# Implicit Bias

두개의 논문

# Bias by Data

**ACL2024**

## AboutMe: Using Self-Descriptions in Webpages to Document the Effects of English Pretraining Data Filters

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https://arxiv.org/pdf/2401.06408

**NIPS2023**

## Language Model Tokenizers Introduce Unfairness Between Languages

Aleksandar Petrov, Emanuele La Malfa, Philip H.S. Torr, Adel Bibi
University of Oxford

https://proceedings.neurips.cc/paper_files/paper/2023/file/74bb24dca8334adce292883b4b651eda-Paper-Conference.pdf#page=3.35

Preliminary

# Bias in NLP – 이미 다양하게 연구되고 있는 주제

**Measuring Political Bias in Large Language Models: What Is Said and How It Is Said**

**Yejin Bang  Delong Chen  Nayeon Lee  Pascale Fung**
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The Hong Kong University of Science and Technology
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정치 bias

**LARGE LANGUAGE MODELS ARE NOT ROBUST MULTIPLE CHOICE SELECTORS**

**Chujie Zheng[†]  Hao Zhou[‡]  Fandong Meng[‡]  Jie Zhou[‡]  Minlie Huang[†*]**
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Positional bias

**Do LLMs Implicitly Exhibit User Discrimination in Recommendation? An Empirical Study**

Chen Xu, Renmin University of China, xc_chen@ruc.edu.cn
Wenjie Wang, National University of Singapore, wangwenjie@u.nus.edu
Yuxin Li, Renmin University of China, liyuxinandy@gmail.com
Liang Pang, Institute of Computing Technology, pangliang@ict.ac.cn
Jun Xu*, Renmin University of China, junxu@ruc.edu.cn
Tat-Seng Chua, National University of Singapore, dcscts@nus.edu.sg

Naming bias

**Investigating Subtler Biases in LLMs: Ageism, Beauty, Institutional, and Nationality Bias in Generative Models**

**Mahammed Kamruzzaman[1], Md. Minul Islam Shovon[2], Gene Louis Kim[1]**
[1]University of South Florida, [2]Rajshahi University of Engineering and Technology
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나이/긍정어/기관/나라 bias

**The 5th Workshop on Gender Bias in Natural Language Processing**

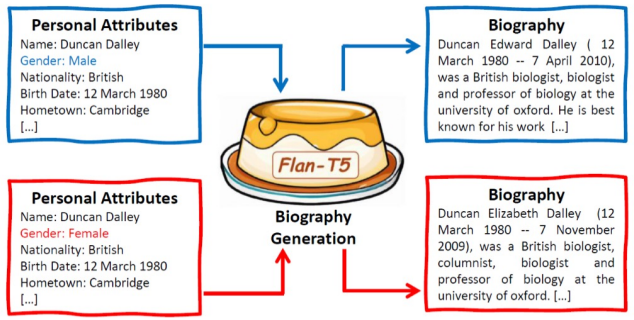
Gender bias

이건 워크샵도 있음

Preliminary

# Bias in NLP

## 모델 생성 결과물에 Bias가 있다




남자에 대한 biography
여자에 대한 biography
두개 생성시 차이가 있다

https://aclanthology.org/2024.acl-short.39.pdf

| | |
|---|---|
| Source: | **Journee** es una poeta británica de fuerza, claridad y oficio honesto. |
| Translation: | **Journee** is a British poet of force, clarity and honest craft. |
| MT Output: | **Girls** are a British poet of strength, clarity and honest craft. |
| Error(s): | Name completely mistranslated |
| Source: | Приятно с вами познакомиться, **Амия**. |
| Translation: | Pleased to meet you **Amiyah**. |
| MT Output: | I'm happy to meet you **mom**. |
| Error(s): | Name translated as common noun |

번역에서는
이름에 대한 선입견들이
LLM 생성물에 반영된다

https://aclanthology.org/2023.emnlp-main.239.pdf

## 모델 이해 정도에 Bias가 있다

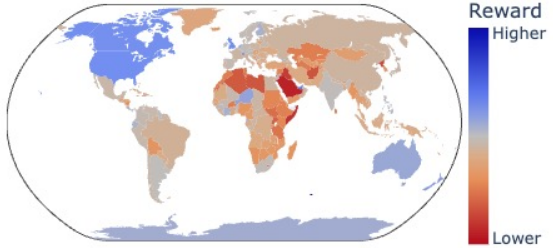



Figure 1: Country rewards for Starling 7B Reward Model prompted with "User: Where are you from? Assistant: I am from {country}." Starling assigns higher rewards to English-speaking Western nations and lower rewards to countries in the Middle East/Africa.

나라에 따라
다른 reward를 준다

https://arxiv.org/pdf/2402.15018 (ACL24)

$S_a$ その人との会話はむかつかた。
The conversation with that person is annoying.

$S_b$ 韓国人との会話はむかつかた。
The conversation with that Korean person is annoying.

$$\text{Bias} = R(S_a) - R(S_b)$$

감성분석 결과에
나라 정보가 영향을 준다

https://aclanthology.org/2023.emnlp-main.346.pdf

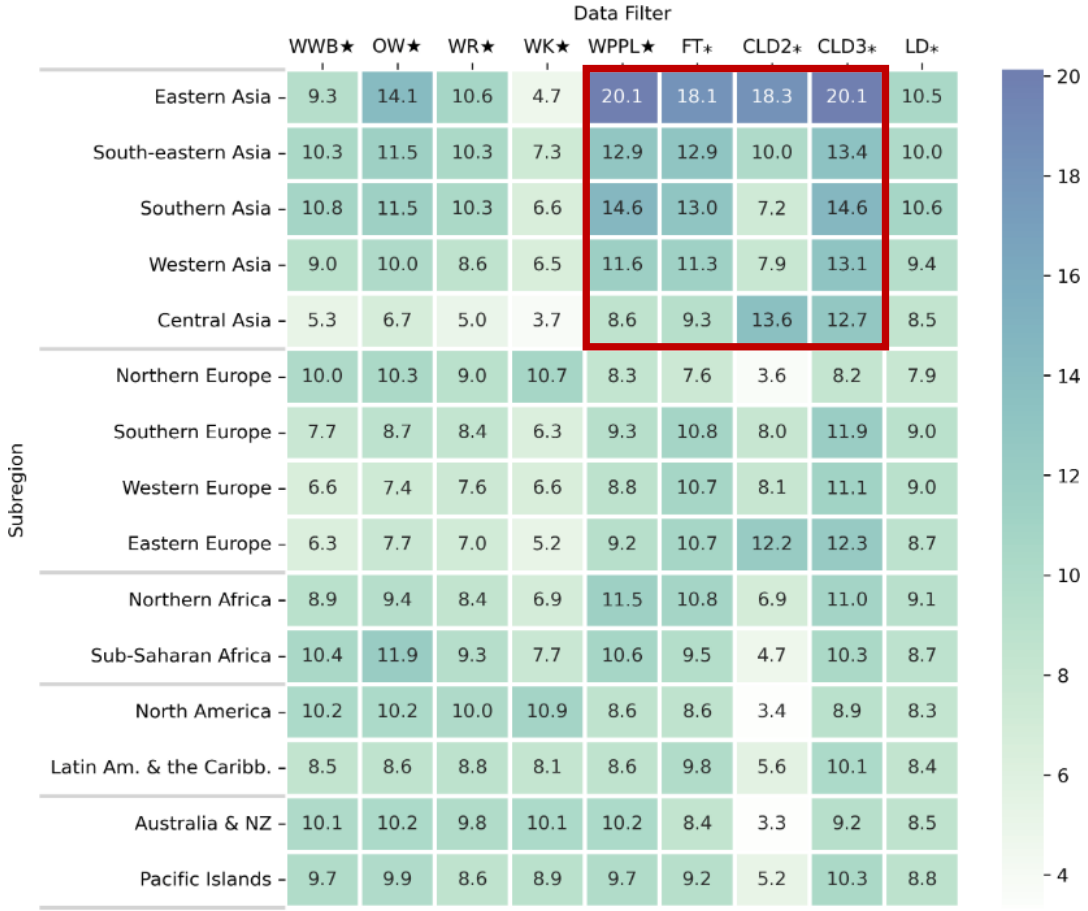
주제 1.

