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Partial data querying through racing algorithms

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Abstract

The paper studies the problem of actively learning from instances characterized by imprecise features or imprecise class labels, where by actively learning we understand the possibility to query the precise value of imprecisely specified data. We differ from classical active learning by the fact that in the later, data are either fully precise or completely missing, while in our case they can be partially specified. Such situations can appear when sensor errors are important to encode, or when experts have only specified a subset of possible labels when tagging data. We provide a general active learning technique that can be applied in principle to any model. It is inspired from racing algorithms, in which several models are competing against each others. The main idea of our method is to identify the query that will be the most helpful in identifying the winning model in the competition. After discussing and formalizing the general ideas of our approach, we illustrate it by studying the particular case of binary SVM in the case of interval valued features and set-valued labels. The experimental results indicate that, in comparison to other baselines, racing algorithms provide a faster reduction of the uncertainty in the learning process, especially in the case of imprecise features.

Keywords: partial data, interval-valued data, set-valued labels, data querying, active learning, racing algorithms

1. Introduction

Although classical learning schemes assume that every instance is fully specified, there are situations where such an assumption is unlikely to hold, and where the data can be qualified of *partial* or *imprecise*. By “partial data”, we refer to the situation where either some features or the labels are imperfectly known, that is are specified by sets of possible values rather than a precise one. For example, when the label of some training instances is only known to belong to a set of labels, or when some features are imprecisely given in the form of intervals.

Classical statistical solutions to solve this problem include the use of different imputation techniques [5] or the use of likelihood-based techniques such as the

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20 EM algorithm [4] and its extensions. The use of such techniques however implies
21 to satisfy specific statistical assumptions about the missingness process (e.g.,
22 missing-at-random assumption), that can be very hard or impossible to check
23 in practice, especially since we do not have access to the original precise data.
24 More recently, the problem of learning from partial data has gained an increasing
25 interest within the machine learning community, and many methods [2, 3, 10]
26 that have shown their efficiency for different problems have been developed.
27 Yet, even if these methods can handle partial data, their performances usually
28 degrade as data become more and more partial or imprecise, as more and more
29 uncertainty is present in the learning process.

30 This work explores the following question about learning from partial data: if
31 we have the possibility to gain more information on some of the partial instances,
32 which instance and what feature of this instance should we query? In the
33 case of a completely missing label (and to a lesser extent of missing features),
34 this problem known as active learning has already been largely treated [16]
35 and applied in different fields like natural language processing, text or image
36 classification, recommender systems [6, 14, 23, 19]. However, we are not aware
37 of similar works concerning the case of partial data. Note that for the case of
38 features, there is even very few active learning methods addressing the problem
39 of missing features. In this work, we provide a new general active learning
40 technique that can be applied in principle to any model and partially missing
41 input/features, and illustrate it on the case of SVM. It is inspired from the
42 concept of racing algorithms [12], in which several models are competing against
43 each others. They were initially introduced to select an optimal configuration
44 of a given lazy learning model (e.g., K-nn methods), and since then have been
45 applied to other settings such as multi-armed bandits [9]. The idea of such
46 racing algorithms is to oppose a (finite) set of alternatives in a race, and to
47 progressively discard losing ones as the race goes along. In our case, the set
48 of alternatives will be different possible models, and the race will consist in
49 iteratively querying the precise value of some partial features or labels. Indeed,
50 as data are partial, the performance of each model is uncertain and several
51 candidate models can be optimal. By iteratively making queries, i.e. asking to
52 an oracle the precise value of a partial data, these performances will become less
53 and less uncertain, and more models will be discarded from the race. The key
54 question is then to identify those data that will be the most helpful in reducing
55 the set of possible winners in the race, in order to converge as quickly as possible
56 to the optimal model.

57 The rest of this paper is organized as follows: we present in Section 2 the
58 basic notations used in this paper. Section 3 introduces the general principles
59 of racing algorithms and formalizes the problem of quantifying the influence of
60 a query on the race. We then study the application of our approach using the
61 particular case of a binary SVM. Section 4 is focused on interval-valued features,
62 while Section 5 explores the case of set-valued labels. Some experiments are
63 then performed in Section 6 to demonstrate the effectiveness of our proposals.
64 Before concluding the paper, Section 7 discusses some computational issues
65 of the presented approaches, generalizing some of the results concerning SVM

66 method. Note that this paper is an extension of [13], with full proofs, larger
 67 experiments as well as the addition of the set-valued label case for binary SVM
 68 and a discussion about the complexity of the approach.

69 2. Preliminaries

In classical supervised setting, the goal of the learning approach is to find a model $m : \mathcal{X} \rightarrow \mathcal{Y}$ within a set \mathcal{M} of models from a set $\mathbf{D} = \{(\mathbf{x}_i, y_i) \in \mathcal{X} \times \mathcal{Y} \mid i = 1, \dots, n\}$ of n input/output samples, where \mathcal{X} and \mathcal{Y} are respectively the input and the output spaces¹. The empirical risk $R(m)$ associated to a model m is then evaluated as

$$R(m) = \sum_{i=1}^n \ell(y_i, m(\mathbf{x}_i)) \quad (1)$$

where $\ell : \mathcal{Y} \times \mathcal{Y} \rightarrow \mathbb{R}$ is the loss function, and $\ell(y, m(\mathbf{x}))$ is the loss of predicting $m(\mathbf{x})$ when observing y . The selected model is then the one minimizing (1), that is

$$m^* = \arg \min_{m \in \mathcal{M}} R(m). \quad (2)$$

Another way to see the model selection problem that will be useful in this paper is to assume that a model m_l is said to be better than m_k (denoted $m_l \succ m_k$) if

$$R(m_k) - R(m_l) > 0, \quad (3)$$

70 or in other words if the risk of m_l is lower than the risk of m_k . Given the
 71 relation \succ on \mathcal{M} , Equation (1) then simply amounts to take as best model the
 72 maximal element of \succ , or in case of equality due to indifference, one of the
 73 maximal model chosen arbitrarily.

In this work, we are however interested in the case where data are partial, that is where general samples are of the kind $(\mathbf{X}_i, Y_i) \subseteq \mathcal{X} \times \mathcal{Y}$. Here and in the rest of this paper, capital letters are used for partial data and small letters will denote precise one, and bold letters will represent vectors and Cartesian products of feature values. When the data is partial, Equations (1), (2) and (3) are no longer well-defined, and can be extended in multiple different ways. Two of the most common ways to extend them is either to use a minimin (optimistic) or a maximin (pessimistic) approach [20, 22]. That is, if we extend Equation (1) to a lower bound

$$\begin{aligned} \underline{R}(m) &= \inf_{(\mathbf{x}_i, y_i) \in (\mathbf{X}_i, Y_i)} \sum_{i=1}^n \ell(y_i, m(\mathbf{x}_i)) \\ &= \sum_{i=1}^n \inf_{(\mathbf{x}_i, y_i) \in (\mathbf{X}_i, Y_i)} \ell(y_i, m(\mathbf{x}_i)) := \sum_{i=1}^n \underline{\ell}(Y_i, m(\mathbf{X}_i)) \end{aligned} \quad (4)$$

¹As \mathcal{X} is often multi-dimensional, we will denote its elements and subsets by bold letters.

and an upper bound

$$\begin{aligned} \bar{R}(m) &= \sup_{(\mathbf{x}_i, y_i) \in (\mathbf{X}_i, Y_i)} \sum_{i=1}^n \ell(y_i, m(\mathbf{x}_i)) \\ &= \sum_{i=1}^n \sup_{(\mathbf{x}_i, y_i) \in (\mathbf{X}_i, Y_i)} \ell(y_i, m(\mathbf{x}_i)) := \sum_{i=1}^n \bar{\ell}(Y_i, m(\mathbf{X}_i)) \end{aligned} \quad (5)$$

then the optimal minimin m_{mm}^* and maximin m_{Mm}^* models are

$$m_{mm}^* = \arg \min_{m \in \mathcal{M}} \underline{R}(m) \quad \text{and} \quad m_{Mm}^* = \arg \min_{m \in \mathcal{M}} \bar{R}(m).$$

74 The minimin approach usually assumes that data are distributed according to
 75 the model, and tries to find the best data replacement (or disambiguation)
 76 combined with the best possible model [10]. Conversely, the maximin approach
 77 assumes that data are distributed in the worst possible way, and select the
 78 model performing the best in the worst situation, thus guaranteeing a minimal
 79 performance of the model [21]. However, such an approach, due to the overly
 80 conservative nature of its assumptions, will often lead to sub-optimal model, so
 81 we will prefer the first principle.

It should be noted that both the minimin and maximin approaches lead to choose a unique optimal model, despite the uncertainty present in the data. Our work focuses on a different approach, where we do not search for an optimal model right away, but rather consider sets of potentially optimal models to then try to identify the best one through querying. In this case, we consider that a model m_l is better than m_k (still denoted $m_l \succ m_k$) if

$$\underline{R}(m_{k-l}) = \inf_{(\mathbf{x}_i, y_i) \in (\mathbf{X}_i, Y_i)} R(m_k) - R(m_l) > 0, \quad (6)$$

which is a direct extension of Equation (3). That is, $m_l \succ m_k$ if and only if it is better under every possible precise replacement (\mathbf{x}_i, y_i) consistent with the partial instances (\mathbf{X}_i, Y_i) . We can then denote by

$$\mathcal{M}^* = \{m \in \mathcal{M} : \nexists m' \in \mathcal{M} \text{ s.t. } m' \succ m\} \quad (7)$$

82 the set of undominated models within \mathcal{M} , that is the set of models that are
 83 maximal with respect to the partial order \succ . The practical computation of (4)-
 84 (6) depends on the type of classifier considered in the race and will be explained
 85 in details in section 4 for the particular case of binary SVM.

86 *Example 1.* Figure 1 illustrates a situation where \mathcal{Y} consists of two different
 87 classes (grey and white), and \mathcal{X} of two dimensions. Only imprecise data are
 88 numbered: squares are assumed to have precise features, and unknown labels are
 89 represented by striped squares (i.e., a data with partial label and features would
 90 be a striped rectangle). Assuming that we only have two models $\mathcal{M} = \{m_1, m_2\}$
 91 to compare (the models in Figure 1 could be decision stumps, or one-level deci-
 92 sion trees), we would choose $m_2 = m_{Mm}^*$ as the maximin model and $m_1 = m_{mm}^*$
 93 as the minimin one. The two models would however be incomparable according
 94 to (6), as both $\underline{R}(m_{1-2})$ and $\underline{R}(m_{2-1})$ are negative, hence $\mathcal{M}^* = \mathcal{M}$ in this case.
 95 The rest of the paper then deals with the data to query in order to reduce \mathcal{M}^*

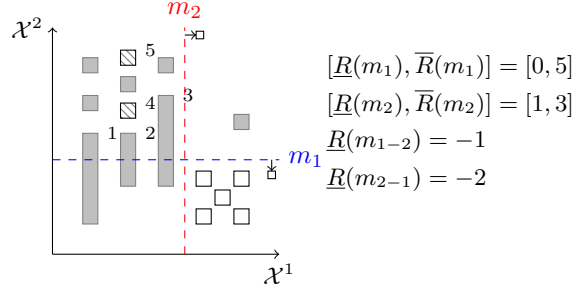


Figure 1: Illustration of partial data and competing models

96 3. Partial data querying: a racing approach

97 Both the minimin and maximin approaches pursue the same goal: obtaining
 98 a unique model from partially specified data. In this sense, they are quite close
 99 to approaches using imputation or EM algorithms. The idea we defend in this
 100 paper is different: we want to identify and query those data that will be the most
 101 helpful in reducing the set \mathcal{M}^* . In order to this, we will try to quantify how
 102 useful an information is to decide what is the best model among those in \mathcal{M}^* .
 103 We will now formalise this idea. We first assume that $\mathcal{X} = \mathcal{X}^1 \times \dots \times \mathcal{X}^p$ is a
 104 Cartesian product of p spaces, and that a partial data (\mathbf{X}_i, Y_i) can be expressed
 105 as $(\times_{j=1}^p X_i^j, Y_i)$, and furthermore that if $\mathcal{X}^j \subseteq \mathbb{R}$ is a subset of the real line,
 106 then X_i^j is an interval. The data who have imprecise features in Figure 1 could
 107 be of this kind.

