INTRO TO BAYESIAN NETWORKS AND CAUSALITY

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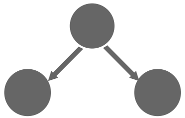
2020

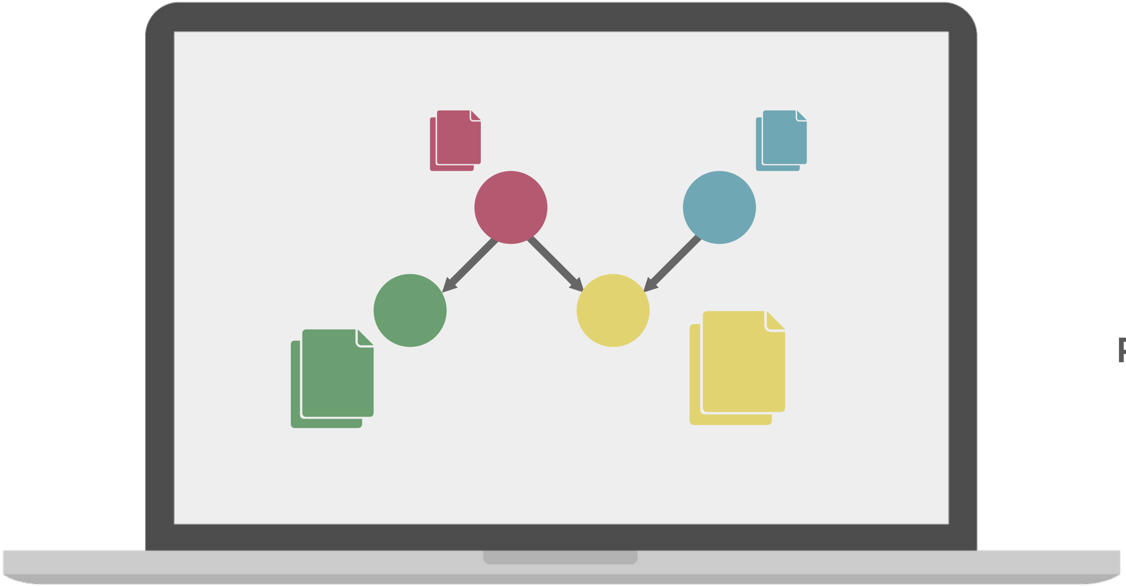
BAYESIAN NETWORKS

PROBABILISTIC GRAPHICAL MODEL



DIRECTED ACYCLIC GRAPH

DAG



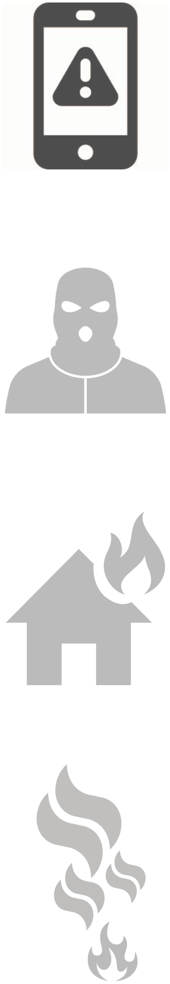
CONDITIONAL PROBABILISTIC TABLES

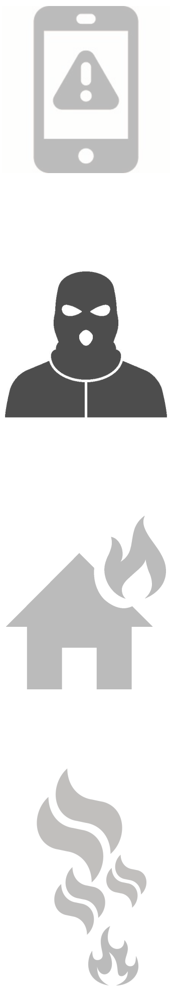
CPTs

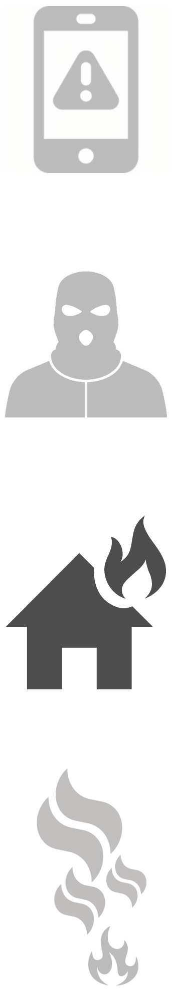
Pearl

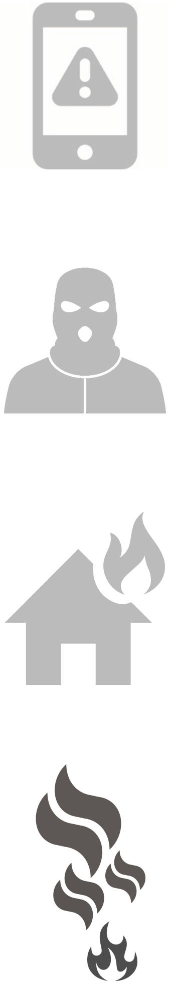
1988


SECURITY
ALARM



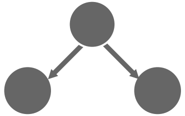


BAYESIAN NETWORKS

PROBABILISTIC GRAPHICAL MODEL



DIRECTED ACYCLIC GRAPH

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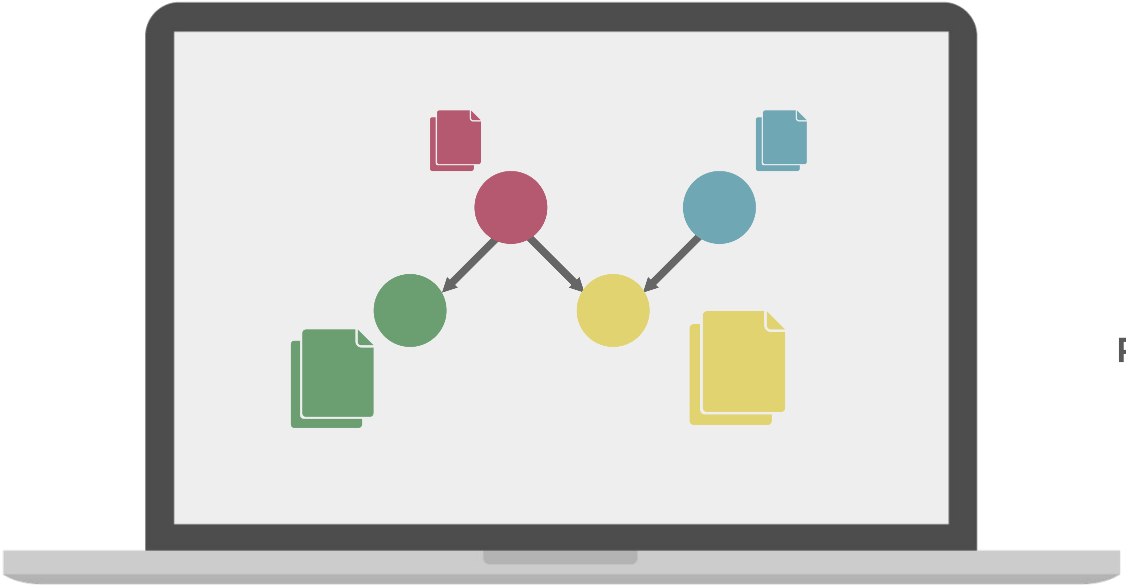

