Shallow2Deep: Restraining Neural Networks Opacity through Neural Architecture Search

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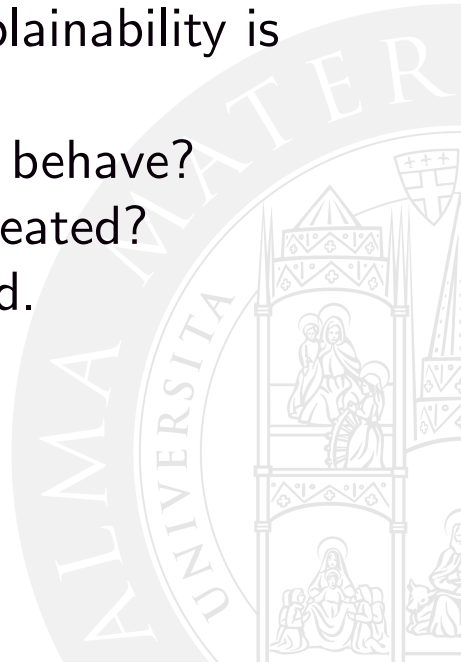


Next in Line...

1. Context & Motivations
2. Shallow2Deep design
3. Experiments & Results
4. Conclusions & future works

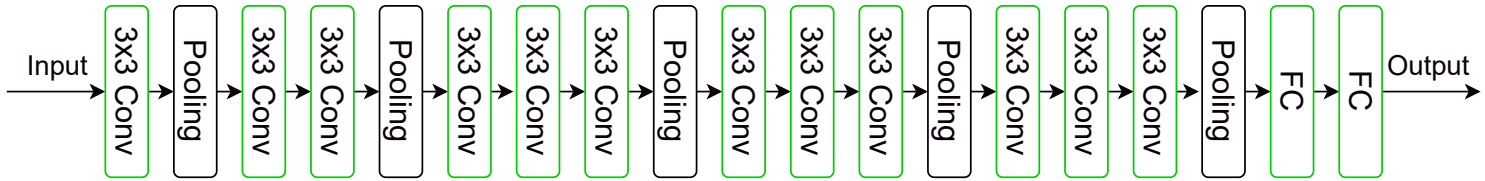
Context

- Neural Networks (NNs) have human-like performances.
- NNs not explainable nor transparent.
- Complexity of NN exaplainability factors:
  - NNs structures obtained via automatic search. $\rightarrow$ Explainability is second thought.
  - Architecture role in performance $\rightarrow$ How NN sections behave?
  - NNs structures are complex. $\rightarrow$ How information is treated?
  - Modern NNs are very deep. $\rightarrow$ Information is modified.

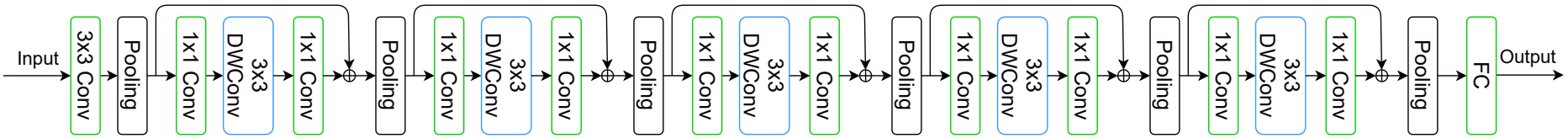


Motivations

- Performance of NNs vastly depend on their structure.



VGG16



MobileNet

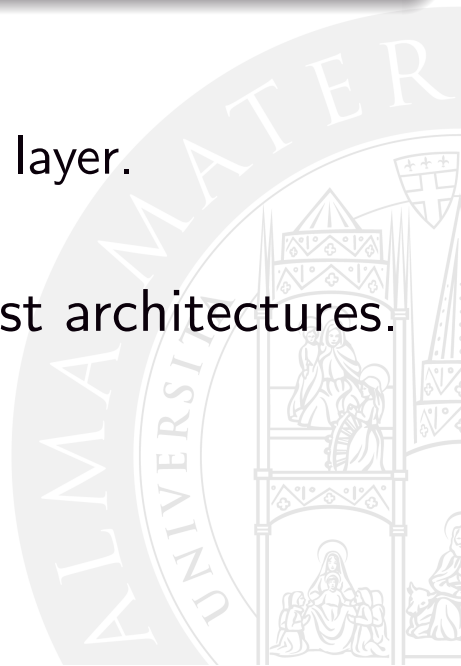
- Neural Architecture Search (NAS) used to build NNs architectures.
- No knowledge about how architecture influences performance.

