Product based on a Deep Learning model (by fastai v2)

> **Use case**: Dog & Cat Breeds Recognizer for Veterinary Clinics

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- **Date**: 10/22/2020
- **Post in Medium**: Product based on a Deep Learning model (by fastai v2)
- Github folder of the Web App v1
- Version 1 of the Web App

Overview

This is the notebook of the post Product based on a Deep Learning model (by fastai v2).

Read this post to understand the context and objective of this notebook.

1. Initialization

In [1]:
```
# Import fastai v2 for computer vision
from fastai.vision.all import *
from fastai.vision.widgets import *
```

In [2]:
```
# Check for CUDA & GPU
if torch.cuda.is_available():
    print(f'gpu: {torch.cuda.current_device()} ({torch.cuda.get_device_name()})')
```

```
gpu: 0 (Tesla V100-PCIE-32GB)
```

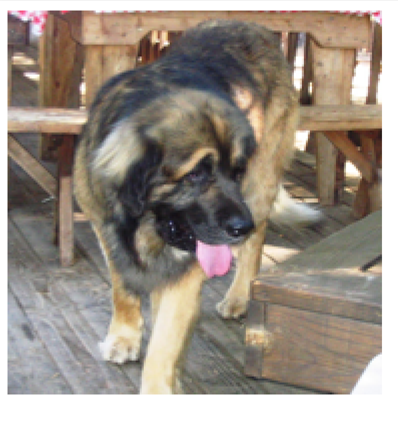
2. Data

In [3]:
```
# Get path to data
path = untar_data(URLs.PETS)
path.ls()
```

Out[3]:
```
(#2) [Path('/mnt/home/pierre/.fastai/data/oxford-iiit-pet/annotations'),Path('/mnt/home/pierre/.fastai/data/oxford-ii
it-pet/images')]
```

In [4]:
```
# Check first image
path_to_img = (path/'images').ls()[0]
img = PILImage.create(path_to_img)
img.to_thumb(192)
```

Out[4]:



3. Dataloaders

We will define a `DataBlock()` object using all the recent techniques (see the notebook 07_sizing_and_tta.ipynb):

- **Data Augmentation** with the list of transforms at batch level (`aug_transforms()`).
- **Presizing** (notebook 05_pet_breeds.ipynb).
- **Normalization** with the standard ImageNet mean and standard deviation (`Normalize.from_stats(*imagenet_stats)`).
- **Progressive Resizing**: Gradually using larger and larger images as you train (`get_dls()`).

In [5]:
```
def get_dls(bs, size):
    dblock = DataBlock(blocks = (ImageBlock, CategoryBlock),
                       get_items=get_image_files,
                       splitter=RandomSplitter(seed=42),
                       get_y=using_attr(RegexLabeller(r'(.+)_\d+.jpg$'), 'name'),
                       item_tfms=Resize(460),
                       batch_tfms=[*aug_transforms(size=size, min_scale=0.75),
                                   Normalize.from_stats(*imagenet_stats)])
    return dblock.dataloaders(path/"images", bs=bs)
```

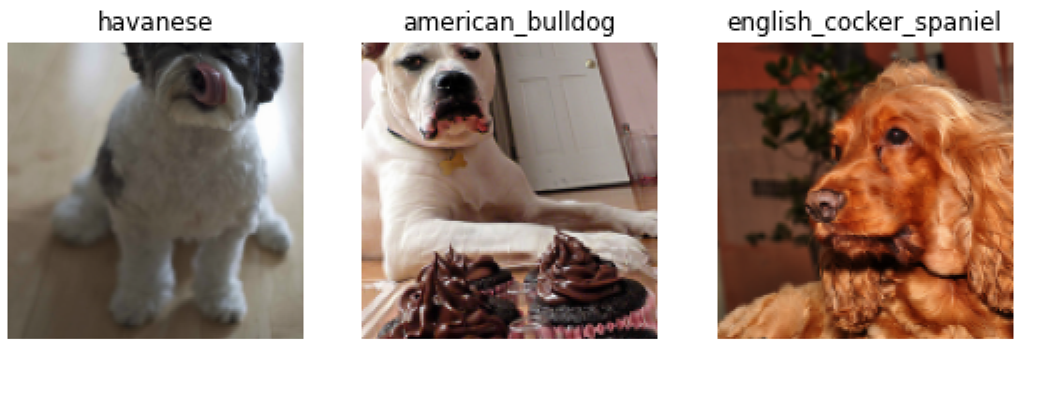
In [6]:
```
# Get Dataloaders
dls = get_dls(128, 128)
```

In [7]:
```
# Check number of categories and list
dls.vocab
```

Out[7]:
```
(#37) ['Abyssinian','Bengal','Birman','Bombay','British_Shorthair','Egyptian_Mau','Maine_Coon','Persian','Ragdoll','R
ussian_Blue'...]
```

In [8]:
```
# Batch size and Check images in training batch
dls.bs, dls.show_batch(nrows=1, ncols=3)
```

Out[8]:
```
(128, None)
```



4. First model (baseline)

To encourage our model to be less confident, we'll use `label smoothing` that will make our training more robust, even if there is mislabeled data. The result will be a model that generalizes better (see the notebook 07_sizing_and_tta.ipynb).

Let's train our model with the following fine-tuning techniques:

- **gradual unfreezing** of layers from the last one to the first ones.
- **Discriminative Learning Rates** (notebook 05_pet_breeds.ipynb).
- **Deeper Architectures**: let's start with resnet34 as baseline, and then resnet152 as final model.

4.1 Images of size 128

In [9]:
```python
# Learner with model resnet34
dls = get_dls(128, 128)
model = resnet34
loss_func=LabelSmoothingCrossEntropy()

learn = cnn_learner(dls, model, loss_func=loss_func, metrics=[accuracy])
```

Freeze all layers but the last (new) one

In [10]:
```python
# Check model and frozen layers
learn.freeze()
learn.summary()
```

epoch	train_loss	valid_loss	accuracy	time
0	None	None		00:00

Out[10]:
```
Sequential (Input shape: ['128 x 3 x 128 x 128'])
================================================================
Layer (type)         Output Shape         Param #    Trainable
================================================================
Conv2d               128 x 64 x 64 x 64   9,408      False
BatchNorm2d          128 x 64 x 64 x 64   128        True
ReLU                 128 x 64 x 64 x 64   0          False
MaxPool2d            128 x 64 x 32 x 32   0          False
Conv2d               128 x 64 x 32 x 32   36,864     False
BatchNorm2d          128 x 64 x 32 x 32   128        True
ReLU                 128 x 64 x 32 x 32   0          False
Conv2d               128 x 64 x 32 x 32   36,864     False
BatchNorm2d          128 x 64 x 32 x 32   128        True
Conv2d               128 x 64 x 32 x 32   36,864     False
BatchNorm2d          128 x 64 x 32 x 32   128        True
ReLU                 128 x 64 x 32 x 32   0          False
Conv2d               128 x 64 x 32 x 32   36,864     False
BatchNorm2d          128 x 64 x 32 x 32   128        True
Conv2d               128 x 64 x 32 x 32   36,864     False
BatchNorm2d          128 x 64 x 32 x 32   128        True
ReLU                 128 x 64 x 32 x 32   0          False
Conv2d               128 x 64 x 32 x 32   36,864     False
BatchNorm2d          128 x 64 x 32 x 32   128        True
Conv2d               128 x 128 x 16 x 16  73,728     False
BatchNorm2d          128 x 128 x 16 x 16  256        True
ReLU                 128 x 128 x 16 x 16  0          False
Conv2d               128 x 128 x 16 x 16  147,456    False
BatchNorm2d          128 x 128 x 16 x 16  256        True
Conv2d               128 x 128 x 16 x 16  8,192      False
BatchNorm2d          128 x 128 x 16 x 16  256        True
Conv2d               128 x 128 x 16 x 16  147,456    False
BatchNorm2d          128 x 128 x 16 x 16  256        True
ReLU                 128 x 128 x 16 x 16  0          False
Conv2d               128 x 128 x 16 x 16  147,456    False
BatchNorm2d          128 x 128 x 16 x 16  256        True
Conv2d               128 x 128 x 16 x 16  147,456    False
BatchNorm2d          128 x 128 x 16 x 16  256        True
ReLU                 128 x 128 x 16 x 16  0          False
Conv2d               128 x 128 x 16 x 16  147,456    False
BatchNorm2d          128 x 128 x 16 x 16  256        True
Conv2d               128 x 128 x 16 x 16  147,456    False
BatchNorm2d          128 x 128 x 16 x 16  256        True
ReLU                 128 x 128 x 16 x 16  0          False
Conv2d               128 x 128 x 16 x 16  147,456    False
BatchNorm2d          128 x 128 x 16 x 16  256        True
Conv2d               128 x 256 x 8 x 8    294,912    False
BatchNorm2d          128 x 256 x 8 x 8    512        True
ReLU                 128 x 256 x 8 x 8    0          False
Conv2d               128 x 256 x 8 x 8    589,824    False
BatchNorm2d          128 x 256 x 8 x 8    512        True
Conv2d               128 x 256 x 8 x 8    32,768     False
BatchNorm2d          128 x 256 x 8 x 8    512        True
Conv2d               128 x 256 x 8 x 8    589,824    False
BatchNorm2d          128 x 256 x 8 x 8    512        True
ReLU                 128 x 256 x 8 x 8    0          False
Conv2d               128 x 256 x 8 x 8    589,824    False
BatchNorm2d          128 x 256 x 8 x 8    512        True
Conv2d               128 x 256 x 8 x 8    589,824    False
BatchNorm2d          128 x 256 x 8 x 8    512        True
ReLU                 128 x 256 x 8 x 8    0          False
Conv2d               128 x 256 x 8 x 8    589,824    False
BatchNorm2d          128 x 256 x 8 x 8    512        True
Conv2d               128 x 256 x 8 x 8    589,824    False
```

