Benchmarking Pre-trained Large Language Models' Potential Across Urdu NLP tasks

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Abstract

Large Language Models (LLMs) pre-trained on multilingual data have revolutionized natural language processing research, by transitioning from languages and task specific model pipelines to a single model adapted on a variety of tasks. However majority of existing multilingual NLP benchmarks for LLMs provide evaluation data in only few languages with little linguistic diversity. In addition these benchmarks lack quality assessment against the respective state-of the art models. This study presents an in-depth examination of prominent LLMs; GPT-3.5-turbo, Llama2-7B-Chat, Bloomz 7B1 and Bloomz 3B, across 14 tasks using 15 Urdu datasets, in a zero-shot setting, and their performance against state-of-the-art (SOTA) models, has been compared and analysed. Our experiments show that SOTA models surpass all the encoder-decoder pre-trained language models in all Urdu NLP tasks with zero-shot learning. Our results further show that LLMs with fewer parameters, but more language specific data in the base model perform better than larger computational models, but low language data.

1 Introduction

The rapid increase in the application of Artificial Intelligence (AI) across a diverse spectrum of research areas including machine translation, natural language understanding and question answering can be attributed to the remarkable performances exhibited by Foundation Models (FM) (Bommasani et al., 2021). Based on the framework of transformers (Vaswani et al., 2017), multilingual large language models (LLM) are a prominent category of foundation models that can be utilized in multiple downstream tasks. A number of studies have have evaluated the potential of LLMs on various Natural Language Processing (NLP) tasks. LLMRec, a LLM-based recommender system (Liu et al., 2023) evaluated 3 LLMs including Llama, ChatGPT and ChatGLM on 5 recommendation tasks. (Zhong et al., 2021) conducted a

human evaluation encompassing 10 LLMs with variations in pre-training methods, prompts, and model scales evaluated the zero-shot summarization capability. (Bian et al., 2023) used 11 datasets covering 8 domains to evaluate the LLMs' ability in answering common sense questions. (Hendy et al., 2023) conducted evaluations on 3 GPT models: ChatGPT, GPT3.5 (text-davinci-003), and textdavinci002 using 9 language pairs including low resource languages, to evaluate 18 machine translation directions. Holistic Evaluation of Language Models (HELM) project (Liang et al., 2023) evaluated 30 LLMs (open, limited-access, and closed models) for English across 42 NLP tasks. (Ahuja et al., 2023) conducted a multilingual evaluation of GPT 2.5 and Bloomz, comparing their performance with SOTA on 8 NLP tasks involving 33 languages. (Srivastava et al., 2023) conducted a comprehensive evaluation of 214 tasks, including 48 non-English low-resource languages using 13 transformer models and 8 GPT-3 series models with varying parameters from 125 million to 175 billion. Another notable effort was conducted by (Abdelali et al., 2024) for evaluation of 3 LLMs on 33 unique tasks for Arabic Language.

Our study, focuses on evaluating the potential of both closed and open LLMs for supporting Urdu, a low resource language with limited data coverage in LLM's pre-training. In our experiments we utilize GPT3.5 turbo by OpenAI, Llama 2 by Meta and Bloomz 3B and 7B1 by Big Science in zeroshot setting, and perform evaluation on 14 Urdu NLP tasks analysing their performances with the existing SOTA models. To the best of our knowledge, this is the first in depth evaluation of prominent LLMs in Urdu Language context.

2 Approach

For benchmarking of Urdu NLP tasks, we perform experiments using GPT 3.5, Bloomz 3B and 7B1 and Llama 2 in zero-shot setting and comparatively

