A random forest system combination approach for error detection in digital dictionaries

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Abstract

When digitizing a print bilingual dictionary, whether via optical character recognition or manual entry, it is inevitable that errors are introduced into the electronic version that is created. We investigate automating the process of detecting errors in an XML representation of a digitized print dictionary using a hybrid approach that combines rule-based, feature-based, and language model-based methods. We investigate combining methods and show that using random forests is a promising approach. We find that in isolation, unsupervised methods rival the performance of supervised methods. Random forests typically require training data so we investigate how we can apply random forests to combine individual base methods that are themselves unsupervised without requiring large amounts of training data. Experiments reveal empirically that a relatively small amount of data is sufficient and can potentially be further reduced through specific selection criteria.

1 Introduction

Digital versions of bilingual dictionaries often have errors that need to be fixed. For example, Figures 1 through 5 show an example of an error that occurred in one of our development dictionaries and how the error should be corrected. Figure 1 shows the entry for the word "turfah" as it appeared in the original print copy of (Qureshi and Haq, 1991). We see this word has three senses with slightly different meanings. The third sense is "rare". In the original digitized XML version of (Qureshi and Haq, 1991) depicted in Figure 2, this was misrepresented as not being the meaning

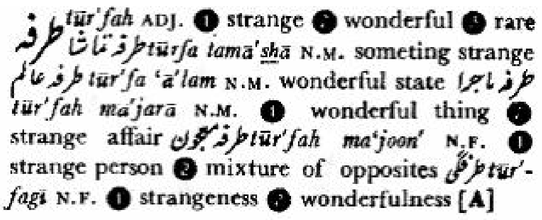

طرفہ *tūr'fah* ADJ. ❶ strange ❷ wonderful ❸ rare طرفہ تماشا *tūrfa tamā'shā* N.M. someting strange طرفہ عالم *tūr'fa 'ā'lam* N.M. wonderful state طرفہ ماجرا *tūr'fah ma'jarā* N.M. ❶ wonderful thing ❷ strange affair طرفہ معجون *tūr'fah ma'joon'* N.F. ❶ strange person ❷ mixture of opposites طرفگی *tūr'-fagī* N.F. ❶ strangeness ❷ wonderfulness [A]

Figure 1: Example dictionary entry

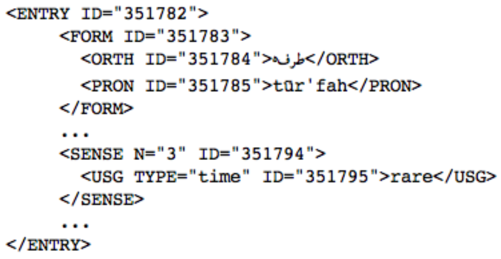

```
<ENTRY ID="351782">
    <FORM ID="351783">
      <ORTH ID="351784">طرفہ</ORTH>
      <PRON ID="351785">tūr'fah</PRON>
    </FORM>
    ...
    <SENSE N="3" ID="351794">
      <USG TYPE="time" ID="351795">rare</USG>
    </SENSE>
    ...
</ENTRY>
```

Figure 2: Example of error in XML

of "turfah" but instead being a usage note that frequency of use of the third sense was rare. Figure 3 shows the tree corresponding to this XML representation. The corrected digital XML representation is depicted in Figure 4 and the corresponding corrected tree is shown in Figure 5.

Zajic et al. (2011) presented a method for repairing a digital dictionary in an XML format using a dictionary markup language called DML. It remains time-consuming and error-prone however to have a human read through and manually correct a digital version of a dictionary, even with languages such as DML available. We therefore investigate automating the detection of errors.

