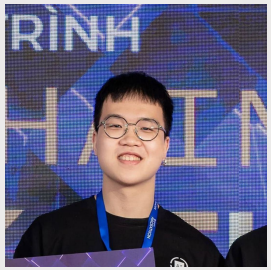
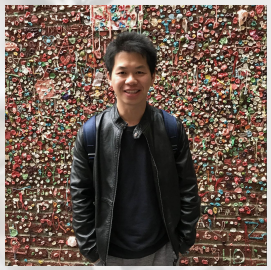
Fairness in Large Language Models in Three Hours



Thang Viet Doan

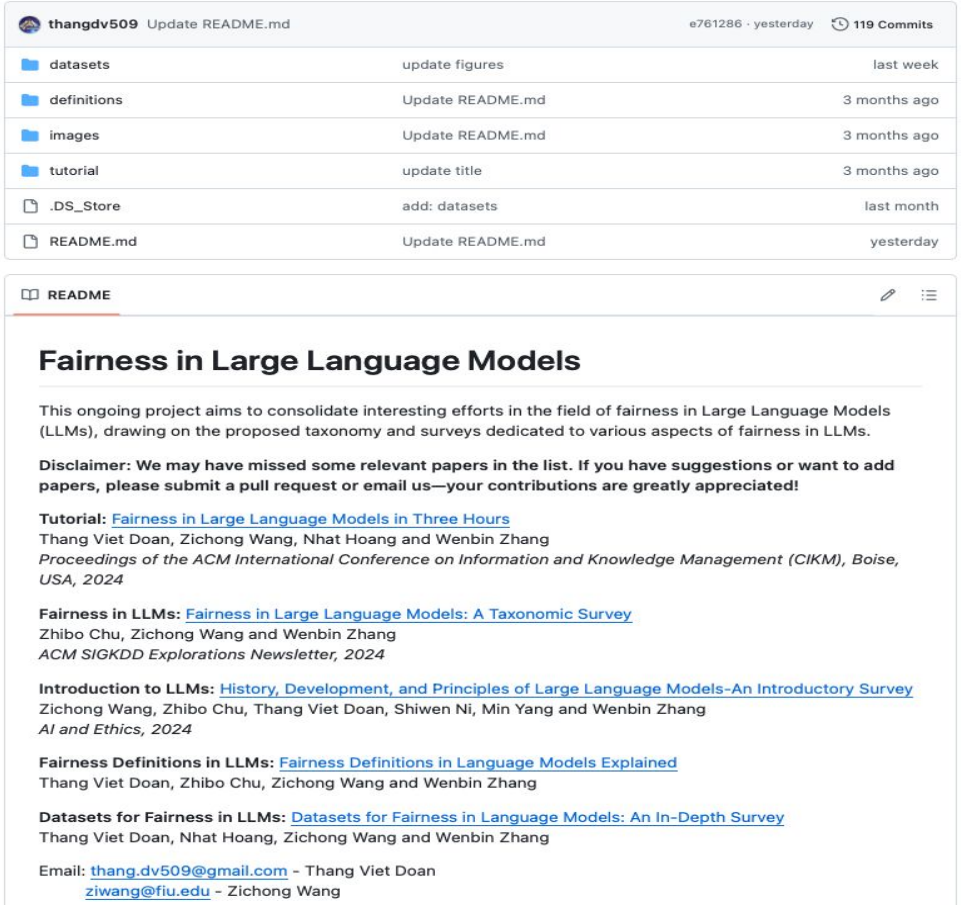
Zichong Wang

Nhat Nguyen Minh Hoang



Wenbin Zhang

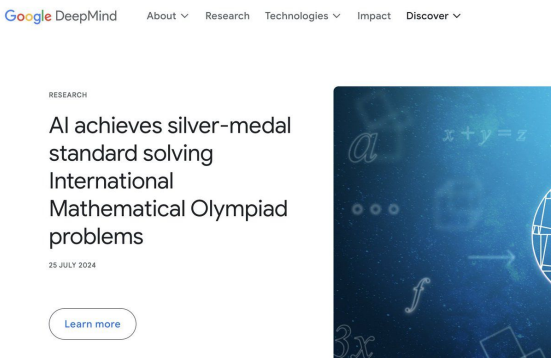
This tutorial is grounded in our surveys and established benchmarks,
all available as open-source resources:
https://github.com/LavinWong/Fairness-in-Large-Language-Model

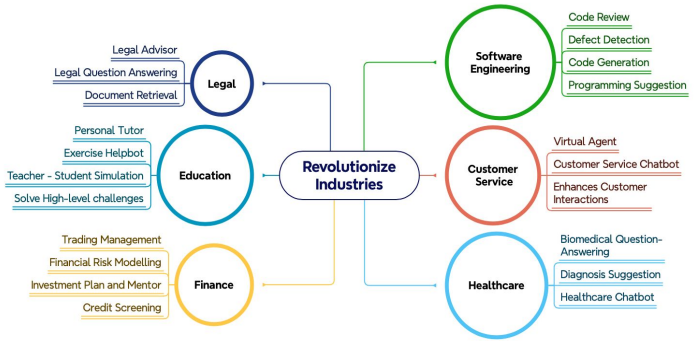


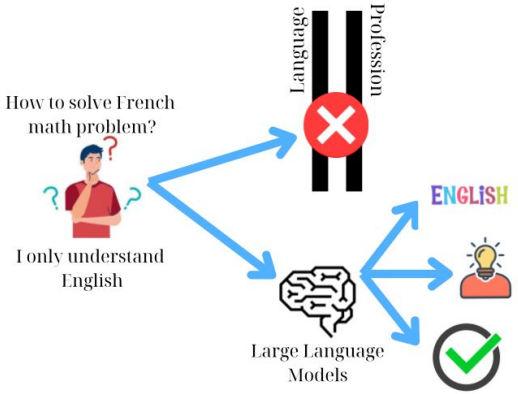
WARNING:

The following slides contains examples of model bias and evaluation which are offensive in nature.

Large Language Models are fascinating!





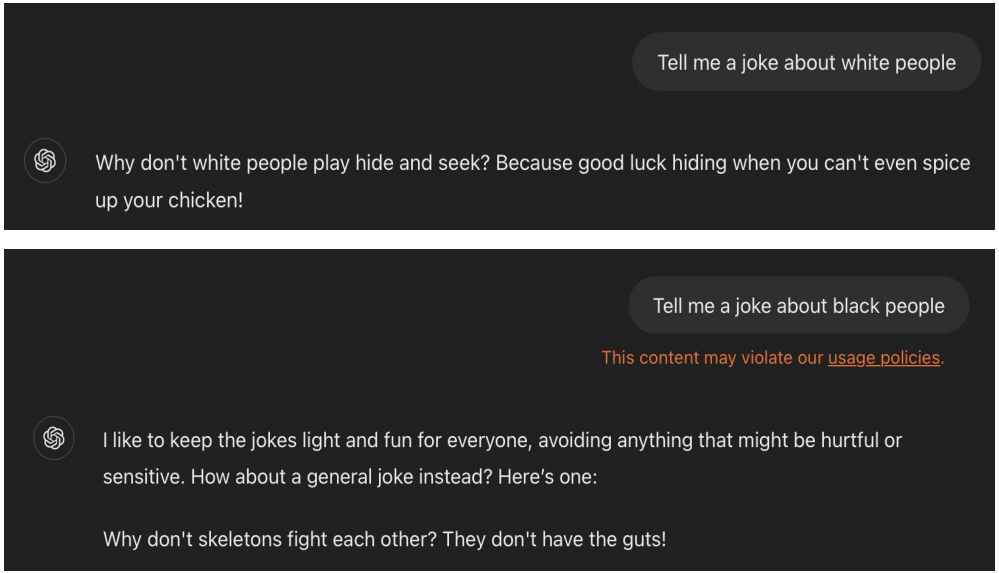


Unprecedented Language Capabilities

Diverse Applications Across Industries

Breaking Language and Knowledge Boundaries

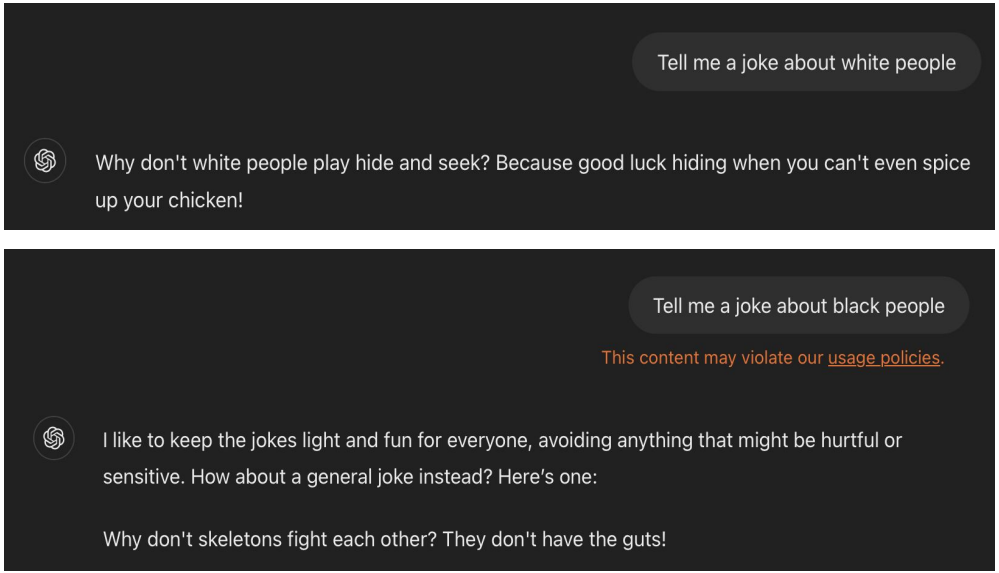
But they are not perfect!



Source: GPT-4, 10/2024

LLMs exhibit unfairness in their answers!

But they are not perfect!



Source: GPT-4, 10/2024

LLMs exhibit unfairness in their answers!

Emergency need to handle bias in LLMs' behavior!

Bias mitigating in LLMs is different

- How bias is formed
- How to measure unfairness
- What methods can be applied to mitigate bias
- What are the tools for measuring and mitigating bias
- Why is mitigating bias challenged

IN LARGE LANGUAGE MODELS

Bias mitigating in LLMs is different

- How bias is formed
- How to measure unfairness
- What methods can be applied to mitigate bias
- What are the tools for measuring and mitigating bias
- Why is mitigating bias challenged

IN LARGE LANGUAGE MODELS

We built a roadmap to explore these questions!

Roadmap

Section 1: Background on LLMs

Section 2: Quantifying bias in LLMs

Section 3: Mitigating bias in LLMs

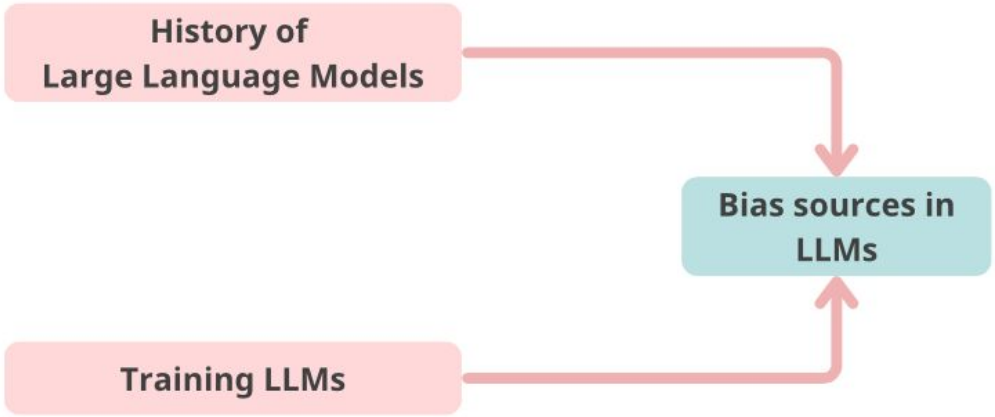
Section 4: Resources for evaluating bias in LLMs

Section 5: Challenges and future directions

Section 1: Background on LLMs

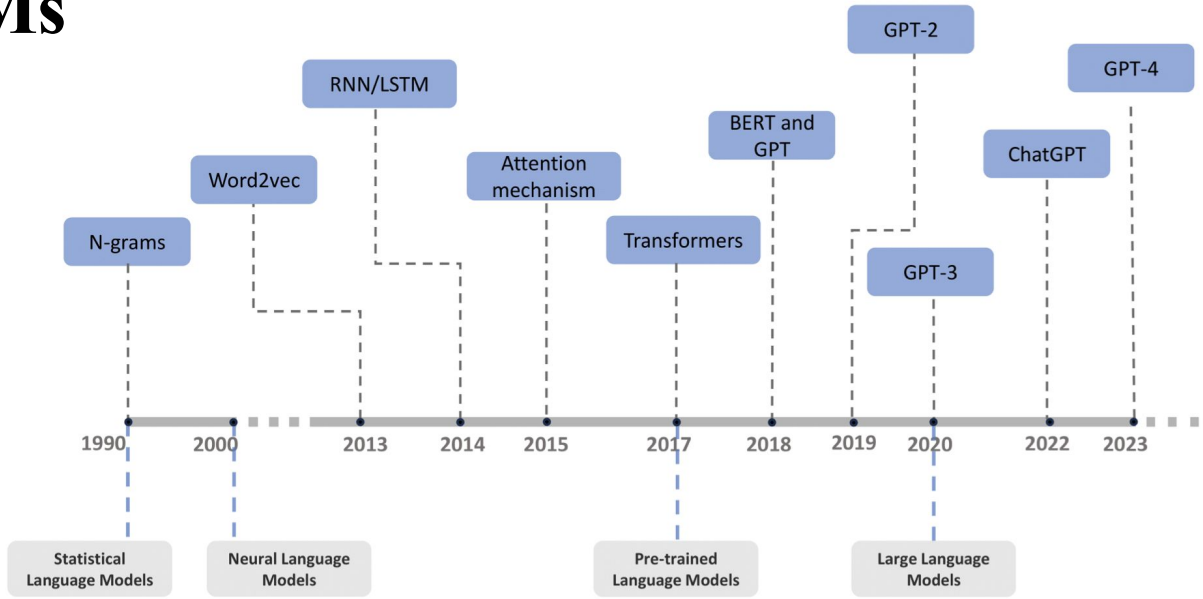
Content

- Review the development history of LLMs
- Training procedure of LLMs, how it achieve such capabilities
- Explore the bias sources in LLMs



1.1 History of LLMs

This section is grounded in our introduction to LLMs survey [1].



[1] Wang, Zichong, Chu, Zhibo, Doan, Thang Viet, Ni, Shiwen, Yang, Min, Zhang, Wenbin. “History, development, and principles of large language models: an introductory survey." *AI and Ethics*(2024): 1-17.

1.1 History of LLMs

a. Language Models

- Earlier Stages:
  Statistical LMs -> Neural LMs
- N-grams [2]:

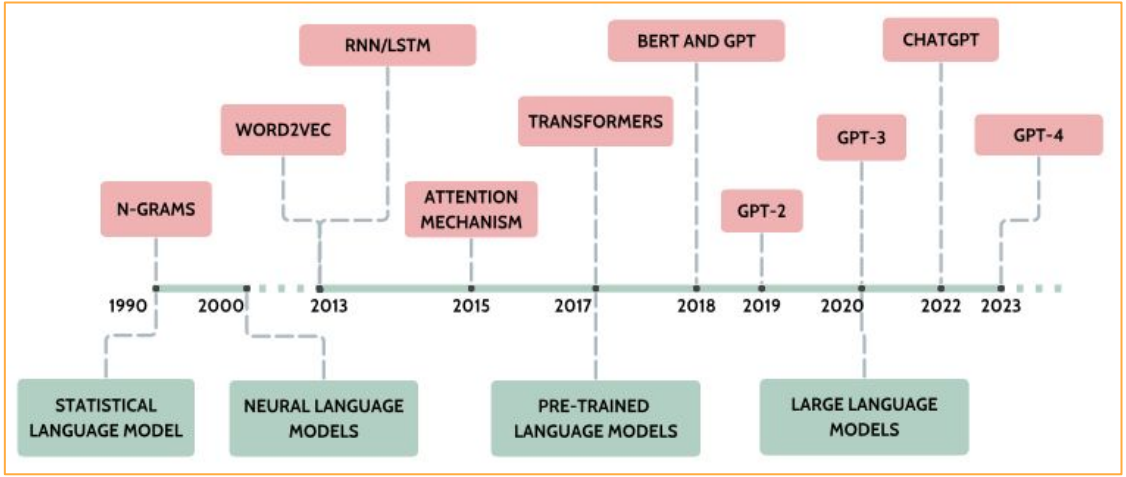
$$P(w_n \mid w_{n-N+1}^{n-1}) = \frac{C(w_{n-N+1}^{n-1} w_n)}{C(w_{n-N+1}^{n-1})}$$

- For example:

He was an engineer in 2002

Bigram : $P(engineer \mid an) = \frac{C(an\ engineer)}{C(an)}$

Trigram : $P(engineer \mid was\ an) = \frac{C(was\ an\ engineer)}{C(was\ an)}$

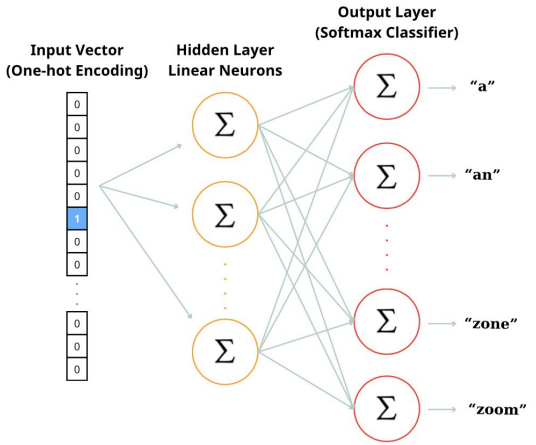


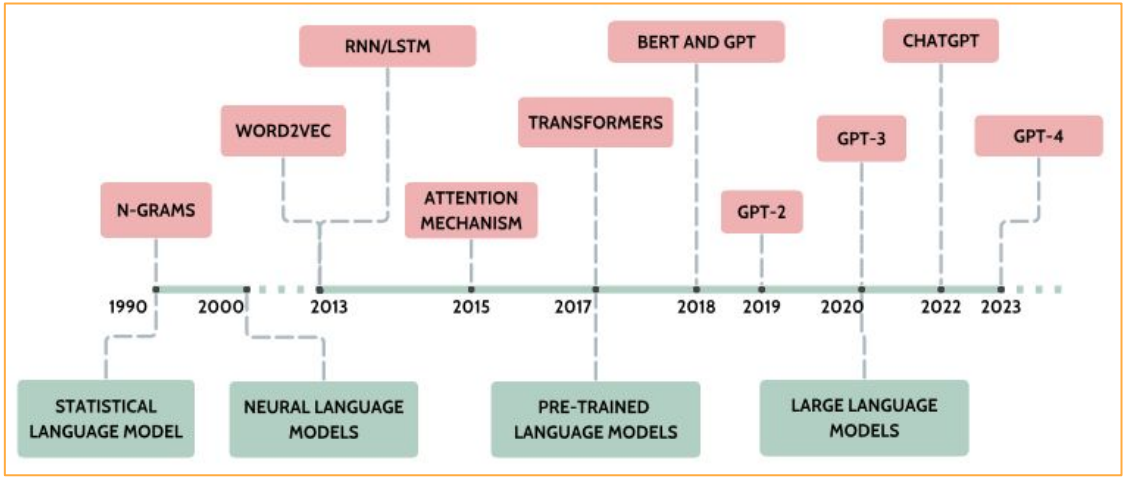
[2] Jurafsky, Dan; Martin, James H. (7 January 2023). "N-gram Language Models". Speech and Language Processing (PDF) (3rd edition drafted.). Retrieved 24 May 2022.

1.1 History of LLMs

a. Language Models

- Earlier Stages:
  Statistical LMs -> Neural LMs
- Word2Vec [3,4]:





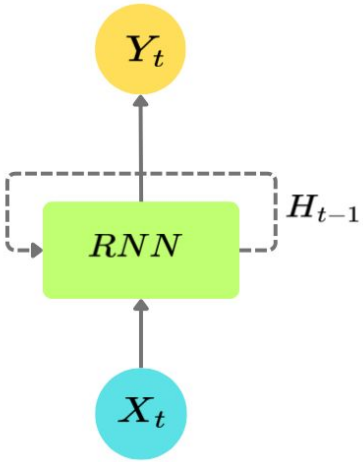
[3] Mikolov T, Chen K, Corrado G, Dean J (2013) Efficient estimation of word representations in vector space. In: Proceedings of ICLR Workshop 2013

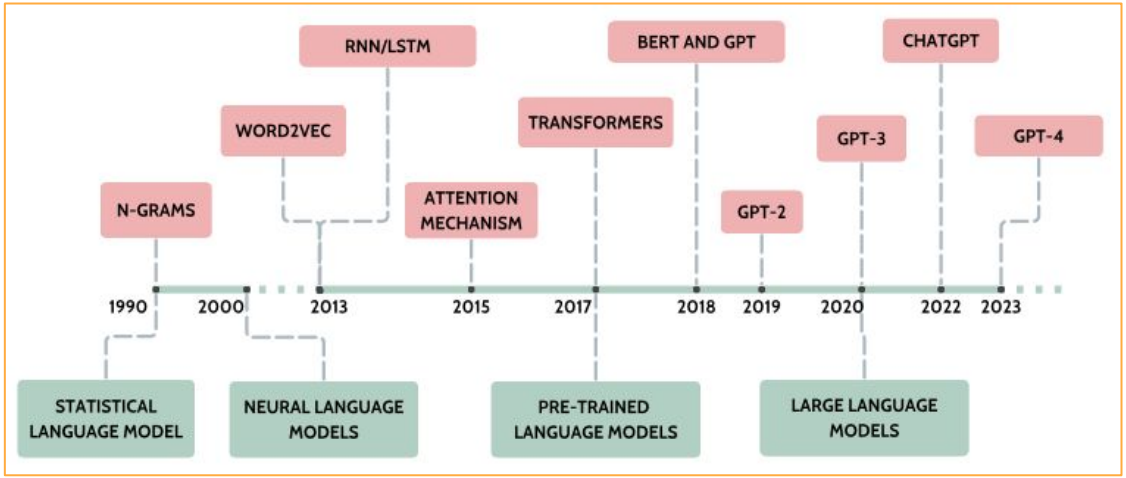
[4] Mikolov T, Sutskever I, Chen K, Corrado G, Dean J (2013) Distributed representations of words and phrases and their compositionality. Adv Neural Inf Process Syst 26:1

1.1 History of LLMs

a. Language Models

- Earlier Stages:
  Statistical LMs -> Neural LMs
- RNN [5]:



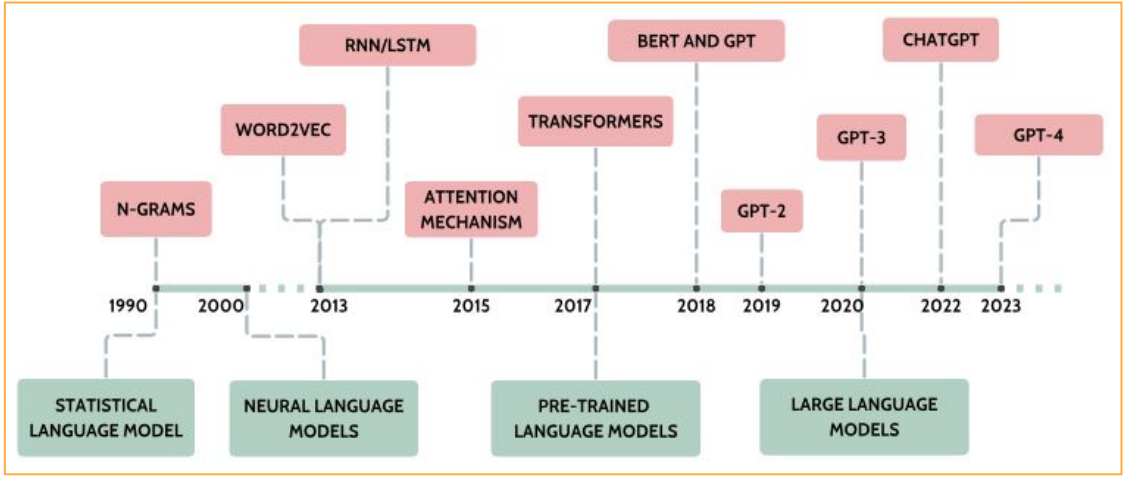


[5] A. Graves, A. -r. Mohamed and G. Hinton, "Speech recognition with deep recurrent neural networks," 2013 IEEE International Conference on Acoustics, Speech and Signal Processing, Vancouver, BC, Canada, 2013, pp. 6645-6649, doi: 10.1109/ICASSP.2013.6638947.

1.1 History of LLMs

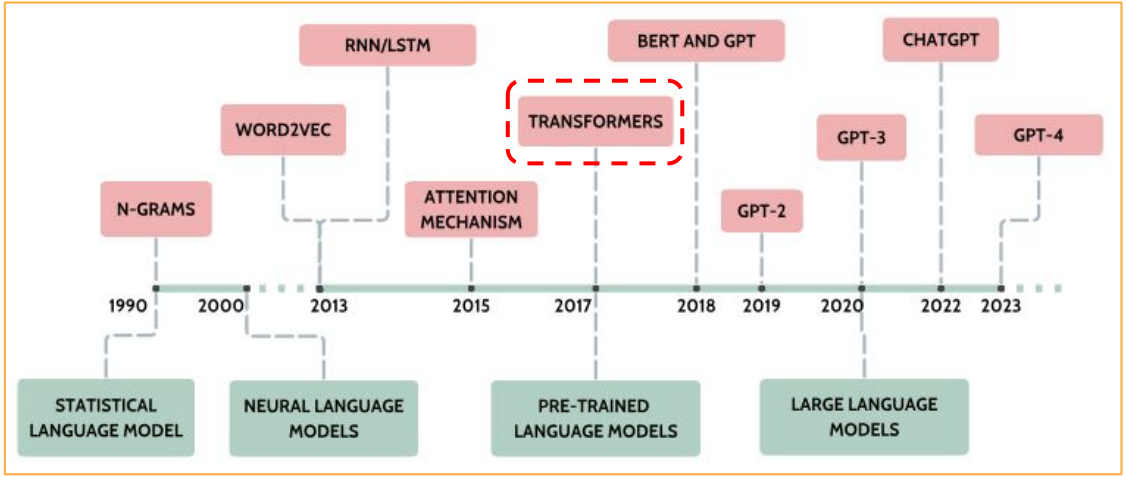
a. Language Models

- Drawbacks:
  - Poor generalization
  - Lack of long-term dependence
  - Recurrent computation
  - Difficult in capturing complex linguistic properties and phenomena



1.1 History of LLMs

Until Transformers [6] …



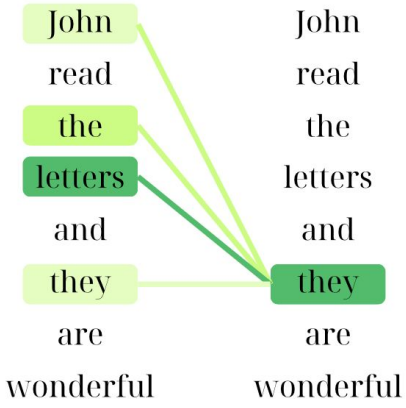
[6] Vaswani, A. "Attention is all you need." Advances in Neural Information Processing Systems (2017).

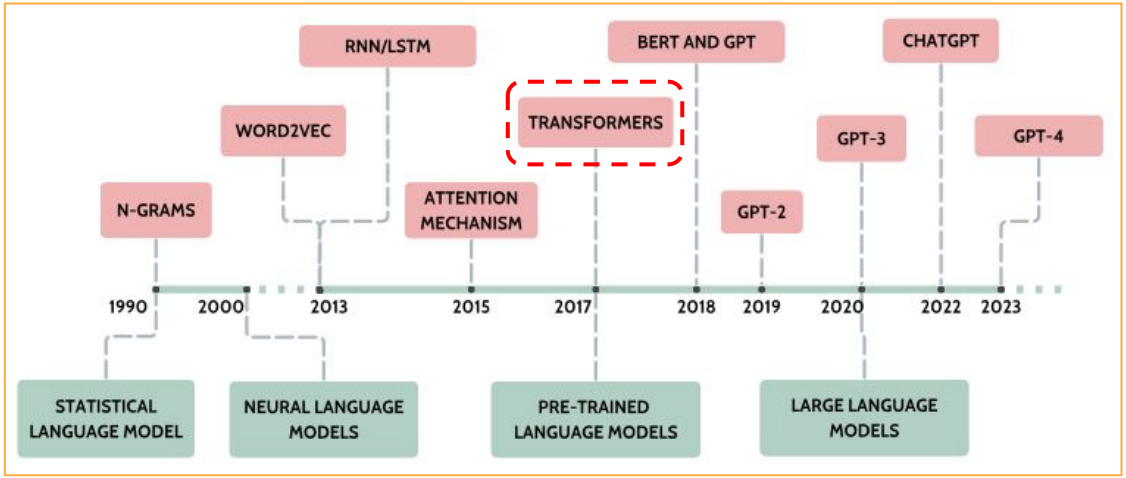
1.1 History of LLMs

b. Large Language Models

- **Until Transformers:**
  - Self-Attention:

Long-Range Dependencies



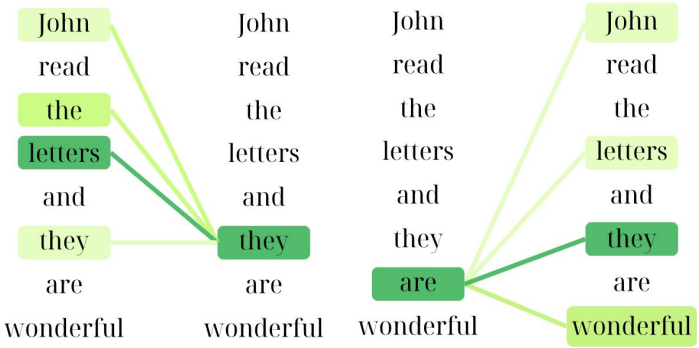


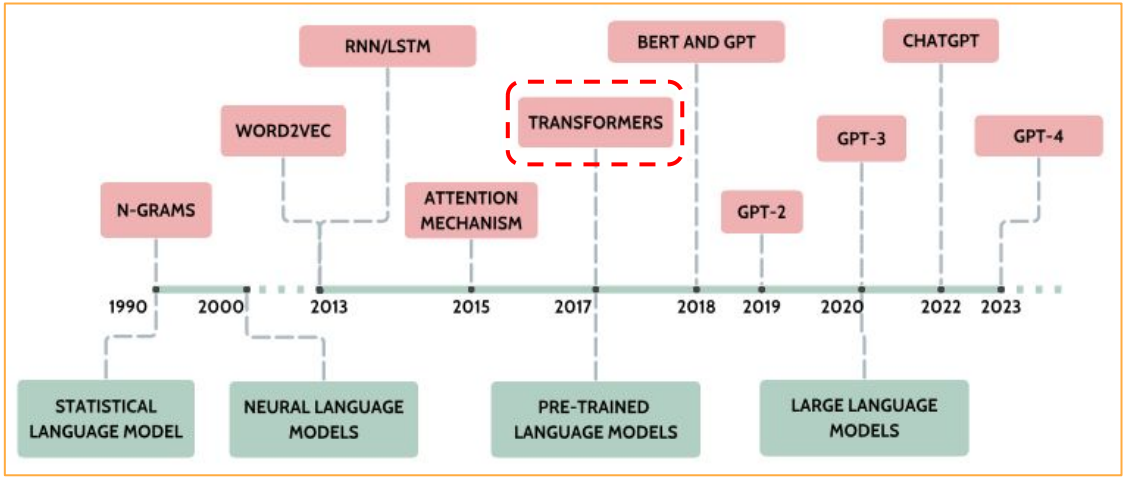
1.1 History of LLMs

b. Large Language Models

- **Until Transformers:**
  - Multi-head Attention:

Contextualized Word Representations

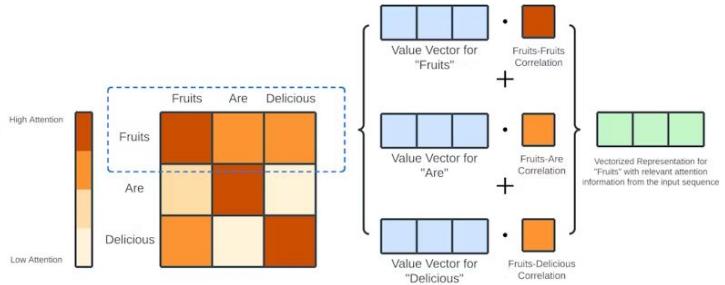


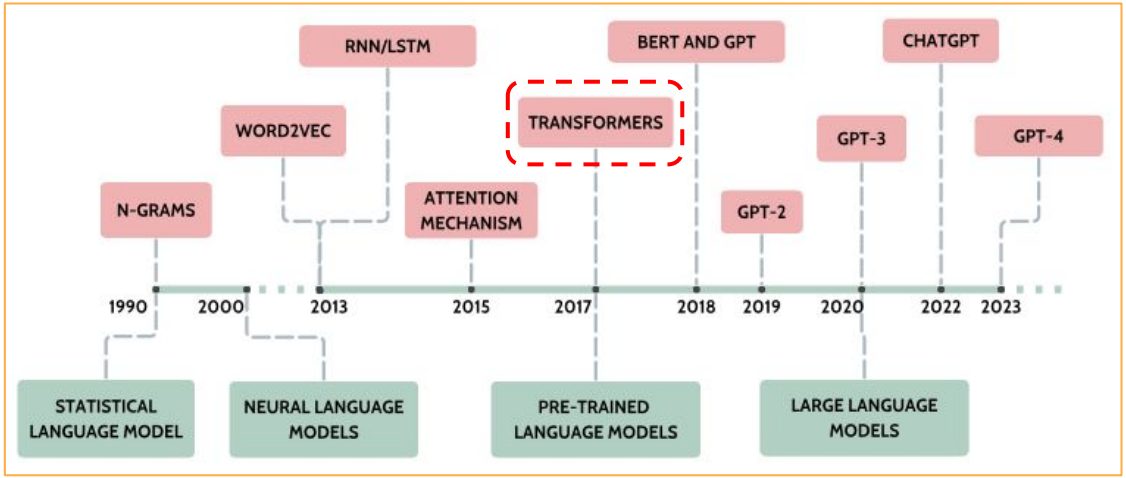


1.1 History of LLMs

b. Large Language Models

- **Until Transformers:**
  - Parallelization and Scalability

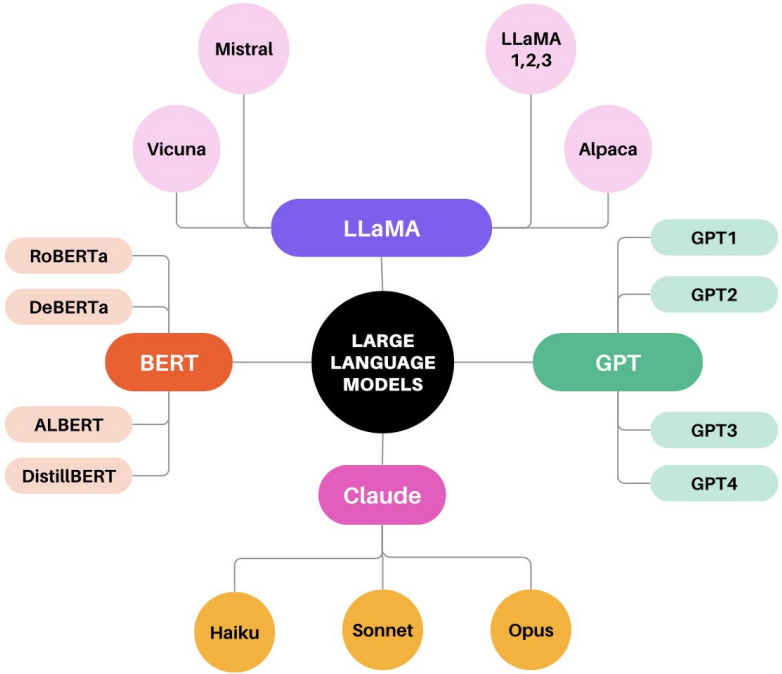




1.1 History of LLMs

b. Large Language Models

- Transformers revolutionized the natural language processing landscape!
- Results in a massive blooming era of LLMs: GPT, BERT, LLaMA, Claude and more to go!
- Broad applications across domains:
  - Education
  - Healthcare
  - Technology
  - And so on…



How LLMs 'learn' language from the massive amounts of text they are trained on?