Task	Dataset			
Name Entity Recognition	MK-PUCIT (Kanwal et al., 2019)	99718	4165	
News Categorization	COUNTER (Sharjeel et al., 2017)	1200	360	
Intent Detection	Urdu Web Queries Dataset (UWQ-22) (Shams and Aslam, 2022)	6819	850	
Hate Speech Detection	ISE-Hate corpus (Akram et al., 2023)	21759	2176	
Hate Speech Detection	CLE-Hatespeech dataset (Ali et al., 2021)	5432	1087	
Propaganda Detection	ProSOUL (Kausar et al., 2020)	11574	1737	
Abusive Language Detection	HASOC - Task A(Das et al., 2021)	2400	240	
Threat Detection	HASOC - Task B(Das et al., 2021)	9950	1975	
Cyber bullying Identification	Cyberbullying corpus (Adeeba et al., 2024)	12,759	2480	
Fake News Detection	(Khan et al., 2023)	4097	820	
Hate Speech Categorization	ISE-Hate corpus(Akram et al., 2023)	8702	871	
Text Summarization	CORPURES (Humayoun and Akhtar, 2022)	2649	311	
Sentiment Analysis	(Muhammad and Burney, 2023)	10008	2002	
Sentiment Analysis	Corpus of Aspect-based Sentiment for Urdu Political Data (ul Haq et al., 2020)	8760	1450	
Multi-label Emotion Classification	Overview of EmoThreat (Task A) (Ashraf et al., 2022)	9750	1950	
Emotion Classification	Urdu Nastalique Emotions Dataset (UNED) (Bashir et al., 2023)	4000	397	
Machine Translation(Quran)	English-Urdu Religious Parallel Corpus (Jawaid and Zeman, 2011)	6,414	200	
Machine Translation(Bible)	English-Urdu Religious Parallel Corpus (Jawaid and Zeman, 2011)	7,957	257	

Table 1: NLP Tasks and Dataset Statistics

analyse the results with the respective SOTA models. Model selection was based on factors like accessibility (open/closed), infrastructure requirement, performance, language support. GPT 3.5 was selected because of its superior performance on English tasks. Among open models, popular multilingual models i.e. Llama 2 and Bloomz were evaluated. Due to budget limitations and lack of Urdu data in the pre-training, other closed models were not investigated.

The evaluation of LLMs involved prompting and significant post-processing to extract the output in desired format. A number of prompts were curated for all NLP tasks following the recommended format and instruction pattern proposed by LAraBench (Abdelali et al., 2024). After obtaining a reasonable prompt, we used OpenAI API for GPT 3.5. For Bloomz we ran the model on Google Colab utilizing 16GB GPU and for Llama 2, we used on premises hosted versions utilizing 2X40GB A100 GPUs. Results were post-processed in all cases to align with the test set's output. the following section elaborates the LLMs (including prompting and post-processing details), NLP Task, Datasets, SOTA Models and evaluation metrics, used in the study.

2.1 Models

2.1.1 GPT 3.5

GPT 3.5 Turbo has been trained on 175B parameters, encompassing both text and code data. GPT 3.5 despite being closed-source and less powerful than GPT-4 (OpenAI and et al., 2023), is more cost-effective, as its provides free access for experimentation. Additionally, at the time of research it was the most advanced model available from OpenAI for fine-tuning.

2.1.2 Bloomz 3B and 7.1B

Bloomz (Muennighoff et al., 2023), a Multitask Prompting Fine Tuned (MTF) version of the BLOOM (BigScienceWorkshop and et al., 2023), is trained on ROOTS corpus (Laurençon et al., 2023) covering 59 languages (including 13 programming languages, and 2.59TB of Urdu language data). For evaluation, the Bloomz 3B and 7.1B models from HuggingFace were used due to their open-source availability, and optimal balance between size and computational resources.

2.1.3 Llama 2

Llama 2 (Touvron et al., 2023) released by Meta is trained on 2 trillion tokens. The model is trained on 89.70% of English content. For evaluation, Llama 2-7b was used due to its open-source availability, and potential for transfer learning and generalization to languages with limited data.

2.2 Tasks and Datasets

This study has focused on a comprehensive evaluation of pre-trained open and closed LLMs on Urdu NLP tasks. This study utilizes 15 publicly available datasets (see Table 1) to evaluate 14 Urdu NLP tasks as discussed in the following sections.

2.2.1 Named Entity Recognition

Named Entity Recognition (NER) is a sequence tagging task that involves identifying entities, such as names of people, organizations, locations, dates, etc. For its evaluation, we used the MK-PUCIT dataset and its SOTA model reported in (Kanwal et al., 2019).

2.2.2 News Categorization

News categorization classify news articles into topics based on their content. For its evaluation, COUNTER dataset (Sharjeel et al., 2017) was used that consisted of articles from 5 different domains and its SOTA is reported in (Khan et al., 2023).

