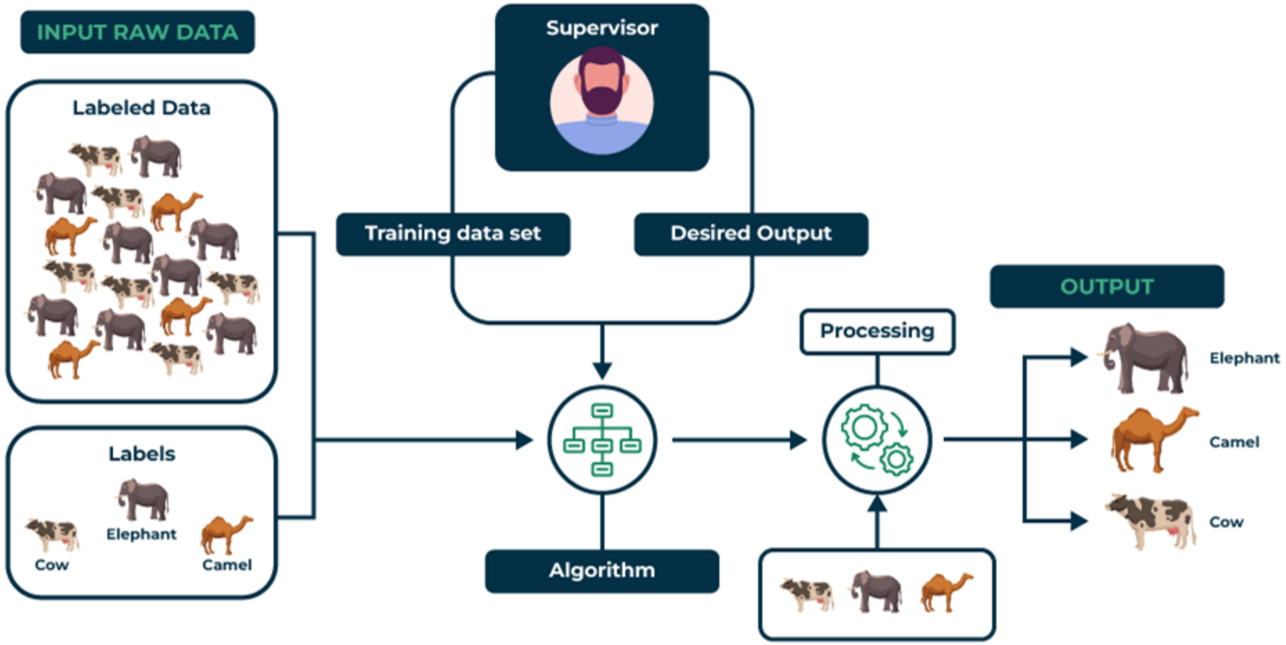
Learning Strategies

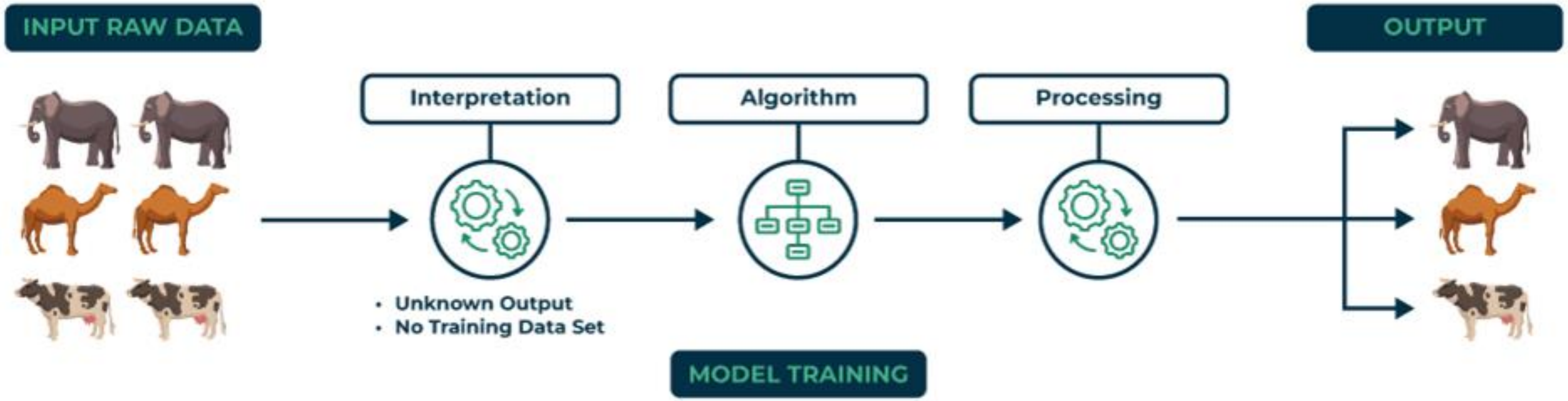
Supervised Learning

- When you have labels or ground-truth so you can find the difference between the predicted and actual



