Addressing Class Imbalance in Grammatical Error Detection with Evaluation Metric Optimization

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Abstract

We address the problem of class imbalance in *supervised* grammatical error detection (GED) for non-native speaker text, which is the result of the low proportion of erroneous examples compared to a large number of error-free examples. Most learning algorithms maximize *accuracy* which is not a suitable objective for such imbalanced data. For GED, most systems address this issue by tuning hyperparameters to maximize metrics like F_β. Instead, we show that learning classifiers that directly learn model parameters by optimizing evaluation metrics like F_1 and F_2 score deliver better performance on these metrics as compared to traditional sampling and cost-sensitive learning solutions for addressing class imbalance. Optimizing these metrics is useful in recall-oriented grammar error detection scenarios. We also show that there are inherent difficulties in optimizing precision-oriented evaluation metrics like $F_{0.5}$. We establish this through a systematic evaluation on multiple datasets and different GED tasks.

1 Introduction

The task of *grammatical error detection* (GED) and *grammatical error correction* (GEC) refers to the identification and repair of grammatical errors in text generated by speakers of a language (native/non-native). Many techniques, rule-based as well as machine learning based, have been proposed for addressing this task. A common and successful method for building *grammatical error detection* (GED) systems is to apply *supervised learning* on annotated learner corpora. For instance, the problem of noun number error detection can be formulated as a task of classifying if the head noun of a noun phrase has the `correct` or `incorrect` grammatical number. As opposed to rule-based methods, classification methods can easily incorporate complex and arbitrary evidence as features. Some of the best performing systems for the most frequent grammatical errors, *viz.* noun number, article and preposition errors, are classification systems (Ng et al., 2013).

Task	**Errors**	**Tokens**	**Error Rate**
Article	6658	234,695	2.84%
Noun Number	3379	245,026	1.38%
Preposition*	1955	123,419	1.58%

Table 1: Error rates for GED tasks (NUCLE)
* statistics for 10 most frequent prepositions

However, a major problem in learning classifiers from an annotated learner corpus is the very low **error rate** (number of errors per token) in the corpus (Chodorow et al., 2012). For instance, the error rates are less than 3% for noun-number, article and preposition errors in the NUCLE annotated learner corpus (Dahlmeier et al., 2013) as shown in Table 1. Such low error rates (less than 5%) have been observed across various learner corpora (see Table 2) *viz.* the NUCLE corpus (Dahlmeier et al., 2013), HOO12 corpus (Dale et al., 2012) and NICT-JLE corpus (Izumi et al., 2004). Thus, learning classifiers for GEC/GED from annotated learner corpora is a case of learning a classifier from an **imbalanced dataset** *i.e.* a dataset where the class ratios are highly skewed (He and Garcia, 2009). In contrast to many imbalanced problems studied in datamining literature, GED tasks are characterized by large and sparse features spaces and very high imbalance ratios.

Since it is easy to achieve high accuracy by simply assigning all training examples to the majority class, *accuracy* as the optimization objective performs poorly for classification on imbal-

Corpus	**Tokens**	**Errors**	**%Error Rate**
NUCLE	1,161,567	46,597	3.82
HOO12	374,680	8,432‡	2.25‡
NICT-JLE	169,662	14,407	8.49

Table 2: Errors statistics for learner corpora
‡ articles and prepositions errors only

anced datasets. Moreover, accuracy is not the right evaluation metric for GED. Non-native language learners require a GED system with a **high precision** so that they are not misguided by wrong error notifications. On the other hand, professional copy-editors and language instructors will require a **high recall** system that helps improve productivity and quality of service by identifying all potential errors that need review, even at the cost of flagging some spurious errors. Hence, a precision oriented optimization objective like $F_{0.5}$ and a recall oriented objective like F_2 would be appropriate for non-native speakers and copy-editors respectively. *In this paper, we explore the hypothesis that by directly optimizing the desired evaluation metric, we can satisfy the requirements of asymmetric misclassification cost and customization of the recall/precision trade-off.*

The following are the contributions of our work:

- Sampling and example-weighting methods have been traditionally applied to overcome this limitation. We systematically investigate different solutions to the class imbalance problem for three GED tasks (noun number, article and preposition) over multiple annotated learner corpora. We compare the following sampling methods over a range of sampling ratios: *random undersampling, Synthetic Minority Over-sampling Technique (SMOTE) and example weighting*. We analyze and present experimental results to demonstrate the limitations of these traditional methods in addressing class imbalance.