Neural Architecture Search

Idea

Structure of performing NNs can be discovered via automatic search of a space $\mathcal{S}$.

- The search space $\mathcal{S}$ defines:
  - The operations set $\mathcal{O} \rightarrow$ Functions applicable at each layer.
  - A set of design rules $\mathcal{D} \rightarrow$ Define layers connection.
- NAS algorithm defines how $\mathcal{S}$ is explored to obtain best architectures.



Contribution of the paper

Our contributions

1. Preliminary study on the applicability of NAS in XAI.
2. Use NAS to extract role of local structure variability in NNs.
3. Local variability promotes NN complexity reduction.



Next in Line...

1 Context & Motivations

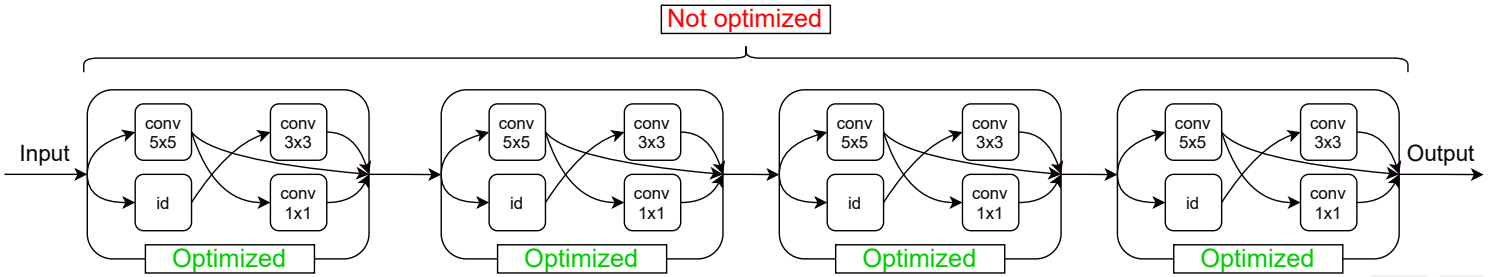
2 Shallow2Deep design

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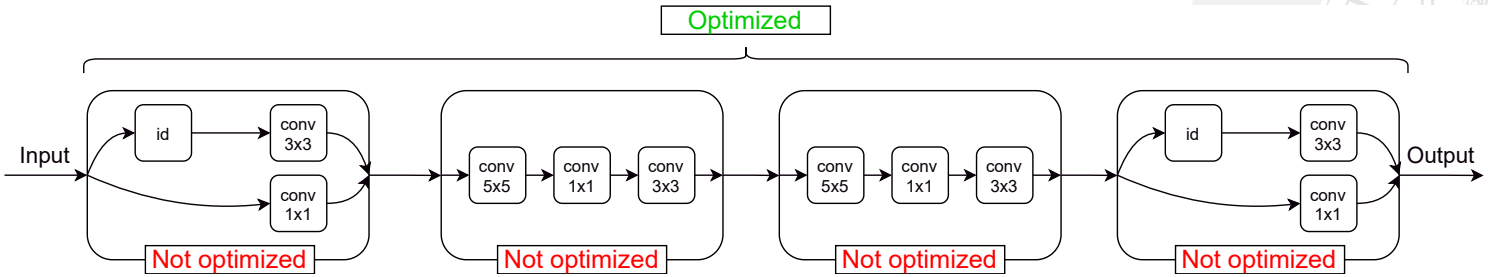
4 Conclusions & future works

Common NAS design

- State-of-the-art NAS can be categorized into:
  - *Local NAS*. NN built repeating *N* times the same *cell*. Best cell is searched [3, 4].



  - *Global NAS*. NN built by concatenating *N* predefined *cells*. The best concatenation is searched [1, 6].

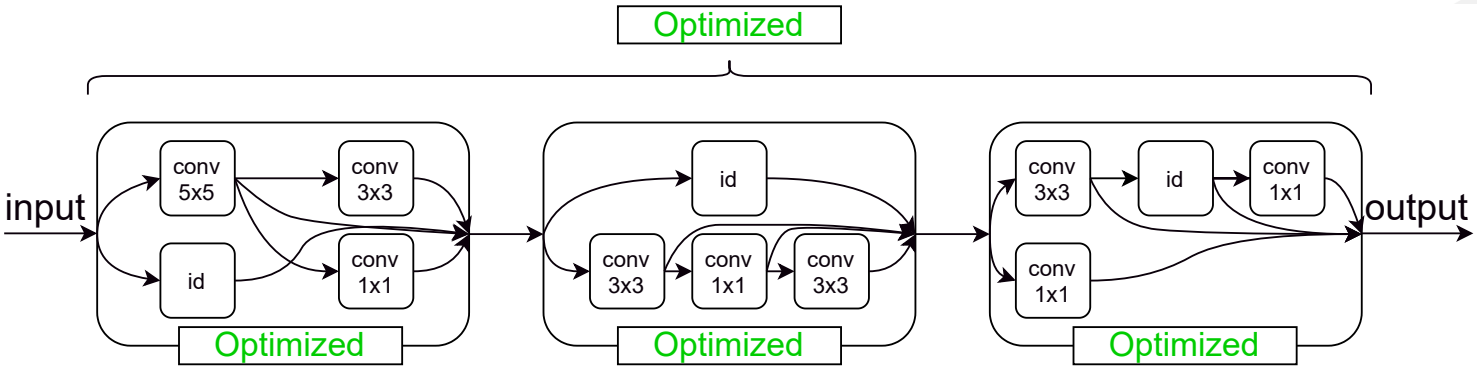


Shallow2Deep design

Idea

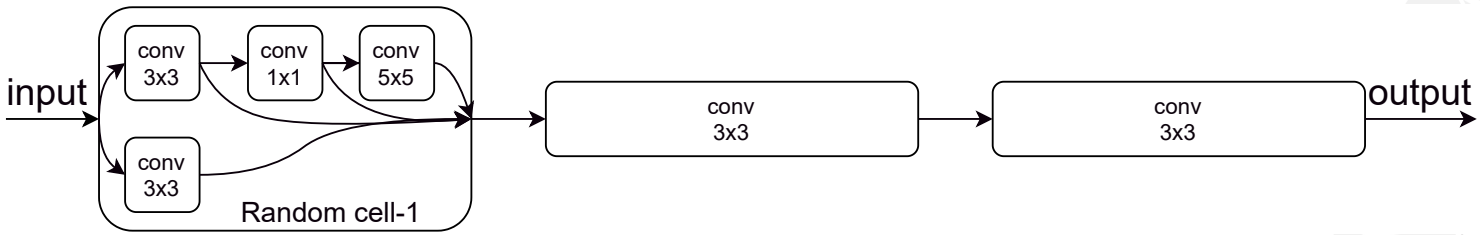
Cells should have different roles. $\Rightarrow$ Cells should have different structures.

- Avoid cell repetition while searching local structures.



