BRIDGING LAUGHTER ACROSS LANGUAGES: GENERATION OF HINDI-ENGLISH CODE-MIXED PUNS

1ST WORKSHOP ON COMPUTATIONAL HUMOR (CHUM 2025)

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Overview

- Introduction
- Related Work
- Methodology
  - Pun Generation (Word Pair)
  - Annotation and Pun Detection
  - Pun Generation Pipeline (Single Word)
- Future Work and Limitation

Introduction

Background

- Puns are a linguistic tool that exploit phonetic or semantic ambiguity to create humor through dual interpretations.
- They are widely used in entertainment, advertising, and literature for engagement.

Challenges

- Generating humor in code-mixed texts is harder due to the need for phonetic alignment and contextual coherence across languages.
- Current research lacks exploration into pun generation in low-resource, code-mixed settings such as Hindi-English text.

Introduction

Contribution

- Propose three novel methods for pun generation on word pairs using Large Language Models.
- Explore the performance of pre-trained multilingual models (XLM-R, mBERT) on detecting puns within code-mixed contexts.
- Introduce a new dataset, HECoP, containing 2,000 machine-generated sentences with human annotations for humor and naturalness.
- Develop a structured pun generation pipeline to generate puns from a single input word.

Related Work

Template-Based Approaches

Early systems like JAPE-1 (Binsted and Ritchie, 1994) relied on manually crafted templates to generate puns based on phonetic or semantic similarity

T-Peg (Hong and Ong, 2008) automated the creation of templates from human-generated puns.

Neural-Based Approaches

Yu et al. 2018 introduced a neural language model capable of generating homographic puns without specialized training data.

Sun et al. 2019 proposed a system with separate modules for pun word retrieval and generation, emphasizing contextual relevance.

AmbiPun(2022) used dictionary search and one-shot GPT-3 for creating ambiguous contexts, achieving a 52% pun success rate.

Task Formulation

A pun is a form of wordplay in which one sign (e.g., a word or a phrase) suggests two or more meanings by exploiting polysemy, homonymy, or phonological similarity to another sign, for an intended humorous or rhetorical effect.

My watch is stuck between 2 and 2.30. It's a do or ***dhai*** situation. Here the pun word is dhai and the alternative word is die.

Humor arises from the phonetic similarity between the Hindi word ***dhai*** (which means two and a half, referencing 2:30 in this context) and the English word die.

Steps in Pun Generation

- Identification of similar sounding words across a language pair
- Generation of candidate sentences with alternate word A_w
- Replacement of A_w with P_w within these candidate sentences

Pun-Alternate Word list Collection

IPA Transcriptions

- Words were transcribed into IPA using the epitrans library.
- American English IPA symbols were mapped to Indian English IPA which Improved the relevance of phonetic matches between Hindi and English words.

Edit Distance

- Employed Levenshtein edit distance with custom substitution costs based on phonetic features.
- The insertion and and deletion cost was set to infinity.
- Pairs with edit distance less than equal to 1 were collected.

Hindi	IPA	English	IPA	Edit
पीपल (pīpal)	/piːpəl/	people	/piːpəl/	0
दिल (dil)	/dil/	deal	/diːl/	0
बिक (bik)	/bik/	big	/big/	0
शौक (shock)	/ʃɔːk/	shack	/ʃæk/	1
गुस्से (gusse)	/gusse/	goose	/guːs/	∞

Tab: Word Pairs Collected

$$c_{\text{sub}}(x,y) = \begin{cases} 0, & \text{if } x \text{ and } y \text{ are same phones ,} \\ 0, & \text{if } x \text{ and } y \text{ are allophones,} \\ 0, & \text{if } x \text{ and } y \text{ are long/short vowel pairs,} \\ 0, & \text{if } x \text{ and } y \text{ are voiced/unvoiced pairs,} \\ 1, & \text{otherwise.} \end{cases}$$

Eq: Custom Substitution cost

Pun Generation Approaches

1. Contextually Aligned Pun Generation

- GPT-4o is prompted to generate five sentences, each ending with the English word A_w
- Each sentence must include a context word C_w , the English translation of P_w .
- For (A_w, P_w, C_w) the prompt is structured as follows: Generate 5 creative Hindi-English code-mixed sentences ending with A_w. Include C_w as context in each sentence.
- Additional filtering phase employed to ensure fluent puns:
  - Part-of-Speech compatibility: ensuring. P_w and A_w share the same POS tag.
  - Candidates are prioritized based on the placement of P_w at the sentence's end.

