PET: Optimizing Tensor Programs with Partially Equivalent Transformations and Automated Corrections

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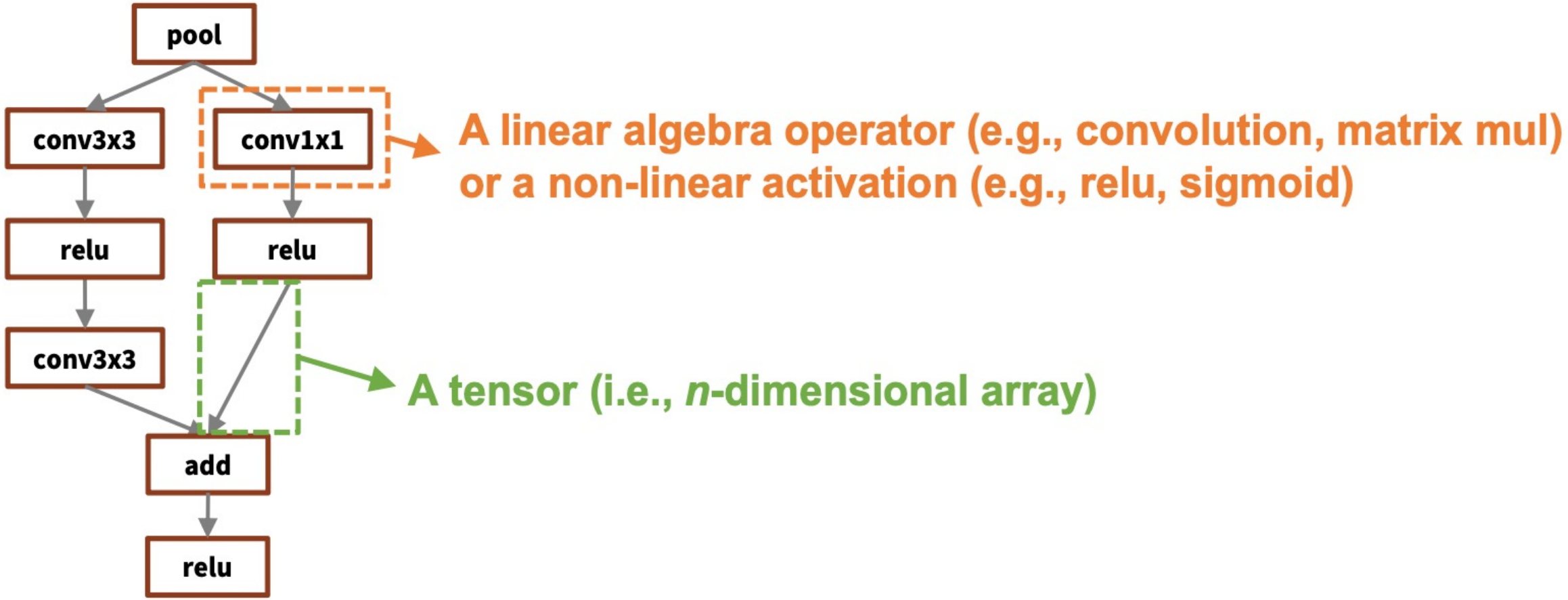
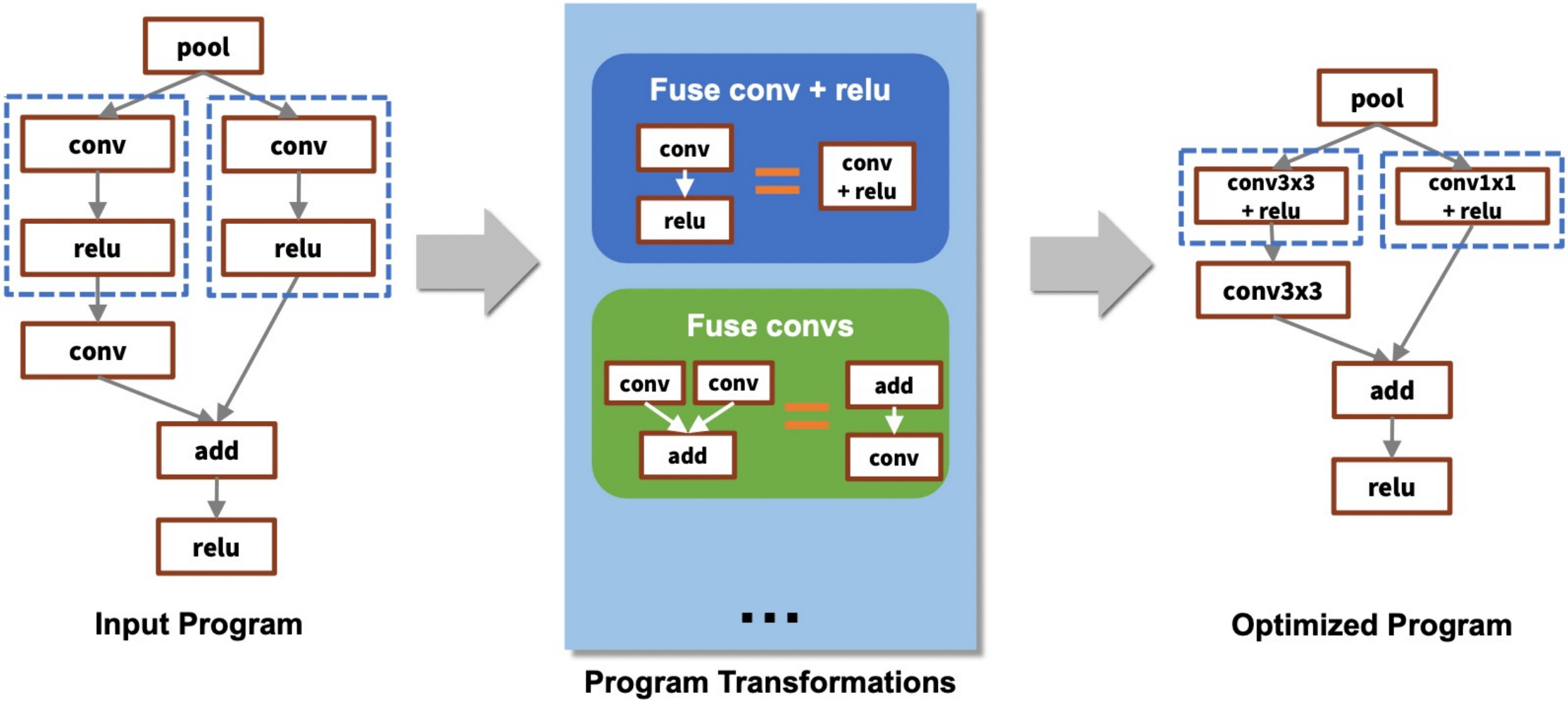
OSDI 2021

Background: Tensor Program



Source: Zhihao Jia. (2021).

Background: Tensor Program Transformations



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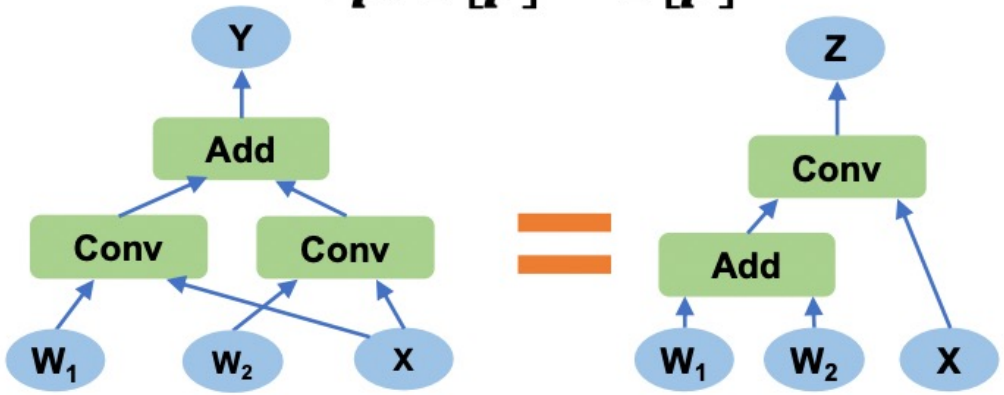
Background: Current Systems Consider only Fully Equivalent Transformations

$$\forall p.\ Y[p] = Z[p]$$

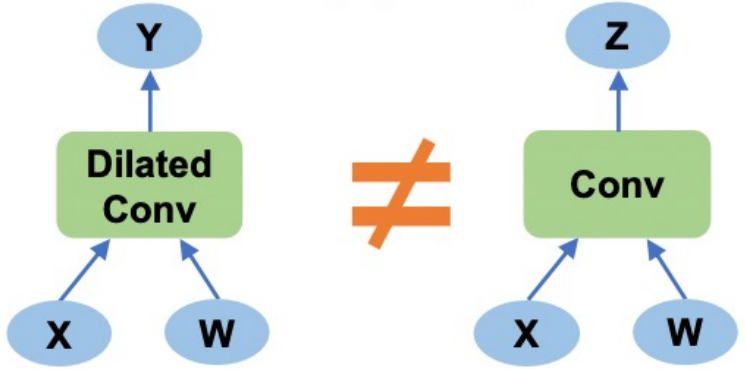


Fully Equivalent Transformations

👍Pro: preserve functionality

👎Con: miss optimization opportunities

$$\exists p.\ Y[p] \neq Z[p]$$



Partially Equivalent Transformations

👍Pro: better performance

- Faster ML operators
- More efficient tensor layouts
- Hardware-specific optimizations

👎Con: potential accuracy loss

Source: Zhihao Jia. (2021).

Current Systems Consider only Fully Equivalent Transformations

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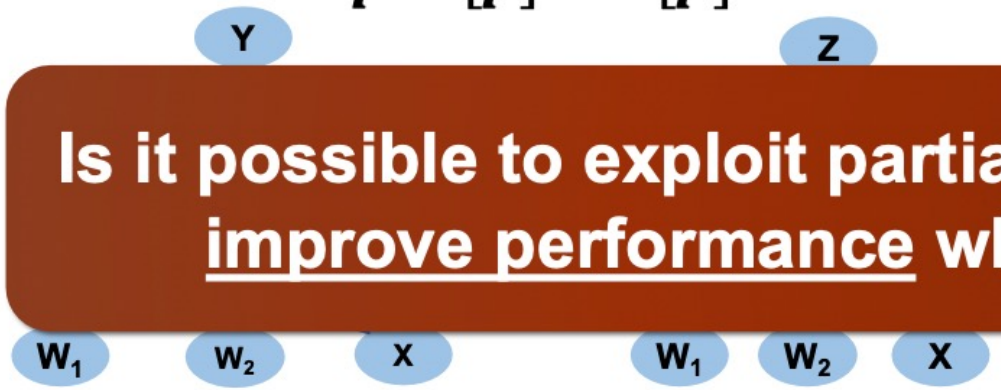

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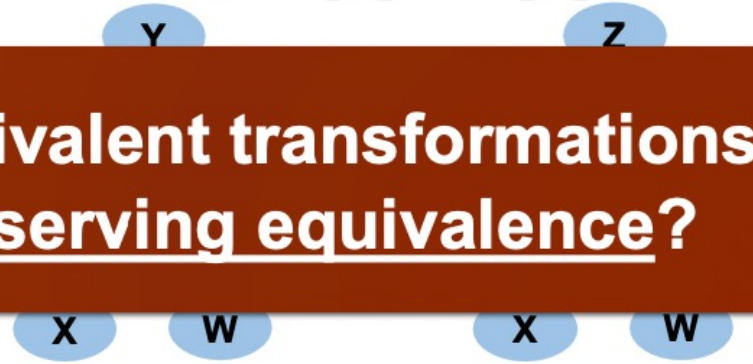

Partially Equivalent Transformations

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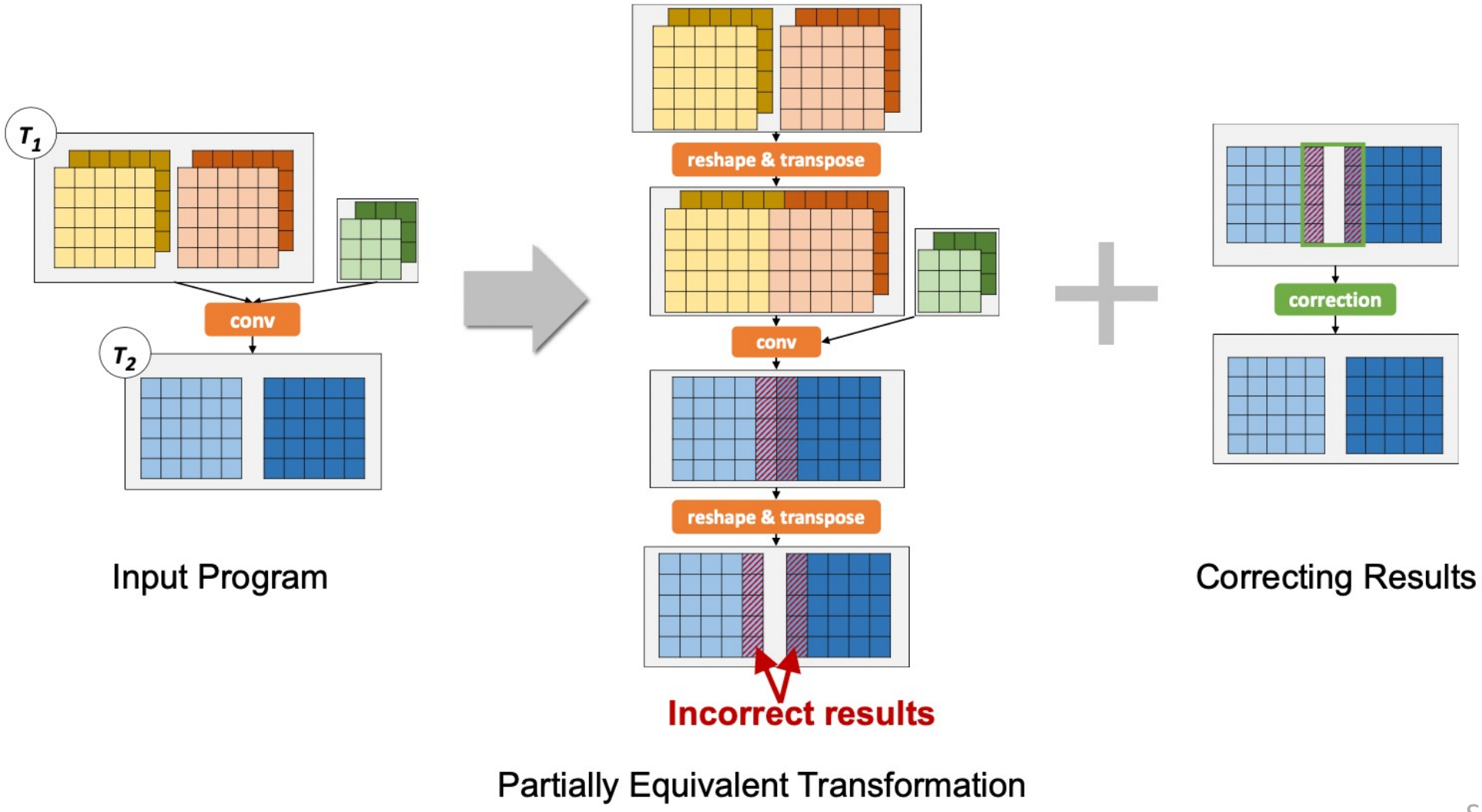
- Hardware-specific optimizations

👎 Con: potential accuracy loss

Is it possible to exploit partially equivalent transformations to improve performance while preserving equivalence?

