# Active Learning with SVM



**Jun Jiang**
*City University of Hong Kong, Hong Kong*

**Horace H. S. Ip**
*City University of Hong Kong, Hong Kong*

## INTRODUCTION

With the increasing demand of multimedia information retrieval, such as image and video retrieval from the Web, there is a need to find ways to train a classifier when the training dataset is combined with a small number of labelled data and a large number of unlabeled one. Traditional supervised or unsupervised learning methods are not suited to solving such problems particularly when the problem is associated with data in a high-dimension space. In recent years, many methods have been proposed that can be broadly divided into two groups: **semi-supervised** and **active learning** (AL). Support Vector Machine (SVM) has been recognized as an efficient tool to deal with high-dimensionality problems, a number of researchers have proposed algorithms of Active Learning with SVM (ALSVM) since the turn of the Century. Considering their rapid development, we review, in this chapter, the state-of-the-art of ALSVM for solving classification problems.

## BACKGROUND

The general framework of AL can be described as in Figure 1. It can be seen clearly that its name – **active learning** – comes from the fact that the learner can improve the classifier by actively choosing the "optimal" data from the potential query set $Q$ and adding it into the current labeled training set $L$ after getting its label during the processes. The key point of AL is its sample selection criteria.

AL in the past was mainly used together with neural network algorithm and other learning algorithms. Statistical AL is one classical method, in which the sample minimizing either the variance (D. A. Cohn, Ghahramani, & Jordan, 1996), bias (D. A. Cohn, 1997) or generalisation error (Roy & McCallum, 2001) is queried to the oracle. Although these methods have strong theoretical foundation, there are two common problems limiting their application: one is how to estimate the posterior distribution of the samples, and the other is its prohibitively high computation cost. To deal with the above two problems, a series of **version space based AL** methods, which are based on the assumption that the target function can be perfectly expressed by one hypothesis in the version space and in which the sample that can reduce the volume of the version space is chosen, have been proposed. Examples are query by committee (Freund, Seung, Shamir, & Tishby, 1997), and SG AL (D. Cohn, Atlas, & Ladner, 1994). However the complexity of version space made them intractable until the version space based ALSVMs have emerged.

The success of SVM in the 90s has prompted researchers to combine AL with SVM to deal with the semi-supervised learning problems, such as distance-based (Tong & Koller, 2001), RETIN (Gosselin & Cord, 2004) and Multi-view (Cheng & Wang, 2007) based ALSVMs. In the following sections, we summarize existing well-known ALSVMs under the framework of **version space theory**, and then briefly describe some mixed strategies. Lastly, we will discuss the research trends for ALSVM and give conclusions for the chapter.

## VERSION SPACE BASED ACTIVE LEARNING WITH SVM

The idea of almost all existing heuristic ALSVMs is explicitly or implicitly to find the sample which can reduce the volume of the **version space**. In this section, we first introduce their theoretical foundation and then review some typical ALSVMs.

*Figure 1. Framework of active learning*

**Initialize Step:** An classifier $h$ is trained on the initial labeled training set $L$

**step 1:** The learner evaluates each data $x$ in potential query set $Q$ (subset of or whole unlabeled data set $U$) and query the sample $x^*$ which has lowest *EvalFun*($x$, $L$, $h$, $H$) to the oracle and get its label $y^*$;

**step 2:** The learner update the classifier $h$ with the enlarged training set $\{L + (x^*, y^*)\}$;

**step 3:** Repeat step 1 and 2 until stopping training;

Where

- *EvalFun*($x$, $L$, $h$, $H$): the function of evaluating potential query $x$ (the lowest value is the best here)
- $L$: the current labeled training set
- $H$: the hypothesis space

## Version Space Theory

Based on the Probability Approximation Correct learning model, the goal of machine learning is to find a consistent classifier which has the lowest generalization error bound. The Gibbs generalization error bound (McAllester, 1998) is defined as

$$\varepsilon_{Gibbs}(m, P_H, z, \delta) = \frac{1}{m}\left(\ln\left(\frac{1}{P_H(V(z))}\right)\right) + \ln\left(\frac{em^2}{\delta}\right)$$

where $P_H$ denotes a prior distribution over hypothesis space $H$, $V(z)$ denotes the version space of the training set $z$, $m$ is the number of $z$ and $\delta$ is a constant in [0, 1]. It follows that the generalization error bound of the consistent classifiers is controlled by the volume of the version space if the distribution of the version space is uniform. This provides a theoretical justification for version space based ALSVMs.

