Comparison of Data Selection Strategies for Online Support Vector Machine Classification

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Abstract: It is often the case that practical applications of support vector machines (SVMs) require the capability to perform online learning under limited availability of computational resources. Enabling SVMs for online learning can be done through several strategies. One group thereof manipulates the training data and limits its size. We aim to summarize these existing approaches and compare them, firstly, on several synthetic datasets with different shifts and, secondly, on electroencephalographic (EEG) data. During the manipulation, class imbalance can occur across the training data and it might even happen that all samples of one class are removed. In order to deal with this potential issue, we suggest and compare three balancing criteria. Results show, that there is a complex interaction between the different groups of selection criteria, which can be combined arbitrarily. For different data shifts, different criteria are appropriate. Adding all samples to the pool of considered samples performs usually significantly worse than other criteria. Balancing the data is helpful for EEG data. For the synthetic data, balancing criteria were mostly relevant when the other criteria were not well chosen.

1 INTRODUCTION

The support vector machine (SVM) has become a well known classification algorithm due to its good performance (Cristianini and Shawe-Taylor, 2000; Müller et al., 2001; Schölkopf and Smola, 2002; Vapnik, 2000). SVM is a static batch learning algorithm, i.e., it uses all training data to build a model and does not change when new data is processed. Despite having the advantage of being a powerful and reliable classification algorithm, SVM can run into problems when dataset shifts (Quionero-Candela et al., 2009) occur due to its static nature. The issues that arise from dataset shifts are amplified when the algorithm is run using limited resources, e.g., on a mobile device, because a complete retraining is not possible anymore.

In the context of SVM learning applied to encephalographic data (EEG), as used for brain-computer interfaces (BCIs)(Blankertz et al., 2011; Zander and Kothe, 2011; Kirchner et al., 2013; Wöhrle et al., 2015), dataset shifts are a major issue. The source of the problem lies in the fact that the observed EEG pattern changes over time, e.g., due to inherent conductivity fluctuations, sensor displacement, or subject tiredness. The issue of dataset shifts also occurs in other applications like robotics. A classic example of a dataset shift would be that of a machine vision classifier being trained during daylight and then used to classify image data taken during the night. Temperature fluctuations, wear and debris inside the robotic frame can lead to a different behavior in certain robotic systems. The behavioral change then impacts measurement results, which is further reflected in the occurrence of a dataset shift.

In any case, it is often possible to adapt the classifier for new incoming data to handle continuous dataset shifts. A straightforward approach would be to integrate a mechanism that labels[1] the incoming data, and afterwards retrain the SVM. Such a re-

[1]When predicting movements with the help of EEG or the electromyogram (EMG) in rehabilitation the labeling is straightforward. For example, by means of a tracking device, or an orthosis, it can be checked whether there is a "true" movement. After a short period of time, the data can be labelled and used for updating the classifier.

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training approach is used by (Steinwart et al., 2009), whereby the optimization problem is given a warm start. Note that there is a large corpus of other algorithms to implement these strategies more efficiently but they are not subject of this paper (Laskov et al., 2006; Liang and Li, 2009). Nevertheless, there are however computational drawbacks that come with this approach, since the SVM update leads to an increase in both processing time (especially when kernels are used), as well as in memory consumption which is the larger problem. Taking into account that for applications like for example BCIs and robotics, mobile devices are often used for processing (Wöhrle et al., 2013; Wöhrle et al., 2014), the scarcity of computing resources conflicts with a high computational cost. Additionally, the online classifier adaptation scheme should be faster than the time interval between two incoming samples.

In the following, we focus on a small subgroup of online learning algorithms which limit the size of the training dataset, such that powerful generalization capabilities of SVM are not lost. In Section 2, we provide a systematic overview over the different strategies for restricting the size of the training set. In the context of data shifts, class imbalance is a major issue which has not yet been sufficiently addressed for online learning paradigms (Hoens et al., 2012). Hence, we additionally suggest approaches which tackle this specific problem, namely the case in which:

1. The class ratio is *ignored*.
2. After the initialization, the class ratio is kept *fixed*.
3. A *balanced* ratio is sought throughout the learning process.