BatchNorm2d	128 x 256 x 8 x 8	512	True
ReLU	128 x 256 x 8 x 8	0	False
Conv2d	128 x 256 x 8 x 8	589,824	False
BatchNorm2d	128 x 256 x 8 x 8	512	True
Conv2d	128 x 256 x 8 x 8	589,824	False
BatchNorm2d	128 x 256 x 8 x 8	512	True
ReLU	128 x 256 x 8 x 8	0	False
Conv2d	128 x 256 x 8 x 8	589,824	False
BatchNorm2d	128 x 256 x 8 x 8	512	True
Conv2d	128 x 256 x 8 x 8	589,824	False
BatchNorm2d	128 x 256 x 8 x 8	512	True
ReLU	128 x 256 x 8 x 8	0	False
Conv2d	128 x 256 x 8 x 8	589,824	False
BatchNorm2d	128 x 256 x 8 x 8	512	True
Conv2d	128 x 512 x 4 x 4	1,179,648	False
BatchNorm2d	128 x 512 x 4 x 4	1,024	True
ReLU	128 x 512 x 4 x 4	0	False
Conv2d	128 x 512 x 4 x 4	2,359,296	False
BatchNorm2d	128 x 512 x 4 x 4	1,024	True
Conv2d	128 x 512 x 4 x 4	131,072	False
BatchNorm2d	128 x 512 x 4 x 4	1,024	True
Conv2d	128 x 512 x 4 x 4	2,359,296	False
BatchNorm2d	128 x 512 x 4 x 4	1,024	True
ReLU	128 x 512 x 4 x 4	0	False
Conv2d	128 x 512 x 4 x 4	2,359,296	False
BatchNorm2d	128 x 512 x 4 x 4	1,024	True
Conv2d	128 x 512 x 4 x 4	2,359,296	False
BatchNorm2d	128 x 512 x 4 x 4	1,024	True
ReLU	128 x 512 x 4 x 4	0	False
Conv2d	128 x 512 x 4 x 4	2,359,296	False
BatchNorm2d	128 x 512 x 4 x 4	1,024	True
AdaptiveAvgPool2d	128 x 512 x 1 x 1	0	False
AdaptiveMaxPool2d	128 x 512 x 1 x 1	0	False
Flatten	128 x 1024	0	False
BatchNorm1d	128 x 1024	2,048	True
Dropout	128 x 1024	0	False
Linear	128 x 512	524,288	True
ReLU	128 x 512	0	False
BatchNorm1d	128 x 512	1,024	True
Dropout	128 x 512	0	False
Linear	128 x 37	18,944	True

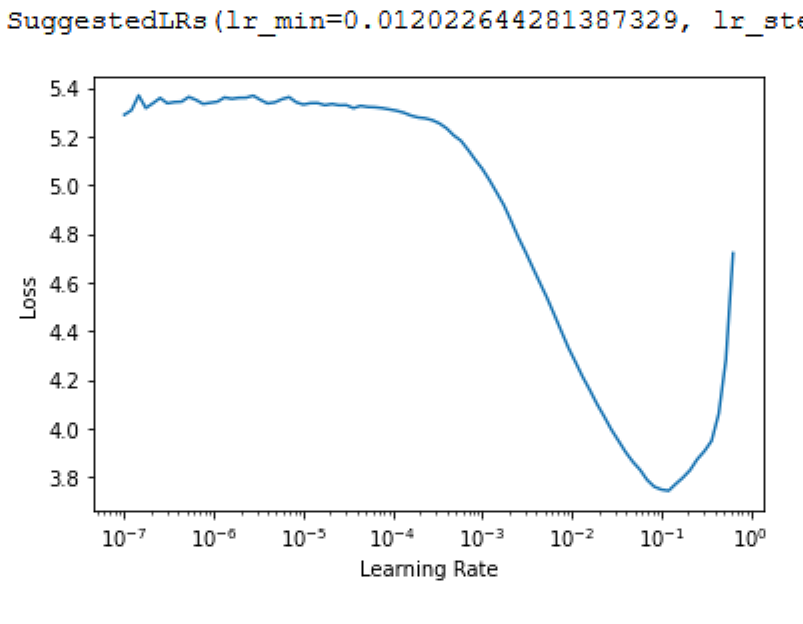
```
Total params: 21,830,976
Total trainable params: 563,328
Total non-trainable params: 21,267,648

Optimizer used: <function Adam at 0x7f84dc655670>
Loss function: LabelSmoothingCrossEntropy()

Model frozen up to parameter group #2

Callbacks:
  - TrainEvalCallback
  - Recorder
  - ProgressCallback
```

In [11]:

```
# Learning rate
learn.lr_find()
```

Out[11]:

```
SuggestedLRs(lr_min=0.012022644281387329, lr_steep=0.0063095735386013985)
```



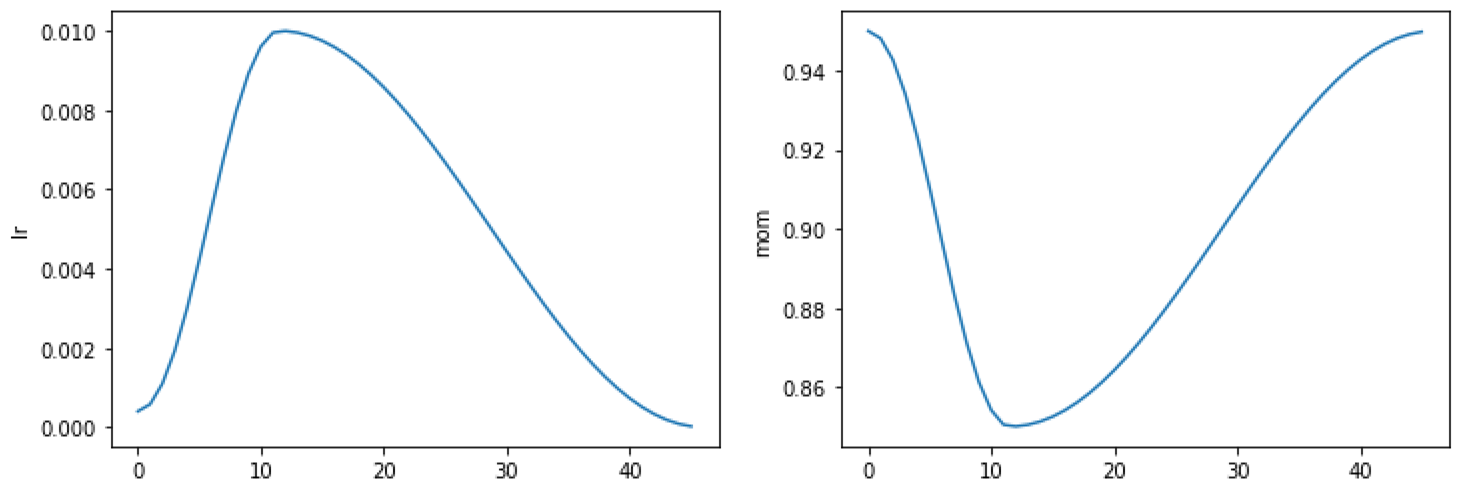
As only the last layer is unfrozen, **let's choose the learning rate 10 times less than the one of the loss minimum as lr_max (1e-2)**.

