

Special Course in Computational Logic
Tutorial 11
Solutions

1. The CURRENT-BEST-LEARNING algorithm produces hypotheses listed in the following table (not necessarily unique). In the second column, FP and FN denote *false positive* and *false negative* examples, respectively.

(a) Starting from the hypothesis $\forall x (WillWait(x) \leftrightarrow Hun(x))$:

Ex		Hypothesis:
x_1		$\forall x (WillWait(x) \leftrightarrow Hun(x))$
x_2	FP	$\forall x (WillWait(x) \leftrightarrow Hun(x) \wedge Est(x, 0-10))$
x_3	FN	$\forall x (WillWait(x) \leftrightarrow Est(x, 0-10))$
x_4	FN	$\forall x (WillWait(x) \leftrightarrow Est(x, 0-10) \vee Est(x, 10-30))$
x_5		$\forall x (WillWait(x) \leftrightarrow Est(x, 0-10) \vee Est(x, 10-30))$
x_6		$\forall x (WillWait(x) \leftrightarrow Est(x, 0-10) \vee Est(x, 10-30))$
x_7	FP	$\forall x (WillWait(x) \leftrightarrow (Est(x, 0-10) \wedge Pat(x, some)) \vee Est(x, 10-30))$
x_8		$\forall x (WillWait(x) \leftrightarrow (Est(x, 0-10) \wedge Pat(x, some)) \vee Est(x, 10-30))$
x_9		$\forall x (WillWait(x) \leftrightarrow (Est(x, 0-10) \wedge Pat(x, some)) \vee Est(x, 10-30))$
x_{10}	FP	$\forall x (WillWait(x) \leftrightarrow (Est(x, 0-10) \wedge Pat(x, some)) \vee (Est(x, 10-30) \wedge \neg Price(x, $$$)))$
x_{11}		$\forall x (WillWait(x) \leftrightarrow (Est(x, 0-10) \wedge Pat(x, some)) \vee (Est(x, 10-30) \wedge \neg Price(x, $$$)))$
x_{12}	FN	$\forall x (WillWait(x) \leftrightarrow (Est(x, 0-10) \wedge Pat(x, some)) \vee (Est(x, 10-30) \wedge \neg Price(x, $$$)) \vee (Est(x, 30-60) \wedge Type(x, burger)))$

(b) For the hypothesis $\forall x (WillWait(x) \leftrightarrow \neg Est(x, 30-60))$:

Ex		Hypothesis:
x_1	FN	$\forall x (WillWait(x) \leftrightarrow Est(x, 30-60) \vee Pat(x, some))$
x_2	FP	$\forall x (WillWait(x) \leftrightarrow Pat(x, some))$
x_3		$\forall x (WillWait(x) \leftrightarrow Pat(x, some))$
x_4	FN	$\forall x (WillWait(x) \leftrightarrow Pat(x, some) \vee Hun(x))$
x_5		$\forall x (WillWait(x) \leftrightarrow Pat(x, some) \vee Hun(x))$
x_6		$\forall x (WillWait(x) \leftrightarrow Pat(x, some) \vee Hun(x))$
x_7		$\forall x (WillWait(x) \leftrightarrow Pat(x, some) \vee Hun(x))$
x_8		$\forall x (WillWait(x) \leftrightarrow Pat(x, some) \vee Hun(x))$
x_9		$\forall x (WillWait(x) \leftrightarrow Pat(x, some) \vee Hun(x))$
x_{10}	FP	$\forall x (WillWait(x) \leftrightarrow Pat(x, some) \vee (Hun(x) \wedge \neg Price(x, $$$)))$
x_{11}		$\forall x (WillWait(x) \leftrightarrow Pat(x, some) \vee (Hun(x) \wedge \neg Price(x, $$$)))$
x_{12}		$\forall x (WillWait(x) \leftrightarrow Pat(x, some) \vee (Hun(x) \wedge \neg Price(x, $$$)))$

Note: the choices made above are not unique (other solutions exist)!

