Z 9 BCNN 2D 2D

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1 Date: 7 2022

2 Method: 2D 2D BCNN

3 Data: Pavia

4 Results v.03

```
[]: # Libraries
     import pandas as pd
     import numpy as np
     import seaborn as sn
     import keras
     from keras.layers import Conv2D, Conv3D, Flatten, Dense, Reshape,
     →BatchNormalization, Lambda
     from keras.layers import Dropout, Input
     from keras.models import Model
     from keras.optimizers import Adam
     from keras.callbacks import ModelCheckpoint
     from keras.utils import np_utils
     from sklearn.decomposition import PCA
     from sklearn.model_selection import train_test_split
     from sklearn.metrics import confusion_matrix, accuracy_score,_
     ⇒classification_report, cohen_kappa_score
     import time
     from plotly.offline import init_notebook_mode
     import numpy as np
     import matplotlib.pyplot as plt
     import scipy.io as sio
     import os
     import spectral
```

```
import tensorflow as tf
    import tensorflow_probability as tfp
    from tensorflow.keras.layers import Dense, Conv2D, MaxPooling2D, Flatten,
     →Dropout
    from tensorflow.keras.layers import Input, Dense, Conv1D, MaxPooling1D,
     →Dropout, Flatten
    from tensorflow.keras.models import Sequential
    from tensorflow.keras.utils import to_categorical
    tfd = tfp.distributions
    tfpl = tfp.layers
[]: ## VARIABLES
    test ratio = 0.3
    test_val_ratio=0.6
    train_ratio = 1-test_ratio
    #train_val_ratio = 0.8
    windowSize = 9 # 25
    dimReduction = 80 # dimReduction
    drop = 0.4
[]: # Split Data
    def splitTrainTestSet(X, y, testRatio, randomState=345):
        X_train, X_test, y_train, y_test = train_test_split(X, y,__
     →test_size=testRatio, random_state=randomState,stratify=y)
        return X_train, X_test, y_train, y_test
[ ]: # PCA
    def applyPCA(X, numComponents): # numComponents=64
        newX = np.reshape(X, (-1, X.shape[2]))
        print(newX.shape)
        pca = PCA(n_components=numComponents, whiten=True)
        newX = pca.fit_transform(newX)
        newX = np.reshape(newX, (X.shape[0],X.shape[1], numComponents))
        return newX, pca, pca.explained_variance_ratio_
[]: # pading With Zeros
    def padWithZeros(X, margin=2):
        newX = np.zeros((X.shape[0] + 2 * margin, X.shape[1] + 2* margin, X.
     x offset = margin
```

```
y_offset = margin
newX[x_offset:X.shape[0] + x_offset, y_offset:X.shape[1] + y_offset, :] = X
return newX
```

```
[]: # Split the hyperspectral image into patches of size windowSize-by-windowSize_u
     \hookrightarrow pixels
     def Patches_Creating(X, y, windowSize, removeZeroLabels = True): #__
      \rightarrow windowSize=15, 25
         margin = int((windowSize - 1) / 2)
         zeroPaddedX = padWithZeros(X, margin=margin)
         # split patches
         patchesData = np.zeros((X.shape[0] * X.shape[1], windowSize, windowSize, X.
      ⇔shape[2]),dtype="float16")
         patchesLabels = np.zeros((X.shape[0] * X.shape[1]),dtype="float16")
         patchIndex = 0
         for r in range(margin, zeroPaddedX.shape[0] - margin):
             for c in range(margin, zeroPaddedX.shape[1] - margin):
                 patch = zeroPaddedX[r - margin:r + margin + 1, c - margin:c +__
      →margin + 1]
                 patchesData[patchIndex, :, :, :] = patch
                 patchesLabels[patchIndex] = y[r-margin, c-margin]
                 patchIndex = patchIndex + 1
         if removeZeroLabels:
             patchesData = patchesData[patchesLabels>0,:,:,:]
             patchesLabels = patchesLabels[patchesLabels>0]
             patchesLabels -= 1
         return patchesData, patchesLabels
[]: # channel_wise_shift
     def channel_wise_shift(X,numComponents):
         X_copy = np.zeros((X.shape[0] , X.shape[1], X.shape[2]))
         half = int(numComponents/2)
         for i in range(0,half-1):
             X_{copy}[:,:,i] = X[:,:,(half-i)*2-1]
         for i in range(half,numComponents):
             X_{copy}[:,:,i] = X[:,:,(i-half)*2]
         X = X_{copy}
         return X
[]: # Read data
     from scipy.io import loadmat
     def read HSI():
       X = loadmat('PaviaU.mat')['paviaU']
       y = loadmat('PaviaU_gt.mat')['paviaU_gt']
       print(f"X shape: {X.shape}\ny shape: {y.shape}")
```