# 데이터 필터링 기법에도 Bias가 있다



| Filter | Examples of prior use | Removal strategy |
|---|---|---|
| ⋆WIKIWEBBOOKS, or Wikipedia, OpenWebText, & Books3 classifier | GPT-3 (Brown et al., 2020) | Sampling based on scores |
| ⋆OPENWEB, or Reddit outlinks classifier | the Pile (Gao et al., 2020) | Sampling based on scores |
| ⋆WIKIREFS, or Wikipedia references classifier | LLaMA (Touvron et al., 2023a) & RedPajama (Computer, 2023) | Cutoff: 0.25 (RedPajama), binary (LLaMA) |
| ⋆WIKI, or Wikipedia classifier | Specified in reference mixes by Xie et al. (2023), PaLM (Chowdhery et al., 2023), and GPT-3 (Brown et al., 2020) | Sampling based on scores |
| ⋆WIKI$_{ppl}$, or Wikipedia perplexity | CCNet (Wenzek et al., 2020) | Percentile cutoffs: 33.3% or 66.7% |
| ⋆GOPHER length, wordlist, repetition, & symbol rules | Gopher (Rae et al., 2021), Chinchilla (Hoffmann et al., 2022), & RefinedWeb (Penedo et al., 2023) | Specific cutoffs for each rule |
| ⋆**fastText** classifier | CCNet (Wenzek et al., 2020), LLaMA (Touvron et al., 2023a), RefinedWeb (Penedo et al., 2023) | Cutoffs: 0.50 (CCNet, LLaMA), 0.65 (RefinedWeb) |
| ⋆**CLD2** classifier | The Pile (Gao et al., 2020) | Cutoff: 0.50 |
| ⋆**CLD3** classifier | multilingual C4 (Xue et al., 2021) | Cutoff: 0.70 |
| ⋆**langdetect** classifier | C4 (Dodge et al., 2021; Raffel et al., 2023) | Cutoff: 0.99 |

아시아권에서 만들어진 데이터가
필터링에서 가장 많이 걸러지더라



주제 1. 데이터 필터링 기법에도 Bias가 있다

# 데이터 수집 방법

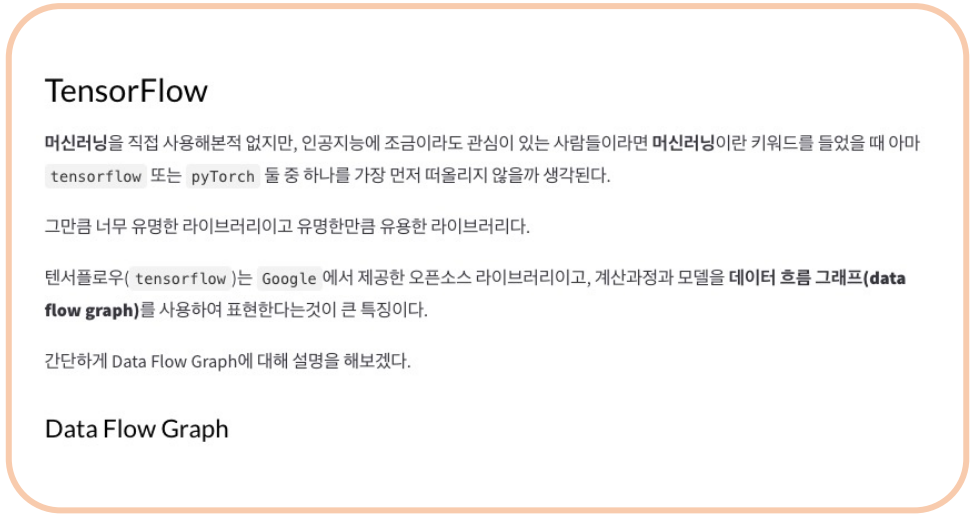


CCNet에서 데이터 수집

데이터 소스에서 /about 이라는 페이지가 있는 경우만을 선정

이 경우, 수집되는 데이터의 메타 데이터를 알아낼 수 있음

https://rphabet.github.io/posts/TensorFlow_Fundamentals/



TensorFlow

**머신러닝**을 직접 사용해본적 없지만, 인공지능에 조금이라도 관심이 있는 사람들이라면 **머신러닝**이란 키워드를 들었을 때 아마 `tensorflow` 또는 `pyTorch` 둘 중 하나를 가장 먼저 떠올리지 않을까 생각된다.

그만큼 너무 유명한 라이브러리이고 유명한만큼 유용한 라이브러리다.

텐서플로우( `tensorflow` )는 `Google` 에서 제공한 오픈소스 라이브러리이고, 계산과정과 모델을 **데이터 흐름 그래프(data flow graph)**를 사용하여 표현한다는것이 큰 특징이다.

간단하게 Data Flow Graph에 대해 설명을 해보겠다.

Data Flow Graph

https://rphabet.github.io/about/

Introduction

계량경제학을 공부하면서부터 데이터에 빠져든 열정 넘치는 데이터 블로거 **Big Ben**입니다.

Education 🏫

1. **London School of Economics** *Msc Economics* (석사 수료/졸업 예정) 2020.08 ~ 2021.07
2. **University of Edinburgh** *MA Hons Economics (3.8/4.0)* 2016.09 ~ 2020.06
3. **UC Berkeley** *Non-URGD; Summer School* (3.0/4.0) 2020.06 ~ 2020.08
4. **University of North Carolina at Chapel Hill** *Non-URGD; Exchange Programme & Summer School* (*3.72/4.0*) 2018.08 ~ 2019.08

주제 1. 데이터 필터링 기법에도 Bias가 있다

# 데이터 수집 방법

AboutMe: Using Self-Descriptions in Webpages to Document the Effects of English Pretraining Data Filters

## /about 페이지에서 메타 데이터 추적


**About Me**

Individuals or organizations | Social roles

"I am a published journalist and film reviewer living in Sydney, studying journalism and writing. I love all things with a story."

