Transfer Learning: how to learn from little data

The biggest constraint in training a model is obtaining a sufficient amount of training data.

The deeper (greater number of layers) your model

- the more weights/parameters need to be estimated
- increases the quantity of training data

Recall our lecture on Interpreting the layers of a Neural Network

- layers close to the input seem to learn simple features
- layer l creates new features that are combinations of features of layer $(l-1)$

Is it possible that we can "re-use" feature transformations ?

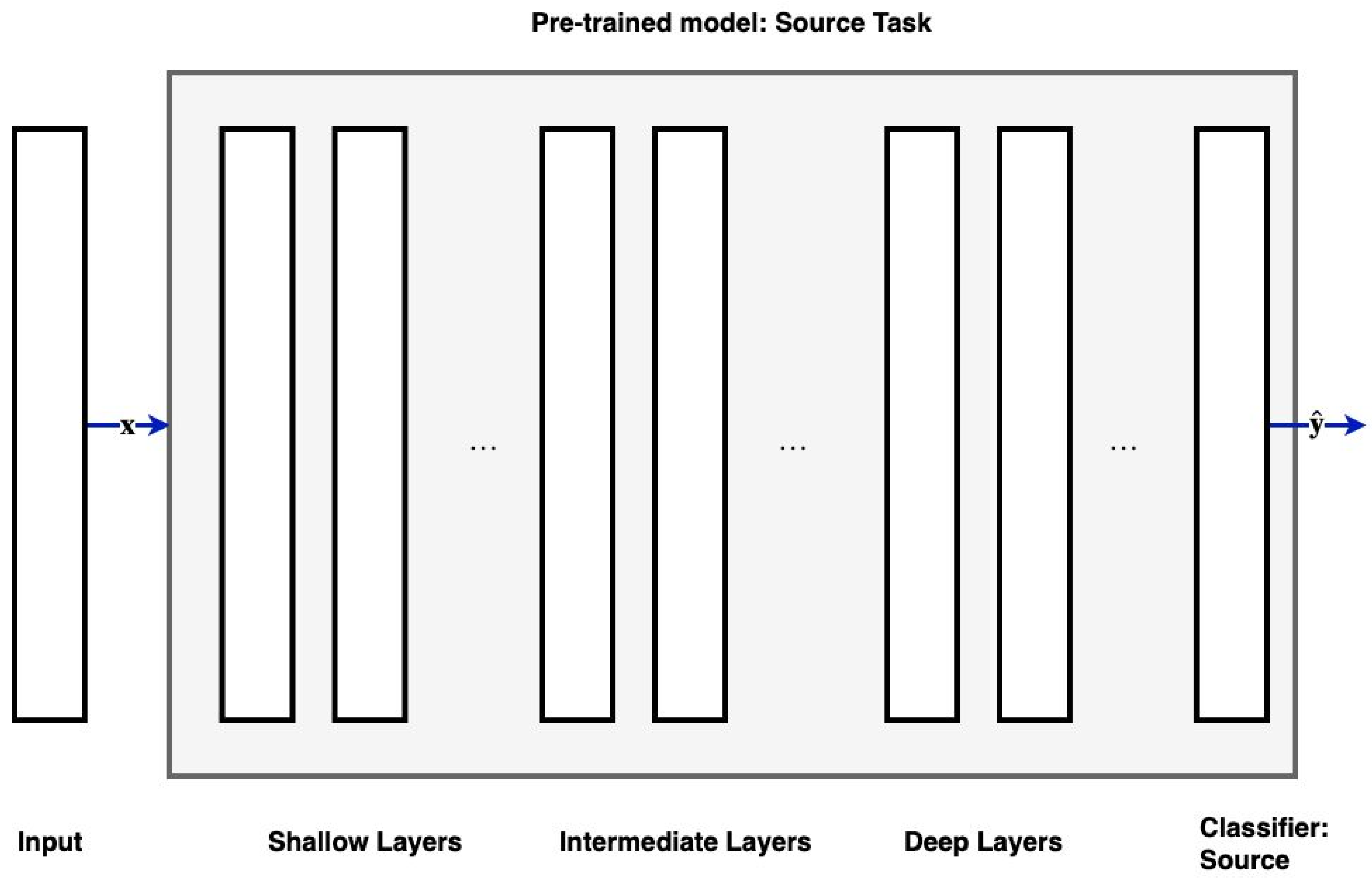
- Use the layers closest to input for a NN trained on a "source" Task
- But apply these layers (and their transformations on input) to a new "target" Task ?

