

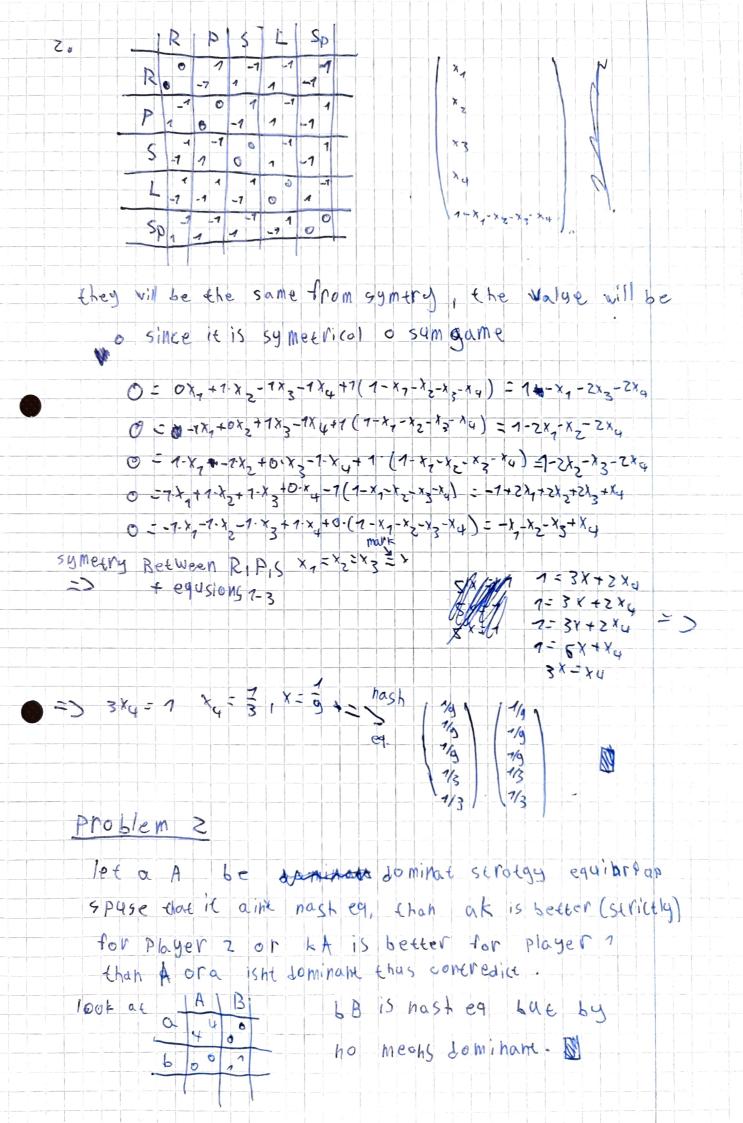
lets see adouble that for any player (13) is

nash equilibria, let sons there is a strategy

(13) that those better and lets goes

say that  $x > \frac{1}{3}$ , and  $x - x - y < \frac{1}{3}$  with be regard dry  $x \ge y > 1 - x - y > 1$ to generalety then couler strateg (1) x > y > 1 - x - y > 1

will get a positive net value in a symetric zero sum game, thus (%) nash equilibrium for both.



Problem 3 all pure hash ex are as followed (A, a), (C, c) for player > B is dominated by A for player 2 when the base game there and only sominated strategys on the surface sinc if P1 Plays A then a is the best, if Por Plous B b is the best and if P1 Plays c then a is the best how ever since Py wont play R (dominated by A) then on the appared matrix 6 wold be dominated by e A dominate D 2 B

Cominates b A 43 2 2 2 8 2 3 8

## Problem [4]: Decision Trees:

## **PlayTennis**

- Four attributes used for classification:
  - 1. Outlook = {Sunny, Overcast, Rain}
  - 2. Temperature = {Hot, Mild, Cool}
  - 3. Humidity = {High, Normal}
  - 4. Wind = {Weak, Strong}
- One predicted (target) attribute (binary): PlayTennis = {Yes,No}
- Given 14 Training examples:9 positive, 5 negative.

