Sentiment analysis of agricultural product e-commerce review data based on deep learning

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***Abstract*: The relevant comment texts of agricultural products sold on the e-commerce platform contain various and complex emotions of consumers, and reflect customers' consumer experience and views on those products. Compared with the features and advantages of English text segmentation structure, the analysis of Chinese sentiment polarity in a complex context has always been a problem in deep learning. This article explores the issue of sentiment polarity analysis of short texts of Chinese reviews of agricultural products by constructing Text-CNN, Bi-LSTM and BERT to fine-tune three deep learning models. The research object adopted is the review data of agricultural products on the e-commerce platform obtained based on crawler technology. The experimental results show that, compared with the Bi-LSTM and BERT fine-tuning models, the Text-CNN model's accuracy, precision, recall, and F1 value are all about 3 to 8 percentage points higher. The classification effect gradient gap between the three models is obvious. The accuracy of the Text-CNN convolutional neural network reached 99.92%. The results confirmed that Text-CNN has high sentiment analysis accuracy and good sentiment polarity classification effect in processing agricultural short text comment data, as an agricultural product e-commerce The emotional classification model of sales review data can provide an important reference for manufacturers to accurately distinguish user feedback and enhance market competitiveness.**

Keywords: Sentiment analysis; deep learning; Text-CNN; BERT; Bi-LSTM

I. INTRODUCTION

With the gradual acceleration of the construction and development of China's agricultural e-commerce network platform, a large number of agricultural enterprises have begun to settle in the e-commerce platform or build their own e-commerce. The online shopping trend of agricultural product consumption has resulted in a large amount of consumer review data on e-commerce platforms. There is a large amount of comment data generating from the growing trend of online shopping for agricultural products. Feedback from users is an important consideration for agricultural production and operation companies to increase market competitiveness and achieve sustainable profitability. To improve the company's product sales strategy, increase the company's marketing competitiveness, and optimize in the agricultural consumer market environment, it is often inaccurate to rely on traditional rating methods as the overall product evaluation results. It is particularly necessary to obtain accurate and comprehensive evaluation results from massive amounts of data.

In the field of agricultural product e-commerce sales, the focus has always been on the emotional expression of consumers. For example, "Although the packaging box has several damages, it tastes very good, crispy and juicy, sweet and delicious", which reflects different aspects based on sentiment analysis (ABSA). As shown in Figure 1, "very good" is positive emotion, "broken" refers to negative emotions. Aspect-based sentiment analysis can help managers understand users' emotional expressions based on contextual information and emotional information.

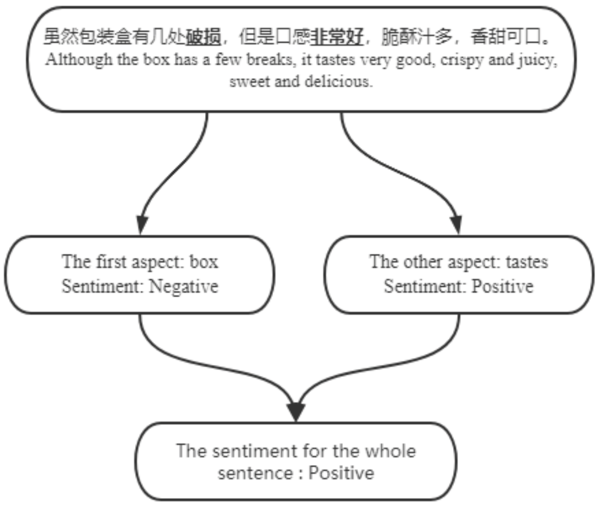

Fig. 1. The example of aspect-based of sentiment analysis

II. RELATION WORK

Sentiment analysis is an important application direction of natural language processing (NLP). Its main purpose is to analyze the sentiment polarity of the text proponent from a large number of subjective texts, and judge whether the sentiment is positive or negative, whether it is positive or negative. In recent years, sentiment analysis systems have been applied to many different types of texts, including comment data [1-6], news [7] and tweets on Twitter and Weibo platforms [8,9]. The research methods of sentiment analysis are mainly divided into the following three categories.