CONDITIONAL PROBABILISTIC TABLES

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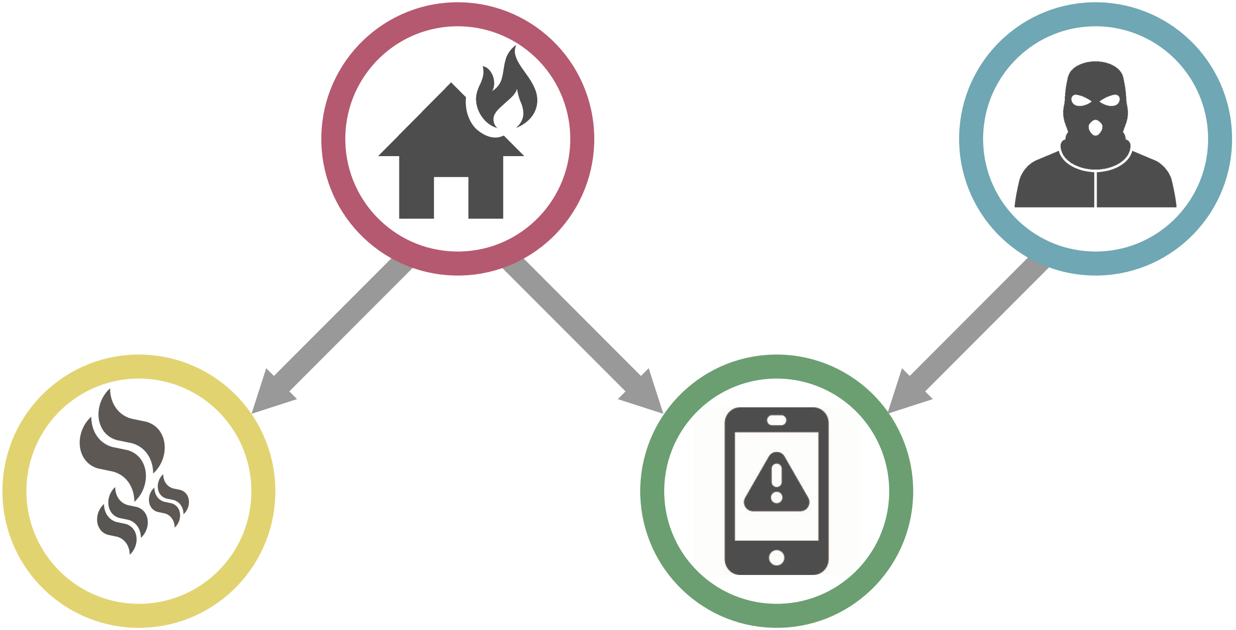
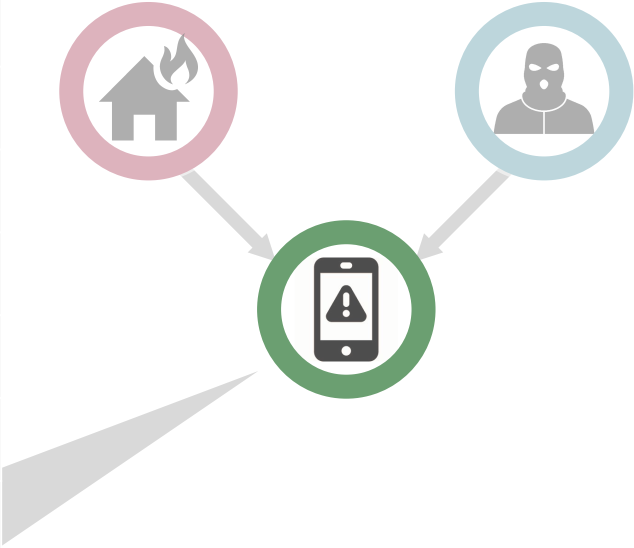
BN EXAMPLE