Source: Zhihao Jia. (2021).

Motivating Example



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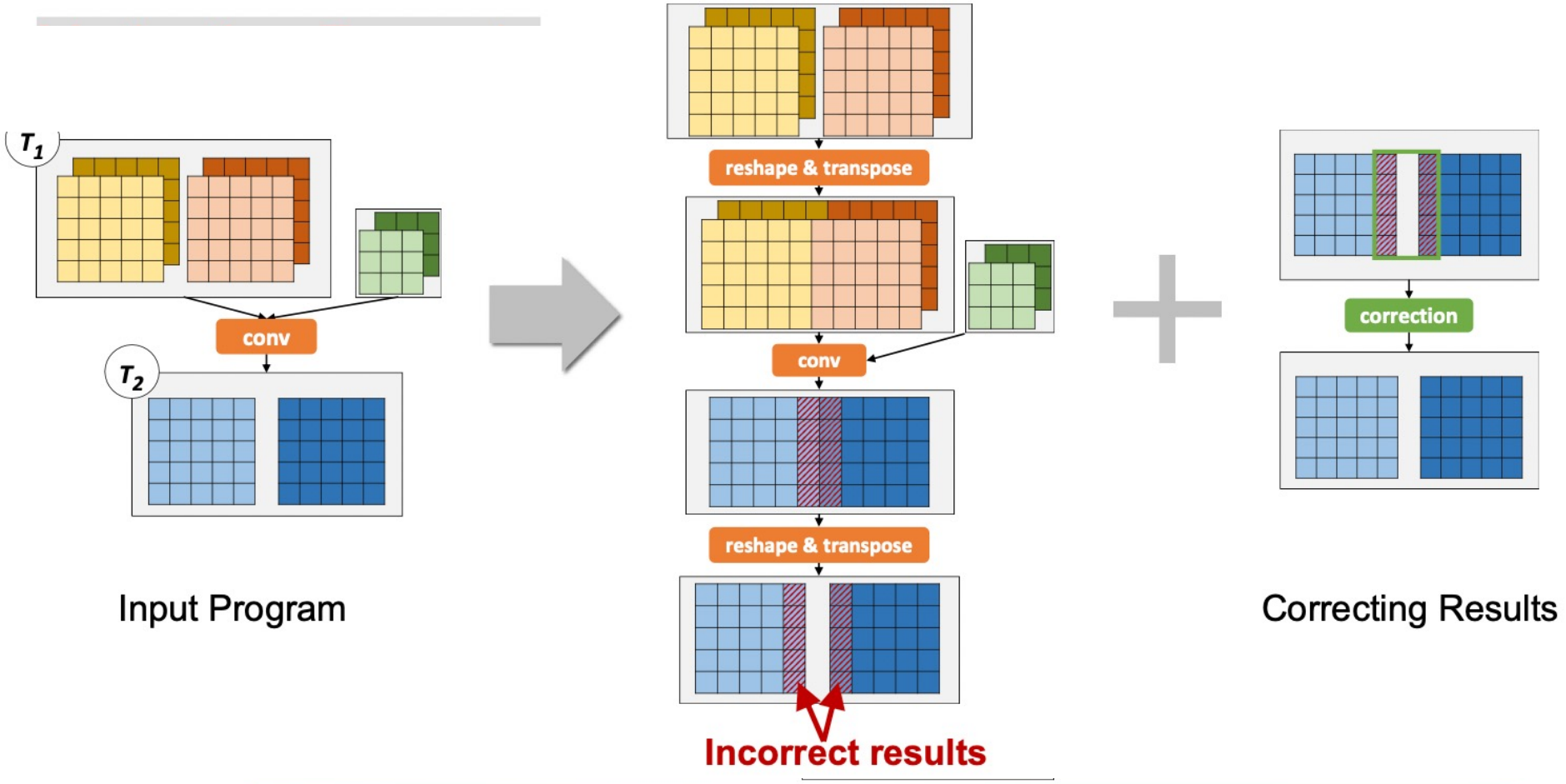


- Transformation and correction lead to **1.2x** speedup for ResNet-18
- Correction preserves end-to-end equivalence

Source: Zhihao Jia. (2021).

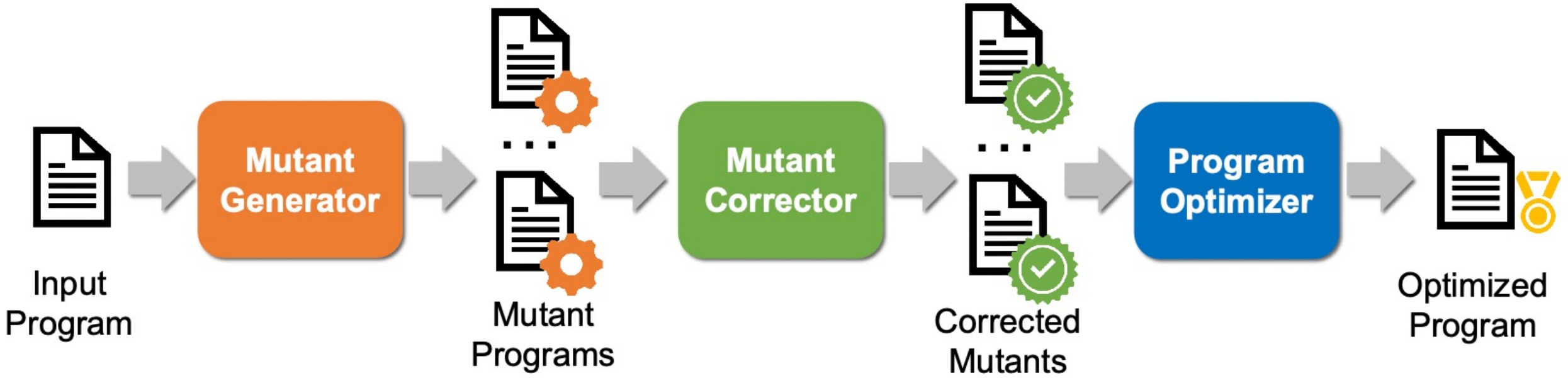
PET

- **First tensor program optimizer** with partially equivalent transformations

- **Larger optimization space** by combining fully and partially equivalent transformations
- **Better performance**: outperform existing optimizers by up to **2.5x**
- **Correctness**: automated corrections to preserve end-to-end equivalence

Source: Zhihao Jia. (2021).

PET Overview



Source: Zhihao Jia. (2021).