In Section 3, we provide a comparison of the numerous strategies by testing them, firstly, on synthetic datasets with different shifts and, secondly, on a more complex classification task with EEG data. Finally, we conclude in Section 4.

2 REVIEW OF TRAINING DATA SELECTION STRATEGIES

This section introduces SVM and the different methods for manipulating its training data for online learning. The data handling methods for SVM can be divided into criteria for adding samples, criteria for removing samples, and further variants which influence both.

2.1 Support Vector Machine

The main part of the SVM concept is the maximum margin which results in the regularization term $\left(\frac{1}{2}\langle w,w\rangle\right)$. Given the training data

$$D = \left\{(x_j, y_j) \in \{-1,+1\} \times \mathbb{R}^m \middle| j \in \{1,\ldots,n\}\right\}, \tag{1}$$

the objective is to maximize the distance between two parallel hyperplanes which separate samples x_i with positive labels $y_i = +1$ from samples with negative labels. The second part is the soft margin which allows for some misclassification by means of the loss term, $\sum t_j$. Both parts are weighted with a cost hyperparameter C. Since the data is usually normalized, the separating hyperplane can be expected to be close to the origin with only a small offset, b. Hence, the solution is often simplified by minimizing b (Hsieh et al., 2008; Mangasarian and Musicant, 1998; Steinwart et al., 2009). The resulting model reads:

$$\begin{aligned} \min_{w,b,t} \quad & \left(\tfrac{1}{2}\|w\|_2^2 + \tfrac{1}{2}b^2 + C\sum t_j\right) \\ \text{s.t.} \quad & y_j(\langle w, x_j\rangle + b) \geq 1 - t_j \quad ,\forall j : 1 \leq j \leq n, \\ & t_j \geq 0 \quad ,\forall j : 1 \leq j \leq n. \end{aligned} \tag{2}$$

Here, $w \in \mathbb{R}^m$ is the classification vector which, together with the offset b, defines the classification function $f(x) = \langle w, x\rangle + b$. The final label is assigned by using the signum function on f. The decision hyperplane is $f \equiv 0$, and the aforementioned hyperplanes (with maximum distance) correspond to $f \equiv +1$ and $f \equiv -1$. In order to simplify the constraints, and to ease the implementation of SVM, the dual optimization is often used:

$$\min_{C \geq \alpha_j \geq 0} \left(\frac{1}{2}\sum_{i,j}\alpha_i\alpha_j y_i y_j (k(x_i,x_j)+1) - \sum_j \alpha_j\right). \tag{3}$$

The scalar product is replaced by a symmetric, positive, semi-definite kernel function k, which is the third part of the SVM concept and allows for nonlinear separation with the decision function

$$f(x) = \sum_{i=1}^{n} \alpha_i y_i (k(x,x_i)+1). \tag{4}$$

A special property of SVM is its sparsity in the sample domain. In other words, there is usually a low number of samples which lie exactly on the two separating hyperplanes (with $C \geq \alpha_i > 0$), or on the wrong side of their corresponding hyperplane ($\alpha_i = C$). These samples are the only factors influencing the definition of f. All samples with $\alpha > 0$ are called *support vectors*.

For the mathematical program of SVM, it can be seen from its definition that all training data is required. When a new sample is added to the training set, the old sample weights can be reused and

updated; the fact that all the data is relevant is not changed by a new incoming sample. In the case of a linear kernel, one approach for online learning is to calculate only the optimal α_{n+1} if a new sample x_{n+1} comes in and leave the other weights fixed. This update is directly integrated into the calculation of w and b, and then the information can be removed from memory, since it is not required anymore. The resulting algorithm is also called online passive-aggressive algorithm (PA) (Crammer et al., 2006; Krell, 2015). Another possibility is to add the sample, remove another sample and then retrain the classifier with a limited number of iterations. The numerous existing criteria for this manipulation strategies are introduced in the following sections.

