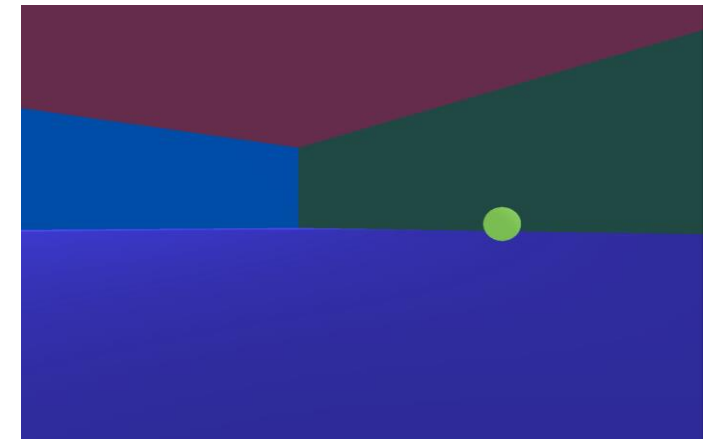
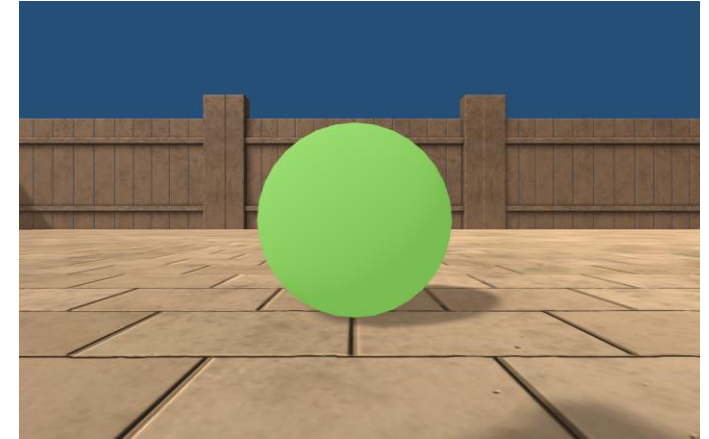


M Crosby, B Beyret, M Shanahan, J Hernández-Orallo, L Cheke, M Halina “The animal-AI testbed and competition” NeurIPS 2019 Competition and Demonstration Track, Proceedings of Machine Learning Research, 2020

animalai.org

Identifying features of interest

- ❑ Relevant
 - ❑ Reward size
 - ❑ Reward distance
 - ❑ Reward in view (i.e., in front vs behind)
- ❑ Irrelevant
 - ❑ Reward side (left vs right)
 - ❑ Reward colour (green vs yellow)



Dimensions and agent characteristic curves

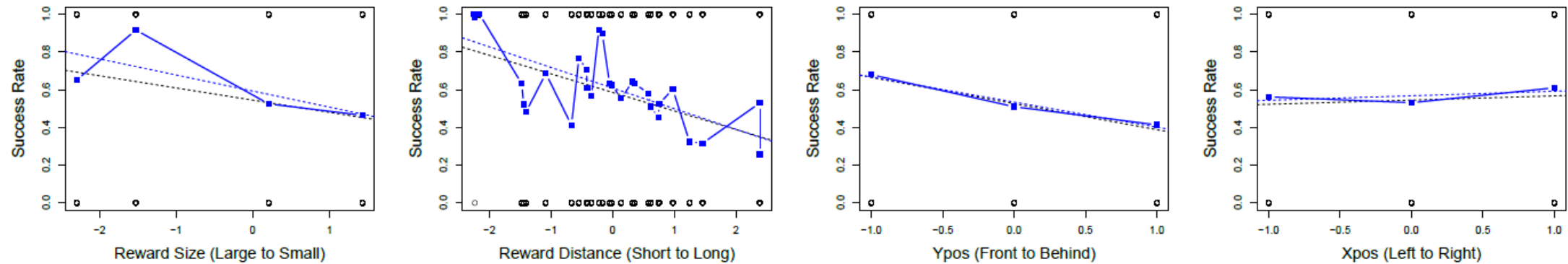
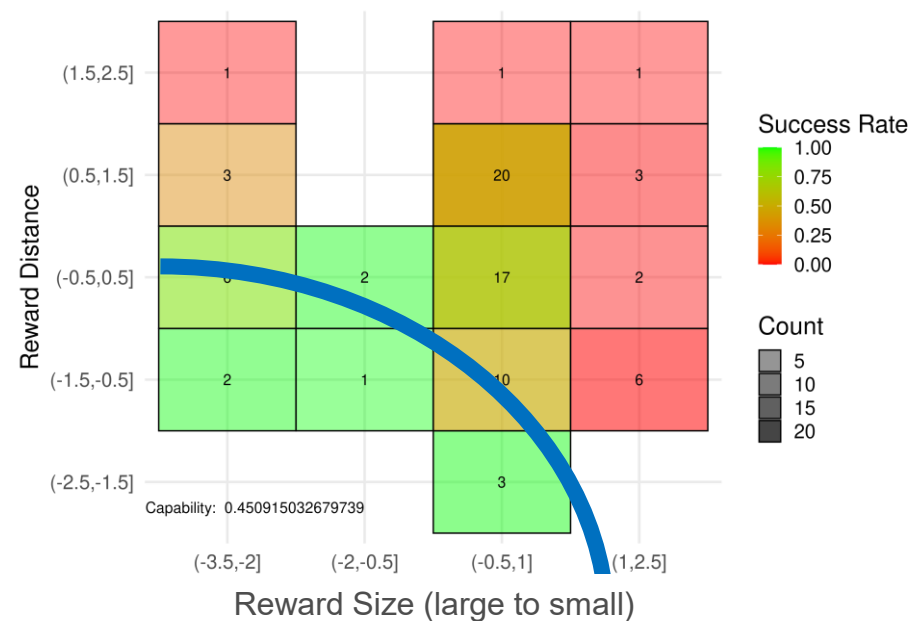


Figure 5: Characteristic curves of all competition entrants (agents) according to three relevant features (size, distance and Ypos) and one irrelevant feature (Xpos). Black dashed lines show the linear regression for the black points (pass/fail), while blue dashed lines interpolate the blue points (binned success rate). The conformances (Spearman correlations against monotonic sequence) are 0.80, 0.60, 1.00 and -0.50 , respectively.

