Colombian Celebrity Classifier

You could define and build a CNN from scratch using Keras. At the other end of the spectrum, you could use a service like AWS Rekogni works entirely behind the scenes and requires almost no input from you. In this exercise, we're going to use an intermediate tool: `fast.` library has vast functionality and acceptable documentation. To learn more about how to use the library for a variety of deep learning ta recommend their free course Practical Deep Learning for Coders.

This exercise will run very slowly on most laptops, so we're going to run it using the free resources of Google Colab. It would also work o but we found this setup to be faster and easier. We have designed this case so that you can either run the optimization on Colab or simp trained versions of the CNN to see how they perform.

Notebook setup for Colab

If you have this notebook in your Google Drive, you can open it with Google Colab. Run the following cells to mount your Drive and make accessible from within the notebook. You will be prompted to open an URL and retrieve a code, which you'll paste in the field below.

```
# This cell will prompt you to connect this notebook with your google account.

from google.colab import drive
drive.mount('/content/gdrive', force_remount=True)
root_dir = "/content/gdrive/My Drive/"
base_dir = root_dir + 'Colab Notebooks/case_18.2'
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6qk8qdgf4n4g

Enter your authorization code:
··········
Mounted at /content/gdrive
```

```
# Set up Colab to have the ideal settings for fast.ai

!curl -s https://course.fast.ai/setup/colab | bash
```

```
Updating fastai...
Done.
```

Go to `Runtime > Change Runtime Type` and make sure that you have enabled GPU acceleration for this notebook.

Setup for Jupyter Notebooks

Run this cell if operating locally or on AWS as a Jupyter notebook.

```
import os
base_dir = os.getcwd()
```

Setup for everyone

```
from fastai.vision import *
np.random.seed(42)
```

```
# Define folders for photos and models
data_path = Path(base_dir + '/photos')
model_path = Path(base_dir + '/models')

# Print for confirmation
data_path
```

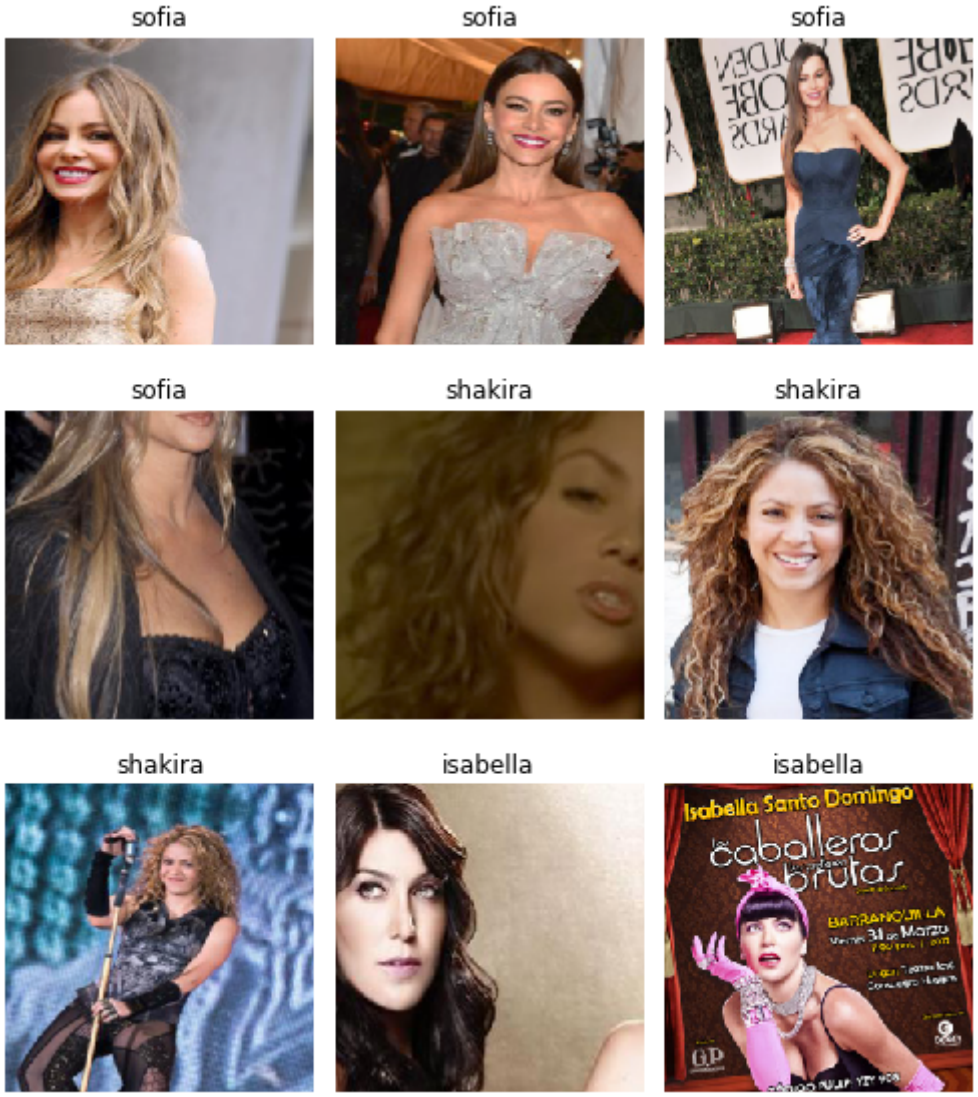
```
PosixPath('/content/gdrive/My Drive/Colab Notebooks/case_18.2/photos')
```

Data prep

In fastai we don't feed our data directly to the model. Instead, we package it into a ImageDataBunch object that will contain the data, kn labels for classification, and know which data is for training/testing/validation. There are many ways to populate a DataBunch object.

The following syntax will populate the ImageDataBunch from our folder structure (docs), apply standard ImageNet image augmentation dataset (docs), resize the modified images to a standard size of 224 pixels, and normalize them using the standard ImageNet statistics

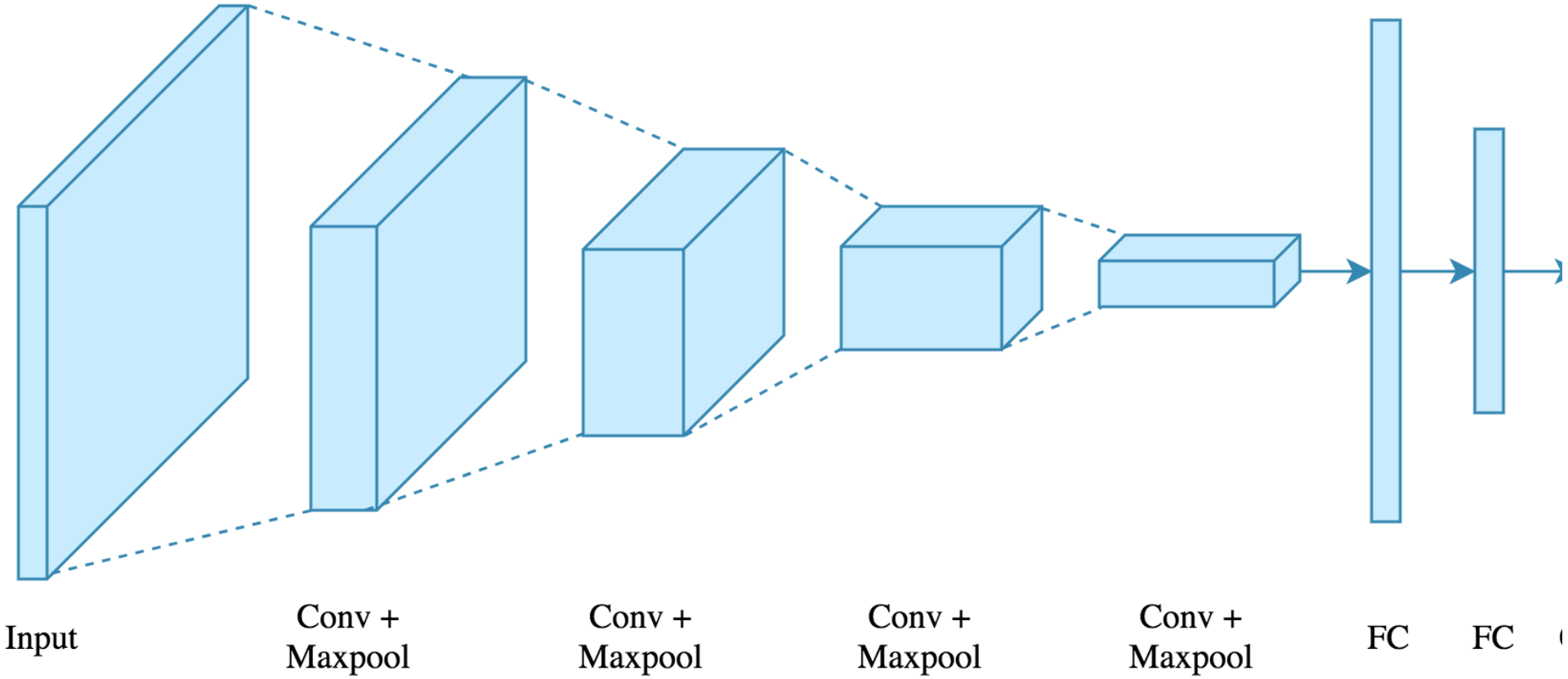
```
# Create a data bunch from the folder of images.
data = ImageDataBunch.from_folder(\
        path=data_path,              # Use the path defined earlier
        ds_tfms=get_transforms(),    # Use standard ImageNet data augmentation
        size=224)\
        .normalize(imagenet_stats)   # Use standard ImageNet normalization

# Show a sample of the pictures
data.show_batch(rows=3, figsize=(7,8))
```



Notice how our images are now all the same size, and labeled according to our folders. Image augmentation involves cropping, and may occasionally cut out important parts of the image. You can also sometimes see mirror padding added at the edges of the images.

Import a pre-trained model

We'll go more into the structure of CNNs later, but for now know that CNNs consist of a stack of layers that detect increasingly complica patterns, followed at the end by a handful of fully-connected layers that use those features to produce a final decision.



Source: Applied Deep Learning - Part 4: Convolutional Neural Networks

Today we'll use ResNet34, a 34-layer CNN architecture that was the clear state of the art in May of 2016. Training these networks from s takes a lot of images and a lot of time, but luckily there's no need to do that. This pre-trained network has already learned to see all sorts basic and complex patterns. We will re-train only the last layers, the ones that actually combined earlier patterns into end results.

We import the architecture of ResNet34 into a cnn_learner. Fastai keeps all the pre-trained convolutional layers from ResNet34, and ther few more layers at the end (one 2D pooling layer, one flattening layer, and blocks of fully-connected layers with batch normalization, dro

and ReLu activation). All the pre-trained layers are frozen at the start, so that their weights won't update during training. We'll train the ne layers first, since they have been initialized with random weights.

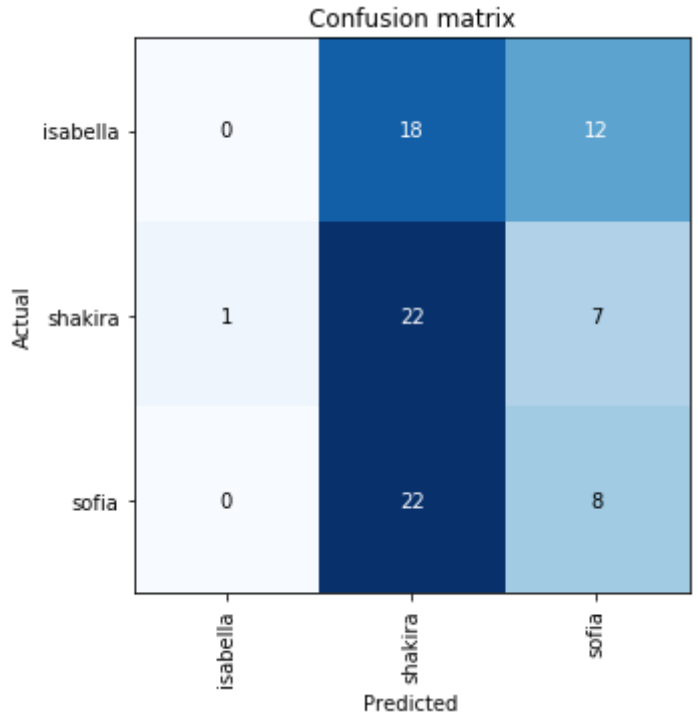
```
# Define a new learner, based on the pre-trained ResNet34 CNN

learn = cnn_learner(data=data,                    # Our ImageDataBunch from above
                    pretrained=True,
                    base_arch = models.resnet34,  # Base architecture
                    metrics=error_rate);
```

```
Downloading: "https://download.pytorch.org/models/resnet34-333f7ec4.pth" to /root/.cache/torch/checkpoints/res
100%|██████████| 83.3M/83.3M [00:01<00:00, 54.6MB/s]
```

In order to investigate how well our model is doing, we will create a ClassificationInterpretation object from the learner. First we'll see a confusion matrix, and then we'll use plot_top_losses to see which pictures the model classified most incorrectly.

```
# Print out the current state of the model
interp = ClassificationInterpretation.from_learner(learn)
print('Confusion Matrix:')
print(interp.confusion_matrix())
interp.plot_confusion_matrix(figsize=(5,5))
# interp.plot_top_losses(9, figsize=(15,11))
```

```
Confusion Matrix:
[[ 0 18 12]
 [ 1 22  7]
 [ 0 22  8]]
```



For a working model, the confusion matrix would have dark squares along the diagonal and lighter squares elsewhere. Here we can see many images a totally untrained model gets right by sheer luck.

Train the new layers

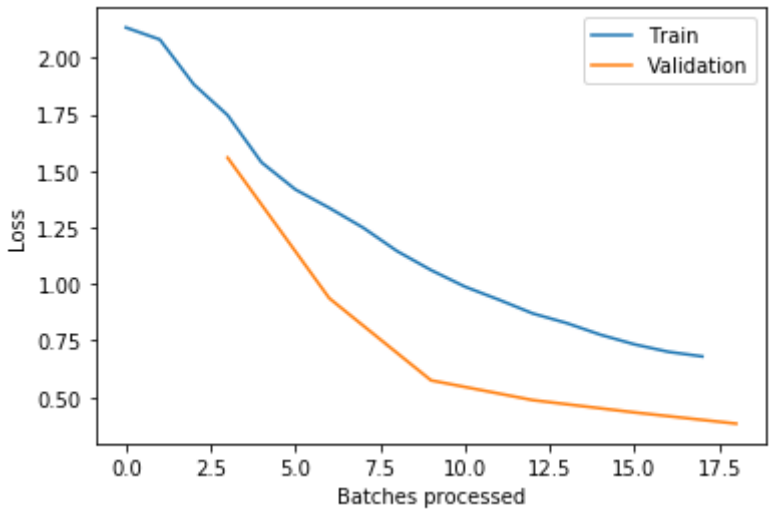
We train using the 1cycle policy, a method that varies the learning rate so as to achieve super fast convergence. We train with all the convolutional layers still frozen, updating weights only in the new layers. Each epoch means that the learner trained on all the data, and its weights accordingly.

```
learn.fit_one_cycle(6)
```

epoch	train_loss	valid_loss	error_rate	time
0	1.882097	1.557969	0.533333	00:57
1	1.417378	0.936620	0.333333	00:06
2	1.144963	0.573917	0.166667	00:04
3	0.930420	0.486677	0.144444	00:04
4	0.775473	0.432344	0.122222	00:04
5	0.679738	0.382795	0.122222	00:04

Even just training the last few layers, we can bring the classification error rate down from 53% to 12%.

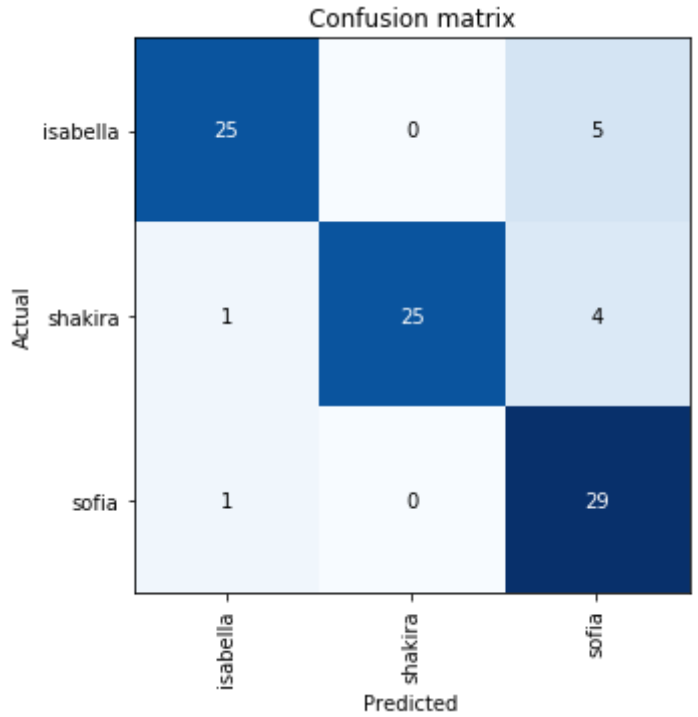
```
learn.recorder.plot_losses()
```




```
# Print out the current state of the model
interp = ClassificationInterpretation.from_learner(learn)
print('Confusion Matrix:')
print(interp.confusion_matrix())
interp.plot_confusion_matrix(figsize=(5,5))
```

```
interp.plot_top_losses(9, figsize=(15,11))
```

```
Confusion Matrix:
[[25  0  5]
 [ 1 25  4]
 [ 1  0 29]]
```

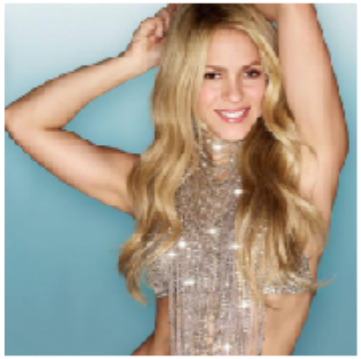


Prediction/Actual/Loss/Probability

isabella/shakira / 6.98 / 0.00

sofia/isabella / 4.34 / 0.01

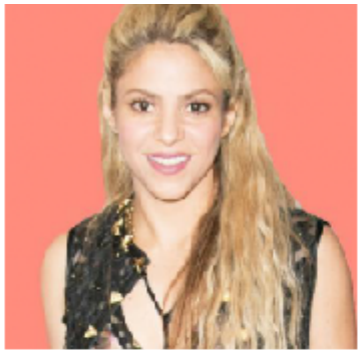
sofia/shakira / 4.25 / 0.01



sofia/isabella / 4.04 / 0.02

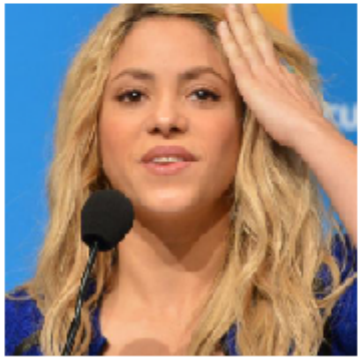
sofia/shakira / 3.06 / 0.05

sofia/isabella / 2.40 / 0.09



sofia/isabella / 1.66 / 0.19

sofia/shakira / 1.33 / 0.26



isabella/sofia / 1.23 / 0.29

It's useful to divide your overall training into multiple steps with intermediate saves, so that you can go back to an earlier version if you o your model or otherwise messed up.

