

# Coursework : Practical Data Analysis using Python

## Overview

The coursework for the Intelligent Data Analysis and Probabilistic Inference Course has two objectives. Firstly it is intended to help you fully understand some of the algorithms covered in the course by doing some practical data analysis work, and secondly it serves as an introduction to Python which is an excellent environment for doing numerical analysis. Python has a powerful syntax that allows you to write code that looks very much like the equations found in the notes. It provides an interface to a highly robust and fast numerical programming library. The syntax has some similarities to Matlab but Python is available for free. There are many good online tutorials which you may want to work through if you find the coursework notes too terse.

## Dates

The coursework is divided into four parts with hand in dates spaced fairly evenly throughout the term. The suggested start dates and the hand in dates are as follows:

Part	Start	Hand In
1	after lecture 2: (16th Jan)	30th Jan
2	after lecture 6: (30th Jan)	13th Feb

Note that we have yet to finalise the third and fourth parts of the coursework. Full details full details of the third and fourth parts will be given in a separate handout.

## Group Working

You are encouraged to work in pairs or in groups of three. Group working can be enjoyable and is an effective way of learning providing everybody in the group participates. If you work in a group then you submit just one solution to CATE for each exercise. You don't have to be in the same group for all four courseworks. For example you could do number one by yourself and the other three in a group with two of your friends.

## Submitting work

All four courseworks will be submitted electronically only. For each you will submit two files. One will be your python script in text format. The other will be a results file. For courseworks 1 this is a simple text file, but for courseworks 2 you will need to submit a .pdf file.

## Assessment

There is a total of 100 marks available for the coursework. The handouts for each exercise give you a breakdown of the marks available for each part. The intention is that you can score up to 60% easily, and with a bit more effort get an A grade, however after that the going gets a little harder. Some of the parts are marked as hard, so you may choose to leave them out if you are under pressure to meet other deadlines, though most students in the past have done everything and received high overall marks. As a compensation to those who want to work alone each exercise will have two bonus marks for individual solutions and one bonus mark for groups of 2. This means that if you work in a group of 2 you can score a maximum of 96% and in a group of 3 you can score a maximum of 92%. On the other hand you may well be able to complete more of the exercises in a group.

Some of the exercises were set last year so please if you do by chance get access to a solution destroy it and work the exercises from scratch. I have copies of all last year's submissions and can automatically check for any copying. Also if you work as a group please don't try to claim individual submissions. This would be considered as plagiarism by the college and can result in severe penalties.

## Coursework Files

The files that you need for the coursework are available from the course web page:

<http://www.doc.ic.ac.uk/dfg/ProbabilisticInference>.

You should download copies of these to your working directory. The files are as follows:

- There are two python scripts with extension .py. One is a library of functions for doing input and output of different kinds of data. The other is a skeleton solution for the first two courseworks, to which you will add your own code. You should look through these to work out what they are doing.
- There are two files of discrete data. One is a small and highly dependent data set for recognition of four developmental stages of neurones grown in culture from five measured variables. The other is a larger data set of measurements on patients suffering from Hepatitis C.

The format of the last two files is as follows:

*Number of Variables*

*Number of Root nodes*

for each variable *The number of states of each variable*

*Number of Data Points*

for each data point

for each variable *the state*

All data items (shown *in italics* above) are integers and are separated either by a space or a carriage return. The states and variables are numbered consecutively from 0 upwards.

Example:

4	the data file has four variables
2	there are two root nodes (the root nodes will always be placed first in the variables)
5 2 4 2	variable 0 has 5 states, variable 1 has 2 states etc
7	there are seven data points
2 0 3 1	data point 1 variable 0 (a root) is in state 2, variable 1 (a root) is in state 0 etc.
4 1 3 1	data point 2
4 0 0 1	etc.
0 0 3 0	
3 0 2 1	
1 1 2 1	
2 0 2 1	

## Working Environment

The suggested environment for doing this coursework is Ubuntu Linux, but you can also do it in the windows and mac operating systems. On Ubuntu it is convenient to use 'Kate' which you can start from the Applications/Other menu, or by right clicking on a .py file and choosing 'Kate' from the 'open with' option. When kate is running, open the terminal at the bottom of the window by clicking on it. You can then edit the file in the top window, save it and then execute it by typing 'python myprog.py' in the terminal.

## Coursework Part 1: The Naive Bayesian Network

In the first coursework we will look at calculating joint and conditional probability tables (link matrices) and making inferences with a naive Bayesian network.

Take a look at the first four functions in `DAPICourseworkLibrary.py` to make sure you understand what is going on. You may find the python syntax self explanatory, but if not you can find several good online tutorials through google. The first function reads a data file in the above format, extracting the data so that it can be used. It is extensively commented to help you understand what is going on. The second writes a data array to a file, appending it to what is there already. The data is written out in a fixed floating point format which is suitable for printing probabilities. The third appends a list (one dimensional array or vector) to a text file and the fourth appends a string to a text file. These allow you to save your results in a text file and add comments to them. Thus you can put together your results in a suitable form for submitting your solution to CATE.

Now take a look at the file `DAPICourseworkSkeleton.py`. The first five functions are to be completed for coursework 1 as detailed below. They are all quite short, the longest part in my solution is 11 lines.

### Task 1.1: 4 marks

Complete the definition of function `Prior`. It should calculate the prior distribution over the states of the variable passed as the parameter 'root' in the data array. The first line simply sets up an array for the result with zero entries.

### Task 1.2: 5 marks

Complete the definition of `CPT` which calculates a conditional probability table (or link matrix) between two variables indicated by parameters `varP` (the parent) and `varC` (the child). In the skeleton the conditional probability table is simply initialised to zeros.

