# Remove_Drift+Class_Reweighing+Bi-LSTM

April 23, 2020

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[1]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
import math
import tensorflow.keras.layers as layers
from tensorflow.keras import Model
from sklearn.metrics import f1_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from tensorflow.keras import callbacks
import scipy.stats as stats
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import SMOTE
from sklearn.utils import class_weight
from sklearn.metrics import confusion_matrix
```

```
Using TensorFlow backend.
```

# 1 Reading the CSV files

[3]:
```
train = pd.read_csv("../input/datawithoutdrift/train_clean.
 ↪csv",index_col=['time'])
test = pd.read_csv("../input/datawithoutdrift/test_clean.
 ↪csv",index_col=['time'])
submission = pd.read_csv("../input/liverpool-ion-switching/sample_submission.
 ↪csv", dtype=dict(time=str))
```

[4]:
```
len(train), len(test)
```

[4]:
```
(5000000, 2000000)
```

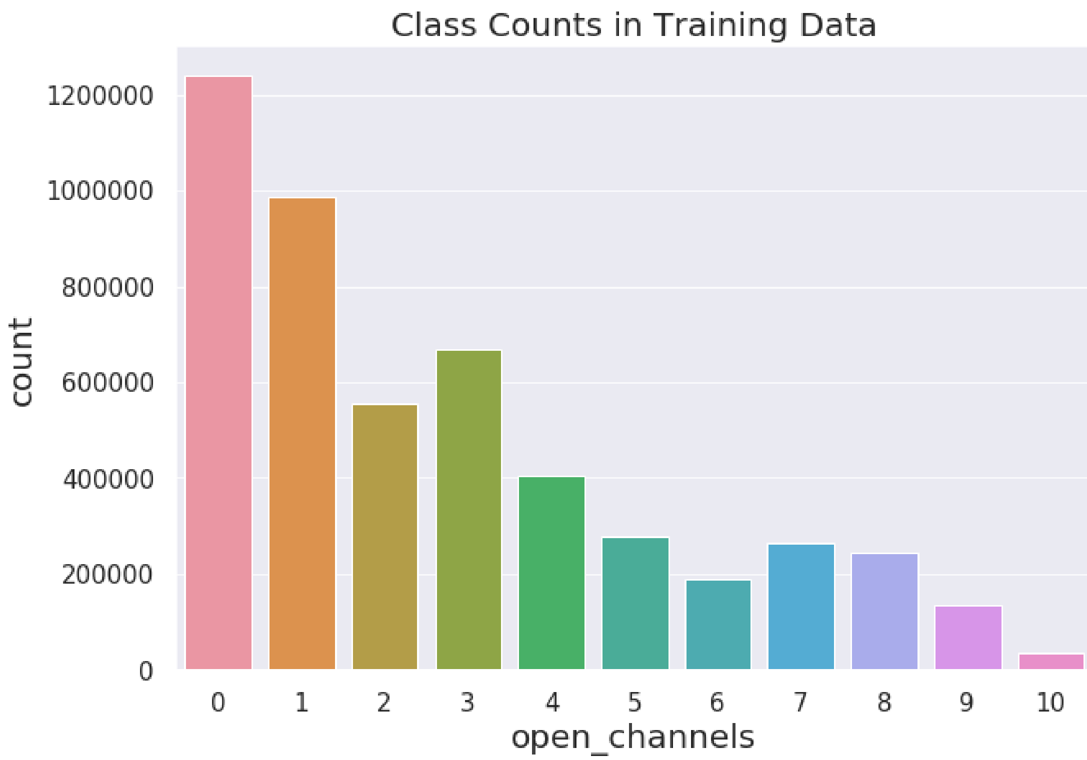
# 2 Plot settings

[5]:
```
plt.rcParams['axes.labelsize'] = 20
plt.rcParams['xtick.labelsize'] = 15
plt.rcParams['ytick.labelsize'] = 15
plt.rcParams['legend.fontsize'] = 23
plt.rcParams['figure.titlesize'] = 26
plt.rcParams['xtick.major.size'] = 10
plt.rcParams['xtick.major.width'] = 1
plt.rcParams['ytick.major.size'] = 10
plt.rcParams['ytick.major.width'] = 1
plt.rcParams['xtick.minor.width'] = 1
plt.rcParams['ytick.minor.size'] = 5
plt.rcParams['ytick.minor.width'] = 1
plt.rcParams['xtick.minor.size'] = 5
