Classification of Text Corrected by the Crowd using Support Vector Machines

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Abstract

Optical Character Recognition (OCR) is a commonly used method of digitizing printed texts so that they can be searched and displayed online, stored compactly and used in text mining applications.
The text generated from OCR devices, however, is often garbled due to variations in quality of the input paper, size and style of the font and column layout. This adversely affects retrieval effectiveness; hence the techniques for cleaning the OCR need to be improvised. Often such techniques involve laborious and time consuming manual processing of data.
This paper shows the need to devise an algorithm that is scalable for a large dataset. The current state of the art algorithm used for performing multi class classification is not yet scalable. The current algorithm takes a long time to converge in a particular parameter setting.

1 Introduction

Crowdsourcing is used extensively in cultural heritage and digital history related projects in recent years to digitize, create and process content and provide editorial or processing interventions. For example, the Australian Newspapers Digitization Program (ADNP 2008) enables communities to explore their rich newspaper heritage by enabling free online public access to over 830,000 newspaper pages containing 8.4 million articles. The public enhanced the data by correcting over 7 million lines of text and adding 200,000 tags and 4600 comments (Holley Nov2009). Picture Australia (NLA 2006) harvests digital images from other heritage institutions and encourages the public to upload their own images and tag them. FamilySearch (LDS 2005) made available handwritten digital images of births, deaths and marriage records for transcription by the public. The New York Public Library has 1,277,616 dishes transcribed to date from 17,079 menus. Galaxy Zoo (Community)is an online collaborative astronomy project in which users are invited to classify millions of galaxies from digital photos.

In all of the above crowdsourcing projects, large volumes of data are generated by users. These include tags, folksonomies, flagged content, information on history, relationship and preference data, structured labels describing objects and creative responses (Ridge 2011). In most citizen science projects, however, little statistical analysis is done of the user generated content. Thus assessment of data quality obtained by leveraging the "wisdom of the crowd" remains an open problem.

In this paper, we focus on understanding what kind of text corrections are done by users of an old historic newspaper archive. The newspapers are made available for searching on the Internet after the following processes 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 OCR scanning process is far from perfect and the documents generated from it contains a large amount of garbled text. A user is presented with erroneous or distorted text from the newspaper article along with a high resolution image and s/he is expected to read and correct the garbled words as required. Our goal is to answer simple questions such as "What are the different kinds corrections proposed by users?".

Our study used log files generated from text correction software in use at the California Digital Newspaper Collection (CDNC)[1], which contains over 400,000 pages of newspapers published in California between 1846-1922. The corrections are primarily categorized as changes in spellings, punctuation rectification, addition of content or capitalization. A semi-automatic engine for classifying corrections based on support vector machines is designed. To the best of our knowledge, this is the first attempt to statistically analyze and model OCR error corrections provided by the crowd. We posit that such a classification system will be beneficial when attempting to compensate the annotators; it can also be used for task allocation if some users are more comfortable with certain type of corrections than others.

Organization: Section 2 discusses related work in OCR text correction with particular emphasis on systems requiring human intervention. Section 3 describes the data obtained from crowd sourcing and pre-processing steps; Section 4 presents the design of the semi-automatic error correction classifier

[1]http://cdnc.ucr.edu/cgi-bin/cdnc

and Section 5 presents empirical and scalability results using real-world data collected at CDNC. Finally, Section 6 concludes the paper.

2 Related Work

Optical Character Recognition

Optical Character Recognition (OCR) is a commonly used method of digitizing printed texts so that they can be searched and displayed online, stored compactly and used in text mining applications. The text generated from OCR devices is often garbled due to variations in quality of the input paper, size and style of the font and column layout, its condition at the time of microfilming, choice of scanner, and the quality of the OCR software. Several techniques for post processing garbled OCR have been designed. These include:
Human interventions.
Dictionary based schemes.

The other initiatives that include human intervention is (Abdulkader and Casey 2009). This work gives a low cost approach for digitizing textual data by using learning methods like neural network classifier to estimate OCR errors, clustering similar errors, designing a user interface and using active learning to tune the error estimation by using user labeled data. Another learning algorithm used for mining wikipedia edit history includes baseline Hidden Markov Model which was further augmented with perceptron reranking (Yamangil and Nelken 2008). Since the model was trained on wikipedia edits, it was attuned to human corrections. An important work (Velagapudi) that uses a combination of classifiers, a kNN classifier, a multilayer perceptron and SVM discusses the the effects of error correction on the classification accuracy of each method. In another work (Laroum1 et al. 2011), instead of error classification OCR documents were classified into fixed number of categories based on their content. The accuracy of their approach was best when evaluated using SVM among other algorithms including KNN, Naive Bayes.

Multi-class SVM

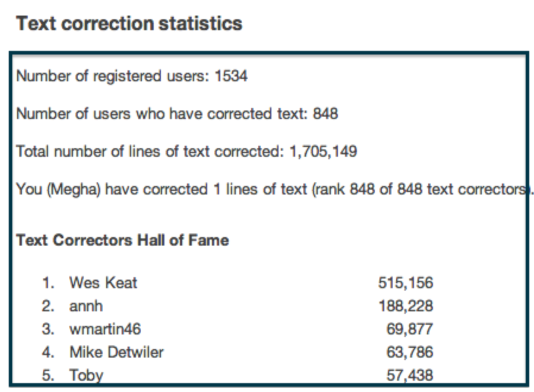
Among the different methods used for solving SVM multi classification problem, we present some of the relevant works in related areas. a) *one-versus-all (OVA classification)* uses winner-takes-all strategy where the classifier with highest output function assigns the label. It generates k classifiers for a k class problem. b) *one-versus-one* uses the majority voting strategy where each classifier assigns the new instance one of the two class, thereby increasing the vote of the assigned class. Finally the class with the majority votes determines the instance classification. It generates k(k-2)/2 models for a k class problem. This approach is not practical for large-scale classification because of the memory required for storing k(k-1)/2 models. c) *Directed Acyclic Graph SVM* in its training phase is the same as the one-against-one method by solving k(k-1)/2 binary SVMs. However, in the testing phase, it uses a rooted binary directed acyclic graph which has k(k-1)/2 internal nodes and k leaves. This is superior to other multiclass SVM algorithms in both training and testing time. d)*error correcting output codes* The other alternative is by using *pairwise classification* (Brunner et al. 2012), where a two class classifier is build on the two input example. The class of training example might be unknown but the mandatory condition is to know whether the examples belong to the same class or not. The input pair is positive pair when the both belong to the same class, otherwise its called as negative pair.
The (Crammer and Singer 2002) approach was to pose the multi class classification problem into a single optimization problem, rather than decomposing it into multiple binary classification problems. A comparison of the above approaches can be referred here (Hsu and Lin 2002).

3 The Data

Newspaper

Figure 1(a) shows a scanned page of "The Amador Ledger" published on January 26, 1900. It is available from the (Collection 2009) archive and the article to be corrected by a user is highlighted. The raw OCR text of the article and the tool used by patrons to correct text is shown in figure 1(b). All the corrections performed by the annotators were recorded in the log files.

The text correction statistics consisting of total number of annotators involved in the the data enrichment process are shown in figure 1. The total number of lines corrected by 848 users are 1,705,149.



Text correction statistics

Number of registered users: 1534

Number of users who have corrected text: 848

Total number of lines of text corrected: 1,705,149

You (Megha) have corrected 1 lines of text (rank 848 of 848 text correctors).

Text Correctors Hall of Fame

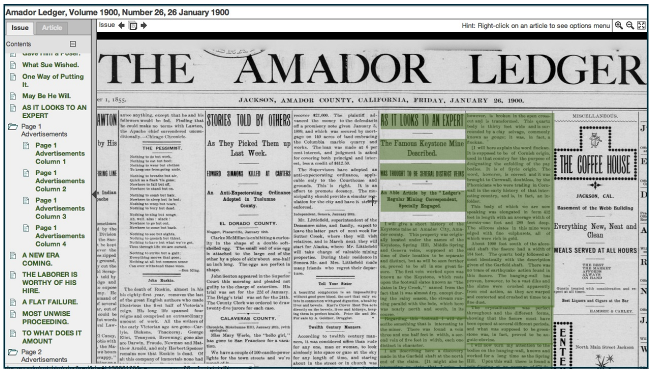
1.	Wes Keat	515,156
2.	annh	188,228
3.	wmartin46	69,877
4.	Mike Detwiler	63,786
5.	Toby	57,438

Figure 1: Text correction statistics

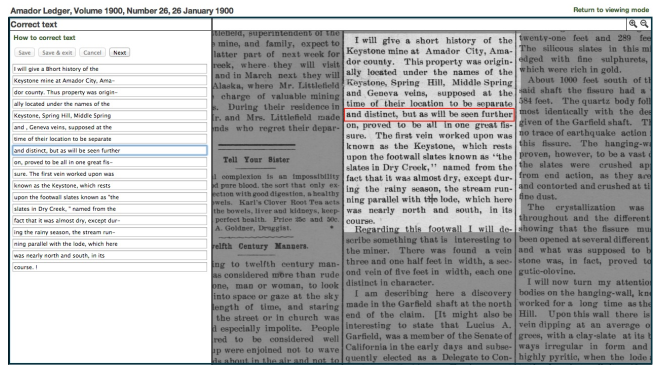
Log-files

The log files are the files that maintain the history of raw OCR and its corresponding corrected OCR text. These files were generated using a third party software issued by *Veridian*[2], a digital library software. Each of the log file was generated at an issue-level, containing xml data about the multiple pages in the issue. The table 1 describes the structure and the format of the log file. The following information is provided about the corrections made by the patrons:
a) *Page Id* representing the id of the page in which editing was done. b) *Block Id* representing the id of the paragraph containing the line corrected by the user. c) *Line Id* is the

[2]http://www.dlconsulting.com/



(a) Scanned newspaper "The Amador Ledger" highlighting an article to be corrected by a user.



(b) The tool used by patrons to annotate articles.

id of the particular line edited by the user. d) *Old text* is the garbled text generated by the OCR device and replaced by the user. e) *New text* is the corrected text with which the old text was replaced.

<TextCorrectedLine lineID="P2_TL00800">
<OldTextValue>**Spll, Stales**</OldTextValue>
<NewTextValue>**Union Stables**</NewTextValue>
</TextCorrectedLine>
<TextCorrectedLine lineID="P2_TL00801">
<OldTextValue>****?** Under Webb Hall ***</OldTextValue>
<NewTextValue>**Under Webb Hall** </NewTextValue>
</TextCorrectedLine>

Table 1: A segment of the log file

There were in total 235 log files of which we worked on 191.

Preprocessing

In order to make use of the full text data, we did some preprocessing on the data stored in the log files. We extracted the old text and the corresponding new text from the log file and tokenized them into words. These tokens were separated by whitespaces. There were in total 44,023 tokens of which 21,113 were corrected by the annotators. The errors rectified by the users were categorized as spellcheck error , addition of a new word, capitalization error, typo, punctuation error. The distribution of the these classes in the dataset is shown in figure 2

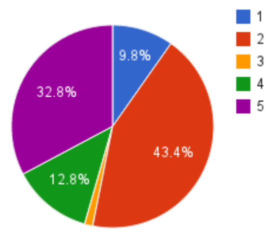


Figure 2: Error Classification

4 Methodology

We are performing automatic text correction by modelling it through a machine learning algorithm, called multi class Support Vector Machines (Joachims 2008). In this formulation, multi class problem is posed as a constrained optimization problem with a quadratic objective function. The multi class formulation is stated as

$$min 1/2 \sum_{i=1}^{k} w_i * w_i + C/n \sum_{i=1}^{n} \xi_i \tag{1}$$

$$s.t. \forall y \leq k : [x_1 \cdot w_{yi}] \geq [x_1 \cdot w_y] + 100 * \Delta(y_1, y) - \xi_1$$

. . . .

$$s.t. \forall y \leq k : [x_n \cdot w_{yn}] \geq [x_n \cdot w_y] + 100 * \Delta(y_n, y) - \xi_n$$

Here C is the regularization parameter that trades off margin error and training error. $\Delta(y_1, y)$ is the loss function that returns 0 if y_n equals y, and 1 otherwise. ξ_i are the non negative slack variables which measure the degree of misclassification of the data x_i.
(Joachims 2008) has to two modules, *svm_multiclass_learn* and *svm_multiclass_classify*. The learning module learns the model given the parameters and the training data whereas the classification module applies the learned model to the test data to find the error. When the data is not linearly separable, the original finite dimensional space is mapped to a much higher dimensional space in order to make the separation easier in that space. The mappings used by SVM schemes are designed to ensure that the dot products may be computed easily in terms of the variables in the original space, by defining them in terms of a Kernel function selected to suit the problem. The types of kernel function used can be described as follows:
a) Linear Kernel (default) : It is the basic kernel function given by the inner product <x,y>plus an optional constant c. K(x,y) = x^Ty + c

b) Polynomial Kernel : It is a non-stationary kernel which is well suited for problems where the training data is normalized.
K(x,y) = $(\alpha x^T y + c)^d$
c) Radial Basis Kernel : The (Gaussian) radial basis function kernel on two samples x and y represented as feature vectors in some input space is defined as
K(x,y) = exp($-||x-y||^2$/2σ^2)

5 Empirical Evaluation

Preprocessing & Data Generation

Feature Construction Originally, there were two features in the dataset, that is old text and new text. Further features were manually crafted looking at the types of errors. In our dataset, we have six binary features consisting of SameLength, EditDist_0, EditDistAbove1, EditDistBelow3, EditDist_1andCaseChange, PunctuationDiff.

