

logistic regression model

$$P(y=1 | x, w) = \psi(w^t x) = \frac{1}{1 + \exp(w^t x)} = \frac{\exp(w^t x)}{1 + \exp(w^t x)}$$

Fit the model by the maximum log-likelihood criterion

$$J_L(w) = \sum_{k=1}^n \log P(y_k | x_k, w)$$

$$= \sum_{k=1}^n \left[ y_k \log P(y_k=1 | x_k, w) + (1-y_k) \log (1 - P(y_k=1 | x_k, w)) \right]$$

$$= \sum_{k=1}^n \left[ y_k (w^t x_k - \log(1 + \exp(w^t x_k))) \right.$$

$$\left. + (1-y_k) \log \frac{1}{1 + \exp(w^t x_k)} \right]$$

$$= \sum_{k=1}^n y_k w^t x_k - \log(1 + \exp(w^t x_k))$$

Thus, we set the derivatives of  $J_L(w)$  w.r.t. the parameters to zero.

$$\frac{\partial J_L(w)}{\partial w_0} = \sum_{k=1}^n y_k - \frac{\exp(w^t x_k)}{1 + \exp(w^t x_k)} = \sum_{k=1}^n y_k - P(y_k=1 | x_k, w) = 0$$

$$\frac{\partial J_L(w)}{\partial w_j} = \sum_{k=1}^n y_k x_{kj} - \frac{\exp(w^t x_k) x_{kj}}{1 + \exp(w^t x_k)} = \sum_{k=1}^n (y_k - P(y_k=1 | x_k, w)) x_{kj} = 0$$

errors:

$$e_k = (y_k - P(y_k=1 | x_k, w)) \quad , k=1, \dots, n$$

stochastic gradient ascent ( $J_L(w)$  is concave)

$$w \leftarrow w + \eta \cdot \frac{\partial}{\partial w} J_L^{(k)}(w)$$

$$= w + \eta \cdot (y_k - P(y_k=1 | x_k, w)) x_k$$

$\eta$  is the learning rate.

# Tutorial 8: Linear Classifiers

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# Outline

- 1 Logistic Regression
- 2 Support Vector Machine

# Support Vector Machine

## Programming Toolkits

Lots of packages for SVM are available with interfaces including Matlab, Java, Python, R, Perl, Julia, etc. We list mostly used ones

- LibSVM

<http://www.csie.ntu.edu.tw/~cjlin/libsvm/>

- Extensions of LibSVM, e.g., LibLinear, multi-class classification, support large training set, etc.

- SVM<sup>light</sup>

<http://svmlight.joachims.org/>

- Extensions of SVM<sup>light</sup>, e.g., SVM<sup>struct</sup>, SVM<sup>perf</sup>, SVM<sup>rank</sup>, etc.

Open source at: <https://github.com/cjlin1/libsvm>

Language: support Matlab/Octave/Python/Java Documentation:

- 1 Setup
- 2 Data format
- 3 Function options
- 4 Example in hand

# LibSVM-Matlab/Octave

## Setup:

- 1 Environment: Matlab, C/C++ compiler (MSVS in Windows or gcc in Linux/Unix)
- 2 Build mex binaries: type in command window `mex -setup` to choose a suitable compiler, and `mex *.c`

## Function usage:

- 1 `model = svmtrain(label_train, data_train, options);`  
label\_train $_{n \times 1}$ : training label (dtype: double)  
data\_train $_{n \times d}$ : training data stacked by row (dtype: double)  
options: string of training options in LibSVM format.
- 2 `[label_pred, acc, decision/prob] = svmpredict(label_test, data_test, model, options);`  
label\_test $_{n \times 1}$ : testing label (dtype: double)  
data\_test $_{n \times d}$ : testing data stacked by row (dtype: double)  
options: string of training options in LibSVM format.

## Function options:

### 1 svmtrain()

https:

[//raw.githubusercontent.com/cjlin1/libsvm/master/README](https://raw.githubusercontent.com/cjlin1/libsvm/master/README)

```
Usage: svm-train [options] training_set_file [model_file]
options:
-s svm_type : set type of SVM (default 0)
    0 -- C-SVC                (multi-class classification)
    1 -- nu-SVC                (multi-class classification)
    2 -- one-class SVM
    3 -- epsilon-SVR           (regression)
    4 -- nu-SVR                (regression)
-t kernel_type : set type of kernel function (default 2)
    0 -- linear: u'*v
    1 -- polynomial: (gamma*u'*v + coef0)^degree
    2 -- radial basis function: exp(-gamma*|u-v|^2)
    3 -- sigmoid: tanh(gamma*u'*v + coef0)
    4 -- precomputed kernel (kernel values in training_set_file)
-d degree : set degree in kernel function (default 3)
-g gamma : set gamma in kernel function (default 1/num_features)
-r coef0 : set coef0 in kernel function (default 0)
-c cost : set the parameter C of C-SVC, epsilon-SVR, and nu-SVR (default 1)
-n nu : set the parameter nu of nu-SVC, one-class SVM, and nu-SVR (default 0.5)
-p epsilon : set the epsilon in loss function of epsilon-SVR (default 0.1)
-m cachesize : set cache memory size in MB (default 100)
-e epsilon : set tolerance of termination criterion (default 0.001)
-h shrinking : whether to use the shrinking heuristics, 0 or 1 (default 1)
-b probability_estimates : whether to train a SVC or SVR model for probability
estimates, 0 or 1 (default 0)
-wi weight : set the parameter C of class i to weight*C, for C-SVC (default 1)
```

Function options:

## 2 `svmpredict()`

`https:`

`//raw.githubusercontent.com/cjlin1/libsvm/master/README`

Usage: `svm-predict [options] test_file model_file output_file`

options: `-b probability_estimates`: whether to predict probability estimates, 0 or 1 (default 0); for one-class SVM only 0 is supported



```
% read provided data heart\_scale
[heart_label , heart_data] = libsvmread('../heart_scale');

% SVM training
model = svmtrain(heart_label , heart_data , '-c1-g0.07');

% test the training data
[predict_label , accuracy , dec_values] ...
= svmpredict(heart_label , heart_data , model);
```

## Setup:

- 1 Environment: Python, C/C++ compiler (MSVS in Windows or gcc in Linux/Unix).
- 2 Build binaries  
Type *make* in terminal if in Linux/Unix, copy `../windows/libsvm.dll` to `C:/WINDOWS/system32/` if in Windows.
- 3 Use other python interface of LibSVM like scikit-learn  
<http://scikit-learn.org/stable/modules/svm.html>

Quick start:

```
# import libsvm packages
```

```
>>> from svmutil import *
```

```
# Read data in LIBSVM format
```

```
>>> y, x = svm_read_problem('../heart_scale')
```

```
# SVM training
```

```
>>> m = svm_train(y[:200], x[:200], '-c_4')
```

```
# SVM testing
```

```
>>> p_label, p_acc, p_val = svm_predict(y[200:], x[200:], m)
```