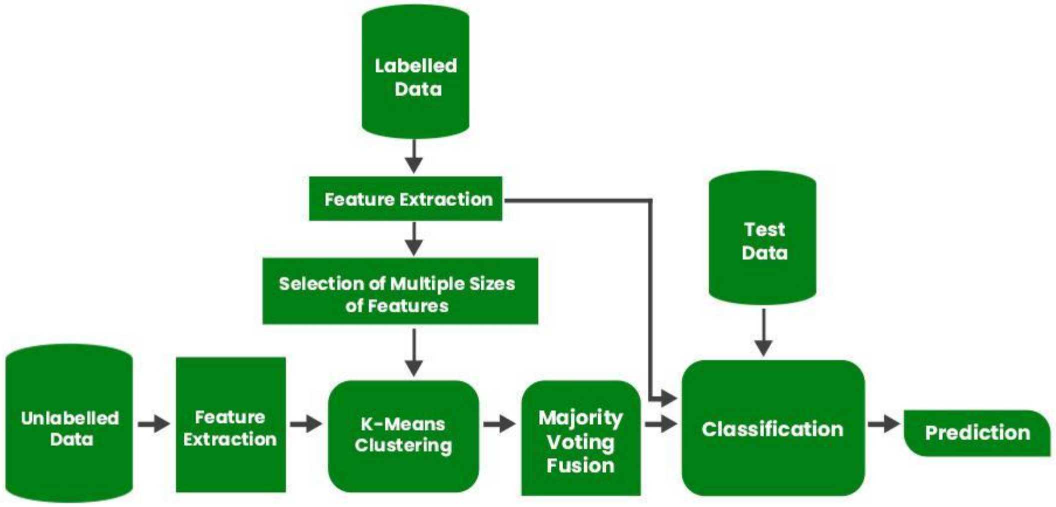
Unsupervised learning

- When labels or ground-truth are not present



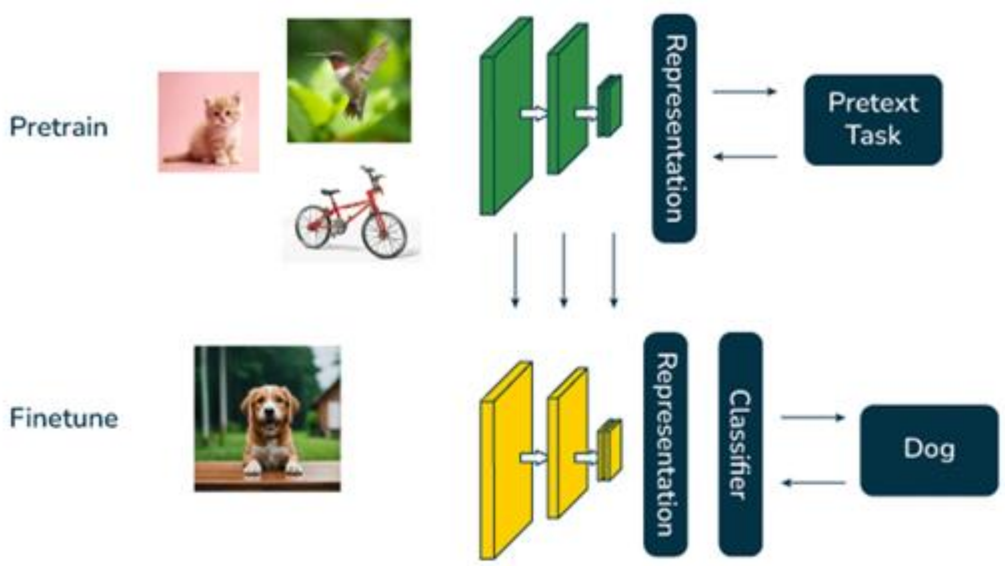
Semi-supervised learning

- uses a small amount of labeled data and a large amount of unlabeled data to train a model



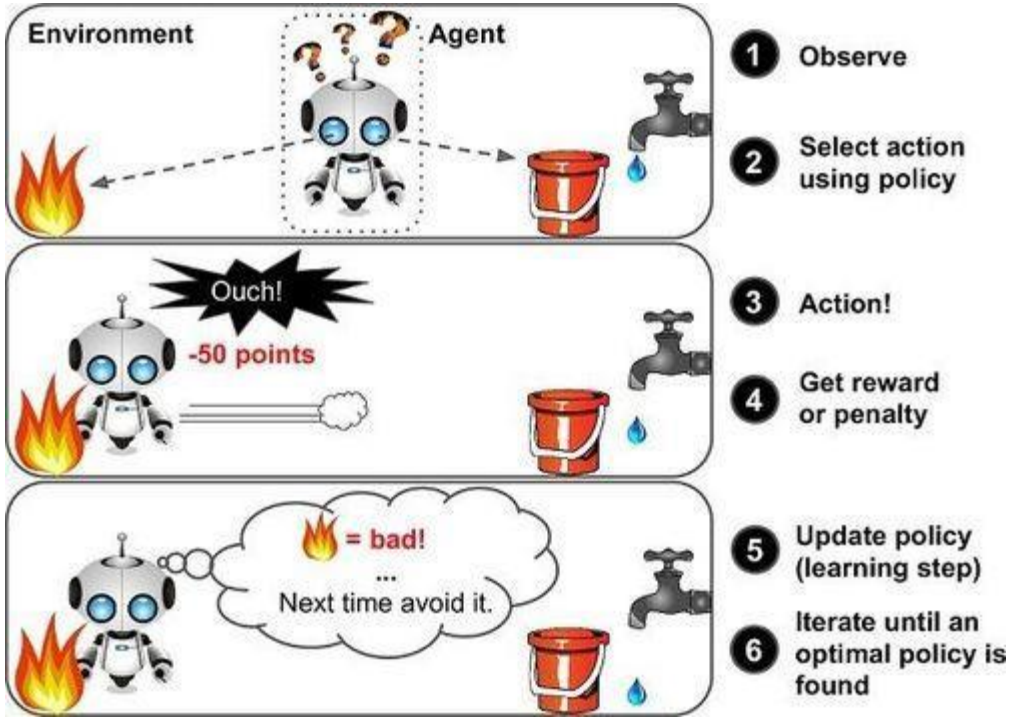
Self-supervised learning

- where a **model is pre-trained using unlabelled data** and the data labels are generated automatically, which are further used in subsequent iterations as ground truths