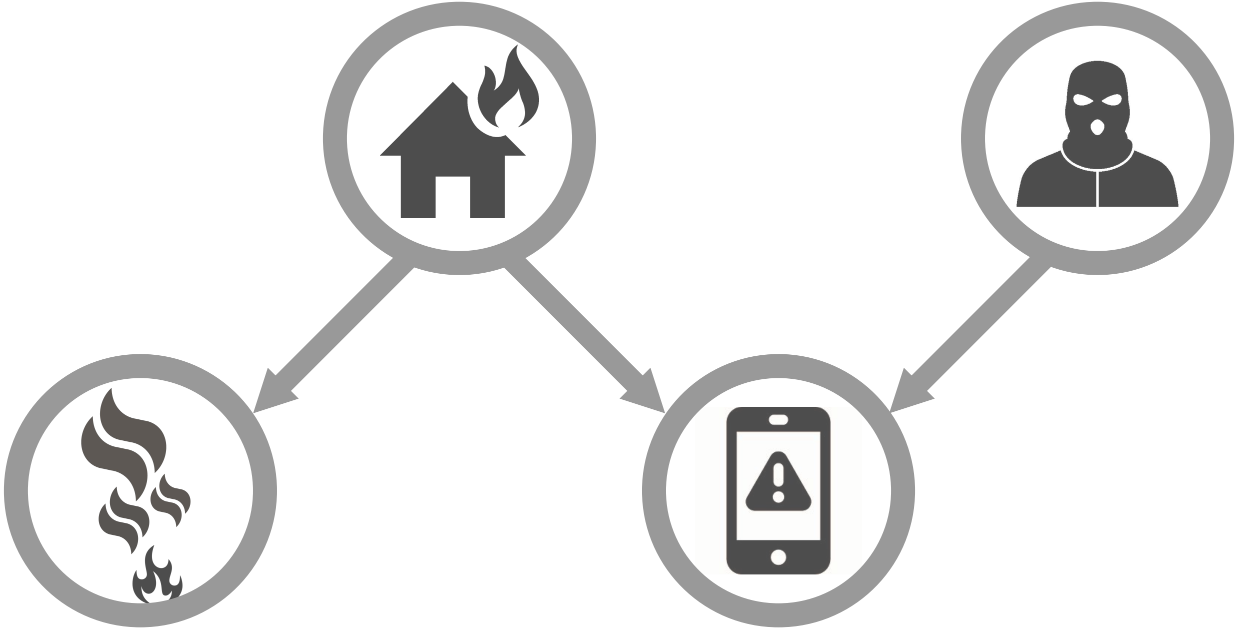
U = { fire, burglar, smoke, app }

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



BN EXAMPLE

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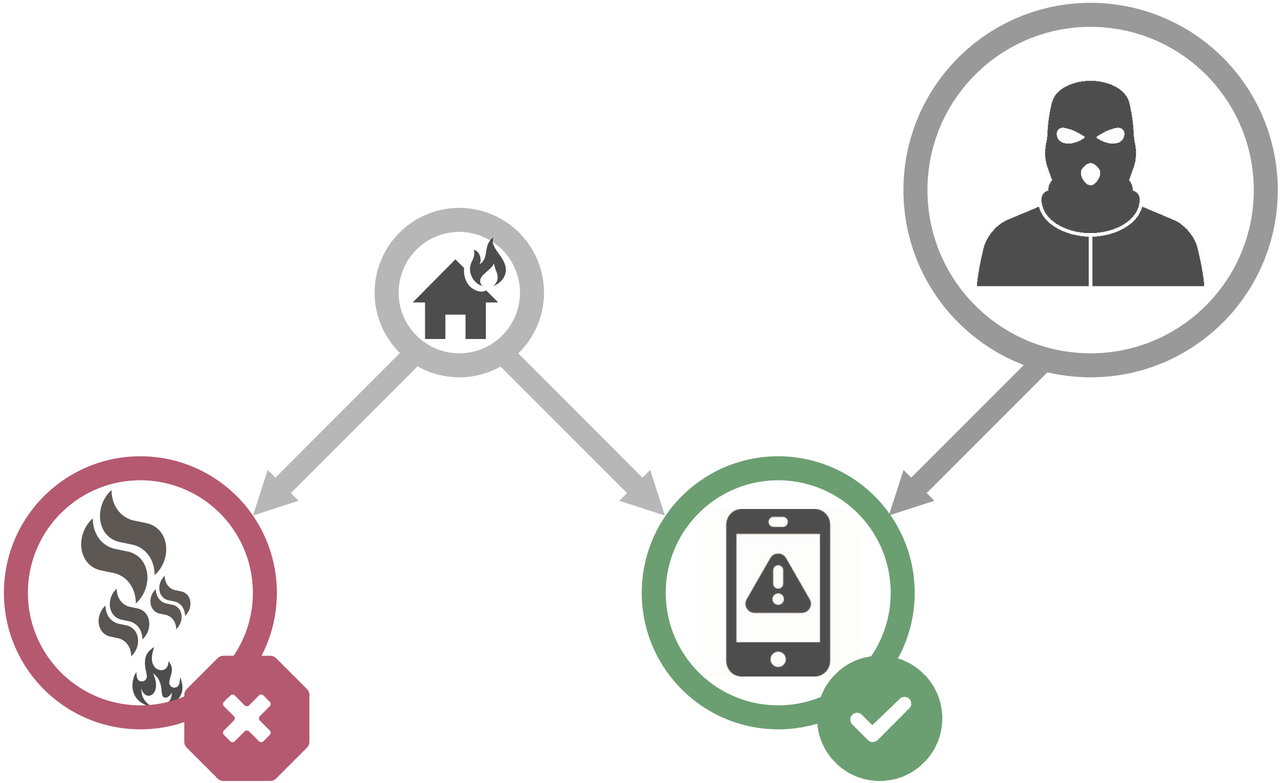
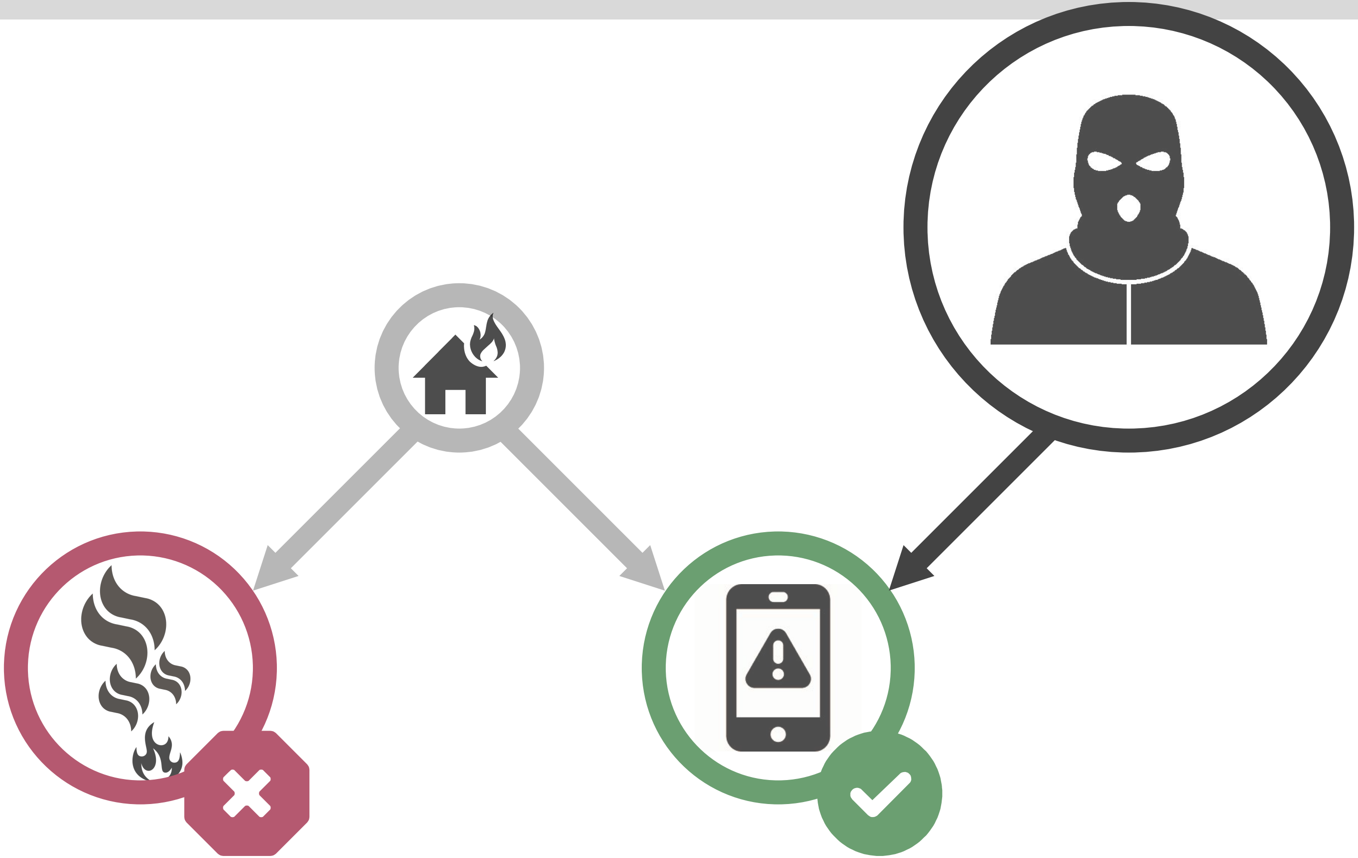
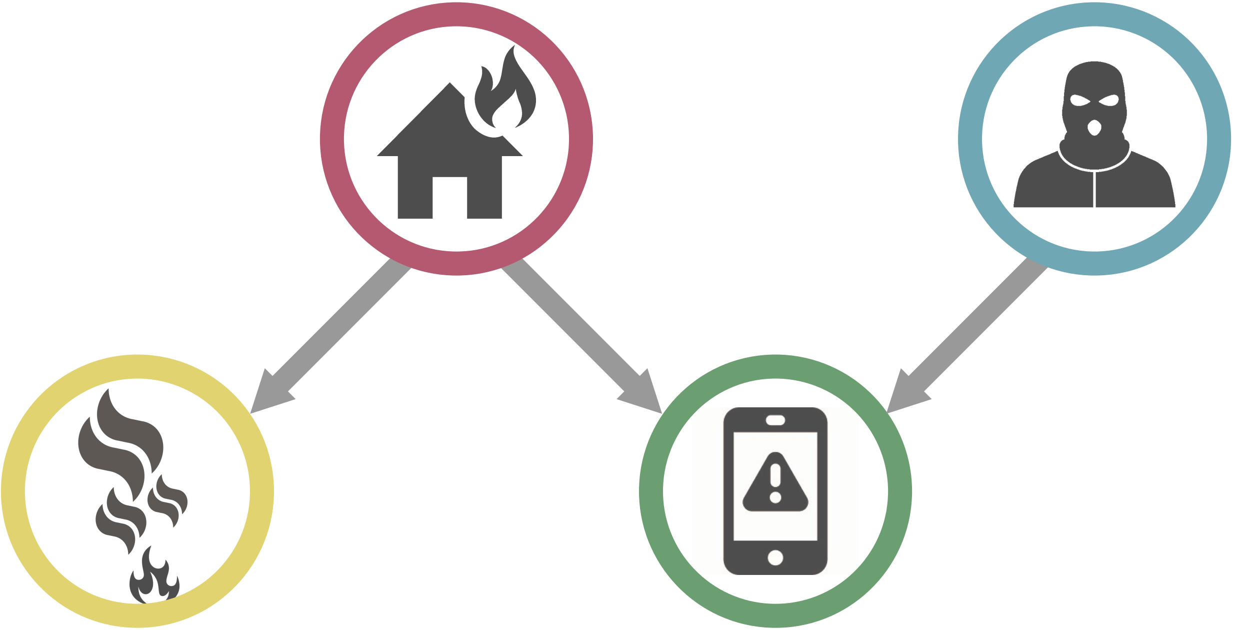