A query on a partial data $(\times_{j=1}^p X_i^j, Y_i)$ consists in transforming one of its di-
 mension X_i^j or Y_i into the true precise value (x_i^j or y_i) provided by an oracle (an
 expert, a precise measuring device). More precisely, Q_i^j denotes the query made
 on X_i^j or Y_i , with $j = p + 1$ for Y_i . Given a model m_l and a data $(\times_{j=1}^p X_i^j, Y_i)$,
 the result of a query can have an effect on the interval $[\underline{R}(m_l), \overline{R}(m_l)]$, depend-
 ing on whether it changes the interval $[\underline{\ell}(Y_i, m_l(\mathbf{X}_i)), \overline{\ell}(Y_i, m_l(\mathbf{X}_i))]$. Similarly,
 when assessing whether the model m_l is preferred to m_k , the query can have
 an influence on the value $\underline{R}(m_{k-l})$ or not. We formalise this by two functions,
 $E_{Q_i^j} : \mathcal{M} \rightarrow \{0, 1\}$ and $J_{Q_i^j} : \mathcal{M} \times \mathcal{M} \rightarrow \{0, 1\}$ such that:

$$E_{Q_i^j}(m_l) = \begin{cases} 1 & \text{if } \exists x_i^j \in X_i^j \text{ that reduces } [\underline{R}(m_l), \overline{R}(m_l)] \\ 0 & \text{else} \end{cases} \quad (8)$$

and

$$J_{Q_i^j}(m_k, m_l) = \begin{cases} 1 & \text{if } \exists x_i^j \in X_i^j \text{ that increases } \underline{R}(m_{k-l}) \\ 0 & \text{else.} \end{cases} \quad (9)$$

108 When $j = p + 1$, X_i^j is to be replaced by Y_i . $E_{Q_i^j}(m_l)$ simply tells us whether
 109 or not the query can affect our evaluation of the model m_l , while $J_{Q_i^j}(m_k, m_l)$
 110 informs us whether the query can help to tell apart m_l from m_k .

111 *Example 2.* In Figure 1, questions related to partial classes (points 4 and 5)
 112 and to partial features (points 1, 2 and 3) have respectively the same potential
 113 effect, so we can restrict our attention to Q_4^3 (the class of point 4) and to Q_1^2
 114 (the second feature of point 1). For these two questions, we have

115 - $E_{Q_4^3}(m_1) = E_{Q_4^3}(m_2) = 1$ and $J_{Q_4^3}(m_1, m_2) = J_{Q_4^3}(m_2, m_1) = 0$.

116 - $E_{Q_1^2}(m_1) = 1$, $E_{Q_1^2}(m_2) = 0$ and $J_{Q_1^2}(m_1, m_2) = J_{Q_1^2}(m_2, m_1) = 1$.

117 This example shows that while some questions may reduce our uncertainty about
 118 many model risks (Q_4^3 reduce risk intervals for both models), they may be less
 119 useful than other questions to tell two models apart (Q_1^2 can actually lead to
 120 declare m_2 better than m_1), hence it is useful to consider both individual and
 121 pairwise effects of a unique query.

122 Following the idea of racing algorithms, which concentrate on the best po-
 123 tential model, Definitions (8) and (9) allow us to define the value of query as
 124 follows:

Definition 1. Given m_{k^*} the best current potential model, the value of a query Q_i^j is defined as

$$\text{Value}(Q_i^j) = E_{Q_i^j}(m_{k^*}) + \sum_{k \neq k^*} J_{Q_i^j}(m_k, m_{k^*}). \quad (10)$$

125 We can now finally propose our querying method inspired by racing algo-
 126 rithms, that consists in building an initial set $\{m_1, \dots, m_R\}$ of models, and then
 127 make them race against each other. The initial set can be instantiated by sam-
 128 pling several precise data sets $(\mathbf{x}_i, y_i) \in (\mathbf{X}_i, Y_i)$, and then learning an optimal
 129 model from each of these precise selection. Algorithm 1 summarises the general
 130 procedure applied to find the best query and to update the race once this set
 131 is built. This algorithm simply searches the query that will have the biggest
 132 impact on the minimin model and its competitors, adopting the optimistic at-
 133 titude of racing algorithms. Once a query has been made, the data set as well
 134 as the set of competitors are updated, so that only potentially optimal models
 135 remain.

136 Notice that the best model (learned from fully precise data) may not be in the
 137 set \mathcal{M} of competitors. This is also true for some active learning techniques such
 138 as Query-by-committee. This means that, at the end of the querying process,
 139 two solutions arise: either retain the best model m_{k^*} within \mathcal{M} , or retrain a new
 140 model from the completed data. Note that since we will not query all partial
 141 data in practice (otherwise trying to find best queries is meaningless), we will
 142 have to use learning techniques able to cope with such data [11]

143 In the next sections, we illustrate our proposed setting and its potential
 144 interest with the popular SVM algorithm. We separate the two cases of interval-
 145 valued features from set-valued labels, for three reasons: (i) we can expect that
 146 imprecision in both aspects is less likely to happen in practice, (ii) this makes
 147 the exposure of the methods easier to follow, and (iii) considering both cases at

148 once would quickly induce a too important imprecision in the results. We leave
 149 the combination of the two approaches to the reader, especially since binary
 150 SVM are here used as an illustration of our general approach.

Algorithm 1: One iteration of the racing algorithm to query data.

Input: data (X_i, Y_i) , set $\{m_1, \dots, m_R\}$ of models
Output: updated data and set of models

- 1 $k^* = \arg \min_{k \in \{1, \dots, R\}} \underline{R}(m_k)$;
- 2 **foreach** query Q_i^j **do**
- 3 $\lfloor \text{Value}(Q_i^j) = E_{Q_i^j}(m_{k^*}) + \sum_{k \neq k^*} J_{Q_i^j}(m_k, m_{k^*})$;
- 4 $Q_i^{j*} = \arg \max_{Q_i^j} \text{Value}(Q_i^j)$;
- 5 Get value $x_{i^*}^{j*}$ of $X_{i^*}^{j*}$;
- 6 **foreach** $k, l \in \{1, \dots, R\} \times \{1, \dots, R\}$, $k \neq l$ **do**
- 7 \lfloor Compute $\underline{R}(m_{k-l})$;
- 8 **if** $\underline{R}(m_{k-l}) > 0$ **then** remove m_k from $\{m_1, \dots, m_R\}$;

151 4. Application to binary SVM: interval-valued features

In the binary SVM setting [1], the input space $\mathcal{X} = \mathbb{R}^p$ is the real space and the binary output space is $\mathcal{Y} = \{-1, 1\}$, where $-1, 1$ encode the two possible classes. The model $m_l = (\mathbf{w}_l, c_l)$ corresponds to the “maximum-margin” hyperplane $\mathbf{w}_l \mathbf{x} + c_l$ with $\mathbf{w}_l \in \mathbb{R}^p$ and $c_l \in \mathbb{R}$. For convenience sake, we will use (\mathbf{w}_l, c_l) and m_l interchangeably from now on. We will also focus in this section on the case of imprecise features and precise labels, and will denote y_i the label of training instances. We will also focus on the classical 0 – 1 loss function defined as follows for an instance (\mathbf{x}_i, y_i) :

$$\ell(y_i, m_l(\mathbf{x}_i)) = \begin{cases} 0 & \text{if } y_i \cdot m_l(\mathbf{x}_i) \geq 0 \\ 1 & \text{if } y_i \cdot m_l(\mathbf{x}_i) < 0, \end{cases} \quad := \ell_l(y_i, \mathbf{x}_i) \quad (11)$$

152 where $m_l(\mathbf{x}_i) = \mathbf{w}_l \mathbf{x}_i + c_l$, and $\ell_l(y_i, \mathbf{x}_i)$ is used as a short notation for $\ell(y_i, m_l(\mathbf{x}_i))$.

153 4.1. Instances inducing imprecision in empirical risk

154 Before entering into the details of how single risk bounds $[\underline{R}(m_l), \overline{R}(m_l)]$
 155 and pairwise risk bounds $\underline{R}(m_{k-l})$ given by Equations (4)-(6), and query ef-
 156 fects $E_{Q_i^j}(m_l)$ and $J_{Q_i^j}(m_k, m_l)$ given by Equations (8)-(9) can be estimated in
 157 practice, we will first investigate under which conditions an instance (\mathbf{X}_i, y_i)
 158 induces imprecision in the empirical risk. Such instances are the only ones of
 159 interest here, since if $\underline{\ell}_l(y_i, \mathbf{X}_i) = \overline{\ell}_l(y_i, \mathbf{X}_i) = \ell_l(y_i, \mathbf{X}_i)$, then $E_{Q_i^j}(m_l) = 0$ for
 160 all $j = 1, \dots, p$. Furthermore, if an instance (\mathbf{X}_i, y_i) is precise w.r.t both m_k and
 161 m_l , then $J_{Q_i^j}(m_k, m_l) = 0$ for all $j = 1, \dots, p$. Thus, only instances which are
 162 imprecise w.r.t at least one model are interested when determining $J_{Q_i^j}(m_k, m_l)$.

Definition 2. Given a SVM model m_l , an instance (\mathbf{X}_i, y_i) is called an imprecise instance w.r.t. m_l if and only if

$$\exists \mathbf{x}'_i, \mathbf{x}''_i \in \mathbf{X}_i \text{ s.t. } m_l(\mathbf{x}'_i) \geq 0 \text{ and } m_l(\mathbf{x}''_i) < 0. \quad (12)$$

163 Instances that do not satisfy Definition 2 will be called precise instances
 164 (w.r.t. m_l). Being precise means that the sign of $m_l(\mathbf{x}_i)$ is the same for all
 165 $x_i \in \mathbf{X}_i$, which implies that the loss $\underline{\ell}_l(y_i, \mathbf{X}_i) = \bar{\ell}_l(y_i, \mathbf{X}_i)$ is precisely known.
 166 The next example illustrates the notion of (im)precise instances.

167 *Example 3.* Figure 2 illustrates a situation with two models and where the two
 168 different classes are represented by grey ($y = +1$) and white ($y = -1$) colours.
 169 From the figure, we can say that (\mathbf{X}_1, y_1) is precise w.r.t both m_1 and m_2 ,
 170 (\mathbf{X}_2, y_2) is precise w.r.t m_1 and imprecise w.r.t m_2 , (\mathbf{X}_3, y_3) is imprecise w.r.t
 171 both m_1 and m_2 and (\mathbf{X}_4, y_4) is imprecise w.r.t m_1 and precise w.r.t m_2 .

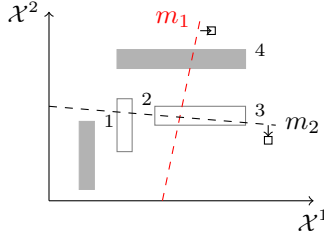


Figure 2: Illustration of interval-valued instances

172 Determining whether an instance is imprecise w.r.t. m_l is actually very easy
 173 in practice. Let us denote by

$$\underline{m}_l(\mathbf{X}_i) := \inf_{\mathbf{x}_i \in \mathbf{X}_i} m_l(\mathbf{x}_i) \text{ and } \bar{m}_l(\mathbf{X}_i) := \sup_{\mathbf{x}_i \in \mathbf{X}_i} m_l(\mathbf{x}_i) \quad (13)$$

174 the lower and upper bounds reached by model m_l over the space \mathbf{X}_i . The
 175 following result characterizing imprecise instances, as well as when a hyperplane
 176 $m_l(\mathbf{x}_i) = 0$ intersects with a region \mathbf{X}_i , follows from the fact that the image of
 177 a compact set by a continuous function is also compact.

Proposition 1. Given $m_l(\mathbf{x}_i) = \mathbf{w}_l \mathbf{x}_i + c_l$ and the set \mathbf{X}_i , then (\mathbf{X}_i, y_i) is imprecise w.r.t. m_l if and only if

$$\underline{m}_l(\mathbf{X}_i) < 0 \text{ and } \bar{m}_l(\mathbf{X}_i) \geq 0. \quad (14)$$

178 Furthermore, we have that the hyperplane $m_l(\mathbf{x}_i) = 0$ intersects with the region
 179 \mathbf{X}_i if and only if (14) holds. In other words, $\exists \mathbf{x}_i \in \mathbf{X}_i$ s.t. $m_l(\mathbf{x}_i) = 0$.