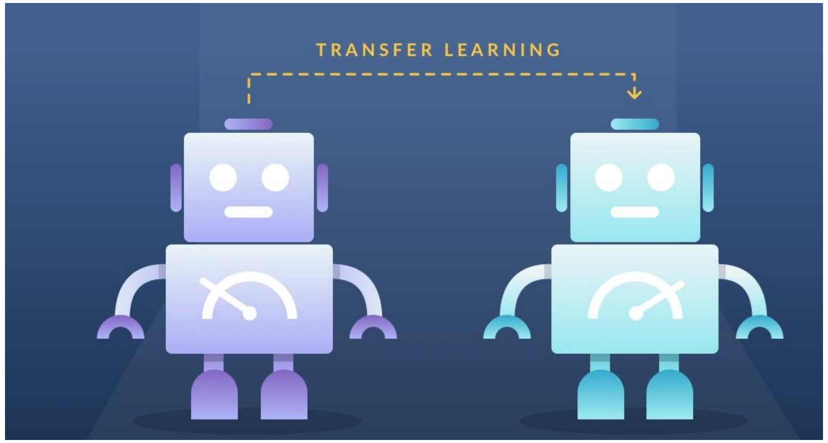
Reinforcement learning

- Based on reward-penalty mechanism to train the model.



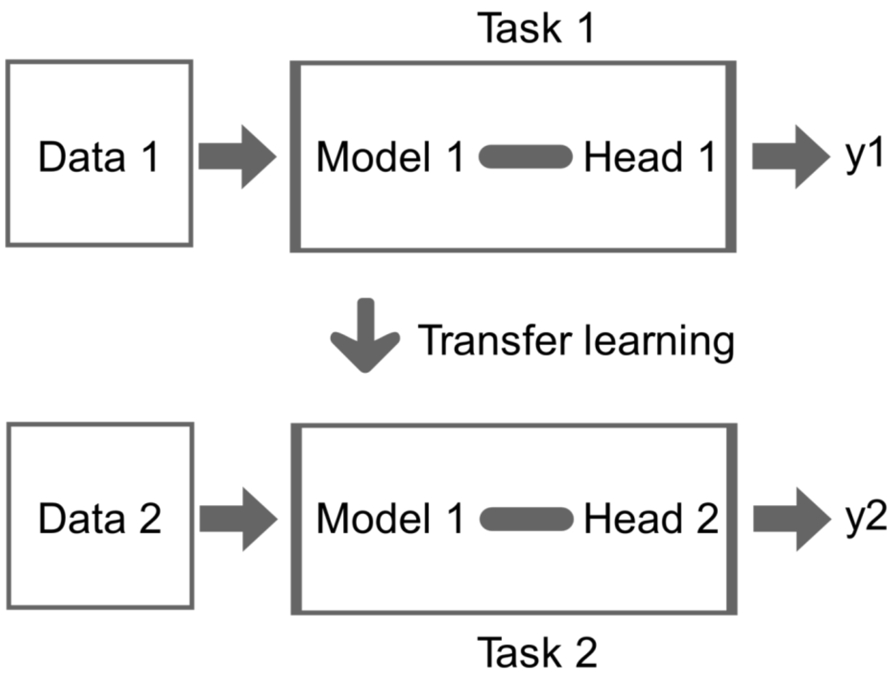
Transfer Learning

- Humans don’t learn from scratch but we use previous knowledge to learn new tasks
- For instance, learning to drive a car after learning a bike



Transfer Learning

- The reuse of a pre-trained model on a new problem is known as transfer learning

