

Lecture 22 announcements

- HW 12 will be posted.
- Tomorrow's discussion has been pre-recorded
 - will be played back tomorrow at usual time and place
 - archive is available online as usual
- Graded midterm exams - handed back today
- Complete midterm exam solution will be posted
 - Problems 2 and 3 were already given in Discussion 10

Lecture 22 outline

- Boosting and Adaboost (part 2)

BOOSTING (pt. 2)

WANT TO FIND:

$$\hat{f}(x) = \underset{f(x)}{\operatorname{argmin}} \sum_{i=1}^N L_{\exp} [\tilde{y}_i, f(x_i)]$$

$$\rightarrow \underset{f_0, \beta_m, \gamma_m \forall m=1, 2, \dots, M.}{\operatorname{argmin}} \sum_{i=1}^N L_{\exp} [\tilde{y}_i, f_0 + \sum_{m=1}^M \beta_m \cdot \phi(x_i, \gamma_m)]$$

EASIER TO MIN. EACH TERM, SEQUENTIALLY:

AT m^{th} ITERATION:

$$\underset{\beta_m, \gamma_m}{\operatorname{argmin}} \sum_{i=1}^N L_{\exp} [\tilde{y}_i, \hat{f}_{m-1}(x_i) + \beta_m \phi(x_i, \gamma_m)]$$

FORWARD STAGEWISE ADDITIVE MODELING

1. INITIALIZE $f_0 = 0$.

2. FOR $m = 1$ TO M :

(i) FIND:

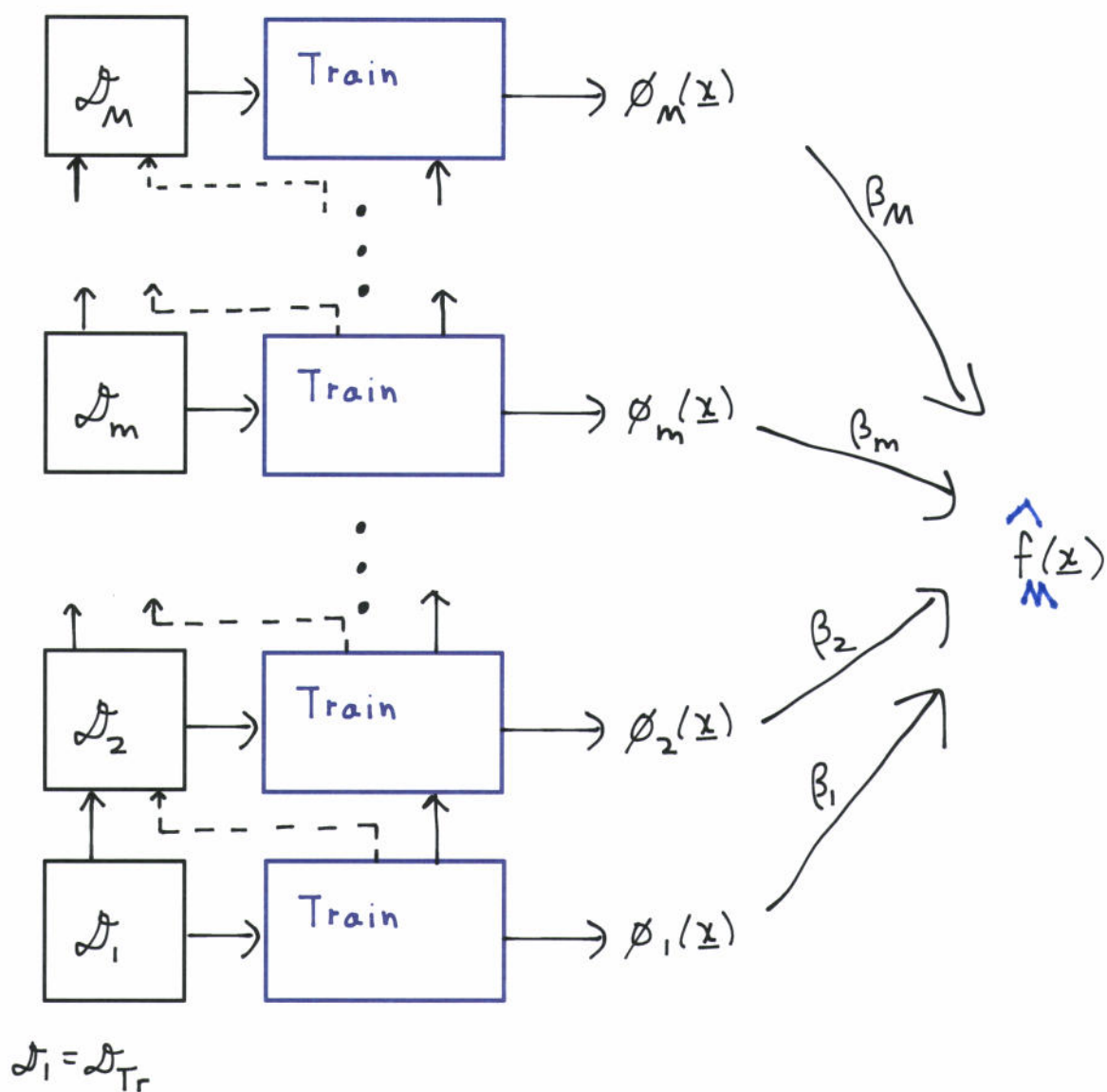
$$(\beta_m, \gamma_m) = \underset{\beta_m, \gamma_m}{\operatorname{argmin}} \left[\sum_{i=1}^N L[\tilde{y}_i, \hat{f}_{m-1}(x_i) + \beta_m \phi(x_i, \gamma_m)] \right]$$

