Repeated Labeling Using Multiple Noisy Labelers*

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Abstract

This paper addresses the repeated acquisition of labels for data items when the labeling is imperfect. We examine the improvement (or lack thereof) in data quality via repeated labeling, and focus especially on the improvement of training labels for supervised induction. With the outsourcing of small tasks becoming easier, for example via Amazon's Mechanical Turk, it often is possible to obtain less-than-expert labeling at low cost. With low-cost labeling, preparing the unlabeled part of the data can become considerably more expensive than labeling. We present repeated-labeling strategies of increasing complexity, and show several main results. (i) Repeated-labeling can improve label quality and model quality, but not always. (ii) When labels are noisy, repeated labeling can be preferable to single labeling even in the traditional setting where labels are not particularly cheap. (iii) As soon as the cost of processing the unlabeled data is not free, even the simple strategy of labeling everything multiple times can give considerable advantage. (iv) Repeatedly labeling a carefully chosen set of points is generally preferable, and we present a set of robust techniques that combine different notions of uncertainty to select data points for which quality should be improved. The bottom line: the results show clearly that when labeling is not perfect, selective acquisition of multiple labels is a strategy that data miners should have in their repertoire; for certain label-quality/cost regimes, the benefit is substantial.

1 Introduction

There are various costs associated with the *preprocessing* stage of the KDD process, including costs of acquiring features, formulating data, cleaning data, obtaining expert labeling of data, and so on (Turney, 2000; Weiss and Provost, 2003). For example, in order to build a model to recognize whether two products described on two web pages are the same, one must extract the product information from the pages, formulate features for comparing the two along relevant dimensions, verify that the features are correct for these products, and label product pairs as identical or not; this process involves costly manual intervention at several points. To build a model that recognizes whether an image contains an object of interest, one first needs to take pictures in appropriate contexts, sometimes at substantial cost.

This paper focuses on problems where it is possible to obtain certain (noisy) data values ("labels") relatively cheaply, from multiple sources ("labelers"). A main focus of this paper is the use of these values as training labels for supervised modeling.[1] For our two examples above, once we have constructed the unlabeled portion of the data point, for relatively low cost one can obtain non-expert opinions on whether

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[1]This setting is in direct contrast to the setting motivating active learning and semi-supervised learning, where unlabeled points are relatively inexpensive, but labeling is expensive.

Figure 1: An example of a micro-task submitted to the Amazon Mechanical Turk marketplace.

two products are the same or whether an image contains a person or a storefront or a building. These cheap labels may be noisy due to lack of expertise, dedication, interest, or other factors. Our ability to perform non-expert labeling cheaply and easily is facilitated by on-line micro-outsourcing systems, such as Amazon's Mechanical Turk (Snow et al, 2008)[2] or txtEagle (Eagle, 2009),[3] which match workers with arbitrary (well-defined) tasks, as well as by creative labeling solutions like the ESP game (von Ahn and Dabbish, 2004).[4] These on-line outsourcing systems allow hundreds (or more) of human labelers to look at objects (i.e., articles) and label them, using an interface as the one in Figure 1. Using such marketplaces, it is possible to outsource small parts of the process at very low cost—parts that prior to the introduction of such systems would have incurred much higher (in-house) cost, or would have been avoided altogether.

In the face of noisy labeling, as the ratio increases between the cost of preprocessing a data point and the cost of labeling it, it is natural to consider *repeated labeling* (or re-labeling): obtaining multiple labels for some or all data points. This paper explores whether, when, and for which data points one should obtain multiple, noisy training labels, as well as what to do with them once they have been obtained. Consider a data miner facing the question of how to expend her data preprocessing budget: (i) acquiring multiple cheap labels for existing data to reduce labeling error versus (ii) acquiring potentially informative new data points at higher cost. Given a data set for supervised classifier induction, ceteris paribus, noisy labels will decrease the generalization performance of induced models (e.g., Quinlan, 1986).

Figure 2 shows learning curves under different labeling qualities for the classic *mushroom* data set (see Section 4.1). Specifically, for the different quality levels of the *training* data,[5] the figure shows learning curves relating the classification accuracy—which is measured by the area under the ROC curve in this paper—of a Weka J48 model (Witten and Frank, 2005) to the number of training data. This data set is illustrative because with zero-noise labels one can achieve perfect classification after some training, as demonstrated by the $q = 1.0$ curve. Figure 2 illustrates that the performance of a learned model depends both on the quality of the training labels and on the number of training examples. Of course if the training labels are uninformative ($q = 0.5$), no amount of training data helps. As expected, for a given labeling quality ($q > 0.5$), more training examples lead to better performance, and the higher the quality of the training data, the better the performance of the learned model. However, the relationship between the two factors is complex: the marginal increase in performance for a given change along each dimension is quite

[2] `http://www.mturk.com`
[3] `http://txteagle.com/`
[4] `http://www.espgame.org`
[5] The test set has perfect quality with zero noise.

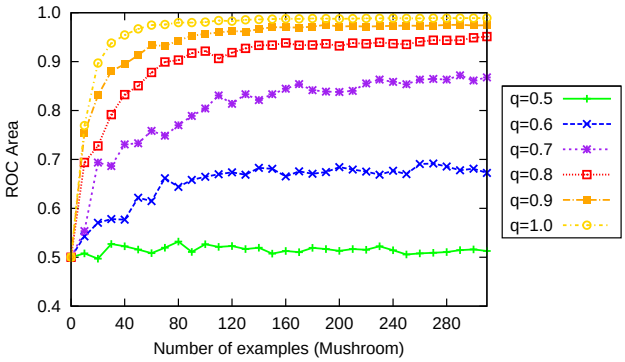


Figure 2: Learning curves under different quality levels of training data (q is the probability of a label being correct).

different for different combinations of values for both dimensions. To this, one must overlay the different costs of acquiring only new labels versus whole new examples, as well as the expected improvement in quality when acquiring multiple new labels.

This paper makes several contributions. First, under gradually weakening assumptions, we assess the impact of repeated-labeling on the quality of the resultant labels, as a function of the number and the individual qualities of the labelers. We derive analytically the conditions under which repeated-labeling will be more or less effective in improving resultant label quality. We then consider the effect of repeated-labeling on the accuracy of supervised modeling. As demonstrated in Figure 2, the relative advantage of increasing the quality of labeling, as compared to acquiring new data points, depends on the position on the learning curves. We show that there are times when repeated-labeling is preferable compared to getting labels for unlabeled data items, even in the case where one ignores the cost of obtaining the unlabeled part of a data item. Furthermore, when we do consider the cost of obtaining the unlabeled portion, repeated-labeling can give considerable advantage.

We present a comprehensive experimental analysis of the relationships between quality, cost, and technique for repeated-labeling. The results show that even a straightforward, round-robin technique for repeated-labeling can give substantial benefit over single-labeling. We then show that selectively choosing the data items to label repeatedly yields substantial extra benefit. A key question is: How should we select data points for repeated-labeling? We argue that the *uncertainty* of a data item's label is a good indicator of where we should allocate our (repeated) labeling efforts. We present various techniques for measuring the uncertainty, and show how these various techniques improve over round-robin repeated labeling.

Although this paper covers a good deal of ground, there is much left to be done to understand how best to label using multiple, noisy labelers; so, the paper closes with a summary of the key limitations, and some suggestions for future work.

2 Related Work

Repeatedly labeling the same data point is practiced in applications where labeling is not perfect (e.g., Smyth et al, 1994a,b). We are not aware of a systematic assessment of the relationship between the resultant quality of supervised modeling and the number of, quality of, and method of selection of data points for repeated-labeling. To our knowledge, the typical strategy used in practice is what we call "round-robin"

repeated-labeling, where cases are given a fixed number of labels—so we focus considerable attention in the paper to this strategy. A related important problem is how in practice to assess the generalization performance of a learned model with uncertain labels (Smyth et al, 1994b), which we do not consider in this paper. Prior research has addressed important problems necessary for a full labeling solution that uses multiple noisy labelers, such as estimating the quality of labelers (Dawid and Skene, 1979; Donmez et al, 2009, 2010; Smyth, 1996; Smyth et al, 1994b), and learning with uncertain labels (Lugosi, 1992; Silverman, 1980; Smyth, 1995). Raykar et al (2009, 2010) recently presented a model that built on and expanded this line of work, and showed how to integrate the process of concurrently building classifier and learning the quality of the labelers. So we treat these topics quickly when they arise, and lean on the prior work.

Repeated-labeling using multiple noisy labelers is different from multiple label classification (Boutell et al, 2004; McCallum, 1999), where one example could have multiple *correct* class labels. As we discuss in Section 7, repeated-labeling can apply regardless of the number of true class labels. The key difference is whether the labels are noisy. A closely related problem setting is described by Jin and Ghahramani (2002). In their variant of the multiple label classification problem, each example presents itself with a set mutually exclusive labels, one of which is correct. The setting for repeated-labeling has important differences: labels are acquired (at a cost); the same label may appear many times, and the true label may not appear at all. Again, the level of error in labeling is a key factor.

The consideration of data acquisition costs has seen increasing research attention, both explicitly (e.g., cost-sensitive learning; Turney, 2000), (utility-based data mining; Provost, 2005) and implicitly, as in the case of active learning (Cohn et al, 1994). Turney (2000) provides a short but comprehensive survey of the different sorts of costs that should be considered, including data acquisition costs and labeling costs. Most previous work on cost-sensitive learning does not consider labeling cost, assuming that a fixed set of labeled training examples is given, and that the learner cannot acquire additional information during learning (e.g., Domingos, 1999; Elkan, 2001; Turney, 1995).

Active learning (Cohn et al, 1994) focuses on the problem of costly label acquisition, although often the cost is not made explicit. Active learning (cf., optimal experimental design, Whittle, 1973) uses the existing model to help select additional data for which to acquire labels (Baram et al, 2004; Margineantu, 2005; Saar-Tsechansky and Provost, 2004). The usual problem setting for active learning is in direct contrast to the setting we consider for repeated-labeling. For active learning, the assumption is that the cost of labeling is considerably higher than the cost of obtaining unlabeled examples (essentially zero for "pool-based" active learning).

Some previous work studies data acquisition cost explicitly. For example, several authors (Kapoor and Greiner, 2005; Lizotte et al, 2003; Melville et al, 2004, 2005; Saar-Tsechansky and Provost, 2004; Weiss and Provost, 2003; Zhu and Wu, 2005) study the costly acquisition of feature information, assuming that the labels are known in advance. Saar-Tsechansky and Provost (2004) consider acquiring both costly feature and label information.

None of this prior work considers selectively obtaining multiple labels for data points to improve labeling quality, and the relative advantages and disadvantages for improving model performance. An important difference from the setting for traditional active learning is that labeling strategies that use multiple noisy labelers have access to potentially relevant additional information. The multisets of existing labels intuitively should play a role in determining the examples for which to acquire additional labels. For example, presumably one would be less interested in getting another label for an example that already has a dozen identical labels, than for one with just two, conflicting labels.

The work presented in this paper is an extension to a previously published conference paper (Sheng et al, 2008). In the present paper, we present and evaluate two additional algorithms for selectively allocating labeling effort (*NLU* and *NLMU*; see Sections 6.3 and 6.4). These new algorithms have better theoretical justification and often outperform the techniques in (Sheng et al, 2008). The results in this paper are all new, although many qualitative conclusions are the same as in the conference version. Specifically, in this paper we use as measure of predictive performance the area under the ROC curve (AUC), which is a more robust indicator of performance than the accuracy metric that we used in (Sheng et al, 2008), especially for imbalanced data sets. Additional completely new results include the following. In Section 6.4.1 we provide a justification why a technique that relies purely on model uncertainty can improve data quality and predictive performance; this contrasts with the implication in (Sheng et al, 2008) that the reason it works is because it is essentially doing active learning. We also present extensive experimental results that demonstrate when soft-labeling can be beneficial in a setting with noisy labelers (Section 5.3) and examine the effect of weighted sampling for selecting examples to label (Section 6.6.2).

