MaLLaM - Malaysia Large Language Model

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Abstract

Addressing the gap in Large Language Model pretrained from scratch with Malaysian context, We trained models with 1.1 billion, 3 billion, and 5 billion parameters on a substantial 349GB dataset, equivalent to 90 billion tokens based on our pretrained Byte Pair Encoding (BPE) tokenizer for a single epoch. MaLLaM contributes to enhanced natural language understanding and generation tasks in the Malay language.

Although trained on a smaller dataset of 90 billion tokens, our instruction-tuned MaLLaM models perform competitively. When compared to ChatGPT3.5 and Malaysian Mistral, MaLLaM's instruction-tuned models demonstrate notable proficiency, underscoring the effectiveness of our approach in capturing and understanding the nuances of the Malaysian language.

MaLLaM models mark a significant contribution to the field, providing comprehensive language representations grounded in Malaysian context. This endeavor aims to pave the way for enhanced natural language understanding and generation tasks specific to the linguistic nuances present in Malaysia. We discuss the training methodology, dataset composition, and the potential impact of MaLLaM in advancing the capabilities of large language models within the context of the Malay language.

All models released at HuggingFace Mesolitica MaLLaM Collection.

1 Introduction

The landscape of large language models (LLMs) has predominantly been shaped by models trained on English, with subsequent adaptations and fine-tunings for languages like Tamil and Malaysian. Existing models such as Tamil-LLama [1] and Malaysian-Mistral [2] have emerged as valuable assets, leveraging the foundation of English-based LLMs for further optimization in non-English languages. However, despite their commendable contributions, these models still carry traces of English nuances, presenting a unique challenge in achieving a fully language-specific representation.

This introduction underscores the significance of mitigating residual English influences in language models tailored for specific linguistic contexts. While the adaptation of English-based LLMs has facilitated advancements in various languages, it falls short of capturing the intricacies and nuances unique to languages like Tamil and Malaysian. To address this gap, we embark on a novel approach by pre-training a large language model entirely from scratch, with a specific focus on the Malaysian language. This deliberate endeavor aims to establish a model that is inherently attuned to the linguistic subtleties and idiosyncrasies of Malaysian, overcoming the limitations posed by models with English-centric origins.

The presence of such inherent English biases becomes particularly pertinent when envisioning the creation of a dedicated large language model for Malaysian linguistic contexts. The prevailing influence of English-centric sources, prevalent in public English news and articles, poses a potential challenge to the development of a truly indigenous language model. The need for a linguistic model devoid of these biases

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is underscored by the desire to accurately capture the unique nuances and intricacies of the Malaysian language.

In light of these considerations, our initiative introduces MaLLaM, a large language model specifically pre-trained from scratch using a robust dataset equivalent to 90 billion tokens sourced from Malaysian contexts. The distinctiveness of MaLLaM lies in its genesis, free from the shadow of English-centric biases pervasive in existing language models. By cultivating a language model that is inherently attuned to Malaysian linguistic idiosyncrasies, we aim to address the gap left by models that, despite being fine-tuned for Malaysian languages, retain traces of English nuances. MaLLaM stands as a testament to our commitment to fostering linguistic authenticity and overcoming the challenges posed by the dominance of English-centric biases in current language modeling paradigms.

- **Pre-training MaLLaM:** We utilized a powerful infrastructure consisting of 10 nodes of the Standard_ND96amsr_A100_v4 Azure instance, with each node featuring 8 A100 80 GPUs. This configuration efficiently facilitated the pre-training of language models with 1.1 billion, 3 billion, and 5 billion parameters on a substantial 349GB dataset of Malaysian texts.
- **Multi-turn Instruction-Tuned MaLLaM:** To ensure a seamless and meaningful comparison, we opted to employ the exact chat instruction dataset from Malaysian Mistral [2]. This approach enables us to replicate the same experimental setup, facilitating a direct and accurate comparison of our work with the existing model.

