For Amazon and Other E-Online commerce's Reviews, Emotional Analysis Using FastText and RNN Variants with Support NLP

Dr. Sumanth S[1] Edna Margaret B[2]
[1]Associate Professor, Department of Computer Science and Computer Applications,
Government College for Women, (Affiliated to Bengaluru North University), Kolar - 563 101.
[2]Assistant Professor, Department of Computer science and Computer Applications,
Smt. V.H.D. Central Institute of Home Science, Bengaluru - 560 001.

ABSTRACT
Emotional analysis refers to the process of extracting content from a text that helps an entity understand the public feelings about its product or product while monitoring online conversations. E-commerce has seen tremendous growth in usage. There is a need to analyze the thousands of product reviews offered to customers to get an accurate view of customer needs and this will help analyze the market styles of any product. The purpose of this study is to explore different approaches to deep learning in an appropriate way Rate customer feedback based on mobile updates from Amazon.com based on measures analyzethese reviews and classify them as good, bad, or neutral. In-depth learning algorithms are different Used and tested as simple, four-dimensional RNN, namely Long Short Term Memory Networks(LRNN). Short-Term Memory Network (GLRNN) is a recurring unit (GRNN), and a recurring unit (UGRNN). Five different algorithms have three modes for extracting features, with accuracy, memory, and precision, andyour F-1 score for both balance and balance datasets found an unequal set of data. It has been determined that GLRNN algorithms with the Quick Text feature to get high accuracy of 93.75%

Keywords: Emotional Analysis, Amazon and Other E-commerce, Product Reviews, FastText, Customer Feedback

1. INTRODUCTION

Thousands of people leave comments on products e-commerce sites (e.g. Amazon, eBay, Flipkart) and updates about services such as restaurants or places of interest (e.g. Travel Advisor, Rotten Tomatoes, and Yelp) and social almost non-existent media (for example, Facebook and Twitter) anything else. thus, sharing reviews and feedback from customers about products or services used online to influence the ideas of new customers in their products, services, organizations, or institutions. Generally, our views are on ourbehavior, ideas, and choices influenced by other experiences and ideas. In particular, feedback or review when we encounter something new informed individuals is requested. (we dream of millions part of users who share their knowledge with online updates about products and services; This will have a profound effect by encouraging or discouraging other people it is very important to try these products or services. Verify the authenticity of the seller. Done over time, consumers expand their ideas and feelings about the product through invisible communities, social networks, and social media communities. Classification and division of adults the amount of random data from the internet is growing on a very challenging journey; so feeling Analysis, as well as Indigenous Languages Processing (NLP) methods, are being developed to perform such tasks analysis of text data from reviews or surveys. (These methods predict the diversity of ideas (positive, negative, or neutral) best effect on the product. In this study, Emotional analysis will be performed for testing products on the website (i.e. unlocked cell phone) amazon.com Also; this analysis will help customers make the right decision to buy or not to buy. Also, companies can understand how their customers feel about products and satisfaction levels to maintain a level of comfort, keeping their functionality as well improving their resources.

1.1. Problem Statement

Use of the internet today has grown to the level of electronic trading websites where customers trust to buy and sell

- As these websites allow consumers to write their responses numerous reviews of different goods and services are now available.
- As a result, the need for analysis of these updates to understand feedback from consumers. it has been raised to both sellers and buyers. However, with so many comments it is hard to read all the answers to something, especially the famous objects.
- Will the study explore different emotions? Cellular data analytics methods reviews predict customer satisfaction mobile reviews using in-depth learning algorithms, including five different RNN models to be based on their performance. However, this will also help consumers make better decisions when considering a purchase of a specific cellphone.

1.2 Related Previous Work

The internet has a huge impact on our daily lives. The Internet provides a wealth of information provides information on a variety of topics.Customers often check for updates before buying a product online. Millions of comments are made every day online about a product, person, or place number and size make it very difficult to manage and analyze reviews. In the process of analyzing emotions, we draw attention to specific revisions using natural language analysis (NLP), integrated language learning, textual analysis, and differentiation of point of view. In the field of emotional analysis, there are many ways to solve NLP problems.

