EECS491 - A3 - tdm47

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0.1 EECS491 A3

0.1.1 Tristan Maidment (tdm47)

Goal The goal of to analyze relationships made in a large Bayesian Network. For the purpose of this exercise, I will be using a free data set found online about car crash statistics.

```
In [1]: from pgmpy.models import BayesianModel as bysmodel
        from pgmpy.factors.discrete import TabularCPD as tcpd
        import csv
        import numpy as np
        import itertools
        from IPython.display import Image
```

Implementation Seven binary variables will be taken from the database. Each entry in the database represents a single person in a crash. The variables used are:

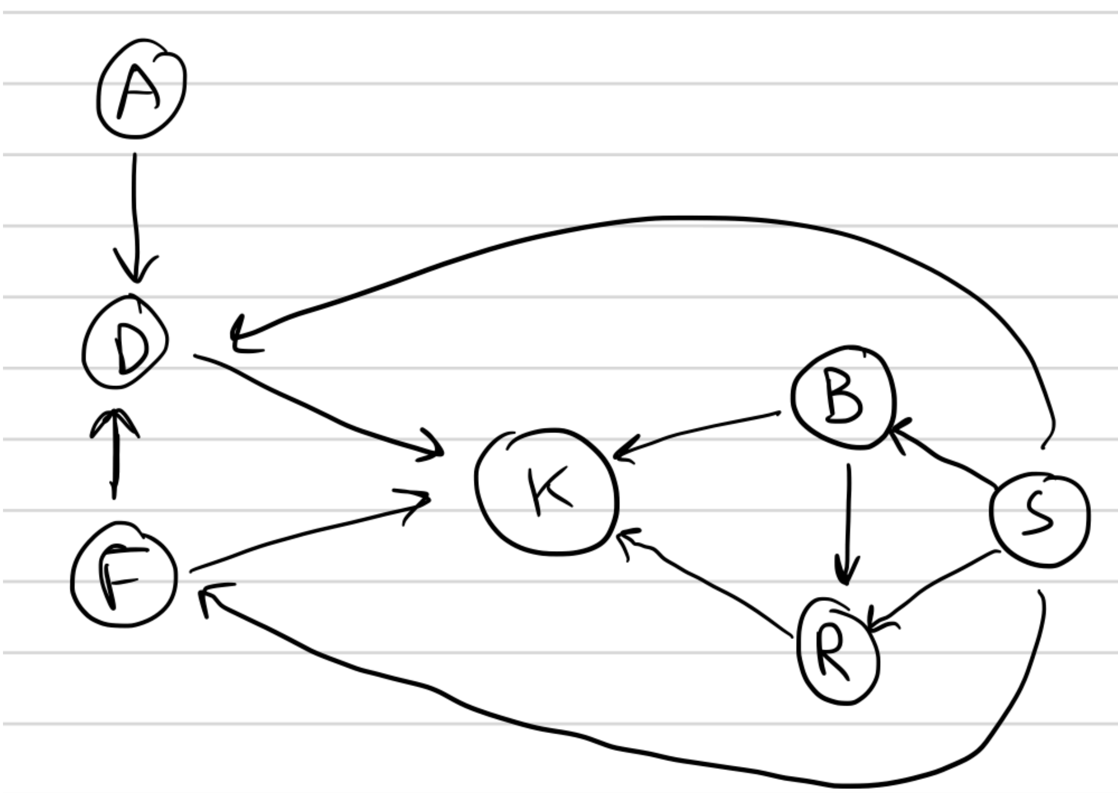
Killed - Whether or not the individual died in the crash.
Airbag - Whether or not the car has an airbag. (This dataset is fairly old, before airbags were a requirement)
Belt - Whether or not the individual was wearing their seatbelt.
Frontal - Whether or not the vehicle was hit in the front.
Sex - Gender of the individual.
Deploy - Whether or not the airbag was deployed. Only true for cars with airbags.
Role - Whether or the the individual was the driver or a passenger.
The bolded letter represents the variable name used in code.

```
In [2]: k, a, b, f, s, d, r = [], [], [], [], [], [], []
        with open('./crashes.csv') as csvfile:
            crashes = csv.reader(csvfile)
            for row in crashes:
                k.append(row[3]) #Killed
                a.append(row[4]) #Airbag
                b.append(row[5]) #Belt
                f.append(row[6]) #Front
                s.append(row[7]) #Sex
                r.append(row[12]) #Deply
                d.append(row[13]) #Role
```

Graph In order to model the network, I have included a visual representation of the the model I being represented in this exercise. Many of the variables require multiple evidence values.

```
In [3]: Image("./graph.png")
```

Out[3]:



This function is used to determine the probability of a binary variable, with no evidence. The reason there is a `true` and `false` parameter, instead of doing a noise or, for instance, is due to the fact that the data set has some errors within it.

```
In [4]: def binary_prob(data, true, false):
            value, length = 0, 0
            for i in range(len(data)):
                if(data[i] == true):
                    length += 1
                    value += 1
                elif(data[i] == false):
                    length += 1
            probability = value/length
            #print("Probability of",true,"is",probability)
            return probability
```

```
In [5]: K = binary_prob(k, 'dead', 'alive')
        print("Probability that a person dies in a crash: %.1f%%" % (K * 100))
```

```
Probability that a person dies in a crash: 4.5%
```

The second thing that we need to define is a function that can calculate the condition probability of a function given a variable amount of evidence variable. `cond_prob` takes in the variable in question, and a list of evidence variables. The list needs to be formatted specifically, and the syntax is shown as a comment.

```
In [6]: #(var, "false", "true"), ((ev1, "false", "true"),(ev2, "false", "true"))
        def cond_prob(data, args):
            #print(args)
            value, length, arg_len = 0, 0, len(args)
            for i in range(len(data[0])):
                if(data[0][i] == data[1]):
                    conds = 0
                    for arg in range(arg_len):
                        if(len(args[arg]) % 3 != 0):
                            print("INCORRECT NUMBER OF ARGS")
                        if(args[arg][0][i] == args[arg][1]):
                            length += 1
                            conds += 1
                        elif(args[arg][0][i] == args[arg][2]):
                            length +=1
                    if(conds == arg_len):
                        value += 1
            probability = value/length
            return probability
```

```
In [7]: D_A = cond_prob([d, '1', '0'], [[f, '1', '0'], [a, 'airbag', 'none']])
        print("Prob of airbag deployment, given the car has an airbag, and the crash was fronta
```

```
Prob of airbag deployment, given the car has an airbag, and the crash was frontal: 4.5%
```

`tcpd` requires that the conditional probability values be insert in a certain order. To the input of these values easier, this function was designed to properly format the value of each cpd.

Due to the nature of the inputs, it requires a binary counter to ensure that the order of inputs is correct.

```
In [8]: def create_values(var, evidence):
            ev_len = len(evidence)
            #print("num args",ev_len)
            width = 2**ev_len
            layout = []
            for i in itertools.product([0,1],repeat=ev_len + 1):
                layout.append(i)
```

```
    #print(layout[::-1]) #reverse the list
    #print(layout)
    #print(evidence)
    values = np.empty((2, width))
    for i in range(2):
        for j in range(width):
            comb = layout[width*i + j]
            ev_val = []
            for k in range(ev_len):
                ev_list = []
                ev_list.append(evidence[k][0])
                ev_list.append(evidence[k][comb[k+1] + 1])
                ev_list.append(evidence[k][2 - comb[k+1]])
                ev_val.append(ev_list)
            values[i, j] = cond_prob((var[0], var[comb[0] + 1], var[comb[0]]), ev_val)
    values[0,:] = 1-values[1,:] # make sure probabilities = 1
    return values
```

A test of this function is shown below. This is the correct format for the input of the data to the model.

```
In [9]: values = create_values([f, "0", "1"], [[s, "f", "m"]])
        print(values)
```

```
[[0.55573343 0.44426657]
 [0.44426657 0.55573343]]
```

Model The next step is to define the model. Each connection in the graph define earlier must be included in the models definition.

```
In [10]: model = bysmodel([('A', 'D'), ('F', 'D'), ('F', 'K'), ('D', 'K'),
                          ('B', 'K'), ('R', 'K'), ('B', 'R'), ('S', 'B'),
                          ('S', 'R'), ('S', 'D'), ('S', 'F')])
```

In addition, the variables must be defined. Variables that are based on some evidence must be defined as such at this point.

```
In [11]: priorA = tcpd(variable='A', variable_card=2, values=[[binary_prob(a, 'airbag', 'none')
         priorS = tcpd(variable='S', variable_card=2, values=[[binary_prob(s, 'm', 'f'), binar

         cpdF = tcpd(variable='F', variable_card=2,
                     evidence=['S'], evidence_card=[2],
                     values=create_values([f, "0", "1"], [[s, "f", "m"]]))

         cpdK = tcpd(variable='K', variable_card=2,
                     evidence=['D', 'F', 'B', 'R'], evidence_card=[2, 2, 2, 2],
                     values=create_values([k, "alive", "dead"], [[d, "0", "1"], [f, "0", "1"],
         cpdB = tcpd(variable='B', variable_card=2,
```

```
                evidence=['S'], evidence_card=[2],
                values=create_values([b, "none", "belted"], [[s, "f", "m"]]))

cpdD = tcpd(variable='D', variable_card=2,
                evidence=['S', 'A', 'F'], evidence_card=[2, 2, 2],
                values=create_values([d, "0", "1"], [[s, "f", "m"],[a, "none", "airbag"],

cpdR = tcpd(variable='R', variable_card=2,
                evidence=['S', 'B'], evidence_card=[2, 2],
                values=create_values([r, "pass", "driver"], [[s, "f", "m"],[b,"none","bel
```

Then, the model must be checked for consistency.

```
In [12]: model.add_cpds(priorA, priorS, cpdF, cpdK, cpdB, cpdR, cpdD)
         model.check_model()

Out[12]: True
```

0.1.2 Analysis

We will be using a variety of methods to execute inference on the network. The first method being tested is `Variable Elimination`

Variable Elimination

```
In [13]: from pgmpy.inference import VariableElimination

         VESolver = VariableElimination(model)

In [14]: print('Deployed|Killed,WearingBelt : %.1f%%' % (VESolver.query(['D'], evidence={'K' :
         print('Driver|Killed,WearingBelt  : %.1f%%' % (VESolver.query(['R'], evidence={'K' :
         print('Frontal|Killed,Deployed    : %.1f%%' % (VESolver.query(['F'], evidence={'K' : 1

Deployed|Killed,WearingBelt : 1.5%
Driver|Killed,WearingBelt  : 36.0%
Frontal|Killed,Deployed    : 79.5%
```

Another method for exact inference is Belief Propegation. We get the exact same answers as `Belief Propegation`, indicating that the model is consistent and the methods work properly.

Belief Propegation

```
In [15]: from pgmpy.inference import BeliefPropagation

         BPSolver = BeliefPropagation(model)

In [16]: BPSolver.calibrate()
```

```
In [17]: print('Deployed|Killed,WearingBelt : %.1f%%' % (BPSolver.query(['D'], evidence={'K' :
         print('Driver|Killed,WearingBelt  : %.1f%%' % (BPSolver.query(['R'], evidence={'K' : 1
         print('Frontal|Killed,Deployed    : %.1f%%' % (BPSolver.query(['F'], evidence={'K' : 1
```

```
Deployed|Killed,WearingBelt : 1.5%
Driver|Killed,WearingBelt  : 36.0%
Frontal|Killed,Deployed    : 79.5%
```

Bayesian Model Sampling

```
In [18]: from pgmpy.factors.discrete import State
         from pgmpy.sampling import BayesianModelSampling

         SMPSolver = BayesianModelSampling(model)

         nsamples = 100
         evdKB  = [State('K', 1), State('B', 1)]
         smpKB  = SMPSolver.rejection_sample(evidence=evdKB, size=nsamples)
         evdKD = [State('K', 1), State('D', 1)]
         smpKD = SMPSolver.rejection_sample(evidence=evdKD, size=nsamples)
```

```
In [19]: from pandas.core.frame import DataFrame

         def calcCondProb(trace, event, cond):
             if type(trace) is DataFrame:
                 trace = trace.transpose().to_dict().values()
             # find all samples satisfy conditions
             for k, v in cond.items():
                 trace = [smp for smp in trace if smp[k] == v]
             # record quantity of all samples fulfill condition
             nCondSample = len(trace)
             # find all samples satisfy event
             for k, v in event.items():
                 trace = [smp for smp in trace if smp[k] == v]
             # calculate conditional probability
             return len(trace) / nCondSample
```

```
In [20]: print('Deployed|Killed,WearingBelt  : %.1f%%' % (calcCondProb(smpKB, {'D' : 1}, {}) *
         print('Driver|Killed,WearingBelt  : %.1f%%' % (calcCondProb(smpKB, {'R' : 1}, {}) * 10
         print('Frontal|Killed,Deployed  : %.1f%%' % (calcCondProb(smpKD, {'F' : 1}, {}) * 100)
```

```
Deployed|Killed,WearingBelt  : 1.0%
Driver|Killed,WearingBelt  : 42.0%
Frontal|Killed,Deployed  : 79.0%
```

Note that my computer is *especially slow* when sampling this model. For that reason I only use 100 samples when printing this notebook. With more samples, the probabilities will converge toward the true value. With 100 samples, this process took a whopping 6 minutes.

0.1.3 Conclusion

Overall, the implementation of a variety of inference methods on a Bayesian Network was fairly straightforward once the model was defined. Due to how the package is designed, creating such a model takes a majority of the time, and analysis is fairly straightforward. For models similar to the size of the one defined, exact inference is a fairly fast method, and sampling takes a fair bit longer. However, for larger models, sampling should be faster.