# Computing the Shapley value to share ressources in cooperative games

#### François Lamothe and Sandra U. Ngueveu

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#### Focus

• Study a more environmentally/socially friendly online retail





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## Context



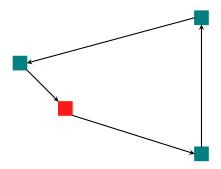
#### Focus

- Study a more environmentally/socially friendly online retail
- Industrial partner : One Stock
- Main participants
  - Sandra U. Ngueveu (Holder)
  - Francois Lamothe (Post-doc)
  - Théo Le Brun (PhD Student)
- Open to new collaborators

## Cost sharing indicator

Package delivery system

- Service to a set of customers  $\rightarrow$  cost
- Economies of scale

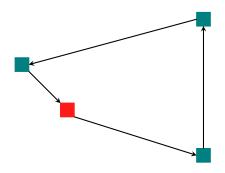


Vehicle routing problem

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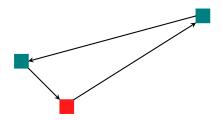


Question : How to divide the total cost amongst the users?

## Cost sharing indicator

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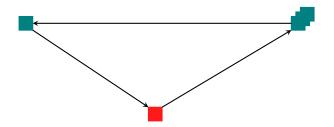
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Dividing equally among the customers?

Package delivery system

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Dividing dividing proportionally to the distance to the depot?

Cooperative game

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    - Linearity : works well with sum of games

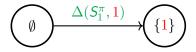
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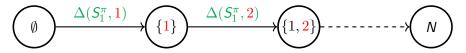
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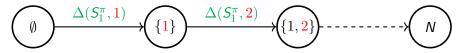
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- Average over all possible orders :
  - $\phi(\mathbf{v}, i) = \frac{1}{n!} \sum_{\pi \in \Pi(\mathbf{N})} \Delta(S_i^{\pi}, i)$
- NP-Hard to compute  $\rightarrow$  approximation

Shapley value :  $\phi(\mathbf{v}, i) = \frac{1}{n!} \sum_{\pi \in \Pi(\mathbf{N})} \Delta(S_i^{\pi}, i)$ 

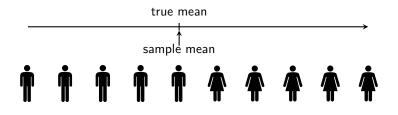
Shapley value as an expectation :  $\phi(\mathbf{v}, i) = \mathbb{E}_{\pi}[\Delta(S_i^{\pi}, i)]$ 

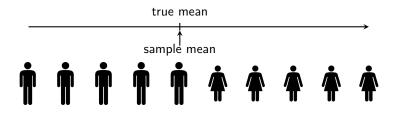
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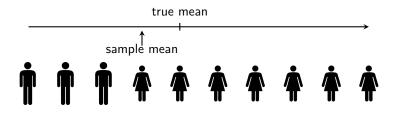
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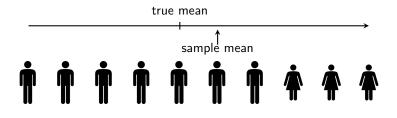
Classical approximation method :

- Expectation  $\rightarrow$  average over samples
- Sampling a set of permutations  $\Pi$
- $\phi(\mathbf{v}, \mathbf{i}) \approx \frac{1}{|\Pi|} \sum_{\pi \in \Pi} \Delta(\mathbf{S}_{\mathbf{i}}^{\pi}, \mathbf{i})$

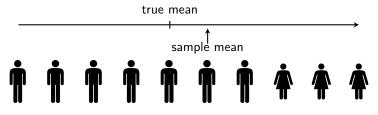




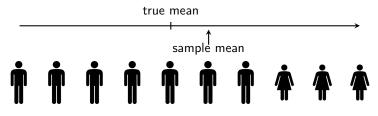




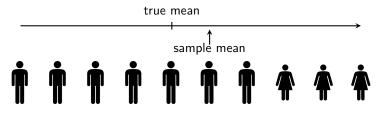
#### Example : estimating mean human size



• Stratified sampling = dividing the samples into groups; averaged separately

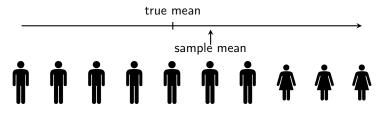


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Law of total expectations :  $\mathbb{E}[\hat{\theta}] = P(A) \mathbb{E}[\hat{\theta}|A] + P(\bar{A}) \mathbb{E}[\hat{\theta}|\bar{A}]$ Stratified estimator :  $\frac{P(A)}{|\Theta_A|} \sum_{\theta \in \Theta_A} \theta + \frac{P(\bar{A})}{|\Theta_{\bar{A}}|} \sum_{\theta \in \Theta_{\bar{A}}} \theta$  Shapley value :  $\phi(\mathbf{v}, i) = \frac{1}{n!} \sum_{\pi \in \Pi(\mathbf{N})} \Delta(S_i^{\pi}, i)$ 

Groups :

- What is the position of player *i* in permutation  $\pi$ ?  $\rightarrow$  |N| groups
- Is player j before or after player  $i ? \rightarrow 2$  groups

How to use and combine all this groups/stratifications?

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• Estimate  $\mathbb{E}[\theta|A \cap B]$  and  $\mathbb{E}[\theta|A \cap \overline{B}]$  and  $\mathbb{E}[\theta|\overline{A} \cap B]$  and  $\mathbb{E}[\theta|\overline{A} \cap \overline{B}]$  $\rightarrow 2^n$  estimates Problem : we can't stratify according to 2 events independently.

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- Estimate  $\mathbb{E}[\theta|A]$  and  $\mathbb{E}[\theta|\bar{A}]$  and  $\mathbb{E}[\theta|B]$  and  $\mathbb{E}[\theta|\bar{B}]$  $\rightarrow$  How to combine them ?

## Flexible stratification with optimization

New paradigm :

- We are estimating the expectation  $\mathbb{E}[\theta]$  with a weighted average of sample
- Each sample  $\sigma$  has a weight  $w_{\sigma}$
- If we know the proba P(A) of event A : we want  $\sum_{\sigma \in \Sigma_A} w_{\sigma} = P(A)$

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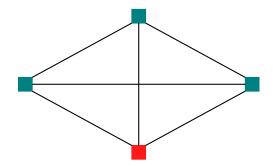
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Modeling with a QP :

$$\begin{split} \min_{w_{\sigma}} \sum_{A} (W(A) - P(A))^2 + \epsilon \sum_{\sigma} (w_{\sigma})^2 \\ s.t. \ \sum_{\sigma} w_{\sigma} = 1 \end{split}$$

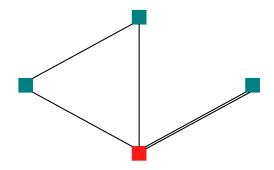
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Example : all length = 1; vehicule capacity = 2



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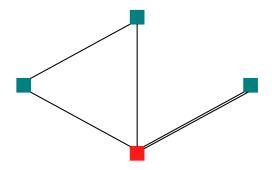
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• Best value = 5; Shapley value = 5/3

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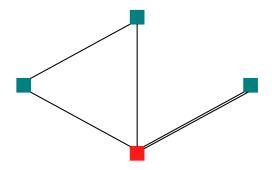
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- Best value = 5; Shapley value = 5/3
- Best 2 size coalition : 3; Shapley value = 3/2
- Core can be non-empty but not contain the Shapley value

# Thank you for your attention

Package https://github.com/TwistedNerves/shapley\_approximation

Paper :

Approximating the Shapley value with sampling : survey and new stratification techniques, Francois Lamothe, Sandra U. Ngueveu