A Summary of Aspect-based Sentiment Analysis

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Abstract. Aspect-based sentiment analysis is a subclass of sentiment analysis tasks, focusing on judging the sentiment tendency of entities or attributes, and has received extensive attention due to fine-grained analysis results. The current research mostly summarizes the research from a single point of aspect extraction or sentiment classification, and lacks of research on the methods and problems in aspect-based sentiment analysis from the overall perspective. By using the method of literature investigation, an in-depth overview of the typical methods and solutions is given in the field of aspect-based sentiment analysis from three aspects: aspect information extraction, aspect information sentiment classification and aspect-based sentiment analysis joint modeling. Then, we discuss some of the most challenging problems existing in the field in terms of model adaptability, error transmission, knowledge and reasoning, and proposes future research opportunities in terms of strengthening knowledge representation, multi-task learning and integrating knowledge and reasoning from the overall perspective of practical application.

Keywords: Sentiment analysis; Aspect extraction; Deep learning; Aspect sentiment classification; Joint modeling.

1. Introduction
Driven by information technology, the Internet-based social media platform has been developed significantly, attracting more and more people to participate in content distribution and interaction depending on its open and free access, convenient communication and rich content, which dramatically promotes increasing the volume of information. The information includes a large quantity of viewpoints held by individuals to a particular issue, which is of great research value in grasping the public attitudes to the issue as well as judging the develop trend of it. How to extract valuable information from the quickly-generated one has increasingly become the concern of enterprises, institutions and even countries. It could be best illustrated by e-commerce. The platforms usually provide consumers with the ability to review products, which include their subjective judgments on every side of the products. From the perspectives of consumers, they could compare the degree of acceptance of the products by reading the comments which could also help to identify the product matching to the consumer’s requirements; regarding the e-commerce platforms, these reviews can help them integrate and visualize the results of sentiment analysis, or be considered as basis of recommendation system to make the shopping experiences more convenient; for the developers, these reviews make them obtain the advantages and disadvantages of the products, helping to improve the products pointedly, so as to increase sales and consumer recognition. This reflects that the information of the public opinion can guidance the decision-making processes and behaviors of all levels of groups, signifying great potential value.

Sentiment analysis is the area that analyzes people’s viewpoints, sentiments, reviews, attitudes and emotion forms to the entity and its attributes[1], and can be divided into three subclasses based on the granules of research, which are document-based sentiment analysis, sentence-based sentiment analysis and aspect-based sentiment analysis. Document-based sentiment analysis and sentence-based sentiment...
analysis focus more on the tendentiousness of overall sentiment of one document or sentence, Aspect-based Sentiment Analysis (ABSA) helps to obtain comprehensive sentiment information by making a clear judgment on finding the entity in one text and the tendentiousness of sentiment of its attributes, providing the foundation for decision-making, which has become a hot research topic in recent years.

The purpose of ASBA task is to extract viewpoint information from text. Viewpoint information can be formalized into a four-tuple, $(g, s, h, t)^{[1]}$. Among the four-tuple, the $g$ is known as aspect information, representing the object of the viewpoint, which could be viewed as the entity, attributes of the entity or one side of the entity. The $s$ represents the sentiment polarity which could be classified into positive sentiment, negative sentiment and neutral sentiment. The $h$ represents the holder of the viewpoint. The $t$ represents the time the viewpoint was made. In practical research, more attention is paid to the information in the two-tuple, $(g, s)$, because the information about time and holder of the viewpoint can be obtained outside the viewpoint text. The aspect information in the text can be divided into explicit and implicit aspect information. Explicit aspect information is explicitly mentioned in the text, just as in the previous example where the words or phrases that are used to represent aspect information clearly appear in the text. Implicit aspect information cannot directly extract a word or phrase from the text, which needs to be summarized by the context.

The general processing flow of ABSA task consists of three steps: aspect information extraction, aspect sentiment classification and aspect information integration. Among these three subtasks, aspect information extraction and aspect information sentiment classification are the key tasks, while aspect information integration often needs to be carried out according to the actual application requirements. In recent studies, some researchers have put the first two subtasks into one model framework and make them work simultaneously to improve the overall task performance with the relation between the two subtasks.