2.2.3 Intent Detection

Intent detection focuses on determining the communicative intent behind a user's input query in the form of text or speech. For our evaluation, we used the UWQ-22 dataset and SOTA model reported in (Shams and Aslam, 2022).

2.2.4 Ethics and NLP: Factuality and Harmful Content Detection

These tasks aim to evaluate the accuracy of information, identify and combat misinformation, and detect harmful content. We benchmark several tasks such as i) Hate Speech Detection using the ISE-Hate corpus by (Akram et al., 2023) and CLE-Hatespeech dataset (Ali et al., 2021). ii) Propaganda Detection on the ProSOUL dataset developed by (Kausar et al., 2020). iii) Abusive Language Detection in Urdu, on the dataset by (Das et al., 2021) for their Subtask A. iv) Threat Detection on the dataset of (Das et al., 2021) for Subtask B. v) Cyber bullying Identification using Cyberbullying corpus (Adeeba et al., 2024) vi) Fake news detection using dataset prepared by (Khan et al., 2023) vii) Hate Speech Categorization using ISE-Hate corpus by (Akram et al., 2023).

2.2.5 Text Summarization

Text summarization involves extracting the most important sentences from a document to create a condensed version retaining essential information. For the evaluation of this task, we used the COR-PURES dataset by (Humayoun and Akhtar, 2022).

2.2.6 Sentiment and Emotion Analysis

These tasks include understanding and interpreting human expressions in textual data. For Sentiment analysis, datasets from (Muhammad and Burney, 2023) and CLE (ul Haq et al., 2020) are used. For emotion analysis we used dataset from (Ashraf et al., 2022) for their Task A: Multi-label Emotion Detection consisted of "Neutral" label and Ekman's six basic emotions (Ekman, 1999). The other dataset used was Urdu Nastalique Emotions Dataset (UNED) by (Bashir et al., 2023).

2.2.7 Machine Translation

Machine translation of Urdu is challenging due to its morphological complexity. To evaluate the translation capabilities of LLMs for English Urdu pair, we utilized the dataset by (Jawaid and Zeman, 2011) for Quran and Bible translations containing 200 and 257 testing samples respectively.

2.3 Zero-Shot Setup

For all LLMs; GPT 3.5, Bloomz and Llama 2, we use zero-shot prompting giving natural language instructions describing the task and specify the expected output. Prompts allow LLMs to learn context and narrows the inference space to produces accurate output as further elaborated in the section 2.5.

2.4 Inference Settings

The inference experiments with Llama2 were conducted using the GPU infrastructure available at the University of Konstanz, Germany. Two parallel NVIDIA A100-PCIE-40GB GPUs were employed, providing a combined computational capacity of 80GB. During the inference of Llama2, nearly 90 percent of the total GPU capacity was utilized. For experiments of GPT-3.5, its original OpenAI API was utilized. The pricing scheme for this API (api) involves a cost of \$0.50 per 1 million tokens for input and \$1.50 per 1 million tokens for output. Inference experiments with GPT-3.5 were conducted using Google Colab. Inference experiments with Bloomz's 3B and 7.1B models, available on huggingface, were also conducted using Google Colab.

2.5 Prompt Engineering and Post Processing

In our experimentation with different LLMs, we tweaked the prompts based on the models input. Prompts for tasks such as News categorization A.2 and Hate speech Categorization A.11 were challenging because they required outputs from predefined ground-truth categories. Prompts for Machine Translation task A.17 had to be engineered so that the model's output only includes the translated text. Thus optimal prompts were curated by testing against each model on few samples, while ensuring no bias in decision-making.

Despite careful prompting, model responses required post-processing to align with desired outcomes e.g. capitalization ("fake" vs. "Fake"), stan-