A. A method based on a sentiment dictionary

S. Zhang [11] proposed the extraction and construction of related dictionaries based on degree adverb dictionary, network vocabulary dictionary, negative word dictionary and other related dictionaries to expand the sentiment dictionary and obtain the emotion of Weibo text through weight calculation Value-based sentiment dictionary analysis method. Tan, Cheng Fang [12] built a Weibo sentiment dictionary based on the CNKI sentiment dictionary, combined with currently commonly used online vocabulary dictionary to increase Weibo sentiment and Sina' API access data, and analyzed Chinese Weibo sentiment information. Vandana Jha[13] uses multiple domain data to create an emotion aware dictionary, which increases the number of words in the target domain by 23% to 24%. And finally, a sentiment analysis method based on the sentiment dictionary of the Dalian University of Technology, the sentiment dictionary of National Taiwan University and the HowNet dictionary are proposed.

B. Algorithms based on traditional machine learning

Sisi Liu & Ickjai Lee [14] proposed a hybrid framework for email data sentiment analysis based on word frequency-inverse document frequency word weight model for feature extraction, k-means tagging and support vector machine classifier. Veny Amilia Fitri [15] uses the naive Bayes algorithm in the RapidMiner tool to obtain an accuracy of 86.43% from the Twitter case test data, which is higher than the 82.91% of other algorithms (decision tree and random forest). Xie[16] proposed a PLSA model based on Wikipedia and the maximum entropy of the training corpus for sentiment analysis.

C. Deep learning-based methods

To obtain higher classification accuracy in Chinese sentiment analysis, Su Y [17] proposed the LMAEB-CNN model in the research, which combines Bi LSTM [18] and CNN, and introduced a multi-head attention mechanism. Experiments show that the model not only solves the problem of overfitting but also improves the accuracy of emotional polarity classification. Cheng[19] proposed a public opinion analysis framework based on sentiment analysis, which expressed and annotated the opinion target and the corresponding sentiment together to avoid the mismatch between the two. Besides, the sentiment analysis problem of Weibo sentences is reduced to a sequence labeling problem, and different RNN recurrent neural network models are used to train and reason the model. Wei Li [20] proposed a deep learning-based sentiment analysis model. The model is called the lexicon integrated two-channel CNN-LSTM series model, which combines CNN[21] and LSTM/Bi-LSTM branches in parallel. The model has achieved good results on some challenging data sets such as the Stanford sentiment treebank.

Compared with traditional machine learning methods and sentiment dictionary analysis methods, deep learning[22,23] has high classification accuracy, strong learning ability, strong ability to automatically extract features, strong fault tolerance, and excellent effects in processing nonlinear complex data, which have gradually become the newest trend of sentiment analysis. Numerous research scholars have confirmed that the abstract features of deep learning, the ability to flexibly adjust the structure, and better simulate the relationship between words, these advantages can make it more accurate than traditional methods in emotion classification rate[24,25]. It is of little significance to select machine learning models and traditional sentiment dictionary methods for related research, so this paper builds a mainstream model in the field of deep learning sentiment analysis, starting from the perspective of agricultural product sentiment review classification, and constructs a review data set based on agricultural product consumption, where Pos stands for positive and Neg stands for negative. Deep learning BERT model, Text-CNN model and Bi-LSTM neural network model are used to explore the optimal sentiment analysis model for sentiment classification of agricultural product review data sets. The experimental results prove that the Text-CNN model is the best for the sentiment classification effect of the agricultural product review data set, and we can use the Text-CNN model to get a good sentiment polarity analysis effect.

III. METHOD

A. Data acquisition

This article uses the R language to build a crawler framework to crawl the agricultural product consumption review data of the e-commerce platform, collect the review text with user sentiment words for processing, and then perform sentiment annotations on part of the data to develop an sentiment analysis model. The results of sentiment polarity determination and comment data segmentation are shown in Table 1:

TABLE I

THE PARTIAL DATA SETS

Sentiment tendency	Comment data
Pos	满意 及时 味道 好 长期 购买 推荐 Satisfied / Timely / Taste / Good / Long term / Buy / Recommend
Neg	很少 买 这次 感受 不好 头 瘪 新鲜 Rarely / Buy / This time / Feeling / Not good / Head / Flat / Fresh
Pos	挺好吃 包装 精细 没坏 泡沫 互相 隔 有点 小 挺 甜 Very delicious / Packaging / Fine / Not bad / Foam / Each other / Separated / A bit / Small / Very / Sweet
Neg	很差 初体验 不会 再 买 Very poor / First experience / No / Again / Buy
Pos	脆甜 水分 足 买 几次 不错 Crisp and sweet / Moisture / Enough / Buy / A few times / Good
Pos	快递 小哥 还要 表扬 帮 送到 楼下 昨天晚上 点 下单 今天 一点 不到 收到 快递 好 没话 说 点赞 新鲜 口感 好 Express / Brother / Also / Praise / Help / Deliver / Downstairs / Last night / Order / Today / Received / Nothing to say / Like / Fresh / Taste / Good
Neg	失望 表示 以后 不会 买 微酸 不甜 破损 吃 三个 里面 烂 Disappointed / Said / Future / Will not / Buy / Slightly sour / Not sweet / Broken / Eat / Three / Inside / Rotten
Neg	生鲜 库房 包装 不好 磕烂 Treasury/ Packaging / Not good / Smashed
Pos	东西 好吃 煮 出来 颜色 蓝 建议 购买 Stuff / Delicious / Cooked / Out / Color / Blue / Recommended / Buy

To be able to verify that the model is comprehensively effective for agricultural products, this article selects agricultural products such as bananas, peaches, dragon fruit, potatoes, tomatoes, cucumbers, green vegetables and other agricultural products to construct a data set of 23,418 agricultural product reviews for emotional two classification test and verification, of which 14,888 positive emotion sentences, 8,530 negative emotion sentences, 80% of all data are selected for test data, and 20% of all data are selected for test data. The data structure is shown in Table 2:

TABLE Ⅱ

COMPOSITION OF AGRICULTURAL PRODUCT REVIEW DATA

Dataset	**Pos**	**Neg**
Train	11910(80%)	6824(80%)
Test	2978(20%)	1706(20%)
Total	14888(63.58%)	8530(36.42%)

B. *BERT fine-tuning classification model based on pre-training*

BERT (Bidirectional Encoder Representations from Transformers) is a pre-trained language representation model proposed by Devlin J [26]. BERT is a Transformer encoder that implements multi-layer bidirectional based on Transformer. Unlike other recent language representation models, BERT aims to pre-train deep bidirectional representations by jointly adjusting the context in all layers. The pre-trained BERT means that it can be fine-tuned through an additional output layer, and is suitable for the construction of the most advanced model for a wide range of tasks, without the need for major architectural modifications for specific tasks. BERT has refreshed 11 natural language processing tasks as soon as it was proposed. In the field of sentiment analysis, many foreign scholars have applied it to English sentiment analysis and achieved good results. Anindya Sarkar [27] proposed to use BERT's hierarchical attention network for document sentiment classification and achieved good results. Xie Q [28] used the pre-trained model BERT embedded multilingual preprocessing of bidirectional encoding representation and potential Dirichlet allocation (LDA) topic model, which analyzes the topic evolution under monolingual and multilingual topic similarity settings. The BERT model is very effective in the field of natural language processing and can be used as a model for Chinese sentiment analysis and testing.

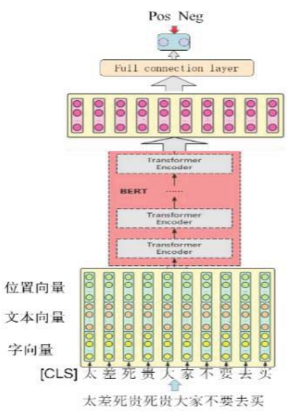

Fig. 2. BERT-based fine-turning classification model

The agricultural product review data in this article is processed into a text with a length of 35 after a long cut and short supplement. The text is processed into 35 tokens plus 1 [cls] token through BERT's word segmentation function tokenization. Vector embedding takes the sum of word vector, text vector and position vector as the model input. Randomly cover or replace 15% of the tokens (characters that are randomly erased) in the data. The covered or replaced content allows the model to predict based on the contextual semantics. Take out the vector corresponding to [cls], then map it to a value and activate it with the sigmoid function. Through joint training of the random mask prediction task and sentence prediction task, the token outputs the feature vector through the BERT model.

$$sigmod: \sigma(z) = \frac{1}{1+e^{-z}} \quad \sigma \in (0,1) \tag{1}$$

In the model of this experiment, the initial learning rate is 1e-5, and the transformer (fully connected layer) is added to the output of the BERT model for fine-tuning. The result of the model output is Test- Loss (test set loss rate) = 0.1629, Test Acc (test set accuracy)=0.9539.