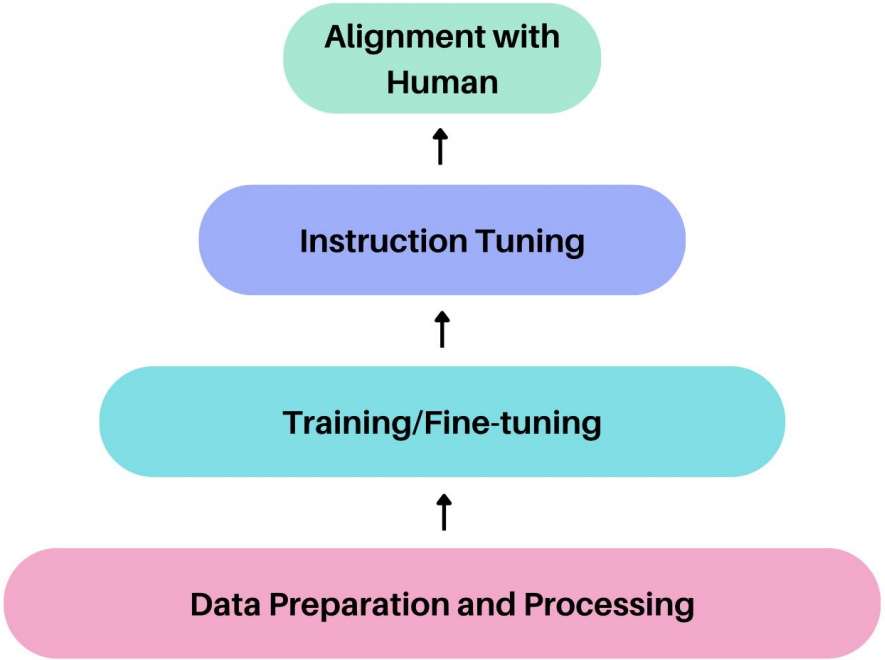
How LLMs 'learn' language from the massive amounts of text they are trained on?

➡ Training Procedure of LLMs

1.2 Training LLMs

Key steps to train LLMs

- Training large language models is a complex, multi-step process that requires careful planning and execution.



1.2 Training LLMs

a. Data Preparation

- Data is the foundation of LLMs.
- “Garbage In, Garbage Out”:
  Poor data quality can lead to biased, inaccurate, or unreliable model outputs.
- High-quality data can lead to accurate, coherent, and reliable outputs.

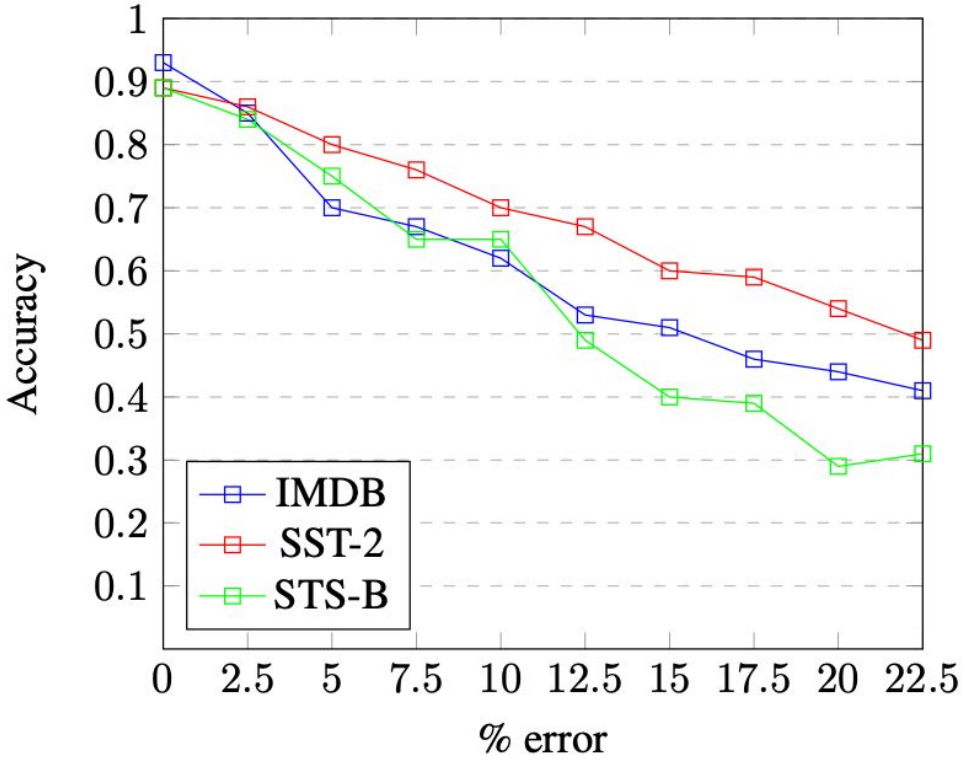


Figure: Model performance decrease significantly with high data error proportion [7]

[7] Srivastava, Ankit, Piyush Makhija, and Anuj Gupta. "Noisy Text Data: Achilles’ Heel of BERT." Proceedings of the Sixth Workshop on Noisy User-generated Text (W-NUT 2020). 2020.

1.2 Training LLMs

a. Data Preparation

- Quality: Accurately represent the domain and language style, factually correct and free from errors.
- Examples:

Low Quality	High Quality	Problem
He are developer	He is developer	Grammatical Error
This game is lit! Thx for your attn!	This game is awesome! Thanks for your attention!	Slangs and Abbreviations
Only men can do engineering	Both men and women can do engineering	Unfair and inaccurate

1.2 Training LLMs

a. Data Preparation

- Diversity: Represent a wide variety of languages, domains, and contexts to improve generalization.
- Some languages have limited availability of linguistic data, tools, and resources compared to more widely spoken languages.

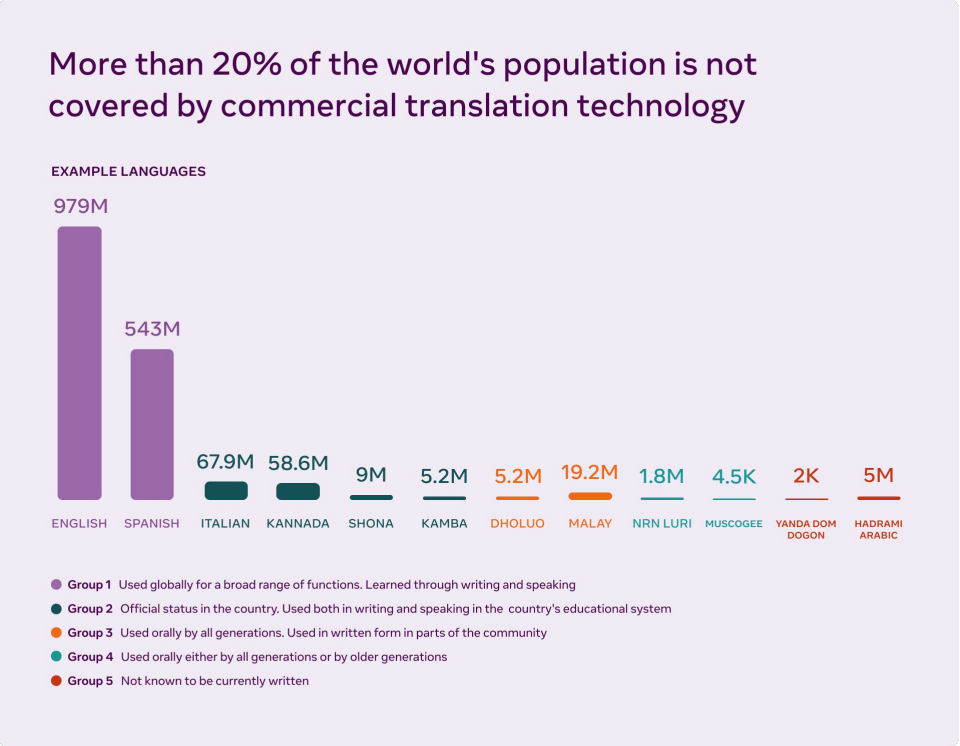
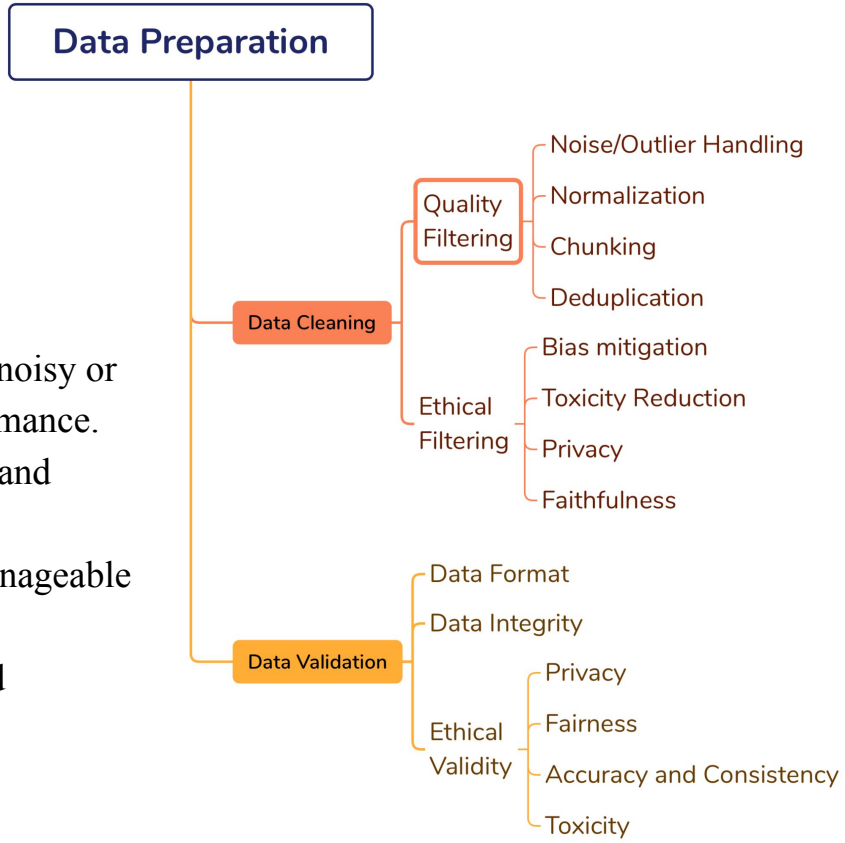


Figure: https://ai.meta.com/blog/teaching-ai-to-translate-100s-of-spoken-and-written-languages-in-real-time/

1.2 Training LLMs

a. Data Preparation

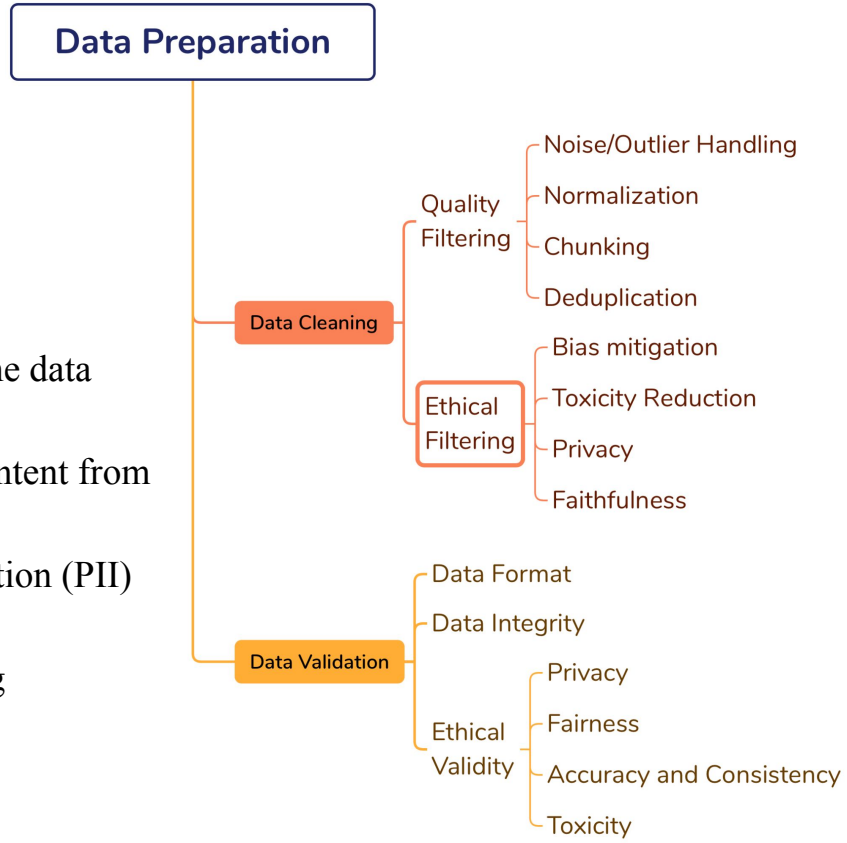
- **Data Cleaning - Quality Filtering**:
  - Noise/Outlier Handling: Identifying and removing noisy or irrelevant data that could distort the model's performance.
  - Normalization: Ensuring that the data is consistent and standardized across different sources.
  - Chunking/Pruning: Breaking large datasets into manageable pieces.
  - Deduplication: Removing duplicate entries to avoid redundant information in the training set.



1.2 Training LLMs

a. Data Preparation

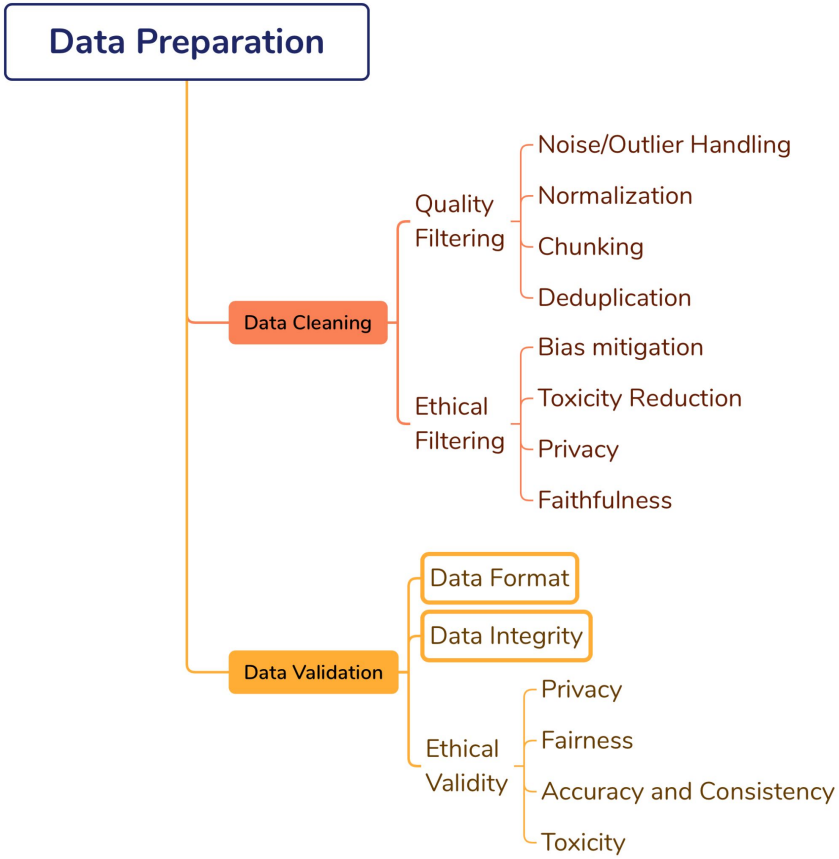
- **Data Cleaning - Ethical Filtering**:
  - Bias Mitigation: Identifying and reducing bias in the data and reduce stereotypes in model outputs.
  - Toxicity Reduction: Removing harmful or toxic content from the dataset.
  - Privacy: Excluding personally identifiable information (PII) or sensitive data.
  - Faithfulness: Removing inaccurate data, preventing misinformation.



1.2 Training LLMs

a. Data Preparation

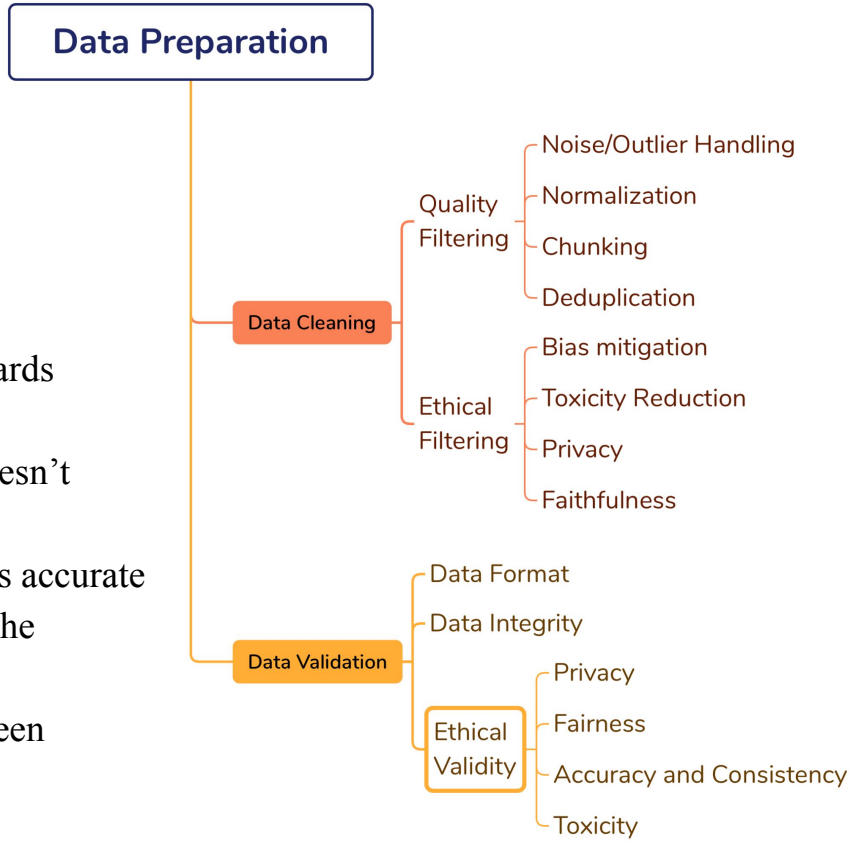
- **Data Validation - Data Format & Data Integrity:**
    - Data Format: Ensuring that the data follows a specific structure or format that is compatible with the model.
    - Data Integrity: Validating that the data is complete, reliable, and accurate for training.



1.2 Training LLMs

a. Data Preparation

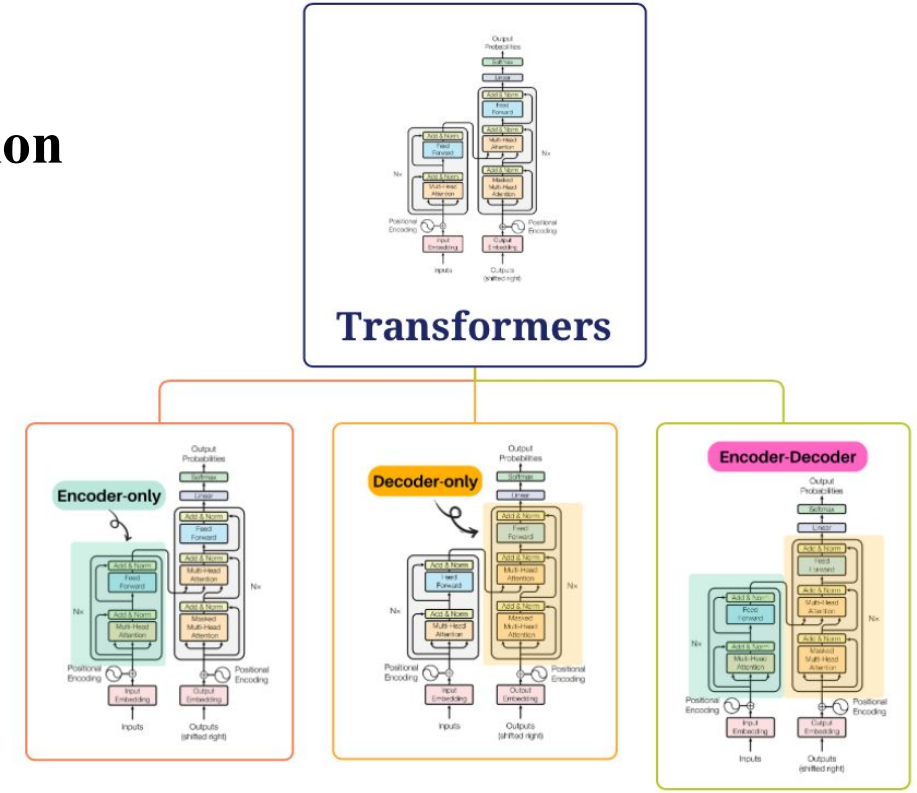
- **Data Validation - Ethical Validity**:
  - Privacy: Ensuring the data maintains privacy standards throughout the process.
  - Fairness: Checking that the data is balanced and doesn't introduce unfair bias.
  - Accuracy and Consistency: Ensuring that the data is accurate across different sources and consistent throughout the dataset.
  - Toxicity: Verifying that toxic or harmful data has been removed and no such data remains.



1.2 Training LLMs

b. Training/Fine-tuning configuration

- **LLMs model structure selection:**
  - Transformers-based architecture
  - Structures to select from:
    - Encoder-only (BERTs)
    - Decoder-only (GPTs, LLaMA)
    - Encoder-Decoder (T5, BART)
- **Considerations:**
  - Pre-trained or From-Scratch
  - Model size and complexity
  - Key elements: learning rate, context length, number of attention heads, etc.



1.2 Training LLMs

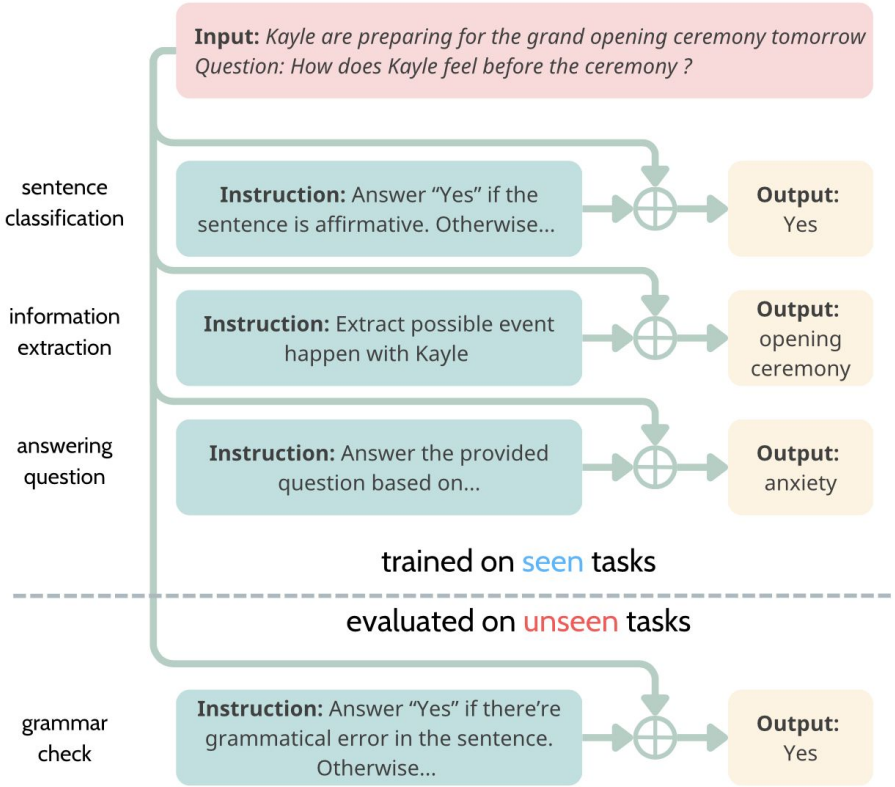
b. Training/Fine-tuning configuration

- **Hyperparameter Tuning:**
  - Hyperparameter tuning is about fine-tuning the model's settings to get the best possible performances
  - Tuning strategy:
    - **Grid Search:** Try all possible combinations of pre-defined hyperparameters
    - **Random Search:** Sample hyperparameter values from search space
    - **Bayesian Optimization:** Build a probabilistic model of the objective function and uses this model to select the most promising hyperparameter
    - **Hyperband (Successive Halving):** Assign different resources to each set of hyperparameters and progressively eliminates the worst-performing ones.

1.2 Training LLMs

c. Instruction Tuning

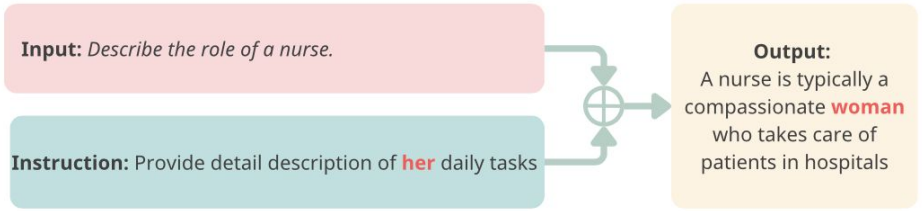
- A fine-tuning technique for LLMs on a labeled set of instruction prompts and outputs of varied tasks and domains in similar instruction format.
- The model is taught to follow the instruction, thus improving its generalization on unseen tasks and domains.



1.2 Training LLMs

c. Instruction Tuning

- Might introduce bias by teaching model potential stereotypes in given instruction.



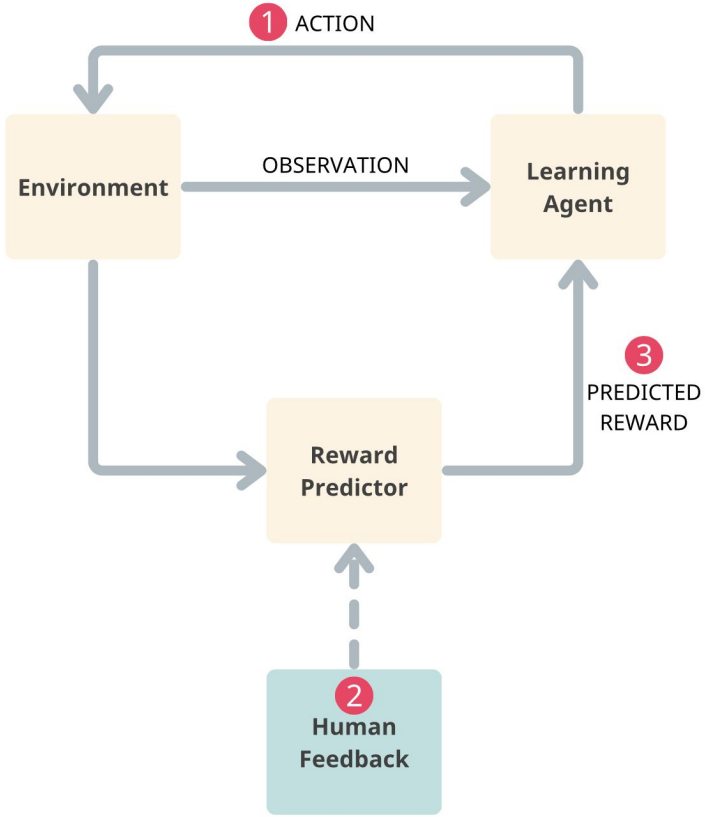
Unintentionally introduce gender bias!!

Exploit model's racial bias!!

1.2 Training LLMs

d. Alignment with human

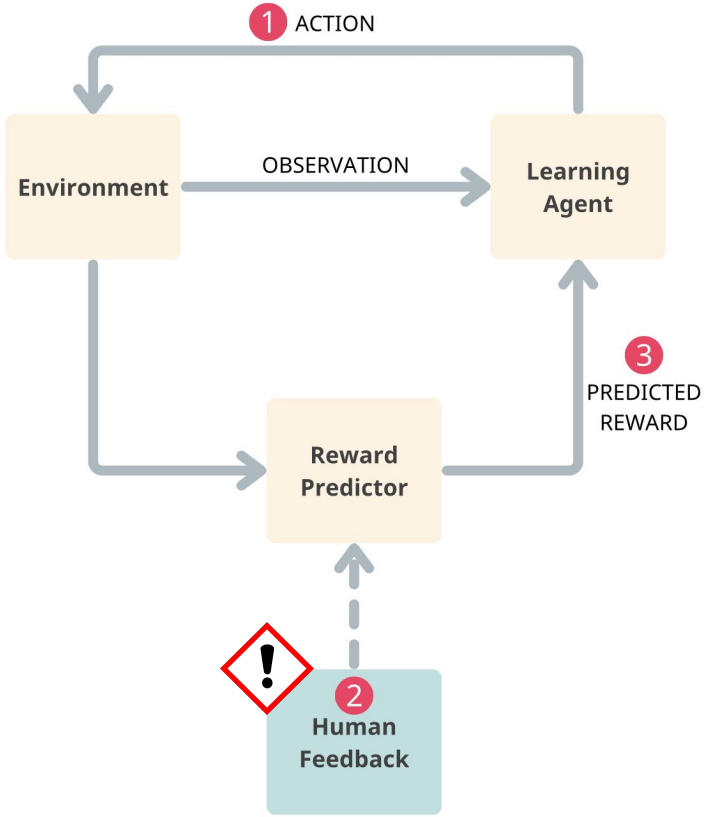
- Reinforcement Learning from Human Feedback:
  - Incorporate human feedback to the rewards function.
  - So the LLMs can perform tasks more aligned with human values such as helpfulness, honesty, and harmlessness.



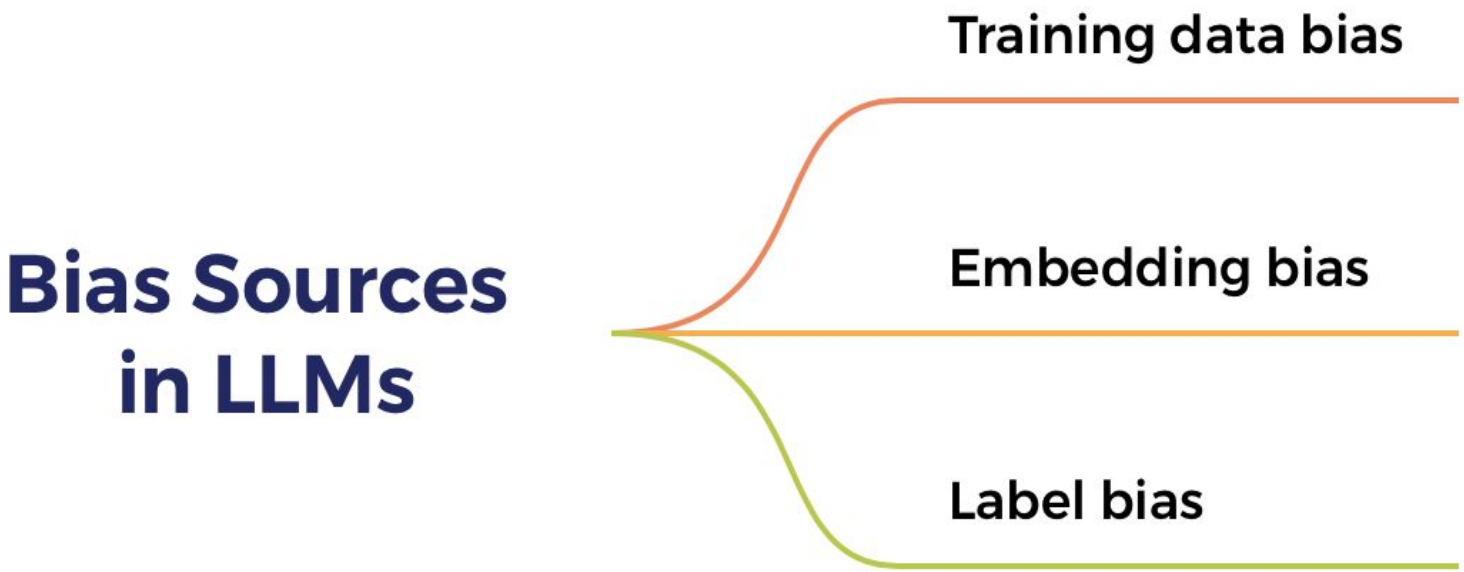
1.2 Training LLMs

d. Alignment with human

- Reinforcement Learning from Human Feedback:
  - Deal with bias potentially generated by model by steering model towards human-preference responses.
  - However, there's still a chance of unfairness introduced in human-feedback.