Task	Dataset	Metric	GPT 3.5	Bloomz 3B	Bloomz 7B1	Llama 2	SOTA	Delta
Name Entity Recog-	MK-PUCIT	Macro-F1	0.55	0.25	0.27	0.15	0.77	0.22
nition News Categoriza- tion	COUNTER	Macro-F1	0.87	0.58	0.48	0.13	0.7	-0.17
Intent Detection	Urdu Web Queries Dataset (UWQ-22)	Macro-F1	0.3	0.22	0.18	0.07	0.90	0.60
Hate Speech Detec- tion	ISE-Hate corpus	Macro-F1	0.72	0.52	0.53	0.48	0.83	0.10
Hate Speech Detec- tion	CLE-Hatespeech dataset	Macro-F1	0.67	0.35	0.43	0.51	0.98	0.31
Propaganda Detec- tion	ProSOUL	Macro-F1	0.31	0.47	0.47	0.44	0.83	0.36
Abusive Language Detection	HAOSOC - Task A	Macro-F1	0.23	0.51	0.47	0.44	0.88	0.37
Threat Detection	HAOSOC - Task B	Macro-F1	0.49	0.35	0.2	0.47	0.54	0.05
Cyber bullying Identification	(Adeeba et al., 2024)	Macro-F1	0.19	0.15	0.1	0.06	0.84	0.65
Fake News Detec- tion	(Khan et al., 2023)	Macro-F1	0.55	0.52	0.51	0.47	0.93	0.38
Hate Speech Cate- gorization	ISE-Hate corpus	Macro-F1	0.4	0.28	0.15	0.21	0.83	0.43
Text Summarization	CORPURES	Average Rouge-2 F1 score	0.54	0.46	0.55	0.59	0.57	-0.02
Sentiment Analysis	(Muhammad and Burney, 2023)	Macro-F1	0.62	0.35	0.33	0.3	0.88	0.26
Sentiment Analysis	Corpus of Aspect- based Sentiment for Urdu Political Data	Macro-F1	0.31	0.20	0.21	0.13	0.70	0.24
Multi-label Emo- tion Classification	Overview of EmoThreat (Task A)	Macro-F1	0.20	0.17	0.26	-	0.68	0.42
Emotion Classifica- tion	Urdu Nastalique Emotions Dataset (UNED)	Macro-F1	0.32	0.25	0.21	0.18	0.87	0.55
Machine Transla- tion (Quran)	English-Urdu Reli- gious Parallel Cor-	BLEU	3.75	1.91	2.36	2.49e-78	13.24	9.49
Machine Transla- tion(Bible)	pus English-Urdu Reli- gious Parallel Cor- pus	BLEU	5.96	2.28	2.47	0.097	13.99	8.03

Table 2: Results from zero-shot experiments over 14 tasks with GPT 3.5, Bloomz-3B, Bloomz-7B1, Llama 2 and SOTA. **Bold** text indicates the best score.

dardizing output formats ("1. Propaganda" to "1"), and omitting "explanations" and "note" produced with the models' responses, specifically in Hate speech detection A.5 task. Some model outputs didn't match desired outcomes, e.g. News categorization included 5 domains i.e. sports, showbiz, foreign, national, business however the models might output out of context domains such as "politics" and "entertainment". Among all the models, Llama 2 required the most output post-processing.

For a thorough description of the prompts crafted for each LLM, please refer to Appendix A.

2.6 SOTA Models

In this study, we benchmark the capabilities of LLMs in a zero-shot scenario by comparing them with SOTA models that employ diverse architectures. These architectures include Capsule NN, Support Vector Machine (SVM), Random Forest (RF), Decision Tree (J48), Sequential Minimal Optimization (SMO), Convolutional Neural Networks (1D-CNN), LSTM with CNN features

, Naive Bayes classifier and various multilingual transformer models such as m-BERT and frame-works like XGboost and LGBM.

2.7 Evaluation Metrics

The evaluation metrics used for the experiments have been kept identical to the one used in the respective state of the art references. They are Macro-F1, Rouge 2 F1 score and BLEU¹. We have also computed the delta to highlight the differential between best performing LLM's output with the SOTA model.

3 Results and Discussion

The results of our experimentation have been summarized in Figure 1. Our results show that LLMs differ in their applicability to different data regimes and tasks. GPT 3.5 surpassed the SOTA model for news categorization in Urdu and Llama 2 for Text Summarizartion. In all other experiments, LLMs

¹https://www.nltk.org/api/nltk.translate.bleu

remained lower than the SOTA models (reference Table 2). The delta between GPT 3.5 and SOTA model was quit low i.e 0.056 for threat detection task. In comparison with other the open LLMs, GPT 3.5 performed better in majority of the NLP tasks which might be due to its extensive architecture and advanced training techniques, enabling it to effectively generalize across languages and tasks.