Yes !

This is called *Transfer Learning*

Create a NN for the new Task by

- using some number of layers (closest to input) of a *trained* model for some source task
- appending new *untrained* layers for the target task
    - final "head": regression, classification


Pre-trained model: Source Task
x
ŷ
...
...
...
Input
Shallow Layers
Intermediate Layers
Deep Layers
Classifier:
Source

Quite often, the Source task's model

- has been trained on lots of data
- has been trained for large amounts of time
    - 2-3 weeks for image models
- has a very large number of parameters

The Transfer Learning approach imports the Source task's layer (with weights) at no cost !

The new layers added for the Target task might be able to benefit from the feature transformations created by the Source Task.

This means

- the Target task training modifies *only* the parameters of the new layers
    - *freeze* the weights of the imported Source layers
- By using a small number of parameters
    - Target task can be trained on a small amount of training data

How to choose the prefix of the Source task

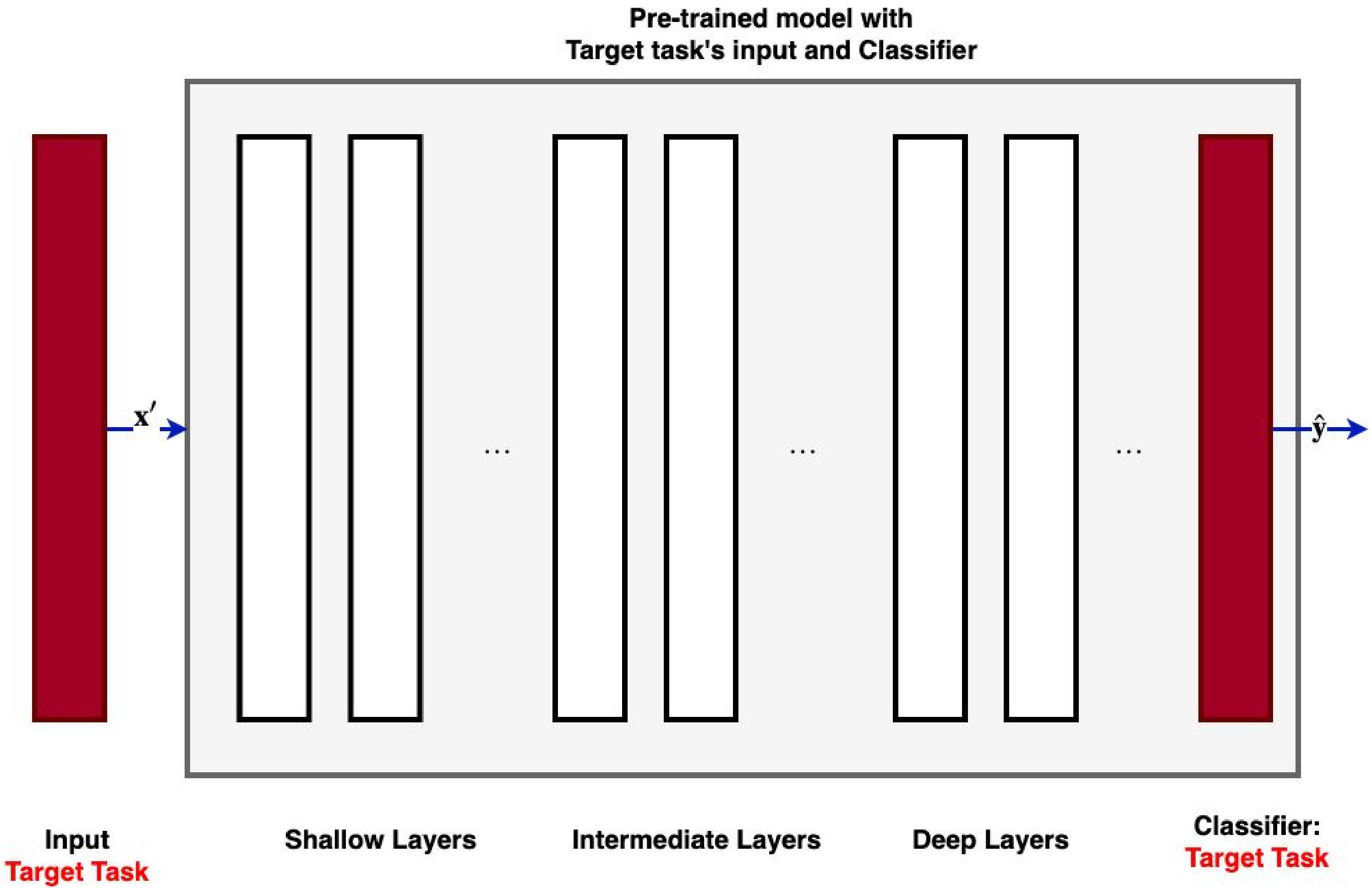
Where do we truncate the Source task's model ?

In other words: how deep should the prefix of the Source model's NN be ?

Consider the features created at the final layer of the prefix:

- Very shallow
    - Features learned may be too simple
    - Target may be able to benefit from deeper prefix
- Too deep
    - Features learned may be *too specialized* to the Source task

In other words: experiment !


Pre-trained model with
Target task's input and Classifier
x′
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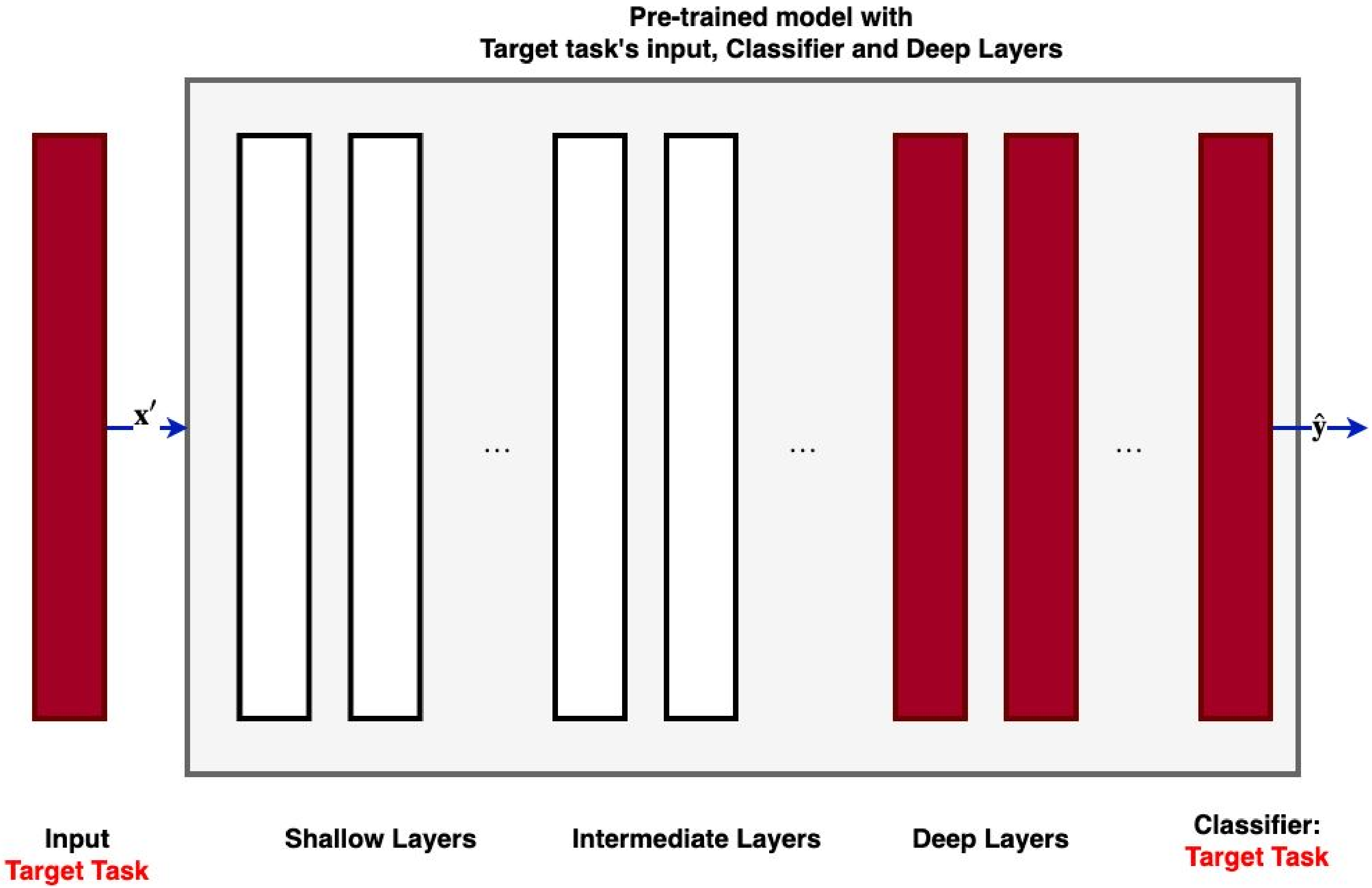
Input
Target Task
Shallow Layers
Intermediate Layers
Deep Layers
Classifier:
Target Task