BN EXAMPLE

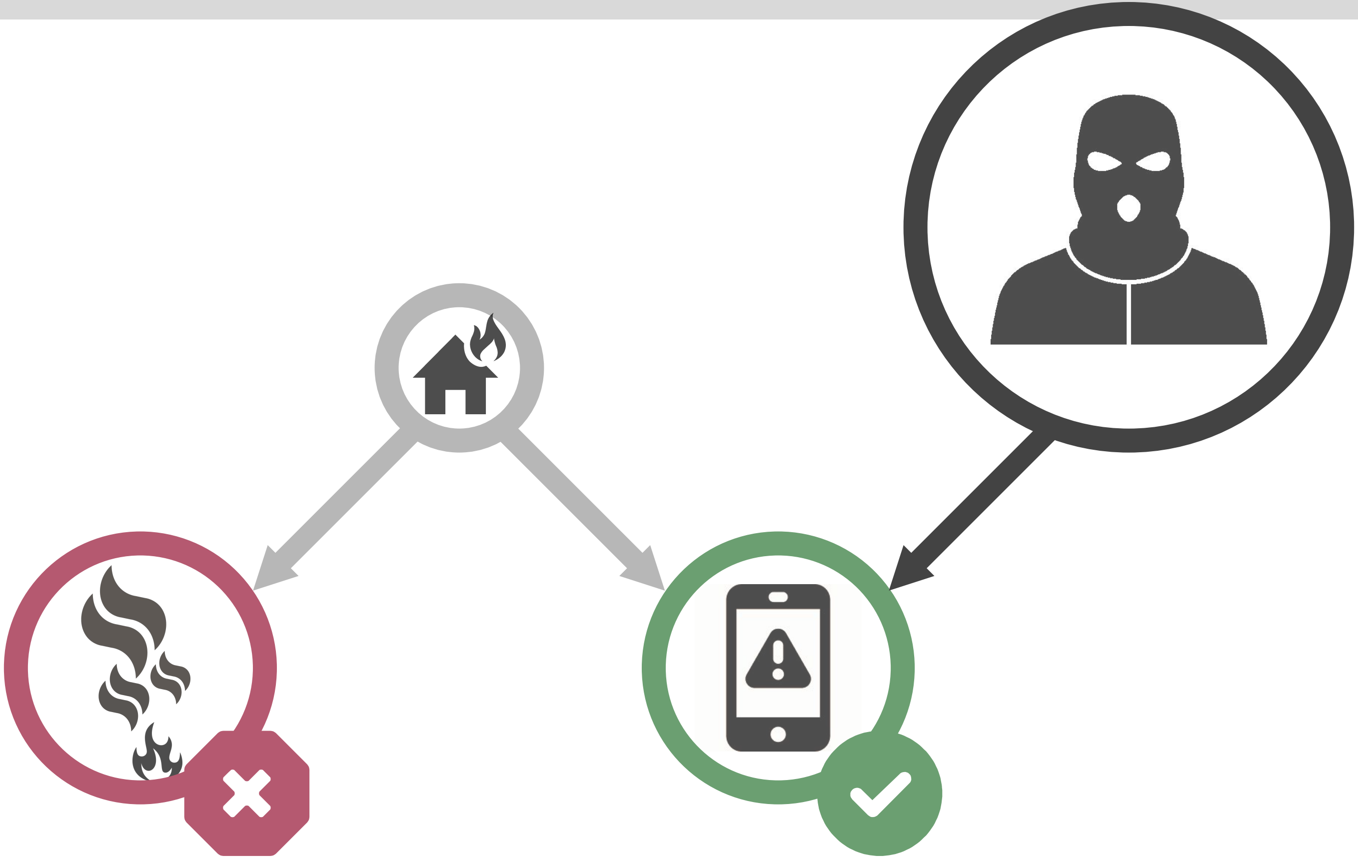


The ∏ of the CPTs is a **joint probability distribution** ρ(**U**)

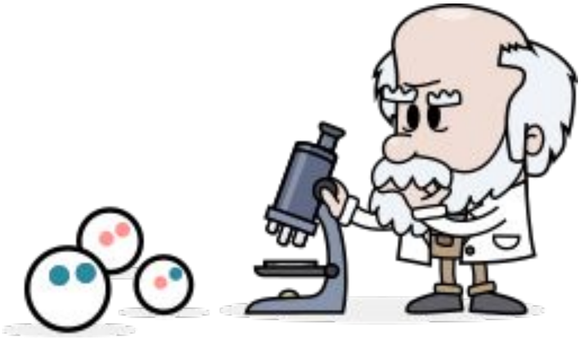


$\rho(\mathbf{U}) = \rho(\mathbf{fire}) \cdot \rho(\mathbf{burglar}) \cdot \rho(\mathbf{smoke} \mid \mathbf{fire}) \cdot \rho(\mathbf{app} \mid \mathbf{fire}, \mathbf{burglar})$

BN EXAMPLE



DARWINIAN NETWORKS LAB



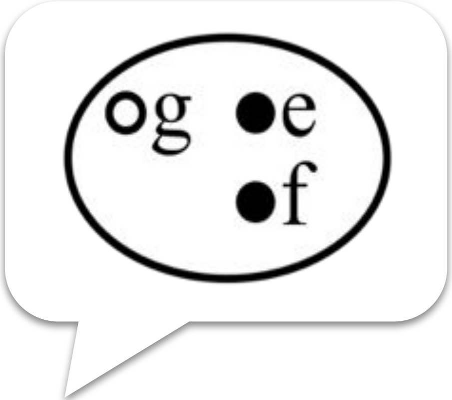
Scan me

DARWINIAN NETWORKS

DARWINIAN NETWORKS

(CAI 2015, CI 2016)

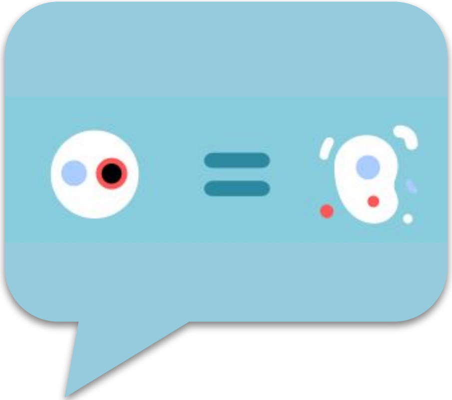
CLEVER WAY TO VIEW CPTs



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

DARWINIAN NETWORKS

POPULATION OF MICROORGANISMS

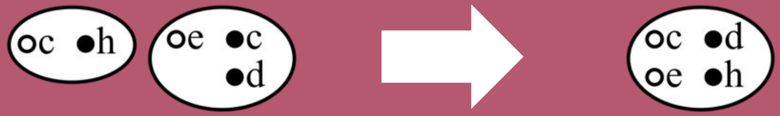


$$P(g|e,f)$$

MULTIPLICATION IS

MERGE

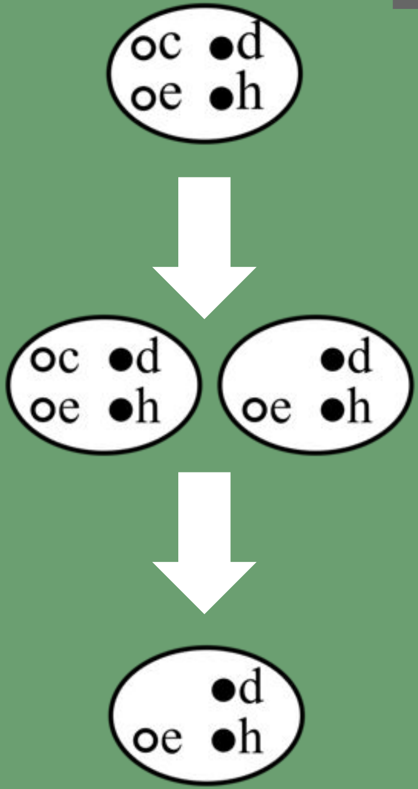
○ white	+	● black	=	○ white
● black	+	○ white	=	○ white
● black	+	● black	=	● black
○ white	+	○ white	=	● black



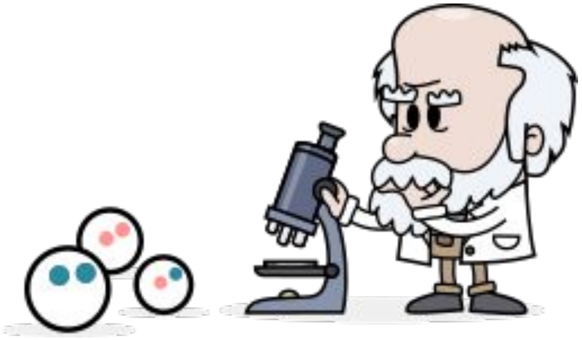
$$P(c|h) \cdot P(e|c, d) \quad = \quad P(c, e|d, h)$$

MARGINALIZATION IS REPLICATION AND NATURAL SELECTION

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



Darwinian Networks
Lab



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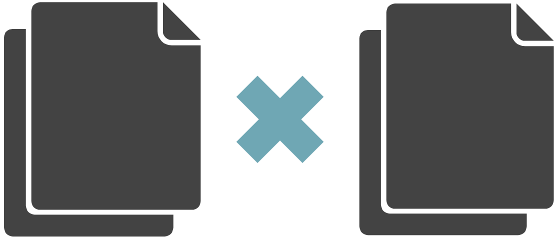
BayesFraud Predictive Analytics

