Table of Contents

In [102]:

```
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
from tensorflow.keras.models import load_model
import scipy.stats as stats
from sklearn.model_selection import train_test_split
from imblearn import under_sampling
from sklearn.utils import class_weight
from sklearn.metrics import confusion_matrix
```

In [63]:

```
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))
```

In [64]:

```
len(train), len(test)
```

Out[64]:

```
(5000000, 2000000)
```

Plot settings

In [65]:

```
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
```

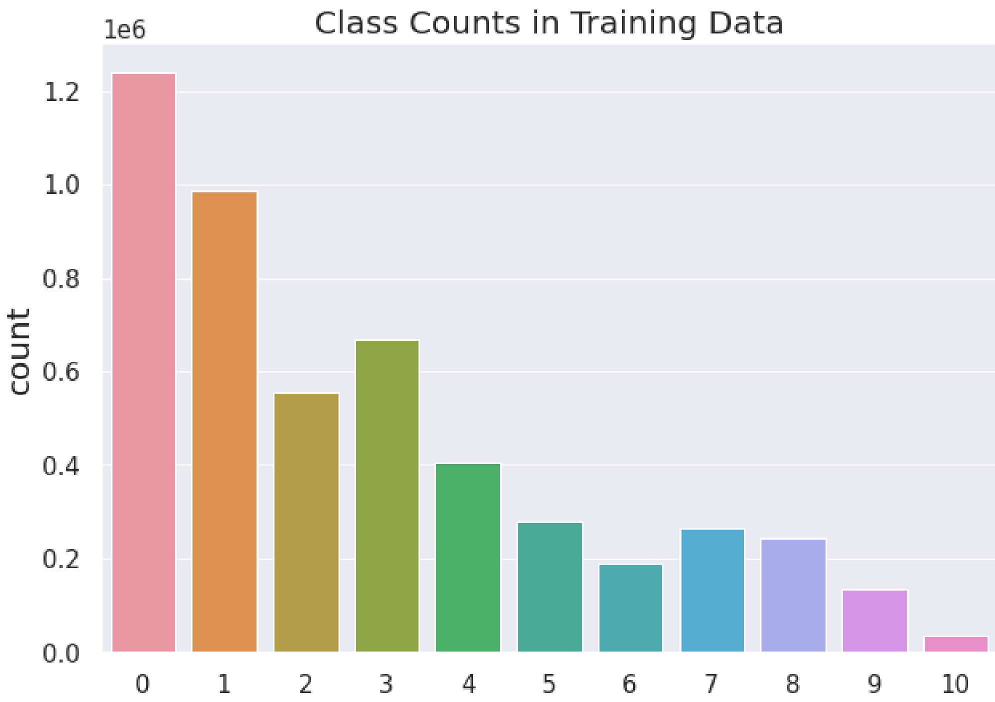
```
plt.rcParams['ytick.minor.width'] = 1
plt.rcParams['xtick.minor.size'] = 5
sns.set_style('darkgrid')
```

In [67]:

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

Out[67]:

```
Text(0.5, 1.0, 'Class Counts in Training Data')
```

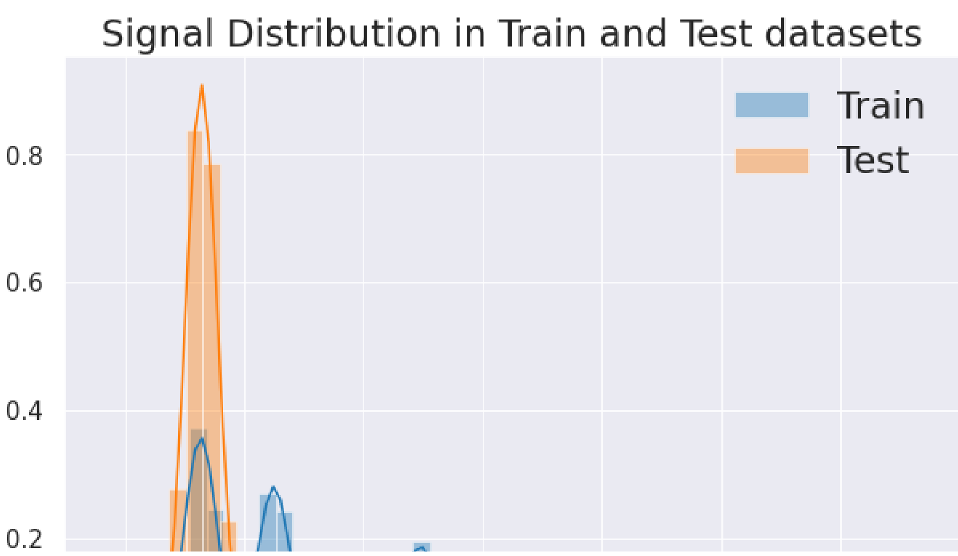


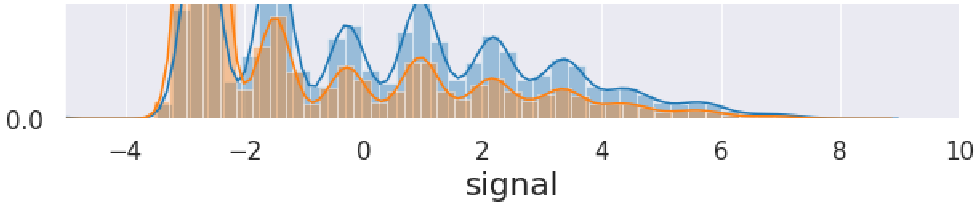
In [68]:

```
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)
```

Out[68]:

```
<matplotlib.legend.Legend at 0x7f8134f1d5d0>
```





As lot of us might have seen the signal and open_channels data shares a very strong correlation after removing the drift. I noted that pearson correlation cofficient increase from `0.81` to `0.96` after removing the data.