2.2 Inclusion Criteria (ADD)

The most common approach is to *add all* samples to the training data set (Bordes et al., 2005; Funaya et al., 2009; Gretton and Desobry, 2003; Oskoei et al., 2009; Tang et al., 2006; Van Vaerenbergh et al., 2010; Van Vaerenbergh et al., 2006; Yi et al., 2011). If the new sample is already on the correct side of its corresponding hyperplane ($y_{n+1}f(x_{n+1}) > 1$), the classification function will not change with the update. When a sample is on the wrong side of the hyperplane, the classification function will change and samples which previously did not have any influence might become important. To reduce the number of updates, there are approaches which only add the samples with importance to the training data. One of these approaches is to add only *misclassified* samples (Bordes et al., 2005; Dekel et al., 2008; Oskoei et al., 2009).

If the true label is unknown, the unsupervised approach by (Spüler et al., 2012) suggests to use the improved Platt's probability fit (Lin et al., 2007) to obtain a probability score from SVM. If the probability exceeds a certain predefined threshold (0.8 in (Spüler et al., 2012)) the label is assumed to be true and the label, together with the sample, are added to the training set. This approach is computationally expensive, since the probability fit has to be calculated anew after each classifier update. Furthermore, it its quite inaccurate, because it is calculated on the training data (Lin et al., 2007). Note that, in this approach, samples within the margin are excluded from the update, and that this approach does not consider the maximum margin concept of SVM.

In contrast to the previous approach, if the true label is known, samples *within the margin* are especially relevant for an update of SVM (Bordes et al., 2005; Oskoei et al., 2009); PA does the same intrinsically. Data outside the margin gets assigned a weight of zero ($\alpha_{n+1} = 0$), and so the sample will not be integrated into the classification vector w. This method is also closely connected to a variant where all data, which is not a support vector, is removed.

In (Nguyen-Tuong and Peters, 2011) a sample is added to the dataset if it is sufficiently linearly independent. This concept is generalized to classifiers with kernels. In case of low dimensional data, this approach is not appropriate, while for higher dimensional data, it is computationally expensive. Furthermore, it does not account for the SVM modeling perspective where it is more appropriate to consider the support vectors. For example, in the case of n-dimensional data, $n+1$ support vectors could be sufficient for defining the separating hyperplane.

To save resources, a variant for adding samples would be to add a change detection test (CDT), as an additional higher-level layer (Alippi et al., 2014). The CDT detects if there is a change in the data, and then activates the update procedure. When working with datasets with permanent/continuous shifts over time, this approach is not appropriate, since the CDT would always activate the update.

2.3 Exclusion Criteria (REM)

To keep the size of the training set bounded, in the context of a fixed batch size, samples have to be removed. One extreme case is the PA which removes the sample directly after adding its influence to the classifier. In other words, the sample itself is discarded, but the classifier remembers its influence. If no additional damping factor in the update formula is used, the influence of the new sample is permanent.

In (Funaya et al., 2009), older samples get a lower weight in the SVM model (exponential decay with a fixed factor). This puts a very large emphasis on new training samples and, at some stage, the weight for the oldest samples is so low, that these samples can be removed. In (Gretton and Desobry, 2003), the *oldest* sample is removed for one-class SVM (Schölkopf et al., 2001). Removing the oldest sample is also closely related to batch updates (Hoens et al., 2012). Here, the classification model remains fixed, while new incoming samples are added to a new training set with a maximum batch size. If this basket is full, all the old data is removed and the model is replaced with a new one, trained on the new training data.

The farther away a sample is from the decision boundary, the lower will the respective dual variable be. Consequently, it is reasonable, to remove the farthest sample (Bordes et al., 2005), because it has the lowest impact on the decision function f. If the sample x has the function value $|f(x)| > 1$, the respective

weight is zero.

In the case of a linear SVM with two strictly separable datasets corresponding to the two classes, the SVM can be also seen as the construction of a separating hyperplane between the convex hulls of the two datasets. So, the *border points* are most relevant for the model, and might become support vectors in future updates. Hence, another criterion for removing data points is to determine the centers of the data and remove all data outside of the two annuli around the centers (Yi et al., 2011). If the number of samples is to high, the weighted distance from the algorithm could be used as a further criterion for removal. Alternatively, we suggest to construct a ring instead of an annulus, samples could be weighted by their distance to the ring and thus, be removed if they are not close enough to the respective ring. Drawbacks of this method are the restriction to linear kernels, the (often wrong) assumption of circular shapes of the datasets, and the additional parameters which are difficult to determine.