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

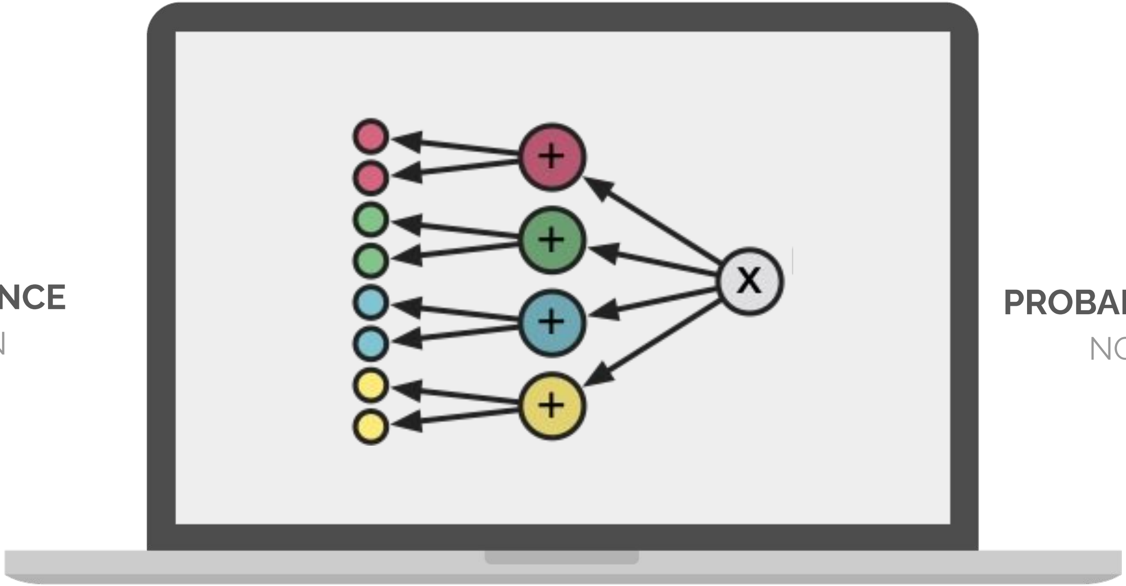
NP-hard Inference



Inference in BNs is a NP-hard task

SUM-PRODUCT NETWORKS

GENERATIVE DEEP LEARNING MODEL



EFFICIENT INFERENCE

UNDER CERTAIN CONDITIONS

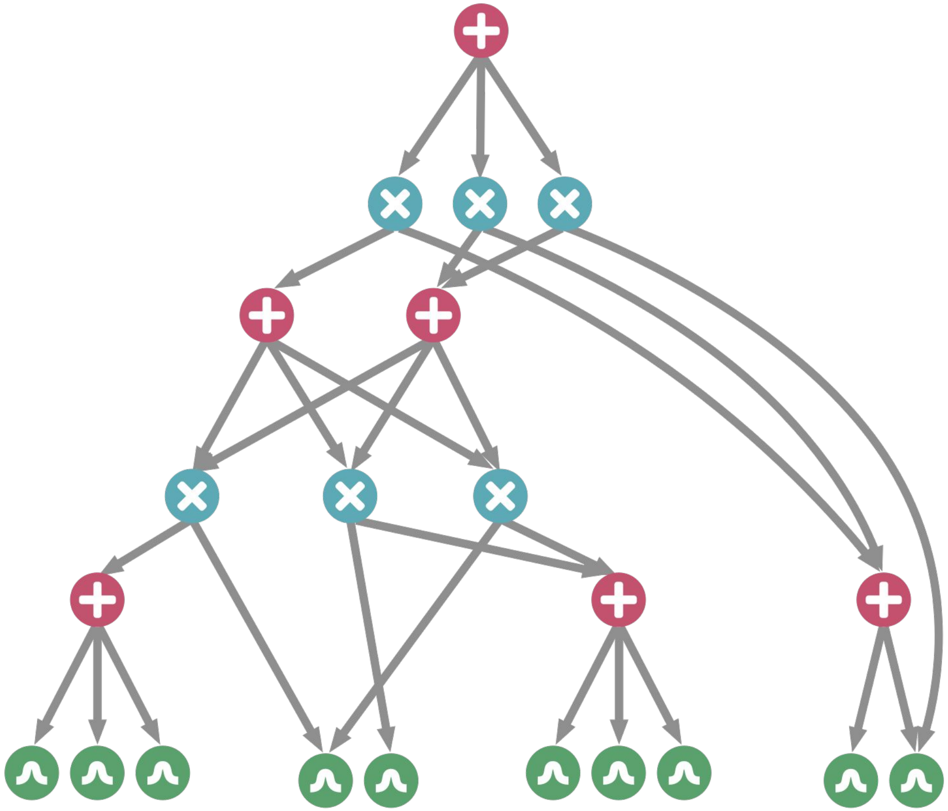
PROBABILISTIC REASONING

NOT A "BLACK BOX"