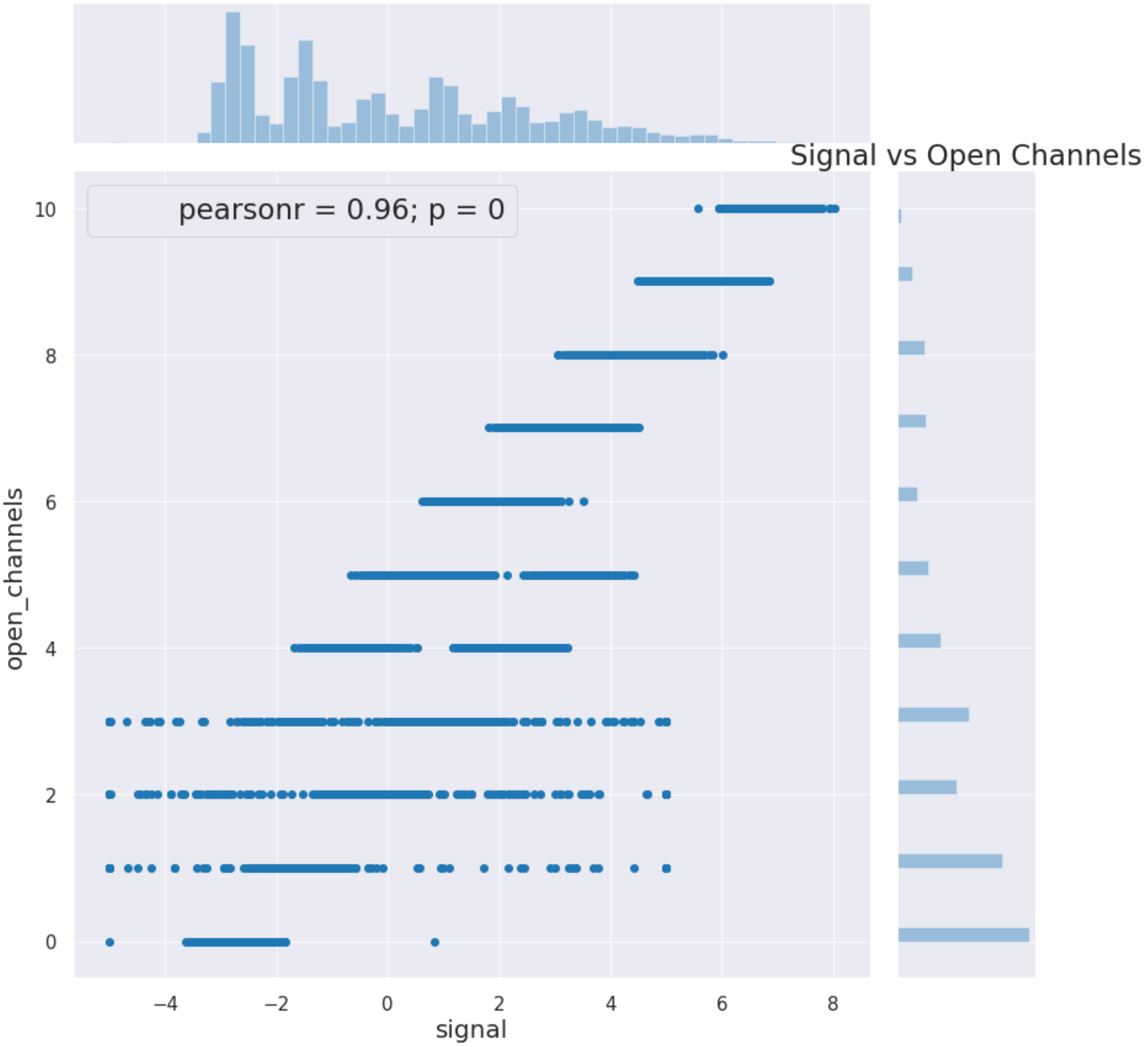
In [69]:

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

```
/opt/conda/lib/python3.7/site-packages/seaborn/axisgrid.py:1848: UserWarning: JointGrid annotation is deprecated and will be removed in a future release.
  warnings.warn(UserWarning(msg))
```

Out[69]:

```
Text(0.5, 1.0, 'Signal vs Open Channels')
```



Pearson Correlation in the various batches

Pearson Correlation in the various batches

In [70]:

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

In [71]:

```
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))
```

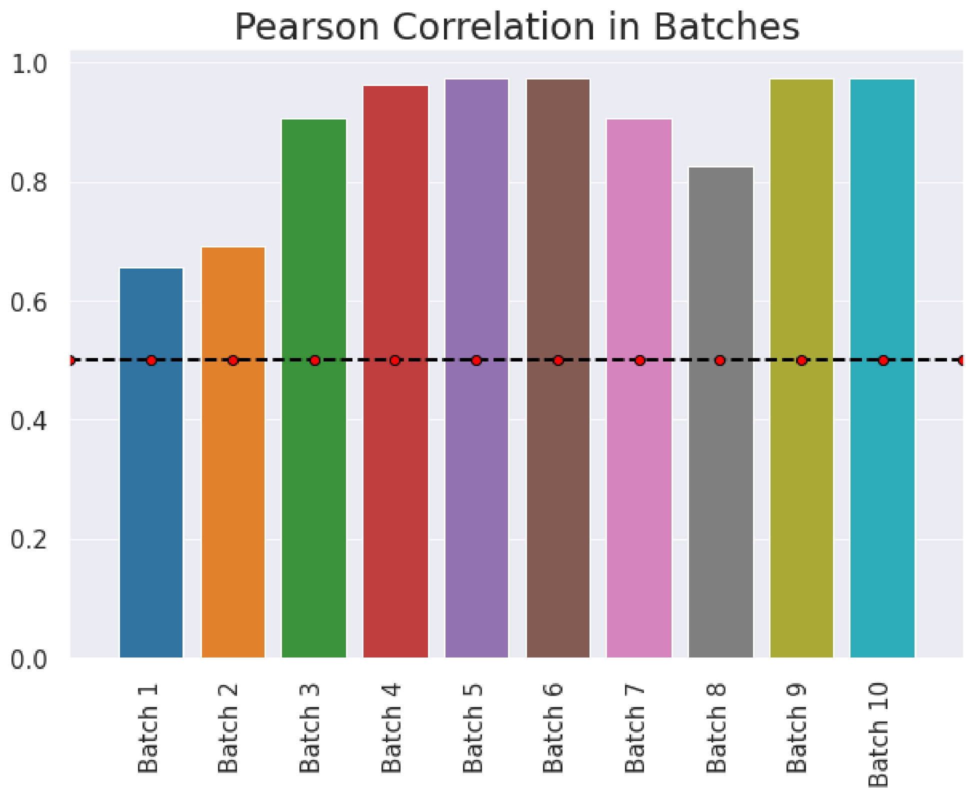
- There is a very strong correlation in every batch of the data except Batch 1 and Batch 2 (i.e. first 1000,000 lines of data)

In [72]:

```
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 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)
```

Out[72]:

```
(-1.0, 10.0)
```



In [86]:

```
X_res = train.signal.values
y_res = train.open_channels.values
```

Undersampling using TomekLinks

- I did some experimentation with the sampling strategy. `samplings_strategy='auto'` gives me the best results.
- According to the documentation [here](): `sampling_strategy='auto'` removes the samples from the majority class.

In [74]:

```
sm = under_sampling.TomekLinks(sampling_strategy='auto')
X_res, y_res = sm.fit_resample(train.signal.values.reshape(-1,1), train.open_channels.values.ravel(
))
```

In [75]:

```
X_res=X_res[318:]
y_res=y_res[318:]
```

In [76]:

```
X_res.shape ,y_res.shape
```

Out[76]:

```
((4690000, 1), (4690000,))
```

In [87]:

```
seq_len = 1000

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

- **I reduced the test size to 0.1 to improve training on minority classes.**

In [88]:

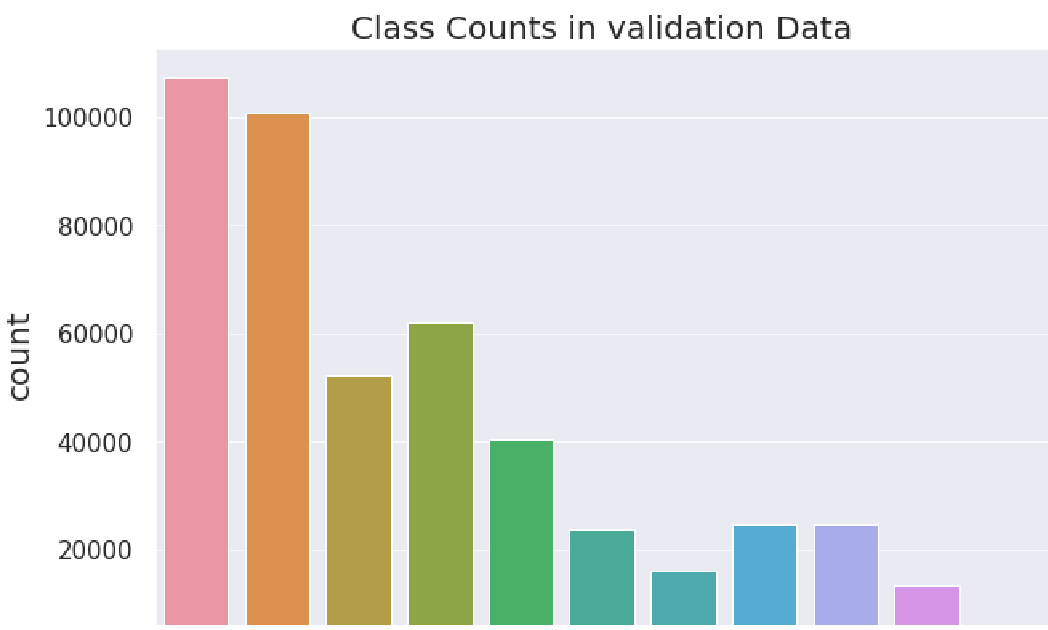
```
X_train, X_valid, y_train, y_valid = train_test_split(X_res, y_res, test_size=0.1)
X_test= test.signal.values.reshape(-1, seq_len, 1)
```

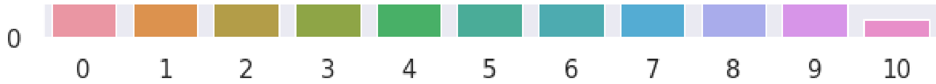
In [79]:

```
plt.figure(figsize=(10,7))
sns.countplot(y_valid.reshape(-1))
plt.title('Class Counts in validation Data',size=20)
```

Out[79]:

```
Text(0.5, 1.0, 'Class Counts in validation Data')
```





Creating a Bi-LSTM Model

- ## With undersampling

In [80]:

```
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.Bidirectional(layers.LSTM(n_units, return_sequences=True))(outputs)
outputs = layers.Dropout(0.5)(outputs)
outputs= layers.Bidirectional(layers.LSTM(n_units, return_sequences=True))(outputs)
outputs = layers.Dropout(0.5)(outputs)
outputs = layers.Bidirectional(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{}+undersampling.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-{batcl
}+undersampling.csv")],
                      validation_data=(X_valid, y_valid)
                      #class_weight=generate_sample_weights(y_train, class_weight)
                      )
```

```
Train on 4221 samples, validate on 469 samples
Epoch 1/30
4221/4221 [==============================] - 40s 9ms/sample - loss: 1.0028 - accuracy: 0.6099 - va
l_loss: 0.6848 - val_accuracy: 0.7140
Epoch 2/30
4221/4221 [==============================] - 32s 7ms/sample - loss: 0.5905 - accuracy: 0.7525 - va
l_loss: 0.5294 - val_accuracy: 0.7782
Epoch 3/30
4221/4221 [==============================] - 32s 7ms/sample - loss: 0.5215 - accuracy: 0.7855 - va
l_loss: 0.4300 - val_accuracy: 0.8271
Epoch 4/30
4221/4221 [==============================] - 32s 7ms/sample - loss: 0.3078 - accuracy: 0.8833 - va
l_loss: 0.1850 - val_accuracy: 0.9412
Epoch 5/30
4221/4221 [==============================] - 32s 7ms/sample - loss: 0.1592 - accuracy: 0.9444 - va
l_loss: 0.1135 - val_accuracy: 0.9619
Epoch 6/30
4221/4221 [==============================] - 32s 7ms/sample - loss: 0.1198 - accuracy: 0.9564 - va
l_loss: 0.1004 - val_accuracy: 0.9646
Epoch 7/30
4221/4221 [==============================] - 32s 7ms/sample - loss: 0.1103 - accuracy: 0.9592 - va
l_loss: 0.0891 - val_accuracy: 0.9682
Epoch 8/30
4221/4221 [==============================] - 32s 7ms/sample - loss: 0.1286 - accuracy: 0.9524 - va
l_loss: 0.1746 - val_accuracy: 0.9328
Epoch 9/30
4221/4221 [==============================] - 32s 7ms/sample - loss: 0.1200 - accuracy: 0.9549 - va
l_loss: 0.0883 - val_accuracy: 0.9681
Epoch 10/30
4221/4221 [==============================] - 32s 7ms/sample - loss: 0.0971 - accuracy: 0.9635 - va
l_loss: 0.0842 - val_accuracy: 0.9692
Epoch 11/30
4221/4221 [==============================] - 32s 8ms/sample - loss: 0.0921 - accuracy: 0.9653 - va
l_loss: 0.0825 - val_accuracy: 0.9697
Epoch 12/30
```

```
4221/4221 [==============================] - 32s 7ms/sample - loss: 0.0891 - accuracy: 0.9663 - va
l_loss: 0.0807 - val_accuracy: 0.9701
Epoch 13/30
4221/4221 [==============================] - 32s 8ms/sample - loss: 0.0869 - accuracy: 0.9671 - va
l_loss: 0.0787 - val_accuracy: 0.9708
Epoch 14/30
4221/4221 [==============================] - 32s 7ms/sample - loss: 0.0850 - accuracy: 0.9678 - va
l_loss: 0.0791 - val_accuracy: 0.9704
Epoch 15/30
4221/4221 [==============================] - 32s 8ms/sample - loss: 0.0835 - accuracy: 0.9684 - va
l_loss: 0.0772 - val_accuracy: 0.9711
Epoch 16/30
4221/4221 [==============================] - 32s 7ms/sample - loss: 0.0823 - accuracy: 0.9687 - va
l_loss: 0.0766 - val_accuracy: 0.9714
Epoch 17/30
4221/4221 [==============================] - 32s 8ms/sample - loss: 0.0819 - accuracy: 0.9690 - va
l_loss: 0.0784 - val_accuracy: 0.9705
Epoch 18/30
4221/4221 [==============================] - 32s 8ms/sample - loss: 0.0806 - accuracy: 0.9695 - va
l_loss: 0.0759 - val_accuracy: 0.9716
Epoch 19/30
4221/4221 [==============================] - 32s 8ms/sample - loss: 0.0797 - accuracy: 0.9698 - va
l_loss: 0.0776 - val_accuracy: 0.9708
Epoch 20/30
4221/4221 [==============================] - 32s 8ms/sample - loss: 0.0788 - accuracy: 0.9700 - va
l_loss: 0.0751 - val_accuracy: 0.9718
Epoch 21/30
4221/4221 [==============================] - 32s 8ms/sample - loss: 0.0779 - accuracy: 0.9704 - va
l_loss: 0.0745 - val_accuracy: 0.9720
Epoch 22/30
4221/4221 [==============================] - 32s 8ms/sample - loss: 0.0774 - accuracy: 0.9706 - va
l_loss: 0.0738 - val_accuracy: 0.9722
Epoch 23/30
4221/4221 [==============================] - 32s 7ms/sample - loss: 0.0767 - accuracy: 0.9708 - va
l_loss: 0.0748 - val_accuracy: 0.9717
Epoch 24/30
4221/4221 [==============================] - 32s 8ms/sample - loss: 0.0764 - accuracy: 0.9710 - va
l_loss: 0.0734 - val_accuracy: 0.9724
Epoch 25/30
4221/4221 [==============================] - 32s 8ms/sample - loss: 0.0763 - accuracy: 0.9709 - va
l_loss: 0.0736 - val_accuracy: 0.9721
Epoch 26/30
4221/4221 [==============================] - 32s 8ms/sample - loss: 0.0752 - accuracy: 0.9715 - va
l_loss: 0.0725 - val_accuracy: 0.9727
Epoch 27/30
4221/4221 [==============================] - 32s 8ms/sample - loss: 0.0749 - accuracy: 0.9716 - va
l_loss: 0.0727 - val_accuracy: 0.9725
Epoch 28/30
4221/4221 [==============================] - 32s 7ms/sample - loss: 0.0748 - accuracy: 0.9716 - va
l_loss: 0.0738 - val_accuracy: 0.9720
Epoch 29/30
4221/4221 [==============================] - 32s 7ms/sample - loss: 0.0742 - accuracy: 0.9719 - va
l_loss: 0.0728 - val_accuracy: 0.9725
Epoch 30/30
4221/4221 [==============================] - 32s 7ms/sample - loss: 0.0736 - accuracy: 0.9720 - va
l_loss: 0.0722 - val_accuracy: 0.9727
```

Out[80]:

```
<tensorflow.python.keras.callbacks.History at 0x7f85b3fce690>
```

- ## **Without Undersampling**

In [89]:

```
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.Bidirectional(layers.LSTM(n_units, return_sequences=True))(outputs)
outputs = layers.Dropout(0.5)(outputs)
outputs= layers.Bidirectional(layers.LSTM(n_units, return_sequences=True))(outputs)
outputs = layers.Dropout(0.5)(outputs)
outputs = layers.Bidirectional(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-{batcl
}.csv")],
                      validation_data=(X_valid, y_valid)
                      #class_weight=generate_sample_weights(y_train, class_weight)
                      )
```

```
Train on 4500 samples, validate on 500 samples
Epoch 1/30
4500/4500 [==============================] - 41s 9ms/sample - loss: 1.0781 - accuracy: 0.5771 - va
l_loss: 0.7160 - val_accuracy: 0.6994
Epoch 2/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.6534 - accuracy: 0.7274 - va
l_loss: 0.5240 - val_accuracy: 0.7788
Epoch 3/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.4641 - accuracy: 0.8087 - va
l_loss: 0.3218 - val_accuracy: 0.8780
Epoch 4/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.2806 - accuracy: 0.8948 - va
l_loss: 0.1436 - val_accuracy: 0.9511
Epoch 5/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.1588 - accuracy: 0.9414 - va
l_loss: 0.1079 - val_accuracy: 0.9613
Epoch 6/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.1323 - accuracy: 0.9500 - va
l_loss: 0.0971 - val_accuracy: 0.9643
Epoch 7/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.1229 - accuracy: 0.9530 - va
l_loss: 0.0908 - val_accuracy: 0.9662
Epoch 8/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.1169 - accuracy: 0.9549 - va
l_loss: 0.0939 - val_accuracy: 0.9643
Epoch 9/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.1119 - accuracy: 0.9567 - va
l_loss: 0.0883 - val_accuracy: 0.9665
Epoch 10/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.1089 - accuracy: 0.9579 - va
l_loss: 0.0846 - val_accuracy: 0.9676
Epoch 11/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.1055 - accuracy: 0.9591 - va
l_loss: 0.0828 - val_accuracy: 0.9683
Epoch 12/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.1060 - accuracy: 0.9589 - va
l_loss: 0.0843 - val_accuracy: 0.9680
Epoch 13/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.1031 - accuracy: 0.9600 - va
l_loss: 0.0819 - val_accuracy: 0.9685
Epoch 14/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.1013 - accuracy: 0.9607 - va
l_loss: 0.0813 - val_accuracy: 0.9687
Epoch 15/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.0992 - accuracy: 0.9615 - va
l_loss: 0.0806 - val_accuracy: 0.9689
Epoch 16/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.0980 - accuracy: 0.9620 - va
l_loss: 0.0795 - val_accuracy: 0.9693
Epoch 17/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.0969 - accuracy: 0.9624 - va
l_loss: 0.0803 - val_accuracy: 0.9690
Epoch 18/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.0963 - accuracy: 0.9626 - va
l_loss: 0.0841 - val_accuracy: 0.9674
Epoch 19/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.0963 - accuracy: 0.9625 - va
l_loss: 0.0805 - val_accuracy: 0.9687
Epoch 20/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.0956 - accuracy: 0.9628 - va
```

```
l_loss: 0.0806 - val_accuracy: 0.9688
Epoch 21/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.0947 - accuracy: 0.9633 - va
l_loss: 0.0786 - val_accuracy: 0.9694
Epoch 22/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.0952 - accuracy: 0.9629 - va
l_loss: 0.0817 - val_accuracy: 0.9681
Epoch 23/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.0943 - accuracy: 0.9634 - va
l_loss: 0.0791 - val_accuracy: 0.9695
Epoch 24/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.0927 - accuracy: 0.9640 - va
l_loss: 0.0788 - val_accuracy: 0.9695
Epoch 25/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.0934 - accuracy: 0.9637 - va
l_loss: 0.0789 - val_accuracy: 0.9694
Epoch 26/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.0927 - accuracy: 0.9640 - va
l_loss: 0.0789 - val_accuracy: 0.9694
Epoch 27/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.0926 - accuracy: 0.9641 - va
l_loss: 0.0781 - val_accuracy: 0.9697
Epoch 28/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.0918 - accuracy: 0.9644 - va
l_loss: 0.0817 - val_accuracy: 0.9682
Epoch 29/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.0911 - accuracy: 0.9646 - va
l_loss: 0.0770 - val_accuracy: 0.9701
Epoch 30/30
4500/4500 [==============================] - 34s 8ms/sample - loss: 0.0908 - accuracy: 0.9648 - va
l_loss: 0.0774 - val_accuracy: 0.9699
```

Out[89]:

```
<tensorflow.python.keras.callbacks.History at 0x7f85b742c1d0>
```

Evaluate Bi-LSTM model without Undersampling

In [90]:

```
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), av
erage='macro')))
print('Recall Score : {}'.format(recall_score(y_valid.reshape(-1), valid_pred.reshape(-1), average=
'macro')))
```

```
Accuracy Score : 0.969872
F1 Score : 0.9385079735266779
Precision Score : 0.9373987518778595
Recall Score : 0.9396668194200064
```

In [91]:

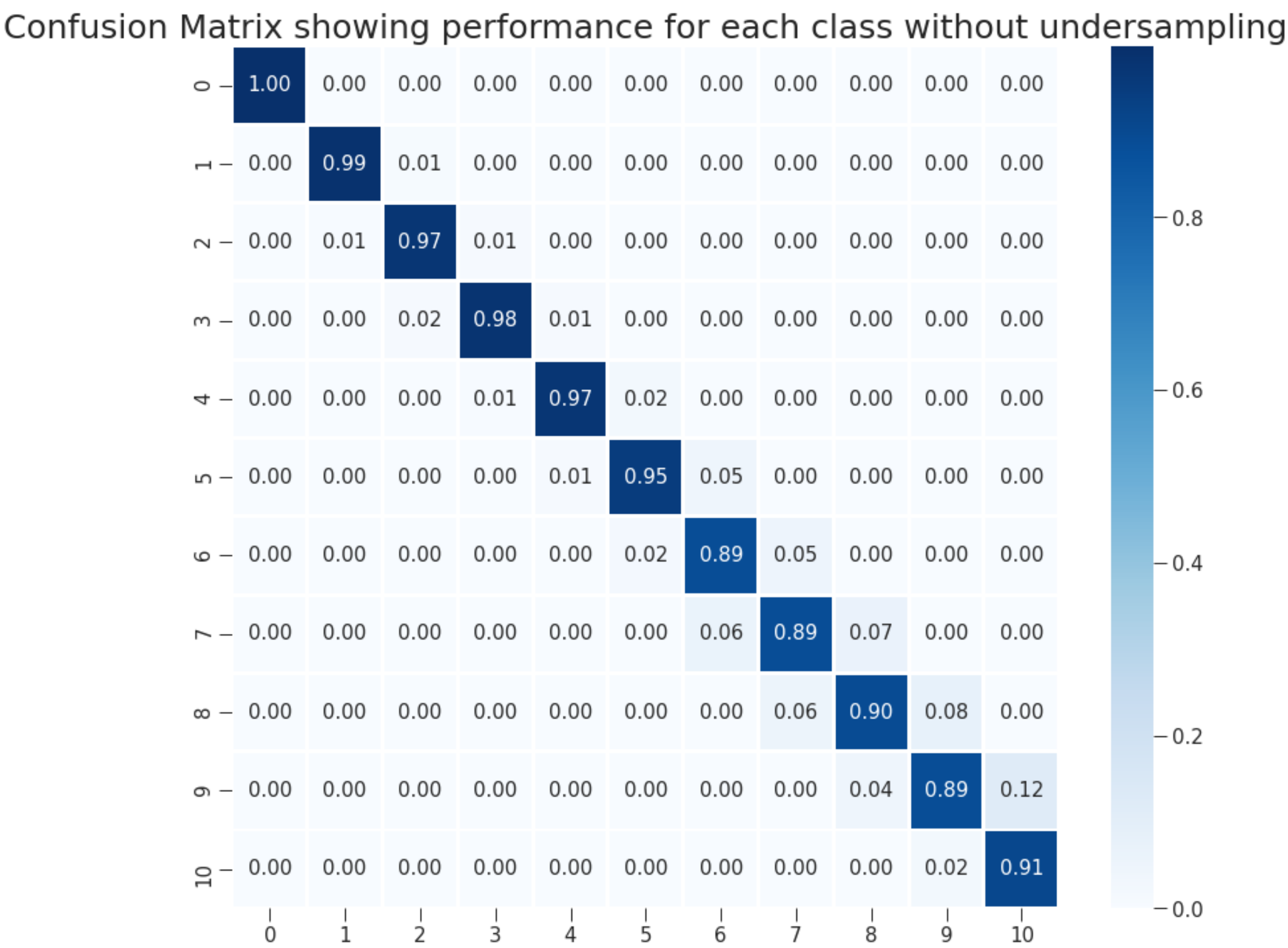
```
conf_mat=confusion_matrix(y_valid.reshape(-1), valid_pred.reshape(-1))
_ , counts= np.unique(y_valid, return_counts=True)
normalized_conf_mat = conf_mat/counts
```

In [92]:

```
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 without undersampling',size=25)
```

Out[92]:

```
Text(0.5, 1.0, 'Confusion Matrix showing performance for each class without undersampling')
```



In [93]:

```
class_performance_without_us = dict(zip(_, np.diagonal(normalized_conf_mat)))
class_performance_without_us=pd.DataFrame(class_performance_without_us, index=range(0,1))
```

Evaluate Bi-LSTM model with Undersampling

In [81]:

```
model.load_weights('BiLSTM-N256-D0.5-B128+undersampling.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), av
erage='macro')))
print('Recall Score : {}'.format(recall_score(y_valid.reshape(-1), valid_pred.reshape(-1), average=
'macro')))
```

```
Accuracy Score : 0.9726695095948827
F1 Score : 0.9441009813425524
Precision Score : 0.9423617641630572
Recall Score : 0.9459572719343883
```

In [82]:

```
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
```

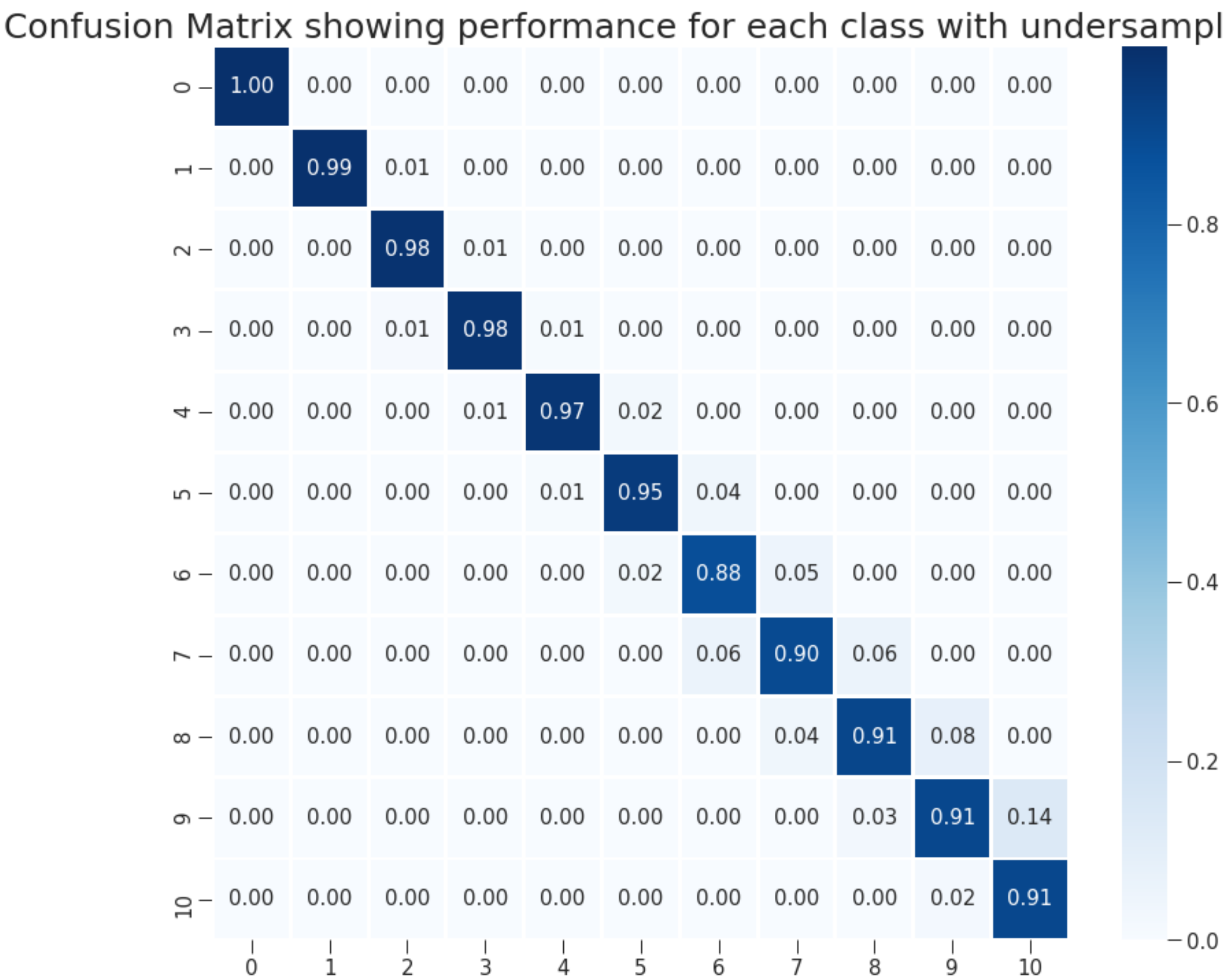
In [83]:

```
sns.set_style('ticks')
```

```python
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 with undersampling',size=25)
```

Out[83]:

```
Text(0.5, 1.0, 'Confusion Matrix showing performance for each class with undersampling')
```



In [84]:

```python
class_performance_with_us = dict(zip(_, np.diagonal(normalized_conf_mat)))
class_performance_with_us=pd.DataFrame(class_performance_with_us, index=range(0,1))
```

In [94]:

```python
class_performance=pd.concat([class_performance_without_us,class_performance_with_us]).T
class_performance.columns=['Without Undersampling','With Undersampling']
```

In [99]:

```python
class_performance.style.background_gradient()
```

Out[99]:

	Without Undersampling	With Undersampling
0	0.998189	0.998789
1	0.989881	0.993653
2	0.973042	0.983527
3	0.979115	0.982480
4	0.972628	0.974330
5	0.950599	0.953874

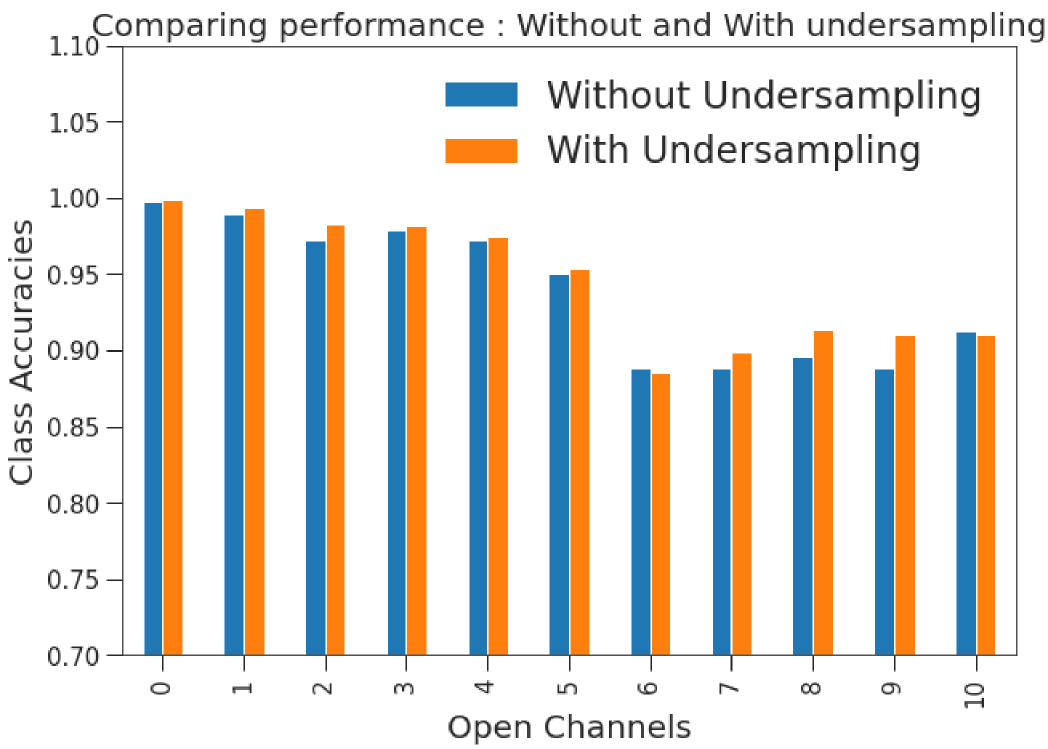
	Without Undersampling	With Undersampling
6	0.888204	0.884921
7	0.887973	0.899492
8	0.896151	0.913548
9	0.888338	0.910087
10	0.912216	0.910828

In [100]:

```
class_performance.plot.bar(figsize=(10,7))
plt.legend(frameon=False, bbox_to_anchor=(1.0,1))
plt.ylabel('Class Accuracies')
plt.xlabel('Open Channels')
plt.title('Comparing performance : Without and With undersampling',size=20)
plt.ylim([0.7,1.1])
```

Out[100]:

```
(0.7, 1.1)
```



Conclusion

- From the above plot, it seems that the undersampling using `TomekLinks` does improve the performance on individual classes.

Generating the submission csv

In [103]:

```
model=load_model('BiLSTM-N256-D0.5-B128+undersampling.h5')
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)
```