

Introduction to Transfer Learning

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MLDA@EEE

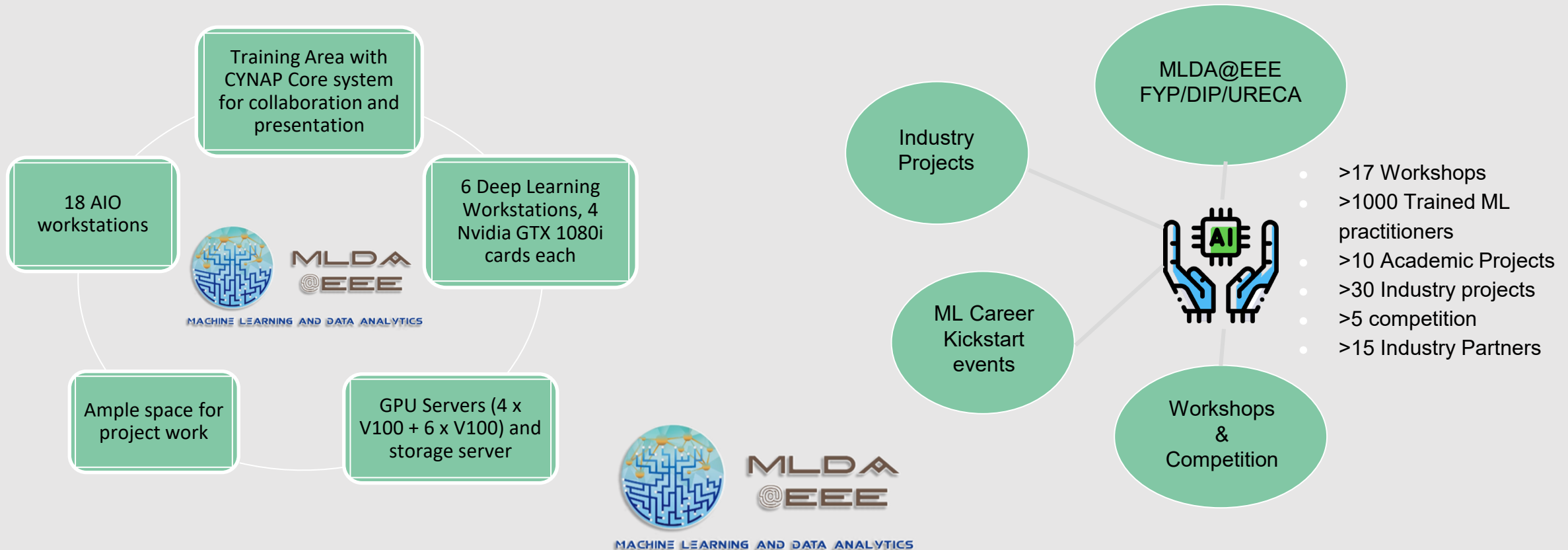


MLDA
@EEE

MACHINE LEARNING AND DATA ANALYTICS

Our Mission

Provide an integrated platform for EEE/IEM students to learn and implement Machine Learning, Data Science & AI, as well as facilitate connections with the industry.



Agenda

- Theory of Transfer learning
- Transfer Learning workflow
- Hands-on: implement Transfer Learning with TensorFlow Keras

