

Sequential Information Acquisition and Optimal Search

Nawaaz Khalfan¹ Rakesh Vohra²

¹Monash University

²University of Pennsylvania

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Allocating without transfers

A principal has something of value to an agent.

Information relevant to the principal for allocation is known to the agent and not the principal.

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Examples

- management **promoting** from a pool of candidates
- governments **funding** selected municipalities
- trade commissions **allowing** merger requests

Instruments

Other papers,

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This paper,

information acquisition: the agent is able to report their private information, and the principal can *acquire additional information* for a *cost*

→ Call this instrument **inspection** and think of the agents information as *noisy*.

Inspection

A core economic activity

- management **interview** candidates
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Why **inspect**?

1. discovery or *information acquisition*
2. verification or *screening*

Today's setup

Each agent's true value to the principal is binary: high, h , and low, ℓ .

The likelihood agent i is of value h is $p_i \in [0, 1]$, and is the agent's **private information** or *type*.

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The principal can inspect an agent and discover their true value for a **cost** $c > 0$.

The principal can elicit reports, commit to an inspection and allocation mechanism, but cannot use **transfers**.

Mechanism space and objective

Suppose the principal has inspected a set of agents S and realized a vector of rewards x_S . At this point, she has the following choices:

- inspect $i \notin S$, realise x_i and re-initialise with the set $S \cup \{i\}$
- stop and allocate to $j \in S \cup \{0\}$

Mechanism space and objective

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If the principal does decide to stop and allocate to her highest value agent, she receives that value net any inspection costs incurred, making her stopping value:

$$v(S, x_S) = \max_{i \in S \cup \{0\}} x_i - \sum_{j \in S} c_j$$

The objective is to select a sequential, *nonanticipative* inspection and allocation policy that maximizes her expected stopping value.

Benchmarks

Two benchmark cases to be aware of:

Weitzman (1979) or **Pandora's problem**: if types are known to the principal ex ante, assign each agent an index, inspect agents sequentially from high index to low index until the value of keeping the best agent found exceeds the next highest index.

Ben-Porath, Dekel and Lipman (2014): if agents are perfectly informed, *verify* the agent with the highest reported type and allocate only to them if they match that report.[†]

Forced inspection

Note that the principal **must** inspect (or search) the agent if they are to allocate to them.

There are a few reasons why we are comfortable studying this problem:

1. Institutional requirements like *due diligence* are common.
2. Pandora's problem is tractable, and our construction relies on the assumption. See Doval (2018).
3. With one agent and no forced inspection, the inspection-free allocation never occurs at the top and is used at the bottom only to save costs. See Khalfan (2023).

Solution for one agent

Full information benchmark:

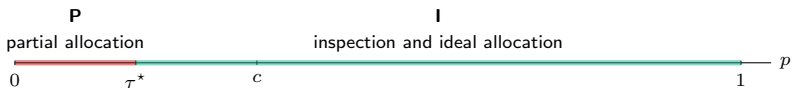


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Optimal **separating** mechanism:



Solution for multiple agents

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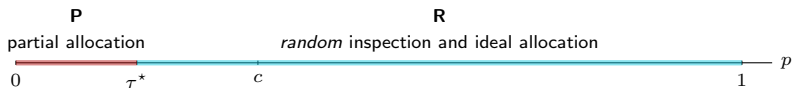


Solution for multiple agents

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Technical innovations

To show this result we:

1. recast Pandora's problem as a dynamic scheduling problem, and
2. show there are necessary and sufficient restrictions on interim allocations that guarantee ex-post implementation.

The first is due to a characterisation by Bertsimas and Niño-Mora (1996), and the second is a similar treatment as Che, Kim and Mierendorff (2013) but dates back to Hassin (1982).

Both however are in the spirit of the reduced form approach e.g. Border (1991).

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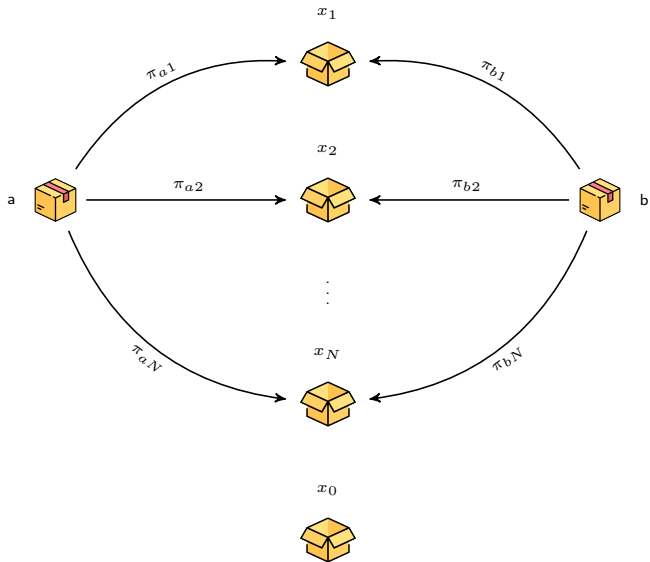
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Weitzman (1979) showed that if Pandora must open a box before being allowed to select it, then the optimal *ordering* and *stopping rule* is *indexable*.

2 box, N prize illustration



A dynamic scheduling problem

We can re-imagine Pandora's problem as an *infinite horizon dynamic scheduling problem* by following the lead of Bertsimas and Niño-Mora (1996).

A *class* is a particular state, and if a *job* is in class $j \in \mathcal{J}$ and is *serviced*, then the scheduler receives a *service reward* r_j and the job transitions to a new class $k \in \mathcal{J}$ with *transition probability* p_{jk} .

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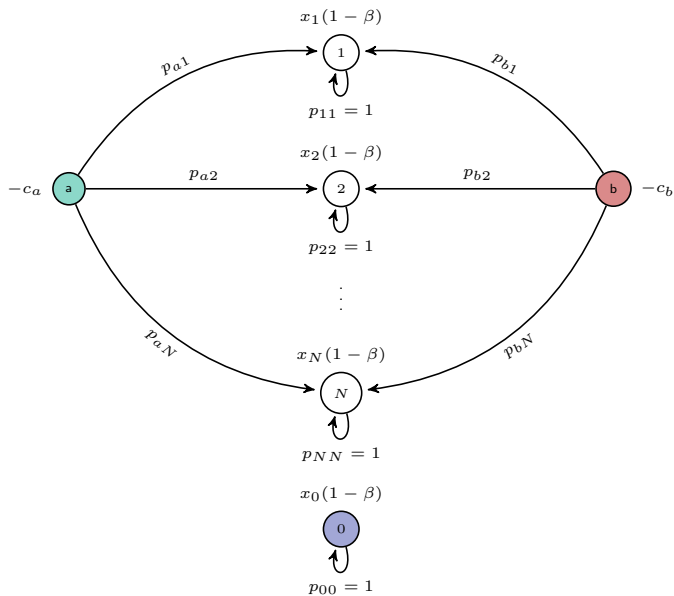
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- if $j = 0$, *keep the outside option*: $r_j = x_0(1 - \beta)$ and $p_{00} = 1$.

with $\beta \in (0, 1)$ the associated discount factor over the infinite time horizon.

2 box, N prize scheduling



Service time formulation

Service time formulation

Define λ_j as the expected discounted number of times a job in class j , and Λ the space where these service times live. Then the optimal mathematical program to solve is:

$$\mathcal{Z} = \max \sum_{j \in \mathcal{J}} r_j \lambda_j \quad \text{s.t.} \quad (\lambda_j)_{\mathcal{J}} \in \Lambda$$

And it turns out that Λ is fully characterized by a (relatively) small number of conservation laws . . .

Pandora's linear program

... and maximising a linear objective over Λ admits an indexable and decomposable solution!

Theorem 1 (Bertsimas and Niño-Mora)

The performance region, Λ , is an extended polymatroid, and for each class $j \in \mathcal{J}$ there exists indices, z , depending only on characteristics of that class, such that an optimal policy is to schedule a job with the largest current index.

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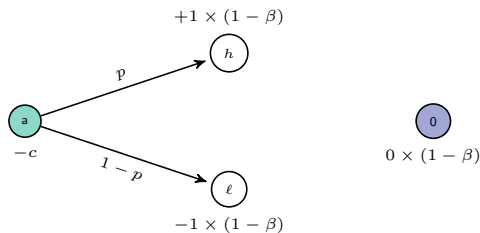
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In its generality (Bertsimas and Niño-Mora, 1996), this reproves the celebrated result of Gittins and Jones (1974).

1 box, 2 prize scheduling problem



$$\begin{aligned}
 V = \max_{\lambda \geq 0} \quad & -c\lambda_a \quad + \quad (1 - \beta)\lambda_h \quad - \quad (1 - \beta)\lambda_\ell \\
 \text{s.t.} \quad & \lambda_a \quad + \quad \lambda_h \quad + \quad \lambda_\ell \quad + \quad \lambda_o \quad = \quad \frac{1}{1 - \beta} \\
 & \lambda_a \quad \leq \quad 1 \\
 & -\frac{p\beta}{1 - \beta}\lambda_a \quad + \quad \lambda_h \quad \leq \quad 0 \\
 & -\frac{(1-p)\beta}{1 - \beta}\lambda_a \quad \quad \quad + \quad \lambda_\ell \quad \leq \quad 0
 \end{aligned}$$

Full information

Suppose Pandora knows p . Then, following our formulation, Pandora's **interim first best value** is given by:

$$\begin{aligned} \bar{v}(p) = \max_{\lambda \geq 0} & \quad -c\lambda_a & + & \quad (1 - \beta)\lambda_h & - & \quad (1 - \beta)\lambda_\ell \\ \text{s.t.} & \quad \lambda_a & + & \quad \lambda_h & + & \quad \lambda_\ell & + & \quad \lambda_0 & = & \quad \frac{1}{1-\beta} \\ & \quad \lambda_a & & & & & & & \leq & \quad 1 \\ & \quad -\frac{p\beta}{1-\beta}\lambda_a & + & \quad \lambda_h & & & & & \leq & \quad 0 \\ & \quad -\frac{(1-p)\beta}{1-\beta}\lambda_a & & & + & \quad \lambda_\ell & & & \leq & \quad 0 \end{aligned}$$

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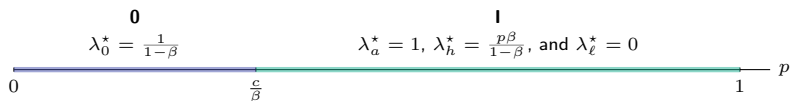
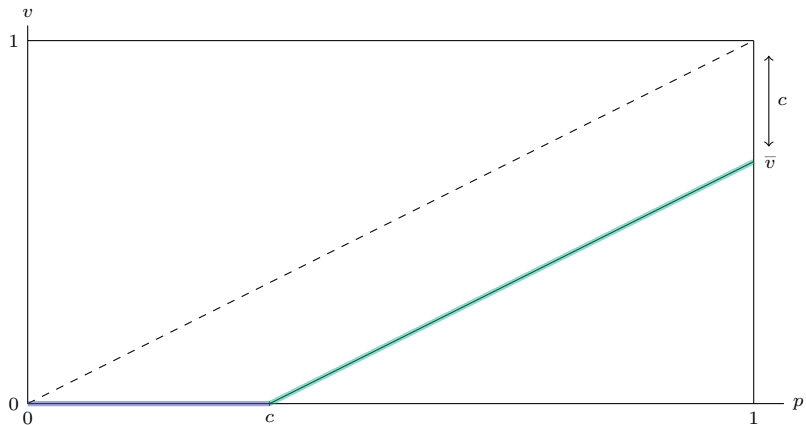
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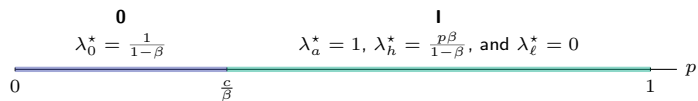
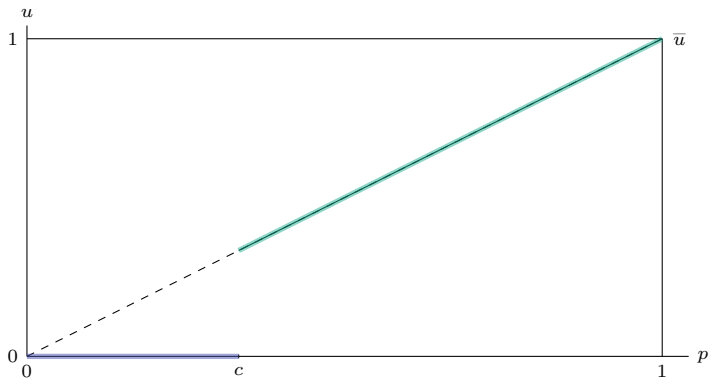
A solution to this problem is λ^* , where:

- if $p\beta - c \geq 0$, then $\lambda_a^* = 1$, $\lambda_h^* = \frac{p\beta}{1-\beta}$, and $\lambda_\ell^* = 0$, and
- if $p\beta - c < 0$, then $\lambda_0^* = \frac{1}{1-\beta}$.

First best value and policy



First best payoff is not incentive compatible



Incentive compatibility

The allocations, $\lambda_h(q)$ and $\lambda_\ell(q)$, are only ever given after h or ℓ has been observed, and so, the deviation payoff for a type p reporting q is:

$$u(q|p) = \frac{p}{q} \lambda_h(q) + \frac{1-p}{1-q} \lambda_\ell(q)$$

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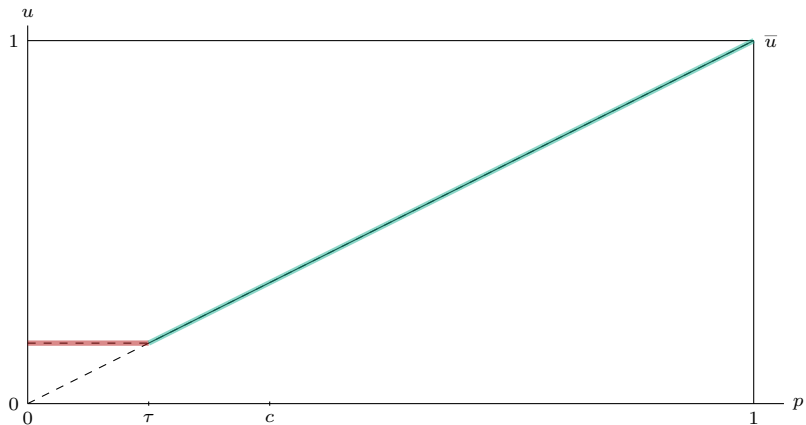
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Let the **guarantee** for report q be denoted by $y_\ell(q)$ and the **differential** for q be denoted by $\Delta(q)$. The **incentive compatibility constraints** can be written as:

$$IC_{pq} : u(p|p) = y_\ell(p) + p\Delta(p) \geq y_\ell(q) + p\Delta(q) = u(q|p) \quad \forall p, q \in \mathcal{P}$$

Second-best payoff and policy



a

$$\lambda_0^* = \frac{p\tau}{1-\beta}$$

l

$$\lambda_a^* = 1, \lambda_h^* = \frac{p\beta}{1-\beta}, \text{ and } \lambda_\ell^* = 0$$



Multiple agents

Now suppose there are n agents, indexed $i \in \{1, \dots, n\} =: N$ and let T be the set of possible types of an agent.

Denote by $\lambda_{ij}(t)$ the allocation to agent $i \in N$ at state $j \in \Omega$ at the profile $t = (t_1, \dots, t_n)$ of types. In our case, there is a special state, denoted '0' and the probability of transitioning from state 0 to state $j \in \Omega \setminus \{0\}$ for agent i of type t_i is denoted $p(j|t_i)$.

Denote the set of all profiles of types by T^n , and the likelihood of any particular type as $\pi(t)$. We will assume that types are independently drawn so that: $\pi(t) = \pi(t_i)\pi(t_{-i})$.

The reduced form

Let Q denote the interim allocation variables so that:

$$\pi(t_i)Q_{ij}(t_i) = \sum_{t_{-i}} \pi(t_i)\pi(t_{-i})\lambda_{ij}(t_i, t_{-i})$$

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The objective function can now be rewritten as:

$$\begin{aligned} V &= \sum_{t \in T^n} \pi(t) \sum_{i \in N} \sum_{j \in \Omega} r_j \lambda_{ij}(t) \\ \Rightarrow V &= \sum_{i \in N} \sum_{t_i \in T} \pi(t_i) \sum_{j \in \Omega} r_j Q_{ij}(t_i) \end{aligned}$$

This says that any two policies that have the same average, or *interim*, service times, are equivalent in terms of their value to the principal.

Transport formulation

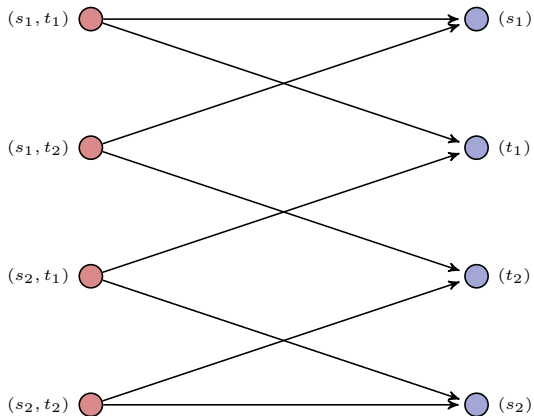
Let $\Delta := N \times T \times \Omega$ be the set of interim states or *demand nodes* and $S := T^n \times \Omega$ be the set of ex post states or *supply nodes*.

Let $\lambda(s) = (\lambda(s, d))_{d \in N(s)}$ be the ex post allocation or *supply* at node $s \in S$, and $Q(d)$ be the interim allocation or *demand* at node $d \in \Delta$.

The total *supply* from node s to a collection of *demand* nodes $D \subseteq N(s)$ is, by our first theorem, bounded by a submodular function g :

$$\sum_{d \in D} \lambda(s, d) \leq g(D|s)$$

A 2 agent, 2 type transport problem



A general solution

Those familiar with transport problems - e.g. Gale and Shapley (1962) - will recognise the type of result we get here.

Theorem 2 (Hassin, Che, Kim and Mierendorff)

There exists a λ such that,

- $\sum_{s \in N(d)} \pi(s, d) \lambda(s, d) = Q(d) \quad \forall d \in \Delta, \text{ and}$
- $0 \leq \sum_{d \in D} x(s, d) \leq g(D|s) \quad \forall D \subseteq N(s), s \in S$

if and only if,

$$0 \leq \sum_{d \in D} \pi(d) Q(d) \leq \sum_{s \in N(D)} \pi(s) g(D \cap N(s)|s) \quad \forall D \subseteq \Delta$$

Note that this essentially reproves Border (1991).

Optimal multiple agent mechanism

This means our proof for the one agent case carries through, so long as we respect these new upper bounds on interim allocations.

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Theorem 3 (Threshold Rule)

The optimal separating mechanism is characterised by a threshold τ , such that for each agent i with type p ,

- if $p \geq \tau$, $Q_{i0}(p) = \bar{Q}$, $Q_{il}(p) = 0$ and $Q_{ih}(p) = \frac{\beta p}{1-\beta} \bar{Q}$, and
- if $p < \tau$, $Q_{i0}(p) = \frac{\beta \tau}{1-\beta} \bar{Q}$, $Q_{il}(p) = \frac{\beta(1-p)}{1-\beta} \bar{Q}$ and $Q_{ih}(p) = \frac{\beta p}{1-\beta} \bar{Q}$,

where \bar{Q} is set maximally given n and π .

Optimal separating mechanism:



Sequential Information Acquisition and Optimal Search

Optimally **informed** search balances *discovery* and *verification*, at most only partially exploiting private information to guide search.

To show this we:

1. recast Pandora's problem as a dynamic scheduling problem, and
2. show there are necessary and sufficient restrictions on interim allocations that guarantee ex-post implementation.

Limitations?

- Forced inspection → seems innocuous
- Binary prizes → need *some* flattening e.g. MLRP
- Comparative statics → missing from this treatment

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Pandora's rule

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1. Set the *reserve value* as the value of the outside option, x_0 .
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3. If the realized prize exceeds the reserve value, replace the reserve value with this new prize and return to step 2.

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Refer to this policy as **Pandora's rule** and the index, z_i , as **Weitzman's index**.

Indexable and decomposable problems

A dynamic problem is:

1. **indexable** if optimal behaviour is described by assigning all potential options an index, and exercising the highest ranked option available at any decision point, and
2. **decomposable** if the index of each option depends on characteristics of that option alone.

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For Pandora, her potential options are:

- *open box i* , for each $i \in \Omega$, and
- *stop and select prize n* , for each $n \in \mathcal{N} \cup \{0\}$.

Assigning opened boxes with an index $z_n = x_n$ for each n , we can see that Pandora's problem is both indexable and decomposable!

A primer on polymatroids

For \mathcal{J} , a finite set, and $f : 2^{\mathcal{J}} \rightarrow \mathbb{R}_+$, a non-decreasing submodular function, a **polymatroid**, \mathcal{P} , is defined as the following polytope:

$$\mathcal{P} = \{x \in \mathbb{R}_+^{\mathcal{J}} \mid \sum_{j \in S} x_j \leq f(S) \forall S \subseteq \mathcal{J}\}$$

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An **extended polymatroid** is a polymatroid with coefficients, $a_{j,S}$, that do not break this greedy characterisation:

$$\mathcal{P}_\varepsilon = \{x \in \mathbb{R}_+^{\mathcal{J}} \mid \sum_{j \in S} a_{j,S} \cdot x_j \leq f(S) \forall S \subseteq \mathcal{J}\}$$

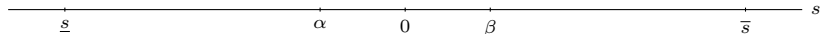
Khalfan (2023)

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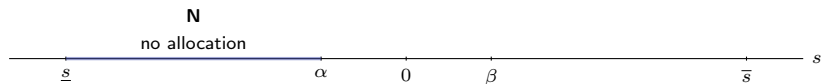
Symmetric information benchmark:



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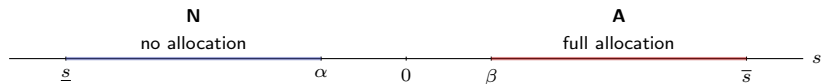
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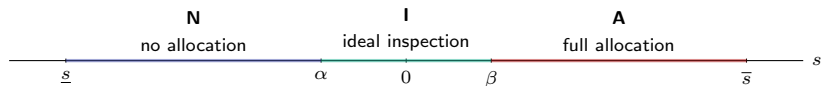
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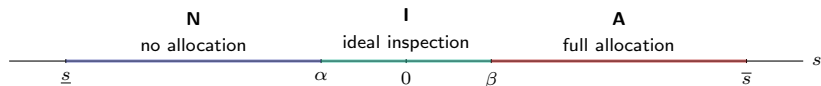
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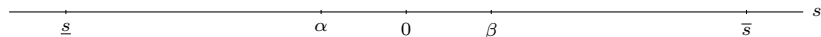
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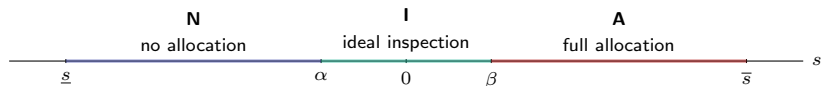
Optimal mechanism:



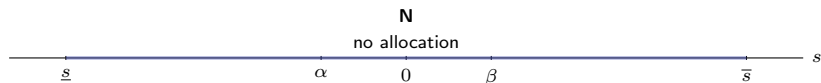
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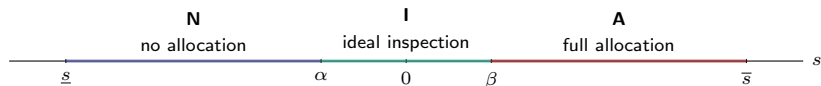
Optimal pooling mechanism:



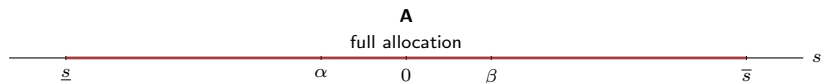
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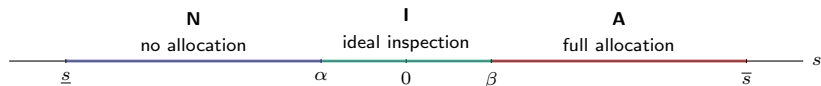
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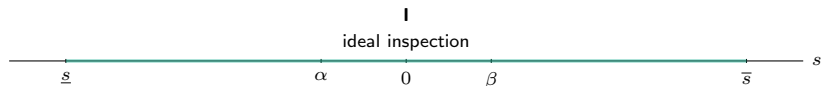
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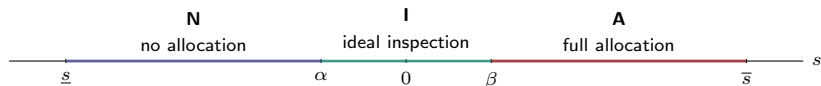
Optimal pooling mechanism:



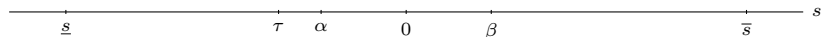
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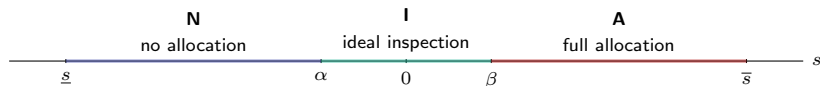
Optimal **separating** mechanism:



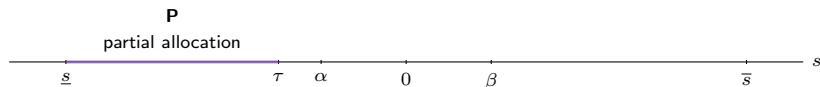
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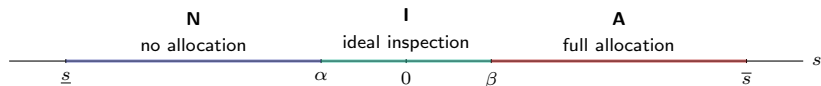
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