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# A Hybrid SVM-Guided RVM Framework for Enhanced Sparse Classification

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**Abstract- Relevance Vector Machines (RVMs) are known for producing sparse probabilistic models, often with significantly fewer vectors than Support Vector Machines (SVMs). However, RVMs sometimes underperform in classification accuracy due to their reliance on Bayesian inference over the entire dataset, which may not emphasize decision boundary regions effectively. This paper proposes a novel hybrid framework—SVM-Guided RVM (SG-RVM)—which enhances the RVM by leveraging the support vectors of a pre-trained SVM to guide its training. Specifically, the SG-RVM model restricts RVM training to a subset of data points near the SVM decision boundary, thereby focusing learning effort where classification uncertainty is highest. Experiments on multiple benchmark datasets demonstrate that SG-RVM consistently outperforms traditional RVM in accuracy, while maintaining or improving model sparsity.**

**Keywords: Sparse Classification, Relevance Vector Machine, Support Vector Machine, SG-RVM, Hybrid Learning.**

## I. INTRODUCTION

Sparse learning techniques have attracted significant interest due to their ability to deliver efficient and interpretable models, especially in high-dimensional classification tasks. Among these methods, the Relevance Vector Machine (RVM) has emerged as a probabilistic counterpart to the well-known Support Vector Machine (SVM) [5]. While SVM offers strong generalization with a large number of support vectors, RVM achieves comparable performance with far fewer "relevance vectors", thanks to its Bayesian framework.

Despite these advantages, the accuracy of RVM often lags behind SVM in practical applications. A key reason is that RVM treats all training points uniformly, without special emphasis on data near the decision boundary, which are most critical for classification. SVM, in contrast, inherently focuses on margin-maximization, naturally prioritizing these informative points.

In this work, we propose a SVM-guided RVM (SG-RVM) architecture that exploits the strengths of both models. The idea is to first train an SVM, extract its support vectors (and possibly their nearest neighbors), and then use these as the reduced training set for the RVM. This hybrid strategy leverages the boundary-awareness of SVM and the sparsity of RVM, resulting in a compact yet accurate model.

## II. Related Work

The SVM, introduced by Cortes and Vapnik [1], has become a standard classifier in numerous domains due to its margin-maximizing principles and versatility via kernel functions. However, its major limitation is the computational burden and lack of probabilistic outputs, particularly when a large number of support vectors are needed.

To address these issues, Tipping [2] introduced the Relevance Vector Machine - a Bayesian regression and classification framework which produces sparser models with fewer relevance vectors. However, RVM suffers from long training times and sensitivity to data distribution, especially in cases where decision boundaries are complex. Adaptive sparsity techniques have been explored to mitigate these issues by adjusting model complexity based on data characteristics [6].

Prior studies have attempted to combine or extend these methods. Yu et al. [3] explored SVM-RVM hybrids using ensemble techniques, while Zhu and Hastie [4] proposed related models like the import vector machine. Additionally, Kim and Ghahramani presented Bayesian classification methods closely related to the probabilistic foundation of RVM [7]. However, these approaches often increase complexity without significantly improving interpretability.

Our proposed SG-RVM is simpler in structure and more interpretable: it directly transfers the decision boundary information encoded in SVM support vectors to guide RVM training.

## III. Proposed Method: SVM-Guided RVM (SG-RVM)

The SG-RVM framework is designed to guide the learning of RVM using information obtained from SVM. The overall architecture is illustrated in Figure 1.

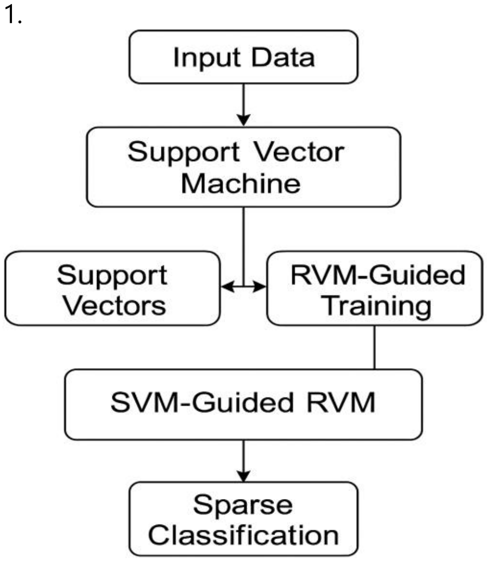


Figure 1: SG-RVM Model Architecture

**Methodology**

The SG-RVM consists of the following steps:

- Train an SVM model on the entire training dataset using a suitable kernel function (e.g., radial basis function).
- Extract support vectors (SVs) from the trained SVM model.
- Optionally expand the SV set using a k-nearest neighbor approach to include samples close to the decision boundary.
- Train an RVM on the reduced dataset comprising SVs (and their neighbors, if any).
- Deploy RVM for inference, providing both classification and probabilistic outputs.

