Workflow Application in Deep Learning: Custom Datasets with PyTorch

Artificial Intelligence

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“What is a custom dataset?”

“I’ve got my own dataset, can I build a model with PyTorch to predict on it?”

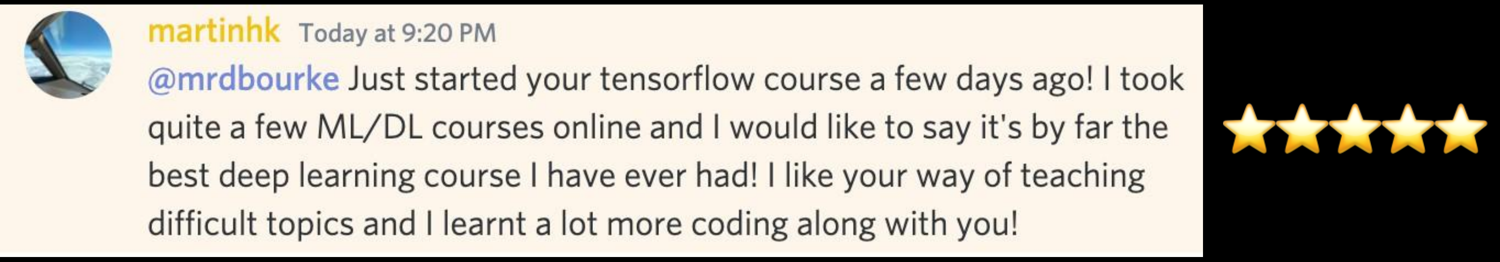
Yes.

PyTorch Domain Libraries

"Is this a photo of pizza, steak or sushi?"

TorchVision

"Are these reviews positive or negative?"



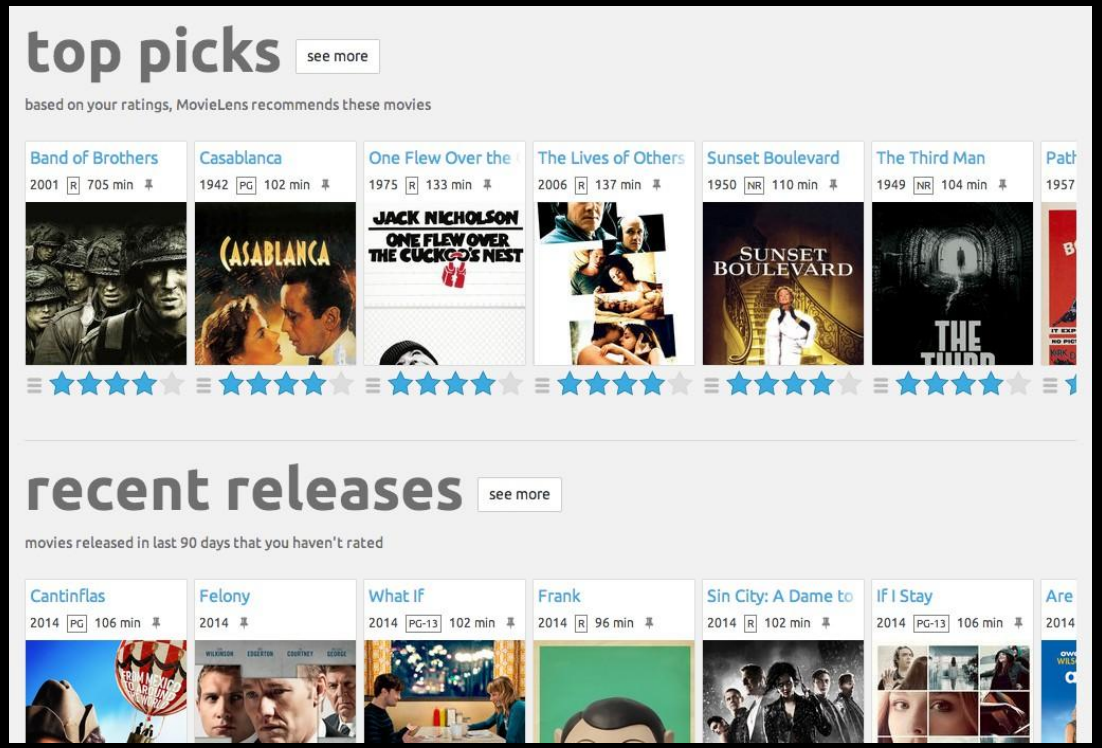
TorchText

"What song is playing?"

