

# Linear Models for Classification (part 2)

T-61.6020: Machine Learning, Basic Principles



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# Outline

- Probabilistic Discriminative Models
  - Logistic Regression
  - Iterative Reweighted LS
  - Multiclass Logistic Regression
  - Probit Regression
- Laplace Approximation
- Bayesian Logistic Regression



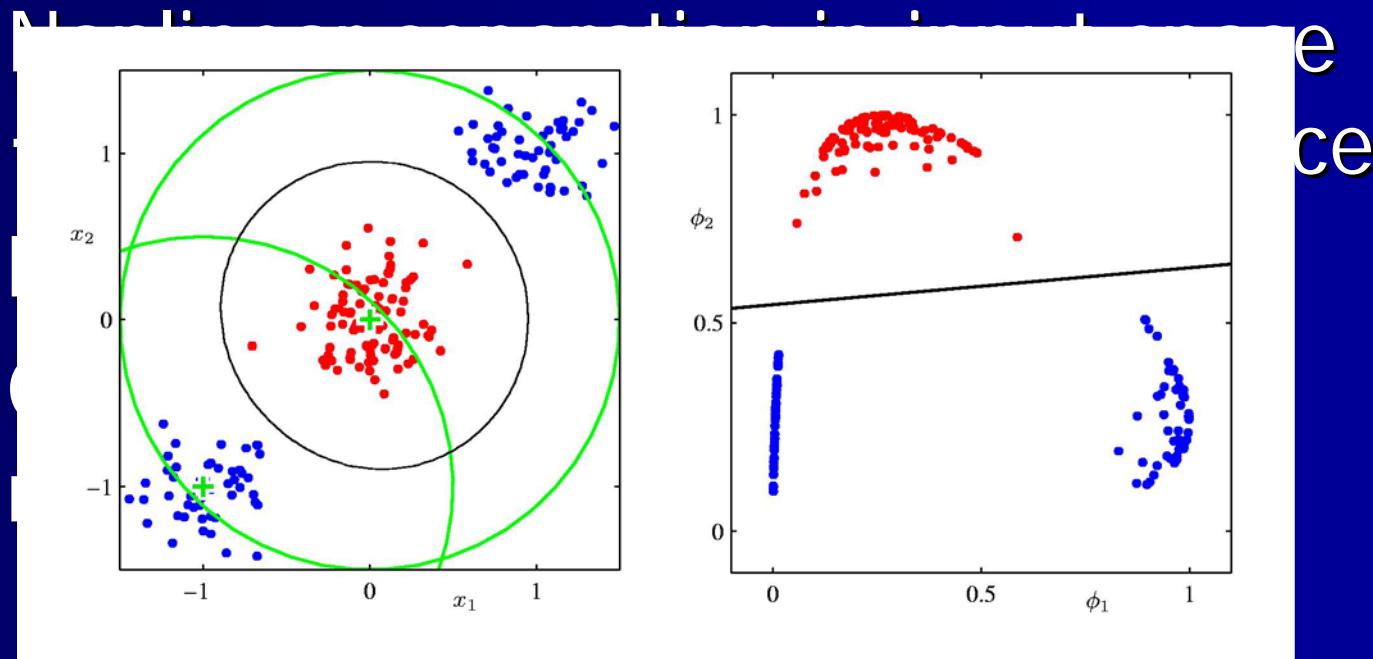
# Probabilistic Discriminative Models

- Direct approach
  - Maximize the conditional probability directly without going through prior and likelihood
- Fewer parameters to be determined
- Better predictive performance
- Enables the usage of basis functions



# Nonlinear Basis Functions

- Transform input space to feature space through basis function



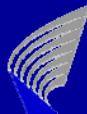
# Logistic Regression

- Classification to two classes using logistic sigmoid function
- Linearly increasing number of parameters, not quadratic like Gaussians
- For linearly separable data, overfitting might occur
  - Needs regularization
  - Or prior and MAP solution



# Iterative Reweighted LS

- No closed-form solution for logistic regression
  - Nonlinearity of logistic Sigmoid
  - Iterative procedure needed
- Error function has unique minimum
- Efficient algorithm: Newton-Raphson
  - Iterative, using local approximation of log likelihood



# IRLS (2)

- Ordinary linear regression

$$\mathbf{w}^{new} = (\Phi^T \Phi)^{-1} \Phi^T \mathbf{t}$$

- Exact solution, same as OLS

- IRLS

$$\mathbf{w}^{new} = \mathbf{w}^{old} - (\Phi^T \mathbf{R} \Phi)^{-1} \Phi^T (\mathbf{y} - \mathbf{t})$$

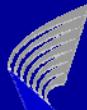


# Multiclass Logistic Regression

- Two-class → Sigmoid Function
- Multiclass → Softmax Function
- IRLS algorithm used again
- Error function nearly the same than with 2-class case

