

# Error Classification in OCR Historic Newspaper Archive using multi-class Support Vector Machine

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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

The *California Digital Newspaper Collection*<sup>1</sup> is an initiative of the Center for Bibliographical Studies and Research (CBSR) which is supported in part by the U.S. Institute of Museum and Library Services. It is also supported by the National Endowment for the Humanities (NEH) to digitise California newspapers for the National Digital Newspaper Program (NDNP). It contains over 400,000 pages of significant historical California newspapers published from 1846-1922.

OCR devices are widely used in electronic conversion of scanned images which are handwritten or printed text into a machine encoded text. The scanning generates It finds most successful applications in the field of machine Learning, Artificial Intelligence and Pattern recognition. It deals with the problem of recognising optically generated characters be it offline or online. The performance directly depends on the quality of input document. The more constrained the input is the better will be the performance of the system. But when it comes to unconstrained handwriting, the performance is far from satisfactory. The main application areas for (Eikvil 1993) like Automatic number plate readers, form readers, signature verification.

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<sup>1</sup><http://cdnc.ucr.edu/cgi-bin/cdnc>

This project deals with printed text in the form of Historical Newspaper Articles in the holdings of (Collection 2009). One such newspaper, The Amador Ledger published in the early 1900s by the Amador Publishing Company appealed to the community's interests by covering issues unique to gold mining. Patrons of the (Collection 2009) continue to be interested in studying about the status of the local mining industry and consequently read the Amador Ledger on a regular basis even to this day and correct (Eikvil 1993) errors as they come across them.

In this paper, we perform error classification using Joachims multi-class Support Vector Machine algorithm called *SVM<sup>multiclass</sup>*<sup>2</sup>. We chose this algorithm as its the state of the art algorithm till now. But the experiments give altogether a different view on this algorithm. This algorithm do not converge quickly on certain parameters which are shown in table 4

## 2 Related Work

### OCR correction

The OCR enables searching of full text data but it is not 100% accurate. Its accuracy largely depends on paper quality of the original issue, font style, column layouts, its condition at the time of microfilming, choice of scanner (Jeffrey Esakov and Zhou ), and the quality of the OCR software. The OCR errors are widely classified as non-word errors and real-word errors. A non-word error takes place when the erroneous word is not a dictionary word whereas in real-word error the erroneous word is correctly spelt and therefore can be found in the dictionary but incorrectly used in context. A related work on the OCR error classification is done by (Niklas ). It gives a more exhaustive classification with respect to OCR errors that helps in classifying real words not contained in any of the dictionary, e.g. names, outdated or historic spelling variations. Segmentation errors, Hyphenation error, Misrecognition of characters, Punctuation errors, Case sensitivity, Changed word meaning are the classes required for better classification of OCR errors.

### Multi-class SVM

SVMs are inherently binary classifiers. To solve the multi class problem, construction of several binary classifiers is

<sup>2</sup>[http://www.cs.cornell.edu/people/tj/svm.light/svm\\_multiclass.html](http://www.cs.cornell.edu/people/tj/svm.light/svm_multiclass.html)

required and the result from each classifier is combed. The traditional approaches to do multi class classification are: a) *one-versus-all (OVA classification)* classifies the new instances is done by 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* 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.

### 3 The Data

#### Newspaper

Figure 1 shows a scanned newspaper (*The Amador Ledger*, January 26,1900) from the (Collection 2009) archive highlighting the article to be corrected by the user. The raw OCR text of the highlighted article is displayed by clicking on the specific article headline from the list of headlines seen on the left side of the issue in figure 1.

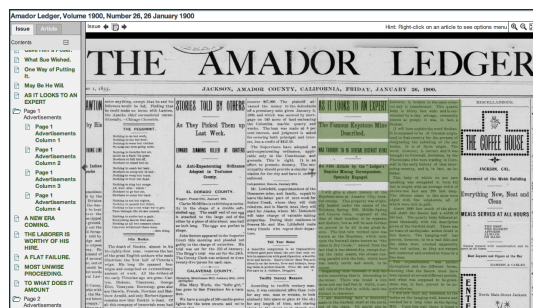


Figure 1: Amador Ledger

The tool used by patrons to correct OCR text is shown in figure 2. 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 3. The total number of lines corrected by 848 users are 1,705,149.

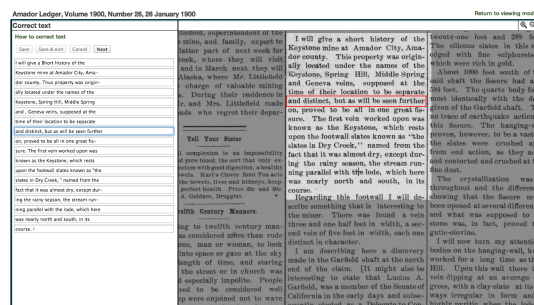


Figure 2: Text correction tool

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 3: 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*<sup>3</sup>, 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 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>Spill, 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

<sup>3</sup><http://www.dlconsulting.com/>

## Preprocessing

In order to make use of the full text data, we did some pre-processing 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.

## 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

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

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

.....

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

Here C is the regularisation 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.  $\xi_i$  are the non negative slack variables which measure the degree of misclassification of the data  $x_i$ .

(?) 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  $\langle x, y \rangle$  plus an optional constant c.  $K(x, y) = x^T y + c$

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

$$K(x, y) = \exp(-||x - y||^2 / 2\sigma^2)$$

## 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, punct\_diff.

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. “punct\_diff” is 1 if both the old text and new text differ in any of the following punctuation marks !"#%&'()\*+,-./:;<=>?@[\\]^\_`{|}~

**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 (!"#%&'()\*+,-./:;<=>?@[\\]^\_`{|}~). 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

The errors rectified by the users were categorised 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 4

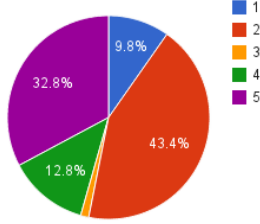


Figure 4: Error Classification

### Experiment Setup

Experiments were performed by randomly partitioning the data into 70% and 30% of training and testing data respectively. For each experiment, the regularisation 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 ±0.149	32.06±0.149	11.96±0.101
.01	32.06±0.149	32.06±0.149	12.04±0.199
.1	32.06±0.149	29.10±0.133	12.04±0.199
1	29.10±0.133	28.99±0.264	6.36±0.142
10	29.20±0.133	8.338±0.107	6.36±0.142
100	29.20±0.133		

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

### Discussion

As can be seen in table ?? , the error is minimum when the C has value (1 and 10) and when the kernel type is radial basis

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		

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

function (gaussian). But the time taken to train the model for these parameters, when C is 1 is 16468 cpu sec and when C is 10 is 55308 cpu sec.

## 6 Conclusion & Future Work

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