

Contract Design Under Uncertainty

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Computation and Economics Seminar

The Hebrew University of Jerusalem

Feb 25, 2024

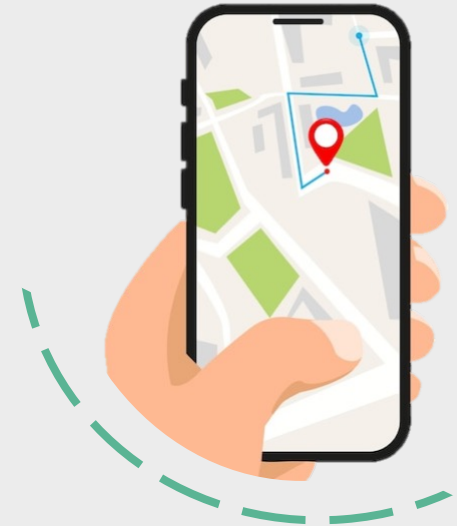


Overview

- Algorithms in society
- Incentivizing **truthfulness** versus incentivizing **effort**
- The **principal-agent** model [GH83]
- Contract design with **types**

Modern Algorithms in Society

- Interactions with **self-interested** individuals
- In algorithmic game theory, we take **incentives** into account



Social Media Marketing

- **Paid Ads** - in the social platform feed
- **Influencer Marketing** - a brand hires popular users

Paid Ads

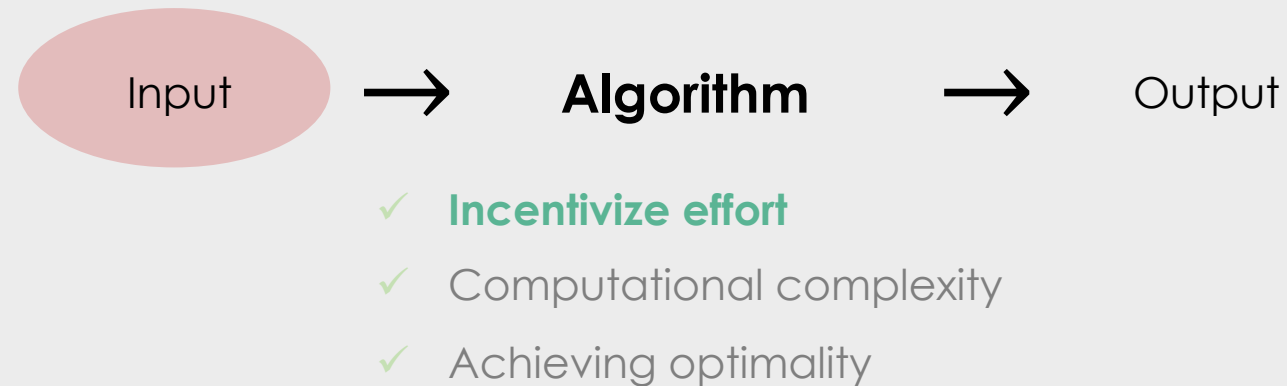
- Algorithmic **auction** - advertisers bid → allocation and payment
- Hidden type or adverse selection



- ✓ **Incentivize truthfulness**
- ✓ Computational complexity
- ✓ Achieving optimality

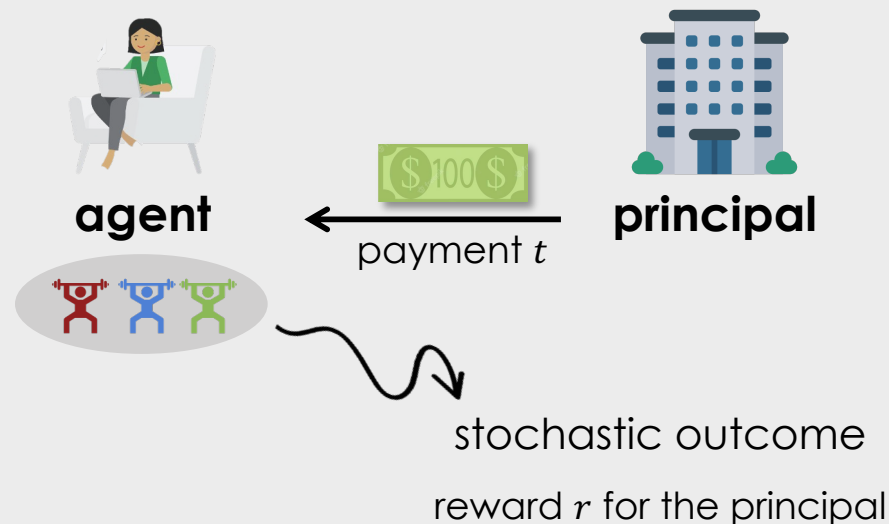
Influencer Marketing

- The algorithm determines a **contract** to incentivize effort

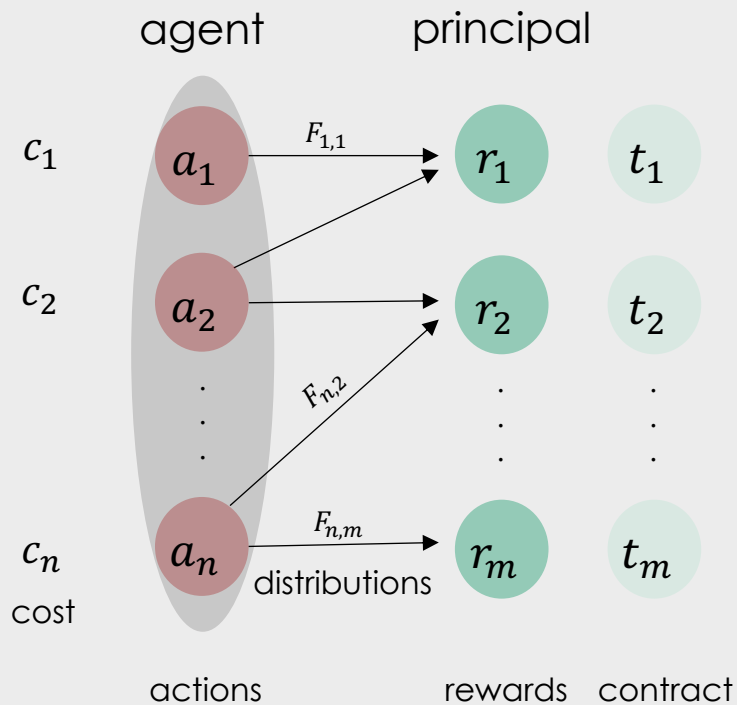


The Principal-Agent Model [GH83]

- **Moral hazard** - the agent's actions cannot be observed
- **Objective:** a contract maximizing expected **rewards minus payment** $\mathbb{E}[r - t]$



