

Machine Learning 6.867 - Pset 2

October 27, 2015

1 Logistic Regression

1.1 Implementation

We implemented L_2 -regularized logistic regression using gradient descent. The objective function to be minimized over is:

$$\sum_{i=1}^n \log(1 + e^{-y^{(i)}(\mathbf{w}^T \mathbf{x}^{(i)} + w_0)}) + \lambda \mathbf{w}^T \mathbf{w} \quad (1)$$

We used both our implementation of gradient descent and the MATLAB function `fminunc`. Convergence criterion is reached within reasonable iterations in both implementations.

1.2 Performance on data with $\lambda = 0$

We run the logistic regression on the four data sets, setting the regularization parameter $\lambda = 0$. The estimated coefficients are listed in Table 1.

Table 1: Estimated logistic regression coefficients and accuracy, $\lambda = 0$

Data	w_0	w_1	w_2	Train accuracy	Valid accuracy	Test accuracy
stdev1	-66.3378	95.2461	101.1527	1.0000	1.0000	0.9975
stdev2	-0.0466	0.7636	1.1148	0.9075	0.9200	0.9250
stdev4	-0.0093	0.2363	0.2034	0.7400	0.7525	0.7825
nonsep	0.0006	-0.0247	-0.0237	0.5150	0.4925	0.4975

The decision boundaries at various thresholds are plotted in Figure 1. We observe the following phenomenon:

1. As data become more linearly non-separable, the accuracy is lower in training, validation, and testing.
2. As data become more linearly non-separable, the estimated logistic function is also less steep, reflected in the wider distance between the contours in the plots and lower norm of \mathbf{w} . This is reasonable because the classifier is not as certain about how to classify the data points in the mix zone.
3. In the non-separable case, logistic regression fails to classify, barely reaching the 50% baseline.

1.3 Performance on data with positive λ

Similarly, we run logistic regression with other values of λ . As demonstrated in Figure 2, with higher values of λ , the decision boundary is flatter, especially in more separable data. The training accuracy is lower, and the validation accuracy typically increases (or stays the same) and then decreases, as shown in Figure 3. We use the cross-validation technique to select best value of λ using the validation set accuracy. In particular, for the

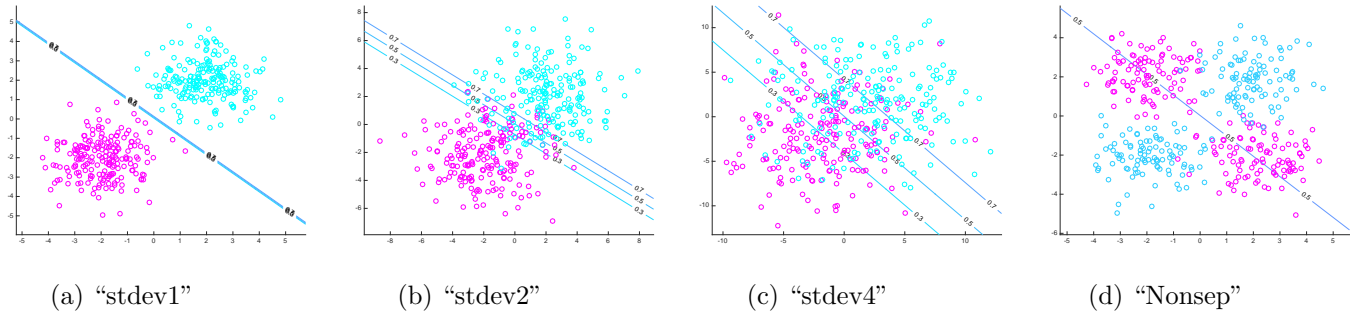


Figure 1: Plots of decision boundaries from logistic regression with $\lambda = 0$ from training sets.

four datasets, we choose $\lambda = 0$, $\lambda = 0$, $\lambda = 100$, and $\lambda = 1000$ respectively. The corresponding accuracy in test sets are 0.9975, 0.9250, 0.7850, and 0.5025. Compared to not regularizing, the test set accuracies are slightly higher. The accuracy for the non-separable data set remains relatively constant regardless of how we regularize.