1. “SameLength” is 1 if both the old word and new word have same length
2. “EditDist_0” is 1 if both the words are exactly same
3. “EditDistAbove1” is 1 if more than one edit operation is required to convert old word to new word
4. “EditDistBelow3” is 1 if less than three edit operations are required to convert old word to new word
5. “EditDist_1andCaseChange” is 1 if the two words have edit distance is exactly 1 and the first character of one string change from upper case to lower case or vice versa.
6. “PunctuationDiff” is 1 if both the old text and new text differ in any of the following punctuation marks !”#$%&’()*+,-./:;<=>?@[\]ˆ_‘{|}˜

Label Construction The error classes were restricted to 6 classes including Spellcheck Error, Addition of a new word, Capitalization Error, Typo, Punctuation Error and No correction These labels were assigned according to the flow graph as shown in figure

1. Spellcheck error : When the edit distance is between 1 and 3. For example, mounten and mountain.
2. Addition of a new word : When the edit distance is more than 3. For example, at and attend.
3. Capitalization error : When the edit distance of two strings is exactly 1 and first letter of both the strings changes from upper to lower case or vice versa. For example, largest and Largest.
4. Typo : When the edit distance is exactly one and case change is 0. For example, teh and the
5. Punctuation error : When the two strings differ by special characters contained in the set (!”#$%&’()*+,-./:;<=>?@[\]ˆ_‘{|}˜). For example, “residents” and residents
6. No correction : When the old and new text are same. For example, plant and plant

The dataset was parsed to a format used by the Joachim’s multi class SVM algorithm which is represented as
<target> <feature>:<value>......<feature>:<value>
The number of rows in the dataset is 44,022. The class distribution in the dataset is shown in table 2

$Class$	$no.of instances$
1	1970
2	8732
3	261
4	2572
5	6602
6	23885
Total	44022

Table 2: Class Distribution

Experiment Setup

Experiments were performed by randomly partitioning the data into 70% (30,815 instances) and 30% (13,207 instances) of training and testing data respectively. For each experiment, the regularization parameter (C) and the type of kernel (t) was varied to (0.001,0.01,0.1,1,10,100) and (Linear, Polynomial and Radial basis kernel) respectively. The experiments were performed on two machines, one of which was a linux server and the other was a dual core Mac machine with Intel Core i7 processor, 8GB RAM, 2.9 GHz of processor speed. Each experiment was ran for 5 iterations. The average loss on the test set and CPU runtime were noted to analyse the experiments. Table 3 describes how the average loss on test set varies for different values of ‘C’ and ‘t’. Here, AE_L, AE_P, AE_R describes the average loss error of linear, polynomial and rbf kernels respectively. Table 4 shows the average runtime (cpu sec) required to learn a model for various values of C and for different kernels. Here, AT_L, AT_P, AT_R refers to the average run time of linear, polynomial and rbf kernels respectively.

Results

C	AE_L	AE_P	AE_R
.001	32.06 $\pm$0.149	32.06$\pm$0.149	11.96$\pm$0.101
.01	32.06$\pm$0.149	32.06$\pm$0.149	12.04$\pm$0.199
.1	32.06$\pm$0.149	29.10$\pm$0.133	12.04$\pm$0.199
1	29.10$\pm$0.133	28.99$\pm$0.264	6.36$\pm$0.142
10	29.20$\pm$0.133	8.338$\pm$0.107	6.36$\pm$0.142
100	29.20$\pm$0.133	0.58$\pm$.034	6.35$\pm$0.16

Table 3: Experiment Results : Average loss error (test set)

Discussion

As can be seen in table 3 , the error is minimum when the C = 100 and when the kernel type is polynomial. But the time taken as shown in table 4 to train the model for these parameters, when C is 100 is 106753 cpu sec.

C	AT_L	AT_P	AT_R
.001	0.218	5192	4596
.01	0.202	5166	4460
.1	0.208	72225	4377
1	0.678	81251	16468
10	0.672	260316	55308
100	0.998	106753	48734

Table 4: Experiment Results : Training time (cpu sec)

Known Defects

The (Joachims 2008) algorithm converges quickly for linear type kernel but the its performance on test set is poor. For non linear kernels, this algorithm does not scale well for large scale datasets but gives better performance than linear kernels.

6 Conclusion & Future Work

The California Digital Newspaper Collection has an archive of 400,000 pages of historical California newspapers published between 1846 to 1922. This archive which has been subjected to OCR and is currently stored in an online database making them accessible to patrons. The OCR scanning process generates lot of garbled text which needs to be corrected to make the online newspaper repository more accessible to general public. An automatic OCR error correction technique is implemented using machine learning technique, multi class Support Vector Machine used to build a model for predicting errors in the dataset generated. State-of -the-art algorithm (Joachims 2008) was used to for our experiments to predict the errors. The labels generated using the approach mentioned in section 5 served as the groundtruth against which labels generated by the algorithm were compared. Our results indicate that even the state-of-the-art algorithm is not scalable for large scale learning as it takes 106753 cpu sec to learn a model on data with 30,185 instances. Our Future work involves careful analysis of the current algorithm to scale the non-linear kernels for large scale learning.

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