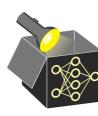
Interpretable Machine Learning

Shapley Values



Learning goals

- Learn cooperative games and value functions
- Define the marginal contribution of a player
- Study Shapley value as a fair payout solution
- Compare order and set definitions



Interpretable Machine Learning

Shapley Shapley Values



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- Learn cooperative games and value functions
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COOPERATIVE GAMES IN GAME THEORY • Shapley (1951)

- **Game theory:** Studies strategic interactions among "players" (who act to maximize their utility), where outcomes depend on collective behavior
- Cooperative games: Any subset $S \subseteq P = \{1, ..., p\}$ can form a coalition to cooperate in a game, each achieving a payout v(S)



COOPERATIVE GAMES IN GAME THEORY

► SHAPLEY_195

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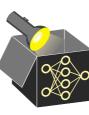
Interpretable Machine Learning - 1 / 11

Interpretable Machine Learning - 1 / 11

COOPERATIVE GAMES IN GAME THEORY Shapley (1951)

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- Cooperative games: Any subset $S \subseteq P = \{1, \dots, p\}$ can form a coalition to cooperate in a game, each achieving a payout v(S)
- Value function: $v: 2^P \to \mathbb{R}$ assigns each coalition S a payout v(S)
 - Convention: $v(\emptyset) = 0 \Leftrightarrow$ Empty coalitions generate no gain
 - v(P): Total achievable payout when all players cooperate → Forms the game's budget to be fairly distributed
- Marginal contribution: Measure how much value player j adds to coalition S by

$$\Delta(j,S) := v(S \cup \{j\}) - v(S) \quad \text{(for all } j \in P \ S \subseteq P \setminus \{j\})$$



COOPERATIVE GAMES IN GAME THEORY

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Interpretable Machine Learning - 1 / 11 Interpretable Machine Learning - 1 / 11

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- Challenge: Players vary in their contributions & how they influence each other
- **Goal:** Fairly distribute v(P) among players by accounting for player interactions \rightsquigarrow Assign each player $j \in P$ a fair share ϕ_i (**Shapley value**)



COOPERATIVE GAMES IN GAME THEORY

► SHAPLEY_1951

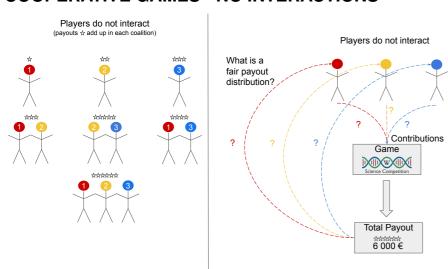
- Game theory: Studies strategic interactions among "players" (who act to maximize their utility), where outcomes depend on collective behavior
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- Challenge: Players vary in their contrib. & how they influence each other
- **Goal:** Distribute v(P) among players by considering player interactions \rightsquigarrow Assign each player $i \in P$ a fair share ϕ_i (Shapley value)



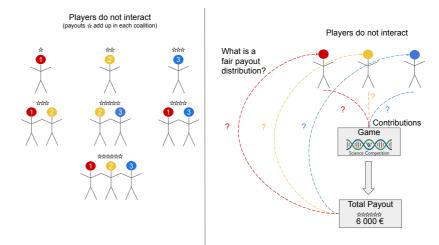
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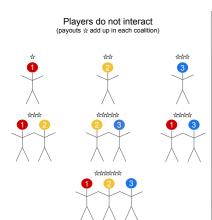


COOPERATIVE GAMES - NO INTERACTIONS

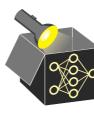


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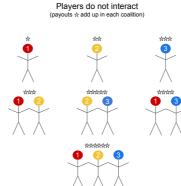
Question: What are individual marginal contributions and what's a fair payout?



Player	Coalition S	$v(S \cup \{j\})$	v(S)	$\Delta(j,S)$
0	Ø	1000	0	1000
0	{② }	3000	2000	1000
0	(3)	4000	3000	1000
1	$\{ 2, 3 \}$	6000	5000	1000
2	Ø	2000	0	2000
2	(1) }	3000	1000	2000
2	(3)	5000	3000	2000
2	$\{ m{0}, m{6} \}$	6000	4000	2000
8	Ø	3000	0	3000
3	(1) }	4000	1000	3000
3	{❷ }	5000	2000	3000
3	$\{ m{0}, m{2} \}$	6000	3000	3000



