Adaptive View Validation: A First Step Towards Automatic View Detection

Ion Muslea MUSLEA@ISI.EDU
University of Southern California, Information Sciences Institute, 4676 Admiralty Way, Marina del Rey, CA 90292, USA

Steven Minton MINTON@FETCH.COM
Fetch Technologies, 4676 Admiralty Way, Marina del Rey, CA 90292, USA

Craig A. Knoblock KNOBLOCK@ISI.EDU
University of Southern California, Information Sciences Institute, 4676 Admiralty Way, Marina del Rey, CA 90292, USA

Abstract

Multi-view algorithms reduce the amount of required training data by partitioning the domain features into separate subsets or *views* that are sufficient to learn the target concept. Such algorithms rely on the assumption that the views are *sufficiently compatible* for multi-view learning (i.e., *most* examples are labeled identically in all views). In practice, it is unclear whether or not two views are sufficiently compatible for solving a new, unseen learning task. In order to cope with this problem, we introduce a *view validation* algorithm: given a learning task, the algorithm predicts whether or not the views are sufficiently compatible for solving that particular task. We use information acquired while solving several exemplar learning tasks to train a classifier that discriminates between the tasks for which the views are *sufficiently* and *insufficiently compatible* for multi-view learning. Our experiments on wrapper induction and text classification show that view validation requires only a modest amount of training data to make high accuracy predictions.

1. Introduction

In a multi-view problem, one can partition the domain's features into subsets (*views*) each of which are *sufficient* for learning the target concept. For instance, one can classify segments of televised broadcasts based *either* on the video *or* on the audio information; or one can classify Web pages based on the words that appear *either* in the pages *or* in the hyperlinks pointing to them. Blum and Mitchell (1998) proved that by bootstrapping the views from each other, the target concept can be learned from a few labeled and many unlabeled examples. Their proof relies on the assumption that the views are *compatible* and *uncorrelated* (i.e., every example is identically labeled in each view; *and*, given the label of any example, its descriptions in each view are independent).

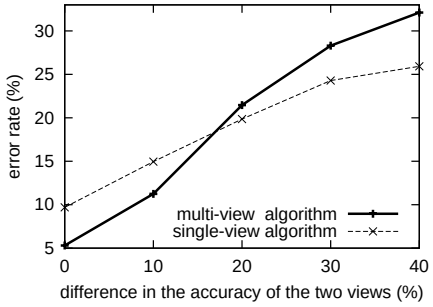

Figure 1. **As the difference in the accuracy of the two views increases, the views become more incompatible, and the single-view algorithm outperforms its multi-view counterpart.**

In real-world problems, both assumptions are often violated for a variety of reasons such as correlated or insufficient features. In a companion paper (Muslea et al., 2002), we introduced an active learning algorithm that performs well even when the independence assumption is violated. We focus here on the view incompatibility issue, which is closely related to the accuracy of the hypotheses learned in the two views: the more accurate the views, the fewer examples can be incompatible (i.e., labeled differently in the two views). Figure 1, which is based on our results in (Muslea et al., 2002), illustrates the relationship between the incompatibility of the views and the applicability of the multi-view algorithms: as the difference between the accuracy of the hypotheses learned in the two views increases (i.e., the views become more incompatible), the single-view algorithm outperforms its multi-view counterpart. This observation immediately raises the following question: for a new, unseen learning task, should we use a multi-view or a single-view learning algorithm?

The question above can be restated as follows: given two views and a set of learning tasks, how can one identify the

tasks for which these two views are *sufficiently compatible* for multi-view learning? In order to answer this question, we introduce a *view validation algorithm* that, for a given pair of views, discriminates between the tasks for which the views are *sufficiently* and *insufficiently compatible* for multi-view learning. In other words, view validation judges the usefulness of the views for a particular learning task (i.e., *it validates the views for a task of interest*).

View validation is suitable for applications such as wrapper induction (Muslea et al., 2000) and Web page classification (Blum & Mitchell, 1998), where the same views are repeatedly used to solve a variety of unrelated learning tasks. Consider, for instance, the Web page classification problem, in which the two views consist of "words that appear in Web pages" and "words in hyperlinks pointing to them". Note that, in principle, we can use these two views in learning tasks as diverse as distinguishing between homepages of *professors* and *students* or distinguishing between articles on *economics* and *terrorism*. However, for any of these learning tasks, it may happen that the text in the hyperlinks is so short and uninformative that one is better off using just the words in the Web pages. To cope with this problem, one can use view validation to predict whether or not multi-view learning is appropriate for a task of interest.

This paper presents a general, meta-learning approach to view validation. In our framework, the user provides several exemplar learning tasks that were solved using the *same views*. For each solved learning task, our algorithm generates a *view validation example* by analyzing the hypotheses learned in each view. Then it uses the `C4.5` algorithm to identify common patterns that discriminate between the learning tasks for which the views are *sufficiently* and *insufficiently compatible* for multi-view learning. An illustrative example of such a pattern is the following: "**IF** for a task T the difference in the training errors in the two views is larger than 20% *and* the views agree on less than 45% of the unlabeled examples **THEN** the views are *insufficiently compatible* for applying multi-view learning to T". We consider two application domains: text classification and wrapper induction (a commercially important multi-view problem). On both domains, the view validation algorithm makes high accuracy predictions based on a modest amount of training data.

View validation represents a first step towards our long-term goal of automatic *view detection*, which would dramatically widen the practical applicability of multi-view algorithms. Instead of having to rely on user-provided views, one can use view detection to search for adequate views among the possible partitions of the domain's features. In this context, a view validation algorithm becomes a key component that verifies whether or not the views that are generated during view detection are sufficiently compatible for applying multi-view learning to a learning task.

2. Background

2.1. Terminology

The *multi-view setting* (Blum & Mitchell, 1998) applies to learning tasks that have a natural way to partition their features into subsets (*views*), each of which are *sufficient* to learn the target concept. In such tasks, an example x is described by a different set of features in each view. For example, in a domain with two views V_1 and V_2, any example x can be seen as a triple $[x_1, x_2, l]$, where x_1 and x_2 are its descriptions in the two views, and l is its label.

A *multi-view problem* is a collection of learning tasks that use the same views; each such task is called an *instance of the multi-view problem* or a *problem instance*. To illustrate these concepts, let us reconsider the idea of classifying Web pages based on the views "words in Web pages" and "words in hyperlinks pointing to the pages". Then the multi-view problem P_1 consists of all learning tasks that use these two views. Each of these tasks (e.g., learning a classifier that distinguishes between homepages of *professors* and *students*) represents an instance of P_1.

Blum and Mitchell (1998) proved that by using two views to bootstrap each other, a target concept can be learned from a few labeled and many unlabeled examples, provided that the views are *compatible* and *uncorrelated*. The former requires that all examples are labeled identically by the target concepts in each view. The latter means that for any example $[x_1, x_2, l]$, x_1 and x_2 are independent given l.

In practice, one cannot expect two views to be sufficiently compatible and uncorrelated for *all* learning tasks. For instance, in the problem P_1 above, a problem instance may have incompatible views because the text in the hyperlinks is too short and uninformative for the text classification task. Similarly, there may be problem instances in which the views are correlated because all the words in the hyperlinks also appear in the Web pages to which they point.

2.2. Incompatible Views and Multi-view Learning

The theoretical foundation of multi-view learning (Blum & Mitchell, 1998) is based on the following idea: one can learn a weak hypothesis h_1 in V_1 based on the few labeled examples and then apply h_1 to all unlabeled examples. If the views are uncorrelated, these newly labeled examples are seen in V_2 as a random training set with classification noise, based on which one can learn the target concept in V_2. The same principle holds for some (low) level of view incompatibility, provided that the views are uncorrelated.

However, as shown in (Muslea et al., 2002), in practice one cannot ignore view incompatibility because one rarely, if ever, encounters real world domains with uncorrelated views. Intuitively, view incompatibility affects multi-view

Given:
- a learning task with two views V_1 and V_2
- a learning algorithm $\mathcal{L}$
- the sets T and U of labeled and unlabeled examples

LOOP for k iterations
- use $\mathcal{L}$, $V_1(T)$, and $V_2(T)$ to learn classifiers h_1 and h_2
- FOR EACH class C_i DO
  - let E_1 and E_2 be the e unlabeled examples on which h_1 and h_2 make the most confident predictions for C_i
  - remove E_1 and E_2 from U, label them according to h_1 and h_2,respectively, and add them to T
- combine the prediction of h_1 and h_2

Figure 2. **The Co-Training algorithm.**

learning in a straightforward manner: if the views are incompatible, the target concepts in the two views *label differently* a large number of examples. Consequently, from V_2's perspective, h_1 may "mislabel" so many examples that learning the target concept in V_2 becomes impossible.

To illustrate how view incompatibility affects an actual multi-view algorithm, let us consider Co-Training (Blum & Mitchell, 1998), which is a semi-supervised, multi-view algorithm.[1] Co-Training uses a small set of labeled examples to learn a (weak) classifier in the two views. Then each classifier is applied to all unlabeled examples, and Co-Training detects the examples on which each classifier makes the most confident predictions. These high-confidence examples are labeled with the estimated class labels and added to the training set (see Figure 2). Based on the updated training set, a new classifier is learned in each view, and the process is repeated for several iterations.

When Co-Training is applied to learning tasks with compatible views, the information exchanged between the views (i.e., the high-confidence examples) is beneficial for both views because most of the examples have the same label in each view. Consequently, after each iteration, one can expect an increase in the accuracy of the hypotheses learned in each view. In contrast, Co-Training has a poor performance on domains with incompatible views: as the difference between the accuracy of the two views increases, the low-accuracy view feeds the other view with a larger amount of mislabeled training data.

3. View Validation

In real world problems, because of corrupted or insufficient features, it is unrealistic to expect the views to be *sufficiently compatible* for applying multi-view learning to all problem instances. In order to cope with this problem, we introduce a *view validation* algorithm: for any problem instance, our algorithm predicts whether or not the views are sufficiently compatible for using multi-view learning for that particular task. In this section we first describe our view validation algorithm, and then we present the features used for view validation.

[1] View incompatibility affects in a similar manner other semi-supervised, multi-view algorithms such as Co-EM (Nigam & Ghani, 2000) or Co-Boost(Collins & Singer, 1999).

Given:
- a multi-view problem P with views V_1 and V_2
- a learning algorithm $\mathcal{L}$
- a set of pairs $\{ \langle I_1, L_1 \rangle, \langle I_2, L_2 \rangle, \ldots, \langle I_n, L_n \rangle \}$, where I_k are instances of P, and L_k labels I_k as having or not views that are *sufficiently compatible* for multi-view learning

FOR each instance I_k DO
- let T_k and U_k be labeled and unlabeled examples in I_k
- use $\mathcal{L}$, $V_1(T_k)$, and $V_2(T_k)$ to learn classifiers h_1 and h_2
- $CreateViewValidationExample(h_1, h_2, T_k, U_k, L_k)$

- train C4.5 on the view validation examples
- use the learned classifier to discriminates between problem instances for which the views are *sufficiently* and *insufficiently compatible* for multi-view learning

Figure 3. **The View Validation Algorithm.**

3.1. The View Validation Algorithm

In practice, the level of "acceptable" view incompatibility depends on both the domain features and the algorithm $\mathcal{L}$ that is used to learn the hypotheses in each view. Consequently, in our approach, we apply view validation to a given multi-view problem (i.e., pair of views) and learning algorithm $\mathcal{L}$. Note that this is a natural scenario for multi-view problems such as text classification and wrapper induction, in which the same views are used for a wide variety of learning tasks.

Our view validation algorithm (see Figure 3) implements a three-step process. First, the user provides several pairs $\langle I_k, L_k \rangle$, where I_k is a problem instance, and L_k is a label that specifies whether or not the views are sufficiently compatible for using multi-view learning to solve I_k. The label L_k is generated automatically by comparing the accuracy of a single- and multi-view algorithm on a test set. Second, for each instance I_k, we generate a *view validation example* (i.e., a feature-vector) that describes the properties of the hypotheses learned in the two views. Finally, we apply C4.5 to the view validation examples; we use the learned decision tree to discriminate between learning tasks for which the views are sufficiently or insufficiently compatible for multi-view learning,

In keeping with the multi-view setting, we assume that for each instance I_k the user provides a (small) set T_k of labeled examples and a (large) set U_k of unlabeled examples. For each instance I_k, we use the labeled examples in T_k to learn a hypothesis in each view (i.e., h_1 and h_2). Then we generate a *view validation example* that is labeled L_k

and consists of a feature-vector that describes the hypotheses h_1 and h_2. In the next section, we present the actual features used for view validation.

