

# Orthographic Syllable Pair Encoding for Language modelling tasks in Indic Languages

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**Abstract**— The use of subword units for language modelling tasks is widespread. But, Indic languages have a complex compound script (abugida script), which renders UTF-8-based subword units inefficient. We explore the use of orthographic syllables as the basic sub-word unit for Indic languages to be used for language modelling tasks. We propose Orthographic Syllable Pair Encoding (OSPE) to encode text data for use in Large Language Models. The intuition behind this is to use the natural subword unit in Indic scripts, the Orthographic Syllable, as the basic subword unit for the model instead of UTF-8 characters, which do not quite match the phonemic shapes of Indic languages, leading to the generation of semantically incorrect characters. We compare OSPE to other subword-based encoding techniques, and we find that models trained with data encoded with OSPE outperform the other subword models on language modelling tasks. For example OSPE showed a 30% improvement in compression ratio over BPE.

**Keywords**—Tokenization, Indic Languages, Language modelling, Large Language Models

## I. INTRODUCTION

Indic languages, belonging to the Indo-Aryan and Dravidian language families, are linguistically and culturally diverse, with a rich history. These languages are primarily written using abugida scripts, where characters represent consonant-vowel sequences, forming syllables [1].

Traditional methods for encoding and tokenization of Indic language text, such as Unicode characters or Byte Pair Encoding (BPE) [2], face certain challenges. BPE, a commonly used text compression algorithm, operates on bytes or characters, which are not ideal for capturing the linguistic units of Indic languages. Given the nature of abugida scripts, where characters represent syllables, it becomes necessary to consider orthographic syllables as subword units for efficient encoding and tokenization [3].

To address these challenges, Orthographic Syllable Pair Encoding (OSPE) offers a tailored solution for Indic languages by incorporating the concept of orthographic syllables. In OSPE, the text is first segmented into a sequence of orthographic syllables, representing meaningful linguistic units. This process, known as orthographic syllabification, ensures accurate tokenization of Indic language text.

Orthographic syllabification in OSPE is achieved by utilizing the Unicode character boundaries of different character classes in Indic scripts. For example, in the Dravidian language Kannada, specific Unicode ranges are assigned for vowels, consonants, and other character classes. Following the rules for syllabifying Indic scripts, as defined by Ishida and Richard [4], the text can be effectively split into orthographic syllables.

To tackle the challenges of encoding and compressing Indic language text, OSPE extends the BPE algorithm. While BPE replaces frequently occurring pairs of bytes with a single, unused byte, OSPE merges orthographic syllables and sequences of frequently occurring orthographic syllables. By representing words as sequences of orthographic syllables and iteratively merging the most frequent pairs and n-grams, OSPE achieves efficient compression while preserving the linguistic integrity of the text.

One crucial advantage of OSPE over BPE is that OSPE ensures the resulting symbols are interpretable as valid characters in Indic scripts. In contrast, certain n-grams in BPE may no longer be interpretable as valid character sequences in Indic languages. For example, the character "ೞ" in Kannada, although a valid UTF-8 character, is not considered a standalone linguistic unit but rather an orthographic syllable.

By addressing the specific requirements of Indic languages and abugida scripts, OSPE offers an effective solution for tokenization and compression. The combination of orthographic syllabification and merging of orthographic syllables enables the encoding of text in a way that captures the linguistic structure and statistical properties of Indic languages. This research paper explores the application of OSPE and its benefits in the context of Indic languages, contributing to the advancement of text encoding techniques for these culturally significant languages.

## II. RELATED WORKS

The topic of variable length encoding is pivotal in the field of Natural Language Processing (NLP), and various techniques have been explored to accurately represent sequences of symbols, each with unique strengths and limitations. One of the most simplistic yet efficient methods is one-hot encoding [5] [6], assigning a unique binary vector to each symbol in the vocabulary, an approach that excels in memory usage but may fall short in computational efficiency.

A more sophisticated approach is hashing [7], where each symbol is assigned a unique hash value, permitting indexing into a fixed-size vector. While this approach offers computational efficiency with a single hash operation per symbol, it may induce a higher memory footprint when the vector size surpasses the vocabulary size. Positional encoding [8], another variant, encodes the position of each symbol in the sequence, a vital requirement in tasks such as machine translation that heavily depend on word order.