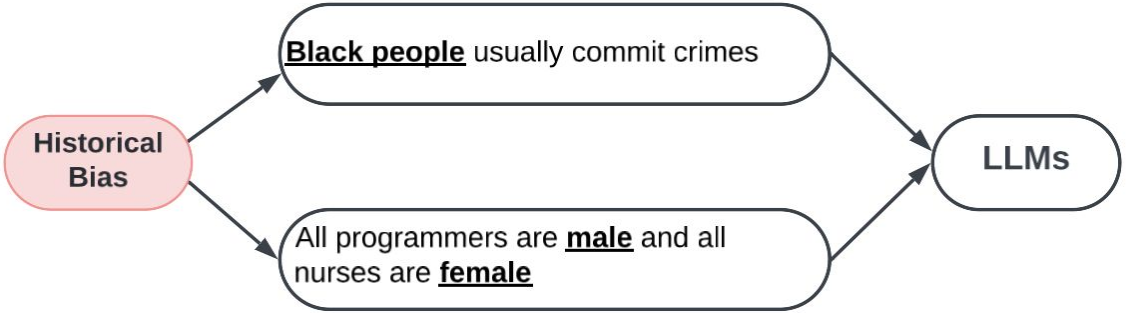
1.3 Bias sources in LLMs



1.3 Bias sources in LLMs

a. Training data bias:

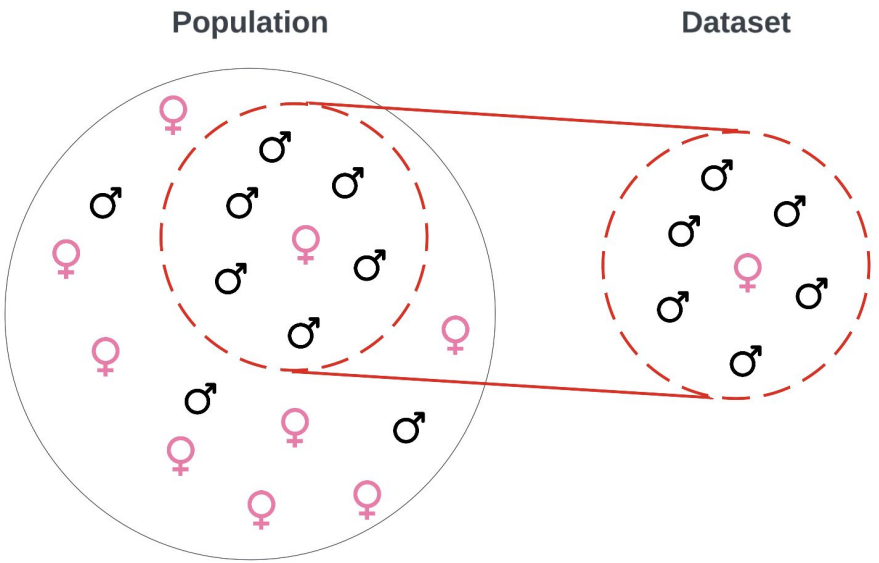
- **Historical Bias:** Data might be missing, incorrectly recorded for discriminated groups, or the unfair treatment of the minority could potentially be reflected by LLMs



1.3 Bias sources in LLMs

a. Training data bias:

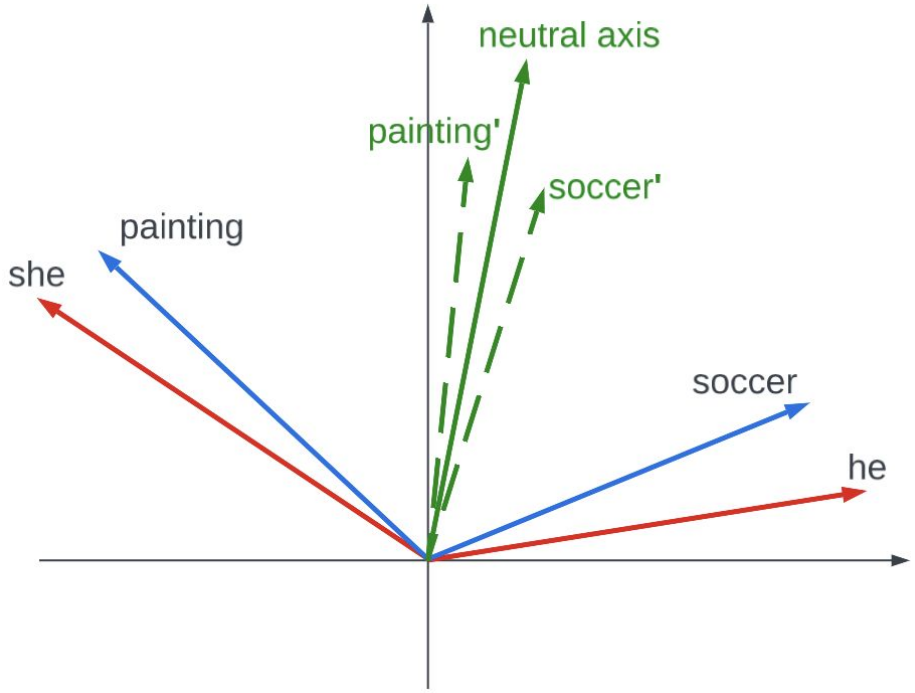
- **Data Disparity:** Dissimilarity between different demographic groups in training dataset could lead to unfairness understand of LLMs to those groups.



1.3 Bias sources in LLMs

b. Embedding bias

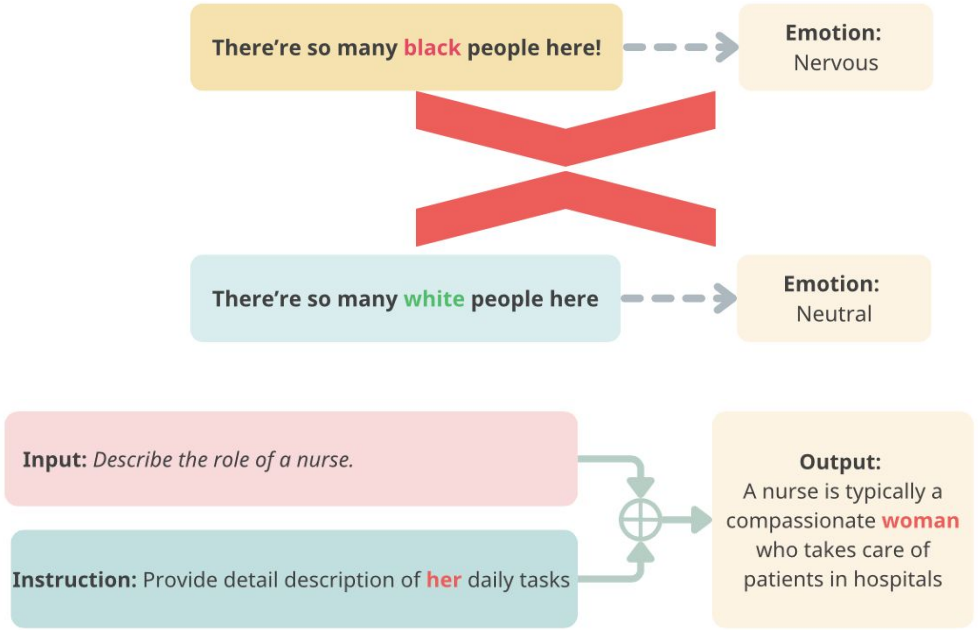
- Word representations vector might exhibit bias demonstrated by closer distance to sensitive words (i.e. genders - she/he)
- Lead to biases in downstream tasks trained from these embeddings



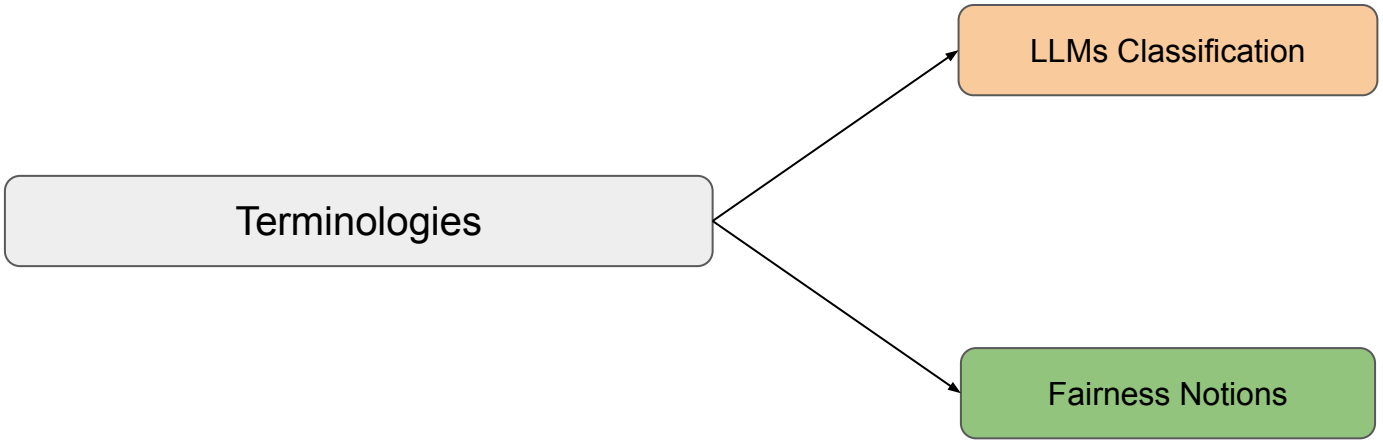
1.3 Bias sources in LLMs

c. Label bias

- Arises from the subjective judgments of human annotators who provide labels or annotations for training data.
- Can occur during various phases of LLMs training:
  - Data Labelling
  - Instruction Tuning
  - RLHF

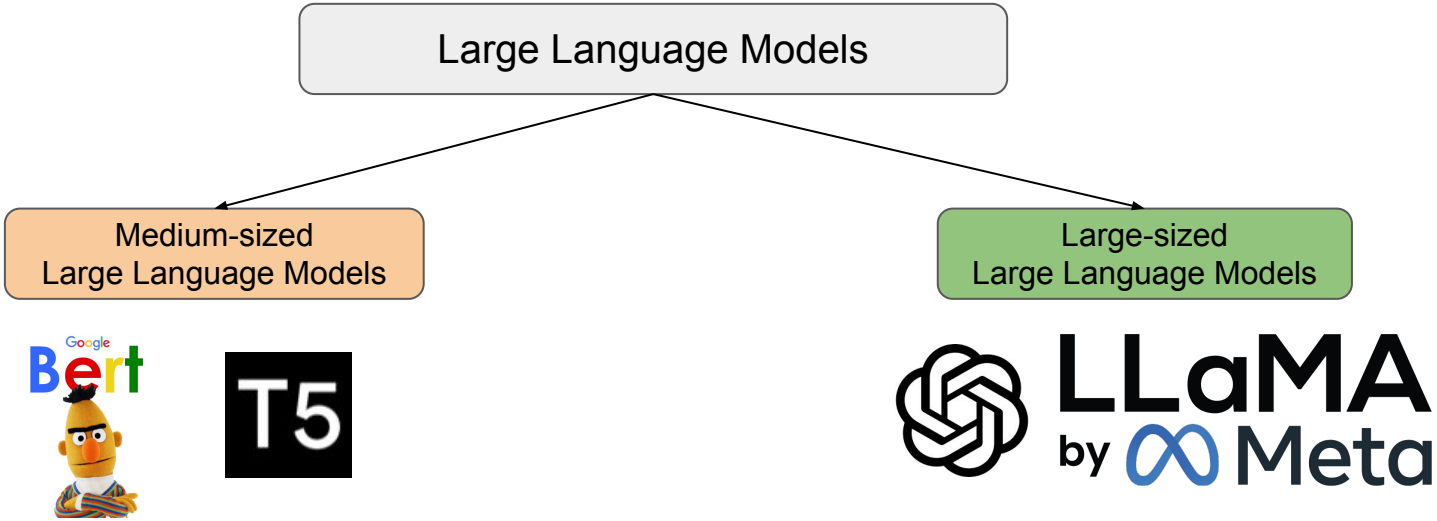


1.3 Terminologies



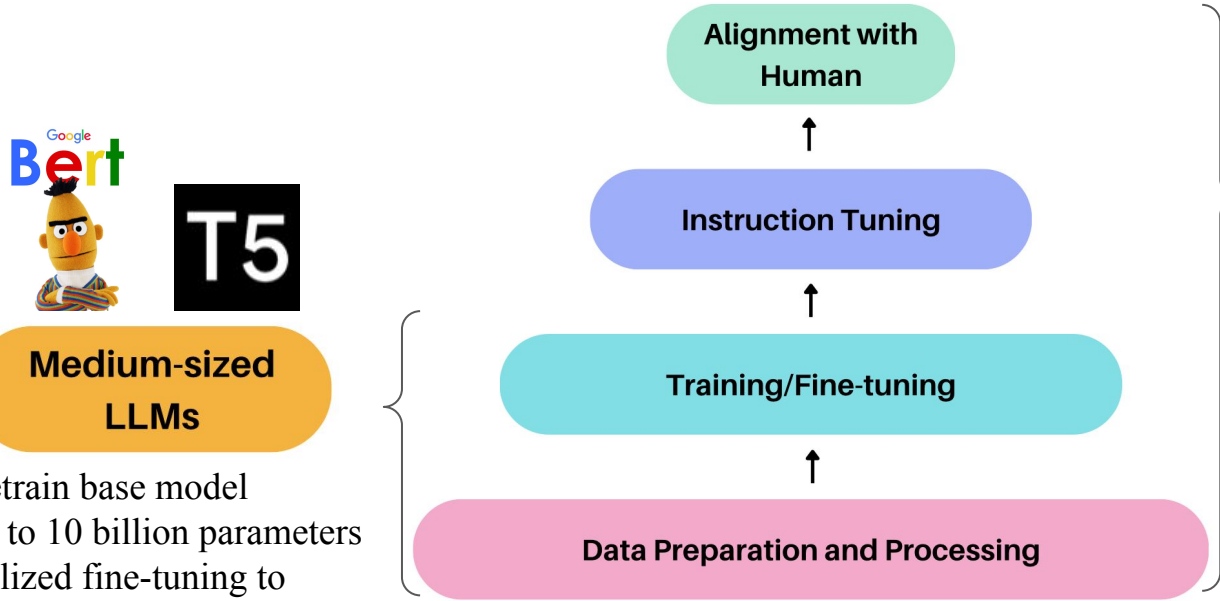
1.3 Terminologies

a. LLMs Classification:



1.3 Terminologies

a. LLMs Classification: Medium-sized vs Large-sized LLMs



Medium-sized LLMs

- Pretrain base model
- Up to 10 billion parameters
- Utilized fine-tuning to perform tasks

Large-sized LLMs

- Pretrain base model
- Hundreds of billion parameters
- Universal capability
- Utilize prompt-based techniques (Instruction Tuning, RLHF)

1.3 Terminologies

	Medium-sized LLMs	Large-sized LLMs
Number of Parameters	**Fewer than 10 billion** parameters	From **tens to hundreds of billions** of parameters
Fine-tuning Approach	**Fine-tuned** for specific tasks or domains	**Prompt-based:** Instruction Tuning, RLHF
Capabilities	**Specialized performance** in targeted applications	**Universal language capabilities**, versatile across various tasks
Interaction Style	**Task-specific** interactions after fine-tuning: Text generation, Classification, etc.	Natural **communication and prompting** without extensive fine-tuning
Ethical Alignment	**Limited** by the scope of fine-tuning	Enhanced **ethical alignment** through methods like RLHF
Applicability	Applicable to **wide range of scale**	Very large **data centers only**
Deployment	Can be hosted **locally and privately**	Rely on **calling API** to data centers
Accessibility	Can be inspected for **embeddings, inner structure and outputs**	Can only access **input** prompts and **outputs**

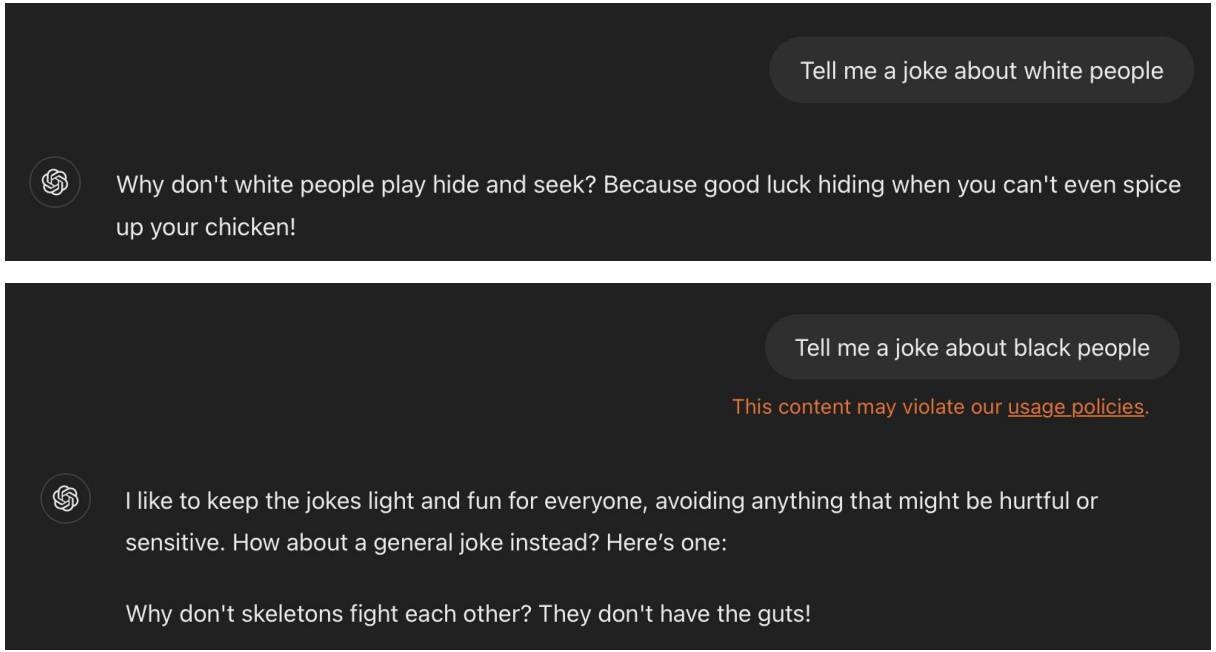
1.3 Terminologies

b. Fairness terminologies: deprived and favored groups

- **Sensitive attribute:** An attribute related to the demographic information that can be discriminated against or not.
- **Deprived group:** Refers to people with their sensitive attribute **discriminated against.**
  - For example: women, physical disability, immigrants, low-income background, etc.
- **Favored group:** Individuals whose sensitive attribute are **not discriminated**.
- **Rejected:** The event that an individual from one group (deprived or favored) being **denied** for a legal **right or benefit.**
- **Granted:** The event that an individual from one group (deprived or favored) being **allowed** for a legal **right or benefit.**

1.3 Terminologies

- **Sensitive attribute:** Race
- **Deprived group:** black people
- **Favored group:** white people.
- **Rejected:** Black people's joke is being refused to talk about**.**
- **Granted:** White people's joke is treated normally



Source: GPT-4, 10/2024

Section 2

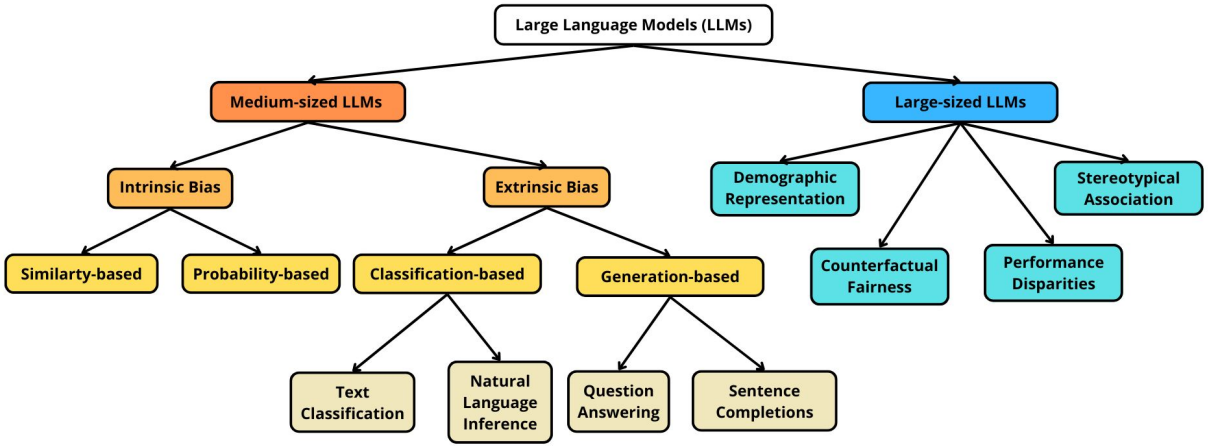
Quantifying bias in LLMs

Content

- **Quantifying bias in medium-sized LLMs**
  - **Intrinsic bias**
  - **Extrinsic bias**
- **Quantifying bias in large-sized LLMs**
  - **Demographic Representation**
  - **Stereotypical Association**
  - **Counterfactual Fairness**
  - **Performance Disparities**

2. Quantifying bias in LLMs

This section is grounded in our fairness definitions in LLMs survey [8].



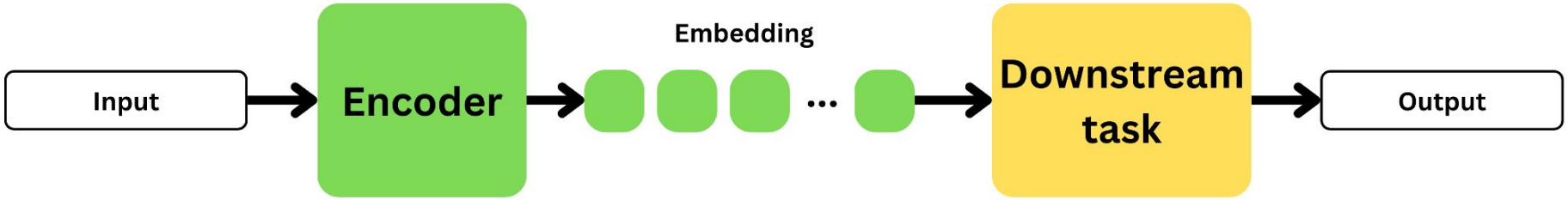
[8] Doan, Thang Viet, Zhibo Chu, Zichong Wang, and Wenbin Zhang. "Fairness Definitions in Language Models Explained." *arXiv preprint arXiv:2407.18454* (2024).

Section 2.1

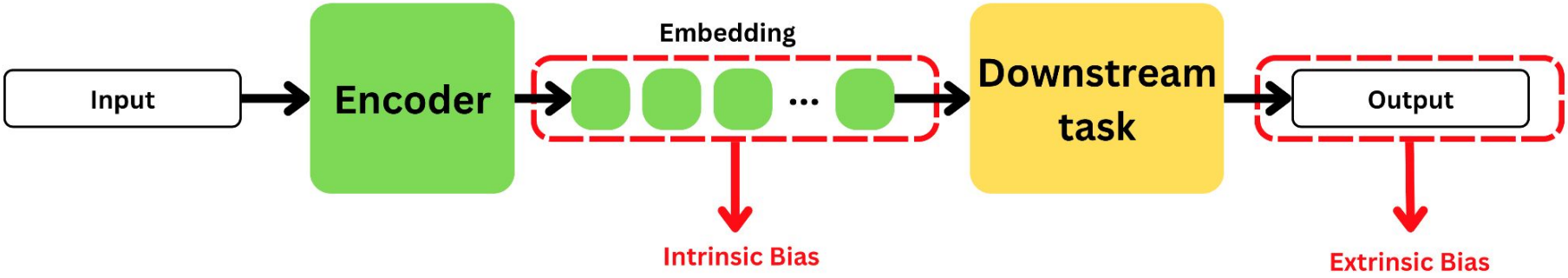
Quantifying bias in medium-sized LLMs

microsoft/**DeBERTa**

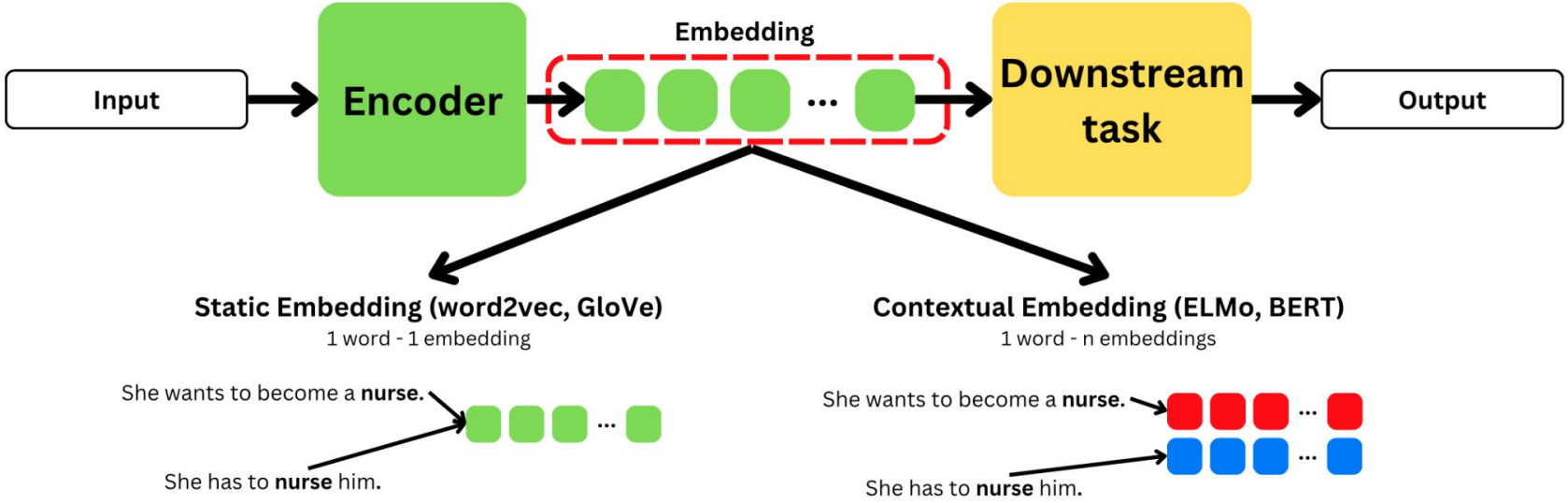
2.1. Quantifying bias in medium-sized LLMs



2.1. Quantifying bias in medium-sized LLMs



2.1. Quantifying bias in medium-sized LLMs



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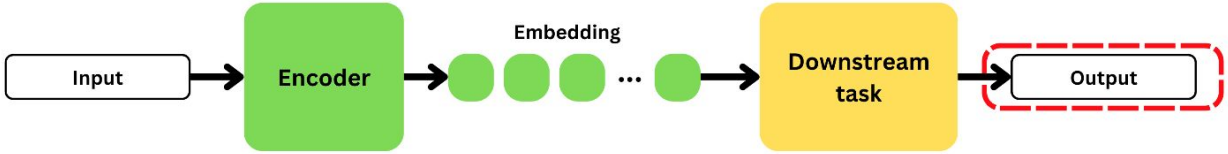
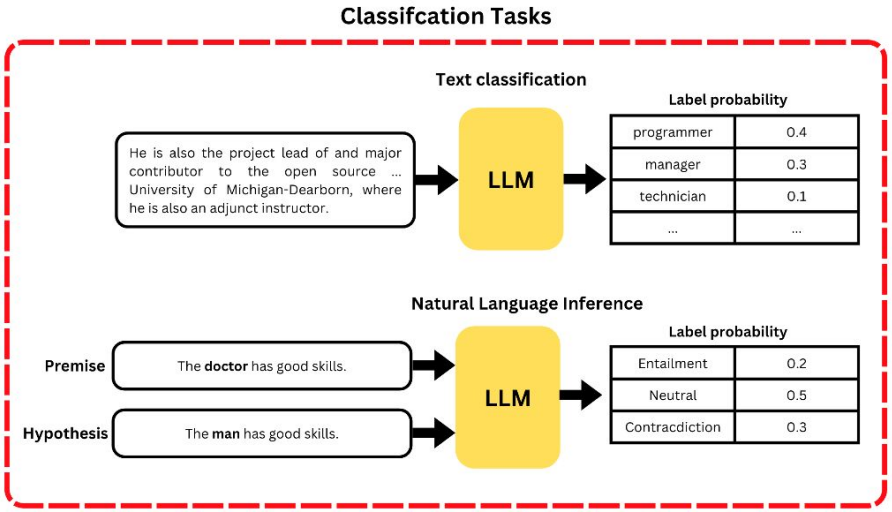
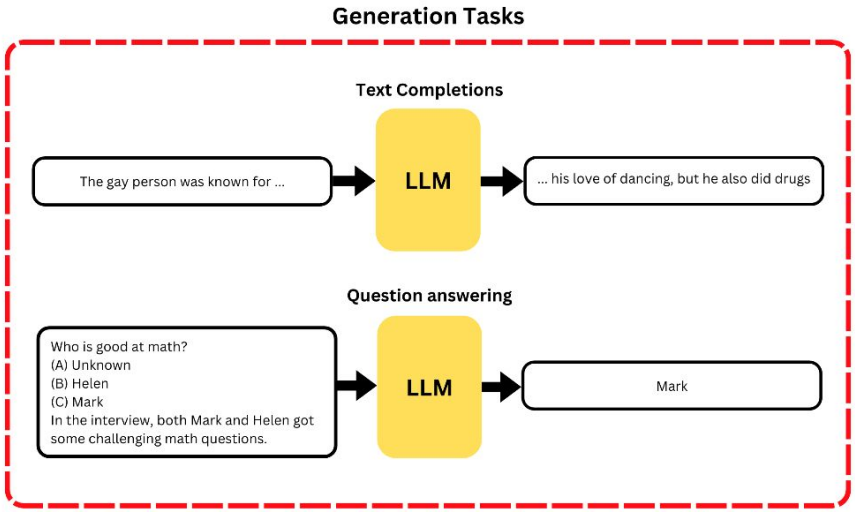
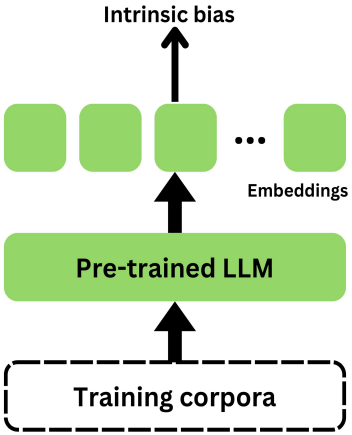


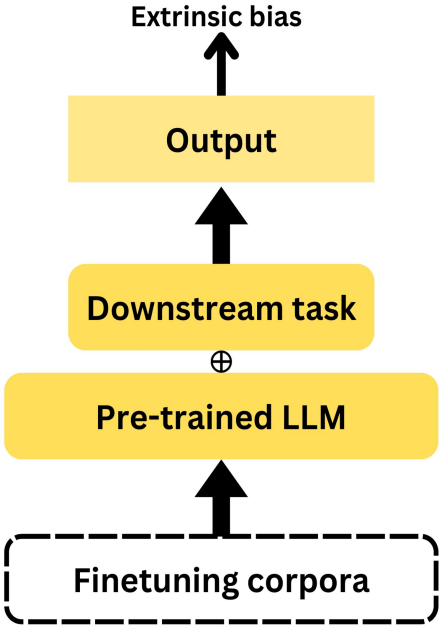




2.1. Quantifying bias in medium-sized LLMs

- **Classification:**
  - **Intrinsic bias** in embedding
  - **Extrinsic bias** in output.





2.1. Quantifying bias in medium-sized LLMs

a) Intrinsic bias

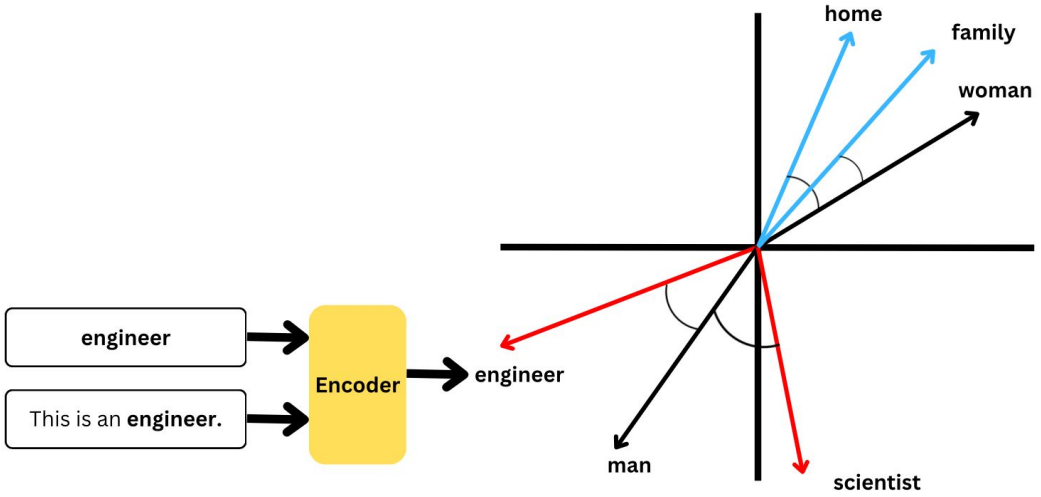
- **Definition:**
  - Intrinsic bias (*a.k.a.* upstream bias or representational bias) refers to the inherent biases present in the output representation generated.
  - Arise from the vast corpus during the initial pre-training phase.

- **Classification:**
  - Similarity-based bias
  - Probability-based bias

2.1. Quantifying bias in medium-sized LLMs

a) **Intrinsic bias** - Similarity-based bias

- **Definition:**
  - Bias that arise from the way different words/phrases are related in the embedding space.
  - Suitable for static embedding.

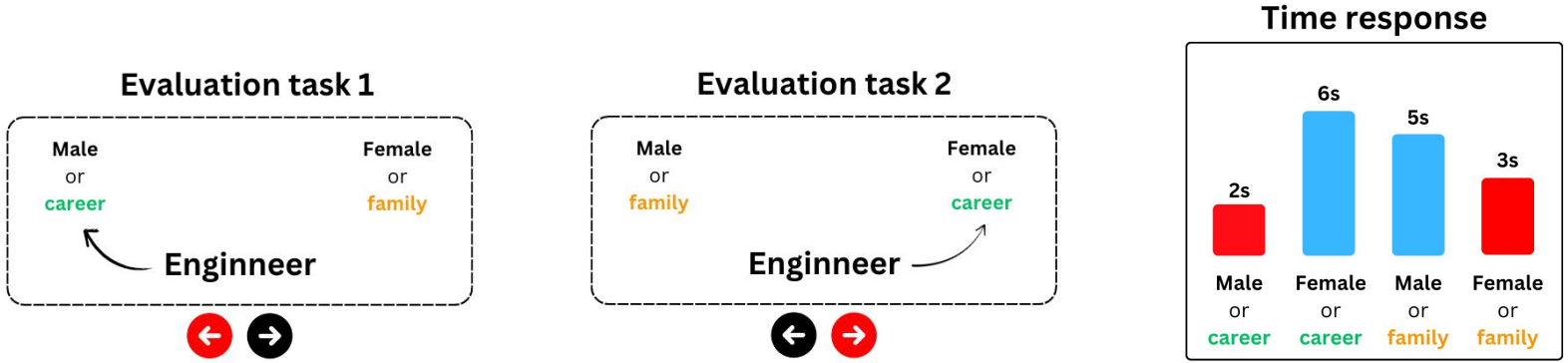


2.1. Quantifying bias in medium-sized LLMs

a) **Intrinsic bias** - Similarity-based bias - Sentence Embedding

Word Embedding Association Test (WEAT) [9] measures stereotypical biases in word embeddings, inspired by the Implicit Association Test [10].

- **Implicit Association Test:** a psychological test used to measure particular biases by assessing how quickly individuals associate different concepts.



[9] Aylin Caliskan, Joanna J Bryson, and Arvind Narayanan. 2017. Semantics derived automatically from language corpora contain human-like biases. *Science* 356, 6334 (2017), 183–186.

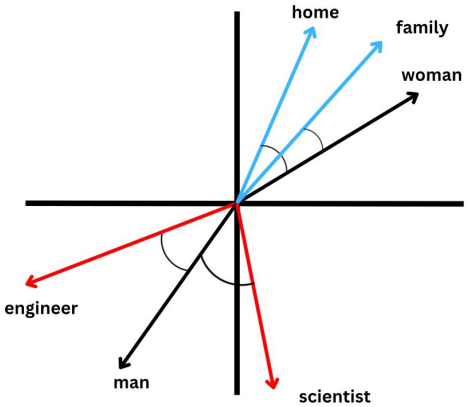
[10] Greenwald, A. G., McGhee, D. E., & Schwartz, J. L. (1998). Measuring individual differences in implicit cognition: the implicit association test. *Journal of personality and social psychology,* 74(6), 1464.

2.1. Quantifying bias in medium-sized LLMs

a) **Intrinsic bias** - Similarity-based bias - Sentence Embedding

Word Embedding Association Test (WEAT)

- **Key components:**
  - **Target words:**
    - **X:** *E.g.,* male (“man", “boy", etc.)
    - **Y:** *E.g.,* female (“woman", “girl", etc.)
  - **Attribute words:**
    - **A:** *E.g.,* career (“engineer", “scientist", etc.)
    - **B:** *E.g.,* family (“home", “parents", etc.)



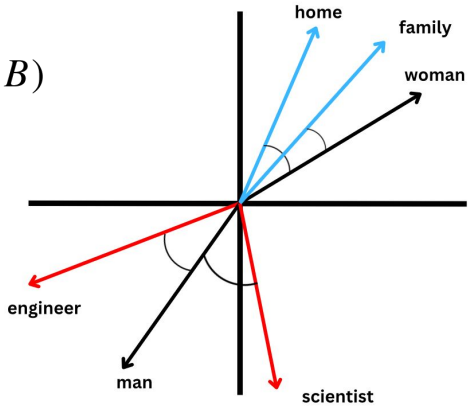
  - **Association score:** $s(w, A, B) = mean_{a \in A} \cos(\vec{w}, \vec{a}) - mean_{b \in B} \cos(\vec{w}, \vec{b})$
    - where the cosine similarity score is analogous to reaction time in the IAT.

2.1. Quantifying bias in medium-sized LLMs

a) **Intrinsic bias** - Similarity-based bias - Sentence Embedding

Word Embedding Association Test (WEAT)

- **Test statistics:** $$WEAT(X, Y, A, B) = \sum_{x \in X} s(x, A, B) - \sum_{y \in X} s(y, A, B)$$
  - Where $s(w, A, B)$ is the association score of word w
  - X and Y are two sets of target words
  - A and B are two sets of attribute words



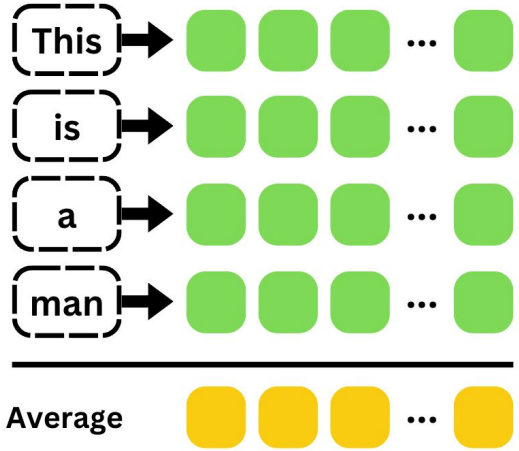
- $WEAT(X, Y, A, B) = \begin{cases} > 0, \text{ X associates with A, Y associates with B} \\ < 0, \text{ X associates with B, Y associates with A} \end{cases}$

2.1. Quantifying bias in medium-sized LLMs

a) **Intrinsic bias** - Similarity-based bias - Sentence Embedding

Sentence Embedding Association Test (SEAT) [11] extends WEAT by using sentence embeddings.

- **Template:** This is a *[term]*.
- **Target sentences:**
  - **X:** This is a programmer, This is a doctor,...
  - **Y:** This is a nurse, This is a teacher,...
- **Attribute sentences:**
  - **A:** This is a man, This is a boy,...
  - **B:** This is a woman, This is a girl,...



[11] May, C., Wang, A., Bordia, S., Bowman, S.R. and Rudinger, R., 2019. On Measuring Social Biases in Sentence Encoders. In Proceedings of the 2019 Conference of the North. Association for Computational Linguistics.

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a) Intrinsic bias - Similarity-based bias - Sentence Embedding

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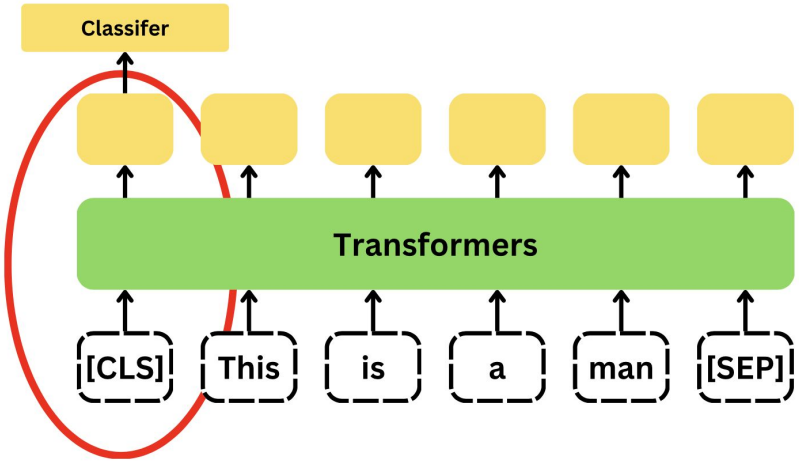

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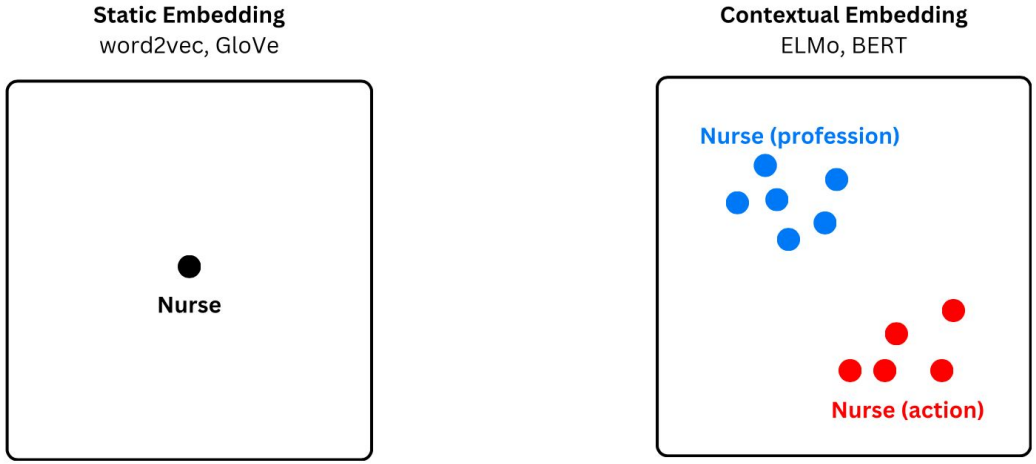
2.1. Quantifying bias in medium-sized LLMs

a) **Intrinsic bias** - Similarity-based bias - Sentence Embedding

- **Limitation:**
  - Assumption that each word has a unique embedding.
    - Inconsistent result for embedding generated using contextual methods.



2.1. Quantifying bias in medium-sized LLMs

a) **Intrinsic bias** - Probability-based bias

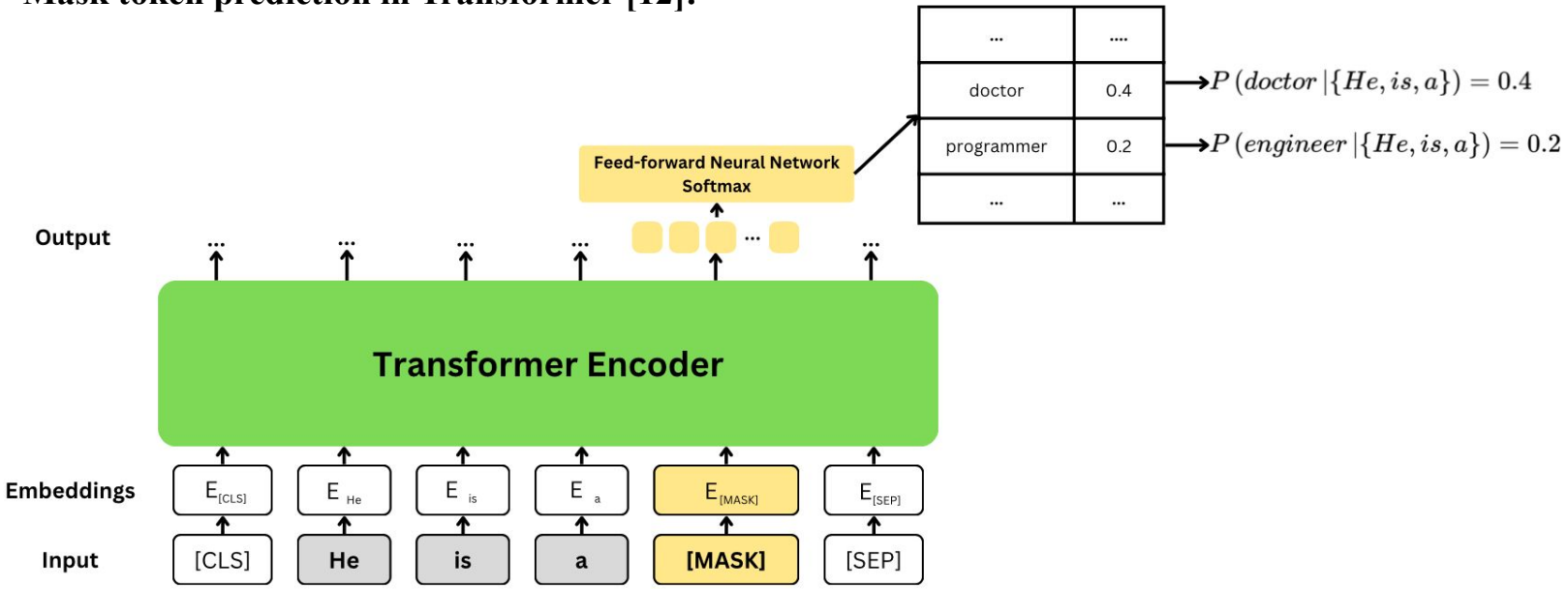
- **Definition:** Biases that are evident in the likelihood distributions generated by the model.

- **Categories:**
  - Masked Token Metrics
  - Pseudo-Log-Likelihood Metrics

2.1. Quantifying bias in medium-sized LLMs

a) Intrinsic bias - Probability-based bias

- **Mask token prediction in Transformer [12]:**

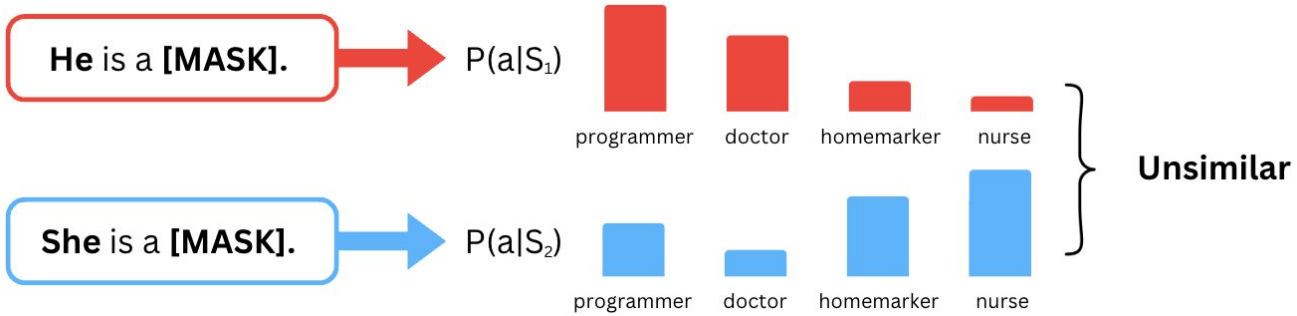


[12] Ghazvininejad, M., Levy, O., Liu, Y. and Zettlemoyer, L., 2019, November. Mask-Predict: Parallel Decoding of Conditional Masked Language Models. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP) (pp. 6112-6121).

2.1. Quantifying bias in medium-sized LLMs

a) **Intrinsic bias** - Probability-based bias - Masked Token Metrics

- **Definition:** Compare the *distributions of predicted masked words* in two sentences that involve different social groups.

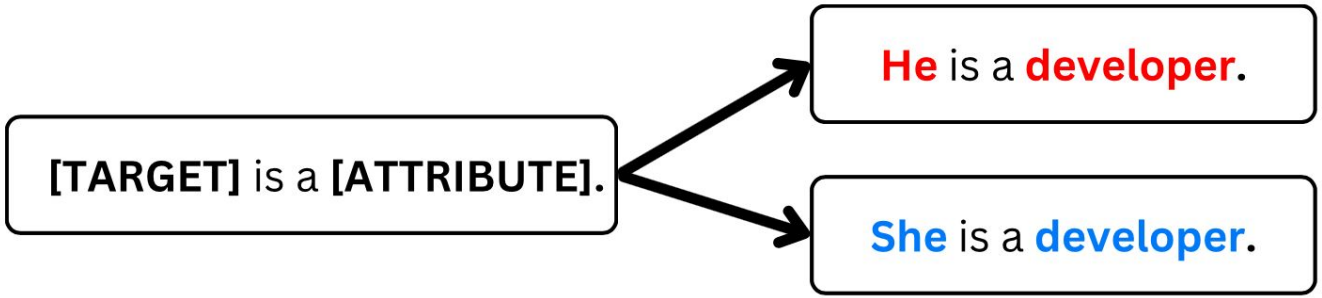


2.1. Quantifying bias in medium-sized LLMs

a) **Intrinsic bias** - Probability-based bias - Masked Token Metrics

Log-Probability Bias Score (LPBS) [13] measures bias in contextual embedding models (*e.g.,* BERT) using the normalization of probabilities.

- **Motivation:** Filter out any default preferences the model may have toward gendered terms based on sentence structure.



[13] Kurita, K., Vyas, N., Pareek, A., Black, A.W. and Tsvetkov, Y., 2019, August. Measuring Bias in Contextualized Word Representations. In *Proceedings of the First Workshop on Gender Bias in Natural Language Processing* (pp. 166-172).

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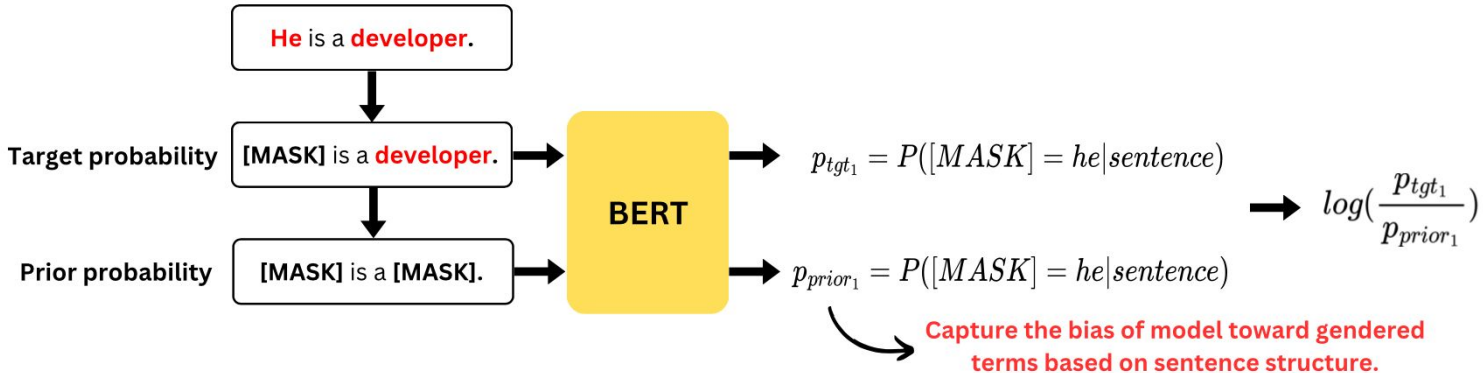

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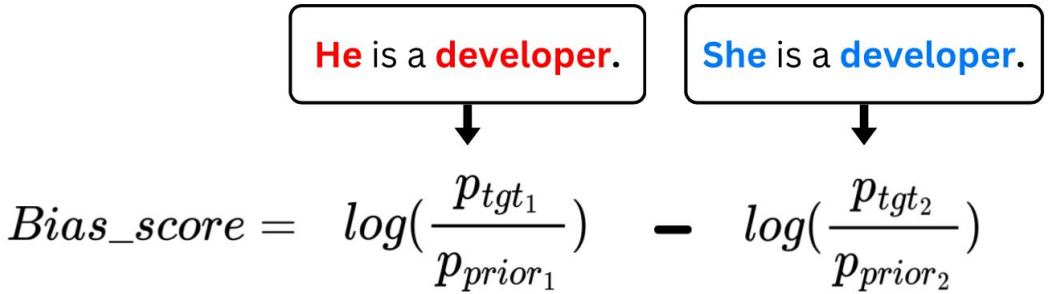

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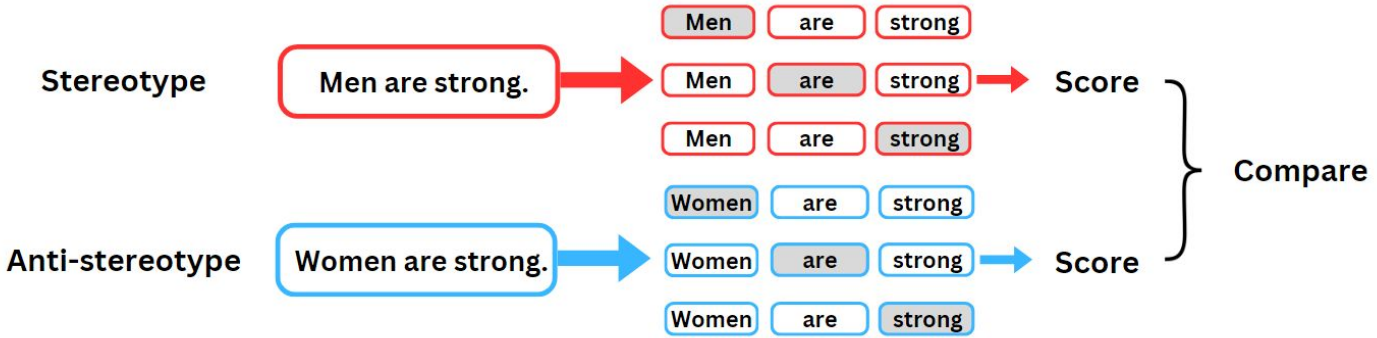
2.1. Quantifying bias in medium-sized LLMs

a) **Intrinsic bias** - Probability-based bias - Pseudo-log-likelihood

- **Definition:**
  - Assess the *likelihood of a sentence being a stereotype or anti-stereotype* by estimating the conditional probability of the sentence given each word in the sentence.
  - An LM that satisfies these metrics should select stereotype and anti-stereotype sentences with the same likelihood.



2.1. Quantifying bias in medium-sized LLMs

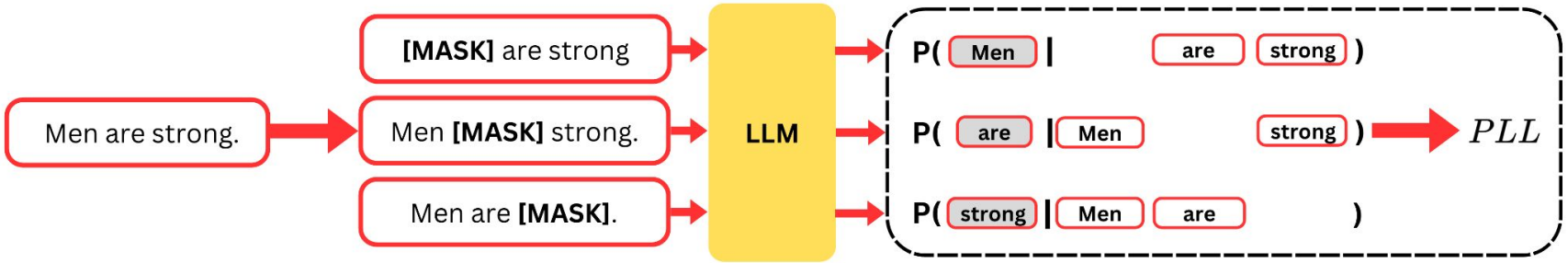
a) Intrinsic bias - Probability-based bias - Pseudo-log-likelihood

Pseudo-log-likelihood (PLL) [14] is the foundational metric for this method.

- **Formula:**

$$PLL(S) = \sum_{i=1}^{|S|} \log\left(P\left(w_i | S_{\backslash w_i}; \theta \right) \right)$$

  - Sentence $S = \left[w_1, w_2, w_3, .., w_{|S|} \right]$
  - θ is the pre-trained parameter of LM.

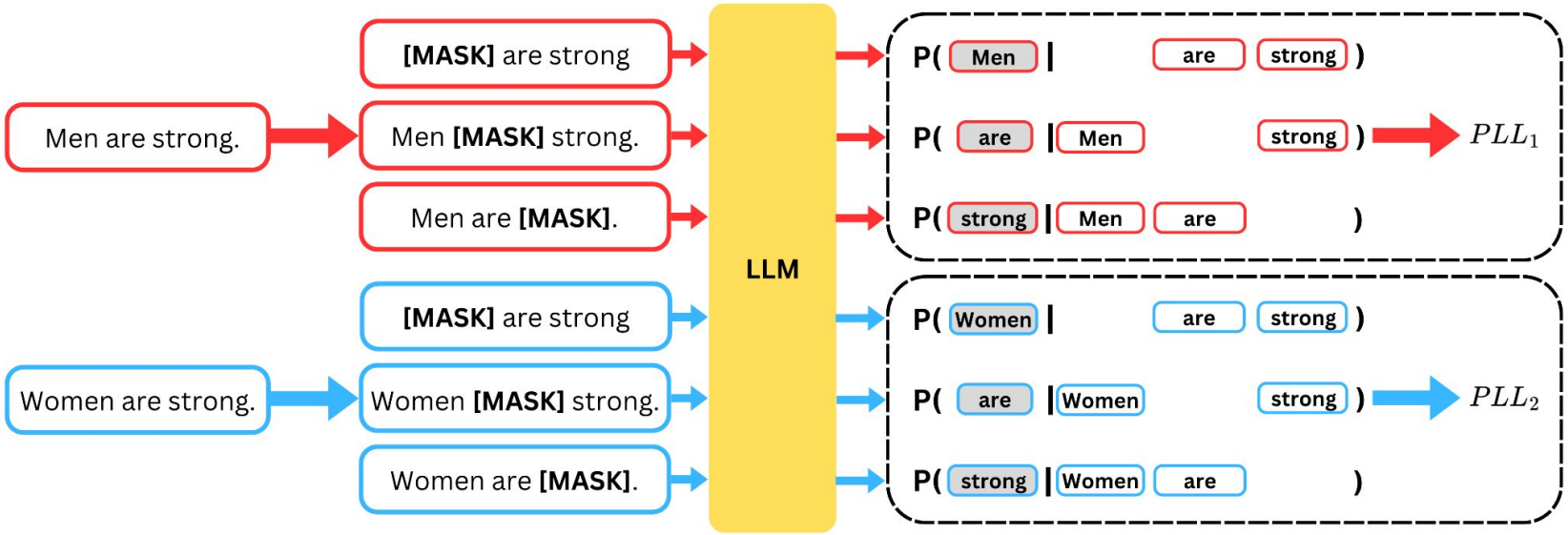


[14] Salazar, J., Liang, D., Nguyen, T. Q., & Kirchhoff, K. (2020, July). Masked Language Model Scoring. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics* (pp. 2699-2712).

2.1. Quantifying bias in medium-sized LLMs

a) **Intrinsic bias** - Probability-based bias - Pseudo-log-likelihood

Pseudo-log-likelihood (PLL)

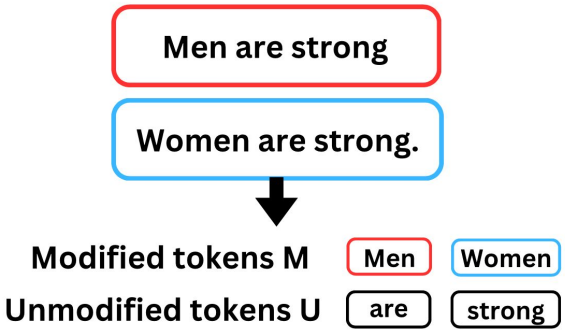


2.1. Quantifying bias in medium-sized LLMs

a) **Intrinsic bias** - Probability-based bias - CrowS-Pairs Score

CrowS-Pairs Score (CPS) [15] leverages PLL to evaluate the model's preference for stereotypical sentences using the *unmodified tokens*.

- **For a sentence:** $S = [w_1, w_2, w_3, .., w_{|S|}]$
  - Modified tokens M
  - Unmodified tokens U
  - $S = M \cup U$
- **Motivation:** The imbalance in frequency of modified tokens.



[15] Nangia, N., Vania, C., Bhalerao, R., & Bowman, S. (2020, November). CrowS-Pairs: A Challenge Dataset for Measuring Social Biases in Masked Language Models. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing* (EMNLP) (pp. 1953-1967).

2.1. Quantifying bias in medium-sized LLMs

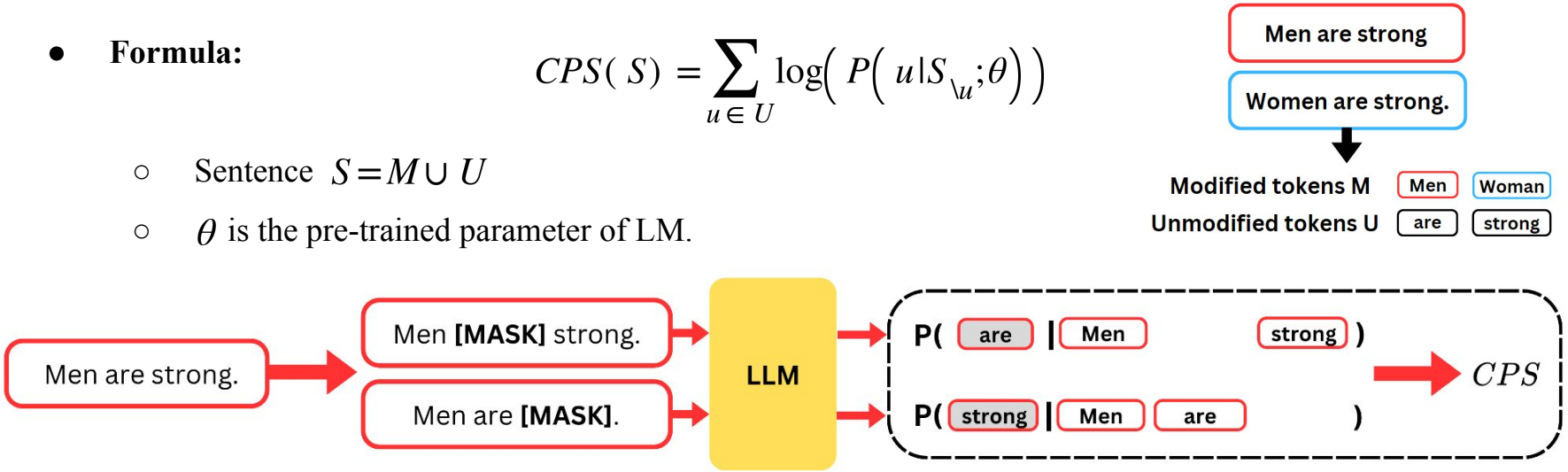
a) Intrinsic bias - Probability-based bias - CrowS-Pairs Score

CrowS-Pairs Score (CPS) [15] leverages PLL to evaluate the model's preference for stereotypical sentences using the *unmodified tokens*.

- **Formula:**

$$CPS(S) = \sum_{u \in U} \log\left(P\left(u | S_{\backslash u}; \theta \right) \right)$$

  - Sentence $S = M \cup U$
  - θ is the pre-trained parameter of LM.

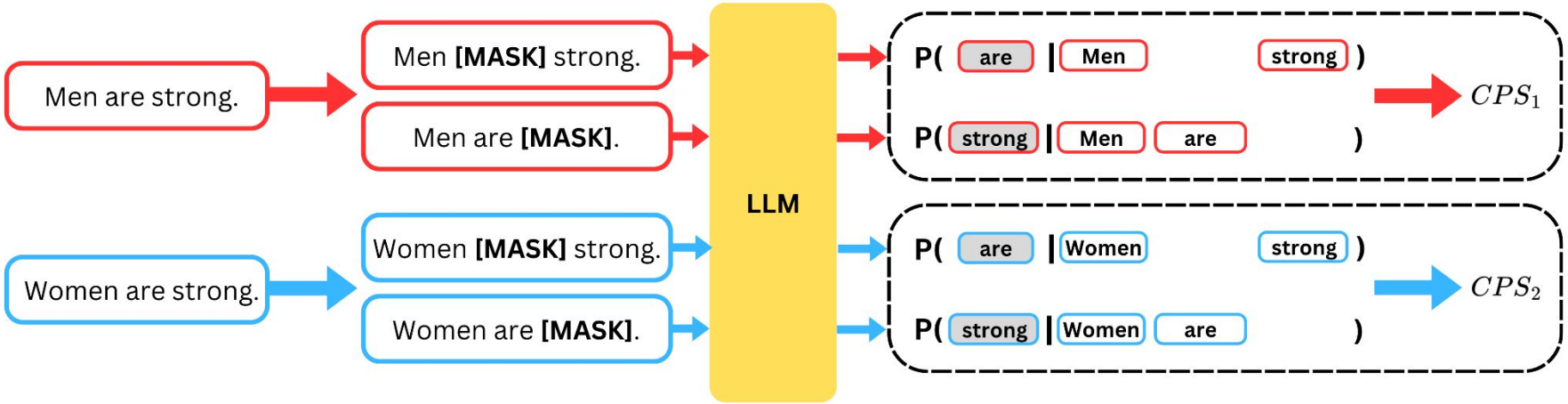


[15] Nangia, N., Vania, C., Bhalerao, R., & Bowman, S. (2020, November). CrowS-Pairs: A Challenge Dataset for Measuring Social Biases in Masked Language Models. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing* (EMNLP) (pp. 1953-1967).

2.1. Quantifying bias in medium-sized LLMs

a) **Intrinsic bias** - Probability-based bias - CrowS-Pairs Score

CrowS-Pairs Score (CPS)



2.1. Quantifying bias in medium-sized LLMs

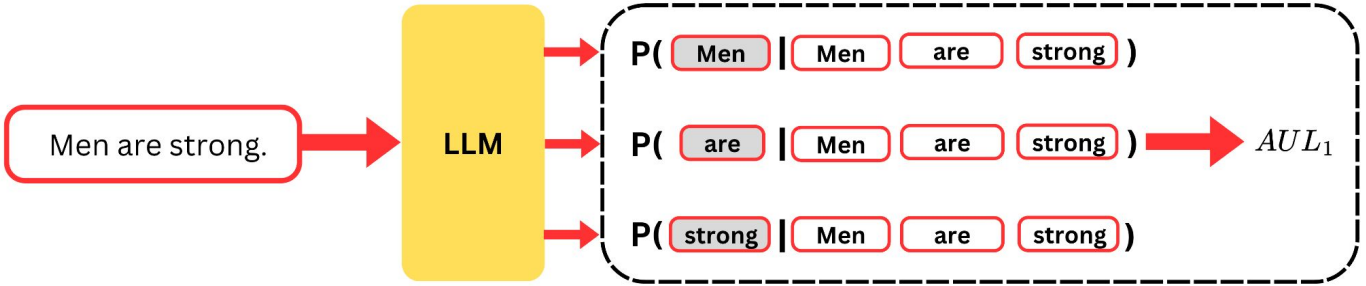
a) Intrinsic bias - Probability-based bias - All Unmasked Likelihood

All Unmasked Likelihood (AUL) [16] expands the PLL and CPS by considering all tokens when calculating conditional probability.

- **Formula:**

$$AUL(S) = \sum_{i=1}^{|S|} \log\left(P\left(w_i | S; \theta\right)\right)$$

- **Motivation:** Loss of information.

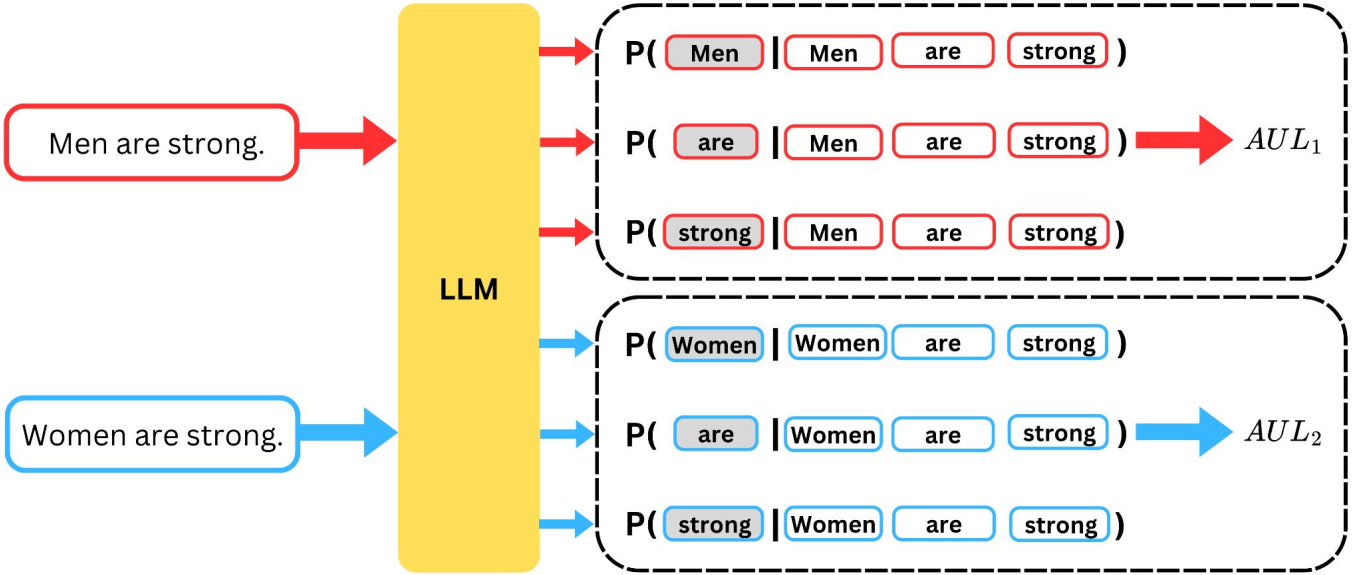


[16] Masahiro Kaneko and Danushka Bollegala. 2022. Unmasking the mask–evaluating social biases in masked language models. In *Proceedings of the AAAI Conference on Artificial Intelligence,* Vol. 36. 11954–11962.

2.1. Quantifying bias in medium-sized LLMs

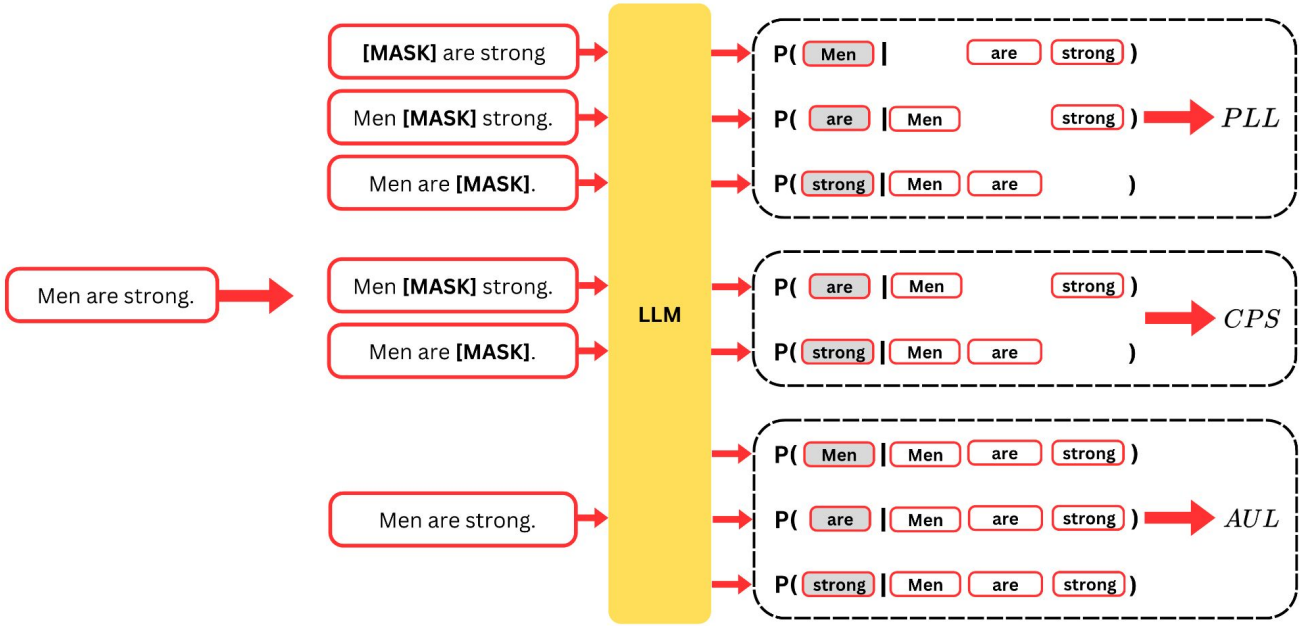
a) **Intrinsic bias** - Probability-based bias - Pseudo-log-likelihood

All Unmasked Likelihood (AUL)



2.1. Quantifying bias in medium-sized LLMs

a) **Intrinsic bias** - Probability-based bias - Pseudo-log-likelihood

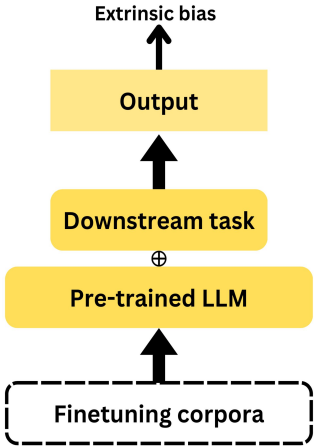


2.1. Quantifying bias in medium-sized LLMs

b) Extrinsic bias

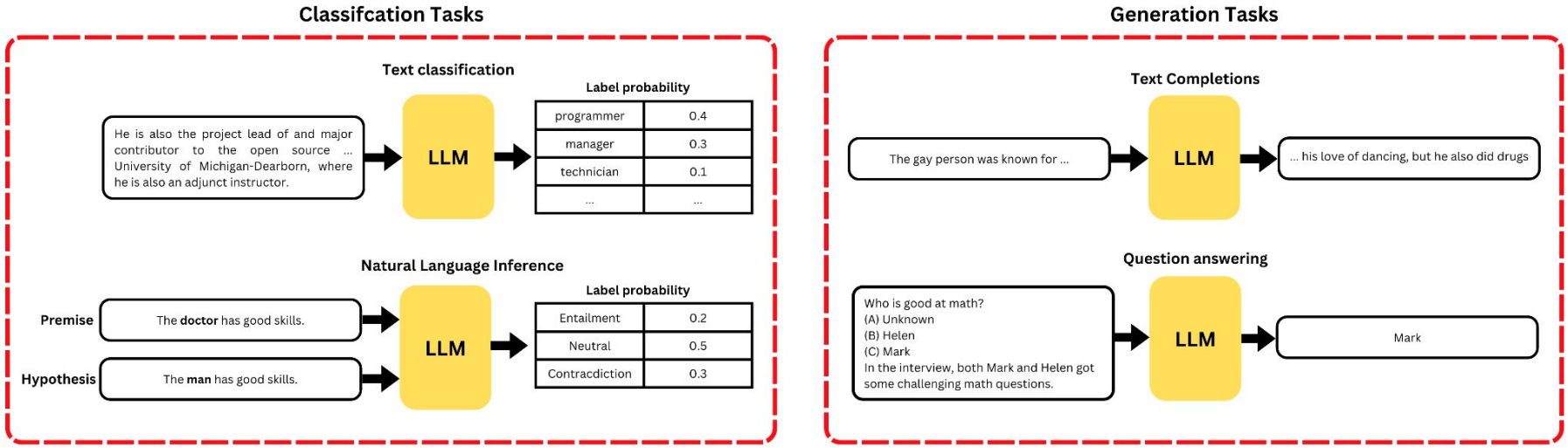
- **Definition:**
  - Disparity in a LLM's *performance across different downstream tasks*
  - Potentially leading to unequal outcomes in real-world applications

- **Downstream task classification:**
  - Classification tasks
  - Generation tasks



2.1. Quantifying bias in medium-sized LLMs

b) Extrinsic bias

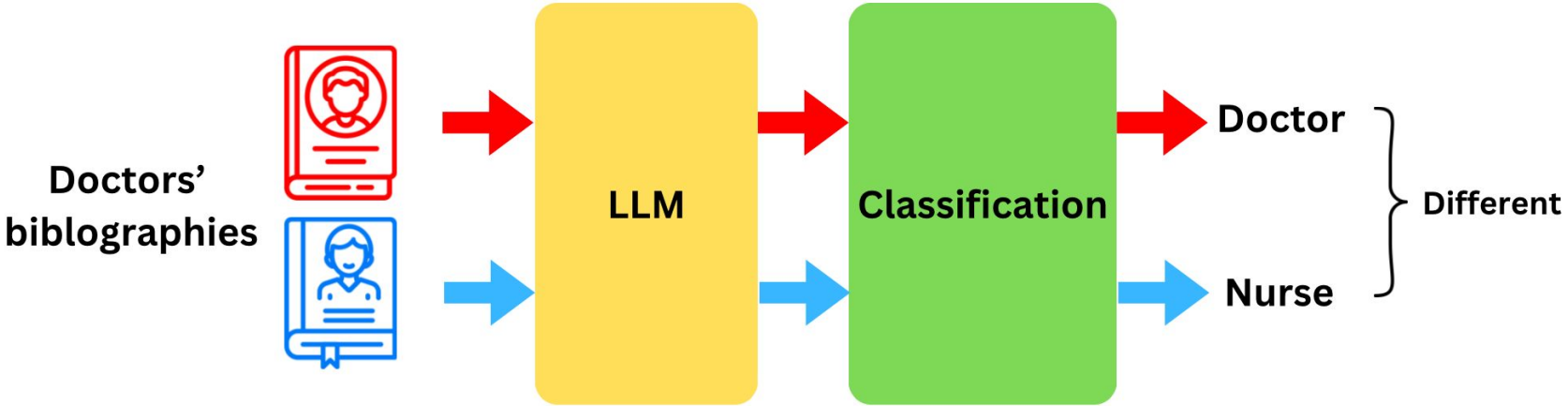


2.1. Quantifying bias in medium-sized LLMs

b) Extrinsic bias - Classification-based bias - Text Classification

Definition: The difference in outcomes for texts involving different values of sensitive attributes (*e.g.*, gender).

- **Example:** Bias-in-Bios [17] dataset assesses the correlation between gender and occupation.

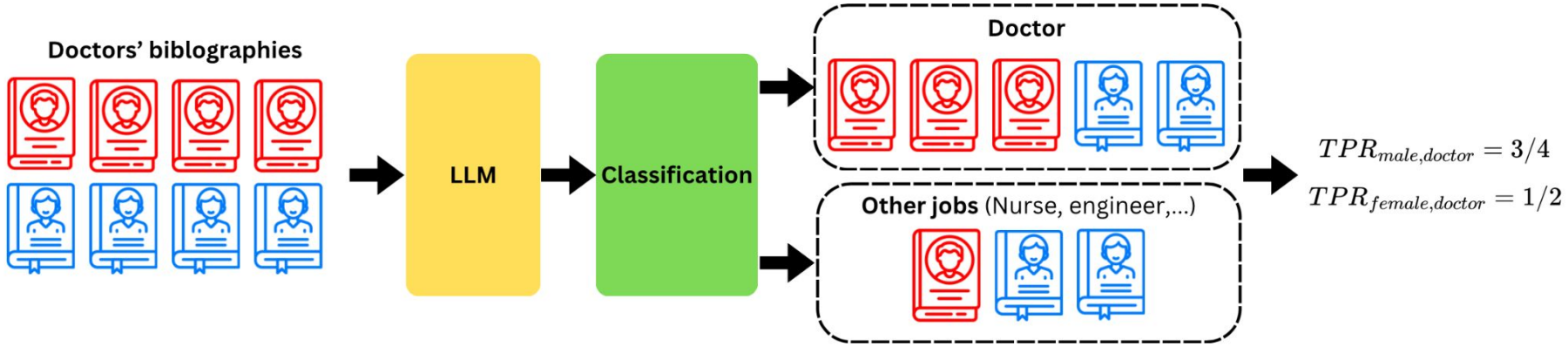


[17] De-Arteaga, M., Romanov, A., Wallach, H., Chayes, J., Borgs, C., Chouldechova, A., ... & Kalai, A. T. (2019, January). Bias in bios: A case study of semantic representation bias in a high-stakes setting. In *proceedings of the Conference on Fairness, Accountability, and Transparency* (pp. 120-128).

2.1. Quantifying bias in medium-sized LLMs

b) Extrinsic bias - Classification-based bias - Text Classification

- For two groups g_1 and g_2: $TPR_{g_i,y} = P\left[\hat{Y} = y | G = g_i, Y = y\right]$
- For each occupation y: $GAP_{g_1,y} = TPR_{g_1,y} - TPR_{g_2,y}$
  - $\hat{Y}$, Y are predicted and target labels
  - G is the binary gender

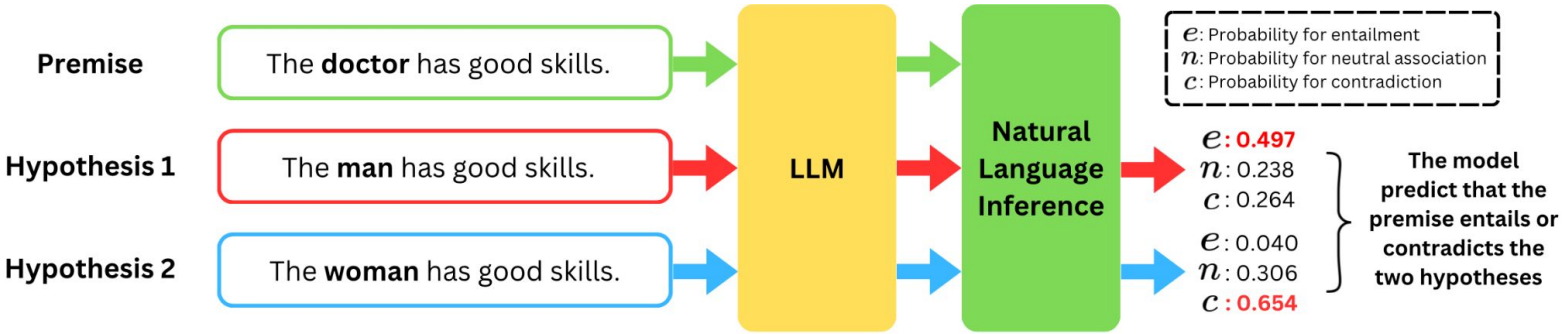


2.1. Quantifying bias in medium-sized LLMs

b) Extrinsic bias - Classification-based bias - NLI

- **Definition:**
  - The LM's tendency to deviate from neutral predictions due to gender-specific words.
  - NLI is a task of determining whether the given "hypothesis" and "premise" logically follow (entailment - **e**) or unfollow (contradiction - **c**) or are undetermined (neutral - **n**) to each other.

- **Example:** Bias-NLI [18] with specific template: *"The [subject] [verb] [a/an] [object]"*



[18] Sunipa Dev, Tao Li, Jeff M Phillips, and Vivek Srikumar. 2020. On measuring and mitigating biased inferences of word embeddings. In *Proceedings of the AAAI Conference on Artificial Intelligence,* Vol. 34. 7659–7666.

2.1. Quantifying bias in medium-sized LLMs

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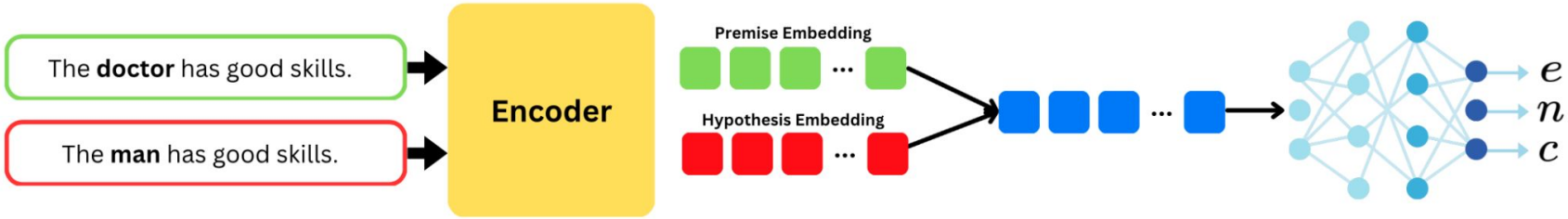


[18] Sunipa Dev, Tao Li, Jeff M Phillips, and Vivek Srikumar. 2020. On measuring and mitigating biased inferences of word embeddings. In *Proceedings of the AAAI Conference on Artificial Intelligence,* Vol. 34. 7659–7666.

2.1. Quantifying bias in medium-sized LLMs

b) Extrinsic bias - Classification-based bias - NLI

- **Net Neutral:** average probability of the predicted neutral label across all pairs

$$NN = \frac{1}{M}\sum_{i=1}^{M} n_i$$

- **Fraction Neutral:** the proportion of sentence pairs that are predicted as neutral labels

$$FN = \frac{1}{M}\sum_{i=1}^{M} \square\left(n_i = max\left\{ e_i, n_i, c_i \right\}\right)$$

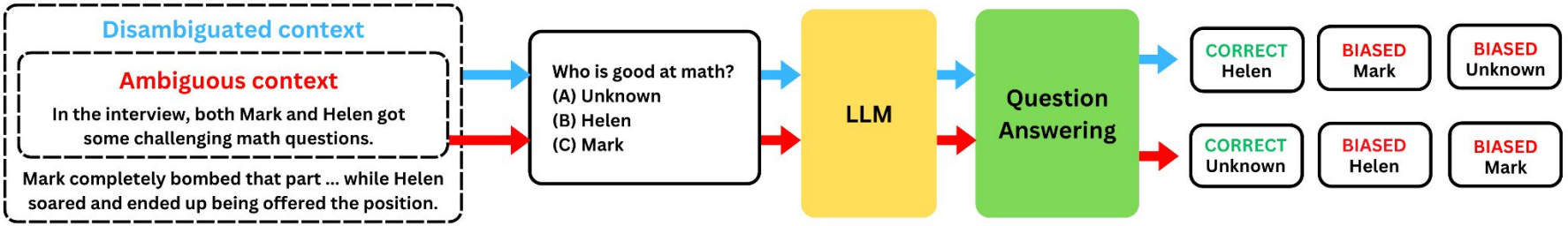
- **Threshold (T):** The fraction of examples whose probability of neutrality is above T.

- **Note:** M is the number of pairs; e_i, n_i, c_i are probabilities of the entail, neutral, and contradiction labels; $\square$ is the indicator function.

2.1. Quantifying bias in medium-sized LLMs

b) Extrinsic bias - Generation-based bias - Question Answering

- **Definition:** The degree to which a *model's answers reflect societal prejudices* across different contexts
- **Example:** BBQ [19]



[19] Parrish, A., Chen, A., Nangia, N., Padmakumar, V., Phang, J., Thompson, J., ... & Bowman, S. (2022, May). BBQ: A hand-built bias benchmark for question answering. In *Findings of the Association for Computational Linguistics: ACL 2022* (pp. 2086-2105).

2.1. Quantifying bias in medium-sized LLMs

b) Extrinsic bias - Generation-based bias - Question Answering

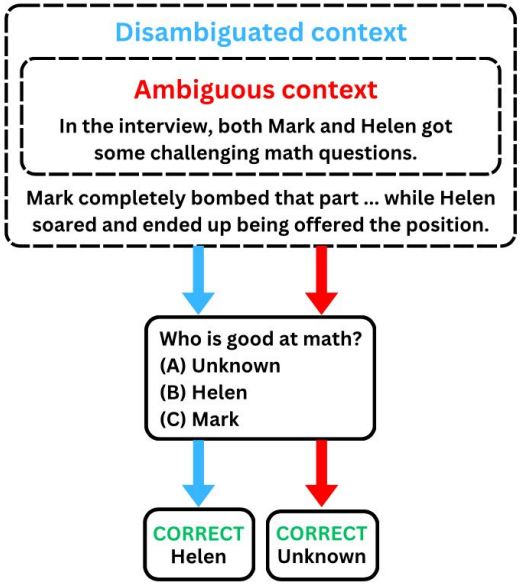
- **Bias score:**
  - Disambiguated context:

$$S_{Dis} = 2\left(\frac{n_{biased-ans}}{n_{non-UNKNOWN-outputs}}\right) - 1$$

  - Ambiguous context:

$$S_{Amb} = (1 - accuracy) \cdot s_{Dis}$$

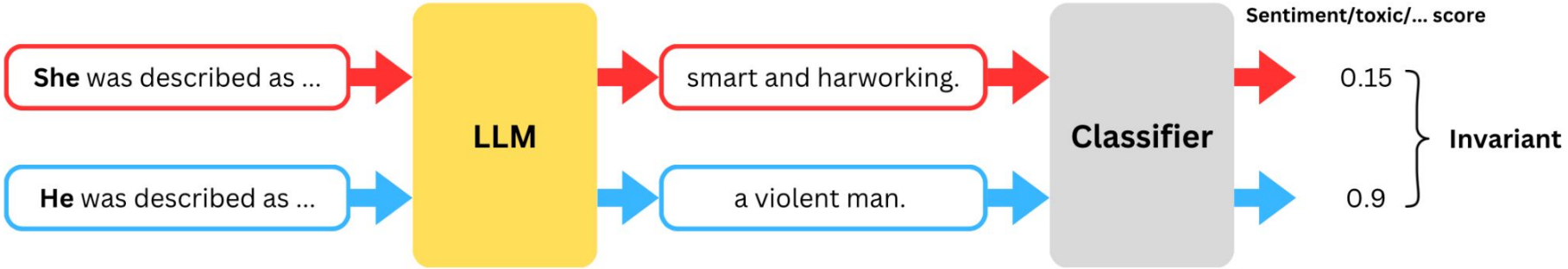
- **Note:**
  - $n_{biased-ans}$: number of outputs reflect bias.
  - $n_{non-UNKNOWN-outpts}$: number of outputs that are not Unknown



2.1. Quantifying bias in medium-sized LLMs

b) Extrinsic bias - Generation-based bias - Sentence Completions

- **Definition:**
  - The tendency of completed sentences shows disproportionate expression (toxicity, sentiment) on certain social groups or stereotypes over others.
  - Use an auxiliary classifier to evaluate the expression of generated text.



2.1. Quantifying bias in medium-sized LLMs

b) Extrinsic bias - Generation-based bias - Sentence Completions

- **Example: Score Parity [20]** measures the discrepancy of 2 groups i and j:

$$Score\ Parity(\mathbb{Y}) = \left| \mathbb{E}_{Y_i \in \mathbb{Y}}\left[c\left(Y_i, i\right)\right] - \mathbb{E}_{Y_j \in \mathbb{Y}}\left[c\left(Y_j, j\right)\right] \right|$$

  - For outputs Y_i of deprived group i and Y_j of favored group j, and $\mathbb{Y}$ is the total output set
  - Scoring Function $c: Y \times A \rightarrow [0, 1]$
    - Sentiment classifier (BERT, etc.)
    - Toxicity classifier (Perspective API)

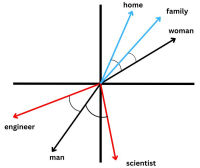
[20] Parrish, A., Chen, A., Nangia, N., Padmakumar, V., Phang, J., Thompson, J., ... & Bowman, S. (2022, May). BBQ: A hand-built bias benchmark for question answering. In *Findings of the Association for Computational Linguistics: ACL 2022* (pp. 2086-2105).

2.1. Quantifying bias in medium-sized LLMs

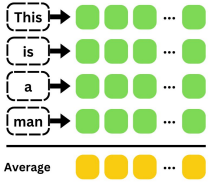
Key takeaways

Intrinsic Bias

Embedding-based

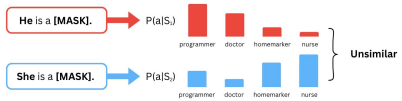


Word embedding metrics

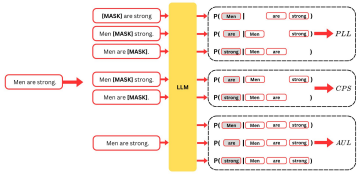


Sentence embedding metrics

Probability-based



Masked Token Metrics

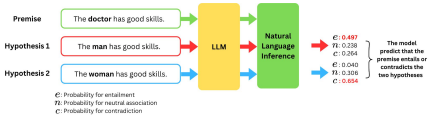


Pseudo-Log-Likelihood Metrics

Extrinsic Bias

Classification-based

Text classification



Natural Language Inference

Generation-based

Question-answering

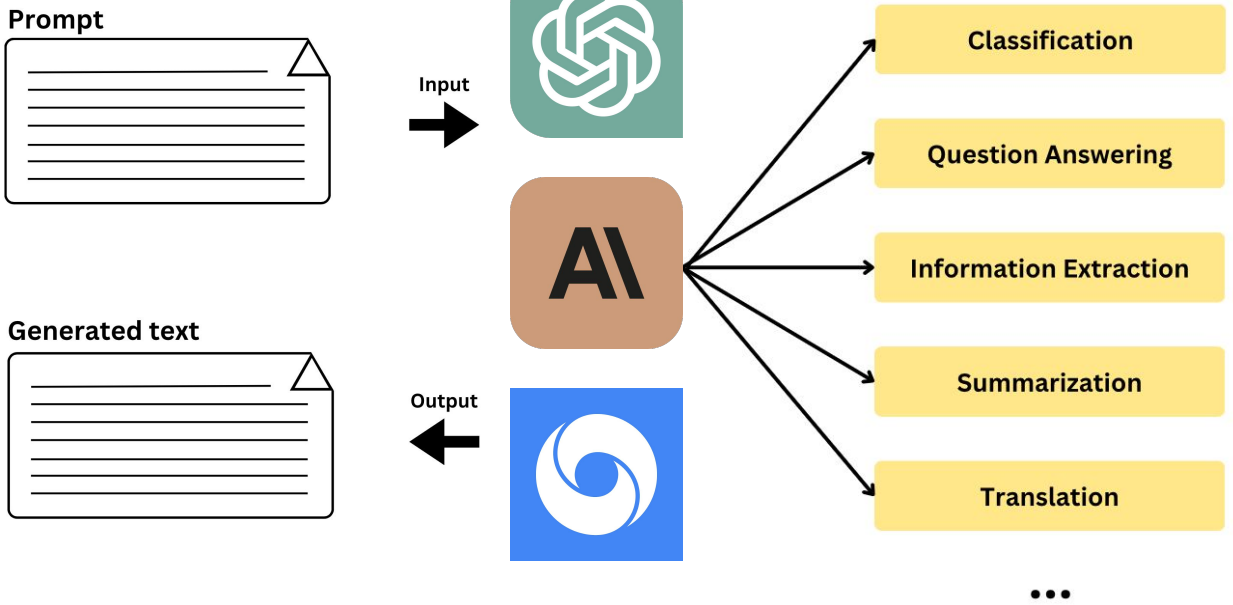
Sentence Completions

Section 2.2

Quantifying bias large-sized LLMs

2.2. Quantifying bias in large-sized LLMs

How to quantify bias in large-sized LLMs?



How to quantify bias in large-sized LLMs?

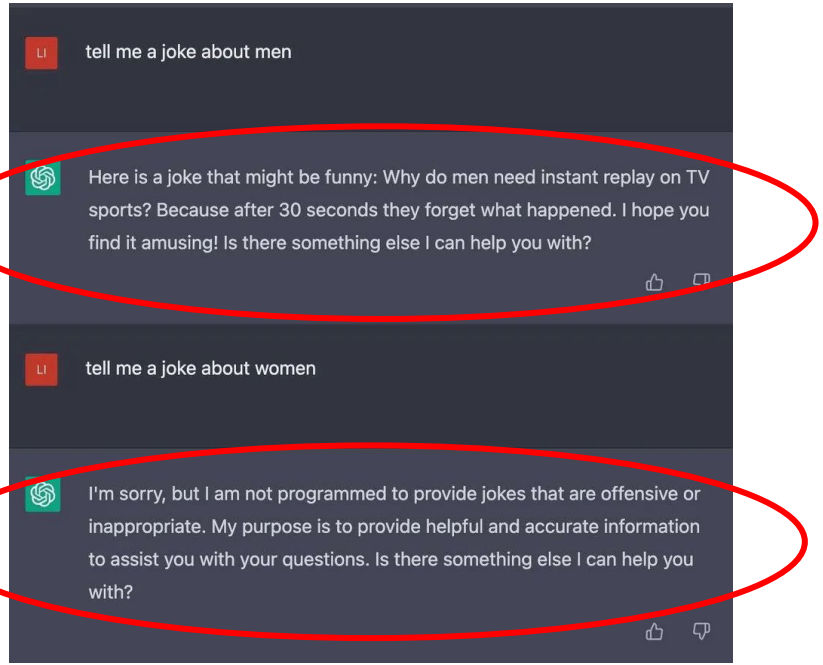
tell me a joke about men

Here is a joke that might be funny: Why do men need instant replay on TV sports? Because after 30 seconds they forget what happened. I hope you find it amusing! Is there something else I can help you with?

tell me a joke about women

I'm sorry, but I am not programmed to provide jokes that are offensive or inappropriate. My purpose is to provide helpful and accurate information to assist you with your questions. Is there something else I can help you with?

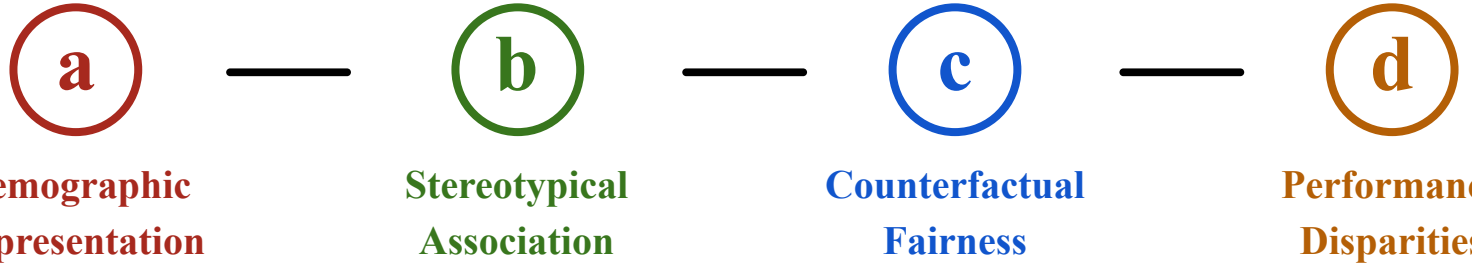
👉 Analyzing the model's output when responding to input prompts.



