

# Evaluation of spell correction on noisy OCR data

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## Abstract

Optical Character Recognition (OCR) of historical text often leads to several kinds of spelling errors. Existing spell correction algorithms do not present a rigorous performance evaluation of the spell correction process. In this paper, we present a novel N-gram based algorithm for evaluation of spell correction which can handle noisy and cleaned text of different lengths. The algorithm relies on appropriately choosing a window of N-words and aligning them in three parallel corpora - noisy OCR, corrected, and cleaned and annotated text (ground truth). Empirical results of spell correction on 300 news articles from the “The Sun” newspaper, Nov- Dec 1894 are presented on edit distance and context sensitive based spell correctors. The Spell Correction Evaluation (SCE) algorithm evaluates their AUC values to be 0.49 and 0.56 respectively. We posit that this novel algorithm for spell correction evaluation has a wide applicability for comparing multiple spell correction algorithms which can play a crucial role in analyzing large volumes of digitized OCR text.

*Keywords:* OCR, Spell Correction, Spell Correction Evaluation, Historical Newspaper Archives

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## 1. Introduction

OCR of typed, handwritten or printed text is widely used to obtain digitized text which can be edited, searched, stored and displayed efficiently([1, 2]). It is used in various applications such as banking, digital libraries [3] and repositories, number plate recognition, and handwriting recognition [4]. However, the OCR scanning of printed text generates a lot of garbled text which renders them inadequate for any such tasks. //DOUBT: Should it be mentioned that OCR of specifically historical documents generates garbled text?

Refinement of such noisy OCR text through spell correction can make them useful for text mining tasks ([5], [6]).

//////////DOUBT: Can we say that the USP of our algorithm is that it can be easily used to compare amongst multiple spell correction algorithms and our algorithm will tell which one is suited to a user’s application best?

Most spell correction algorithms have focused on improving the correction model and either do not give a detailed performance evaluation of the algorithm post spell correction or the evaluation measures used are not able to completely analyze the performance of such algorithms. A major problem that surfaces when evaluating a spell corrector for OCR text is that the text has to be verified against the original text (ground truth) to estimate its performance. This one-to-one verification may lead to word alignment problems, since the corrected and original text can be of different lengths because of the variety of errors in the OCR text. In this paper, we describe the development of an N-word grams Spell Correction Evaluation (SCE) algorithm that can automatically evaluate a spell correction algorithm by using an N-word window to align three parallel corpora - the noisy OCR, corrected and original/ manually cleaned text. We present the performance evaluation results of applying our SCE algorithm on two commonly used spell correction techniques - Edit distance and Context Sensitive spelling correction on 300 OCR historical newspaper articles of “The Sun” newspaper published in Nov-Dec 1894.

**Organization:** This paper is organized as follows: related work is described in Section 2; characteristics of the OCR data and its annotation in Section 3; spelling correction and evaluation algorithms in Section 4; empirical evaluation in Section 5 followed by discussion and future work in Section 7.

## 2. Related Work

Spelling correction algorithms have been vastly discussed in literature but either their evaluation measures and data analysis are not accurate or they do not take all types of OCR errors into consideration. Kukich[7] comprehensively discusses various spelling correction techniques based on non word, isolated word and real word spelling errors. N-gram analysis, dictionary lookup and probabilistic techniques ([8], [9]) are used for correcting isolated and nonword errors while context-dependent techniques are used mostly for correcting real word errors including the correction of word split and join errors [10]. N-gram techniques work by examining each n-gram in the text string and comparing against a pre-compiled table of n-gram statistics to retrieve the correct word while dictionary look up techniques directly check whether the text string appears in the dictionary using string

matching algorithms. Both techniques require a dictionary or a large text corpus and take frequency of n-grams or word occurrence into account in order to find the correct spelling. Probabilistic techniques use transition and word confusion probabilities to estimate likelihood of the correction in order to rank and retrieve correct word spelling. On the other hand, Context-dependent techniques require contextual information and use either extensive NLP techniques or Statistical Language Modeling (SLM) for spelling correction. Bassil and Alwani[11] use Google 1-5 gram word dataset to gain context information in order to determine the correct words sequence in the text for correction. Tong and Evans[12] use Statistical Language Modeling (SLM) approach involving information from letter n-grams, character confusion and word bi-gram probabilities to perform context sensitive spelling correction obtaining a 60 percent error reduction rate. All these spelling correction techniques have developed over time and have been used in combination to achieve improved accuracy [13]. Agarwal et al.[14] use a combination of Google suggestions, LCS and character confusion probabilities for choosing the correct spelling on a small set of historical newspaper data and achieve recall and precision of 51% and 100% respectively.