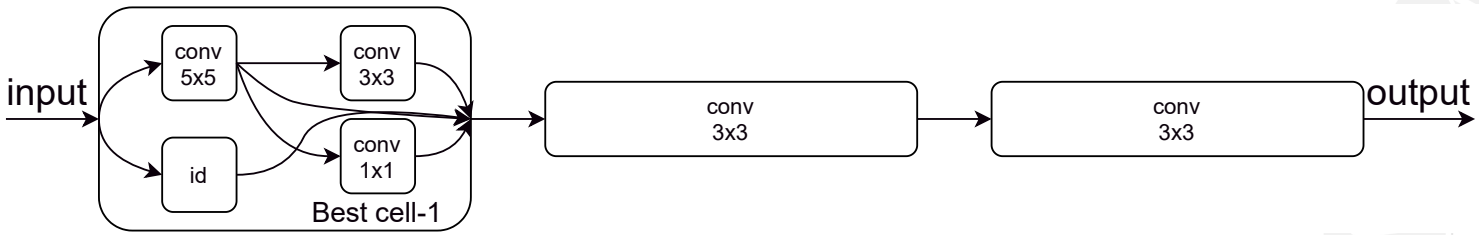
Shallow2Deep search algorithm

- Shallow2Deep searches for the best structure of each cell.
- Cells searched consecutively from closest to input to closest to output.
- When $cell_i$ is searched $cell_j$ with $j \in [i+1, \ldots, C]$ have 3×3 convolution.
- When $cell_i$ is searched $cell_j$ with $j \in [1, \ldots, i-1]$ are not trained.



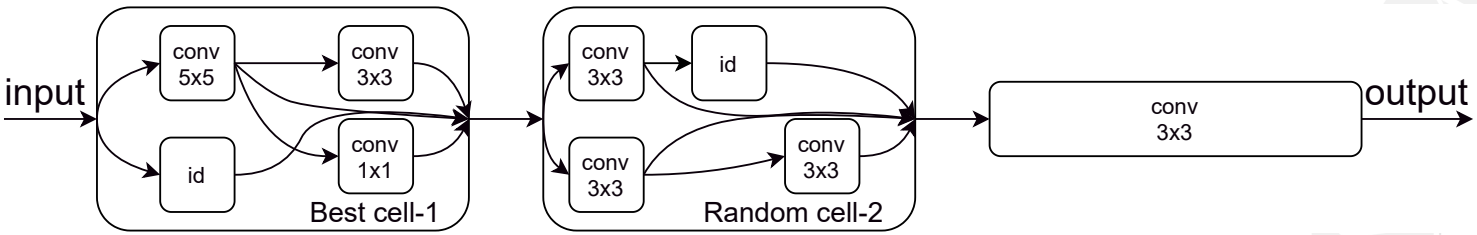