Proof. Since continuous functions preserve compactness and connectedness [7], then the image $f(\mathbf{X}) = Y$ of a compact and connected set \mathbf{X} is compact and

connected. Furthermore, a set on \mathbf{R}^p is compact if and only if it is closed and bounded (Heine–Borel Theorem [15]), then \mathbf{X} is a closed, bounded and connected set which is exactly a closed interval. Or in other words, we have that

$$m_l(\mathbf{X}_i) = \left[\underline{m}_l(\mathbf{X}_i), \overline{m}_l(\mathbf{X}_i) \right],$$

180 is an interval consisting of every possible values that can take $m_l(\mathbf{x}_i)$ for $\mathbf{x}_i \in \mathbf{X}_i$.
 181 That (14) is equivalent to (12) then immediately follows. Also, we have that
 182 $\exists \mathbf{x}_i \in \mathbf{X}_i$ s.t. $m_l(\mathbf{x}_i) = 0$ if and only if $0 \in \left[\underline{m}_l(\mathbf{X}_i), \overline{m}_l(\mathbf{X}_i) \right]$. \square

183 This proposition means that to determine whether an instance (\mathbf{X}_i, y_i) is
 184 imprecise, we only need to compute values $\underline{m}_l(\mathbf{X}_i)$ and $\overline{m}_l(\mathbf{X}_i)$, which can be
 185 easily done using Proposition 2.

Proposition 2. *Given (\mathbf{X}_i, y_i) with $X_i^j = [a_i^j, b_i^j]$ and SVM model (\mathbf{w}_l, c_l) , we have*

$$\begin{aligned} \overline{m}_l(\mathbf{X}_i) &= \sum_{w_l^j \geq 0} w_l^j b_i^j + \sum_{w_l^j < 0} w_l^j a_i^j + c_l \\ \underline{m}_l(\mathbf{X}_i) &= \sum_{w_l^j \geq 0} w_l^j a_i^j + \sum_{w_l^j < 0} w_l^j b_i^j + c_l. \end{aligned}$$

186 *Proof.* Since $m_l(\mathbf{x}_i)$ is a linear function, it is monotonic in each dimension, hence
 187 the extreme values are obtained at points $\mathbf{x}_i \in \times_{j=1}^p \{a_i^j, b_i^j\}$. Furthermore,
 188 $m_l(\mathbf{x}_i)$ decreases (increases) w.r.t \mathbf{x}_i^j if $w_l^j < 0$ ($w_l^j > 0$). Hence, Proposition 2
 189 holds. \square

190 Again, it should be noted that only imprecise instances are of interest here,
 191 as these are the only instances that, once queried, can result in an increase of
 192 the lower empirical risk bounds. We will therefore focus on those in the next
 193 sections.

Example 4. Consider the model m_l on a 3-dimensional space given by $\mathbf{w}_l = (2, -1, 1)$ and the partial instance $\mathbf{X}_i = [1, 3] \times [2, 5] \times [1, 2]$. In this case, we have

$$\begin{aligned} \underline{m}_l(\mathbf{X}_i) &= 1 \times 2 + 5 \times -1 + 1 \times 1 = -2, \\ \overline{m}_l(\mathbf{X}_i) &= 3 \times 2 + 2 \times -1 + 2 \times 1 = 6, \end{aligned}$$

194 hence the instance \mathbf{X}_i is imprecise with respect to m_l

195 4.2. Empirical risk bounds and single effect

We are now going to investigate the practical computation of $\underline{R}(m_l)$, $\overline{R}(m_l)$, as well as the value $E_{\mathcal{Q}_i^j}(m_l)$ of a query on a model m_l . Equations (4) (resp. (5)) implies that the computation of $\underline{R}(m_l)$ (resp. $\overline{R}(m_l)$) can be done by first

computing $\underline{\ell}_l(y_i, \mathbf{X}_i)$ (resp. $\bar{\ell}_l(y_i, \mathbf{X}_i)$) for $i = 1, \dots, n$ and then summing the obtained values. This means that we can focus our attention on computing $\underline{\ell}_l(y_i, \mathbf{x}_i)$ and $\bar{\ell}_l(y_i, \mathbf{x}_i)$ for a single instance, as obtaining $\underline{R}(m_l)$, $\bar{R}(m_l)$ from them is straightforward. Note that we have $\underline{\ell}_l(y_i, \mathbf{X}_i) = 0$ and $\bar{\ell}_l(y_i, \mathbf{X}_i) = 1$ if and only if \mathbf{X}_i is imprecise w.r.t. m_l , a fact that can easily be checked using Proposition 1. The bounds of the loss interval for the model m_l and datum (\mathbf{X}_i, y_i) is

$$[\underline{\ell}_l(y_i, \mathbf{X}_i), \bar{\ell}_l(y_i, \mathbf{X}_i)] = \begin{cases} [0, 0] & \text{if } \min(y_i \cdot \bar{m}_l(\mathbf{X}_i), y_i \cdot \underline{m}_l(\mathbf{X}_i)) \geq 0 \\ [0, 1] & \text{if } \bar{m}_l(\mathbf{X}_i) \cdot \underline{m}_l(\mathbf{X}_i) < 0 \\ [1, 1] & \text{if } \max(y_i \cdot \bar{m}_l(\mathbf{X}_i), y_i \cdot \underline{m}_l(\mathbf{X}_i)) < 0 \end{cases} \quad (15)$$

196 Let us now focus on estimating the effect of a query. As with the loss
 197 bounds, the only situation where a query Q_i^j can affect the empirical risk
 198 bounds, and hence the only situation where $E_{Q_i^j}(m_l) = 1$, is when the interval
 199 $[\underline{\ell}_l(y_i, \mathbf{X}_i), \bar{\ell}_l(y_i, \mathbf{X}_i)]$ can be reduced by querying X_i^j . Therefore we can also
 200 focus on a single instance to evaluate it. In the case of 0-1 loss, the only case
 201 where $E_{Q_i^j}(m_l) = 1$ is the one where $[\underline{\ell}_l(y_i, \mathbf{X}_i), \bar{\ell}_l(y_i, \mathbf{x}_i)]$ goes from $[0, 1]$ before
 202 the query to a precise value after it, or in other words if there is $x_i^j \in X_i^j$ such
 203 that $\mathbf{X}_i' = \times_{j' \neq j} X_i^{j'} \times \{x_i^j\}$ is precise w.r.t. m_l . According to Proposition 1,
 204 this means that either $\underline{m}_l(\mathbf{X}_i')$ should become positive, or $\bar{m}_l(\mathbf{X}_i')$ should become
 205 negative after a query Q_i^j . The conditions to check whether this is possible are
 206 given in the next proposition.

Proposition 3. *Given (\mathbf{X}_i, y_i) with $X_i^j = [a_i^j, b_i^j]$ and a model m_l s.t. \mathbf{X}_i is imprecise, then $E_{Q_i^j}(m_l) = 1$ if and only if one of the following conditions holds*

$$\underline{m}_l(\mathbf{X}_i) \geq -|w_l^j|(b_i^j - a_i^j) \quad (16)$$

or

$$\bar{m}_l(\mathbf{X}_i) < |w_l^j|(b_i^j - a_i^j). \quad (17)$$

Proof. Let us concentrate on the first condition (the second one can be proved similarly). If we denote by $\underline{m}_l^{Q_i^j}$ the lower bound reached by m_l on \mathbf{X}_i' (the set resulting from the query answer), then we have the following inequality

$$\underline{m}_l^{Q_i^j}(\mathbf{X}_i') \leq \underline{m}_l(\mathbf{X}_i) + |w_l^j|(b_i^j - a_i^j)$$

207 giving us a tight upper bound for it. Indeed, if $w_l^j \geq 0$, then \underline{m}_l is obtained for
 208 $x_i^j = a_i^j$ (by Proposition 2), and it can increase by at most $w_l^j(b_i^j - a_i^j)$ if the
 209 result of the query Q_i^j is $x_i^j = b_i^j$ (the case $w_l^j \leq 0$ is similar). Since $\underline{m}_l(\mathbf{X}_i)$ is
 210 known to be negative (from Proposition 1 and the fact that \mathbf{X}_i is imprecise), it
 211 can only become positive after a query Q_i^j if $\underline{m}_l(\mathbf{X}_i) + |w_l^j|(b_i^j - a_i^j)$ is positive.

212 Finally, by investigating the change of $\text{sign}(w_l^j)$, we have:

213 **B1:** Q_i^j can change the sign of $\underline{m}_l(\mathbf{x}_i)$ iff

$$\begin{cases} \underline{m}_l(\mathbf{x}_i) + w_l^j(b_i^j - a_i^j) \geq 0 & \text{if } w_l^j \geq 0, \\ \underline{m}_l(\mathbf{x}_i) - w_l^j(b_i^j - a_i^j) \geq 0 & \text{if } w_l^j < 0. \end{cases}$$

B2: Q_i^j can change the sign of $\overline{m}_l(\mathbf{x}_i)$ iff

$$\begin{cases} \overline{m}_l(\mathbf{x}_i) - w_l^j(b_i^j - a_i^j) < 0 & \text{if } w_l^j \geq 0 \\ \overline{m}_l(\mathbf{x}_i) + w_l^j(b_i^j - a_i^j) < 0 & \text{if } w_l^j < 0. \end{cases}$$

214

□

215 $\underline{R}(m_l), \overline{R}(m_l)$, needed in the line 1 of Algorithm 1 to identify the most
 216 promising model k^* , are computed easily by summing over all training instances
 217 the intervals $[\underline{\ell}_l(y_i, \mathbf{X}_i), \overline{\ell}_l(y_i, \mathbf{X}_i)]$ given by Equation (15), while Equations (16)-
 218 (17) give easy ways to estimate the values of $E_{Q_i^j}(m_{k^*})$, needed in line 3 of
 219 Algorithm 1.

Example 5. Let us consider again Example 4, and check whether querying the
 last ($j = 3$) or second dimension may induce some effect on the empirical risk
 bounds. Using Proposition 3, we have for Q_i^3 that

$$\underline{m}_l(\mathbf{X}_i) = -2 < -1 \times (2 - 1) \text{ and } \overline{m}_l(\mathbf{X}_i) = 6 > 1 \times (2 - 1),$$

hence $E_{Q_i^3}(m_l) = 0$, as none of the conditions are satisfied. We do have, on the
 contrary, that

$$\underline{m}_l(\mathbf{X}_i) = -2 \geq -1 \times (5 - 2),$$

220 hence $E_{Q_i^2}(m_l) = 1$. Indeed, if $x_i^2 = 2$ (the query results in the lower bound),
 221 then the model becomes positive for any replacement of $\mathbf{X}_i' = [1, 3] \times 2 \times [1, 2]$.

222 4.3. Pairwise risk bounds and effect

Let us now focus on how to compute, for a pair of models m_k and m_l ,
 whether a query Q_i^j will have an effect on the value $\underline{R}(m_{k-l})$. For this, we will
 have to compute $\underline{R}(m_{k-l})$, which is a necessary step to estimate the indicator
 $J_{Q_i^j}(m_k, m_l)$ of a possible effect of Q_i^j . To do that, note that $\underline{R}(m_{k-l})$ can be
 rewritten as

$$\underline{R}(m_{k-l}) = \inf_{\mathbf{x}_i \in \mathbf{X}_i, i=1, \dots, n} (R(m_k) - R(m_l)) = \sum_{i=1}^n \underline{\ell}_{k-l}(y_i, \mathbf{X}_i) \quad (18)$$

with

$$\underline{\ell}_{k-l}(y_i, \mathbf{X}_i) = \inf_{\mathbf{x}_i \in \mathbf{X}_i} \left(\ell_k(y_i, \mathbf{x}_i) - \ell_l(y_i, \mathbf{x}_i) \right), \quad (19)$$

223 meaning that computing $\underline{R}(m_{k-l})$ can be done by summing up $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i)$ over
 224 all \mathbf{X}_i , similarly to $\underline{R}(m_l)$ and $\overline{R}(m_l)$. Also, $J_{Q_i^j}(m_k, m_l) = 1$ if and only if Q_i^j
 225 can increase $\underline{R}(m_{k-l})$. We can therefore focus on the computation of $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i)$
 226 and its possible changes. First note that if \mathbf{X}_i is precise w.r.t. both m_k and m_l ,
 227 then $\ell_k(y_i, \mathbf{X}_i) - \ell_l(y_i, \mathbf{X}_i)$ is a well-defined value, as each loss is precise, and in
 228 this case $J_{Q_i^j}(m_k, m_l) = 0$. Therefore, the only cases of interest are those where
 229 \mathbf{X}_i is imprecise w.r.t. to at least one model. We will first treat the case where
 230 it is imprecise for only one, and then we will proceed to the more complex one
 231 where it is imprecise w.r.t. both. Note that imprecision with respect to each
 232 model can be easily established using Proposition 1.

233 4.3.1. Imprecision with respect to one model

234 Let us consider the case where \mathbf{X}_i is imprecise w.r.t. either m_k or m_l . In
 235 each of these two cases, the loss induced by (\mathbf{X}_i, y_i) on the model for which
 236 it is precise is fixed. Hence, to estimate the lower loss $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i)$, as well
 237 as the effect of a possible query Q_i^j , we only have to look at the model for
 238 which (\mathbf{X}_i, y_i) is imprecise. The next proposition establishes the lower bound
 239 $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i)$, necessary to compute $\underline{R}(m_{k-l})$.

Proposition 4. *Given (\mathbf{X}_i, y_i) with $X_i^j = [a_i^j, b_i^j]$ and two models m_k and m_l
 s.t. (\mathbf{X}_i, y_i) is imprecise w.r.t. one and only one model, then we have*

$$\underline{\ell}_{k-l}(y_i, \mathbf{X}_i) = \ell_k(y_i, \mathbf{X}_i) - 1 \quad \text{if } \mathbf{X}_i \text{ imprecise w.r.t. } m_l \quad (20)$$

$$\underline{\ell}_{k-l}(y_i, \mathbf{X}_i) = 0 - \ell_l(y_i, \mathbf{X}_i) \quad \text{if } \mathbf{X}_i \text{ imprecise w.r.t. } m_k. \quad (21)$$

240 *Proof.* We will only prove Equation (20), the proof for Equation (21) being simi-
 241 lar. First note that if \mathbf{X}_i is precise with respect to m_k , then $\ell_k(y_i, \mathbf{X}_i)$ is precise.
 242 Second, the value of $\ell_l(y_i, \mathbf{X}_i) \in \{0, 1\}$, since \mathbf{X}_i is imprecise with respect to
 243 m_l , hence the lower bound is obtained for $\mathbf{x}_i \in \mathbf{X}_i$ such that $\ell_l(y_i, \mathbf{x}_i) = 1$. \square

244 We kept the 0 in Equation (21) to make clear that we take the lower bound
 245 of the loss w.r.t. m_k , and the precise value of $\ell_l(y_i, \mathbf{X}_i)$. Let us now study
 246 under which conditions a query Q_i^j can increase $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i)$, hence under which
 247 conditions $J_{Q_i^j}(m_k, m_l) = 1$. The two next propositions respectively address
 248 the case of imprecision w.r.t. m_k and m_l . Given a possible query Q_i^j on \mathbf{X}_i ,
 249 the only possible way to increase $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i)$ is for the updated \mathbf{X}_i' to become
 250 precise w.r.t. to the model for which \mathbf{X}_i was imprecise, and moreover to be so
 251 that $\ell_l(y_i, \mathbf{X}_i') = 0$ ($\ell_k(y_i, \mathbf{X}_i') = 1$) if \mathbf{X}_i is imprecise w.r.t. m_l (m_k).

Proposition 5. *Given (\mathbf{X}_i, y_i) with $X_i^j = [a_i^j, b_i^j]$ and two models m_k and m_l
 s.t. (\mathbf{X}_i, y_i) is imprecise w.r.t. m_l , the question Q_i^j is such that $J_{Q_i^j}(m_k, m_l) = 1$
 if and only if one of the two following conditions holds*

$$y_i = 1 \text{ and } \underline{m}_l(\mathbf{X}_i) \geq -|w_l^j|(b_i^j - a_i^j) \quad (22)$$

or

$$y_i = -1 \text{ and } \overline{m}_l(\mathbf{X}_i) < |w_l^j|(b_i^j - a_i^j). \quad (23)$$

252 *Proof.* First note that if \mathbf{X}_i is imprecise w.r.t. m_l , then the only case where
 253 $\underline{\ell}_{k-l}(\mathbf{X}_i)$ increases is when the updated instance \mathbf{X}_i' is precise w.r.t. m_l after
 254 the query Q_i^j is performed and the precise loss becomes $\ell_l(y_i, \mathbf{X}_i') = 0$.

255 Let us consider the case $y_i = 1$ (the case $y_i = 0$ is similar). To have
 256 $\ell_l(y_i, \mathbf{X}_i') = 0$, we must have $\underline{m}_l(\mathbf{X}_i') \geq 0$. Using the same argument as in
 257 Proposition 3, we easily get the result. \square

Proposition 6. *Given (\mathbf{X}_i, y_i) with $X_i^j = [a_i^j, b_i^j]$ and two models m_k and m_l
 s.t. (\mathbf{X}_i, y_i) is imprecise w.r.t. m_k , the query Q_i^j is such that $J_{Q_i^j}(m_k, m_l) = 1$
 if and only if one of the two following condition holds*

$$y_i = 1 \text{ and } \overline{m}_k(\mathbf{X}_i) < |w_k^j|(b_i^j - a_i^j) \quad (24)$$

or

$$y_i = -1 \text{ and } \underline{m}_k(\mathbf{X}_i) \geq -|w_k^j|(b_i^j - a_i^j). \quad (25)$$

258 The proof is analogous to the one of Proposition 5. In summary, if \mathbf{X}_i is
 259 imprecise w.r.t. only one model, estimating $J_{Q_i^j}(m_k, m_l)$ comes down to identify
 260 whether the \mathbf{X}_i can become precise with respect to such a model, in such a way
 261 that the lower bound is possibly increased. Propositions 5 and 6 show that this
 262 can be checked easily using our previous results of Section 4.1 concerning the
 263 empirical risk. Actually, in this case, the problem essentially boils down to the
 264 problem of Section 4.2.

265 4.3.2. Imprecision with respect to both models

Given \mathbf{X}_i and two models m_k, m_l , we define :

$$m_{k-l}(\mathbf{X}_i) = m_k(\mathbf{X}_i) - m_l(\mathbf{X}_i). \quad (26)$$

We thus have:

$$m_{k-l}(\mathbf{X}_i) > 0 \text{ if } m_k(\mathbf{x}_i) - m_l(\mathbf{x}_i) > 0 \quad \forall \mathbf{x}_i \in \mathbf{X}_i \quad (27)$$

$$m_{k-l}(\mathbf{X}_i) < 0 \text{ if } m_k(\mathbf{x}_i) - m_l(\mathbf{x}_i) < 0 \quad \forall \mathbf{x}_i \in \mathbf{X}_i. \quad (28)$$

266 In the other cases, this means that there are $\mathbf{x}_i', \mathbf{x}_i'' \in \mathbf{X}_i$ for which the model
 267 difference have different signs. The reason for introducing such differences is
 268 that, if $m_{k-l}(\mathbf{X}_i) > 0$ or $m_{k-l}(\mathbf{X}_i) < 0$, then not all combinations in $\{0, 1\}^2$
 269 are possible for the pair $(\ell_k(y_i, \mathbf{x}_i), \ell_l(y_i, \mathbf{x}_i))$, while they are in the other case.
 270 These various situations are depicted in Figure 3, where the white class is again
 271 the negative one ($y_i = -1$).

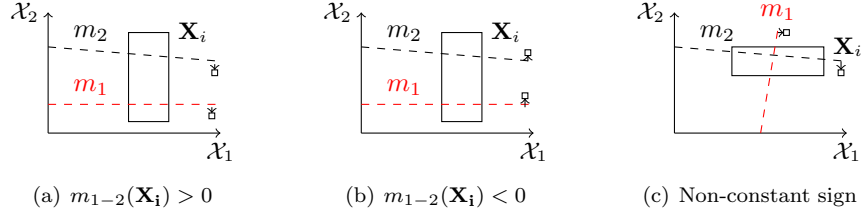


Figure 3: Illustrations for the different possible cases corresponding to the difference $m_1(\mathbf{x}) - m_2(\mathbf{x})$

Since $m_k(\mathbf{x}_i) - m_l(\mathbf{x}_i)$ is also of linear form (with weights $w_k^j - w_l^j$), we can easily determine whether the sign of $m_{k-l}(\mathbf{X}_i)$ is constant: it is sufficient to compute the interval

$$\left[\inf_{\mathbf{x}_i \in \mathbf{X}_i} (m_k(\mathbf{x}_i) - m_l(\mathbf{x}_i)), \sup_{\mathbf{x}_i \in \mathbf{X}_i} (m_k(\mathbf{x}_i) - m_l(\mathbf{x}_i)) \right]$$

272 that can be computed similarly to $[\underline{m}_k(\mathbf{X}_i), \overline{m}_k(\mathbf{X}_i)]$ in Section 4.1 (Proposition
 273 2). If zero is not within this interval, then $m_{k-l}(\mathbf{X}_i) > 0$ if the lower bound
 274 is positive, otherwise $m_{k-l}(\mathbf{X}_i) < 0$ if the upper bound is negative. The next
 275 proposition indicates how to easily compute the lower bound $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i)$ for
 276 the different possible situations.

Proposition 7. *Given (\mathbf{X}_i, y_i) with $X_i^j = [a_i^j, b_i^j]$ and two models m_k, m_l s.t. (\mathbf{X}_i, y_i) is imprecise w.r.t. both models, then the minimal difference value is*

$$\underline{\ell}_{k-l}(y_i, \mathbf{X}_i) = \begin{cases} \min(0, -y_i) & \text{if } m_{k-l}(\mathbf{X}_i) > 0 \\ \min(0, y_i) & \text{if } m_{k-l}(\mathbf{X}_i) < 0 \\ -1 & \text{if } m_{k-l}(\mathbf{X}_i) \text{ can take both signs} \end{cases} \quad (29)$$

277 *Proof.* First note that when neither $m_{k-l}(\mathbf{X}_i) > 0$ nor $m_{k-l}(\mathbf{X}_i) < 0$ hold, then
 278 there are values \mathbf{x}_i for which $m_k(\mathbf{x}_i)$ and $m_l(\mathbf{x}_i)$ are either positive and negative,
 279 or negative and positive, or of the same sign. Hence there is always a value \mathbf{x}_i
 280 such that $\ell_k(y_i, \mathbf{x}_i) = 0$ and $\ell_l(y_i, \mathbf{x}_i) = 1$.

281 Let us then deal with the situation where $m_{k-l}(\mathbf{X}_i) > 0$ (the case $m_{k-l}(\mathbf{X}_i) <$
 282 0 can be treated similarly). In this case, there are values $\mathbf{x}_i \in \mathbf{X}_i$ such that
 283 $m_k(\mathbf{x}_i)$ and $m_l(\mathbf{x}_i)$ have the same sign (0/1 loss difference is then null), or
 284 $m_k(\mathbf{x}_i)$ is positive and $m_l(\mathbf{x}_i)$ negative, but no values for which $m_k(\mathbf{x}_i)$ is nega-
 285 tive and $m_l(\mathbf{x}_i)$ positive. When $m_k(\mathbf{x}_i)$ is positive and $m_l(\mathbf{x}_i)$ negative, the loss
 286 difference is -1 if $y_i = +1$, and 1 if $y_i = -1$. \square

287 The next question is to know under which conditions a query Q_i^j can increase
 288 $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i)$ (or equivalently $\underline{R}(m_{k-l})$), or in other words to determine a pair
 289 (i, j) s.t $J_{Q_i^j}(m_k, m_l) = 1$. Proposition 7 tells us that $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i)$ can be either 0
 290 or -1 if $m_{k-l}(\mathbf{X}_i) > 0$ or $m_{k-l}(\mathbf{X}_i) < 0$, and is always -1 if $m_{k-l}(\mathbf{X}_i)$ can take
 291 both signs. The next proposition establishes conditions under which $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i)$
 292 can increase.