Similar to the inclusion criterion, linear independence could also be used for removing the "least linearly independent" samples (Nguyen-Tuong and Peters, 2011). This approach suffers from the drawbacks of computational cost and additional hyperparameters, too.

2.4 Further Criteria (KSV, REL, BAL)

As already mentioned, support vectors are crucial for the decision function. A commonly used selection criterion is that of *keeping only support vectors* (KSV) (Bordes et al., 2005; Yi et al., 2011) and removing all the other data from the training set.

While in the supervised setting, there might be some label noise from the data sources, in the unsupervised case labels might be assigned completely wrong. For compensation, (Spüler et al., 2012) suggests to *relabel* (REL) every sample with the predicted label from the updated classifier. This approach is also repeatedly used by (Li et al., 2008) for the semi-supervised training of an SVM.

Insofar, the presented methods did not consider the class distribution. The number of samples of one class could be drastically reduced, when the inclusion criteria mostly add data from one class and/or the exclusion criteria mostly remove data from the other class. Furthermore, when removing samples, it might occur that older data ensured a balance in the class distribution while the incoming data belongs to only one class. Hence, we suggest three different mantras for *data balancing* (BAL). *Don't handle* the classes differently. *Keep the ratio* as it was when first filling the training data basket, i.e., after the initialization always remove a sample from the same class type as it was added in the current update step. For us, the most promising approach is to strive for a *balanced ratio* when removing data, by always removing samples from the overrepresented class.

Note that these three criteria can be combined with each other, as well as with all inclusion and exclusion criteria.

3 EVALUATION

This section describes an empirical comparison of a selection of the aforementioned methods on synthetic and EEG data. We start by describing the data generation (for synthetic data), or acquisition (for EEG data). Afterwards, we present the processing methods and describe the results of the analysis.

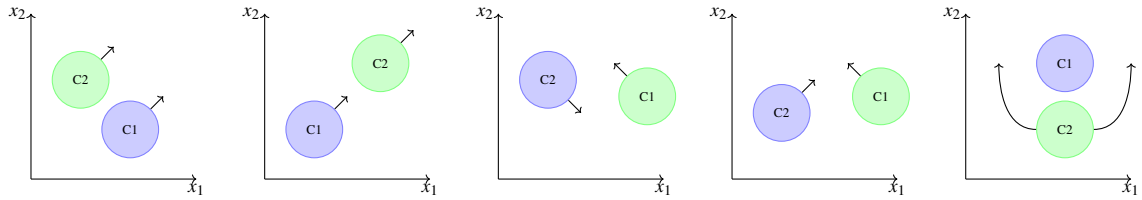
3.1 Data

For the synthetic data, we focus on linearly separable data. The first case that we consider is that of a data shift which is parallel to the separating hyperplane ("Parallel"). In all the other cases, the decision function is time dependent. Five datasets with different shifts are depicted in Figure 1. The data was randomly generated with Gaussian distributed noise and shifting means. Since class distributions are usually unbalanced in reality, we used a ratio of 1:3 between the two classes, with the underrepresented class labeled as C2.

For a three dimensional example, we followed the approach by (Street and Kim, 2001) in order to create a dataset with an abrupt concept change every 100 samples, in contrast to the continuous shifts. The data was randomly sampled in a three-dimensional cube. Given a three dimensional sample (p_1, p_2, p_3), a two step procedure is implemented to define the class label. For samples of the first class, initially, $p_1 + p_2 \leq \theta$ has to hold. Next, 10% class noise is added for both classes. p_3 only introduces noise and has no influence on the class. Theta is randomly changed every 100 samples in the interval $(6, 14)$.

The six datasets have a total of 10000 samples. Of these, the first 1000 samples are taken for training and hyperparameter optimization while the remaining 9000 samples are used for testing. The same synthetic data was used for all evaluations.

