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Detecting Defective Expressions in Turkish Sentences Using a Hybrid Deep Learning Method

Hibrit bir Derin Öğrenme Yöntemi Kullanarak Türkçe Cümlelerdeki Anlatım Bozukluklarının Tespiti

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Abstract

Defective expression is a grammatical term that refers to both semantic and morphologic ambiguities in Turkish sentences. In earlier studies, Natural Language Processing (NLP) techniques have been used by constructing rule-based language-specific models. However, despite less demanding annotations requirements and ease of incorporating external knowledge, rule-based systems have some significant obstacles in terms of processing efficiency. Deep learning techniques such as long short-term memory (LSTM) or convolutional neural network (CNN) have made significant advances in recent years, which led to an unprecedented boost in NLP applications in terms of performance. In this study, a hybrid approach of LSTM and CNN (C-LSTM) for detecting defective expressions in addition to traditional machine learning classifiers such as support vector machine (SVM) and random forest (RF) to compare the results in terms of accuracy are proposed. The proposed hybrid approach achieved higher accuracy than the existing deep neural models of CNN and LSTM, in addition to the traditional classifiers of SVM and random forest. This study shows that deep neural approaches come into prominence for text classification compared to traditional classifiers.
Keywords: *Defective Expression, Machine Learning, NLP, Semantic ambiguity, Turkish*

Öz

Anlatım bozukluğu, Türkçe cümlelerde hem anlamsal hem de biçimsel belirsizlikleri ifade eden bir dilbilgisi terimidir. Daha önceki çalışmalarda, kural tabanlı dile özgü modeller oluşturularak Doğal Dil İşleme (DDİ) teknikleri kullanılmıştır. Bununla birlikte, daha az talepkar açıklama gereksinimlerine ve harici bilgiyi birleştirme kolaylığına rağmen, kural tabanlı sistemler, işleme verimliliği açısından bazı büyük engellere sahiptir. Uzun Kısa-Süreli Bellek (UKSB (ing: LSTM)) veya Evrişimsel Sinir Ağları (ESA (ing: CNN)) gibi derin öğrenme teknikleri son yıllarda büyük ilerlemeler kaydetmiş, bu da DDİ uygulamalarında performans açısından benzeri görülmemiş bir artışa yol açmıştır. Bu çalışmada, anlatım bozukluklarını tespit etmek için UKSB ve ESA'nın hibrit modeli olan bir derin öğrenme yaklaşımı (E-UKSB (ing: C-LSTM)) ve buna ek olarak sonuçları doğruluk açısından karşılaştırmak için Destek Vektör Makinesi (DVM (ing: SVM)) ve Rastgele Orman (RO (ing: RF)) gibi geleneksel makine öğrenmesi sınıflandırıcıları önerilmiştir. Önerilen hibrit model, geleneksel DVM ve rastgele orman sınıflandırıcılarına ek olarak, ESA ve UKSB'nin mevcut modellerinden daha yüksek başarım elde etmiştir. Bu durum, metin sınıflandırma için geleneksel sınıflandırıcılara kıyasla derin sinirsel yaklaşımların daha çok ön plana çıktığını göstermektedir.

Anahtar Kelimeler: *Anlatım Bozukluğu, Makine Öğrenmesi, Doğal Dil İşleme, Anlamsal Belirsizlik, Türkçe*

1. Introduction

A language is an essential tool for communication among the member of a society [1] which enables to address the feelings and opinions of others. A proper interaction among people and having awareness of the innovations in the developing world directly depend on good communication [2]. Improper use of this tool leads to narrowness or ambiguities in meanings, therefore the ideas and thoughts cannot be expressed clearly. The role of ambiguities in a language has been comprehensively analyzed in other high-risk industries, such as aviation [3], and the failure caused by the misunderstanding has been unfortunately concluded with fatal errors [4].