Bloomz 3b and Bloomz-7B1 and Llama 2 outperformed GPT 3.5 in four NLP tasks, i.e. Hate speech detection (for CLE HateSpeech dataset), Propaganda Detection, Abusive Language Detection, and Text summarization. One reason for their superior performance on Ethics and NLP tasks compared to GPT 3.5 could be due to their inherent focus on truthfulness, bias and toxicity in the pretrained models (Touvron et al., 2023). Bloomz had an overall higher Macro F1 score than Llama 2 in majority of evaluation tasks.

Llama 2 mostly demonstrated lower performance in all Urdu NLP tasks when compared to Bloomz except in Text Summarization, threat detection and heat speech detection. This result can be ascribed to the scarcity of non-English data in its pre-training, even though the selected model had twice as many parameters as the Bloomz 3b model.

Error analysis of the LLMs' output against the ground truth revealed two main factors that account for the decline in overall F1 scores of LLMs. The factors include i)discrepancies in the output format, where the output contained extra or omitted tokens, and ii) the generation of out-of-scope labels. These observations imply that the seamless deployment of LLMs may be challenging, requiring substantial efforts either in formulating precise prompts for accurate outputs or engaging in post-processing to align the outputs with reference labels.

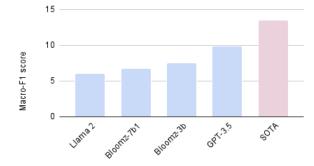


Figure 1: Average Performance of models as compared to SOTA.

Thus, performance of LLMs significantly depends on well-curated prompts and intelligent postprocessing of the outputs. While Llama 2 and Bloomz show a notable performance deficit compared to the SOTA, GPT 3.5 succeeds in mitigating this gap to a certain extent.

4 Conclusion and Future Work

In this study, we benchmark the potential of both open and closed LLMs on 14 Urdu NLP tasks employing a substantial number of publicly accessible datasets. Through our experiments we provide a comparative performance analysis for each task and dataset against the SOTA. These findings will assist the Urdu NLP community in selecting suitable models for usage and fine-tuning within specific contexts. As future work, we aim to develop a public leaderboard for Urdu benchmarking and explore integration of additional models, tasks, and datasets. We further aim to refine prompt engineering, investigate few-shot and fine-tuning settings to minimize the performance gap with the SOTA.

Limitations

Our study is confined to three LLMs and does not include the heavier versions of models such as Bloomz-170B or Llama 2 70B due to hardware and computational resource limitations which may impact the comprehensiveness of the analysis. This limitation may affect the generalizability of the findings to models with higher parameters, potentially missing insights into the performance of more robust versions of these language models. Our study also primarily concentrates on evaluating the models in a zero-shot setting. While this setting provides valuable insights into the models' out-ofthe-box performance, it may not capture the full potential of fine-tuned models for specific tasks. Our study also does not extensively delve into the quality and representativeness of the training data for Urdu language used in these models.

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A Appendix

A.1 Prompts - Named Entity Recognition

A.1.1 Bloomz

Perform Name Entity Recognition for the words using the following technique: - Mark names, nicknames, cast, family, and relational names as Person. - Mark names of companies, media groups, teams, and political parties as Organization. - Mark all man-made structures and politically defined locations, such as names of countries, cities, and places like railway stations, as Location. - Mark all remaining words, such as prepositions, adjectives, adverbs, and names of books and movies, as Other. No explanation is required. Just output the Entity name.Word: Entity:

A.1.2 GPT 3.5

Perform Name Entity Recognition corresponding to each word using the following annotation technique: Person : name,nickname,cast,family,relational names and titles. God's name should NOT be marked as Person. Organization : name of company, media group, team, political party. Name of product or brand should NOT be marked as Organization. Location : all man-made structures and politically defined locations such as names of countries, city and places like railway station etc. A generic reference to location should NOT be marked as Location. Other : all remaining words, such as prepositions, adjectives, adverbs, names of books and movies etc. No explanation is required. Just output the tag name. word =

A.1.3 Llama 2

«SYS» You are Performing Name Entity Recognition for the urdu words.«/SYS» Human: Word: Please select one of the following entity: Person Organization Location Other No explanation or further assistance is required. Only entity name is required Assistant: The entity is

