

VoteKit: A Python package for computational social choice research

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Summary

The scholarly study of elections, known as *social choice theory*, centers on the provable properties of voting rules. The practical study of democracy reform focuses on designing or selecting systems of election to produce electoral outcomes that promote legitimacy and broad-based representation. For instance, the dominant electoral system in the United States is a one-person-one-vote/winner-take-all system, sometimes known as PSMD (plurality in single member districts), but there is considerable reform momentum in favor of ranked choice voting because it is thought to mitigate the effects of vote-splitting and strengthen prospects for minority representation.¹ Across the world, systems of election—and prospects for system change—vary substantially. From both a scholarly and a practical perspective, many questions arise about comparing the properties and tendencies of diverse systems of election in a rigorous manner.

VoteKit ([MGGG Redistricting Lab, n.d.-b](#)) is a Python package designed to facilitate just that kind of analysis, bringing together multiple types of functionality. Users can:

1. Create synthetic *preference profiles* (collections of ballots) with a choice of generative models and behavioral parameters;
2. Read in real-world *cast vote records* (CVRs) as observed examples of preference profiles; clean and process ballots, including by deduplication and handling of undervotes and overvotes;
3. Run a variety of *voting rules* to ingest preference profiles and output winner sets and rankings; and
4. Produce a wide range of *summary statistics* and *data visualizations* to compare and analyze profiles and election outcomes.

Statement of need

Social choice theory grew out of welfare economics in the mid-twentieth century and has been recognized as a deep and highly applicable area of economic theory, forming part of the basis for at least four Nobel Prize awards.² Since the 1990s, a new fusion of economics and computer science has emerged under the name of *computational social choice*, studying

¹Recent ranked-choice voting reforms include the adoption of instant runoff voting (IRV) in Maine, Alaska, New York City, and single transferable vote (STV) in Portland, Oregon. Advocacy groups claiming various pro-democratic properties of ranked choice include [Campaign Legal Center](#), [FairVote](#), and many others.

²Nobel Laureates with significant work in social choice include Arrow, Sen, Maskin, and Myerson.

34 questions of complexity and design and further advancing the axiomatic study of elections.³
35 But most of these innovations have been highly abstract, and there has been a significant gap
36 in the literature—and in the landscape of software—between the theory and the practice of
37 democracy.

38 On the software side, researchers have built a multitude of different packages for generating and
39 analyzing elections, and users have had to invest substantial work in cleaning CVRs to make
40 them usable across multiple packages.⁴ VoteKit is built to provide an end-to-end pipeline.

41 Area of need: Generative models

42 For one concrete example of a literature and software gap, consider the construction of
43 *generative models*. This term is often associated with large language models as paradigms
44 of artificial intelligence; here, what is being generated is realistic voting rather than realistic
45 language. In this setting, a generative model of voting is a probability distribution on the
46 set of all possible ballots that can be cast in a given election style; profiles can be sampled
47 from a generative model to produce simulated or synthetic elections. Having sources of rich,
48 varied, and realistic data is essential to an empirically grounded research program to probe
49 the properties of voting rules. Good generative models are also essential to advise reformers
50 deciding between options in a new locality, as they enable generation of synthetic profiles keyed
51 to the scale, demographics, and election specs of that specific place. But most of the models
52 in the literature, like the Impartial Culture model (all permutations of candidates are equally
53 likely) or the Impartial Anonymous Culture model (sampling proportional to volume measure
54 on the simplex of weighted averages of permutations) are mathematically tractable but highly
55 unrealistic. This is bluntly described by Tideman and Plassman in a survey of generative
56 methods: in their words, “None of the 11 models discussed so far are based on the belief that
57 the associated distributions [...] might actually describe rankings in actual elections” (Tideman
58 & Plassmann, 2010). They therefore recommend *spatial models* instead, which themselves are
59 of dubious realism for the selection of political candidates.⁵