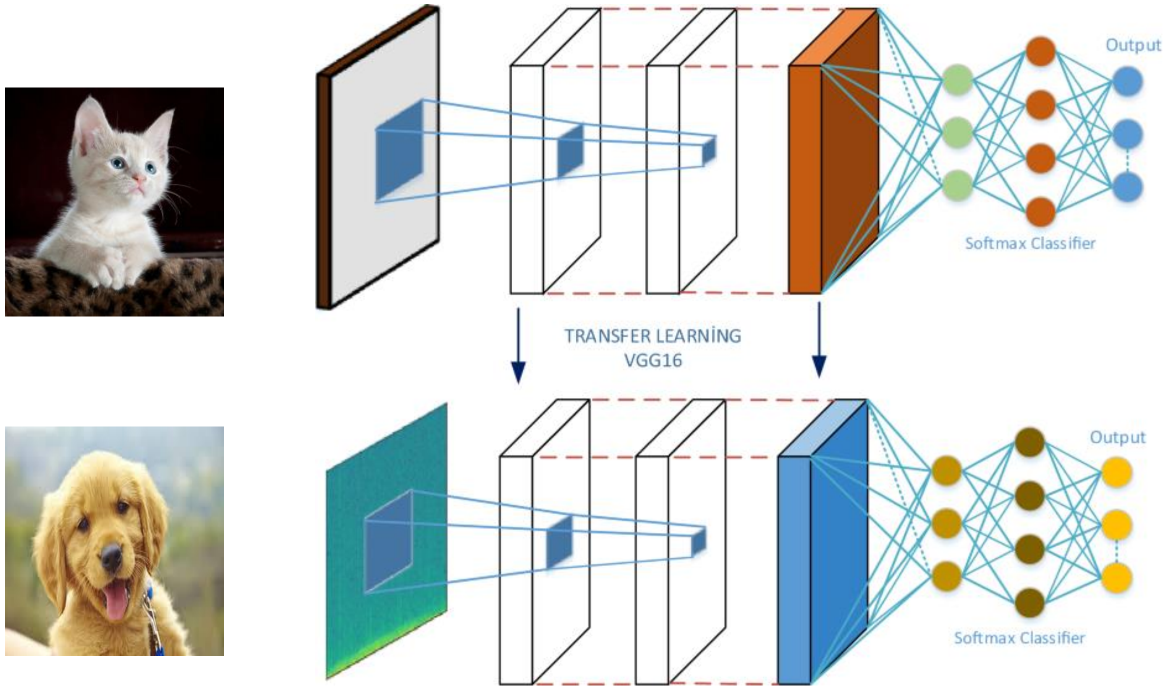


Transfer Learning

- With transfer learning, we basically try to use what we’ve learned in one task to better understand the concepts in another. weights are being automatically being shifted to a network performing “task A” from a network that performed new “task B.”

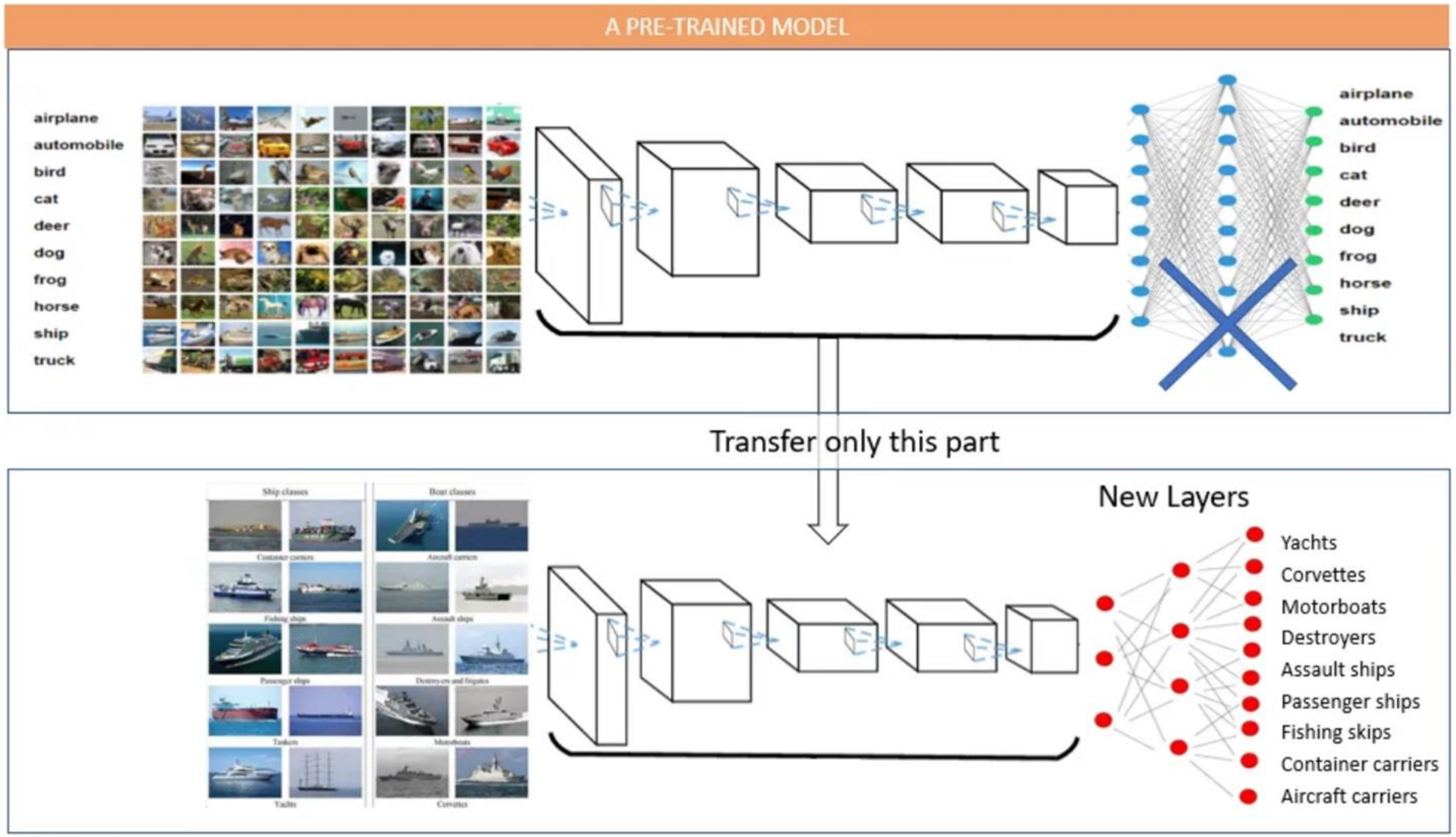
How Transfer Learning Works

- If the shallow features of both the task are similar then they can be used directly without re-learning
- Only deep features of last few layers will be re-learned