3.2. Features Used for View Validation

Ideally, besides the label L_k, a *view validation example* would consist of a single feature: the percentage of examples that are labeled differently in the two views. Based on this unique feature, one could learn a *threshold value* that discriminates between the problem instances for which the views are sufficiently/insufficiently compatible for multi-view learning. In Figure 1, this threshold corresponds to the point in which the two learning curves intersect. In practice, using this unique feature requires knowing the labels of *all* examples in a domain. As this is an unrealistic scenario, we have chosen instead to use several features that are indicators of the how incompatible the views are.

In this paper, each view validation example is described by the following seven features:

- f_1: the percentage of unlabeled examples in U_k that are classified identically by h_1 and h_2;
- f_2: $min(TrainingErrors(h_1), TrainingErrors(h_2))$;
- f_3: $max(TrainingErrors(h_1), TrainingErrors(h_2))$;
- f_4: $f_3 - f_2$;
- f_5: $min(Complexity(h_1), Complexity(h_2))$;
- f_6: $max(Complexity(h_1), Complexity(h_2))$;
- f_7: $f_6 - f_5$.

Note that features f_1-f_4 are measured in a straightforward manner, regardless of the algorithm $\mathcal{L}$ used to learn h_1 and h_2. By contrast, features f_5-f_7 dependent on the representation used to describe these two hypotheses. For instance, the complexity of a boolean formula may be expressed in terms of the number of disjuncts and literals in the disjunctive or conjunctive normal form; or, for a decision tree, the complexity measure may take into account the depth and the breadth (i.e., number of leaves) of the tree.

The intuition behind the features f_1-f_7 is the following:

- the fewer unlabeled examples from U_k are labeled identically by h_1 and h_2, the larger the number of potentially incompatible examples;
- the larger the difference in the training error of h_1 and h_2, the less likely it is that the views are equally accurate;
- the larger the difference in the complexity of h_1 and h_2, the likelier it is that the most complex of the two hypotheses overfits the (small) training set T_k. In turn, this may indicate that the corresponding view is significantly less accurate than the other one.

In practice, features f_1-f_4 are measured in a straightforward manner; consequently, they can be always used in the view validation process. In contrast, measuring the complexity of a hypothesis may not be always possible or meaningful (consider, for instance, the case of a Naive Bayes or a k nearest-neighbor classifier, respectively). In such situations, one can simply ignore features f_5-f_7 and rely on the remaining features.

4. The Test Problems for View Validation

We describe now the two problems that we use as case studies for view validation. First we present the *wrapper induction* problem, which consists of a collection 33 information extraction tasks that originally motivated this work. Then we describe a family of 60 parameterized text classification tasks (for short, PTCT) that we used in (Muslea et al., 2002) to study the influence of view incompatibility and correlation on multi-view learning algorithms.

4.1. Multi-View Wrapper Induction

To introduce our approach to wrapper induction (Muslea et al., 2000), let us consider the illustrative task of extracting phone numbers from documents similar to the Web-page fragment in Figure 4. In our framework, an *extraction rule* consists of a *start rule* and an *end rule* that identify the beginning and the end of the item, respectively; given that start and end rules are extremely similar, we describe here only the former. For instance, in order to find the beginning of phone number, we can use the start rule

R1 = $SkipTo$**(** `Phone:<i>` **)**.

This rule is applied *forward*, from the beginning of the page, and it ignores everything until it finds the string `Phone:<i>`. For a slightly more complicated extraction task, in which only the toll-free numbers appear in italic, one can use a disjunctive start rule such as

R1′ = EITHER $SkipTo$**(** `Phone:<i>` **)**
OR $SkipTo$**(** `Phone:` **)**

An alternative way to detect the beginning of the phone number is to use the start rule

R2 = $BackTo$**(** `Cuisine` **)** $BackTo$**(** ($Number$) **)**

which is applied *backward*, from the end of the document. **R2** ignores everything until it finds "`Cuisine`" and then, again, skips to the first number between parentheses.

As described in (Muslea et al., 2001), rules such as **R1** and **R2** can be learned based on user-provided examples of items to be extracted. Note that **R1** and **R2** represent

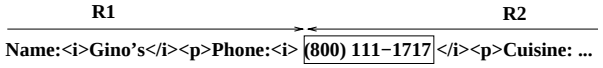

Figure 4. **Extracting the phone number.**

descriptions of the same concept (i.e., start of phone number) that are learned in two different views. That is, the views V_1 and V_2 consist of the sequences of characters that *precede* and *follow* the beginning of the item, respectively.

For wrapper induction, the view validation features are measured as follows: f_1 represents that percentage of (unlabeled) documents from which the two extraction rules extract the same string; for f_2-f_4, we count the labeled documents from which the extraction rules do not extract the correct string. Finally, to measure f_5-f_7, we define the complexity of an extraction rule as the maximum number of disjuncts that appear in either the start or the end rule.

4.2. Multi-View Text Classification

As a second case study, we use the PTCT family of parameterized text categorization tasks described in (Muslea et al., 2002).[2] PTCT contains 60 text classification tasks that are evenly distributed over five levels of view incompatibility: 0%, 10%, 20%, 30%, or 40% of the examples in a problem instance are made incompatible by corrupting the corresponding percentage of labels in one of the views.

PTCT is a text classification domain in which one must predict whether or not various newsgroups postings are of interest for a particular user. In PTCT, a multi-view example's description in each view consists a document from the `20-Newsgroups` dataset (Joachims, 1996). Consequently, we use the Naive Bayes algorithm (Nigam & Ghani, 2000) to learn the hypotheses in the two views. As there is no obvious way to measure the complexity of a Naive Bayes classifier, for PTCT we do not use the features f_5-f_7. The other features are measured in a straightforward manner: f_1 represents the percentage of unlabeled examples on which the two Naive Bayes classifiers agree, while f_2-f_4 are obtained by counting the training errors in the two views.

5. Empirical Results

5.1. Generating the WI and PTCT Datasets

To label the 33 problem instances for wrapper induction (WI), we compare the single-view STALKER algorithm (Muslea et al., 2001) with its multi-view version described in (Muslea et al., 2000). On the six extraction tasks in which the difference in the accuracy of the rules learned in the two views is larger than 10%, single-view STALKER does at least as well as its multi-view counterpart. We label these six problem instances as having views that are insufficiently compatible for multi-view learning.

In order to label the 60 instances in PTCT, we compare single-view, semi-supervised EM with Co-Training, which is the most widely used semi-supervised multi-view algorithm (Collins & Singer, 1999) (Pierce & Cardie, 2001) (Sarkar, 2001). We use the empirical results from (Muslea et al., 2002) to identify the instances on which semi-supervised EM performs at least as well as Co-Training. We label the 40 such instances as having views that are insufficiently compatible for multi-view learning.

For both WI and PTCT, we have chosen the number of examples in T_k (i.e., $Size(T_k)$) according to the experimental setups described in (Muslea et al., 2001) and (Muslea et al., 2002), in which WI and PTCT were introduced. For WI, in which an instance I_k may have between 91 and 690 examples, $Size(T_k)$=6 and U_k consists of the remaining examples. For PTCT, where each instance consists of 800 examples, the size of T_k and U_k is 70 and 730, respectively.

5.2. The Setup

In contrast to the approach described in Figure 3, where a *single* view validation example is generated per problem instance, in our experiments we create *several* view validation examples per instance. That is, for each instance I_k, we generate $ExsPerInst = 20$ view validation examples by repeatedly partitioning the examples in I_k into randomly chosen sets T_k and U_k of the appropriate sizes. The motivation for this decision is two-fold. First, the empirical results should not reflect a particularly (un)fortunate choice of the sets T_k and U_k. Second, if we generate a single view validation example per instance, for both WI and PTCT we obtain a number of view validation examples that is too small for a rigorous empirical evaluation (i.e., 33 and 60, respectively). To conclude, by generating $ExsPerInst = 20$ view validation examples per problem instance, we obtain larger number of view validation examples (660 and 1200, respectively) that, for each problem instance I_k, are representative for a wide variety of possible sets T_k and U_k.

To evaluate view validation's performance, for both WI and PTCT, we partition the problem instances into *training* and *test instances*. For each such partition, we create the *training* and *test sets* for `C4.5` as follows: all $ExsPerInst = 20$ view validation examples that were created for a *training instance* are used in the `C4.5` *training set*; similarly, all 20 view validation examples that were created for a *test instance* are used in the `C4.5` *test set*. In other words, all view validation examples that are created based on the same problem instance belong either to the training set or to the test set, and they cannot be split be-

[2] We would have preferred to use a real-world multi-view problem instead of PTCT. Unfortunately, given that multi-view learning represents a relatively new field of study, most multi-view algorithms were applied to just a couple problem instances.

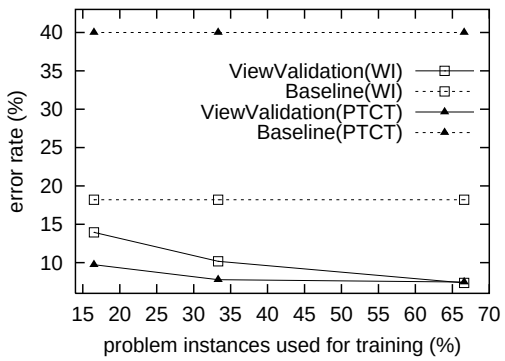

Figure 5. **View validation clearly outperforms a baseline algorithm that predicts the most frequent label.**

tween the two sets. In our experiments, we train on $\frac{1}{6}$, $\frac{1}{3}$, and $\frac{2}{3}$ of the instances and test on the remaining ones. For each of these three ratios, we average the error rates obtained over $N = 20$ random partitions of the instances into training and test instances.

Figure 5 shows the view validation results for the WI and PTCT datasets. The empirical results are excellent: when trained on 66% of the available instances, the view validation algorithm reaches an accuracy of 92% on both the WI and PTCT datasets. Furthermore, even when trained on just 33% of the instances (i.e., 11 and 20 instances for WI and PTCT, respectively), we still obtain a 90% accuracy. Last but not least, for both WI and PTCT, view validation clearly outperforms a baseline algorithm that simply predicts the most frequent label in the corresponding dataset.

5.3. The Influence of $ExsPerInst$ and $Size(T_k)$

The results in Figure 5 raise an interesting practical question: how much can we reduce the user's effort without harming the performance of view validation? In other words, can we label only a fraction of the $ExsPerInst$ view validation examples per problem instance and a subset of T_k, and still obtain a high-accuracy prediction? To answer this question, we designed two additional experiments in which we vary one of the parameters at the time.

To study the influence of the $ExsPerInst$ parameter, we keep $Size(T_k)$ constant (i.e., 6 and 70 for WI and PTCT, respectively), and we consider the values $ExsPerInst = 1, 5, 10, 20$. That is, rather than including all 20 view validation examples that we generate for each instance I_k, the `C4.5` training sets consist of (randomly chosen) subsets of one, five, 10, or 20 view validation examples for each training instance. Within the corresponding `C4.5` test sets, we continue to use all 20 view validation examples that are available for each test instance.

Figure 6 displays the learning curves obtained in this experiment. The empirical results suggest that the benefits of increasing $ExsPerInst$ become quickly insignificant: for both WI and PTCT, the difference between the learning curves corresponding to $ExsPerInst = 10$ and 20 is not statistically significant, even though for the latter we use twice as many view validation examples than for the former. This implies that a (relatively) small number of view validation examples is sufficient for high-accuracy view validation. For example, our view validation algorithm reaches a 90% accuracy when trained on 33% of the problem instances (i.e., 11 and 20 training instances, for WI and PTCT, respectively). For $ExsPerInst = 10$, this means that `C4.5` is trained on just 110 and 200 view validation examples, respectively.

In order to study the influence of the $Size(T_k)$ parameter, we designed an experiment in which the hypotheses h_1 and h_2 are learned based on a fraction of the examples in the original set T_k. Specifically, for WI we use two, four, and six of the examples in T_k; for PTCT we use 20, 30, 40, 50, 60, and 70 of the examples in T_k. For both WI and PTCT, we keep $ExsPerInst = 20$ constant.

Figure 7 shows the learning curves obtained in this experiment. Again, the results are extremely encouraging: for both WI and PTCT we reach an accuracy of 92% without using all examples in T_k. For example, the difference between $Size(T_k) = 4$ and 6 (for WI) or $Size(T_k) = 60$ and 70 (for PTCT) are *not* statistically significant.

The experiments above suggest two main conclusions. First, for both WI and PTCT, the view validation algorithm makes high accuracy predictions. Second, our approach requires a modest effort from the user's part because both the number of view validation examples and the size of the training sets T_k are reasonably small.

5.4. Understanding the Predictions

In practice, it is important to provide users with the intuition behind a view validation prediction. The decision trees learned by `C4.5` are extremely useful with this respects. Figure 8 shows two illustrative pruned decision trees (one for each domain) that were learned using 66% of the problem instances. For each node in the trees, we show the following information: the view validation feature used to make the decision (i.e., one of the seven features described in Section 4); the error rate on the test set; and the number of test examples that are classified based on the node's descendents.

Consider, for instance, the PTCT decision tree, which misclassifies 4.5% of the 400 test examples (see the tree's root). The decision tree reads as follows: if the hypotheses h_1 and h_2 agree on more than 62% of the unlabeled examples in U_k (i.e., if $f_1 > 62\%$), then the problem instance has views that are sufficiently compatible for multi-view

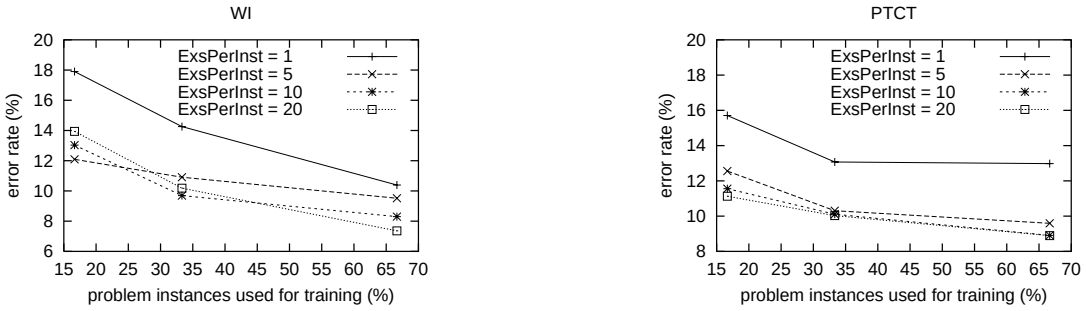

Figure 6. **We keep $Size(T_k)$ constant and vary the value of $ExsPerInst$ (1, 5, 10, and 20).**

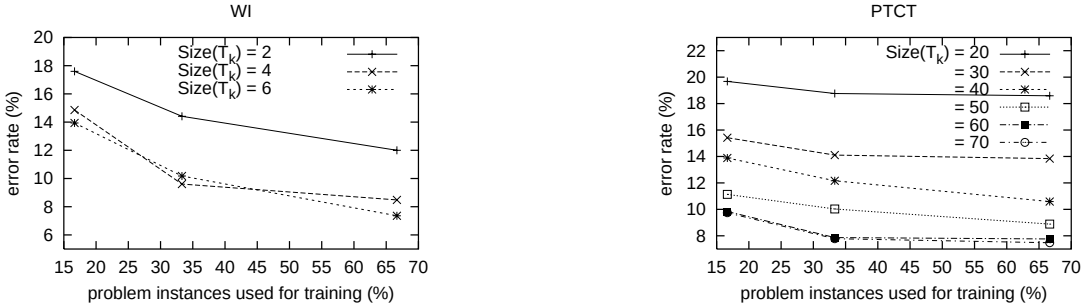

Figure 7. **For $ExsPerInt = 20$, we consider several values for $Size(T_k)$: 2/4/6 for WI, and 20/30/40/50/60/70 for PTCT.**

learning. Based on this criterion, 150 of the 400 examples are labeled "sufficiently compatible", with an error rate of 2.67% (i.e., only four examples are misclassified).

If the two hypotheses agree on at most 59% of the unlabeled examples (i.e., $f_1 \leq 59\%$), the views are insufficiently compatible for learning. Finally, if the agreement level is between 59% and 62%, the decision is taken based on the feature f_4: the views are sufficiently compatible if and only if the difference in training error in the two views is larger than 10% (i.e., seven of the 70 examples in T_k). This counter-intuitive decision, which is due to overfitting, produces half the errors on the entire test set (i.e., nine of the 18 misclassified examples).

6. Limitations and Future Work

In this section we discuss the limitations of our algorithm and possible approaches to address them. First, view validation can be applied only to problems in which the same views are used to solve a large number of learning tasks. For wrapper induction, which motivates our work, this is a natural scenario: we currently maintain a library of almost 900 extraction tasks, and we add several dozen new tasks each month. For scenarios in which one tries to solve a *single* instance of a *new* multi-view problem, view validation cannot be applied. To address this issue, we plan to investigate the use of training sets that consist of labeled instances from several multi-view problems that use the same learning algorithm $\mathcal{L}$ (see Figure 2).

Second, we applied view validation only to the two multi-view problems for which there is a large collection of learning tasks. In order perform additional experiments, we plan to collect data for several other problems, such as Web page classification (Blum & Mitchell, 1998), advertisement removal and discourse tree parsing (Muslea et al., 2000). These problems share a common trait: their views can be used to solve hundreds of real world learning tasks. We expect view validation to be successful on such problems because the decision trees learned in our experiments correspond to a powerful intuition: if the views are compatible, the hypotheses learned in each view should agree on many unlabeled examples, and they should have similar complexity and training errors.

Third, in this paper we used only seven view validation features. We are investigating several additional features that describe the dynamics of the learning process in each view. More precisely, we partition the training set T_k in several subsets, and we record the changes in the values of features f_1-f_7 as more of these subsets are used for training. Intuitively, these new features monitor the difference in the speed of convergence towards the target concept in each view. Preliminary experiments indicate that the additional features reduce the error rate by almost 50%.

Finally, to broaden the practical applicability of view validation, we plan to reduce the number of labeled problem

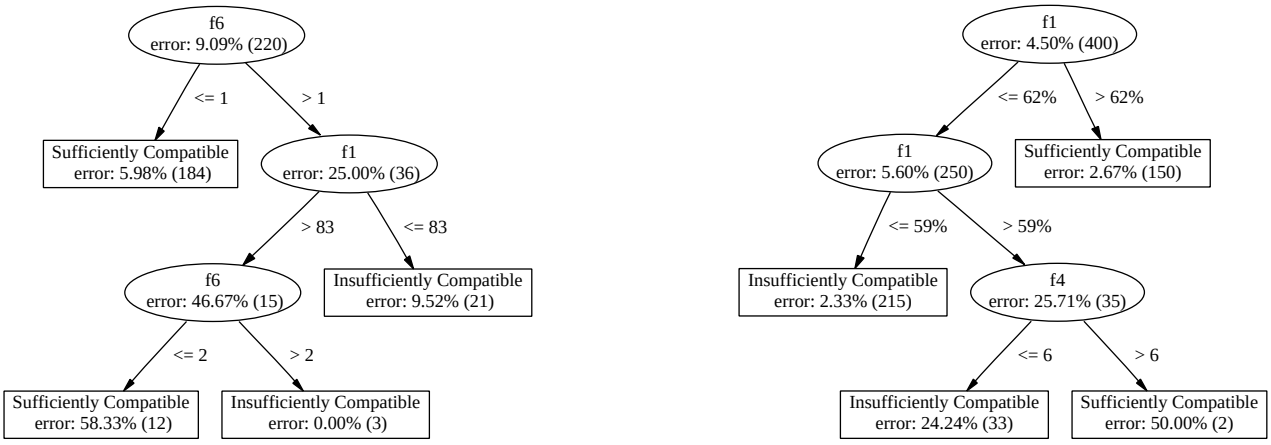

Figure 8. **Illustrative trees for** WI **(left) and** PTCT **(right).**

instances required for training. We intend to replace the C4.5 algorithm in Figure 3 with a semi-supervised algorithm that combines both labeled and unlabeled examples, thus reducing the need for labeled problem instances.

7. Conclusions

In this paper we describe the first approach to view validation. We use several solved problem instances to train a classifier that discriminates between instances for which the views are *sufficiently/insufficiently compatible* for multi-view learning. For both wrapper induction and text classification, view validation requires a modest amount of training data to make high-accuracy predictions. View validation represents a first step towards our long-term goal to create a *view detection* algorithm that partitions the domain's features in views that are adequate for multi-view learning.

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