

# Algorithmic Persuasion with No Externalities

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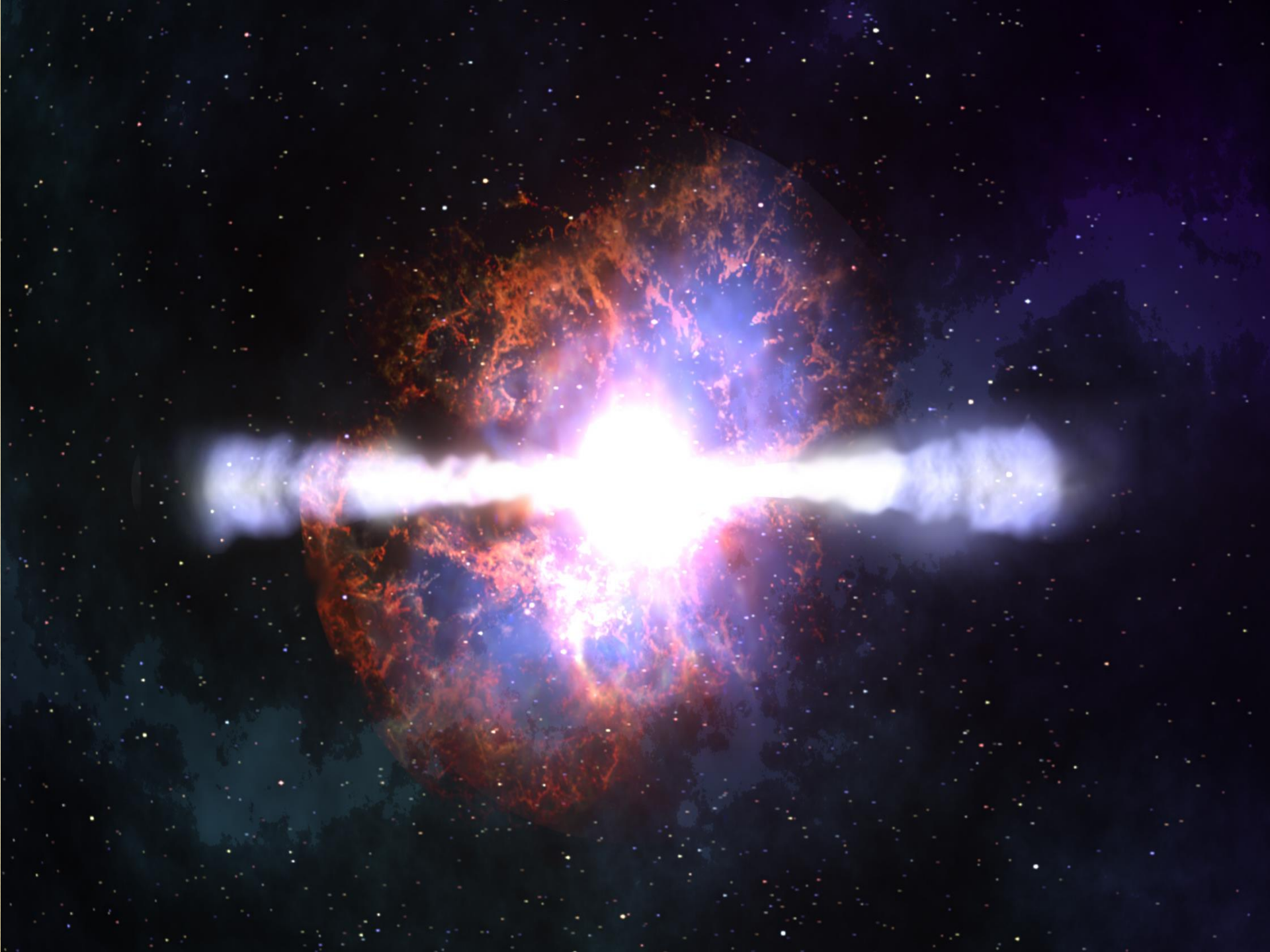
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# The Central Paradigm of Computer Science



