

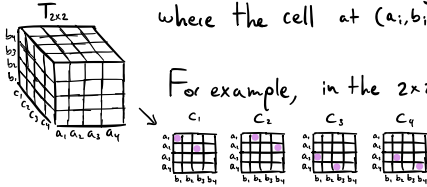
This is a personal TLDR of the following paper
 Discovering faster matrix multiplication algorithms with RL - DeepMind

The crux of the paper is a perspective shift on matrix multiplications

Ex. $\begin{pmatrix} a_1 & a_2 \\ a_3 & a_4 \end{pmatrix} \begin{pmatrix} b_1 & b_2 \\ b_3 & b_4 \end{pmatrix} = \begin{pmatrix} c_1 & c_2 \\ c_3 & c_4 \end{pmatrix}$

now clearly $c_1 = a_1 b_1 + a_2 b_3$ ①
 $c_4 = a_3 b_2 + a_4 b_4$

The authors represent the eqs ① as a binary tensor T_n
 where the cell at (a_i, b_j, c_k) is 1 if $c_k = a_i b_j + \dots$
 0 otherwise



For example, in the 2x2 case above,

Now the cool part of their algo is through finding decompositions of T_n , they implicitly find diff procedures to perform the mat mul.

$T_n = \sum_{i=1}^k u^{(i)} \otimes v^{(i)} \otimes w^{(i)}$, \otimes is outer product

↳ This is similar to SVD of $A^{n \times n}$ but here we are doing it for $A^{n \times n \times n}$.

So imagine $U, V, W \in \{-1, 0, 1\}^{i \times j \times k}$ are given, how do you use them?

$T_n = u^{(1)} \otimes v^{(1)} \otimes w^{(1)} + \dots$ geometrically therefore, u_s correspond to a
 v_s correspond to b
 w_s correspond to c

Thus the algo to actually perform mat mul given U, V, W is

Algo 1

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for r=1 to R do
    m_r ← (u^{(r)} a_1 + ... + u_n^{(r)} a_n) (v_1^{(r)} b_1 + ... + v_n^{(r)} b_n)
for i=1, ..., n^2 do
    C_i ← w_i^{(1)} m_1 + ... + w_i^{(R)} m_R
return C
    
```

The RL agent has to find U, V, W and the authors construct a game, which is
 Let $S_0 = T_n$, the agent outputs (u', v', w') , thus $S_i = S_0 - u^{(i)} \otimes v^{(i)} \otimes w^{(i)}$ and so on
 until $S_i = 0$. The agent is penalized for each step to encourage it
 to find shortest path (minimize R). The RL algo is based on AlphaZero
 where they do MCTS with a policy and value network.