Capabilities vs no-capabilities

Capability boundary



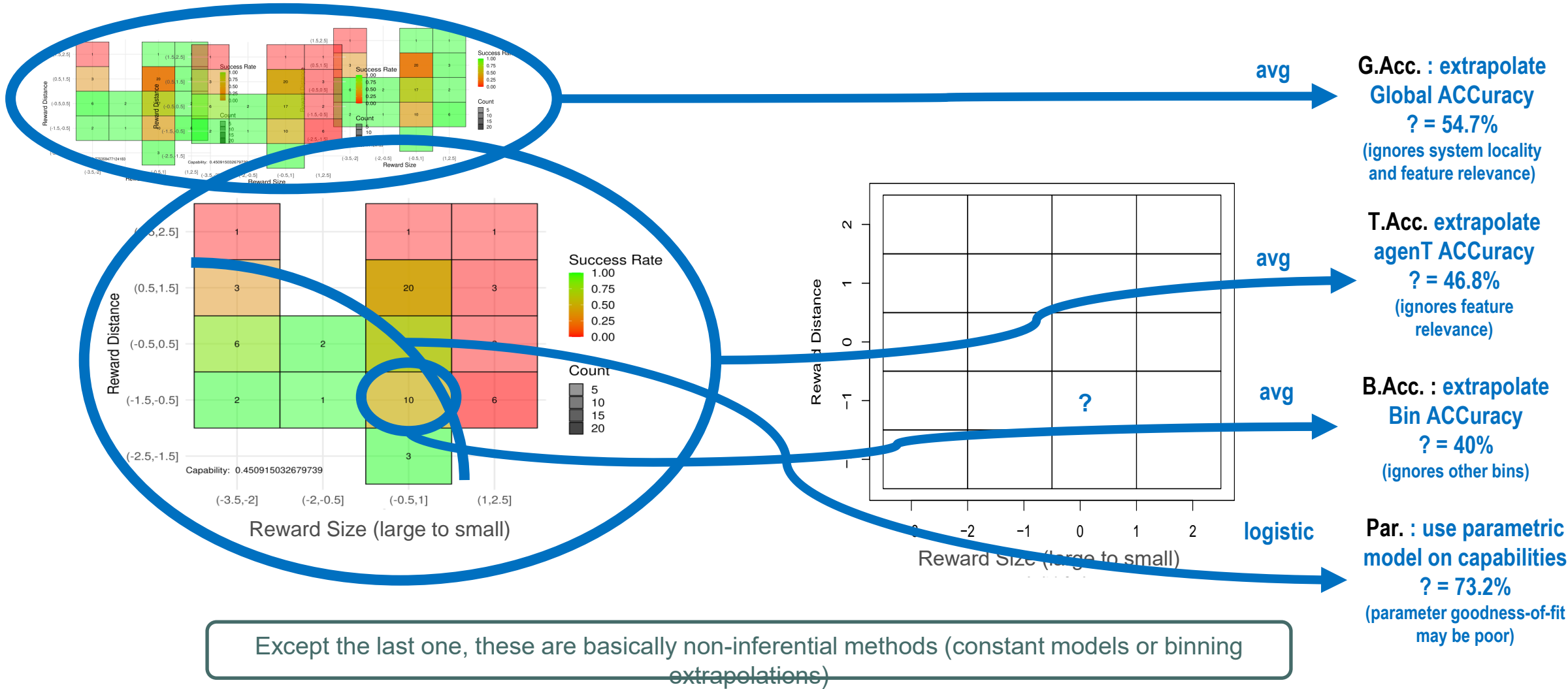
Conformant System
Juohmaru

This system doesn't show monotonicity.
We can't identify any level of capability robustly.



Non-Conformant System
y.yang

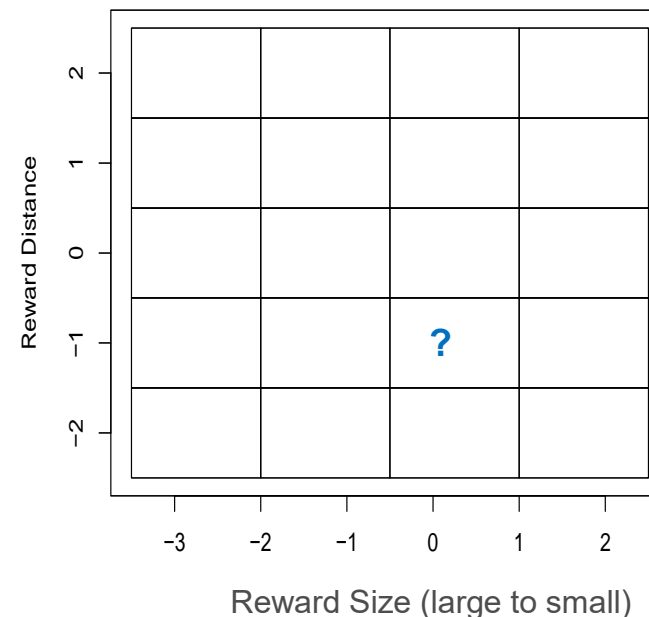
Predicting performance POSSIBLE



Predicting performance NOT POSSIBLE?



A : use assessor models
(Using all variables or only the relevant ones?)