2. In the candy domain, hypotheses are based on the following five mixings of the two flavours:

h_1 : 100% cherry
 h_2 : 75% cherry and 25% lime
 h_3 : 50% cherry and 50% lime
 h_4 : 25% cherry and 75% lime
 h_5 : 100% lime

After unwrapping four pieces of the surprise candy we note that three pieces are cherry flavoured.

- (a) To find out the most likely (ML) hypothesis let us denote the observed data, i.e., three cherry candies and one lime candy, by \mathbf{d} . The probability of \mathbf{d} (given each hypothesis h_i in turn) varies as follows:

$$\begin{aligned} P(\mathbf{d} | h_1) &= 0 \\ P(\mathbf{d} | h_2) &= 4 \cdot \left(\frac{3}{4}\right)^3 \cdot \frac{1}{4} = \frac{27}{64} \approx 0.42 \\ P(\mathbf{d} | h_3) &= 4 \cdot \left(\frac{1}{2}\right)^3 \cdot \frac{1}{2} = 0.25 \\ P(\mathbf{d} | h_4) &= 4 \cdot \left(\frac{1}{4}\right)^3 \cdot \frac{3}{4} = \frac{3}{64} \approx 0.047 \\ P(\mathbf{d} | h_5) &= 0 \end{aligned}$$

Thus h_2 is the most likely hypothesis.

- (b) Let us then suppose that the prior distribution of the bags is

$$\langle 0.1, 0.1, 0.1, 0.6, 0.1 \rangle.$$

In order to determine the maximum a posteriori (MAP) hypothesis we calculate:

$$\begin{aligned} P(h_1) &= 0.1 \\ P(h_2) &= 0.1 \\ P(h_3) &= 0.1 \\ P(h_4) &= 0.6 \\ P(h_5) &= 0.1 \\ P(h_1 | \mathbf{d}) &= \alpha P(\mathbf{d} | h_1) P(h_1) = 0 \\ P(h_2 | \mathbf{d}) &= \alpha P(\mathbf{d} | h_2) P(h_2) \approx 0.042\alpha \\ P(h_3 | \mathbf{d}) &= \alpha P(\mathbf{d} | h_3) P(h_3) \approx 0.025\alpha \\ P(h_4 | \mathbf{d}) &= \alpha P(\mathbf{d} | h_4) P(h_4) \approx 0.028\alpha \\ P(h_5 | \mathbf{d}) &= \alpha P(\mathbf{d} | h_5) P(h_5) = 0 \\ P(h_1 | \mathbf{d}) &= 0 \\ P(h_2 | \mathbf{d}) &= \frac{0.042}{0.042+0.025+0.028} \approx 0.44 \\ P(h_3 | \mathbf{d}) &= \frac{0.025}{0.042+0.025+0.028} \approx 0.26 \\ P(h_4 | \mathbf{d}) &= \frac{0.028}{0.042+0.025+0.028} \approx 0.29 \\ P(h_5 | \mathbf{d}) &= 0 \end{aligned}$$

We conclude that the maximum a posteriori hypothesis is h_2 , i.e., the prior distribution does not affect the dominating hypothesis.

- (c) Next we estimate the probability that the fifth piece of candy is lime:

$$P(\text{lime} | \mathbf{d}) = P(\text{lime} | h_2)P(h_2 | \mathbf{d}) + P(\text{lime} | h_3)P(h_3 | \mathbf{d}) + P(\text{lime} | h_4)P(h_4 | \mathbf{d}).$$

Using the prior distribution of bags given in item (b) we may calculate the probability of getting a lime for the fifth draw:

$$P(\text{lime} | \mathbf{d}) = 0.25 \cdot 0.44 + 0.5 \cdot 0.26 + 0.75 \cdot 0.29 \approx 0.46.$$