Probabilitistic Graphical Models for Fraud and Anomaly Detection in Insurance

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6 July 2016

How to Build a Model with No Data and No Domain Knowledge...

Structure of Talk

- Conditional Dependence, Independence and Bayesian Networks
- The Sprinkler Network
- Medical Non-disclosure
- Building a Model
- Expanding the Model
- Beyond Bayesian Networks
- Summary

Conditional Probability

Probability of 2D6 totalling 11?

$$(5, 6) \text{ or } (6, 5)$$

$$P(T = 11) = \frac{2}{36} = 0.05556$$

Conditional Probability

Probability of 2D6 totalling 11 if first dice is 5?

$$(5, 6)$$

$$P(T = 11 | D_1 = 5) = \frac{5}{6} = 0.8333$$

Conditional Dependence and Independence

Three variables, A, B, C:

A and B are independent
C depends on A
C depends on B

What happens if we learn information about C?

A and B are *conditionally dependent* on C.

2D6 Example

Define variables D_1, D_2 and T.

D_1 and D_2 are independent, T depends on both

What happens to D_2 if $T = 7$, $D_1 = 4$?

$$P(D_2 = X) = \begin{cases} 1 \text{ iff } X = 3 \\ 0 \text{ otherwise} \end{cases}$$

2D6

$T = 9$

$P(D_2)$:

1	2	3	4	5	6
0	0	0.5	0.5	0	0

$P(D_1)$:

1	2	3	4	5	6
0	0	0	0	0.5	0.5

Conditional Independence

Now suppose we have T as before, but define

$$X_1 = \begin{cases} 1 \text{ iff } T \text{ even} \\ 0 \text{ otherwise} \end{cases} \qquad X_2 = \begin{cases} 1 \text{ iff } T >= 9 \\ 0 \text{ otherwise} \end{cases}$$

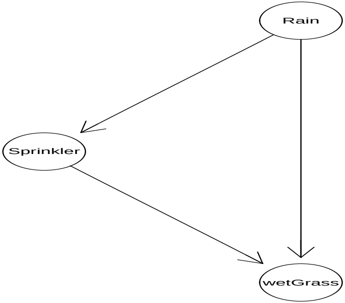
T NOT KNOWN, $X_1 \not\perp X_2$ $\qquad$ T KNOWN, $X_1 \perp X_2$

X_1 and X_2 are *conditionally independent* on T

Probabilistic Graphical Models represent structural dependence amongst variables

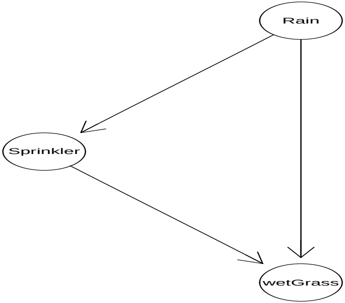
Bayesian Networks

PGM where graph is a *directed, acyclic graph* (DAG):



Dependencies represented via *Conditional Probability Tables* (CPTs)

The Sprinkler Network



Variables: (R)aining, (S)prinkler, wet(G)rass

The Sprinkler Network

```
print(sprinkler_grain$cptlist$Rain)


## Rain
## yes  no
## 0.2 0.8


ftable(sprinkler_grain$cptlist$Sprinkler, row.vars = 'Rain')


##      Sprinkler  yes   no
## Rain
## yes            0.01 0.99
## no             0.40 0.60


ftable(sprinkler_grain$cptlist$wetGrass, row.vars = c('Rain', 'Sprinkler'))


##                wetGrass  yes   no
## Rain Sprinkler
## yes  yes                0.99 0.01
##      no                 0.90 0.10
## no   yes                0.80 0.20
##      no                 0.00 1.00
```

Some Questions

What is the probability of the grass being wet?

```
querygrain(sprinkler_grain, nodes = 'wetGrass')$wetGrass
```

```
## wetGrass
##     yes      no
## 0.43618 0.56382
```

If the grass is wet, what is the probability that it is raining?

```
querygrain(sprinkler_grain, evidence = list(wetGrass = 'yes'), nodes = 'Rain')$Rain
```

```
## Rain
##      yes       no
## 0.413086 0.586914
```

Medical Non-disclosure

SSQ Financial Group

REQUEST FOR OPTIONAL LIFE INSURANCE

PLEASE COMPLETE THIS FORM IN BLOCK LETTERS USING INK

A. EMPLOYER INFORMATION

Policy Holder Name:	SSQ Group #:
Division Name:	Certificate #:

B. PARTICIPANT INFORMATION

Last Name:	First Name:	S.I.N.:
Mailing Address: (including postal code)		
Telephone: Home	Work	Language Preference: ☐ English ☐ French
Gender: ☐ M ☐ F	Date of Birth: D M Y	Salary: $

C. REQUEST FOR OPTIONAL LIFE INSURANCE COVERAGE

IMPORTANT: Optional Life Insurance units of $10,000 are only available to plans that currently offer this benefit.