293 **Proposition 8.** Given (\mathbf{X}_i, y_i) with $X_i^j = [a_i^j, b_i^j]$ and two models m_k and m_l
 294 s.t (\mathbf{X}_i, y_i) is imprecise w.r.t both of the given models, then $J_{Q_i^j}(m_k, m_l) = 1$ if
 295 the following conditions hold

if $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i) = -1$ **and** $y_i = 1$:

$$\overline{m}_k(\mathbf{X}_i) < |w_l^j|(b_i^j - a_i^j) \text{ or } \underline{m}_l(\mathbf{X}_i) \geq -|w_l^j|(b_i^j - a_i^j) \quad (30)$$

if $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i) = -1$ **and** $y_i = -1$:

$$\underline{m}_k(\mathbf{X}_i) \geq -|w_k^j|(b_i^j - a_i^j) \text{ or } \overline{m}_l(\mathbf{X}_i) < |w_l^j|(b_i^j - a_i^j). \quad (31)$$

if $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i) = 0$ **and** $m_{k-l}(\mathbf{X}_i) < 0$:

$$\overline{m}_k(\mathbf{X}_i) < |w_l^j|(b_i^j - a_i^j) \text{ and } \underline{m}_l(\mathbf{X}_i) \geq -|w_l^j|(b_i^j - a_i^j) \quad (32)$$

if $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i) = 0$ **and** $m_{k-l}(\mathbf{X}_i) > 0$:

$$\underline{m}_k(\mathbf{X}_i) \geq -|w_k^j|(b_i^j - a_i^j) \text{ and } \overline{m}_l(\mathbf{X}_i) < |w_l^j|(b_i^j - a_i^j). \quad (33)$$

296 *Proof.* Let us first investigate the case where $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i) = -1$ and $y_i = 1$ (the
 297 case $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i) = -1$ and $y_i = -1$ is similar). In this case, $J_{Q_i^j}(m_k, m_l) = 1$ if
 298 and only if Q_i^j can either increase $\underline{\ell}_k(y_i, \mathbf{X}_i) = 0$ or decrease $\overline{\ell}_l(y_i, \mathbf{X}_i) = 1$, that
 299 is become precise for at least one of them, with $\underline{\ell}_k(y_i, \mathbf{X}_i') = 1$ or $\overline{\ell}_l(y_i, \mathbf{X}_i') = 0$.
 300 The conditions are then obtained by following arguments similar to those of
 301 Proposition 3.

302 The second case $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i) = 0$ only happens when either $m_{k-l}(\mathbf{X}_i) < 0$
 303 or $m_{k-l}(\mathbf{X}_i) > 0$, and we will treat the first case. According to Proposition 7,
 304 this means that $y_i = -1$. Also, since according to Proposition 4 the value 0 is
 305 an upper bound of $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i)$ when \mathbf{X}_i is imprecise with either m_k or m_l , to
 306 go from $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i) = 0$ to $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i') = 1$, we need a value $x_i^j \in X_i^j$ such that
 307 $m_k(\mathbf{X}_i') < 0$ and $m_l(\mathbf{X}_i') > 0$, as $y_i = -1$. Again, we can get the conditions to
 308 have such a value by deriving arguments similar to those of Proposition 3. \square

309 For instance, in Figure 3(a) and 3(b), $J_{Q_i^1}(m_2, m_1) = 0$ and $J_{Q_i^2}(m_2, m_1) =$
 310 1 for both cases. The whole procedure is summed up in the Algorithm 1.
 311 Algorithm 2 summarizes how to determine the query effect Q_i^j , which can be
 312 considered as the main computational difficulty when performing the querying
 313 step (line 2 – 3 in Algorithm 1). Determining the set of undominated models
 314 (line 6 – 8 in Algorithm 1) is summarized in Algorithm 3.

315 Let us now study the complexity of the whole approach. Lines 2 and 4 of
 316 Algorithm 2 are in $\mathcal{O}(p)$, since they correspond to linear operations. Iterations
 317 from 5-10 are in $\mathcal{O}(R \times p)$, since we must check all undominated models once.
 318 Iterations from 13-15 are also in $\mathcal{O}(R \times p)$, for the same reason. Thus, one run of
 319 Algorithm 2 is in $\mathcal{O}(R \times p)$. If we have I partial features in the data, then loop

320 2-3 of Algorithm 1 takes $\mathcal{O}(I \times R \times p)$ in the case of SVM, so it remains linear
321 in each of the parameter. Algorithm 3 corresponds to lines 6-8 of Algorithm 1,
322 and computing $\underline{R}(m_{k-l})$ can be done in $\mathcal{O}(n \times p)$ since we must compute $\underline{\ell}$ for
323 each data point. Finally, since this must be done for every pair of models in
324 the worst case, performing Algorithm 3 is in $\mathcal{O}(R^2 \times n \times p)$, which is quadratic
325 in R and linear in the other parameters. This can be approximated by only
326 comparing intervals $[\underline{R}(m_k), \bar{R}(m_k)]$ of every models, that would bring down
327 the complexity to $\mathcal{O}(R \times n \times p)$, but would provide a super-set of the set of
328 undominated models.

Algorithm 2: Determining the query effect $Value(Q_i^j)$

Input: partial data (\mathbf{X}_i, y_i) , set $\mathcal{M} = \{m_1, \dots, m_R\}$ of models, the best
potential model m_{k^*}
Output: the query effect $Value(Q_i^j)$

- 1 initialize $E_{Q_i^j}(m_{k^*}) = 0$, $J_{Q_i^j}(m_k, m_{k^*}) = 0$, $Value(Q_i^j) = 0$, $\forall k \neq k^*$;
- 2 check whether (\mathbf{X}_i, y_i) is imprecise w.r.t m_{k^*} using Prop. 1 and 2;
- 3 **if** (\mathbf{X}_i, y_i) is imprecise w.r.t m_{k^*} **then**
- 4 compute $E_{Q_i^j}(m_{k^*})$ using Prop. 3 ;
- 5 **foreach** $k \neq k^*$ **do**
- 6 **if** (\mathbf{X}_i, y_i) is imprecise w.r.t m_k **then**
- 7 use Prop. 7 to get $\underline{\ell}_{k-k^*}(y_i, \mathbf{X}_i)$;
- 8 use Prop. 8 to get $J_{Q_i^j}(m_k, m_{k^*})$;
- 9 **else**
- 10 use Prop. 5 to get $J_{Q_i^j}(m_k, m_{k^*})$;
- 11 compute $Value(Q_i^j)$ using Definition 1;
- 12 **else**
- 13 **foreach** $k \neq k^*$ **do**
- 14 **if** (\mathbf{X}_i, y_i) is imprecise w.r.t m_k **then**
- 15 use Prop. 6 to get $J_{Q_i^j}(m_k, m_{k^*})$;
- 16 compute $Value(Q_i^j)$ using Definition 1;

329 **5. Application to binary SVM: set-valued labels**

330 This section investigates the computations of racing algorithms to query set-
331 valued labels when using binary SVM with precise features and when labels are
332 partially given. Let us first note that, in the binary case, the problem of querying
333 partial label data is identical to classical active learning as label data is either
334 precise or fully partial (completely missing). One suitable technique in such a
335 case is query-by-committee [17]. However, the strategies of query-by-committee
336 technique and our racing technique are different. The previous one focus on

Algorithm 3: Determining the undominated set

Input: data (\mathbf{X}_i, y_i) , set $\mathcal{M} = \{m_1, \dots, m_R\}$ of models
Output: the set of undominated model \mathcal{M}^*

```

1 foreach  $k, l \in \{1, \dots, R\} \times \{1, \dots, R\}, k \neq l$  do
2    $\underline{R}(m_{k-l}) = 0$ ;
3   foreach data  $(\mathbf{X}_i, y_i)$  do
4     if  $(\mathbf{X}_i, y_i)$  is imprecise w.r.t both  $m_k$  and  $m_l$  then
5        $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i)$ ;
6     else if  $(\mathbf{X}_i, y_i)$  is imprecise w.r.t only one of  $m_k$  and  $m_l$  then
7        $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i)$ ;
8     else
9        $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i) = \ell_k(y_i, \mathbf{X}_i) - \ell_l(y_i, \mathbf{X}_i)$  using (15)
10     $\underline{R}(m_{k-l}) = \underline{R}(m_{k-l}) + \underline{\ell}_{k-l}(y_i, \mathbf{X}_i)$ ;
11  if  $\underline{R}(m_{k-l}) > 0$  then remove  $m_k$  from  $\{m_1, \dots, m_R\}$ ;
  
```

337 missing labels that are the least consensual or the most ambiguous among a
 338 given set of models, while racing algorithms focus on labels having the most
 339 effect on reducing the uncertainty about the best potential model performance,
 340 as well as its difference to other models. From such intuitions, we could hope
 341 that, in practice, query-by-committee provide a quick reduction on the size of the
 342 set of undominated models while racing algorithms give faster convergence on
 343 determining the best potential model. In any case, it is worth exploring whether
 344 the two techniques perform similarly or if they show significant differences.

Before investigating the detailed computations of racing algorithms, let us
 recall that we focus here on binary SVM with 0/1 loss function (11). Also,
 as the output is partially given and inputs are precise, from now on and to
 facilitate exposure, we will adopt the notation (\mathbf{x}_i, Y_i) where $Y_i \subseteq \{-1, 1\} = \mathcal{Y}$
 and $\mathbf{x}_i \in \mathcal{X}$. Let us first note that, in case of precise label (i.e, $Y_i = \lambda$), it is
 clear that the corresponding loss score is precisely given as in (34) and querying
 such an instance is redundant.

$$\ell_l(Y_i, \mathbf{x}_i) = \underline{\ell}_l(Y_i, \mathbf{x}_i) = \bar{\ell}_l(Y_i, \mathbf{x}_i) = \begin{cases} 0 & \text{if } Y_i * m_l(\mathbf{x}_i) \geq 0, \\ 1 & \text{otherwise.} \end{cases} \quad (34)$$

We are now going to determine the imprecise loss function,

$$[\underline{\ell}_l(Y_i, \mathbf{x}_i), \bar{\ell}_l(Y_i, \mathbf{x}_i)]$$

345 and investigate under which conditions an imprecise label can have an effect on
 346 the risk bounds.

347 **Proposition 9.** *Given a model m_l and an instance (\mathbf{x}_i, Y_i) , if $Y_i = \{-1, 1\}$,*
 348 *then the following results hold*

349 **A1.** $[\underline{\ell}_l(Y_i, \mathbf{x}_i), \bar{\ell}_l(Y_i, \mathbf{x}_i)] = [0, 1]$

350 **A2.** $E_{Q_i}(m_l) = 1.$

Proof. It is clear that, in the binary case, if $Y_i = \{-1, 1\}$, whatever the prediction of the given model is (either 1 or -1), there always exist element λ and λ' in Y_i s.t

$$\ell_l(\lambda, \mathbf{x}_i) = 0 \text{ and } \ell_l(\lambda', \mathbf{x}_i) = 1,$$

351 or in other words, $[\underline{\ell}_l(Y_i, \mathbf{x}_i), \bar{\ell}_l(Y_i, \mathbf{x}_i)] = [0, 1]$. Furthermore, querying Y_i always
 352 help to modify $[\underline{\ell}_l(Y_i, \mathbf{x}_i), \bar{\ell}_l(Y_i, \mathbf{x}_i)]$ into single value (either to 0 or 1). Or, in
 353 other words, A2 holds. \square

354 Proposition 9 simply points out that all partial labels give the same (interval-
 355 valued) losses and have an effect on modifying the corresponding losses. In the
 356 next Proposition, we show that if the predictions of two given models for a
 357 partially labelled instance are different, then the corresponding lower pairwise
 358 difference is -1 and the effect of querying such labels is 1. Otherwise, both
 359 values are 0.