2 Pre-Training Data

2.1 Public Data

Malay Wikipedia, we incorporated the Malay Wikipedia dump, enriching the linguistic diversity by partially converting it into Jawi script. Utilizing the Ejawi converter, we ensured that the model is not only proficient in understanding the standard Malay script but also adept at comprehending the intricacies of Jawi.

Malay Language study articles, We enriched our dataset with content from the Malay dictionary and public articles from Dewan Bahasa Pustaka. This inclusion ensures our language model is well-versed in word meanings, usages, and various linguistic styles prevalent in Malaysian literature.

Malaysia Government public documents, We included public government documents from the official Malaysia government website and Google searches to enrich our dataset. This ensures that our language model is exposed to formal language and communication styles used in official government contexts, enhancing its ability to understand and generate text relevant to administrative, legal, and policy domains in Malaysia.

Malaysian public articles, We gathered a varied dataset by scraping articles from Malaysian sources. This process exposed our language model to different topics, writing styles, and language nuances found in Malaysian articles, contributing to a model well-versed in the Malaysian language across diverse domains.

Malaysian public social media, We gathered diverse data by scraping content from specific Facebook pages, filtering tweets based on location and keywords, and extracting information from platforms like c.cari.com.my, b.cari.com.my, carigold, lowyat, and transcripts of Malaysian YouTube videos. This approach broadens our dataset to include various language styles and colloquial expressions from online Malaysian communities.

Malaysia public journals, We added content from reputable Malaysian journals like `https://mjpharm.org`, `https://myjgeosc.com`, and `https://www.akademisains.gov.my` to our dataset. This ensures our language model is familiar with formal and technical language used in academic contexts, covering a variety of subjects.

Malaysian related public research papers, We refined our dataset by filtering CrossRef using keywords like 'malaysia,' 'malay,' and 'melayu.' This targeted approach ensures that our language model is exposed to scholarly literature closely tied to Malaysia.

Complete list of gathered data at Github Project - Prepare LLM dataset.

2.2 Coding Data

Incorporating a coding dataset is a crucial component of our diverse training data. For this purpose, we utilized the original dataset available at bigcode/the-stack-dedup. To ensure relevance and efficiency, we selectively picked specific programming languages, including Python, Julia, C, C++, HTML, CSS, JavaScript, Go, Rust, Java, SQL, Markdown, R, Dockerfile, Ruby, Typescript, and YAML. To manage the dataset size, each programming language was limited to a maximum of 10GB.

2.3 Instruction-tuned Data

To augment the comprehensiveness of our training dataset, we devised a synthetic Malay instruction dataset. This encompassed diverse linguistic aspects, including the conversion between Rumi and Jawi scripts, dependency and constituency parsing, grammatical error generation (kesalahan tatabahasa), and coding instruction datasets related to various programming paradigms. Additionally, we included instructional content relevant to educational levels such as UPSR, PT3, and SPM, providing a broad coverage of language proficiency levels. The incorporation of syntactic and semantic elements, coupled with coding instructions, contributes to a well-rounded language model capable of handling a diverse array of linguistic tasks and understanding instructions across different domains.

Complete list of Instruction-tuned Data at instruction-dataset.

3 Deduplicating and Postprocessing Data

We removed duplicate entries from our public data from 2.1 using the MinHash implementation from `https://github.com/ChenghaoMou/text-dedup`.

We configured the MinHash algorithm with the following parameters:

Parameter	Value
num_perm	256
threshold	0.95
hash_func	sha1
hash_bits	64

Complete deduplicating data implementation at here. All deduped dataset published at malaysia-ai/dedup-text-dataset.

After removing duplicates, we employed the postprocessing technique mentioned in Malaysian Mistral section 3.3 [2].