return X, y

```
X, y = read_HSI()
    X shape: (610, 340, 103)
    y shape: (610, 340)
[]: # Load and reshape data for training
     X0, y0 = read HSI()
     #X=X0
     #y=y0
     InputShape=(windowSize, windowSize, dimReduction)
     #X, y = loadData(dataset) channel_wise_shift
     X1,pca,ratio = applyPCA(X0,numComponents=dimReduction)
     X2 shifted = channel_wise_shift(X1,dimReduction) # channel-wise shift
     \#X2 = X1
     #print(f"X0 shape: {X0.shape}\ny0 shape: {y0.shape}")
     #print(f"X1 shape: {X1.shape}\nX2 shape: {X2.shape}")
     X3, y3 = Patches_Creating(X2_shifted, y0, windowSize=windowSize)
     Xtrain, Xtest, ytrain, ytest = splitTrainTestSet(X3, y3, test_ratio)
     print(f"Xtrain shape: {Xtrain.shape}\nytrain shape : {ytrain.shape}")
     #print(f"Xtest shape: {Xtest.shape}\nytest shape : {ytest.shape}")
    X shape: (610, 340, 103)
    y shape: (610, 340)
    (207400, 103)
    Xtrain shape: (29943, 9, 9, 80)
    ytrain shape : (29943,)
[]: # split data for Training and Testing
     Xtrain = Xtrain.reshape(-1, windowSize, windowSize, dimReduction)
     ytrain = np_utils.to_categorical(ytrain)
     #Xvalid, Xtest, yvalid, ytest = splitTrainTestSet(Xtest, ytest,
     → (test_ratio-train_ratio/train_val_ratio)/test_ratio)
     Xvalid, Xtest, yvalid, ytest = splitTrainTestSet(Xtest, ytest, test_val_ratio)
     Xvalid = Xvalid.reshape(-1, windowSize, windowSize, dimReduction)
     yvalid = np_utils.to_categorical(yvalid)
[]: # Function to define the spike and slab distribution
     # => To be used in prior
```

```
def spike_and_slab(event_shape, dtype):
         distribution = tfd.Mixture(
             cat=tfd.Categorical(probs=[0.5, 0.5]),
             components=[
                 tfd.Independent(tfd.Normal(
                     loc=tf.zeros(event_shape, dtype=dtype),
                     scale=1.0*tf.ones(event_shape, dtype=dtype)),
                                 reinterpreted_batch_ndims=1),
                 tfd.Independent(tfd.Normal(
                     loc=tf.zeros(event_shape, dtype=dtype),
                     scale=10.0*tf.ones(event_shape, dtype=dtype)),
                                 reinterpreted_batch_ndims=1)],
         name='spike_and_slab')
         return distribution
[ ]: # Testing Model_ NO1
     from tensorflow.keras.optimizers import RMSprop
     def nll(y_true, y_pred):
         return -y_pred.log_prob(y_true)
```

```
[]: #Testing Model_ NO1
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint,

→TensorBoard

def negative_log_likelihood(y_true, y_pred):
    return -y_pred.log_prob(y_true)
```

