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Reasoning Under Uncertainty: Differential Diagnosis of Diseases March 20, 2020

Introduction

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Today's Agenda

Introduction

Webinar Series: Reasoning Under Uncertainty

- Part 1: Differential Diagnosis of Diseases
- Part 2: Temporal Modeling of an Epidemic
- Part 3: "Test and Treat" vs. Presumptive Treatment

Motivation

Probabilistic Reasoning with Bayesian Networks

- Diagnostic Reasoning
- Differential Diagnosis of Lung Diseases



Slides and Screen Recording: forum.bayesia.us



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Webinar Series — Reasoning Under Uncertainty (Part 1): Differential Diagnosis of Diseases



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This is a placeholder post. The webinar recording plus all presentation materials will be posted here by the end of March 20, 2020.

Webinar Overview

With the outhreak of the COVID-19 punchanic, reasoning about diseases has gone mainstream. No longer is hight healthcare professionals that perform differential diagnoses. Newspapers and accial media have been publicating charts that compare synotrams of COVID-35 years are requirer fau, and the common colds or individuals can potentially self-diagnose and reduce the builden on healthcare providers.

While a chart can list symptoms, it is not an "Inference engine." Deliberate real happen in the mind of the self-diagnosting individual to reach a concithe difficult part, as humans are ill-equipped to handle probabilistic the cause, is, from symptom to disease.

In this webinar, we present Bayesian networks as a framework for e diseases and symptoms. Given this knowledge base, we then use B algorithms to update the probabilities of the potential conditions gi A very similar model, the so-called 'Visit Asia' metwork, was one of lustrated the reaconing capabilities of Bayesian networks.

Please note that this webinar does not constitute medical advice. Although the o on current events, we focus solely on the reasoning process. Thus, all numerical probabilities shown in the presentation should be considered fictional.

Please post all your questions and comments below

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Warning

- The medical, healthcare, and health policy topics presented in this webinar are strictly for methodological illustration purposes.
- No medical advice is provided.
- No part of this seminar should be interpreted as a research finding or policy recommendation.
- All numerical values shown throughout the presentation should be considered fictional.



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MAKING DATA-DRIVE DECISIONS

DATA-DRIVEN HEALTHCA

How Apolytics and DL are Transforming the Industry

FIRST OPINION

A fiasco in the making? As the coronavirus pandemic takes hold, we are making decisions without reliable data

By JOHN P.A. IOANNIDIS / MARCH 17, 2020



A nurse holds swabs and a test tube to test people for Covid-19 at a drive-through station set up in the parking lot of the Beaumont Hospital in Royal Oak, Mich. PAUL SANCYA/AP



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Medical data is a hot soot for venture investing and product innovation. The goal: better care.





Testing to the Rescue

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Human Reasoning Experiment*

- A new and serious infectious disease appears in a population.
- At this time, the prevalence of infection is believed to be 0.1%.
- A test is available to detect the infection long before any symptoms appear. This test has a
 - sensitivity of 99.9% and a
 - specificity of 99.9%.
- As a disease control measure, you are tested for the disease.







*adapted from Kahneman

& Tversky, 1980





Are you infected?

- Prevalence of infection in population: 0.1%
- Test Performance:
 - Sensitivity: 99.9%
 - Specificity: 99.9%
- The test results come back, and you are positive.



Are you infected?

- More specifically, what is your probability of being infected?
 - P(Infection=true | Test=positive)=99.9%
 - P(Infection=false | Test=negative)=99.9%
 - P(Infection=true | Test=negative)=0.1%
 - P(Infection=false | Test=positive)=0.1%

SO, WHY DO YOU EVEN ASK?



Your probability of being infected is...





The Prosecutor's Fallacy

Judgment under uncertainty: Heuristics and biases

Edited by DANIEL KAHNEMAN PAUL SLOVIC AMOS TVERSK HUMAN REASONING

Human Cognitive Limitations and Biases Under Uncertainty



Rev. Thomas Bayes

Bayes' Theorem for Conditional Probabilities

H: Hypothesis E: Evidence $P(H | E) = \frac{P(E | H)P(H)}{P(E)}$ "Probability of the Hypothesis given the Evidence"



J Bayes.

1763 PHILOSOPHICAL TRANSACTIONS

[370] quodque folum, certa nitri figna præbere, fed plura concurrere debere, ut de vero nitro producto dubium non relinquatur.

LII. An Effay towards folving a Problem in the DoEtrine of Chances. By the late Rev. Mr. Bayes, F. R. S. communicated by Mr. Price, in a Letter to John Canton, A. M. F. R. S.

Dear Sir,

Read Dec. 25, I Now fend you an effay which I have 1763. I found among the papers of our deceafed friend Mr. Bayes, and which, in my opinion, has great merit, and well deferves to be preferved. Experimental philofophy, you will find, is nearly interefted in the fubject of it; and on this account there feems to be particular reafon for thinking that a communication of it to the Royal Society cannot be im-

proper. He had, you know, the honour of being a member of that illuftrious Society, and was much efteemed by many in it as a very able mathematician. In an introduction which he has writ to this Effay, he fays, that his defign at firft in thinking on the fubject of it was, to find out a method by which we might judge concerning the probability that an event has to happen, in given circumftances, upon fuppofition that we know nothing concerning it but that, under the fame circum-

• Bayes' Rule allows us to compute the probability *P*(*Infection=true | Test=positive*)

$$P(H \mid E) = \frac{P(E \mid H)P(H)}{P(E)}$$



J Bayes

 $P(Infection = true | Test = positive) = \frac{P(Test = positive | Infection = true)P(Infection = true)}{P(Test = positive)} = \frac{P(Test = positive)}{P(Test = positive)}$

P(*Test* = *positive* | *Infection* = *true*)*P*(*Infection* = *true*)

P(Test = positive | Infection = true)P(Infection = true) + P(Test = positive | Infection = false)P(Infection = false)

correct, but cumbersome, even in trivial cases.

Bayesian Networks to the Rescue!

Overcoming our Limitations





Bayesian Networks



We encode our knowledge regarding the problem domain



We encode our knowledge regarding the problem domain

False	True	
99.900		0.100

	uomam	Probability Table			
Disease	Negative		Positive		
False	99	9.900	0.100		
True	(0.100	99.900		

Conditional



We use this Bayesian network to perform inference



We use this Bayesian network to perform inference



We use this Bayesian network to perform inference



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New graph ...







Infections Over Time



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Differential Diagnosis of Lung Diseases



Example

- Decision support for the differential diagnosis of lung diseases that have common symptoms:
 - Bronchitis
 - Pneumonia
 - Tuberculosis
 - Lung Cancer



Case courtesy of Radswiki, Radiopaedia.org, rID: 12040

This is an inference task!

- $P(Bronchitis | Symptom_1,..., Symptom_n, Risk Factor_1,..., Risk Factor_n) = ?$
- $P(Pneumonia | Symptom_1,..., Symptom_n, Risk Factor_1,..., Risk Factor_n) = ?$

Probability of s | Symptom₁,..., Symptom_n, Risk Factor₁,..., Risk Factor_n)=?

P(Lung Cancer | Symptom₁,..., Symptom_n, Risk Factor₁,..., Risk Factor_n)=?
given

Bayesian Networks







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Node:	Lung Cancer	
Variable of	TRUE	FALSE
Interest	5.5%	94.5%

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All numerical values provided in this example are fictional.

Differential Diagnosis Conditional **Fictional Values Probability Table Discrete & Nonparametric** Lung Cancer Smoker FALSE TRUE **Probabilistic Relationship** FALSE 99% 1% P(Lung Cancer|Smoker) TRUE 90% 10% Arc Smoker Lung Cancer

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Example of a Patient

- 19-year-old smoker
- No known comorbidities
- 1. Visit to general practitioner:
 - Reports cough
 - Diagnosis: bronchitis
- 2. Visit to general practitioner, one week later:
 - Reports cough, fever, chest pain, and shortness of breath
 - X-Ray is positive for lung lesions
 - Diagnosis: pneumonia
 - Treatment: antibiotics





- Patient dies one week later
- Autopsy reveals cause of death: tuberculosis



- Parents of deceased file lawsuit against treating physician claiming wrongful death as a result of negligence.
- The plaintiff states that all common symptoms of tuberculosis were present in the patient, which the physician should have recognized.





Replicating the Diagnosis Steps of First Visit

- Season=Winter
- Age<20
- Smoker=True
- Cough (Patient Report)=True
- Temperature (Patient Report)=Low-Grade Fever
- Temperature (Measured in Office)=No Fever
- Patient Credibility=Low

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1 0.00% .00% Spring 0.00% Summe 0.00% 0.00% Fall Dyspnea Temperature Lung Lesions 100.00% Winter Patient Credibility Value: 0.750 X-Ray Abnormalities Value: 0.177 (+0.021) 25.00% 75.00% 82.34% False 17.66% True Patient Credibility Measurement Accuracy Interpretation Measurement Accuracy Value: 0.900 (+0.000) Reliability Temperature (Measured in Office) Value: 0.271 (+0.043) 10.00% 90.00% 79.50% No Fever 13.87% Low-Grade 6.63% High Fever Temperature Temperature (Measured in Cough Dyspnea X-Ray Abnormalities Office) (Patient-Reported) (Patient-Reported) (Patient-Reported) 1. Visit < % 🖬 🌗 Asia6.xbl

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Tornado Diagrams



Tornado Diagrams



Bayesian Networks = Artificial Intelligence



Knowledge Base

- Declarative/Propositional Knowledge
- Associational Knowledge
- Causal Knowledge

Inference Engine



Bayesian Networks = Transparent Expert System



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Bayesian Networks = Transparent Expert System



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In Conclusion...



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