

# Fast ai lesson 1 : notes

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## For viewing various documentation of the functions

```
!pip install nbdev
From nbdev.showdoc import *

# for viewing the documentation
Help(function/ method)
```

## For loading the fast ai into colab notebook

```
!pip install fastai --upgrade
from fastai.vision.all import *
```

## Getting file names from file\_path

```
Path_img = get_file_names(path)
```

## Getting the labels from filenames

```
ImageDataLoaders.from_path_re : get's the labels from the file names
Takes Parameters as path, filenames , pattern ( re )
Valid_pct ( valid percentage )
Seed = for controlling randomness
Bs = batch_size
Shuffle = for shuffling the data
Device += "gpu or cpu "
The compulsory parameters are path, filenames and patterns
```

## Creating the simple cnn model with fast ai

```
Learn = cnn_learner(dls, resnet34, metrics = error_rate).to_fp_16
To_fp_sixteen : for mixed precision we are specifying the model to use floatpoint 16
predictions
So that the model will load faster with GPU access
Dls = data loaders
Resnet34 : model architecture
Metrics = error_rate, accuracy
Normalization and pretrained = normalization does the normalization of the data
Pretrained is the model which is already built and the data is loaded and normlized with
the help of the data which pretrained model really wants
```

## Viewing model layers ;

```
Model_name.model
Returns the total architecture of the model
```

## Fitting the model :

```
Model_name.fit_one_cycle(no of epochs )
Fit_one_cycles decides the learning rate from cosine annealing form
```

## Saving the model :

```
Model_name.save('path')
Saves the model in .pth format
Another way

Save_model(file,model,opt,with_opt,pickle_protocol)
File : name of the file which you want to save your model in
Opt :
Pickle_protocol :for saving in pkl format
```

**Laoding the model :**

Load\_model(file\_path , model , opt , with\_opt, device = None, strict = True)  
 Device : if passed nothing then loads of CPU otherwise gpu can be passesd

Strict : true : all file must exactly contain certain weights for every parameter key in model  
 If it's false : only key that are in the saved model are loaded in the model

**To evaluate and see when the model is performing most of wrong predictions :**

Interp = ClassificationInterpretation.from\_learner(learn)  
 From\_learner is to pass the model  
 Learn : the model which you want to pass

Getting indexes and the losses of the model  
 Loss, indexes = interp.top\_losses()  
 # the top losses model did

**For plotting where the model is getting wrong mostly**

Interp.plot\_top\_losses(9, figsize=(15,11))  
 9 : no of figures which we want to display  
 Figsize : the size of the figure

**For plotting the confusion matrix :**

Interp.plot\_confusion\_matrix(figsize= (12,12), dpi= 60)  
 It just plots the confusion matrix just like scikitlearn's confusion matrix function

**For viewing the most wrong predictions :**

Interp.most\_confused(min\_val= 2 )  
 Min\_val paramter : it to show the confusion between the number fo values it's like the model is confused between those 2 classes

**Fine tuning model procedures :**

For unfreezing the model :  
 Learn.unfreeze()  
 Learn – model\_name which is already pretrained  
 Unfreezing the whole model layers ( setting it for fine tuning )

For fitting the unfreezed model  
 Learn.fit\_one\_cycle(no\_of\_epochs)  
 Train whole model again

**For loading the model with weights we can do like :**

Learn.load(path)  
 It loads the model in learn  
 It takes parameter as device so we can specify device which we want to load it on

**For finding the learning rate of the model :**

Learn.lr\_find()  
 This will give us the valley or suggesting learning rates on which we can see the loss is kind of decreasing

**For fitting in between certain learning rate ranges ;**

Learn.fit\_one\_cycle(no\_of\_epochs lr\_max = slice(1e-6,1e-4))  
 Slice object : provides the iterable object as the output of the we can slice string with this iterable object  
 So here the slice is giving out the object which will cut the learning rate from 1e-6 to 1e-4

**Training the resnet model :**

The steps are same

1. To define the data loaders

- i. `ImageDataLoaders.from_path_re(image_paths, file_names, pattern(re), transformations as batch_tfms = [*aug_transforms(size = 299, max_warp = 0)])`
- ii. `Normalize.from_stats(*imagenet_stats))`
2. Defining the model `learn = cnn_learner(dls, reset, metcrics = error_rate) .to_fp16()`
3. `Learn.lr_find()`
4. `Learn.fit_one_cycle(10)`
5. `Learn.save(filepath)` for saving the model
6. Then unfreezing the layers
7. Fitting for some more epochs
8. If doesn't help then we can again roll back to the previous model  
`learn.load(filePath);`
9. `Interp = ClassificationInterpretation.from_learner(learn)`
10. `Interp.most_confused(min_val = 2)`
11. `Interp.plot_confusion_matrix(figsize = (, ), dpi = 60)`

Experimenting with the other data formats same way we can import data from folders	<code>ImageDataLoaders.from_folder(path, batch_tfms, size, bs)</code>
Experimenting and we want to load the data from csv files	<code>ImageDataLoaders.from_csv(path), batch_tfms, size)</code>
From dataframe	<code>ImageDataLoaders.from_df(df, path, batch_tfms = tfms, size = 24)</code>
From path functions	<code>ImageDataLoaders.from_path_func(path, fn_paths, tfms = tfms, size, label_func = lambda x : '3' if '/3/' in str(x) else '7')</code>
From lists	<code>ImageDataLoaders.from_lists(path, fn_paths, labels, batch_tfms)</code>