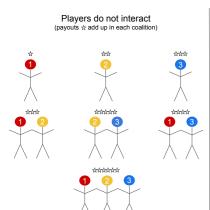
COOPERATIVE GAMES - NO INTERACTIONS



Player	Coalition S	$v(S \cup \{j\})$	v(S)	$\Delta(j,S)$
1	Ø	1000	0	1000
0	{② }	3000	2000	1000
0	(8)	4000	3000	1000
0	$\{ {f Q}, {f G} \}$	6000	5000	1000
2	Ø	2000	0	2000
2	{● }	3000	1000	2000
2	(6) }	5000	3000	2000
2	$\{ oldsymbol{0}, oldsymbol{6} \}$	6000	4000	2000
3	Ø	3000	0	3000
3	{① }	4000	1000	3000
3	{ <mark>②</mark> }	5000	2000	3000
3	$\{0, 2\}$	6000	3000	3000



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Player	Coalition S	$v(S \cup \{j\})$	v(S)	$\Delta(j,S)$
0	Ø	1000	0	1000
0	{② }	3000	2000	1000
0	(3)	4000	3000	1000
0	$\{ 2, 6 \}$	6000	5000	1000
2	Ø	2000	0	2000
2	{● }	3000	1000	2000
2	(3)	5000	3000	2000
2	$\{oldsymbol{0}, oldsymbol{3}\}$	6000	4000	2000
6	Ø	3000	0	3000
(3)	{● }	4000	1000	3000
(3)	{② }	5000	2000	3000
(3)	{♠ , ❷ }	6000	3000	3000



- No interactions: Each player contributes the same fixed value to each coalition

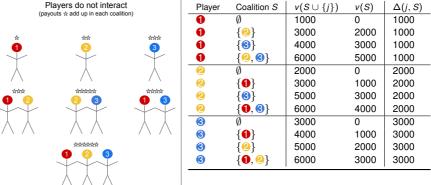
 → Player ① always adds 1000, ② adds 2000, and ③ adds 3000
 - \sim Marginal contributions are constant across all coalitions S
- **Conclusion:** Fair payout = average marginal contribution across all *S*
 - \sim Total value v(P) = 6000 splits proportionally by individual contributions:

$$0 = \frac{1}{6}, \quad 2 = \frac{1}{3}, \quad 3 = \frac{1}{2}$$





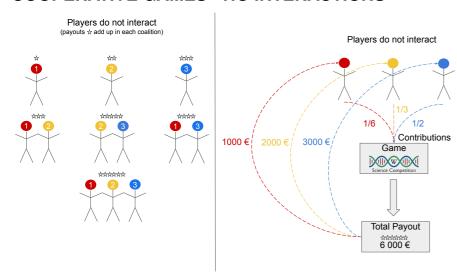






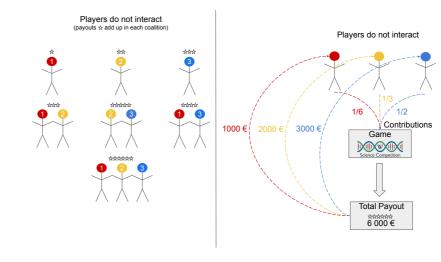
- No interactions: Each player contrib.s same fixed value to each coalition
- → Player **1** always adds 1000, **2** adds 2000, and **3** adds 3000
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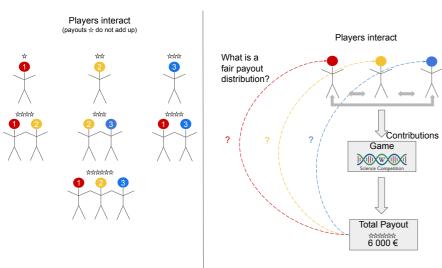
⇒ Fair payouts are trivial without interactions

COOPERATIVE GAMES - NO INTERACTIONS



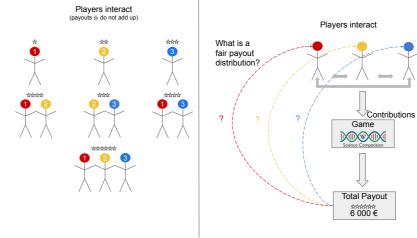


⇒ Fair payouts are trivial without interactions



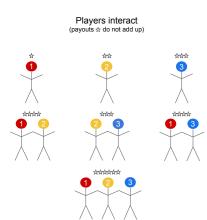
⇒ Unclear how to fairly distribute payouts when players interact