The edit distance approach, suggested initially by Wagner and Fischer[15], is a dictionary lookup approach commonly used for OCR data correction because of the large number of substitution errors in OCR data [7][16] which can be corrected using this technique. String edit distance approaches with faster correction are discussed in [17],[18] with variants like Levenshtein automata and normalized edit distance. All of the above algorithms are evaluated based on the percentage of spelling errors corrected or reduction in the word error rate and do not consider the word alignment problem arising due to word split and join errors in the OCR text.

Semi-automatic spelling correction systems [19] require user interaction in order to perform complete correction and system evaluation. Rice[20] discusses OCR errors similar to the ones in our dataset. Their algorithm evaluates edit distance spelling correction by estimating word accuracy; the length of LCS between correct and incorrect strings on a page-by-page level is used as the relevant metric. The evaluation strategy works correctly but the definition of accuracy does not give a complete coverage of the spell correction as it does not provide any information on the errors missed by the spelling corrector due to lack of word by word comparison/alignment during the evaluation procedure.

—ADD RELATED WORK REGARDING LINGPIPE BASED CONTEXT SENSITIVE SPELL CORRECTION HERE.

—ADD RELATED WORK REGARDING RECENT PAPERS READ

ON SPELLING CORRECTION EVALUATION. (REYNAERT PAPERS, Compound words paper)

—specifically mention that most of the evaluation mechanisms use OCR and true word pairs for measuring the algorithm performance which is not suitable for a complete evaluation of the spelling correction algorithm where the dataset has word split and join errors.

### 3. Data

#### 3.1. Data Characteristics

The dataset used for empirical evaluation of the algorithm has been obtained from the Chronicling America<sup>1</sup> website. It contains scanned newspaper pages published in New York between 1890 to 1920. OCR software is run over high resolution images to create searchable full text of the newspaper articles.

In order to make a newspaper available for searching on the Internet, the following processes used in [5] must take place: (1) the microfilm copy or paper original is scanned; (2) master and Web image files are generated; (3) metadata is assigned for each page to improve the search capability of the newspaper; (4) OCR software is run over high resolution images to create searchable full text and (5) OCR text, images, and metadata are imported into a digital library software program. The scanned newspaper holdings of the NYPL offers a wealth of data and opinion for researchers and historians. The newspaper titles and digitized pages available through the Chronicling America website can be searched using the OpenSearch protocol<sup>2</sup>. Unfortunately, the current search facilities are rudimentary and irrelevant documents are often more highly ranked than relevant ones. The newspapers are scanned on a page-by-page basis and article level segmentation is poor or non-existent; the OCR scanning process is far from perfect and the documents generated from it contains a large amount of garbled text. In a bid to serve its patrons better, the New York Public Library employed human annotators to clean headlines of articles and text, but the process of manually reading all the old newspapers article-by-article and cleaning them soon became very expensive.

An individual OCR text article has at least one or more of the following types of spelling errors:

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<sup>1</sup><http://chroniclingamerica.loc.gov/>

<sup>2</sup><http://www.opensearch.org/Home>

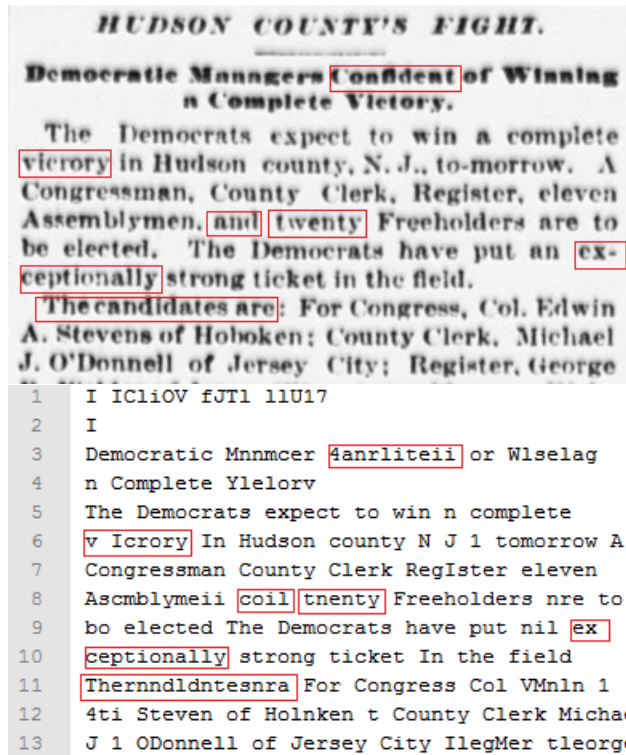


Figure 1: Scanned Image of a Newspaper article (left) and its OCR raw text (right)