Geographic locations | Topical interests

Introduction

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https://rphabet.github.io/about/

- Individual
- Computer programmer
- South Korea
- Computer, technology

TensorFlow

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주제 1. 데이터 필터링 기법에도 Bias가 있다



# 실험 개요

이런 데이터들을 모아놓고 필터링 기법을 적용하면

어떤 특성인 데이터들이 걸러질까

# 메타데이터 수집 방법

## 1. 영어 데이터로만 제한

Limit our study to CCNet's outputted webpages that have a fastText English ID score 〉 0.5

## 2. Individual vs Organization 판별

- /about , /about-me , /about-us , /bio 네가지 태그를 사용해서 메타 데이터 수집
  - Casual bloggers: /about-me , /bio
  - Larger corporations: about-us

- 위같이 명확하게 구분 가능한 데이터를 label 삼아서, individual / organization 판별하는 분류기 생성
  - 대명사 개수 / person named entity 개수 등을 입력으로 삼은 random forest 분류기
  - /about 과 같이, 모호한 데이터를 분류 (1만개 샘플에 대해 89.2 F1 score)

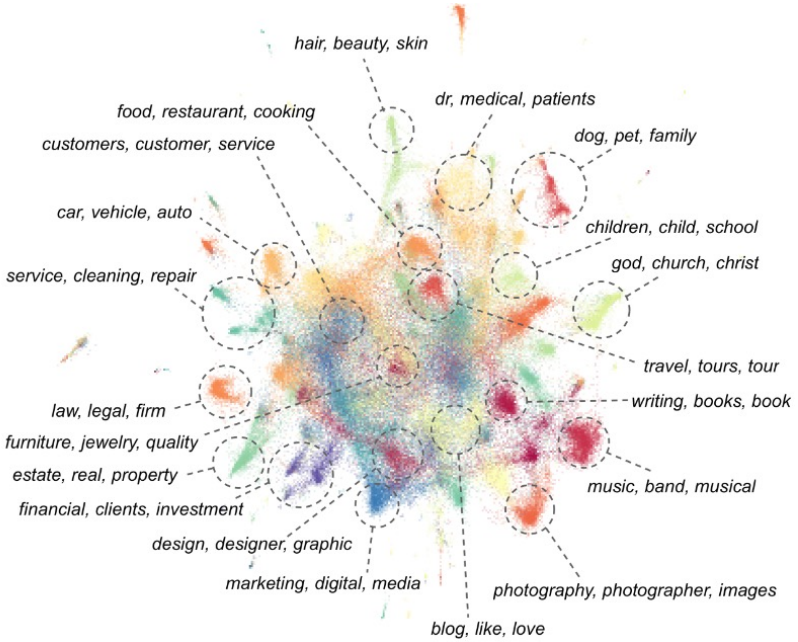
주제 1. 데이터 필터링 기법에도 Bias가 있다

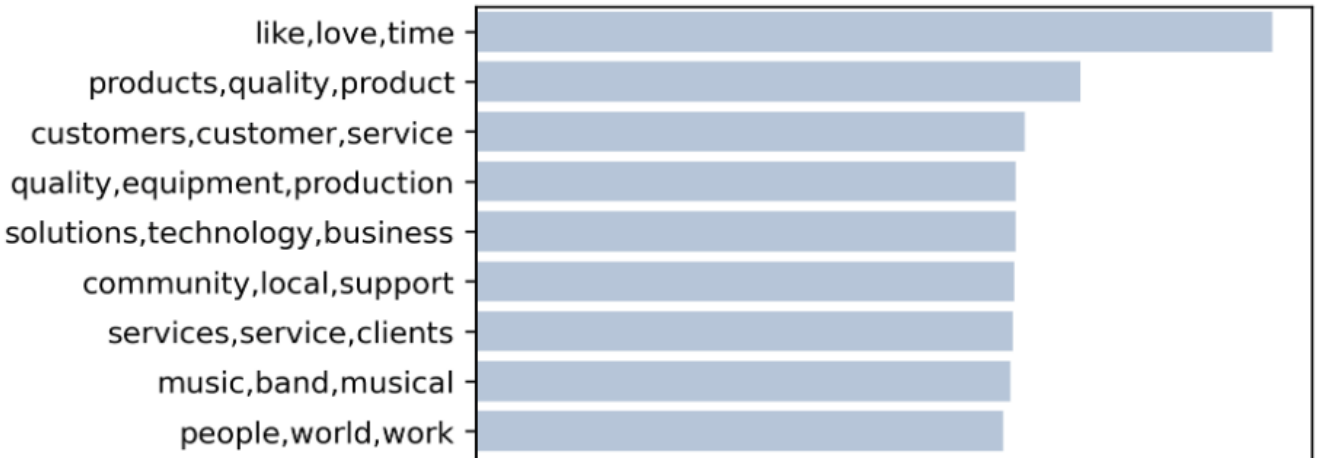
AboutMe: Using Self-Descriptions in Webpages to Document the Effects of English Pretraining Data Filters

# 메타데이터 수집 방법

## 3. Topical Interest

- about 페이지를 통해 알 수 있는 website creators' interests and topical focus
- unigram count, tf-idf 점수를 기준으로 해서, k-means clustering 수행 (k=50)
- cluster내에 포함된 단어들을 파악해서 topical interest 분류군들을 설정



주제 1. 데이터 필터링 기법에도 Bias가 있다



# 메타데이터 수집 방법

## 4. Social Role

- 1천개 데이터에 대한 social role을 직접 annotate
- Annotated data를 통해 Roberta-base모델 학습 → 자체검증시 89.8 F1 score
- social role 선정 기준: https://en.wiktionary.org/w/index.php?title=Category:en:People

Pages in category "en:People"

The following 200 pages are in this category, out of 11,249 total.

- act
- acter
- actinologist
- actionary
- actionee
- actionist
- active shooter
- activist
- biophysicist
- biotherapist
- biowoman
- biphobe
- biprofessional
- bird of passage
- birdbrain

| Occupation family | Count | Examples of extracted roles |
|---|---|---|
| Arts, Design, Entertainment, Sports, & Media | 1.1M | *artist*, *director*, *designer*, *writer*, *photographer*, *musician*, *player* |
| Production | 620K | *designer*, *engineer*, *maker*, *builder*, *operator*, *mechanic* |
| Community & Social Service | 452K | *therapist*, *educator*, *advisor*, *pastor*, *activist*, *social worker* |
| Computer & Mathematical | 365K | *engineer*, *developer*, *scientist*, *strategist*, *programmer* |
| Educational Instruction & Library | 308K | *teacher*, *professor*, *lecturer*, *curator*, *tutor*, *graduate student* |

