

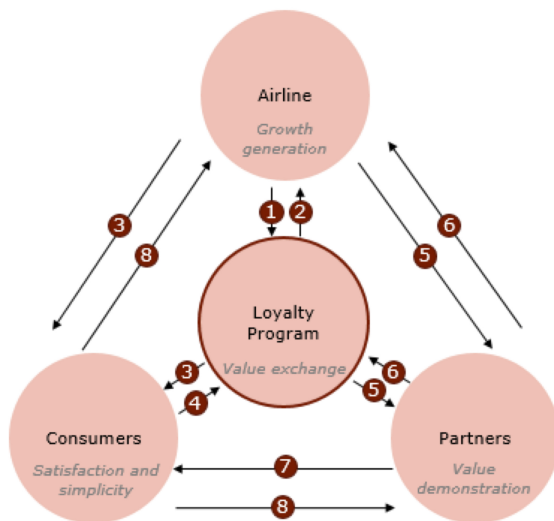
# Optimizing the design of a loyalty program

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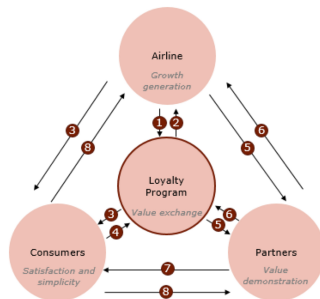
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Centre de recherches mathématiques  
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# Aeroplan Loyalty Program



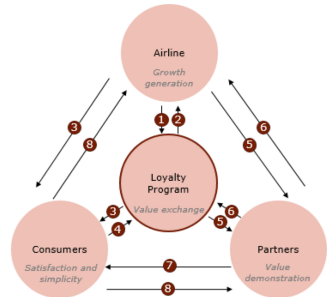
# Aeroplan Loyalty Program



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## Accumulation

- ▶ Use Aeroplan-linked credit cards.
- ▶ Buy Air Canada (and other) flight tickets.



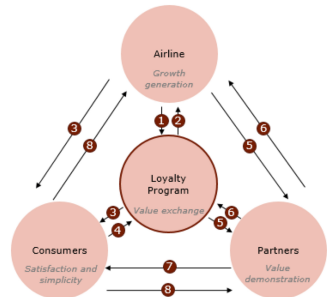
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## Redemption

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- ▶ Buy toasters etc.



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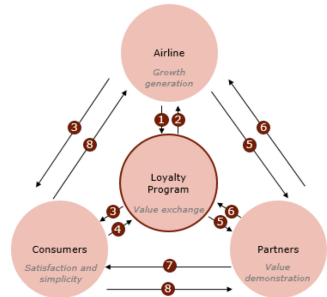
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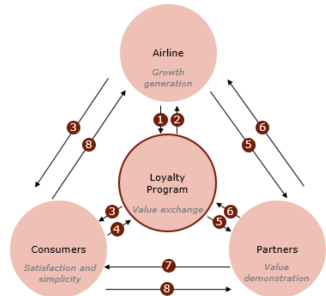
- ▶ Use Aeroplan-linked credit cards.
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- 1 *Members* collect points from *partners*.
- 2 *Partners* buy points from Aeroplan.

## Redemption

- ▶ Buy Air Canada (and other) flight tickets.
- ▶ Buy toasters etc.

- 1 Members use miles to get free tickets or toasters from Aeroplan.
- 2 Aeroplan pays the partner for the tickets and toasters.



# Aeroplan's problem

$$\begin{array}{l} \max \\ \text{Miles per toaster} \\ \text{from member,} \\ \text{Budget, promotion,} \\ \text{etc.} \end{array} : \sum_{p,j} (\text{Revenue} - \text{Costs})$$

Subject to

- ▶ Some meaningful constraints



# Aeroplane's problem

$$\begin{array}{l} \max \\ \text{Miles per toaster} \\ \text{from member,} \\ \text{Budget, promotion,} \\ \text{etc.} \end{array} : \sum_{p,j} (\text{Accumulated miles} \times P \rightarrow \text{AE Price} - \text{Costs})$$

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# Aeroplan's problem

$$\begin{array}{l} \max \\ \text{Miles per toaster} \\ \text{from member,} \\ \text{Budget, promotion,} \\ \text{etc.} \end{array} : \sum_{p,j} \left( d_{p,j}^{acc} \times \pi_{p,j}^{P \rightarrow AE} - \text{Costs} \right)$$