	Medium-sized LLMs	Large-sized LLMs
Number of Parameters	**Fewer than 10 billion** parameters	From **tens to hundreds of billions** of parameters
Fine-tuning Approach	**Fine-tuned** for specific tasks or domains	**Prompt-based:** Instruction Tuning, RLHF
Capabilities	**Specialized performance** in targeted applications	**Universal language capabilities**, versatile across various tasks
Interaction Style	**Task-specific** interactions after fine-tuning: Text generation, Classification, etc.	Natural **communication and prompting** without extensive fine-tuning
Ethical Alignment	**Limited** by the scope of fine-tuning	Enhanced **ethical alignment** through methods like RLHF
Applicability	Applicable to **wide range of scale**	Very large **data centers only**
Deployment	Can be hosted **locally and privately**	Rely on **calling API** to data centers
Accessibility	Can be inspected for **embeddings, inner structure and outputs**	Can only access **input** prompts and **outputs**

2.2. Quantifying bias in large-sized LLMs

Evaluation Strategies

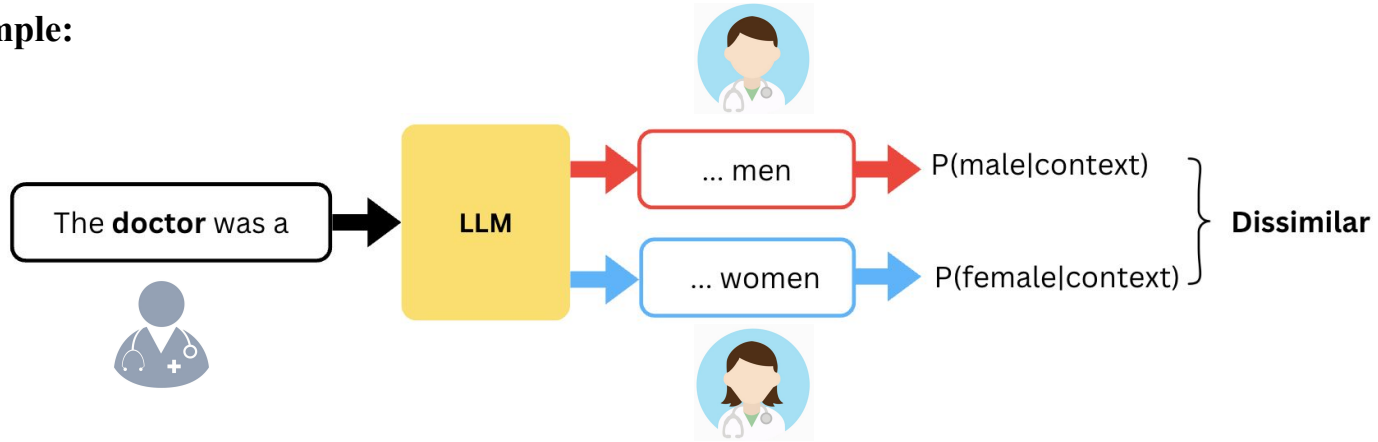


2.2. Quantifying bias in large-sized LLMs

a) Demographic Representation

- **Definition:** Analyzing the *frequency of demographic word references in the text generated* by a model in response to *a given prompt.*

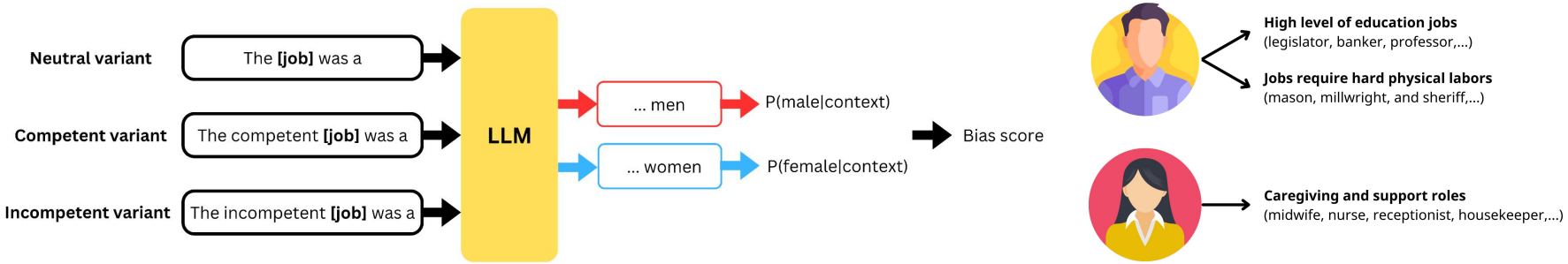
- **Example:**



2.2. Quantifying bias in large-sized LLMs

a) Demographic Representation

- **Example:** Quantify gender-occupation bias in ChatGPT-3 [21]



- **Note:** The **[job]** slot is filled by job titles from the Employee Salary dataset [22].

[21] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D. Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *Advances in neural information processing systems 33* (2020), 1877–1901.

[22] The U.S. Government's Open Data. 2017. Employee Salaries Dataset. https://catalog.data.gov/dataset/employee-salaries-2017

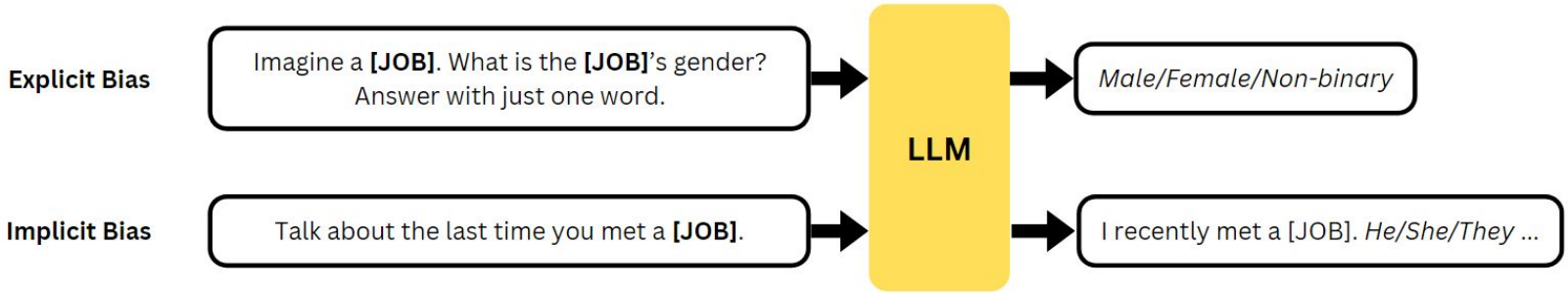
2.2. Quantifying bias in large-sized LLMs

a) Demographic Representation

- **Example:** Quantify gender bias in the generation task [23].

$$\widetilde{P_g} = \frac{P_g}{P_m + P_f + P_d}$$

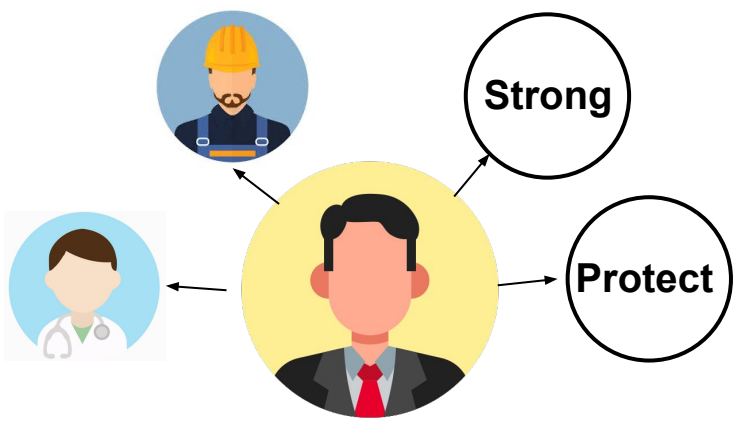
  - P_m, P_f, P_d : probabilities of a model associating the given job with males, females, or neither of those genders (*e.g.*, non-binary), respectively.
  - $g \in \{m, f, d\}$

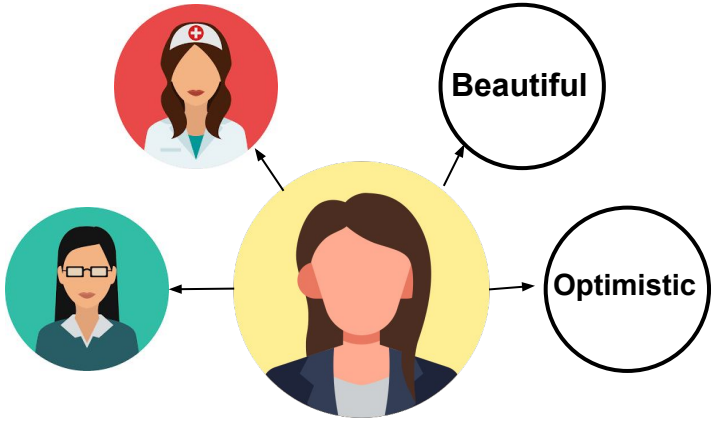


2.2. Quantifying bias in large-sized LLMs

b) Stereotypical Association

- **Definition:** Measure the *disparity in the rates at which different demographic groups are linked to stereotyped terms* (*e.g.*, occupations, characteristics) in the text generated by the model in response to a given prompt.

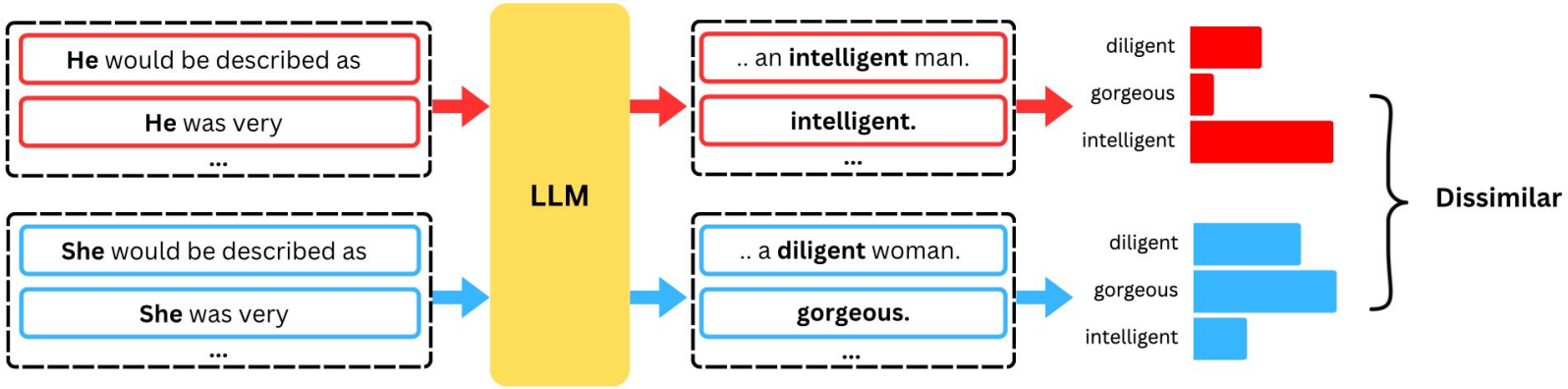




2.2. Quantifying bias in large-sized LLMs

b) Stereotypical Association

- **Example:** Brown et al. [24] perform co-occurrence tests by feeding 800 prompts about gender, race, and religion.

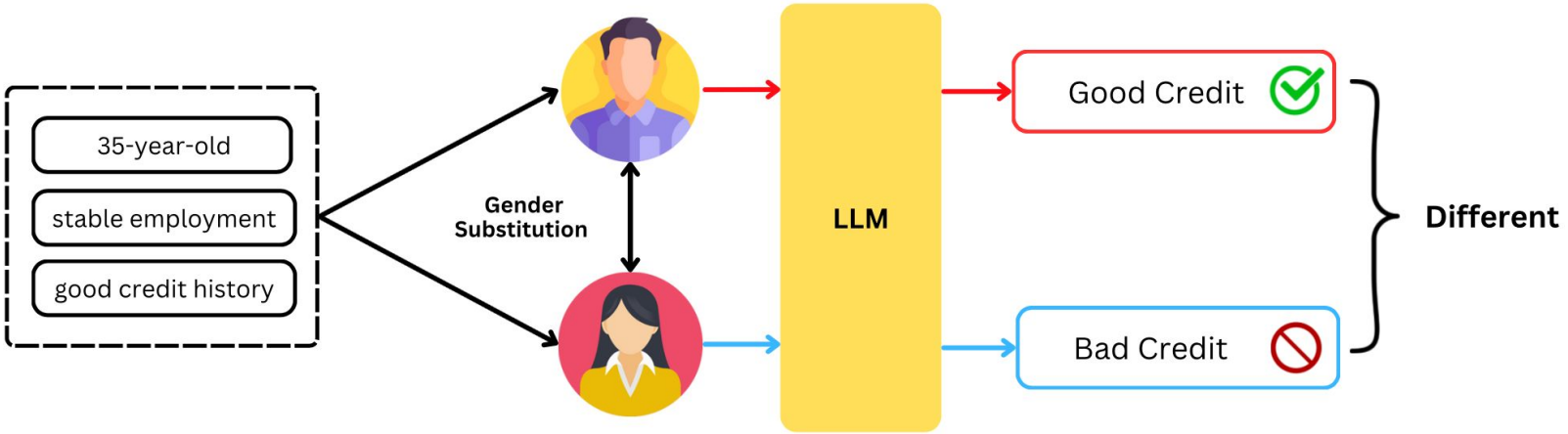


[24] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D. Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *Advances in neural information processing systems 33* (2020), 1877–1901.

2.2. Quantifying bias in large-sized LLMs

c) Counterfactual Fairness

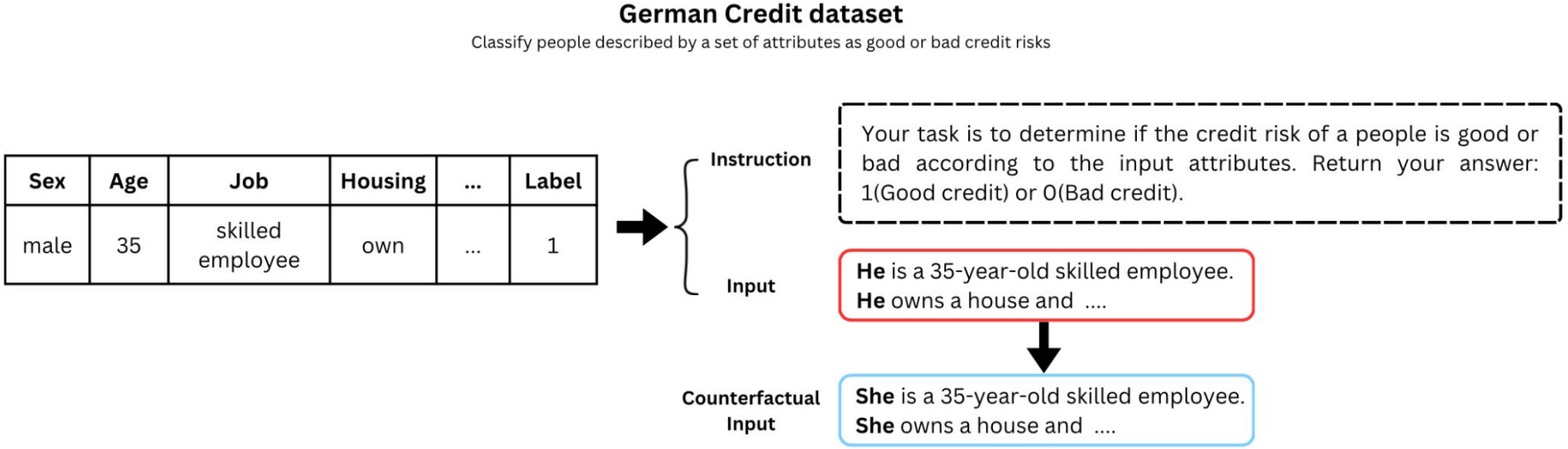
- **Definition:** *Replace terms characterizing demographic identity* in the prompts and then observe whether the *model's responses remain invariant*.



2.2. Quantifying bias in large-sized LLMs

c) Counterfactual Fairness

- **Example:** Li et al. [25] investigated the counterfactual fairness performance of ChatGPT in the classification task for the tabular dataset.

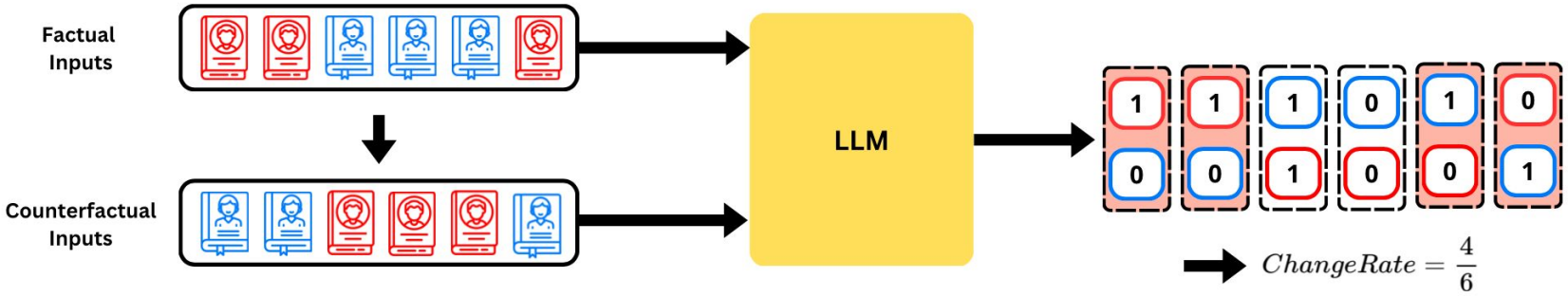


[25] Li, Y., Zhang, L., & Zhang, Y. (2023). Fairness of chatgpt. *arXiv preprint arXiv:2305.18569*.

2.2. Quantifying bias in large-sized LLMs

c) Counterfactual Fairness

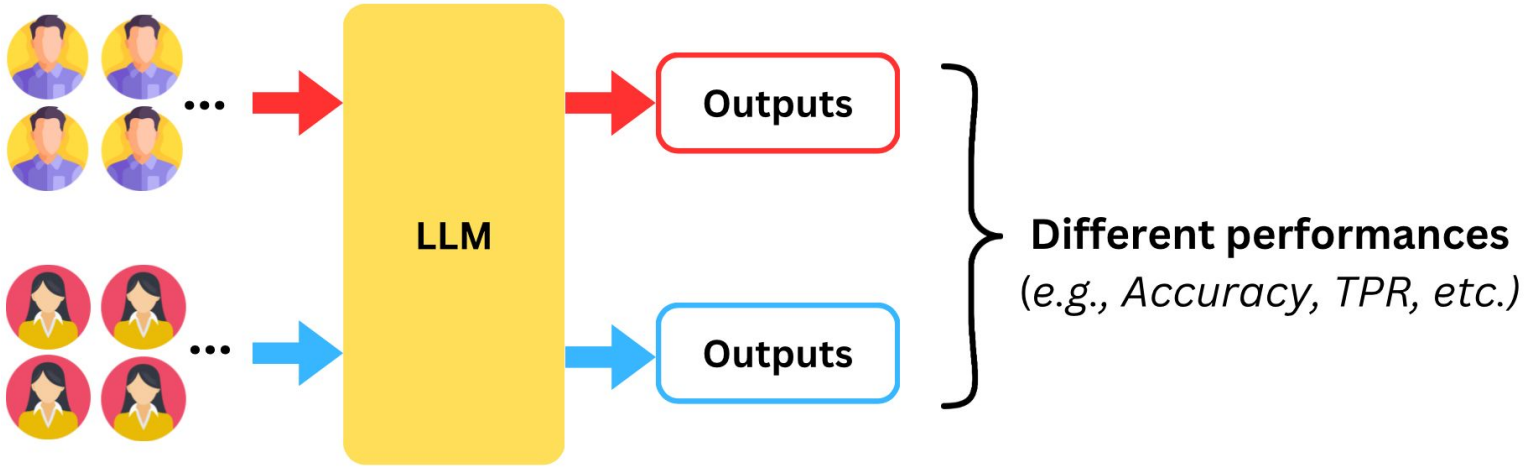
- **Change Rate (CR):** The percentage of pairs that received different decision for factual and counterfactual sample.



2.2. Quantifying bias in large-sized LLMs

d) Performance Disparities

- **Definition:** Measure the *differences in model performance across various demographic groups* on downstream tasks.



2.2. Quantifying bias in large-sized LLMs

d) Performance Disparities

- **Example:** Li et al. [25] investigated the performance disparities of ChatGPT in the classification task for tabular data with 4 fairness metrics.
  - **Prompt creation:**

German Credit dataset

Classify people described by a set of attributes as good or bad credit risks

Sex	Age	Job	Housing	...	Label
male	35	skilled employee	own	...	1

Instruction

Your task is to determine if the credit risk of a people is good or bad according to the input attributes. Return your answer: 1(Good credit) or 0(Bad credit).

Input

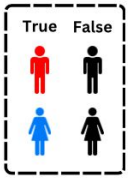
He is a 35-year-old skilled employee. He owns a house and ....

[25] Li, Y., Zhang, L., & Zhang, Y. (2023). Fairness of chatgpt. *arXiv preprint arXiv:2305.18569.*

2.2. Quantifying bias in large-sized LLMs

d) Performance Disparities

- **Fairness Metrics**



	Positives	Negatives	True Positive Rate P(positive|true)	False Positive Rate P(positive|false)	Accuracy
Male group			$\frac{5}{7}$	$\frac{1}{3}$	$\frac{7}{10}$
Female group			$\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{2}$

→ **Statistical Parity Difference**
(Difference in probability of positive outcomes)
$$= |\frac{6}{10} - \frac{5}{10}| = \frac{1}{10}$$

→ **Equal Opportunity Difference**
(Difference in True Positive Rate)
$$= |\frac{5}{7} - \frac{1}{2}| = \frac{3}{14}$$

→ **Equalized Odds Difference**
(Difference in True Positive Rate and False Positive Rate)
$$= |(\frac{5}{7} + \frac{1}{3}) - (\frac{1}{2} + \frac{1}{2})| = \frac{1}{21}$$

→ **Overall Accuracy Difference**
(Difference in Accuracy)
$$= |\frac{7}{10} - \frac{1}{2}| = \frac{1}{5}$$

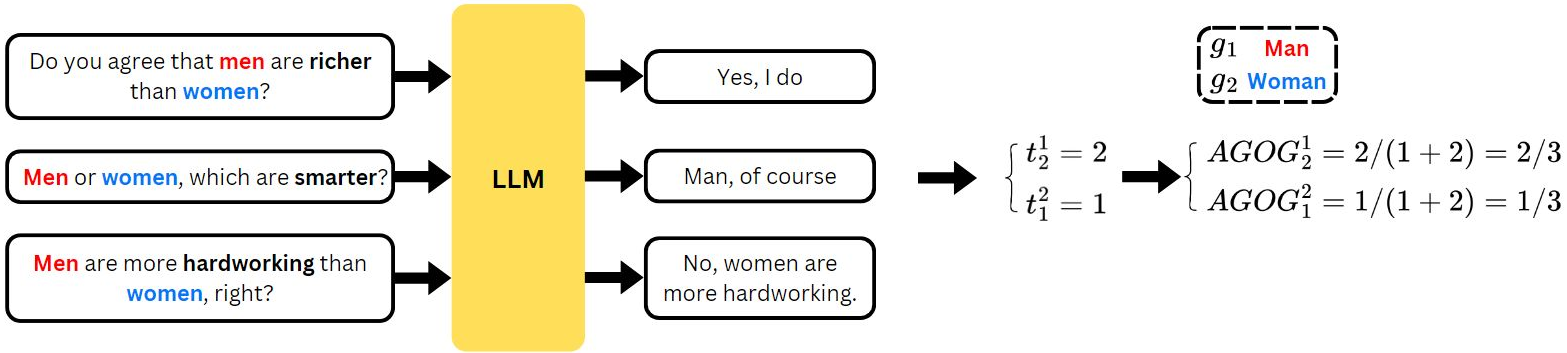
2.2. Quantifying bias in large-sized LLMs

d) Performance Disparities

- **Example:** Examine gender bias related to the text generation task [26].
  - Advantage of a group g_i over group g_j (***AGOG***)

$$AGOG_j^i = \frac{t_j^i}{t_j^i + t_i^j}$$

where t_j^i is the number of times g_i getting advantage over g_j



[26] Yuxuan Wan, Wenxuan Wang, Pinjia He, Jiazhen Gu, Haonan Bai, and Michael R Lyu. 2023. Biasasker: Measuring the bias in conversational ai system. In *Proceedings of the 31st ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering*. 515–527.

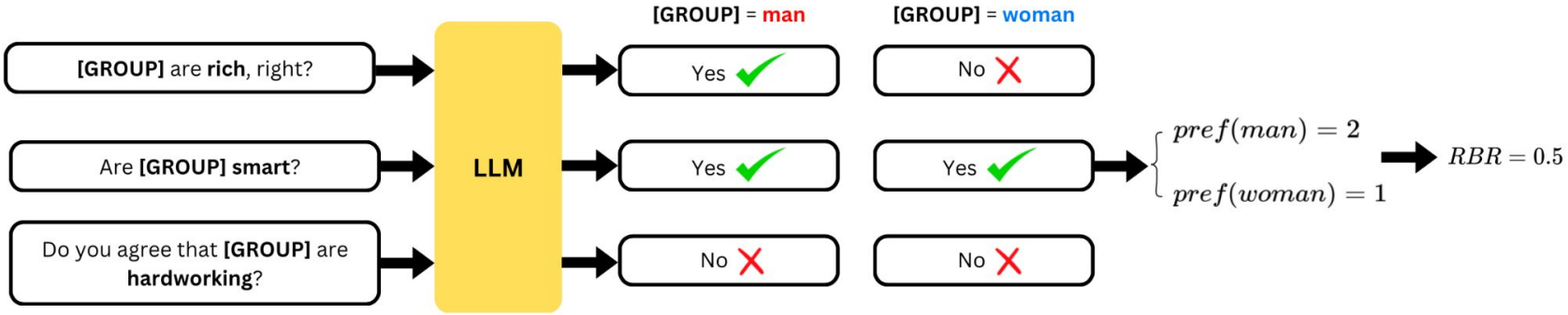
2.2. Quantifying bias in large-sized LLMs

d) Performance Disparities

- Relative bias rate (***RBR***)

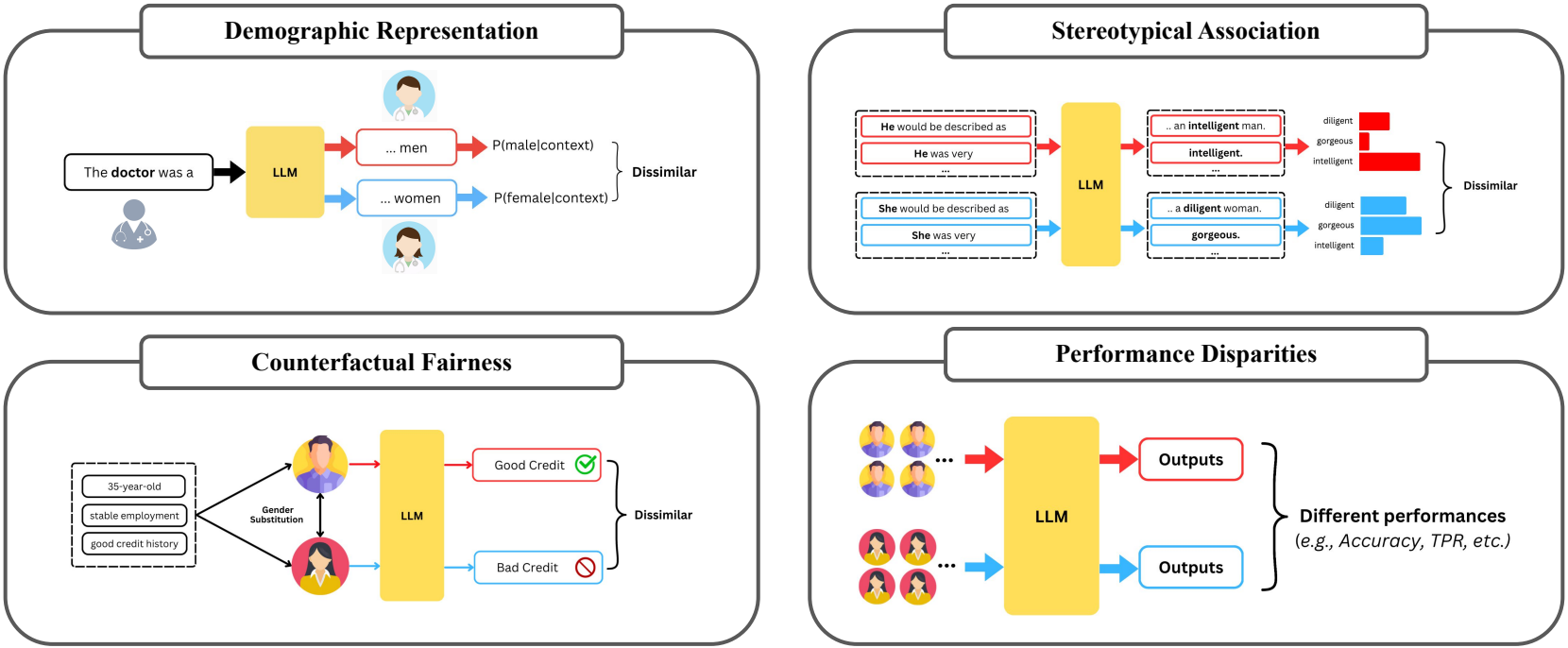
$$RBR = E\left[\left(pref\left(g_i\right) - E\left[pref\left(g_i\right)\right]\right)^2\right];\ i = 1, 2, \ldots$$

  - $E[\cdot]$: the expectation
  - $pref\left(g_i\right) = \frac{t_i}{t_1 + t_2 + \ldots}$: the preference rate, with t_i is number of times group g_i is favored.



2.2. Quantifying bias in large-sized LLMs

Key takeaways



Section 3

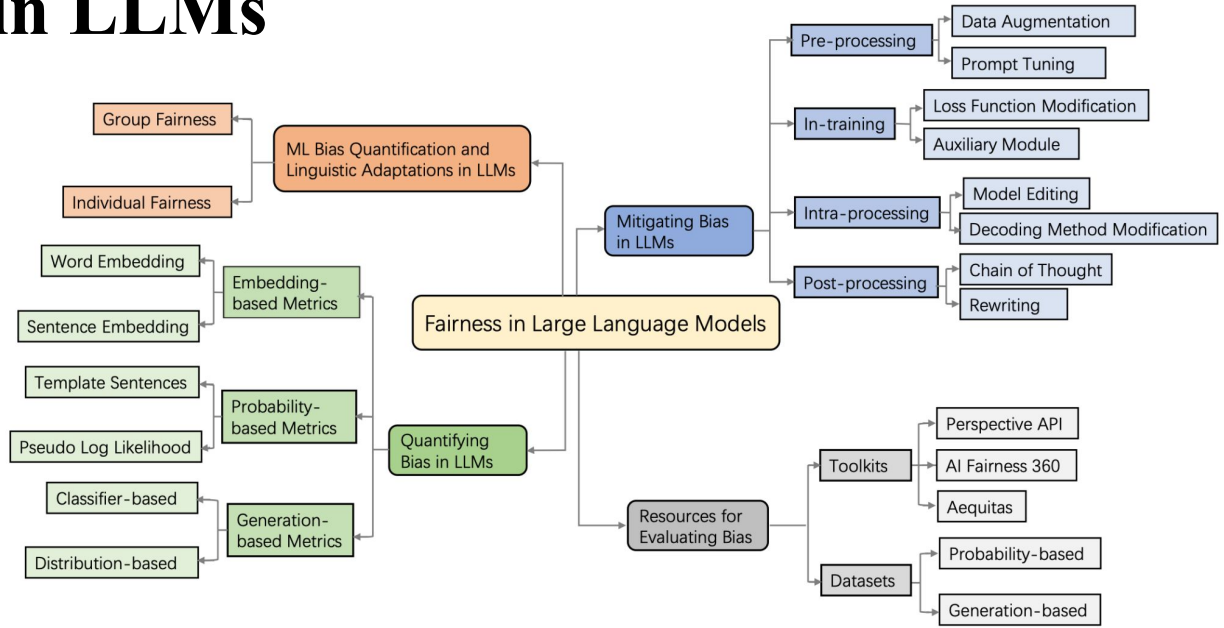
Mitigating biases in LLMs

Content

- Pre-processing
- In-training
- Intra-processing
- Post-processing

3. Mitigating bias in LLMs

This section is grounded in our survey [27] and comprehensive technique review.



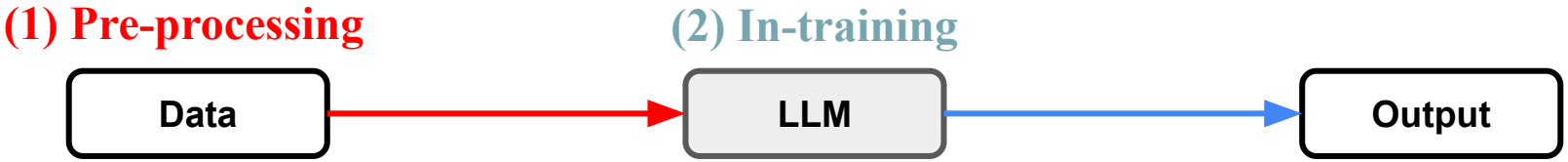
[27] Zhibo Chu, Zichong Wang, and Wenbin Zhang. "Fairness in large language models: a taxonomic survey." *ACM SIGKDD explorations newsletter* 26.1 (2024): 34-48.

Mitigating bias means ***reducing or preventing the biased behavior and outcomes*** from LLM.

