

EX. 1 6 min

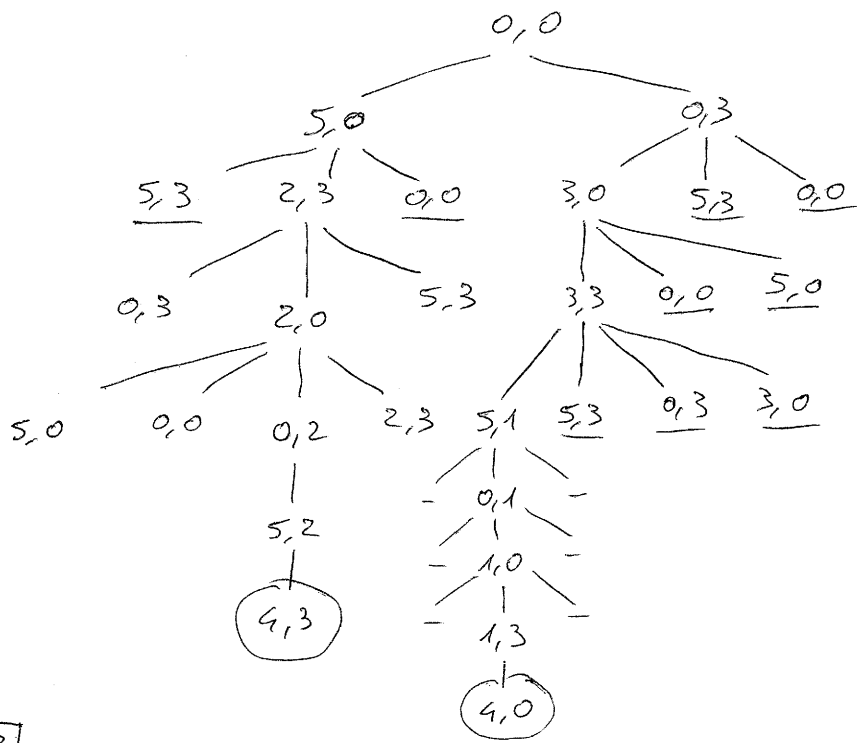
representation: 2 digits for the liters in the 2 containers

init-state: 0,0

operators (successor function):
 fill 5-lit. container
 fill 3-lit. cont.
 empt. 5-lit. cont.
 empt. 3-lit. cont.
 pour 3 in 5
 pour 5 in 3

goal state 4,4

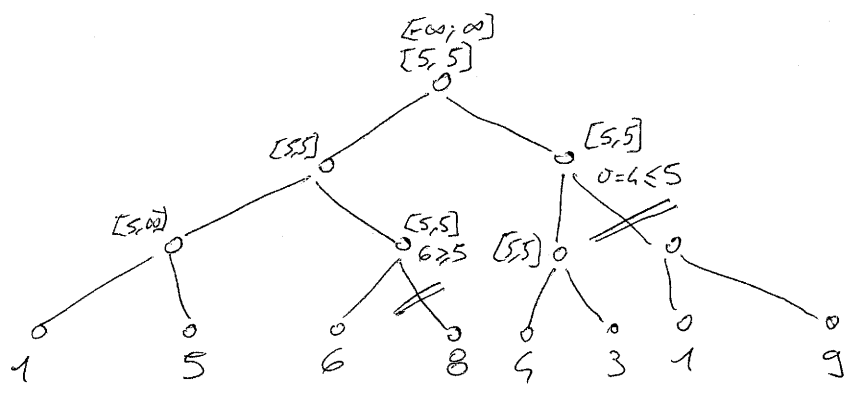
Search tree:



- pruned because repeated state.

EX. 3

MAX
 MIN
 MAX
 MIN



Ex.2

20 min

Uniq. cost

A	6	8
I	8	8
B	8	9
M	9	15
J	9	10
N	10	15
L	11	15
F	17	17
G	17	18
O	18	18
C	18	23
H	18	19
K	18	18
E	18	18
D	18	18

Best Cost

A	6+6=12	8+7=15
I	10	15
J	15	16
B	16	16
M	16	19
N	17	18
O	18	19
L	18	19
K	19	22
F	23	26
H	23	26
C	24	27
E	24	27
G	26	27
D	26	27

Greedy

- A
- I
- J
- K

We cannot say that the best cost heuristic is an A^* search unless we have information on the type of heuristic used. If the heuristic is admissible then we can claim that the best cost heuristic is an A^* search.

ES.4

45 min

- (a) i) $\forall x, y, z \text{ Owns}(x, y) \wedge \text{In}(z, y) \Rightarrow \text{Owns}(x, z) \wedge \text{File}(z)$
- ii) $\forall x \text{ Ne}(x) \Leftrightarrow \exists z \text{ File}(z) \wedge \text{In}(z, x)$
- iii) $\exists x \text{ Ne}(x) \wedge \text{Owns}(J, x)$
- iv) $\exists z \text{ File}(z) \wedge \text{Owns}(J, z)$

b) We can show that $KB \neq \alpha$ by showing that $KB \wedge \neg \alpha$ leads to a contradiction. To prove $KB \wedge \neg \alpha$ false we use FOL inference rules: transform in CNF, apply resolution with unification, show that the resolution closure contains the empty clause.

If $KB \neq \alpha$ holds then the set of interpretations under which KB holds is a subset of the set of interpretations under which α holds.

c) From the last sentence in (b) it follows that we can show $KB \neq \alpha$ by showing that there exists an interpretation under which α holds but KB not. Showing that the procedure via resolution of (b) cannot reach a contradiction does not work in general because it may not terminate due to undecidability of FOL.

d) Transform i-iv in CNF:

i): $\forall x, y, z \neg [\text{Owns}(x, y) \wedge \text{In}(z, y)] \vee \text{Owns}(x, z)$

$\neg \text{Owns}(x, y) \vee \neg \text{In}(z, y) \vee \text{Owns}(x, z)$ ¹

ii): $\forall x, \text{Ne}(x) \Rightarrow \exists z \text{ File}(z) \wedge \text{In}(z, x)$

$\forall x \neg \text{Ne}(x) \vee (\text{File}(f(x)) \wedge \text{In}(f(x), x))$

$\neg \text{Ne}(x) \vee \text{File}(f(x))$ ² \wedge $\neg \text{Ne}(x) \vee \text{In}(f(x), x)$ ³

$\forall x [\exists z \text{ File}(z) \wedge \text{In}(z, x)] \Rightarrow \text{Ne}(x)$

$\forall x \neg [\exists z \text{ File}(z) \wedge \text{In}(z, x)] \vee \text{Ne}(x)$

$\forall x (\forall z \neg \text{File}(z) \vee \neg \text{In}(z, x)) \vee \text{Ne}(x)$

$\neg \text{File}(z) \vee \neg \text{In}(z, x) \vee \text{Ne}(x)$ ⁴

iii): $\text{Ne}(H)$ ⁵ \wedge $\text{Owns}(J, H)$ ⁶

~~XXXXXXXXXX~~



$$\neg(\forall) : \neg \exists z \text{File}(z) \wedge \text{Owns}(J, z)$$

$$\forall z \neg \text{File}(z) \vee \neg \text{Owns}(J, z)$$

$$\neg \text{File}(z) \vee \neg \text{Owns}(J, z) \quad ?$$

Here we have 7 clauses.

$$7: \neg \text{File}(z) \vee \neg \text{Owns}(J, z)$$

$$6: \text{Owns}(J, H)$$

$$8 \therefore \neg \text{File}(H) \quad \theta: \{z/H\}$$

$$2: \neg \text{Ne}(x) \vee \text{File}(f(x))$$

$$5: \text{Ne}(H)$$

$$9 \therefore \text{File}(f(H)) \quad \theta: \{x/H\}$$

$$3: \neg \text{Ne}(x) \vee \text{In}(f(x), x)$$

$$5: \text{Ne}(H)$$

$$10 \therefore \text{In}(f(H), H) \quad \theta: \{x/H\}$$

$$7: \neg \text{File}(z) \vee \neg \text{Owns}(J, z)$$

$$9: \text{File}(f(H))$$

$$11: \therefore \neg \text{Owns}(J, f(H)) \quad \theta: \{z/f(H)\}$$

$$1: \neg \text{Owns}(x, y) \vee \neg \text{In}(z, y) \vee \text{Owns}(x, z)$$

$$6: \text{Owns}(J, H)$$

$$12 \therefore \neg \text{In}(H, H) \vee \text{Owns}(J, H) \quad \theta: \{x/J, y/H\}$$

$$12: \neg \text{In}(z, H) \vee \text{Owns}(J, z)$$

$$10: \text{In}(f(H), H)$$

$$13: \therefore \text{Owns}(J, f(H)) \quad \theta: \{z/f(H)\}$$

$$13: \text{Owns}(J, f(H))$$

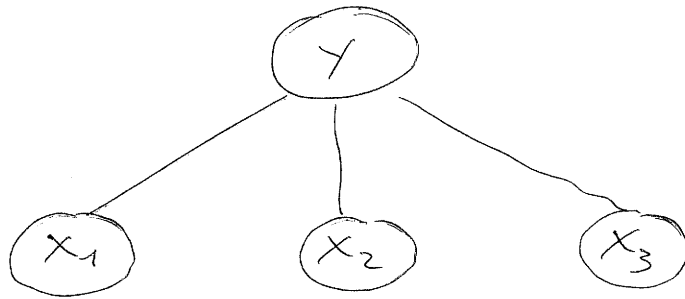
$$11: \neg \text{Owns}(J, f(H))$$

$$\therefore \emptyset$$

EX. 5

30 min

2)



	y=0	y=1
x ₁ =1	7	7
x ₂ =1	1	1
x ₃ =1	3	5

$h_{\bar{\sigma}}: \bar{\sigma} = (\sigma_{10}, \sigma_{11}, \sigma_{20}, \sigma_{21}, \dots)$

$P(y=1) = 0$

P ₂	y=0	y=1
x ₁ =1	σ_{10}	σ_{11}
x ₁ =0	$1-\sigma_{10}$	$1-\sigma_{11}$

P ₂	y=0	y=1
x ₂ =1	σ_{20}	σ_{21}
x ₂ =0	$1-\sigma_{20}$	$1-\sigma_{21}$

P ₂	y=0	y=1
x ₃ =1	σ_{30}	σ_{31}
x ₃ =0	$1-\sigma_{30}$	$1-\sigma_{31}$

$P(h_{\bar{\sigma}} | \bar{d}) = \alpha P(\bar{d} | h_{\bar{\sigma}}) P(h_{\bar{\sigma}})$ product rule

$P(\bar{d} | h_{\bar{\sigma}}) = \prod_{j=1}^{18} P(\bar{d}_j | h_{\bar{\sigma}}) = \prod_j P(x_j, y_j | h_{\bar{\sigma}}) = \prod_j P(x_j | y_j, h_{\bar{\sigma}}) P(y_j | h_{\bar{\sigma}}) =$

Card-indep. $\frac{18}{11} \prod_{j=1}^3 P(x_{ij} | y_j, h_{\bar{\sigma}}) \cdot P(y_j | h_{\bar{\sigma}}) =$

$= \sigma_{10}^7 (1-\sigma_{10})^{8-7} \cdot \sigma_{11}^7 (1-\sigma_{11})^{8-7} \cdot \sigma_{20}^1 (1-\sigma_{20})^{8-1} \cdot \sigma_{21}^1 (1-\sigma_{21})^{8-1} \cdot \sigma_{30}^3 (1-\sigma_{30})^{8-3} \cdot \sigma_{31}^5 (1-\sigma_{31})^{8-5} \cdot \sigma_{32}^8 (1-\sigma_{32})^{8-8}$

$L(\sigma) = \log(P(\bar{d} | h_{\bar{\sigma}})) = 7 \log \sigma_{10} + \log(1-\sigma_{10}) + 7 \log \sigma_{11} + \log(1-\sigma_{11}) + \dots$

$\frac{dL}{d\sigma} = \frac{8}{\sigma} - \frac{8}{1-\sigma} = \frac{8-8\sigma-8\sigma}{\sigma(1-\sigma)} > 0 \Rightarrow \sigma = \frac{1}{2}$

$\frac{dL}{d\sigma_{10}} = \frac{7}{\sigma_{10}} - \frac{1}{1-\sigma_{10}} = \frac{7-7\sigma_{10}-\sigma_{10}}{\sigma_{10}(1-\sigma_{10})} = 0 \Rightarrow \sigma_{10} = \frac{7}{8}$

$\frac{dL}{d\sigma_{21}} = \frac{1}{\sigma_{21}} - \frac{7}{1-\sigma_{21}} = \frac{1-\sigma_{21}-7\sigma_{21}}{\sigma_{21}(1-\sigma_{21})} = 0 \Rightarrow \sigma_{21} = \frac{1}{8}$

$\frac{dL}{d\sigma_{30}} = \frac{3}{\sigma_{30}} - \frac{5}{1-\sigma_{30}} = \frac{3-3\sigma_{30}-5\sigma_{30}}{\sigma_{30}(1-\sigma_{30})} = 0 \Rightarrow \sigma_{30} = \frac{3}{8}$

$1 - \sigma_{30} = 1 - \frac{3}{8} = \frac{5}{8}$

$\sigma_{11} = \frac{7}{8}$

$\sigma_{31} = \frac{5}{8}$

$\sigma_{20} = \frac{1}{8}$

REMOVED

$$P(y|\bar{x}, \theta) \stackrel{\text{Bayes}}{=} \frac{P(\bar{x}|y, \theta_0) P(y, \theta_0)}{P(\bar{x})} \stackrel{\text{cond. indep. }^3}{=} \frac{\prod_{i=1}^3 P(x_i|y, \theta_{i0}) P(y, \theta_{i0})}{P(\bar{x})} =$$

$$= \alpha \prod_{i=1}^3 P(x_i|y, \theta_{i0}) P(y, \theta_{i0}) =$$

$$= \alpha \langle P(x_1=0|y=1)P(x_2=1|y=1)P(x_3=1|y=1)P(y=1); P(x_1=0|y=0)P(x_2=1|y=0)P(x_3=1|y=0)P(y=0) \rangle$$

$$= \alpha \langle (1-\theta_{11})\theta_{21}\theta_{31}\theta; (1-\theta_{10})\theta_{20}\theta_{30}(1-\theta) \rangle =$$

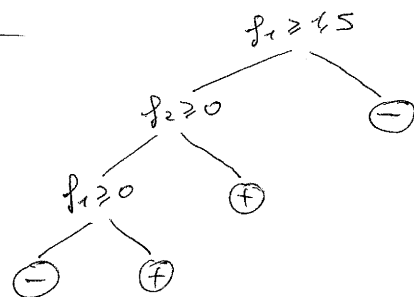
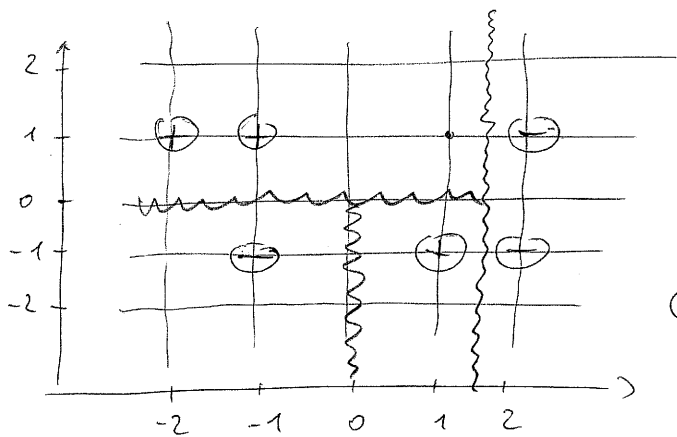
$$= \alpha \langle \frac{1}{8} \frac{1}{8} \frac{5}{8} \cdot \frac{1}{2}; \frac{1}{8} \cdot \frac{1}{8} \cdot \frac{3}{8} \cdot \frac{1}{2} \rangle =$$

$$= \alpha \langle \dots; \dots \rangle$$

$y=1$ is more likely than $y=0$
 hence we conclude that $y=1$
 is the most probable prediction.

Ex. 6 30 min

⇒



Ⓛ We calculate the inf. gain at each split point of f_1 and f_2 .

$$I(P(v_1), P(v_2)) = \sum_{i=1}^2 -P(v_i) \log_2 P(v_i) \quad \leftarrow \text{entropy}$$

$$\text{Gain}(\text{attr}(s_i)) = I\left(\frac{P}{P+u}; \frac{u}{P+u}\right) - \text{Remainder}(\text{attr}(s_i))$$

$\text{attr}(s_i)$ split attribute in s_i ↙ before split ↘ after split

$$\text{Remainder}(\text{attr}(s_i)) = \sum_{i=1}^2 \frac{P_i + u_i}{P + u} I\left(\frac{P_i}{P_i + u_i}; \frac{u_i}{P_i + u_i}\right)$$

↓
prob. of choosing that branch
↙ inf. in the branch.

$$\begin{aligned} \text{gain}(f_1(+1.5)) &= I\left(\frac{3}{6}; \frac{3}{6}\right) - \left(\frac{2}{6} I(0,1) + \frac{4}{6} I\left(\frac{3}{4}; \frac{1}{4}\right)\right) = \\ &= +\frac{1}{2} \log_2 \frac{1}{2} - \frac{1}{2} \log_2 \frac{1}{2} - \left(\frac{1}{3} (-0 \log_2 0 - 1 \log_2 1) + \frac{2}{3} \left(-\frac{3}{4} \log_2 \frac{3}{4} - \frac{1}{4} \log_2 \frac{1}{4}\right)\right) = \\ &= +1 - \frac{2}{3} (0.91 + 0.5) = 0.46 \end{aligned}$$

$$\begin{aligned} \text{gain}(f_1(0)) &= I\left(\frac{3}{6}; \frac{3}{6}\right) - \left(\frac{3}{6} I\left(\frac{1}{3}; \frac{2}{3}\right) + \frac{3}{6} I\left(\frac{2}{3}; \frac{1}{3}\right)\right) = 1 - \left(\frac{1}{2} (0.91 + 0.91) + \frac{1}{2} (0.91 + 0.91)\right) = \\ &= 1 - (0.92) = 0.08 \end{aligned}$$

$$\text{gain}(f_1(1.5)) = 1 - \left(\frac{1}{6} I(4,0) + \frac{5}{6} I\left(\frac{2}{5}; \frac{3}{5}\right)\right) = 1 - \left(\frac{5}{6} (0.91 + 0.44)\right) = 0.191$$

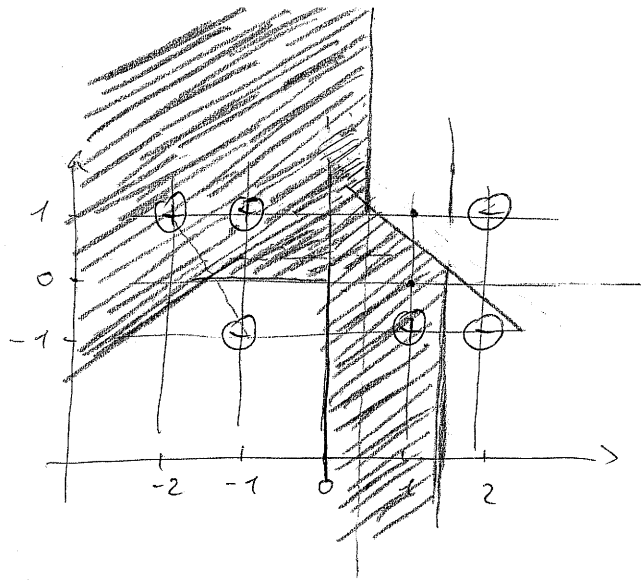
$$\text{gain}(f_2(0)) = 1 - \left(\frac{1}{2} I\left(\frac{2}{3}; \frac{1}{3}\right) + \frac{1}{2} I\left(\frac{1}{3}; \frac{2}{3}\right)\right) = 1 - 0.92 = 0.08$$

Hence we select $f_1(+1.5)$ because it maximizes the gain.

c) Prediction for 1,1 is ⊕

Nearest Neigh.

e)



b) prediction in $(1,1) \rightarrow \ominus$

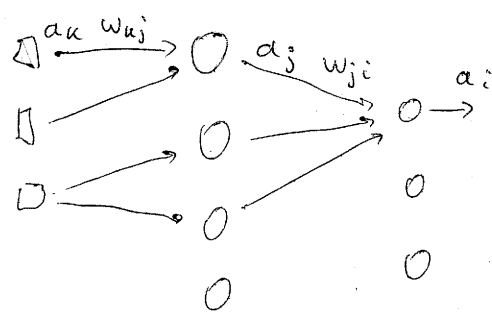
c) prediction by 3-NN $\rightarrow \ominus$ for majority rule

d) by crossvalidation

Perceptron

e) The algorithm would not converge because the points are not linearly separable

EX. 7 10 marks



activation function
 $g(x) = cx + d$

$$\begin{aligned}
 a_i &= g\left(\sum_j a_j w_{ji}\right) = c \sum_j a_j w_{ji} + d = c \sum_j w_{ji} g\left(\sum_k w_{kj} a_k\right) + d = \\
 &= c \sum_j w_{ji} \left(c \sum_k w_{kj} a_k + d\right) + d = c^2 \sum_j w_{ji} \sum_k w_{kj} a_k + c \sum_j w_{ji} d + d = \\
 &= c^2 \sum_k \sum_j a_k w_{ji} w_{kj} + \underbrace{\left(c \sum_j w_{ji} + 1\right)}_e d = \\
 &= f \sum_k w_{ki} a_k + e
 \end{aligned}$$

where $\sum_k w_{ki} = \sum_k \sum_j w_{ji} w_{kj}$

Hence we could substitute with a single layer network and weights appropriately chosen.

