36fPANet

September 24, 2019

[1]:
```python
#Define libraries
import tensorflow as tf
import keras
from keras.models import Sequential
from keras.layers import Dense, Dropout, Conv1D, MaxPooling1D,␣
 ↪BatchNormalization, Flatten
from sklearn.model_selection import KFold
from keras.utils import multi_gpu_model
#from sklearn.cross_validation import StratifiedKFold
from contextlib import redirect_stdout

from keras.utils import plot_model
from IPython.display import Image
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
from sklearn.metrics import auc

from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
from sklearn.metrics import cohen_kappa_score
from sklearn.metrics import roc_auc_score
from sklearn.metrics import confusion_matrix

import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from keras.utils.vis_utils import plot_model
from IPython.display import SVG
import datetime
from keras.utils.vis_utils import model_to_dot
from keras.callbacks import EarlyStopping, ModelCheckpoint

gpu_options = tf.GPUOptions(allow_growth=True)
sess =tf.Session(config=tf.ConfigProto(gpu_options=gpu_options))
```

```
tf.keras.backend.set_session(sess)

NBname='_36fPANet'
%matplotlib inline

# =======
# 441PANet2
# epochs 40
# np.random.seed(100)
# kernel_len 25
# half (3,6, 9, 12, 15)
# epochs 20
# FC 2x56
# lr=0.0000125
# decay=0.0000125
# dropout 0.25
# # # diff b/w 441PANet2 & 5p361PANet2
# FC 2x36
# patience 5
# epochs 50
# lr=0.0000125
# # # diff b/w 5p361PANet2 & 5m_36FC
# lr=0.00000625*5 (0.00003125)
# =======
```

```
Using TensorFlow backend.
```

[2]:

```
SMALL_SIZE = 10
MEDIUM_SIZE = 15
BIGGER_SIZE = 18

# font = {'family' : 'monospace',
#         'weight' : 'bold',
#         'size'   : 'larger'}

#plt.rc('font', **font)  # pass in the font dict as kwargs
plt.rc('font', size=MEDIUM_SIZE,family='normal',weight='normal')          #␣
↪controls default text sizes
plt.rc('axes', titlesize=MEDIUM_SIZE,)     # fontsize of the axes title
plt.rc('axes', labelsize=MEDIUM_SIZE,)    # fontsize of the x and y labels
plt.rc('xtick', labelsize=MEDIUM_SIZE)    # fontsize of the tick labels
plt.rc('ytick', labelsize=MEDIUM_SIZE)    # fontsize of the tick labels
plt.rc('legend', fontsize=SMALL_SIZE)    # legend fontsize
plt.rc('figure', titlesize=BIGGER_SIZE,titleweight='bold')  # fontsize of the␣
↪figure title
#plt.rc('xtick', labelsize=15)
#plt.rc('ytick', labelsize=15)
```

[3]:
```python
print(str(datetime.datetime.now()))
```

```
2019-06-12 15:42:25.286689
```

[4]:
```python
def plot_perform1(mod, metric, last,ttl):
    plt.figure(figsize=(11,11))
    name='final'
    plt.plot(mod.epoch, mod.history[metric], label=name.
 ↪title()+'_Train',linewidth=1.5)
    plt.xlabel('Epochs')
    plt.ylabel(metric.replace('_',' ').title())
    plt.ylabel(metric.title())
    plt.title(ttl)
    plt.legend(loc='best')

    plt.xlim([0,max(mod.epoch)])
    figname=metric+last+'.png'
    plt.savefig(figname,dpi=500)
```

[5]:
```python
# def save_models(mod, last):
#   for i in range(len(mod)):
#     name=str(i+1)+last
#     mod[i].model.save(name)
```

[6]:
```python
# def plot_perform2(mod, metric, last,ttl):
#   #plt.figure(figsize=(13,13))
#   plt.figure(figsize=(11,11))
#   for i in range(len(mod)):
#     name=str(i+1)
#     val = plt.plot(mod[i].epoch, mod[i].history['val_'+metric],
#                          '--', label=name.title()+'_Val',linewidth=1.5)
#     plt.plot(mod[i].epoch, mod[i].history[metric],
#                     color=val[0].get_color(), label=name.
 ↪title()+'_Train',linewidth=1.2)

#   plt.xlabel('Epochs')
#   plt.ylabel(metric.replace('_',' ').title())
#   plt.ylabel(metric.title())
#   plt.title(ttl)
#   plt.legend(loc='best')

#   plt.xlim([0,max(mod[i].epoch)])
#   figname=metric+last+'.png'
#   plt.savefig(figname,dpi=500)
```

[7]:
```python
def create_model0(shape1):
```

```
    model0 = Sequential()

    model0.add(Conv1D(3, 25, strides=1,padding='same',activation='relu',␣
↪batch_input_shape=(None,shape1,1)))
    model0.add(BatchNormalization())
    model0.add(Conv1D(3, 25, strides=1,padding='same',activation='relu'))
    model0.add(MaxPooling1D(2))

    model0.add(Conv1D(6, 25, strides=1,padding='same',activation='relu'))
    model0.add(BatchNormalization())
    model0.add(Conv1D(6, 25, strides=1,padding='same',activation='relu'))
    model0.add(MaxPooling1D(2))

    model0.add(Conv1D(9, 25, strides=1,padding='same',activation='relu'))
    model0.add(BatchNormalization())
    model0.add(Conv1D(9, 25, strides=1,padding='same',activation='relu'))
    model0.add(MaxPooling1D(2))

    model0.add(Conv1D(12, 25, strides=1,padding='same',activation='relu'))
    model0.add(BatchNormalization())
    model0.add(Conv1D(12, 25, strides=1,padding='same',activation='relu'))
    model0.add(MaxPooling1D(2))

    model0.add(Conv1D(15, 25, strides=1,padding='same',activation='relu'))
    model0.add(BatchNormalization())
    model0.add(Conv1D(15, 25, strides=1,padding='same',activation='relu'))
    model0.add(MaxPooling1D(2))

    model0.add(Flatten())
    model0.add(Dense(36, activation='relu'))
    model0.add(Dense(36, activation='relu'))
    #model0.add(Dense(8, activation='relu'))
    model0.add(Dropout(0.25))
    model0.add(Dense(2, activation='softmax'))

    return model0
```

[8]:

```
%%time

batch_size = 10
N_epochs = 12
N_folds=4
np.random.seed(100)
kf = KFold(n_splits=N_folds, shuffle=False)

# fmd='train_x.npy'
# fld='train_y.npy'
```

```
# data=np.load(os.path.abspath(fmd))
# dlabels=np.load(os.path.abspath(fld))


rm='res_x.npy'
rl='res_y.npy'
rdata=np.load(os.path.abspath(rm))
rlabels=np.load(os.path.abspath(rl))

sm='sen_x.npy'
sl='sen_y.npy'
sdata=np.load(os.path.abspath(sm))
slabels=np.load(os.path.abspath(sl))

fmtim='testim_x.npy'
fltim='testim_y.npy'
testim=np.load(os.path.abspath(fmtim))
tlabelsim=np.load(os.path.abspath(fltim))

fmtb='testb_x.npy'
fltb='testb_y.npy'
testb=np.load(os.path.abspath(fmtb))
tlabelsb=np.load(os.path.abspath(fltb))




# =================
# Do once!
# =================
sen_batch = np.random.RandomState(seed=45).permutation(sdata.shape[0])
bins = np.linspace(0, 200, 41)
digitized = np.digitize(sen_batch, bins,right=False)
# ================



# ===============================
# # FINAL TRAIN
# ===============================
train_idx_k=np.random.permutation(rdata.shape[0])
s_x=sdata[np.isin(digitized,train_idx_k+1)]
s_y=slabels[np.isin(digitized,train_idx_k+1)]
r_x=np.
 ↪concatenate((rdata[train_idx_k],rdata[train_idx_k],rdata[train_idx_k],rdata[train_idx_k],rdat
r_y=np.
 ↪concatenate((rlabels[train_idx_k],rlabels[train_idx_k],rlabels[train_idx_k],rlabels[train_idx

f_train_x, f_train_y = np.concatenate((s_x,r_x)), np.concatenate((s_y,r_y))
```

```
train_shuf_idx = np.random.permutation(f_train_x.shape[0])
x_train, y_train = f_train_x[train_shuf_idx], f_train_y[train_shuf_idx]


model0 = create_model0(rdata.shape[1])
model0.compile(optimizer=keras.optimizers.Adamax(lr=0.00003125, beta_1=0.9,␣
 ↪beta_2=0.999, epsilon=None, decay=0.0000125),
                              loss='categorical_crossentropy',
                              metrics=['accuracy','categorical_crossentropy'])
fmodel=model0.fit(x_train, y_train, epochs=N_epochs, batch_size=batch_size,␣
 ↪verbose=2)

# =======================
# # ONLY FOR CROSS-VAL
# =======================

# i=0
# adamax=[]
# callbacks = [EarlyStopping(monitor='val_loss', patience=10),
#              ModelCheckpoint(filepath='best_model'+NBname+'.h5',␣
 ↪monitor='val_loss', save_best_only=True)]

# for train_idx_k, val_idx_k in kf.split(rdata):
#     print ("Running Fold", i+1, "/", N_folds)

#     # ================================
#     # select train
#     # ================================

#     s_train_x=sdata[np.isin(digitized,train_idx_k+1)]
#     s_train_y=slabels[np.isin(digitized,train_idx_k+1)]
#     r_train_x=np.
 ↪concatenate((rdata[train_idx_k],rdata[train_idx_k],rdata[train_idx_k],rdata[train_idx_k],rdat
#     r_train_y=np.
 ↪concatenate((rlabels[train_idx_k],rlabels[train_idx_k],rlabels[train_idx_k],rlabels[train_idx

#     # ================================
#     # select val
#     # ================================

#     s_val_x=sdata[np.isin(digitized,val_idx_k+1)]
#     s_val_y=slabels[np.isin(digitized,val_idx_k+1)]

#     r_val_x=np.
 ↪concatenate((rdata[val_idx_k],rdata[val_idx_k],rdata[val_idx_k],rdata[val_idx_k],rdata[val_id
```

```
#     r_val_y=np.
 ↪concatenate((rlabels[val_idx_k],rlabels[val_idx_k],rlabels[val_idx_k],rlabels[val_idx_k],rlab

#     # ===============================
#     # concatenate F_train/val_x/y
#     # ===============================

#     f_train_x, f_train_y = np.concatenate((s_train_x,r_train_x)), np.
 ↪concatenate((s_train_y,r_train_y))
# #     train_shuf_idx = np.random.permutation(f_train_x.shape[0])
# #     F_train_x, F_train_y = f_train_x[train_shuf_idx],␣
 ↪f_train_y[train_shuf_idx]

#     f_val_x, f_val_y = np.concatenate((s_val_x,r_val_x)), np.
 ↪concatenate((s_val_y,r_val_y))
# #     val_shuf_idx = np.random.permutation(f_val_x.shape[0])
# #     F_val_x, F_val_y = f_val_x[val_shuf_idx], f_val_y[val_shuf_idx]

#     # ===============================
#     # shuffle just because we can?
#     # ===============================

#     train_shuf_idx = np.random.permutation(f_train_x.shape[0])
#     x_train_CV, y_train_CV = f_train_x[train_shuf_idx],␣
 ↪f_train_y[train_shuf_idx]

#     val_shuf_idx = np.random.permutation(f_val_x.shape[0])
#     x_val_CV, y_val_CV = f_val_x[val_shuf_idx], f_val_y[val_shuf_idx]

#     # ===============================
#     # clear and create empty model
#     # ===============================

#     model0 = None # Clearing the NN.
#     model0 = create_model0(rdata.shape[1])

# #    x_train_CV, y_train_CV, = data[train_idx_k], dlabels[train_idx_k]
# #    x_val_CV, y_val_CV, = data[val_idx_k], dlabels[val_idx_k]

# #     parallel_model = None
# #     parallel_model = multi_gpu_model(model0, gpus=2)
# #     #default
# #     #parallel_model.compile(optimizer=keras.optimizers.Adamax(lr=0.002,␣
 ↪beta_1=0.9, beta_2=0.999, epsilon=None, decay=0.0),
# #     parallel_model.compile(optimizer=keras.optimizers.Adamax(lr=0.004,␣
 ↪beta_1=0.9, beta_2=0.999, epsilon=None, decay=0.005),
```

```
# #                              loss='categorical_crossentropy',
# #                              metrics=['accuracy','categorical_crossentropy'])
# #     model0_adamax = parallel_model.fit(x_train_CV, y_train_CV,
# #                                           epochs=N_epochs,
# #                                           batch_size=batch_size,
# #                                                                                  ␣
 ↪validation_data=(x_val_CV,y_val_CV),
# #                                           verbose=1)

#     #default
#     #parallel_model.compile(optimizer=keras.optimizers.Adamax(lr=0.002,␣
 ↪beta_1=0.9, beta_2=0.999, epsilon=None, decay=0.0),
#     model0.compile(optimizer=keras.optimizers.Adamax(lr=0.00003125, beta_1=0.
 ↪9, beta_2=0.999, epsilon=None, decay=0.0000125),
#                              loss='categorical_crossentropy',
#                              metrics=['accuracy','categorical_crossentropy'])
#     model0_adamax = model0.fit(x_train_CV, y_train_CV,
#                                           epochs=N_epochs,
#                                           batch_size=batch_size,
#                                           validation_data=(x_val_CV,y_val_CV),
#                                           verbose=2,callbacks=callbacks)

#     adamax.append(model0_adamax)
#     i=i+1
```

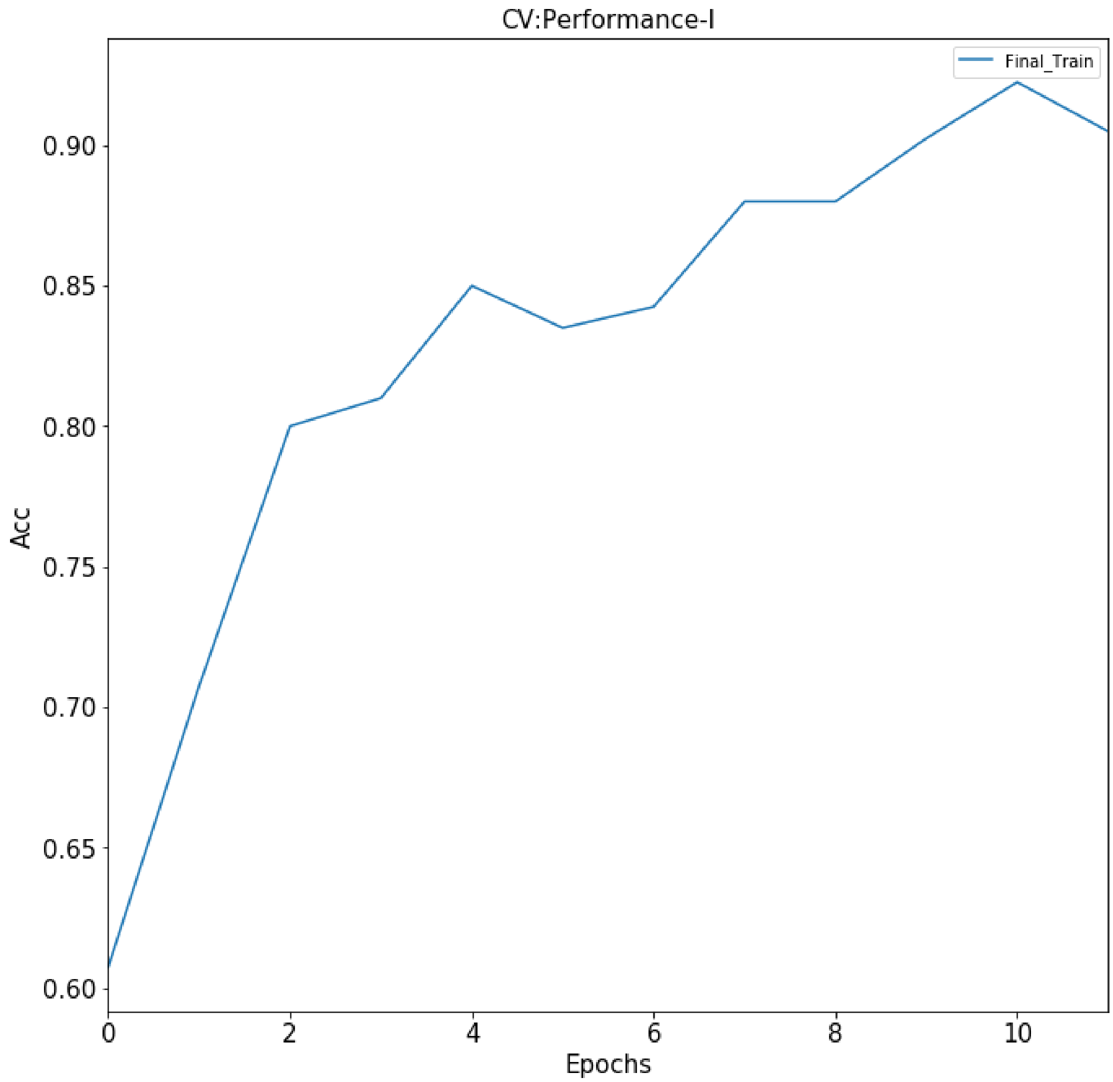
```
Epoch 1/12
 - 32s - loss: 0.6999 - acc: 0.6075 - categorical_crossentropy: 0.6999
Epoch 2/12
 - 25s - loss: 0.5996 - acc: 0.7075 - categorical_crossentropy: 0.5996
Epoch 3/12
 - 26s - loss: 0.4401 - acc: 0.8000 - categorical_crossentropy: 0.4401
Epoch 4/12
 - 25s - loss: 0.3718 - acc: 0.8100 - categorical_crossentropy: 0.3718
Epoch 5/12
 - 25s - loss: 0.3003 - acc: 0.8500 - categorical_crossentropy: 0.3003
Epoch 6/12
 - 25s - loss: 0.3159 - acc: 0.8350 - categorical_crossentropy: 0.3159
Epoch 7/12
 - 25s - loss: 0.3023 - acc: 0.8425 - categorical_crossentropy: 0.3023
Epoch 8/12
 - 26s - loss: 0.2699 - acc: 0.8800 - categorical_crossentropy: 0.2699
Epoch 9/12
 - 25s - loss: 0.2788 - acc: 0.8800 - categorical_crossentropy: 0.2788
Epoch 10/12
 - 26s - loss: 0.2526 - acc: 0.9025 - categorical_crossentropy: 0.2526
Epoch 11/12
 - 26s - loss: 0.2132 - acc: 0.9225 - categorical_crossentropy: 0.2132
```

```
Epoch 12/12
 - 25s - loss: 0.2273 - acc: 0.9050 - categorical_crossentropy: 0.2273
CPU times: user 40min 57s, sys: 4min 22s, total: 45min 20s
Wall time: 5min 20s
```

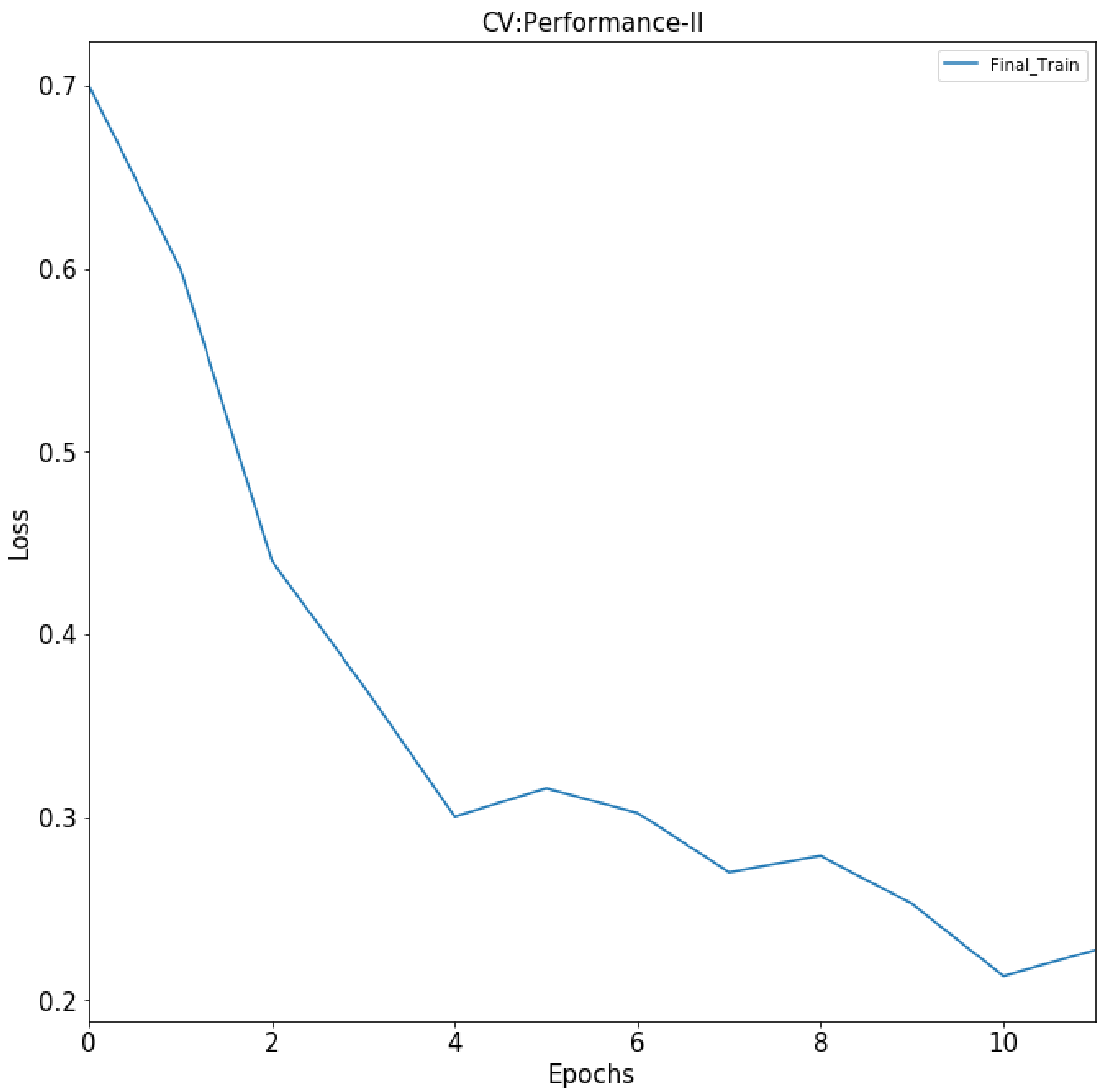
[9]:
```
mname='final'+NBname+'.h5'
fmodel.model.save(mname)
```

[10]:
```
plot_perform1(fmodel,'acc',NBname,'CV:Performance-I')
```

```
/home/uu_bio_amrdl/dprasad/miniconda3/envs/TFgpu/lib/python3.6/site-
packages/matplotlib/font_manager.py:1241: UserWarning: findfont: Font family
['normal'] not found. Falling back to DejaVu Sans.
  (prop.get_family(), self.defaultFamily[fontext]))
```



[11]:
```python
plot_perform1(fmodel,'loss',NBname,'CV:Performance-II')
```



[12]:
```python
with open('summary'+NBname+'.txt', 'w') as f:
    with redirect_stdout(f):
        fmodel.model.summary()
```

[13]:
```python
fmodel.model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv1d_1 (Conv1D)            (None, 1152012, 3)        78
_________________________________________________________________
batch_normalization_1 (Batch (None, 1152012, 3)        12
```

```
_________________________________________________________________
conv1d_2 (Conv1D)            (None, 1152012, 3)        228
_________________________________________________________________
max_pooling1d_1 (MaxPooling1 (None, 576006, 3)         0
_________________________________________________________________
conv1d_3 (Conv1D)            (None, 576006, 6)         456
_________________________________________________________________
batch_normalization_2 (Batch (None, 576006, 6)         24
_________________________________________________________________
conv1d_4 (Conv1D)            (None, 576006, 6)         906
_________________________________________________________________
max_pooling1d_2 (MaxPooling1 (None, 288003, 6)         0
_________________________________________________________________
conv1d_5 (Conv1D)            (None, 288003, 9)         1359
_________________________________________________________________
batch_normalization_3 (Batch (None, 288003, 9)         36
_________________________________________________________________
conv1d_6 (Conv1D)            (None, 288003, 9)         2034
_________________________________________________________________
max_pooling1d_3 (MaxPooling1 (None, 144001, 9)         0
_________________________________________________________________
conv1d_7 (Conv1D)            (None, 144001, 12)        2712
_________________________________________________________________
batch_normalization_4 (Batch (None, 144001, 12)        48
_________________________________________________________________
conv1d_8 (Conv1D)            (None, 144001, 12)        3612
_________________________________________________________________
max_pooling1d_4 (MaxPooling1 (None, 72000, 12)         0
_________________________________________________________________
conv1d_9 (Conv1D)            (None, 72000, 15)         4515
_________________________________________________________________
batch_normalization_5 (Batch (None, 72000, 15)         60
_________________________________________________________________
conv1d_10 (Conv1D)           (None, 72000, 15)         5640
_________________________________________________________________
max_pooling1d_5 (MaxPooling1 (None, 36000, 15)         0
_________________________________________________________________
flatten_1 (Flatten)          (None, 540000)            0
_________________________________________________________________
dense_1 (Dense)              (None, 12)                6480012
_________________________________________________________________
dense_2 (Dense)              (None, 12)                156
_________________________________________________________________
dropout_1 (Dropout)          (None, 12)                0
_________________________________________________________________
dense_3 (Dense)              (None, 2)                 26
=================================================================
Total params: 6,501,914
```

```
Trainable params: 6,501,824
Non-trainable params: 90
_________________________________________________________________
```

[14]:
```
print(str(datetime.datetime.now()))
```

```
2019-06-12 15:47:51.373972
```

[ ]:
```

```

[15]:
```
# testim=np.load(os.path.abspath(fmtim))
# tlabelsim=np.load(os.path.abspath(fltim))

# testb=np.load(os.path.abspath(fmtb))
# tlabelsb=np.load(os.path.abspath(fltb))
```

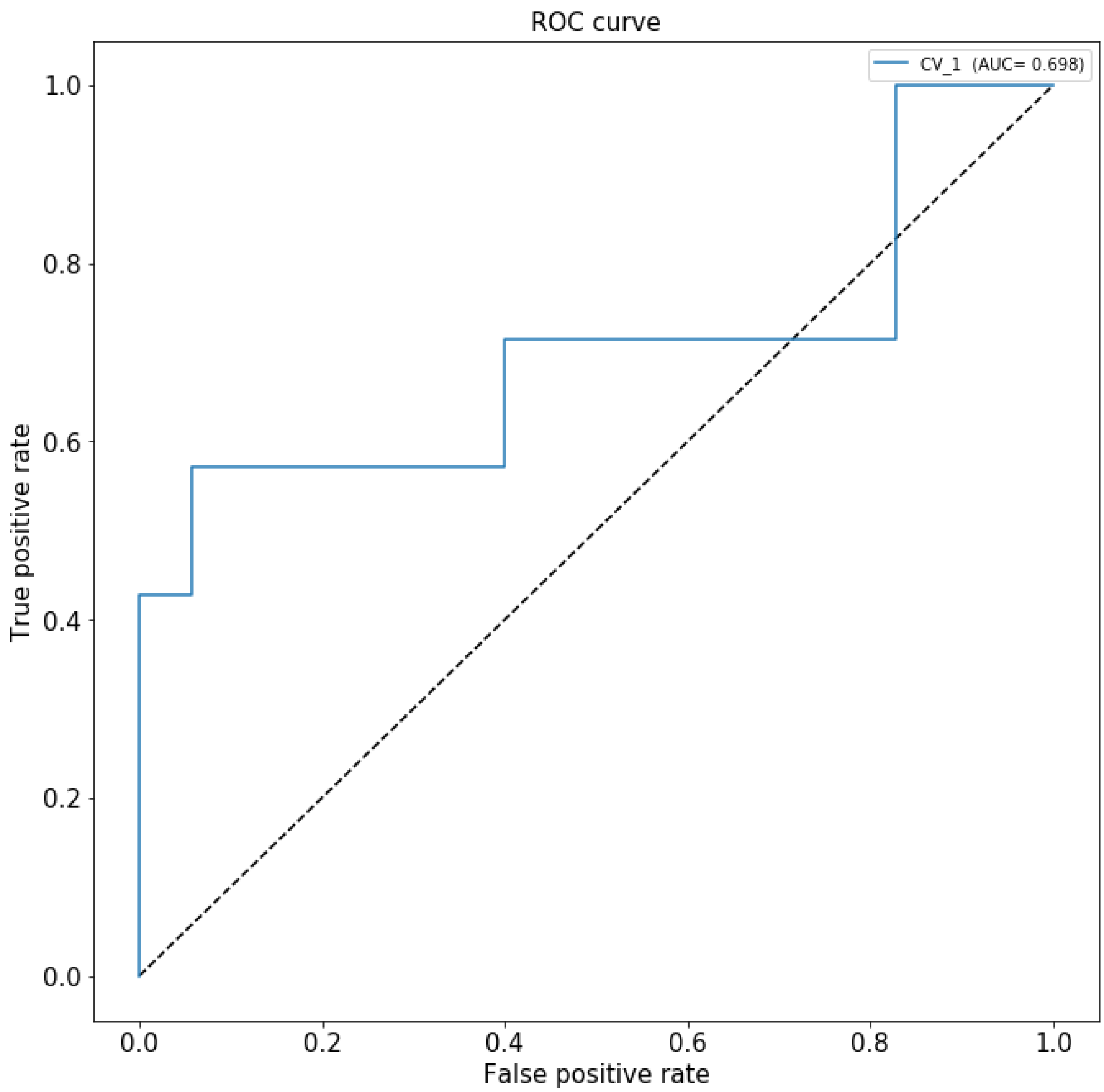
[16]:
```
# ==========================================================================
# # DO NOT UNCOMMENT UNTIL THE END; DECLARES FUNCTION FOR AN UNBIASED TEST
# ==========================================================================

def plot_auc(aucies,fprs,tprs, last):
  #plt.figure(figsize=(13,13))
  plt.figure(figsize=(11,11))
  plt.plot([0, 1], [0, 1], 'k--')
  for i in range(len(aucies)):
    st='CV_'+str(i+1)+' '
    if i==0:
        st='Balanced'
    elif i ==1:
        st='Imbalanced'
    plt.plot(fprs[i], tprs[i], label='{} (AUC= {:.3f})'.
 ↪format(st,aucies[i]),linewidth=1.5)

  plt.xlabel('False positive rate')
  plt.ylabel('True positive rate')
  plt.title('ROC curve')
  plt.legend(loc='best')

  figname='ROC'+last+'.png'
  plt.savefig(figname,dpi=500)
```

[17]:
```
# ==========================================================================
# # THIS IS THE FUCKING UNBIASED TEST; DO NOT UNCOMMENT UNTIL THE END
# ==========================================================================

fpr_x=[]
tpr_x=[]
thresholds_x=[]
auc_x=[]
```

```
pre_S=[]
rec_S=[]
f1_S=[]
kap_S=[]
acc_S=[]
mat_S=[]
```

[18]:
```
NBname='_12fPANetb'
y_predb = fmodel.model.predict(testb)#.ravel()
fpr_0, tpr_0, thresholds_0 = roc_curve(tlabelsb[:,1], y_predb[:,1])
fpr_x.append(fpr_0)
tpr_x.append(tpr_0)
thresholds_x.append(thresholds_0)
auc_x.append(auc(fpr_0, tpr_0))

# predict probabilities for testb set
yhat_probs = fmodel.model.predict(testb, verbose=0)
# predict crisp classes for testb set



yhat_classes = fmodel.model.predict_classes(testb, verbose=0)
# reduce to 1d array
testby=tlabelsb[:,1]

#testby1=tlabels[:,1]
#yhat_probs = yhat_probs[:, 0]
#yhat_classes = yhat_classes[:, 0]

# accuracy: (tp + tn) / (p + n)
acc_S.append(accuracy_score(testby, yhat_classes))
#print('Accuracy: %f' % accuracy_score(testby, yhat_classes))

#precision tp / (tp + fp)
pre_S.append(precision_score(testby, yhat_classes))
#print('Precision: %f' % precision_score(testby, yhat_classes))

#recall: tp / (tp + fn)
rec_S.append(recall_score(testby, yhat_classes))
#print('Recall: %f' % recall_score(testby, yhat_classes))

# f1: 2 tp / (2 tp + fp + fn)
f1_S.append(f1_score(testby, yhat_classes))
#print('F1 score: %f' % f1_score(testby, yhat_classes))

# kappa
```

```
kap_S.append(cohen_kappa_score(testby, yhat_classes))
#print('Cohens kappa: %f' % cohen_kappa_score(testby, yhat_classes))

# confusion matrix
mat_S.append(confusion_matrix(testby, yhat_classes))
#print(confusion_matrix(testby, yhat_classes))

with open('perform'+NBname+'.txt', "w") as f:
    f.writelines("AUC \t Accuracy \t Precision \t Recall \t F1 \t Kappa\n")
    f.writelines(map("{}\t{}\t{}\t{}\t{}\t{}\n".format, auc_x, acc_S, pre_S,␣
 ↪rec_S, f1_S, kap_S))
    for x in range(len(fpr_x)):
        f.writelines(map("{}\n".format, mat_S[x]))
        f.writelines(map("{}\t{}\t{}\n".format, fpr_x[x], tpr_x[x],␣
 ↪thresholds_x[x]))

# =============================================================================
# # THIS IS THE FUCKING UNBIASED testb; DO NOT UNCOMMENT UNTIL THE END
# =============================================================================

plot_auc(auc_x,fpr_x,tpr_x,NBname)
```



[17]:

```

```

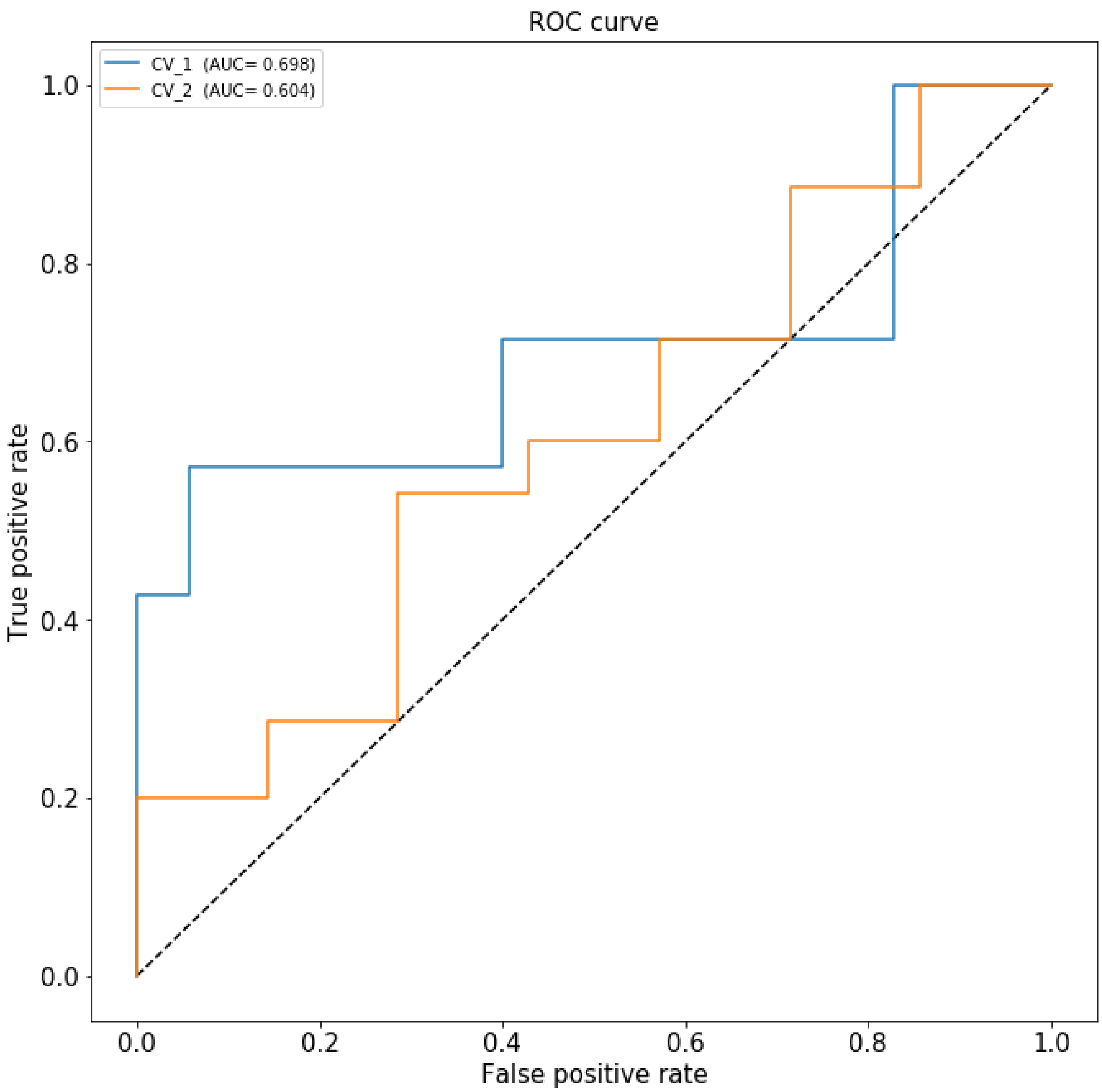
[ ]:

```

```

[19]:

```
NBname='_12fPANetim'
y_pred = fmodel.model.predict(testim)#.ravel()
fpr_0, tpr_0, thresholds_0 = roc_curve(tlabelsim[:,1], y_pred[:,1])
fpr_x.append(fpr_0)
tpr_x.append(tpr_0)
thresholds_x.append(thresholds_0)
auc_x.append(auc(fpr_0, tpr_0))

# predict probabilities for testim set
yhat_probs = fmodel.model.predict(testim, verbose=0)
# predict crisp classes for testim set
```

```python
yhat_classes = fmodel.model.predict_classes(testim, verbose=0)
# reduce to 1d array
testimy=tlabelsim[:,1]

#testimy1=tlabels[:,1]
#yhat_probs = yhat_probs[:, 0]
#yhat_classes = yhat_classes[:, 0]

# accuracy: (tp + tn) / (p + n)
acc_S.append(accuracy_score(testimy, yhat_classes))
#print('Accuracy: %f' % accuracy_score(testimy, yhat_classes))

#precision tp / (tp + fp)
pre_S.append(precision_score(testimy, yhat_classes))
#print('Precision: %f' % precision_score(testimy, yhat_classes))

#recall: tp / (tp + fn)
rec_S.append(recall_score(testimy, yhat_classes))
#print('Recall: %f' % recall_score(testimy, yhat_classes))

# f1: 2 tp / (2 tp + fp + fn)
f1_S.append(f1_score(testimy, yhat_classes))
#print('F1 score: %f' % f1_score(testimy, yhat_classes))

# kappa
kap_S.append(cohen_kappa_score(testimy, yhat_classes))
#print('Cohens kappa: %f' % cohen_kappa_score(testimy, yhat_classes))

# confusion matrix
mat_S.append(confusion_matrix(testimy, yhat_classes))
#print(confusion_matrix(testimy, yhat_classes))

with open('perform'+NBname+'.txt', "w") as f:
    f.writelines("AUC \t Accuracy \t Precision \t Recall \t F1 \t Kappa\n")
    f.writelines(map("{}\t{}\t{}\t{}\t{}\t{}\n".format, auc_x, acc_S, pre_S, rec_S, f1_S, kap_S))
    for x in range(len(fpr_x)):
        f.writelines(map("{}\n".format, mat_S[x]))
        f.writelines(map("{}\t{}\t{}\n".format, fpr_x[x], tpr_x[x], thresholds_x[x]))

# =============================================================================
# # THIS IS THE FUCKING UNBIASED testim; DO NOT UNCOMMENT UNTIL THE END
# =============================================================================

plot_auc(auc_x,fpr_x,tpr_x,NBname)
```



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[20]:

```
#model = load_model('final_fPANet.h5')
```

[21]:

```
# produces extremely tall png, that doesn't really fit into a screen
# plot_model(model0, to_file='model'+NBname+'.png',␣
↪show_shapes=True,show_layer_names=False)
```

[22]:

```
# produces crappy SVG object. dont uncomment until desperate
# SVG(model_to_dot(model0, show_shapes=True,show_layer_names=False).
↪create(prog='dot', format='svg'))
```

[ ]:

[ ]:

```

```

[23]:

```
# # =====================================
# # Legacy block, life saver truly
# # =====================================

# # sdata.shape
# # (200, 1152012, 1)
# print('\n')
# sen_batch = np.random.RandomState(seed=45).permutation(sdata.shape[0])
# print(sen_batch)

# print('\n')
# bins = np.linspace(0, 200, 41)
# print(bins.shape)
# print(bins)

# print('\n')
# digitized = np.digitize(sen_batch, bins,right=False)
# print(digitized.shape)
# print(digitized)

# # #instead of 10, run counter
# # print(np.where(digitized==10))
# # print(sdata[np.where(digitized==10)].shape)
# # # (array([  0,  96, 101, 159, 183]),)
# # # (5, 1152012, 1)

# # dig_sort=digitized
# # dig_sort.sort()
# # # print(dig_sort)
# # # [ 1  1  1  1  1  2  2  2  2  2  3  3  3  3  3  4  4  4  4  4  5  5  5  5
# # #   5  6  6  6  6  6  7  7  7  7  7  8  8  8  8  8  9  9  9  9  9 10 10 10
# # #  10 10 11 11 11 11 11 12 12 12 12 12 13 13 13 13 13 14 14 14 14 14 15 15
# # #  15 15 15 16 16 16 16 16 17 17 17 17 17 18 18 18 18 18 19 19 19 19 19 20
# # #  20 20 20 20 21 21 21 21 21 22 22 22 22 22 23 23 23 23 23 24 24 24 24 24
# # #  25 25 25 25 25 26 26 26 26 26 27 27 27 27 27 28 28 28 28 28 29 29 29 29
# # #  29 30 30 30 30 30 31 31 31 31 31 32 32 32 32 32 33 33 33 33 33 34 34 34
# # #  34 34 35 35 35 35 35 36 36 36 36 36 37 37 37 37 37 38 38 38 38 38 39 39
# # #  39 39 39 40 40 40 40 40]
# # print(val_idx_k)
# # # array([ 2,  3,  8, 10, 14, 15, 23, 24, 30, 32])
# # print(val_idx_k+1)
# # # array([ 3,  4,  9, 11, 15, 16, 24, 25, 31, 33])
# # print('\n')
# # print(sdata[np.isin(digitized,train_idx_k+1)].shape)
# # # (150, 1152012, 1)
```

```
# # print(sdata[np.isin(digitized,val_idx_k+1)].shape)
# # # (50, 1152012, 1)
```

[ ]:

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[ ]:

[24]:
```
# plt.figure(figsize=(16,10))
# plt.plot([0, 1], [0, 1], 'k--')
# plt.plot(fpr_x[0], tpr_x[0], label='CV1 (area= {:.3f})'.format(auc_x[0]))
# plt.plot(fpr_x[1], tpr_x[1], label='CV2 (area= {:.3f})'.format(auc_x[1]))
# plt.plot(fpr_x[2], tpr_x[2], label='CV3 (area= {:.3f})'.format(auc_x[2]))
# plt.xlabel('False positive rate')
# plt.ylabel('True positive rate')
# plt.title('ROC curve')
# plt.legend(loc='best')
# figname='model0_011GWAS'+'_ROC.png'
# plt.savefig(figname,dpi=400)
```

[ ]:

[25]:
```
# As index starts from 0, changed from general form
# [(M*(k-i)):(M*k-1)]
for train_idx,val_idx in kf.split(rdata):
    print(train_idx)
    print(5*train_idx)
    print(5*train_idx+4)
    print('\n')
    print(val_idx)
    print(5*val_idx)
    print(5*val_idx+4)
    print('\n \n')
```

```
[10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33
 34 35 36 37 38 39]
[ 50  55  60  65  70  75  80  85  90  95 100 105 110 115 120 125 130 135
 140 145 150 155 160 165 170 175 180 185 190 195]
[ 54  59  64  69  74  79  84  89  94  99 104 109 114 119 124 129 134 139
 144 149 154 159 164 169 174 179 184 189 194 199]


[0 1 2 3 4 5 6 7 8 9]
[ 0  5 10 15 20 25 30 35 40 45]
[ 4  9 14 19 24 29 34 39 44 49]



[ 0  1  2  3  4  5  6  7  8  9 20 21 22 23 24 25 26 27 28 29 30 31 32 33
```

```
 34 35 36 37 38 39]
[  0   5  10  15  20  25  30  35  40  45 100 105 110 115 120 125 130 135
 140 145 150 155 160 165 170 175 180 185 190 195]
[  4   9  14  19  24  29  34  39  44  49 104 109 114 119 124 129 134 139
 144 149 154 159 164 169 174 179 184 189 194 199]


[10 11 12 13 14 15 16 17 18 19]
[50 55 60 65 70 75 80 85 90 95]
[54 59 64 69 74 79 84 89 94 99]



[ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 30 31 32 33
 34 35 36 37 38 39]
[  0   5  10  15  20  25  30  35  40  45  50  55  60  65  70  75  80  85
  90  95 150 155 160 165 170 175 180 185 190 195]
[  4   9  14  19  24  29  34  39  44  49  54  59  64  69  74  79  84  89
  94  99 154 159 164 169 174 179 184 189 194 199]


[20 21 22 23 24 25 26 27 28 29]
[100 105 110 115 120 125 130 135 140 145]
[104 109 114 119 124 129 134 139 144 149]



[ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
 24 25 26 27 28 29]
[  0   5  10  15  20  25  30  35  40  45  50  55  60  65  70  75  80  85
  90  95 100 105 110 115 120 125 130 135 140 145]
[  4   9  14  19  24  29  34  39  44  49  54  59  64  69  74  79  84  89
  94  99 104 109 114 119 124 129 134 139 144 149]


[30 31 32 33 34 35 36 37 38 39]
[150 155 160 165 170 175 180 185 190 195]
[154 159 164 169 174 179 184 189 194 199]
```

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```
```

[ ]:

```
```

[26]:

```
# plot_perform([#('1_nadam', nadam[0]),
#                 ('1_adamax', adamax[0]),
```

```
#               #('2_nadam', nadam[1]),
#               ('2_adamax', adamax[1]),
#               #('3_nadam', nadam[2]),
#               ('3_adamax', adamax[2])],
#               #('3_nadam', nadam[2]),
#               #('4_adamax', adamax[3]),
#               #('3_nadam', nadam[2]),
#               #('5_adamax', adamax[4])],
#     'acc','model0_011GWAS')
```

[27]:
```
# plot_perform([#('1_nadam', nadam[0]),
#               ('1_adamax', adamax[0]),
#               #('2_nadam', nadam[1]),
#               ('2_adamax', adamax[1]),
#               #('3_nadam', nadam[2]),
#               ('3_adamax', adamax[2])],
#               #('3_nadam', nadam[2]),
#               #('4_adamax', adamax[3]),
#               #('3_nadam', nadam[2]),
#               #('5_adamax', adamax[4])],
#     'loss','model0_011GWAS')
```

[28]:
```
# adamax[0].model.save('adamax_1_011GWAS')
# adamax[1].model.save('adamax_2_011GWAS')
# adamax[2].model.save('adamax_3_011GWAS')
# # adamax[3].model.save('adamax_4_011GWAS')
# # adamax[4].model.save('adamax_5_011GWAS')
```

[29]:
```
# # plot_perform([#('1_nadam', nadam[0]),
# #               ('1_adamax', adamax[0]),
# #               #('2_nadam', nadam[1]),
# #               ('2_adamax', adamax[1]),
# #               #('3_nadam', nadam[2]),
# #               ('3_adamax', adamax[2])],
# #               #('3_nadam', nadam[2]),
# #               #('4_adamax', adamax[3]),
# #               #('3_nadam', nadam[2]),
# #               #('5_adamax', adamax[4])],
# #     'acc','model0_011GWAS')
# def plot_perform(histories, metric,initial):
#   plt.figure(figsize=(16,10))

#   for name, history in histories:
#     val = plt.plot(history.epoch, history.history['val_'+metric],
#                    '--', label=name.title()+' Val')
#     #print(val) [<matplotlib.lines.Line2D object at 0x7fbb1899a940>]
#     #print(val[0]) Line2D(Baseline Val)
#     #print(val[0].get_color()) #1f77b4
```

```
#     plt.plot(history.epoch, history.history[metric],
#              color=val[0].get_color(), label=name.title()+' Train')

#   plt.xlabel('Epochs')
#   plt.ylabel(metric.replace('_',' ').title())
#   plt.ylabel(metric.title())
#   plt.legend()

#   plt.xlim([0,max(history.epoch)])
#   figname=initial+"_"+metric+".png"
#   plt.savefig(figname,dpi=400)
```