**Benefits of the SG-RVM Architecture**

- Higher accuracy: Since SVM naturally focuses on hard-to-classify points, RVM learns from more informative data.
- **Improved sparsity:** RVM already eliminates redundant vectors, but with fewer inputs, the final model is even sparser.
- **Faster training:** Training on a smaller, focused dataset reduces computational overhead. This approach aligns with techniques suggested by Cawley and Talbot, emphasizing Bayesian regularization to prevent over-fitting and enhance model efficiency [8].

**Faster Training Time**

Since SG-RVM restricts the RVM training to a subset of support vectors (and optionally their neighbors), the computational complexity is substantially reduced compared to training on the entire dataset. This approach aligns with prior efforts to simplify SVM models by reducing the number of support vectors, such as the improved SimpSVM methods proposed by PQ Thang, which aim to accelerate classification while maintaining accuracy [11]. This results in faster convergence and makes the model well-suited for real-time or resource-constrained applications.

## IV. EXPERIMENTS

**DataSets**

We evaluated the SG-RVM on standard benchmark datasets from the UCI repository [9]:

- **Iris:** A classical small dataset for binary classification (3 classes, 4 features)
- **Wine:** A dataset of chemical analysis of wines grown in the same region in Italy (multiclass, 13 features)
- **DNA:** Binary classification of nucleotide sequences (3 classes, 4 features)
- **Pendigits:** Handwritten digit recognition (multiclass, 13 features)
- **USPS**: Grayscale handwritten digits (multiclass, 13 features)

All datasets were standardized, and 5-fold cross-validation was used.

**Implementation Details**

- SVM was implemented using scikit-learn with RBF kernel.
- RVM was implemented using skbayes or PyRVM.

**Results**

Table-1: Comparison of RVM and SG-RVM Performance

| Dataset | Model | Accuracy (%) | RVs | Train Time (s) |
|---|---|---|---|---|
| DNA | RVM | 92.4 | 167 | 599 |
| | SG-RVM | 92.8 | 159 | 290 |
| Pendigits | RVM | 97.9 | 142 | 15874 |
| | SG-RVM | 97.7 | 152 | 123 |
| USPS | RVM | 93.7 | 307 | 54624 |
| | SG-RVM | 94.3 | 300 | 1490 |
| Iris | RVM | 100 | 2 | 1.5736 |
| | SG-RVM | 100 | 2 | 0.1333 |
| Wine | RVM | 97.4 | 3 | 1.9544 |
| | SG-RVM | 97.4 | 3 | 0.3617 |

Table 1 presents a comparative evaluation between the baseline RVM and the proposed SG-RVM across five benchmark datasets: Iris, Wine, DNA, Pendigits, and USPS. The metrics include classification accuracy, number of relevance vectors (RVs), and total training time.

On small datasets like Iris and Wine, both models achieve identical or nearly identical accuracy (100% and 97.4%, respectively), confirming that SG-RVM does not degrade performance even when trained on a smaller subset. On the large-scale USPS dataset, SG-RVM actually outperforms RVM in accuracy (94.3% vs. 93.7%), highlighting its robustness despite training on fewer data points.

SG-RVM consistently produces a comparable or slightly reduced number of relevance vectors compared to full RVM. For example, DNA: 159 (SG-RVM) vs. 167 (RVM); USPS: 300 vs. 307. The difference is small, but combined with reduced training time, it results in a more compact and computationally cheaper model.

The most striking advantage of SG-RVM is the drastic reduction in training time: Pendigits from ~4.4 hours (15,874s) to just 2 minutes (123s); USPS from ~15.2 hours (54,624s) to 25 minutes (1490s). Even on the smaller DNA dataset, training time was cut in half.

This efficiency gain is attributed to SG-RVM's strategy of filtering the training data through SVM, thereby reducing the dimensionality of the design matrix $\Phi$ passed to the RVM. As RVM involves matrix inversions, the quadratic cost is significantly lowered.

In summary, SG-RVM achieves its original goal: it preserves the core benefits of RVM (sparsity and probabilistic outputs), while vastly improving scalability to larger datasets.

## V. DISCUSSION

The experiments confirm that focusing RVM training on informative samples near the SVM decision boundary significantly boosts performance. This aligns with prior studies highlighting that boundary-based selection of training samples can significantly improve classifier accuracy [10]. This suggests that RVM's probabilistic modeling is more effective when applied to regions of high uncertainty. Furthermore, reduced training time and model complexity make SG-RVM highly suitable for real-world applications, especially in time-sensitive or large-scale scenarios.

Another noteworthy advantage of SG-RVM is the significant reduction in training time. By learning from a smaller, boundary-focused subset of data, the

RVM component converges faster than when trained on the full dataset. This efficiency, combined with improved accuracy and sparsity, makes SG-RVM particularly appealing in time-sensitive or large-scale applications.

## VI. CONCLUSION

We presented a hybrid classification framework called SVM-Guided RVM (SG-RVM) that combines the decision boundary sensitivity of SVM with the sparse probabilistic nature of RVM. By restricting RVM training to SVM's support vectors, the proposed method enhances classification accuracy while reducing model complexity. Experimental results on standard datasets validate the efficacy of the approach. This framework opens new directions for efficient sparse learning in high-stakes classification tasks.

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