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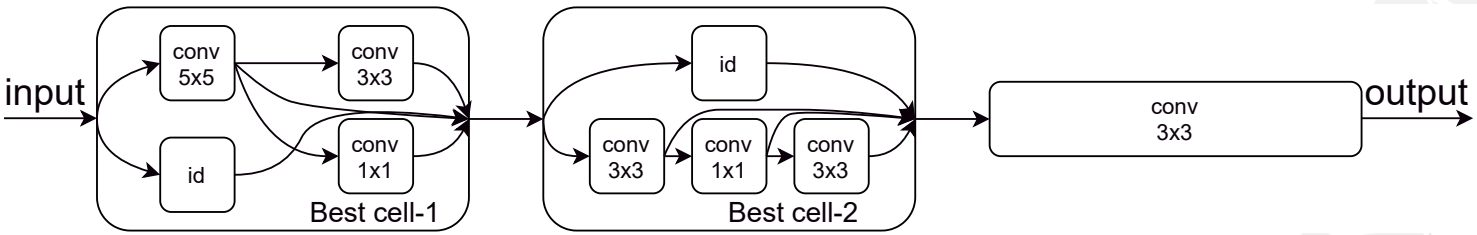
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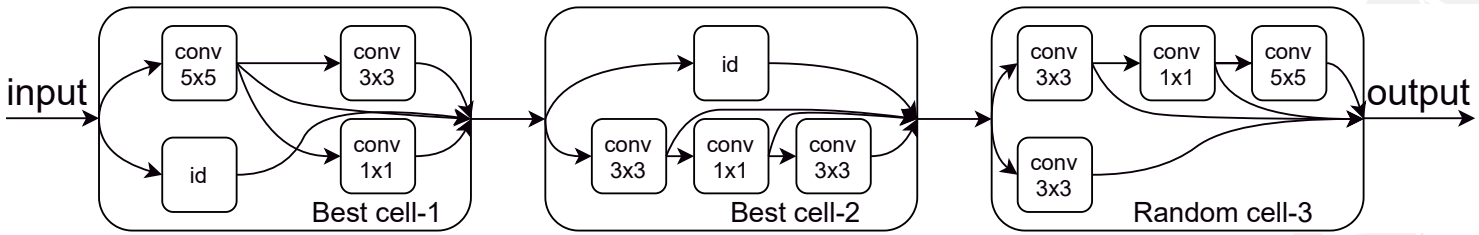
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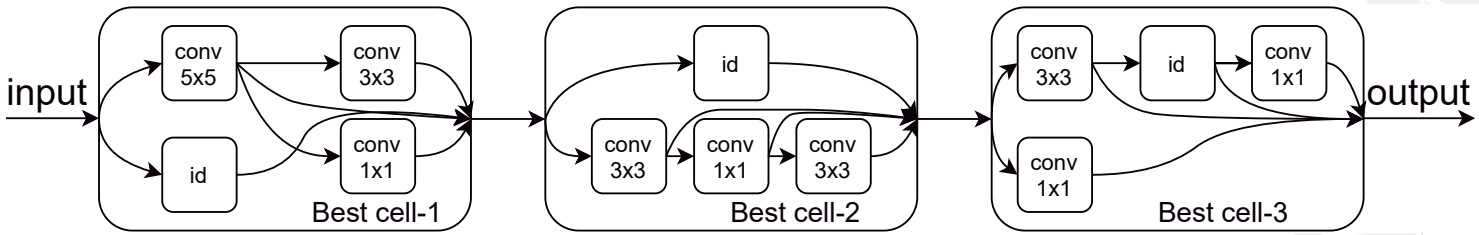
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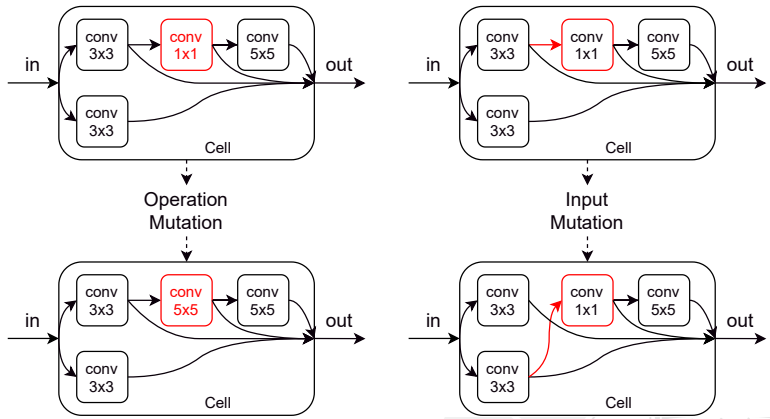
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Shallow2Deep search algorithm

