

Figure 2: Deterministic algorithm: Average percentage of tried add/delete combinations.

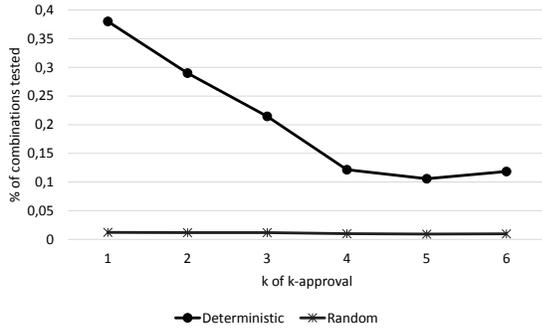
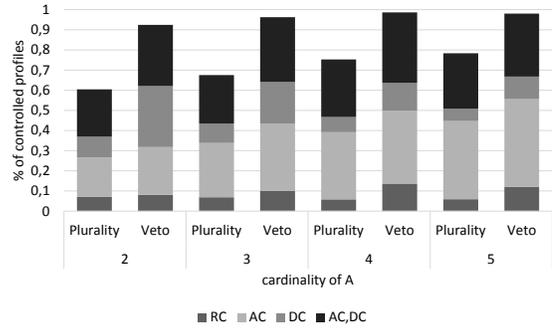


Figure 3: Deterministic and non-deterministic algorithm: comparison.

main trend of these charts and not in the small differences that they can report, because these small differences are connected to the structure of the preferences in the dataset. What is really interesting is once again that the larger are  $k$  and  $|A|$ , the smaller is the computational effort of this algorithm.

We also considered a non-deterministic algorithm which the chair of the election could use to change the winner by replacing candidates. Such an algorithm consists of picking an add/delete combination randomly (over all possible combinations), and checking whether the winner changes. From the experimental data, we count the percentage of profiles where the winner changes (see Fig. 1) and we use this as the probability of success of this approach. If  $p$  is the probability that picking one profile is enough to change the winner, it is easy to see that  $1/p$  is the expected number of profiles to be picked up before changing the winner. We therefore show this  $1/p$  number as a measure of how many combinations should be tested by this non-deterministic algorithm before changing the result (or discovering that it cannot change).

Figure 3 compares the difficulty of the DCRC problem as measured in Fig.2 to this measure of the difficult of DCRC via the non-deterministic algorithm. We used the sushi dataset, with 10 voters,  $|C| = 7$  and  $|A| = 3$ . The  $x$  axis has the value of  $k$  in  $k$ -approval, which varies from 1 to 6, while the  $y$  axis shows the percentage of add/delete combinations that the algorithm tries before stopping.



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Figure 4: Deterministic algorithm: RC compared to AC, DC, and AC+DC.

We also compared the power of replacing candidates with respect to just adding or deleting candidates. We consider the profiles where the winner changes using RC, and we count in how many of these profiles

- the winner changes using AC but does not change using DC (denoted by “AC only”);
- the winner changes using DC but does not change using AC (denoted by “DC only”);
- the winner changes using either DC or AC (denoted by “AC only and DC only”);
- the winner changes only using RC (denoted by “RC only”).

Notice that “AC only” and “DC only” do not add up to “AC only and DC only” because all these categories represent disjoint sets of profiles.

Figure 4 shows the percentage of profiles where the winner changes using RC. We use a stacked bar histogram that report the percentage of profiles where the winner change using RC only, AC only, DC only, or AC only and DC only, for Plurality and Veto. We used the sushi dataset, with 10 voters,  $|C| = 5$  and  $|A|$  varies over the  $x$  axis from 1 to 4.

It can be seen that RC improves the vulnerability of the voting rule since the number of controllable profiles increases by about 9%, this is a significant increase in controllability compared to AC or DC alone that is not reported in this chart and which is around 0,3%, thus making the voting rule much more vulnerable to this kind of control action.

Data from experiment over t-shirt dataset show that the structure of the preferences made veto almost resistant to AC only but the voting rule shows the same trend about the vulnerability to RC. Once again RC improves the vulnerability of the voting rule since the number of controllable profiles increases by about 7%, this is a significant increase in controllability compared to AC or DC alone that is not reported in this chart and which is around 0,2%, thus making the voting rule much more vulnerable to this kind of control action.

We also run some experiments using Borda. Theorem 1 shows that Borda is vulnerable to DCRC. Surprisingly, the deterministic algorithm for checking whether the winner can

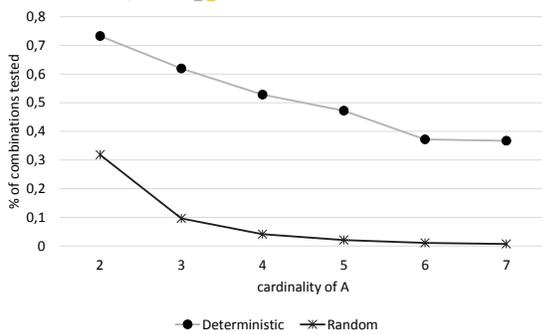


Figure 5: Borda deterministic and non-deterministic algorithm: comparison.

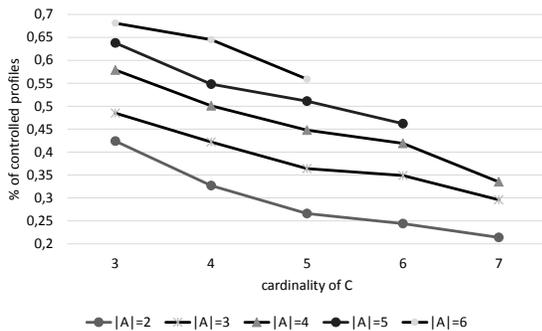


Figure 6: Borda: percentage of profiles (over 1000) with successful DCRC.

be changed by replacing candidates needs to test many combinations, as shown in Figure 5. Also, the number of profiles where the control succeeds decreases when the cardinality of  $C$  increases, as shown in Figure 6.

These results suggest that, even if the worst case theoretical analysis tells us that a voting rule is vulnerable to a certain control action, or resistant, the conditions that make it susceptible to the control action could be difficult to find in real-world scenarios, and this could sometimes lead to a reverse situation in practice. Veto, for instance, is resistant to DCRC, but in practice it is very easy to control and this can be done in almost all the profiles. On the other hand, Borda is vulnerable to DCRC, but in practice, when the size of the profile grows, it is unlikely to find a combination that changes the winner.

We also performed experiments with the data collected using the AGH course selection dataset. However, we do not report them here since they show the same trends as the ones of the other datasets.

## Conclusions

After reporting theoretical results that show that Plurality and Veto are difficult to control, while Borda is easy, with respect to DCRC, we also performed an extensive experimental work, using real-world data sets, to test if  $k$ -approval and Borda are really difficult in practice to control via replacing

candidates. Our experiments show that plurality is more resistant to DCRC than other versions of  $k$ -approval. Furthermore, the results show that Borda becomes more resistant to replacement control when the size of the profile grows. Also, a non-deterministic algorithm seems to be the most convenient for the chair to control the election. Finally, RC is significantly more powerful than just AC or DC alone in terms of giving the chair control over the election. These results suggest that the study of computational complexity in the worst case is not enough to ensure a significant protection to the system, as reported in many works such as (Bartholdi, Tovey, and Trick 1992; Faliszewski and Procaccia 2010; Faliszewski et al. 2009; Faliszewski, Hemaspaandra, and Hemaspaandra 2011; Walsh 2010). Experimental analysis is needed to get a deep comprehension of the likelihood of the conditions that make the system vulnerable/resistant to the control action.

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