Improving the Computational Efficiency of Adaptive Audits of IRV Elections*

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Abstract. AWAIRE is one of two extant methods for conducting risklimiting audits of instant-runoff voting (IRV) elections. In principle AWAIRE can audit IRV contests with any number of candidates, but the original implementation incurred memory and computation costs that grew superexponentially with the number of candidates. This paper improves the algorithmic implementation of AWAIRE in three ways that make it practical to audit IRV contests with 55 candidates, compared to the previous 6 candidates. First, rather than trying from the start to rule out all candidate elimination orders that produce a different winner, the algorithm starts by considering only the final round, testing statistically whether each candidate could have won that round. For those candidates who cannot be ruled out at that stage, it expands to consider earlier and earlier rounds until either it provides strong evidence that the reported winner really won or a full hand count is conducted, revealing who really won. Second, it tests a richer collection of conditions, some of which can rule out many elimination orders at once. Third, it exploits relationships among those conditions, allowing it to abandon testing those that are unlikely to help. We provide real-world examples with up to 36 candidates and synthetic examples with up to 55 candidates, showing how audit sample size depends on the margins and on the tuning parameters. An open-source Python implementation is publicly available.

1 Introduction

Risk-limiting audits (RLAs) are gaining attention in the world of election se-curity and assurance.^{[5](#page-0-0)} An RLA is any procedure with a guaranteed minimum

[⋆] We thank Vanessa Teague for helpful discussions. This work was supported by the Australian Research Council (Discovery Project DP220101012, OPTIMA ITTC IC200100009) and the US National Science Foundation (SaTC 2228884).

 5 [https://www.ifes.org/publications/risk-limiting-audits-guide-global-use,](https://www.ifes.org/publications/risk-limiting-audits-guide-global-use) and [https:](https://www.ncsl.org/elections-and-campaigns/risk-limiting-audits) [//www.ncsl.org/elections-and-campaigns/risk-limiting-audits](https://www.ncsl.org/elections-and-campaigns/risk-limiting-audits) (visited 15 May 2024)

probability of correcting the reported outcome of an election if the reported out-come is wrong, and that never alters a correct outcome.^{[6](#page-1-0)} Outcome means who or what won, not the vote tallies. The risk limit α is the maximum chance that a wrong outcome will not be corrected. RLAs generally involve sampling cast ballot cards at random and manually reading the votes on those cards. RLAs can use a broad variety of sampling designs and can use a variety of information from the voting system to improve efficiency [\[7,](#page-15-0)[8](#page-15-1)[,9\]](#page-15-2).

Improving the efficiency of RLAs—i.e., reducing the sample size an RLA requires when the reported outcome is correct—is an active field of research. Efficient RLAs for instant-runoff voting (IRV), a common form of ranked-choice voting, were developed relatively recently. IRV is tallied in rounds. The least popular candidate is eliminated in each round until only one candidate remains: the winner. In each round, each ballot's most preferred choice among the remaining candidates is counted as a vote for that candidate. Tabulating an IRV election produces an elimination order ; the last candidate in the order is the winner.

IRV is used in political contests in several countries: the federal House of Representatives in Australia, along with most analogues at the state-level; the president of India; single-winner contests in Ireland such as the president of Ireland and by-elections to Dail Eireann (the Irish lower house); and various contest in U.S. states including Alaska, California, Colorado, Maine, and Nevada, and by some political parties for statewide primary elections.

RAIRE $[3]$ and AWAIRE $[6]$ are the only extant methods for conducting RLAs of IRV elections. Both confirm the outcome by ruling out all elimination orders that yield a different winner (alt-orders). Both involve constructing 'assertions' which, if true, collectively rule out all alt-orders.^{[7](#page-1-1)} These assertions are then checked statistically using tools available in the SHANGRLA frame-work for RLAs [\[7](#page-15-0)[,8\]](#page-15-1). RAIRE is a two-stage approach: generate a sufficient set of assertions before any sampling (offline), then test the assertions by sampling. AWAIRE perform both steps simultaneously (online), using the sample to 'learn' a sufficient set of assertions that can be tested efficiently, while testing them.

Another difference between the two methods is that RAIRE requires cast vote records (CVRs, the voting equipment's internal record of the preferences expressed on each ballot) to select the set of assertions to minimize expected workload if the CVRs are accurate.^{[8](#page-1-2)}

⁶ The collection of ballot cards from which the audit sample is drawn must be a demonstrably complete and trustworthy record of the validly cast votes; otherwise, no audit procedure can guarantee a nonzero chance of catching and correcting wrong outcomes. See, e.g., Appel & Stark [\[1\]](#page-15-5).

⁷ The assertions used by RAIRE may also rule out some orders that correspond to the reported winner indeed winning, but through an elimination order that differs from the reported order.