Since the publication of the conference paper, a significant amount of work has been published in the area. Donmez and Carbonell (2008) presented an active learning model where the labelers are imperfect, have expertise on different parts of the space, and have various costs, depending on the uncertainty of the labeler: Donmez et al. focus on the problem of selecting the labelers to ask for given examples. In contrast to our work, Donmez and Carbonell (2008) do not use repeated labeling to improve the quality of the data. In subsequent extensions, Donmez et al (2009, 2010) learn the labeler quality in order to better guide the labeling strategy and show that techniques that exploit the labeler quality perform better than the round robin repeated labeling strategy (see Section 5). (There is no comparison against the selective labeling strategies that we presented in (Sheng et al, 2008) and which we also discuss in Section 6.)

Carpenter (2008) presented a Bayesian model for estimating the quality of the labelers, and Whitehill et al (2009) presented a graphical model in which both labelers vary in quality and the examples have varying degree of difficulty for being classified. Ipeirotis et al. Ipeirotis et al (2010) described an algorithm that measures the inherent quality of a labeler using a scalar metric that takes into consideration the misclassification costs and also separates the error computation from the potential biases exhibited by the labelers. Again, the focus is not on cost-sensitive acquisition of data, but rather on building Bayesian models that account for the expertise of the workers and the difficulty of labeling given examples.

3 Repeated Labeling: The Basics

Figure 2 illustrates that the quality of the labels can have a marked effect on classification accuracy. Intuitively, using repeated-labeling to shift from a lower-q curve to a higher-q curve can, under some settings, improve learning considerably. In order to treat this more formally, we first introduce some terminology and simplifying assumptions.

3.1 Notation and Assumptions

We consider a problem of supervised induction of a (binary) classification model. The setting is the typical one, with some important exceptions. For each training example $\langle y_i, x_i \rangle$, procuring the *unlabeled* "feature" portion, x_i, incurs cost C_U. The action of *labeling* the training example with a label y_i incurs cost C_L. For simplicity, we assume that each cost is constant across all examples. Each example $\langle y_i, x_i \rangle$ has a true label

y_i, but labeling is error-prone. Specifically, each label y_{ij} comes from a labeler j exhibiting an individual labeling quality p_j, which is $Pr(y_{ij} = y_i)$; since we consider the case of binary classification, the label assigned by labeler j will be incorrect with probability $1 - p_j$.

In the current paper, we work under a set of assumptions that allows us to focus on a certain set of problems that arise when labeling using multiple noisy labelers. First, we assume that $Pr(y_{ij} = y_i|x_i) = Pr(y_{ij} = y_i) = p_j$, that is, individual labeling quality is independent of the specific data point being labeled. Note that we do *not* assume that all labelers have the same quality: each labeler has an individual quality p_j. We sidestep the issue of knowing p_j: the techniques we present do not rely on this knowledge and are largely agnostic about the quality of the labelers. Inferring p_j accurately should lead to improved techniques; Dawid and Skene (1979) and Smyth et al. (Smyth, 1996; Smyth et al, 1994b) have shown how to use an expectation-maximization framework for estimating the quality of labelers. We also assume for simplicity that each labeler j only gives one label, but that is not a restrictive assumption in what follows. We further discuss limitations and directions for future research in Section 7.

3.2 Majority Voting and Label Quality

To investigate the relationship between labeler quality, number of labels, and the overall quality of labeling using multiple labelers, we start by considering the case where, for induction, each repeatedly-labeled example is assigned a *single* "integrated" label $\hat{y}_i$, inferred from the individual y_{ij}'s by majority voting. For simplicity, and to avoid having to break ties, we assume that we always obtain an odd number of labels. The quality $q_i = Pr(\hat{y}_i = y_i)$ of the integrated label $\hat{y}_i$ will be called the *integrated quality*. Where no confusion will arise, we will omit the subscript i for brevity and clarity.

3.2.1 Uniform Labeler Quality

We first consider the case where all labelers are independent and exhibit the same quality, that is, $p_j = p$ for all j. (We will relax the assumption of uniform quality later.). Using $2N + 1$ labelers with uniform quality p, the integrated labeling quality q is:

$$q = Pr(\hat{y} = y) = \sum_{i=0}^{N} \binom{2N+1}{i} \cdot p^{2N+1-i} \cdot (1-p)^i \tag{1}$$

which is the sum of the probabilities that we have more correct labels than incorrect (the index i corresponds to the number of incorrect labels).

Not surprisingly, from the formula above, we can infer that the integrated quality q is greater than p only when $p > 0.5$. When $p < 0.5$, we have an adversarial setting where $q < p$, and, not surprisingly, the quality decreases as we increase the number of labelers.

Figure 3 demonstrates the analytical relationship between the integrated quality and the number of labelers, for different individual labeler qualities. As expected, the integrated quality improves with larger numbers of labelers, when the individual labeling quality $p > 0.5$; however, the marginal improvement decreases as the number of labelers increases. Moreover, the benefit of getting more labelers also depends on the underlying value of p. Figure 4 shows how integrated quality q increases compared to the case of single-labeling, for different values of p and for different numbers of labelers. For example, when $p = 0.9$, there is little benefit when the number of labelers increase from 3 to 11. However, when $p = 0.7$, going just from single labeling to three labelers increases integrated quality by about 0.1, which in Figure 2 would

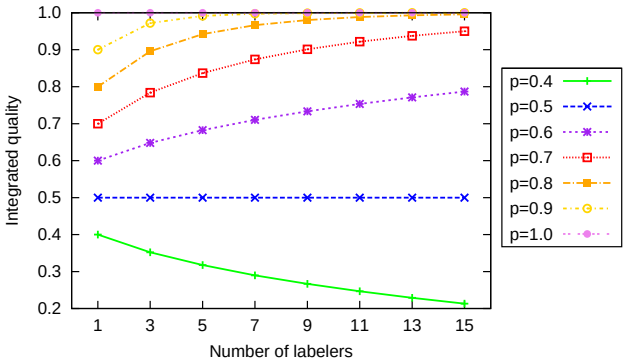


Figure 3: The relationship between integrated labeling quality, individual quality, and the number of labelers.

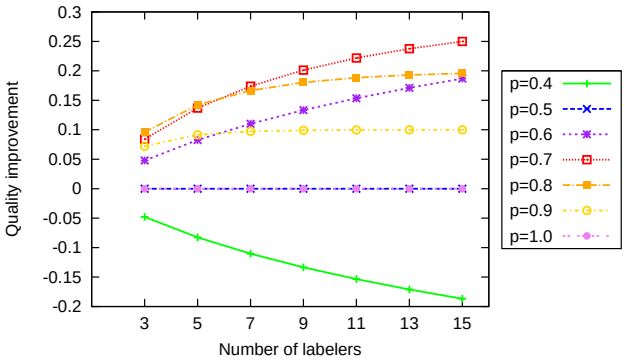


Figure 4: Improvement in integrated quality compared to single-labeling, as a function of the number of labelers, for different labeler qualities.

yield a substantial upward shift in the learning curve (from the $q = 0.7$ to the $q = 0.8$ curve); in short, a small amount of repeated-labeling can have a noticeable effect for moderate levels of noise.

Therefore, for cost-effective labeling using multiple noisy labelers we need to consider: (a) the effect of the integrated quality q on learning, and (b) the number of labelers required to increase q under different levels of labeler quality p; we will return to this later, in Sections 5 and 6.

3.2.2 Different Labeler Quality

If we relax the assumption that $p_j = p$ for all j, and allow labelers to have different qualities, a new question arises: what is preferable: using multiple labelers or using the best individual labeler? A full analysis is beyond the scope of this paper; Kuncheva et al (2003) provide an extensive analysis, and also examine the cases where the labelers are not independent. Let us consider, though, the special case that we have a group of three labelers, where the middle labeling quality is p, the lowest one is $p - d$, and the highest one

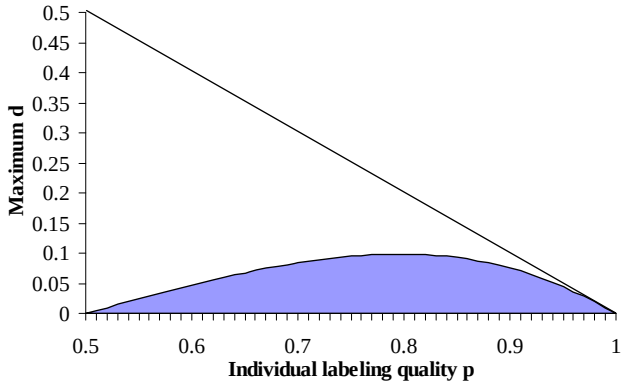


Figure 5: Repeated-labeling improves quality when d is below the curve (see text).

is $p + d$. In this case, the integrated quality q is:

$$\begin{aligned}(p-d)\cdot p\cdot(p+d)+(p-d)\cdot p\cdot(1-(p+d))+\\ (p-d)\cdot(1-p)\cdot(p+d)+(1-(p-d))\cdot p\cdot(p+d)=\\ -2p^3+2pd^2+3p^2-d^2\end{aligned}$$

When is this quantity greater than that of the best labeler $p + d$? Figure 5 plots the values of d that satisfy this relationship. If d is below the curve, using multiple labelers improves quality; otherwise, it is preferable to use the single highest-quality labeler.

3.3 Uncertainty-preserving Labeling

Majority voting is a simple and straightforward method for integrating the information from multiple labels, but clearly with its simplicity comes a potentially serious drawback: information is lost about label uncertainty. In principle, an alternative is to move to some form of *"soft" labeling*, with the multiset of labels resulting in a probabilistic label, for example (Smyth, 1995). One concern with soft labeling is that even in cases where, in principle, modeling techniques should be able to incorporate soft labeling directly (which would be true for techniques such as naive Bayes, logistic regression, tree induction, and beyond), existing software packages do not accommodate soft labels. Fortunately, we can finesse this.

Consider the following straightforward method for integrating labels from multiple labelers. For each unlabeled example x_i, the *multiplied examples (ME)* procedure considers the multiset of existing labels $L_i = \{y_{ij}\}$. *ME* creates one replica of x_i labeled by each unique label appearing in L_i. Then, for each replica, *ME* assigns a weight $1/|L_i|$, where $|L_i|$ is the number of occurrences of this label in L_i. Alternative ways of integrating the labels may rely on computing the uncertainty about the class of the example and assigning the weights appropriately. These weighted replicas can be used in different ways by different learning algorithms: for instance, in algorithms that take weights directly, such as cost-sensitive tree (Ting, 2002), or in techniques like naive Bayes that naturally incorporate uncertain labels. Moreover, any importance-weighted classification problem can be reduced to a uniform-weighted classification problem (Zadrozny et al, 2003), often performing better than hand-crafted weighted-classification algorithms. We examine the effect of uncertainty-preserving labeling (a.k.a. "soft labeling") in Sections 5.3 and 6.6.1.

Data Set	#Attributes	#Examples	Pos	Neg
kr-vs-kp	37	3196	1669	1527
mushroom	22	8124	4208	3916
sick	30	3772	231	3541
spambase	58	4601	1813	2788
splice	61	3190	1535	1655
thyroid	30	3772	291	3481
tic-tac-toe	10	958	332	626
waveform	41	5000	1692	3308

Table 1: The eight data sets used in the experiments: the numbers of attributes and examples in each, and the split into positive and negative examples.

4 Experimental Setup and Design

The previous section examined when repeated-labeling can improve data quality. We now consider when repeated-labeling should be chosen for *modeling*. What is the relationship to label quality? (Since we see that for $p = 1.0$ and $p = 0.5$, repeated-labeling adds no value.) How cheap (relatively speaking) does labeling have to be? For a given cost setting, is repeated-labeling much better or only marginally better? Can selectively choosing data points to label improve performance?