## Query by Committee with SVM

This algorithm was proposed by (Freund et al., 1997) in which 2$k$ classifiers were randomly sampled and the sample on which these classifiers have maximal disagreement can approximately halve the **version space** and then will be queried to the oracle. However, the complexity of the structure of the version space leads to the difficulty of random sampling within it. (Warmuth, Ratsch, Mathieson, Liao, & Lemmem, 2003) successfully applied the algorithm of playing billiard to randomly sample the classifiers in the SVM version space and the experiments showed that its performance was comparable to the performance of **standard distance-based ALSVM** (SD-ALSVM) which will be introduced later. The deficiency is that the processes are time-consuming.

## Standard Distance Based Active Learning with SVM

For SVM, the **version space** can be defined as:

$$V = \left\{w \in W \mid \|w\| = 1, \quad y_i(w \bullet \Phi(x_i)) > 0, \quad i = 1,\ldots,m\right\}$$

where $\Phi(.)$ denotes the function which map the original input space $X$ into a high-dimensional space $\Phi(X)$, and $W$ denotes the parameter space. SVM has two properties which lead to its tractability with AL. The first is its duality property that each point $w$ in $V$ corresponds to one hyperplane in $\Phi(X)$ which divides $\Phi(X)$ into two parts and vice versa. The other property is that the solution of SVM $w^*$ is the center of the **version space** when the version space is symmetric or near to its center when it is asymmetric.

Based on the above two properties, (Tong & Koller, 2001) inferred a lemma that the sample nearest to the

*Figure 2. Illustration of standard distance-based ALSVM*

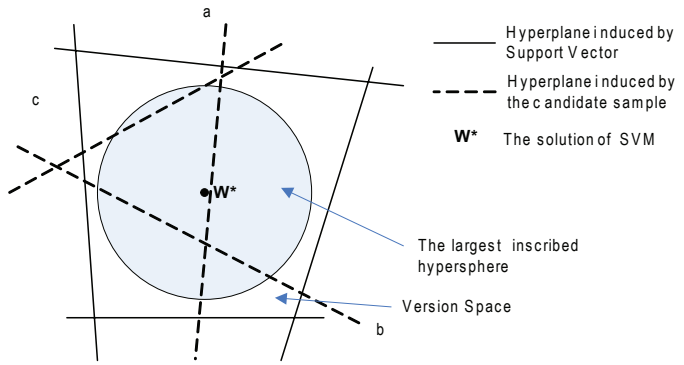



*Figure 2a. The projection of the parameter space around the Version Space*

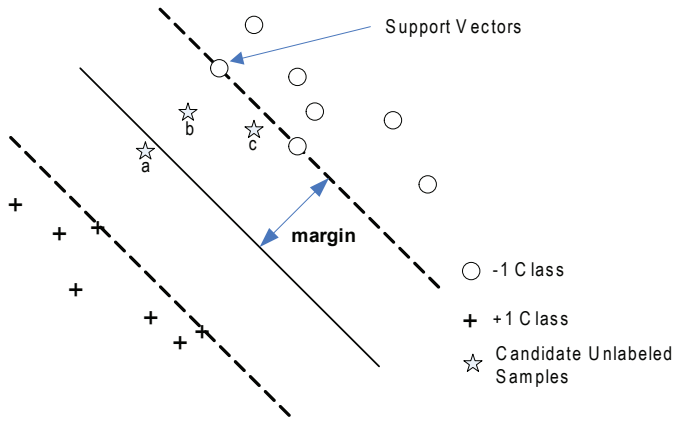



*Figure 2b. In the induced feature space*

decision boundary can make the expected size of the version space decrease fastest. Thus the sample nearest to the decision boundary will be queried to the oracle (Figure 2). This is the so-called SD-ALSVM which has low additional computations for selecting the queried sample and fine performance in real applications.

## Batch Running Mode Distance Based Active Learning with SVM

When utilizing batch query, (Tong & Koller, 2001) simply selected multiple samples which are nearest to the decision boundary. However, adding a batch of such samples cannot ensure the largest reduction of the size of version space, such as an example shown in figure 3. Although every sample can nearly halve the version space, three samples together can still reduce about 1/2, instead of 7/8, of the size of the version space. It can be observed that this was ascribed to the small angles between their induced hyperplanes.