We investigate the use of three individual methods. The first is a supervised feature-based method trained using SVMs (Support Vector Machines). The second is a language-modeling

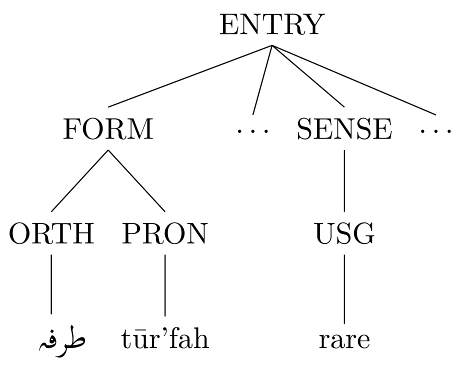


Figure 3: Tree structure of error

```
<ENTRY ID="351782">
     <FORM ID="351783">
       <ORTH ID="351784">طرفه</ORTH>
       <PRON ID="351785">tūr'fah</PRON>
     </FORM>
     ...
     <SENSE N="3" ID="351794">
       <TRANS ID="351794+1">
         <TR ID="351795">rare</TR>
       </TRANS>
     </SENSE>
     ...
</ENTRY>
```

Figure 4: Example of error in XML, fixed

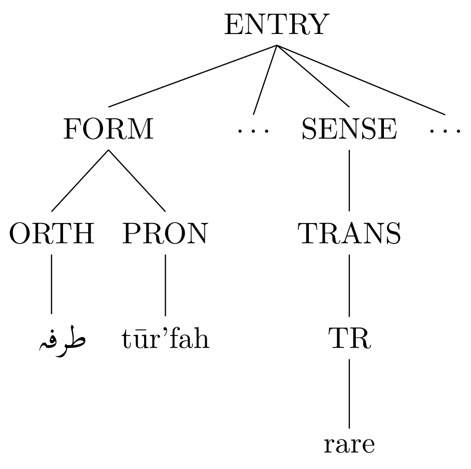


Figure 5: Tree structure of error, fixed

method that replicates the method presented in (Rodrigues et al., 2011). The third is a simple rule inference method. The three individual methods have different performances. So we investigate how we can combine the methods most effectively. We experiment with majority vote, score combination, and random forest methods and find that random forest combinations work the best.

For many dictionaries, training data will not be available in large quantities a priori and therefore methods that require only small amounts of training data are desirable. Interestingly, for automatically detecting errors in dictionaries, we find that the unsupervised methods have performance that rivals that of the supervised feature-based method trained using SVMs. Moreover, when we combine methods using the random forest method, the combination of unsupervised methods works better than the supervised method in isolation and almost as well as the combination of all available methods. A potential drawback of using the random forest combination method however is that it requires training data. We investigated how much training data is needed and find that the amount of training data required is modest. Furthermore, by selecting the training data to be labeled with the use of specific selection methods reminiscent of active learning, it may be possible to train the random forest system combination method with even less data without sacrificing performance.

In section 2 we discuss previous related work and in section 3 we explain the three individual methods we use for our application. In section 4 we explain the three methods we explored for combining methods; in section 5 we present and discuss experimental results and in section 6 we conclude and discuss future work.

2 Related Work

Classifier combination techniques can be broadly classified into two categories: mathematical and behavioral (Tulyakov et al., 2008). In the first category, functions or rules combine normalized classifier scores from individual classifiers. Examples of techniques in this category include Majority Voting (Lam and Suen, 1997), as well as simple score combination rules such as: sum rule, min rule, max rule and product rule (Kittler et al., 1998; Ross and Jain, 2003; Jain et al., 2005). In the second category, the output of individual classifiers are combined to form a feature vector as the input to a generic classifier such as classification trees (P. and Chollet, 1999; Ross and Jain, 2003) or the k-nearest neighbors classifier (P. and Chollet, 1999). Our method falls into the second category, where we use a random forest for system combination.

The random forest method is described in (Breiman, 2001). It is an ensemble classifier consisting of a collection of decision trees (called a random forest) and the output of the random forest is the mode of the classes output by the individual trees. Each single tree is trained as follows: 1) a random set of samples from the initial training set is selected as a training set and 2) at each node of the tree, a random subset of the features is selected, and the locally optimal split is based on only this feature subset. The tree is fully grown without pruning. Ma et al. (2005) used random forests for combining scores of several biometric devices for identity verification and have shown encouraging results. They use all fully supervised methods. In contrast, we explore minimizing the amount of training data needed to train a random forest of unsupervised methods.

The use of active learning in order to reduce training data requirements without sacrificing model performance has been reported on extensively in the literature (e.g., (Seung et al., 1992; Cohn et al., 1994; Lewis and Gale, 1994; Cohn et al., 1996; Freund et al., 1997)). When training our random forest combination of individual methods that are themselves unsupervised, we explore how to select the data so that only small amounts of training data are needed because for many dictionaries, gathering training data may be expensive and labor-intensive.