4.1 Experimental Setup

Practically speaking, the answers to these questions rely on the conditional distributions being modeled, and so we shift to an empirical analysis based on experiments with benchmark data sets.

To investigate the questions above, we present experiments on 8 real-world data sets from (Blake and Merz, 1998) and (Zheng and Padmanabhan, 2006). These data sets were chosen because they are classification problems with a moderate number of examples, allowing the development of learning curves based on a large numbers of individual experiments. Furthermore, we use only data sets for which the performance (AUC) was above 0.7 running with cross-validation on the original full data set—so that there is room to differentiate different labeling strategies. The data sets are described in Table 1. If necessary, we convert the target to binary (for *thyroid* we keep the negative class and integrate the other three classes into positive; for *splice*, we integrate classes IE and EI; for *waveform*, we integrate classes 1 and 2).

For each data set, 30% of the examples are held out, in every run, as the test set from which we calculate generalization performance. The rest is the "pool" from which we acquire unlabeled and labeled examples. To simulate noisy label acquisition, we first hide the labels of all examples for each data set. At the point in an experiment when a label is acquired, we generate a label according to the labeler quality p: we assign the example's original label with probability p and the opposite value with probability $1 - p$.

After obtaining the labels, we add them to the training set to induce a classifier. For the results presented, models are induced with J48, the implementation of C4.5 (Quinlan, 1992) in WEKA (Witten and Frank, 2005). The classifier is evaluated on the test set (with the true labels). Each experiment is repeated 50 times with a different random data partition, and average results are reported.

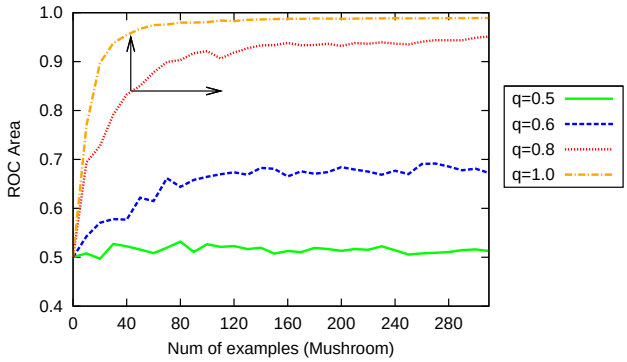


Figure 6: Learning curves under different quality levels of training data (q is the probability of a label being correct).

4.2 Design Choices for Repeated Labeling

In our experimental setup, we examine a set of basic design choices that can be varied to create different repeated labeling algorithms. Specifically, the design choices that we explore are the following:

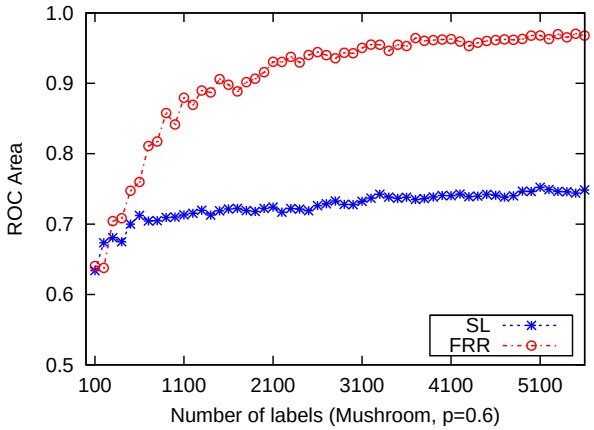
- Choice of next example to (re-)label:
  - Selection policy: The choice of the next example to (re-)label is based on a policy that determines the priority with which we choose the next example. First, in Section 5 we explore policies that assume uniform prioritization across all examples. In Section 6 we examine versions that use heterogeneous (and dynamic) prioritization schemes.
  - Deterministic vs. Randomized order: Is the choice of the next example to (re-)label based on a deterministic order or is the next example sampled from a distribution over the data set? Most of our work relies on deterministic order, but we also explore sampling schemes in Section 6.6.2.
- Choice of labeling scheme: Use a "hard" label for each example, inferred using majority voting? Or use a "soft" label that preserves the uncertainty about the class label? We examine the effect of uncertainty-preserving labeling (a.k.a. "soft labeling") in Sections 5.3 and 6.6.1.

5 Basic Repeated-Labeling Strategies

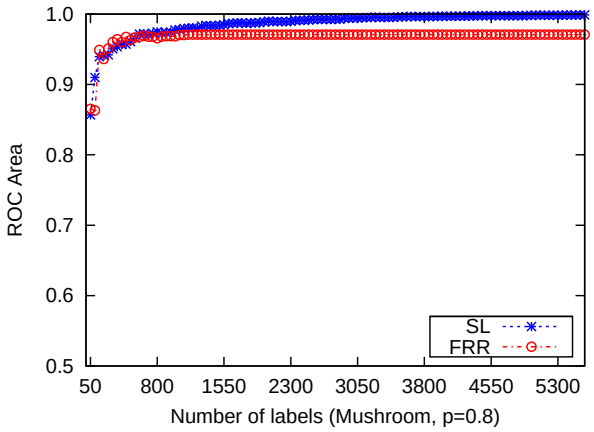
Figure 6 shows the learning curves for the *mushroom* data set. As a case in point, assume that we have processed 50 examples with quality $q = 0.8$; we have different choices for how to proceed. The two basics choices are: (i) get more examples with a single label each (horizontal arrow), or (ii) improve the quality of the existing examples by repeatedly labeling the existing examples (vertical arrow).

We call the first strategy *single labeling* (*SL*): getting as many examples as possible, one label for each example. The second strategy is the most straightforward repeated labeling strategy: assign additional labels to the labeled examples, in a round-robin fashion. We can keep *adding labels* to a *fixed* number of examples, until exhausting our labeling budget. We call this strategy *fixed round-robin* (*FRR* in short). The *FRR* strategy strategy corresponds to the vertical arrow in Figure 6. A slight generalization of *FRR* is to always give the next label to the example with the fewest labels; we call this labeling strategy *generalized*

round-robin (*GRR* in short). For the experiments below, we assume that we receive a new example every k labels, so in this case *GRR* simply assigns k labels to each new example. We evaluate these basic labeling strategies (*SL*, *FRR*, and *GRR*) in the next sections.



(a) $p = 0.6$, *#examples* $= 100$, for *FRR*



(b) $p = 0.8$, *#examples* $= 50$, for *FRR*

Figure 7: Comparing the increase in accuracy for the *mushroom* data set as a function of the number of labels acquired, when the cost of an unlabeled example is negligible. The simplest repeated-labeling strategy *FRR* with majority vote starts with an existing set of examples and only acquires additional labels for them, and single labeling (*SL*) acquires additional examples. Other data sets show similar results.

5.1 Fixed Round-robin Strategy *FRR*

We assume for this section that we select randomly a *fixed* set of examples from the unlabeled pool and *FRR* repeated-labeling re-labels examples in a *fixed round-robin* fashion: Specifically, given a fixed set L of to-be-labeled examples (a subset of the entire set of examples) the next label goes to the example in L with the fewest labels, with ties broken according to some rule (in our case, by cycling through a fixed order).

Figure 7 shows the generalization performance of *FRR* with majority vote, compared to that of single labeling, *SL*, as a function of the *number of labels*, acquired for a fixed labeler quality. Both *FRR* and *SL* start with the same number of single-labeled examples. Then, *FRR* starts acquiring additional labels *only* for the *existing* examples, while *SL* acquires new examples and labels them (once).

Generally, the decision regarding whether to invest in another whole training example or another label depends on the gradient of generalization performance, as a function of obtaining another label or a new example. (We will return to this when we discuss future work.) Figure 7 shows, for our example problem, scenarios where each strategy is preferable to the other. Consider Figure 7(a). From Figure 2 we see that for $p = 0.6$, and with 100 examples, there is a lot of headroom for repeated-labeling to improve generalization performance by improving the overall labeling quality. Figure 7(a) indeed shows that for $p = 0.6$, repeated-labeling does improve generalization performance (per label) as compared to single-labeling new examples. On the other hand, for high initial quality or steep sections of the learning curve, repeated-labeling may not compete with single labeling. Figure 7(b) shows that single labeling performs better than repeated-labeling when we have a fixed set of 50 training examples with labeling quality $p = 0.8$. Particularly, repeated-labeling could not further improve its performance after a certain amount of labeling (cf., the $q = 1$ curve in Figure 2). This happens because all the examples end up having perfect quality (so further repeated labeling cannot help) and the size of the training set is simply not sufficient to reach higher accuracy.

The results for other data sets are similar to Figure 7: under noisy labels, the fixed round-robin repeated-labeling *FRR* can perform better than single-labeling when there are enough training examples, i.e., after the learning curves are not so steep (cf., Figure 2).

5.2 Generalized Round-robin Strategies *GRR*, Introducing Costs

We illustrated above that repeated-labeling (e.g., *FRR*) is a viable alternative to single-labeling, when the labels that we get are noisy. In our comparison of *FRR* with *SL*, we effectively ignored the cost of acquiring the "feature" part of each new example for *SL*. However, as described in the introduction, often the cost of (noisy) label acquisition C_L is low compared to the cost C_U of acquiring an unlabeled example. In this case, clearly repeated-labeling should be considered: using multiple labels can shift the learning curve up significantly.

We now study the setting where we have the choice of either:

- acquiring a new training example for cost $C_U + C_L$, (C_U for the *unlabeled* portion, and C_L for the label), or
- get another label for an existing example for cost C_L.

To compare any two strategies on equal footing, we calculate generalization performance "per unit cost" of acquired data; we then compare the different strategies for combining multiple labels, under different individual labeling qualities. We start by defining the data acquisition cost C_D:

$$C_D = C_U \cdot T_r + C_L \cdot N_L \tag{2}$$

to be the sum of the cost of acquiring T_r unlabeled examples ($C_U \cdot T_r$), plus the cost of acquiring the associated N_L labels ($C_L \cdot N_L$). For single labeling we have $N_L = T_r$, but for repeated-labeling $N_L > T_r$.

We extend the setting of Section 5.1 slightly and we consider the generalized round-robin strategy, *GRR*, which can acquire and label new examples; single labeling *SL* is unchanged. For each new example acquired, repeated labeling acquires a fixed number of labels k, and in this case $N_L = k \cdot T_r$. Thus, for *GRR*, in these experiments the cost setting can be described compactly by the cost ratio $\rho = \frac{C_U}{C_L}$, and in this case $C_D = \rho \cdot C_L \cdot T_r + k \cdot C_L \cdot T_r$, i.e.,

$$C_D \propto \rho + k \tag{3}$$

Figure 8 shows the generalization performance of the *GRR* round-robin repeated-labeling strategy with majority vote compared to that of single labeling *SL*, as a function of data acquisition cost. Figure 8(a) shows the case where the unlabeled part of a new example is still free ($\rho = 0$, i.e., $C_U = 0$) for both *GRR* and *SL*. Here we just have in the horizontal axis the data acquisition cost instead of the number of labels. In this example, *GRR* gets 10 labels per example. For the same cost, *SL* gets 10 examples. In this higher noise scenario, it is much better to get examples with 10 labels, as this reduces significantly the noise. Another issue is the size of the pool of available examples. For the *mushroom* data set, we have eight thousands examples; so, *SL* runs out of examples to label and this is the reason for the early termination show in the *SL* curve. This case shows that *GRR* can be better than single labeling even when the labels are not particularly cheap.

Figure 8(b) and 8(c) illustrate scenarios where there is a cost for obtaining the unlabeled part of the example, with $\rho = 3, k = 5$ and $\rho = 10, k = 12$, respectively. We can see that *GRR* outperforms *SL*, even though *GRR* allocates a significant amount of resources to re-labeling the examples. The results are similar across other data sets, in high-noise settings.

