Decision trees optimization for ultrasound detection of fetal abnormalities.

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Context and Objectives : Prenatal Diagnosis.

There are three compulsory ultrasound test during pregnancy in France. Some classical measures are done for every women, for example the research of trisomy 21 is well known and mastered. On the contrary there is no strict protocol defined for the research of rare diseases. This is why we want to help obstetricians to improve/systematize ultrasonic diagnostic.

From Marginals to Joint Distribution via Maximum Entropy Heuristic :

We have $P[S | A_i]$ but we need to know $P[A_1, ..., A_n | S]$. We face the problem to assign values to probabilities in presence of partial information. We want to add as few information as possible so we will choose the model with less additional information compatible with our data.

We use entropy to measure information contained in a distribution, less information meaning more entropy [4].

![FIGURE 1: An ultrasound view of a 12 weeks embryo.](image1)

![FIGURE 2: A binary decision tree.](image2)

**Data :**

Each disease manifests itself by a combination of abnormalities visible by ultrasound (symptoms). Some symptoms are more probable than others. We know the probability of each disease and the probability of each symptoms knowing the disease. These probabilities come from the literature (acknowledgment to Emmanuel Spaggiari, Physician in Gynecology obstetric at Necker).

Here an extract of our data :

<table>
<thead>
<tr>
<th>id</th>
<th>disease</th>
<th>symptom</th>
<th>probability of symptom knowing the disease</th>
</tr>
</thead>
<tbody>
<tr>
<td>16</td>
<td></td>
<td></td>
<td>0.39</td>
</tr>
<tr>
<td>16</td>
<td></td>
<td></td>
<td>0.67</td>
</tr>
<tr>
<td>16</td>
<td></td>
<td></td>
<td>0.50</td>
</tr>
<tr>
<td>16</td>
<td></td>
<td></td>
<td>0.16</td>
</tr>
<tr>
<td>16</td>
<td></td>
<td></td>
<td>0.50</td>
</tr>
<tr>
<td>16</td>
<td></td>
<td></td>
<td>0.75</td>
</tr>
</tbody>
</table>

Notation : $P[A_i | S]$ is the probability to have the abnormalities $i$ knowing that we have the disease $S$.

![FIGURE 3: Entropy of Bernoulli distribution X.](image3)

![FIGURE 4: Comparison between distribution obtained via maximum heuristic (blue) and distribution obtained via independence hypothesis (green).](image4)

![FIGURE 5: Reinforcement learning scheme](image5)

Our algorithm memorise what he observed in his experience considering it more likely to happen again but still consider possible combinations he never observed (just as would a physician).

Best strategy learning.

Our objective is to determine in which order we have to ask the questions so as to minimize the average number of question necessary to diagnose patient’s disease (just as in a 20 question game).

We propose to formulate it in the reinforcement learning framework where someone take actions in a sequential way, receive rewards from the environment and try to maximize his long-term (cumulative) reward [3].

We want to learn a diagnostic policy which associate to each state of knowledge a question to ask.

$$\pi : S \rightarrow A.$$ We are looking for $\pi^*$ the best diagnostic strategy, that is the strategy that goes the fastest to terminal states (i.e who maximize rewards).

This kind of problems are well-known and can be solved with algorithm such that Policy Iteration (see [3]). However we face a problem of high dimension (300 questions possible) so to use Policy Iteration algorithm or even store $\pi^*$ is hopeless.

To face this issue we propose a energy-based policy (as in [2]) :

$$\pi(s,a) \propto \exp(\theta(s,a)) \prod_{b \in \mathcal{S}} \exp(\phi(b)).$$

$\pi(s,a)$ is the probability to take the action $a$ when we are in state $s$. $(s,a)$ is a vector of features which quantify the interest of taking action $a$ when we are in state $s$.

The optimal parameters $\theta^*$ will be learned doing a stochastic gradient descent solving the problem of maximization of cumulative reward.

Acknowledgment

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Références