360 **Proposition 10.** *Given two models m_k and m_l and an imprecise instance*
 361 *(\mathbf{x}_i, Y_i) ($Y_i = \{-1, 1\}$) then the following properties hold*

B1. *if $m_k(\mathbf{x}_i) = m_l(\mathbf{x}_i)$ then*

$$\underline{\ell}_{k-l}(Y_i, \mathbf{x}_i) = 0 \text{ and } J_{Q_i}(m_k, m_l) = 0.$$

B2. *if $m_k(\mathbf{x}_i) \neq m_l(\mathbf{x}_i)$ then*

$$\underline{\ell}_{k-l}(Y_i, \mathbf{x}_i) = -1 \text{ and } J_{Q_i}(m_k, m_l) = 1.$$

362 *Proof.* **B1** follows from the fact that if $m_k(\mathbf{x}_i) = m_l(\mathbf{x}_i)$, then $\ell_{k-l}(\lambda, \mathbf{x}_i) = 0$
 363 for all $\lambda \in Y_i$. Furthermore, for any $\lambda^* \in Y_i$ to be returned after performing Q_i ,
 364 we always have $\ell_{k-l}(\lambda^*, \mathbf{x}_i) = 0$, or in other words $J_{Q_i}(m_k, m_l) = 0$.

365 We are now going to give the proof for **B2**. Let us first notice that when
 366 $m_k(\mathbf{x}_i) \neq m_l(\mathbf{x}_i)$, there always exists $\lambda \in Y_i$ (i.e $\lambda = m_l(\mathbf{x}_i)$) s.t $\ell_{k-l}(\lambda) = -1$.
 367 Then it is clear that $\underline{\ell}_{k-l}(Y_i, \mathbf{x}_i) = -1$. Furthermore, if $\lambda^* = m_l(\mathbf{x}_i)$ is the given
 368 label after performing Q_i , then the pairwise difference $\ell_{k-l}^{Q_i}(\lambda^*, \mathbf{x}_i) = 1$. In other
 369 words, we have $J_{Q_i}(m_k, m_l) = 1$. \square

370 Propositions 9 and 10 provide an interesting property of $Value(Q_i)$. In
 371 fact, for any given partial label Y_i , the corresponding total effect ($Value(Q_i)$)
 372 is exactly $1 + u_i$ where u_i is the number of models in the undominated set that
 373 give predictions against the best potential model (m^*). This means that while
 374 query-by-committee do consider consensus between all models for each instance,
 375 racing algorithms are based on the consensus of each model w.r.t. to the best
 376 potential model, for all instances. Again, we can see similarities and differences
 377 between the two approaches, and comparing them makes sense.

378 The whole procedure is again summed up in the Algorithm 1. Similar to the
 379 case of interval-valued features, we summarize how to determine the query effect
 380 Q_i (line 2 – 3 in Algorithm 1) and the set of undominated models (line 6 – 8
 381 in Algorithm 1) in Algorithm 4 and 5, respectively. The complexity analysis is
 382 similar to the one of interval-valued features.

Algorithm 4: Determining the query effect $Value(Q_i)$

Input: partial data (\mathbf{x}_i, Y_i) with $Y_i = \{-1, 1\}$, set $\mathcal{M} = \{m_1, \dots, m_R\}$ of models, the best potential model m_{k^*}

Output: the query effect $Value(Q_i)$

- 1 initialize $E_{Q_i}(m_{k^*}) = 1$;
 - 2 **foreach** $k \neq k^*$ **do**
 - 3 | use Prop. 10 to get $J_{Q_i}(m_k, m_{k^*})$;
 - 4 compute $Value(Q_i)$ using Definition 1;
-

Algorithm 5: Determining the undominated set

Input: data (\mathbf{x}_i, Y_i) , set $\mathcal{M} = \{m_1, \dots, m_R\}$ of models

Output: the set of undominated model \mathcal{M}^*

- 1 **foreach** $k, l \in \{1, \dots, R\} \times \{1, \dots, R\}$, $k \neq l$ **do**
 - 2 | $\underline{R}(m_{k-l}) = 0$;
 - 3 | **foreach** data (\mathbf{x}_i, Y_i) **do**
 - 4 | **if** (\mathbf{x}_i, Y_i) is imprecise **then**
 - 5 | use Prop. 10 to get $\underline{\ell}_{k-l}(Y_i, \mathbf{x}_i)$;
 - 6 | **else**
 - 7 | compute $\underline{\ell}_{k-l}(Y_i, \mathbf{x}_i) = \ell_k(Y_i, \mathbf{x}_i) - \ell_l(Y_i, \mathbf{x}_i)$ using (34)
 - 8 | $\underline{R}(m_{k-l}) = \underline{R}(m_{k-l}) + \underline{\ell}_{k-l}(Y_i, \mathbf{x}_i)$;
 - 9 | **if** $\underline{R}(m_{k-l}) > 0$ **then** remove m_k from $\{m_1, \dots, m_R\}$;
-

383 **6. Experiments**

384 We run experiments on a “contaminated” version of 7 standard benchmark
 385 (binary classes) data sets that are described in Table 1. The next two Sections
 386 present the details of the experiments and the results obtained in the two cases
 387 of interval-valued features and set-valued labels.

388 *6.1. Interval-valued features case*

389 Given a data set, we randomly chose a training set \mathbf{D} consisting of 10% of
 390 instances and the rest (90%) as a test set \mathbf{T} . For each training instance $\mathbf{x}_i \in \mathbf{D}$,
 391 and each dimension $j = 1, \dots, p$, a biased coin is flipped in order to decide
 392 whether or not x_i^j will be contaminated; the probability of contamination is α (α

Table 1: Data set used in the experiments

Name	# instances	# features
parkinsons	197	22
vertebral-column	310	6
ionosphere	351	34
climate-model	540	18
breast-cancer	569	30
blood-transfusion	784	4
banknote-authentication	1372	4

393 is fixed to 0.4 in all the experiments). Note that the probability that an instance
394 has at least one contaminated feature is equal to $1 - 0.6^p$ (the complement of
395 having no features contaminated), which is quite high: 0.87 when $p = 4$, our
396 lowest number of features in any data set. In case x_i^j is contaminated, a width
397 q_i^j will be generated from a uniform distribution. Then, the generated interval
398 valued data is $X_i^j = [x_i^j + q_i^j(\underline{D}^j - x_i^j), x_i^j + q_i^j(\overline{D}^j - x_i^j)]$ where $\underline{D}^j = \min_i(x_i^j)$
399 and $\overline{D}^j = \max_i(x_i^j)$.

400 The set of undominated models is generated as follows: we randomly choose
401 100 precise replacements from the interval-valued training data. From each
402 replacement, one linear SVM model is trained. The set of such 100 models is
403 considered as the initial set \mathcal{M} of undominated models.

404 After each query, the efficiency of the querying scheme is assessed based on
405 the two following criteria:

- 406 - the proportion on the test set of identical predictions between the current
407 best potential model and a reference model. The reference model is chosen
408 to be the one in the initial undominated set that has the best accuracy
409 on the fully precise training set. It is thus the model towards which the
410 race must converge. The best potential model is the minimin model in the
411 race. In case of multiple minimal risk models, the one with the minimum
412 value of $\overline{R}(m)$ will be chosen as the best potential model;
- 413 - the size of the undominated set.

414 To make comparisons about the convergence of the two criteria, two base-line
415 algorithms are also used to query interval-valued features:

- 416 - a random querying strategy where, each time, an interval feature to be
417 queried is chosen randomly;
- 418 - the most partial querying strategy i.e, each time, the feature with the
419 largest imprecision (i.e., the largest sampled value q) is queried.

420 Because the training set is randomly chosen and contaminated, the results
421 may be affected by random components. Then, for each data set, we repeat the
422 above procedure 10 times and compute the average results.

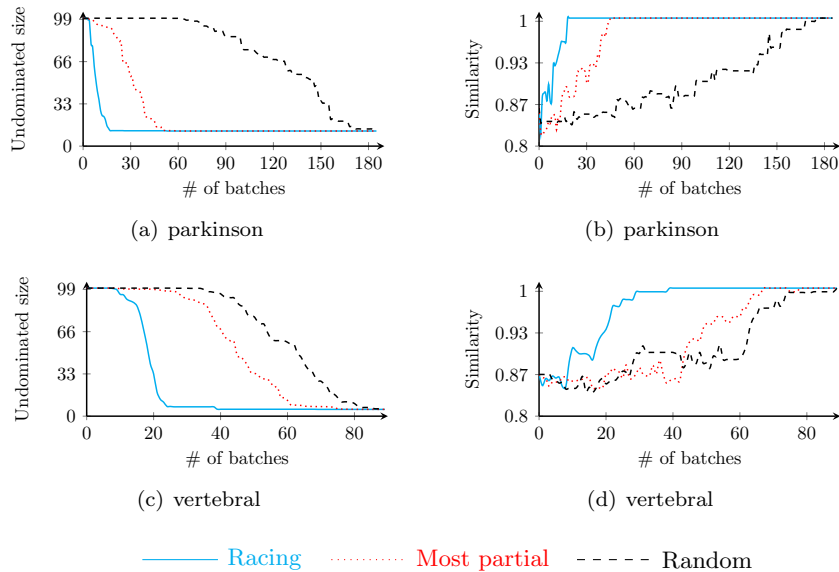


Figure 4: Experiments for interval-valued features data with preferred model

423 *6.2. Set-valued labels case*

424 Experiments for the case of set-valued labels is performed in a similar way.
 425 Firstly, we randomly chose a training set \mathbf{D} consisting of 20% of instances and
 426 the rest (of 80%) as a test set \mathbf{T} . Then, each label y_i in the training set \mathbf{D} will be
 427 contaminated with probability α (α is fixed to 0.8 in all the experiments). Since
 428 the label is binary, if a label is contaminated, it becomes completely missing.

429 To make comparisons, the two following base-line querying schemes are also
 430 used:

- 431 - a random querying strategy, where, each time, a set-valued label is chosen
 432 randomly
- 433 - and a query-by-committee (QBC) strategy which picks up the instance
 434 with a set-valued label associated to the highest disagreement among the
 435 predictions given by the models in the race;

436 For each cases, we only show the results for two data sets (Parkinsons and
 437 Veretbral), as all data sets display similar behaviours. The experimental results
 438 for the case of interval-valued features and set-valued labels are given in Figures
 439 4 and 5, respectively. The other results can be found in the Appendix.

440 In the case of set-valued labels, we can see that there are only slight dif-
 441 ferences between the methods. This result was expected, since, in the case of
 442 binary classification, partial labels are completely missing labels. Querying par-
 443 tial labels is thus equivalent to standard active learning methods like QBC. A
 444 lot of queries are needed to significantly reduce the set of undominated models

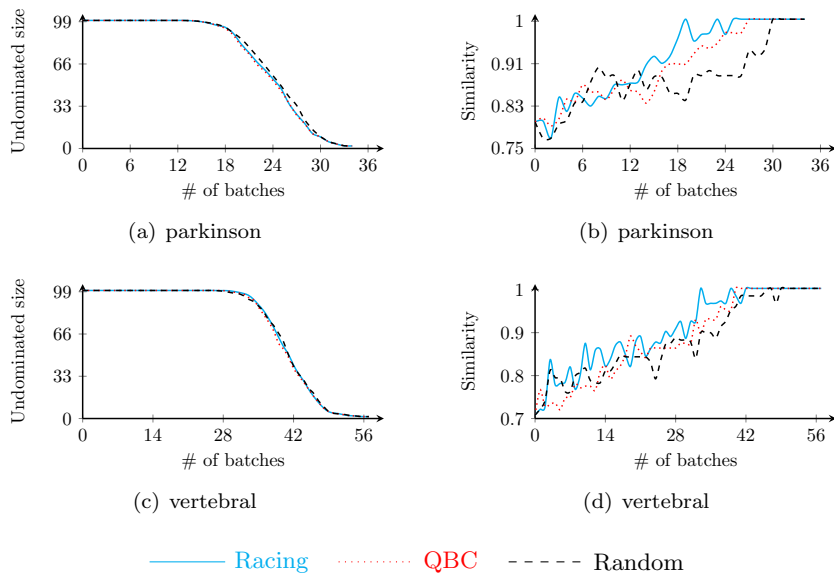


Figure 5: Experiments for set-valued labels data with preferred model

445 and to converge through the best model. Also, the random strategy has per-
 446 formances that are often comparable to the active learning ones. In contrast,
 447 the performances of our approach are much better than the others in the case
 448 of interval-valued features. One can see that the size of the set of undominated
 449 models is very quickly reduced and that our racing algorithm converges faster
 450 than the other approaches to the winning model.