60 VoteKit implements many of the models described in those surveys, as well as newer mathe-
61 matical models that give users the ability to generate profiles that are designed to comport
62 with real-world ranking behavior and particularly to generate polarized elections. Two leading
63 choices are based on classic statistical ranking mechanisms, called the Plackett–Luce (PL) and
64 Bradley–Terry (BT) models; another model called the Cambridge Sampler (CS) draws from
65 historical ranking data in Cambridge, MA city council elections. These models have flexible
66 parameters, allowing users to vary voting bloc proportions, candidate strength within slates,
67 and polarization between blocs. These parameters can be specified or randomly sampled.

³For example, a very active research direction in computational social choice theory has been the development of fairness axioms for approval elections, such as the definition called JR (justified representation) and its relatives, which have been extended to rankings. See (Aziz et al., 2017; Skowron et al., 2017) and their references.

⁴See for instance the extensive array of open-source tools on the Computational Social Choice (COMSOC) community page (Ulle Endriss and Simon Rey, n.d.) including the widely used collection of ranked data called PrefLib (Ulle Endriss and Simon Rey, n.d.). See also the materials provided by FairVote, including their DataVerse and GitHub (FairVote, n.d.). The ArXiv preprint (Boehmer et al., n.d.) provides an impressively comprehensive list of numerical experiments on elections. The PRAGMA Project (<https://perma.cc/2P6V-8ZER>) echoes our statement of need, noting that the current literature and software falls short in practical applicability and that the understanding of real and synthetic data is “very limited.”

⁵Spatial models assume voters rank by proximity in a metric space defined by issue positions or other attributes; the metric space may be latent, or unknown to voters, but it is presumed to universally govern the way voters rank candidates. See for instance (Burden, 1997), which introduces probabilistic voting keyed to proximity. Though spatial models have been argued to perform adequately to model roll call voting in Congress, their efficacy for selecting political representation is debatable. In a meta-analysis of 163 papers (Boehmer et al., n.d.), the authors report that Impartial Culture and Euclidean (spatial) models make up more than 75% of the election experiments found in 163 papers.

68 Area of need: Comparison and communication

69 In the realm of democracy reform, groups of stakeholders often ask researchers to provide
70 modeling studies to decide on what shift to make in electoral systems, as the project list below
71 makes clear. VoteKit implements voting rules that stakeholders often seek to compare, with
72 parameters designed to be tailored by the user to the specific locality under study. Available
73 voting rules include:

- 74 ■ **Ranking-based (ordinal).** Plurality/SNTV, STV and IRV, (generalized) Borda, Alaska⁶,
75 Top-Two, Dominating sets/Smith method, Condo-Borda⁷, Sequential RCV.
- 76 ■ **Score-based (cardinal).** Range voting, Cumulative, Limited.
- 77 ■ **Approval-based (set).** Approval voting, Bloc plurality.

78 See generally (Amorós et al., 2016; Emerson, 2013; McCune et al., 2023; Reynolds et al.,
79 2008; Tideman, 1995) for references.

80 Reform advocates also need to describe voting mechanisms and their likely outcomes effectively
81 to members of their communities. The end-to-end pipeline provided by VoteKit allows
82 advocates to toggle different system settings and compare expected outcomes.

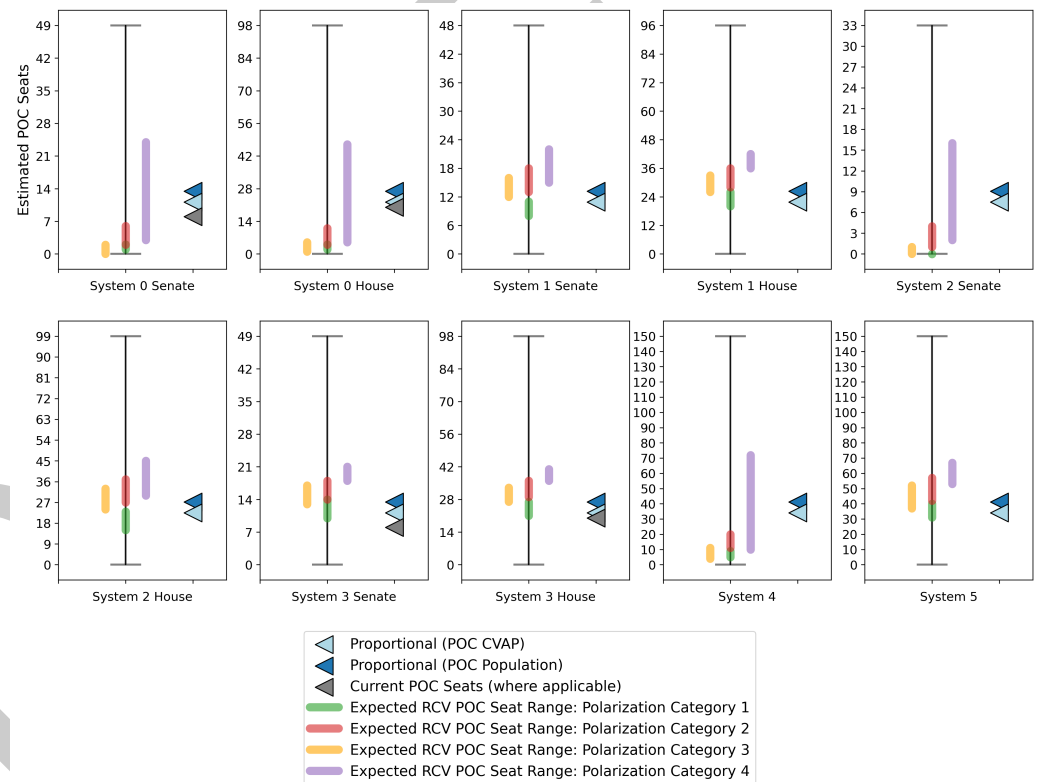


Figure 1: A comparison of a variety of electoral systems and their effect on minority representation in a case study of the Washington state legislature (MGGG Redistricting Lab, 2021d).

⁶Our model of the Alaska method is an SNTV/STV hybrid that uses single non-transferable vote to choose a set of finalists, then runs STV on the same preference profile to fill the seats. Alaska's elections run this with four finalists and one seat; the top-two system runs this with two finalists and one seat.

⁷This system orders candidates within dominating sets by Borda score. Note that this is distinct from Black's method (Black, 2012), which uses Borda score as a backup system in case the smallest dominating set is not a singleton.

83 Area of need: Resources for research

84 Previous research works such as (Elkind et al., 2017) have compared properties of earlier
85 generative models; VoteKit facilitates robust comparisons across a more comprehensive and
86 up-to-date list of alternatives. It also offers new analytical tools that will support research
87 on elections. Some examples of more sophisticated functionality are shown in Figure 2. At
88 left is a *ballot graph*, where nodes are ballots weighted by their frequency in the profile; a
89 recent research paper shows that ballot graphs can be metrized to realize classical statistical
90 ranking distances, like Kendall tau and the Spearman footrule (Duchin & Tapp, 2024). VoteKit
91 also implements a class of election distances, as surveyed in (Boehmer et al., 2022). Choices
92 for measuring the difference between two profiles on the same set of candidates include L^p
93 distance and Wasserstein (earth-mover) distance. At right is a multidimensional scaling (MDS)
94 plot of a different set of data, showing mutual L^1 differences between generated profiles across
95 various selections of model (shown in colors) and candidate strength parameters (shown with
96 symbols), enabling comparisons in the style of (Szufa et al., 2020).

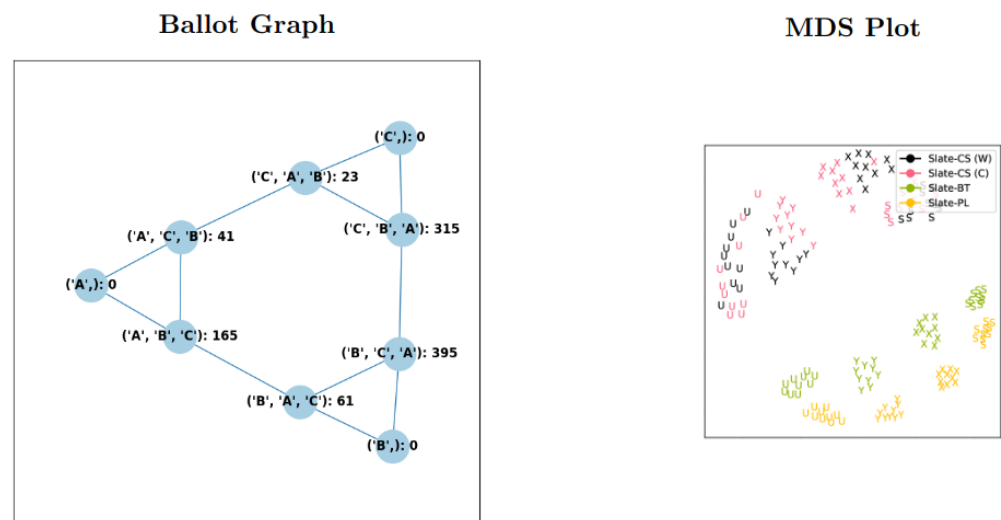


Figure 2: At left, the ballot graph for a 3-candidate election. There is one node per possible ballot, and the weights show the number of instances of that ballot in the profile. At right, a multidimensional scaling (MDS) plot for 160 synthetic profiles made with various generative models and candidate strength parameters for two slates of 3 candidates each. The MDS plot is a low-distortion planar embedding of those 160 profiles and their pairwise differences.

97 Finally, VoteKit interacts seamlessly with a wide range of actual vote data, such as thousands
98 of political elections collected by FairVote and a cleaned repository of over 1000 Scottish STV
99 local government elections (FairVote, n.d.; MGGG Redistricting Lab, n.d.-a). Previously, the
100 use of real data in election research was often extremely limited; for instance, a recent survey
101 reports that the single most popular “real-life” dataset has been a survey of 5000 respondents’
102 sushi preferences (Boehmer et al., n.d.).

103 Projects

104 A significant number of white papers and scholarly articles have used VoteKit (and its prede-
105 cessor codebase) in recent years. These include the following.

- 106 ■ A large number of case studies in ranked-choice modeling, such as studies for the city
107 councils of Chicago, IL (MGGG Redistricting Lab, 2019b) and Lowell, MA (MGGG
108 Redistricting Lab, 2019a); the state legislatures of Oregon and Washington (MGGG

- 109 [Redistricting Lab, 2021a, 2021d](#)), and a range of county commissions and school boards
 110 across the Pacific Northwest ([MGGG Redistricting Lab, 2021c, 2021b](#));
- 111 ■ A study modeling the impact of proposed legislation called the Fair Representation Act,
 112 which would convert U.S. Congressional elections to the single transferable vote system
 113 ([MGGG Redistricting Lab, 2022](#));
 - 114 ■ A detailed study isolating the impacts of varying hypotheses about voter behavior and
 115 candidate availability on the Massachusetts legislature ([MGGG Redistricting Lab, 2024](#));
 - 116 ■ A peer-reviewed article for an election law audience on the impact of STV elections on
 117 minority representation ([Benadè et al., 2021](#));
 - 118 ■ A peer-reviewed article for a CS/econ audience that probes whether STV delivers
 119 proportional representation ([Benadè et al., 2024](#)); and
 - 120 ■ A peer-reviewed article for an CS/operations research audience on optimizing to “learn”
 121 blocs and slates in real-world elections ([Duchin & Tapp, 2024](#)).

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