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# Aeroplan's problem

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— Promotion budget

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- ▶ Budget balance constraints.
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– Promotion budget – Budget to get new partners/members

Subject to

- ▶ Budget balance constraints.
- ▶ Miles Accumulated in a year  $\geq$  Miles redeemed in a year
- ▶ Contract based promotions fulfilled.

$$\begin{aligned}
& \max_{m_{p,j}^{red}, B_{AE}, a_{p,j}, \Psi} \lambda \left( \sum_k \left( \sum_{p \in \{FI, O\}} \sum_{j \in J_p} d_{M_k, p, j}^{acc} \frac{P \rightarrow AE}{\pi_{p,j}} - \sum_{p \in \{AC, FI, O\}} \sum_{j \in J_p^{red}} d_{M_k, p, j}^{red} \frac{AE \rightarrow P}{\pi_{p,j}} \right) \right. \\
& \quad \left. - B_{AE} + f(\Psi) + \sum_k \sum_{j \in J_{AC}} (p_{j,k}^{acc} s_{j,k}^{acc} + p_{j,k}^{red} s_{j,k}^{red}) - B_{AC} \right) \\
& \quad + (1 - \lambda) \left( \sum_k \sum_{p \in \{AC, FI, O\}} \sum_{j \in J_p} g(d_{M_k, p, j}^{acc}) \right) \tag{1a}
\end{aligned}$$

subject to

$$\sum_{p \in \{AC, FI, O\}} \sum_{j \in J_p} a_{p,j} + \Psi \leq B_{AE} \tag{1b}$$

$$\sum_k \sum_{p \in \{AC, FI, O\}} \sum_{j \in J_p} d_{M_k, p, j}^{red} \leq \sum_k \sum_{p \in \{AC, FI, O\}} \sum_{j \in J_p} d_{M_k, p, j}^{acc} \tag{1c}$$

$$a_{p,j} \geq l_{p,j} \quad \forall p, j \tag{1d}$$

# Partners' problem

$$\max_{\substack{\text{Miles acc} \\ \text{per toaster,} \\ \text{Budget, promotion,} \\ \text{etc.}}} : \sum \text{Addnl profit due to partnership} - \text{Cost of partnership}$$

Subject to

- ▶ Some meaningful constraints

# Partners' problem

$$\begin{array}{l} \max \\ \text{Miles acc} \\ \text{per toaster,} \\ \text{Budget, promotion,} \\ \text{etc.} \end{array} : \sum \text{Accum profit} + \text{Redem profit} - \text{Cost of partnership}$$

Subject to

- ▶ Some meaningful constraints

# Partners' problem

$$\begin{array}{l} \max \\ \text{Miles acc} \\ \text{per toaster,} \\ \text{Budget, promotion,} \\ \text{etc.} \end{array} : \sum p_j^{acc} s_j^{acc} + p_j^{red} s_j^{red} - \text{Cost of partnership}$$

Subject to

- ▶ Some meaningful constraints

# Partners' problem

$$\begin{array}{l} \max \\ \text{Miles acc} \\ \text{per toaster,} \\ \text{Budget, promotion,} \\ \text{etc.} \end{array} : \sum p_j^{acc} s_j^{acc} + p_j^{red} s_j^{red} - (\text{Accum miles} \times P \rightarrow \text{AE Price} + B)$$

Subject to

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Subject to

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Subject to

$$\triangleright d_{p,j}^{acc} = s_j^{acc} m_{p,j}^{acc}$$

$$\triangleright d_{p,j}^{red} = s_j^{red} m_{p,j}^{red}$$



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Subject to

- ▶  $d_{p,j}^{acc} = s_j^{acc} m_{p,j}^{acc}$
- ▶  $d_{p,j}^{red} = s_j^{red} m_{p,j}^{red}$
- ▶ Budget balance constraint.

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- ▶ Budget balance constraint.
- ▶ Stock availability constraint

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- ▶ Stock availability constraint  $s_j^{acc} + s_j^{red} \leq \alpha_j$  and  $s_j^{red} \leq \beta_j$ .

# Partners' problem

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**Note:** Air Canada's problem can be concatenated with Aeroplan's.

$$\max_{m_{p,j}^{acc}, B_p, b_{p,j}} \sum_k \left( \sum_{j \in J_p} \left( p_{j,k}^{acc} s_{j,k}^{acc} - d_{M_k,p,j}^{acc} \frac{P \rightarrow AE}{\pi} p_{p,j} \right) + \sum_{j \in J_p^{red}} p_{j,k}^{red} s_{j,k}^{red} \right) - B_p \quad (2a)$$

subject to

$$\sum_{j \in J_p} b_{p,j} \leq B_p \quad (2b)$$

$$d_{M_k,p,j}^{acc} = s_{j,k}^{acc} m_{p,j}^{acc} \quad (2c)$$

$$d_{M_k,p,j}^{red} = s_{j,k}^{red} m_{p,j}^{red} \quad (2d)$$

$$\sum_k s_{j,k}^{acc} + s_{j,k}^{red} \leq \alpha_j \quad (2e)$$

$$\sum_k s_{j,k}^{red} \leq \beta_j \quad (2f)$$

## A regression model

$$s_{k,p,j,t}^{acc} = \mathcal{R} \left( \{m_{p,j,t-1}^{red}\}_{p,j}, m_{p,j,t}^{acc}, a_{p,j}, b_{p,j} \right) \quad (3a)$$

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One predicts the number of each product bought for the sake of accumulating miles or for redeeming miles using a regression model (perhaps a neural network), given

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- ▶ Promotion efforts by Aeroplan
- ▶ Promotion efforts by the partner

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- ▶ Other interesting parameters?

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Welcome to Game theory

## Example: Prisoner's dilemma

The prisoners simultaneously select their strategy.

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		Prisoner B			
		silent		betray	
Prisoner A	silence	-1	-1	-3	0
	betray	0	-3	-2	-2

# Example: Prisoner's dilemma

The prisoners simultaneously select their strategy.

There is a unique Nash equilibrium:

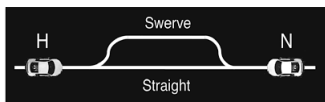
*(betray, betray)*

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Prisoner A	silence	-1	-1	-3	0
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# Example: game of chicken

Simultaneously, the cars decide to swerve and straight.

		Car B			
		Swerve		Straight	
Car A	Swerve	tie 0	tie 0	lose -1	win +1
	Straight	win +1	lose -1	accident -1000	accident -1000



origem: [www.researchgate.net/publication/261351299\\_The\\_effects\\_of\\_neuromodulation\\_on\\_human-robot\\_interaction\\_in\\_games\\_of\\_conflict\\_and\\_cooperation/figures?lo=1&utm\\_source=google&utm\\_medium=organic](http://www.researchgate.net/publication/261351299_The_effects_of_neuromodulation_on_human-robot_interaction_in_games_of_conflict_and_cooperation/figures?lo=1&utm_source=google&utm_medium=organic)

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Simultaneously, the cars decide to swerve and straight.

There are 3 equilibria:

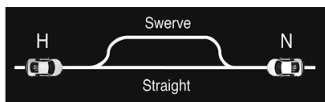
Car A: swerve and Car B: straight

Car A: straight and Car B: swerve

Car A: swerve with prob  $\frac{999}{1000}$  and straight with prob  $\frac{1}{1000}$

Car B: swerve with prob  $\frac{999}{1000}$  and straight with prob  $\frac{1}{1000}$

		Car B			
		Swerve		Straight	
Car A	Swerve	tie 0	tie 0	lose -1	win +1
	Straight	win +1	lose -1	accident -1000	accident -1000

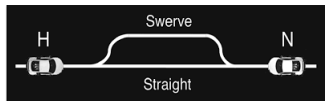


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# Example: game of chicken

Simultaneously, the cars decide to swerve and straight.

There is a correlated equilibrium where:

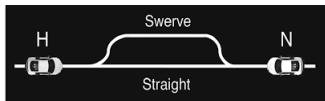
Car A and Car B get a positive utility!

Car A plays *swerve* and Car B plays *swerve* with prob  $\frac{998}{1000}$ ,

Car A plays *swerve* and Car B plays *straight* with prob  $\frac{997}{1000^2}$

Car A plays *straight* and Car B plays *swerve* with prob  $\frac{999}{1000^2}$

		Car B			
		Swerve		Straight	
Car A	Swerve	tie 0	tie 0	lose -1	win +1
	Straight	win +1	lose -1	accident -1000	accident -1000



origem: [www.researchgate.net/publication/261351299\\_The\\_effects\\_of\\_neuromodulation\\_on\\_human-robot\\_interaction\\_in\\_games\\_of\\_conflict\\_and\\_cooperation/figures?lo=1&utm\\_source=google&utm\\_medium=organic](http://www.researchgate.net/publication/261351299_The_effects_of_neuromodulation_on_human-robot_interaction_in_games_of_conflict_and_cooperation/figures?lo=1&utm_source=google&utm_medium=organic)

# Example: game of chicken

Simultaneously, the cars decide to swerve and straight.

**Moral:** by sending signals players can find a more balanced solutions.

There is a correlated equilibrium where:

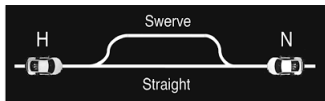
Car A and Car B get a positive utility!

Car A plays *swerve* and Car B plays *swerve* with prob  $\frac{998}{1000}$ ,

Car A plays *swerve* and Car B plays *straight* with prob  $\frac{997}{1000^2}$

Car A plays *straight* and Car B plays *swerve* with prob  $\frac{999}{1000^2}$

		Car B			
		Swerve		Straight	
Car A	Swerve	tie 0	tie 0	lose -1	win +1
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## Algorithmic approach: literature

Normal form games can be solved *reasonably fast* to obtain a *mixed-strategy Nash or correlated equilibrium*.

Players have a finite number of strategies and the game is represented through a multidimensional matrix with an entry for each pure profile of strategies.

		Player 2		
		rock	scissors	paper
Player 1	rock	(0,0)	(1,-1)	(-1,1)
	scissors	(-1,1)	(0,0)	(1,-1)
	paper	(1,-1)	(-1,1)	(0,0)

Table: Rock-scissors-paper game

## Algorithmic approach: overview

- Step 1 Compute an initial set of strategies for each player.
- Step 2 Obtain the normal-form game associated with the enumerated strategies.
- Step 3 Compute the equilibria of the current normal-form game.
- Step 4 Determine whether there is a player with incentive to deviate. If the deviation incentive is greater than a certain tolerance, update the normal-form game with new strategies and go back to **Step 3**. Else, **return** the current equilibrium.

## Step 1: Initial set of strategies

- ▶ Current strategies of the players.
- ▶ Strategies that guarantee a minimum profit for each player.
- ▶ Optimal strategies if each player controlled the remaining ones.
- ▶ Equilibrium strategies for subsets of players.
- ▶ etc...

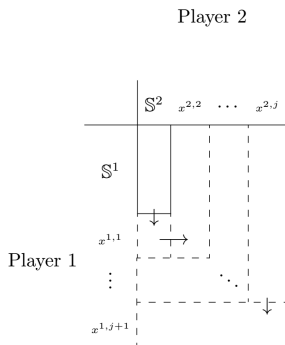
Depending on this initialization the algorithm convergence rate will vary.

Let  $\mathbb{S}_p$  be the initial set of pure strategies for player  $p$ .

## Step 2: Normal-form Game

Compute the utility of each player for any combination of strategies and build the associated multidimensional matrix.

## Step 3: Compute the Equilibria



Nash equilibria: there are solvers available.

Correlated equilibria: there is a solver for 2-player game.

## Step 4: Verify Nash Equilibria

For an equilibrium  $x^*$ , for each player  $p$  solve

$$\hat{x}_p = \operatorname{argmax}_{x_p \in X_p} f_p(x_p, x_{-p}^*)$$

If  $f_p(\hat{x}_p, x_{-p}^*) - f(x^*) \leq \epsilon \quad \forall p$  then return  $x^*$ .

Otherwise, add  $\hat{x}_p$  to the normal-form game.



## Step 4: Verify Correlated Equilibria

For an equilibrium  $\sigma^*$  (probability distribution over any outcome of the normal-form game), for each player  $p$  and for each  $x_p \in \mathbb{S}_p$  (strategies in the current normal-form game) solve

$$z_p = \min_{\hat{x}_p \in X_p} \sum_{x_{-p} \in \mathbb{S}_{-p}} \sigma^*(x_p, x_{-p}) f_p(x_p, x_{-p}) - \sum_{x_{-p} \in \mathbb{S}_{-p}} \sigma^*(x_p, x_{-p}) f_p(\hat{x}_p, x_{-p})$$

If  $z_p$  is negative then  $\sigma^*$  is not a correlated equilibrium and  $\hat{x}_p$  must be added to the game.

Otherwise, if  $z_p \geq 0 \quad \forall p \forall x_p \in \mathbb{S}_p$ , return  $\sigma^*$ .

# Probability based Strategy

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- ▶ If the game is only played a few times, maximizing *expected* returns does not make sense.
- ▶ A deterministic equilibrium might fail to exist! (Example: Rock-Paper-Scissors).
- ▶ Are there intelligent hacks to implementing the equilibrium?

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- ▶ Each partner's presence increases the total value generated.
- ▶ The grand coalition between Aeroplan and *all* the partners creates a total increased utility.
- ▶ How can the dollar value of the utility be distributed among the partners and Aeroplan - in a fair and acceptable way?

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  - ▶ Downside: No existence guarantees! (But in practice, many interesting games have a core)
- ▶ These notions give indications to Aeroplan on who has the market power and where the fair rates are for each partner.

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  - ▶ Highly nonlinear and nonconvex function leading to a *nasty* feasible set.
  - ▶ Ideas from Vielma et. al. (2018) [arxiv:1811.01988].
- ▶ Interesting hacks to implement a probability-based equilibrium.

Thank you

# Solution Concepts

## Definition (Correlated Equilibrium. Aumann 1974)

Let  $\Gamma = \langle I, (A_i)_{i \in I}, (u_i)_{i \in I} \rangle$  be a strategic form game. A *Correlated Equilibrium* is a distribution  $\mu \in \Delta(A)$  such that

$$\forall i \in I, \forall a_i, a'_i \in A_i, \sum_{a_{-i} \in A_{-i}} \mu(a_i, a_{-i}) [u_i(a_i, a_{-i}) - u_i(a'_i, a_{-i})] \geq 0.$$



**Figure:** An example of a Correlated Equilibrium.

# Nash Equilibrium

## Definition (Nash Equilibrium. Nash, 1950)

Let  $\Gamma = \langle I, (A_i)_{i \in I}, (u_i)_{i \in I} \rangle$  be a strategic form game. A mixed strategy of player  $i$  is a probability measure over  $A_i$ , we denote the set of mixed strategy profiles of player  $i$  as  $\Delta_i$ . A mixed strategy profile  $\delta^* = (\delta_i^*)_{i \in I}$  is a mixed Nash Equilibrium iff

$$\forall i \in I, \forall \delta_i \in \Delta_i, u_i(\delta_i^*, \delta_{-i}) - u_i(\delta_i, \delta_{-i}) \geq 0.$$

**Remark** A mixed Nash Equilibrium is a Correlated Equilibrium where the players' mixed strategies are independent.



# Cooperative Game Theory - Core

## Definition (Core)

For a Cooperative Game  $(N, v)$ , a payoff distribution

$\mathbf{x} = (x_1, \dots, x_n) \in \mathbb{R}^n$  is

- ▶ *efficient* if  $\sum_{i \in N} x_i = v(N)$ ,
- ▶ *individually rational* if for every  $i \in N$ ,  $x_i \geq v(\{i\})$ ,
- ▶ *coalitionally rational* if for every  $B \in 2^N \setminus \emptyset$ ,  $\sum_{i \in B} x_i \geq v(\{B\})$ .

The *Core* of  $(N, v)$  is the set

$C(N, v) = \{\mathbf{x} \in \mathbb{R}^n \mid \mathbf{x} \text{ is efficient and coalitionally rational}\}$

**Remark** The Core could be large, small or even empty.

# Shapley value

## Definition (Shapley value)

The Shapley value of a cooperative game  $(N, v)$  is a payoff vector  $\Phi(N, v)$  whose  $i$ -th coordinate is

$$\Phi_i(N, v) = \sum_{B \subseteq N: i \notin B} \frac{|B|!(n-|B|-1)!}{n!} [v(B \cup \{i\}) - v(B)].$$

**Remark** The Shapley value assigns to each player her average marginal contribution to the game.

Note that the Shapley value might not be in the Core.