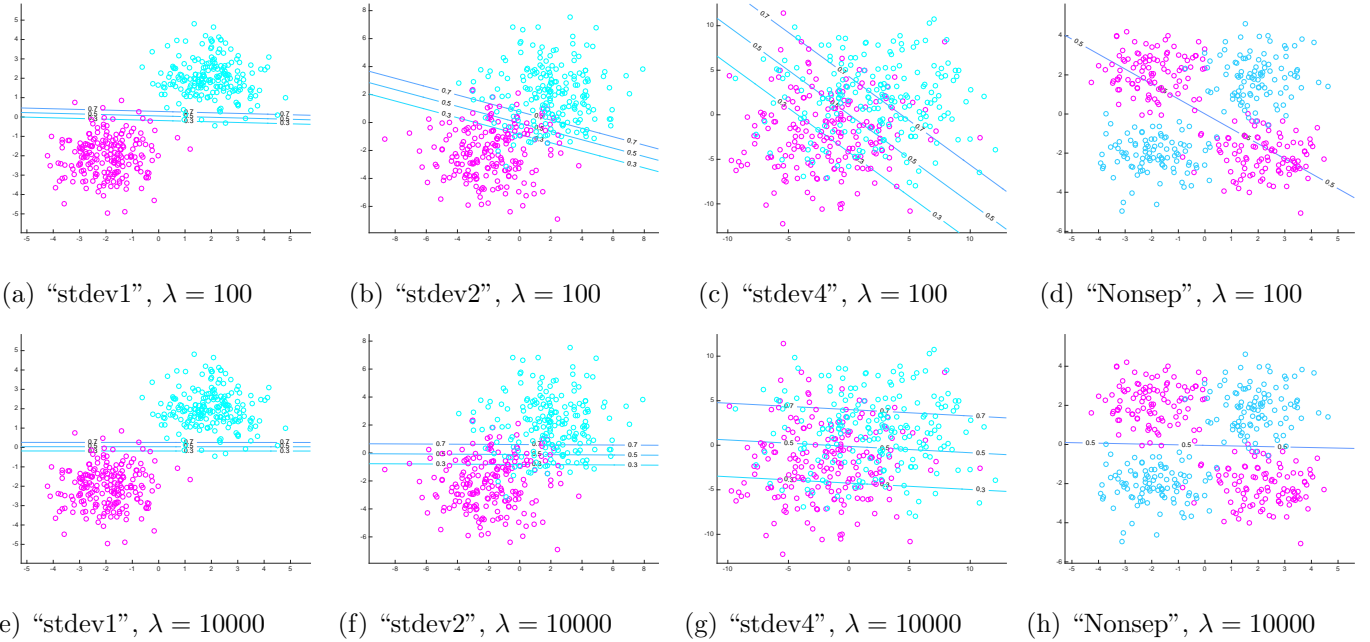


Figure 2: Plots of decision boundaries from logistic regression with $\lambda = 100$ and $\lambda = 10000$ from training sets.

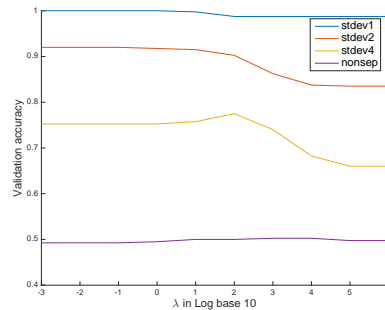


Figure 3: Cross validation error with respect to λ

2 Support Vector Machine

Support Vector Machines are a popular classification method to construct linear or nonlinear decision boundaries by solving a convex optimization problem. There are two common forms of the optimization problem considered for SVM, which we refer to as the primal and dual. In this paper, we only consider the dual form, because it is computationally more tractable for many problems, and this method has the ability to generalize to different choices of kernel. The dual form of SVM for a general kernel function $k : \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$ is as follows:

$$\begin{aligned} \max_{\alpha \in \mathbb{R}^n} \quad & \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j y^{(i)} y^{(j)} k(x^{(i)}, x^{(j)}) \\ \text{s.t.} \quad & 0 \leq \alpha_i \leq C, \quad i = 1, \dots, n, \\ & \sum_{i=1}^n \alpha_i y^{(i)} = 0. \end{aligned} \quad (2)$$