Different domain libraries contain data loading functions for different data sources

TorchAudio

"How do we recommend similar products?"



TorchRec

Source: movielens.org

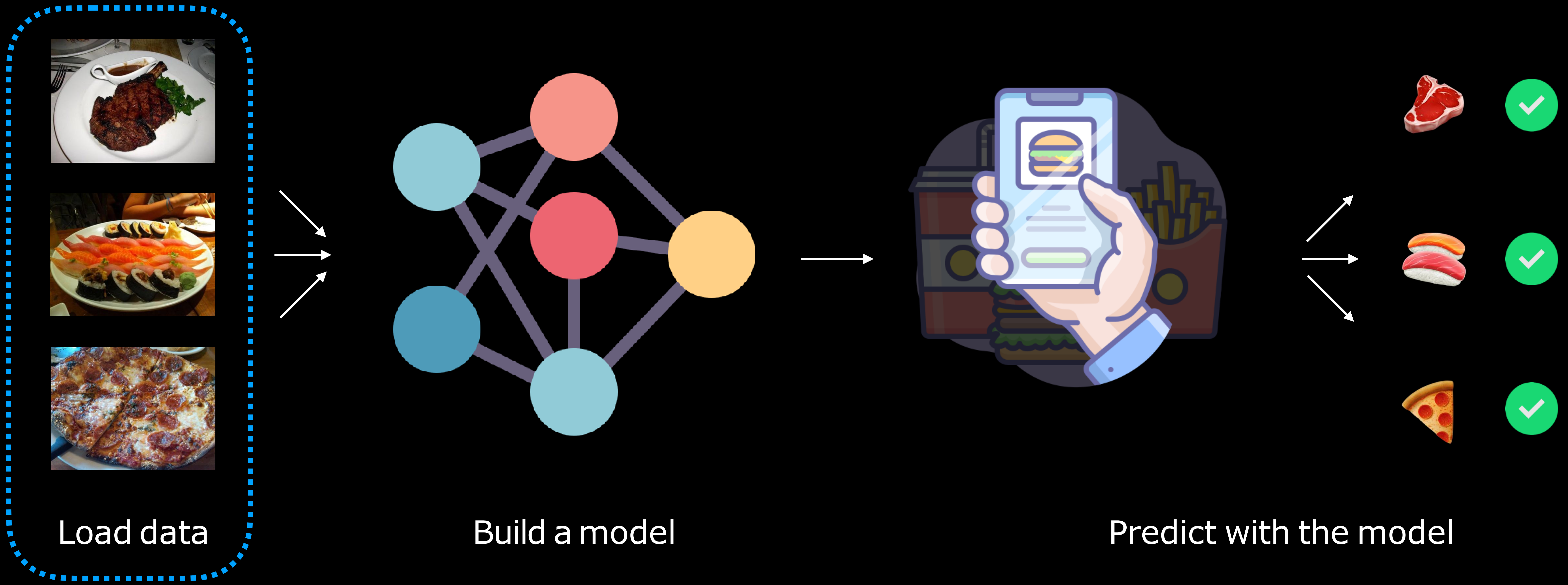
PyTorch Domain Libraries

Problem Space	Pre-built Datasets and Fuctions
Vision	`torchvision.datasets`
Text	`torchtext.datasets`
Audio	`torchaudio.datasets`
Recommendation system	`torchrec.datasets`
Bonus	`TorchData`*