451 It should be noted that the two previous sections provide an illustration of
 452 our approach to a particular learning method, i.e., binary SVM, but that the
 453 method can be applied in principle to any other learning method. Of course,
 454 whether or not the racing can be efficiently achieved or can improve quickly the
 455 prediction qualities vary from models to models, and can even depend on the
 456 aspects of data that are partial: in the case of binary SVM, our method is much
 457 more interesting when features are partial. We think it is however mainly due
 458 to two reasons: binary SVM are rather robust with respect to changes in the
 459 labels of data, as their learning rely only on a handful of precise points (the
 460 support vectors), and partial labels take a very restricted form (in contrast with
 461 partial features) that is equivalent to having missing labels. Therefore, what
 462 happens for SVM and labels will not necessarily happen for multi-class methods
 463 more sensitive to misspecified labels, such as decision trees.

464 In order to provide some insights about the potential difficulties of adapting
 465 our method to other models, the next section discuss briefly computational
 466 issues by building upon the results obtained for SVM.

467 **7. Discussion on computational issues**

468 The reader may have noticed that the section devoted to SVM with interval-
 469 valued features was quite longer, and presented more complex methods than the
 470 one about set-valued labels. Such an observation extends beyond SVM, and we
 471 try in this section to give some reasons why we may expect the problem of
 472 interval-valued features to be more complex than the problem of set-valued
 473 labels. As with the previous sections, we will stick to the case of 0 – 1 loss
 474 functions. We will first provide some general remarks about the implementation
 475 of our generic approach, and then will shortly discuss how results obtained for
 476 the SVM case could be extended to monotone models in general.

477 *7.1. General discussion*

478 A first remark is that when we have a partial data (\mathbf{X}_i, y_i) with interval-
 479 valued features, a query Q_i^j will not make the data precise unless only one feature
 480 is partial, but will transform \mathbf{X}_i into $\mathbf{X}'_i = \times_{k \neq j} X_i^k \times x_i^j$. In contrast, querying
 481 a partial data (\mathbf{x}_i, Y_i) with set-valued label Y_i guarantees that the queried data
 482 becomes the precise data (\mathbf{x}_i, y_i) , hence guaranteeing that the loss with respect
 483 to any model m_l will also become precise.

484 Let us now consider the problem of computing bounds of loss functions and
 485 potential effect of queries, with a focus on pairs of models and on the case
 486 where partial data will induce imprecision in the loss functions of both models,
 487 which constitute the most difficult aspects of our approach (our conclusions
 488 also apply to other calculations, yet these are typically easier to solve for both
 489 interval-valued features and set-valued labels).

Let us first consider the computations of $\underline{\ell}_{k-l}$: in the case of set-valued label Y_i , we do have

$$\underline{\ell}_{k-l}(Y_i, \mathbf{x}_i) = \begin{cases} 0 & \text{if } m_k(\mathbf{x}_i) = m_l(\mathbf{x}_i) \vee \{m_k(\mathbf{x}_i), m_l(\mathbf{x}_i)\} \cap Y_i = \emptyset \\ -1 & \text{else} \end{cases} \quad (35)$$

as the first case describes the only situations where we cannot find a label $\lambda \in Y_i$ such that $m_k(\mathbf{x}_i) = \lambda$ and $m_l(\mathbf{x}_i) \neq \lambda$. These conditions are rather easy to check in practice. In contrast, when one has interval-valued features, or more generally set-valued features \mathbf{X}_i with a precise label y_i , we have that

$$\underline{\ell}_{k-l}(y_i, \mathbf{X}_i) = \begin{cases} 1 & \text{if } \forall \mathbf{x}_i \in \mathbf{X}_i, m_k(\mathbf{x}_i) \neq y_i \wedge m_l(\mathbf{x}_i) = y_i \\ -1 & \text{if } \exists \mathbf{x}_i \in \mathbf{X}_i \text{ s.t. } m_k(\mathbf{x}_i) = y_i \wedge m_l(\mathbf{x}_i) \neq y_i \\ 0 & \text{else} \end{cases} \quad (36)$$

490 with the last case corresponding to the situation where we can only find² $\mathbf{x}_i \in \mathbf{X}_i$
 491 such that either $m_k(\mathbf{x}_i) = m_l(\mathbf{x}_i) = y_i$, or $m_k(\mathbf{x}_i) \neq y_i$ and $m_l(\mathbf{x}_i) \neq y_i$.
 492 In contrast with Equation (35) whose conditions are easily checked provided

²In addition to those possible \mathbf{x}_i for which $m_k(\mathbf{x}_i) \neq y_i$ and $m_l(\mathbf{x}_i) = y_i$.

493 $m_k(\mathbf{x}_i)$ and $m_l(\mathbf{x}_i)$ are easy to compute (this is the greatest majority of model-
 494 based learning methods), identifying which case of Equation (36) does apply is
 495 more complex and highly depends on the properties of the considered learning
 496 method.

Similar conclusions can be drawn to compute the effect $J_{Q_i^j}(m_l, m_k)$ of a possible query. In the case of a set-valued label Y_i , we can directly extend the observation made in Proposition 10 for SVM to have that

$$J_{Q_i}(m_k, m_l) = 1 \text{ iff } \underline{\ell}_{k-l}(Y_i, \mathbf{x}_i) = -1$$

497 where $\underline{\ell}_{k-l}(Y_i, \mathbf{x}_i) = -1$ is given by the general and usually easy to esti-
 498 mate Equation (35). In contrast, we cannot extend Proposition 8 to arbitrary
 499 models when we have interval-valued features. Of course we still have that
 500 $J_{Q_i^j}(m_k, m_l) = 0$ when $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i) = 1$, as it cannot be increased by any query.
 501 Yet, in the other cases, one must check that the conditions to have an increase
 502 of $\underline{\ell}_{k-l}(y_i, \mathbf{X}_i)$ are met at least for one value $x_i^j \in X_i^j$, and we do not see how
 503 to provide a generic, efficient algorithmic procedure to check them without con-
 504 sidering the specificities of the considered model.

505 7.2. The case of monotone models

506 In the case of the SVM methods, Proposition 7 uses the fact that linear
 507 functions are monotonic in every dimension \mathcal{X}^j . Note that our analysis should
 508 extend easily to all monotonic models, such as logistic regression or models based
 509 on the Choquet [18] and more generally on non-additive and fuzzy integrals [8].

As an illustration of this fact, let us consider the case of the logistic regression model. Keeping $\mathcal{X} = \mathbb{R}^p$ and the output space $\mathcal{Y} = \{-1, 1\}$ encoding the two possible classes, the logistic regression corresponding to a model m_k can be read³ as

$$m_k(\mathbf{x}_i) = \ln \frac{P_k(1|\mathbf{x}_i)}{P_k(-1|\mathbf{x}_i)} = \sum_{j=0}^p w_k^j x_i^j,$$

with $P_k(\cdot|\mathbf{x}_i)$ the posterior probabilities induced by model m_k , and vector \mathbf{w}_k its parameters with the convention $x_i^0 = 1$. This model obviously shares with the SVM that it is monotone in each of its parameters, and in the case of the 0 – 1 loss function, we also have

$$\ell_k(y_i, \mathbf{x}_i) = \begin{cases} 0 & \text{if } y_i \cdot m_k(\mathbf{x}_i) \geq 0 \\ 1 & \text{if } y_i \cdot m_k(\mathbf{x}_i) < 0. \end{cases} \quad (37)$$

Indeed, if $m_k(\mathbf{x}_i) > 0$, we have $P_k(1|\mathbf{x}_i) \geq P_k(-1|\mathbf{x}_i)$, hence predicting $\hat{y}_i = 1$. If we consider now that the features \mathbf{x}_i are imprecisely known (as said in the previous section, the major computational difficulties will mostly happen in the case of set-valued features), and that $X_i^j = [a_i^j, b_i^j]$ (note that we still have

³The adopted formulation allows us to better shows the similarities with the SVM case.

$X_i^0 = [1, 1]$, we can again easily determine when (\mathbf{X}_i, y_i) will be imprecise (1) w.r.t. a model m_k and (2) w.r.t. both models m_k and m_ℓ . Clearly, for the first case, we will have

$$[\underline{m}_k(\mathbf{X}_i), \overline{m}_k(\mathbf{X}_i)] = \left[\sum_{w_k^j \geq 0} w_k^j b_i^j + \sum_{w_k^j < 0} w_k^j a_i^j, \sum_{w_k^j \geq 0} w_k^j a_i^j + \sum_{w_k^j < 0} w_k^j b_i^j \right],$$

and (\mathbf{X}_i, y_i) will be imprecise w.r.t. m_k if and only if it contains the value 0 (arguments are similar to the one of the SVM case). Let us now consider the case of not one but two models m_k and m_ℓ , (\mathbf{X}_i, y_i) being imprecise w.r.t. both of them (in the other situations, the same remarks as the one done for the SVM case apply). Without loss of generality, we can assume that $y_i = 1$, and we then have that

$$\underline{\ell}_{k-\ell}(y_i, \mathbf{X}_i) = \begin{cases} 1 & \text{if } \forall \mathbf{x}_i, m_k(\mathbf{x}_i) < 0 \wedge m_\ell(\mathbf{x}_i) > 0 \\ -1 & \text{if } \exists \mathbf{x}_i, m_k(\mathbf{x}_i) > 0 \wedge m_\ell(\mathbf{x}_i) < 0 \\ 0 & \text{else .} \end{cases}$$

It is clear that the first case will never happen, as (\mathbf{X}_i, y_i) is imprecise w.r.t. m_k (so there is an \mathbf{x}_i for which m_k is positive). To check the second condition, we have to know whether we can find \mathbf{x}_i with $m_\ell(\mathbf{x}_i) < 0$, under the constraint that $m_k(\mathbf{x}_i) > 0$. This comes down to solve the following linear optimisation problem

$$\inf_{\substack{\mathbf{x}_i \in \mathbf{X}_i \\ m_k(\mathbf{x}_i) > 0}} \sum_{j=0}^p w_\ell^j x_i^j$$

510 and to check whether it is negative, in which case the lower bound is -1 , and 0
 511 otherwise. The methodology is here slightly different than in the SVM case, but
 512 still takes advantage of the monotonicity and linearity of the model. Completely
 513 implementing our proposal in the case of logistic regression would of course
 514 require some additional work (left here to the interested reader), but seems
 515 quite doable in the light of the above remarks.

516 8. Conclusion

517 This paper has explored an issue related to partially specified data: what
 518 is the best information to query so that an optimal model can be quickly der-
 519 ived. We have proposed a generic method, inspired from the idea of racing
 520 algorithms, to identify what partial data, feature or label should be queried
 521 (i.e., whose precise value should be obtained). The method search to differen-
 522 tiate, as soon as possible, different competing models. In principle, it can be
 523 applied to any learning method, but the computational complexity of applying it
 524 may vary between different learning methods, especially in the case of partially
 525 specified features, while the case of set-valued labels should present comparable
 526 complexities for most learning methods.

527 To illustrate this generic method, we have detailed its implementation for
528 the specific case of binary SVM, and have performed various experiments to
529 demonstrate the efficiency of our method. While it clearly outperformed other
530 approaches in the case of partial features, demonstrating the potential usefulness
531 of our approach in some cases, all tested approaches (including the random one)
532 were comparable in the case of set-valued labels. However, it should be kept
533 in mind that in the specific case of binary labels, learning and querying from
534 partial data comes down to classical active learning. The picture may be quite
535 different for multi-class problems.

536 Our future research efforts will mainly concentrate on applying this approach
537 to various learning methods. Decision trees seem particularly interesting, as we
538 are optimistic about the possibility to propose implementation that are compu-
539 tationally reasonable, and as those multi-class classifiers are well known to be
540 highly sensitive to training data. This means that they could strongly benefit
541 from our approaches. Logistic regression models, or their extension to non-linear
542 functions [18] could also be explored, as in this case we can probably use the
543 same monotonicity properties as in the SVM case.

