PyCon 2017 Delhi, India

Applying Transfer Learning on Your Data

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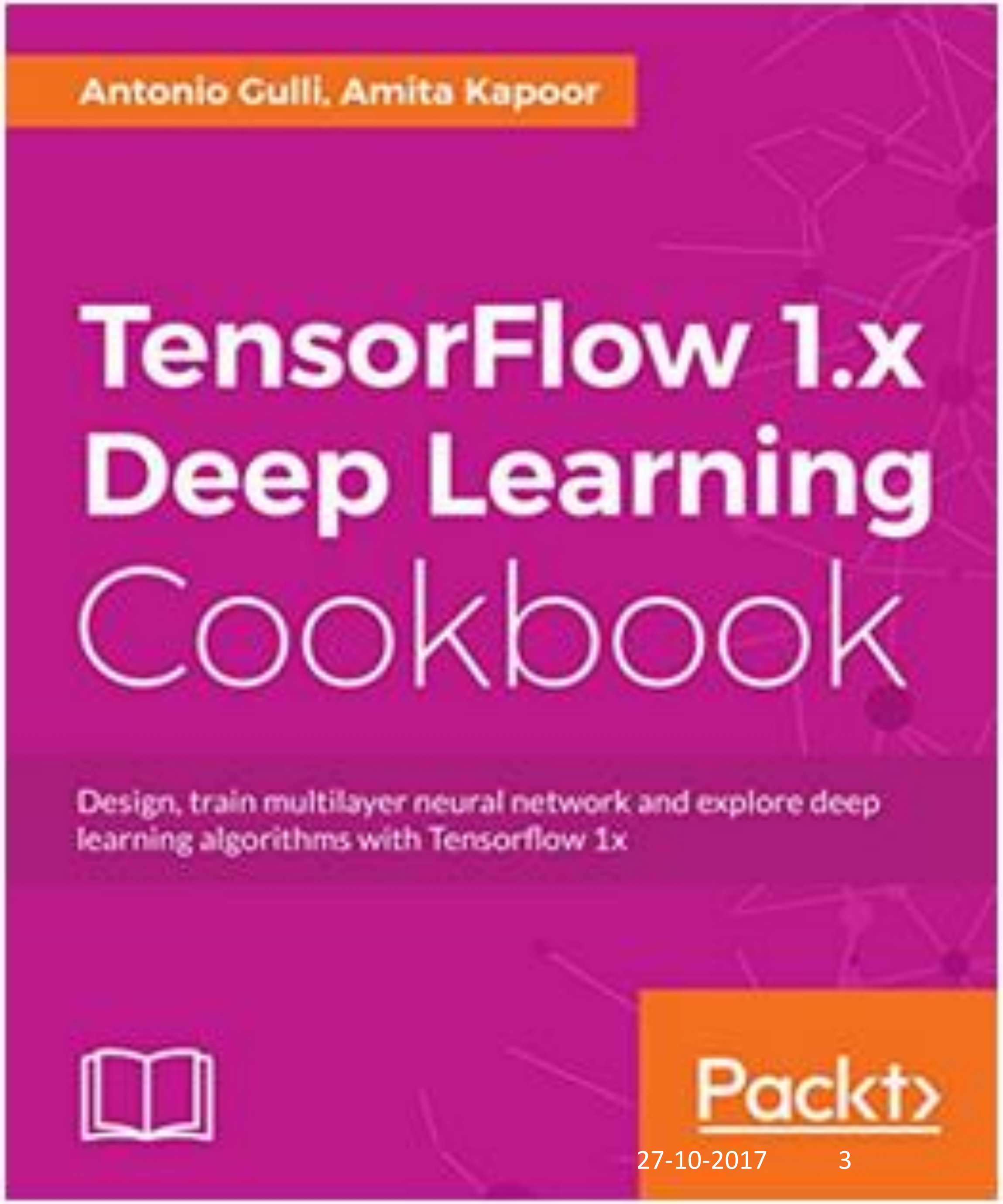
A little About Amita Kapoor

- 20+ years of experience of teaching Neural Networks and Artificial Intelligence.
- Masters in Electronics from Jamia Milia Islamia in the year 1996,
- PhD from the University of Delhi in the year 2011.
  - Joint Co-Supervision:
    - Prof Wolfgang Freude, IPQ, KIT, Karlsruhe, Germany
    - Prof Enakshi K Sharma, UDSC, Delhi, India.
  - Awarded the prestigious DAAD fellowship.
  - Awarded best Presentation Award at International Conference Photonics 2008.
- At present I am Associate Professor in University of Delhi College.
- Supervises PhD students in the area of Artificial Intelligence, Machine Learning, and Robotics.
- Have more than 40 publication in the international journals and conferences.
- Recently co-Authored a book Tensorflow 1.x Deeplearning Cookbook (More than 90 recipes, and we go from basic MLP, CNN, RNN, LSTMs, GANs, AE, RBMs, SOMs, DBN, DQN, Policy Gradients)