Model N02

```
bias_prior_fn = tfpl.
 →default_multivariate_normal_fn,
                                            bias_posterior_fn=tfpl.
 →default mean field normal fn(is singular=False),
                                            bias_divergence_fn = divergence_fn),
    MaxPooling2D(2,1),
    Conv2D(32, (2,2), activation='relu'),
    MaxPooling2D(2,1),
    Conv2D(16, (2,2), activation='relu'),
    MaxPooling2D(2,1),
    Conv2D(16, (2,2), activation='relu'),
    MaxPooling2D(1,1),
    Flatten(),
    Dense(512, activation='relu'),
    Dropout(0.2),
    # Statistical Dense-
    tfpl.DenseReparameterization(units=tfpl.OneHotCategorical.params_size(9),_
 →activation=None,
                                     kernel_prior_fn = tfpl.
 →default_multivariate_normal_fn,
                                     kernel_posterior_fn=tfpl.
 →default_mean_field_normal_fn(is_singular=False),
                                     kernel_divergence_fn = divergence_fn,
                                     bias_prior_fn = tfpl.
 →default_multivariate_normal_fn,
                                     bias_posterior_fn=tfpl.
 →default_mean_field_normal_fn(is_singular=False),
                                     bias_divergence_fn = divergence_fn
                                 ),
    # output-
    tfpl.OneHotCategorical(9)
model_bayes.summary()
Model: "sequential_15"
c:\Users\kifah\anaconda3\lib\site-
packages\tensorflow_probability\python\layers\util.py:95: UserWarning:
`layer.add_variable` is deprecated and will be removed in a future version.
Please use the `layer.add_weight()` method instead.
c:\Users\kifah\anaconda3\lib\site-
packages\tensorflow_probability\python\layers\util.py:105: UserWarning:
`layer.add_variable` is deprecated and will be removed in a future version.
Please use the `layer.add_weight()` method instead.
```

conv2d_reparameterization_1 5 (Conv2DReparameterization) max_pooling2d_60 (MaxPoolin g2D) conv2d_45 (Conv2D)	(None, 8, 8, 8)	
g2D)	(None, 7, 7, 8)	0
conv2d_45 (Conv2D)		
	(None, 6, 6, 32)	1056
<pre>max_pooling2d_61 (MaxPoolin g2D)</pre>	(None, 5, 5, 32)	0
conv2d_46 (Conv2D)	(None, 4, 4, 16)	2064
<pre>max_pooling2d_62 (MaxPoolin g2D)</pre>	(None, 3, 3, 16)	0
conv2d_47 (Conv2D)	(None, 2, 2, 16)	1040
<pre>max_pooling2d_63 (MaxPoolin g2D)</pre>	(None, 2, 2, 16)	0
flatten_15 (Flatten)	(None, 64)	0
dense_15 (Dense)	(None, 512)	33280
dropout_15 (Dropout)	(None, 512)	0
dense_reparameterization_15 (DenseReparameterization)	(None, 9)	9234
<pre>one_hot_categorical_15 (One HotCategorical)</pre>	((None, 9), (None, 9))	0