2.1 Implementation

First, we implemented the dual form of the SVM with a linear kernel, where k is the usual dot product $k(x, z) = \langle x, z \rangle$ for all $x, z \in \mathcal{X}$. In MATLAB, we created a function with inputs: data $X \in \mathbb{R}^{n \times p}$, labels $Y \in \{-1, 1\}$, and cost parameter $C \in \mathbb{R}^+$. Within the function, we use the quadratic solver `quadprog` to solve the SVM dual problem (2) with these parameters to find the optimal α 's. Since `quadprog` requires that the problem fit into a certain functional form, we reformulate the problem (2) as follows:

$$\begin{aligned} - \min_{\alpha \in \mathbb{R}^n} \quad & \frac{1}{2} \alpha^T H \alpha - \sum_{i=1}^n \alpha_i \\ \text{s.t.} \quad & 0 \leq \alpha_i \leq C, \quad i = 1, \dots, n, \\ & \sum_{i=1}^n \alpha_i y^{(i)} = 0, \end{aligned} \quad (3)$$

where: $H \in \mathbb{R}^{n \times n}$ is a matrix with $(i, j)^{th}$ entry $H_{ij} = y^{(i)} y^{(j)} k(x^{(i)}, x^{(j)})$. Given the optimal solution $\alpha \in \mathbb{R}^n$ for the SVM problem with a linear kernel, the chosen linear decision boundary $\theta^T x + \theta_0 = 0$ is given by:

$$\theta = \sum_{i=1}^n \alpha_i y^{(i)} x^{(i)} \quad (4)$$

$$\theta_0 = \frac{1}{\mathcal{M}} \left(\sum_{j \in \mathcal{M}} \left(y^{(j)} - \sum_{i \in \mathcal{S}} \alpha_i y^{(i)} (x^{(j)})^T x^{(i)} \right) \right) \quad (5)$$

where $\mathcal{M} = \{i : 0 < \alpha_i < C\}$ and $\mathcal{S} = \{i : \alpha_i > 0\}$. The output of our linear SVM function is $[\theta, \theta_0]$. We tested our function on the 2D example $X = \{(1, 2), (2, 2), (0, 0), (-2, 3)\}$, $Y = \{1, 1, -1, -1\}$. For this problem, the objective function generated for minimization problem (3) is:

$$\frac{1}{2} \alpha^T H \alpha - \sum_{i=1}^4 \alpha_i, \quad (6)$$

where:

$$H = \begin{bmatrix} 5 & 6 & 0 & -4 \\ 6 & 8 & 0 & -2 \\ 0 & 0 & 0 & 0 \\ -4 & -2 & 0 & 13 \end{bmatrix}$$

The constraints are:

$$0 \leq \alpha_i \leq C, \quad i = 1, \dots, 4, \quad (7)$$

$$\alpha_1 + \alpha_2 - \alpha_3 - \alpha_4 = 0. \quad (8)$$

2.2 Performance on datasets

We tested our linear SVM function on the same 2D datasets from the previous section, with parameter $C = 1$. The estimated coefficients are listed in Table 2.