For real world, experimental data, we used data from a controlled P300 oddball paradigm (Courchesne et al., 1977), as described in (Kirchner et al.,



(a) Parallel (b) LinearShift (c) Opposite (d) Cross (e) Parabola

Figure 1: Synthetic two-dimensional datasets with the classes $C1$ and $C2$ (underrepresented target class) with shifting Gaussian distribution depicted by arrows.

2013). In the experimental paradigm, which is intended for use in a real BCI, the subject sees an unimportant piece of information every second, with some jitter. With a probability of $1/6$, an important piece of information is displayed, information which requires an action from the subject. This task-relevant event leads to a specific pattern in the brain, called P300. The goal of the classification task is to discriminate the different patterns in the EEG. In this paradigm it is possible to infer the (probably) true label, due to the reaction of the subject.

For the data acquisition process, we had 5 subjects, with 2 recording sessions per subject. The recording sessions were divided into 5 parts, where each part yielded 720 samples of unimportant information and 120 samples of important information. For the evaluation, we used 1 part for training, and the 4 remaining parts for testing.

3.2 Processing Chain and Implementation

The chosen classifier was a SVM implementation with a linear kernel, as suggested by (Hsieh et al., 2008). We limited the number of iterations to 100 times the number of samples. The regularization hyperparameter C of the SVM was optimized using 5 fold cross validation, with two repetitions, and the values $[10^0, 10^{-0.5}, \ldots, 10^{-4}]$.

For the synthetic data as well as for the EEG data, a normalization based on the training data was performed, such that the dataset would exhibit a mean $\mu = 0$ and standard deviation $\sigma = 1$ for every feature. In the case of the EEG data, further preprocessing was done by means of a standard processing chain, as described in (Kirchner et al., 2013).

For the evaluation part, each sample was first classified, and then the result was forwarded to the performance calculation routine. *Afterwards, the correct label was provided to the algorithm for manipulating the training data of the classifier, and, if necessary, the classifier was updated.* In order to save time, the SVM was only updated when the data led to a change which required an update. If, for example, data outside of the margin is added and removed, no update is required.

A preceding analysis was performed on the synthetic data to analyze the unsupervised label assignment parameter (Spüler et al., 2012). The analysis revealed that all data should be added for the classification. Hence, we did not consider unsupervised integration of new data any further. For comparison, we used batch sizes $[50, 100, \ldots, 1000]$ for the synthetic data and $[100, 200, \ldots, 800]$ for the EEG data. We implemented and tested the criteria "all", "misclassified", "within margin" for adding samples, "oldest", "farthest", "border points" with tour variant for removing samples and the (optional) variants to "relabel" the data, "keep only support vectors", and "data balancing".[2] For the details to the methods refer to Section 2.

To account for class imbalance, we used *balanced accuracy (BA)* as a performance measure (Straube and Krell, 2014), which is the arithmetic mean of true positive rate, and true negative rate. As baseline classifiers, we used online PA and static SVM.

We did not test an unsupervised setting for the update of the classifier. In this case either semi-supervised classifiers could be used or the classified label could be assumed to be the true label. In the latter case, all aforementioned strategies could be applied and the relabeling is especially important (Spüler et al., 2012). For classical BCIs the true label is often not available, especially when using spellers for patients with locked-in syndrome (Mak et al., 2011). In contrast, with embedded brain reading (Kirchner et al., 2014) the true label can be often inferred from the behavior of the subject. If the subject perceives and reacts to an important rare stimulus, the respective data can be labeled as P300 data. For simplicity, the reaction in our experiment was a buzzer press. Another example is movement prediction where the true label can be inferred by other sensors like EMG or force sensors. Supervised settings should be preferred if possible because they usually

[2]The code is publicly available, including the complete processing script and the generators for the datasets at the repository of the software pySPACE (Krell et al., 2013).

Table 1: Comparison of different data selection strategies for each dataset. For further details refer to the description in Section 3.3.