544 **References**

- 545 [1] C. J. Burges. A tutorial on support vector machines for pattern recognition.
546 *Data mining and knowledge discovery*, 2(2):121–167, 1998.
- 547 [2] T. Cour, B. Sapp, C. Jordan, and B. Taskar. Learning from ambiguously
548 labeled images. In *Computer Vision and Pattern Recognition, 2009. CVPR*
549 *2009. IEEE Conference on*, pages 919–926. IEEE, 2009.
- 550 [3] T. Cour, B. Sapp, and B. Taskar. Learning from partial labels. *The Journal*
551 *of Machine Learning Research*, 12:1501–1536, 2011.
- 552 [4] A. P. Dempster, N. M. Laird, and D. B. Rubin. Maximum likelihood
553 from incomplete data via the em algorithm. *Journal of the royal statistical*
554 *society. Series B (methodological)*, pages 1–38, 1977.
- 555 [5] A. R. T. Donders, G. J. van der Heijden, T. Stijnen, and K. G. Moons.
556 Review: a gentle introduction to imputation of missing values. *Journal of*
557 *clinical epidemiology*, 59(10):1087–1091, 2006.
- 558 [6] M. Elahi, F. Ricci, and N. Rubens. A survey of active learning in collabo-
559 rative filtering recommender systems. *Computer Science Review*, 20:29–50,
560 2016.
- 561 [7] P. Fitzpatrick. *Advanced calculus*, volume 5. American Mathematical Soc.,
562 2006.
- 563 [8] M. Grabisch and J.-M. Nicolas. Classification by fuzzy integral: Perform-
564 ance and tests. *Fuzzy sets and systems*, 65(2-3):255–271, 1994.

- 565 [9] V. Heidrich-Meisner and C. Igel. Hoeffding and Bernstein races for selecting
566 policies in evolutionary direct policy search. In *Proceedings of the 26th Annual International Conference on Machine Learning*, pages 401–408. ACM,
567 2009.
568
- 569 [10] E. Hüllermeier. Learning from imprecise and fuzzy observations: Data dis-
570 ambiguation through generalized loss minimization. *International Journal*
571 *on Approximate Reasoning*, 55(7):1519–1534, 2014.
- 572 [11] E. Hüllermeier and J. Beringer. Learning from ambiguously labeled exam-
573 ples. *Intelligent Data Analysis*, 10(5):419–439, 2006.
- 574 [12] O. Maron and A. W. Moore. The racing algorithm: Model selection for
575 lazy learners. In *Lazy learning*, pages 193–225. Springer, 1997.
- 576 [13] V.-L. Nguyen, S. Destercke, and M.-H. Masson. Partial data querying
577 through racing algorithms. In *Integrated Uncertainty in Knowledge Mod-*
578 *elling and Decision Making: 5th International Symposium, IUKM 2016*,
579 pages 163–174. Springer, 2016.
- 580 [14] F. Olsson. A literature survey of active machine learning in the context of
581 natural language processing. Technical report t2009:06, Swedish Institute
582 of Computer Science, 2009.
- 583 [15] M. Raman-Sundström. A pedagogical history of compactness. *The Amer-*
584 *ican Mathematical Monthly*, 122(7):619–635, 2015.
- 585 [16] B. Settles. Active learning literature survey. Computer Sciences Technical
586 Report 1648, University of Wisconsin–Madison, 2009.
- 587 [17] H. S. Seung, M. Opper, and H. Sompolinsky. Query by committee. In
588 *Proceedings of the fifth annual workshop on Computational learning theory*,
589 pages 287–294. ACM, 1992.
- 590 [18] A. F. Tehrani, W. Cheng, K. Dembczyński, and E. Hüllermeier. Learning
591 monotone nonlinear models using the Choquet integral. *Machine Learning*,
592 89(1-2):183–211, 2012.
- 593 [19] S. Tong and D. Koller. Support vector machine active learning with ap-
594 plications to text classification. *Journal of Machine Learning Research*,
595 2:45–66, 2002.
- 596 [20] M. C. Troffaes. Decision making under uncertainty using imprecise prob-
597 abilities. *International Journal of Approximate Reasoning*, 45(1):17–29,
598 2007.
- 599 [21] L. V. Utkin and F. P. Coolen. Classification with support vector machines
600 and Kolmogorov–Smirnov bounds. *Journal of Statistical Theory and Prac-*
601 *tice*, 8(2):297–318, 2014.

- 602 [22] A. Wiencierz and M. Cattaneo. On the validity of minimin and minimax
603 methods for support vector regression with interval data. In *9th inter-*
604 *national symposium on imprecise probability: Theories and applications*,
605 pages 325–332, 2015.
- 606 [23] Z. Ye, P. Liu, J. Liu, X. Tang, and W. Zhao. Practice makes perfect: An
607 adaptive active learning framework for image classification. *Neurocomput-*
608 *ing*, 196:95–106, 2016.

609 **Appendix A. Experimental results**

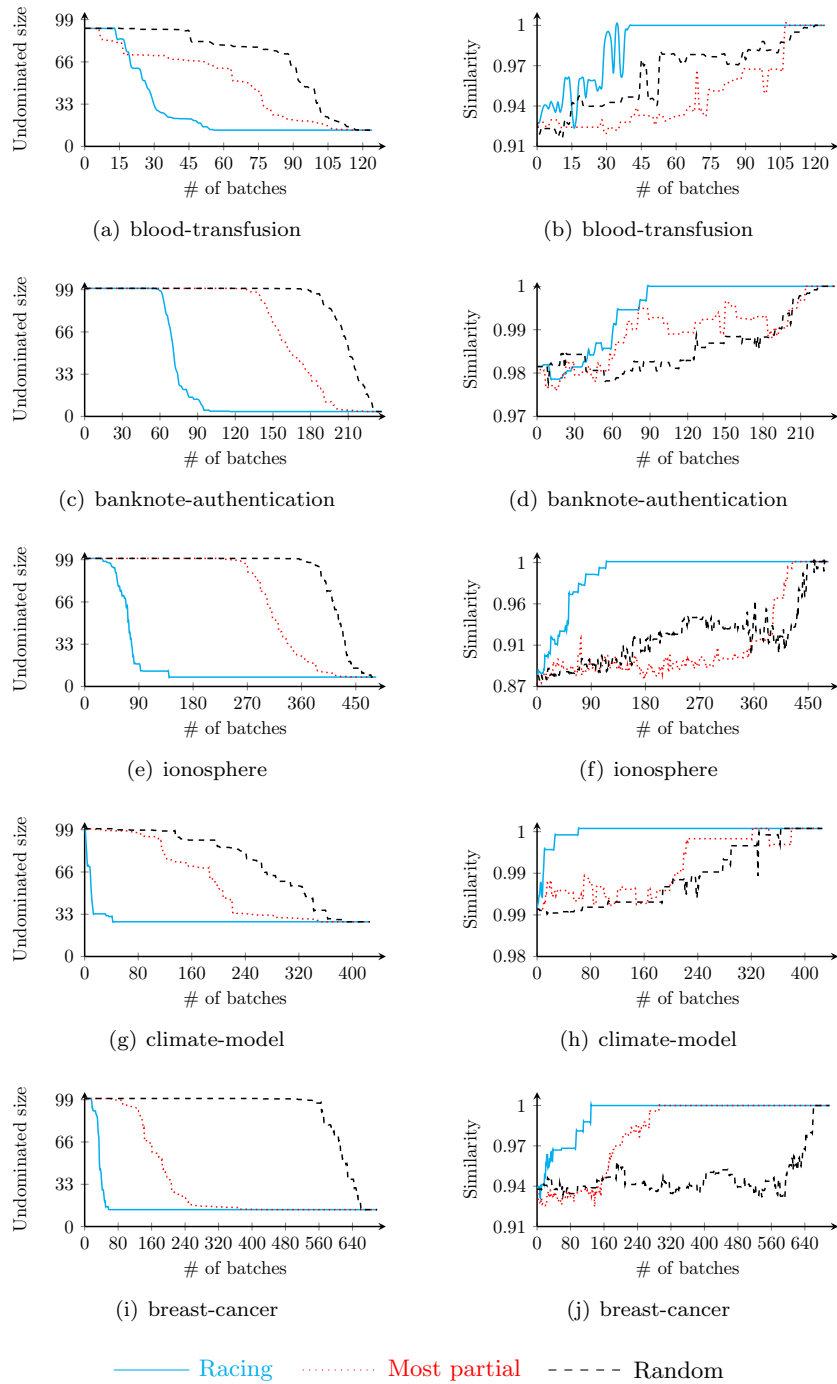


Figure A.6: Experiments for interval-valued features data with preferred model

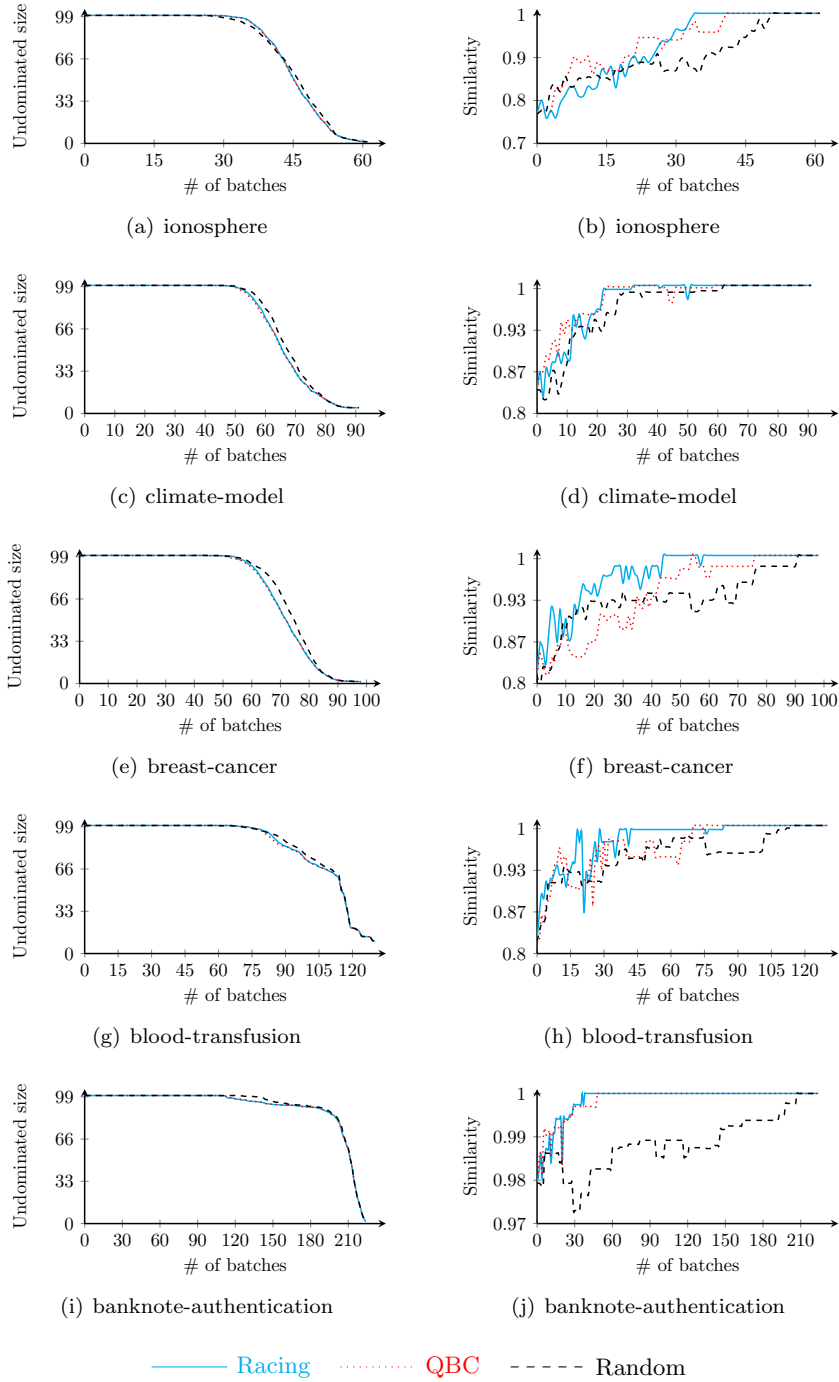


Figure A.7: Experiments for set-valued labels data with preferred model