⁸ If the CVRs are linked to the corresponding ballot cards, RAIRE and AWAIRE can use ballot-level comparison auditing, increasing efficiency. See, e.g., Blom et al. [\[2\]](#page-15-6). ONEAudit [\[9\]](#page-15-2) can also be used with RAIRE and AWAIRE to take advantage batch subtotals or linked CVRs.

AWAIRE has benefits over RAIRE, leveraging the insight that one can decompose every alt-order into a set of requirements that must all be true for the alt-order to be true, and let the sample dictate which requirements to use to reject the alt-order, while, RAIRE pre-commits to a subset of requirements to test. Because of this, AWAIRE can adaptively identify the requirements that are easiest to disprove, even when the CVRs are not accurate; it does not require CVRs, but can use them if they are available; and it is more resilient than RAIRE if the CVRs imply an incorrect elimination order but the reported winner is correct.

Here, we address the main drawback of AWAIRE as presented so far: its computational performance. For contests with k candidates, the original implementation of AWAIRE tracked and tested all $k! - (k-1)!$ alt-orders and their numerous requirements. That limited it to elections with at most 6 candidates, fewer than many real-world IRV elections. We show how to vastly decrease the computational resources AWAIRE needs.

The new implementation tracks a frontier of suffixes of alt-orders. Often, the sample allows AWAIRE to reject a suffix that an exponential number of alt-orders share. Otherwise, the new approach extends the suffix, replacing it in the frontier with all suffixes with one more candidate. As the suffixes grow in length, they entail more requirements, which may make them easier to reject. By parsimoniously expanding suffixes, the algorithm never needs to consider very many at a time, and most of the possible requirements may never need to be tested. We also consider forms of requirements that RAIRE uses but that were not used in the original implementation of AWAIRE. As a result, the new version of AWAIRE is computationally tractable for IRV elections with more than 50 candidates.

2 Background

We refer the reader to the original AWAIRE paper [\[6\]](#page-15-4) for details of the notation and terminology, but we summarize the key objects and ideas here: alt-orders, requirements, test supermartingales (TSMs), base TSMs, and intersection TSMs.

Let C denote the set of candidates, $k = |\mathcal{C}|$ the number of candidates, and B the number of *ballot cards*^{[9](#page-2-0)} cast in the contest. We identify each ballot card *b* with an ordering of a subset of candidates, possibly the empty set.

An *alt-order* is a candidate elimination order in which someone other than the reported winner is last—i.e., the reported winner did not win. There are $(k-1)(k-1)! = k! - (k-1)!$ alt-orders: for each of the $k-1$ candidates who were not reported to have won, there are $(k-1)!$ elimination orders for the the other $k-1$ candidates that would make that candidate the winner.

Example 1. Consider a four-candidate election, with candidates W, X, Y, Z, where W is the reported winner. The outcome is confirmed if we can rule out every elimination order in which any candidate other than W is last (every $alt-order$):

 $[W, X, Y, Z], [W, X, Z, Y], [W, Y, X, Z], [W, Y, Z, X], [W, Z, X, Y], [W, Z, Y, X],$

⁹ In some countries, a ballot may comprise more than one piece of paper (card).

 $[X, W, Y, Z], [X, W, Z, Y], [X, Y, W, Z], [X, Z, W, Y], [Y, W, X, Z], [Y, W, Z, X],$ $[Y, X, W, Z], [Y, Z, W, X], [Z, W, X, Y], [Z, W, Y, X], [Z, X, W, Y], [Z, Y, W, X].$ The other 6 elimination orders lead to W winning: they are not alt-orders. ⊓⊔

Each alt-order is characterized by a set of requirements, all of which must be true for that alt-order to be the actual elimination order. If any requirement for an alt-order fails, that rules out the alt-order—and every other alt-order that shares that requirement. AWAIRE used a single form of requirement:

Directly Beats. DB (i, j, S) holds if candidate i has more votes than candidate j when the only candidates remaining are $S \supseteq \{i, j\}$: i cannot be the next candidate eliminated when exactly the candidates S remain.

If $DB(i, j, \mathcal{S})$ is false, j has more votes than i when only S remain standing. In that case, j cannot be the next eliminated: i would be eliminated before it.

Each requirement is associated with a test supermartingale (TSM) called a base TSM. (A TSM is a stochastic process starting at 1 that, if the requirement is true, is a nonnegative supermartingale. A nonnegative supermartingale is like the fortune of a bettor in a series of games that are fair or biased against the bettor, when the bettor is not allowed to go into debt. Ek et al. [\[6\]](#page-15-4) explains how TSMs are used in AWAIRE.)

In turn, each alt-order is associated with a TSM called an intersection TSM, a weighted average of the base TSMs for the requirements that characterize that alt-order. If every requirement for that alt-order is true, the intersection TSM for the alt-order is a nonnegative supermartingale starting at 1. The weights in the average are chosen adaptively to try to minimize the sample size required to confirm the reported outcome (i.e., to reject every alt-order) when the reported outcome is indeed correct.