DATASET	ADD	REM	BAL	KSV	REL	SIZE	PERF	SVM/PA
LinearShift	m	o	n	f	f	1000	87.1	50.2
	m	o	k	-	t			94.5
Parallel	w	n	n	f	t	150	96.4	55.9
	m	f	b	f	-			88.7
Opposite	m	f	n	-	-	200	95.4	39.4
	m	o	n	f	t			68.4
Cross	m	o	n	-	-	150	95.2	55.7
	m	o	b	-	-			67.6
Parabola	a	o	k	f	t	50	96.8	66.2
	m	f, o	b	t	t			61.3
3D (Street and Kim, 2001)	a, w	o	n	-	-	50	87.7	81.1
	w	o	n, b	f	-			51.0
EEG	m	f	b	f	f	600	84.7 ± 0.3	83.7 ± 0.3
	w	o	b	f	f	300, 400	84 ± 0.4 84.1 ± 0.3	83.0 ± 0.4

result in better performance.

3.3 Results and Discussion

For the synthetic data, the results were analyzed by repeated measure ANOVA with 5 within-subjects factors (criteria): inclusion (ADD), exclusion (REM), data balancing (BAL), support vector handling (KSV), and relabeling (REL). For the EEG data, the basket *size* was considered as an additional factor. Here, we looked for more general good performing algorithms independently from subject, session or repetition. Where necessary, the Greenhouse-Geisser correction was applied. For multiple comparisons, the Bonferroni correction was used.

In Table 1, the different strategies of how to

- **ADD**: all (a), within margin (w), misclassified (m) and
- **REM**ove: oldest (o), farthest (f), not a border point (n) samples,
- for data **BAL**ancing: no handling (n), balancing the ratio (b), or keep it fixed (k),
- **K**eeping only **S**upport **V**ectors (KSV): active (t) and not active (f), and
- **REL**abeling: active (t) and not active (f)

are compared. For each dataset, first the best combination of strategies with the respective batch size and performance (balanced accuracy in percent) are given based on the descriptive analysis. The performance for SVM and PA are provided as baselines. In addition, the best strategy was selected separately for each criterion which was statistically estimated irrespective of the interaction between criteria (second row). In case, that strategies of criteria did not differ from each other, it is not reported (-).

Although the best approach is different depending on the dataset, some general findings could be extracted from descriptive and inference statistics.

First, for all datasets, the best combination of strategies with a limited batch size outperformed the static SVM and the PA except for the "LinearShift" dataset (Table 1: first row). The SVM is static and cannot adapt to the drift and the PA is adapting to the drift but it does not forget its model modifications from previous examples.

Second, specific approaches were superior compared to other approaches (Table 1: second row). For most cases, it was best to *add* only misclassified samples. A positive side effect of adding only misclassified samples is the reduced processing time, due to a lower number of required updates. *Removing* the oldest samples often gave good results, because a continuous shifts of a dataset leads to a shift of the optimal linear separation function and older samples would violate the separability. Not removing the border points showed bad performance in every case. Mostly, *balancing* the data led to higher performance. Often, the remaining two criteria had less influence but there is a tendency for *relabeling* data and not *keeping only support vectors*.

Third, the investigation of the interaction between the criteria could help to understand why there is some discrepancy between the best combination of strategies (first row) and the best choice for each individual criterion (second row). For example, if a good joint selection of inclusion and exclusion criteria is made, there are several cases where relabeling is no longer necessary (possibly because the data is already