- **Real word errors** include words that are spelled correctly in the OCR text but still incorrect when compared to the original newspaper article image. For example: In Figure 1, the word “coil” has been correctly spelled in the OCR text but should have been “and” according to the original newspaper article.
- **Non-real word errors** include words that have been misspelled due to some insertion, deletion, substitution or transposition of characters from a word. For eg. In Figure 1, the word “tnenty” in the OCR text has a substitution error (‘n’ should have been ‘w’) which is actually “twenty” according to the original newspaper article.
- **Non-word errors** include words that have been spelled incorrectly and are a combination of alphabets and numerical characters. For example: In Figure 1, the word “4anrliteii” which is a combination of alphabets and number and should have been “confident” as per the

original newspaper article.

- **New Line errors** include words that are separated by hyphens where part of a word is written on one text line and remaining part in the next line. For example: In Figure 1, the word “ex-ceptionally” where “ex” occurs on one line while “ceptionally” in the next and due to no punctuation in the text, they are treated as separate words in OCR text.
- **Word Split and Join errors** include words that either get split into one of more parts or some words in a sentence get joined to make a single word. For example: In Figure 1, the word “Thernndldntesnra” in the OCR text is actually a combination of three words “The candidates are” while the words “v Icrory” are actually equivalent to a single word “victory” when compared with the original news article.

### 3.2. Data Statistics

Our corpus consists of 300 OCR text articles from the “The Sun” newspaper issues of November-December 1894 taken from the Chronicling America website. The text does not have any punctuation and contains a large amount of garbled text containing OCR errors mentioned in Section 3. Spelling correction is performed on this corpus to obtain spell corrected text. We also used manually cleaned OCR text to check and validate the correctness of spelling correction procedure.

Two months of articles of “The Sun” newspaper from November-December 1894 consisting of 14020 news articles with a total of 8,403,844 tokens are used for empirical evaluation.

Due to the word split and join errors and new line errors in the OCR text, the 3 parallel corpora, i.e., OCR text, its spell corrected version and the original correct version need to be aligned so that a word by word correspondence could be made among all versions and the spelling correction algorithm could be evaluated.

### 3.3. Manual Annotation of Data

For the evaluation of spelling correction on spell corrected data, cleaned/original newspaper text is required so that a word by word matching can be done to see how well the spelling corrector performs. Due to unavailability of a spell corrected and original correct word pairs list, manual annotation of the OCR text articles needs to be done so that the spelling correction evaluation can be done accordingly. In order to obtain the original cleaned

text from the OCR text, we used manual annotators who annotated the OCR articles from their newspaper images. For this purpose, we recruited 5 annotators each of whom were given 50 OCR articles and their corresponding images to annotate. For every OCR article, they had to write the corresponding clean line text called as the original newspaper article version by looking at the OCR article’s newspaper image/s. The annotators were also asked not to consider any punctuation in their writing of clean text since the OCR text from *Chronicling America* is devoid of the same. DOUBT: Does this need to be mentioned here: The OCR text article was given as reference so that the number of linetexts in the correctly written version from newspaper image and the OCR text article remain same. Each annotator was given a different set of articles to work with ranging from November-December issue of “The Sun” newspaper and after the annotation process was complete, one more annotator was asked to verify whether the resulting original article was completely error free or not.

## 4. Theory

This section first describes the two types of algorithms- Edit Distance and Context Sensitive Spell Correction Algorithms followed by a detailed description of the N-Gram based Spell Correction Evaluation (SCE) Algorithm on which the first two algorithms are tested.

### 4.1. *Edit Distance Spelling Corrector*

The Edit Distance algorithm based on Levenshtein distance[21] has been used for spelling correction. It is an isolated word correction technique that uses dictionary based-look up and the distance between strings for matching the text and correcting it. An “edit distance”<sup>3</sup> corresponds to the minimum number of insertions, deletions, and substitutions required to transform one string into another.

