Photon and Electron classification for barrel region (EB) with and without tracking information

In [1]:
```
import uproot
import numpy as np
import pandas as pd
import h5py
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.optimizers import SGD
from tensorflow.keras.layers import Input, Activation, Dense, Convolution2D, MaxPooling2D, Dropout, Flatten
from tensorflow import keras
from tensorflow.keras.callbacks import ReduceLROnPlateau
```

Reading the root file with uprood and coverting them to pandas data frame

In [2]:
```python
# fix random seed for reproducibility
seed = 7
np.random.seed(seed)

treename = 'fTree' # this is the name of the tree in the root file
filename = {}
upfile = {}
df = {}


filename['photon'] = 'data/Signal.root' # this the the file which contains photons (diphotons)
filename['electron'] = 'data/Background.root' # this is the file which contains electrons and positron.

branches1 = ['Photon1']


upfile['photon1'] = uproot.open(filename['photon'])
upfile['electron1'] = uproot.open(filename['electron'])
df['photon1'] = upfile['photon1'][treename].arrays(branches1, library='pd')
df['electron1'] = upfile['electron1'][treename].arrays(branches1, library='pd')
df['photon1']['isPhoton'] = np.ones(len(df['photon1']))
df['electron1']['isPhoton'] = np.zeros(len(df['electron1']))

branches2 = ['Photon2']


upfile['photon2'] = uproot.open(filename['photon'])
upfile['electron2'] = uproot.open(filename['electron'])
df['photon2'] = upfile['photon2'][treename].arrays(branches2, library='pd')
df['electron2'] = upfile['electron2'][treename].arrays(branches2, library='pd')
df['photon2']['isPhoton'] = np.ones(len(df['photon2']))
df['electron2']['isPhoton'] = np.zeros(len(df['electron2']))
```

Selecting Photon and electron which passes certain condition and creating separate data frame for them, this data frame is not used for training purpose. This is only for analysis of data

In [3]:
```
df['electron1_pashipt'] = df['electron1'][(df['electron1'][('Photon1','pt')] >= 30.0)
    & (df['electron1'][('Photon1','pt')] <= 1800)
    & (df['electron1'][('Photon1','isEB')] ==1) & (df['electron1'][('Photon1','passHighPtID')] == 1)]
# len(df['electron1_pashipt'])

df['photon1_pashipt'] = df['photon1'][(df['photon1'][('Photon1','pt')] >= 30.0) &
                              (df['photon1'][('Photon1','pt')] <= 1800)
     & (df['photon1'][('Photon1','isEB')] ==1) & (df['photon1'][('Photon1','passHighPtID')] ==1)]
# len(df['photon1_pashipt'])

df['electron2_pashipt'] = df['electron2'][(df['electron2'][('Photon2','pt')] >= 30.0) & (df['electron2'][('Photon2','pt')] <= 1800)
     & (df['electron2'][('Photon2','isEB')] ==1) & (df['electron2'][('Photon2','passHighPtID')] ==1)]
# len(df['electron2_pashipt'])

df['electron2_pashipt'] = df['electron2'][(df['electron2'][('Photon2','pt')] >= 30.0) &
                                  (df['electron2'][('Photon2','pt')] <= 1800)
     & (df['electron2'][('Photon2','isEB')] ==1) & (df['electron2'][('Photon2','passHighPtID')] ==1)]
# len(df['electron2_pashipt'])
```

Selecting the particles with high transeve momentum in EB region

In [4]:
```
df['electron1'] = df['electron1'][(df['electron1'][('Photon1','pt')] >= 30.0) &
                (df['electron1'][('Photon1','pt')] <= 1800) & (df['electron1'][('Photon1','isEB')] ==1)]

df['photon1'] = df['photon1'][(df['photon1'][('Photon1','pt')] >= 30.0) &
                (df['photon1'][('Photon1','pt')] <= 1800) & (df['photon1'][('Photon1','isEB')] ==1)]

df['electron2'] = df['electron2'][(df['electron2'][('Photon2','pt')] >= 30.0) &
                (df['electron2'][('Photon2','pt')] <= 1800) & (df['electron2'][('Photon2','isEB')] ==1)]


df['photon2'] = df['photon2'][(df['photon2'][('Photon2','pt')] >= 30.0) &
                (df['photon2'][('Photon2','pt')] <= 1800) & (df['photon2'][('Photon2','isEB')] ==1)]
```

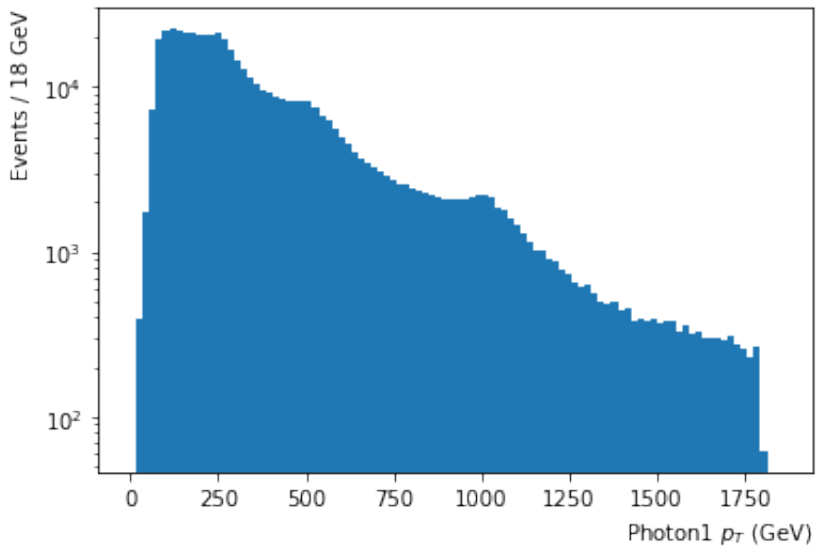
In [5]:
```
# df["photon2"]['isPhoton']
```

In [6]:
```
# df['electron1'].isnull().sum().sum()
```

Lets plot few parameters

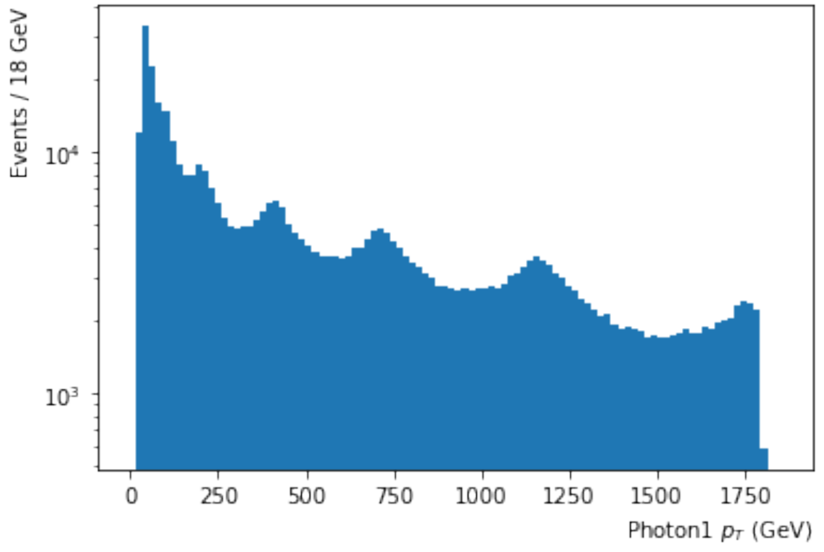
In [7]:

```
n_bins_pt = 100;
df['photon1'][('Photon1','pt')].plot.hist(bins=n_bins_pt,range=(0,1850),log=1);
plt.xlabel('Photon1 $p_T$ (GeV)', horizontalalignment='right', x=1.0);
plt.ylabel('Events / '+str(int(1850/n_bins_pt))+' GeV', horizontalalignment='right', y=1.0);
```