In [12]:

```
# Train the model with lr_max and the fit_one_cycle() function on 1 epoch
lr_max = 1e-2
learn.fit_one_cycle(1, lr_max=lr_max)
```

epoch	train_loss	valid_loss	accuracy	time
0	2.204725	1.470944	0.784844	00:10

In [13]:
```python
# Display the Learning rate and momentum values used in training
learn.recorder.plot_sched()
```



In [14]:
```python
# Save the model
learn.save('petbreeds_1')
```

Out[14]: Path('models/petbreeds_1.pth')

Unfreeze all layers and Discriminative Learning Rates

In [15]:
```python
# Load model, unfreeze layers and check it
learn = learn.load('petbreeds_1')
learn.unfreeze()
learn.summary()
```

epoch	train_loss	valid_loss	accuracy	time
0	None	None	00:00	

Out[15]:
```
Sequential (Input shape: ['128 x 3 x 128 x 128'])
================================================================
Layer (type)         Output Shape         Param #    Trainable
================================================================
Conv2d               128 x 64 x 64 x 64   9,408      True
BatchNorm2d          128 x 64 x 64 x 64   128        True
ReLU                 128 x 64 x 64 x 64   0          False
MaxPool2d            128 x 64 x 32 x 32   0          False
Conv2d               128 x 64 x 32 x 32   36,864     True
BatchNorm2d          128 x 64 x 32 x 32   128        True
ReLU                 128 x 64 x 32 x 32   0          False
Conv2d               128 x 64 x 32 x 32   36,864     True
BatchNorm2d          128 x 64 x 32 x 32   128        True
Conv2d               128 x 64 x 32 x 32   36,864     True
BatchNorm2d          128 x 64 x 32 x 32   128        True
ReLU                 128 x 64 x 32 x 32   0          False
Conv2d               128 x 64 x 32 x 32   36,864     True
BatchNorm2d          128 x 64 x 32 x 32   128        True
Conv2d               128 x 64 x 32 x 32   36,864     True
BatchNorm2d          128 x 64 x 32 x 32   128        True
ReLU                 128 x 64 x 32 x 32   0          False
Conv2d               128 x 64 x 32 x 32   36,864     True
BatchNorm2d          128 x 64 x 32 x 32   128        True
Conv2d               128 x 128 x 16 x 16  73,728     True
BatchNorm2d          128 x 128 x 16 x 16  256        True
ReLU                 128 x 128 x 16 x 16  0          False
Conv2d               128 x 128 x 16 x 16  147,456    True
BatchNorm2d          128 x 128 x 16 x 16  256        True
Conv2d               128 x 128 x 16 x 16  8,192      True
BatchNorm2d          128 x 128 x 16 x 16  256        True
Conv2d               128 x 128 x 16 x 16  147,456    True
BatchNorm2d          128 x 128 x 16 x 16  256        True
ReLU                 128 x 128 x 16 x 16  0          False
Conv2d               128 x 128 x 16 x 16  147,456    True
BatchNorm2d          128 x 128 x 16 x 16  256        True
Conv2d               128 x 128 x 16 x 16  147,456    True
BatchNorm2d          128 x 128 x 16 x 16  256        True
ReLU                 128 x 128 x 16 x 16  0          False
Conv2d               128 x 128 x 16 x 16  147,456    True
BatchNorm2d          128 x 128 x 16 x 16  256        True
Conv2d               128 x 128 x 16 x 16  147,456    True
BatchNorm2d          128 x 128 x 16 x 16  256        True
ReLU                 128 x 128 x 16 x 16  0          False
Conv2d               128 x 128 x 16 x 16  147,456    True
BatchNorm2d          128 x 128 x 16 x 16  256        True
Conv2d               128 x 256 x 8 x 8    294,912    True
BatchNorm2d          128 x 256 x 8 x 8    512        True
ReLU                 128 x 256 x 8 x 8    0          False
Conv2d               128 x 256 x 8 x 8    589,824    True
BatchNorm2d          128 x 256 x 8 x 8    512        True
Conv2d               128 x 256 x 8 x 8    32,768     True
BatchNorm2d          128 x 256 x 8 x 8    512        True
Conv2d               128 x 256 x 8 x 8    589,824    True
BatchNorm2d          128 x 256 x 8 x 8    512        True
ReLU                 128 x 256 x 8 x 8    0          False
```

Conv2d	128 x 256 x 8 x 8	589,824	True
BatchNorm2d	128 x 256 x 8 x 8	512	True
Conv2d	128 x 256 x 8 x 8	589,824	True
BatchNorm2d	128 x 256 x 8 x 8	512	True
ReLU	128 x 256 x 8 x 8	0	False
Conv2d	128 x 256 x 8 x 8	589,824	True
BatchNorm2d	128 x 256 x 8 x 8	512	True
Conv2d	128 x 256 x 8 x 8	589,824	True
BatchNorm2d	128 x 256 x 8 x 8	512	True
ReLU	128 x 256 x 8 x 8	0	False
Conv2d	128 x 256 x 8 x 8	589,824	True
BatchNorm2d	128 x 256 x 8 x 8	512	True
Conv2d	128 x 256 x 8 x 8	589,824	True
BatchNorm2d	128 x 256 x 8 x 8	512	True
ReLU	128 x 256 x 8 x 8	0	False
Conv2d	128 x 256 x 8 x 8	589,824	True
BatchNorm2d	128 x 256 x 8 x 8	512	True
Conv2d	128 x 256 x 8 x 8	589,824	True
BatchNorm2d	128 x 256 x 8 x 8	512	True
ReLU	128 x 256 x 8 x 8	0	False
Conv2d	128 x 256 x 8 x 8	589,824	True
BatchNorm2d	128 x 256 x 8 x 8	512	True
Conv2d	128 x 512 x 4 x 4	1,179,648	True
BatchNorm2d	128 x 512 x 4 x 4	1,024	True
ReLU	128 x 512 x 4 x 4	0	False
Conv2d	128 x 512 x 4 x 4	2,359,296	True
BatchNorm2d	128 x 512 x 4 x 4	1,024	True
Conv2d	128 x 512 x 4 x 4	131,072	True
BatchNorm2d	128 x 512 x 4 x 4	1,024	True
Conv2d	128 x 512 x 4 x 4	2,359,296	True
BatchNorm2d	128 x 512 x 4 x 4	1,024	True
ReLU	128 x 512 x 4 x 4	0	False
Conv2d	128 x 512 x 4 x 4	2,359,296	True
BatchNorm2d	128 x 512 x 4 x 4	1,024	True
Conv2d	128 x 512 x 4 x 4	2,359,296	True
BatchNorm2d	128 x 512 x 4 x 4	1,024	True
ReLU	128 x 512 x 4 x 4	0	False
Conv2d	128 x 512 x 4 x 4	2,359,296	True
BatchNorm2d	128 x 512 x 4 x 4	1,024	True
AdaptiveAvgPool2d	128 x 512 x 1 x 1	0	False
AdaptiveMaxPool2d	128 x 512 x 1 x 1	0	False
Flatten	128 x 1024	0	False
BatchNorm1d	128 x 1024	2,048	True
Dropout	128 x 1024	0	False
Linear	128 x 512	524,288	True
ReLU	128 x 512	0	False
BatchNorm1d	128 x 512	1,024	True
Dropout	128 x 512	0	False
Linear	128 x 37	18,944	True

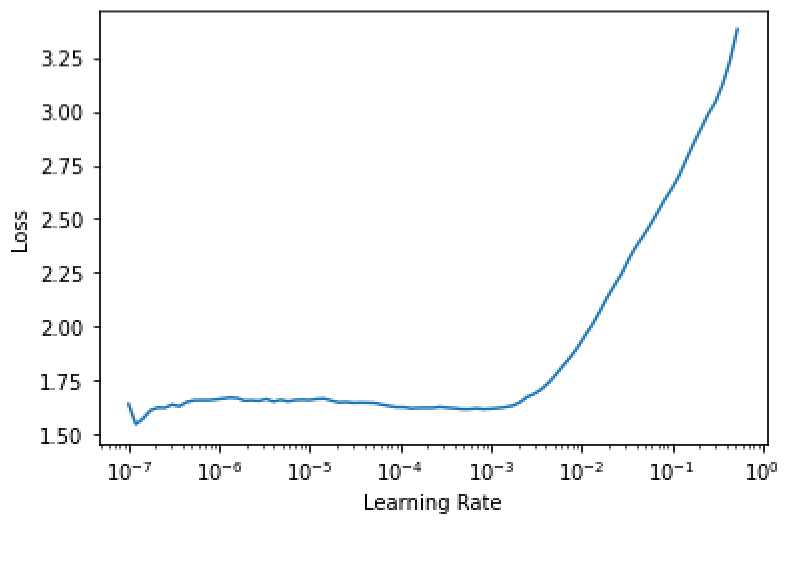
```
Total params: 21,830,976
Total trainable params: 21,830,976
Total non-trainable params: 0

Optimizer used: <function Adam at 0x7f84dc655670>
Loss function: LabelSmoothingCrossEntropy()

Model unfrozen

Callbacks:
  - TrainEvalCallback
  - Recorder
  - ProgressCallback
```

In [16]:

```
# Learning rate
learn.lr_find()
```

Out[16]:

```
SuggestedLRs(lr_min=8.317637839354575e-05, lr_steep=1.5848931980144698e-06)
```



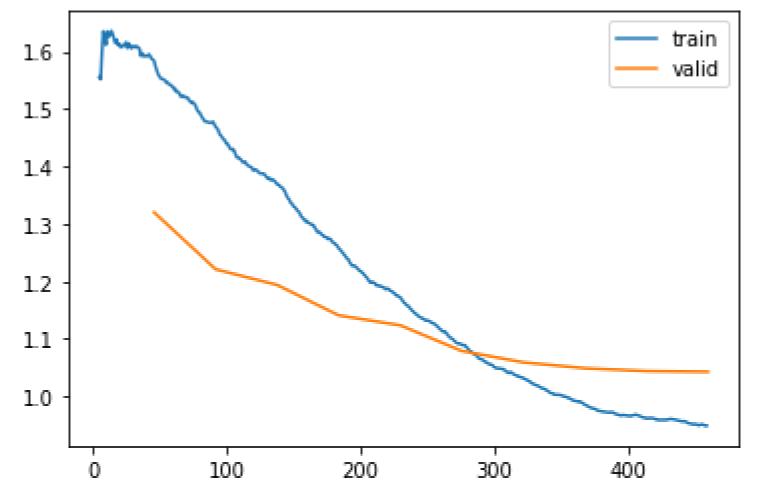
As we unfroze all layers of the model, **let's choose the learning rate of the loss minimum as lr_max (1e-3)**.

In [17]:
```
# Train the model with lr_max and the fit_one_cycle() function on 1 epoch
lr_max = 1e-3
lr_min = lr_max / 100
learn.fit_one_cycle(10, lr_max=slice(lr_min,lr_max))
```

epoch	train_loss	valid_loss	accuracy	time
0	1.586308	1.320002	0.826116	00:10
1	1.473428	1.220881	0.859269	00:10
2	1.371713	1.193700	0.859269	00:10
3	1.261236	1.140758	0.875507	00:10
4	1.173585	1.123551	0.864682	00:10
5	1.091030	1.078906	0.887010	00:10
6	1.032797	1.059132	0.889039	00:10
7	0.986927	1.048918	0.886333	00:10
8	0.962747	1.043976	0.889039	00:10
9	0.949135	1.042742	0.893099	00:10

Baseline model accuracy: **89.31%**

In [18]:
```
# Display the training and validation loss
learn.recorder.plot_loss()
```



In [19]:
```
# Save the model
learn.save('petbreeds_2')
```

Out[19]: `Path('models/petbreeds_2.pth')`

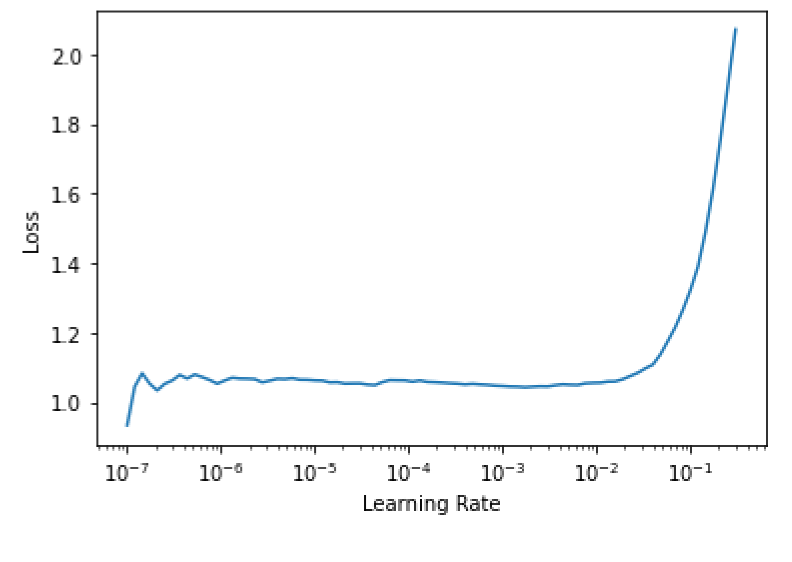
4.2 Images of size 224

In [20]:
```
# Learner with model resnet34
dls = get_dls(64, 224)
model = resnet34
loss_func=LabelSmoothingCrossEntropy()

learn = cnn_learner(dls, model, loss_func=loss_func, metrics=[accuracy])
learn = learn.load('petbreeds_2')
```

Freeze all layers but the last (new) one

In [21]:
```
# Learning rate
learn.freeze()
learn.lr_find()
```

Out[21]: `SuggestedLRs(lr_min=0.00017378007760271 43, lr_steep=7.585775847473997e-07)`



As only the last layer is unfrozen, **let's choose the learning rate 10 times less than the one of the loss minimum as lr_max (2e-4)**.

In [22]:
```
# Train the model with lr_max and the fit_one_cycle() function on 1 epoch
lr_max = 2e-4
learn.fit_one_cycle(1, lr_max=lr_max)
```

epoch	train_loss	valid_loss	accuracy	time
0	1.036574	0.962142	0.933694	00:14

In [23]:
```
# Save the model
learn.save('petbreeds_3')
```

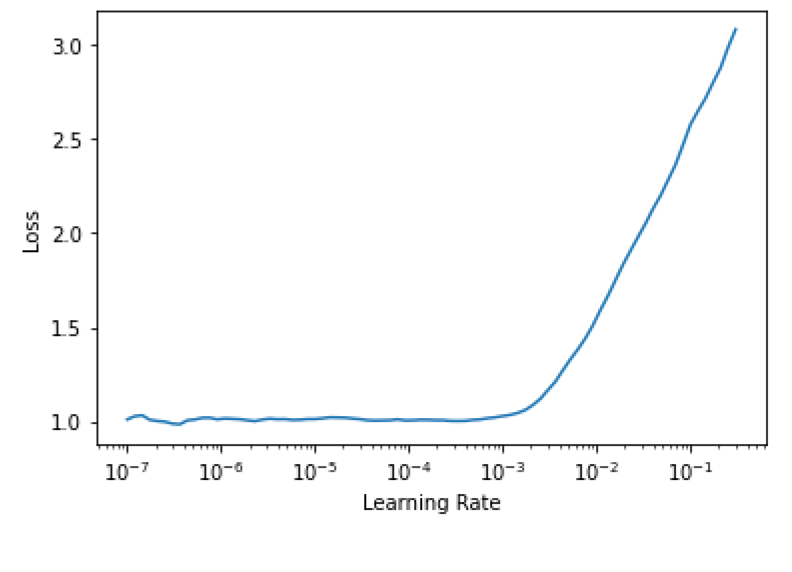
Out[23]: `Path('models/petbreeds_3.pth')`

Unfreeze all layers and Discriminative Learning Rates

In [24]:
```
# Load model, unfreeze layers and check it
learn = learn.load('petbreeds_3')
learn.unfreeze()
```

In [25]:
```
# Learning rate
learn.lr_find()
```

Out[25]: `SuggestedLRs(lr_min=2.2908675418875645e-07, lr_steep=7.585775847473997e-07)`



As we unfroze all layers of the model, **let's choose the learning rate of the loss minimum as lr_max (2e-4)**.

In [26]:
```
# Train the model with lr_max and the fit_one_cycle() function on 1 epoch
lr_max = 2e-4
lr_min = lr_max / 100
learn.fit_one_cycle(10, lr_max=slice(lr_min,lr_max))
```

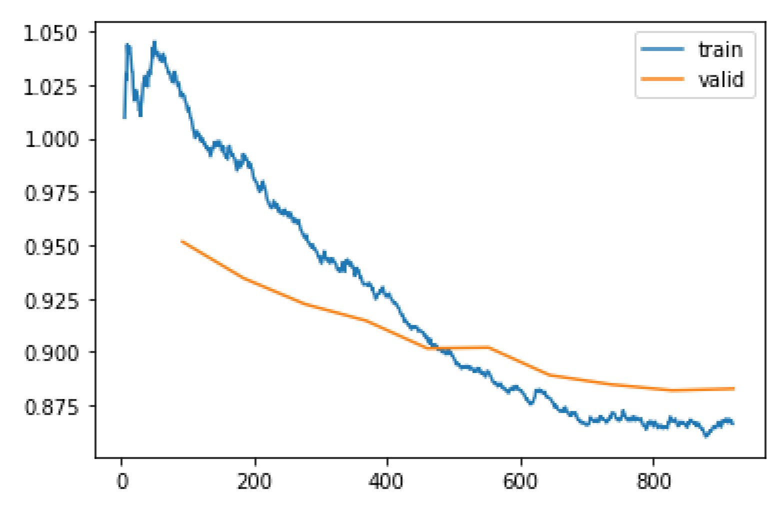
epoch	train_loss	valid_loss	accuracy	time
0	1.021168	0.951557	0.935724	00:17
1	0.992551	0.934461	0.940460	00:16
2	0.953975	0.922366	0.936401	00:16
3	0.931800	0.914601	0.937754	00:17
4	0.906766	0.901651	0.947903	00:16
5	0.890850	0.902056	0.944520	00:17
6	0.878638	0.889122	0.945196	00:16
7	0.869708	0.884780	0.946549	00:17
8	0.868199	0.881976	0.951962	00:17
9	0.866460	0.882781	0.948579	00:16

In [77]:
```
# Test Time Augmentation
# notebook: https://github.com/fastai/fastbook/blob/master/07_sizing_and_tta.ipynb
learn.epoch = 0
preds,targs = learn.tta()
accuracy(preds, targs).item()
```

Out[77]: 0.9539918899536133

Baseline model accuracy: **95.40%**

In [27]:
```
# Display the training and validation loss
learn.recorder.plot_loss()
```

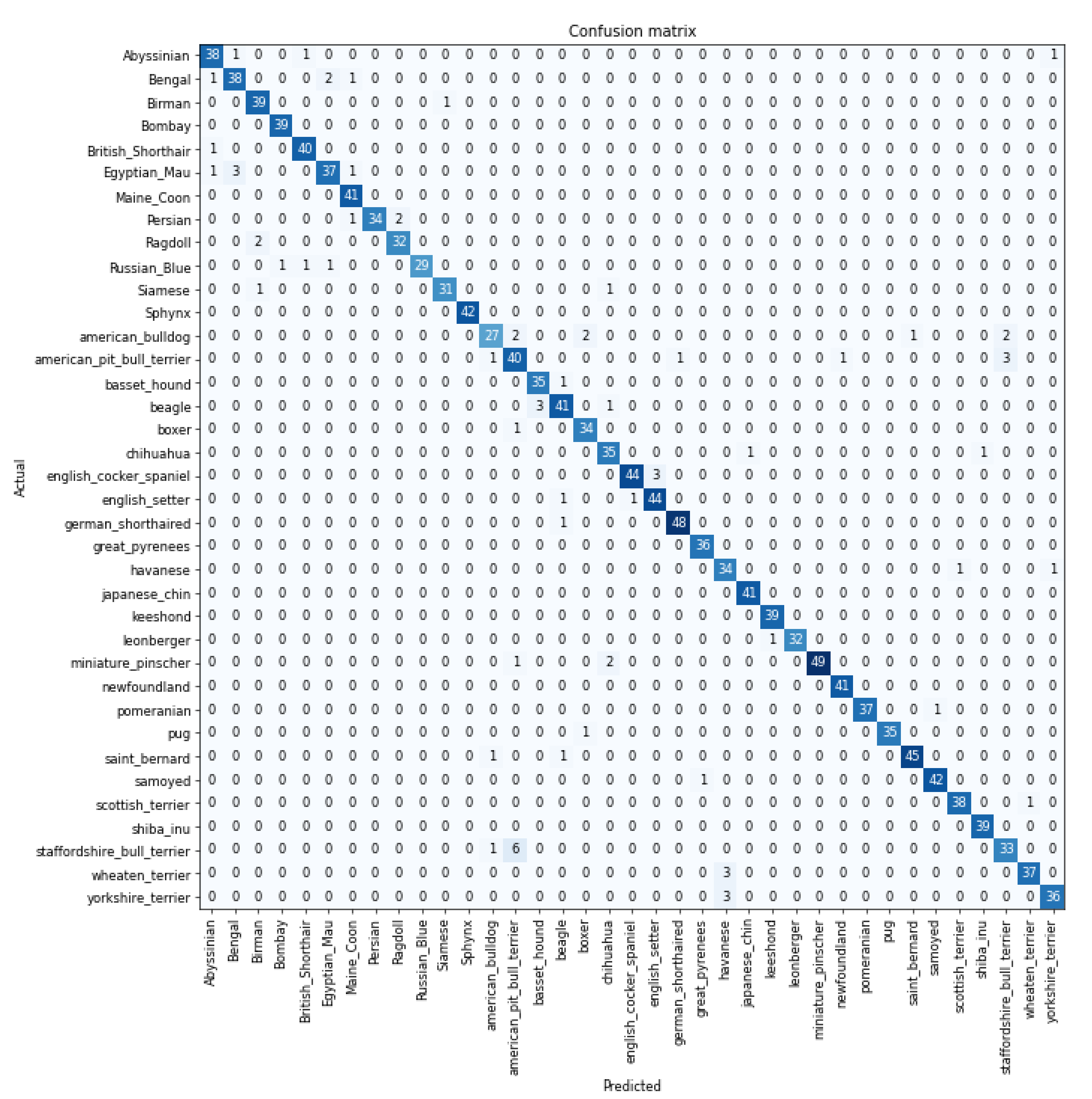


In [28]:
```
# Save the model
learn.save('petbreeds_4')
```

Out[28]: Path('models/petbreeds_4.pth')

5. Results analysis

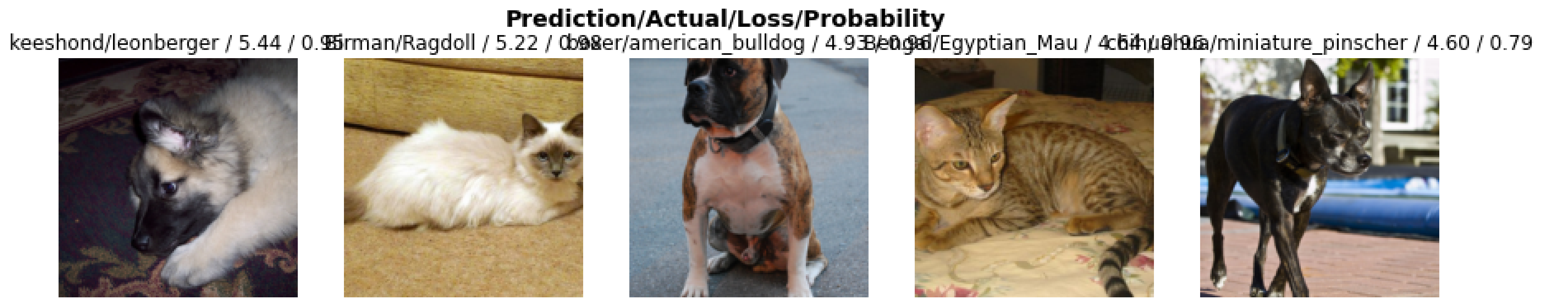
In [41]:
```
# Load model and display the Confusion Matrix
learn = learn.load('petbreeds_4')
interp = ClassificationInterpretation.from_learner(learn)
interp.plot_confusion_matrix(figsize=(12,12), dpi=60)
```



In [42]:
```
# Get categories with the most errors
interp.most_confused(min_val=3)
```

Out[42]:
```
[('staffordshire_bull_terrier', 'american_pit_bull_terrier', 6),
 ('Egyptian_Mau', 'Bengal', 3),
 ('american_pit_bull_terrier', 'staffordshire_bull_terrier', 3),
 ('beagle', 'basset_hound', 3),
 ('english_cocker_spaniel', 'english_setter', 3),
 ('wheaten_terrier', 'havanese', 3),
 ('yorkshire_terrier', 'havanese', 3)]
```

In [43]:
```
# Get the images with highest loss between prediction and true category
interp.plot_top_losses(5, nrows=1)
```



In [44]:
```
# Clean training and validation datasets
cleaner = ImageClassifierCleaner(learn)
cleaner
```

In [ ]:
```
# for idx in cleaner.delete(): cleaner.fns[idx].unlink()
# for idx,cat in cleaner.change(): shutil.move(str(cleaner.fns[idx]), path/cat)
```

6. Deeper model

6.1 Images of size 128

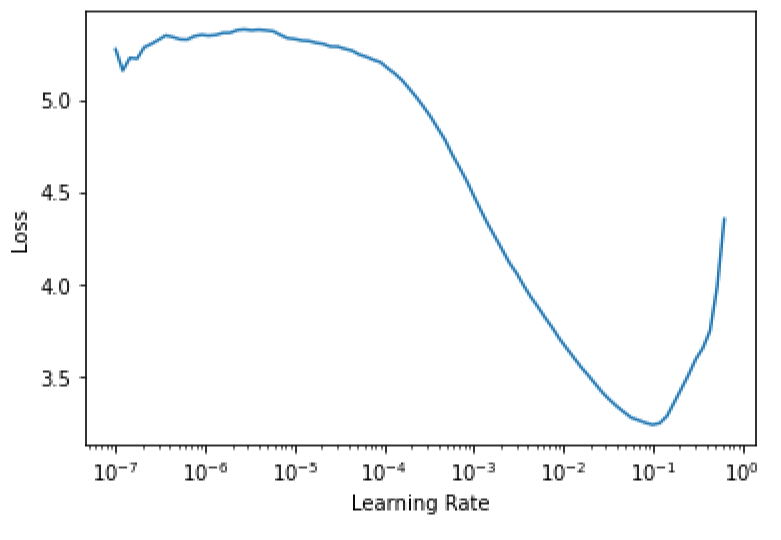
In [45]:
```
# Learner with model resnet152
dls = get_dls(128, 128)
model = resnet152
loss_func=LabelSmoothingCrossEntropy()

learn = cnn_learner(dls, model, loss_func=loss_func, metrics=[accuracy])
```

Freeze all layers but the last (new) one

In [46]:
```
# Check model and frozen layers
learn.freeze()
```

In [47]:
```
# Learning rate
learn.lr_find()
```

Out[47]:
```
SuggestedLRs(lr_min=0.010000000149011612, lr_steep=0.0008317637839354575)
```



As only the last layer is unfrozen, **let's choose the learning rate 10 times less than the one of the loss minimum as lr_max (1e-2)**.

In [48]:
```
# Train the model with lr_max and the fit_one_cycle() function on 1 epoch
lr_max = 1e-2
learn.fit_one_cycle(1, lr_max=lr_max)
```

epoch	train_loss	valid_loss	accuracy	time
0	1.984388	1.491735	0.803789	00:20

In [49]:
```
# Save the model
learn.save('petbreeds_5')
```

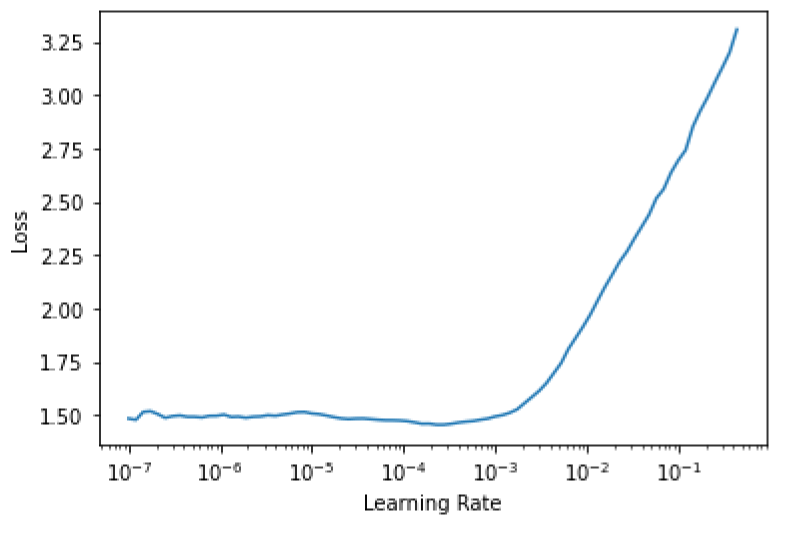
Out[49]:
```
Path('models/petbreeds_5.pth')
```

Unfreeze all layers and Discriminative Learning Rates

In [50]:
```
# Load model, unfreeze layers and check it
learn = learn.load('petbreeds_5')
learn.unfreeze()
```

In [51]:
```
# Learning rate
learn.lr_find()
```

Out[51]:
```
SuggestedLRs(lr_min=2.2908677055966611e-05, lr_steep=1.0964781722577754e-06)
```



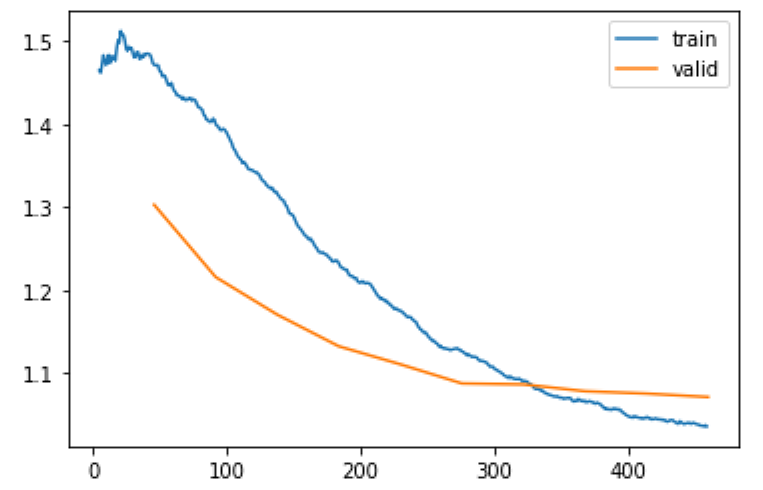
As we unfroze all layers of the model, **let's choose the learning rate of the loss minimum as lr_max (2e-4)**.

In [52]:
```
# Train the model with lr_max and the fit_one_cycle() function on 1 epoch
lr_max = 2e-4
lr_min = lr_max / 100
learn.fit_one_cycle(10, lr_max=slice(lr_min,lr_max))
```

epoch	train_loss	valid_loss	accuracy	time
0	1.473513	1.302816	0.835589	00:25
1	1.405306	1.215646	0.861299	00:25
2	1.318926	1.170392	0.866712	00:24
3	1.234848	1.132229	0.886333	00:24
4	1.175394	1.110505	0.890392	00:24
5	1.127627	1.087428	0.896482	00:25
6	1.090511	1.086275	0.897158	00:24
7	1.065642	1.078029	0.895805	00:25
8	1.045674	1.075211	0.897835	00:24
9	1.035725	1.071048	0.897835	00:25

Deeper model accuracy: **89.78%**

In [53]:
```
# Display the training and validation loss
learn.recorder.plot_loss()
```



In [54]:
```
# Save the model
learn.save('petbreeds_6')
```

Out[54]: `Path('models/petbreeds_6.pth')`

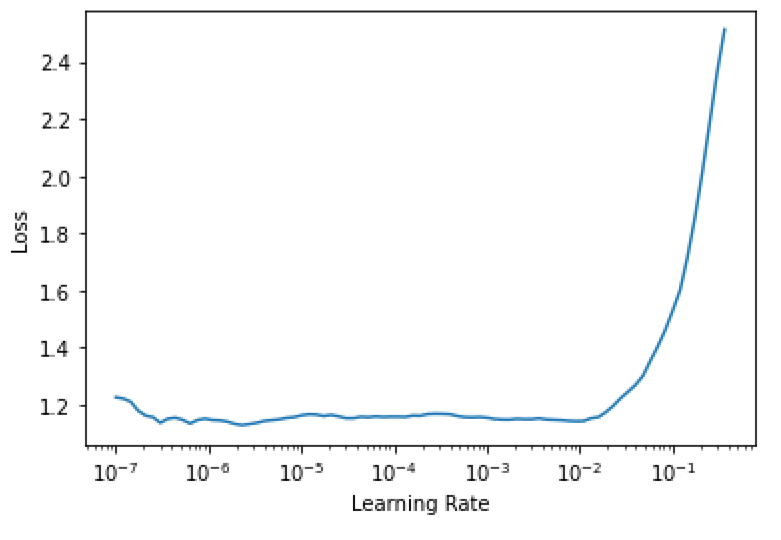
6.2 Images of size 224

In [55]:
```
# Learner with model resnet152
dls = get_dls(64, 224)
model = resnet152
loss_func=LabelSmoothingCrossEntropy()

learn = cnn_learner(dls, model, loss_func=loss_func, metrics=[accuracy])
learn = learn.load('petbreeds_6')
```

Freeze all layers but the last (new) one

In [56]:
```
# Learning rate
learn.freeze()
learn.lr_find()
```

Out[56]: `SuggestedLRs(lr_min=2.2908675418875645e-07, lr_steep=1.5848931980144698e-06)`



As only the last layer is unfrozen, **let's choose the learning rate 10 times less than the one of the loss minimum as lr_max (1e-3)**.

In [58]:
```
# Train the model with lr_max and the fit_one_cycle() function on 1 epoch
lr_max = 1e-3
learn.fit_one_cycle(1, lr_max=lr_max)
```

epoch	train_loss	valid_loss	accuracy	time
0	1.070695	0.979857	0.931664	00:43

In [59]:
```
# Save the model
learn.save('petbreeds_7')
```

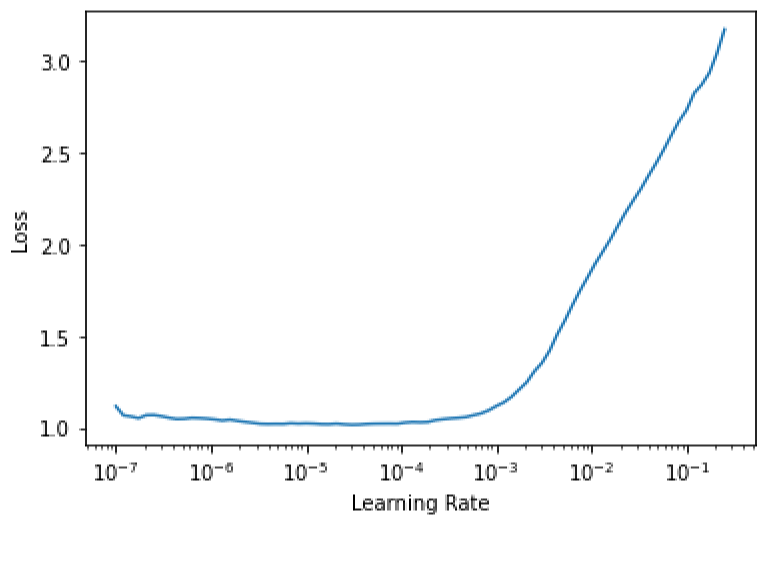
Out[59]: `Path('models/petbreeds_7.pth')`

Unfreeze all layers and Discriminative Learning Rates

In [60]:
```
# Load model, unfreeze layers and check it
learn = learn.load('petbreeds_7')
learn.unfreeze()
```

In [61]:
```
# Learning rate
learn.lr_find()
```

Out[61]: `SuggestedLRs(lr_min=3.0199516913853586e-06, lr_steep=1.5848931980144698e-06)`



As we unfroze all layers of the model, **let's choose the learning rate of the loss minimum as lr_max (2e-5)**.

In [62]:
```
# Train the model with lr_max and the fit_one_cycle() function on 1 epoch
lr_max = 2e-5
lr_min = lr_max / 100
learn.fit_one_cycle(10, lr_max=slice(lr_min,lr_max))
```

epoch	train_loss	valid_loss	accuracy	time
0	1.017913	0.970047	0.935047	00:56
1	1.026601	0.959922	0.934371	00:56
2	1.014295	0.955836	0.938430	00:56
3	0.989764	0.949453	0.939107	00:56
4	0.990386	0.946892	0.939784	00:56
5	0.976985	0.943799	0.939784	00:55
6	0.987667	0.940762	0.940460	00:56
7	0.974066	0.947678	0.940460	00:56
8	0.969518	0.941596	0.939107	00:55
9	0.960903	0.940221	0.941813	00:56

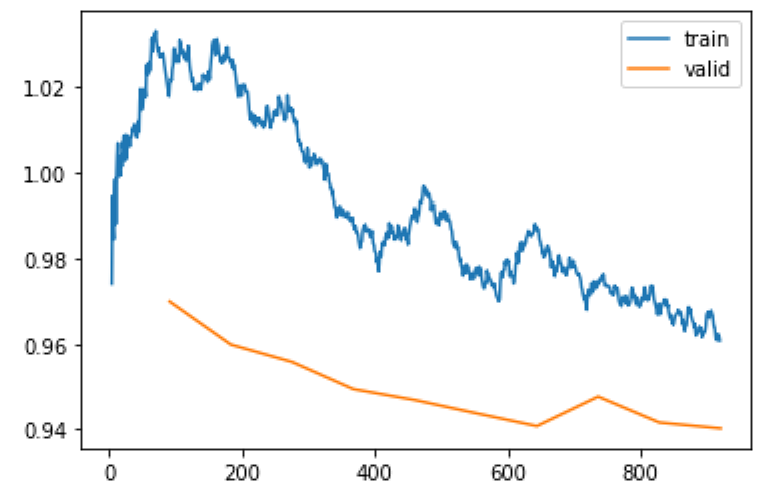
In [75]:
```
# Test Time Augmentation
# notebook: https://github.com/fastai/fastbook/blob/master/07_sizing_and_tta.ipynb
learn.epoch = 0
preds,targs = learn.tta()
accuracy(preds, targs).item()
```

Out[75]: 0.9492557644844055

Deeper model accuracy: **94.92%**. Within our dataset, the use of a Deeper model does not help (accuracy of our baseline model: 95.4%).

Let's test regularization techniques in the following paragraph.

