Composed Fine-Tuning: Freezing Pre-trained Denoising Autoencoders for Improved Generalization

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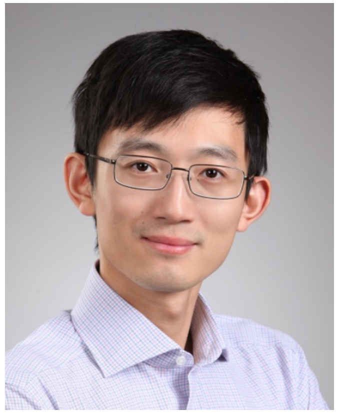


High-dimensional output spaces

```python
def partition(array, start, end):
    pivot = array[start]
    low = start + 1
    high = end
    while True:
        while low <= high and array[high] >= pivot:
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        while low <= high and array[low] <= pivot:
            low = low + 1
        if low <= high:
            array[low], array[high] = array[high], array[low]
        else:
            break
    array[start], array[high] = array[high], array[start]
    return high

def quick_sort(array, start, end):
    if start >= end:
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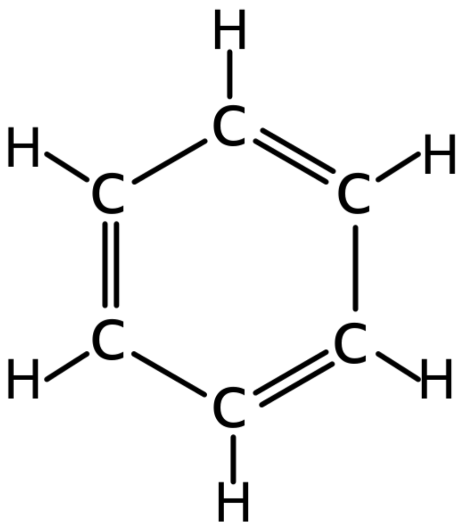
    p = partition(array, start, end)
    quick_sort(array, start, p-1)
    quick_sort(array, p+1, end)
```

Code



Molecules

Language

Natural Images

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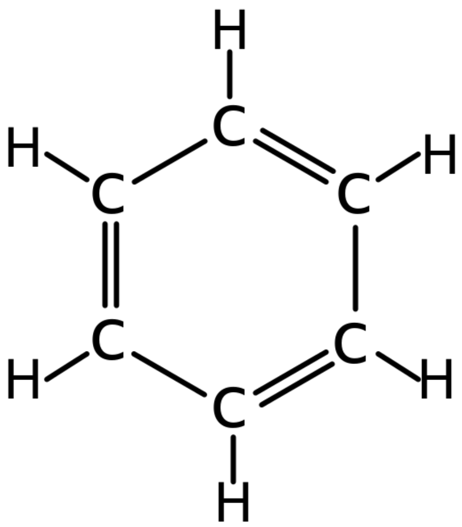
Code

Compiles/Executes



Molecules

Forms a stable molecule

Language

Grammar/syntax

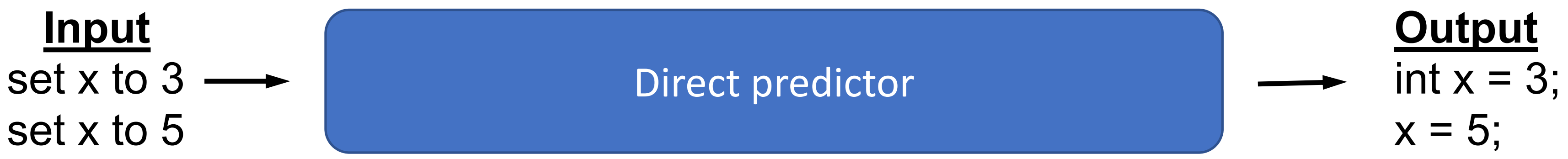
Natural Images

Physical constraints, familiar objects, sharp lines

Output structure: only some outputs are valid

Supervised learning

- Example: Pseudocode-to-code (Kulal et al. 2019)



Supervised learning

- Example: Pseudocode-to-code (Kulal et al. 2019)

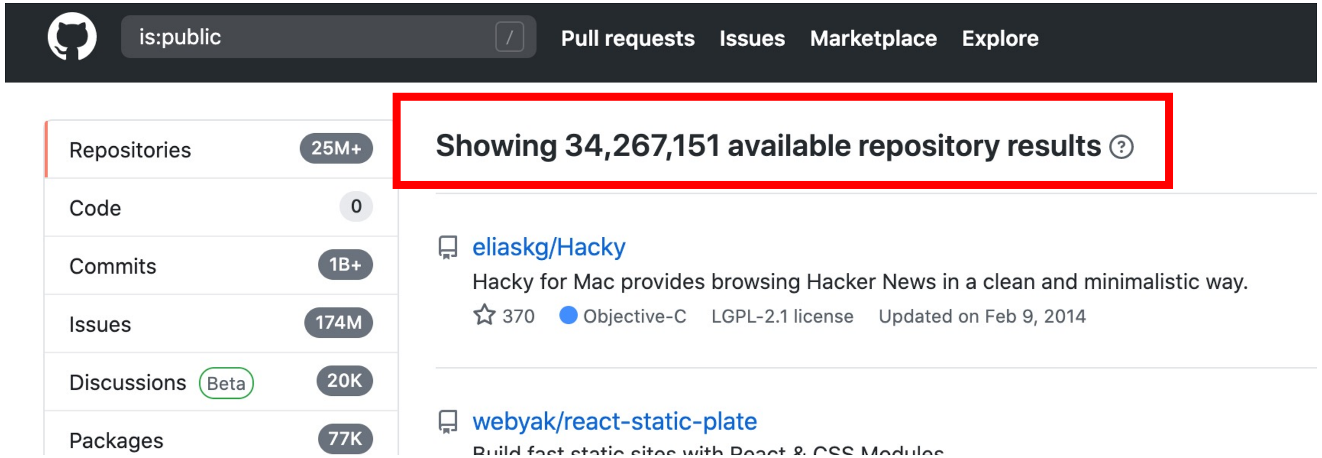
Input
set x to 3
set x to 5

Direct predictor

Output
int x = 3;
x = 5;

Predictor handles both **input-output mapping** and **output structure**

”Unlabeled” output data is abundant



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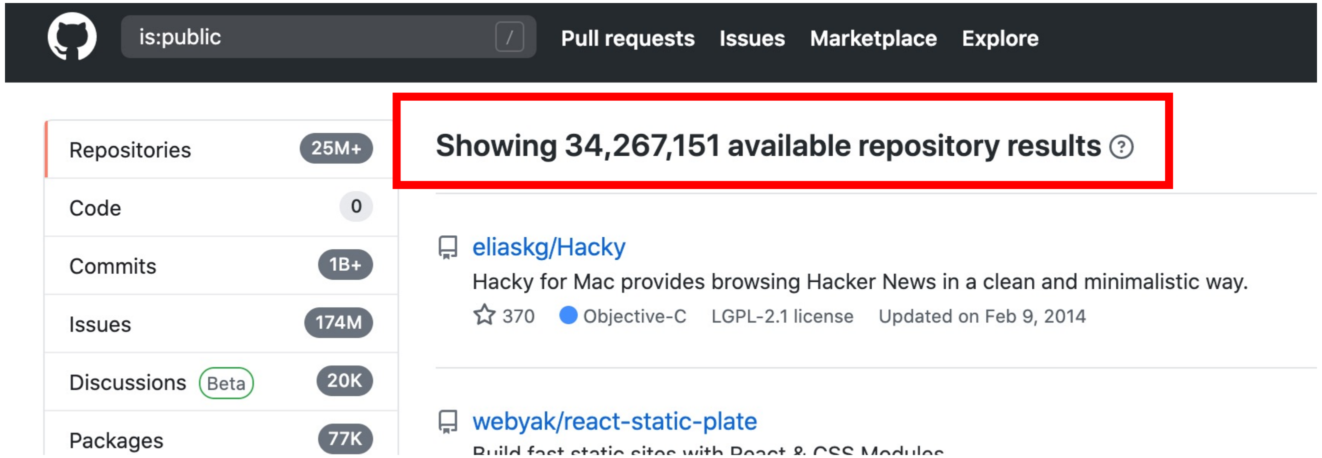
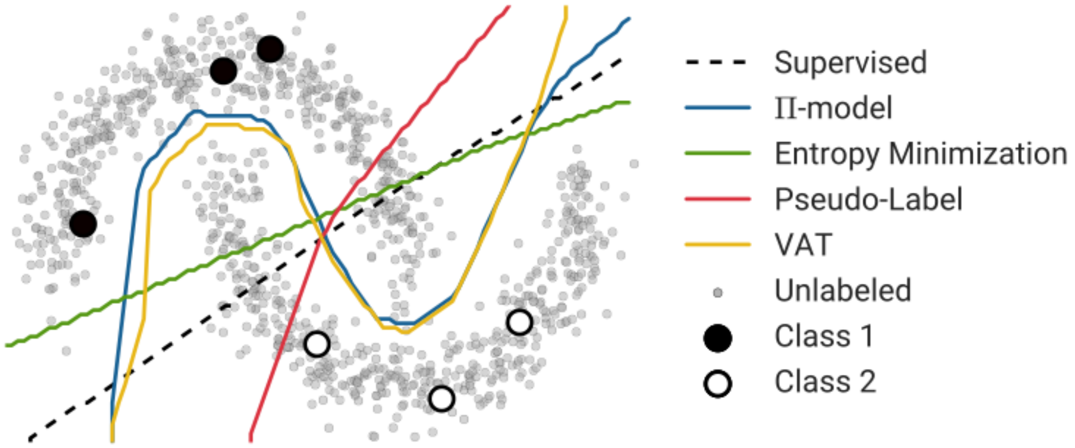


Unlabeled output data can be used for learning the output structure

Unlabeled outputs: not standard SSL

- Standard semi-supervised learning: unlabeled inputs for improving classifier



Oliver et al. 2018

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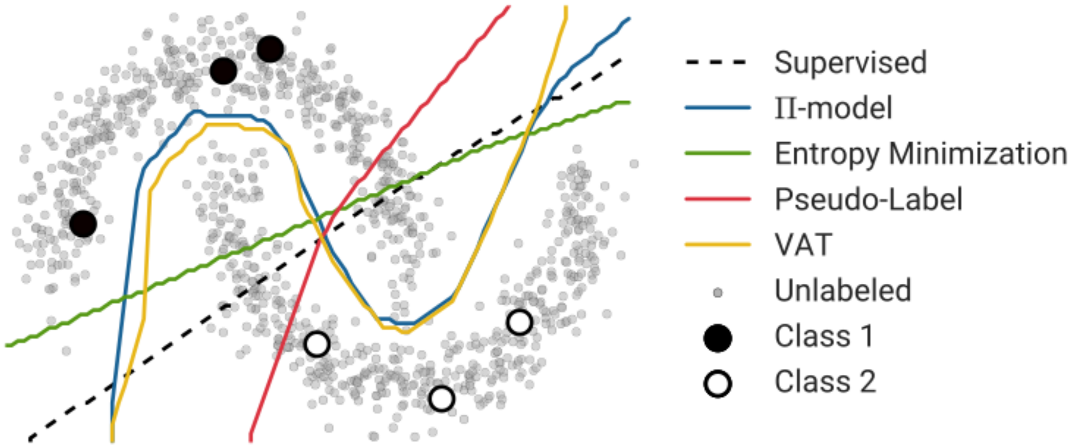
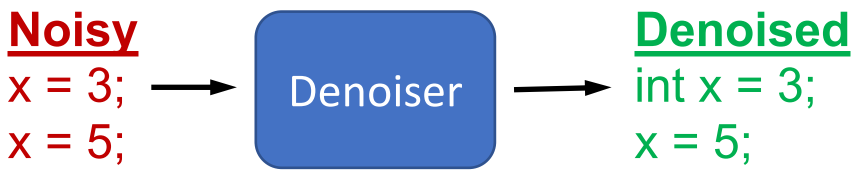


Oliver et al. 2018

- Leveraging unlabeled outputs requires a different way of thinking

Pre-train + Fine-tune paradigm

- Output structure: Pre-train a denoising autoencoder (denoiser) on large unlabeled data
  - (BART/T5 Lewis et al. 2020, Raffel et al. 2019)



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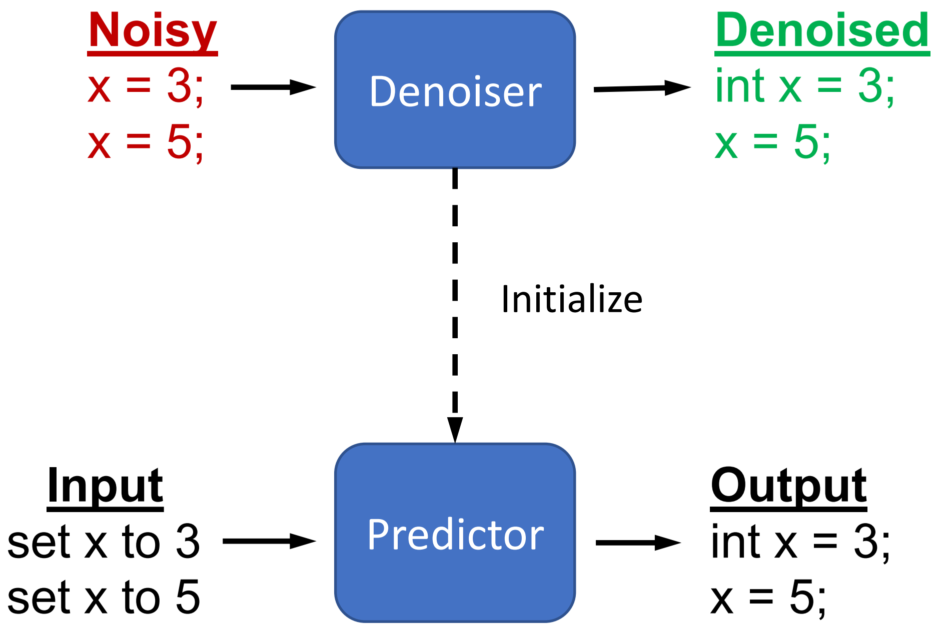