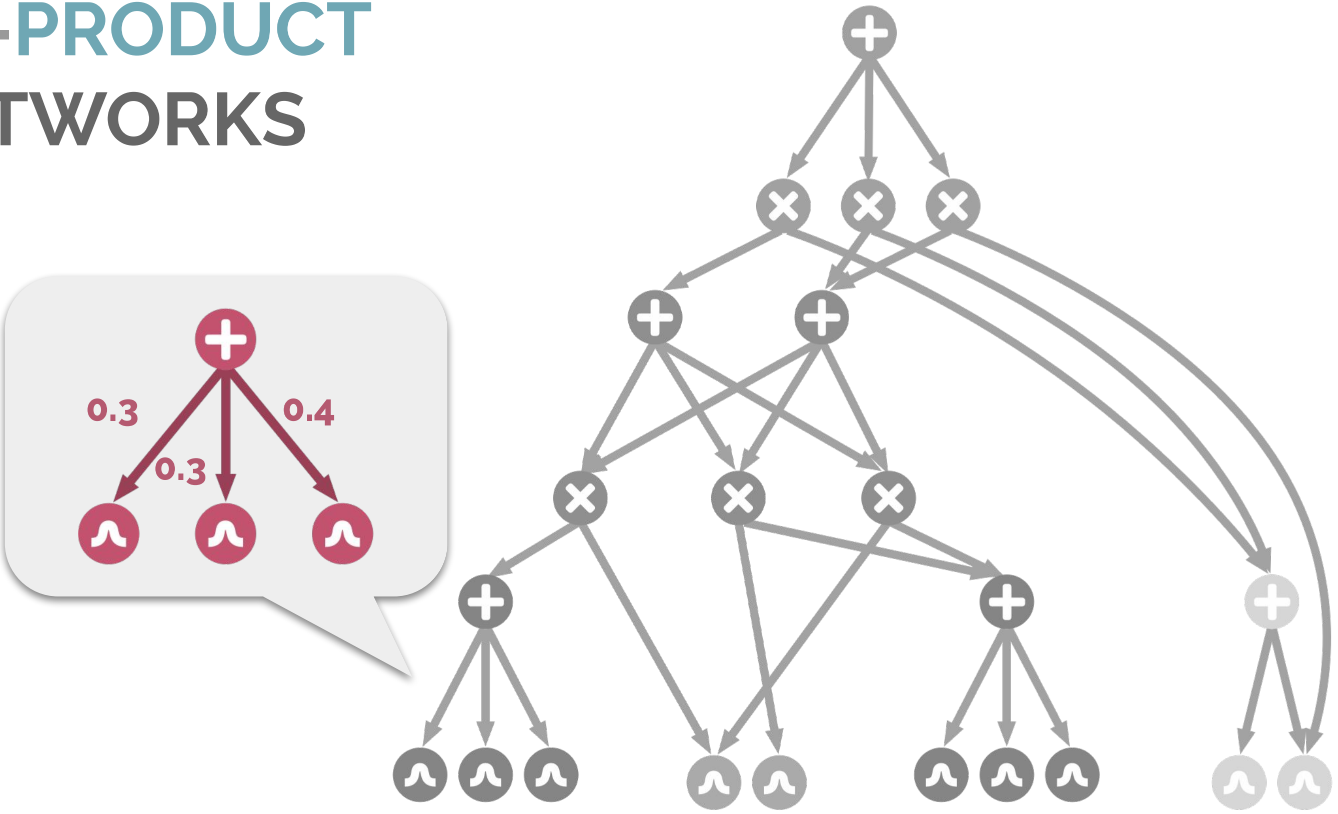
Poon and Domingos

2011

SUM-PRODUCT NETWORKS



SUM-PRODUCT NETWORKS



SUM-PRODUCT NETWORKS

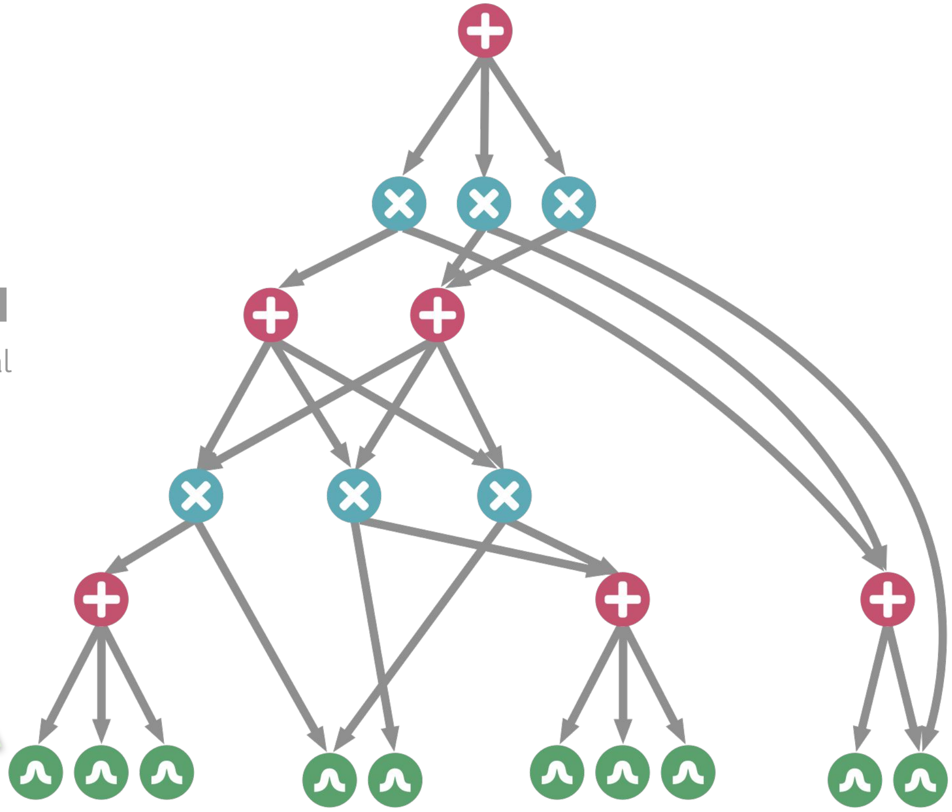
DIFFERENTIAL APPROACH

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.

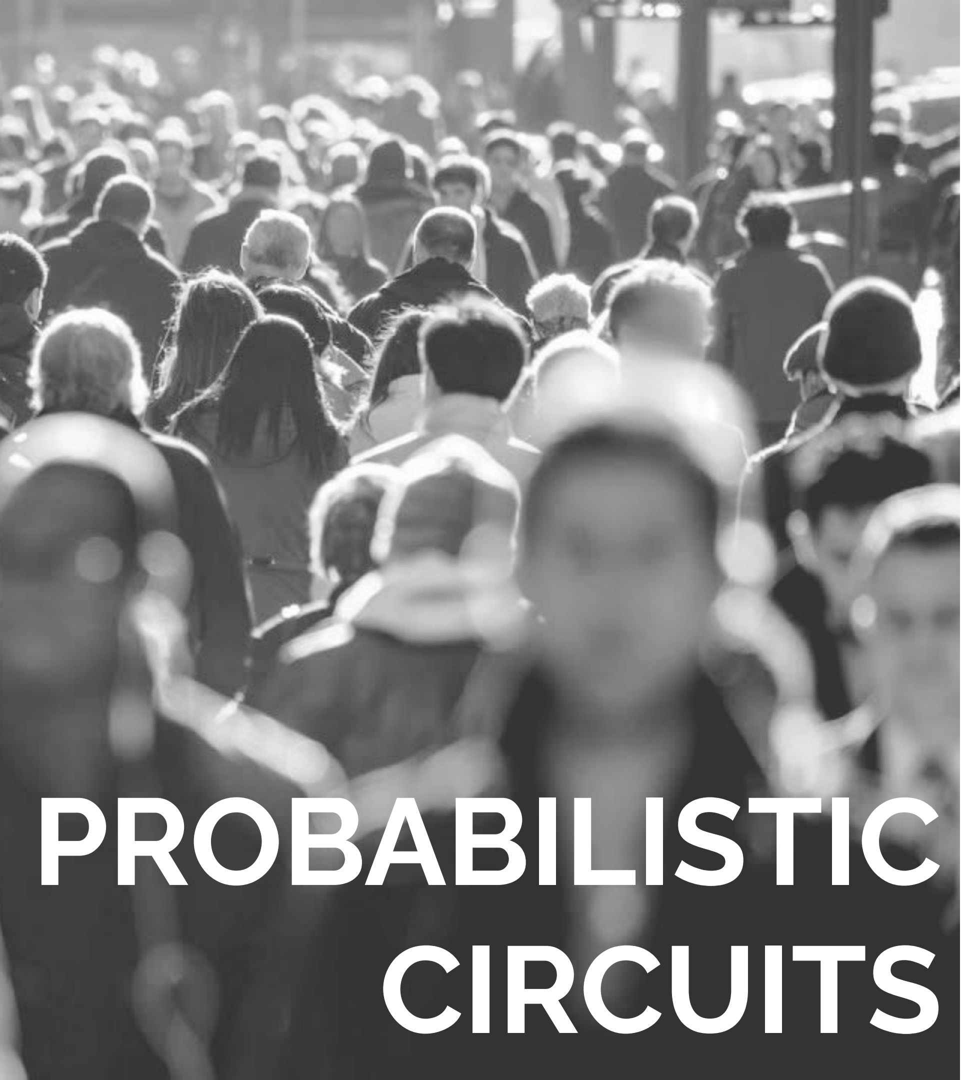
2015

Sharir et al.

2018

Butz et al.

2019



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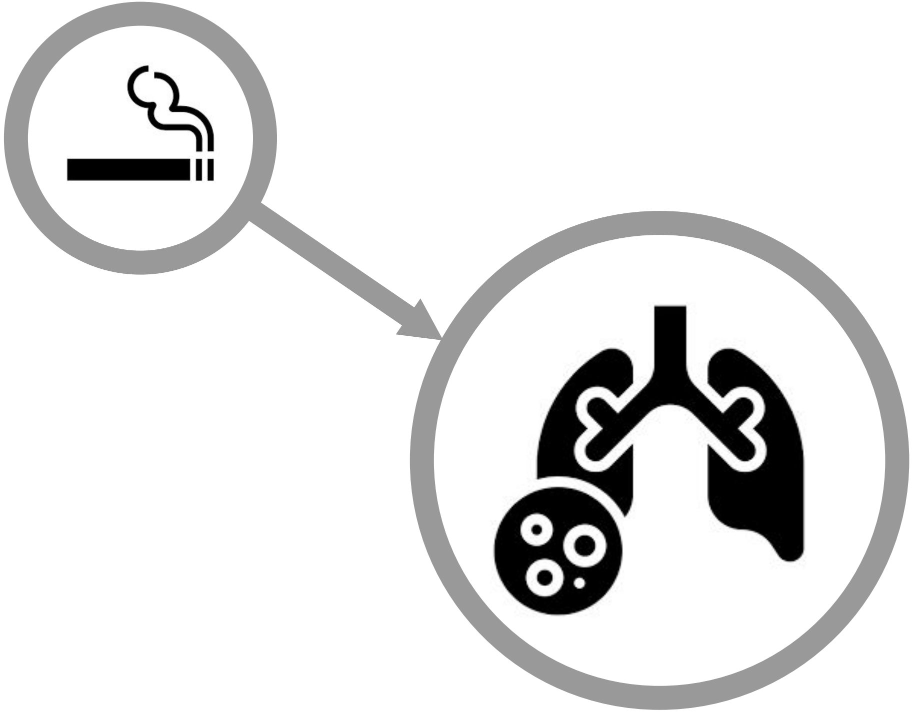
Does smoking cause cancer?