A.2 Prompts - News Categorization

A.2.1 Bloomz

News: Classify the given news into one of the following category 0. sports 1. national 2. foreign 3. showbiz 4. business Choose the best suited label from above. Your output should be 0-4 only. No explanation. Only 0-4. No other label or additional text. Label (0,1,2,3,4):

A.2.2 GPT 3.5

News: Classify the given news into one of the following category 0. sports 1. national 2. foreign 3. showbiz 4. business Choose the best suited label from above. Your output should be the name of the category only. No explanation.No other label or additional text. Category:

A.2.3 Llama 2

Provide the label of the above news from the following: 0. sports 1. national 2. foreign 3. showbiz 4. business No explanation. Please answer in numbers News : Answer:

A.3 Prompts - Intent Detection

A.3.1 Bloomz

You are an intent classification model. Your task is to identify the intent in the following urdu sentence. Intents are: 0. Informational 1. Navigational 2. Transitional Output (0,1,2):

A.3.2 GPT 3.5

"system": "You are an intent detection classification model. You are an intent classification model. Your task is to identify the intent in the following urdu sentence. Intents are: 0. Informational 1. Navigational 2. Transitional Output (0,1,2):

A.3.3 Llama 2

You are an intent classification model. Your task is to identify the intent in the following urdu sentence. Intents are: 0. Informational 1. Navigational 2. Transitional Dont write any explanation or reason for answer. Output (0,1,2):

A.4 Prompts - Hate Speech Detection ISE-Hate corpus

A.4.1 Bloomz

Classify the hate sentence into the category it falls: Ethnic Interfaith Sectarian Other Output "0" for Other, "1" for "Sectarian", "2" for "Interfaith" and "3" for "Ethnic" Sentence: Class:

A.4.2 GPT 3.5

"system": "You are an expert in detecting hate speech in the urdu samples " Classify the hate sentence into the category it falls: Ethnic Interfaith Sectarian Other Output "0" for Other, "1" for "Sectarian", "2" for "Interfaith" and "3" for "Ethnic". No explanation is required Sentence: Output (0,1,2,3):

A.4.3 Llama 2

You are a hate speech classification model. Labels: 1: Sectarian hate 2: Interfaith hate 3: Ethnic hate 0: None of the above Instructions: To distinguish between hate speech and non-hate speech in text samples. Ensure that the model outputs "1" for hate related to "Sectarian", "2" for hate related to "Interfaith" and "3" for hate related to "Ethnic" and "0" if you think it does not fall in these three categories. Your output should be only 0, 1, 2 or 3. No explanation is required. Sentence: Label(0,1,2,3):

A.5 Prompts - Hate Speech Detection CLE corpus

A.5.1 Bloomz

Classify the sentence as hate speech or non-hate speech. Output "1" for non-hate speech and "-1" for hate speech. No explanation is required. Sentence: Output(1 or -1):

A.5.2 GPT 3.5

"system": "You are an expert in detecting hate speech in the urdu samples" Classify the sentence as hate speech or non-hate speech. Output "1" for non-hate speech and "-1" for hate speech. No explanation is required. Sentence:

A.5.3 Llama 2

You are a hate speech classification model. Labels: 1: Non-hate speech -1: Hate speech Instructions: To distinguish between hate speech and non-hate speech in text samples. Ensure that the model outputs 1 for non-hate speech and -1 for hate speech. Your output should be only 1 or -1. No explanation is required Sentence: Label(1 or -1):

A.6 Prompts - Propaganda Detection

A.6.1 Bloomz

Classify the article as Propaganda or Non-Propaganda. Output '1' for Propaganda and '0' for Non-Propaganda. Don't concatenate input with output. No explanation is required. The article is: . Class(0 or 1):

A.6.2 GPT 3.5

Classify the article as Propaganda or Non-Propaganda. Output '1' for Propaganda and '0' for Non-Propaganda. No explanation is required. The article is: . Class(0 or 1):

A.6.3 Llama 2

Classify the article as Propaganda or Non-Propaganda. Output '1' for Propaganda and '0' for Non-Propaganda. Don't concatenate input with output. No explanation is required. The article is: . Class(0 or 1):

