International Journal of Aquatic Science
ISSN: 2008-8019
Vol 12, Issue 03, 2021

Designing the Neural Model for POS Tag Classification and Prediction of Words from Ancient Stone Inscription Script

S.Ezhilarasi[1] And Dr.P.Uma Maheswari[2]

[1]Junior Research Fellow, Department of Computer Science and Engineering College of Engineering, Guindy Campus, Anna University, Chennai, TamilNadu, India

[2]Associate Professor, Department of Computer Science and Engineering College of Engineering, Guindy Campus, Anna University, Chennai, TamilNadu, India

Email: ezhilarasise@gmail.com[1], dr.umasundar@gmail.com[2]

Abstract. POS (Part-of-Speech) Tagging is essential to indicate labeling the words in the corpus into grammatical categories in text analysis and marking up linguistic words in a text. According to the inflections and combinations in the words of Tamil language, there is still difficulty in POS Tagging classification and prediction of Tags of the words as the automated tools are very rare compared to the aspects of rich English language. As if there are tools for modern Tamil language there is a lack of such statistical methods and techniques for the Ancient Tamil language such as the texts from inscriptions and scripts of stone where the words are lengthy and combined without splitting up into morphemes or lemmas. Package supportiveness and availability also considerably have some issues in dealing with it as the words of Ancient Tamil script differs from modern Tamil. The proposed work overcomes the complexity of classifying ancient words. The proposed work is based on designing the Neural Model for POS Tag Classification and Prediction of Words from the Ancient 11th century stone inscription script. Bi-LSTM model is implemented with the embedding layer of vectors of words for training the POS Tagging model based on pattern generation of regular expressions and classifying the words into tags and prediction of Tags of words for any novel script given that involves syntactic tag assigning and predicting tag for concerning words efficiently. The proposed model provides 88.88% accuracy compared to the existing works in the stream.

Keywords: POS Tagging, pattern, Bi-LSTM classification and prediction.

1. INTRODUCTION

In ancient Tamil language, a part of speech (POS) tagging is a difficult undertaking as its miles each inflectionally and derivationally wealthy morphological language. The implementation of deep learning fashions for Ancient Tamil POS tagging undertaking with a well-balanced language-impartial function set and to spotlight numerous demanding situations which reason Tamil language POS undertaking a difficult one. Part of speech (POS) tagging undertaking is carried out thru using taggers, and taggers are composed of a large set of linguistic policies and the process of those taggers is to assign a corresponding syntactic tag to every phrase in a given textual content withinside the script. It is located that the scale of the training information and the exceptional of tagset used are the 2 predominant elements that substantially affect the overall performance of fashions which learns thru computerized method deep

learning fashions. Therefore, we can say that the POS tagging undertaking now no longer completely relies upon the dataset accustomed in the training section of the model, however, besides the tagset used withinside the annotation is likewise similarly important. The predominant element this is of utmost vital for the improvement of a specific POS tagger is a set of rules for suitable POS tags prediction and its affiliation with taking a test at information. POS tagging undertaking is more difficult in the Ancient Tamil language having fewer linguistic resources.

In our proposed work the 11th century ancient stone inscription text scripts from the Thanjavur Brihadeeswarar Temple were taken as a dataset that contains a continuous sequence of characters. The raw character sequence of the script after recognizing, the transliterated characters are extracted by mapping with the recognized character sequence repository. The words are recognized based on semantic, syntactic, and linguistic rules. The extraction of ancient words from the ancient script is done by referring to the ancient materials, historical documents, Tamil stone inscription books, and artifacts. The Thanjavur Brihadeeswarar Temple inscriptions script predicts the history of RajaRaja Chola –I, Rajendra Chola Empires and kingdoms. The extracted words are also consulted with the well-established epigraphists of the Tamil language. Ancient Tamil word corpus is created and generated and this is the dataset taken for further Tag classification. Bidirectional Long Short Term Memory (LSTM) sequence model is implemented for the POS Tagged words in model building and evaluation after POS Tagging the words from the script.