3 Three Single Method Approaches for Error Detection

Before we discuss our approaches for combining systems, we briefly explain the three individual systems that form the foundation of our combined system.

First, we use a supervised approach where we train a model using SVM^{light} (Joachims, 1999) with a linear kernel and default regularization parameters. We use a depth first traversal of the XML tree and use unigrams and bigrams of the tags that occur as features for each subtree to make a classification decision.

We also explore two unsupervised approaches. The first unsupervised approach learns rules for when to classify nodes as errors or not. The rule-based method computes an anomaly score based on the probability of subtree structures. Given a structure A and its probability P(A), the event that A occurs has anomaly score 1-P(A) and the event that A does not occur has anomaly score P(A). The basic idea is if a certain structure happens rarely, i.e. P(A) is very small, then the occurrence of A should have a high anomaly score. On the other hand, if A occurs frequently, then the absence of A indicates anomaly. To obtain the anomaly score of a tree, we simply take the maximal scores of all events induced by subtrees within this tree.

The second unsupervised approach uses a reimplementation of the language modeling method described in (Rodrigues et al., 2011). Briefly, this methods works by calculating the probability a flattened XML branch can occur, given a probability model trained on the XML branches from the original dictionary. We used (Stolcke, 2002) to generate bigram models using Good Turing smoothing and Katz back off, and evaluated the log probability of the XML branches, ranking the likelihood. The first 1000 branches were submitted to the hybrid system marked as an error, and the remaining were submitted as a non-error. Results for the individual classifiers are presented in section 5.

4 Three Methods for Combining Systems

We investigate three methods for combining the three individual methods. As a baseline, we investigate simple majority vote. This method takes the classification decisions of the three methods and assigns the final classification as the classification that the majority of the methods predicted.

A drawback of majority vote is that it does not weight the votes at all. However, it might make sense to weight the votes according to factors such as the strength of the classification score. For example, all of our classifiers make binary decisions but output scores that are indicative of the confidence of their classifications. Therefore we also explore a score combination method that considers these scores. Since measures from the different systems are in different ranges, we normalize these measurements before combining them (Jain et al., 2005). We use z-score which computes the arithmetic mean and standard deviation of the given data for score normalization. We then take the summation of normalized measures as the final measure. Classification is performed by thresholding this final measure.[1]

Another approach would be to weight them by the performance level of the various constituent classifiers in the ensemble. Weighting based on performance level of the individual classifiers is difficult because it would require extra labeled data to estimate the various performance levels. It is not clear how to translate the different performance estimates into weights, or how to have those weights interact with weights based on strengths of classification. Therefore, we did not weigh based on performance level explicitly.

We believe that our third combination method, the use of random forests, implicitly captures weighting based on performance level and strengths of classifications. Our random forest approach uses three features, one for each of the individual systems we use. With random forests, strengths of classification are taken into account because they form the values of the three features we use. In addition, the performance level is taken into account because the training data used to train the decision trees that form the forest help to guide binning of the feature values into appropriate ranges where classification decisions are made correctly. This will be discussed further in section 5.

5 Experiments

This section explains the details of the experiments we conducted testing the performance of the various individual and combined systems. Subsection 5.1 explains the details of the data we experiment on; subsection 5.2 provides a summary of the main results of our experiments; and subsection 5.3 discusses the results.

5.1 Experimental Setup

We obtained the data for our experiments using a digitized version of (Qureshi and Haq, 1991), the same Urdu-English dictionary that Zajic et al. (2011) had used. Zajic et al. (2011) presented DML, a programming language used to fix errors in XML documents that contain lexicographic data. A team of language experts used DML to correct errors in a digital, XML representation of the Kitabistan Urdu dictionary. The current research compared the source XML document and the DML commands to identify the elements that the language experts decided to modify. We consider those elements to be errors. This is the ground truth used for training and evaluation. We evaluate at two tiers, corresponding to two node types in the XML representation of the dictionary: ENTRY and SENSE. The example depicted in Figures 1 through 5 shows an example of SENSE. The intuition of the tier is that errors are detectable (or learnable) from observing the elements within a tier, and do not cross tier boundaries. These tiers are specific to the Kitabistan Urdu dictionary, and we selected them by observing the data. A limitation of our work is that we do not know at this time whether they are generally useful across dictionaries. Future work will be to automatically discover the meaningful evaluation tiers for a new dictionary. After this process, we have a dataset with 15,808 Entries, of which 47.53% are marked as errors and 78,919 Senses, of which 10.79% are marked as errors. We perform tenfold cross-validation in all experiments. In our random forest experiments, we use 12 decision trees, each with only 1 feature.

[1]In our experiments we used 0 as the threshold.

	Recall	Precision	F1-Measure	Accuracy
LM	11.97	89.90	21.13	57.53
RULE	99.79	70.83	82.85	80.37
FV	35.34	93.68	51.32	68.14

Table 1: Performance of individual systems at ENTRY tier.

5.2 Results

This section presents experimental results, first for individual systems and then for combined systems.

5.2.1 Performance of individual systems

Tables 1 and 2 show the performance of language modeling-based method (LM), rule-based method (RULE) and the supervised feature-based method (FV) at different tiers. As can be seen, at the ENTRY tier, RULE obtains the highest F1-Measure and accuracy, while at the SENSE tier, FV performs the best.

	Recall	Precision	F1-Measure	Accuracy
LM	9.85	94.00	17.83	90.20
RULE	84.59	58.86	69.42	91.96
FV	72.44	98.66	83.54	96.92

Table 2: Performance of individual systems at SENSE tier.

5.2.2 Improving individual systems using random forests

In this section, we show that by applying random forests on top of the output of individual systems, we can have gains (absolute gains, not relative) in accuracy of 4.34% to 6.39% and gains (again absolute, not relative) in F1-measure of 3.64% to 11.39%. Tables 3 and 4 show our experimental results at ENTRY and SENSE tiers when applying random forests with the rule-based method.[2] These results are all obtained from 100 iterations of the experiments with different partitions of the training data chosen at each iteration. Mean values of different evaluation measures and their standard deviations are shown in these tables. We change the percentage of training data and repeat the experiments to see how the amount of training data affects performance.

It might be surprising to see the gains in performance that can be achieved by using a random forest of decision trees created using only the rule-based scores as features. To shed light on why this is so, we show the distribution of RULE-based output scores for anomaly nodes and clean nodes in Figure 6. They are well separated and this explains why RULE alone can have good performance. Recall RULE classifies nodes with anomaly scores larger than 0.9 as errors. However, in Figure 6, we can see that there are many clean nodes with anomaly scores larger than 0.9. Thus, the simple thresholding strategy will bring in errors. Applying random forest will help us identify these errorful regions to improve the performance. Another method for helping to identify these errorful regions and classify them correctly is to apply random forest of RULE combined with the other methods, which we will see will even further boost the performance.

[2]We also applied random forests to our language modeling and feature-based methods, and saw similar gains in performance.

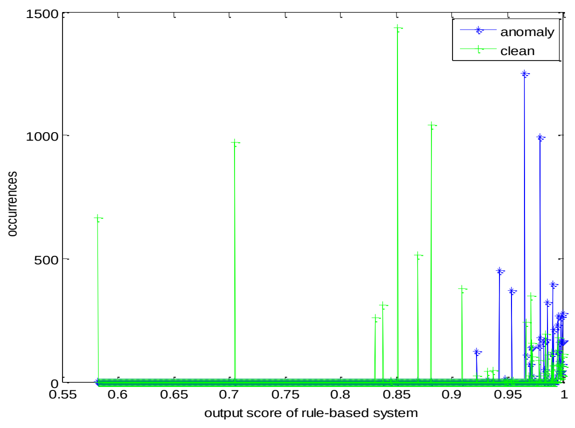


Figure 6: Output anomalies score from RULE (ENTRY tier).

5.2.3 System combination

In this section, we explore different methods for combining measures from the three systems. Table 5 shows the results of majority voting and score combination at the ENTRY tier. As can be seen, majority voting performs poorly. This may be due to the fact that the performances of the three systems are very different. RULE significantly outperforms the other two systems, and as discussed in Section 4 neither majority voting nor score combination weights this higher performance appropriately.