How Transfer Learning Works

Another example,



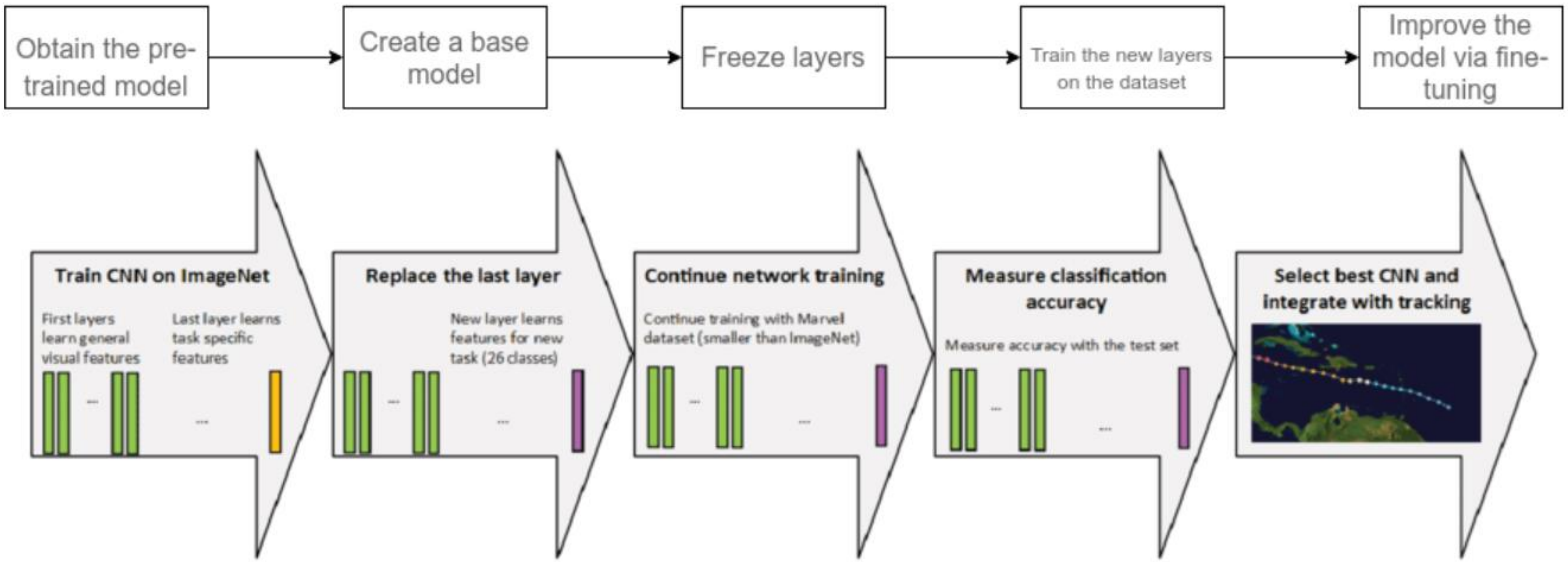
Why it is useful?

- The convergence of deep model require a lot of training data and computational complexity is high
- Transfer learning reduces training time as the data is less compared to model from which we are learning. For example, VGG 16 pre-trained on ImageNet requires a lot of training time due to high number of training parameter and billions of images in train set.

Why it is useful?

- On the other hand using features from VGG-16 to build a cat-dog classifier can be build few fewer parameters and less training time.
- Further transfer learning improves neural network performance (in most circumstances), and model can be optimized in the absence of a large amount of data.

Steps of Transfer Learning



Steps of Transfer Learning

1. Obtain the pre-trained model: Transfer learning requires a strong correlation between the knowledge of the pre-trained source model and the target task domain for them to be compatible.’

2. Create a base model: The base model is one of the architectures such as ResNet or Xception which we have selected in the first step to be in close relation to our task.

Steps of Transfer Learning

3. Freeze layers: Freezing the starting layers from the pre-trained model is essential to avoid the additional work of making the model learn the basic features.

- If we do not freeze the initial layers, we will lose all the learning that has already taken place. This will be no different from training the model from scratch and will be a loss of time, resources, etc.