- The central paradigm in computer science is that an algorithm  $\mathcal{A}$  is good if:
  - $\mathcal{A}$  runs in *polynomial time* in the input size  $n$ .
- That is,  $\mathcal{A}$  runs in time  $T(n) = O(n^k)$  for some constant number  $k$ .  
e.g.  $T(n) = 100n + 55$        $T(n) = \frac{1}{2}n^2 + 999 \log n$   
 $T(n) = 6n^7 - n^3 + 899890n^2 - \sqrt{n}$
- An algorithm is **bad** if it runs in *exponential time*.  
e.g.  $T(n) = 2^n + 100n^5$        $T(n) = 1.000000001^n - n^3 - n$







example

- An agent wants to discover its *preference ordering* over  $n$  outcomes.
  - This is simply the problem of sorting  $n$  numbers.

A Good Algorithm: **MergeSort** runs in time  $O(n \cdot \log n)$

A Bad Algorithm: **ExhaustiveSearch** runs in time  $O(n \cdot n!) \gg 2^n$

- The functionality of our economic system is based on this paradigm!
  - **Public-Key Cryptography**: *Message senders and recipients* have good algorithms to encrypt and decrypt.
  - An *eavesdropper* has a bad algorithm to decrypt [prime factorization].



# An Equivalent Characterization

○ This central paradigm has an equivalent formulation:

- $\mathcal{A}$  runs in **polynomial time** in the input size  $n$ .



- The input sizes that  $\mathcal{A}$  can solve, *in a fixed amount  $T$  of time*, scales **multiplicatively** with increasing computational power.



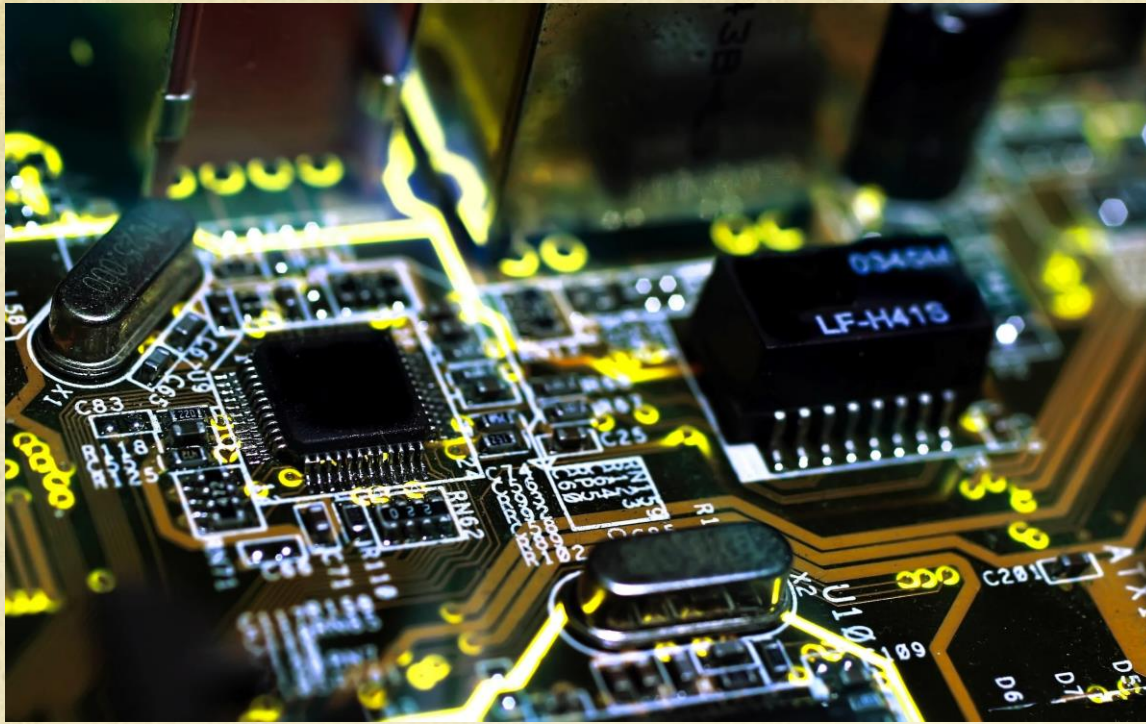
# Multiplicative Scalability

- An algorithm  $\mathcal{A}$  is good if the input sizes it can solve, in a fixed amount  $T$  of time, scales multiplicatively with increasing computational power.

		Input Sizes solved in Time $T$	
		Power = 1	Power = 2
Runtime of Algorithm	$n$	$T$	$2T$
	$n^2$	$\sqrt{T}$	$\sqrt{2} \cdot \sqrt{T}$
	$2^n$	$\log T$	$1 + \log T$







# Software versus Hardware

- Thus, improvements in hardware will never overcome *bad algorithm design*.
- Indeed, the current dramatic breakthroughs in computer science are based upon better (faster and higher performance) algorithmic techniques.



# Computational Complexity



- Therefore, a basic aim of computer science is to understand which problems have **good algorithms** and which problems don't.
- As a first step, we do this by assigning problems to complexity classes in the computational hierarchy.

e.g. **P** The set of decision problems that can always be solved in polynomial time by a (deterministic) computer.

**NP** The set of decision problems that can always be solved in polynomial time by a nondeterministic computer.

- The hardest problems in these groups form an equivalence class called **complete** problems.

# The $P \neq NP$ Conjecture

- This conjecture states that computation is harder than verification.

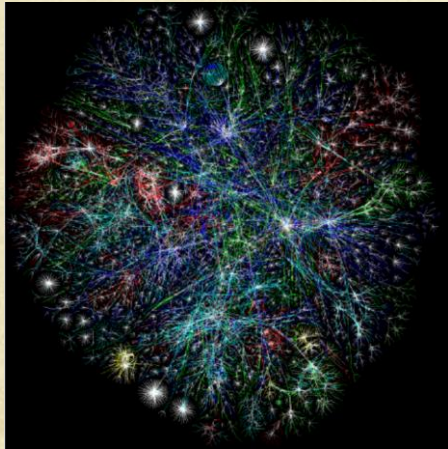
**Informally 1:** If  $P = NP$  then the existence of a bad algorithm (i.e. exhaustive search) implies the existence of a good algorithm.



**Informally 2:** If  $P = NP$  then having a wizard who can magically find you an optimal solution does not help you in your search!



- Traditionally, computer scientists have studied computation in the context of an *optimizer* designing fast code in problem solving.
- However, recently there has been an strong interest in dealing with situations where there *multiple decision-makers*.







- Why should Economists or Game Theorists or Bayesian Persuaders care about computation?

- ~~Because it explains why every example in economics textbooks and academic papers have only two agents and at most two time periods!~~
- Because it applies beyond computers to every decision-maker and decision-making process and to all mechanisms and markets.
- For example, we have no **good algorithms** for
  - *Nash equilibria in Bimatrix Games.*
  - *Market Equilibria.*
  - *Combinatorial Auctions.*
  - *Fair Division, etc.*



# Comments and Questions

- The main result shows, for any monotone set function  $f$ , a computational equivalence between optimizing the private signal and the maximizing  $f$  plus an additive function.
  - *The proof is cleverly pieced together in via the techniques of reduction, LP duality and separation oracles.*
  
- Bayesian Persuasion relates very closely to Correlated Equilibria.
  - *Can you explain why Bayesian persuasion is a more general problem?*
  - *The techniques used in the paper also relate closely to approaches taken to find welfare maximizing correlated equilibria.*
    - *How do your methods differ?*
    - *Can your methods be used to obtain stronger results for correlated equilibria or other problems?*