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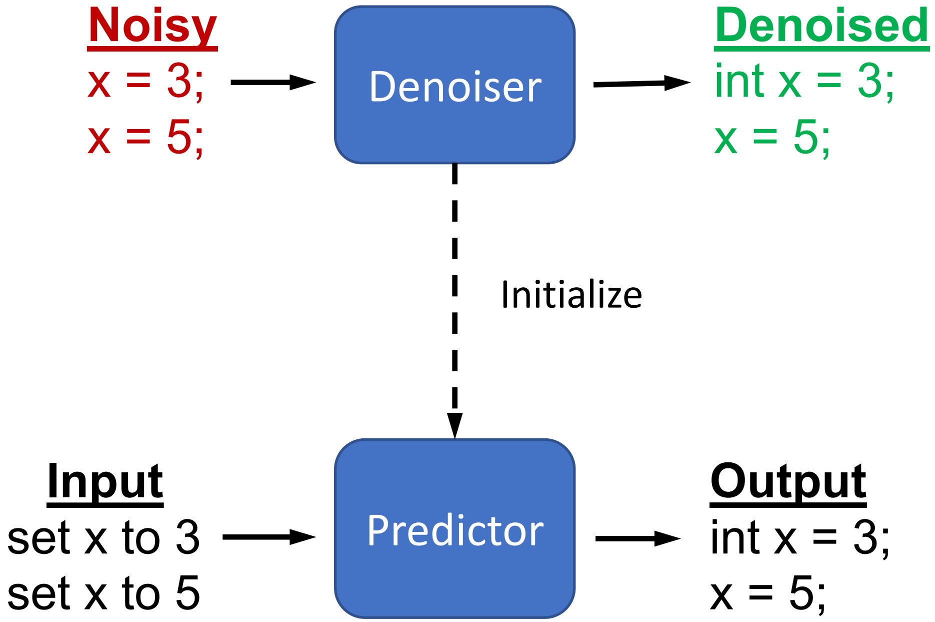

Highly accessible: don’t need unlabeled data during fine-tuning

How well does standard fine-tuning use pre-trained information?

Experiment:

1. Train standard fine-tuned model initialized from pre-trained denoiser

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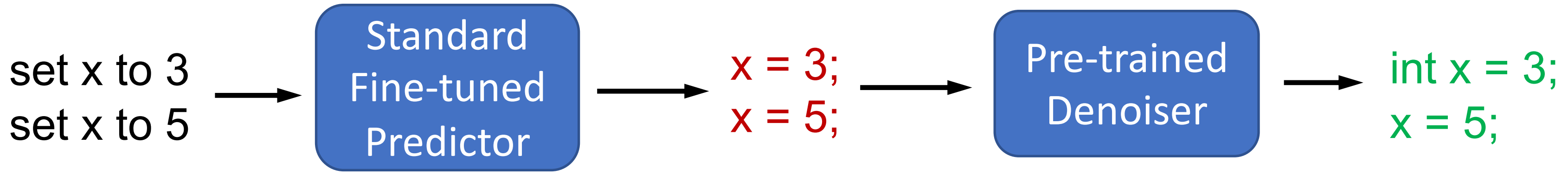
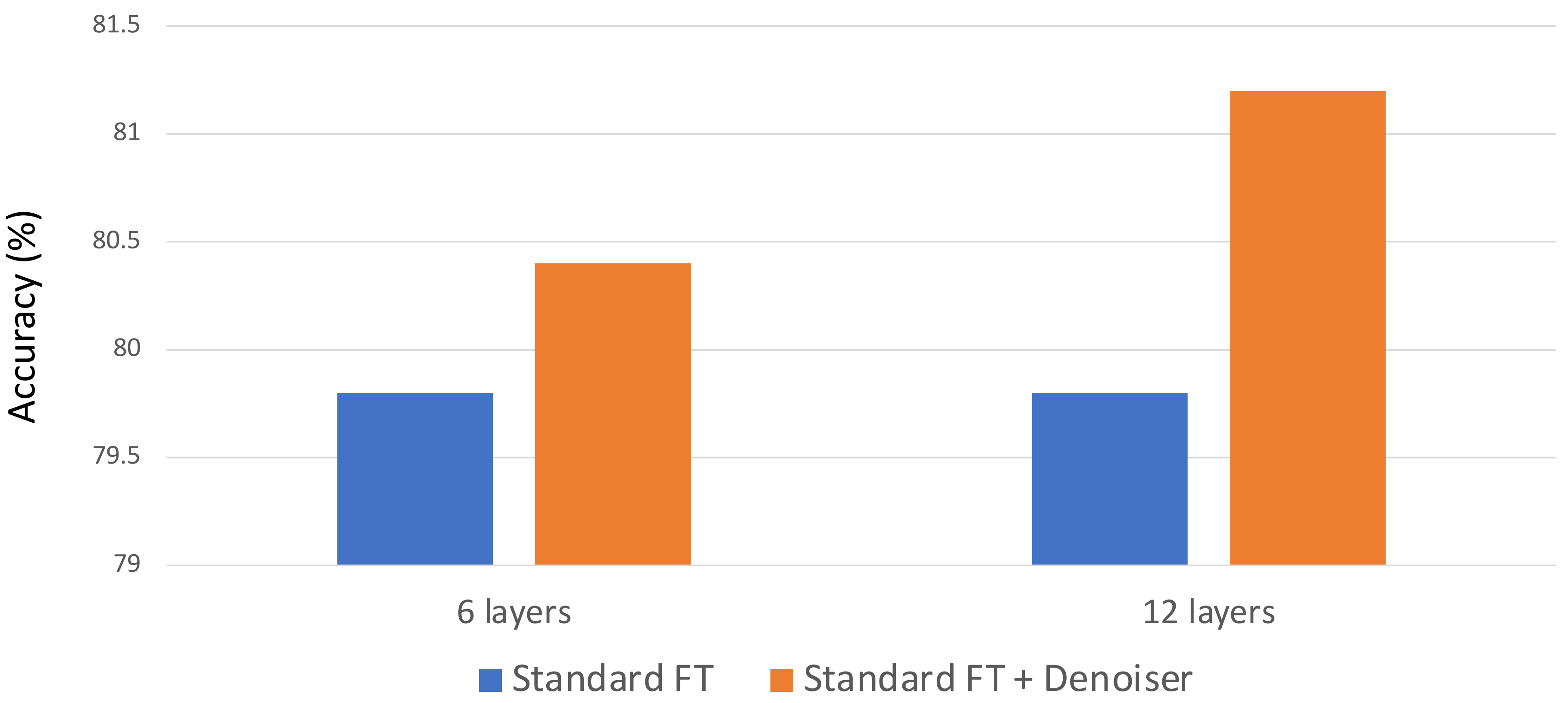
Experiment:

1. Train standard fine-tuned model initialized from pre-trained denoiser
2. Apply the denoiser to the predictions at test-time



Standard fine-tuning destroys some pre-trained output structure

In our SansType pseudocode-to-code dataset, re-applying the denoiser post-hoc improves accuracy by 0.5% to 1.5%



Outline

- Algorithm: Composed fine-tuning
- Analysis: Composing can reduce complexity
- Experiments: pseudocode-to-code and image generation

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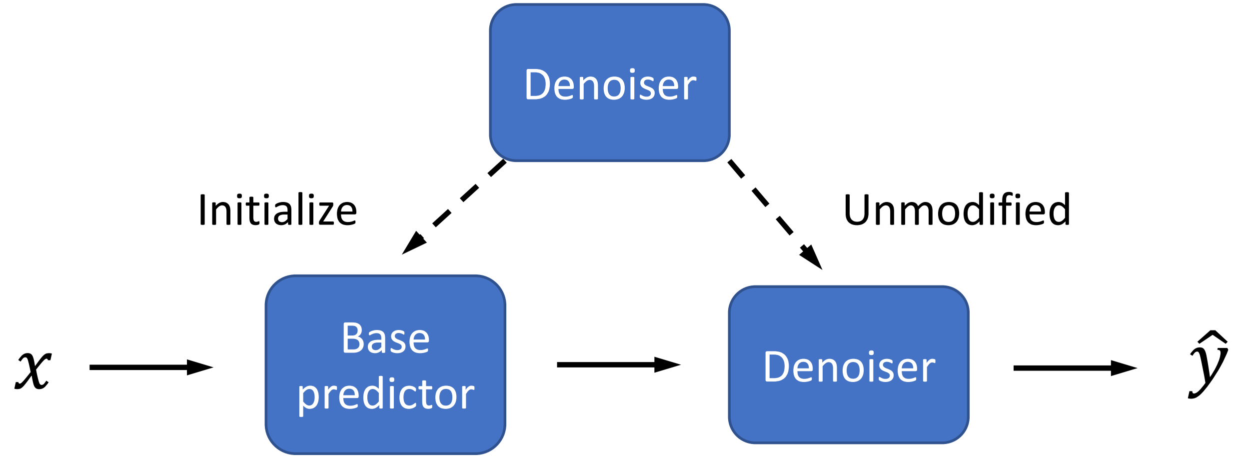
Composed Fine-Tuning

Given pre-trained denoiser Π, learn the base predictor f_θ composed with denoiser on labeled data:



$$Loss(x, y, \theta) = \ell(\Pi \circ f_\theta(x), y) + \lambda \ell(f_\theta(x), y)$$

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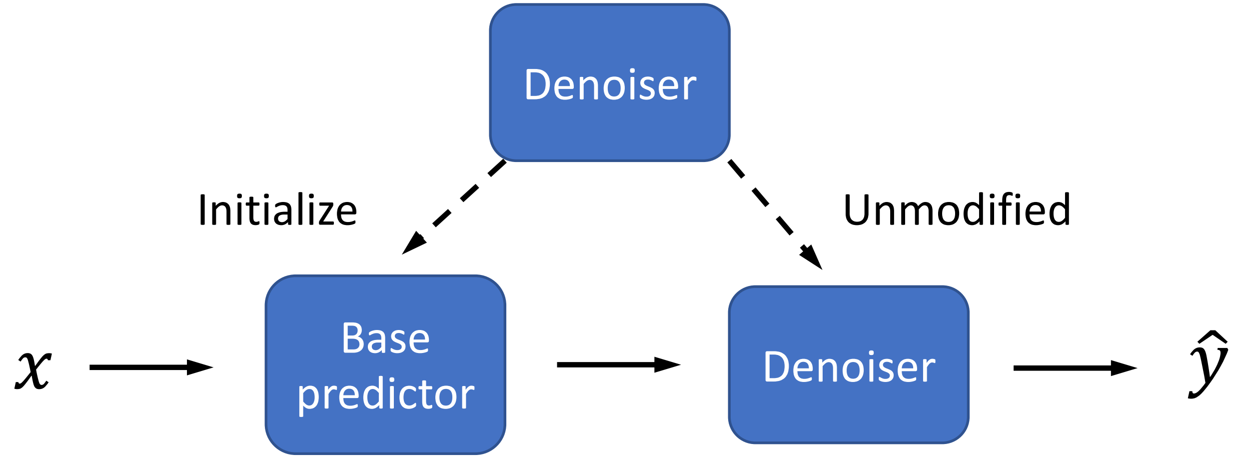

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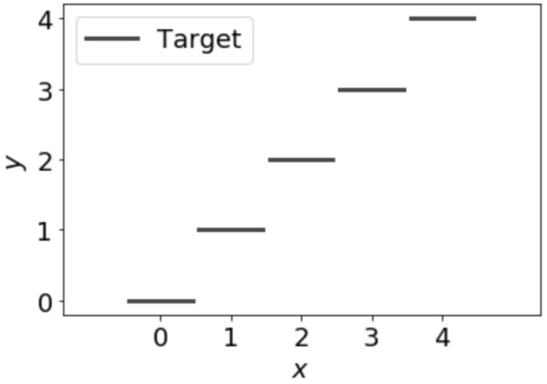
Offload complexity of learning output structure to the pre-trained denoiser

Composed fine-tuning simplifies models

- Target function: staircase function
  - valid outputs are integers



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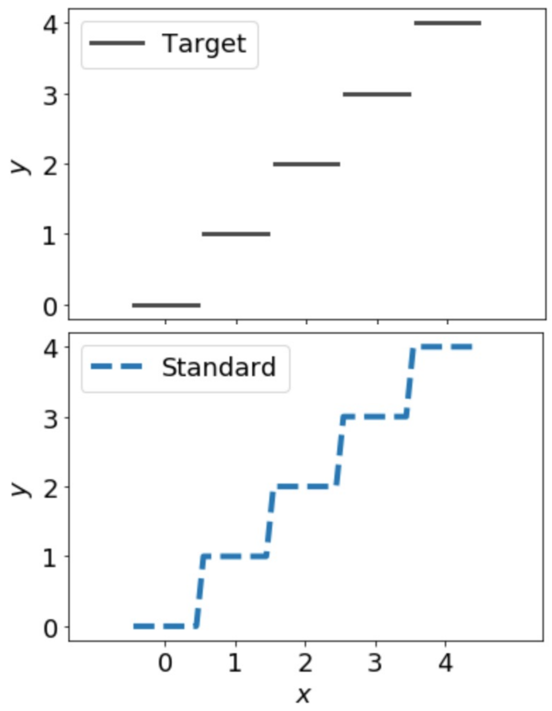

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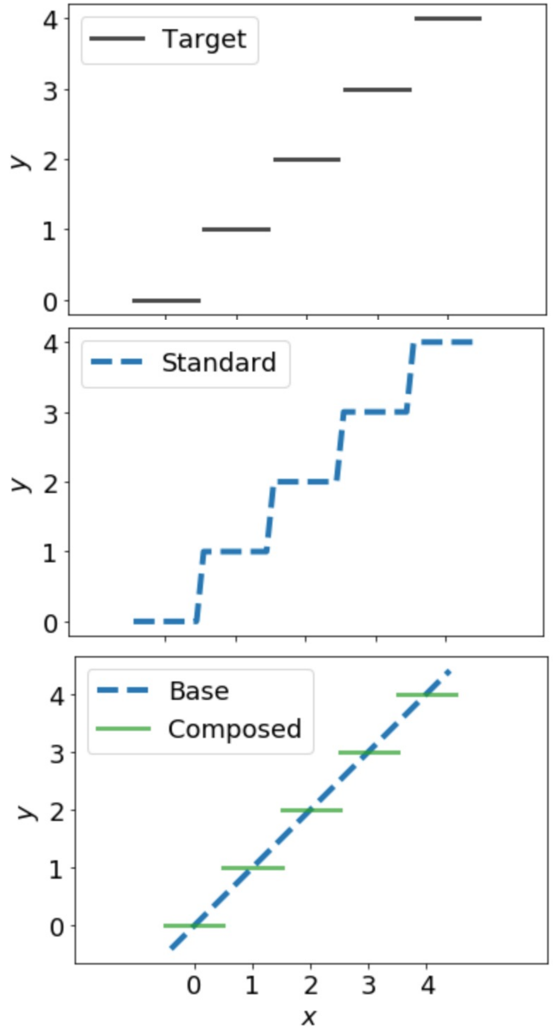

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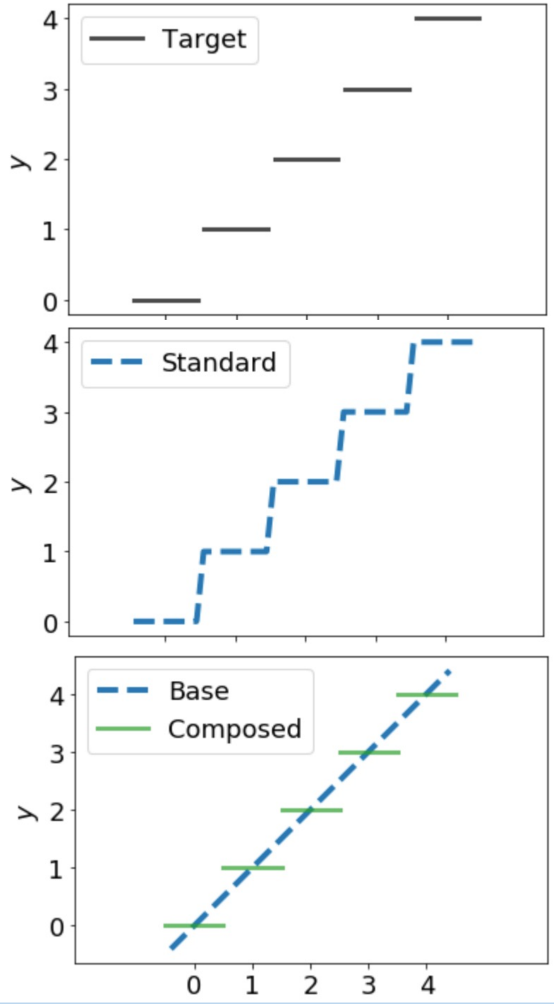

Base predictor is simple (linear) and extrapolates perfectly

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- Analysis: Composing can reduce complexity
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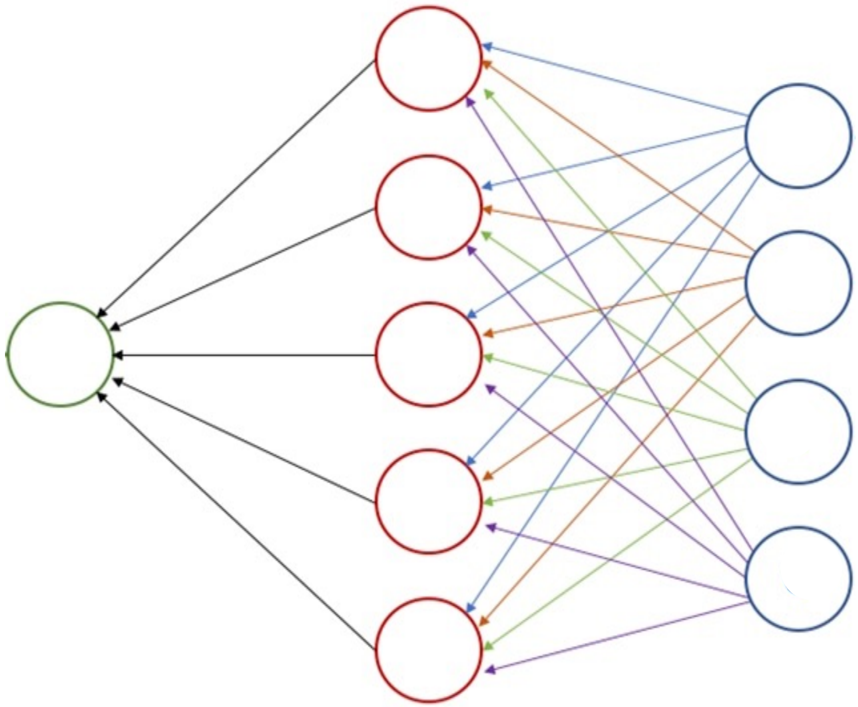
Analysis of composed fine-tuning

Setup

- Base model f_θ: 2 layer ReLU net with high-dim output
- Denoiser Π: projects to the nearest valid output
- Complexity measure $C(\theta)$: L2 norm of weights θ



Lower complexity -> better generalization

Analysis of composed fine-tuning

Can composed learning increase complexity?

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$$C(\theta_{std}) = \min_\theta\{C(\theta): f_\theta = f^*\}$$
$$C(\theta_{composed}) = \min_\theta\{C(\theta): \Pi \circ f_\theta = f^*\}$$

then

$$C(\theta_{composed}) \leq C(\theta_{std})$$

since $f_{\theta_{std}}$ is a feasible solution of the composed problem.

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since $f_{\theta_{std}}$ is a feasible solution of the composed problem.

Composing with a denoiser never increases the complexity

Composing can reduce model complexity

How much does composing decrease complexity?

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- We prove that composing can arbitrarily reduce complexity, depending on the stability of the target function

$$\frac{C(\theta_{std})}{C(\theta_{composed})} \rightarrow \infty \text{ as target function is more stable}$$

Composing can reduce model complexity

How much does composing decrease complexity?

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More stability in input-output mapping -> composing helps more

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Pseudocode-to-code

Example: from our generated SansType dataset, where pseudocode specifies all but the types

```
set var_8 to "str_2";
instantiate var_2;
read var_2 from stdin;
add "str_4" to the beginning of var_8;
set var_2 to false;
set var_5 to true;
if var_2 is true, ↩
        swap the values of var_2 and var_5;
if var_2 is true↩
        , set var_2 to the value of var_5↩
         and var_5 to the value of var_2;
output var_8 to stdout;
print var_2;
output var_5 to stdout;
```

Input pseudocode

```
int main () {
  string var_8 = "str_2";
  bool var_2;
  cin >> var_2;
  var_8 = "str_4" + var_8;
  var_2 = false;
  var_5 = true;
  if ( var_2 ) {
    string temp = var_2;
    var_2 = var_5;
    var_5 = temp; }
  if ( var_2 ) {
    bool temp = var_2;
    var_2 = var_5;
    var_5 = temp; }
  cout << var_8;
  cout << var_2;
  cout << var_5;
  return 0; }
```

Base predictor

```
int main () {
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  bool var_2;
  cin >> var_2;
  var_8 = "str_4" + var_8;
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Composed

Pseudocode-to-code

- **Task**: *full-program* pseudocode-to-code translation with Transformers (Vaswani et al. 2017) – correct code passes test cases
  - Previous works consider line-by-line translation and compiler side information (Kulal et al 2019, Yasunaga and Liang 2020)

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  - Previous works consider line-by-line translation and compiler side information (Kulal et al 2019, Yasunaga and Liang 2020)
- **Validity**: code must compile & execute

SansType: synthetic pseudocode-to-code

- Dataset generation: generate pseudocode and code from templates
- Test sets
  - In-distribution (ID): same templates as training
  - Out-of-distribution (OOD): mix-and-matched ID pseudocode templates

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  - In-distribution (ID): same templates as training
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- Example:
  - ID templates: `print <var>`, `output <var> to stdout`
  - OOD templates: `print <var> to stdout`, `output <var>`, `stdout <var>`

SPoC dataset for pseudocode-to-code

- Crowdsourced pseudocode for programming competition code from codeforces.com

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- Crowdsourced pseudocode for programming competition code from codeforces.com
- Two test sets:
  - ID: test generalization to new pseudocode for previously seen programs
  - OOD: test generalization to new programs

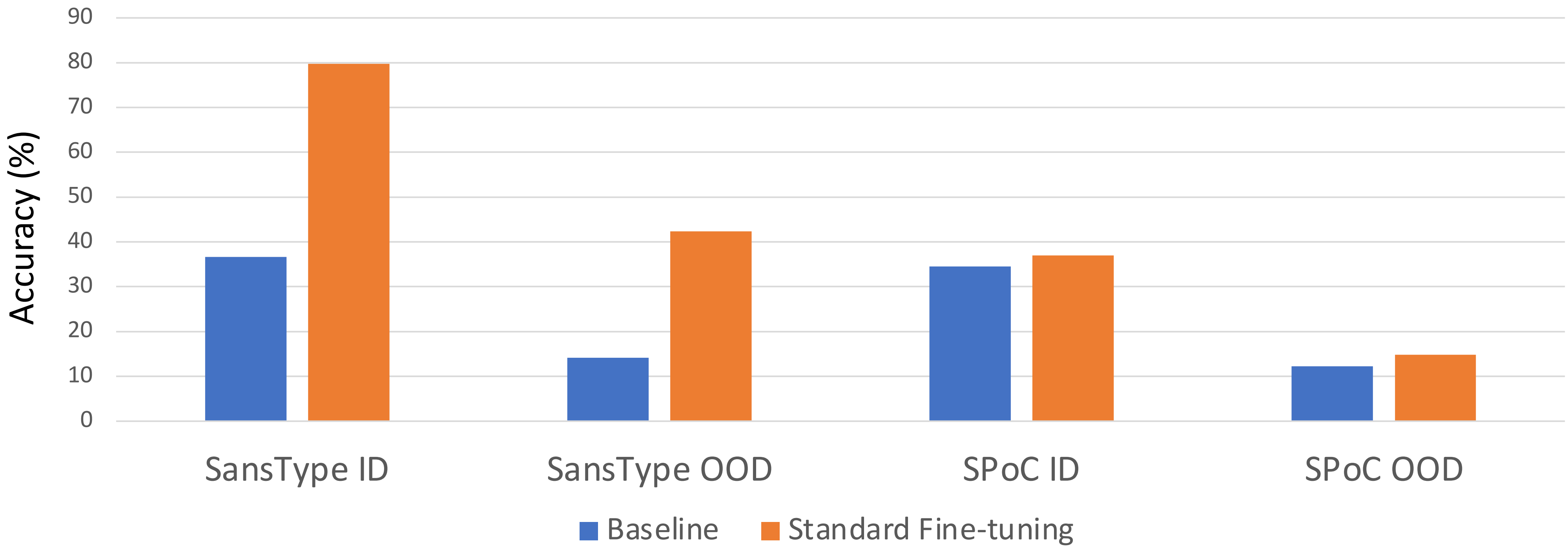
```
in function main
  let n be integer
  read n
  let A be vector of integers
  set size of A = n
  read n elements into A
  for all elements in A
    set min_i to i
    for j = i + 1 to size of A exclusive
      set min_i to j if A[min_i] > A[j]
    swap A[i], A[min_i]
  print all elements of A
```

```
int main() {
  int n;
  cin >> n;
  vector<int> A;
  A.resize(n);
  for(int i = 0; i < A.size(); i++) cin >> A[i];
  for(int i = 0; i < A.size(); i++) {
    int min_i = i;
    for(int j = i+1; j < A.size(); j++) {
      if(A[min_i] > A[j]) { min_i = j; }
    swap(A[i], A[min_i]);
  for(int i=0; i<A.size(); i++) cout<<A[i]<<" ";
}
```

Kulal et al. 2019

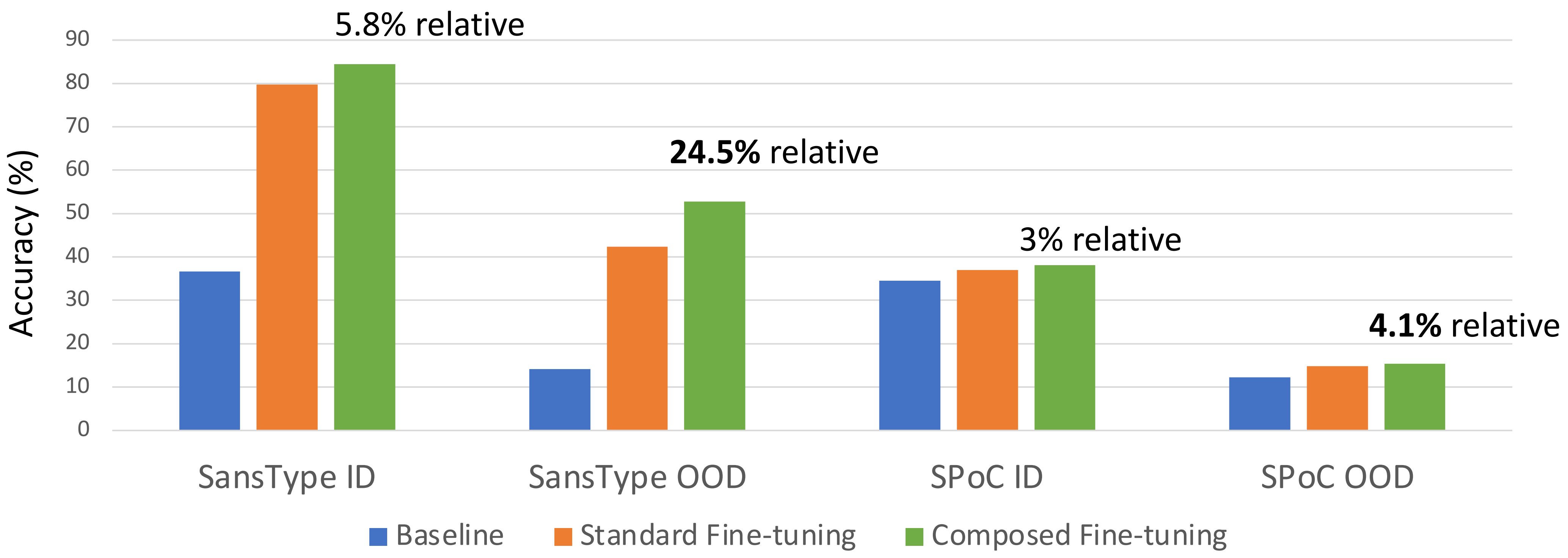
Pseudocode-to-code results

- Standard fine-tuning improves over baseline (no pretraining)



Pseudocode-to-code results

- Standard fine-tuning improves over baseline (no pretraining)
- Composed fine-tuning improves both ID and OOD, but especially OOD



Stronger baselines

- **Scaled-up baseline**: double the number of layers
  - Note: pre-trained denoiser is also doubled for these models
- **Test-time denoiser**: apply denoiser post-hoc to baseline/standard fine-tuning

Stronger baselines

- **Scaled-up baseline**: double the number of layers
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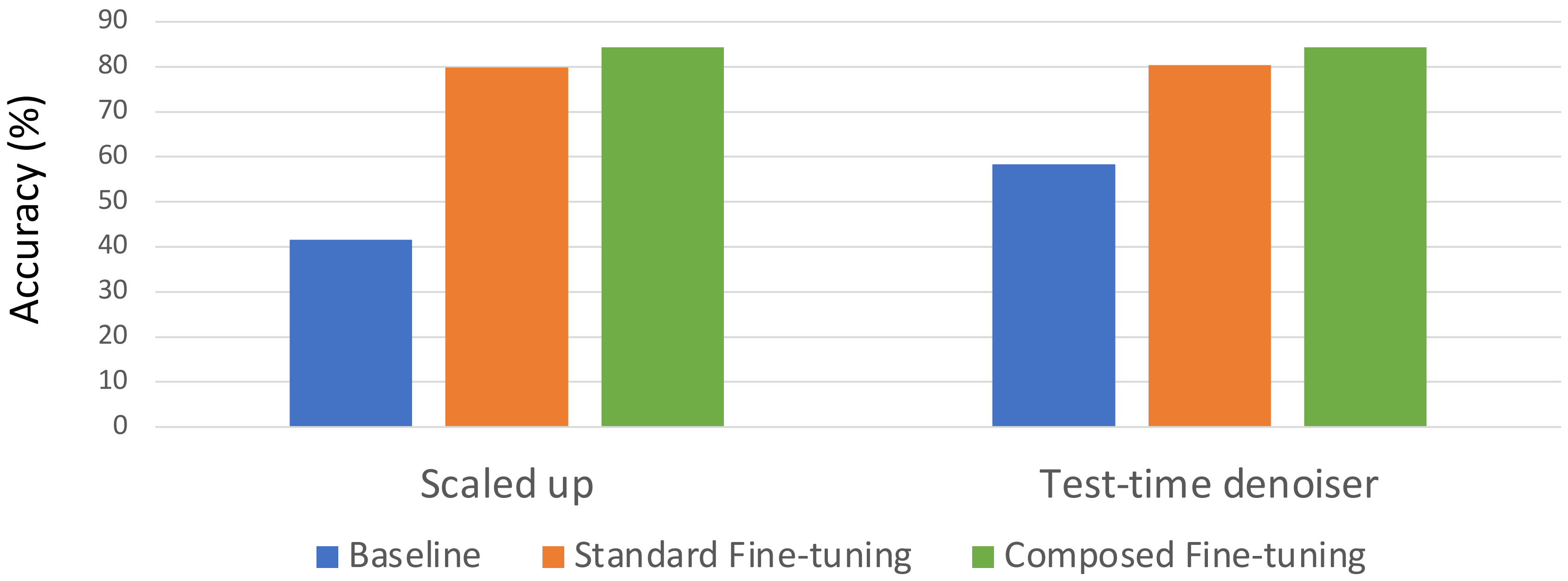
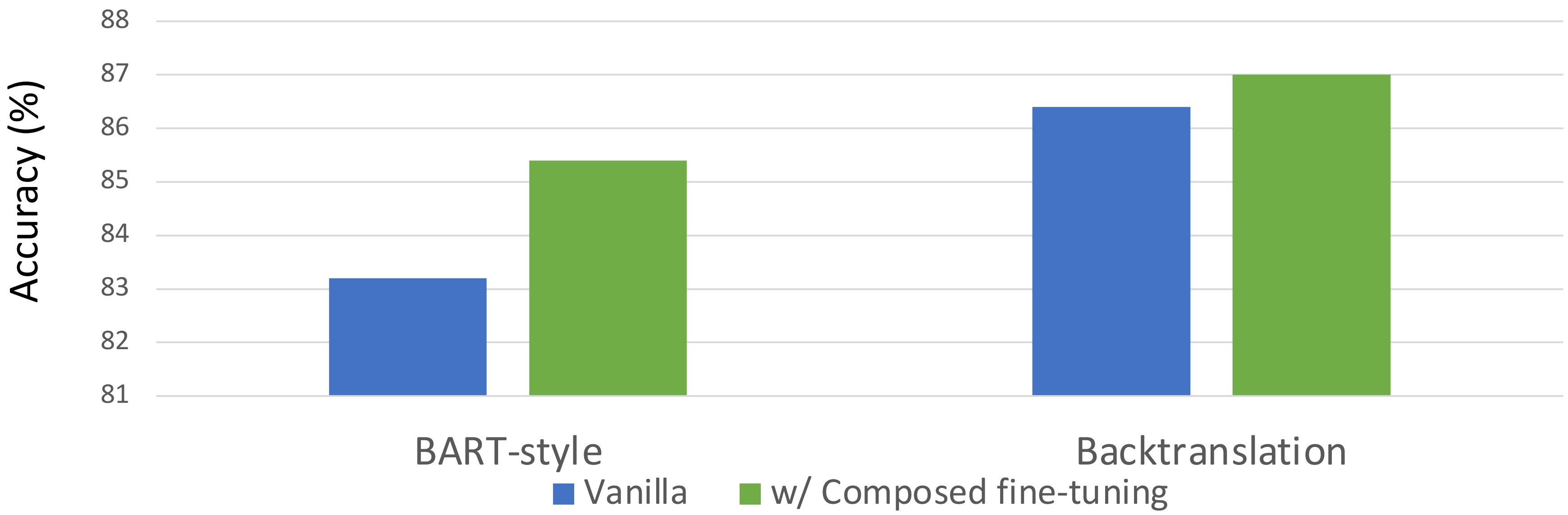
- **Test-time denoiser**: apply denoiser post-hoc to baseline/standard fine-tuning
- Composed fine-tuning still improves over these (SansType)



Composed fine-tuning is complementary with fancier methods

- BART-style fine-tuning
  - Two-stage process: freeze later layers first, then fully finetune
- Backtranslation (Sennrich et al. 2015)
  - Use unlabeled output data during fine-tuning to create synthetic inputs



OOD conditional image generation

Train

[D, Disney font] → 

Test

[i, Disney font] → 

- **Task**: given font family and character, output a font image
- **Validity**: font images have sharp lines, adhere to font styling

OOD conditional image generation

Train

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Test

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- **Validity**: font images have sharp lines, adhere to font styling

- Useful for prototyping new fonts: supply a few characters and the model fills in the rest
- Extrapolate to new character-font pairs at test time

OOD conditional image generation

- Image generations for some random fonts (MLP base model)

(a) Direct

OOD conditional image generation

- Image generations for some random fonts (MLP base model)

(a) Direct

(b) Composed

OOD conditional image generation

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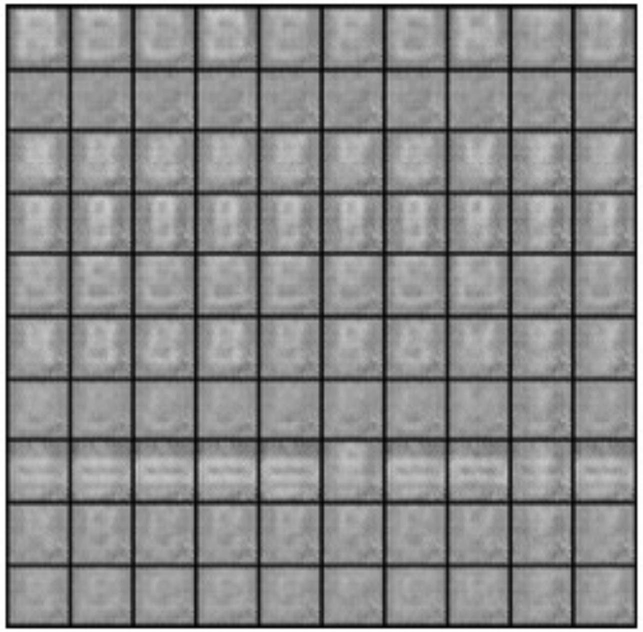

(c) Base

Base predictor is simpler – gray and blobby outputs

Takeaways

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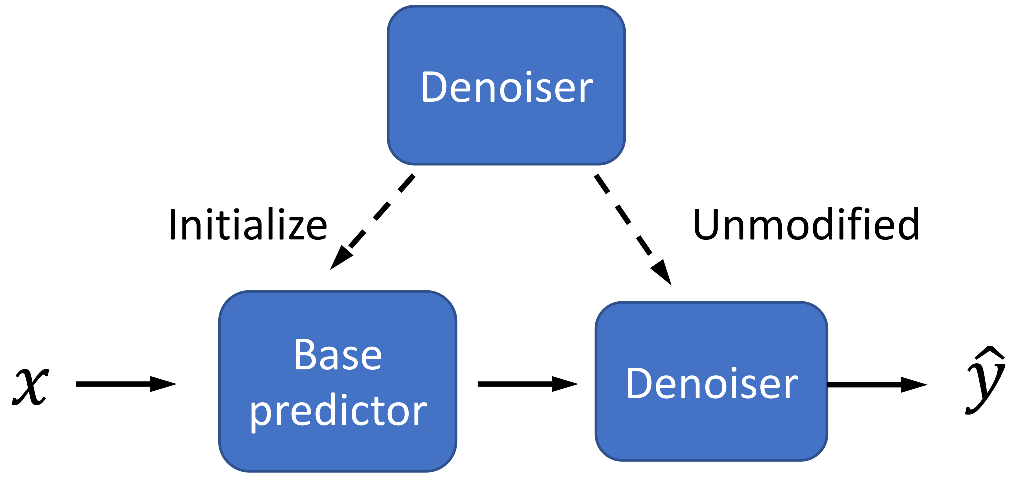

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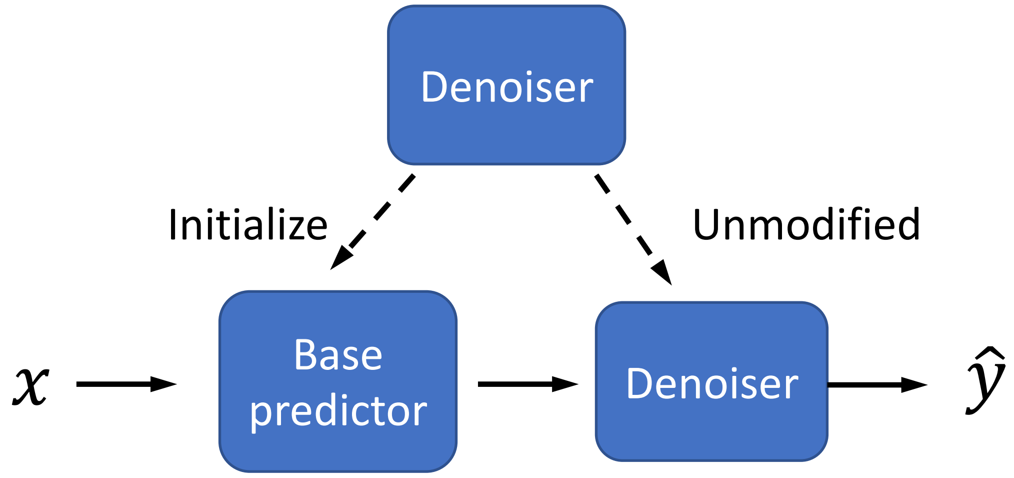
- **Composed fine-tuning** preserves it by freezing the denoiser. Base predictor only needs to learn the input-output mapping
- Composed fine-tuning leads to **reduced complexity** and **better generalization**, especially **OOD**!



Thanks!

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