Example

Tuple (P_w, A_w, C_w) = (डेढ़(one and a half), dead, one and a half)
Prompt: Generate 5 creative Hindi-English sentences ending with the word 'dead'. Have the word 'one and a half' as a context in each of these sentences.
Final Pun: मैने(I) one and a half litre दूध ख़रीदा(milk buy), but when i opened it, it was already डेढ़(one and a half)."

Pun Generation Approaches

2. Question-Answer Pun Generation

- Structured approach used to generate puns in question answer format.
- The process consists of three key stages:
  - Generating a short phrase containing A_w
  - Replacing A_w with P_w in the generated phrase
  - Formulating a question based on the transformed phrase.

Example

Pun Alternate word pair (P_w, A_w) = (गाय(cow), guy)

Generated Small Phrase: A cool guy
Replaced Pun Word: A cool गाय(cow)
Generated Question: What do you call a cow wearing sunglasses?
Generated Translated Question: Sunglasses पहने हुए(wearing) cow को आप क्या कहते हैं?(what do you call)
Final Pun: Sunglasses पहने हुए(wearing) cow को आप क्या कहते हैं(what do you call)? A cool गाय(cow).

Pun Generation Approaches

3. Subject-Masked Pun Generation

- Generate puns by incorporating a subject-masking step,
- The process consists of three key stages:
  - Generating a sentence with A_w
  - Replacing the A_w with P_w
  - Masking and replacement of the subject to add relevance to the pun.

Example

Pun Alternate word pair (P_w, A_w) = (लाख(lakh), luck)

Generated Short Sentence: The man attributed all his success to luck
Replaced Alternate Word: The man attributed all his success to लाख(lakh)
Masked Subject: [MASK] attributed all his success to लाख(lakh)
Final Pun Sentence: The lucky अमीर(rich) businessman attributed all his success to लाख(lakh)

Pun Evaluation Criteria

Pun Success

Binary metric assessing successful incorporation of wordplay (Yes/No).

Funniness

Assessed on a 5-point Likert scale from “Not Funny” to “Hilarious.”

Acceptability

Assessed on 5-point scale from “Definitely Unacceptable” to “Definitely Acceptable and Very Fluent.”

Evaluation Results

Model	Suc(%)	Fun.	Accep.
Contextually Aligned	38.8	2.32	4.32
Question-Answer	62.6	2.59	4.28
Subject-Masked	43	2.24	4.54
Baseline	19.8	2.17	4.48

Tab: Comparison of Success percentage(Suc%), Mean Funniness score rated out of 5(Fun.), and Mean Acceptability score rated out of 5(Accep.) for different pun generation methods

Pun Detection

Task-Specific Fine Tuning

Encoder-based models (e.g., XLM-R, mBERT) fine-tuned for pun detection.

Transfer Learning + Task-Specific Fine Tuning

Encoder-based models continued pre-trained on large scale code-mixed corpora and then fine-tuned for pun detection.

NLI-Based Models

NLI-based models, including BART-nli, were assessed for their capacity to produce sentence embeddings, which may help capture semantic nuances crucial for understanding puns.

Few-Shot Learning

Both decoder-only models and encoder-decoder models were employed using few-shot learning to detect puns leveraging minimal labeled data.