- As an alternative to sampling methods, we propose that a GED classifier be learnt by directly optimizing the evaluation metrics, typically F_1, F_2 or $F_{0.5}$. For copy-editors, F_2 is a suitable evaluation measure which addresses the need for high recall in GED. We use the performance measure optimization framework proposed by Joachims (2005) for optimizing these metrics. For the three GED tasks under consideration, we show that optimizing the F_2 metric of the `incorrect` class gives better performance compared to sampling methods.

- We also show that evaluation metric optimization, as well as sampling methods, are not suitable for improving precision. While evaluation metric optimization helps improve recall and obtain a reasonable precision-recall trade-off, improving precision remains a challenge.

The rest of the paper is organized as follows. Section 2 describes the limitations of sampling methods, motivates the use of evaluation metrics optimization for imbalanced data problems, and the use of F_2 as an evaluation metric for GED. Sections 3 and 4 discuss the related work and the learning algorithm used for directly optimizing evaluation metrics. Section 5 explains classifiers for the GED tasks under consideration, while Section 6 describes our experimental setup. We analyze results in Section 7. Section 8 summarizes our contributions and describes possible future directions.

2 Motivation

There are many GED applications where users do not consider false positive and false negative errors as equally damaging. To copy-editors, false negative errors are costlier than false positive errors. They would not mind evaluating a few false alarms, but cannot afford to miss genuine errors since that would affect the quality of service. They would prefer the GED system to err on the side of higher recall. Similarly, translators using computer-aided translation systems would prefer to have most errors pointed out. Even an automatic post-editing system for MT would prefer to have most errors identified since alternatives can then be evaluated for these potential errors in a post-editing stage.

We hypothesize that by directly optimizing the desired evaluation metric, we can satisfy the requirements of asymmetric loss and customization of the recall/precision trade-off. For a GED system designed to help copy-editors, F_2 would be a reasonable choice as an optimization objective since it is biased towards recall. Similarly, $F_{0.5}$ would be a reasonable choice for a GED system designed for language learners. Our choice of

$\beta = 0.5, 2$ follows the conventional choices mentioned in literature for evaluating precision and recall bias.

Traditionally, sampling and example-weighting have been the most common methods to handle class imbalance. **Sampling** involves either *undersampling* the `correct` examples or *oversampling* the `incorrect` examples in the training set (Van Hulse et al., 2007; Domingos, 1999). In **example-weighting**, misclassification costs are associated with the training examples, with higher misclassification costs for wrongly classifying `incorrect` examples (Zadrozny et al., 2003). In theory, example-weighting and sampling techniques can be shown to be equivalent (Zadrozny et al., 2003), and in the rest of the paper we use *sampling* to refer to both. However, sampling methods have a few limitations which direct optimization of the performance metrics does not suffer from:

- Even the choice of sampling ratio is arbitrary and its effect on the evaluation metrics is not obvious. A validation set may be used to select the appropriate ratio which maximizes the evaluation metric, at the cost of setting aside some valuable training data for tuning. On the other hand, while optimizing an evaluation metric, it naturally induces a loss function.

- A high degree of undersampling is required to negate the effect of the very low error rate in GED tasks. However, this results in a drastic reduction in the examples available for training. Random undersampling has been reported to work reasonably on some datasets with a dense feature space and a small number of features (Van Hulse et al., 2007). In contrast, the classification problems for GED results are characterized by large and sparse feature spaces leading to a loss of many features due to undersampling. Optimizing evaluation metrics directly does not incur this loss since data is not sampled prior to learning.

- Oversampling with repetition of `incorrect` class instances generally does not improve classification performance and results in overfitting. Informed oversampling through introduction of synthetic instances belonging to the minority class (SMOTE) by interpolation of minority class instances in the training set has shown good improvement in many applications (Chawla et al., 2002). For large feature spaces, the generation of synthetic examples can be computationally expensive since it involves a k-nearest neighbourhood search. Optimizing evaluation metrics directly does not incur this computational overhead.

3 Related Work

The most common methods to handle **imbalanced datasets** in GED involve undersampling the `correct` instances (Dahlmeier et al., 2012; Putra and Szabo, 2013; Kunchukuttan et al., 2013) or oversampling the `incorrect` instances (Xing et al., 2013). Rozovskaya et al. (2012) propose an *error inflation* method for preposition error correction, where a fraction of the correct prepositions are marked as incorrect prepositions and these new "erroneous" instances are distributed among different possible erroneous prepositions. This method is similar to the *MetaCost* (Domingos, 1999) approach of re-labelling examples in the training set according to a cost function. Some whole-sentence correction approaches (Kunchukuttan et al., 2014; Junczys-Dowmunt and Grundkiewicz, 2014; Dahlmeier and Ng, 2012) are tuned to maximize the F_β scores.

