

Machine learning assignment

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1. a) Optimization function: $y_i (w^T x_i + b) \geq 1$
 $i = 1, \dots, n$

$$\min_{\gamma, w, b} \frac{1}{2} \|w\|^2$$

WKT,

Lagrange dual $\Theta_D(\alpha, \beta) = \min_w L(w, \alpha, \beta)$

Re-writing the constraints

$$g(w) = y_i (w^T x_i + b) - 1 \leq 0$$

When we substitute in our Lagrangian formula we get:

$$f(w) = \frac{1}{2} \|w\|^2 \quad \left(\max_{\|w\|} \frac{1}{\|w\|} \approx \min \|w\| \approx \min \frac{1}{2} \|w\|^2 \right)$$

$$g_i(w) = y_i (w^T x_i + b) - 1$$

$$L(w, \alpha, \beta) = \frac{1}{2} \|w\|^2 + \sum_{i=1}^m \alpha_i [y_i (w^T x_i + b) - 1]$$

$$\boxed{\frac{\partial L}{\partial w} = w - \sum_{i=1}^m \alpha_i y_i x_i}$$

Calculating for extremum we get

$$w - \sum_{i=1}^m \alpha_i y_i x_i = 0$$

$$w = \sum_{i=1}^m \alpha_i y_i x_i$$

diff. w.r.t b

$$\frac{\partial L}{\partial b} = \sum_{i=1}^m \alpha_i y_i$$

Solving for extremum we get:

$$\frac{\partial L}{\partial b} = 0 \Rightarrow \sum_{i=1}^m \alpha_i y_i = 0$$

Placing them into Lagrange formula:

$$L(w, \alpha, b) = \frac{1}{2} \left(\sum_{i=1}^m \alpha_i y_i \bar{x}_i \right) \cdot \left(\sum_{j=1}^m \alpha_j y_j \bar{x}_j \right) - \sum_{i=1}^m \alpha_i y_i \cdot \left(\sum_{j=1}^m \alpha_j y_j \bar{x}_j \right)$$
$$= - \sum_{i=1}^m \alpha_i y_i b + \sum_{i=1}^m \alpha_i$$

$$L(w, \alpha, b) = \sum_{i=1}^m \alpha_i - \frac{1}{2} \sum_{i=1}^m \sum_{j=1}^m \alpha_i \alpha_j y_i y_j (\bar{x}_i)^T \cdot \bar{x}_j$$

$$\Rightarrow \max_{\alpha} W(\alpha) = \sum_{i=1}^m \alpha_i - \frac{1}{2} \sum_{i=1}^m \sum_{j=1}^m y_i y_j \alpha_i \alpha_j \langle x_i, x_j \rangle$$