Table 2: Estimated SVM coefficients and accuracy, $C = 1$

Data	w_0	w_1	w_2	Train accuracy	Valid accuracy	Test accuracy
stdev1	1.2333	1.2409	-0.4204	1.0000	1.0000	0.9975
stdev2	0.4573	0.7552	-0.1410	0.9050	0.9200	0.9175
stdev4	0.1998	0.1820	-0.0470	0.7450	0.7650	0.7800
nonsep	-0.2194	-0.2118	-0.4280	0.6975	0.6950	0.7000

The decision boundaries at various thresholds are plotted in Figure 4. We observe the following phenomenon:

1. As data become more linearly non-separable, the accuracy is lower, and the width of the margin increases for the same value of C .
2. In the totally non-separable case, SVM achieves close to 70% accuracy, which is higher than logistic regression. These two methods yield different results because they use different loss functions. SVM uses a hinge loss function which is piecewise linear, while logistic regression uses a logistic loss function which is nonlinear convex.

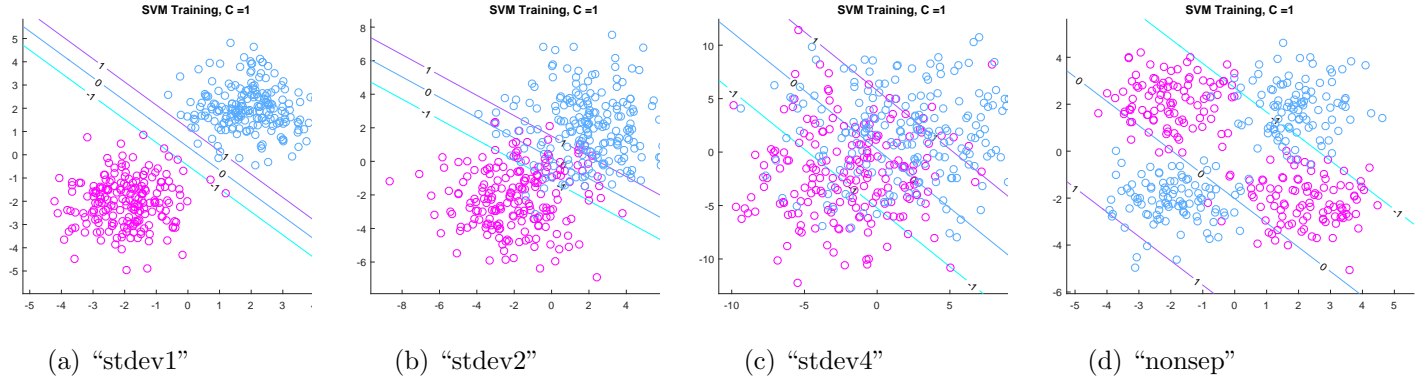


Figure 4: Plots of decision boundaries from SVM with $C = 1$ from training sets.

2.3 Kernel SVM

We extended our SVM implementation in MATLAB to operate with more general kernels, taking the kernel function or kernel matrix as input. We tested our SVM method for linear kernel varying $C = \{0.01, 0.1, 1, 10, 100\}$, and for gaussian kernel varying $C = \{0.01, 0.1, 1, 10, 100\}$ and the squared bandwidth $\sigma^2 = \{0.1, 1, 10, 100\}$. Plots illustrating the resulting decision boundaries on the 2D datasets for different parameters are shown in Figure 5. As σ^2 decreases, the decision boundary becomes more jagged to fit the training data more exactly.

Questions:

- (a) As C increases, the geometric margin $1/\|\mathbf{w}\|$ decreases. If the data is not linearly separable, then the geometric margin $1/\|\mathbf{w}\|$ decreases strictly monotonically as C increases. However, if the data is linearly separable, then this does not always happen as we increase C . In this case, once the margin is sufficiently small such that all points are correctly classified, then it will not decrease further even as C approaches infinity.

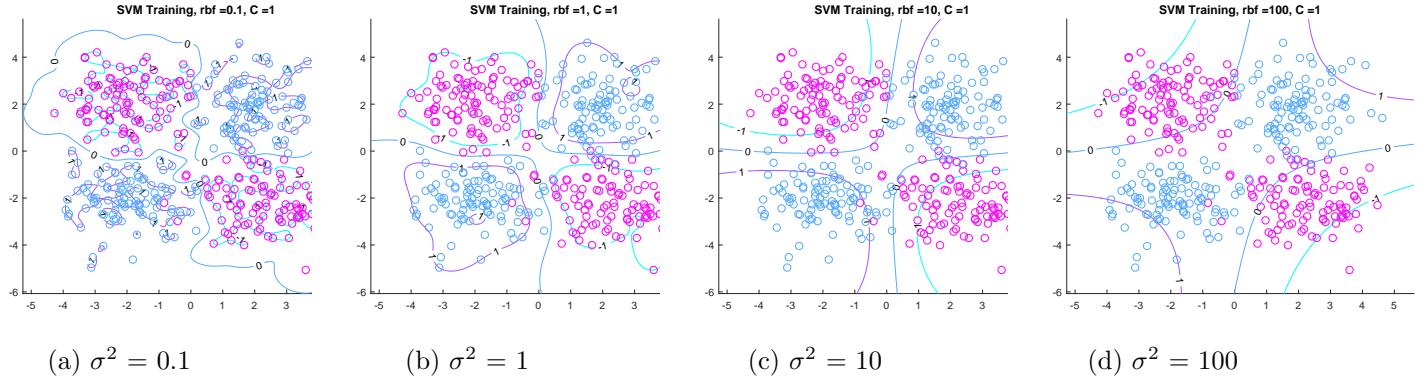


Figure 5: Plots of decision boundaries from SVM with gaussian kernel, $C = 1$ on “nonsep” dataset, varying values of the bandwidth parameter.

- (b) As C increases, the number of support vectors generally decreases. This is because the larger penalty on misclassified points leads to a decision boundary with fewer misclassifications on the training data. The number of the support vectors is bounded below by two as C approaches infinity, because there will always be at least one support vector on each side of the decision boundary. However, there are pathological examples where the number of support vectors increases as C increases for some values, which we observe for the nonseparable dataset.
- (c) Maximizing the geometric margin $1/\|\mathbf{w}\|$ on the training data is not an appropriate criterion for selecting C because this leads to a classifier which is overfit to the training set. To obtain a classifier which generalizes well on test data, we should use out-of-sample data to select an appropriate value for C . To do this, we can train the SVM model with $C = \{0.01, 0.1, 1, 10, 100\}$, and then select the value for C which yields the classifier with the highest accuracy on the validation set.

3 Titanic Data

We apply our methods to **Titanic**, a real-world dataset from Kaggle competition on the Titanic shipwreck of 1912. The classification task is to predict which passengers survived based on features such as age, gender, and ticket class. Before running logistic regression or SVM, we scale the features in two ways: 1) standardizing using mean and standard deviation by $(X_j^{(i)} - \mu(X_j))/\sigma(X_j)$; 2) scale so each dimension is within the $[0, 1]$ range using min and max: $(X_j^{(i)} - \min X_j)/(\max X_j - \min X_j)$. We find the scaling constants in the training sets only, and use the same constants in the validation and testing sets.

3.1 Logistic Regression

We first use logistic regression on the Titanic data to make predictions on survivor results. With no regularization, we obtain a testing set accuracy of 77.78% in both cases of scaling methods. To find the best λ , we use cross-validation. The validation set accuracy with respect to λ is presented in Figure 6a. We therefore choose $\lambda = 10$ in standard-deviation-based scaling, and $\lambda = 0.1$ in range-based scaling. The test set accuracy is then 75.13% and 76.19%, respectively. Unfortunately neither is as good as the non-regularized logistic regression. Furthermore, the way how one scales the features can also impact the accuracy.

3.2 SVM

Next, we run SVM with a linear kernel on the Titanic data, and use cross-validation to select C . Validation set accuracies are presented in Figure 6b, and we choose $\lambda = 0.01$ in standard-deviation-based scaling, and $\lambda = 0.1$ in range-based scaling. The test set accuracy is then 76.19% and 75.66%, respectively.