sns.set_style('darkgrid')
```

# 3 Graphs

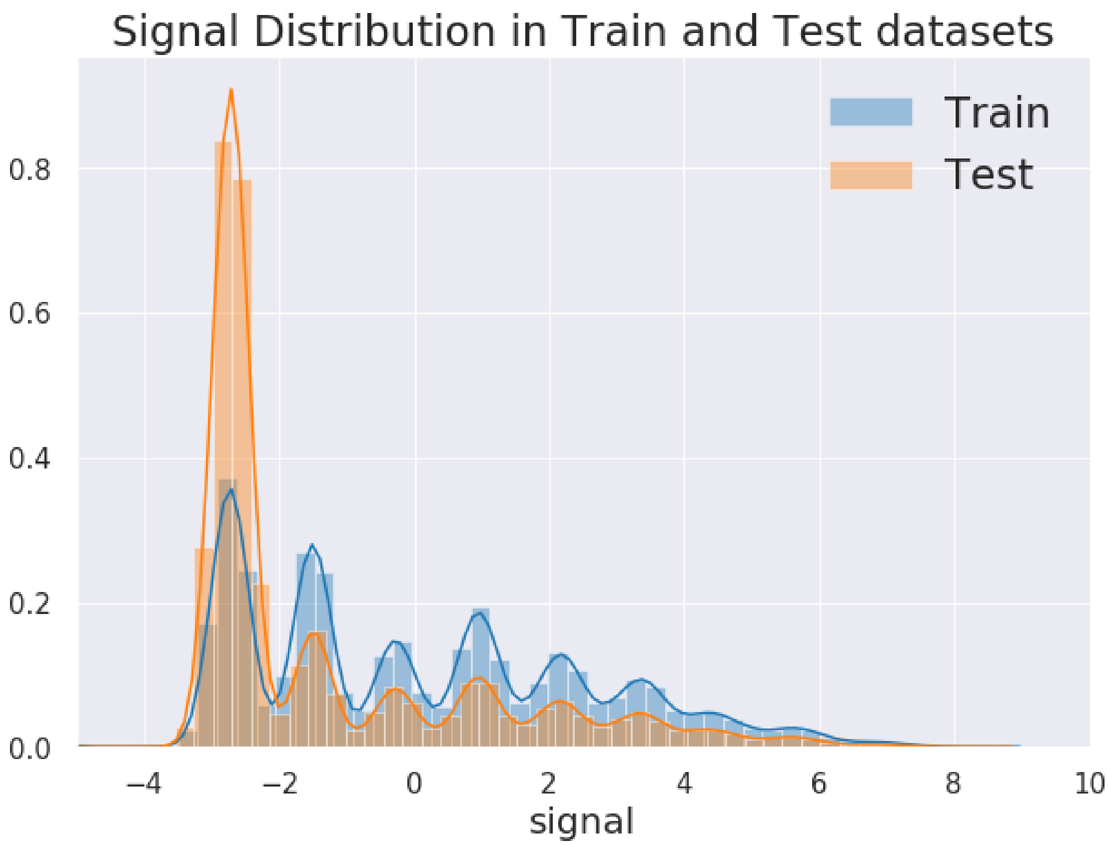
[6]:
```
plt.figure(figsize=(10,7))
sns.countplot(train.open_channels)
plt.title('Class Counts in Training Data',size=20)
```

[6]:
```
Text(0.5, 1.0, 'Class Counts in Training Data')
```




[7]:
```
plt.figure(figsize=(10,7))
sns.distplot(train.signal)
sns.distplot(test.signal)
plt.xlim([-5,10])
plt.title('Signal Distribution in Train and Test datasets',size=23)
plt.legend(['Train','Test'],frameon=False)
```

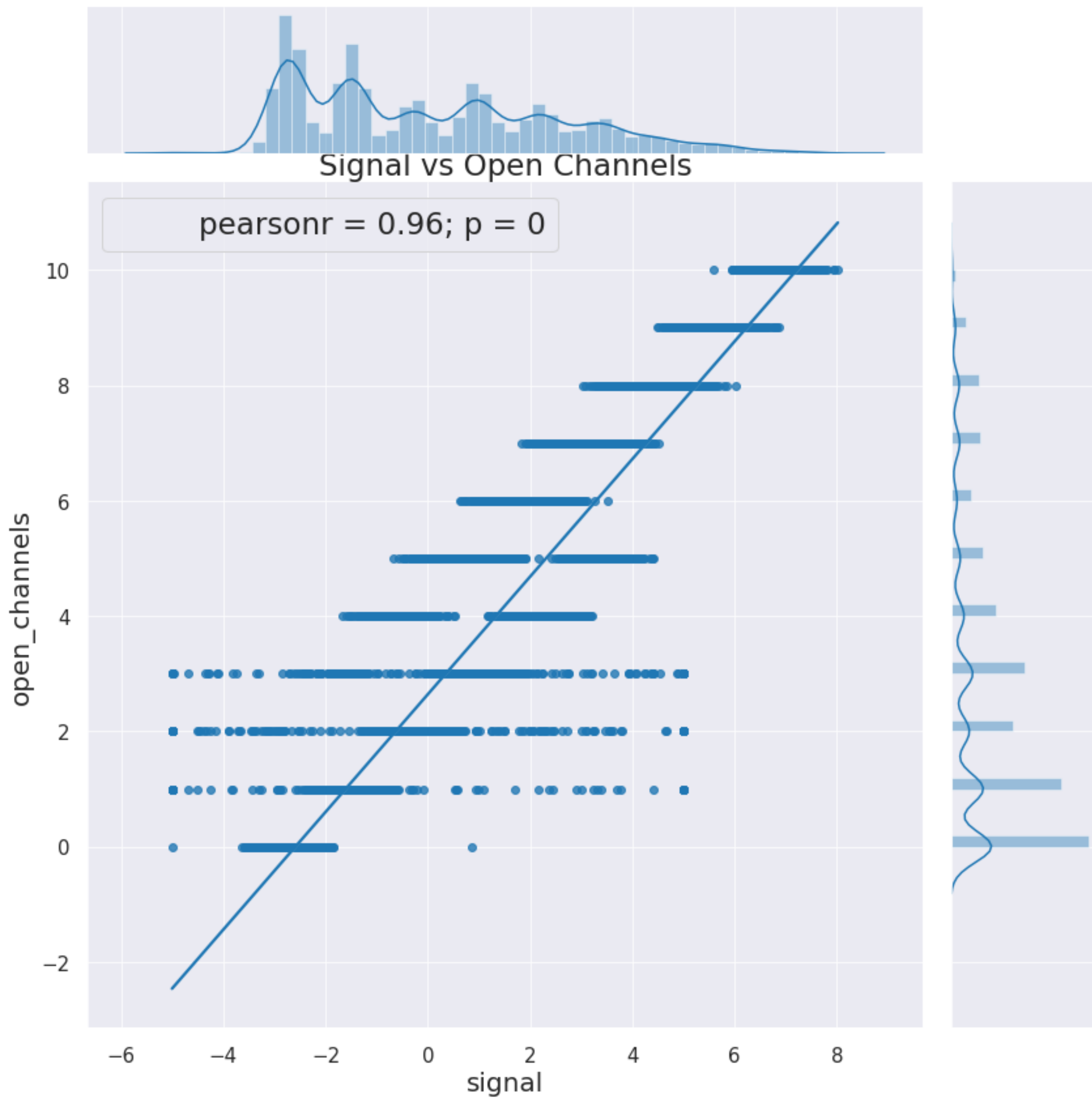
[7]:
```
<matplotlib.legend.Legend at 0x7fe12e275cc0>
```




[8]:
```
g=sns.jointplot(x='signal', y='open_channels' ,data=train[::100], height=12,␣
 ↪kind='reg')
g.annotate(stats.pearsonr)
plt.title('Signal vs Open Channels',size=23)
```