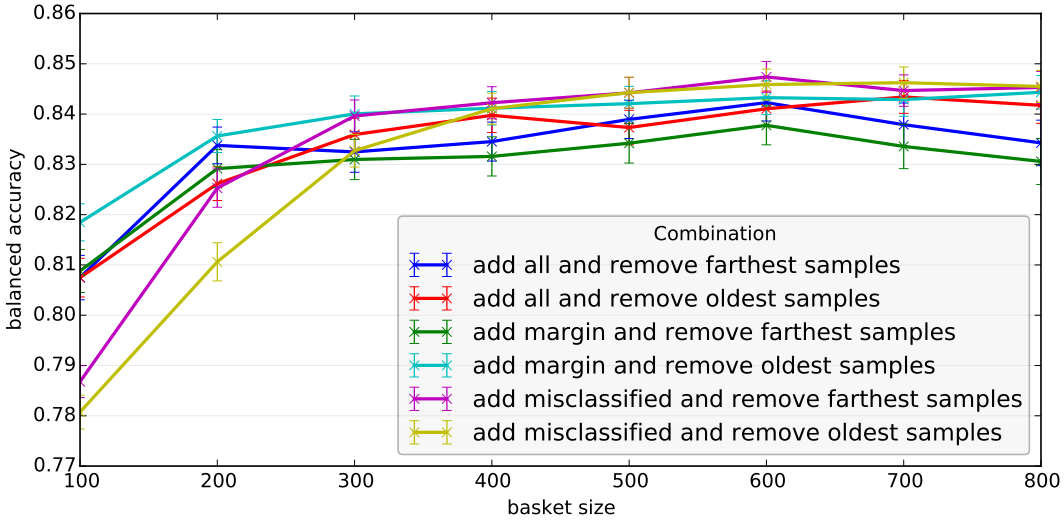


Figure 2: Comparison of all combinations of strategies from three different criteria (inclusion/exclusion/basket size) with data balancing (BAL-b) but without relabeling (REL-f) or keeping more than just support vectors (KSV-f). The mean of classification performance and standard error are depicted.

well separated), or the data should not have to be balanced anymore (maybe because a good representative choice is already made). Two more detailed examples are given in the following.

For the "Opposite" dataset, the BAL criterion had a clear effect. All combinations with not handling the class ratios (BAL-n) were better than the other combinations with BAL-b and BAL-k. In contrast, the KSV criterion had no strong effect. In combination with KSV-t, removing no boarder points (REM-n) improved the performance but the performance decreased for a few other combinations of in-/exclusion criteria with KSV-t. On the other hand, the KSV criterion had an interaction with the relabeling criterion (REL). In combination with KSV-f, REL had no effect but REL-t improved performance for some combinations with KSV-t.

For the EEG data, the handling of support vector affected classification performance, i.e., the performance was significantly worse when keeping only support vectors (KSV-t) compared to keeping more than just the support vectors (KSV-f). The effect of the support vector handling dominated the other criteria. The performance of combinations with KSV-f was always higher than the combinations with KSV-t. Thus, it makes less sense to choose the combinations with KSV-t. The similar pattern was observed in the handling of relabeling (REL) and data balancing (BAL). When not relabeling the samples (REL-f) and when keeping a balanced class ratio (BAL-b) the performance was superior compared to other strategies of REL and BAL. Hence, we chose a fixed strategy of these three criteria (KSV-f, REL-f, BAL-b) for the following visualization. Figure 2 illustrates the comparison of the respective combinations of criteria. The best combination was obtained when combining the inclusion of misclassified samples with the exclusion of oldest or farthest samples for the basket size of 600. This inclusion has a low number of updates. Implementing the removal of oldest samples is straightforward whereas removing the farthest samples requires some additional effort. Hence, these combinations are beneficial in case of using a mobile device, which requires a trade off between efficiency and performance.

4 CONCLUSION

In this paper, we reviewed numerous data selection strategies and compared them on synthetic and EEG data. As expected, we could verify that online learning can improve the performance. This even holds when limiting the amount of used data. Depending on the kind of data (shift), different methods are superior. Considering that usually more data is expected to improve performance or at least not to reduce it is surprising that adding only misclassified data is often a good approach and it is in most cases significantly better than adding all incoming data. Furthermore, this approach comes with the advantage of requiring the lowest processing costs. Our suggested variant of balancing the class ratios was beneficial in several cases, but the benefit was dependent on the type of the shift and the chosen inclusion/exclusion criterion,

because some variants balance the data intrinsically, or keep the current class ratio. Hence, it should always be considered, especially since it makes the algorithms robust against long time occurrence of only one class. Last but not least, we observed that it is always important to look at the interaction between the selection strategies.

In future, we want to analyze different hybrid approaches between the selection strategies from SVM and PA. Some inclusion strategies can be applied to the PA and when removing samples from the training set, their weights could be kept integrated into the linear classification vector. Additionally, we will compare the most promising approaches on different data, such as movement prediction with EEG or EMG, and on different transfer setups which will come with other kinds of data shifts. Last but not least, different implementation strategies for efficient updates and different strategies for unsupervised online learning could be compared. In the latter, the relabeling criterion is expected to be much more beneficial than in our evaluation.

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