What is Transfer Learning

- Apply knowledge learned from **one task** to another **related task**

CAR CLASSIFIER



Car



No car

TRUCK CLASSIFIER

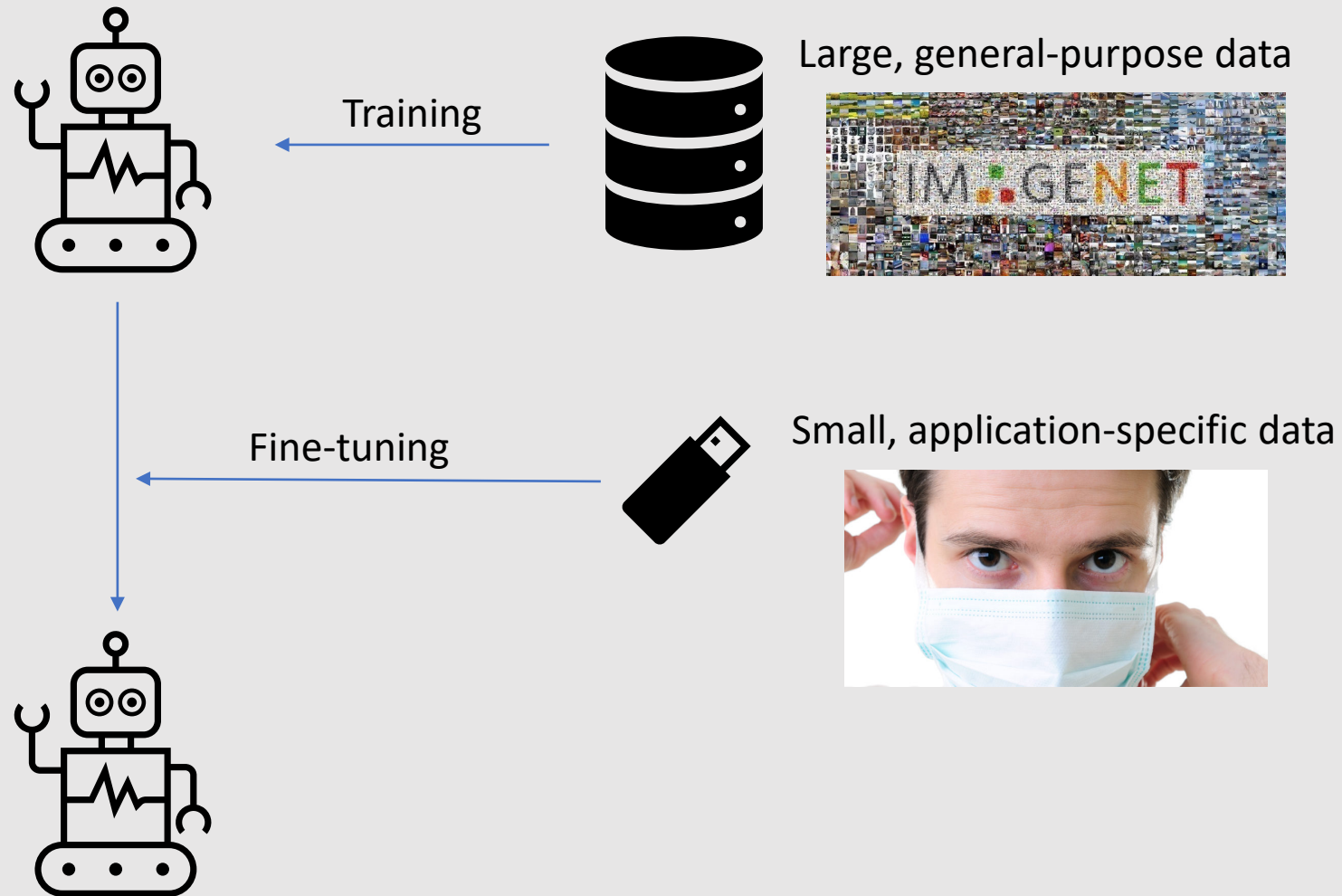


Truck



No truck

What is Transfer Learning



Motivations



Lack of training data

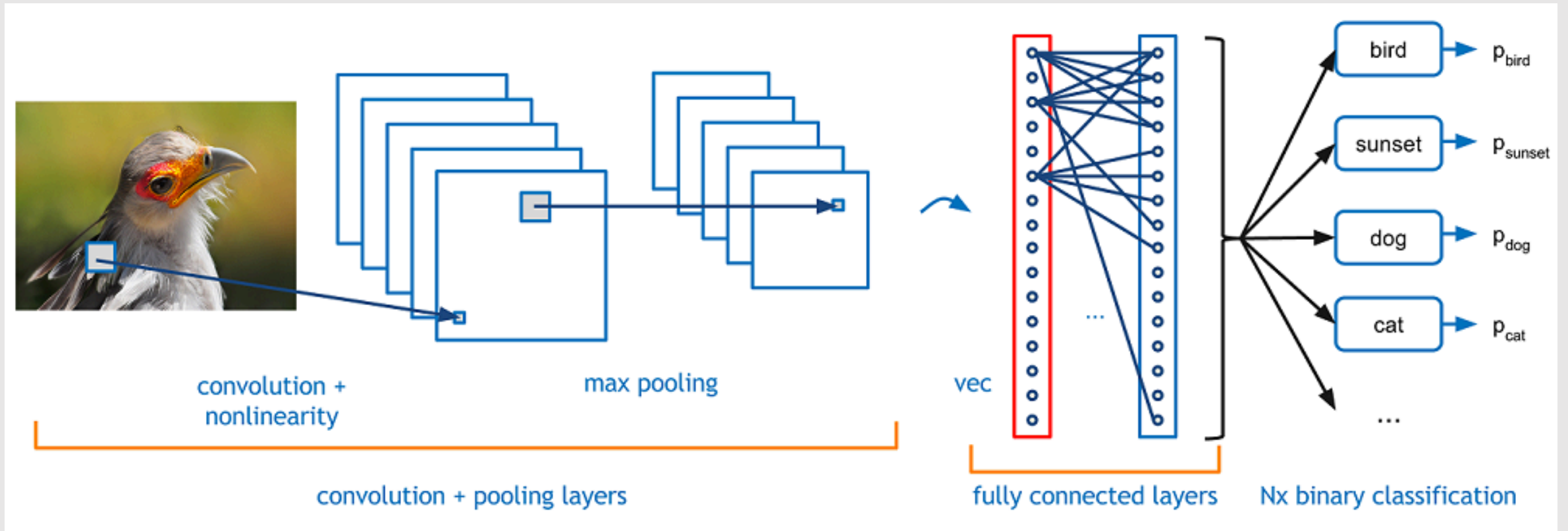


Reduce training time



More robust to unseen data

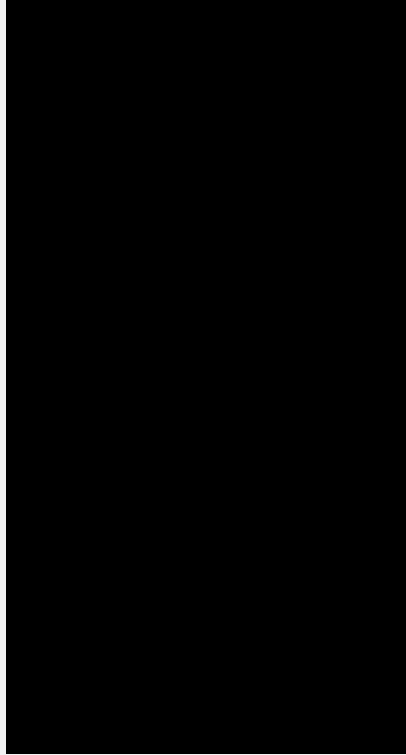
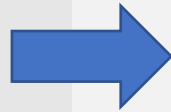
Transfer Learning – Learning the features



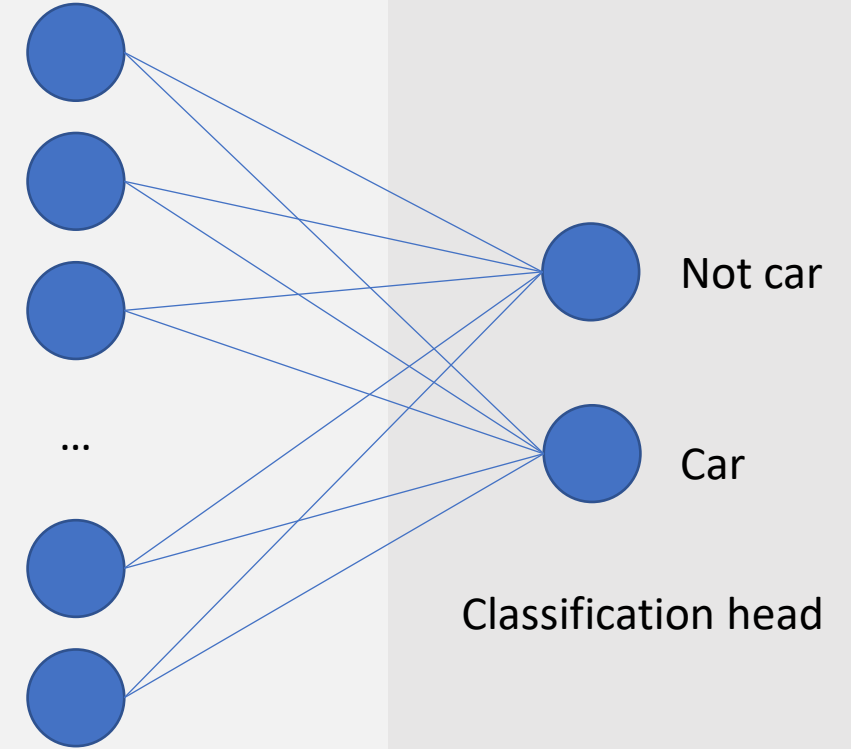
Transfer Learning – Black box



Input – Rank 3 Tensor

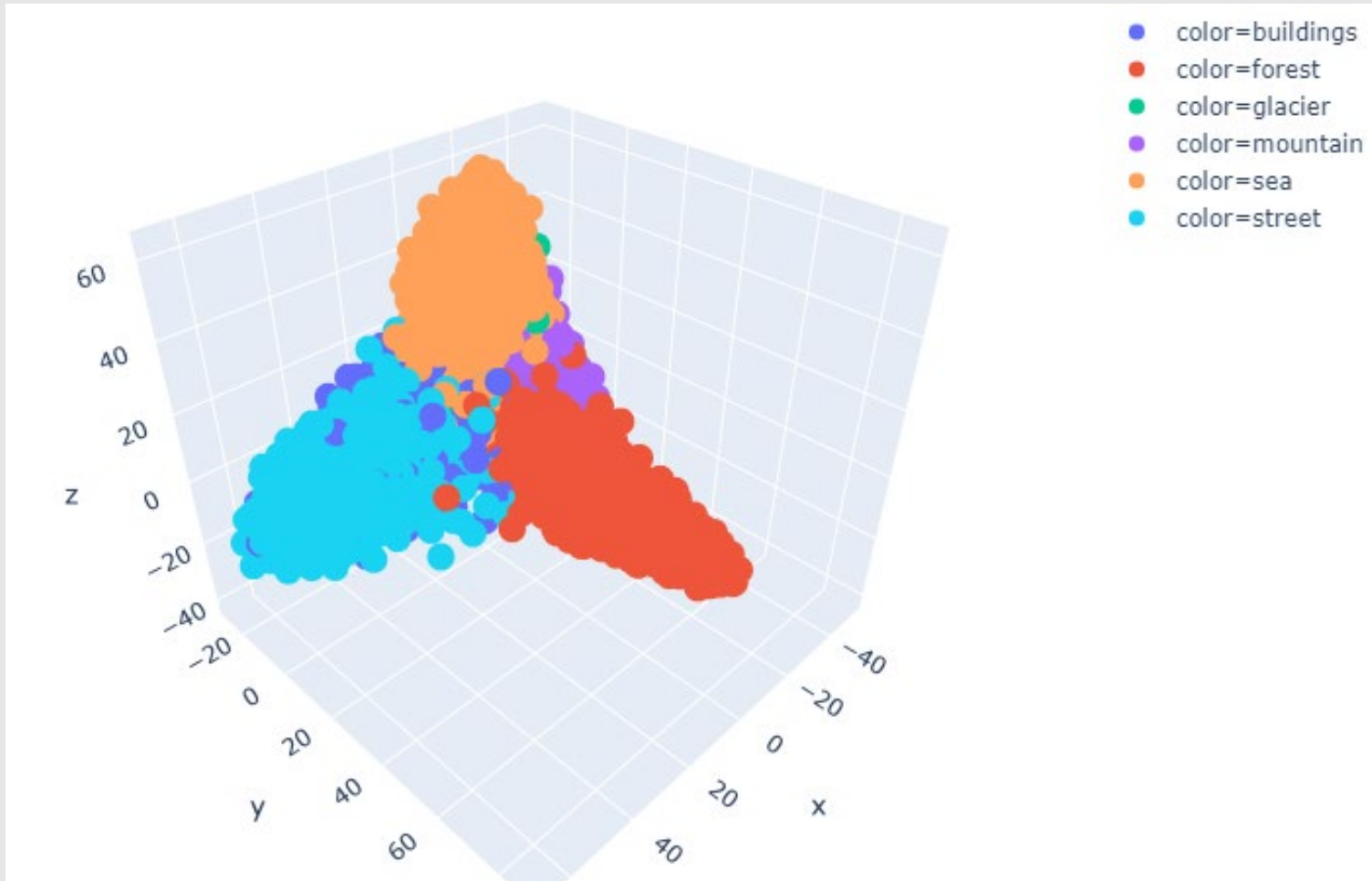


Black box – Pre-trained model



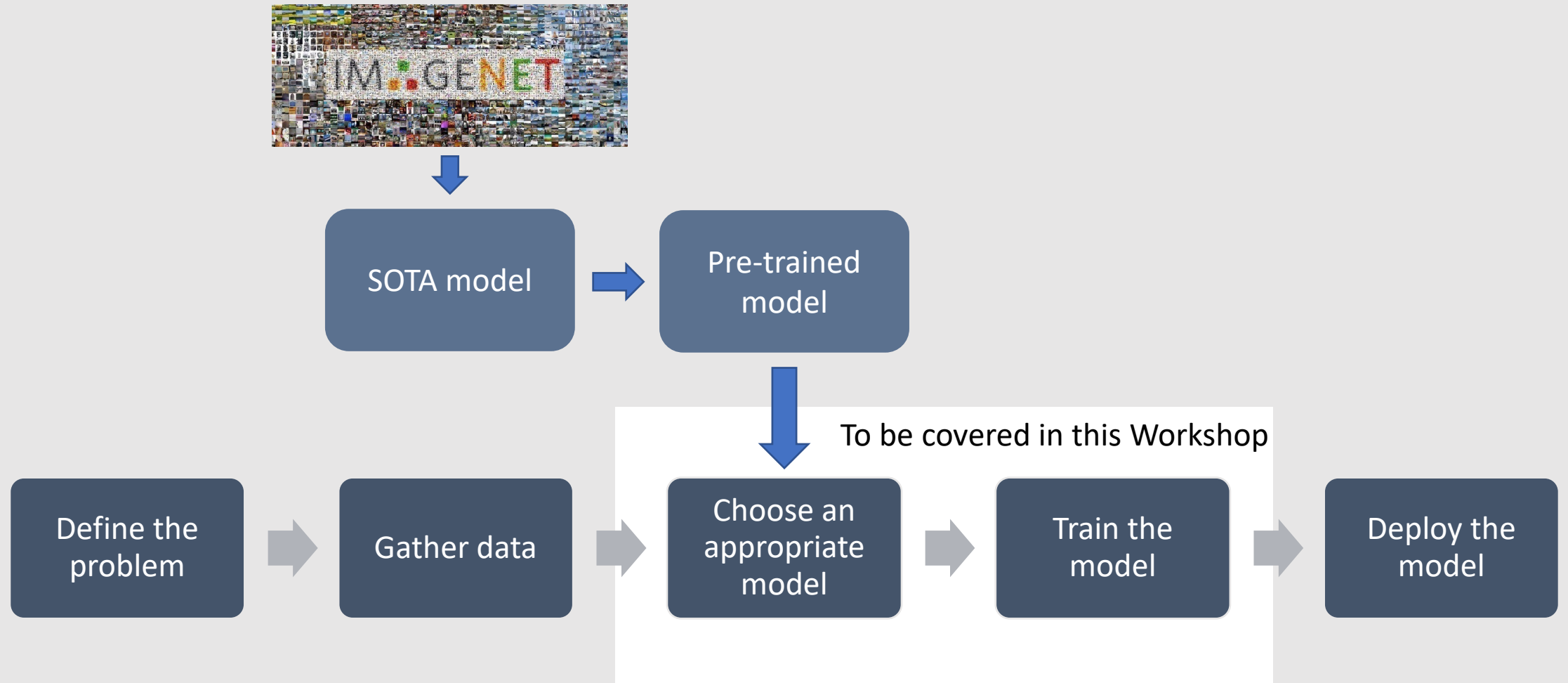
Output - Features vector

Transfer Learning – Black box



Features vectors of Intel Image
Classification dataset in 3D space
(Generated from Google's BiT-M model)

Sample Transfer Learning Workflow



Upstream Training - ImageNet

- ImageNet: a database of images for visual object recognition research
 - 14 million images, hand-annotated
 - 20,000 categories (classes)
 - The standard dataset for evaluating neural network architecture in research
 - <http://image-net.org/explore>



Upstream Training - ImageNet

Geological formation, formation

(geology) the geological features of the earth


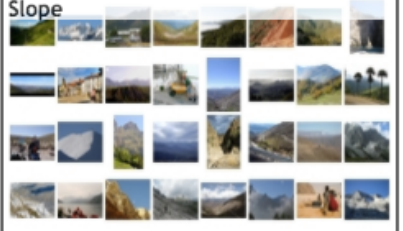
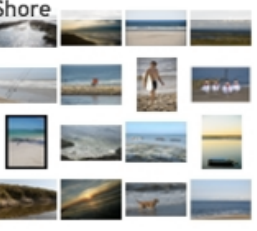

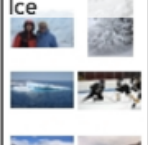




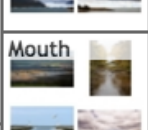





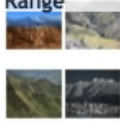

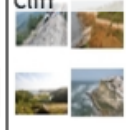






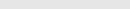
1808 pictures 86.24% Popularity Percentile Wordnet IDs

Numbers in brackets: (the number of synsets in the subtree).

- ImageNet 2011 Fall Release (32326)
 - plant, flora, plant life (4486)
 - geological formation, formation (17)
 - aquifer (0)
 - beach (1)
 - cave (3)
 - cliff, drop, drop-off (2)
 - delta (0)
 - diapir (0)
 - folium (0)
 - foreshore (0)
 - ice mass (10)
 - lakefront (0)
 - massif (0)
 - monocline (0)
 - mouth (0)
 - natural depression, depression (0)
 - natural elevation, elevation (41)
 - oceanfront (0)
 - range, mountain range, range of mountains (0)
 - relict (0)
 - ridge, ridgeline (2)
 - ridge (0)
 - shore (7)
 - slope, incline, side (17)
 - spring, fountain, outflow, outpouring (0)
 - talus, scree (0)
 - vein, mineral vein (1)
 - volcanic crater, crater (2)
 - wall (0)

Treemap Visualization

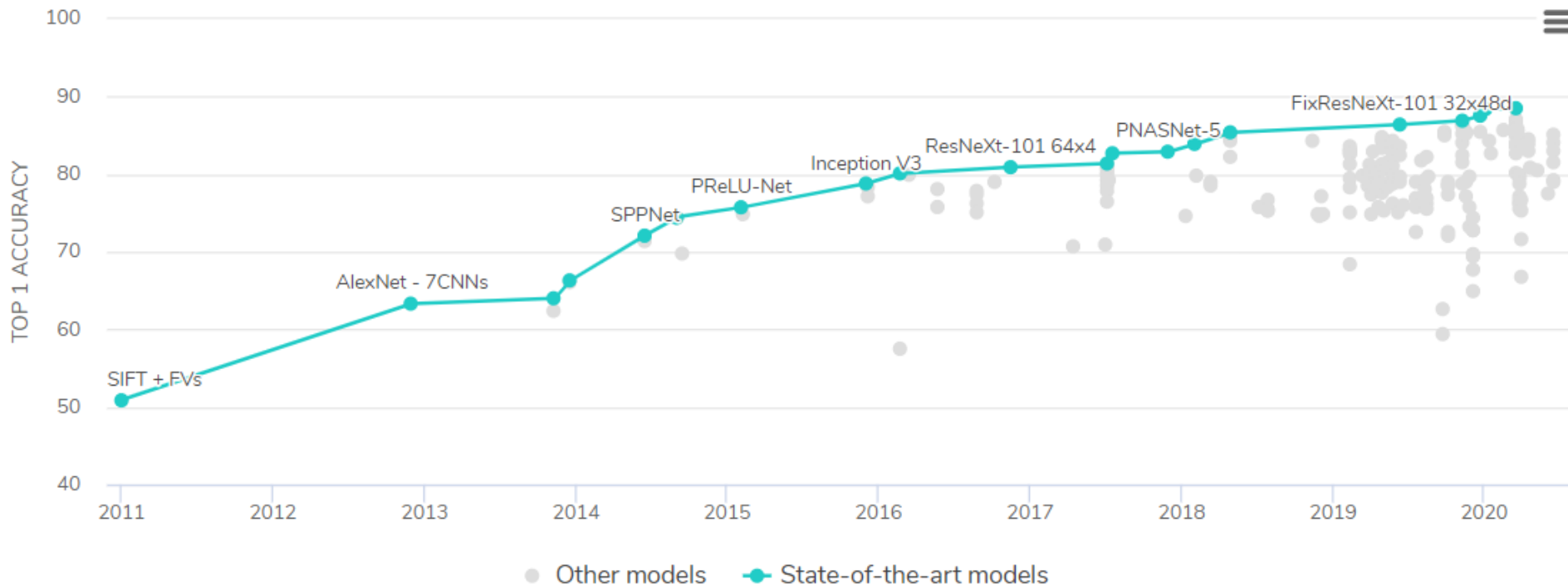
ImageNet 2011 Fall Release Geological formation, formation

Natural 	Slope 	Shore 
Natural 	Ice 	Water 
	Vein 	Delta 
	Foreshore 	
	Massif 	Talus 
	Volcanic 	Beach 
	Mouth 	
	Lakefront 	Range 
	Diapir 	Cliff 
	Wall 	
	Monocline 	Oceanfront 
	Aquifer 	Cave 
		Spring 
		Ridge 

SOTA models

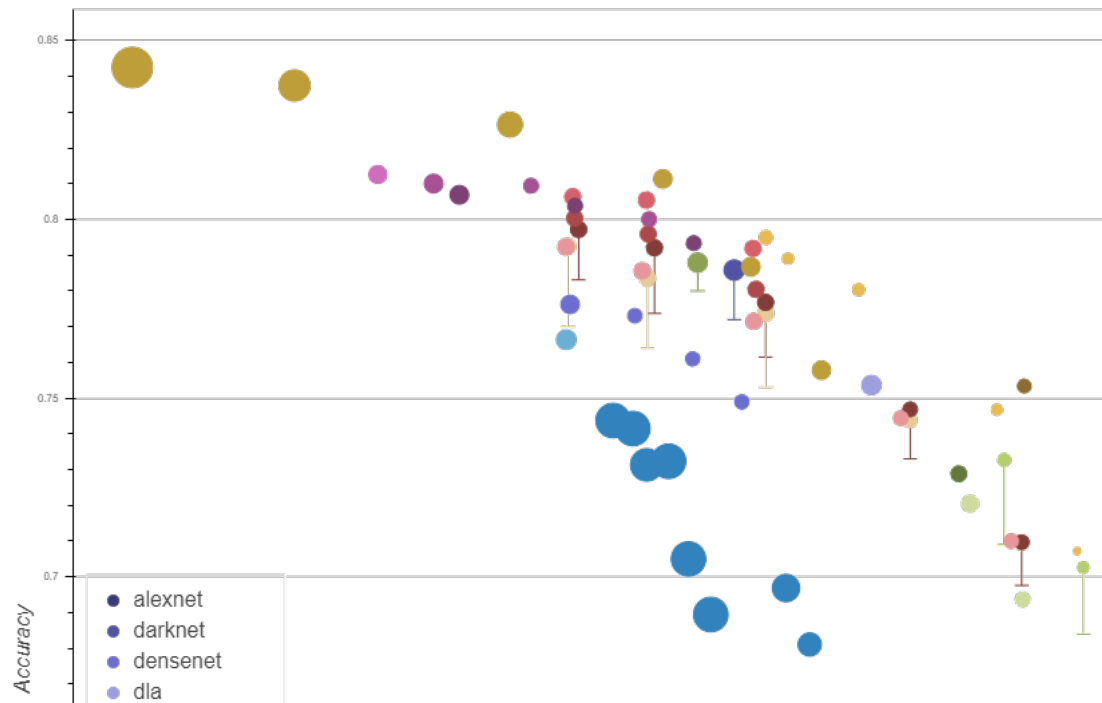
Model	Top-1 accuracy
AlexNet (2012)	63.3%
VGG-19 (2015)	74.5%
ResNet-152 (2016)	77.8%
ResNeXt-101 (2017)	80.9%
EfficientNet-B7 (2019)	84.4%
FixEfficientNet-L2 (2020)	88.5%

Image Classification on ImageNet

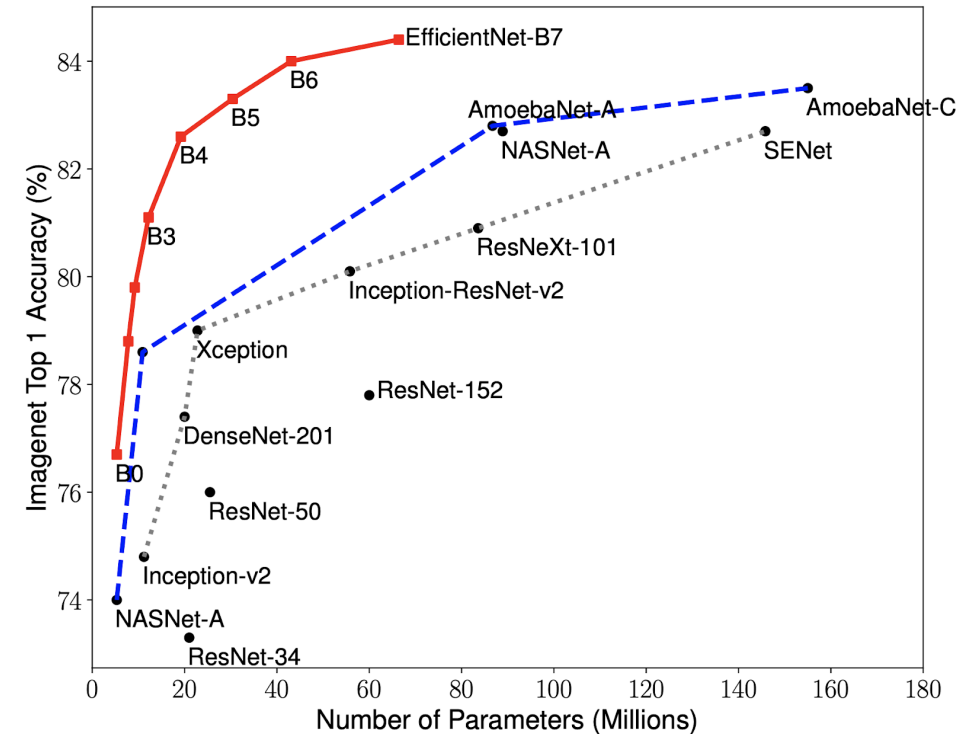


Source: <https://paperswithcode.com/sota/image-classification-on-imagenet>

Choose a model



Accuracy vs Throughput Trade-off



Model size

Define the
problem

Gather data

Choose an
appropriate
model

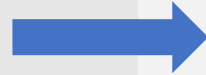
Train the
model

Deploy the
model

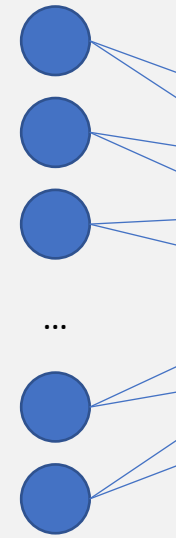
Prepare the model



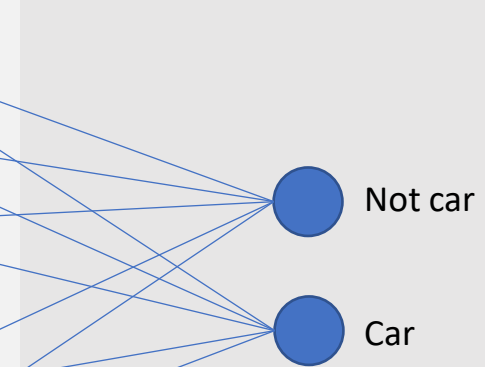
Prepare image input
according to how the pre-trained model was trained



Other layers
(Convolution...)



Features vector
(Dense layer)



Add classification head
based on the number of
output classes

Pre-trained model

Define the
problem



Gather data



Choose an
appropriate
model



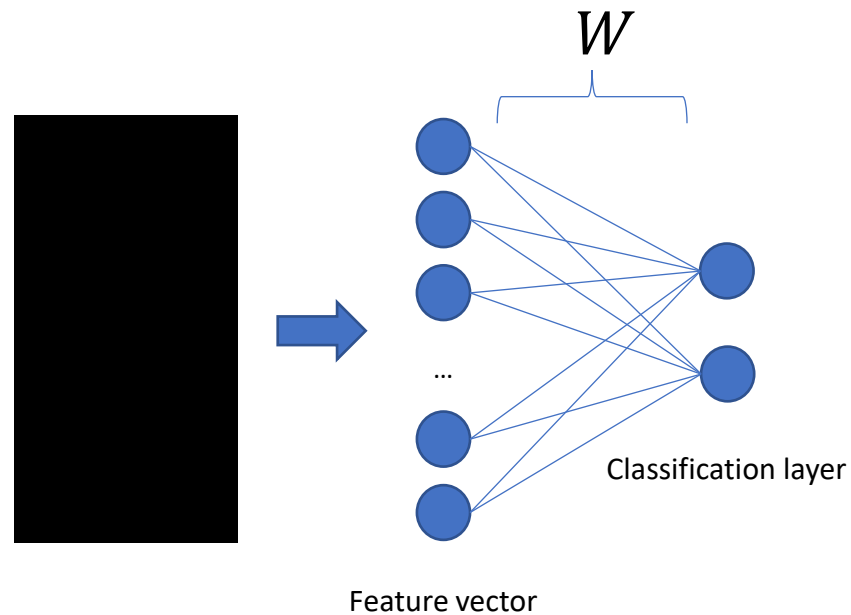
Train the
model



Deploy the
model

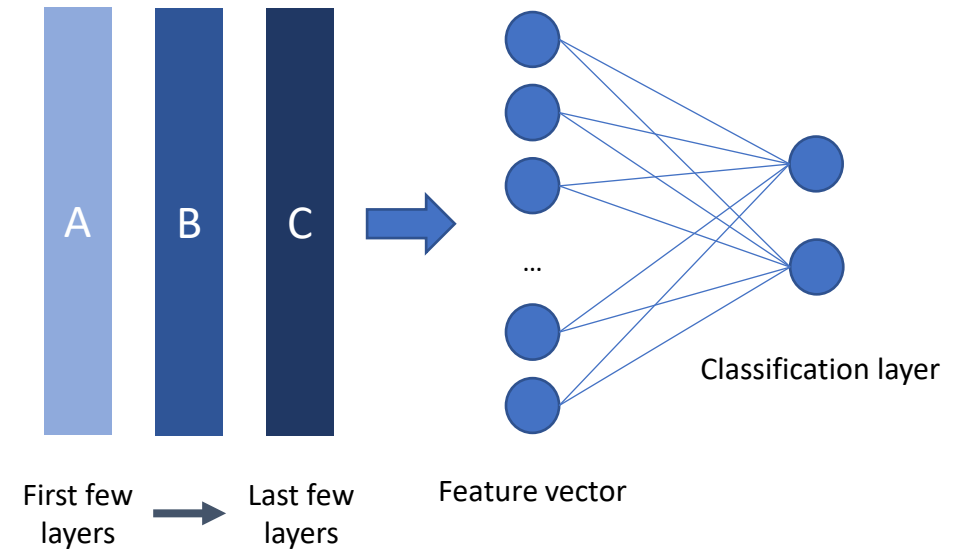
Classification layer and Fine-tuning

Train the classification layer only



Train the whole network

Train selectively the last few layers



(Will not be covered during Hands-on)

Define the
problem

Gather data

Choose an
appropriate
model

Train the
model

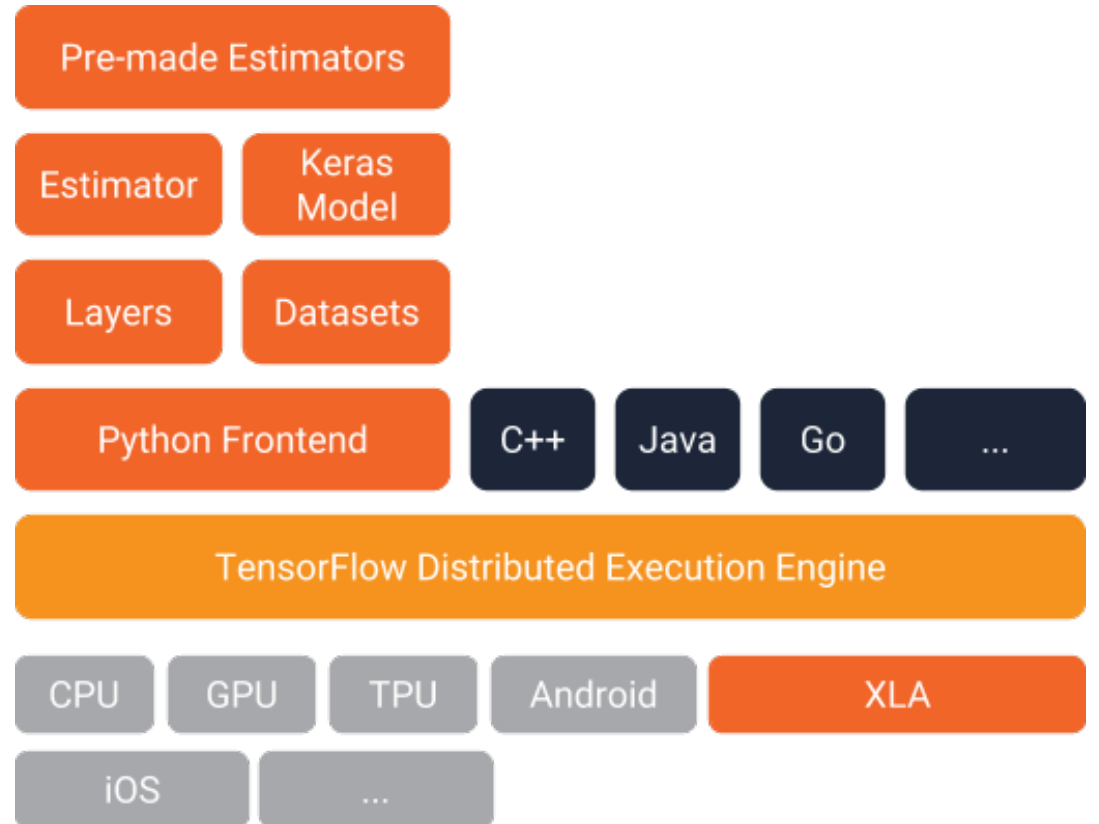
Deploy the
model

TensorFlow and Keras

TensorFlow's **high-level APIs** are based on the Keras API standard for defining and training neural networks.

Keras enables **fast** prototyping, state-of-the-art research, and production—all with **user-friendly APIs**.

TensorFlow Architecture



TensorFlow and Keras

```
import tensorflow as tf
mnist = tf.keras.datasets.mnist

(x_train, y_train), (x_test, y_test) = mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0

model = tf.keras.models.Sequential([
    tf.keras.layers.Flatten(input_shape=(28, 28)),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Dense(10, activation='softmax')
])

model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

model.fit(x_train, y_train, epochs=5)
model.evaluate(x_test, y_test)
```

[Run code now](#)[Try in Google's interactive notebook](#)

```
class MyModel(tf.keras.Model):
    def __init__(self):
        super(MyModel, self).__init__()
        self.conv1 = Conv2D(32, 3, activation='relu')
        self.flatten = Flatten()
        self.d1 = Dense(128, activation='relu')
        self.d2 = Dense(10, activation='softmax')

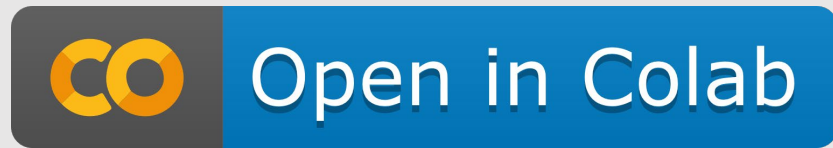
    def call(self, x):
        x = self.conv1(x)
        x = self.flatten(x)
        x = self.d1(x)
        return self.d2(x)

model = MyModel()

with tf.GradientTape() as tape:
    logits = model(images)
    loss_value = loss(logits, labels)
    grads = tape.gradient(loss_value, model.trainable_variables)
    optimizer.apply_gradients(zip(grads, model.trainable_variables))
```

[Run code now](#)[Try in Google's interactive notebook](#)

Hands-on session



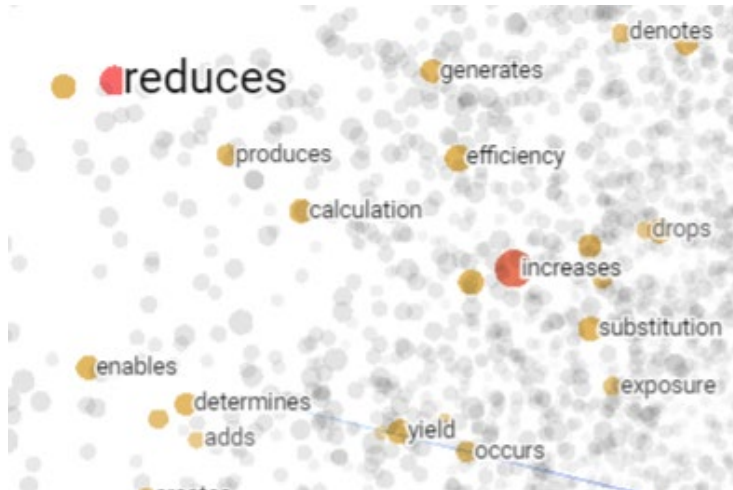
<https://github.com/MLDA-NTU/Transfer-Learning-DL2020>

Transfer Learning for NLP tasks

Upstream training with Wikipedia data



Word embeddings



Word2Vec 10K

<https://projector.tensorflow.org>

Language models

GPT-3
BERT
Turing-NLG
RoBERTa

Using Language models



Hugging Face

Feedback



[MLDA Transfer Learning Workshop Feedback Form \(google.com\)](#)

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