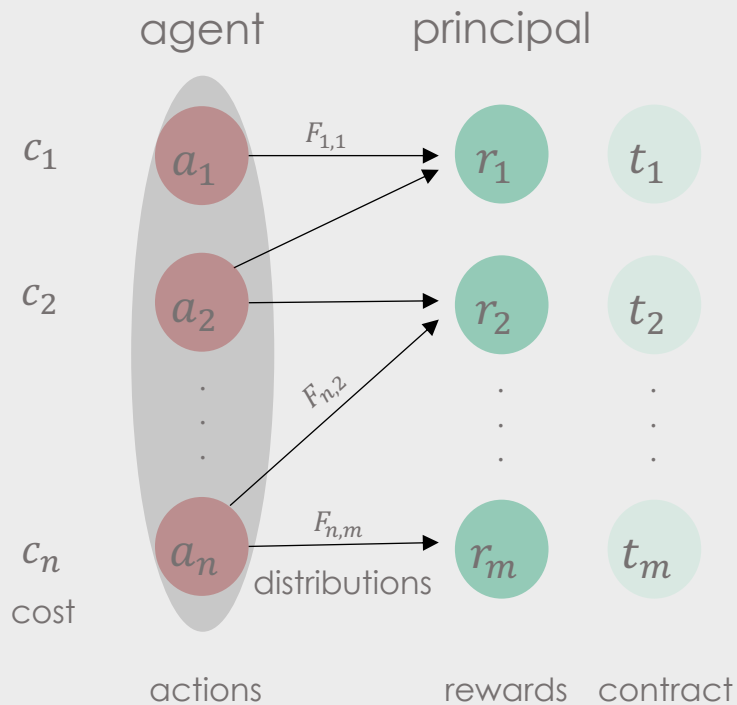
The Principal-Agent Model [GH83]



○ Agent's **action i^*** maximizes $\sum_{j \in [m]} F_{i,j} t_j - c_i$

○ Principal's **revenue** $\sum_{j \in [m]} F_{i^*,j} r_j - \sum_{j \in [m]} F_{i^*,j} t_j$

The Principal-Agent Model [GH83]



○ Agent's **action** i^* maximizes $\sum_{j \in [m]} F_{i,j} t_j - c_i$

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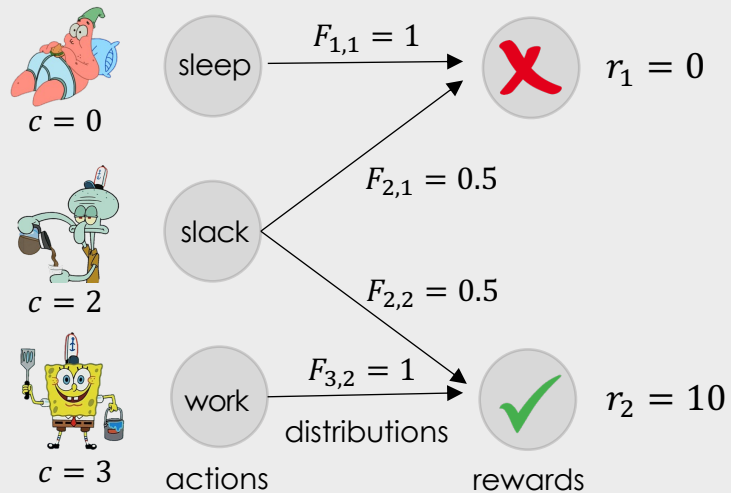
Min-payment LP for incentivizing action i :

$$\min_{t_1, \dots, t_m} \sum_{j \in [m]} F_{i,j} t_j$$

$$s. t. \quad \sum_{j \in [m]} F_{i,j} t_j - c_i \geq \sum_{j \in [m]} F_{i',j} t_j - c_{i'} \quad \forall i' \in [n] \quad (IC)$$

$$t_j \geq 0 \quad \forall j \in [m] \quad (LL)$$

Simple Example



Min-payment LP for incentivizing **working**:

$$\begin{aligned}
 \min_{t_1, t_2} \quad & t_2 \\
 \text{s. t.} \quad & t_2 - 3 \geq t_1 - 0 \quad (IC - \text{sleep}) \\
 & t_2 - 3 \geq 0.5 \times t_1 + 0.5 \times t_2 - 2 \quad (IC - \text{slack}) \\
 & t_1, t_2 \geq 0
 \end{aligned}$$

The **optimal contract**: $(t_1, t_2) = (0, 3)$

Agenda

Generalizations of the classic model:

- **Personalization** for participants from diverse population (with **types**)
- **Multilateral** contracts involving multiple principals or agents
- The need for **simple** contracts

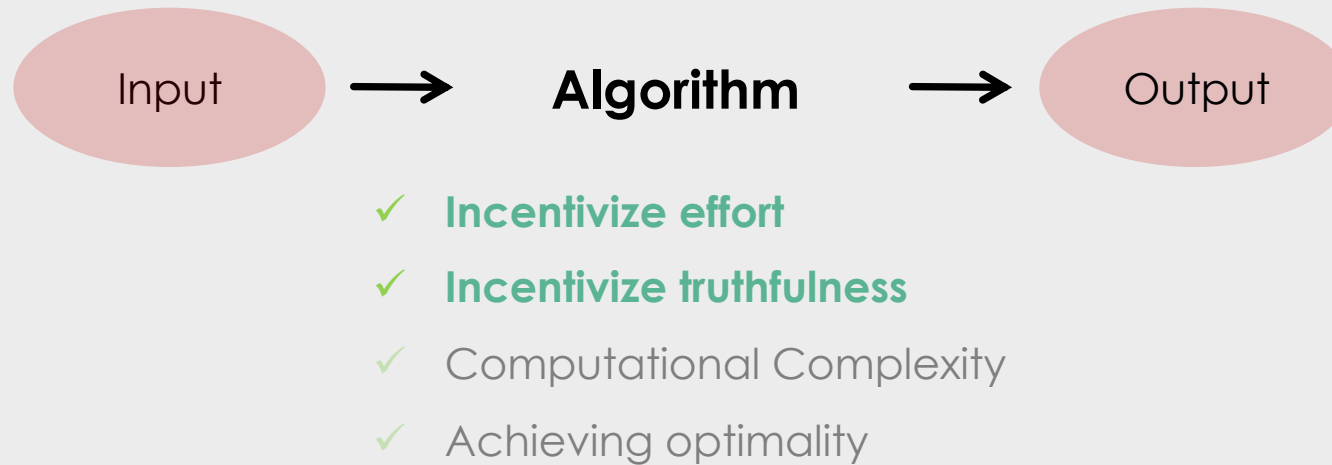
Agenda

Generalizations of the classic model:

- **Personalization** for participants from diverse population (with **types**)
- **Multilateral** contracts involving multiple principals or agents
- The need for **simple** contracts

Agenda

- Combine **moral hazard** and **adverse selection**



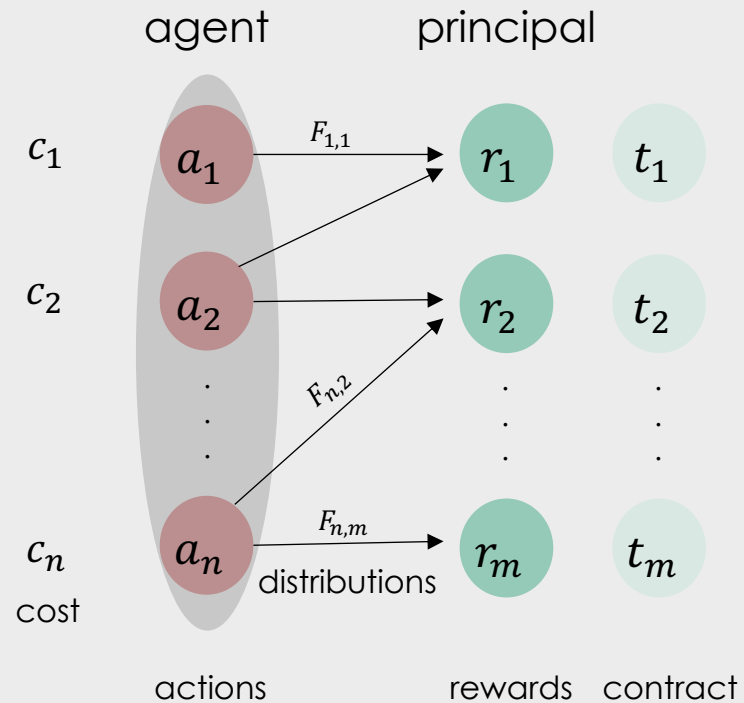
Outline

- **Single-parameter** model of types [ADT.C. EC'21]
 - Motivated by single-parameter auction design
- **Characterization** of the design space [ADT.C. EC'21]
- Counter-intuitive and **undesirable** properties of **optimal contracts** [ADLT.C. EC'23]
- **Linear contracts** (aka commission-based) are near-optimal [ADLT.C. EC'23]

Recent works on contracts with types. Myerson (1982), Guruganesh et al. (2021), Castiglioni et al. (2021), Gottlieb and Moreira (2022), Casto-Pire et al. (2022).

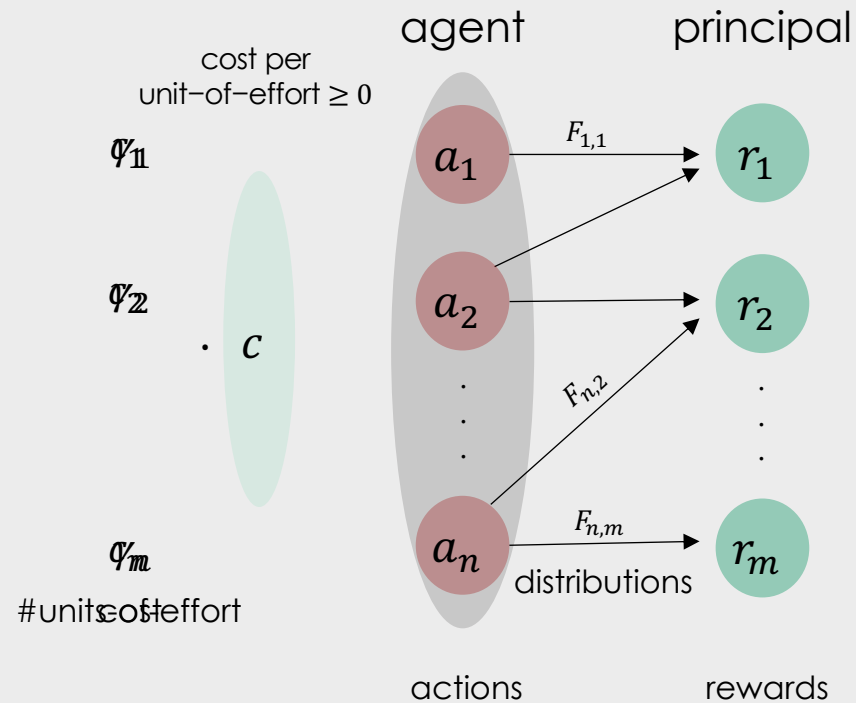
The Model

- o The classic principal-agent model by Grossman-Hart (1983)



The Model

- Type is drawn from G with density g supported on $\mathcal{C} = [\underline{c}, \bar{c}]$



The Model

- A **contract** (x, t) consists of two mappings:
 - **Payment rule** $t: \mathcal{C} \rightarrow \mathbb{R}^m$ from types to a **paymet** scheme
 - **Allocation rule** $x: \mathcal{C} \rightarrow [n]$ from types to an **action** recommendation

Notation. $T_i^c = \mathbb{E}_{j \sim F_i}[t(c)_j]$

- **Agent** c report \hat{c} and action $i^*(c)$ maximize $T_{i^*(c)}^{\hat{c}} - \gamma_{i^*(c)} c$
- A contract (x, t) is **incentive compatible (IC)** if $c = \hat{c}$ and $x(c) = i^*(c)$
- **Principal's contract** maximizes **revenue** $\mathbb{E}_{c \sim G}[R_{x(c)} - T_{x(c)}^c]$ s.t. IC
- **Welfare** sum of utilities $\mathbb{E}_{c \sim G}[R_{i^*(c)} - \gamma_{i^*(c)} c]$

Design Space Characterization

Definition. Allocation rule x is **implementable** if exists payment rule t s.t. (x, t) is IC

Q. How do implementable allocation rules look like?

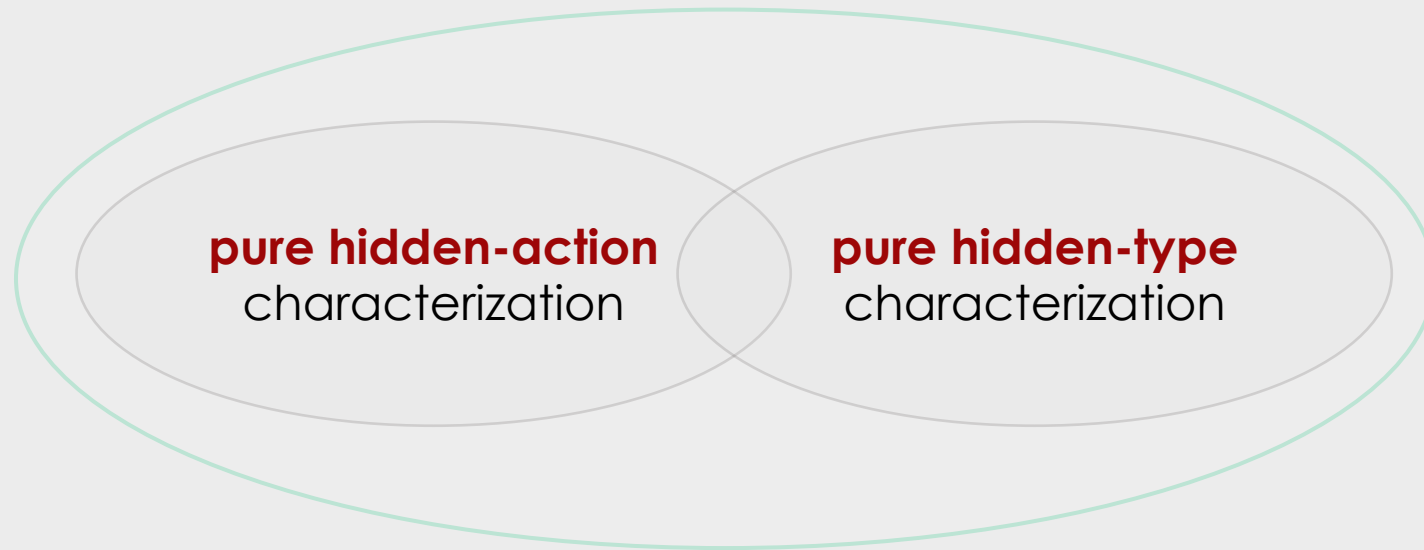
pure hidden-action
characterization

pure hidden-type
characterization

Design Space Characterization

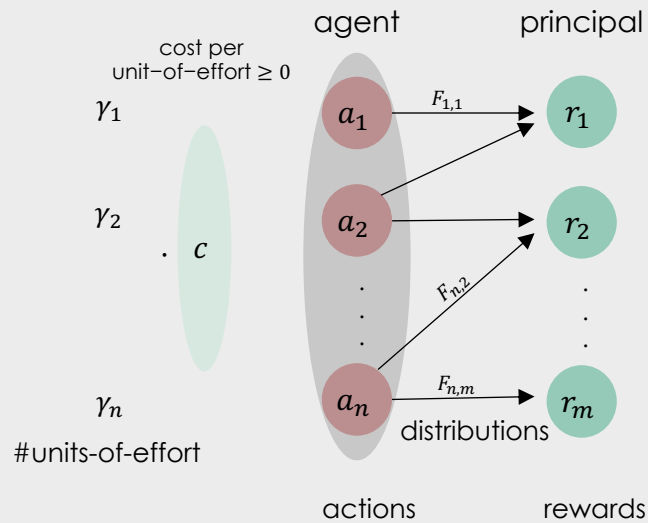
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Design Space Characterization

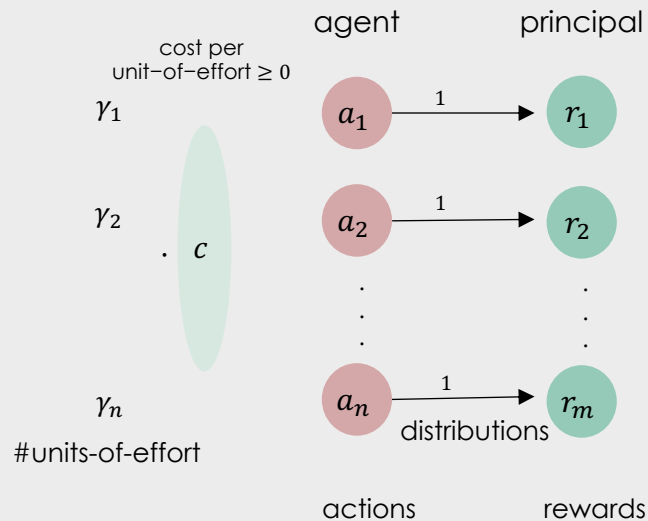
Pure hidden type



Design Space Characterization

Pure hidden type

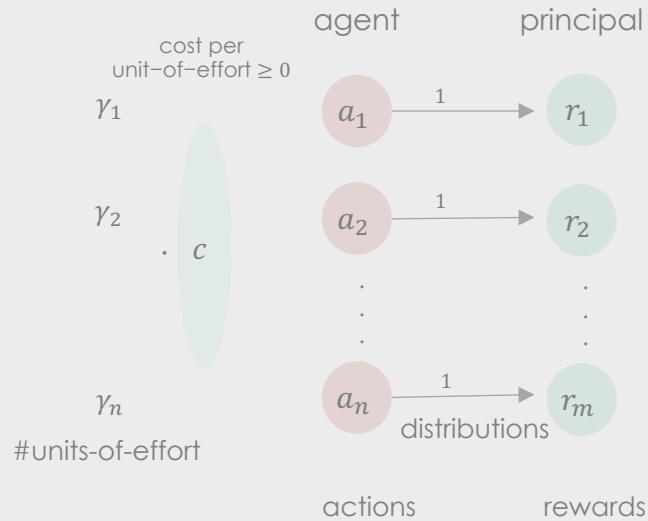
- x is **implementable** $\Leftrightarrow x$ is **monotone** [Myerson 1981]



Design Space Characterization

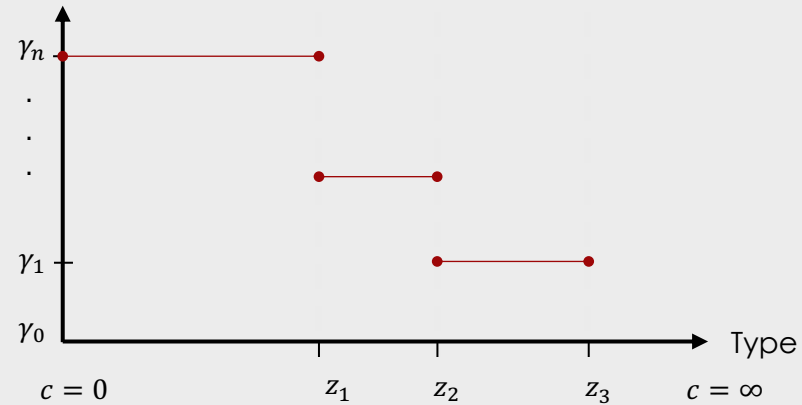
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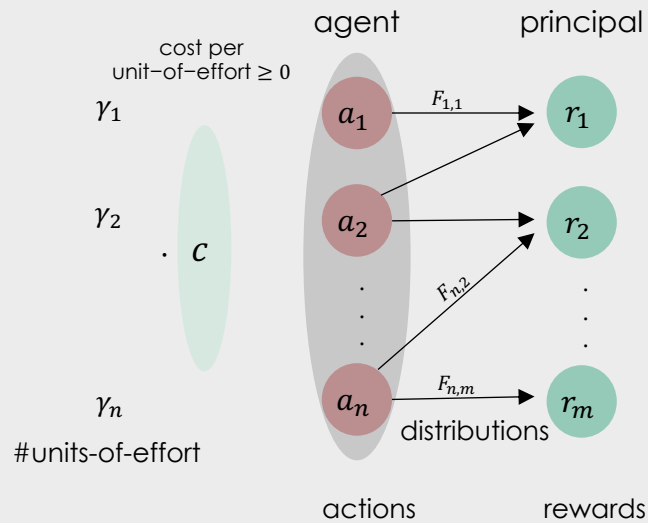
Monotone allocation rule $x: \mathcal{C} \rightarrow [n]$

Units-of-Effort



Design Space Characterization

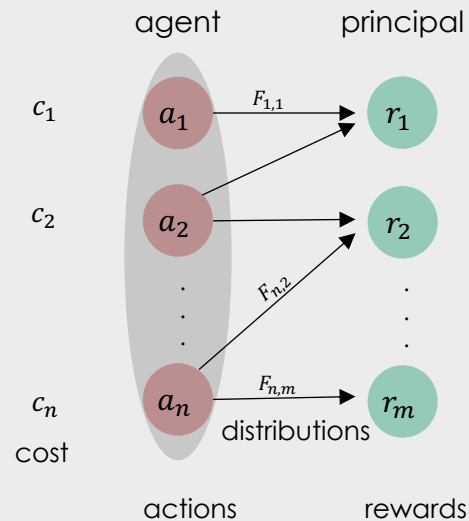
Pure hidden action



Design Space Characterization

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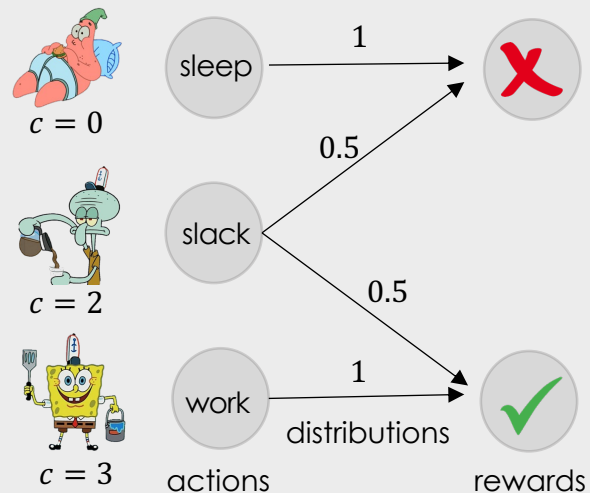
- x is **implementable** $\Leftrightarrow \nexists$ **deviation scheme** $\lambda = (\lambda_1, \dots, \lambda_n)$ s.t. $\sum_{k \in [n]} \lambda_k = 1$ and:



Design Space Characterization

Pure hidden action

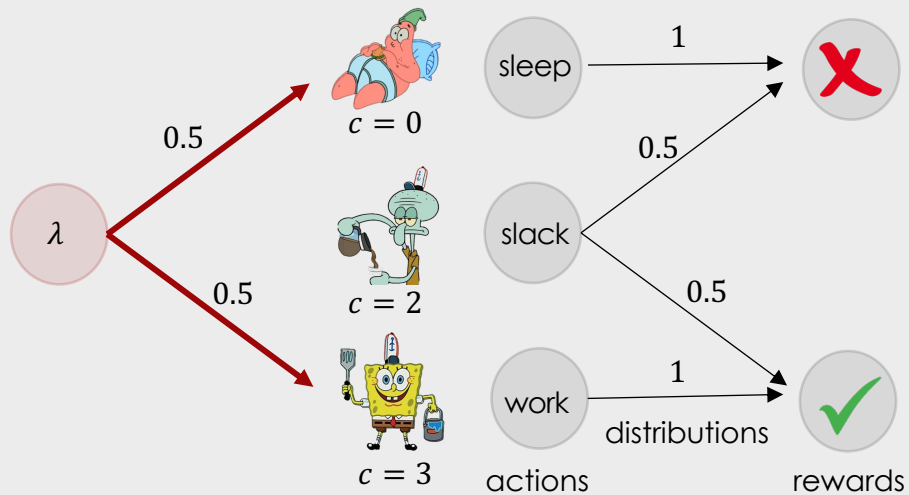
- x is **implementable** $\Leftrightarrow \nexists$ **deviation scheme** $\lambda = (\lambda_1, \dots, \lambda_n)$ s.t. $\sum_{k \in [n]} \lambda_k = 1$ and:
 - (1) $\sum_k \lambda_k F_k \geq F_x$ (dominant distribution)
 - (2) $\sum_k \lambda_k c_k < c_x$ (strictly lower cost)



Design Space Characterization

Pure hidden action

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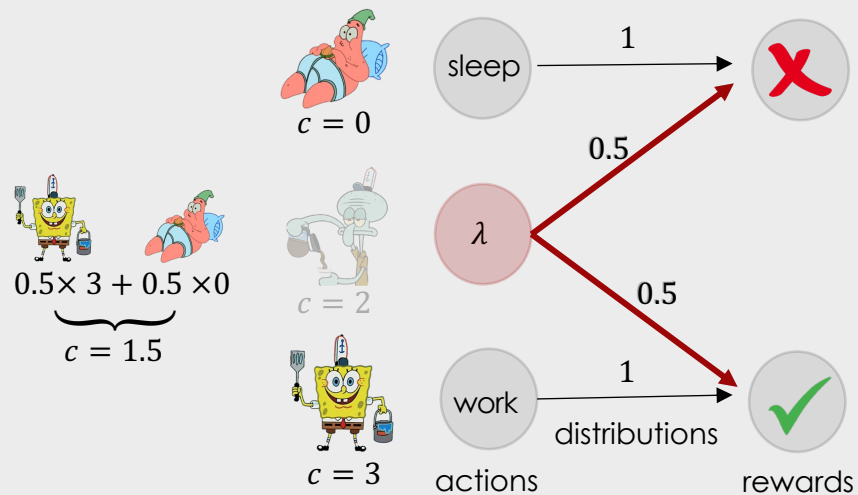



is not implementable

Design Space Characterization

Pure hidden action

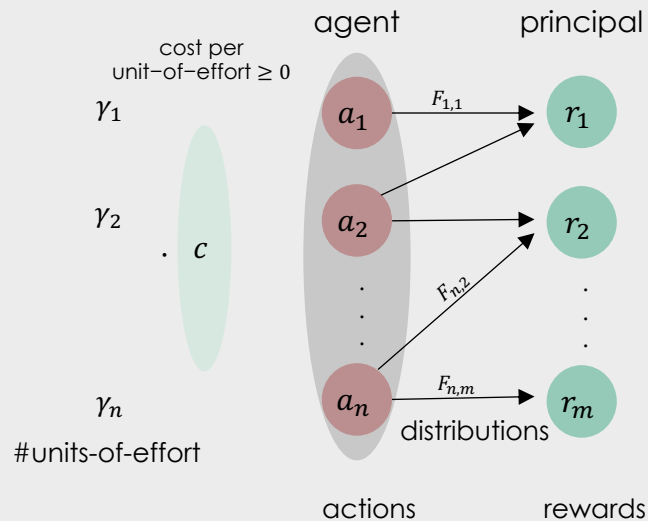
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Design Space Characterization

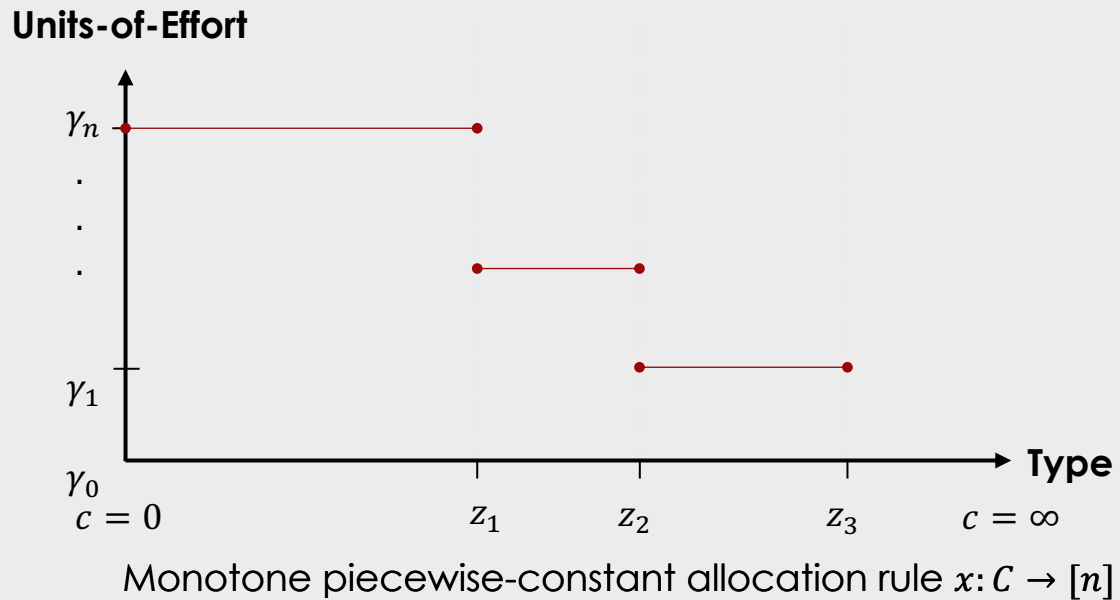
Hidden type and hidden action



Design Space Characterization

Hidden type and hidden action

Proposition [ADT EC'21]. If x is implementable, it is **monotone**



Design Space Characterization

Theorem [ADT EC'21]. x **implementable** \Leftrightarrow exists no **deviation scheme** $\lambda_{(z,k)}$ s.t.

Corollary [ADT EC'21]. Optimal contract is **polytime computable** for const #actions

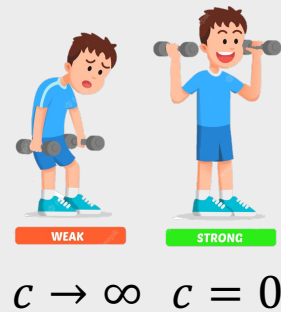
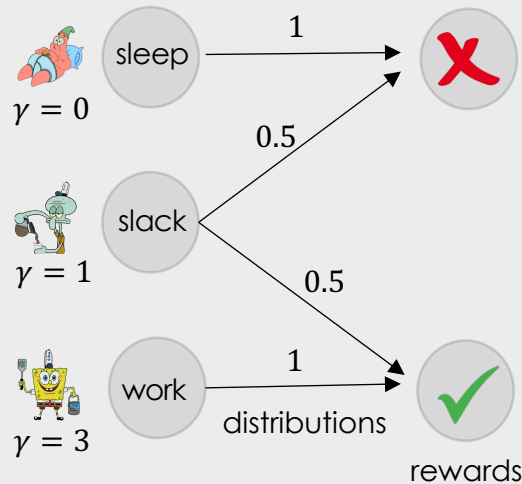
Hardness for constant #actions in the multi-parameter model [Guruganesh-Schneider-Wang'21]

Back to Our Example

Theorem [ADT EC'21]. x implementable \Leftrightarrow exists no **deviation scheme** $\lambda_{(z,k)}$ s.t.

(1) $\sum_{z,k} \lambda_{(z,k)} F_k \geq \sum_z F_{x(z)}$ (dominant sum of distributions)

(2) $\sum_{z,k} \lambda_{(z,k)} \gamma_k z < \sum_z \gamma_{x(z)} z$ (strictly lower joint cost)

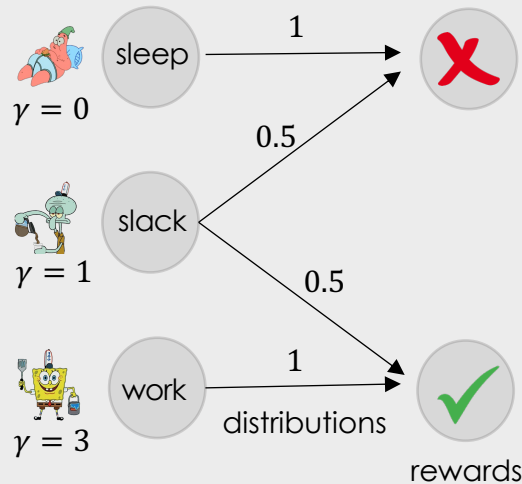





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allocation rule:   \rightarrow 

$c \rightarrow \infty$ $c = 0$ $\gamma = 1$

(1) distributions sum (1,1)

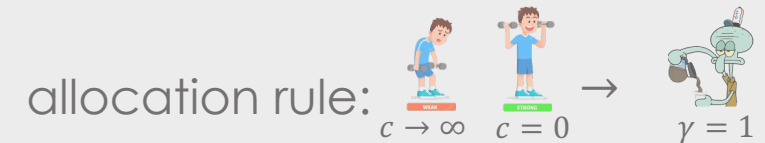
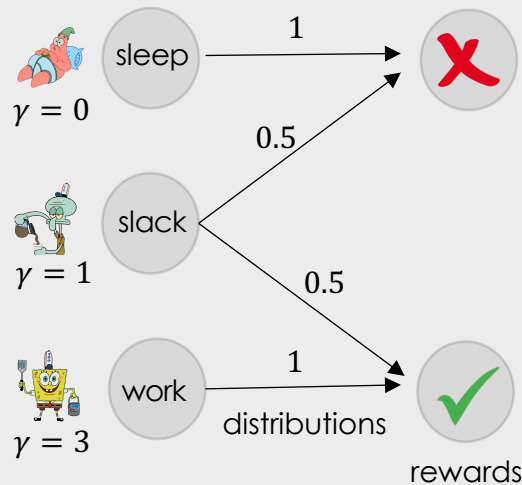
(2) joint cost ∞

Back to Our Example

Theorem [ADT EC'21]. x implementable \Leftrightarrow exists no **deviation scheme** $\lambda_{(z,k)}$ s.t.

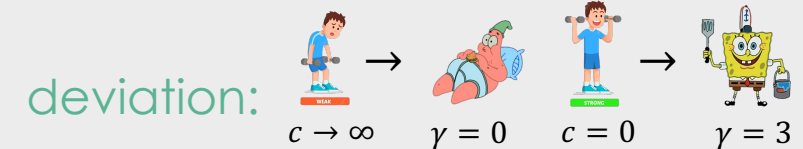
(1) $\sum_{z,k} \lambda_{(z,k)} F_k \geq \sum_z F_{x(z)}$ (dominant sum of distributions)

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(1) distributions sum (1,1)

(2) joint cost ∞



(1) distributions sum (1,1)

(2) joint cost 0

Optimal Contracts and Their Issues

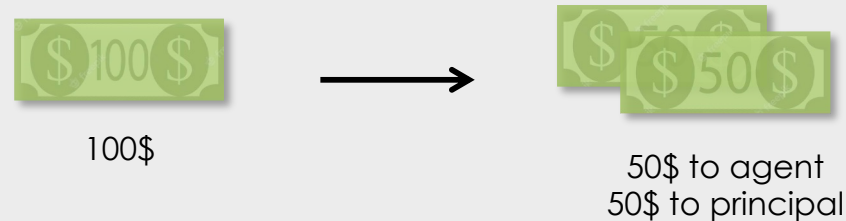
- Informational requirements, extensive analysis, etc.
- Unintuitive, e.g., non-monotonicity in rewards [DRT EC'19]

Theorem [ADLT EC'23]. In the single dimensional typed model

- Large **menu-size complexity**
- Revenue **non-monotonicity** w.r.t type distribution

Simple Contracts

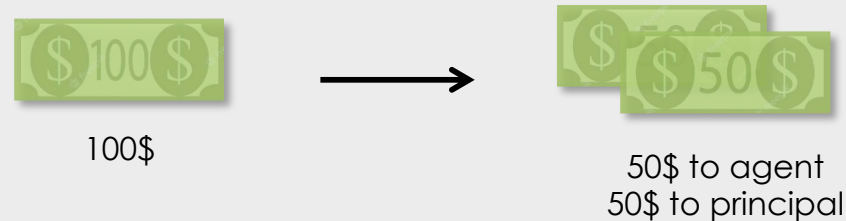
- In a **linear contract**, the principal offers a fixed share $\alpha \in [0,1]$ of the rewards



“It is probably **the great robustness of linear rules** based on aggregates **that accounts for their popularity**. That point is not made as effectively as we would like by our model; we suspect that it cannot be made effectively in any traditional Bayesian model.” [Milgrom and Holmstrom 1987]

Simple Contracts

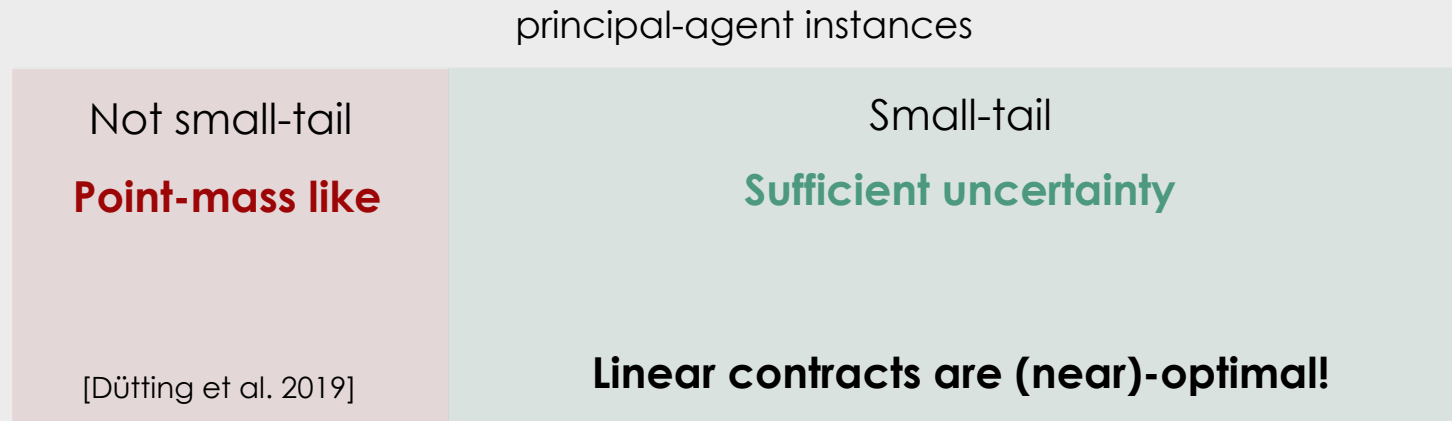
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- **Robustness of linear contracts.** Carroll (2015), Dütting et al. (2019), Yu and Kong (2020), Dai and Toikka (2022), Walton and Carroll (2022)
- **Approximation of linear contracts.** Dütting et al. (2019), Castiglioni et al. (2021), Guruganesh et al. (2021)

Near-Optimality of Linear Contracts

- $\theta(n)$ separation for **point-mass** distributions [DRT EC'19]
 - Boundary case
- **Approximately optimal** with **sufficient uncertainty**
 - The small-tail assumption



Near-Optimality of Linear Contracts

Theorem [ADLT EC'23]. Revenue benchmark:

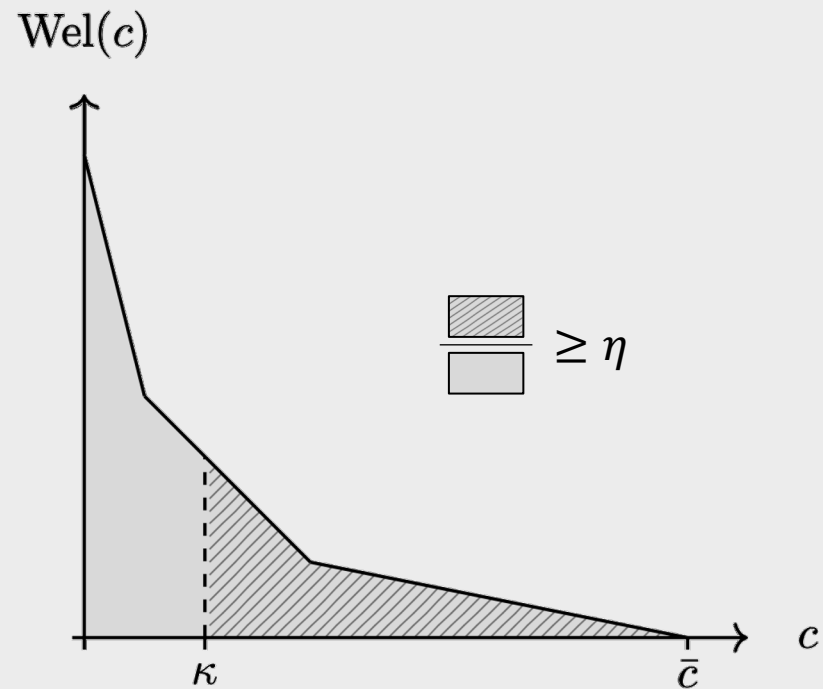
- **3-approximation** for **normal** $\mathcal{N}(\mu, \sigma^2)$ truncated at $c = 0$ with $\sigma \geq 5\eta/2\sqrt{2}$
- **2-approximation** for **uniform** $U[0, \bar{c}]$
 - **Optimal** when $i^*(r, \bar{c}) = 0$
- **2-approximation** for **decreasing densities** (e.g., exponential)

- **Constant** approximation w.r.t optimal **welfare benchmark** [ADLT EC'23]

The Small-Tail Assumption

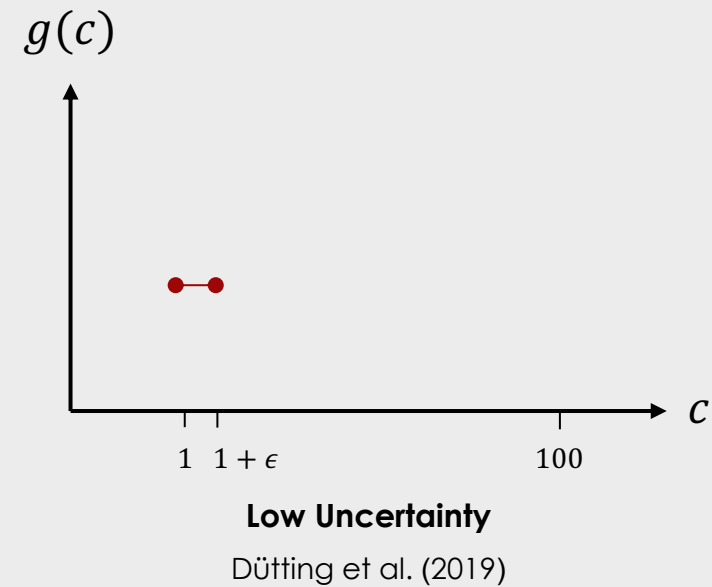
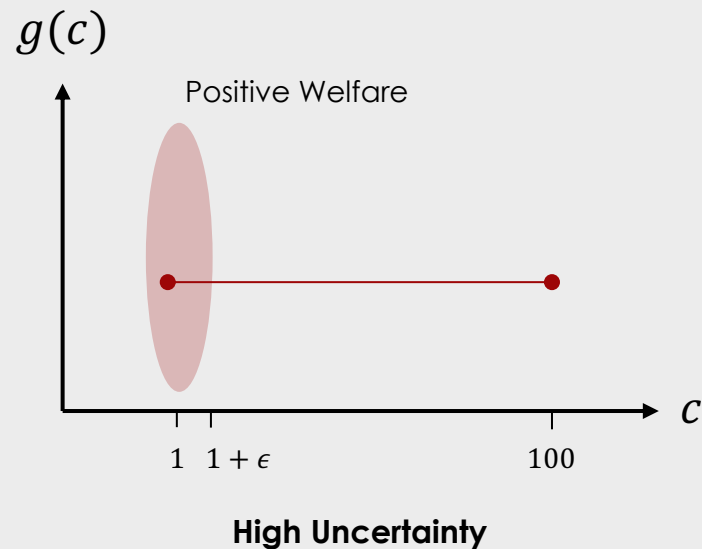
Definition [ADLT EC'23]. Let $\kappa \in [\underline{c}, \bar{c}]$, $\eta \in [0,1]$.

An instance is **(κ, η) -small-tail** if $\text{Wel}_{[\kappa, \bar{c}]} \geq \eta \text{Wel}_{[\underline{c}, \bar{c}]}$



The Small-Tail Assumption

Depends on the entire principal-agent setting



Universal Approximation Guarantee

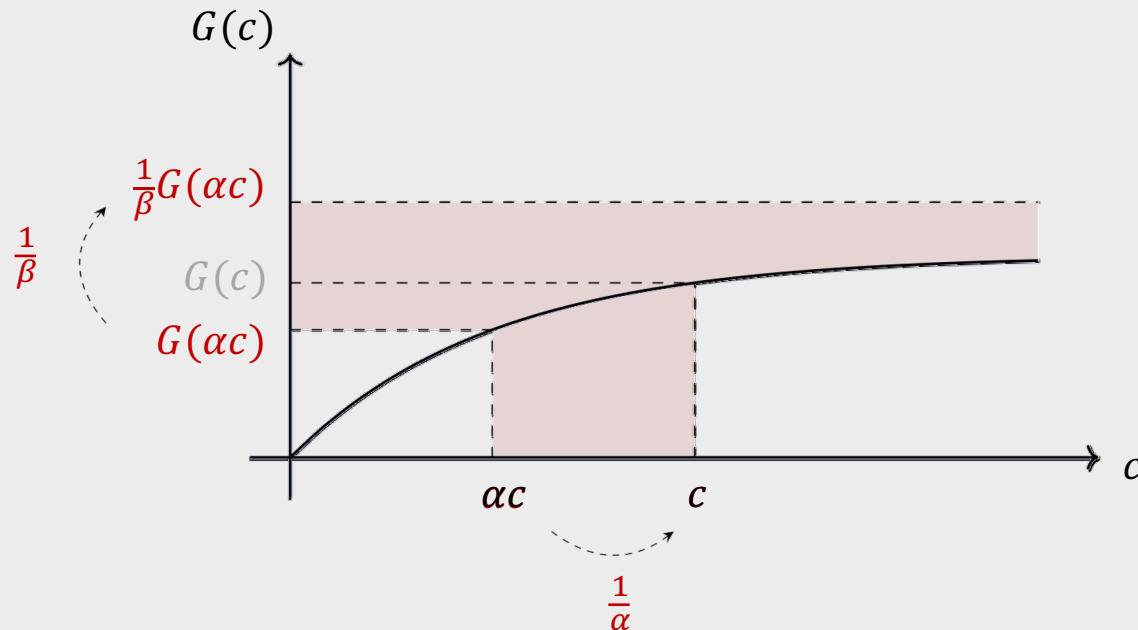
Theorem [ADLT EC'23]. Let $q \in (0,1)$ and $G(c_q) = q$. If for $\alpha, \eta \in (0,1)$ the settings is $(\frac{c_q}{\alpha}, \eta)$ -small-tail then linear contract α is at least $(1 - \alpha)\eta q$ of the **optimal welfare**

Slowly-Increasing Distributions

- Applies to any CDF and captures its **rate of increase**
- Parametric **approximation** of linear contracts
- Any distribution is slowly-increasing for **some parameters**

Slowly-Increasing Distributions

Definition [ADLT EC'23]. Let $\alpha, \beta \in (0,1)$, and $\kappa \in [\underline{c}, \bar{c}]$. A distribution G is (α, β, κ) -**slowly-increasing** if $G(c) \leq \frac{1}{\beta} G(\alpha c) \forall \kappa \leq c$



Approximation for Slowly Increasing

Theorem [ADLT EC'23]. Let $\alpha, \beta, \eta \in (0,1)$, and $\kappa \in [\frac{c}{\alpha}, \bar{c}]$.

Under (α, β, κ) -slowly-increasing and (κ, η) -small-tail
linear contract α is $(1 - \alpha)\beta\eta$ of the optimal welfare

$$\text{linear contract revenue} \geq (1 - \alpha) \times \beta \times \text{optimal welfare}$$

Proof Idea for Slowly Increasing

$$\text{linear contract revenue} \geq (1 - \alpha) \times \text{linear contract welfare} \geq (1 - \alpha) \times \beta \times \text{optimal welfare}$$

Proof Idea for Slowly Increasing

$$\text{linear contract revenue} \geq (1 - \alpha) \times \text{linear contract welfare} \geq (1 - \alpha) \times \beta \times \text{optimal welfare}$$

Step 1. Revenue of linear contract α is at least $1 - \alpha$ of its welfare

$$\begin{array}{l} \text{revenue of linear contract} \\ \mathbb{E}_{c \sim G}[(1 - \alpha)R_{x(c)}] \end{array} \geq (1 - \alpha) \times \begin{array}{l} \text{welfare of linear contract} \\ \mathbb{E}_{c \sim G}[R_{x(c)} - \gamma_{x(c)}c] \end{array}$$

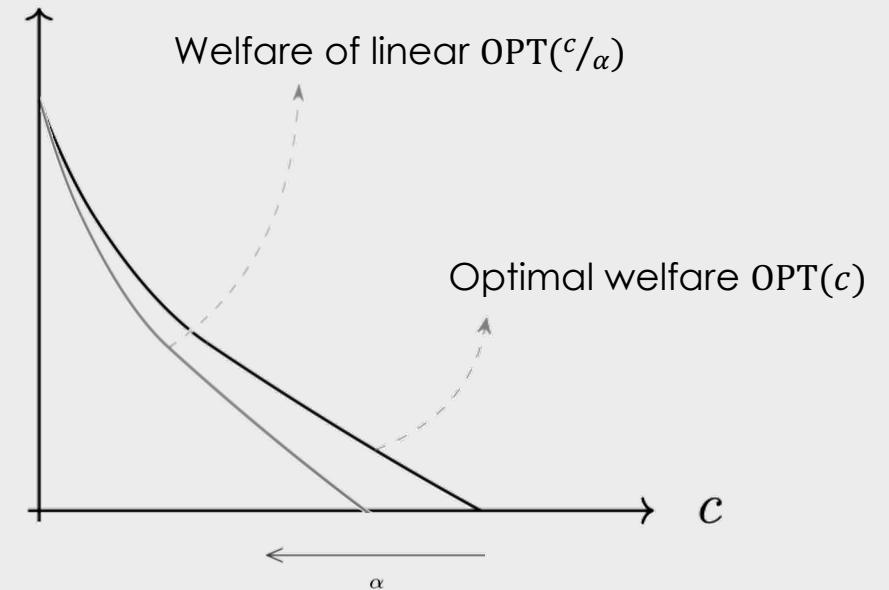
Proof Idea for Slowly Increasing

$$\text{linear contract revenue} \geq (1 - \alpha) \times \text{linear contract welfare} \geq (1 - \alpha) \times \beta \times \text{optimal welfare}$$

Step 2. Welfare of linear contract α is at least β of the optimal welfare

- When maximizing welfare, the agent maximizes $R_i - \gamma_i c$
- For linear contract α :

The agent maximizes $\alpha R_i - \gamma_i c$ which is $R_i - \gamma_i \frac{c}{\alpha}$



Approximation for Slowly Increasing

Theorem [ADLT EC'23]. Let $\alpha, \beta, \eta \in (0,1)$, and $\kappa \in [\frac{c}{\alpha}, \bar{c}]$.

Under (α, β, κ) -slowly-increasing and (κ, η) -small-tail
linear contract α is $(1 - \alpha)\beta\eta$ of the optimal welfare

Summary and Future Directions

- **Single-parameter** model of types
- **Characterization** of the design space
- Counter-intuitive and **undesirable** properties of **optimal contracts**
- **Linear contracts** are near-optimal

Future directions:

- Other **forms of simple contracts** that are near-optimal
- Contracts that involve **multiple agents**
- **Applications** of this theory

Thank You!

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