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# Adapting Safe-for-Work Classifier for Malaysian Language Text: Enhancing Alignment in LLM-Ops Framework

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## Abstract

As large language models (LLMs) become increasingly integrated into operational workflows (LLM-Ops), there is a pressing need for effective guardrails to ensure safe and aligned interactions, including the ability to detect potentially unsafe or inappropriate content across languages. However, existing safe-for-work classifiers are primarily focused on English text. To address this gap for the Malaysian language, we present a novel safe-for-work text classifier tailored specifically for Malaysian language content. By curating and annotating a first-of-its-kind dataset of Malaysian text spanning multiple content categories, we trained a classification model capable of identifying potentially unsafe material using state-of-the-art natural language processing techniques. This work represents an important step in enabling safer interactions and content filtering to mitigate potential risks and ensure responsible deployment of LLMs. To maximize accessibility and promote further research towards enhancing alignment in LLM-Ops for the Malaysian context, the model is publicly released at [malaysia-ai/malaysian-sfw-classifier](https://malaysia-ai/malaysian-sfw-classifier).

## 1 Introduction

The AI field, especially natural language processing, has seen remarkable progress with significant breakthroughs like transformer-based architectures, multimodality integration to chatbot applications, and reinforcement learning from human feedback. This has led to the rise of open-domain dialogue systems, known as chatbots or conversational agents, which are now increasingly integrated into our daily lives.

Due to the nature of how large language models are trained, using internet data, it is prevalent that there may be harmful contents

However, as users, especially children and teenagers, engage with these chatbots, exposure to harmful and provocative text can have significant adverse effects, impacting individuals' mental well-being, relationships, and emotional state. Therefore, ensuring safe and beneficial interactions has become critically important.

The scarcity of data for identifying not safe for work content, particularly in the Malay language, hinders the advancement of undesired content filtration. In this paper, titled *Adapting Safe-for-Work Classifier for Malaysian Language Text: Enhancing Alignment in LLM-Ops Framework*, we

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address this challenge by initiating the data gathering process to create a comprehensive dataset of harmful texts. Our methodology involves mining data representative of harmful text categories. Our categorization includes the following labels: pornography, harassment, sexist, racist, religious insult, self-harm, psychiatric or mental illness, and safe for work.

We aim to create a robust classifier tailored for Malaysian language text, enhancing the alignment of our large language model operations framework with safety and ethical standards. This classifier serves as a necessary guardrail within the LLM-Ops framework, providing a cost-effective solution for ensuring safe AI. By systematically identifying and filtering out inappropriate content, this classifier will help create a safe and respectful interaction environment for users.

Furthermore, to the best of our knowledge, there is currently no existing local dataset for the Malaysian language that addresses these specific categories of harmful content. Our work thus represents a pioneering effort in developing and applying this crucial safety measure.

## 2 Taxonomy

Designing a universal taxonomy for safe for work guardrails is challenging due to the context-dependent nature of language. Below, we outline our taxonomy for safe-for-work categorization, which will guide the application of guardrails to our large language model or chatbot system. Each category is described to clarify the scope and specifics of what constitutes undesired content:

- **Pornography:** Content that includes explicit sexual descriptions, depictions of sexual acts, or nudity intended to arouse sexual interest. This category covers sexually explicit text, adult content descriptions, and any language or media that depicts sexual activity.
- **Harassment:** Content that targets individuals or groups with the intent to demean, intimidate, or threaten. This includes abusive language, threats, stalking, or any form of verbal harassment aimed at causing emotional or psychological distress.
- **Sexist:** Content that promotes discrimination or prejudice based on gender. This includes sexist remarks, derogatory comments about any gender, and language that reinforces harmful gender stereotypes or inequality.
- **Racist:** Content that discriminates or promotes hatred based on race, ethnicity, or nationality. This includes racial slurs, derogatory remarks about ethnic groups, and any language that supports racial superiority or inferiority.
- **Religious Insult:** Content that disrespects or mocks religious beliefs, practices, or figures. This includes blasphemy, offensive jokes about religions, and language intended to insult or offend individuals based on their religious affiliations.
- **Self-Harm:** Content that depicts or encourages self-injurious behavior or suicide. This includes descriptions of self-harm methods, discussions promoting suicide, and any language that glorifies or encourages self-destructive actions.
- **Psychiatric or Mental Illness:** Content that stigmatizes or discriminates against individuals with mental health conditions. This includes derogatory terms for mental health issues, insensitive jokes, signs of mental distress or illness, and any language that trivializes or mocks mental illness.
- **Violence:** Content that promotes or glorifies violence or celebrates the suffering or humiliation of others.
- **Safe for Work:** Content that is appropriate for a professional or public environment, free from explicit, offensive, or discriminatory material. This includes clean language, respectful discourse, and content that does not contain any of the above-mentioned undesired elements.

This taxonomy will help us systematically identify and filter out inappropriate content, where additional redirection can be made to ensure a safe and respectful interaction environment for users.

## 3 Data Source

The data for this study was collected from various platforms, including social media, public forums, and publicly available datasets. The majority of the data is in the Malay language and relevant

to the malay context. By utilizing these comprehensive datasets from multiple sources, we have strengthened the robustness and accuracy of our classification model, enabling it to effectively tackle the challenges of identifying self-harm and sexism in online content.

### 3.1 Social Media

Data was collected from popular social media platforms such as Twitter and Facebook. Two main approaches were employed to gather relevant data:

1. Keyword-based scraping: a list of keywords associated with explicit content was compiled. These keywords were used to extract tweets from the platform.
2. Profile-based scraping: a list of profiles known for regularly posting NSFW content was curated. Posts from these profiles were then scraped to obtain a more targeted dataset.

The combination of these two scraping methods resulted in a comprehensive and diverse dataset from social media, capturing both keyword-specific content and data from profiles that frequently share explicit material.

### 3.2 Public Articles

For public articles, we have collected data from various articles and blogs which are [b.cari](#), which hosts a wide range of user-generated content in Malay.

The collected dataset consists of human dialogues extracted from these articles and blog posts. It notably includes some dialogues that contain nsfw content. The inclusion of such dialogues, while potentially controversial, is important to allow the trained classifier to effectively detect explicit content that may realistically occur in open-ended dialogue systems.

### 3.3 Public Datasets

We have also collected data from publicly available dataset on kaggle such as [Kaggle: Suicide and Depression Detection](#) datasets. The dataset is a collection of posts from the "SuicideWatch" and "depression" subreddits of the Reddit platform. This dataset contains a wide range of suicide ideation contexts, providing valuable insights for our research.

We also leverage [Explainable Detection of Online Sexism \(EDOS\)](#) from github and [EXIST: sEXism Identification in Social neTwork \(EXIST\)](#) from web that contain a diverse collection of sexism statements, which have significantly contributed to the success of our classifier in identifying and categorizing such content.

## 4 Methodology

Supervised text classification requires reliable class labels for training data. However, obtaining these labels can be complex and expensive. Typically, labels are added sequentially by querying an annotator until satisfactory performance is achieved. We introduced an approach that leverages active learning, knowledge distillation of large language models, and text clustering to reduce annotation effort and construct a collection of labeled not safe for work (NSFW) data from our gathered data.

Following figure illustrates the overall flow employed in our methodology to collect NSFW dataset aims to label malaysian dataset for alignment in LLMOps framework.

### 4.1 Manual Labeling

Relying on large language models (LLMs) for data labeling can present challenges, such as inaccuracies and biases introduced by the model. To address these issues and enhance the quality of our dataset, we employed manual labeling using Label Studio.

Label Studio is an open-source data labeling tool that allows for efficient and precise annotation of data. We used Label Studio to manually label approximately 200 data points, which were then added to our dataset as a baseline.

