

Contextual Semantics:
From Quantum Mechanics to Logic, Databases,
Constraints, and Complexity
Lecture 2

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A Possibilistic Model Of An Experiment

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Can we explain this behaviour using a classical source?

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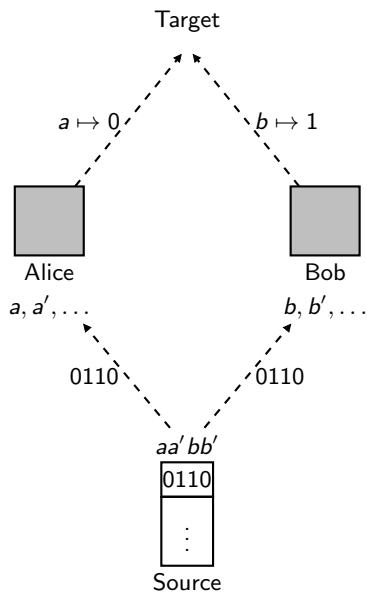
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This point of view is called **non-contextuality**. It is equivalent to the assumption of a classical source.

However, this view is **impossible to sustain** in the light of our **actual observations of (micro)-physical reality**.

Hidden Variables: The Mermin instruction set picture



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Hardy models: those whose support satisfies

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$$\lambda : a_1 \mapsto 0, \quad b_1 \mapsto 0.$$

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Thus Hardy models are **contextual**. They cannot be explained by a classical source.

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A	B	(0,0)	(1,0)	(0,1)	(1,1)
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a'	b	$3/8$	$1/8$	$1/8$	$3/8$
a	b'	$3/8$	$1/8$	$1/8$	$3/8$
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Each row of the table specifies a **probability distribution** on events O^C for a given choice of measurements C .

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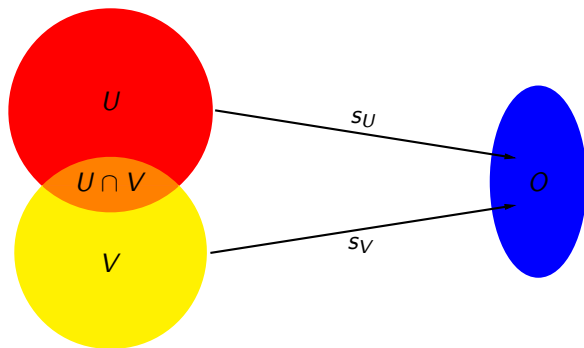
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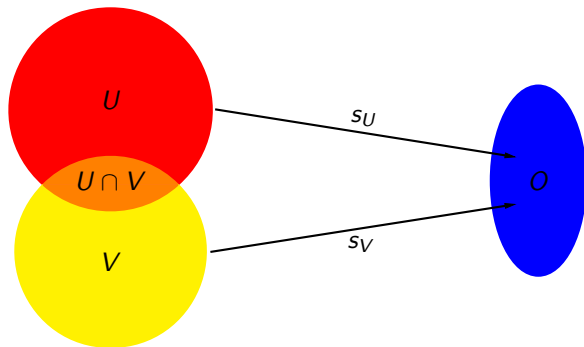
The different sets of compatible measurements correspond to the different contexts of measurement and observation of the physical system.

The fact that the behaviour of these observable outcomes cannot be accounted for by some context-independent global description of reality corresponds to the geometric fact that these local sections cannot be glued together into a **global section**.

Gluing functional sections



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If $s_U|_{U \cap V} = s_V|_{U \cap V}$, they can be glued to form

$$s : U \cup V \longrightarrow O$$

such that $s|_U = s_U$ and $s|_V = s_V$.

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Examples: $\mathbb{R}_{\geq 0}$ (probability distributions), \mathbb{B} (non-empty subsets), \mathbb{R} (signed measures).

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$$\mathcal{D}_R(O^{U'}) \rightarrow \mathcal{D}_R(O^U) :: d \mapsto d|_U,$$

where for each $s : U \rightarrow O$:

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In fact, it is the composition of $U \mapsto O^U$ and the covariant distribution functor \mathcal{D}_R .

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Example: Bell scenarios

If X_A, X_B are disjoint sets of labels for measurements by Alice and Bob, the set of contexts will be

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N.B. Vorob'ev theorem.

Example: the 18-vector configuration in \mathbb{R}^4

This uses the following measurement cover $\mathcal{U} = \{U_1, \dots, U_9\}$:

U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9
A	A	H	H	B	I	P	P	Q
B	E	I	K	E	K	Q	R	R
C	F	C	G	M	N	D	F	M
D	G	J	L	N	O	J	L	O

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<i>B</i>	<i>E</i>	<i>I</i>	<i>K</i>	<i>E</i>	<i>K</i>	<i>Q</i>	<i>R</i>	<i>R</i>
<i>C</i>	<i>F</i>	<i>C</i>	<i>G</i>	<i>M</i>	<i>N</i>	<i>D</i>	<i>F</i>	<i>M</i>
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Yields a proof of the **Kochen-Specker theorem**.

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$$\sum_{x \in X} \phi(x) = 1.$$

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Functorial action: Given a function $f : X \rightarrow Y$, we define

$$\mathcal{D}_R(f) : \mathcal{D}_R(X) \rightarrow \mathcal{D}_R(Y) :: d \mapsto [y \mapsto \sum_{f(x)=y} d(x)].$$

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Contextual Probability Theory!

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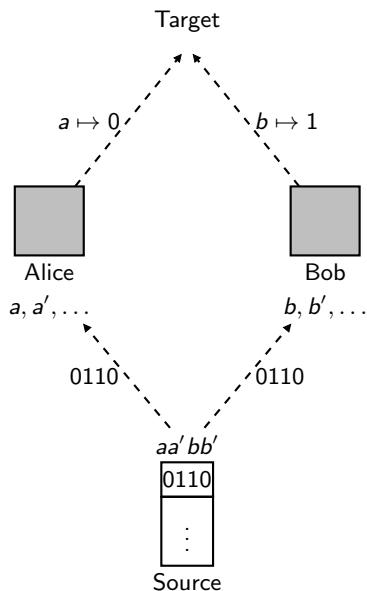
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This says that the probability for Alice to get the outcome $s_0(m_a)$ is the same, whether we marginalize over the possible outcomes for Bob with measurement m_b , or with m'_b .

In other words, Bob's choice of measurement cannot influence Alice's outcome.

Hidden Variables: The Mermin instruction set picture



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If d is a global section for the model $\{e_C\}$, we recover the predictions of the model by **averaging over the values of these hidden variables**:

$$e_C(s) = d|C(s) = \sum_{s' \in \mathcal{E}(X), s'|C=s} d(s') = \sum_{s' \in \mathcal{E}(X)} \delta_{s'|C}(s) \cdot d(s').$$

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Any factorizable (i.e. local) hidden-variable model defines a global section.

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So:

existence of a local hidden-variable model for a given empirical model
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Hence:

No such h.v. model exists (the empirical model is **non-local/contextual**)
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Thus in terms of well-known examples, we have

Bell $<$ Hardy $<$ GHZ

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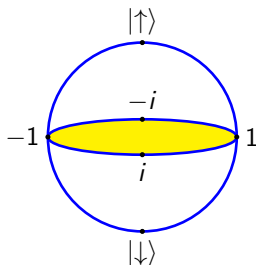
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This computation is controlled by the product of the $|\downarrow\rangle$ -coefficients of the basis vectors: cyclic group generated by $i \cong \mathbb{Z}_4$.



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NB: a model with these properties can be realized in quantum mechanics.

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Thus for any $Y^{(i)}, Y^{(j)}$ assigned the **same** value, if we substitute X 's in those positions they must receive **different** values. Similarly, for any $Y^{(i)}, Y^{(j)}$ assigned different values, the corresponding $X^{(i)}, X^{(j)}$ must receive the same value.

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Suppose not all $Y^{(i)}$ are assigned the same value. Then for some i, j, k , $Y^{(i)}$ is assigned the same value as $Y^{(j)}$, and $Y^{(j)}$ is assigned a different value to $Y^{(k)}$. Thus $Y^{(i)}$ is also assigned a different value to $Y^{(k)}$. Then $X^{(i)}$ is assigned the same value as $X^{(k)}$, and $X^{(j)}$ is assigned the same value as $X^{(k)}$. By transitivity, $X^{(i)}$ is assigned the same value as $X^{(j)}$, yielding a contradiction.

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The remaining cases are where all Y 's receive the same value. Then any pair of X 's must receive different values. But taking any 3 X 's, this yields a contradiction, since there are only two values, so some pair must receive the same value.

Degrees of contextuality/non-locality for quantum states

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- Finally, a state is weakly non-local if it is non-local, but neither of the previous two cases apply.

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We believe that an answer to this problem will shed considerable light on the structure of multipartite states, not least because it will necessitate solving the following task:

Given a multipartite state, find local observables which witness its highest degree of non-locality.

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Proposition

*All bipartite entangled states **except** the maximally entangled ones are logically non-local.*

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However, as we shall see, for $n > 2$ a different picture emerges.

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The general result is proved non-constructively.

Permutation Symmetric States

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For each $n \geq 2$, $0 < k < n$ the Dicke state $S(n, k)$ is defined as:

$$S(n, k) := K \sum_{\text{perm}} |0^k 1^{n-k}\rangle.$$

where $K = \binom{n}{k}^{-1/2}$ is a normalization constant, and we sum over all products of k 0-kets and $n - k$ 1-kets.

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All permutation symmetric states are logically non-local.

Functionally dependent balanced states

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A balanced $n + 1$ -qubit quantum state with a functional dependency given by an n -ary Boolean function $F : \{0, 1\}^n \rightarrow \{0, 1\}$ has the form

$$\Psi_F = \frac{1}{\sqrt{2^n}} \sum_{q_1 q_2 \dots q_n = 00 \dots 0}^{11 \dots 1} |q_1 q_2 \dots q_n F(q_1, q_2, \dots, q_n)\rangle$$

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All balanced functionally dependent states are in $P(n)$ or $L(n)$.