To overcome this problem, (Brinker, 2003) proposed a new selection strategy by incorporating **diversity** measure that considers the angles between the induced hyperplanes. Let the labeled set be $L$ and the pool query set be $Q$ in the current round, then based on the diversity criterion the further added sample $x_q$ should be

$$x_q = \min_{x_j \in Q} \max_{x_i \in L} \frac{\left|k(x_j, x_i)\right|}{\sqrt{k(x_j, x_j)k(x_i, x_i)}}$$

$$\frac{\left|k(x_j, x_i)\right|}{\sqrt{k(x_j, x_j)k(x_i, x_i)}}$$

*Figure 3. One example of simple batch querying with "a", "b" and "c" samples with pure SD-ALSVM*

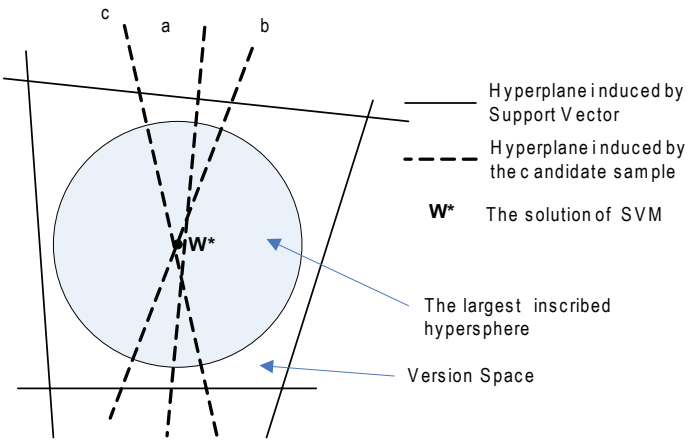
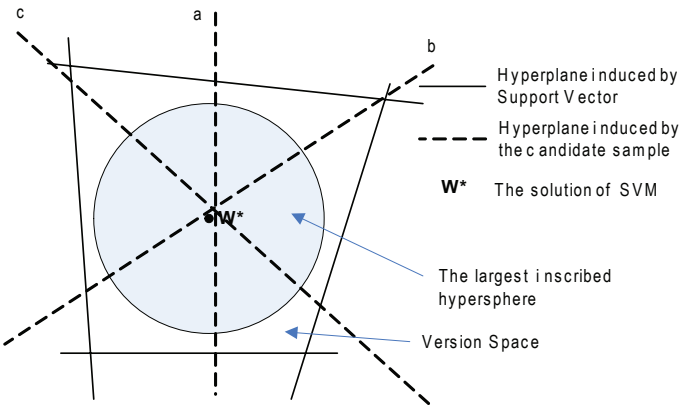



*Figure 4. One example of batch querying with "a", "b" and "c" samples by incorporating diversity into SD-ALSVM*




where  denotes the cosine value of the angle between two hyperplanes induced by $x_j$ and $x_i$, thus it is known as angle diversity criterion. It can be observed that the reduced volume of the version space in figure 4 is larger than that in Figure 3.

## RETIN Active Learning

Let $(I_j)_{j\in[1...n]}$ be the samples in a potential query set $Q$, and $r(i, k)$ be the function that, at iteration $i$, codes the position $k$ in the relevance ranking according to the distance to the current decision boundary, then a sequence can be obtained as follows:

$$\underbrace{I_{r(i,1)}}_{most\ relevant},I_{r(i,2)},\ldots,\underbrace{I_{r(i,s(i)},\ldots,I_{r(i,s(i)+m-1}}_{queried\ data},\ldots,\underbrace{I_{r(i,n)}}_{least\ relevant}$$

In SD-ALSVM, $s(i)$ is such as $I_{r(i,s(i)},\ldots,I_{r(i,s(i)+m-1}$ are the $m$ closest samples to the SVM boundary. This strategy implicitly relies on a strong assumption: an accurate estimation of SVM boundary. However, the decision boundary is usually unstable at the initial iterations. (Gosselin & Cord, 2004) noticed that, even if the decision boundary may change a lot during the earlier iterations, the ranking function $r()$ is quite stable. Thus they proposed a balanced selection criterion that

is independent on the frontier and in which an adaptive method was designed to tune $s$ during the feedback iterations. It was expressed by

$$s(i+1) = s(i) + h(r_{rel}(i)\ r_{irr}(i)$$

where $h(x, y) = k \times (x - y)$ which characterizes the system dynamics ($k$ is a positive constant), $r_{rel}(i)$ and $r_{irrl}(i)$ denote the number of relevant and irrelevant samples in the queried set in the *ith* iteration. This way, the number of relevant and irrelavant samples in the queried set will be roughly equal.