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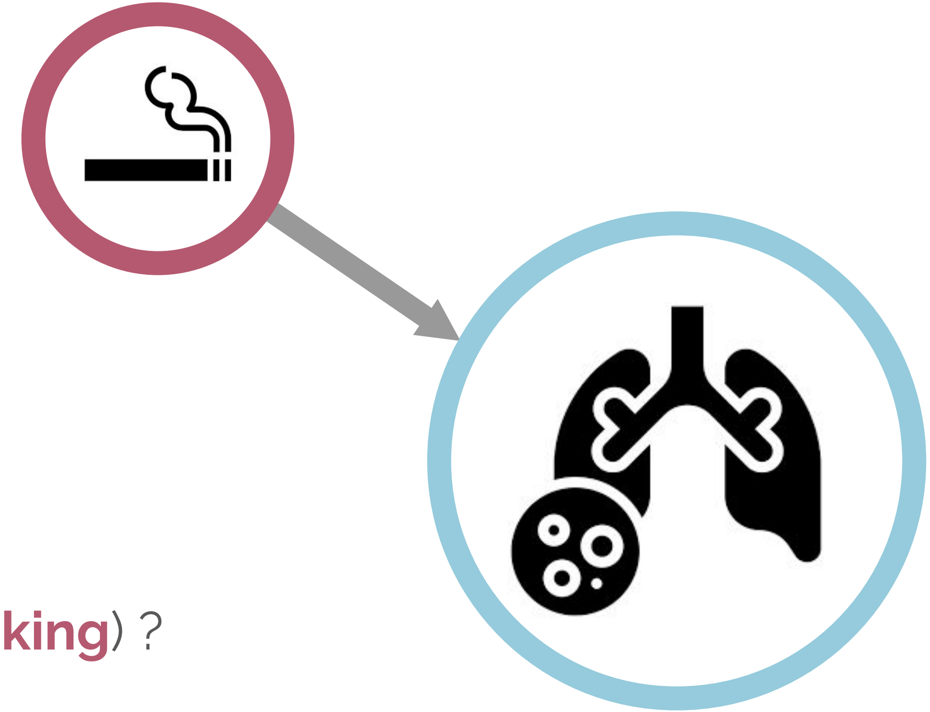


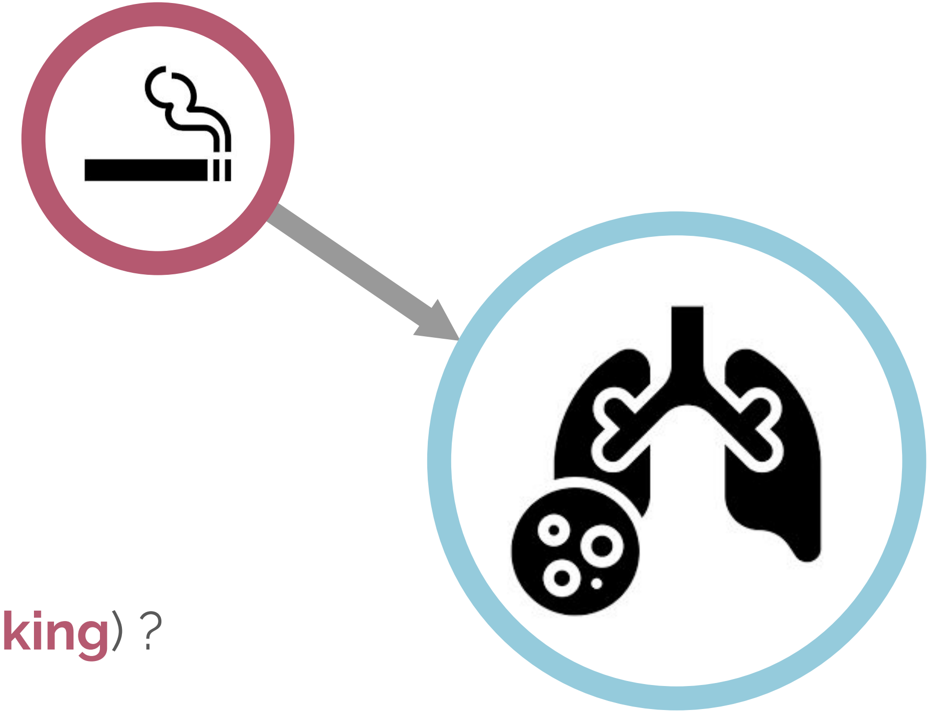
ρ(cancer | smoking) ?

Causality

Causality

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

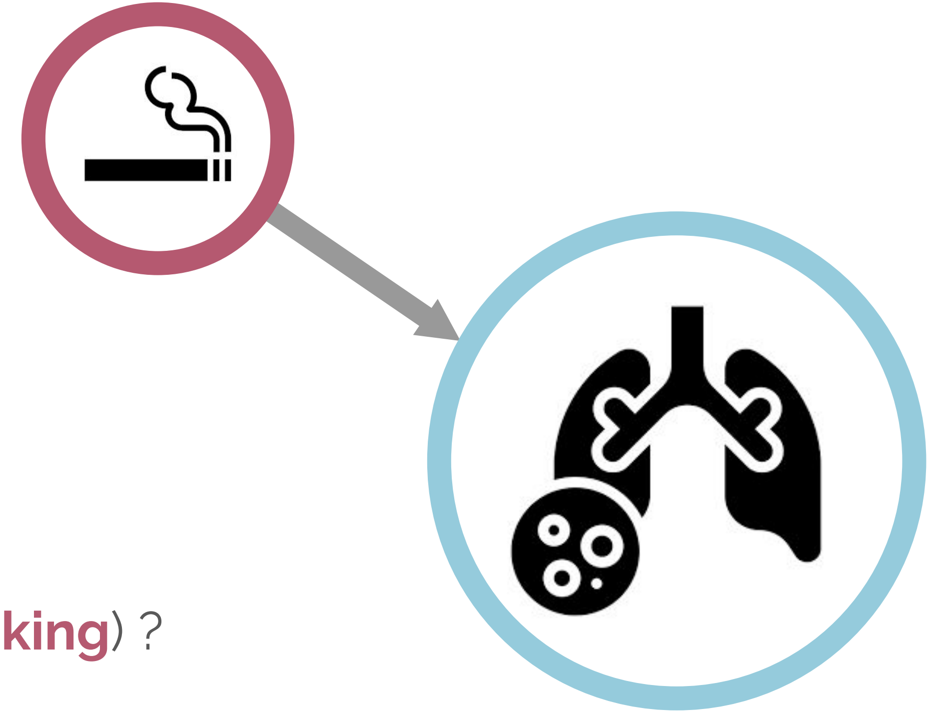
Does smoking cause cancer?



p(cancer | smoking) ?

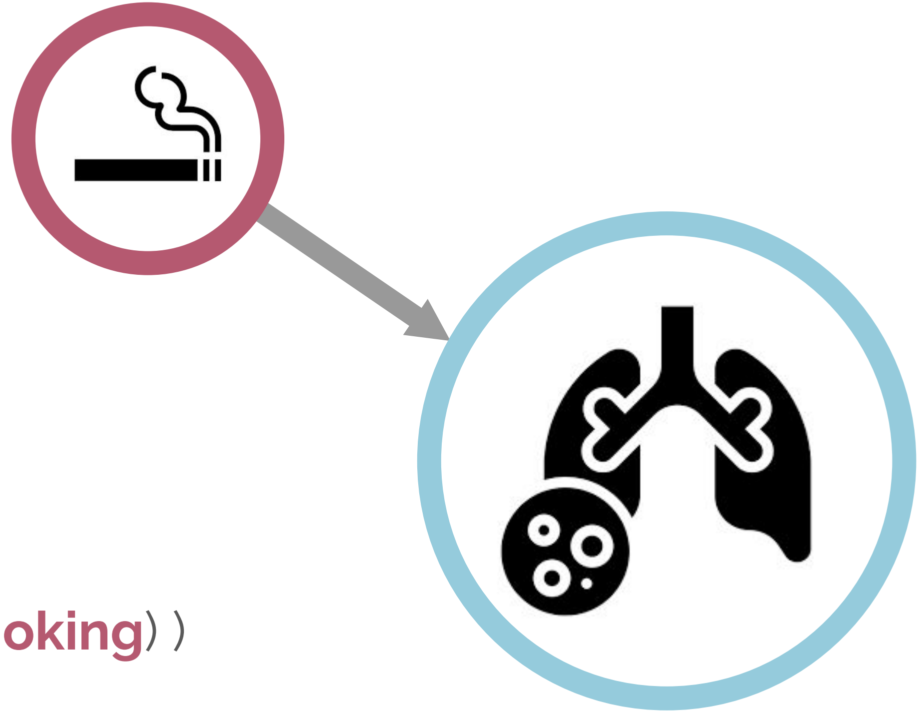

15

Does smoking cause cancer?