```
/opt/conda/lib/python3.6/site-packages/seaborn/axisgrid.py:1848: UserWarning:
JointGrid annotation is deprecated and will be removed in a future release.
  warnings.warn(UserWarning(msg))
```

[8]:
```
Text(0.5, 1.0, 'Signal vs Open Channels')
```



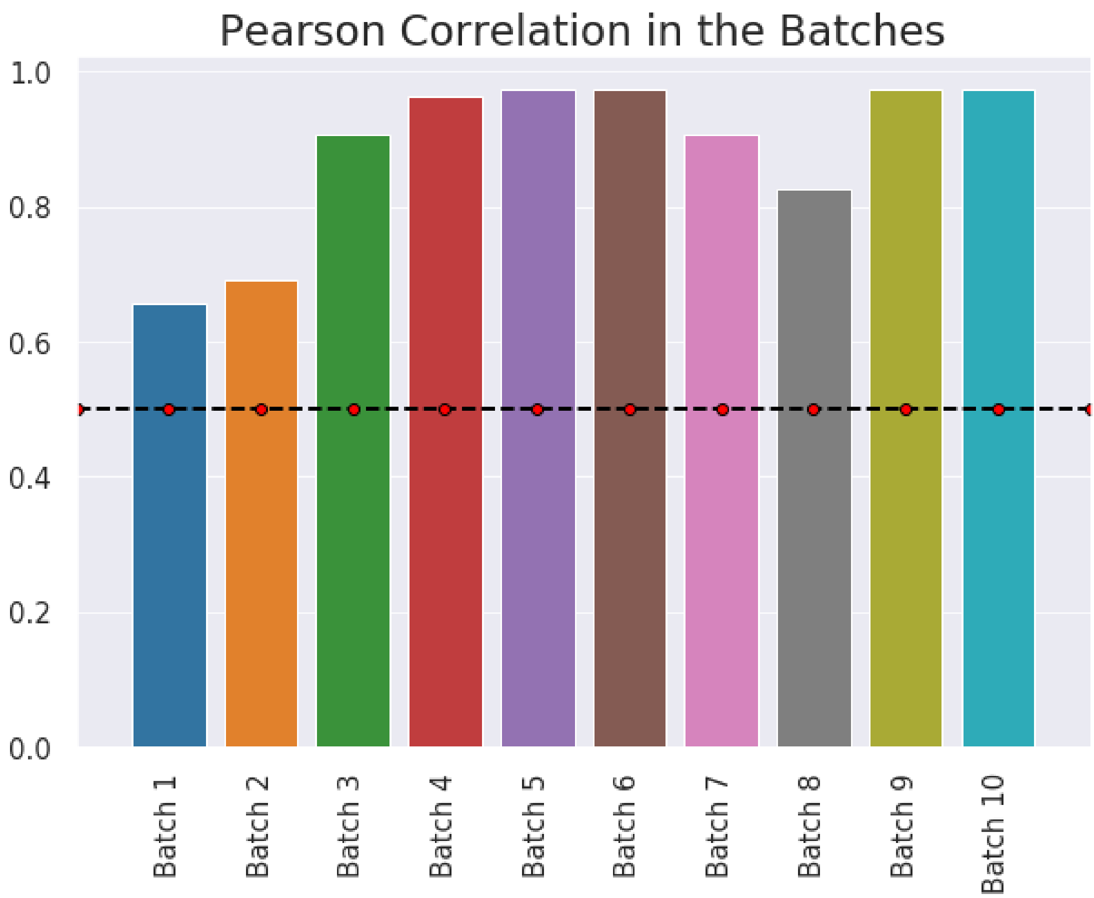

```
[9]: def BATCH_CORRELATION(df):
         return stats.pearsonr(df.values[:,0], df.values[:,1])[0]
```

```
[10]: STEP_SIZE=500000
      sp=np.arange(0, len(train),STEP_SIZE)
      correlation=[BATCH_CORRELATION(train.iloc[s:(s+STEP_SIZE)]) for s in sp]
      batches=['Batch {}'.format(i) for i in range(1,11)]
      batch_correlations=dict(zip(batches,correlation))
```

```
[11]: plt.figure(figsize=(10,7))
      sns.barplot(data=pd.DataFrame(batch_correlations, index=range(0,10)))
      plt.xticks(rotation=90)
      plt.title('Pearson Correlation in the Batches',size=23)
```

```
xx=np.arange(-1,11)
yy=xx*0 + 0.5
plt.plot(xx,yy, lw=2, ls='--', color='k', marker='o', markerfacecolor='r')
plt.xlim(-1,10)
```

[11]: (-1, 10)




## 4 Creating Weightes for the Classes

[13]:
```
def create_class_weight(labels_dict,mu=0.15):
    total = np.sum(list(labels_dict.values()))
    keys = list(labels_dict.keys())
    class_weight = dict()
    for key in keys:
        score = math.log(mu*total/float(labels_dict[key]))
        class_weight[key] = score if score > 1.0 else 1.0
    return class_weight
```

[14]:
```
class_weight=create_class_weight(dict(train.open_channels.value_counts()))
```

[15]:
```
def generate_sample_weights(training_data, class_weight_dictionary):
    sample_weights = [class_weight_dictionary[key] for key in training_data.
↪ravel()]
    return np.asarray(sample_weights)
```

# 5 Reshaping and Splitting the data

[24]:
```
sm = SMOTE(random_state=1, sampling_strategy='minority')
X_res, y_res = sm.fit_resample(train.signal.values.reshape(-1,1), train.
↪open_channels.values.ravel())
```

[25]:
```
X_res.shape ,y_res.shape
```

[25]:
```
((6204419, 1), (6204419,))
```

[26]:
```
X_res=X_res[419:]
y_res=y_res[419:]
```

[27]:
```
X_res.shape ,y_res.shape
```

[27]:
```
((6204000, 1), (6204000,))
```

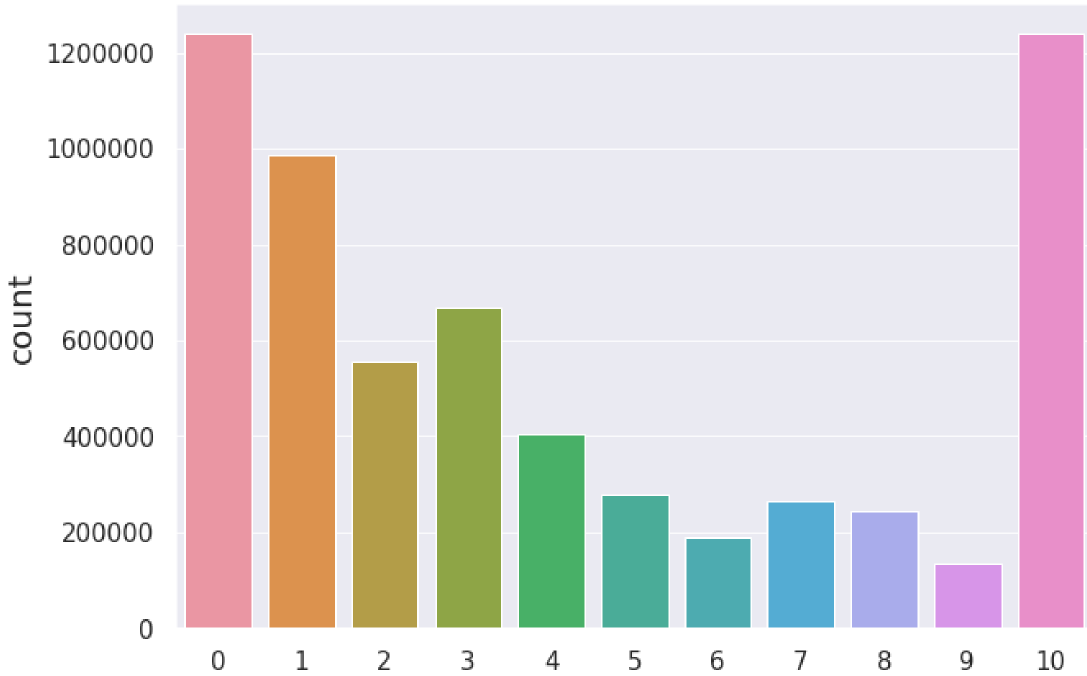
[28]:
```
seq_len = 1000

X_res = X_res.reshape(-1, seq_len, 1)
y_res = y_res.reshape(-1, seq_len, 1)
```

[29]:
```
#seq_len = 1000
#X_res = train.signal.values.reshape(-1, seq_len, 1)
#y_res = train.open_channels.values.reshape(-1, seq_len, 1)
```

[30]:
```
plt.figure(figsize=(10,7))
sns.countplot(y_res.reshape(-1))
```

[30]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe12de70748>
```




[31]:
```
X_train, X_valid, y_train, y_valid = train_test_split(X_res, y_res, test_size=0.
↪2)
X_test= test.signal.values.reshape(-1, seq_len, 1)
```

# 6 Creating a Bi-LSTM Model

[32]:
```
X_train.shape
```

[32]: (4963, 1000, 1)