Constructing the statistical tests of alt-orders from TSMs provides sequential validity: the evidence that the outcome is correct can be evaluated after each sampled ballot card is examined, with no statistical penalty for looking at the data repeatedly. For any requirement that is true, the chance that its base TSM ever reaches or exceeds $1/\alpha$ is at most α , by Ville's inequality. If any alt-order is true, the chance that its intersection TSM ever reaches the value $1/\alpha$ is at most α . Thus, if the audit stops without a full hand count only if every intersection TSM hits or exceeds $1/\alpha$, the audit has risk limit α .

Requirements are expressed in terms of the means of lists of numbers, one number per ballot card (for each requirement). An *assorter* (see Stark [\[7\]](#page-15-0)) assigns a number to each card, depending on the vote preferences on the card and on the requirement. The assorter assigns the numbers in such a way that if its requirement is true, the mean of the list of numbers is no larger than 1/2.

Example 2. Consider the requirement $DB(X, Y, C)$ that candidate X beats candidate Y on first preferences. The corresponding assorter assigns a card the value 1 if it shows a first preference for candidate Y, the value 0 if it shows a first preference for X, and the value 1/2 otherwise. If the mean of the resulting list of all B numbers is less than 1/2, then the requirement $DB(X, Y, C)$ holds. □

Each requirement can be tested by testing the statistical hypothesis that the mean of its assorter values is at most $1/2$ from a random sample of values of its assorter. That is done by drawing ballot cards at random and computing the value of the assorter corresponding to the requirement from the preferences on each sampled card. The same sample can be used to test all requirements by computing the value of every assorter for each sampled card.

As in the previous implementation of AWAIRE, we use the ALPHA TSM with the truncated shrinkage estimator to test requirements and intersections of requirements from the sample of assorter values. See Stark [\[8\]](#page-15-1) for more about ALPHA and Ek et al. [\[6\]](#page-15-4) for details on how ALPHA is used in AWAIRE. Given the cards sampled in draws $t = 1, \ldots, \ell$, let $(X_t)_{t=1}^{\ell}$ denote the values assigned by the assorter of a particular requirement. Let M_{ℓ} be the TSM for the requirement, evaluated after the ℓ th card is drawn. It can be written as a product: M_{ℓ} := $\prod_{t=0}^{\ell} m_t$. Here, $m_0 = 1$ is the initial value of the TSM and m_t reflects the evidence X_t provides about the requirement: if $m_t > 1$, X_t is evidence against the requirement. The TSMs for individual requirements are called base TSMs.

To test an alt-order statistically, we could test each of its requirements separately and reject the alt-order if we reject at least one of its requirements. However, doing this naively would increase the risk limit; this is an instance of the well-known problem of multiple testing in statistics. AWAIRE addresses multiple testing by forming a weighted average of the base TSMs called an intersection TSM, which is a nonnegative supermartingale starting at 1 if every requirement for that alt-order is true.

The weights are chosen *predictably*: the weights at time t depend on the data collected up to time $t-1$, but not on anything that has not been observed before the tth card is drawn. The intersection TSM is a product of weighted means of the terms of the base TSMs. When all the requirements hold, the intersection TSM is a nonnegative supermartingale starting at 1.

Multiple weighting schemes were investigated in [\[5\]](#page-15-7). One of the best and the simplest for AWAIRE was 'Largest,' which puts all weight on the base TSM that is largest at time $t-1$ (in the case of ties, it gives equal weight to the largest). We use 'Largest' below because of its simplicity and good empirical performance.

If every intersection TSM hits or exceeds $1/\alpha$, we can reject every alt-order: the audit stops without a full hand count and the reported outcome is certified. Otherwise, AWAIRE continues until the sample contains every ballot card: a full hand count. The chance the audit stops without a full hand count if any alt-order is correct is at most α , the risk limit.

RAIRE avoids multiple testing by pre-commiting, before sampling commences, to a sufficient set of requirements^{[10](#page-4-0)} that covers all alt-orders. RAIRE uses the CVRs to select a set of requirements that minimizes the expected number of ballot cards required to be sampled to certify the contest, on the assumption that the CVRs are accurate.

¹⁰ RAIRE uses the terminology 'assertions' in place of 'requirements'.

3 Improving AWAIRE

The original implementation of AWAIRE tracked all $k! - (k-1)!$ alt-orders separately. The requirements characterizing each alt-order were all DB. Because there are so many alt-orders, the implementation became computationally impractical for more than 6 candidates.

