Introduction to Transfer Learning

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MLDA@EEE

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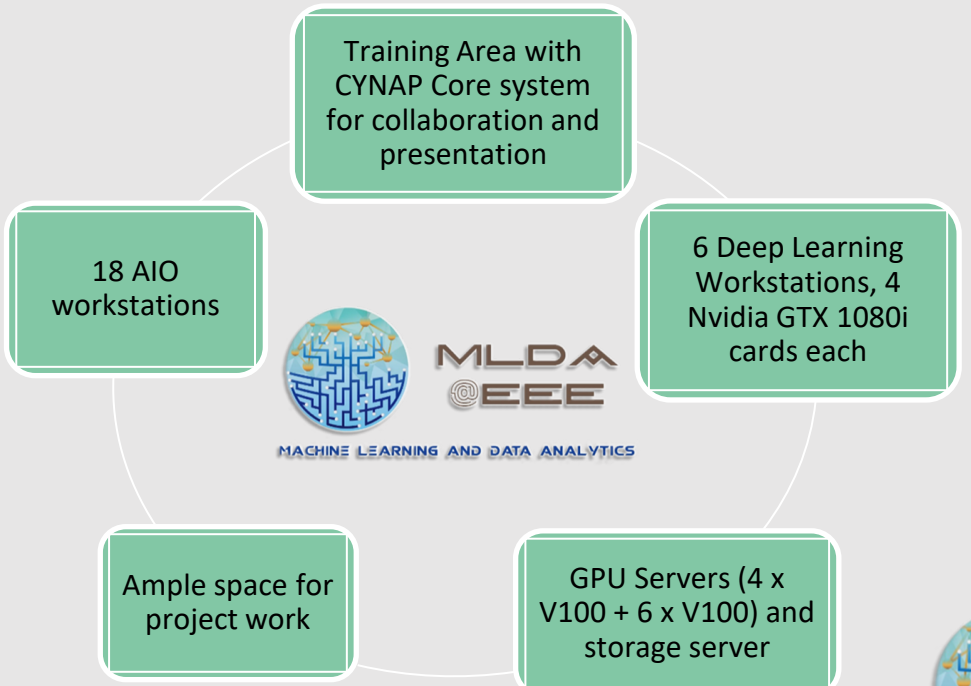
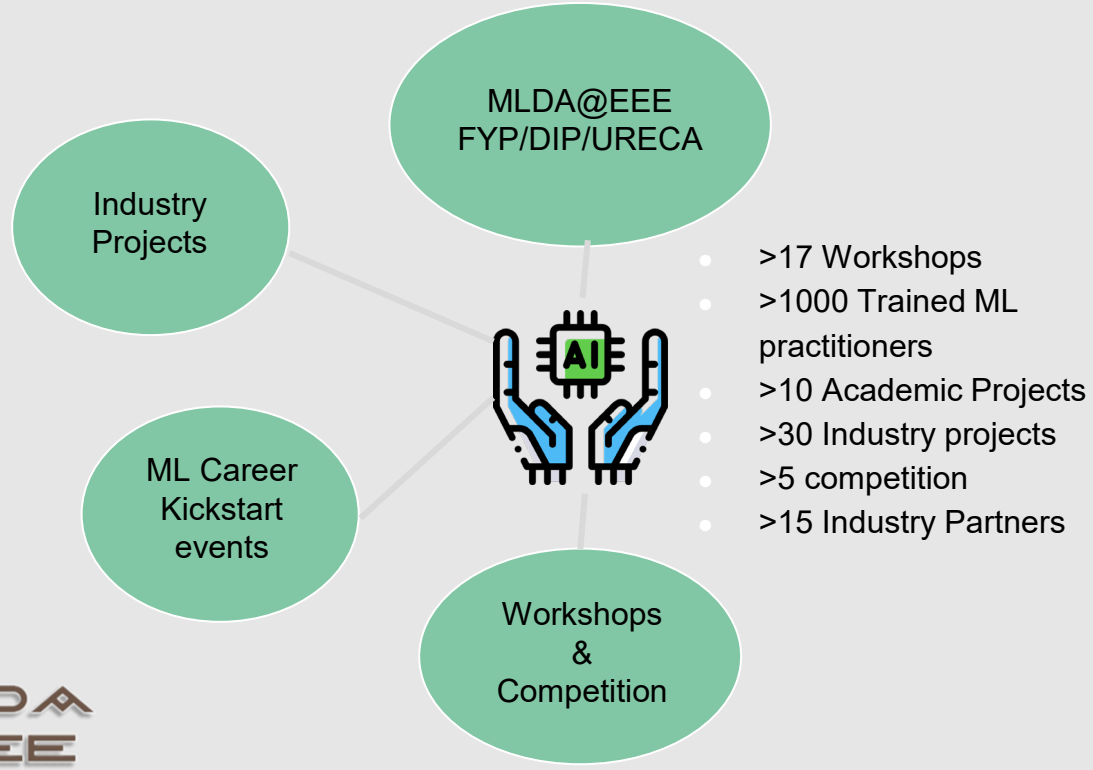
MACHINE LEARNING AND DATA ANALYTICS

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.