Key Challenges

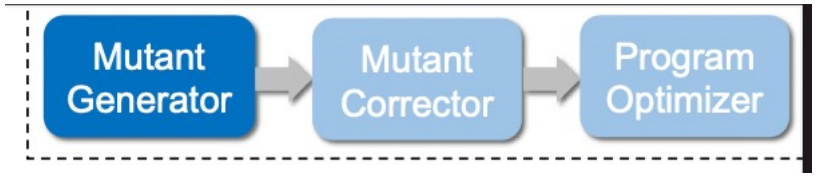
1. How to generate partially equivalent transformations?

Superoptimization

2. How to correct them?

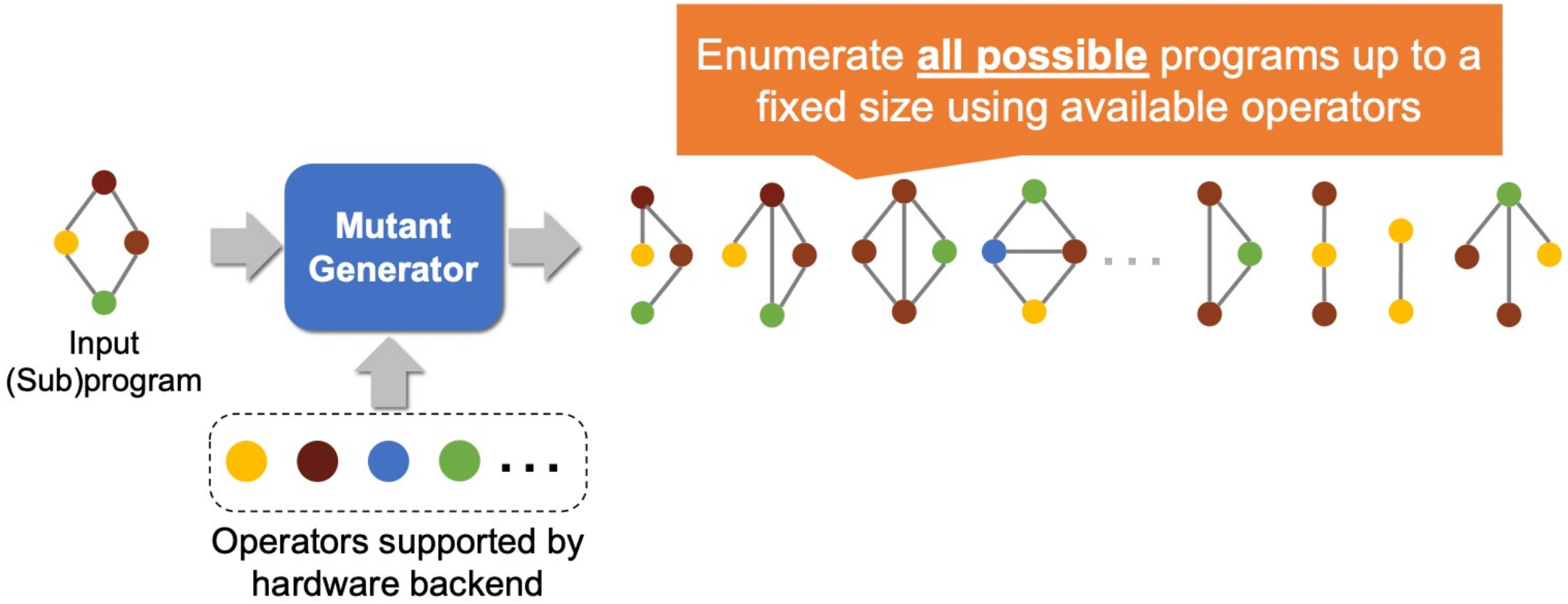
Multi-linearity of DNN computations

Source: Zhihao Jia. (2021).



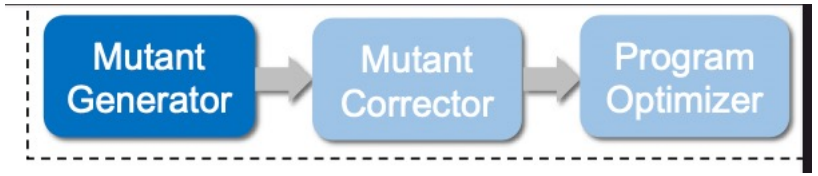
Mutant Generator

Superoptimization adapted from TASO[1]



1. TASO: Optimizing Deep Learning Computation with Automated Generation of Graph Substitutions. SOSP'19.

Source: Zhihao Jia. (2021).



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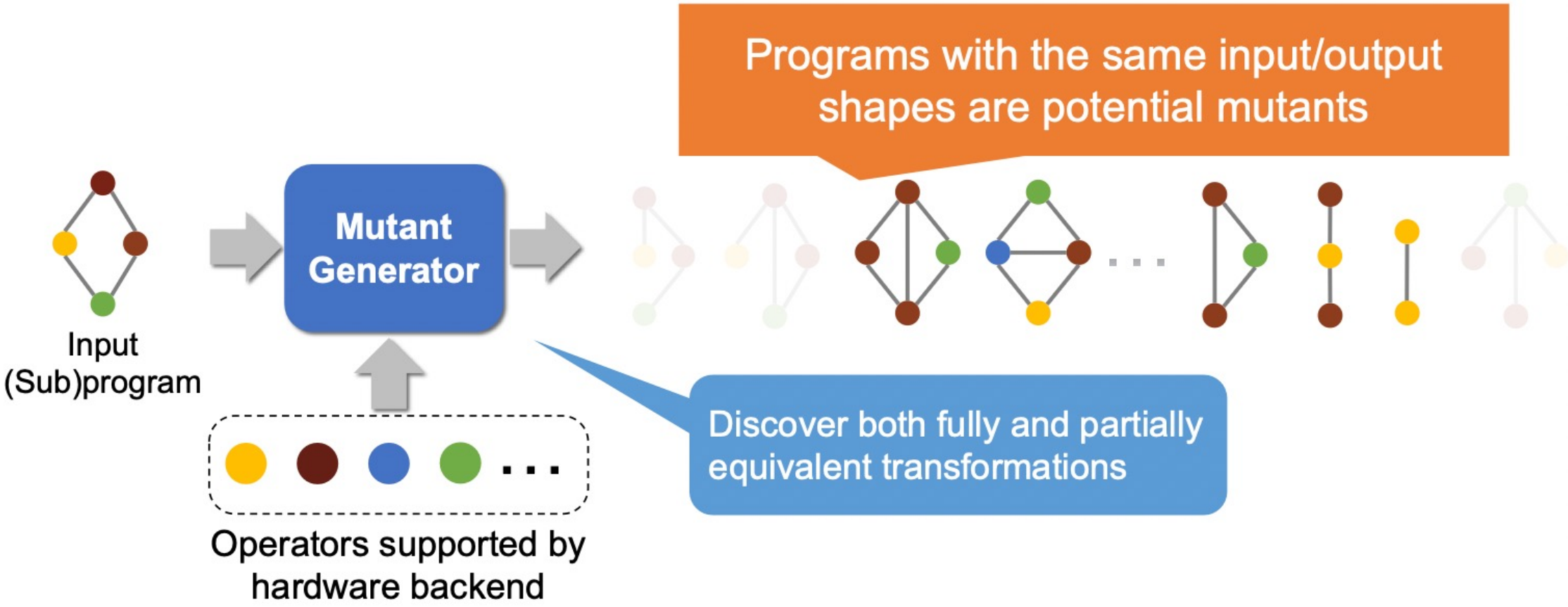

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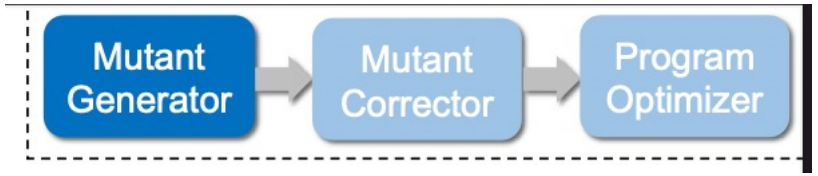
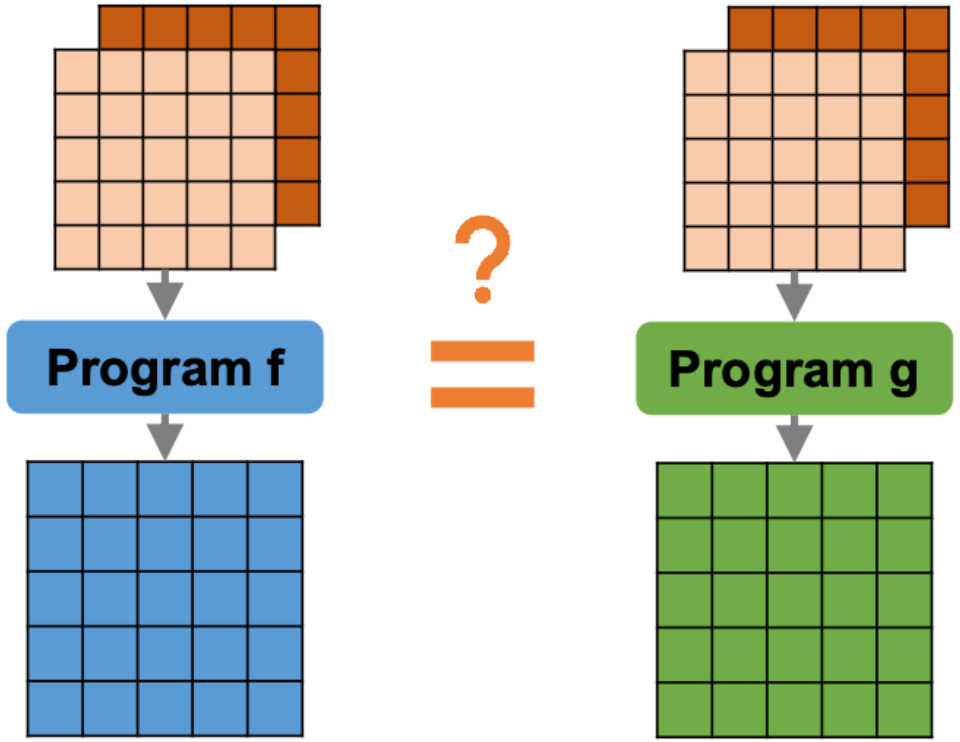


Challenges: Examine Transformations

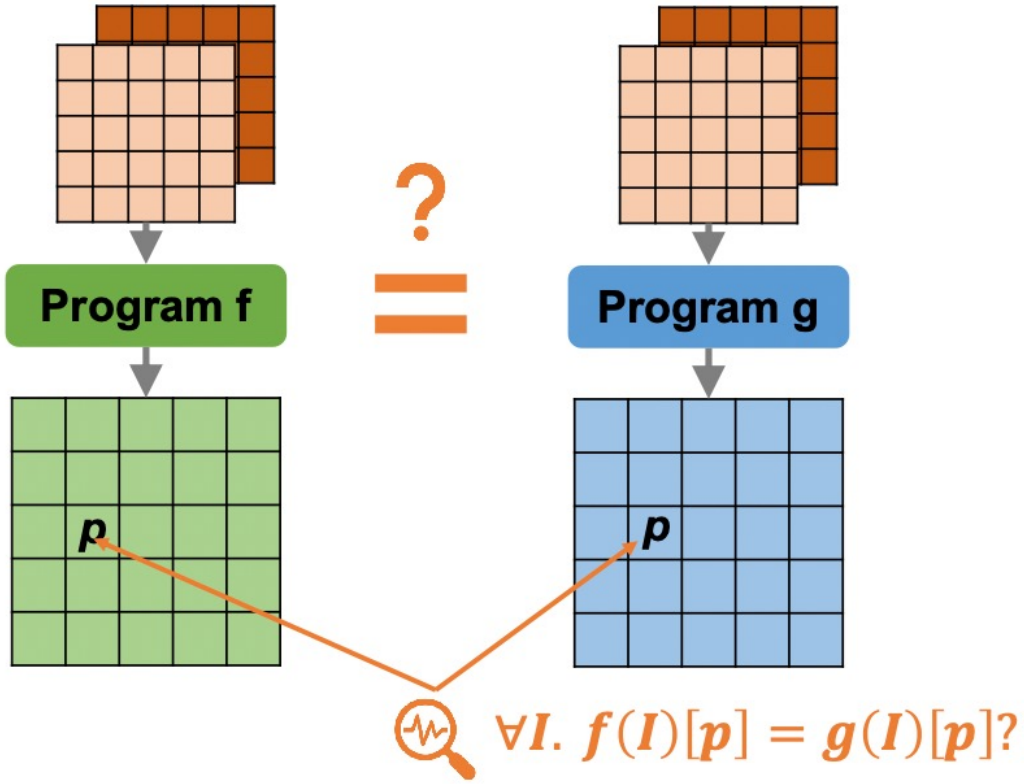


1. Which part of the computation is not equivalent?
2. How to correct the results?

Source: Zhihao Jia. (2021).

A Strawman Approach

- **Step 1**: Explicitly consider all output positions (m positions)
- **Step 2**: For each position ***p***, examine all possible inputs (n inputs)



Require O(m * n) examinations, but both m and n are too large to explicitly enumerate

Source: Zhihao Jia. (2021).

Multi-Linear Tensor Program (MLTP)

- A program $\boldsymbol{f}$ is multi-linear if the output is linear to all inputs
  - $\boldsymbol{f}(I_1, \ldots, X, \ldots, I_n) + \boldsymbol{f}(I_1, \ldots, Y, \ldots, I_n) = \boldsymbol{f}(I_1, \ldots, X + Y, \ldots, I_n)$
  - $\alpha \cdot \boldsymbol{f}(I_1, \ldots, X, \ldots, I_n) = \boldsymbol{f}(I_1, \ldots, \alpha \cdot X, \ldots, I_n)$

- DNN computation = MLTP + non-linear activations

Majority of the computation

O(m * n) examinations in strawman approach

O(1) examinations in PET's approach

Source: Zhihao Jia. (2021).

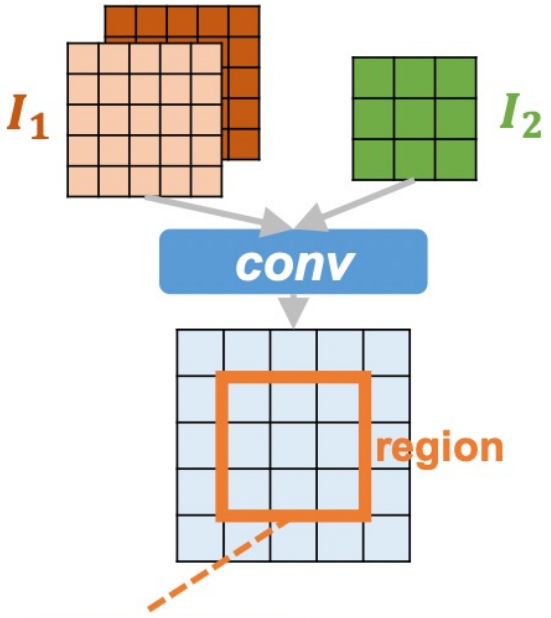
No Need to Enumerate All Output Positions

Group all output positions with an identical summation interval into a region

***Theorem 1**: For two MLTPs **f** and **g**, if **f=g** for **O(1)** positions in a region, then **f=g** for all positions in the region

Only need to examine **O(1)** positions for each region.

Complexity: **O(m * n) → O(n)**



$$conv(c,h,w) = \sum_{d=0}^{D-1} \sum_{x=-1}^{1} \sum_{y=-1}^{1} I_1(d, h+x, w+y) \times I_2(d,c,x,y)$$

Summation interval

*Proof details available in the paper

Source: Zhihao Jia. (2021).

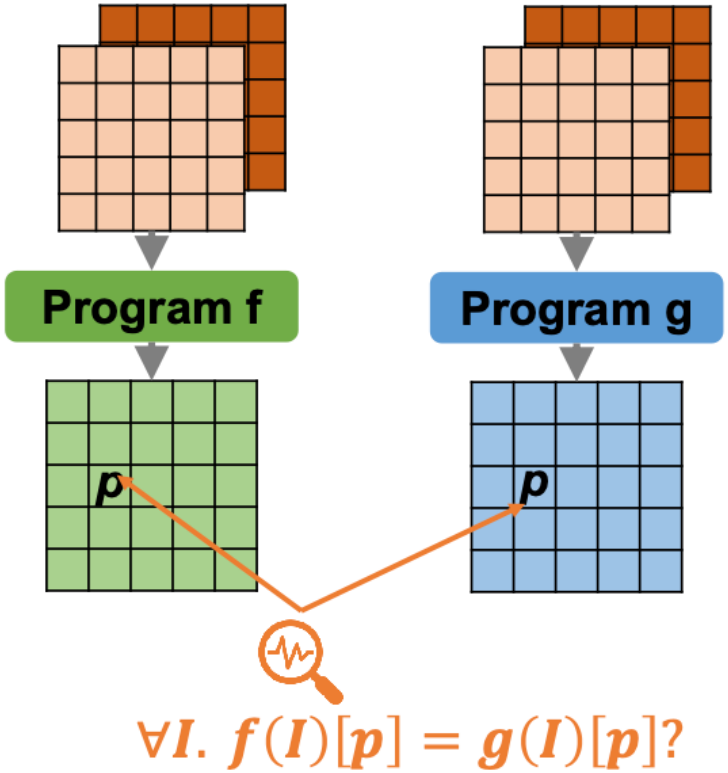
No Need to Consider All Possible Inputs

Examining equivalence for a single position is still challenging

***Theorem 2**: If $\exists I.\ f(I)[p] \neq g(I)[p]$, then the probability that **f** and **g** give identical results on t random integer inputs is $(\frac{1}{2^{31}})^t$

Run t random tests for each position p

Complexity: **O(n) → O(t) = O(1)**



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Mutant Corrector

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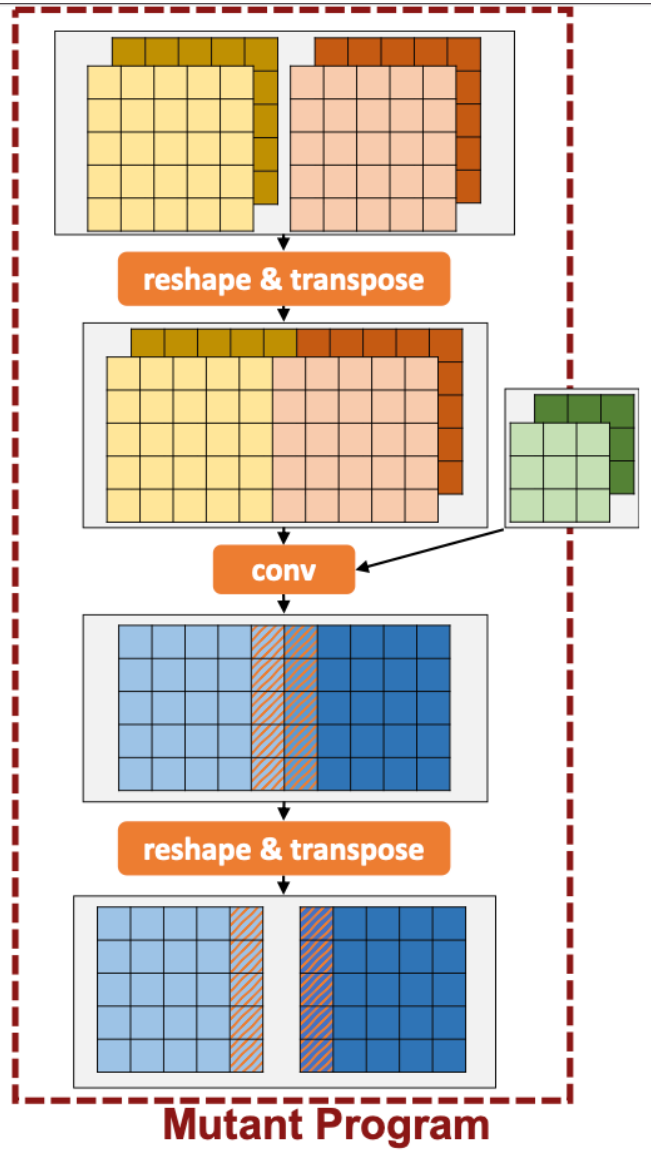
Goal: **quickly** and **efficiently** correcting the outputs of a mutant program



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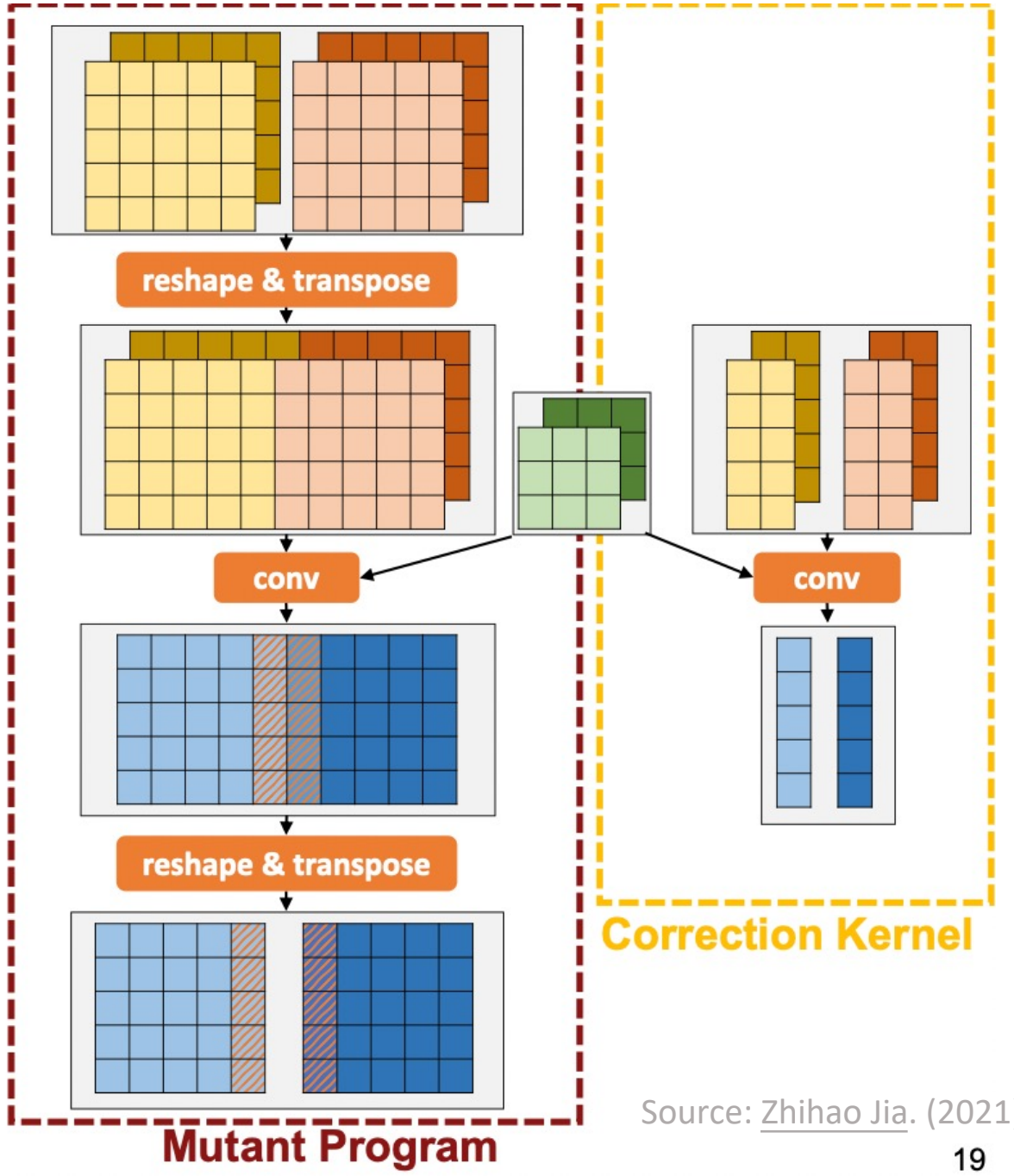
Mutant Corrector

Goal: **quickly** and **efficiently** correcting the outputs of a mutant program

Step 1: recompute the incorrect outputs using the original program



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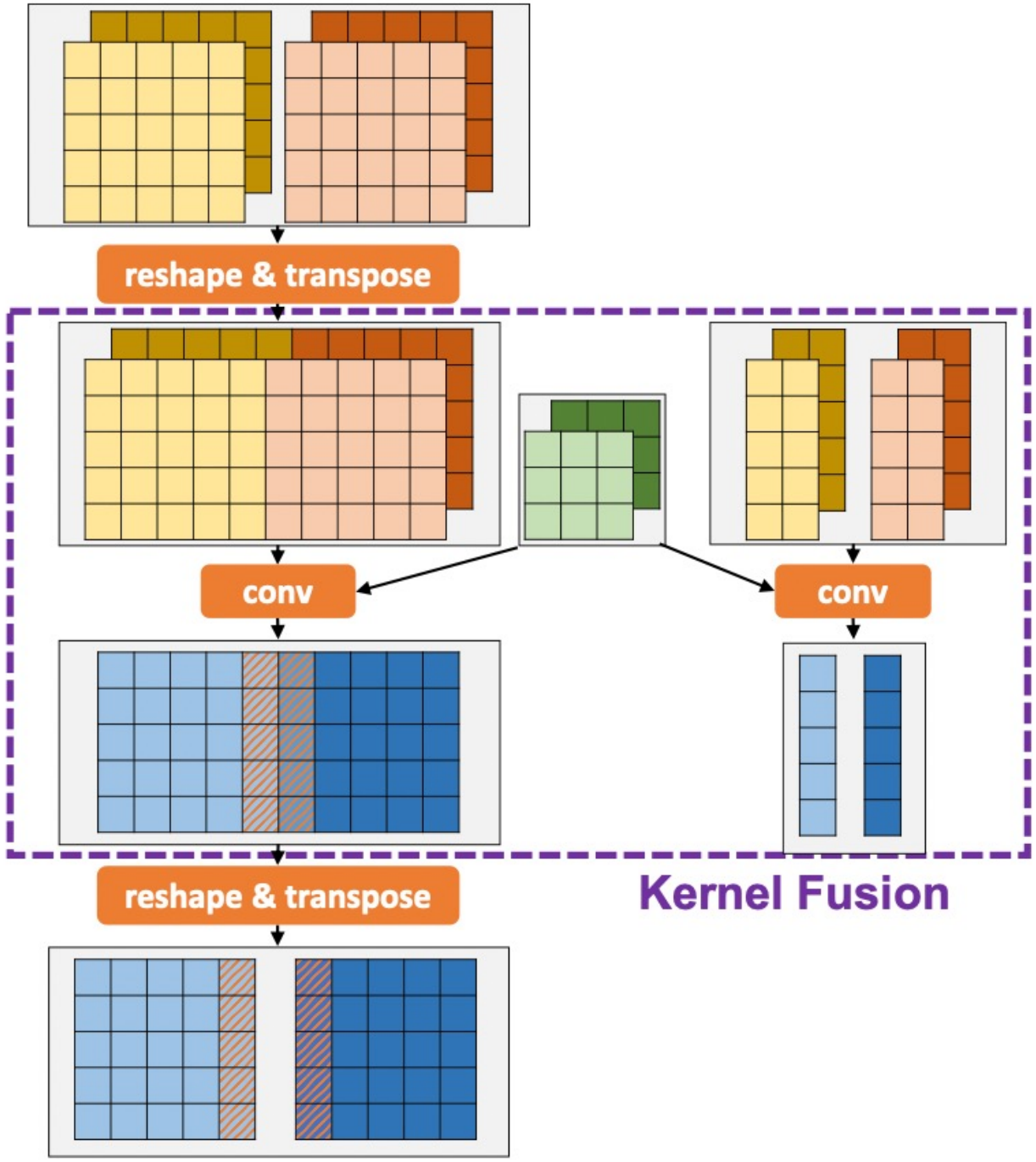
Mutant Corrector

