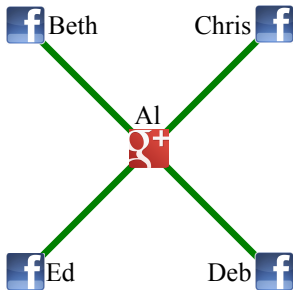


# Computing Shapley Value in Supermodular Coalitional Games

David Liben-Nowell (CS, Carleton College),  
Alexa Sharp (CS, Oberlin College),  
Tom Wexler (CS, Oberlin College),  
**Kevin Woods** (Math, Oberlin College).



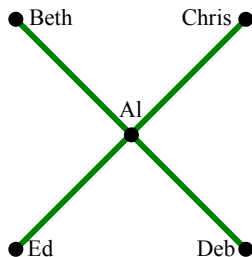
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Players are in a **social network**  
(edges = friends).

Deciding whether to **adopt** a social  
technology (cell phone plan, Google+).

Each player has a cost,  $c$ , to adopt.

Each player gets benefit,  $b$ , for each friend who has also adopted.



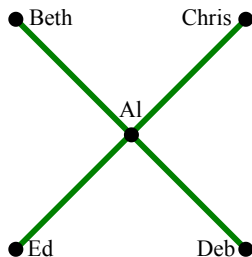
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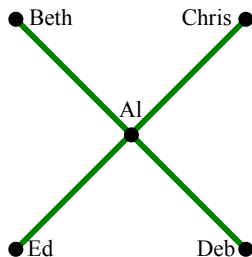
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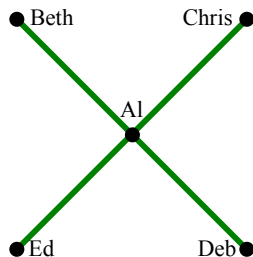
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All players **want** to adopt.

Leaf players have utility  $b - c = 2$ .

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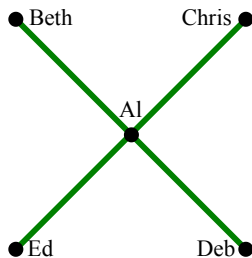
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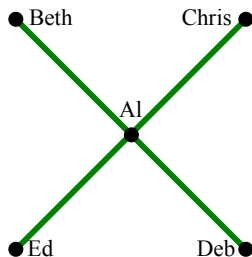
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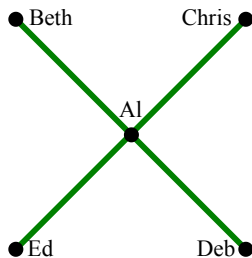
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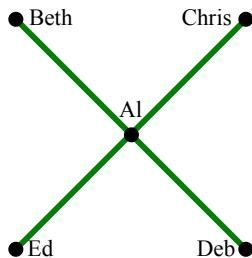
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But total surplus is:  $8b - 5c = 22$ .

AI should pay the other players to entice them.



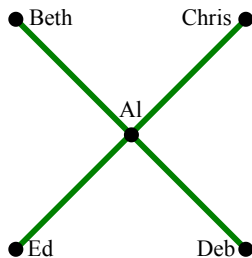
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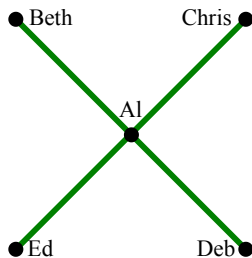
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How much?

How should the total surplus be divided?



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**Definition:** For **any subset**,  $S$ , of players, associate a **value**,  $v(S)$ .

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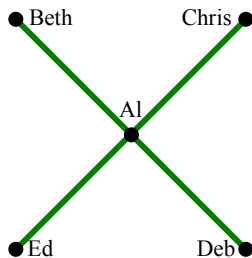
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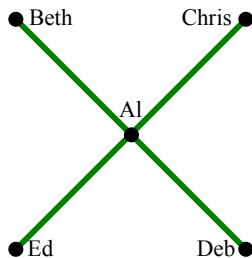
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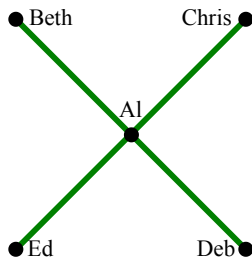
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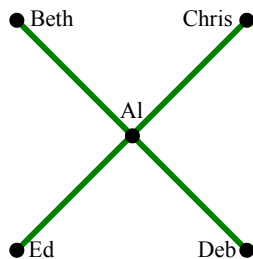
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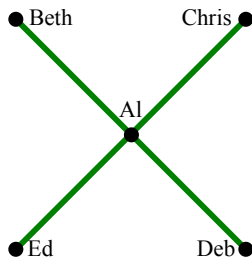
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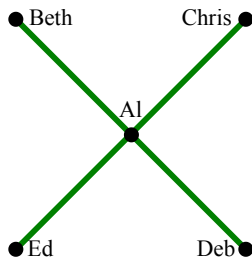
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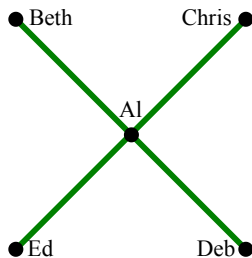
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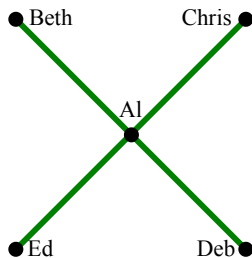
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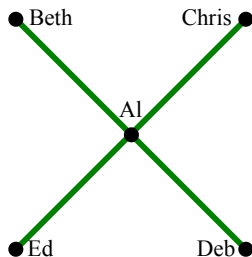


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Imagine players arrive in some **order**,  $\sigma$ .

Player receives **marginal contribution**:  
what he adds to players already present.



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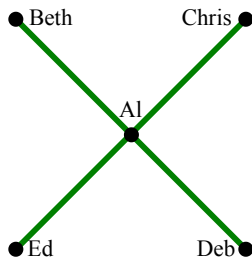
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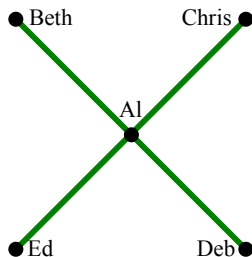
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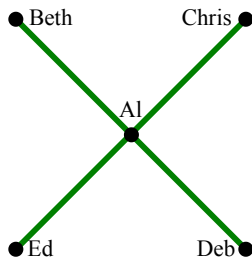
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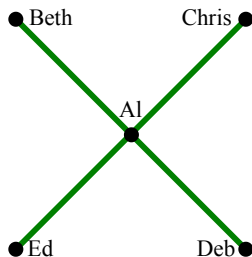
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**Definition:** For all  $S, T$ ,  $v(S \cup T) + v(S \cap T) \geq v(S) + v(T)$ .

or: For all  $S \subseteq T$ , for all  $i \notin T$ ,

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Increasing marginal contributions.

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**Bad Example:** Let  $\mathcal{C}$  be a collection of subsets of  $\{1, \dots, n\}$ , each of cardinality  $n/2$ .

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**Probabilistic Algorithm:** For some  $m$ , choose  $m$  permutations, uniformly at random, and average the marginal contributions of a player.

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**Probabilistic Algorithm:** For some  $m$ , choose  $m$  permutations, uniformly at random, and average the marginal contributions of a player.

**Theorem:** For supermodular games, oracle access, this gives a fully polynomial-time randomized approximation scheme (FPRAS).

For  $n$  players, given  $\epsilon > 0$ , let  $m = 4n(n - 1)/\epsilon^2 \in \text{poly}(n, 1/\epsilon)$ .

With probability  $3/4$ , the computed values of all players will be within a  $1 \pm \epsilon$  multiplicative factor of the correct values.

To replace  $3/4$  with  $1 - \delta$ , need  $m \in \text{poly}(n, 1/\epsilon, \log(1/\delta))$ .

# Shapley Value for Supermodular Games

**Key:** Supermodularity implies that can't get huge values with tiny probability.

Indeed, largest marginal contribution is when player appears last, which happens with probability  $1/n$ .

**Assumption:**  $v(\{i\}) \geq 0$ , for all  $i$ .

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# Shapley Value for Supermodular Games

## Theorem:

- ▶ No deterministic algorithm can do **as well** as  $\text{poly}(n, 1/\epsilon)$ .
- ▶ No other probabilistic algorithm can do **better** than  $\text{poly}(n, 1/\epsilon)$ .
- ▶ Doesn't depend on  $P \neq NP$ .

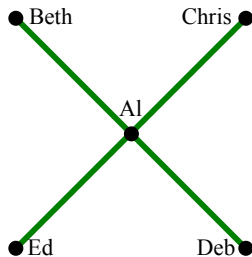
Similar bad example as before shows these facts.

## The Kernel

In example, suppose have decided to allocate 6 to AI and 4 to each leaf player.

Beth can threaten AI that she will “go alone”,

Cost of threat to Beth:  $4 - 0 = 4$ .

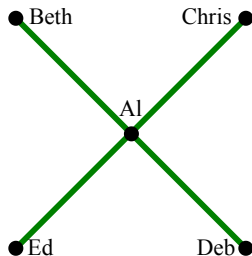


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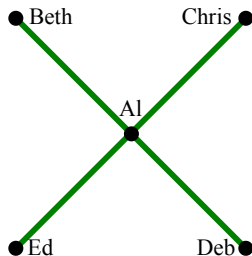


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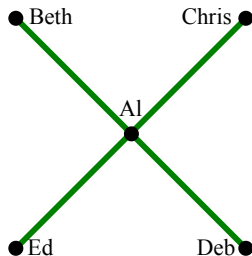
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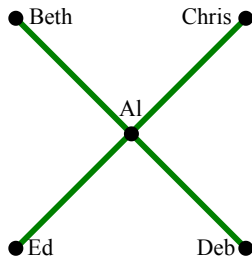
In example, suppose have decided to allocate 6 to Al and 4 to each leaf player.

Beth can threaten Al that she will “go alone”,

Cost of threat to Beth:  $4 - 0 = 4$ .

Or Al can threaten that he will only cooperate with C, D, and E. Then  $v(ACDE) = 14$ , but Al must continue paying C, D, and E each 4, leaving 2 for himself.

Cost of threat to Al:  $6 - 2 = 4$ .



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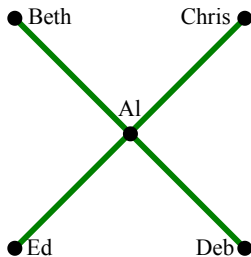
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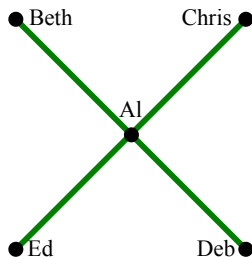
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Best threats are in **equilibrium**. Called the **kernel**.



# The Kernel

Kernel **exists** and **is unique** for supermodular games [Shapley].

Kernel = Stable Outcome,  
Shapley = Fair Outcome.

Unlike Shapley value, kernel of supermodular games can be exactly computed, in polynomial time [Kuipers].

## Key Difference:

- ▶ Shapley value depends on the values of all  $2^n$  subsets.
- ▶ Kernel only depends on the values of the  $n(n - 1)$  best threats of player  $i$  to player  $j$ .

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# Open Questions

- ▶ For **specific** supermodular games, like our example, can the Shapley value be **computed efficiently**?
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# Thank You!