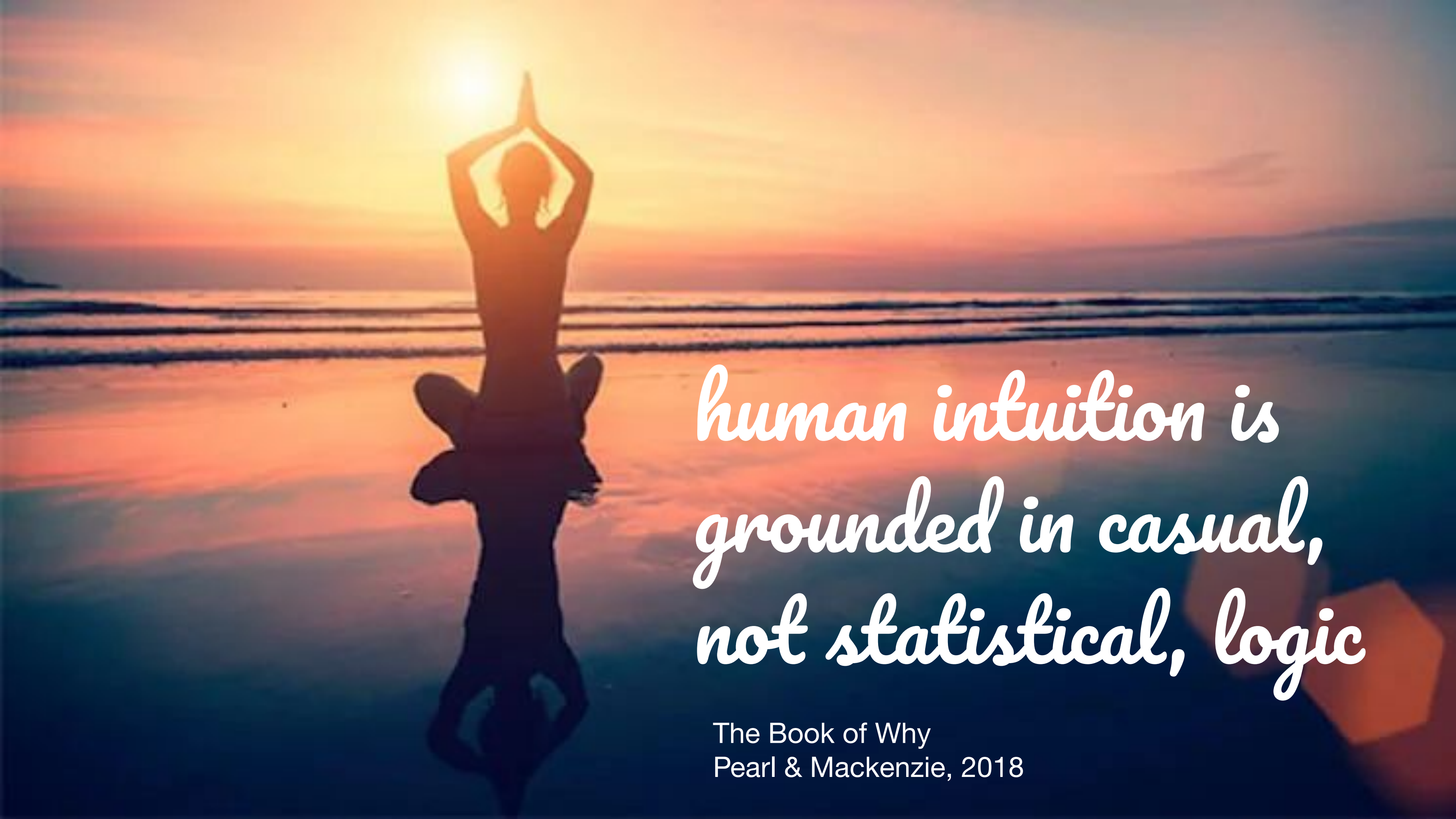


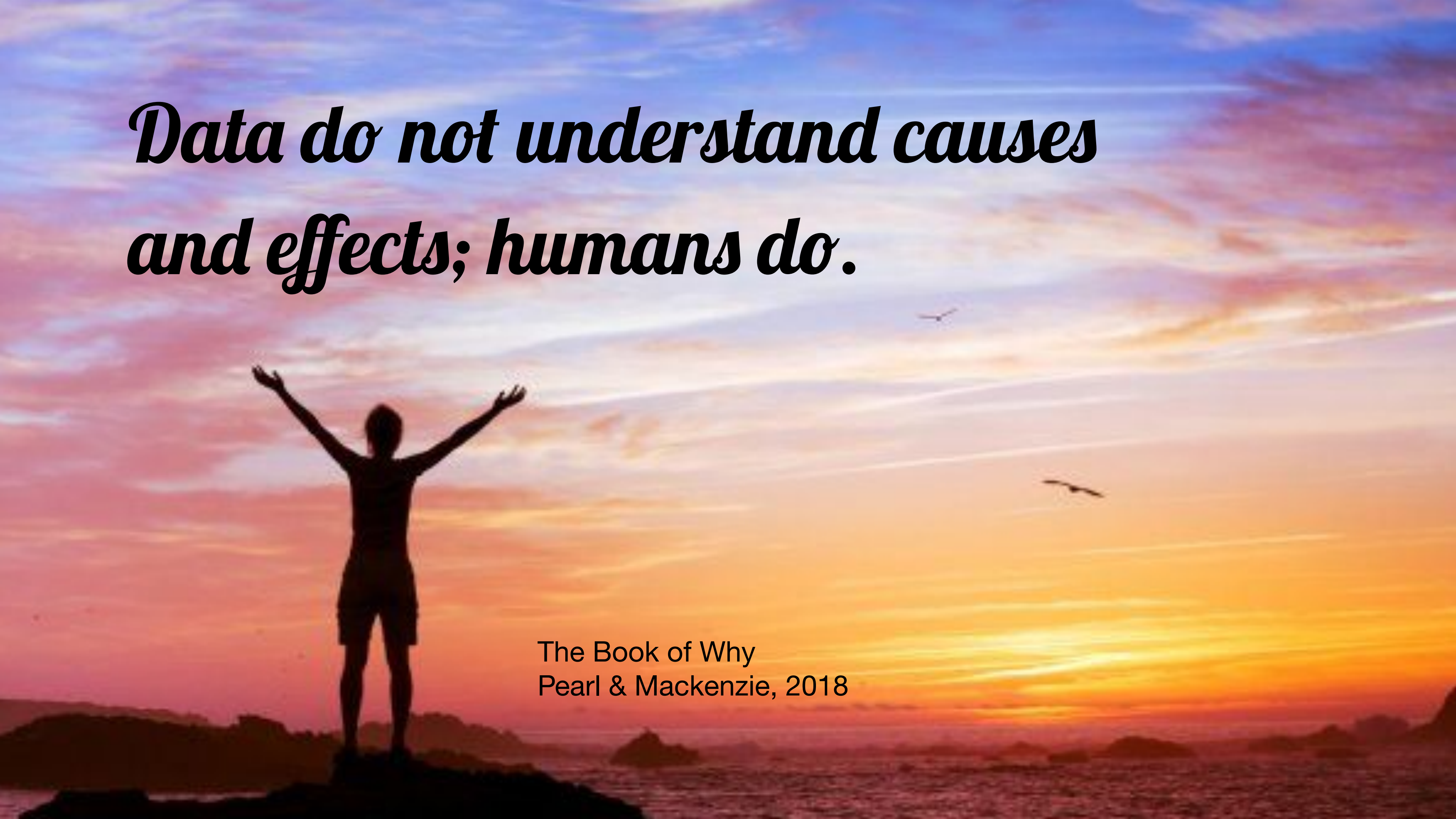
p(cancer | smoking) ?

smoking does cause cancer!



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


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