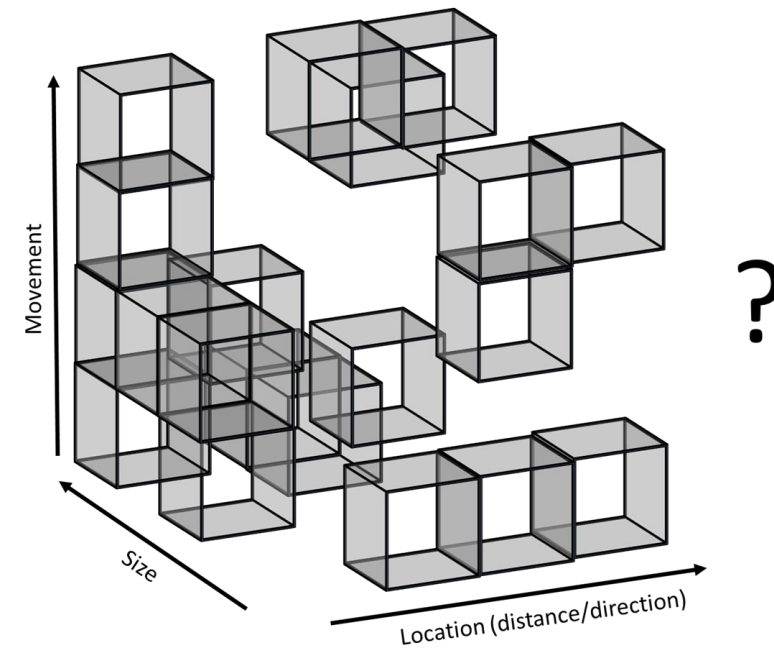
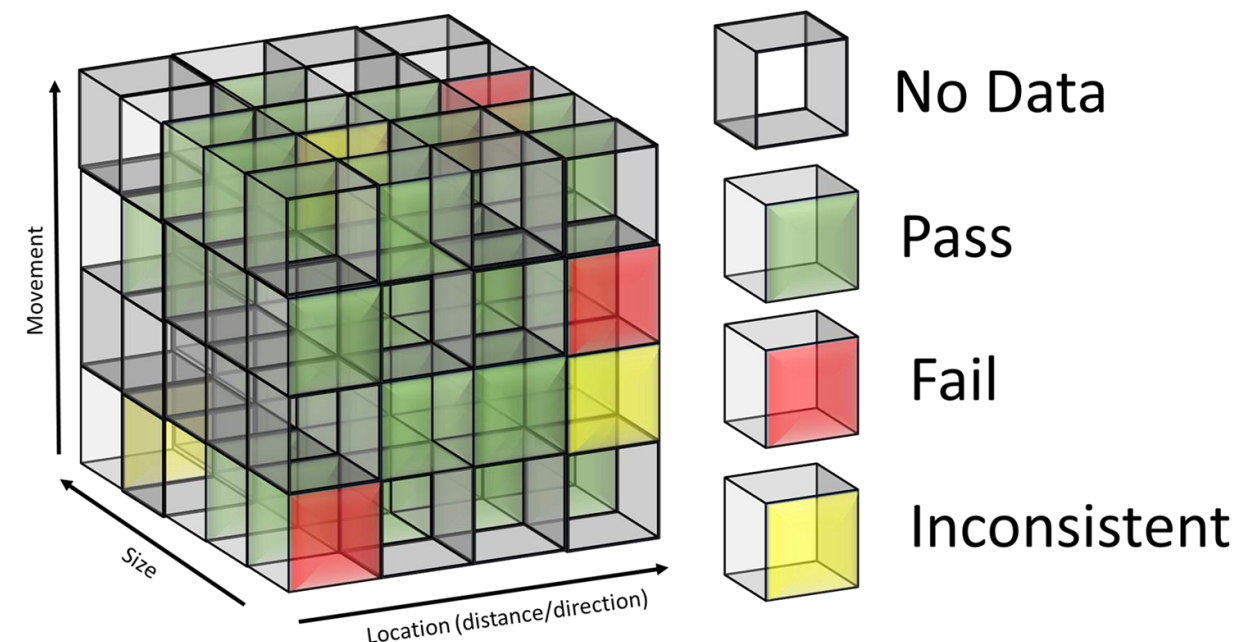
assessors = let's use all the power of ML to characterise the system's performance!!

Predicting performance (comparison)

	Maj. (1)	G.Acc.	T.Acc.	~All+A	~Rel+A
Error	45.3%	48.0%	33.6%	19.7%	20.6%
MAE	45.3%	49.6%	34.9%	29.3%	30.2%
MSE	45.3%	24.8%	17.6%	14.8%	15.4%

Animal AI Competition Data: 99 instances x 68 agents

We need data at the granular level!



Need for granular data!

- ❑ Instance-level data:
 - ❑ For building good predictive models of AI validity, we need evaluation results at the instance level.

Is sharing code open source (github) enough?
Re-running the experiments is not
feasible/sustainable anymore.

- ❑ Demands for each instance:
 - ❑ We can use LLMs for annotation!

Rethink reporting of evaluation results in AI

Aggregate metrics and lack of access to results limit understanding

By Ryan Burnell¹, Wout Schellaert², John Burden^{1,3}, Tomer D. Ullman⁴, Fernando Martinez-Plumed², Joshua B. Tenenbaum⁵, Danaja Rutar¹, Lucy G. Cheke^{1,6}, Jascha Sohl-Dickstein⁷, Melanie Mitchell⁸, Douwe Kiela⁹, Murray Shanahan^{10,11}, Eleni M. Voorhees¹², Anthony G. Cohn^{13,14,15,16}, Joel Z. Leibo¹⁰, Jose Hernandez-Orallo^{12,23}

Artificial intelligence (AI) systems have begun to be deployed in high-stakes contexts, including autonomous driving and medical diagnosis. In contexts such as these, the consequences of system failures can be devastating. It is therefore vital that researchers and policy-makers have a full understanding of the capabilities and weaknesses of AI systems so that they can make informed decisions about where these systems are safe to use and how they might be improved. Unfortunately, current approaches to AI evaluation make it exceedingly difficult to build such an understanding, for two key reasons. First, aggregate metrics make it hard to predict how a system will perform in a particular situation. Second, the instance-by-instance evaluation results that could be used to unpack these aggregate metrics are rarely made available (1). Here, we propose a path forward in which results are presented in more nuanced ways and instance-by-instance evaluation results are made publicly available.

Across most areas of AI, system evaluations follow a similar structure. A system is first built or trained to perform a particular set of functions. Then, the performance of the system is tested on a set of tasks relevant to the desired functionality of the system. In many areas of AI, evaluations use standardized sets of tasks known as “benchmarks.” For each task, the system will be tested on a number of example “instances” of the task. The system would then be given a score for each instance based on its performance, e.g., 1 if it classified an image correctly, or 0 if it

was incorrect. For other systems, the score for each instance might be based on how quickly the system completed its task, the quality of its outputs, or the total reward it obtained. Finally, performance across the various instances and tasks is usually aggregated to a small number of metrics that summarize how well the system performed, such as percentage accuracy.

But aggregate metrics limit our insight into performance in particular situations, making it harder to find system failure points and robustly evaluate system safety. This problem is also worsening as the increasingly broad capabilities of state-of-the-art systems necessitate ever more diverse benchmarks to cover the range of their capabilities. This problem is further exacerbated by a lack of access to the instance-by-instance results underlying the aggregate metrics, making it difficult for researchers and policy-makers to further scrutinize system behavior.

AGGREGATE METRICS

Use of aggregate metrics is understandable. They provide information about system performance “at a glance” and allow for simple comparisons across systems. But aggregate performance metrics obfuscate key information about where systems tend to succeed or fail (2). Take, for example, a system that was trained to classify faces as male or female that achieved classification accuracy of 90% (3). Based on this metric, the system appears highly competent. However, a subsequent breakdown of performance revealed that the system misclassified females with darker skin types a staggering 34.5% of the time, while erring only 0.8% of the time for males with lighter skin types. This example demonstrates how aggregation can make it difficult for policymakers to determine the fairness and safety of AI systems.

Compounding this problem, many benchmarks include disparate tasks that are ultimately aggregated together. For

example, the Beyond the Imitation Game Benchmark (BIG-bench) for language models includes over 200 tasks that evaluate everything from language understanding to causal reasoning (4). Aggregating across these disparate tasks—as the BIG-bench leaderboard does—reduces the rich information in the benchmark to an overall score that is hard to interpret.

It is also easy for aggregation to introduce unwarranted assumptions into the evaluation process. For example, a simple average across tasks implicitly treats every task as equally important—in the case of BIG-bench, a sports understanding task has as much bearing on the overall score as a causal reasoning task. These aggregation decisions have huge implications for the conclusions that are drawn about system capabilities, yet are seldom considered carefully or explained.

Aggregate metrics depend not only on the capability of the system but also on the characteristics of the instances used for evaluation. If the gender classification system above were reevaluated by using entirely light-skinned faces, accuracy would skyrocket, even though the system’s ability to classify faces has not changed. Aggregate metrics can easily give false impressions about capabilities when a benchmark is not well constructed.

Problems and trade-offs that arise when considering aggregate versus granular data and metrics are not specific to AI, but they are exacerbated by the challenges inherent in AI research and the research practices of the field. For example, machine learning evaluations usually involve randomly splitting data into training, validation, and test sets. An enormous amount of data is required to train state-of-the-art systems, so these datasets are often poorly curated and lack the detailed annotation necessary to conduct granular analyses. In addition, the research culture in AI is centered around outdoing the current state-of-the-art performance, as evidenced by the many lea-

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From characteristic grids to measurement layouts

- ❑ Building upon IJCAI “Not A Number” paper
- ❑ Go beyond defining characteristic patterns of performance across limited number of distributions
- ❑ Extracting **cognitive profile** of agents across range of capabilities - incorporating specific limitations and weaknesses (e.g. bias, lack of robustness etc).

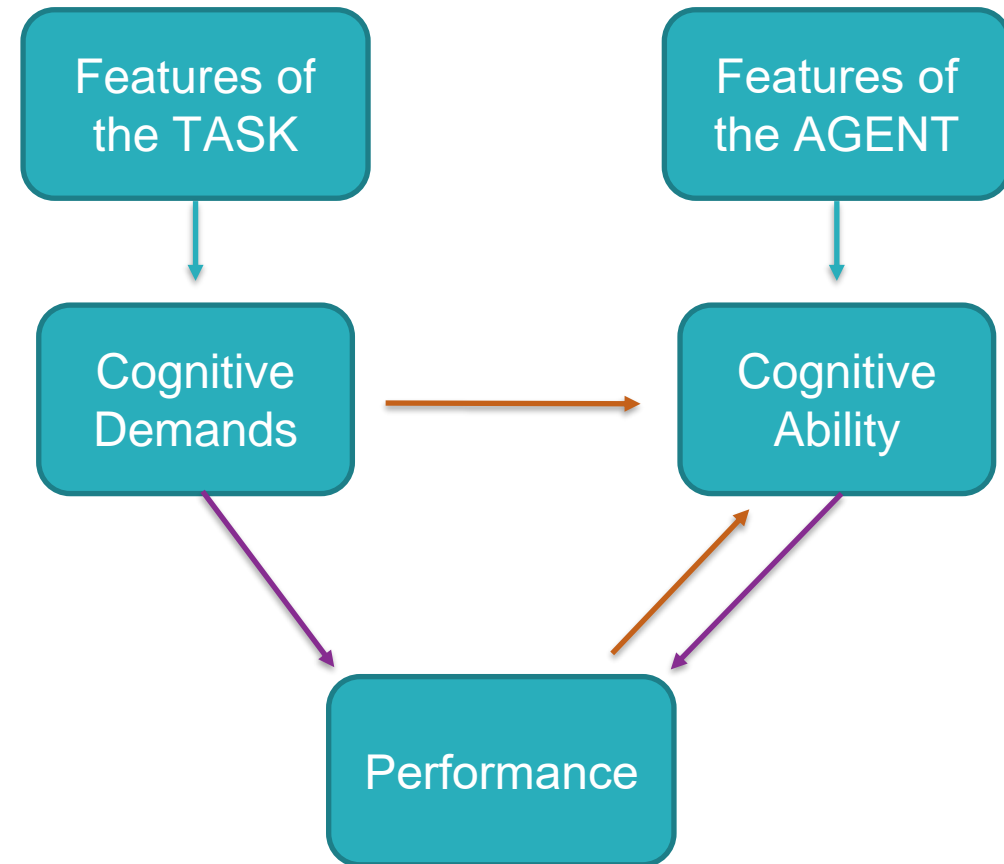
Modelling capabilities

We build on:

- The cognitive demands for each task instance
- Performance dictated from agent abilities meeting demands
- The assumed relationship between demands and abilities

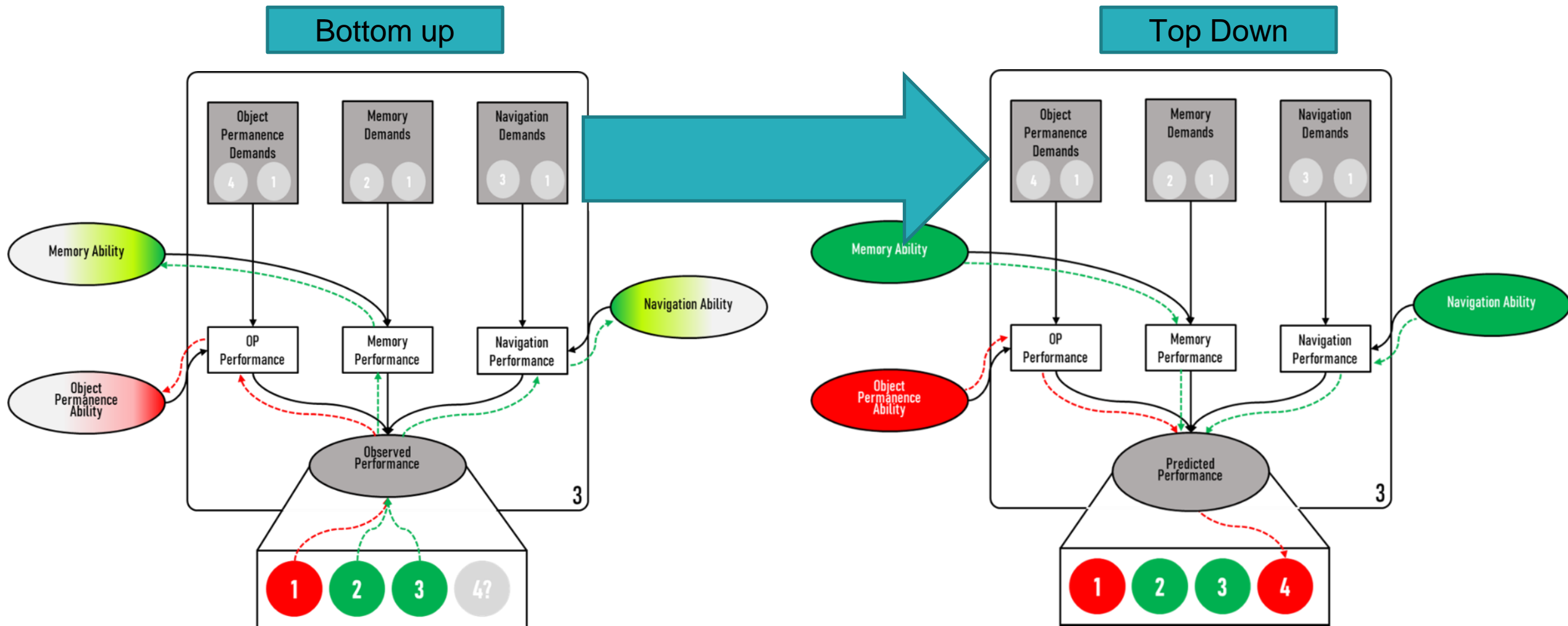
...to **infer** the cognitive profile of a subject from the performance data of that subject only across a number of diverse instances.

The Measurement Layouts are Hierarchical Bayesian networks, implemented in PyMC, a probabilistic programming language for building Bayesian models and fitting them with Markov Chain Monte Carlo (MCMC) methods.



Simplest linking function:
 $\text{performance} = f(\text{ability} - \text{demand})$

Bi-directional inference



Thank you!