In all the work mentioned above, the systems maximize F_β by tuning only the "hyper-parameters" like sampling threshold, features weights for scores of underlying components —classifier (Dahlmeier and Ng, 2012) or SMT component scores (Kunchukuttan et al., 2014; Junczys-Dowmunt and Grundkiewicz, 2014) —on a tuning dataset using *approximate* methods like MERT (Och, 2003), PRO (Hopkins and May, 2011) and grid search. In contrast, we optimize all the model parameters *exactly and efficiently* to maximize F_β.

4 Optimizing Performance Measures

A loss function like the induced F_β loss is non-decomposable *i.e.* it cannot be expressed as the sum of losses over individual instances. We use the max-margin formulation proposed by Joachims (2005) for *exactly* optimizing such non-decomposable loss functions which can be computed from the contingency table[1]. It is applicable only to binary classification problems.

The training loss is described in terms of a loss function (Δ) which measures the discrepancy between the expected output vector ($\bar{\mathbf{y}}$) and observed output vector ($\bar{\mathbf{y}}'$) on training data of size m:

$$\Delta : (y_1 ... y_i ... y_m) \times (y'_1 ... y'_i ... y'_m) \rightarrow \mathbb{R} \qquad (1)$$

For a decomposable loss functions like 0-1 loss, hinge loss, *etc.* we can express the loss as:

$$\Delta(\mathbf{y}, \bar{\mathbf{y}}) = \sum_{i=1}^{m} \Delta'(y_i, y'_i) \qquad (2)$$

where, Δ' is the loss function for a single instance:

$$\Delta' : y \times y' \rightarrow \mathbb{R} \qquad (3)$$

In the max-margin framework, a decomposable loss function (hinge loss in the example below) can be minimized by solving the following objective function for support vector machines (SVM):

$$\min \frac{1}{2}\mathbf{w}.\mathbf{w} + C\sum_{i=1}^{n} \xi_i \qquad (4)$$

$$s.t : \forall_{i=1}^{n} : y_i[\mathbf{w}.\mathbf{x_i}] \geq 1 - \xi_i \qquad (5)$$

Here, $\xi_i = 1 - y_i[\mathbf{w}.\mathbf{x_i}]$ is an upper bound on the loss (Δ') for the i^{th} training instance.

However, non-decomposable loss functions cannot be modeled in this framework since the constraint, and hence the loss, is defined per instance. We need a framework to represent the problem in terms of loss over the entire training set (*i.e.* the observed and expected label vector) using a custom loss function. The *StructSVM* framework (Tsochantaridis et al., 2005) provides the ability to define custom loss functions over arbitrary output structures like vectors, trees, etc. Joachims (2005) framed the binary classification problem with non-decomposable loss functions as a structured prediction problem, where the entire training set becomes a single instance. The input ($\bar{\mathbf{x}}$) is a tuple of the original features vectors ($\mathbf{x_i}$) and output is the label vector ($\bar{\mathbf{y}}$) . The training objective can be represented as:

$$\min \frac{1}{2}\mathbf{w}.\mathbf{w} + C\xi \qquad (6)$$

[1]`http://en.wikipedia.org/wiki/Confusion_matrix`

Noun Number	
O: It was great to see the **excitements** on the child's face.	
C: It was great to see the **excitement** on the child's face.	
Article	*Preposition*
O: I want to buy pen.	Keep the pen **in** the table.
C: I want to buy **a** pen.	Keep the pen **on** the table.
O: original,	*C: corrected*

Table 3: Examples of grammatical errors
O: original, C: corrected

subject to the following constraints

$$\forall \bar{\mathbf{y}}' \in \mathcal{Y} \backslash \bar{\mathbf{y}} : \langle \mathbf{w}, \delta\Psi(\bar{\mathbf{x}}, \bar{\mathbf{y}}') \rangle \geq \Delta(\bar{\mathbf{y}}, \bar{\mathbf{y}}') - \xi \qquad (7)$$

where,

$$\delta\Psi(\bar{\mathbf{x}}, \bar{\mathbf{y}}') = \Psi(\bar{\mathbf{x}}, \bar{\mathbf{y}}) - \Psi(\bar{\mathbf{x}}, \bar{\mathbf{y}}') \qquad (8)$$

$$\Psi(\bar{\mathbf{x}}, \bar{\mathbf{y}}') = \sum_{i=1}^{m} y'_i \mathbf{x_i} \qquad (9)$$