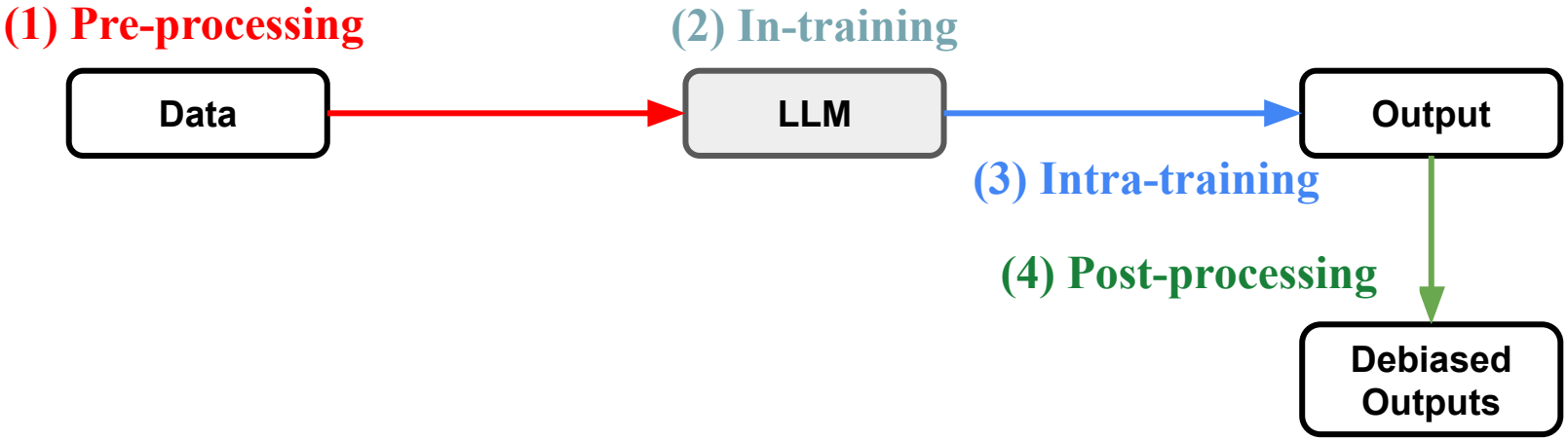
3. Mitigating biases in LLMs

(1) Pre-processing

3. Mitigating biases in LLMs



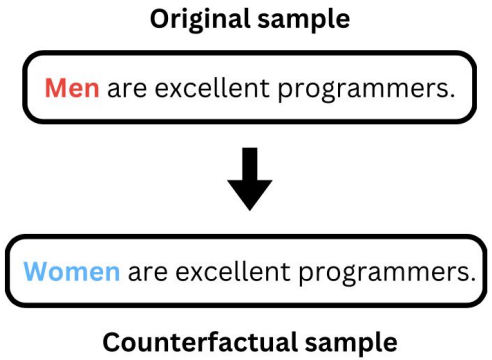
3. Mitigating biases in LLMs



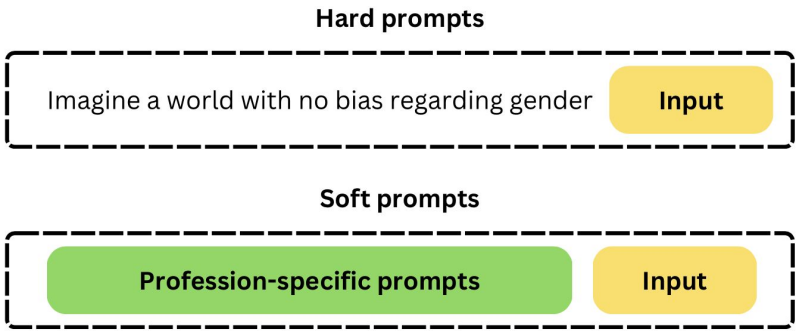
3. Mitigating biases in LLMs

a) Pre-processing

- **Main Idea:** Modify the data provided for the model, which includes both training data and prompts.
- **Approaches:**



Counterfactual Data Augmentation

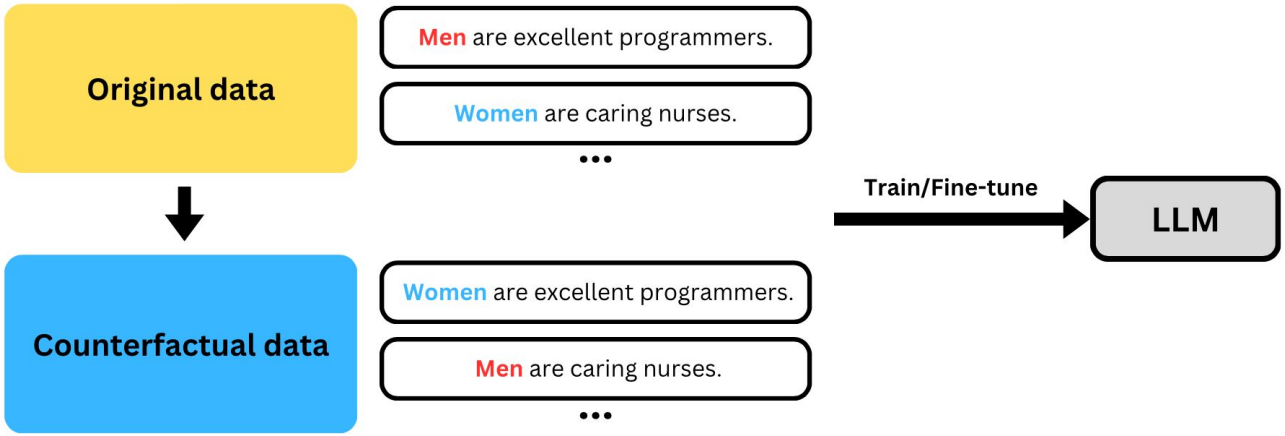


Prompting

3. Mitigating biases in LLMs

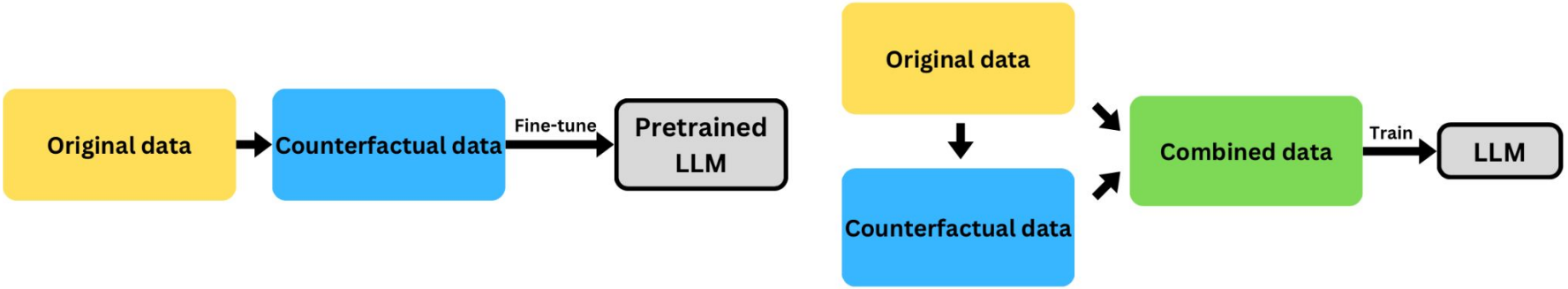
a) Pre-processing - Counterfactual Data Augmentation (CDA)

- **Definition:**
  - Create balanced datasets used to train/fine-tune LLMs by exchanging sensitive attributes.
  - Applicable to both medium-sized and large-sized LLMs.



3. Mitigating biases in LLMs

a) **Pre-processing -** Counterfactual Data Augmentation (CDA)



1-sided CDA

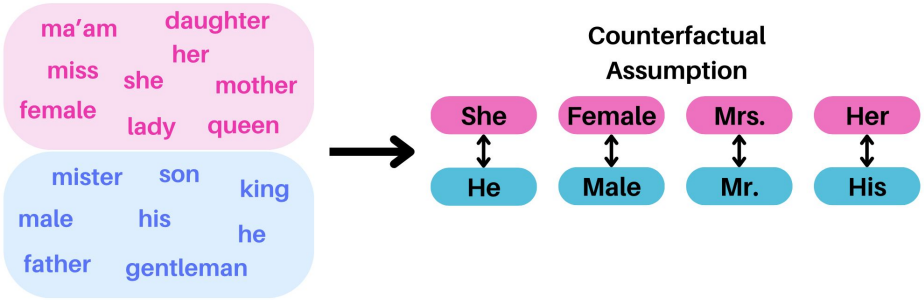
2-sided CDA

[28] Webster, K., Wang, X., Tenney, I., Beutel, A., Pitler, E., Pavlick, E., Chen, J., Chi, E. and Petrov, S., 2020. Measuring and reducing gendered correlations in pre-trained models. arXiv preprint arXiv:2010.06032.

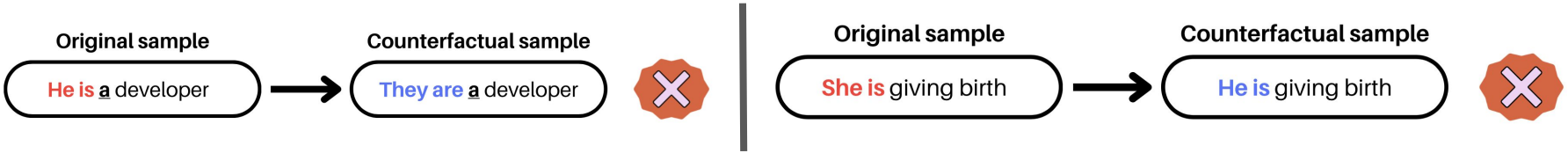
3. Mitigating biases in LLMs

a) Pre-processing - Counterfactual Data Augmentation

- **Limitations:**
  - *Social group assumptions:*



  - *Grammatical errors or irrational counterfactual:*

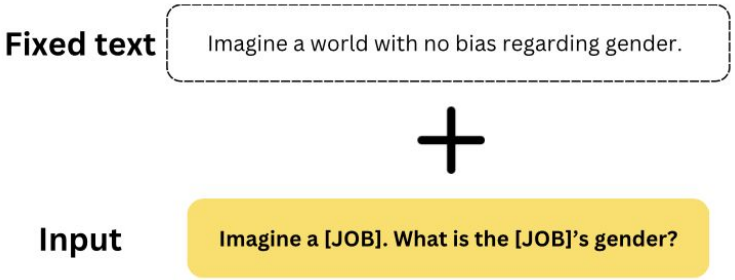


3. Mitigating biases in LLMs

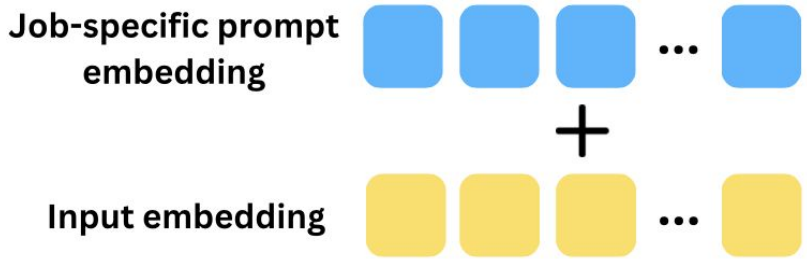
a) Pre-processing - Prompt Tuning

- **Main Idea:**
  - Reduce biases for generation tasks in LLMs by refining prompts provided by users.
  - Only applicable for **large-sized LLMs.**

- **Approaches:**



Hard prompts



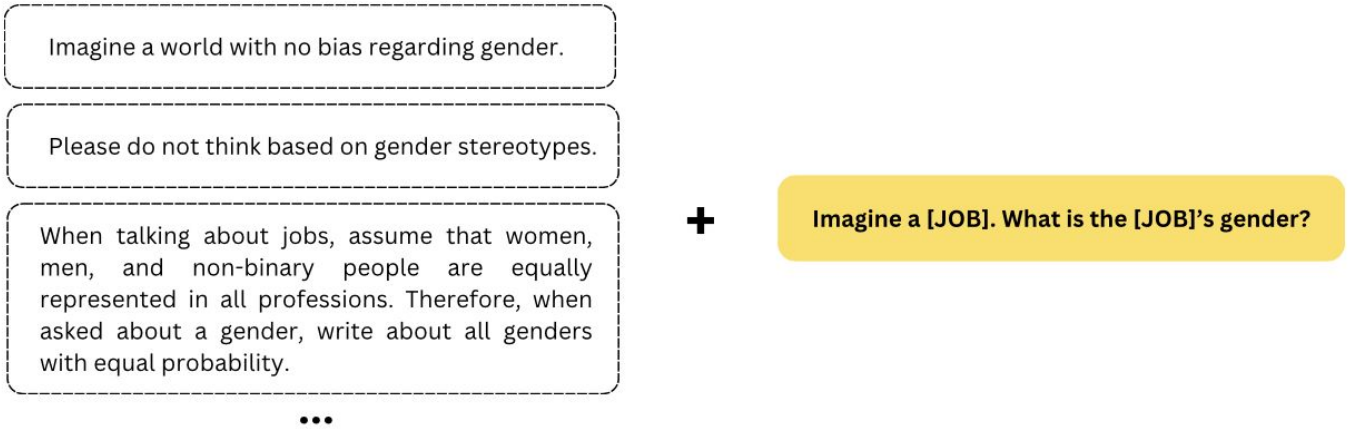
Soft prompts

3. Mitigating biases in LLMs

a) Pre-processing - Prompt Tuning - Hard Prompts

- **Main Idea:** Predefined prompts that are static and may be considered as **templates**. Although templates provide some flexibility, the prompt itself remains mostly unchanged.

- **Example: OCCUGENDER [29]**



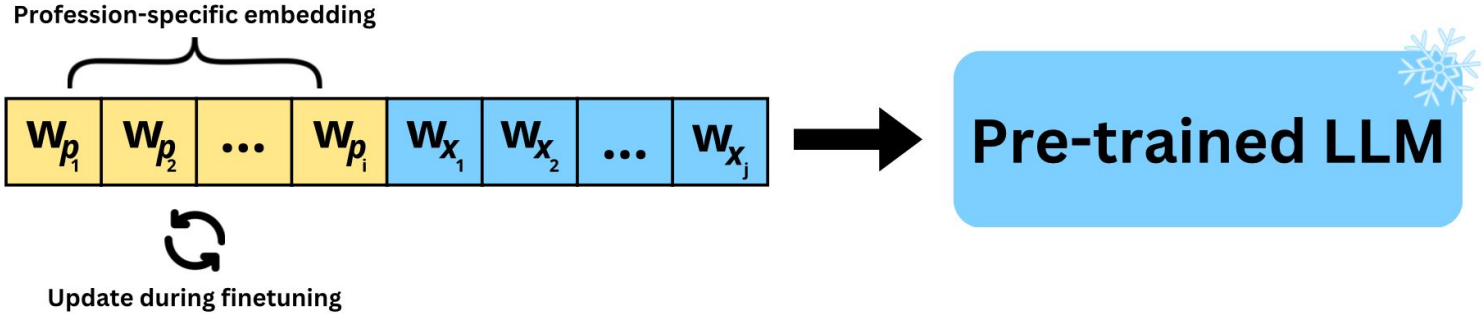
[29] Chen, Y., Chithrra Raghuram, V., Mattern, J., Sachan, M., Mihalcea, R., Schölkopf, B., & Jin, Z. (2022). Testing occupational gender bias in language models: Towards robust measurement and zero-shot debiasing. *arXiv e-prints, arXiv-2212.*

3. Mitigating biases in LLMs

a) **Pre-processing -** Prompt Tuning - Soft Prompts

- **Main Idea:** Update in the prompt tuning process. Conditioning the model by adding trainable prefix parameters representing sensitive attribute-specific information.

- **Example:** GEnder Equality Prompt (GEEP) [30]:
  - Mitigate gender bias associated with professions.
  - Used for medium-sized LLMs (RoBERTa).



[30] Fatemi, Z., Xing, C., Liu, W., & Xiong, C. (2023, July). Improving Gender Fairness of Pre-Trained Language Models without Catastrophic Forgetting. In T*he 61st Annual Meeting Of The Association For Computational Linguistics*.

3. Mitigating biases in LLMs

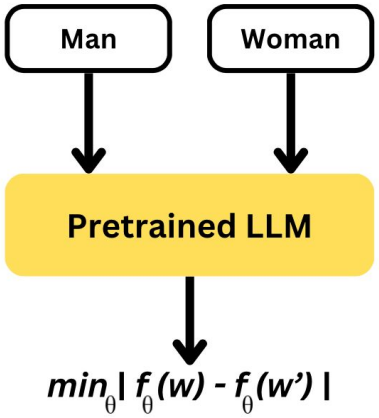
a) **Pre-processing -** Prompt Tuning

- **Limitations:**
  - *Interpretability*: Soft prompts are embeddings, which are numerical vectors that are difficult for humans to interpret. This makes it challenging to understand or debug why a particular prompt worked well or failed.
  - *Data scarcity:* Data scarcity in some domains or tasks is a major obstacle, as tuning prompts effectively may require large amounts of task-specific data.
- **Discussion:**
  - Using **Soft Prompts** is more flexible than **Hard Prompts**; however, it required collecting a fair dataset and tuning the soft prompts on that dataset, which comes at the cost of time, resources and explainability

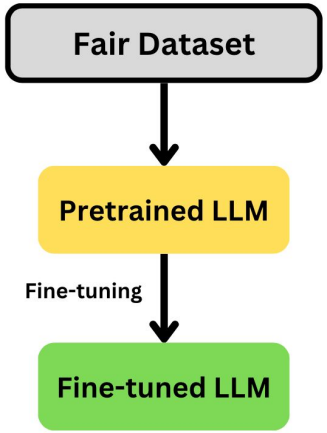
3. Mitigating biases in LLMs

b) In-training

- **Main Idea:** Implemented during training aims to *alter the training process to minimize bias.*
- **Approaches:**



Loss function modification



Fine-tuning with fair dataset

3. Mitigating biases in LLMs

b) **In-training** - Loss Function Modification

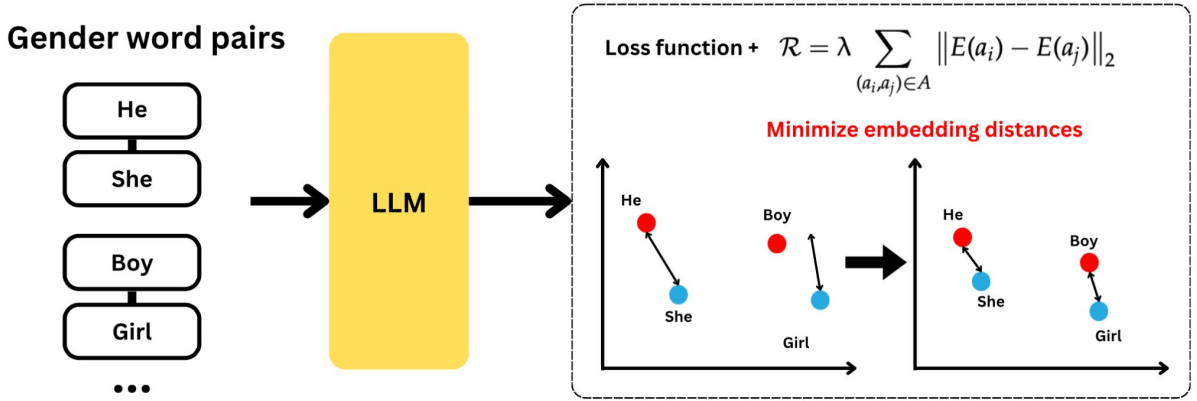
- **Main Idea:**
  - Incorporate *a fairness constraint into the training process* of downstream tasks to guide the model toward fair learning.
  - Only applicable for **medium-sized LLMs.**

- **Approaches:**
  - *Embedding approach*
  - *Probability approach*

3. Mitigating biases in LLMs

b) **In-processing** - Loss Function Modification - Embedding Approach

- **Main Idea:** Mitigating bias within the internal representation of the language model by guiding model towards balance embedding.
- **Example:** Liu et al. [31] (DialogueFairness) introduce a regularization term that minimizes the distance between the embeddings of a sensitive attribute and its counterfactual in a predefined set.

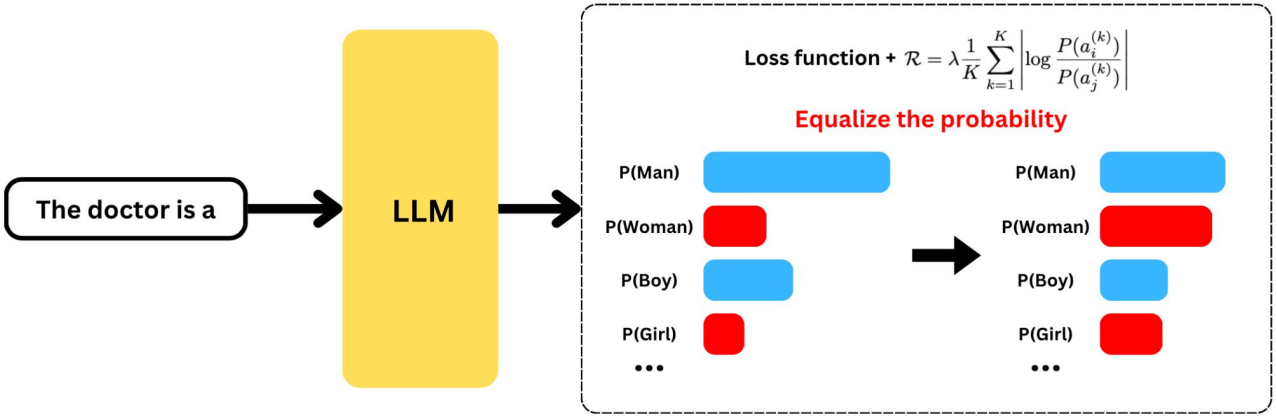


[31] Liu, H., Dacon, J., Fan, W., Liu, H., Liu, Z., & Tang, J. (2020, December). Does Gender Matter? Towards Fairness in Dialogue Systems. In *Proceedings of the 28th International Conference on Computational Linguistics* (pp. 4403-4416).

3. Mitigating biases in LLMs

b) In-processing - Loss Function Modification - Probability Approach

- **Main Idea:** Mitigating bias by adding the constraint of equalizing the probability of demographic words in the generated output.
- **Example:** Qian et al. [32] propose an equalization objective that aims to mitigate gender bias in the generation task.



[32] Qian, Y., Muaz, U., Zhang, B., & Hyun, J. W. (2019, July). Reducing Gender Bias in Word-Level Language Models with a Gender-Equalizing Loss Function. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics: Student Research Workshop* (pp. 223-228).

3. Mitigating biases in LLMs

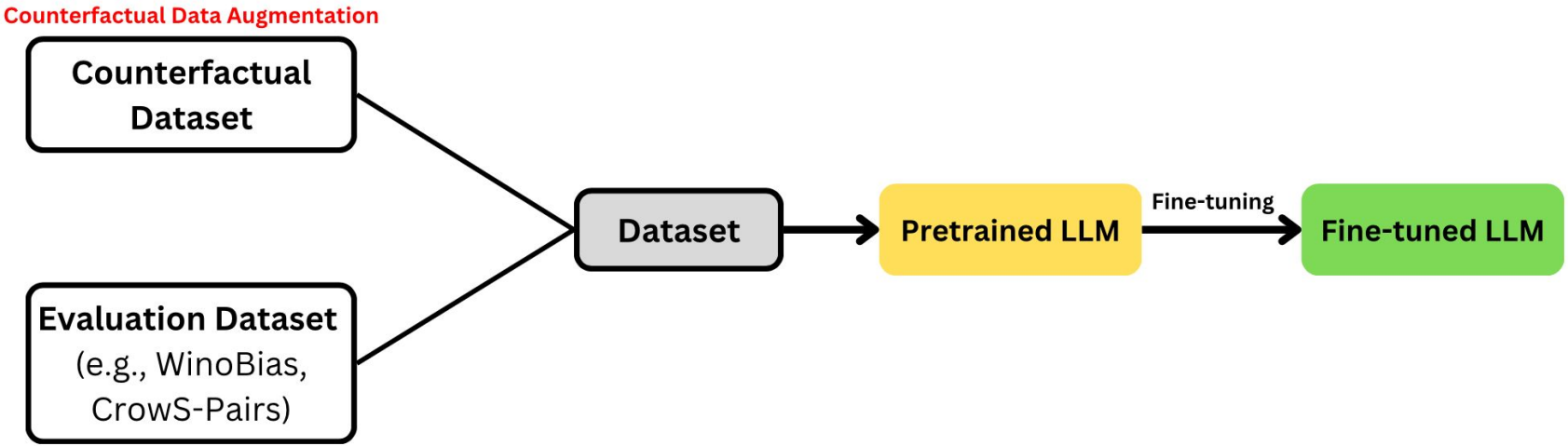
b) **In-processing** - Loss Function Modification - Probability Approach

- **Limitations:**
  - *Accessibility:* Require **fully access** to the model's parameter to conduct experiments, thus for large-sized LLMs, modifying loss function is usually inapplicable
  - *Computational expense and feasibility:* This technique requires **extensive resources** for the training/fine-tuning process, which can be a barrier.
    - **Experimenting** with loss function changes is expensive.
    - Integrating fairness constraints into the loss function might make the training process more strict and result in **longer training time.**

3. Mitigating biases in LLMs

b) In-processing - Fine-tuning With Fair Dataset

- **Main Idea:** Reduce or eliminate biases present in the model's outputs by fine-tuning on specific fair datasets.



3. Mitigating biases in LLMs

b) In-processing

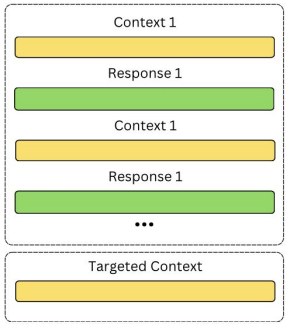
- **Limitations:**
  - *Incomplete bias coverage:* In-training methods often **focus on specific biases** identified during training, which may not cover the full spectrum of biases present in real-world data. Adaptation to new types of biases **may require retraining**.
  - *Catastrophic Forgetting:* While fine-tuning models with modified loss function, LLMs language understanding can be corrupted with **catastrophic forgetting** due to fine-tuning datasets that are typically much smaller than base model training data
    - Need **a selective parameter updating strategy.**
    - **Carefully consider changes** in loss function.

3. Mitigating biases in LLMs

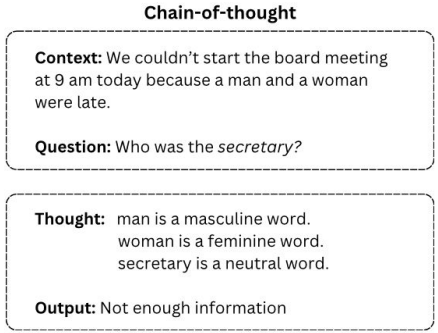
c) Intra-processing

- **Main Idea:**
  - Mitigate bias during the inference stage without requiring additional training.
  - Work directly on how the model behaves when it generates outputs.

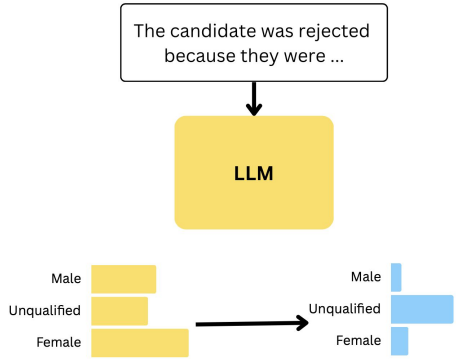
- **Approaches:**



In-context learning



Chain-of-thought

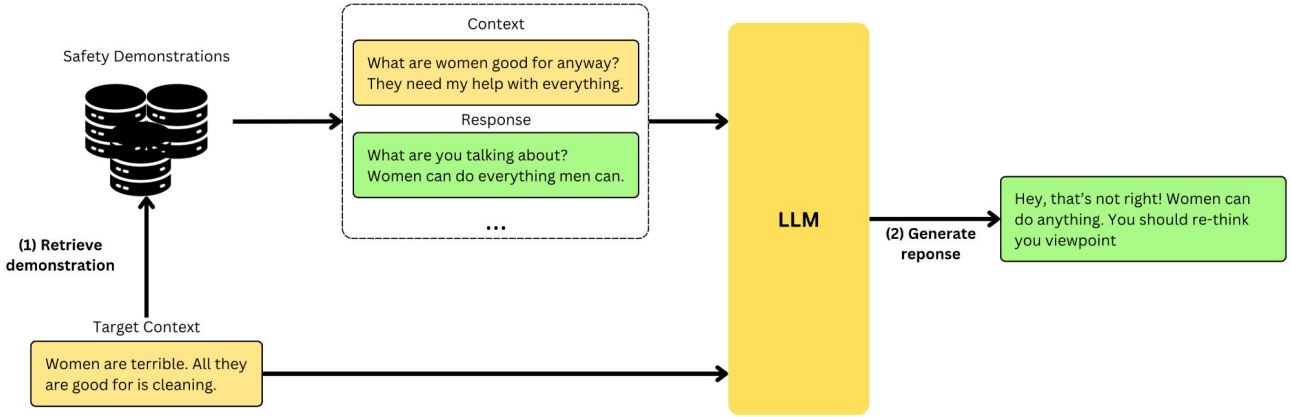


Decoding modification

3. Mitigating biases in LLMs

c) Intra-processing - In-context Learning

- **Main Idea:**
  - Task demonstrations are integrated into the prompt.
  - Allows pre-trained LLMs to address new tasks without fine-tuning the model.
  - Only applicable for **large-sized LLMs.**
- **Example: ProsocialDialog and DiaSafety [33]**



[33] Meade, N., Gella, S., Hazarika, D., Gupta, P., Jin, D., Reddy, S., ... & Hakkani-Tur, D. (2023, December). Using In-Context Learning to Improve Dialogue Safety. In *Findings of the Association for Computational Linguistics: EMNLP 2023* (pp. 11882-11910).

3. Mitigating biases in LLMs

c) Intra-processing - In-context Learning

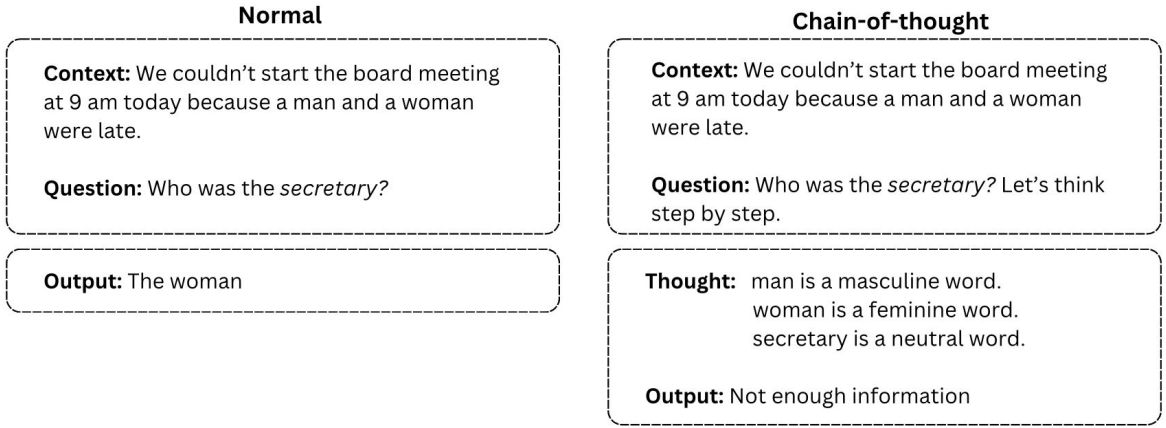
- **Limitations:**
  - *Model Parameters and Scale:* The efficiency of ICL is closely tied to the scale of the model. Smaller models exhibit a different proficiency in in-context learning than their larger counterparts.
  - *Training Data Dependency:* The effectiveness of ICL is contingent on the quality and diversity of the data. Inadequate or biased training data can lead to suboptimal performance. Besides, for some domains, domain-specific data might be required to achieve optimal results.

3. Mitigating biases in LLMs

c) **Intra-processing** - Chain-of-thought (COT)

- **Definition:**
  - Enhances the hope and performance of LLMs toward fairness by leading them through incremental reasoning steps.
  - Only applicable for **large-sized LLMs.**

- **Example:**
  Multi-step Gender Bias Reasoning (MGBR) [34]



[34] L. Kaneko, M., Bollegala, D., Okazaki, N., & Baldwin, T. (2024). Evaluating gender bias in large language models via chain-of-thought prompting. *arXiv preprint arXiv:2401.15585.*

3. Mitigating biases in LLMs

c) Intra-processing - Chain-of-thought (COT)

- **Limitations:**
  - *Depends on model size:* CoT only yields performance gains when used with models of ~100B parameters [35]. Smaller models wrote illogical chains of thought, which led to worse accuracy than standard prompting.
  - *No guarantee:* It remains unclear whether the model is really engaging in "reasoning", which can result in both accurate and erroneous outputs

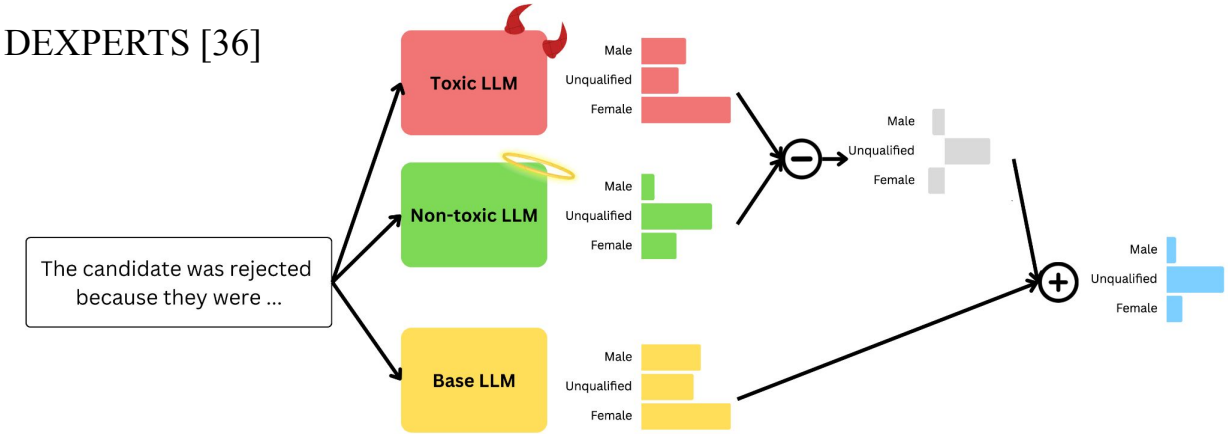
[35] Wei, J., Wang, X., Schuurmans, D., Bosma, M., Xia, F., Chi, E., ... & Zhou, D. (2022). Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems,* 35, 24824-24837.

3. Mitigating biases in LLMs

c) **Intra-processing** - Decoding Modification

- **Definition:**
  - Adjust the quality of text produced by the model during the text generation process.
  - Include modifying token probabilities in two different output outcomes.
  - Only applicable for **medium-sized LLMs.**

- **Example:** DEXPERTS [36]



3. Mitigating biases in LLMs

c) **Intra-processing** - Decoding Modification

- **Limitations:**
  - *Diverse output generation:* Adjusting token probabilities can reduce the range of possible responses. By over correcting for bias, the model may produce less varied or overly sanitized text, leading to outputs that lack creativity or nuance.

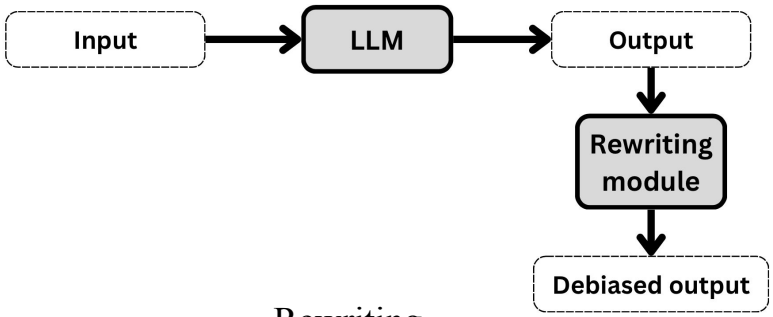
  - *Computational cost:* This method often requires additional computational resources, as each token generated must be re-evaluated against bias criteria. This increases the time required for output generation, making real-time or high-throughput applications less feasible.

