

MULTIMODE UTILITY THEORY: A theory of rational subjectivity

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Rationality

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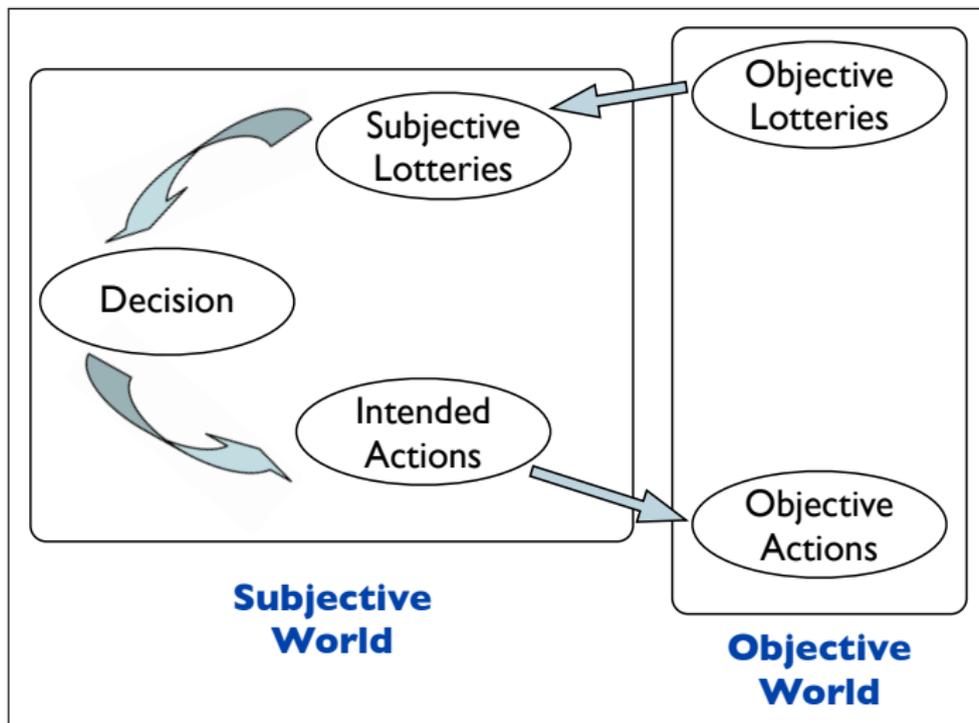
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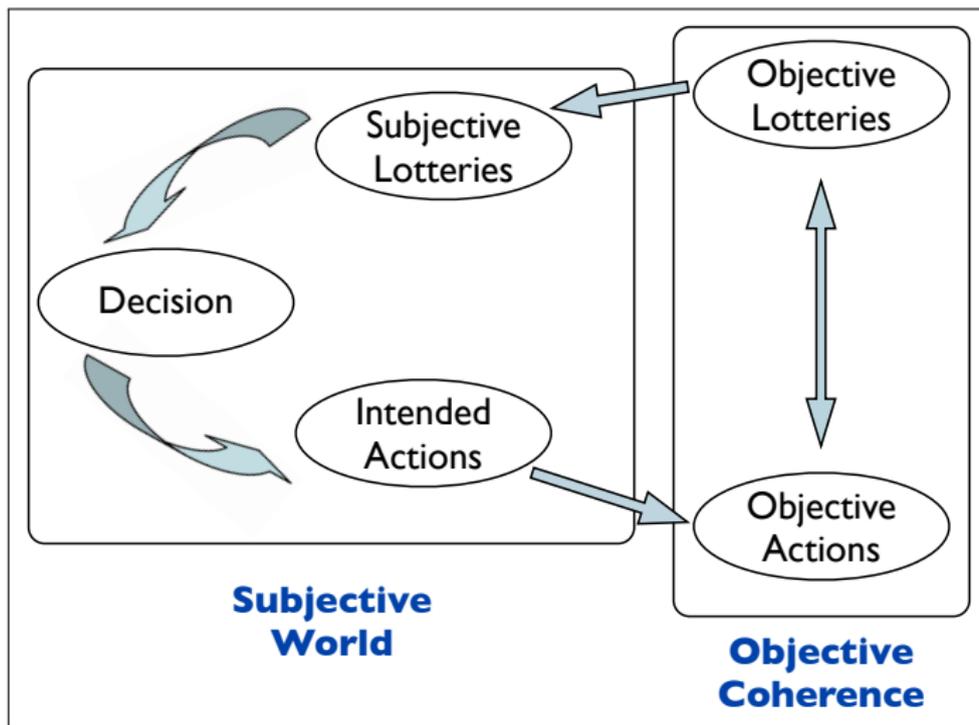
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A number of modifications of SEU for capturing various concepts of risk has been suggested in the economic literature. Some of these give up uncertainty being measured by a finitely additive probability function. They all, however, retain the boolean algebra structure of events.

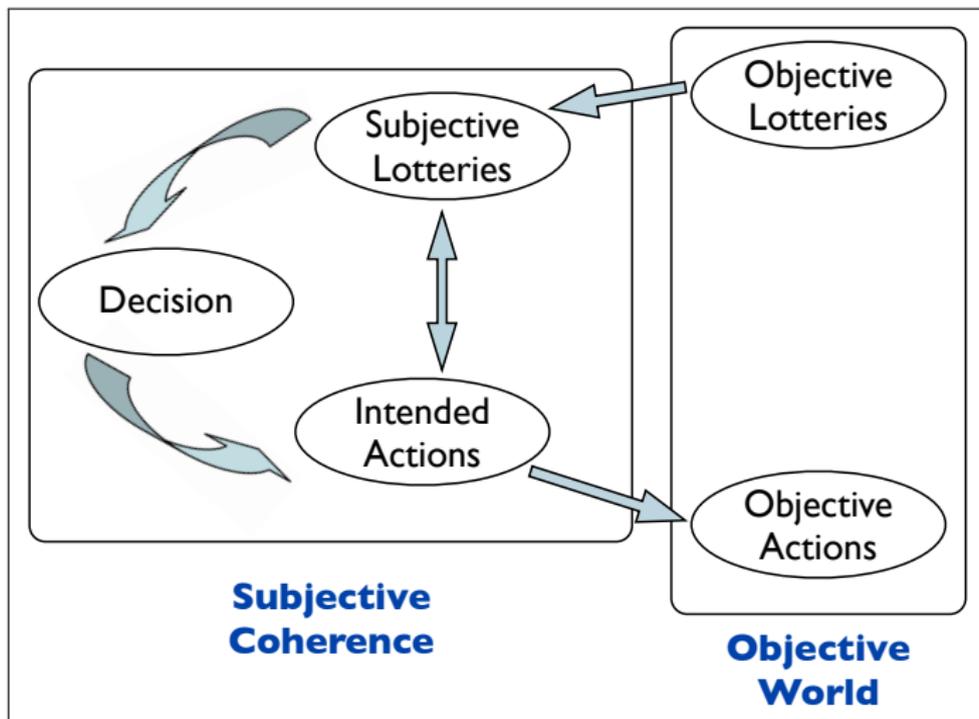
Decision Making with Subjective Stages



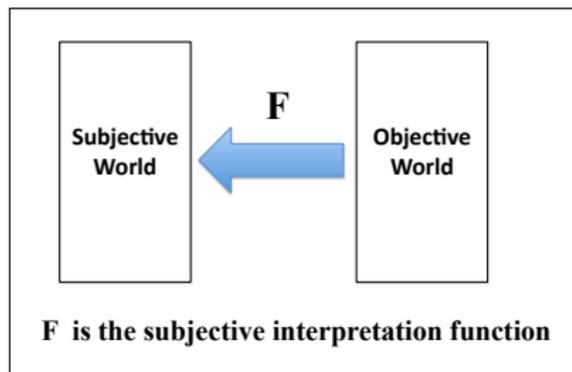
Objective Rationality



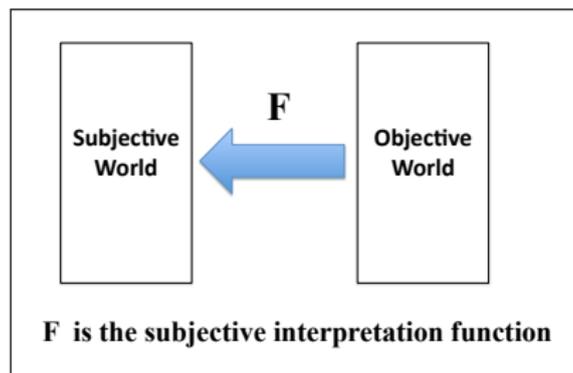
Subjective Rationality



Subjective Interpretation Function

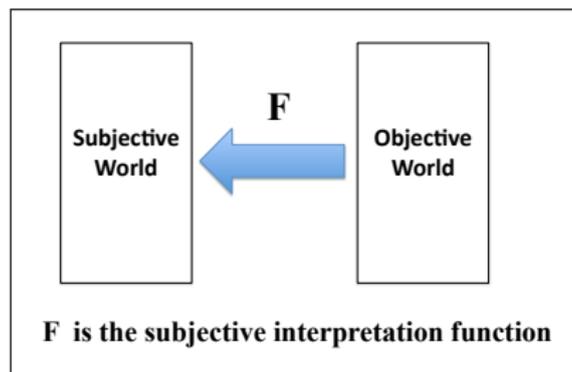


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For the purposes of this lecture it will be assumed that *the subjective interpretations of gambles are themselves gambles*.

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Certainty condition: 70% of participants preferred the cash over the kiss.

Low-probability condition: 65% of participants preferred the kiss lottery over the cash lottery.

Rationality and Human Normative Behavior

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Instead of arguing about term “rational”, I will reformulate (1) as (1’): *Human normative behavior should be formulated to include human emotions.*

Normativeness and Rationality

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Figure: Normative

Normativeness and Rationality



Figure: Normative



Figure: Rational

Normative Behavior

Key idea of this talk: Normativeness for human decisions making under uncertainty should be formulated in terms of subjective coherence.

Boolean Event Spaces and Logic

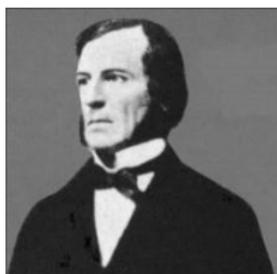


Figure: Boole

Boolean event spaces were originally developed for describing the algebra inherent in classical logic, which is the logic appropriate for Platonism.

Quantum Event Spaces and Logic



Figure: von Neumann

Von Neumann in the 1930's realized (i.e., proved to himself) that the phenomena in quantum mechanics could not be described using boolean logic and an boolean event space. He provided a probabilistic foundation for quantum mechanics using a different kind of event space.

Intuitionistic Mathematics



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Heyting formulated a logic that could account for the deductions that Brouwer made in his new radical mathematics. His axiomatization became known as *intuitionistic logic*.

Topological Semantics for Intuitionistic Logic



Figure: Rasiowska and Sikorski

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The concepts and properties of event spaces used in my research are based on ideas and methods of Rasiowska and Sikorski.

Anticipation Event Spaces

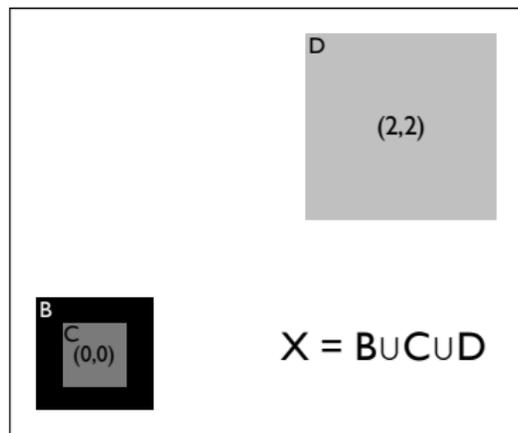
$\langle \mathcal{X}, \cup, \cap, \dot{-}, X, \emptyset \rangle$ is said to be an **anticipation event space** if and only if

- X and \emptyset are in \mathcal{X} and $X \neq \emptyset$
- all elements of \mathcal{X} are subsets of X ,
- for all A and B in \mathcal{X} , $A \cup B$ and $A \cap B$ are in \mathcal{X} ,
- $\dot{-}$ is an operation on \mathcal{X} , called **pseudo complementation**, such that

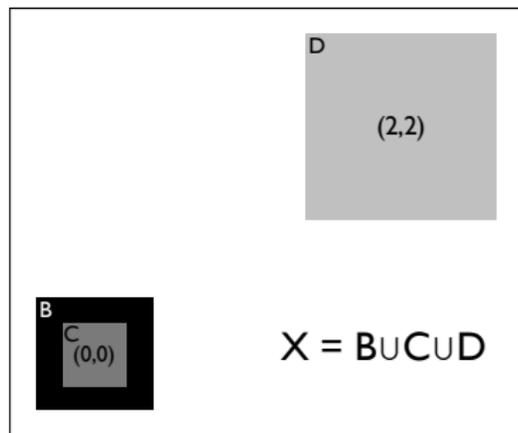
$\dot{-}A =$ the largest element B of \mathcal{X} such that $B \subseteq X - A$,

i.e., if C is in \mathcal{X} and $C \subseteq X - A$ then $C \subseteq B$.

Example of an Anticipation Algebra that is not Boolean



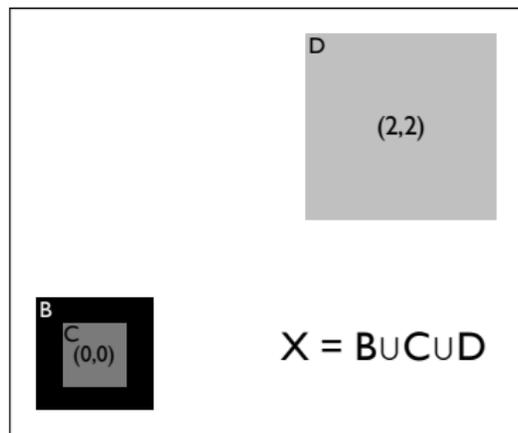
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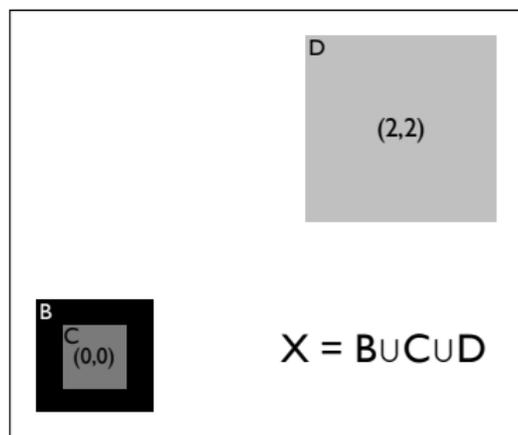


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Note that $\dot{\cdot} C = \dot{\cdot} B = D$ and that $\dot{\cdot} D = B$. Thus, $C \neq B$, but $\dot{\cdot}\dot{\cdot} C = \dot{\cdot}\dot{\cdot} B$.

Probability and Topological Interpretation

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Suppose $\langle \mathcal{X}, \cup, \cap, \dot{-}, X, \emptyset \rangle$ is an anticipation event space. Then \mathbb{P} is said to be a *probability function* on \mathcal{X} if and only if \mathbb{P} is a function from \mathcal{X} into $[0, 1]$ such that

- ▶ $\mathbb{P}(X) = 1$ & $\mathbb{P}(\emptyset) = 0$,
- ▶ for all A and B in \mathcal{X} ,

$$\mathbb{P}(A \cup B) = \mathbb{P}(A) + \mathbb{P}(B) - \mathbb{P}(A \cap B).$$

Descriptions

A typical description of the lottery

$$L = (a_1, A_1; \dots; a_i, A_i; \dots; a_m, A_m)$$

has the form,

$$\mathbf{L} = (\mathbf{a}_1, \mathbf{A}_1; \dots; \mathbf{a}_i, \mathbf{A}_i; \dots; \mathbf{a}_m, \mathbf{A}_m).$$

L is called the *objective interpretation* of L and is denoted by $\mathcal{I}_O(\mathbf{L})$.

Similarly, the *objective interpretations* of \mathbf{A}_i and \mathbf{a}_i are, respectively, A_i and a_i , and are denoted by, respectively, $\mathcal{I}_O(\mathbf{A}_i)$ and $\mathcal{I}_O(\mathbf{a}_i)$.

Interpretations

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In MUT (*Multimode Utility Theory*), the decision maker can be in many states and her interpretation of a description can vary with with state.

$\mathcal{I}_i(\mathbf{A})$ denotes the decision maker's interpretation of \mathbf{A} when she is in state M . Similarly for $\mathcal{I}_M(\mathbf{a})$ and $\mathcal{I}_M(\mathbf{L})$.

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$$u(\mathbf{L}) = \sum_{i=1}^m \frac{P[\mathcal{I}_{M_i}(\mathbf{A}_i)]u(\mathbf{a}_i)}{P[\mathcal{I}_{M_1}(\mathbf{A}_1)] + \cdots + P[\mathcal{I}_{M_m}(\mathbf{A}_m)]},$$

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- The formula

$$M_i = F(\mathbf{a}_i, \mathbf{A}_i)$$

for specifying the decision maker's state. (*A DSEU restriction*)

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A consequence of the above is that if $\mathcal{I}_M(\mathbf{A})$ and $\mathcal{I}_N(\mathbf{B})$ are defined and $A \cap B = \emptyset$, then $\mathcal{I}_M(\mathbf{A}) \cap \mathcal{I}_N(\mathbf{B}) = \emptyset$.

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Thus the interpretation of a lottery remains a lottery with the outcomes in the same order.

DSEU Modeling

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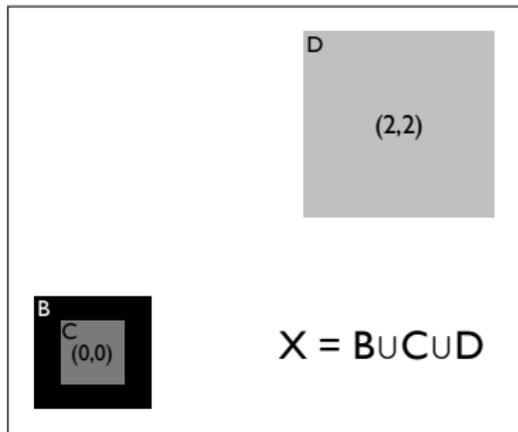
When this, and other DSEU restrictions are met, then DSEU models generally have fewer or the same number parameters than other models for the same kind of cognitive decision phenomenon.

Example: Kissing Your Favorite Movie Star Experiment

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Low probability condition participants were asked to imagine that they could take part in either a lottery offering a 1% chance of winning “the opportunity to meet and kiss your favorite movie star” or a lottery offering a 1% chance of winning \$50 in cash.

T1 = (Kiss, Winning Ticket; \$0, Losing Ticket), T2 = (\$50, Wining Ticket; \$0, Losing Ticket).



Kiss in T1 puts the decision maker into mode M and $\mathcal{I}_M(\mathbf{Winning\ Ticket}) = B$; **\$50 in T2** put the decision maker into mode N and $\mathcal{I}_N(\mathbf{Winning\ Ticket}) = C$; **\$0 in both T1 and T2** puts the decision maker in mode N and $\mathcal{I}_N(\mathbf{Losing\ Ticket}) = D$.

Example: Fear

Chichilnisky (2009) presents a generalization of classical subjective expected utility theory that emphasizes the special role that catastrophes play in human decision processes.

Her intent is “to define rational behavior more broadly, and more in tune with the way humans behave.”

Fear

In this example \mathcal{M} has two modes, a rational mode, R , and a fear mode F , which are related as follows: : For all lottery event descriptions \mathbf{A} ,

$$\mathcal{I}_F(\mathbf{A}) = [\dot{\cdot} \dot{\cdot} \mathcal{I}_R(\mathbf{A})] = [\dot{\cdot} \dot{\cdot} \mathcal{I}_O(\mathbf{A})] \supset \mathcal{I}_R(\mathbf{A}) = \mathcal{I}_O(\mathbf{A}) = A.$$

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The outcome \mathbf{a} in the term description (\mathbf{a}, \mathbf{A}) puts the decision maker into one of the states R or F .

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This raises the question about how states in $[\dot{\cdot}\dot{\cdot}\mathcal{I}_R(\mathbf{A})] - \mathcal{I}_R(\mathbf{A})$ are to be interpreted. Three approaches are considered:

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(2) The adding of states in $[\dot{\cdot}\dot{\cdot}\mathcal{I}_F(\mathbf{A})] - \mathcal{I}_R(\mathbf{A})$ to those of $\mathcal{I}_R(\mathbf{A})$ is a mathematical way of increasing the decision maker's perceived probability of \mathbf{A} . The states in $[\dot{\cdot}\dot{\cdot}\mathcal{I}_R(\mathbf{A})] - \mathcal{I}_R(\mathbf{A})$ are *fictitious* (called *virtual* in some literatures).

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(3) The adding of states in $[\dot{\cdot}\dot{\cdot}\mathcal{I}_F(\mathbf{A})] - \mathcal{I}_R(\mathbf{A})$ to those of $\mathcal{I}_R(\mathbf{A})$ is a result of the decision maker's beliefs: Fear produces illusions involving the existence of such states, and she takes these illusions into account in the computation of $u(\mathbf{L})$.

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A theorem shows the following: Each DSEU model is isomorphically imbeddable in a SEU model.

- (1) I take this theorem as showing that DSEU **within the subjective world** has the **same formal properties** that are used to characterize rationality in the objective world.
- (2) This alone does not imply that DSEU will pass pragmatic tests carried out in the **objective world** of rationality designed for SEU.

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In SEU, the straight jacket takes the form of a rigid structure that only allows subjectivity for the importance of outcomes and the size of probabilities. Generally the sizes of probabilities are highly constrained by symmetry and other structural considerations. Other decision theories, to keep a rational appearance, cut SEU into separate pieces and re-tailor them into a slightly less stifling garment.

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In contrast, the decision theory discussed in this lecture, DSEU, sees instead a colorful individual in need of a new kind of clarity to reveal his or her rational intent.