Thus any label vector of the training set ($\bar{\mathbf{y}}'$) other than the expected label vector ($\bar{\mathbf{y}}$) would incur a loss upper bounded by:

$$\xi = \Delta(\bar{\mathbf{y}}, \bar{\mathbf{y}}') + \Psi(\bar{\mathbf{x}}, \bar{\mathbf{y}}') - \Psi(\bar{\mathbf{x}}, \bar{\mathbf{y}}) \qquad (10)$$

where, Δ is a custom loss function between the expected and observed label vectors.

The number of constraints is exponential in m, since there are $2^m - 1$ possible values of $\bar{\mathbf{y}}'$. However, the above optimization problem can be solved efficiently in a polynomial number of iterations using an iterative, cutting plane algorithm. The efficiency of the overall algorithm depends on the efficiency of finding the most violated constraint, *i.e.* finding the $\bar{\mathbf{y}}'$ which maximizes Equation 10. This *loss-augmented inference problem* can be solved in polynomial time for binary classification problems involving loss functions which can be computed from the contingency table *e.g.* F_β, precision, recall loss.

5 Grammatical Error Detection Classifiers

The GED tasks and the classifiers under study are described in this section.

5.1 Tasks

We consider the following three GED tasks: Noun Number (`NN`), Article (`Art`) and Preposition (`Prep`)

ARTICLE and NOUN NUMBER features
Head Noun
Is the noun capitalized?
Is the noun an acronym?
Is the noun a named entity?
Is the noun a (i) mass noun, (ii)*pluralia tantum*?
Observed number of the noun
POS of the noun
Start letter of noun ‡
Suffixes of the noun (length 1-4) ‡
Noun Phrase (NP)
Does the NP have: (i) article (ii) demonstrative (iii) quantifier?
What (i) article (ii) demonstrative (iii) quantifier does the NP have?
Number of tokens in the NP
Start letter of the word to the right of article ‡
Contextual
(i)Token (ii) POS (iii) Chunk tag in ± 2 word-window around head noun
(i)Token (ii) POS (iii) Chunk tags in ± 2 word-window around article ‡
Are there words indicating plurality in the context of the noun?
Is the noun a part of a list of nouns?
Grammatical Number of majority of nouns in noun list
Sentence
The first two words of the sentence and their POS tags
Has the noun been referenced earlier in the sentence?
PREPOSITION features
Contextual
(i) Token (ii) POS tag in ± 4 word-window around preposition
2-4 grams of (i) Token (ii) POS tag around preposition
‡: *features used only for articles*

Table 4: Feature set for various GED tasks

error detection. A few examples of these errors are shown in Table 3.

Each is a binary classification task which labels an instance as grammatically `correct` (*negative*) or `incorrect` (*positive*). The training instances for each task are defined as follows. For **noun number**, each noun phrase is an instance. For **articles**, each noun phrase containing the articles $\{a, an, the, \phi\}$ is an instance. For **preposition**, we consider only preposition deletion and substitution errors. We consider only the ten most frequent prepositions as instances: $\{on, from, for, of, about, to, at, in, with, by\}$ (Rozovskaya and Roth, 2010). The top 10 prepositions account for 78% of all prepositions in the NUCLE corpus and 81% of all the preposition errors. The feature sets for the GED tasks are shown in Table 4.

5.2 Directly optimizing evaluation metrics

We directly optimize F_β using the support vector method for optimizing performance measures (**SVM-Perf**) proposed by Joachims (2005). We chose this method since it can *exactly* and *efficiently* optimize non-decomposable evaluation metrics which can be computed from the contingency table *e.g.* F_β. We train different classifiers corresponding to $\beta = 0.5, 1, 2$.

5.3 Sampling Methods

Sampled datasets were created from the original training set using three sampling methods. In **random undersampling** (Van Hulse et al., 2007), the `correct` instances are undersampled at random and all `incorrect` instances are retained in the training set. In **SMOTE** (Chawla et al., 2002), `incorrect` class examples are oversampled by generating synthetic examples for every `incorrect` instance using linear interpolation with one of its five nearest incorrect neighbours. In **cost-sensitive learning** (Zadrozny et al., 2003), misclassifying `incorrect` instances incurs a higher cost as compared to misclassifying `correct` instances.

For each sampling method, sampled datasets were created using different representative sampling ratios ($p = 0.3, 0.5, 1.0$) which span the entire range. The sampling ratio (p) refers to the ratio of `incorrect` to `correct` examples in the sampled dataset. For cost-senstive learning, the corresponding misclassification cost ratio (J) can be computed as $J = pR$, where R is the ratio of `correct` to `incorrect` instances in training set. An SVM is trained with hinge loss on each of these sampled datasets.

6 Experimental Setup

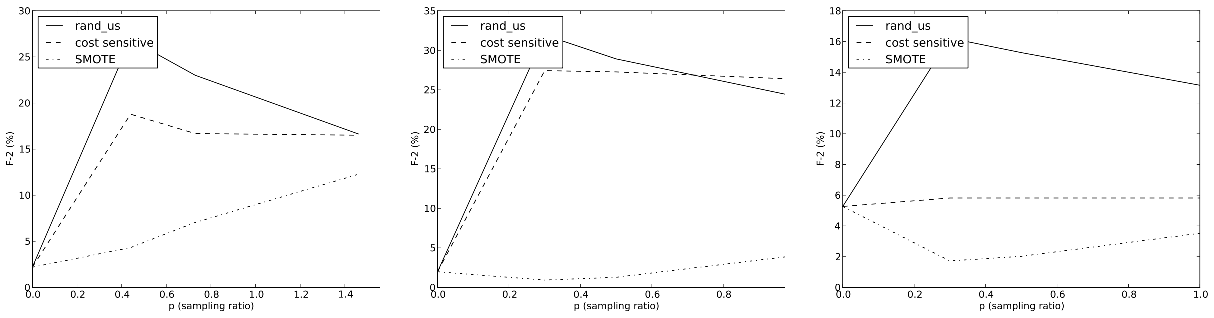
We tested our GED systems on three annotated learner corpora: NUCLE (Dahlmeier et al., 2013), HOO11 (Dale and Kilgarriff, 2011) and HOO12 (Dale et al., 2012) shared task corpora. For the HOO12 dataset, noun number error detection was not done since the dataset did not have these annotations.

For hinge loss, the classifiers were trained using the *SVMLight* package (Joachims, b). For other loss functions, classifiers were trained using the *SVM-Perf* package (Joachims, a) with extensions to optimize recall, precision and F_β. We used a linear kernel for all our experiments.The evaluation was done using Precision, Recall, $F_{0.5}$, F_1 and F_2 metrics. The average scores over a 5-fold cross-validation are reported.

7 Results and Discussion

7.1 Limitations of sampling methods

Figure 1 shows the F_2 scores of sampling methods for different GED tasks on the NUCLE dataset as a function of the sampling ratio. We can see



(a) Noun Number (b) Articles (c) Preposition

Figure 1: Comparison of sampling methods on NUCLE dataset (scores in %)

Dataset	Method	Noun Number			Article			Preposition		
		$F_{0.5}$	F_1	F_2	$F_{0.5}$	F_1	F_2	$F_{0.5}$	F_1	F_2
NUCLE	Hinge Loss	7.80	3.42	2.19	6.92	3.07	1.98	**15.37**	7.85	5.27
	Random Undersampling (p=0.3)	11.01	15.62	26.89	14.57	20.01	**31.94**	6.75	9.53	16.23
	Cost-Sensitive (p=0.3)	10.46	13.43	18.79	**18.58**	22.15	27.43	13.53	8.14	5.82
	SMOTE (p=1.0)	**18.91**	14.74	12.27	10.50	5.78	4.00	10.52	5.28	3.52
	SVM-Perf $F_{0.5}$	14.93	19.17	26.82	17.74	22.34	30.17	6.39	9.41	17.84
	SVM-Perf F_1	15.72	**19.92**	27.24	17.95	**22.65**	30.72	6.60	**9.70**	**18.28**
	SVM-Perf F_2	13.72	18.43	**28.08**	18.02	22.65	30.51	6.55	9.63	18.15
HOO-11	Hinge Loss	**18.48**	**14.15**	11.64	**35.55**	**29.87**	25.85	**28.90**	16.92	12.22
	Random Undersampling (p=0.3)	3.55	5.36	10.98	14.64	19.54	29.42	9.90	11.96	15.20
	Cost-Sensitive (p=0.3)	**18.48**	**14.15**	11.64	33.88	29.49	26.23	**28.90**	16.92	12.22
	SMOTE (p=1.0)	**18.48**	**14.15**	11.64	34.28	29.64	26.19	**28.90**	16.92	12.22
	SVM-Perf $F_{0.5}$	4.42	6.45	11.98	25.86	27.89	30.44	26.67	**17.69**	13.32
	SVM-Perf F_1	4.42	6.45	11.98	24.06	28.12	33.88	24.84	17.19	13.21
	SVM-Perf F_2	4.70	6.96	**13.42**	18.58	24.01	**34.05**	12.69	14.39	**16.81**
HOO-12	Hinge Loss				7.66	3.74	2.47	**17.63**	10.14	7.12
	Random Undersampling (p=0.3)				10.11	13.75	21.50	12.26	15.91	22.66
	Cost-Sensitive (p=0.3)				**14.66**	**16.79**	19.65	17.58	11.47	8.51
	SMOTE (p=1.0)				7.28	3.90	2.66	12.74	6.83	4.68
	SVM-Perf $F_{0.5}$				11.37	15.05	**22.29**	12.79	**17.01**	**25.42**
	SVM-Perf F_1				11.69	15.22	21.83	10.84	15.11	24.91
	SVM-Perf F_2				11.94	15.48	22.02	9.48	13.80	25.32

Table 5: Comparison of SVM-Perf with best sampling methods (scores in %)

that *the scores vary sharply with sampling ratio*, making the choice of the right sampling ratio extremely important. Undersampling techniques show a sharp increase in recall with increasing sample ratios (up to 20%), but a sharp drop in precision with increase in sampling ratio (halving the precision in some cases). Thus, the methodology does not offer much in terms of achieving a good precision-recall trade-off. The drastic variation indicates that the bias introduced by the sampling ratio is driving the classifier's decision and the training data's role is made irrelevant due to sampling loss.

In general, we can observe a trend that *undersampling and cost-sensitive techniques perform best at low sampling ratios (p=0.3), whereas SMOTE performs best at higher sampling ratios (p=1.0).* This is a consequence of the high imbalance ratio for GED tasks. However, there is no sampling method that is uniformly best across tasks and evaluation metrics. *Empirical cross-validation is the only way to determine the best sampling method and configuration for a particular task.*

7.2 SVM-Perf vs. sampling methods

Table 5 shows F_1, F_2 and $F_{0.5}$ evaluation for various SVM-Perf classifiers (optimized for F_β=0.5,1,2) and compares them with the classic hinge loss classifier and the best undersampling, oversampling and cost-sensitive learning methods on three datasets.

For the F_2 evaluation metric, optimizing F_2 is clearly better than the sampling techniques in all but one out of 8 cases (NUCLE, `Art`). Even in this case, the performance of F_β optimization is comparable to the best sampling method (96% of the undersampling score). Improvements up to 15% in F_2 score over the best sampling techniques have been observed. For instance, on the HOO11 dataset, the F_2 scores improve by about 15%, 15% and 10% over the best sampling methods for the `NN`, `Art` and `Prep` tasks respectively. Using F_2 optimization, the precision is generally higher than that of the best performing sampling technique. Only in 3 cases, F_2 optimization gives slightly lower F_2 scores than F_1 or $F_{0.5}$ optimizations ($\approx$ 1% lesser). *A GED system designed to achieve high recall can thus benefit from optimizing the F_2 metric.*

F_1 optimization gives the best F_1 score on the NUCLE dataset for all tasks, and on some tasks on other datasets. For instance, the F_1 scores improve by 27.52%, 2.26% and 1.78% over the best sampling methods for the `NN`, `Art` and `Prep` tasks respectively on the NUCLE dataset. Only on the `NN` task for the HOO-11 dataset, the sampling methods vastly outperform F_1 optimization. On the remaining tasks, the performance is comparable to the best performing sampling method. *In most cases, we can conclude that F_1 optimization would yield a good F_1 score.*

Finally, none of the F_β optimizers perform well for $F_{0.5}$ as the evaluation metric. The precision/recall analysis in the next section explains this issue.

7.3 Precision, Recall and Accuracy Analysis

Table 6 shows the accuracy, precision and recall for the classic hinge loss classifier and the best undersampling, oversampling, cost-sensitive and SVM-Perf classifiers on the NUCLE dataset. Other datasets also show similar trends.

Undersampling methods achieve higher recall (more than 70% for all tasks with $p = 1.0$), which can be attributed to the strong inductive bias that alters the class prior in favour of the minority class. But there is a substantial reduction in precision and accuracy. The classic SVM with no sampling achieves the highest precision for all tasks (more than 40% for all tasks), while SMOTE also shows higher precision (between 25-32%). But the recall is as low as 5%. The SVM-Perf classifier maintains a comparatively high precision ($\approx$ 15%, except preposition GED task) as well recall (between 35-45%), while the accuracy drop compared to the classic hinge is comparatively less.