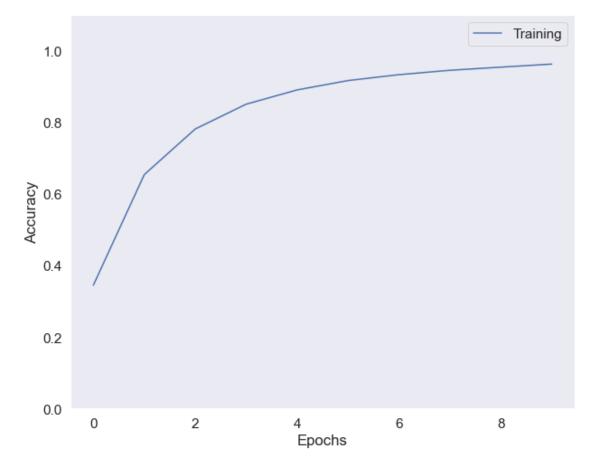
Trainable params: 51,810

Non-trainable params: 0

```
[]: # Testing Model_ NO2 # Comiple
```

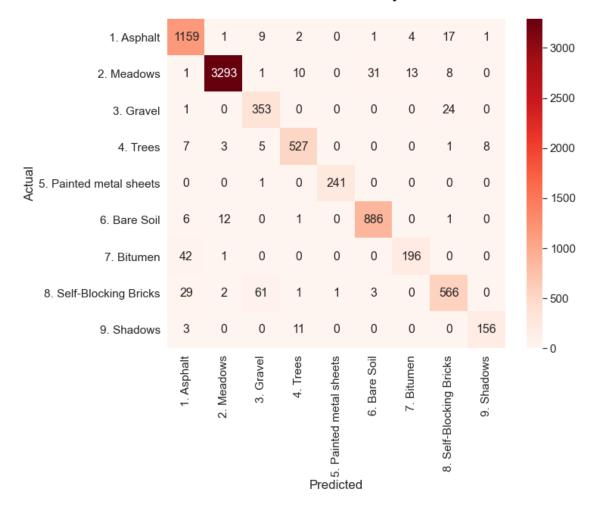
```
model_bayes.compile(loss = negative_log_likelihood,
           optimizer = Adam(learning_rate=0.001), #0.005
           metrics = ['accuracy'],
           experimental_run_tf_function = False)
[]: # Testing Model_ NO2
   # Train
   hist = model_bayes.fit(Xtrain,
                 ytrain,
                 epochs = 10,
                 batch size = 512,
                 validation_data = (Xvalid, yvalid)
  Epoch 1/10
  0.3452 - val_loss: 1.6012 - val_accuracy: 0.5371
  Epoch 2/10
  59/59 [============= ] - 3s 54ms/step - loss: 1.3280 - accuracy:
  0.6545 - val_loss: 1.0661 - val_accuracy: 0.7551
  Epoch 3/10
  0.7820 - val_loss: 0.8994 - val_accuracy: 0.8188
  Epoch 4/10
  0.8514 - val_loss: 0.8271 - val_accuracy: 0.8798
  0.8913 - val_loss: 0.7493 - val_accuracy: 0.9110
  0.9174 - val_loss: 0.7043 - val_accuracy: 0.9330
  Epoch 7/10
  59/59 [============ ] - 3s 51ms/step - loss: 0.7099 - accuracy:
  0.9340 - val loss: 0.6895 - val accuracy: 0.9427
  Epoch 8/10
  0.9462 - val_loss: 0.6758 - val_accuracy: 0.9527
  Epoch 9/10
  0.9549 - val_loss: 0.6554 - val_accuracy: 0.9532
  Epoch 10/10
  0.9636 - val_loss: 0.6659 - val_accuracy: 0.9511
[]: # Plot accuracy
   plt.figure(figsize=(10,8))
   plt.ylim(0,1.1)
   plt.grid()
```

```
plt.plot(hist.history['accuracy'])
plt.ylabel('Accuracy')
plt.xlabel('Epochs')
plt.legend(['Training','Validation'])
plt.savefig("acc_curve.pdf")
plt.show()
```



```
df_cm.index.name = 'Actual'
df_cm.columns.name = 'Predicted'
plt.figure(figsize = (10,8))
sn.set(font_scale=1.4)#for label size
sn.heatmap(df_cm, cmap="Reds", annot=True,annot_kws={"size": 16}, fmt='d')
plt.savefig('cmap.png', dpi=300)
```