Defective expression is a grammatical term that refers to both semantic and morphologic ambiguities in Turkish sentences. The importance of defective expressions can be clearly understood in the areas such as Turkish education at schools, the use of Turkish in mass media or in literal publications and even almost any competitive exams held in Turkey for the entrances to high schools or universities [5]. In this study, we focus on detecting semantic defective expressions which are morphologically accurate expressions, however they damage the sentences in terms of semantics and are caused by seven grammatical reasons, categorized as follows:

- Using a redundant word
- Using a semantically opposed word
- Using a semantically incorrect word
- Using words in the wrong place
- Using semantically incorrect idiom
- Uncertainty in the meaning
- Error in logic and order

The following sentence has a defective expression of 'uncertainty in the meaning'; because the noun 'gömleğini' has meanings of both 'your shirt' and 'his shirt'; (gömlek [root] + i [accusative] + n [possession] + i [acc. of poss.]). The suffix '-n' provides the meaning of possession for both 'your' and 'his'.

- Yavuz, kırmızı **gömleğini** giydi. *(Yavuz has worn **[his or your]** red shirt.)*

In order to fix the defectiveness of the sentence, a possessive pronoun must describe the noun such as 'senin (your)' or 'onun (his)', shown as follows:

- Yavuz, **senin** kırmızı gömleğini giydi. (*Yavuz has worn **your** red shirt.*)

- Yavuz, **onun** kırmızı gömleğini giydi. (*Yavuz has worn **his** red shirt.*)

Another example of the following sentence has a defective expression of 'using a semantically opposed word'; because the word 'Elbette' means 'Of course' and 'olabilir' has the meaning of 'might'.

- **Elbette** Ali de Ahmet ile gitmiş **olabilir**. *(**Of course** Ali **might** also have gone with Ahmet)*

To disambiguate the sentence, one of the aforementioned words must be omitted and the rest of the sentence must be optimized in terms of grammar, as follows:

- **Elbette** Ali de Ahmet ile gitmiştir. *(**Of course** Ali has also gone with Ahmet.)*

- Ali de Ahmet ile gitmiş **olabilir**. *(Ali **might** also have gone with Ahmet.)*

There has been a substantial amount of research available in the literature for ambiguities in natural languages. To give example, the study of Ferrari and Esuli [6] analyzes the ambiguous terms in requirements elicitation using a domain-specific language model with word embeddings. The meanings of those technical terms may vary from area to area, which ends in frustration and distrust in the meetings. In addition, the ambiguities in the documents of requirement engineering have been analyzed by Bano [7] using NLP techniques. Hoecini, et al. [8] has performed an empirical study for the disambiguation of no-vowel- Arabic texts using the combination of natural language processing

(NLP) and Multiple Criteria Decision-Aid (MCDA). On the other hand, the fact that defective expressions in Turkish may occur due to the wrong suffixes, wrongly oriented words, extra words and etc., they are quite different from the aforementioned ambiguities. The study of Suncak and Aktaş [57] deals with Turkish defective expressions using deep learning techniques such as CNN. However, this study has main difference from that study by providing both machine learning classifiers and a hybrid deep neural approach. Apart from the computer scientists, linguists of education science have performed several studies for detecting defective expressions such as the study of Büyükikiz [9] which includes the manual investigation of compositions of 8th-degree students in terms of analyzing what kind of defective expressions the students have been used in the sentences. The study of Bahar [10] has performed a similar study with Büyükikiz and investigated the compositions of 8th grade students in terms of morphological defections in Turkish sentences. Özdem [11] has performed an investigation in nine daily and two weekly regional newspapers in terms of defective expressions. It is understood from the literature that other language ambiguities, especially English, are neither semantically nor morphologically related to the sui generis ambiguities of Turkish. To conclude, the absence of studies for this subject directed us to introduce NLP and deep learning approaches.

NLP is an artificial intelligence (AI) technology that deals with several operations such as event extraction [12], question answering [13], big data analytics [14], generating a naturalistic response [15-17] and etc. In earlier studies, NLP techniques have been used by constructing rule-based language-specific models. However, despite less demanding annotations requirements and ease of incorporating external knowledge, rule-based systems have some major obstacles in terms of processing efficiency [18]. Moreover, adjusting regular expressions to define the rules of the language requires an excessive knowledge of grammar in order not to cause inaccuracy in the results.