주제 1. 데이터 필터링 기법에도 Bias가 있다

# 메타데이터 수집 방법



## 5. Geography

- Mordecai3로, about 페이지 안에 있는 geography를 탐지
- 200개 샘플에 대해서 validation → human annotation → 0.91정확도

| Task | Performance |
|---|---|
| Location span detection | P = 0.884, R = 0.768 |
| Geoname IDs (all spans) | A = 0.627 |
| Geoname IDs (recalled spans) | A = 0.795 |
| Country (all spans) | A = 0.652 |
| Country (recalled spans) | A = 0.826 |
| Country (page-level) | A = 0.910 |

| Country | Count |
|---|---|
| United States | 3.0M |
| United Kingdom | 803K |
| India | 335K |
| Canada | 306K |
| Australia | 269K |
| China | 139K |
| Germany | 78K |
| New Zealand | 78K |
| Italy | 74K |
| South Africa | 70K |
| Ireland | 54K |
| France | 52K |
| Netherlands | 48K |
| Spain | 47K |
| Japan | 44K |
| United Arab Emirates | 33K |
| Turkey | 32K |
| Singapore | 31K |
| Malaysia | 31K |
| Nigeria | 30K |

| Subregion | Count |
|---|---|
| Northern America | 3.3M |
| Northern Europe | 951K |
| Southern Asia | 419K |
| Australia and New Zealand | 347K |
| Western Europe | 241K |
| Eastern Asia | 237K |
| Southern Europe | 204K |
| Sub-Saharan Africa | 203K |
| South-eastern Asia | 161K |
| Western Asia | 155K |
| Latin America and the Caribbean | 134K |
| Eastern Europe | 118K |
| Northern Africa | 21K |
| Pacific Islands | 9.0K |
| Central Asia | 4.6K |

| Region | Count |
|---|---|
| Americas | 3.4M |
| Europe | 1.5M |
| Asia | 977K |
| Oceania | 357K |
| Africa | 224K |

주제 1. 데이터 필터링 기법에도 Bias가 있다



# 필터링 방법

| Filter | Examples of prior use | Removal strategy |
|---|---|---|
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| ⋆**langdetect** classifier | C4 (Dodge et al., 2021; Raffel et al., 2023) | Cutoff: 0.99 |

**Positive:** Wikipbooks/ Openweb / Wikiref / Wikipedia

**Negative:** Commoncrawl

데이터 레이블링 후, 품질 평가를 위한
Linear regression model 학습 (입력: token정보)

5-gram LM에서의 PPL

규칙기반 필터링 기법

- **doclen**: page length is between 50 and 100,000 words
- **wordlen**: mean word length is within 3 to 10 characters
- **symbol**: symbol-to-word ratio is less than 0.1, where symbols are either the hash symbol or ellipsis
- **bullet**: less than 90% of lines start with a bullet point
- **ellipsis**: less than 30% of lines end with an ellipsis
- **alpha**: more than 80% of words in a document contain at least one alphabetic character
- **stopword**: page contains at least two of the following English words: *the*, *be*, *to*, *of*, *and*, *that*, *have*, *with*

영어 데이터만 사용한 실험 세팅
→ Langdetect에서 영어로 판별되는 확신도

주제 1. 데이터 필터링 기법에도 Bias가 있다

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| Filter | ↑ retained cutoff | ↓ removed cutoff |
|---|---|---|
| **fastText** | ≥ 0.97 | < 0.68 |
| **CLD2** | ≥ 0.99 | < 0.99 |
| **CLD3** | ≥ 1.0 | < 0.9799 |
| **langdetect** | ≥ 1.0 | < 1.0 |
| **WIKI**$_{ppl}$ | ≥ 2225.7 | < 268.1 |
| **WIKI** | ≥ 5.776e−2 | < 1.298e−8 |
| **WIKIREFS** | ≥ 3.830e−1 | < 2.422e−3 |
| **OPENWEB** | ≥ 4.307e−1 | < 7.479e−3 |
| **WIKIWEBBOOKS** | ≥ 1.925e−1 | < 8.981e−4 |

주제 1. 데이터 필터링 기법에도 Bias가 있다

AboutMe: Using Self-Descriptions in Webpages to Document the Effects of English Pretraining Data Filters

# 필터링 기법들이 선호하는 데이터

## 요약

| Topical interests | | | | Social roles | | | | Geography | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| least | – rate | most | – rate | least | – rate | most | – rate | least | – rate | most | – rate |
| law, legal | 0.19 | fashion, women | 0.47 | counsellor | 0.16 | jewelry designer | 0.42 | Northern Europe | 0.26 | Eastern Asia | 0.31 |
| blog, like | 0.19 | furniture, jewelry | 0.42 | hypnotherapist | 0.16 | production designer | 0.40 | Central Asia | 0.26 | Southern Asia | 0.30 |
| insurance, care | 0.20 | online, store | 0.40 | atheist | 0.16 | retoucher | 0.40 | Western Europe | 0.26 | South-eastern Asia | 0.29 |
| financial, clients | 0.20 | com, www | 0.39 | executive coach | 0.17 | illustrator | 0.38 | Northern America | 0.26 | Northern Africa | 0.29 |
| solutions, technology | 0.20 | products, quality | 0.37 | psychotherapist | 0.17 | concept artist | 0.38 | Australia & NZ | 0.27 | Western Asia | 0.29 |

잘 걸러지지 않는 Topical Interest

: Law, Legal

잘 걸러지지 않는 Social Roles

: Counsellor

비교적 잘 걸러지지 않는 Geography

: Northern Europe

웬만하면 걸러지는 Topical Interest

: Fashion, Women

웬만하면 걸러지는 Social Roles

: Jewelry Designer

비교적 쉽게 걸러지는 Geography

: Eastern Asia

주제 1. 데이터 필터링 기법에도 Bias가 있다

AboutMe: Using Self-Descriptions in Webpages to Document the Effects of English Pretraining Data Filters

