An aerial photograph of a city, likely Toronto, showing a large park (Roncesvalles Park) with a lake (Roncesvalles Lake) in the foreground. The city skyline is visible in the background, with various buildings and greenery. The image is in black and white, except for the text which is in color.

INTRO TO BAYESIAN NETWORKS AND CAUSALITY

ANDRÉ E. DOS SANTOS

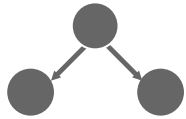
andreedsgithub.io

dossantos@ualberta.ca

2020

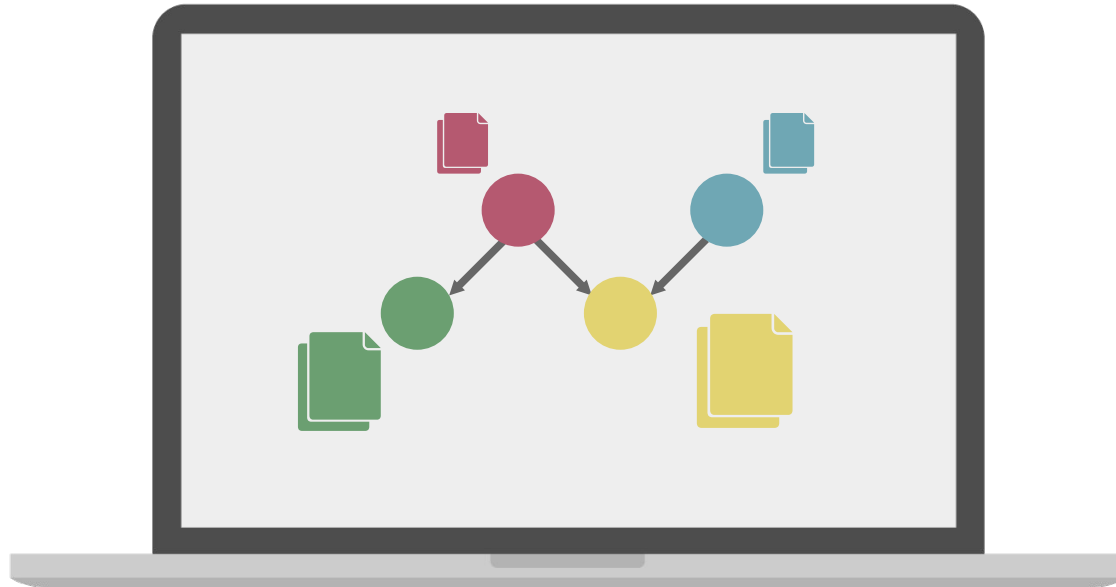
BAYESIAN NETWORKS

PROBABILISTIC GRAPHICAL MODEL



**DIRECTED
ACYCLIC
GRAPH**

DAG



**CONDITIONAL
PROBABILISTIC
TABLES**

CPTs

Pearl
1988