Tables 6 and 7 show the results of combining RULE and LM. This is of particular interest since these two systems are unsupervised. Combining these two unsupervised systems works better than the individual methods, including supervised methods. Tables 8 and 9 show the results for combinations of all available systems. This yields the highest performance, but only slightly higher than the combination of only unsupervised base methods.

The random forest combination technique does require labeled data even if the underlying base methods are unsupervised. Based on the observation in Figure 6, we further study whether choosing more training data from the most errorful regions will help to improve the performance. Experimental results in Table 10 show how the choice of training data affects performance. It appears that there may be a weak trend toward higher performance when we force the selection of the majority of the training data to be from ENTRY nodes whose RULE anomaly scores are

Training %	Recall	Precision	F1-Measure	Accuracy
0.1	78.17(14.83)	75.87(3.96)	76.18(7.99)	77.68(5.11)
1	82.46(4.81)	81.34(2.14)	81.79(2.20)	82.61(1.69)
10	87.30(1.96)	84.11(1.29)	85.64(0.46)	86.10(0.35)
50	89.19(1.75)	83.99(1.20)	86.49(0.34)	86.76(0.28)

Table 3: Mean and std of evaluation measures from 100 iterations of experiments using RULE+RF. (ENTRY tier)

Training %	Recall	Precision	F1-Measure	Accuracy
0.1	60.22(12.95)	69.66(9.54)	63.29(7.92)	92.61(1.57)
1	70.28(3.48)	86.26(3.69)	77.31(1.39)	95.55(0.25)
10	71.52(1.23)	91.26(1.39)	80.18(0.41)	96.18(0.07)
50	72.11(0.75)	91.90(0.64)	80.81(0.39)	96.30(0.06)

Table 4: Mean and std of evaluation measures from 100 iterations of experiments using RULE+RF. (SENSE tier)

larger than 0.9. However, the magnitudes of the observed differences in performance are within a single standard deviation so it remains for future work to determine if there are ways to select the training data for our random forest combination in ways that substantially improve upon random selection.

5.3 Discussion

Majority voting (at the entry level) performs poorly, since the performance of the three individual systems are very different and majority voting does not weight votes at all. Score combination is a type of weighted voting. It takes into account the confidence level of output from different systems, which enables it to perform better than majority voting. However, score combination does not take into account the performance levels of the different systems, and we believe this limits its performance compared with random forest combinations.

Random forest combinations perform the best, but the cost is that it is a supervised combination method. We investigated how the amount of training data affects the performance, and found that a small amount of labeled data is all that the random forest needs in order to be successful. Moreover, although this requires further exploration, there is weak evidence that the size of the labeled data can potentially be reduced by choosing it carefully from the region that is expected to be most errorful. For our application with a rule-based system, this is the high-anomaly scoring region because although it is true that anomalies are often errors, it is also the case that some structures occur rarely but are not errorful.

RULE+LM with random forest is a little better than RULE with random forest, with gain of about 0.7% on F1-measure when evaluated at the ENTRY level using 10% data for training.

An examination of examples that are marked as being errors in our ground truth but that were not detected to be errors by any of our systems suggests that some examples are decided on the basis of features not yet considered by any system. For example, in Figure 7 the second FORM is well-formed structurally, but the Urdu text in the first FORM is the beginning of the phrase transliterated in the second FORM. Automatic systems detected that the first FORM was an error, however did not mark the second FORM as an error whereas our ground truth marked both as errors.

Examination of false negatives also revealed cases where the systems were correct that there was no error but our ground truth wrongly indicated that there was an error. These were due to our semi-automated method for producing ground truth that considers elements mentioned in DML commands to be errors. We discovered instances in which merely mentioning an element in a DML command does not imply that the element is an error. These cases are useful for making refinements to how ground truth is generated from DML commands.

Examination of false positives revealed two categories. One was where the element is indeed an error but was not marked as an element in our ground truth because it was part of a larger error

Method	Recall	Precision	F1-Measure	Accuracy
Majority voting	36.71	90.90	52.30	68.18
Score combination	76.48	75.82	76.15	77.23

Table 5: LM+RULE+FV (ENTRY tier)

Training %	Recall	Precision	F1-Measure	Accuracy
0.1	77.43(15.14)	72.77(6.03)	74.26(8.68)	75.32(6.71)
1	86.50(3.59)	80.41(1.95)	83.27(1.33)	83.51(1.11)
10	88.12(1.12)	84.65(0.57)	86.34(0.46)	86.76(0.39)
50	89.12(0.62)	87.39(0.56)	88.25(0.30)	88.72(0.29)

Table 6: System combination based on random forest (LM+RULE). (ENTRY tier, mean (std))

Training %	Recall	Precision	F1-Measure	Accuracy
0.1	65.85(12.70)	71.96(7.63)	67.68(7.06)	93.38(1.03)
1	80.29(3.58)	84.97(3.13)	82.45(1.36)	96.31(0.28)
10	82.68(2.49)	90.91(2.37)	86.53(0.41)	97.22(0.07)
50	83.22(2.43)	92.21(2.29)	87.42(0.35)	97.42(0.04)

Table 7: System combination based on random forest (LM+RULE). (SENSE tier, mean (std))

Training %	Recall	Precision	F1-Measure	Accuracy
20	91.57(0.55)	87.77(0.43)	89.63(0.23)	89.93(0.22)
50	92.04(0.54)	88.85(0.48)	90.41(0.29)	90.72(0.28)

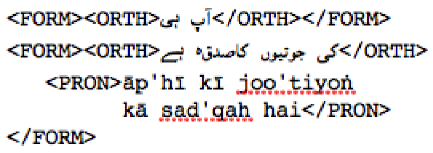
Table 8: System combination based on random forest (LM+RULE+FV). (ENTRY tier, mean (std))

Training %	Recall	Precision	F1-Measure	Accuracy
20	86.47(1.01)	90.67(1.02)	88.51(0.26)	97.58(0.06)
50	86.50(0.81)	92.04(0.85)	89.18(0.30)	97.73(0.06)

Table 9: System combination based on random forest (LM+RULE+FV). (SENSE tier, mean (std))

	Recall	Precision	F1-Measure	Accuracy
50%	85.40(4.65)	80.71(3.49)	82.82(1.57)	82.63(1.54)
70%	86.13(3.94)	80.97(2.64)	83.36(1.33)	83.30(1.21)
90%	85.77(3.61)	81.82(2.72)	83.65(1.45)	83.69(1.35)
95%	85.93(3.46)	82.14(2.98)	83.89(1.32)	83.94(1.18)
random	86.50(3.59)	80.41(1.95)	83.27(1.33)	83.51(1.11)

Table 10: Effect of choice of training data based on rule based method (Mean evaluation measures from 100 iterations of experiments using RULE+LM at ENTRY tier). We choose 1% of the data for training and the first column in the table specifies the percentage of training data chosen from Entries with anomalous score larger than 0.9.



```
<FORM><ORTH>آپ ہی</ORTH></FORM>
<FORM><ORTH>کی جرتیوں کاصدقہ ہے</ORTH>
   <PRON>āp'hī kī joo'tiyoṅ
         kā sad'qah hai</PRON>
</FORM>
```

Figure 7: Example of error in XML

that got deleted and therefore no DML command ever mentioned the smaller element but lexicographers upon inspection agree that the smaller element is indeed errorful. The other category was where there were actual errors that the dictionary editors didn't repair with DML but that should have been repaired.

A major limitation of our work is testing how well it generalizes to detecting errors in other dictionaries besides the Urdu-English one (Qureshi and Haq, 1991) that we conducted our experiments on.

6 Conclusions

We explored hybrid approaches for the application of automatically detecting errors in digitized copies of dictionaries. The base methods we explored consisted of a variety of unsupervised and supervised methods. The combination methods we explored also consisted of some methods which required labeled data and some which did not.

We found that our base methods had different levels of performance and with this scenario majority voting and score combination methods, though appealing since they require no labeled data, did not perform well since they do not weight votes well.

We found that random forests of decision trees was the best combination method. We hypothesize that this is due to the nature of our task and base systems. Random forests were able to help tease apart the high-error region (where anomalies take place). A drawback of random forests as a combination method is that they require labeled data. However, experiments reveal empirically that a relatively small amount of data is sufficient and the amount might be able to be further reduced through specific selection criteria.

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