Ramsey’s Test, Adams’ Thesis, and Left-Nested Conditionals

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17 Sept 2009
Outline

1. Ramsey’s Test, Adams’ Thesis, and Left-Nested Conditionals
2. The Judy Benjamin Case, and Other Types of Cases
3. An Argument from McGee-Type Probabilism
4. An Argument from Weak Centering
Indicative conditionals

If Kennedy was not murdered by Oswald, he was murdered by somebody else.

If it does rain, it won’t pour.

Default characterisation

*Indicative* conditionals are conditional sentences that presuppose that the domain of possibilities relevant to acceptability is a subset of the domain of epistemically possible worlds [Stalnaker 1975:145 f].
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Graded belief

- Belief regarding conditionals comes in degrees;
- when saying that an epistemic subject believes (is confident, accepts) to a certain degree $x$ that $\varphi \rightarrow \psi$, we can equivalently say that her degree of belief (confidence, or acceptability) for the sentence $\llbracket \varphi \rightarrow \psi \rrbracket$ is $x$.

General problem

How to model graded belief for conditionals?

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Narrowing down the focus: left-nested conditionals (LN)

Simple conditionals: \( A \rightarrow B \)

If it does rain it won’t pour. \( \text{(1)} \)

Conditionals in the scope of Boolean connectives (\( \neg, \wedge, \vee \))

It won’t rain, but if it does rain it won’t pour. \( \text{(2)} \)

Right-nested conditionals (RN): \( \varphi \rightarrow (\psi \rightarrow \chi) \)

If you leave your umbrella behind you’ll get soaked if it rains. \( \text{(3)} \)

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If you’ll get soaked if it rains, then you’ll get soaked. \( \text{(4)} \)
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When two people are arguing ‘If p will q?’ and are both in doubt as to p, they are adding p hypothetically to their stock of knowledge and arguing on that basis about q; so that in a sense ‘If p, q’ and ‘If p, ¬q’ are contradictories. We can say they are fixing their degrees of belief in q given p. If p turns out false, these degrees of belief are rendered void. (‘General propositions and causality’, p. 155, n)
Ramsey’s footnote [1929]

- Degree of belief for a given conditional $\varphi \rightarrow \psi$ amounts to the associated conditional degree of belief (for the consequent $\psi$ given $\varphi$);

- an operational characterisation of conditional degree of belief: To fix the degree of belief for $\psi$ given $\varphi$, consider the degree of belief distribution that is obtainable from your actual one by hypothetically adding $\varphi$ to what you already know, and take the degree of belief for $\psi$ relative to that hypothetical new distribution.
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Ramsey’s test (RT)

- We refer to Ramsey’s footnote under the above interpretation as *Ramsey’s Test* (RT);
- we use *conditional degree of belief* in the informal sense as characterised in RT.

The problem put more specifically: How to explicate instances of RT for LN?
Ramsey’s test (RT)

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The problem put more specifically: How to explicate instances of RT for LN?
Roman upper case letters “A,” “B,” “C,” … are metavariables for *factive* sentences, that is conditional-free sentences, in the relevant language;

Greek lower case letters “ϕ,” “ψ,” “χ,” … are metavariables for any sort of sentence in the relevant language.
Syntax: languages

\( \mathcal{L}_0 \) Conditional-free language of propositional logic (\( \neg, \wedge, \lor \)), that is, a language that contains \( \neg \varphi, \varphi \land \psi, \) and \( \varphi \lor \psi \), whenever it contains \( \varphi \) and \( \psi \), and that contains only factive sentences;

\( \mathcal{L}_1 \) Language of propositional logic that embeds \( \mathcal{L}_0 \) and that contains a sentence \( \varphi \rightarrow \psi \), whenever it contains \( \varphi \) and \( \psi \);

\( \mathcal{L}_{2_{SL}} \) Language of propositional logic that embeds \( \mathcal{L}_1 \) and that contains a sentence \( \varphi \rightarrow \psi \), whenever it contains \( \varphi \) and \( \psi \), with \( \varphi \) being either a factive sentence or a simple conditional;

\( \mathcal{L}_{2_R} \) Language of propositional logic that embeds \( \mathcal{L}_1 \) and that contains a sentence \( \varphi \rightarrow \psi \), whenever it contains \( \varphi \) and \( \psi \);

\( \mathcal{L} \) Language of propositional logic that embeds \( \mathcal{L}_1 \) and that contains a sentence \( \varphi \rightarrow \psi \) whenever it contains \( \varphi \) and \( \psi \).
Two core principles of standard Bayesianism

Probabilism

Degree of belief obeys standard laws of probability with respect to Boolean connectives.