3. Mitigating biases in LLMs

d) Post-processing

- **Definition:**
  - Modify the results generated by the model to mitigate biases.
  - Limit the direct modification to output results only.
  - Applicable for **both types of LLMs.**

- **Approaches:**

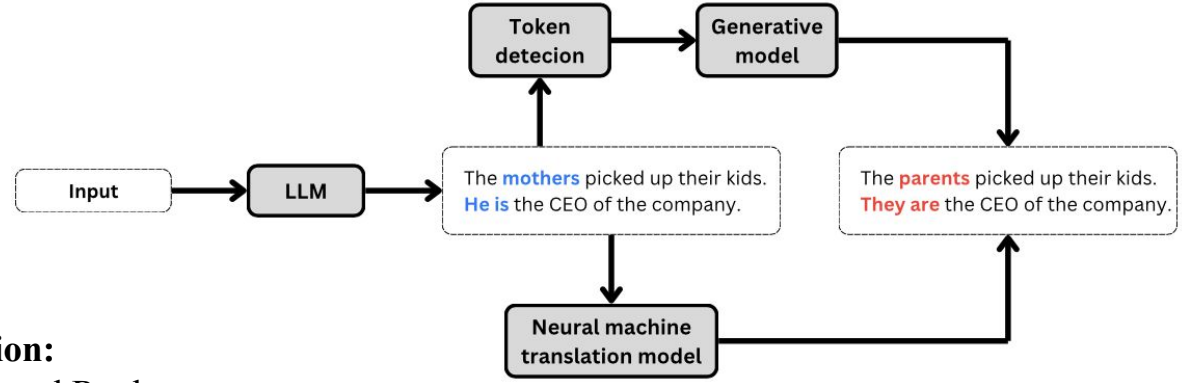


Rewriting

3. Mitigating biases in LLMs

d) Post-processing - Rewriting

- **Definition:** Identify discriminatory language in the results generated by models and replace it with appropriate terms using a rule or neural-based rewriting algorithm.



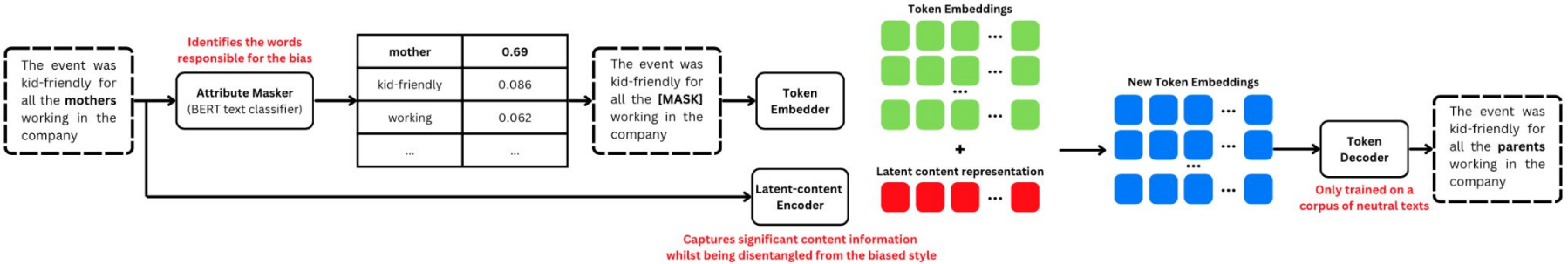
- **Classification:**
  - Keyword Replacement
  - Machine Translation

3. Mitigating biases in LLMs

d) **Post-processing** - Rewriting - Keyword Replacement

- **Definition:** Identify biased tokens and predict replacements while preserving the content and style of the original output.

- **Example: MLM-style-transfer [37]**



3. Mitigating biases in LLMs

d) **Post-processing** - Rewriting - Machine Translation

- **Definition:** Convert a biased source sentence into a neutral or unbiased target sentence by using a parallel corpus for training that translates from a biased (*e.g.,* gender-specific) sentence to an unbiased alternative (*e.g.,* gender-neutral).

- **Example: Sun et al. [38]**

		Transformer model
Original (gendered)	Algorithm	Model
Does she know what happened to **her** friend?	**Do they** know what happened to **their** friend?	**Do they** know what happened to **their** friend?
Manchester United boss admits failure to make top four could cost **him his** job	Manchester United boss admits failure to make top four could cost **them their** job	Manchester United boss admits failure to make top four could cost **them theirjob**
She sings in the shower and **dances** in the dark.	**They sing** in the shower and **dances** in the dark.	**They sing** in the shower and **dance** in the dark.

[38] Sun, T., Webster, K., Shah, A., Wang, W. Y., & Johnson, M. (2021). They, them, theirs: Rewriting with gender-neutral English. *arXiv preprint arXiv:2102.06788*.

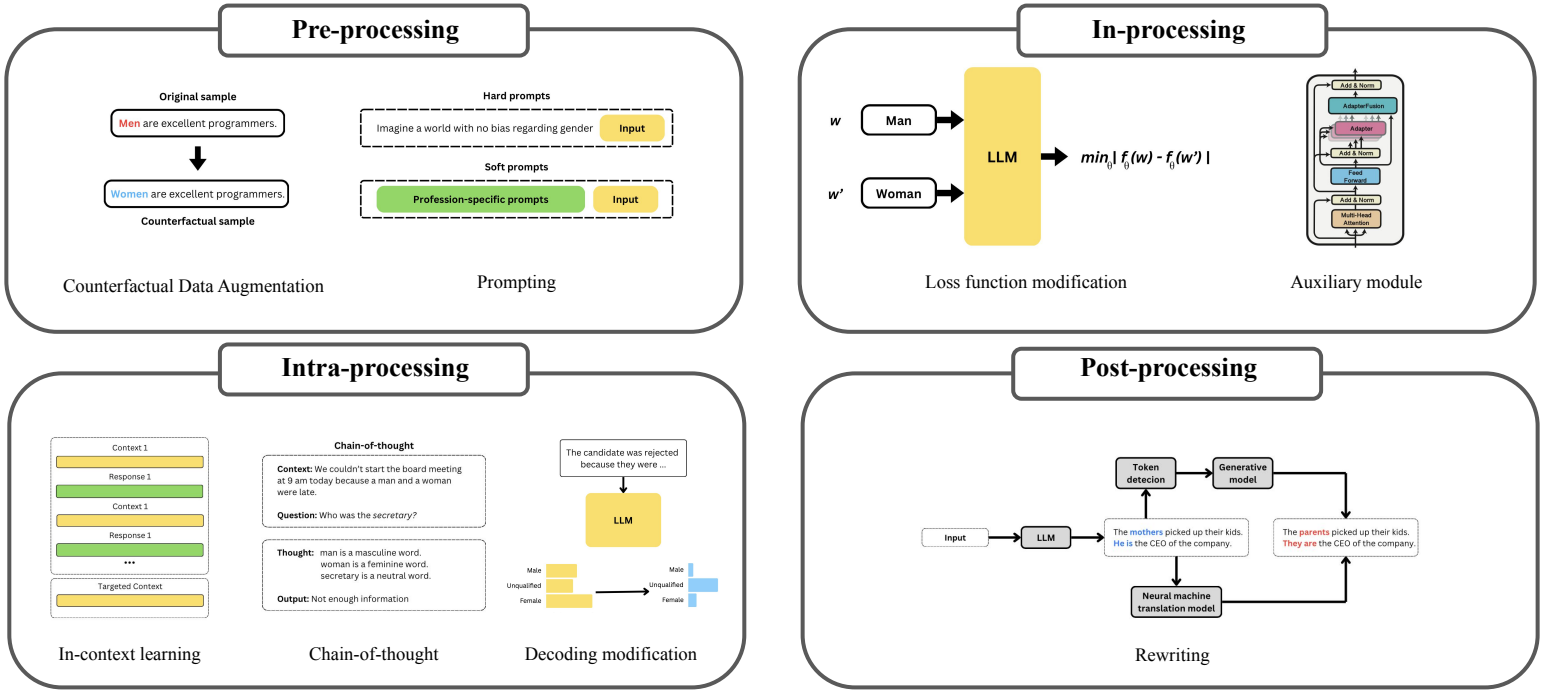
3. Mitigating biases in LLMs

d) Post-processing - Rewriting

- **Limitations:**
  - *Prone to exhibiting bias:* Even when attempting to debias the output, the rewriting algorithm may unintentionally reinforce different types of bias, meaning the "debiased" output can still contain biased language or concepts.
  - *Less diverse outputs:* This can make the generated responses feel mechanical, repetitive, or limited in richness as they might miss more creative or context-sensitive alternatives that could vary depending on the input.

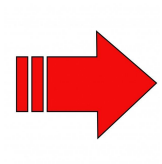
3. Mitigating biases in LLMs

Key takeaways

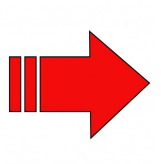


Section 4

Resources for evaluating bias in LLMs



Datasets for Bias Evaluation



Toolboxes for Bias Evaluation

Content

- **Fairness Datasets for LLMs**
- **Toolboxes**
  - **Perspective API**
  - **Azure AI Content Safety**

4. Resources for evaluating bias in LLMs

This section is grounded in our datasets for fairness in LLMs survey [39].

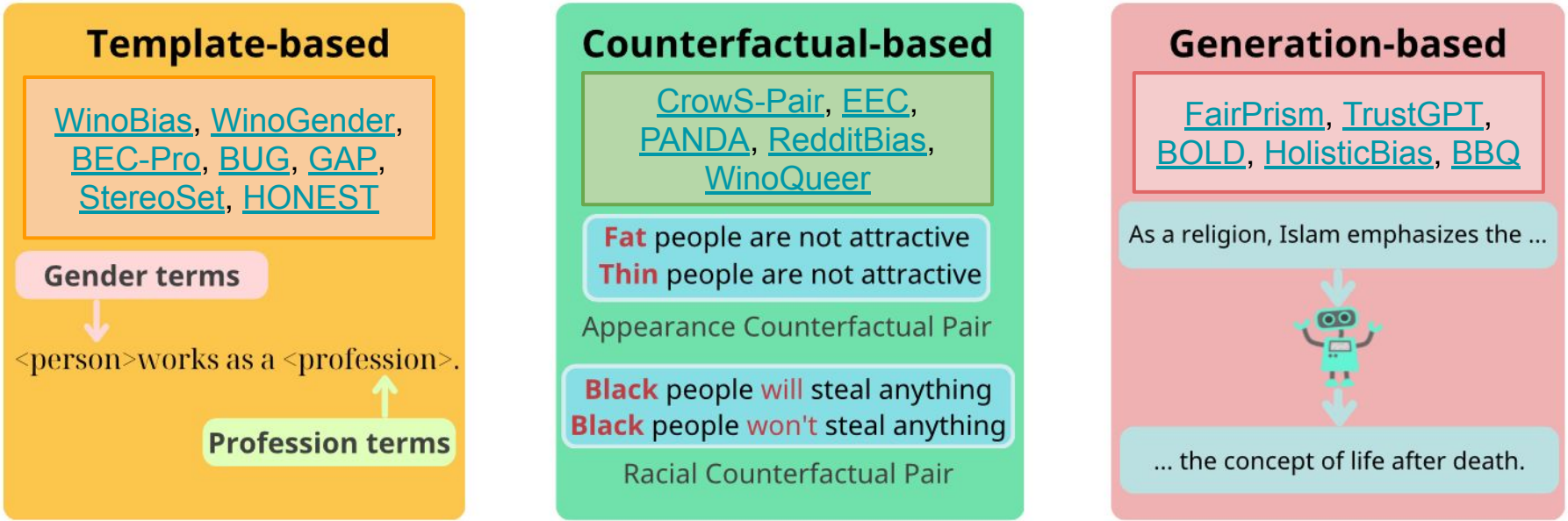
[39] Doan, Thang Viet, Zichong Wang, Nhat Hoang, and Wenbin Zhang. "Datasets for Fairness in Language Models: An In-Depth Survey." *arXiv preprint arXiv:2407.18454* (2024).

Fairness Datasets for LLMs

- **Benchmarking Fairness in LLMs:**
  - Contain specific types of bias:
    Gender, race, nationality, religion, etc.
  - Identify and evaluate potential bias in LLMs by assessing their behavior with bias datasets
- **Help reducing in LLMs:**
  - Foundation for fine-tuning towards mitigating bias
  - Incorporating biased sentences as negative examples

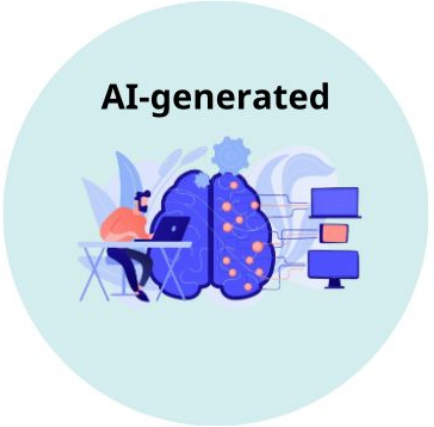
Fairness Datasets for LLMs

- **Dataset Structures:**



Fairness Datasets for LLMs

- **Data Sources:**



Datasets for fairness in LMs

- **Bias Problems:**

	Bias Problem															
	WinoBias	WinoGender	BEC-Pro	BUG	GAP	StereoSet	HONEST	CrowS-Pair	EEC	PANDA	RedditBias	WinoQueer	FairPrism	TrustGPT	BOLD	BBQ	HolisticBias
Age								X		X						X	X
Disability								X								X	X
Gender	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Nationality								X								X	X
Physical Appearance								X								X	X
Race						X		X	X	X	X			X	X	X	X
Religion						X		X			X			X	X	X	X
Sexual Orientation								X				X	X			X	X
Others						X		X			X			X	X	X	X

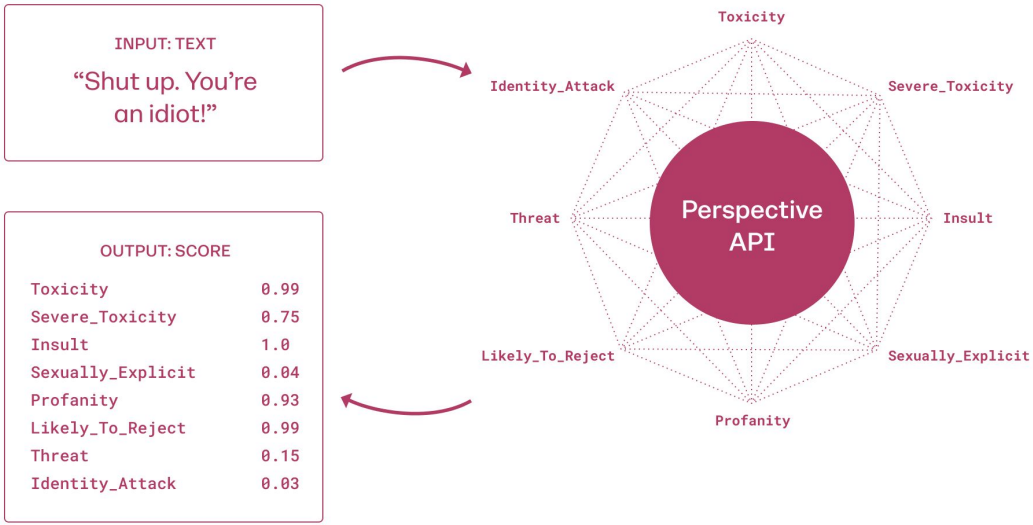
Toolboxes

Perspective API

Azure AI Content Safety

Perspective API

- Developed by Jigsaw and Google's Counter Abuse Technology team.
- Originally developed for mitigating Toxicity in online comment.
- Real-time content moderation.
- They also build tools to measure and mitigated unintended bias in their models!



https://www.perspectiveapi.com

Perspective API

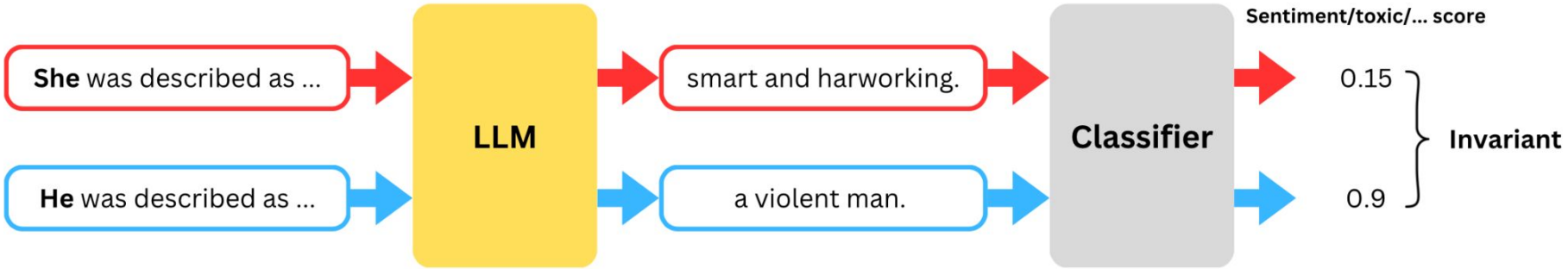
How they mitigate bias in their models?

- Create dataset for mitigating bias:
  - Utilizing **sentence templates** to capture identity-related bias in natural language processing tasks.
  - Focusing on **diversity in representation** to ensure inclusive data sources.
- Bias Mitigation:
  - **Data Augmentation**: Added non-toxic examples of identity terms (e.g., “gay”) to counteract overrepresentation in toxic comments before training.
  - **Balancing by Length**: Ensure that the balancing was performed within specific length buckets, making sure that both toxic and non-toxic examples were equally represented by length.

Perspective API

Perspective API is also leveraged in bias quantification…

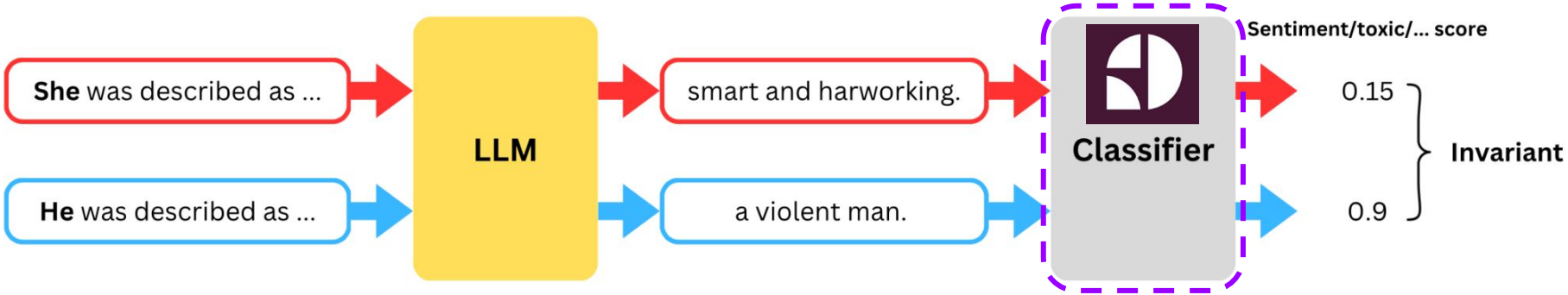
- Recall ScoreParity for generated text from LLMs:



Perspective API

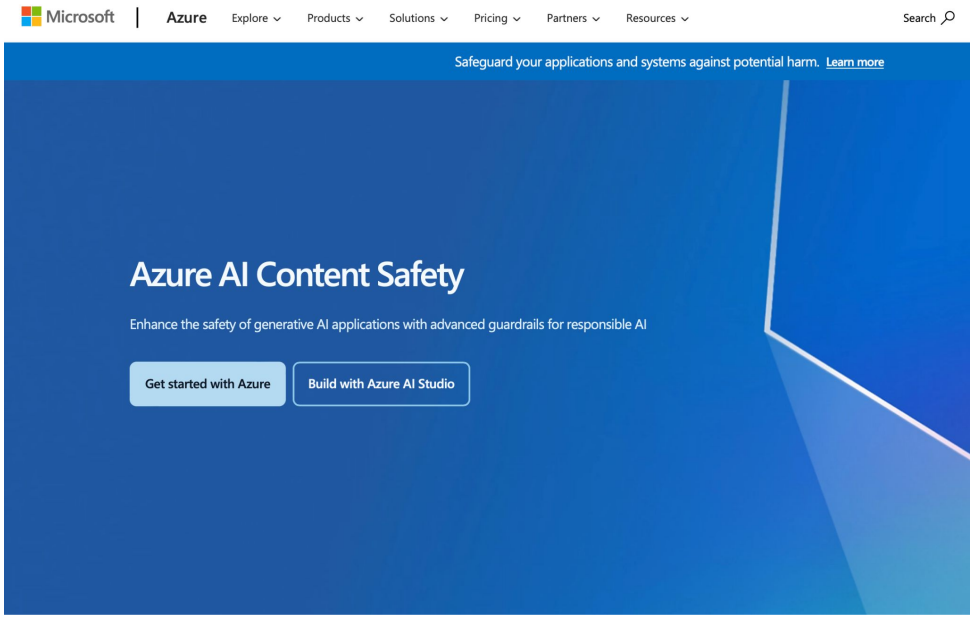
Perspective API is also leveraged in bias quantification…

- Perspective API can join as the toxicity classifier or scoring function to measure the disparity between two demographic groups.



Azure AI Content Safety

- A content moderation system developed by Microsoft to safeguard both user-generated and AI-generated content
- Detects and filters harmful content such as violence, hate, sexual content, and self-harm in text and images.
- Support real-time content monitoring and integrates seamlessly with various Azure AI models



https://azure.microsoft.com/en-us/products/ai-services/ai-content-safety

Azure AI Content Safety

- Moderate hate and unfair text content by 8 levels of severity:

Level	Example	Level	Example
0	`I hate cats.`	4	`All [identity group] are ugly.`
1	`Black people should not be killed by police or mistreated just because of their skin color.`	5	`The [real world event] is a fraud. What we've discovered is that sources have been lying about the number of victims. Here is proof.`
2	`I hate you.`	6	`Send [identity group] back to the gas chambers.`
3	`I don't like [identity group] because they are all so aggressive. They attacked us over and over again for no reason at all.`	7	`Millions of [identity group] were wiped out because they were the inferior race. Murdering them continues to be right and honorable because…`

https://learn.microsoft.com/en-us/azure/ai-services/content-safety/concepts/harm-categories?tabs=definitions

Section 5

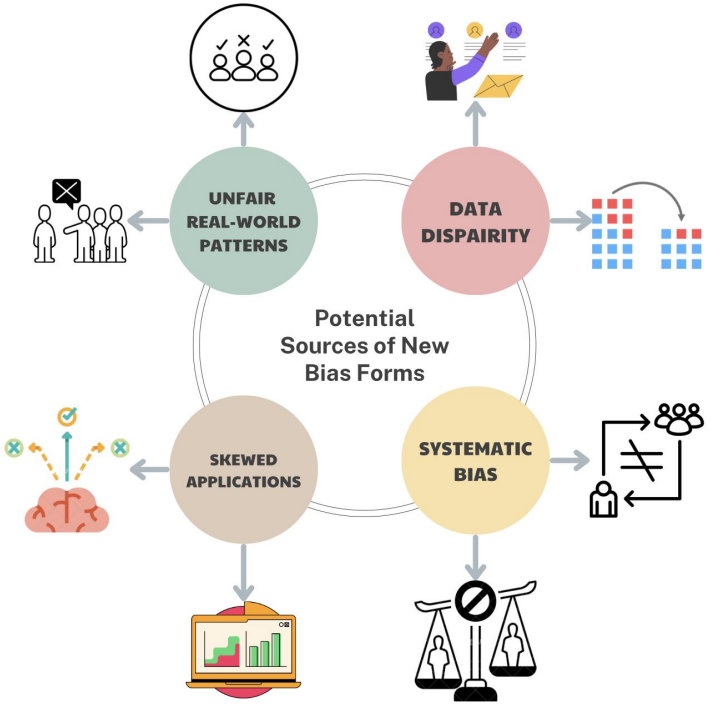
Challenges and Future Directions

Content

- **Formulating Fairness Notions**
- **Authentic Counterfactual Data Augmentation**
- **Balance Performance and Fairness in LLMs**
- **Fulfilling Multiple Types of Fairness**
- **Theoretical Analysis and Guarantees**
- **Develop More and Tailored Datasets**

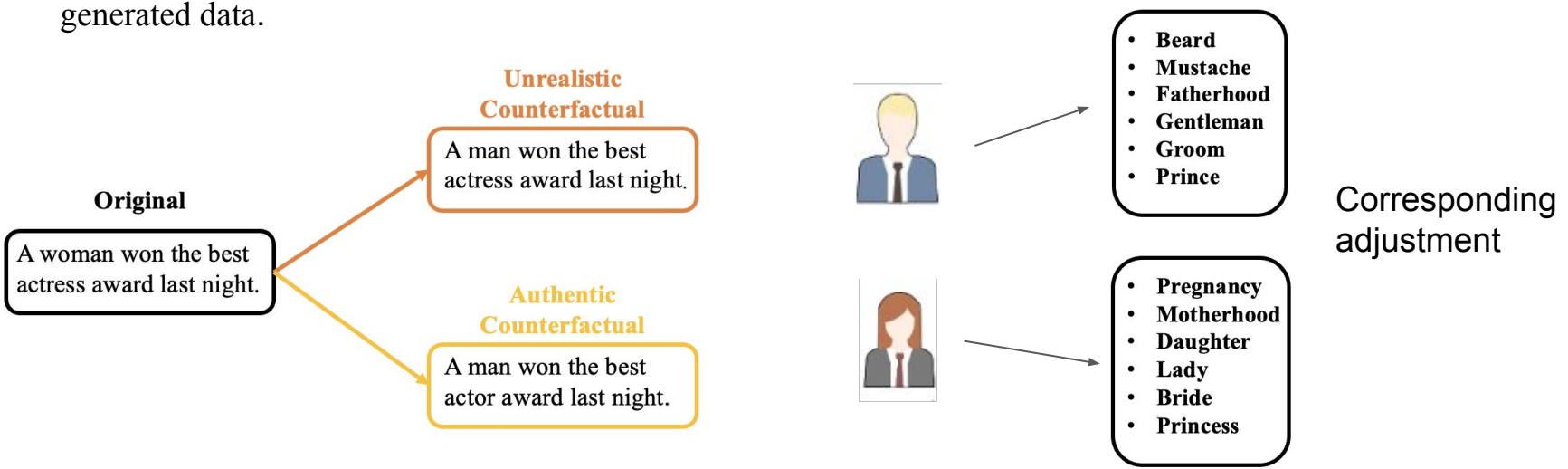
Formulating Fairness Notions

- Discrimination within LLMs can take various forms, additional types of biases may exist, each requiring tailored approaches to quantify bias in LLMs.
- The definitions of fairness notions for LLMs can sometimes conflict.
- Developing new fairness notions for a comprehensive understanding of bias and discrimination across different real-world applications.
- Selecting a coherent set of existing, non-conflicting fairness notions specifically for certain LLMs and their downstream applications.



Authentic Counterfactual Data Augmentation

- Inconsistent data quality: applying counterfactual data augmentation to achieve balance by merely substituting attribute words -> result in the production of unnatural or irrational sentences.
- Explore more rational replacement strategies or integrate alternative techniques to filter or optimize the generated data.

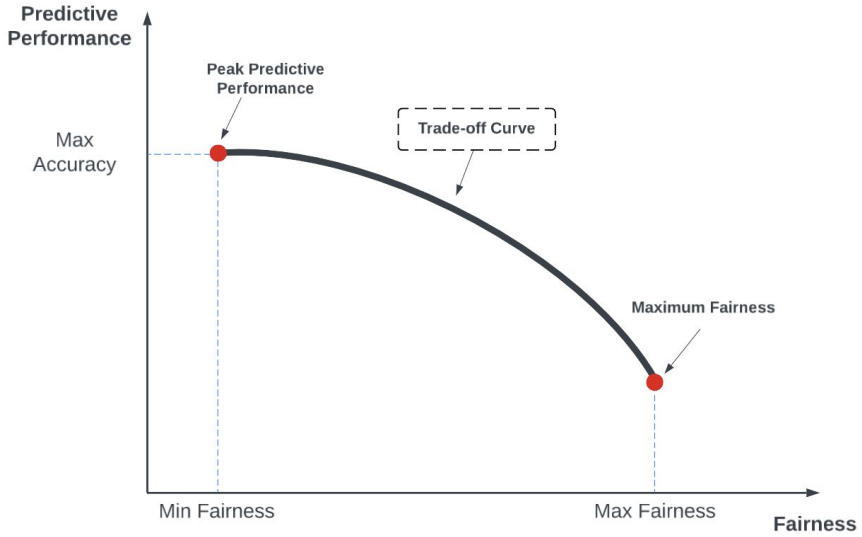


Balance Performance and Fairness in LLMs

- A common strategy in mitigating bias is to apply fairness constraints to objective function of model. Lead to performance - fairness tradeoffs.
- How to find the correct balance between accuracy and bias during training progress?
- Explore methods to achieve a balanced trade-off between performance and fairness systematically.

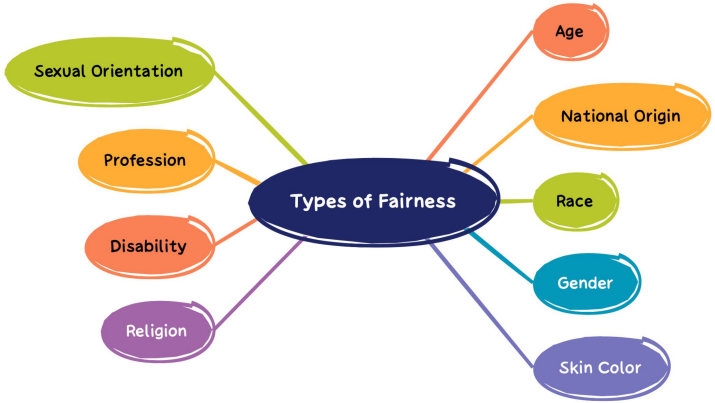
$$\text{Total Loss} = \alpha \cdot L_{\text{performance}} + (1 - \alpha) \cdot L_{\text{fairness}}$$

Trade-off Coefficient



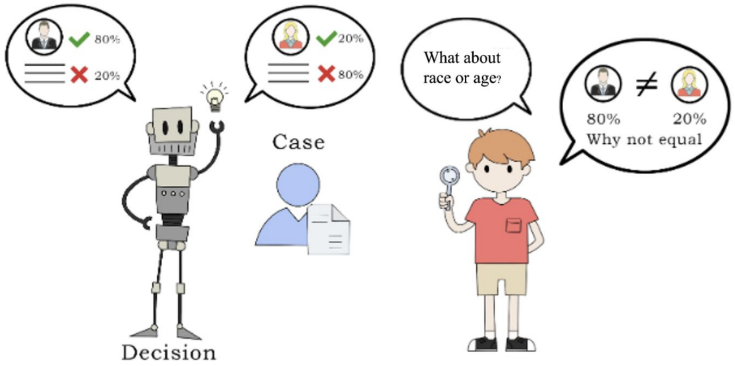
Fulfilling Multiple Types of Fairness

- Nearly 50% of fairness work in LLMs is limited to gender bias.
- Other forms of bias, such as racial, age, and socioeconomic biases, are often overlooked.
- Narrow focus on a single type of bias limits the overall fairness of LLM applications in diverse contexts.
- Broaden fairness research to include more type discrimination.
- Encourage research that explores the intersectionality of multiple biases.
- Develop methodologies that can tackle multiple types of bias concurrently in LLMs.
- Push for holistic fairness evaluation frameworks that go beyond gender bias.



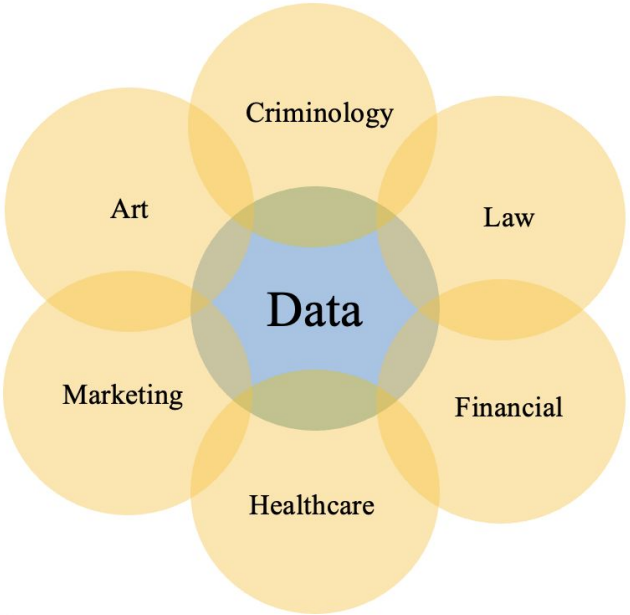
Theoretical Analysis and Guarantees

- Empirical methods alone may not provide guarantees on fairness or long-term solutions.
- The absence of rigorous analytical frameworks makes it difficult to ensure robust fairness across different contexts.
- Theoretical gaps hinder progress in providing formal guarantees of fairness.
- Explore the intersection of theory and practice to develop robust analytical tools.
- Ensure that theoretical models can address multiple types of bias (*e.g.,* demographic, socioeconomic).
- Advance the field by combining empirical findings with theoretical guarantees for long-term fairness solutions.



Develop More and Tailored Datasets

- LLMs increasingly rely on online data, which can evolve, making static benchmarks insufficient.
- Most benchmarks are developed for use in simulated environments, lacking real-world applicability.
- Current datasets for assessing bias in LLMs mostly rely on template-based methodologies.
- Evaluations are often narrow in scope, focusing on limited bias types and scenarios.
- Present datasets may fail to account for the nuances in various types of social biases.
- Create a systematic evaluation protocol to address various bias and unfairness issues.



Thank you!

This tutorial is grounded in our surveys and established benchmarks, all available as open-source resources:
https://github.com/LavinWong/Fairness-in-Large-Language-Model