We also investigated if SVM-Perf is effective in obtaining high precision or recall by directly optimizing precision and recall respectively (see Table 7 for results). Optimizing recall significantly increases the recall over F_β optimization, with recall of more than 50% achieved on all tasks. However, optimizing precision does not show much improvement over the F_β optimization and is clearly far worse than the precision obtained with the baseline SVM. Precision loss can be represented as $FP/(FP + TP)$. We can see that $FP = 0$ can easily be achieved by assigning all examples to the `correct` class, since FN does not affect the precision. This loss function does not provide a sufficient bias for increasing precision. This also explains why optimizing F_1, F_2 are more effective than optimizing $F_{0.5}$ which is precision oriented.

8 Conclusion and Future work

We have shown on multiple GED tasks and datasets that optimizing F_1 and F_2 outperforms sampling for these evaluation metrics, while maintaining accuracy and precision above what is achieved through sampling methods. Directly optimizing evaluation metrics scores over sampling since: (i) the optimization objective can incorporate precision requirements and needs no empirical determination of hyper-parameters, and (ii) no data loss/corruption due to sampling.

It is beneficial to use F_2 optimization to learn GED classifiers designed for recall-oriented use-cases like copyediting. The gains are largely due to improvement in recall, and we show the inherent difficulties in optimizing a precision-oriented metric. Future directions of work include improving precision and direct optimization of evaluation metrics for grammatical error **correction**.

A natural extension is to apply this method to error detection in native speaker text and machine translation output. Our method also has wider applicability to other problems in NLP which encounter the imbalanced dataset problem *e.g.* sarcasm detection, sentiment thwarting detection, WSD, NER, *etc*.

References

Nitesh V. Chawla, Kevin W. Bowyer, Lawrence O. Hall, and W. Philip Kegelmeyer. 2002. SMOTE:

Method	**Noun Number**			**Article**			**Preposition**		
	A	**P**	**R**	**A**	**P**	**R**	**A**	**P**	**R**
Hinge Loss	**98.54**	**54.29**	1.77	**97.50**	**42.39**	1.60	**98.41**	**42.91**	4.32
Random Undersampling (p=0.3)	91.79	9.20	**51.88**	89.44	12.33	**53.06**	90.92	5.65	30.54
Cost-Sensitive(p=0.3)	95.16	9.11	25.63	94.29	16.78	32.62	98.27	24.26	4.89
SMOTE (p=1.0)	98.16	25.00	11.07	97.34	24.15	3.32	98.38	31.46	2.88
SVM-Perf $F_{0.5}$	95.46	13.02	36.67	93.17	15.60	39.40	86.60	5.26	44.46
SVM-Perf F_1	95.72	13.79	36.22	93.16	15.77	40.30	87.01	5.44	**44.63**
SVM-Perf F_2	94.39	11.72	43.19	93.26	15.86	39.68	86.97	5.40	44.24

Table 6: NUCLE dataset: Comparison of Accuracy (A), Precision (P), Recall (R) (scores in %)

Method	Noun Number		Article		Preposition	
	Precision	Recall	Precision	Recall	Precision	Recall
SVM-Perf Precision	12.60	39.92	15.97	39.26	7.52	0.45
SVM-Perf Recall	3.93	63.16	7.35	56.37	4.02	52.76

Table 7: NUCLE dataset: Optimizing Precision and Recall (scores in %)

Synthetic Minority Over-sampling Technique. *Journal of Artificial Intelligence Research*, 16(1).

Martin Chodorow, Markus Dickinson, Ross Israel, and Joel R Tetreault. 2012. Problems in evaluating grammatical error detection systems. In *COLING*, pages 611–628. Citeseer.

Daniel Dahlmeier and Hwee Tou Ng. 2012. A beam-search decoder for grammatical error correction. In *Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning*.

Daniel Dahlmeier, Hwee Tou Ng, and Eric Jun Feng Ng. 2012. NUS at the HOO 2012 Shared Task. In *Proceedings of the Seventh Workshop on Building Educational Applications Using NLP*.

Daniel Dahlmeier, Hwee Tou Ng, and Siew Mei Wu. 2013. Building a Large Annotated Corpus of Learner English: The NUS Corpus of Learner English. In *Proceedings of the 8th Workshop on Innovative Use of NLP for Building Educational Applications*.