Participant: *(Please check N/A if request is only for spouse)*		Spouse:	
Current amount of coverage (in force)	Additional amount of coverage (requested)	Current amount of coverage (in force)	Additional amount of coverage (requested)
☐ None ☐ 1x salary ☐ 2x salary ☐ 3x salary ______ units of $10,000	☐ N/A ☐ 1x salary ☐ 2x salary ☐ 3x salary ______ units of $10,000	☐ None ☐ 25% ______ units of $10,000	☐ 25% ☐ 50% ______ units of $10,000
Spouse:	Last Name:		First Name:
	Gender: ☐ M ☐ F	Date of Birth: D M Y	

D. SMOKING HABITS

Participant: Non-Smoker ☐ Smoker ☐ **Spouse:** Non-Smoker ☐ Smoker ☐

"I declare that I do not smoke and have not smoked any tobacco products such as cigarettes, cigars, cigarillos or pipes, or any drugs during the past 12 months. This statement is an affirmative guarantee on my part." It is understood that the insurer may periodically require confirmation of non-smoker status. The participant must be in a position to meet the requirements then in force and return the confirmation within 30 days of the request, failing which the participant shall lose non-smoker status and the associated premium reduction shall cease to apply as of the date of the insurer's request. "I also acknowledge that a false or incomplete statement may cause the coverage to be null and void."

Participant: ______________________ Spouse: ______________________

Problems

Doing Outlier / Anomaly Detection:

- Data is sparse/missing
- Lack of output variables
- Low incidence rate
- Semi-supervised Learning

Fraud Detection

Fraud Detection

Fraud Detection

Fraud Detection

Full automation difficult!

Create filter instead

Build a Model

We want a model which, given the data observed in the policy application, allows us to estimate the probability of a subsequent medical exam changing the underwriting decision on the policy.

The model should incorporate our assumptions of the process and be as simple as possible.

Consequences

- Applicant may be unaware
- Is the nondisclosure relevant?
- Is the juice worth the squeeze?

Consequences

Conditions:

(S)moker: Smoker, Quitter, Non-smoker

(B)MI: Normal, Overweight, Obese

Family (H)istory: None, HeartDisease

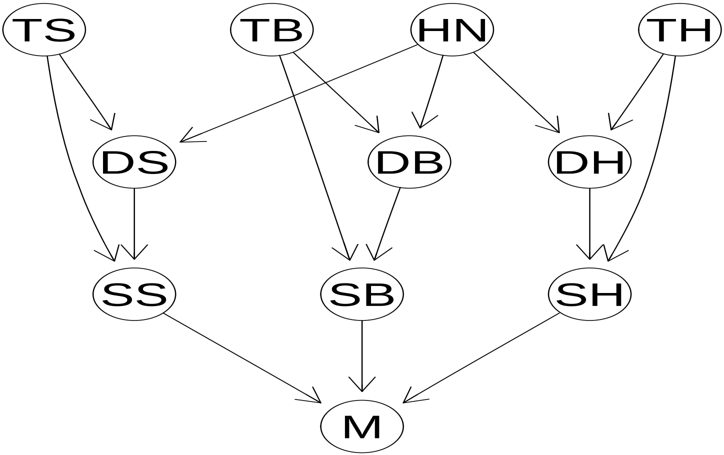
Aspects:

T True state

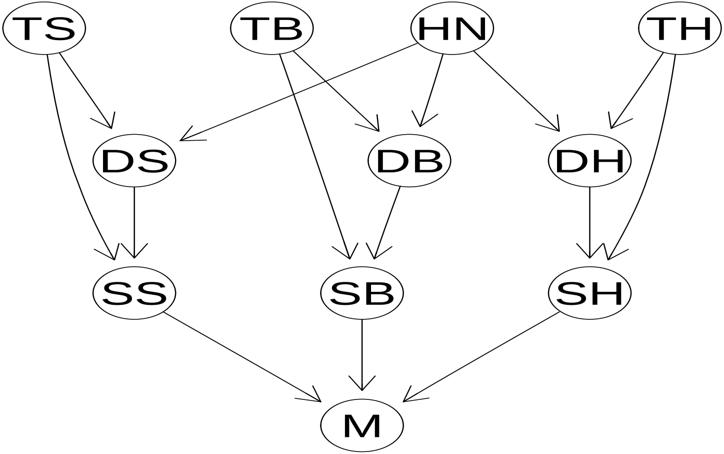
D Declared state

S Seriousness of condition's impact on decision

Medical Exam Network



Bad Teacher Syndrome


TS
TB
HN
TH
DS
DB
DH
SS
SB
SH
M

```
print(underwriting_grain$cptlist$TH)
```

```
## TH
##        None HeartDisease
##        0.95         0.05
```

```
ftable(underwriting_grain$cptlist$DH, row.vars = c('HN', 'TH'))
```

```
##                          DH None HeartDisease
## HN        TH
## Dishonest None                0.9          0.1
##           HeartDisease        0.5          0.5
## Honest    None                0.9          0.1
##           HeartDisease        0.1          0.9
```

```
ftable(underwriting_grain$cptlist$SH, row.vars = c('TH', 'DH'))
```

```
##                               SH Serious NotSerious
## TH           DH
## None         None                   0.01       0.99
##              HeartDisease           0.20       0.80
## HeartDisease None                   0.60       0.40
##              HeartDisease           0.10       0.90
```

Medical Exam

```
ftable(underwriting_grain$cptlist$M, row.vars = c('SS', 'SB', 'SH'))
```

```
##                                   M Medical NoMedical
## SS         SB         SH
## Serious    Serious    Serious          0.99      0.01
##                       NotSerious       0.85      0.15
##            NotSerious Serious          0.95      0.05
##                       NotSerious       0.60      0.40
## NotSerious Serious    Serious          0.90      0.10
##                       NotSerious       0.60      0.40
##            NotSerious Serious          0.85      0.15
##                       NotSerious       0.10      0.90
```

What is the unconditional probability of a medical exam finding something?

```
querygrain(underwriting_grain, nodes = 'M')$M

## M
##   Medical NoMedical
##  0.177515  0.822485
```

Too high?

Probably flawed

Assess the Model

Declares a clean bill of health (DS = Nonsmoker, DB = Normal, DH = None)?

```
querygrain(underwriting_grain, nodes = 'M'
          ,evidence = list(DS = 'Nonsmoker'
                          ,DB = 'Normal'
                          ,DH = 'None'))$M


## M
##   Medical NoMedical
##  0.146951  0.853049
```

Assess the Model

Declares history of heart disease? ($DH =$ HeartDisease)?

```
querygrain(underwriting_grain, nodes = 'M'
          ,evidence = list(DS = 'Nonsmoker'
                          ,DB = 'Normal'
                          ,DH = 'HeartDisease'))$M
```

```
## M
##   Medical  NoMedical
##  0.257899  0.742101
```

Expanding the Model

Current model built by guessing CPTs

Use Data?

CPTs assist this - subsets of variables available

Bootstrap to assess calculation validity?

Expanding Variable Levels

Add states/levels to variables – `HeartDisease`?

Limitations:

- Model separately?
- CPT specification complicated
- More data

Add Variables

Add variables to model

- Family history?
- Work on honesty modelling
- Split exam types

Potential for bias

Further Uses

- Underwriting fraud for car insurance
- Claims fraud
- Product recommendations
- Problematic customers
- Regulatory issues

Beyond Bayesian Networks

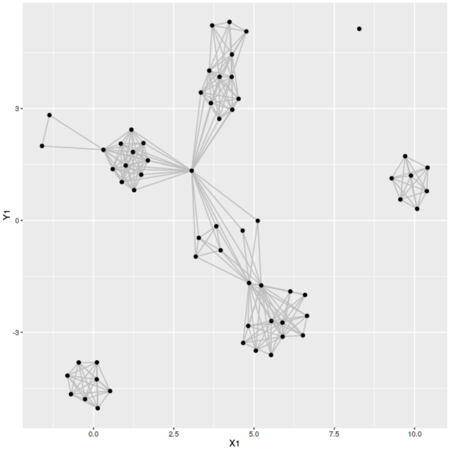
Require categorical variables

Binning continuous data loses information

- Markov Random Fields
- Chain graphs
- Conditional Random Fields

Semi-supervised Learning

One Last Thing...



Conclusions

- Classification very difficult
- Highly speculative – nowhere near production-ready
- Use as filter – no automation
- Outputs often counter-intuitive
- Work unfinished - lots more avenues to explore

Get In Touch

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Slides and code available on GitHub:
`https://www.github.com/kaybenleroll/dublin_r_workshops`