Garcia et al. have developed an agent-based model for the emotional analysis of product reviews [1]. In this way, the authors developed an agent-based model that uses a framework to reflect the emergence of cohesive emotions in online communities [2]. The framework modifies user interaction in online communities using two valences that describe happiness and awakening, which define the level of agency activity. In this way, the main focus of the authors was to balance the power of users and communities of product reviews. Santosh Kumar et al. conducted a comparative study of other emotional analysis methods [3]. The authors found the Naive Bayes division work much better compared to SentiWord.Net and Logistic retreats. F1 score was used to compare methods. Zhou et al. proposed a method based on a neuralnetwork of textual segregation called C-LSTM [4]. The authors describe a new method based on the neural network of emotional analysis. Haque et al. 10 vector support systems used for amazon review reviews were used [5]. A method similar to the one above was developed by Soliman et al. emotional analysis [6]. Vanja et al. suggested an emotional analysis based on e-commerce data visibility. The attribute removal in the aspect-level of product reviews is done by the authors. They compared the performance of SVM with the Naive Bayes and found that the latter was more accurate [7]. Wijayanto et al. use the Gaussian Naive Bayes in the emotional analysis [8]. Nithya et al. have proposed a way to conduct emotional analysis in random reviews[9]. They used TANAGRA software to differentiate. The authors explored 4 aspects, namely. A Recommended way to find out which feature is most important and which is the smallest customer in the list of features of each of their products is Display, Accessories, Battery life, weight, and cellphone costs. In this article, we have used the NLP library of Facebook FastText [10]. It is an open-source library. This library is specially designed for classification [11]. FastText is famous for its distributed representation. It is also used to embed words. The Fasttext has some advantages over its peers in separating text and word placement. It trains models very quickly in comparison. The Fasttext uses a hierarchical method that makes it very fast. It is a learning model of a monitored machine. Returns text and related tags of some kind and trains the model. This model also helps in separating the text.

1.3 Purpose and Scope of Work

The paper aims to explore different models of in-depth reading measuring the polarity of text reviews for mobile phones From Amazon.com. Five different versions of RNN algorithms used RNN, LSTM-RNN, GLSTM-RNN, GRU-RNN, and UG-RNN and are compared in terms of three terms embedding extraction features: Glove, Word2vec, and FastText. The placement of words plays a very important role in text fragmentation by converting text into displayed numbers presentations that allow us to use it as an input machine learning algorithm. E-commerce plays an important role in our daily lives. We are becoming more and more dependent on internet marketing to buy things. Thousands of comments are left on e-commerce sites every day. These updates provide valuable information about people's perceptions ofthe product. Therefore, it has become necessary to develop an appropriate approach to implementing and analyzing these updates to effectively and efficiently understands market trends and customer needs.

2. LITERATURE REVIEW

On the other hand, in the field of emotional analysis, using in-depth learning methods, a comprehensive set of information 10,662 records were used to produce sensitivity analysis From the IMDb database [6] deep integration method unsupervised machine learning and learning Rewards provided better results and better analysis. alternatives available [3]. (in-depth reading feature Convolutional Neural Network (CNN) section, on the other hand, the machine learning aspect of the analysis used Kun supervised learning was used to train and study CNN K-mean after data and output feature Integration algorithm used to classify updates good or bad collections.

3. METHODOLOGY

Methods and techniques used in this section, the division of mobile updates has also discussed the steps taken during the test are specified. Figure 1 shows the stages of this study starting with the Data set for online updates until each update is split into good, bad, or neutral Pre-processing. (Previous processing methods are used to Prepare the data to model and conclude very good results which include issuing pre-processing steps Nulls, lower case, spelling correction, token making, word order, punctuation, and punctuation. EachUpdate to the database is labeled based on the review ratings. If the rating is more than three stars, it will be labeled positive, if the ratio is equal to three stars, it is neutral, and anything less than three stars is considered negative. Also, the database is divided into 80% training and 20% testing.

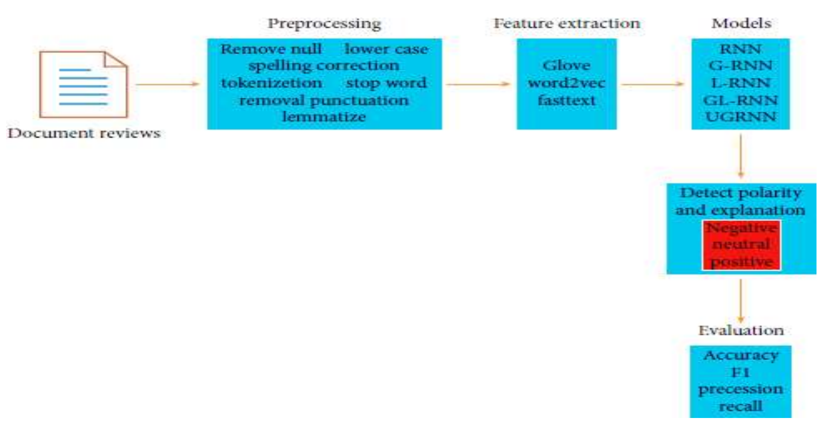

Figure 1:Categories of the proposed route

A. Data Collection
This section includes the compilation of a relevant database of emotional training analysis models. We have used the "Amazon Comments Sentiment Analysis" database, which is freely accessible at Kaggle.com. This database contains 3.6 million comments from amazon.com.

B. Previous processing of data
This included the task of converting the database into the required format by removing any reuse from the database. This category includes functions such as case modification, word removal, punctuation, Stem focus, Lemmatization, and POS tagging. Each update to the database is appropriately labeled according to its feelings (bad or good).

C. Feature Domain
This includes extracting the required information from pre-processed data to help classify the review as negative or positive. This was done using the fastest library.

D. Separation
This step involves training the emotional analysis model using the quick text library. This model is further evaluated in comparison with the test data to ensure the accuracy of the model.

3.1. Types of Section Models
3.1.1. RNN Model
Initially, we used the Camera library for in-depth reading. We started setting some parameters for our RNN model. First, we applied the RNN layers. A dense network with 150 hidden units was used and then Softmax. Enabling function to predict 3 classes; in fact, Activation function Soft max determines the final classes. Here we keep a decrease of 0.2. We passed them all embedding types (Glove, Word2vec, and FastText) vectors model and transfer them as a layer in a dense layer. In mathematics, also known as the Softmax function softargmax, or the standard interpreter function is a function that takes the vector of the real number K as the input again It is accustomed to the possible distribution of K Equal opportunities and input elements numbers. (Meanwhile, before installing Soft max, some vectors parts can be worse or bigger than one, too not total in 1; but, after the use of Softmax, each component will be in width{\ display style(0,1)} (0,1),and sections will be added upto 1 for interpretation as opportunities. In addition, large input components will go hand in hand with great potential. Softmax is commonly used on neural networks, to create an unusual exit map distribution of opportunities over predicted output from the network class. Additionally, we used an Adam optimizer to customize its model to determine the distance between the forecast and actual value. Adam optimizer calculates the reading rate by distance. If the distance is large, the Adam optimizer will increase the level of learning. Finally, we spent 30 seasons' data.

3.1.2. LSTM Based RNN(LRNN)
In neural networks, Softmax is also an unusual network output in distribution opportunities over a limited output Class. We also tried to get in this way. Original text embedded in Word2vec, Glove, and FastText data were trained 30 times in experimental use of LSTM. The period is a defined hyperparameter before model training. Onetime, all data is transmitted both front and back via the neural network only once. Adam optimizer was used to improve limits, reading rate of 0.01 and bulk size is 32. A drop-out rate of 0.2 is setto prevent overcrowding it is in an LSM layer with 150 hidden units man a pattern of flexible learning levels. Individual accounts learning levels of various parameters comes the word the amount of time that corresponds to why it is named Adam used the first and second measure to change the learning level of the weight of each neural network. In repair, refers to the amount of weight that is set for it such as "reading level" or step size.

3.1.3. GRU Based RNN(GRNN)

In this model, we use a GRU block cell to create a basic GRU with 150 hidden units this article, a cell with an output size of 100 and a pull rate of 0.2 received e-output is transmitted to RNN via a program. 62 and 31 lengths of training and test data, respectively. Finally all (Glove, Word2vec, and FastText) embedding vectors in the model, sequentially, as well are used interchangeably as they are placed in a dense layer ReLu activation function and output, Soft max classifier for the final emotional separation.

3.1.4. LSTM Based RNN(GLRNN)Group

Group LSTM RNN paper based on the effective LSM Group cell Size 150 and 0.2 drop point Group of LSTM cells contains a small LSTM cell for each group, in which each small cell operates in a sub-vector with the same output size. (Ku the output is transferred to RNN. Finally, a thick layer Included is the ReLu activation function; a Very high value of RELU the opening function commonly used in sensory networks; ReLU is usually a good first-step output transferred in the Softmax separator for the final sensitivity, separation.

3.1.5. Update RNN-Based Gateway(UGRNN).

GRU-LSTM RNN-based use of your network structure for both LSTM cells with GRU used for 150 output size and a decrease of 0.2 cells is a combination of LSTM and GRU units, there is only one department here. To decide, to decide even if the unit needs a faster computer or compound, this is a repetitive concept feed-forward highway network output taken Switch to RNN with unit lengths 62 and31 characters training and test data, respectively. In the end, the big layer is used with the function of activating the Relu as well output is transferred to the softmax separator emotional separation.

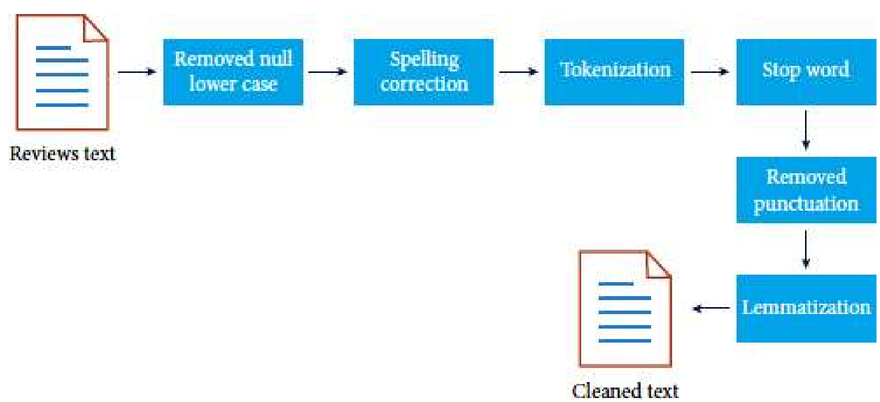

Figure2:e-stepsof thepre-processing

4. ANALYSIS AND RESULT

First, we identified and received a different test best model for measuring test polarity from previous tests comparing the effectiveness of an engineering feature; for example, FastText, Glove, and Word2vec use the jump gram for each model before making comparisons between models. and decide which method is best Veza. (Algorithms used in our experiments are RNN, LRNN, GRNN, GLRNN, and UGRNN. However, all reviews are considered good in this article, negative or neutral based on the star rating (label). (We, four scales and five stars are classified as positive while two and one-star ratings are classified as: negative ratings and three-star ratings are classified as neutral. (Ku The first tests were performed on unequal 4K data. Comments (second analysis estimates data means we have fixed the problem Unbalanced data set using a combination of two strategies: sub-samples and bulk samples.

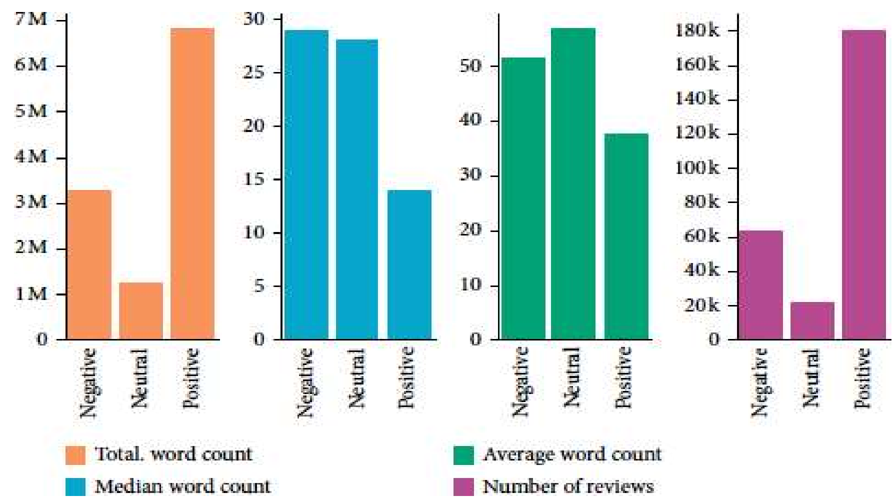

Figure3:e-reviewssummarystatistics for positive ,neutral, and negative rating

However, Oversampling was used to increase the size of unusual sample examples. Instead of throwing away a lot of examples, Unusual new events are created using repetition (done minority oversampling technique used in neutral reviews, the lower category contains Only 21,000 comments. Thus, we increase the size of the neutral Negative reviews by doing multiple samples to get 64165 reviews. Also, under-sampling used to compensate for data by reducing the size of the overflowing class method used when a data value is sufficient; As a result, we used smaller samples. Positive reviews because they were higher than negative and biased reviews. Note the number of positive comments. It was 18, 0686. Therefore, we are under a good review sample negative is equal to 64,165. Finally, balance the data collection contains each good, negative, and neutral item has 64,165 reviews. The balance of balance sheet includes 192,495 reviews.

4.1. Results from Unequal Data

Tables 1-5 represent Results for RNNGRU, LSTM, GLSTM, and UGRNN using a three-factor domain, respectively strategies. In five algorithms used in unequal systems in databases, it turns out that the GL-RNN algorithm has had a very good performance and very bad GRU-RNN. For this in thedata set, GL-RNN and LSTM-RNN same performance; it may be related to their reality having the same structures. Usually, FastText name insertion where the feature output provides the highest accuracy compared to other methods of removal feature UG-RNN, Glove provides low accuracy in all tests algorithms high accuracy achieved FastText Feature domain used in the RSTN-based LSTM group 93.75% accuracy low accuracy achieved Gloves Feature domain uses GRU-RNN algorithm 53.87% accuracy. (In Glove Medium Accuracy, Word2vec and FastText feature extraction features 75.1%, 82.6% and, 83.7%, respectively). There is limited Accuracy according to thealgorithms suggested in its unequal data; it is clear that FastText is working best and Gloves.

4.2. Results Received With Limited Data

From the beginning, if you look at the estimated data set, three ways to extract a feature with similar points However, the maximum number of five proposed algorithms 88.39% accuracy was obtained. The LSTM-RNN algorithm uses the FastText feature way. Collect LSTM – RNN using FastText feature discharge was 0.01%different from the LSRM RNN algorithm; and, this is both algorithms share similar properties. Usually, Gloves the method had the highest accuracy among the four algorithms. However, it obtained very high scores used with the GRU-RNN algorithm (Glove, Word2vec, and FastText download methods according to five algorithms 71.4%, 80.1%, and 79%, respectively). Ku as opposed to unequal data in which the accuracy is moderate. It was the highest value of the FastText method, balanced data had Word2vec as the highest accuracy of the rating. Table 6-10 represents the results of the RNN GRU, Three LSTMs are used, and GLSTM and UGRNN respectively install removal method.

4.3 Comparison

Comparing our work with other related research, in this paper, the results were obtained as follows previous analyzes were performed in different ways, discussed earlier in the literature. Various methods and algorithms for machine learning have been used in it.

	Accuracy(%)	**Precision(%)**	**Recall(%)**	**F1-score(%)**
Word2Vec	71.88	67.98	71.87	67.23
GloVe	68.45	59.33	68.84	61.22
FastText	75.89	54.12	75.15	74.10

Table 1: Results from the nonlinear data analysis of RNN, an algorithm with three methods for extracting features.

	Accuracy(%)	**Precision(%)**	**Recall(%)**	**F1-score(%)**
Word2Vec	92.13	92.15	91.10	90.44
GloVe	83.44	83.78	82.11	83.67
FastText	92.67	93.27	92.90	93.13

Table 2: Results from the nonlinear data analysis for LSTM Based on an RNN algorithm with three methods for extracting features.

	Accuracy(%)	**Precision(%)**	**Recall(%)**	**F1-score(%)**
Word2Vec	65.89	49.34	65.45	56.20
GloVe	53.77	29.77	53.98	37.90
FastText	70.67	63.45	70.44	65.33

Table 3: Results from the unlimited GRU data analysis Based on an RNN algorithm with three methods for extracting features.

	Accuracy(%)	**Precision(%)**	**Recall(%)**	**F1-score(%)**
Word2Vec	92.23	92.78	92.56	92.00
GloVe	86.33	86.44	86.10	85.34
FastText	93.45	93.22	93.12	93.10

Table 4:Unequal data analysis results GLSTM-based RNN algorithm with three components methods

	Accuracy(%)	Precision(%)	Recall(%)	F1-score(%)
Word2Vec	90.34	90.67	90.33	90.77
GloVe	82.11	81.78	82.94	81.98
FastText	85.77	85.88	85.22	85.99

Table 5:Results from UGRU non- statistical data analysis Based on an RNN algorithm with three methods for extracting features.

	Accuracy(%)	Precision(%)	Recall(%)	F1-score(%)
Word2Vec	77.34	06.45	77.23	11.98
GloVe	62.77	58.33	62.58	59.44
FastText	70.33	59.55	70.44	63.90

Table 6:Results from the analysis of the RNN balance data an algorithm with three methods for extracting features.

	Accuracy(%)	Precision(%)	Recall(%)	F1-score(%)
Word2Vec	87.33	87.56	86.55	87.33
GloVe	69.44	63.56	69.70	63.98
FastText	88.99	88.46	87.33	88.34

Table 7:Results from the analysis of the balanced LSTM data Based on an RNN algorithm with three methods for extracting features.

	Accuracy(%)	Precision(%)	Recall(%)	F1-score(%)
Word2Vec	61.77	66.55	61.47	58.44
GloVe	66.44	71.33	66.45	70.23
FastText	61.55	66.77	61.44	58.89

Table 8:Results from the GRU Unbalanced Data Analys is RNN Based algorithm with three methods for extracting features.

	Accuracy(%)	Precision(%)	Recall(%)	F1-score(%)
Word2Vec	87.44	87.77	86.32	87.45
GloVe	80.56	80.47	80.58	79.44
FastText	88.56	88.54	88.47	87.67

Table 9: Results from the GLSTM balance data analysis Based on an RNN algorithm with three methods for extracting features.

	Accuracy(%)	Precision(%)	Recall(%)	F1-score(%)
Word2Vec	86.44	86.98	86.34	85.90
GloVe	77.46	78.44	77.98	75.34
FastText	87.34	87.55	87.58	86.95

Table 10: Results obtained from balanced data analysis for UGRNN based RNN algorithm with three feature extraction methods.

The same database used in this study of the three FastText feature domains depending on the survey used with the LSTM team based on the RNN method Maximum 93.75% accuracy (work in [10] was able to Get 92.73%accuracy using the Glove removal feature With CNN algorithm; However, the Glove feature provided the removal Severe side effects when used under RNN algorithms (Kulow accuracy obtained by heavy unigrams [4] Feature domain with accuracy under the SVM algorithm 81.2%. On the other hand, the study in [7] gets 90.7% accuracy using a continuous word bag on how to extract a feature under the random forest algorithm. Positive results are obtained recommended method, under the FastText as set domain GLRNN.

CONCLUSION

The most difficult part is text fragmentation because the meaning of the words should be understood when the ambiguity is removed looks at human language data displayed to gain a better understanding; processed afterward and is designed for use as an input into five different RNN algorithms. However, the data was processed for later processing limited data to solve the problem of having too many good reviews compared to neutral and bad. Otherwise, previous research has focused on unstable databases as well has been able to achieve good results. In five algorithms, GLSTM-based RNN with FastText feature can give the best results when tested in terms of accuracy, precision, memory, and F1 score of inequality LSTM–RNN also has data sets of 93.75% accuracy. FastText provided the best results in the form of a feature removal for a balanced database with an accuracy of 88.39%. The result can be drawn here that they get the highest points for sharing. similar structures; but, on a set of measured data, There was a 0.01% difference between GLSTM and LSTM-RNN algorithms accuracy makes them very similar to this type of analysis (Ku Unlimited data set produced better results, probably because of it. large size. (i.e., results were compared with previous tests in books; As a result, the purpose of this article successfully achieved and all objectives achieved; and, a better model is built than the results to the reliability of previous tests with great accuracy The rate obtained using the Glove removal feature is 92.75%. On the other hand, the Glove feature with the CNN algorithm extraction produced very low results when used with the RNN algorithm method of extracting a feature or machine learning cannot be individually tested emotional analysis; therefore, the algorithm needs to be adjusted to suit the situation Requirements, inputs, and output algorithm.

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