Multi-label Classification

September 7, 2018

0.1 Multi-label Classification (Planet Dataset)

```
In [10]: %reload_ext autoreload
         %autoreload 2
         %matplotlib inline
```

```
In [11]: # import convolution tools
         from fastai.conv_learner import *
         # import pandas for csv visualization
         import pandas as pd
```

```
In [12]: # set our path to the planet data set
         PATH = 'data/planet/'
```

```
In [13]: # list our sub directories
         !ls {PATH}
```

```
models        test-jpg  tmp  train-jpg  train_v2.csv
```

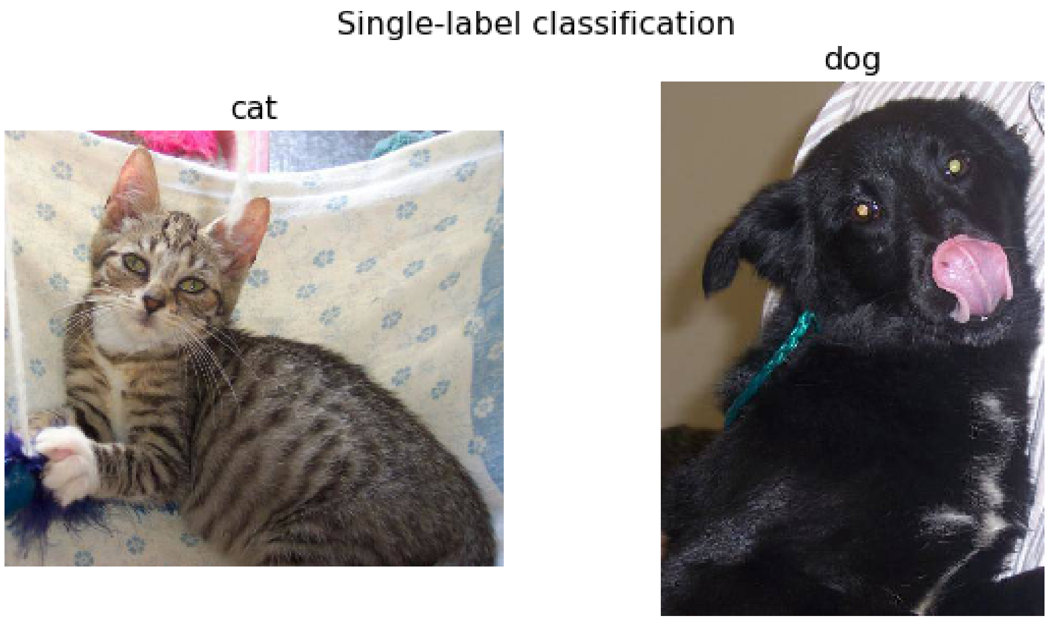
```
In [14]: df = pd.read_csv("data/planet/train_v2.csv")
         print(df.head())
```

```
  image_name                                       tags
0    train_0                               haze primary
1    train_1             agriculture clear primary water
2    train_2                              clear primary
3    train_3                              clear primary
4    train_4  agriculture clear habitation primary road
```

```
In [15]: # plotting library from fastai
         from fastai.plots import *
```