Pun Detection Results

Model	Validation				Test			
	F1	Precision	Recall	Accuracy	F1	Precision	Recall	Accuracy
1. Task-Specific Fine Tuning								
XLM-R (Conneau et al., 2020)	$\mathbf{67.8}_{1.18}$	$\mathbf{69.5}_{1.16}$	$\mathbf{69.0}_{0.96}$	$\mathbf{69.0}_{0.96}$	$\mathbf{67.1}_{1.12}$	$\mathbf{68.0}_{1.14}$	$\mathbf{69.0}_{1.25}$	$\mathbf{69.0}_{1.25}$
mBERT (Devlin et al., 2019)	$65.28_{1.82}$	$65.4_{1.79}$	$66.0_{2.01}$	$66.0_{2.01}$	$63.4_{1.78}$	$63.5_{1.82}$	$64.0_{1.66}$	$64.0_{1.66}$
IndicBERT (Kakwani et al., 2020)	$61.74_{0.73}$	$62.3_{0.71}$	$62.9_{0.83}$	$62.9_{0.83}$	$62.0_{3.11}$	$62.4_{2.77}$	$63.5_{2.59}$	$63.5_{2.59}$
2. Transfer Learning + Task-Specific Fine Tuning								
Hing-mBERT (Nayak and Joshi, 2022a)	$64.5_{2.22}$	$65.3_{1.57}$	$65.2_{1.65}$	$65.2_{1.65}$	$65.1_{1.74}$	$66.4_{0.64}$	$65.4_{2.19}$	$65.4_{2.19}$
Hing-Roberta (Nayak and Joshi, 2022a)	$64.10_{0.30}$	$64.5_{0.56}$	$64.4_{0.24}$	$64.4_{0.24}$	$63.9_{1.25}$	$65.0_{0.81}$	$64.1_{1.46}$	$64.1_{1.46}$
GCM-XLMR (Kodali et al., 2024)	$61.63_{2.00}$	$63.2_{2.12}$	$63.9_{1.59}$	$63.9_{1.59}$	$60.1_{1.27}$	$62.2_{0.69}$	$62.6_{0.63}$	$62.6_{0.63}$
GCM-mBERT (Kodali et al., 2024)	$62.63_{1.22}$	$63.0_{1.56}$	$62.8_{0.71}$	$62.8_{0.71}$	$61.3_{0.70}$	$61.7_{0.98}$	$61.3_{0.48}$	$61.3_{0.48}$
ACL-XLMR (Das et al., 2023)	$64.01_{0.79}$	$64.2_{0.43}$	$64.9_{0.52}$	$64.9_{0.52}$	$63.3_{2.05}$	$63.8_{2.11}$	$64.5_{2.15}$	$64.5_{2.15}$
ACL-mBERT (Das et al., 2023)	$59.97_{3.65}$	$60.4_{3.43}$	$61.6_{3.02}$	$61.6_{3.02}$	$61.3_{2.55}$	$61.7_{2.23}$	$62.6_{1.46}$	$62.6_{1.46}$
3. NLI-Based Models								
BART-large-nli (Lewis et al., 2020)	$64.90_{1.42}$	$65.5_{1.79}$	$66.2_{1.95}$	$66.2_{1.95}$	$62.0_{1.92}$	$62.5_{2.11}$	$63.6_{2.28}$	$63.6_{2.28}$
roberta-large-nli (Liu et al., 2019)	$62.73_{2.29}$	$62.7_{2.40}$	$63.3_{2.76}$	$63.3_{2.76}$	$63.1_{1.59}$	$63.1_{1.65}$	$63.6_{1.27}$	$63.6_{1.27}$
4. Few-Shot Learning								
IndicBART (Dabre et al., 2022)	$54.5_{1.71}$	$54.5_{1.71}$	$55.8_{1.78}$	$55.8_{1.78}$	$53.6_{1.69}$	$53.1_{1.65}$	$53.9_{1.70}$	$53.9_{1.70}$
mBART (Liu et al., 2020)	$55.5_{1.81}$	$55.2_{1.74}$	$54.3_{1.73}$	$54.3_{1.73}$	$54.3_{1.73}$	$54.0_{1.71}$	$54.6_{1.74}$	$54.6_{1.74}$
Llama-3.2-1B (Touvron et al., 2023)	$50.5_{2.09}$	$50.1_{2.46}$	$53.5_{2.09}$	$53.5_{2.09}$	$51.5_{2.98}$	$52.2_{1.85}$	$56.5_{1.89}$	$56.5_{1.89}$
Airavata (Gala et al., 2024)	$51.9_{2.79}$	$51.8_{4.27}$	$56.7_{2.41}$	$56.7_{2.41}$	$60.5_{3.11}$	$60.7_{2.36}$	$61.1_{2.34}$	$61.1_{2.34}$

Tab: Performance comparison of different models for pun detection, grouped by model type

Pun Generation Pipeline

01 **Phonetically Similar Word Selection:**

- Identifies English words phonetically aligned with the input Hindi pun word.
- Utilizes the custom phonetic edit distance metric proposed to select top 5 candidates.