[34]:
```
n_units=256
batch=128
n_classes=len(train.open_channels.unique())
inputs = layers.Input(shape=(seq_len, X_train.shape[2]))
outputs = layers.Dense(n_units, activation='linear')(inputs)
outputs= layers.LSTM(n_units, return_sequences=True)(outputs)
outputs = layers.Dropout(0.5)(outputs)
outputs= layers.LSTM(n_units, return_sequences=True)(outputs)
outputs = layers.Dropout(0.5)(outputs)
outputs = layers.LSTM(n_units, return_sequences=True)(outputs)
outputs = layers.Dense(n_classes, activation='softmax')(outputs)
model = Model(inputs=inputs, outputs=outputs)
```

```
model.compile('adam',␣
↪loss='sparse_categorical_crossentropy',metrics=['accuracy'])
model.fit(X_train, y_train,
          batch_size=batch,
          epochs=30,
          callbacks=[ callbacks.ReduceLROnPlateau(),
                      callbacks.ModelCheckpoint('BiLSTM-N{}-D0.5-B{}.h5'.
↪format(n_units,batch)),
                      callbacks.EarlyStopping(monitor='val_loss', mode='min',␣
↪verbose=1, patience=10),
                      callbacks.
↪CSVLogger(f"BiLSTM-log-Nodes-{n_units}-dropout-0.5-batchsize-{batch}.csv")],
                      validation_data=(X_valid, y_valid),
                      class_weight=generate_sample_weights(y_train,␣
↪class_weight)
                      )
```

```
Train on 4963 samples, validate on 1241 samples
Epoch 1/30
4963/4963 [==============================] - 21s 4ms/sample - loss: 1.1300 -
accuracy: 0.5890 - val_loss: 0.8041 - val_accuracy: 0.6830
Epoch 2/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.7726 -
accuracy: 0.6884 - val_loss: 0.7393 - val_accuracy: 0.7019
Epoch 3/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.7091 -
accuracy: 0.7118 - val_loss: 0.6327 - val_accuracy: 0.7329
Epoch 4/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.5988 -
accuracy: 0.7490 - val_loss: 0.5395 - val_accuracy: 0.7749
Epoch 5/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.4912 -
accuracy: 0.8034 - val_loss: 0.4061 - val_accuracy: 0.8508
Epoch 6/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.3410 -
accuracy: 0.8778 - val_loss: 0.2365 - val_accuracy: 0.9262
Epoch 7/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.2336 -
accuracy: 0.9177 - val_loss: 0.1729 - val_accuracy: 0.9448
Epoch 8/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.1908 -
accuracy: 0.9315 - val_loss: 0.1438 - val_accuracy: 0.9530
Epoch 9/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.1720 -
accuracy: 0.9371 - val_loss: 0.1339 - val_accuracy: 0.9545
Epoch 10/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.1563 -
```

```
accuracy: 0.9425 - val_loss: 0.1209 - val_accuracy: 0.9584
Epoch 11/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.1433 -
accuracy: 0.9469 - val_loss: 0.1115 - val_accuracy: 0.9610
Epoch 12/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.1474 -
accuracy: 0.9456 - val_loss: 0.1195 - val_accuracy: 0.9574
Epoch 13/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.1483 -
accuracy: 0.9448 - val_loss: 0.1040 - val_accuracy: 0.9625
Epoch 14/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.1277 -
accuracy: 0.9521 - val_loss: 0.0990 - val_accuracy: 0.9641
Epoch 15/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.1212 -
accuracy: 0.9542 - val_loss: 0.0944 - val_accuracy: 0.9655
Epoch 16/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.1187 -
accuracy: 0.9551 - val_loss: 0.0929 - val_accuracy: 0.9660
Epoch 17/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.1138 -
accuracy: 0.9569 - val_loss: 0.0916 - val_accuracy: 0.9664
Epoch 18/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.1123 -
accuracy: 0.9574 - val_loss: 0.0895 - val_accuracy: 0.9671
Epoch 19/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.1095 -
accuracy: 0.9584 - val_loss: 0.0876 - val_accuracy: 0.9676
Epoch 20/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.1088 -
accuracy: 0.9587 - val_loss: 0.1019 - val_accuracy: 0.9615
Epoch 21/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.1179 -
accuracy: 0.9552 - val_loss: 0.0866 - val_accuracy: 0.9679
Epoch 22/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.1075 -
accuracy: 0.9592 - val_loss: 0.0856 - val_accuracy: 0.9679
Epoch 23/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.1042 -
accuracy: 0.9604 - val_loss: 0.0842 - val_accuracy: 0.9685
Epoch 24/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.1020 -
accuracy: 0.9612 - val_loss: 0.0837 - val_accuracy: 0.9685
Epoch 25/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.1076 -
accuracy: 0.9592 - val_loss: 0.0901 - val_accuracy: 0.9667
Epoch 26/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.1033 -
```

```
accuracy: 0.9607 - val_loss: 0.0848 - val_accuracy: 0.9681
Epoch 27/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.0999 -
accuracy: 0.9621 - val_loss: 0.0824 - val_accuracy: 0.9689
Epoch 28/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.0978 -
accuracy: 0.9628 - val_loss: 0.0823 - val_accuracy: 0.9689
Epoch 29/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.0969 -
accuracy: 0.9631 - val_loss: 0.0823 - val_accuracy: 0.9688
Epoch 30/30
4963/4963 [==============================] - 17s 3ms/sample - loss: 0.0960 -
accuracy: 0.9634 - val_loss: 0.0810 - val_accuracy: 0.9693
```