- **Annotation Process:** Our team meticulously reviewed and annotated the data points to ensure high-quality labels. This process involved cross-checking by multiple annotators to minimize errors and biases.
- **Baseline Dataset:** The manually labeled data serves as a baseline for our model. By starting with a small, accurately labeled dataset, we provide the model with a strong foundation for learning.

ID	Completed	Date	Annotation results
35	May 22 2024, 21:29:05	1	[[{"start": 0, "end": 100, "label": "safe for work"}]]
36	May 22 2024, 21:30:06	1	[[{"start": 0, "end": 100, "label": "safe for work"}]]
37	May 22 2024, 21:30:14	1	[[{"start": 0, "end": 100, "label": "safe for work"}]]
38	May 22 2024, 21:30:23	1	[[{"start": 0, "end": 100, "label": "safe for work"}]]

Figure 1: Manual labeling process using Label Studio.

## 4.2 Knowledge Distillation of Large Language Models

Data annotation using knowledge distillation from a large language model (LLM) involves prompting a teacher LLM to generate a label  $y$  for a given input  $x$  as the foundational knowledge. This paper primarily explores the zero-shot paradigm, where the LLM receives only the input  $x$  and an instruction  $I$  without any labeled examples or demonstrations. This straightforward yet effective method of extracting knowledge from teacher LLMs has been widely applied to various tasks and applications. It only requires an input dataset, which is then processed by the LLM to produce the desired label  $y$ .

In this annotation stage, we utilized two different large language models: mistral-7b and mallam-small [?]. By leveraging mistral-7b, which excels with English-centric prompts, we translated our scraped data into English to provide better context and achieve reliable outputs from the model. While for mallam, we provided inputs from the original malay text as it has better contextual meaning compared to the other models. Below is the prompt we used to generate the labels from the models:

text: <text content>

If the text shows any sign of prejudice, stereotyping, or discrimination on the basis of sex:, label it as 'sexist'.

If the text shows any sign of content that threatens, incites, glorifies, or expresses desire for violence or harm., label it as 'violence'.

If the text shows any sign of prejudice, discrimination, or antagonism by an individual, community, or institution against a person or people on the basis of their membership of a particular racial or ethnic group, label it as 'racist'.

If the text shows any sign of content depicting adult nudity or sexual behavior that is pornographic or intended to cause sexual arousal, label it as 'porn'.

If the text shows any sign of psychiatric or mental illness, label it as 'psychiatric or mental illness'.

If the text shows any sign of promotion, or otherwise encourage, suicide or self-harm, label it as 'self-harm'.

If the text shows any sign of harassment, label it as 'harassment'.

If the text does not show any sign of violation and safe for work, label it as 'safe for work'

Only use the label from above choice.

return the result in JSON format {'label', 'explain'}

### 4.3 Centroid Based Filtering

We utilize labeled data obtained from a large language model (LLM) to enhance the quality and consistency of our dataset. First, we compute the centroid of the feature vectors for the labeled data, representing the central point in the feature space. The determination of similarity is guided by the Euclidean distance formula, where lower values indicate greater similarity and higher values signify greater dissimilarity.

By measuring the distance of each data point from this centroid, we can identify and filter out data points that are far from the centroid. These distant points are likely to be outliers or less representative of the core topic data distribution. This ensures that the labels encapsulate the nuanced semantics of the specific topic. This filtering process enhances the dataset by retaining data that is more coherent and relevant, thereby improving the performance of the classifier.