Steps of Transfer Learning

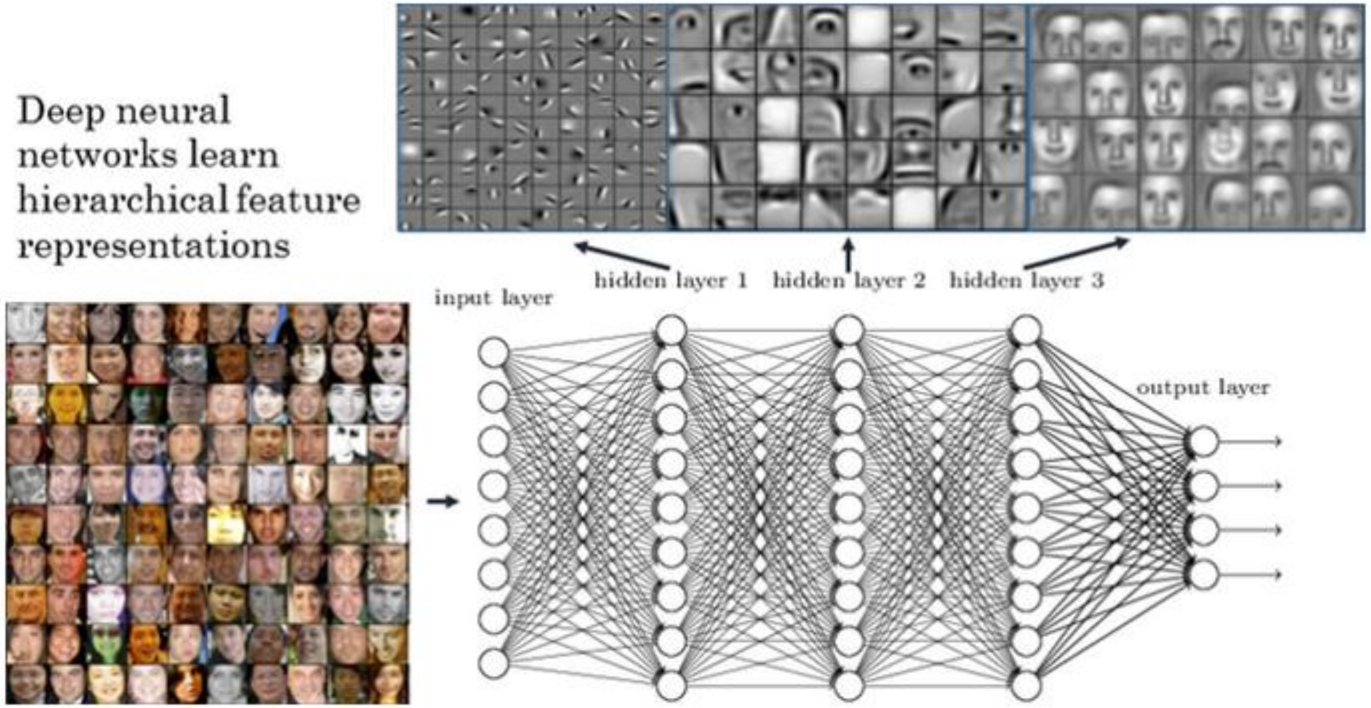
4. Add new Trainable Layers: Add additional layers on top of them to predict the specialized tasks of the model.

5. Train the new layers: The pre-trained model’s final output will most likely differ from the output we want for our model. We have to train the model with a new output layer in place.

6. Fine-Tune Your model: Fine-tuning involves unfreezing some part of the base model and training the entire model again on the whole dataset at a very low learning rate. The low learning rate will increase the performance of the model on the new dataset while preventing overfitting.

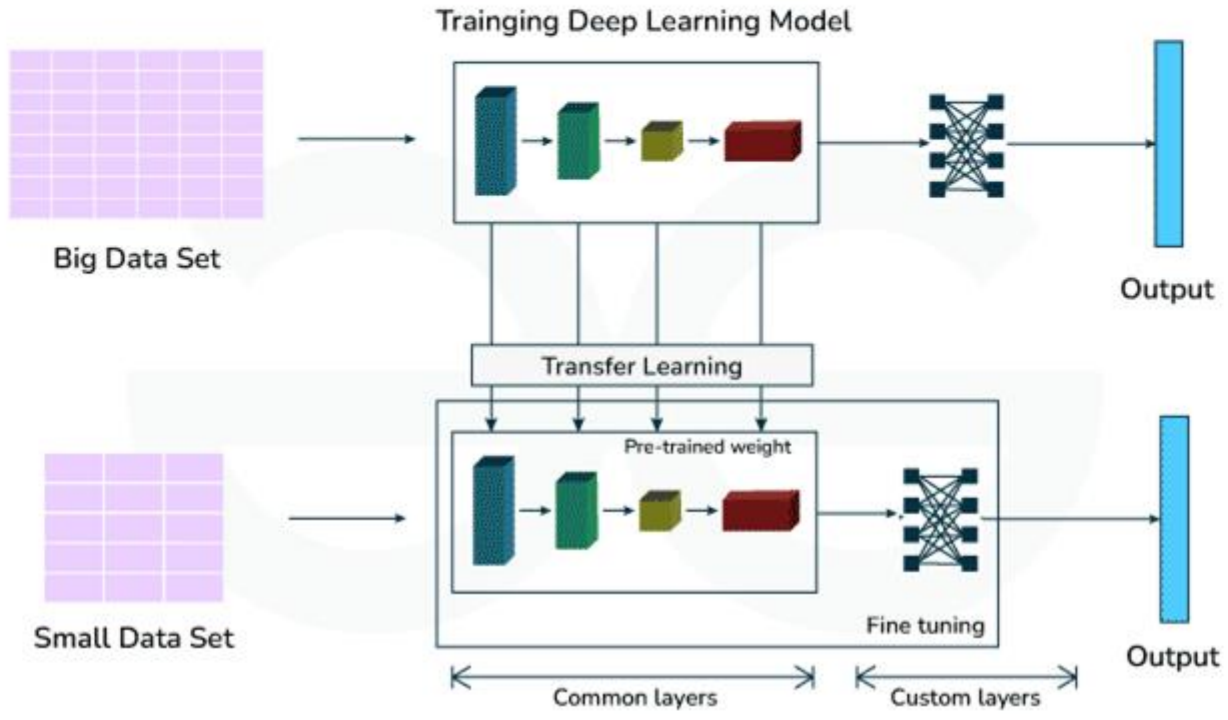
Freezing

- Preventing the model's layers to update the weights during training is said to be freezing