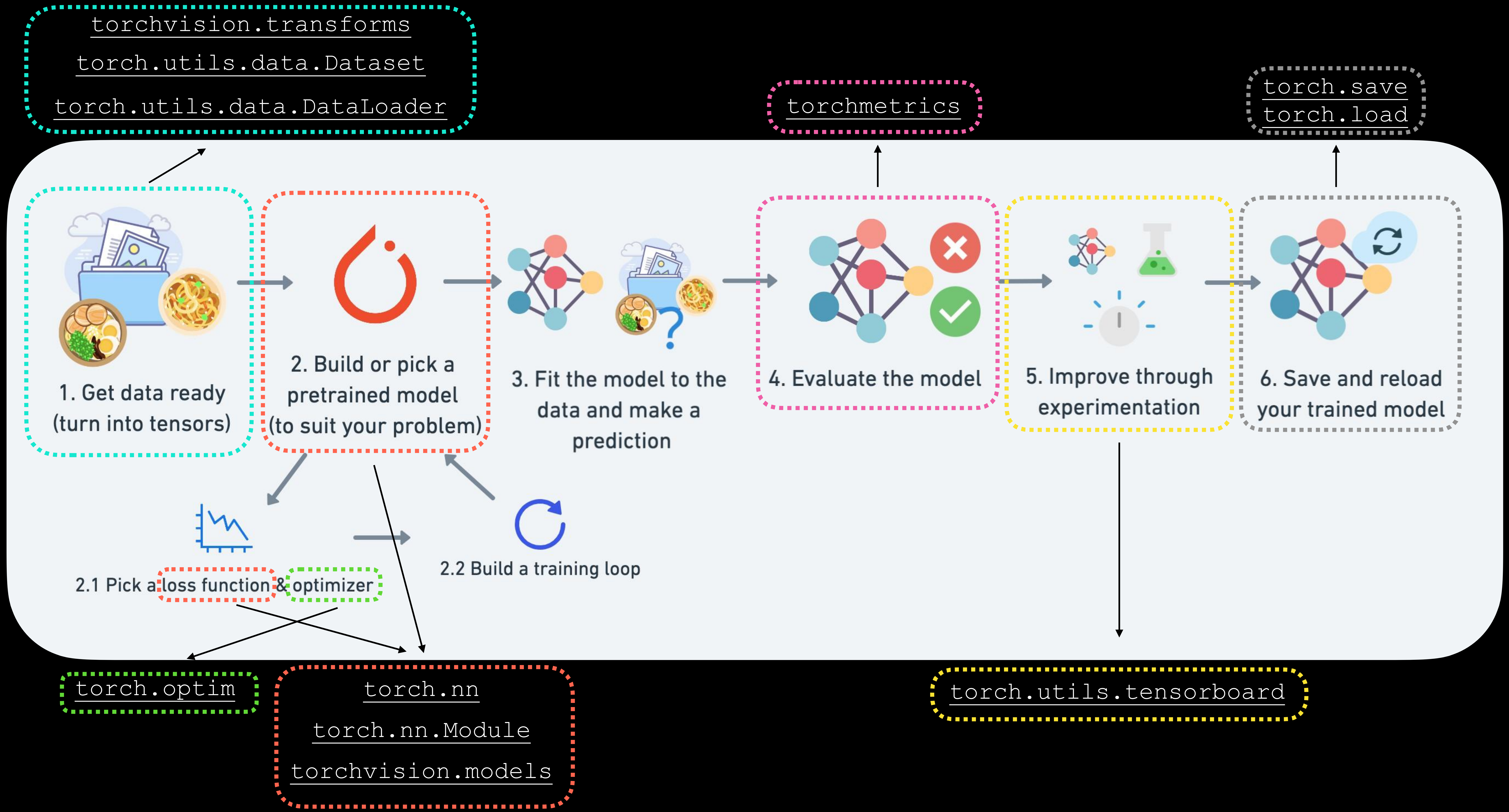
*`TorchData` contains many diKerent helper functions for loading data and is currently in beta as of April 2022.

What we're going to build

FoodVision Mini



We're going to write code to load images of food (our own custom dataset for FoodVision Mini)



See more: https://pytorch.org/tutorials/beginner/ptcheat.html

What we're going to cover

- Getting a custom dataset with PyTorch
- Becoming one with the data (preparing and visualising)
- Transforming data for use with a model
- Loading custom data with pre-built functions and custom functions
- Building FoodVision Mini to classify 🍕🥩🍣 images
- Comparing models with and without data augmentation
- Making predictions on custom data

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

How: 👩‍🍳 👩‍🔬

Let’s code!

Daniel Bourke
@mrdbourke

"If I had 8 hours to build a machine learning model, I'd spend the first 6 hours preparing my dataset."

- Abraham Lossfunction

12:35 PM · Nov 4, 2021 · Twitter Web App

Standard image classification data format

Your own data format will depend on what you're working

```
pizza_steak_sushi/ # <- overall dataset folder
    train/ # <- training images
        pizza/ # <- class name as folder name
            image01.jpeg
            image02.jpeg
            ...
        steak/
            image24.jpeg
            image25.jpeg
            ...
        sushi/
            image37.jpeg
            ...
    test/ # <- testing images
        pizza/
            image101.jpeg
            image102.jpeg
            ...
        steak/
            image154.jpeg
            image155.jpeg
            ...
        sushi/
            image167.jpeg
            ...
```

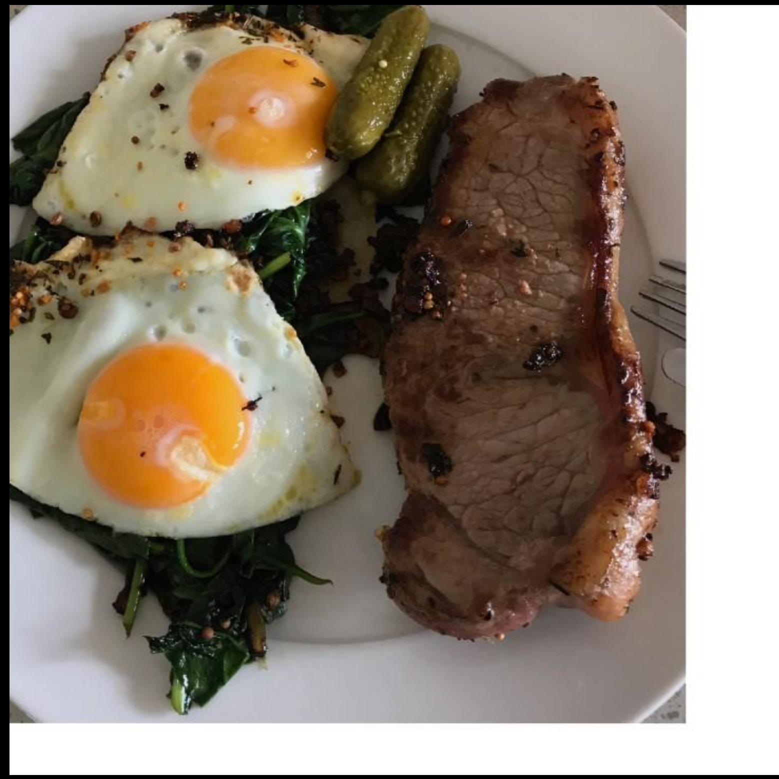
The premise remains: write code to get your data into tensors for use with PyTorch

What is data augmentation?

Looking at the same image but from different perspective(s)*. To artificially increase the diversity of a dataset.

Original

Rotate



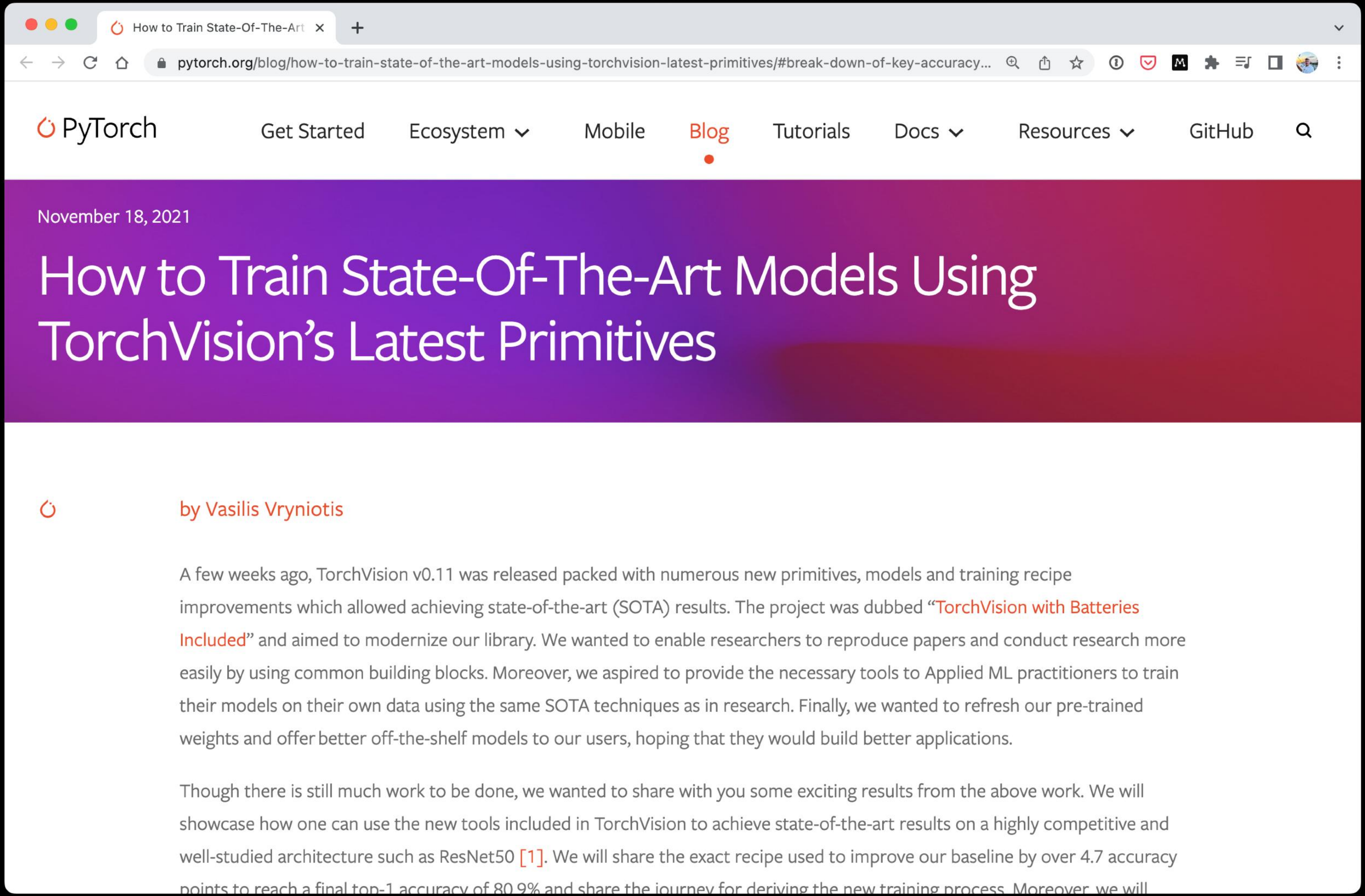
Shift

Zoom

***Note:** There are many more different kinds of data augmentation such as, cropping, replacing, shearing. This slide only demonstrates a few.

PyTorch State of the Art Recipe

Research comes out often on how best to train models, state-of-the-art (SOTA) methods are always changing).



November 18, 2021

How to Train State-Of-The-Art Models Using TorchVision's Latest Primitives

by Vasilis Vryniotis

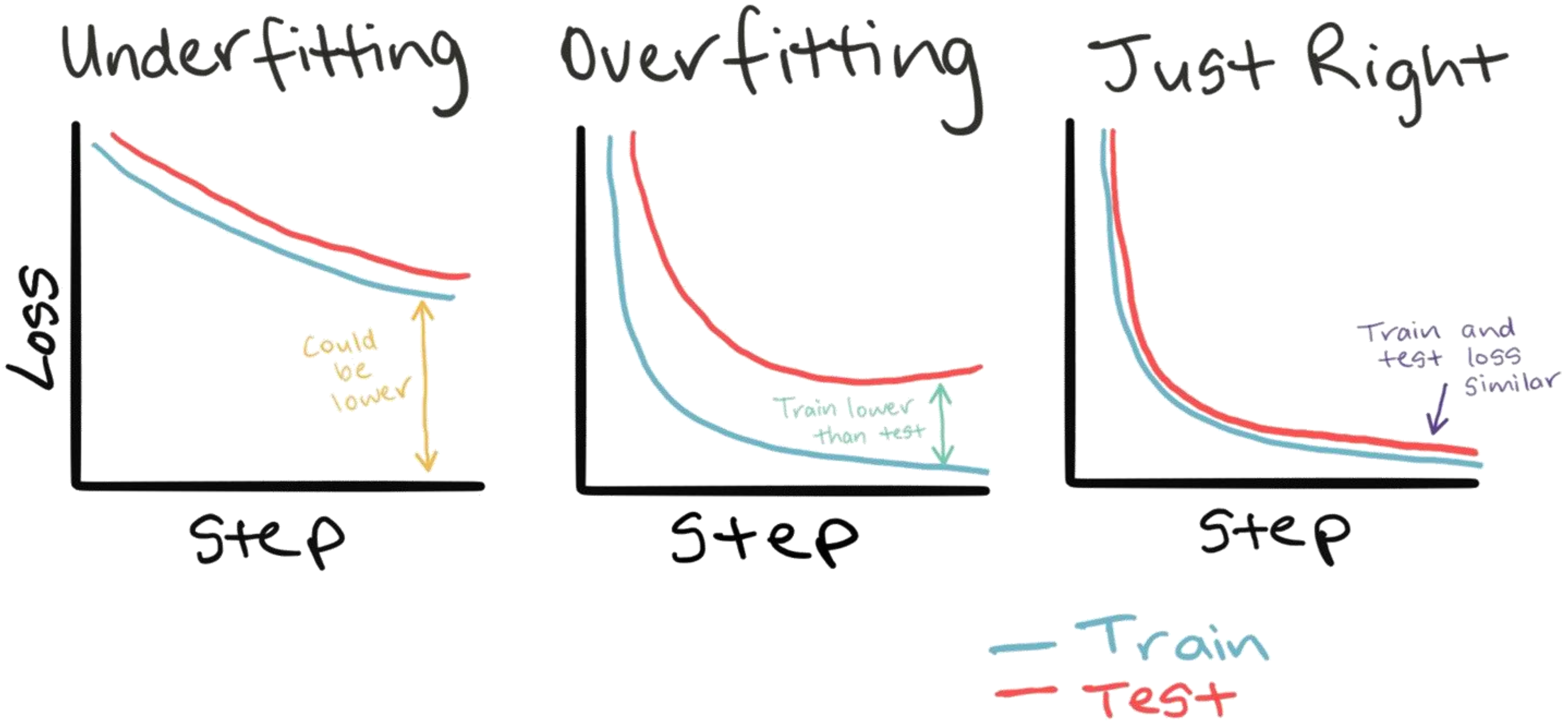
A few weeks ago, TorchVision v0.11 was released packed with numerous new primitives, models and training recipe improvements which allowed achieving state-of-the-art (SOTA) results. The project was dubbed "TorchVision with Batteries Included" and aimed to modernize our library. We wanted to enable researchers to reproduce papers and conduct research more easily by using common building blocks. Moreover, we aspired to provide the necessary tools to Applied ML practitioners to train their models on their own data using the same SOTA techniques as in research. Finally, we wanted to refresh our pre-trained weights and offer better off-the-shelf models to our users, hoping that they would build better applications.

Though there is still much work to be done, we wanted to share with you some exciting results from the above work. We will showcase how one can use the new tools included in TorchVision to achieve state-of-the-art results on a highly competitive and well-studied architecture such as ResNet50 [1]. We will share the exact recipe used to improve our baseline by over 4.7 accuracy points to reach a final top-1 accuracy of 80.9% and share the journey for deriving the new training process. Moreover, we will

Source: Training state-of-the-art computer vision models with `torchvision` from the PyTorch blog.

