

#### Cause and Chance

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# Overview

Propose a framework for a propensity theory of chance

Will answer questions such as:



# Overview (cont'd)

- When do you have a propensity?
- How do you get probabilities from propensities?
- How are propensities related to credences?
- What information is inadmissible?



# Overview (cont'd)

#### Will not answer:

• What makes the propensity for heads on a coin toss (e.g.) take the specific value .51 rather than .49?



### Overview (cont'd)

- Will motivate approach with some problems for propensity theories, as well as for Lewis's Principal Principle
- Make use of formal apparatus of causal Bayes nets



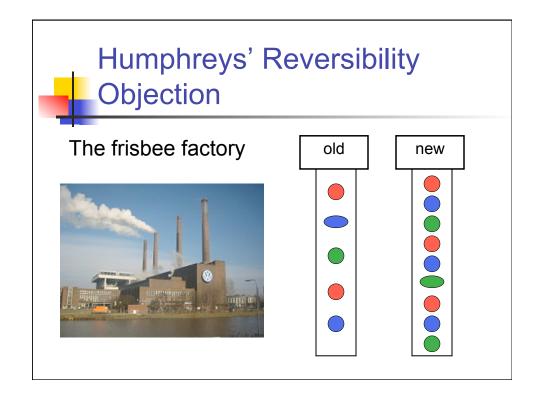
# Propensity Interpretation of Chance

- Introduced by Popper; defended by Miller, Fetzer, Giere
- Propensities are measures of the strength of partial dispositions
- The disposition is grounded in a causal basis
- E.g. propensity of a coin to land heads;
   causal basis = constitution of coin, movement
   of thumb, constitution of landing surface, etc.



# Three Problems for Propensities

- Humphreys' reversibility objection
- Identifying the causal basis
- The source of mathematical structure





# Humphreys' Reversibility Objection (cont'd)

Pr(f is defective | f is made by new machine) could be a propensity

Pr(f is made by new machine | f is defective) is not a propensity



# Identifying the Causal Basis

Which sets of causes give rise to propensities?

Standard answer:

Complete time-slice



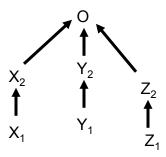
# Identifying the Causal Basis (cont'd)

Problems with the standard answer:

- Too demanding:
   We rarely know the complete state at a time
- Too restricitive:
   Non-simultaneous causes can confer a propensity



# Identifying the Causal Basis (cont'd)





#### The Source of Structure

Why think that propensities have the mathematical structure of probability?

- Propensity theorists often compare propensities to physical parameters like mass, force, and charge
- It is an empirical matter that charge is discrete, has positive and negative values
- But we can't imagine discovering that chances can be negative or greater than 1



# The Source of Structure (cont'd)

Three potential solutions

Propensities inherit their structure from:

- Frequencies (early Popper, Gillies)
- Ratios of possible outcomes (Giere, McCall)
- Rational credences (Mellor, Skyrms, Lewis)



# The Principal Principle

PP (Lewis)

$$Cr(A \mid Ch(A) = r \& E) = r$$

- 'Cr' is the credence of a rational agent
- · 'Ch' is chance
- 'E' is admissible relative to 'A' and 'Ch'



# The Principal Principle (cont'd)

#### PP tells us

- what it is for a rational agent to take 'Ch' to be chance
- how evidence bears on hypotheses about chance
- how beliefs about chance guide decisions



# The Principal Principle (cont'd)

PP posits a screening-off relation:

$$Cr(A \mid Ch(A) = r \& E) = r$$

'Ch(A) = r' screens off 'A' from admissible 'E'



# The Principal Principle (cont'd)

Problem: when is 'E' admissible?

Why it matters:

- There is not one PP, but many
- Different objective probability concepts give rise to versions of PP
- They differ with respect to admissibility relations



# The Principal Principle (cont'd)

Finite frequencies obey a PP-like principle:

- Knowing only that Pat is British, and 15.7% of Britons are aged 65 or older, what credence should I have that Pat is 65 or older?
- .157
- Many propositions are inadmissible whether Pat plays bridge or listens to Lady Gaga



### The Project

The problem of defining admissibility (for propensities) and finding appropriate causal bases are inter-related:

- A suitable causal basis will screen off inadmissible information
- Admissibility can be characterized causally



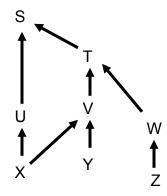
# Causal Bayes Nets

A causal structure  $S = \langle V, G \rangle$ 

- V is a set of variables
- **G** is a *directed acyclic graph* on **V**
- An arrow from X to Y represents that X
  has a causal influence on Y that is
  direct relative to V