The present contribution makes AWAIRE tractable for contests with far more candidates, using three tools: incremental expansion, use of new requirements, and requirement abandonment. The first of these helps the most, but for clarity we begin by describing the second. The new implementation of AWAIRE and the code and output for the figures and tables in this paper are at [https://github.](https://github.com/aekh/awaire) [com/aekh/awaire.](https://github.com/aekh/awaire)

3.1 Another Type of Requirement

We introduce a new requirement to AWAIRE, related to a RAIRE assertion. Candidate *i dominates* candidate *j* if *i* has more first-preference votes than there are ballots that rank j ahead of i (including ballots that mention j but not i). In other words, i has more votes before any candidate is eliminated than j could ever possibly get, no matter who else is eliminated. The new type of requirement is the complement of this condition: $¹¹$ $¹¹$ $¹¹$ </sup>

Does Not Dominate. DND (i, j) holds if candidate i does not dominate candidate j : there might be an elimination sequence that results in j having more votes than *i*.

If the requirement is false, i dominates $j: j$ cannot possibly have more votes than i . The original implementation of AWAIRE used only \bf{DB} requirements. Including DND requirements can reduce sample sizes and runtimes because the requirement $\text{DND}(i, j)$ is shared by all alt-orders in which candidate i is eliminated before candidate j . Although **DND** requirements may need larger samples to reject than **DB** requirements, they still reduce runtime and there are only $k(k-1)$ of them.

Like **DB**, the assorter for the requirement $\text{DND}(X, Y)$ assigns a ballot card the value 0 if it shows a first preference for candidate X (so that card will be counted for candidate X), the value 1 if it shows a preference for candidate Y before candidate X or shows a preference for candidate Y and does not mention candidate X (so the card may eventually contribute a vote to in Y before X is eliminated), and the value 1/2 otherwise.

3.2 Suffix Representation and Incremental Expansion

Instead of tracking all alt-orders, we track suffixes of alt-orders. Each suffix of a set of alt-orders can be represented by a set of requirements that are shared

¹¹ Blom et al. [\[3\]](#page-15-3) originally defined 'WO' assertions, later renamed to 'NEB' $[2]$. **DND** is the negation of these.

Fig. 1. The suffix tree for alt-orders with alternate winner X.

by all alt-orders with that suffix. As the audit progresses, either it finds enough evidence to reject a suffix (along with all alt-orders that include it), or it extends that suffix by one in all possible ways and tests those extended suffixes.

Example 3. Consider the alt-orders in [Example 1](#page-2-1) where X wins. [Figure 1](#page-6-0) illustrates how these alt-orders can be represented by a suffix tree. On the first level of the tree, the suffix $[\ldots, X]$ encompasses all alt-orders where X wins (listed at the bottom of the tree). One step below are three suffixes, $[\ldots, Y, X], [\ldots, Z, X],$ $[\ldots, \mathbf{W}, \mathbf{X}]$, denoting the winner X but also the possible runner-ups $(\mathbf{Y}, \mathbf{Z}, \mathbf{A})$ respectively). The first of these represents the two complete alt-orders $[W, Z, Y, X]$ and $[Z, W, Y, X]$. □

Each suffix has an associated intersection TSM, a weighted combination of the base TSMs for requirements shared by all alt-orders with that suffix. If that intersection TSM hits or exceeds $1/\alpha$, we reject every alt-order with that suffix.

The base TSM for each active requirement is only computed once and stored in a dictionary (i.e., hash table). The test for each suffix can access a set of base TSM values and can determine weights to combine them into an intersection TSM for that suffix. The code can also remove from the database every requirement that is no longer useful, further reducing memory and CPU usage. [Figure 2](#page-7-0) shows the structure of the algorithm. The figure caption summarizes the steps, many of which are described below in more detail.

Suffix trees. The alt-orders of a given k -candidate election can be represented by a forest of $k - 1$ suffix trees, each rooted at the supposed winning candidate according to that alt-order. Each alt-order corresponds to the unique path from a leaf node to a root node. Recall the alt-orders defined in [Example 1.](#page-2-1) The forest consists of 3 suffix trees rooted by the candidates other than the reported winner: X, Y and Z. The one for X is shown in [Figure 1;](#page-6-0) the other two are analogous. Each node in the forest corresponds to a suffix of alt-orders. For example, the node pictured under the root corresponds to suffix $[\ldots, Z, X]$ and subsumes (is the suffix of) the two alt-orders $[W, Y, Z, X]$ and $[Y, W, Z, X]$.

Fig. 2. An overview of the new implementation of AWAIRE. The process begins by (1) sampling some ballots at random. Then, the controller (2) prompts the requirement database, which (3) processes each requirement in the database. Each requirement has (4) a base TSM, the value of which is (5) calculated from the ballots seen so far. Once all requirements have been processed, the controller (6) prompts the frontier, which (7) processes and keeps track of all the nodes. Each node represents a suffix and has (8) an intersection TSM associated with it. To calculate the current value of the intersection TSM, it (9) requests the previous values of the node's associated base TSMs (used as weights) and how their values changed to reach the current values (used as returns). If a node's intersection TSM is above the risk threshold, we remove it; further, if a node's intersection TSM and/or base TSM(s) are not increasing enough or at all, the frontier may expand this node, introducing several children of longer suffixes. Once all nodes have been processed, AWAIRE either (10) continues sampling if nodes and unseen ballots remain, (11) certifies the election if no nodes remain, or (12) terminates as a full hand count if no unseen ballots remain but nodes remain. At any point in this process, auditors may decide to perform a full hand count instead of continuing to sample ballots at random; this cannot increase the risk.

Node frontier. We keep track of a dynamic frontier of nodes in this forest of suffixes, the nodes for which we calculate intersection TSMs to test alt-orders. Every alt-order has a suffix in the frontier. If we can rule out each node in a frontier, we have ruled out every alternative winner of the election.^{[12](#page-7-1)}

Before sampling commences, the frontier is initialized with $|\mathcal{C}| - 1$ suffixes of the form $[\ldots, c]$, for each candidate c other than the reported winner, i.e., the roots of the forest of alt-orders. The requirements for the root node labelled

 12 RAIRE also uses suffix trees, but it computes a *static* frontier of the alt-order forest using the CVRs (before observing any sampled ballot cards).

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c are $\{DND(c', c): c' \in C - \{c\}\},\$ since, for c to have won, no other candidate could have dominated c.

Example 4. Continuing with [Example 1,](#page-2-1) the requirements for the suffix $[\ldots, \mathbf{X}]$ are $\{DND(Y, X), DND(Z, X), DND(W, X)\}\$. The requirements for the other suffixes [...,Y] and $\lbrack \ldots, Z \rbrack$ are similar. □

Each node m has a watchlist of requirements that are necessarily true if its suffix is true. These are the requirements that are shared among the alt-orders represented by m. The weighting scheme for m is in essence no different than for the original implementation of AWAIRE except it uses only the base TSMs from the watchlist of requirements. Thus, some requirements and their base TSM values are ignored. If the intersection TSM for node m ever reaches $1/\alpha$, we can reject all elimination orders with that suffix. We remove node m from the frontier, its subtree is pruned.

Expanding nodes. If none of a node's requirements appears to be false (e.g., all the base TSMs have decreased for a long time or are less than 1), we split that node. Given a node representing suffix $[\ldots, S]$ we split it to create the child nodes $\{[\ldots, c] \oplus S : c \in \mathcal{C} \setminus S\}$, where \oplus represents sequence concatenation. Thus, we create a child node for each candidate not appearing in the suffix S of the expanded parent node.

Consider a suffix $[\ldots, c_{\ell}, c_{\ell-1}, \ldots, c_1]$ with the unmentioned candidates, implicitly eliminated before this suffix, represented by the set U . The requirements of this suffix are given by: $\{DND(c_j, c_i): \ell \geq j > i \geq 1\}$, i.e., each candidate c_j eliminated before c_i does not dominate c_i ; together with $\{\mathbf{DND}(c, c_i) : \ell \geqslant i \geqslant i\}$ $1, c \in \mathcal{U}$, i.e., every unmentioned candidate c does not dominate any candidate c_i in the suffix; and $\{DB(c_i, c_j, \{c_\ell, \ldots, c_1\}) : \ell \geq j > i \geq 1\}$, i.e., just before c_j is eliminated, every other remaining candidate c_i directly beats c_j .

Each node inherits all the requirements of its parent node, and adds more specific requirements relating to the newly added candidate $c_{\ell+1}$. We only need to add the requirements $\{DND(c, c_{\ell+1}): c \in \mathcal{U} \setminus \{c_{\ell+1}\}\}$ and $\{DB(c_i, c_{\ell+1}, \{c_{\ell+1}, \ldots, c_1\})$: $\ell \geq i \geq 1$ to the parent nodes requirements.

Example 5. Continuing our running example of [Example 1,](#page-2-1) assume we decide to expand the node $[\ldots, X]$. We add three child nodes: $[\ldots, Y, X]$, $[\ldots, Z, X]$, $[\ldots, W, X]$. The requirements for $[\ldots, Y, X]$ adds $\{DND(Z, Y), DND(W, Y), DB(X, Y, \{X, Y\})\}$ to those inherited from its parent $[\ldots, X]$. □

When a node is expanded, its intersection TSM (up to the latest sample) is copied to all its children. This step ensures that its continued use will remain risk-limiting.

A critical ingredient for the improved AWAIRE is when and which nodes to expand. To decide which node to expand we score nodes by the value of its best performing base TSM. The higher the score the more likely we will be able to reject this suffix. So when we choose to expand a node we always choose one with the lowest score.

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To decide when to expand a node we consider a few policies:

Every (i) . We expand a node after every non-zero multiple of i ballots sampled. **Below(x).** After every ballot, we expand every node that has a score below x.

These policies are quite myopic, only looking at the current node's score. We can also impose a look-ahead rule to avoid unnecessary expansions. If we choose a node m for potential expansion, we examine the child suffixes of node m and determine what their scores would be (by computing the base TSM for any newly introduced requirements). We only allow the expansion if:

Loose. Some child node has a better score than m. **Tight** (y) . Some child has a better score than m, and is also higher than y.

3.3 Requirement Database and Requirement Abandonment

The requirement database is a critical data structure of the algorithm as the number of requirements is $k(k-1)2^{k-2}$.^{[13](#page-9-0)} Thus, we have to aggressively restrict the number of requirements we track.

The requirement database is initially empty but nodes can *request* requirements needed for their intersection TSM, adding them to their watch-list and the database (if not already added). This happens when the frontier is created or a node is expanded. Adding a requirement to the database involves calculating its base TSM from ballot card 1 to the latest observed.

We can leverage some logical implications between requirements to decrease computation time, by deciding to abandon (i.e., set weight to 0 for the remaining samples) particular requirements when there is sufficiently strong evidence that they are true. Note that this will not compromise the risk limit, but it may increase the sample size required to terminate the audit (if a requirement that is actually false is erroneously abandoned). The two relationships we use are:

 $\neg \mathbf{DB}(i, j, S) \longleftrightarrow \mathbf{DB}(j, i, S)$ and $\neg \mathbf{DB}(i, j, S) \longrightarrow \mathbf{DND}(i, j).$

Considering the requirement on the left-hand side of these rules, if its base TSM exceeds $1/\alpha$ (our threshold of 'enough evidence' that the requirement is false^{[14](#page-9-1)}), we abandon the requirements on the right-hand side, since the evidence now suggests that they ought to be true.

Another way a requirement can be abandoned is when it has been mathematically proven to be true (i.e., we can show that the requirement must be true given the number of remaining samples).

Finally, if, due to node pruning, a requirement is no longer part of any node's watch-list, we need not process its base TSM. In that case we *park* the requirement to save computation time. If at another point this parked requirement is requested, we simply unpark it and calculate its base TSM values from the time it was parked to the latest observed ballot.

 $\frac{13}{13}$ This is fewer than the number of alt-orders due to the *order* of elimination being irrelevant for requirements; only the set of eliminations is relevant.

¹⁴ Due to multiple testing, this does not necessarily allow us to reject the alt-orders it is part of. To do that we need to use intersection TSMs.

Table 1. Size of the final frontier for AWAIRE v2, showing the mean and 99th percentile frontier size across all experiments on contests with a given number of candidates. The second column shows the number of contests summarized in each row, and the third column shows the total number of alt-orders (max. possible frontier size). The three subcolumns refer to different ways to specify η_0 in ALPHA: either to 0.51, to the last-round margin (LRM), or to the reported assorter margins (AM).

				Mean			99 th percentile			
Candidates	Contests	Alt-orders	0.51	LRM	AМ	0.51	LRM	AM		
4	5	18	5			11	11	11		
5	50	96	7	9	10	36	37	40		
6	25	600	10	15	16	34	60	55		
7	17	4,320	31	38	44	379	372	455		
8	7	35,280	13	35	35	57	218	259		
11	$\overline{2}$	4×10^7	5,005	5,471	6,194	21,171	24,190	25,762		
18		6×10^{15}	17	937	81	17	22,711	694		
19	$\overline{2}$	1×10^{17}	794	6,879	1,299	3,068	82,947	10,889		
36		4×10^{41}	170	3,463	740	1,318	51,669	5,075		

4 Analyses and Results

We used the data from the 93 New South Wales Legislative Assembly Contests and 14 contests in the USA used by $[3].^{15}$ $[3].^{15}$ $[3].^{15}$ $[3].^{15}$ We also used datasets for three contests for Minneapolis Mayor (in 2013, 2017, and 2021), ^{[16](#page-10-1)} for a total of 110 contests.

The reported margin (in cards) of an election is the minimum number of cards that must have been mistabulated if the reported winner really lost. We use margin to mean reported diluted margin, the reported margin in cards divided by the number of cards from which the sample is drawn. We used margin-irv $[4]$ to find margins for 109 of the contests; it did not find the margin for 2021 Minneapolis Mayor (19 candidates) in a week.

When the reported outcome is correct, audit sample sizes can generally be reduced by exploiting information about the tabulation available before auditing, for instance, the reported last-round margin. Often, the reported last-round margin is close to or equal to the actual reported margin in cards.^{[17](#page-10-2)}

We simulated 500 ballot-polling audits for every contest, with each audit corresponding to a randomly sampled (without replacement) order of the ballots. The same 500 sampled orders for each contest were used across all methods. The ballots were selected one at a time. After each ballot, the method under

¹⁵ <https://github.com/michelleblom/margin-irv/> (visited 16 May 2024).

¹⁶ <https://vote.minneapolismn.gov/results-data/election-results/> (16 May 2024).

 17 Of the 109 contests for which we calculated the margin, 8 had last-round margins greater than their actual margin. The difference ranged from 11 to 2, 539 ballots, equating up to a few percentage points in margin relative to the total number of ballots.

Fig. 3. Mean sample size (as a fraction of the total number of ballots) comparing AWAIRE v2, AWAIRE v1, and RAIRE at risk limit 0.05. All used the ALPHA test supermartingale with $d = 200$ in the truncated shrinkage estimator and $\eta_0 = 0.51$, the last-round margin (LRM), or the reported assorter margins (AM). We omitted the San Francisco Mayor 2007 contest (the margin was much larger than for the other contests), but see [Table 2.](#page-13-0)

experiment was used to determine whether to terminate and certify the contest (with risk limit $\alpha = 0.05$), or continue sampling.

We compared the old and new implementations of AWAIRE (v1 and v2, respectively) and RAIRE. Each simulation had access to 32GB of RAM. For the tuning parameters in the truncated shrinkage estimator for ALPHA, we used $d = 200$ and three choices of η_0 :

- $-$ 0.51; setting $\eta_0 = 0.51$, as recommended by [\[5\]](#page-15-7)
- LRM : setting η_0 for all requirements using the last-round margin
- AM : setting η_0 to the reported assorter margin (for each requirement separately), which requires CVRs.

All experiments with RAIRE used AM.

In earlier extensive comparisons of expansion schemes in AWAIRE v2, Be- $\text{low}(1)$ -Tight $(e^{0.5})$ consistently performed the best. We used this scheme for all AWAIRE v2 experiments reported here. Additional experiments with and without requirement abandonment and **DNDs** showed some performance improvements (without affecting sample sizes) when using the above expansion scheme. We have omitted the details due to space constraints.

4.1 Computational Performance

Incremental expansion lets the audit 'group reject' many alt-orders by rejecting nodes they share, rather than having to reject all $k!-(k-1)!$ alt-orders separately.

Fig. 4. Average number of cards sampled by AWAIRE v2 minus average number sampled by RAIRE, as a function of contest margin, to audit 109 contests at risk limit 0.05. Omitted: Lismore (left pane, AWAIRE v2 AM samples 91 fewer cards than RAIRE on average), Minneapolis Mayor 2013 using LRM (right pane, relative differences are beyond $4\times$), and San Francisco Mayor 2007 (both panes, margin too large).

One measure of the computation saved is the final frontier size (the number of nodes that were not expanded but instead pruned) compared to $k! - (k-1)!$, the total number of alt-orders and thus the maximum possible frontier size; see [Table 1.](#page-10-3) Incremental expansion saves an exponential amount of memory.^{[18](#page-12-0)}

AWAIRE $v2$ was substantially faster, scaling exponentially better in k . For elections with 4–8 candidates it saved seconds for the smaller elections and up to 20 minutes on the larger elections. AWAIRE v1 could not complete the audit of any contest with more than 8 candidates (6 of the contests) regardless of the margin of victory, for lack of memory. AWAIRE v2 could complete all but 36 simulated audits (two using $\eta = 0.51$, 33 using LRM, and one using AM; all for the Minneapolis contests) out of 165,000, for lack of memory or time (48 hours). This could be resolved by further experimentation with expansion schemes. We treated those 36 audits as full hand counts.

To stress-test the implementation, we added 'fake' candidates to a handful of contests. These candidates never get any votes, but the audit cannot foresee that, so it must include them in the search tree. The new implementation could easily handle 55 candidates in those simulations, and possibly more. The runtime was always within a minute per ballot on average, and only reached an hour per audit on average in the toughest cases. The largest real IRV election to the authors' knowledge had 36 candidates (Minneapolis Mayor 2013). CPU time per audit for RAIRE and our implementation of AWAIRE v2 were similar.

¹⁸ The result for 18 candidates represents a single contest (San Francisco Mayor 2007) that was inexpensive to audit. There is little expansion with 0.51 and AM but quite a bit with LRM. Nonetheless, with LRM, the audit terminated after 24 ballots on average, compared to 60 for 0.51, since LRM expanded to nodes that were easy to reject. Using AM expanded to fewer nodes but on average terminated after 20 ballots.

$\mathcal{A}_{\mathit{S}\mathit{P}\mathit{e}\mathit{n}}$ $\mathit{C}_{\mathit{i}\mathit{t}\mathit{y}}$ $\mathit{C}_{\mathit{O}\mathit{u}\mathit{n}\mathit{c}\mathit{i}\mathit{l}}$				$M_{\footnotesize{ac}}_{\footnotesize{quar}_{\footnotesize{ieFe}}_{\footnotesize{li}q_{\footnotesize{S}}}$					
	Contest:			$M_{\mathrm{O}\eta_{\mathrm{d}\varrho_{O}}}$			$M_{\ensuremath{a_{\ensuremath{r_{0}}}}\xspace_{l}}$		$\, S_{\bar{a}_R} \, F_{\bar{r}a_{\bar{R}c_{\bar{l}s_{\bar{C}O}}} \, M_{\bar{a}_{\bar{j}c_{\bar{O}r}}}}$
	Candidates:	6	11	5	6	7	5	5	18
	Margin:	0.44%	1.38%	2.43\%	5.15%	7.43\%	10.1%	20.0%	34.0%
	Ballots:	47,208	2,544	46,236	44,011	47,381	46,533	45,942	149,465
AWAIRE	v10.51	28,088	$\qquad \qquad -$	3,642	803	438	264	102	
	$v1$ LRM	28,596	$\overline{}$	3,758	826	420	222	56	
	$v1$ AM	27,851	$\overline{}$	3,660	709	357	196	46	
	v20.51	27,204	2,200	3,446	794	440	286	110	60
	$v2$ LRM	27,282	2,303	3,245	626	317	191	47	24
	$v2$ AM	27,095	2,175	3,453	656	342	191	48	20
	RAIRE	27,186	2,129	2,850	539	269	143	36	16
	Std. err. (max.)	410.0	8.5	112.9	27.5	13.4	7.9	1.8	0.7

Table 2. Contest sizes, no. candidates, margins, and audit sample sizes for 8 contests. Rows 5–11: mean sample size for AWAIRE with various settings and RAIRE. Bottom row: largest standard error of the mean sample sizes in each column.

4.2 Statistical Performance

To quantify the statistical efficiency we used the sample size required to certify each contest, averaged across simulated audits.

The mean sample size as a proportion of the total number of ballots is shown in [Figure 3.](#page-11-0) Unsurprisingly, RAIRE is typically the most efficient since it uses CVRs, but AWAIRE v2 is close or on par (for Lismore). Having more information (LRM) is better than default (0.51) for both AWAIRE v1 and v2; v2 was slightly better than v1. The mean sample size for AWAIRE v2 was never more than v1 by more than 1.8% of the total number ballots or 55 ballots (despite having less information at the start), and was often slightly more efficient (likely due to the difference in initial bets).

For larger elections we can only compare RAIRE to AWAIRE v2. [Figure 4](#page-12-1) shows the absolute and relative increase in mean sample sizes for RAIRE (using error-free CVRs) and the new implementation. While the difference in the number of cards can be large for large elections with tiny margins, the relative difference is small; and while the relative difference is large for small elections, the difference in cards is small.

[Table 2](#page-13-0) shows detailed results for a few elections with various margins. The narrower the margin, the better RAIRE typically does (since it takes advantage of the accurate CVRs), but the relative difference is small. For the new implementation, using the LRM usually helps, but using individual assorter margins did not help more.

Table 3. Average number of ballots required to certify the winner in the Strathfield (top, 46,644 cards cast) and Ballina (bottom, 47,865 cards cast) contests at risk limit 0.05 when the candidates are re-labeled, for RAIRE and the new implementation of AWAIRE (v2) with different ways of choosing η_0 . 'F' means the audit led to a full hand count in every run. Notation for reported elimination orders: an integer means the candidate with that number is in that place in the order; a crossed-out integer means the given candidate is not in that place; and a dot (\cdot) means any unmentioned candidate can be in that place. The final row is the only order with a different winner. Ranges span the lowest and highest mean sample size of all permutations of a row.

4.3 Robustness to CVR errors

Ek et al. [\[6\]](#page-15-4) illustrated the robustness of AWAIRE v1 compared to RAIRE when the CVRs have errors. We repeated that experiment using AWAIRE v2 for the Strathfield and Ballina contests; see [Table 3.](#page-14-0) For each contest we re-labelled the candidates on the ballots and ran 200 simulated audits for each re-labeling and method. In all renumberings but the last, the winner is unchanged. The workload for approaches that do not use (erroneous) information to set assorter margins was unchanged by renumberings that do not change the winner. RAIRE become much worse as the CVRs increasingly became less accurate; AWAIRE v2 using AM was affected less. For Ballina, RAIRE often led to an unnecessary full hand count.

5 Discussion

The new implementation of AWAIRE (v2) has comparable statistical efficiency to the original (v1) but requires substantially lower computational resources,

allowing audits of IRV elections with up to 55 candidates. Using an incremental expansion strategy for AWAIRE does not undermine its risk-limiting properties. It amounts to giving zero weight to the base TSMs for a subset of requirements for a group of alt-orders. Expanding the frontier is equivalent to changing the weights from zero to something positive, using past samples to inform the choice of weights. Because only past samples are used to select the weights, the stochastic process is still a TSM.

Future work includes understanding how to better leverage CVRs in AWAIRE when using incremental expansion, e.g., how to 'pre-expand' the frontier, perhaps guided by RAIRE-produced assertions; using AWAIRE for comparison audits including those based on assorter means for groups of CVRs [\[9\]](#page-15-2); experimenting with expansion strategies and other weighting schemes and ALPHA tuning parameters; and experimenting with more varieties of CVR errors.

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