

## Proof of the Zermelo's Theorem (with several additional comments)

Let  $\sigma$  be the strategy profile derived through backward induction.

Let  $i \in N$ , and let  $\hat{\sigma}_i$  be player  $i$ 's strategy under which he deviates from  $\sigma_i$ . We now prove that  $v_i(\sigma) \geq v_i(\hat{\sigma}_i, \sigma_{-i})$  by induction.

**Notation** For each decision node  $x$ , let  $Z(x)$  be the set of terminal nodes that succeed  $x$ . Given a decision node  $x$  and  $z \in Z(x)$ , let  $n(x, z)$  be the number of decision nodes between  $x$  and  $z$ . We also define  $n(x) \equiv \max_{z \in T(x)} n(x, z)$ , which is called “distance” (see the figure on page 3).

Let  $N$  be  $\max\{n(x) | x \text{ is a decision node of } \Gamma\}$ . Because  $\Gamma$  is finite,  $N$  is finite.

**How to play** Given  $n \in \{0, 1, \dots, N\}$ , we define  $\hat{\sigma}_i(\cdot; n)$  for player  $i$ 's strategy such that for all player  $i$ 's decision node  $x$ ,

$$\hat{\sigma}_i(x; n) = \begin{cases} \sigma_i(x) & \text{if } n(x) \leq n, \\ \hat{\sigma}_i(x) & \text{if } n(x) > n. \end{cases}$$

This means as follows: Given that we set  $n$ , if the distance of decision node  $x$  is smaller than or equal to  $n$ , player  $i$ 's action at  $x$  follows  $\sigma_i(x)$ , otherwise, his action at  $x$  follows  $\hat{\sigma}_i(x)$ .

The following table summarizes the strategy  $\hat{\sigma}_i(\cdot; n)$  for each decision node when we set  $n$ :

Distance	0	$\dots$	$n$	$n+1$	$\dots$	$\dots$
$\hat{\sigma}_i(\cdot; n)$	$\sigma_i(\cdot)$	$\dots$	$\sigma_i(\cdot)$	$\hat{\sigma}_i(\cdot)$	$\dots$	$\hat{\sigma}_i(\cdot)$

Note that  $\hat{\sigma}_i(\cdot; N) = \sigma_i$  because player  $i$ 's strategy is  $\sigma_i(x)$  for any decision node  $x$  when  $n = N$ .

**What we do** By induction, we establish that for all  $n \in \{0, \dots, N\}$ ,

$$v_i(\hat{\sigma}(\cdot; n), \sigma_{-i}) \geq v_i(\hat{\sigma}_i, \sigma_{-i}),$$

which implies that  $v_i(\sigma) \geq v_i(\hat{\sigma}_i, \sigma_{-i})$  because  $\hat{\sigma}_i(\cdot; N) = \sigma_i$ .

**Step I ( $n = 0$ ):** Let  $y$  be the final decision node reached by the strategy profile  $(\hat{\sigma}_i(\cdot; 0), \sigma_{-i})$ .

1. If  $y$  is not  $i$ 's decision node,  $v_i(\hat{\sigma}_i(\cdot; 0), \sigma_{-i}) = v_i(\hat{\sigma}_i, \sigma_{-i})$  because the outcome does not differ.
2. If  $y$  is  $i$ 's decision node,  $v_i(\hat{\sigma}_i(\cdot; 0), \sigma_{-i}) \geq v_i(\hat{\sigma}_i, \sigma_{-i})$  due to the construction of  $\sigma$  through the backward induction (at  $y$ , player  $i$  must choose one of the best action(s)).

Therefore,  $v_i(\hat{\sigma}_i(\cdot; 0), \sigma_{-i}) \geq v_i(\hat{\sigma}_i, \sigma_{-i})$  when  $n = 0$ .

**Step II:** Assume that  $v_i(\hat{\sigma}_i(\cdot; n-1), \sigma_{-i}) \geq v_i(\hat{\sigma}_i, \sigma_{-i})$ .

Let  $x'$  be the decision node on the path of strategy profile  $(\hat{\sigma}_i(\cdot; n), \sigma_{-i})$  such that  $n(x') = n$ . Note that  $x'$  is also on the path of strategy profile  $(\hat{\sigma}_i(\cdot; n-1), \sigma_{-i})$  because the actions at nodes whose distance is larger than or equal to  $n+1$  in the latter strategy profile are the same with those in the former strategy profile (see the red colored  $\hat{\sigma}_i(\cdot)$  whose distance is larger than or equal to  $n+1$  in the following table).

Distance	0	$\dots$	$n-1$	$n$	$n+1$	$\dots$
$\hat{\sigma}_i(\cdot; n-1)$	$\sigma_i(\cdot)$	$\dots$	$\sigma_i(\cdot)$	$\hat{\sigma}_i(\cdot)$	$\hat{\sigma}_i(\cdot)$	$\dots$
$\hat{\sigma}_i(\cdot; n)$	$\sigma_i(\cdot)$	$\dots$	$\sigma_i(\cdot)$	$\sigma_i(\cdot)$	$\hat{\sigma}_i(\cdot)$	$\dots$

Note also that for all decision nodes  $x''$  that succeed  $x'$  (the distance of  $x''$  is smaller than or equal to  $n-1$ ),  $\hat{\sigma}_i(x''; n) = \sigma_i(x'') = \hat{\sigma}_i(x''; n-1)$  (see the blue colored  $\sigma_i(\cdot)$  whose distance is smaller than or equal to  $n-1$  in the above table).

1. If  $x'$  is not  $i$ 's decision node,  $v_i(\hat{\sigma}_i(\cdot; n), \sigma_{-i}) = v_i(\hat{\sigma}_i(\cdot; n-1), \sigma_{-i})$  because the outcome does not differ.
2. If  $x'$  is  $i$ 's decision node,  $v_i(\hat{\sigma}_i(\cdot; n), \sigma_{-i}) \geq v_i(\hat{\sigma}_i(\cdot; n-1), \sigma_{-i})$  due to the construction of  $\sigma$  through the backward induction (at  $x'$ , player  $i$  must choose one of the best action(s)).

Therefore,  $v_i(\hat{\sigma}_i(\cdot; n), \sigma_{-i}) \geq v_i(\hat{\sigma}_i(\cdot; n-1), \sigma_{-i})$ .

Also, by the induction hypothesis,  $v_i(\hat{\sigma}_i(\cdot; n), \sigma_{-i}) \geq v_i(\hat{\sigma}_i(\cdot; n-1), \sigma_{-i}) \geq v_i(\hat{\sigma}_i, \sigma_{-i})$ , thus,  $v_i(\hat{\sigma}_i(\cdot; n), \sigma_{-i}) \geq v_i(\hat{\sigma}_i, \sigma_{-i})$ . We know the fact that  $\hat{\sigma}_i(\cdot; N) = \sigma_i$ . Therefore,  $v_i(\sigma_i, \sigma_{-i}) \geq v_i(\hat{\sigma}_i, \sigma_{-i})$ , that is, the deviation does not improve the payoff of player  $i$ . Q.E.D.

See also the proof in MWG pp.272-3.