### 4.2. *Context Sensitive Spelling Corrector*

We use LingPipe’s spelling correction algorithm for spelling correction based on context. It is based on a noisy-channel model, which models user

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<sup>3</sup>Our edit distance algorithm corrects non-real word spelling errors by making at most 2 operations of insertion, deletion and substitution of letters in the word. The choice of 2 is governed by the trade off between algorithm runtime and quality of spelling correction. The spelling corrector has been designed as suggested by Peter Norvig <http://norvig.com/spell-correct.html>.

mistakes (typos and brainos) and expected user input (based on the data). Mistakes are modeled by weighted edit distances and expected input by a character language model. Spelling corrections are motivated by the indexed dictionary which make the algorithm domain sensitive. The dictionary words are added to the search index and a language model. The language model stores seen phrases and maintains statistics about them. When a word is submitted for correction, the spell corrector looks for possible character edits, namely substitutions, insertions, replacements, transpositions, and deletions, that make the word to be corrected a better fit for the language model. The spell corrector is also able to split and combine tokens during spelling correction due to which Word Split and Join errors can also be corrected by this algorithm.

#### 4.3. Spelling Correction Algorithm Evaluation

For evaluating the performance of spell correction, the raw OCR text and OCR text after application of spelling correction algorithm (corrected text) needs to be compared with the original newspaper text. The OCR text is extremely garbled with Word Split and Join errors due to which word-to-word alignment with the original newspaper text is impossible, i.e., the raw OCR and original newspaper text are of different lengths. A novel algorithm, Spelling Correction Evaluation (SCE) based on N-gram approach is proposed for automatic evaluation of the corrected text. The SCE algorithm can be used for evaluation of any type of spelling correction algorithm - dictionary look up, context sensitive or probabilistic spell correction algorithms. The following metrics are used for estimating the performance: (1) **Accuracy** This requires calculation of the number of OCR errors that got corrected when compared to the original newspaper text. Specifically,  $Accuracy = \frac{TP+TN}{TP+FP+TN+FN}$  where,  $TP$ =Number of True Positives,  $TN$ =Number of True Negatives,  $FP$ =Number of False Positives,  $FN$ =Number of False Negatives. Reynaert and Martin[22] suggest a way to define these terms by distinguishing between correct words and incorrect words in the text through the set of non-target, target and selected words and use Precision and Recall evaluation measures for measuring performance of spelling correction which we adapt for this work. (2) **Time taken for Spelling Correction** The time for correcting the text is also noted for benchmarking correction of large datasets.

#### **N-Word Grams Spelling Correction Evaluation(SCE) Algorithm**

To make the correspondence between corrected and original OCR text, a window of N-word grams in the original newspaper text is considered which can be seen in a diagrammatic representation in Figure 2. For each token



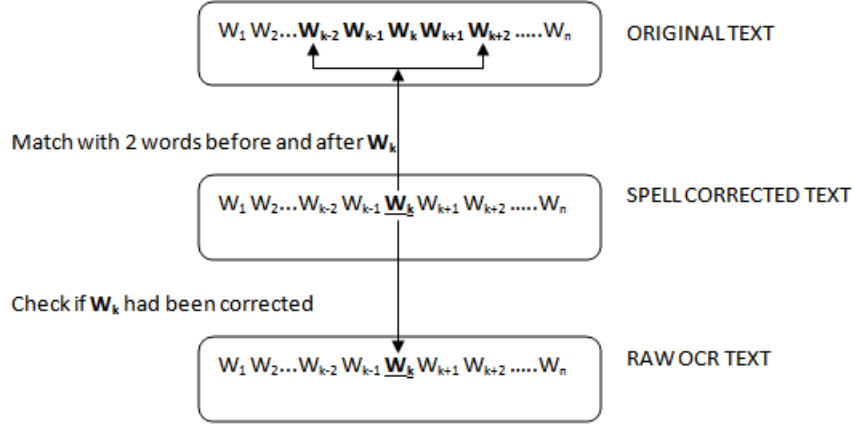


Figure 2: Schematic diagram for alignment of spell corrected article text with original article text for a word  $W_k$

in the spell corrected text, the corresponding token in the original text article along with 2 tokens before and 2 tokens after it are considered for alignment<sup>4</sup>. If the token being considered matches with any word in the original text article word’s window and its spelling has been corrected when compared to the corresponding token in raw OCR text, then it is marked as a “True Positive” which is actually rewarding the Spell corrector for making the correct spelling change. A “False Positive” is marked if it does not match any of the words despite its spelling being corrected. Table 1 describes the the process of marking each token in the corrected text as a TP, TN, FP or FN in each text article for calculation of accuracy. The final values of TP, TN, FP and FN are accumulated throughout the dataset to calculate accuracy.