2. BACKGROUND SURVEY

A.M.Natarajan and M.Selvam as in [7] have proposed Improvement of POS Tagging and Morphological Analysis which is Rule-Based and in the Tamil Language through Induction and Projection Techniques. Morphological evaluation and a part of speech tagging are much substantial for vocabulary tactics and dealing with a maximum of the words with morphological derivative and inflectional. The order primarily based totally POS tagging and morphological interpretation is so hard and could not contain every combos thru the policies because of exceptions and inflections specifically in vocabulary like Tamil. Mathematical techniques are mere essential that in a big quantity of digital corpus and automatic which might be very uncommon in Tamil. The rule primarily based totally POS tagger and morph analyzer may be constructed from nicely described structural policies of Tamil language. They may be also progressed via way of means of the root phrases prompted from English language to Tamil language thru the series of tactics mere sequence order, induction, and lemmatization with the assistance of corpora that is sentence aligned like newspaper materials, Television news, Bible corpora considering that locating the basis withinside the modulated phrases could be mere hard and ends in uncertainty. POS tagger and order primarily based morphology tester has 85.56 accuracies. Sentences that are POS Tagged in Tamil had been acquired for the Bible corpora thru projection and order sequence strategies and express records were acquired.

1. REVIEW of Existing Work

Wahab Khan et.al. as in [1] have proposed POS Tagging in Urdu as it is a difficult venture as it's far each inflectionally and derivationally wealthy morphological language. Verbs are normally conceived a surprisingly inflected item in Urdu relatively to nouns. POS tagging is used as an initial linguistic textual content evaluation in various natural language processing domain names which include speech processing, fact extraction, system translation, and others. It is a venture that first identifies suitable syntactic classes for every phrase in going for walks textual content and second assigns the expected syntactic tag to all worried words. However, withinside the contemporary observes, they offered: 1) the implementation of each system and deep gaining knowledge of fashions for the Urdu POS tagging venture with a well-balanced language-impartial function set and 2) to spotlight various demanding situations which motive Urdu POS venture a difficult one. In this research, they confirmed the effectiveness of the system gaining knowledge of and deep gaining knowledge of fashions for Urdu POSventure.

Pengfei Zhang et.al. as in [2] have proposed Combining Self-attention mechanism POS Tags for recognition of simile where a phrase might also additionally have extraordinary part-of-speech labels in extraordinary sequences. It is crucial for the popularity of simile venture must become aware of a sure POS statistics for every phrase in a sentence. Here, they suggest a neural model community structure particularly incorporating the POS statistics into popularity venture of simile, with supplementary self-interest system to higher seize deep time dependencies among any words in the sentences. The empirical effects display that their work system fashions considerably performs well in preceding statistical techniques withinside the popularity venture of simile.

Liner Yang et.al. as in [3] have proposed Joint Dependency Parsing and POS Tagging with Neural Networks that are transition based where parsing based on dependency and POS tagging are located to be carefully connected, current paintings on combined designing with manually devised process templates affected from the process paucity and insufficiency issues. In this proposed work, they suggest a method to joint parsing based on dependency and POS tagging the usage of change over-primarily based totally neural models. The Neural model community firstly based wholly three classifiers are formed to solve tagging based on shift/reduce, and naming issues. Investigations display that their method extensively performed well than the preceding techniques throughout quite a few languages.

Meishan Zhang et.al. in [4] have proposed an effective and simple Neural based Model for POS Tagging and Joint Word Segmentation where Joint fashions have proven more potent talents for POS tagging and phrase segmentation of Chinese words, feature received first-rate pursuits withinside the network of language processing Chinese language. Here, they observe providing an easy but powerful collection-to-collection neural version for the combined work, primarily based totally on a better described change over system, with the aid of using the usage of lengthy memory (LSTM) neural network structures. They have analyzed the behavior experiments on 5 specific datasets.

Zhengua Li et.al. as in [5] have proposed POS Tagging that is coupled on Heterogeneous Annotations where the restrained scale and style of categorized information significantly prevents the capability of supervised methodologies. To efficiently make use of a couple of categorized corpus with annotations that are in heterogeneous manner for the identical job, here they proposed a joint collection naming version that could precisely analyze and assume annotations that are in heterogeneous manner concurrently, the use of POS tagging of Chinese language as their case study. The version on datasets that are non-overlapping has

most effective tags of one-aspect ratio, they rework a tag of one-aspect into bundled tags set via way of means of combining the tag with each likely tag on the lacking aspect in line with a predefined framework-unfastened tag-to-tag matching, for that reason generating ambiguous labeling as susceptible supervision. The layout and look at 4 different framework-unfastened tag-to-tag matching, and discover that the joint form attains its exceptional overall attainment while every one side tag is matched with all the tags at the alternative aspect (particularly entire matching), displaying that the version can efficiently analyze heterogeneous annotations, context-conscious on line pruning approach that could more as it should be seize matching connections among elucidations primarily based totally on evidence of context and for that reason efficiently remedy the severe inability hassle with their joint form beneath neath entire matching, similar with CRF version.
Min Zhang et.al. as in [6] have proposed Joint Optimization for Parsing based on dependency and POS Tagging of Chinese language where parsing based on dependency has received increasing processing of natural languages in currently because of its monotony and fashionable appropriateness for numerous vocabularies. However, because of little structural alterations, POS tagging in Chinese language has verified to be extra difficult than other languages including English. Hence it results in uncompromising mistakes propagation for parsing based dependency of Chinese language[11]. They proposed for their joint fashions numerous programming primarily based totally decoding techniques that may include wealthy POS tagging and syntactic functions[12]. They had provided a powerful pruning method to decrease the quest area of POS tags, main to sizeable development of speed of parsing. The POS tags evolved into extra dependable and useful for syntactic functions that are utilized in POS tagging.

3. LANGUAGE SPECIFICATIONS

In agglutinative Tamil grammar, marking class, range, and instances connected to the word noun by suffixes[8]. Tamil phrase might also additionally have a root lemma or extra affixes are joined together. Large Tamil suffixes and affixes can be inflectional and derivational[9]. The quantity of agglutination and length are lengthier in Tamil ensuing in lengthier phrases that has more suffixes. The issues are morpho-phonology such as insertion of sandhi, deletion of sandhi and morphological sandhi substitution rules, complicated verb and noun patterns, and OOV value due to poetry script inscriptions called "Mei Keerthi" are extra complicated than a normal script.

4. PROPOSED METHODOLOGY FOR POS TAGGING

The proposed POS Tagging methodology is frame worked based on the various morphological analysis, forms, stems, and suffix patterns and also deeply rely on rule- based formats[10]. The modules of the methodology of POS Tagging stats from corpus generation, word tokenization with POS tagger with the implementation of Bi LSTM model for building classifiers and predictors of tagged words from the new script also. The architecture block is shown in fig.1 as shown.

a. Corpus Creation

The raw character sequence of the script after recognizing, the transliterated characters are extracted by mapping with the recognized character sequence repository. The words are recognized based on semantic, syntactic, and linguistic rules[13]. The extraction of ancient words from the ancient script is done by referring to the ancient materials, historical documents, Tamil stone inscription books, and artifacts[14][15]. The extracted words are also consulted with the well-established epigraphists of Tamil language. Ancient Tamil word corpus is created and generated and this is the dataset taken for further Tag classification. It is done by implementing Natural Language ToolKit (NLTK) package and the corpus file can be read by a corpus reader as specified in algorithm 1.

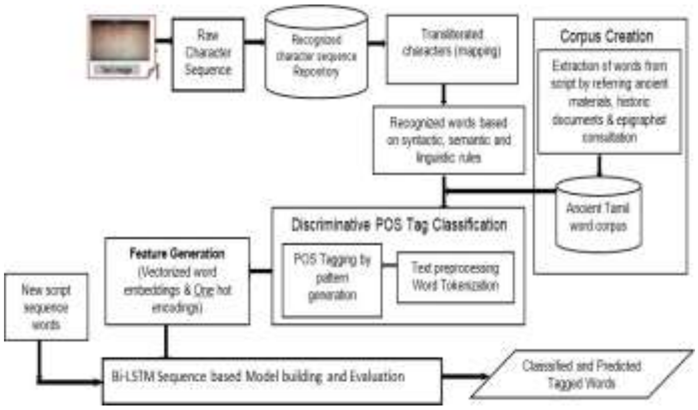

Fig. 1. The Architecture of POS Tag Classification and Prediction

Algorithm 1: Corpus Creation Input: Recognized words RW **Output:** Word corpus WC

i. **begin**
ii. **for** all Recognized words RW from recognized sequence repository
iii. Generate the list of words from the script in a corpus file
iv. Read the Wordcorpus WC with NLTK WordListCorpusReader
v. **end for**
vi. **end**

b. Word Tokenization

The script consisting words are fed as the input file for text pre-processing steps that involve tokenization of the sentences in the script to tokens or words using Word Level Tokenization initially and sub word-level tokenization later. Word leveltokenization splits the sentences into words or lemma with word tokenizer as specified in algorithm 2.

