

Statistical Mechanics of Support Vector Networks

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Using methods of Statistical Physics, we investigate the generalization performance of support vector machines (SVMs), which have been recently introduced as a general alternative to neural networks. For nonlinear classification rules, the generalization error saturates on a plateau, when the number of examples is too small to properly estimate the coefficients of the nonlinear part. When trained on simple rules, we find that SVMs overfit only weakly. The performance of SVMs is strongly enhanced, when the distribution of the inputs has a gap in feature space.

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Statistical Mechanics provides an important approach to analyzing and understanding the ability of neural networks to learn and generalize from examples (see e.g. [1–3]). The majority of this work has been devoted to the simplest network architecture, the perceptron. This network however has limited power, because it classifies examples with a simple linear separating hyperplane and is able to learn only linear separable rules. More complicated multilayer neural nets can realize general nonlinear rules (when the size of their hidden layer is large enough) but have also practical and theoretical disadvantages. Learning in these networks results in a usually nonconvex optimization problem and there is no guarantee that an algorithm will find the minimum of the training cost function. The complexity of the training error surface reflects itself in the theoretical analysis by Statistical Mechanics. The occurrence of phases of broken ergodicity [4] makes their analysis a complicated task. Finally, network parameters must be chosen carefully in order to adapt the network's complexity on the task and to avoid overfitting.

Recently, a new type of learning machine has been introduced by V. Vapnik and his collaborators [5,6] which may become a reasonable alternative to neural networks. These *support vector machines* (SVMs) seem to have several advantages over neural networks. Being generalizations of perceptrons, their training involves only simple convex optimization. Further, for several applications, it has been shown that SVMs do not have a strong tendency to overfit.

In this letter, we present a detailed analysis of the typical performance of SVMs by methods of Statistical Mechanics. To understand the basic idea behind the SVM approach, assume a nonlinear mapping $\vec{\Psi}(\mathbf{x})$ from vec-

tors $\mathbf{x} \in \mathbb{R}^N$ onto vectors $\vec{\Psi}$ which belong to an M -dimensional feature space. A nonlinear classification of inputs \mathbf{x} can be defined by a linear separation of feature vectors $\vec{\Psi}(\mathbf{x})$ using a perceptron with weight vector $\vec{w} \in \mathbb{R}^M$ perpendicular to the separating hyperplane via $\text{sign}(\vec{\Psi}(\mathbf{x}) \cdot \vec{w})$. The dot denotes the standard inner product of vectors in \mathbb{R}^M . The vector \vec{w} can be adapted to a set of example data by any learning algorithm for perceptrons. This simple approach has major problems which result from the typical high dimensionality of the feature space. Assuming e.g., that the vector $\vec{\Psi}$ contains all bilinear expressions of components of the input vector \mathbf{x} (in addition to linear ones), the dimension M is of order N^2 . First, there is a big computational problem in storing and learning the weights and second, one can expect that there is also a large tendency of these machines to overfit, because there are much less training data than adjustable parameters in this model. The main idea to overcome these problems is to use the optimal stability learning algorithm, which has also been studied extensively in the Statistical Mechanics approach to neural networks (see e.g. [3]). The goal of this algorithm is to find a vector of weights \vec{w} which allows for a separation of positive and negative example points with the maximal margin defined by

$$\kappa := \max_{\vec{w}} \min_{\mu} \{h_{\mu} / \sqrt{\vec{w} \cdot \vec{w}}\}. \quad (1)$$

The local fields h_{μ} are defined by

$$h_{\mu} = \sigma_{\mu} \vec{\Psi}(\mathbf{x}^{\mu}) \cdot \vec{w} \quad (2)$$

Here $\sigma_{\mu} \in \{-1, 1\}$ is the classification of the point \mathbf{x}^{μ} , for $\mu = 1, \dots, m$, and m is the total number of labelled examples in the training set. This maximization problem is found to be equivalent to a quadratic minimization problem for the function $\frac{1}{2} \vec{w} \cdot \vec{w}$ under the constraints that $h_{\mu} \geq 1$ for all examples in the training set. According to convex optimization theory the solution vector can be expanded as a linear combination of example feature vectors via

$$\vec{w} = \sum_{\mu} \alpha^{\mu} \sigma_{\mu} \vec{\Psi}(\mathbf{x}^{\mu}) \quad (3)$$

where $\alpha^{\mu} \geq 0$ are Lagrange parameters which account for the m inequality constraints. Hence, the number of adjustable parameters α^{μ} for this algorithm never exceeds

the number of examples. The α^μ are nonzero only for those examples, for which $h_\mu = 1$, defining the *support vectors* (SVs) of the data set. If the remaining examples ($\alpha^\mu = 0$) would be discarded from the training set, the SVM would predict their correct label σ_μ . Hence, if the relative number of SVs is small, we can expect that the SVM generalizes well. In fact, a simple argument [5] shows that the expected ratio of the number of support vectors over m yields an upper bound on the generalization error. We will see later within the average case scenario of Statistical Mechanics that this mechanism prevents a complex SVM from overfitting when learning a simple rule.

The expansion (3) also reduces the computational cost of the algorithm drastically because any inner product of \vec{w} with vectors $\vec{\Psi}(\mathbf{x})$ in the feature space (including $\vec{w} \cdot \vec{w}$) is entirely expressed in terms of the so called kernel $K(\mathbf{x}, \mathbf{y}) = \vec{\Psi}(\mathbf{x}) \cdot \vec{\Psi}(\mathbf{y}) = \sum_\rho \Psi_\rho(\mathbf{x}) \Psi_\rho(\mathbf{y})$. In particular, for any \mathbf{x} , we have

$$\vec{w} \cdot \vec{\Psi}(\mathbf{x}) = \sum_\mu \alpha^\mu \sigma_\mu K(\mathbf{x}, \mathbf{x}^\mu). \quad (4)$$

Hence, both learning and prediction on novel inputs depend only on the feature vectors $\vec{\Psi}$ through the kernel K . In fact, there is no need to specify the high dimensional mapping $\vec{\Psi}(\cdot)$ explicitly. Instead, one can directly take any reasonable positive semidefinite operator kernel K , which by Mercer's theorem has a decomposition $K(\mathbf{x}, \mathbf{y}) = \sum_\rho \lambda_\rho \phi_\rho(\mathbf{x}) \phi_\rho(\mathbf{y})$ in terms of eigenvalues λ_ρ and orthonormal eigenfunctions $\phi_\rho(\mathbf{x})$ and identify Ψ_ρ with $\sqrt{\lambda_\rho} \phi_\rho$. This approach even allows to take kernels with feature space dimension $M = \infty$ without problems.

We will now study the generalization performance of SVMs within the framework of Statistical Mechanics. We define the partition function

$$Z = \int \prod_{\rho=1}^M dw_\rho e^{-\frac{\beta}{2} \vec{w} \cdot \vec{w}} \prod_{\mu=1}^m \Theta \left(\sigma_\mu \sum_{\rho=1}^M \sqrt{\lambda_\rho} w_\rho \phi_\rho(\mathbf{x}^\mu) - 1 \right) \quad (5)$$

which for $\beta \rightarrow \infty$ is dominated by the solution vector \vec{w} of the SVM algorithm. The properties of the SVM can be computed from the average free energy $F = -\frac{1}{\beta} \langle \ln Z \rangle$, in the zero temperature limit $\beta \rightarrow \infty$, where the brackets denote the average over the distribution of m training examples. The main difference from the Statistical Mechanics of learning in a simple perceptron with M weights is that in the SVM, each coupling w_ρ is weighted by $\sqrt{\lambda_\rho}$, which typically diminishes the influence of the more complex, higher order degrees of freedom in the eigenvector expansion. As we will see, this makes the generalization behavior of the SVM rather different from that of a simple perceptron in the thermodynamic limit $N \rightarrow \infty$, when the rule to be learnt has a similar eigenvector expansion. We will consider here a rule of the