Robert Dale and Adam Kilgarriff. 2011. Helping our own: The HOO 2011 pilot shared task. In *Proceedings of the 13th European Workshop on Natural Language Generation*.

Robert Dale, Ilya Anisimoff, and George Narroway. 2012. HOO 2012: A report on the preposition and determiner error correction shared task. In *Proceedings of the Seventh Workshop on Building Educational Applications Using NLP*.

Pedro Domingos. 1999. Metacost: A general method for making classifiers cost-sensitive. In *Proceedings of the fifth ACM SIGKDD international conference on Knowledge Discovery and Data Mining*.

Haibo He and Edwardo A Garcia. 2009. Learning from imbalanced data. *IEEE Transactions on Knowledge and Data Engineering*, 21(9).

Mark Hopkins and Jonathan May. 2011. Tuning as ranking. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*, pages 1352–1362. Association for Computational Linguistics.

Emi Izumi, Kiyotaka Uchimoto, and Hitoshi Isahara. 2004. The NICT JLE Corpus: Exploiting the Language Learners Speech Database for Research and Education. *International Journal of the Computer, the Internet and Management*.

Thorsten Joachims. Svm-perf: Support vector machine for multivariate performance measures. `http://www.cs.cornell.edu/People/tj/svm_light/svm_perf.html/`.

Thorsten Joachims. Svmlight: Support vector machine. `http://svmlight.joachims.org/`.

Thorsten Joachims. 2005. A Support Vector Method for Multivariate Performance Measures. In *Proceedings of the 22nd International Conference on Machine Learning*.

Marcin Junczys-Dowmunt and Roman Grundkiewicz. 2014. The AMU System in the CoNLL-2014 Shared Task: Grammatical Error Correction by Data-Intensive and Feature-Rich Statistical Machine Translation. In *Proceedings of the Eighteenth Conference on Computational Natural Language Learning: Shared Task*.

Anoop Kunchukuttan, Ritesh Shah, and Pushpak Bhattacharyya. 2013. IITB System for CoNLL 2013 Shared Task: A Hybrid Approach to Grammatical Error Correction. In *Proceedings of the Seventeenth Conference on Computational Natural Language Learning: Shared Task*.

Anoop Kunchukuttan, Sriram Chaudhury, and Pushpak Bhattacharyya. 2014. Tuning a Grammar Correction System for Increased Precision. In *Proceedings of the Eighteenth Conference on Computational Natural Language Learning: Shared Task*.

Hwee Tou Ng, Siew Mei Wu, Yuanbin Wu, Christian Hadiwinoto, and Joel Tetreault. 2013. The CoNLL-2013 Shared Task on Grammatical Error Correction. In *Proceedings of the Seventeenth Conference on Computational Natural Language Learning: Shared Task*.

Franz Josef Och. 2003. Minimum error rate training in statistical machine translation. In *Proceedings of the 41st Annual Meeting on Association for Computational Linguistics-Volume 1*.

Desmond Darma Putra and Lili Szabo. 2013. UdS at CoNLL 2013 Shared Task. In *Proceedings of the Seventeenth Conference on Computational Natural Language Learning: Shared Task*.

Alla Rozovskaya and Dan Roth. 2010. Generating confusion sets for context-sensitive error correction. In *Proceedings of the 2010 Conference on Empirical Methods in Natural Language Processing*.

Alla Rozovskaya, Mark Sammons, and Dan Roth. 2012. The UI system in the HOO 2012 shared task on error correction. In *Proceedings of the Seventh Workshop on Building Educational Applications Using NLP*.

Ioannis Tsochantaridis, Thorsten Joachims, Thomas Hofmann, and Yasemin Altun. 2005. Large margin methods for structured and interdependent output variables. In *Journal of Machine Learning Research*.

Jason Van Hulse, Taghi M Khoshgoftaar, and Amri Napolitano. 2007. Experimental perspectives on learning from imbalanced data. In *Proceedings of the 24th International Conference on Machine learning*.

Junwen Xing, Longyue Wang, Derek F. Wong, Lidia S. Chao, and Xiaodong Zeng. 2013. UM-Checker: A Hybrid System for English Grammatical Error Correction. In *Proceedings of the Seventeenth Conference on Computational Natural Language Learning: Shared Task*.

Bianca Zadrozny, John Langford, and Naoki Abe. 2003. Cost-sensitive learning by cost-proportionate example weighting. In *Third IEEE International Conference on Data Mining*.