Deep learning techniques such as long short-term memory (LSTM) or convolutional neural network (CNN) have made great advances in recent years, which led to an unprecedented boost in NLP applications in terms of performance [19]. In machine translation, for instance, the phrase-based statistical approaches gave their place gradually to huge deep neural networks which generate better performance [20]. Furthermore, early models of named entity recognition were based on grammar rules, ontologies, or dictionaries, but today, deep learning approaches and iterative architectures have replaced them to achieve better performance.

In this study, we propose a hybrid deep neural approach of LSTM and CNN (C-LSTM) for detecting defective expressions in addition to traditional machine learning classifiers such as support vector machine (SVM) and random forest in order to compare the results in terms of accuracy. For model training and validation, a dataset containing approximately 30000 sentences labelled as 'defective' and 'non-defective' was collected one by one.

2. Methodology

This chapter tells about the deep learning models and the traditional classifiers that have been benefited from the study in detail. The models and classifiers have all been implemented using the Python programming language with the adequate libraries such as Keras [58] and Tensorflow [59]. Moreover, in order to benefit the Word2Vec technique, a corpus of word embeddings have also been created from the sentences in the dataset.

2.1. Dataset

In order to train and test the detection models, a dataset containing 29756 sentences have been collected from several sources one by one and each sentence has been tagged as ‘NON-DEF’ ,which means it has no defective expression, or ‘DEF’ , if it has defective expression, by the expert linguists. After that a corpus of word embeddings has been created from those sentences to vectorize the input data.

2.1.1. Data collection

In NLP, although it is tough, challenging and superlatively time consuming, one of the most important processes is collecting the data for the sake of better development and performance [21]. Besides a machine learning model is as successful as the quality and quantity of its input data. Therefore, a dataset containing a great quantitative number of Turkish sentences with their class tags was needed, however after comprehensive research, it has been found out that there has been no such dataset or data collection study performed earlier. That is why we had to bring all the adequate number of sentences together, analyze and label them whether they have defective expressions or not.

First, approximately 50 different open-access websites of courses, schools and education centers in addition to the official exam center of Turkey (OSYM) have been researched and the sentences which are related to defective expressions have been collected one by one. After that, those collected sentences have been analyzed in terms of defective expressions and labelled either 'DEF' or 'NON-DEF'. A sample of the collected data is given in Table 1.

Table 1. Sample of the sentences in dataset.

SENTENCE	LABEL
Bu konuda yapılan açıklamaların anlaşılmayacak bir yanı bulunmuyor.	DEF
Teknoloji ne kadar artarsa da el emeğinin önemi azalmıyor.	NON-DEF
Ortada, karamsar olmayı gerektirecek bir durum yoktu.	DEF
Bu, kendi resimleri için açtığı ilk kişisel sergisi olacağı için çok heyecanlıydı.	NON-DEF
Çok yorgun olduğu için o akşam erkenden yatmak istedi.	DEF
Burada, tiyatro salonundan internet kafeye kadar birçok etkinlik bulunuyor.	NON-DEF
Kentteki yaşam, öğretim kurumlarının sayısı arttıkça hareketleniyor.	DEF

However, the number of collected sentences was 9710, whose 4299 of them have defective expressions, and that amount of data is pretty insufficient for training a deep learning model. For this reason, a data augmentation operation was performed by using the Turkish Synonym Dictionary [22] and as a result, the data have been augmented up to 29756, 13398 of them have defective expressions and 16358 of them are proper sentences. The flow of the augmentation algorithm is depicted in Figure 1 and explained as follows:

- Each sentence from the dataset is split into words, which is called tokenization.
- The sentence itself is held as a whole in a variable before tokenization.
- Each word of the sentence is searched for its correspondent synonym one in the Turkish Synonym Dictionary.
- When found, the synonym word in the dictionary is replaced with the original word in the sentence that is held, and added to a file.
- Then these operations are applied to other words of the sentence.
- Then these operations are applied to other sentences of the dataset.
- As a result, a unique sentence can generate at least 3 to 5 new sentences depending on the word count.

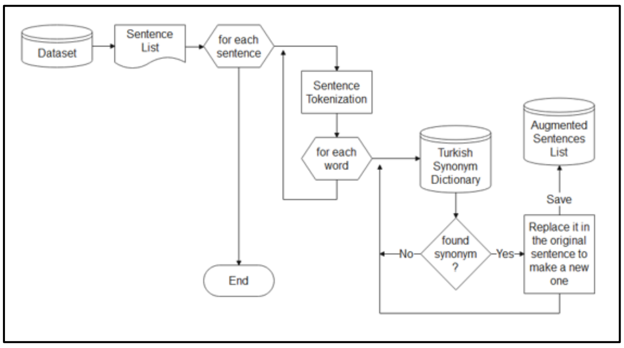

Figure 1. The flow of data augmentation

The augmentation process is shown on an example sentence, “Bu güz harika bir tatil yapacağız. (We are going to have a great holiday in this fall.)” below, the synonym words are listed in Table 2:

Table 2. Sample of the words in the sentence with their correspondent synonyms.

Word	Synonym
güz (fall)	sonbahar (autumn)
harika (great)	muhteşem (magnificent)
tatil (holiday)	dinlence (vacation)

• Bu sonbahar harika bir tatil yapacağız. (We are going to have a great holiday in this autumn.)

• Bu güz muhteşem bir tatil yapacağız. (We are going to have a magnificent holiday in this fall.)

• Bu güz harika bir dinlence yapacağız. (We are going to have a great vacation in this fall.)

2.1.2. Dataset preparation

After data collection, some preprocess operations on the sentences to prepare the dataset have been performed for the quality of the data such as morphological normalization, stop-word and punctuation omitting, lowering the letters, removing the similar sentences and etc., as shown in Figure 2.

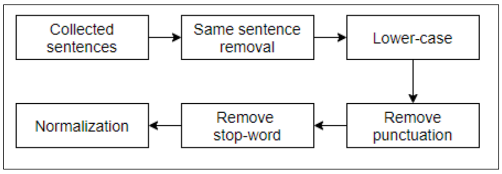

Figure 2. The flow diagram of data preprocess operations

However, this must be pointed out that we did not perform a stemming operation, because some of the defective expressions may be caused by using the wrong suffixes. Moreover, we did not remove all the stop-words such as conjunction words and personal pronouns since they may severely cause defective expressions, however since numbers, years, indefinite articles, indefinite pronouns and etc. do not affect the sentences, they have been removed from sentences in the dataset.

2.1.3. Corpus of word embeddings

Word embedding is a term that refers to using vectors to represent document vocabulary [23]. Word2vec is one of the techniques that vectorizes the words, introduced by Mikolov et al. [24]. This technique creates word vectors by considering the context of the reference words in the sentence by two separate algorithms: continuous bag-of-words (CBOW) and skip-gram. CBOW predicts the target word considering the surrounding words (context) and skip-gram, which notably performs better for infrequent words, predicts the context using the target word [25].

In this study, for the purpose of better learning performance in comparison to the existing Turkish word embedding, skip-gram algorithm with 200-dimension have been used to create our own word embeddings as corpus file which is then benefited to generate embedding matrix to train the models.

2.2. Detection models and classifiers

This subsection explains the model architecture of each deep learning model and traditional classifiers that have been implemented to detect defective expressions in Turkish in addition to their evaluation metrics.

2.2.1. Long short-term memory (LSTM)

Deep learning models can process complex patterns of time series and change their internal variables using back propagation techniques while conventional artificial neural networks (ANN) can only performs data process in a raw form, which makes deep learning a state of the art method [26]. Recurrent neural network (RNN) is a type of deep neural network and RNNs are widely used due to the capability of predicting time-series since they are capable of using previous time steps for predicting current information. LSTM is the most appropriate network in terms of handling a long sequence of data among RNNs [27,28], introduced by Hochreiter and Schmidhuber [29]. LSTM avoids long terms dependencies and vanishing gradient problems, which is major obstacles of regular RNNs, since it can decide whether to forget or remember the information by using its own forget gate and memory cells [30]. That is why LSTM is used extensively for NLP tasks with time-variant data such as handwriting recognition [31,32], machine translation [33] and etc. [34].

2.2.2. Convolutional neural network (CNN)

CNN and its derivatives are the most popular models among deep learning models in terms of visual tasks such as semantic segmentation, object detection and image classification [35, 36]. CNN model has shown notable efficiency for image diagnostics [37-41], however it is possible that by processing the data in the form of 1-dimension, CNN is also applicable to text data [42] such as text classification [43,44], text fragment categorization [45], character level classification [46] and etc.

Today, researchers of NLP focus on optimizing deep neural networks for achieving better performances since both CNN and LSTM approaches on single structure have certain weaknesses, therefore a hybrid model construction using advantages of each model makes important boost in terms of performance and time duration of tasks [47].

2.2.3. Support vector machine (SVM)

SVM is a supervised learning method for classification and regression tasks, introduced by Vapnik [48]. SVMs are derived from a robust theory of structural risk minimization, which aims at minimizing the structural risk, instead of the training error [49,50]. This classifier is widely used in text classification and clustering tasks with acceptable efficiency results [51-53].

2.2.4. Random forest

Random Forest is an ensemble learning model and an advanced decision tree method, introduced by Breiman [54] that is widely used for classification and regression tasks [55]. Since the high variance makes a decision tree model unstable, random forest is excessively preferred as it creates many decision trees having different sets of samples at each node and it gets a more accurate final score by averaging the scores of each tree [56].

2.2.5. Model evaluation metrics

Evaluation of the deep learning hybrid model have been measured by using the accuracy (validation accuracy) and loss (Mean Squared Error) metrics, defined as Eqs.(1)-(2)

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \tag{1}$$

Mean Squared Error (MSE) is calculated by taking the average of the square of the difference between the original and predicted values of the data, defined as:

$$MSE = \frac{1}{N}\sum_{i=0}^{n}(actual\ v. - predicted\ v.)^2 \tag{2}$$

where N is the total number of samples in the dataset and the abbreviation of ‘v.’ refers to ‘values’. The sigma symbol denotes that the difference between actual and predicted values taken on each i value ranging from 1 to n.

In addition to the metrics above, precision, recall and f1 score metrics have also been applied to measure the performances of the proposed models. The equations of the aforementioned metrics are given in Eqs (3)-(5). The abbreviations of TP, TN, FP and FN are True-Positive, True-Negative, False-Positive and False-Negative respectively.

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

$$F1\ Score = \frac{2 * precision * recall}{precision + recall} \tag{5}$$

3. Results and Discussion

This chapter represents and discusses the results of the aforementioned methods for detecting defective expressions in Turkish. The overall learning flow for each model is depicted in Figure 3.

As aforementioned in previous chapters, C-LSTM model is a hybrid approach of 1-dimensional CNN (Conv1D) and LSTM deep learning models. After the data is processed with CNN, then the output becomes the input of LSTM layer and the

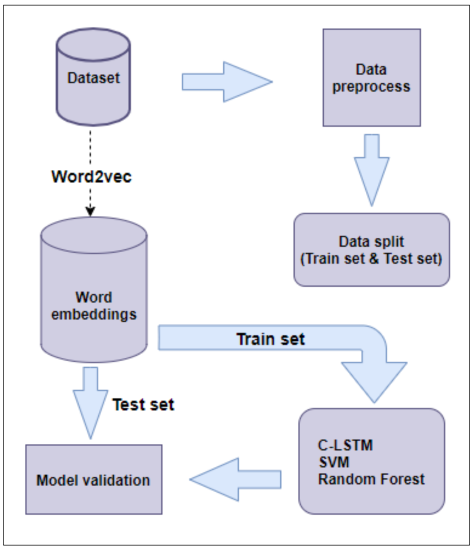

Figure 3. The flow diagram of the learning models

product is the final output of C-LSTM model, as shown in Figure 4.

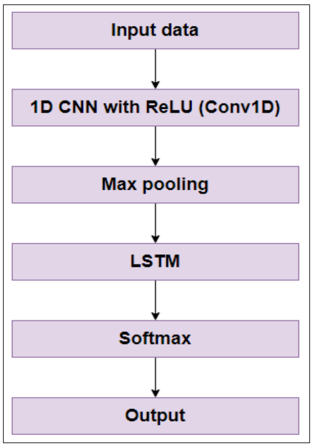

Figure 4. The layer architecture of the hybrid model (C-LSTM)

In order to implement the most optimized C-LSTM hybrid model, the hyperparameters of each model such as the number of filters, kernel size and the pooling size of CNN in addition to the number of hidden layers of LSTM model have been analyzed with several configurations. At the end of the empirical trials, the optimized hyper parameters of C-LSTM model are adjusted, as seen in Table 3.

Table 3. The parameters of C-LSTM model with the corresponding values.

PARAMETERS	**VALUES**
CNN Filters	256
CNN Kernel size	3
CNN Pool size	2
LSTM number of hidden layers	256
Dropout	0,3
Conv1D activation	Relu (Rectified Linear Unit)
Model activation	Softmax
Optimizer	Adam
Loss function	MSE
Learning rate	0,001
Epochs	50
Batch size	85

3.1. Results

Table 4 represents the performance results of random forest and SVM classifiers using the evaluation metrics.

Table 4. Model performances of the classifiers.

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**
SVM	0.5850	0.60	0.75	0.66
Random Forest	0.7812	0.79	0.85	0.81

The results of the classifiers clearly show that Random Forest provides more successful classification in comparison to SVM. This is because random forest creates many variations of decision trees during the classification and each final score is averaged to get higher accuracy. In the following, Table 5 represents the results of deep learning models using evaluation metrics.

Table 5. Model performances of the deep learning models.

Model	Validation accuracy	Validation loss	Precision	Recall	F1 Score
LSTM	0.8794	0.0992	0.88	0.89	0.88
CNN	0.8433	0.1217	0.80	0.88	0.84
C-LSTM	0.8854	0.0884	0.87	0.86	0.87

The results clearly show that all the deep neural approaches of this study perform by far more accurate than traditional machine learning classifiers. In addition, although separate deep learning approaches provide quite acceptable performances, a hybrid model of those approaches shows a slight increase in accuracy. The accuracy comparison of the models is shown in Figure 5.

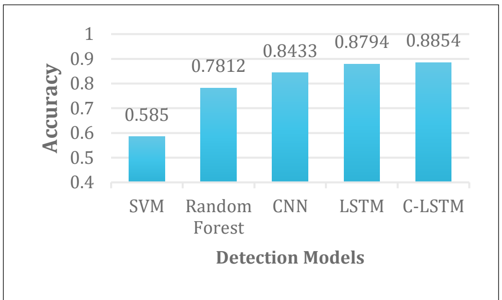

Figure 5. Accuracy comparison of each model in the study

3.2. Discussion

The model proposed in this paper has demonstrated a slight improvement in performance compared to the existing separate deep learning models and traditional classifiers. This hybrid approach addresses the data-loss and long-term dependencies which also affect LSTM and CNN separately due to the high size of data. On the other hand, traditional classifiers show quite insufficient performance, especially SVM, since they have no capabilities of learning long-term dependencies. In addition, one of the limitations of this study is the inadequacy of input data, because a machine learning model requires a great number of training and test data to be more effective in terms of model accuracy.

This can also be pointed out from this study that traditional classifiers are not the best options for some tasks belonging to specific languages such as Turkish, since Turkish has a superlatively complex structure in terms of both morphologic grammar and semantic context. Even though deep neural-based models provide acceptable performances, more NLP studies on Turkish will ensure better performances and more promising results.

Defective Expression is a significantly crucial issue for Turkish people in the fields of mass media such as newspapers or TVs, literal publications such as books or magazines, educations at schools from primary schools to universities and even almost any competitive exams held in Turkey for attending high schools or universities. All the aforementioned issues clearly show the importance of practising the Turkish language without defective expressions. Developing a machine learning system for this issue will surely provide Turkish teachers and linguists a better and efficient solution to analyze defective expression for improving Turkish education and practice.

4. Conclusion

In this paper, we proposed a hybrid model of CNN and LSTM for detecting defective expressions in Turkish. Evaluation experiments have been performed using the dataset that has been collected sentence by sentence from several sources since there has been no such domain-specific data collection performed before.

The proposed model achieved higher accuracy than the existing deep neural models of CNN and LSTM, in addition to the traditional classifiers of SVM and random forest. In general, this study also shows that deep neural approaches come into prominence for text classification in comparison to traditional classifiers.

In conclusion, this study is a great contribution to Turkish NLP and an excellent source for other researchers studying this area. In future, a more comprehensive dataset must be considered for improving the model performance.

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