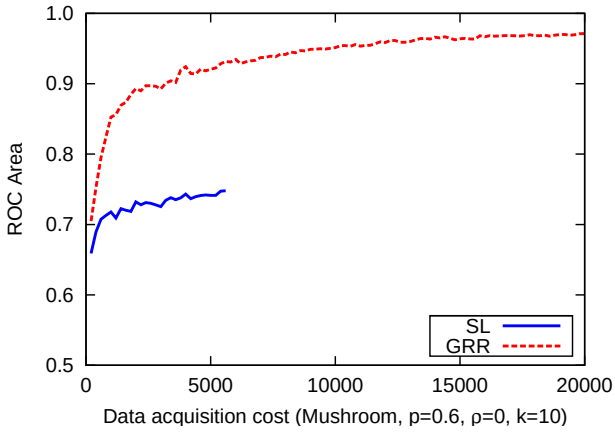
The high-level conclusion: as the cost ratio ρ increases, the improvement of *GRR* over *SL* also increases. So when the labels actually are cheap, we can actually get significant advantage from using a repeated labeling strategy, such as *GRR*.

5.3 Different Label Integration Methods

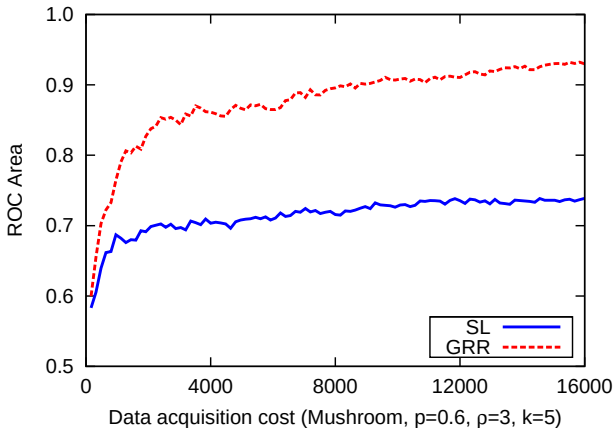
In all experiments shown above, both for *FRR* and *GRR*, we use majority voting for creating the integrated label from multiple labels. Obviously, some information (such as label uncertainty) is lost during this process. Soft labeling (described above) does not lose this information, and therefore may improve performance. In this section, we examine these two label integration methods (majority voting and soft labeling) by applying them to *GRR*. *GRR* with majority voting is called *MV* for short, and *GRR* with soft labeling is called *ME* for short. For *ME*, we generate *multiple examples* with different weights to preserve the uncertainty of the label multiset as described in Section 3.3.

Figure 9 plots the generalization accuracy of the models as a function of data acquisition cost. Here $\rho = 3$, $k = 5$, and we see very clearly that, for $p = 0.6$, both versions of repeated-labeling are preferable to single labeling. *MV* and *ME* outperform *SL* consistently (on all but waveform, where *MV* ties with *SL*) and, interestingly, the comparative performance of repeated-labeling tends to increase as one spends more on labeling. Furthermore, from the results in Figure 9, we can see that the uncertainty-preserving repeated-labeling *ME* outperforms *MV* in all cases, to greater or lesser degrees.

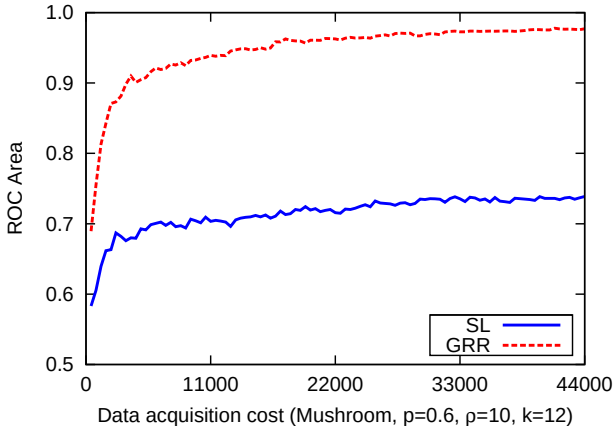
In other results (not shown) we see that when labeling quality is substantially higher (e.g., $p = 0.8$), repeated-labeling still is increasingly preferable to single labeling as ρ increases; however, we no longer see an advantage for *ME* over *MV*. These results suggest that when labeler quality is low, inductive modeling often can benefit from the explicit representation of the uncertainty incorporated in the multiset of labels for each example. When labeler quality is relatively higher, this additional information apparently is superfluous, and straight majority voting is sufficient.



(a) $p = 0.6$, $\rho = 0$ (i.e., $C_U = 0$), $k = 10$, for *GRR*



(b) $p = 0.6$, $\rho = 3$, $k = 5$, for *GRR*



(c) $p = 0.6$, $\rho = 10$, $k = 12$, for *GRR*

Figure 8: Comparing the increase in accuracy for the *mushroom* data set as a function of data acquisition cost. *SL* is single labeling; *GRR* is generalized round-robin repeated-labeling, acquiring one new training example at a time, and using majority voting. Other data sets show similar results.

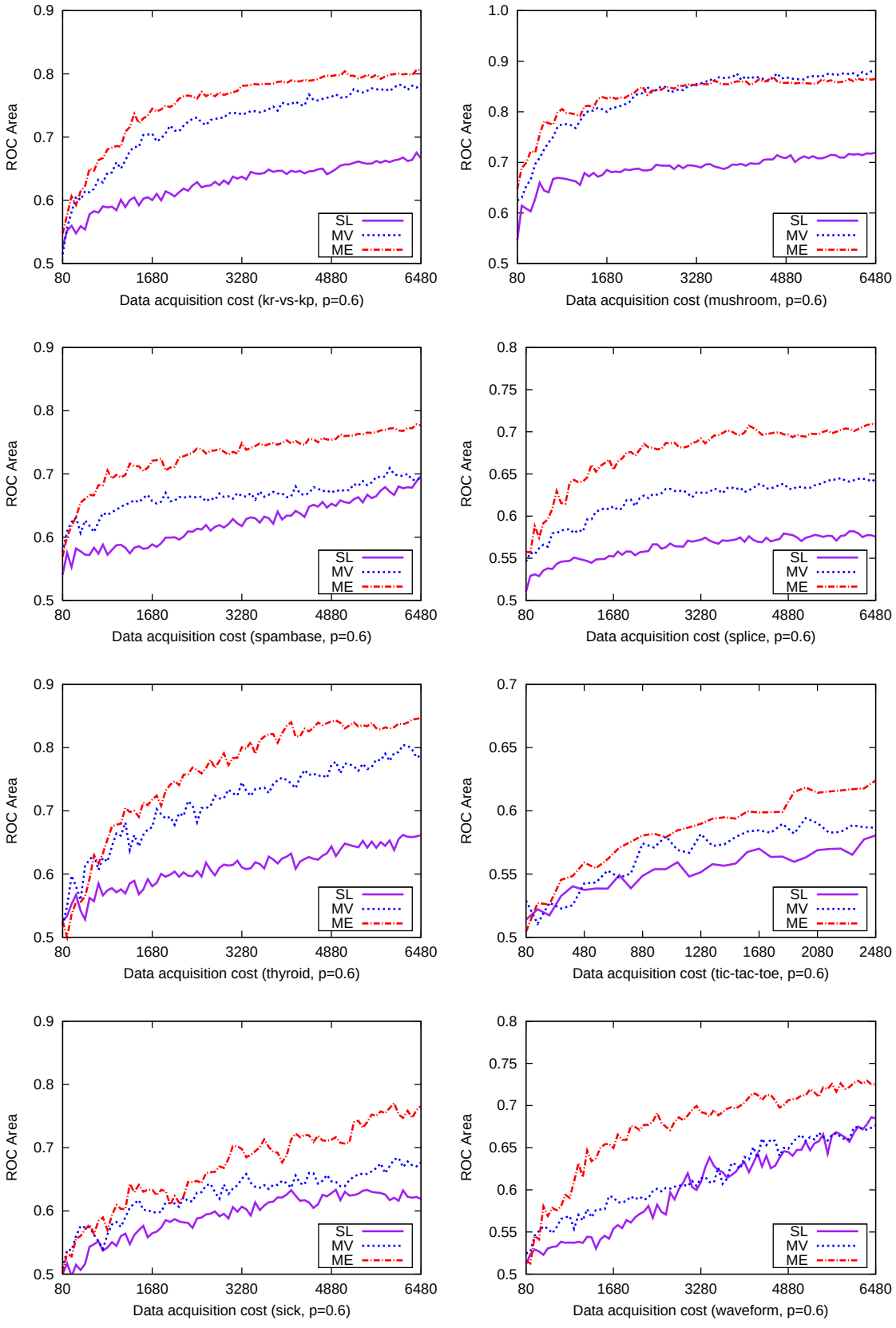


Figure 9: Increase in model accuracy as a function of data acquisition cost for the 8 data sets; ($p = 0.6$, $\rho = 3$, $k = 5$). *SL* is single labeling; *MV* is repeated-labeling with majority voting, and *ME* is uncertainty-preserving repeated-labeling. Both *MV* and *ME* are based on *GRR*.

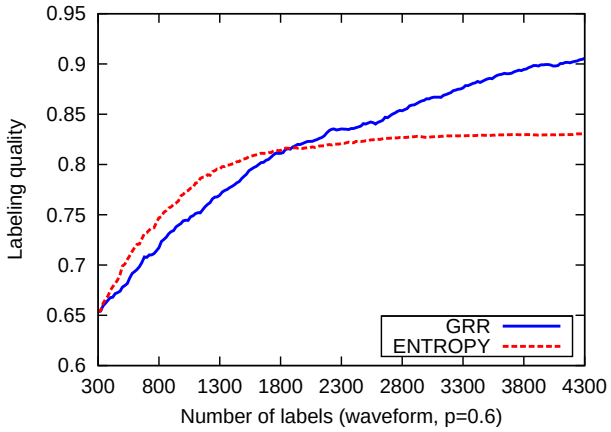


Figure 10: What not to do: data quality improvement for an entropy-based selective repeated-labeling strategy vs. round-robin repeated-labeling.

6 Selective Repeated-Labeling Strategies

So far, we have considered repeated labeling as a uniform process across all examples. Now, we examine (i) whether selective allocation of labeling resources can further improve performance, and (ii) if so, how should the examples be selected. For example, intuitively it would seem better to augment the label multiset $\{+,-,+\}$ than to augment $\{+,+,+,+,+\}$.

6.1 What Not To Do

The example above suggests a straightforward procedure for selective repeated-labeling: acquire additional labels for those examples where the current multiset of labels is impure. Two natural measures of purity are:

- the entropy of the multiset of labels, and
- how close the frequency of the majority label is to the decision threshold (here, 0.5).

For our binary classification setting, these two measures generate the same example ranking. Unfortunately, there is a clear problem: under noise these measures do not really measure the uncertainty in the estimation of the class label. For example, $\{+,+,+\}$ is perfectly pure, but the true class is not certain (e.g., with $p = 0.6$ one is not 95% confident of the true label). Applying a small-sample shrinkage correction (e.g., Laplace) to the probabilities is not sufficient.

Figure 10 (dashed line) demonstrates how labeling quality increases as a function of assigned labels, using the (Laplace-corrected) entropy-based estimation of uncertainty (*ENTROPY*). For small amounts of repeated-labeling, the *ENTROPY* technique does indeed select useful examples to label, but the fact that the estimates are not true estimates of uncertainty hurts the procedure in the long run—generalized round-robin repeated-labeling (GRR) from Section 5 outperforms the entropy-based approach. This happens because with ENTROPY most of the labeling resources are wasted, with the procedure labeling a small set of examples very many times. Note that with a high level of noise, the long-run label mixture will be quite impure, even though the true class of the example may be quite certain (e.g., consider the case of 600

positive labels and 400 negative labels with $p = 0.6$). Less impure, but incorrect, label multisets are never revisited.

