Introspective Active Learning for Scalable Semantic Mapping

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***Abstract*—This paper proposes an active learning framework for semantic mapping in mobile robotics. In particular, our work explores the benefits of an introspective classifier over that of a more traditional non-introspective approach for active data selection. We extend the notion of introspection to a particular sparse Gaussian Process classifier, the Informative Vector Machine (IVM), and show that the use of an IVM leads to more informative questions being asked during active learning. We further leverage the information-theoretic nature of the IVM to formulate a principled mechanism for forgetting stale data. The result is an efficient and highly effective end-to-end active learning framework which outperforms both passive approaches as well as active approaches based on the more commonly used Support Vector Machine (SVM) in terms of classification performance and learning rate on a publicly available dataset.**

I. Introduction

The training of classifiers for application on large, continuous data streams is a challenging problem particularly pertinent to mobile robotics. As we aspire to robust, long-term autonomy, our systems have to contend with vast amounts of data from which information needs to be assimilated. In addition, the assumption of independent, identically distributed (i.i.d.) data common in detection and classification tasks is routinely violated as the dataset evolves. The ability to efficiently and repeatedly select an informative subset of data for further processing and, subsequently, learning therefore becomes increasingly indispensable in mobile robotics.

For our work, the task of offline semantic mapping serves as a concrete example. Significant progress in autonomous driving in recent years has inspired a view that successful autonomous operation in complex, dynamic environments critically depends on *a-priori* available semantic maps representing ostensibly permanent aspects of the environment such as lane markings, traffic light positions and road sign information (see, for example, [2, 4]). Owing to their safety-critical nature, these maps are commonly created manually specific to particular routes [5]. This is, of course, an expensive process which scales badly with the number of routes for which autonomous operation is to be provided. Much, therefore, stands to be gained by minimising human involvement in this process, thus providing a robust and scalable solution.

A prominent approach to tackling these challenges is that of active learning, where classification results are refined iteratively by asking for ground-truth labels in ambiguous cases and incorporating the added information into the classifier. To the best of our knowledge this paper is the first in robotics to present an efficient and scalable active learning framework for the task of offline semantic mapping. Crucially, however, our work is also set apart from the vast majority of the related works in active learning by the unusual stance we take with regards to uncertainty estimates in the system. Generally, active learning relies on being able to select data for labelling using confidence measures derived from a classifier's output: if the classification of a datum is insufficiently confident it will be passed to an oracle (often a human labeller) to obtain ground truth class information. This is then incorporated into the classifier by retraining. It has recently been shown, however, that several of the classification frameworks commonly used in robotics are unrealistically overconfident in their assessment of class membership [7]. In this context, Grimmett *et al.* [7] have motivated and introduced the notion of an *introspective capacity* of a classification framework: the ability to mitigate potentially overconfident classifications by an appropriate assessment of how qualified the system is to make a judgement on the current test datum. In this paper we show that *introspective classification* harbours significant benefits for active learning as compared to more traditional, non-introspective approaches. In particular, the contributions of this paper are

- the application of an active learning framework to semantic mapping in robotics,
- the application of the notion of introspection to the Informative Vector Machine (IVM) [10] as an efficient extension to [7],
- the application of the IVM specifically to achieve *introspective* active learning, which is demonstrated to lead to more effective information extraction over more traditional approaches, and
- the introduction of a principled mechanism for the IVM to *forget* less important data to provide for scalable, life-long active learning.

We apply our framework to the detection of traffic lights in a real, third-party image dataset and demonstrate iteratively improved semantic mapping, which makes efficient use of available label information. A typical qualitative example of our system output is shown in Fig. 1.

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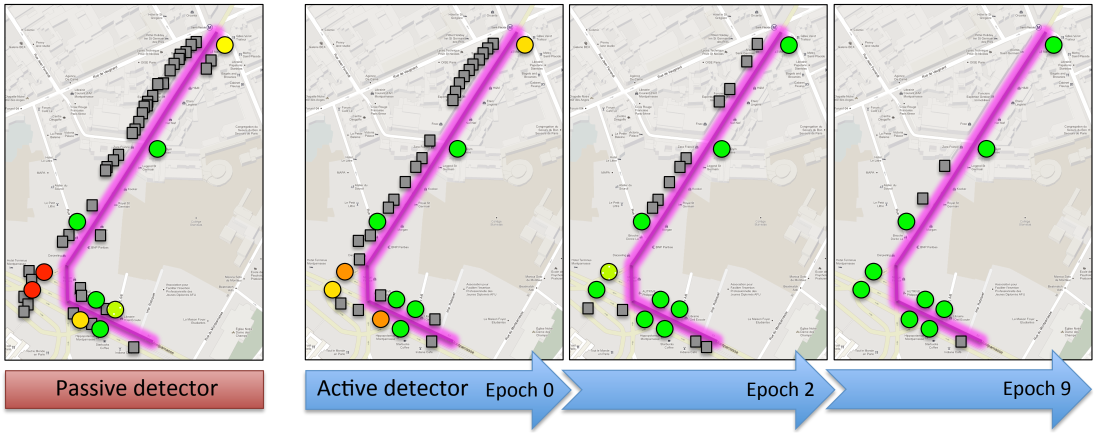

Fig. 1: Active learning in a semantic mapping context. This figure shows semantic maps indicating the positions of traffic lights along a street in Paris. Circles denote the locations of ground-truth traffic lights. The shading encodes the correctness of the classification output as provided by a probabilistic classifier: red denotes the *background* component, green denotes the *traffic light* component. False positives are shown as grey squares. From left to right, we first see a typical passive detector, followed by our active-learning framework at epochs 0, 2, and 9 respectively. Note that in the active learning setting the shading of the circles progresses from red to green as a greater proportion traffic lights are correctly detected with increasing confidence. Similarly the number of false positives reduces dramatically. By epoch 2 the active learning framework already outperforms the passive detector. In this paper we show that our formulation of an *introspective* active learning approach provides for more efficient information extraction – and thus a higher learning rate – over conventional active learning approaches. (This figure is best viewed in colour.)

II. Related Works

Active learning is an established and vibrant field of research spanning a significant number of application domains. Consequently, a variety of methods have been proposed for selecting informative measurements for labelling and/or for incrementally training a learning algorithm. For example, Freund *et al.* [6] propose disagreement among a committee of classifiers as a criterion for active data selection. McCullum and Nigam [11] apply this to text classification using high label inconsistency as a query criterion coupled with expectation maximisation (EM) for online learning. More recently, Joshi *et al.* [8] address multi-class image classification using SVMs and propose criteria based on entropy and best-versus-second-best (BvSB) measures based on the hyperplane-margin for determining uncertain points. Tong and Koller [17] pick unlabelled data for query based on minimising the version space within a margin-based SVM formulation. Kapoor *et al.* [9] propose an active learning system for object categorization using a GP classifier where data points possessing large uncertainty (using posterior mean and variance) are queried for labels and used to improve classification.

Within the robotics community, active learning and directed information acquisition has received attention in recognition, planning and mapping tasks. For example, Dima *et al.* [3] present unlabelled data filtering for outdoor terrain classification tasks with the aim of reducing the amount of training data to be human-labelled. The approach relies on kernel density estimation over unlabelled data and estimating a "surprise" score for image patches, hence only querying the least likely samples given the density estimate for human labelling. In [13] the authors present a learning approach for continually improving place recognition perfomance by actively learning an appearance model of a robot's operating environment. The method uses probabilistic topic models and a measure of perplexity to identify least explained images which further drives retrieval of thematically linked samples leading to an improved workspace representation. Recent work by Tellex *et al.* [16] explores active information gathering for human-robot dialog. The authors formulate an information-theoretic strategy for asking targeted clarifying questions to disambiguate the robot's belief over the mapping between phrases and aspects of the workspace.

While, to the best of our knowledge, this is the first work in robotics applying active learning to a semantic mapping task, our work is also set apart significantly from prior art in active learning in that we introduce and demonstrate the benefits of efficient *introspective* active learning. In this respect, the work most closely related to ours is that of [9] above, in which an inherently introspective classifier is used but its use is not motivated by its introspective qualities.

III. Efficient Introspective Classification

The introspective capacity of a classifier characterises its ability to *realistically* estimate the uncertainty in its predictions. Grimmett *et al.* [7] define the introspective capacity as a classifier's ability to moderate its output by an appropriate measure as to how 'qualified' it is to make a call given its own prior experience, usually in the form of training data. The intuition is that test data, which are in some form 'similar' to that seen in training, are classified with higher certainty than data which are more dissimilar. This points towards non-parametric approaches potentially being more introspective than parametric ones, as all the training data are available for inference in the former, whereas inference in the latter is based on parametric models learned from the data. Grimmett *et al.* [7] investigated several commonly used classification frameworks providing probabilistic output and found that a Gaussian Process classifier (GPC) [15] indeed is significantly more introspective than, for example, the more commonly used Support Vector Machine (see, for example, [1]) with a probabilistic calibration (such as, for example, provided by [14]).

The authors of [7] attribute this quality to a GPC's Bayesian treatment of predictive variance. Consider a set of training data $\{\mathcal{X}, \mathcal{Y}\}$, where $\mathcal{X} = \{\mathbf{x}_1, \ldots, \mathbf{x}_{|\mathcal{X}|}\}$ denotes the set of feature vectors and $\mathcal{Y}$ denotes the set of corresponding class labels. Probabilistic predictions for a test point, $\mathbf{x}_*$, are obtained in two steps. First, the distribution over the latent variable corresponding to the test input is obtained by

$$p(f_* \mid \mathcal{X}, \mathcal{Y}, \mathbf{x}_*) = \int p(f_* \mid \mathcal{X}, \mathbf{x}_*, f) p(f \mid \mathcal{X}, \mathcal{Y}) df, \quad (1)$$

where $p(f \mid \mathcal{X}, \mathcal{Y})$ is the posterior distribution over latent variables. This is followed by applying a sigmoid function $\sigma(\cdot)$, which in our implementation is the cumulative Gaussian, and *marginalising* over the latent f_* to yield the class likelihood $p(y_* \mid \mathcal{X}, \mathcal{Y}, \mathbf{x}_*)$ as

$$p(y_* \mid \mathcal{X}, \mathcal{Y}, \mathbf{x}_*) = \int \sigma(f_*) p(f_* \mid \mathcal{X}, \mathcal{Y}, \mathbf{x}_*) df_*. \quad (2)$$

It is this *marginalisation* over all models induced by the training set, as opposed to relying on a single *minimisation*-based estimate, which accounts for an accurate estimate of the inherent uncertainty in class distribution, and therefore endows GP classification with a high introspective capacity.

A. Information-Theoretic Sparsification

A key drawback of a GPC is its significant computational demand in terms of memory and run time. This is due to the fact that the GP maintains a mean $\boldsymbol{\mu}$, as well as a covariance matrix Σ, which is computed from a kernel function and of size squared in the number of training samples. A number of sparsification methods have been proposed in order to mitigate this computational burden. For efficiency, in this work we adopt one such sparsification method: the Informative Vector Machine (IVM) [10]. The main idea of this algorithm is to only use a sub-set of the training points denoted the *active set*, $\mathcal{I}$, from which an approximation of the posterior covariance $q(f \mid \mathcal{X}, \mathcal{Y}) = \mathcal{N}(f \mid \boldsymbol{\mu}, \Sigma)$ is computed. The IVM algorithm computes $\boldsymbol{\mu}$ and Σ incrementally and at every iteration, j, selects the training point $(\mathbf{x}_k, y_k)$ for inclusion into the active set, which maximizes the entropy difference ΔH_{jk} between q_{j-1} and q_j. As q is Gaussian, ΔH_{jk} can be computed by

$$\Delta H_{jk} = -\frac{1}{2} \log|\Sigma_{jk}| + \frac{1}{2} \log|\Sigma_{j-1}|. \quad (3)$$

The algorithm stops when the active set has reached a desired size. In our implementation, we choose this value as a fixed fraction of the training set.

To find the kernel hyper-parameters $\boldsymbol{\theta}$ of an IVM, two steps are processed in a loop for a given number of times: estimation of $\mathcal{I}$ from $\boldsymbol{\theta}$ and minimising the marginal likelihood $q(\mathbf{y} \mid \mathcal{X})$, thereby keeping $\mathcal{I}$ fixed. Although there are no convergence guarantees, in practice already a small number of iterations are sufficient to find good kernel hyper-parameters.

Importantly for our work, since inference with the IVM is similar to that with a GPC, the IVM retains the model averaging described in Eq. (2). We argue, therefore, that the IVM provides a significant and well-established improvement in processing speed over a GPC while maintaining its introspective properties.

IV. Scalable Active Learning

The power of an active learning framework lies in its ability to select a suitable training set in an application-oriented way. It thus inherently allows the system to naturally adapt to the non-stationarity of the data often encountered in long-term robotics applications. The active learning framework considered here provides for supervised learning where a human operator furnishes class labels for selected test data that are then fed back into classifier training to improve the classification result of the next round. We therefore consider progress in terms of consecutive *epochs*, which each consist of (re-)training, classification and user-feedback. The implementation of a scalable active learning framework requires two problems to be addressed: firstly, a sub-set of test data have to be selected for re-training such that classification performance increases in the next epoch. Secondly, measures have to be taken that guarantee that the active set is bounded in size, since otherwise the algorithm will sooner or later exhaust the resources of a finite-memory, real robotic system. We now provide details of both our data selection strategy and our approach to forgetting (bounding the active set size), before outlining the specific active learning algorithm employed in this work.

A. Data Selection Strategy

The key element of an active learning algorithm is the strategy by which a new test point $\mathbf{x}^*$ is considered for re-training. In this work we adopt a greedy strategy which simply adds the r top-ranked data points to the classifier training set as long as these data also exceed a threshold indicating suitability.

An intuitive and well-explored indicator of which data might be suitable for inclusion is the classification *uncertainty* associated with $\mathbf{x}^*$. To characterise the uncertainty of the classification from the given class prediction $z = p(y_* \mid \mathcal{X}, \mathbf{y}, \mathbf{x}_*)$, we adopt the measure of *normalised entropy* $H(z)$, such that for the binary case,

$$H(z) = -z \cdot \log_2(z) - (1 - z) \cdot \log_2(1 - z). \quad (4)$$

The normalized entropy ranges between 0 and 1, with high values representing high uncertainty.

This, indeed is central to our work. While, in principle, any classification framework which provides a distribution over class labels as output can be used in our active learning framework, intuitively we expect those with more realistic estimates of these probabilities to be more effective for active learning. Thus, we expect more introspective classifiers to perform better in the sense that they will ask more informative questions, leading to a higher learning rate. In Sec. V, we will show that this is indeed the case when comparing the proposed framework based on an IVM with one based on a more commonly used, probabilistically calibrated SVM.

B. Bounding the Active Set Size by Forgetting

The main problem with the active learning framework as we presented it so far is that in theory the training set can grow arbitrarily. The reason for this is that there are no guarantees that the algorithm will stop asking new questions at some point. This makes the algorithm less flexible, especially if the input data can not be guaranteed to be within certain locality bounds, for example in a life-long learning application. Therefore, and for run time efficiency, we bound the size of the training set by removing points from it when it exceeds a given target size t. To decide which points to remove, we leverage the information-theoretic instruments that the IVM already provides. After each training round, we keep the entropy differences given in Eq. (3) for all training points and sort them in increasing order. Those training data which correspond to the first $n_i - t$ values, where n_i is the current training set size, are then removed. Intuitively, this method discards the data that were least informative during the last training round, those which influence the classification performance the least. One caveat with this method is that it assumes independence between the training data, which is not generally given. For example, two data may both have small individual ΔH-values, but when removing both of them, the entropy could change significantly. In this work we acknowledge but do not explore this phenomenon. Instead, we note that in our experiments we did not observe a deterioration in classification performance when we applied our method for forgetting.

C. The Active Learning Algorithm

Algorithm 1 describes our active learning framework which, for reasons given in Section III, uses an IVM as the underlying classifier. It requires five different input parameters: the initial hyper-parameters $\boldsymbol{\theta}_0$ used for training the IVM, the fraction q of active points that are used for sparsification, the batch size b, the normalised entropy threshold ϑ that a test point needs to exceed to be considered for retraining, and the maximum number of questions r that the algorithm may ask. The latter is intended to minimise nuisance to a human operator due to being asked too many questions. The sub-routines in the algorithm are explained as follows. `TrainIVM` uses the current training set, the active set fraction q, and the initial kernel parameters to find optimal kernel parameters $\boldsymbol{\theta}_{i+1}$ and an active set $\mathcal{I}_{i+1}$ as described in Sec. III-A. Throughout this work we employ a squared exponential kernel with additive white noise, such that

$$k(\mathbf{x}_i, \mathbf{x}_j) = \sigma_f^2 e^{-\frac{(\mathbf{x}_i - \mathbf{x}_j)^2}{2l^2}} + \sigma_n^2 \delta_{ij}, \quad (5)$$

where δ_{ij} is the Kronecker delta, and $\boldsymbol{\theta} = \{\sigma_f^2, l, \sigma_n^2\}$ are the signal variance, the length scale, and the noise variance. `IVMPrediction` returns an estimate of the probability z that the next test data point $\mathbf{x}^*$ has a particular class label, as given in Eq. (2). Based on this probability, the normalised

Algorithm 1: Active Learning with an IVM

Data: training data $\mathcal{D} = (\mathcal{X}, \mathbf{y})$, stream of test data $\mathcal{X}^*$
Input: initial kernel parameters $\boldsymbol{\theta}_0$, batch size b, active set size fraction q, minimal retraining score ϑ, maximum number of questions r
Output: stream of output labels $\mathbf{y}^*$

```
i ← 0
while X* ≠ ∅ do
    (θ_{i+1}, I_{i+1}) ← TrainIVM(X, y, q, θ_0)
    move next b test points from X* into X*_i
    P ← ∅
    forall the x* ∈ X*_i do
        z ← IVMPrediction(I_{i+1}, θ_{i+1}, x*)
        s ← ComputeRetrainingScore(z)
        if s > ϑ then  P ← P ∪ {(x*, s)}
    sort P by decreasing values of s
    D+ ← ∅
    for j ← 1 to MIN(r, |P|) do
        (x+_j, s_j) ← element j of P
        y+_j ← AskLabelFromUser(x+_j)
        D+ ← D+ ∪ (x+_j, y+_j)
    D ← D ∪ D+,   i ← i + 1
```

entropy measure is then computed. The top ranked r test data exceeding the retraining threshold ϑ are labelled by the user and added to the training set for the next epoch.

V. Experimental Results

In this section we investigate the performance of our introspective active learning approach in terms of learning rate, data selection strategy, classification performance and tractability. We compare and contrast our approach with one based on the much more commonly used SVM classifier (calibrated to provide probabilistic output). The task we set both learners is to detect traffic lights in a third-party image dataset. Specifically, we use the publicly available Traffic Lights Recognition (TLR) data set [12], which comprises 11,179 colour images taken at 25 Hz from a car driven through central Paris at speeds under 31 mph. It has ground-truth labels for traffic light positions and subtype labels 'green', 'orange', 'red', 'ambiguous' (though here we are only concerned with the detection of traffic lights, irrespective of their state). As recommended by the authors of the dataset, we disregard labels of type 'ambiguous' and exclude sections where the vehicle was stationary for long periods of time. We use data from the first 7,200 frames for training and the remainder for testing. We compute a template-based feature set inspired by Torralba *et al.* [18] which has a successful track record in the detection of traffic lights [7]. From each of the training partition and the test partition we extract 1,000 positive windows and 10,000 negative windows, giving rise to 22,000 feature vectors of dimension 200.

As described in Sec. IV, our active learning algorithm is retrained after having seen a fixed number of test points, as opposed to running the training algorithm after every new datum encountered. During our experiments, the classifiers each go through 10 epochs. Every epoch consists of a training phase, a classification phase, and a feedback phase. At the very start of epoch 0, the classifiers are trained on a randomly chosen 5% of the training set. During each classification phase, the classifiers are then tested on a batch of 1,000 points randomly drawn from the test set. Then the 10 points with the highest normalised entropy (providing they are over a threshold empirically set to be $\vartheta = 0.97$) are greedily added to the training set, ready for retraining at the start of the next epoch. Note that each classifier (IVM and SVM) makes its own choices regarding which points to add for the next epoch.

A. Active Learning and the Benefit of Introspection

One of the central claims of this paper is that the use of an introspective classifier will lead to more informative questions being asked when selecting data for human labelling and inclusion into the training set. In order to test this claim both an IVM and an SVM are initially trained on the same data. Then, 1,000 new data are shown to both classifiers for testing. Each chooses 10 data to add to the training set for the next round, resulting in *two* new and different training sets: the 'IVM set' and the 'SVM set'. A new IVM and SVM are now trained on *each* of the two new sets and evaluated on a further 1,000 held out data points. This process thus gives rise to four classifiers: two IVMs trained on data selected by an IVM and a SVM respectively, and two equivalent SVMs. We compute precision and recall for all four classifiers. The results after 100 repetitions of this experiment are shown in Fig. 2. As expected, both the IVM and the SVM perform better when trained on the dataset chosen, introspectively, by the initial IVM, suggesting that the questions asked by the IVM tend to be significantly more informative. An unpaired t-test shows this result to be significant to a level of over 99.9%. The overall effect of introspection in an active learning setting is therefore an increased learning rate, as shown in Fig. 3, where the IVM learner based on a normalised entropy selection policy outperforms the equivalent SVM based method both in absolute terms per epoch as well as in terms of relative increase (information gained) per epoch.

Fig. 3 further serves to justify empirically our choice of normalised entropy as a valid criterion for data selection by comparing it to randomly selecting new training data. Intuitively, both methods should improve classification by virtue of the fact that they increase the training set size. However, the results indicate that for both the IVM and the SVM, using normalised entropy leads to more rapidly improving classification performance.

B. Tractability

Our work aims to contribute an introspective active learning algorithm that is efficient in terms of computational effort and scalable with respect to its memory requirements. In this section we investigate the efficacy of the mechanism we have put in place to provide this tractability: forgetting. In experiments thus far new training data were added in each epoch. The IVM active set size is a fixed proportion of the training set size, $q = 0.2$. This has the benefit of increasing

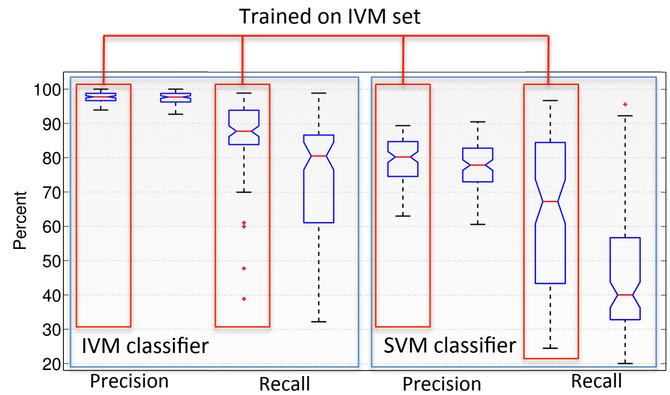

Fig. 2: The benefit of introspection. Data selected by an introspective classifier lead to an improved learning rate in terms of precision and recall for both and IVM and and SVM over that selected by a non-introspective classifier. Results are shown for 100 experimental runs. See text for more details.

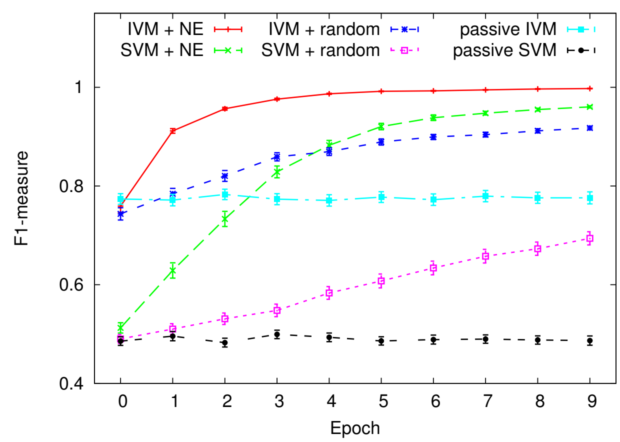

Fig. 3: Classification performance and (learning rates) for both IVM and SVM variants as indicated by the f_1-measure after each epoch. Measurements are averaged over 100 runs. Error bars indicate one standard error of the mean. The IVM using a normalised entropy-based data selection strategy (IVM+NE) consistently outperforms all other active learning variants in terms of overall performance and learning rate.

classification performance, but to the detriment of processing time. In the context of a life-long-learner, this is not a scalable solution.

We therefore elect to cap the size of the training set at 550 data, which in turn makes the computational effort constant at every epoch. This *IVM+forgetting* learner can add new data, but only by simultaneously discarding a similar number. Fig. 4 (left) shows the level of sparsity for three different active learners: IVM, SVM, and IVM+forgetting. The SVM sparsity is unbounded, and so grows rapidly with training set size. The IVM active set size also grows at 20% of the training set, but the IVM+forgetting is constant past epoch 2. Fig. 4 (right) shows the corresponding classification performance as characterised by the f_1 measure. It indicates that, in this case, the IVM+forgetting mechanism performs no worse than the

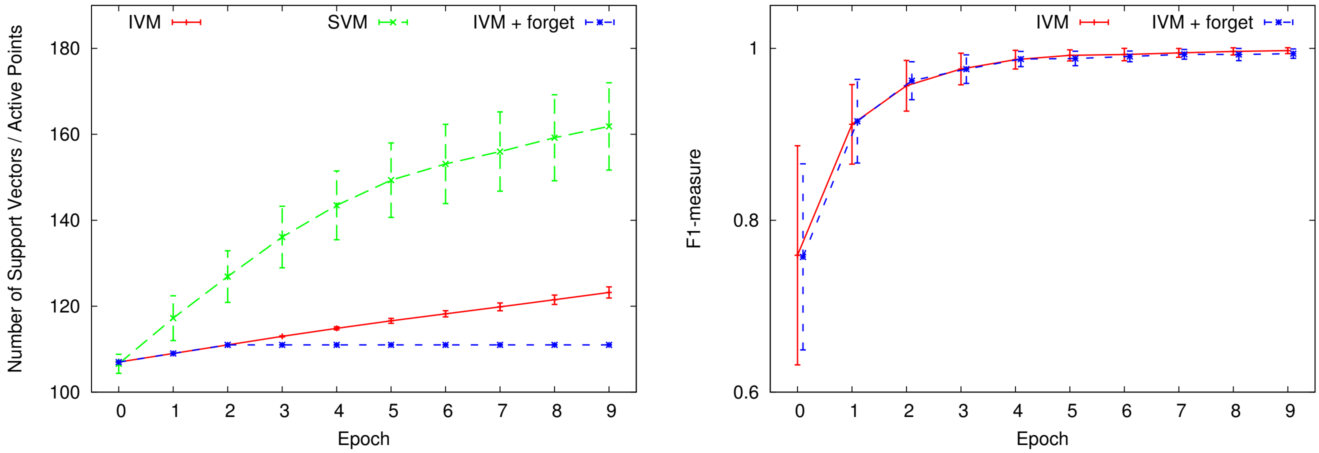

Fig. 4: *Forgetting* results in commensurate classification performance while successfully bounding the active set size of the classifier. Each datum represents the mean (and associated standard deviation) over 100 experimental runs. **Left:** The evolution of sparsity (number of support vectors for the SVM, active set size for the IVM) over several epochs. **Right:** Classification performance with and without *forgetting*. For corresponding SVM results, see Fig. 3.

original IVM.

VI. Conclusion

This paper investigates the benefits of an introspective active learning framework in the context of a semantic mapping task in mobile robotics. In contrast to related works on active learning our approach leverages an *introspective* classifier for data selection, which moderates its uncertainty estimates by accounting for the predictive variance associated with the datum. This results in increased learning rates compared to more commonly used, non-introspective approaches, since a more accurate estimate of predictive variance leads to more effective use of class information contained in the data. This is a key contribution of our work.

Efficiency and tractability are achieved by several mechanisms: firstly, we extend the argument for the introspective qualities of a GPC to a sparse GPC variant, the IVM. To the best of our knowledge this is the first work to consider introspective - and more specifically, IVM-based - active learning. This, therefore, constitutes another key contribution of our work. Secondly, we introduce an information theoretic mechanism for *forgetting*, which bounds the size of the IVM active set and thus leads to constant time inference. This was found to perform well on the data used in this work and, overall, results in an efficient and effective active learning scheme, which outperforms more traditional approaches in terms of learning rate and absolute classification performance per epoch.

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