- https://www.amazon.in/TensorFlow-1-x-Deep-Learning-Cookbook-ebook/dp/B0753KP6S4
- **Key Features**
  - Develop your skills to implement advance techniques in deep learning using Google's Tensorflow 1.x
  - Implement real-world and practical examples to illustrate deep learning techniques.
  - Hands-on recipes to learn how to design and train a multi-layer neural network with TensorFlow 1.x



A little About Narotam Singh

- Narotam Singh has been with India Meteorological Department, Ministry of Earth Sciences, India since 1996.
- He has been actively involved with various technical programs and training of officers of GOI in the field of Information Technology and Communication.
- He did his post-graduation in the field of Electronics in 1996 and both Post graduate diploma and Diploma in the field of Computer Engineering, in 1997 and 1994 respectively.
- He is currently working in the enigmatic field of Neural Networks.

Bio-inspired Machine Learning

- Neural Networks → Brain (Biological Neurons)
- Convolutional Neural Networks (CNNs) -> Visual Neo Cortex
- Learning Paradigms:
  - Supervised Learning
  - Unsupervised Learning
  - Reinforcement Learning
- Transfer Learning

What is Transfer Learning?

- Transfer knowledge to new conditions.
- Reuse of some or all of the training (data) of a prior model:
  - feature representations
  - neural-node layering
  - Weights
  - training method
  - loss function
  - learning rate etc.
- Tap into the knowledge gained on prior projects: Supervised, Unsupervised, Reinforcement Learning
- Extracts knowledge from one or more source tasks and apply the knowledge to a target task.

What is Transfer Learning?

- People can intelligently apply knowledge learned previously to solve new problems.
- Not a new concept:
  - NIPS-95 Learning to Learn: *Need for lifelong machine learning methods that retain and reuse previously learned knowledge*.
  - DARPA 2005: *The ability of a system to recognize and apply knowledge and skills learned in previous task to novel tasks*.

Transfer Learning

Transfer learning will become a key driver of Machine Learning success in industry.

-Andrew Ng (NIPS 2016)

Transfer Learning- ML Commercial Success-Key?

- Traditional Models have reported Super human performance in certain tasks.
- Yet, when they are used in production, the performance deteriorates.
- Real world is very different from the structured data used for training and testing.
- Individual users can have slightly different preferences.
- Transfer Learning can help deal with these and allow us to use ML beyond tasks and domains where
  - labelled data is plentiful,
  - data is outdated
- Boost productivity by reducing time to implement new projects

Applications of Transfer Learning

- Learning from simulations and then applying to real world:
  - Real world data is hard to come by. Generate data using simulator: Data has similar feature space, slightly different in marginal probability distributions, and different in conditional probability distributions.
  - E.g.: Self driving Car, Robots, AGI Agents
- Data becoming outdated:
  - Wi-Fi Localization: Locating a mobile device in an indoor environment, position of device changes
- Sentiment Classification:
  - Learn sentiment classification on one topic and apply the model learned on other topics
- Cross Domain Activity Recognition
  - Knowledge about activity learned in one domain (Cleaning Indoor) can be applied to other domain (Doing Laundry).

Transfer Learning: Formal Definition[1]

- **Domain** *D* consists of two components: Feature Space χ and marginal Probability Distribution *P(X)* where $X = \{x_1, \ldots, x_n\} \in \chi$

$$D = \{\chi, P(X)\}$$

- **Task** *T* also consists of two components: a Label Space *Y* and an objective predictive function *f*(.)

$$T = \{Y, f(\cdot)\}$$

- In terms of probability the objective predictive function *f(x)* can be written as *P(y|x)*.
- Consider one source domain D_s and corresponding source task T_s and one target domain D_T and target task T_T

Transfer Learning: Formal Definition[1]

- Consider one source domain D_s and corresponding source task T_s and one target domain D_T and target task T_T
- Traditional Machine Learning:

$$D_S = D_T \quad and \quad T_S = T_T$$

- Transfer Learning:

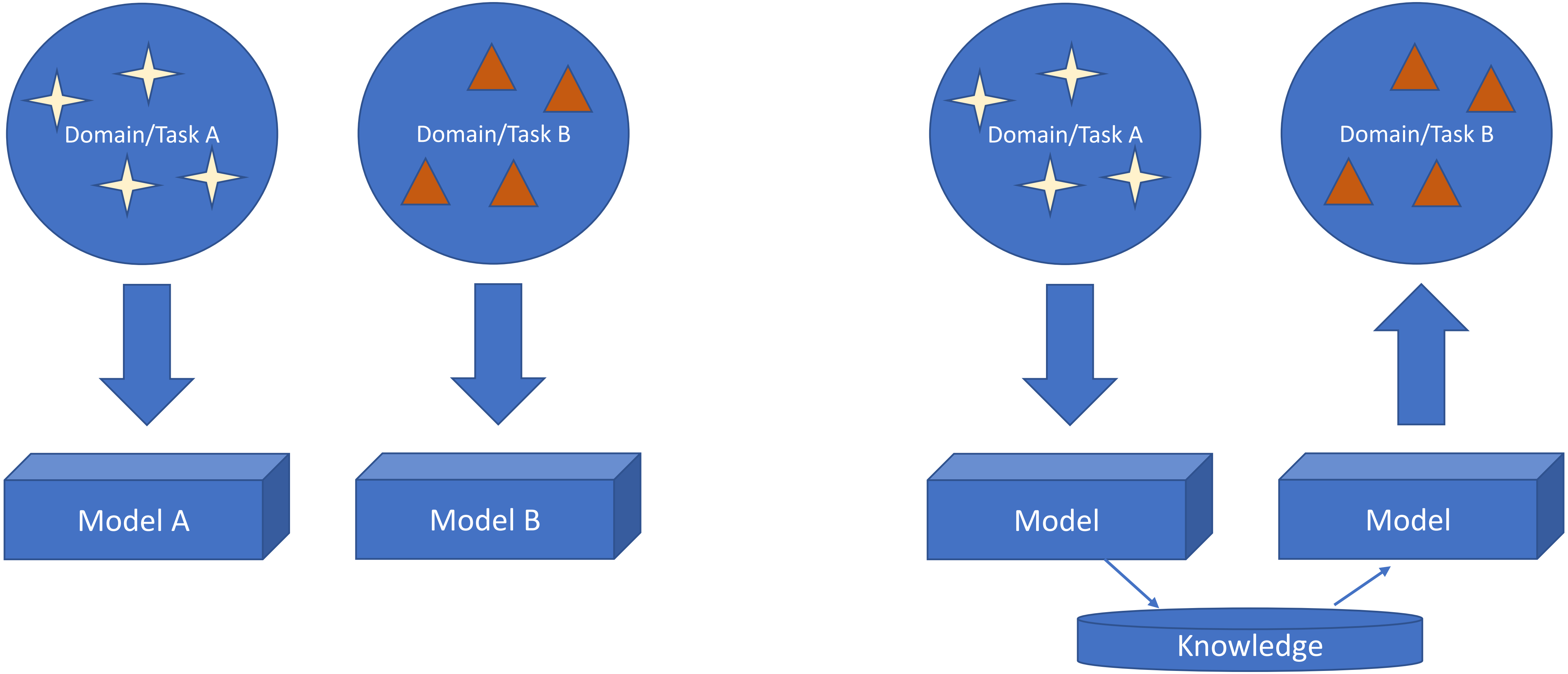
$$D_S \neq D_T \quad or \quad T_S \neq T_T$$

Source and target conditions can vary in four ways =>

Four Scenarios

Traditional vs Transfer Learning

$D_S = D_T \quad and \quad T_S = T_T$ $\qquad$ $D_S \neq D_T \quad or \quad T_S \neq T_T$



Training and Evaluation on same task/domain $\qquad$ Training and Evaluation on same task/domain

Transductive Transfer Learning

Source Domain and Target Domain different: $D_S \neq D_T$

- $\chi_S \neq \chi_T$: Heterogenous Transfer Learning
  - E.g. Source and Target languages are different
- $P(X_S) \neq P(X_T)$: Frequency Feature Bias/Domain Adaption
  - E.g. Source and target documents are on different topics.

