

Independence in counterfactuals: Premise semantics, causality, and lumping

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Outline	Goodman	Premise semantics	Causality	Integration	Conclusion





2 Premise semantics









- (1) If that match had been scratched, it would have lighted.
 - "When we say (1), we mean that conditions are such—i.e. the match is well made, is dry enough, oxygen enough is present, etc.—that "The match lights" can be inferred from "The match is scratched."



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- "When we say (1), we mean that conditions are such—i.e. the match is well made, is dry enough, oxygen enough is present, etc.—that "The match lights" can be inferred from "The match is scratched."
- "Thus the connection we affirm may be regarded as joining the consequent with the conjunction of the antecedent and other statements that truly describe relevant conditions."



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 - *Q*: What sentences are to be taken in conjunction with the antecedent as a basis for inferring the consequent?



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- *Q*: What sentences are to be taken in conjunction with the antecedent as a basis for inferring the consequent?
- A: True sentences with which the antecedent is cotenable.

A is cotenable with with $S \dots$ if it is not the case that S would not be true if A were true.

i.e., if A were true, S would (still) be true

Outline	Goodman	Premise semantics	Causality	Integration	Conclusion
This talk	ς				

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Outline	Goodman	Premise semantics	Causality	Integration	Conclusion
This ta	lk				

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 - Premise semantics for adding sentences to the antecedent
 - Causal networks

for choosing which sentences to add

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- Two ingredients of a Goodmanian theory:
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for choosing which sentences to add

• One way to combine the two.

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Premis	e semanti	CS			

Adding sentences to the antecedent Veltman (1976), Kratzer (1981, 1989)



• Model $\mathcal{M} = \langle W, V \rangle$, where

- W is a non-empty set of possible worlds;
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$$\llbracket \neg \varphi \rrbracket_{w}^{\mathcal{M}} = 1 \Leftrightarrow \llbracket \varphi \rrbracket_{w}^{\mathcal{M}} = 0$$

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Counte	rfactuals				

- Premise set: set of propositions
 - representing one way of adding true sentences to the antecedent consistently

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Count	terfactuals	\$			

- Premise set: set of propositions
- $Prem_w(\varphi)$: set of premise sets
 - representing *all* relevant ways of adding true_w sentences to φ consistently

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- Prem_w(φ): set of premise sets
- Would-counterfactual: □→

 $\varphi \square \rightarrow \psi$ is true at *w* if and only if every set in $\operatorname{Prem}_w(\varphi)$ has a superset in $\operatorname{Prem}_w(\varphi)$ which entails ψ .

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• Fact: $\varphi \Box \rightarrow \psi$ iff $\neg(\varphi \diamondsuit \neg \psi)$



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- The premise sets are the place to tweak the theory.



Flavors of premise semantics

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 - Invariably: For all X in $Prem_w(\varphi)$,
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 - All X in $\operatorname{Prem}_{w}(\varphi)$ must be subsets of f(w).
- Different versions, characterized by f:
 - $\Box \xrightarrow{n}$, $\overleftarrow{\rightarrow}$: *Naïve* premise semantics
 - $\stackrel{p}{\mapsto}$, $\stackrel{p}{\leftrightarrow}$: Partition semantics
 - $\Box \rightarrow$, $\diamond \rightarrow$: Lumping semantics

Outline	Goodman	Premise semantics	Causality	Integration	Conclusion			
Naïve	Naïve premise semantics							

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Naïve	premise	semantics			

• f(w): all propositions that are true at w.

 $f(w) = \{p \subseteq W | w \in p\}$



- f(w): all propositions that are true at w.
- $\operatorname{Prem}_{w}^{n}(\varphi)$: all consistent subsets of $f(w) \cup \{\varphi\}$ containing φ .

$$\mathsf{Prem}_w^n(\varphi) = \{ X \subseteq f(w) | \bigcap X \neq \emptyset \land \varphi \in X \}$$



- f(w): all propositions that are true at w.
- Prem^{*n*}_{*w*}(φ): all consistent subsets of $f(w) \cup \{\varphi\}$ containing φ .
- Problem: This can't be right.
 If φ is false at w, then
 - $\varphi \xrightarrow{n} \psi$ comes down to $\Box(\varphi \to \psi)$. (strict implication)
 - $\varphi \Leftrightarrow \psi$ comes down to $\Diamond (\varphi \land \psi)$ (logically consistency)



