Linear methods of classification

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Linear discriminant functions

- Classification of two classes ω_1 and ω_2.
- Linear discriminant function:

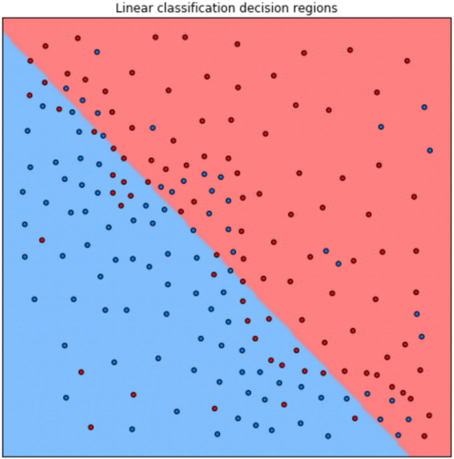
$$g(x) = w^T x + w_0$$

- Decision rule:

$$x \to \begin{cases} \omega_1, & g(x) \geq 0 \\ \omega_2, & g(x) < 0 \end{cases}$$

- Decision boundary $B = \{x : g(x) = 0\}$ is linear.

Example: decision regions



Properties

- $x_A, x_B \in B \Rightarrow \begin{cases} g(x_A) = w^T x_A + w_0 = 0 \\ g(x_B) = w^T x_B + w_0 = 0 \end{cases} \Rightarrow$
  $w^T(x_A - x_B) = 0$, so $w \perp B$.
- Distance from the origin to B is equal to absolute value of the projection of $x \in B$ on $\frac{w}{\|w\|}$:

$$\langle x, \frac{w}{\|w\|} \rangle = \frac{\langle x, w \rangle}{\|w\|} = \{w^T x + w_0 = 0\} = -\frac{w_0}{\|w\|}$$

- So $\rho(0, B) = \frac{w_0}{\|w\|}$, and w_0 determines the offset from the origin.

Distance from x to B

Denote $x_\perp$ - the projection of x on B, and $r = \langle \frac{w}{\|w\|}, x - x_\perp \rangle$ - the signed length of the orthogonal complement of x on B:

$$x = x_\perp + r\frac{w}{\|w\|}$$

After multiplication by w and addition of w_0:

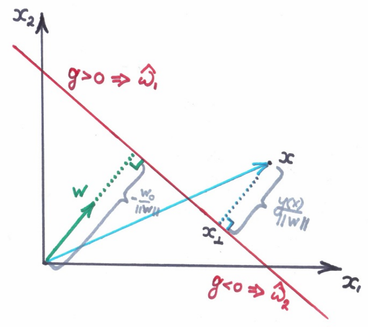
$$w^T x + w_0 = w^T x_\perp + w_0 + r\frac{\langle w, w \rangle}{\|w\|}$$

Using $w^T x + w_0 = g(x)$ and $w^T x_\perp + w_0 = 0$, we obtain:

$$r = \frac{g(x)}{\|w\|}$$

So from one side of the hyperplane $r > 0 \Leftrightarrow g(x) > 0$, and from the other side of the hyperplane $r < 0 \Leftrightarrow g(x) < 0$.

Illustration



Linear decision rule:

$$\widehat{c}(x) = \begin{cases} \omega_1, & g(x) > 0 \\ \omega_2, & g(x) < 0 \end{cases}$$

Decision boundary: $g(x) = 0$, confidence of decision: $|g(x)| / \|w\|$.

Multiple classes classification - solution

- Classification among $\omega_1, \omega_2, ...\omega_C$.
- Use C discriminant functions $g_c(x) = w_c^T x + w_{c0}$
- Decision rule:

$$\widehat{c}(x) = \arg\max_c g_c(x)$$

- Decision boundary between classes ω_i and ω_j is linear:

$$\left(w_i - w_j\right)^T x + \left(w_{i0} - w_{j0}\right) = 0$$

- Decision regions are convex.

