SVM classification using k-times Markov sampling

*Ayush Raj(IIT2018188), Harsh Bajaj (IIT2018190), Utkarsh Priyam (IIT2018197)*

*Semester VI, Department of IT, Indian Institute of Information Technology, Allahabad, India.*

***Abstract: One of the most widely used algorithms in machine learning classification techniques is Support vector machine (SVM). SVM is versatile and effective in practical scenarios but its complexity increases with dataset size. In this paper, we summarise the approach [1] of k-times Markov sampling based SVM classification. This approach provides improved time efficiency for training and sampling , smaller misclassification rates.***

**INTRODUCTION**

Support vector machine (SVM) algorithms find large applicability in the domain of pattern recognition problems [2]. SVM is flexible and performs well in practical applications. SVM performs well with i.i.d. Samples , but this is not the case with the various practical applications, such as system diagnosis, speech recognition etc, which are time dependent in nature[3]. The generalization ability of SVMC with uniformly ergodic Markov chain (u.e.M.c.)

Samples has been studied in [4], with further advancements in the optimality of the learning rate of Gaussian kernels performed in [5].

SVMC model with markov sampling, has low error but higher total time required for sampling and training is longer compared with the classical SVMC. In order to reduce this time , researchers in [1], implement a k-times sampling which enhances the classical SVMC,by improving its learning rate . The authors also present the numerical studies on this model for standard data sets. A comparative study based on the classic SVMC model, sampling model and k-times sampling model is performed in [6]. The results show that k-times sampling model has less misclassification and takes less time to obtain a sparse model.

1. **ALGORITHM DESCRIPTION**

Input: ST , N, k, q, n2

Output: sign( fk )

1. Draw randomly N samples Siid := {zj}j=1N from ST. Train Siid by SVMC and obtain a preliminary

learning model f0. Let i = 0.

1. Let N+ = 0, N− = 0, t = 1.
2. Draw randomly a sample zt from ST , called it the current sample. Let N+ = N++1 if the label of zt is +1, or let N− = N− + 1 if the label of zt is −1.
3. Draw randomly another sample z∗ from ST , called it the candidate sample, and calculate the ratio α, α = e−( fi ,z∗)/e−( fi ,zt).
4. If α ≥ 1, yty∗ = 1 accept z∗ with probability α1 = e−y∗ fi /e−yt fi. If α = 1 and yty∗ = −1 or α < 1, accept z∗ with probability α. If there are n2 candidate samples can not be accepted continually, then set α2 = qα and accept z∗ with probability α2. If z∗ is not accepted, go to Step 4, else let zt+1 = z∗, N+ = N+ + 1 if the label of zt+1 is +1 and N+ < N/2, or let zt+1 = z∗, N− = N−+1 if the label of zt+1 is −1 and N− < N/2 (if the value α (or α1, α2) is bigger than 1, accept the candidate sample z∗ with probability 1 ).
5. If N++N− < N, return to Step 4, else we obtain N Markov chain samples SMar. Let i = i + 1. Train SMar by SVMC and obtain a learning model fi .
6. If i < k, go to Step 2, else output sign( fk ).
7. **RESULTS AND OBSERVATIONS**

The above model was able to achieve approx. 84.3% to 87.5% accuracy on the provided datasets.

1. **CONCLUSION**

The results suggest that the provided approach provides better classification performance than the SVMC in terms of misclassification rates, training computational time, etc.

1. **REFERENCES**

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