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- More generally:

$$\varphi \xrightarrow{n} \psi \Leftrightarrow (\varphi \to \psi) \land (\neg \varphi \to \Box(\varphi \to \psi))$$
$$\varphi \xrightarrow{n} \psi \Leftrightarrow (\varphi \land \psi) \lor (\neg \varphi \land \diamondsuit(\varphi \land \psi))$$

Outline	Goodman	Premise semantics	Causality	Integration	Conclusion		
Partition semantics							

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- f(w) subject only to the condition that it uniquely identify {w}.

$$\bigcap f(W) = \{W\}$$



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- Prem^p_w(φ): all consistent subsets of f(w) ∪ {φ} containing φ (as before).

$$\mathsf{Prem}^{p}_{w}(\varphi) = \{ X \subseteq f(w) | \bigcap X \neq \emptyset \land \varphi \in X \}$$



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 - Which piece of the logical machinery regulates membership in $\operatorname{Prem}_w^p(\varphi)$?
- Kratzer (1989): Closure conditions on sets in $\operatorname{Prem}_{w}^{p}(\varphi)$
 - Closure under logical consequence and *lumping*.
 - Doesn't quite work as expected; see Kanazawa, Kaufmann and Peters (2005).



Premise semantics:

 Closely related to Stalnaker/Lewis ordering semantics (Lewis, 1981)



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- Question: How to define premise sets

Premise semantics:

- Closely related to Stalnaker/Lewis ordering semantics (Lewis, 1981)
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- Question: How to define premise sets
- Next section: Some ideas from AI and psychology



- Recall: ' $\varphi \square \rightarrow \psi$ ' is true iff ψ follows from φ together with true sentences which
 - are cotenable with φ

(Goodman)

• would (still) be true if φ were true



• Recall: ' $\varphi \square \rightarrow \psi$ ' is true iff ψ follows from φ together with true sentences which

> are counterfactually independent of φ

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- Recall: ' $\varphi \Box \rightarrow \psi$ ' is true iff ψ follows from φ together with true sentences which
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Hume: ... [w]e may define a cause to be

- an object, followed by another, and where all the objects similar to the first are followed by objects similar to the second.
- Or in other words where, if the first object had not been, the second never had existed.



- Recall: ' $\varphi \square \rightarrow \psi$ ' is true iff ψ follows from φ together with true sentences which
 - are counterfactually independent of φ
 - \blacktriangleright are causally independent of φ

(Goodman)

(Hume)



- Recall: ' $\varphi \square \rightarrow \psi$ ' is true iff ψ follows from φ together with true sentences which
 - are counterfactually independent of φ (Goodman)
 - The are causally independent of φ (Hume)
- Lewis: Counterfactual analysis of causality

(see also Collins, Hall and Paul, 2004)

- Counterfactuals interpreted in terms of overall comparative similarity between possible worlds
- Counterfactuals provide evidence about causal relations



- Recall: ' $\varphi \square \rightarrow \psi$ ' is true iff ψ follows from φ together with true sentences which
 - are counterfactually independent of φ (Goodman)

(Hume)

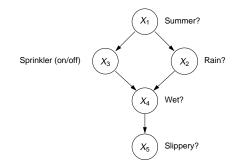
- **>** are causally independent of φ
- Lewis: Counterfactual analysis of causality
- Why not take causality as basic?
 - (not that all counterfactuals assert causal relationships)

Pearl (2000):

In the last decade, owing partly to advances in graphical models, causality has undergone a major transformation: from a concept shrouded in mystery into a mathematical object with well-defined semantics and well-founded logic ... Put simply, causality has been mathematized.

Bayesian Network:

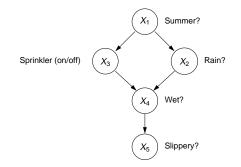
- Directed Acyclic Graph (DAG) $\langle U, E \rangle$
 - U: set of random variables
 - E: relation over U whose transitive closure is asymmetric



Bayesian Network:

- Directed Acyclic Graph (DAG) $\langle U, E \rangle$
- Probability distribution over the values assignments

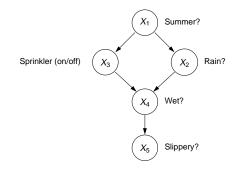
Notation: $(P(x_1, ..., x_n))$ for $(P(X_1 = x_1, ..., X_n = x_n))$