Combined with the focus of current researches, we summarize the typical methods and solutions to solve existing problems from three aspects: aspect information extraction, aspect information sentiment classification and aspect-based sentiment analysis joint modeling, point out the existing problems, and give some suggestions for future study.

2. The Research Status of Aspect Information Extraction Technology

Methods based on frequency and rules are the main methods to extract the aspect information in early days. Among them, the method based on rules refers to when words or phrases in the text conform to a predefined pattern, they are regarded as aspect information. At present, the typical methods are proposed based on topic model, conditional random field, deep learning and so on, while methods based on frequency and rules are mostly used as the supplement of main machine learning methods. In addition, some scholars use corpus resources or dictionary resources to match and extract aspect information. We will study and analyze the following five methods: method based on frequency, method based on rule, method based on topic model, method based on conditional random field and method based on deep learning, and then we'll summarize the current situations of information extraction research.

2.1. Method Based on Frequency

Method of aspect information extraction based on frequency is based on the following assumption: in a large amount of texts that review the same entity, nouns or nominal phrases that represent entities and entity attributes will appear at a higher frequency. This kind of method uses the frequency characteristic of aspect information in the text. Hu et al.$^{[2]}$ firstly explore the aspect information extraction through observing the review expression, and it was found that the reviewers often use relatively fixed or similar words to express their sentiment for a certain attribute, thus proposing the aspect information extraction method using association rules to extract nouns or phrases frequently appearing in the text as aspect information; Li Shi et al.$^{[3]}$ also use association rules to find frequent items in the text as candidate aspect information, and get the final aspect information through modification, filtering and other operations; Ku et al.$^{[4]}$ use term frequency-inverse document frequency(TF-IDF) algorithm to assess the importance of a word to a document, and to extract aspect information accordingly. Although the method based on frequency is simple and easy, it will fail or make mistakes in the face of aspect information that does not
conform to the above assumptions, such as low-frequency aspect information and high-frequency nouns or nominal phrases with non-aspect information.

2.2. Method Based on Rule

The definition of language in CiShu is a collection of expressions, conventions and rules used to convey information. It can be seen from the definition that language conforms to certain rules in organization. Aspect information is a specific component of language expression, must conform to certain rules with context, such as the modification relationship between nominal aspect information and adjective sentimental words, the parallel relationship between aspect information in the same component in compound sentences, etc. From this point of view, researchers propose a method based on rule to extract aspect information. Zhuang et al.[5] use a series of pre-established syntactic templates to match the text and extract the sentiment word and attribute word in the text; Qi et al.[6, 7] propose a double propagation (DP) algorithm, which uses the dependency relation between the attribute word and the sentiment word to extract aspect information; Poria et al.[8] use the method based on syntax dependency, and add common sense knowledge into the model, to extract the implied aspect information. The main task of using a rule-based approach is to establish a series of valid rule sets, and this process often needs manual construction. Under this situation, Liu et al.[9] propose a method to automatically select aspect extraction rule sets. By testing and calculating the accuracy rate and recall rate of each rule on the training data, the rules were sorted and the appropriate rule subsets were automatically selected.

2.3. Method Based on Topic Model

Topic model is an unsupervised learning method for modeling document topics. Its basic assumption is that the document topic is the implicit information in the text, while the document and the words in the document are connected by several topics, with each topic representing a semantic content. The purpose of using the topic model is to establish the topic distribution under the given document condition and the word distribution under the given topic condition. Common topic models include latent semantic analysis (LSA) and latent Dirichlet allocation (LDA). With the continuous application of topic model in topic analysis, some researchers apply this method to the task of aspect information extraction. However, using the topic model alone to extract the aspect information will produce some results that are difficult to explain[10]. In order to solve the above problems, some scholars put forward the semi-supervised topic model. For example, Andrzejewski et al.[11] propose the DF-LDA (LDA with Dirichlet Forest prior) model, by establishes a series of Must-Links and Cannot-Links constraints to guide topic classification. Lu et al.[12] propose a weak supervised learning algorithm by adding seed words in the process of extracting information when using the topic model, to enhance consistency between topic and aspect. Pointing to the fact that it finds no way in solving problems of polysemy based on DF-LDA model and seed words as priori knowledge and so on, Chen et al.[13] propose an improved algorithm MC-LDA(LDA with M-set and C-set), by using M-sets and C-sets to replace two constraints in DF-LDA algorithm. Based on the observation of the overlapping phenomenon of aspect information in different fields, Chen et al.[14] propose another method to generate aspect information by using LDA and its variant, AKL (Automated Knowledge LDA). The advantage of aspect information extraction technology based on topic model is that it is an unsupervised or a semi-supervised learning method, which can improve the extraction of implicit aspect information, has low requirements for labeled data, and low degree of application limitation in the open field. The disadvantage is that extracting the explicit aspect information directly from the text is not very easy, and the extraction is generally affected in the face of social media review data that is often very short.

2.4. Method Based on Conditional Random Field

Conditional random field (CRF) is a supervised machine learning method based on the undirected graph model of Markov network. It is often used to deal with the problem of sequence labeling, that is, when given the observation sequence \( x \), by manually selecting the task related features, and defining the feature function, researchers could work out the conditional probability distribution \( P(y|x) \) of the tag sequence \( y \), and select the tag combination with the greatest probability as the aspect extraction
The key problem of using CRF model for aspect extraction is to build rich feature sets which will affect the final marking effect. For example, Jakob et al.\[15\] complete aspect extraction task by using CRF model based on current words, part of speech tags, syntactic dependency, word spacing and other basic features; Chernyshevich\[16\] also use CRF model for aspect extraction, but constructed 15 different sub-features of three types features which are participle, nominal phrase and semantic role; Shu et al.\[17\] propose a Longlife CRF (Longlife CRF, L-CRF) model based on the understanding of longlife machine learning (LML) and information overlapping phenomenon of different fields, using the model trained on the labeled training data to extract the textual aspect information in the field having not been labeled, and applying the information to the following new filed for the same goal. The disadvantage of this method is that it relies heavily on feature engineering, and the complexity, randomness and fallibility of review language pose many challenges for feature extraction and application, which limits the further improvement of information extraction performance of this kind of methods.

2.5. Method Based on Deep Learning

In recent years, Deep learning become popular methods in various fields of natural language processing tasks. There has been also many more methods proposed, all of which were based on deep learning to solve the task of aspect information extraction. In these methods, models and technologies based on Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), Attention Mechanism and Pre-trained Word Embedding are often used. The advantage of methods based on neural network is that it can automatically capture the features of words, phrases or sentences without human designs.

At present, there are three main ways to extract aspect information based on deep learning. (1) exploiting semantic information encoded in the Pre-training words embedding. The words representation is the basis of using neural network to deal with natural language problems. Words embedding that trained through a large number of text resources can better retain the semantic characteristics of words, and words’ position are relatively close in the word embedding space with similar semantic. For example, He et al.\[18\] propose an unsupervised model, using independent aspect word embedding in representation of reconstructive sentence, and taking the difference between representation of reconstructive sentence and representation of original sentence as the minimum goal, learning to get reasonable aspect information. (2) using syntactic dependency between words among sentence. Syntactic dependency information is the dependency between different components in a sentence, while aspect information is often the specific component in a particular syntactic dependency structure. For example, Yin et al.\[19\] put forward learning the vector of dependency path between two words in the words embedding to construct features as the input of CRF; (3) using the feature of co-occurrence of viewpoint information and aspect information. Aspect information and viewpoint information often appear in a complete expression at the same time, and the co-occurrence relationship can be used to enhance the extraction effect of both. For example, Li et al.\[20\] use two LSTM networks with memory modules to process the extraction of aspect information and viewpoint information respectively, and the relationship between viewpoint and aspect was built interactively through the memory modules of the two networks.

3. The Research Status of Aspect Sentiment Polarity Classification

Aspect sentiment polarity classification is the task which given the text sequence

\[ S = \{w_1, w_2, \ldots, w_n\} \quad (1) \]

and aspect information sequence in sentences

\[ A = \{w_{ni}, w_{ni+1}, \ldots, w_{ni+k}\} \quad (k \leq i) \quad (2) \]

to decide the sentimental polarity \( C \) of aspect information \( A \) equals to which one in the aggregate, \{negative, positive, neutral\}. Method based on dictionary, method based on traditional machine learning and method based on support vector machine (SVM) and method based on deep learning are often used.
3.1. Method Based on Dictionary

Method based on dictionary makes use of the feature that sentimental dictionary gives sentiment polarity or sentiment score to the words with sentiment. For example, Multiple-Perspective Question Answering\cite{21} subjective dictionary entitles sentimental words to positive, negative or neutral sentiment, and specifies the strength of sentiment. Different from document-based or sentence-based sentiment classification tasks, processing aspect sentiment classification task with sentiment dictionary need to deal with problems like sentiment correspondence among multi-aspects, denying sentiment discrimination and how to aggregate sentimental score of specific aspect information and so on. Hu et al.\cite{22} sum up the sentimental score of sentimental words in sentences to express the sentimental score of aspect information, which is obviously not suitable for aspect sentimental classification of single sentence with multiple aspect information; Zhu et al.\cite{23} divided the sentence into sub-sentences, so that each sub-sentence contains only one aspect information. Kessler et al.\cite{24} use syntax analysis to determine the corresponding relationship between aspect information and sentimental information, and then model the sentimental score of aspect information more accurately. Generally speaking, the method based on dictionary has better adaptability of crossing-fields, but it requires a large number of dictionaries and rules, and cannot give good results in the face of complex sentence structure, implicit sentimental expression, sentimental expression depend on target and so on.

3.2. Method Based on Support Vector Machine

SVM is one of the best algorithms to solve the classification problem before the method based on deep learning is widely used. It is a supervised learning algorithm. In fact, traditional supervised machine learning algorithms such as Naïve Bayesian Classifier, Maximum Entropy Classifier and Random Forest Classifier can also solve this problem, but SVM has been widely used in aspect sentiment classification due to its excellent performance. The basic idea of using SVM classifier to construct aspect sentiment classification model is to map the sentimental features of specific aspect into spatial features. On the linear separable training data, the key goal is to solve the corresponding convex quadratic programming problem and acquire the hyper-plane of the separated data. In these studies, systems submitted by teams called NRC-Canada\cite{25} and DCU\cite{26} in the ABSA task of SemEval2014 has achieved the best classification among the 28 teams. NRC-Canada proposes a classifier using linear SVM, which combines aspect information, context word features, part of speech features, syntactic dependency features, grammatical features and features based on various dictionaries, while DCU presents a system that combines bag features, rule features and dictionary features. Obviously, the method based on SVM relies on feature engineering in the process of working, and is vulnerable to noisy data.

3.3. Method Based on Deep Learning

Neural network model can extract abstract features from the original text features for text semantic analysis or sentimental analysis. In the aspect information extraction task, the extraction target is the special features of the aspect information itself, such as the semantic features of the aspect information, the specific syntactic features of the aspect information in the text and so on, while in the aspect sentiment classification, the target is to extract the features that can be used to express the aspect sentiment information, and how to transmit the sentiment information in the text to the final feature representation becomes a main concerned issues.

At present, there are three ways to settle down the task of aspect information sentiment classification based on deep learning. (1) Extract the aspect sentiment features from semantics of the whole text. The semantic expression of text is the carrier of sentiment. Therefore, semantic features can be used as sentimental features to classify aspect sentiment polarity. At the same time, aspect information is very important to distinguish different aspect information’s sentimental features. Therefore, aspect information has to be taken into consideration in the process of constructing sentimental feature representation. For example, Tang et al.\cite{27} put forward two methods TD-LSTM and TC-LSTM to construct sentimental features of specific aspect information by capturing semantic information from the left side and right side of the sentence respectively to get the final sentimental feature representation; Xue et al.\cite{28} extracted the sentimental features of the text by using CNN, and further eliminated the
unimportant sentimental information by using the max pooling operation along the sequence direction, which overcomes the problems of LSTM network like structure complexity and sequence dependence. (2) Use aspect information and context to extract features of aspect sentiment. The expression of aspect sentiment information is often part of the sentence with strong sentimental information, such as adjectives or phrases with rhetorical relationship. For example, Tang et al.\cite{29} use MN and Multi-layer Attention Mechanism to extract sentimental information from memory for many times; Wang et al.\cite{30} proposed five ways in the process of forming the final sentimental feature representation with a non-linear transformation, improving the model's performance of classifying the sentiment polarity of aspect information with context of target sensitive sentimental words; aspect information is often expressed as multi-word phrases rather than independent words, and each word has different effects on the overall information meaning. Based on this consideration, Huang et al.\cite{31, 32} propose the method to use cross attention to get aspect sentimental features with preference by making context and words in aspect information pay attention to each other. (3) Extract aspect sentiment feature by considering the relation between sentences. In the task of aspect sentiment classification, the whole review is often taken as the analysis object, but the relationship between sentences also has a great influence on aspect sentiment information. For example, Ruder et al.\cite{33} propose a Bi-LSTM model, in which the first layer of Bi-LSTM network captures the sentimental information inside the sentence, while the second layer of Bi-LSTM network captures the sentimental information transmitted by other sentences; similarly, Wang et al.\cite{34} propose that reviews should be divided into clauses according to some conjunctions.

4. The Research Status of Aspect-based Sentiment Analysis Joint Modeling
As mentioned before, aspect information extraction and aspect information sentiment classification are generally implemented as two sub-tasks separately in aspect sentiment analysis. Most researches only focus on one sub-task. In fact, aspect information extraction task can be regarded as word segmentation level classification task, aspect information sentiment classification can also be regarded as a sequence annotation task, and the association between two tasks can promote each other, such as label dependency between tasks, parameters sharing between models, etc. Some researchers have explored the joint modeling of the two tasks.

The method of joint modeling is basically based on the framework of information extraction and classification methods mentioned above. Through different but interpretable combinations, the information of aspect and corresponding sentiment are extracted at the same time. There are two specific ideas: (1) in a model, two subtasks are constructed at the same time, and the relationship between them is established. The total loss of each task is used as the overall loss update of the model parameters. For example, He et al.\cite{35} established an interactive multi-task learning network (IMN), which integrates document-based classification tasks into current aspect information extraction and sentiment classification tasks, not only makes use of the relationship between tasks, but also benefits from the input of multi-task learning to relevant field information. (2) Combine two sub-tasks into one task, blur the boundary between tasks, and establish a joint marking scheme. This kind of joint marking method can distinguish the aspect information boundary and the sentiment polarity. For example, Li et al.\cite{36} have used binary layers Bi-LSTM network to extract the information of both boundary and sentiment at the same time, and output joint labeling information with the help of three auxiliary modules responsible for boundary, sentiment and target detection.

5. Existing Problems of Aspect-based Sentiment Analysis
Aspect-based sentiment analysis has been paid more and more attention because of its fine-grained sentiment analysis results, which has important application value in various fields. By combing the methods of aspect-based sentiment analysis, we found that there are still the following problems need to be solved.

5.1. Model Adaptability in Complex Language Environment
As a fine-grained sentiment analysis style, aspect-based sentiment analysis task needs to abstract and extract entity information, attribute information, sentiment information and overall semantic
information in the text. However, these information are often distributed in complex language environment, which brings great difficulties to recognition and makes it very challenging to use programs to carry out such tasks. The complex language environment is reflected in the following two aspects: (1) the complexity of language itself. Language is the crystallization of human wisdom, with flexible forms of expression, such as implication, satire, metaphor, rhetorical questions, etc., and different people often have different habits in language expression, resulting in the complexity of language expression. (2) The arbitrariness of language expression in social media. As the main information source of aspect-based emotion analysis, the information produced by social media, such as reference, idiom, idiomatic expressions and other language phenomena, as well as grammar and spelling errors and other problems, often appear in the review text.

5.2. Error Delivery in Continuous Tasks
In practical application, aspect-based sentiment analysis needs to go through the process of aspect information extraction, sentiment classification and information integration, and needs to use external resources to assist to solve each sub-problem. The errors in one link will be transferred to the next link, which has a great influence to the overall effect of sentiment analysis. For example, at present, most aspect-based sentiment analysis methods treat aspect information extraction and aspect sentiment polarity classification as two independent sub-tasks, and errors in aspect extraction tasks will be amplified in aspect sentiment polarity classification tasks; in methods based on syntactic dependency analysis, errors in syntactic analysis will be directly transmitted to classification or markup models; in the method proposed by He et al.[37], using the document-based sentiment classification data training model with more labeled data, and initializing the aspect-based task model with the obtained underlying parameters, can reduce the impact of lack of labeled data in the aspect-based sentiment analysis task, but there is also the problem of wrong transfer.

5.3. Lack of Knowledge Learning, Understanding and Reasoning Ability
In the process of evolution, human beings have acquired the ability of knowledge learning, understanding and reasoning, which makes it easy to understand the rich connotations and logical relations expressed in words. In aspect-based sentiment analysis, whether through rules, features, or various supervised machine learning methods, it is often limited to the use or acquisition of certain patterns in the language to process unfamiliar data. This process is a kind of mechanized processing flow, which lacks the understanding and flexible use of knowledge and the logical reasoning based on language context, and the correct emotional judgment cannot be completed in the face of complex language phenomena.

6. Future Development Direction of Aspect-based Sentiment Analysis
In view of the above problems, we believe that the following three directions are worthy of further exploration in aspect-based sentiment analysis in the future:

6.1. Enhancing Knowledge Representation Based on Pretraining Model
In fact, word embedding, which is widely used in aspect-based sentiment analysis based on deep learning, is a kind of pretraining model, such as Word2Vec[38] and Glove[39] models commonly used. Recently, the pretraining models such as EMLO[40] and Bert[41] have achieved the best results of multiple tasks in the field of natural language processing. The advantage of the pretraining model is that it can obtain abundant information of language patterns by constructing a complex model with large-scale parameters and training on large-scale text corpus resources. For example, the work of Sun et al.[42] has initially demonstrated the powerful advantages of Bert, a pretraining model, in aspect-based sentiment analysis task, improving the knowledge representation ability of pretraining model, exploring the efficient integration of pretraining model and aspect sentiment analysis task will be an effective way to improve aspect sentiment analysis effect.
6.2. Exploring Multi-task Learning of Aspect Sentiment Analysis

Natural language processing is based on language representation, which integrates various information such as semantics, context, etc. These information are consistent in various natural language tasks. Using this feature, effect of aspect-based sentiment analysis can be enhanced. For example, at present, the document-based classification task in the field has the characteristics of high accuracy and many tag data. By adding the document-based classification task to the aspect-based sentiment analysis task, will realize multi-task learning, it will effectively reduce noisy interference and error transmission, and integrate more rich and accurate language features into the language representation at the bottom of the model. Some researchers have made relevant explorations\cite{20, 35, 43}, proving that this method can effectively reduce the over fitting problem in the model training process and improve the effect of aspect-based sentiment analysis.

6.3. Explore the Method of Integrating Knowledge and Reasoning

The development of natural language processing technology must deal with the application of knowledge. As a knowledge representation model integrating information such as entity, relationship and attribute, knowledge graph has recently attract more and more attention in the field of natural language processing. For example, Zhang et al.\cite{44} proposed to add the information of knowledge map to the training of Bert model. The experimental results on the task of entity type and relationship recognition show that the integration of knowledge map into the task of natural language processing can not only use large-scale language to obtain rich semantics, but also get more fine-grained through the prior knowledge stored in the knowledge map The knowledge representation of degree, the completion of knowledge reasoning and other more complex and abstract language processes. In aspect-based sentiment analysis, how to use common sense knowledge and the information in knowledge map to solve the affective analysis of complex sentences such as metaphor and satire is worthy of in-depth study.

7. Conclusion

This paper systematically reviews the methods and progress in the research of aspect level emotion analysis, summarizes the typical model methods of aspect level emotion analysis tasks and the thinking of dealing with related problems from three aspects: aspect information extraction, aspect information sentiment classification, and aspect-based sentiment analysis joint modeling, and analyzes the problems still existing in research. At the same time, combining with the current research progress of artificial intelligence and deep learning, we can make a judgment on the possible promotion path of aspect level emotion analysis in the future. As a basic task of natural language processing, the development of aspect-based sentiment analysis is closely related to the development of related technologies of natural language processing. The current research is still in the primary stage. The main problem is that at this stage, aspect-based sentiment analysis still takes text features as the main starting point of various tasks, and the expression and utilization of the relationship between features are still very limited, and relationship modeling is an important step to turn the task of natural language processing from the modeling of grammar and semantics to the modeling of pragmatics, and it is an important foundation of knowledge application and reasoning. With the in-depth study of artificial intelligence and natural language processing technology, the effect of aspect-based sentiment analysis will be further improved.

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