- Cells searched using evolutionary algorithm:
  1. Train all NNs in the population.
  2. Select m best performing architectures.
  3. Incubate new NN via mutation.
- Mutations:
  - *Operation mutation*.
  - *Input mutation*.



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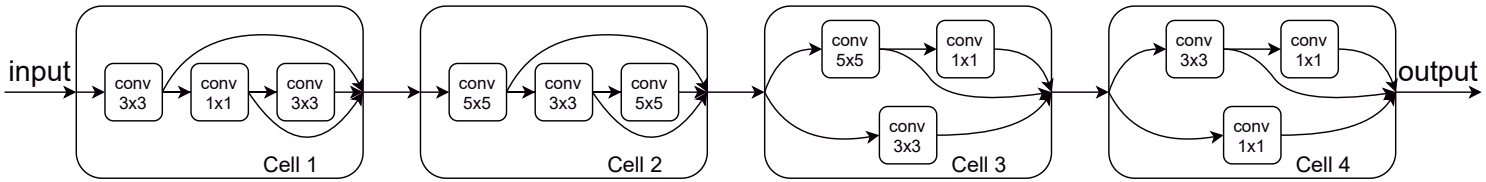
4 Conclusions & future works

Experiments setup

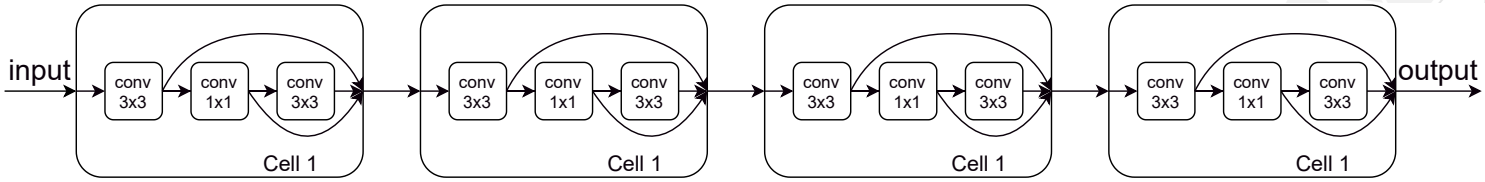
- Test on MNIST fashion [7].
- $\mathcal{O} = \{$ identity, 1×1 conv, 3×3 conv, 5×5 conv $\}$
- Number of architectures $|\mathcal{N}| = |\mathcal{S}|^C = \left((B+1)! \cdot |\mathcal{O}|^B\right)^C$ where:
  - $\mathcal{S}$ is the search space.
  - C is the number of cells.
  - B is the number of blocks in a cell.
- $B = 3,\ C = 4 \quad \Rightarrow \quad |\mathcal{N}| = 5.57 \cdot 10^{12}$.

Results

- Novel architecture *S2DNN* does not resemble well-known NNs.



- *S2DNN* compared with NN built repeating its own cells.



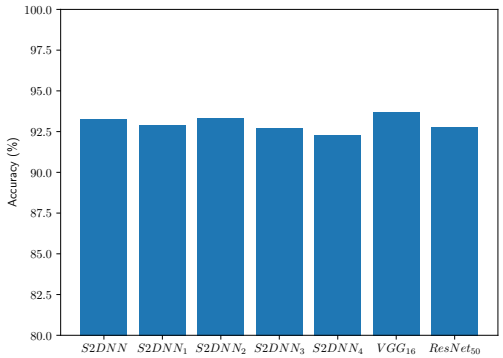
$S2DNN_1$

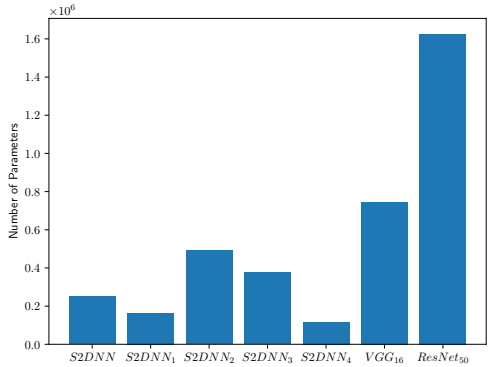
Results

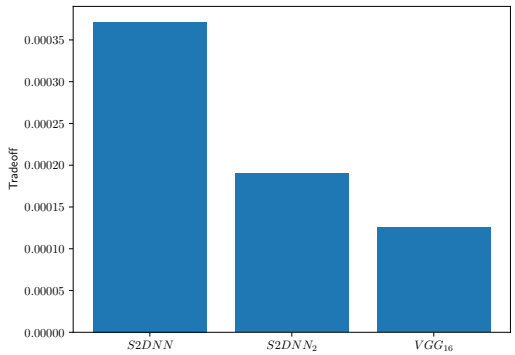
- *S2DNN* performes better than ResNet50 [2].
- *S2DNN* similar to VGG16 [5] while one third of parameters.
- *S2DNN* performes better than most $S2DNN_i$.
- *S2DNN* best model w.r.t. performance/footprint trade-off.

$$\Downarrow$$

Structure variability is desirable.







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Conclusions

Summing up

- We propose an exhaustive NAS algorithm.
- S2DNN comparable to state-of-the-art models while smaller.
- Prooved local structure variability is desirable w.r.t. performance/footprint trade-off.
- NAS can be used to check for NN properties.



Future works

Future research directions

- Test Shallow2Deep on a more challenging dataset.
- Test Shallow2Deep over a larger $\mathcal{O}$.
- Test iterative search of cells with dynamic C.



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