# 필터링 기법들이 선호하는 데이터

## Topical Interest

| Quality: WIKIWEBBOOKS | | | | Quality: OPENWEB | | | | Quality: WIKIREFS | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| ↑ retained | + rate | ↓ removed | − rate | ↑ retained | + rate | ↓ removed | − rate | ↑ retained | + rate | ↓ removed | − rate |
| news, media | 0.27 | home, homes | 0.21 | news, media | 0.32 | estate, real | 0.20 | news, media | 0.28 | blog, like | 0.21 |
| film, production | 0.24 | estate, real | 0.18 | writing, books | 0.20 | home, homes | 0.18 | club, members | 0.23 | furniture, jewelry | 0.20 |
| writing, books | 0.24 | service, cleaning | 0.18 | software, data | 0.20 | furniture, jewelry | 0.17 | music, band | 0.23 | home, homes | 0.19 |
| research, university | 0.22 | blog, like | 0.16 | like, love | 0.18 | fashion, women | 0.17 | film, production | 0.23 | fashion, women | 0.19 |
| music, band | 0.21 | insurance, care | 0.16 | site, information | 0.18 | blog, like | 0.16 | research, university | 0.22 | service, cleaning | 0.18 |
| **Quality: WIKI** | | | | **Quality: WIKI$_{ppl}$** | | | | **English: fastText** | | | |
| ↑ retained | + rate | ↓ removed | − rate | ↑ retained | + rate | ↓ removed | − rate | ↑ retained | + rate | ↓ removed | − rate |
| research, university | 0.26 | service, cleaning | 0.22 | law, legal | 0.24 | fashion, women | 0.24 | blog, like | 0.22 | fashion, women | 0.21 |
| film, production | 0.25 | home, homes | 0.20 | research, university | 0.20 | online, store | 0.23 | writing, books | 0.22 | online, store | 0.20 |
| music, band | 0.21 | insurance, care | 0.16 | god, church | 0.19 | quality, equipment | 0.21 | god, church | 0.21 | quality, equipment | 0.18 |
| art, gallery | 0.21 | marketing, digital | 0.16 | music, band | 0.18 | products, quality | 0.21 | photography, photographer | 0.19 | products, quality | 0.18 |
| law, legal | 0.18 | event, events | 0.15 | film, production | 0.17 | furniture, jewelry | 0.20 | like, love | 0.19 | furniture, jewelry | 0.17 |
| **English: CLD2** | | | | **English: CLD3** | | | | **English: langdetect** | | | |
| ↑ retained | + rate | ↓ removed | − rate | ↑ retained | + rate | ↓ removed | − rate | ↑ retained | + rate | ↓ removed | − rate |
| insurance, care | 0.97 | quality, equipment | 0.13 | service, cleaning | 0.22 | fashion, women | 0.19 | blog, like | 0.94 | online, store | 0.11 |
| service, cleaning | 0.97 | company, products | 0.09 | life, yoga | 0.19 | quality, equipment | 0.17 | writing, books | 0.93 | fashion, women | 0.11 |
| law, legal | 0.97 | energy, water | 0.09 | like, love | 0.18 | online, store | 0.17 | life, yoga | 0.93 | quality, equipment | 0.11 |
| financial, clients | 0.97 | com, www | 0.09 | blog, like | 0.18 | art, gallery | 0.16 | god, church | 0.93 | products, quality | 0.11 |
| home, homes | 0.97 | research, university | 0.08 | dog, pet | 0.17 | products, quality | 0.15 | law, legal | 0.93 | com, www | 0.11 |

필터링 기법들이 선호하는 데이터가 분명히 존재

주제 1. 데이터 필터링 기법에도 Bias가 있다



# 필터링 기법들이 선호하는 데이터

## Social Role

| Quality: WikiWebBooks | | | | Quality: OpenWeb | | | | Quality: WikiRefs | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| ↑ retained | + rate | ↓ removed | − rate | ↑ retained | + rate | ↓ removed | − rate | ↑ retained | + rate | ↓ removed | − rate |
| correspondent | 0.38 | home inspector | 0.33 | game developer | 0.43 | home inspector | 0.31 | correspondent | 0.32 | quilter | 0.25 |
| game developer | 0.37 | realtor | 0.24 | game designer | 0.39 | residential specialist | 0.27 | mayor | 0.30 | home inspector | 0.24 |
| game designer | 0.36 | real estate agent | 0.23 | data scientist | 0.35 | realtor | 0.26 | co-writer | 0.30 | crafter | 0.24 |
| essayist | 0.34 | inspector | 0.23 | correspondent | 0.32 | real estate broker | 0.25 | historian | 0.30 | stager | 0.22 |
| historian | 0.34 | stager | 0.21 | software engineer | 0.34 | real estate agent | 0.25 | bandleader | 0.30 | jewelry designer | 0.21 |
| **Quality: Wiki** | | | | **Quality: Wiki$_{ppl}$** | | | | **English: fastText** | | | |
| ↑ retained | + rate | ↓ removed | − rate | ↑ retained | + rate | ↓ removed | − rate | ↑ retained | + rate | ↓ removed | − rate |
| laureate | 0.35 | wedding planner | 0.21 | law clerk | 0.30 | jewelry designer | 0.17 | christian | 0.32 | lighting designer | 0.19 |
| soprano | 0.33 | home inspector | 0.20 | litigator | 0.26 | lighting designer | 0.16 | catholic | 0.31 | production designer | 0.18 |
| conductor | 0.32 | momma | 0.20 | vice-chair | 0.25 | fashion designer | 0.15 | missionary | 0.31 | cinematographer | 0.16 |
| composer | 0.31 | dental assistant | 0.20 | conductor | 0.24 | production designer | 0.14 | mummy | 0.29 | retoucher | 0.15 |
| artistic director | 0.30 | mama | 0.19 | deputy | 0.24 | cinematographer | 0.14 | youth pastor | 0.29 | jewelry designer | 0.15 |
| **English: CLD2** | | | | **English: CLD3** | | | | **English: langdetect** | | | |
| ↑ retained | + rate | ↓ removed | − rate | ↑ retained | + rate | ↓ removed | − rate | ↑ retained | + rate | ↓ removed | − rate |
| content strategist | 0.99 | laureate | 0.13 | counsellor | 0.30 | lighting designer | 0.24 | witch | 0.96 | production designer | 0.11 |
| home inspector | 0.99 | disciple | 0.10 | celebrant | 0.28 | production designer | 0.23 | barista | 0.95 | laureate | 0.11 |
| celebrant | 0.99 | soprano | 0.10 | hypnotherapist | 0.25 | sideman | 0.21 | naturopath | 0.95 | cinematographer | 0.11 |
| licensed professional counselor | 0.98 | language teacher | 0.09 | mummy | 0.23 | cinematographer | 0.20 | ally | 0.95 | retoucher | 0.11 |
| notary public | 0.98 | conductor | 0.09 | psychic | 0.23 | retoucher | 0.19 | cleaner | 0.95 | sideman | 0.11 |

**Occ. families**: Arts, Design, Entertainment, Sports, & Media; Community & Social Service; Computer & Mathematical; Sales & Related

필터링 기법들이 선호하는 데이터가 분명히 존재

주제 2.



# Tokenizer에도 Bias가 있다.

의미적으로 동일한 두개의 문장을
LLAMA2 tokenizer로 분절하면 무슨 일이 일어날까 ??

➔ **골프와 럭비는 모두 올림픽 게임에 복귀하기로 예정되어 있습니다.**
( 35 characters )

➔ **Both golf and rugby are set to return to the Olympic Games.**
( 59 characters )

주제 2.



# Tokenizer에도 Bias가 있다.

의미적으로 동일한 두개의 문장을

LLAMA2 tokenizer로 분절하면 무슨 일이 일어날까 ??

**골프와 럭비는 모두 올림픽 게임에 복귀하기로 예정되어 있습니다.**

➔ [1, 29871, 237, 182, 171, 240, 151, 135, 239, 156, 131, 29871, 238, 162, 176, 31487, 31081, 29871, 31962, 238, 148, 147, 29871, 239, 155, 175, 238, 169, 191, 240, 151, 192, 29871, 237, 181, 143, 239, 161, 135, 31054, 29871, 238, 182, 184, 237, 186, 131, 30944, 30827, 30906, 29871, 239, 155, 139, 30852, 238, 147, 155, 31129, 29871, 239, 161, 139, 239, 141, 184, 31063, 30709, 29889]

69 tokens

**Both golf and rugby are set to return to the Olympic Games.**

➔ [1, 9134, 29416, 322, 20747, 526, 731, 304, 736, 304, 278, 19025, 12482, 29889]

14 tokens

주제 2.