Inductive Transfer Learning

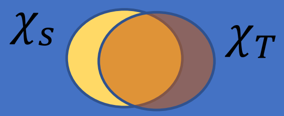
Source Task and Target Task different: $T_S \neq T_T$

- $Y_S \neq Y_T$: **Main focus of this talk**
  - E.g. Source documents had with binary classification and Target documents have multiple classification.
- $P(Y_S|X_S) \neq P(Y_T|X_T)$: Context Feature Bias:

Transfer Learning Approach

Instance based approach:

Source and target domains have lot of overlapping features



Feature-based approach:

Source and target have some overlapping features

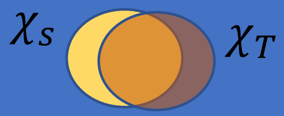
Parameter-based approach

Relational Approach

Transfer Learning Approaches

Instance based approach:

Source and target domains have lot of overlapping features



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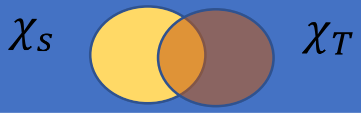


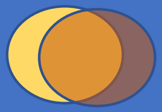
Parameter-based approach

Relational Approach

Transfer Learning Approaches

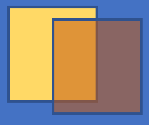
Instance based approach:

Source and target domains have lot of overlapping features

χ_S  χ_T

Feature-based approach:

Source and target have some overlapping features

$\varphi(\chi_S)$  $\varphi(\chi_T)$

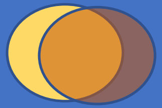
Parameter-based approach

Relational Approach

Transfer Learning Approaches

Instance based approach:

Source and target domains have lot of overlapping features

χ_S  χ_T

Feature-based approach:

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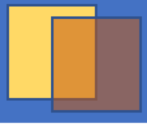
$\varphi(\chi_S)$  $\varphi(\chi_T)$

Parameter-based approach:

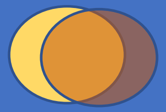
Source and target tasks are related, and so what has been learned from source can be transferred to target.

Relational Approach

Transfer Learning Approaches

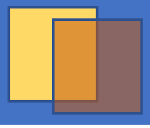
Instance based approach:

Source and target domains have lot of overlapping features

χ_S  χ_T

Feature-based approach:

Source and target have some overlapping features

$\varphi(\chi_S)$  $\varphi(\chi_T)$

Parameter-based approach:

Source and target tasks are related, and so what has been learned from source can be transferred to target.

Relational Approach:

If two relational domains are related, they may share similar relations among Objects.

Transfer Learning Techniques

Using pre-trained models: Useful when new task has different label space.	• Training an entire convolutional neural network from scratch requires a very large dataset and time, instead use a pretrained CNN
Learn domain-invariant representations: Useful for Heterogenous transfer learning and Domain Adaptation.	• Use models to learn representations that do not change based on the domain: Find a Common Latent Feature Space. Use Denoised Autoencoders
Make representations more similar	• Pre-process such that representations of both domains become more similar to e/o
Domain Confusion	• Add an objective function to existing model that confuses the two domains.

Pre-trained Models

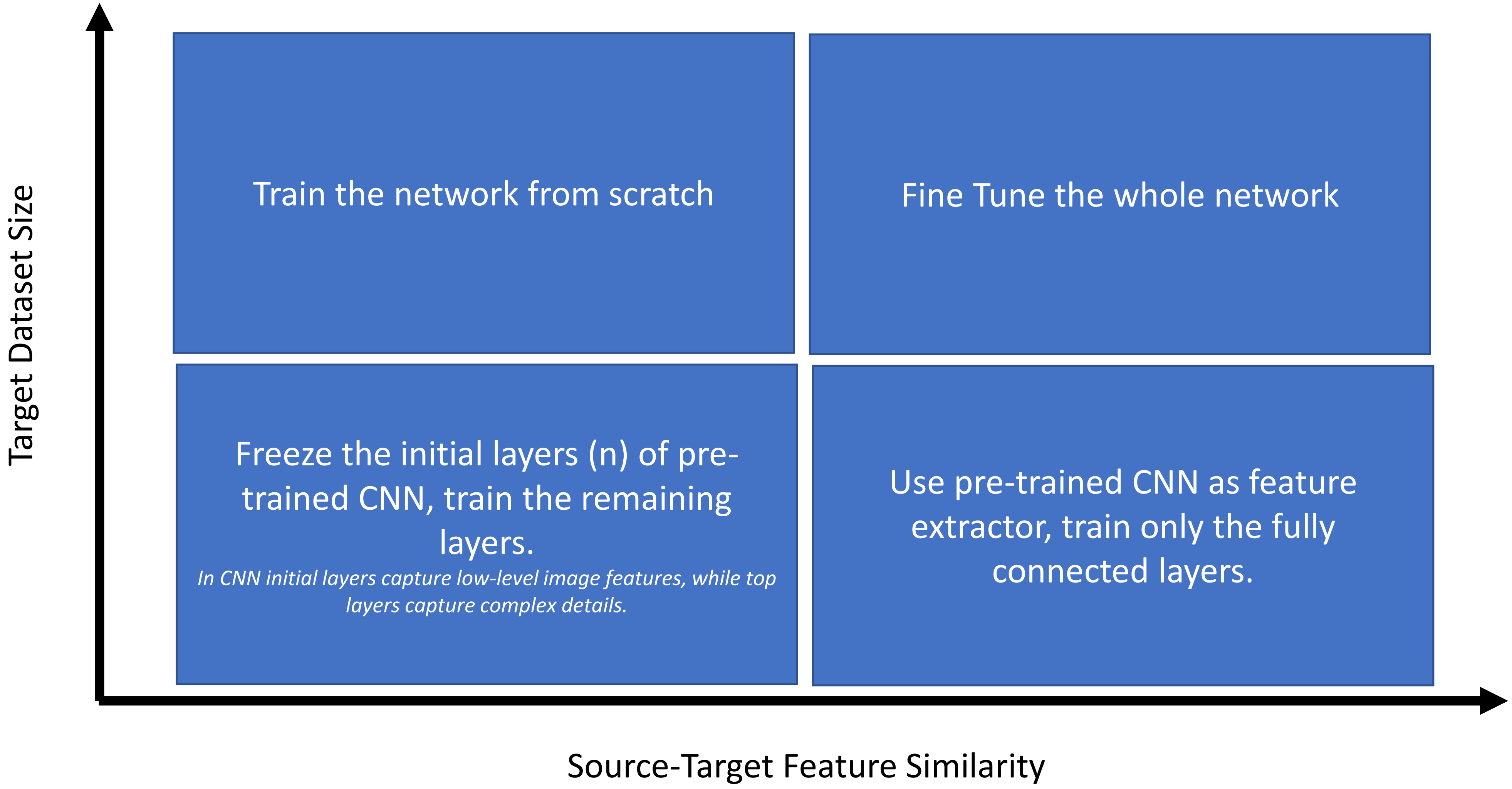
Pre-trained CNN as feature extractor:

Take a pre-trained CNN model, remove the last fully connected layers, use the remaining CNN as feature extractor for the new dataset. The output of this CNN feature extractor is fed to a classifier. The classifier is trained for the new dataset.

Fine tune pre-trained CNN:

The weights of both the pre-trained CNN layers (all or some) and fully connected classifier layer/s are fine tuned using backpropagation.

Which method to employ?



Pre-trained Models in Keras/Tensorflow

Models for Image classification
with weights trained on ImageNet

- Xception
- VGG16
- VGG19
- ResNet50
- InceptionV3
- MobileNet

Import Models:

```
from keras.applications.model_name    import model_name
From keras.applications.model_name  import preprocess_input, decode_predictions

from keras.applications.vgg16    import VGG16
```

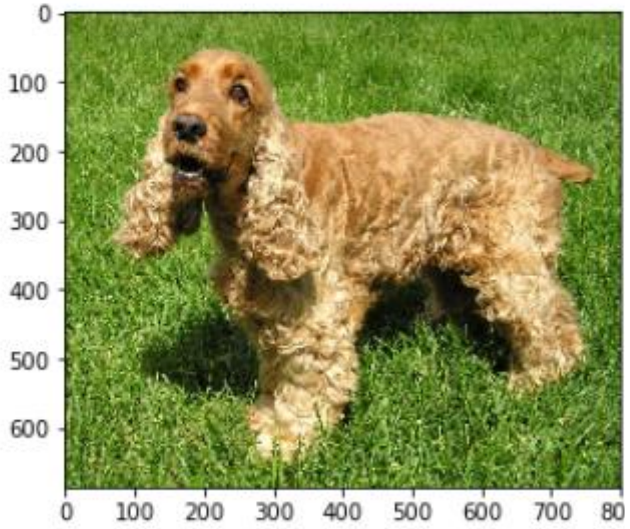
Predicting Dog Breed Using Xception

- Prediction Using the Model

```
Wow, Wow you are a Dog!
And your breed is
Labrador_retriever
```


```
Correct breed is
Chesapeake_bay_retriever
```

```
Wow, Wow you are a Dog!
And your breed is
English_cocker_spaniel
```




```
Correct breed is
English_cocker_spaniel
```

```
Wow, Wow you are a Dog!
And your breed is
Greater_swiss_mountain_dog
```


```
Correct breed is
Greater_swiss_mountain_dog
```

```
Wow, Wow you are a Dog!
And your breed is
Chihuahua
```


```
Correct breed is
Chihuahua
```

Further Research

One/Zero shot learning

Aim to learn from only a few/one/zero shot learning.

Multi Task learning

Learn more than one task. Use knowledge acquired by learning from related tasks to do well on target. Source and Target are jointly trained.

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