Goal: **quickly** and **efficiently** correcting the outputs of a mutant program

Step 1: recompute the incorrect outputs using the original program

Step 2: opportunistically fuse correction kernels with other operators

Correction introduces less than **1%** overhead



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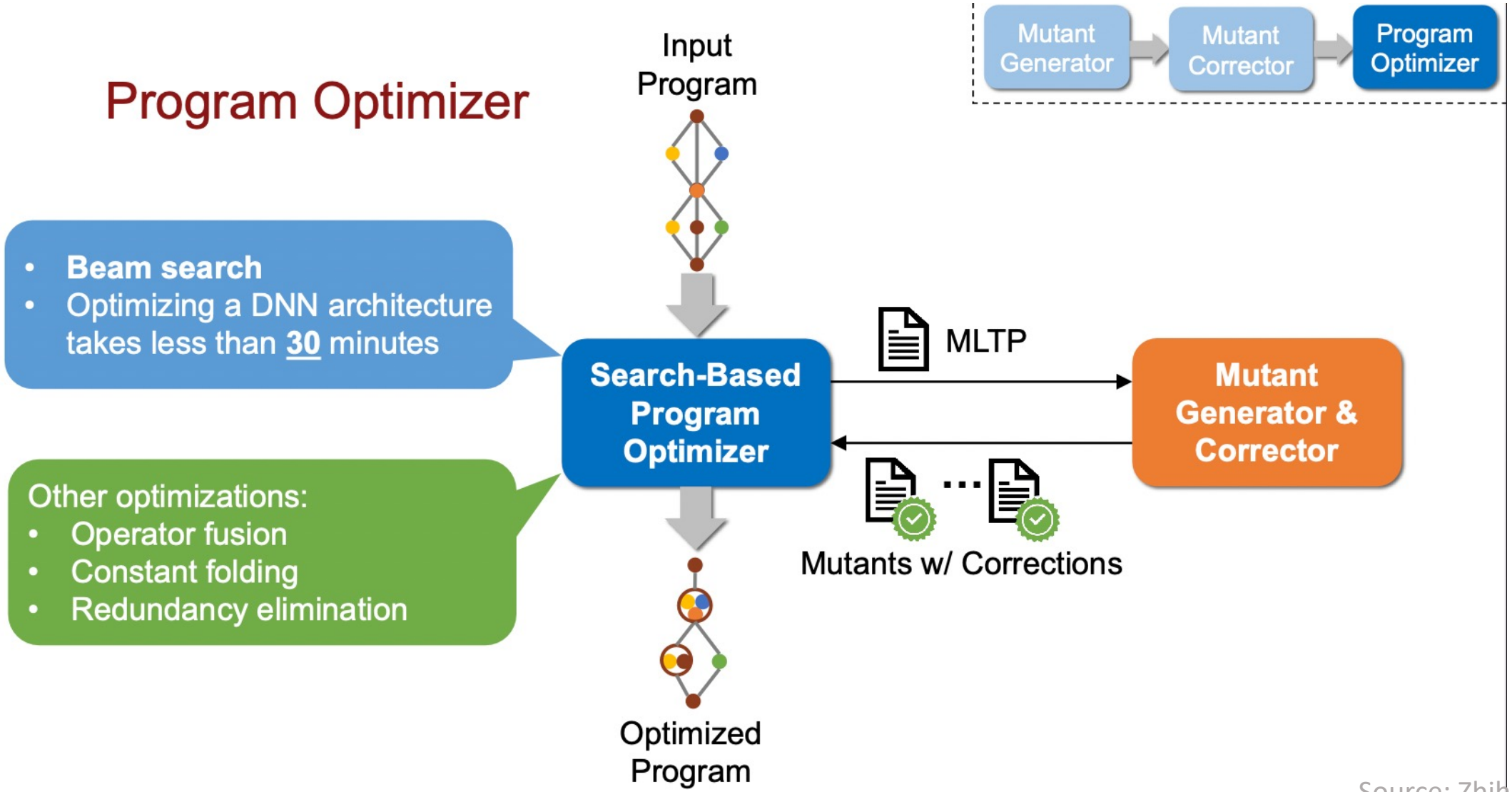
Program Optimizer



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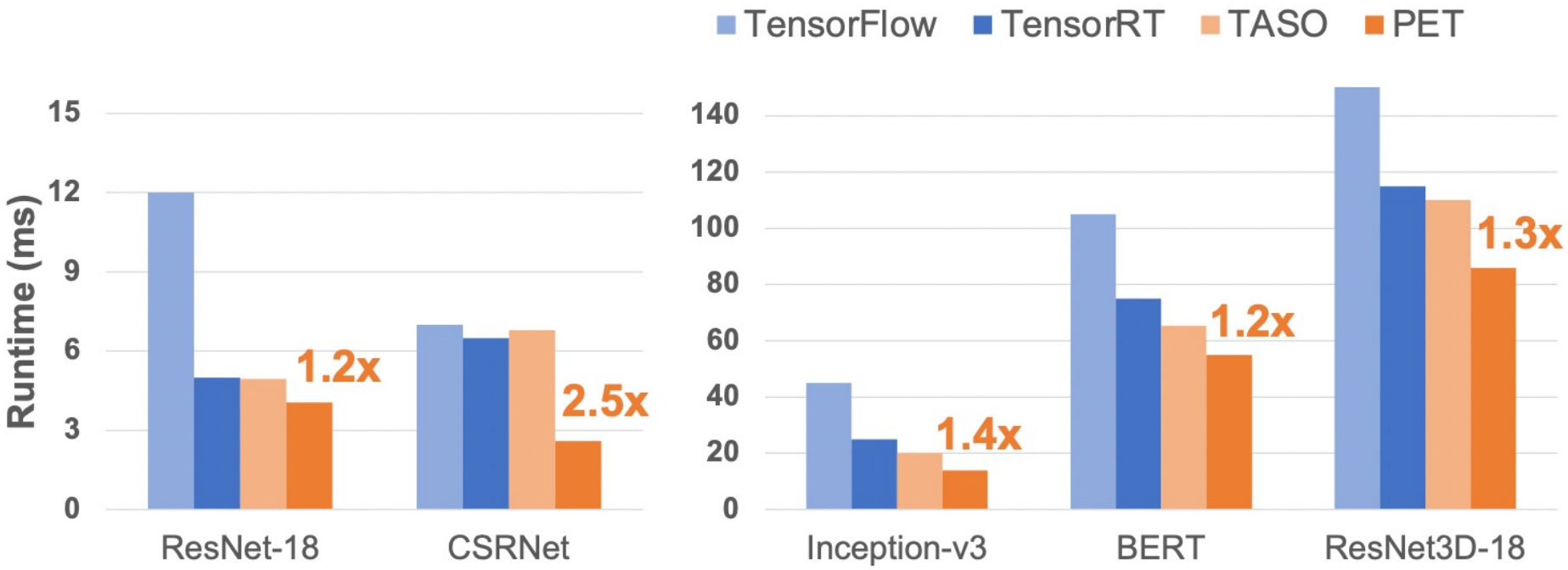
End-to-end Inference Performance (Nvidia V100 GPU)



PET outperforms existing optimizers by 1.2-2.5x
by combining fully and partially equivalent transformations

Source: Zhihao Jia. (2021).

More Evaluation in Paper

1. A case study on tensor-, operator-, and graph-level optimizations discovered by PET

2. Both fully and partially equivalent transformations are critical to performance

3. PET consistently outperforms existing optimizers on various backends (cuDNN/cuBLAS, TVM, Ansor)

4. Partially equivalent transformations w/ corrections can directly benefit existing optimizers

Source: Zhihao Jia. (2021).

PET

- A tensor program optimizer with partially equivalent transformations and automated corrections

- **Larger optimization space** by combining fully and partially equivalent transformations
- **Better performance**: outperform existing optimizers by up to **2.5x**
- **Correctness**: automated corrections to preserve end-to-end equivalence

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Criticism - pros/cons

- While PET outperforms rule-based optimizers, it only discovers transformations between expressions that can be constructed using only the predefined operators.

- PET attempts to save human effort in DNN optimization by searching for optimised transformations given a set of operators. PET then introduces inequivalent transformations and correction mechanisms to find even more optimizations.

- Existing attempts to improve a DNN's tensor algebra expression only address expressions representable by a fixed set of predefined operators (e.g. matrix multiplication), leaving out possible optimization opportunities between general expressions.

- We can improve the design to explore a much larger search space of general expressions. By deriving tensor algebra expressions, we can broaden the search space from predefined operator representable (POR) expressions to **general expressions.**