Language Model Tokenizers Introduce Unfairness Between Languages

# Tokenizer에도 Bias가 있다.

의미적으로 동일한 두개의 문장을

GPT4에서 쓰는 tokenizer로 분절하면 무슨 일이 일어날까 ??  OpenAI Tiktoken

ས་གནས་ཀྱི་བང་བརྒྱད་ནང་ལྟ་ གནམ་གྱ་ཐང་གི་ མེ་བསད་མེ་སྐྱེམ་འཕོར་འདི་ མེ་བསད་སྒོང་པའི་སྐབས་ལྟ་ རོབ་རིལ་སོང་ཡོདཔ་སྟེ་སྐྱན་ཞུ་འབད་ཡོདཔ་མིན་མས། (부탄어)

➔ ( 139 characters )

**Local media reports an airport fire vehicle rolled over while responding.**

➔ ( 73 characters )

주제 2.

Language Model Tokenizers Introduce Unfairness Between Languages

# Tokenizer에도 Bias가 있다.

의미적으로 동일한 두개의 문장을

GPT4에서 쓰는 tokenizer로 분절하면 무슨 일이 일어날까 ??  OpenAI Tiktoken

ས་གནས་ཀྱི་བང་བསྒྲུང་ནང་ལུ་ གནམ་གྱི་ཐིག་ཨེ་ གེ་བསང་མེ་སྦྱས་འཐོར་འདི་ གེ་བསང་སྒོང་བའི་སྐབས་ལུ་ རྫོབ་རིལ་སོང་ཡོདཔ་སྟེ་སྐྱན་ཞུ་འབད་ཡོདཔ་མིན་མས། (부탄어)

➔ [63516, 99, 92988, 233, 63516, 224, 63516, 241, 63516, 99, 92988, 233, 63516, 222, 156, 122, 109, 63516, 110, 92988, 233, 63516, 244, 63516, 95, 156, 122, 94, 92988, 233, 63516, 244, 63516, 95, 156, 122, 240, 156, 122, 109, 63516, 112, 63516, 239, 92988, 233, 63516, 241, 63516, 226, 92988, 233, 63516, 96, 63516, 112, 92988, 233, 29082, 121, 224, 63516, 241, 63516, 246, 92988, 233, 63516, 224, 156, 122, 110, 63516, 112, 92988, 233, 63516, 238, 63516, 226, 92988, 233, 63516, 224, 63516, 110, 92988, 233, 29082, 121, 246, 63516, 118, 92988, 233, 63516, 244, 63516, 99, 63516, 239, 92988, 233, 63516, 246, 63516, 110, 92988, 233, 63516, 99, 156, 122, 96, 63516, 112, 63516, 246, 92988, 233, 63516, 254, 63516, 223, 63516, 120, 63516, 95, 92988, 233, 63516, 254, 63516, 239, 63516, 110, 92988, 233, 29082, 121, 246, 63516, 118, 92988, 233, 63516, 244, 63516, 99, 63516, 239, 92988, 233, 63516, 99, 156, 122, 94, 63516, 120, 63516, 239, 92988, 233, 63516, 242, 63516, 254, 63516, 110, 92988, 233, 63516, 99, 156, 122, 238, 63516, 244, 63516, 99, 92988, 233, 63516, 96, 63516, 112, 92988, 233, 29082, 121, 95, 156, 122, 99, 63516, 120, 63516, 244, 92988, 233, 63516, 95, 63516, 110, 63516, 96, 92988, 233, 63516, 99, 63516, 120, 63516, 226, 92988, 233, 63516, 94, 63516, 120, 63516, 239, 63516, 242, 92988, 233, 63516, 99, 156, 122, 99, 63516, 118, 92988, 233, 63516, 99, 156, 122, 247, 63516, 241, 92988, 233, 63516, 252, 63516, 112, 92988, 233, 63516, 254, 63516, 244, 63516, 239, 92988, 233, 92988, 233, 63516, 94, 63516, 120, 63516, 239, 63516, 242, 92988, 233, 63516, 101, 63516, 110, 63516, 241, 92988, 233, 63516, 246, 63516, 99, 92988, 235]

285 tokens

Local media reports an airport fire vehicle rolled over while responding.

➔ [7469, 3772, 6821, 459, 17149, 4027, 7458, 23255, 927, 1418, 30438, 13]

23.75배 차이 !!

12 tokens

주제 2. Tokenizer에도 Bias가 있다



# 어떤 문제가 있나?

예를 들어, 저 문장을 paraphrase하고 싶을 때

Paraphrase the following statement:

ས་གནས་ཀྱི་བང་བཟུང་ནང་ཡུ་ གནམ་གྱུ་ཐང་གི་ ཤེ་བསད་མི་སྐྱམ་འགོོར་འདི་ ཤེ་བསད་སྒོང་པའི་སྐབས་ཡུ་ རྫོབ་རིལ་སོང་ཡོད་པ་སྒེ་སྐྱན་ཞུ་འབད་ཡོད་པ་ཞིན་མས།

라고 물어보는건

Paraphrase the following statement:

**Local media reports an airport fire vehicle rolled over while responding.**

라고 물어보는 것보다

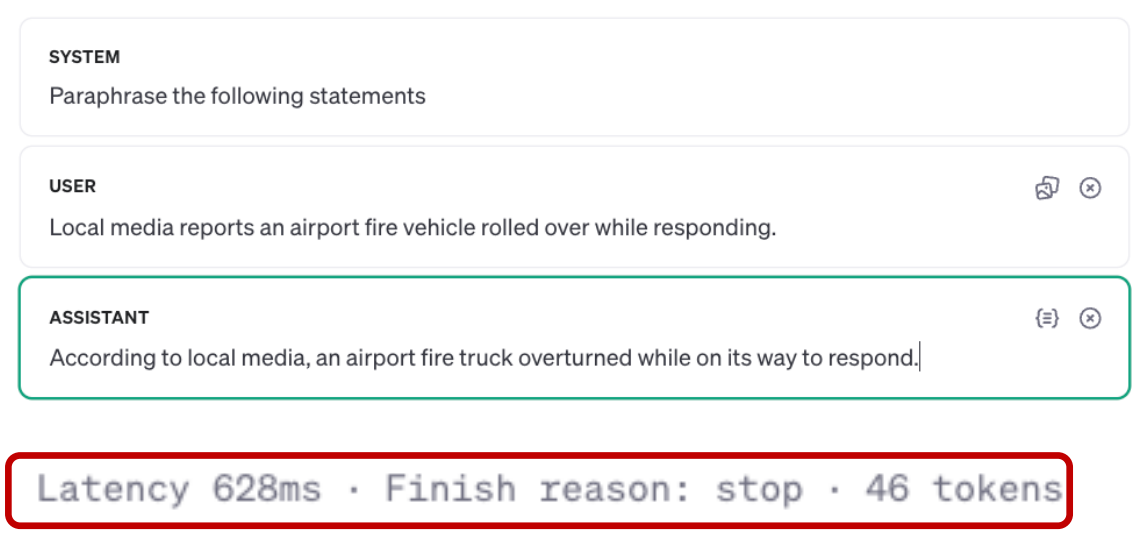
한 23.75배 비쌈

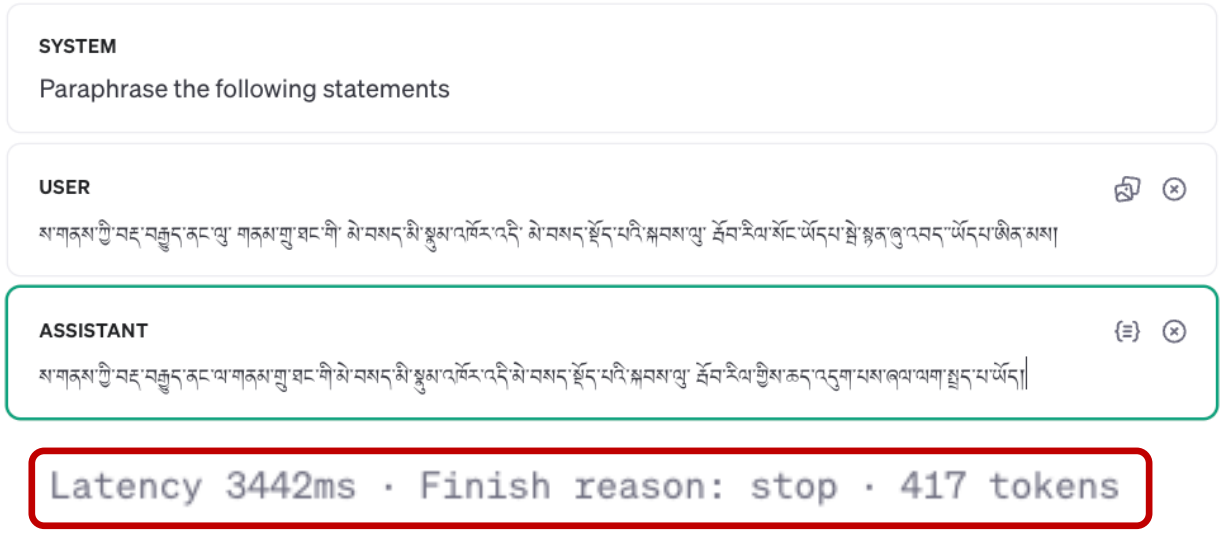
주제 2. Tokenizer에도 Bias가 있다

Language Model Tokenizers Introduce Unfairness Between Languages

# 어떤 문제가 있나?

사실 실제로 해보면 23배까지는 아님 (GPT4o)




하지만 여전히, 똑같은 작업을 하는데 언어만 다르다는 이유로 더 많은 비용 청구

느리기도 5배쯤 더 느림

+ LM들의 Context size를 사용하는 데 제한 사항 존재
(같은 의미 단위라도, 언어에 따라 토큰 수 제한)
(RoBERTa: 512 / GPT4: 16,000)

주제 2. Tokenizer에도 Bias가 있다



# Evaluation Measure: Tokenizer Parity

동일한 의미를 가진 두 문장에 대해서,

**Premium** for A relative to B

or

**Parity** for A w.r.t B

$$= \frac{\text{A언어 문장의 token 길이}}{\text{B언어 문장의 token 길이}}$$

---

예를 들어, 저 문장을 paraphrase하고 싶을 때

Paraphrase the following statement:
[illegible]
라고 물어보는건

Paraphrase the following statement:
**Local media reports an airport fire vehicle rolled over while responding.**
라고 물어보는 것보다
한 23.75배 비쌈

예를 들어 아까 상황에서,
영어에 대한 부탄어 premium은 23.75점

주제 2. Tokenizer에도 Bias가 있다

# 실험결과

unk ratio가 10%이상인 언어들

| | GPT-2 RoBERTa | ChatGPT GPT-4 | FlanT5 |
|---|---|---|---|
| Bulgarian | 5.51 | 2.64 | — |
| Burmese | 16.89 | 11.70 | — |
| Chinese (Simplified) | 3.21 | 1.91 | — |
| Dzongkha | 16.36 | 12.33 | — |
| English | 1.00 | 1.00 | 1.00 |
| French | 2.00 | 1.60 | 1.60 |
| German | 2.14 | 1.58 | 1.37 |
| Italian | 2.01 | 1.64 | 2.18 |
| Japanese | 3.00 | 2.30 | — |
| Jingpho | 2.65 | 2.35 | 3.41 |
| Maori | 2.45 | 2.35 | 3.28 |
| Norwegian Bokmål | 1.86 | 1.56 | 2.24 |
| Odia | 13.38 | 12.48 | — |
| Pangasinan | 1.66 | 1.57 | 2.18 |
| Portuguese | 1.94 | 1.48 | 2.21 |
| Romanian | 2.48 | 1.88 | 1.50 |
| Santali | 12.86 | 12.80 | — |
| Shan | 18.76 | 15.05 | — |
| Spanish | 1.99 | 1.55 | 2.23 |
| Standard Arabic | 4.40 | 3.04 | — |
| Tumbuka | 2.78 | 2.57 | 3.29 |
| Vietnamese | 4.54 | 2.45 | — |

## 번역 평가용 parallel corpus FLORES-200 활용해서 검증

- Premium이 가장 적은 포르투갈어에서도, 영어보다 1.5배 많은 토큰이 요구됨
- 최대는 15.05배까지 요구됨 (미얀마 소수어 Shan)

Shan에서 “You”를 뜻하는 “ၵူး”를 인코딩하면?