$$(ii) \hat{f}_m(x) = \hat{f}_{m-1}(x) + \beta_m \phi_m(x, \gamma_m)$$

3. FINAL CLASSIFIER IS:

$$\hat{y}(x) = \operatorname{sign} \{ \hat{f}_M(x) \}$$

L COULD BE L_{exp} OR OTHER LOSS FCN.



$$\hat{y}(x) = \text{sign}\{\hat{f}_M(x)\} = \text{sign}\left\{\sum_{m=1}^M \beta_m \phi_m(x)\right\}$$

ADABOOST

→ USE $L = L_{\text{exp}}$

FROM ABOVE:

2. (i) FIND $(\beta_m, \underline{x}_m)$

$$= \underset{\beta'_m, \underline{x}'_m}{\operatorname{argmin}} \sum_{i=1}^N L_{\text{exp}} \left[\tilde{y}_i, \hat{f}_{m-1}(x_i) + \beta'_m \phi(x_i, \underline{x}'_m) \right]$$

$$(5) \left\{ L_m = \sum_i \exp \left\{ -\tilde{y}_i \left[\hat{f}_{m-1}(x_i) + \beta'_m \phi(x_i, \underline{x}'_m) \right] \right\} \right\}$$

$w_{i,m}$ (const. of β_m, \underline{x}_m)

$$(6) \text{ LET } w_{i,m} \triangleq \exp \left\{ -\tilde{y}_i \hat{f}_{m-1}(x_i) \right\}$$

$$(7) L_m = \sum_{i=1}^N w_{i,m} \exp \left[-\tilde{y}_i (\beta'_m \phi(x_i, \underline{x}'_m)) \right]$$

sum over all data pts.

weight on i^{th} data pt. at m^{th} iteration.

$\beta'_m > 0$, behaves like regular exp. loss

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L_m CAN BE MINIMIZED ALGEBRAICALLY.
[see Murphy].

CAN RE-ARRANGE L_m ABOVE (see Murphy),
to get EQNS. FOR ADABOOST ALGORITHM.

\Rightarrow

(*) $\phi(x_i, \gamma_m)$ IS CHOSEN TO MINIMIZE A
SUM OF WEIGHTS OF MISCLASSIFIED DATA
POINTS,

(**) $\beta_m = \frac{1}{2} \log \frac{1 - \text{err}_m}{\text{err}_m}$, with:

$$(***) \text{err}_m = \frac{\sum_{i=1}^N w_{i,m} \mathbb{I}[\tilde{y}_i \neq \phi(x_i, \gamma_m)]}{\sum_{i=1}^N w_{i,m}}$$

= SAMPLE-WEIGHTED ERROR RATE
(AT m^{th} ITERATION)

ALGORITHM: ADABOOST. M1

1. INITIALIZE $w_i = \frac{1}{N} \quad \forall i$.

2. FOR $m = 1$ TO M :

(i) TRAIN CLASSIFIER $\phi_m(x)$ [1-NODE CART]
ON WEIGHTED DATASET \mathcal{D}_m (WEIGHTS w_i)
PER (*).

(ii) COMPUTE [FROM (**)]:

$$\text{err}_m = \frac{\sum_{i=1}^N w_i \mathbb{I}[\tilde{y}_i \neq \phi_m(x_i)]}{\sum_{i=1}^N w_i}$$

(iii) COMPUTE

$$\alpha_m = \log \left[\frac{1 - \text{err}_m}{\text{err}_m} \right] = 2 \beta_m \text{ in (**),}$$

(iv) UPDATE $w_i \leftarrow w_i \exp[\alpha_m \mathbb{I}(\tilde{y}_i \neq \phi_m(x_i))]$
 $\forall i$.

3. RETURN $\hat{f}(x) = \sum_{m=1}^M \alpha_m \phi_m(x)$

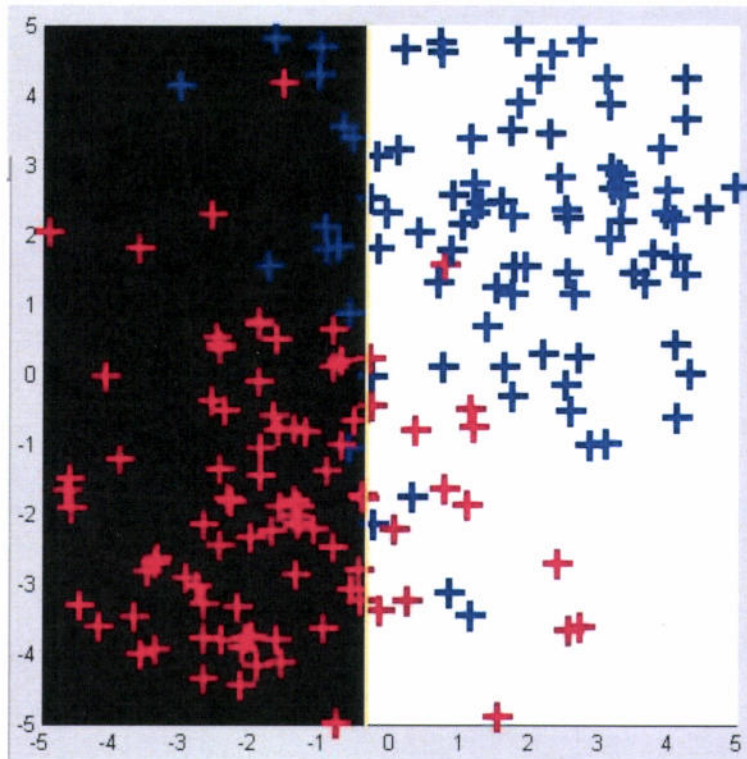
AND $\hat{y}(x) = \text{sign}\{\hat{f}(x)\}$.

NOTE: ERROR IN MURPHY, ALG. 16.2 (Adaboost^{.m1})

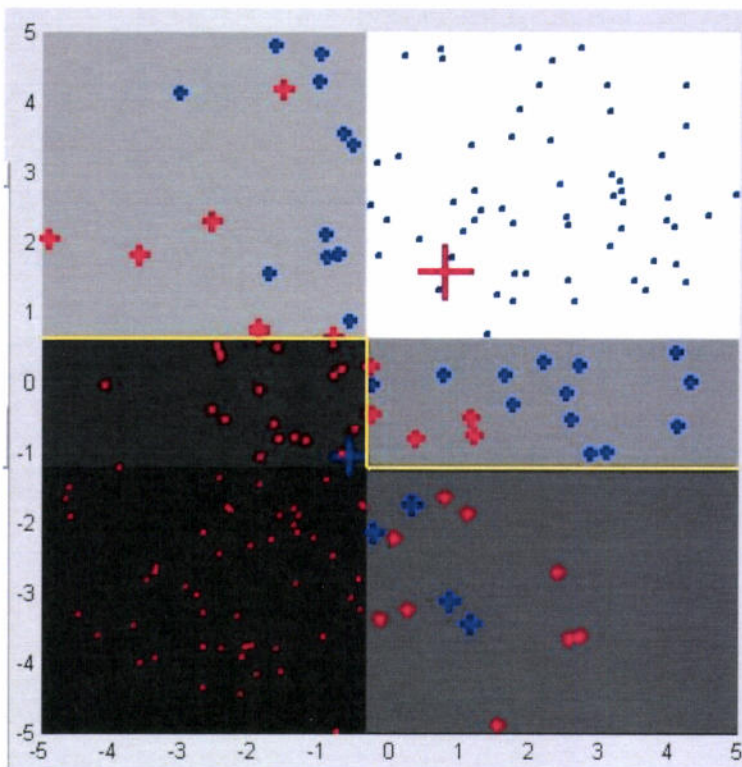
$$7 \text{ RETURN } \text{sgn}\{f(x)\} = \text{sgn}\left[\sum_{m=1}^M \alpha_m \phi_m(x)\right]$$

Murphy Fig. 16.10 :

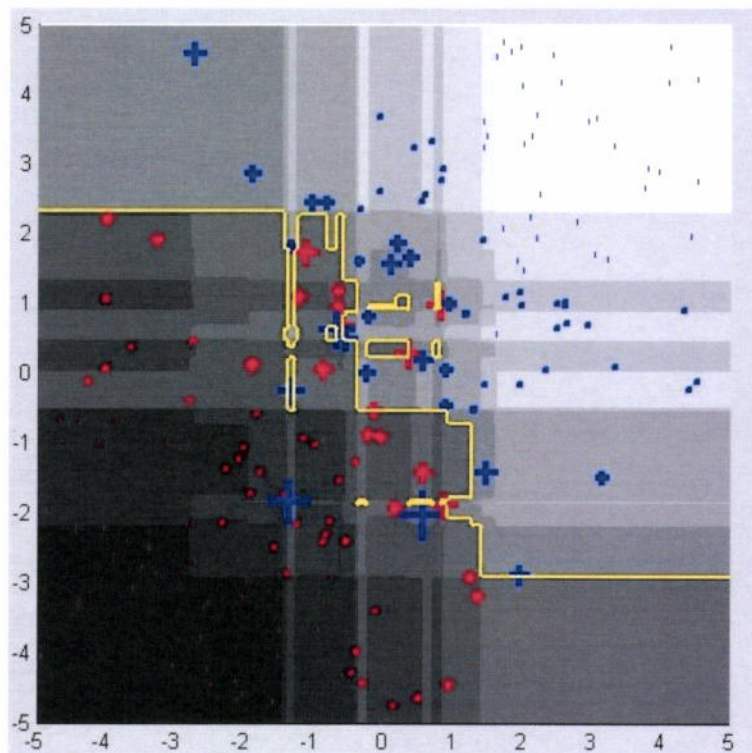
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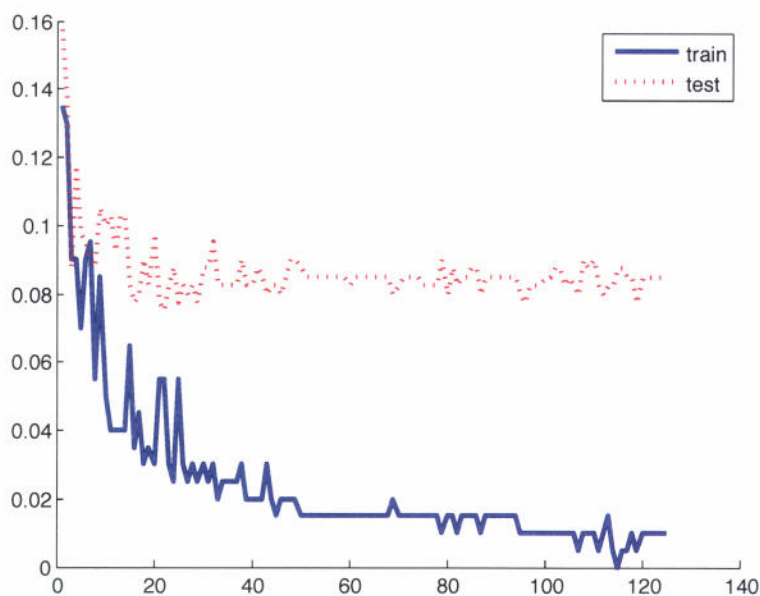
$m=1$



$m=3$



$m = 120$



Murphy
Fig. 16.8.

also - [Hastie Fig. 15.1]