## Mean Version Space Criterion

(He, Li, Zhang, Tong, & Zhang, 2004) proposed a selection criterion by minimizing the **mean version space** which is defined as

$$C_{MVS}(x_k) = Vol(V_i^+(x_k))\ P(y_k = 1 \mid x_k) + Vol(V_i^-(x_k))\ P(y_k = -1 \mid x_k)$$

where $Vol(V_i^+(x_k))$ ($Vol(V_i^-(x_k))$) denotes the volume of the version space after adding an unlabelled sample $x_k$ into the *ith* round training set. The mean version space includes both the volume of the version space and the posterior probabilities. Thus they considered that the criterion is better than the SD-ALSVM. However, the computation of this method is time-consuming.

## Multi-View Based Active Learning

Different from the algorithms which are based only on one whole feature set, **multi-view** methods are based on multiple sub-feature ones. Several classifiers are first trained on different sub-feature sets. Then the samples on which the classifiers have the largest disagreements comprise the contention set from which queried samples are selected. first (I. Muslea, Minton, & Knoblock, 2000) applied in AL and (Cheng & Wang, 2007) implemented it with ALSVM to produce a Co-SVM algorithm which was reported to have better performance than the SD-ALSVM.

Multiple classifiers can find the rare samples because they observe the samples with different views. Such property is very useful to find the diverse parts belonging to the same category. However, multi-view based methods demand that the relevant classifier can classify the samples well and that all feature sets are uncorrelated. It is difficult to ensure this condition in real applications.

# MIXED ACTIVE LEARNING

Instead of single AL strategies in the former sections, we will discuss two mixed AL modes in this section: one is combining different selection criteria and another is incorporating **semi-supervised learning** into AL.

## Hybrid Active Learning

Contrast to developing a new AL algorithm that works well for all situations, some researchers argued that combining different methods, which are usually complementary, is a better way, for each method has its advantages and disadvantages. The intuitive structure of the hybrid strategy is parallel mode. The key point here is how to set the weights of different AL methods.

The simplest way is to set fixed weights according to experience and it was used by most existing methods. The Most Relevant/Irrelevant (L. Zhang, Lin, & Zhang, 2001) strategies can help to stabilize the decision boundary, but have low learning rates; while standard distance-based methods have high learning rates, but have unstable frontiers at the initial feedbacks. Considering this, (Xu, Xu, Yu, & Tresp, 2003) combined these two strategies to achieve better performance than only using a single strategy. As stated before, the **diversity** and distance-based strategies are also complementary and (Brinker, 2003), (Ferecatu, Crucianu, & Boujemaa, 2004) and (Dagli, Rajaram, & Huang, 2006) combined angle, inner product and entropy **diversity** strategy with standard distance-based one respectively.

However, the strategy of the fixed weights can not fit well into all datasets and all learning iterations. So the weights should be set dynamically. In (Baram, El-Yaniv, & Luz, 2004), all the weights were initialized with the same value, and were modified in the later iterations by using EXP4 algorithm. In this way, the resulting AL algorithm is empirically shown to consistently perform almost as well as and sometimes outperform the best algorithm in the ensemble.

### Semi-Supervised Active Learning

1. Active Learning with Transductive SVM

In the first stages of SD-ALSVM, a few labeled data may lead to great deviation of the current solution from the true solution; while if unlabeled samples are considered, the solution may be closer to the true solution. (Wang, Chan, & Zhang, 2003) showed that the closer the current solution is to the true one, the larger the size of the version space will be reduced. They incorporated Transductive SVM (TSVM) to produce more accurate intermediate solutions. However, several studies (T. Zhang & Oles, 2000) challenged that TSVM might not be so helpful from unlabeled data in theory and in practice. (Hoi & Lyu, 2005) applied the semi-supervised learning techniques based on the Gaussian fields and Harmonic functions instead and the improvements were reported to be significant.

2. Incorporating EM into Active Learning

(McCallum & Nigam, 1998) combined Expectation Maximization (EM) with the strategy of querying by committee. And (Ion Muslea, Minton, & Knoblock, 2002) integrated Multi-view AL algorithm with EM to get the Co-EMT algorithm which can work well in the situation where the views are incompatible and correlated.

