

# Going Beyond the Traditional Complexity Analysis

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# What will I talk about?

- ▶ Investigating computational complexity issues in computational social choice using tools capable of **subtler analysis** leads to more useful insights
- ▶ Classical complexity theory has a **negative bias**
- ▶ This is problematic when using **intractability** as a barrier
- ▶ What to watch out for when using finer tools to reduce this negative bias

# What's Next?

Overview

Complexity in Computational Social Choice

# Complexity in Computational Social Choice

- ▶ Computational complexity is an important aspect of research in computational social choice
  - ▶ To know in what cases some algorithmic approaches are possible
    - ▶ e.g., efficient algorithms for computing the winner of an election
  - ▶ To know in what cases some algorithmic approaches are impossible
    - ▶ e.g., using intractability results as a barrier against strategic behavior

# General Methodology of Computational Complexity

- ▶ Theoretical, mathematical framework to classify how hard it is to solve computational problems
  - ▶ distinguish tractable from intractable
- ▶ To do this productively, an abstract model is used:
  - ▶ Inputs are strings over some alphabet
  - ▶ Consider how the running time grows with the input size  $n$
  - ▶ For each  $n$ , count the maximum over any input of size  $n$
- ▶ Theoretical distinction between P and NP-hard (or worse)
  - ▶ Idea: this distinction corresponds by and large to the border between tractable and intractable in practice

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Negative Bias of Complexity Theory

# Intractability Results can be Overly Negative

- ▶ Intractability results (e.g., NP-hardness) indicate that all algorithms require exponential time **in the worst case**
  - ▶ i.e., there is no algorithm that is efficient **for all inputs**
- ▶ There could still be an algorithm that works efficiently for a **large subclass of inputs**
- ▶ In fact, for many NP-complete problems, important classes of inputs have been found with efficient algorithms
  - ▶ **Vertex Cover**: given a graph  $G = (V, E)$ , is there a subset of vertices of size  $m$  that touches each edge?
  - ▶ If  $m$  is small, this can be solved, even for large graphs

## Example: Manipulation in Voting

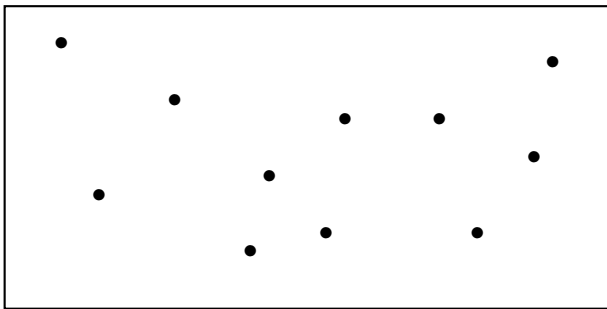
- ▶ Consider voting using Single Transferable Vote (STV)
- ▶ The problem of manipulation is **NP-complete**
  - ▶ So: each algorithm to compute a manipulation policy takes time  $2^{\Omega(n)}$
- ▶ However, this could give a **false sense of safety!**
- ▶ Strategic manipulation is solvable in time  $m! \cdot \text{poly}(n)$ , where  $m$  is the number of candidates
  - ▶ Whenever  $m$  is small, this is feasible



# The Need for Stronger Intractability Results

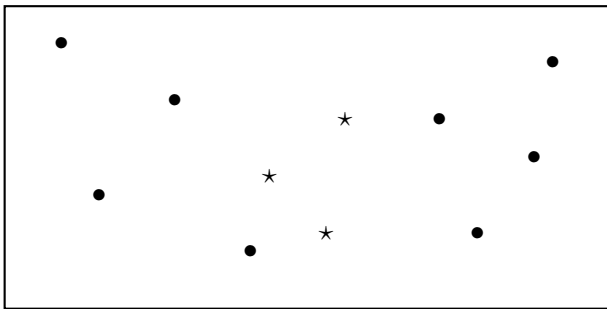
- ▶ **Negative bias** in intractability results:
  - ▶ **Good** when looking for algorithms that are (guaranteed to be) efficient
- ▶ When using intractability to argue that strategic behavior is obstructed, it is **naive to disregard this bias**
- ▶ Classical theory of computational complexity gives **weak intractability results**
- ▶ We need **stronger intractability results** to argue for complexity barriers against strategic behavior

# The Need for Stronger Intractability Results.. in pictures



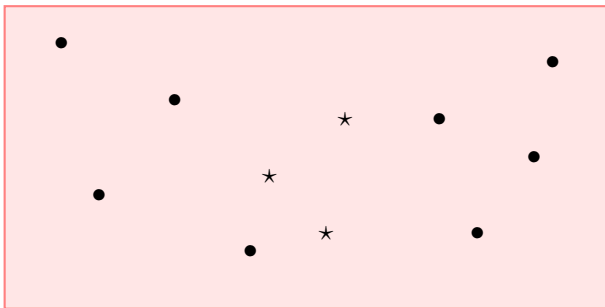
Imagine these are all possible inputs

# The Need for Stronger Intractability Results.. in pictures



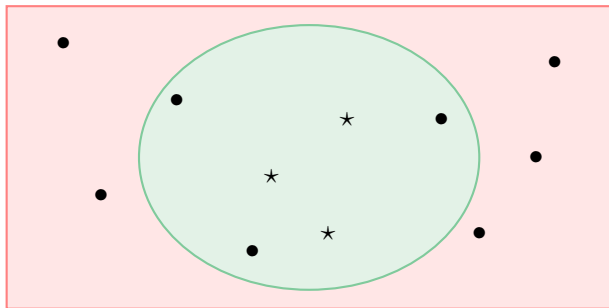
Suppose you care about the  $\star$ 's

# The Need for Stronger Intractability Results.. in pictures



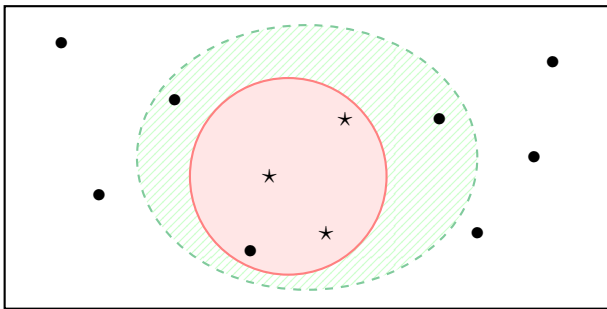
Classical intractability..

# The Need for Stronger Intractability Results.. in pictures



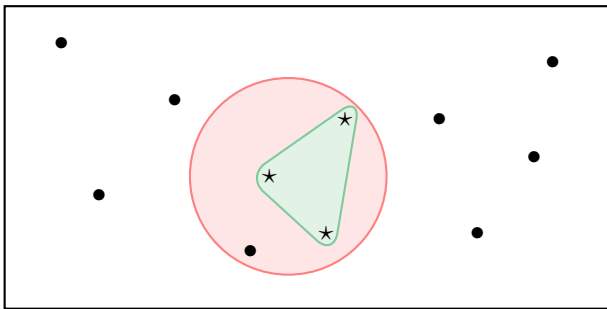
does not rule out an efficient algorithm for a subset of inputs

# The Need for Stronger Intractability Results.. in pictures



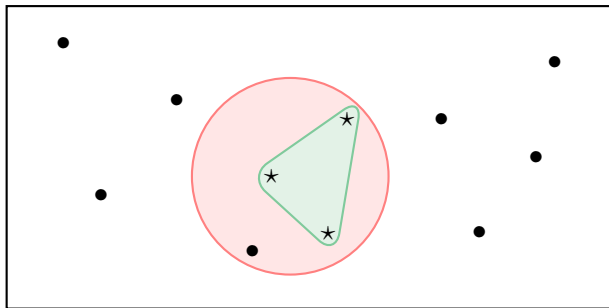
Stronger intractability results can rule out such an algorithm

# The Need for Stronger Intractability Results.. in pictures



But careful.. there could always be algorithms  
for more restricted classes of inputs

# The Need for Stronger Intractability Results.. in pictures



Intuitively, **stronger intractability** results leave less space for undiscovered efficient algorithms



## A typical pitfall

- ▶ When **modelling**, you consider an abstraction of the scenario you care about
- ▶ Typically, you 'err' on the side of **generality**
- ▶ **Example: judgment aggregation**, with issues  $\varphi_1, \dots, \varphi_n$  represented by **arbitrary** propositional formulas
- ▶ In this setting, intractability results are **everywhere!**
- ▶ These results might not say much if your scenario contains logical relations expressible by statements of the form:  
(if  $a$ , then  $b$ )

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**What to do?**

# Going Beyond Showing NP-Hardness

- ▶ Investigate the possibilities of more intricate methods offered by (theoretical) computer science, e.g.:
  - ▶ Investigate the problem for fragments of inputs
  - ▶ Consider approximation algorithms
  - ▶ Use the framework of parameterized complexity theory
  - ▶ Encode problem inputs into SAT, and use SAT solvers
  - ▶ Employ typical-case complexity
  - ▶ Empirically investigate how algorithmic methods perform

# Parameterized Complexity in a Nutshell

- ▶ Traditional complexity theory measures running time **only** in terms of the input size  $n$
- ▶ To reduce the **worst-case negative bias**, take into account more than just this number  $n$ :
- ▶ **Parameterized complexity** measures running times in terms of input size  $n$  and a **parameter**  $k$
- ▶ The parameter captures *structure* that is present in the input
  - ▶ the smaller  $k$ , the more structure
- ▶ **Fixed-parameter tractability**: running time of  $f(k) \cdot \text{poly}(n)$ , for some (computable) function  $f$
- ▶ (Idea: worst-case over inputs of size  $n$  and with small  $k$ )

## People have been parameterizing...

- ▶ Many parameterized complexity results in computational social choice
  - ▶ *parameters*, e.g.: number of candidates, number of voters
- ▶ *Example*: manipulation of STV with a small number of candidates
  - ▶ *Relativizes* the NP-hardness result for manipulation of STV
  - ▶ Solvable in time  $m! \cdot \text{poly}(n)$ , where  $m$  is the number of candidates
  - ▶ Whenever  $m$  is small, this is feasible

# But stay on your toes!

- ▶ Remember from the picture:
  - ▶ Whenever you have **intractability for a 'small circle'**..
  - ▶ there could be an **efficient algorithm for an 'even smaller circle'**
- ▶ Parameterized intractability results still have a **negative bias**
- ▶ Keep trying to 'reduce the circle' as much as possible for your application:
  - ▶ Add another parameter
  - ▶ Restrict to a fragment of the inputs
  - ▶ ...

## Example: Manipulating the Kemeny JA Procedure

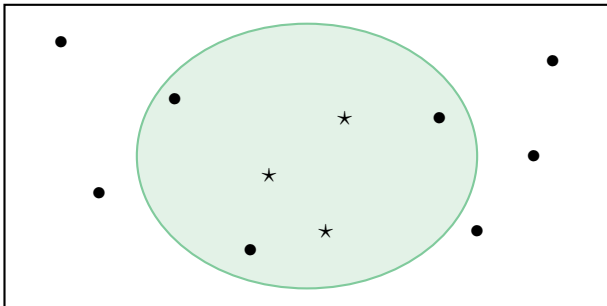
- ▶ **Strategic manipulation:** can an individual report an insincere judgment to obtain a *better* group outcome?
- ▶ For the Kemeny JA procedure, this is  $\Sigma_2^P$ -complete
  - ▶ (worse than NP-complete..)
- ▶ Even when parameterized by # of issues, the problem remains **intractable**
- ▶ **But**, with if-then logical constraints, manipulation becomes tractable

# Stricter Parameters

- ▶ For **tractability** results, loose (or general) parameters—as few as possible together—are ideal



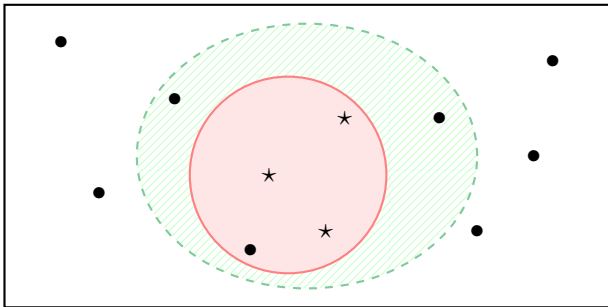
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- ▶ For **intractability** results, combinations of as many as possible strict parameters are ideal

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- ▶ For **tractability** results, loose (or general) parameters—as few as possible together—are ideal
- ▶ For **intractability** results, combinations of as many as possible strict parameters are ideal
- ▶ To get useful, strong intractability results, consider parameters that **severely restrict structure**, e.g.:
  - ▶ treewidth (and others, e.g., clique-width)
  - ▶ backdoors
  - ▶ distance to **single-peakedness** or **unidimensional alignment**
  - ▶ **maximum distance** between any two votes
  - ▶ **maximum range** of candidates (in voting)

# Strict Parameters for the Example of Kemeny in JA

- ▶ **Example** of judgment aggregation
  - ▶ **restriction**: all issues are propositional variables
  - ▶ **restriction**: integrity constraint contains no additional variables
  - ▶ **parameter**: maximum distance  $h$  between any two individual judgments
  - ▶ **parameter**: number  $p$  of individuals
- ▶ **Intractability** in this constrained setting is much **more powerful** than
- ▶ **But**: even in this case, further restrictions could lead to efficient algorithms

# Combining Various Methods

- ▶ Negative theoretical results rule out one type of algorithmic approach
- ▶ Idea of strong negative results: try to rule out approaches that are as specialized as possible
- ▶ Investigate combinations of algorithmic methods
- ▶ For example: combination of parameterized algorithms and SAT encodings

# SAT Encodings

- ▶ **General idea:**
  - ▶ encode your problem input as an instance of SAT
  - ▶ use a SAT solving algorithm to solve the problem
  
- ▶ Applicable for problems in NP
  
- ▶ No worst-case guarantees
  
- ▶ Works well in many practical settings

# Possibilities for the Example of Kemeny in JA

- ▶ **Previous example:** strategic manipulation in judgment aggregation for the Kemeny procedure
  - ▶ parameter: number of issues
- ▶ **Parameterized intractability result:** no efficient parameterized algorithm for this case
- ▶ **But:** can be solved in **fixed-parameter tractable time** by encoding into a small number of SAT instances



# The Holy Grail

- ▶ Study your application setting
- ▶ Consider **all** algorithmic methods (that we know about)
- ▶ Give theoretical (**intractability**) results that these methods are not possible in your application
- ▶ Give experimental evidence that these methods really do not work well
  
- ▶ (Compare this to just showing NP-hardness)

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- ▶ Classical complexity theory has a **negative bias**
- ▶ This is problematic when using **intractability** as a barrier
- ▶ Use finer tools to reduce this negative bias
- ▶ **Be much more demanding** when using negative results as a barrier!!

**Thanks!**

**Questions?**

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