6.2 Estimating Label Uncertainty

Instead, for a given multiset of labels, we can compute Bayesian estimates of the uncertainty in the class of the example. Specifically, we would like to estimate our uncertainty that the true class y of the example is the majority class y_m of the multiset. Consider a Bayesian estimation of the probability that y_m is incorrect. Here we do not assume that we know (or have estimated well) the labeler quality,[6] and so we presume the prior distribution over the true label (quality) $p(y)$ to be uniform in the $[0, 1]$ interval. Thus, after observing p positive labels and n negative labels, the posterior probability $p(y)$ follows a Beta distribution $B(p + 1, n + 1)$ (Gelman et al, 2003).

For our first measure of label uncertainty, we compute the level of uncertainty as the tail probability below the labeling decision threshold. Formally, the uncertainty is equal to the CDF at the decision threshold of the Beta distribution, which is given by the regularized incomplete beta function:

$$I_x(\alpha, \beta) = \sum_{j=a}^{\alpha+\beta-1} \frac{(\alpha+\beta-1)!}{j!(\alpha+\beta-1-j)!} x^j (1-x)^{\alpha+\beta-1-j} \tag{4}$$

In our case, the decision threshold is $x = 0.5$, and $\alpha = p + 1, \beta = n + 1$. Thus, we set:

$$S_{LU} = \min\{I_{0.5}(p+1, n+1), 1 - I_{0.5}(p+1, n+1)\} \tag{5}$$

We compare selective repeated-labeling based on S_{LU} to round-robin repeated-labeling (GRR), which we showed to perform well in Section 5. To compare repeated-labeling strategies, we followed the experimental procedure of Section 5, with the following modification. Since we are asking whether label uncertainty can help with the selection of examples for which to obtain additional labels, each training example starts with three initial labels (selected as above). Then, each repeated-labeling strategy iteratively selects examples for which it acquires additional labels (two at a time in these experiments).

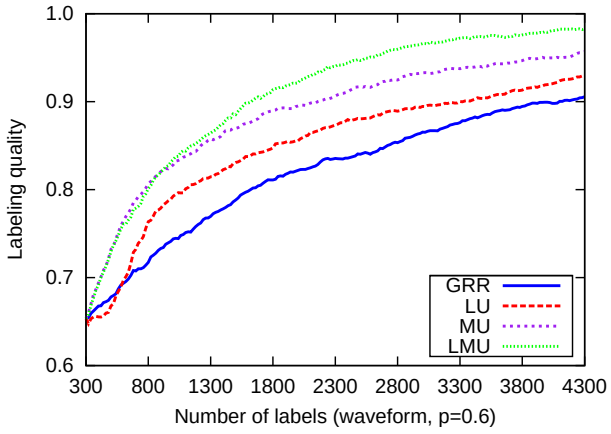
Comparing selective repeated-labeling using S_{LU} (call that **Label Uncertainty (LU)**) to *GRR*, we observed similar patterns across all twelve data sets; therefore we only show the results for the *waveform* data set (Figure 11; ignore the *MU* and *LMU* lines for now, we discuss these techniques below), which are representative. The results indicate that *LU* performs substantially better than *GRR*, identifying the examples for which repeated-labeling is more likely to improve quality.

6.3 Estimating Label Uncertainty using Example-Specific Labeler Quality

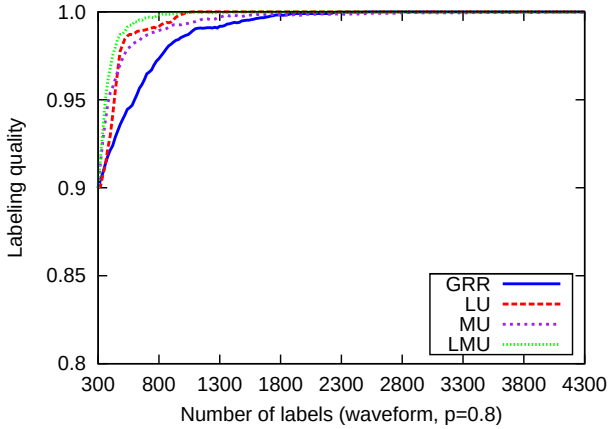
The *LU* method, described above, estimates the probability of an example being labeled correctly. So the distribution estimated by *LU* is a distribution of possible "labeler quality" values *for the given example*. Using *LU* relies on the assumption that we do not have adversarial labelers, so the quality will not be below 0.5. Hence, with *LU* we can use the uncertainty about the quality of the labelers as a proxy for estimating the true label of the example.

Instead of relying on this assumption, we can use the estimation of the labeler quality distribution from Section 6.2 to estimate directly the uncertainty about the class label. Specifically, suppose that we have

[6] Doing so may improve the results presented below.



(a) $p = 0.6$



(b) $p = 0.8$

Figure 11: The data quality improvement of the four strategies (*GRR*, *LU*, *MU*, and *LMU*) for the *waveform* data set.

an example that has been labeled $p + n$ times, receiving p positive labels and n negative ones. If we had available the quality of the labelers q (assuming for simplicity a common q; labeler-and-example-specific $q_{i,j}$ would entail the natural expansion), it is straightforward to compute the probability $Pr(y_i|p,n)$, i.e., infer the true label given the p positive labels and n negative labels. Specifically, we have:

$$\begin{aligned} Pr(+|p,n) = \frac{Pr(p,n|+) \cdot Pr(+)}{Pr(p,n)} &= q^p \cdot (1-q)^n \frac{Pr(+)}{Pr(p,n)} \\ Pr(-|p,n) = \frac{Pr(p,n|-) \cdot Pr(-)}{Pr(p,n)} &= q^n \cdot (1-q)^p \frac{Pr(-)}{Pr(p,n)} \end{aligned} \tag{6}$$

In reality, the labeler quality q is unknown. However, given a sequence of p positive labels and n negative labels, we can apply Bayesian estimation to compute the distribution of possible values for q. After seeing p positive and n negative labels, the quality q, *for that example* follows a beta distribution. The distribution is $B(p+1, n+1)$ if $p > n$, or follows a beta distribution $B(n+1, p+1)$ if $p < n$. In other words:

$$Pr(q) = \begin{cases} \frac{\Gamma(p+n+2)}{\Gamma(p+1)\Gamma(n+1)} \cdot q^p \cdot (1-q)^n & : p \geq n \\ \\ \frac{\Gamma(p+n+2)}{\Gamma(p+1)\Gamma(n+1)} \cdot q^n \cdot (1-q)^p & : p < n \end{cases} \tag{7}$$

Assuming $p \geq n$, and without loss of generality, we use the derivation of $Pr(+|p,n)$ from above, and integrate over all possible values of q:

$$\begin{aligned} Pr(+|p,n) &= \frac{Pr(p,n|+) \cdot Pr(+)}{Pr(p,n)} \\ &= \int_0^1 q^p \cdot (1-q)^n \frac{Pr(+)}{Pr(p,n)} Pr(q) dq \\ &= \frac{Pr(+)}{Pr(p,n)} \int_0^{1.0} q^p \cdot (1-q)^n \cdot \frac{\Gamma(p+n+2)}{\Gamma(p+1)\Gamma(n+1)} \cdot q^p \cdot (1-q)^n dq \\ &= \frac{Pr(+)}{Pr(p,n)} \cdot \frac{\Gamma(p+n+2)}{\Gamma(p+1)\Gamma(n+1)} \int_0^1 q^{2p} \cdot (1-q)^{2n} dq \\ &= \frac{Pr(+)}{Pr(p,n)} \cdot \frac{\Gamma(p+n+2)}{\Gamma(p+1)\Gamma(n+1)} \frac{\Gamma(2n+1)\Gamma(2p+1)}{\Gamma(2+2n+2p)} \end{aligned}$$

and similarly for $Pr(-|p,n)$. Using $Pr(+|p,n)$ and $Pr(-|p,n)$, and for $p \geq n$ we get:

$$Pr(+|p,n) = \left(1 + \frac{1-Pr(+)}{Pr(+)} \cdot \frac{\big(\Gamma(n+p+1)\big)^2}{\Gamma(2n+1) \cdot \Gamma(2p+1)}\right)^{-1} \tag{8}$$

Since p and n are integers, and $\Gamma(k) = (k-1)!$ for $k \in N$, we have:

$$Pr(+|p,n) = \left(1 + \frac{1-Pr(+)}{Pr(+)} \cdot \frac{\big((n+p)!\big)^2}{(2n)! \cdot (2p)!}\right)^{-1} \tag{9}$$

where p is the number of positive labels, n is the number of negative labels (with $p \geq n$), $Pr(+)$ is the prior probability for the positive class, and $\Gamma(\cdot)$ is the Gamma function. (For $p < n$, it is symmetric.) So, our **New Label Uncertainty (*NLU*)** metric should be now $S_{NLU} = 1 - Pr(+|p,n)$.

From Equation 9, we can see that we need to know the prior probability $Pr(+)$ to calculate the posterior probability $Pr(+|p,n)$, which is typically unknown. However, we can use a simple expectation-maximization algorithm over the collected data, to compute an estimate of $Pr(+)$:

1. Pick a random prior for positive class (e.g., $Pr(+) = 0.5$)
2. Compute the conditional probabilities $Pr(x_i = +|p,n)$ for each example x_i, using the current prior estimate
3. Compute the $Pr(+)$ as the average value of $Pr(x_i = +|p,n)$
4. Go to step 2

Experiments show that *NLU* improves *LU*, in terms of labeling quality and the model performance (accuracy), on the data sets where the class distribution is unbalanced, such as *sick and thyroid* (Figure 12). For the data sets (*kr-vs-kp, mushroom, spambase, splice, tic-tac-toe, and waveform*), *NLU* has a similar performance

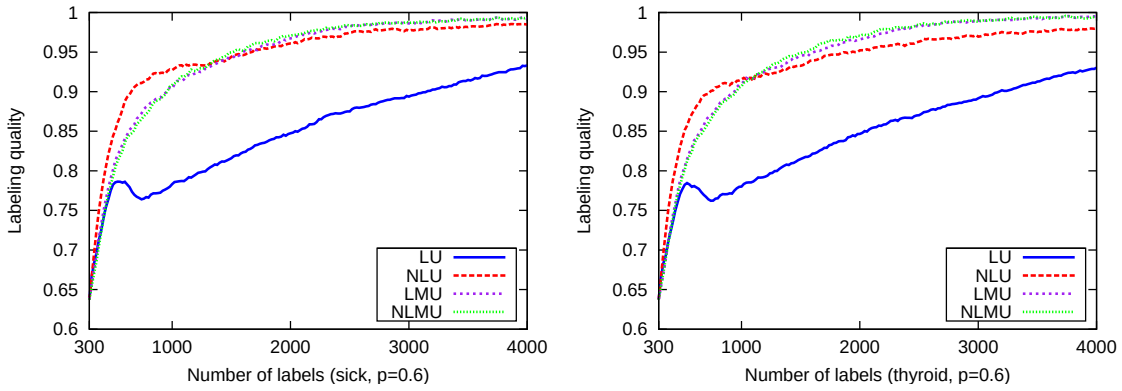


Figure 12: Comparing the strategies (*NLU* and *NLMU*) with their previous version (*LU* and *LMU*) in terms of the improvement of integrated labeling quality on imbalanced data sets (*sick* and *thyroid*).