COOPERATIVE GAMES - INTERACTIONS

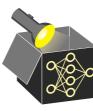




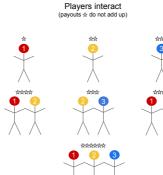




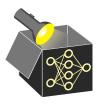
Player	Coalition S	$v(S \cup \{j\})$	v(S)	$\Delta(j,S)$
0	Ø	1000	0	1000
0	{② }	4000	2000	2000
0	(3)	4000	3000	1000
0	$\{ 2, 6 \}$	6000	3000	3000
2	Ø	2000	0	2000
2	{● }	4000	1000	3000
2	(3)	3000	3000	0
2	$\{ oldsymbol{0}, oldsymbol{6} \}$	6000	4000	2000
(3)	Ø	3000	0	3000
3	{● }	4000	1000	3000
3	{② }	3000	2000	1000
3	$\{ oldsymbol{0}, oldsymbol{arrho} \}$	6000	4000	2000

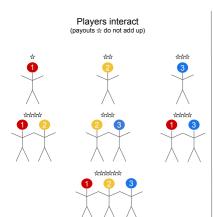


COOPERATIVE GAMES - INTERACTIONS



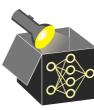
Player	Coalition S	$v(S \cup \{j\})$	v(S)	$\Delta(j,S)$
0	Ø	1000	0	1000
0	{② }	4000	2000	2000
0	(3)	4000	3000	1000
0	$\{2, 3\}$	6000	3000	3000
2	Ø	2000	0	2000
2	{① }	4000	1000	3000
2	(3)	3000	3000	0
2	$\{ oldsymbol{0}, oldsymbol{6} \}$	6000	4000	2000
3	Ø	3000	0	3000
3	{① }	4000	1000	3000
3	{ <mark>②</mark> }	3000	2000	1000
3	(1) , (2) }	6000	4000	2000
	0 0 0 0 2 2 2 2 2 6 6	(a) {(a) {(b) {(a) {(b) {(b) {(b) {(b) {(b) {(b) {(b) {(b	 ∅ 1000 (2) 4000 (3) 4000 (4) (2) (6) (7) (8) (8) (9) (1) (1) (2) (3) (4) (5) (6) (7) (8) (9) (10) 	 ∅ 1000 0 4000 2000 4000 3000 4000 3000 6000 4000 <l< th=""></l<>



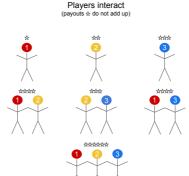


Player	Coalition S	$v(S \cup \{j\})$	v(S)	$\Delta(j,S)$
1	Ø	1000	0	1000
1	{② }	4000	2000	2000
0	(3)	4000	3000	1000
0	$\{ 2, 6 \}$	6000	3000	3000
2	Ø	2000	0	2000
2	{● }	4000	1000	3000
2	(3)	3000	3000	0
2	$\{ oldsymbol{0}, oldsymbol{6} \}$	6000	4000	2000
3	Ø	3000	0	3000
3	{● }	4000	1000	3000
3	{② }	3000	2000	1000
@	JA 🙉l	6000	4000	2000

- With interactions: Players contribute different amounts depending on coalition
 → Marginal contributions vary across coalitions S (e.g., due to overlap, synergy)
- Averaging over subsets does not recover total payout v(P) → unfair payout distr.
 → average contrib. (1) = 1750, (2) = 1750, (3) = 2250 do not sum to v(P) = 6000
- Value a player adds depends on joining order, not just who else is in the coalition
 Shapley values fairly average over all possible joining orders



COOPERATIVE GAMES - INTERACTIONS



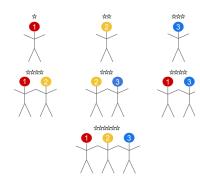
Player	Coalition S	$v(S \cup \{j\})$	v(S)	$\Delta(j, S)$
0	Ø	1000	0	1000
0	{② }	4000	2000	2000
0	(8)	4000	3000	1000
0	{② , ❸ }	6000	3000	3000
2	Ø	2000	0	2000
2	{① }	4000	1000	3000
2	(3)	3000	3000	0
2	$\{ oldsymbol{0}, oldsymbol{6} \}$	6000	4000	2000
8	Ø	3000	0	3000
3	{① }	4000	1000	3000
3	{ <mark>②</mark> }	3000	2000	1000
8	{1 , ⊘ }	6000	4000	2000



- With interactions: Players contribute differently depending on coalition
- \rightsquigarrow Marginal contribs vary across coalitions S (e.g. overlap, synergy)
- Averaging ever subsets does not recover total payout $\nu(D)$
- Averaging over subsets does not recover total payout v(P)
- → unfair payout distribution
- \rightarrow avg. contrib. \bigcirc = 1750 \bigcirc = 1750 \bigcirc = 2250 don't sum to $\nu(P)$ = 6000
- Value a player adds depends on joining order, not just who's in coalition

Shapley values fairly average over all possible joining orders

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Ordering 1: $\textcircled{3} \rightarrow \textcircled{2} \rightarrow \textcircled{1}$

joins alone: 3 ☆

 \bigcirc joins: total = 3 $\stackrel{\triangle}{\Rightarrow}$, marginal = 0

• joins: total = 6 $\stackrel{\triangle}{\Rightarrow}$, marginal = +3

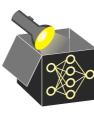
But what if 1 joins before 2?

Ordering 2: $\textcircled{3} \rightarrow \textcircled{1} \rightarrow \textcircled{2}$

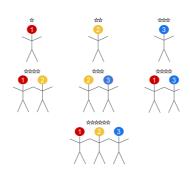
ioins alone: 3 ☆

1 joins: total = 4 ☆, marginal = +1

② joins: total = 6 %, marginal = +2



COOPERATIVE GAMES - INTERACTIONS



Ordering 1: $3 \rightarrow 2 \rightarrow 1$

③ joins alone: 3 ☆

joins: total = 3 ☆, marginal = 0

1 joins: total = 6 $\stackrel{\triangle}{\Rightarrow}$, marginal = +3

But what if 1 joins before 2?

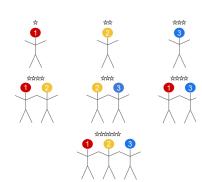
Ordering 2: $\textcircled{3} \rightarrow \textcircled{1} \rightarrow \textcircled{2}$

3 joins alone: 3 ☆

• joins: total = 4 %, marginal = +1

 \bigcirc joins: total = 6 $\stackrel{\triangle}{\Rightarrow}$, marginal = +2





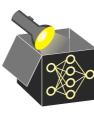
Ordering 1: $\bigcirc \rightarrow \bigcirc \rightarrow \bigcirc$

- 6 joins alone: 3 ☆
- \bigcirc joins: total = 3 \rightleftharpoons , marginal = 0
- 1 joins: total = 6 \Leftrightarrow , marginal = +3

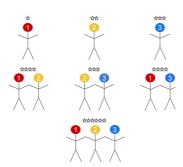
But what if 1 joins before 2?

- joins alone: 3 ☆
- joins: total = 4 %, marginal = +1
- 2 joins: total = 6 %, marginal = +2
- Order sensitivity: A player's marginal contribution depends on when they join S
- Shapley value: Averages each player's contribution over all possible join orders
 - Resolves redundancy (e.g., 6)'s contribution/skill overlaps with 2's)

 - Ensures fairness (no player is advantaged or penalized by order of joining)



COOPERATIVE GAMES - INTERACTIONS



- ③ joins alone: 3 ☆
- joins: total = 3 ☆, marginal = 0
- joins: total = 6 $\stackrel{\triangle}{\Rightarrow}$, marginal = +3

But what if 1 joins before 2?

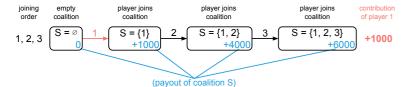
Ordering 2: (3) \rightarrow (1) \rightarrow (2)

- joins alone: 3 ☆
- joins: total = $4 \stackrel{\triangle}{\Rightarrow}$, marginal = +1
- 2 joins: total = 6 %, marginal = +2
- Order sensitivity: A player's marginal contribution depends on when they join S
- Shapley value: Averages each player's contribution over all possible
- join orders

 → Resolves redundancy (e.g., ③'s contribution/skill overlaps with ⊘'s)
- → Accounts for order sensitivity (e.g., obrings more value if added last)
- → Ensures fairness (order of joining gives no advantage/disadvantage)



- Generate all possible joining orders of players (all permutations of full set *P*)
- For each order: track player *j*-th marginal contribution when *j* joins a coalition