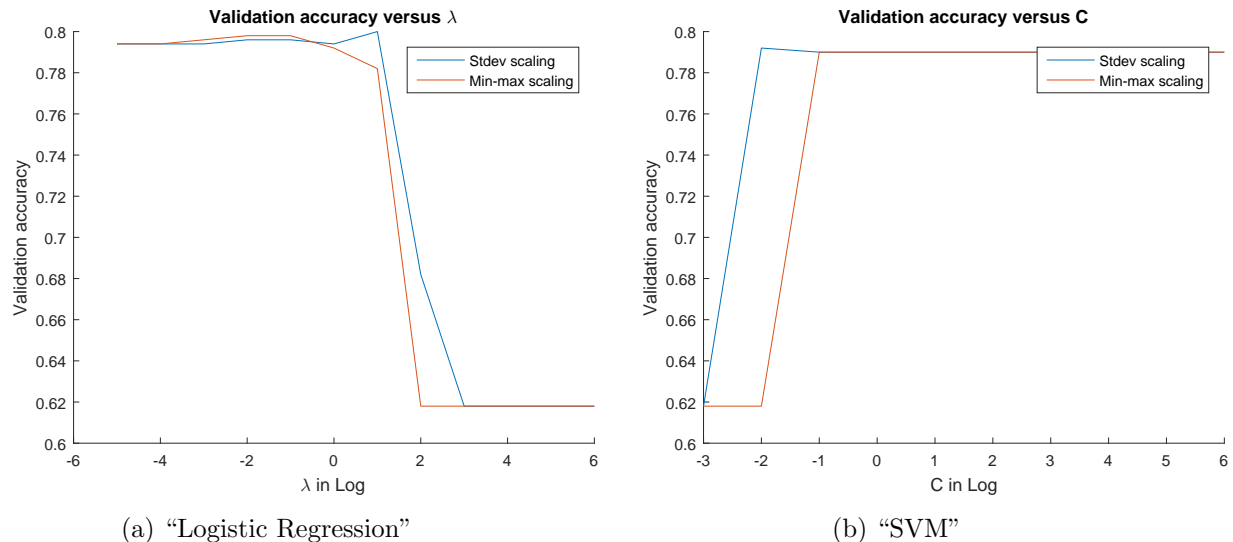


Figure 6: Titanic Data, Cross validation error in logistic regression with respect to λ and in SVM with respect to C , under two different scaling methods.

3.3 Comparison

The estimated coefficients for logistic regression and SVM are presented in Table 3. Since we do not have standard error and confidence interval information, we can only rely on the magnitude of the estimator (even if they are not statistically significant). For logistic regression, we observe that being woman, higher class and higher fare are associated with higher likelihood of survival, whereas being 3rd class is strongly associated with death. We observe similar results for SVM coefficients, except the absolute values of the coefficients are slightly smaller for all parameters. The three most significant parameters for SVM by absolute magnitude were Sex, Number of parents/children aboard, and Passenger class 3, respectively. By far, gender is the most significant feature for both methods. The sign of the coefficients are the same for both methods, except for w_{11} , in which case both are near zero.

Table 3: Estimated coefficients for logistic regression, $\lambda = 10$, and SVM, $C = 0.01$, on Titanic data under feature-scaling method (1).

Coefficient	Description	Logistic estimator	SVM estimator
w_0	Constant	-0.6289	-0.3976
w_1	Passenger class 1	0.1680	0.0350
w_2	Passenger class 2	0.2013	0.0774
w_3	Passenger class 3	-0.3245	-0.0982
w_4	Sex	0.7795	0.6714
w_5	Age	-0.1417	-0.0643
w_6	Num siblings/Spouses aboard	-0.0477	-0.0397
w_7	Num parents/children aboard	0.1422	0.1152
w_8	Pasenger fare	0.1533	0.0793
w_9	Port of embarkation = Southampton	-0.0955	-0.0632
w_{10}	Port of embarkation = Cherbourg	0.1090	0.0758
w_{11}	Port of embarkation = Queenstown	0.0393	-0.0052