4 Pre-Training Tokenizer

To ensure an efficient and versatile tokenizer, we conducted pretraining on a BPE (Byte Pair Encoding) tokenizer using diverse datasets, including Malay Wikipedia, synthetic Jawi, public articles, translated code instructions, Google-translated Tamil and Google-translated Punjabi. The objective was to develop a tokenizer capable of handling longer subwords for languages such as Malay, Mandarin, Tamil, Jawi, English, and Arabic. The decision to use BPE was motivated by certain limitations observed in SentencePiece, where newline characters caused issues, some Tamil and Jawi characters were missing, and the processing speed for very long texts was suboptimal. By opting for BPE, we addressed these challenges, ensuring a robust and efficient tokenizer for our language model training.

The BPE tokenizer was trained on a deduplicated text dataset of 85GB, with a vocabulary size of 32,000.

The decision to train our own BPE tokenizer was driven by the goal of minimizing token sizes during both input and output. To illustrate the efficiency gained, we conducted a comparison using the Malaysian Ultrachat AstroAwani dataset. Our pre-trained BPE tokenizer achieved a notable reduction of up to 43%

in token size when compared to tokenizers employed by Llama2 and Mistral. This reduction in token size enhances the efficiency and resource optimization of our language model, offering advantages in terms of computational performance and memory usage during processing.

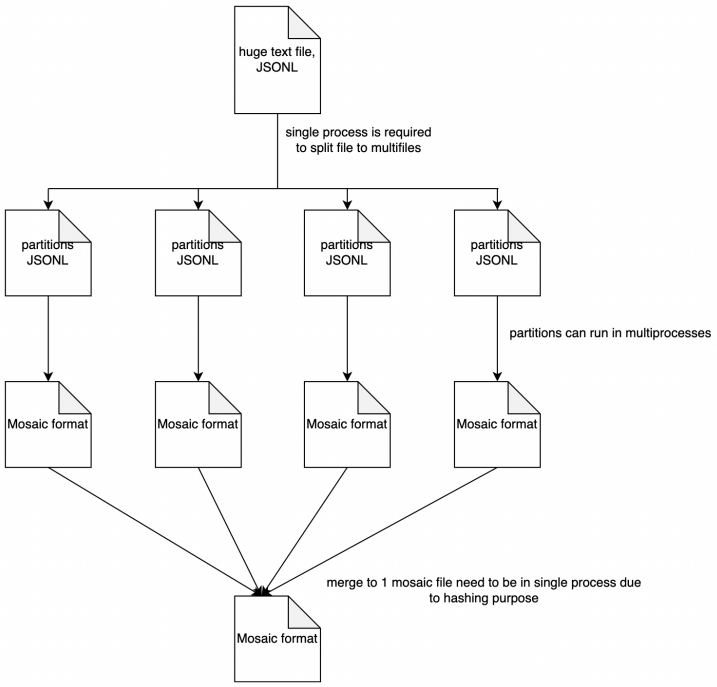
Complete pre-training tokenizer implementation at here

5 Tokenizing Data

Our dataset comprises a substantial 349GB of text in JSONL format, amounting to 90 billion tokens. The following table breaks down the distribution of token sizes within the dataset:

Distribution	Tokens (B)
deduped text Dataset	31.7
Filtered StarCoder [3]	40.98
Unfiltered MS Madlad 400 [4]	14.98
Instruction-tuned Dataset	1.58
Malaysia journals and research papers	1.14

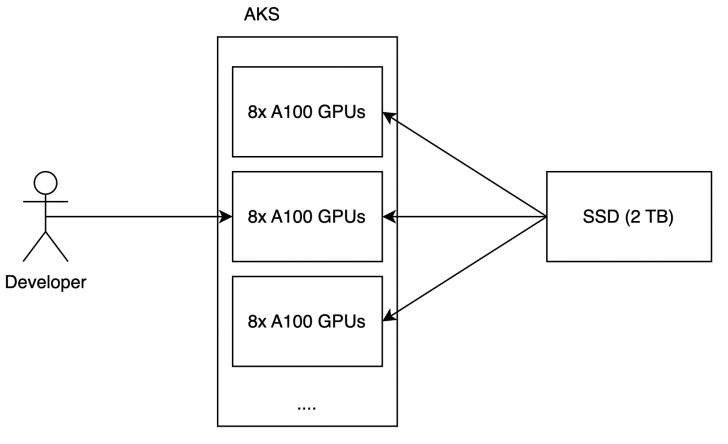
To optimize data processing efficiency, we use MosaicML Streaming library [5], by using hashing technique. Recognizing the complexity of our dataset, we implemented data distribution processing to transform it into the MosaicML streaming format,