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Linear discriminant functions

- Consider binary classification of classes ω_1 and ω_2.
- Denote classes ω_1 and ω_2 with $y = +1$ and $y = -1$.
- Linear discriminant function: $g(x) = w^T x + w_0$,

$$\widehat{\omega} = \begin{cases} \omega_1, & g(x) \geq 0 \\ \omega_2, & g(x) < 0 \end{cases}$$

- Decision rule: $y = \operatorname{sign} g(x)$.
- Define constant feature $x_0 \equiv 1$, then $g(x) = w^T x = \langle w, x \rangle$ for $w = [w_0, w_1, ..w_D]^T$.
- Define the margin $M(x) = g(x)y$
  - $M(x) \geq 0$ <=> object x is correctly classified
  - $|M(x)|$ - confidence of decision

Weights selection

- Target: minimization of the number of misclassifications:

$$Q_{accurate}(w|X) = \sum_i \mathbb{I}[M(x_i|w) < 0] \to \min_w$$

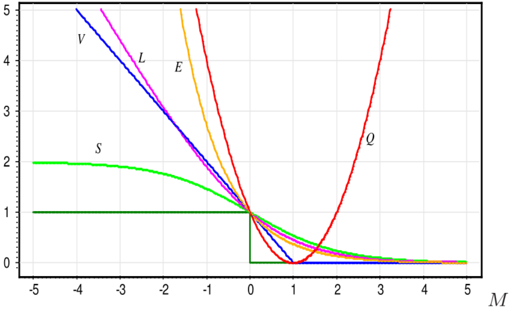
- Problem: standard optimization methods are inapplicable, because $Q(w,X)$ is discontinuous.
- Idea: approximate loss function with smooth function $\mathcal{L}$:

$$\mathbb{I}[M(x_i|w) < 0] \le \mathcal{L}(M(x_i|w))$$

Approximation of the target criteria

We obtain the upper boundary on the empirical risk:

$$
\begin{aligned}
Q_{accurate}(w|X) &= \sum_i \mathbb{I}[M(x_i|w) < 0] \\
&\leq \sum_i \mathcal{L}(M(x_i|w)) = F(w)
\end{aligned}
$$



$$
\begin{aligned}
Q(M) &= (1-M)^2 \\
V(M) &= (1-M)_+ \\
S(M) &= 2(1+e^M)^{-1} \\
L(M) &= \log_2(1+e^{-M}) \\
E(M) &= e^{-M}
\end{aligned}
$$

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Optimization

- Optimization task to obtain the weights:

$$F(w) = \sum_{i=1}^{N} \mathcal{L}(\langle w, x_i \rangle y_i) \to \min_{w}$$

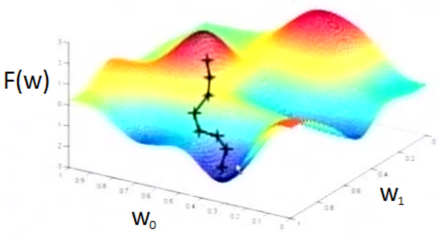
- Gradient descend algorithm:

INPUT:
η - parameter, controlling the speed of convergence
stopping rule

ALGORITHM:
initialize w_0 randomly
while stopping rule is not satisfied:
    $w_{n+1} \leftarrow w_n - \eta \frac{\partial F(w_n)}{\partial w}$
    $n \leftarrow n + 1$

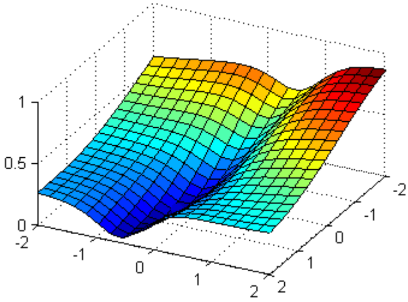
Gradient descend

- Possible stopping rules:
  - $|w_{n+1} - w_n| < \varepsilon$
  - $|F(w_{n+1}) - F(w_n)| < \varepsilon$
  - $n > n_{max}$
- Suboptimal method of minimization in the direction of the greatest reduction of $F(w)$:



Recommendations for use

- Convergence is faster for normalized features
  - feature normalization solves the problem of «elongated valleys»



Convergence acceleration

Stochastic gradient descend method

set the initial approximation w_0
calculate $\widehat{Q}_{approx} = \sum_{i=1}^{n} \mathcal{L}(M(x_i|w_0))$
iteratively until convergence $\widehat{Q}_{approx}$:

1. select random pair (x_i, y_i)
2. recalculate weights: $w_{n+1} \leftarrow w_n - \eta_n \mathcal{L}'(\langle w_n, x_i \rangle y_i) x_i y_i$
3. estimate the error: $\varepsilon_i = \mathcal{L}(\langle w_{n+1}, x_i \rangle y_i)$
4. recalculate the loss $\widehat{Q}_{approx} = (1-\alpha)\widehat{Q}_{approx} + \alpha\varepsilon_i$
5. $n \leftarrow n+1$

Variants for selecting initial weights

- $w_0 = w_1 = ... = w_D = 0$
- For logistic $\mathcal{L}$ (because the horizontal asymptotes):
    - randomly on the interval $[-\frac{1}{2D}, \frac{1}{2D}]$
- For other functions $\mathcal{L}$:
    - randomly
- $w_i = \frac{\langle x^i, y \rangle}{\langle x^i, x^i \rangle}$

Discussion of SGD

Advantages

- Easy to implement
- Works online
- A small subset of learning objects may be sufficient for accurate estimation

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Drawbacks

- For non-convex $\mathcal{L}(M)$ may converge to local optimum
- Needs selection of η_n:
  - too big: divergence
  - too small: very slow convergence
- Overfitting possible for large D and small N
- When $\mathcal{L}(u)$ has left horizontal asymptotes (e.g. logistic), the algorithm may «get stuck» for large values of $\langle w, x_i \rangle$.

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Regularization for SGD

- L_2-regularization for upperbound approximation:

$$Q_{approx}^{regularized}(w) = Q_{approx}(w) + \frac{\tau}{2}|w|^2$$

- SGD weights modification: $w \leftarrow w(1 - \eta\tau) - \eta Q'_{approx}(w)$

Regularization

- Useful technique to control the trade-off between bias and variance, can be applied to any algorithm.

$$Q^{regularized}(w) = Q(w) + \tau ||w||_2$$

$$Q^{regularized}(w) = Q(w) + \tau ||w||_1$$

$$||w||_1 = \sum_{d=1}^{D} |w^d|, \quad ||w||_2 = \sqrt{\sum_{d=1}^{D} (w^d)^2}$$

- Examples:
  - LASSO: least-squares regression, using $||w||_1$
  - Ridge: least-squares regression, using $||w||_2$
  - Elastic Net: : least-squares regression, using both

L_1 norm

- $||w||_1$ regularizer will do feature selection.
- Consider

$$Q(w) = \sum_{i=1}^{n} \mathcal{L}_i(w) + \frac{1}{C} \sum_{d=1}^{D} |w_d|$$

- if $\frac{1}{C} > \sup_w \left| \frac{\partial \mathcal{L}(w)}{\partial w_i} \right|$, then it becomes optimal to set $w_i = 0$
- For smaller C more inequalities will become active.
- L_2 does not filter features.

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Maximum probability estimation

- $X=\{x_1,x_2,...x_n\}$, $Y=\{y_1,y_2,...y_n\}$ - training sample of i.i.d. observations, $(x_i,y_i)\sim p(y|x,w)$
- ML estimation $\widehat{w}=\arg\max_w p(Y|X,w)$
- Using independence assumption:

$$\prod_{i=1}^{n} p(y_i|x_i,w)=\sum_{i=1}^{n}\ln p(y_i|x_i,w)\to\max_w$$

- Approximated misclassification:

$$\sum_{i=1}^{n}\mathcal{L}(g(x_i)y_i|w)\to\min_w$$

- Interrelation:

$$\mathcal{L}(g(x_i)y_i|w)=-\ln p(y_i|x_i,w)$$

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Binary classification

- Linear classifier:

$$score(\omega_1|x) = w^T x$$

- +relationship between score and class probability is assumed:

$$p(\omega_1|x) = \sigma(w^T x)$$

where $\sigma(z) = \frac{1}{1+e^{-z}}$ - sigmoid function

Binary classification: estimation

Using the property $1-\sigma(z)=\sigma(-z)$ obtain that

$$p(y=+1|x)=\sigma(w^T x) \Longrightarrow p(y=-1|x)=\sigma(-w^T x)$$

So for $y\in\{+1,-1\}$

$$p(y|x)=\sigma(y\langle w,x\rangle)$$

Therefore ML estimation can be written as:

$$\prod_{i=1}^{N}\sigma(\langle w,x_i\rangle y_i)\to\max_w$$

Multiple classes

Multiple class classification:

$$\begin{cases} score(\omega_1|x) = w_1^T x \\ score(\omega_2|x) = w_2^T x \\ \cdots \\ score(\omega_C|x) = w_C^T x \end{cases}$$

+relationship between score and class probability is assumed:

$$p(\omega_c|x) = softmax(w_c^T x | x_1^T x, ... x_C^T x) = \frac{exp(w_c^T x)}{\sum_i exp(w_i^T x)}$$

Multiple classes

Weights ambiguity:

w_c, $c = 1, 2, ...C$ defined up to shift v:

$$\frac{exp((w_c - v)^T x)}{\sum_i exp((w_i - v)^T x)} = \frac{exp(-v^T x) exp(w_c^T x)}{\sum_i exp(-v^T x) exp(w_i^T x)} = \frac{exp(w_c^T x)}{\sum_i exp(w_i^T x)}$$

To remove ambiguity usually $v = w_C$ is subtracted.

Estimation with ML:

$$\begin{cases} \prod_{n=1}^N softmax(w_{y_n}^T x_n | x_1^T x, ... x_C^T x) \to \max_{w_1, ... w_C - 1} \\ w_C = \mathbf{0} \end{cases}$$

Loss function for 2-class logistic regression

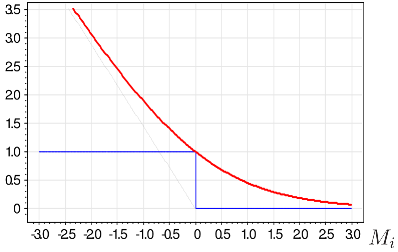
For binary classification $p(y|x) = \sigma(\langle w, x\rangle y)$ $w = [\beta_0', \beta]$, $x = [1, x_1, x_2, ...x_D]$.

Estimation with ML:

$$\prod_{i=1}^{n} \sigma(\langle w, x_i\rangle y_i) \to \max_w$$

which is equivalent to

$$\sum_i^n \ln(1 + e^{-\langle w, x_i\rangle y_i}) \to \min_w$$



So loss function for logistic regression is $\mathcal{L}(M) = \ln(1 + e^{-M})$.

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Problem statement

- Standard linear classification decision rule

$$\widehat{c} = \begin{cases} 1, & w^T x \geq -w_0 \\ 2, & w^T x < w_0 \end{cases}$$

  is equivalent to

  1. dimensionality reduction to 1-dimensinal space (defined by w)
  2. making classification in this space

- Idea of Fisher's LDA: find direction, giving most discriminative projections.

Possible realization

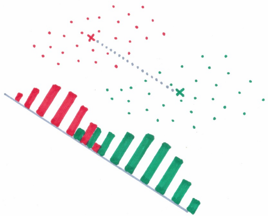
- Classification between ω_1 and ω_2.
- Define $C_1 = \{i : x_i \in \omega_1\}, \quad C_2 = \{i : x_i \in \omega_2\}$ and

$$m_1 = \frac{1}{N_1} \sum_{n \in C_1} x_n, \quad m_2 = \frac{1}{N_1} \sum_{n \in C_2} x_n$$

$$\mu_1 = w^T m_1, \quad \mu_2 = w^T m_2$$

Naive solution:

$$\begin{cases} (\mu_1 - \mu_2)^2 \to \max_w \\ \|w\| = 1 \end{cases}$$



Fisher's LDA

- Define projected within class variances:

$$s_1 = \sum_{n \in C_1} (w^T x_n - w^T m_1)^2, \quad s_2 = \sum_{n \in C_2} (w^T x_n - w^T m_2)^2$$

- Fisher's LDA criterion: $\frac{(\mu_1 - \mu_2)^2}{s_1^2 + s_2^2} \to \max_w$