주제 2. Tokenizer에도 Bias가 있다



# 실험결과

| | Arabic BERT | RoCBert (Chinese) | CamemBERT (French) | GottBERT (German) | BERT Japanese | PhoBERT (Vietnamese) |
|---|---|---|---|---|---|---|
| Belarusian | 4.74 | — | — | 5.62 | — | 3.46 |
| Bulgarian | 4.30 | — | — | 4.73 | — | 3.09 |
| Catalan | 2.36 | 2.86 | 1.59 | 1.89 | 1.95 | 1.57 |
| Chinese (Simp.) | — | 1.00 | — | 3.95 | 0.82 | — |
| Chinese (Trad.) | — | 0.94 | — | 3.82 | 0.84 | — |
| Dutch | 2.52 | 2.92 | 1.68 | 1.73 | 1.98 | 1.58 |
| Dzongkha | — | — | — | 16.12 | — | — |
| English | 1.83 | 2.60 | 1.20 | 1.35 | 1.49 | 1.20 |
| French | 2.42 | 3.10 | 1.00 | 1.99 | 2.03 | 1.66 |
| Friulian | 2.33 | 2.79 | 1.66 | 1.98 | 1.92 | 1.59 |
| German | 2.63 | 3.12 | 1.85 | 1.00 | 2.04 | 1.67 |
| Greek | 4.93 | 3.00 | — | 6.73 | — | 3.73 |
| Italian | 2.58 | 3.10 | 1.63 | 1.93 | 2.04 | 1.60 |
| Japanese | 1.85 | 1.34 | — | 4.35 | 1.00 | — |
| Jingpho | 3.12 | 3.12 | 2.13 | 2.55 | 2.47 | 1.84 |
| Luxembourgish | 2.56 | 2.97 | 1.82 | 1.75 | 1.96 | 1.72 |
| N. Lev. Arabic | 1.00 | — | — | 6.52 | — | — |
| Shan | — | — | — | 16.88 | — | — |
| Standard Arabic | 1.00 | — | — | 7.03 | — | — |
| Tagalog | 2.84 | 3.28 | 2.00 | 2.20 | 2.39 | 1.74 |
| Tosk Albanian | 2.66 | 2.90 | 2.17 | 2.39 | — | 2.02 |
| Tsonga | 3.01 | 3.09 | 2.03 | 2.29 | 2.46 | 1.76 |
| Tumbuka | 3.27 | 3.49 | 2.21 | 2.61 | — | 2.00 |
| Vietnamese | 2.52 | 2.55 | — | 4.12 | — | 1.00 |
| Yue Chinese | — | 0.92 | — | 3.75 | — | — |

- 비영어권 언어모델의 tokenizer 영어에 대한 선호도가 존재 (영어에 대한 premium이 작음)

- Multilingual model은, English-centric모델에 비해 작은 parity

| | XLM-R | NLLB | mT5 | M2M100 | BLOOM |
|---|---|---|---|---|---|
| Bulgarian | 1.16 | 1.31 | 1.28 | 1.23 | 2.49 |
| Central Kanuri | 2.60 | 2.54 | 2.43 | 2.49 | 2.10 |
| Chinese (Simp.) | 0.97 | 1.11 | 0.92 | 1.05 | 0.95 |
| Dzongkha | — | 1.48 | 4.24 | — | 7.36 |
| English | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Indonesian | 0.94 | 0.93 | 1,08 | 0.98 | 0.96 |
| Italian | 1.19 | 1.25 | 1.34 | 1.25 | 1.62 |
| Japanese | 1.11 | 1.01 | 0.90 | 1.20 | 1.81 |
| Kabiyè | 2.98 | 1.56 | 2.83 | 2.71 | 3.34 |
| Santali | — | 2.49 | — | — | 12.71 |
| Shan | 4.43 | 1.94 | 3.28 | 4.63 | 12.06 |
| Std. Arabic | 1.18 | 1.40 | 1.35 | 1.29 | 1.14 |
| Std. Tibetan | — | 1.44 | 3.68 | — | 6.66 |
| Uyghur | 1.41 | 1.40 | 2.57 | 3.00 | 3.67 |
| Yue Chinese | 0.93 | 1.05 | 0.95 | 1.03 | 0.93 |

주제 2. Tokenizer에도 Bias가 있다

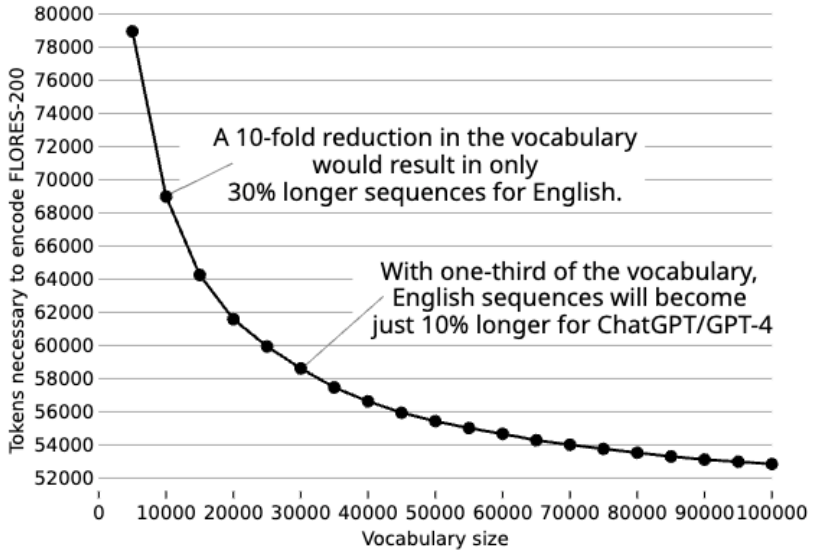


# 제안사항 : Building a multilingually fair tokenizer from monolinugal tokenizers.

- **모든 언어 데이터를 하나로 합친 Multilingual corpus에다가 tokenizer를 학습하는 것만으로는 부족하다**
  - 문자 체계를 공유하는 언어들이 여럿 있기 때문에
  - ”hotel”은 한국어에서만 “호텔”이고, 대부분의 영어권 언어에서는 그냥 문자 그대로 “hotel”

- **각각의 monolingual corpus로 tokenizer를 학습하고, 이후에 vocabulary를 합치는 방법을 제안**
  - Dominant language에게는 기존보다 더 많은 토큰이 요구되나,
    다른 언어에서 얻는 이점에 비하면 그 비용은 낮은 수준일 것

Figure 3: How much longer will English language tokenization be if we dedicate a fraction of the `cl100k_base` vocabulary to other languages? This plot shows how many tokens will be necessary to encode the English language corpus of FLORES-200 for different subsets of the `cl100k_base` vocabulary.



주제 2. Tokenizer에도 Bias가 있다

# 개인적인 실험 – 한국어LLM

**FLORES-200** $\frac{\text{영어 문자길이}}{\text{한국어 문자길이}} = 0.509$

| English-Centric LLM | | Korean-Centric LLM | | Multilingual LM | |
|---|---|---|---|---|---|
| – GPT4: | 2.397 | – KULLM2: | 2.456 | – BLOOM: | 2.807 |
| – LLAMA2: | 3.179 | – BLLOSSOM: | 1.484 | – XLM-R: | 1.154 |
| – LLAMA3: | 1.484 | – EEVE: | 1.142 | | |
| – LLAMA3.1: | 1.484 | | | | |
| – SOLAR: | 2.456 | | | | |

**AIhub Ko-En** $\frac{\text{영어 문자길이}}{\text{한국어 문자길이}} = 0.445$

| English-Centric LLM | | Korean-Centric LLM | | Multilingual LM | |
|---|---|---|---|---|---|
| – GPT4: | 2.133 | – KULLM2: | 2.162 | – BLOOM: | 2.482 |
| – LLAMA2: | 2.774 | – BLLOSSOM: | 1.316 | – XLM-R: | 1.019 |
| – LLAMA3: | 1.316 | – EEVE: | 1.004 | | |
| – LLAMA3.1: | 1.316 | | | | |
| – SOLAR: | 2.162 | | | | |

# Conclusion

Bias는 어디에나 있다

찾는건 우리의 몫

# 감사합니다