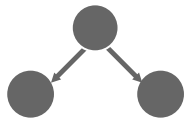






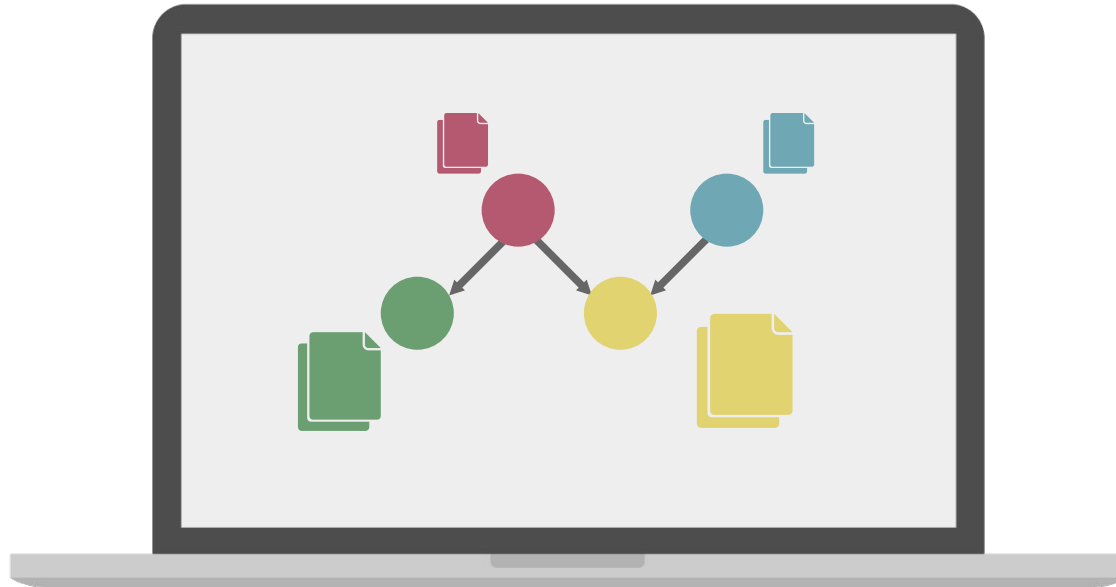
BAYESIAN NETWORKS

PROBABILISTIC GRAPHICAL MODEL



**DIRECTED
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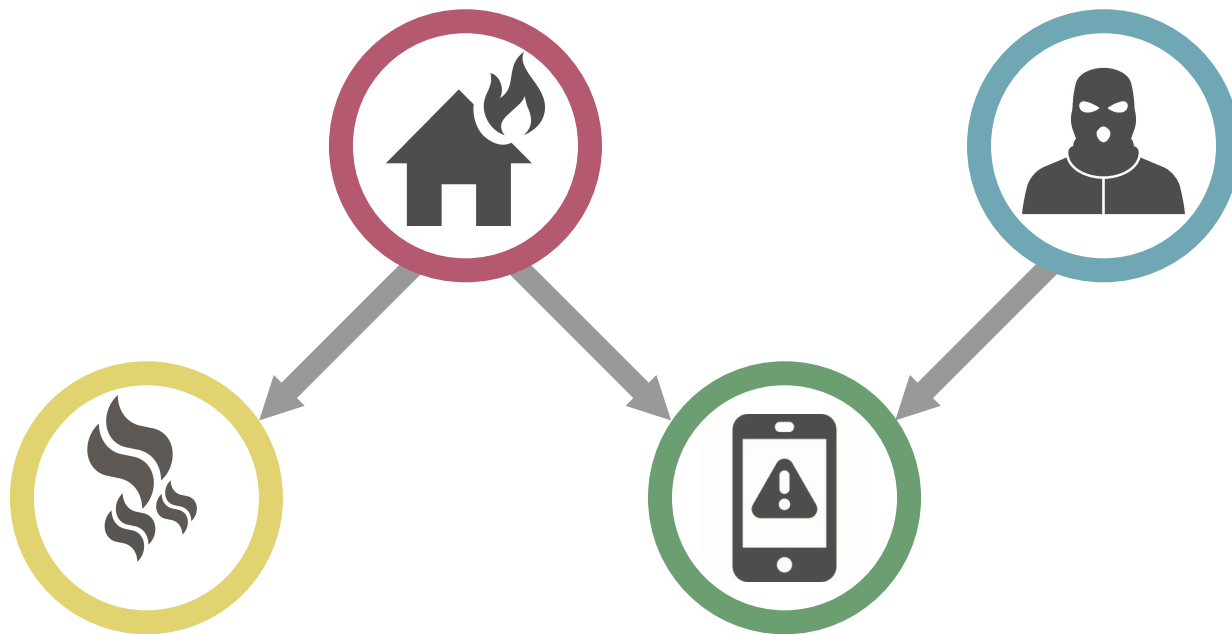


**CONDITIONAL
PROBABILISTIC
TABLES**

CPTs

Pearl
1988

BN EXAMPLE



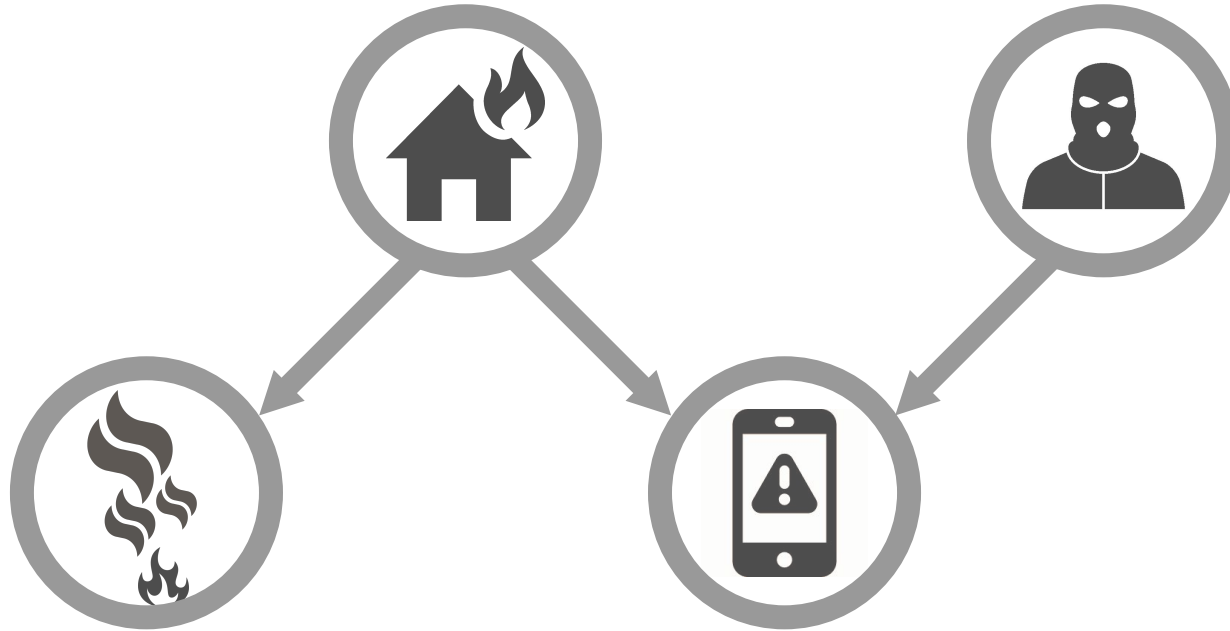
$U = \{ \text{fire}, \text{burglar}, \text{smoke}, \text{app} \}$

CPT EXAMPLE

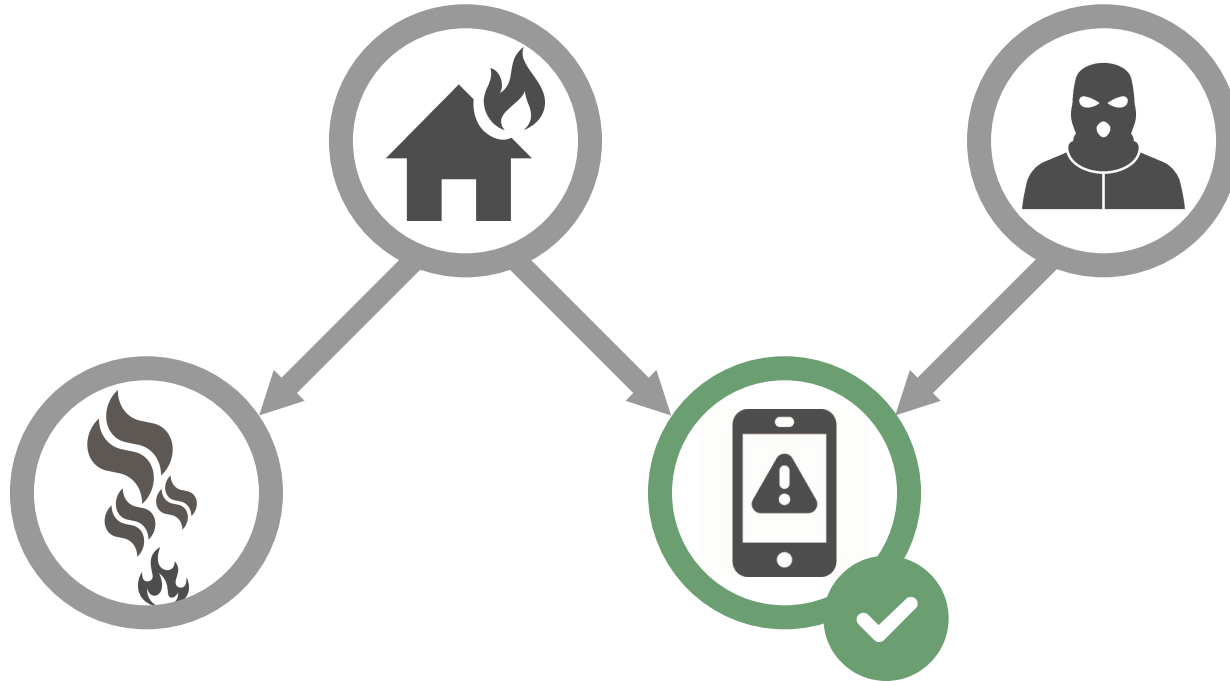
app	fire	burglar	$\rho(\text{app} \mid \text{fire}, \text{burglar})$
T	T	T	1.0
F	T	T	0.0
T	F	T	0.8
F	F	T	0.2
T	T	F	0.9
F	T	F	0.1
T	F	F	0.01
F	F	F	0.99



BN EXAMPLE



BN EXAMPLE



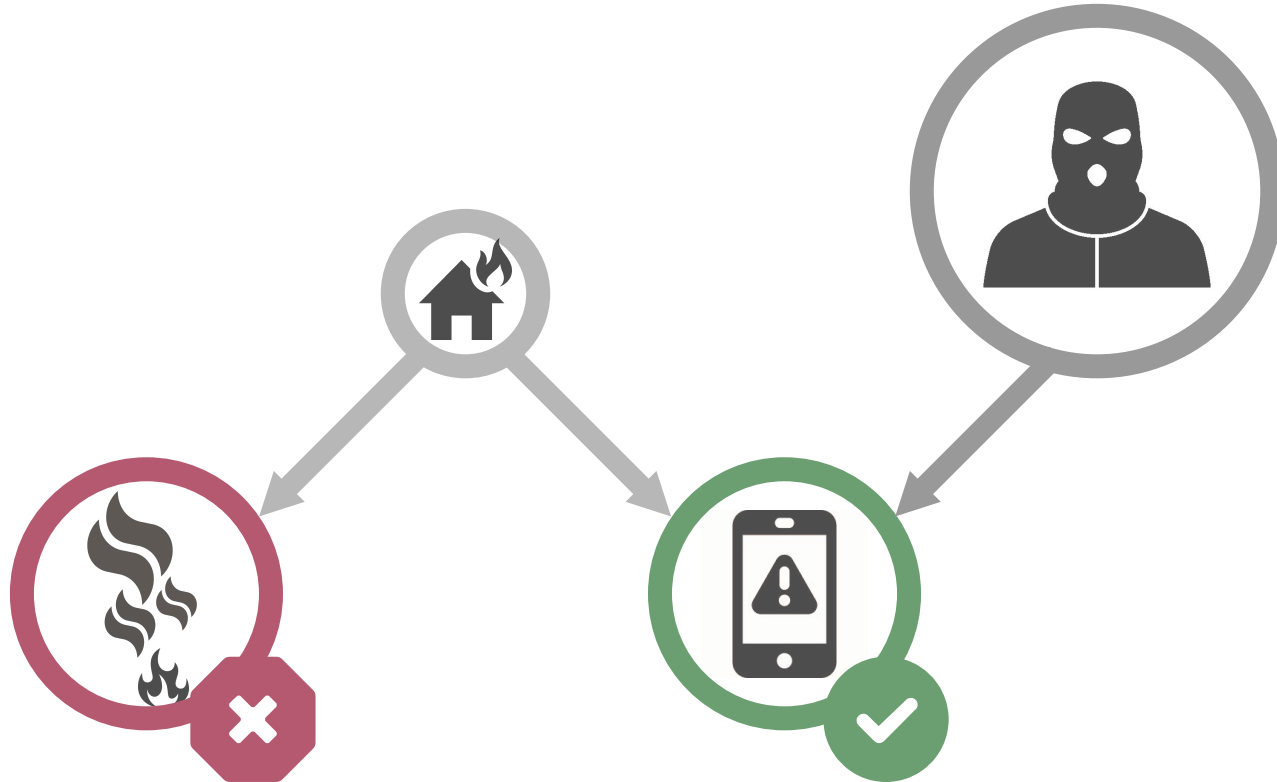
BN EXAMPLE



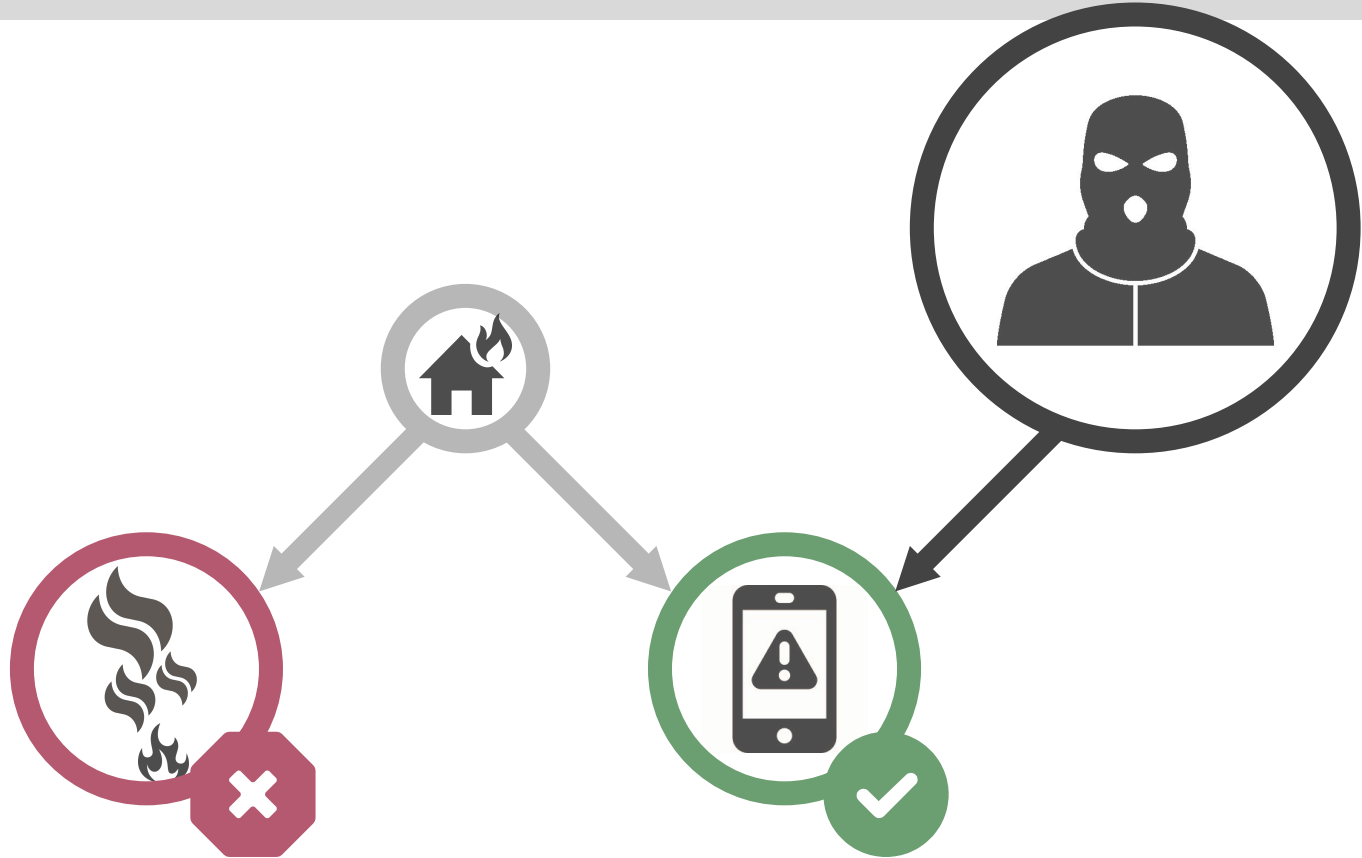
BN EXAMPLE



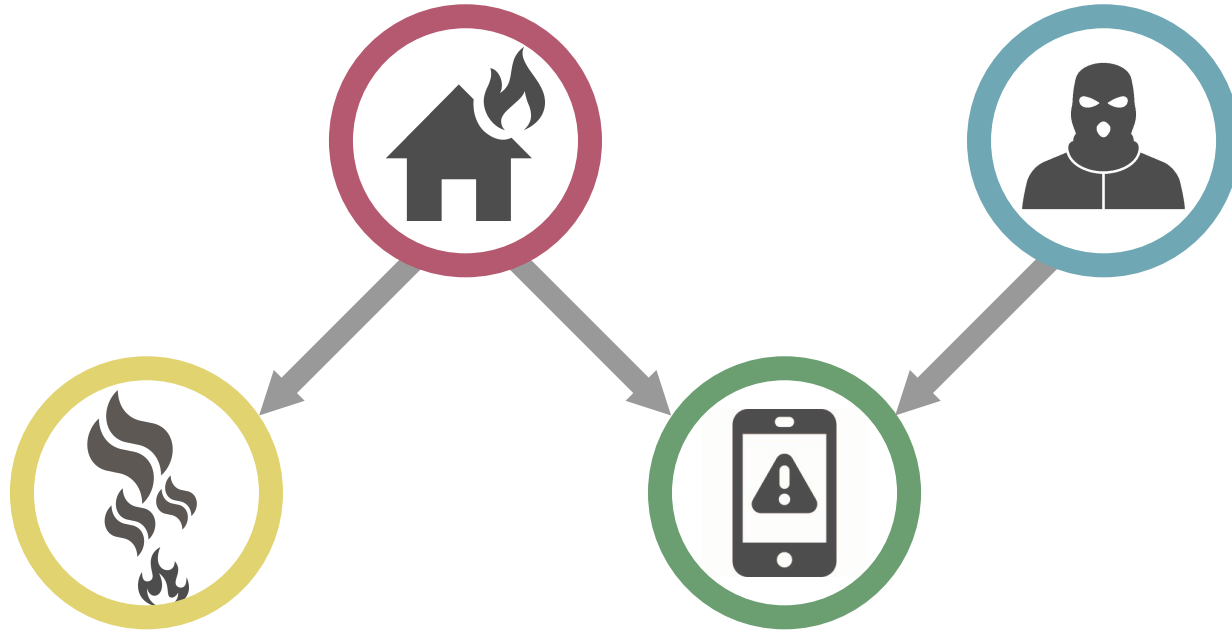
BN EXAMPLE



BN EXAMPLE

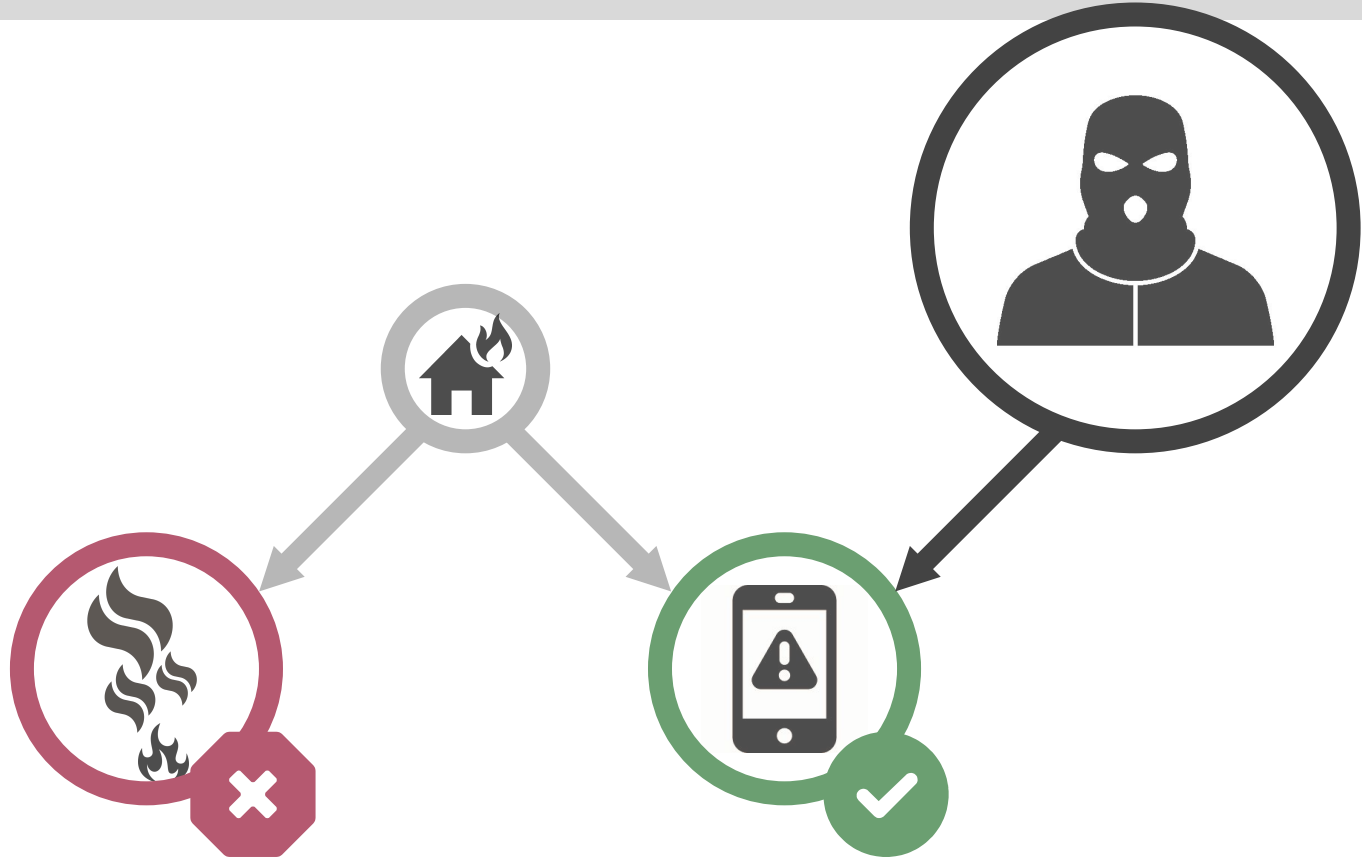


The \prod of the CPTs is a **joint probability distribution** $\rho(\mathbf{U})$

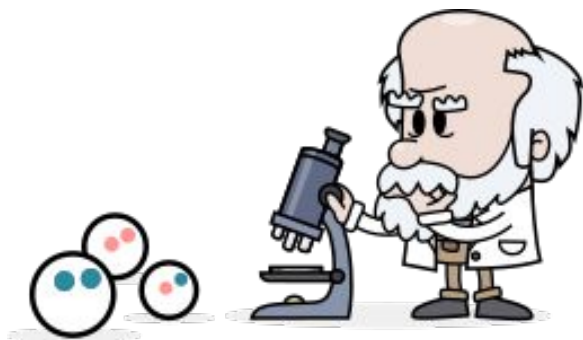


$$\rho(\mathbf{U}) = \rho(\text{fire}) \cdot \rho(\text{burglar}) \cdot \rho(\text{smoke} \mid \text{fire}) \cdot \rho(\text{app} \mid \text{fire}, \text{burglar})$$

BN EXAMPLE



DARWINIAN NETWORKS LAB



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DARWINIAN NETWORKS

DARWINIAN NETWORKS

(CAI 2015, CI 2016)



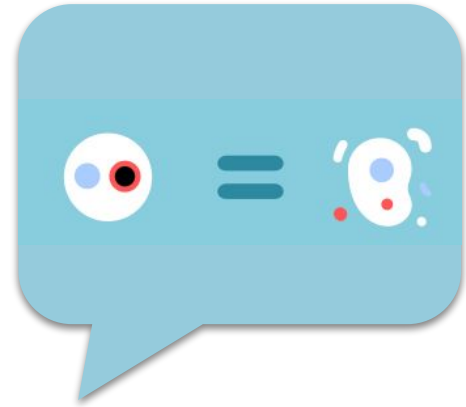
CLEVER WAY TO VIEW CPTs



$$P(g|e, f)$$

DARWINIAN NETWORKS

POPULATION OF MICROORGANISMS



$$P(g|e, f)$$



MULTIPLICATION IS MERGE

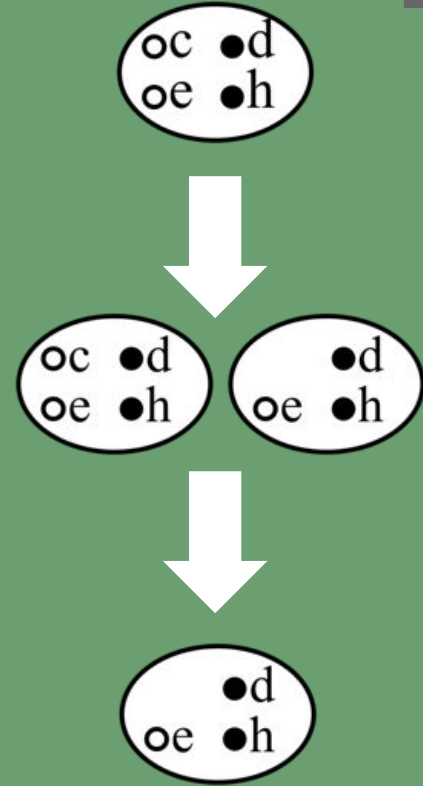


$$P(c|h) \cdot P(e|c, d) = P(c, e|d, h)$$

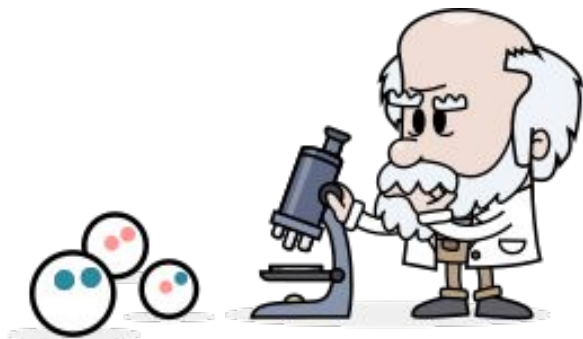
○ white + ● black = ○ white
● black + ○ white = ○ white
● black + ● black = ● black
○ white + ○ white = ● black

MARGINALIZATION IS REPLICATION AND NATURAL SELECTION

$$\sum_c P(c, e|d, h) = P(e|d, h)$$



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BayesFraud Predictive Analytics

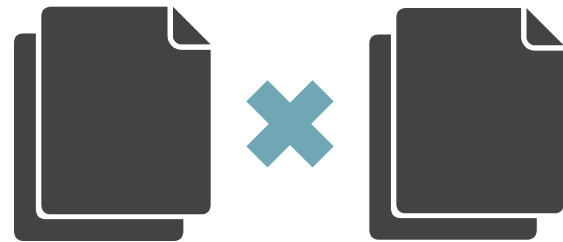


*Identify Fraud, **improve efficiency** and **reduce losses** with the advanced computing power of **BayesFraud Analytics**. The results of implementing BayesFraud are compelling: more attempted fraud is exposed, and claims costs and premiums are kept at a minimum.*

[READ MORE](#)[GET FREE DEMO](#)



NP-hard Inference



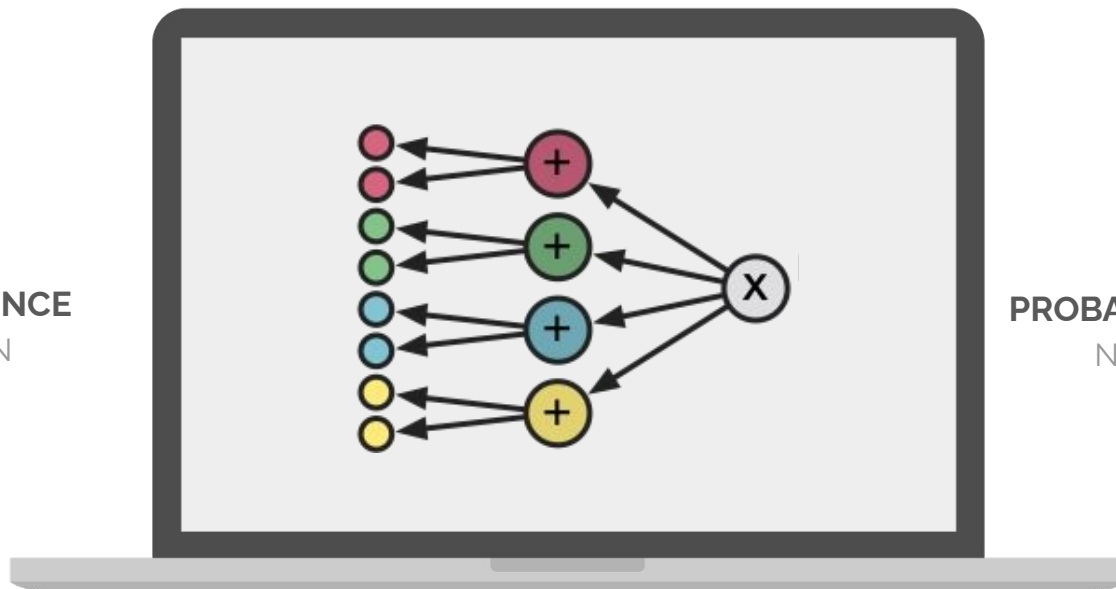
Inference in BNs is a NP-hard task

SUM-PRODUCT NETWORKS

GENERATIVE DEEP LEARNING MODEL



EFFICIENT INFERENCE
UNDER CERTAIN
CONDITIONS

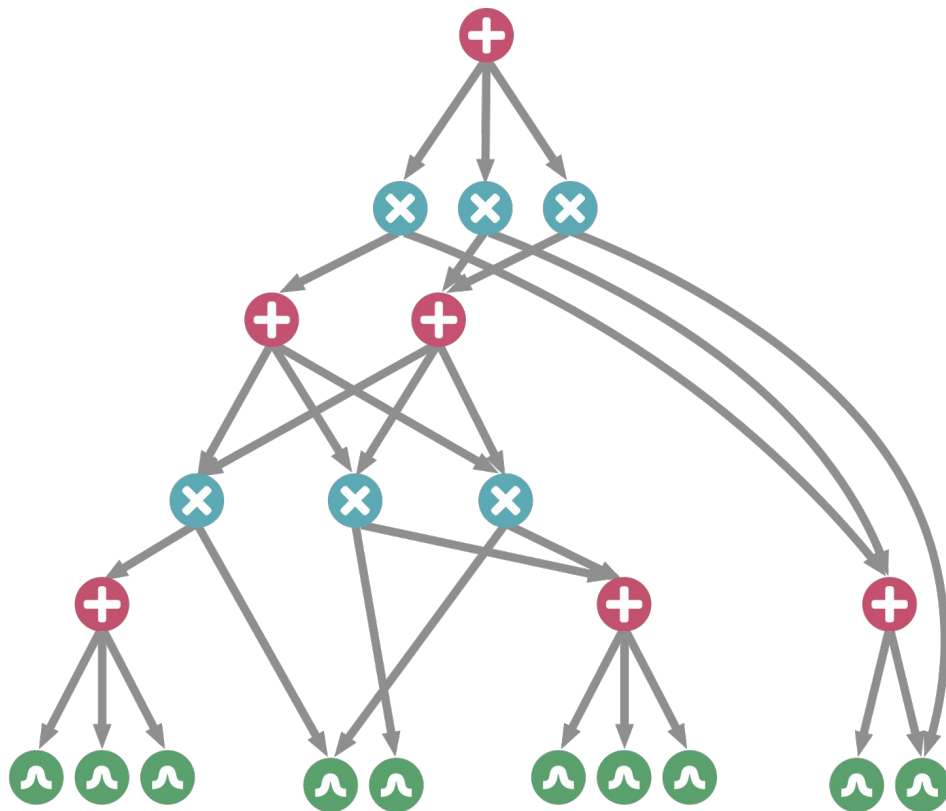


PROBABILISTIC REASONING
NOT A "BLACK BOX"

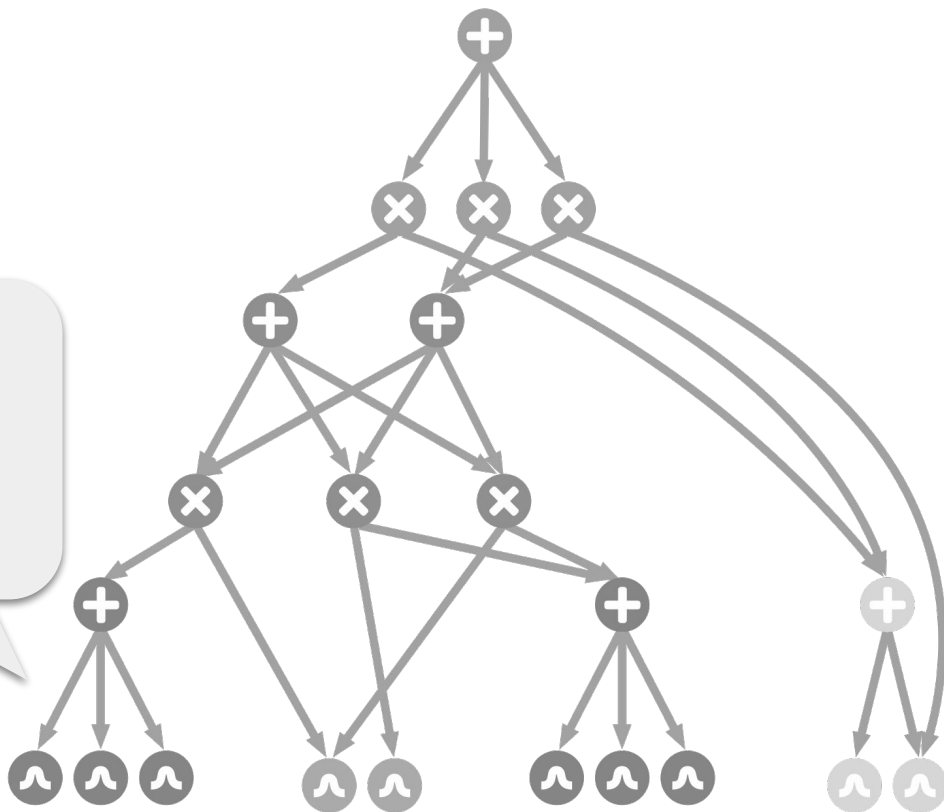
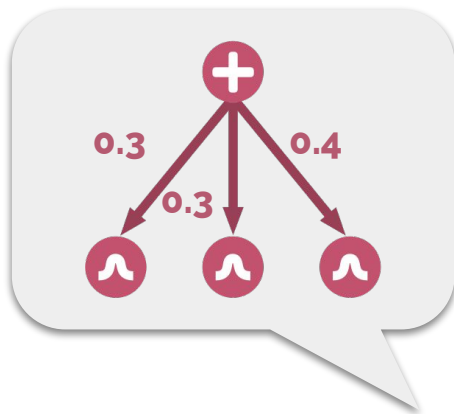
Poon and Domingos

2011

SUM-PRODUCT NETWORKS



SUM-PRODUCT NETWORKS



SUM-PRODUCT NETWORKS

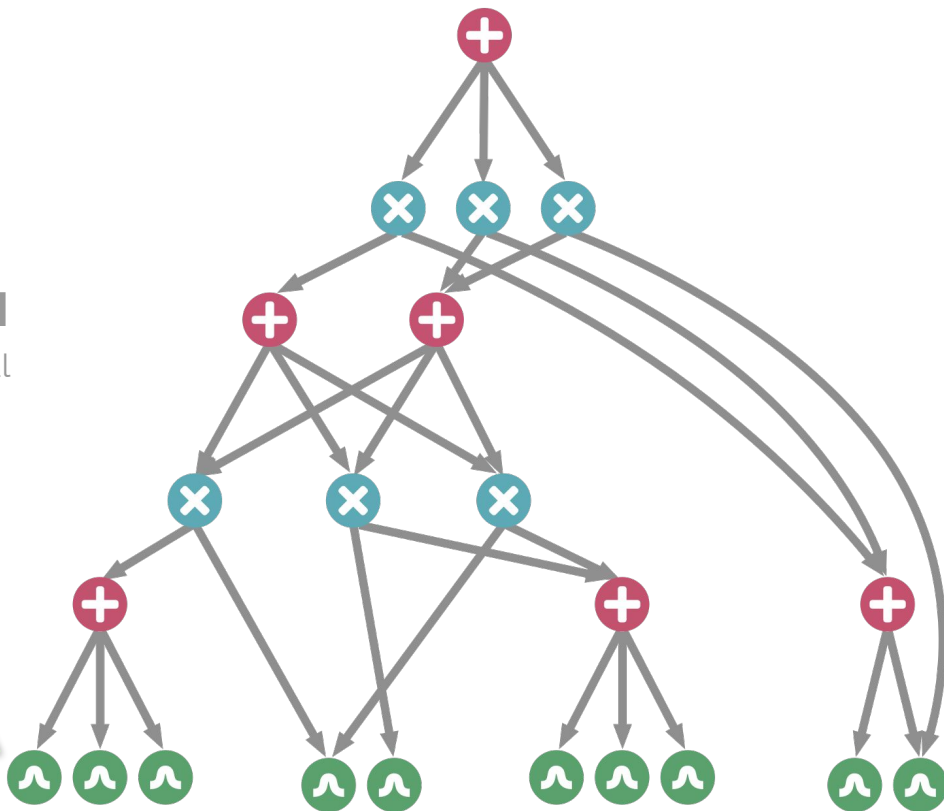
DIFFERENTIAL APPROACH

SPN can represent a network polynomial

BACK PROPAGATION

derivatives can be evaluated for all random variables of the model

$$\frac{\partial \mathcal{S}(\mathbf{e})}{\partial \lambda_{X=x}} = \mathcal{S}(X = x, \mathbf{e} \setminus X)$$





tractable inference



SPNs follows a rigorous probabilistic structure with the benefit of tractable inference in the size of the network



RELATED WORK



NNFs

Darwiche

1999, 2001

Darwiche and Marquis

2002



AND/OR graphs

Dechter and Mateescu

2007



ACs

Darwiche

2003



NNs

Poon and Domingos

2011

Vergari et al.

2015

Sharir et al.

2018

Butz et al.

2019

PROBABILISTIC CIRCUITS

RELATED WORK



NNFs

Darwiche

1999, 2001

Darwiche and Marquis

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AND/OR graphs

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2019

An aerial photograph of a city, likely Toronto, showing a large park (Roncesvalles Park) with a lake (Roncesvalles Lake) in the foreground. The city skyline is visible in the background, including several high-rise buildings. The image is in black and white, with the text overlaid in color.

INTRO TO BAYESIAN NETWORKS AND CAUSALITY

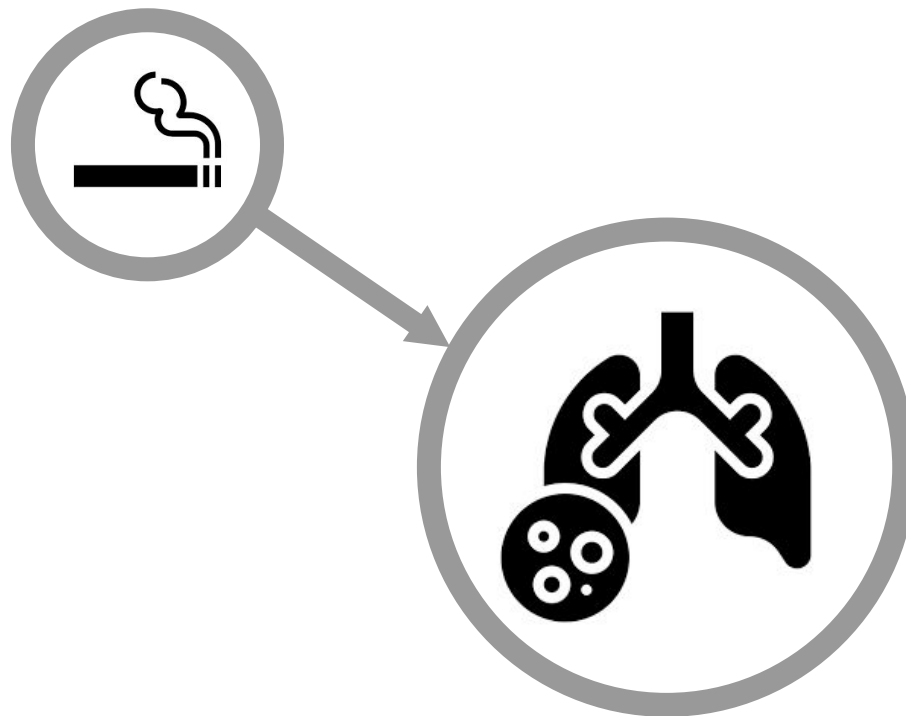
ANDRÉ E. DOS SANTOS

andreedsgithub.io

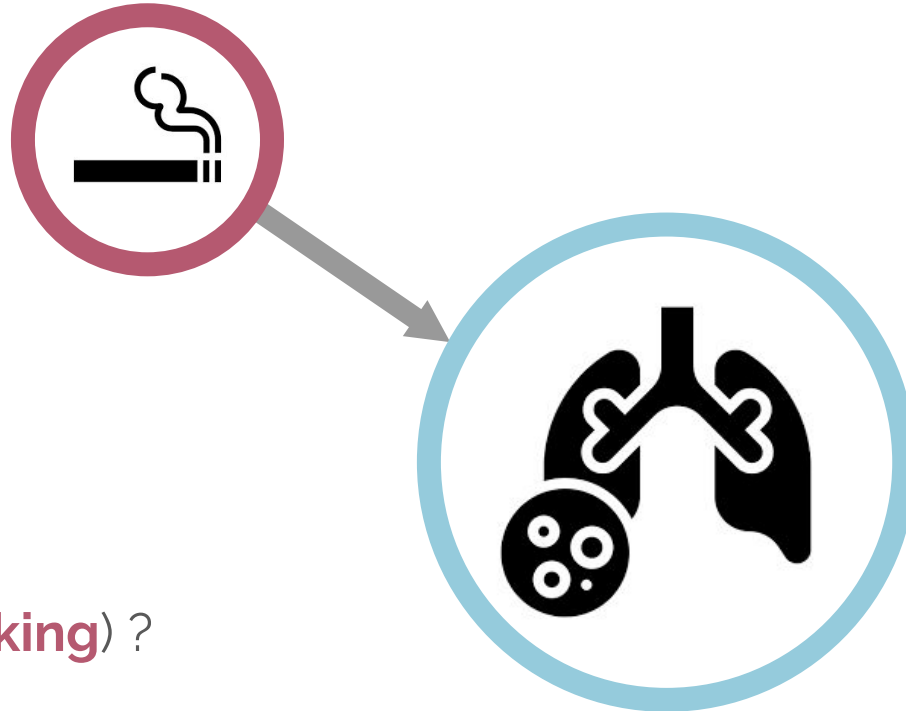
dossantos@ualberta.ca

2020

Does smoking cause cancer?



Does smoking cause cancer?



$p(\text{cancer} \mid \text{smoking}) ?$

Causality

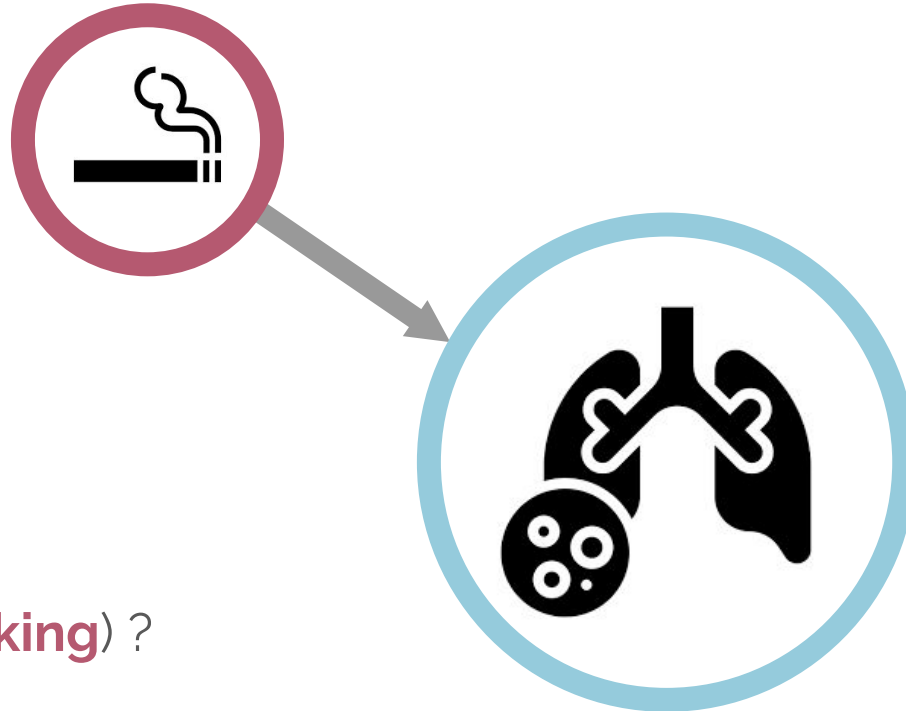


Causality

- Gives proper vocabulary for causation
- Difference with **correlation**
- Ladder of Causation: Association, Intervention, and Counterfactuals
- **seeing** vs **doing**



Does smoking cause cancer?

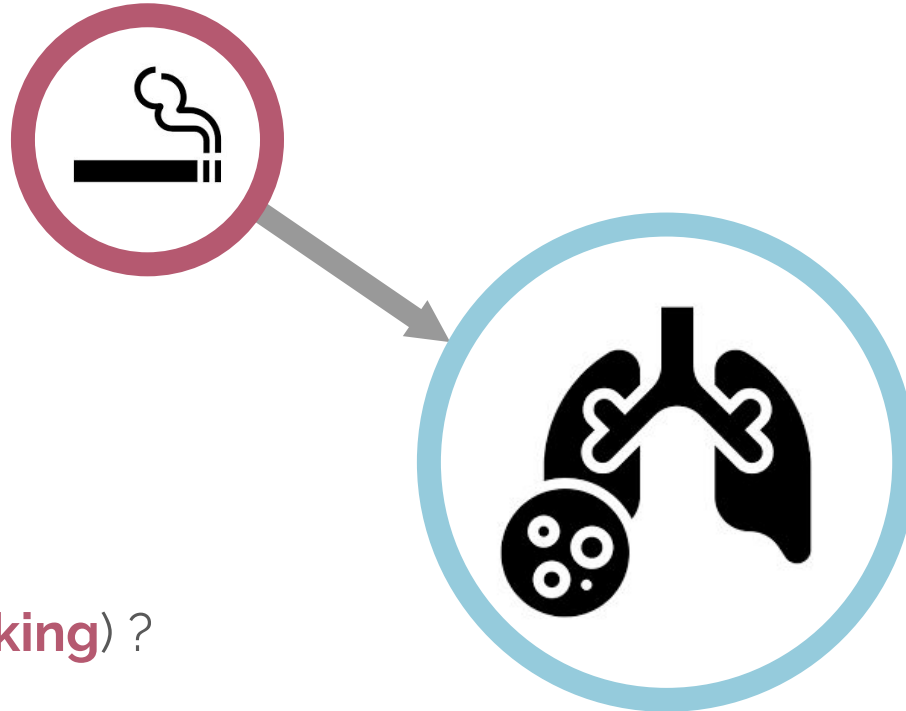


$p(\text{cancer} \mid \text{smoking}) ?$



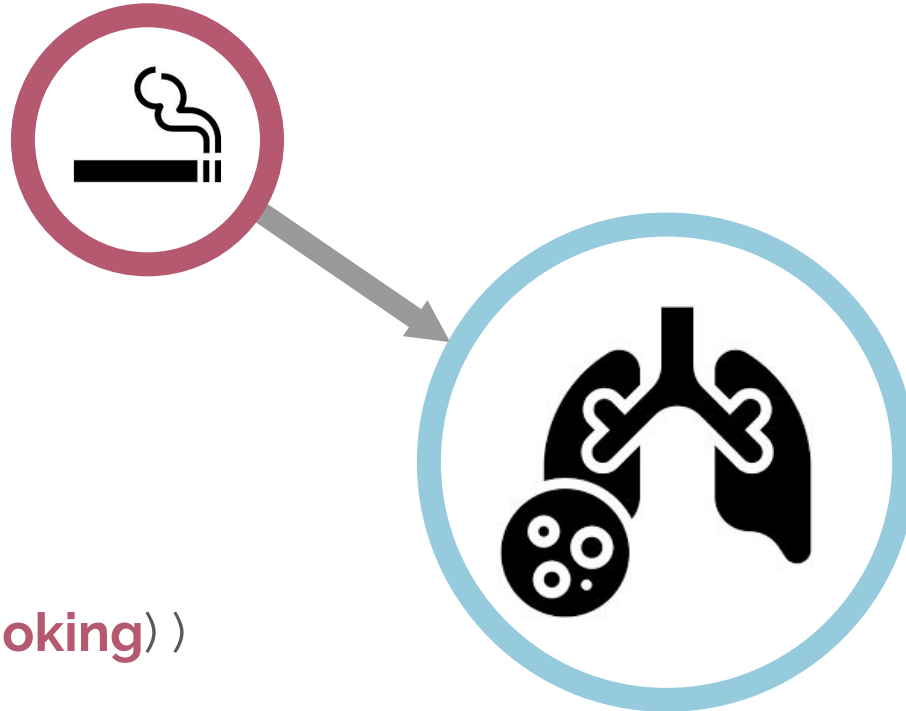


Does smoking cause cancer?

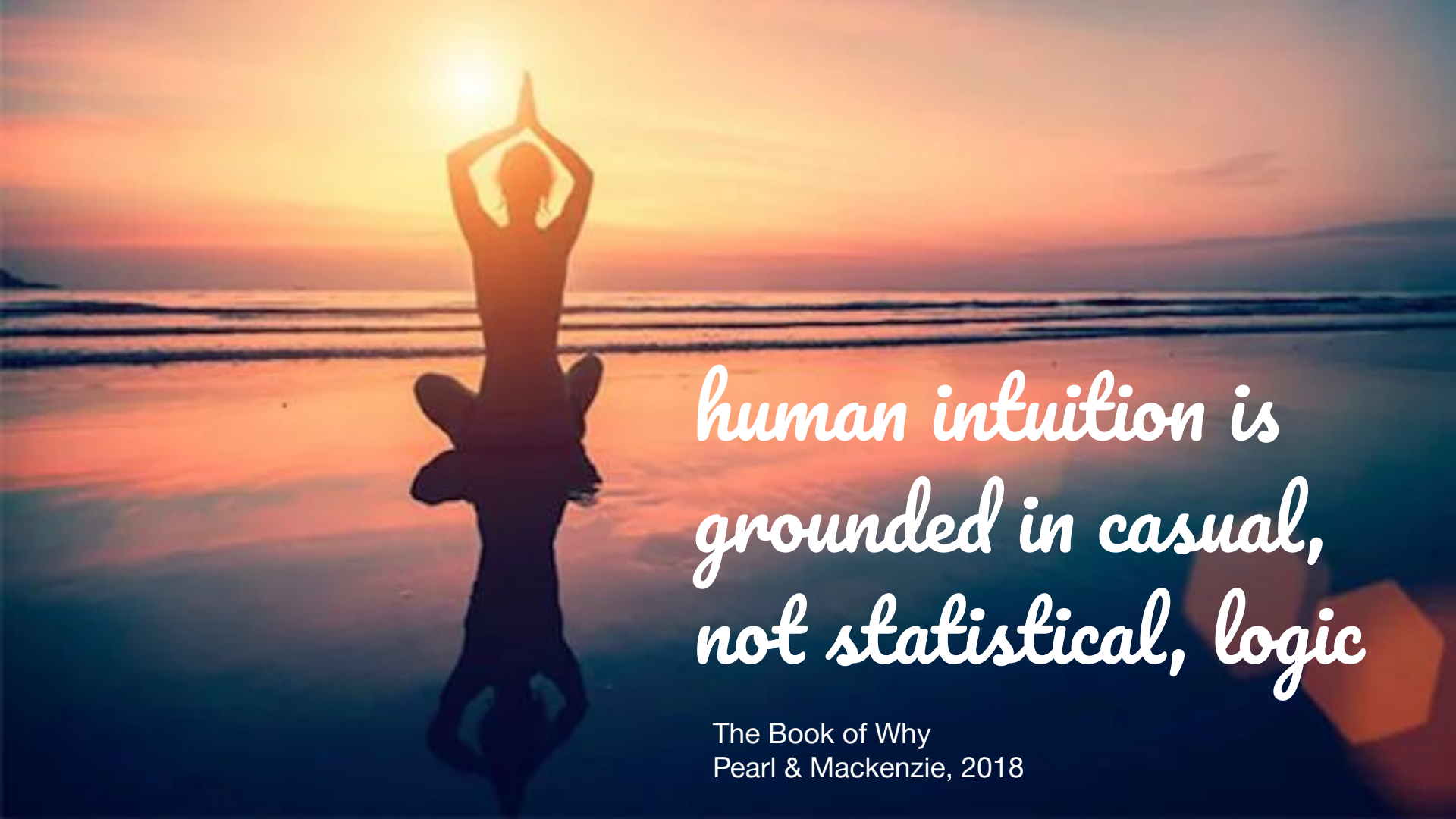


$p(\text{cancer} \mid \text{smoking}) ?$

smoking does cause cancer!



$p(\text{cancer} \mid \text{do}(\text{smoking}))$

The background of the slide is a photograph of a sunset over a body of water. Two people are silhouetted against the bright sun, which is low on the horizon. They are in a yoga pose, with one person standing on the shoulders of the other, both with their arms raised and hands joined in a prayer position (Anjali Mudra) directly in front of the sun. The water in the foreground is calm, reflecting the colors of the sky and the silhouettes of the people. The sky transitions from a deep blue at the top to a bright orange and yellow near the horizon.

*human intuition is
grounded in casual,
not statistical, logic*

The Book of Why
Pearl & Mackenzie, 2018

***Data do not understand causes
and effects; humans do.***



The Book of Why
Pearl & Mackenzie, 2018

data are profoundly dumb

The Book of Why
Pearl & Mackenzie, 2018