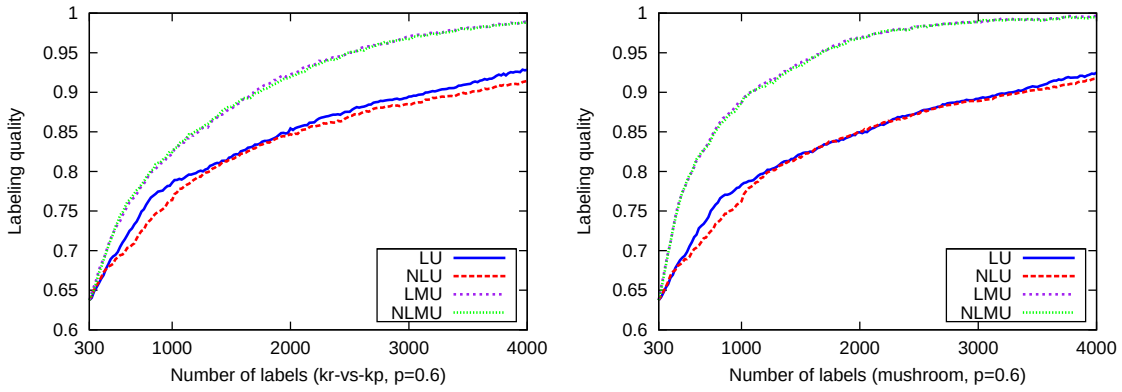


Figure 13: Comparing the strategies (*NLU* and *NLMU*) with their previous version (*LU* and *LMU*) in terms of the improvement of integrated labeling quality on balanced data sets (*kr-vs-kp* and *mushroom*).

to *LU* (Figure 13). The results indicate that *LU*, although less principled in nature compared to *NLU*, works well for balanced data sets. However, for unbalanced data sets, the derivation of *NLU* suggests that taking into consideration the prior class distribution during the uncertainty estimation should improve the results, and the experiments demonstrate that it indeed does so.

We can also compare the the performance of *LU* and *NLU* based on their ability to identify and separate the correctly and incorrectly labeled examples. Ideally, all incorrectly labeled examples should have higher uncertainty scores than the correctly labeled ones. The method that better separates the two classes will be a better choice. In order to examine the differences of *LU* and *NLU* , we employ the Mann-Whitney-Wilcoxon (MWW) test, a non-parametric test for assessing whether two independent samples of observations can be separated. Specifically, we conduct the following experiment:

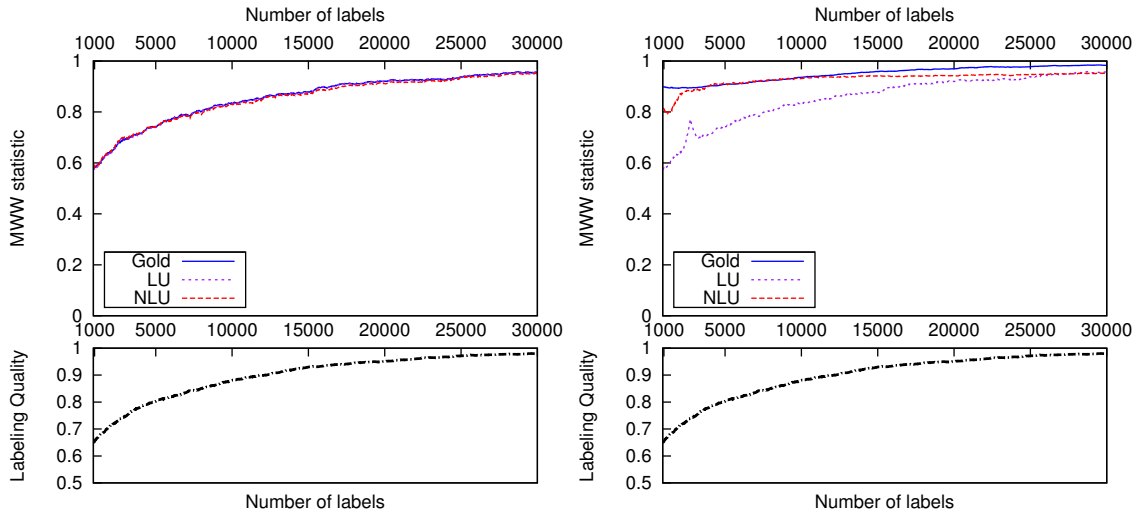
1. Pick a random prior for the positive class (e.g., $Pr(+) = 0.7$)
2. Generate n positive and negative examples (in our case, $n = 300$), following the prior value from the previous step.
3. Assign three initial labels to each example; the labeler quality is p.
4. Assign an increasing number of labels to the examples, following the GRR strategy.[7]
5. Compute the uncertainty scores for *LU*, and *NLU*; also, we compute the "*Gold*" uncertainty score, which assumes knowledge of the quality of the labelers and uses Equation 6 to compute the uncertainty for each example. Note that this is the best possible uncertainty metric that we can have when we only know about the multiset of the assigned labels.
6. Compute the uncertainty scores for correctly and incorrectly labeled examples, and compute the MWW statistic for the two sets of points (the correctly and incorrectly labeled examples). Higher values of MWW indicate better separating ability.
7. Go to step 4 until the total number of labels are used up.

Figure 14 gives us the results of the experiment. When the dataset is balanced (i.e., ($Pr(+) \approx 0.5$), the performance of *LU*, *NLU*, and *Gold* are similar. This indicates that *LU* and *NLU*, are almost optimal. However, in imbalanced data sets, *NLU* outperforms *LU* by a wide margin. *NLU* has a performance much closer to *Gold*, especially when we have only a few labels per example.

6.4 Using Model Uncertainty

The two techniques described above, *LU* and *NLU*, assume that the different examples that are being labeled are independent of each other. In other words, the labels assigned to an example do not give any information about the labels that should be assigned to a different example. One approach to overcome this limitation is to learn a classification model using the existing labeled examples, and use the resulting classifier to get information about the potential class for each example. One can envision different ways to instantiate this approach. We devise and experiment with one here: producing a measure of "model

[7] We do *not* use selective labeling strategies for this experiment, as we want to keep the labeling allocation strategy constant, and independent of the two uncertainty scoring strategies. The goal is to see which uncertainty score can separate best the correctly from the incorrectly labeled examples.



(a) $Pr(+) = 0.5$ (b) $Pr(+) = 0.1$

Figure 14: MWW statistic for three uncertainty scores (*NLU*, *NLMU* and *Gold*) and the corresponding Labeling quality ($p = 0.6$)

uncertaintly" for an example: An example becomes a candidate for (re-)labeling when a learned model's uncertainty about its class is high.

More specificaly, **Model Uncertainty (MU)** ignores the current multiset of labels. It learns a set of models, each of which predicts the probability of class membership. The MU score is:

$$S_{MU} = 0.5 - \left| \frac{1}{m} \sum_{i=1}^{m} Pr(+|x, H_i) - 0.5 \right| \tag{10}$$

where $Pr(+|x, H_i)$ is the probability of classifying the example x into $+$ by the learned model H_i, and m is the number of learned models. In our experiments, $m = 10$, and the model set is a *random forest* (Breiman, 2001) (generated by Weka). We compare *MU* to other strategies below, but first let us address its obvious drawback.

Of course, by ignoring the label set, *MU* has the complementary problem to *LU*: even if the model is uncertain about a case, should we acquire more labels if the existing label multiset is very certain about the example's class? The investment in these labels would be wasted, since they would have a small effect on either the integrated labels or the learning.

A hybrid strategy, called **Label and Model Uncertainty (LMU)**, combines the uncertainty scores from *LU* and *MU*, to *avoid examples where either model is certain*. This is done by computing the score S_{LMU} as the geometric average[8] of S_{LU} and S_{MU}. That is:

$$S_{LMU} = \sqrt{S_{MU} \cdot S_{LU}} \tag{11}$$

Similarly, we combined the score of *NLU* with the score of *MU*, to create the **New Label and Model Uncertainty (NLMU)** method, for which:

[8]Subsequent to these experiments, we also experimented with other approaches for combining probabilities from multiple sources, following the discussion in Clemen and Winkler (1990). For our experiments, taking the geometric mean was the best performing and most robust approach for combining the uncertainty scores, even after transforming the uncertainty scores into proper probability scores.

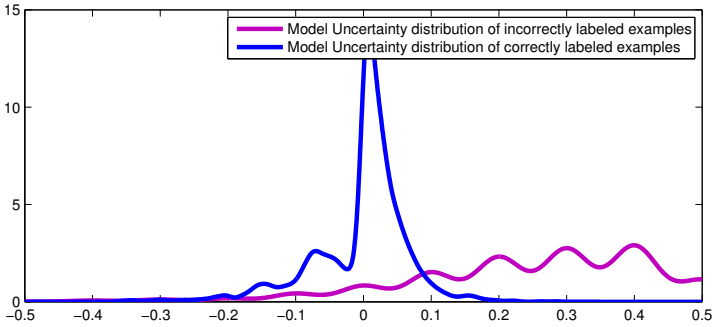


Figure 15: Why MU works: Model uncertainty distribution of correctly and incorrectly labeled examples for the *bmg* data set.

$$S_{NLMU} = \sqrt{S_{MU} \cdot S_{NLU}} \tag{12}$$

Figure 11 demonstrates the improvement in data quality when using model information, which is typical of the results across our data sets. We can observe that the *LMU* model strongly dominates all other strategies. In high-noise settings ($p = 0.6$) *MU* also performs well compared to *GRR* and *LU*, indicating that when noise is high, using learned models helps to focus the investment in improving quality. In settings with low noise ($p = 0.8$), *LMU* continues to dominate, but *MU* no longer outperforms *LU* and *GRR*.

6.4.1 Why Model Uncertainty *MU* Works

Our *Model Uncertainty* approach was inspired by active learning. However, it works for a very different reason. Unlike traditional active learning, which builds models from the labeled examples and uses these models to predict the uncertainty of each *unlabeled* example, our *MU* strategy applies a sort of of self-healing (Brodley and Friedl, 1999). It builds models on the noisy data and uses the models to predict the uncertainty of each example within these same noisy data. The idea is that poorly labeled examples will make modeling difficult in their own region of the example space—model uncertainties are due at least in part to the quality of the labels of the examples in the training data. (Contrast this with active learning, where the *model* is applied specifically to a different, unlabeled set of data.) In our case, the examples that affect the modeling the most are the more important examples to re-label, in case the effect is due to poor labeling. So, we expect that incorrectly labeled examples will tend to have higher *MU* uncertainty scores, compared to correctly labeled oned. Figure 15 shows a representative result: We computed the uncertainty scores of correctly and incorrectly labeled examples for the *bmg* dataset ($m = 10$). Figure 15 illustrates that the uncertainty scores of the correctly labeled examples are centered around 0, while the distribution of scores for incorrectly labeled examples has a much higher mean.

To assess the relative contribution of this self-healing property of *MU*, we compare our *MU* with versions corresponding to traditional active learning. Specifically, the latter uses 10-fold cross-validation; every fold is treated as active learning's unlabeled set, and the remaining 9 as the labeled set (training set) for building models. (We refer to this active learning strategy as *MUCV*.) *MUCV* follows a similar procedure as *MU*. However, *MUCV* builds a random forest using the training data, unlike *MU*, which builds a random forest from the whole data. This comparison isolates the contribution of applying the model back to the training

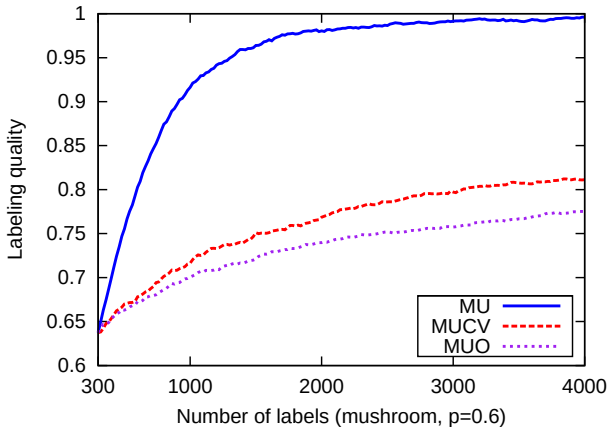


Figure 16: The data quality improvement on three versions of model uncertainty (*MU*, *MUCV*, and *MUO*) for the *mushroom* data set.

data (for self-healing), as opposed to active learning's attempt to concentrate on parts of the space near the classification boundary, or that otherwise are not (yet) modeled well. As a point of further comparison, we also build a strategy called Model Uncertainty with Oracle (*MUO*): we use all the original data with perfect labels (provided by a perfect Oracle, but unknown to the re-labeling procedure except through the resultant model) and build a random forest; we use this random forest to predict the uncertainty of each example in the noisy data. For all strategies, the uncertainty score is also defined in Equation 10 with $m = 10$.

