LangFair: A Python Package for Assessing Bias and Fairness in Large Language Model Use Cases

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Abstract

Large Language Models (LLMs) have been observed to exhibit bias in numerous ways, potentially creating or worsening outcomes for specific groups identified by protected attributes such as sex, race, sexual orientation, or age. To help address this gap, we introduce langfair, an open-source Python package that aims to equip LLM practitioners with the tools to evaluate bias and fairness risks relevant to their specific use cases. The package offers functionality to easily generate evaluation datasets, comprised of LLM responses to use-case-specific prompts, and subsequently calculate applicable metrics for the practitioner's use case. To guide in metric selection, LangFair offers an actionable decision framework.

Keywords: large language models, algorithmic fairness, artificial intelligence, machine learning, Python

1. Introduction

Traditional machine learning (ML) fairness toolkits like AIF360 (Bellamy et al., 2018), Fairlearn (Weerts et al., 2023), Aequitas (Saleiro et al., 2018) and others (Vasudevan and Kenthapadi, 2020; Wexler et al., 2019; Tensorflow, 2020) have laid crucial groundwork. These toolkits offer various metrics and algorithms that focus on assessing and mitigating bias and fairness through different stages of the ML lifecycle. While the fairness assessments offered by these toolkits include a wide variety of generic fairness metrics, which can also apply to certain LLM use cases, they are not tailored to the generative and context-dependent nature of LLMs.¹

LLMs are used in systems that solve tasks such as recommendation, classification, text generation, and summarization. In practice, these systems try to restrict the responses of the LLM to the task at hand, often by including task-specific instructions in system or user prompts. When the LLM is evaluated without taking the set of task-specific prompts into account, the evaluation metrics are not representative of the system's true performance. Representing the system's actual performance is especially important when evaluating its

^{1.} The toolkits mentioned here offer fairness metrics for classification. In a similar vein, the recommendation fairness metrics offered in FaiRLLM (Zhang et al., 2023) can be applied to ML recommendation systems as well as LLM recommendation use cases.

outputs for bias and fairness risks because they pose real harm to the user and, by way of repercussions, the system developer.

Most evaluation tools, including those that assess bias and fairness risk, evaluate LLMs at the model-level by calculating metrics based on the responses of the LLMs to static benchmark datasets of prompts (Rudinger et al., 2018; Zhao et al., 2018; Webster et al., 2018; Levy et al., 2021; Nadeem et al., 2020; Bartl et al., 2020; Nangia et al., 2020; Felkner et al., 2024; Barikeri et al., 2021; Kiritchenko and Mohammad, 2018; Qian et al., 2022; Gehman et al., 2020; Dhamala et al., 2021; Huang et al., 2023; Nozza et al., 2021; Parrish et al., 2022; Li et al., 2020; Krieg et al., 2023) that do not consider prompt-specific risks and are often independent of the task at hand. Holistic Evaluation of Language Models (HELM) (Liang et al., 2023), DecodingTrust (Wang et al., 2023), and several other toolkits (Srivastava et al., 2022; Huang et al., 2024; Gao et al., 2024; Nazir et al., 2024; Huggingface, 2022) follow this paradigm.

In this paper, we introduce langfair, an open-source Python package for conducting bias and fairness assessments of LLM use cases.² LangFair complements the aforementioned frameworks because it follows a bring your own prompts (BYOP) approach, which allows users to tailor the bias and fairness evaluation to their use case by computing metrics using LLM responses to user-provided prompts. This addresses the need for a task-based bias and fairness evaluation tool that accounts for prompt-specific risk for LLMs.³ To guide the selection of bias and fairness metrics, LangFair offers an actionable decision framework, discussed in detail in the project's companion paper, Bouchard (2024).

Furthermore, LangFair is designed for real-world LLM-based systems that require governance audits. LangFair focuses on calculating metrics from LLM responses only, which is more practical for real-world testing where access to internal states of model to retrieve embeddings or token probabilities is difficult. An added benefit is that output-based metrics, which are focused on the downstream task, have shown to be potentially more reliable than metrics derived from embeddings or token probabilities (Goldfarb-Tarrant et al., 2021; Delobelle et al., 2022).