Algorithm 2: Word Level Tokenization Input: Sequence of script words SW **Output:** Tokenized words TW

i. **begin**
ii. **for** all sequence of words SW from the script file
iii. Preprocess the text
iv. Apply word-level tokenization with NLTK word tokenize method
v. Generate a list of Tokenized words TW
vi. **end for**
vii. **end**

c. Implementation Of POS Tagging

International Journal of Aquatic Science
ISSN: 2008-8019
Vol 12, Issue 03, 2021

Before performing the POS Tagging operations the general pattern after analyzing the grammar and morphology of the ancient words from the script, analyzing the suffixes of the words, and classifying the overall Tags into sub categorical tags are generated. The general pattern is generated with regular expressions and the POS tagging is done with the regular expression tagger as specified in algorithm 3. POS in Tamil has extra inflections and morphemes. Lexicon words and tags are bracketed for all word pairs via which a tag shape is constrained. POS Tagging is finished many of the phrases to morphemes. A few of the proposed POS tags for Ancient script Tamil words are categorized and is shown in Table I.

Algorithm 3: POS Tagging with pattern generation Input: Tokenized words T_W
Output: POS Tagged words POS_W

i. **begin**
ii. **for** all Tokenized words T_W
iii. Generate pattern Pi with regular expression
iv. Tag the words with regular expression tagger reg_exp
v. Based on the pattern Pi, classify the words into categorical tags
vi. Generate the list of POS Tagged words POS_W
vii. **end for**
viii. **end**

Main POS Tag	**Sub POS Tag Categories**
	Noun (NOUN)
	Noun Case Marker (NOUNCM)
	Noun Instrumental Case Marker (NOUNICM)
	Noun Benefactive Case Marker (NOUNBCM)
Noun	Noun Dative Case Marker (NOUNDCM)
	Noun Genetive Case Marker (NOUNGCM)
	Noun Locative Case Marker (NOUNLCM)
	Noun Plural Case Marker (NOUNPLCM)
	Noun Sandhi (NOUNSAN)
	Verb (VERB)
Verb	Verb Plural Marker (VERBPM)

Table1. POS Tags

	Adjective (ADJ)
Adjective	Adjective Case Marker (ADJCM)
Adverb	Adverb (ADV)
	Adverb oblique (ADV OBL)
Auxillary verb	Auxillary verb (AUXVERB)
Post Position	Post Position (PP)
	Echo Post Position (ECHOPP)
Day/Year	Day/Year (DAY/YEAR)
	Numeral (NUM)
	Numeral Selective Case Marker (NUMSECM)
	Numeral Case Marker (NUMCM)
	Numeral Sociative Case Marker (NUMSCM)
Numeral	Numeral Instrumental Case Marker (NUMICM)
	Numeral Sandhi (NUMSAN)

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ISSN: 2008-8019
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	Quantity (QUANT)
Quantity	Quant Benefactive Case Marker (QUANTBCM)
	Quant Acusuative Case Marker (QUANTACM)
	Quant Vocative Case Marker (QUANTVCM)
Determiner	Determiner (DET)
Verb Infinitive	Verb Infinitive (VERBIF)
Clitics	Clitics (CLITICS)
Gender Marker	Gender Marker (GM)

d. Bi-LSTM Model building for Classification and Prediction

The sentences in the script are processed and the words are tagged to fom tagged sentences and they are combined and known as sentence tags. The model is implemented by splitting up into training sentences, testing sentences, training tags, and testing tags before training the model. The POS tagger is implemented using Keras and Bi-directional LSTM layer. The words and the tags are defined in the form of sets and they are implemented in the words to index form. As Keras works with numbers the words and tags are assigned to a unique integer. A Set of unique words and tags computation is done and transforming to index form and these are considered as word vocabulary and tag vocabulary. After adding the value of padding sequences and assigning out of vocabulary (OOV) for unknown words the maximum length of the longest sequence is identified and making the other sequences to the same length by padding operations to the corresponding words and tags. For the words, the embedding layer the word vector model is computed and the Bidirectional LSTM layer inputs the next words in the sequence and the fully connected layer or dense layer chooses the POS Tag appropriately. By adding the TimeDistributed modifier and using Softmax of the activation layer the model is built and categorical entropy for loss and Adam optimizer to optimize it. The sequence of tags is transformed into one hot encoded tag as specified in algorithm 4. The tags are classified by training the model. The test sentences are taken and transform words into indexes and padding sequences and the prediction model is built.

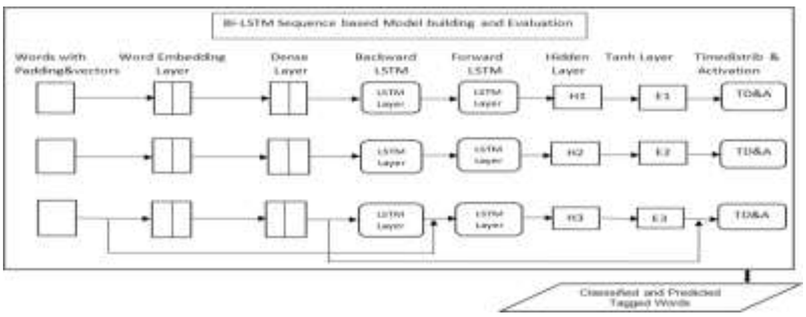

Fig. 2. The Block Architecture of Bi-LSTM Sequence model Building

The Bi-LSTM state of forget state (1), cell memory state (2), input state (3), combined cell state (5,6) with the tanh function (4) are computed as in the following equation

$f_{ot} = \ (W_{fo} [h_{it-1}, x_{it}] + b_{fo})$ (1)

$C^{f} = C_{t-1} * f_{ot}$ (2)

$$in_t = (W_{in} [h_{it-1}, x_{it}] + b_{in}) \quad (3)$$
$$C_l = \tanh (W_c [h_{it-1}, x_{it}] + b_C) \quad (4)$$
$$C^i = C_l * i_t \quad (5)$$
$$C_t = C^f + C^i \quad (6)$$

The Bi-LSTM state of output state (7), hidden layer (8), embedding layer (9) are computed as follows

$$o_t = (W_o [h_{it-1}, x_{it}] + b_o) \quad (7)$$
$$hid_t = o_t * \tanh (C_t) \quad (8)$$
$$e_t = LSTM (e_{t-1} , C_t) \quad (9)$$

Algorithm 4: Bi-LSTM for Classification and Prediction Input: POS Tagged words POS_W
Output: Classified Tagged words CT_W , Predicted Tagged words PT_W

- **i.** **begin**
- ii. **for** all POS Tagged words POS_W
- iii. Split into train_sent, test_sent, train_tag, test_tag
- iv. Combine the words into Sets of words w[] and tags t[]
- v. **for** all words w[] and tags t[] in sets
- vi. Transform into word to index unique vector form v_i
- vii. Assign vocabulary of sequences OOV_i and padding of sequences pad_i
  1. Find max_len of sequences and make other sequences equal by computing max_len: = len + pad_i
- viii. **for** all tagged sequence
- ix. One_hot_encoding := encoded tags one_hot_t
- x. Build the model with Bi-LSTM, Dense, Time_Distributed layer
- xi. Activation:= softmax
- xii. Loss:= categorical_cross_entropy
- xiii. Optimizer:=adam
- xiv. Classify the tags, tagged words:= CT_W
- xv. **for** all-new sequence of words in the script
- xvi. Predict the tags with the model, predicted tagged words:= PT_W
- **xvii.** **end for**
- **xviii.** **end**

5. EXPERIMENTAL RESULTS

The sentences in the given script are tokenized and POS Tagged as tagged sentences based on the pattern implementing Regular Expression Tagger. The tagged sentences sample result is given as below

[('ஸ்ர ீர ாஜர ாஜதேவர்','NOUN'),('த ாம ானையும்','NOUNCM'),('பாண்டியர ்கனை யும்','NOUNCM'),('மனைநாட்டு','NOUN'),('எரிந்து','VERB'),('ககாண்ட','AUXVERB'),('பண்டாரங்கைில்','NOUNPLCM'),('யாண்டு','DAY/YEAR'),('இருபத்ே ாறாவது',' NUMERALSCM')]

Transforming of Word to index and tag to the index is done and the special value of the padding sequence –PAD- is 0 and Out of vocabulary –OOV- is 1. The train_sent, test_sent, train_tag, and test_tag are split accordingly considering exception on Key Error. The vectorized form of the sample sentences is as occurred below.