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**Algorithm 1** Centroid-Based Filtering

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```
1: Input: Labeled text data, LLM for embeddings
2: Output: Filtered dataset
3: Generate embeddings for the specific topic labeled by LLM
4: Compute the centroid of the embeddings for each embedding do
5:
    end
    Calculate the Euclidean distance to the centroid
6: Observe the distribution of distances
7: Set a threshold based on the distance distribution
8: Filter out texts with distances more than the threshold
9: return Filtered dataset
```

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### 4.4 Active Learning

We use relevant data from a specific category to train a classifier model. The trained model is then used to classify unlabeled data, a process known as pseudolabeling. The outputs given by the classifier are reviewed before feeding all the unlabeled data into a larger classifier model. This iterative process continues until the desired accuracy is achieved.

The following algorithm outlines the active learning process:

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**Algorithm 2** Active Learning for Single Label Classifier

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```
1: Input: Labeled data  $D_L$ , Unlabeled data  $D_U$ , Classifier model  $M$ , Desired accuracy  $A_{desired}$ 
2: Output: Trained classifier model  $M$ 
   while Accuracy  $A < A_{desired}$  do
3:
   end
   Train classifier  $M$  on  $D_L$ 
4: Predict labels for  $D_U$  using  $M$  (pseudolabeling)
5: Filter high-confidence predictions from  $D_U$  to create a new labeled dataset  $D_{L_{new}}$ 
6: Update labeled dataset:  $D_L \leftarrow D_L \cup D_{L_{new}}$ 
7: Retrain classifier  $M$  on the updated  $D_L$ 
8: Manually evaluate the accuracy  $A$  of  $M$ 
9: return Trained classifier model  $M$ 
```

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## 5 Result

In this section, we evaluate the performance of our finetuned model using the training set. I ran evaluation of all the models on the subset of the. The evaluation metrics used are accuracy, precision, recall, F1 score, and ROC-AUC. These metrics provide a comprehensive view of the model's performance across different aspects.

### 5.1 Evaluation Metrics

- **Accuracy** measures the overall correctness of the model, indicating the proportion of true results (both true positives and true negatives) among the total number of cases examined.
- **Precision** is the ratio of correctly predicted positive observations to the total predicted positives, reflecting the model’s ability to identify only the relevant instances.
- **Recall** (or Sensitivity) is the ratio of correctly predicted positive observations to all observations in the actual class, showing the model’s ability to capture all relevant instances.
- **F1 Score** is the weighted average of Precision and Recall, providing a balance between the two metrics, especially useful for imbalanced datasets.
- **ROC-AUC** (Receiver Operating Characteristic - Area Under Curve) represents the model’s ability to distinguish between classes, with higher values indicating better performance.

### 5.2 Model Comparison

Table ?? summarizes the performance metrics for different models. Each model was trained and evaluated under the same conditions to ensure a fair comparison.

Model	Accuracy	Precision	Recall	F1 Score
malaysian-mistral-191M-MLM	0.8768	0.8601	0.8854	0.8714
t5-small-bahasa-cased	0.85	0.84	0.86	0.85
roberta-small-bahasa-cased	0.88	0.87	0.88	0.87
bert-small-bahasa-cased	0.92	0.91	0.93	0.92

Table 1: Evaluation on Malaysian NSFW Dataset

The results indicate that

### 5.3 Analysis

## 6 Acknowledgement

We would like to express our gratitude to Mesolitica for providing us with the resources and NVIDIA Inception for generously providing us with the opportunity to train our model on the Azure cloud. Their support has played a crucial role in the success of our research, enabling us to leverage advanced technologies and computational resources.

We extend our thanks to the wider research community for their valuable insights and collaborative discussions, which have greatly influenced our work. This paper reflects the collective efforts and contributions from both NVIDIA Inception and the broader research community.

## 7 Conclusion

In conclusion, our work has presented a novel approach to moderating harmful content in AI safety through the introduction of a Safe For Work (SFW) classifier. By harnessing the power of large language models and data mining techniques, we have constructed a valuable dataset annotated with harmful topics. This pioneering research fills a significant gap in the field, as there is no available data with harmful contents labelled as no prior studies have explored this specific approach. Moving forward, our efforts lay the foundation for further advancements in AI safety and the responsible development of conversational agents and chatbots.