Save the learner -- CAUTION!

The save learner cell below overrides any existing saved file with the same name. We've provided pre-trained snapshots of the learner, w you may load below. Don't run the `save` cell unless you want to override what we provided.

```
# # Save the trained model
# learn.save(model_path/'stage-1')
```

```
learn.load(model_path/'stage-1');
```

Train the whole CNN

Now that we're done with all these, we can finally unfreeze the whole network and allow for further convergence.

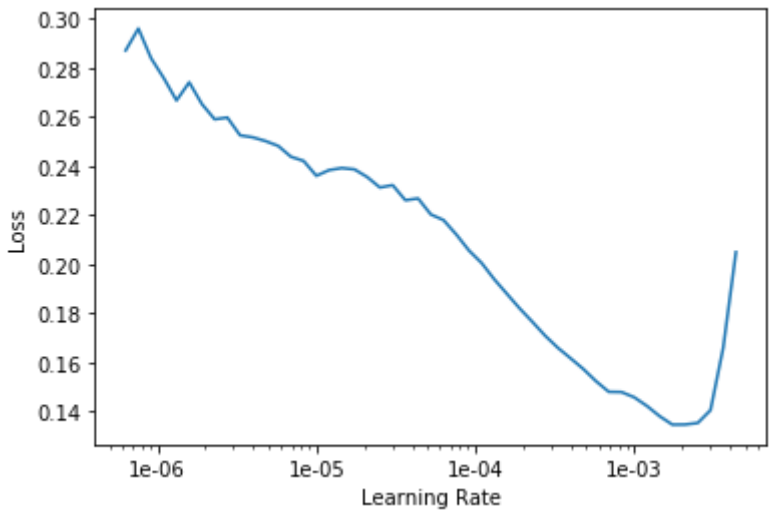
```
# Unfreeze the whole CNN for further training
learn.unfreeze()
```

For training the whole unfrozen model, at this point we're going to use a built-in fastai tool for finding the optimal learning rate. This will learning progress optimally.

```
# Find the optimal learning rate
learn.lr_find()
```

```
LR Finder is complete, type {learner_name}.recorder.plot() to see the graph.
```

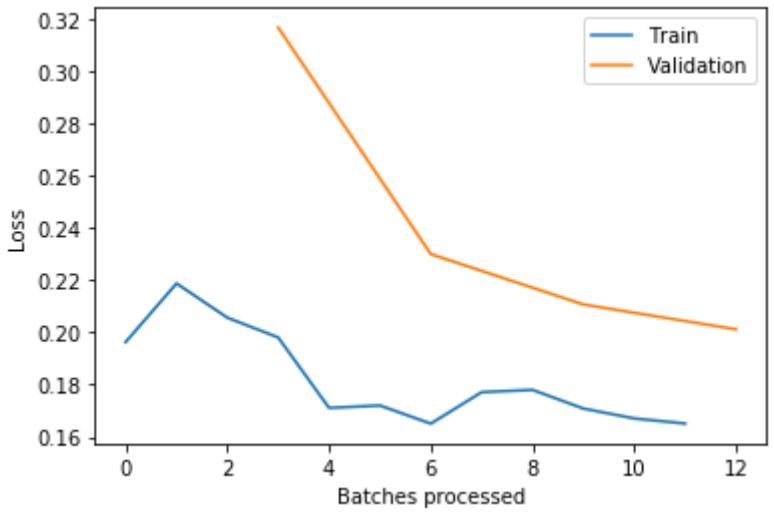
```
# Plot the optimal learning rate
learn.recorder.plot()
```




```
# I choose a range that ends about one order of magnitude before the bottom of the
# valley, and starts one order of magnitude before that.
learn.fit_one_cycle(4, max_lr=slice(2e-5,2e-4))
```

epoch	train_loss	valid_loss	error_rate	time
0	0.205653	0.316800	0.100000	00:04
1	0.171999	0.230005	0.077778	00:04
2	0.177997	0.210711	0.088889	00:04
3	0.165102	0.201188	0.077778	00:04

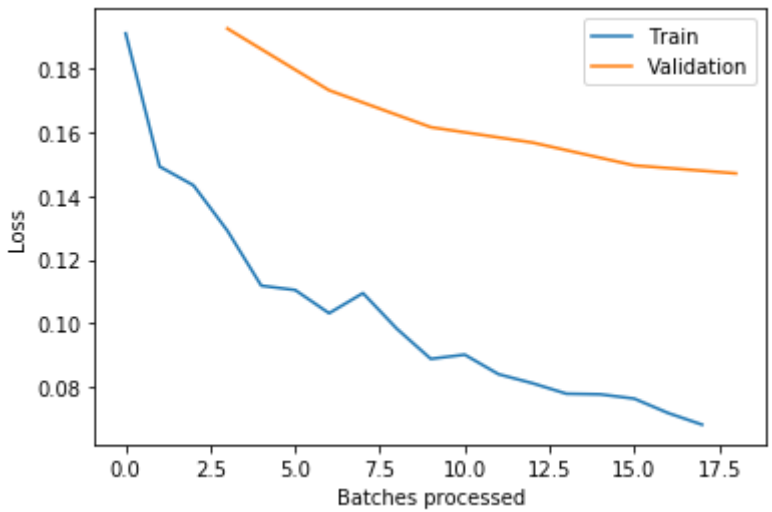
```
learn.recorder.plot_losses()
```




```
# Let's train for a few more epochs
learn.fit_one_cycle(6, max_lr=slice(2e-5,2e-4))
```

epoch	train_loss	valid_loss	error_rate	time
0	0.143370	0.192596	0.088889	00:04
1	0.110487	0.173213	0.088889	00:04
2	0.098306	0.161616	0.066667	00:04
3	0.084039	0.156793	0.055556	00:04
4	0.077723	0.149609	0.055556	00:04
5	0.068209	0.147112	0.055556	00:04

```
learn.recorder.plot_losses()
```



CAUTION!

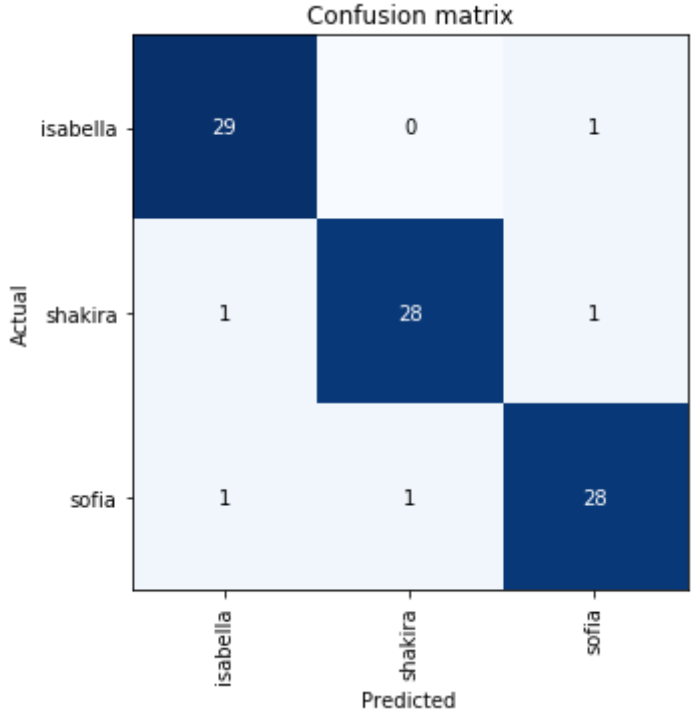
The save learner cell below overrides any existing saved file with the same name. We've provided pre-trained snapshots of the learner, w
you may load below. Don't run the `save` cell unless you want to override what we provided.

```
# # Save the current state of the learner
# learn.save(model_path/'stage-2')
```

```
learn.load(model_path/'stage-2');
```

```
# Print out the current state of the model
interp = ClassificationInterpretation.from_learner(learn)
print('Confusion Matrix:')
print(interp.confusion_matrix())
interp.plot_confusion_matrix(figsize=(5,5))
interp.plot_top_losses(9, figsize=(15,11))
```

```
[ 1 28  1]
[ 1  1 28]]
```



Prediction/Actual/Loss/Probability

isabella/shakira / 4.18 / 0.02

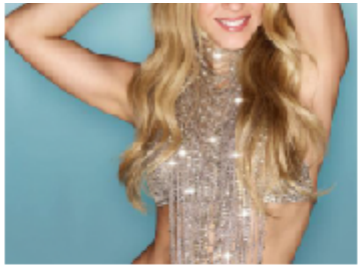
sofia/isabella / 3.01 / 0.05

isabella/sofia / 1.38 / 0.25

shakira/sofia / 1.01 / 0.37

sofia/shakira / 0.95 / 0.39

isabella/isabella / 0.55 / 0.57

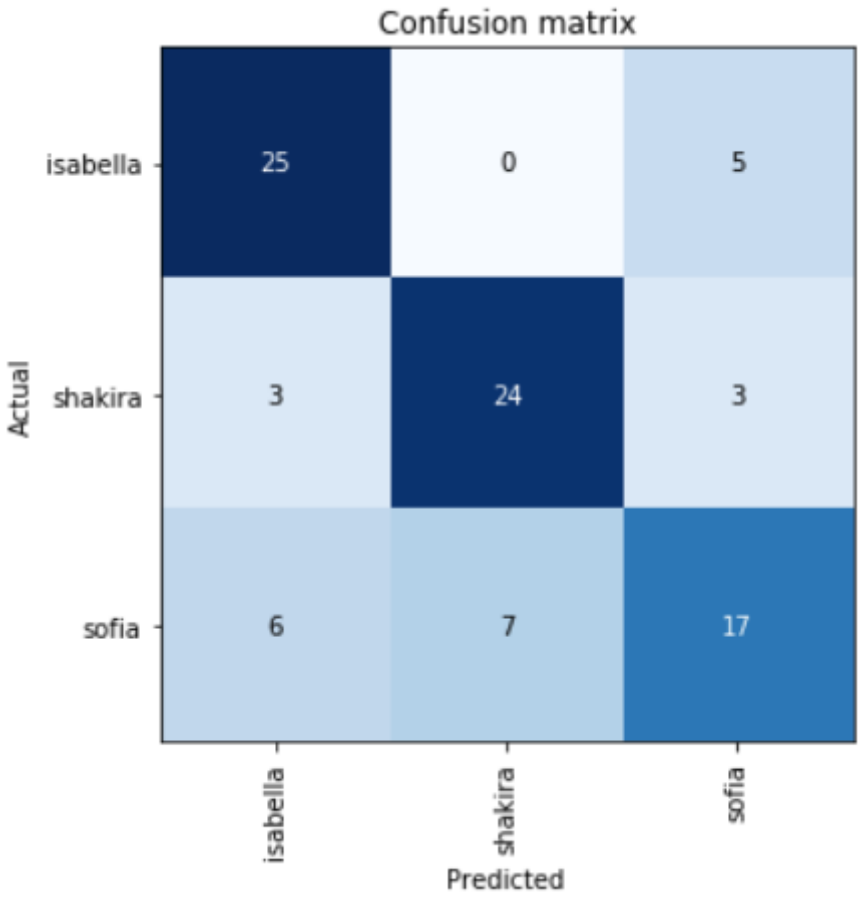

isabella/isabella / 0.48 / 0.62

isabella/isabella / 0.31 / 0.73

shakira/shakira / 0.30 / 0.74

Way fewer training pictures

Just to show how much juice you can get out of pre-trained networks, I trained the same one on just 10 pictures of each celebrity. The re are less good, but still pretty impressive.


Confusion matrix
isabella
shakira
sofia
Actual
25
0
5
3
24
3
6
7
17
isabella
shakira
sofia
Predicted