[34]: <tensorflow.python.keras.callbacks.History at 0x7fe1155d2748>

## 7 Evaluate Bi-LSTM model

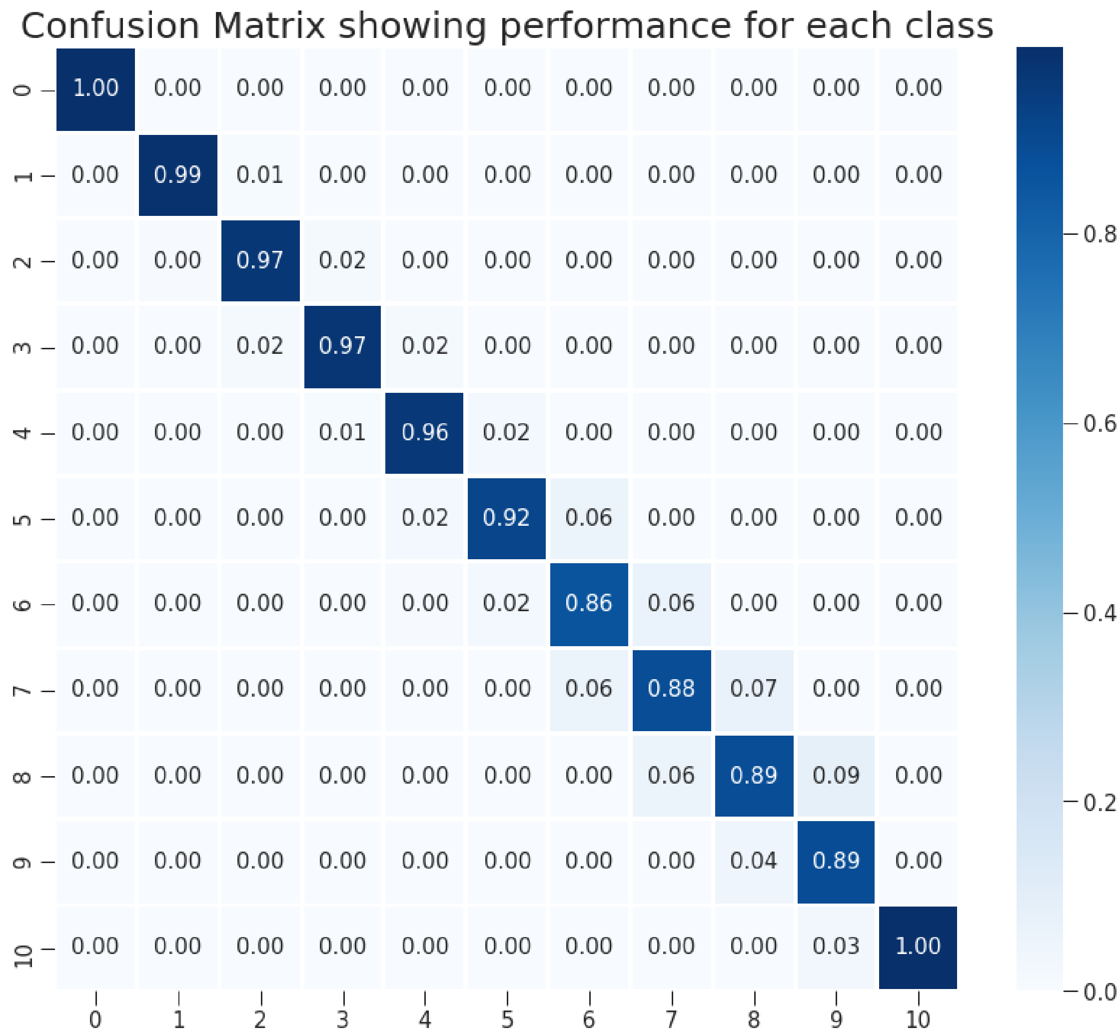
[35]:
```
model.load_weights('BiLSTM-N256-D0.5-B128.h5')
valid_pred = model.predict(X_valid, batch_size=128).argmax(axis=-1)
print('Accuracy Score : {}'.format(accuracy_score(y_valid.reshape(-1),␣
 ↪valid_pred.reshape(-1))))
print('F1 Score : {}'.format(f1_score(y_valid.reshape(-1), valid_pred.
 ↪reshape(-1), average='macro')))
print('Precision Score : {}'.format(precision_score(y_valid.reshape(-1),␣
 ↪valid_pred.reshape(-1), average='macro')))
print('Recall Score : {}'.format(recall_score(y_valid.reshape(-1), valid_pred.
 ↪reshape(-1), average='macro')))
```

```
Accuracy Score : 0.9692514101531023
F1 Score : 0.9393087464479225
Precision Score : 0.9397573584053949
Recall Score : 0.9389226929417588
```

[36]:
```
conf_mat=confusion_matrix(y_valid.reshape(-1), valid_pred.reshape(-1))
_ , counts= np.unique(y_valid, return_counts=True)
normalized_conf_mat = conf_mat/counts
```

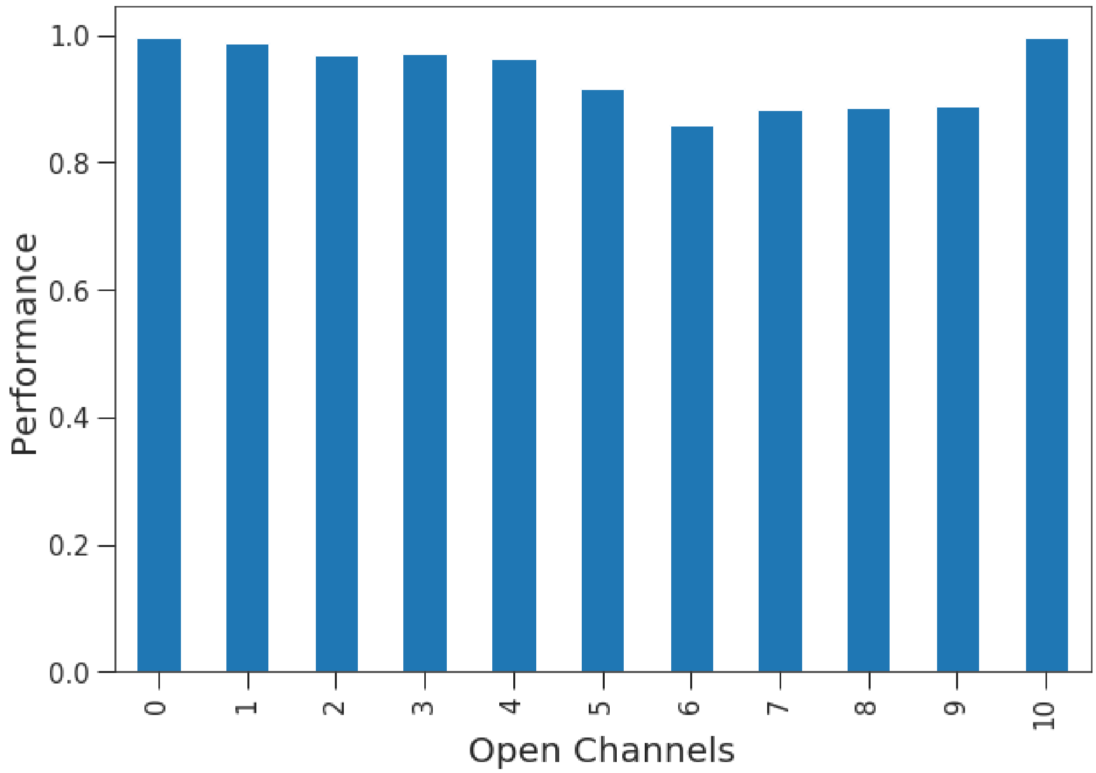
[37]:
```
sns.set_style('ticks')
plt.figure(figsize=(14,12))
sns.heatmap(normalized_conf_mat, lw=2, cmap='Blues', annot=True, fmt='.2f',␣
 ↪annot_kws={'size':15} )
plt.title('Confusion Matrix showing performance for each class',size=25)
```

[37]: Text(0.5, 1.0, 'Confusion Matrix showing performance for each class')




[38]:
```python
class_performance = dict(zip(_, np.diagonal(normalized_conf_mat)))
class_performance=pd.DataFrame(class_performance, index=range(0,1))
class_performance.T.plot.bar(legend=False,figsize=(10,7))
plt.xlabel('Open Channels')
plt.ylabel('Performance')
```

[38]: Text(0, 0.5, 'Performance')




[39]:
```
test_pred = model.predict(X_test, batch_size=128).argmax(axis=-1)
submission.open_channels = test_pred.reshape(-1)
submission.to_csv('submission.csv', index=False)
```

[ ]:
```
```