Pre-trained model with
Target task's input, Classifier and Deep Layers
x′
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...
...
...
Input
Target Task
Shallow Layers
Intermediate Layers
Deep Layers
Classifier:
Target Task

Transfer

Limitations of Transfer Learning

There is no guarantee that the features learned by the Source task will be useful for the Target task

- greater chance if tasks/domains are similar

Training the Target task

Why do we freeze the weights of the imported Source prefix ?

- the weights of the Target task's suffix are uninitialized
    - large gradients to start
- so early in traing: we don't to destroy the weights in the prefix

After the suffix is trained, we sometimes

- unfreeze the latter layers of the prefix
- train with a *much lower* learning rate than the suffix

In other words: we try to "fine-tune" the prefix.

The key is fine-tuning

- wait until Suffix has been trained enough to generate small gradients
- differential learning rates per layer
    - the Prefix has been trained on lots of examples
    - don't want to alter these weights based on the small number of Target training examples

Transfer learning in Keras

target_model = Sequential() # Import the prefix of source_model # - Import the architecture # - and the weights # Freeze the imported weights for layer in source_model.layer[:num_prefix_layers]: target_model.add(layer, trainable=False) # Add the Suffix of the target task to the model target_model.add(...)

Pre-trained Models in Keras

Image

[ImageNet pre-trained models (https://keras.io/applications/)](https://keras.io/applications/)

NLP

[Pre-trained word embeddings (https://keras.io/examples/pretrained_word_embeddings/)](https://keras.io/examples/pretrained_word_embeddings/)

Model zoo

Open source, pre-trained models (https://modelzoo.co)

Conclusion

Transfer learning is a method to make you highly productive

- Leverage an existing model that may have been very expensive to train
    - Revolutionized Image Processing and Natural Language Processing
- "Cut off the head" and retrain *new head* on smaller number of examples

But there is still an element of art in knowing how much of the head to cut off

- Deeper layers may have over-specialized; best to cut them off
- Shallower layers may only recognize generic features; best to keep more of them

In [4]:

```
print("Done")
```

Done