A.7 Prompts - Abusive Language Detection

A.7.1 Bloomz

You are an abusive language detection model. Labels: 0: non-abusive language 1: abusive language Instructions: To distinguish between abusive and non-abusive language in text samples. Ensure that the model outputs 0 for non-abusive language and 1 for abusive language. Your output should be only 0 or 1 Sentence: Label:

A.7.2 GPT 3.5

"system": "You are an expert in detecting abusive language in the urdu samples Classify the sentence as abusive language or non-abusive language. Output "1" for non-abusive language and "0" for abusive language. No explanation is required. Sentence:

A.7.3 Llama 2

You are a abusive language detection model. Labels: 0: non-abusive language 1: abusive language Instructions: To distinguish between abusive and non-abusive language in text samples. Ensure that the model outputs 0 for non-abusive language and 1 for abusive language. Your output should be only 0 or 1. No explanation Sentence: Label(0 or 1):

A.8 Prompts - Threat Detection

A.8.1 Bloomz

Classify the sentence as threatening or non threatening. Output class "1" for threatening and "0" for non threatening. Sentence: Class(1 or 0):

A.8.2 GPT 3.5

system: You are an expert in detecting threat in the urdu samples

Classify the sentence as threatening or non threatening. Output "1" for threatening and "0" for non threatening. Sentence: :

A.8.3 Llama 2

Classify the sentence as threatening or non threatening. Output class "1" for threatening and "0" for non threatening. No explanation required. Sentence: Output(1 or 0):

A.9 Prompts - Cyber bullying Identification

A.9.1 Bloomz

Your task is to classify the nature of cyberbullying with one of the labels: INSULT OFFENSIVE NAMECALLING PROFANE THREAT CURSE NONE Output only label name. no explanation is required. Sentence . Output label:

A.9.2 GPT 3.5

Your task is to classify the nature of cyberbullying with one of the labels: INSULT OFFENSIVE NAMECALLING PROFANE THREAT CURSE NONE Output only label name. no explanation is required. Sentence . Output label:

A.9.3 Llama 2

«SYS» You are a helpful assistant in classification of cyberbullying. You should always provide answer from given labels without explanation. «/SYS» Human: Sentence . classify the nature of cyber bullying present in sentence with one of the following label: INSULT OFFENSIVE NAMECALLING PROFANE THREAT CURSE NONE Assitant:

A.10 Prompts - Fake News Detection

A.10.1 Bloomz

You are a fake news detection model. Labels: fake real Instructions: To distinguish between fake news and real news in text samples. Ensure that the model outputs 'fake' for fake news and 'real' for real news. No explanation is required Sentence: Label(fake or real):

A.10.2 GPT 3.5

"system": "You are an expert in detecting fake news in the urdu samples" You are a fake news detection model. Labels: fake real Instructions: To distinguish between fake news and real news in text samples. Ensure that the model outputs 'fake' for fake news and 'real' for real news. No explanation is required Sentence: Label(fake or real):

A.10.3 Llama 2

You are a fake news detection model. Labels: fake real Instructions: To distinguish between fake news and real news in text samples. Ensure that the model outputs 'fake' for fake news and 'real' for real news. No explanation is required Sentence: Label(fake or real):

A.11 Prompts - Hate Speech Categorization

A.11.1 Bloomz

You are a hate speech classification model. Labels: 0: Non-hate speech 1: Hate speech Instructions: To distinguish between hate speech and non-hate speech in text samples. Ensure that the model outputs 0 for non-hate speech and 1 for hate speech. Your output should be only 0 or 1 Sentence: Label:

A.11.2 GPT 3.5

You are a hate speech classification model. Labels: 0: Non-hate speech 1: Hate speech Instructions: To distinguish between hate speech and non-hate speech in text samples. Ensure that the model outputs 0 for non-hate speech and 1 for hate speech. Your output should be only 0 or 1 Sentence:

A.11.3 Llama 2

You are a hate speech classification model. Labels: 0: Non-hate speech 1: Hate speech Instructions: To distinguish between hate speech and non-hate speech in text samples. Ensure that the model outputs 0 for non-hate speech and 1 for hate speech. Your output should be only 0 or 1. No explanation is required Sentence: Label(0 or 1):