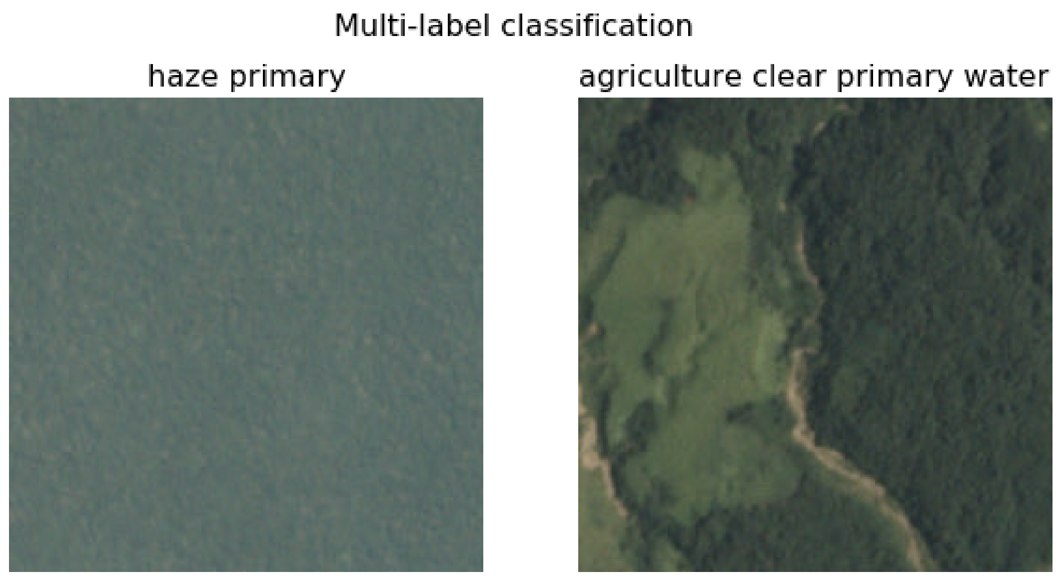
```
In [16]: # gets the first picture in a path
         def get_1st(path):
             # glob lets you return potentially empty file locs without throwing an error
             # this just says give me the first of anything.anything in PATH
             return glob(f'{path}/*.*')[0]
```

```
In [17]: # go to the valid dogs and cats this is to showcase the difference between single and
         # classification
         dc_path = "data/dogscats/valid/"

         # creates a list of things we will later plot
         list_paths = [get_1st(f"{dc_path}cats"), get_1st(f"{dc_path}dogs")]

         # plots the list above with sub and main titles
         plots_from_files(list_paths, titles=["cat", "dog"], maintitle="Single-label classifica
```



Remember to use A sigmoid instead of Softmax for multilabel classification

```
In [18]: # this does the same as above
         list_paths = [f"{PATH}train-jpg/train_0.jpg", f"{PATH}train-jpg/train_1.jpg"]

         titles=["haze primary", "agriculture clear primary water"]

         plots_from_files(list_paths, titles=titles, maintitle="Multi-label classification")
```




```
In [19]: from fastai.imports import *
         from fastai.transforms import *
         from fastai.dataset import *
         from sklearn.metrics import fbeta_score
         import warnings

         # this a predifined metric by Jeremy for checking error using beta score
         def f2(preds, targs, start=0.17, end=0.24, step=0.01):
             with warnings.catch_warnings():
                 warnings.simplefilter("ignore")
                 return max([fbeta_score(targs, (preds>th), 2, average='samples')
                             for th in np.arange(start,end,step)])
```

```
In [20]: # f2 is like a confusion matrix
         # there are lots of different ways you can turn that confusion matrix into a score
         # f2 is f beta with beta=2, the kaggle competition wanted this
         #
         metrics=[f2]
         f_model = resnet34
```

```
In [21]: # The csv file containing our labels
         label_csv = f'{PATH}train_v2.csv'

         #o = open(label_csv)
         #li = list(o)
         #n = len(li)-1
```

```
n = len(list(open(label_csv)))-1

val_idxs = get_cv_idxs(n)
```

In [22]:
```
# takes in the size of the image and returns a ImageClassifierData object
def get_data(sz):
    # apply transforms
    tfms = tfms_from_model(f_model, sz, aug_tfms=transforms_top_down, max_zoom=1.05)
    return ImageClassifierData.from_csv(PATH, 'train-jpg', label_csv, tfms=tfms,
                    suffix='.jpg', val_idxs=val_idxs, test_name='test-jpg')
```

In [23]:
```
# the images are 256 x 256
data = get_data(256)
```

In [24]:
```
# ds is data set
# this will give you a single image back

# dl is data loader
# a data loader gives you back a minibatch
# specifically a transformed minibatch
# also you can only get the next minibatch so a good practice
# would be to loop through and grab a minibatch at a time

# for more info google pytorch data set and data loader


x,y = next(iter(data.val_dl))
```

In [25]:
```
# batch size by default is 64 in the function
# so its 64 by 17 possible classes or labels
# this also seems to be transposed so its index x class
y
```

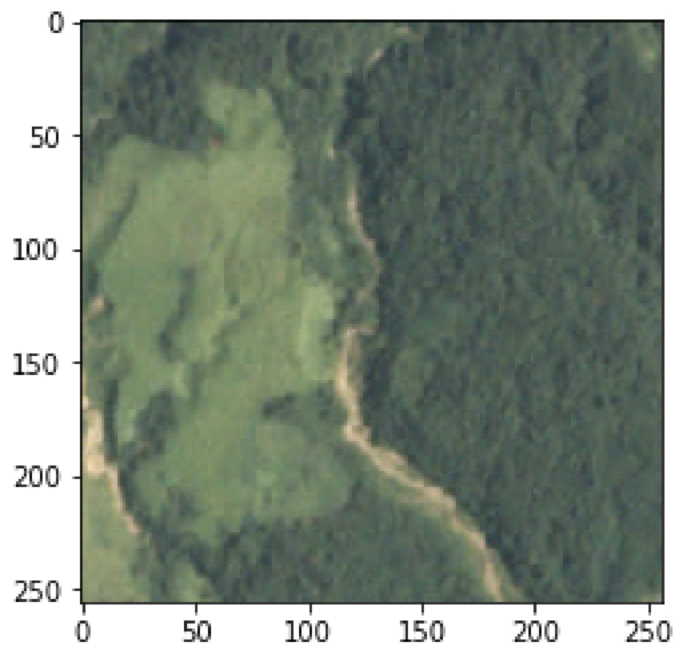
Out[25]:
```

    1     0     0  ...      0     0     1
    1     0     0  ...      0     0     0
    0     0     0  ...      0     0     0
       ...                     ...
    0     0     0  ...      0     0     1
    1     0     0  ...      0     0     0
    1     0     0  ...      0     0     0
[torch.cuda.FloatTensor of size 64x17 (GPU 0)]
```

In [26]:
```
# zip will combine lists
# so you will get the 0th thing from the first list and the 0th thing from the second
list(zip(data.classes, y[0]))
```

Out[26]:
```
[('agriculture', 1.0),
 ('artisinal_mine', 0.0),
```

```
('bare_ground', 0.0),
('blooming', 0.0),
('blow_down', 0.0),
('clear', 1.0),
('cloudy', 0.0),
('conventional_mine', 0.0),
('cultivation', 0.0),
('habitation', 0.0),
('haze', 0.0),
('partly_cloudy', 0.0),
('primary', 1.0),
('road', 0.0),
('selective_logging', 0.0),
('slash_burn', 0.0),
('water', 1.0)]
```

In [27]:
```
plt.imshow(data.val_ds.denorm(to_np(x))[0]*1.4);
```



In [28]:
```
# we do this here since there is nothing like satellite images in the imagenet model
# we wouldn't do this with the cats and dogs because we would destroy the weights
sz=64
```

In [29]:
```
# create data object
data = get_data(sz)
```

In [30]:
```
# this speeds things up by saying
# I won't be needing anything bigger than sz*1.3
```

```
data = data.resize(int(sz*1.3), 'tmp')
```

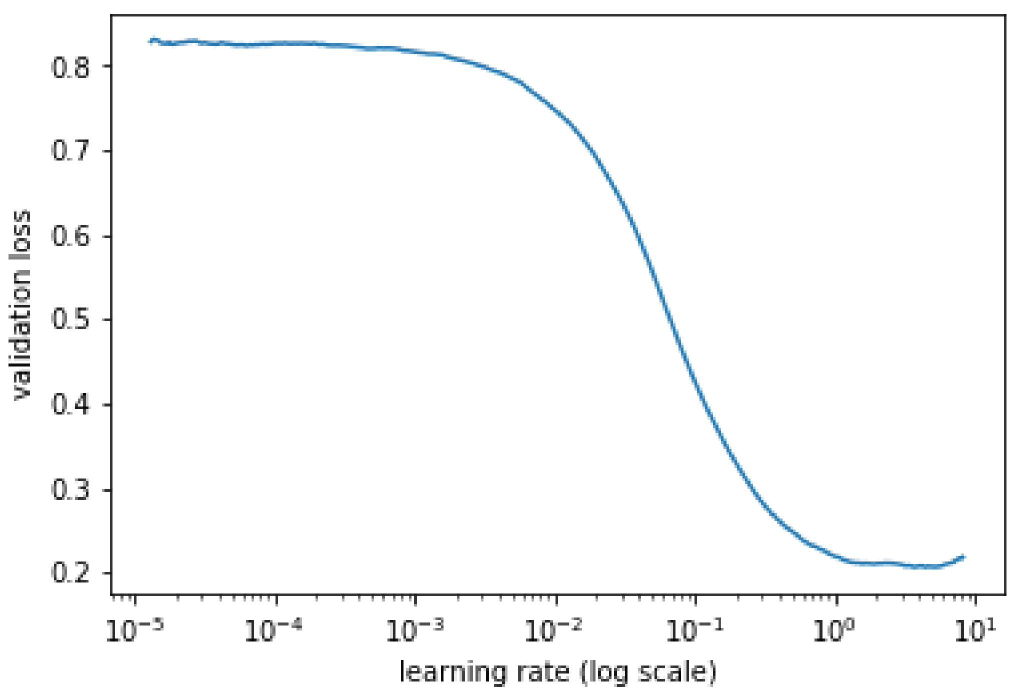
```
HBox(children=(IntProgress(value=0, max=6), HTML(value='')))
```

```
In [31]: learn = ConvLearner.pretrained(f_model, data, metrics=metrics)
```

```
In [32]: lrf=learn.lr_find()
         learn.sched.plot()
```

```
HBox(children=(IntProgress(value=0, description='Epoch', max=1), HTML(value='')))
```

```
epoch      trn_loss   val_loss   f2
    0      0.223709   0.269339   0.825095
```




```
In [33]: lr = 0.2
```

```
In [34]: learn.fit(lr, 3, cycle_len=1, cycle_mult=2)
```

```
HBox(children=(IntProgress(value=0, description='Epoch', max=7), HTML(value='')))


epoch      trn_loss   val_loss   f2
    0      0.147102   0.133033   0.883338
    1      0.141103   0.127185   0.889755
    2      0.139051   0.125667   0.892151
    3      0.137805   0.124761   0.892294
    4      0.136067   0.122831   0.89526
    5      0.132859   0.121276   0.896396
    6      0.131545   0.121369   0.895219
```

```
Out[34]: [array([0.12137]), 0.8952189648278935]
```

```
In [35]: # notice the learning rate is greater for all 3 layers compared to the cats and dogs
         # this is because imagenet was more suited for the cats and dogs model
         # satellite data is much different so we set a higher learning rate
         # at lower layers, but still less than our top layers

         # Also notice how we don't do this right away
         # this is because our layers would be random
         # we should train our layers first then unfreeze the imagenet layers
         # for retraining
         lrs = np.array([lr/9,lr/3,lr])
```

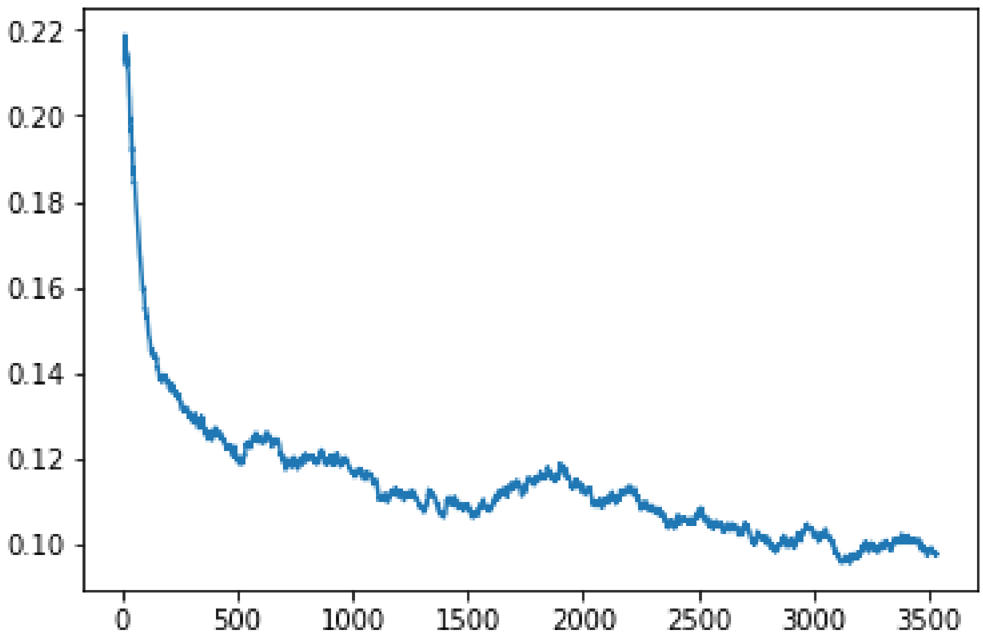
```
In [36]: learn.unfreeze()
         learn.fit(lrs, 3, cycle_len=1, cycle_mult=2)
```

```
HBox(children=(IntProgress(value=0, description='Epoch', max=7), HTML(value='')))


epoch      trn_loss   val_loss   f2
    0      0.120365   0.109936   0.907705
    1      0.116826   0.107446   0.907156
    2      0.107001   0.101385   0.915106
    3      0.112509   0.102195   0.913443
    4      0.105939   0.101563   0.915094
    5      0.102347   0.097551   0.917749
    6      0.097418   0.097372   0.918057
```

```
Out[36]: [array([0.09737]), 0.9180571787743648]
```

```
In [37]: learn.save(f'{sz}')
```

```
In [38]: learn.sched.plot_loss()
```



In [39]:
```
sz=128
```

In [40]:
```
learn.set_data(get_data(sz))
learn.freeze()
learn.fit(lr, 3, cycle_len=1, cycle_mult=2)
```

```
HBox(children=(IntProgress(value=0, description='Epoch', max=7), HTML(value='')))
```

epoch	trn_loss	val_loss	f2
0	0.09867	0.094844	0.91859
1	0.097065	0.093558	0.920441
2	0.095911	0.092839	0.920789
3	0.09785	0.092624	0.921624
4	0.098201	0.092687	0.920607
5	0.09571	0.091823	0.92184
6	0.094101	0.09177	0.921351

Out[40]:
```
[array([0.09177]), 0.9213513015617453]
```

In [41]:
```
learn.unfreeze()
learn.fit(lrs, 3, cycle_len=1, cycle_mult=2)
learn.save(f'{sz}')
```

```
HBox(children=(IntProgress(value=0, description='Epoch', max=7), HTML(value='')))
```

```
epoch      trn_loss   val_loss   f2
    0      0.094061   0.087197   0.926153
    1      0.092818   0.086996   0.928174
    2      0.091056   0.084689   0.929947
    3      0.091446   0.089575   0.92483
    4      0.087511   0.085343   0.929945
    5      0.085561   0.08384    0.930323
    6      0.083966   0.083565   0.930993
```

In [47]:
```
sz=256
```

In [43]:
```
learn.set_data(get_data(sz))
learn.freeze()
learn.fit(lr, 3, cycle_len=1, cycle_mult=2)
```

```
HBox(children=(IntProgress(value=0, description='Epoch', max=7), HTML(value='')))
```

```
epoch      trn_loss   val_loss   f2
    0      0.093788   0.088406   0.925103
    1      0.092152   0.087738   0.926359
    2      0.089541   0.086787   0.927078
    3      0.090457   0.087079   0.925858
    4      0.088064   0.086749   0.926517
    5      0.091159   0.085939   0.927563
    6      0.08619    0.085856   0.92778
```

Out[43]:
```
[array([0.08586]), 0.9277797506975684]
```

In [44]:
```
learn.unfreeze()
learn.fit(lrs, 3, cycle_len=1, cycle_mult=2)
learn.save(f'{sz}')
```

```
HBox(children=(IntProgress(value=0, description='Epoch', max=7), HTML(value='')))
```

```
epoch      trn_loss   val_loss   f2
    0      0.087228   0.082125   0.931622
    1      0.090669   0.083097   0.929711
    2      0.083937   0.08099    0.932874
    3      0.087432   0.083413   0.930149
    4      0.083918   0.082244   0.932266
```

5	0.079948	0.08139	0.932267
6	0.077498	0.080706	0.933599

In [45]:
```
multi_preds, y = learn.TTA()
preds = np.mean(multi_preds, 0)
```

In [46]:
```
f2(preds,y)
```

Out[46]: 0.9316254029148617