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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

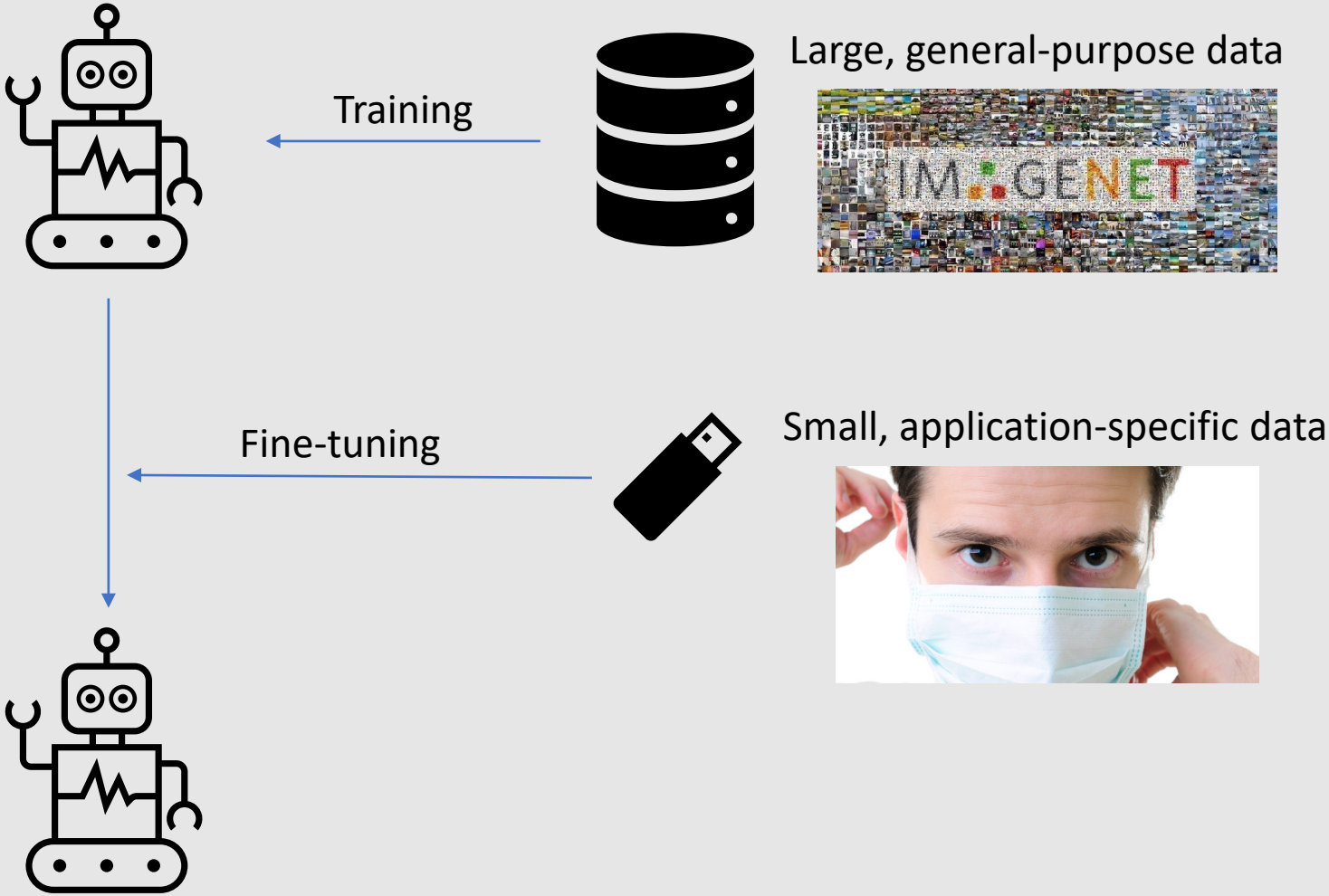
No car

TRUCK CLASSIFIER

Truck

No truck

What is Transfer Learning



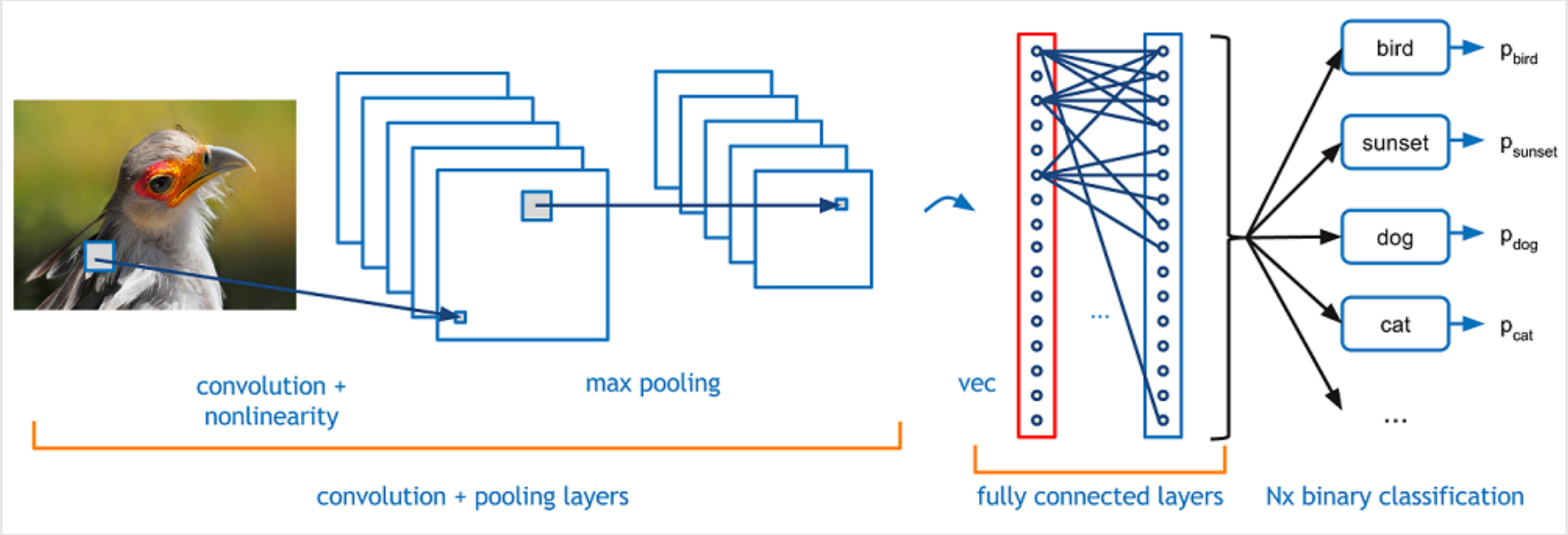
Motivations

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

...