form $\sigma_\mu = \text{sign} \left(\sum_\rho \sqrt{\lambda_\rho} B_\rho \phi_\rho(\mathbf{x}^\mu) \right)$, where the teacher weight vector is given by $B_\rho = \pm 1$. We will further average the performance over all teachers of this form with equal probability for all nonzero components. We will specialize on a family of kernels of the form $K(\mathbf{x}, \mathbf{y}) = k \left(\frac{\mathbf{x} \cdot \mathbf{y}}{N} \right)$, where the only constraint on the function $k(\cdot)$ is the non-negativity of the eigenvalues. These kernels are permutation symmetric in the components of the input vectors and contain the simple perceptron as a special case, when k is a linear function. This choice has the nice feature that for binary input vectors $\mathbf{x} \in \{-1, 1\}^N$ the eigenvalue decomposition of $K(\mathbf{x}, \mathbf{y})$ can be explicitly calculated [7]. The eigenfunctions are labelled by subsets $\rho \subseteq \{1, \dots, N\}$. We have $\phi_\rho(\mathbf{x}) = 2^{-N/2} \prod_{i \in \rho} x_i$. The eigenvalues are $\lambda_\rho = 2^{N/2} \sum_{\mathbf{x}} K(\mathbf{e}, \mathbf{x}) \phi_\rho(\mathbf{x})$ where $\mathbf{e} = (1, \dots, 1)^T$, which depend on the cardinality $|\rho|$ only and show for large N an exponential decay with $|\rho|$ like $\frac{2^N}{N^{|\rho|}} k^{(|\rho|)}(0)$. The corresponding degeneracy grows exponentially: $n_{|\rho|} = \binom{N}{|\rho|} \simeq N^{|\rho|} / |\rho|!$.

We expect that a decay of the generalization error, ϵ_g , to zero should occur only on the scale of $m = \mathcal{O}(M)$, since M is the number of learnable parameters. However, as we will show, ϵ_g may drop to small values already on a scale of $m = \alpha N$ examples. Hence, we make the general ansatz $m = \alpha N^l$, $l \in \mathbb{N}$ and calculate $f_l := \lim_{\beta \rightarrow \infty} \lim_{N \rightarrow \infty} N^{-l} F$.

If we assume that the inputs \mathbf{x}^μ are drawn at random with respect to a uniform probability distribution $D(\mathbf{x})$ on $\{-1, 1\}^N$, we can perform the average over the input distribution by the replica method [1–3]. This becomes tractable by the fact that the eigenfunctions are orthonormal with respect to $u(\mathbf{x})$ and we have $2^N \langle \phi_\rho(\mathbf{x}) \phi_{\rho'}(\mathbf{x}) \rangle_u = \sum_{\mathbf{x}} \phi_\rho(\mathbf{x}) \phi_{\rho'}(\mathbf{x}) = \delta_{\rho\rho'}$. Furthermore, all but the constant eigenfunctions have zero mean under the uniform distribution. By restricting the kernels to having $k(0) = 0$, the average over the inputs is expressed in the thermodynamic limit $N \rightarrow \infty$ by expectations over Gaussian random variables. These averages can be further expressed by the order parameters

$$\begin{aligned} q_0 &= \sum_\rho \Lambda_\rho \langle (w_\rho)^2 \rangle, \\ q &= \sum_\rho \Lambda_\rho \langle w_\rho \rangle^2 \\ R &= \sum_\rho \Lambda_\rho \langle w_\rho \rangle B_\rho \end{aligned}$$

where $\Lambda_\rho := \lambda_\rho / 2^N$, and $\langle \dots \rangle$ denotes a statistical mechanical averaging specified by Eq. (5). The generalization error is $\epsilon_g = \frac{1}{\pi} \arccos \frac{R}{\sqrt{Bq}}$, where the $B = \sum_\rho \Lambda_\rho = k(1)$ is the squared norm of the teacher vector. In replica symmetry (which is expected to be exactly fulfilled by the convexity of the phase space) we obtain f_l by extremizing the function

$$f_l(q, R, \chi) = \alpha \int_{-\infty}^{1/\sqrt{q}} Dt \Phi\left(\frac{Rt}{\sqrt{Bq - R^2}}\right) \frac{(1 - \sqrt{qt})^2}{\chi} + \frac{1}{2N^l} \left(\frac{n_l}{\Lambda^{(+)} - \chi} + \frac{1}{\Lambda_l}\right) \times \left(q - \frac{R^2}{B^{(-)} + B_l^2(n_l \Lambda_l + \Lambda^{(+)} - \chi)}\right) \quad (6)$$

with respect to the order parameters q, R and χ . Further, $Dt = \frac{dt}{\sqrt{2\pi}} e^{-t^2/2}$, $\Phi(x) = \int_{-\infty}^x Dt$ and $\chi := \lim_{\beta \rightarrow \infty} \beta(q_0 - q)$. $\Lambda^{(+)} := \sum_{|\rho| > l} \Lambda_\rho$ denotes the sum over the higher order components and $B^{(-)} := \sum_{|\rho| < l} \Lambda_\rho$.

As a general result of solving the order parameter equations we find that all high order components $|\rho| > l$ of the teacher vector are completely *undetermined* by learning only $\mathcal{O}(N^l)$ examples, in the sense that $R^{(+)} := \sum_{|\rho| > l} \Lambda_\rho w_\rho B_\rho = 0$, and also that $q_0^{(+)} := \sum_{|\rho| > l} \Lambda_\rho (w_\rho)^2 = 0$, in the large N limit. However, as we will see, the values of the corresponding weights w_ρ are not zero but are determined by the expansion (3). On the other hand, all lower order components are *completely* determined, in the sense that $w_\rho = cB_\rho$ for all $|\rho| < l$, where c depends on α only. The only components which are actually learnt at a scale l are those for $|\rho| = l$. We will illustrate these results for quadratic kernels of the form $k(x) = (1 - d)x^2 + dx$, where the parameter d , $0 < d < 1$, tunes the degree of nonlinearity in the SVM's decision boundary. On a scale of $m = \alpha N$ examples (left side of Fig. 1), the SVM is able to learn the linear part of the teacher's rule. However, since there is not enough information to infer the remaining $\mathcal{O}(N^2)$ weights of the teacher's quadratic part, the generalization error of the SVM reaches a nonzero plateau with $\epsilon_g(\alpha) - \epsilon_g(\infty) \sim \alpha^{-1}$, where $\epsilon_g(\infty) = \pi^{-1} \arccos(d)$. This scaling may be understood from the fact that the undetermined components w_ρ and B_ρ , with $|\rho| = 2$ act as a noise term during classification similar to learning of perceptrons with weight noise [3]. For comparison, we also show the performance of a simple *linear* SVM (i.e. a perceptron) for which $w_\rho = 0$ when $|\rho| > 1$. The better performance of the nonlinear SVM does not contradict the fact that, on the linear scale, its higher order weights w_ρ for $|\rho| = 2$ are uncorrelated with the corresponding teacher values. Those weights are needed to learn the training examples perfectly which is not possible for the linear machine when α exceeds a critical value $= \alpha_c(d)$, given by $\pi/\alpha_c = \arctan \pi/(\alpha_c d)$.

Increasing the number of examples to a scale of $m = \alpha N^2$ (right side of Fig. 1), the well known [8] $1/\alpha$ asymptotic vanishing of ϵ_g is found. A similar stepwise learning has been obtained for the case of Gibbs learning in higher order perceptrons [9]. In general, for kernels which are polynomials of order z , more plateaus will appear. On the scale of $m = \alpha = N^{l-1}$ examples, the generalization error decays to a plateau at $\alpha \rightarrow \infty$ given by

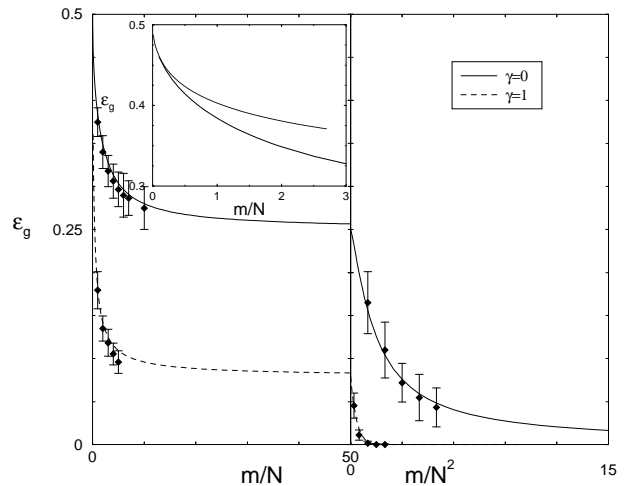


FIG. 1. Decrease of the generalization error on different scales of examples, for quadratic SVM-kernel learning a quadratic teacher rule ($d = 0.5$, $B = 1$) and various gaps γ . The inset compares the SVM to a linear perceptron (upper curve), trying to learn the same task. Simulations were performed with $N = 201$ and averaged over 50 runs (left and next figure), and $N = 20, 40$ runs (right).

$$\epsilon_g = \frac{1}{\pi} \arccos \sqrt{\frac{B^{(-)}}{B}} = \frac{1}{\pi} \arccos \sqrt{\frac{\sum_{j=1}^{l-1} \frac{k^{(j)}(0)}{j!}}{k(1)}}. \quad (7)$$

Finally, at the highest scale $m = \alpha N^z$, the generalization error converges to zero as $\epsilon_g \approx \frac{0.500489}{z!} \alpha^{-1}$. This form is in accordance with general results [5] which show that (in the worst case) the number of examples must be larger than the capacity of the classifier in order to achieve a small generalization error. The capacity $m_c = \alpha_c N^z$ is found from (6) by solving the order parameter equations with the restriction $R = 0$, as the value of α where q_0 diverges. We obtain $\alpha_c = \frac{z!}{z!}$ which agrees with the results in [10] for polynomial separation surfaces in the large N limit.

As the next problem, we study the ability of the SVM to cope with the problem of overfitting when learning a simple rule. We keep the SVM quadratic, but choose a simpler, linear teacher rule according to $|B_\rho| = 1$ for $|\rho| = 1$ and $|B_\rho| = 0$ else. The results for the generalization error are shown in Fig. 2, where the number of examples is scaled as $m = \alpha N$. Surprisingly, although the student has of $\mathcal{O}(N^2)$ adjustable parameters, this does not lead to any strong overfitting. The SVM is able to learn the N teacher weights on the scale of $m = \alpha N$ examples far below capacity. For comparison, we have also shown ϵ_g for a simple linear SVM (i.e. with $w_\rho = 0$ for $|\rho| = 2$). While for the latter case, the decay of the generalization error is of the well known form $\epsilon_g \sim \alpha^{-1}$, the quadratic SVM shows the somewhat slower decay $\epsilon_g \sim \alpha^{-2/3}$. The same scaling is obtained for higher order SVMs which learn a low order *e.g.*, a linear, rule.

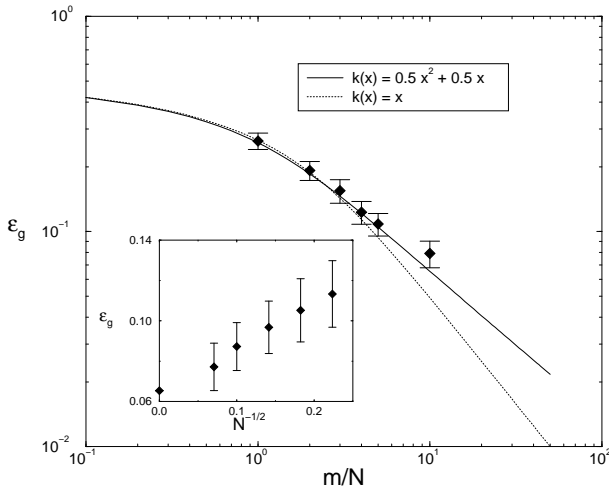


FIG. 2. Learning curves for linear student and quadratic SVM-kernels, all learning a linear teacher rule ($B = d$). For $\alpha = 10$, a finite size scaling is shown as inset.

We can shed further light on this interesting result by showing that the number of SVs increases like $\alpha^{2/3}$, hence the relative number of SVs (which is a crude upper bound on ϵ_g) decreases like $\alpha^{-1/3}$. This can be understood from the following analysis, which is valid for more general classes of input distributions. For simplicity, we restrict ourselves to the quadratic SVM learning a linear rule. We assume that the inputs have zero mean and are sufficiently weakly correlated such that the off-diagonal elements of the quadratic part of the kernel matrix $K_{\mu\nu}^{(2)} = (1-d)(N^{-1}\mathbf{x}^\mu \cdot \mathbf{x}^\nu)^2$ for $\mu \neq \nu$ are typically $\mathcal{O}(1/N)$. The diagonal elements are $K_{\mu\mu}^{(2)} = 1-d$. Evaluating $h_\mu = \vec{w} \cdot \vec{\Psi}(\mathbf{x}^\mu)$ using Eq. (4) one finds that the relative contributions of the off-diagonal elements of K are $\mathcal{O}\left((m/N^2)^{\frac{1}{2}}\right)$ and can be neglected on the linear scale $m = \alpha N$. Hence we obtain $h_\mu = v_\mu + (1-d)\alpha^\mu$ with v_μ being the contribution from the linear weights, namely, $v_\mu = \sigma_\mu \sqrt{d/N} \mathbf{w} \cdot \mathbf{x}$, where \mathbf{w} consists of w_ρ ; $|\rho| = 1$. Solving for the coefficients α^μ , noting that they are nonzero only when $h_\mu > 1$, we obtain

$$\alpha^\mu = (1-d)^{-1}(1-v^\mu)\Theta(1-v^\mu). \quad (8)$$

When α is small, all $\alpha^\mu \approx 1/(1-d)$ and the SVM acts like a Hebbian classifier. With increasing number of examples v^μ will grow and the probability that $\alpha^\mu > 0$ (an example is a SV) will decrease. The exact asymptotic scaling can be calculated selfconsistently assuming that for large α , $w_\rho \simeq cB_\rho$ for $\rho = 1$ and $c = N^{-1} \sum_{|\rho|=1} w_\rho B_\rho = \frac{1}{N} \sum_{\mu=1}^{\alpha N} \alpha^\mu u^\mu$ where u^μ the linear contribution to the local field of the teacher vector. Using Eq. (8) and noting that $v_\mu \approx cu_\mu$ we obtain

$$c \sim \alpha \int_0^{1/c} du p(u) u (1-cu) \quad (9)$$

valid for large α . Here $p(u)$ denotes the density of the teacher linear fields u . Solving Eq. (9) for c in limit of $\alpha \rightarrow \infty$ yields $c \sim (\alpha p(0)/6)^{1/3}$. Similarly, the relative number of SVs scales as $p(0)/c \sim \alpha^{-1/3} p(0)^{2/3}$.

The dependence on $p(0)$ suggests that the density of inputs at the teacher's decision boundary should play a crucial role for the generalization ability of the SVM. When this density vanishes close to the teacher's separating hypersurface, a much faster decay of the generalization error can be expected. To study this property in more detail, we have analyzed the Statistical Mechanics for an input distribution correlated with the teacher weights such that $D(\mathbf{x}) \sim \Theta\left(\sigma \sum_\rho \sqrt{\Lambda_\rho} B_\rho \phi_\rho(\mathbf{x}) - \gamma\right)$ which have a gap of zero density with size 2γ around the teacher's decision boundary. As expected, the generalization performance of a quadratic SVM which learns from a quadratic teacher is enhanced, but the asymptotic decay towards the plateau on the linear scale (see Fig. 1) is still of the form $\epsilon_g(\alpha) - \epsilon_g(\infty) \sim \alpha^{-1}$. The effect of the gap is more dramatic on the quadratic scale $m = \alpha N^2$, where instead of an inverse power law, we now find a fast drop of the generalization error like $\epsilon_g \sim \alpha^{-3} e^{-\hat{c}(\gamma)\alpha^2}$.

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