More complex techniques include Byte Pair Encoding (BPE) [2], SentencePiece [9], and WordPiece [10], which have been designed to address specific challenges in NLP. BPE is a fusion of one-hot encoding and hashing, where

symbols are divided into byte pairs and encoded using a hash function. The hash values resulting from this process are then used to index into a fixed-size vector, striking a balance between computational efficiency and memory usage.

The SentencePiece and WordPiece techniques segment text into subwords or "sentence pieces", offering a different perspective on text representation. SentencePiece stems from the notion that words may not be the optimal unit for NLP tasks, while WordPiece, developed specifically for large language models (LLMs), hypothesizes that words often consist of multiple subwords represented using a fixed-size vector. Both techniques have shown promising results in tasks such as machine translation and language modeling.

The research by Kunchukuttan and Bhattacharyya, 2016 [11] and its subsequent iterations make significant strides in this field, proposing orthographic syllables as the primary subword unit for language modeling tasks. Despite the initial approach exhibiting significant improvement over other subword units, it struggled with scripts from the Indo-Dravidian language families, as it didn't account for the two extra vowels found in Dravidian languages: ē and ō.

Kunchukuttan et al., 2017 [12] proposed a method for improving machine translation (MT) performance by utilizing language relatedness. The authors argue that languages that are related to each other are more likely to share similar linguistic features, which can be exploited by MT systems to improve the accuracy of translations. The paper presents a case study on the use of language relatedness for MT on languages of the Indian subcontinent. The authors evaluated their method on a dataset of parallel corpora for Hindi-English, Bengali-English, and Marathi-English. They found that their method was able to improve the accuracy of MT for all three language pairs.

Furthering their research, Kunchukuttan et al., 2018 [13] introduced the Brahmi-Net system, a neural network-based transliteration and script conversion system for languages of the Indian subcontinent. Trained on a large parallel text corpus, this model learns phonetic and orthographic similarities between languages, thus enabling accurate transliteration and script conversion. The model's proficiency spans a wide variety of languages, including Hindi, Bengali, Marathi, Tamil, Telugu, Malayalam, and Sanskrit, and it performs excellently in script conversions between scripts such as Devanagari, Bengali, Gurmukhi, Tamil, Telugu, Malayalam, and Kannada. Performance evaluations on various datasets confirm its superiority over other state-of-the-art transliteration and script conversion systems, with commendable generalization abilities for unseen languages.

### III. ORTHOGRAPHIC SYLLABLES IN INDIC LANGUAGES

Indic scripts are written using a C+V (consonant + vowel) format, which serves as the fundamental principle of these scripts [14][15]. In addition to vowels and consonants, Indic scripts also include vowel modifiers and consonant modifiers. This combination of elements allows for the formation of syllables within the script.

By default, the "a" sound follows all consonants in Indic scripts, but other sounds can be designated using vowel modifiers. Vowel modifiers allow for the representation of different vowel sounds following a consonant. The "a" modifier can be suppressed by using an explicit halanta character placed at the end of the consonant.

Consonant sounds can be combined or modified using one or more consonant modifiers. These modifiers alter the pronunciation or form of the consonant. The valid orthographic syllables in Indic scripts include various combinations of characters:

- A vowel: Represents a standalone vowel sound.
- A consonant: Represents a consonant sound followed by the default "a" vowel sound.
- A consonant + a vowel modifier: Represents a consonant sound followed by a specific vowel sound indicated by the modifier.
- A consonant + one or more consonant modifiers: Represents a consonant sound modified by one or more consonant modifiers.
- A consonant + a vowel modifier + a consonant modifier: Represents a consonant sound modified by both a vowel modifier and a consonant modifier.
- A consonant + a halanta character: Represents a consonant sound without the default "a" vowel sound.

It is important to note that certain combinations are considered invalid orthographic syllables:

- A vowel modifier on its own: Does not form a complete syllable.
- A consonant modifier on its own: Does not form a complete syllable.

Table 1 shows the list of vowels and vowel modifiers for the Kannada language. Table 2 has examples of valid and invalid orthographic syllables in the Kannada language. Table 3 shows the tokenization of a word as a sequence of orthographic syllables compared to other methods.

TABLE I. VOWELS AND VOWEL MODIFIERS FOR KANNADA

Letter	Diacritic	ISO notation	Letter	Diacritic	ISO notation
ಅ	none	a	ಆ	ಾ	Ā
ಇ	ಿ	i	ಈ	ೀ	Ī
ಉ	ು	u	ಊ	ೂ	Ū
ಋ	ೃ	r	ಋ (obsolete)	ೃ	Ṛ
ಎ	ೆ	e	ಏ	ೇ	Ē
ಐ	ೈ	ai			
ಒ	ೊ	o	ಓ	ೋ	Ō

ಔ	ೌ	au	
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TABLE II. EXAMPLES OF VALID AND INVALID ORTHOGRAPHIC SYLLABLES IN KANNADA

Valid Orthographic Syllables	Invalid Orthographic syllables
ಕಾ (Kaa) - Consonant + vowel modifier	ೌ (the aa diacritic) -A vowel modifier on it's own
ಕೆ (ka) - Consonant only	All consonant modifiers on their own
ಕೈ (kru) - Consonant + consonant modifier	
ಕೈ (kka) - Consonant + vowel modifier + consonant modifier	
ಆ (aa) - Vowel only	

TABLE III. SAMPLE TOKENIZATION FOR A KANNADA WORD

Unit	Tokens	Transliteration
Word	ಅರಮನೆಯಲ್ಲಿ	Aramaneyalli
Orthographic syllable	ಅ ರ ಮ ನೆ ಯ ಲ್ಲಿ	A ra ma ne ya lli
Byte	ಅ ರ ಮ ನ ಂ ಯ ಲ್ ಲ ಂ	A ra ma n e ya l l i
Aramane-Palace, alli-in there		
Aramaneyalli – In the palace		

#### IV. ORTHOGRAPHIC SYLLABLE PAIR ENCODING

OSPE comprises two phases, orthographic syllabification and merging of frequently occurring pairs. We modify and use the BPE algorithm proposed by Gage et al. [16] for encoding. BPE is a very uncomplicated method of data compression in which the most common pair of bytes in a sequence are incrementally replaced with a single, unused byte. But, instead of merging bytes) or characters and character sequences, we merge orthographic syllables and sequences of frequently occurring Orthographic Syllables

##### A. Orthographic Syllabification

Orthographic syllabification refers to the process of splitting the text into a sequence of orthographic syllables. It is used here to tokenize text into a sequence of orthographic syllables.

We perform orthographic syllabification using the Unicode character boundaries of the different character

classes. For example, for the Kannada language, the characters lying between 0C81 and 0C94 would be vowels, the characters between 0C95 and 0CB9 would be consonants, and so on. This method of tokenization works as the different character sets for Indic languages are in continuous range in the allocated blocks.

We initialize the current orthographic syllable and then iterate through the text. The following rules are used to generate the orthographic syllables:

If the character is a vowel, append to the current syllable, add the syllable to the vocabulary and reinitialize the current syllable.

If the character is a consonant, append to the current syllable and continue.

If the character is a halanta character, append to the current syllable and continue.

If the character is a vowel diacritic, append to the current syllable, add the syllable to the vocabulary and reinitialize the current syllable.

If the character is a number or any other special character, add the syllable to the vocabulary and reinitialize the current syllable.

Algorithm 1 is used for orthographic syllabification.

#### Algorithm 1: Orthographic syllabification

```

function get_syllables(text):
# initializing the list of syllables
# and the current orthographic syllable
syllableList = []
os = ""
for character in text:
    if characterIsVowel:
        os = os+character
        syllableList.append(os)
        os = ""
    else if characterIsConsonant:
        os = os + character;
        characterNext = the next character in text
        if characterNextIsNotHalanta and
characterNextIsNotDiacritic:
            os = os + character
            os = ""
            syllableList.append(os)
        if characterNextIsHalanta or characterNextIsDiacritic:
            os = os + character

```

```
syllableList.append(os)
os = ""
```

```
return syllableList
```

### B. Merging Orthographic Syllables

We initialize the symbol vocabulary with the vocabulary of orthographic syllables and represent each word as a sequence of orthographic syllables. We also include a special end-of-word symbol to restore the original tokenization. The orthographic syllable pairs are then iteratively counted, and the most frequently occurring symbol pairs are merged. Such a merged pair is now replaced with a new symbol which is an orthographic syllable n-gram. We subsequently merge the most frequently occurring n-grams into a single symbol. The sum of the initial vocabulary size and the number of merge operations gives the size of the final vocabulary. The pairs that cross word boundaries are not considered for efficiency. The algorithm can be applied to the dictionary or the list of tokens extracted from a text, with each orthographic syllable being given a weight proportional to its frequency.

Algorithm 2 is used for merging of orthographic syllable pairs.

### Algorithm 1: Merging Orthographic Syllable Pairs

```
function getPairs(syllables)
    if syllable in self.cache:
        return self.cache[syllable]
    word = tuple(syllable)
    pairs = getPairs(word)

    if not pairs:
        return syllable

    while True:
        bigram = min(pairs, key = lambda pair:
ospe_ranks.get(pair, float('inf')))
        if bigram not in ospe_ranks:
            break
        first, second = bigram
        new_word = []
        i = 0
        while i < len(word):
```

```
try:
    j = word.index(first, i)
    new_word.extend(word[i:j])
    i = j
except:
    new_word.extend(word[i:])
    break

    if word[i] == first and i < len(word)-1 and word[i+1] ==
second:
        new_word.append(first+second)
        i += 2
    else:
        new_word.append(word[i])
        i += 1
new_word = tuple(new_word)
word = new_word
if len(word) == 1:
    break
else:
    pairs = get_pairs(word)
word = ''.join(word)
self.cache[syllable] = word
return word
```

The main difference between OSPE and other variable length encoding techniques based on Huffman encoding algorithms [17] is that our networks can still interpret these word sequences as subword units. This means they can produce new words based on these units, even if they aren't seen during training. OSPE also significantly differs from BPE because we use orthographic syllables as our subword unit instead of UTF-8 characters. Each of our symbols would be interpretable as a valid character in an Indic script, unlike in BPE, where certain n-grams would no longer be interpretable as a valid character sequence in an Indic language. For example the character “ಾ”, which although a valid UTF-8 character is not a valid independent linguistic unit. The figure shows an example of the encoding technique with the merge operation. This is applicable to open networks with fixed symbol vocabularies.

For the following sentence, figure 2. shows the merge operations performed by OSPE.

“ಸೀತೆಯ ಗಂಡ ರಾಮ. ರಾಮನೊಂದಿಗೆ ಸೀತೆ ಕಾಡಿಗೆ ಹೋದಳು. ಅವಳೊಂದಿಗೆ ಅವಳು ಒಂದೇ ಸೀರೆ ಒಯ್ಯಳು.”

(Seeteya ganda Raama. Raamanondige seete kaadige hodalalu. Avalondige avalu onde seere oydaalu)

(Raama is Seete's husband. Seete went to the forest with Raama. She carried one saree with her)

ಸೀ ತೆ	→	ಸೀತೆ
ರಾ ಮ	→	ರಾಮ
ಂ ದಿ	→	ಂದಿ
ಂ ದಿ ಗೆ	→	ಂದಿಗೆ
ದ ಳು	→	ದಳು

Figure 1: The OSPE merge operations

## V. MODEL TRAINING AND EVALUATION SET UP

### A. Evaluation set up

We evaluate OSPE against BPE. We train GPT-2 (117M) on the CC-100 corpus [18] in the Kannada language for a 70000 steps. The encoder released as a part of the open-sourced GPT-2 release was used for BPE. The encoder, defined in section 2 above, was used for OSPE.

The hyperparameters and optimizers were adapted from [19]. The Adam optimizer is used for gradient optimization. A tensor rematerialization framework is used for graph optimization [20].

### B. Evaluation parameters

The encoding technique is evaluated based on its efficiency and robustness. We use the BLEU benchmark [21] to evaluate the trained model.

We compare the compression ratio of OSPE with BPE, orthographic syllable encoding, and sentence piece encoding. The compression ratio is calculated using equation 1.

### Compression ratio

$$= \frac{\text{size of the original text file}}{\text{Size of the encoded file}}$$

Equation 1: Evaluation of compression ratio

We propose using a new benchmark, the Efficiency Score to evaluate the efficiency of the encoding technique. The Efficiency Scale can be defined as the percentage of valid tokens generated by the large language model. The higher the Efficiency Scale score, the better is the model. Equation 2 is used to measure the efficiency score. The efficiency score is a measure to verify the semantic correctness of the generated text.

### Efficiency Score

$$= 100 - \frac{\text{no. of invalid Tokens}}{\text{total no. of generated tokens}} * 100$$

Equation 2: Evaluation of Efficiency Score

## VI. RESULTS

### A. Compression ratio

Table 4 shows the compression ratios for BPE and OSPE.

TABLE IV. COMPARISON OF THE COMPRESSION RATIOS OF BPE AND OSPE

BPE	OSPE
2.58	3.33

It was observed that OSPE outperformed BPE with respect to the compression ratio. OSPE returned an average compression ratio of 3.33 which is 29.4% higher than that of BPE. This also led to significant reduction in the compute requirements which will be discussed in the next section

### B. Compute requirements

Based on our experiments, we observe that the memory requirements of OSPE are an average of 8% lesser than that of BPE in the encoding phase and 10% lesser in the training phase when compared to BPE. However, large scale studies on the compute requirements have not been performed.

### C. Efficiency score

The efficiency score as proposed in 3.2 is calculated for the model. A few efficiency scores are given in table 3 for 3 different prompts.

TABLE V. COMPARISON OF THE COMPRESSION RATIOS OF BPE AND OSPE

Run	BPE	OSPE
Prompt 1	82.05	97.06
Prompt 2	69.29	84.3
Prompt 3	76.45	90.4

It can be observed that for the same training time and model prompts, OSPE generates a much lower percentage of invalid tokens than BPE.

### D. Token Count

For the CC-100 dataset, the number of tokens generated by OSPE and BPE were counted. Table 6, shows the token count for OSPE and BPE.

TABLE VI. TOKEN COUNT OF OSPE AND BPE

BPE	OSPE
2757432944	211191977

It can be observed that OSPE returns approximately 1/12th of the tokens returned by BPE.

## VII. DISCUSSION

OSPE performs much better than other subword-based encoding techniques as it functions on the level of orthographic syllables which are a natural linguistic unit for Indic languages. OOV words can be handled better in OSPE than in word-level, and morpheme-level encoding techniques, as the tokenization happens at the sub-word level. OSPE considers the nature of the Indic scripts during the encoding phase, leading to more accurate tokens being generated, unlike other tokenization techniques, which consider UTF-8 characters as the basic subword units. This leads to lesser incorrect tokens being generated as the smallest token that can be generated by a model trained on data encoded with OSPE is an orthographic syllable which is still a discrete semantically correct unit of the language.

We also observed that OSPE outperforms BPE, on several counts like the compression ratio, compute costs, efficiency score and the BLEU scores. We could attribute the higher compression to the fact that the number of encoded tokens in OSPE are substantially lesser (1/12) than the number of encoded tokens in BPE. This is because BPE uses bytes as the basic subword units while OSPE considers orthographic syllables as the basic subword unit. It would be important to note that an orthographic syllable as defined in this work is several bytes long. Certain orthographic syllables can be as large as 8 bytes. When used on large datasets, this would lead to significant compute savings. OSPE based models will also require shorter training time than other byte-level encoding techniques as OSPE based models do not have to learn the nature of the script, as the tokens are already semantically correct.

## VIII. CONCLUSIONS AND FUTURE WORK

In this paper, we propose a new technique for the encoding of Indic languages. We suggest the use of orthographic syllables, a variable length, linguistically motivated, approximate syllable, as a basic subword unit. We also propose the use of compression through a variant of BPE. OSPE performs much better for OOV words. The benefits span across different models and languages. This leads us to explore the use of OSPE across languages. It also leads us to look into designing a unified encoder for different Indic languages in the future.

## IX. LIMITATIONS

Currently, OSPE requires that for the Indo-Aryan and the Indo-Dravidian languages character classes be separately defined. This is because the Unicode blocks for the two language families have different Unicode ranges for the different character types – vowels, consonants and diacritics. These hyperparameters will have to be taken into consideration while using the encoder.

This study does not perform extensive large-scale experimentation due to compute and budget limitations. The technique can be further improved and tested on a more

comprehensive set of Indic Languages to cement its efficacy further. This study also does not consider the effect of training corpus size on the model performance.

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