## FUTURE TRENDS

### How to Start the Active Learning

AL can be regarded as the problem of searching target function in the version space, so a good initial classifier is important. When the objective category is diverse, the initial classifier becomes more important, for bad one may result in converging to a local optimal solution, i.e., some parts of the objective category may not be correctly covered by the final classifier. Two-stage (Cord, Gosselin, & Philipp-Foliguet, 2007), long-term learning (Yin, Bhanu, Chang, & Dong, 2005), and pre-cluster (Engelbrecht & BRITS, 2002) strategies are promising.

### Feature-Based Active Learning

In AL, the feedback from the oracle can also help to identify the important features, and (Raghavan, Madani, & Jones, 2006) showed that such works can improve the performance of the final classifier significantly. In (Su, Li, & Zhang, 2001), Principal Components Analysis was used to identify important features. To our knowledge, there are few reports addressing the issue.

### The Scaling of Active Learning

The scaling of AL to very large database has not been extensively studied yet. However, it is an important issue for many real applications. Some approaches have been proposed on how to index database (Lai, Goh, & Chang, 2004) and how to overcome the concept complexities accompanied with the scalability of the dataset (Panda, Goh, & Chang, 2006).

## CONCLUSION

In this chapter, we summarize the techniques of ALSVM which have been an area of active research since 2000. We first focus on the descriptions of heuristic ALSVM approaches within the framework of the theory of version space minimization. Then mixed methods which can complement the deficiencies of single ones are introduced and finally future research trends focus on techniques for selecting the initial labeled training set, feature-based AL and the scaling of AL to very large database.

## REFERENCES

Baram, Y., El-Yaniv, R., & Luz, K. (2004). Online Choice of Active Learning Algorithms. *Journal of Machine Learning Research, 5*, 255-291.

Brinker, K. (2003). *Incorporating Diversity in Active Learning with Support Vector Machines.* Paper presented at the International Conference on Machine Learning.

Cheng, J., & Wang, K. (2007). Active learning for image retrieval with Co-SVM. *Pattern Recognition, 40*(1), 330-334.

Cohn, D., Atlas, L., & Ladner, R. (1994). Improving Generalization with Active Learning. *Machine Learning, 15*, 201-221.

Cohn, D. A. (1997). Minimizing Statistical Bias with Queries. In *Advances in Neural Information Processing Systems 9, Also appears as AI Lab Memo 1552, CBCL Paper 124*. M. Mozer et al, eds.

Cohn, D. A., Ghahramani, Z., & Jordan, M. I. (1996). Active Learning with Statistical Models. *Journal of Artificial Intelligence Research, 4*, 129-145.

Cord, M., Gosselin, P. H., & Philipp-Foliguet, S. (2007). Stochastic exploration and active learning for image retrieval. *Image and Vision Computing, 25*(1), 14-23.

Dagli, C. K., Rajaram, S., & Huang, T. S. (2006). *Utilizing Information Theoretic Theoretic Diversity for SVM Active Learning.* Paper presented at the International Conference on Pattern Recognition, Hong Kong.

Engelbrecht, A. P., & BRITS, R. (2002). Supervised Training Using an Unsuerpvised Approach to Active Learning. *Neural Processing Letters, 15*, 14.

Ferecatu, M., Crucianu, M., & Boujemaa, N. (2004). *Reducing the redundancy in the selection of samples for SVM-based relevance feedback*

Freund, Y., Seung, H. S., Shamir, E., & Tishby, N. (1997). Selective Sampling Using the Query by Committee Algorithm. *Machine Learning, 28*, 133-168.

Gosselin, P. H., & Cord, M. (2004). *RETIN AL: an active learning strategy for image category retrieval.* Paper presented at the International Conference on Image Processing.

He, J., Li, M., Zhang, H.-J., Tong, H., & Zhang, C. (2004). *Mean version space: a new active learning method for content-based image retrieval.* Paper presented at the International Multimedia Conference Proceedings of the 6th ACM SIGMM International Workshop on Mulitimedia Information Retrieval.

Hoi, S. C. H., & Lyu, M. R. (2005). *A semi-supervised active learning framework for image retrieval.* Paper presented at the IEEE Computer Society Conference on Computer Vision and Pattern Recognition.

Lai, W.-C., Goh, K., & Chang, E. Y. (2004, June). *On Scalability of Active Learning for Formulating Query Concepts (long version of the ICME invited paper).* Paper presented at the Workshop on Computer Vision Meets Databases (CVDB) in cooperation with ACM International Conference on Management of Data (SIGMOD), Paris.

McAllester, D. A. (1998). *Some PAC Bayesian Theorems.* Paper presented at the Proceedings of the 11th Annual Conference on Computational Learning Theory, Madison, Wisconsin.

McCallum, A. K., & Nigam, K. (1998). *Employing EM and Pool-Based Active Learning for Text Classification.* Paper presented at the Proceedings of 15th International Conference on Machine Learning.

Muslea, I., Minton, S., & Knoblock, C. A. (2000). *Selective Sampling with Redundant Views.* Paper presented at the Proceedings of the 17th National Conference on Artificial Intelligence.

Muslea, I., Minton, S., & Knoblock, C. A. (2002). *Active+Semi-Supervised Learning = Robust Multi-View Learning.* Paper presented at the Proceedings of the 19th International Conference on Machine Learning.

Panda, N., Goh, K., & Chang, E. Y. (2006). Active Learning in Very Large Image Databases *Journal of Multimedia Tools and Applications Special Issue on Computer Vision Meets Databases*.

Raghavan, H., Madani, O., & Jones, R. (2006). Active Learning with Feedback on Both Features and Instances. *Journal of Machine Learning Research, 7*, 1655-1686.

Roy, N., & McCallum, A. (2001). *Toward Optimal Active Learning Through Sampling Estimation of Error Reduction.* Paper presented at the Proceedings of 18th International Conference on Machine Learning.

Su, Z., Li, S., & Zhang, H. (2001). *Extraction of Feature Subspaces for Content-based Retrieval Using Relevance Feedback.* Paper presented at the ACM Multimedia, Ottawa, Ontario, Canada.

Tong, S., & Koller, D. (2001). Support Vector Machine Active Learning with Application to Text Classification. *Journal of Machine Learning Research*, 45-66.

Wang, L., Chan, K. L., & Zhang, Z. (2003). *Bootstrapping SVM active learning by incorporating unlabelled images for image retrieval.* Paper presented at the Proceeding of IEEE Computer Vision and Pattern Recognition.

Warmuth, M. K., Ratsch, G., Mathieson, M., Liao, J., & Lemmem, C. (2003). Active Learning in the Drug Discovery Process. *Journal of Chemical Information Sciences, 43*(2), 667-673.

Xu, Z., Xu, X., Yu, K., & Tresp, V. (2003). *A Hybrid Relevance-feedback Approach to Text Retrieval.* Paper presented at the Proceedings of the 25th European Conference on Information Retrieval Research, Lecture Notes in Computer Science.

Yin, P., Bhanu, B., Chang, K., & Dong, A. (2005). Integrating Relevance Feedback Techniques for Image Retrieval Using Reinforcement Learning *IEEE Transactions on Pattern Analysis and Machine Intelligence, 27*(10), 1536-1551.

Zhang, L., Lin, F., & Zhang, B. (2001). *Support Vector Machine Learning for Image Retrieval.* Paper presented at the International Conference on Image Processing.

Zhang, T., & Oles, F. (2000). *A Probability Analysis on The Value of Unlabeled Data for Classification Problems.* Paper presented at the Proceeding of 17th International Conference of Machine Learning, San Francisco, CA.

## KEY TERMS

**Heuristic Active Learning:** The set of active learning algorithms in which the sample selection criteria is based on some heuristic objective function. For example, version space based active learning is to select the sample which can reduce the size of the version space.

**Hypothesis Space:** The set of all hypotheses in which the objective hypothesis is assumed to be found.

**Semi-Supervised Learning:** The set of learning algorithms in which both labelled and unlabelled data in the training dataset are directly used to train the classifier.

**Statistical Active Learning:** The set of active learning algorithms in which the sample selection criteria is based on some statistical objective function, such as minimization of generalisation error, bias and variance. Statistical active learning is usually statistically optimal.

**Supervised Learning:** The set of learning algorithms in which the samples in the training dataset are all labelled.

**Unsupervised Learning:** The set of learning algorithms in which the samples in training dataset are all unlabelled.

**Version Space:** The subset of the hypothesis space which is consistent with the training set.