In [63]:
```
# Display the training and validation loss
learn.recorder.plot_loss()
```



In [64]:
```
# Save the model
learn.save('petbreeds_8')
```

Out[64]: Path('models/petbreeds_8.pth')

7. Deeper model with regularisation

In [65]:
```
# Learner with model resnet152
dls = get_dls(64, 224)
model = resnet152
loss_func=LabelSmoothingCrossEntropy()

learn = cnn_learner(dls, model, loss_func=loss_func, metrics=[accuracy])
learn = learn.load('petbreeds_7')
```

Dropout

In [66]:
```
# The model has already a value of 50% of dropout
learn.model[1][7]
```

Out[66]: Dropout(p=0.5, inplace=False)

Weight Decay

In [67]:
```
# Load model, unfreeze layers and check it
learn.unfreeze()
learn.opt_func
```

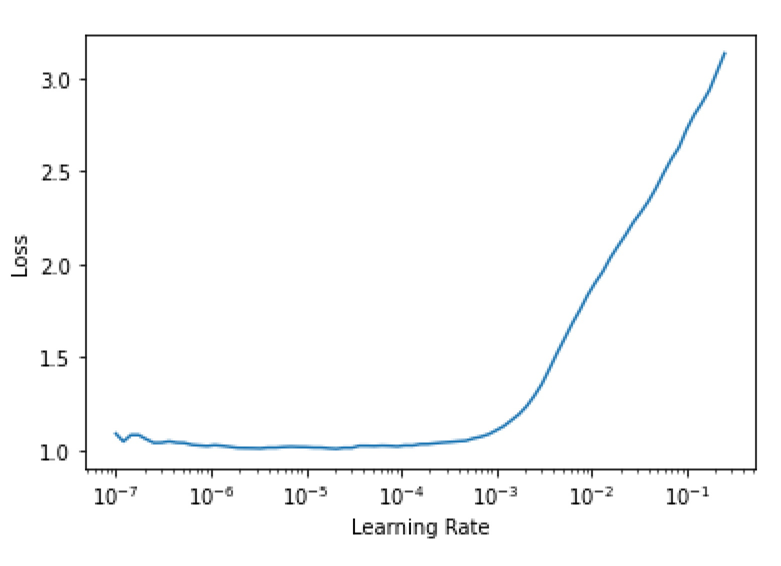
Out[67]: <function fastai.optimizer.Adam(params, lr, mom=0.9, sqr_mom=0.99, eps=1e-05, wd=0.01, decouple_wd=True)>

In [68]:
```
# let's increase weight decay from 0.01 to 0.1
wd = 0.1
learn.opt_func = partial(Adam, sqr_mom=0.99, eps=1e-05, wd=wd, decouple_wd=True)
learn.opt_func
```

Out[68]: functools.partial(<function Adam at 0x7f84dc655670>, sqr_mom=0.99, eps=1e-05, wd=0.1, decouple_wd=True)

In [69]:
```
# Learning rate
learn.lr_find()
```

Out[69]: SuggestedLRs(lr_min=2.0892961401841602e-06, lr_steep=1.5848931980144698e-06)



As we unfroze all layers of the model, **let's choose the learning rate of the loss minimum as lr_max (2e-5)**.

In [70]:
```
# Train the model with lr_max and the fit_one_cycle() function on 1 epoch
lr_max = 2e-5
lr_min = lr_max / 100
learn.fit_one_cycle(10, lr_max=slice(lr_min,lr_max))
```

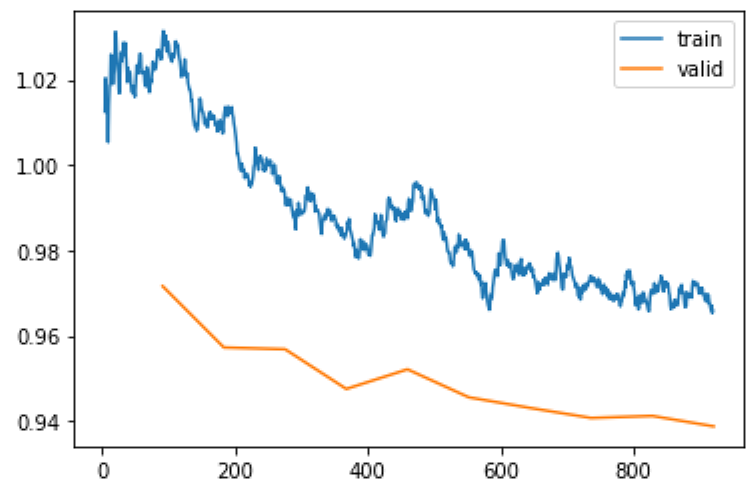
epoch	train_loss	valid_loss	accuracy	time
0	1.027706	0.971606	0.931664	00:56
1	1.007818	0.957255	0.935724	00:55
2	0.993733	0.956846	0.937754	00:56
3	0.983502	0.947544	0.941813	00:56
4	0.989188	0.952140	0.937077	00:56
5	0.981377	0.945588	0.937754	00:56
6	0.976960	0.943102	0.937077	00:56
7	0.974034	0.940747	0.935724	00:56
8	0.970089	0.941225	0.937077	00:56
9	0.965893	0.938787	0.939784	00:56

In [74]:
```
# Test Time Augmentation
# notebook: https://github.com/fastai/fastbook/blob/master/07_sizing_and_tta.ipynb
learn.epoch = 0
preds,targs = learn.tta()
accuracy(preds, targs).item()
```

Out[74]: 0.9465494155883789

The accuracy did not improve. **The thing to do to improve it is certainly to get more training data ... as always with Deep Learning models!**

In [71]:
```
# Display the training and validation loss
learn.recorder.plot_loss()
```



In [72]:
```
# Save the model
learn.save('petbreeds_9')
```

Out[72]:
```
Path('models/petbreeds_9.pth')
```

8. Export best model

According to the accuracy, **we keep our baseline model as the best one with a validation accuracy of 95.4%**.

In [95]:
```
# Export best model
learn = learn.load('petbreeds_4')
learn.export()
```

9. Turning your model into a Web App

Fonte: notebook [02_production.ipynb]

In [79]:
```
# Get model for inference
learn_inf = load_learner('export.pkl')
```

Creating a notebook App from the model

In [80]:
```
# Button to upload image
btn_upload = widgets.FileUpload()

# Button to classify
btn_run = widgets.Button(description='Classify')

# Display a thumb of the image
out_pl = widgets.Output()
out_pl.clear_output()

# Calculation and display of the category prediction
lbl_pred = widgets.Label()
def on_click_classify(change):
    img = PILImage.create(btn_upload.data[-1])
    out_pl.clear_output()
    with out_pl: display(img.to_thumb(128,128))
    pred,pred_idx,probs = learn_inf.predict(img)
    lbl_pred.value = f'Prediction: {pred}; Probability: {probs[pred_idx]:.04f}'
btn_run.on_click(on_click_classify)
```

In [81]:
```
# Run app
VBox([widgets.Label('Select your animal!'),
      btn_upload, btn_run, out_pl, lbl_pred])
```

Turning your notebook into a (real) Web App

fastai explains in the notebook [02_production.ipynb] how to create a Web App using your `export.pkl` file on a free Web service like [Binder] + [Voilà]. You can as well read and apply this [Guide on how to duplicate the fastai bear_voila app on Binder] (if you need help about git, read this [git - the simple guide]).

This is a great way for your first *well-chosen users* (parents or friends for example, or even a first client) to use your Web App, which will give you initial feedback and new data, which in turn will allow you to improve both your model and your Web App interface (this is *The Virtuous Cycle of AI* of Andrew Ng explained in the [AI Transformation Playbook]).

Of course, this free service is not sufficient for a professional Web App that you are going to develop alongside this first version.

To do that, check the following paragraph for tips and have fun!

Version 1 of our "Dog & Cat Breeds Recognizer for Veterinary Clinics"

- Github: https://github.com/piegu/petsbreeds_voila
- Web App: https://mybinder.org/v2/gh/piegu/petsbreeds_voila/master?urlpath=%2Fvoila%2Frender%2Fpets_classifier.ipynb

Dog & Cat Breeds Recognizer for Veterinary Clinics

Select your pets!

Upload (1)

Prediction: american_bulldog; Probability: 0.9039

10. Turning your Web App into a startup product

This paragraph is written in the post [Product based on a Deep Learning model (by fastai v2)].

End of the notebook but about our startup product: to be continued...

In [ ]: