

Lewis' theory of convention

Convention: *A behavioural regularity the conformity to which instantiates one out of multiple strict coordination equilibria, made salient by precedent and operational by this being common knowledge*

Game 1: *A pure coordination game*

		player 2	
		<i>l</i>	<i>r</i>
player 1	<i>l</i>	1, 1	0, 0
	<i>r</i>	0, 0	1, 1

Game 2: *The telephone tag game*

		player 2	
		<i>c</i>	<i>w</i>
player 1	<i>c</i>	0, 0	1, 1
	<i>w</i>	1, 1	0, 0

- reformulating action descriptions
- equilibrium selection and the problem of salience:
 - (a) underdetermination, (b) lack of reason to chose the salient

Learning and convention

Best reply models of learning

- *maximize expected payoff given expectations*
- *learning rules for forming these expectations given observations*
 - *stationarity assumption: agents learn on the assumption that other agents are playing some stationary (possibly mixed) strategy*

In this model, an agent k updates his probability distribution $\mu_k^n(\cdot)$ according to the following formula: If one of m possible outcomes A_1, \dots, A_m can occur in each of n rounds, and n_{A_i} is the number of times that A_i is observed to occur in the n rounds of the game, then

$$(1) \quad \mu_k^n(A_i) = \frac{n_{A_i} + \gamma_{A_i}}{n + \sum_j \gamma_{A_j}},$$

where $\gamma_{A_i} \geq 0$, $1 \leq j \leq m$ and $\sum_j \gamma_{A_j} > 0$. Notice that the value of γ_{A_i} reflects the strength of k 's initial expectation that A_i will occur in any given round. Hence before any rounds have occurred, that is, when $n = 0$, the quotient $\gamma_{A_i} / \sum_j \gamma_{A_j}$ determines an agents *prior probability* that A_i occurs.

Learning and convention

Best reply models of learning

- *maximize expected payoff given expectations*
- *learning rules for forming these expectations given observations*
 - *stationarity assumption: agent learn on the assumption that other agents are playing some stationary (possibly mixed) strategy*
- **Successes and failures**
- **Convention as correlated equilibrium**

$$f(\omega) = \begin{cases} (A_{k_1}, A_{i_2}) & \text{if } \omega = \omega_1 \\ (A_{k_2}, A_{i_1}) & \text{if } \omega = \omega_2 \end{cases}.$$

Presumptuous learning

stationarity assumption:

learning under the assumption that other agents are playing some stationary (possibly mixed) strategy

minimal universe:

unique and salient partition of W which is common knowledge

common inductive standards:

unique projections of past observations into the future

Framing theory

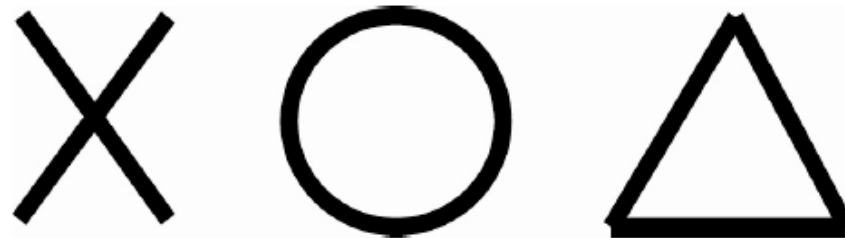


Figure 2: Three symbols

In general, let $S = \{x_1, \dots, x_n\}$ be a set of objects of choice and $P = \{\phi_1, \dots, \phi_n\}$ be a set of predicates. A frame $F \subseteq P$, then, is a set of predicates suitable for describing the objects in S , where if $\phi_i \in F$, then $E(\phi_i)$ is a function that denotes the *extension* of ϕ in S , that is the (possibly empty) subset of S which satisfy ϕ . We say that x and $y \in S$ are *F-equivalent*, written $x = Fy$, if

$$(1) \quad y \in E(\phi) \quad \text{iff} \quad x \in E(\phi) \quad \forall \phi \in F$$

That is, equation (1) says that if x and y are F-equivalent, then the predicates of a frame do not suffice to discriminate x from y . In this way a frame F induces a partition, P_F , on S , whose cells are F-equivalence classes [Bacharach 2003, 63].