Loss curves

(a way to evaluate your model's performance over time)



Dealing with overfitting

Method to improve a model (reduce overKtting)	What does it do?
Get 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 a 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.
Simplify your model	If the current model is already overfitting the training data, it may be too complicated of a model. This means it's learning the patterns of the data too well and isn't able to generalize well to unseen data. One way to simplify a model is to reduce the number of layers it uses or to reduce the number of hidden units in each layer.
Use learning rate decay	The idea here is to slowly decrease the learning rate as a model trains. This is akin to reaching for a coin at the back of a couch. The closer you get, the smaller your steps. The same with the learning rate, the closer you get to convergence, the smaller you'll want your weight updates to be.
Use early stopping	Early stopping stops model training *before* it begins to overfit. As in, say the model's loss has stopped decreasing for the past 10 epochs (this number is arbitrary), you may want to stop the model training here and go with the model weights that had the lowest loss (10 epochs prior).

Dealing with underfitting

Method to improve a model (reduce underKtting)	What does it do?
Add more layers/units to your model	If your model is underfitting, it may not have enough capability to **learn* the required patterns/weights/representations of the data to be predictive. One way to add more predictive power to your model is to increase the number of hidden layers/units within those layers.
Tweak the learning rate	Perhaps your model's learning rate is too high to begin with. And it's trying to update its weights each epoch too much, in turn not learning anything. In this case, you might lower the learning rate and see what happens.
Train for longer	Sometimes a model just needs more time to learn representations of data. If you find in your smaller experiments your model isn't learning anything, perhaps leaving it train for a more epochs may result in better performance.
Use transfer learning	Take a 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.
Use less regularization	Perhaps your model is underfitting because you're trying to prevent overfitting too much. Holding back on regularization techniques can help your model fit the data better.

Predicting on custom data

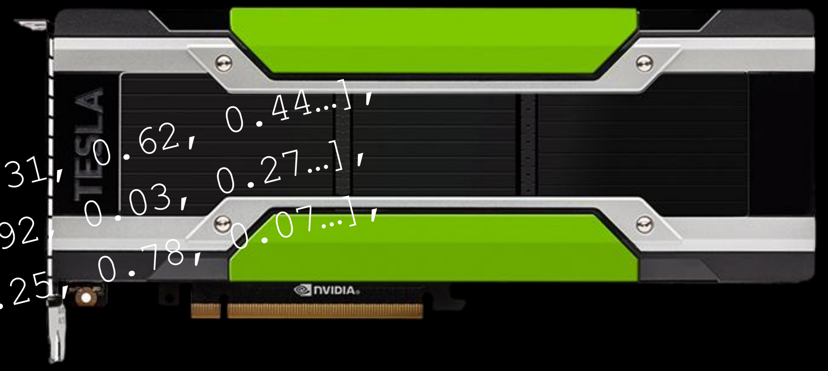
(3 things to make sure of…)

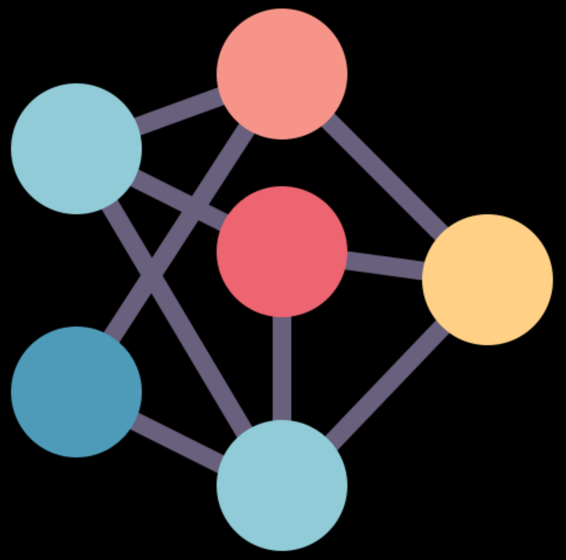
Custom image

[[0.31, 0.62, 0.44…],
[0.92, 0.03, 0.27…],
[0.25, 0.78, 0.07…],
…,

torch.float32

Is the model on the GPU?





Original

Shape = [64, 64, 3]

Add batch dimension & rearrange if needed

Shape = [None, 64, 64, 3] (NHWC)
Shape = [None, 3, 64, 64] (NCHW)

Same as model input

1. Data in right datatype

2. Data on same device as model

3. Data in correct shape