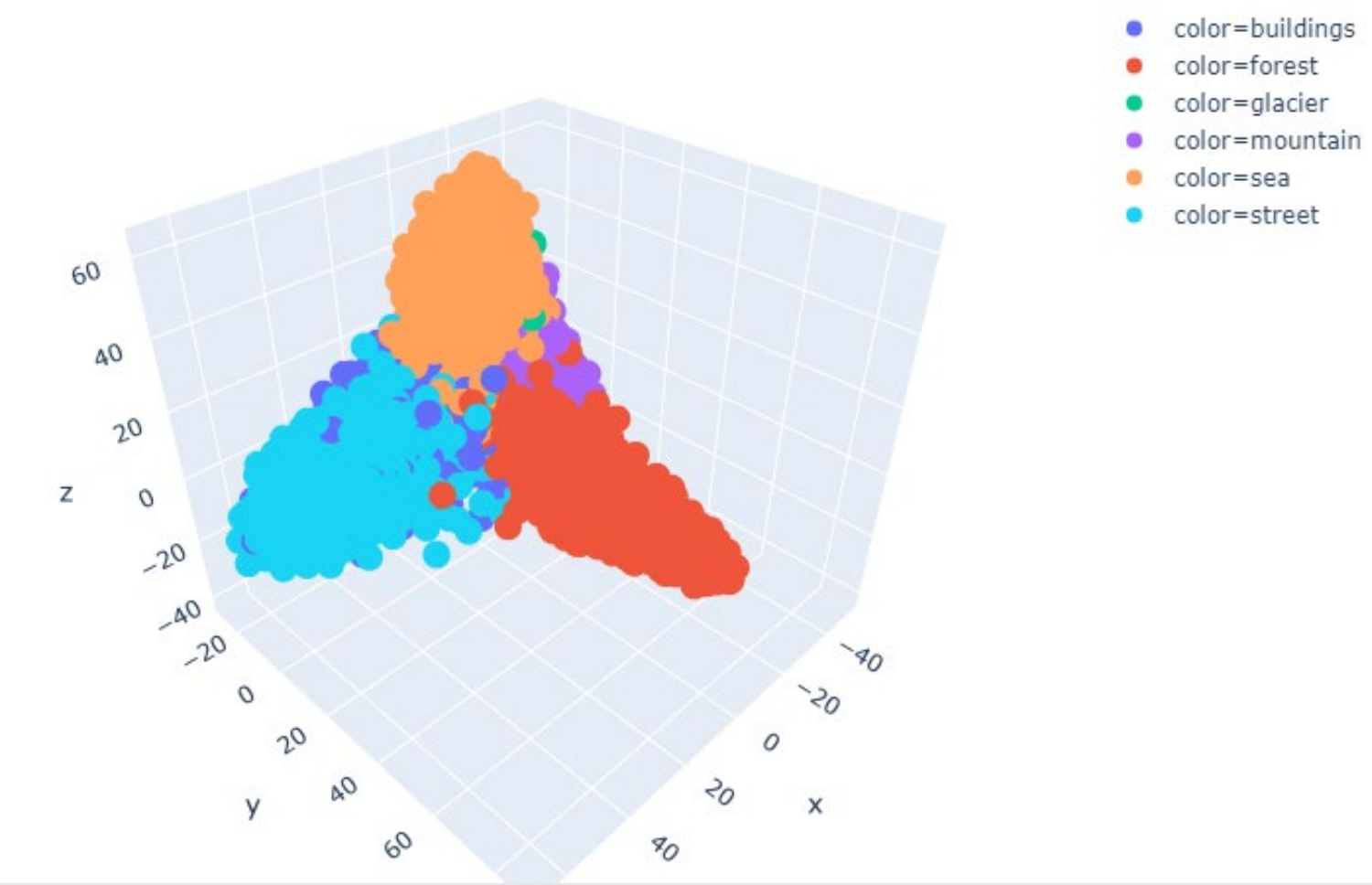
Not car

Car

Classification head

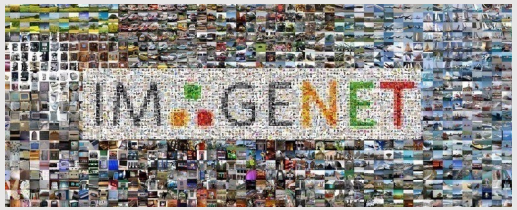
Output - Features vector

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