We will choose the variable to split on such that the corresponding information gain is maximal. We will use the formula from Tirgul (10):

$$IG_{Ex}(Goal; a) = H_{Ex}(Goal) - \sum_{v \in val(a)} \frac{|Ex_{a,v}|}{|Ex|} H_{Ex_{a,v}}(Goal)$$

The entropy of a random variable X is:

$$H(X) = -\sum_{x} p(x) \log_b p(x)$$

So the initial entropy of the training sample:

$$H_{Ex}(Goal) = -\left(\frac{5}{14}log_2\frac{5}{14} + \frac{9}{14}log_2\frac{9}{14}\right) = 0.9403$$

The information gains of the attributes are:

$$\begin{split} &IG_{Ex}(Goal; \text{Outlook}\,) = 0.9403 - \left[\frac{5}{14}H\left(\frac{2}{5},\frac{3}{5}\right) + \frac{4}{14}H\left(\frac{4}{4},\frac{0}{4}\right) + \frac{5}{14}H\left(\frac{3}{5},\frac{2}{5}\right)\right] = 0.2468 \\ &IG_{Ex}(Goal; \text{Temperature}\,\,) = 0.9403 - \left[\frac{4}{14}H\left(\frac{2}{4},\frac{2}{4}\right) + \frac{6}{14}H\left(\frac{4}{6},\frac{2}{6}\right) + \frac{4}{14}H\left(\frac{3}{4},\frac{1}{4}\right)\right] = 0.0292 \\ &IG_{Ex}(Goal; \text{Humidity}\,\,) = 0.9403 - \left[\frac{7}{14}H\left(\frac{4}{7},\frac{3}{7}\right) + \frac{7}{14}H\left(\frac{6}{7},\frac{1}{7}\right)\right] = 0.1518 \\ &IG_{Ex}(Goal; \text{Wind}\,\,) = 0.9403 - \left[\frac{8}{14}H\left(\frac{6}{8},\frac{2}{8}\right) + \frac{6}{14}H\left(\frac{3}{6},\frac{3}{6}\right)\right] = 0.0481 \end{split}$$

**Outlook** is selected as the decision attribute for the root node, and branches are created below the root for each of its possible values (i.e., Sunny, Overcast, and Rainy). Next, we choose an attribute to split on in every leaf of the tree:

## First, the **Sunny** leaf:

$$H_{Ex_{Outlook,Sunny}}(Goal) = H\left(\frac{2}{5}, \frac{3}{5}\right) = 0.971$$

$$IG_{Ex_{Outlook,Sunny}}(Goal; Temperature) = 0.971 - \left[\frac{2}{5}H\left(\frac{0}{2}, \frac{2}{2}\right) + \frac{2}{5}H\left(\frac{1}{2}, \frac{1}{2}\right) + \frac{1}{5}H\left(\frac{1}{1}, \frac{0}{1}\right)\right]$$
  
= 0.570

$$IG_{Ex_{Outlook,Sunny}}(Goal; Humidity) = 0.971 - \left[\frac{3}{5}H\left(\frac{0}{3}, \frac{3}{3}\right) + \frac{2}{5}H\left(\frac{2}{2}, \frac{0}{2}\right)\right] = 0.971$$

$$IG_{Ex_{Outlook,Sunny}}(Goal; Wind) = 0.971 - \left[\frac{3}{5}H\left(\frac{1}{3}, \frac{2}{3}\right) + \frac{2}{5}H\left(\frac{1}{2}, \frac{1}{2}\right)\right] = 0.019$$

*Humidity* is selected as the leftmost son of the root node, and branches are created below it for each of its possible values (i.e., High and Normal).

Second, the *Overcast* leaf. Notice that because the training examples associated with this leaf all have same target attribute value (i.e., True) we stopped expanding this node.

Third, the *Rainy* leaf. Calculations are similar to those we've done before:

$$H_{Ex_{Outlook,Rainy}}(Goal) = H\left(\frac{3}{5}, \frac{2}{5}\right) = 0.971$$

 $IG_{Ex_{Outlook,Rainy}}(Goal; Temperature) = 0.019$ 

 $IG_{Ex_{Outlook,Rainy}}(Goal; Humidity) = 0.019$ 

 $IG_{Ex_{Outlook\ Rainy}}(Goal; Wind) = 0.971$ 

*Wind* is selected as the rightmost son of the root node, and branches are created below it for each of its possible values (i.e., Strong and Week).

And because the training examples associated with each one of the current leaves, which are, Humidity attributes and Wind attributes, have the same target attribute value, (High-> False, Normal->True, Strong->True, Weak->False), our algorithm will stop at this point.

The complete decision tree will look like:

