Timing:
2:00 - 3:30
4:00 - 6:00

Experiments in Computational Social Choice
(Using Maps of Elections)

Niclas Boehmer

Piotr Faliszewski

Stanisław Szufa

Tomasz Wąs

Timing:
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Using Maps of Elections

Experiments in Computational Social Choice

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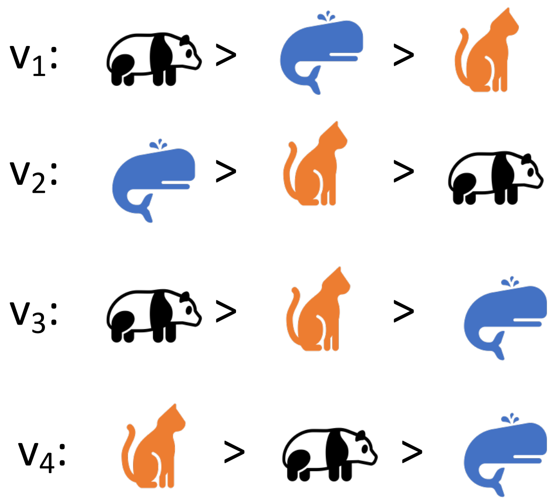
An Election

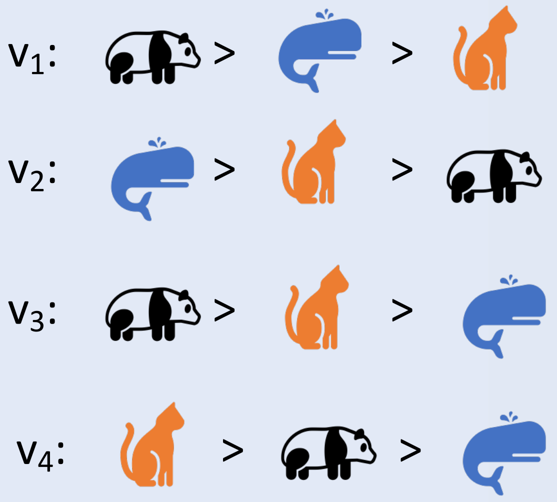


$$E = (C,V)$$

C = {  }

$$V = (v_1, v_2, v_3, v_4)$$

An Election

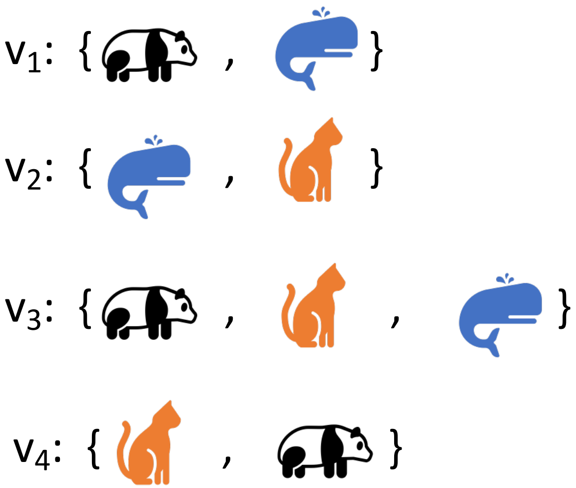


$$E = (C,V)$$

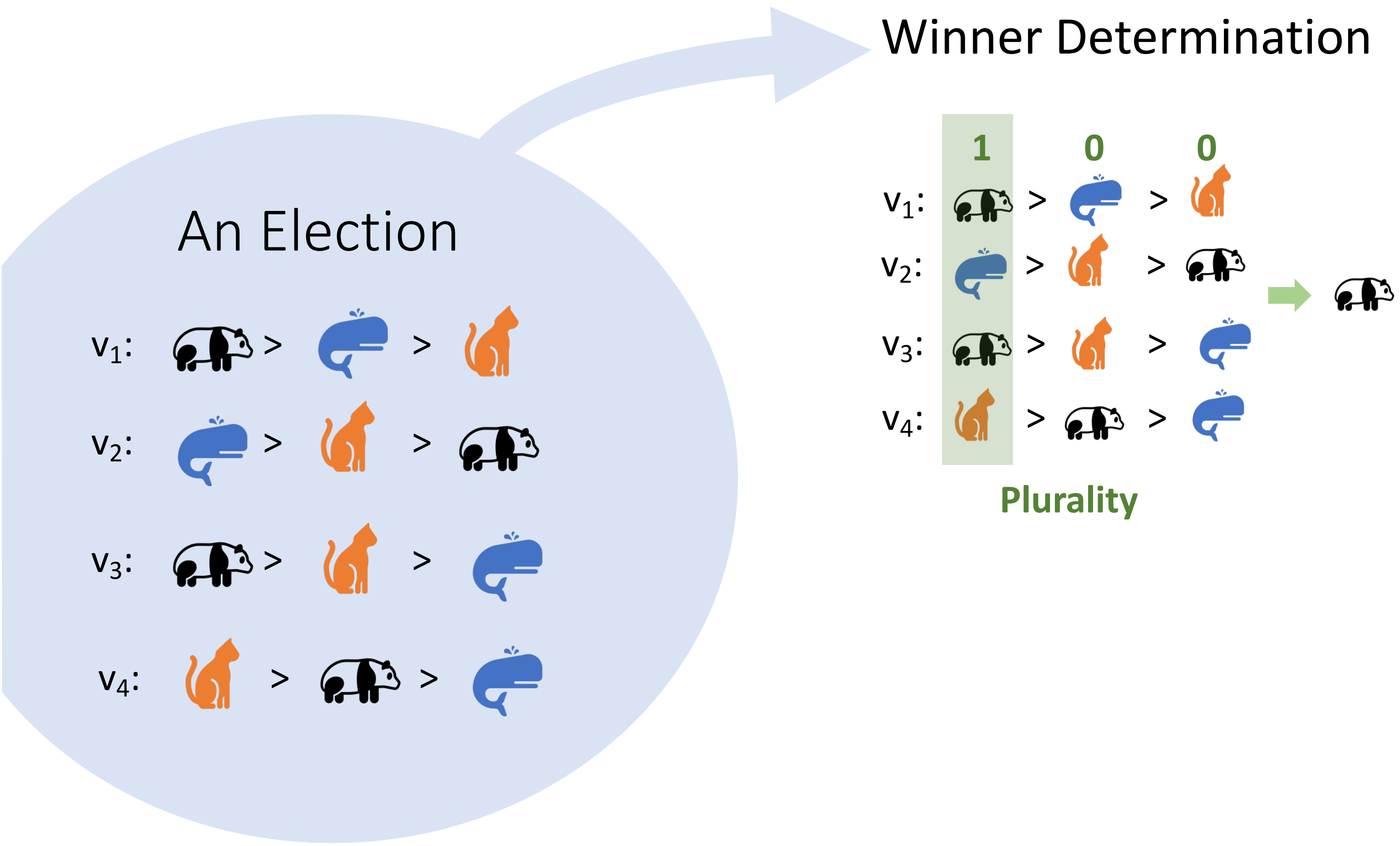
$C = \{$  $\}$

$$V = (v_1, v_2, v_3, v_4)$$

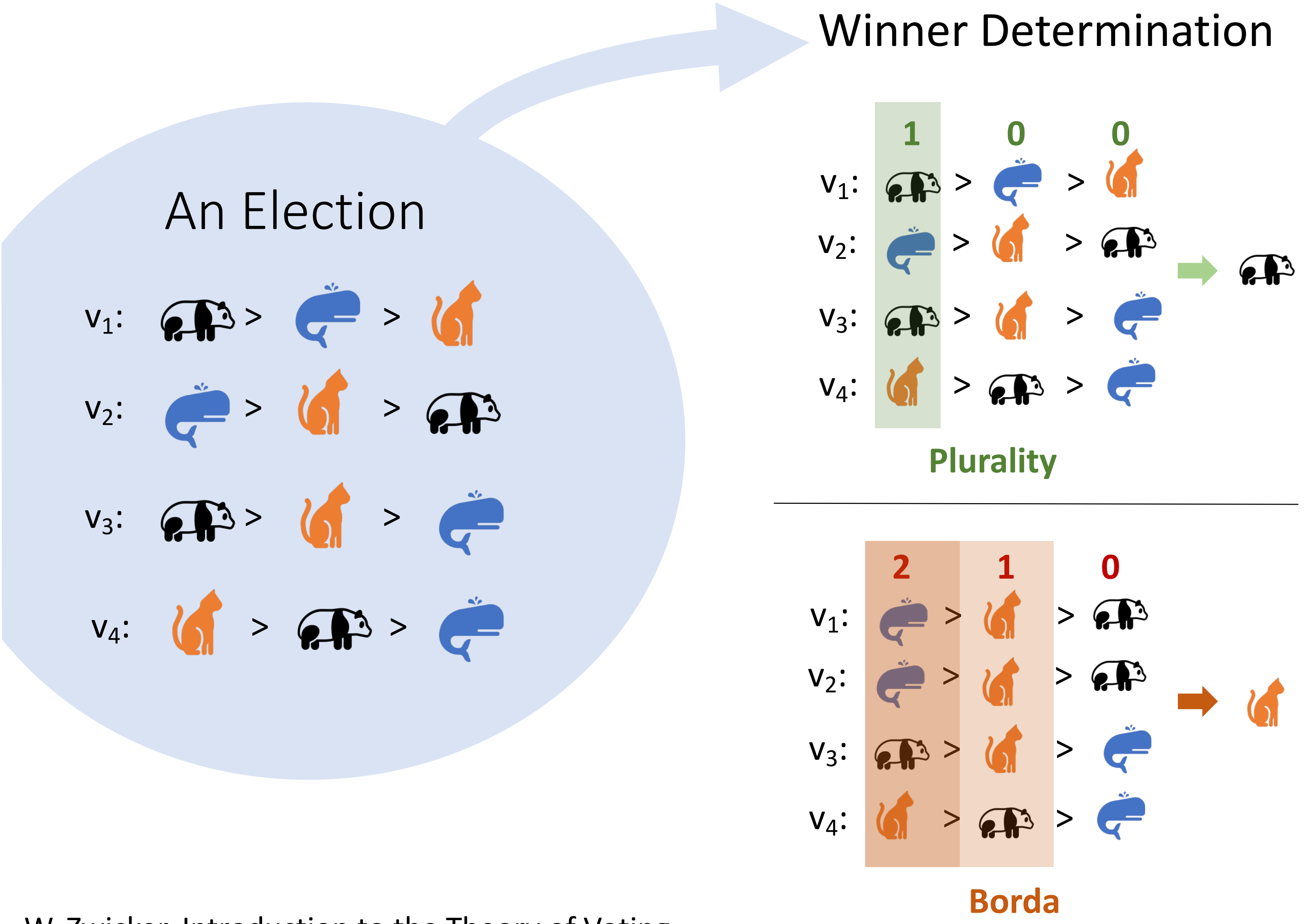
Also an election



We mostly focus on the ordinal setting, but approvals will come!



W. Zwicker, Introduction to the Theory of Voting.
Handbook of Computational Social Choice 2016



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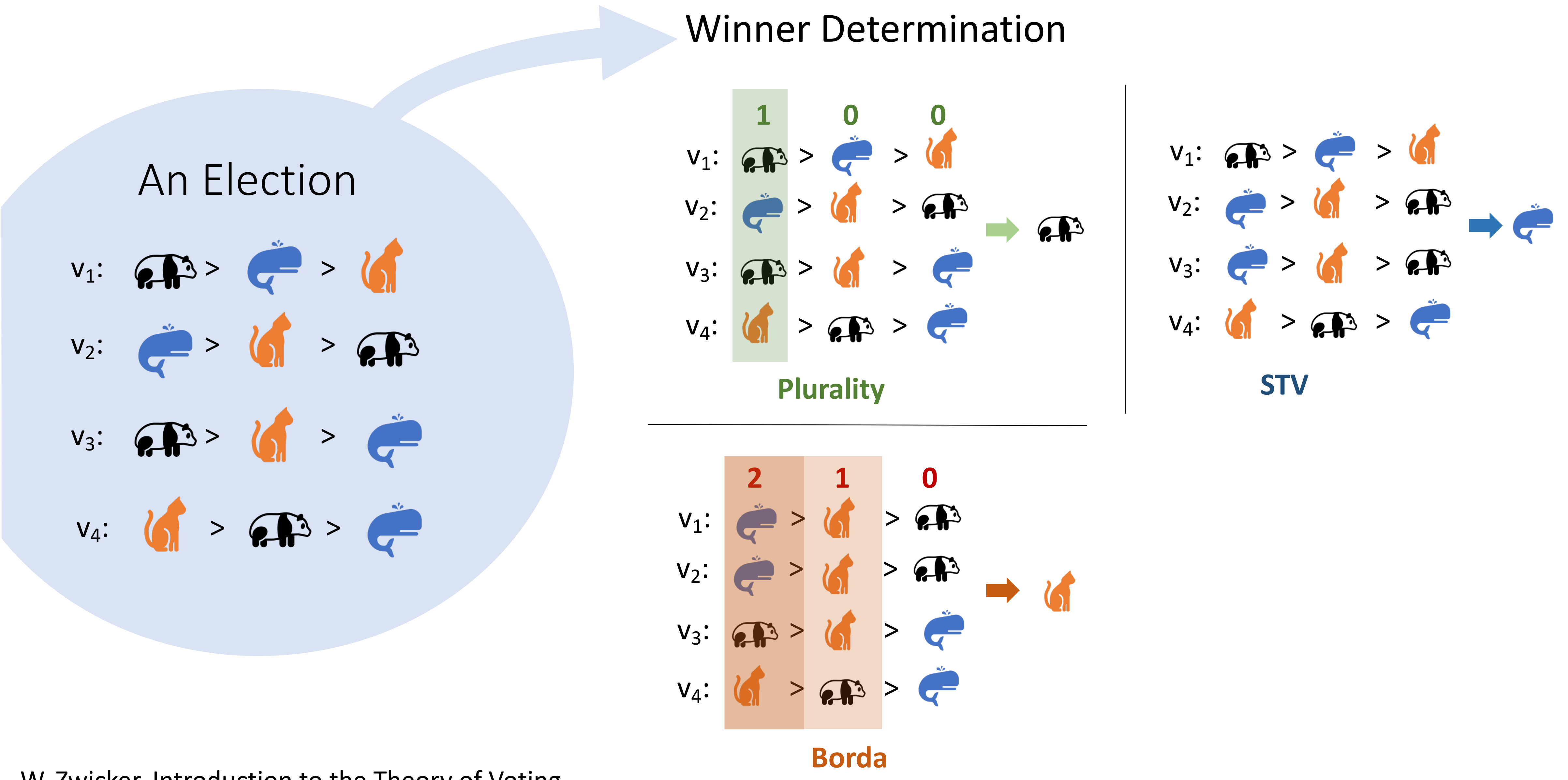

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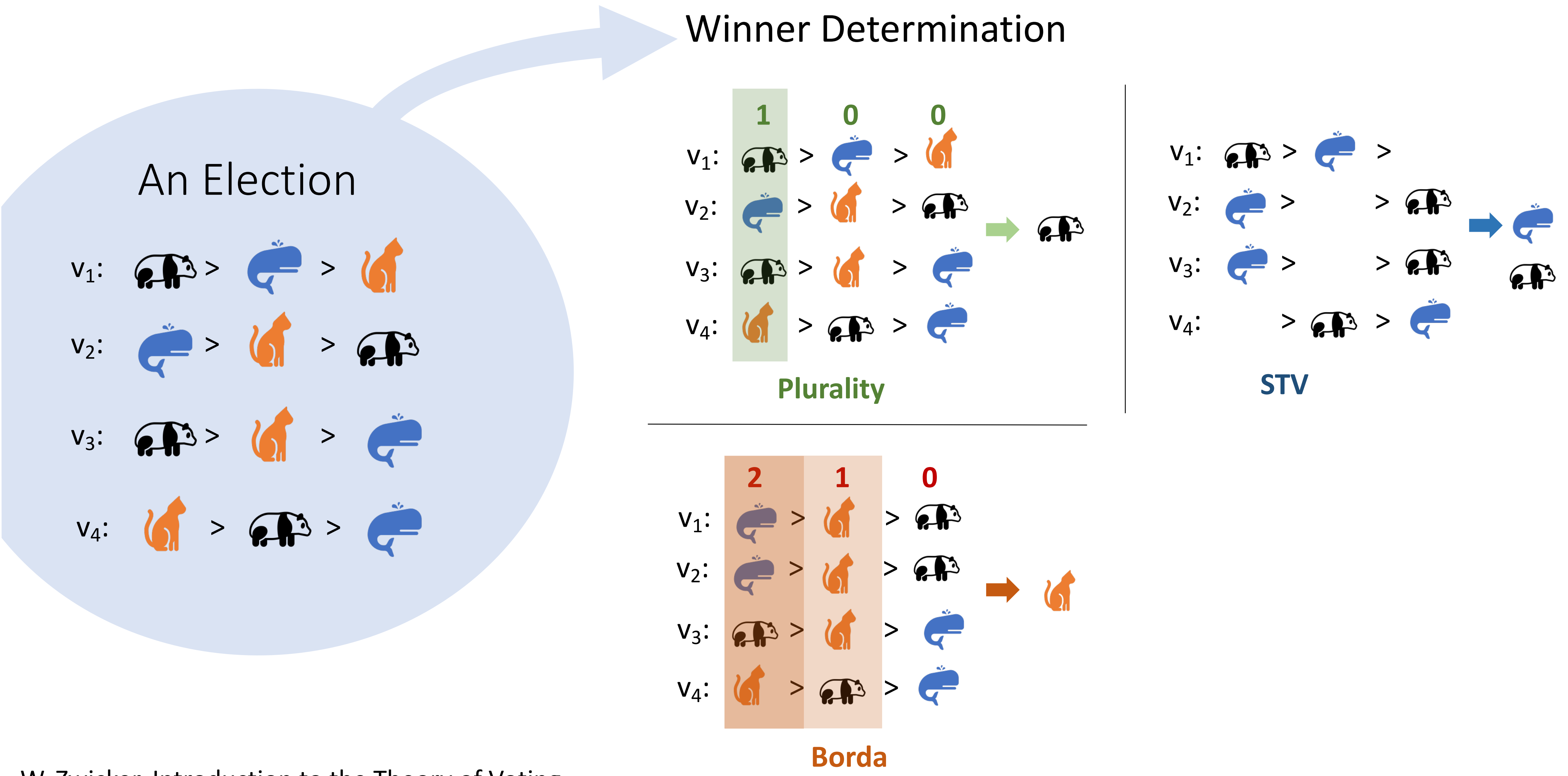

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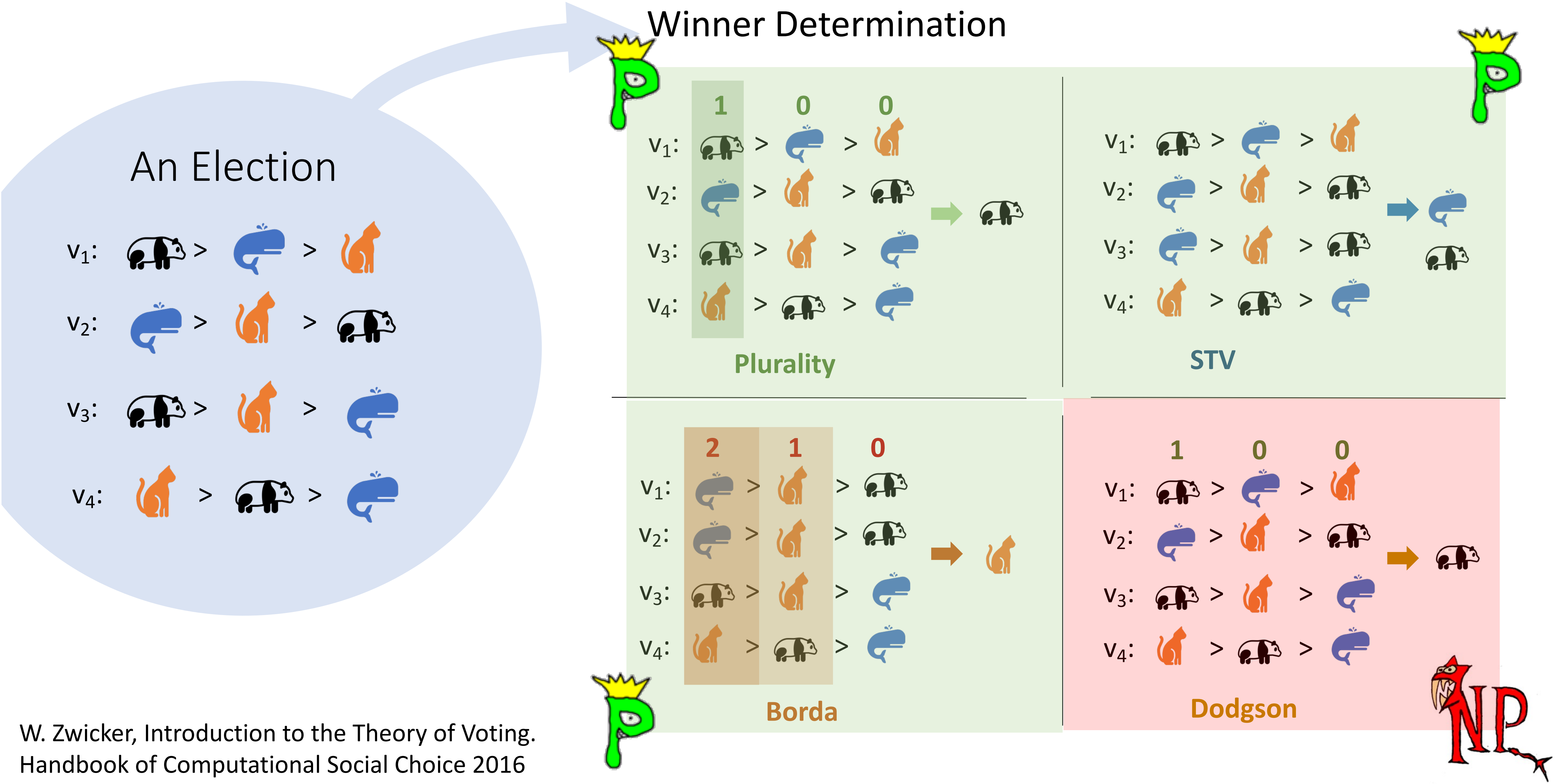

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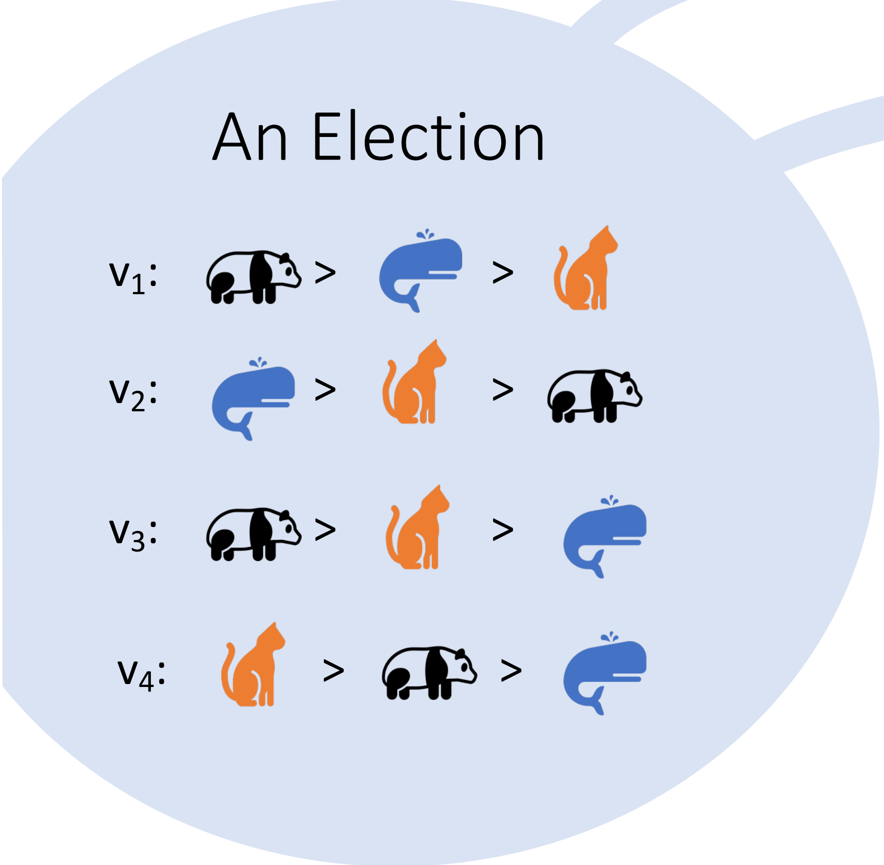
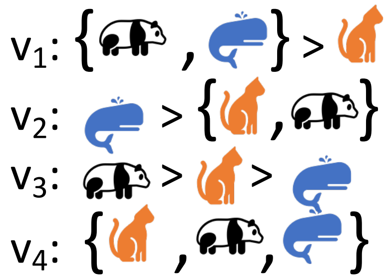
Winner Determination

Result Modification/Analysis

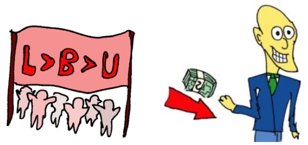


Possible/Necessary Winner (in various shapes)



Manipulating Elections

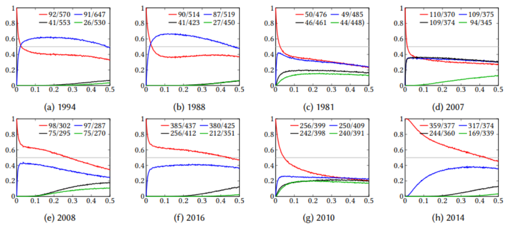
Bribery/Campaign Management



Electoral Control

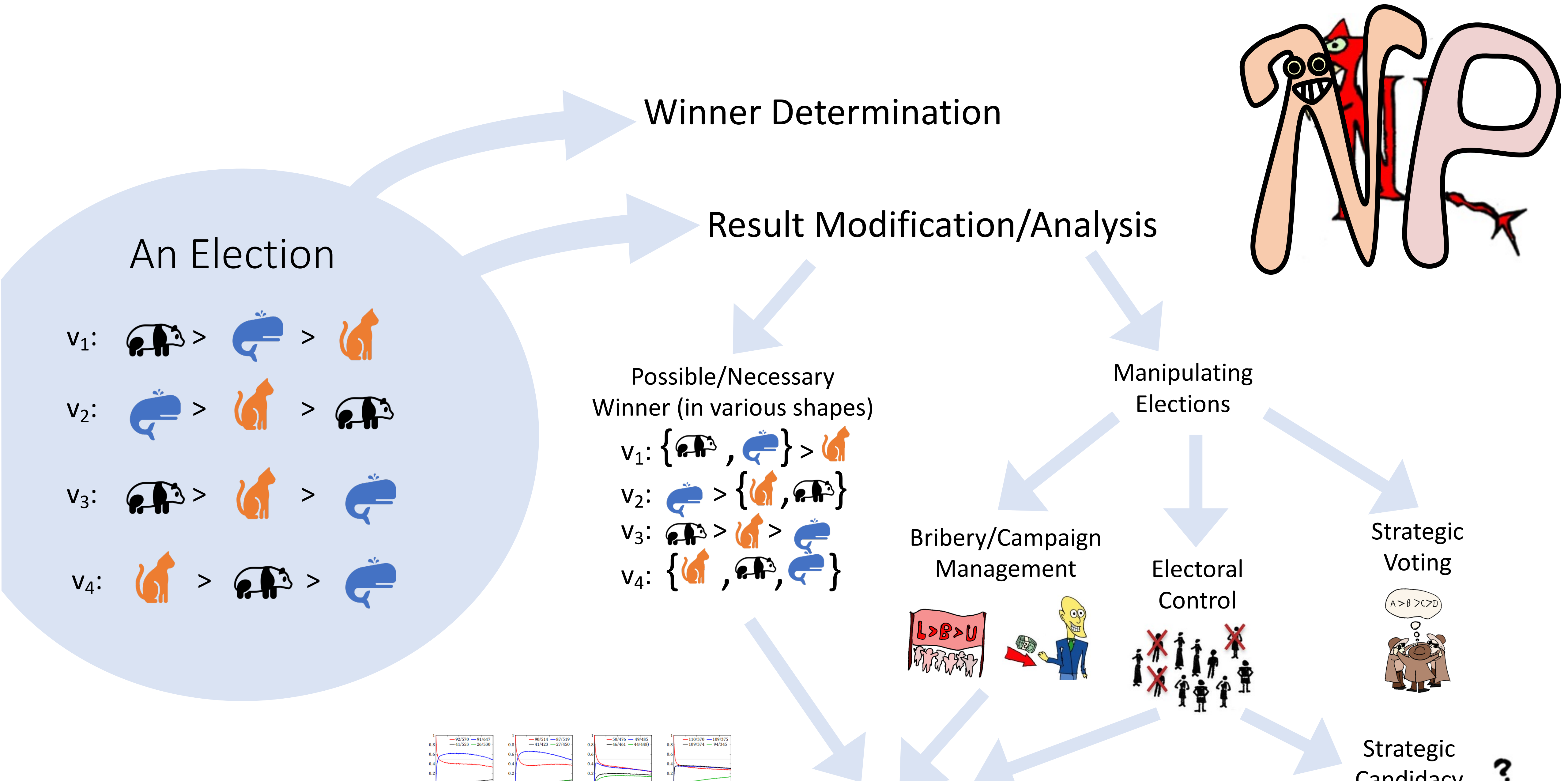
Strategic Voting

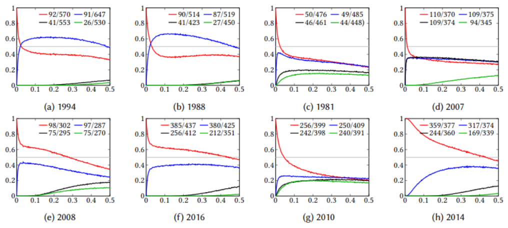
Strategic Candidacy



Robustness / Winner Assessment / Margin of Victory

B. Dutta, M. Jackson, M. Le Breton, Strategic Candidacy ar
K. Konczak, J. Lang. Voting procedures with incomplete pr
V. Conitzer, T. Walsh, Barriers to Manipulation in Voting. I
P. Faliszewski, J. Rothe, Control and Bribery in Voting. Har





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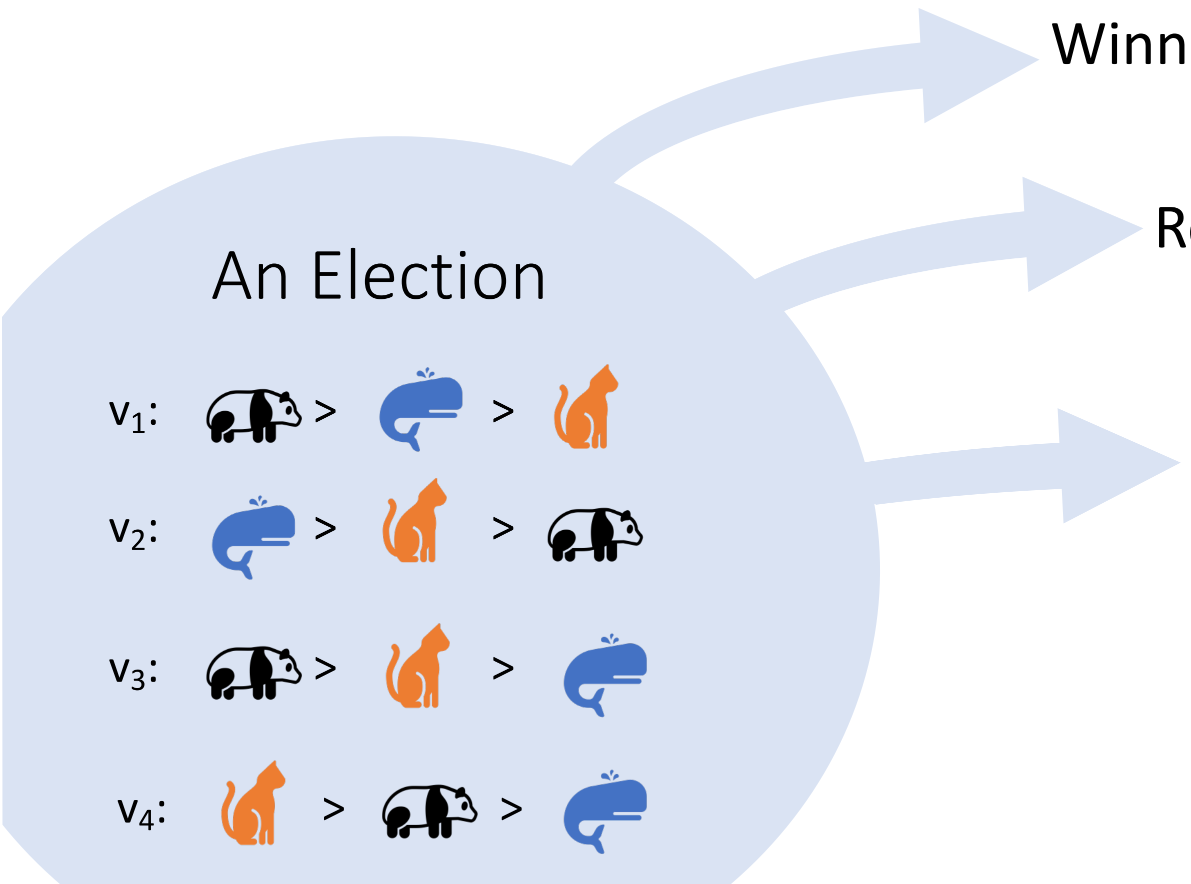


Winner Determination

Rule	Complexity	JR/PJR/EJR	PR	SMWPI	SMWOPI	Com. Mon.
AV	P [a]	No [d]	No [k]	Str. [Thm. 3.4]	Str. [Thm. 3.6]	Yes
SAV	P [a]	No [d]	No [k]	Str. [Thm. 3.4]	Str. [Thm. 3.6]	Yes
CC	NP-comp. [b]	JR [d]	Yes [g, k]	Str. [Thm. 3.4]	Wk. [Thm. 3.5]	No [Ex. 4.2]
Monroe	NP-comp. [b]	JR [d,e]	Yes [h]	No [Ex. 3.10]	Wk. [Thm. 3.9]	No [Ex. 4.2]
PAV	NP-comp. [a]	EJR [d]	No [h]	Str. [Thm. 3.4]	Wk. [Thm. 3.5]	No [j]
max-Phragmén	NP-comp. [c]	PJR [c,f]	Yes [c]	Wk. [i, Thm. 3.12]	Wk. [i, Thm. 3.12]	No [i]

[a] Results by Aziz et al. [4] and Skowron et al. [31].
[b] Results by Procaccia et al. [28].
[c] Results by Brill et al. [7].
[d] Results by Aziz et al. [2].
[e] Monroe satisfies PJR if k divides n [29].
[f] max-Phragmén satisfies PJR when combined with certain tie-breaking rule [7].
[g] CC satisfies PR if ties are broken always in favour of the candidates subsets that provide PR.
[h] Results by Sánchez-Fernández et al. [29].
[i] Results by Janson [15], Mora and Oliver [21], and Phragmén [26].
[j] Results by Thiele [33].
[k] Results by Sánchez-Fernández and Fisteus [30].

Table 1: Properties of approval-based multi-winner voting rules

Result Modification/Analysis

Comparison of preferential electoral systems [hide]

System	Monotonic	Condorcet winner	Majority	Condorcet loser	Majority loser	Mutual majority	Smith	ISDA	LIIA	Independence of clones	Reversal symmetry	Participation, consistency	Later-no-harm	Later-no-help	Polynomial time	Resolvability
Schulze	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	No	Yes	Yes
Ranked pairs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	Yes	Yes
Tideman's Alternative	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No	No	No	No	Yes	Yes
Kemeny–Young	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No	No	No	No	Yes
Copeland	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	No	No	No	Yes	No
Nanson	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	Yes	No	No	No	Yes	Yes
Black	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	Yes	No	No	No	Yes	Yes
Instant-runoff voting	No	No	Yes	Yes	Yes	Yes	No	No	No	Yes	No	No	Yes	Yes	Yes	Yes
Smith/IRV	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No	No	No	No	Yes	Yes
Borda	Yes	No	No	Yes	Yes	No	No	No	No	No	Yes	Yes	No	Yes	Yes	Yes
Baldwin	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	Yes	Yes
Bucklin	Yes	No	Yes	No	Yes	Yes	No	No	No	No	No	No	No	Yes	Yes	Yes
Plurality	Yes	No	Yes	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Contingent voting	No	No	Yes	Yes	Yes	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Coombs[32]	No	No	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No	Yes	Yes
Mini-Max[specify]	Yes	Yes	Yes	No	No	No	No	No	No	No	No	No	No	No	Yes	Yes
Anti-plurality[32]	Yes	No	No	No	Yes	No	No	No	No	No	No	Yes	No	No	Yes	Yes
Sri Lankan contingent voting	No	No	Yes	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Supplementary voting	No	No	Yes	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Dodgson[32]	No	Yes	Yes	No	No	No	No	No	No	No	No	No	No	No	No	Yes

Normative Properties

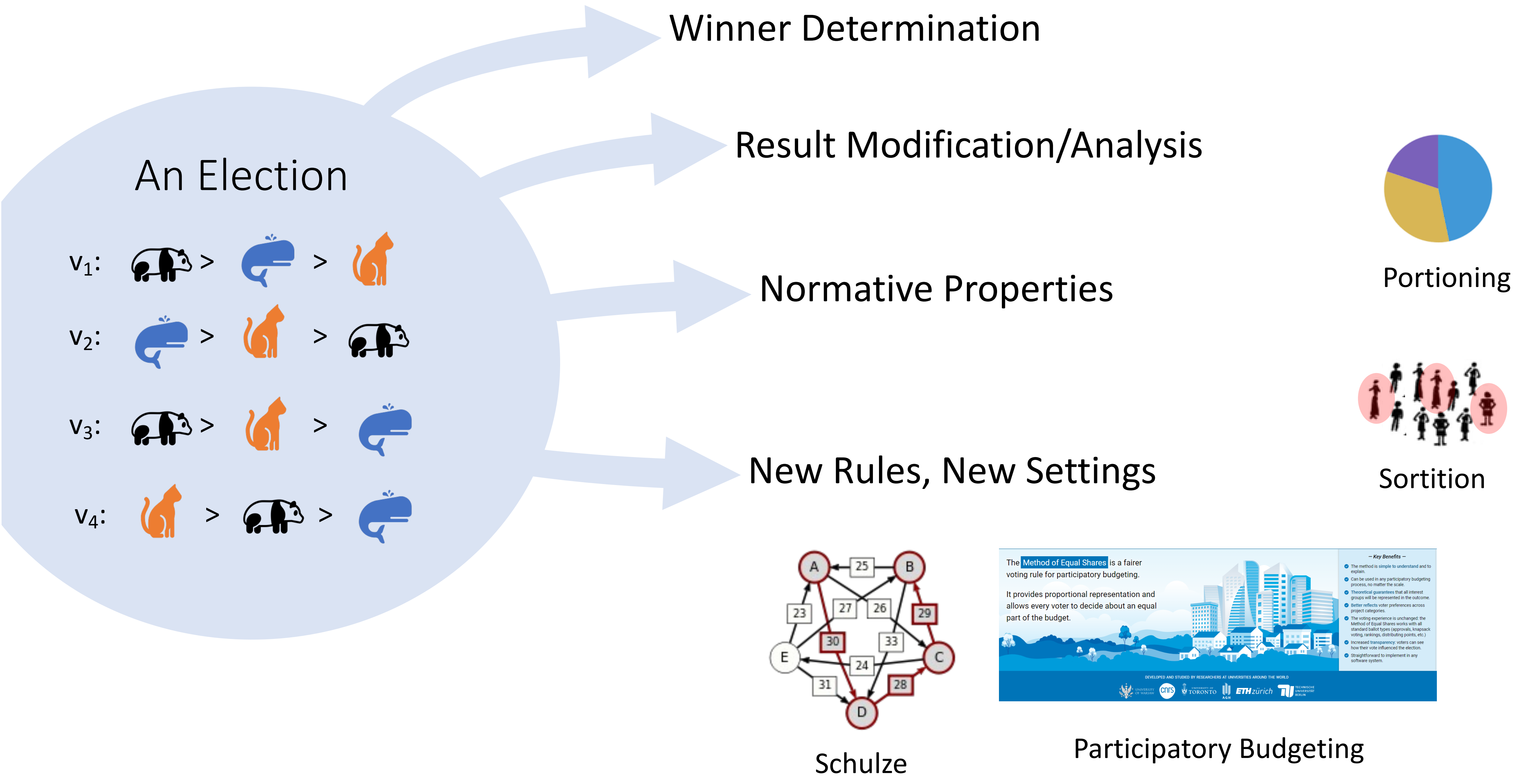
- Monotonicity
- Homogeneity
- Consistency
- Condorecet Consistency
- (Something) Justified Representation
- Core
- Priceability

	Pareto efficiency	committee monoton.	support monot. with / without add. voters			consist.	inclusion-strategypr.	comput. complexity
AV	strong	✓	✓	/	✓	✓	✓	P
CC	weak	×	✓	/	cand	✓	?	NP-hard
PAV	strong	×	✓	/	cand	✓	×	NP-hard
seq-PAV	×	✓	≥cand	/	cand	×	×	P
seq-CC	×	✓	?	/	?	×	×	P
rev-seq-PAV	×	✓	≥cand	/	cand	×	×	P
Monroe	×	×	×	/	cand	×	×	NP-hard
Greedy Monroe	×	×	×	/	?	×	×	P
seq-Phragmén	×	✓	cand	/	cand	×	×	P
lexmin-Phragmén	×	×	cand	/	cand	×	?	NP-hard
Rule X	?	×	×	/	?	×	×	P
MAV	weak	×	?	/	?	×	×	NP-hard
SAV	strong	✓	✓	/	✓	✓	×	P

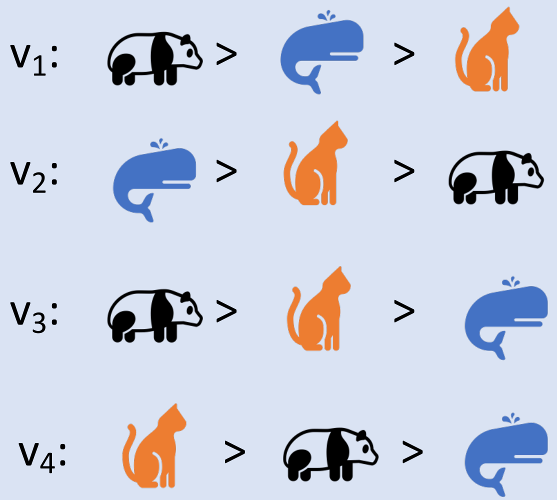
	symmetry	consistency	weak efficiency	efficiency	continuity	indep. of irr. alt.	monotonicity	D'Hondt prop.	disjoint equality	disjoint diversity
ABC counting rules	+	+	+	+	+					
Thiele Methods	+	+	+	+	+	+				
Dissatisfaction counting rules	+	+	+	+	+		+			
Multi-winner Approval Voting (AV)	+	+	+	+	+	+	+		+	
Proportional Approval Voting (PAV)	+	+	+	+	+	+		+		
Approval Chamberlin–Courant (CC)	+	+	+	+	+	+				+
Constant Threshold Methods	+	+	+	+	+	+				
Satisfaction Approval Voting	+	+	+	+	+					
Sequential Thiele Methods	+		+	+	+	+				
Reverse-sequential Thiele Methods	+		+	+	+					
Sequential PAV	+		+	+	+	+		+		
Reverse-Sequential PAV	+		+	+	+			+		

	M	PO	IAWP	CC	IALP	ICLP
Lexicographic rule	✓	✓	✓			
Condorcet's practical method	✓	✓($m = 3$)	✓		✓($m \leq 4$)	
Fallback Bargaining	✓	✓				
Majoritarian Compromise	✓	✓	✓		✓	
Obata and Ishii's method	✓	✓	✓			
Contreras, Hinojosa and Mármol's method	✓	✓	✓			
Geometric rule	✓	✓				

M: Monotonicity, PO: Pareto-optimality, IAWP: Immunity to the absolute winner paradox, CC: Condorcet consistency, IALP: Immunity to the absolute loser paradox, ICLP: Immunity to the Condorcet loser paradox.


Winner Determination
Result Modification/Analysis
Normative Properties
New Rules, New Settings
An Election
v1: > >
v2: > >
v3: > >
v4: > >
Portioning
Sortition
A
B
C
D
E
25
23
27
26
29
30
33
24
31
28
Schulze
The Method of Equal Shares is a fairer voting rule for participatory budgeting.
It provides proportional representation and allows every voter to decide about an equal part of the budget.
Participatory Budgeting

An Election

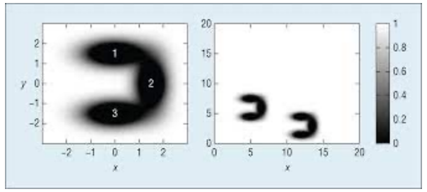


Winner Determination

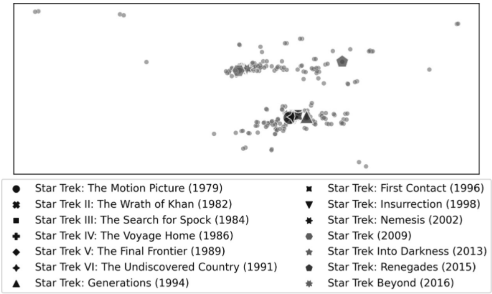
Result Modification/Analysis

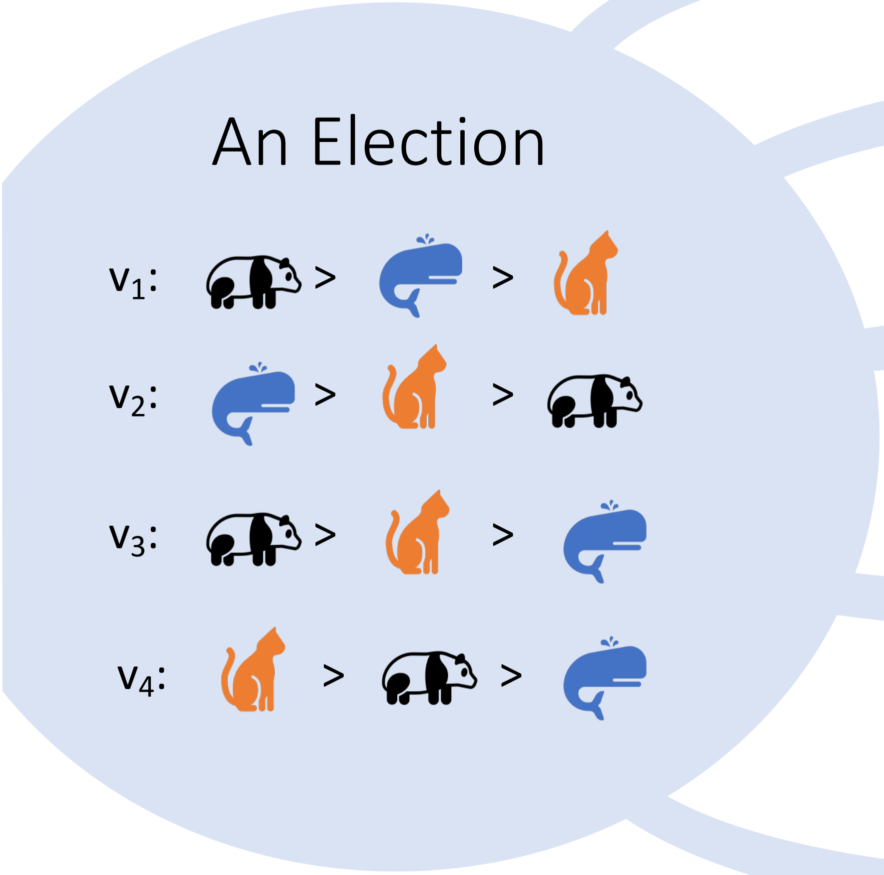
Normative Properties

New Rules, New Settings



Applications





Largely studied theoretically

We want more experiments!

N. Mattei, T. Walsh, PrefLib: A Library For Preferences, ADT 2013

Benefits of Experiments

- More complex settings
- More precise results
    - Exact running time vs asymptotic running time
- Observe actual phenomena instead of merely predicting their possibility
    - Condorcet winners often exist
    - No-show paradox is/is-not a problem
    - Voting rules do/do-not give very different results

Problems with Experiments

- They don't generalize
- May be misleading
- Some insights are impossible to get experimentally
- You never really know…

We want more experiments!

Data!

- Real-Life Data
    - Preflib
    - Pabulib
    - Others…
- Synthetic Data
    - Impartial Culture
    - Urn, Mallows
    - Euclidean, and more

N. Mattei, T. Walsh, PrefLib: A Library For Preferences, ADT 2013

We want more experiments!

Real-Life Data

- Preflib
- Pabulib
- Others...

Real data is real

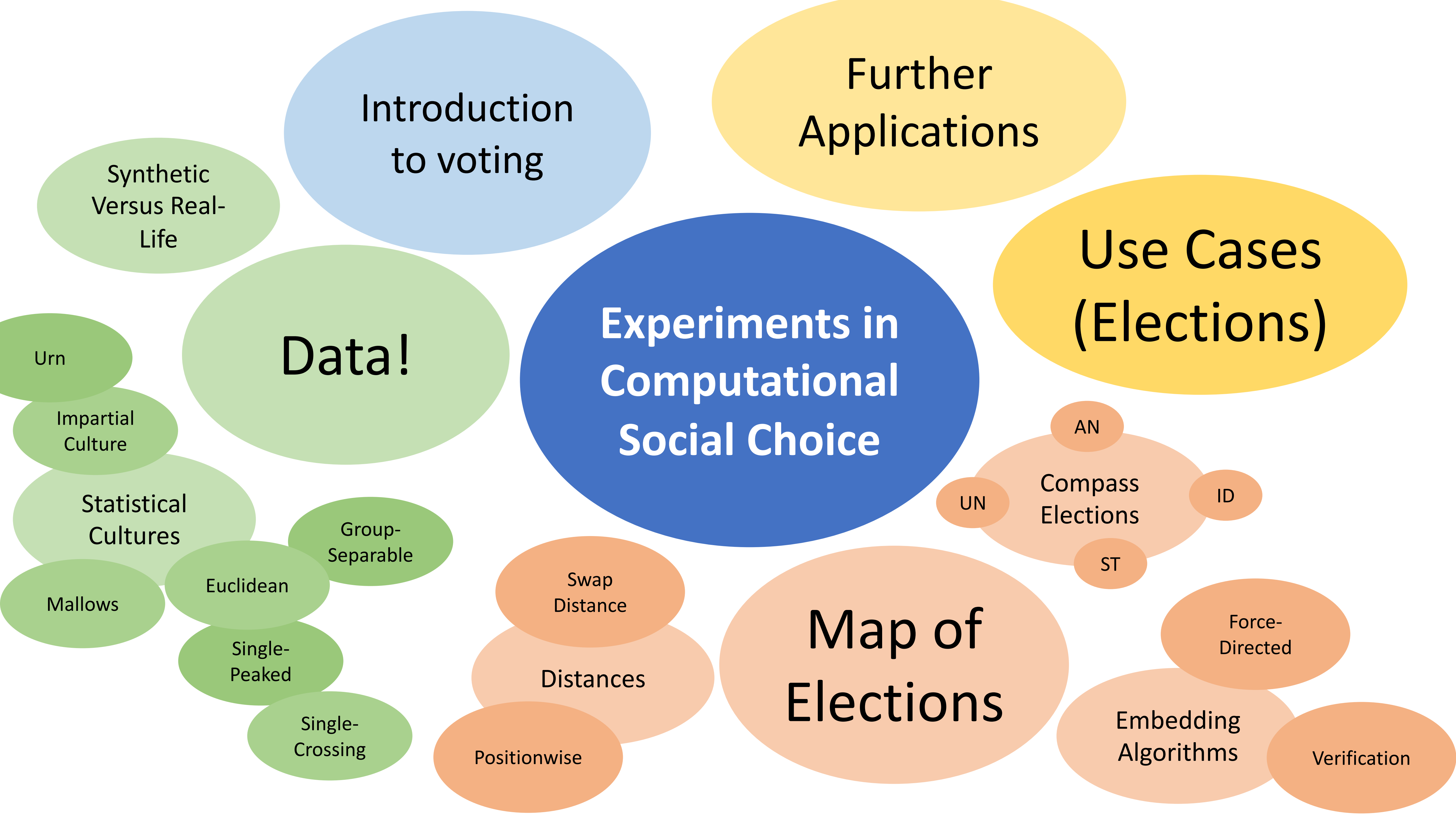
- Fixed, hard to control number of candidates/voters
- Collected under specific circumstances
- Often incomplete
- But it's real!

Synthetic Data

- Impartial Culture
- Urn, Mallows
- Euclidean, and more

Easy to control!

- Arbitrary size
- Perfect information
- Unrealistic...
  - All models are wrong but some are wronger than others ;)
- Hard to choose a model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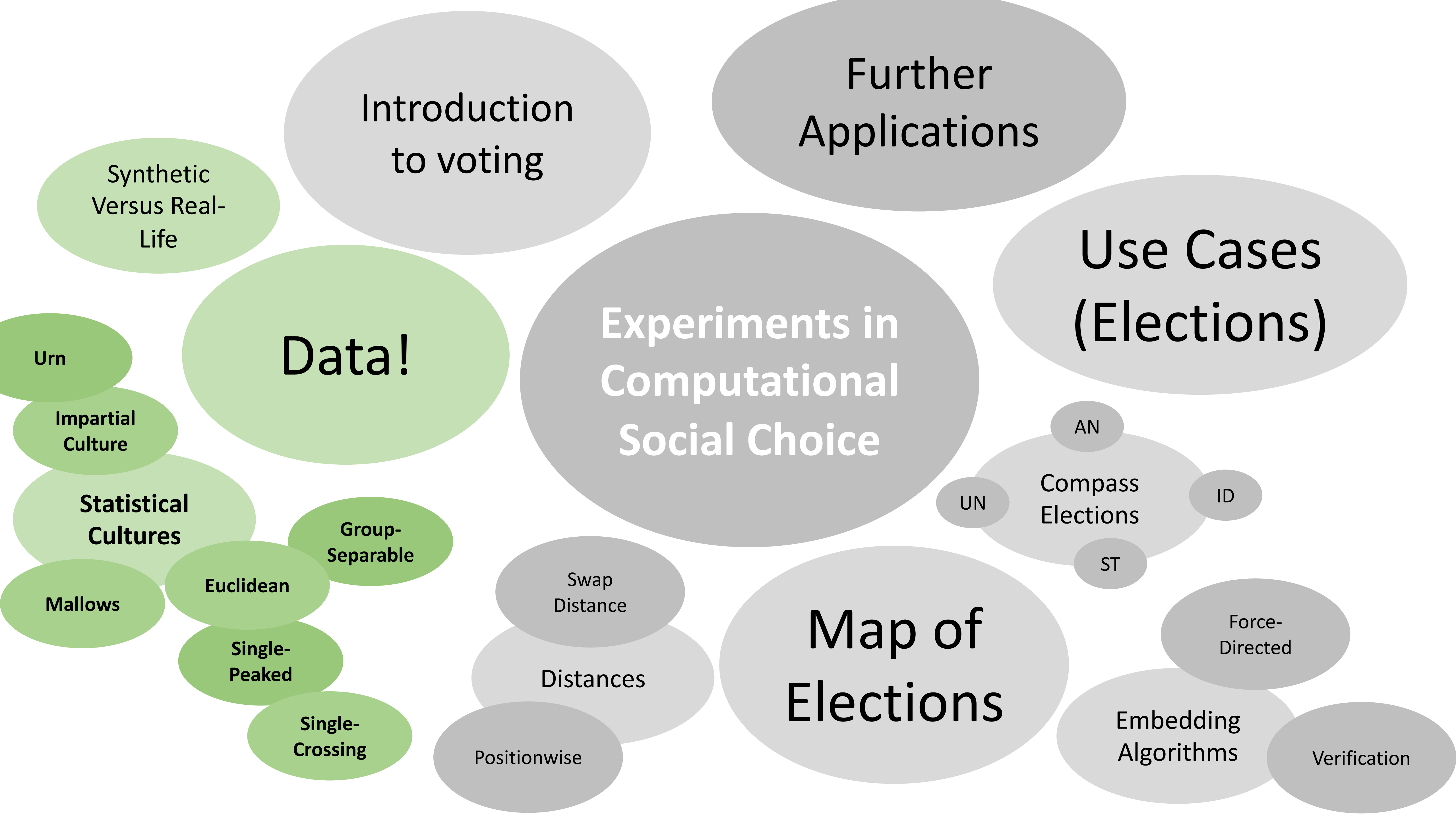
Further Applications
Synthetic Versus Real-Life
Use Cases (Elections)
Data!
Experiments in Computational Social Choice
Urn
Impartial Culture
Statistical Cultures
Group-Separable
Mallows
Euclidean
Single-Peaked
Single-Crossing
AN
Compass Elections
UN
ID
ST
Swap Distance
Distances
Positionwise
Map of Elections
Force-Directed
Embedding Algorithms
Verification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Force-Directed
Embedding Algorithms
Verification

5 minutes

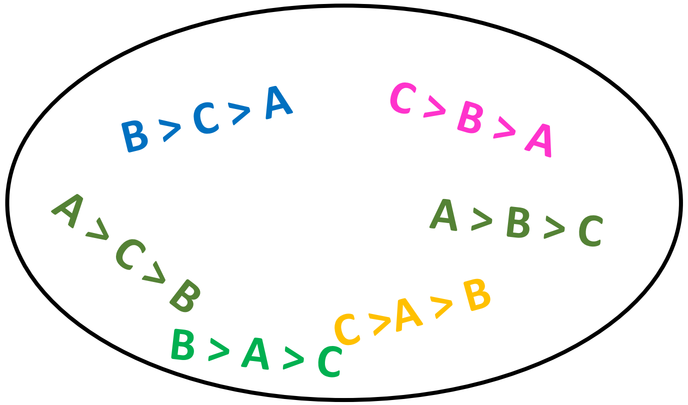
Basic Statistical Cultures

Statistical Cultures

Impartial Culture (IC): Every preference order comes with the same proba-bility (a.k.a. **uniform distribution**)

Polya-Eggenberger Urn Model:
Form an urn of **all possible m! votes**. To generate a vote:

1) Choose a vote from the urn and add it to your election
2) **Return** the vote to the urn, together with **α·m! copies**.



S. Berg. Paradox of voting under an urn model: The effect of homogeneity. Public Choice, 1985.
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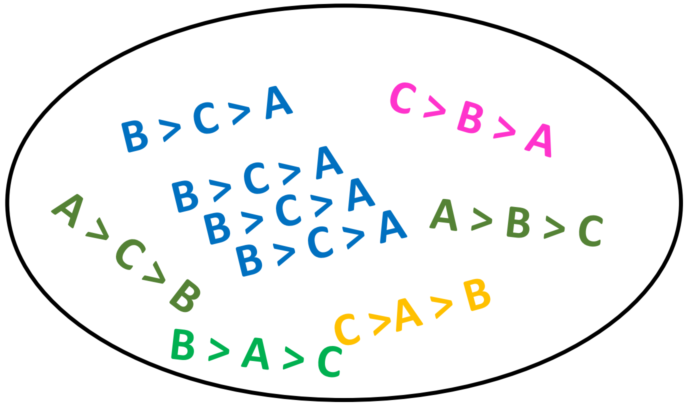

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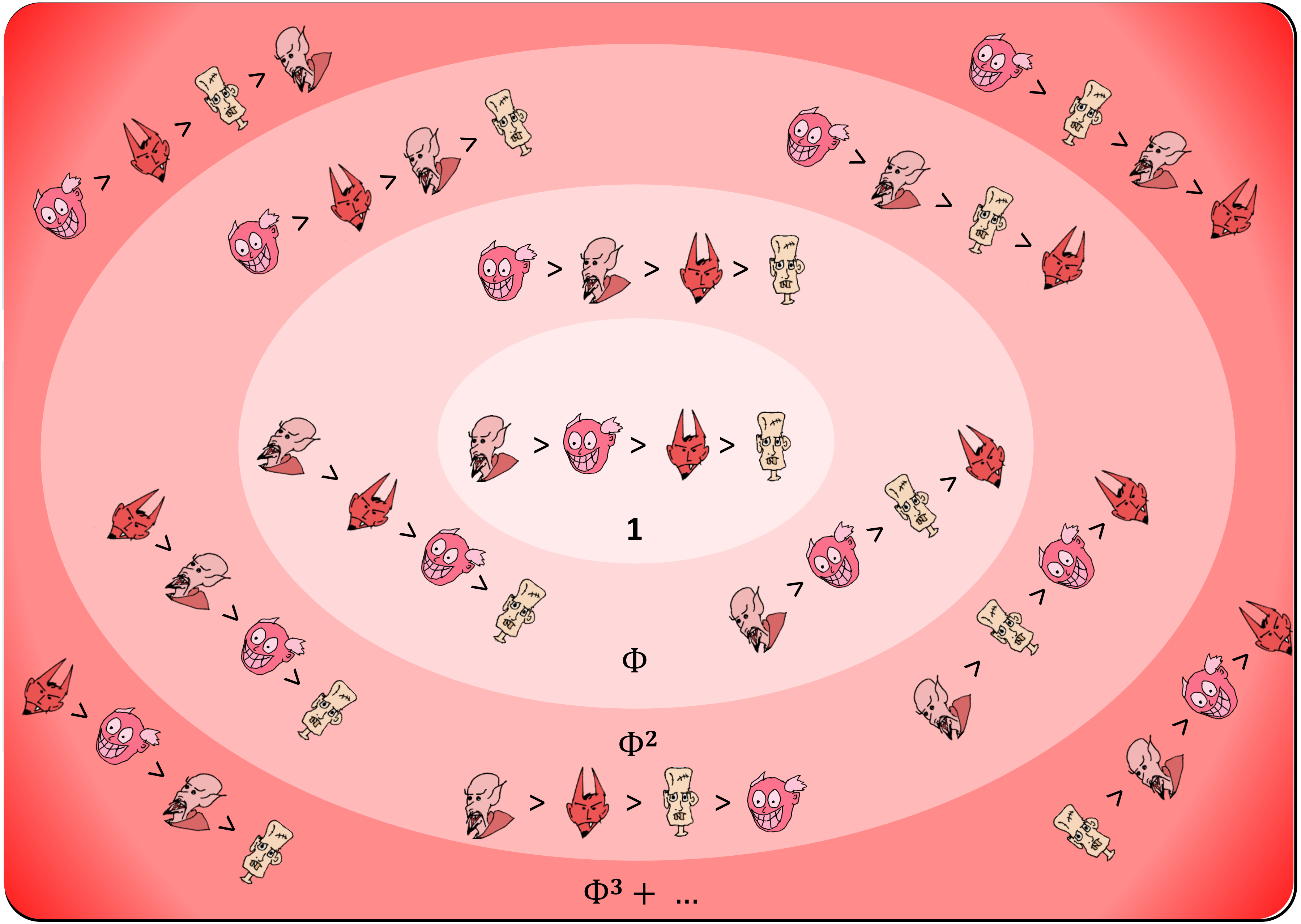
Mallows Model: Choose a center vote u. The probability of generating vote v is:

$$\frac{1}{Z}\Phi^{swap(u,v)}$$

(There are some algorithms that generate votes from this distribution… effectively.)



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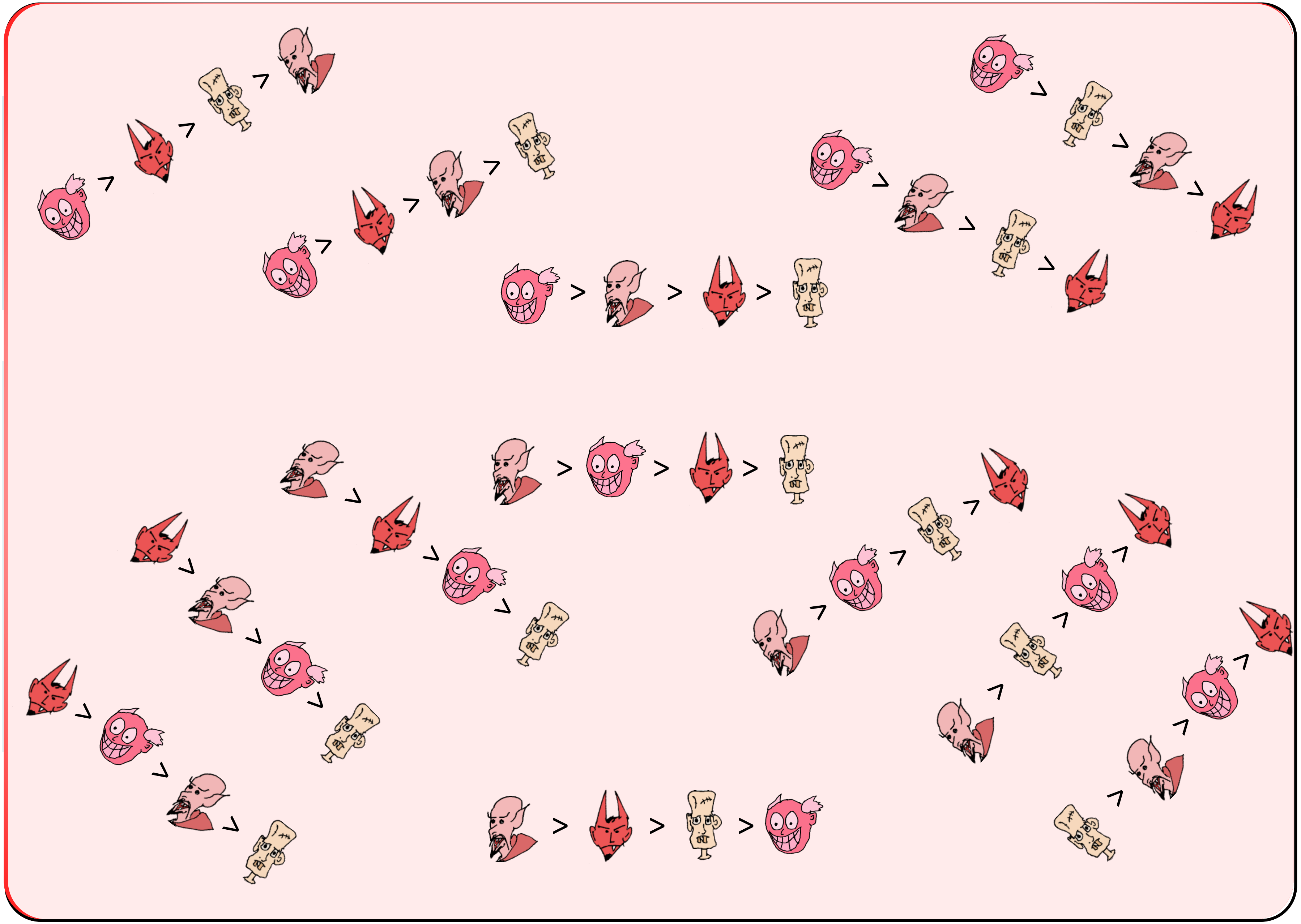
There are fast sampling algorithms.

Φ = 1



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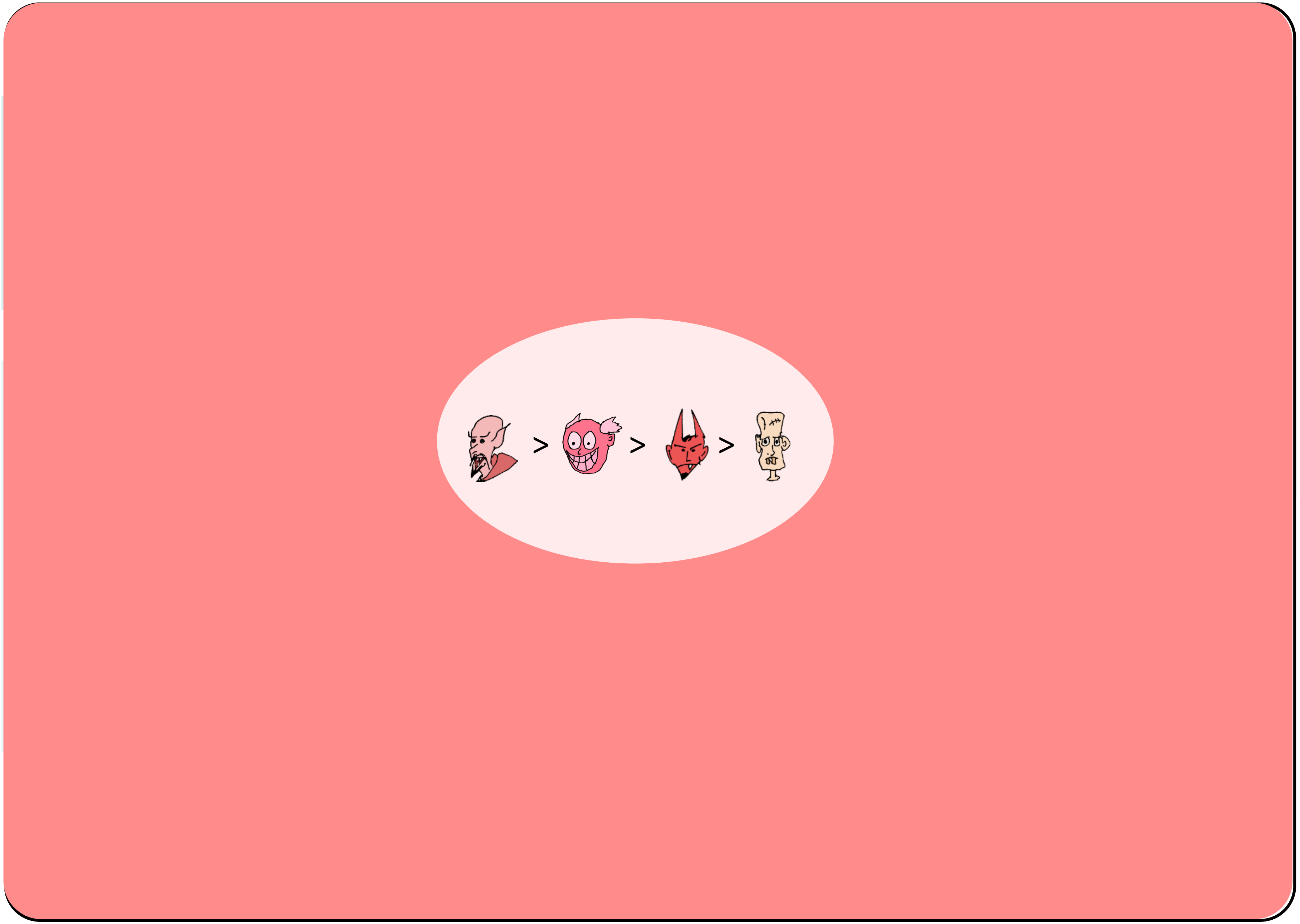
$$\frac{1}{Z}\Phi^{swap(u,v)}$$

There are fast sampling algorithms.

$\Phi = 0$



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So… what do these models actually do?

15 minutes

Microscope View of Statistical Cultures

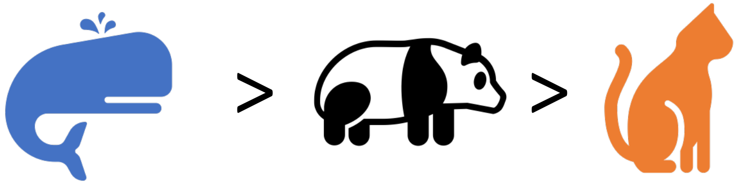
Swap Distance

Number of swaps of adjacent candidates needed to transform one preference order into the other

Swap Distance

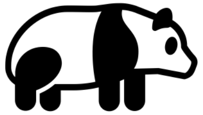
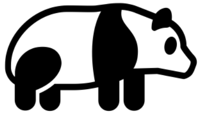
Number of swaps of adjacent candidates needed to transform one preference order into the other

Swap Distance

$d_{swap}($  ,  $) = 0$

Number of swaps of adjacent candidates needed to transform one preference order into the other

Swap Distance

$d_{swap}($  $>$  $>$  ,  $>$  $>$  $) = 0$

Number of swaps of adjacent candidates needed to transform one preference order into the other

Election microscope:

1. Generate an election from a statistical culture
2. Compute swap distances between all pairs of votes
3. Represent each vote as a dot in 2D space, so that Euclidean distances are similar to the swap distances → **map!**

The Map Idea

We have some objects:

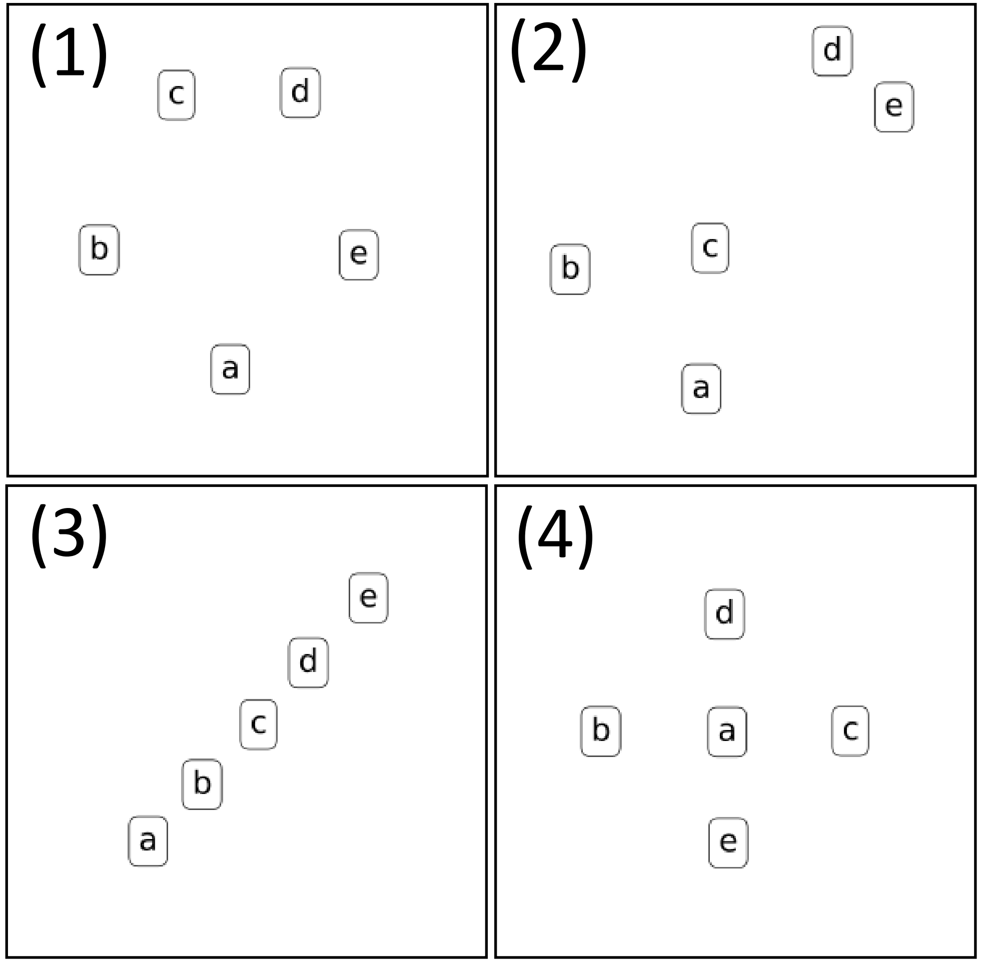
a, b, c, d ,e

We (somehow) know the distances between each pair

—	a	b	c	d	e
a	—	2	2	4	4
b	2	—	2	4	4
c	2	2	—	3	3
d	4	4	3	—	1
e	4	4	3	1	—

(a) Distance Matrix

Can we arrange them in 2D space?



The Map Idea

We have some objects:

a, b, c, d ,e

We (somehow) know the distances between each pair

–	a	b	c	d	e
a	–	2	2	4	4
b	2	–	2	4	4
c	2	2	–	3	3
d	4	4	3	–	1
e	4	4	3	1	–

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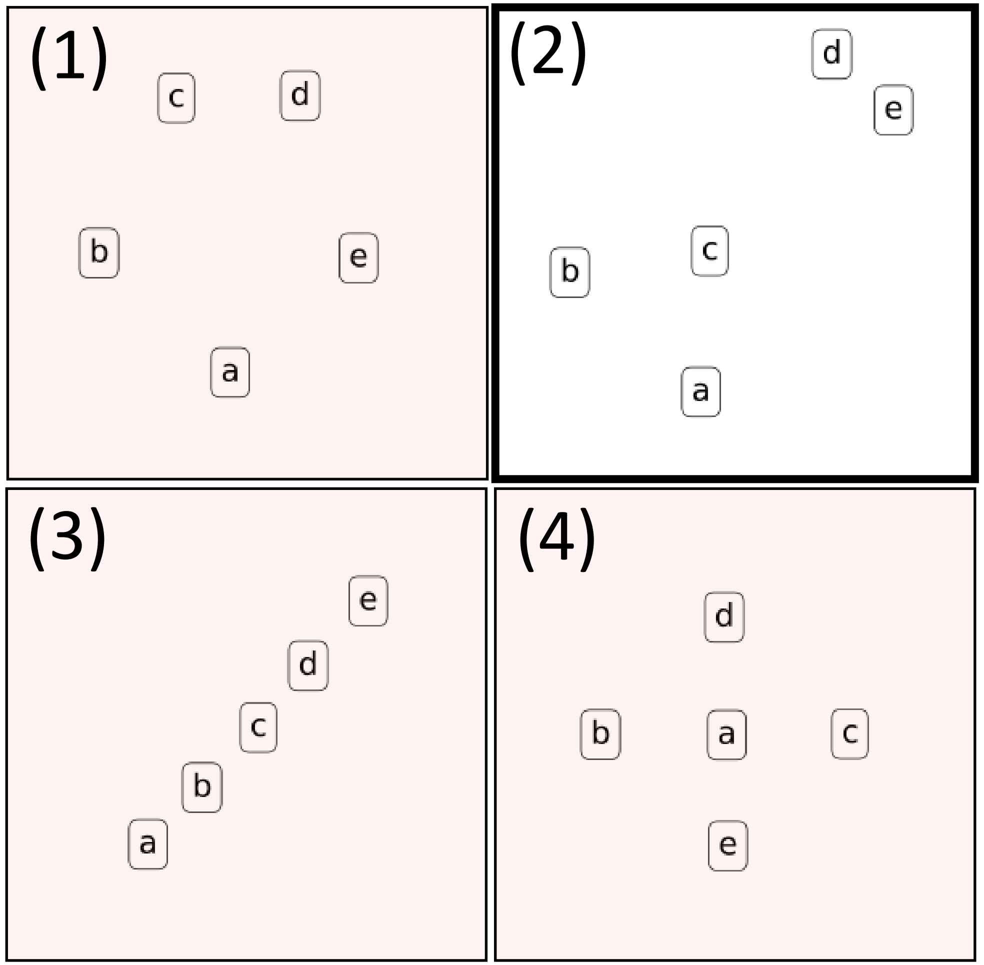


The Map Idea: Sometimes You Fail

Consider objects:

$$z_1, z_2, z_3, \ldots, z_{100}$$

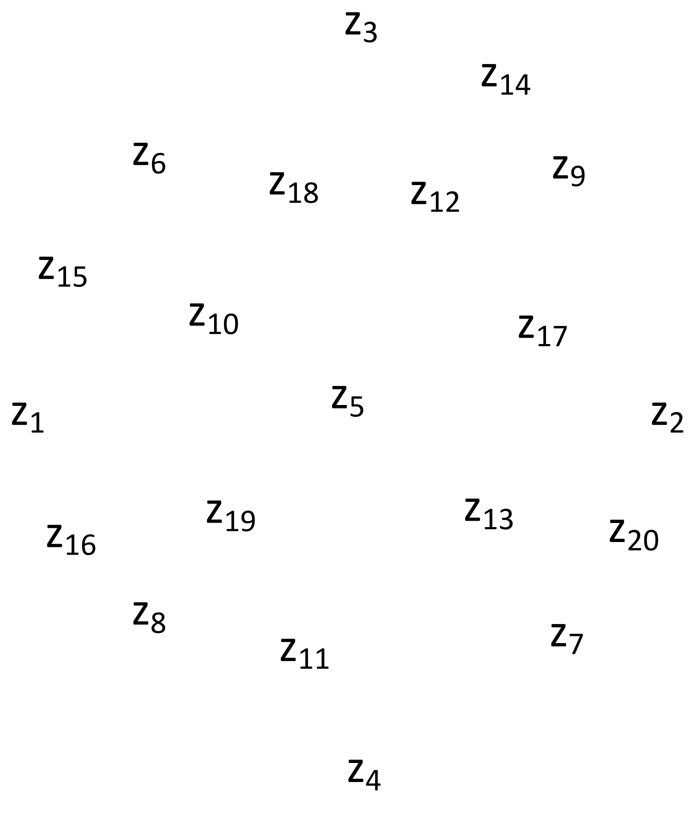
For each $i, j \in [100]$, we have:

$$d(z_i, z_j) = 1$$

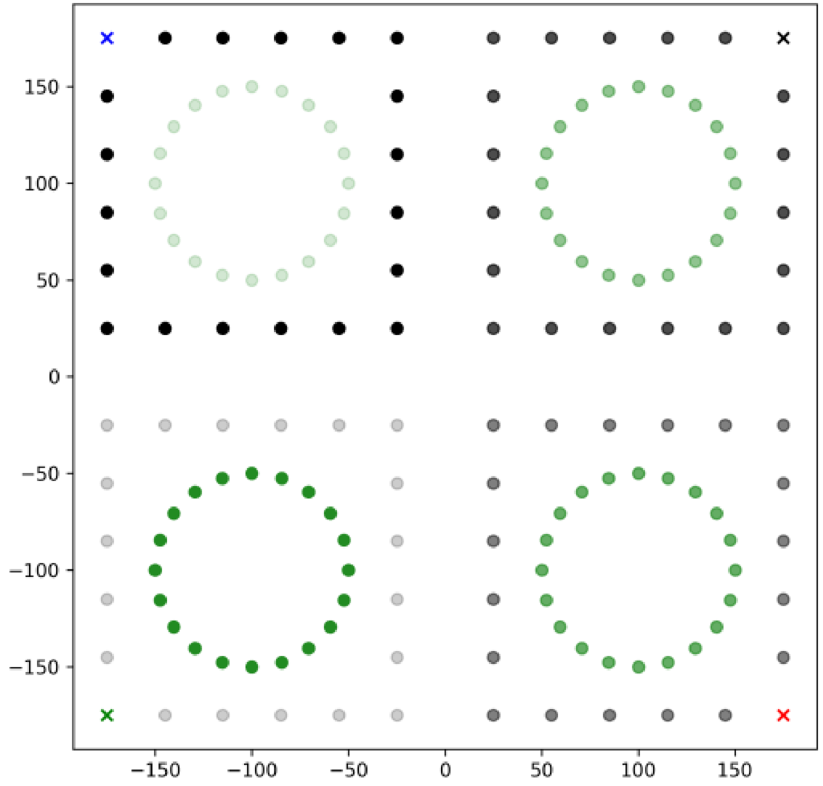
How to arrange these in the 2D space?

Not much you can do without errors…

But we still do it



The Map Idea: Computing The Embedding



simple geometric dataset
(embedding algorithms only have Euclidean distances of points as inputs)

$$\begin{bmatrix} a_{00} & a_{01} & a_{02} & a_{03} & a_{04} & a_{05} & a_{06} & a_{07} \\ a_{10} & a_{11} & a_{12} & a_{13} & a_{14} & a_{15} & a_{16} & a_{17} \\ a_{20} & a_{21} & a_{22} & a_{23} & a_{24} & a_{25} & a_{26} & a_{27} \\ a_{30} & a_{31} & a_{32} & a_{33} & a_{34} & a_{35} & a_{36} & a_{37} \\ a_{40} & a_{41} & a_{42} & a_{43} & a_{44} & a_{45} & a_{46} & a_{47} \\ a_{50} & a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & a_{56} & a_{57} \\ a_{60} & a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} & a_{67} \\ a_{70} & a_{71} & a_{72} & a_{73} & a_{74} & a_{75} & a_{76} & \\ a_{80} & a_{81} & a_{82} & a_{83} & a_{84} & a_{85} & & \\ a_{90} & a_{91} & a_{92} & a_{93} & a_{94} & a_{95} & & \end{bmatrix}$$

K. Sapała, Algorithms for Embedding Metrics in Euclidean Spaces, MSc thesis AGH 2022 (specialized implementation of Kamada-Kawai algorithm)

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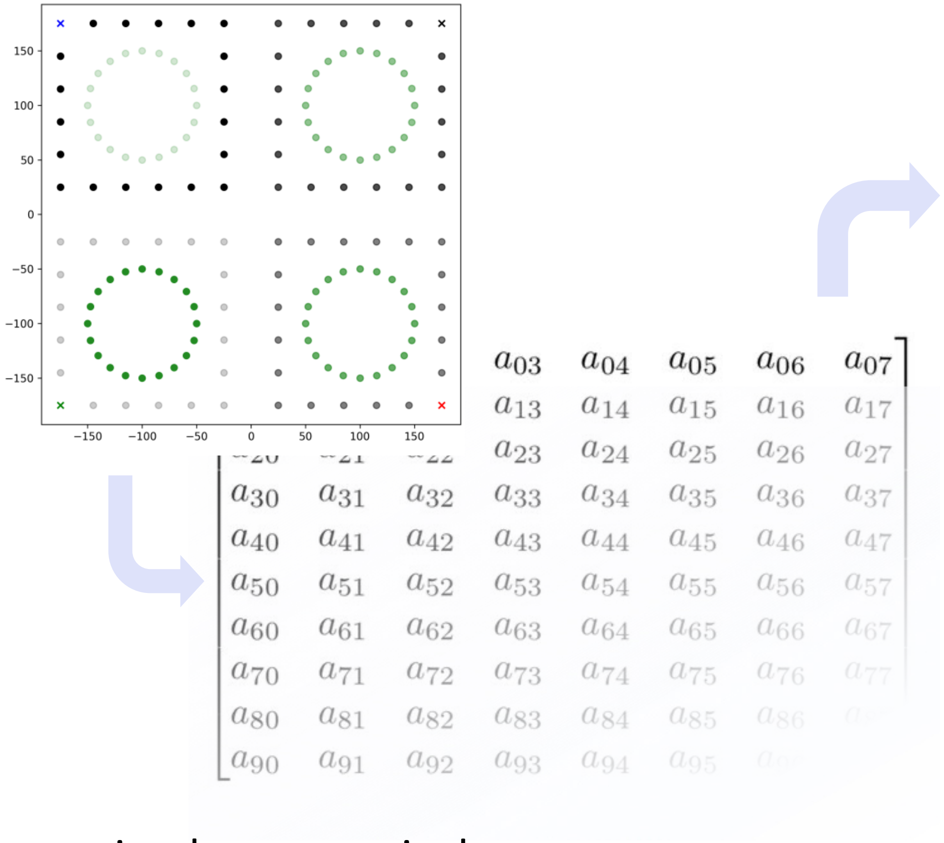

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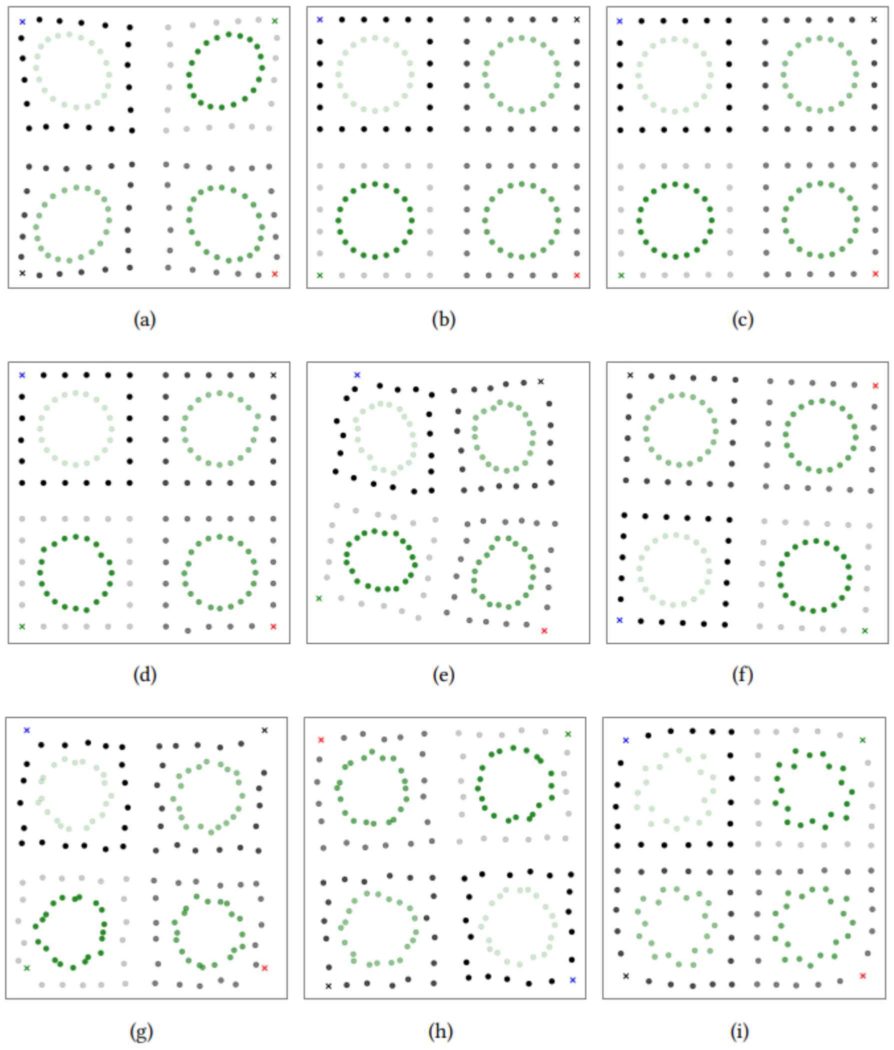

Examples of embeddings

(a) ISOMAP
(b) Kamada-Kawai (KK) with positions of corner points fixed
(c) KK wihtout fixing
(d) KK with Newton-Rhapson + fixing
(e) KK with Newton-Rhapson without fixing
(f) MDS
(g) Simulated annealing with fixing
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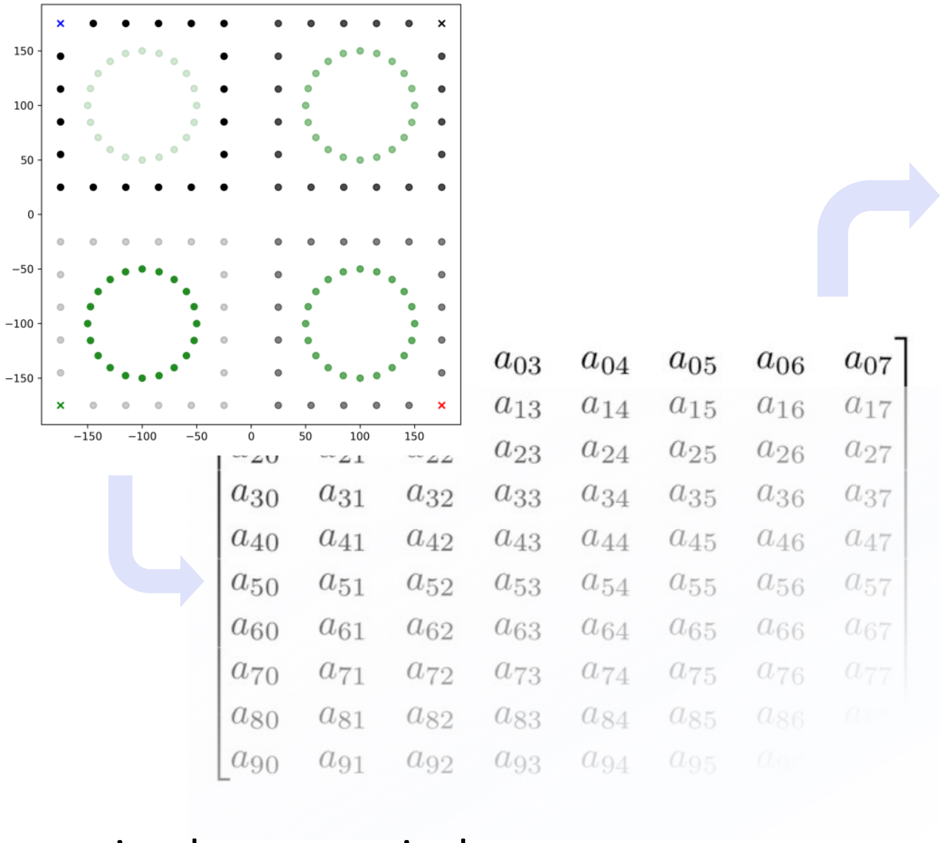

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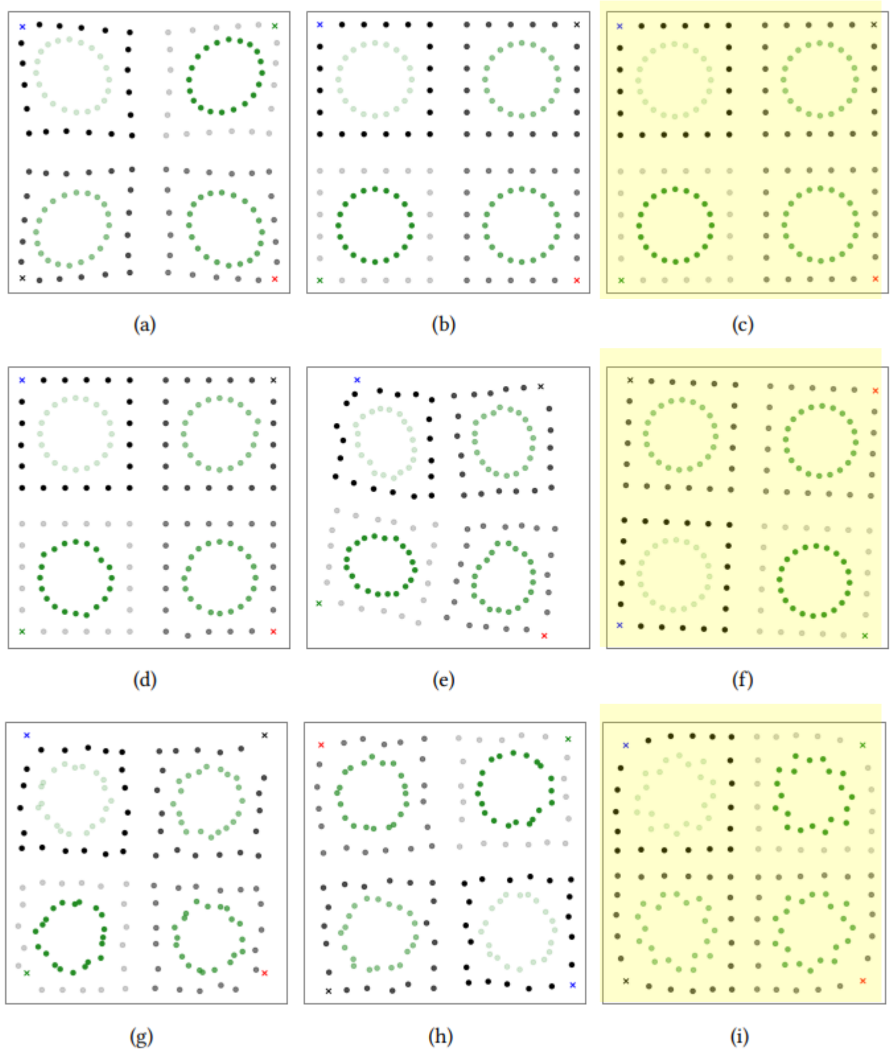

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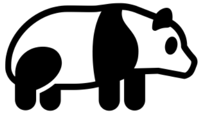
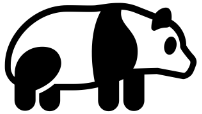
Swap Distance

$d_{swap}($  >  >  ,  >  >  $) = 0$

Number of swaps of adjacent candidates needed to transform one preference order into the other

Election microscope:

1. Generate an election from a statistical culture
2. Compute swap distances between all pairs of votes
3. Represent each vote as a dot in 2D space, so that Euclidean distances are similar to the swap distances → **map!**

Microscope

Impartial Culture (IC): Every preference order comes with the same proba-bility (a.k.a. **uniform distribution**)

Polya-Eggenberger Urn Model: Form an urn of **all possible m! votes**. To generate a vote:

1) Choose a vote from the urn and add it to your election
2) **Return** the vote to the urn, together with **α·m! copies**.

Mallows Model: Choose a center vote u. The probability of generating vote v is:

$$\frac{1}{Z}\Phi^{swap(u,v)}$$

(There are some algorithms that generate votes from this distribution… effectively.)

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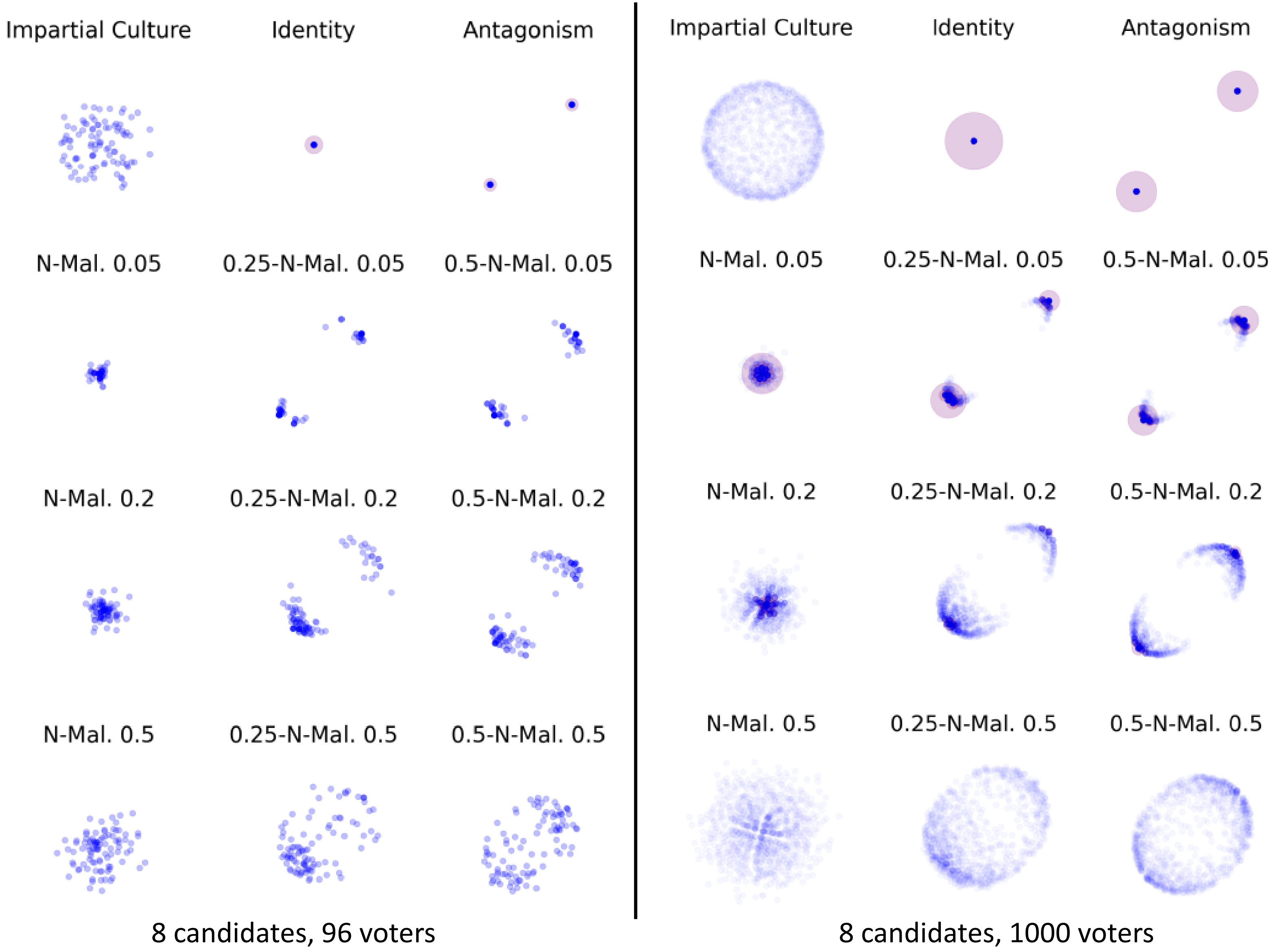

P. Faliszewski, A. Kaczmarczyk, K. Sornat, S. Szufa, T. Wąs, Diversity, Agreement and Polarization in Elections, IJCAI 2023

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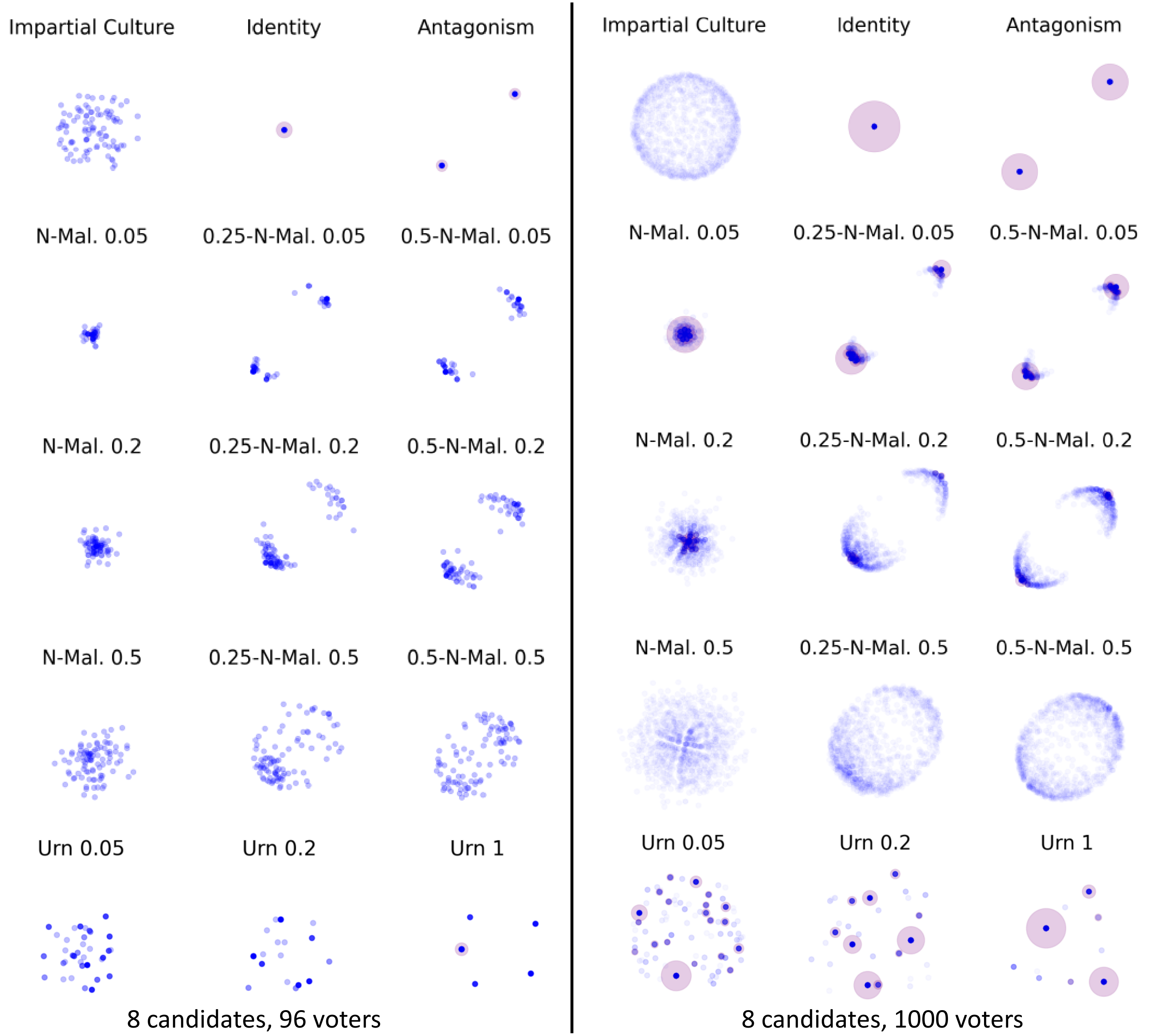

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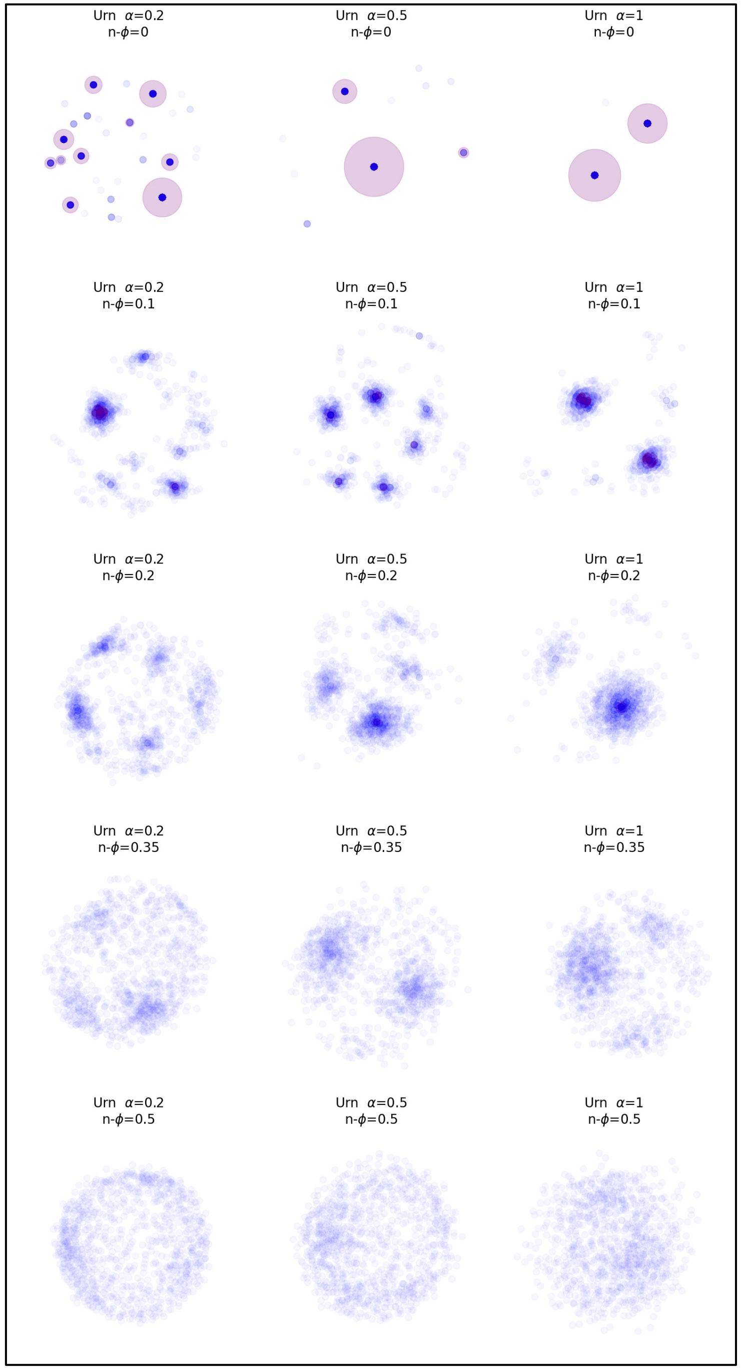

Urn-Mallows Model: First generate an election according to the urn model and then replace each vote *v* with one generated using Mallows model, with *v* as the center vote.

Comparison to real-life elections: Sushi contains preferences about sushi types. Grenoble and Irish are political elections

10 minutes

Restricted Domains

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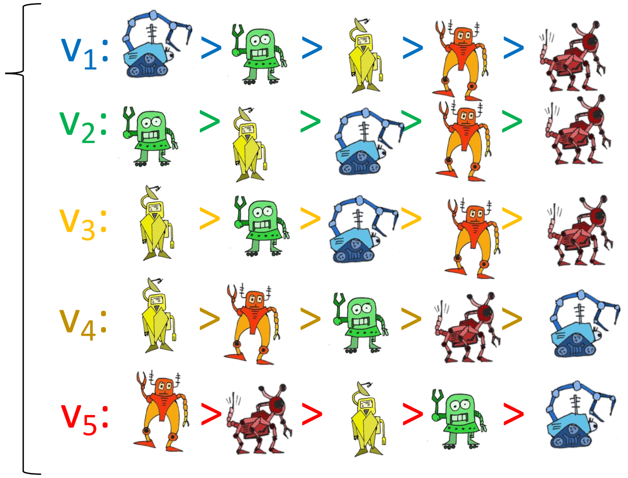
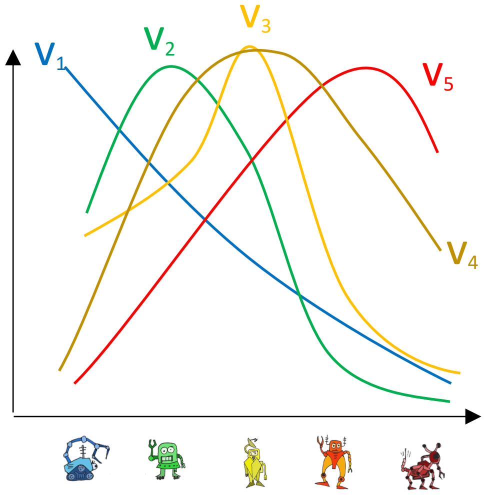
Single-Peaked (SP): Fix a societal axis, e.g., the following ordering of the candidates. Every single-peaked vote for this axis satisfies the property that „for each t, the top t candidates form an interval on the axis).

single-peakedness





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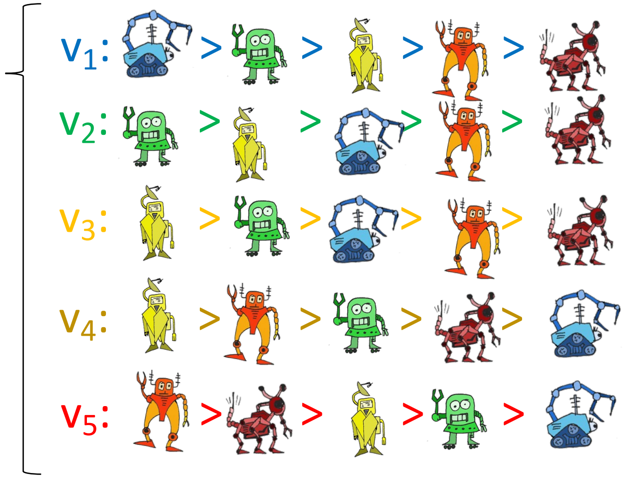
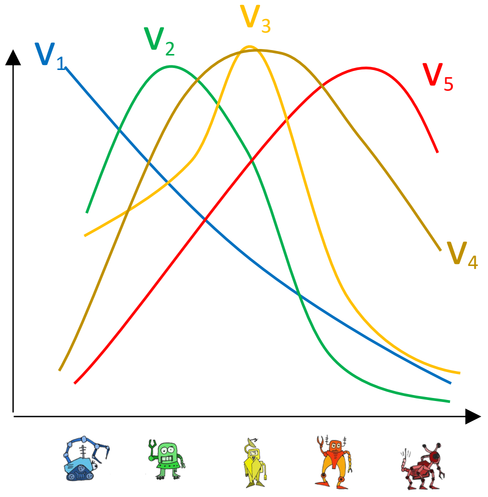
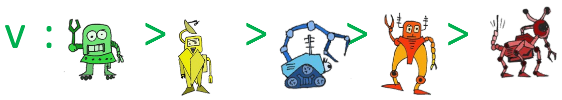




Conitzer model (top-down)

1/n * 1/2 * 1/2 * 1 * 1



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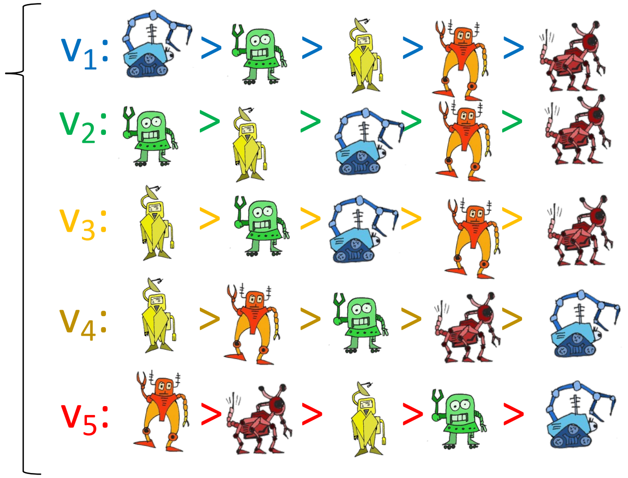
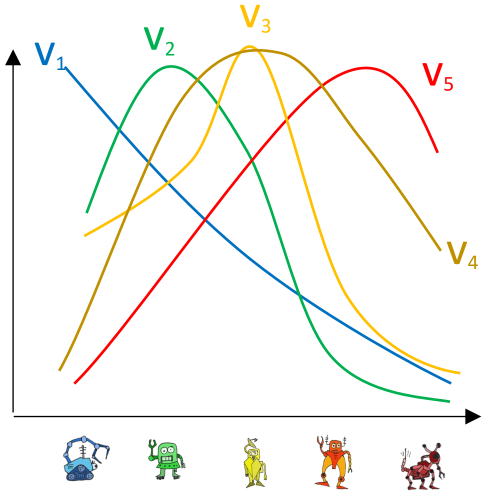
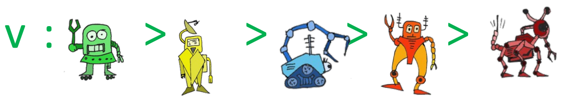




Conitzer model (top-down)

1/5 * 1/2 * 1/2 * 1 * 1



Walsh model (bottom-up)

Uniform distribution

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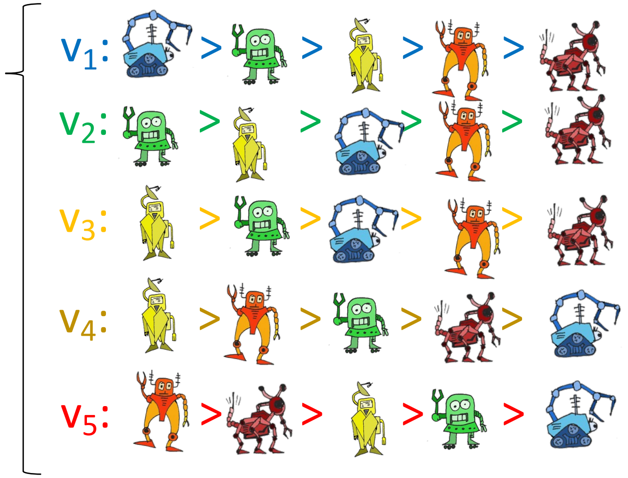
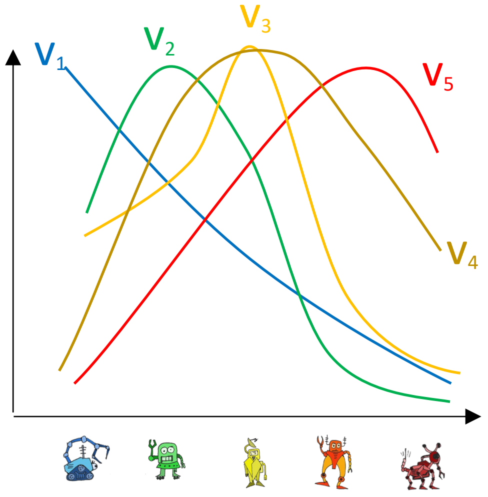
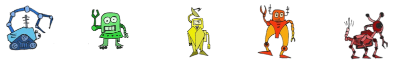
Single-Crossing: Order voters so going from top to bottom, each pair of candidates crosses at most once.

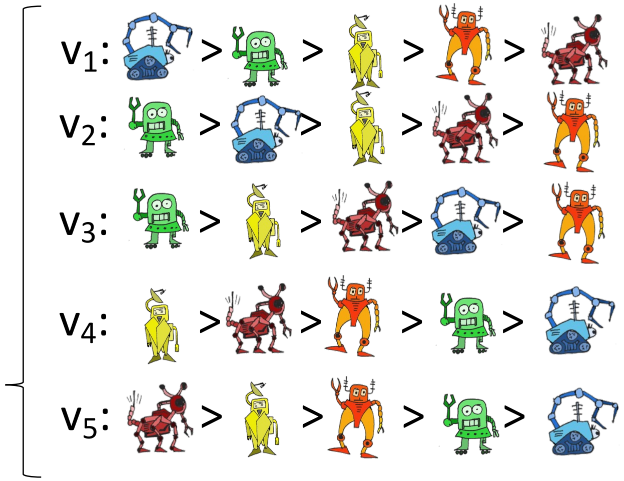
single-peakedness







single-crossingness



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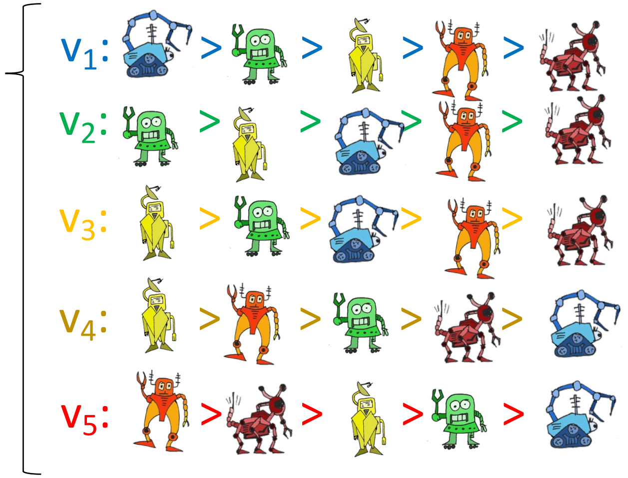

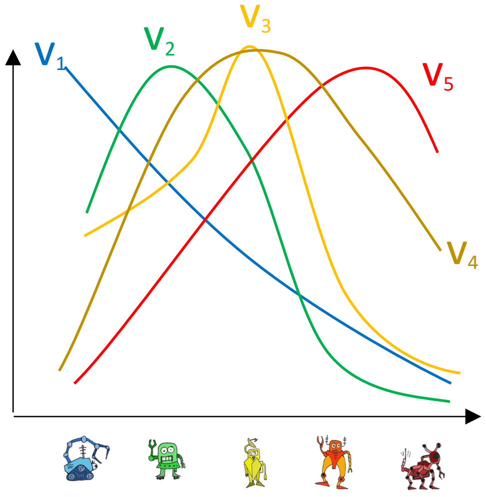

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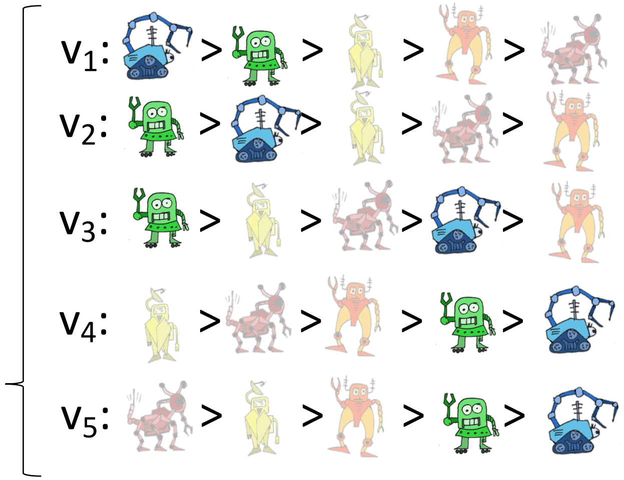

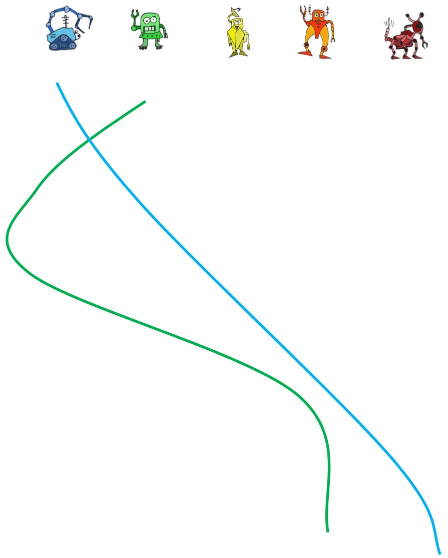

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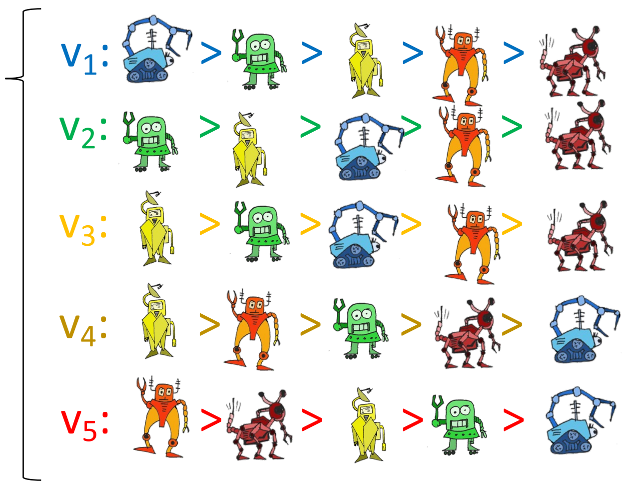

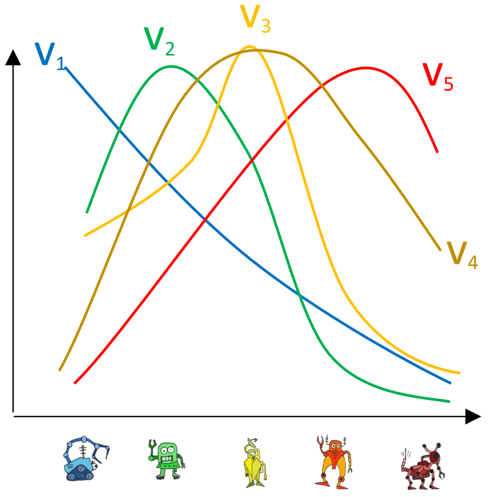

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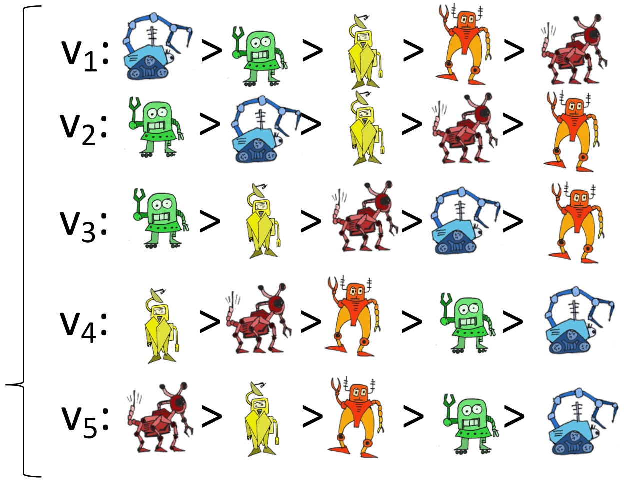

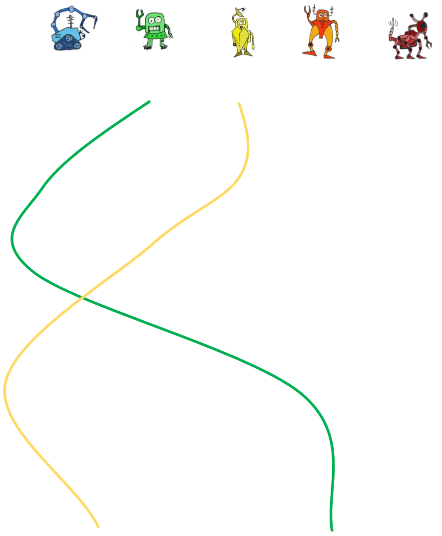

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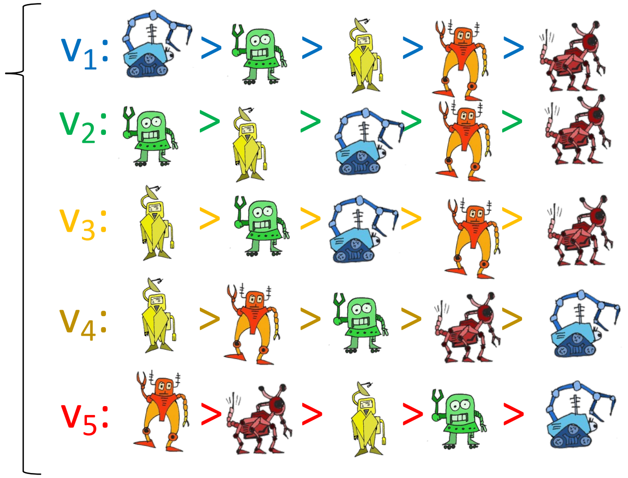

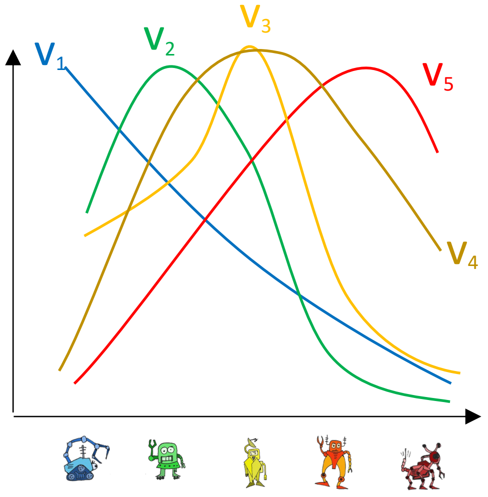

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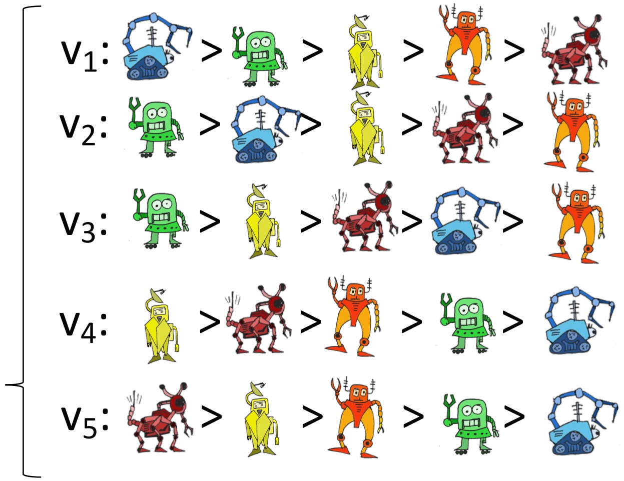

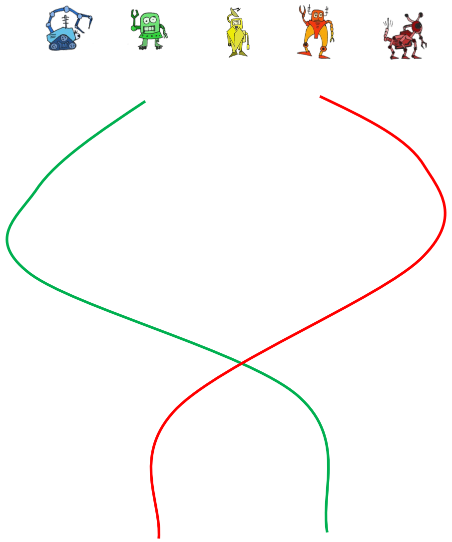

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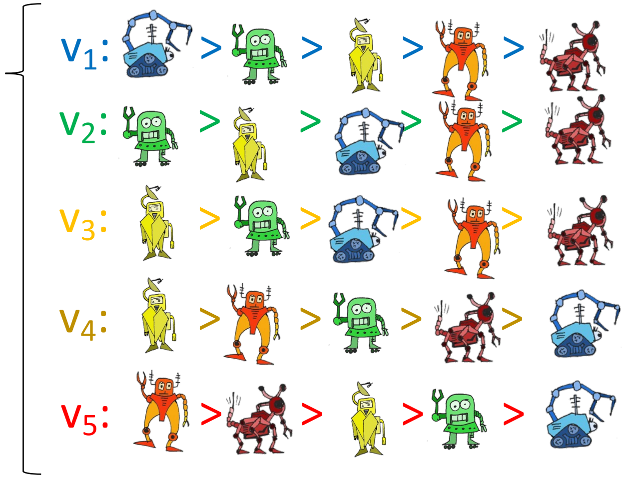
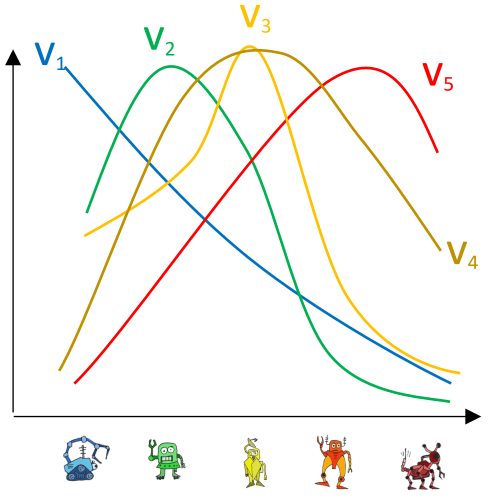
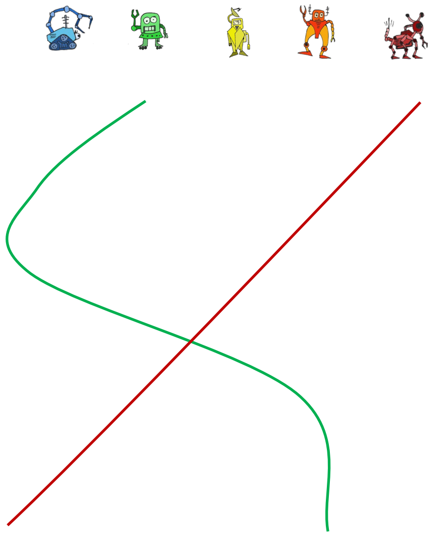
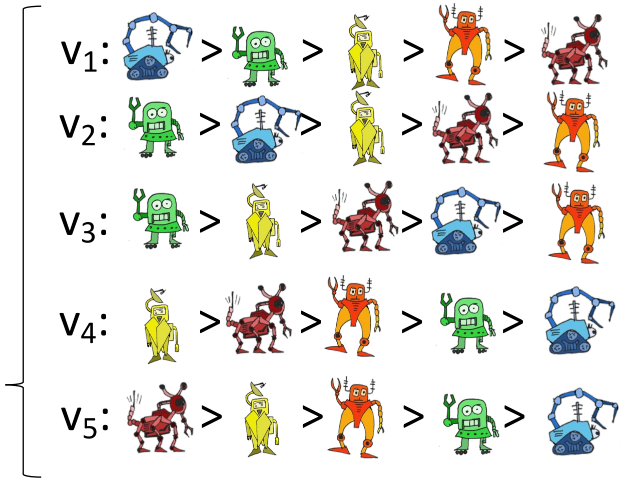




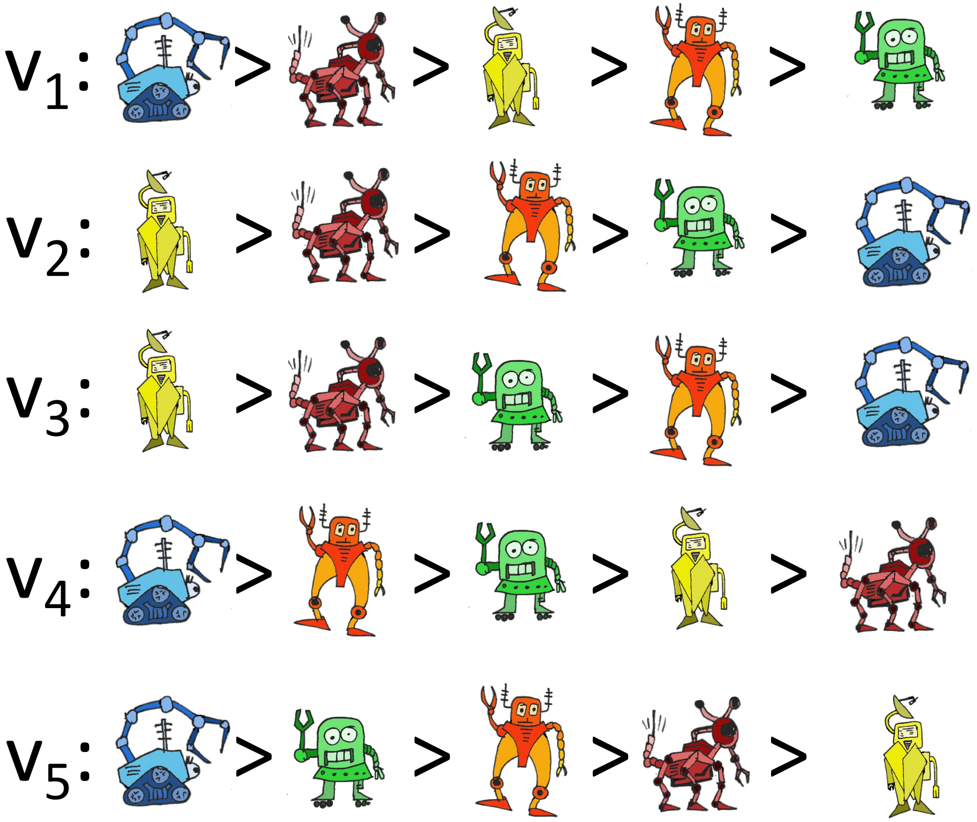


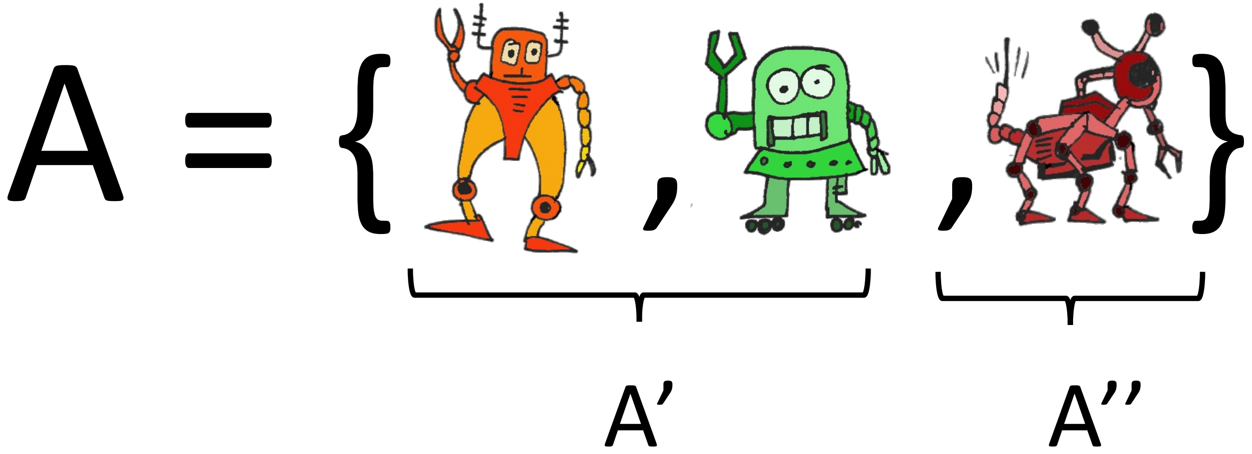


single-crossingness

Group-Separable Preferences

A profile is group-separable if each subset A, |A| ≥ 2, of candidates can be partitioned into A’ and A’’ so that each voter prefers all members of one to all members of the other





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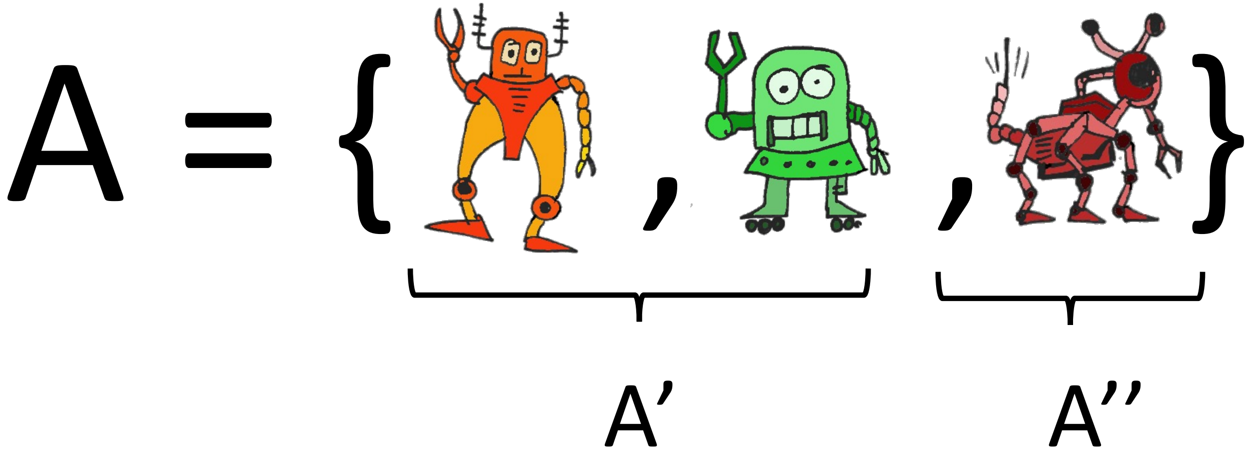

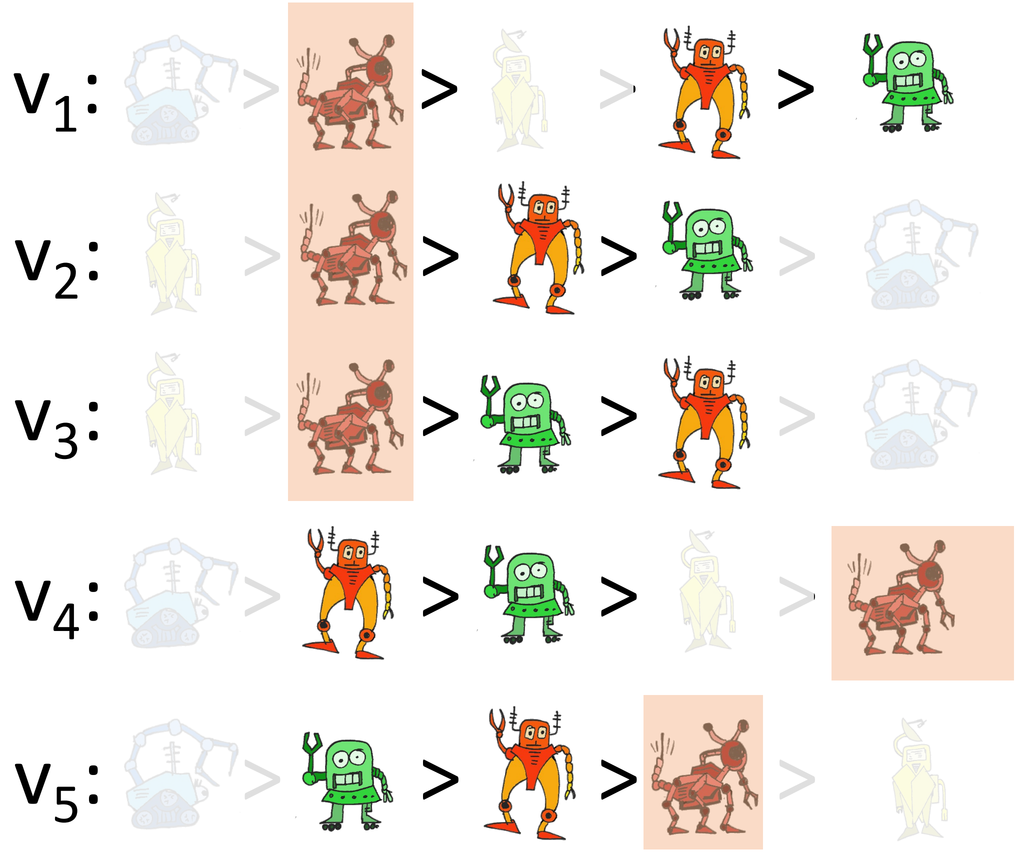

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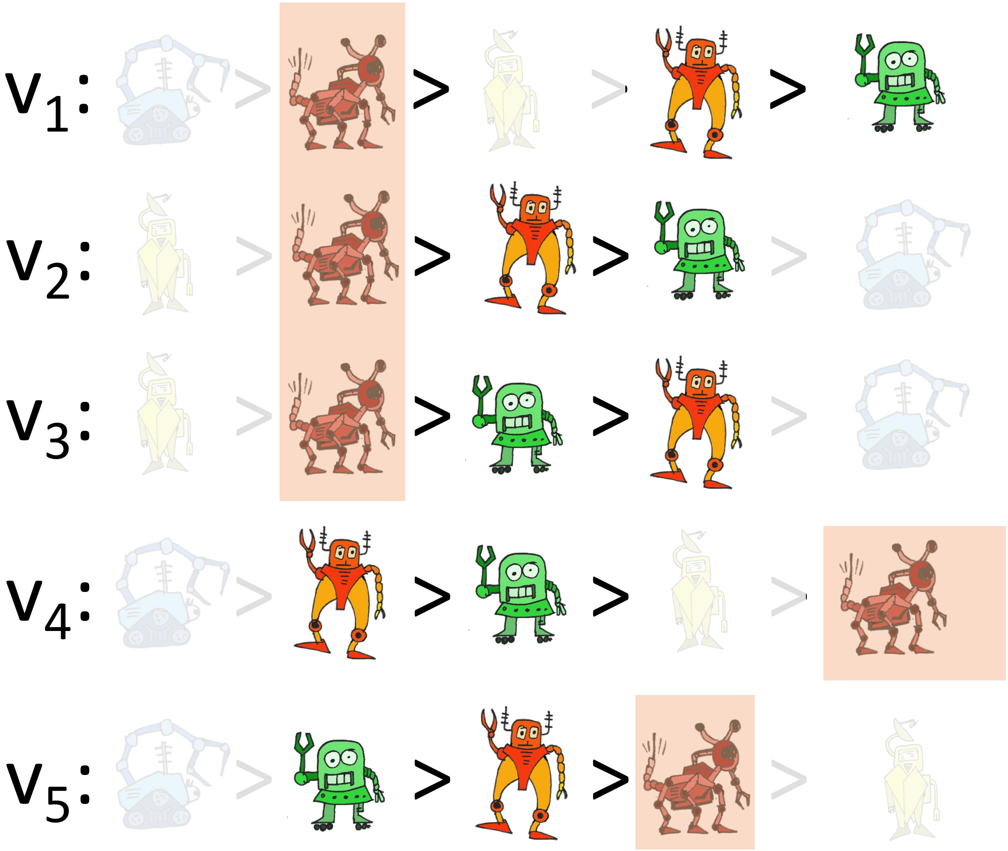

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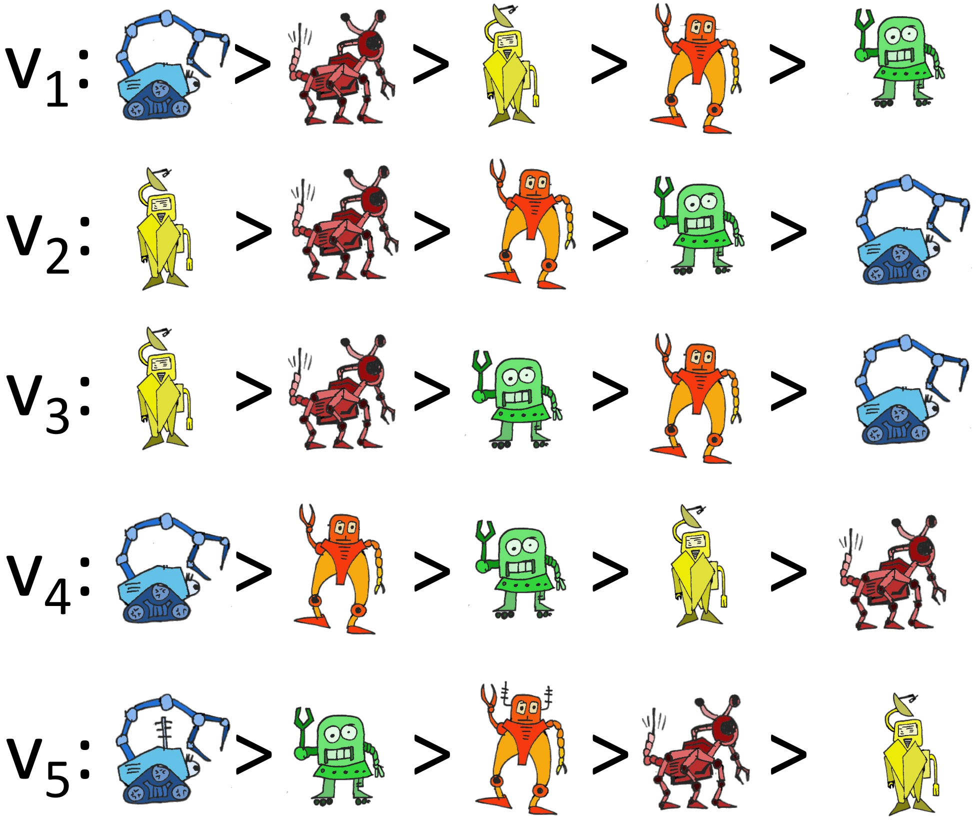
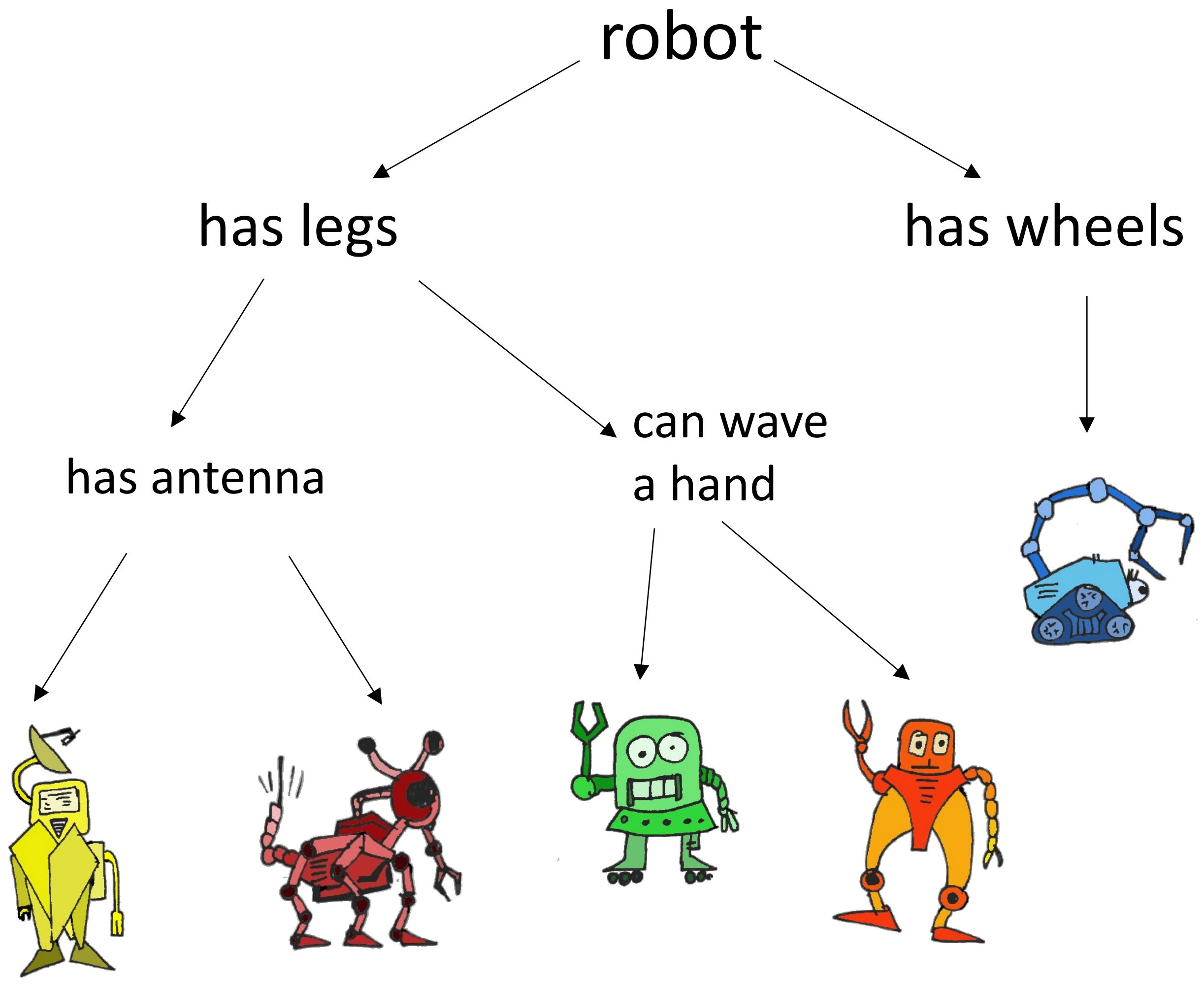
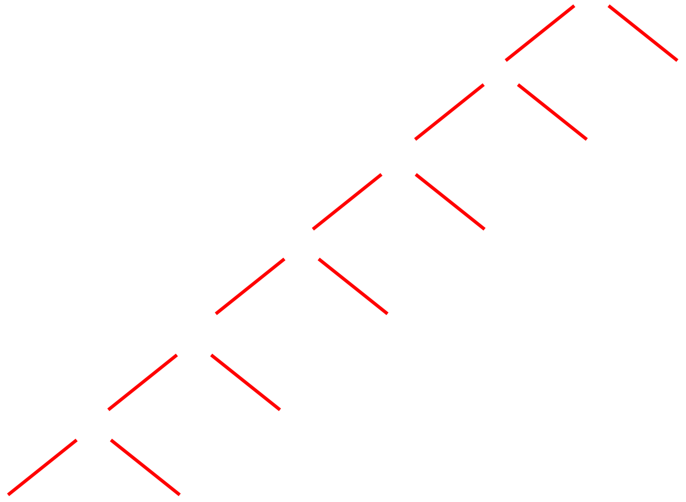




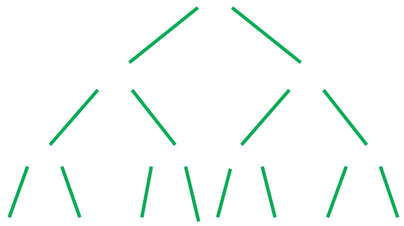
A. Karpov, On the Number of Group-Separable Preference Profiles, Group Decision and Negotiation, 2019

Group-Separable Preferences

Caterpillar Trees

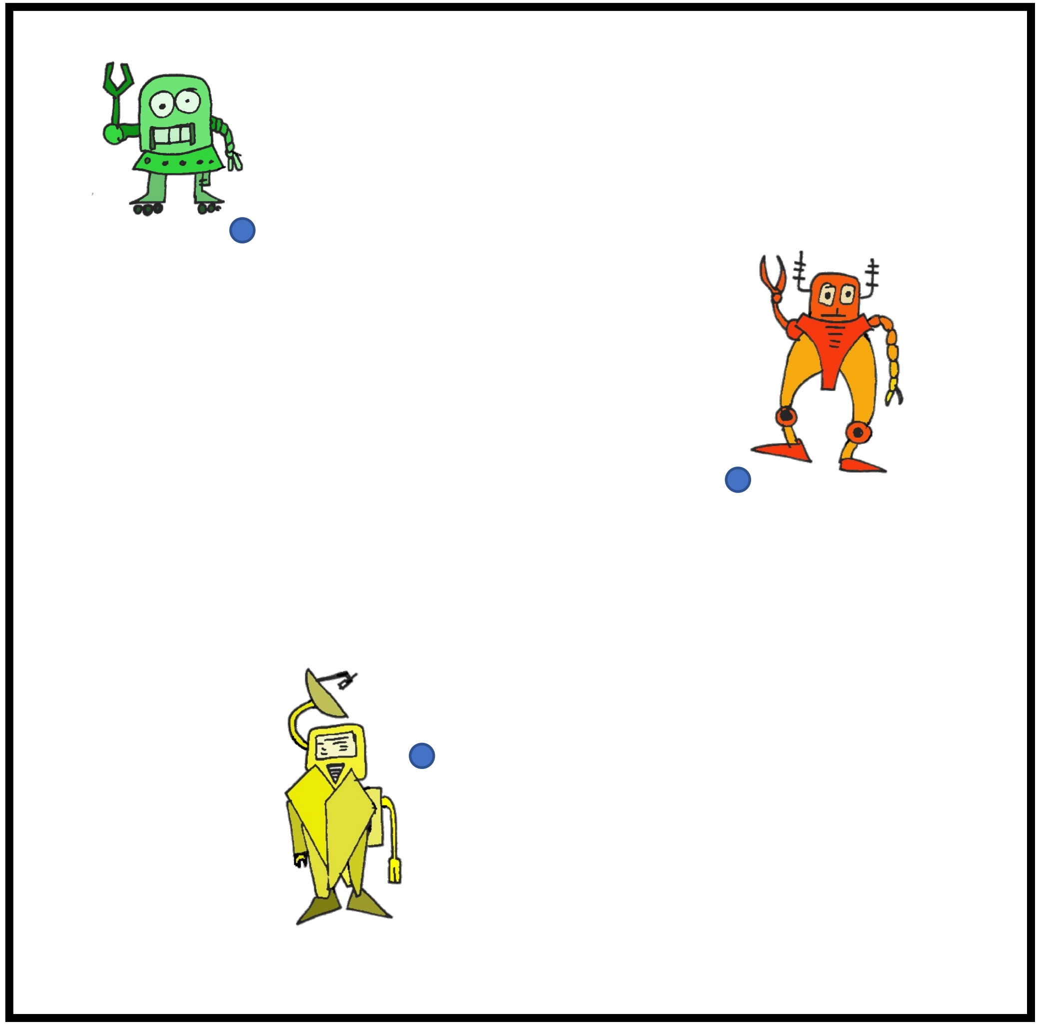


Balanced Trees



Euclidean Preferences

Euclidean Model: Choose points for the voters and candidates from Euclidean space $\mathbb{R}^t$. Voter v prefers candidate x to y if x's point is closer to v than y's.



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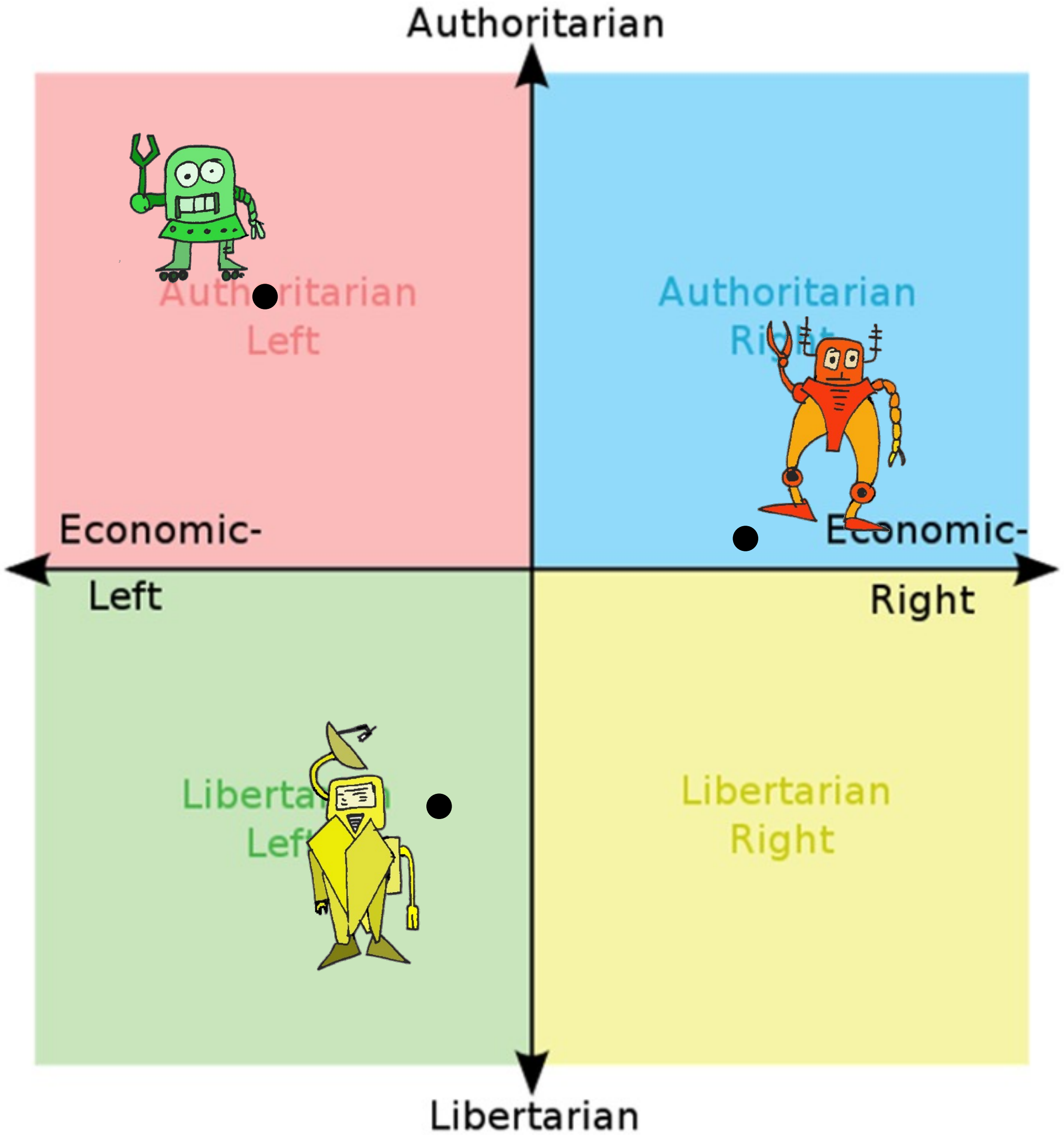
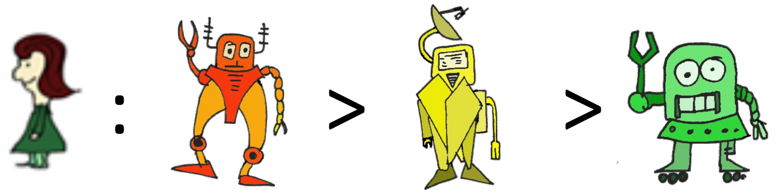
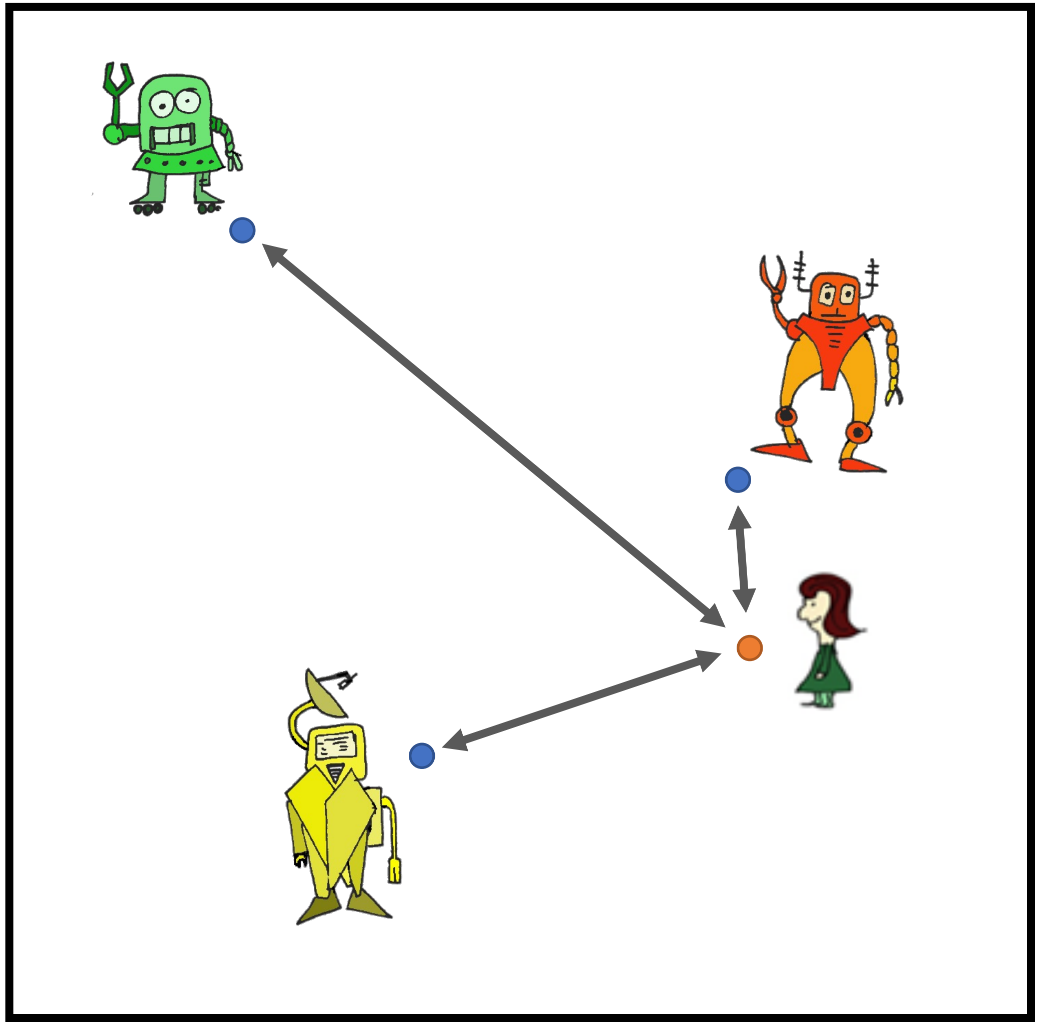
Euclidean Model: Choose points for the voters and candidates from Euclidean space $\mathbb{R}^t$. Voter *v* prefers candidate *x* to *y* if *x*'s point is closer to *v* than *y*'s.



Euclidean Preferences

Euclidean Model: Choose **points** for the voters and candidates from **Euclidean space** $\mathbb{R}^t$. Voter *v* prefers candidate *x* to *y* if *x*'s point is **closer** to *v* than *y*'s.





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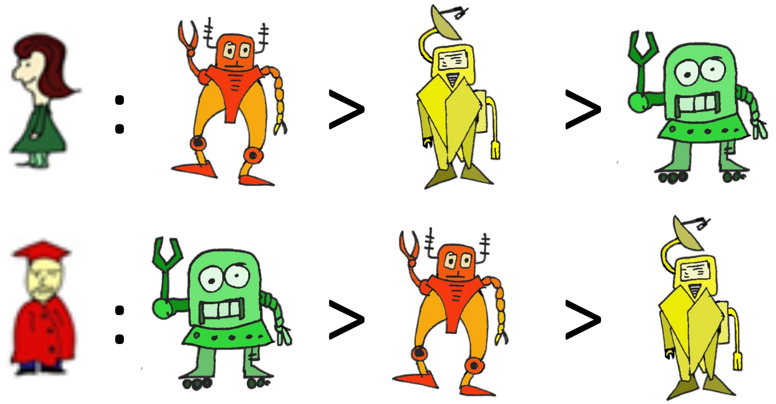
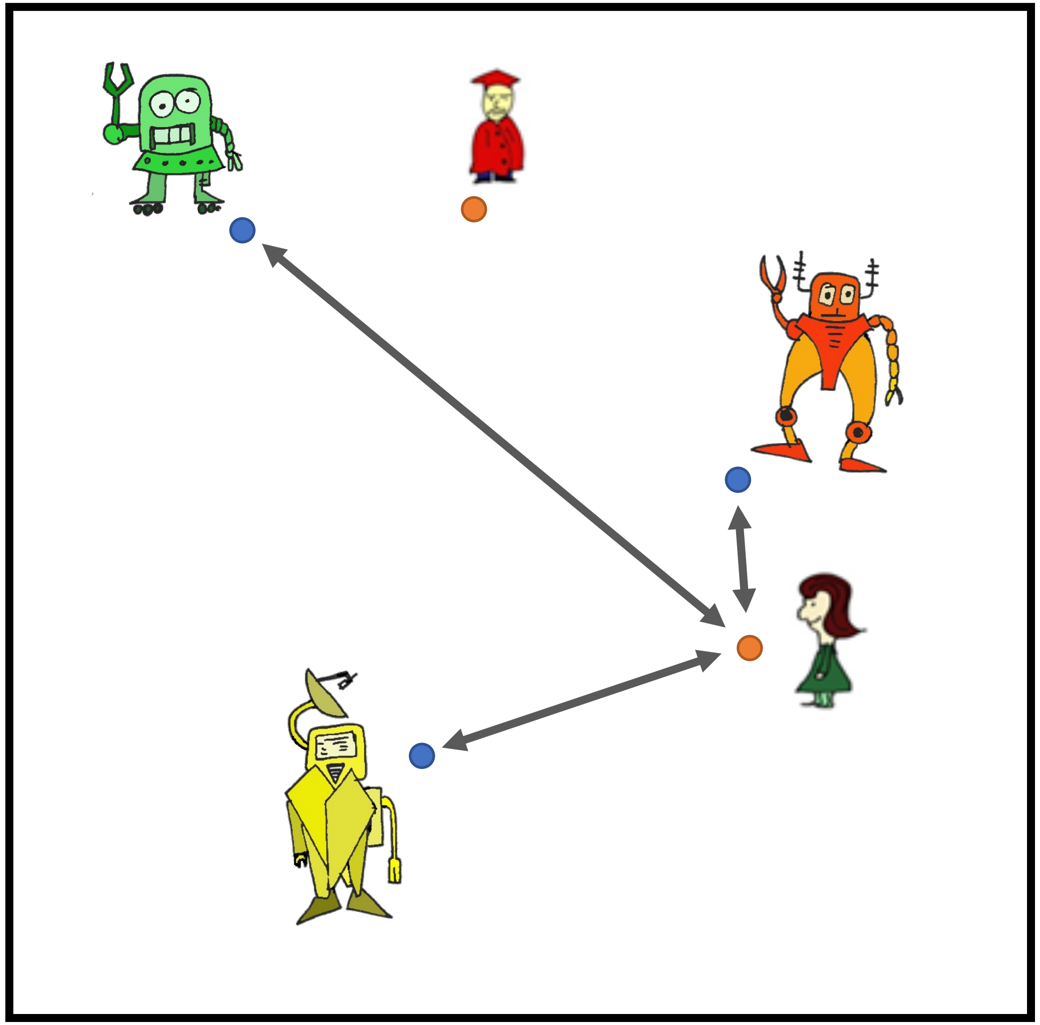




Microscope of Structured Domains

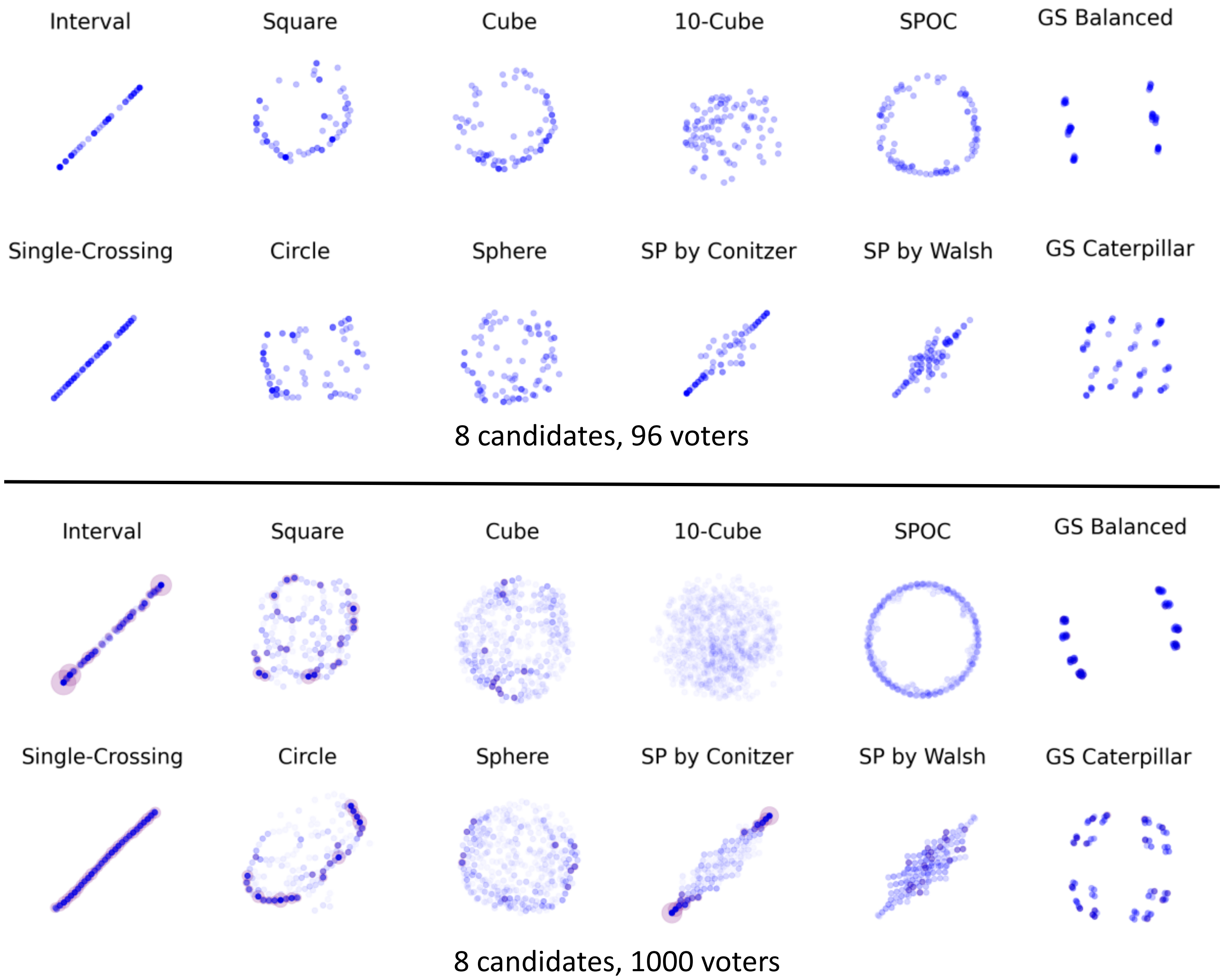
Euclidean Model: Choose points for the voters and candidates from Euclidean space $\mathbb{R}^t$. Voter *v* prefers candidate *x* to *y* if *x*'s point is closer to *v* than *y*'s.

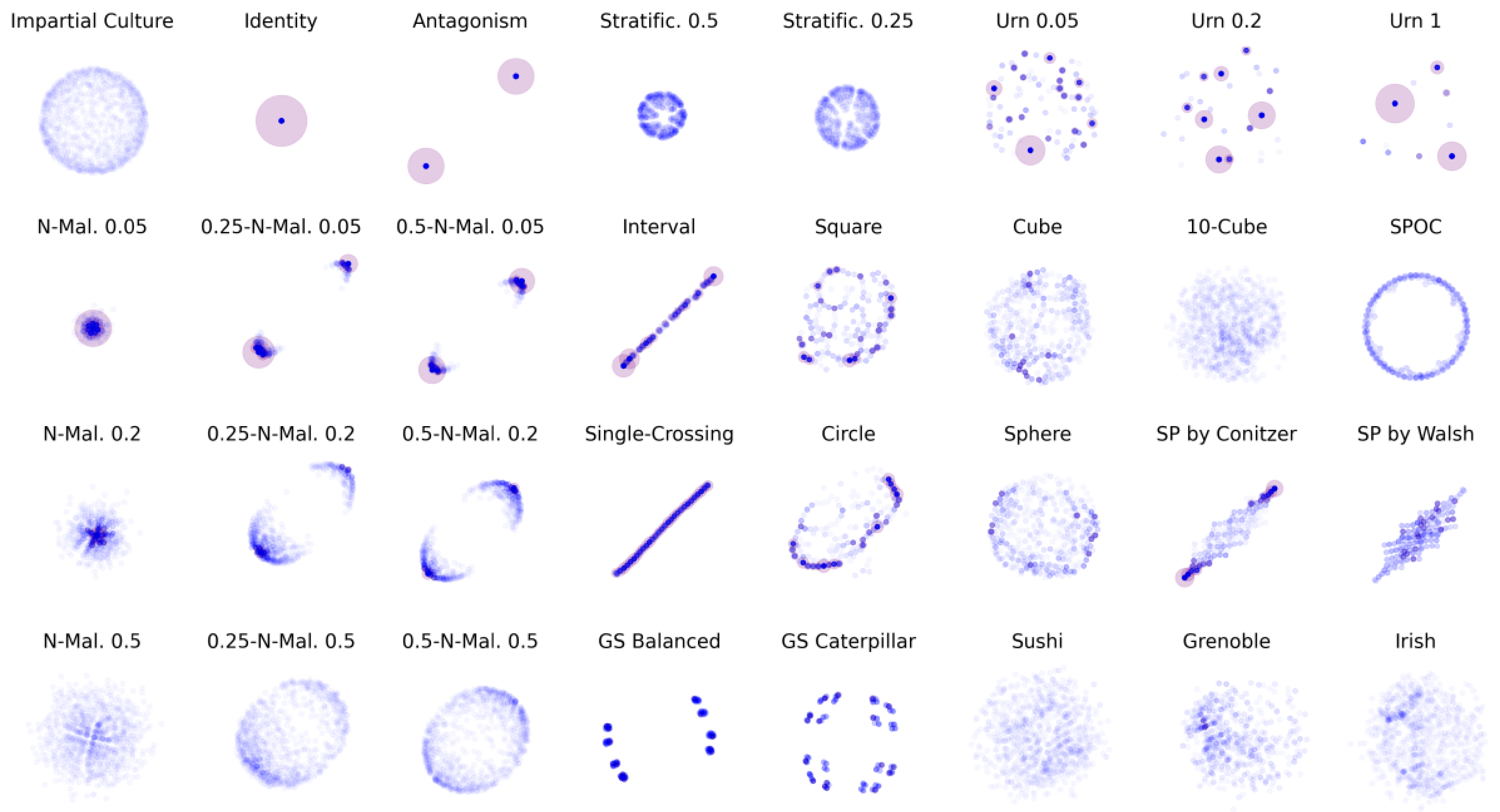
Single-Peaked: There is societal axis (order of the of the candidates). Every single-peaked vote for this axis satisfies the property that „for each t, the top t candidates form an interval on the axis".

SPOC: Like SP, but the axis is cyclic

Single-Crossing: It is possible to order the voters so that as we go along this order, the relative ranking of two candidates changes at most once

Group-Separable: Trees, trees everywhere!





P. Faliszewski, A. Kaczmarczyk, K. Sornat, S. Szufa, T. Wąs, Diversity, Agreement and Polarization in Elections, IJCAI 2023

10 minutes

What’s Used?

Collecting the Data

Papers

- AAAI, AAMAS, IJCAI
- 2010—2023
- Downloaded all the papers using the XML file from DBLP (September 2023)

Screening Process

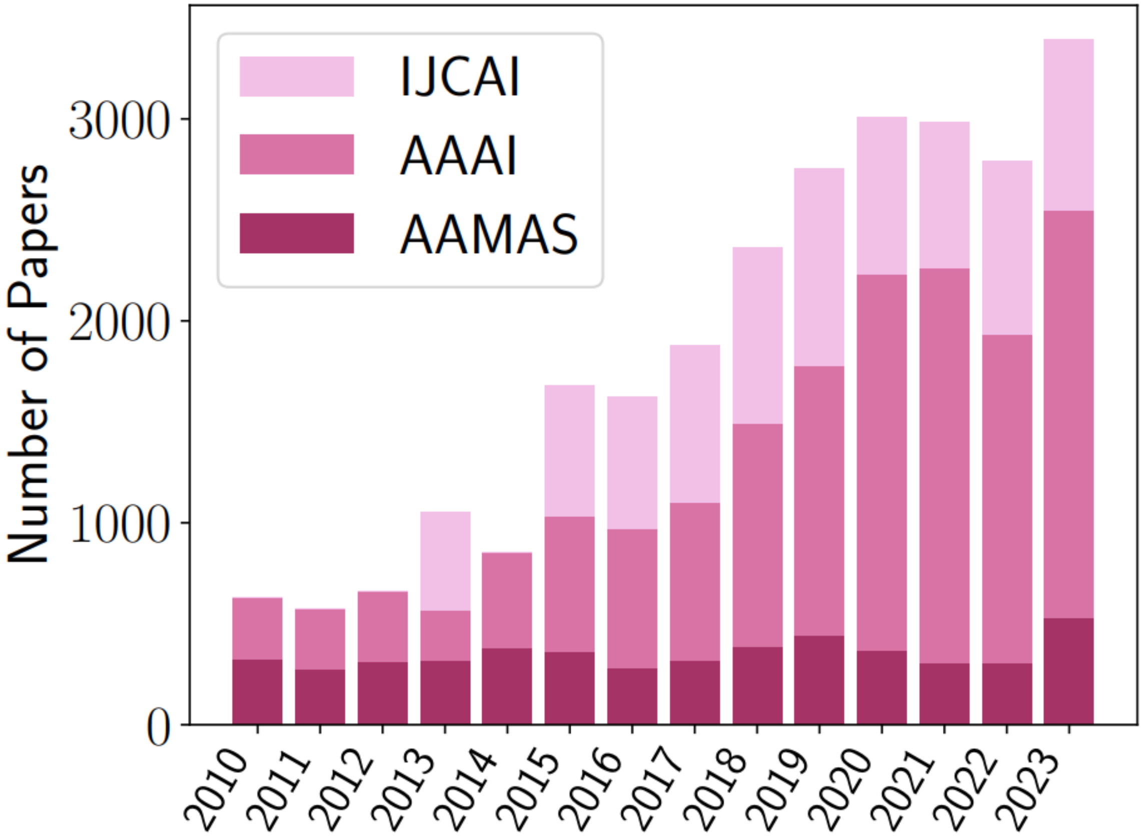
- Automated script looking for election- and experiment-related keywords
  - `election, vote, ballot`
  - `experiment, empirical, simulation`
- Manual check of the shortlist
- E.g., IJCAI-23:
  - 846 papers
  - Script shortlisted 41
  - Manual check retained 7

Basic Statistics

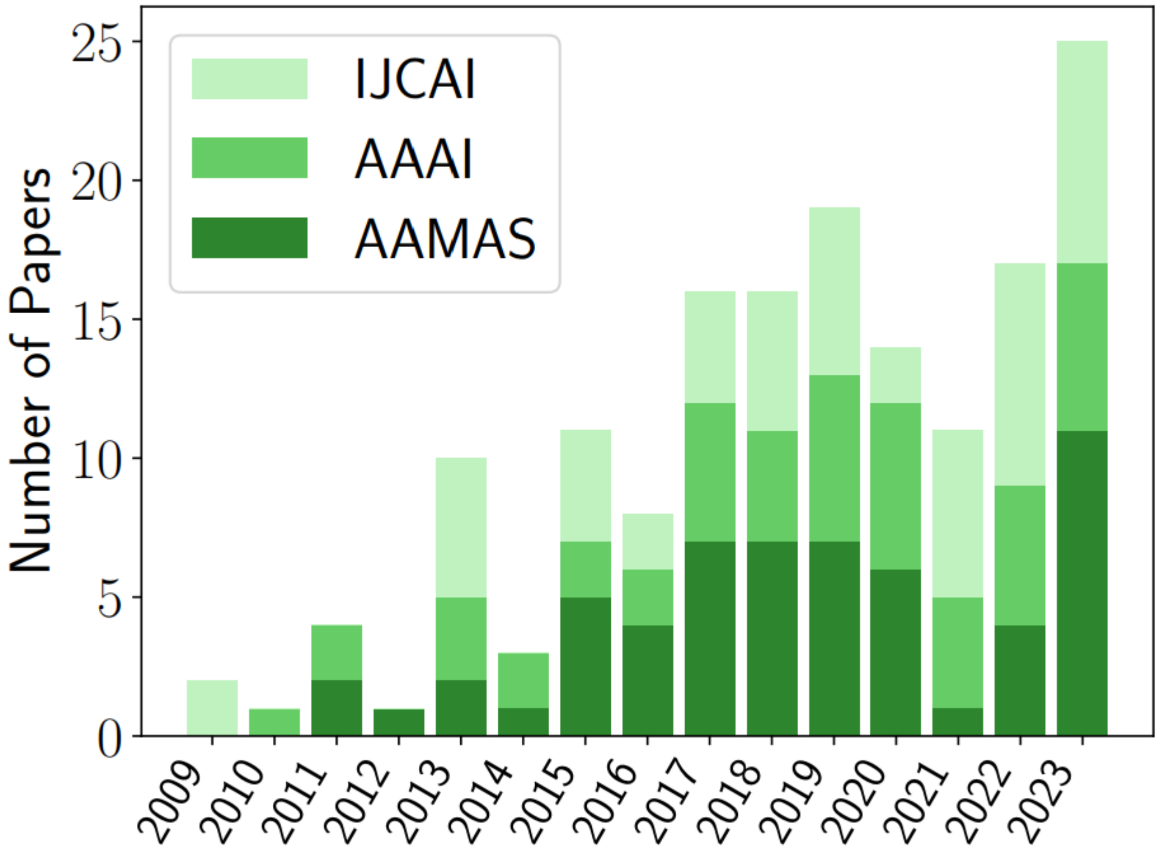
- Papers: 163
  - 130 ordinal
  - 35 approval
  - **Puzzle?**
- Experiments: 257
  - 211 ordinal
  - 46 approval
- Authors: 273 (+/-)

P. Faliszewski --> 26 paper(s) (18 ordinal, 8 approval)
P. Skowron --> 14 paper(s) (8 ordinal, 6 approval)
N. Talmon --> 14 paper(s) (11 ordinal, 3 approval)
M. Lackner --> 12 paper(s) (3 ordinal, 9 approval)
S. Szufa --> 11 paper(s) (8 ordinal, 3 approval)
A. Procaccia --> 8 paper(s) (ordinal)
A. Slinko --> 8 paper(s) (7 ordinal, 1 approval)
N. Boehmer --> 7 paper(s) (ordinal)
N. Mattei --> 7 paper(s) (5 ordinal, 2 approval)
N. Shah --> 7 paper(s) (6 ordinal, 1 approval)
L. Xia --> 7 paper(s) (ordinal)
C. Boutilier --> 6 paper(s) (ordinal)
U. Endriss --> 6 paper(s) (4 ordinal, 2 approval)
J. Lang --> 6 paper(s) (3 ordinal, 3 approval)
O. Lev --> 6 paper(s) (ordinal)
D. Peters --> 6 paper(s) (4 ordinal, 2 approval)
T. Walsh --> 6 paper(s) (ordinal)
R. Bredereck --> 5 paper(s) (4 ordinal, 1 approval)
M. Brill --> 5 paper(s) (2 ordinal, 3 approval)
E. Elkind --> 5 paper(s) (3 ordinal, 2 approval)
R. Meir --> 5 paper(s) (3 ordinal, 3 approval)
R. Niedermeier --> 5 paper(s) (4 ordinal, 1 approval)
J. Rosenschein --> 5 paper(s) (ordinal)
F. Rossi --> 5 paper(s) (ordinal)
H. Aziz --> 4 paper(s) (ordinal)
F. Brandt --> 4 paper(s) (ordinal)
I. Caragiannis --> 4 paper(s) (ordinal)
S. Kraus --> 4 paper(s) (ordinal)
Y. Lewenberg --> 4 paper(s) (ordinal)
S. Nath --> 4 paper(s) (ordinal)
K. Sornat --> 4 paper(s) (2 ordinal, 2 approval)
A. Wilczynski --> 4 paper(s) (ordinal)

Experiments on Elections in COMSOC

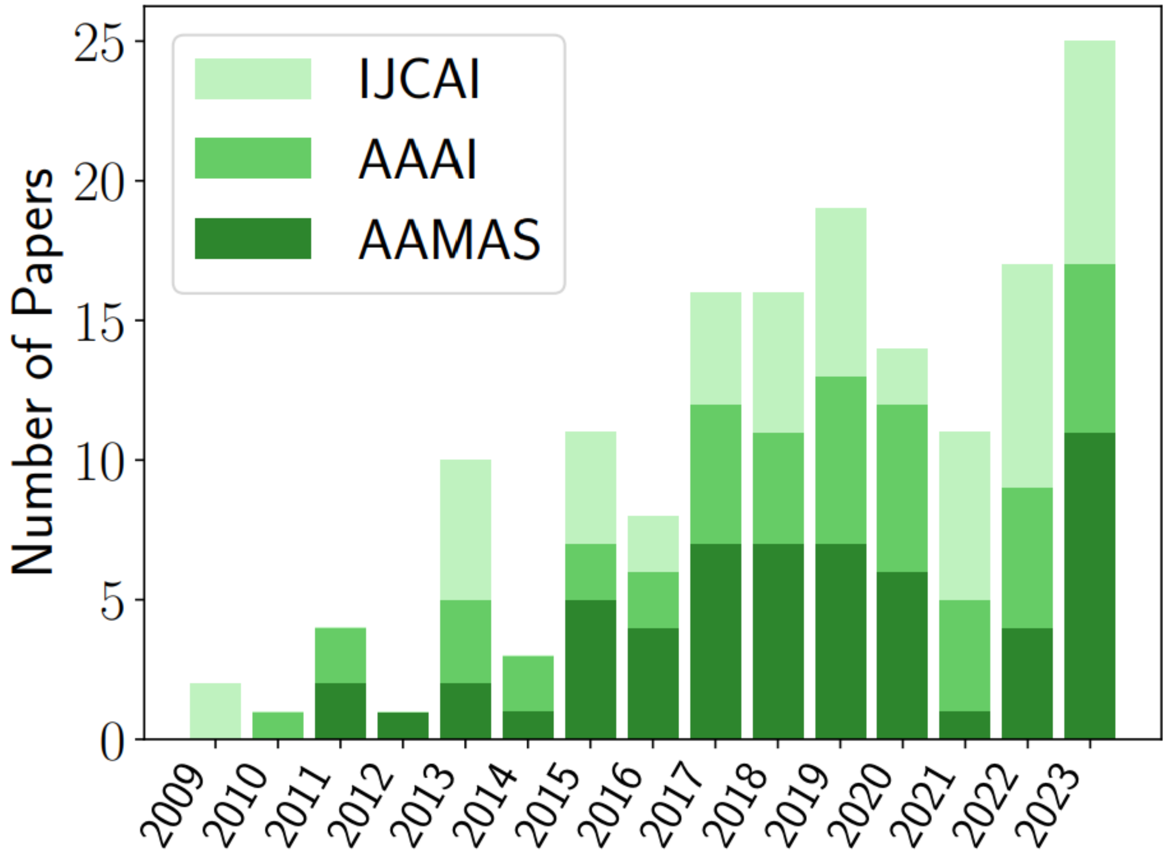


Papers in recent AI conferences



Papers in recent AI conferences that include experiments on elections*

Experiments on Elections in COMSOC



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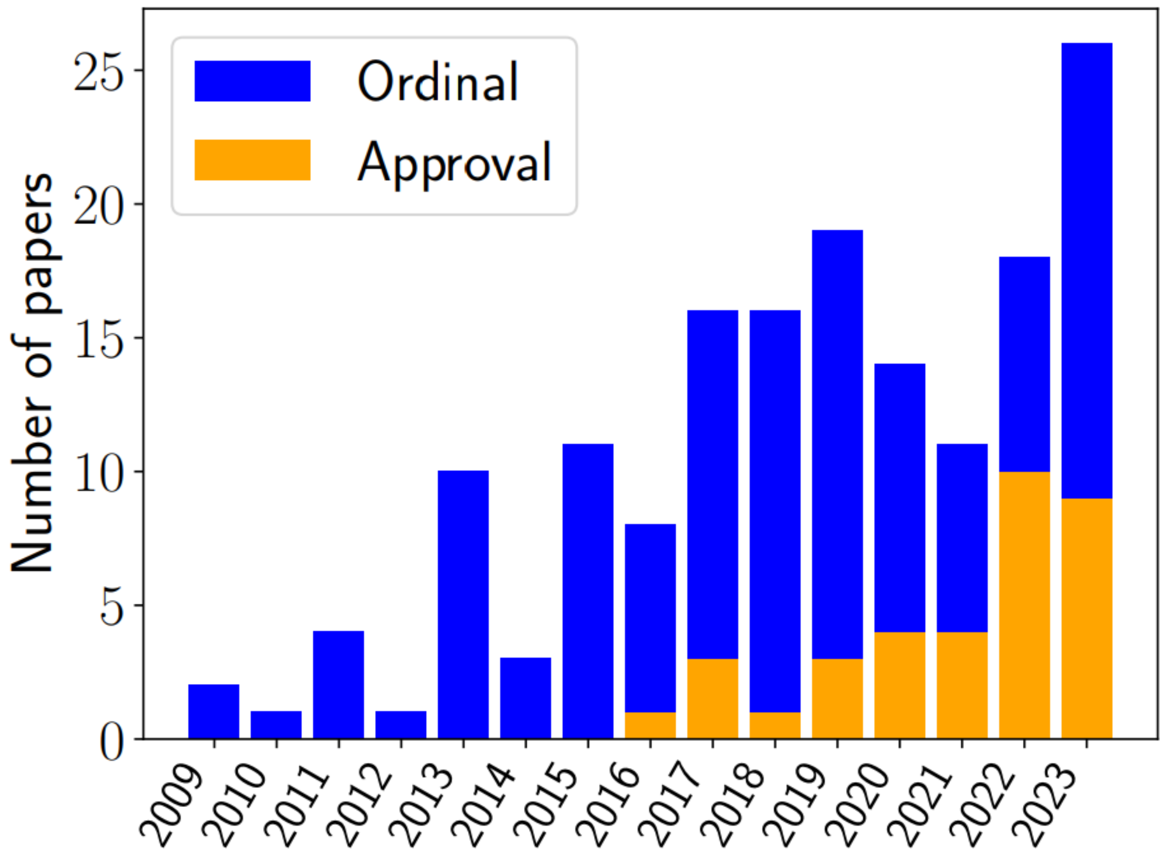
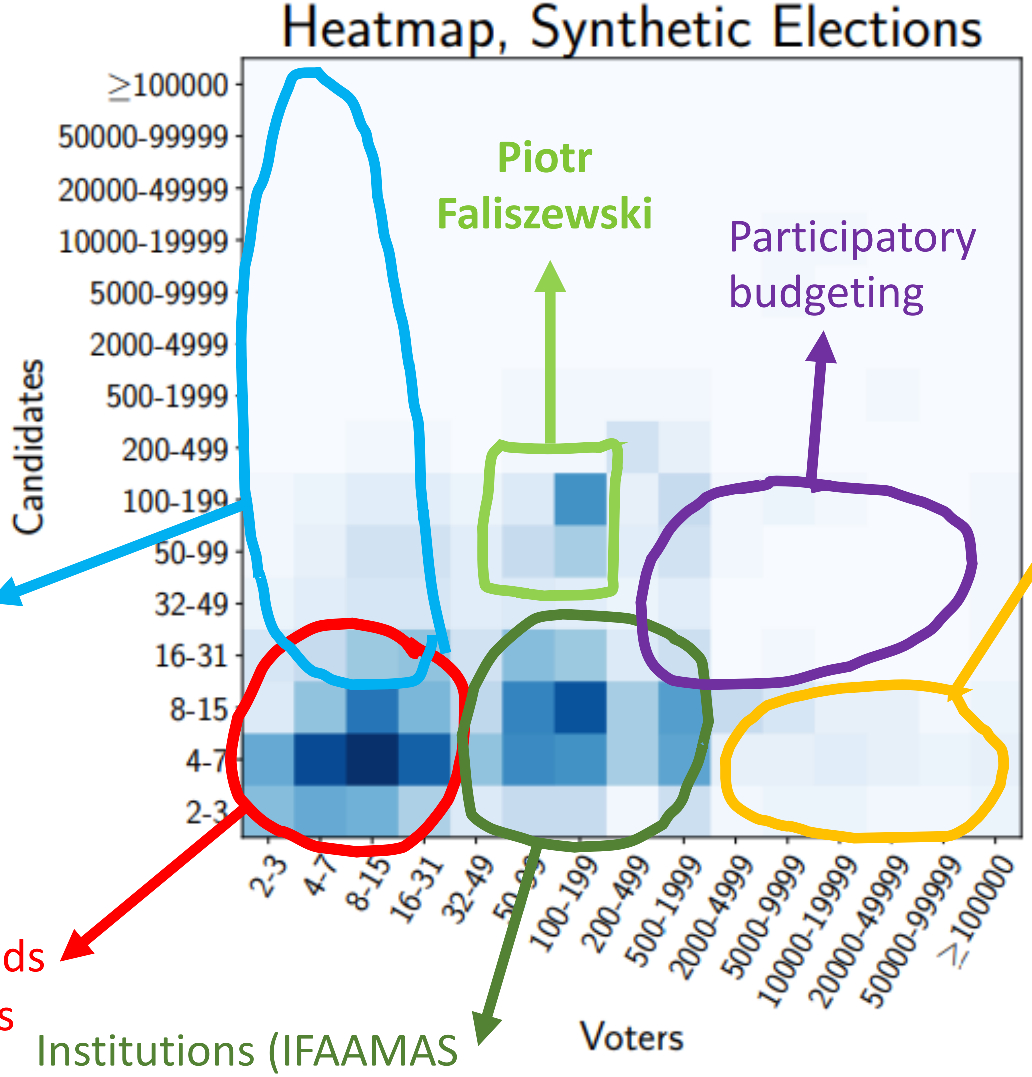


Ordinal preferences versus approval (as covered in the papers)

What Elections to Study?

Structure of the preference orders?

Reasonable numbers of candidates and voters?

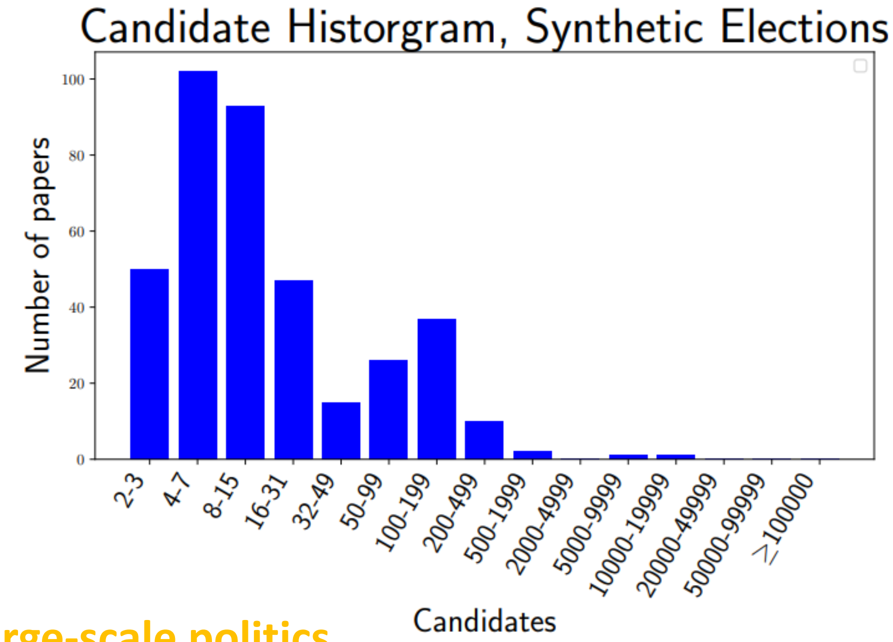


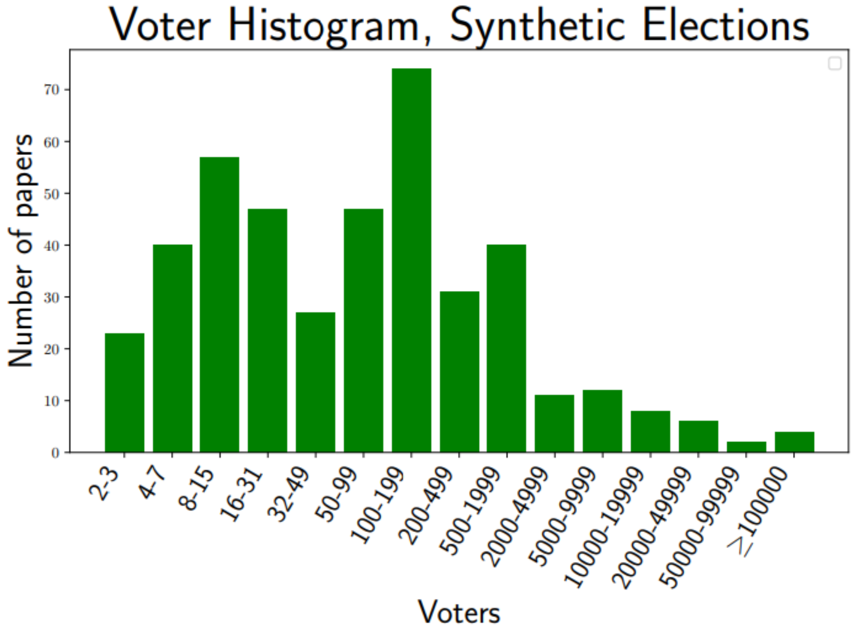
Ground-truth search (sporting events, meta-search engines, recommendation systems, etc.)

Small committees (e.g., hiring), friends voting on frivolous stuff, „usual life"

Institutions (IFAAMAS board elections, choosing electors at universities, etc.)

Large-scale politics





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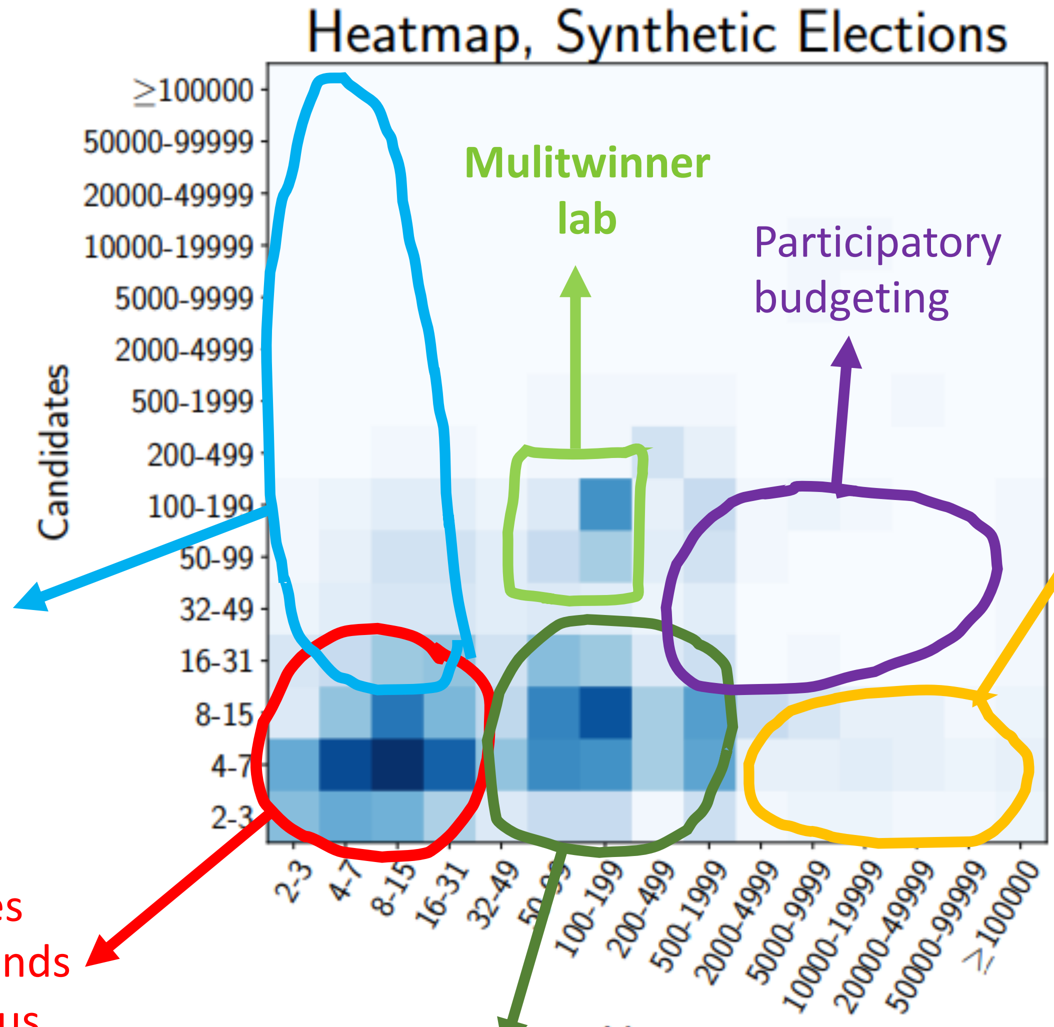

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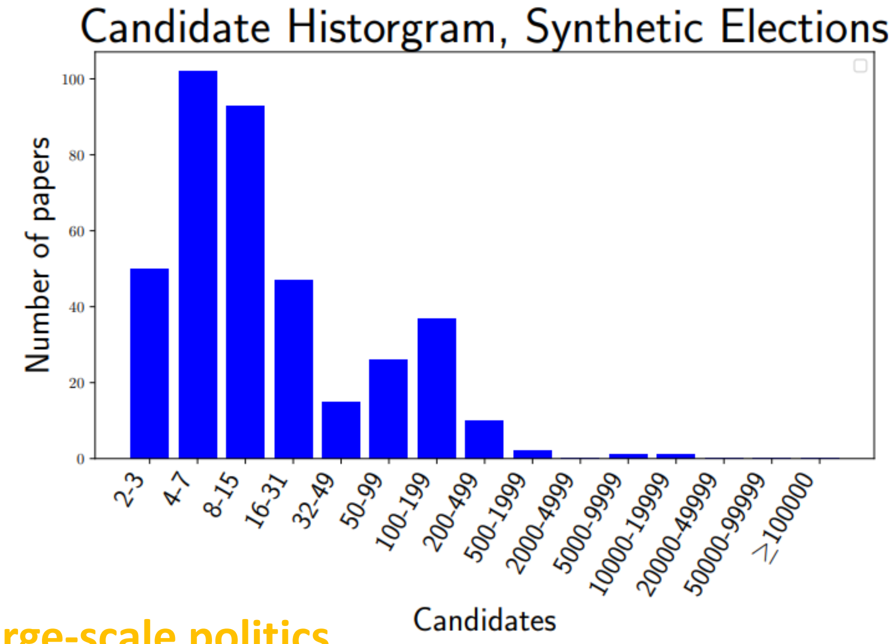

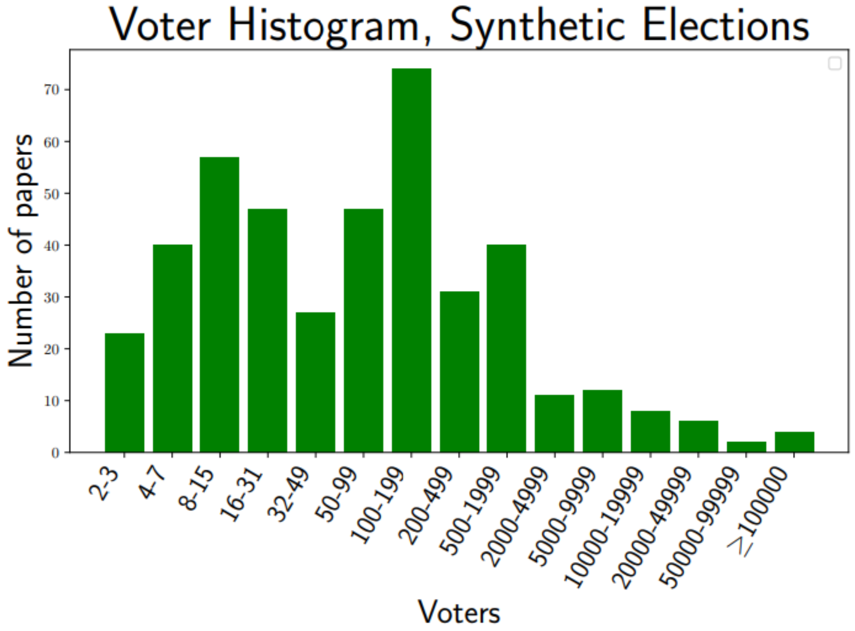

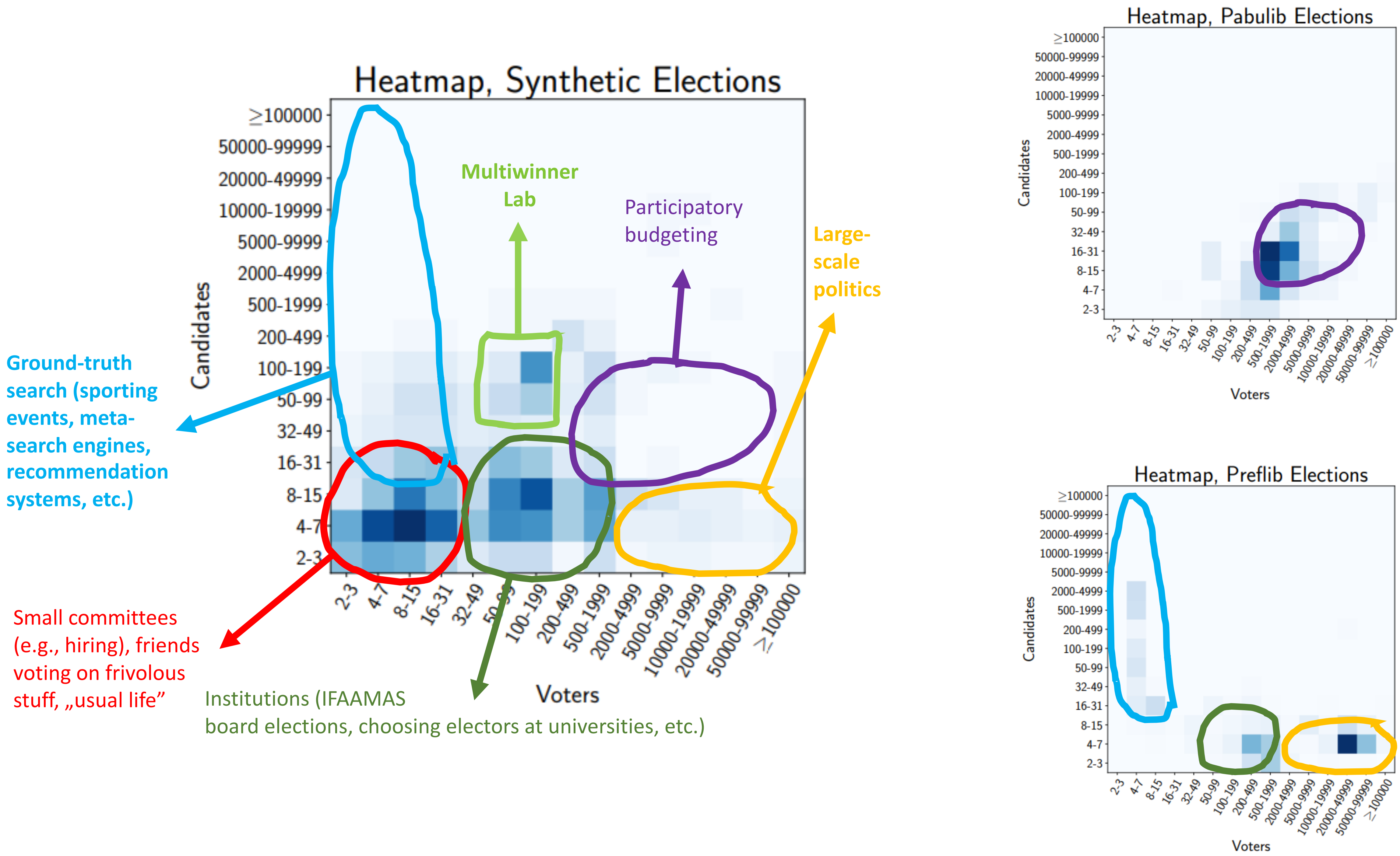

Heatmap, Synthetic Elections
Candidates
Voters
Multiwinner Lab
Participatory budgeting
Large-scale politics
Ground-truth search (sporting events, meta-search engines, recommendation systems, etc.)
Small committees (e.g., hiring), friends voting on frivolous stuff, „usual life”
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Heatmap, Pabulib Elections
Candidates
Voters
Heatmap, Preflib Elections
Candidates
Voters

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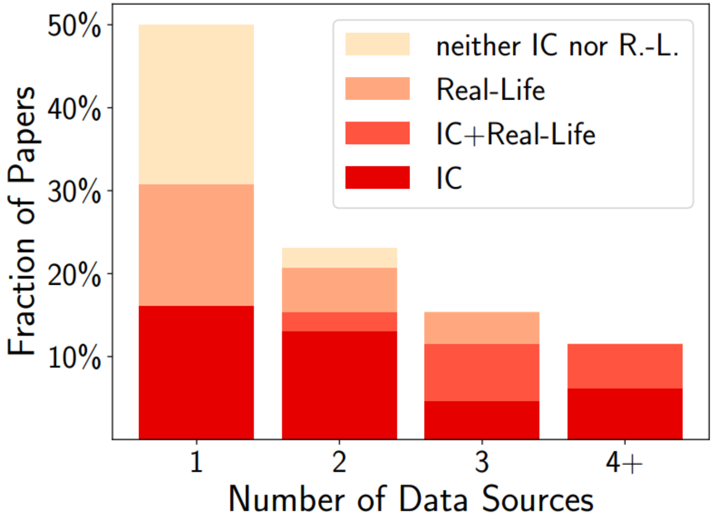
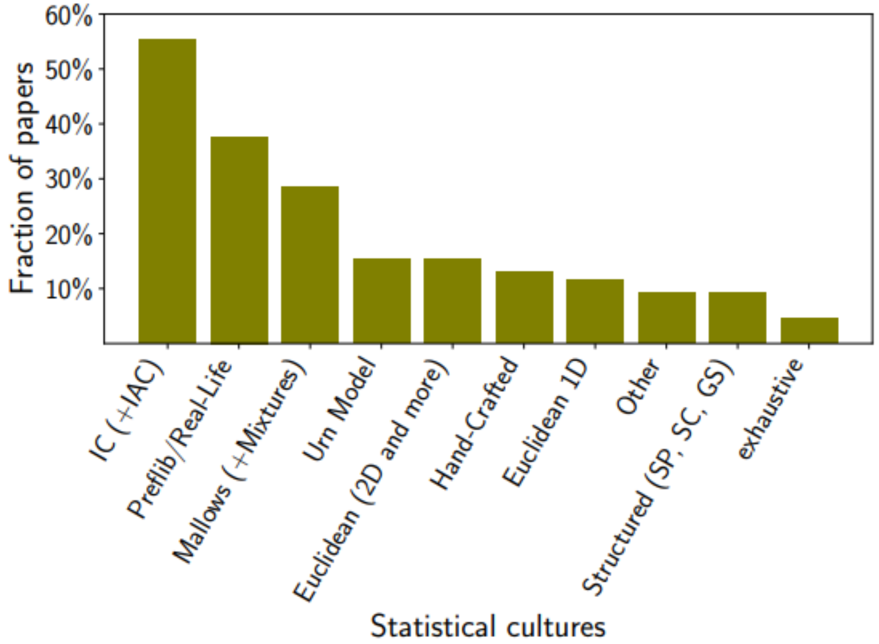
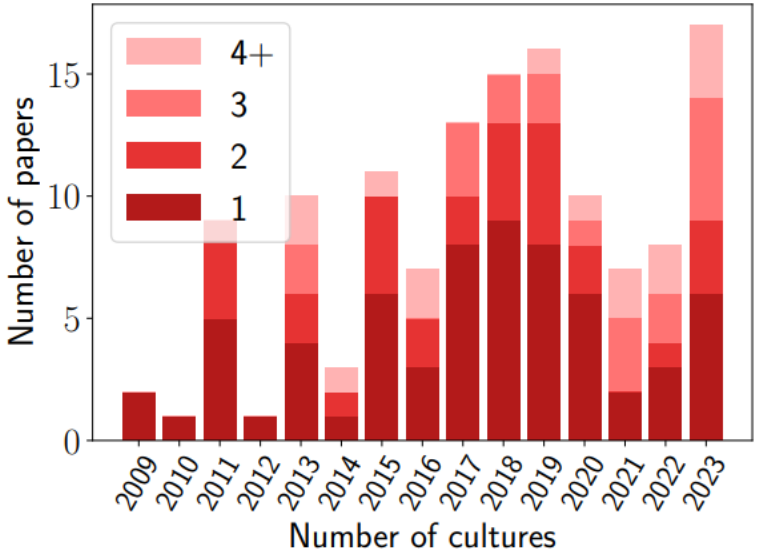
Reasonable numbers of candidates and voters?

Structure of the preference orders?

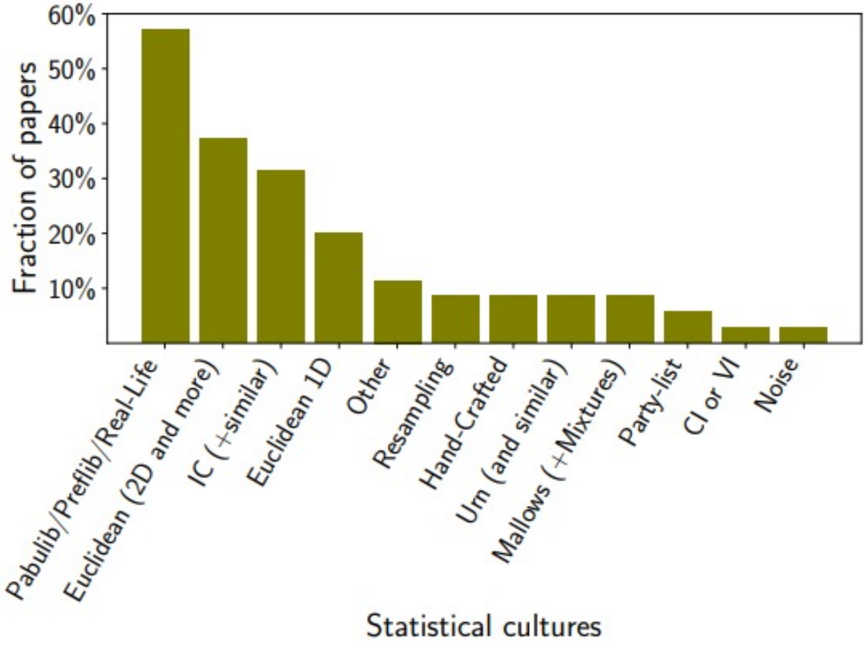


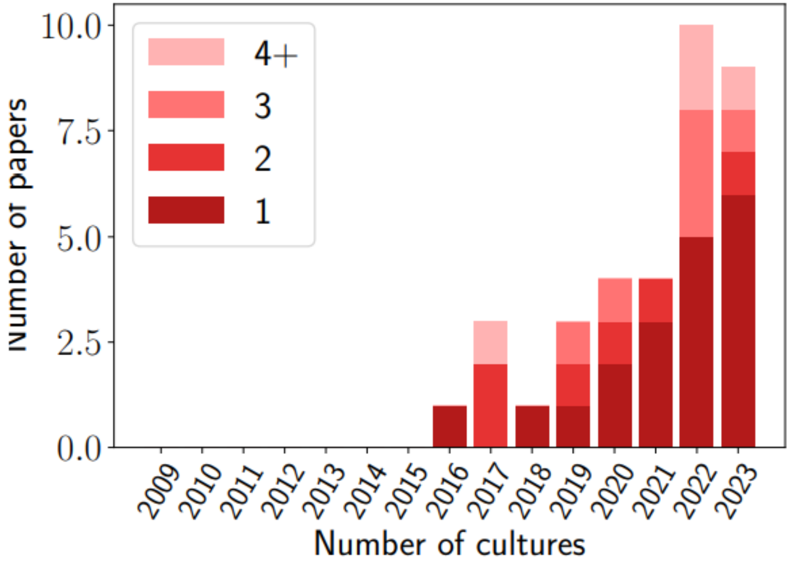




Ordinal

Approval

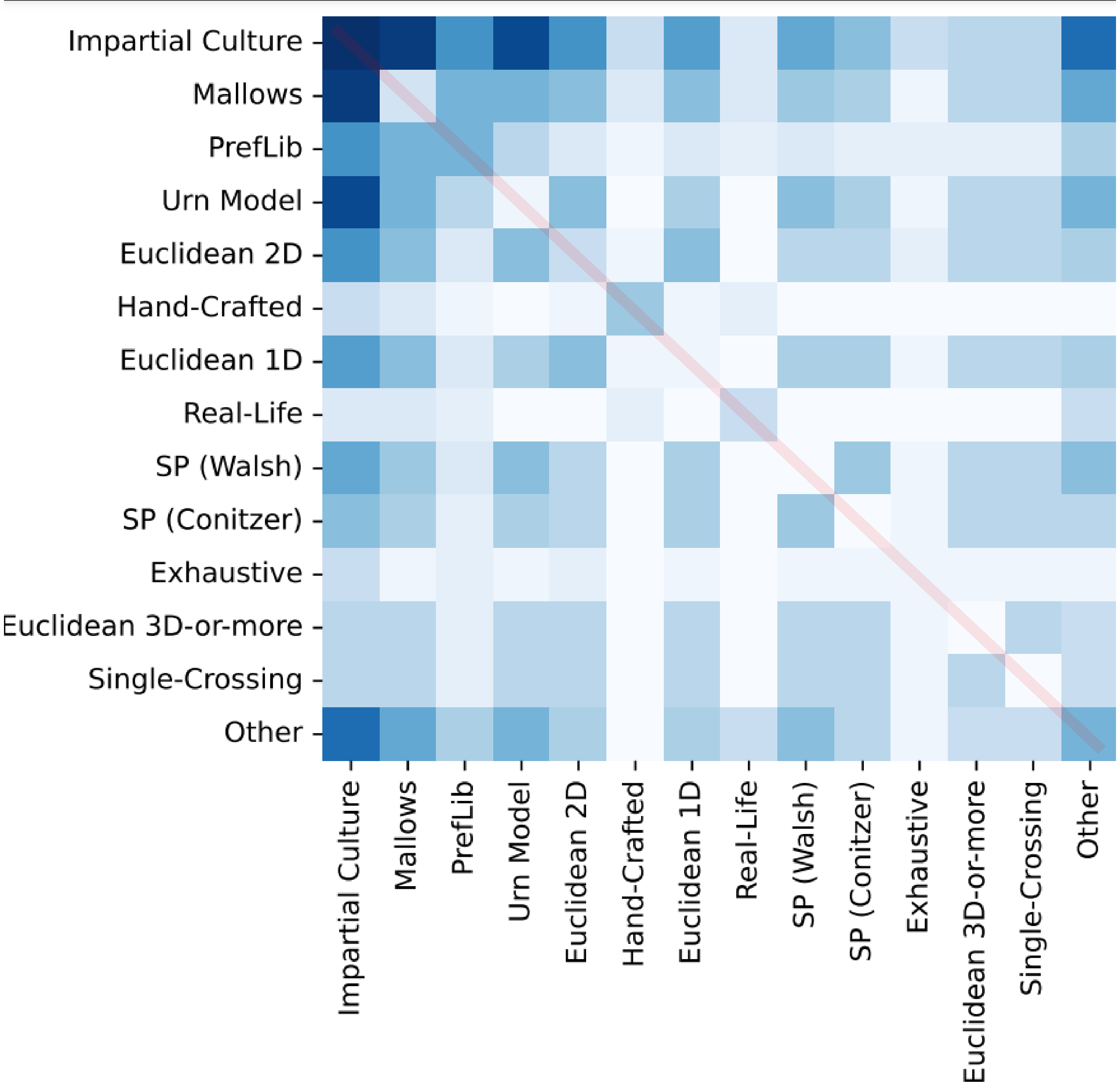


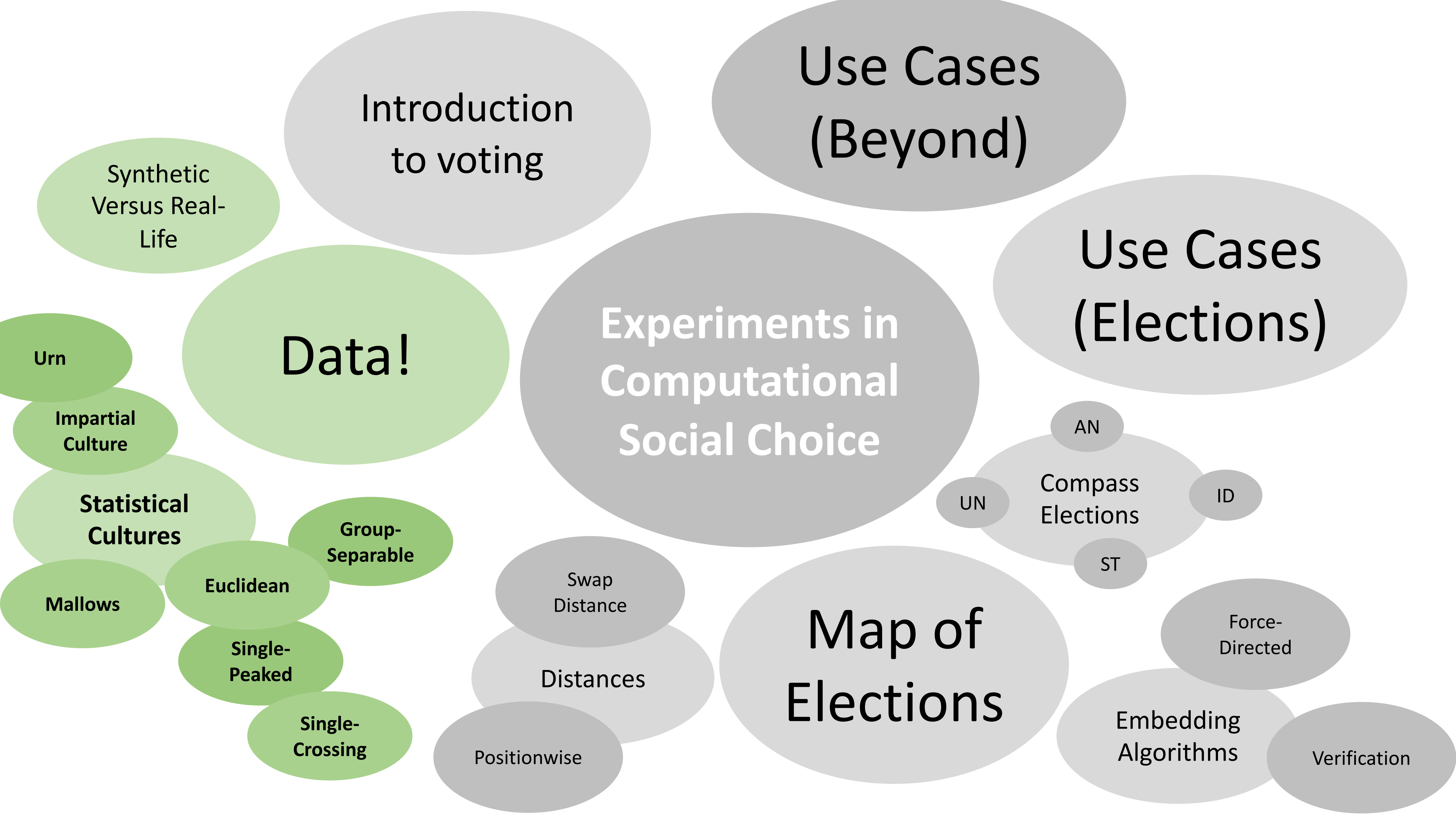


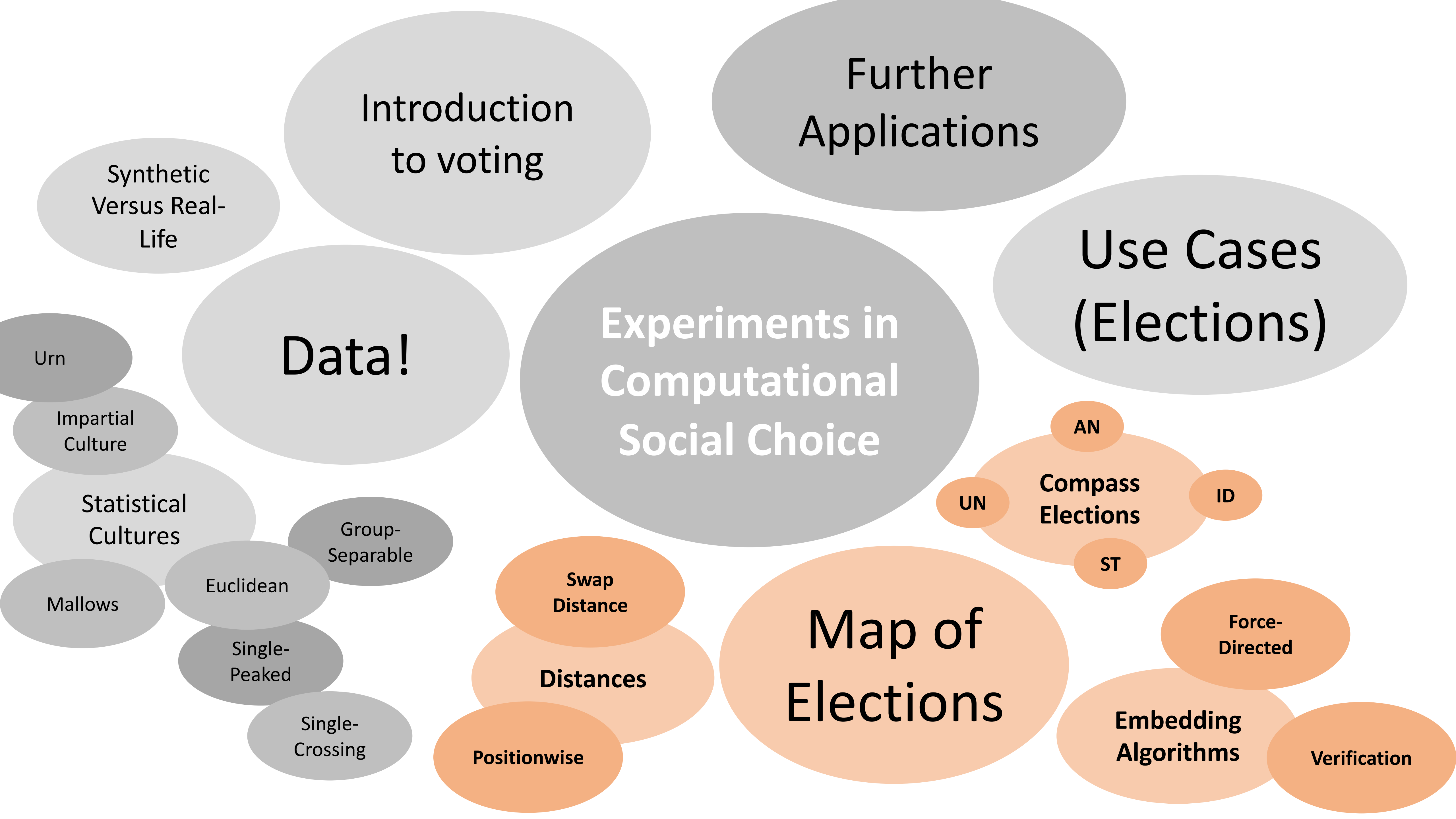
Co-Occurence of Cultures

Matrix entries – How frequently two given cultures happen together

Diagonal – How frequently a given culture is used alone




Introduction to voting
Use Cases (Beyond)
Synthetic Versus Real-Life
Use Cases (Elections)
Data!
Experiments in Computational Social Choice
Urn
Impartial Culture
AN
Compass Elections
UN
ID
ST
Statistical Cultures
Group-Separable
Euclidean
Mallows
Swap Distance
Distances
Map of Elections
Force-Directed
Single-Peaked
Single-Crossing
Embedding Algorithms
Positionwise
Verification


Introduction to voting
Further Applications
Synthetic Versus Real-Life
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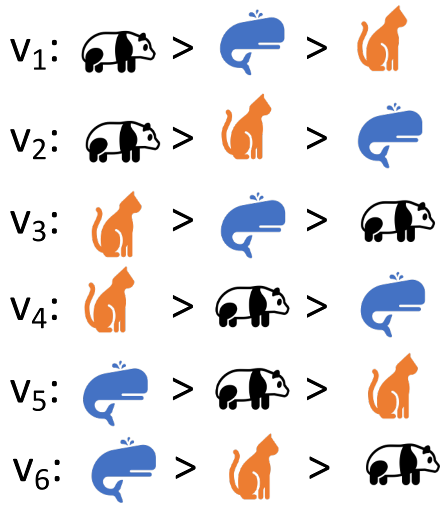
Map of Elections
Single-Peaked
Force-Directed
Embedding Algorithms
Single-Crossing
Positionwise
Verification

30 minutes

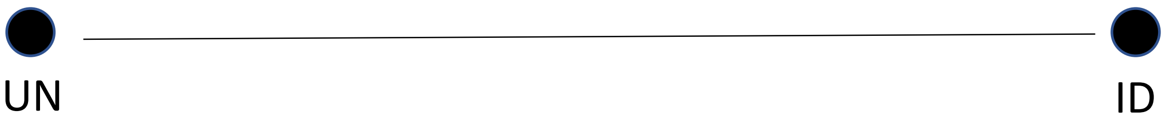
Map of Elections

How different?

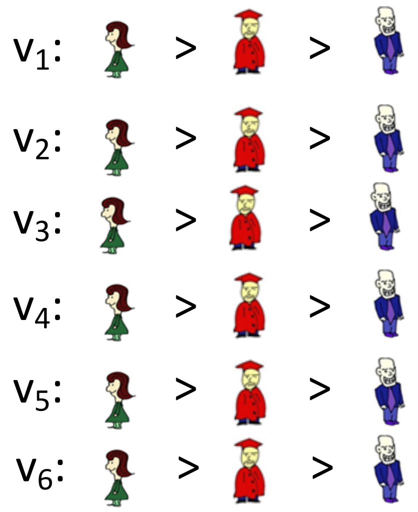


all possible preference orders

uniformity



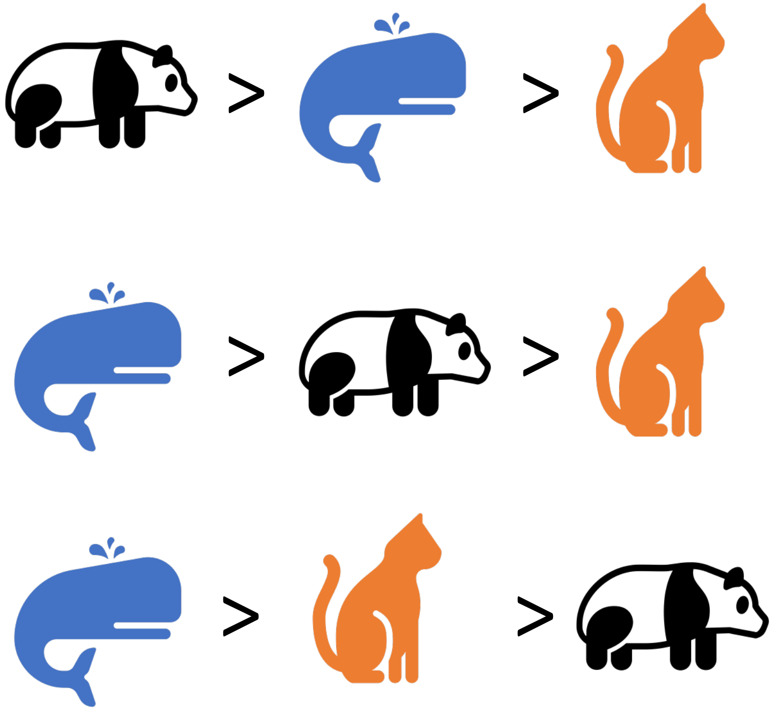
Count the number of swaps that make the elections isomorphic (i.e., identical up to renaming the candidates and reordering the voters)

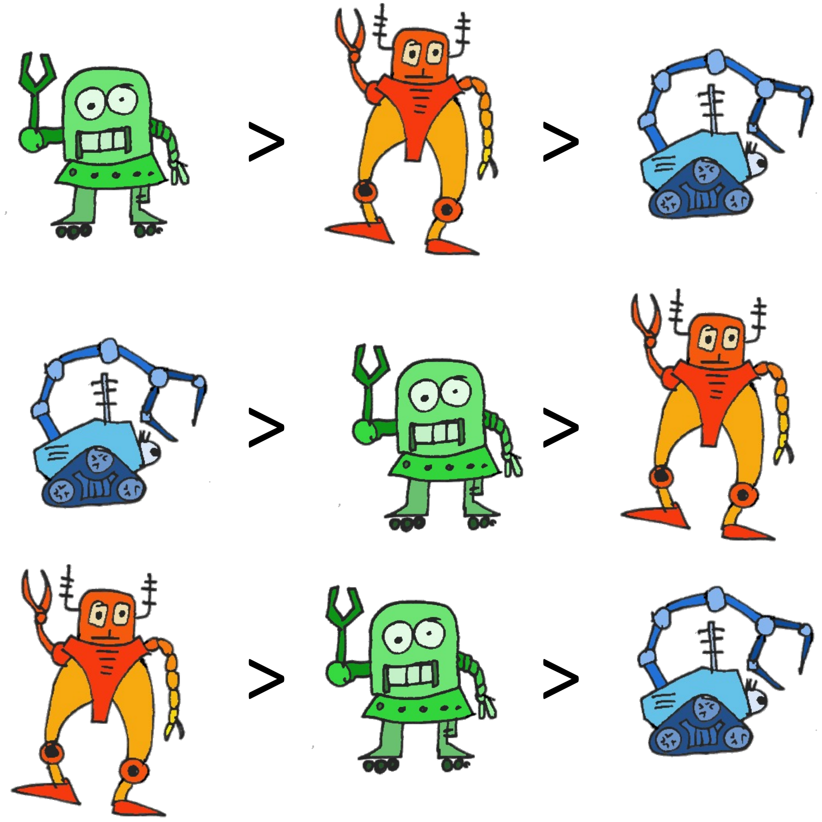


Identical preference orders

identity

Isomorphic Swap Distance

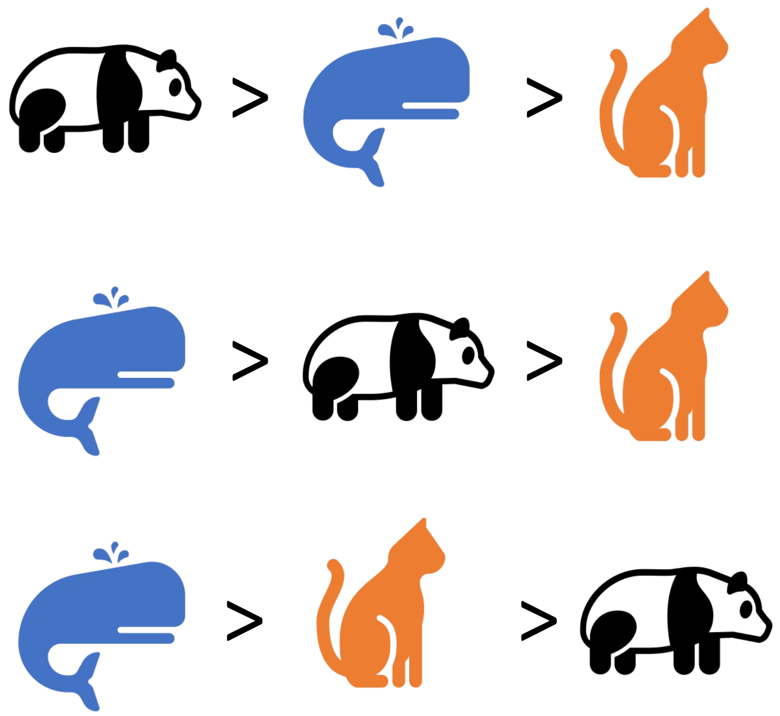


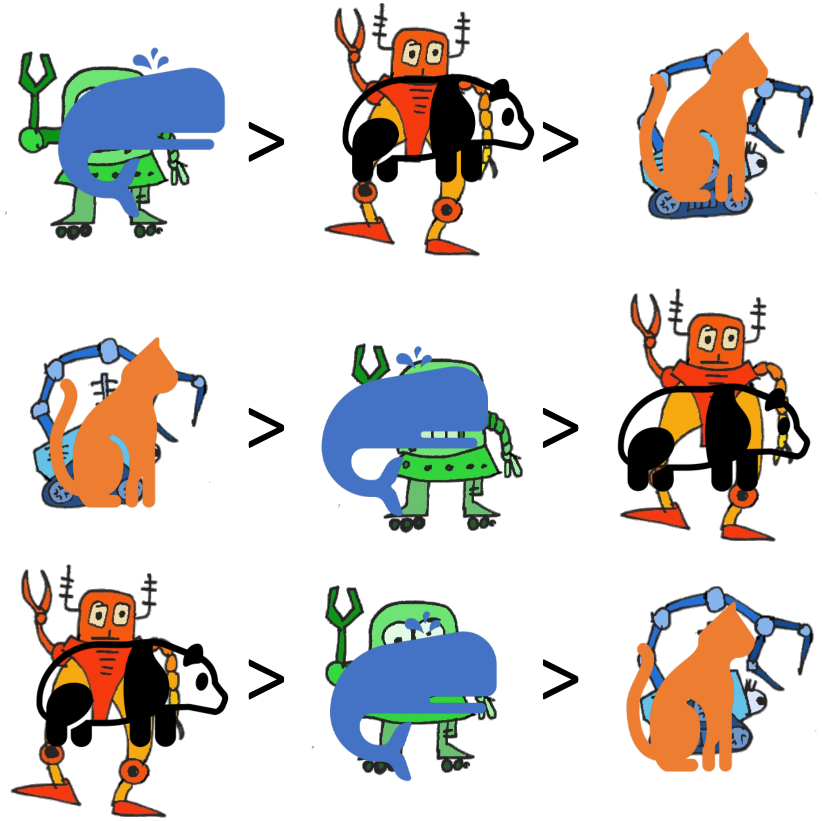


1. Match the candidates
2. Match the voters
3. Count the swaps

P. Faliszewski, P. Skowron, A. Slinko, S. Szufa, N. Talmon: How Similar Are Two Elections? AAAI 2019

Isomorphic Swap Distance





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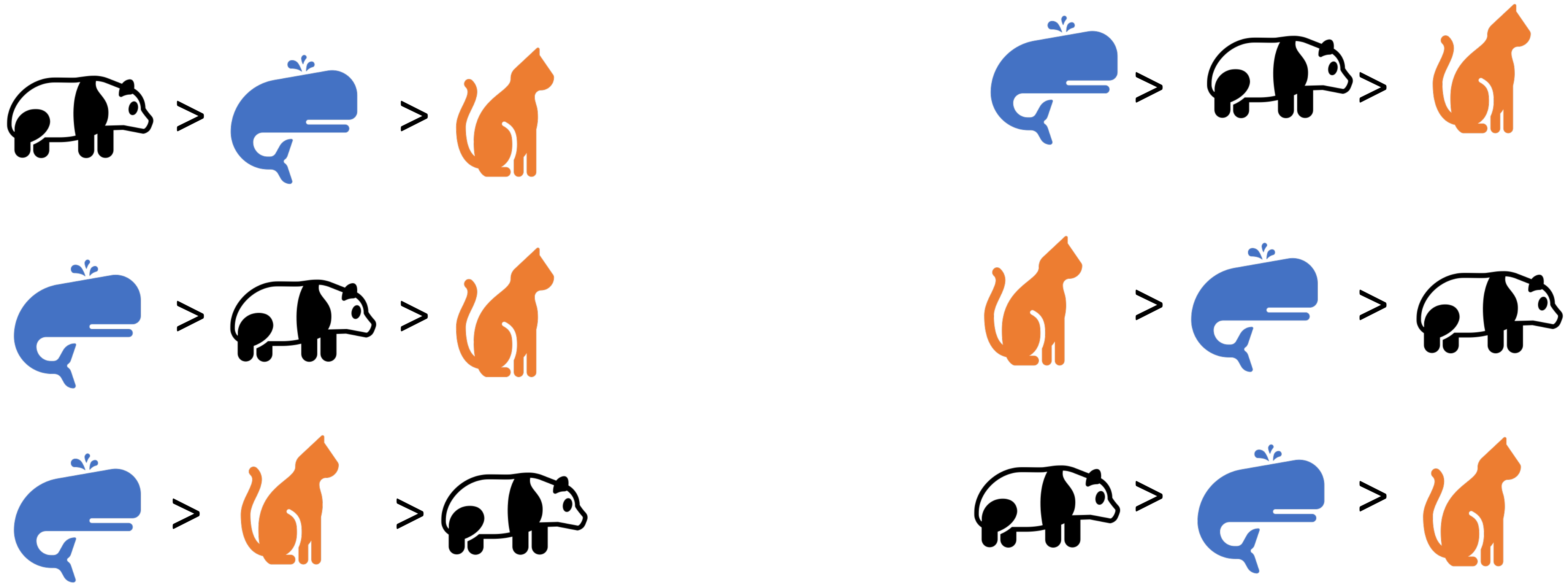

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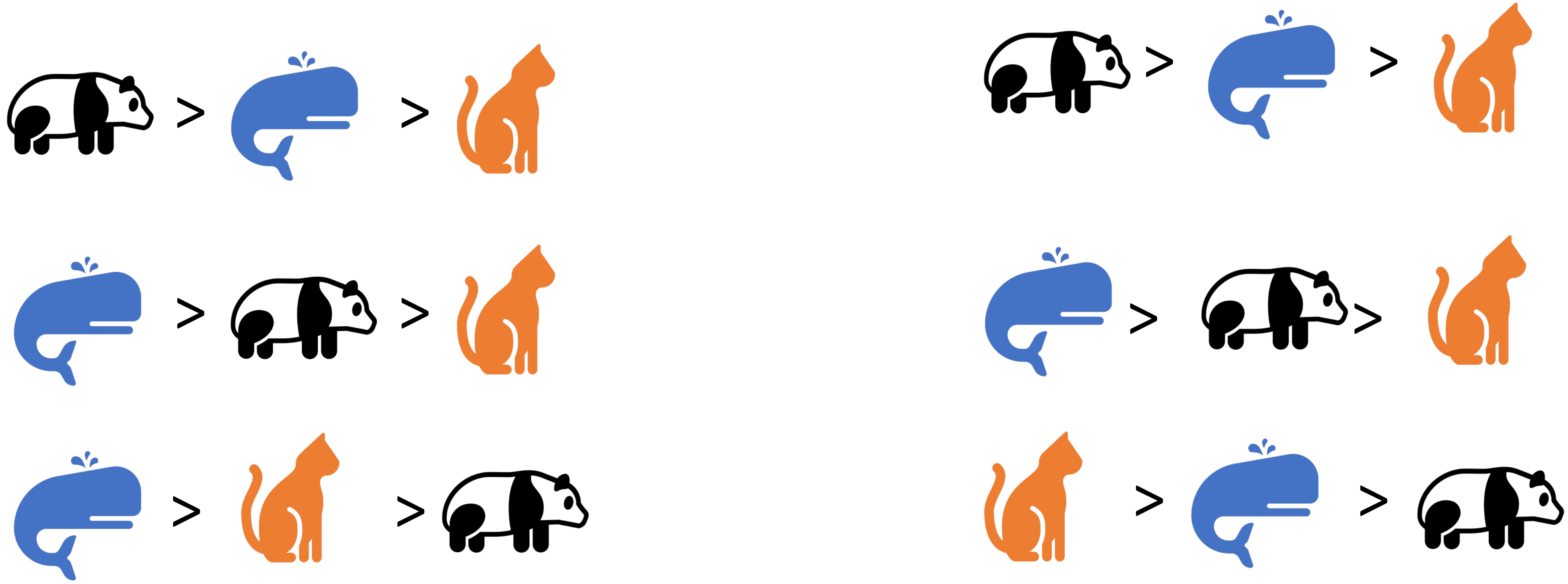

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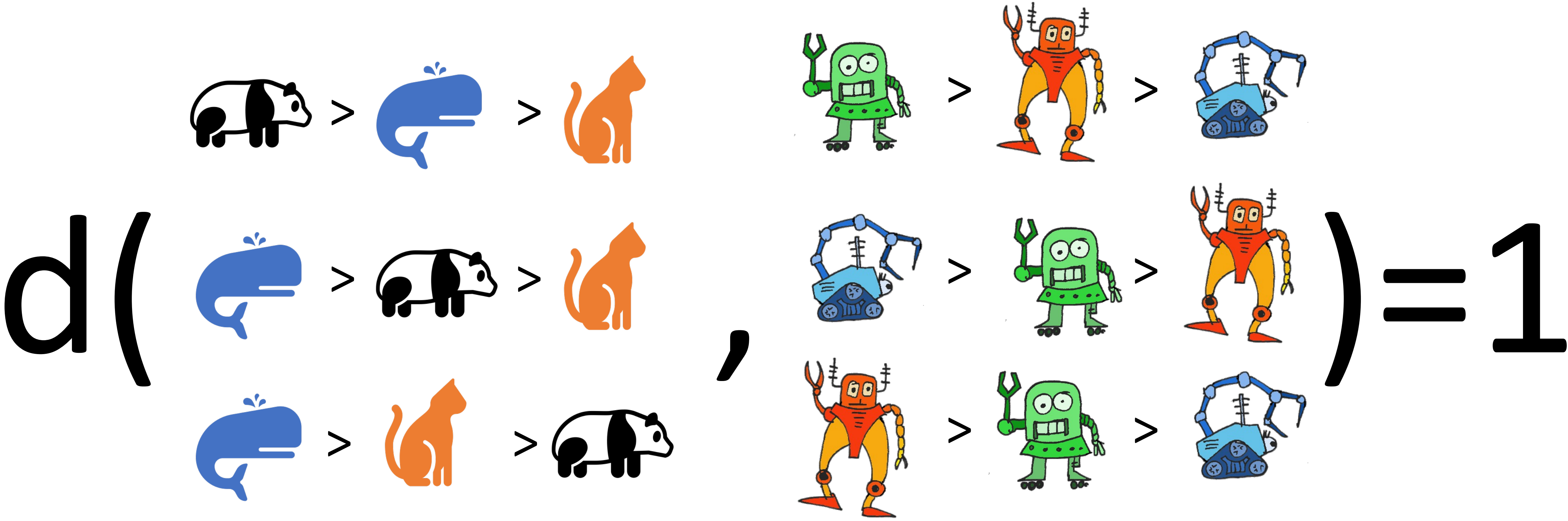

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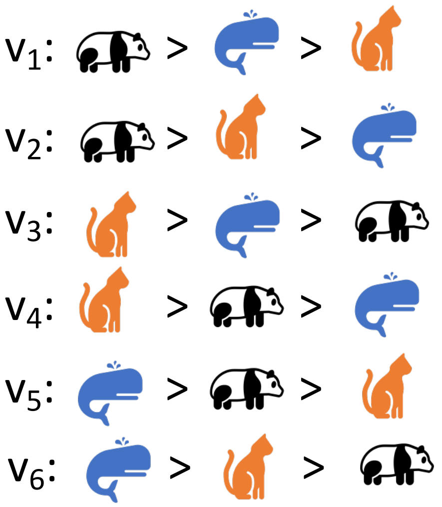
P. Faliszewski, P. Skowron, A. Slinko, S. Szufa, N. Talmon: How Similar Are Two Elections? AAAI 2019

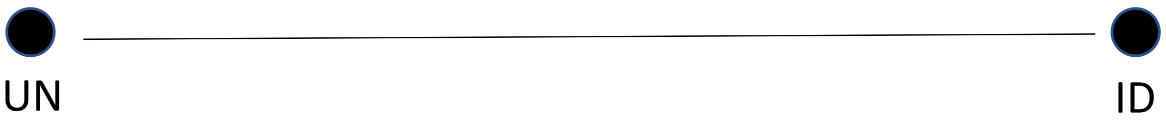
Thm. In an election with m candidates and $n = t*m!$ votes, every two elections are at distance at most $\frac{1}{4} n(m^2-m)$.



all possible preference orders

uniformity

$\frac{1}{4} n(m^2-m)$



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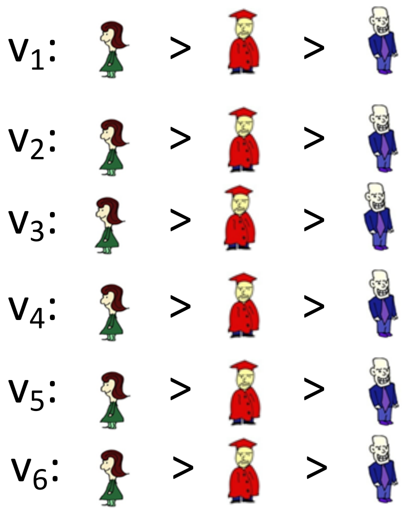
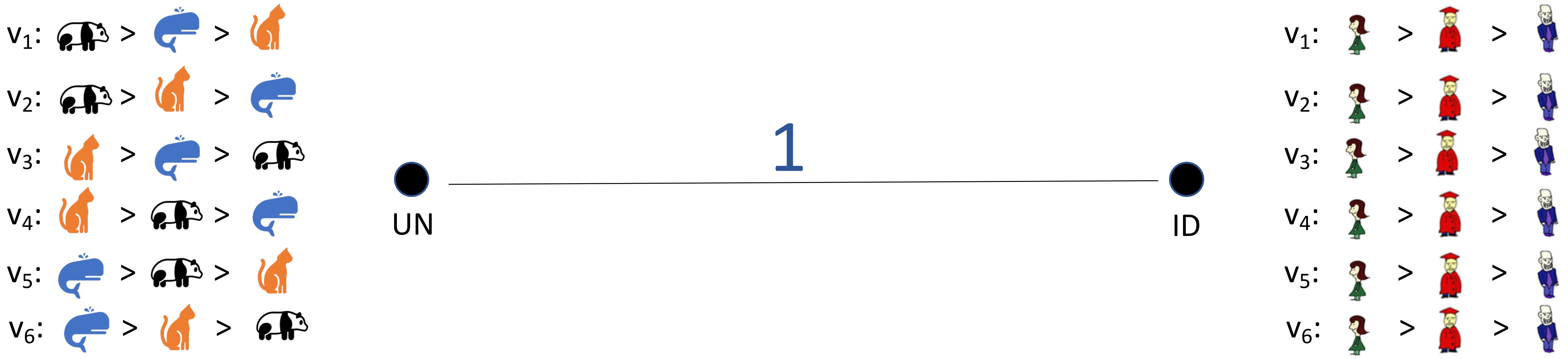


Identical preference orders

identity

N. Boehmer, P. Faliszewski, R. Niedermeier, S. Szufa, T. Wąs, Understanding Distance Measures Among Elections, IJCAI 2022

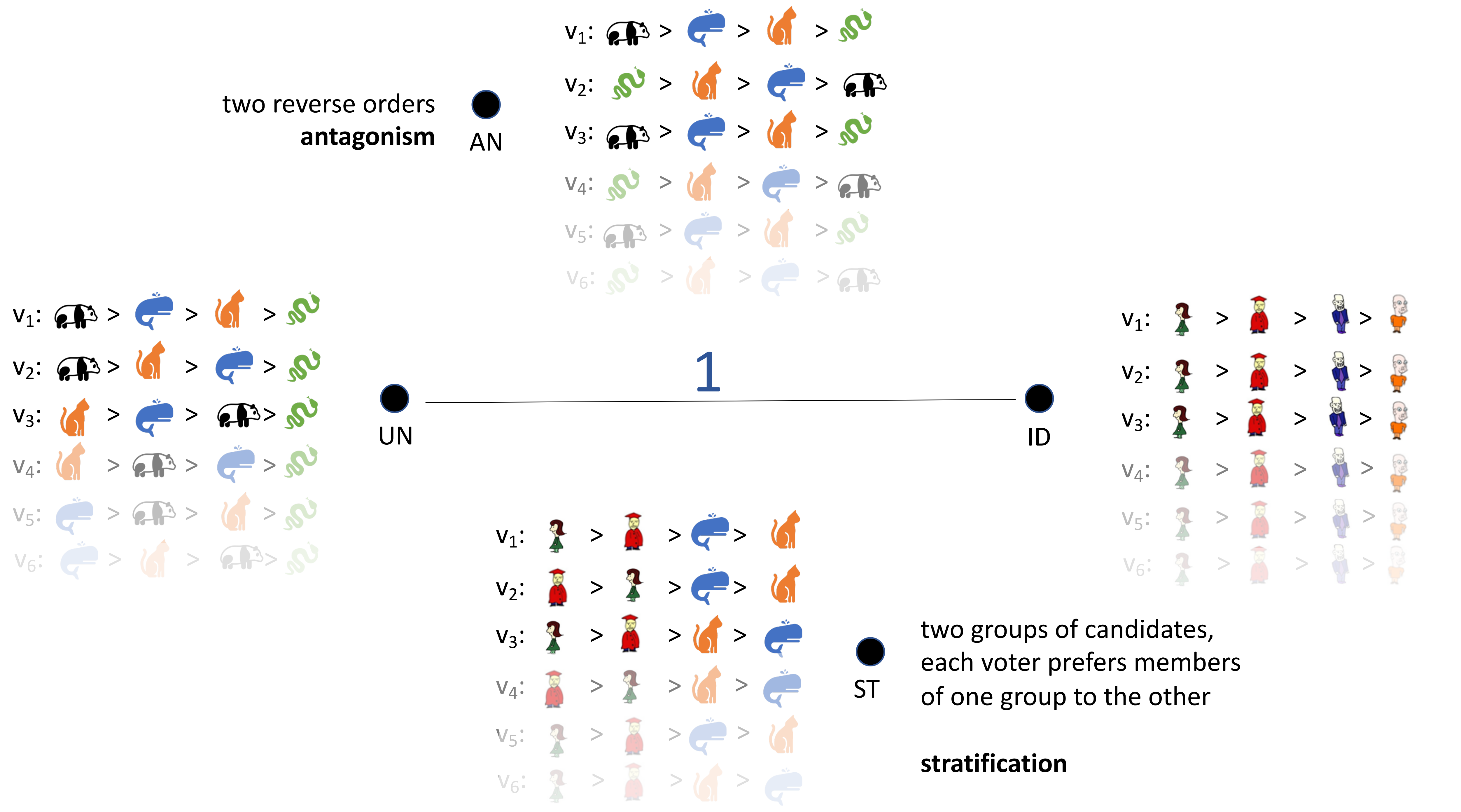


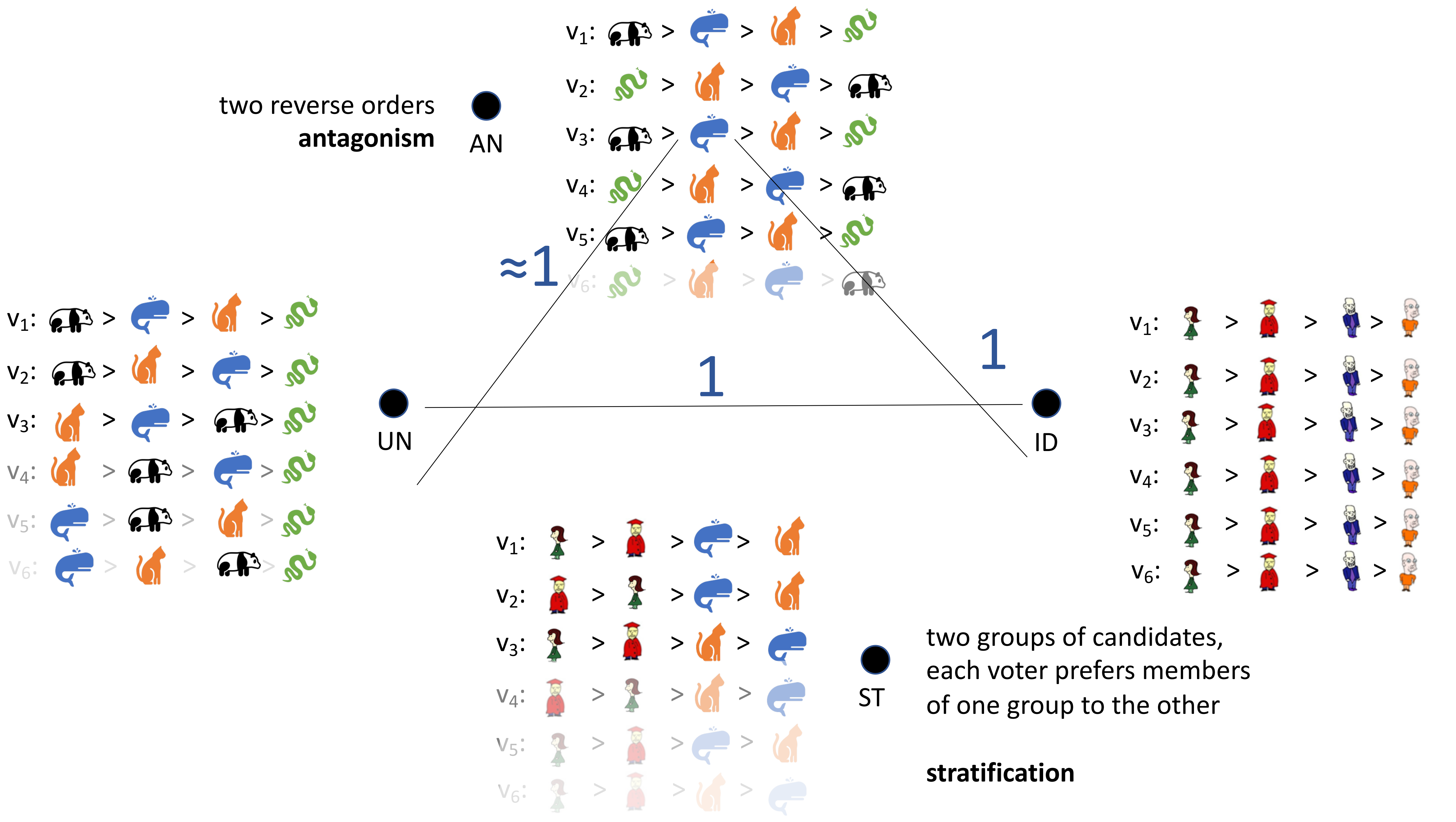
all possible preference orders

Identical preference orders

uniformity

identity

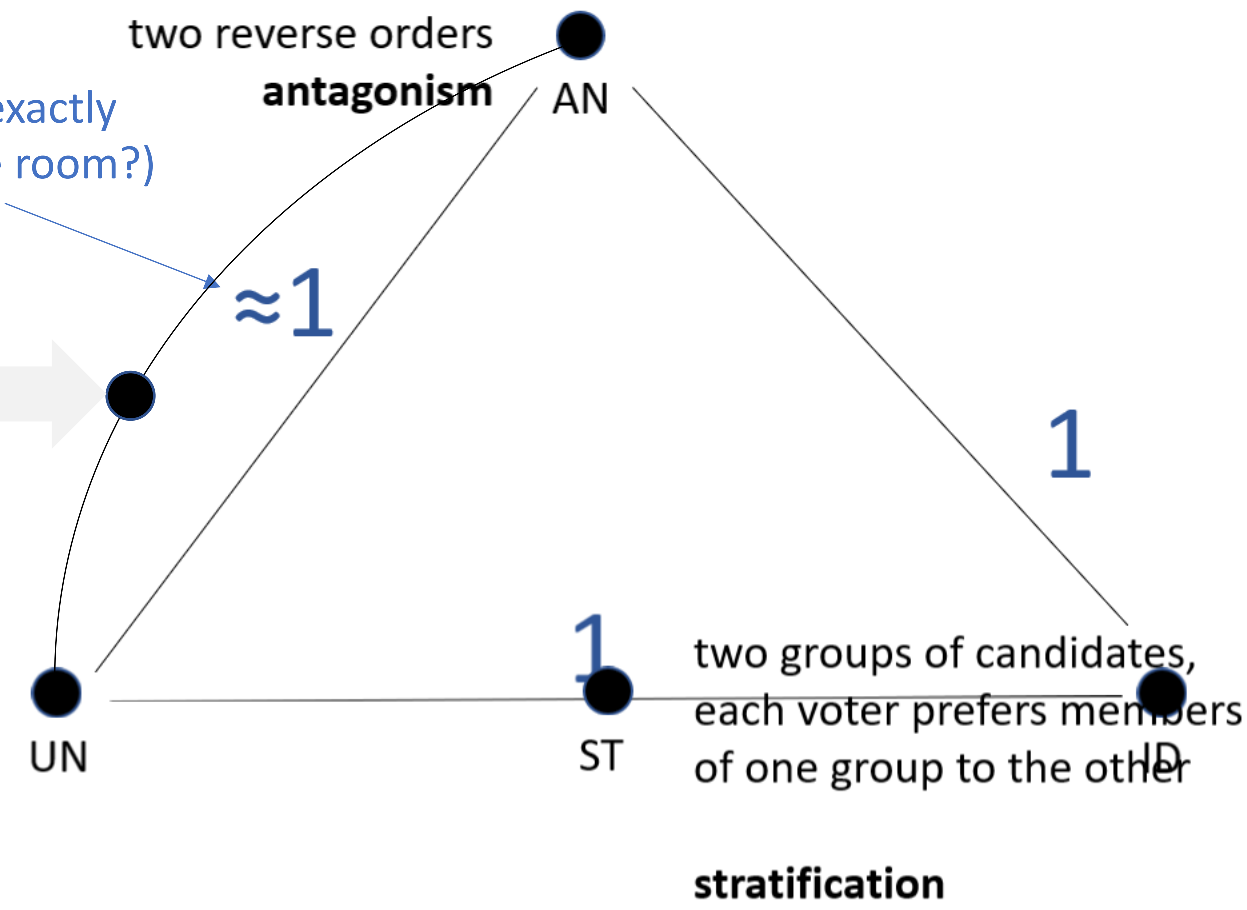

two reverse orders
antagonism
AN
UN
1
ID
ST
two groups of candidates, each voter prefers members of one group to the other
stratification



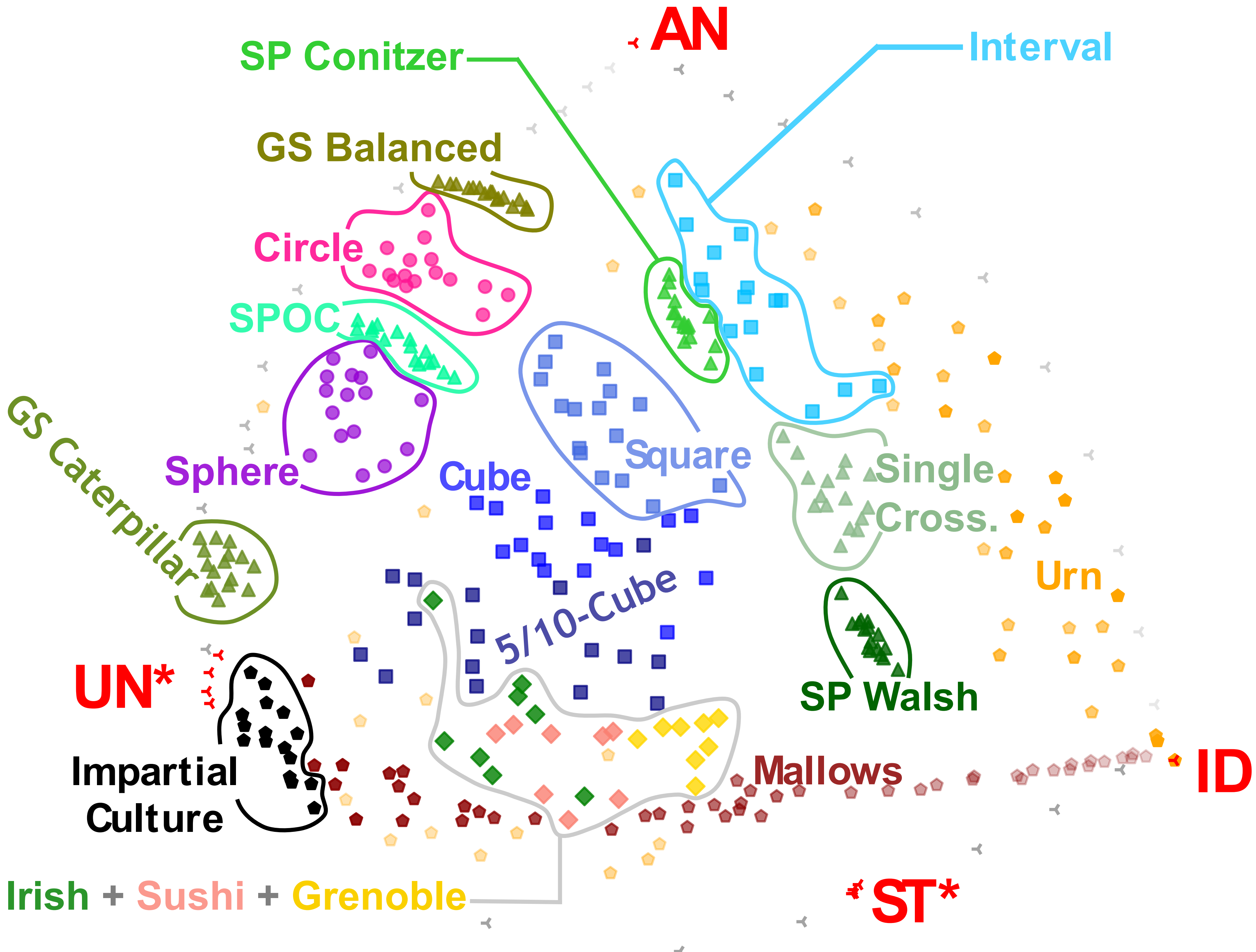
two reverse orders
antagonism
AN
≈1
1
1
UN
ID
ST
two groups of candidates, each voter prefers members of one group to the other
stratification

Somehow difficult to compute exactly
(is there a mathematician in the room?)

Thm. An election is at (normalized) distance 1 from ID if and only if for all pairs of candidates *a* and *b*, half of the voters prefer *a* to *b*, and half of the voters prefer *b* to *a*.



v_6: > > >



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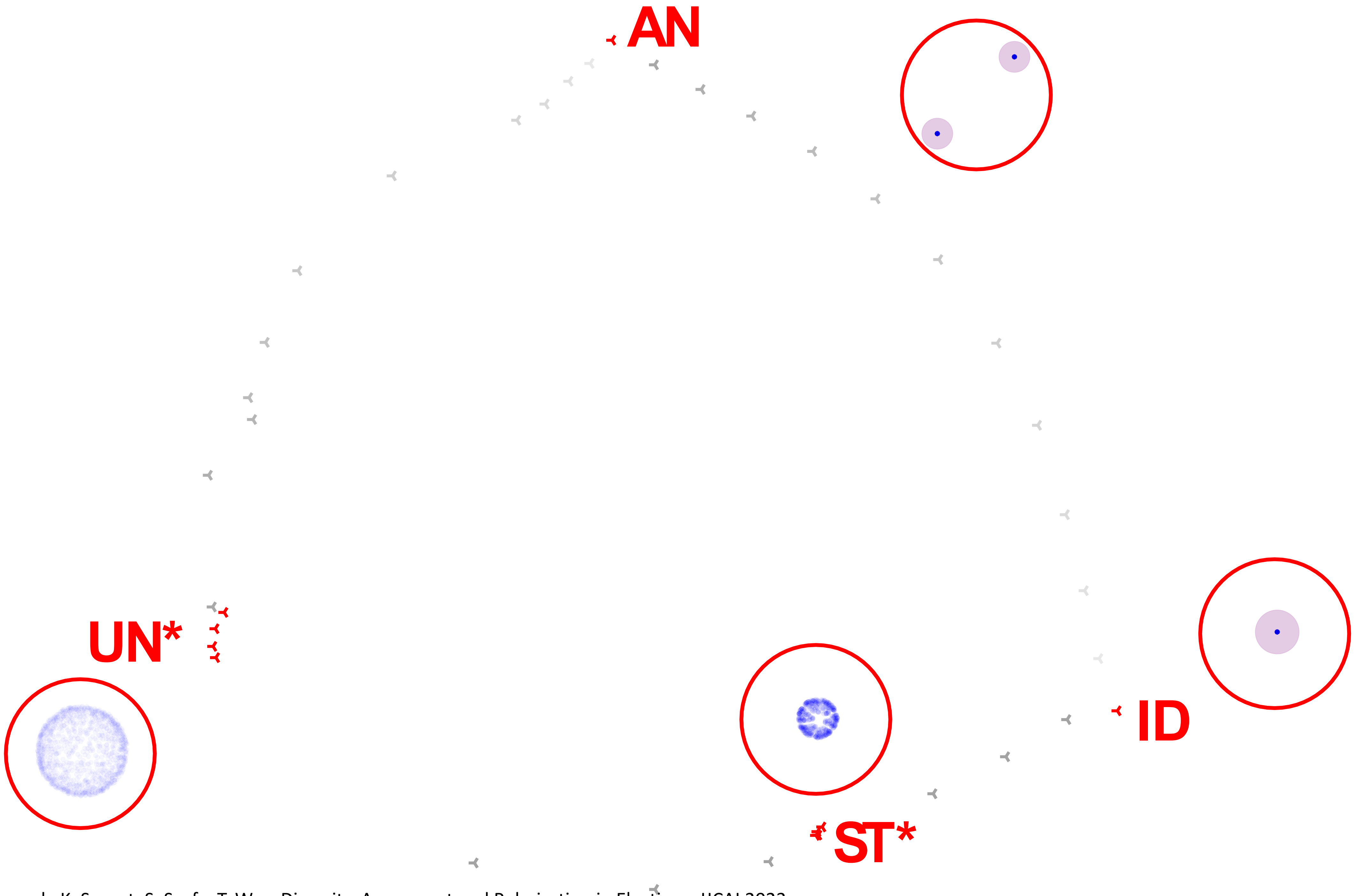

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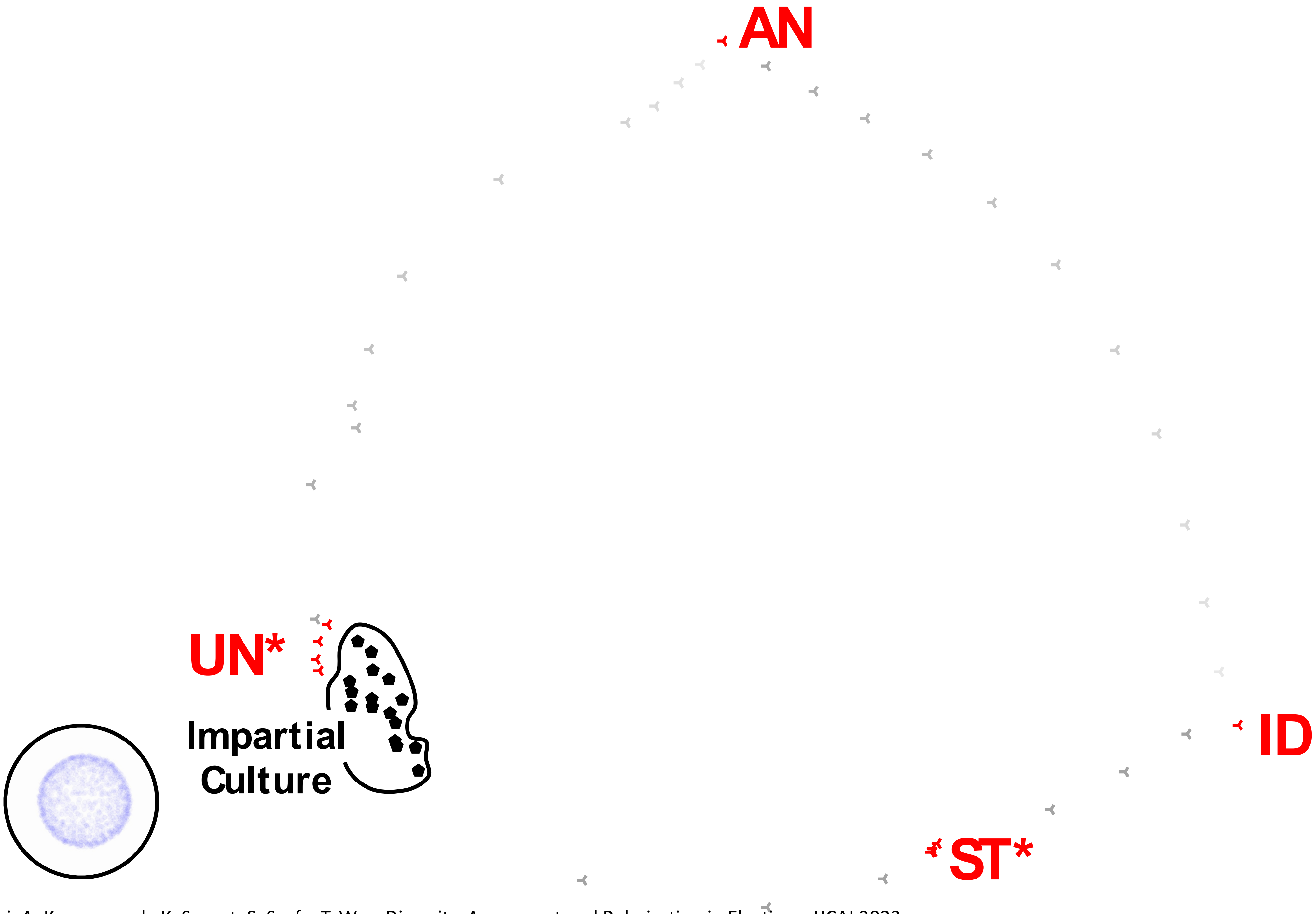

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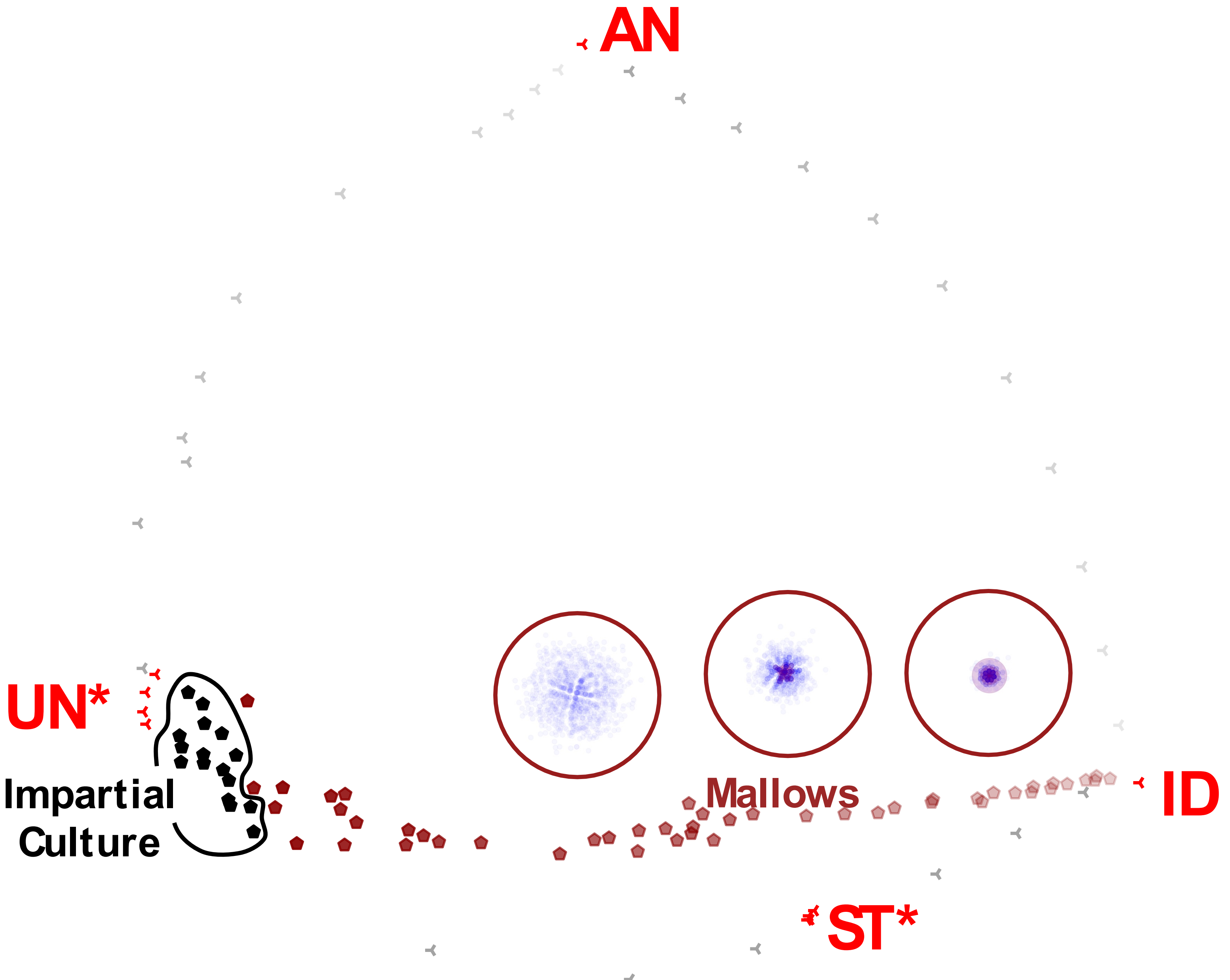

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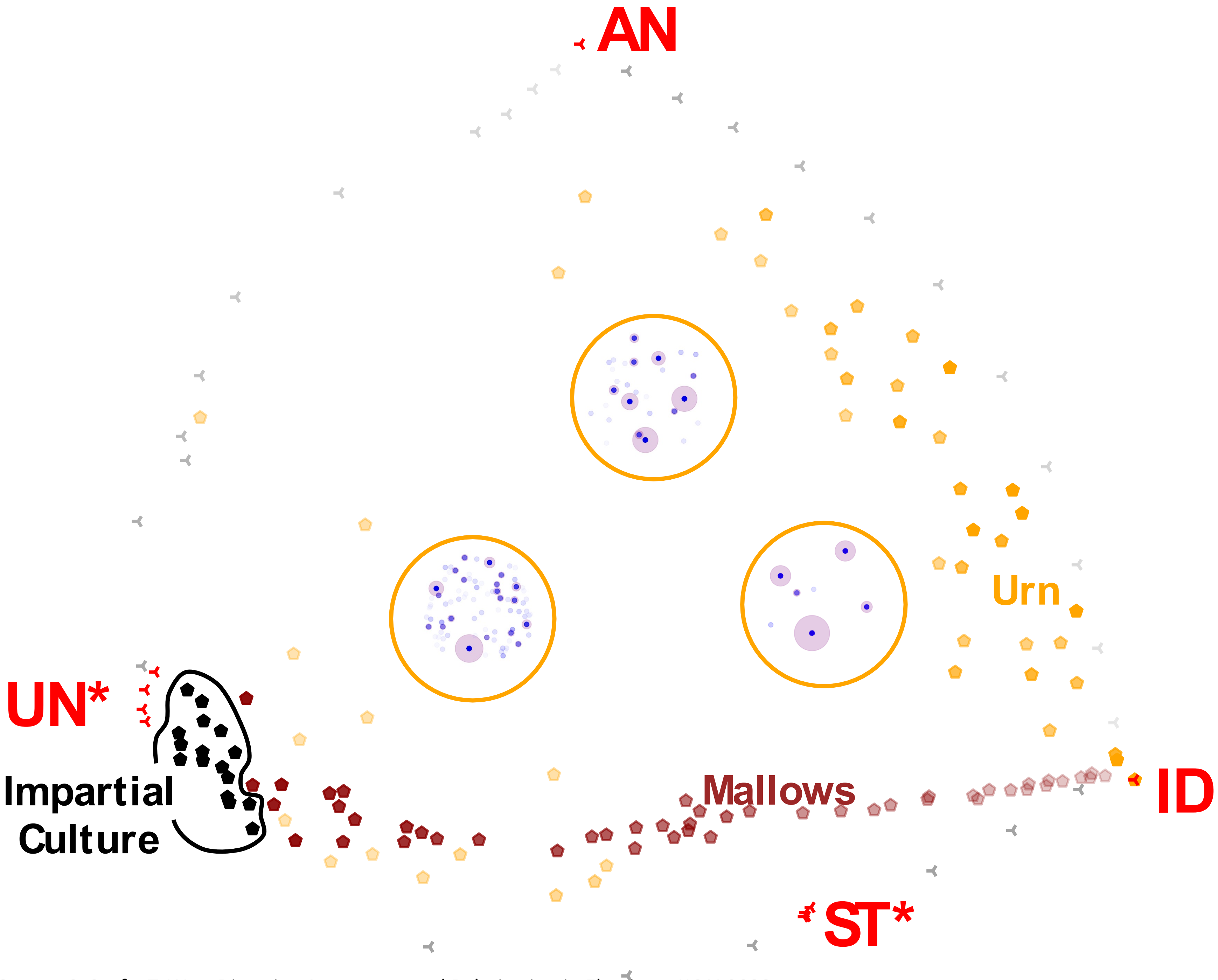

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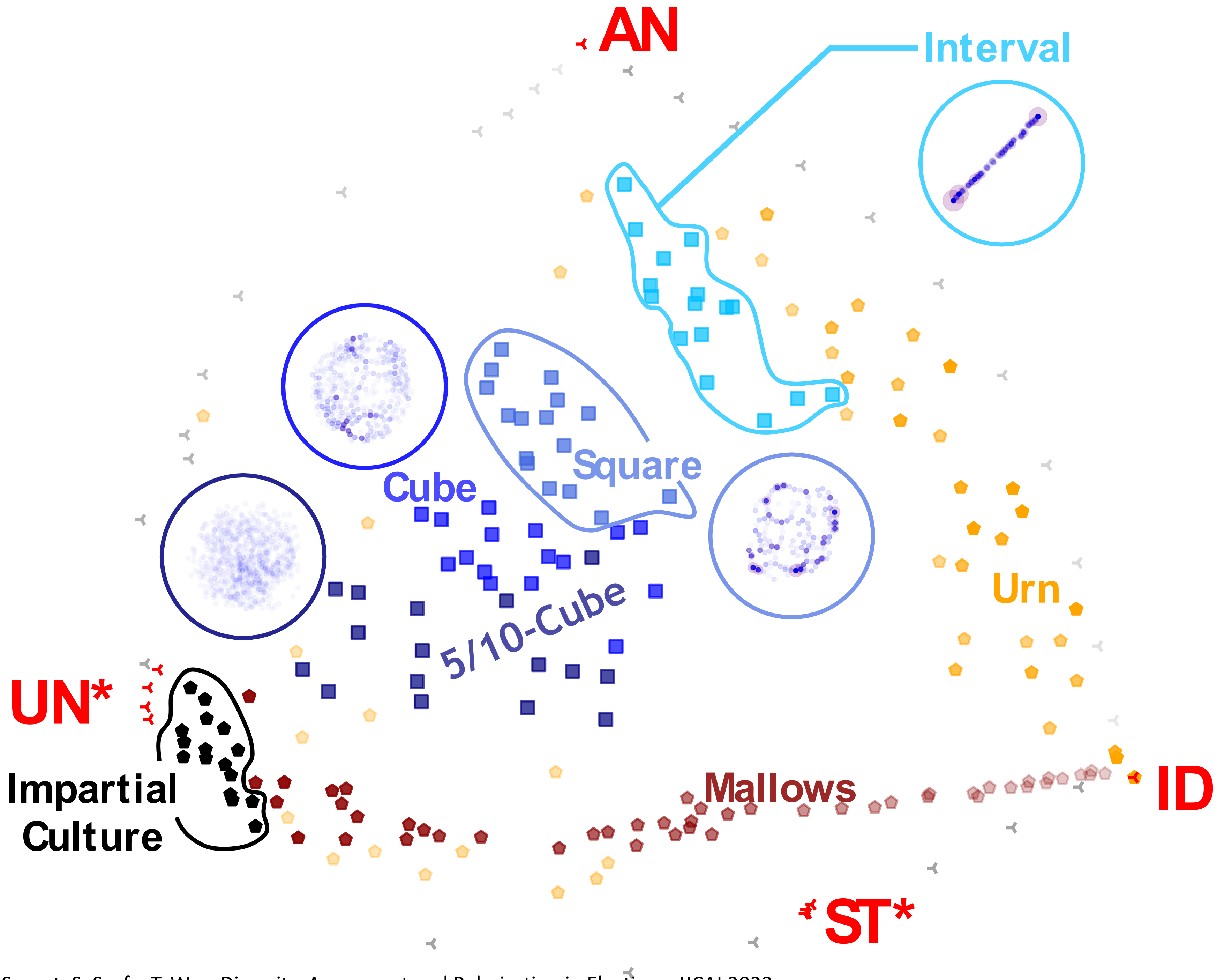

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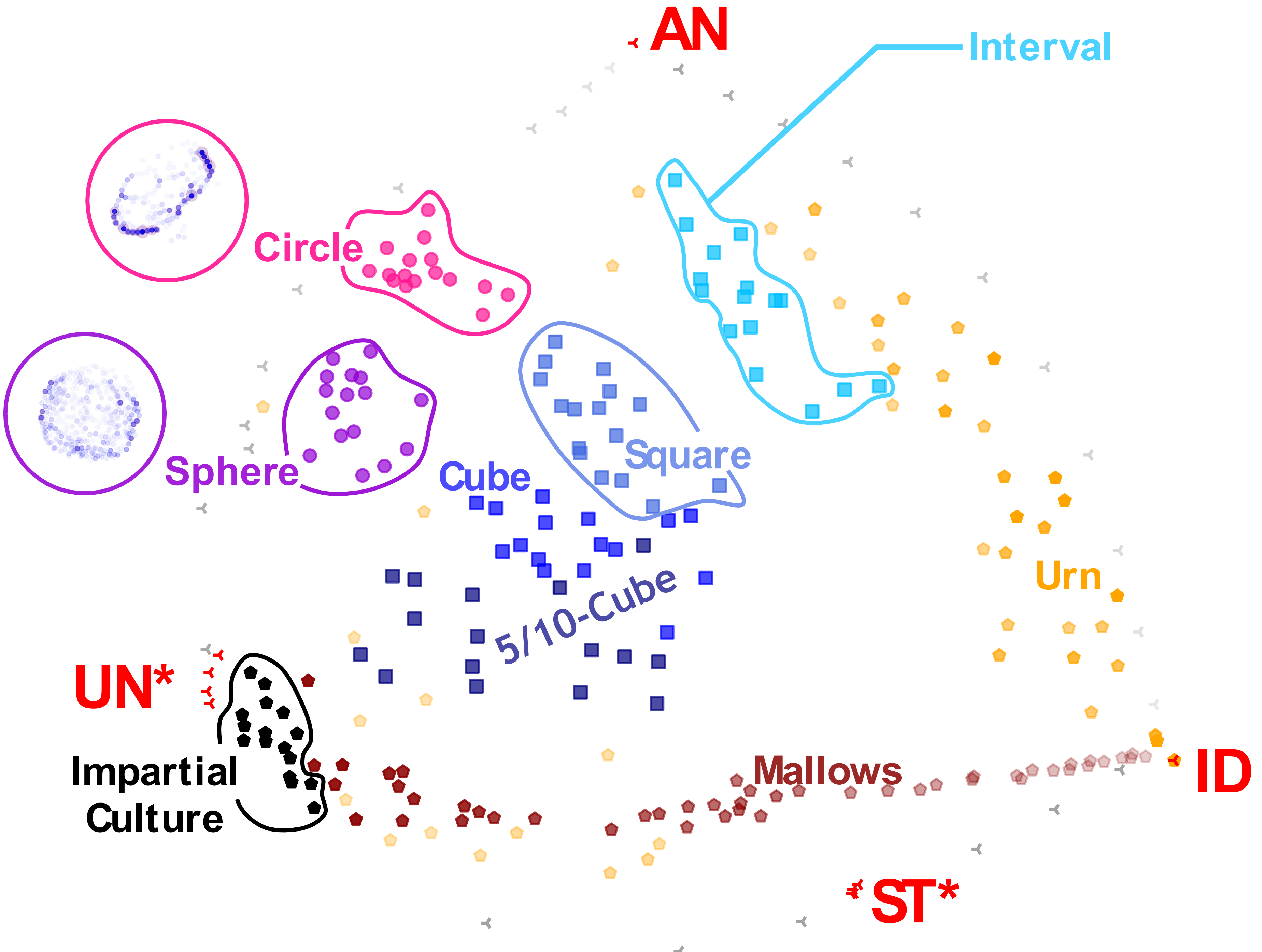

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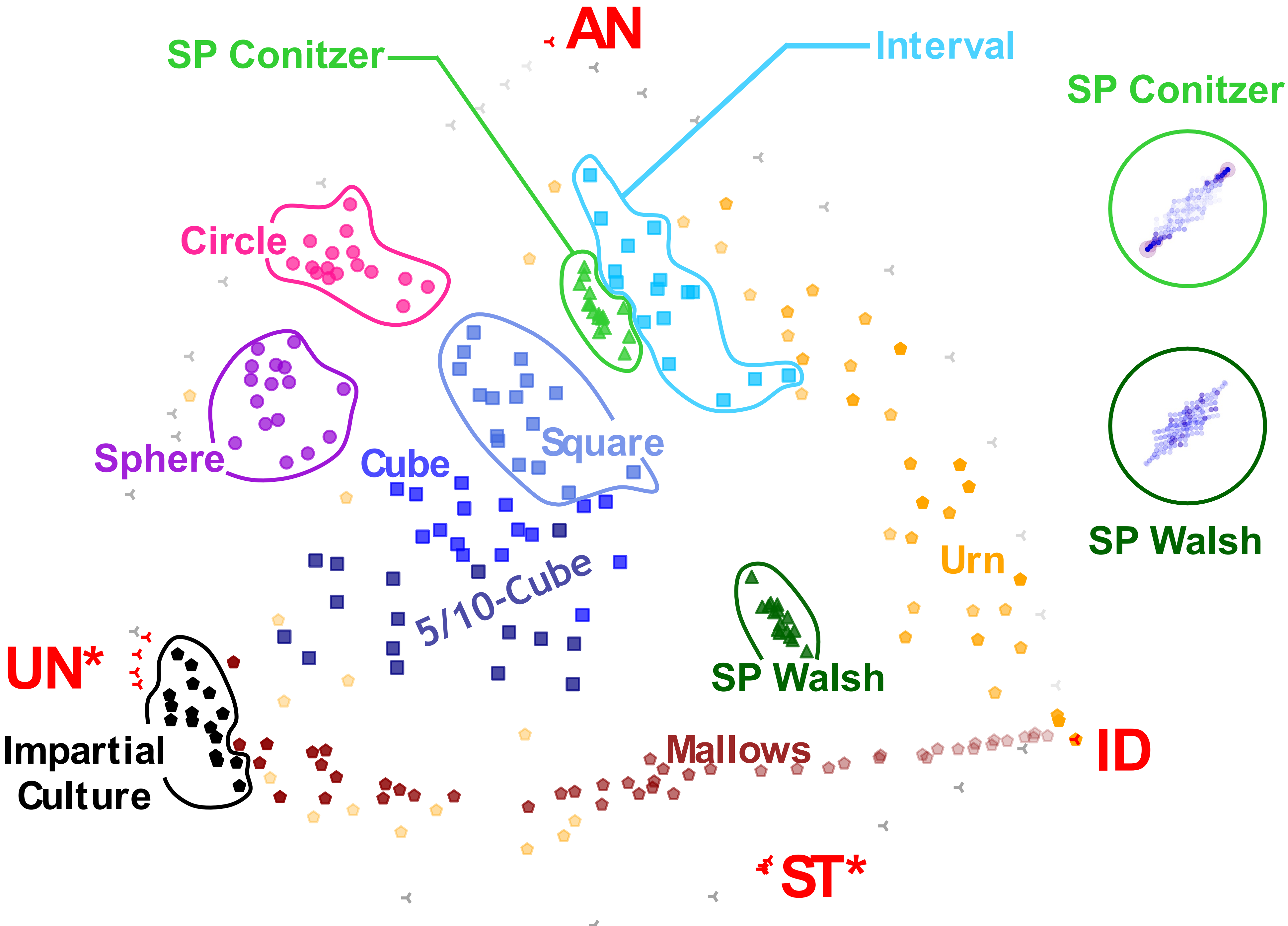

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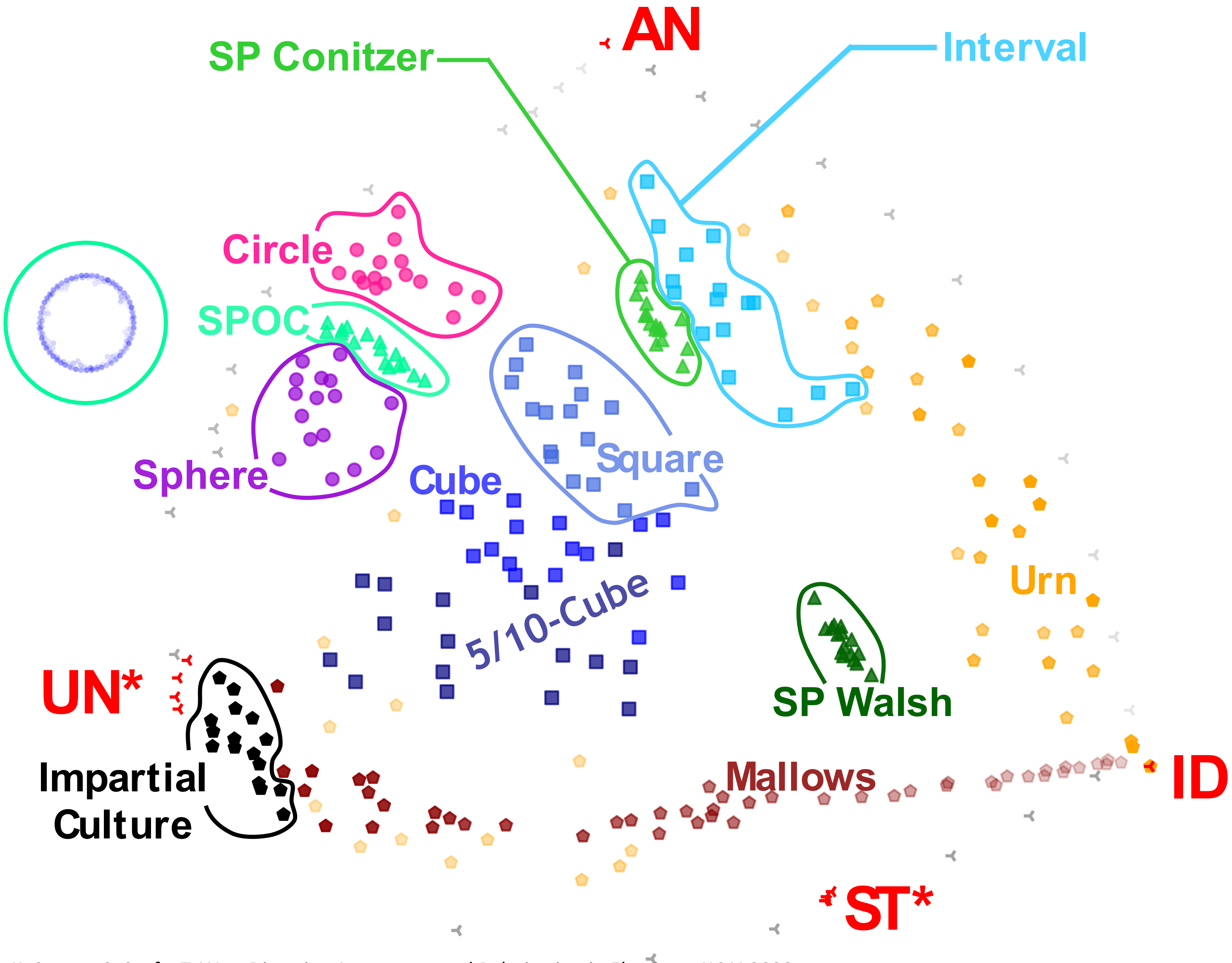

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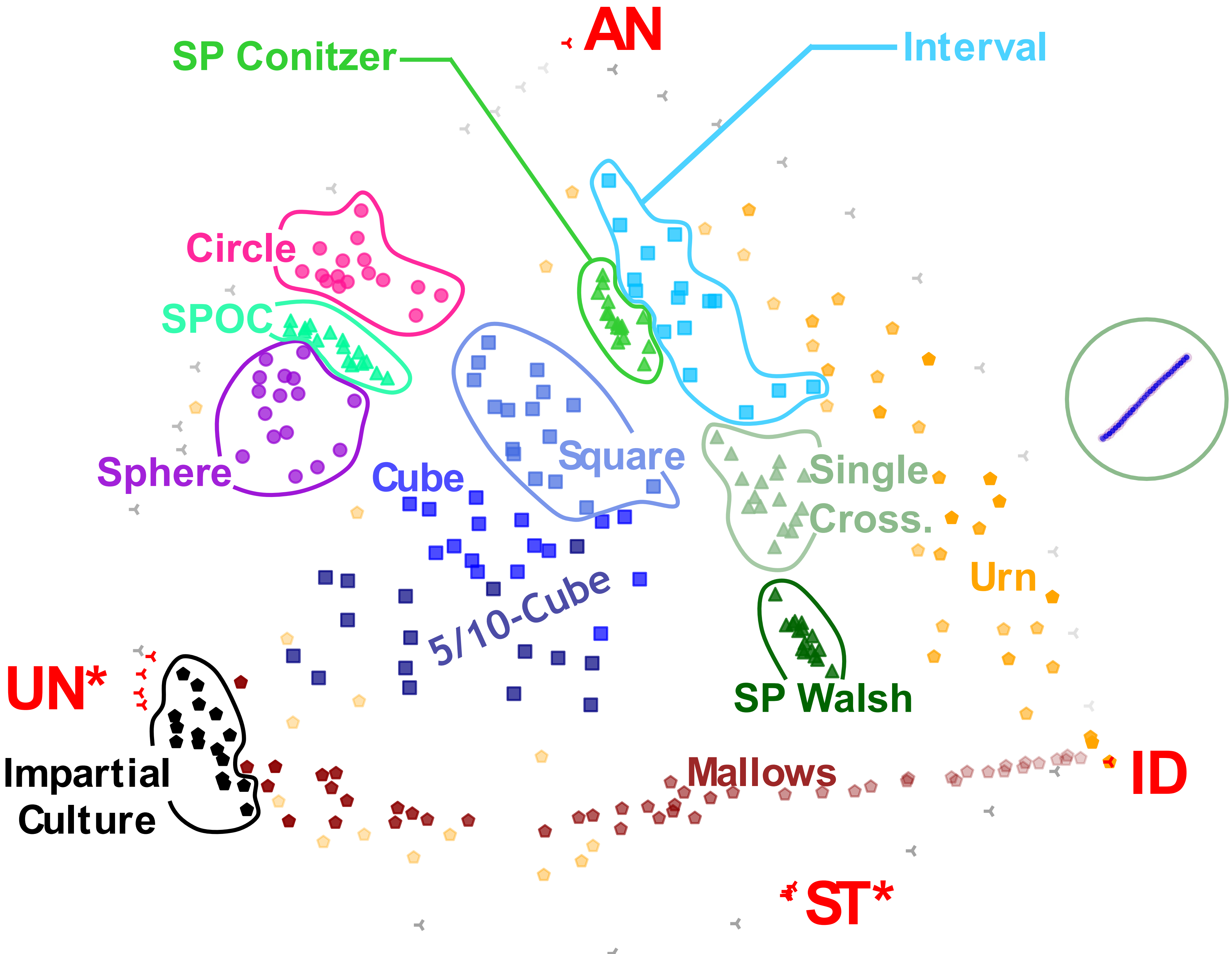

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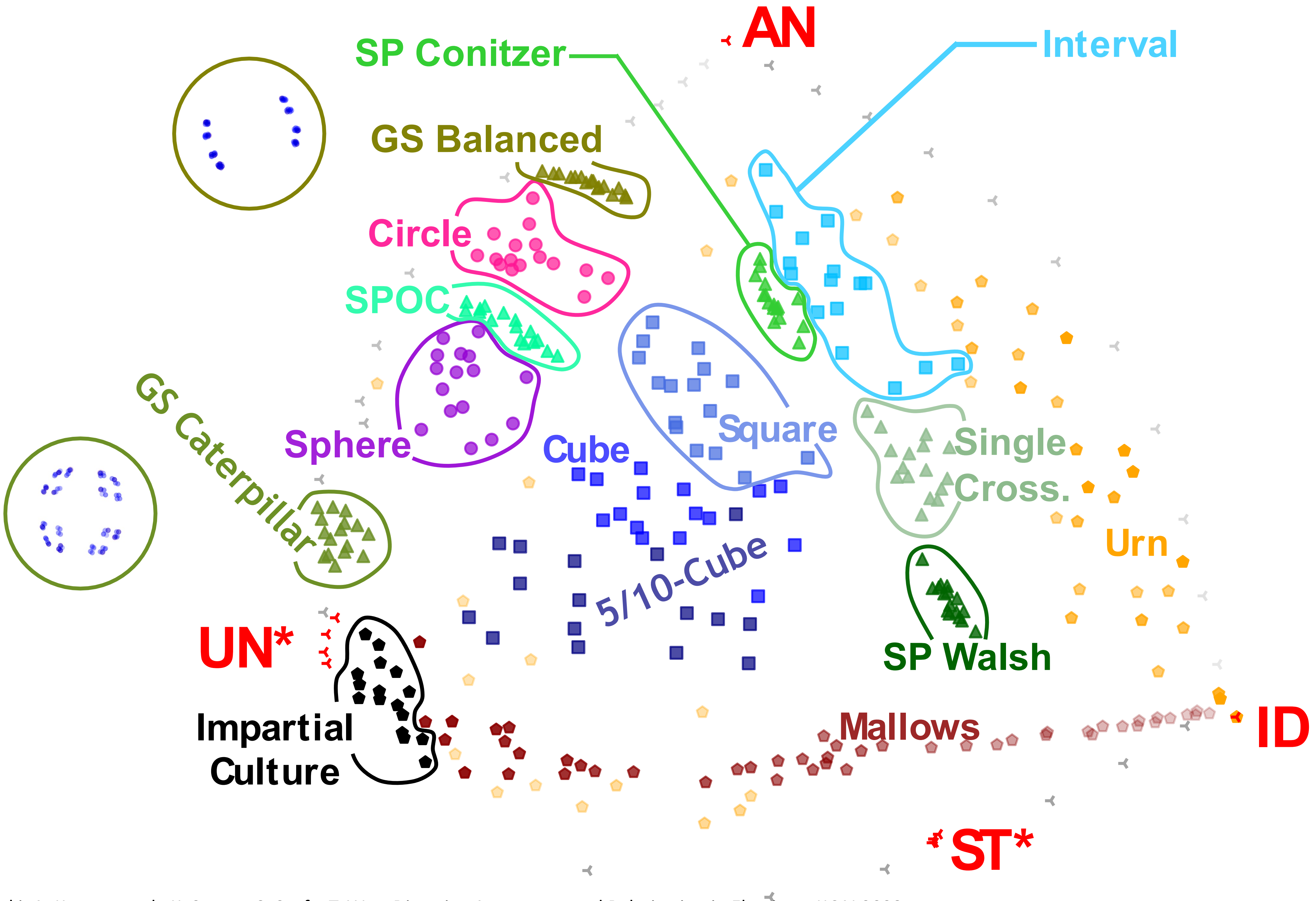

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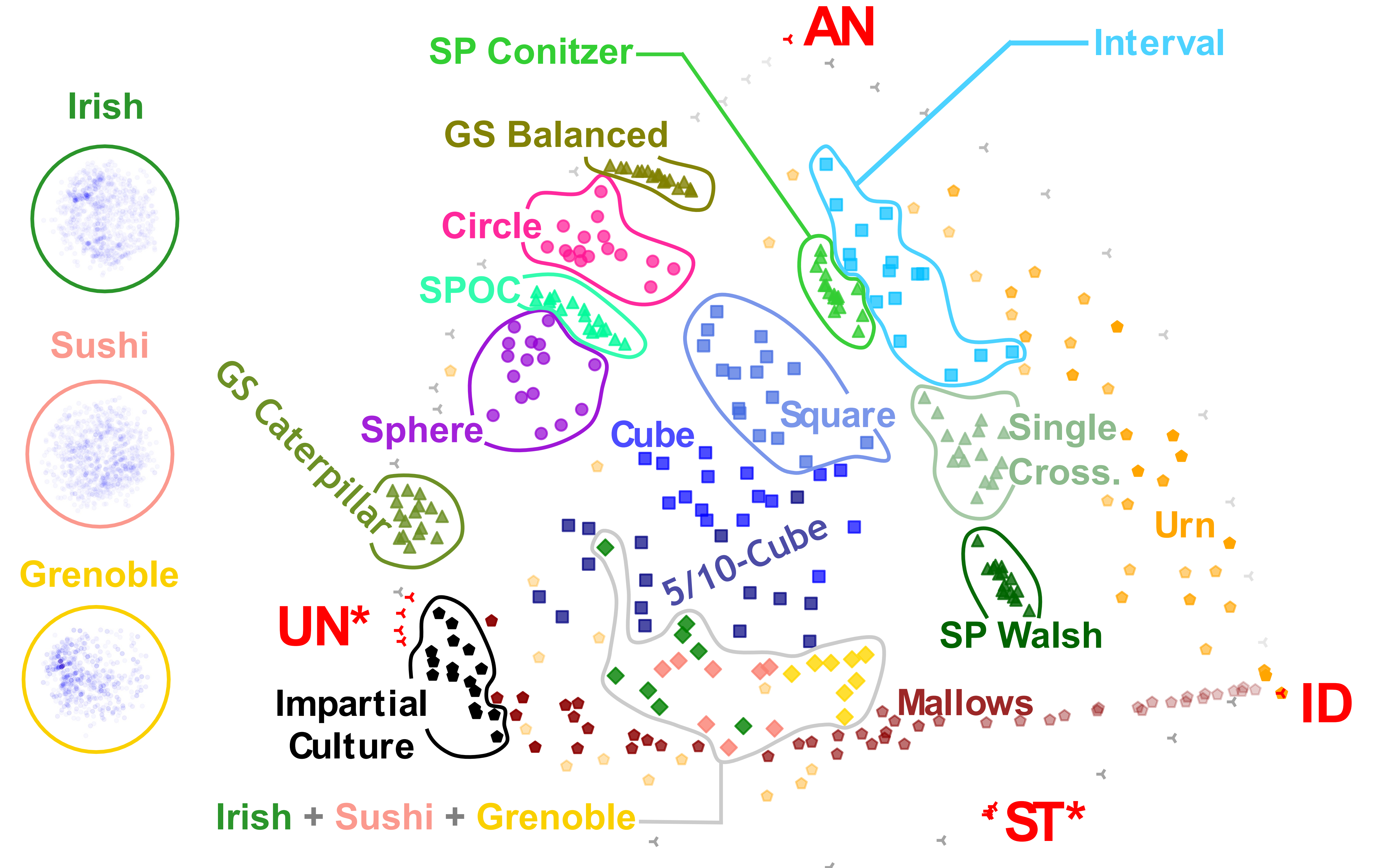


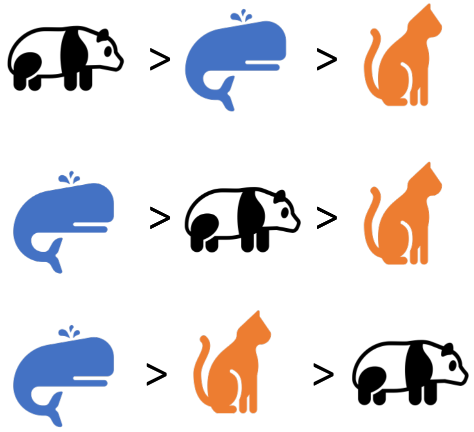
P. Faliszewski, A. Kaczmarczyk, K. Sornat, S. Szufa, T. Wąs, Diversity, Agreement and Polarization in Elections, IJCAI 2023

Computing Isomorphic Swap distance is:

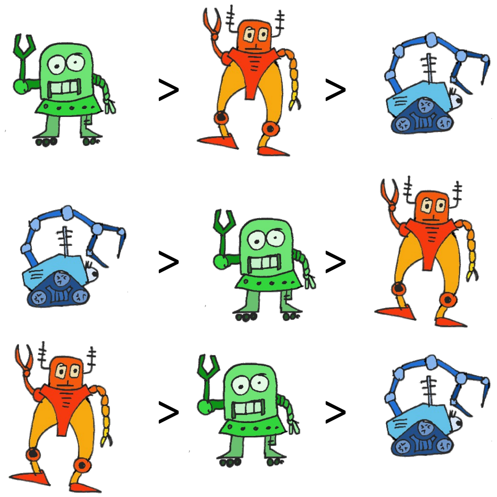
- NP-hard
- Hard to approximate
  - O(m)-approx. and no better
- FPT-computable, but impractical
- Infeasible using ILP
- Just plain tough!
- Bruteforce works up to 10x50 elections, if you have hundreds of cores and plenty of time…

P. Faliszewski, P. Skowron, A. Slinko, S. Szufa, N. Talmon: How Similar Are Two Elections? AAAI 2019

How to Go Around Isomorphic Swap Distance?

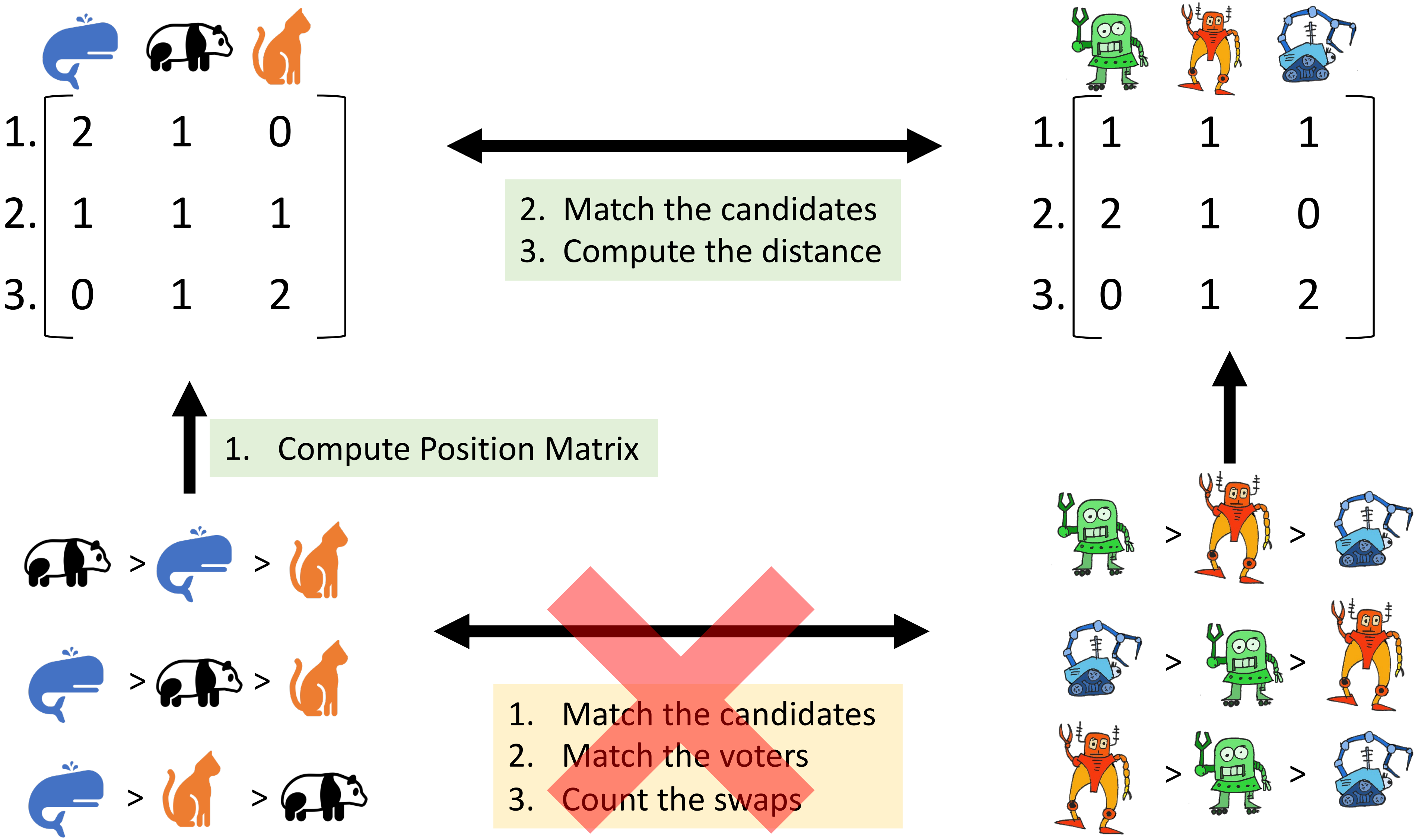


1. Match the candidates
2. Match the voters
3. Count the swaps



S. Szufa, P. Faliszewski, P. Skowron, A. Slinko, N. Talmon, Drawing a map of elections in the space of statistical cultures, AAMAS 2020

How to Go Around Isomorphic Swap Distance?



S. Szufa, P. Faliszewski, P. Skowron, A. Slinko, N. Talmon, Drawing a map of elections in the space of statistical cultures, AAMAS 2020

Distance Between Vectors

$$\begin{bmatrix} 3 & 1 & 0 & 1 & 1 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 3 & 0 & 1 & 0 & 1 \end{bmatrix}$$

N. Boehmer, P. Faliszewski, R. Niedermeier, S. Szufa, T. Wąs, Understanding Distance Measures Among Elections, IJCAI 2022

Distance Between Vectors

ℓ_1-distance

$$\begin{bmatrix} 3 & 1 & 0 & 1 & 1 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 3 & 0 & 1 & 0 & 1 \end{bmatrix}$$

$$\begin{bmatrix} 2 & 2 & 0 & 0 & 1 & 1 \end{bmatrix} \quad 6$$

N. Boehmer, P. Faliszewski, R. Niedermeier, S. Szufa, T. Wąs, Understanding Distance Measures Among Elections, IJCAI 2022

Distance Between Vectors

ℓ_1-distance

$$\begin{bmatrix} 3 & 1 & 0 & 1 & 1 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 1 & 0 & 3 & 0 & 1 \end{bmatrix}$$

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N. Boehmer, P. Faliszewski, R. Niedermeier, S. Szufa, T. Wąs, Understanding Distance Measures Among Elections, IJCAI 2022

Distance Between Vectors

ℓ_1-distance

$$\begin{bmatrix} 3 & 1 & 0 & 1 & 1 & 0 \end{bmatrix}$$

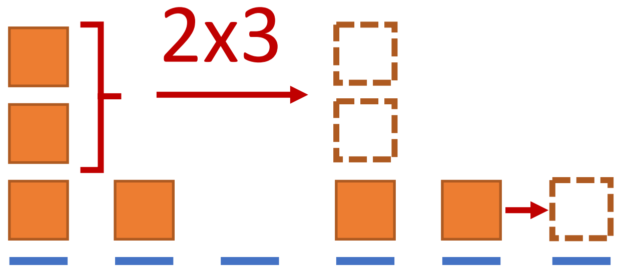
$$\begin{bmatrix} 1 & 1 & 0 & 3 & 0 & 1 \end{bmatrix}$$

$$\begin{bmatrix} 2 & 0 & 0 & 2 & 1 & 1 \end{bmatrix} \quad 6$$

Earth Mover’s Distance (EMD)

$$\begin{bmatrix} 3 & 1 & 0 & 1 & 1 & 0 \end{bmatrix}$$

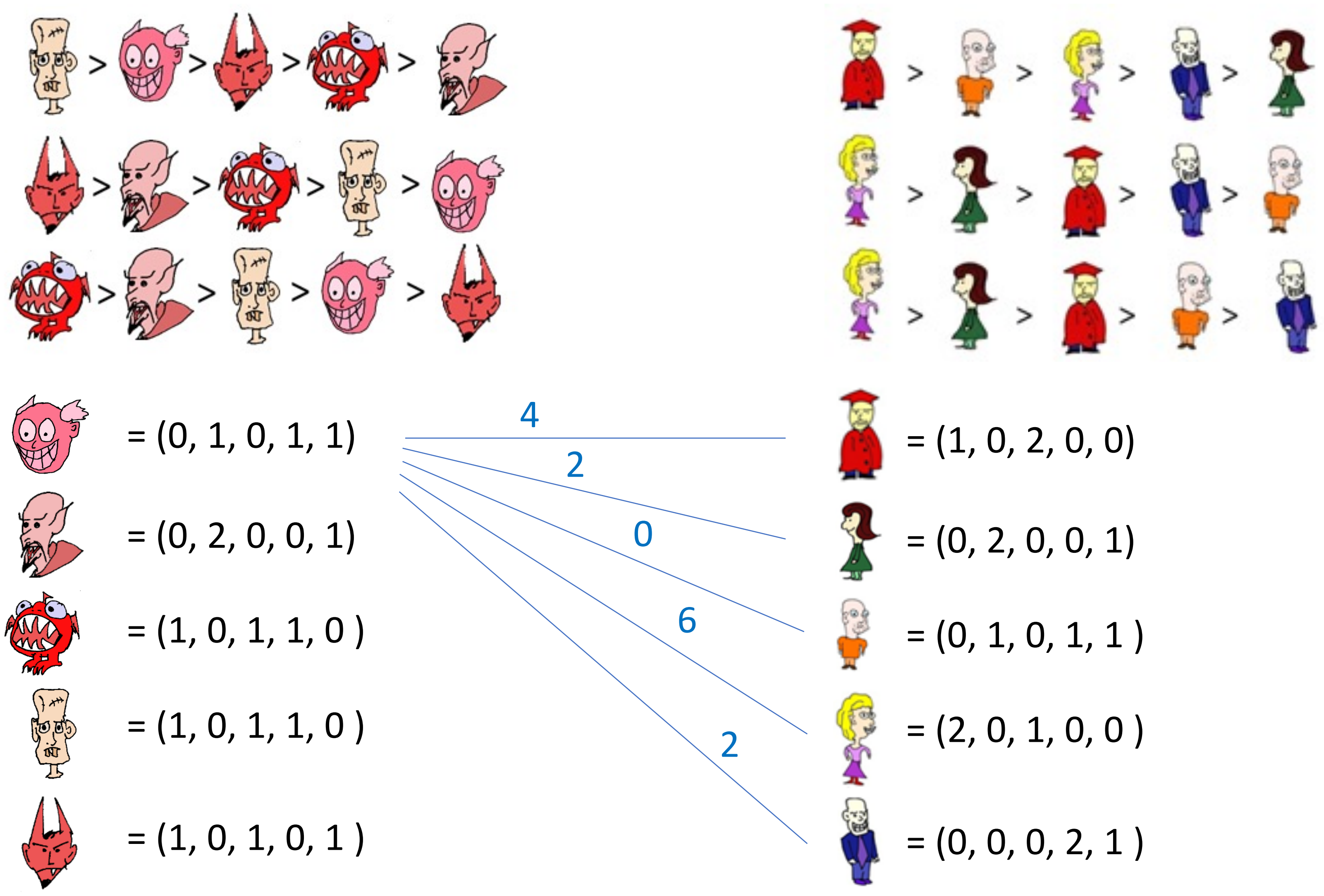
$$\begin{bmatrix} 1 & 1 & 0 & 3 & 0 & 1 \end{bmatrix}$$



7

N. Boehmer, P. Faliszewski, R. Niedermeier, S. Szufa, T. Wąs, Understanding Distance Measures Among Elections, IJCAI 2022

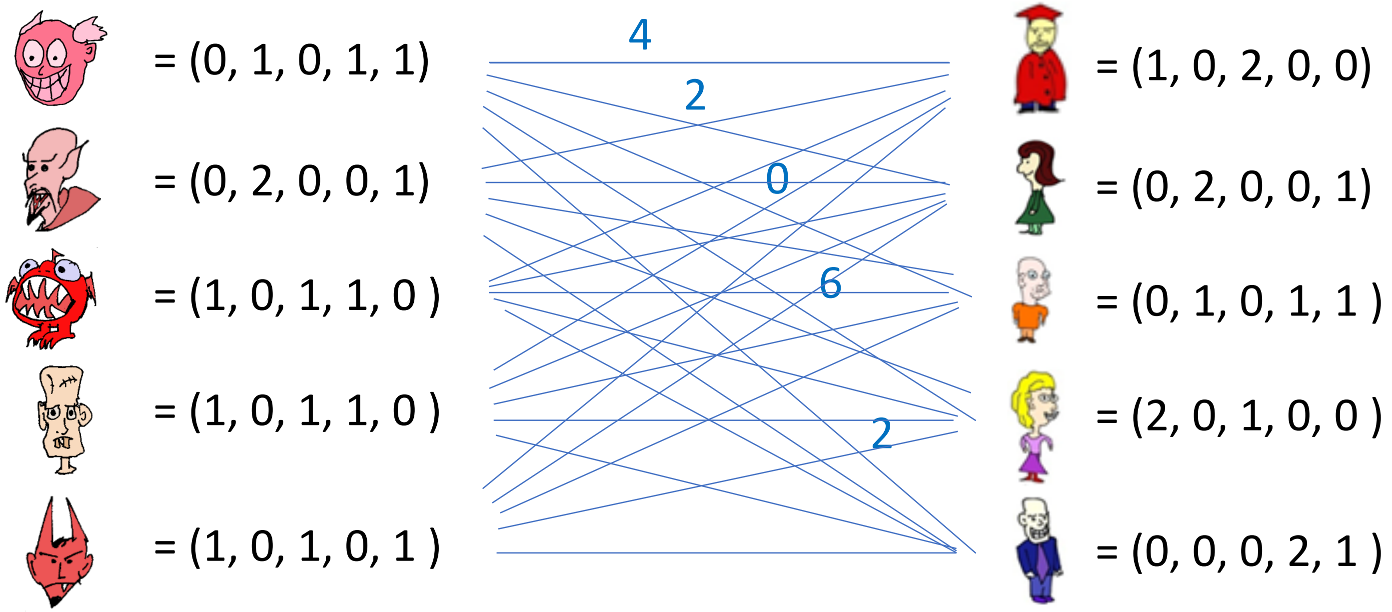
Positionwise Distance



Earth mover distances

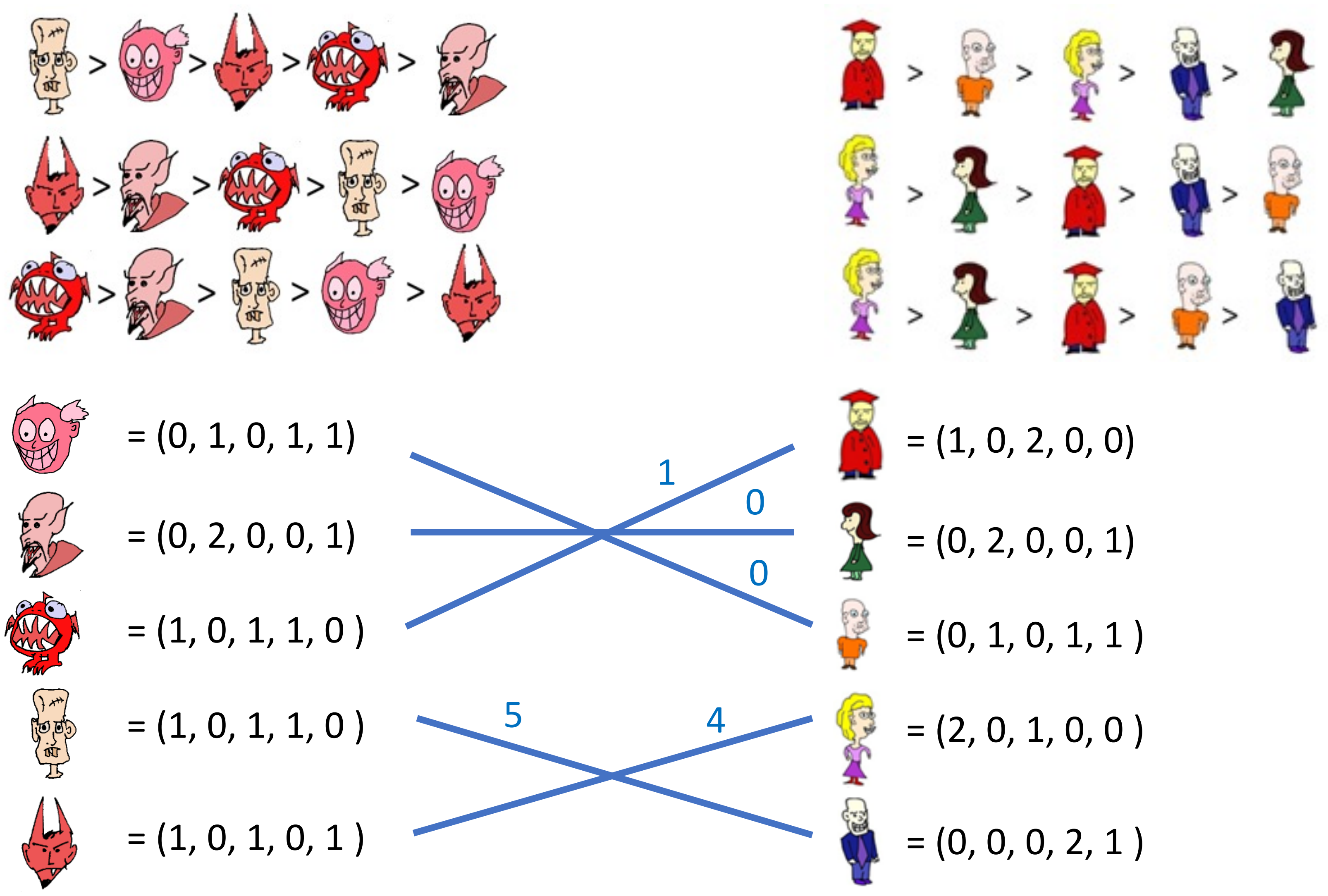
S. Szufa, P. Faliszewski, P. Skowron, A. Slinko, N. Talmon, Drawing a Map of Elections in the Space of Statistical Cultures, AAMAS 2022

Positionwise Distance

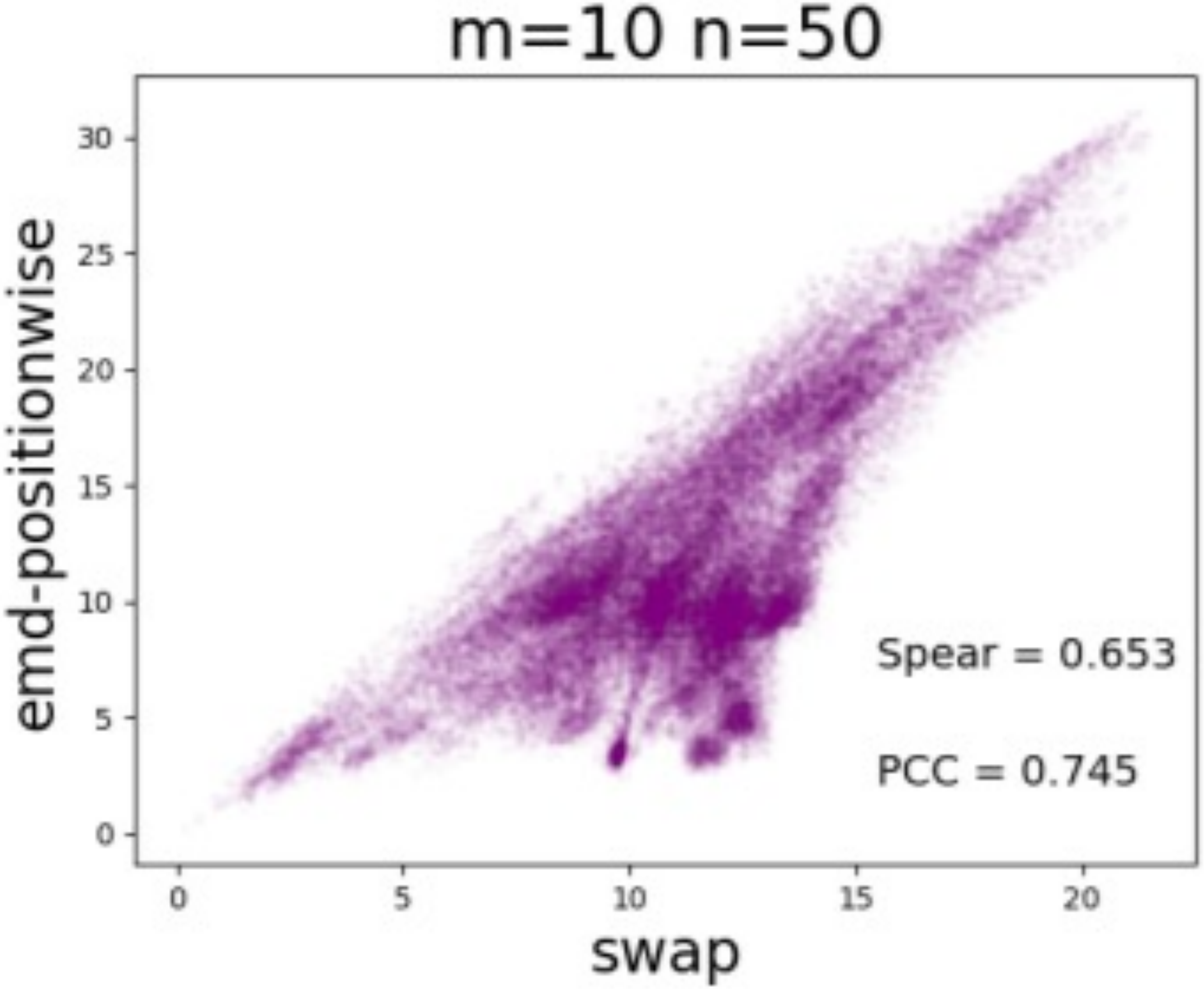


S. Szufa, P. Faliszewski, P. Skowron, A. Slinko, N. Talmon, Drawing a Map of Elections in the Space of Statistical Cultures, AAMAS 2022

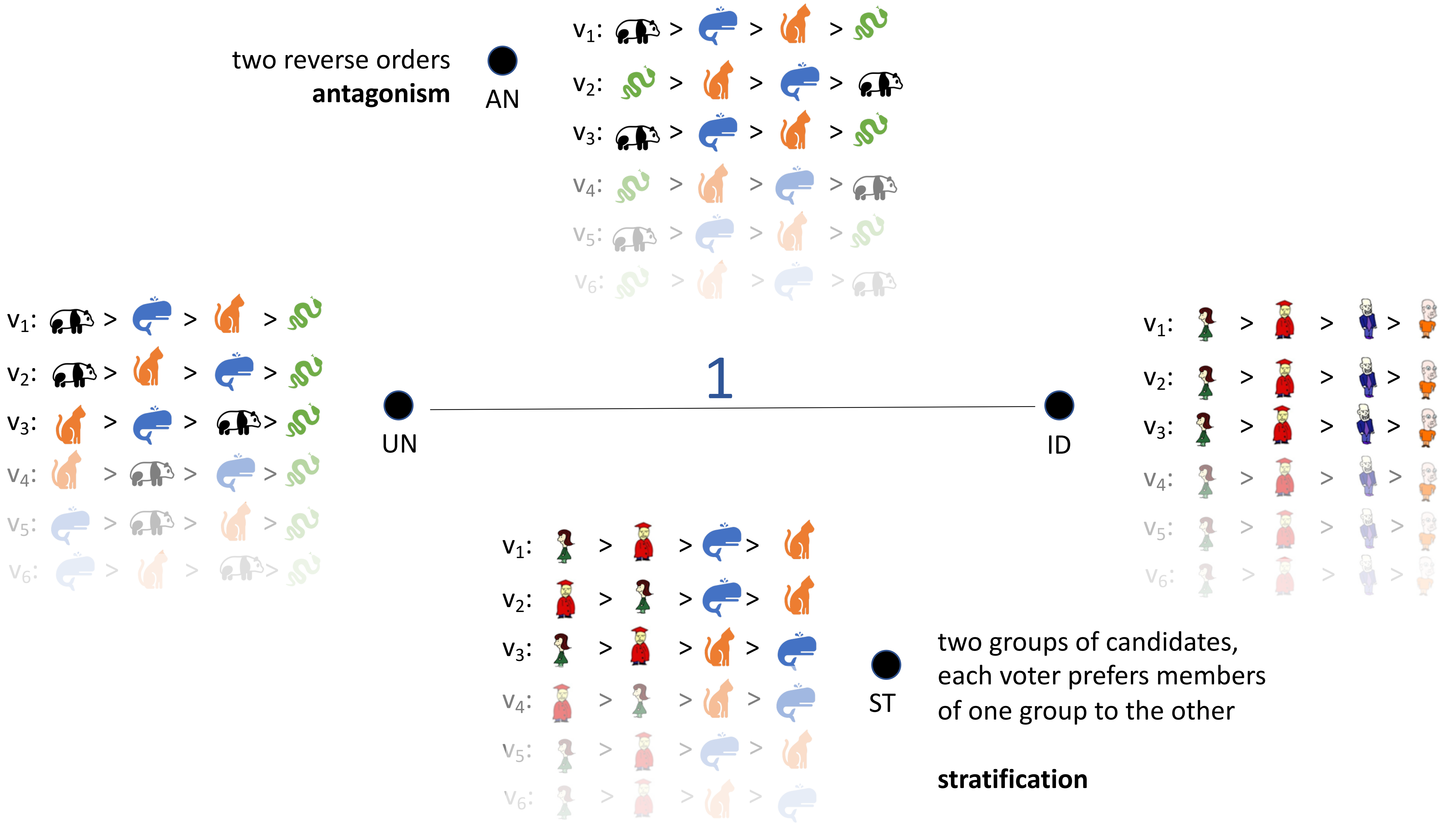
Positionwise Distance



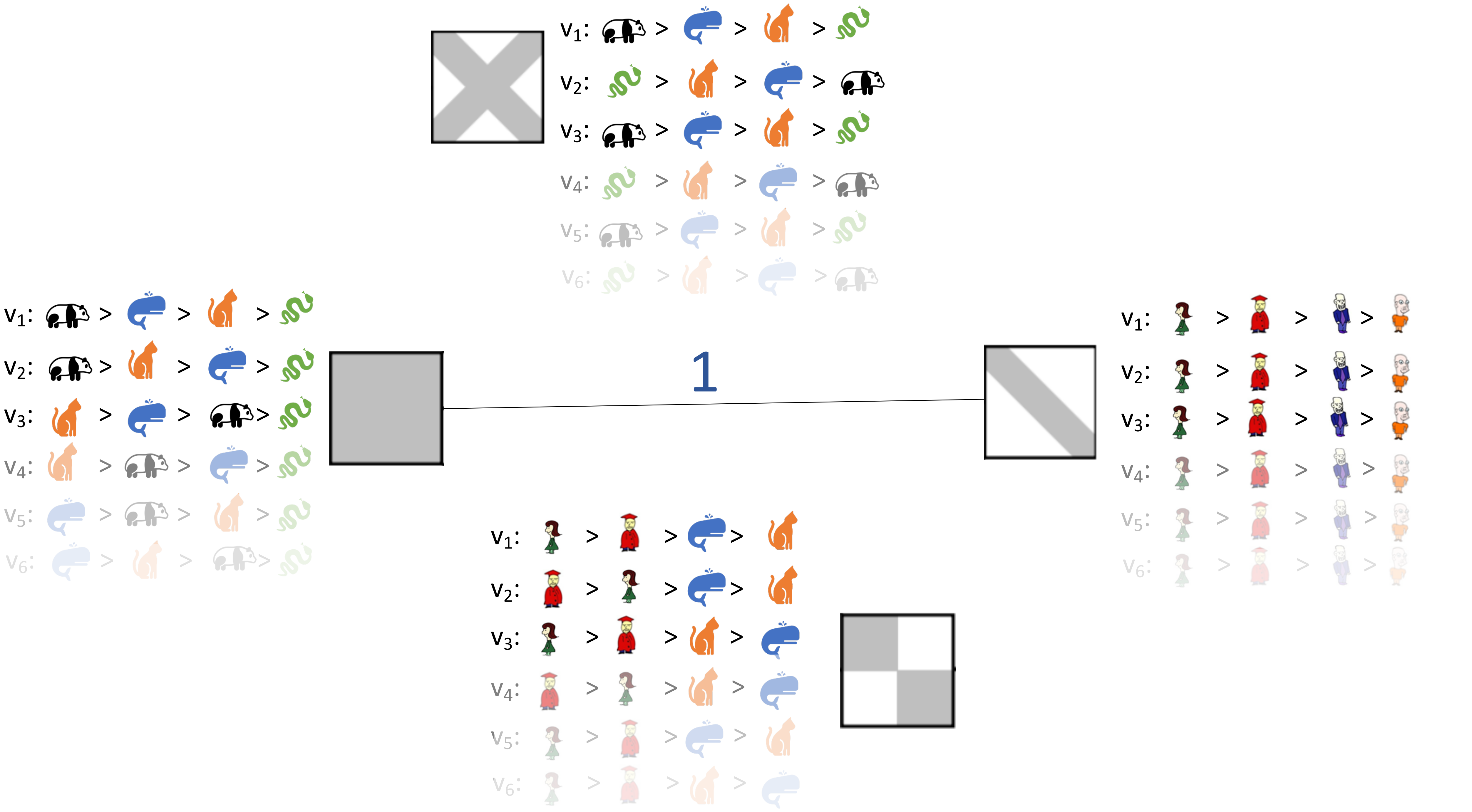
distance = 1+0+0+5+4 = 10

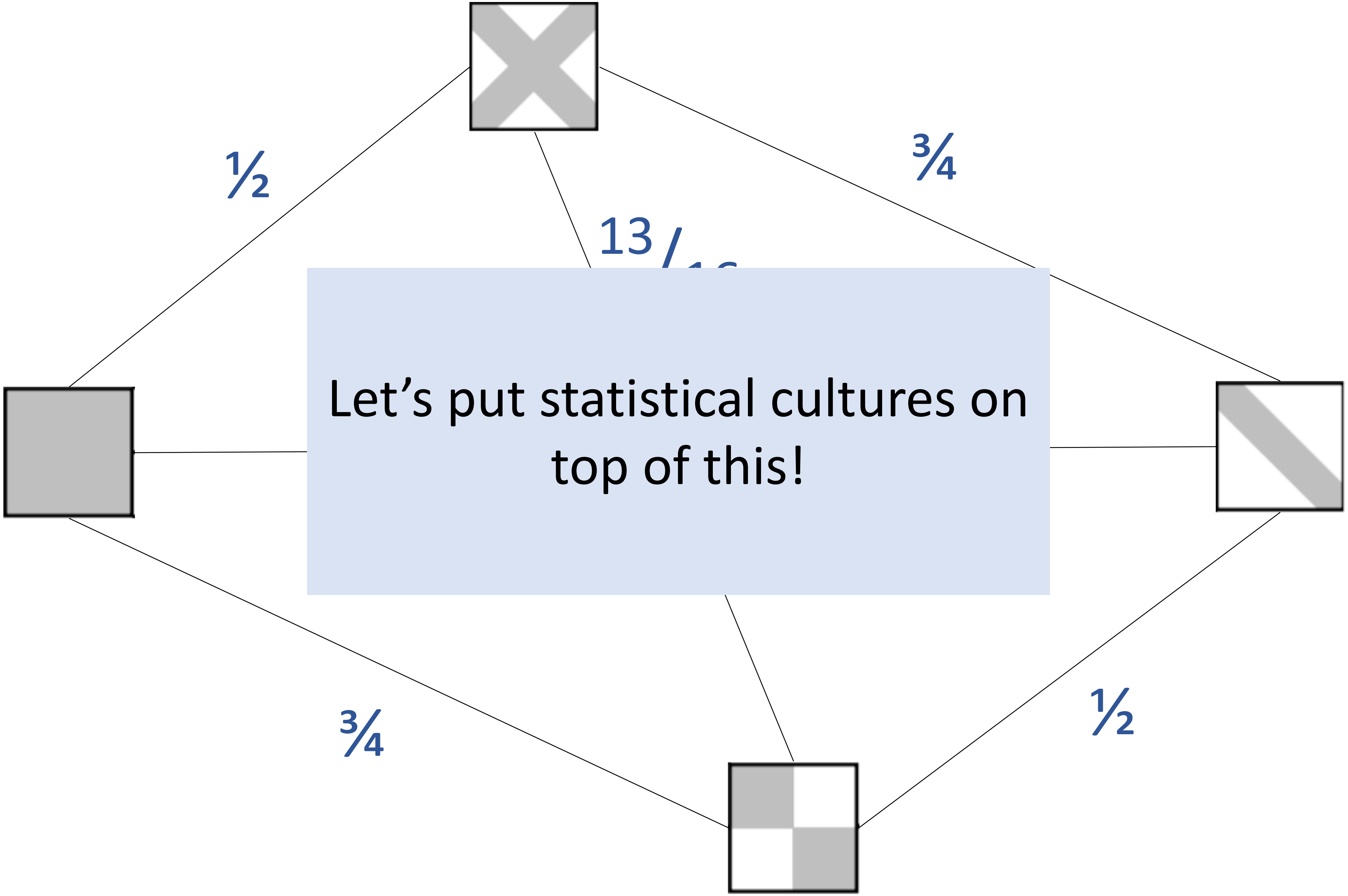


m=10 n=50
emd-positionwise
swap
Spear = 0.653
PCC = 0.745
0
5
10
15
20
25
30
0
5
10
15
20

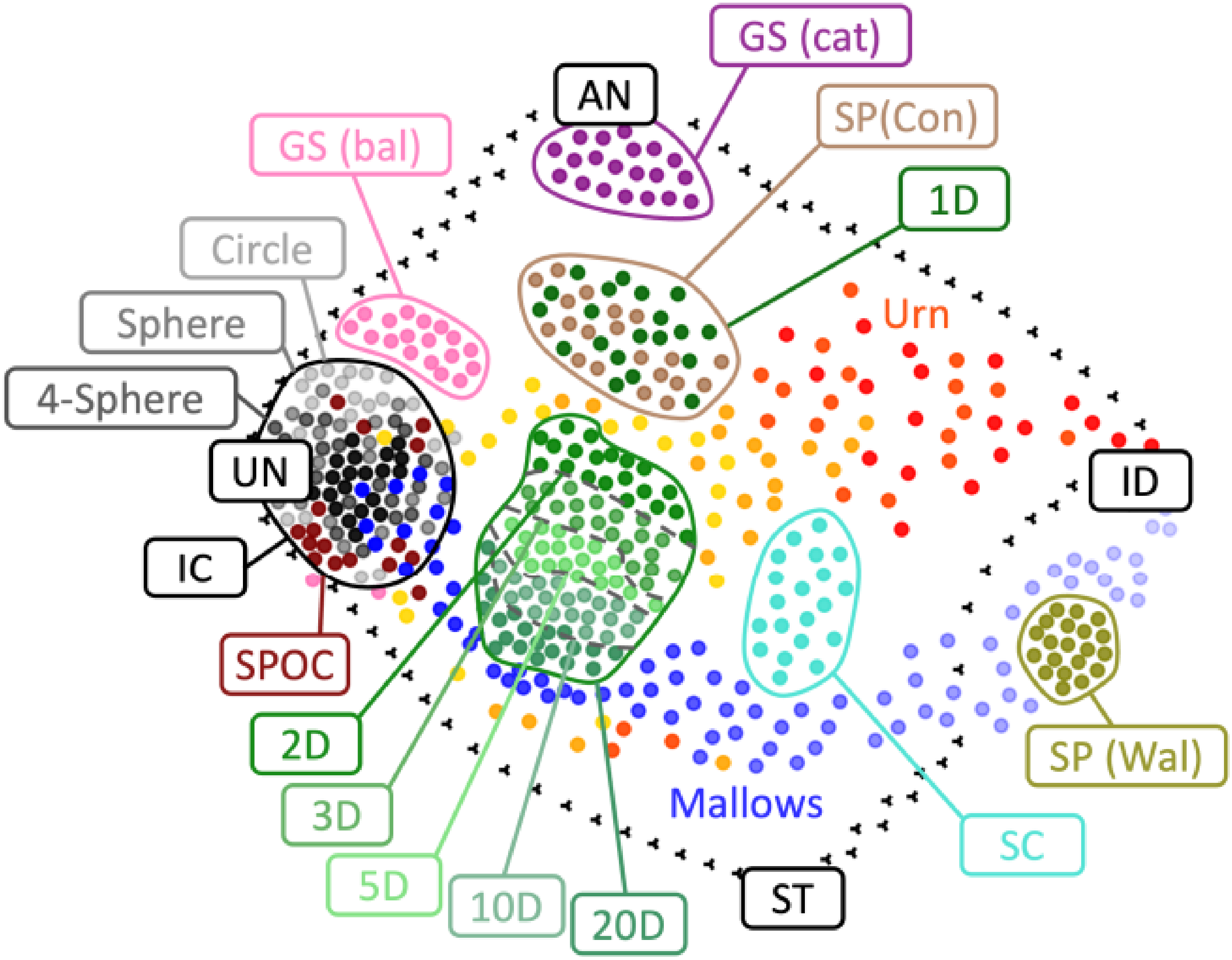


two reverse orders
antagonism
AN
v1: > > >
v2: > > >
v3: > > >
v4: > > >
v5: > > >
v6: > > >
UN
1
ID
ST
two groups of candidates, each voter prefers members of one group to the other
stratification


v1: > > >
v2: > > >
v3: > > >
v4: > > >
v5: > > >
v6: > > >
1

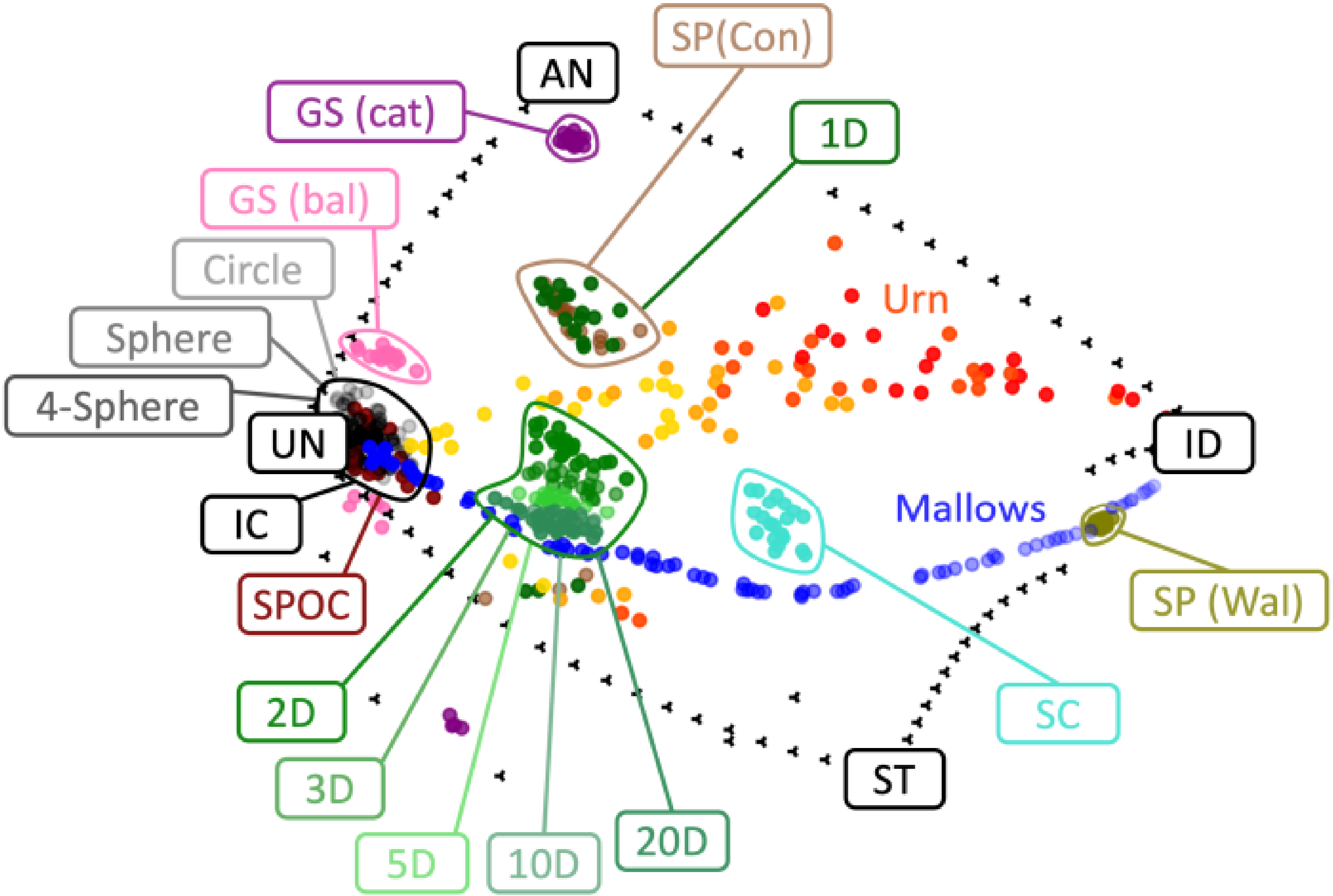


Let’s put statistical cultures on top of this!

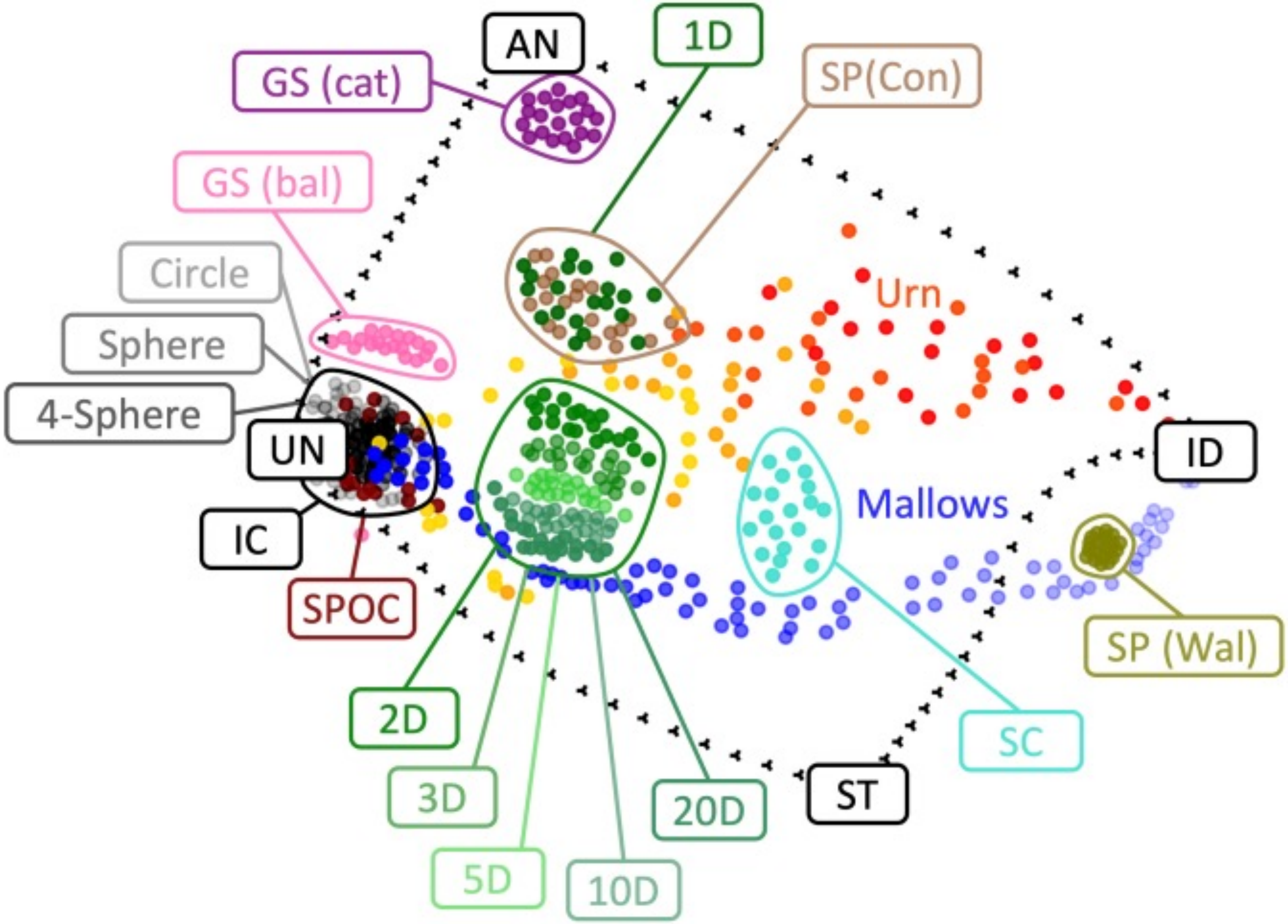


(a) FR

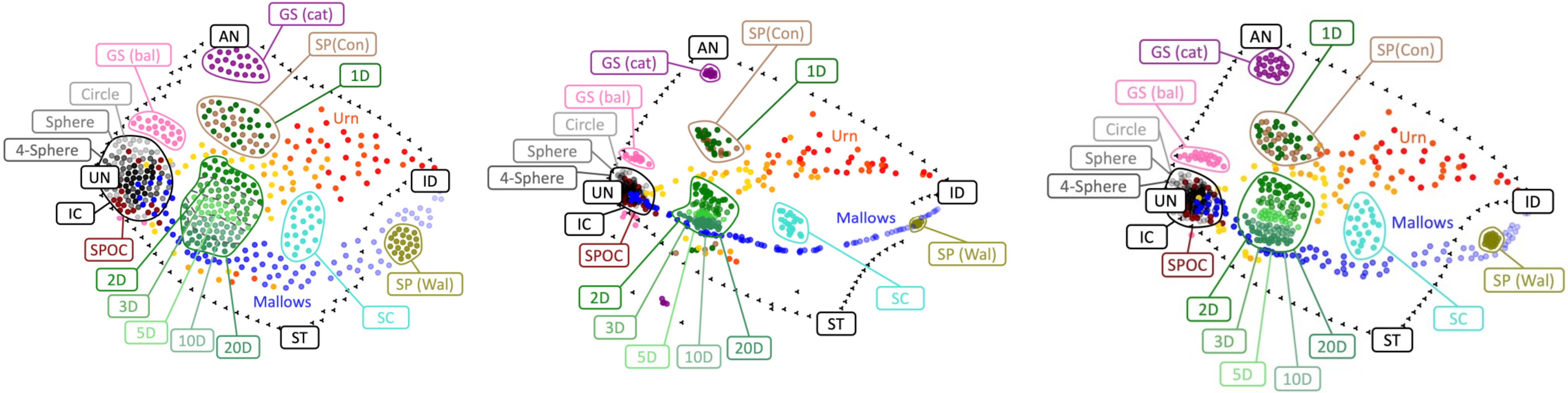
N. Boehmer, R. Bredereck, P. Faliszewski, R. Niedermeier, S. Szufa: Putting a Compass on the Map of Elections, IJCAI 2021


SP(Con)
AN
GS (cat)
1D
GS (bal)
Circle
Urn
Sphere
4-Sphere
UN
ID
Mallows
IC
SPOC
SP (Wal)
2D
SC
3D
ST
5D
10D
20D

(b) MDS


AN
1D
GS (cat)
SP(Con)
GS (bal)
Circle
Urn
Sphere
4-Sphere
UN
ID
Mallows
IC
SPOC
SP (Wal)
2D
SC
3D
ST
20D
5D
10D

(c) KK



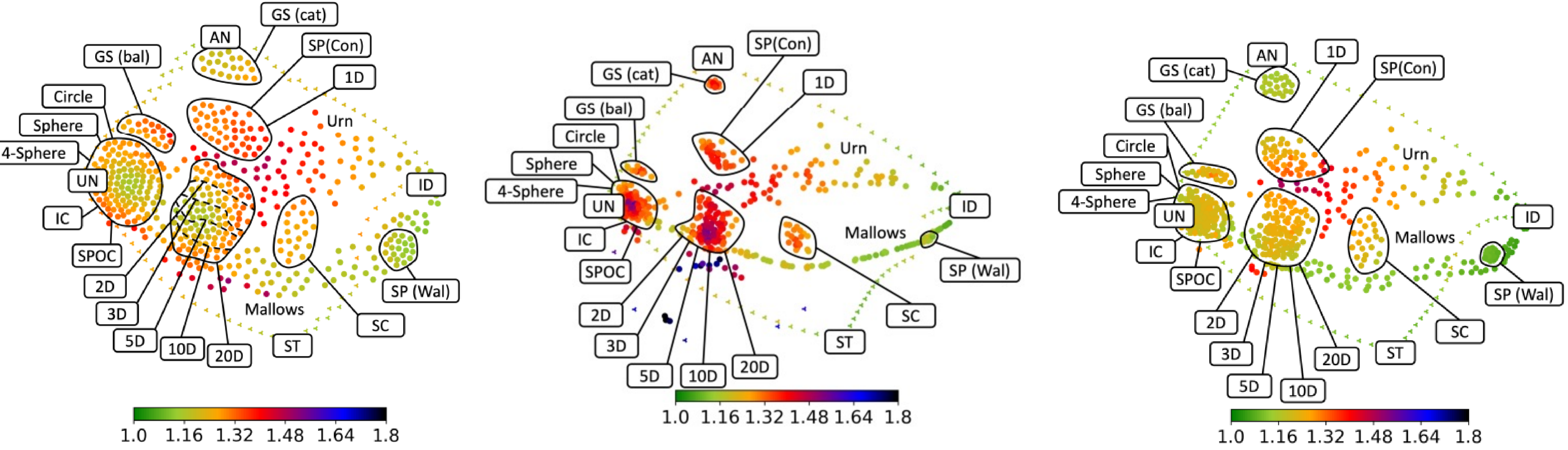
(a) FR

(b) MDS

(c) KK

Which embedding is best?

$$\mathrm{MR}(X,Y) = \frac{\max(\bar{d}_{\mathrm{Euc}}(X,Y), \bar{d}_{\mathcal{M}}(X,Y))}{\min(\bar{d}_{\mathrm{Euc}}(X,Y), \bar{d}_{\mathcal{M}}(X,Y))},$$



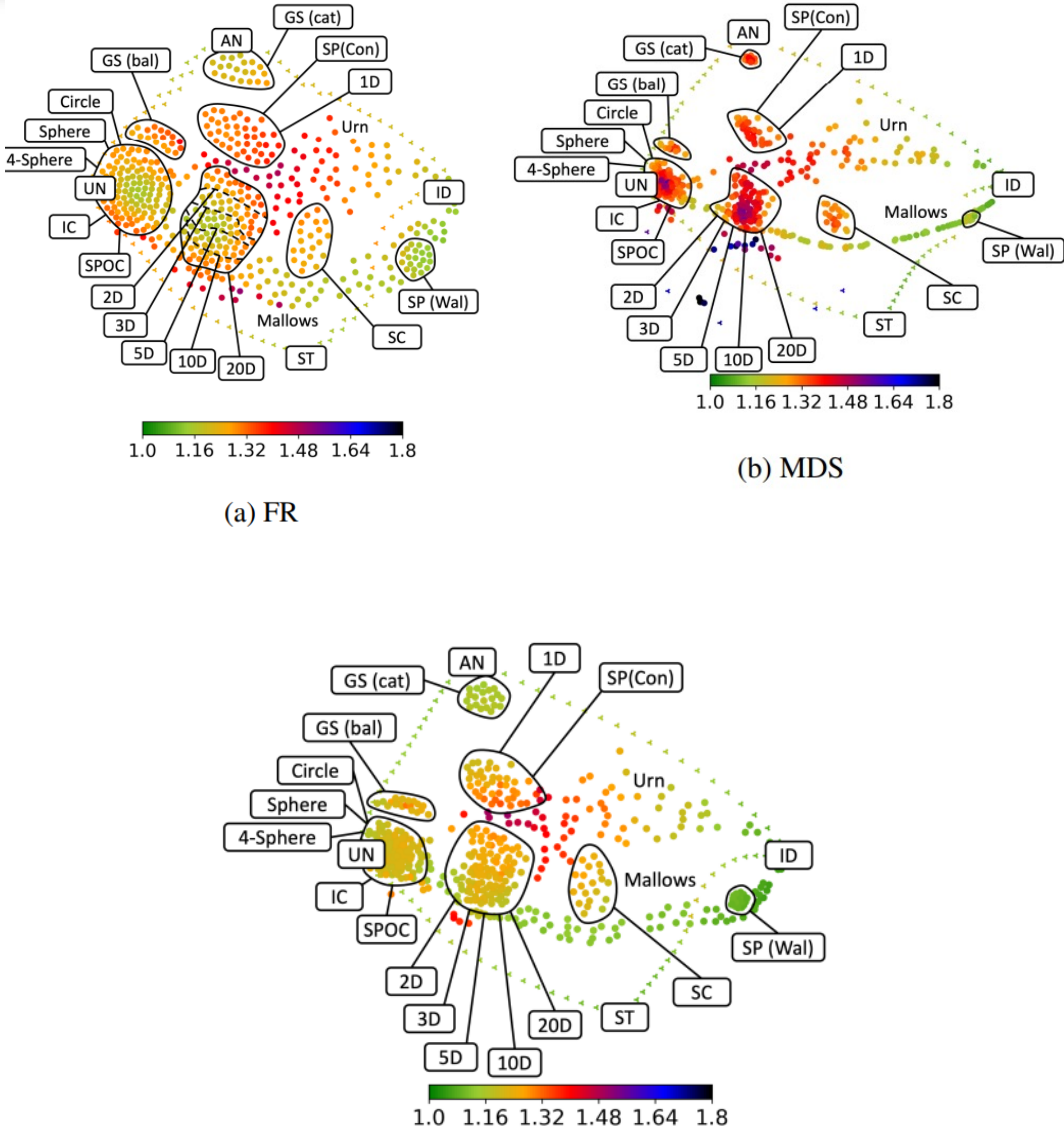
(a) FR

(b) MDS

(c) KK

dataset	average total distortion values		
	FR	MDS	KK
4×100	1.3213 ± 0.0157	1.3099 ± 0.0076	1.2612 ± 0.0158
10×100	1.3119 ± 0.0194	1.3531 ± 0.0108	1.2625 ± 0.0125
20×100	1.2979 ± 0.0195	1.3545 ± 0.0126	1.2406 ± 0.0060
100×100	1.3006 ± 0.0256	1.3225 ± 0.0194	1.2119 ± 0.0123

Model	average total distortion values		
	FR	MDS	KK
Impartial Culture	1.145	1.087	1.07
Single-Peaked (Conitzer)	1.313	1.305	1.244
Single-Peaked (Walsh)	1.114	1.067	1.071
SPOC	1.223	1.094	1.081
Single-Crossing	1.256	1.298	1.225
Interval	1.321	1.3	1.233
Square	1.267	1.274	1.203
Cube	1.216	1.217	1.146
5-Cube	1.155	1.177	1.114
10-Cube	1.2	1.162	1.094
20-Cube	1.252	1.162	1.097
Circle	1.222	1.105	1.101
Sphere	1.187	1.09	1.077
4-Sphere	1.174	1.084	1.072
Group-Separable (Balanced)	1.302	1.298	1.204
Group-Separable (Caterpillar)	1.215	1.218	1.14
Urn	1.338	1.298	1.285
Mallows	1.195	1.121	1.094
All	1.241	1.198	1.159



(a) FR

(b) MDS

(c) KK

Mapel

Matchings

Further Applications

Approval Elections

Map of Rules

Data!

Introduction to voting

Experiments in Computational Social Choice

Preference Learning

Mallows

Real-Life Data

Use Cases (Elections)

Swap Distance

Map of Elections

Distances

Positionwise

Embedding Algorithms

Force-Directed

Verification

AN

UN

Compass Elections

ID

ST

Winners

Approximations

Election Results

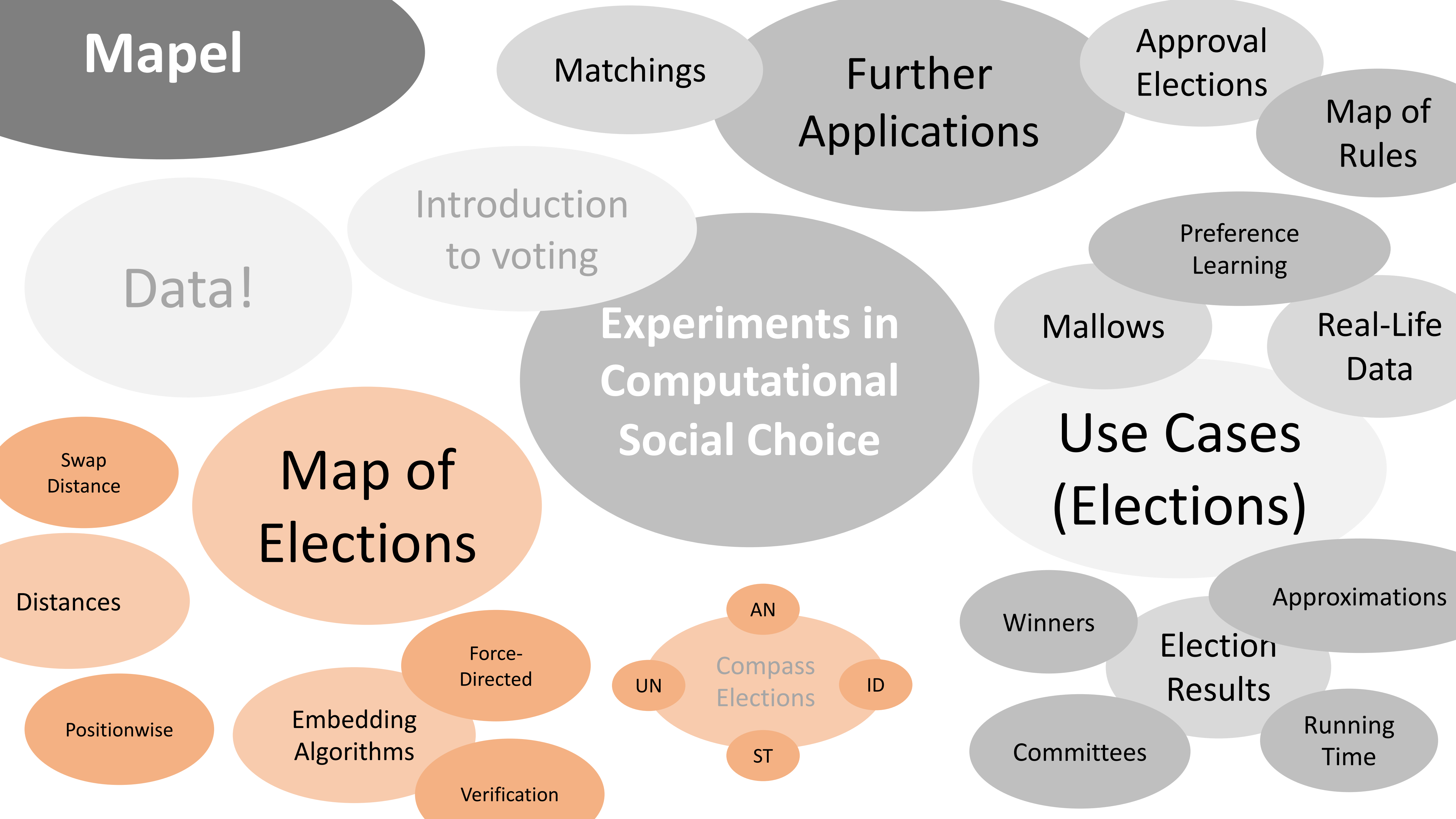
Committees

Running Time

15 minutes

Create your own map of elections!

Introduction to Mapel Software Package 1/2


Mapel
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Further Applications
Approval Elections
Map of Rules
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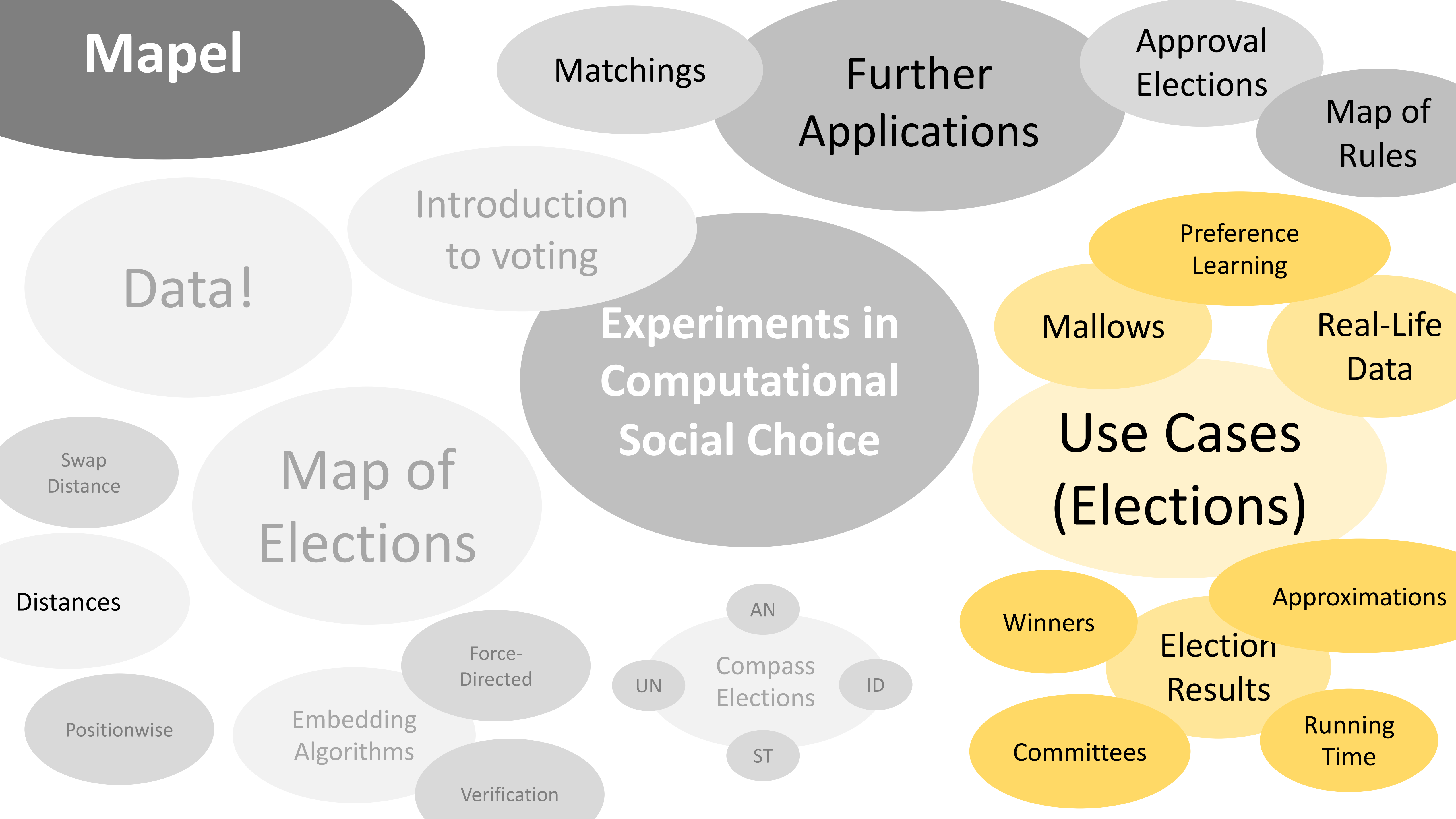
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Winners
Approximations
Election Results
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Running Time

Drawing a Map of Elections in the Space of Statistical Cultures, Szufa et al., AAMAS-20

Map of Elections, S. Szufa, PhD Thesis

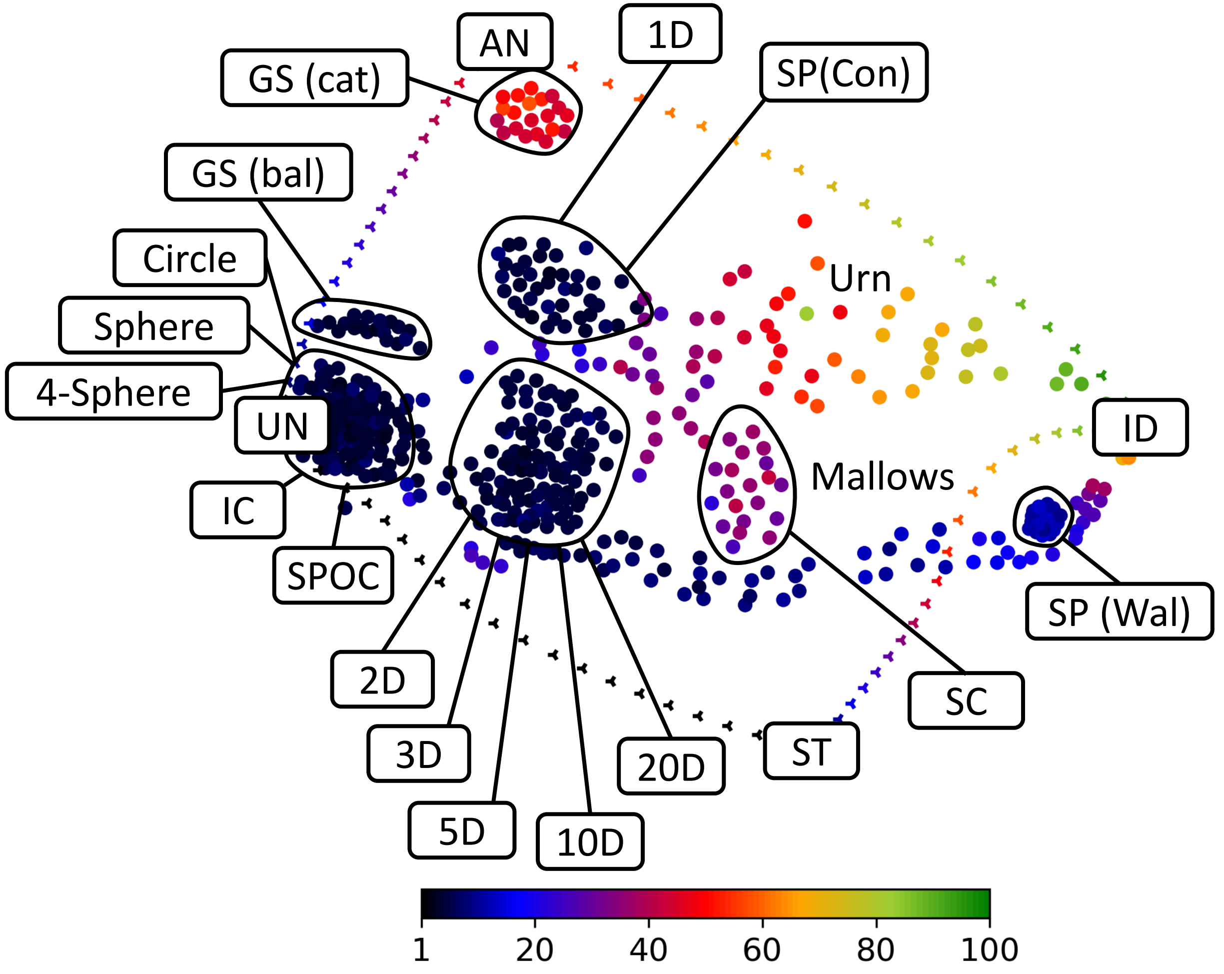
20 minutes

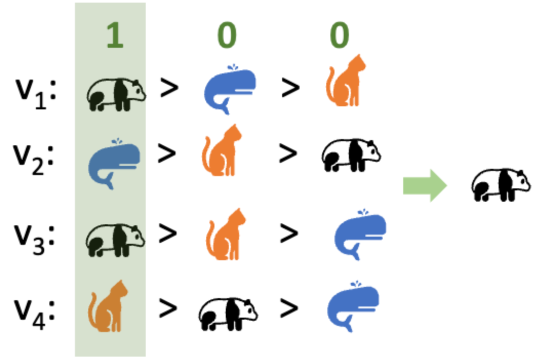
Visualizing Experiment Results

Use Cases

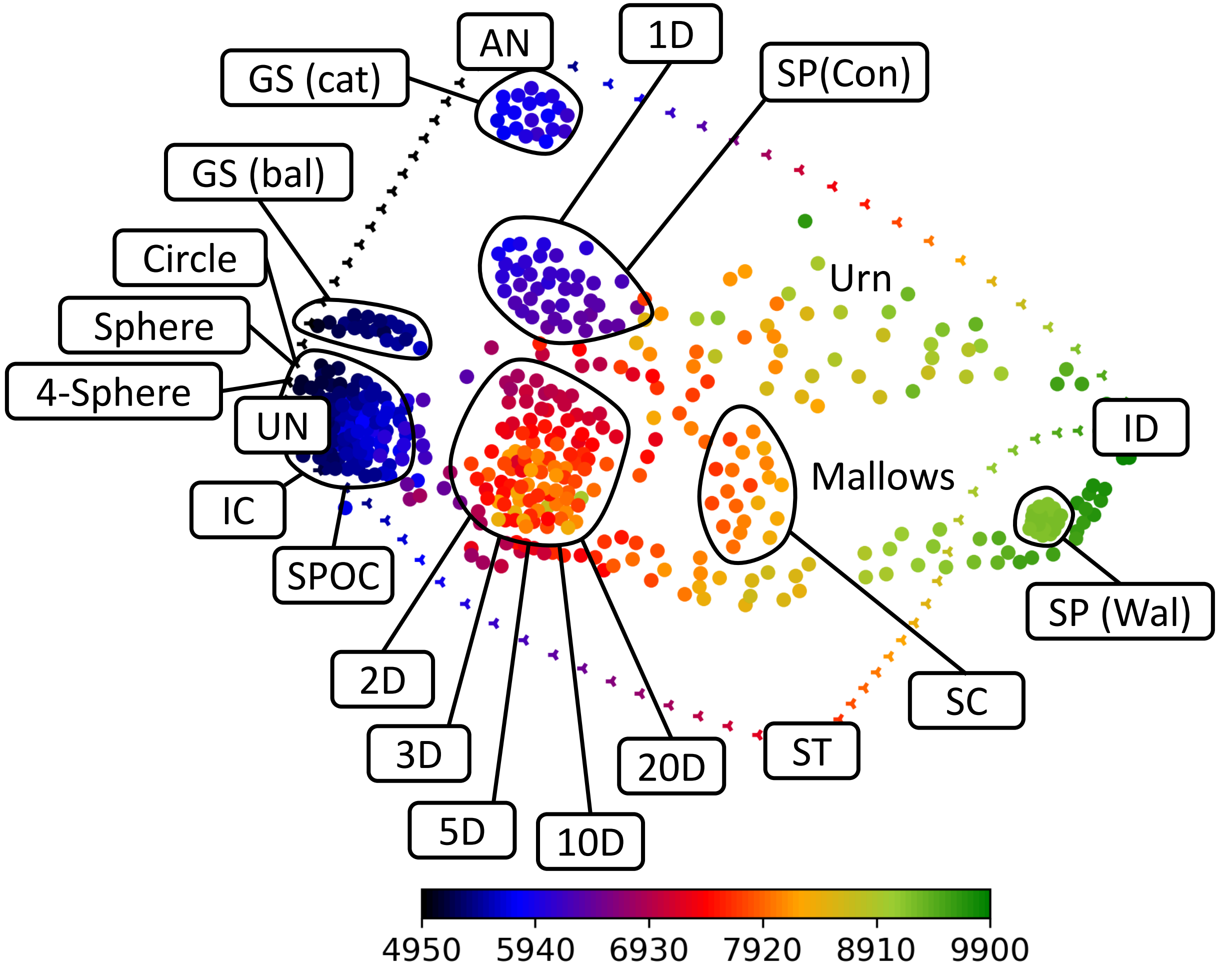
Winner Score

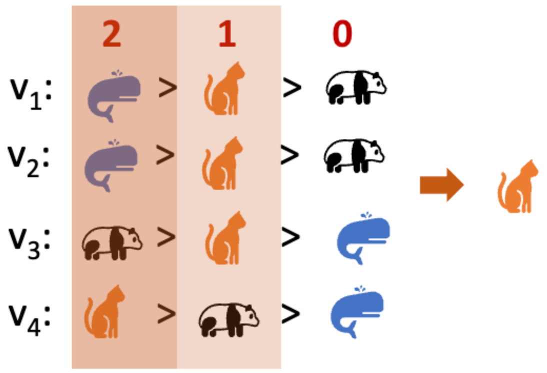
Visualizing Experiment Results





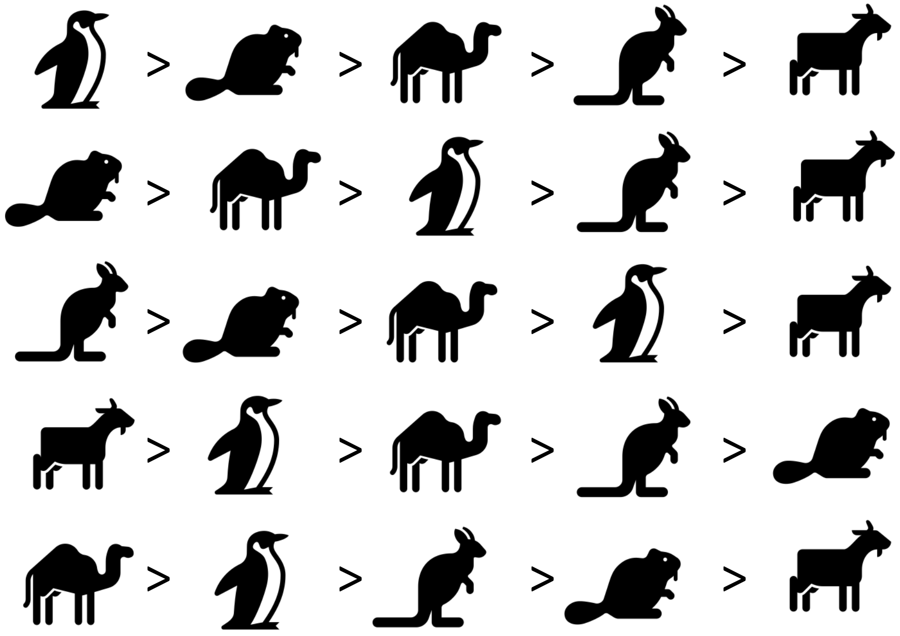
Highest Plurality Score

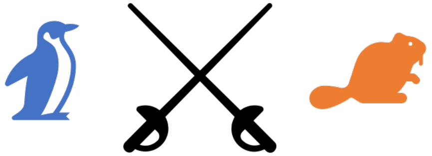




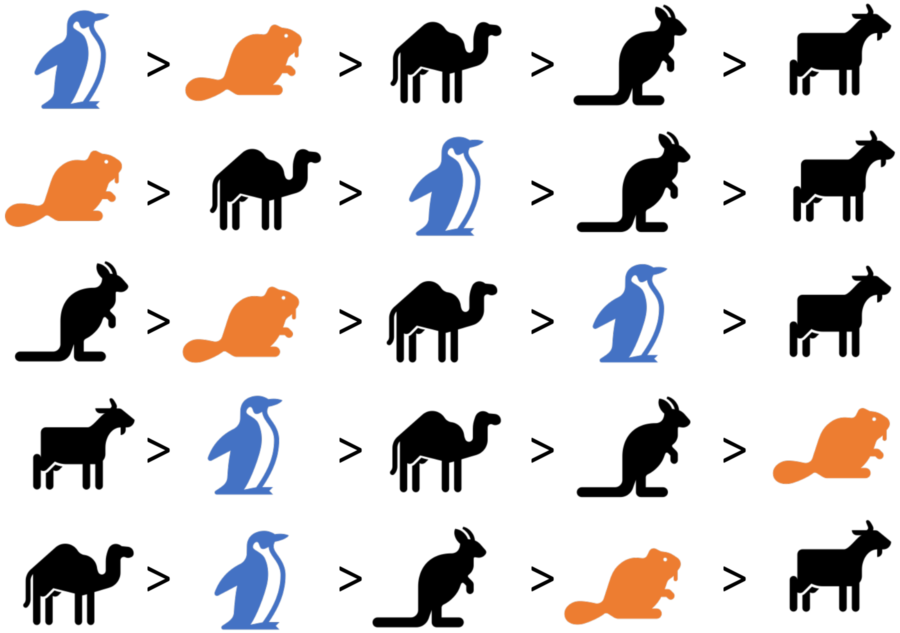
Highest Borda Score

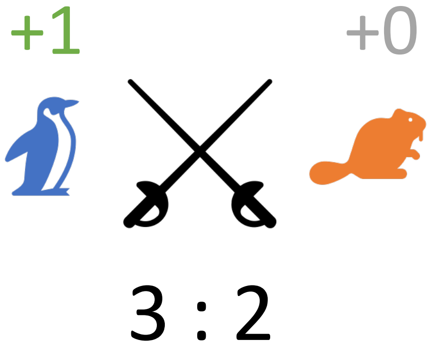
Copeland Rule



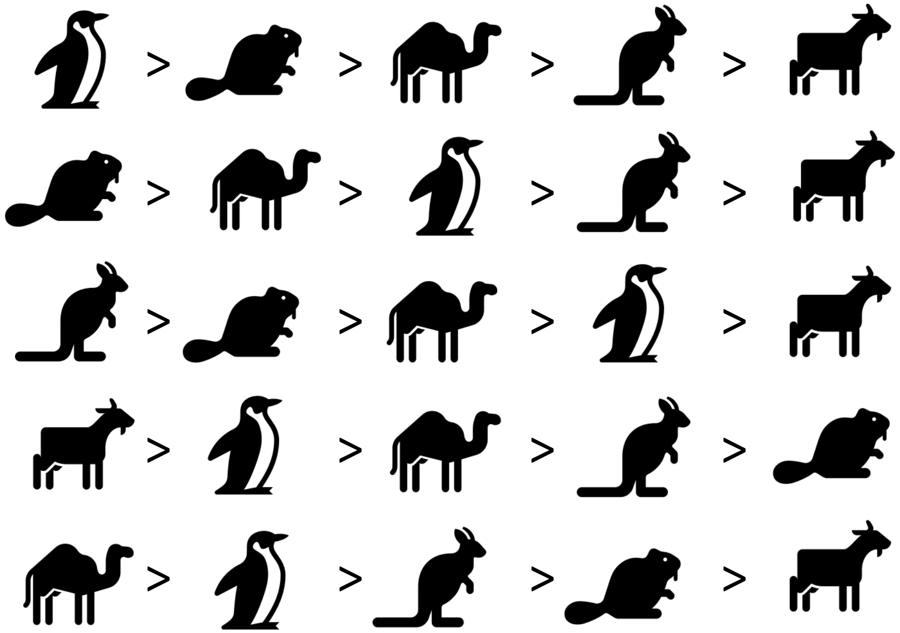


Copeland Rule

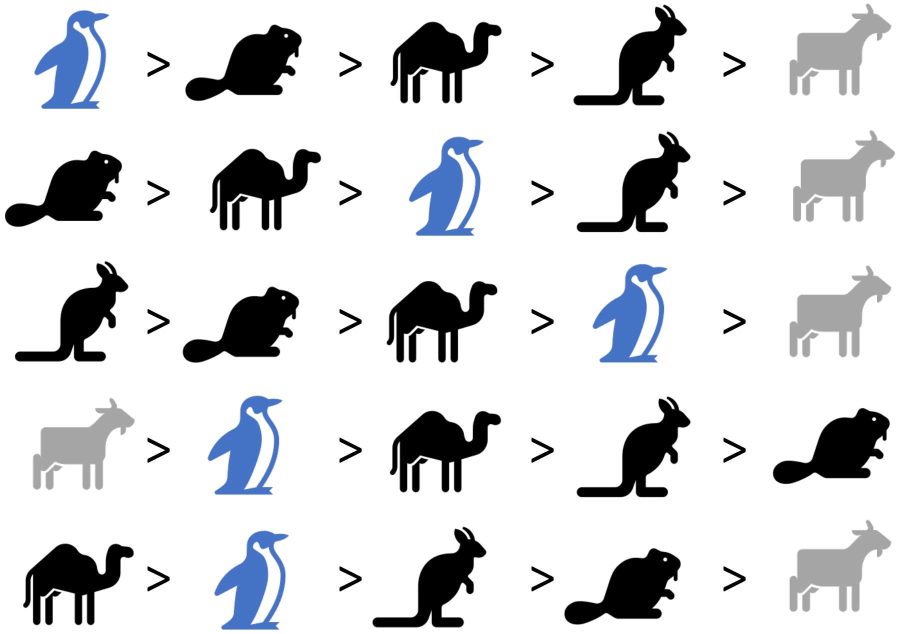




Copeland Rule

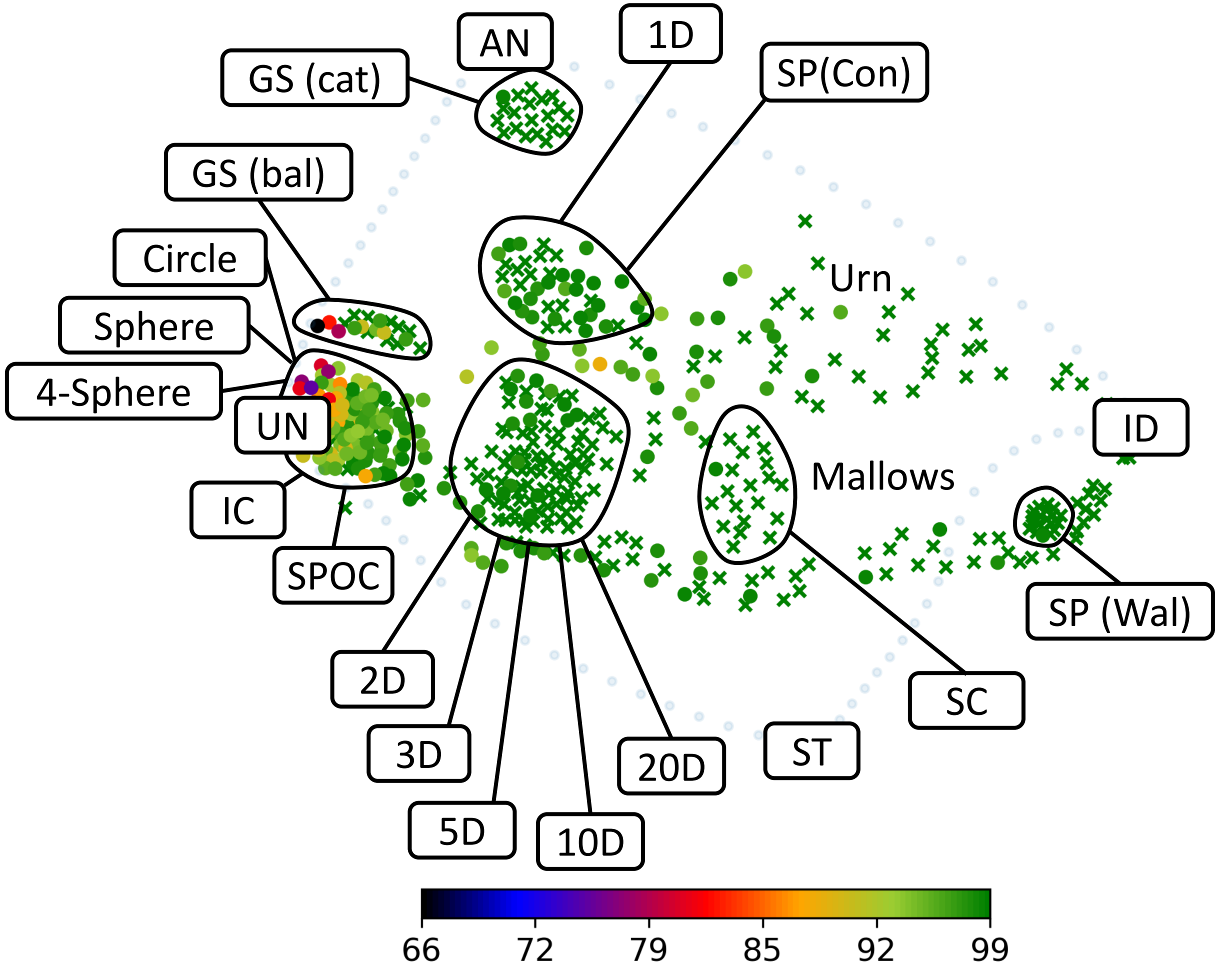


Copeland Rule



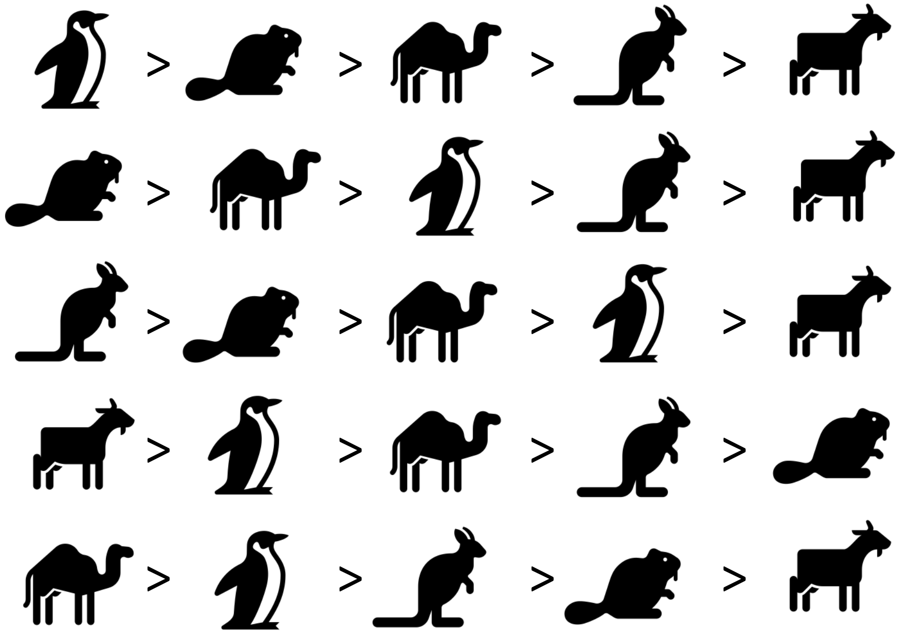
Condorcet winner
A candidate that wins all pairwise comparisons

The candidate with the highest score wins



Highest Copeland Score

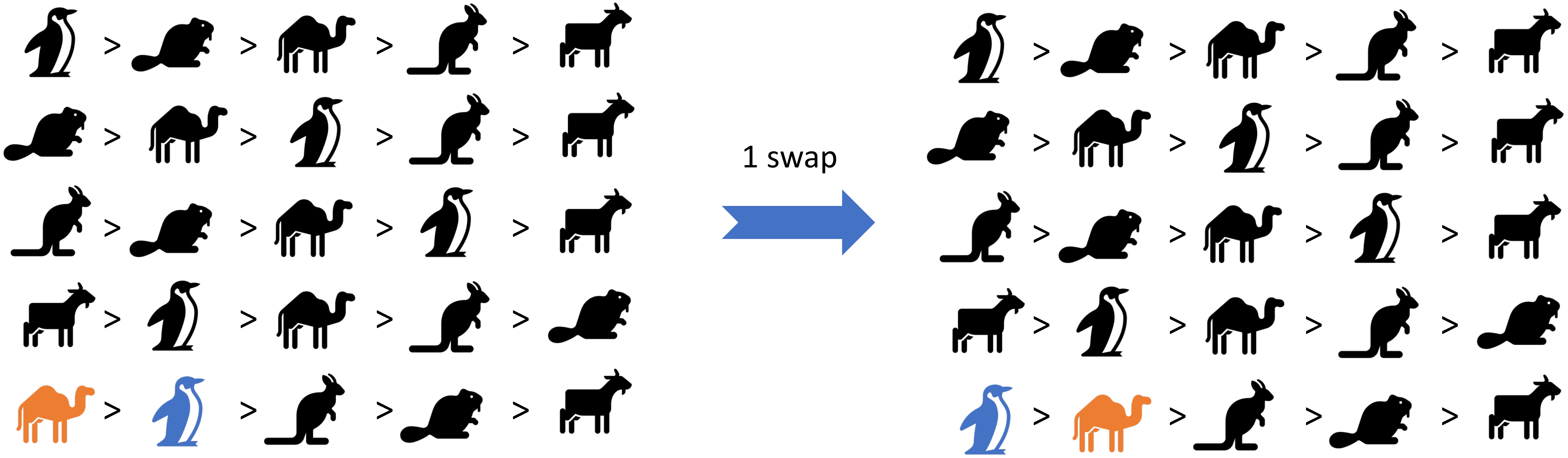
Dodgson Rule



Score of a candidate is the minimal number of swaps needed to make him or her a Condorcet winner

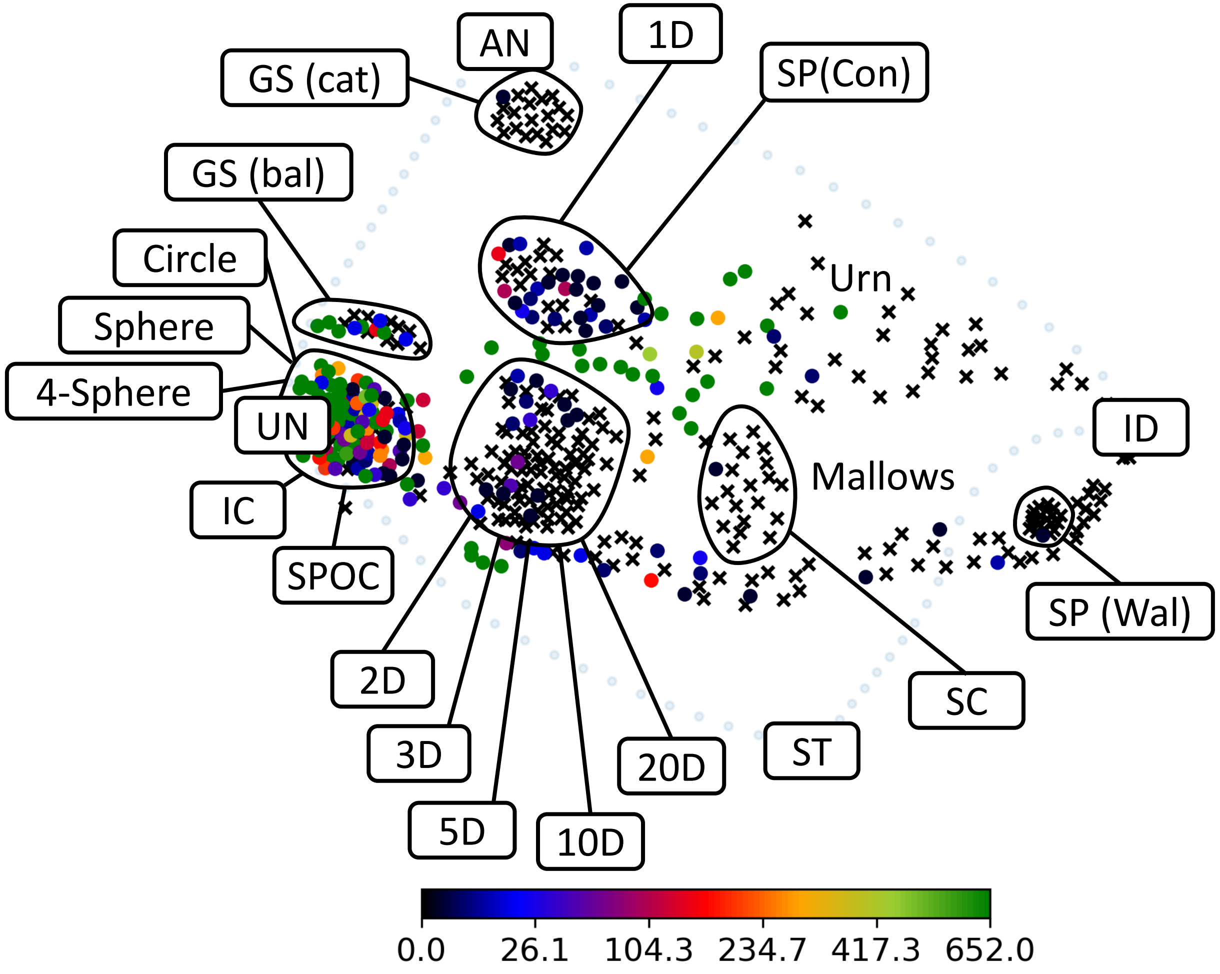
The candidate with the lowest score wins

Dodgson Rule



Score of a candidate is the minimal number of swaps needed to make him or her a Condorcet winner

The candidate with the lowest score wins

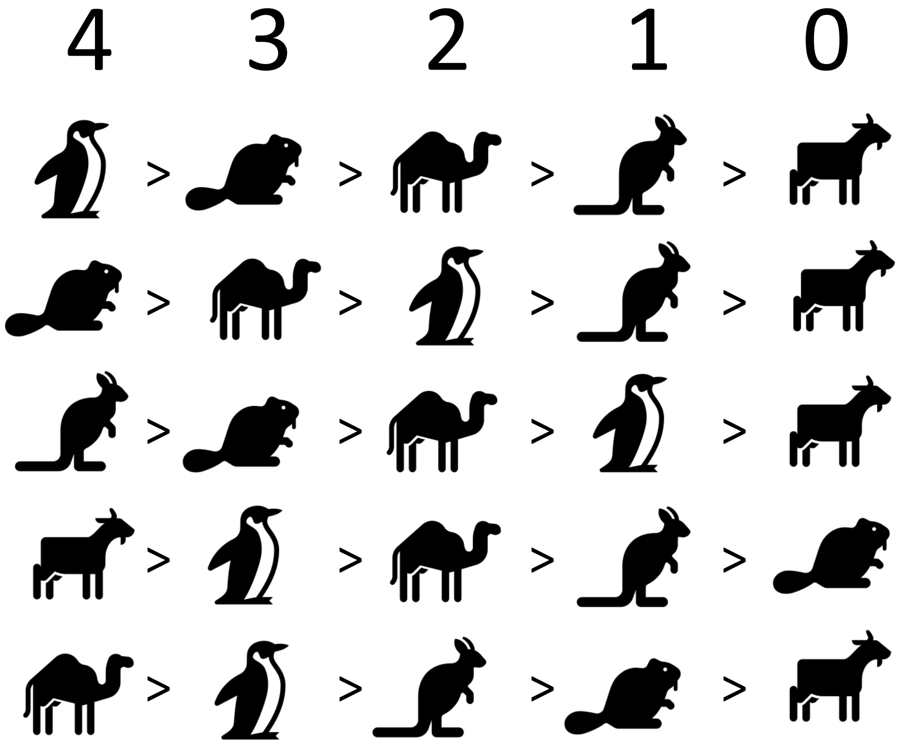


Lowest Dodgson Score

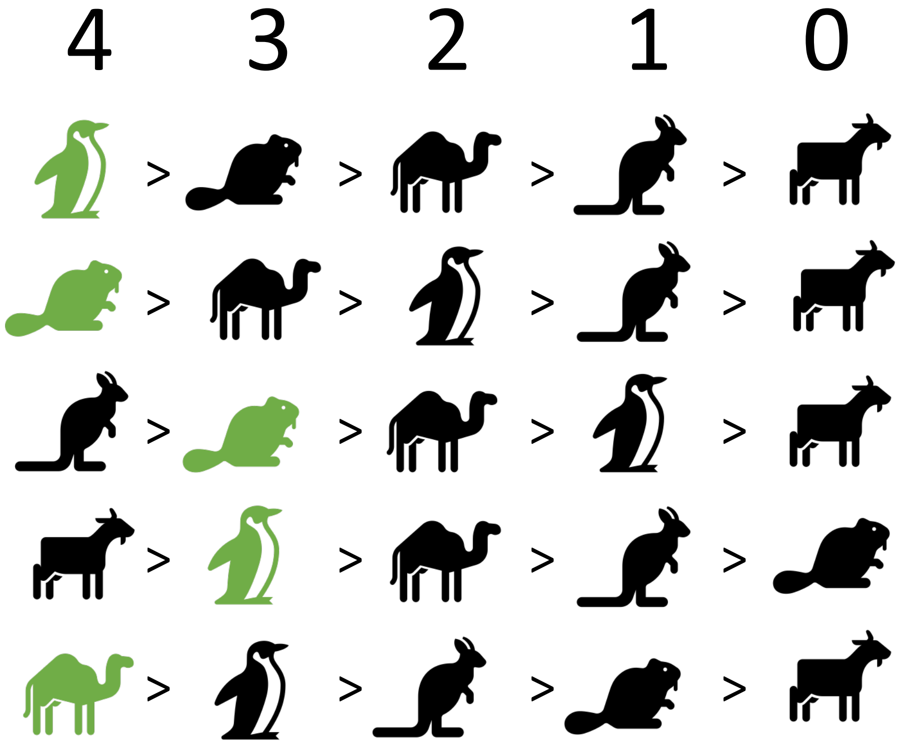
Winning Committee Score

Visualizing Experiment Results

Chamberlin—Courant (CC) Rule

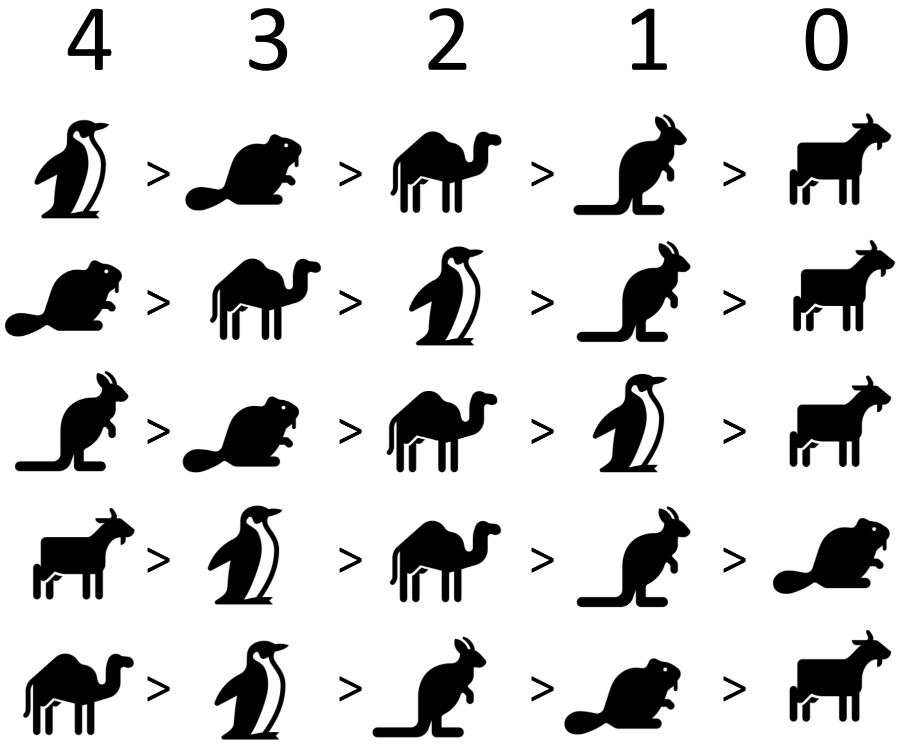


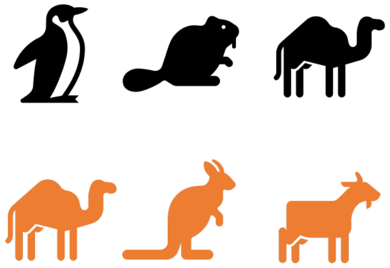
Chamberlin—Courant (CC) Rule



18 = 4+4+3+3+4

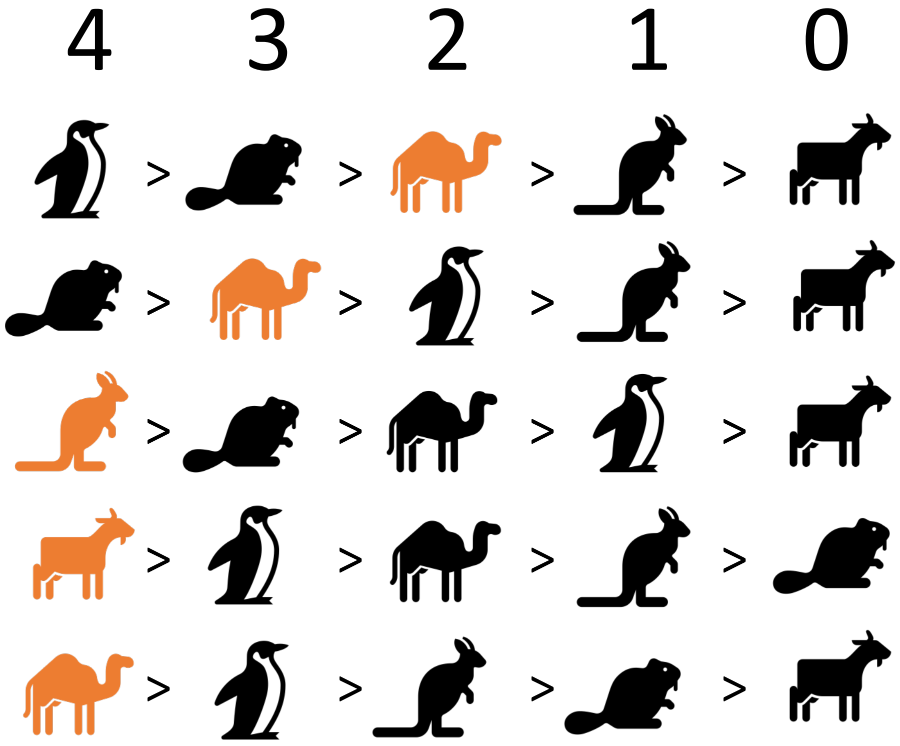
Chamberlin—Courant (CC) Rule

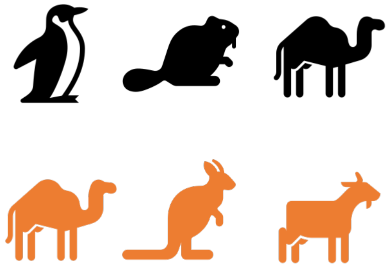




18 = 4+4+3+3+4

Chamberlin—Courant (CC) Rule

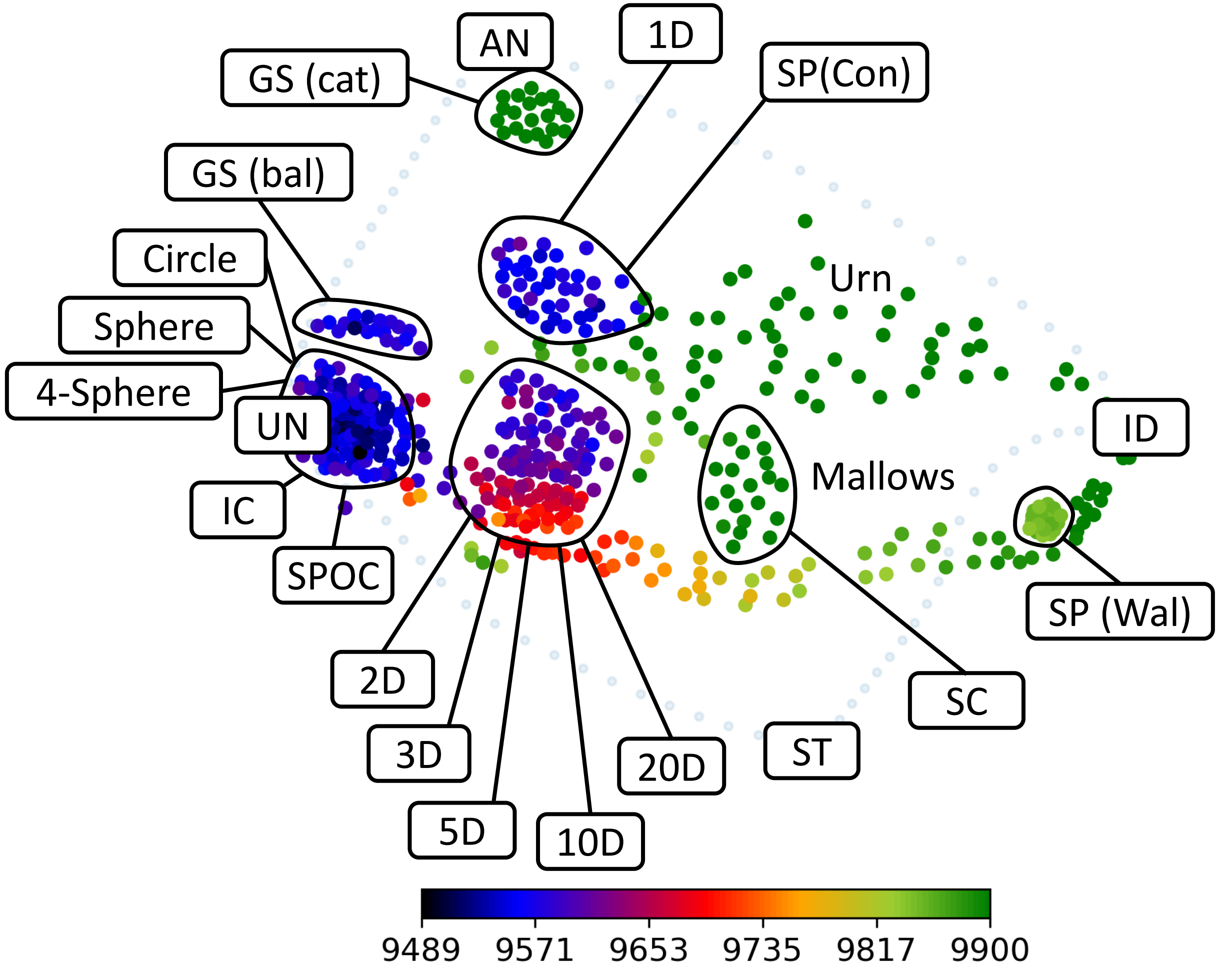




18 = 4+4+3+3+4

17 = 2+3+4+4+4

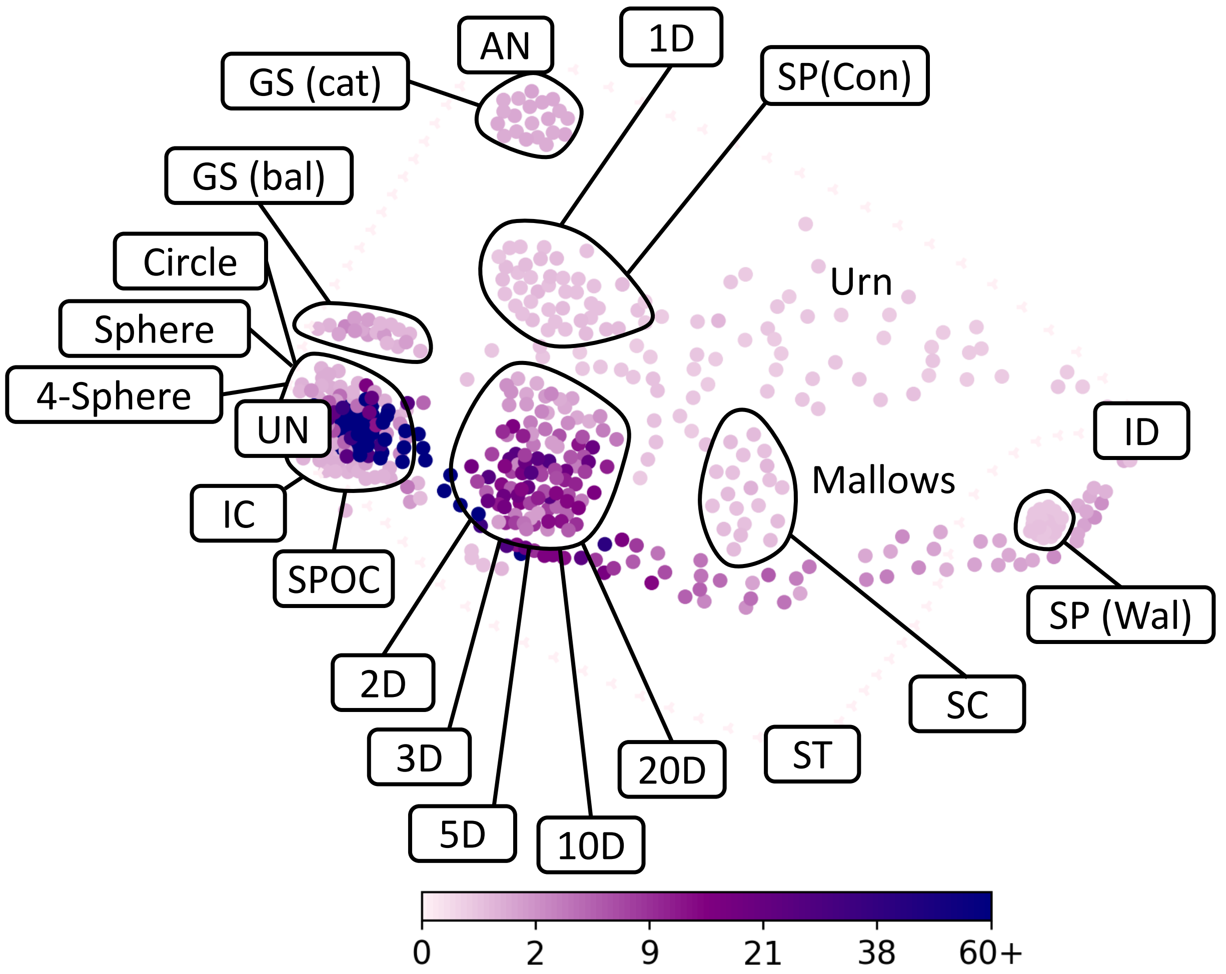
Committee with the highest score wins

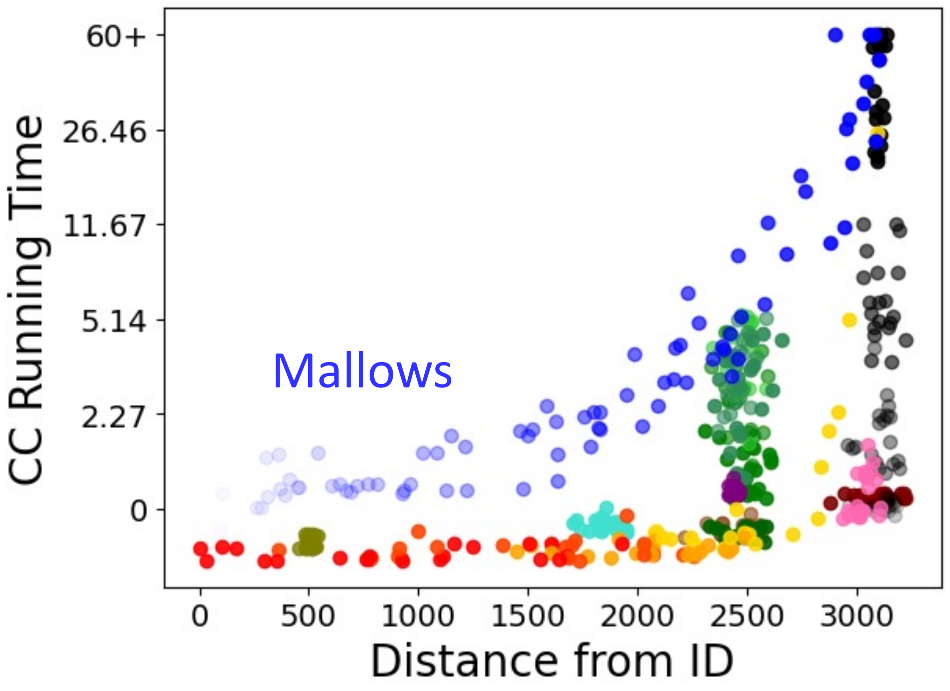


Highest CC Score

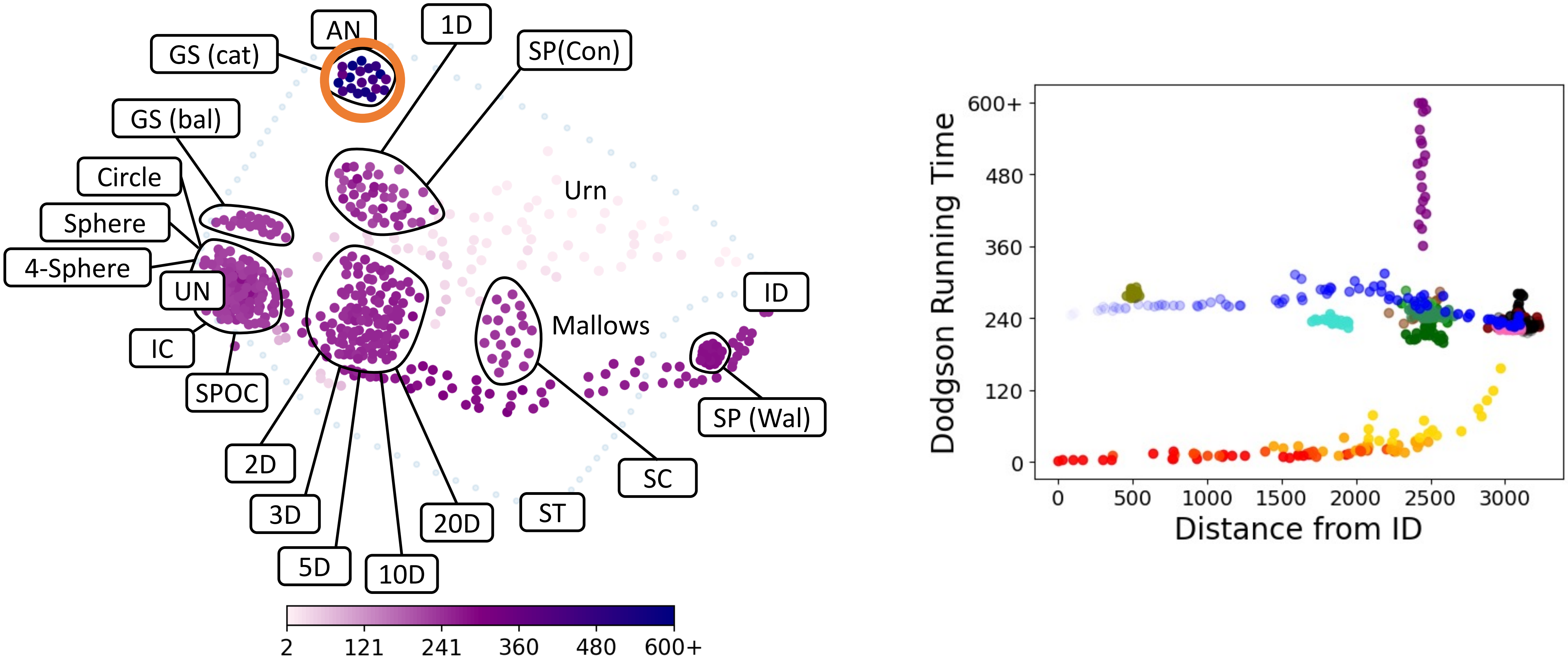
Running Time

Visualizing Experiment Results





CC - Running Time (in seconds)

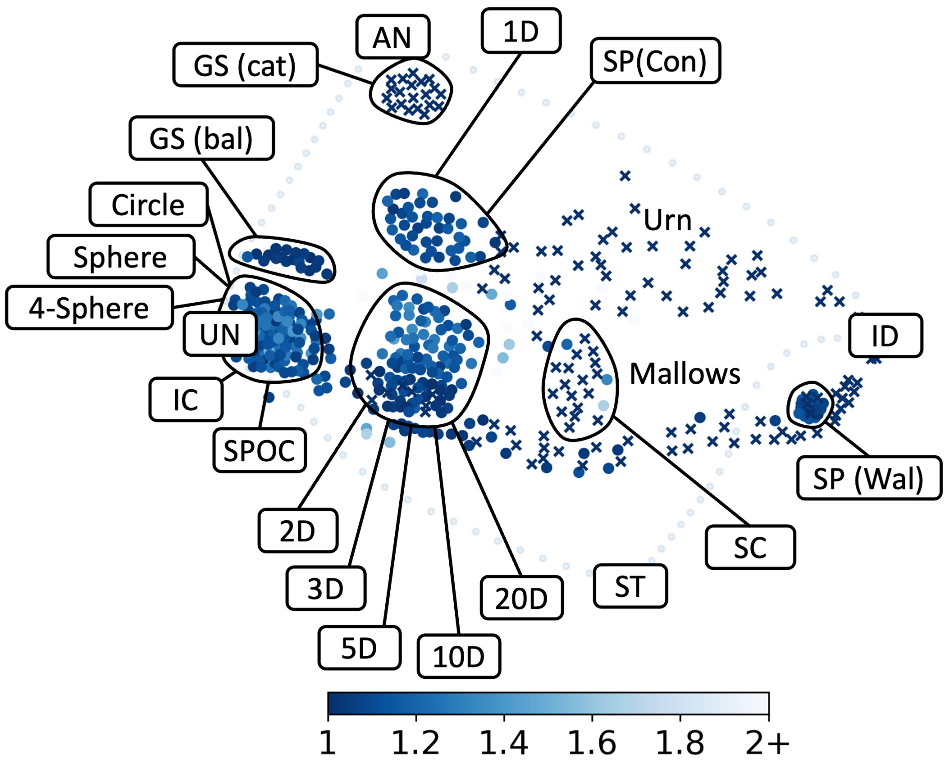


Dodgson - Running Time (in seconds)

Approximation Ratio

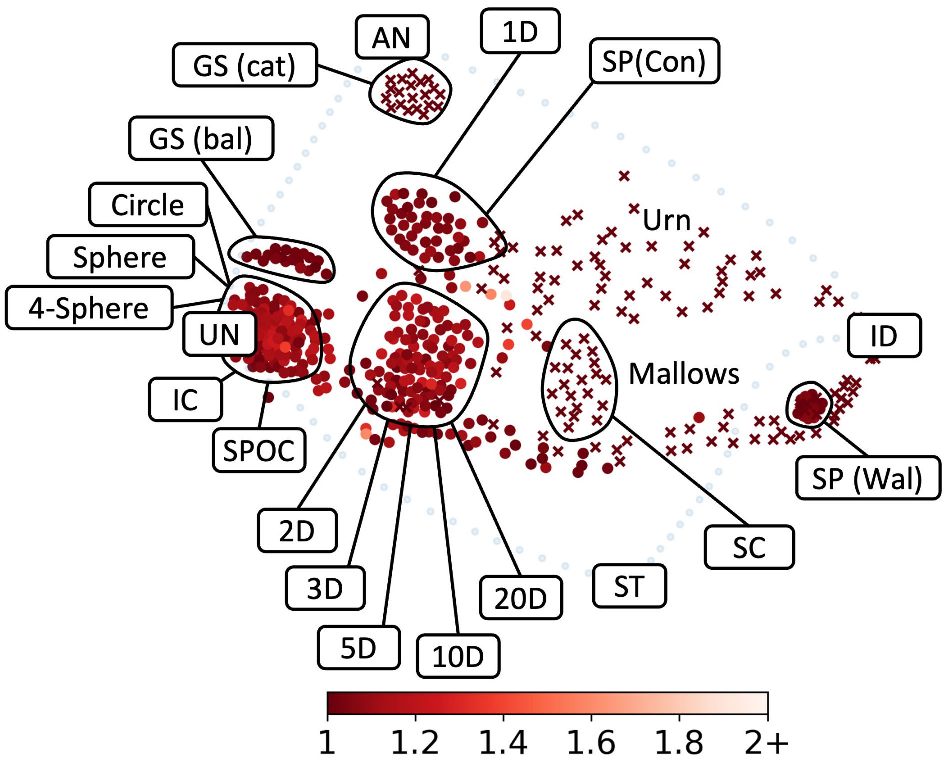
Visualizing Experiment Results

In each step, add the candidate
who increases the committee's score the most

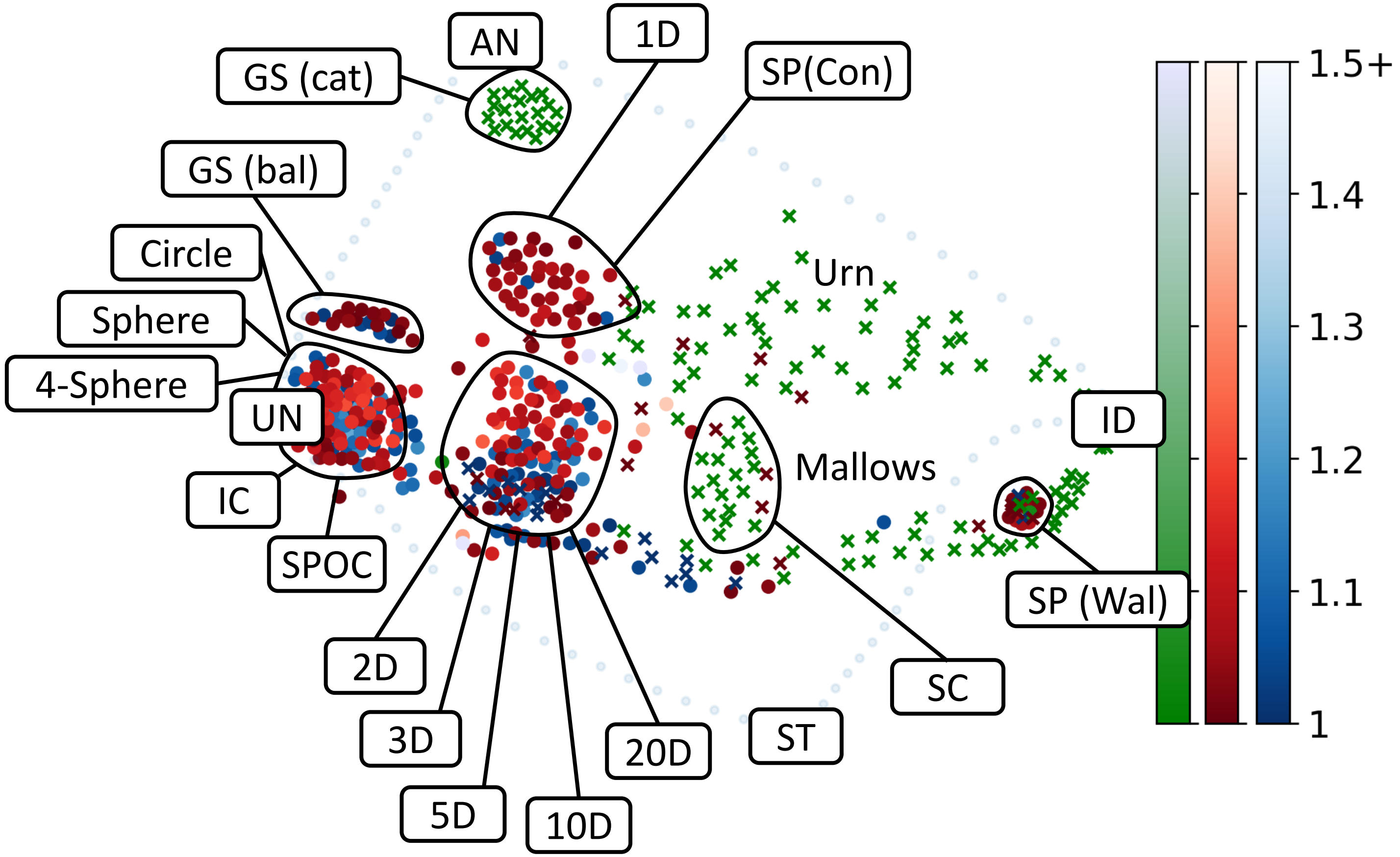


Sequential CC Approx. Ratio

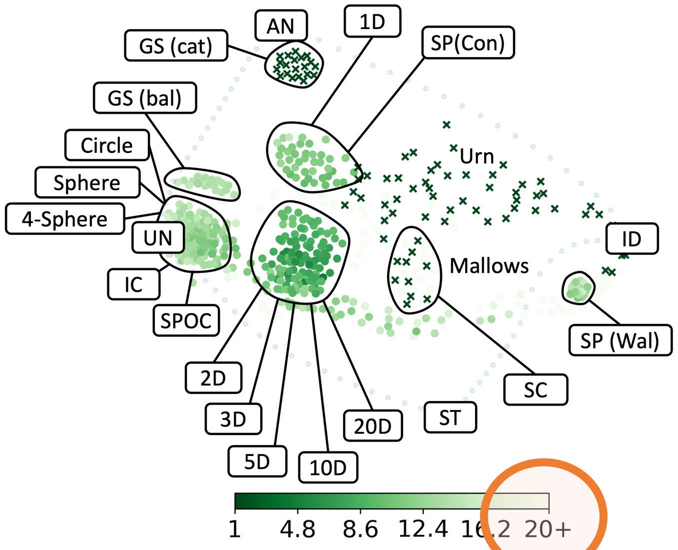
In each step, remove the candidate
who decreases the committee's score the least



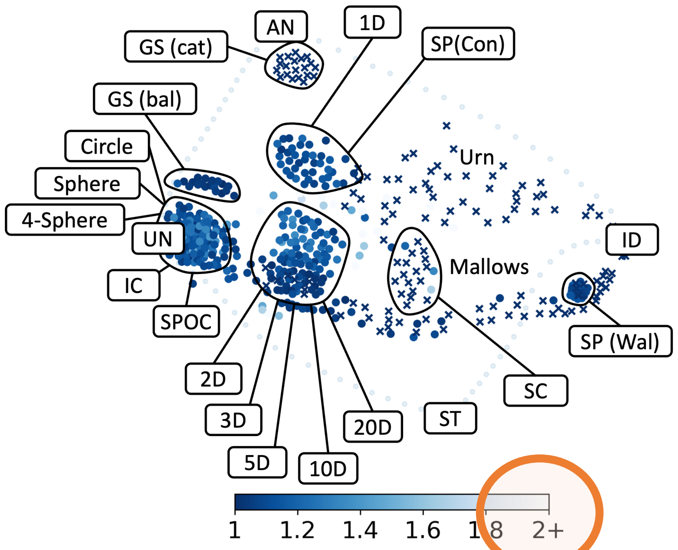
Removal CC Approx. Ratio



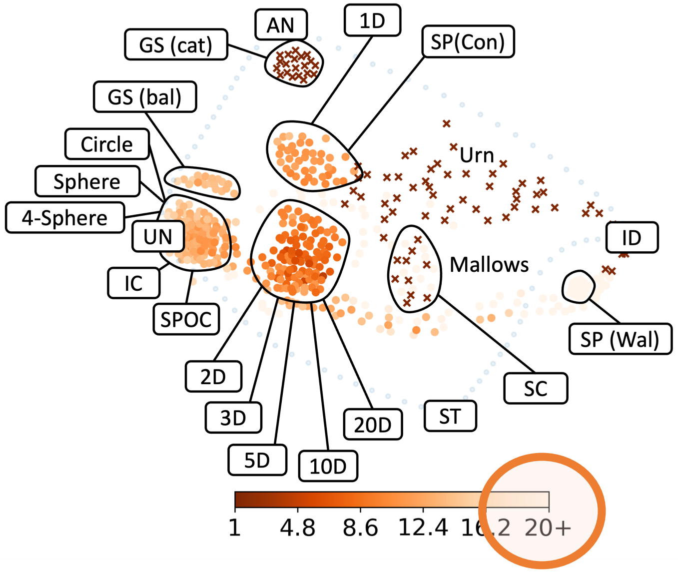
Sequential CC vs Removal CC



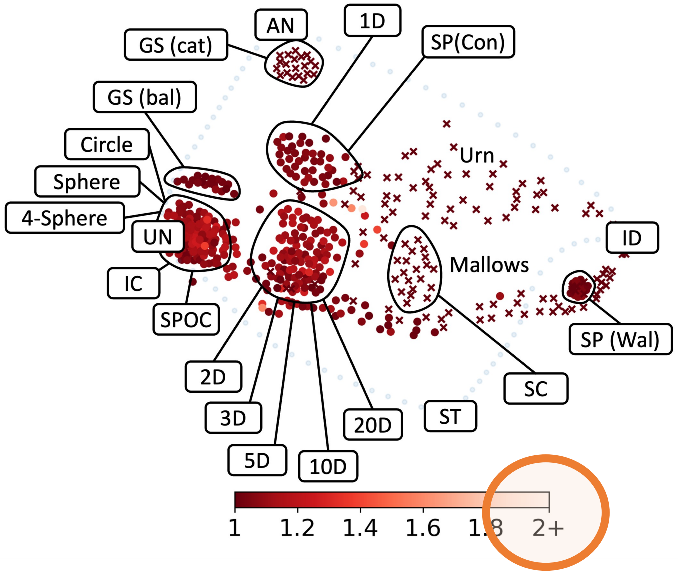
Banzhaf CC Approx. Ratio



Sequential CC Approx. Ratio



Ranging CC Approx. Ratio



Removal CC Approx. Ratio

Collecting, Classifying, Analyzing, and Using Real-World Ranking Data, Boehmer and Schaar, AAMAS-23

Putting a Compass on the Map of Elections, Boehmer et al., IJCAI-21

PrefLib: A Library for Preferences http://www.preflib.org, Mattei and Walsh, ADT-13

10 minutes

Putting Real-World Elections on the Map

Preflib Data

PrefLib ID	Name	Type	#Elections	Avg. m	Avg. n	Avg. Inc
1	Irish	political	3	11.67	46003.67	0.39
2	Debian	survey	8	6.25	419	0.08
3	NASA	survey	1	32	10	0.1
4	Netflix	user ratings	200	3.5	818.79	0.0
5	Burlington	political	2	6	9384	0.27
6	Skate	survey	48	23.31	8.67	0.0
7	ERS	association	87	8.74	409.31	0.25
8	Glasgow	political	21	9.9	8970.29	0.5
9	AGH	survey	2	8	149.5	0.0
10	Ski	sport	2	260.5	4	0.23
11	Web	meta-search	77	1874.74	4.04	0.36
12	T-Shirt	survey	1	11	30	0.0
14	Sushi	survey	1	10	5000	0.0
15	Clean Web	meta-search	79	78.15	4.04	0.0
16	Aspen	political	2	8	2502	0.26
17	Berkley	political	1	4	4173	0.13
18	Minneapolis	political	4	218	34370.5	0.76
19	Oakland	political	7	7	52449.29	0.39
20	Pierce	political	4	5	188627	0.29
21	San Francisco (sf)	political	14	10.43	61635.79	0.51
22	San Leandro (sl)	political	3	5.33	23666	0.27
23	Takoma Park	political	1	4	204	0.13
24	Mechanical Turk dots	human tests	4	4	795.75	0.0
25	Mechanical Turk puzzle	human tests	4	4	795	0.0
26	French Presidental	political	6	16	430.83	0.68
27	Proto French	political	1	15	398	0.7
28	APA	association	12	5	16991.33	0.16
30	UK Labor Leadership	political	1	5	266	0.21
31	Vermont	political	15	3.93	1160.73	0.42
32	Education Survey	survey	7	13.57	21.86	0.39
33	San Sebastian Poster	survey	2	17	61.5	0.59
34	Cities	survey	2	42	392	0.73
35	Breakfast Items	survey	6	15	42	0.0
57	Austrian Parliamentary	political	9	12.22	4792773.11	0.84

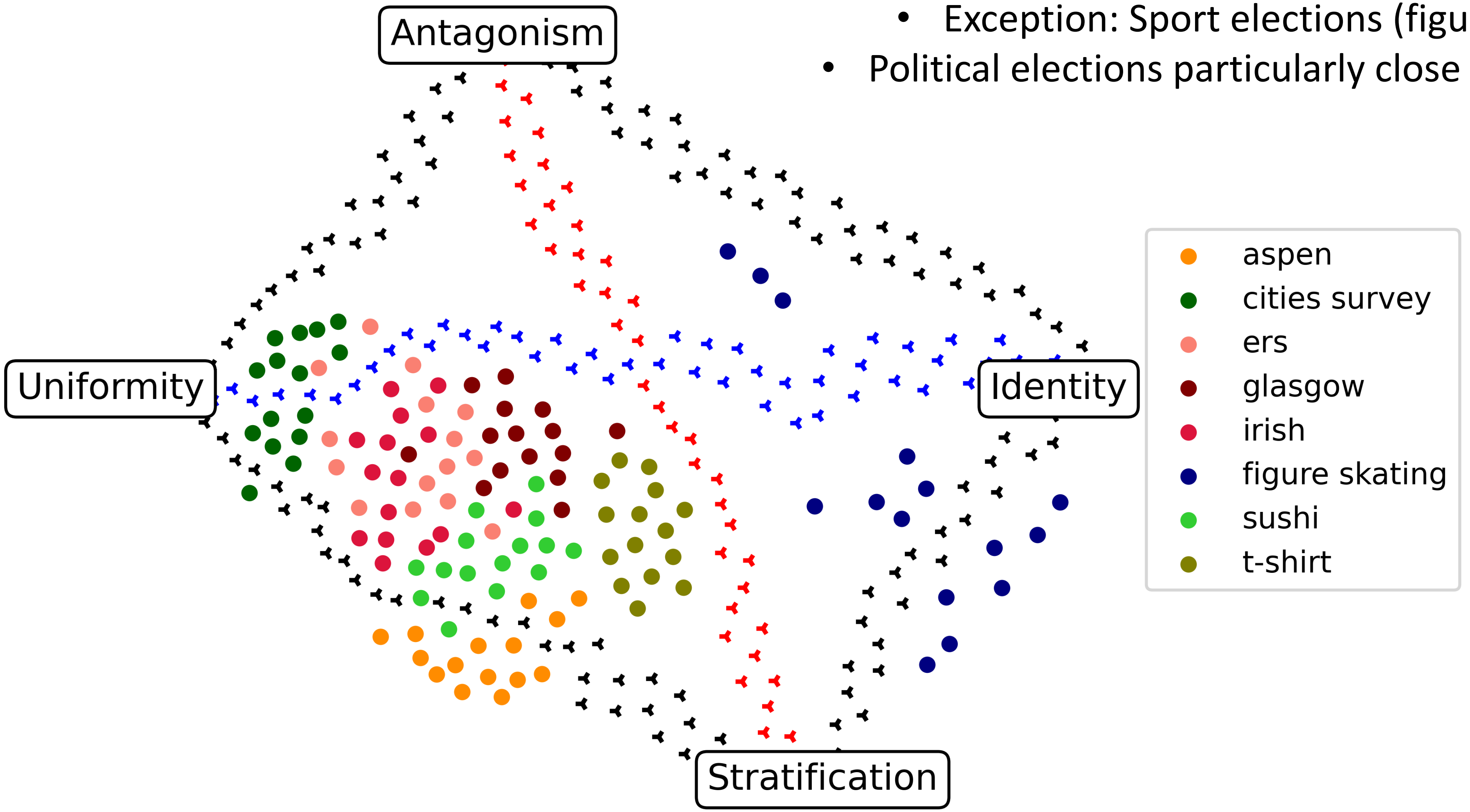
637 elections from 35 datasets:
- Humans expressing opinions concerning candidates for a position (political, association)
- Humans expressing preferences over objects (survey, user ratings)
- Humans ranking items in a test (human tests)

Decisive features:
- Typcially below 10 candidates or below 10 voters.
- Often highly incomplete votes, voters typically rank only small subset of candidates.

Usable for map:
Irish, Skate, ERS, Glasgow, T-Shirt, Sushi, Aspen, and Cities

Map of Preflib Elections

- Most elections fall in bottom left
    - Exception: Sport elections (figure skating)
- Political elections particularly close to each other



A Second Datasource

Collecting, Classifying, Analyzing, and Using Real-World Ranking Data, AAMAS 2023.

Time-Based Elections

- Multi-race competitions (Formula 1 season/Tour de France)
- Top-x rankings at different times (Spotify, boxing, tennis top 100, american football)

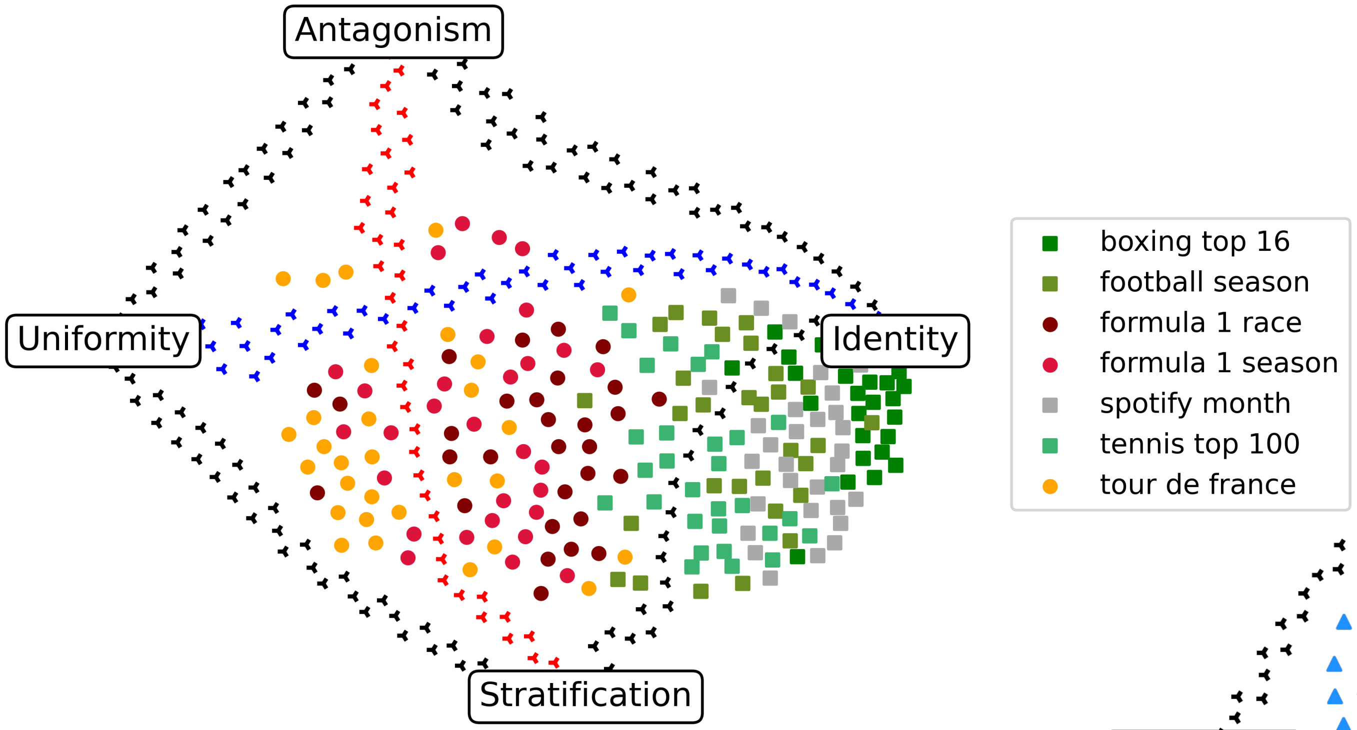
…

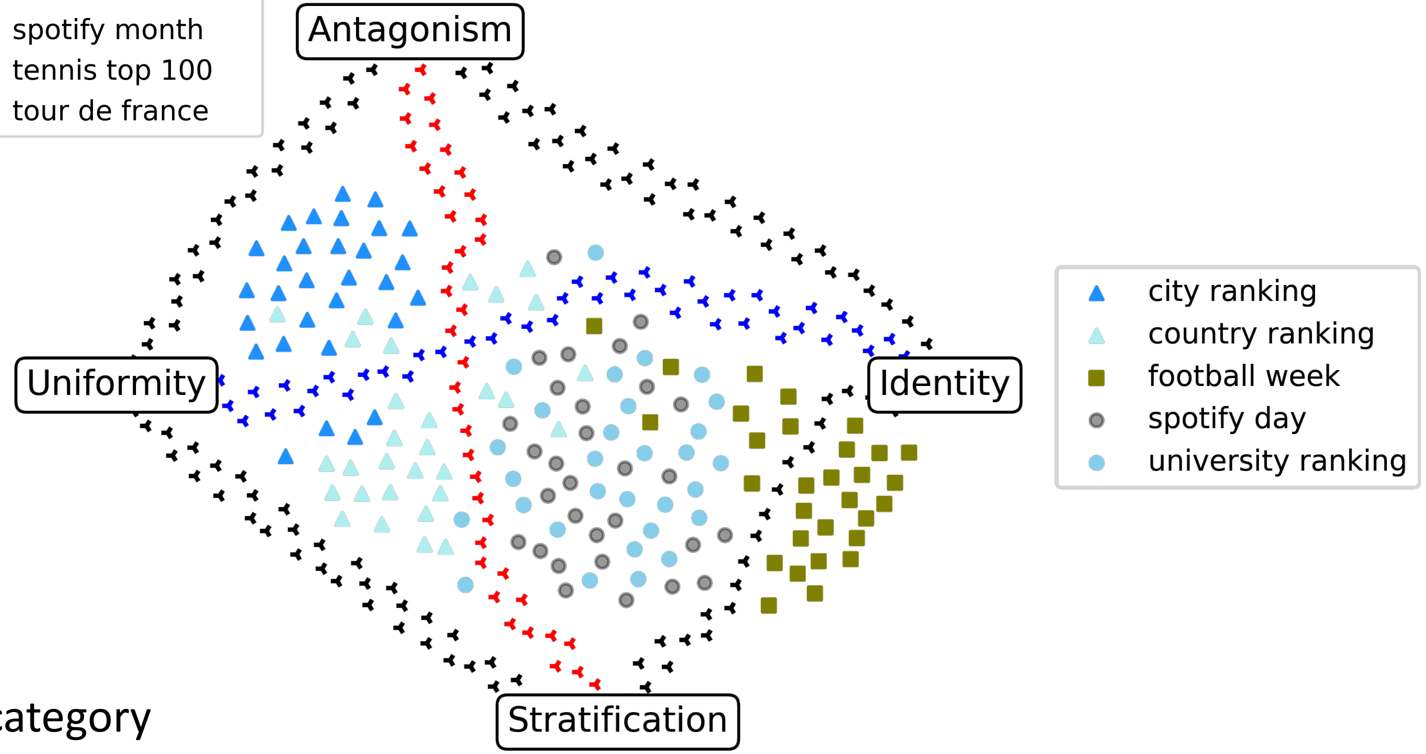
Criterion-Based Elections

- Indicator-based rankings (cities, countries, universities)
- Top-x rankings from different sources (Spotify, american football)

…

Map of Real-World Elections

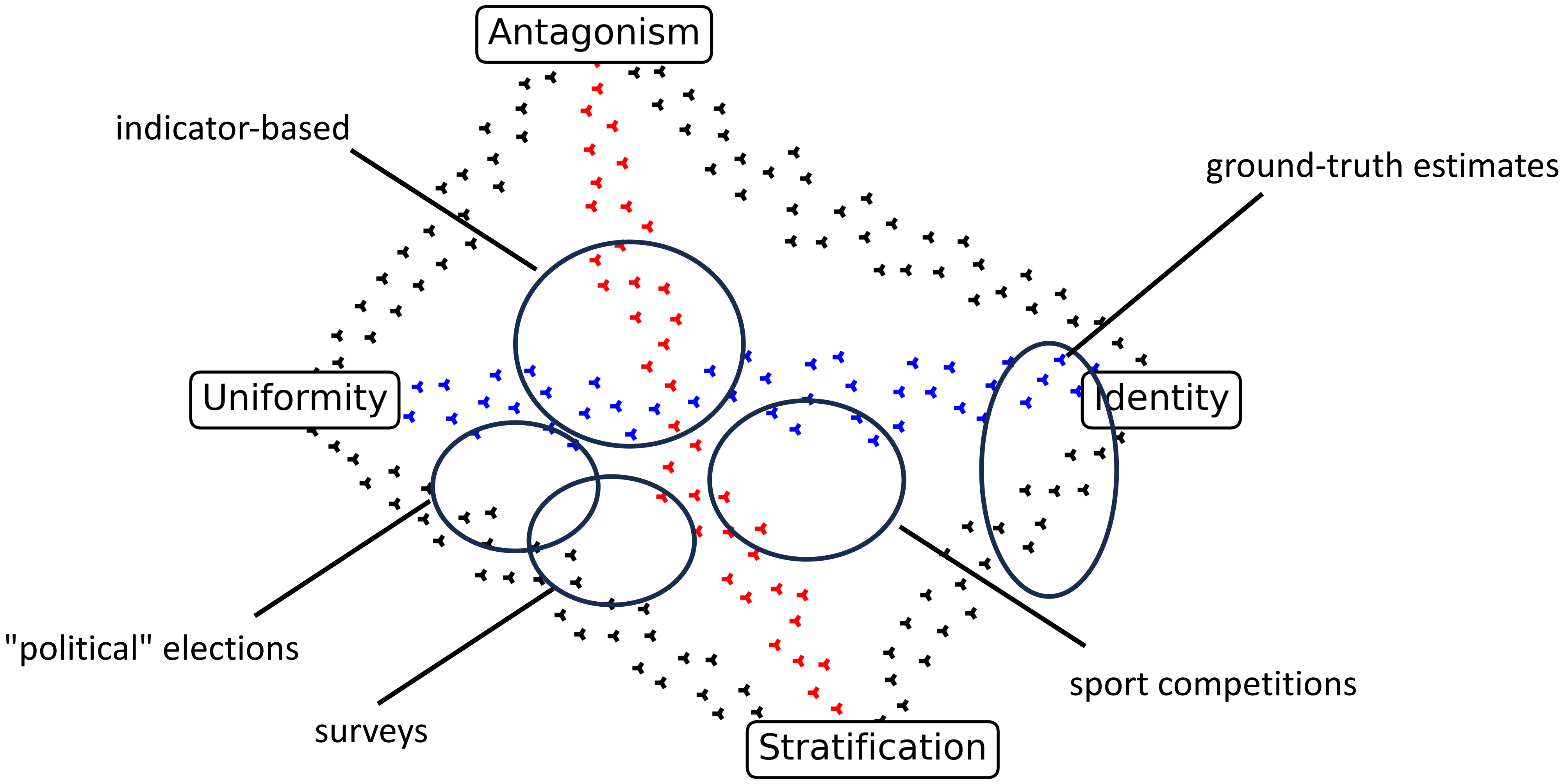




■ Close to Identity elections (mostly time-based)
● Elections from "the middle"
▲ "Outliers" closer to Uniformity

→ very consistent behavior of data sources from one category

Different Types of Real-World Elections

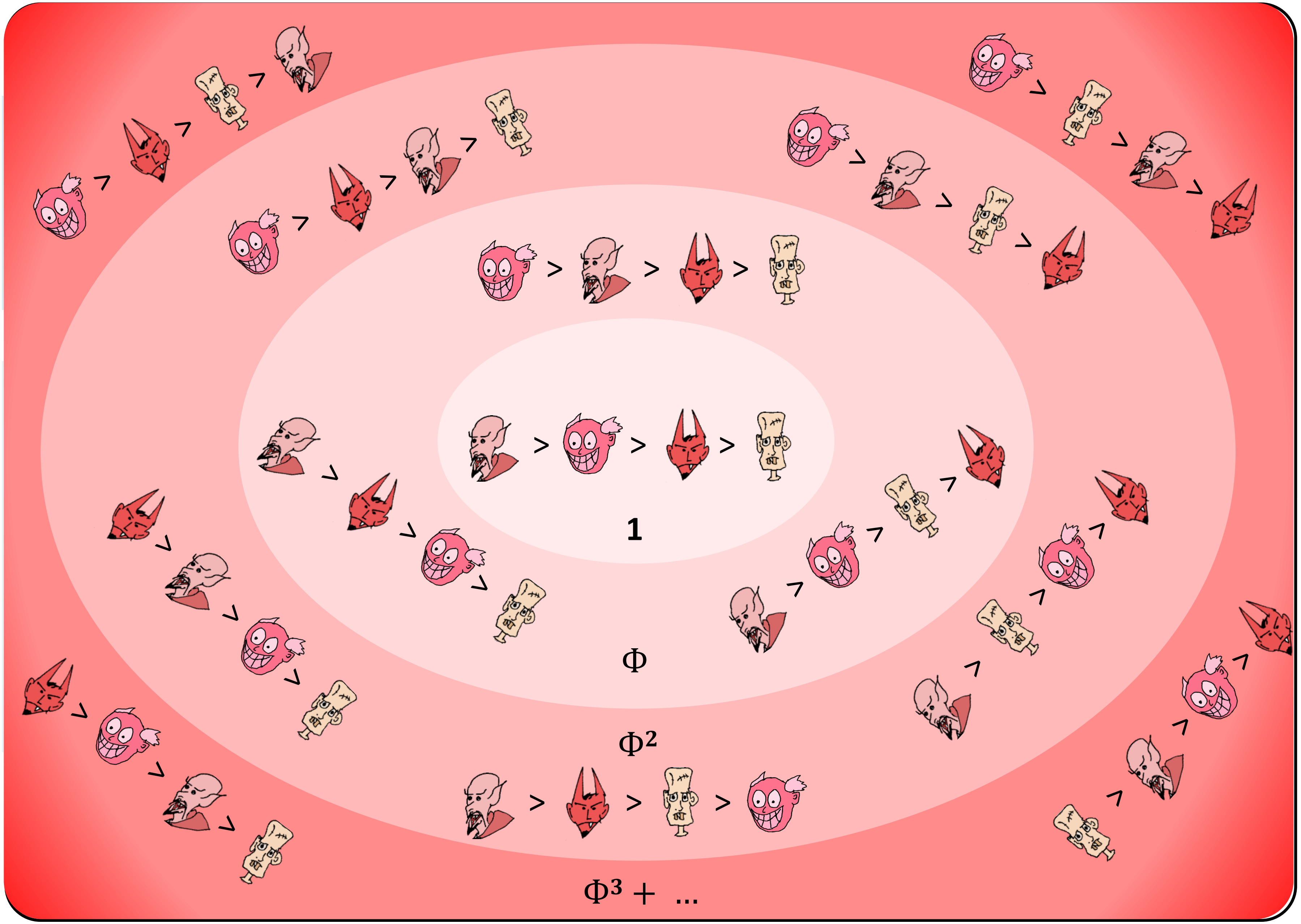


Putting a Compass on the Map of Elections, Boehmer et al., IJCAI-21

Properties of the Mallows Model Depending on the Number of Alternatives: A Warning for an Experimentalist, Boehmer et al., ICMl-23

15 minutes

Using the Map to Generate Realistic Data: (Normalized) Mallows Model



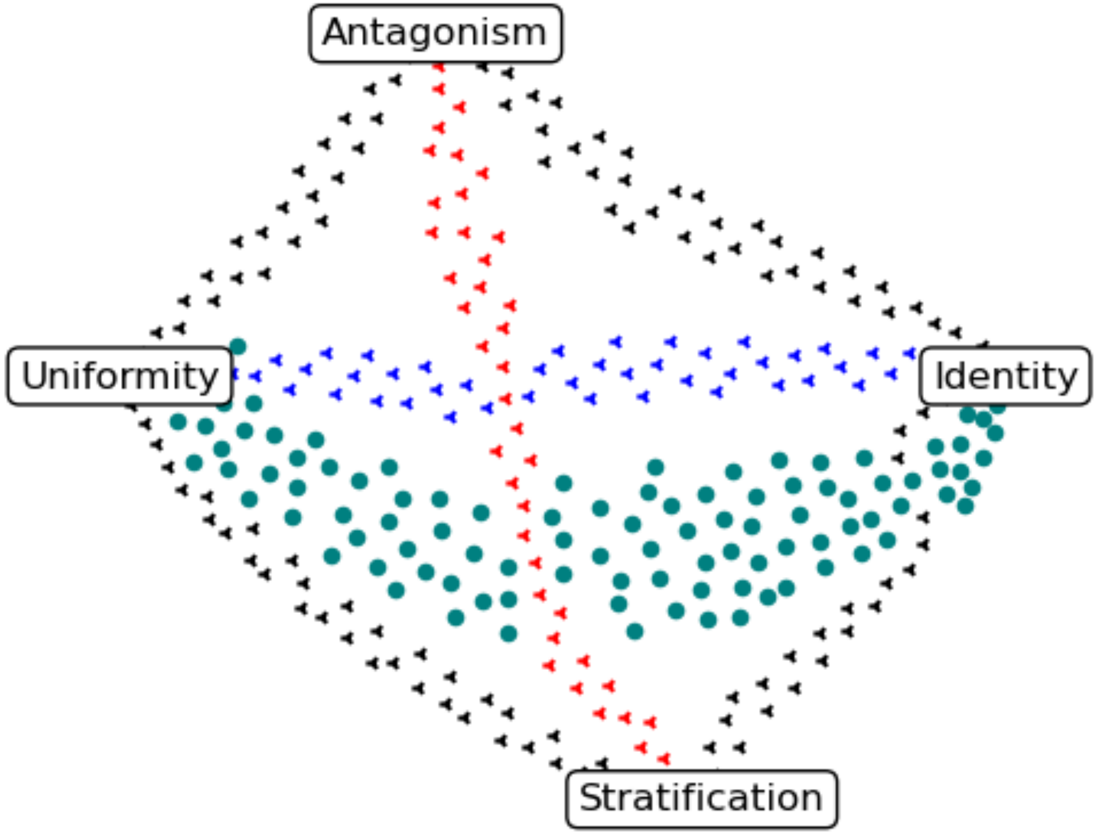
Mallows Model

Input
Central vote v* + dispersion paramter φ

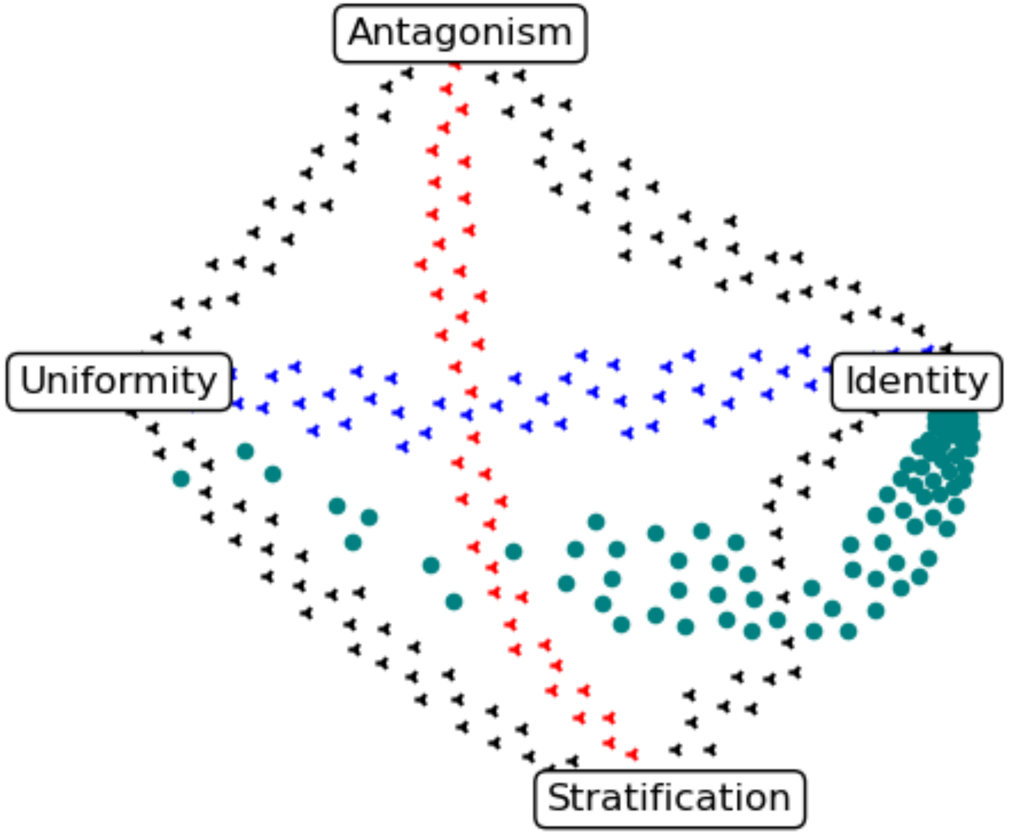
Sampling
Probability of sampling vote v proportional to:

$$\varphi^{swap(v,v^*)}$$

Mallows Model with Uniformly Sampled φ

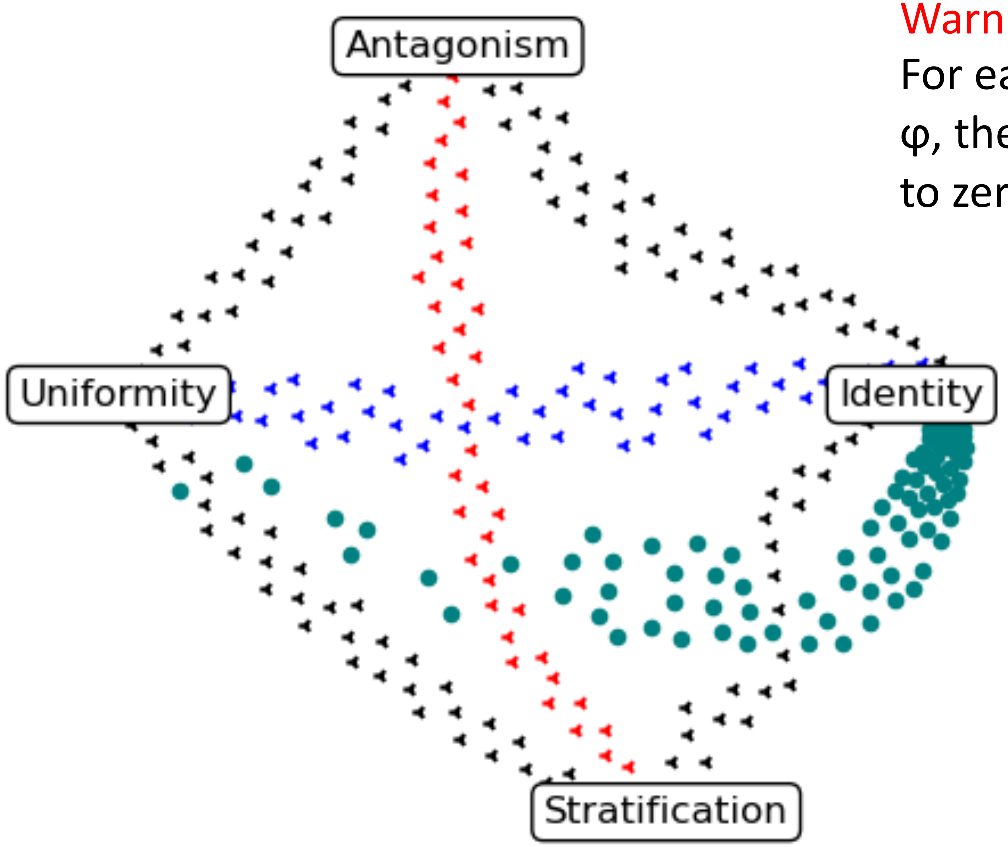


100 voters and 10 candidates



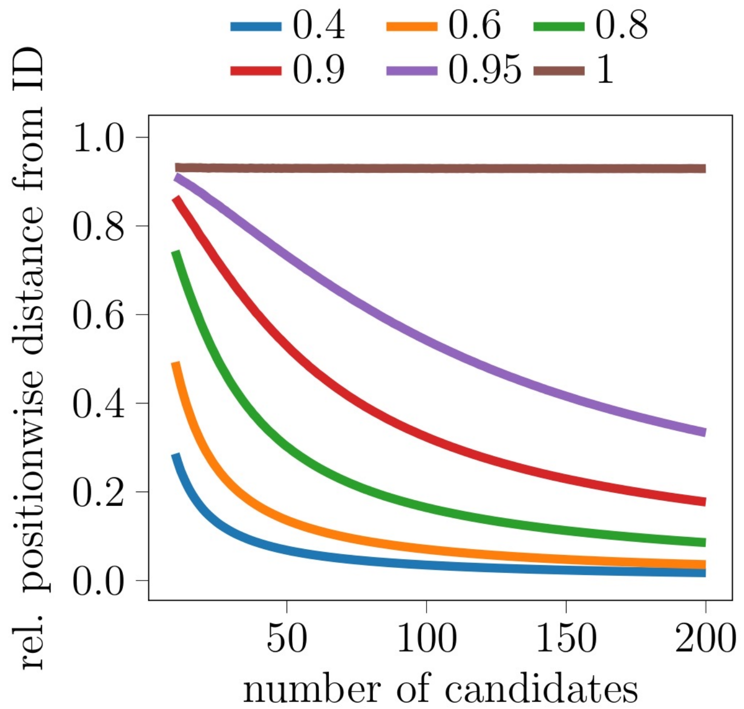
100 voters and 50 candidates

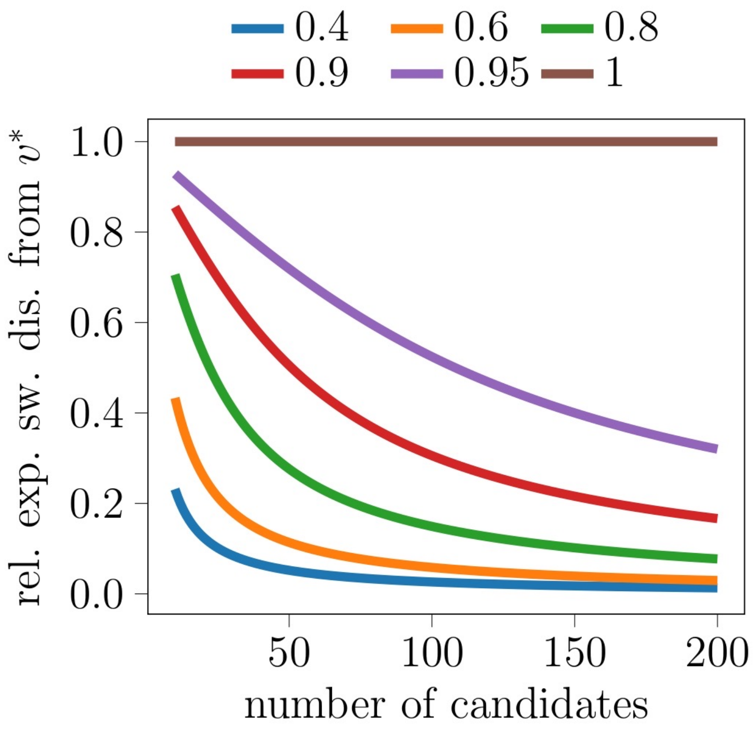
Mallows Model with Uniformly Sampled φ



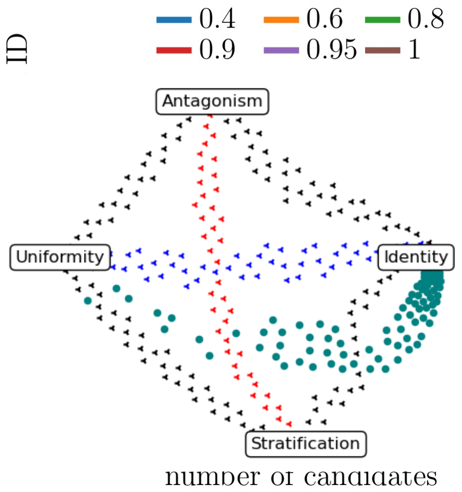
100 voters and 50 candidates

Warning
For each fixed dispersion parameter φ, the relative distance to ID goes to zero.





Problems with Mallows Model



Common Implicit Assumptions

Evidence

A fixed dispersion parameter produces "structurally similar" elections for different candidate numbers.

⇨ Fixed dispersion parameter for different candidate numbers in one experiment.

A uniformly at random chosen dispersion parameter "uniformly covers" the space between identity and uniformity.

⇨ Don’t know what dispersion to use? Just choose uniformly at random, it’s the *natural* agnostic choice.

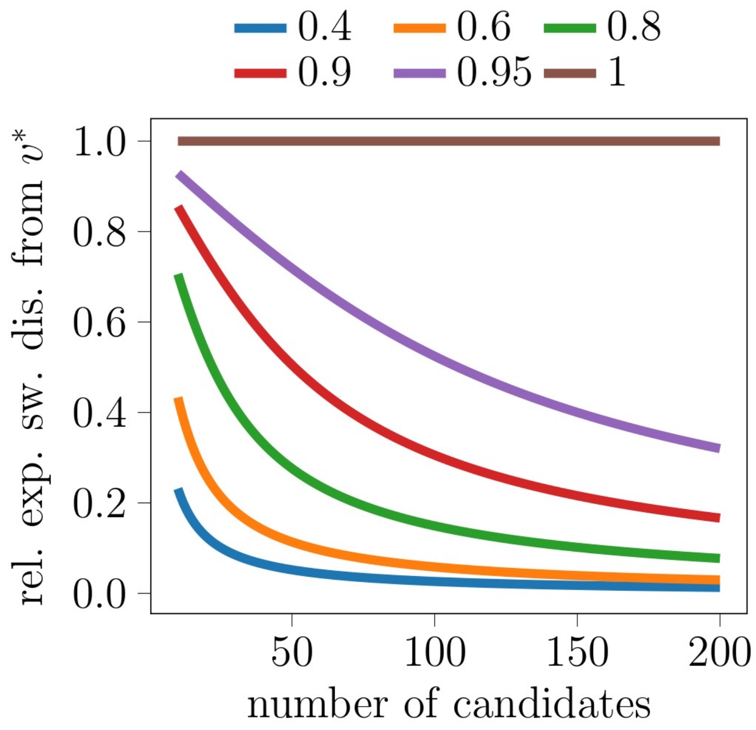
⇩

Possibility for methodological errors!

What Can We Do?

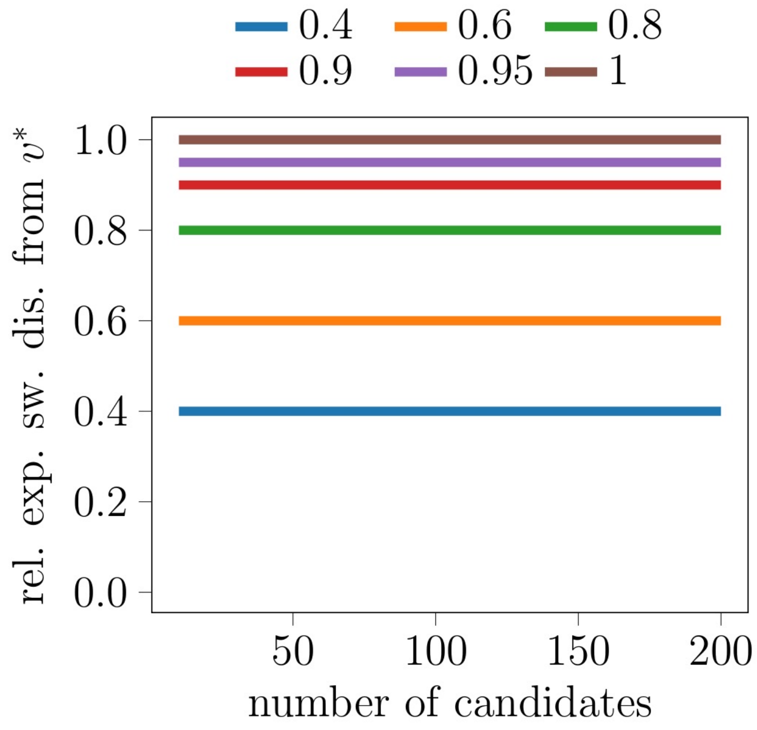
Mallows Model

Sampled votes become more and more similar to central one



Normalized Mallows Model

Keep expected swap distance from central order fixed



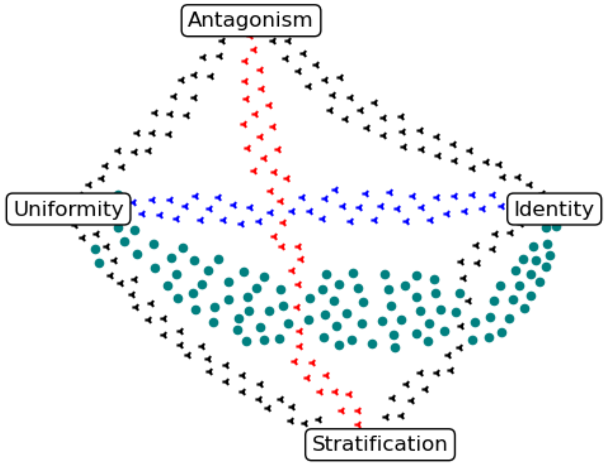
Normalized Mallows Model

Idea

- Keep expected swap distance from central order fixed

Advantage

- Uniform parameter values lead to uniform coverage of election space
- "Consistent" behavior for varying number of candidates
- Easy-to-interpret parameter values



Input

Central vote v* with m candidates + "new" paramter norm-φ

Conversion

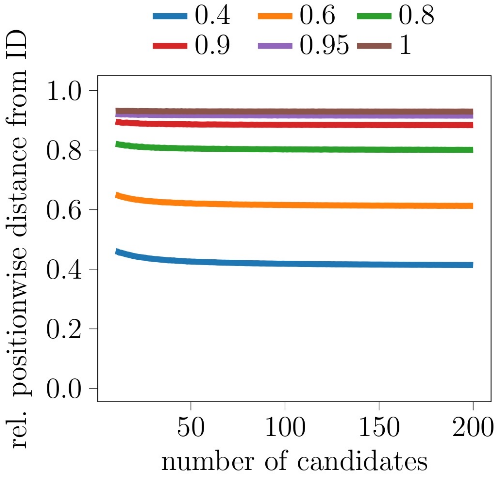
Choose a value φ of the dispersion parameter s.t. expected swap distance between central and sampled vote:

$$\text{norm-}\varphi \cdot \tfrac{1}{4}\, m(m-1)$$

Sampling

Probability of sampling vote v proportional to:

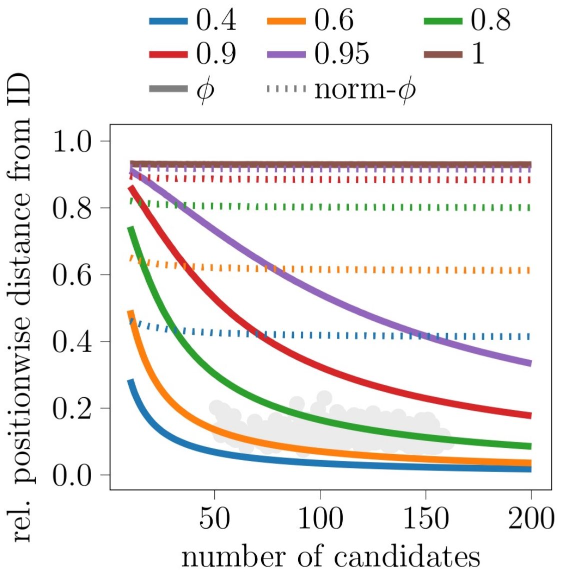
$$\varphi^{\mathrm{swap}(v,v^*)}$$

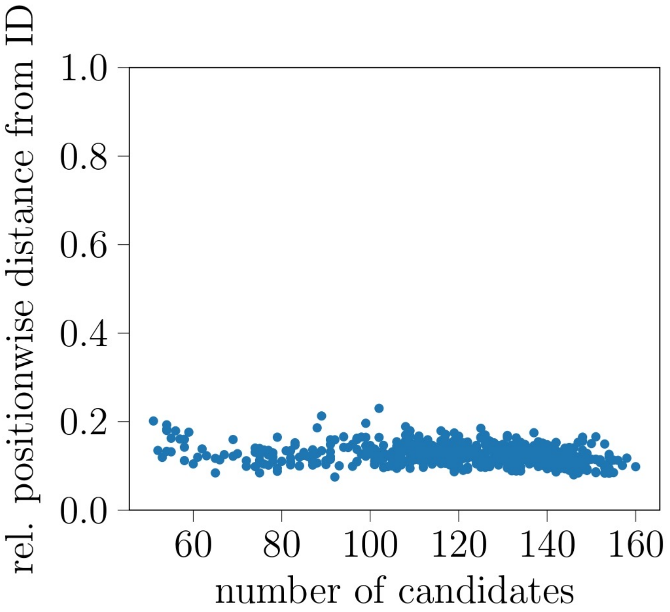


Real-World Evidence

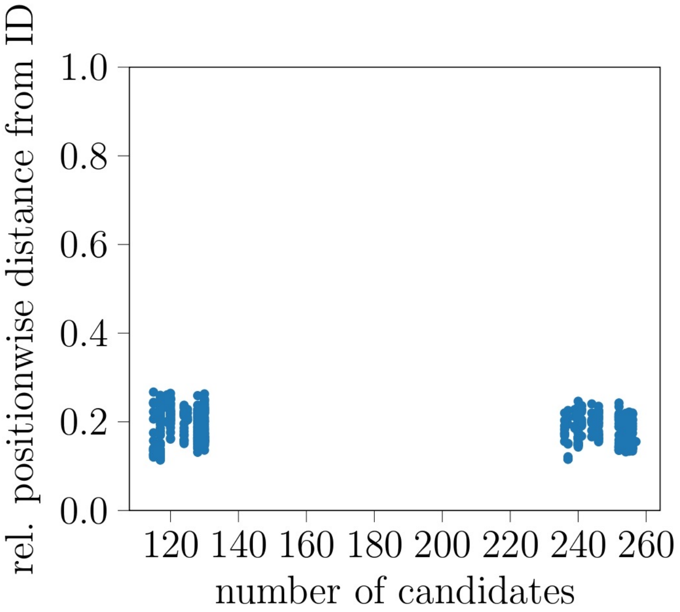
⇩

Behaves as normalized Mallows model

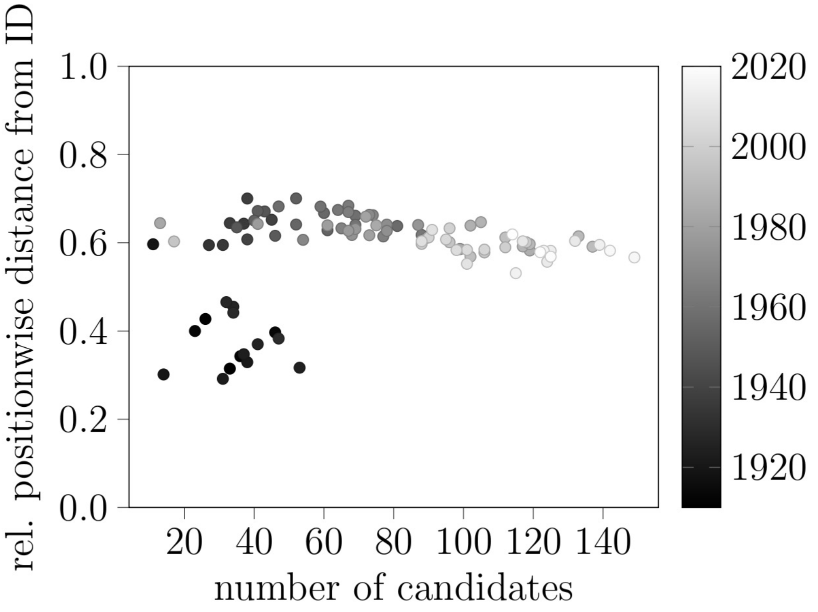




Spotify charts



American football power rankings



Tour de France

Mallows Model: Warnings

- Be careful when varying the number of candidates: Trends could be artifact of Mallows model.
- Statements about certain ranges of dispersion parameter unlikely to generalize for other candidate numbers.
- Be careful how to select values of dispersion parameter in experiments to ensure meaningful coverage.
- Problems get intensified for generalizations such as Mallows mixtures.

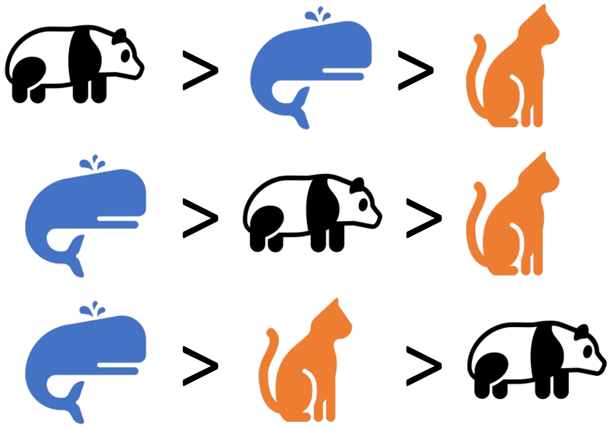
Expected Frequency Matrices of Elections: Computation, Geometry, and Preference Learning, Boehmer et al., NeurIPS-22

Application-Oriented Collective Decision Making, Boehmer, PhD thesis

10 minutes

Understanding Real-World Elections via Preference Learning

Frequency Matrix



Position Matrix

1	2	0	1
2	1	1	1
3	0	2	1

Frequency Matrix

1	2/3	0	1/3
2	1/3	1/3	1/3
3	0	2/3	1/3

Frequency Matrix of Vote Distribution (aka. probability distribution over votes)

Entry (i,j): Probability that j is ranked in position i in a sampled vote.

Learning Real-World Data

Idea

Given parameterized vote distribution and (real-world) election

Compute parameters most likely to produce election

Motivation

- Quantify nature of examined elections
- Identify parameter values leading to realistic data

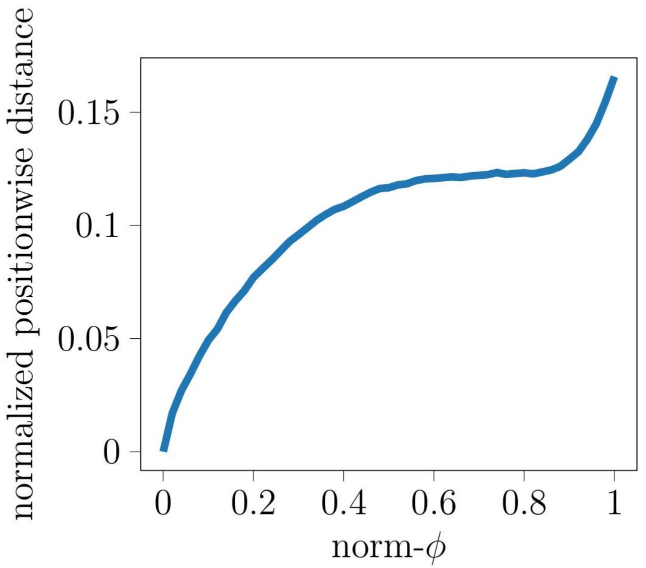
Approach

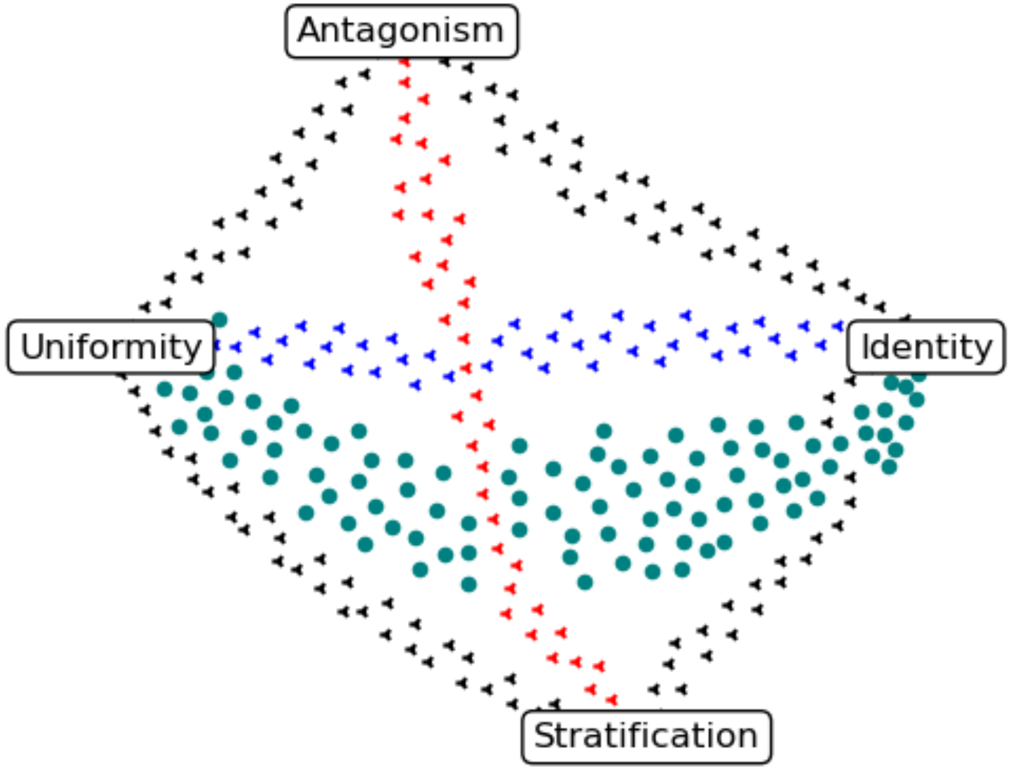
For different distribution parameters:

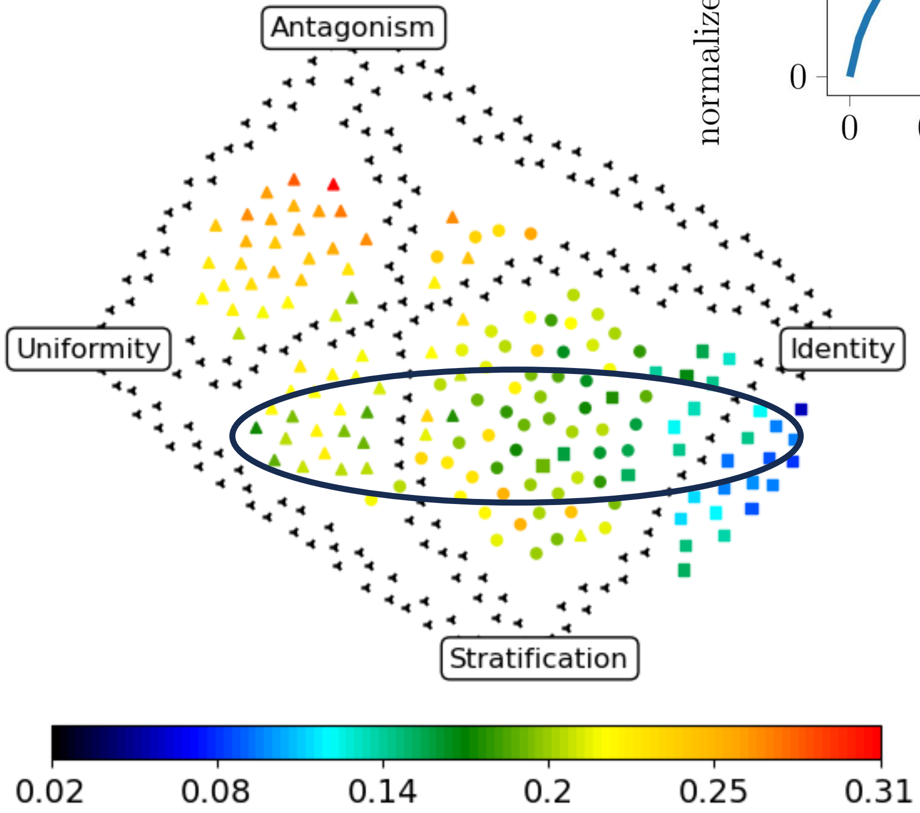
- Compute distance between frequency matrix of distribution and election

Return distribution parameters resulting in smallest distance

Learning Single Mallows Models







Normalized dispersion parameter norm-φ
of closest Mallows model
Avg. 0.49

Normalized EMD-positionwise distance to
closest Mallows matrix
Avg. 0.192

Learning Mixtures of Mallows Model

Idea

Heterogeneous electorate with multiple central votes

Procedure

Given two central votes v_1* and v_2* (over same candidate set), two dispersion parameters norm-φ>norm-ψ, and probability p

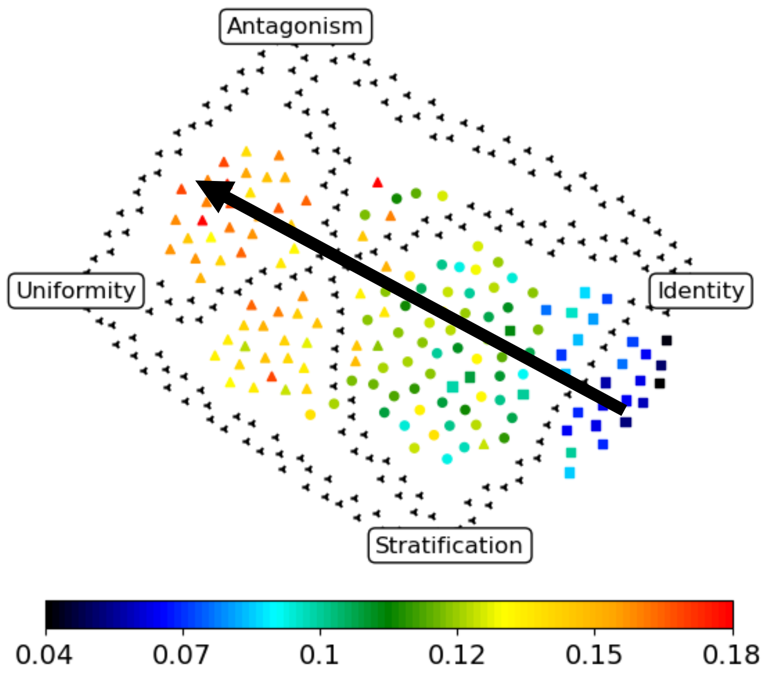
- With probability p, sample from Mallows model with norm-φ and v_1*
- With probability 1-p, sample from Mallows model with norm-ψ and v_2*

Frequency matrix

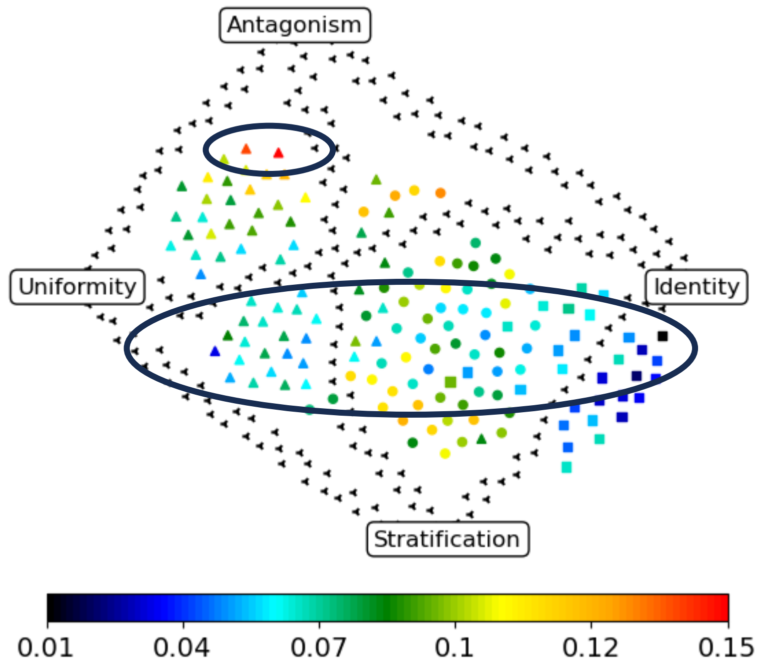
Weighted sum of matrices of individual models

Learning Mixtures of Mallows Model

$p*M(\text{norm-}\varphi, v_1*) +$
$(1-p)*M(\text{norm-}\psi, v_2*)$
with $\text{norm-}\varphi > \text{norm-}\psi$



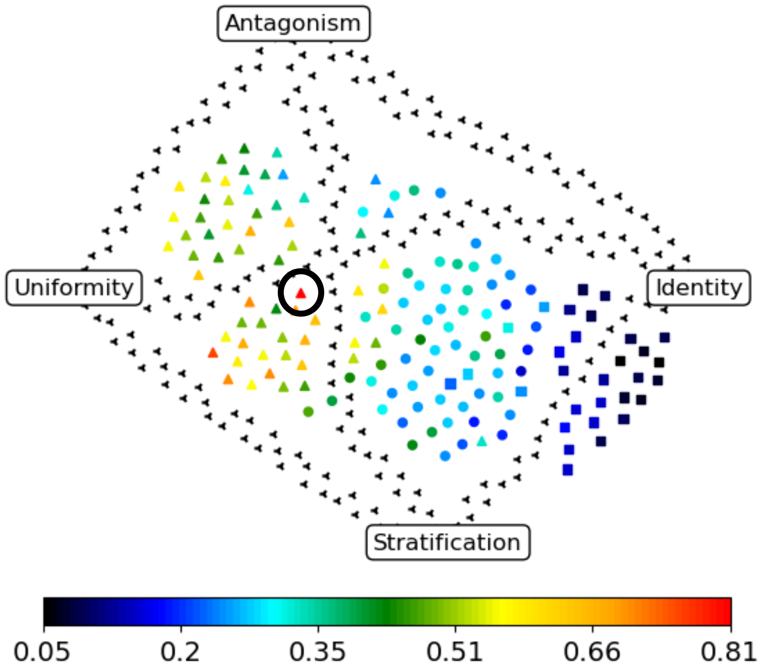
Distance to frequency matrix of closest Mallows mixture
Avg. 0.12 (-0.07)



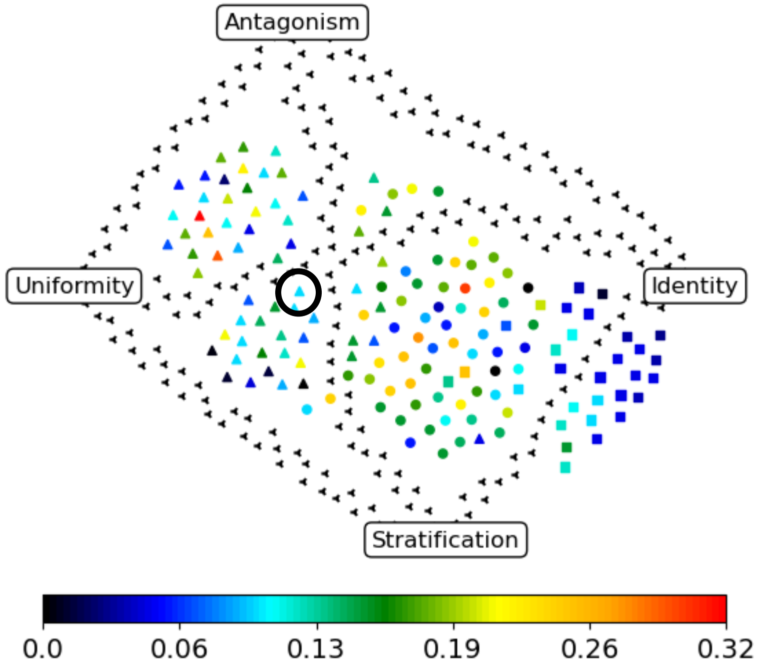
Distance "gain" by using mixture instead of single Mallows model

Learning Mixtures of Mallows Model

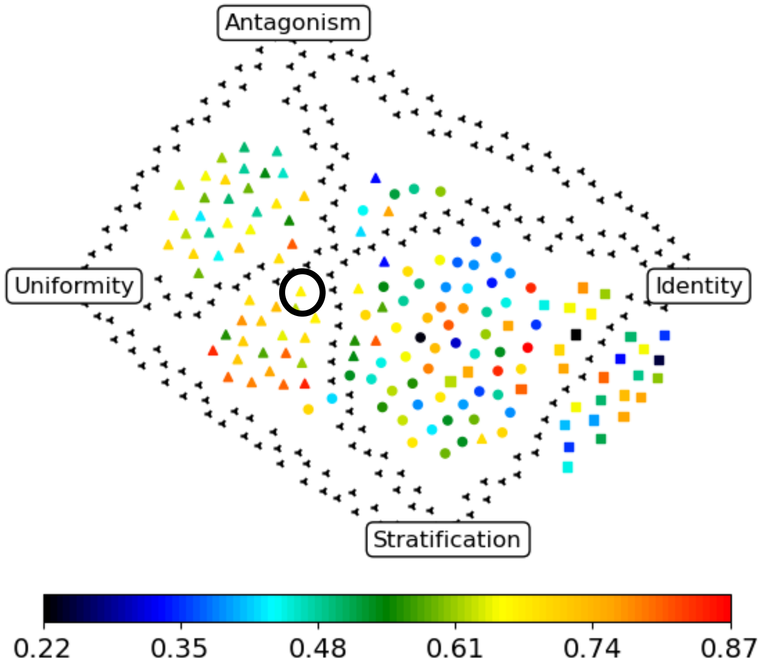
$p*M(\text{norm-}\varphi,v_1^*)+$
$(1-p)*M(\text{norm-}\psi,v_2^*)$
with norm-φ>norm-ψ



Normalized dispersion parameter norm-φ of closest mixture
Avg. 0.353



Normalized dispersion parameter norm-ψ of closest mixture
Avg. 0.128



Sampling probability of closest mixture
Avg. 0.6

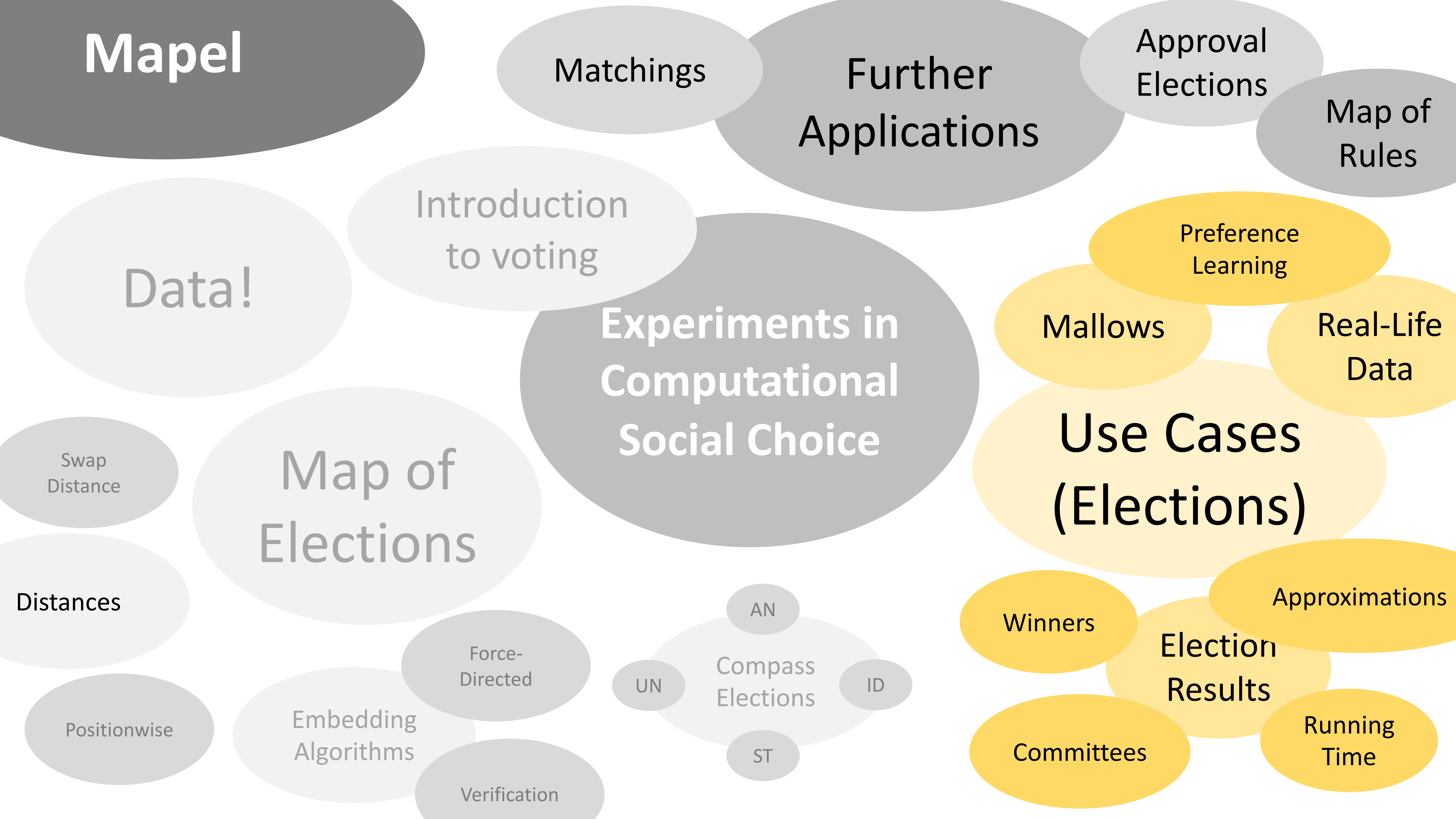
How to Sample Realistic Data Using the Mallows model?

Observations

- Mallows elections capture relevant part of map of elections well
- Mixtures of Mallows models even more powerful/general

Procedure

- Normalized Mallows model with uniformly at random chosen norm-φ between 0 and 0.92
- Mixtures of Mallows models: $p \in [0.35, 0.8]$, norm-$\varphi \in [0.05, 0.6]$, norm-$\psi \in [0, 0.25]$, and swap distance between v_1^* and v_2^* $\in [0.35, 0.6]$


Mapel
Matchings
Further Applications
Approval Elections
Map of Rules
Data!
Introduction to voting
Experiments in Computational Social Choice
Preference Learning
Mallows
Real-Life Data
Use Cases (Elections)
Swap Distance
Map of Elections
Distances
AN
UN
Compass Elections
ID
ST
Force-Directed
Embedding Algorithms
Verification
Positionwise
Winners
Approximations
Election Results
Committees
Running Time

Mapel

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UN

Compass Elections

ID

ST

Winners

Approximations

Election Results

Committees

Running Time

25 minutes

Approval Elections

Further Applications

Instance of Approval Election

Candidates:

Voters:

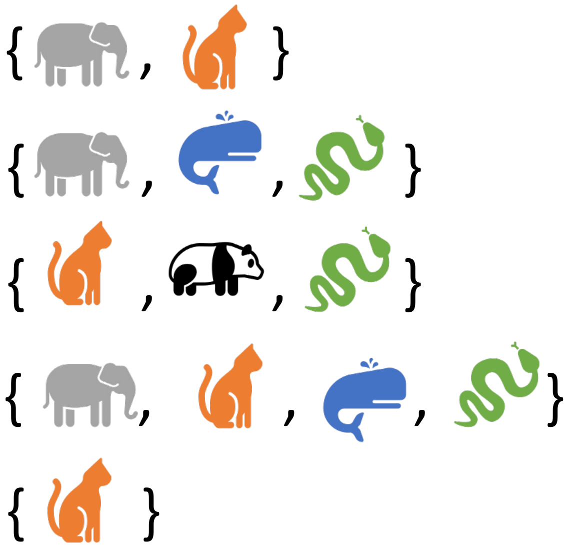
v_1:

v_2:

v_3:

v_4:

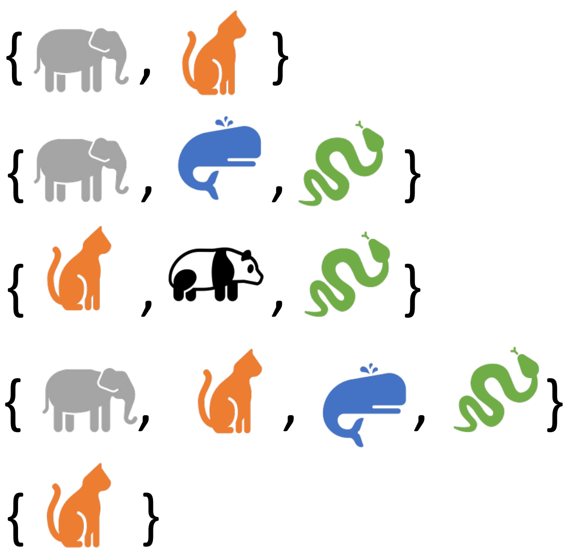
v_5:



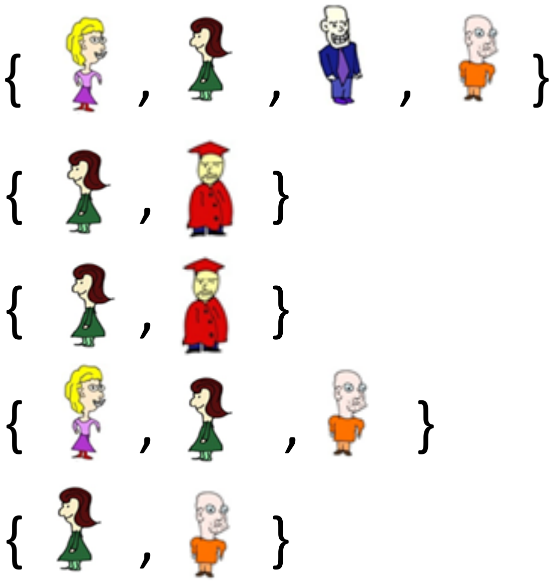
Approvalwise distance

Approvalwise distance

v_1:
v_2:
v_3:
v_4:
v_5:



u_1:
u_2:
u_3:
u_4:
u_5:



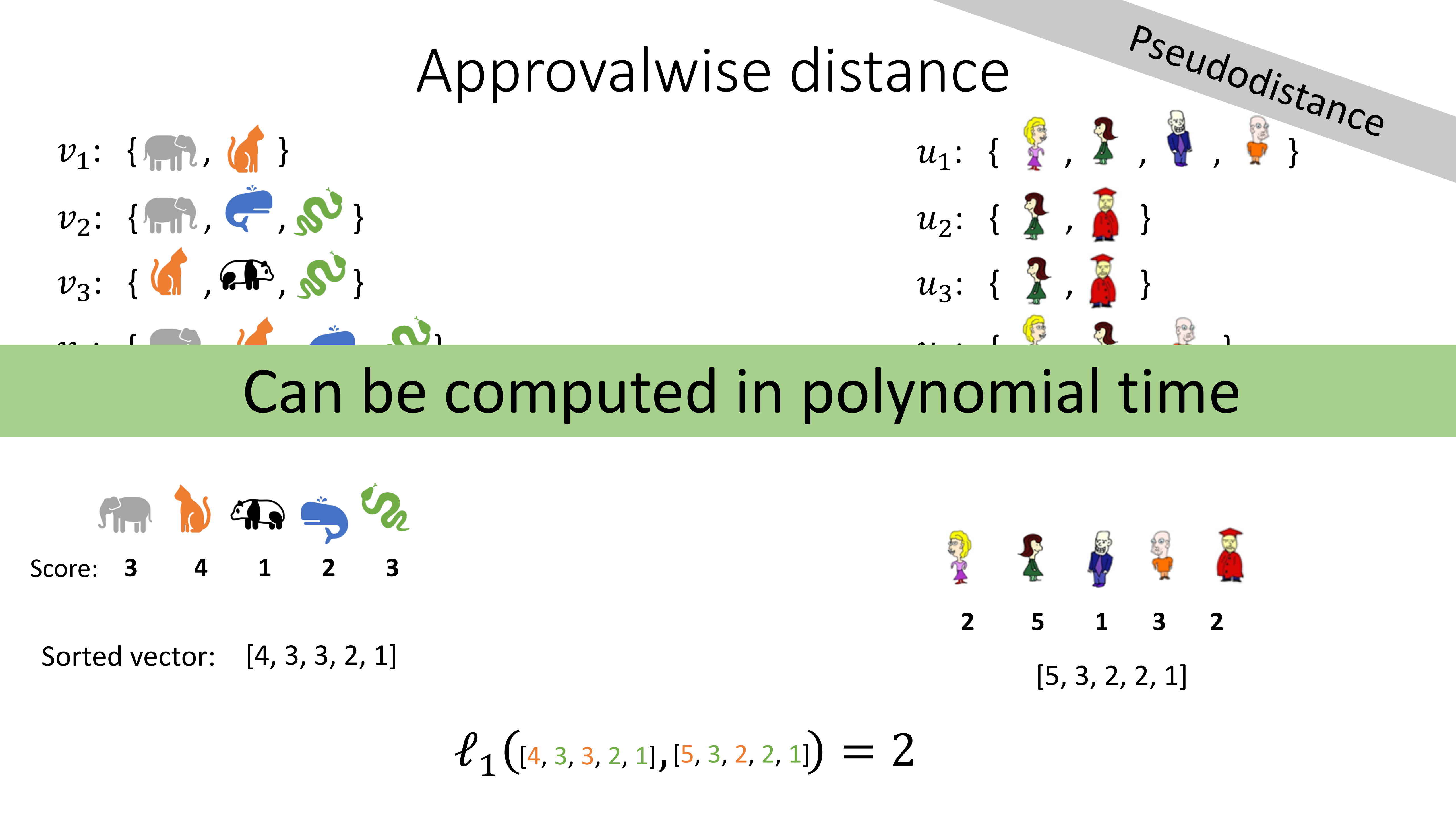
Score: **3** **4** **1** **2** **3**

Sorted vector: [4, 3, 3, 2, 1]

2 **5** **1** **3** **2**

[5, 3, 2, 2, 1]

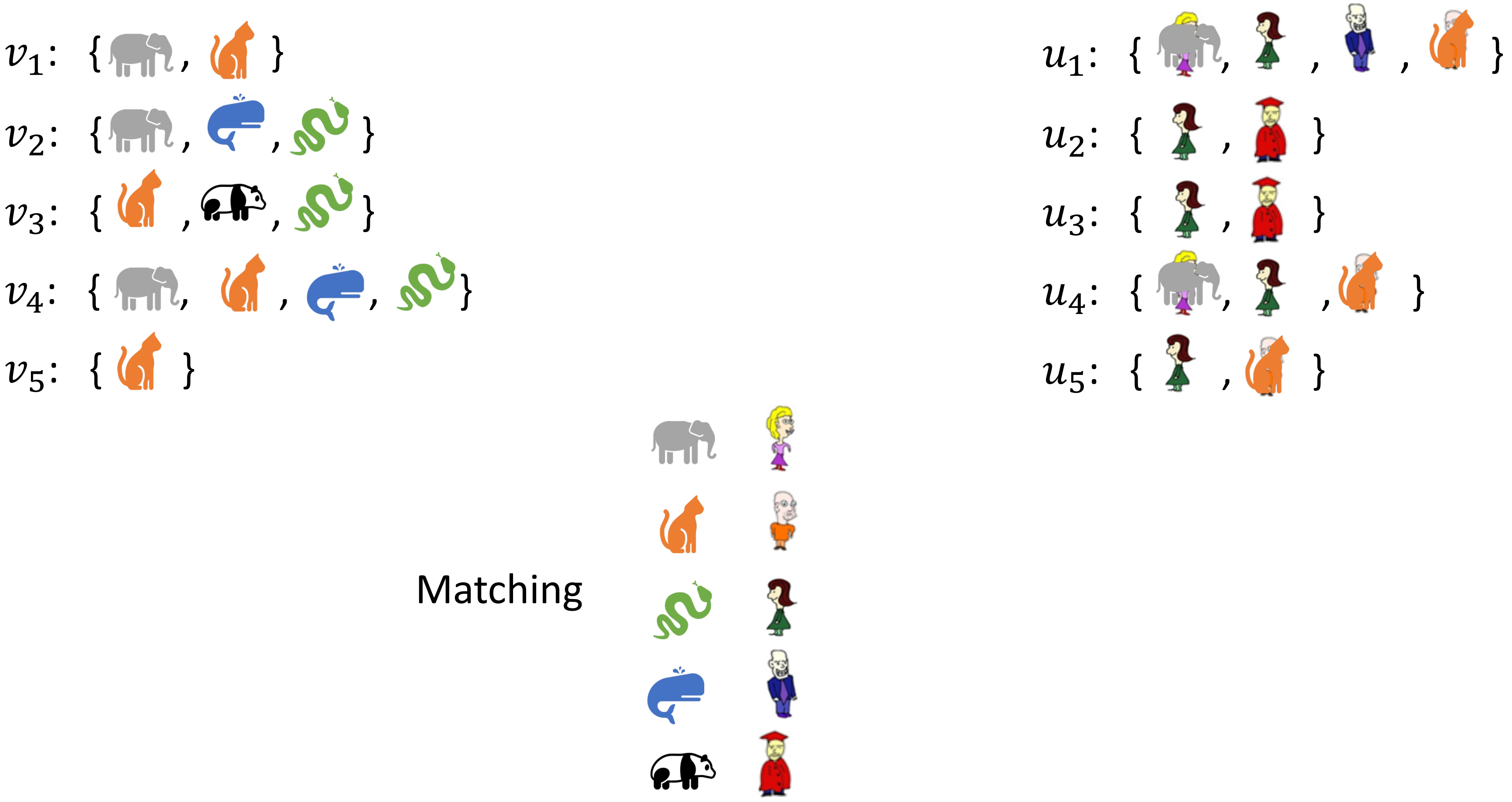
$$\ell_1([4, 3, 3, 2, 1], [5, 3, 2, 2, 1]) =$$



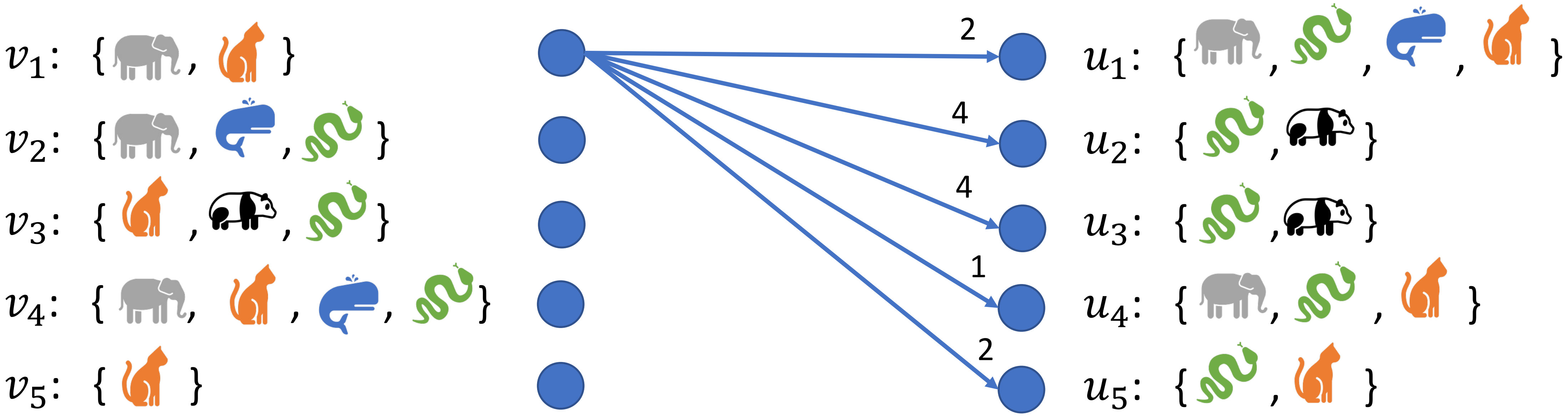
Approvalwise distance
Pseudodistance
v_1: { , }
v_2: { , , }
v_3: { , , }
u_1: { , , , }
u_2: { , }
u_3: { , }
Can be computed in polynomial time
Score: 3 4 1 2 3
Sorted vector: [4, 3, 3, 2, 1]
2 5 1 3 2
[5, 3, 2, 2, 1]
$\ell_1([4, 3, 3, 2, 1], [5, 3, 2, 2, 1]) = 2$

Hamming distance

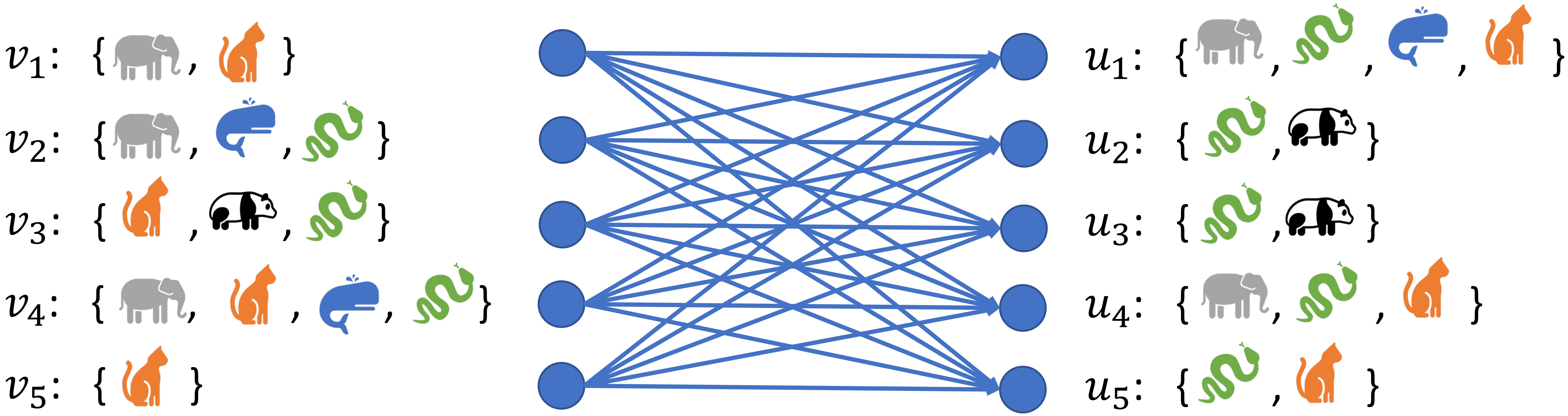
Hamming distance



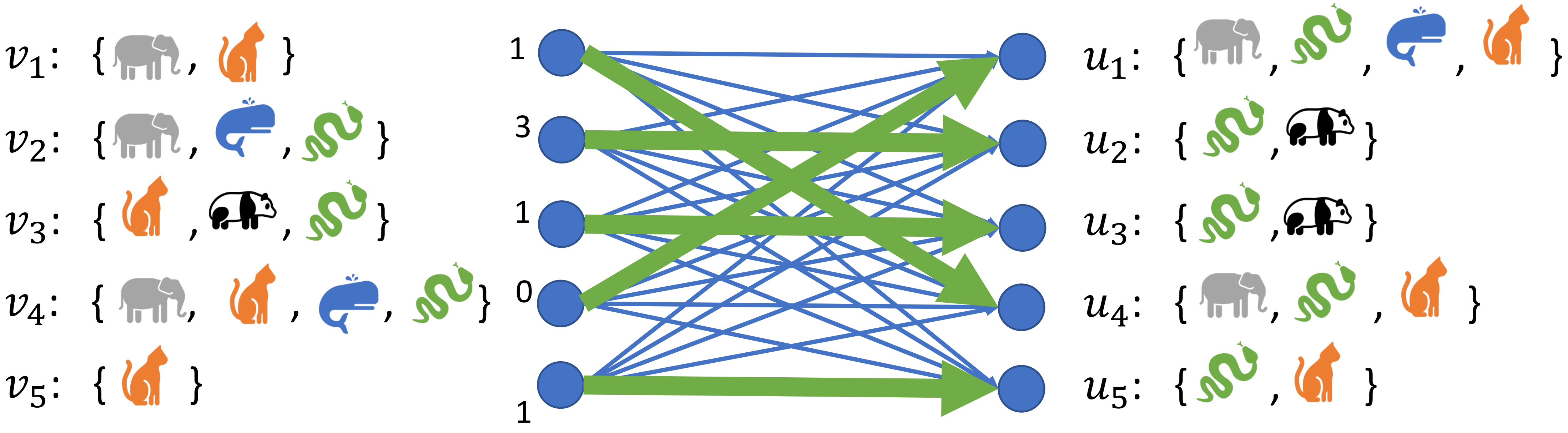
Hamming distance



Hamming distance

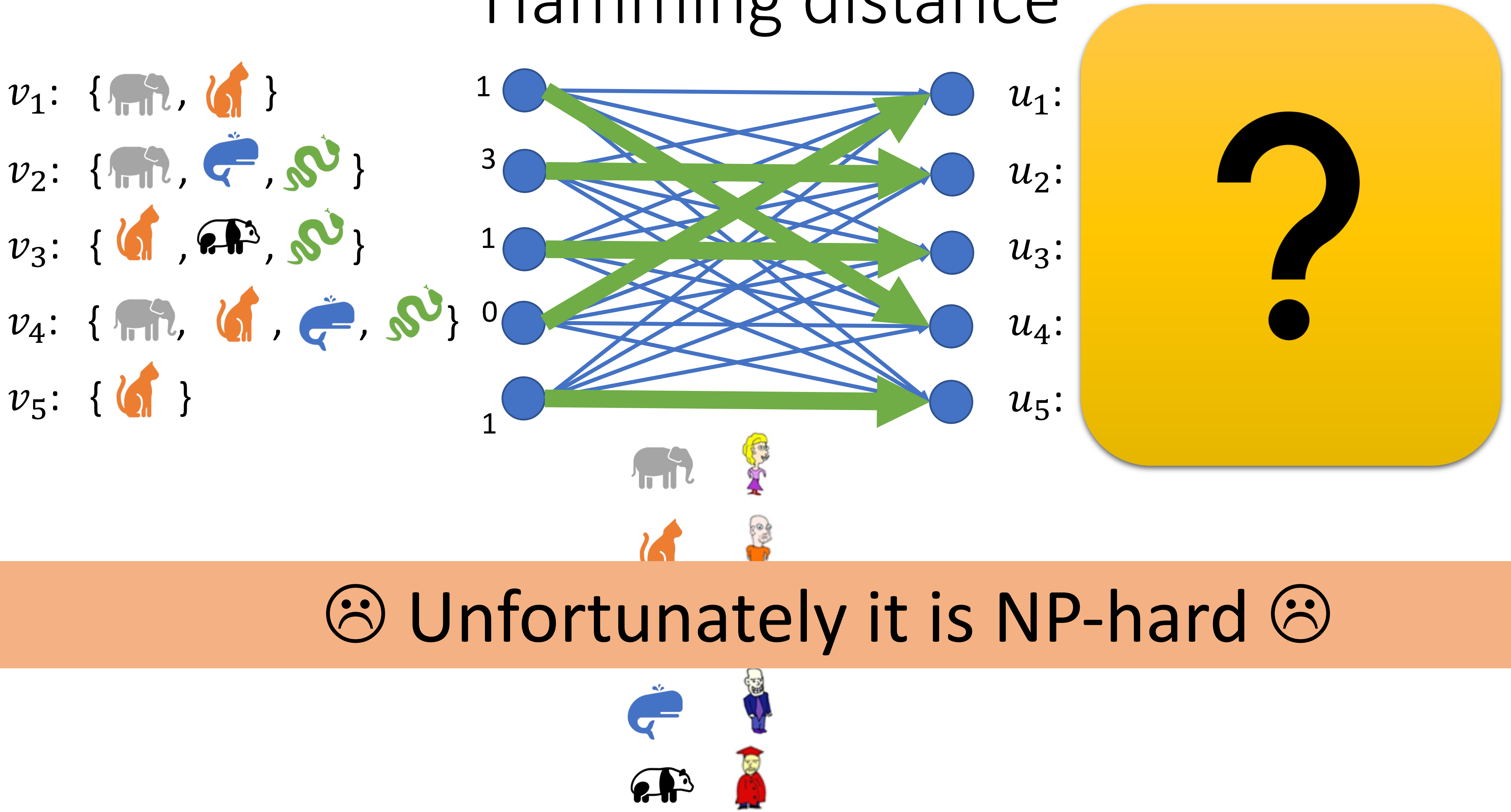


Hamming distance



1 + 3 + 1 + 0 + 1 = 6

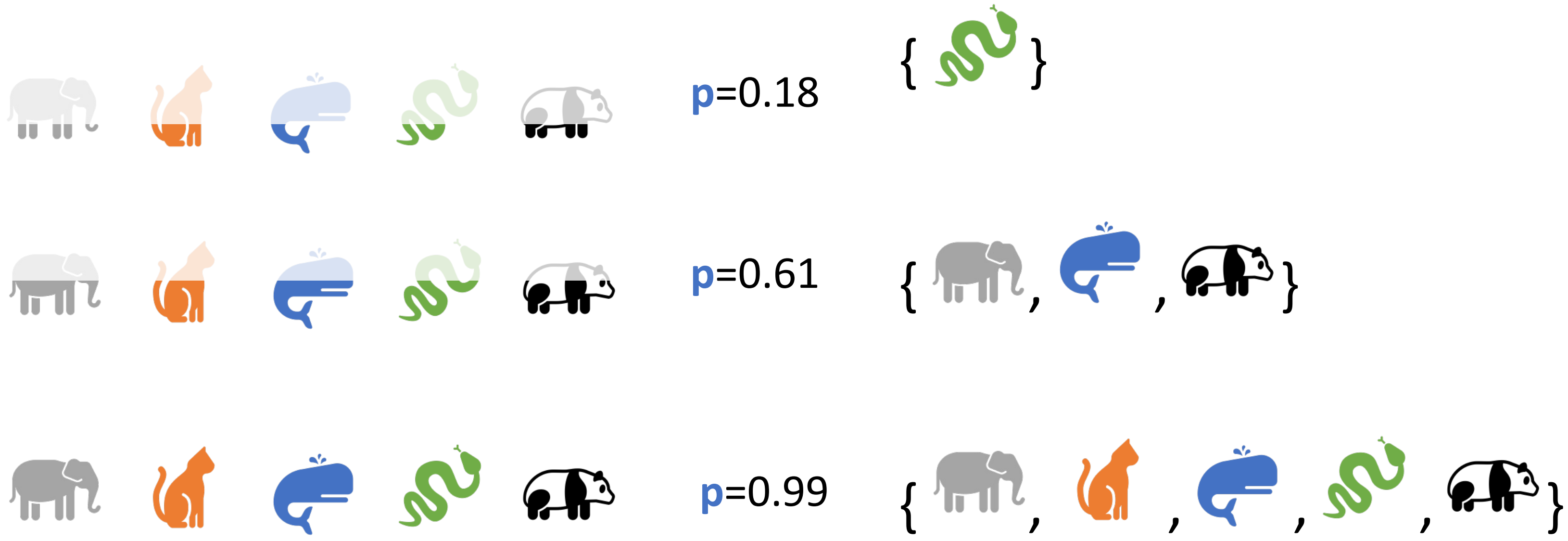
Hamming distance



☹ Unfortunately it is NP-hard ☹

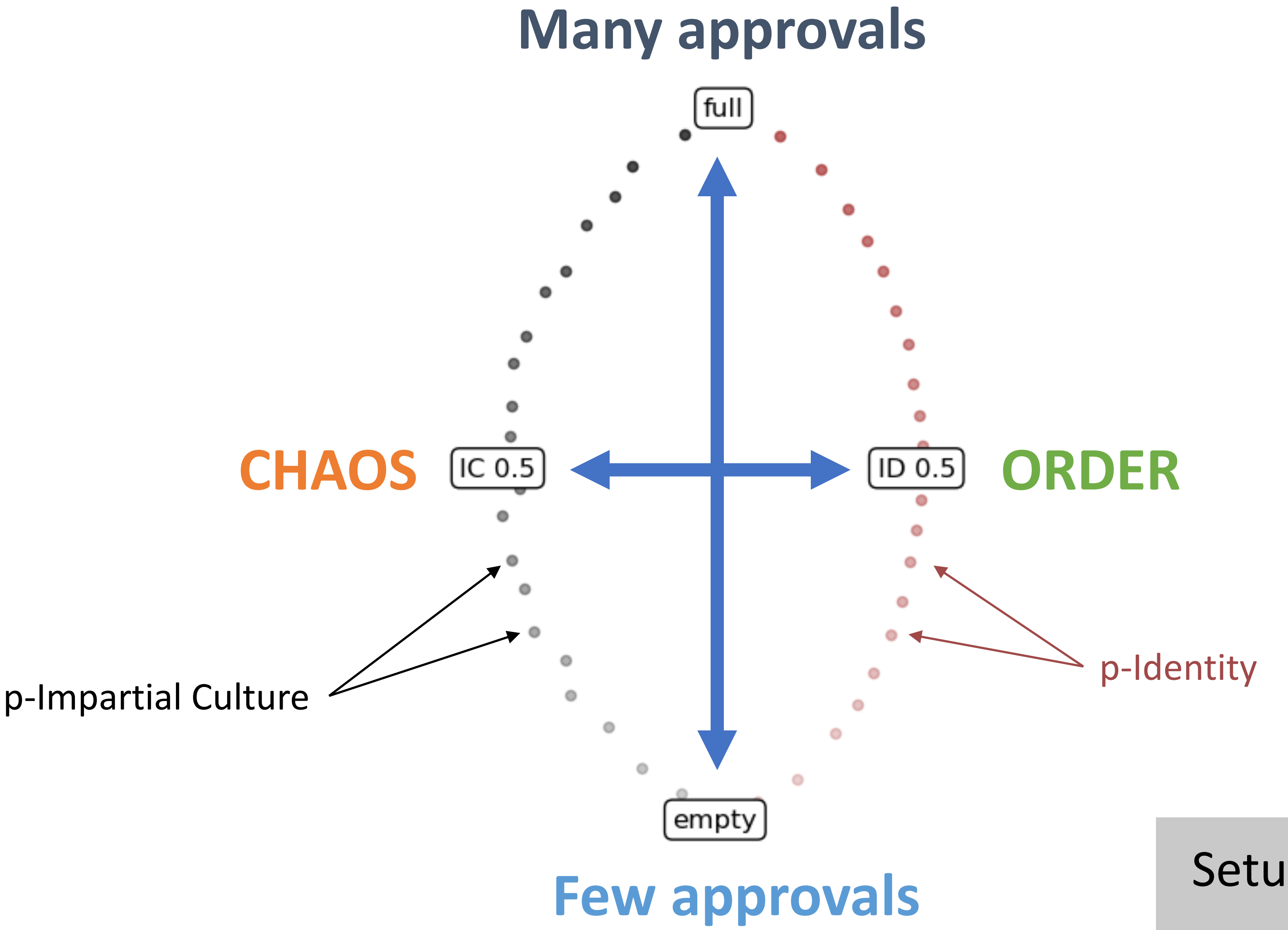
p-Impartial Culture

To generate a vote, for each candidate we flip an assymetric coin,
and with probability p we put that candidate in our ballot



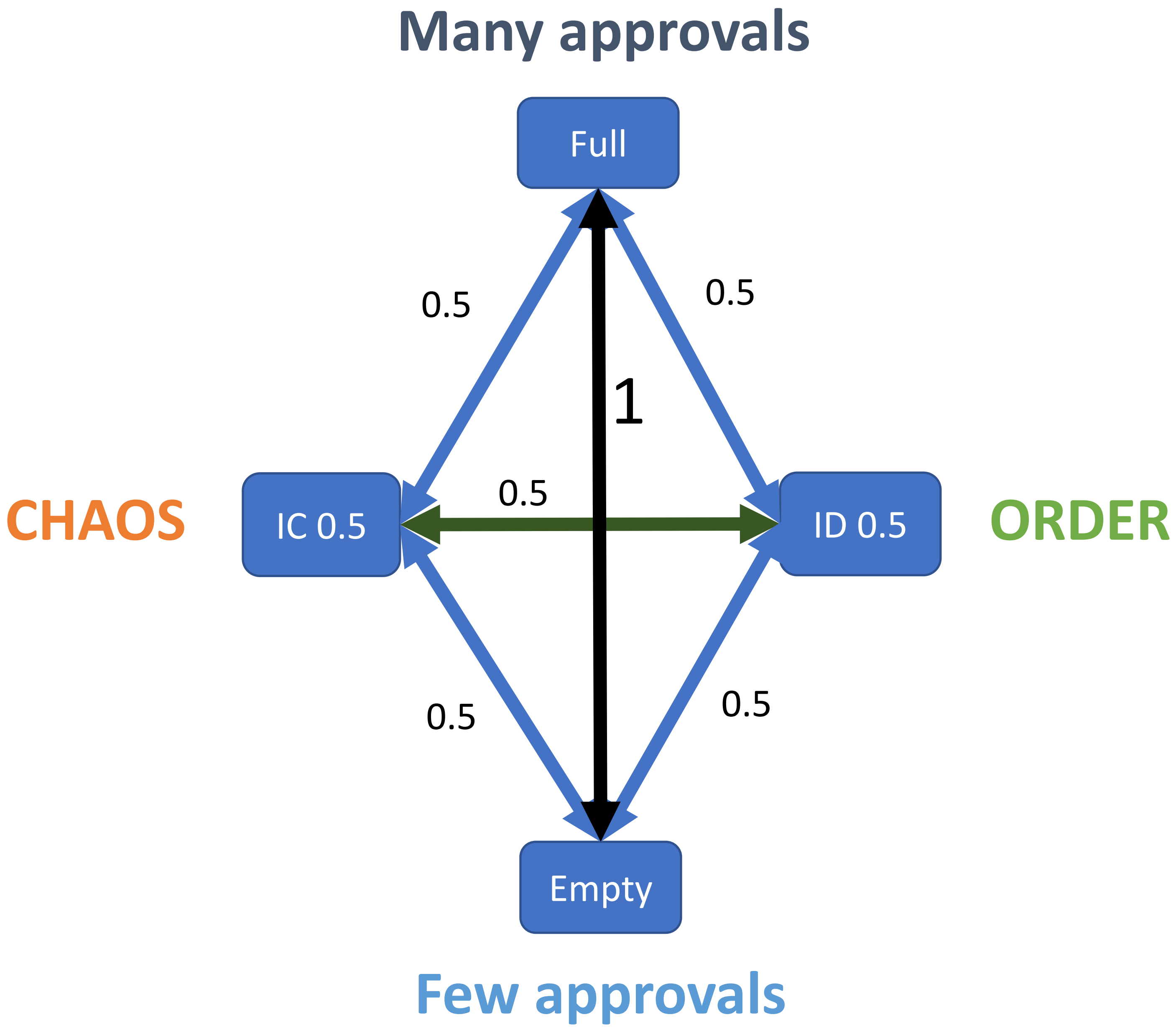
p-Identity

To generate first vote, we approved $\lfloor p \cdot m \rfloor$ candidates selected uniformly at random.
All other votes are its copies.

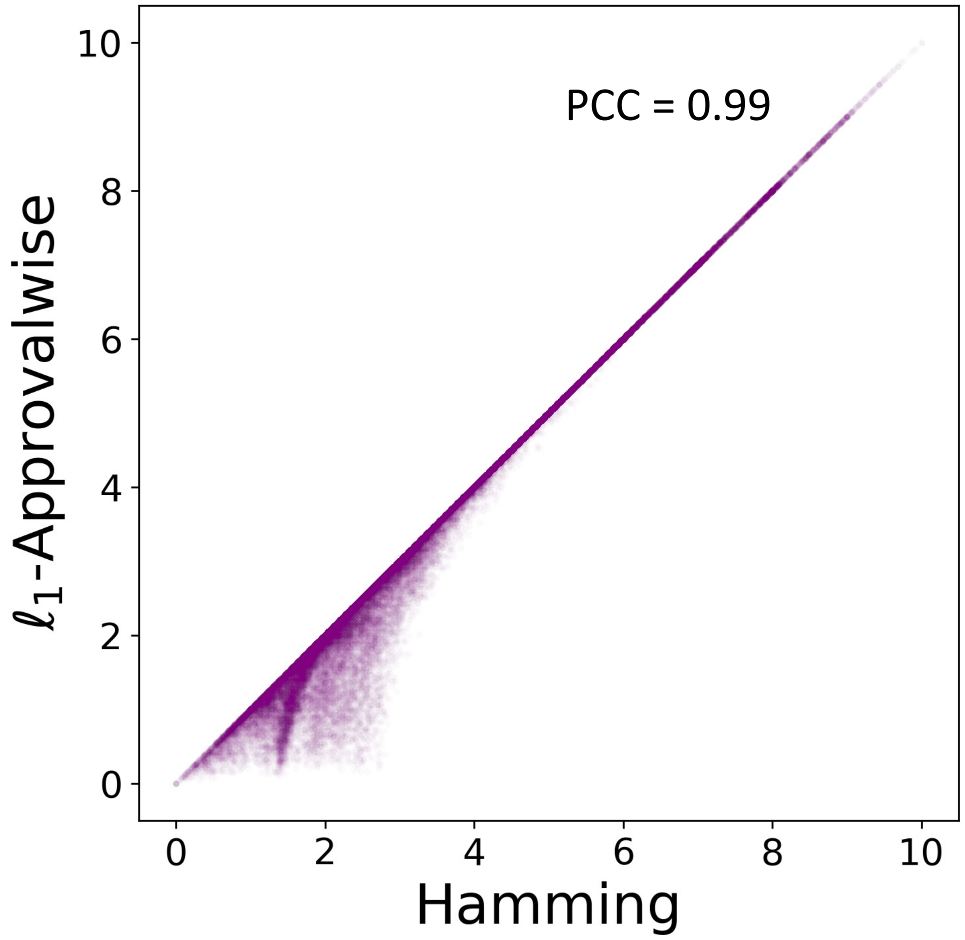


Setup

number of candidates	50
number of voters	100


Many approvals
Full
0.5
0.5
1
CHAOS
IC 0.5
0.5
ID 0.5
ORDER
0.5
0.5
Empty
Few approvals

Correlation

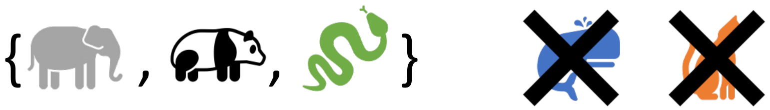


Setup

number of candidates	10
number of voters	50

p-Identity with ϕ-Resampling

Initial ballot (from **p**-ID)

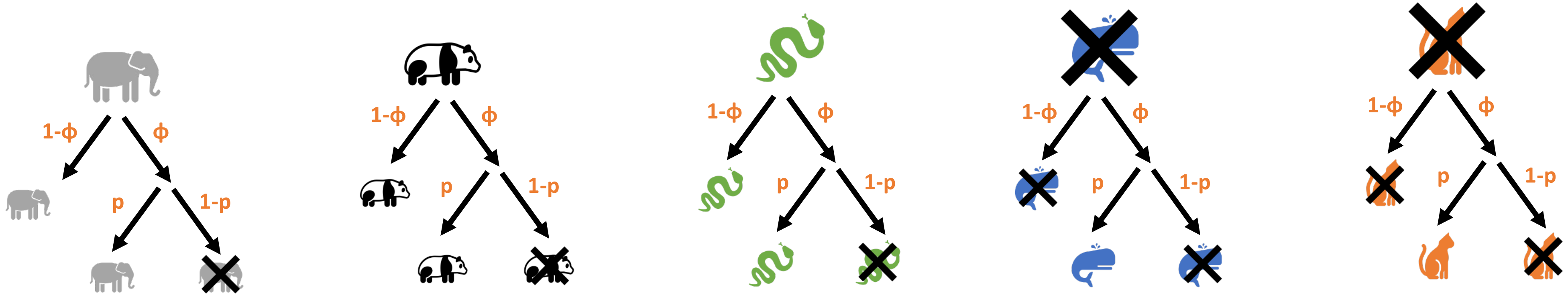


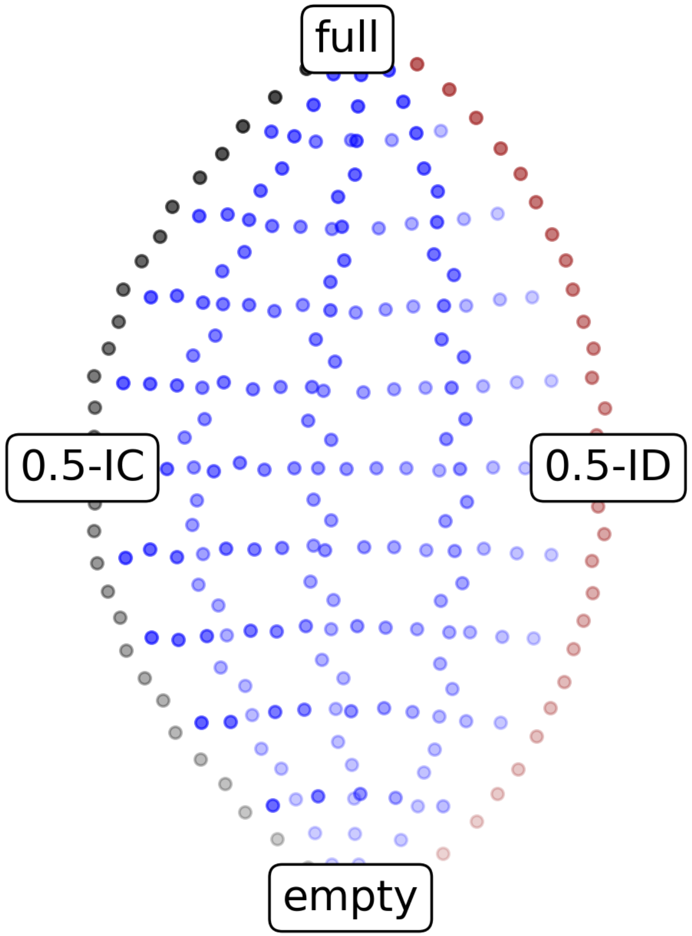
To generate a vote:

Step 0: copy initial ballot
Step 1: for each candidate, **resample** that candidate with probability **ϕ**

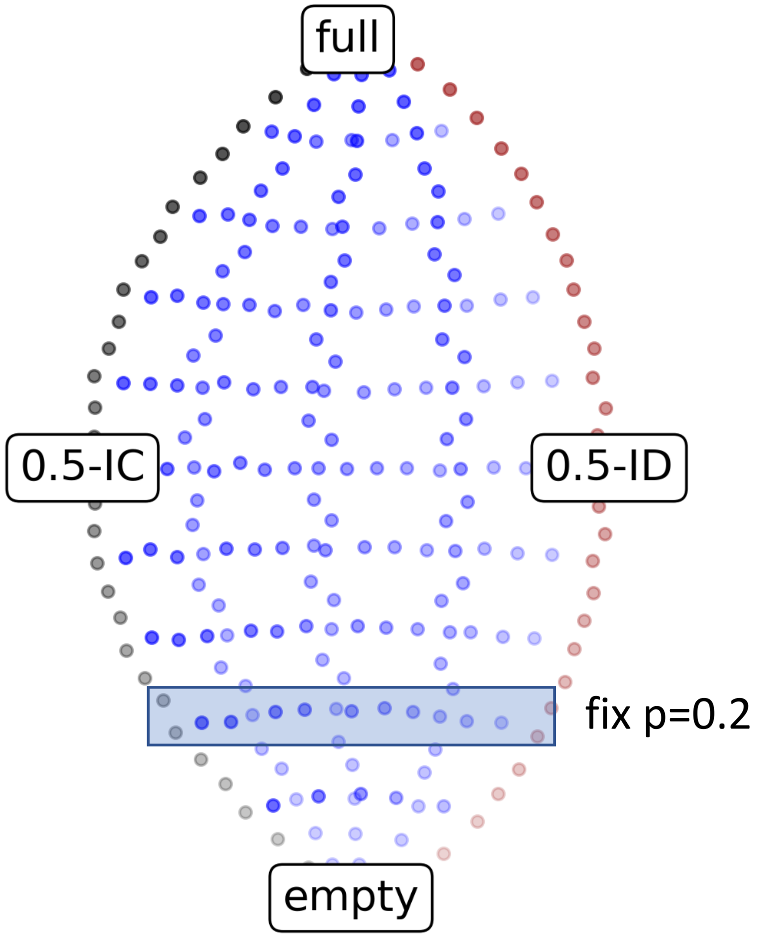
not reverse

(resample = toss an assymetric coin; approve with probability p)

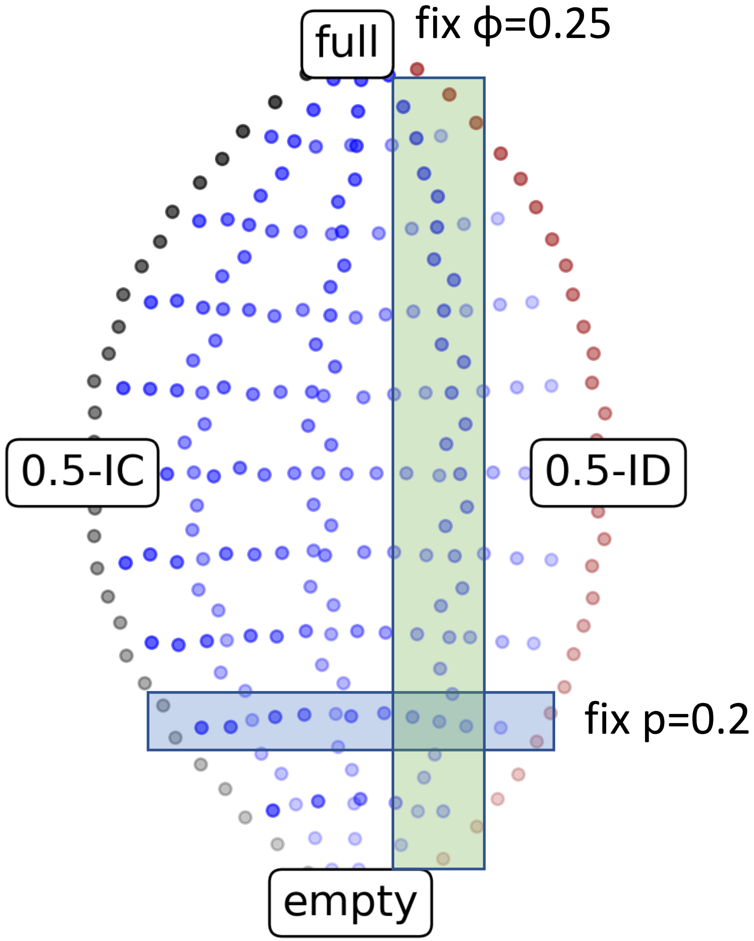




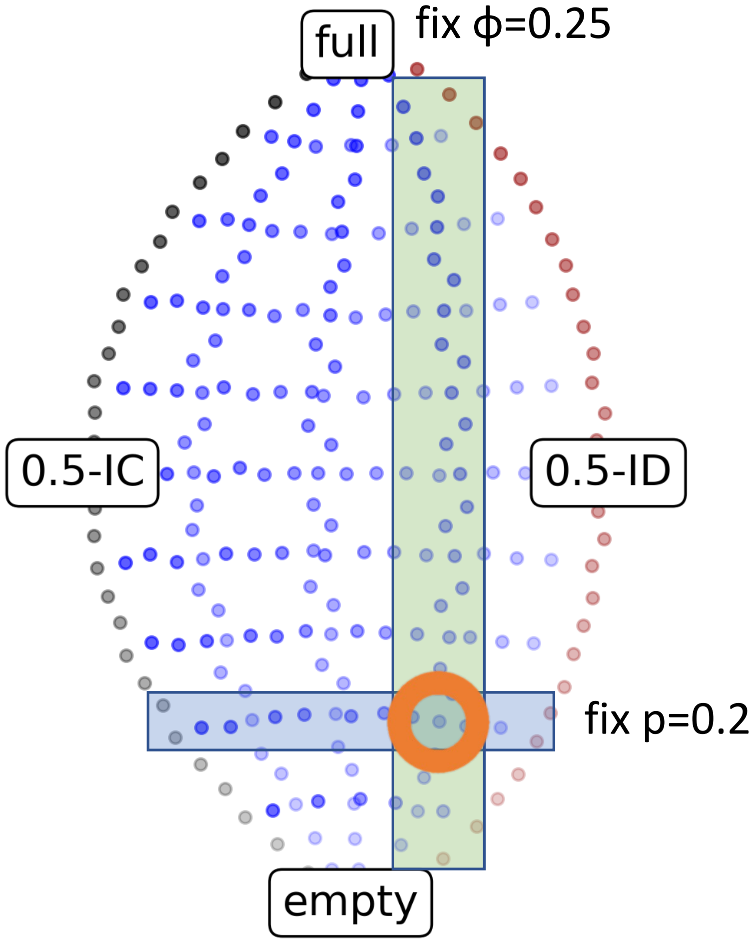
p-Identity with ϕ-Resampling



p-Identity with ϕ-Resampling



p-Identity with ϕ-Resampling

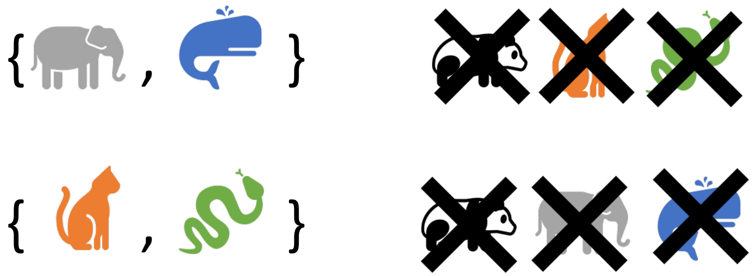


p-Identity with ϕ-Resampling

Disjoint p-Identity with ϕ-Resampling

First initial ballot

Second initial ballot



To generate a vote:

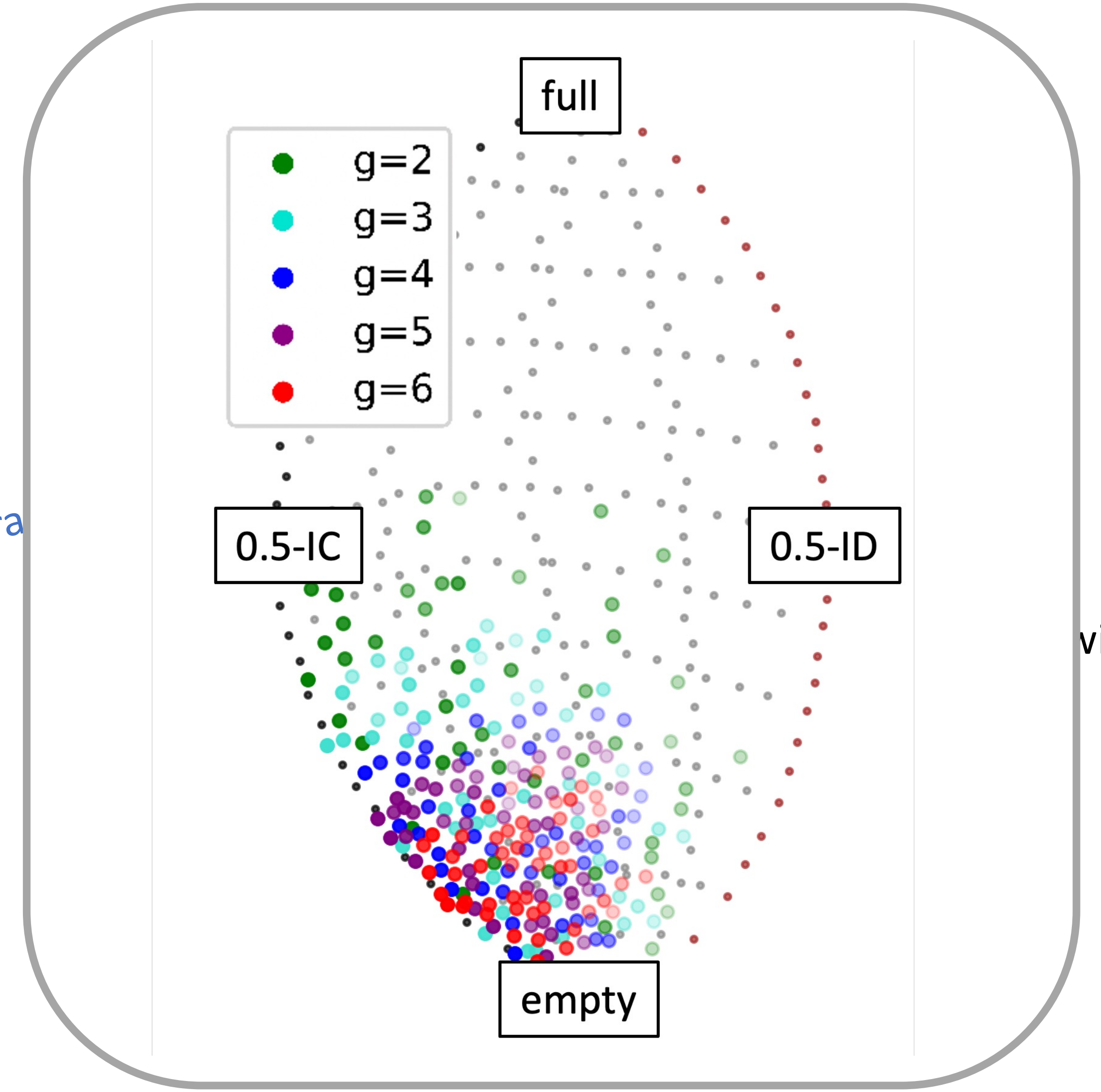
Step 0: copy one of the initial votes
Step 1: for each candidate, **resample** that candidate with probability ϕ

Disjoint p-Identity with ϕ-Resampling

First initial ballot

Second initial ballot

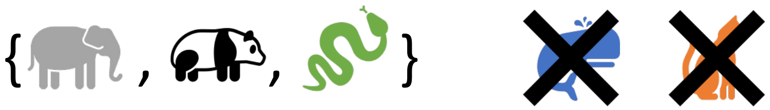
To genera



vith probability ϕ

(p, ϕ) Noise Model

Initial ballot (from **p**-IC)



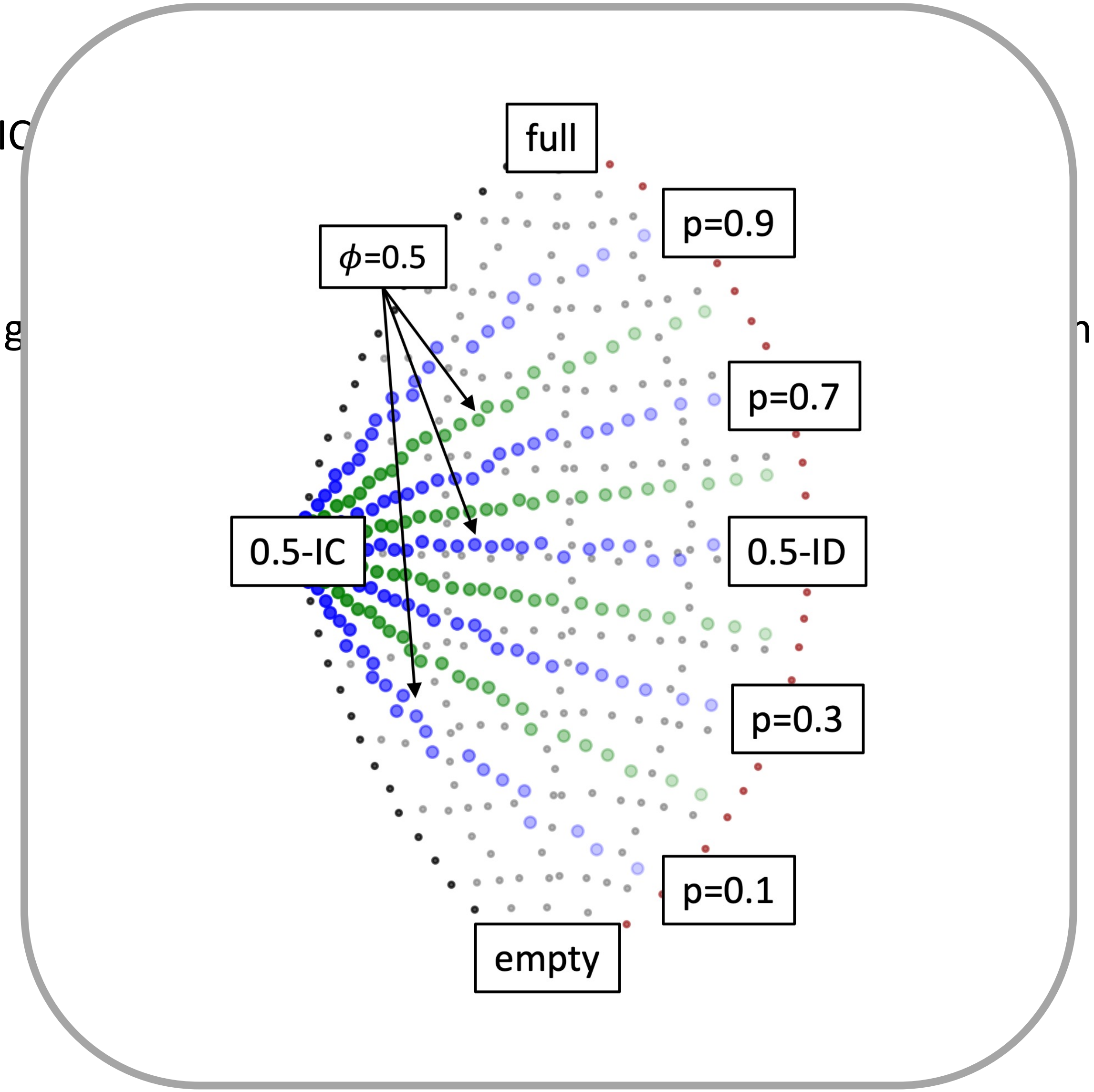
The probability of a given vote is proportional to its **Hamming** distance from the initial ballot

(p, ϕ) Noise Model

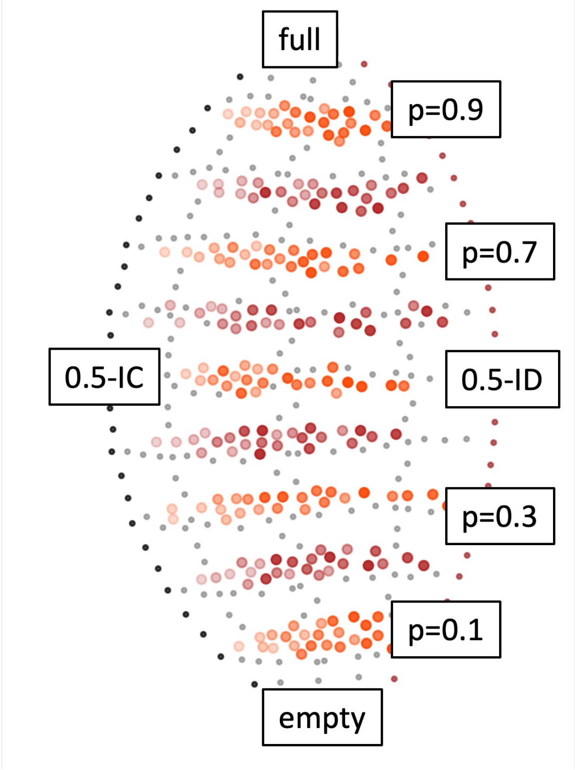
Initial ballot (from **p**-IC

The probability of a g

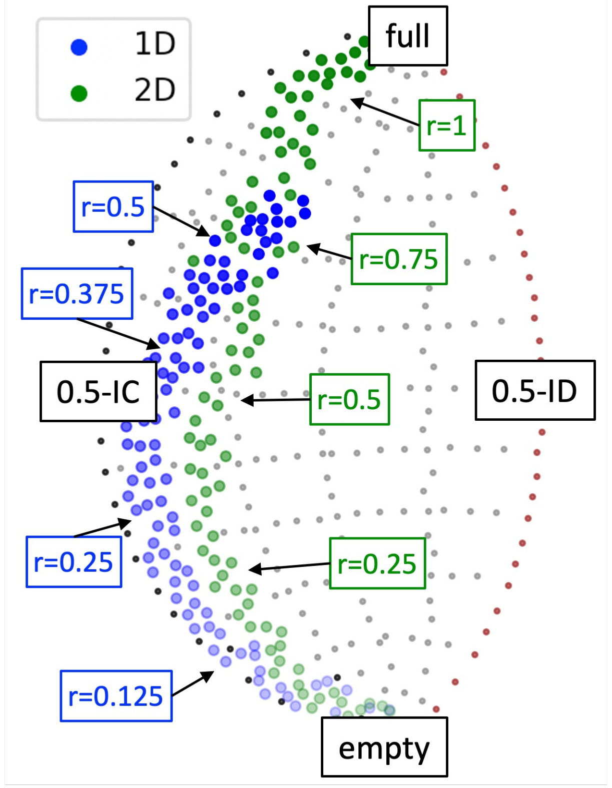
ne initial ballot



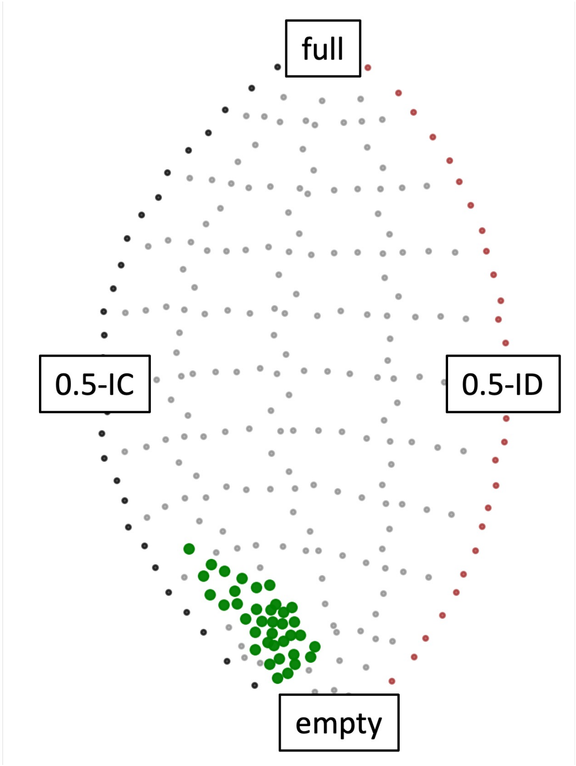
Other Cultures



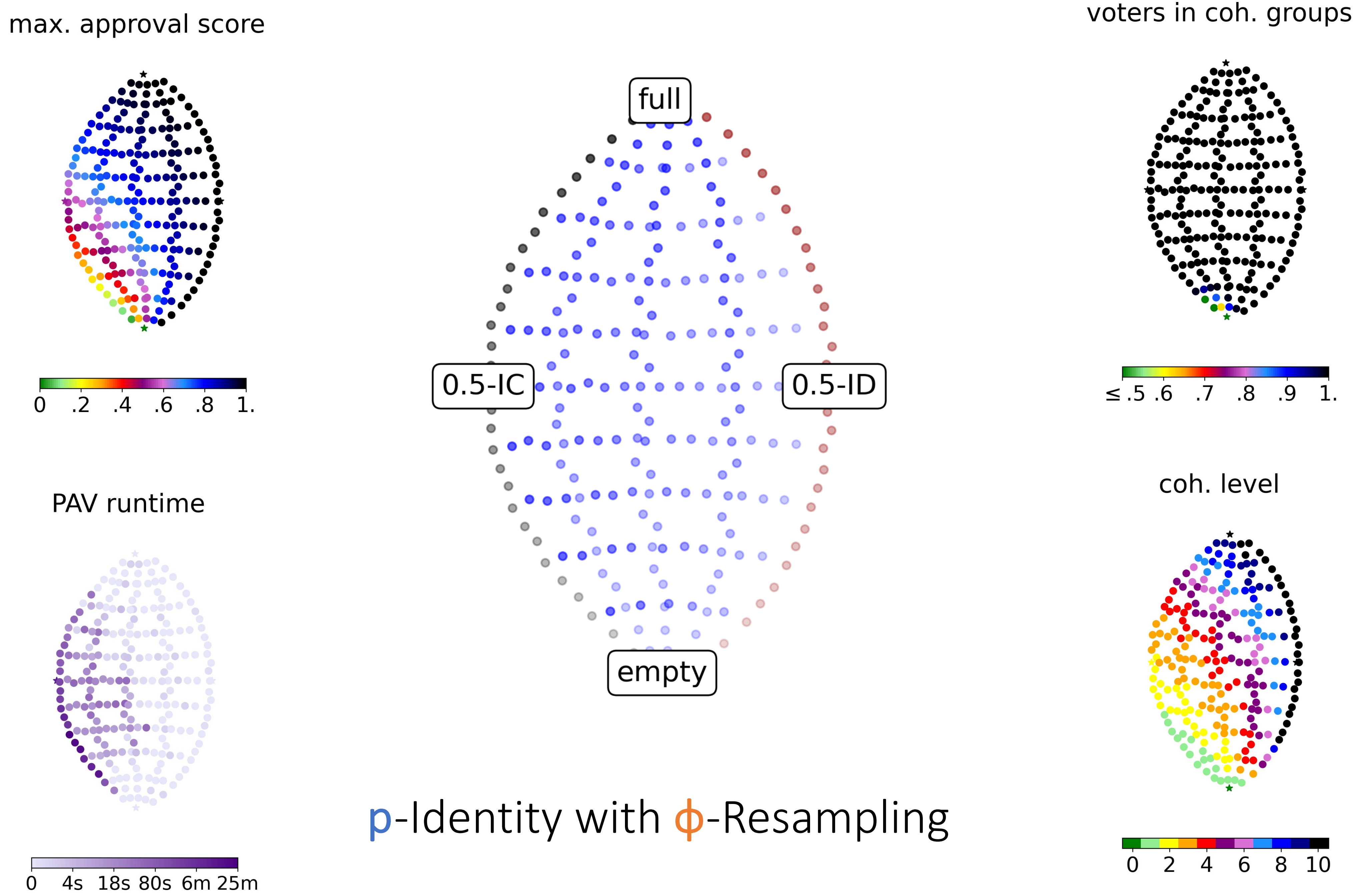
(p, α) Urn Model



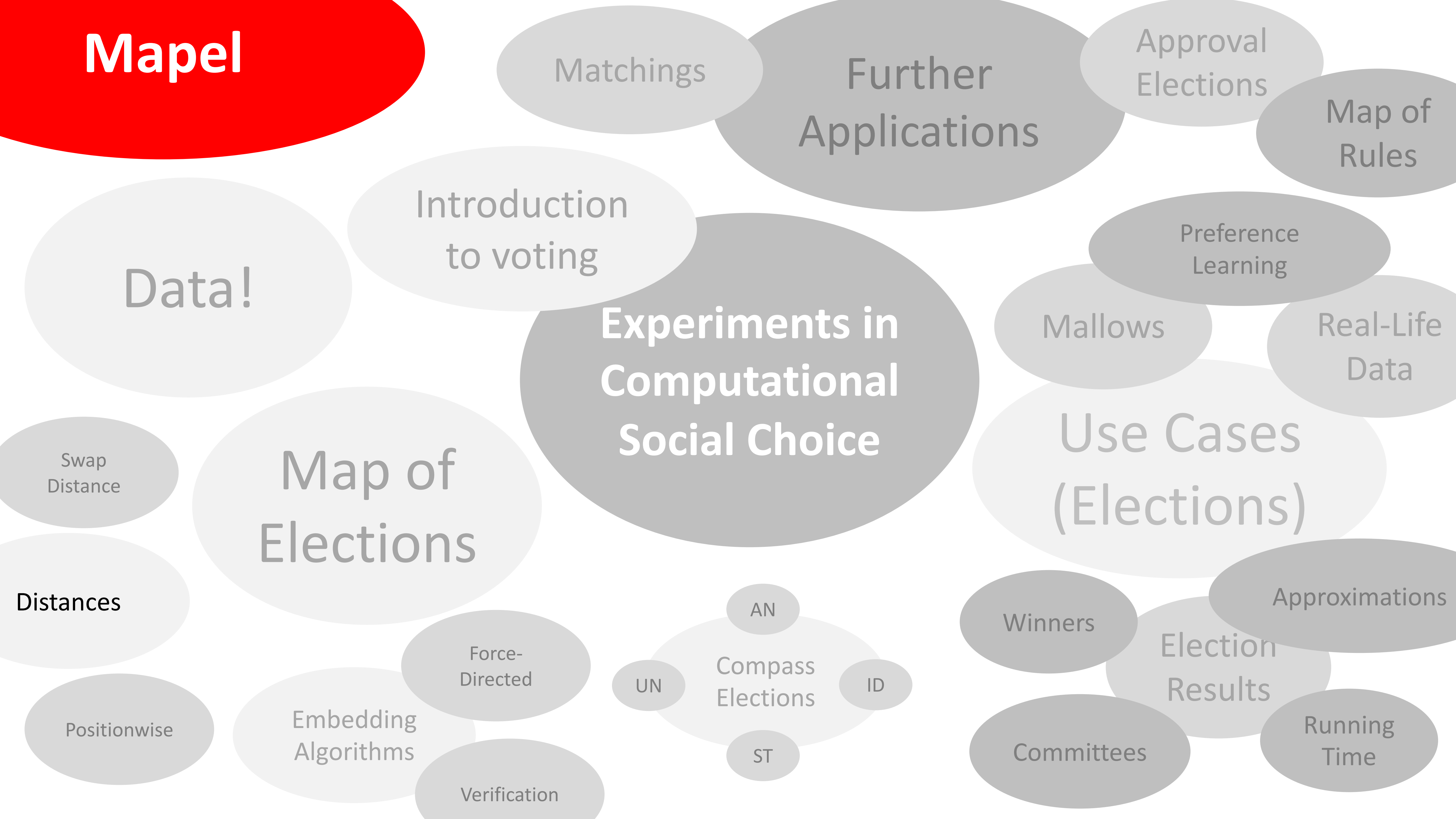
Euclidean



Real life data



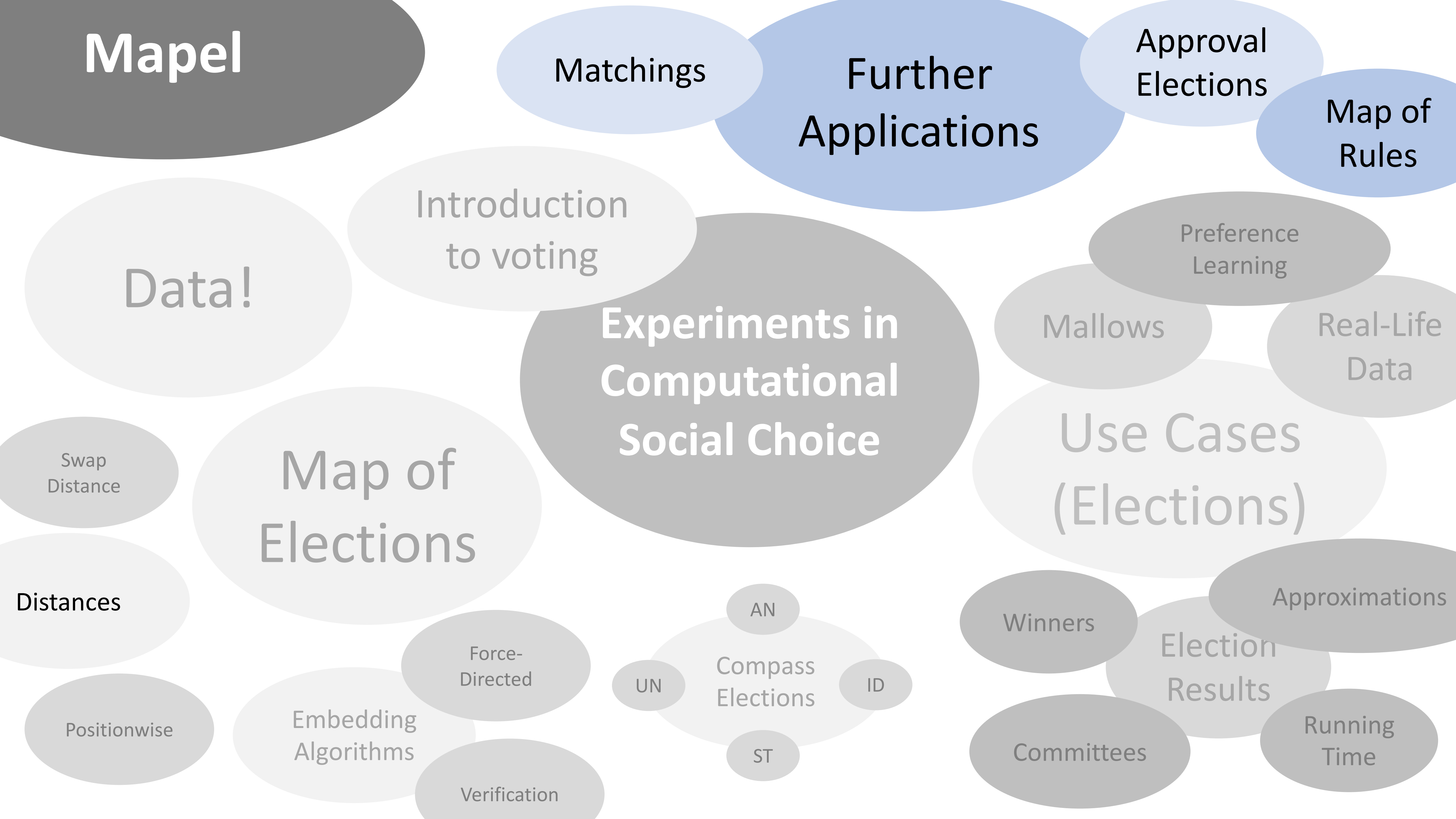
max. approval score
0
.2
.4
.6
.8
1.
PAV runtime
0
4s
18s
80s
6m
25m
full
0.5-IC
0.5-ID
empty
voters in coh. groups
≤ .5
.6
.7
.8
.9
1.
coh. level
0
2
4
6
8
10
p-Identity with ϕ-Resampling


Mapel
Matchings
Further Applications
Approval Elections
Map of Rules
Data!
Introduction to voting
Experiments in Computational Social Choice
Preference Learning
Mallows
Real-Life Data
Use Cases (Elections)
Swap Distance
Map of Elections
Distances
Positionwise
Embedding Algorithms
Force-Directed
Verification
AN
UN
Compass Elections
ID
ST
Winners
Approximations
Election Results
Committees
Running Time

10 minutes

Create your own map of elections!

Introduction to Mapel Software Package 2/2


Mapel
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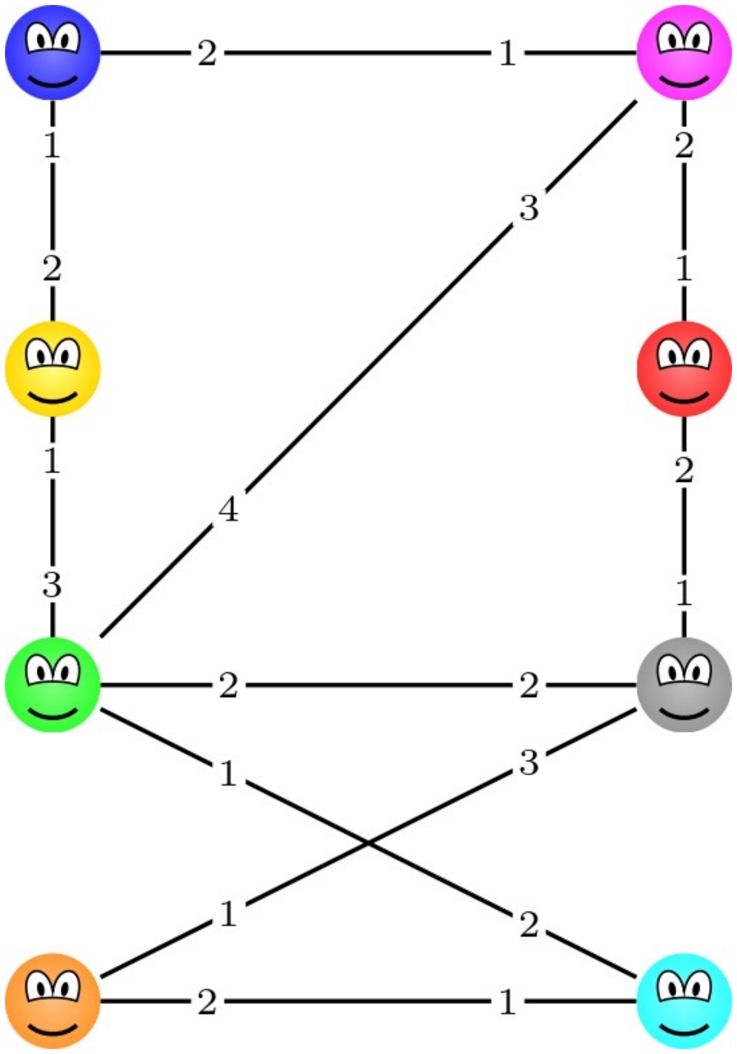
ST
Winners
Election Results
Approximations
Committees
Running Time

A Map of Diverse Synthetic Stable Roommates Instances, Boehmer et al., AAMAS-23

15 minutes

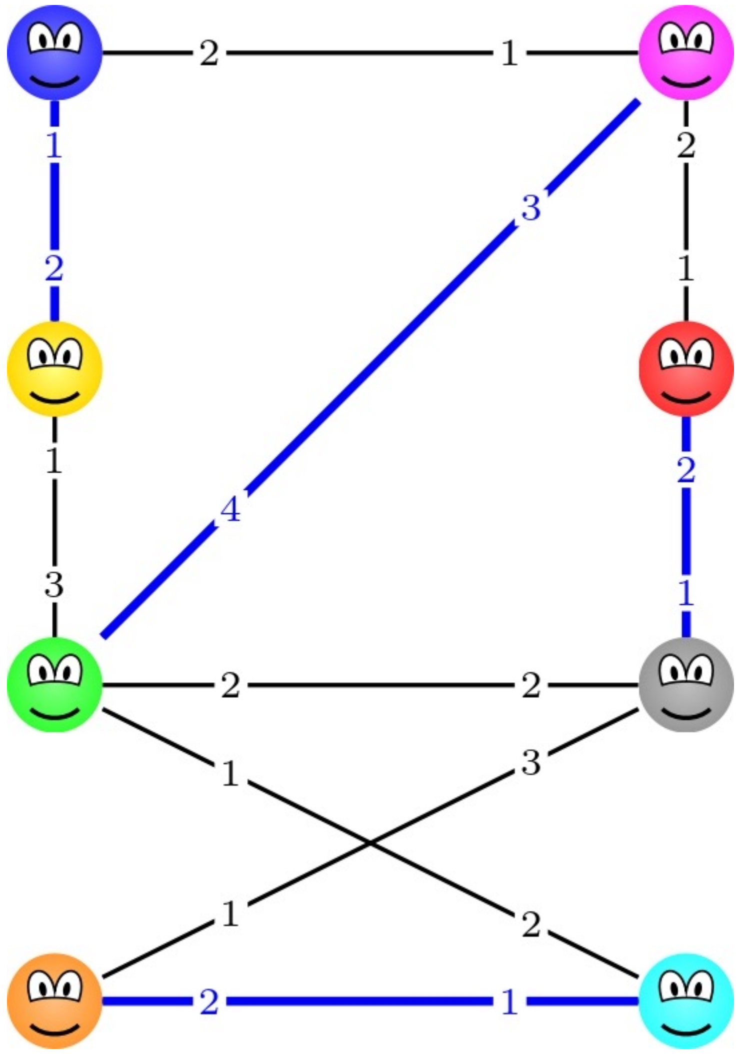
Maps for Matchings under Preferences

Stable Roommates



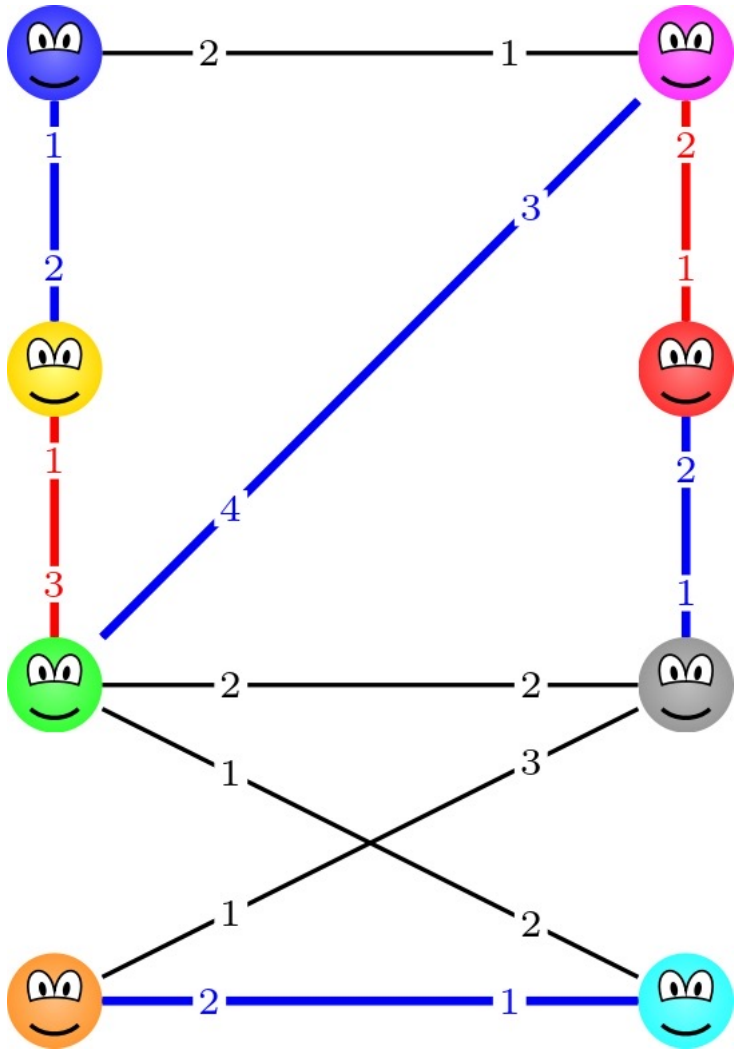
Input: Agents with strict preferences over each other.

Stable Roommates



Input: Agents with strict preferences over each other.

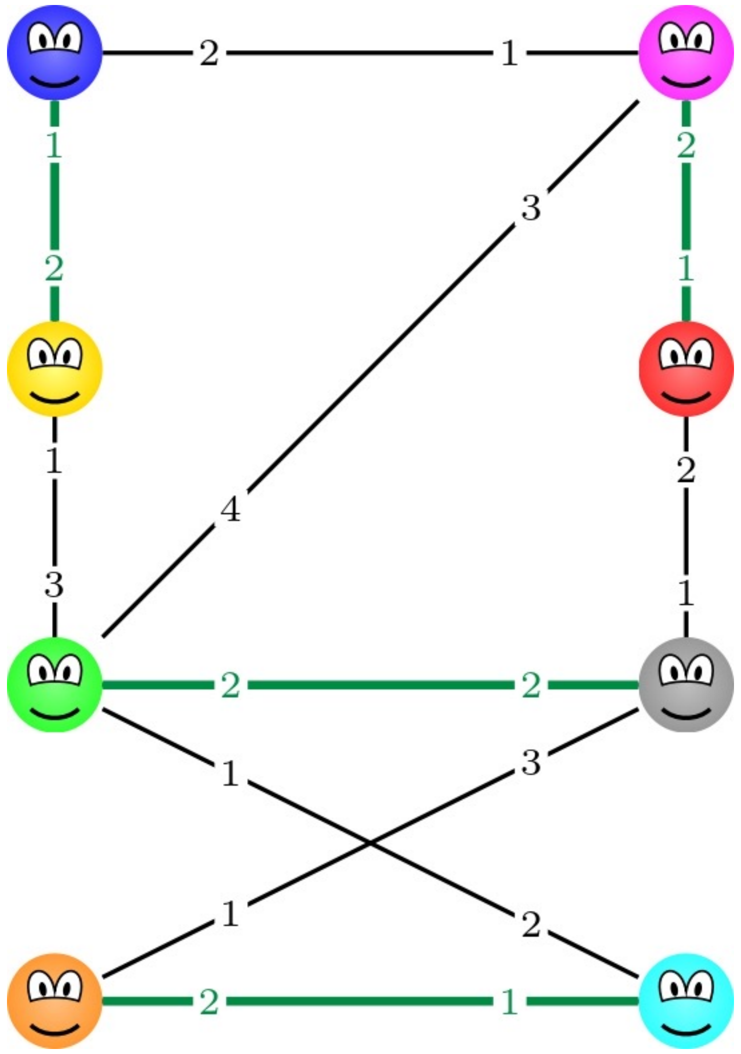
Stable Roommates



Input: Agents with strict preferences over each other.

An agent pair blocks matching M if both agents prefer each other to current partner.

Stable Roommates

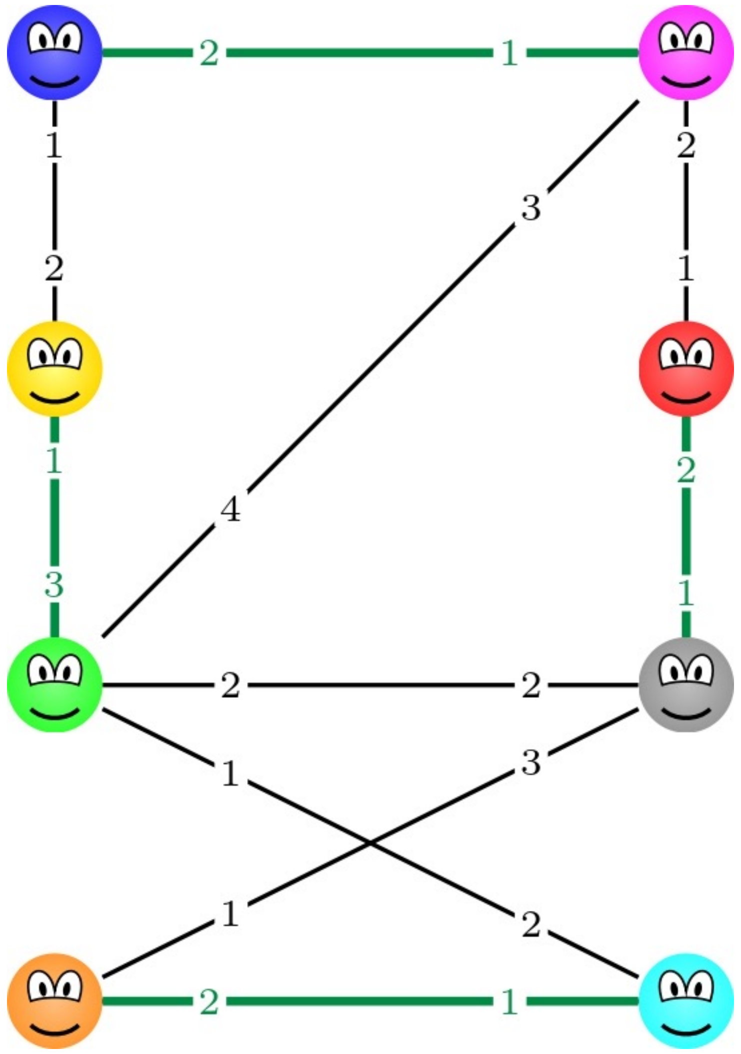


Input: Agents with strict preferences over each other.

An agent pair blocks matching M if both agents prefer each other to current partner.

Goal: Find a stable matching, i.e., a matching without a blocking pair.

Stable Roommates



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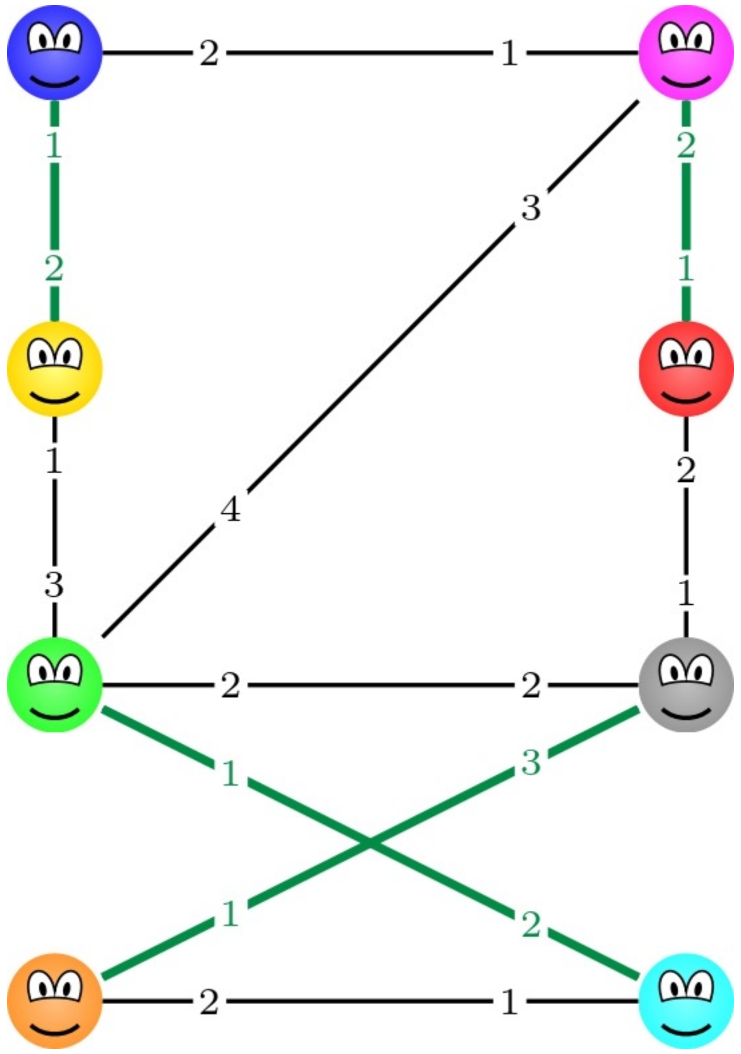
Stable Roommates



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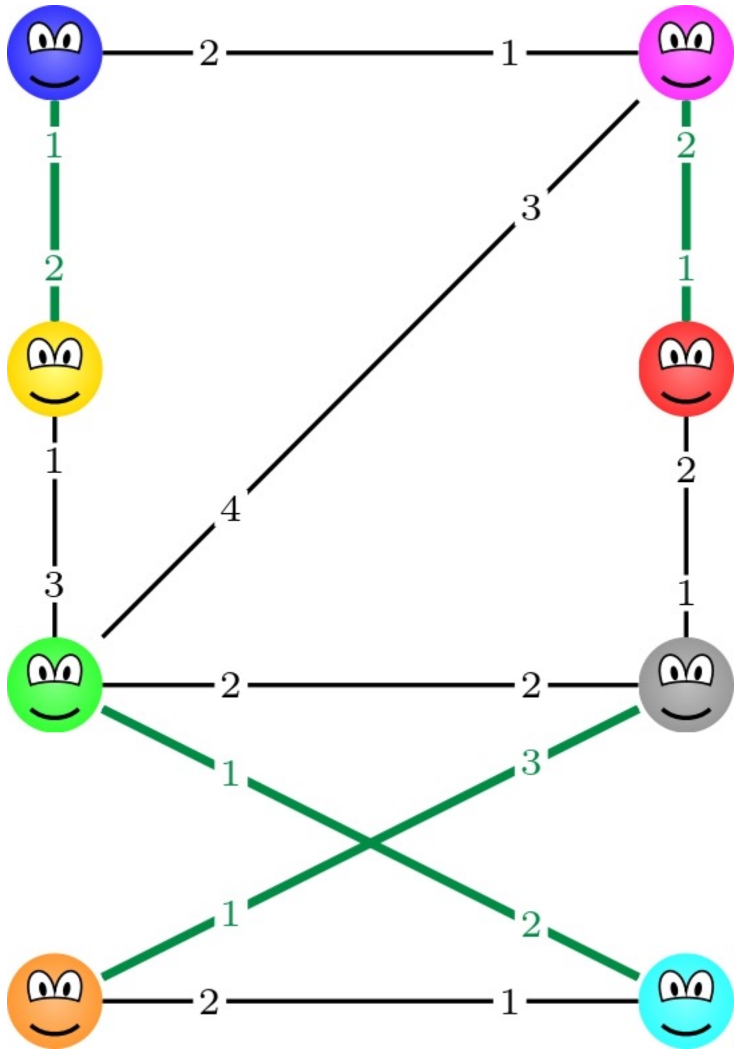
Stable Roommates



Input: Agents with strict preferences over each other.

An agent pair blocks matching M if both agents prefer each other to current partner.

Goal: Find a stable matching, i.e., a matching without a blocking pair.

Status Quo

- Numerous works on theoretical aspects of stable matching problems with real-world impact.
- Some works contain empirical investigations but far away from standard with most of them only using uniformly at random sampled preferences.

Step 1: Distance Measure

Central Question

How to measure the similarity of two Stable Roommates instances?

(Assumption: Both instances have same number of agents)

Positionwise Distance

General popularity/quality of agents in the instance.

Position matrix completely ignores mutual opinions, i.e., what agents think of each other (agents are "voters" and "candidates")

Mutual Attraction Matrix: Aggregate Representation

Intuition For stable matchings, it is important which agents an agent likes, but also whether they like them as well.

Mutual Attraction Vector i-th entry is the position in which *agent a* occurs in the preferences of the agent that *agent a* ranks in position i.

Mutual Attraction Matrix One row for each agent/vector.

a : b ≻ c ≻ d

b : a ≻ c ≻ d

c : a ≻ b ≻ d

d : a ≻ b ≻ c

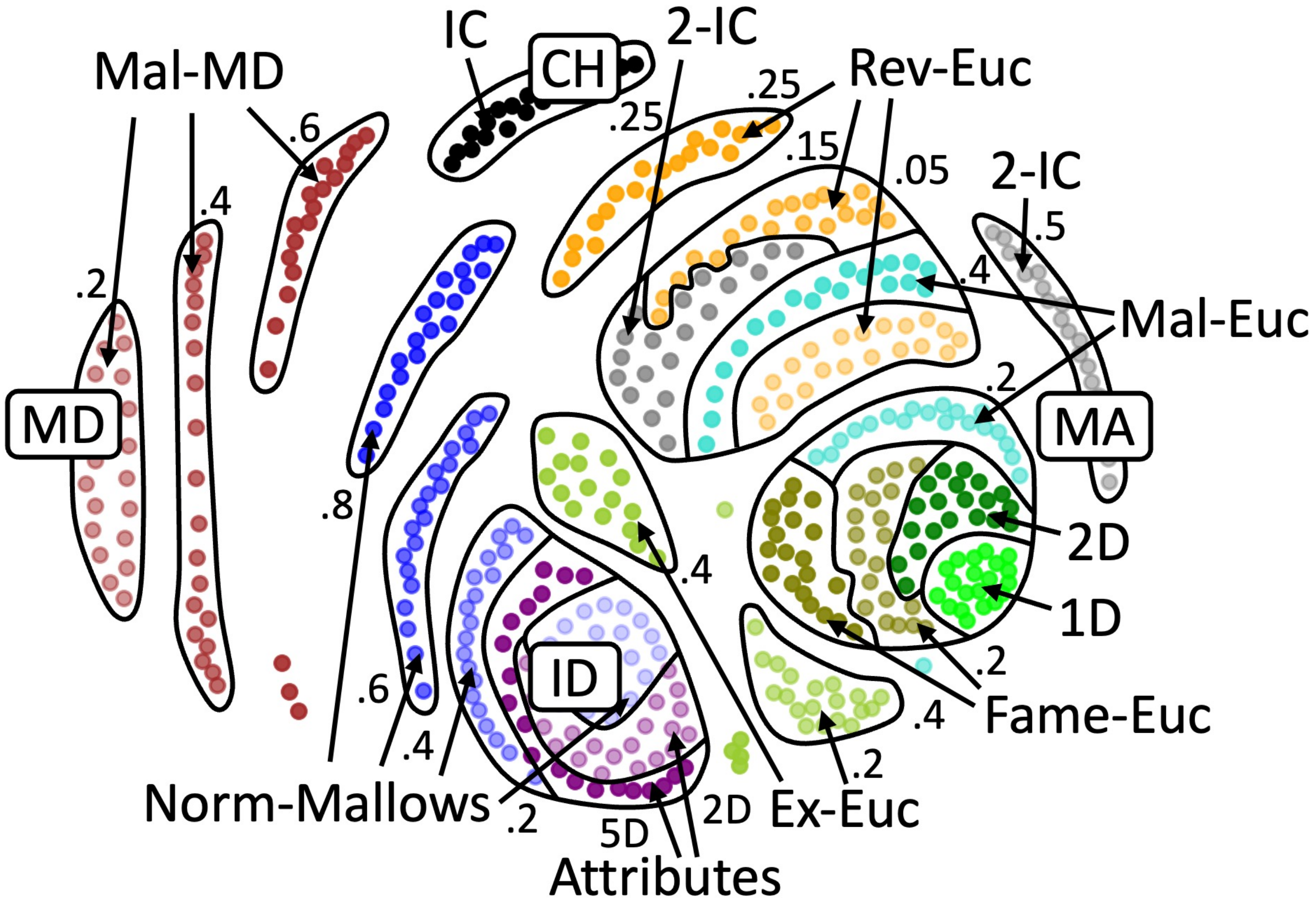
$$\rightsquigarrow \quad \begin{array}{c} \\ a \\ b \\ c \\ d \end{array} \begin{array}{c} \begin{array}{ccc} 1 & 2 & 3 \end{array} \\ \begin{bmatrix} 1 & 1 & 1 \\ 1 & 2 & 2 \\ 2 & 2 & 3 \\ 3 & 3 & 3 \end{bmatrix} \end{array}$$

Step 2: Generating Instances

460 instances generated from 10 statistical cultures (4 known) from:

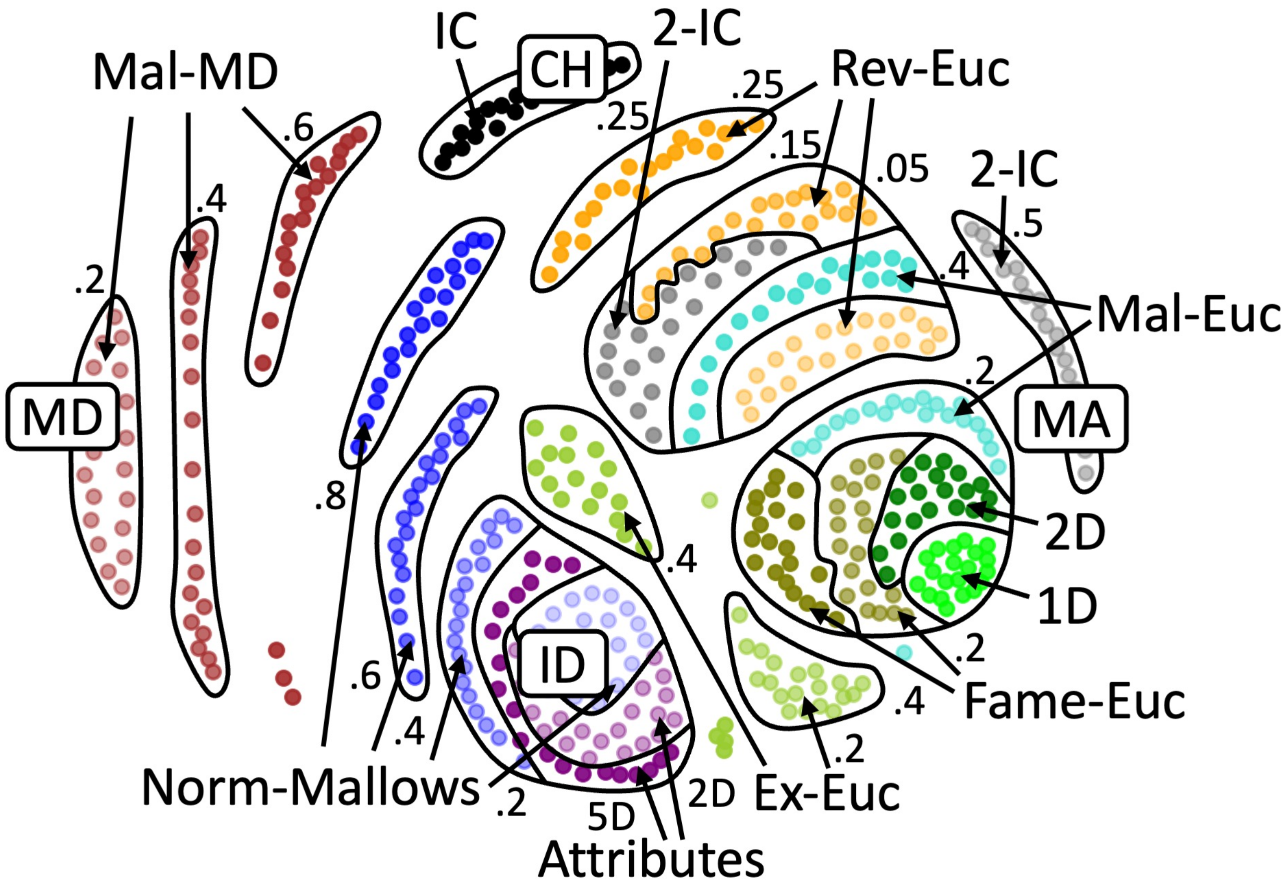
- Impartial Culture Agents draw preferences uniformly at random from set of all possible preferences.
- Mallows There is a central order v*. Probability of sampling preference order v is proportional to $\varphi^{swap(v,v^*)}$.
- Attributes Different objective evaluation criteria but agents assign different importance to them.
- Euclidean Agents are points on line / in square and rank other agents by increasing distance.
- Reverse-Euclidean Like Euclidean but some fraction of agents rank by decreasing distance.
- Fame-Euclidean Like Euclidean but some agents are generally more attractive.

Step 3: Drawing the Map



Computed using variant of forced-directed Kamada-Kawai algorithm

Step 4: Understanding the Map

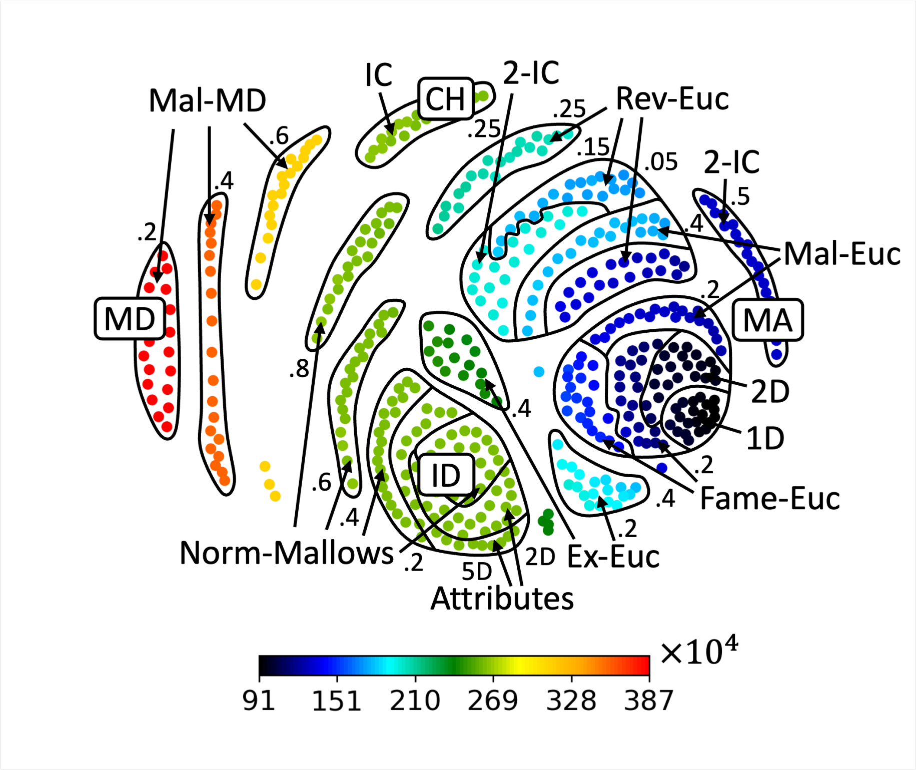


Extreme Matrices

1. Identity (ID) All agents have the same preferences (master list).
2. Mutual Agreement (MA) Agents rank each other in same position.
3. Mutual Disagreement (MD) Evaluations are diametric: a ranks b in position i-b ranks a in position n-i+1.
4. Chaos (CH) "Chaotic" matrix.

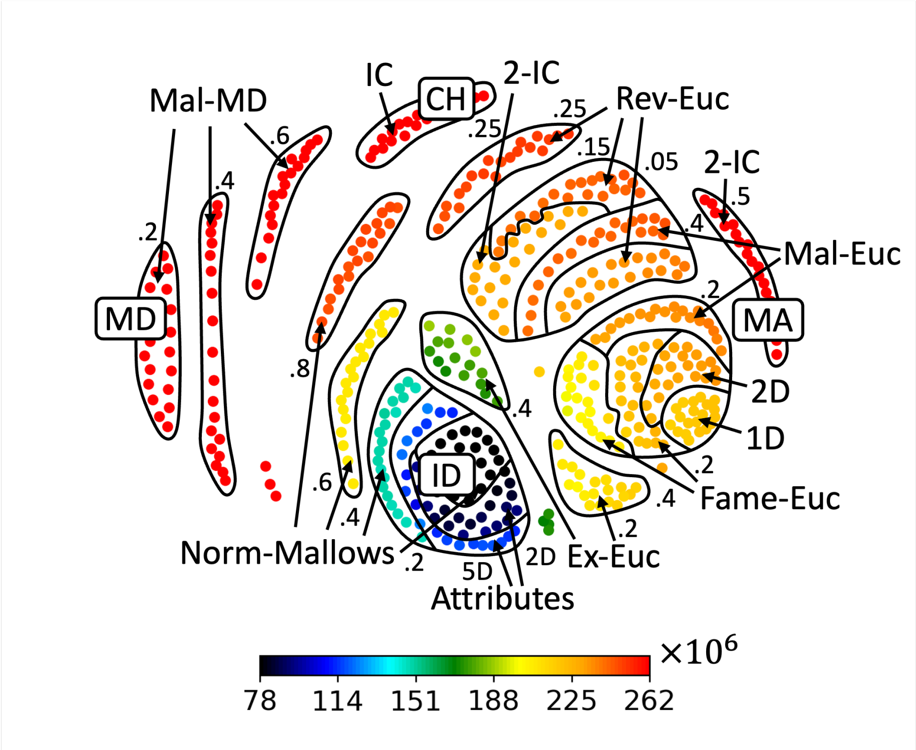
Step 4: Understanding the Map II

Meaning of Axes



Mutuality value

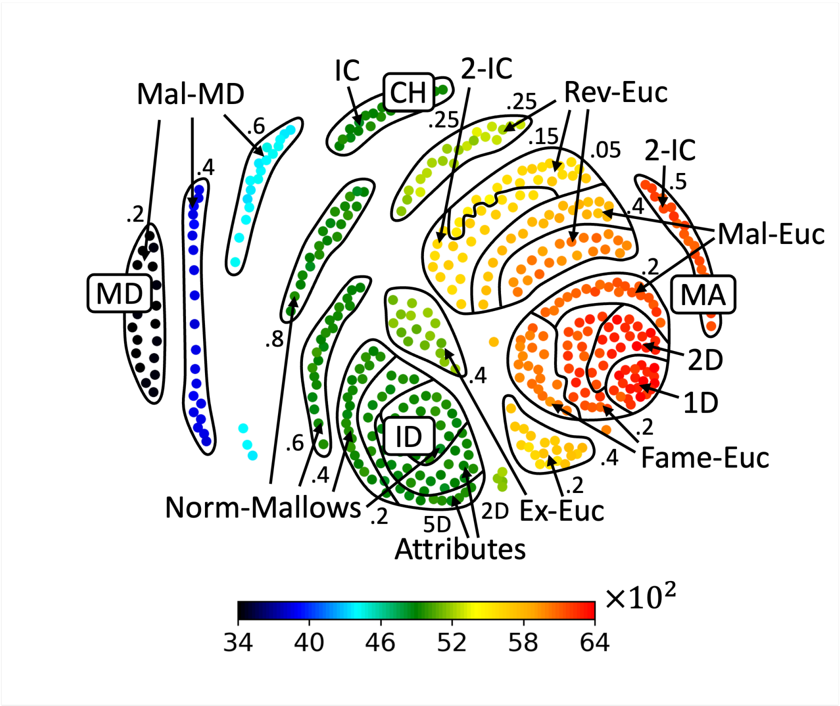
total difference between mutual evaluations of agent pairs



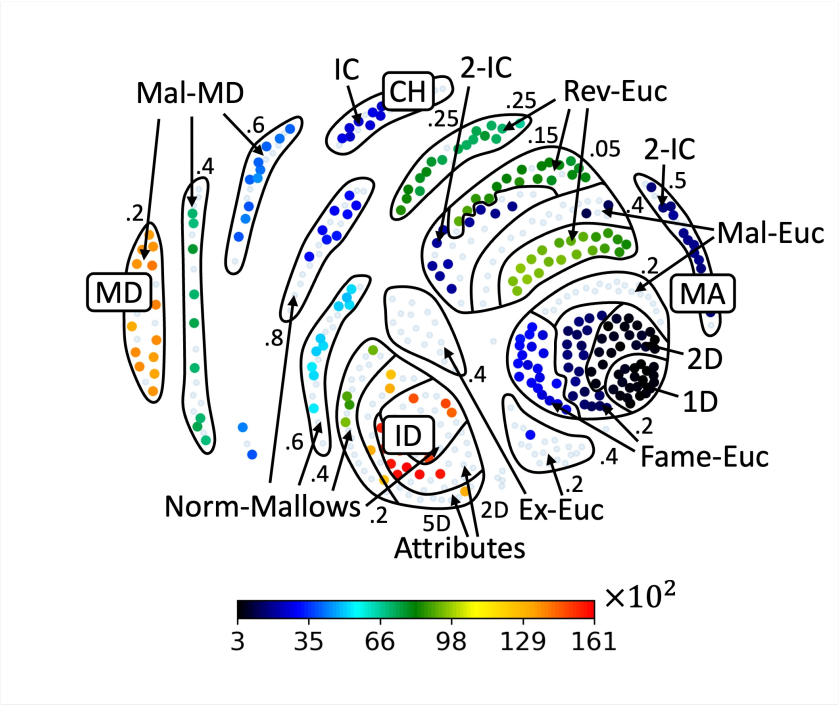
Rank distortion

for each agent we sum up the absolute difference between all pairs of entries in MA vector

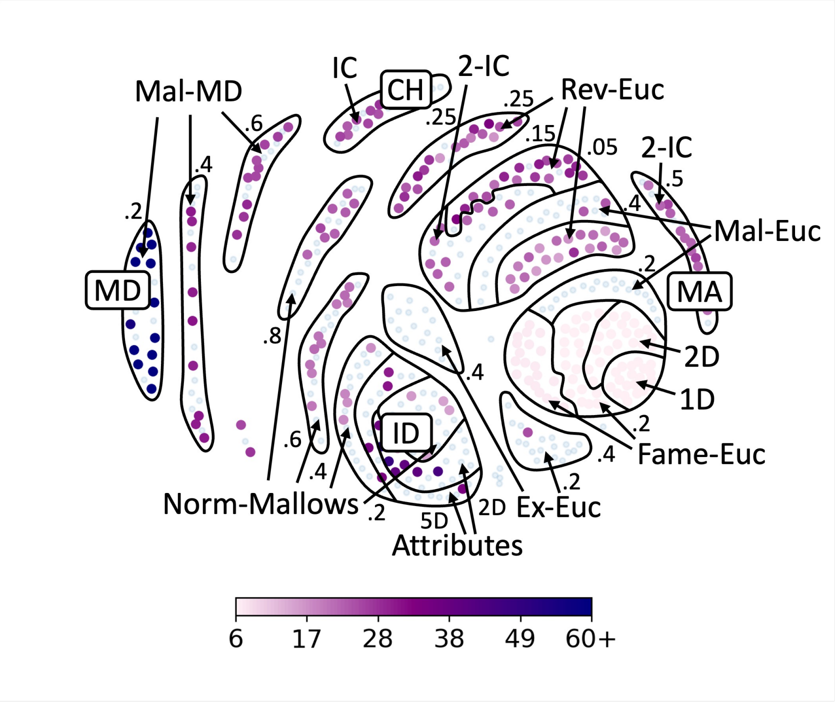
Step 5: Using the Map



Average number of blocking pairs for perfect matching



Minimum summed rank of a stable matching



Running time of ILP for summed rank minimal matching

Conclusion

Take-aways

- General approach for maps applicable beyond voting including "tricks":
  - Aggregate representation
  - Force-directed algorithms
  - Give meaning to axes and regions on the map (plus compass points)
- Instances from one statistical culture placed close to each other and exhibit similar performance in experiments.

→ Usage of multi-source data crucial.

Do
More
Experiments!

Please…