Figures 16 and 17 show representative experimental results for the three versions of model uncertainty, using the *mushroom* data set. Figures 16 and 17, show that *MUCV* and *MUO* are not nearly as effective as *MU* for repeated labeling. *MU* dynamically finds examples that seem to be causing problems with the modeling, and improves their label quality by acquiring more labels. In contrast, *MUO* ignores the characteristics of the noisy data completely and applies the statistical models learned from the original noise-free training data, so *MUO* always acquires more labels for the same small set of examples—producing static models unaffected by the additional labels. *MUCV* is also a dynamic process. However, the benefit of identifying examples that cannot be classified easily (as with active learning) is not nearly as large as the benefit of self-healing with *MU*.

6.5 Classification Performance with Selective Repeated-Labeling

So, finally, let us assess whether selective repeated-labeling accelerates learning (i.e., improves model generalization performance, in addition to data quality). Again, experiments are conducted as described above, except here we compute generalization accuracy averaged over the held-out test sets (as described in Section 4.1). In Figure 18, we show the performances of these four strategies in terms of classification accuracy on the eight data sets.

We report values for $p = 0.6$, a high-noise setting that can occur in real-life training data.[9] Table 2 summarizes the results of the experiments, reporting accuracies averaged across the acquisition iterations for each data set, with the maximum accuracy across all the strategies highlighted in bold, the minimum

[9]From Provost and Danyluk (1995): *"No two experts, of the 5 experts surveyed, agreed upon diagnoses more than 65% of the time. This might be evidence for the differences that exist between sites, as the experts surveyed had gained their expertise at different locations. If not, however, it raises questions about the correctness of the expert data."*

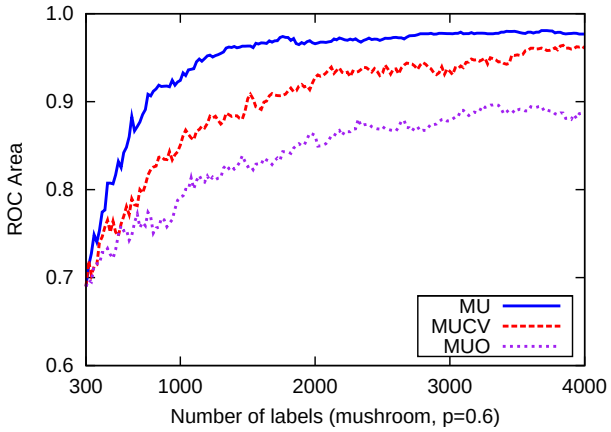


Figure 17: The model quality improvement on three versions of model uncertainty (*MU*, *MUCV*, and *MUO*) for the *mushroom* data set.

Data Set	GRR	LU	NLU	MU	LMU	NLMU
kr-vs-kp	*0.891*	0.908	0.902	0.925	0.941	**0.942**
mushroom	*0.956*	0.964	0.966	**0.980**	**0.980**	**0.980**
sick	*0.637*	0.674	0.685	0.717	**0.764**	0.761
spambase	*0.786*	0.789	0.796	0.825	0.818	**0.825**
splice	*0.747*	0.776	0.766	0.790	**0.800**	0.797
thyroid	*0.844*	0.889	0.875	**0.938**	0.926	0.924
tic-tac-toe	0.625	0.627	0.637	*0.611*	0.637	**0.644**
waveform	*0.672*	0.689	0.686	0.689	0.716	**0.723**
average	*0.770*	0.789	0.789	0.809	0.823	**0.825**

Table 2: Average AUC of the six strategies over 8 data sets, for $p = 0.6$. For each data set, the best performance is in boldface and the worst in italics.

accuracy italicized, and the grand averages reported at the bottom of the columns.

The results are satisfying. The two basic methods that use label uncertainty (*LU* and *NLU*) are consistently better than round-robin repeated-labeling, achieving higher accuracy for every data set. (Recall that in the previous section, round-robin repeated-labeling was shown to be substantially better than the baseline single labeling in this setting.) The performance of model uncertainty alone (*MU*) is more variable: in one case it has the best accuracy, but in another case it does not even reach the accuracy of round-robin repeated-labeling. Overall, combining label and model uncertainty (*LMU* and *NLMU*) produce the best approaches: in these experiments, they always outperform round-robin repeated-labeling, and as hypothesized, generally they are better than the strategies based on only one type of uncertainty (in the case of *LU* and *NLU*, the corresponding combined strategy is better in every case; statistically significant by a sign test at $p < 0.01$).

6.6 Alternative Selective Strategies

In previous sections, we have studied the performance of the selective repeated labeling strategies. The experimental results show that all selective strategies perform better than single labeling. In this section, we examine some alternative strategies, that can be used in conjunction with the techniques that we presented

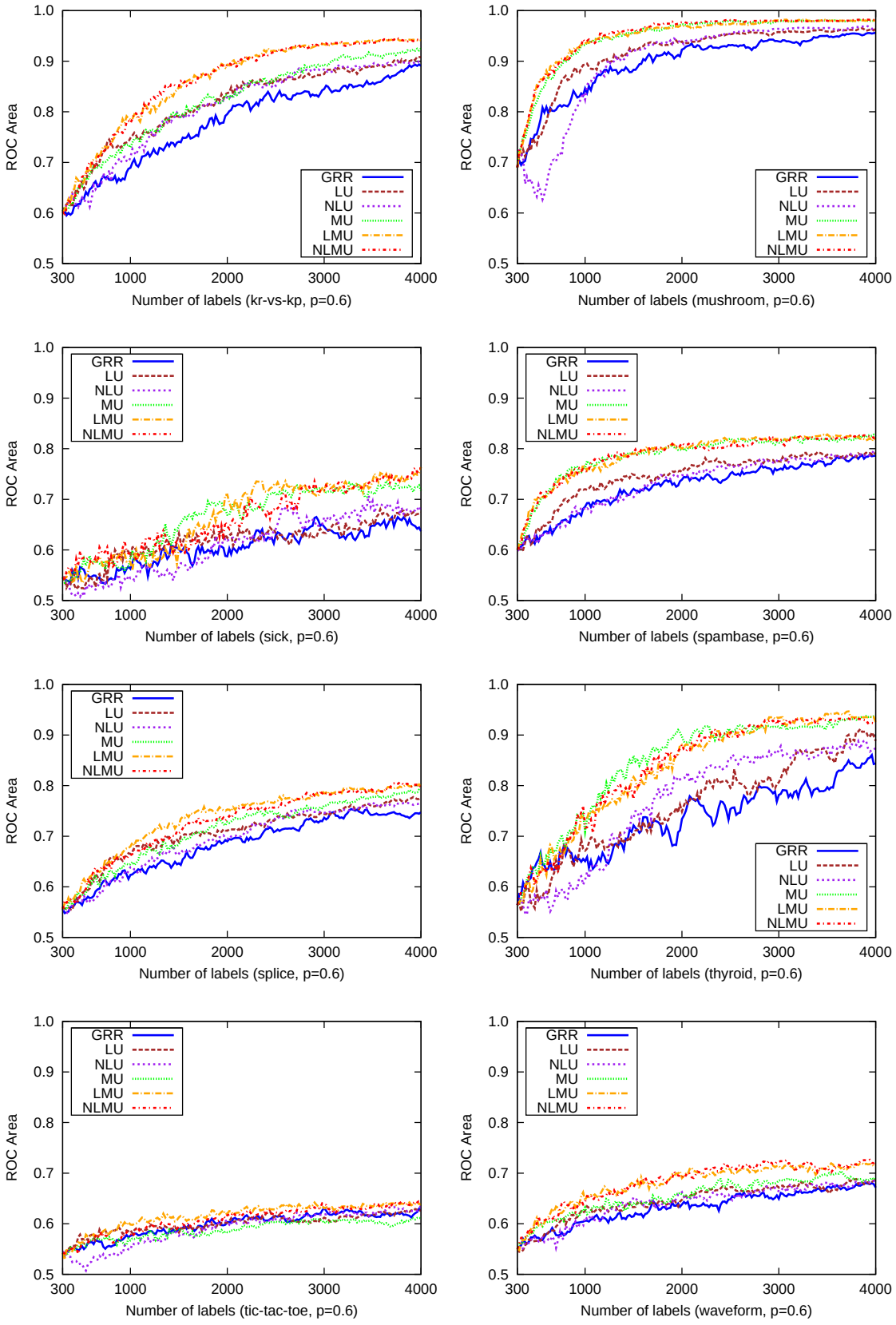


Figure 18: Accuracy as a function of the number of labels acquired for the six selective repeated-labeling strategies for the 8 data sets ($p = 0.6$).

so far. Specifically, we discuss the case of using "soft labels" and the case of using weighted sampling to select the example to label, instead of picking the examples in absolute order according to their uncertainty scores.

6.6.1 Soft-labeling

Majority voting is the most straightforward method for integrating multiple labels for each example. In contrast to majority voting, soft-labeling (refer to Section 3.3) retains the uncertainty in the multiset of labels. Specifically, the *ME* technique produces a fractionally weighted example with each unique label in the set. In Section 5.3, we saw that soft-labeling can improve the performance of the GRR strategy. Now, we investigate whether soft-labeling can improve selective re-labeling.

Curiously, in our experimental results, we did not observe consistent improvements in generalization performance by incorporating soft-labeling, as compared to the majority-voting counterparts. The results from the data sets *mushroom, splice, and thyroid* are representative and shown in Figures 19, 20 and 21. For some data sets (e.g., *mushroom*), the performance of soft-labeling and majority voting are similar. For other data sets (e.g., *splice*), soft-labeling performs a little better, while on others (e.g., *thyroid*), soft-labeling reduces performance significantly.

Based on these results and those from above, we can conclude that soft-labeling is a strategy to consider in environments with high noise and when using basic round-robin labeling strategies. When selective labeling is employed, the benefits of using soft-labeling apparently diminish, and so far we do not have the evidence to recommend using soft-labeling.

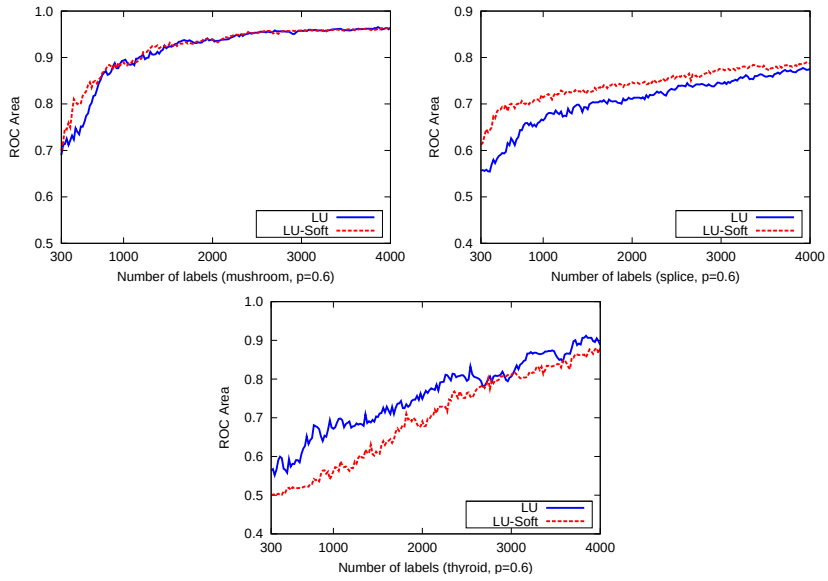


Figure 19: The accuracy improvement of soft-labeling on *LU* on the *mushroom, splice, thyroid* data sets.

6.6.2 Weighted Sampling

Weighted sampling has been shown previously to be a useful tool for improving the performance of active learning (Saar-Tsechansky and Provost, 2004). In this section, we further study whether weighted sampling

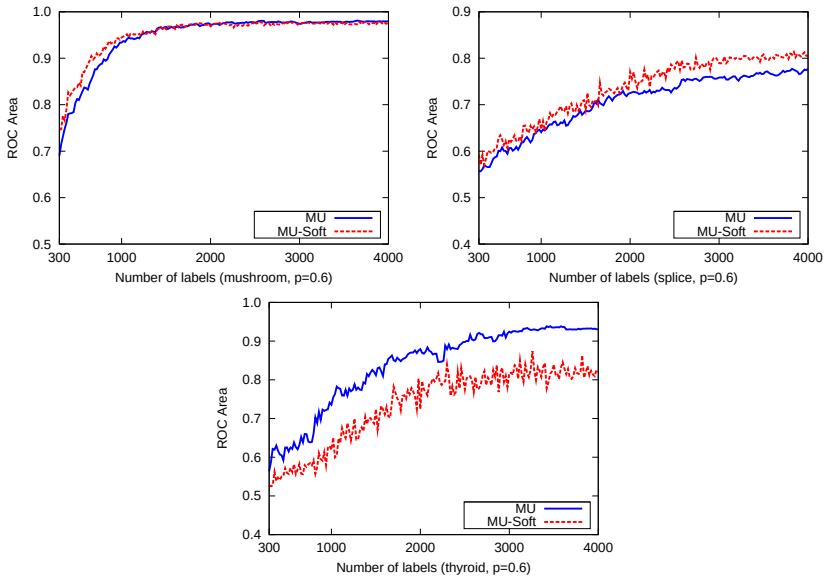


Figure 20: The accuracy improvement of soft-labeling on *MU* on the *mushroom, splice, thyroid* data sets.

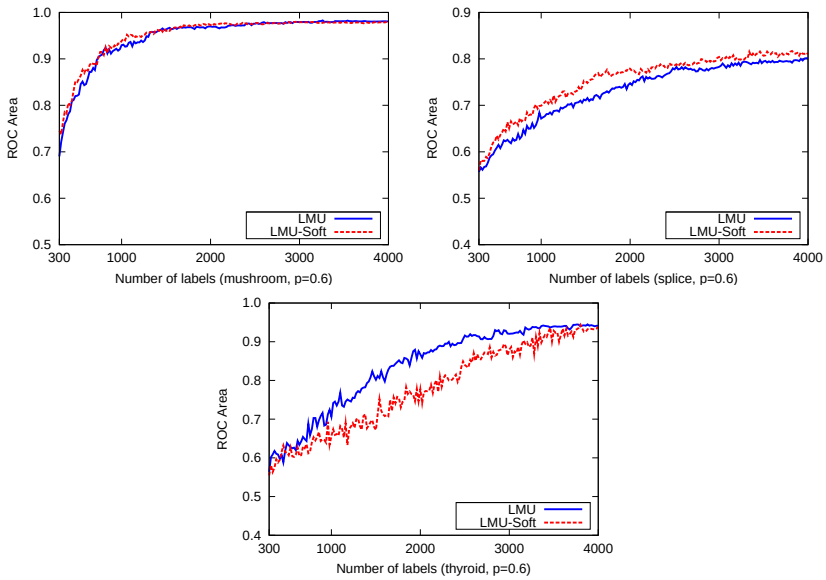


Figure 21: The accuracy improvement of soft-labeling on *LMU* on the *mushroom, splice, thyroid* data sets.

can also improve the performance of the selective repeated-labeling strategies.

So far, all selective repeated-labeling strategies always acquired new labels for the most uncertain examples, in absolute priority. Now we study the technique proposed in (Saar-Tsechansky and Provost, 2004) where an example is selected probabilistically, with a probability proportional to its uncertainty: if the uncertainty score of an example is s_i (where s_i is computed following S_{MU}, S_{LU}, S_{LMU}, S_{NLU}, S_{NLMU}), then the probability of picking that example for labeling is $\frac{s_i}{\sum_j s_j}$. Figure 22 shows the *labeling quality* of the selective repeated-labeling strategies with and without weighted sampling for the *mushroom* data set. Figure 23 shows the change of the *accuracy* of the selective repeated-labeling strategies with and without weighted sampling for the *mushroom* data set. (We only show the experimental results of the *mushroom* data set, but the results are representative across all data sets.)

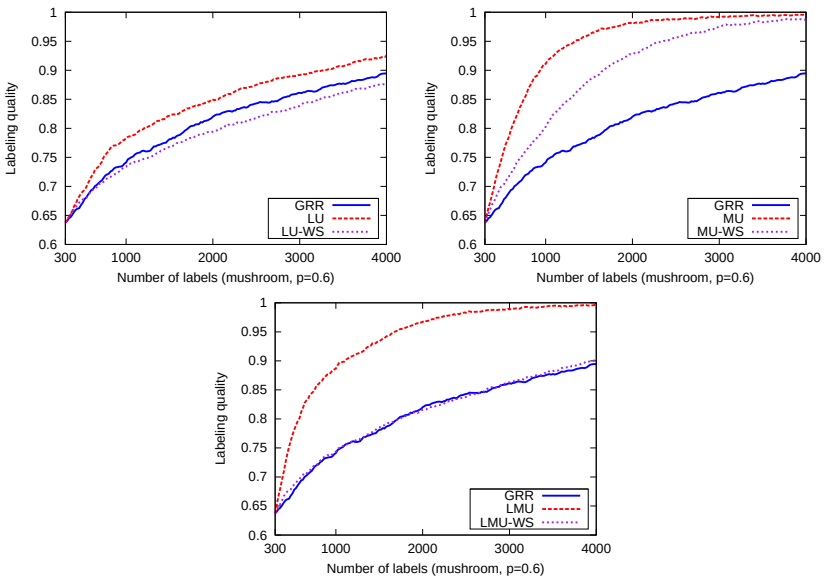


Figure 22: The labeling quality of the three selective repeated-labeling strategies with/without weighted sampling for the *mushroom* data set.

We can see that (this version of) weighted sampling does not improve the performance (labeling quality and accuracy) of the selective repeated-labeling strategies. The three selective repeated-labeling strategies with deterministic selection order perform significantly better than the ones with weighted sampling. The weighted sampling makes the three repeated-labeling strategies worse. Intuitively, this happens because weighted sampling allocates resources to examples that are only marginally uncertain. Due to the large number of examples with low uncertainty, the weighted sampling strategies end up allocating significant amount of labeling resources to re-label examples that are perfectly good and do not need any further labels. Note that the present setting is quite different from that of active learning: here we have direct, albeit noisy, information on the class of the example. Of course, there are alternative ways to use the uncertainty scores to form a sampling distribution. It may be that a version that has a sharper peak at the uncertain end of the spectrum would be effective; such tinkering is left to future work.

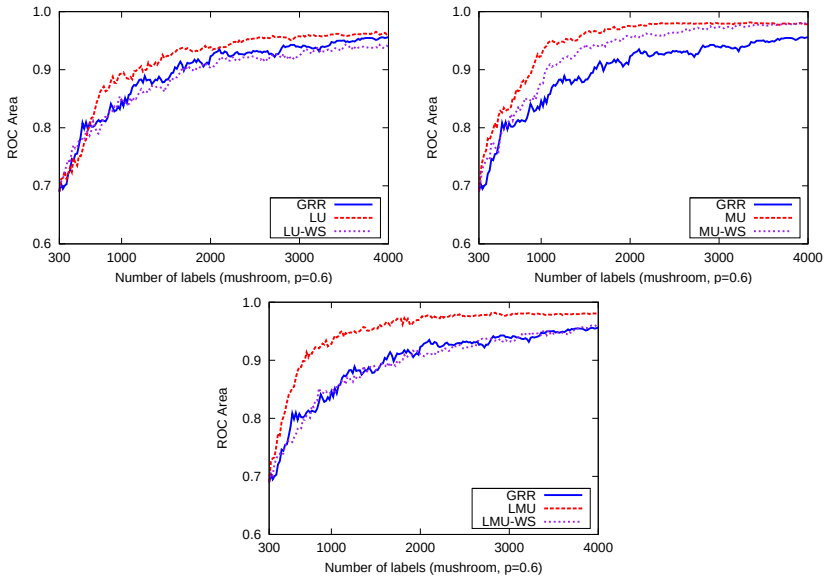


Figure 23: Accuracy of the three selective repeated-labeling strategies with/without weighted sampling for the *mushroom* data set.

7 Conclusions, Limitations, and Future Work

Repeated-labeling is a tool that should be considered whenever labeling might be noisy, but can be repeated. We showed that under a wide range of conditions, it can improve both the quality of the labeled data directly, and the quality of the models learned from the data. In particular, selective repeated-labeling seems to be preferable, taking into account both labeling uncertainty and model uncertainty.

Our focus in this paper has been on improving data quality for supervised learning; however, the results have implications for data mining generally. We showed that selective repeated-labeling improves the data quality directly and substantially. This could be helpful for many data mining applications.

This paper makes important assumptions that should be visited in future work, in order for us to understand practical repeated-labeling and realize its full benefits.

- The techniques we present can be applied no matter if the labelers have the same or different qualities. As we showed briefly in Section 3.2.2, differing qualities complicates the analysis, but suggests that labelers should have somewhat similar qualities in order that it not be better simply to estimate the labeler qualities, and use the results from the best. Furthermore, the NLU and NLMU selective labeling algorithm explicitly account for the quality of the labelers being different across different data points. We have not experimented extensively with the effects of labelers of varying qualities. Moreover, good estimates of individual labelers' qualities inferred by observing the assigned labels (Dawid and Skene, 1979; Smyth, 1996; Smyth et al, 1994b) could allow more sophisticated selective repeated-labeling strategies.

- It would be interesting to see if labelers exhibit higher quality in exchange for a higher payment. (Some recent work by (Mason and Watts, 2009) indicates that this may not be the case.) It would be interesting to observe empirically how individual labeler quality varies as we vary C_U and C_L, and to build models that dynamically increase or decrease the amounts paid to the labelers, depending on

the quality requirements of the task. Morrison and Cohen (2005) determine the optimal amount to pay for noisy information in a decision-making context, where the amount paid affects the level of noise.

- In our experiments, we introduced noise to existing, benchmark data sets. Future experiments, that use real labelers (e.g., using Mechanical Turk) should give a better understanding on how to better use repeated-labeling strategies in a practical setting. For example, in practice we expect labelers to exhibit different levels of noise and to have correlated errors; moreover, there may not be sufficiently many labelers to achieve very high confidence for any particular example.

- We also assumed that C_L and C_U are fixed and indivisible. Clearly there are domains where C_L and C_U would differ for different examples, and could even be broken down into different acquisition costs for different features. Thus, repeated-labeling may have to be considered in tandem with costly feature-value acquisition. Indeed, feature-value acquisition may be noisy as well, so one could envision a generalized repeated-labeling problem that includes both costly, noisy feature acquisition and label acquisition.

- In this paper, we consider the labeling process to be a noisy process over a *single, true label*. An alternative, practically relevant setting is where the label assignment to a case is inherently uncertain. (For example, assesments on whether a racy celebrity gossip website should be classified into an "adult-only" category or into "parental-guidance"). This is a separate setting where repeated-labeling could provide benefits, but we leave it for future analysis.

- In our repeated-labeling strategy we compared repeated-labeling vs. single labeling, and did not consider any hybrid scheme that can combine the two strategies. A promising direction for future research is to build a *"learning curve gradient"-based* approach that decides dynamically which action will give the highest marginal accuracy benefit for the cost. Such an algorithm would compare on-the-fly the expected benefit of acquiring new examples versus selectively repeated-labeling existing, noisy examples and/or features.

Despite these limitations, we hope that this study provides a solid foundation on which future work can build. Furthermore, we believe that both the analyses and the techniques introduced can have immediate, beneficial practical application.

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