2. Generation of Evaluation Datasets

The langfair.generator module offers two classes, ResponseGenerator and CounterfactualGenerator, which aim to enable user-friendly construction of evaluation datasets for text generation use cases.

ResponseGenerator class. To streamline generation of evaluation datasets, the ResponseGenerator class wraps an instance of a langchain LLM and leverages asynchronous generation with asyncio. To implement, users simply pass a list of prompts (strings) to the ResponseGenerator.generate_responses method, which returns a dictionary containing prompts, responses, and applicable metadata.

Counterfactual Generator class. In the context of LLMs, counterfactual fairness can be assessed by constructing counterfactual input pairs (Gallegos et al., 2024; Bouchard, 2024),

^{2.} The repository for langfair can be found at https://github.com/cvs-health/langfair.

^{3.} Experiments in Wang et al. (2023) demonstrate that prompt content has substantial influence on the likelihood of biased LLM responses.

comprised of prompt pairs that mention different protected attribute groups but are otherwise identical, and measuring the differences in the corresponding generated output pairs. These assessments are applicable to use cases that do not satisfy fairness through unawareness (FTU), meaning prompts contain mentions of protected attribute groups. To address this, the CounterfactualGenerator class offers functionality to check for FTU, construct counterfactual input pairs, and generate corresponding pairs of responses asynchronously using a langchain LLM instance.⁴ Off the shelf, the FTU check and creation of counterfactual input pairs can be done for gender and race/ethnicity, but users may also provide a custom mapping of protected attribute words to enable this functionality for other attributes as well.

3. Bias and Fairness Evaluations for Focused Use Cases

Following Bouchard (2024), evaluation metrics are categorized according to the risks they assess (toxicity, stereotypes, counterfactual unfairness, and allocational harms), as well as the use case task (text generation, classification, and recommendation).⁵ Table 1 maps the classes contained in the langfair.metrics module to these risks. These classes are discussed in detail below.

Table 1: Classes for Computing Evaluation Metrics in langfair.metrics

Class	Risk Assessed	Applicable Tasks
ToxicityMetrics	Toxicity	Text generation
StereotypeMetrics	Stereotypes	Text generation
CounterfactualMetrics	Counterfactual fairness	Text generation
RecommendationMetrics	Counterfactual fairness	Recommendation
ClassificationMetrics	Allocational harms	Classification

Toxicity Metrics The ToxicityMetrics class facilitates simple computation of toxicity metrics from a user-provided list of LLM responses. These metrics leverage a pre-trained toxicity classifier that maps a text input to a toxicity score ranging from 0 to 1 (Gehman et al., 2020; Liang et al., 2023). For off-the-shelf toxicity classifiers, the ToxicityMetrics class provides four options: two classifiers from the detoxify package, roberta-hate-speech-dynabench-r4-target from the evaluate package, and toxigen available on HuggingFace. For additional flexibility, users can specify an ensemble of the off-the-shelf classifiers offered or provide a custom toxicity classifier object.

Stereotype Metrics To measure stereotypes in LLM responses, the **StereotypeMetrics** class offers two categories of metrics: metrics based on word cooccurrences and metrics that leverage a pre-trained stereotype classifier. Metrics based on word cooccurrences aim to assess relative cooccurrence of stereotypical words with certain protected attribute words.

^{4.} In practice, a FTU check consists of parsing use case prompts for mentions of protected attribute groups.

^{5.} Note that text generation encompasses all use cases for which output is text, but does not belong to a predefined set of elements (as with classification and recommendation).

^{6.} https://github.com/unitaryai/detoxify; https://github.com/huggingface/evaluate; https://github.com/microsoft/TOXIGEN

On the other hand, stereotype-classifier-based metrics leverage the wu981526092/Sentence-Level-Stereotype-Detector classifier available on HuggingFace (Zekun et al., 2023) and compute analogs of the aforementioned toxicity-classifier-based metrics (Bouchard, 2024).

Counterfactual Fairness Metrics for Text Generation The CounterfactualMetrics class offers two groups of metrics to assess counterfactual fairness in text generation use cases. The first group of metrics leverage a pre-trained sentiment classifier to measure sentiment disparities in counterfactually generated outputs (see Huang et al. (2020) for further details). This class uses the vaderSentiment classifier by default but also gives users the option to provide a custom sentiment classifier object. The second group of metrics addresses a stricter desiderata and measures overall similarity in counterfactually generated outputs using well-established text similarity metrics (Bouchard, 2024).

