

# Using CNN to solve Two player zero-sum games

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# Introduction

### Background

- A two-person zero-sum game can be represented by a matrix, e.g.,
  - $A = \begin{bmatrix} 1 & 7 & 5 \\ 2 & 4 & 3 \\ 3 & 10 & 6 \end{bmatrix}.$
- One of the classical problems is to solve  $v = \min_y \max_x x^T Ay$ , where v denotes the saddle point value and  $(x^*, y^*)$  denotes the saddle point strategy.
- This problem can be solved by linear programming.
- The famous minmax theorem guarantees the existence of a saddle point.

## **Problem formulation**

We consider the matrix *A* to satisfy the following,

- The shape of *A* is given and fixed.
- The elements of *A* come from a given probability distribution.

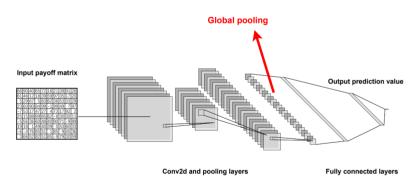
We use a convolutional neural network (CNN) approach to find an estimate  $\hat{v}$  and use a linear system to derive  $(\hat{x}, \hat{y})$  in the corresponding  $\hat{v} = \hat{x}^T A \hat{y}$ .

We evaluate the CNN method results by 1) Accuracy: The predicted  $\hat{v}$  is expected to be as close as possible to the real v. 2) Efficiency: The CNN method is expected to be faster than the classical linear programming method.

# Method

CNN method to predict saddle point value

- 1. Generate a certain number of matrices A according to the given shape and probability distribution. Use linear programming to find v. Multiple (A, v) together form the training set.
- 2. Construct a CNN model in which the number of input channels is 1, like the following,



3. Go training.

# **Experimental results**

#### Linear system to obtain saddle point strategy

After the CNN predicts  $\hat{v}$ , the remaining problem is how to get (x, y) in  $\hat{v} = \hat{x}^T A \hat{y}$ 

Solving the  $\hat{v} = \hat{x}^T A \hat{y}$  problem can be converted to solving down the following linear system problems, where *n*, *m* denote the size of *x* and *y*.

$$\mathbf{A}^T \mathbf{x} \ge \hat{v} \mathbf{e}_{\mathbf{m}} \mathbf{x}^T \mathbf{e}_{\mathbf{n}} = 1, \mathbf{x} \ge 0,$$
 (1)

$$\begin{aligned} \mathbf{A}\mathbf{y} &\leq \hat{v}\mathbf{e}_{\mathbf{n}} \\ \mathbf{y}^{T}\mathbf{e}_{\mathbf{m}} &= 1, \mathbf{y} \geq 0, \end{aligned}$$
 (2)

- when  $\hat{v} = v$ , both (1) and (2) are feasible.
- When  $\hat{v} < v$ , only (1) is feasible, and the corresponding  $\hat{y}$  is the best response of  $-A^T \hat{x}$ .
- When  $\hat{v} > v$ , only (2) is feasible, and the corresponding  $\hat{x}$  is the best response of  $A\hat{y}$ .

## References

We consider the game size to be 1000 \* 1000 and a uniform(-10, 100) probability distribution. Compare the CNN method to linear programming(LP), fictitious play(FP) and EXP3 methods.

1000*1000			
Algorithms	CPU Time	Value	Gap (%)
LP	1.3035	45.0293	-
CNN	0.00086	45.6481	1.3553%
FP	259.3845	47.6020	5.4043%
Exp3	0.7100	45.0431	0.0304%

Table 1: Comparison between LP, CNN and two learning algorithms

[1] Dawen Wu, Abdel Lisser. Using CNN for solving two-player zero-sum games. 2021.  $\langle hal-03341813 \rangle$ 

[2] G. B. Dantzig, Linear programming and extensions, Vol. 48, Princeton university press, 1998.

[3] P. Fischer, A. Dosovitskiy, T. Brox, Image orientation estimation with convolutional networks, in: German Conference on Pattern Recognition, Springer, 2015, pp. 368–378