Fine-Tuning

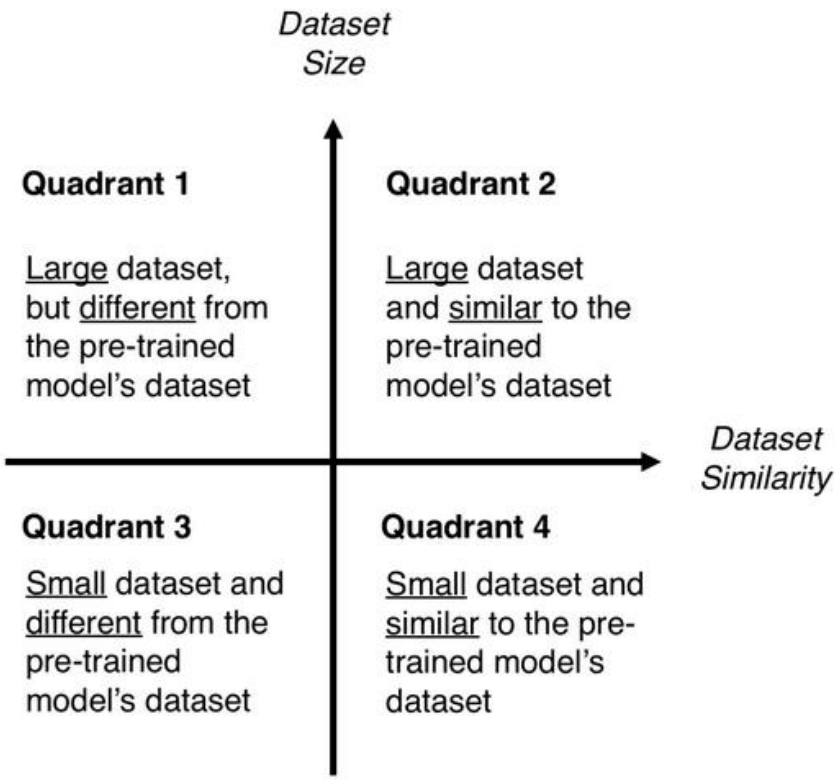
- The models weight can be re-adjusted during training by backpropagation to adapt to change in task

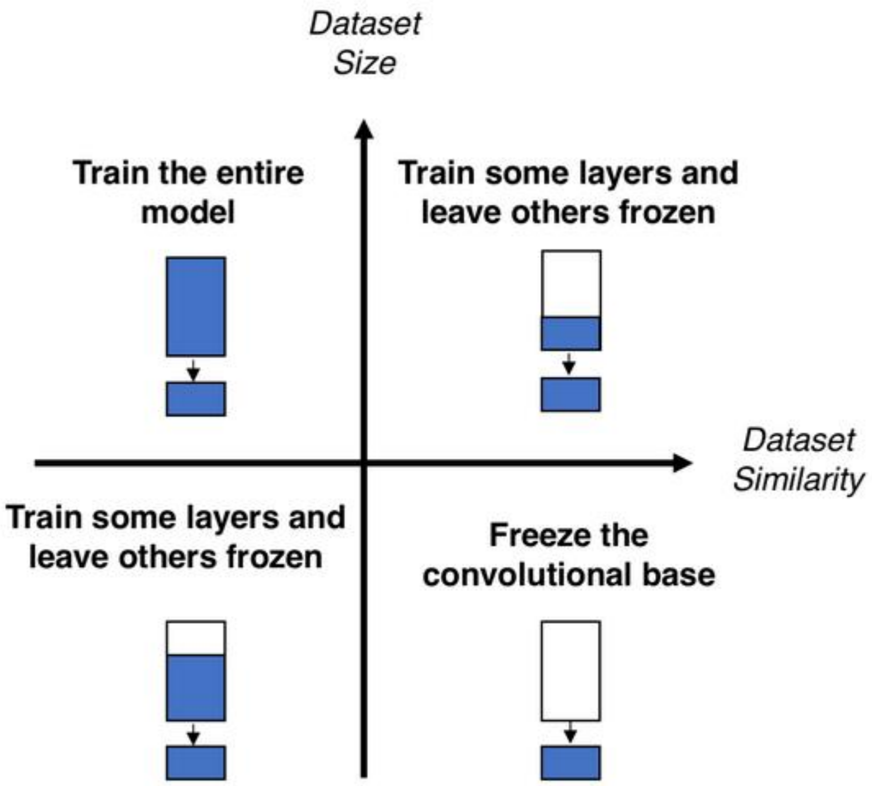


Freezing or Finetuning?

- Freeze: not updated. Used when target label are scarce.
- Fine tune: updated using back propagation. Used when target labels are available for tuning.

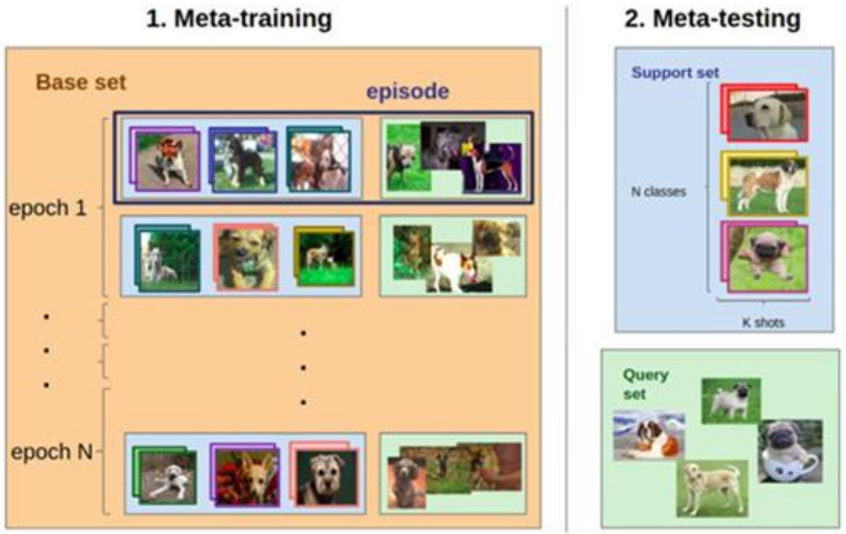
When and how to learn?





