```
In [1]: #hide
!pip install -Uqq fastbook
import fastbook
fastbook.setup_book()

In [2]: #hide
from fastbook import *
```

Image Classification

From Dogs and Cats to Pet Breeds

```
In [3]: from fastai.vision.all import *
        path = untar data(URLs.PETS)
In [4]: #hide
        Path.BASE PATH = path
In [5]: path.ls()
Out[5]: (#2) [Path('images'),Path('annotations')]
In [6]: (path/"images").ls()
Out[6]: (#7393) [Path('images/miniature_pinscher_199.jpg'),Path('images/newfoundland_18
        3.jpg'),Path('images/pomeranian_90.jpg'),Path('images/pomeranian_102.jpg'),Path
        ('images/japanese_chin_74.jpg'),Path('images/yorkshire_terrier_45.jpg'),Path('i
        mages/chihuahua 34.jpg'),Path('images/american pit bull terrier 150.jpg'),Path
        ('images/wheaten terrier 160.jpg'), Path('images/staffordshire bull terrier 91.j
        pg')...]
In [7]: fname = (path/"images").ls()[0]
Out[7]: Path('images/miniature_pinscher_199.jpg')
In [8]: re.findall(r'(.+) \d+.jpg$', fname.name)
Out[8]: ['miniature_pinscher']
```

In [10]: dls.show_batch(nrows = 1, ncols=3)







In [11]: dls.show_batch(nrows=1, ncols = 3, unique = True)







Lets test the model with what we have currently

In [12]: learn = cnn_learner(dls, resnet18, metrics=accuracy) #Notice we didn't choose a l
learn.fit_one_cycle(2)

epoch	train_loss	valid_loss	accuracy	time
0	1.532583	0.412520	0.868065	01:20
1	0.705810	0.353400	0.887010	01:07

In [13]: learn.loss_func #fastAI chose CrossEntropyLoss as the loss func

Out[13]: FlattenedLoss of CrossEntropyLoss()

Presizing

```
In [ ]: dblock1 = DataBlock(blocks=(ImageBlock(), CategoryBlock()),
                           get_y=parent_label,
                           item tfms=Resize(460))
        dls1 = dblock1.dataloaders([(Path.cwd()/'images'/'grizzly.jpg')]*100, bs=8)
        dls1.train.get idxs = lambda: Inf.ones
        x,y = dls1.valid.one batch()
        ,axs = subplots(1, 2)
        x1 = TensorImage(x.clone())
        x1 = x1.affine coord(sz=224)
        x1 = x1.rotate(draw=30, p=1.)
        x1 = x1.zoom(draw=1.2, p=1.)
        x1 = x1.warp(draw x=-0.2, draw y=0.2, p=1.)
        tfms = setup aug tfms([Rotate(draw=30, p=1, size=224), Zoom(draw=1.2, p=1., size=
                               Warp(draw x=-0.2, draw y=0.2, p=1., size=224)])
        x = Pipeline(tfms)(x)
        #x.affine_coord(coord_tfm=coord_tfm, sz=size, mode=mode, pad_mode=pad_mode)
        TensorImage(x[0]).show(ctx=axs[0])
        TensorImage(x1[0]).show(ctx=axs[1]);
```

Cross-Entropy Loss

Viewing Activations and Labels

```
In [15]: x,y = dls.one batch()
In [16]: y #values refer to vocab list
Out[16]: TensorCategory([18, 19, 20, 23, 24, 35, 27, 27, 32, 16, 0, 9, 21, 0, 2, 12,
         26, 10, 24, 20, 32, 27, 18, 28, 8, 18, 23, 21, 30, 29, 9, 26, 25, 29, 14, 11,
         34, 7, 36, 4, 9, 6, 23, 20, 17, 14, 25, 19,
                 23, 8, 18, 2, 11, 7, 9, 19, 19, 31, 1, 29, 1, 31, 7, 33], device
         ='cuda:0')
In [17]: | dls.vocab
Out[17]: ['Abyssinian', 'Bengal', 'Birman', 'Bombay', 'British_Shorthair', 'Egyptian_Ma
         u', 'Maine_Coon', 'Persian', 'Ragdoll', 'Russian_Blue', 'Siamese', 'Sphynx', 'a
         merican_bulldog', 'american_pit_bull_terrier', 'basset_hound', 'beagle', 'boxe
         r', 'chihuahua', 'english_cocker_spaniel', 'english_setter', 'german_shorthaire
         d', 'great_pyrenees', 'havanese', 'japanese_chin', 'keeshond', 'leonberger', 'm
         iniature_pinscher', 'newfoundland', 'pomeranian', 'pug', 'saint_bernard', 'samo
         yed', 'scottish_terrier', 'shiba_inu', 'staffordshire_bull_terrier', 'wheaten_t
         errier', 'yorkshire terrier']
```

```
In [18]: preds,_ = learn.get_preds(dl=[(x,y)])
preds
```

```
Out[18]: TensorImage([[2.1285e-01, 4.7995e-02, 1.1221e-03, ..., 1.4506e-03, 9.0126e-03, 2.4594e-02], [6.9040e-06, 4.3596e-03, 8.7159e-06, ..., 3.3018e-05, 2.8775e-05, 2.50 54e-05], [2.1535e-12, 2.2470e-11, 5.4650e-12, ..., 2.8323e-10, 1.6942e-10, 4.79 21e-11], ..., [1.0889e-07, 3.3818e-07, 1.8115e-05, ..., 4.5040e-07, 3.6186e-06, 5.47 62e-08], [2.5651e-04, 5.6865e-05, 4.7429e-02, ..., 1.0788e-05, 2.0495e-04, 3.38 97e-06], [1.6846e-05, 3.8460e-06, 1.8923e-06, ..., 1.2548e-06, 2.0216e-06, 2.94 12e-07]])
```

```
In [19]: len(preds[0]),preds[0].sum() #37 pred and all add up to 1
#How did we manage to make all the pred add up to 1? Softmax!
```

Out[19]: (37, TensorImage(1.0000))

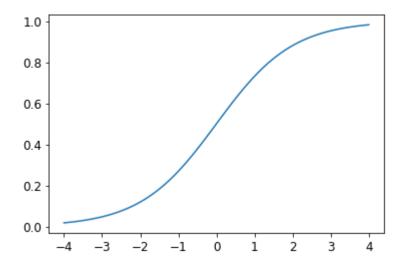
Softmax

Shows why softmax is better than sigmoid when dealing with more classes

```
In [20]: plot_function(torch.sigmoid, min=-4,max=4)
```

/opt/conda/envs/fastai/lib/python3.8/site-packages/fastbook/__init__.py:73: Use rWarning: Not providing a value for linspace's steps is deprecated and will thr ow a runtime error in a future release. This warning will appear only once per process. (Triggered internally at /opt/conda/conda-bld/pytorch_1603729096996/w ork/aten/src/ATen/native/RangeFactories.cpp:23.)

x = torch.linspace(min,max)



```
In [21]: #hide
         torch.random.manual seed(42);
In [22]: acts = torch.randn((6,2))*2 #Getting preds
         acts
Out[22]: tensor([[ 0.6734, 0.2576],
                  [ 0.4689, 0.4607],
                  [-2.2457, -0.3727],
                 [ 4.4164, -1.2760],
                  [0.9233, 0.5347],
                  [ 1.0698, 1.6187]])
In [23]: acts.sigmoid() #using sigmoid to squish pred (Notice that although the values are
Out[23]: tensor([[0.6623, 0.5641],
                  [0.6151, 0.6132],
                  [0.0957, 0.4079],
                  [0.9881, 0.2182],
                  [0.7157, 0.6306],
                  [0.7446, 0.8346]])
```

Can fix by switching to softmax

Unique indexing technique

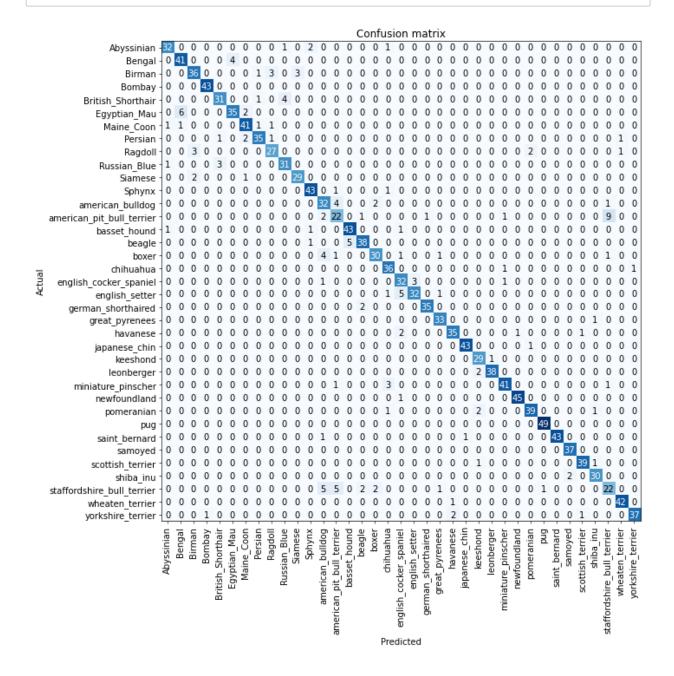
```
In [27]: idx = range(6)
         sm acts[idx, targ]
Out[27]: tensor([0.6025, 0.4979, 0.1332, 0.0034, 0.4041, 0.3661])
In [28]: | from IPython.display import HTML
         df = pd.DataFrame(sm acts, columns=["3","7"])
         df['targ'] = targ
         df['idx'] = idx
         df['loss'] = sm acts[range(6), targ]
         t = df.style.hide index()
         #To have html code compatible with our script
         html = t. repr html ().split('</style>')[1]
         html = re.sub(r'', r'', html)
         display(HTML(html))
               3
                       7 targ idx
                                      loss
          0.602469 0.397531
                                0 0.602469
                            0
          0.502065 0.497935
                                1 0.497935
                            1
          2 0.133188
          0.996640 0.003360
                            1
                                3 0.003360
          0.595949 0.404051
                                4 0.404051
          0.366118  0.633882
                            0
                                5 0.366118
In [29]: |-sm_acts[idx, targ]
Out[29]: tensor([-0.6025, -0.4979, -0.1332, -0.0034, -0.4041, -0.3661])
In [30]: F.nll_loss(sm_acts, targ, reduction='none')
Out[30]: tensor([-0.6025, -0.4979, -0.1332, -0.0034, -0.4041, -0.3661])
```

Taking the Log

```
In [31]: plot_function(torch.log, min=0,max=4)
            1
            0
           -1
           -2
           -3
              0.0
                   0.5
                         1.0
                              1.5
                                   2.0
                                        2.5
                                             3.0
                                                  3.5
                                                        4.0
In [32]: loss_func = nn.CrossEntropyLoss()
In [33]: loss_func(acts, targ)
Out[33]: tensor(1.8045)
In [34]: F.cross_entropy(acts, targ)
Out[34]: tensor(1.8045)
In [35]: nn.CrossEntropyLoss(reduction='none')(acts, targ) #Shows individual Loses before
Out[35]: tensor([0.5067, 0.6973, 2.0160, 5.6958, 0.9062, 1.0048])
```

Model Interpretation

In [40]: interp = ClassificationInterpretation.from_learner(learn)
interp.plot_confusion_matrix(figsize=(12,12), dpi=60)



Prediction/Actual/Loss/Probability boxer/american_bulldgmg-at7_p3/re/ne-₹s/english_setter /ട്ടെമ്റ്റ്റ്/A/batagle / 6b•tagle/german_shorthsataeftb/ds/atiee/_bull⊵terrier/boxer / 5.97 / 0.88











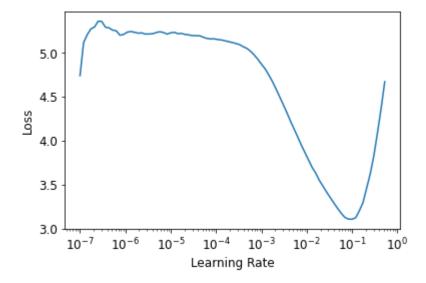
Improving Our Model

The Learning Rate Finder

```
In [36]: learn = cnn_learner(dls, resnet18, metrics=error_rate)
learn.fine_tune(1, base_lr=0.1)
#Current err is 40% - Very bad
```

epoch	train_loss	valid_loss	error_rate	time
0	2.820359	3.461341	0.359269	01:07
epoch	train_loss	valid_loss	error_rate	time
0	0.007474	1.268851	0.00000	04.04

```
In [37]: learn = cnn_learner(dls, resnet34, metrics=error_rate)
lr_min,lr_steep = learn.lr_find() #Finding best Lr
```



```
In [38]: print(f"Minimum/10: {lr_min:.2e}, steepest point: {lr_steep:.2e}")
          Minimum/10: 1.00e-02, steepest point: 3.63e-03
In [43]:
          learn = cnn_learner(dls, resnet34, metrics=error_rate)
          learn.fine_tune(2, base_lr=3e-3) #pick something inbetween
          #error rate dropped down to 7%
           epoch train_loss valid_loss error_rate
                                                time
                  1.285344
                            0.377785
                                      0.117050
                                               01:40
           epoch train_loss valid_loss
                                     error_rate
                                                time
                  0.522819
                            0.429013
                                      0.128552 02:12
               0
                  0.318475
                            0.252019
                                      0.075778 02:12
```

Unfreezing and Transfer Learning

fine_tune()

learn.fine_tune??

freeze() - Freezes the model first
fit_one_cycle(1) - Runs 1 epoch to tune the final layers (Model frozen remember)
base_lr /= 2 - Changes the lr
unfreeze() - Now all parameters can be stepped
self.fit_one_cycle - Now we fit the model on the number of given epochs (Input)

We will now implement fine_tune below

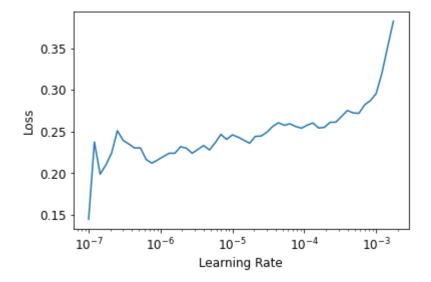
In [49]: learn = cnn_learner(dls, resnet34, metrics=error_rate) #cnn_learner freezes model
learn.fit_one_cycle(3, 3e-3)

epoch	train_loss	valid_loss	error_rate	time
0	1.134641	0.368042	0.112991	01:40
1	0.526193	0.260705	0.083897	01:40
2	0.330762	0.236595	0.075101	01:40

```
In [50]: learn.unfreeze()
```

```
In [51]: learn.lr_find()
```

Out[51]: SuggestedLRs(lr_min=7.585775847473997e-08, lr_steep=0.00013182566908653826)



In [52]: learn.fit_one_cycle(3, lr_max=1e-5) #Update Learning rate again and train some mo

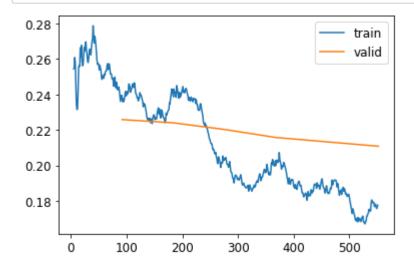
epoch	train_loss	valid_loss	error_rate	time
0	0.276042	0.235768	0.077131	02:12
1	0.237535	0.232880	0.071042	02:20
2	0.216734	0.229787	0.071719	02:15

Discriminative Learning Rates

```
In [10]: learn = cnn_learner(dls, resnet34, metrics=error_rate)
    learn.fit_one_cycle(3, 3e-3)
    learn.unfreeze()
    learn.fit_one_cycle(6, lr_max=slice(1e-6,1e-4)) #can do better using a slice
```

epoch	train_loss	valid_loss	error_rate	time
0	1.136157	0.331316	0.108254	01:44
1	0.526700	0.263616	0.078484	01:41
2	0.318562	0.241009	0.075778	01:41
epoch	train_loss	valid_loss	error_rate	time
0	0.239533	0.225810	0.073072	02:13
1	0.240597	0.223987	0.069689	02:13
2	0.203807	0.220246	0.064276	02:13
3	0.202546	0.215731	0.066306	02:13
4	0.188517	0.213268	0.066306	02:13
5	0.177560	0.210809	0.065629	02:13

In [11]: learn.recorder.plot_loss()



Selecting the Number of Epochs

Deeper Architectures

In [12]: from fastai.callback.fp16 import *
learn = cnn_learner(dls, resnet50, metrics=error_rate).to_fp16() #half as many bi
learn.fine_tune(6, freeze_epochs=3) #First 3 epochs train finals layer, next 6 tr

Downloading: "https://download.pytorch.org/models/resnet50-19c8e357.pth" to /ro ot/.cache/torch/hub/checkpoints/resnet50-19c8e357.pth

HBox(children=(HTML(value=''), FloatProgress(value=0.0, max=102502400.0), HTML
(value='')))

epoch	train_loss	valid_loss	error_rate	time
0	1.426074	0.289685	0.094723	02:23
1	0.630846	0.336782	0.109608	02:23
2	0.421451	0.289481	0.083221	02:23
_				
epoch	train_loss	valid_loss	error_rate	time
0	0.265935	0.293698	0.094046	03:13
1	0.291401	0.294177	0.081867	03:14
2	0.256584	0.271347	0.077131	03:14
3	0.164891	0.258964	0.073072	03:14
4	0.088564	0.210342	0.064953	03:14
5	0.051878	0.209877	0.063599	03:14

Conclusion

Questionnaire

1. Why do we first resize to a large size on the CPU, and then to a smaller size on the GPU?

This process is actually known as presizing. Here a large image is needed because data augmentation often leads to degradation of the image. Therefore, to minize this destruction of the image quality, this technique known as presizing is used.

- 2. If you are not familiar with regular expressions, find a regular expression tutorial, and some problem sets, and complete them. Have a look on the book's website for suggestions.
- 3. What are the two ways in which data is most commonly provided, for most deep learning datasets?

Individual files with data (Ex: Images)

Tabular data (CSV data)

- 4. Look up the documentation for L and try using a few of the new methods that it adds. L is a custom list class by FastAl. It is designed to be a replacement for list in python.
- 5. Look up the documentation for the Python pathlib module and try using a few methods of the Path class.
- 6. Give two examples of ways that image transformations can degrade the quality of the data.

Rotating an image by leaves corner regions of the new bounds with emptiness, which will not teach the model anything.

Many rotation and zooming operations will require interpolation, which leave a lower quality image.

- 7. What method does fastai provide to view the data in a DataLoaders?

 DataLoader.show batch()
- 8. What method does fastai provide to help you debug a DataBlock?

 DataBlock.summary()
- 9. Should you hold off on training a model until you have thoroughly cleaned your data? No. It is better to create a model first and then plot_top_losses to have the model help you clean the data.
- 10. What are the two pieces that are combined into cross-entropy loss in PyTorch? Softmax function and Negative Log Likelihood Loss
- 11. What are the two properties of activations that softmax ensures? Why is this important?

All values add up to 1 and amplifies small changes in the output activations. This overall makes the model more confident when classifying.

- 12. When might you want your activations to not have these two properties? I guess when you have more than one label possible for a class.
- 13. Calculate the exp and softmax columns of <> yourself (i.e., in a spreadsheet, with a calculator, or in a notebook).
- 14. Why can't we use torch where to create a loss function for datasets where our label can have more than two categories?

torch.where can only select between two possibilities.

15. What is the value of log(-2)? Why?

Undefined. Log is the inverse of exp, where all values are pos.

16. What are two good rules of thumb for picking a learning rate from the learning rate finder?

Minimum/10

Subjective choice based on observation

17. What two steps does the fine_tune method do?

Freezes and trains the head for 1 epoch Unfreezes and trains on the input epochs

- 18. In Jupyter Notebook, how do you get the source code for a method or function?
- 19. What are discriminative learning rates?

Trick of using different learning rates for different layers of the model. Here the early layers have a lower Ir and the later layers have a higher Ir.

- 20. How is a Python slice object interpreted when passed as a learning rate to fastai? First val is the initial Ir, final val is the final Ir, and the layers inbetween have a Ir thats equal distant in the range.
- 21. Why is early stopping a poor choice when using 1cycle training?

 The training may not have time to reach lower learning rate values.
- 22. What is the difference between resnet50 and resnet101?

 Number of layers
- 23. What does to fp16 do?

Lowers the floating point precision numbers so you can speed up training.

Further Research

- 1. Find the paper by Leslie Smith that introduced the learning rate finder, and read it.
- 2. See if you can improve the accuracy of the classifier in this chapter. What's the best accuracy you can achieve? Look on the forums and the book's website to see what other students have achieved with this dataset, and how they did it.

Rather than doing this lesson, I decided to do the MNIST, for which I had an accuracy of 61%. After the LR improvement it jumped to 87%.

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