This involves splitting the original JSONL file into smaller ones, and each of these smaller files undergoes multiprocessing for conversion into the Mosaic format. Subsequently, these smaller Mosaic files are merged into a single Mosaic file. It's worth noting that MosaicML streaming accesses one folder at a time, necessitating the consolidation of smaller files into a unified format for seamless training data access.

6 Infrastructure Setup

For infrastructure deployment and efficient node management, we opted for Azure Kubernetes Service (AKS). This choice allows us to manage nodes effortlessly through YAML configurations, ensuring a smooth and standardized deployment process. Leveraging Azure Kubernetes provides benefits such as improved internal networking and the convenience of attaching remote storage using the WriteManyAccess approach. With everything configured through YAML files, our deployment on Azure Kubernetes ensures a well-organized and easily manageable infrastructure for our language model training. Below is the figure of the infrastructure setup,



We use NFS with WriteManyAccess to centralize both the dataset and checkpoint directory. This simplifies the management of these components, making it easy to access them from multiple nodes. The use of NFS ensures efficient loading of checkpoints from various nodes.

Our approach to training involves leveraging the Ray distributed framework [6] for multi-node and multi-GPU setups. Ray provides a user-friendly setup process as only the Ray workers need to connect to the Ray master. Following this straightforward connection, developers can initiate the training session with ease by simply calling the Ray master. This simplicity in setup and execution streamlines the training process, allowing for efficient utilization of multiple nodes and GPUs to enhance the scalability and performance of our language model.

Our Ray cluster setup to efficiently manage a total of 80 A100 80GB GPUs. **Specifically, 40 GPUs are allocated for training the 5-billion-parameter model, while 20 GPUs each are dedicated to the 1.1-billion and 3-billion-parameter models**. The concurrent training of all models, each with distinct parameter sizes, is facilitated by the Ray cluster, enabling a synchronized and optimized training process.

All deployment manifests at here.

7 Pre-Training Phase

To pretrain our language model, we employ a causal language model with the objective of minimizing cross-entropy,

$$P(x_1, x_2, \ldots, x_T) = \prod_{t=1}^{T} P(x_t | x_1, x_2, \ldots, x_{t-1})$$

The training is conducted on a context length of 4096 using Mistral architecture [7], and the hyper-parameters utilized in this process are detailed below,

Hyperparameter	Value
DeepSpeed	ZeRO-3 Offload
Batch Size	24
Learning Rate	1e-4
Learning Rate scheduler	WarmupDecayLR
Warmup Steps	2000
AdamW decay rate	0.1
Precision	bfloat16

Complete pre-training 4096 context length implementation at here.

8 Pre-Training Hiccup

The occurrence detailed in the following paragraphs pertains specifically to the 5-billion-parameter model, as evidenced by the graph below,

To address a stability concern during training, we temporarily reduced the learning rate by 30% and reverted to older checkpoints. Once stability was regained, we reverted back to the initial learning rate

Additionally, we encountered GPU failures during the training process. Restarting the Nvidia plugin daemonset proved effective in resolving the issue in most instances. However, in a particular occurrence, a node restart became necessary, requiring a stop-and-start action within the Kubernetes node through the Azure console to restore normal functioning. These challenges and the corresponding mitigation strategies underscore the complexities inherent in large-scale language model training in a cloud provider.

9 Pre-Training Evaluation

We evaluated our language model using the same tatabahasa test set from Malaysian Mistral [2] and compared its performance with other existing pretrained models,

Model	Tatabahasa 0 shot	Tatabahasa 1 shot	Tatabahasa 3 shots
aisingapore/sealion3b	21.777	21.776	24.641
aisingapore/sealion7b	25.788	27.507	26.074
mesolitica/mallam-1.1B-4096	25.758	25.788	28.08
mesolitica/mallam-3B-4096	24.567	24.641	28.653
mesolitica/mallam-5B-4096	24.074	**27.794**	**28.653**

We also compared with other models and published the benchmark at mesolitica/malay-llm-leaderboard.

10 Supervised Instruction Fine-tuning Procedure

We fine-tuned 1.1 billion and 5 billions parameters models with 20480 context length using an instruction dataset from Malaysian Mistral [2], and use latest checkpoints from 7. Below are the hyperparameters we use during the fine-tuning process:

Hyperparameter	Value
DeepSpeed	ZeRO-3 Offload
Batch Size	6
Learning Rate	constant 2e-5

Complete fine-tuning 20480 context length implementation at here.

11 Result Finetuning

We obtained our results using the fine-tuned model accessible at mesolitica/mallam-1.1b-20k-instructions-v2.

11.1 Multiturn Malaysian context QA

```
User: KWSP tu apa
Assistant: KWSP ialah sebuah syarikat yang menyediakan pelbagai perkhidmatan kewangan kepada
    individu dan organisasi. Mereka menawarkan beberapa produk seperti akaun simpanan,
    pelaburan, insurans, pinjaman perumahan dan banyak lagi. Adakah terdapat sesuatu yang
    khusus yang anda ingin ketahui tentang KWSP?
User: macam mana ko tahu semua ni
Assistant: Untuk mengetahui lebih lanjut mengenai KWSP, anda boleh merujuk laman web rasmi
    mereka di www.kwsp.gov.my atau menghubungi cawangan terdekat untuk mendapatkan maklumat
    terkini. Selain itu, anda juga boleh mengikuti media sosial mereka seperti Facebook,
    Twitter dan Instagram untuk mendapatkan perkembangan terkini dalam industri ini. Jika ada
    soalan lain, jangan teragak-agak untuk bertanya!
User: tak mahu, saya nak tanya awak
Assistant: Tak perlu risau, saya sedia membantu dengan sebarang pertanyaan berkaitan KWSP.
    Apa sahaja yang anda perlukan, sila beritahu saya. Saya akan cuba menjawab sebaik mungkin.
```

11.2 Multiturn Coding QA

```
User: macam mana nak code sentiment python3
Assistant: Untuk mengkodekan sentimen dalam Python 3, anda boleh menggunakan perpustakaan
    seperti nltk atau scikit-learn. Berikut adalah contoh bagaimana untuk melakukan ini:

‘‘‘python
import nltk
from sklearn import svm
from scipy.stats import norm

# Contoh data latihan dan ujian
data = {
    'text': ['Saya suka filem itu!',
             'Filem itu sangat bagus!'],
    # tambahkan ciri lain di sini jika diperlukan
}
```

```
# Buat model SVM dengan algoritma Naive Bayes
model_svm = svm.SVC(kernel='linear') # Gantikan'svm.SVC()' dengan fungsi kernel yang sesuai

# Latih model menggunakan data latihan
model_svm.fit(data['text'])

# Ramalkan label bagi teks baru
new_text = "Ini adalah tajuk berita."
predicted_label = model_svm.predict(new_text)
print("Label ramalan:", predicted_label)
```

Dalam kod di atas, kami mengimport modul `nltk'' dari `sklearn.feature_extraction.text` untuk mendapatkan ciri-ciri teks. Kemudian, kami membuat objek `SVC` dari `sklearn.naive_bayes` untuk melatih model pengelasan binari pada set data yang diberikan. Akhirnya, kami memanggil kaedah predict pada objek `SVC` untuk meramalkan label bagi teks baru berdasarkan ciri-ciri yang telah dipelajari sebelum ini.

User: ada contoh untuk tensorflow sentiment analysis?

Assistant: Tentu saja! Berikut adalah contoh bagaimana menggunakan TensorFlow untuk melakukan analisis sentimen pada dataset MNIST:

```python
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import accuracy_score

# Baca dataset MNIST
df = pd.read_csv('mnist_data.csv') # Gantikan'mnist_data.csv' dengan nama fail CSV sebenar
X = df.iloc[:, :-1].values # Ambil lajur pertama sebagai data latihan
y = df.iloc[:, -1].values # Ambil lajur kedua sebagai data ujian

# Pra-proses data
count_vectorizer = CountVectorizer()
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Inisialisasi model vektorisasi
model = tf.keras.models.Sequential([
  CountVectorizer(), # Tambah lapisan vektor tambahan
  tf.keras.layers.Embedding(len(y_train), 100, input_length=100), # Tambah lapisan embedding tambahan
  tf.keras.layers.Bidirectional(tf.keras.layers.GRU(128, return_sequences=True)), # Tambah lapisan Bidirectional tambahan
  tf.keras.layers.Dense(10, activation="softmax") # Tambah lapisan output tambahan
])

# Kompilasi model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=[accuracy_score])

# Latih model
model.fit(X_train, y_train, epochs=50, batch_size=32)

# Nilai prestasi model
loss, accuracy = model.evaluate(X_test, y_test)
print("Akurasi:", accuracy)
```

```
Pastikan anda menggantikan 'mnist_data.csv' dengan lokasi dan nama fail CSV sebenar yang
    mengandungi dataset MNIST. Kod ini membaca dataset MNIST, memprosesnya menjadi ciri
    berangka, melatih model rangkaian saraf, dan menilai prestasinya menggunakan set
    pengesahan. Hasil penilaian kemudian dicetak. Semoga membantu!
```

Despite being trained on a relatively small coding dataset, the model has demonstrated a commendable capability to generate satisfactory results. This highlights the model's capacity to generalize and glean valuable insights even when exposed to limited coding examples. The effectiveness of the model in producing meaningful outcomes with a smaller dataset underscores its adaptability and efficiency in handling coding-related tasks.

11.3 Malay instruction

```
User: macam mana nak buat nasi ayam yg sedap
Assistant: Untuk membuat Nasi Ayam yang lazat, anda boleh mengikuti langkah-langkah berikut:

Bahan-bahan:

200g daging ayam (dipotong kecil)
1 biji bawang besar, dihiris halus
2 ulas bawang putih, dikisar
3 sudu besar rempah kari
1 cawan air rebusan ayam
Garam dan gula secukup rasa
Minyak masak untuk menumis
Daun ketumbar segar untuk hiasan
Bawang goreng untuk taburan
Sos cili atau sos tomato untuk dihidangkan bersama nasi panas
Cara penyediaan:

Panaskan minyak dalam kuali dan tumis bawang besar hingga naik bau. Masukkan bawang putih dan
    kacau sehingga wangi.
Masukkan rempah kari dan kacau rata supaya bahan menjadi pekat.
Masukkan daging ayam yang telah dipotong kecil ke dalam kuali dan biarkan ia masak selama
    beberapa minit sehingga bertukar warna.
Masukkan air rebusan ayam dan biarkan mendidih.
Selepas itu, masukkan garam dan gula secukup rasa. Kacau lagi sehingga semua bahan bercampur
    dengan baik.
Biarkan nasi sejuk sebelum dihidangkan.
Selamat mencuba!
```

12 Acknowledgement

Special thanks to Malaysia-AI volunteers especially Wan Adzhar Faiq Adzlan, Ammar Azman, M. Amzar, Muhammad Farhan and Syafie Nizam for contributing dataset to train MaLLaM.

13 Conclusion

In conclusion, our open-source language model represents a significant stride toward bridging the research gap in Malaysia. By making our model accessible to the research community, we aim to contribute to the advancement of natural language processing in the Malaysian context. The availability of this model provides researchers, developers, and practitioners with a valuable resource to explore and address linguistic challenges specific to Malaysia. We anticipate that the open-source nature of our model will

foster collaboration and inspire further innovations, ultimately promoting a richer and more nuanced understanding of the Malaysian language landscape.

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