Markov Assumption: The probability of a variable is completely determined by the value(s) of its parent(s) in the graph.

e.g.,
$$P(x_5|x_1, x_2, x_3, x_4) = P(x_5|x_4)$$

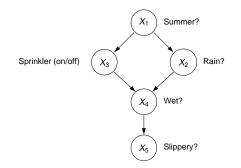


Outline	Goodman	Premise semantics	Causality	Integration	Conclusion
Bayes	ian netwo	orks			

Markov Assumption: Decomposability

$$P(x_1, x_2, x_3, x_4, x_5)$$

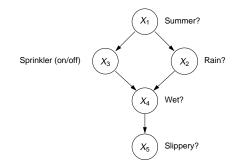
= $P(x_1)P(x_2|x_1)P(x_3|x_1, x_2)P(x_4|x_1, x_2, x_3)P(x_5|x_1, x_2, x_3, x_4)$
= $P(x_1)P(x_2|x_1)P(x_3|x_1)P(x_4|x_2, x_3)P(x_5|x_4)$



Outline	Goodman	Premise semantics	Causality	Integration	Conclusion
Bayesia	an networ	ks			

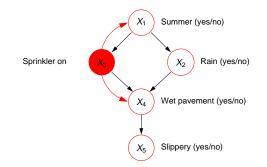
Practical advantages:

- compact representation
- learning from limited data
- efficient inference



Observing that the sprinkler is on:

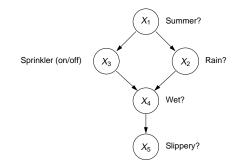
- Set X₃ to 'on'
- Re-calibrate the probabilities of all other variables.
- Affects the probabilities of the seasons



Outline	Goodman	Premise semantics	Causality	Integration	Conclusion
Causal	networks				

Causal Bayesian Network:

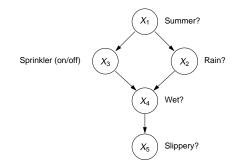
- Bayesian Network under a special interpretation
- All arrows indicate causal influence





Causal Bayesian Network:

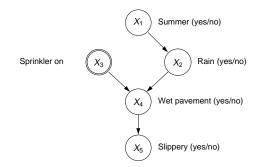
- Bayesian Network under a special interpretation
- All arrows indicate causal influence
- Two modes of inference: Observation and Intervention





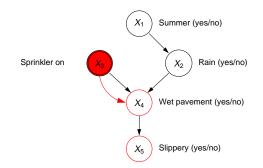
Intervention I: Manipulation

• Manipulate the network structure: Cut all arrows into X₃



Intervention I: Manipulation

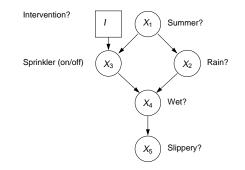
- Manipulate the network structure: Cut all arrows into X₃
- Update as before (now on the modified network)
- Only affects the descendants of X₃ (provided that X₄, X₅ are not observed)





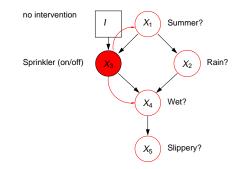
Intervention II: Intervention variable

• A special variable with values $\{idle, do(X_3 = on), do(X_3 = off)\}$



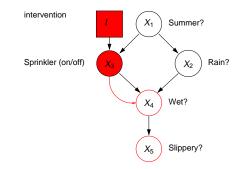
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 - *idle*: The value of X₃ is *observed*



Intervention II: Intervention variable

- A special variable with values $\{idle, do(X_3 = on), do(X_3 = off)\}$
 - *idle*: The value of X₃ is *observed*
 - $do(X_3 = ...)$: The value of X_3 is manipulated



Intervention (either way):

- Prevents backtracking (abductive) inferences
- Similar to Lewisian "miracles"

(Lewis 1973, 1979)

• Simple rule: All non-descendants of the manipulated variable remain unaffected

Outline	Goodman	Premise semantics	Causality	Integration	Conclusion
Obse	rvation vs	. intervention			



- Observation: Conditioning on 'X_i = x_i' [Non-descendants of X_i affected]
- Intervention: Conditioning on 'do(X_i = x_i)' [Non-descendants of X_i not affected]

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Two hypotheses:

- H1: Indicatives involve observation.
- H2: Counterfactuals involve intervention.