C. *Convolutional Neural Network Text-CNN Model*

As one of the important algorithms in the field of deep learning, a convolutional neural network is a type of feedforward neural network that includes convolution calculation and has a deep structure. Text-CNN (Text Convolutional Neural Networks) is an algorithm that uses convolutional neural networks to classify text. It is a variant of CNN. The difference from CNN is that CNN is mainly used for image classification and Text-CNN is mainly used for text classification. Text-CNN was first proposed by Kim Y[29]. The model consists of an input layer, a convolutional layer (feature extraction), a pooling layer (down-sampling), a fully connected layer (classification) and an output layer, and the word vector is constructed to solve related applications of NLP to sentiment analysis tasks. The core idea of Text-CNN is to use multiple different convolution kernels to extract the local key information in the text and accurately capture the local features of the text. The so-called local feature in the text is a sliding window composed of several words. The advantage of a convolutional neural network is that it can automatically filter and combine the sliding window to obtain semantic information of different abstract levels.

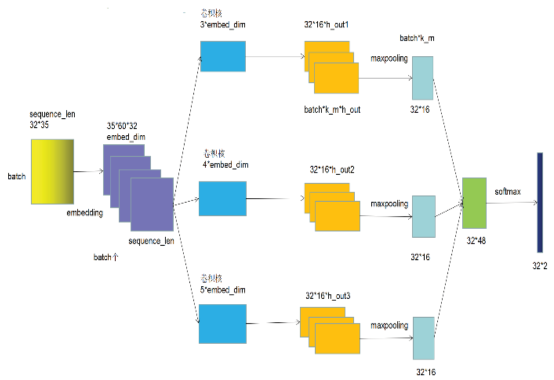

Fig. 3. Text-CNN convolutional neural network

The word segmentation tool Jieba's word segmentation accuracy can generally reach 97%, so in the text-CNN data preprocessing stage of this article, jieba word segmentation is used, and meaningless content is deleted through stop word operations. The Text-CNN model constructed in this paper uses three convolutional layers and uses dropout (negative log-likelihood loss function) to enhance the return capability of the model. The pre-processed data model extracts different feature vectors through the convolutional layer to form a splicing output.The pooling layer pools sentences of different lengths to obtain a fixed-length vector representation output, and finally use the Softmax activation function to output the probability of each category to obtain a two-digit vector, and the values represent the positive and negative possibilities respectively. The final model output result is Test-Loss=0.0040 and Test Acc=0.9992.

D. *Bi-LSTM neural network based on deep learning*

Recurrent Neural Network RNN (Recurrent Neural Network) is a neural network used to process sequence data. Since the gradient disappearance of RNN can only have a short-term memory, scholars have used hidden layer structure modification to avoid the problem of gradient disappearance of RNN, so that the recurrent neural network has long-term memory capabilities. This special type of RNN recurrent neural network is the long- and short-term memory nerve Net LSTM (Long Short Term Memory) [30]. Bi-LSTM (Bi-directional Long-Short Term Memory) is a kind of LSTM, which is composed of two-way LSTM, which is a combination of two-way recurrent neural networks and long- and short-term memory [31]. At each time t, the input will be provided to these two neural networks in opposite directions at the same time, and the output will be jointly determined by the two unidirectional recurrent neural networks. In the field of sentiment analysis, due to the advantages that LSTM can choose to learn or forget, the LSTM neural network model can better capture the long-distance dependencies. And LSTM modeling cannot encode back-to-front problems, but Bi-LSTM can better capture the two-way semantic dependence.

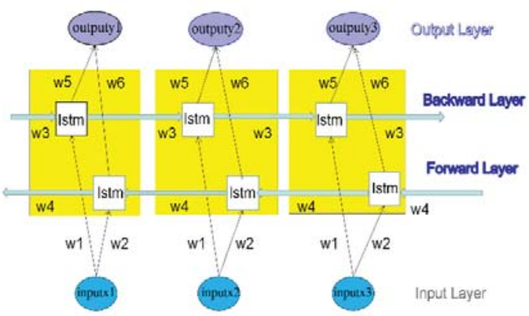

Fig. 4. Bi-LSTM bidirectional long short term memory neural network

Constructing Bi-LSTM to realize sentiment analysis requires constructing a two-layer two-way LSTM network, we need to declare the list of LSTM-Cells firstly. Inside the neural network, the forward and backward calculations are performed on the LSTM of each layer, using concat to the output hidden layer, and then the next layer is input for calculation. After the data is preprocessed, three vectors }, are obtained by inputting the forward LSTM, and the backward vector is obtained by inputting the data into the backward LSTM. The output layer of the model at time t represents the vector representation of the t-th element of the output sequence. The number of neurons in the output layer is consistent with the length of the vector representation. Finally, the forward and backward vectors are spliced into , the final model output result of the model : Test- Loss=0.216, Test Acc=0.936.

IV. Experiment

A. *Experimental Environment*

In this paper, the experimental environment is shown in Table 3:

TABLE Ⅲ

THE EXPERIMENTAL ENVIRONMENT OF SERVER

Operating system	Parameters
CPU	Intel core i7 9700
Memory	500G
GPU	RTX 2070
Keras	2.2.4
Python	3. 7
TensorFlow	2.0
RAM	24G

B. *Experimental Design*

The model to classify data needs to include the following two processes: The first process is to convert these texts into machine-recognizable codes in the data processing stage. The main process is to construct a dictionary and construct a mapping from words to codes. The second process is to convert the original text based on the mapping table and convert the text into a machine-recognizable code.

The experiment of Bi-LSTM/Text-CNN model is divided into three steps: data processing, dictionary making, training and testing. Data processing is to clean, segment, and scramble the text data of Neg and Pos obtained by the crawler, and obtain the text with good words and the text without word segmentation, and the corresponding category files (emotion category Pos or Neg). Make a dictionary is to read the text data of the divided words in the file, take out the words in each line of these data to form a word bag, sort and encode according to word frequency. Write to the dictionary file in the word-order encoding format. Perform training and testing is to read the data to get the comments and categories, digitally encode the comment text, take 80% of the data as the training set and 20% as the test set, load the encoded data into the form of data-loader, and put the data into the model for training test, run directly and get training and test results.

Different from the previous two models, BERT is a deep learning model based on pre-training. The experiment of this model is divided into two steps: data processing and training and training test. Data processing is to configure the hyperparameters of the model to start constructing training data, and the preprocessed data is tagged with emotion. The Tokenizer is divided into BasicTokenizer and WordpieceTokenizer. First, perform BasicTokenizer tokenization to obtain a token list with a relatively coarse tokenization effect, and then use the WordpieceTokenizer tokenizer to process each token to obtain the final tokenization result. The data set is divided into 80% training set and 20 % Test set. Perform training and testing is to use pytorch_pretrained (a pre-training model based on the deep learning framework PyTorch provided by Google) to segment and encode the text, and put the BERT output results in the fully connected layer to output the prediction results.

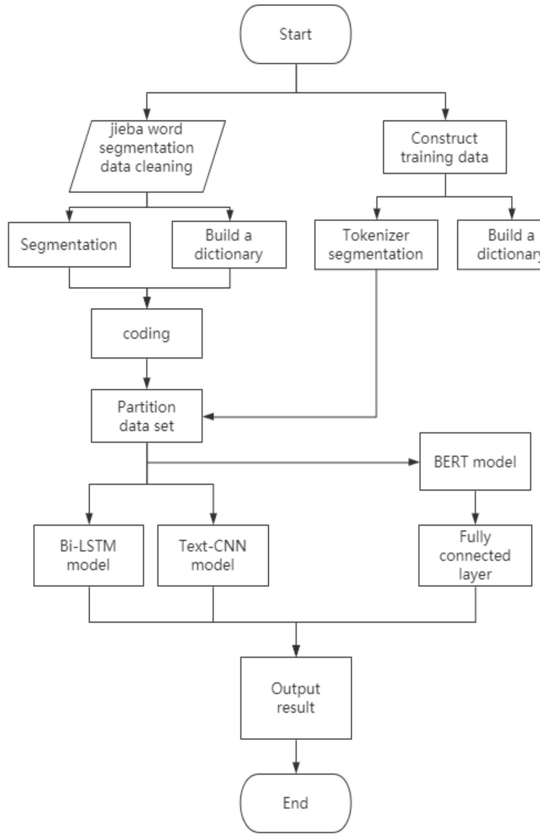

Fig. 5. Experimental design flow chart

V. Result Analysis

The constructed Bi-LSTM two-way long and short-term memory neural network, the BERT-based fine-tuning classification model and the Text-CNN convolutional neural network used the preprocessed Pos data set and Neg data set to perform classification experiments. Table 5 shows the experimental results of each classifier. Precision is an indicator of accuracy, which means that the number of correctly classified by the classifier accounts for the proportion of the correct samples by the classifier. The recall rate (Recall refers to the proportion of the correct number of correctly classified by the classifier in the original data. Accuracy refers to the ratio of correct classification (whether it is correctly classified as Pos or Neg). F1 value (F1 -score) Harmonic average of precision and recall. The calculation method of these four indicators is as follows. The higher the value of the index is, the better the classification effect is. FP, FN, TP and TN represent false positive case, false negative case, real case and true negative case respectively.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (2)$$

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

$$F1 - score = 2 * \frac{Precision * Recall}{Recall + Precision} \quad (5)$$

From the results in the above table, the accuracy of the Text-CNN convolutional neural network reached 99.92%, which is significantly higher than the accuracy of 95.39% of the BERT fine-tuned classification model and the accuracy of 93.60 of the Bi-LSTM bidirectional long-short-term memory neural network. In the results of the training data set, the accuracy of the Bi-LSTM two-way long and short-term memory neural network is 93.60%, but the accuracy is a bit poor compared to the other two models. On the agricultural product review dataset with short text sentences, the classification model is inferior to the other two models in terms of accuracy, precision, recall, and F1 value. In addition, it can be seen that the accuracy, precision, recall, and F1 value of the Text-CNN classification model are about 3 to 8 percentage points higher than the other two models. The classification effect between the three models is gradient. That is, the Text-CNN model is significantly better than the BERT fine-tuned classification model, and the BERT fine-tuned classification model is significantly better than the Bi-LSTM model. In summary, the sentiment classification effect of agricultural product e-commerce review data based on the Text-CNN convolutional neural network model is the best. Although CNN does not have the structure of the LSTM model that can capture long dependencies, nor does it have the word embedding feature based on the BERT fine-tuning classification model that makes full use of contextual semantic information, its convolutional layer's ability to capture local information and the pooling layer's extraction of local important information just proves that the Text-CNN convolutional neural network model has a good sentiment classification for the 35-word agricultural product review short text data set.

TABLE Ⅳ

FINAL RESULT TABLE

Metrics(%) / Model	Type	Accuracy /%	Precision /%	Recall /%	F1-score %
BERT	positive	95.39	94.02	96.77	95.38

	negative		96.79	94.05	95.40
Text-CNN	positive	99.92	99.90	99.95	99.92
	negative		99.95	99.90	99.93
Bi-LSTM	positive	93.60	91.70	95.62	93.62
	negative		95.59	91.65	93.58

VI. CONCLUSION

Compared with traditional sentiment analysis methods, this article uses three mainstream models of deep learning to explore agricultural product e-commerce platform comment data for sentiment classification comparison. To obtain scientific and reasonable test results, this article uses the R language to build a web crawler and grabs 23418 data on agricultural product reviews on the e-commerce platform. In the end, the Text-CNN convolutional deep neural network model we tested got unexpected results: the accuracy of emotion classification reached 99.2% and compared with the Bi-LSTM bidirectional long short-term memory neural network, it was about 6 percentage points higher. The comparison of the BERT classification model is about 4% higher, which proves the excellent sentiment classification performance of Text-CNN in short texts such as agricultural Chinese comment data. The research results of this article provide a valuable and practical reference in the field of emotional classification of agricultural product review data. Agricultural product production and management enterprises can accurately obtain the emotional feedback of agricultural product consumer information, improve product service capabilities, thereby improve market competitiveness, and optimize agricultural products' online sales market environment.

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