Counterfactual Fairness Metrics for Recommendation The RecommendationMetrics class is designed to assess counterfactual fairness for recommendation use cases. Specifically, these metrics measure similarity in generated lists of recommendations from counterfactual input pairs. Metrics may be computed pairwise (Bouchard, 2024), or attribute-wise (Zhang et al., 2023).

Fairness Metrics for Classification When LLMs are used to solve classification problems, traditional machine learning fairness metrics may be applied, provided that inputs can be mapped to a protected attribute. To this end, the ClassificationMetrics class offers a suite of metrics to address unfair classification by measuring disparities in predicted prevalence, false negatives, or false positives. When computing metrics using the ClassificationMetrics class, the user may specify whether to compute these metrics as pairwise differences (Bellamy et al., 2018) or pairwise ratios (Saleiro et al., 2018).

4. Semi-Automated Evaluation

AutoEval class. To streamline assessments for text generation use cases, the AutoEval class conducts a multi-step process (each step is described in detail above) for a comprehensive fairness assessment. Specifically, these steps include metric selection (based on whether FTU is satsified), evaluation dataset generation from user-provided prompts with a user-provided LLM, and computation of applicable fairness metrics. To implement, the user is required to supply a list of prompts and an instance of langchain LLM. Below we provide a basic example demonstrating the execution of AutoEval.evaluate with a gemini-pro instance.⁹

```
from langchain_google_vertexai import ChatVertexAI
from langfair.auto import AutoEval

llm = ChatVertexAI(model_name='gemini-pro')
auto_object = AutoEval(prompts=prompts, langchain_llm=llm)
results = await auto_object.evaluate()
```

Listing 1: AutoEval Example

^{7.} https://huggingface.co/wu981526092/Sentence-Level-Stereotype-Detector

^{8.} https://github.com/cjhutto/vaderSentiment

^{9.} Note that this example assumes the user has already set up their VertexAI credentials and sampled a list of prompts from their use case prompts.

Under the hood, the AutoEval.evaluate method 1) checks for FTU, 2) generates responses and counterfactual responses (if FTU is not satisfied), and 3) calculates applicable metrics for the use case. ¹⁰ This process flow is depicted in Figure 1.

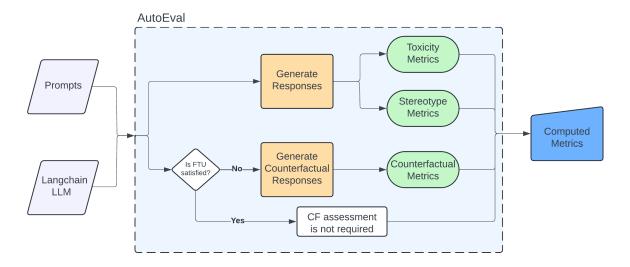


Figure 1: Flowchart of internal design of AutoEval.evaluate method.

5. Conclusions

In this paper, we introduced langfair, an open-source Python package that aims to equip LLM practitioners with the tools to evaluate bias and fairness risks relevant to their specific use cases. The package offers functionality to easily generate evaluation datasets, comprised of LLM responses to use-case-specific prompts, and subsequently calculate applicable metrics for the practitioner's use case. To aid practitioners, we provide numerous supporting resources, including API documentation, tutorial notebooks, and a technical companion paper (Bouchard, 2024).¹¹

Author Contributions

Dylan Bouchard was the principal developer and researcher of the LangFair project, responsible for conceptualization, methodology, and software development of the langfair library. Mohit Singh Chauhan was the architect behind the structural design of the langfair library and helped lead the software development efforts. David Skarbrevik was the primary author of LangFair's documentation, helped implement software engineering best practices, and contributed to software development. Viren Bajaj wrote unit tests, contributed to the software development software engineering best practices. Zeya Ahmad contributed to the software development.

^{10.} The 'AutoEval' class is designed specifically for text generation use cases. Applicable metrics include toxicity metrics, stereotype metrics, and, if FTU is not satisfied, counterfactual fairness metrics.

^{11.} https://cvs-health.github.io/langfair/latest/index.html

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