# Probabilitistic Graphical Models for Detecting Underwriting Fraud

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

# Structure of Talk

Medical Non-disclosure

Bayesian Networks

Building the Model

Conclusions

### Medical Non-disclosure



#### REQUEST FOR OPTIONAL LIFE INSURANCE

Policy Holder Name:  Disson Rame:  B. PARTICIPANT INFORMATION  Last Name:  Molling Address: (including posted code)  Tell-phone:  Home  Gendor:   M   F	First Name:  Work  Date of Birth:		SSQ Group #:  Certificate #:  S.I.N::  Language Preference:	I Sanfeh
E. PARTICIPANT INFORMATION LEST Name:  Mailing Address: (nclusing postal code)  Telephone: Home	Work		S.I.N.:	I Sanish □ Search
Last Name: Mailing Address: (including postal code) Telephone: Home	Work			Il Saalish   T Erech
Mailing Address: (including postal code) Telephone: Home	Work			Sealer Second
(including postal code) Telephone: Home	10000		Language Preference:	Seelish T Seesah
	10000		Language Preference:	English T French
Gender: M F	Date of Birth:		Language Preference: English French  N Y Salary: \$	
		M Y		
C. REQUEST FOR OPTIONAL LIFE INSURA	NCE COVERAGE			
IMPORTANT: Optional Life Insurance units of \$	10,000 are only available to plans that curr	rently offer this b	enefit.	
Participant: (Please check N/A	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 ☐	N/A 1x salary	☐ None	25%	25% 50%
2x salary 3x salary units of \$10,000	2x salary 3x salary units of \$10,000		units of \$10,000	units of \$10,000
Spouse: La	Lest Name: First Name:			
6	ender: 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 sm an affirmative guarantee on my part." It is und the requirements then in force and return the o reduction shall cease to apply as of the date of	erstood that the insurer may periodically re confirmation within 30 days of the request, f	equire confirmation	in of non-smoker status. The participant shall lose non-sm	participant must be in a position to meet oker status and the associated premium
Participant:		Spouse:		

## **Problems**

Data sparse / missing

Partially missing output variable

Low base-rate problem

Semi-supervised learning

#### Fraud Detection

Full automation difficult!

Create filter instead — triage cases

#### 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.

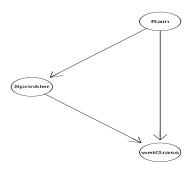
# Is the Juice Worth the Squeeze?



Probabilistic Graphical Model?

# Bayesian Networks

PGM with directed, acyclic graph (DAG):



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

Conditional Probability Tables (CPTs)

# Some Questions

What is the probability of the grass being wet?

```
querygrain(sprinkler_grain, nodes = 'wetGrass')$wetGrass
## wetGrass
## yes no
## 0.44 0.56
```

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
## 0.41 0.59
```

# **Getting Started**

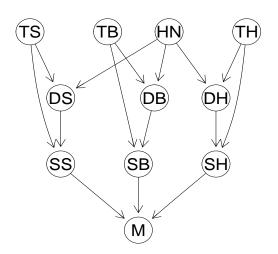
#### Conditions:

- (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



- HN: Honesty
- TS: True Smoking
- DS: Decl Smoking
- SS: Serious Smoking
- TB: True BMI
- DB: Decl BMI
- SB: Serious BMI
- *TH*: True History
- DH: Decl History
- SH: Serious History
- M: Medical Chance

#### Assess

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

```
querygrain(underwriting_grain, nodes = 'M')$M
## M
##
     Medical NoMedical
##
        0.18
                  0.82
```

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
##
        0.15 0.85
##
```

# Expanding the Model

Guessed CPTs — use data?

CPTs assist this - subsets of variables available

Bootstrap to validate?

Add states/levels to variables — HeartDisease?

Add variables: Family History, Medical Exams, Honesty?

#### Conclusions

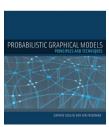
- Classification very difficult
- Highly speculative nowhere near production-ready
- Use as filter no automation
- Outputs often counter-intuitive
- Work unfinished lots more avenues to explore

Other areas: Claims fraud, product recommendations, regulatory issues

#### Further Resources



"Graphical Models with R" Søren Højsgaard.



"Probabalistic Graphical Models: Principles and Techniques" Koller and Friedman

Package Vignettes: gRain and gRbase

Coursera: Probabilistic Graphical Models https://www.coursera.org/course/pgm

#### Get In Touch

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Slides and code available on GitHub: https://www.github.com/kaybenleroll/dublin\_r\_workshops

#### Blogpost Series:

http://blog.applied.ai/probabilistic-graphical-models-for-fraud-detection-part-1 http://blog.applied.ai/probabilistic-graphical-models-for-fraud-detection-part-2 http://blog.applied.ai/probabilistic-graphical-models-for-fraud-detection-part-3