

# Machine Learning: Sixth Home Work

Bayesian Networks

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### Part I

# Introduction

## 1 Scope

I was supposed to familiarise with bayesian networks used in stochastic modelling.

## 2 Objectives

Learning to model graph-like networks with a Bayesian approach for three different cases.

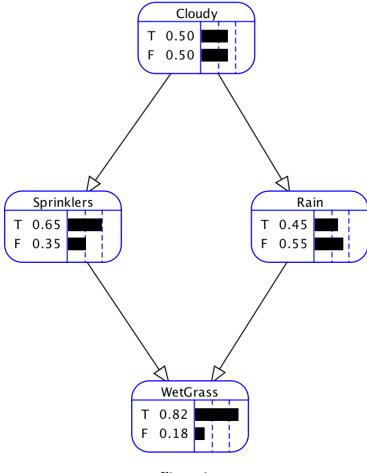


Figure 1

### Part II

# Development

#### 3 First case

I have built a model that represents the conditional bounds between stochastic atoms. In particular, in fig(1), there is the graphical model that corresponds to the following joint probability distribution: P( Cloudy, Sprinklers,

Rain, WetGrass) = P( Cloudy ) P( Sprinklers| Cloudy) P( Rain| Cloudy) P(

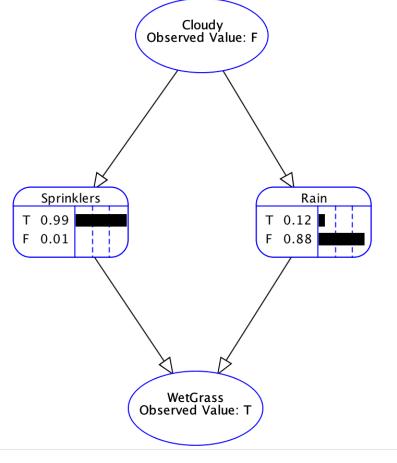


Figure 2

WetGrass | Sprinklers, Rain) In fig(2) there is also the result, according to the conditional probability, after that two observations have been made.

#### 4 Second case

Then I build a model in order to reconstruct the probability distribution of a random coin extraction between three differently weighted coins in terms of probabilities between head and tail outcomes. In fig(3), given a prior knowledge on three trows made with a unique coin, there is the guess of the bayesian network on which coin has been extracted.

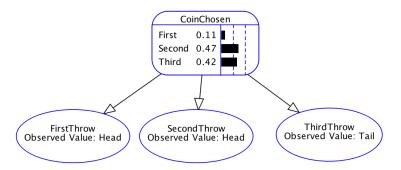
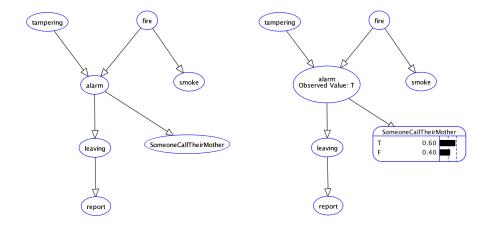


Figure 3

#### 5 Third case

Finally, the last assignment consisted of a modification of an already finished model that describes probabilities of events after that a fire alarm goes on. Essentially, I added a branch to the graph linking two nodes: the former was the node which symbolises that the alarm has gone off, the latter was a new node which represents the probability that someone could call their mother. Accordingly, in fig(4), there is the modified bayesian network corresponding to the joint probability distribution written above:  $P(\text{tampering}, \text{fire}, \text{alarm}, \text{smoke}, \text{leaving}, \text{report}) = P(\text{tampering})^* P(\text{fire})^* P(\text{alarm}| \text{tampering}, \text{fire})^* P(\text{smoke}| \text{fire})^* P(\text{leaving}| \text{alarm})^* P(\text{report}| \text{leaving})$ 



### Part III

# Conclusions

In the final analysis bayesian network approach could be extremely powerful in order to visualise and understand the stochastic representation of complex scenarios. On the other hand, when there would be plenty of conditional dependencies among the nodes, it become a disorienting representation