### Task 1.3: 4 marks

Complete the definition of function `JPT` which calculates the joint probability table of any two variables. The joint probability is simply the frequency of a state pair occurring in the data. So for state  $a_0$  of variable  $A$  and state  $b_3$  of variable  $B$ , if  $N(a_0 \& b_3)$  is the number of data points containing both  $a_0$  and  $b_3$  then  $P(a_0 \& b_3) = N(a_0 \& b_3) / noDataPoints$ . The table should be arranged so that for  $P(A \& B)$  the states of  $A$  are rows and the states of  $B$  are columns.

### Task 1.4: 4 marks

Complete the function `JPT2CPT` which calculates a conditional probability table from a joint probability table. This is purely a matter of normalising each column to sum to 1. In effect we use the equation  $P(A|B) = P(A \& B) / P(B)$ .

### Task 1.5: 6 marks (harder)

Finally complete the function `Query` which calculates the probability distribution over the root node of a naive Bayesian network. To represent a naive network in Python we will use a list containing an entry for each node (in numeric order) giving the associated probability table: [`prior`, `cpt1`, `cpt2`, `cpt3`, `cpt4`, `cpt5`]. You can calculate the prior of the root and the conditional probability tables between each child variable and the root using your solutions to Tasks 1 and 2. A query is a list of the instantiated states of the child nodes, for example `[1,0,3,2,0]`. The returned value is a list (or vector) giving the posterior probability distribution over the states of the root node, for example `[0.1,0.3,0.4,0.2]`.

## Results File

You should finish by writing a main program part at the end of the skeleton file. Some example code is there to help you do this. You should use the `Neurones.txt` data set, and create a results file containing:

1. A title giving your group members
2. The prior probability distribution of node 0 in the data set
3. The conditional probability matrix  $P(2|0)$  calculated from the data.
4. The joint probability matrix  $P(2\&0)$  calculated from the data.
5. The conditional probability matrix  $P(2|0)$  calculated from the joint probability matrix  $P(2\&0)$ .
6. The results of queries [4,0,0,0,5] and [6, 5, 2, 5, 5] on the naive network

Rename your python file “DAPICoursework01.py” and submit it and your results file named “DAPIResults01.txt” using CATE.

### Some confusing things when starting python

Python uses the list as its primary data structure, and this provides a very flexible mechanism for representing and manipulating data. However, in numerical analysis we are primarily concerned with using vectors and matrices. The python module “numpy” provides support for this activity. For example, if we want to use a 2 by 3 array we would define it as a list of lists:

```
myList = [ [3,4,7], [2,1,3]]
```

We can convert it to a Matrix by using

```
myMatrix = numpy.array(myList)
```

This function creates a new data structure with attributes like rows (`myMatrix.shape[0]`) and columns (`myMatrix.shape[1]`), and methods, for example:

```
myMatrix.transpose()
```

Numpy contains many other useful functions, for example to compute a matrix product:

```
myMatrixProd = numpy.dot(myMatrix, myMatrix.transpose())
```

A python module is simply a set of python function definitions. In order to use a module you must import it. There are different ways of doing this. For example:

```
import numpy
```

allows you to use all the functions defined in numpy, but you must explicitly reference them as numpy functions. For example we write `numpy.dot` for the dot product. Numpy contains a reference to the linear algebra module named `linalg` and in coursework part four you need the eigenvector function `eig`. You reference this by writing `numpy.linalg.eig` You can alternatively write:

```
from numpy import *
```

If you do this you can use the functions in numpy without the reference, ie just `dot` for the dot product.

## Coursework Part 2: The Maximally Weighted Spanning Tree

This coursework is concerned with the spanning tree algorithm for finding a singly connected Bayesian network from a data set. The material you need will be completely covered by Lecture 6 of the course. You can use the same skeleton program that was set up for Coursework 1, continuing to fill in code where indicated. You will need to use the function that you wrote to compute the joint probability distribution of a pair of variables. If your original solution was wrong and you are stuck then email me and I will give you some working code to do this (after the hand in date for coursework 1).

### Task 2.1: 6 marks

Complete the function “MutualInformation” which calculates the mutual information (or Kullback Leibler divergence) of two variables from their joint probability table. The process involves marginalising the joint probability table and then applying the formula as described in Lecture 6.

### Task 2.2: 5 marks

Complete the function “DependencyMatrix” which uses mutual information as a measure and creates a symmetric matrix showing the pairwise dependencies between the variables in a data set.

### Task 2.3: 6 marks

Complete the function “DependencyList” which turns the dependency matrix into a list of arcs ordered by their dependency. Your list items should be triplets: [dependency, node1, node2]. Using your dependency list draw by hand the Bayesian network that you would get for the HepatitisC data set. Make an image file of your network (either by scanning your hand drawing or using a drawing package (eg powerpoint or open office)).

### Task 2.4: 6 marks (difficult)

Starting with a dependency list find the maximally weighted spanning tree automatically, and append it as a list to your results file. Don't worry about implementing marginal independence to find the causal directions.

### Results File

You should finish by writing a main program part at the end of the skeleton file which will add the following items to your results file:

1. A title giving your group members
2. The dependency matrix for the HepatitisC data set
3. The dependency list for the HepatitisC data set.
4. The spanning tree found for the HepatitisC data set (if you attempted task 2.4).

Assemble the results listed above with the network picture into a .pdf file (You can do this with word, open office or latex). Rename your python file “DAPICoursework02.py” and submit it and your results file named “DAPIResults02.pdf” using CATE.