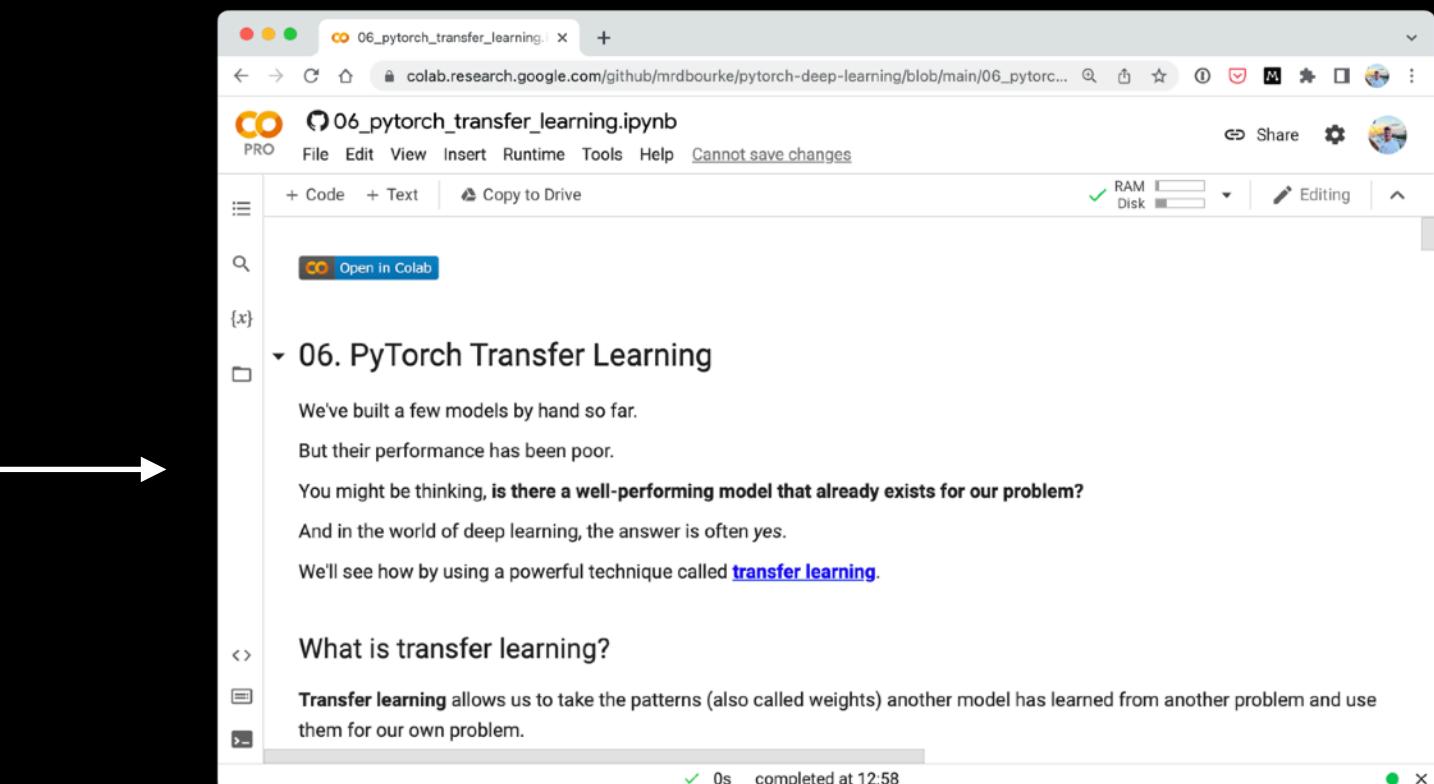


Transfer Learning with



Where can you get help?

- Follow along with the code

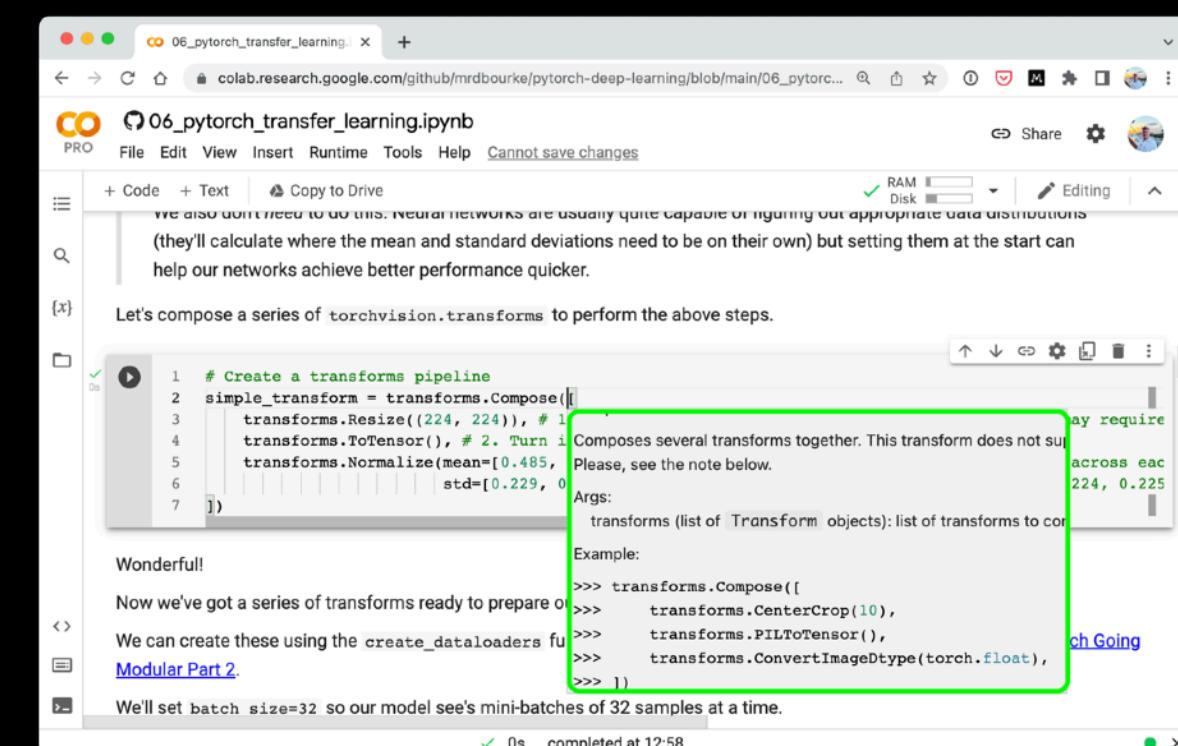


A screenshot of a Google Colab notebook titled "06_pytorch_transfer_learning.ipynb". The notebook contains text explaining transfer learning and its benefits. It also includes a section on what transfer learning is and how it allows us to take patterns from one model and use them in another.

"If in doubt, run the code"

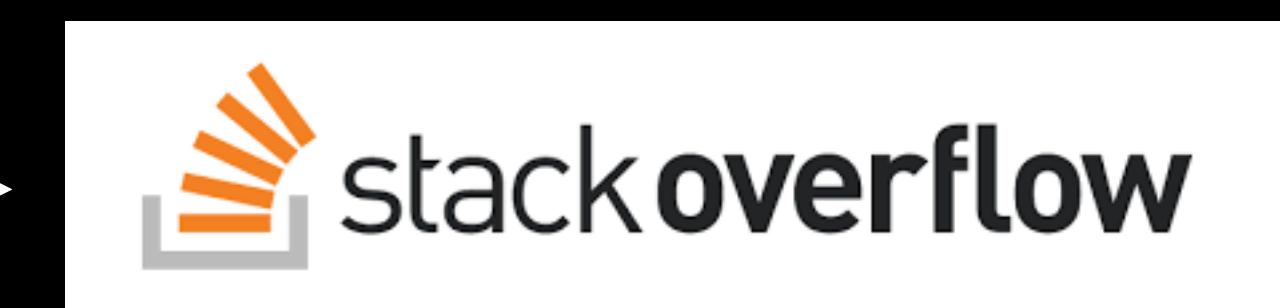
- Try it for yourself

- Press SHIFT + CMD + SPACE to read the docstring



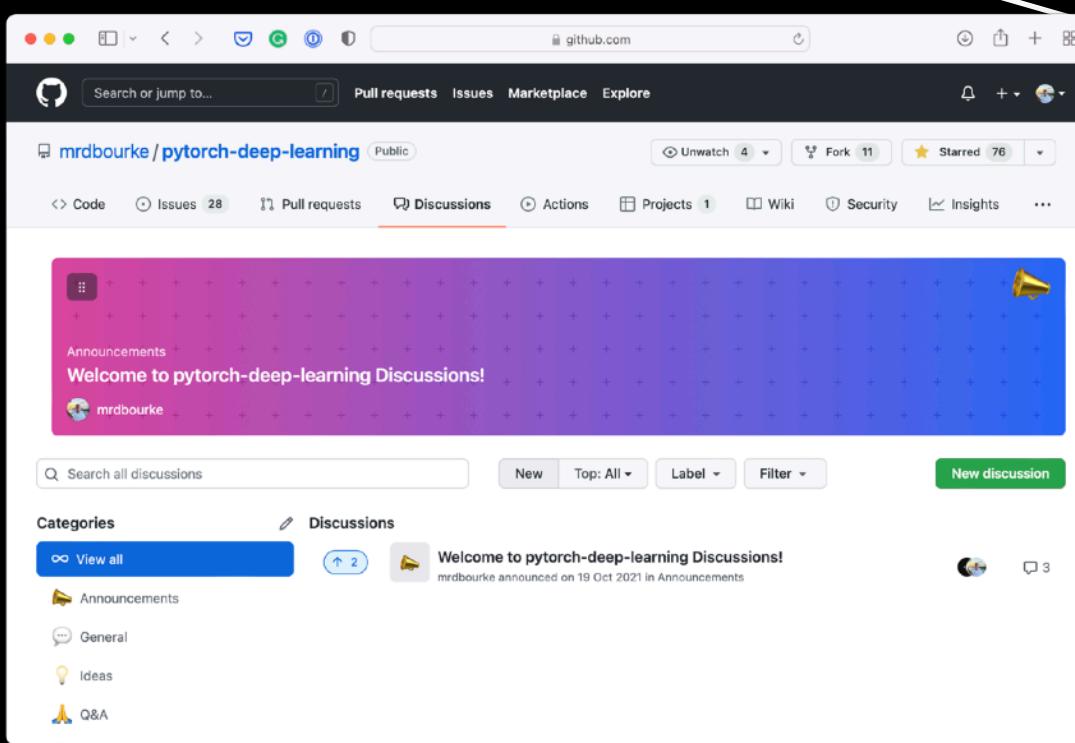
A screenshot of a Google Colab notebook showing a code cell. The code defines a transform pipeline using `transforms.Compose`. A green box highlights the docstring for `transforms.Compose`, which explains that it composes several transforms together. The code cell also includes examples of how to use the transform.

- Search for it

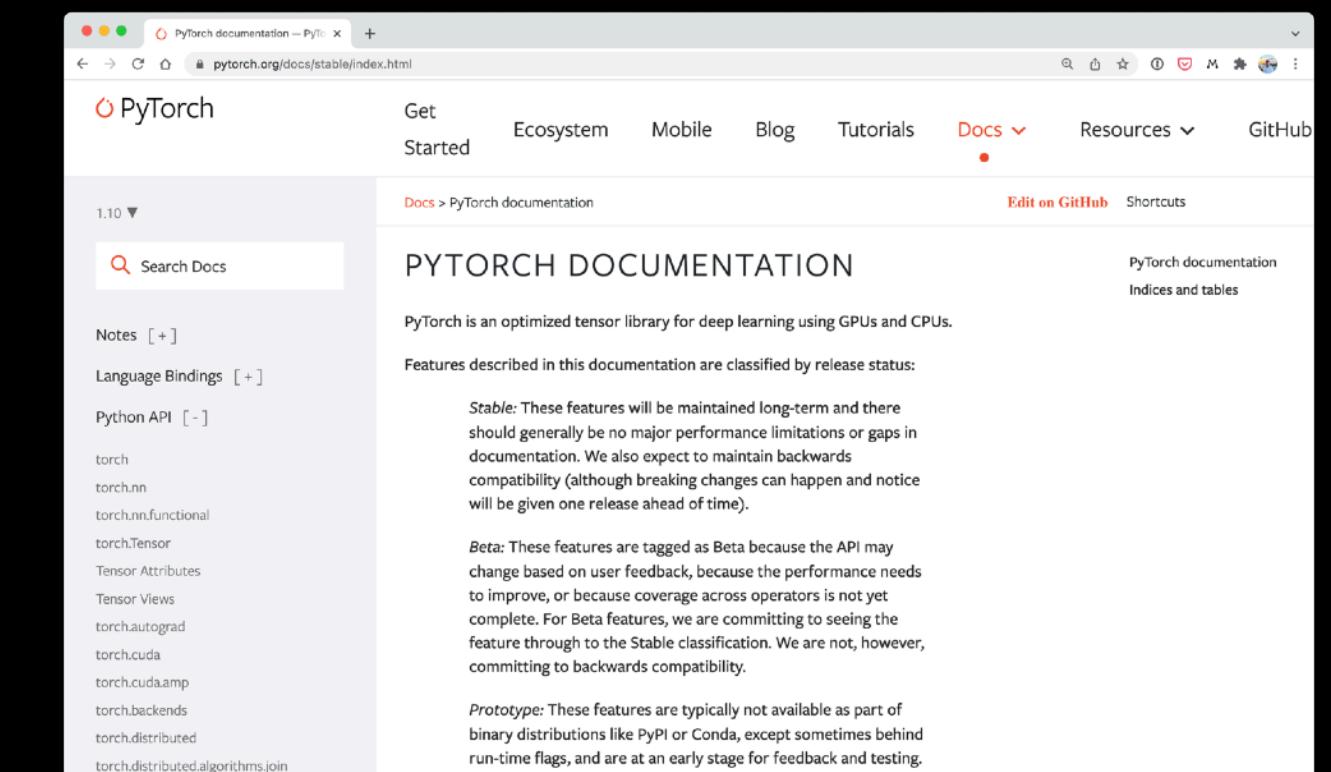


- Try again

- Ask



<https://www.github.com/mrdbourke/pytorch-deep-learning/discussions>

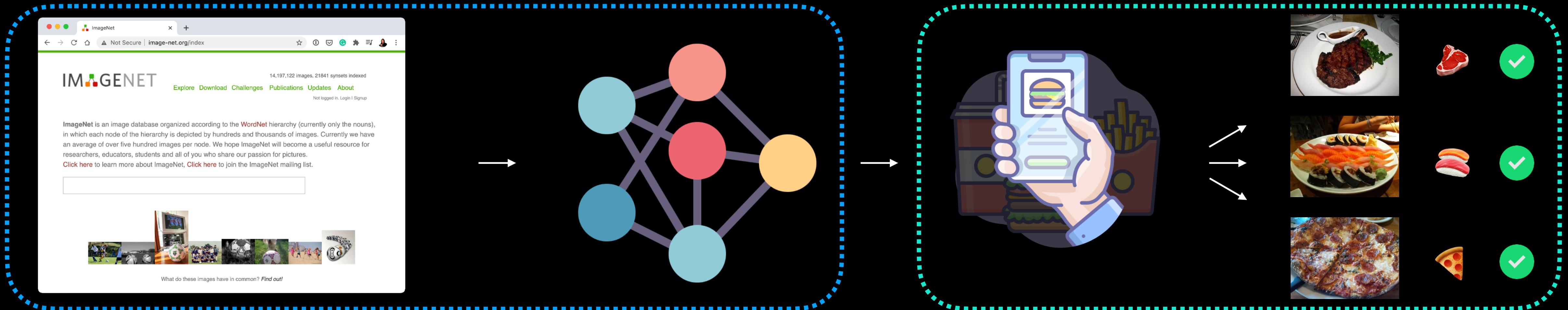


“What is transfer learning?”

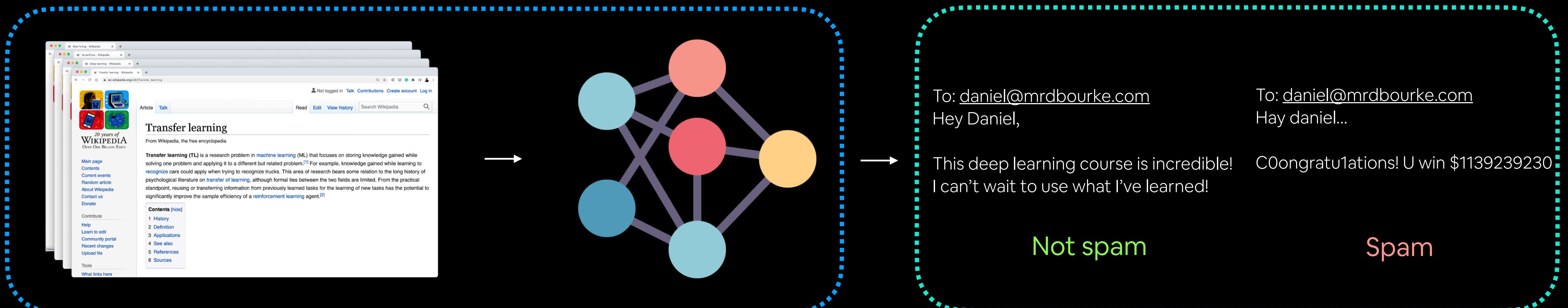
Surely someone has spent the time crafting the right model for the job...

Example transfer learning use cases

Computer vision



Natural language processing



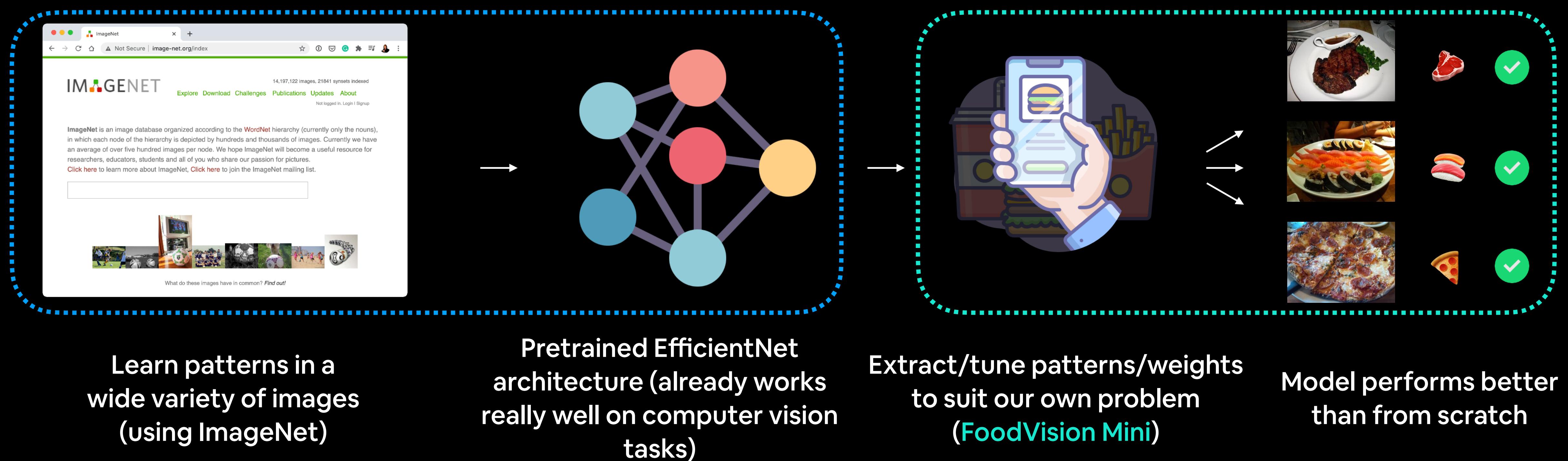
Model learns patterns/weights from similar problem space

Patterns get used/tuned to specific problem

“Why use transfer learning?”

Why use transfer learning?

- Can leverage an existing neural network architecture **proven to work** on problems similar to our own
- Can leverage a working network architecture which has **already learned patterns** on similar data to our own (often results in great results with less data)



Improving a model

Method to improve a model (reduce overfitting)

What does it do?

More data

Gives a model more of a chance to learn patterns between samples (e.g. if a model is performing poorly on images of pizza, show it more images of pizza).

Data augmentation

Increase the diversity of your training dataset without collecting more data (e.g. take your photos of pizza and randomly rotate them 30°). Increased diversity forces a model to learn more generalisation patterns.

Better data

Not all data samples are created equally. Removing poor samples from or adding better samples to your dataset can improve your model's performance.

Use transfer learning

Take an existing model's pre-learned patterns from one problem and tweak them to suit your own problem. For example, take a model trained on pictures of cars to recognise pictures of trucks.

Where to find pretrained models

The screenshot shows the PyTorch documentation page for 'Models and pre-trained weights'. The left sidebar includes links for 'Package Reference', 'Transforming and augmenting images' (with 'Models and pre-trained weights' highlighted), 'Datasets', 'Operators', 'Reading/Writing images and videos', 'Feature extraction for model inspection', 'Examples and training references', 'Example gallery', and 'Training references'. The main content area is titled 'MODELS AND PRE-TRAINED WEIGHTS' and discusses the `torchvision.models` subpackage. It includes a note about backward compatibility and a section on 'Classification'.

PyTorch domains libraries (torchvision, torchtext, torchaudio, torchrec). Source: <https://pytorch.org/vision/stable/models.html>

The screenshot shows the GitHub repository page for 'rwightman/pytorch-image-models'. The repository has 272 stars, 3.1k forks, and 18.6k subscribers. It contains 18 branches and 31 tags. The code tab is selected, showing a list of files and their commit history. The repository description mentions PyTorch image models, scripts, pretrained weights for ResNet, ResNeXT, EfficientNet, EfficientNetV2, NFNet, Vision Transformer, MixNet, MobileNet-V3/V2, RegNet, DPN, and CSPNet.

Torch Image Models (timm library).
Source: <https://github.com/rwightman/pytorch-image-models>

The screenshot shows the HuggingFace Hub interface. The left sidebar lists 'Tasks' (Image Classification, Image Segmentation, Automatic Speech Recognition, Token Classification, Audio Classification, Summarization) and 'Libraries' (PyTorch, TensorFlow, JAX). The main content area displays a list of pre-trained models like 'distilgpt2', 'gpt2', 'bert-base-uncased', 'distilbert-base-uncased-finetuned-sst-2-english', 'roberta-base', and 'SEBIS/code_trans_t5_small_program_synthesize_transfer_lea...'. A search bar at the top right allows users to search for specific models.

HuggingFace Hub.
Source: <https://huggingface.co/models>

The screenshot shows the Paperswithcode SOTA interface. The main header reads 'Browse State-of-the-Art' with statistics: 7,545 benchmarks, 3,092 tasks, and 71,000 papers with code. Below this, there's a section for 'Computer Vision' featuring categories like Semantic Segmentation, Image Classification, Object Detection, Image Generation, and Denoising, each with a thumbnail and some details.

Paperswithcode SOTA.
Source: <https://paperswithcode.com/sota>

What we're going to cover

(broadly)

- Getting setup (**importing previously written code**)
- Introduce **transfer learning** with PyTorch
- **Customise a pretrained model** for our own use case

(FoodVision Mini 🍕🥩🍣)

- **Evaluating** a transfer learning model
- **Making predictions** on our own custom data

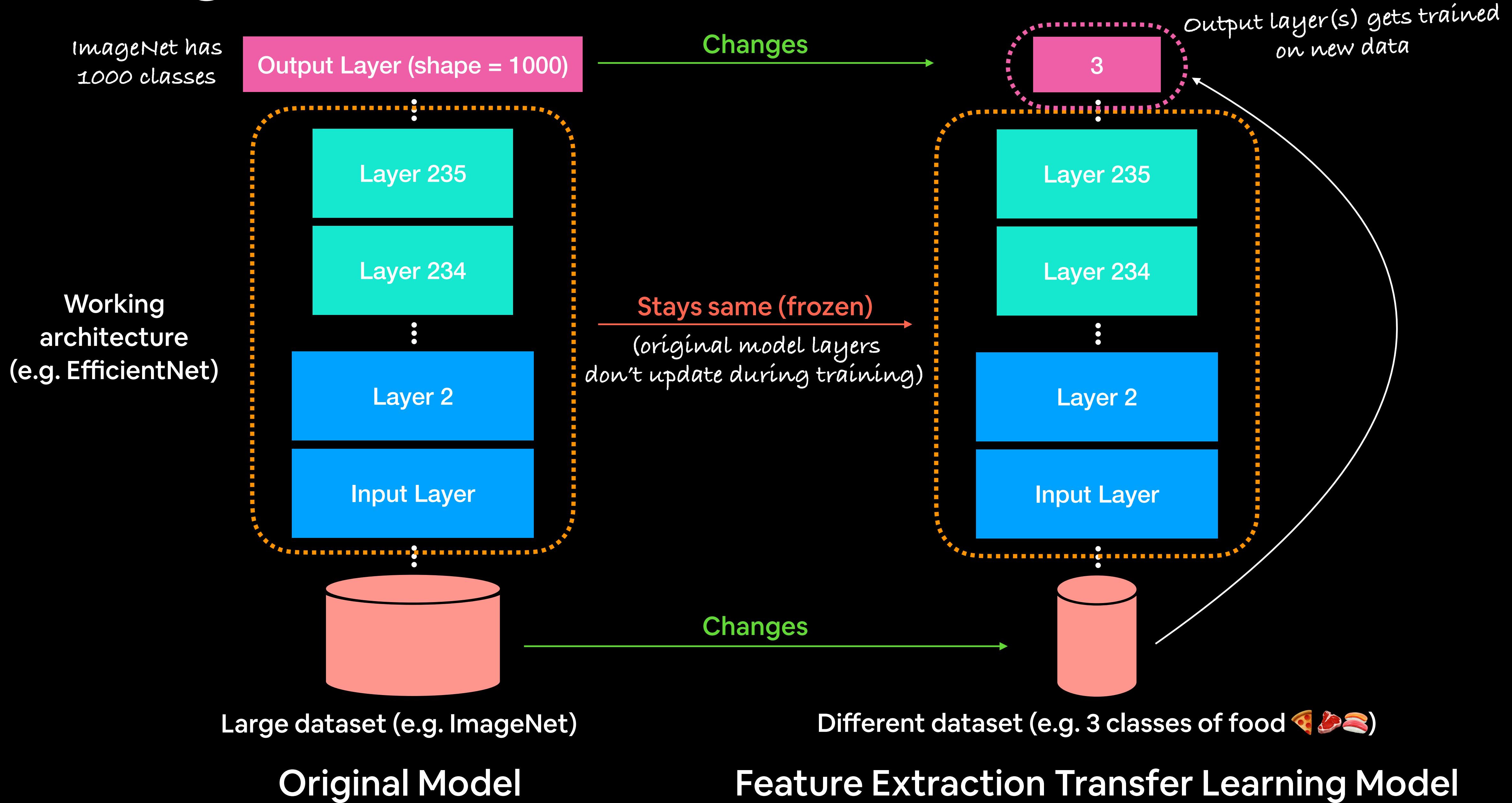
(we'll be cooking up lots of code!)

How:

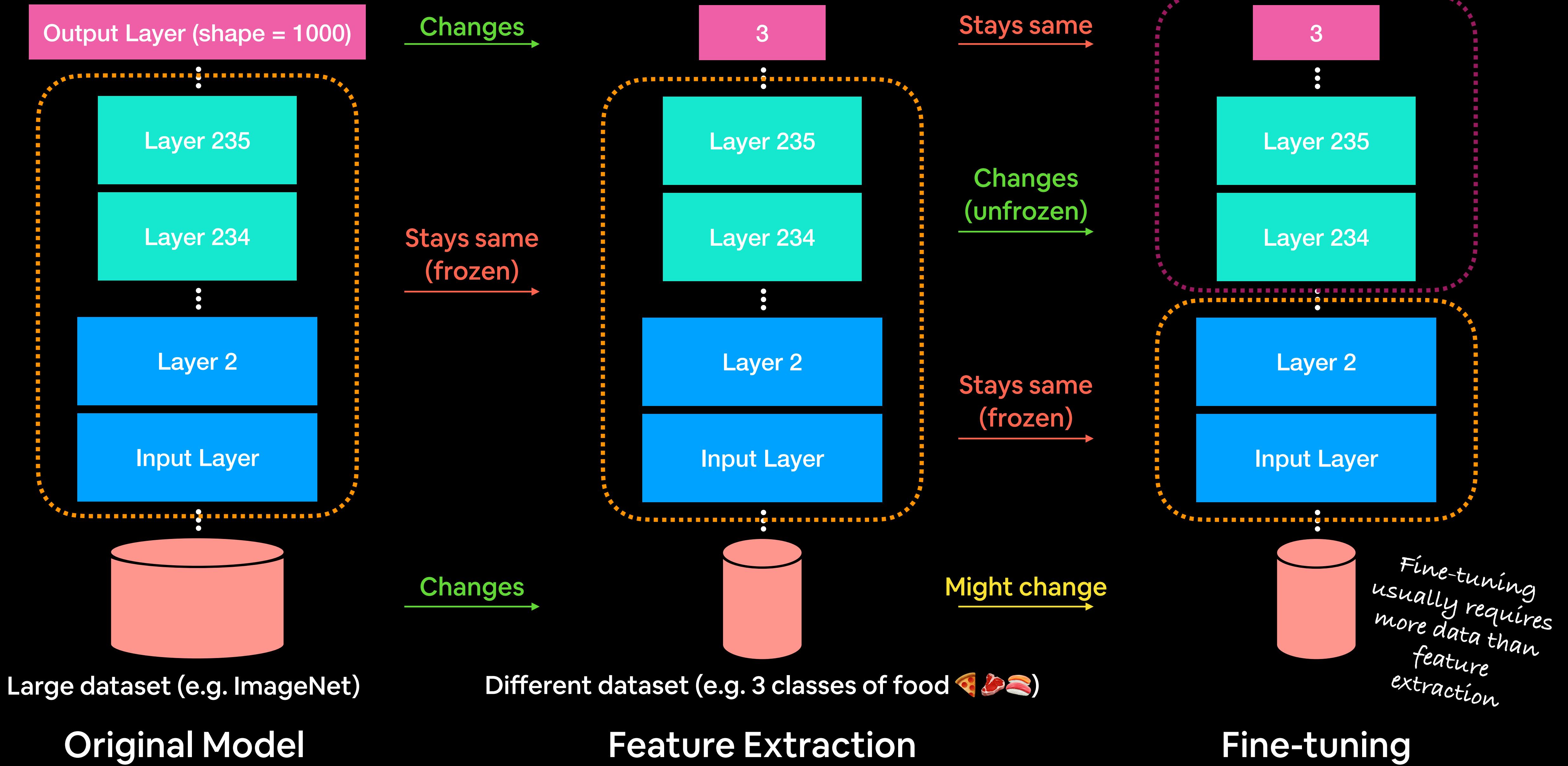


Let's code!

Original Model vs. Feature Extraction



Kinds of Transfer Learning

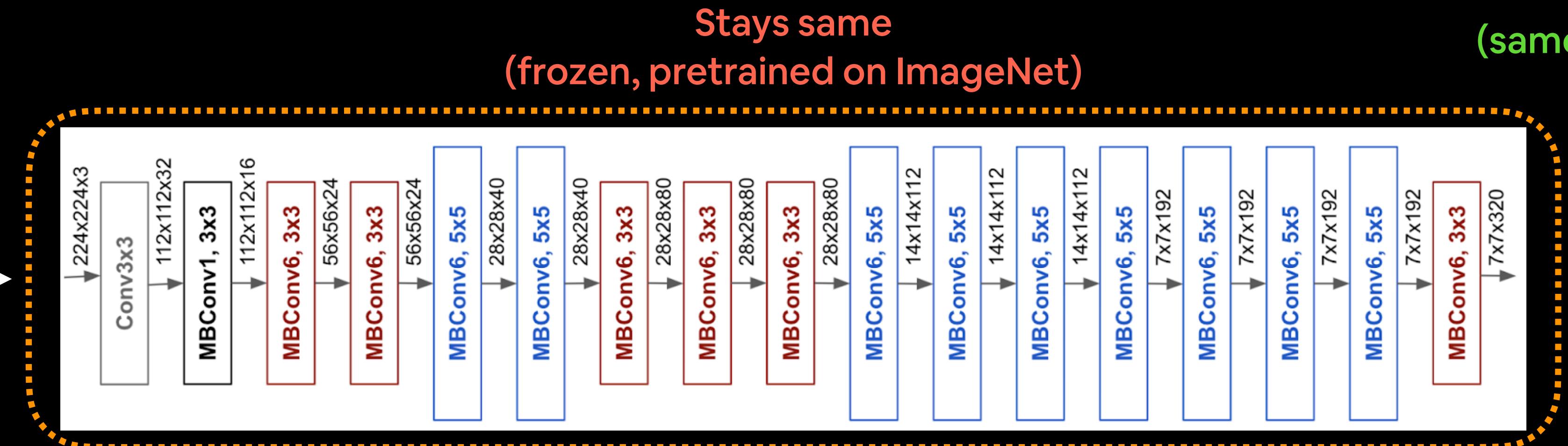


Kinds of Transfer Learning

Type	Description	What happens	When to use
Original model (“As is”)	Take a pretrained model as it is and apply it to your task without any changes.	The original model remains unchanged.	Helpful if you have the exact same kind of data the original model was trained on.
Feature extraction	Take the underlying patterns (also called weights) a pretrained model has learned and adjust its outputs to be more suited to your problem.	Most of the layers in the original model remain frozen during training (only the top 1-3 layers get updated).	Helpful if you have a small amount of custom data (similar to what the original model was trained on) and want to utilise a pretrained model to get better results on your specific problem.
Fine-tuning	Take the weights of a pretrained model and adjust (fine-tune) them to your own problem.	Some, many or all of the layers in the pretrained model are updated during training.	Helpful if you have a large amount of custom data and want to utilise a pretrained model and improve its underlying patterns to your specific problem.

EfficientNet feature extractor

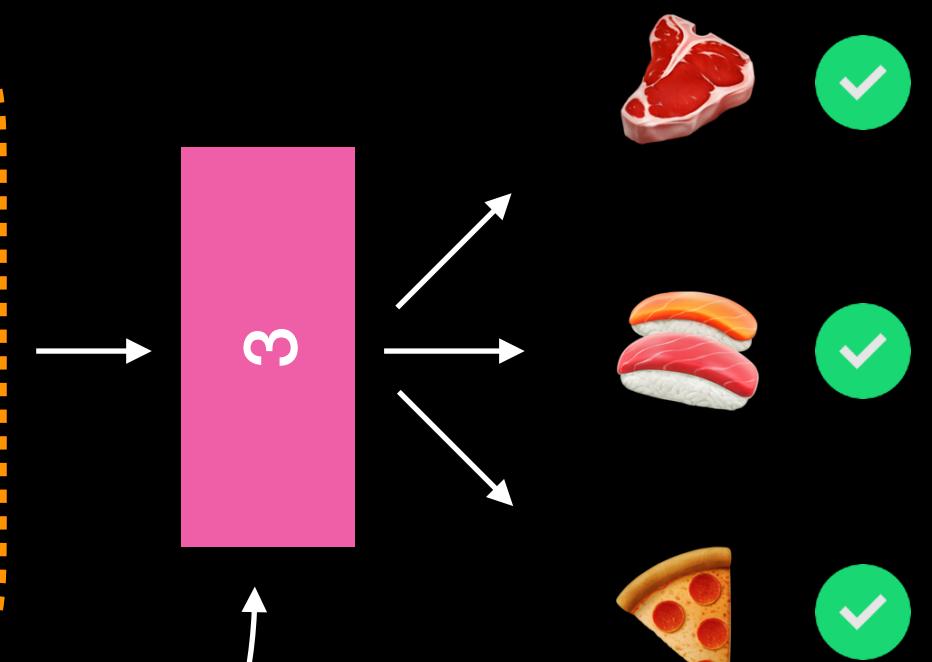
Input data
(Pizza, Steak, Sushi)



EfficientNetB0 architecture. Source: <https://ai.googleblog.com/2019/05/efficientnet-improving-accuracy-and.html>

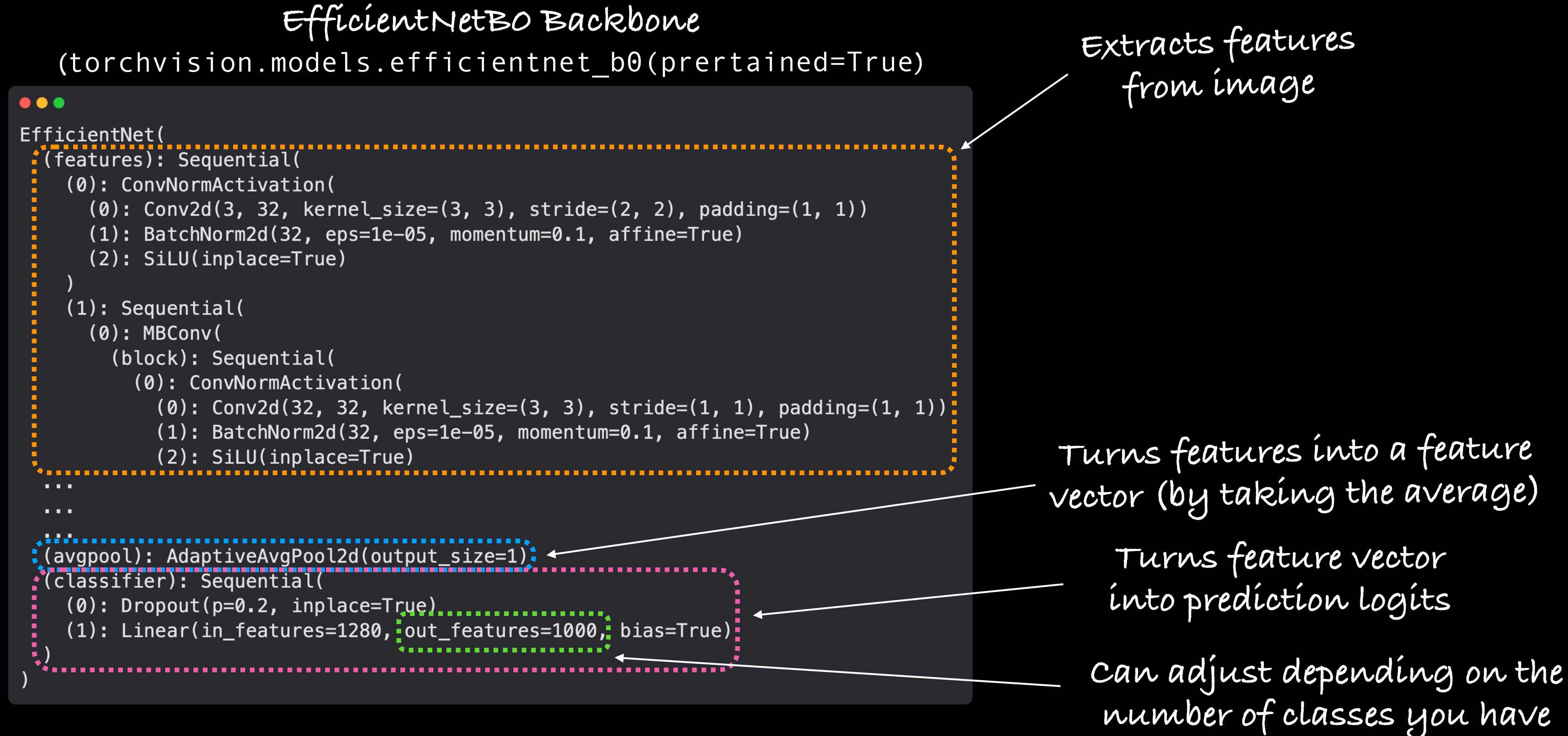
EfficientNetB0 Backbone
(`torchvision.models.efficientnet_b0`)

Changes
(same shape as number
of classes)



Linear classifier layer
(`torch.nn.Linear`)

EfficientNet feature extractor



EfficientNet feature extractor — changing the classifier head

EfficientNetB0 Backbone

(`torchvision.models.efficientnet_b0(prertained=True)`)

```
EfficientNet(  
    features: Sequential(  
        (0): ConvNormActivation(  
            (0): Conv2d(3, 32, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))  
            (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True)  
            (2): SiLU(inplace=True)  
        )  
        (1): Sequential(  
            (0): MBConv(  
                block: Sequential(  
                    (0): ConvNormActivation(  
                        (0): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
                        (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True)  
                        (2): SiLU(inplace=True)  
                    )  
                    ...  
                    ...  
                )  
            )  
            (avgpool): AdaptiveAvgPool2d(output_size=1)  
        )  
        (classifier): Sequential(  
            (0): Dropout(p=0.2, inplace=True)  
            (1): Linear(in_features=1280, out_features=1000, bias=True)  
        )  
    )  
)
```

Same

Changed

```
EfficientNet(  
    features: Sequential(  
        (0): ConvNormActivation(  
            (0): Conv2d(3, 32, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))  
            (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True)  
            (2): SiLU(inplace=True)  
        )  
        (1): Sequential(  
            (0): MBConv(  
                block: Sequential(  
                    (0): ConvNormActivation(  
                        (0): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
                        (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True)  
                        (2): SiLU(inplace=True)  
                    )  
                    ...  
                    ...  
                )  
            )  
            (avgpool): AdaptiveAvgPool2d(output_size=1)  
        )  
        (classifier): Sequential(  
            (0): Dropout(p=0.2, inplace=True)  
            (1): Linear(in_features=1280, out_features=3, bias=True)  
        )  
    )  
)
```

Original Model

(1000 output classes for ImageNet)

Original Model + Changed Classifier Head

(3 output classes for 🍕, 🥩, 🍣)

```
torchinfo.summary(model, input_size=(32, 3, 224, 224))
```

Layer (type (var_name))	Input Shape	Output Shape	Param #	Trainable
EfficientNet	--	--	--	True
Sequential (features)	[32, 3, 224, 224]	[32, 1280, 7, 7]	--	True
ConvNormActivation (0)	[32, 3, 224, 224]	[32, 32, 112, 112]	--	True
Conv2d (0)	[32, 3, 224, 224]	[32, 32, 112, 112]	864	True
BatchNorm2d (1)	[32, 32, 112, 112]	[32, 32, 112, 112]	64	True
SiLU (2)	[32, 32, 112, 112]	[32, 32, 112, 112]	--	--
Sequential (1)	[32, 32, 112, 112]	[32, 16, 112, 112]	--	True
MBConv (0)	[32, 32, 112, 112]	[32, 16, 112, 112]	1,448	True
Sequential (2)	[32, 16, 112, 112]	[32, 24, 56, 56]	--	True
MBConv (0)	[32, 16, 112, 112]	[32, 24, 56, 56]	6,004	True
MBConv (1)	[32, 24, 56, 56]	[32, 24, 56, 56]	10,710	True
Sequential (3)	[32, 24, 56, 56]	[32, 40, 28, 28]	--	True
MBConv (0)	[32, 24, 56, 56]	[32, 40, 28, 28]	15,350	True
MBConv (1)	[32, 40, 28, 28]	[32, 40, 28, 28]	31,290	True
Sequential (4)	[32, 40, 28, 28]	[32, 80, 14, 14]	--	True
MBConv (0)	[32, 40, 28, 28]	[32, 80, 14, 14]	37,130	True
MBConv (1)	[32, 80, 14, 14]	[32, 80, 14, 14]	102,900	True
MBConv (2)	[32, 80, 14, 14]	[32, 112, 14, 14]	--	True
Sequential (5)	[32, 80, 14, 14]	[32, 112, 14, 14]	126,004	True
MBConv (0)	[32, 112, 14, 14]	[32, 112, 14, 14]	208,572	True
MBConv (1)	[32, 112, 14, 14]	[32, 112, 14, 14]	208,572	True
MBConv (2)	[32, 112, 14, 14]	[32, 192, 7, 7]	--	True
Sequential (6)	[32, 112, 14, 14]	[32, 192, 7, 7]	262,492	True
MBConv (0)	[32, 192, 7, 7]	[32, 192, 7, 7]	587,952	True
MBConv (1)	[32, 192, 7, 7]	[32, 192, 7, 7]	587,952	True
MBConv (2)	[32, 192, 7, 7]	[32, 192, 7, 7]	587,952	True
MBConv (3)	[32, 192, 7, 7]	[32, 320, 7, 7]	--	True
Sequential (7)	[32, 192, 7, 7]	[32, 320, 7, 7]	717,232	True
MBConv (0)	[32, 192, 7, 7]	[32, 320, 7, 7]	409,600	True
ConvNormActivation (8)	[32, 320, 7, 7]	[32, 1280, 7, 7]	--	True
Conv2d (0)	[32, 320, 7, 7]	[32, 1280, 7, 7]	2,560	True
BatchNorm2d (1)	[32, 1280, 7, 7]	[32, 1280, 7, 7]	--	--
SiLU (2)	[32, 1280, 7, 7]	[32, 1280, 1, 1]	--	--
AdaptiveAvgPool2d (avgpool)	[32, 1280]	[32, 1000]	--	True
Sequential (classifier)	[32, 1280]	[32, 1280]	--	--
Dropout (0)	[32, 1280]	[32, 1000]	1,281,000	True
Linear (1)	[32, 1280]	[32, 1000]	--	--

Are the layers **trainable**?
(unfrozen)

Input shape of data per layer

Output shape of data per layer

Total number of parameters
and trainable parameters

Total params: 5,288,548
Trainable params: 5,288,548
Non-trainable params: 0
Total mult-adds (G): 12.35

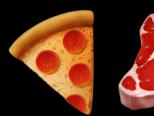
Input size (MB): 19.27
Forward/backward pass size (MB): 3452.35
Params size (MB): 21.15
Estimated Total Size (MB): 3492.77

```
torchinfo.summary(model, input_size=(32, 3, 224, 224))
```

Layer (type (var_name))	Input Shape	Output Shape	Param #	Trainable
EfficientNet	--	--	--	Partial
Sequential (features)	[32, 3, 224, 224]	[32, 1280, 7, 7]	--	False
ConvNormActivation (0)	[32, 3, 224, 224]	[32, 32, 112, 112]	--	False
Conv2d (0)	[32, 3, 224, 224]	[32, 32, 112, 112]	(864)	False
BatchNorm2d (1)	[32, 32, 112, 112]	[32, 32, 112, 112]	(64)	False
SiLU (2)	[32, 32, 112, 112]	[32, 32, 112, 112]	--	--
Sequential (1)	[32, 32, 112, 112]	[32, 16, 112, 112]	--	False
MBConv (0)	[32, 32, 112, 112]	[32, 16, 112, 112]	(1,448)	False
Sequential (2)	[32, 16, 112, 112]	[32, 24, 56, 56]	--	False
MBConv (0)	[32, 16, 112, 112]	[32, 24, 56, 56]	(6,004)	False
MBConv (1)	[32, 24, 56, 56]	[32, 24, 56, 56]	(10,710)	False
Sequential (3)	[32, 24, 56, 56]	[32, 40, 28, 28]	--	False
MBConv (0)	[32, 24, 56, 56]	[32, 40, 28, 28]	(15,350)	False
MBConv (1)	[32, 40, 28, 28]	[32, 40, 28, 28]	(31,290)	False
Sequential (4)	[32, 40, 28, 28]	[32, 80, 14, 14]	--	False
MBConv (0)	[32, 40, 28, 28]	[32, 80, 14, 14]	(37,130)	False
MBConv (1)	[32, 80, 14, 14]	[32, 80, 14, 14]	(102,900)	False
MBConv (2)	[32, 80, 14, 14]	[32, 80, 14, 14]	(102,900)	False
Sequential (5)	[32, 80, 14, 14]	[32, 112, 14, 14]	--	False
MBConv (0)	[32, 80, 14, 14]	[32, 112, 14, 14]	(126,004)	False
MBConv (1)	[32, 112, 14, 14]	[32, 112, 14, 14]	(208,572)	False
MBConv (2)	[32, 112, 14, 14]	[32, 112, 14, 14]	(208,572)	False
Sequential (6)	[32, 112, 14, 14]	[32, 192, 7, 7]	--	False
MBConv (0)	[32, 112, 14, 14]	[32, 192, 7, 7]	(262,492)	False
MBConv (1)	[32, 192, 7, 7]	[32, 192, 7, 7]	(587,952)	False
MBConv (2)	[32, 192, 7, 7]	[32, 192, 7, 7]	(587,952)	False
MBConv (3)	[32, 192, 7, 7]	[32, 192, 7, 7]	(587,952)	False
Sequential (7)	[32, 192, 7, 7]	[32, 320, 7, 7]	--	False
MBConv (0)	[32, 192, 7, 7]	[32, 320, 7, 7]	(717,232)	False
ConvNormActivation (8)	[32, 320, 7, 7]	[32, 1280, 7, 7]	--	False
Conv2d (0)	[32, 320, 7, 7]	[32, 1280, 7, 7]	(409,600)	False
BatchNorm2d (1)	[32, 1280, 7, 7]	[32, 1280, 7, 7]	(2,560)	False
SiLU (2)	[32, 1280, 7, 7]	[32, 1280, 7, 7]	--	--
AdaptiveAvgPool2d (avgpool)	[32, 1280]	[32, 1280]	--	True
Sequential (classifier)	[32, 1280]	[32, 3]	--	True
Dropout (0)	[32, 1280]	[32, 1280]	--	True
Linear (1)	[32, 1280]	[32, 3]	3,843	True
<hr/>				
Total params: 4,011,391				
Trainable params: 3,843				
Non-trainable params: 4,007,548				
Total mult-adds (G): 12.31				
<hr/>				
Input size (MB): 19.27				
Forward/backward pass size (MB): 3452.09				
Params size (MB): 16.05				
Estimated Total Size (MB): 3487.41				
<hr/>				

Many layers
untrainable (frozen)

Only last layers are trainable

Final layer output (same as
number of classes)   

Less trainable parameters
because many layers are
frozen