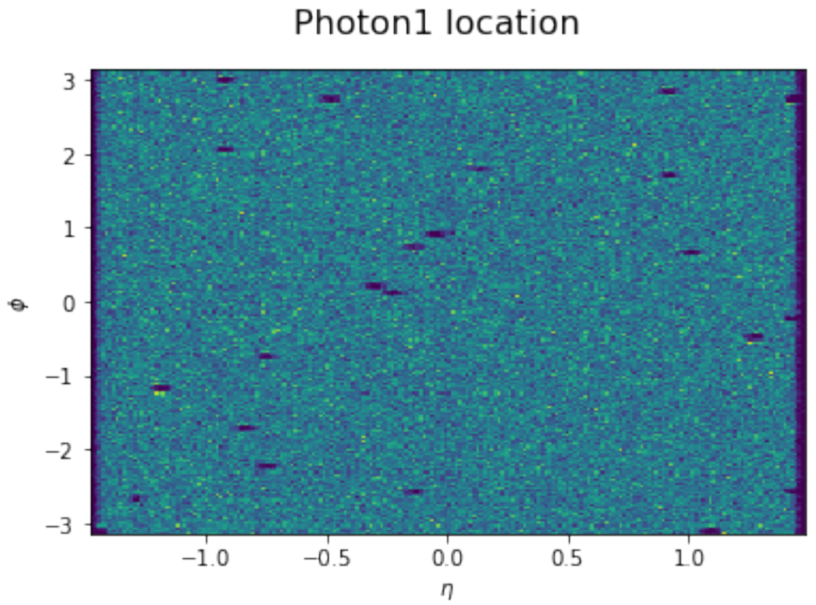
In [8]:

```
n_bins_pt = 100;
df['electron1'][('Photon1','pt')].plot.hist(bins=n_bins_pt,range=(0,1850),log=1);
plt.xlabel('Photon1 $p_T$ (GeV)', horizontalalignment='right', x=1.0);
plt.ylabel('Events / '+str(int(1850/n_bins_pt))+' GeV', horizontalalignment='right', y=1.0);
```



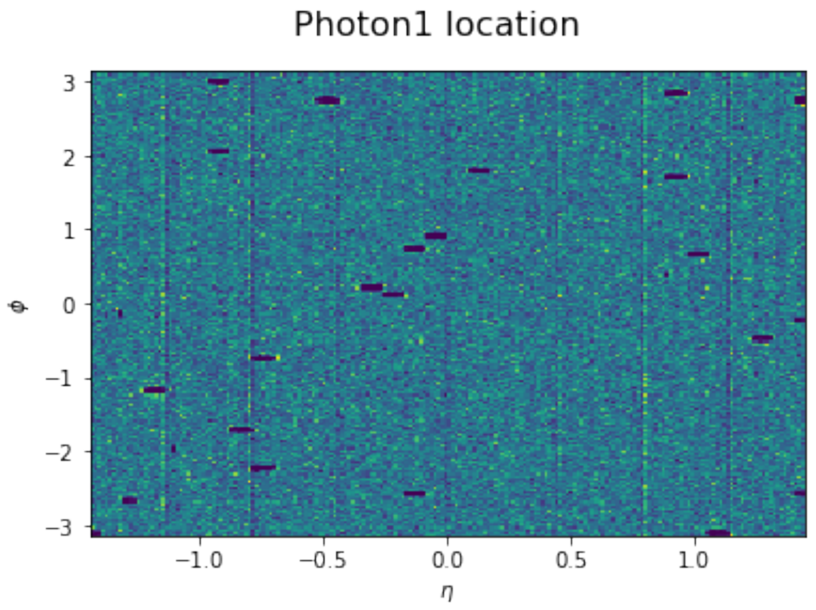
In [9]:

```
plt.hist2d(df['photon1'][('Photon1','eta')],df['photon1'][('Photon1','phi')],bins=200);
plt.suptitle('Photon1 location',fontsize=16)
plt.xlabel('$\eta$');
plt.ylabel('$\phi$');
```

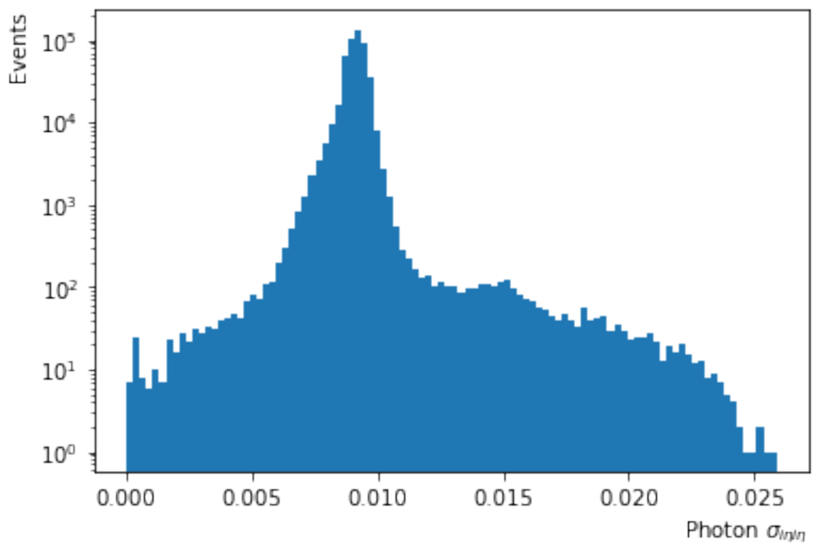


In [10]:

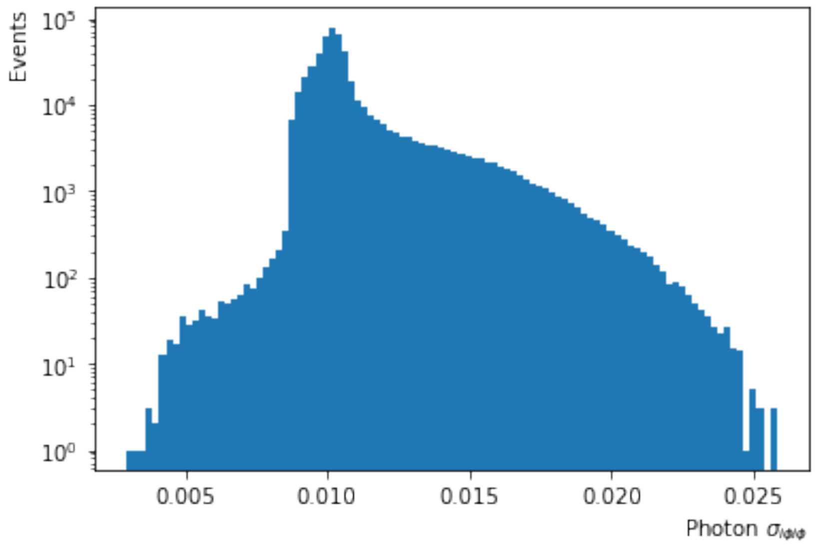
```
plt.hist2d(df['photon1'][('Photon1','scEta')],df['photon1'][('Photon1','scPhi')],bins=200);
plt.suptitle('Photon1 location',fontsize=16)
plt.xlabel('$\eta$');
plt.ylabel('$\phi$');
```



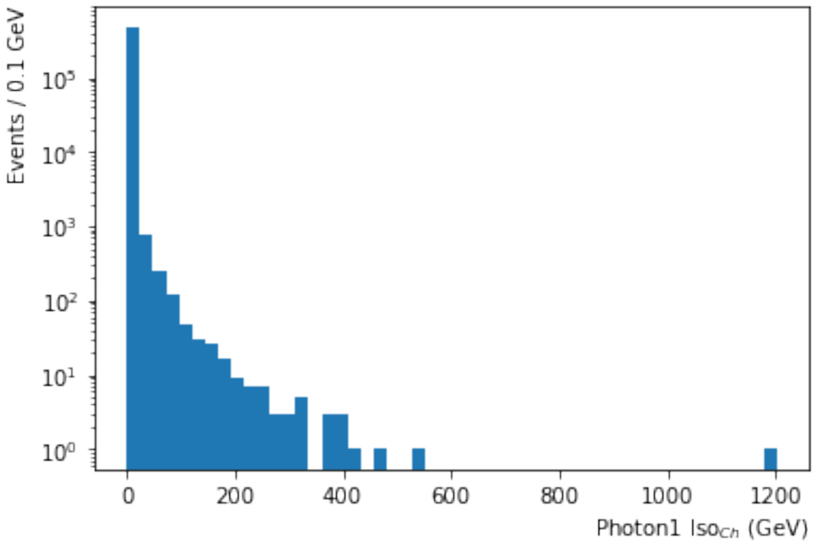
In [11]:
```python
df['photon1'][('Photon1','sigmaIetaIeta5x5')].plot.hist(bins=100,log=1);
plt.xlabel('Photon $\sigma_{i\eta i\eta}$', horizontalalignment='right', x=1.0);
plt.ylabel('Events', horizontalalignment='right', y=1.0);
```



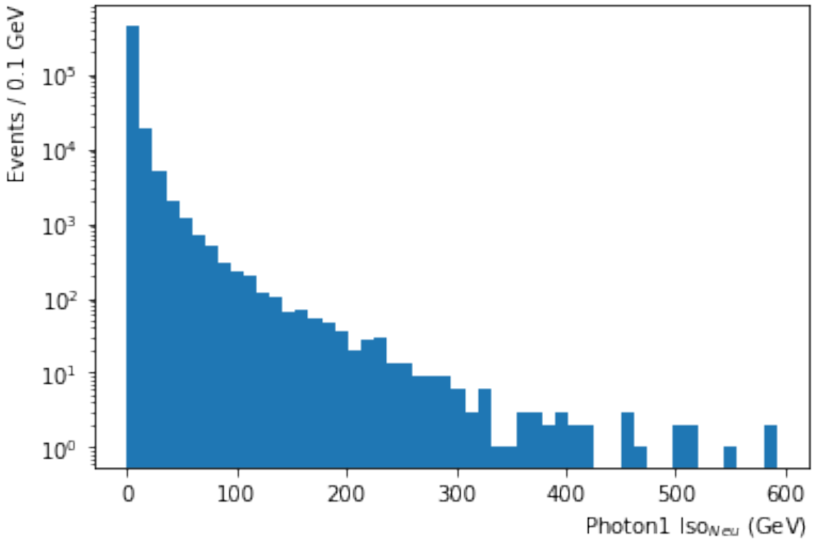
In [12]:
```python
df['photon1'][('Photon1','sigmaIphiIphi5x5')].plot.hist(bins=100,log=1);
plt.xlabel('Photon $\sigma_{i\phi i\phi}$', horizontalalignment='right', x=1.0);
plt.ylabel('Events', horizontalalignment='right', y=1.0);
```



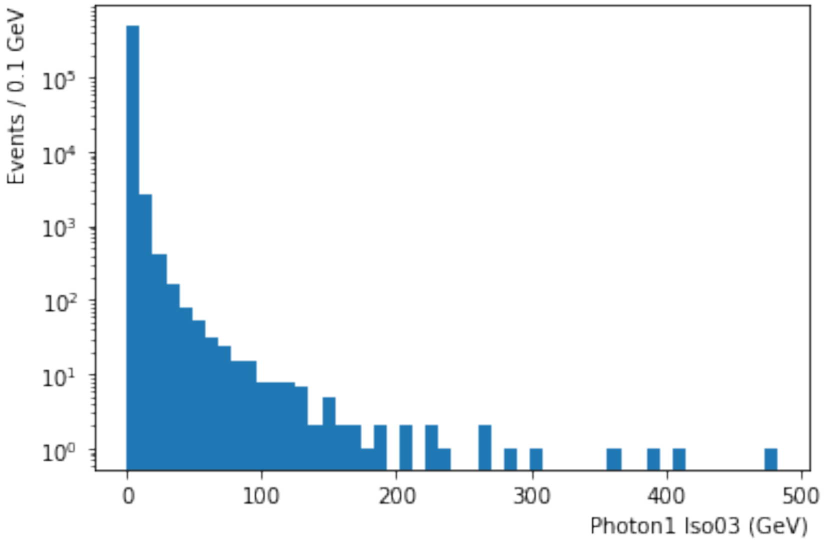
In [13]:
```
df['photon1'][('Photon1','chargedHadIso03')].plot.hist(bins=50,log=True);
plt.xlabel('Photon1 Iso$_{Ch}$ (GeV)', horizontalalignment='right', x=1.0);
plt.ylabel('Events / '+str(5/50)+' GeV', horizontalalignment='right', y=1.0);
```



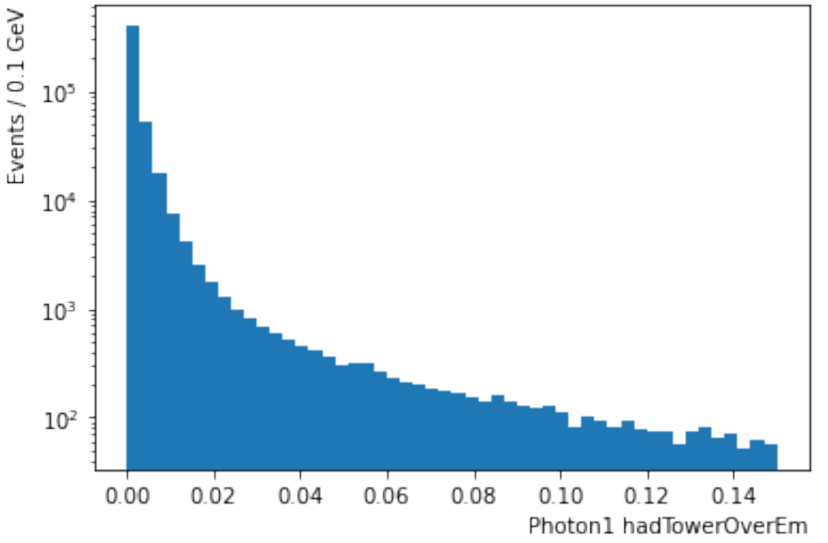
In [14]:
```
df['photon1'][('Photon1','neutralHadIso03')].plot.hist(bins=50,log=True);
plt.xlabel('Photon1 Iso$_{Neu}$ (GeV)', horizontalalignment='right', x=1.0);
plt.ylabel('Events / '+str(5/50)+' GeV', horizontalalignment='right', y=1.0);
```



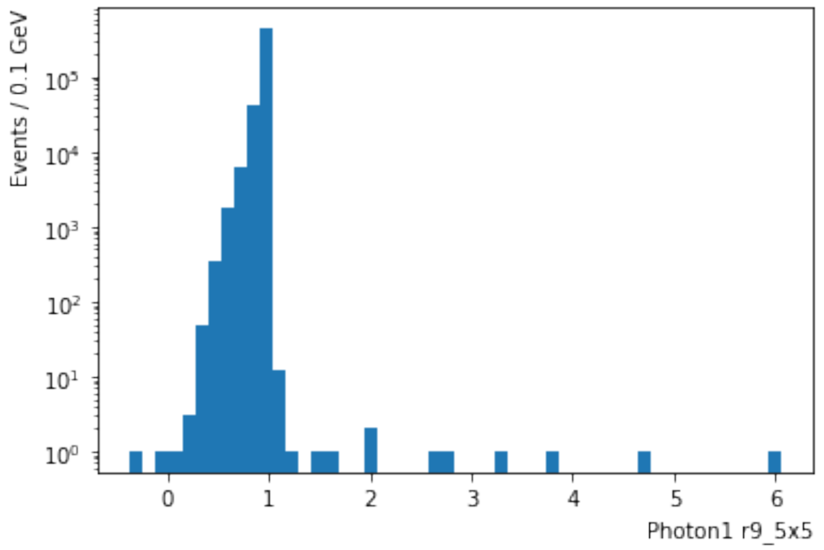
In [15]:
```
df['photon1'][('Photon1','photonIso03')].plot.hist(bins=50,log=True);
plt.xlabel('Photon1 Iso03 (GeV)', horizontalalignment='right', x=1.0);
plt.ylabel('Events / '+str(5/50)+' GeV', horizontalalignment='right', y=1.0);
```



In [16]:
```
df['photon1'][('Photon1','hadTowerOverEm')].plot.hist(bins=50,log=True);
plt.xlabel('Photon1 hadTowerOverEm', horizontalalignment='right', x=1.0);
plt.ylabel('Events / '+str(5/50)+' GeV', horizontalalignment='right', y=1.0);
```

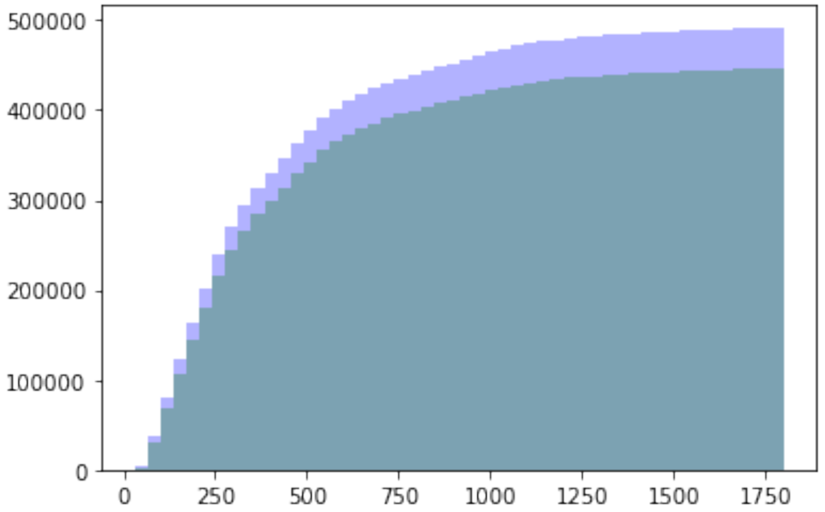


In [17]:
```
df['photon1'][('Photon1','r9_5x5')].plot.hist(bins=50,log=True);
plt.xlabel('Photon1 r9_5x5', horizontalalignment='right', x=1.0);
plt.ylabel('Events / '+str(5/50)+' GeV', horizontalalignment='right', y=1.0);
```

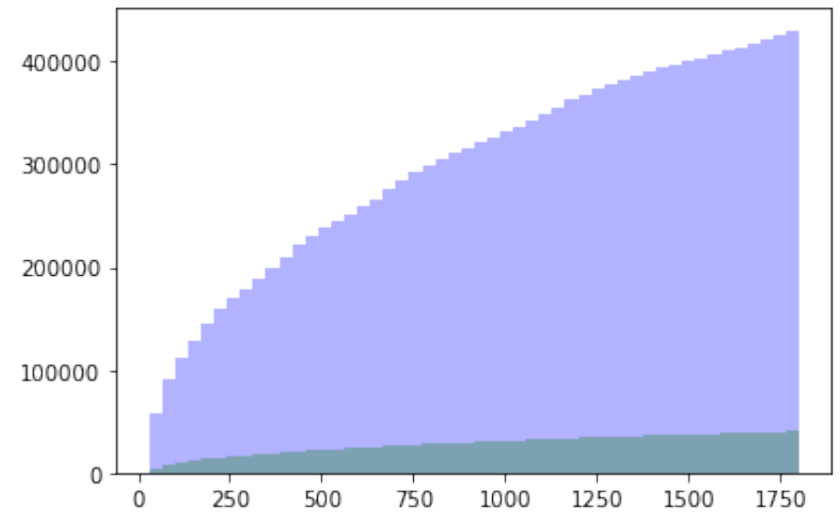


Few plot for efficiency calculation does not related to this project

In [18]:
```
n1,bins1,patches1 = plt.hist(df['photon1'][('Photon1','pt')],bins=50,alpha=0.3,color='blue',cumulative=1,density=0)
n2,bins1,patches1 = plt.hist(df['photon1_pashipt'][('Photon1','pt')],bins=50,alpha=0.3,color='green',cumulative=1,density=0)
```

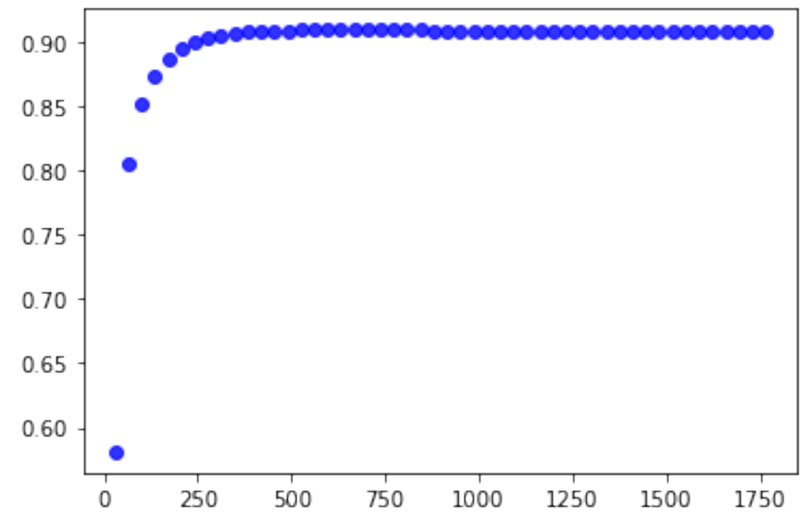


In [19]:
```
n3,bins2,patches1 = plt.hist(df['electron1'][('Photon1','pt')],bins=50,alpha=0.3,color='blue',cumulative=1,density=False)
n4,bins2,patches1 = plt.hist(df['electron1_paship t'][('Photon1','pt')],bins=50,alpha=0.3,color='green',cumulative=1,density=False)
```



In [20]:
```
plt.scatter(bins1[:-1],n2/n1,alpha=0.8,color='blue')
```

Out[20]: <matplotlib.collections.PathCollection at 0x7f9456095b50>



Now lets check corelation between the parameters we are going to use in as input for our DNN

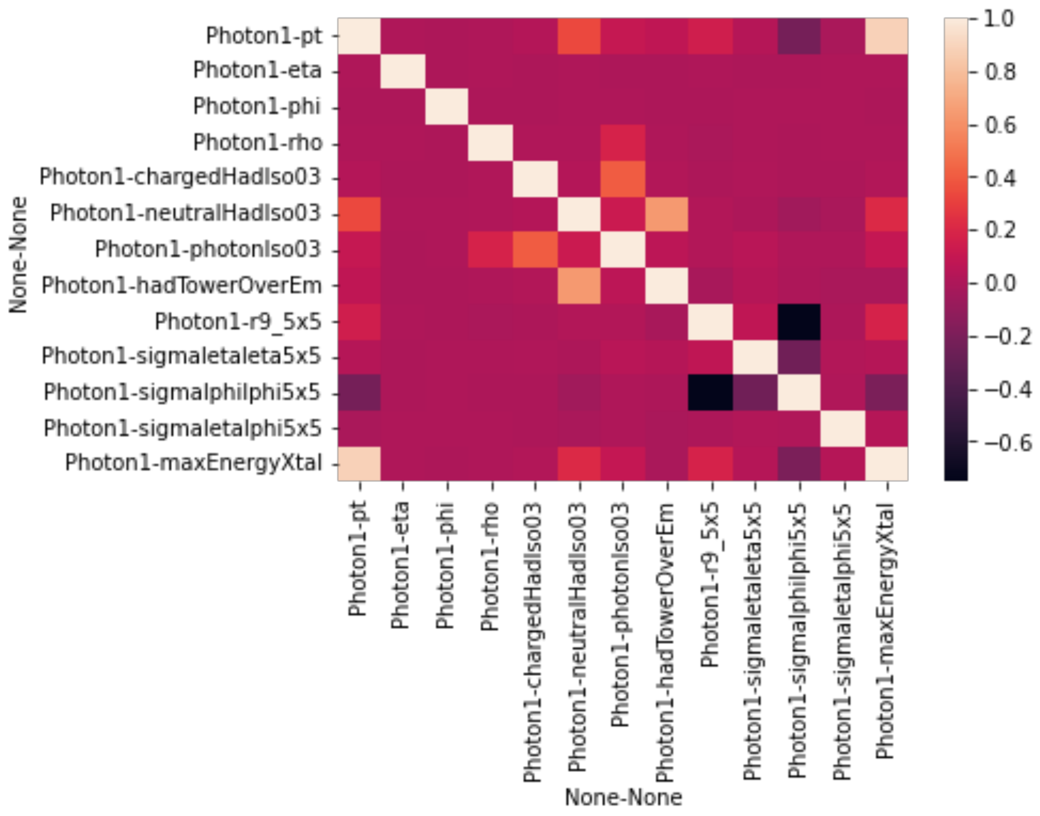
In [21]:
```
features1 = [('Photon1','pt'),('Photon1','eta'),('Photon1','phi'),('Photon1','rho'),('Photon1','chargedHadIso03'),('Photon1','neutralHadIso03'),('Photon1','photonIso03'),(
features2 = [('Photon2','pt'),('Photon2','eta'),('Photon2','phi'),('Photon2','rho'),('Photon2','chargedHadIso03'),('Photon2','neutralHadIso03'),('Photon2','photonIso03'),(
features = [('Photon1','pt'),('Photon1','eta'),('Photon1','phi'),('Photon1','rho'),('Photon1','chargedHadIso03'),('Photon1','neutralHadIso03'),('Photon1','photonIso03'),('
```

In [22]:
```
df['photon1'][('Photon1','iEta')].value_counts()
```

Out[22]:
```
0.0    491900
Name: (Photon1, iEta), dtype: int64
```

In [23]:
```
corr = df['photon1'][features].corr()
```

In [24]:
```
sns.heatmap(corr);
```



Adding new coulmn to extending data frame as "track" whose value is 0 if particle passes to CSEV (passElectronVeto) else 1.

In [25]:
```
def is_track1(row):
    if (row[('Photon1','passElectronVeto')] == 1):
        val = 0
    else:
        val = 1
    return val

def is_track2(row):
    if (row[('Photon2','passElectronVeto')] == 1):
        val = 0
    else:
        val = 1
    return val
df['photon1'][('Photon1','track')] = df['photon1'].apply(is_track1, axis=1)
df['electron1'][('Photon1','track')] = df['electron1'].apply(is_track1, axis=1)
df['photon2'][('Photon2','track')] = df['photon2'].apply(is_track2, axis=1)
df['electron2'][('Photon2','track')] = df['electron2'].apply(is_track2, axis=1)
```

In [26]:
```
# df['electron2'][('Photon2','track')].value_counts()
```

In [27]:
```
# df['photon2'][('Photon2','track')].value_counts()
```

In [28]:
```
df_all1 = pd.concat([df['photon1'], df['electron1']])
df_all2 = pd.concat([df['photon2'], df['electron2']])
```

In [29]:

```
# df_all1[('Photon1','passElectronVeto')]
```

In [30]:

```
# df_all1
```

In [31]:

```
X1 = df_all1[features1].values
Y1 = df_all1['isPhoton']
X2 = df_all2[features2].values
Y2 = df_all2['isPhoton']
X_track=np.concatenate((X1, X2), axis=0)
Y=np.concatenate((Y1, Y2), axis=0)
```

In [32]:

```
from sklearn.model_selection import train_test_split
X_track_train_val, X_track_test, Y_train_val, Y_test = train_test_split(X_track, Y, test_size=0.20, random_state=7)

from sklearn.preprocessing import StandardScaler
scaler_track = StandardScaler().fit(X_track_train_val)
X_track_train_val = scaler_track.transform(X_track_train_val)
X_track_test = scaler_track.transform(X_track_test)
```

In [33]:

```
print ("Number of total examples: " + str(X_track.shape[0]))
print ("Number of training examples: " + str(X_track_train_val.shape[0]))
print ("Number of testing examples: " + str(X_track_test.shape[0]))
print ("X_train_val shape: " + str(X_track_train_val.shape))
print ("Y_train_val shape: " + str(Y_train_val.shape))
print ("X_test shape: " + str(X_track_test.shape))
print ("Y_test shape: " + str(Y_test.shape))
```

```
Number of total examples: 1854806
Number of training examples: 1483844
Number of testing examples: 370962
X_train_val shape: (1483844, 14)
Y_train_val shape: (1483844,)
X_test shape: (370962, 14)
Y_test shape: (370962,)
```

NN Model with tracker information added for EB region

We are traing this model for 13 + 1(track as a parameter) = 14 for this model

In [34]:

```python
keras.backend.clear_session()
model_EB_track = Sequential()
model_EB_track.add(Dense(300, input_dim=14, activation='relu'))
model_EB_track.add(Dropout(.05))
model_EB_track.add(Dense(250, activation='relu'))
model_EB_track.add(Dropout(.05))
model_EB_track.add(Dense(200, activation='relu'))
model_EB_track.add(Dropout(.05))
model_EB_track.add(Dense(150, activation='relu'))
model_EB_track.add(Dropout(.05))
model_EB_track.add(Dense(100, activation='relu'))
model_EB_track.add(Dropout(.025))
model_EB_track.add(Dense(70, activation='relu'))
model_EB_track.add(Dropout(.01))
model_EB_track.add(Dense(50, activation='relu'))
model_EB_track.add(Dense(25, activation='relu'))
model_EB_track.add(Dense(1, activation='sigmoid'))

# compile the model
model_EB_track.compile(optimizer='nadam', loss='binary_crossentropy', metrics=['accuracy'])
# print the model summary
model_EB_track.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense (Dense)                (None, 300)               4500      
_________________________________________________________________
dropout (Dropout)            (None, 300)               0         
_________________________________________________________________
dense_1 (Dense)              (None, 250)               75250     
_________________________________________________________________
dropout_1 (Dropout)          (None, 250)               0         
_________________________________________________________________
dense_2 (Dense)              (None, 200)               50200     
_________________________________________________________________
dropout_2 (Dropout)          (None, 200)               0         
_________________________________________________________________
dense_3 (Dense)              (None, 150)               30150     
_________________________________________________________________
dropout_3 (Dropout)          (None, 150)               0         
_________________________________________________________________
dense_4 (Dense)              (None, 100)               15100     
_________________________________________________________________
dropout_4 (Dropout)          (None, 100)               0         
_________________________________________________________________
dense_5 (Dense)              (None, 70)                7070      
_________________________________________________________________
dropout_5 (Dropout)          (None, 70)                0         
_________________________________________________________________
dense_6 (Dense)              (None, 50)                3550      
_________________________________________________________________
dense_7 (Dense)              (None, 25)                1275      
_________________________________________________________________
dense_8 (Dense)              (None, 1)                 26        
=================================================================
Total params: 187,121
Trainable params: 187,121
```

```
Non-trainable params: 0
_________________________________________________________________

2022-04-19 20:46:24.453479: I tensorflow/core/platform/cpu_feature_guard.cc:142] This TensorFlow binary is optimized with oneAPI Deep Neural Network Library (oneDNN) to u
se the following CPU instructions in performance-critical operations:  SSE4.1 SSE4.2 AVX AVX2 FMA
To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.
```

In [35]:

```
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.2, patience=2, min_delta=0.0001, min_lr=1e-10, mode='auto')
checkpoint_cb = keras.callbacks.ModelCheckpoint("model_EB_track.h5", save_best_only=True)
early_stopping_cb = keras.callbacks.EarlyStopping(patience=4, restore_best_weights = True)
history=model_EB_track.fit(X_track_train_val, Y_train_val,\
        batch_size=256,\
        epochs=50,\
        validation_split=.20,\
        callbacks=[reduce_lr, checkpoint_cb, early_stopping_cb],\
        verbose=1, shuffle=True, initial_epoch=0
        )
```

```
Epoch 1/50

2022-04-19 20:46:24.672766: I tensorflow/compiler/mlir/mlir_graph_optimization_pass.cc:116] None of the MLIR optimization passes are enabled (registered 2)
2022-04-19 20:46:24.673480: I tensorflow/core/platform/profile_utils/cpu_utils.cc:112] CPU Frequency: 2099945000 Hz

4638/4638 [==============================] - 42s 9ms/step - loss: 0.1893 - accuracy: 0.9373 - val_loss: 0.1697 - val_accuracy: 0.9438
Epoch 2/50
4638/4638 [==============================] - 38s 8ms/step - loss: 0.1689 - accuracy: 0.9436 - val_loss: 0.1784 - val_accuracy: 0.9412
Epoch 3/50
4638/4638 [==============================] - 34s 7ms/step - loss: 0.1664 - accuracy: 0.9443 - val_loss: 0.1659 - val_accuracy: 0.9445
Epoch 4/50
4638/4638 [==============================] - 34s 7ms/step - loss: 0.1647 - accuracy: 0.9449 - val_loss: 0.1634 - val_accuracy: 0.9452
Epoch 5/50
4638/4638 [==============================] - 34s 7ms/step - loss: 0.1632 - accuracy: 0.9455 - val_loss: 0.1620 - val_accuracy: 0.9457
Epoch 6/50
4638/4638 [==============================] - 34s 7ms/step - loss: 0.1625 - accuracy: 0.9456 - val_loss: 0.1608 - val_accuracy: 0.9461
Epoch 7/50
4638/4638 [==============================] - 34s 7ms/step - loss: 0.1617 - accuracy: 0.9458 - val_loss: 0.1692 - val_accuracy: 0.9415
Epoch 8/50
4638/4638 [==============================] - 34s 7ms/step - loss: 0.1613 - accuracy: 0.9456 - val_loss: 0.1610 - val_accuracy: 0.9460
Epoch 9/50
4638/4638 [==============================] - 34s 7ms/step - loss: 0.1579 - accuracy: 0.9470 - val_loss: 0.1585 - val_accuracy: 0.9469
Epoch 10/50
4638/4638 [==============================] - 34s 7ms/step - loss: 0.1569 - accuracy: 0.9472 - val_loss: 0.1583 - val_accuracy: 0.9471
Epoch 11/50
4638/4638 [==============================] - 34s 7ms/step - loss: 0.1572 - accuracy: 0.9471 - val_loss: 0.1580 - val_accuracy: 0.9470
Epoch 12/50
4638/4638 [==============================] - 34s 7ms/step - loss: 0.1564 - accuracy: 0.9474 - val_loss: 0.1582 - val_accuracy: 0.9471
Epoch 13/50
4638/4638 [==============================] - 35s 8ms/step - loss: 0.1569 - accuracy: 0.9471 - val_loss: 0.1582 - val_accuracy: 0.9471
Epoch 14/50
4638/4638 [==============================] - 34s 7ms/step - loss: 0.1557 - accuracy: 0.9477 - val_loss: 0.1576 - val_accuracy: 0.9472
Epoch 15/50
4638/4638 [==============================] - 34s 7ms/step - loss: 0.1545 - accuracy: 0.9477 - val_loss: 0.1576 - val_accuracy: 0.9470
Epoch 16/50
4638/4638 [==============================] - 34s 7ms/step - loss: 0.1567 - accuracy: 0.9472 - val_loss: 0.1577 - val_accuracy: 0.9471
Epoch 17/50
4638/4638 [==============================] - 34s 7ms/step - loss: 0.1551 - accuracy: 0.9479 - val_loss: 0.1575 - val_accuracy: 0.9471
Epoch 18/50
```

```
4638/4638 [==============================] - 34s 7ms/step - loss: 0.1553 - accuracy: 0.9475 - val_loss: 0.1575 - val_accuracy: 0.9471
Epoch 19/50
4638/4638 [==============================] - 34s 7ms/step - loss: 0.1546 - accuracy: 0.9478 - val_loss: 0.1575 - val_accuracy: 0.9471
Epoch 20/50
4638/4638 [==============================] - 34s 7ms/step - loss: 0.1558 - accuracy: 0.9474 - val_loss: 0.1575 - val_accuracy: 0.9471
Epoch 21/50
4638/4638 [==============================] - 34s 7ms/step - loss: 0.1554 - accuracy: 0.9477 - val_loss: 0.1575 - val_accuracy: 0.9471
```

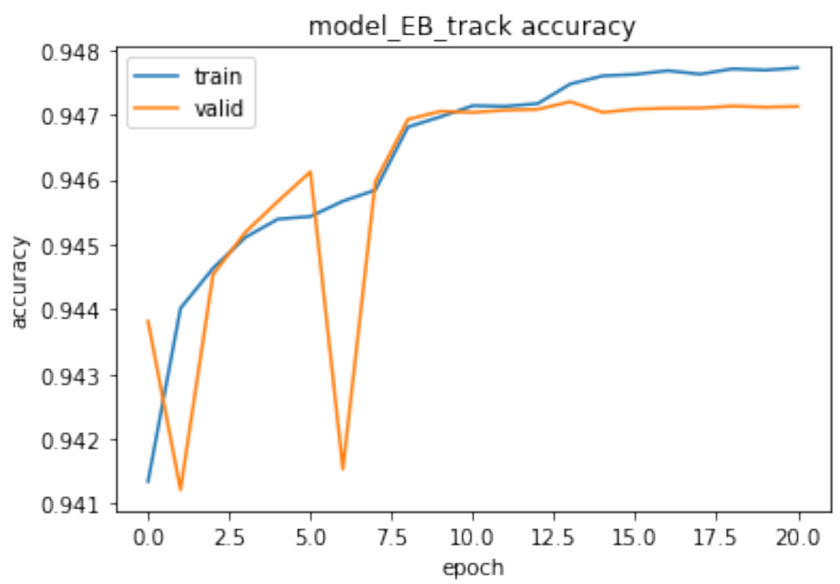
In [36]:
```
model_EB_track = keras.models.load_model("model_EB_track.h5")
```

In [37]:
```
model_EB_track.evaluate(X_track_test, Y_test)
```

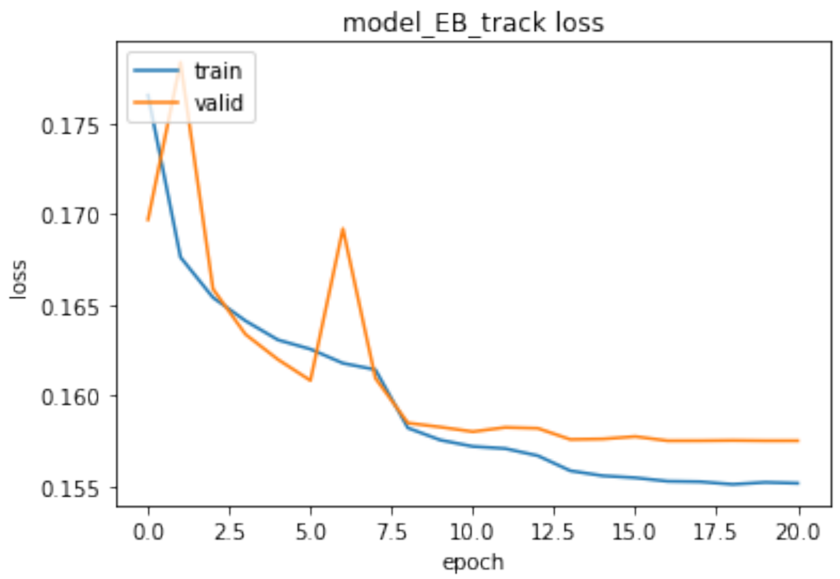
```
11593/11593 [==============================] - 13s 1ms/step - loss: 0.1580 - accuracy: 0.9469
```

Out[37]:
```
[0.1579597294330597, 0.9468652009963989]
```

In [38]:
```
# summarize history for accuracy
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model_EB_track accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'valid'], loc='upper left')
plt.show()
```



In [39]:
```
# summarize history for loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model_EB_track loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'valid'], loc='upper left')
plt.show()
```



In [40]:
```
y_track_pred=model_EB_track.predict(X_track_test)
```

In [41]:
```
from sklearn.metrics import confusion_matrix
confusion_matrix(Y_test, y_track_pred.round())
```

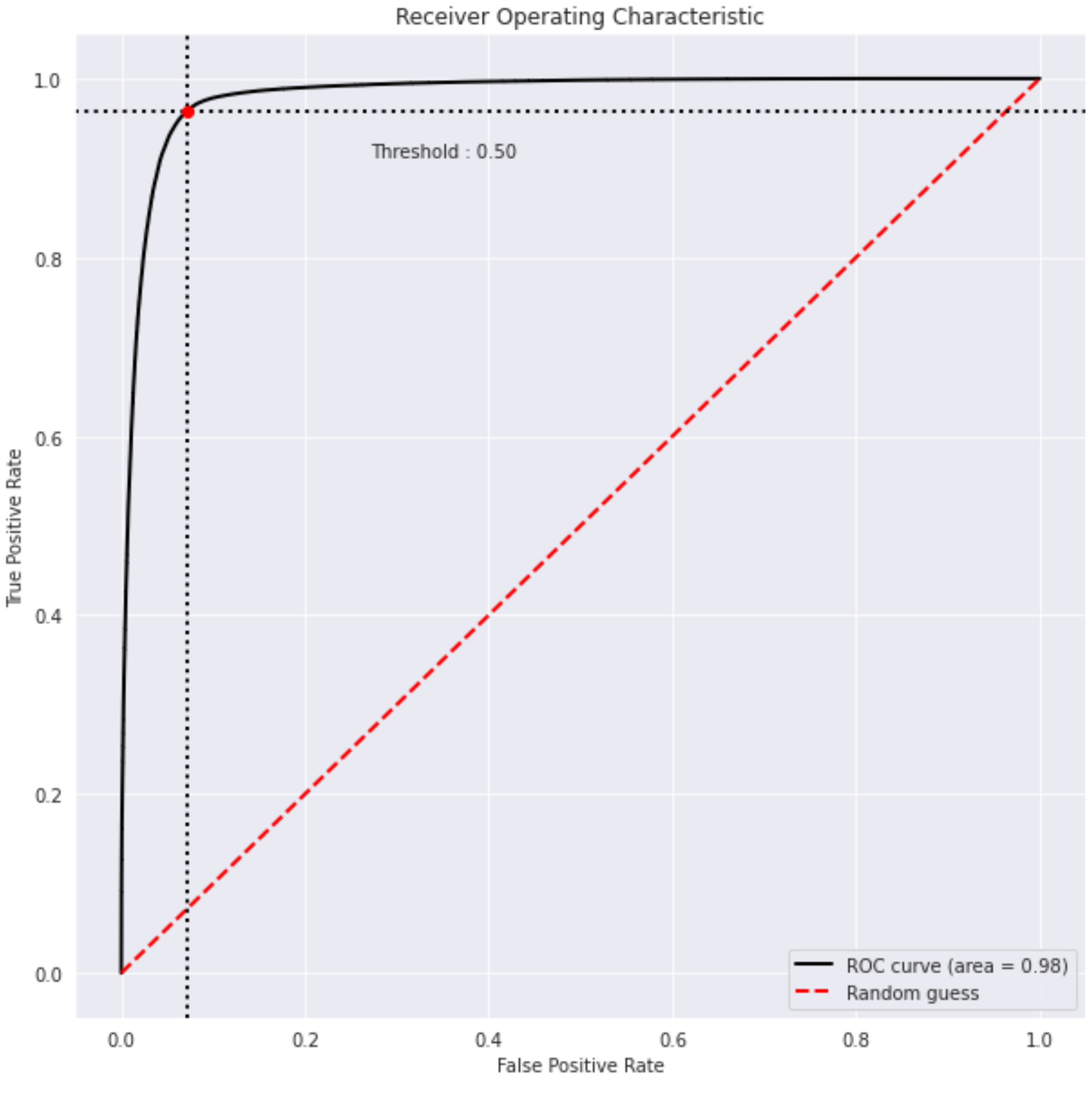
Out[41]:
```
array([[165612,  12696],
       [  7015, 185639]])
```

In [42]:
```
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt

from plot_metric.functions import BinaryClassification


# Visualisation with plot_metric
bc = BinaryClassification(Y_test, y_track_pred, labels=["Class 1", "Class 2"])

# Figures
plt.figure(figsize=(10,10))
bc.plot_roc_curve()
plt.show()
```



Removing tracking information from input data

In [43]:
```
X_notrack_train_val = X_track_train_val[:,0:13]
X_notrack_test = X_track_test[:,0:13]
```

NN Model without tracker information for EB region

We are only training with 13 parameter for this model

In [44]:
```
keras.backend.clear_session()
model_EB_notrack = Sequential()
model_EB_notrack.add(Dense(300, input_dim=13, activation='relu'))
model_EB_notrack.add(Dropout(.05))
model_EB_notrack.add(Dense(250, activation='relu'))
model_EB_notrack.add(Dropout(.05))
model_EB_notrack.add(Dense(200, activation='relu'))
model_EB_notrack.add(Dropout(.05))
model_EB_notrack.add(Dense(150, activation='relu'))
model_EB_notrack.add(Dropout(.05))
model_EB_notrack.add(Dense(100, activation='relu'))
model_EB_notrack.add(Dropout(.025))
model_EB_notrack.add(Dense(70, activation='relu'))
model_EB_notrack.add(Dropout(.01))
model_EB_notrack.add(Dense(50, activation='relu'))
model_EB_notrack.add(Dense(25, activation='relu'))
model_EB_notrack.add(Dense(1, activation='sigmoid'))

# compile the model
model_EB_notrack.compile(optimizer='nadam', loss='binary_crossentropy', metrics=['accuracy'])
# print the model summary
model_EB_notrack.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 300)               4200
_________________________________________________________________
dropout (Dropout)            (None, 300)               0
_________________________________________________________________
dense_1 (Dense)              (None, 250)               75250
_________________________________________________________________
dropout_1 (Dropout)          (None, 250)               0
_________________________________________________________________
dense_2 (Dense)              (None, 200)               50200
_________________________________________________________________
dropout_2 (Dropout)          (None, 200)               0
_________________________________________________________________
dense_3 (Dense)              (None, 150)               30150
_________________________________________________________________
dropout_3 (Dropout)          (None, 150)               0
_________________________________________________________________
dense_4 (Dense)              (None, 100)               15100
_________________________________________________________________
dropout_4 (Dropout)          (None, 100)               0
_________________________________________________________________
dense_5 (Dense)              (None, 70)                7070
_________________________________________________________________
dropout_5 (Dropout)          (None, 70)                0
_________________________________________________________________
```

```
dense_6 (Dense)              (None, 50)                3550
_________________________________________________________________
dense_7 (Dense)              (None, 25)                1275
_________________________________________________________________
dense_8 (Dense)              (None, 1)                 26
=================================================================
Total params: 186,821
Trainable params: 186,821
Non-trainable params: 0
_________________________________________________________________
```

In [45]:
```
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.2, patience=2, min_delta=0.0001, min_lr=1e-10, mode='auto')
checkpoint_cb = keras.callbacks.ModelCheckpoint("model_EB_notrack.h5", save_best_only=True)
early_stopping_cb = keras.callbacks.EarlyStopping(patience=4, restore_best_weights = True)
history=model_EB_notrack.fit(X_notrack_train_val, Y_train_val,\
        batch_size=256,\
        epochs=50,\
        validation_split=.20,\
        callbacks=[reduce_lr, checkpoint_cb, early_stopping_cb],\
        verbose=1, shuffle=True, initial_epoch=0
        )
```

```
Epoch 1/50
4638/4638 [==============================] - 36s 7ms/step - loss: 0.5141 - accuracy: 0.7435 - val_loss: 0.5082 - val_accuracy: 0.7485
Epoch 2/50
4638/4638 [==============================] - 34s 7ms/step - loss: 0.4799 - accuracy: 0.7654 - val_loss: 0.4802 - val_accuracy: 0.7655
Epoch 3/50
4638/4638 [==============================] - 35s 7ms/step - loss: 0.4753 - accuracy: 0.7678 - val_loss: 0.5036 - val_accuracy: 0.7657
Epoch 4/50
4638/4638 [==============================] - 34s 7ms/step - loss: 0.4724 - accuracy: 0.7694 - val_loss: 0.4717 - val_accuracy: 0.7691
Epoch 5/50
4638/4638 [==============================] - 35s 7ms/step - loss: 0.4699 - accuracy: 0.7708 - val_loss: 0.4669 - val_accuracy: 0.7718
Epoch 6/50
4638/4638 [==============================] - 40s 9ms/step - loss: 0.4701 - accuracy: 0.7709 - val_loss: 0.4678 - val_accuracy: 0.7714
Epoch 7/50
4638/4638 [==============================] - 41s 9ms/step - loss: 0.4674 - accuracy: 0.7725 - val_loss: 0.4693 - val_accuracy: 0.7703
Epoch 8/50
4638/4638 [==============================] - 41s 9ms/step - loss: 0.4633 - accuracy: 0.7742 - val_loss: 0.4622 - val_accuracy: 0.7744
Epoch 9/50
4638/4638 [==============================] - 41s 9ms/step - loss: 0.4618 - accuracy: 0.7746 - val_loss: 0.4624 - val_accuracy: 0.7743
Epoch 10/50
4638/4638 [==============================] - 41s 9ms/step - loss: 0.4609 - accuracy: 0.7755 - val_loss: 0.4614 - val_accuracy: 0.7750
Epoch 11/50
4638/4638 [==============================] - 41s 9ms/step - loss: 0.4612 - accuracy: 0.7755 - val_loss: 0.4610 - val_accuracy: 0.7754
Epoch 12/50
4638/4638 [==============================] - 41s 9ms/step - loss: 0.4595 - accuracy: 0.7761 - val_loss: 0.4613 - val_accuracy: 0.7752
Epoch 13/50
4638/4638 [==============================] - 41s 9ms/step - loss: 0.4592 - accuracy: 0.7765 - val_loss: 0.4606 - val_accuracy: 0.7751
Epoch 14/50
4638/4638 [==============================] - 41s 9ms/step - loss: 0.4601 - accuracy: 0.7763 - val_loss: 0.4611 - val_accuracy: 0.7753
Epoch 15/50
4638/4638 [==============================] - 41s 9ms/step - loss: 0.4587 - accuracy: 0.7765 - val_loss: 0.4610 - val_accuracy: 0.7754
Epoch 16/50
4638/4638 [==============================] - 41s 9ms/step - loss: 0.4574 - accuracy: 0.7775 - val_loss: 0.4600 - val_accuracy: 0.7758
Epoch 17/50
4638/4638 [==============================] - 41s 9ms/step - loss: 0.4570 - accuracy: 0.7775 - val_loss: 0.4602 - val_accuracy: 0.7755
Epoch 18/50
```

```
4638/4638 [==============================] - 41s 9ms/step - loss: 0.4579 - accuracy: 0.7775 - val_loss: 0.4600 - val_accuracy: 0.7759
Epoch 19/50
4638/4638 [==============================] - 41s 9ms/step - loss: 0.4573 - accuracy: 0.7773 - val_loss: 0.4597 - val_accuracy: 0.7757
Epoch 20/50
4638/4638 [==============================] - 41s 9ms/step - loss: 0.4566 - accuracy: 0.7781 - val_loss: 0.4598 - val_accuracy: 0.7757
Epoch 21/50
4638/4638 [==============================] - 41s 9ms/step - loss: 0.4561 - accuracy: 0.7781 - val_loss: 0.4598 - val_accuracy: 0.7758
Epoch 22/50
4638/4638 [==============================] - 41s 9ms/step - loss: 0.4566 - accuracy: 0.7776 - val_loss: 0.4598 - val_accuracy: 0.7758
Epoch 23/50
4638/4638 [==============================] - 41s 9ms/step - loss: 0.4566 - accuracy: 0.7773 - val_loss: 0.4598 - val_accuracy: 0.7757
```

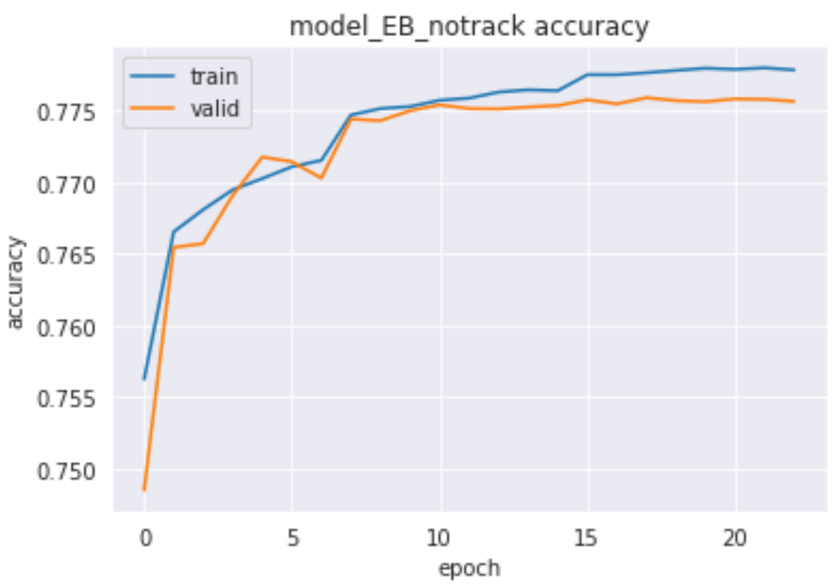
In [46]:
```
model_EB_notrack = keras.models.load_model("model_EB_notrack.h5")
```

In [47]:
```
model_EB_notrack.evaluate(X_notrack_test, Y_test)
```

```
11593/11593 [==============================] - 14s 1ms/step - loss: 0.4610 - accuracy: 0.7745
```

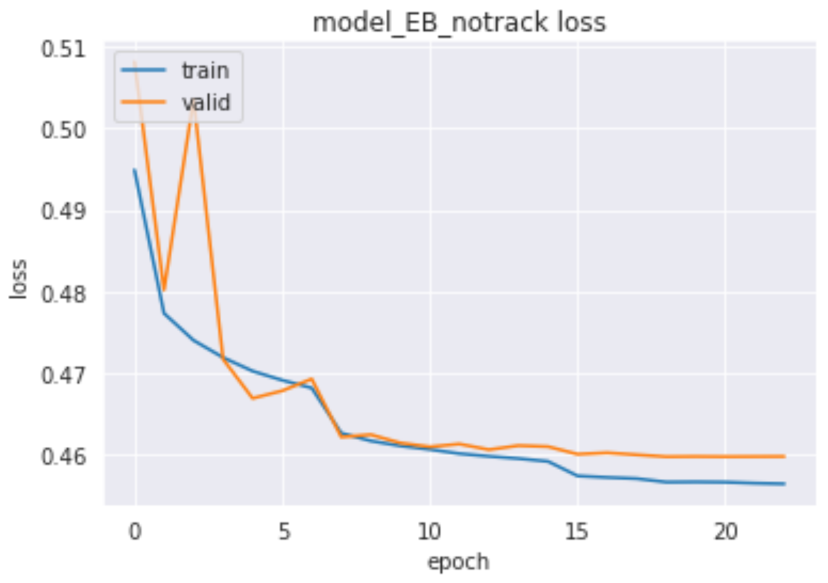
Out[47]:
```
[0.4610247015953064, 0.7744593620300293]
```

In [48]:
```
# summarize history for accuracy
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model_EB_notrack accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'valid'], loc='upper left')
plt.show()
```



In [49]:
```
# summarize history for loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model_EB_notrack loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'valid'], loc='upper left')

plt.show()
```



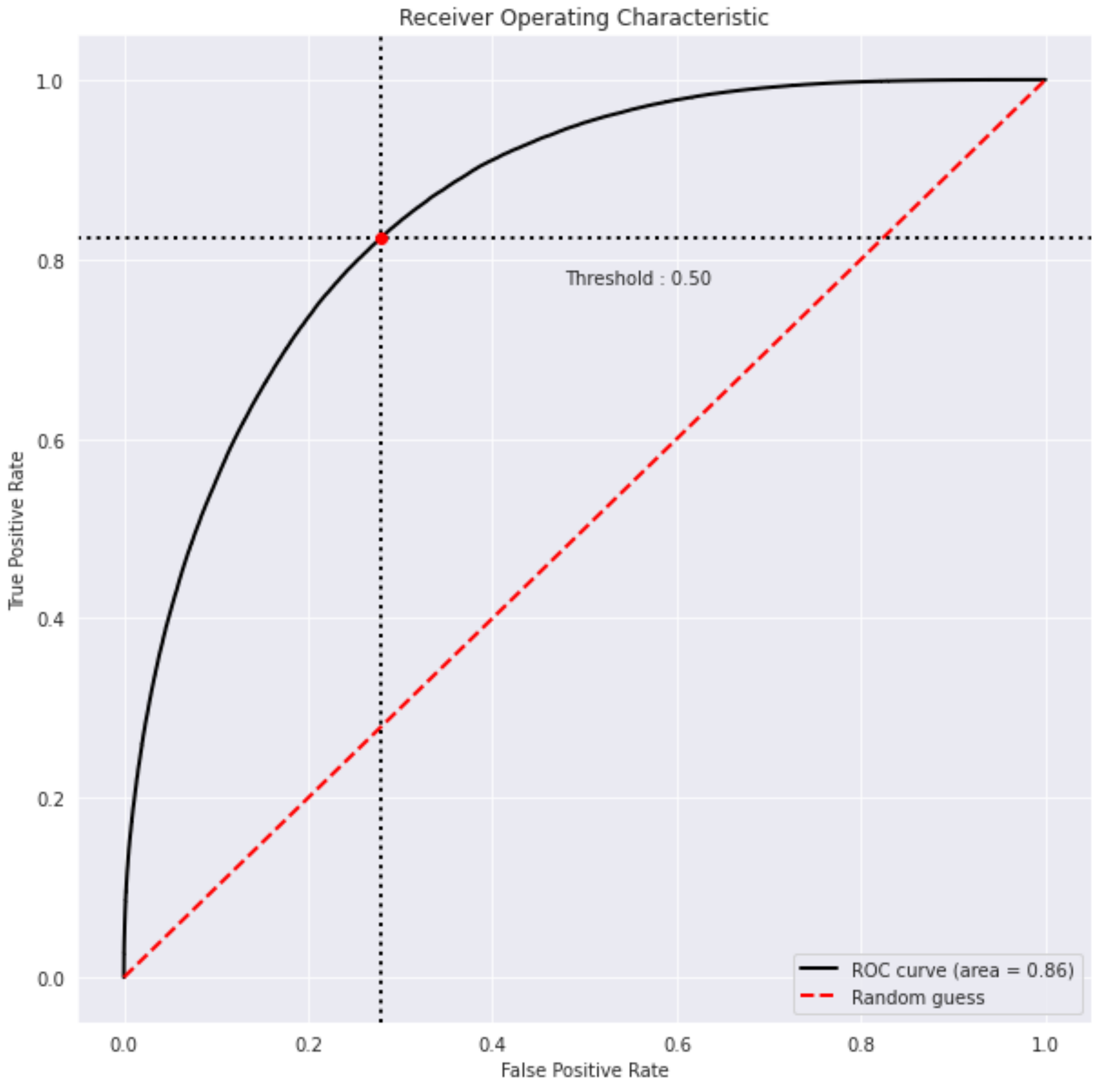
In [50]:
```
y_notrack_pred=model_EB_notrack.predict(X_notrack_test)
```

In [51]:
```
confusion_matrix(Y_test, y_notrack_pred.round())
```

Out[51]:
```
array([[128573,  49735],
       [ 33932, 158722]])
```

In [52]:
```
# Visualisation with plot_metric
bc = BinaryClassification(Y_test, y_notrack_pred, labels=["Class 1", "Class 2"])

# Figures
plt.figure(figsize=(10,10))
bc.plot_roc_curve()
plt.show()
```



In [ ]:

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