Consistent Probabilistic Social Choice

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Preliminaries

Finite set of alternatives A {*a*,*b*,*c*} A is not fixed Linear preference relations $\geq \in \mathscr{L}(A)$ $a \ge b \ge c$ Fractional preference profiles $R \in \Delta(\mathscr{L}(A)) = \mathscr{R}|_A$ 1/2 1/3 1/6 b $\Delta(\mathscr{L}(A))$ denotes the (|A|!-1)-dimensional unit simplex а а h С С implicitly assumes anonymity and homogeneity b Cа will only consider rational fractions Fractional collective preference R(x,y) = $R(\geq)$ R(a,b)=56 $\geq \in \mathscr{L}(A): X \geq V$ Majority margin $g_R(x,y) = R(x,y) - R(y,x)$ $g_R(a,b) = \frac{2}{3}$ (Weak) Condorcet winner x with $g_R(x,y) \ge 0$ for all y а Felix Brand Consistent Probabilistic Social Choice 2

Probabilistic Social Choice Functions

- A probabilistic social choice function (PSCF) f maps a preference profile $R \in \mathscr{R}|_A$ to a non-empty subset of $\Delta(A)$.
 - *f* is (upper hemi-)continuous
 - ► f(R) is a convex set
 - $R \in \mathcal{R}|_{\{x,y\}}$ and R(x,y)=1 imply $f(R) = \{x\}$
 - $\{R \in \mathcal{R}|_A : |f(R)| = 1\}$ is dense in $\mathcal{R}|_A$

- (continuity) (convexity) (unanimity) (decisiveness)
- Non-probabilistic SCFs are PSCFs where, for all $R \in \mathscr{R}|_A$, $f(R) = \Delta(X)$ for some $X \subseteq A$.
- The axioms we propose for PSCFs coincide with classic axioms for the special case of non-probabilistic SCFs.



Random Dictatorship



 One agent is picked uniformly at random and his most preferred alternative is implemented as the social choice.

►
$$RD(R) = \left\{ \sum_{\geq \in \mathscr{L}(A)} R(\geq) \cdot \max_{\geq}(A) \right\}$$

 $(A) = \left\{ \sum_{\geq \in \mathscr{L}(A)} R(\geq) \cdot \max_{\geq}(A) \right\}$
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 $RD(R) = \{\frac{5}{6}a + \frac{1}{6}b\}$

- ► *RD* is a (single-valued) PSCF.
 - It satisfies continuity, convexity, unanimity, and decisiveness.



Population-Consistency



Whenever two disjoint electorates agree on a lottery, this lottery should also be chosen by the union of both electorates.



Population-Consistency

1/2 1/2	1/2 1/2	1/4 1/4 1/2
a b	a b	a a b
b c	C C	bcc
с а	b a	c b a
R	R'	½ R + ½ R'
1/2 a + 1/2 b	$\frac{1}{2}a + \frac{1}{2}b$	$\frac{1}{2}a + \frac{1}{2}b$

- $f(R) \cap f(R') \subseteq f(\lambda R + (1-\lambda)R')$
 - strong population-consistency requires equality (not only inclusion) whenever left-hand-side is non-empty
 - first proposed by Smith (1973), Young (1974), Fine & Fine (1974)
 - also known as "reinforcement" (Moulin, 1988)
 - variants used by Fishburn, Merlin, Myerson, Saari, etc.



Composition-Consistency



Decomposable preference profiles are treated component-wise.



Composition-Consistency

	1⁄3	1⁄6	1⁄2	1/2 1/2	1/3 2/3
	а	а	b	a b	b' b
	b'	b	b'	b a	b b'
	b	b'	а		
		R		$R _{\mathcal{A}'}$	$R _B$
1⁄2 E	2 + 1	/₃ b	+ 1⁄6	b' ½ a + ½ b	⅔b + ⅓b'

- $f(R|_{A'}) \times_b f(R|_B) = f(R)$
 - Laffond, Laslier, and Le Breton (1996)
 - Cloning-consistency precursors: Arrow and Hurwicz (1972), Maskin (1979), Moulin (1986), Tideman (1987)





Chevalier de Borda

Non-Probabilistic Social Choice



Marquis de Condorcet

- All scoring rules satisfy population-consistency. (Smith 1973; Young, 1974)
- No Condorcet extension satisfies population-consistency. (Young and Levenglick, 1978)
- Many Condorcet extensions satisfy compositionconsistency. (Laffond et al., 1996)
- No Pareto-optimal scoring rule satisfies compositionconsistency. (Laslier, 1996)
- Theorem: There is no SCF that satisfies populationconsistency and composition-consistency.
- But: These two axioms uniquely characterize a PSCF.





Maximal Lotteries



Peter C. Fishburn

- Kreweras (1965) and Fishburn (1984)
 - rediscovered by Laffond et al. (1993), Felsenthal and Machover (1992), Fisher and Ryan (1995), Rivest and Shen (2010)
- Extend g_R to lotteries: $g_R(p,q) = \sum_{x,y} p(x) \cdot q(y) \cdot g_R(x,y)$
 - fractional collective preferences over lotteries
- p is a maximal lottery, $p \in ML(R)$, if $g_R(p,q) \ge 0$ for all $q \in \Delta(A)$.
 - probabilistic Condorcet winner
 - always exists due to Minimax Theorem (v. Neumann, 1928)
- Set of profiles with unique maximal lotteries is open and dense.
 - set of profiles with multiple maximal lotteries is negligible
 - always unique for odd number of voters (Laffond et al., 1997)
 - generalized uniqueness conditions by Le Breton (2005)



Examples

- Two alternatives $1 \frac{Maximal lotteries}{p(x)} \frac{p(x)}{p(x)} \frac{p(x)}{p($
- g_R can be interpreted as a symmetric zero-sum game.
 - Maximal lotteries are mixed minimax strategies.

			-
0	1	-1	
	•	•	
-1	0	3	
1	-3	0	
	0 -1 1	0 1 -1 0 1 -3	0 1 -1 -1 0 3 1 -3 0

b

Я

С

• The unique maximal lottery is 3/5 a + 1/5 b + 1/5 c.



Main Result

- Theorem: A PSCF f satisfies population-consistency and composition-consistency iff f=ML.
- Proof structure:
 - Composition-consistency implies neutrality.
 - Two-alternative characterization (via three-alternative profiles)
 - Condorcet-consistency around uniform profile
 - $f \subseteq ML$.
 - Assume for contradiction that *f* yields a lottery that is not maximal.
 - Construct a Condorcet profile in which a uniform lottery is returned.
 - Derive a density violation.
 - $ML \subseteq f$.
 - For any vertex of the set of maximal lotteries in a profile, construct a sequence of profiles that converges to the original profile and whose unique maximal lotteries converge to the original maximal lottery.
 - Apply continuity and convexity.



Two-Alternative Proof

- Lemma: Let f be a composition-consistent PSCF and $A = \{x, y\}$. $p \in f(R)$ with $p \neq x, y$ implies $f(R) = \Delta(A)$.
 - Proof: Let r=R(x,y).

<u>r 1-r</u>	<u>r 1-r</u>	<u>1 1-r</u>
ху	x y	ХУ
y x	<i>X' X'</i>	y x
	y x	
$\lambda x + (1 - \lambda) y$	$\lambda^2 x + \lambda (1 - \lambda) x' + (1 - \lambda) y$	$\lambda^2 x + (1 - \lambda^2) y$

- Hence, $\lambda^2 x + (1 \lambda^2) y \in f(R)$.
- Repeated application, continuity, and convexity imply the statement.
- As a consequence, *RD* violates composition-consistency.



Two-Alternative Proof (ctd.)









Consistent Probabilistic Social Choice

Remarks

- Independence of axioms
 - population, not composition: random dictatorship RD
 - composition, not population: maximal lotteries variant ML³
- ML almost always satisfy strong population-consistency
- Composition-consistency can be weakened to cloningconsistency when also requiring Condorcet-consistency
 - RD satisfies cloning-consistency
- *ML* also satisfy agenda-consistency (Sen's α and γ)
- Axioms imply Fishburn's C2 (pairwiseness) as well as Condorcet-consistency.



Remarks (ctd.)

- Possible non-probabilistic interpretation of outcomes as fractional division (e.g., budget division, time shares)
 - Axioms are equally natural.
- Pareto-dominated alternatives always get zero probability in every maximal lottery.
 - In fact, *ML* is even **SD-efficient** (Aziz et al., 2012).
- ML does not require asymmetry, completeness, or even transitivity of preferences.
 - Random dictatorship requires unique maximum.
- In assignment domain, *ML* are known as popular mixed matchings (Kavitha et al., 2011).
- *ML* can be efficiently computed via linear programming.



	Maximal Lotteries	Random Serial Dictatorship	Borda's Rule
population-consistency		only for strict prefs	
agenda-consistency			
cloning-consistency	even composition-consistency		
Condorcet-consistency			
(weak SD-) strategyproofness			
weak group-strategyproofness			
(weak SD-) participation	even for groups	even very strongly	
(SD-) efficiency		only for strict prefs otherwise only <i>ex post</i>	
efficient computability		#P-complete in P for strict prefs	



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HANDBOOK of COMPUTATIONAL SOCIAL CHOICE

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