241/241 [=========] - 1s 2ms/step



```
[]: # average_acc
from operator import itemgetter
def AA_andEachClassAccuracy(confusion_matrix):
    counter = confusion_matrix.shape[0]
    list_diag = np.diag(confusion_matrix)
    list_raw_sum = np.sum(confusion_matrix, axis=1)
    each_acc = np.nan_to_num((list_diag/ list_raw_sum))
    average_acc = np.mean(each_acc)
```

```
return each_acc, average_acc
[]: # average_acc
     each_acc, aa = AA_andEachClassAccuracy(confusion)
     print("accuracy for each:")
     print (each_acc)
     print("OA accuracy:")
     print(aa)
    accuracy for each:
    [0.97068677 0.98093536 0.93386243 0.95644283 0.99586777 0.97792494
     0.82008368 0.85369532 0.91764706]
    OA accuracy:
    0.934127352191321
[]: # classification report
     print(classification_report(ytest, y_pred, target_names = names, digits = 3))
                             precision
                                           recall f1-score
                                                              support
                 1. Asphalt
                                 0.929
                                            0.971
                                                      0.949
                                                                 1194
                 2. Meadows
                                 0.994
                                            0.981
                                                      0.988
                                                                 3357
                  3. Gravel
                                 0.821
                                            0.934
                                                      0.874
                                                                  378
                   4. Trees
                                 0.955
                                            0.956
                                                      0.956
                                                                  551
    5. Painted metal sheets
                                 0.996
                                            0.996
                                                      0.996
                                                                  242
               6. Bare Soil
                                 0.962
                                            0.978
                                                      0.970
                                                                  906
                 7. Bitumen
                                 0.920
                                            0.820
                                                      0.867
                                                                  239
    8. Self-Blocking Bricks
                                 0.917
                                            0.854
                                                      0.884
                                                                  663
                 9. Shadows
                                 0.945
                                            0.918
                                                      0.931
                                                                  170
                                                      0.958
                                                                 7700
                   accuracy
                                                                 7700
                  macro avg
                                 0.938
                                            0.934
                                                      0.935
               weighted avg
                                 0.959
                                            0.958
                                                      0.958
                                                                 7700
[]: # Calculation the predicted image
     def Patch(data,height index,width index):
         height_slice = slice(height_index, height_index+PATCH_SIZE)
         width_slice = slice(width_index, width_index+PATCH_SIZE)
         patch = data[height_slice, width_slice, :]
         return patch
[]: # Calculation the predicted image
```

PATCH_SIZE = windowSize

#X2_shifted, y0

```
#X,pca,ratio = applyPCA(X0,numComponents=40)

X = padWithZeros(X2_shifted, PATCH_SIZE//2) # PATCH_SIZE=15, PATCH_SIZE//2=7
height = y0.shape[0]
width = y0.shape[1]
```

```
[]: # the predicted image
     outputs = np.zeros((height, width), dtype="float16")
     outputs2 = np.zeros((height, width), dtype="float16")
     for i in range(0,height,1):
         for j in range(0, width, 1):
             target = int(y0[i,j])
             if target == 0 :
                 image_patch=Patch(X,i,j)
                 X_test_image = image_patch.reshape(1,image_patch.

¬shape[0],image_patch.shape[1], image_patch.shape[2]).astype('float32')

                 prediction2 = (model bayes.predict(X test image))
                 prediction2 = np.argmax(prediction2, axis=1)
                 outputs2[i][j] = prediction2+1
                 print(i); print(j)
                 #print(outputs2[i][j])
             else :
                 image_patch=Patch(X,i,j)
                 X_test_image = image_patch.reshape(1,image_patch.

→shape[0],image_patch.shape[1], image_patch.shape[2]).astype('float32')

                 prediction = (model_bayes.predict(X_test_image))
                 prediction = np.argmax(prediction, axis=1)
                 outputs[i][j] = prediction+1
                 outputs2[i][j] = prediction+1
                 #print("target=1")
                 #print(outputs2[i][j])
```

```
[]: import spectral
ground_truth = spectral.imshow(classes = y0,figsize_
→=(10,8),cmap='nipy_spectral'); plt.colorbar()

predict_image = spectral.imshow(classes = outputs.astype(int),figsize_
→=(7,7),cmap='nipy_spectral')
predict_image2 = spectral.imshow(classes = outputs2.astype(int),figsize =(7,7))

#spectral.save_rgb("predictions.png", outputs.astype(int), colors=spectral.
→spy_colors)

#spectral.save_rgb("predictions2.png", outputs2.astype(int), colors=spectral.
→spy_colors)
```

[]:[