Bayes’ Principle (BP)

If $\Pr_0$ is our prior probability distribution, $\varphi$ is the new evidence, and $\Pr_1$ is the posterior probability distribution you should adopt on learning $\varphi$, then for every $\psi$, $\Pr_1$ takes for $\psi$ the prior conditional probability of $\psi$ given $\varphi$—where conditional probability is constrained by:

\[
\Pr(\psi | \varphi) = \frac{\Pr(\varphi \land \psi)}{\Pr(\varphi)},
\]

provided $\Pr(\varphi) > 0$. (Ratio Formula)
### Two core principles of standard Bayesianism

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$$Pr(\psi | \varphi) = Pr(\varphi \land \psi) / Pr(\varphi),$$

provided $Pr(\varphi) > 0$. (Ratio Formula)
A naive Bayesian approach to RT

If BP applies to cases where we \textit{factually} add \( \varphi \) to our stock of knowledge, it should equally apply to RT where we only \textit{hypothetically} add \( \varphi \) to our stock of knowledge. This suggests:

\begin{center}
\textbf{Conditional degree of belief is conditional probability}
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\Pr(\varphi \rightarrow \psi) = \Pr(\psi | \varphi), \text{ if } \Pr(\varphi) > 0.
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Adams’ thesis (AT)

The naive Bayesian approach to RT suggests for simple conditionals:

**The thesis**

If $Pr$ is our subjective probability distribution on the conditional-free fragment of our language, then for any pair of factive sentences $A$ and $B$:

$Pr(A \rightarrow B) = Pr(B \mid A)$, if $Pr(A) > 0$. 
**Lewis’ triviality results (LTR) revisited**

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| \[
| \Pr(A \rightarrow \varphi) = \Pr(\varphi | A), \text{ for any } A \text{ with } \Pr(A) > 0 \text{ and any } \varphi. 
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| **L2** For any \( B \) with \( \Pr(B) > 0 \), the probability function gotten by conditionalising \( \Pr \) on \( B \) in turn satisfies AT-RN. |

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McGee’s [1989] reconstruction of Lewis [1976]

\begin{enumerate}
\item \textbf{L1} Pr is a probability function on $\mathcal{L}_{2R}$ that satisfies the extension of AT to RN (AT-RN):
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McGee’s [1989] reconstruction of Lewis [1976]

**L1** Pr is a probability function on $\mathcal{L}_{2R}$ that satisfies the extension of AT to RN *(AT-RN)*:

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**L2** For any $B$ with $\Pr(B) > 0$, the probability function gotten by conditionalising Pr on $B$ in turn satisfies **AT-RN**.
Lewis’ triviality results revisited

First triviality result

For any $A$ and $C$ with $\Pr(A \land C) > 0$ and $\Pr(A \land \neg C) > 0$:

$$\Pr(C | A) = \Pr(C).$$
Lewis’ triviality results revisited

Skyrms’ [1980:169] observation

The conjunction of $L1$ and $L2$ is equivalent to the conjunction of $L1$ and the principle Import-Export (IE):

$$L3 \quad \Pr(B \rightarrow (A \rightarrow \varphi)) = \Pr((A \land B) \rightarrow \varphi),$$

provided $\Pr(A \land B) > 0$. 
Lewis’ triviality results revisited

Bottom line

- Lewis’ triviality argument from $L_1$ and $L_2$ shows that we can assume both AT-RN and BP for $L_{2_R}$ only on pain of triviality;
- The triviality argument from $L_1$ and $L_3$ shows that even if we keep to BP only for $L_0$, we can assume AT-RN only on pain of triviality—provided IE.
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Van Fraassen’s tenability results [1976]

Stalnaker’s hypothesis schema (SHS)

\[ \Pr(\varphi \rightarrow \psi) = \Pr(\psi | \varphi), \text{ for all } \varphi, \psi \text{ in the domain of } \Pr, \]

\[ \text{with } \Pr(\varphi) > 0 \]

Van Fraassen’s results imply for probability functions on \( \mathcal{L} \)

- There are non-trivial functions that satisfy the restriction of SHS to (i) simple conditionals, (ii) simple RN, and (iii) simple LN, and respect the conditional logic C2;
- There are non-trivial functions that satisfy SHS and respect the conditional logic CE.

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Extending AT to LN?

AT as extended to LN: \( \Pr(\varphi \rightarrow \psi) \rightarrow \chi) = \Pr(\chi | \varphi \rightarrow \psi). \)

We focus on:

\[\text{(AT-SLN)}\]

\( \Pr((A \rightarrow B) \rightarrow C) = \Pr(C | A \rightarrow B) \)
Extending AT to LN?

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We focus on:

\begin{align*}
\text{(AT-SLN)} \\
\Pr((A \rightarrow B) \rightarrow C) &= \Pr(C \mid A \rightarrow B)
\end{align*}
Argument strategy

1. In some RT instances for simple LN, it is perfectly reasonable to violate certain constraints for updates on conditional evidence;

2. whatever type of probabilism for $L_1$ one may plausibly consider, conditional probability given a simple conditional is bound to meet some of these constraints.

Bottom line

- Conditional degree of belief for $C$ given a simple conditional $A \rightarrow B$ is not representable as a conditional probability of $C$ given $A \rightarrow B$;
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The Judy Benjamin (JB) case

- An area that is divided into two halves, Red territory ($R$) and Blue territory ($\neg R$), each of which in turn is divided in equal parts, Second Company area ($S$) and Headquarters Company area ($\neg S$);
- as Judy Benjamin has no information as to her location, her degree of confidence that she is in a particular quarter is the same for each quarter: $\Pr_0$, we have: $\Pr_0(R \land S) = \Pr_0(R \land \neg S) = \Pr_0(\neg R \land S) = \Pr_0(\neg R \land \neg S) = \frac{1}{4}$;
- she then receives a radio message:

  > I can’t be sure where you are. If you are in Red territory, the odds are 3 : 1 that you are in Headquarters Company area.

After this, the radio gives out.
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Three plausible constraints on updating in the JB case

1. \( \Pr_1(\neg S \mid R) = \frac{3}{4} \) and \( \Pr_1(S \mid R) = \frac{1}{4} \), that is, the probability of \( R \land \neg S \) should be 3 times higher than the probability of \( R \land S \);

2. \( \Pr_1(\neg R) = \Pr_0(\neg R) \), that is the probability for \( \neg R \) should be unaffected;

3. \( \Pr_1(C \mid X) = \Pr_0(C \mid X) \), for all \( C \), for all \( X \) with \( X \in \{ \neg R, R \land S, R \land \neg S \} \), that is, none of her conditional degrees of belief given any proposition in \( \{ \neg R, R \land S, R \land \neg S \} \) should change either.
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3. $\Pr_1(C \mid X) = \Pr_0(C \mid X)$, for all $C$, for all $X$ with $X \in \{\neg R, R \land S, R \land \neg S\}$, that is, none of her conditional degrees of belief given any proposition in $\{\neg R, R \land S, R \land \neg S\}$ should change either.
Three plausible constraints on updating in the JB case

1. $\Pr_1(\neg S \mid R) = 3/4$ and $\Pr_1(S \mid R) = 1/4$, that is, the probability of $R \land \neg S$ should be 3 times higher than the probability of $R \land S$;

2. $\Pr_1(\neg R) = \Pr_0(\neg R)$, that is the probability for $\neg R$ should be unaffected;

3. $\Pr_1(C \mid X) = \Pr_0(C \mid X)$, for all $C$, for all $X$ with $X \in \{\neg R, R \land S, R \land \neg S\}$, that is, none of her conditional degrees of belief given any proposition in $\{\neg R, R \land S, R \land \neg S\}$ should change either.
Let $\text{Pr}_0$ be our probability function on $\mathcal{L}_0$. Let 
$\{\neg A, A \land B_1, \ldots, A \land B_n\}$ be a set of sentences in $\mathcal{L}_0$ of pairwise
truth-functionally inconsistent sentences whose disjunction is a
tautology such that, for all $i$, $\text{Pr}_0(B_i \mid A) > 0$. Let $E$ be the new
evidence of the form $\lbrack\lnot \text{If } A, \text{ then the odds for } B_1, \ldots, B_n \text{ are } c_1 : \cdots : c_n \rbrack$. Then any posterior probability function $\text{Pr}_1$ is said to
meet the requirements of a JB case for $\text{Pr}_0$ and $E$ iff for all $C$ in $\mathcal{L}_0$:

\begin{align*}
\text{JB1} & \quad \text{Pr}_1(B_i \mid A) = \frac{c_i}{\sum_{1\leq j \leq n} c_j}; \\
\text{JB2} & \quad \text{Pr}_1(A) = \text{Pr}_0(A); \\
\text{JB3} & \quad \text{Pr}_1(C \mid X) = \text{Pr}_0(C \mid X), \text{ for all } \ X \in \{\neg A, A \land B_1, \ldots, A \land B_n\}.
\end{align*}
Putting odds aside

- The JB requirements seem as correct for the scenario we obtain from the JB case by changing the odds from 3 : 1 to 1 : 0:

  \[
  \begin{align*}
  \text{JB1'} & \quad \text{Pr}_1(B \mid A) = 1; \\
  \text{JB2'} & \quad \text{Pr}_1(A) = \text{Pr}_0(A); \\
  \text{JB3'} & \quad \text{Pr}_1(C \mid X) = \text{Pr}_0(C \mid X), \text{ for all } X \in \{\neg A, A \land B_1, \ldots, A \land B_n\}.
  \end{align*}
  \]

- It makes no difference for the correctness of JB1’-JB3’ whether the new evidence has the form “If you are in Red territory, the odds are 1 : 0 that you are in Headquarters Company Area” or the form “If you are in Red territory, then you are in Headquarters Company Area”.
A case in point for violating JB2’

There was a burglary. A watch has been stolen, and the homeowner has been murdered, but it is not clear at this point that there is a connection between these two events; perhaps someone murdered the house owner, and then someone else saw an opportunity to steal the watch. There is a chance that Bob was the thief. On the other hand, while Bob may be up to theft, it seems less likely that he committed the murder. For in view of his personality, the possibility that he was the murderer seems so remote that we would not consider it seriously—although it cannot be ruled out. Importantly, even supposing that if Bob stole the watch, he also murdered the victim, the possibility that he was the murderer is still smaller than our prior probability for his being the thief.
A case in point for violating JB2’

(Thief) Bob stole the watch.
(Murderer) Bob murdered the victim.
(Evidence 1) If Bob stole the watch, then he also murdered the victim.
A case in point for violating JB2’

Applying RT to our prior probability distribution and (Evidence 1)

- $\Pr_1(\text{Murderer} \mid \text{Thief}) = 1$ (by $\Pr_1(\text{Evidence 1}) = 1$ and AT);
- $\Pr_1(\text{Murderer}) < \Pr_0(\text{Thief})$;
- $\Pr_1(\text{Murderer}) = \Pr_1(\text{Murderer} \mid \text{Thief}) \Pr_1(\text{Thief}) + \Pr_1(\text{Murderer} \mid \neg \text{Thief}) \Pr_1(\neg \text{Thief})$;
- As a result JB2’ fails:
  
  $\Pr_1(\text{Thief}) \leq \Pr_1(\text{Murderer}) < \Pr_0(\text{Thief})$. 

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A case in point for violating JB2'

Applying RT to our prior probability distribution and (Evidence 1)

- \( \Pr_1(\text{Murderer} \mid \text{Thief}) = 1 \) (by \( \Pr_1(\text{Evidence 1}) = 1 \) and AT);
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- \( \Pr_1(\text{Murderer}) = \Pr_1(\text{Murderer} \mid \text{Thief}) \Pr_1(\text{Thief}) + \Pr_1(\text{Murderer} \mid \neg\text{Thief}) \Pr_1(\neg\text{Thief}) \);
- As a result JB2' fails:
  \[ \Pr_1(\text{Thief}) \leq \Pr_1(\text{Murderer}) < \Pr_0(\text{Thief}). \]
A case in point for violating JB2’

Applying RT to our prior probability distribution and (Evidence 1)

- \( \Pr_1(\text{Murderer} \mid \text{Thief}) = 1 \) (by \( \Pr_1(\text{Evidence 1}) = 1 \) and \( \text{AT} \));
- \( \Pr_1(\text{Murderer}) < \Pr_0(\text{Thief}) \);
- \( \Pr_1(\text{Murderer}) = \Pr_1(\text{Murderer} \mid \text{Thief}) \Pr_1(\text{Thief}) + \Pr_1(\text{Murderer} \mid \lnot \text{Thief}) \Pr_1(\lnot \text{Thief}) \);
- As a result JB2’ fails:
  \[ \Pr_1(\text{Thief}) \leq \Pr_1(\text{Murderer}) < \Pr_0(\text{Thief}). \]
A case in point for violating JB2’

Applying RT to our prior probability distribution and (Evidence 1)

- $\Pr_1(\text{Murderer} \mid \text{Thief}) = 1$ (by $\Pr_1(\text{Evidence 1}) = 1$ and AT);
- $\Pr_1(\text{Murderer}) < \Pr_0(\text{Thief})$;
- $\Pr_1(\text{Murderer}) = \Pr_1(\text{Murderer} \mid \text{Thief}) \Pr_1(\text{Thief}) + \Pr_1(\text{Murderer} \mid \neg \text{Thief}) \Pr_1(\neg \text{Thief})$;
- As a result JB2’ fails:
  
  $$\Pr_1(\text{Thief}) \leq \Pr_1(\text{Murderer}) < \Pr_0(\text{Thief}).$$
A case in point for violating JB2’

Applying RT to our prior probability distribution and (Evidence 1)

- \( \text{Pr}_1(\text{Murderer} \mid \text{Thief}) = 1 \) (by \( \text{Pr}_1(\text{Evidence 1}) = 1 \) and AT);
- \( \text{Pr}_1(\text{Murderer}) < \text{Pr}_0(\text{Thief}) \);
- \( \text{Pr}_1(\text{Murderer}) = \text{Pr}_1(\text{Murderer} \mid \text{Thief}) \text{Pr}_1(\text{Thief}) + \) 
  \( \text{Pr}_1(\text{Murderer} \mid \neg \text{Thief}) \text{Pr}_1(\neg \text{Thief}) \);
- As a result JB2’ fails:
  \( \text{Pr}_1(\text{Thief}) \leq \text{Pr}_1(\text{Murderer}) < \text{Pr}_0(\text{Thief}) \).
A case in point for violating JB3’

We live in a house in neighbourhood $N$. Nearby lives a werewolf who assumes her wolf form every full-moon night. We know that before going out to search for prey, the werewolf flips secretly a fair coin. If the coin lands heads, she goes to neighbourhood $N$, and if it lands tails, she goes to neighbourhood $M$. We also know that the werewolf always kills anyone who ventures outside in the neighbourhood she is stalking. Conversely, she never kills beyond the neighbourhood she is stalking. Tonight there is full moon. The odds for the werewolf being in our neighbourhood as against her being in the neighbourhood $M$ are 1 : 1. We suddenly learn that Jones, who was still in our house a few minutes ago, has left the house. There are two doors to the house, the front and the back—either way out leads into neighbourhood $N$. 

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Ramsey’s Test, Adams’ Thesis, and Left-Nested Conditionals
A case in point for violating JB3’

Killing Jones was killed by the werewolf.

Front Jones went out the front door.

Evidence 2 If Jones went out the front door, then he was killed by the werewolf.

What we know strongly suggests that the question of the outcome of the werewolf’s coin toss is independent of the question of what exit was taken by Jones. Importantly, mere supposition of Evidence 2 should not make a difference regarding the independence of these two questions of each other.
A case in point for violating JB3’

Applying RT to our prior probability distribution and Evidence 2

- $Pr_1(Killing) = Pr_1(Killing | Front)$;
- $Pr_1(Killing | Front) = Pr_1(Evidence 2)$ (by AT);
- $Pr_1(Evidence 2) = 1$;
- hence, $Pr_1(Killing) = 1$.
- As a result JB3' fails:
  
  $Pr_1(Killing | \neg Front) = 1 \neq .5 = Pr_0(Killing | \neg Front)$.
A case in point for violating JB3’

Applying RT to our prior probability distribution and Evidence 2

- \( \Pr_1(\text{Killing}) = \Pr_1(\text{Killing} \mid \text{Front}); \)
- \( \Pr_1(\text{Killing} \mid \text{Front}) = \Pr_1(\text{Evidence 2}) \) (by AT);
- \( \Pr_1(\text{Evidence 2}) = 1; \)
- hence, \( \Pr_1(\text{Killing}) = 1. \)
- As a result JB3’ fails:
  \[ \Pr_1(\text{Killing} \mid \neg \text{Front}) = 1 \neq .5 = \Pr_0(\text{Killing} \mid \neg \text{Front}). \]
A case in point for violating JB3’

Applying RT to our prior probability distribution and Evidence 2

- \( \Pr_1(\text{Killing}) = \Pr_1(\text{Killing} \mid \text{Front}) \);
- \( \Pr_1(\text{Killing} \mid \text{Front}) = \Pr_1(\text{Evidence 2}) \) (by AT);
- \( \Pr_1(\text{Evidence 2}) = 1 \);
- hence, \( \Pr_1(\text{Killing}) = 1 \).
- As a result JB3’ fails:

\[ \Pr_1(\text{Killing} \mid \neg \text{Front}) = 1 \neq .5 = \Pr_0(\text{Killing} \mid \neg \text{Front}). \]
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- \( \Pr_1(\text{Evidence 2}) = 1 \);
- hence, \( \Pr_1(\text{Killing}) = 1 \).
- As a result JB3’ fails:

  \[ \Pr_1(\text{Killing} \mid \neg \text{Front}) = 1 \neq 0.5 = \Pr_0(\text{Killing} \mid \neg \text{Front}). \]
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Applying RT to our prior probability distribution and Evidence 2

- $\Pr_1(\text{Killing}) = \Pr_1(\text{Killing} \mid \text{Front})$;
- $\Pr_1(\text{Killing} \mid \text{Front}) = \Pr_1(\text{Evidence 2})$ (by AT);
- $\Pr_1(\text{Evidence 2}) = 1$;
- hence, $\Pr_1(\text{Killing}) = 1$.

As a result JB3’ fails:

$$\Pr_1(\text{Killing} \mid \neg \text{Front}) = 1 \neq 0.5 = \Pr_0(\text{Killing} \mid \neg \text{Front}).$$
A case in point for violating JB3’

Applying RT to our prior probability distribution and Evidence 2

- \( Pr_1(\text{Killing}) = Pr_1(\text{Killing} \mid \text{Front}) \);
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- \( Pr_1(\text{Evidence 2}) = 1 \);
- hence, \( Pr_1(\text{Killing}) = 1 \).
- As a result JB3’ fails:
  \[ Pr_1(\text{Killing} \mid \neg \text{Front}) = 1 \neq .5 = Pr_0(\text{Killing} \mid \neg \text{Front}). \]
First result

- In some RT instances for simple LN, it is perfectly reasonable to violate JB2'.
- In some RT instances for simple LN, it is perfectly reasonable to violate JB3'.
McGee’s probabilism for the fragment $\mathcal{L}_1^*$ of $\mathcal{L}_1$ of Boolean combinations of factive sentences and simple conditionals with a non-zero antecedent [1989]

**Probabilistic Centering (PC)** \[ \Pr(A \land (A \rightarrow B)) \equiv A \land B) = 1. \]

**Independence (IND)** If $C$ is truth-functionally incompatible with each of $A_1, \ldots, A_n$ and, for all $i$, $\Pr(A_i) > 0$, then
\[
\Pr(C \land (A_1 \rightarrow B_1) \land \cdots \land (A_n \rightarrow B_n)) = \\
\Pr(C) \times \Pr((A_1 \rightarrow B_1) \land \cdots \land (A_n \rightarrow B_n)).
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McGee’s probabilism for the fragment $\mathcal{L}_1^*$ of $\mathcal{L}_1$ of Boolean combinations of factive sentences and simple conditionals with a non-zero antecedent [1989]

Probabilistic Centering (PC) $\Pr(A \land (A \to B) \equiv A \land B) = 1$.

Independence (IND) If $C$ is truth-functionally incompatible with each of $A_1, \ldots, A_n$ and, for all $i$, $\Pr(A_i) > 0$, then $\Pr(C \land (A_1 \to B_1) \land \cdots \land (A_n \to B_n)) = \Pr(C) \times \Pr((A_1 \to B_1) \land \cdots \land (A_n \to B_n))$. 

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Ramsey’s Test, Adams’ Thesis, and Left-Nested Conditionals
McGee’s probabilism for $\mathcal{L}_1^*$ [1989]

- **(GEN-AT)** Assuming probability, PC and IND jointly imply AT;
- **(EX)** For every probability function $Pr$ on $\mathcal{L}_0$, there is a probability function $Pr'$ on $\mathcal{L}_1^*$ such that $Pr'$ extends $Pr$ and $Pr'$ meets PC and IND;
- **(UN)** For every probability function $Pr$ on $\mathcal{L}_0$, if there is a probability function $Pr'$ on $\mathcal{L}_1^*$ such that $Pr'$ extends $Pr$ and $Pr'$ meets PC and IND, then there is only one such extension.
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- **(GEN-AT)** Assuming probability, **PC** and **IND** jointly imply **AT**;
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- (UN) For every probability function Pr on $\mathcal{L}_0$, if there is a probability function Pr' on $\mathcal{L}_1^*$ such that Pr' extends Pr and Pr' meets PC and IND, then there is only one such extension.
Simple conditional updating (SCU)

Definition

Let \( \{\neg A, A \land B_1, \ldots, A \land B_n\} \) be a set of pairwise truth-functionally inconsistent sentences whose disjunction is a tautology such that for the prior probability function \( Pr_0 \), \( Pr_0(B_i \mid A) > 0 \), for all \( i \), and suppose that one is caused to change, for all \( i \), one’s degrees of belief from \( Pr_0(A \rightarrow B_i) \) to \( Pr_1(A \rightarrow B_i) \). Then one updates by *simple conditional updating (SCU)* on this change iff for all sentences \( C \) of \( L_0 \),

\[
Pr_1(C) = \sum_{i=1}^{n} Pr_0(C \mid A \rightarrow B_i) \times Pr_1(A \rightarrow B_i).
\]
SCU and AT-SLN

Let $Pr_0$ be our prior distribution on $L_1^*$ and $Pr_1$ be the result of hypothetically updating $Pr_1$ on the hypothetical new evidence $A \rightarrow B$, where $Pr_0(A \rightarrow B) > 0$. Let $Pr_1^*$ be the result of SCU on a change of one’s degree of belief for $A \rightarrow B$ to 1 and of one’s degree of belief for $A \rightarrow \neg B$ to 0. Assuming RT and AT-SLN, it follows then that $Pr_1 = Pr_1^*$.

Bottomline

Assuming McGee’s probabilism and that AT-SLN provides an adequate model of RT for left-nested conditionals, instances of RT for simple left-nested conditionals are instances of SCU.
Simple conditional updating: an appropriate update function for JB cases

Theorem

Let \( \{\neg A, A \land B_1, \ldots, A \land B_n\} \) be a set of pairwise truth-functionally inconsistent sentences of \( \mathcal{L}_0 \) whose disjunction is a tautology such that for the prior probability function \( \Pr_0 \) on \( \mathcal{L}_0 \), \( \Pr_0(B_i \mid A) > 0 \) for all \( i \). Then, if a person’s new degree of belief function \( \Pr_1 \) comes from her old degree of belief function \( \Pr_0 \) by SCU on a change in her degrees of belief in \( A \rightarrow B_i \), for all \( i \), we have for all \( C \in \mathcal{L}_0 \):

1. \( \Pr_1(A) = \Pr_0(A) \);
2. \( \Pr_1(C \mid X) = \Pr_0(C \mid X) \), for all \( X \in \{\neg A, A \land B_1, \ldots, A \land B_n\} \);
3. the restriction of \( \Pr_1 \) to \( \mathcal{L}_0 \) is a probability function.
The argument from McGee’s probabilism

1. Assuming McGee’s probabilism and that AT-SLN provides an adequate model of RT for left-nested conditionals, instances of RT for simple left-nested conditionals are instances of SCU.

2. According to SCU, on updating on simple conditional evidence, we should meet both JB2’ and JB3’.

3. But by the First result, we can make perfect sense of updates on simple conditional evidence that violate JB2’ or JB3’.

4. Hence, assuming McGee’s probabilism, AT-SLN does not provide an adequate model of RT for left-nested conditionals.
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Turning the argument around against IND?

Lance [1991]

\[ \Pr(((\text{Front} \rightarrow \text{Killing}) \land (\neg \text{Front} \land \neg \text{Killing})) = 0. \]

How to motivate this claim without an Adams-type account of Ramsey tests involving simple conditionals?

- \( \Pr( \text{Front} \rightarrow \text{Killing} \mid \neg \text{Front} \land \neg \text{Killing}) = 0? \)
- \( \Pr(\neg \text{Front} \land \neg \text{Killing} \mid \text{Front} \rightarrow \text{Killing}) = 0? \)
Weak centering: logical

(WLC)

\[ \neg A \wedge B \wedge \neg A \wedge (A \to B) \wedge \] are logically equivalent.
## Weak centering: logical

### Standard conditional logics: Stalnaker (C2)

<table>
<thead>
<tr>
<th>Rule</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>RCEC</strong></td>
<td>From $\varphi \equiv \psi$, to infer $(\chi \rightarrow \varphi) \equiv (\chi \rightarrow \psi)$</td>
</tr>
<tr>
<td><strong>RCK</strong></td>
<td>From $(\varphi_1 \land \cdots \land \varphi_n) \supset \psi$, to infer $[(\chi \rightarrow \varphi_1) \land \cdots \land (\chi \rightarrow \varphi_n)] \supset (\chi \rightarrow \psi)$</td>
</tr>
<tr>
<td><strong>ID</strong></td>
<td>$\varphi \rightarrow \varphi$</td>
</tr>
<tr>
<td><strong>MP</strong></td>
<td>$(\varphi \rightarrow \psi) \supset (\varphi \supset \psi)$</td>
</tr>
<tr>
<td><strong>MOD</strong></td>
<td>$(\neg \varphi \rightarrow \varphi) \supset (\psi \rightarrow \varphi)$</td>
</tr>
<tr>
<td><strong>CSO</strong></td>
<td>$[(\varphi \rightarrow \psi) \land (\psi \rightarrow \varphi)] \supset [(\varphi \rightarrow \chi) \equiv (\psi \rightarrow \chi)]$</td>
</tr>
<tr>
<td><strong>CV</strong></td>
<td>$[(\varphi \rightarrow \psi) \land \neg (\varphi \rightarrow \neg \chi)] \supset [(\varphi \land \chi) \rightarrow \psi]$</td>
</tr>
<tr>
<td><strong>CEM</strong></td>
<td>$(\varphi \rightarrow \psi) \lor (\varphi \rightarrow \neg \psi)$</td>
</tr>
</tbody>
</table>
Weak centering: logical

Standard conditional logics: Lewis (VC)

Replace in $C_2$ the principle $CEM$ by:

$$\text{CS} \ (\varphi \land \psi) \supset (\varphi \rightarrow \psi)$$
Weak centering: probabilistic

Assuming probability respects conditional logic, (WLC) implies:

\[ \Pr(A \land B) = \Pr(A \land (A \rightarrow B)) \]  

(WPC)

Probabilism for \( \mathcal{L}_1 \) and richer languages

- van Fraassen [1976]
- McGee [1989]
- Jeffrey and Stalnaker [1994]
- Milne [1997] (non-classical probability)

(Exception: Ellis [1979])
Weak centering: probabilistic

Assuming probability respects conditional logic, \((WLC)\) implies:

\[
\Pr(A \land B) = \Pr(A \land (A \rightarrow B)) \tag{WPC}
\]

Probabilism for \(\mathcal{L}_1\) and richer languages

- van Fraassen [1976]
- McGee [1989]
- Jeffrey and Stalnaker [1994]
- Milne [1997] (non-classical probability)

(Exception: Ellis [1979])
A well-known result [van Fraassen 1976]

Assuming \textbf{WPC, AT} is equivalent to:

\[
\Pr(A | A \rightarrow B) = \Pr(A) \tag{PI}
\]
The argument from weak centering

1. Assuming WPC, AT is equivalent to PI.

2. Assuming that AT-SLN provides an adequate model of RT for left-nested conditionals, PI implies the constraint JB2′.

3. But by the First result, we can make perfect sense of updates on simple conditional evidence that violate JB2′.

4. Hence, assuming weak centering, AT-SLN does not provide an adequate model of RT for left-nested conditionals.
The argument from weak centering

1. Assuming WPC, AT is equivalent to PI.

2. Assuming that AT-SLN provides an adequate model of RT for left-nested conditionals, PI implies the constraint JB2'.

3. But by the First result, we can make perfect sense of updates on simple conditional evidence that violate JB2'.

4. Hence, assuming weak centering, AT-SLN does not provide an adequate model of RT for left-nested conditionals.
The argument from weak centering

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2. Assuming that AT-SLN provides an adequate model of RT for left-nested conditionals, PI implies the constraint JB2'.

3. But by the First result, we can make perfect sense of updates on simple conditional evidence that violate JB2'.

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An afternote on Stalnaker’s hypothesis (SH)

Stalnaker’s hypothesis (SH)—weakest plausible interpretation
For each probability function Pr that could represent a rational subject’s system of beliefs, there is some connective “→” such that:

$$\Pr(\varphi \rightarrow \psi) = \Pr(\psi | \varphi)$$, for all $\varphi, \psi$ in the domain of $\Pr$, with $\Pr(\varphi) > 0$
Van Fraassen [1976] suggests that PI may provide “a new fulcrum for the application of a philosophical critique or defence” of SH.

In view of our material inadequacy result against AT-SLN, we contend that PI provides a “new fulcrum” for the former.
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Thank you!