$$\alpha_i \geq 0 \quad i=1, \dots, m$$

$$\sum_{i=1}^m \alpha_i y_i = 0$$

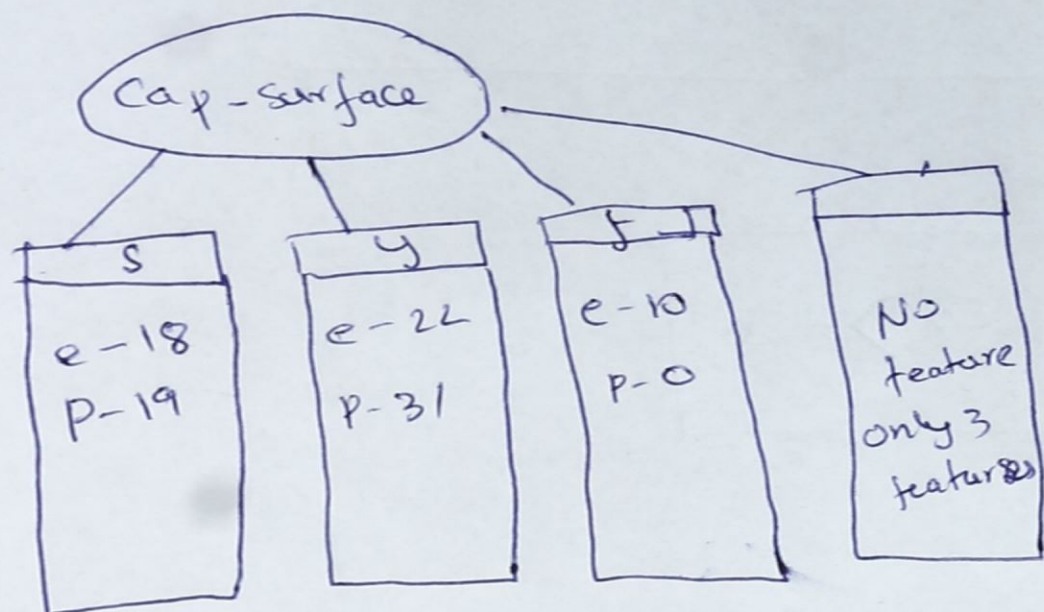
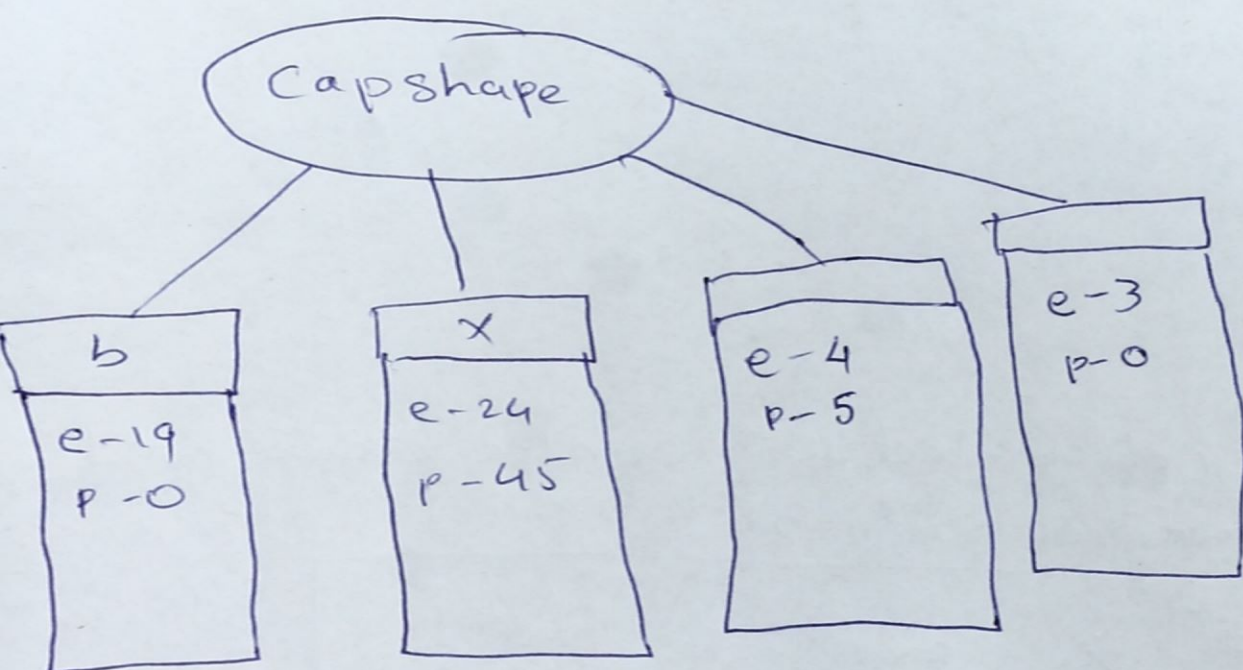
Once α^* has been calculated w^* can be calculated from the dual function with b :

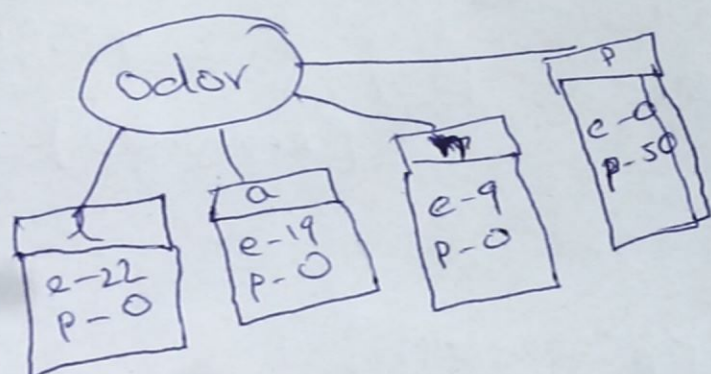
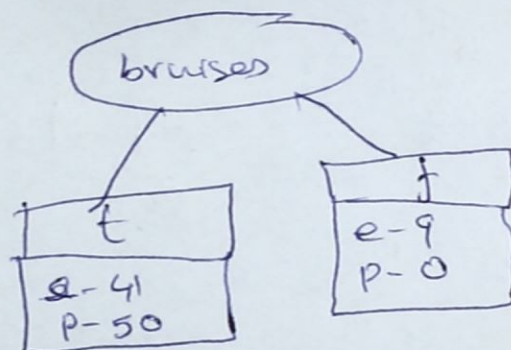
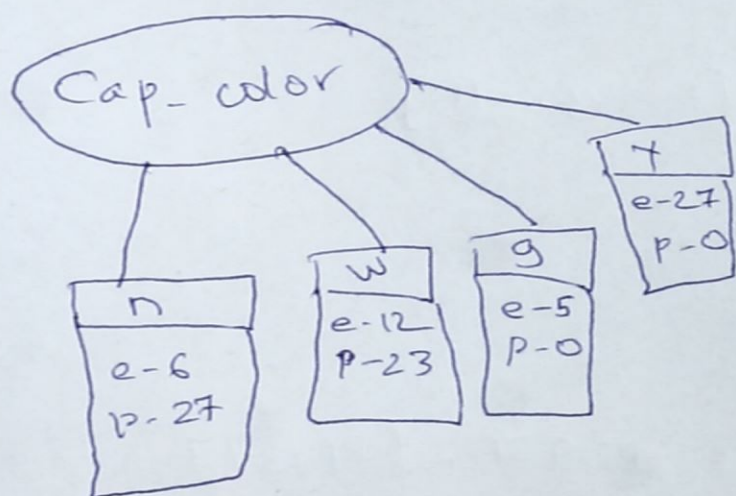
$$b = \frac{-\max_{i: y_i = -1} w^{*T} x_i + \min_{i: y_i = 1} w^{*T} x_i}{2}$$

~~or~~

$$\Rightarrow w^T x + b = \sum_{i=1}^m \alpha_i y_i \langle x^{(i)}, x \rangle + b$$

2. a Writing down number of e's and p's for each feature we get





$$\begin{aligned}
 E(S) &= -P(e) \log_2 P(e) - P(p) \log_2 P(p) \\
 &= -0.5 \times \log_2 0.5 - 0.5 \log_2 0.5 \\
 &= 1
 \end{aligned}$$

$$\begin{aligned}
 E(\text{capshape}=b) &= -P(e) \log_2 P(e) - P(p) \log_2 P(p) \rightarrow \textcircled{1} \\
 &= -1 \log_2 1 - 0 \log_2 0 \\
 &= 0
 \end{aligned}$$

$$\begin{aligned}
 E(\text{capshape}=x) &= -\left(\frac{24}{69}\right) \times -1.523 - \left(\frac{45}{69}\right) \times -0.6168 \quad [\text{Applying } \textcircled{1}] \\
 &= 0.9319
 \end{aligned}$$

$$\begin{aligned}
 E(\text{capshape}=f) &= -\left(\frac{4}{9}\right) \times -1.173 - \left(\frac{5}{9}\right) \times -0.85 \quad [\text{Applying } \textcircled{1}] \\
 &= 0.9918
 \end{aligned}$$

brwise

$$E(\text{brwise} = t) = - \left(\frac{41}{91} \right) (-1.1504) - \left(\frac{50}{91} \right) (-0.86407)$$

[Applying ①]

$$= 0.99307$$

$$E(\text{brwise} = f) = -1.0 - 0 = 0$$

$$E(\text{odor} = \text{all } \overset{\text{properties}}{\text{features}}) = 0 \quad [\text{odor is a pure feature}]$$

Information of capshape

$$I(\text{capshape}) = 0 + \frac{69}{100} \times 0.9319 + \frac{9}{100} \times 0.9918 + 0$$

$$= \sum_{i=1}^n p(\text{first property}) \times E(\text{property}) \rightarrow \textcircled{2}$$

Information of cap surface:

$$I(\text{cap-surface}) = \frac{27}{100} \times 0.9998 + \frac{53}{100} \times 0.98016 \text{ [Applying ②]} \\ = 0.8894$$

$$I(\text{cap-color}) = \frac{33}{100} \times 0.6835 + \frac{35}{100} \times 0.9276 + 0 + 0 \text{ [Applying ②]} \\ = 0.5502$$

Similarly Applying ② for the next two features we get:

$$I(\text{bruise}) = \frac{91}{100} \times 0.99307 + 0 \\ = 0.9036$$

$$I(\text{odour}) = 0$$

After this we find the Information gained from each feature:

$$\text{Gained}(\text{capshape}) = E(S) - I(\text{capshape}) \rightarrow \text{③} \\ = 1 - 0.732273 \\ = 0.267727$$

Applying ③ we get:

$$\text{④ Gained}(\text{cap-surface}) = 1 - 0.8894 \\ = 0.1106$$

$$I(\text{cap-surface}) = \frac{27}{100} \times 0.9998 + \frac{53}{100} \times 0.98016 \text{ [Applying ②]}$$

$$= 0.8894$$

$$I(\text{cap-color}) = \frac{33}{100} \times 0.6835 + \frac{35}{100} \times 0.9276 + 0 + 0$$

$$\text{[Applying ②]}$$

$$= 0.5502$$

Similarly Applying ② for the next two features we get:

$$I(\text{bruise}) = \frac{91}{100} \times 0.99307 + 0$$

$$= 0.9036$$

$$I(\text{odour}) = 0$$

After this we find the Information gained from each feature:

$$\text{Gained}(\text{capshape}) = E(S) - I(\text{capshape}) \rightarrow \text{③}$$

$$= 1 - 0.732273$$

$$= 0.267727$$

Applying ③ we get:

$$\text{④ Gained}(\text{cap-surface}) = 1 - 0.8894$$

$$= 0.1106$$

$$\begin{aligned}\text{Gained}(\text{cap-color}) &= 1 - 0.5502 \\ &= 0.4498\end{aligned}$$

$$\begin{aligned}\text{Gained}(\text{brwise}) &= 1 - 0.9036 \\ &= 0.0964\end{aligned}$$

$$\begin{aligned}\text{Gained}(\text{odor}) &= 1 - 0 \\ &= 1\end{aligned}$$

Since odor feature has the highest Information gain odor becomes the root.

The below tree is as follows.