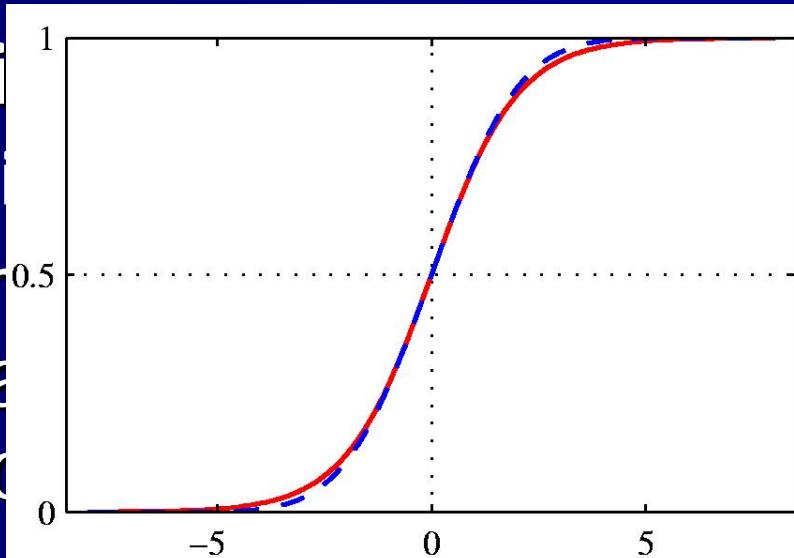
$$\sigma(a) = \frac{1}{1 + e^{-a}}$$

$$y_k(\phi) = \frac{e^{a_k}}{\sum_j e^{a_j}}$$



# Probit Regression

- Very close to the logistic regression
- Probit function used approximating Sigmoid
- Difference is:
  - More sensitive
- In case of non-normal errors, it must be taken into account by changing the probabilistic model.



# Probit (2)

## ■ Probit function

$$\Phi(a) = \int_{-\infty}^a N(\theta | 0,1) d\theta$$

$$\Phi(a) = \frac{1}{2} \left\{ 1 + \frac{1}{\sqrt{2}} \text{erf}(a) \right\}$$

$$\text{erf}(a) = \frac{2}{\sqrt{\pi}} \int_0^a \exp\left(-\frac{\theta^2}{2}\right) d\theta$$



# Canonical Link Functions

- Conditional distribution of target variable from exponential family
- Corresponding choice for activation function
  - Error formula always similar

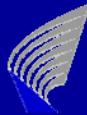
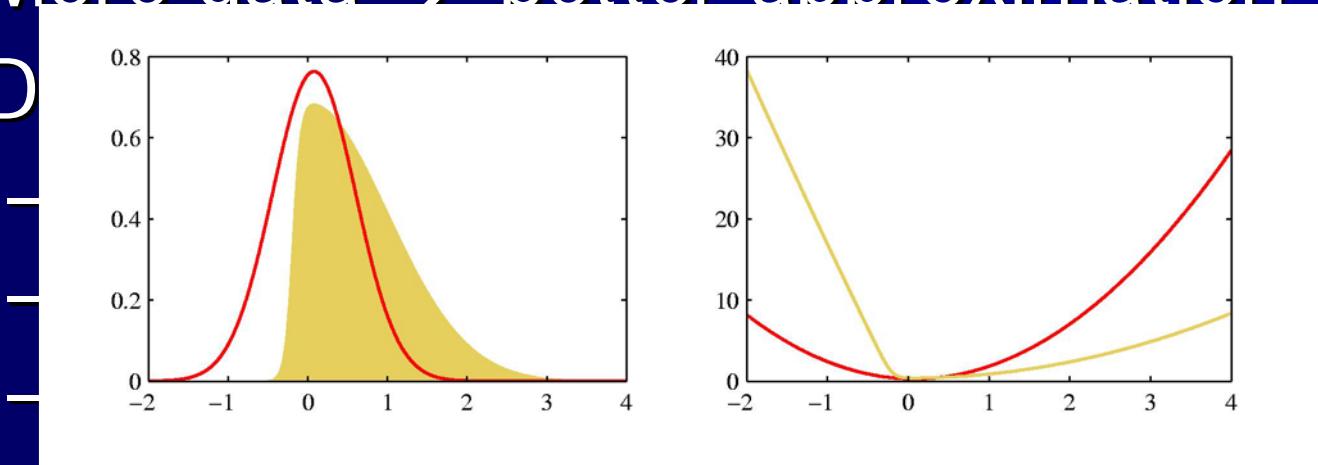
$$\nabla \ln E(w) = \frac{1}{S} \sum_{n=1}^N (y_n - t_n) \phi_n$$



# Laplace Approximation

- Approximation of the integration
  - Posterior no longer Gaussian
- Built around mode of the distribution
- More data → better approximation

■ D



# Bayesian Information Criterion (BIC)

- Same kind of model complexity measure than for example AIC
- Assumptions
  - Prior distributions broad
  - Hessian matrix full rank
  - Assumptions not always valid!
- Approximation rough
  - More accuracy in Section 5.7



# BIC (2)

- BIC

$$\ln p(D) \cong \ln p(D | \theta_{MAP}) - \frac{1}{2}M \ln N$$

- N data points
- M parameters
- Penalizes model complexity harder than AIC



# Bayesian Logistic Regression

- Integration of a product of Sigmoids is intractable → no exact solution
- Laplace approximation used
- Predictive distribution
  - Using Probit function to replace the Sigmoids



# Bayesian Logistic Regression (2)

- Posterior distribution (approximation)

$$q(\mathbf{w}) = N(\mathbf{w} \mid \mathbf{w}_{MAP}, \mathbf{S}_N)$$

$$\mathbf{S}_N = \mathbf{S}_0^{-1} + \sum_{n=1}^N y_n(1-y_n)\phi_n\phi_n^T$$

- Predictive distribution (approximation)

$$p(C_n \mid \phi, \mathbf{t}) = \sigma\left(\kappa\left(\sigma_a^2\right)\mu_a\right) \quad \kappa\left(\sigma^2\right) = \frac{1}{\sqrt{1 + \frac{\pi\sigma^2}{8}}}$$



## ■ Questions?

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Pictures of the presentation, courtesy of C.M. Bishop  
<http://research.microsoft.com/~cmbishop/PRML/webfigs.htm>

