INTRO TO BAYESIAN NETWORKS AND CAUSALITY

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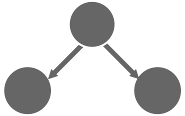
2020

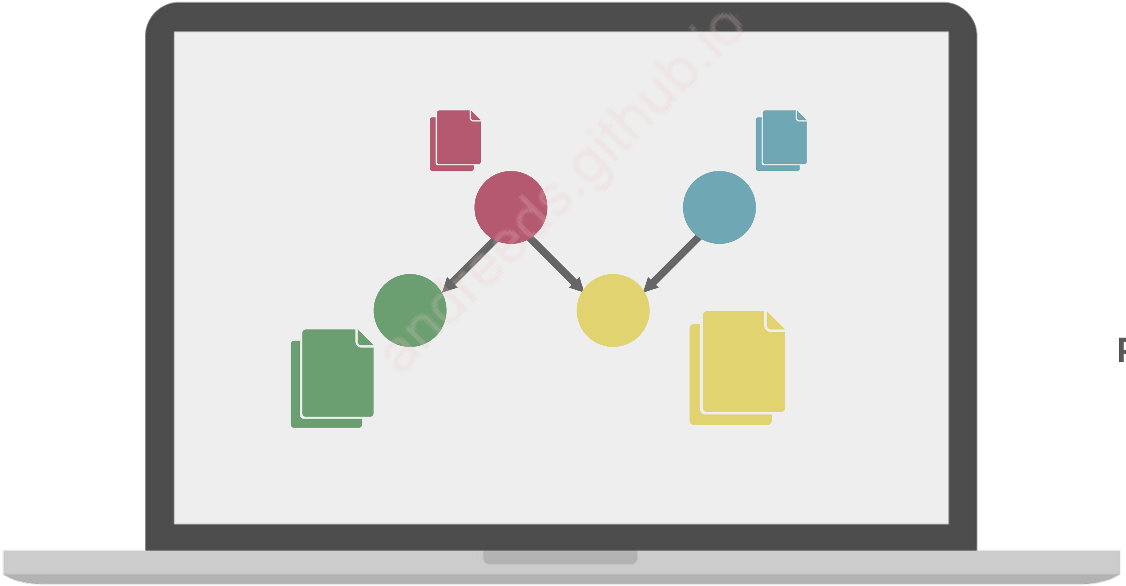
BAYESIAN NETWORKS

PROBABILISTIC GRAPHICAL MODEL



DIRECTED ACYCLIC GRAPH

DAG

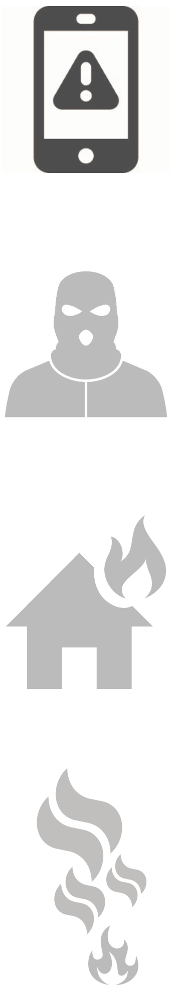


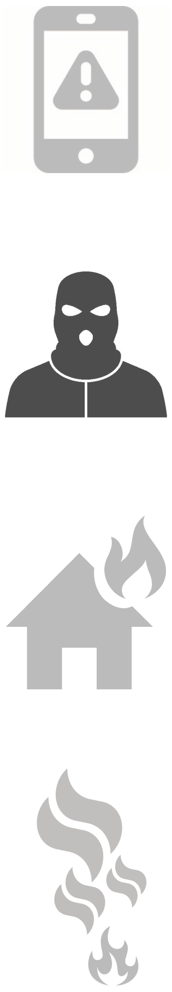
CONDITIONAL PROBABILISTIC TABLES

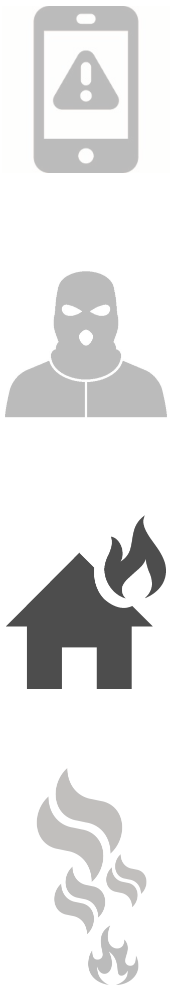
CPTs

Pearl

1988


SECURITY
ALARM


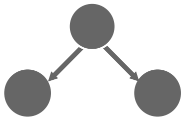







BAYESIAN NETWORKS

PROBABILISTIC GRAPHICAL MODEL



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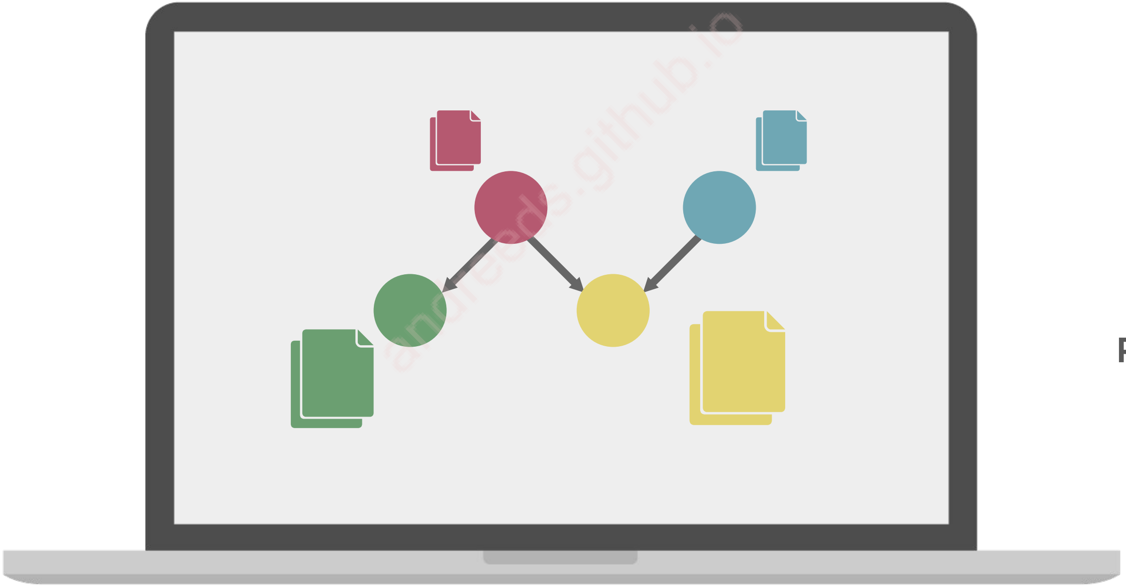

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CPTs

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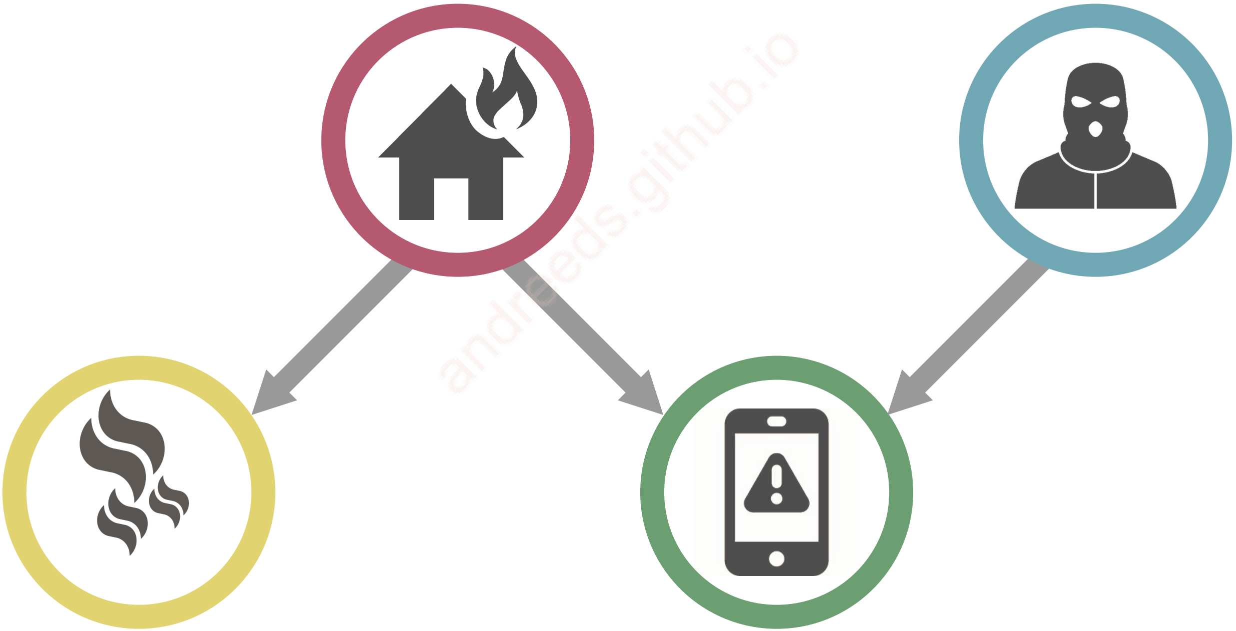
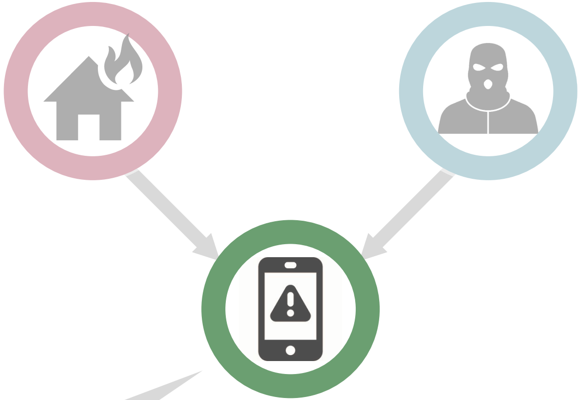
BN EXAMPLE



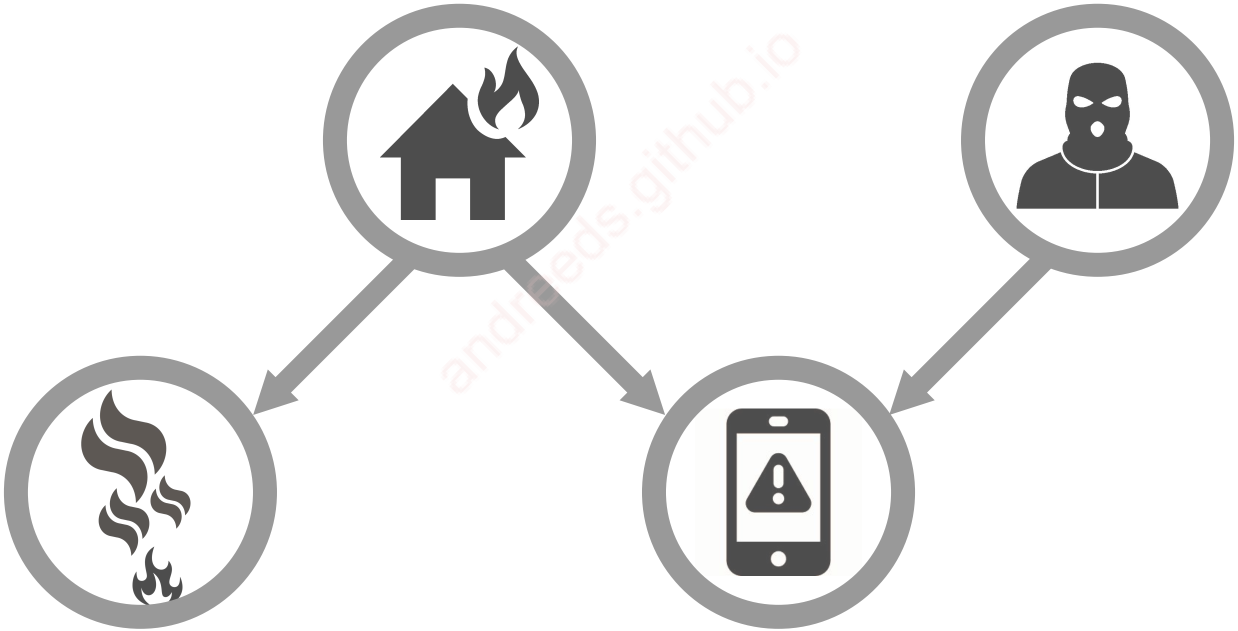
U = { fire, burglar, smoke, app }

CPT EXAMPLE

app	fire	burglar	p(app | fire, 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



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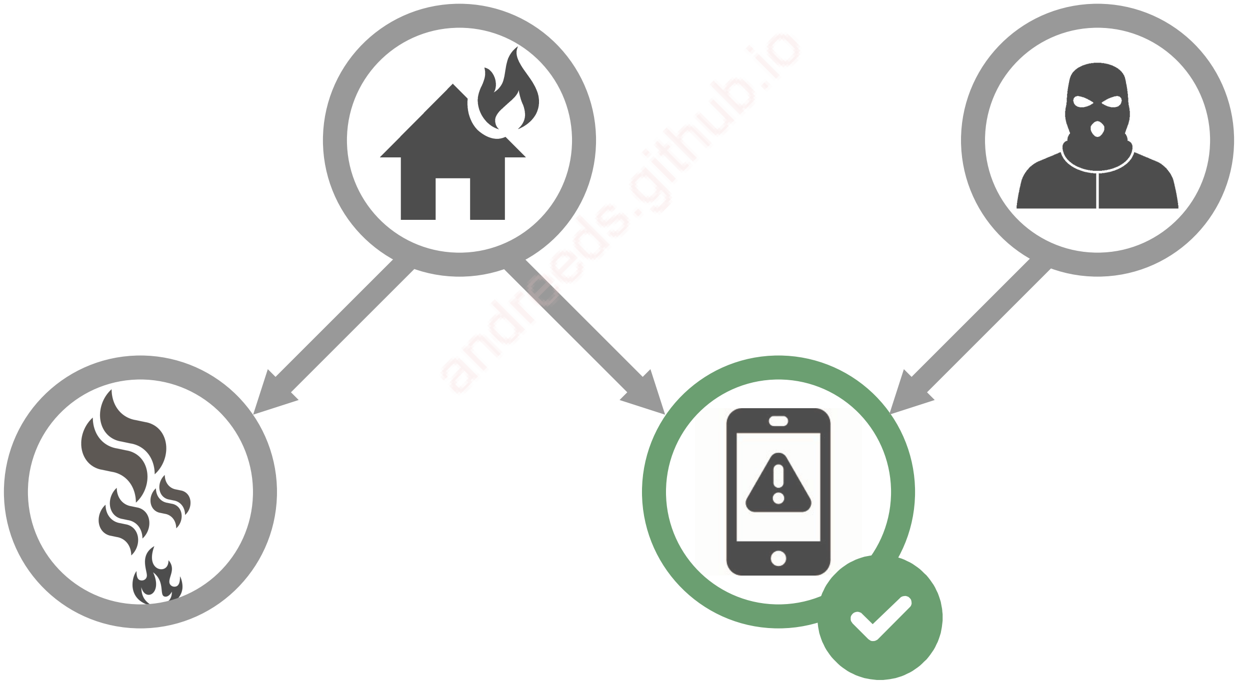

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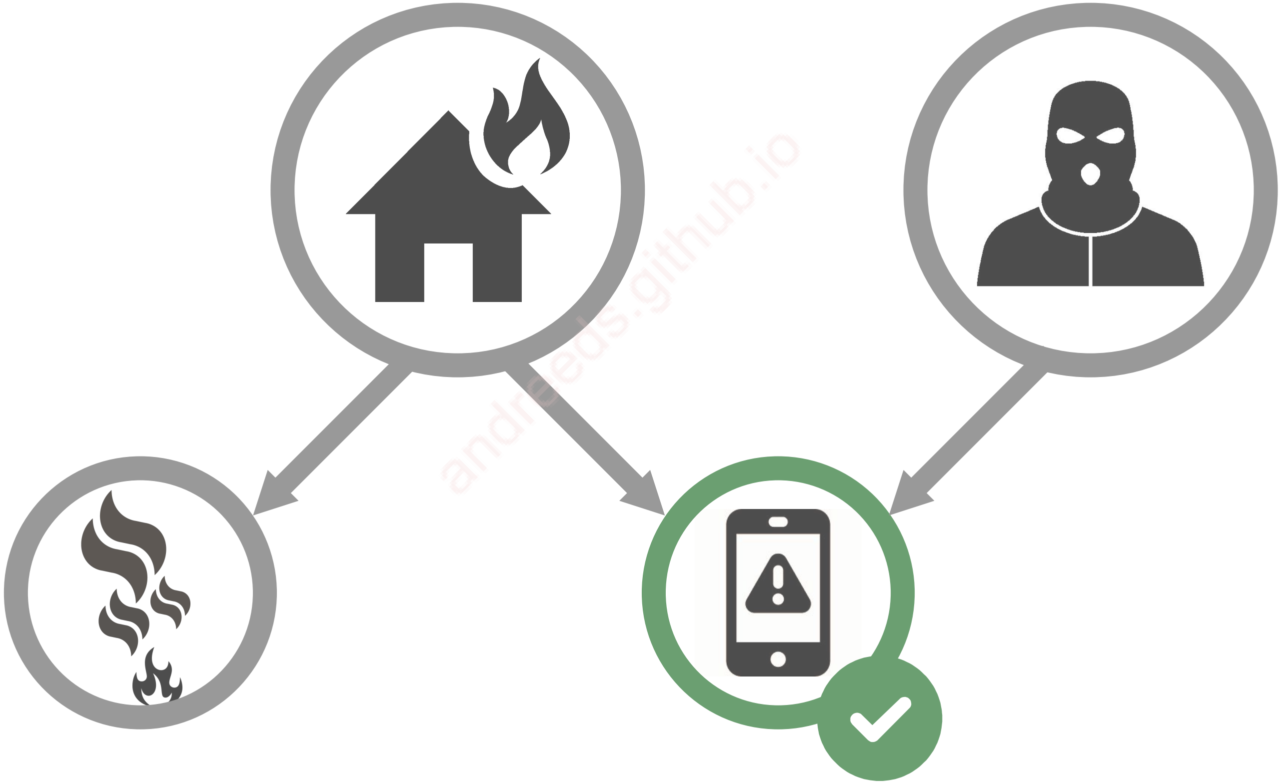

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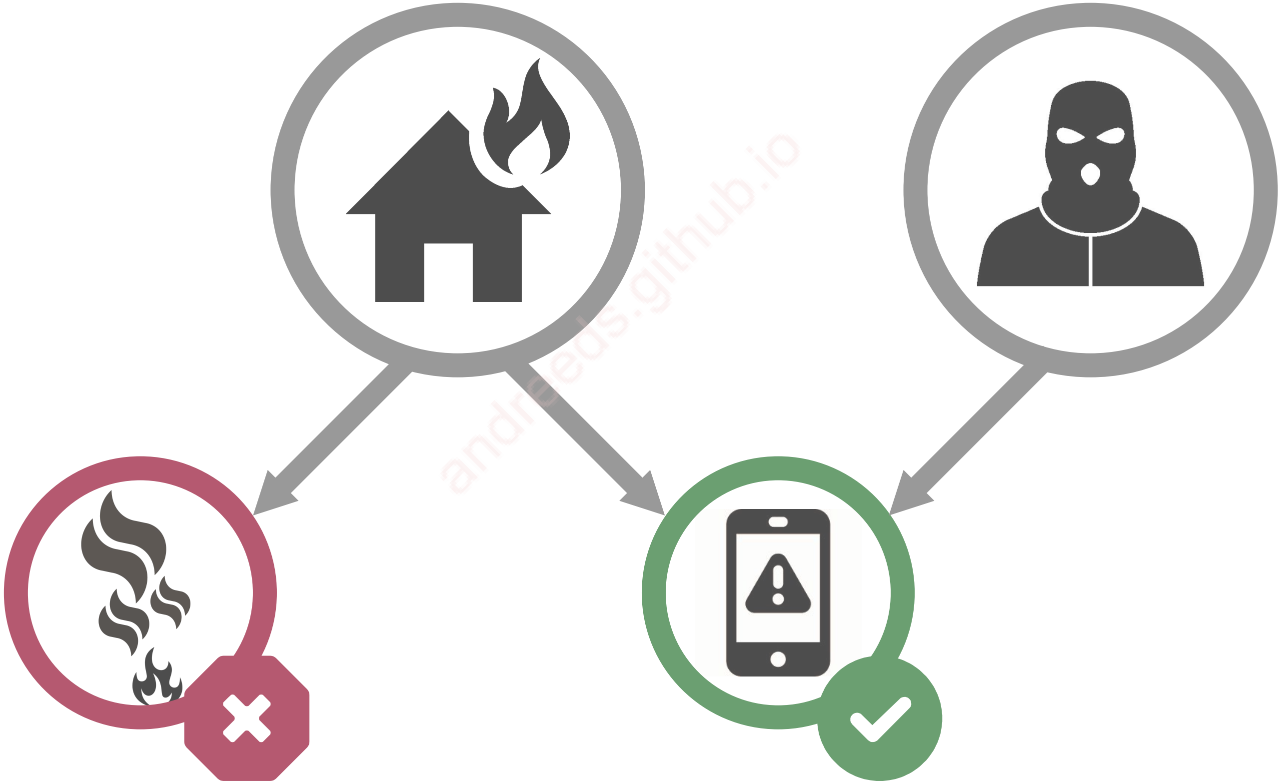

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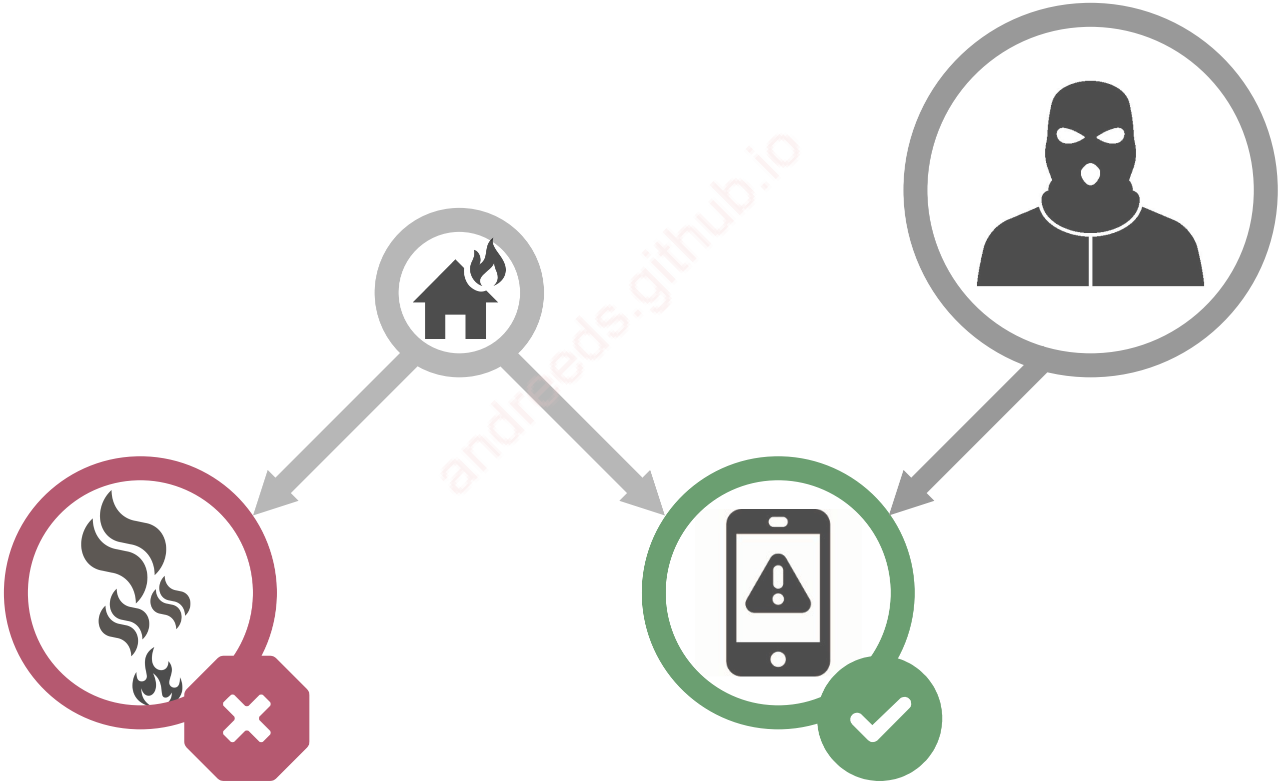

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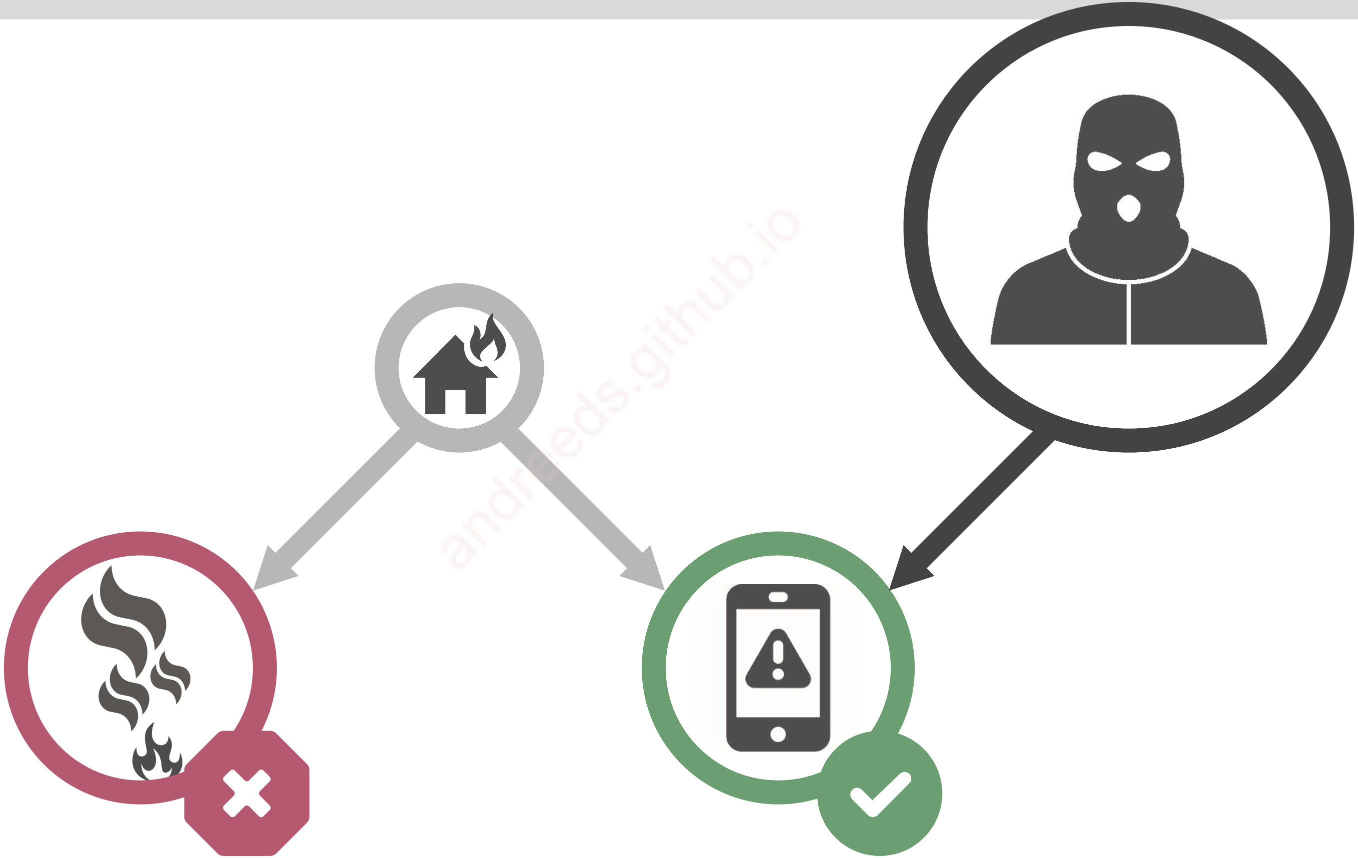
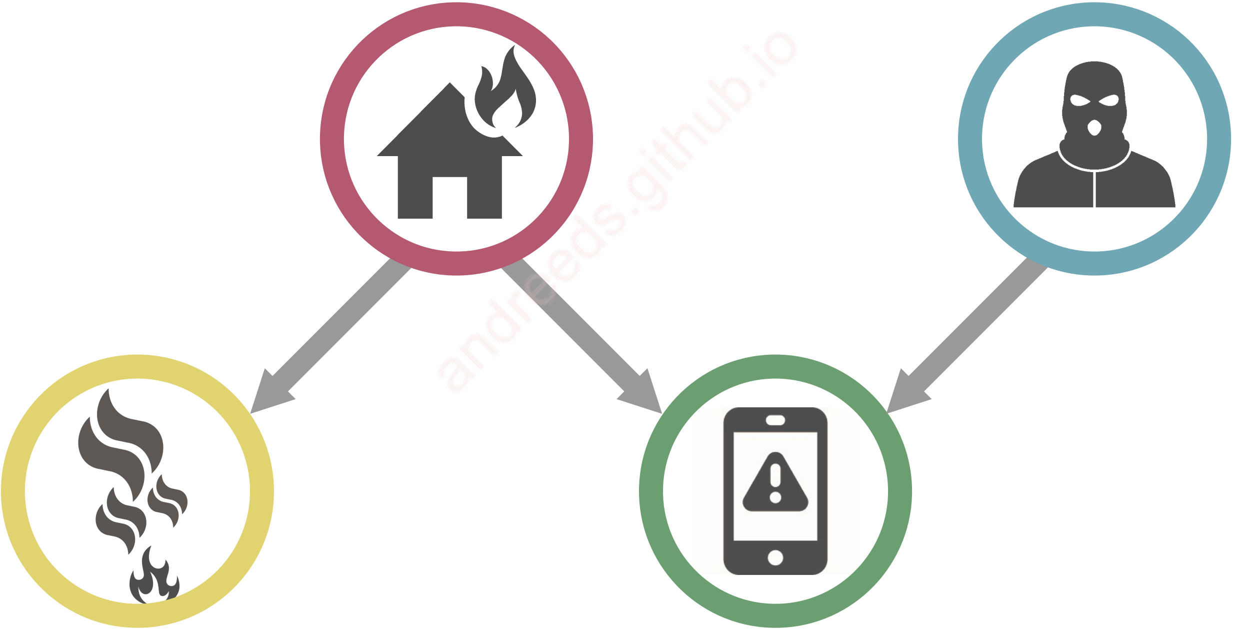
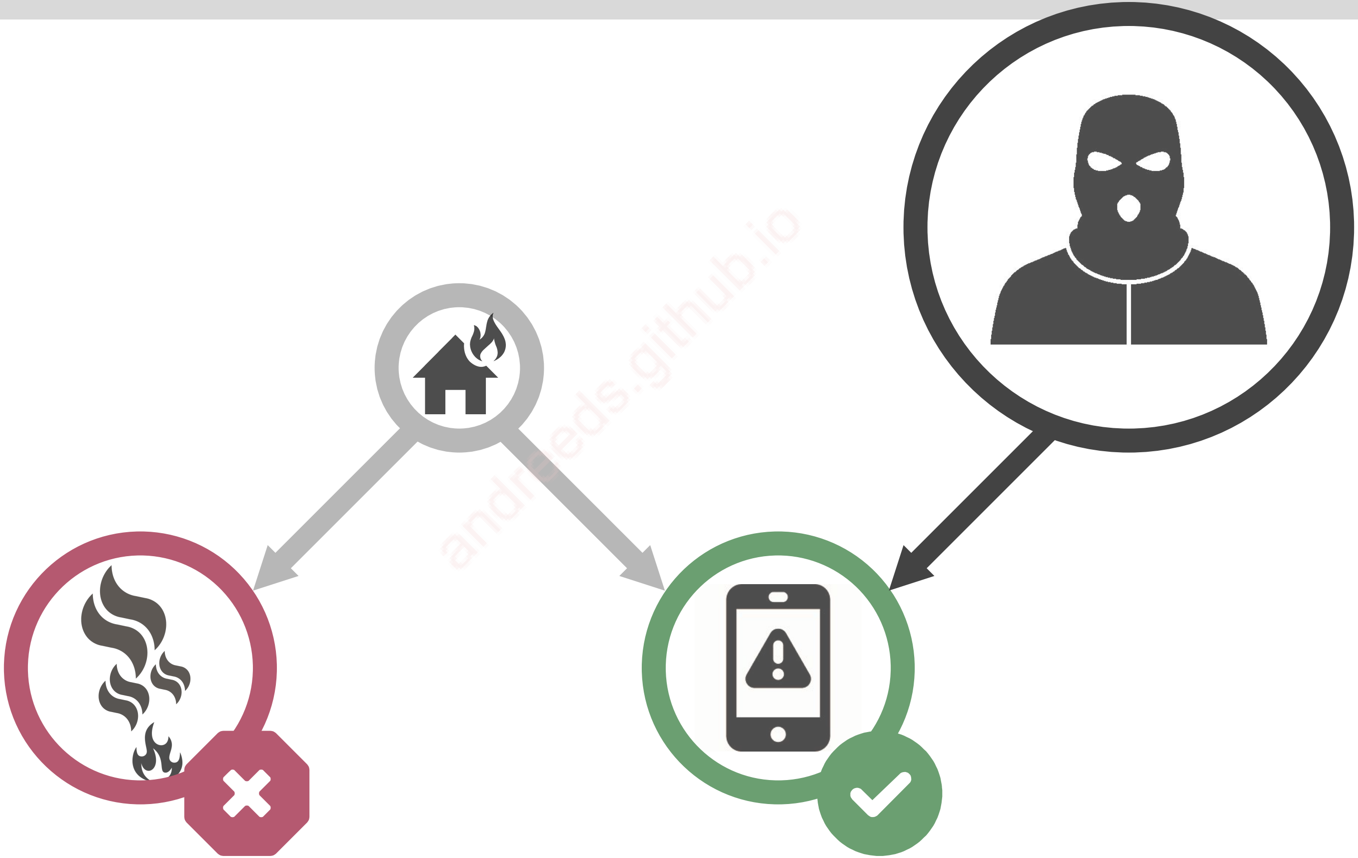


The ∏ of the CPTs is a **joint probability distribution** $\rho(\mathbf{U})$

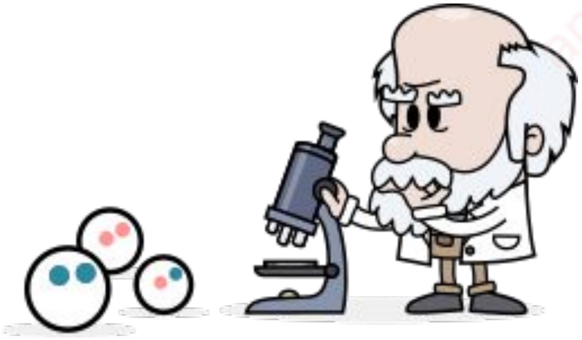


$\rho(\mathbf{U}) = \rho(\text{fire}) \cdot \rho(\text{burglar}) \cdot \rho(\text{smoke} \mid \text{fire}) \cdot \rho(\text{app} \mid \text{fire}, \text{burglar})$

BN EXAMPLE



DARWINIAN NETWORKS LAB



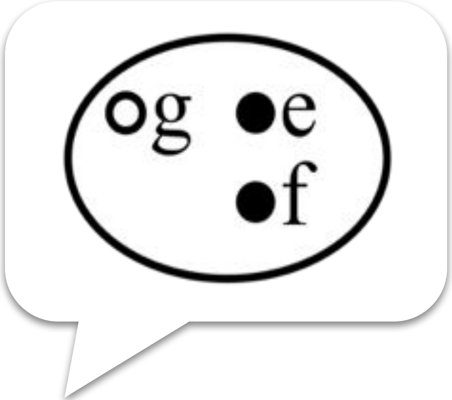
Scan me

DARWINIAN NETWORKS

DARWINIAN NETWORKS

(CAI 2015, CI 2016)

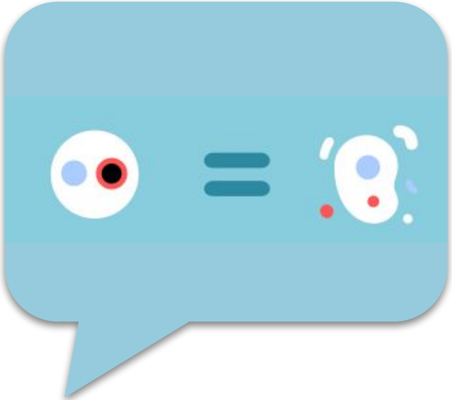
CLEVER WAY TO VIEW CPTs



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

DARWINIAN NETWORKS

POPULATION OF MICROORGANISMS

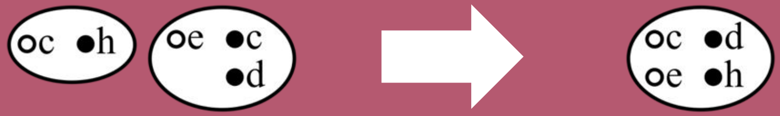


$$P(g|e,f)$$

MULTIPLICATION IS

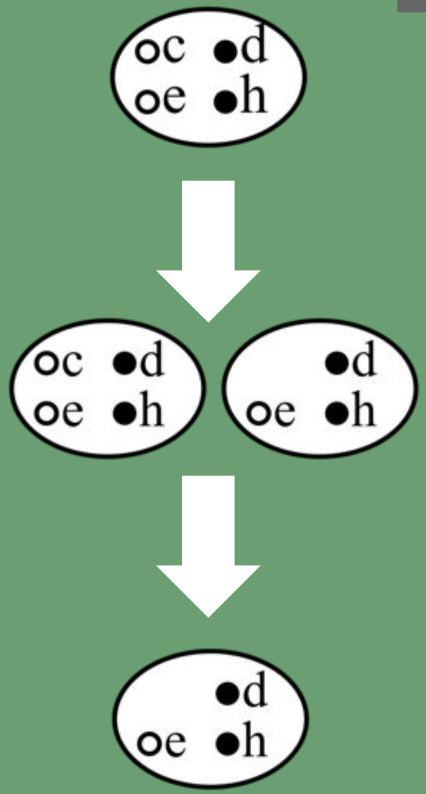
MERGE

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



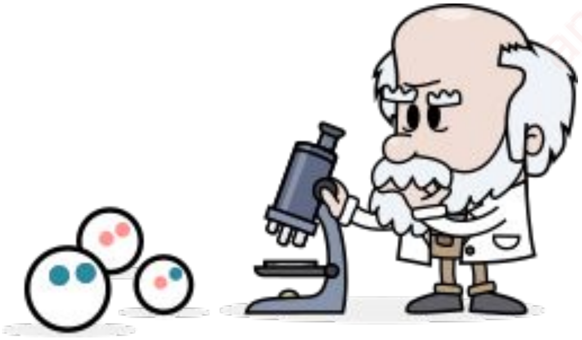
$$P(c|h) \cdot P(e|c,d) \quad = \quad P(c,e|d,h)$$

MARGINALIZATION IS REPLICATION AND NATURAL SELECTION



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

DARWINIAN NETWORKS LAB



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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

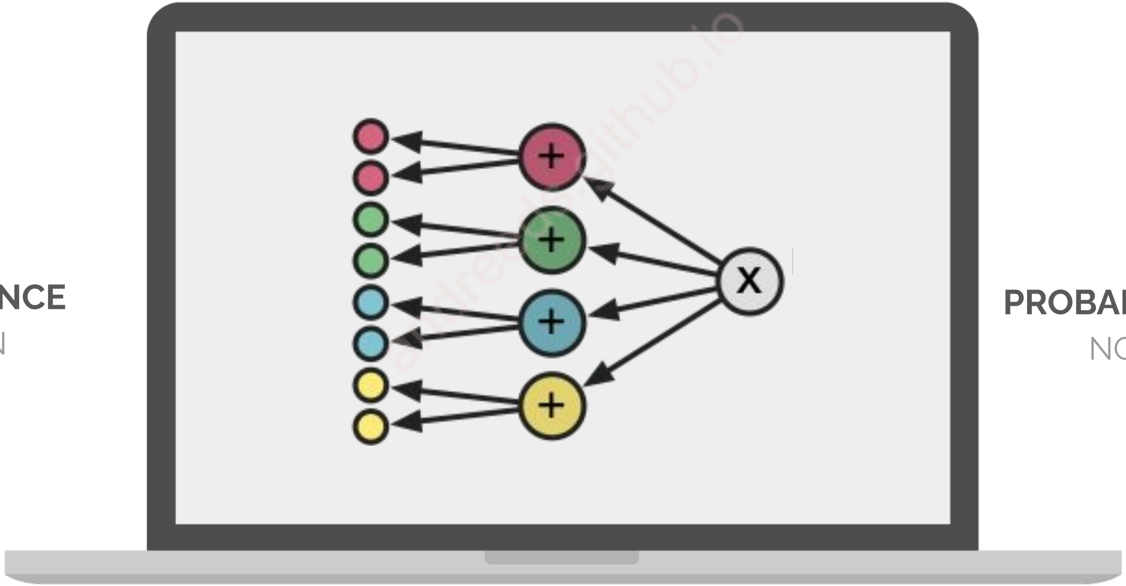
NP-hard Inference

Inference in BNs is a NP-hard task

SUM-PRODUCT NETWORKS

GENERATIVE DEEP LEARNING MODEL

EFFICIENT INFERENCE
UNDER CERTAIN CONDITIONS

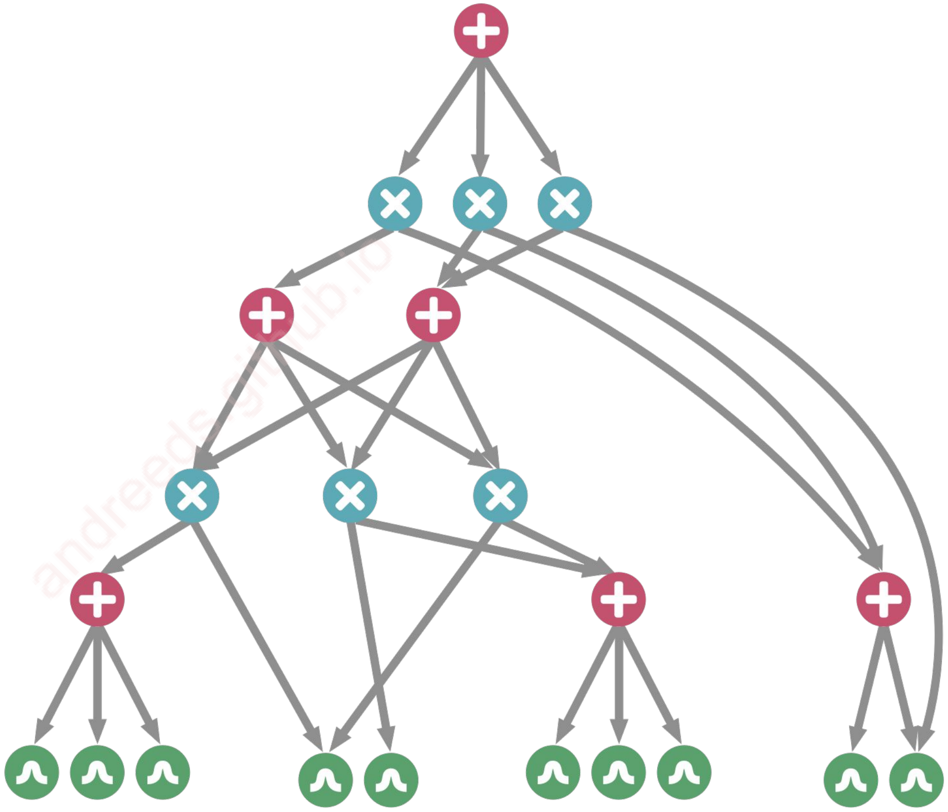


PROBABILISTIC REASONING
NOT A "BLACK BOX"

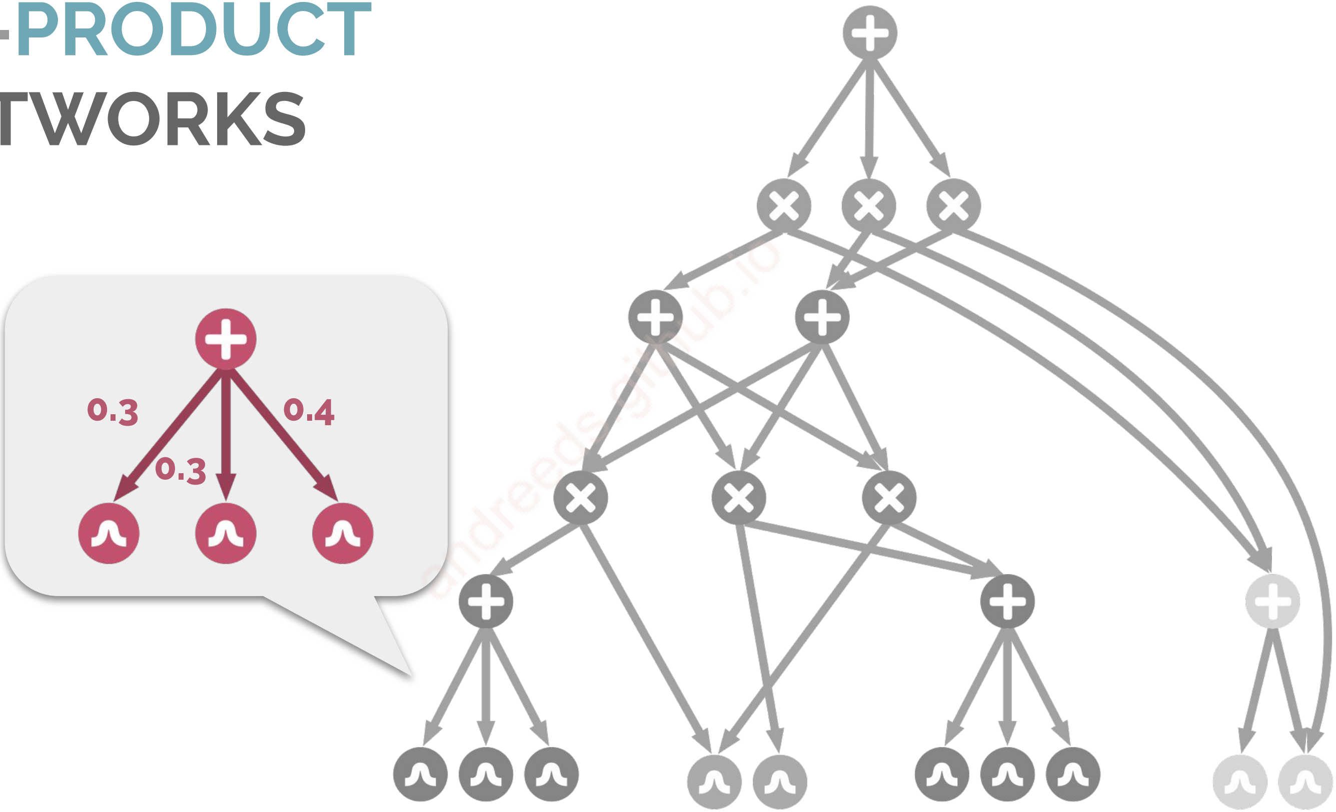
Poon and Domingos

2011

SUM-PRODUCT NETWORKS



SUM-PRODUCT NETWORKS



SUM-PRODUCT NETWORKS

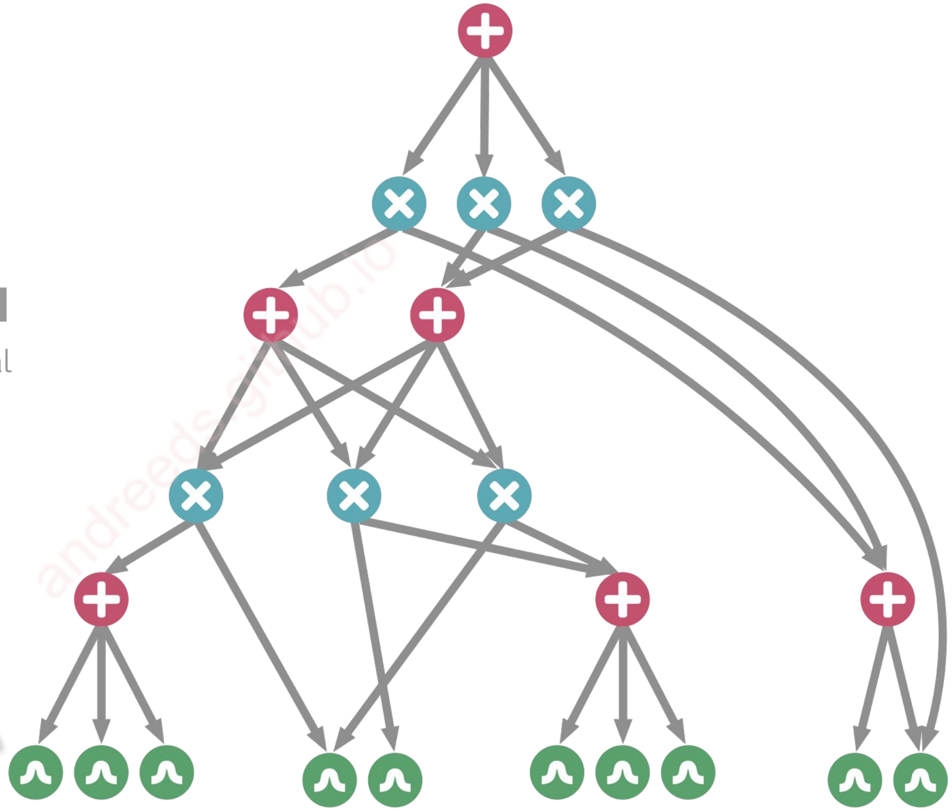
DIFFERENTIAL APPROACH

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 benet of tractable inference in the size of the network

RELATED WORK

NNFs

Darwiche
1999, 2001
Darwiche and Marquis
2002

AND/OR graphs

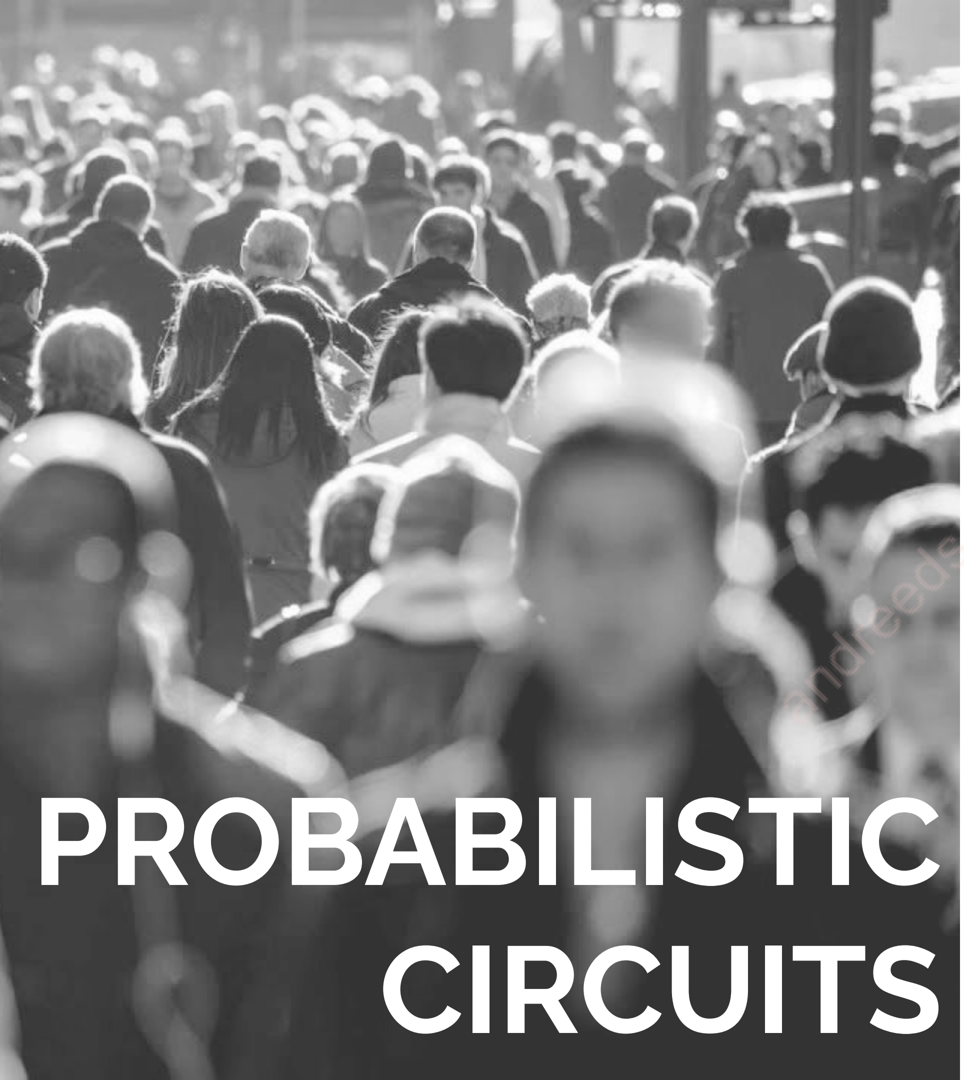
Dechter and Mateescu
2007

ACs

Darwiche
2003

NNs

Poon and Domingos
2011
Vergari et al.
2015
Sharir et al.
2018
Butz et al.
2019



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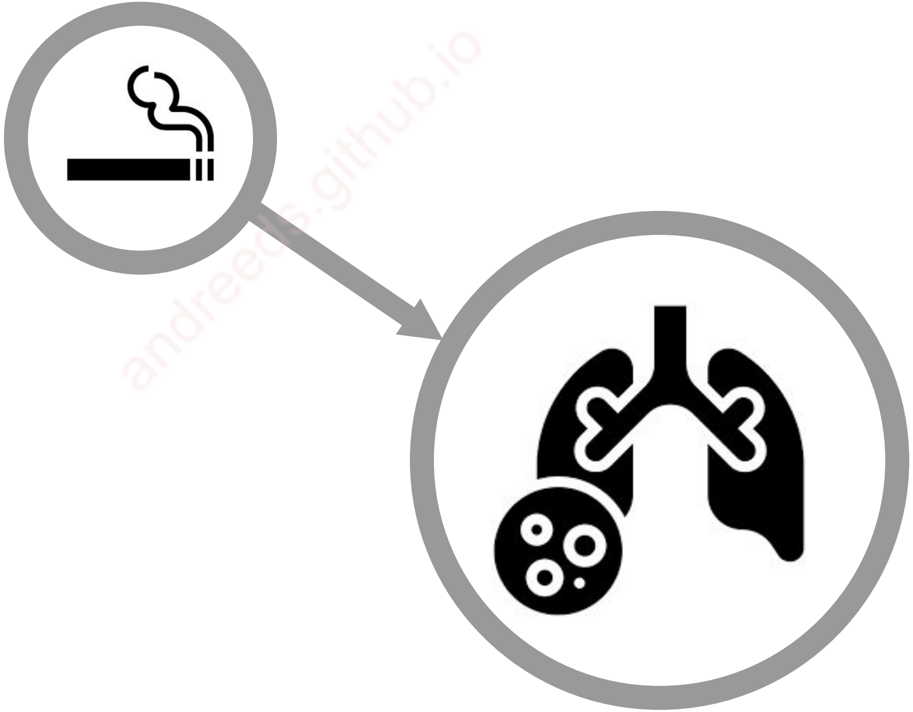
Does smoking cause cancer?



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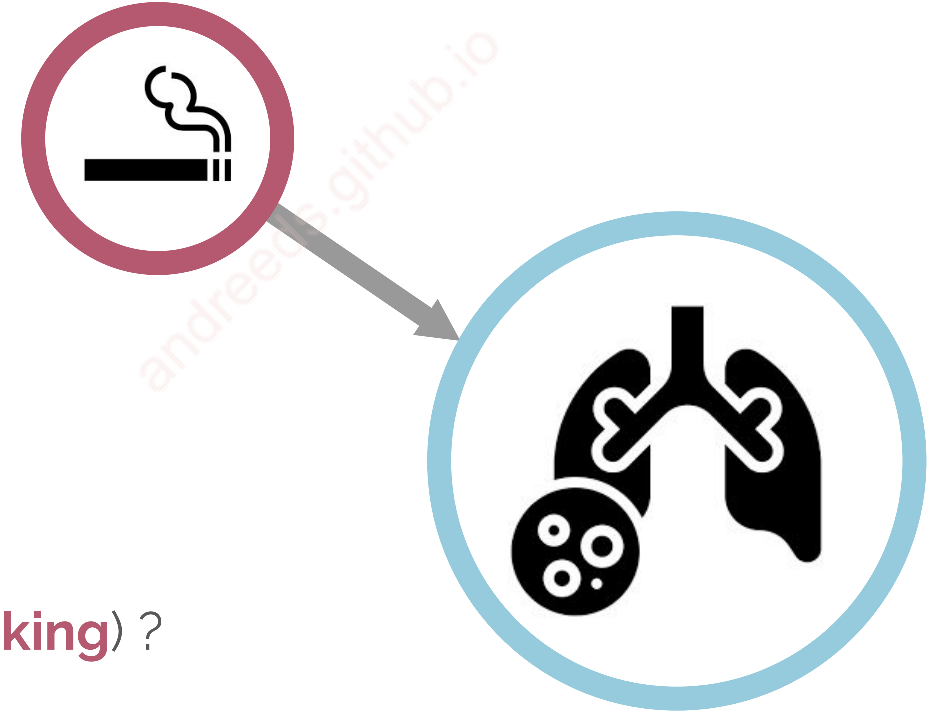


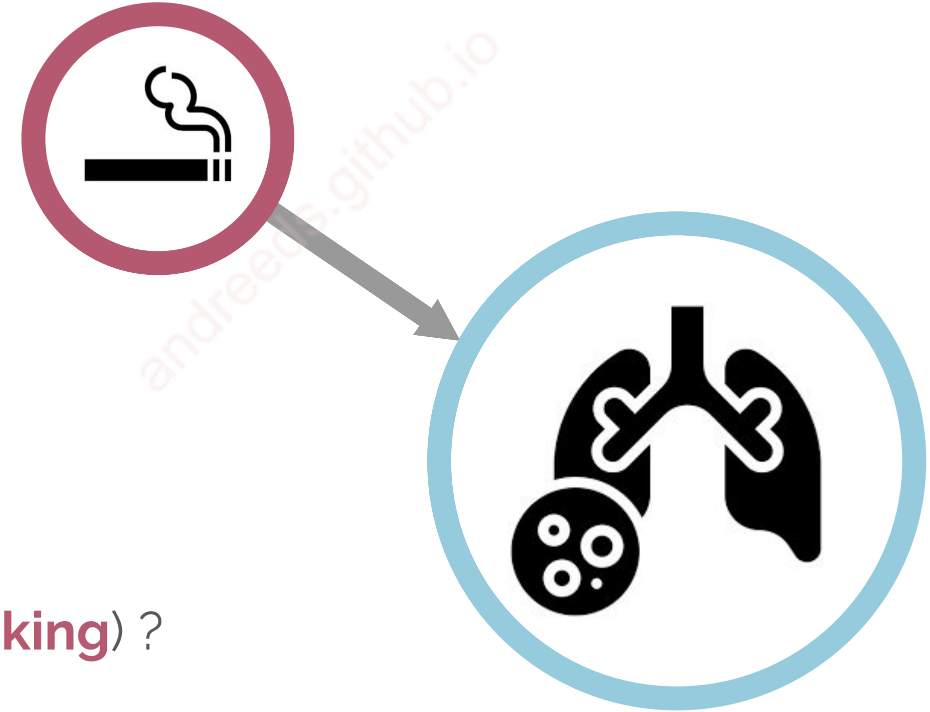
p(cancer | smoking) ?

Causality

Causality

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

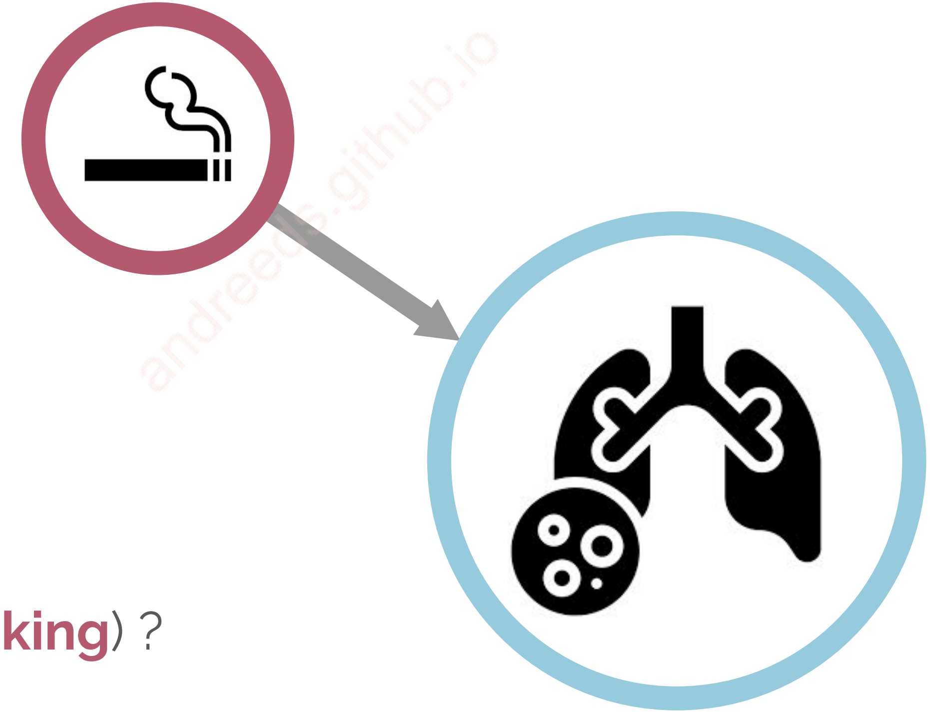
Does smoking cause cancer?



ρ(cancer | smoking) ?

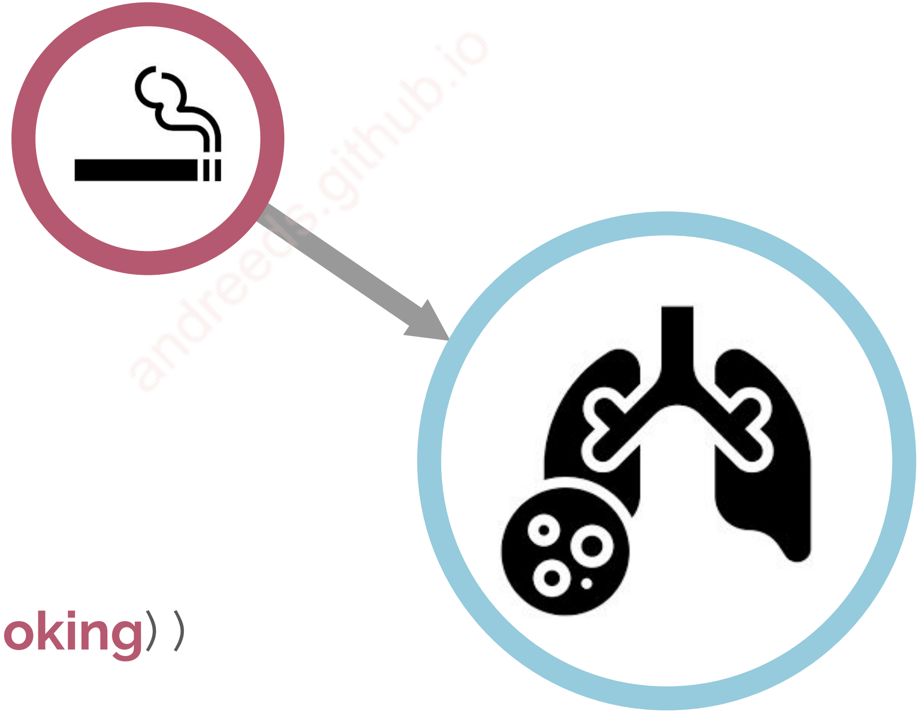

15

Does smoking cause cancer?

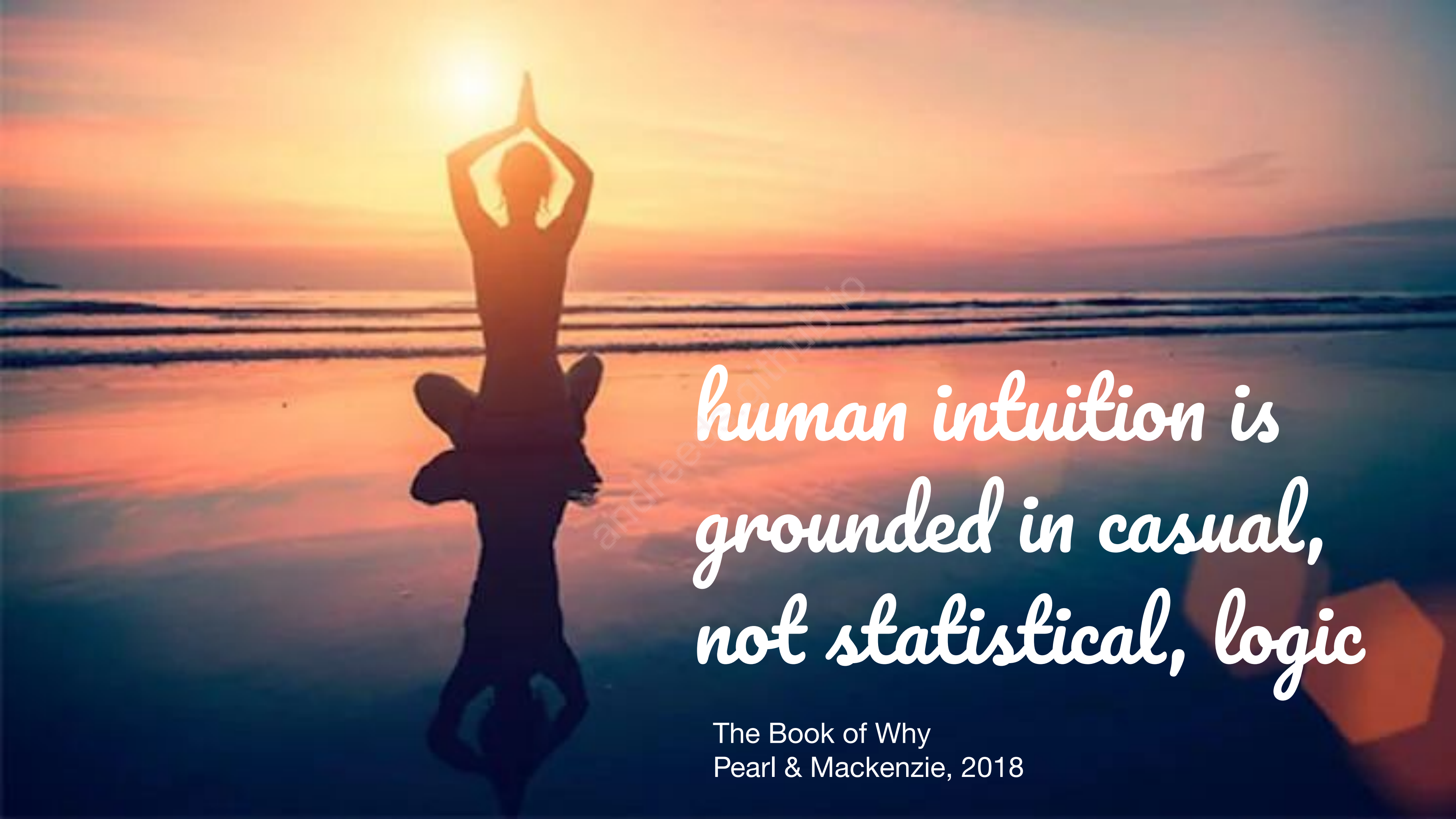


p(**cancer** | **smoking**) ?

smoking does cause cancer!

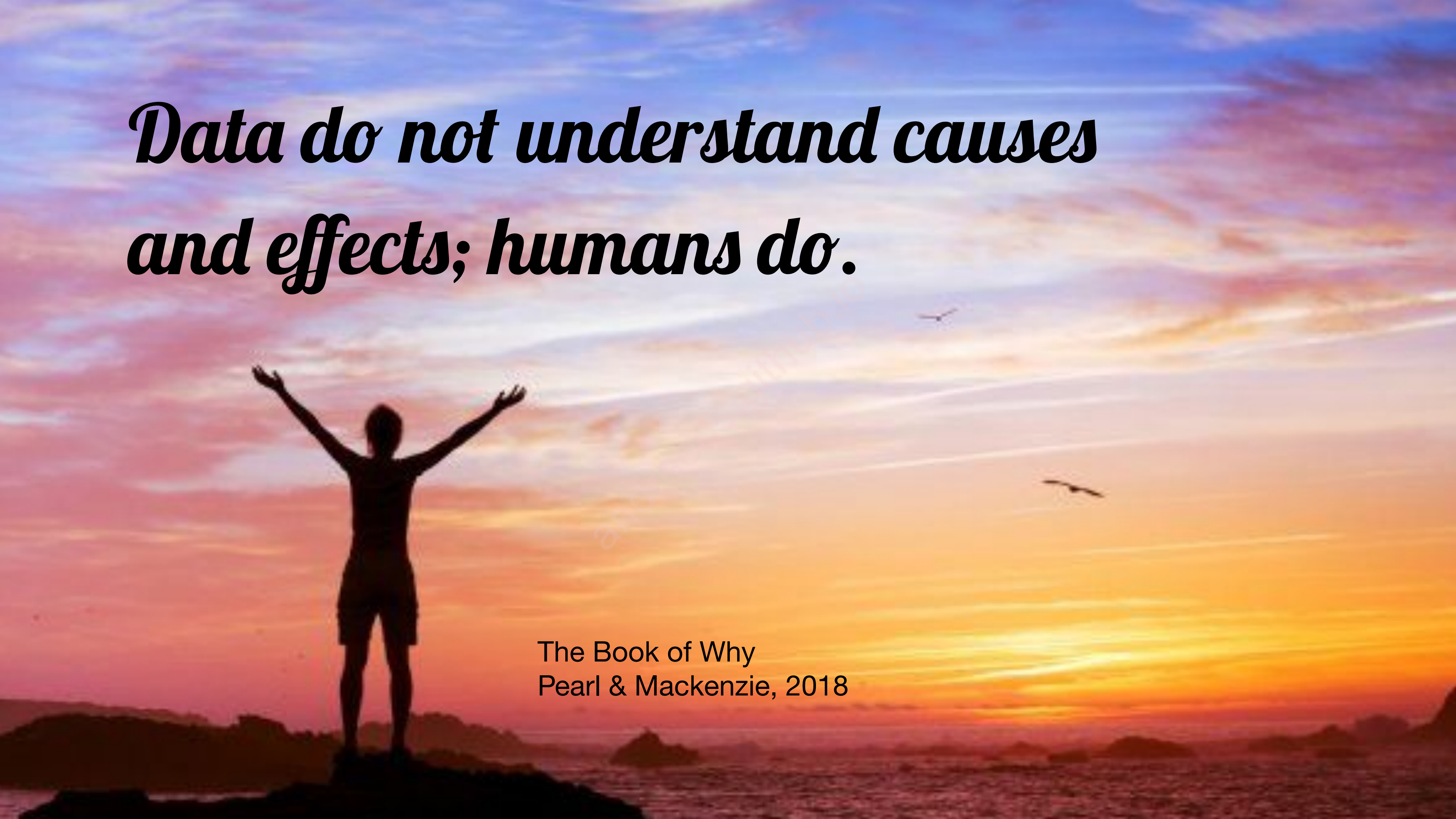


ρ(cancer | *do*(smoking))


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