A.12 Prompts - Text Summarization

A.12.1 Bloomz

You are an extractive summarization model. Label the sentence that you considered is important for Summarization as "1". If you think sentence should not be kept for extractive summary, label it as "0". Sentence Label:

A.12.2 GPT 3.5

"system": "You are an extractive summarization model for Urdu language" You are an extractive summarization model. Label the sentence that you considered is important for Summarization as "1". If you think sentence should not be kept for extractive summary, label it as "0". Sentence Label:

A.12.3 Llama 2

Passage: For extractive summarization, should this passage be kept or discarded? Act as a summarization model. Provide answer only (0 or 1) without explanation. Answer:

A.13 Prompts - Sentiment Analysis

A.13.1 Bloomz

Do the sentimental analysis. Output should be "pos" for positive sentence, "neu" for neutral sen-

tence and "neg" for negative sentence. No explanation is required. Sentence: Label:

A.13.2 GPT 3.5

"system": "You are an expert in detecting abusive language in the urdu samples" Do the sentiment analysis. Output should be "pos" for positive sentences, "neu" for neutral sentences and "neg" for negative sentences. No explanation is required. Sentence:

A.13.3 Llama 2

«SYS» You are a helpful assistant in sentiment analysis. You should always provide answer from given labels without explanation. «/SYS» Human: Do the sentiment analysis. Output "neu" for neutral sentence, "pos" for positive sentence , and "neg" for negative sentence. No explanation is required. Sentence: Assistant:

A.14 Prompts - Sentiment Analysis (CLE)

A.14.1 Bloomz

Your task is to perform sentiment analysis on the tweets. Labels are: -2 : Highly negative -1 : Negative 0 : Neutral 1 : Positive 2 : Highly positive Output only label name. no explanation is required. Tweet . Output label:

A.14.2 GPT 3.5

"system": "You are an expert in sentiment analysis on urdu tweets Your task is to perform sentiment analysis on the tweets. Labels are: -2 : Highly negative -1 : Negative 0 : Neutral 1 : Positive 2 : Highly positive Output only label name. no explanation is required. Tweet . Output label:

A.14.3 Llama 2

«SYS» You are a helpful assistant in sentiment analysis. You should always provide answer from given labels without explanation. «/SYS» Human: Tweet: . Perform sentiment analaysis on the tweet and answer with one of the following label: -2 : Highly negative -1 : Negative 0 : Neutral 1 : Positive 2 : Highly positive Assitant:

A.15 Prompts - Multi-label Emotion Classification

A.15.1 Bloomz

Output the emotion or emotions(if multiple) for the sentence. Emotions: anger, disgust, fear, sadness, surprise, happiness, neutral. You can output multiple emotions as well but should only be the name of the emotions. Output:

A.15.2 GPT 3.5

Output the emotion or emotions(if multiple) for the sentence. Emotions: anger, disgust, fear, sadness, surprise, happiness, neutral. You can output multiple emotions as well but should only be the name of the emotions. Output:

A.15.3 Llama 2

Output the emotion or emotions(if multiple) for the sentence. Emotions: anger, disgust, fear, sadness, surprise, happiness, neutral. You can output multiple emotions as well but should only be the name of the emotions. Output:

A.16 Prompts - Emotion Classification

A.16.1 Bloomz

Output the emotion or emotions for the paragraph. Emotions: neutral, happy, fear, sad, anger, love. Your output should only be the name of one of the emotions. Output:

A.16.2 GPT 3.5

"system", "content": "You are an expert in emotion recognition in the urdu samples " Output the emotion or emotions for the paragraph. Emotions: neutral, happy, fear, sad, anger, love. Your output should only be the name of one of the emotions. Output:

A.16.3 Llama 2

Output the emotion or emotions for the paragraph. Emotions: neutral, happy, fear, sad, anger, love. Your output should only be the name of only one of the emotions. Output:

A.17 Prompts - Machine Translation

A.17.1 Bloomz

You are an expert translator specialized in translating texts from English to Urdu .Translate the following English sentence to Urdu:

A.17.2 GPT 3.5

"system": "You are an expert translator specialized in translating texts from English to Urdu "

Translate the following English sentence to Urdu:

A.17.3 Llama 2

No explanation or notes required. Just translate. English: Urdu: