

A Higher-Order N-gram Model to enhance automatic Word Prediction for Assamese sentences containing ambiguous Words

M.P. Bhuyan, S.K. Sarma

Abstract: Word prediction is a technique which tries to suggest the users' words after knowing the few input letters of the user. This predictive model also tries to generate the future words or next words of a sentence by observing earlier words of the sentence. In this research, two problems are combined, one is word prediction and the next is handling of ambiguous words. A word prediction model predicts the future words of a sentence by using n-gram based model. In general, predictive models use unigram, bigram or trigram models to predict the next words. In case of sentences consisting of ambiguous words, the predictive model by using only bigram or trigram cannot perform well to predict the next words. To enhance this prediction for ambiguous words, maximum of six previous input words are observed and try to predict almost the exact words after the ambiguous words in those particular contexts. Different level of experiments are done and the results are compared for modified or enhanced prediction model with the traditional prediction model, improvement on accuracy and failure rate are found in the enhanced model. The accuracy of the Traditional Model is 60.68% on the hand the accuracy of the Enhanced Model is 66.88%. The failure rate of the Traditional Model is 32.35% and the Enhanced Model is 29.17%.

Keywords: N-gram, ambiguous words, word prediction.

I. INTRODUCTION

Assamese is an official language of India which is used in the north-east part of the country; the language is spoken by nearly 30 million people. Assamese language belongs to the Indo-European language family [1]. There are large numbers of newspapers, magazines, books, etc. are available in Assamese. But, the language is not getting very much focuses in the digital world, i.e. the resources of Assamese language are not easily available to process electronically. Importance of the word prediction model is to increase the productivity or throughput of a user who has typing speed below the average speed so that the user should not annoyed with the computer-system to type his text.

Word Sense Disambiguation (WSD) is a technique to resolve the lexical level of ambiguity of a word i.e. the word which has multiple meaning. It is found that every language has some words which have multiple meanings, because of having multiple meanings the traditional predictive model

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with low context memory will predict some unrelated words with higher probability and the actual word may not be predicted at the first time. This research aims to find the exact next words after the ambiguous word with high probability. Let us consider an Assamese ambiguous word আদি(aadi)

Sentence₁ = তেওঁৰ কথাৰ কোনো আদি অন্ত নাই | (Teor Kothar Konu Aadi Onto Nai), In English the sentence is: *His words do not have any beginning and ending* here the ambiguous word আদি(aadi) is used as *starting*.

Sentence₂ = ল'ৰা আৰু ছোৱালী আদিয়েই হ'ল ইয়াৰ উদাহৰণ | (Lora Aaru Sowali aadiEi hol Iyaar UdaHoron), In English the sentence is: *Boys and girls etc. are the example of this.* Here the ambiguous word আদি (aadi) is used as *etc*.

Assamese is a morphologically rich language and free word order, so, it is very difficult to process the language. There are many critical grammar rules in the language that are very difficult to follow while writing. That is why it is necessary to have a prediction model in Assamese to assist the users.

The rest of the paper is organized as follows: *Section 2* describes the related works, *Section 3* describes the word prediction model, *Section 4* analyzes and discusses about the experimental result and *Section 5* concludes the work and highlight the future direction of this research.

II. RELATED WORKS

In [2], authors have used N-gram language models like unigram, bigram, trigram, deleted interpolation and backoff model to generate prediction for Bangla language. They have used these models and tested at different levels with a corpus of size 0.25 million words to predict the next word in Bangla, 100 sentences are tested with length varies from 5 to 20 and the average accuracies are found:- 21.24%, 45.84%, 63.04%, 63.50%, 62.86% for unigram, bigram, trigram, backoff and deleted interpolation model respectively.

In [3], authors have said that word prediction and completion are helping the people with disability of typing and also automatic word prediction can help the new learners, students etc. by providing the correct word to complete the sentence. The n-gram models like Unigram, Bigram, Trigram, Backoff and Linear interpolation models are compared for accuracy and failure rate. Linear interpolation model is found better than the all other models and another experiment is done to find the optimum prediction list length, which is obtained as 7 along with the accuracy of prediction.

In [4], authors have used an N-gram model to predict word for Assamese language using Unigram, Bigram, Trigram, Quadrigram language models. Keystrokes saving values are tested for these models for both in-domain data and users' data, and the maximum keystrokes saving is found 74.04% and 48.28% for in-domain data and users' data.

In [5], authors have used a hybrid word suggestion model based on Naive Bayes and Latent Semantic Analysis (LSA) and the accuracy achieved is 44.2%, Naive Bayes method uses conditional independent variables which requires less memory and computation power, however Naive Bayes becomes worst because of knowledge loss due to independent assumption; LSA uses techniques to analyze text and try to find relationship among the words at different levels like paragraph, phrase etc. to store the relationship, a relationship table is designed and which stores the frequency of a word w_i appeared in the context of the word w_j . To control the size of relationship table Singular Value Decomposition (SVD) method is used.

In [6], authors have described a predictive form fill-up system depending on the past history of the user so that the amount of time required to fill the form is reduced, model tries to predict sequence of entries of a form not only the current filed entry.

In [7], authors have proposed an exponential interpolation model which combines a Part Of Speech (POS) based language model and an n-gram based language model. They have found the improvement in keystroke saving, perplexity and also the hit rate over traditional n-gram and interpolation model. They have tested their model for Spanish, Portuguese and English. In all the three languages their proposed model has shown significant level of improvement in hit rate, keystrokes saving and perplexity.

In [8], authors have described the problem of large sized language models for on-device keyboards. These large sized language models would cause an overhead for the system to perform the computations. They have proposed on-device neural language model by optimizing the run time memory. Their model size is 7.40MB and the average prediction time is 6.47ms. They claimed that their proposed model was able to show improvement in comparison with the existing methods in terms of keystrokes savings and word prediction rate.

In [9], authors have designed a tool called LuitPad to write Assamese efficiently. They have used two methods to complete a word; first one is by predicting the next character after knowing the previous characters and the second one is a unigram method which generates the current words using the knowledge of previous words. But their method is not able to produce the future words (next words) for the users.

In [10], authors have described an error detection and correction model for Assamese words using n-gram models, like unigram, bigram, and trigrams. They have designed a score based system for each character or letter of Assamese alphabets. In their model they have focused on the point of error in Assamese words and generate the relevant character(s) as suggestion. Their model is basically for the learners' Assamese language and students of Assamese medium schools.

From the above discussion it is seen that the word

prediction model are useful in any language and workings are going on not only the English language but also the local languages like Bangla and other languages, so it will be very much helpful if such types of accurate predictive models are designed for Assamese language. In addition, this research work will also enhance the work done by Bhuyan and Sarma in [4] which is the only work in Assamese to predict words while writing, and also, able to bring a new direction in the field of Assamese writing software or tools.

III. WORD PREDICTION MODEL

N-gram based models are used to predict the next word in a sentence, generally this N-gram model observe the previous all words and suggest the next word; for example: "There is no student in the _____," here in this example the blank space can be filled up by the word 'class' or 'college' or 'school', etc. This process of filling the unknown word by human is a very common task, a human can fill such blank position by observing the previous words of the sentence and the same process of filling the blank space can be taught to machine but a machine does not have infinite memory, so the machine cannot remember all the previous words, so fraction of the previous words are used to predict the next word, for that, N-gram model is reduced to Unigram, Bigram, Trigram model etc. In addition, N-gram model is a probabilistic model which primarily depends on Hidden Markov Model (HMM). In this research N-gram models like Unigram, Bigram, and Trigram are used to predict the next word, Bigram model is known as the 1st order Markov model and Trigram model is known as the 2nd order Markov model. Moreover, in this research to avoid the words having zero probability, a smoothing technique called Katz's backoff model is used which helps to overcome the zero final probability of a sentence. In general, a smoothing technique plays a vital role in such predictive models.

Let us consider the following sentence and understand how the predictive model works:

sentence_i = মই এজন ল'ৰা উত্তৰ ফালে যোৱা দেখিছো | (*Moi Ejon Lora Uttar Fale JooAa Dekhiso meaning is I have seen a boy going towards North*)

In the above example the word উত্তৰ (uttar) is ambiguous which means *North* in this context. Following process explains how the probabilities are calculated in the traditional word-prediction model.

Unigram model:

$$p(\text{sentence}_i) = p(\text{মই}) \times p(\text{এজন}) \times p(\text{ল'ৰা}) \times p(\text{উত্তৰ}) \times p(\text{ফালে}) \times p(\text{যোৱা}) \times p(\text{দেখিছো})$$

Bigram model:

$$p(\text{sentence}_i) = p(\text{মই}) \times p(\text{এজন} | \text{মই}) \times p(\text{ল'ৰা} | \text{এজন}) \times p(\text{উত্তৰ} | \text{ল'ৰা}) \times p(\text{ফালে} | \text{উত্তৰ}) \times p(\text{যোৱা} | \text{ফালে}) \times p(\text{দেখিছো} | \text{যোৱা})$$

Trigram model:

$$p(\text{sentence}_i) = p(\text{মই}) \times p(\text{এজন} | \text{মই}) \times p(\text{ল'ৰা} | \text{মই এজন}) \times p(\text{উত্তৰ} | \text{এজন ল'ৰা}) \times p(\text{ফালে} | \text{ল'ৰা উত্তৰ}) \times p(\text{যোৱা} | \text{উত্তৰ ফালে}) \times p(\text{দেখিছো} | \text{ফালে যোৱা})$$

In the modified or enhanced word prediction model if the system encounters an ambiguous word then from that point the model will look back maximum five previous contexts and using these five previous contexts words the system tries to generate the next suggestion after the ambiguous word. On the other hand, if the five previous words fail to produce the next word then the system reduces the context and uses four previous contexts words to generate the next word and so on. The probability evaluation process for the enhanced model is given below:

Trigram model in the enhance version:

$$p(\text{sentence}_i) = p(\text{মই}) \times p(\text{এজন} \mid \text{মই}) \times p(\text{লাৰা} \mid \text{মই এজন}) \times p(\text{উত্তৰ} \mid \text{এজন লাৰা}) \times p(\text{ফালে} \mid \text{মই এজন লাৰা উত্তৰ}) \times p(\text{যোৱা} \mid \text{উত্তৰ ফালে}) \times p(\text{দেখিছো} \mid \text{ফালে যোৱা})$$

In the above calculation, to predict the next word after the ambiguous word উত্তৰ (*uttar*) all the previous context (*quadrigram contexts*) is searched and the next word ফালে (*FaaLe*) is predicted with a higher probability in comparison with the earlier traditional word-prediction model. If this enhanced model fails then the prediction will go back to the traditional model by reducing the contexts. Actually, the enhancer is on the top of the traditional model to handle such type of ambiguous words. Following *Algorithm-1* and *Algorithm-2* describes the predictive model and enhanced module.

unigram_db = unigram database
bigram_db = bigram database
trigram_db = trigram database
quadrigram_db = quadrigram database
5_gram_db = 5-gram database
6_gram_db = 6-gram database
SL = suggestion list
predictive_model = word prediction model
enhance_model = enhance model for ambiguous words
 w_i = word selected from the *SL* list.
 w_u = word formed using *unigram_db*
 w_b = word formed using *bigram_db*
 w_t = word formed using *trigram_db*
 w_q = word formed using *quadrigram_db*
 w_{ambg} = ambiguous word.
 # = used to comment lines
 + = used to concatenate

Algorithm-1: Predictive Model

Step-1:

- 1.1 $w_u = ''$ #empty string
- 1.2 Input a letter 'L' in $w_u = w_u + L$.
- 1.3 Generate six most frequent words starting with 'L' in a suggestion list *SL* using *unigram_db*.
- 1.4 If the users' word appear in the *SL* list then select the word w_i from *SL* list and $w_u = w_i$ goto *Step-2*.
- 1.5 If the users' word does not appear in the suggestion list goto *Step-1.1* and input more letters or go to *Step-2* skipping the suggestion part.

Step-2:

- 2.1 Using w_u obtained in *Step-1* and the *bigram_db* the predictive model tries to generate the next word w_b , display the suggestion list *SL* with six most frequent words in the context of w_u .
- 2.2 If the users' word appear in the *SL* list then select the word w_i from *SL* list and $w_b = w_i$ goto *Step-3*.
- 2.3 If the users' word does not appear in the suggestion list or the *SL* is empty then goto *Step-1.1* and input more letters to form w_b , after getting w_b goto *Step-3*.

Step-3:

- 3.1 Using w_u and w_b obtained in *Step-1*, *Step-2* and the *trigram_db* the predictive model tries to generate the next word w_t , display the suggestion list *SL* with six most frequent words in the context of w_u and w_b .
- 3.2 If the users' word appear in the *SL* list then select the word w_i from *SL* list and $w_t = w_i$ goto *Step-4*.
- 3.3 If the users' word does not appear in the suggestion list or the *SL* is empty then goto *Step-1.1* and input more letters to form w_t , after getting w_t goto *Step-4*.

Step-4:

Repeat *Step-1* to *Step-3* to form the sentence.

Following algorithm describes how the enhance model works along with the predictive model.

Algorithm-2: Enhancing procedure for the Ambiguous words

Step-1:

- 1.1 An ambiguous word $w_i = w_{ambg}$ is detected while constructing a sentence.
- 1.2 Use $\langle w_{i-5}, w_{i-4}, w_{i-3}, w_{i-2}, w_{i-1}, w_{ambg} \rangle$ maximum six previous context by using *6_gram_db* to get accurate next word(s) w_{i+1} after $w_i = w_{ambg}$ in the *SL* list. If *SL* is empty then goto *Step-1.3*
- 1.3 Use $\langle w_{i-4}, w_{i-3}, w_{i-2}, w_{i-1}, w_{ambg} \rangle$ maximum five previous context by using *5_gram_db* to get accurate next word(s) w_{i+1} after, $w_i = w_{ambg}$ in the *SL* list. If *SL* is empty then goto *Step-1.4*
- 1.4 Use $\langle w_{i-3}, w_{i-2}, w_{i-1}, w_{ambg} \rangle$ maximum four previous context by using *quadrigram_db* to get accurate next word(s) w_{i+1} after, $w_i = w_{ambg}$ in the *SL* list. If *SL* is empty then goto *Step-1.5*
- 1.5 Use $\langle w_{i-2}, w_{i-1}, w_{ambg} \rangle$ maximum three previous context by using *trigram_db* to get accurate next word(s) w_{i+1} after $w_i = w_{ambg}$ in the *SL* list. If *SL* is empty then goto *Step-1.6*
- 1.6 Use $\langle w_{i-1}, w_{ambg} \rangle$ maximum two previous context by using *bigram_db* to get accurate next word(s) w_{i+1} after $w_i = w_{ambg}$ in the *SL* list. If *SL* is empty then goto *Step-2*.

Step-2: If unable to find the word w_{i+1} after $w_i = w_{ambg}$ then goto *Step-1* of **Algorithm-1**.

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For the experimental purpose, a mixed set of corpus is used which contains sentences of ambiguous words as well as the other common sentences. The system is trained with a corpus of size nearly 250,000 words. If the prediction model is tested with new sentences the predictive models tries to predict 5 relevant words as the next word considering the previous context using bigram and trigram for unambiguous words and for ambiguous words quadrigram, 5-gram and 6-gram are also used as enhancement module.

IV. RESULT AND DISCUSSION

In the following *Table-I* a portion of the list of Assamese ambiguous words and their meanings are given which are used in the predictive model as part of the corpus data.

Table- I: List of ambiguous words and their meanings

Words	Ambiguous words	Meaning-1	Meaning-2
W01	উত্তৰ (uttar)	answer	north
W02	আদি (aadi)	starting	etc.
W03	কল (kol)	banana	factory
W04	ঘৰ (ghar)	house	quadrangle
W05	অংক (ongko)	numeric values, maths	an act of drama
W06	অর্থ (ortho)	meaning	money
W07	আচল (aasol)	the root form	the end portion of a wearing cloth
W08	আচাৰ (aachar)	behavior	pickle
W09	কলা (kola)	cultural related	deaf
W10	কাতি (kaati)	seventh month of Assamese calender	inclined
W11	পদ (pod)	designation	the act of singing vocal music
W12	মালিক (maalik)	God	owner
W13	ফল (fol)	result	fruit
W14	গুণ (goon)	characteristics	multiple
W15	মূৰ (moor)	head	boundary
W16	কাপ (cup)	trophy	cup
W17	কান্নি (kaani)	opium made for smoking	cloths
W18	কবি (kobi)	poet	A vegetable

A. Performance Measure-1

18 sentences are tested for different ambiguous words which are shown in *Table-I*. From the table it is clearly visible that the Enhanced Model is able to increase the sentence

probability. On the other hand, the Traditional Model is treating these ambiguous words as the other common words.

Table-II: Comparison of sentence probability between the traditional and enhanced word prediction model

Sentences	Ambiguous words	Sentence Probability (Traditional Model)	Sentence Probability (Enhanced Model)	Improvement (no. of times)
S01	উত্তৰ	4.243E-5	2.354E-4	5.55
S02	আদি	5.241E-5	7.533E-5	1.44
S03	কল	1.342E-6	4.284E-6	3.19
S04	ঘৰ	3.021E-5	6.124E-5	2.03
S05	অংক	4.102E-6	4.102E-6	1.00
S06	অর্থ	5.231E-7	5.231E-7	1.00
S07	আচল	3.248E-5	7.102E-5	2.19
S08	আচাৰ	2.701E-6	6.705E-6	2.48
S09	কলা	8.745E-6	1.637E-5	1.87
S10	কাতি	2.341E-5	2.341E-5	1.00
S11	পদ	5.241E-5	2.143E-4	4.09
S12	মালিক	6.208E-6	7.214E-6	1.16
S13	ফল	4.219E-5	2.874E-4	6.81
S14	গুণ	7.125E-5	8.245E-5	1.16
S15	মূৰ	4.433E-6	6.714E-6	1.51
S16	কাপ	7.112E-6	7.112E-2	1.00
S17	কান্নি	2.401E-7	2.401E-7	1.00
S18	কবি	7.651E-6	3.214E-5	4.20

The probability values and the improvement of the sentence probability values in number of times are shown in the above *Table-II*. To visualize the outcome and the performance more clearly, the improvement result obtained in the experiment are plotted graphically as shown in the above Fig.1. For the sentences: S01, S03, S11, S13, and S18 the improvement is relatively higher than the other sentences. The sentence S13 is showing the highest improvement among the all sentences with the ambiguous word 'ফল' (Fol means Fruit) and the present trained corpus. The sentences: S02, S04, S07, S08, S09, S12, S14, S15 the enhanced model is showing little moderate result and finally for few ambiguous words for the sentences: S05, S06, S10, S16, S17 the enhanced-prediction-model is unable to improve the performance, there are two reason for this non-performance, either the word is not found in the corpus or the position of the word in the sentence (i.e. the context for the word is not more than the trigram). In such situation the enhanced-prediction-model will fall to the trigram model, recalling the concept, this enhanced-prediction-model is working on the top of the traditional trigram model so once

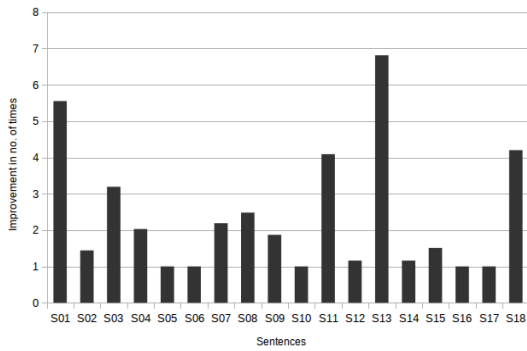


Fig.1. Comparison of sentence probability between the traditional and enhanced word prediction model

the enhanced-prediction-model fails the predictive system will work like the traditional trigram model.

B. Performance Measure-2

The performance of the predictive model can be evaluated using accuracy and failure rate of prediction.

$$Accuracy = \frac{(L+1) - i}{L} \times 100\% \quad (1)$$

Where L is the length of the prediction list and i is the position where the intended word is appeared.

$$FailureRate = \frac{F}{P} \times 100\% \quad (2)$$

Where F is the number of times system fails to predict the intended word out of P predictions [3]. The same 18 sentences are tested in this experiment and the results are shown in the Table -III.

Table-III: Accuracy and Failure rate of the prediction models

Sentence s	Ambiguous words	Accuracy		FailureRate	
		Traditional Model	Enhanced Model	Traditional Model	Enhanced Model
S01	উত্তর	57.16	72.34	32.36	22.41
S02	আদি	62.41	65.23	30.12	30.12
S03	কল	54.23	64.38	35.22	31.47
S04	ঘর	56.71	61.28	32.54	28.74
S05	অংক	62.35	62.35	31.25	31.25
S06	অর্থ	73.14	73.14	27.35	27.35
S07	আচল	61.41	68.25	32.39	29.14
S08	আচার	62.17	66.74	34.56	28.34
S09	কলা	59.31	63.49	30.14	31.55
S10	কাতি	58.71	58.71	36.54	36.54
S11	পদ	54.57	73.22	35.14	24.75
S12	মালিক	58.88	64.45	31.24	31.24
S13	ফল	61.12	75.41	35.21	21.14
S14	গুণ	61.14	65.24	31.25	30.74
S15	মূর্ষ	58.41	62.39	33.76	30.81
S16	কাপ	72.48	72.48	28.36	28.36

S17	কানি	64.18	64.18	30.25	30.25
S18	কবি	53.94	70.61	34.54	30.86
Average		60.68	66.88	32.35	29.17

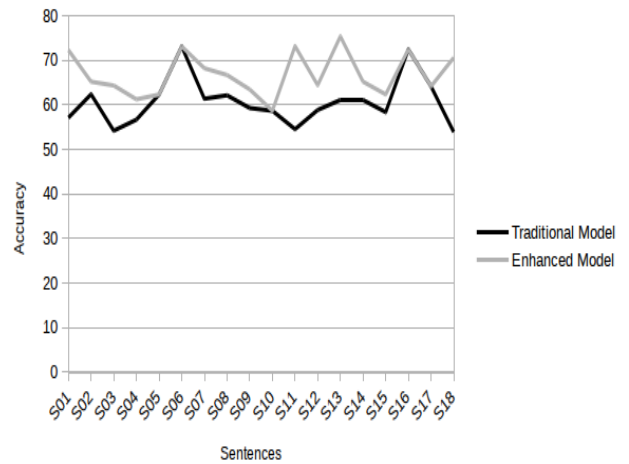


Fig.2. Comparison of accuracy between the traditional and Enhanced word prediction Model

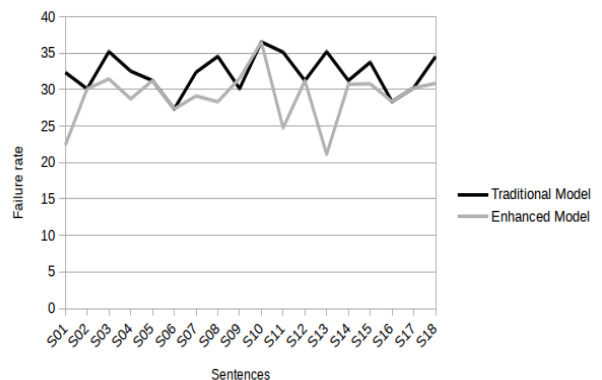


Fig.3. Comparison of failure rate between the Traditional and Enhanced word prediction Model

From the above experiment, it is seen that the enhanced model is performing better than the traditional model for both accuracy and the failure rate. For the sentences: $S05, S06, S10, S16, S17$ both the traditional and enhanced models are showing similar accuracy and failure rate, in reality, for these sentences prediction system is unable to enhance the accuracy and failure rate, this is due not having sufficient context or the ambiguous words may not present in the corpus. From the Fig.2 it can be clearly visualized that the accuracy of the enhanced model is higher than or equal to the traditional model and from Fig.3 it can be easily identified that failure rate of the enhanced model is lower than the traditional model.



V. CONCLUSION AND FUTURE WORK

Word prediction model will help the people who type in Assamese by increasing the productivity of the users. Moreover, the model will also help the differently-abled persons. From the above experiments it is cleared that the enhanced model is able to improve the probability of prediction, accuracy and the failure rate in most of the cases and also this enhanced-prediction-model is an additive to the original model so it will not degrade the performance if it fails to improve the performance. Thus, the Enhanced Model will definitely purify the prediction result for the ambiguous words.

In the future, the same ambiguous words can be tested by placing the word at different positions in the sentences where they can be placed without losing the meaning of the sentence, this placing can be done in Assamese because of its free word order property and the performance of the system can be evaluated again. For all the ambiguous words more number of sentences can be included in the corpus. For both the two models time required to generate the prediction for relatively longer sentences can be evaluated. Lastly, to measure the real-time performance of the system computer typist of Assamese language shall be asked to test the present predictive model.

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REFERENCES

1. G C Goswami. 1982. "Structure of Assamese", Gauhati University, Assam Guwahati, Assam.
2. M. Haque, M. T. Habib, and M. M. Rahman, "Automated word prediction in Bangla language using stochastic language model," *International Journal in foundation Computer Science & Technology (IJFCST)*, vol. 5, Nov. 2015.
3. Md. Tarek Habib , Al-Mamun Abdullah, Rahman Md. Sadekur, Shah Md. Tanvir Siddiquee and Ahmed Farruk, "An Exploratory Approach to Find a Novel Metric Based Optimum Language Model for Automatic Bangla Word Prediction," *International Journal of Intelligent Systems and Applications (IJISA)*, Vol. 10, pp 47-54, February 2018.
4. M. P. Bhuyan & S.K. Sarma, "An N-gram based model for predicting of word-formation in Assamese language," *Journal of Information and Optimization Sciences*, 40:2, 427-440, DOI: [10.1080/02522667.2019.1580883](https://doi.org/10.1080/02522667.2019.1580883).
5. H.X. Goulart, M.D. Tosi , D.S. Gonçalves, R.F. Maia, & G.A. Wachs-Lopes. "Hybrid Model For Word Prediction Using Naive Bayes and Latent Information," CoRR, abs/1803.00985.
6. L. Troiano, C. Birtolo, & R. Armenise, *Soft Comput* (2017) 21: 1583. <https://doi.org/10.1007/s00500-015-1870-7>.
7. D. C. Cavalieri, S. E. Palazuelos-Cagigas, T. F. Bastos-Filho, and M. Sarcinelli-Filho, "Combination of language models for word prediction: an exponential approach," *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, vol. 24, no. 9, pp. 1481–1494, 2016.
8. Yu Seunghak, Nilesh Kulkarni, Haejun Lee, and Ji-hie Kim, "On-device neural language model based word prediction," in COLING 2018, *The 27th International Conference on Computational Linguistics: System Demonstrations*, Santa Fe, New Mexico, August 20-26, 2018, Dongyan Zhao, Ed. 2018, pp. 128–131, Association for Computational Linguistics.
9. N. Saharia, K. M. Konwar, "LuitPad: a fully unicode compatible Assamese writing software," in *Proceedings of the 2nd Workshop on Advances in Text Input Methods (WTIM 2)*, Mumbai, India, 2012, pp. 79-88.
10. M P Bhuyan and S K Sarma, "A statistical model for automatic Error Detection and Correction of Assamese Words", *International Journal of Recent Technology and Engineering (IJRTE)*, vol.8, issue: 2, July 2019, pp: 6111-6116.