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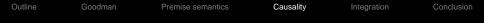
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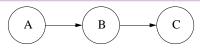
H2: Counterfactuals involve intervention.

Two problems:

- Some indicative conditionals involve intervention. (Kaufmann 2004, 2005b, 2006)
- Not all counterfactual inference involves intervention.

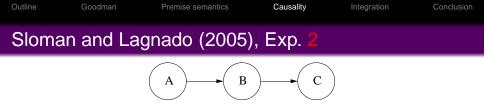


Sloman and Lagnado (2005), Exp. 2



• (abstract) causal condition:

When A happens, it causes B most of the time. When B happens, it causes C most of the time. A happened. C happened.



- Intervention: "Someone intervened directly on B, preventing it from happening. What is the probability that A/C would have happened?"
- Observation: "What is the probability that A/C would have happened if we observed that B did not happen?"
- Unspecified: "What is the probability that A/C would have happened if B had not happened?"



 Intervention: "Someone intervened directly on B, preventing it from happening. What is the probability that A/C would have happened?"

A: 3.9 C: 2.3

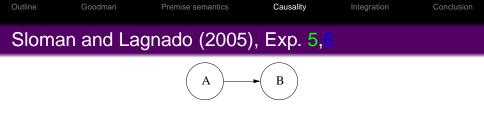
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A: 2.7 C: 2.3

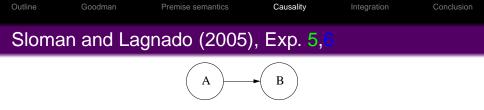
 Unspecified: "What is the probability that A/C would have happened if B had not happened?"

A: 3.2 C: 2.4

(Scale: 1=very low, 2=low, 3=medium, 4=high, 5=high)

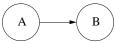


 All rocket ships have two components, A and B. Component A causes Component B to operate. In other words, if A, then B.



- Counterfactual: "Suppose Component B/A were not operating, would Component A/B still operate?"
- Explicit prevention: "Suppose Component B/A were prevented from operating, would Component A/B still operate?"
- Explicit prevention: "Suppose Component B/A were prevented from moving, would Component A/B still be moving?"
- Explicit observation: "Suppose Component B/A were observed to not be moving, would Component A/B still be moving?





 Counterfactual: "Suppose Component B/A were not operating, would Component A/B still operate?"

if not B, A: 68 if not A, B: 2.6

• Explicit prevention: "Suppose Component B/A were prevented from operating, would Component A/B still operate?"

if not B, A: 89 if not A, B: 5.3

• Explicit prevention: "Suppose Component B/A were prevented from moving, would Component A/B still be moving?"

if not B, A: 85 if not A, B: 19

• Explicit observation: "Suppose Component B/A were observed to not be moving, would Component A/B still be moving?

if not B, A: 22 if not A, B: 30



Sloman and Lagnado (2005): Discussion

No simple relationship between counterfactuals and intervention.

"Representing intervention is not always as easy as forcing a variable to some value and cutting the variable off from its causes. Indeed, most of the data reported here show some variability in people's responses. People are not generally satisfied to simply implement a <u>do</u> operation. People often want to know precisely how an intervention is taking place." Causal networks:

- empirically testable
- mathematically elegant
- computationally tractable
- precise statement and testing of hypotheses about causal inference

Causal networks:

- empirically testable
- mathematically elegant
- computationally tractable
- precise statement and testing of hypotheses about causal inference
- Question: What about a "causal premise semantics"?
 And how is all this related to possible, worlds, anyway?



Causal networks and possible worlds

Networks

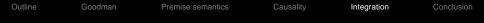
Event

Worlds

Proposition



x	
---	--



Causal networks and possible worlds

Networks

- Event
- Variable

Worlds

- Proposition
- Partition



x	x
---	---

Causality

Causal networks and possible worlds

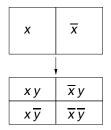
Networks

- Event
- Variable
- Network of variables



Worlds

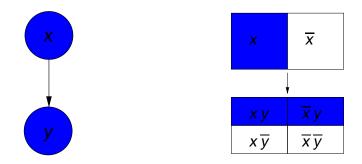
- Proposition
- Partition
- Network of partitions



X cuts across Y, but not vice versa.

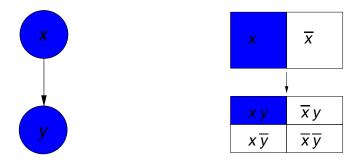


Counterfactual alternatives



Suppose *x* and *y* are both true at world *w*.



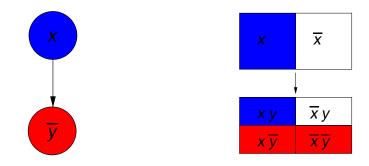


Only x and x y are relevant for the truth of counterfactuals.

•
$$f(w) = \{x, xy\}$$



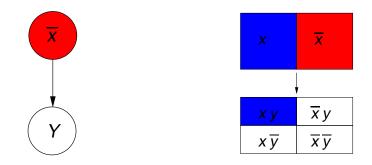
Counterfactual alternatives



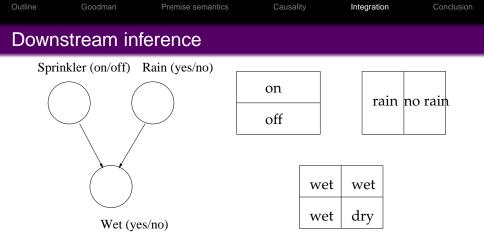
If y were false, x would still be true.



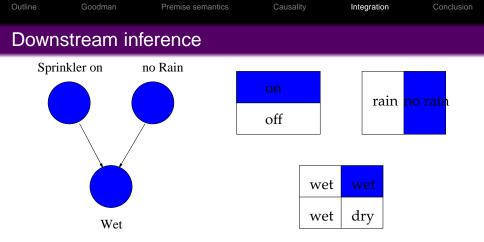
Counterfactual alternatives



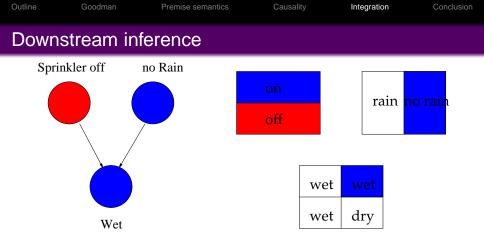
If *x* were false, *y* might also be false.



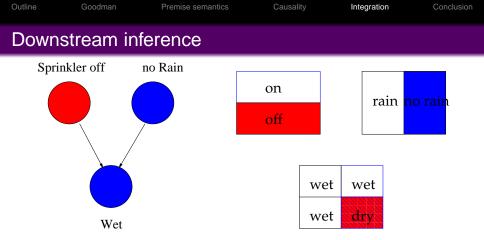
Sprinkler and Rain are independent.



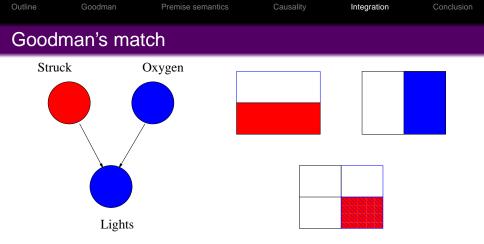
True propositions (at the world of evaluation)



(3) a. If the sprinkler were off ...



- (3) a. \checkmark If the sprinkler were off, it would be dry.
 - b. XIf the sprinkler were off, it would be raining.



- (3) a. \checkmark If the match had been struck, it would have lighted.
 - b. *X*If the match had been struck, there would have been no oxygen.

Summary on downstream inference

Premise semantics and causality:

- Causal structure affects the set *f*(*w*) of propositions relevant for the truth of counterfactuals.
- Whenever $X \to Y$, f(w) contains X_w and $X_w Y_w$ not Y_w .
- Counterfactual reasoning about causes involveses "undoing" their effects; but not vice versa
- Intervention.

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- Counterfactual reasoning about causes involveses "undoing" their effects; but not *vice versa*
- Intervention.

But what about non-intervention counterfactuals?



Kratzer (1989):

King Ludwig of Bavaria likes to spend his weekends at Leoni Castle. Whenever the Royal Bavarian flag is up and the lights are on, the King is in the Castle. At the moment, the lights are on, the flag is down, and the King is away. Suppose now counterfactually that the flag were up.

(4) a. If the flag were up, the King would be in the Castle.

Outline	Goodman	Premise semantics	Causality	Integration	Conclusion
Obser	vation vs	. intervention			

Kratzer (1989):

King Ludwig of Bavaria likes to spend his weekends at Leoni Castle. Whenever the Royal Bavarian flag is up and the lights are on, the King is in the Castle. At the moment, the lights are on, the flag is down, and the King is away. Suppose now counterfactually that the flag were up. Well, then the King would be in the Castle and the lights would still be on. But why wouldn't the lights be out and the King still be away?

(4) a. \checkmark If the flag were up, the King would be in the Castle.



Kratzer (1989):

Let us change the scenario just a little bit ... I say to you: "Suppose I hoisted the flag..." ... Would my hoisting the flag bring the King back into the Castle?

- (4) a. \checkmark If the flag were up, the King would be in the Castle.
 - b. If I hoisted the flag, the King would appear in the Castle.



Let us change the scenario just a little bit ... I say to you: "Suppose I hoisted the flag..." ... Would my hoisting the flag bring the King back into the Castle? No. The counterfactual expressed by [4b] is false.

- (4) a. \checkmark If the flag were up, the King would be in the Castle.
 - b. *X*If I hoisted the flag, the King would appear in the Castle.

Outline	Goodman	Premise semantics	Causality	Integration	Conclusion
Obser	vation vs	. intervention			

• Observation vs. intervention

- · expressed in the linguistic form of the antecedent
- results in truth-conditional difference

- (4) a. \checkmark If the flag were up, the King would be in the Castle.
 - b. *X*If I hoisted the flag, the King would appear in the Castle.

Kratzer called her King of Bavaria example a "simplified variant" of Goodman's match example. Is it?

Kratzer:

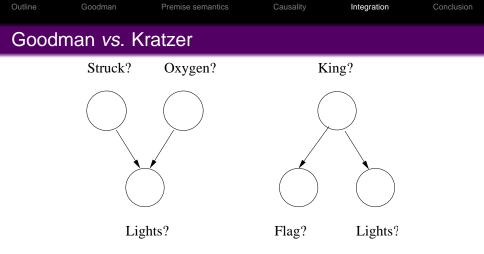
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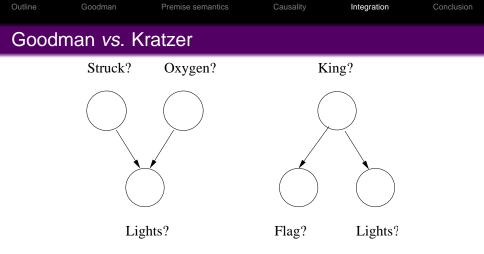
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Goodman's match:

Whenever a match is struck and oxygen is present, the match lights.

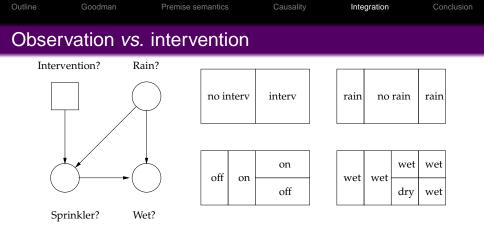


Match: Striking affects lighting King: Flag may or may not affect the king

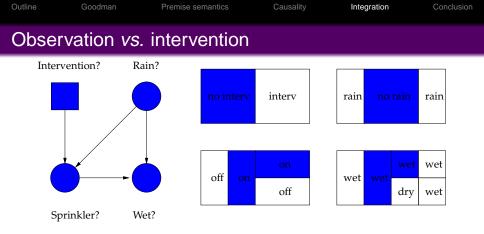


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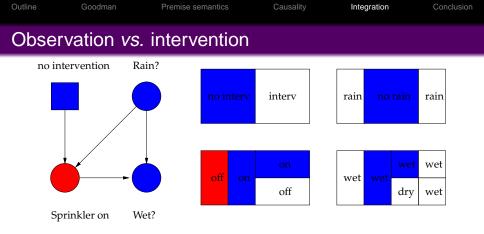
Observation vs. intervention again



- Without intervention, the status of the sprinkler is determined by the weather.
- With intervention, they are independent.

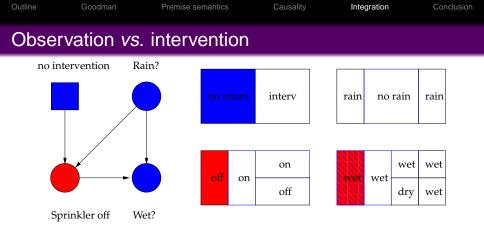


True propositions (at the world of evaluation).



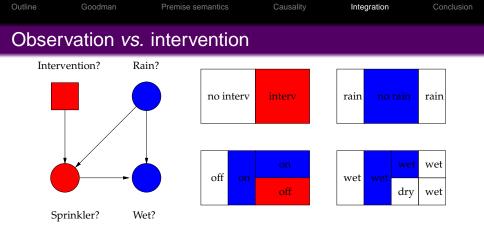
Without intervention:

(5) a. If the sprinkler were off...



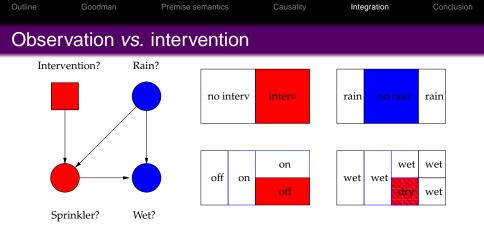
Without intervention:

- (5) a. If the sprinkler were off, it would be raining.
 - b. If the sprinkler were off, it would be wet.



With intervention:

(5) a. If the sprinkler were turned off...



With intervention:

- (5) a. \checkmark If the sprinkler were turned off, it would be dry.
 - b. XIf the sprinkler were turned off, it would be wet.



- (6) a. If I turned the sprinkler off ...b. If the sprinker were off ...
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 - How the difference between intervention and observation expressed linguistically?

Aspectual properties? Thematic roles? Dowty (1979, 1981)



- (6) a. If I turned the sprinkler off ...b. If the sprinker were off ...
 - The two antecedents license different inferences about non-effects
 - How the difference between intervention and observation expressed linguistically?
 - What should a model-theoretic analysis look like?

Intertia worlds? Stereotypical ordering sources?



• Premise semantics: A useful general-purpose framework (not a theory itself)

Outline	Goodman	Premise semantics	Causality	Integration	Conclusion
Conclu	usion				

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- Lots of work ahead.

Outline	Goodman	Premise semantics	Causality	Integration	Conclusion

The End.



How to interpret $\varphi \square \psi$ at world *w*:

• $\langle U, \rightarrow \rangle$: Causal network



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 $[X_w] =_{\mathrm{df}} \{ v \in W | X_v = X_w \}$



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- $\langle U, \rightarrow \rangle$: Causal network
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- $[X_w]$: Proposition that variable X has value X_w
- f(w): Set of relevant propositions restricted by non-descendants

For each variable X, f(w) contains the proposition that

- X has value X_w and
- X's non-descendants Y, Y',... have values Y_w, Y'_w,...

$$f(w) = \left\{ [X_w] \cap [Y_w] \cap [Y'_w] \cap \dots | X \twoheadrightarrow Y^i, X \in U \right\}$$



How to interpret $\varphi \square \rightarrow \psi$ at world *w*:

- $\langle U, \rightarrow \rangle$: Causal network
- \rightarrow : Transitive closure of \rightarrow
- $[X_w]$: Proposition that variable X has value X_w
- *f*(*w*): Set of relevant propositions restricted by non-descendants
- Prem^c_w(φ): all consistent subsets of f(w) ∪ {φ} containing φ and closed under logical consequence (relative to f(w))

For all $X \in \operatorname{Prem}_{w}^{c}(\varphi), p \in f(w)$: If *p* logically follows from $X \cap f(w)$, then $p \in X$

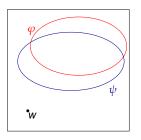
$" \square \rightarrow$ " and strict implication

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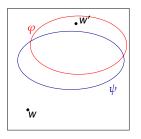
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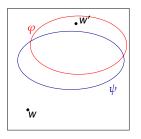
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- Suppose $\Box(\varphi \rightarrow \psi)$ is false.
- Then there is a world w' at which φ is true and ψ is false.



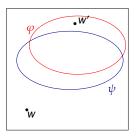
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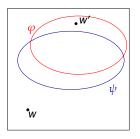
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- $\{w, w'\}$ is a proposition true at w
- *X* = {*φ*, {*w*, *w*'}} is a premise set
 - consistent;
 - contains φ ;
 - all propositions except φ true at w



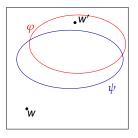
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- $\{w, w'\}$ is a proposition true at w
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- X and all its supersets entail $\neg \psi$
- Hence $\varphi \xrightarrow{n} \psi$ is false