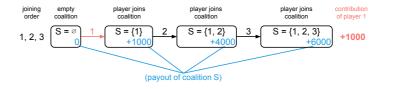




SHAPLEY VALUES - ILLUSTRATION

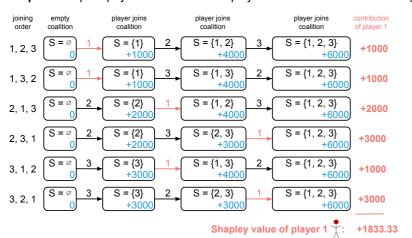
- Generate all possible joining orders (all permutations of full set P)
- For each order: track player *j*-th marginal contrib when *j* joins a coalition





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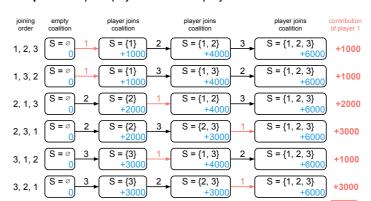
- Generate all possible joining orders of players (all permutations of full set *P*)
- For each order: track player *j*-th marginal contribution when *j* joins a coalition
- Shapley value of *j*: Average this marginal contribution over all joining orders
- Example: Compute payout difference after player 1 enters coalition → average



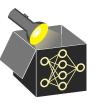


SHAPLEY VALUES - ILLUSTRATION

- Generate all possible joining orders (all permutations of full set *P*)
- For each order: track player *j*-th marginal contrib when *j* joins a coalition
- Shapley value of *j*: Average this marginal contrib over all joining orders
- **Example:** Compute payout diff. after player 1 enters coalition → average

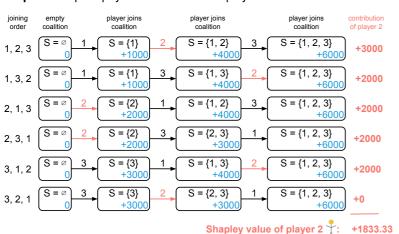


Shapley value of player 1 +1833.33



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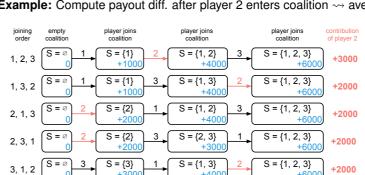
- Generate all possible joining orders of players (all permutations of full set *P*)
- For each order: track player j-th marginal contribution when j joins a coalition
- Shapley value of *j*: Average this marginal contribution over all joining orders
- Example: Compute payout difference after player 2 enters coalition → average





SHAPLEY VALUES - ILLUSTRATION

- Generate all possible joining orders (all permutations of full set *P*)
- For each order: track player *j*-th marginal contrib when *j* joins a coalition
- Shapley value of *j*: Average this marginal contrib over all joining orders
- **Example:** Compute payout diff. after player 2 enters coalition → average



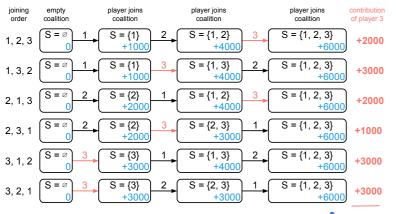
 $S = \{2, 3\}$

S = {1, 2, 3}

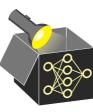
Shapley value of player 2 ★: +1833.33



- Generate all possible joining orders of players (all permutations of full set *P*)
- For each order: track player *j*-th marginal contribution when *j* joins a coalition
- Shapley value of *j*: Average this marginal contribution over all joining orders
- Example: Compute payout difference after player 3 enters coalition → average

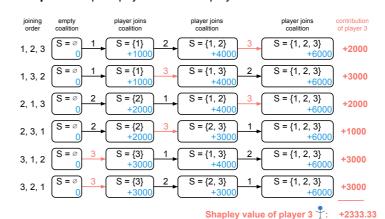


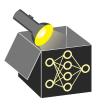




SHAPLEY VALUES - ILLUSTRATION

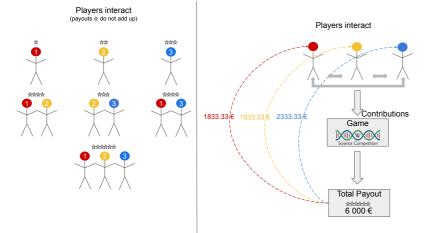
- Generate all possible joining orders (all permutations of full set P)
- For each order: track player *j*-th marginal contrib when *j* joins a coalition
- Shapley value of *j*: Average this marginal contrib over all joining orders
- **Example:** Compute payout diff. after player 3 enters coalition → average

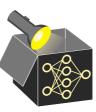




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- Generate all possible joining orders of players (all permutations of full set *P*)
- For each order: track player *j*-th marginal contribution when *j* joins a coalition
- Shapley value of *j*: Average this marginal contribution over all joining orders

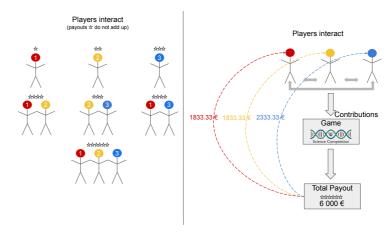




SHAPLEY VALUES - ILLUSTRATION

- Generate all possible joining orders (all permutations of full set P)
- For each order: track player *j*-th marginal contrib when *j* joins a coalition
- Shapley value of *j*: Average this marginal contrib over all joining orders



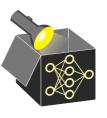


SHAPLEY VALUE - ORDER DEFINITION

The Shapley value order definition averages the marginal contribution of a player across all possible player orderings:

$$\phi_j = \frac{1}{|P|!} \sum_{\tau \in \Pi} (v(S_j^\tau \cup \{j\}) - v(S_j^\tau))$$

• Π : Set of all permutations (joining orders) of the players – there are |P|! in total



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•
$$S_j^{\tau}$$
: Set of players before j joins, for each ordering $\tau = (\tau^{(1)}, \dots, \tau^{(p)})$
E.g.: $\Pi = \{(\mathbf{0}, \mathbf{2}, \mathbf{3}), (\mathbf{0}, \mathbf{3}, \mathbf{2}), (\mathbf{2}, \mathbf{0}, \mathbf{3}), (\mathbf{2}, \mathbf{3}, \mathbf{0}), (\mathbf{3}, \mathbf{0}, \mathbf{2}), (\mathbf{3}, \mathbf{2}, \mathbf{0})\}$

$$\leadsto$$
 For joining order $\tau = (2, \mathbf{0}, \mathbf{0})$ and player $j = \mathbf{0} \Rightarrow S_i^{\tau} = \{2, \mathbf{0}\}$

$$\sim$$
 For joining order $\tau = (\$, 0, 2)$ and player $j = 0 \Rightarrow S_i^{\tau} = \{\$\}$



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 For joining order $\tau = (2, \mathbf{0}, \mathbf{0})$ and player $j = \mathbf{0} \Rightarrow S_i^{\tau} = \{2, \mathbf{0}\}$

$$\rightsquigarrow$$
 For joining order $\tau = (3, 0, 2)$ and player $j = 0 \Rightarrow S_i^{\tau} = \{3\}$

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E.g.: $\Pi = \{(\mathbf{1}, \mathbf{2}, \mathbf{6}), (\mathbf{1}, \mathbf{6}, \mathbf{2}), (\mathbf{2}, \mathbf{1}, \mathbf{6}), (\mathbf{2}, \mathbf{6}, \mathbf{1}), (\mathbf{6}, \mathbf{1}, \mathbf{2}), (\mathbf{6}, \mathbf{2}, \mathbf{1})\}$
 \rightarrow For joining order $\tau = (\mathbf{2}, \mathbf{1}, \mathbf{6})$ and player $j = \mathbf{6} \Rightarrow S_j^{\tau} = \{\mathbf{2}, \mathbf{1}\}$
 \rightarrow For joining order $\tau = (\mathbf{6}, \mathbf{1}, \mathbf{2})$ and player $j = \mathbf{1} \Rightarrow S_i^{\tau} = \{\mathbf{6}\}$

• Order definition allows to approximate Shapley values by sampling permutations \rightsquigarrow Sample a fixed number $M \ll |P|!$ of random permutations and average:

$$\phi_j pprox rac{1}{M} \sum_{ au \in \Pi_{II}} ig(v(S_j^ au \cup \{j\}) - v(S_j^ au) ig)$$

where $\Pi_M \subset \Pi$ is the random sample of M player orderings



SHAPLEY VALUE - ORDER DEFINITION

The Shapley value order definition averages the marginal contribution of a player across all possible player orderings:

$$\phi_j = \frac{1}{|P|!} \sum_{\sigma \in P} (v(S_j^{\tau} \cup \{j\}) - v(S_j^{\tau}))$$



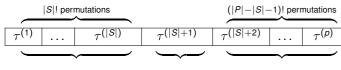
- Π : Set of all permutations (joining orders) of the players -|P|! in total
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 - **E.g.:** $\Pi = \{(\mathbf{0}, \mathbf{2}, \mathbf{8}), (\mathbf{0}, \mathbf{8}, \mathbf{2}), (\mathbf{2}, \mathbf{0}, \mathbf{8}), (\mathbf{2}, \mathbf{8}, \mathbf{0}), (\mathbf{8}, \mathbf{0}, \mathbf{2}), (\mathbf{8}, \mathbf{2}, \mathbf{0})\}$ \rightsquigarrow For joining order $\tau = (\mathbf{2}, \mathbf{0}, \mathbf{8})$ and player $j = \mathbf{8} \Rightarrow S_i^{\tau} = \{\mathbf{2}, \mathbf{0}\}$
 - \sim For joining order $\tau = (0, 0, 0)$ and player $j = 0 \Rightarrow S_j = \{0, 0, 0\}$ and player $j = 0 \Rightarrow S_i^{\tau} = \{0\}$
- Order definition allows to approximate Shapley values by sampling permutations
 - \sim Sample a fixed *M* ≪ |*P*|! random permutations and average:

$$\phi_j pprox rac{1}{M} \sum_{ au \in \Pi_{t+1}} ig(v(S_j^ au \cup \{j\}) - v(S_j^ au) ig)$$

where $\Pi_M \subset \Pi$ is the random sample of M player orderings

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- **Note:** The same subset S_j^{τ} can occur in multiple permutations (joining orders) \rightsquigarrow Its marginal contribution is included multiple times in the sum in ϕ_i
- Example (for set of players $P = \{ \mathbf{0}, \mathbf{0}, \mathbf{0} \}$, player of interest $j = \mathbf{0}$):
 - $\Pi = \{ (\mathbf{0}, \mathbf{2}, \mathbf{3}), \ (\mathbf{0}, \mathbf{3}, \mathbf{2}), \ (\mathbf{2}, \mathbf{0}, \mathbf{3}), \ (\mathbf{2}, \mathbf{3}, \mathbf{0}), \ (\mathbf{3}, \mathbf{0}, \mathbf{2}), \ (\mathbf{3}, \mathbf{2}, \mathbf{0}) \}$
 - \rightsquigarrow In both $(\mathbf{0}, \mathbf{2}, \mathbf{3})$ and $(\mathbf{2}, \mathbf{0}, \mathbf{3})$, player **3** joins after coalition $S_i^T = \{\mathbf{0}, \mathbf{2}\}$
 - \Rightarrow Marginal contribution $v(\{\{0, 2, 3\}\}) v(\{\{0, 2\}\})$ occurs twice in ϕ_i
- **Reason:** Each subset S appears in |S|!(|P|-|S|-1)! orderings before j joins
 - \Rightarrow There are |S|! possible orders of players within coalition S
 - \Rightarrow There are (|P| |S| 1)! possible orders of players without S and j



player *j*

Players before player j

Players after player *j*

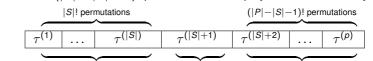


FROM ORDER DEFINITION TO SET DEFINITION

- **Note:** The same subset S_j^{τ} can occur in multiple permutations \rightsquigarrow Its marginal contribution is included multiple times in the sum in ϕ_i
- Example Π (for players $P = \{ \mathbf{0}, \mathbf{0}, \mathbf{0} \}$, player of interest $j = \mathbf{0}$):

$$\{(\textcolor{red}{\textbf{0}},\textcolor{red}{\textbf{2}},\textcolor{red}{\textbf{3}}),\,(\textcolor{red}{\textbf{0}},\textcolor{red}{\textbf{3}},\textcolor{red}{\textbf{2}}),\,(\textcolor{red}{\textbf{2}},\textcolor{red}{\textbf{0}},\textcolor{red}{\textbf{3}}),\,(\textcolor{red}{\textbf{2}},\textcolor{red}{\textbf{3}},\textcolor{red}{\textbf{0}}),\,(\textcolor{red}{\textbf{3}},\textcolor{red}{\textbf{2}},\textcolor{red}{\textbf{0}}),\,(\textcolor{red}{\textbf{3}},\textcolor{red}{\textbf{2}},\textcolor{red}{\textbf{3}})\}$$

- \rightsquigarrow In $(\mathbf{0}, \mathbf{0}, \mathbf{3})$ and $(\mathbf{0}, \mathbf{0}, \mathbf{3})$, player $\mathbf{0}$ joins after coal. $S_i^{\tau} = \{\mathbf{0}, \mathbf{0}\}$
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Players before player i

player *i*

Players after player *i*



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- Order view: Each of the |P|! permutations contributes one term with weight $\frac{1}{|P|!}$ • Same subset $S \subseteq P \setminus \{j\}$ can appear before j in multiple orders
- \rightsquigarrow e.g., $S = \{ \bullet, \bullet \} = \{ \bullet, \bullet \}$
- **Set view:** Group by unique subsets *S*, not permutations
- Each S occurs in |S|!(|P|-|S|-1)! orderings \rightsquigarrow Weight: $\frac{|S|!(|P|-|S|-1)!}{|D|!}$

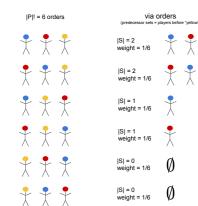


FROM ORDER DEFINITION TO SET DEFINITION





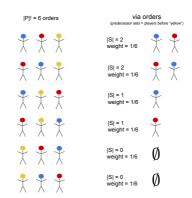
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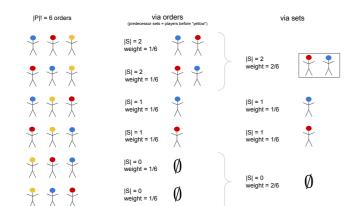


FROM ORDER DEFINITION TO SET DEFINITION

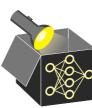




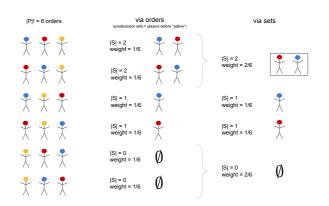
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SHAPLEY VALUE - SET DEFINITION

Shapley value via **set definition** (weighting via multinomial coefficient):

$$\phi_j = \sum_{S \subseteq P \setminus \{j\}} rac{|S|!(|P|-|S|-1)!}{|P|!} (v(S \cup \{j\}) - v(S))$$

The coefficient gives the probability that, when randomly arranging all |P| players, the exact set S appears before player j, and the remaining players appear afterward.

	S ! pern	nutations	player j	(P - S -	-1)! per	mutations
$ au^{(1)}$		$ au^{(S)}$	$ au^{(S +1)}$	$ au^{(S +2)}$		$\tau^{(P)}$



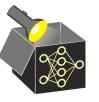
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\$	S ! permutations		player j	j $(P - S -1)!$ permuta		mutations
$\tau^{(1)}$		$ au^{(S)}$	$ au^{(S +1)}$	$ au^{(S +2)}$		$ au^{(P)}$



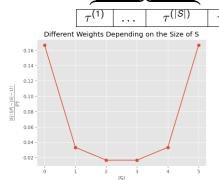
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- player j (|P|-|S|-1)! permutations
- $au^{(|S|+1)} \mid au^{(|S|+2)} \mid \dots \mid au^{(|P|)}$

• |S| = 0: player *j* joins first

- \Rightarrow many permutations \Rightarrow high weight \bullet |S| = |P| 1: player j joins last
- Middle-sized |S|: fewer exact matches
 ⇒ lower weight
- Result: U-shaped weight distribution



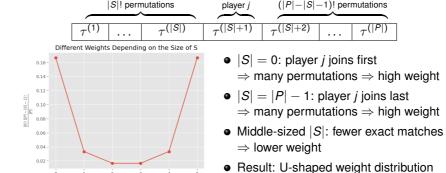
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Interpretable Machine Learning - 10 / 11

Interpretable Machine Learning - 10 / 11

What makes a payout fair? The Shapley value provides a fair payout ϕ_j for each player $j \in P$ and uniquely satisfies the following axioms for any value function v:

• **Efficiency**: Total payout v(P) is fully allocated to players:

$$\sum_{j\in P}\phi_j=v(P)$$



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Interpretable Machine Learning - 11 / 11

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$$v(S \cup \{j\}) = v(S \cup \{k\})$$
 for all $S \subseteq P \setminus \{j, k\}$, then $\phi_i = \phi_k$



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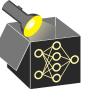
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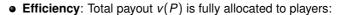
$$\phi_{i,\nu_1+\nu_2} = \phi_{i,\nu_1} + \phi_{i,\nu_2}$$

→ Payout of combined game = payout of the two separate games



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