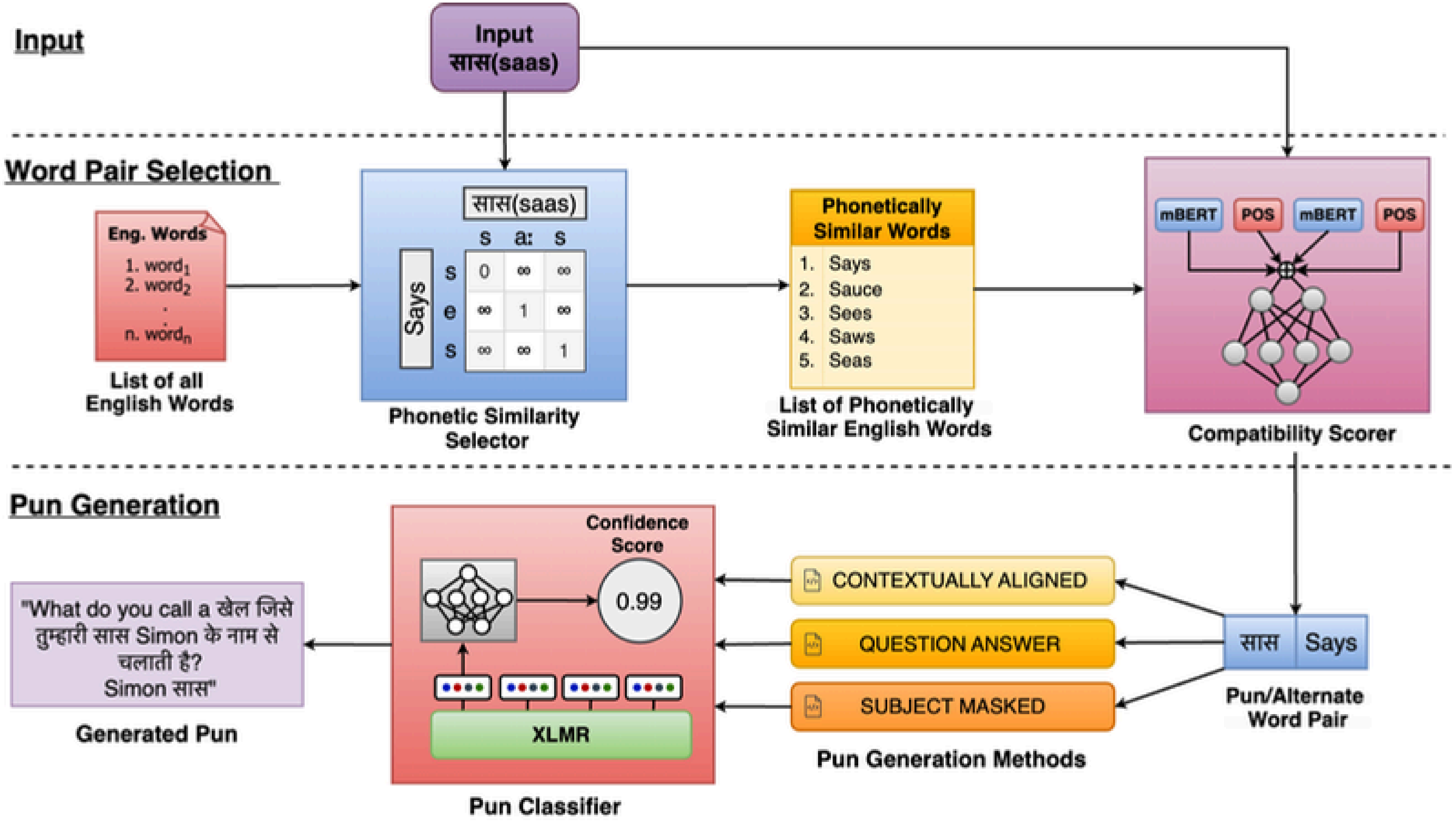
02 **Compatibility Scoring Model:**

- A regression model to compute a compatibility score (0-4) for pun-alternate word pairs.
- Feature set includes:
  - BERT embeddings for P_w and A_w .
  - Part-of-speech tags encoded as one-hot vectors, based on the universal POS tag set

03 **Sentence Generation and Filtering:**

- Generate candidate sentences using obtained word pairs and the three methods described previously.
- Uses XLM-R based pun classifier to filter and select the most effective pun sentence based on confidence score.

Pun Generation Pipeline



Evaluation

- Our pun generation pipeline was compared against a baseline model in which GPT-4o is prompted directly to generate a pun using only the given pun word P_w .
- Annotators were asked to rate the funniness of each output and determine which sentence was the better pun overall.
- Evaluation was done on 50 samples.

Model	Win Rate (%)	Avg. Funniness
Proposed Model	67.65	1.79
Baseline Model	32.35	0.91

Future Work and Limitations

Future Work

- Expand dataset to include other code-mixed language pairs.
- Try advanced frameworks to detect and generate puns.

Limitations

- The reliance on robust models like GPT-4o may be less effective for other low-resource languages
- Challenges in applying this approach to low-resource languages due to unavailable phonetic resources.
- Current focus excludes subword-level puns and complex wordplay.

THANK YOU

For the Attention