Several scenarios could arise during the word alignment process due to difference in the lengths of text between OCR and original text. All such cases are depicted in Table 2 which describes the window size of tokens to match in the original text (from  $j$ =starting index to ending index) for every token  $i$  of the corrected text.

A limitation of the SCE algorithm is that it requires all 3 versions of a

<sup>4</sup>The choice of  $N=2$  is based on the Word Split and Join errors in the dataset. This value can be set appropriately by considering the maximum difference of lengths in each line of OCR and original text in the dataset.

Table 1: Calculation of accuracy in SCE algorithm

Evaluation Metric	TP	TN	FP	FN
Criteria to be checked				
Match found in N-word window?	Yes	Yes	No	No
Spell correction was done?	Yes	No	Yes	No

Table 2: Different cases for word alignment

Token index of OriginalLine	Starting index (j)	Ending index (j)
Token index of CorrectedLine(i)		
Length[CorrectedLine] < 4 or Length[OriginalLine] < 4	0	Length[OriginalLine]
i=0	0	3
i=1	0	4
i=Length[CorrectedLine]-2	i-2	Length[OriginalLine]
i=Length[CorrectedLine]-1	i-2	Length[OriginalLine]
i=Length[CorrectedLine]	i-2	Length[OriginalLine]
i=Length[CorrectedLine]+1	i-2	Length[OriginalLine]
i ≥ Length[CorrectedLine]+2	Length[OriginalLine]-3	Length[OriginalLine]
Any other value of i	i-2	i+3

newspaper article (Original, Corrected and OCR) to have the same number of lines as alignment of line texts is performed. In case of difference in the number of lines of text due to some Word Split and Join errors, the word's window needs to be extended so as to cover previous and next line texts also for alignment.

**An Illustrative Example** The execution of the SCE algorithm can be demonstrated with the help of the following example: Consider 3 versions of a scanned image of a newspaper article – the original text of the scanned image, the raw OCR text and the text after spell correction. Assume, the texts are:

OcrLine= *by tlt n rejmrt of th cepert aaccountauts who*

CorrectedLine= *by than report of the expert accountants who*

OriginalLine= *by the report of the expert accountants who*

Here, for each token of CorrectedLine, we find its index and call the Match-WordGrams function accordingly. For the first token 'by' at index i=0 in CorrectedLine, we consider the word window to be "by the report" (index j=0 to 2) in OriginalLine by matching iteratively with each token to see if there is a match and also if there has been a spelling correction by compar-

ing with the corresponding token in *OcrLine*. Here, no change was made to the spelling of ‘by’ and it matches with a word in words window, so it is marked as a *FN*. For the second token ‘than’ at index  $i=1$ , we consider the word window to be “by the report of” (index  $j=0$  to 3) for which there is no match in the window but there has been a spelling correction from ‘tltn’ to ‘than’, which implies the correction was wrong and the token is marked as a *FP*. For the third token ‘report’ at index  $i=2$ , we consider the window as “by the report of the” (index  $j=0$  to 4) in *Original Line* and find that there is a match in the word window and there has been a spelling correction too from ‘rejmr’ to ‘report’ which makes this token a *TP*. Similarly, rest of the tokens get marked for each line in the *Corrected.txt*.

Another example can be considered from Line 10 in Figure 3 and Figure 4 where the number of tokens is different in *CorrectedLine* and *OriginalLine*. In such a case, direct alignment between tokens is not possible because of which the words window becomes useful. Here, when the last token ‘Richmond’ of *CorrectedLine* is considered at index  $i=3$ , the corresponding words window becomes “Jury now sitting at Richmond” (index  $j=1$  to 5) for which there is a match in the words windows and corresponding spelling has also been changed from ‘tilchmond’ to ‘Richmond’ which makes it a *TP*. Had the word window not been considered, the corresponding token at index  $j=3$  in *OriginalLine* would have been chosen as ‘sitting’ which would have resulted in a *FP*.

## 5. Empirical Evaluation and Results

**Aim:** The aim of our experiments is to answer the following research questions:

RQ1: Which spelling correction algorithm is better?

RQ2: How does the variation of the parameters of SCE affects the result?

RQ3: How do parameters of the spelling correction algorithm affect the evaluation results?

**Materials:** The spelling correction algorithms are used to correct all the 300 OCR raw text articles in the dataset. The dictionary used for look-up is a concatenation of several public domain books from Project Gutenberg and lists of most frequent words from Wiktionary and the British National Corpus<sup>5</sup>. This is augmented with a large people names list which is obtained by running Stanford NER-CRF parser on subsets of the ClueWeb12 dataset

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<sup>5</sup><http://norvig.com/big.txt>

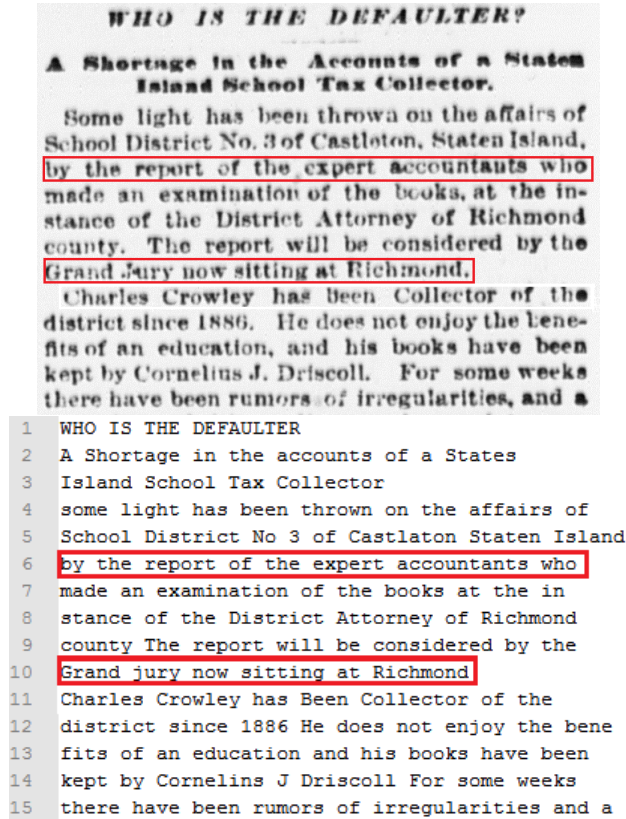


Figure 3: Scanned image of a newspaper article (left) along with its original text (right)

made available in the TREC 2013 Crowdsourcing Track<sup>6</sup>. This enhanced dictionary has been used to give special consideration to correction of person names in the dataset. All our experiments are run on a 4GB RAM machine on Windows platform and the complete implementation of Edit distance and SCE algorithms has been carried out in Java. The context sensitive based spell correction algorithm from LingPipe 4.1.0 version also implemented in Java has been used in our experiments.

////////Mention answer to research questions here

**Methods:** In order to answer RQ1 for comparing the performance of spell correction algorithms, we use AUC score as a metric as described in previous

<sup>6</sup><http://boston.lti.cs.cmu.edu/clueweb12/TRECcrowdsourcing2013/>

1	into Ji Jin tntfAtnTKiit
2	A Hhortim In he Aeeonnt nf HtntMS
3	lalaad Heknol Tux 4ollrelor
4	tome llRlil Imi h cn tlimwa on tho affairs of
5	SVhool District Ko iof Castlolon Staten Island
6	by tltn rejmrst of th cxpert aaccountauts who
7	msdn an examination of tho bcoka nt the In
8	nUnco of tho District Attorney of ltichmon1
9	cntmty Tho report will bo considered by the
10	Irnniluttry iiownlllllnu at tilchmond
11	Chnrles Crowley ha llecli Collector nf the
12	district since 1NNO lie iloe nnt onjoy the lene
13	fltnof nn education nnd his books have been
14	kept by C rnlln J Drlicoll Kor sorao weeks
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1	into Ji Jin tntfAtnTKiit
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3	Leland Henok tax 4ollrelor
4	time Llulll Imi h cn Limca on the affairs of
5	school District Ko of CASTILLON state Island
6	by than report of the expert accountants who
7	Sdn an examination of the Boka it the In
8	lunch of the District Attorney of ltichmon1
9	entity Tho report will bo considered by the
10	Irnniluttry iiownlllllnu at Richmond
11	Charles Crowley ha Lesli Collector of the
12	district since into lie Ilon not enjoy the line
13	fltnof an education and his books have been
14	kept by C roll J Driscoll For Sorbo weeks
15	there have been rumors of Irrecuturiltles and a

Figure 4: OCR raw text (left) and Spell corrected text (right) of the article

section. For answering RQ2, we vary the value of the  $N=2$  in the N-gram SCE algorithm and compare it with the LCS (Lowest Common Substring) algorithm as well to observe the changes in results of evaluation. For addressing RQ3, we modify the parameters of both spell correction algorithms, i.e., value of edit distance=2 in the edit distance algorithm and other parameters in context sensitive algorithm and study the modified spell correction evaluation results.

#### Results:

/////////DOUBT: Should I mention the time taken to run spell correction algo as a parameter in both the algorithms??

The edit distance based spell corrector shows an AUC score of 0.49 when corrected text is compared to OCR text and original article text using our SCE algorithm. We believe that the results are less accurate due to the presence of a large number of non-word, new line, word split and join

errors in the OCR data which can not be corrected by the edit distance spelling corrector used for this research. On the other hand, the Lingpipe based context sensitive spelling corrector has a better AUC score of 0.56 demonstrating that in case of OCR text, this algorithm performs better.

We experimented with different window size for our N-gram based SCE algorithm for which following results were obtained: `////////COMPUTE RESULTS OF SCE ALGORITHM BY CHANGING WINDOW SIZE`

We also compared our N-gram based SCE algorithm with the LCS (Longest Common Subsequence) algorithm<sup>7</sup>. The LCS of corrected and original text gives a list of matching corrected words found in the original text. Following the similar evaluation procedure of calculating accuracy as in the N-word gram approach, it was found that there is no statistically significant difference in accuracy when using either of the two algorithms. We posit that LCS is a special case of the N-word gram algorithm when the window size N is set to the complete text in a line.

`////////COMPUTE RESULTS WHEN PARAMETERS OF SPELL CORRECTION ALGORITHMS ARE CHANGED` We also experimented by changing the parameters of spell correction algorithms used in this study. For Edit distance algorithm, the change in edit distance gives following results: For Context sensitive spell correction algorithm, following parameters were modified:

## 6. Discussion

The edit distance based spell corrector used in this work corrects non-real word errors by focusing on isolated words in the dataset. We believe a better accuracy of spell correction can be obtained by correcting the new line errors in the articles. This can be done by checking for if the word at last index of a linetext or the word at first index of the next linetext is a word not present in the dictionary and combining the two and checking again in the dictionary for a valid word. The new word, if present in the dictionary can be replaced by the two words from which it is formed thereby removing the New Line error. Similar approach can be applied for word split and join errors but would require each word of an article not present in the dictionary to be analyzed along with some window of words before and after it to make a correction. Since edit distance algorithm is governed by the dictionary choice, using a dictionary with historical terms, places and people names

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<sup>7</sup>[https://en.wikipedia.org/wiki/Longest\\_common\\_subsequence\\_problem](https://en.wikipedia.org/wiki/Longest_common_subsequence_problem)

can also help perform spelling correction better and improve its accuracy. The LingPipe based context sensitive spell correction algorithm also employs a corpus dictionary for indexing the terms which suggests that the dictionary choice affects the results of spell correction in this case as well.

## 7. Conclusion and Future Work

In this paper, we presented a novel approach for automatic performance evaluation of spell correction on noisy OCR text through N-word grams alignment of the OCR, corrected and manually cleaned text. Preliminary results of application of our algorithm on an Edit distance based spell corrector evaluate its AUC score to be 0.49 while it evaluates to 0.56 for Context Sensitive based spell corrector. We believe the N-word gram SCE algorithm can be used to evaluate any kind of spell correction algorithm and provide a detailed performance by considering complete text coverage compared to simpler measures like percentage of corrected words or word error rate used previously. It can be further used to examine multiple spell correction algorithms and analyze the best spell correction algorithm suited for OCR data mining tasks. In future, we plan to add more evaluation metrics to our evaluation algorithm.

## 8. Acknowledgement

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