Orchestrating a brighter world



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Motivation

Given a dataset, we consider an AI system as a machine that can generate a solution for a given task. In our work, we tackle the question: How can we assess such systems in a human-centric manner?



Ground truth: The man at the bat readies to swing at the pitch while the umpire looks on.

Prediction: Two men playing baseball

Figure 1: If we have a system that generates captions for given images, how can we properly compare two captions?

Typically in order to evaluate a system solving a task, we compare the generated solution with the ground truth. Through this comparison, we can assess the AI system appropriately on a test set.

Issues with standard approaches: it assumes that the ground truth data can be generated or easily defined, which is not the case for many scenarios. For example, in order to assess an AI framework that generates explanations, we must first answer:

- What is a good ground-truth explanation?
- How do we compare explanations? The comparison is not straightforward.

Generation of ground truth data	Con
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To assess the performance of two systems, we propose a blind experiment with two sides:

- A selected domain expert we call a **lead expert**
- Solvers: Al system or another domain expert



A Human-Centric Assessment Framework for Al

nparison of generated data

ctive guous ult to describe mathematically





Conclusion: Machine explanations can be as good as human explanations, such that a colourblind lead expert would receive adequate assistance from an AI model to recognize colours.



The framework consists of the following steps: The lead expert identifies a task to be solved by one of

• The task is assigned randomly to one of the solvers who tries to solve the task and returns a solution. • The lead expert does not know who the solver is. Following approval guidelines, the lead expert evaluates the solution by accepting or rejecting it.

Figure 2: By monitoring the experiment and by evaluating the acceptance rates for solvers, the AI system can be assessed in

Figure 3: Based on the framework we propose an instantiation to assess the usefulness of explanations by using Ishihara colourblind images.

See our paper for framework instantiations:

- How it is related to assessment measures like classification accuracy.
- How the quality of explanations can be assessed on Ishihara's colorblindness test.