# Causal Bayes Nets (cont'd)





# Causal Bayes Nets (cont'd)

#### Terminology:

X is a parent of Y if there is an arrow from X to Y

PA(X) is the set of parents of X



# Causal Bayes Nets (cont'd)

Y is a descendant of X if there is a directed path from X to Y

- Convenience: X is a descendant of X
- **DE**(X) is the set of descendants of X



# Causal Bayes Nets (cont'd)

A causal Bayes net  $\mathcal{N} = \langle \mathbf{V}, \mathbf{G}, Pr \rangle$ 

- **∨** ⟨V, G⟩ is a causal structure
- Pr is a probability measure on V that satisfies the Markov condition



# Causal Bayes Nets (cont'd)

Markov condition:

For all  $V \in V$ , all  $W \subseteq V \setminus DE(V)$ :

 $Pr(V \mid PA(V), W) = Pr(V \mid PA(V))$ 

PA(V) screens off V from its non-descendants



# Causal Bayes Nets (cont'd)

Fact: Pr satisfies the Markov condition on  $V = \{V_1, ..., V_n\}$  iff Pr 'factorizes':

$$Pr(V_1,...V_n) = \prod_{i=1,...n} Pr(V_i | PA(V_i))$$

*Pr* is uniquely determined by probabilities of the form:

$$Pr(V_i | \mathbf{PA}(V_i))$$



### **Proposal**

Reverse engineering: want to end up with a causal Bayes net

Probabilities of the form  $Pr(V = v \mid \mathbf{PA}(V) = \mathbf{p})$ are interpreted as propensities



# Proposal (cont'd)

Pr can be uniquely constructed out of the probabilities that are directly interpreted as propensities (follows from factorization)

Thus we get all of the probabilities, including backwards conditional probabilities, out of propensities



# Proposal (cont'd)

**PA**(*V*) = **p** is the causal basis for the propensity

$$Pr(V = v \mid \mathbf{PA}(V) = \mathbf{p})$$

(We can liberalize this to allow other causal bases)



# Proposal (cont'd)

Markov condition gives us a purely causal definition of admissibility

A proposition is admissible when it tells us only about variables that are not descendants of *V* 

(This can be modified to allow for other kinds of causal basis)



# The Construction

Doing things in the right order:

Propensity structure  $\mathcal{P} = \langle \mathbf{V}, \mathbf{G}, Prop \rangle$ 

 $Prop(\mathbf{PA}(V) = \mathbf{p}, \ V = v)$ the propensity for causal basis  $\mathbf{PA}(V) = \mathbf{p}$  to yield V = v



### The Construction (cont'd)

PP\*:

$$Cr(V = v \mid PA(V) = p \& P \& E) = r$$
  
=  $Prop(PA(V) = p, V = v)$ 

for all admissible propositions E, where P is the proposition that  $\mathcal{P}$  is an appropriate representation



### The Construction (cont'd)

Define  $Pr(\bullet) = Cr(\bullet|P)$ 

- Pr is a probability function
- Pr satisfies the Markov condition (from definition of admissibility)
- Pr is uniquely determined by Prop (by factorization)

 $\langle V, G, Pr \rangle$  is a causal Bayes net



# Liberalizing the Causal Basis

Allow sets of causes  $\mathbf{U}$  other than  $\mathbf{PA}(V)$  to be causal bases for propensities of V

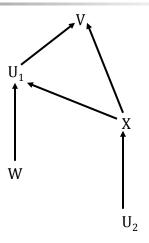
**U** gives rise to a propensity for V = v if it has the right admissibility profile

Only information about variables that are causally downstream of **U** is inadmissible



#### **Causal Bases**

- {U<sub>1</sub>, U<sub>2</sub>} does not form a causal basis for a propensity
- Because information about W is inadmissible
- {W, X} does form the causal basis for a propensity





#### From Framework to Theory

What determines the value of  $Prop(\mathbf{PA}(V) = \mathbf{p}, V = v)$ ?

What makes a propensity structure  $\mathcal{P}$  an appropriate representation?

The framework is compatible with many possible answers

Unlikely to be one answer suitable for all causal systems



### An Under-appreciated Option

Moderate anti-realism:

- The causal structure is real
- The causal basis is real
- Propensities are real; some are stronger than others
- But assigning them precise values is an idealization; like assigning precise values to degrees of belief



# Moderate Anti-realism (cont'd)

PP\* connects propensities with Bayesian confirmation theory and decision theory

There are facts about

- how well  $\mathcal{P}$  fits the data
- lacktriangle whether  $\mathcal P$  has been a good 'guide to life'

But (on this option) no facts about whether  $\mathcal{P}$  is *true*