Meta Learning

- Known as "Learning to learn"
- It aims to develop models that can learn new tasks more quickly and efficiently by utilizing experience from previous tasks
- The focus is on improving the learning algorithm itself.



Meta Learning

- During meta-learning, the model is trained to learn tasks in the meta-training set. Two optimizations:
- The learner, which learns new tasks
- The meta-learner, which trains the learne

Meta Learning vs Transfer Learning

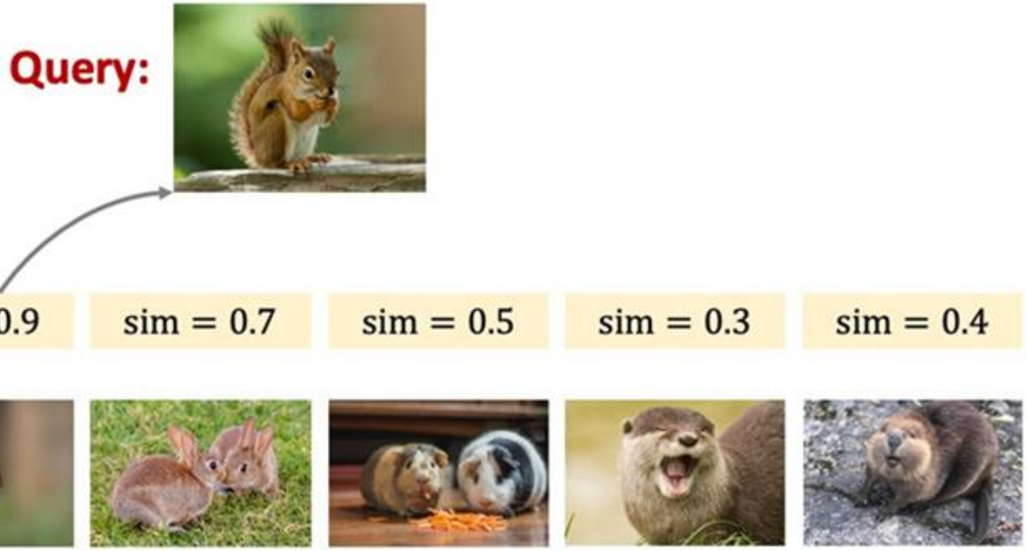
- **Meta-Learning:** Primarily aims to create models that can quickly adapt to new tasks with minimal data, focusing on the learning process itself.
- **Transfer Learning:** Utilizes existing knowledge from related tasks to improve performance on a specific task, focusing on reusing and fine-tuning pre-trained models.

Types of Meta Learning

- Few Shot Learning
- Zero Shot Learning
- One Shot Learning

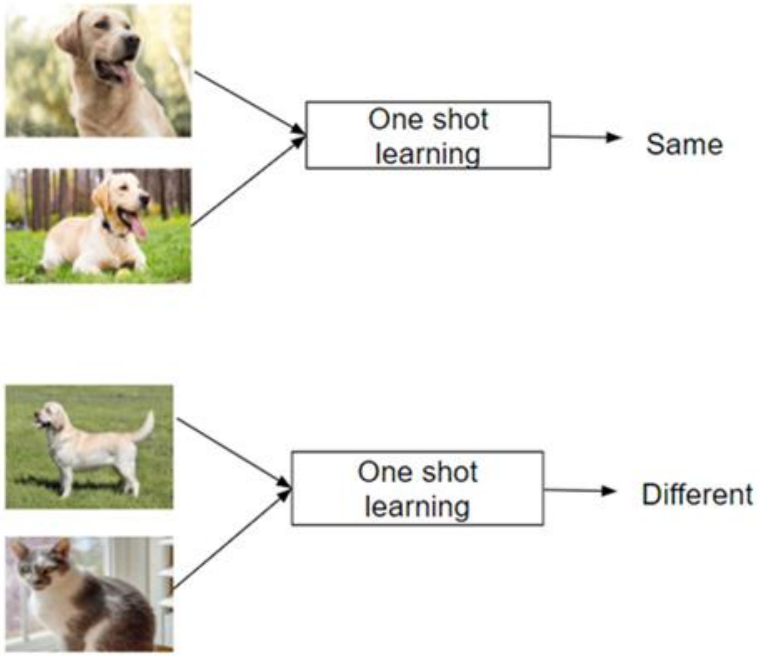
Few Shot Learning

- Learn a model from a large dataset that can be easily adapted to new classes with few instances



One Shot Learning

- compares the similarities and differences between two images



Zero Shot Learning

- Zero-shot learning (ZSL) is a machine learning scenario in which an AI model is trained to recognize and categorize objects or concepts without having seen any examples of those categories or concepts beforehand.