SOTA model → Pre-trained model

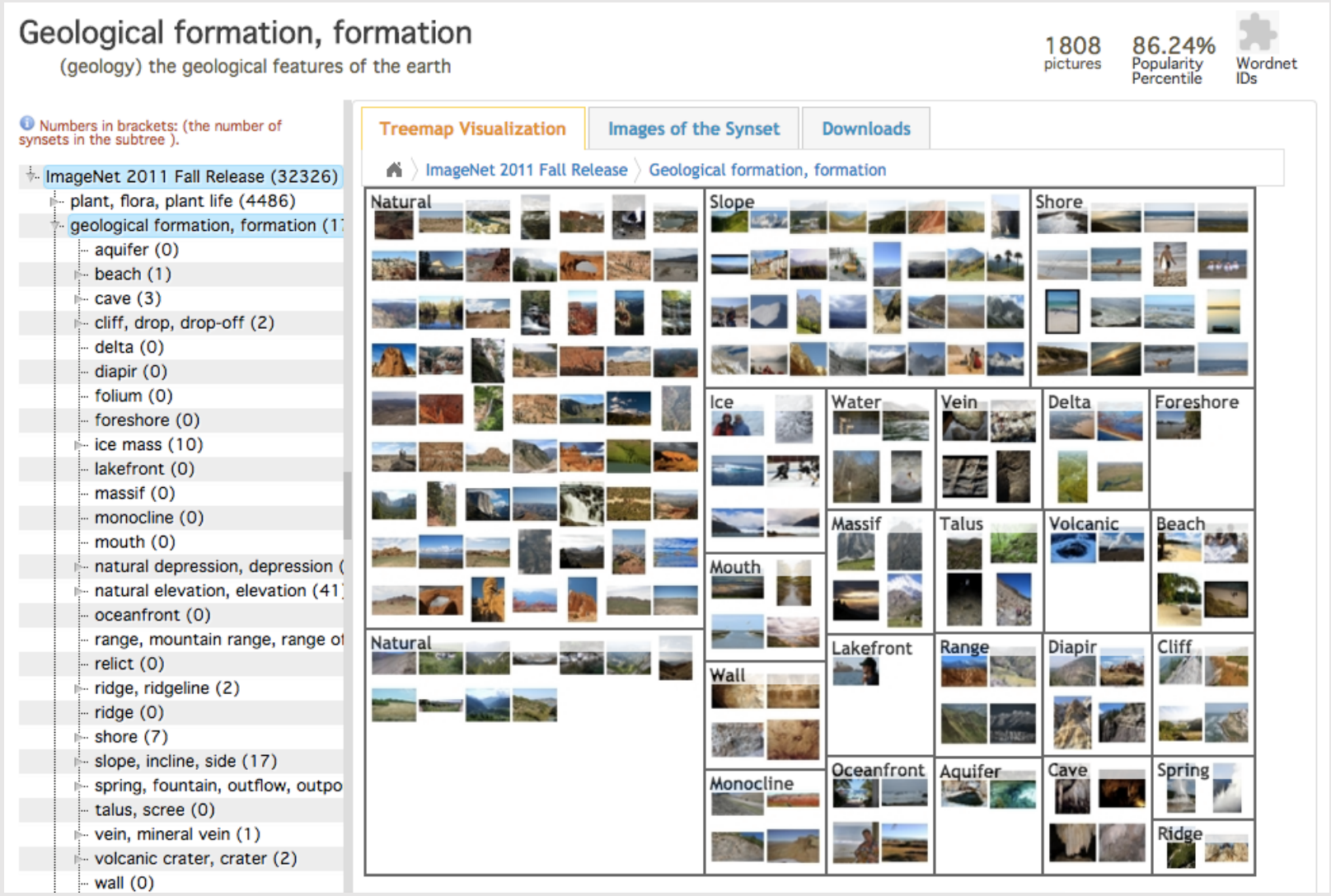
To be covered in this Workshop

Define the problem → Gather data → Choose an appropriate model → Train the model → Deploy the model

Upstream Training - ImageNet

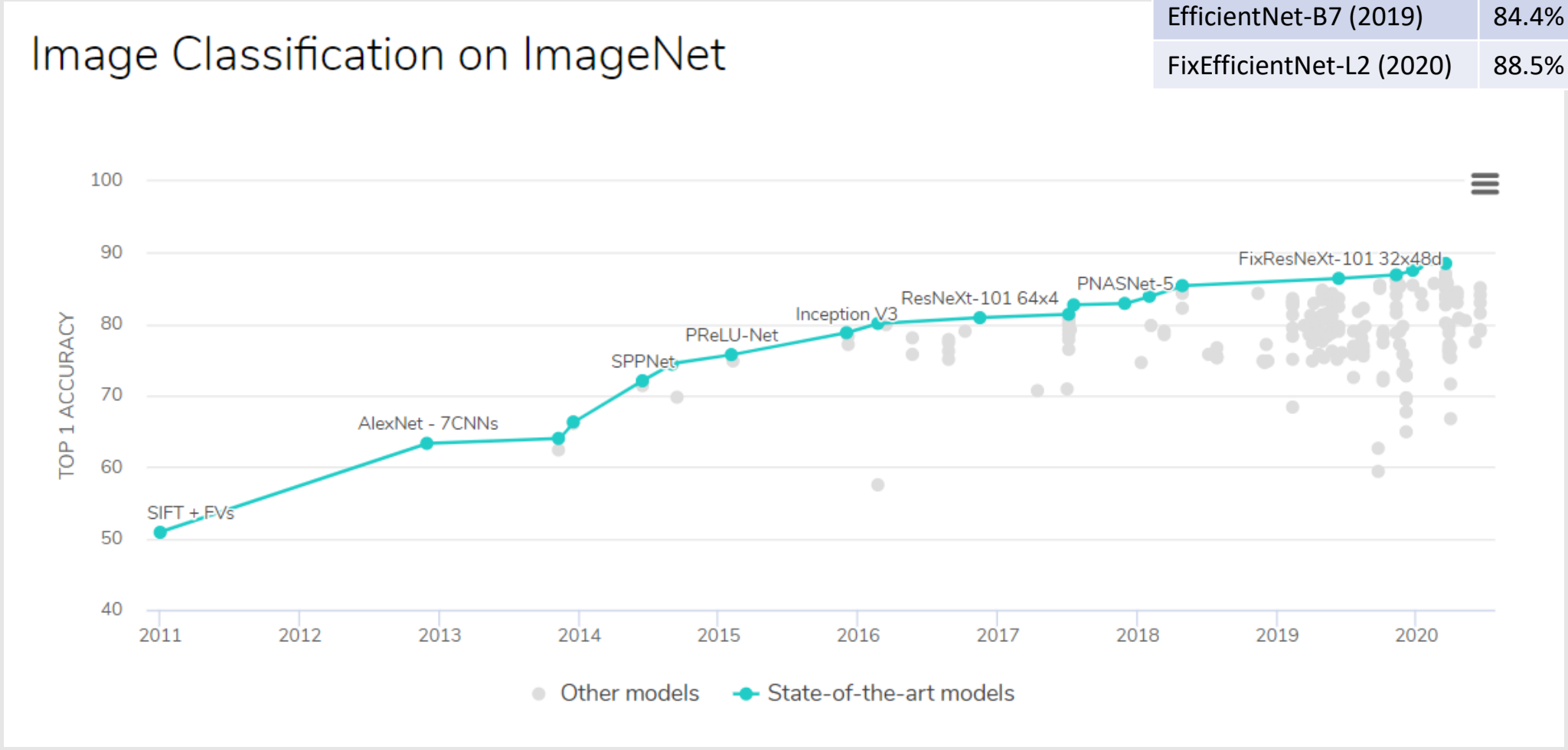
- ImageNet: a database of images for visual object recognition research
  - 14 million images, hand-annotated
  - 20,000 categories (classes)
  - The standard dataset for evaluating neural network architecture in research
  - http://image-net.org/explore

Upstream Training - ImageNet



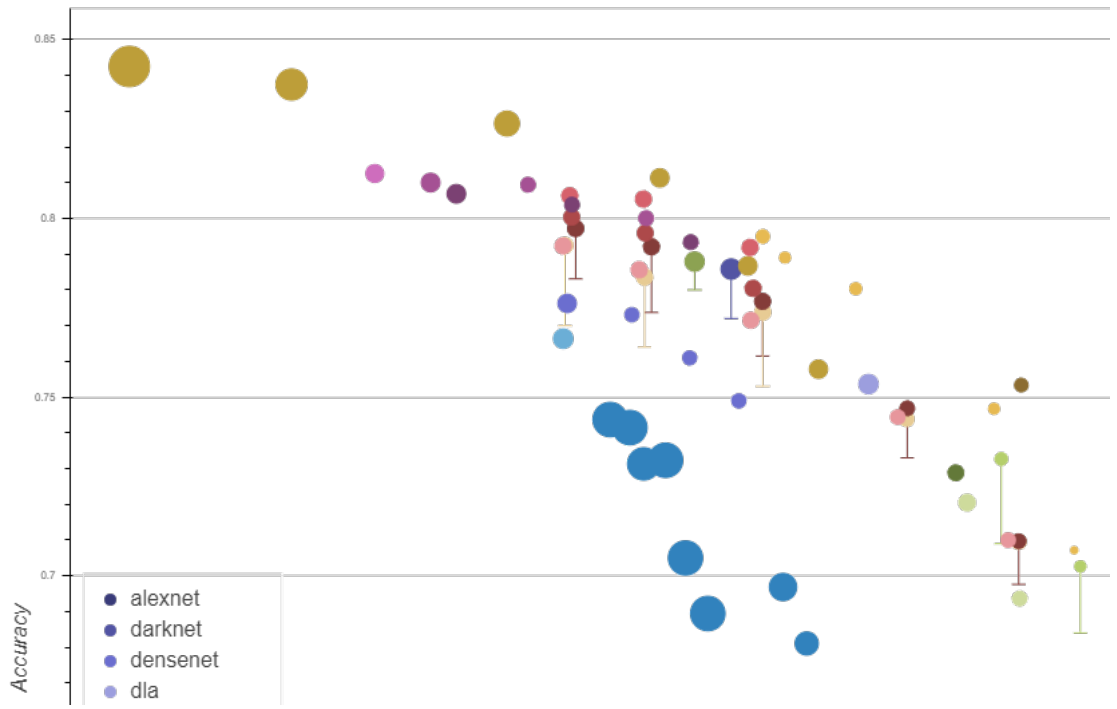
SOTA models

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%

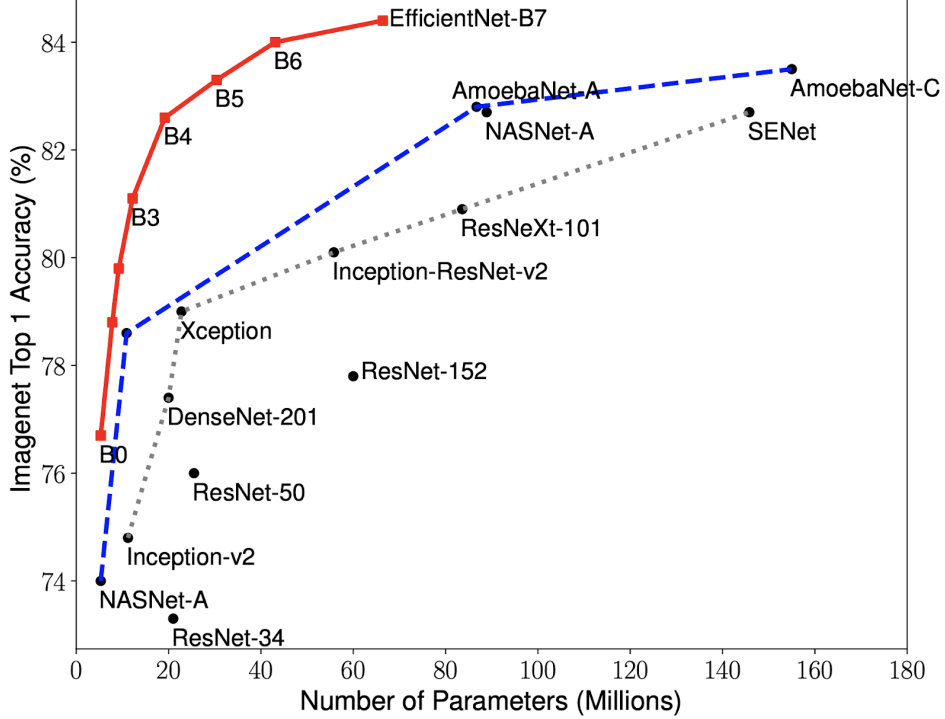


Source: https://paperswithcode.com/sota/image-classification-on-imagenet

Choose a model



Accuracy vs Throughput Trade-off

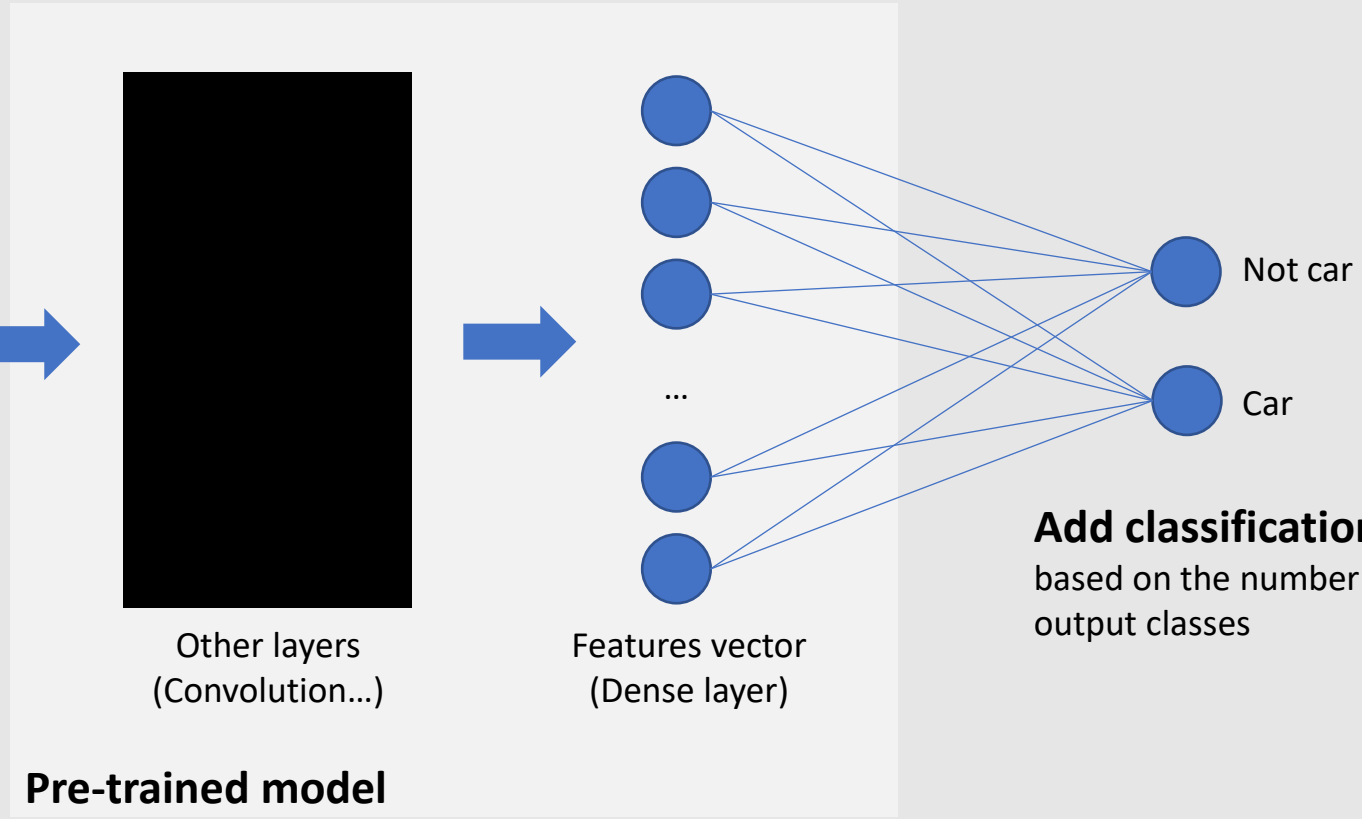


Model size

Define the problem → Gather data → Choose an appropriate model → Train the model → Deploy the model

Prepare the model

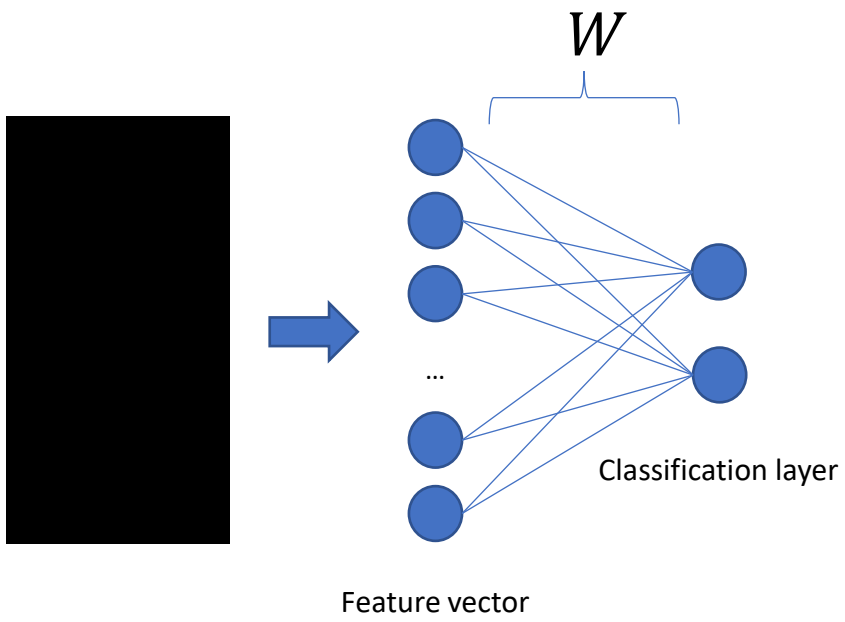
Prepare image input
according to how the pre-trained model was trained



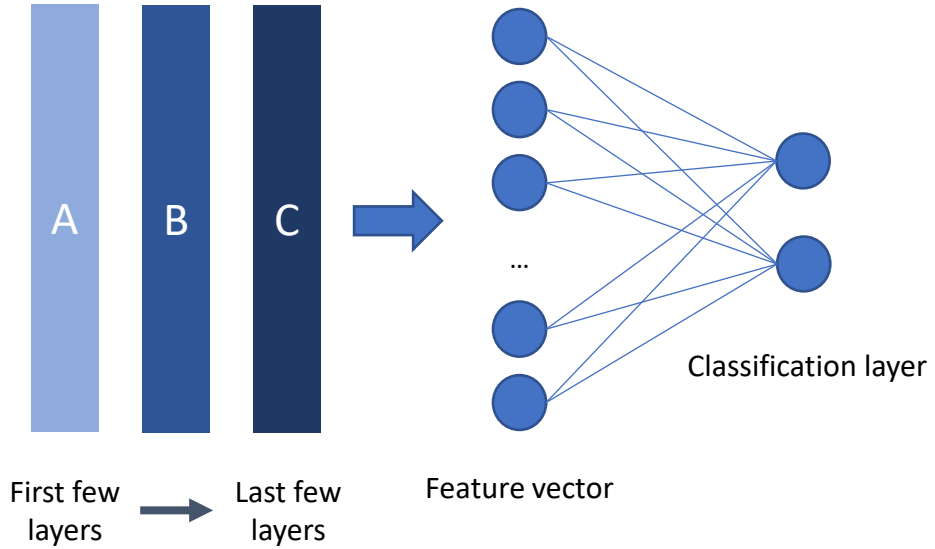
Define the problem → Gather data → Choose an appropriate model → Train the model → Deploy the model

Classification layer and Fine-tuning

Train the classification layer only



Train the whole network
Train selectively the last few layers



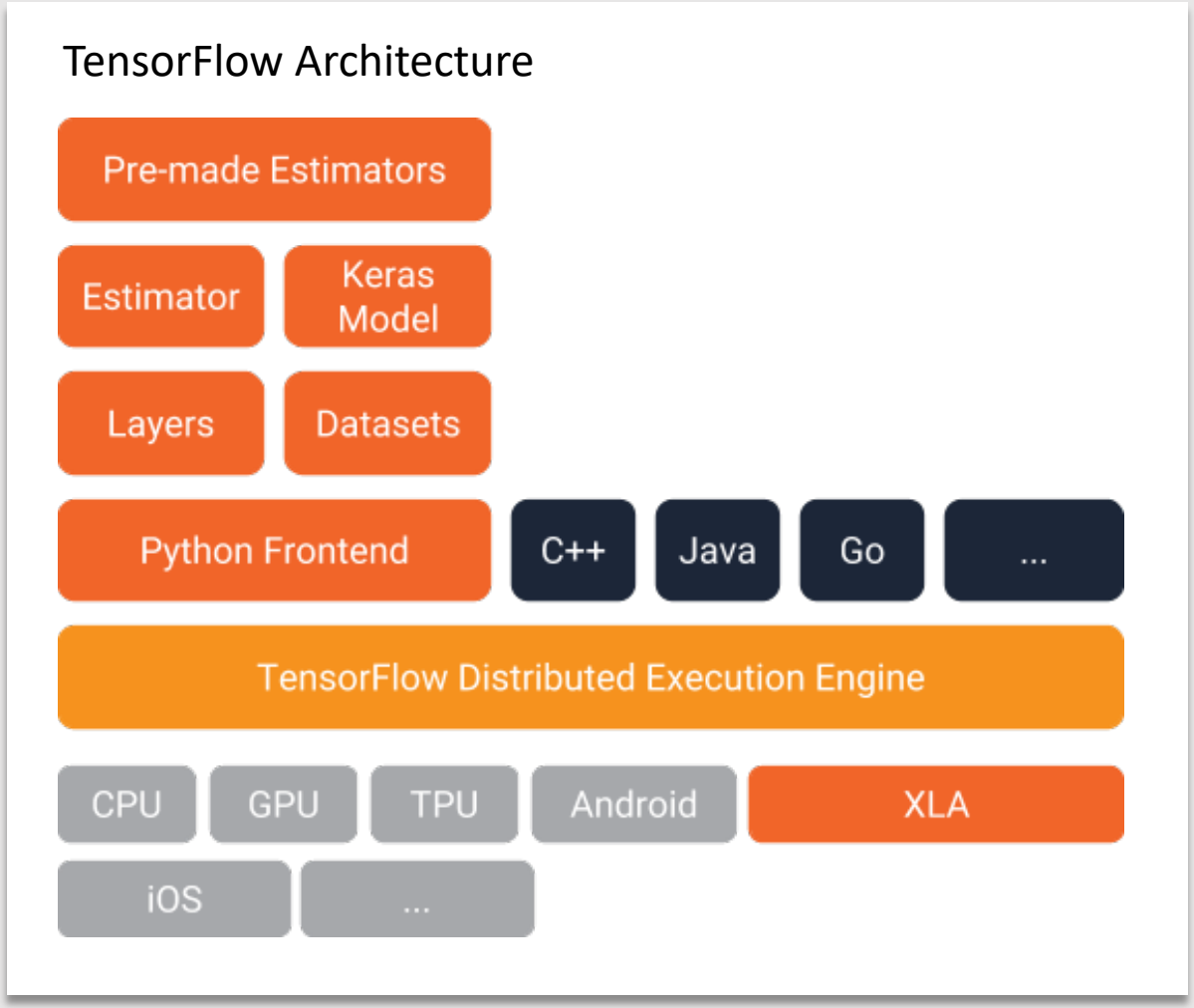
(Will not be covered during Hands-on)

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 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_variable
optimizer.apply_gradients(zip(grads, model.trainable_varia
```

Run code now Try in Google's interactive notebook

Hands-on session

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

Feedback

MLDA Transfer Learning Workshop Feedback Form (google.com)