

# Simple vs. Optimal Contracts

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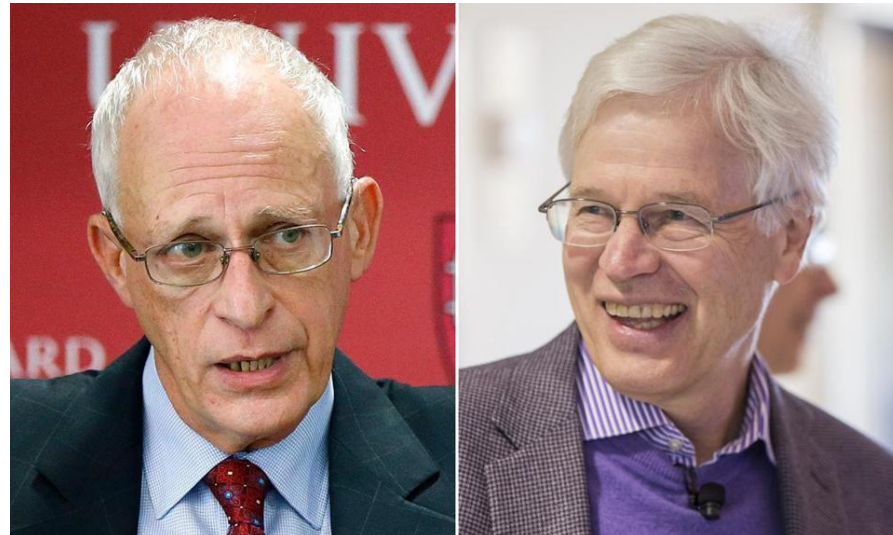
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# Contract Theory

- Contracts **align interests** to enable exploiting gains from cooperation
- “Modern economies are held together by innumerable contracts”

[2016 Nobel Prize Announcement]



Oliver Hart

Bengt Holmström

# Classic Applications

- Employment contracts
- Venture capital (VC) investment contracts
- Insurance contracts
- Freelance (e.g. book) contracts
- Government procurement contracts
- ...

→ Contracts are indeed everywhere

# Modern Applications

Classic applications are moving **online** and/or increasing in **complexity**:

- Crowdsourcing platforms
- Platforms for hiring freelancers
- Online marketing and affiliation
- Complex supply chains
- Pay-for-performance medicare

→ Of interest to AGT; algorithmic approach becoming more relevant

# The Algorithmic Lens

Research agenda: What can we learn about contract design through the algorithmic lens?

1. **Robust** alternatives to average-case / Bayesian analysis
2. **Approximation** guarantees when optimal solutions inappropriate
3. (**Complexity** issues – in different work)

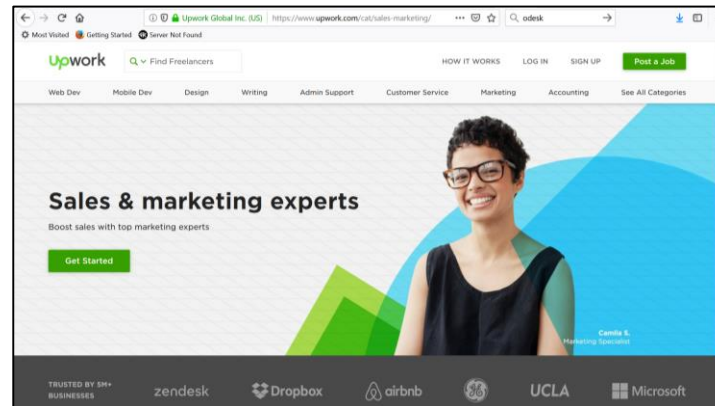
For more information please see our EC'19 tutorial website

# A Building Momentum

- Some pioneering works:
  - Combinatorial agency [Babaioff Feldman and Nisan'12]
  - Contract complexity [Babaioff and Winter'14]
  - Incentivizing exploration [Frazier Kempe Kleinberg and Kleinberg'14]
  - Robustness [Carroll'15]
  - Adaptive design [Ho Slivkins and Vaughan'16]
- Some recent works:
  - Delegated search [Kleinberg and Kleinberg'18]
  - Information acquisition [Azar and Micali'18]
  - Succinct models [Dütting Roughgarden and T.-C.'19b]
- EC'19 papers:
  - [Kleinberg and Raghavan'19, Lavi and Shamash'19, Dütting Roughgarden and T.-C.'19a]

# Basic Contract Setting: An Example

- Website owner (**principal**) hires marketing **agent** to attract visitors



- Two defining features:
  1. Agent's actions are hidden - “moral hazard”
  2. Principal never charges (only pays) agent - “limited liability”

# Relation to other Incentive Problems

- **Mechanism design**
    - Agents have hidden types
  - **Signaling** (Bayesian persuasion)
    - Principal more informed
- **Contracts** [Holstrom'79]
    - No hidden types
    - Principal less informed



# Our Results

- In the model of [Holmstrom'79]:
  1. New **robustness (max-min) justification for simple, linear** contracts
    - “Standing on the shoulders” of [Carroll'15]
  2. **Approximation guarantees** for linear contracts
    - Linear is far from optimal only in **pathological cases**
    - Approximation is **tight even for monotone** contracts

# Model: Contract Setting

- Parameters  $n, m$
- **Agent** has actions  $a_1, \dots, a_n$ 
  - with costs  $0 = c_1 \leq \dots \leq c_n$  (can always choose action with 0 cost)
- **Principal** has rewards  $0 \leq r_1 \leq \dots \leq r_m$
  
- Action  $a_i$  induces distribution  $F_i$  over rewards (“technology”)
  - with expectation  $R_i$
  - Assumption:  $R_1 \leq \dots \leq R_n$
  
- **Contract** = vector of transfers  $\vec{t} = (t_1, \dots, t_m) \geq 0$



Recall two defining features

# Example

Contract:	$t_1 = 0$	$t_2 = 1$	$t_3 = 2$	$t_4 = 5$
	No visitor $r_1 = 0$	General visitor $r_2 = 3$	Targeted visitor $r_3 = 7$	Both visitors $r_4 = 10$
Low effort $c_1 = 0$	0.72	0.18	0.08	0.02 $R_1 = 1.3$
Medium effort $c_2 = 1$	0.12	0.48	0.08	0.32 $R_2 = 5.2$
High effort $c_3 = 2$	0	0.4	0	0.6 $R_3 = 7.2$


# Contract Design Problem

An **optimization** problem with incentive compatibility (IC) constraints

Maximize principal's  $\mathbb{E}[\text{payoff}]$  from **action**  $a_i$   
subject to **action**  $a_i$  maximizing  $\mathbb{E}[\text{utility}]$  for agent

- $\mathbb{E}[\text{payoff}]$  = expected reward  $R_i$  minus expected payment  $\sum_j F_{i,j} t_j$
- $\mathbb{E}[\text{utility}]$  = expected payment  $\sum_j F_{i,j} t_j$  minus cost  $c_i$

# Example: Agent's Perspective

Contract:	$t_1 = 0$	$t_2 = 1$	$t_3 = 2$	$t_4 = 5$
	No visitor $r_1 = 0$	General visitor $r_2 = 3$	Targeted visitor $r_3 = 7$	Both visitors $r_4 = 10$
0.44 Low effort $c_1 = 0$	0.72	0.18	0.08	0.02
1.24 Medium effort $c_2 = 1$	0.12	0.48	0.08	0.32
 High effort $c_3 = 2$	0	0.4	0	0.6

Expected transfers: (0.44, 2.24, 3.4) for (low, medium, high)

# Example: Principal's Perspective

Contract:	$t_1 = 0$	$t_2 = 1$	$t_3 = 2$	$t_4 = 5$
	No visitor $r_1 = 0$	General visitor $r_2 = 3$	Targeted visitor $r_3 = 7$	Both visitors $r_4 = 10$
Low effort $c_1 = 0$	0.72	0.18	0.08	0.02 $R_1 = 1.3$
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$$R_3 - \text{expected transfer} = 7.2 - 3.4 = 3.8$$

# LP-Based Solution

Observation: Can compute optimal contract by solving  $n$  LPs, one per action

$$\begin{aligned} & \text{minimize } \sum_j F_{i,j} t_j && \text{Expected transfer to agent for action } a_i \\ \text{s.t. } & \sum_j F_{i,j} t_j - c_i \geq \sum_j F_{i',j} t_j - c_{i'} \quad \forall i' \neq i && \text{(IC)} \\ & t_j \geq 0 && \text{(LL)} \end{aligned}$$

Agent's expected utility from  $a_i$  given contract  $\vec{t}$

- Caveats: (1) imperfect distribution knowledge (2) impractical contract

# Result 1: Robust Optimality



# Linear Contracts

- Determined by parameter  $\alpha \in [0,1]$ :
    - Given reward  $r_j$ , principal transfers  $\alpha r_j$  to agent
    - Generalization to affine:  $\alpha r_j + \alpha_0$
  - Agent's expected utility from action  $a_i$  is  $\alpha R_i - c_i$
  - Principal's expected payoff is  $(1 - \alpha)R_i$
- } No dependence on details of distribution!
- Really popular in practice

# Robustness

- “It is probably the great robustness of linear rules [...] that accounts for their popularity” [Milgrom-Holmström’87]
- Breakthrough formulation of [Carroll’15]: Linear contracts are optimal in the worst-case over **unknown extra actions** available to agent
- Alternative formulations?
- Standard **CS** formulation of uncertainty when input is stochastic: assume only **first moments** of the distribution are known [Scarf’58]

# Example

	No visitor $r_1 = 0$	General visitor $r_2 = 3$	Targeted visitor $r_3 = 7$	Both visitors $r_4 = 10$
Low effort $c_1 = 0$	0.72	0.18	0.08	0.02 $R_1 = 1.3$
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# Example

	No visitor $r_1 = 0$	General visitor $r_2 = 3$	Targeted visitor $r_3 = 7$	Both visitors $r_4 = 10$
Low effort $c_1 = 0$	?	?	?	? $R_1 = 1.3$
Medium effort $c_2 = 1$	?	?	?	? $R_2 = 5.2$
High effort $c_3 = 2$	?	?	?	? $R_3 = 7.2$

# New Robustness Result

## Theorem:

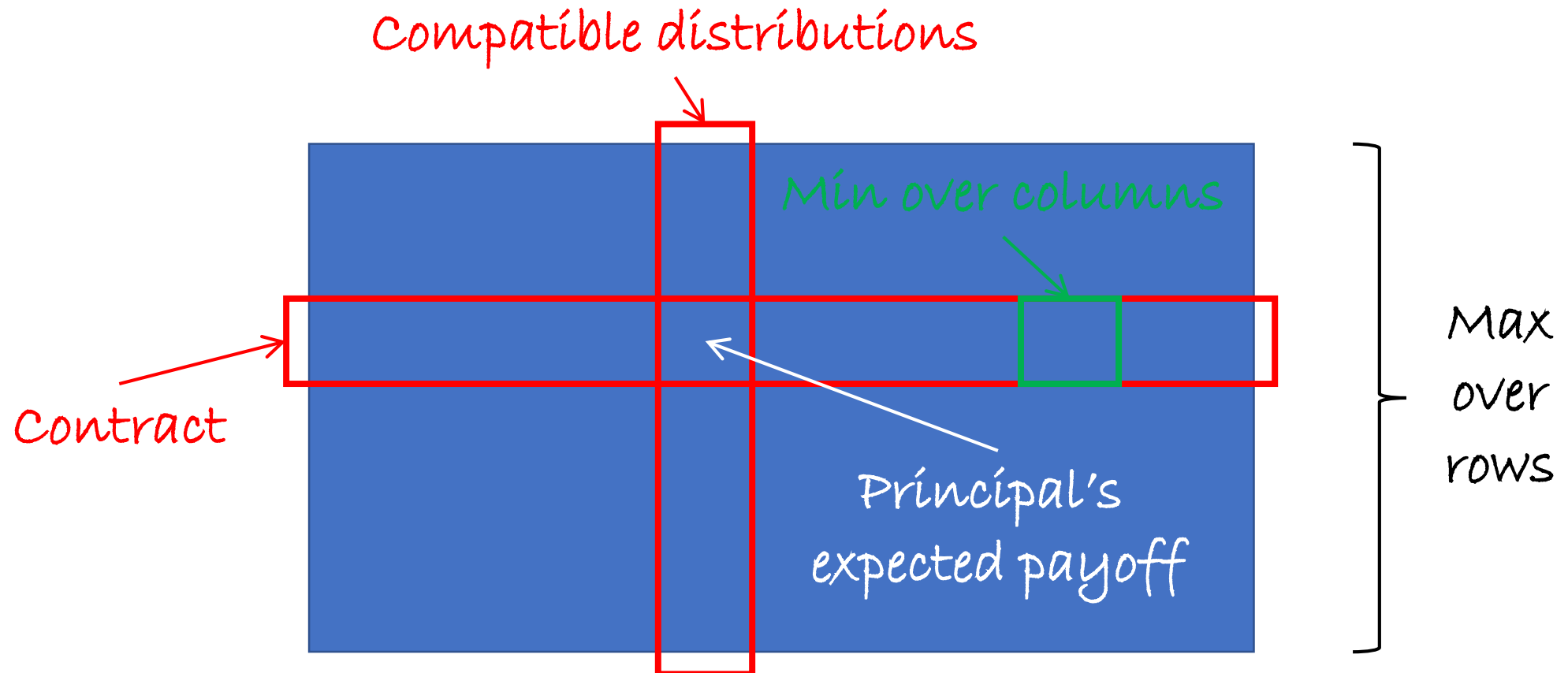
- Given a contract setting with **unknown distributions** but **known expectations**,
- a **linear** contract is **optimal in the worst-case** over all compatible distributions

→ Same conclusion as [Carroll'15], under very different hypothesis!

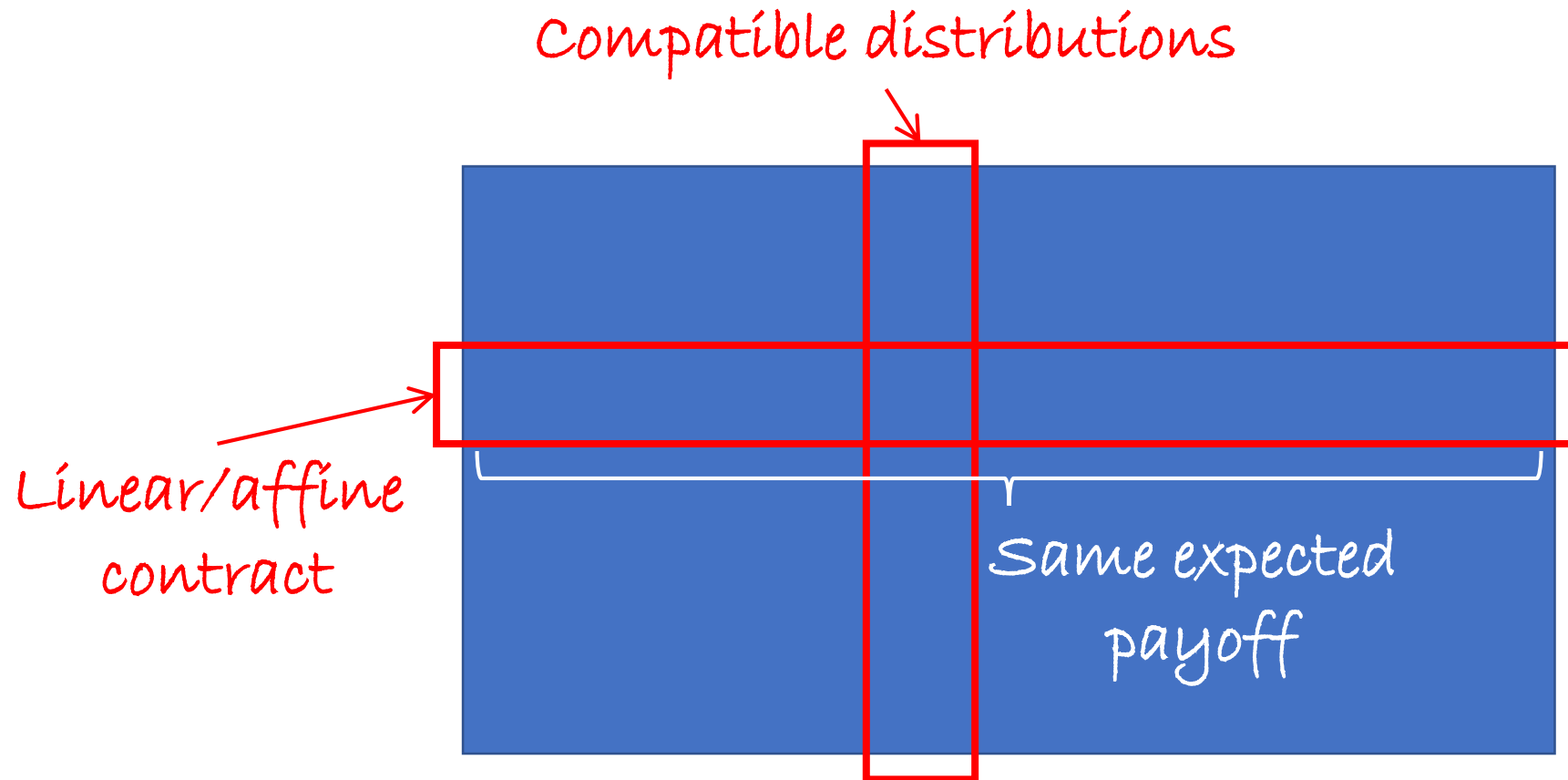
Intuition: If you don't know enough to design a contract depending on anything but the expected rewards, optimize wrt what you know

# Proof Overview: Max-Min Visualization

- Fix a contract setting with known expected rewards

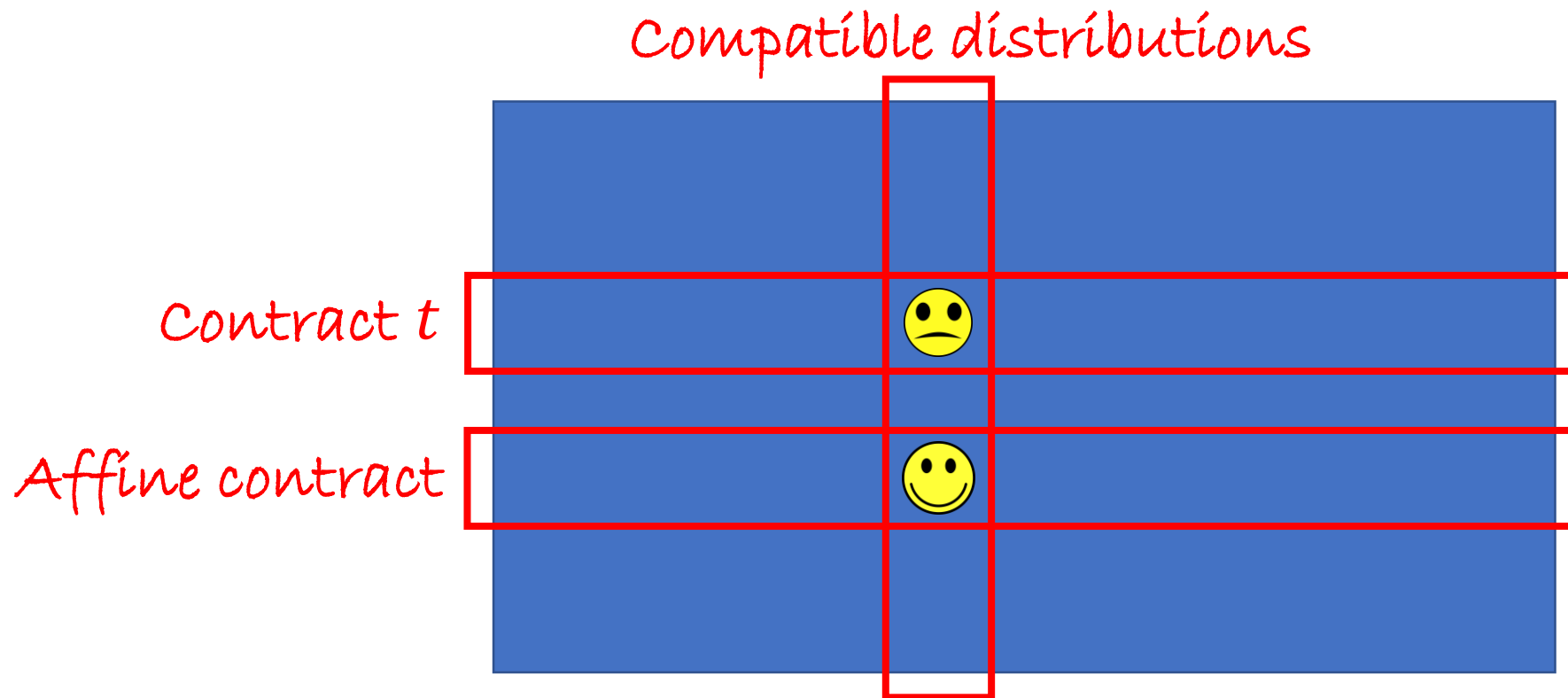


# Proof Overview: Linear Contracts are Robust



# Proof Overview: Key Lemma

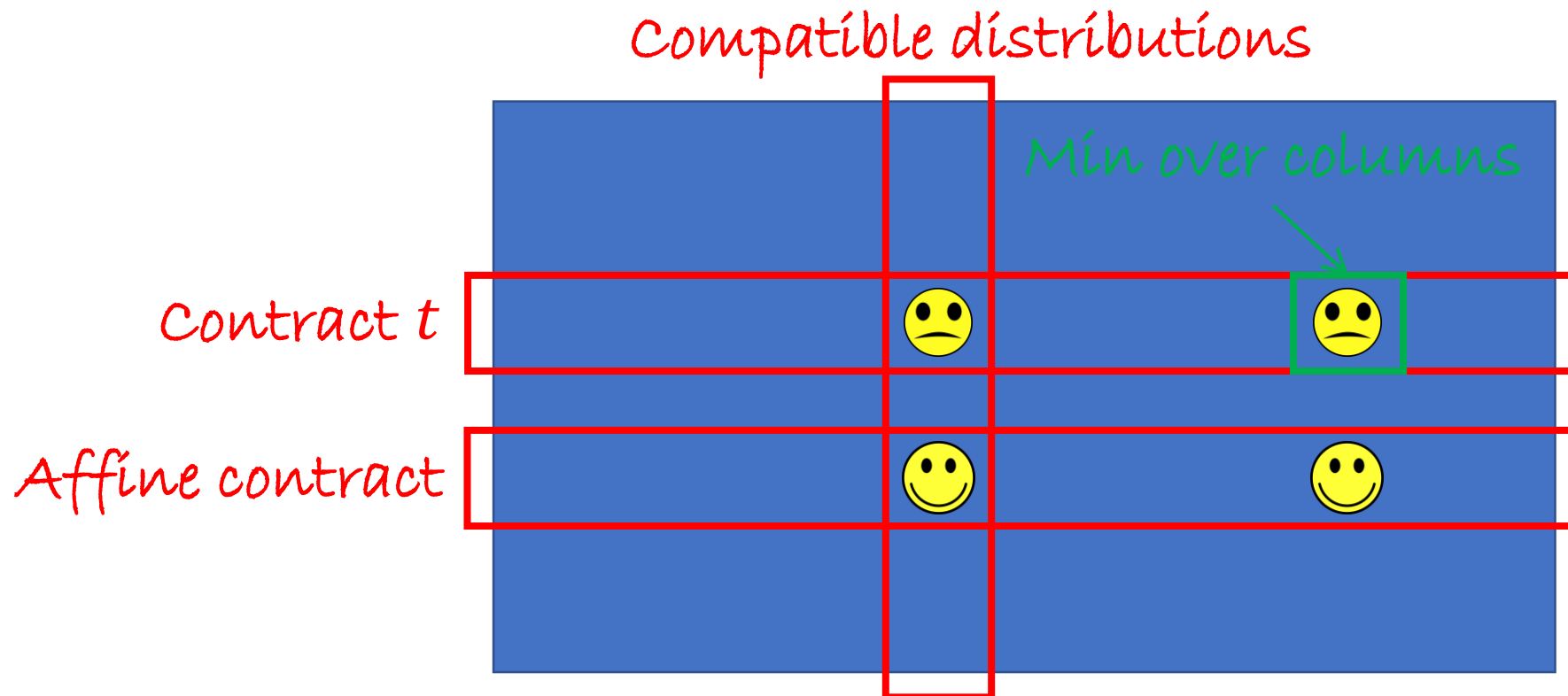
Lemma: For every contract  $t$  there exist compatible distributions and an **affine** contract with  $\alpha_0 \geq 0$  and better expected payoff





# Key Lemma Suffices

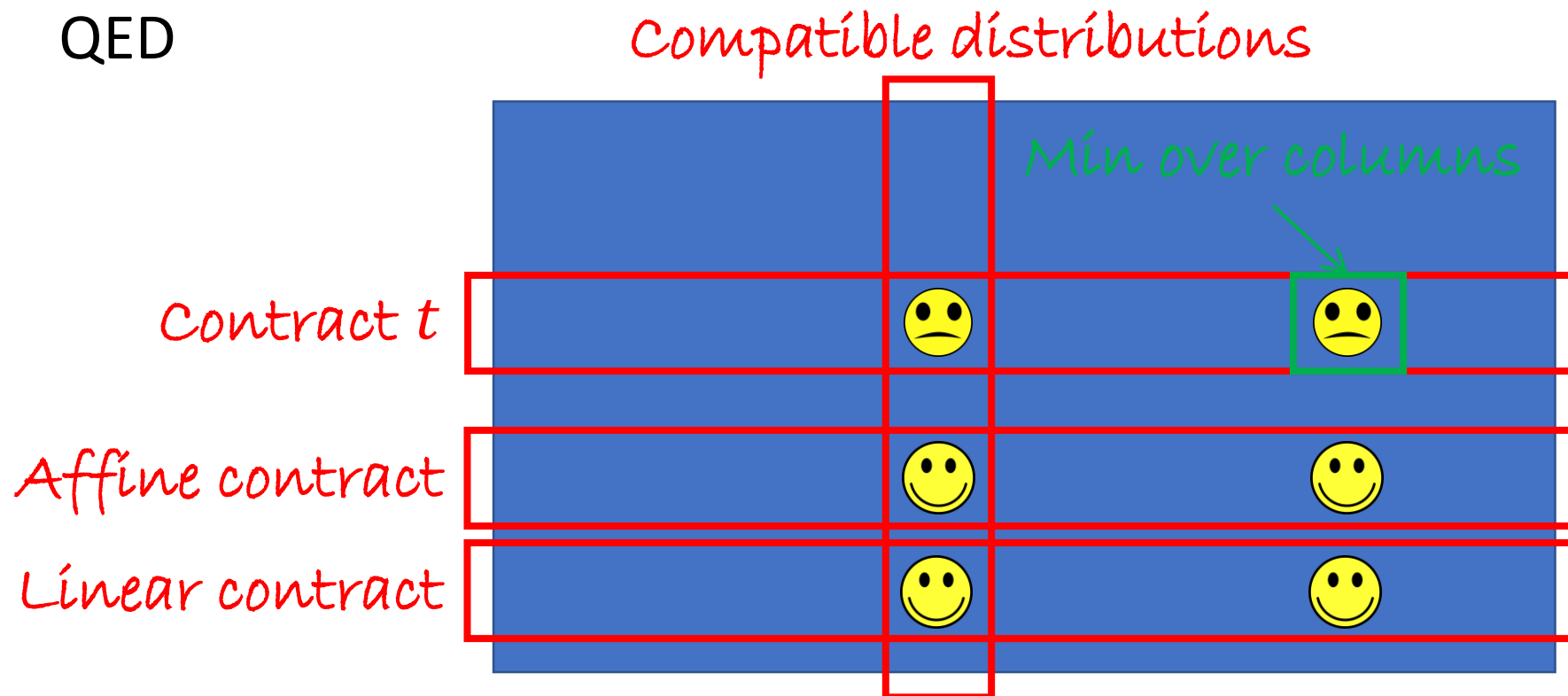
→ For every contract  $t$  there exists an **affine** contract with  $\alpha_0 \geq 0$  and better **worst-case** expected payoff



# Key Lemma Suffices

In an **affine** contract, setting  $\alpha_0 = 0$  increases expected payoff  
→ Optimal **linear** contract has best worst-case expected payoff

QED



# Result 2: Approximation

# Approximation

What fraction of the optimal payoff is achievable by a simple contract?

- Result (informal): Linear contracts achieve constant approximation except in pathological settings with simultaneously:
  - many **actions**;
  - big spread of expected **rewards**;
  - big spread of **costs**

# Example of Pathological Setting

- Let  $\epsilon \rightarrow 0$

$$(R_1, R_2, R_3, \dots) = (1, \frac{1}{\epsilon}, \frac{1}{\epsilon^2}, \dots)$$
$$(c_1, c_2, c_3, \dots) = (0, \frac{1}{\epsilon} - 2 + \epsilon, \frac{1}{\epsilon^2} - 3 + 2\epsilon, \dots)$$

# Formally

## Theorem:

$\rho$  = worst-case ratio of **optimal** contract and best **linear** contract

- with  $n$  actions,  $\rho = n$ ;
- with ratio  $R$  of highest to lowest  $R_i$ ,  $\rho = \Theta(\log R)$ ;
- with ratio  $C$  of highest to lowest  $c_i$ ,  $\rho = \Theta(\log C)$

Bounds are tight even for best **monotone** contract

# Summary

- Contract theory as an interesting new frontier for AGT
- Algorithmic approach can provide new insights, such as:
  - Optimize the contract to available moment information
  - Expect linear contracts to perform well except in pathological cases
- Opportunities for new success stories