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A spelling mistake correction (SMC) model for real-word error correction

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Abstract
Spell Checker is used to identify and correct mistakes made by user while writing text and the mistakes are generally spelling mistakes. This paper aims at creation of spelling correction system mainly focusing on automatically performing the task of identification and correction of spelling mistakes such as real-word spelling mistakes accurately and efficiently. An intelligent spelling correction system SMC, is proposed to automatically correct real-word spelling mistakes using contextual information of the confused word. The system is capable to correct words, which are contextually wrong which belongs to set of confused words fed into it. In this paper, an efficient technique for spelling correction is proposed. An algorithm to identify and correct real-word errors is proposed in the technique. The first part of algorithm uses trigram approach to correct spelling mistakes and the second part of algorithm uses Bayesian approach to correct spelling mistakes. Brown corpus is used as a training set. A set of commonly confused words is used in this case. Selection of words in second part of algorithm uses synonyms derived from dictionary in the scenario when words are not found in the corpus. Comparative analysis of the proposed approach with MS Word 2007 has also been performed to identify the accuracy of SMC. Correction results indicate that SMC gives higher accuracy for spelling mistakes identification and correction for the commonly confused words as compared to other spelling correction algorithms.

Keywords: Real-word errors; Spelling mistakes; Spelling corrector; Modified corpus; Supervised approach; Unsupervised approach.

Introduction

Misspelled word correction refers to recognizing and rectifying the mistakes, which the user generally makes while representing language i.e. while writing text. The need of spell checker arose because mistakes are unavoidable part of writing. Not everyone can be skilful in representing language i.e. in writing process. So, Spelling mistakes correction has become very useful and widely used technology. When the spelling of the word is written incorrectly, then that mistake is called non-word spelling error or mistake [1]. In others words, it can also be described as a word which does not match the list of words in the dictionary e.g. "I am fonde of music" rather than "I am fond of music". The word "fonde" is a non-word error. There is a difference between non-word and real-word errors. When the spelling of the word is written correctly but other word is written in place of actual word then that mistake is called Real-word spelling error [1]. In other words, it can also be described, as a word user does not intended for e.g. "I am font of music" rather than "I am fond of music". The word "font" is a real-word error. Indeed, experimental analysis have evaluated that more than 40% of errors are result of real-word error [1]. It is also known as context-based errors.

Nearly all word processors have a built-in Spelling checker that flags the spelling mistakes. It also provides the solution to correct these spelling mistakes by choosing a possible alternative from a given list. For identification of spelling mistakes, most spellcheckers checks each word drawn separately from the written text against the dictionary-stored words. If the word is found while searching the dictionary, it is considered as correct word regardless of its context. This approach is efficient for identifying the non-word spelling mistakes but other mistakes cannot be identified using this method. The other mistakes such as real-word spelling mistakes i.e. words that are correctly spelled but are not intended by the user. Mistakes falling under this category go unrecognized by most spellcheckers because they handle non-word spelling mistakes by checking against the dictionary word list. This technique is effective to identify the non-word spelling mistakes but not the real-word spelling mistakes. To identify the real-word spelling mistakes, there is a need to utilize the neighbouring contextual information of the target word. Let's take an example of a sentence, "I want to eat a piece of cake" and we have confused word set as (piece, peace),to identify that 'peace' cannot be used in this case, we utilize the neighbouring contextual information 'cake' for word 'piece'.

Spelling correction is a cumbersome task. The difficulty lies in identifying and correcting real-word spelling errors. The non-word spelling errors are not difficult to correct because of the availability of dictionary searching technique. The foremost challenge for spelling correction in text is the development of real-word based correction techniques. Therefore, its correction is challenging and however a very important task that needs to be achieved.

This paper is organized as follows: first, we describe previous work in the field of real-word correction. Implementation of SMC framework is then presented. The experiment result and the comparison with Microsoft Word 2007 are then presented. This paper closes with a conclusion made and plans for future work.

Problem Formation

The need of real-word correction became prominent in the mid of 90's.This gained attention of researchers to usher in the field of real-word error correction. James L. Peterson [3] discussed the errors which spelling checker computer program could not detected. Spell checker works efficiently for identifying and correcting non-word errors but failed to identify and correct context-sensitive errors. For a non-word spell checker, it has performed by checking the word against the list of the given words. If the word exists in the list, then it is considered as correct otherwise flagged it as incorrect word. The addition of extra word in the word list is the solution to this problem. The researchers have tried to increase the list to detect the undetected errors but they found that the percentage of undetected errors increased by increasing the list. The new large list contained not only words but also the code which gives the information regarding the misspelling of a word. The percentage of undetected errors is also increased because of new increased list. It is concluded that word from the word list should be adopted according to the topic and situation for which it is to be used. In addition to it, there is need of intelligent spell checker that detects and corrects both syntax and semantic errors in a sentence.

Eric Mays [4] introduced a statistical approach to deal with the problem of context-spelling error efficiently. In this, the sum of 100 sentences is taken arbitrarily considering that it contains words from our vocabulary, fifty sentences from the documentations of the Parliament of Canada and remaining fifty from the AP newswire. A list of 20000 words is employed from speech recognition project of IBM along with their respective trigram probabilities. The correct sentences are transformed into misspelled sentences. A list of correct sentences and list of 20,000 words are considered as training set and manually transformed incorrect sentences are considered as test sets. The probability of sentences is calculated by using the maximum likelihood estimation of probability.

David Yarowsky [5] introduced a learning algorithm to find out the sense of word that has more than one meaning so that it can be correctly used in a sentence. The learning method used in this case is unsupervised and the training set used here is without tagging. The two concepts used in this case are one sense per discourse and one sense per collocation. The former means one word always reveals one meaning if used in a particular context and the latter means words that are neighbours of the target word, provides the information regarding the recognition of it. Words can exist in more than one collocation, so the advantage of this feature of word has been used to sense disambiguity. The researchers first took only a subset of disambiguate words and then made them learn to differentiate so that a word can be used in an intended situation. The knowledge obtained from a subset of words is applied to the whole sample. In this case, conflicts are fixed by using only one evidence rather than using integration of multiple evidences.

Andrew R. Golding [6] introduced Tribayes, which is based on trigram, and Bayes to correct the context-sensitive spellings errors. Trigram is based on parts-of-speech of words and Bayes is based on features. Tribayes has used the best of both methods to deal with the problem of real-word errors. In case of same POS tagging of confused words, Bayes is used and for different POS tagging, Trigram is used. They used brown corpus as their training set and commonly confused words as their data set. The commonly confused words are repeating words from the brown corpus. After applying Tribayes method, the probability is calculated and appropriate word is substituted.

Andrew R. Golding [7] implemented Bayesian hybrid to resolve the problem of context- sensitive spelling errors. In this, Bayesian classifier method puts forward decision lists to make best use of both context texts and collocations. One big decision list containing all features is created and target word is checked against all features. The features are sorted in decreasing weight and some features are pruned because of their negligible weights. It does not stop after first matching, but continue looking over the whole list and integrating information from all the matched features. The target word with highest probability is substituted. To solve the problem of context-sensitive error, the collected evidences are transformed into a single piece of information. However, when it was applied to the real-word spelling errors correction, it performed much better than the component methods. Lidia Mangu [8] illustrated new way to correct the real-word spelling problem. In this, the newly proposed approach learned the linguistic knowledge automatically to correct the context sensitive spelling errors. Acquiring information in small set of rules is one of the important characteristic of this approach and is easily understandable. Rather than emphasis on large set of features and weight, it focused more on small set of rules. With the help of given technique, the machine can automatically understand and learn the rules. The learning based algorithm that is used to make the machine learn and understand the rules is called Transformation-Based learning.

Andrew R. Golding [9] proposed method called WinSpell to identify and correct context-sensitive spelling mistakes. It is one of the most efficient algorithms till date for correcting real-word or context-sensitive spelling mistakes or errors In Winspell, the features are not pruned unlike Bayspell. The features during the training of Winspell are extracted and their weights are calculated and further assigned to them. In the same way, list of active features is created from the given sentence during the testing of Winspell after learning from the set of learned features. The connection between classifier and active features is created to distinguish one word from other words in the confusion set. The classifiers utilized the variants of Winspell algorithm, applied algorithm called weighted majority, which stored different values. The appropriate connection is created with the help of training, and furthermore their respective weights are learnt. It utilizes information from multiple classifiers (features) rather than using single classifier to decide on the substitution of intended word. One of the best characteristics of Winspell is that it is trained and tested using different corpora and still outperformed other methods that have utilized the same corpus for both purposes. It has used supervised learning for training and unsupervised leaning for testing.

Davide Fossati [10] used mixed trigram model to correct the real-word errors. In this, the POS tagging is performed in order to tag the sentences using the Stanford tagger. The tagged sentences having the confusion words are compared with the HMM (hidden markov model) labeled tags. The difference detected while comparing tags, which means there is a misspelling in the sentence and the mixed trigram is applied to correct it. A new empirical grounded technique is used to create the dataset of confused words. A corpus with large dataset of misspelled words is used and its probability is calculated. A test set is generated artificially by arbitrarily replacing words, as there is unavailability of appropriate test set to test the real-word errors. The precision of context sensitive spell checker is increased .Therefore the outcome of results have exhibited increase in coverage of spell checker using the mixed trigram model.

Ya Zhou [11] proposed a method known as RCW (real-word correction) for the real-word spelling errors based on tribayes. Due to inadequate training set, there is exclusion of essential

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features. In this, Word Net is used to extract the pruned features and the problem of pruned features is solved to a certain degree. Trigram performs well in case of different

tagging of words in data set and Bayes performs well in case of same tagging of word in data set. RCW has used the complementary of both to get the best results. The weight of context words are calculated based on their contextual information, and considered as the determining feature for the correction of real-word spelling mistakes or errors. Furthermore, synonyms from Word Net are used in place of effective features that are pruned in order to improve the accuracy.

Context-based approaches, such as Tribayes [6], Bayesian hybrid method[7], Winnow [9], mixed trigram model[10], RCW (real-word correction with Word Net) based on Tribayes[11] , correction with trigrams[12], have had certain degree of success for the problem of real-word correction. But the scope of correcting errors are limited to only predefined dataset because these all are corpus based methods. The limitation of using currently available corpus is that the contextual information is limited to only the text available in the corpus. Corpus contained contextual information of only limited text but does not cover all the contextual information of the language. Therefore, the scope of correcting mistakes remained limited to only the contextual information available in the corpus. Thus, the real-word error correction is limited to only small data set and its accuracy is also reduced.

It is being concluded after extensive analysis of literature that the identification and correction of real-word spelling errors or mistakes can be performed efficiently with trigram and Bayesian technique. Both techniques work well for real-word spelling correction.

SMC framework

Spelling correction is an application used to identify and correct the spelling mistakes in the text written by the user. Conventional spell checker fix only non-word errors and the real-word errors that gives valid words but are not intended by the user goes undetected. Correcting this kind of problem requires a very different approach from those used in the conventional spell checker.

Considering this problem, SMC method is proposed and this paper addresses SMC method, which is based on trigram, and Bayesian approaches. This method is
able to solve the problem to a certain extent by modifying the present corpus by adding the information in its sample, which is not available in the corpus so that other contextual
able to solve the problem to a certain extent by modifying the present corpus by adding the information in its sample, which is not available in the corpus so that other contextual information can also be included in it. The addition of more information in the corpus resulted in increasing the scalability of correcting large data set. Our approach also aims at retrieving the synonyms of the words, which is not available in the corpus by extracting synonyms from the dictionary of their corresponding words.

Training Feature

Brown corpus [13] is used as a training set in this proposed method but in the modified form to increase the scope of correcting real-word errors. The contextual information (sentences) is tagged with brown corpus [13] tagging and inserted in the samples of brown corpus [13]. The context information, which is added, is different from the information already available in the brown corpus [13].

A. Trigram

Trigram approach takes full benefit of the data that is present in the surroundings of the target word i.e. collocation features. Trigram calculates the probability of collocation of three words in a sentence and adds all the calculated probabilities of a sentence. The probabilities of all the ambiguous words in the confusion set are calculated by substituting them one by one in a sentence. The target word having the highest probability is substituted in the final outcome and is considered as correct word.

$$\mathrm{p}(\mathrm{w3}|\mathrm{w1},\mathrm{w2}) = \frac{f(w1,w2,w3)}{f(w1,w2)} \qquad (1)$$

f(w1,w2,w3)→count of w3 is seen following w2 and w1in brown corpus

f(w1,w2)→count of w2 is seen following w1.

B. Bayesian Approach

Bayesian approach takes full benefit of the data that is present in the surroundings of the target word i.e. context words. It extracts the words surrounding the target word and names it as features. From the training corpus that is containing correct articles, bayesian approach learns the contextual information surrounding the target word. The probabilities of context words is calculated, which is based on corpus i.e. by calculating the frequency of occurrences of features individually and the frequency of occurrences of features along with the target word. If the feature is not found in the corpus then synonym of that particular feature is extracted from the dictionary and its probability is calculated. The synonym having the highest probability is substituted in place of its corresponding feature. The ambiguous word having the highest score is substituted in the final outcome and is considered as correct word.

$$\textbf{Value(f)[10]} = log\left(\frac{p(c,a)}{p(c)*p(a)}\right) \qquad (2)$$

p(w, a)→the joint probability between p(c) and p(a)
p(c)→probability of feature of the target word
p(a)→probability of target word

$$\text{Sum}(w_a) = \sum_{ci \in C} value(fi) + \sum_{sj \in S} max(sj) \quad (3)$$

function max(s_j)→highest value of all synonyms of the feature s_j
function value(f_i) is used to calculate the value of feature c_i
c_a → ambiguous word

Bayesian approach will be used when the POS tagging of ambiguous words are same else, in case of different tagging, its performance will degrade.

The following procedure summarizes the algorithm:

Input: Sentence T =w_1, w_2, w_3..,w_i,...,w_n ∈
w_j → input word
X→ {w_i, $w_i^{\ c}$} is confusion set
Output: Corrected w_i If w_i ∈ X.
If w_j ∈ C
then tag the whole sentence
Goto Step 2
Else
print “ word not found in data set”
For i= 0,1,2....,n where i ∈ X do
If w_j ∈ w_i, having different POS brown corpus tagging
then
trigram is applied
Extract the collocation(T) ∈ A
A→training set
Find fr(col)
fr(col)→frequencies of the collocation of sentences
Combine corresponding collocations and frequencies.
Calculate p(w_i)
p(w_i)→ probability of w_a in the C

$$p(w3|w1, w2) = \frac{f(w1,w2,w3)}{f(w1,w2)} \quad (1)$$

f(w1,w2,w3)→count of w3 is seen following w2 and w1in brown corpus
f(w1,w2)→count of w2 is seen following w1.
Print the word with highest probability
Else If w_j ∈ w_i, having same POS brown corpus tagging
then
bayes is applied
Extract the context words
A→training set
Find the fr(c)
fr(c)→frequencies of the context words
Combine corresponding features and frequencies.
If fr(c) = 0
then
S→Synonyms of w_i
Calculate the sum of w_i

$$\text{Value(f)} = log\left(\frac{p(c,a)}{p(c)*p(a)}\right) \quad (2)$$

p(w, a)→the joint probability between p(c) and p(a)
p(c)→probability of feature of the target word
p(a)→probability of target word

$$\text{Sum}(w_a) = \sum_{ci \in C} value(fi) + \sum_{sj \in S} max(sj) \quad (3)$$

function max(sj)→highest value of all synonyms of the feature sj
function value(fi) is used to calculate the value of feature ci
ca→ambiguous word

Print the word with highest probability

In above algorithm, different corpora is used for training set and testing set. Supervised learning approach is used for the training corpus, which is manually enhanced brown corpus, and unsupervised learning approach is used for testing and the test-set will be manually created incorrect sentences set. We have supposed that the text in training and testing sets contains no spelling mistakes. Frequently occurring words in Brown corpus [13] is selected as the confusion sets. Test set is unsupervised as nobody indicates whether the spelling of the word it checks is correct or incorrect. SMC is better than RCW [11] to adapt because of the utilization of supervised and unsupervised strategy. We have found that, using this strategy, the performance of SMC is able to improve on an unfamiliar test set. Using same corpus for both training and testing, it becomes easy to solve the problem, that’s why we will use two different corpora.

Results and Comparison

In this paper, to evaluate our proposed system two widely used and publicly available datasets are used. These datasets includes brown [13] corpus and set of confused words [14]. Brown corpus contains 1,014,312 words sampled from 15 text categories and set of 30 confused words are used. In SMC method, real-word identification and correction is performed by considering the context information surrounding the target word. Trigram and bayes methods are used. When the POS tagging for ambiguous words are different then trigram is used and when it is different, then bayes method is used. Trigram used the context information in the form of collocation and bayes used context information in the form of features. The probabilities for ambiguous words are calculated in both cases of trigram and bayes and word having highest probability is selected. To evaluate our method, SMC method for real-word correction is compared with MS word 2007 that has the feature of context-sensitive checking.

A. Calculations of results

The calculation of probabilities for one of the confused words is shown in Table 5.1

1. Input: They do not accept checks.

TABLE 5.1: The information of the features and values of the ambiguous words- (accept, except)

Collocation features			**Total**
They do not	do not accept	not accept checks	
0.43859646	0.4385965	0.20	1.07719296
They do not	do not except	not except checks	
0.4385965	0.4385965	0	0.877193

TABLE 5.2: The result of real-word error correction in SMC and Word 2007

S.No.	**Confus-ion items**	**No. of test cases**	**SMW**		**MS Word 2007**	
			No. of correct	**Accuracy**	**No. of correct**	**Accuracy**
1.	accept, except	20	19	95%	14	70%
2.	capital, capitol	20	19	95%	12	60%
3.	among, between	20	18	90%	15	75%
4.	brake, break	20	19	95%	16	80%
5.	desert, dessert	20	19	95%	15	75%
6.	device, devise	20	18	90%	13	65%
7.	farther, further	20	18	90%	18	90%
8.	formerly, formally	20	19	95%	18	90%
9.	hear, here	20	19	95%	15	75%
10.	instance, instant	20	19	95%	15	75%
11.	passed, past	20	18	90%	12	60%
12.	peace, piece	20	18	90%	15	75%
13.	principal, principle	20	19	95%	10	50%
14.	raise, rise	20	19	95%	12	60%
15.	sea, see	20	17	85%	13	65%
16.	stationary, stationery	20	17	85%	14	70%
17.	waist, waste	20	19	95%	15	75%
18.	weak, week	20	18	90%	16	80%
19.	than, then	20	18	90%	15	75%
20.	adverse, averse	20	18	90%	14	70%
21.	altar ,alter	20	19	95%	12	60%
22.	appraise ,apprise	20	19	95%	11	55%
23.	loose, lose	20	19	95%	15	75%
24.	pour, pore	20	18	90%	13	65%
25.	bare, bear	20	18	90%	15	75%
26.	censure, censor	20	19	95%	14	70%
27.	curb, kerb	20	18	95%	11	55%
28.	currant, current	20	18	90%	12	60%
29.	duel, dual	20	17	85%	13	65%
30.	storey, story	20	19	95%	14	70%
	Average	/	/	92.17 %	/	69.50%

The results of comparison are shown in above table. Number of test cases implies number of times confused words occurred in test corpus. Number of correct implies the number of cases SMC method corrected. The accuracy achieved for SMC is 92.17% according to the results obtained as compared to MS word 2007, which is 69.50%. The SMC method is obviously a better method as it achieved a better accuracy. According to the results, MS word 2007 is too prudent to identify and correct the real-word errors. To enhance the overall accuracy, our method balances recall rate and precision.

Conclusion

Misspelled words, which are present in article created by human, are a common phenomenon and these misspelled words can be characterized as non-word errors and real-word errors. In this paper, we proposed SMC system for automatically identifying and correcting real-word spelling mistakes. We integrated both non-word spelling mistakes correction and real-word spelling mistakes correction and tested in a realistic setting using a suitable user interface as word processor. Considering real-word errors, we identify the ambiguous words in the confusion set by context information consisting of collocation and context words. To deal with the problem of real-word errors, we proposed an algorithm using trigram and bayes methods. Supervised and unsupervised learning strategy is used in this work. Supervised learning is used for training and unsupervised is used for testing. Unsupervised learning is used so that this work can be applied to any context of the text. Brown corpus [13] is used as a training set and manually created sentences are used as a test set because of unavailability of test sets. The algorithm is run on the data of 30 confused sets that is extracted from “Words Commonly Confused” [14]. Generally, when we use supervised learning technique for both training and testing, the scope of correcting misspelled word is limited to context of text used in corpus or context of text written by author and becomes insufficient in correcting text apart from the context of the corpus.

Therefore, in this paper, we used supervised and unsupervised learning strategy so that evaluation is done on different context of text from the training set. We have modified the brown corpus by increasing the content in the sample files of it to increase the scalability of correcting the real-word errors. The trigram method is used when POS tagging of ambiguous words in the confusion set are different and bayes method is used when POS tagging of ambiguous words in the confusion set are same. The algorithm also takes an advantage of the synonyms of the context words, which are not found in the brown corpus. The synonyms are extracted from the dictionary. We have empirically evaluated and compared SMC with MS word 2007 and achieved an error correction accuracy of 92.17% for real-word errors. Our work showed significantly higher performance for real-word errors when compared with MS word 2007.

Future Scope

Although the SMC system developed in this research has gained some course of success in identifying and correcting the real-word spelling mistakes, it has also suggested several issues that needs to be addressed in the future development. Implementation and comparison with existing real-word spell checker such as MS Word 2007.Identification and correction of real-word errors is limited to small confusion sets. Therefore, the scalability of correction needs to be improved so that large set of words could be corrected. A large corpus is required that includes text of all possible contextual information. The number of real-word correction per sentence at a time is one; hence, algorithm has to be modified to do multiple corrections per sentence. Integration of proposed approach with the conventional spell checker needs to be done.

References

[1] Yinghao Huang, Yi Lu Murphey and Yao Ge, “Automotive diagnosis typo correction using domain knowledge and machine learning.” IEEE Symposium Series on Computational Intelligence, pp 267-274 (2013).
[2] Kukich K. Technique for Automatically Correcting Words in Text. *ACM Computing Surveys (CSUR)* ,vol. 24, pp. 377-439 (1992).
[3] Peterson, James L. "A note on undetected typing errors." Communications of the ACM 29.7, pp 633-637, Year 1986.
[4] Mays, Eric, Fred J. Damerau, and Robert L. Mercer. "Context based spelling correction." Information Processing & Management 27.5, pp 517-522 (1991).
[5] Yarowsky, David. "Unsupervised word sense disambiguation rivaling supervised methods." Proceedings of the 33rd annual meeting on Association for Computational Linguistics. Association for Computational Linguistics,pp 189-196 (1995).
[6] Golding, Andrew R., and Yves Schabes. "Combining trigram-based and feature-based methods for context-sensitive spelling correction." Proceedings of the 34th annual meeting on Association for Computational Linguistics. Association for Computational Linguistics, pp 71-78 (1996).
[7] Golding, Andrew R. "A Bayesian hybrid method for context-sensitive spelling correction." arXiv preprint cmp-lg/9606001, pp 1-15 (1996).
[8] Mangu, Lidia, and Eric Brill. "Automatic rule acquisition for spelling correction."ICML, Vol. 97, pp 187-194 (1997).
[9] Golding, Andrew R., and Dan Roth. "A winnow-based approach to context-sensitive spelling correction." Machine learning 34.1-3, pp 107-130 (1999).
[10] Fossati, Davide, and Barbara Di Eugenio. "I saw TREE trees in the park: How to Correct Real-Word Spelling Mistakes." LREC, pp 896-901 (2008).
[11] Zhou, Ya, et al. "A Correcting Model Based on Tribayes for Real-Word Errors in English Essays." Computational Intelligence and Design (ISCID), 2012 Fifth International Symposium on IEEE, Vol. 1, pp 407-410 (2012).
[12] Wilcox-O’Hearn, Amber, Graeme Hirst, and Alexander Budanitsky. "Real-word spelling correction with trigrams: A reconsideration of the Mays, Damerau, and Mercer model." Computational Linguistics and Intelligent
[13] Text Processing. Springer Berlin Heidelberg, pp 605-616 (2008).
[14] Francis, W. Nelson, and Henry Kucera. "Brown corpus manual." Brown University (1979).
[15] Oxford University Press, “Oxford American Large Print Dictionary", Year 2008.