[51, 37, 43, 52, 10, 57, 55, 20]

International Journal of Aquatic Science
ISSN: 2008-8019
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[10, 36, 1, 1, 1, 52, 1, 10, 1]
[7, 18, 9, 7, 9, 7, 7, 18]
[9, 7, 7, 18, 9, 7, 3, 9, 7]

After finding the maximum length of the sequence of the sentence the padding sequence is added to make all the sentences equal length for sequential model building in Keras, the sample vectorized form of sentences occurred as below.

[51 37 43 52 10 57 55 20 0]
[10 36 1 1 1 52 1 10 1]
[7 18 9 7 9 7 7 18 0]
[9 7 7 18 9 7 3 9 7]

The test samples sentences are given and the vectorized form of those sequences after adding padding sequence occurred as follows
[['உனடயார்','ஸ்ரீராஜராஜதேவர்','குடுத்ே','கபான்ைி ன்'],['கல்ைி ல்','கவட்டிை' ,'இருபத்னேஞ் ாவது','படிகாைாஞ் ி','ஒன்று','கபான்','ஸ்ரீராஜராஜதேவர்']

[[6 5 56 16 0 0 0 0 0]
[1 42 1 24 1 6 5 0 0]]

The prediction model is fit, built, and evaluated and the token sequences of the test samples are predicted and tagged as follows.
[['NOUN', 'NOUN', 'VERB','NOUNGCM','-PAD-','-PAD-','-PAD-','-PAD-','-PAD-'], ['NOUNLCM', 'VERBPM', 'NOUNSCM','QUANT','NUM','NOUN',‘NOUN’,'-PAD-','-PAD-']]
The sequential model is fit, built, and evaluated and we get an accuracy of 88.8888 % as this accuracy is improved compared to the existing work as shown in Table 2.

Experiments	**Rule-based POS Tagging Morphological analysis (Exist)**
Bible corpora (Tamil)test case	85.56%
CIIL corpora (Tamil) test case	83%
Experiments	**Pattern-based POS Tagging with Bi-LSTM (Proposed)**
11th century Ancient Tamil stone inscriptions script words	88.8888%

Table. 2. Comparison of Proposed work with Existing work

The plot for model accuracy in training and validation and plot for model loss in training and validation is shown in fig.3 as follows

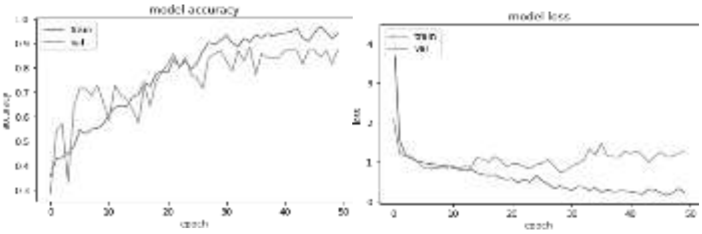

Fig. 3. Plot for model accuracy and model loss in training and validation

6. CONCLUSION AND FUTURE WORK

The proposed work is based on designing the Bi-LSTM Sequential Model for POS Tag Classification and Prediction of Words from the Ancient 11th century stone inscription script. It is implemented efficiently with embedding layers of vectors of words for training the POS Tagging model based on pattern generation of regular expressions and classifying the words into tags and prediction of Tagged words for any new script given that involves tag assigning and predicting for the concerned sequence of sentenced words. The proposed model provides 88.88% accuracy compared to the existing work of the morphological POS tagging approach. The accuracy of predicting tags can be improved by ignoring the class accuracy and validation accuracy categorical value and also by implementing Bi-LSTM with the Conditional Random Fields model which will be the future enhancement of our work
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