Machine Learning (2016 Fall) HW3 Report

Semi-supervised Learning in Picture Classification

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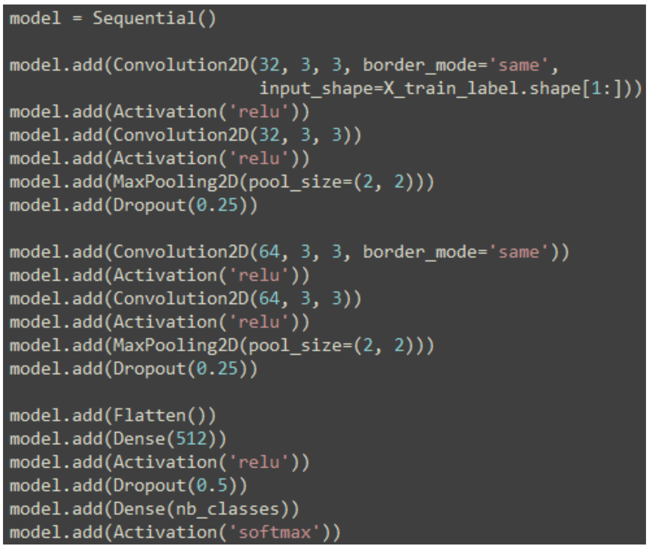
A. Supervised learning

a. Layer structure



```
model = Sequential()

model.add(Convolution2D(32, 3, 3, border_mode='same',
                        input_shape=X_train_label.shape[1:]))
model.add(Activation('relu'))
model.add(Convolution2D(32, 3, 3))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Convolution2D(64, 3, 3, border_mode='same'))
model.add(Activation('relu'))
model.add(Convolution2D(64, 3, 3))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Flatten())
model.add(Dense(512))
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(nb_classes))
model.add(Activation('softmax'))
```

b. Performance

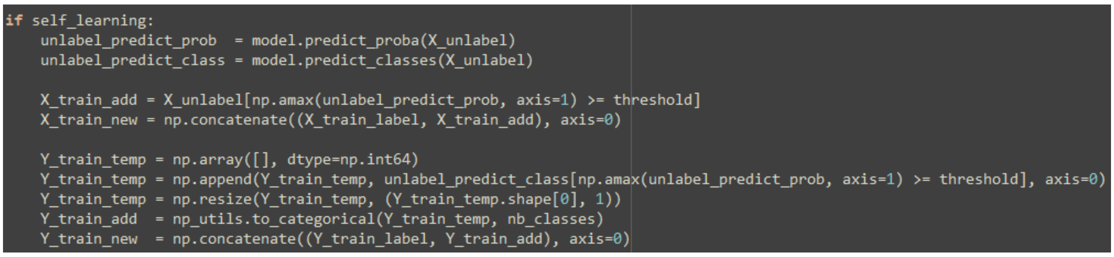
acc_train	acc_valid	acc_public
0.8807	0.7260	0.7090

c. Description

Batch size	32	Optimizer	Adam
Epoch	200	Training set	4500
Data augment	Apply	Validation set	500

B. Semi-supervised learning (1) – self-learning

a. Predict and add unlabel data to training set if confident enough



```
if self_learning:
    unlabel_predict_prob  = model.predict_proba(X_unlabel)
    unlabel_predict_class = model.predict_classes(X_unlabel)

    X_train_add = X_unlabel[np.amax(unlabel_predict_prob, axis=1) >= threshold]
    X_train_new = np.concatenate((X_train_label, X_train_add), axis=0)

    Y_train_temp = np.array([], dtype=np.int64)
    Y_train_temp = np.append(Y_train_temp, unlabel_predict_class[np.amax(unlabel_predict_prob, axis=1) >= threshold], axis=0)
    Y_train_temp = np.resize(Y_train_temp, (Y_train_temp.shape[0], 1))
    Y_train_add  = np_utils.to_categorical(Y_train_temp, nb_classes)
    Y_train_new  = np.concatenate((Y_train_label, Y_train_add), axis=0)
```

b. Performance

(a) Without using testing data

acc_train	acc_valid	acc_public
0.9024	0.7440	0.7150

(b) Use testing data meanwhile

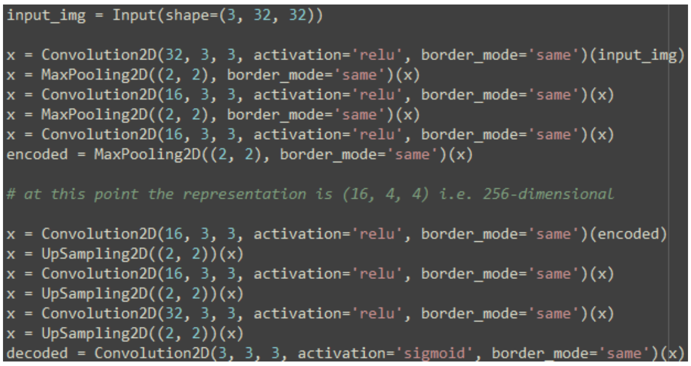
acc_train	acc_valid	acc_public
0.9120	0.7240	0.7174

c. Description

Batch size	32	Optimizer	Adam
Epoch	200	Training set	4500
Data augment	Apply	Validation set	500
Threshold	0.9	Iteration	2

C. Semi-supervised learning (2) – clustering

a. Train an autoencoder to extract feature



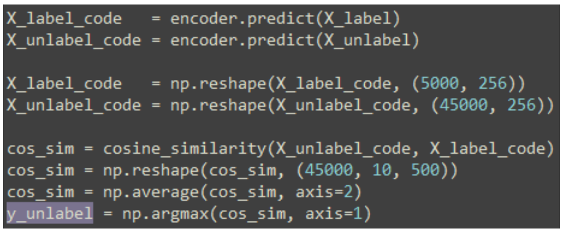
```
input_img = Input(shape=(3, 32, 32))

x = Convolution2D(32, 3, 3, activation='relu', border_mode='same')(input_img)
x = MaxPooling2D((2, 2), border_mode='same')(x)
x = Convolution2D(16, 3, 3, activation='relu', border_mode='same')(x)
x = MaxPooling2D((2, 2), border_mode='same')(x)
x = Convolution2D(16, 3, 3, activation='relu', border_mode='same')(x)
encoded = MaxPooling2D((2, 2), border_mode='same')(x)

# at this point the representation is (16, 4, 4) i.e. 256-dimensional

x = Convolution2D(16, 3, 3, activation='relu', border_mode='same')(encoded)
x = UpSampling2D((2, 2))(x)
x = Convolution2D(16, 3, 3, activation='relu', border_mode='same')(x)
x = UpSampling2D((2, 2))(x)
x = Convolution2D(32, 3, 3, activation='relu', border_mode='same')(x)
x = UpSampling2D((2, 2))(x)
decoded = Convolution2D(3, 3, 3, activation='sigmoid', border_mode='same')(x)
```

b. Clustering by cosine similarity



```
X_label_code   = encoder.predict(X_label)
X_unlabel_code = encoder.predict(X_unlabel)

X_label_code   = np.reshape(X_label_code, (5000, 256))
X_unlabel_code = np.reshape(X_unlabel_code, (45000, 256))

cos_sim = cosine_similarity(X_unlabel_code, X_label_code)
cos_sim = np.reshape(cos_sim, (45000, 10, 500))
cos_sim = np.average(cos_sim, axis=2)
y_unlabel = np.argmax(cos_sim, axis=1)
```

c. Performance

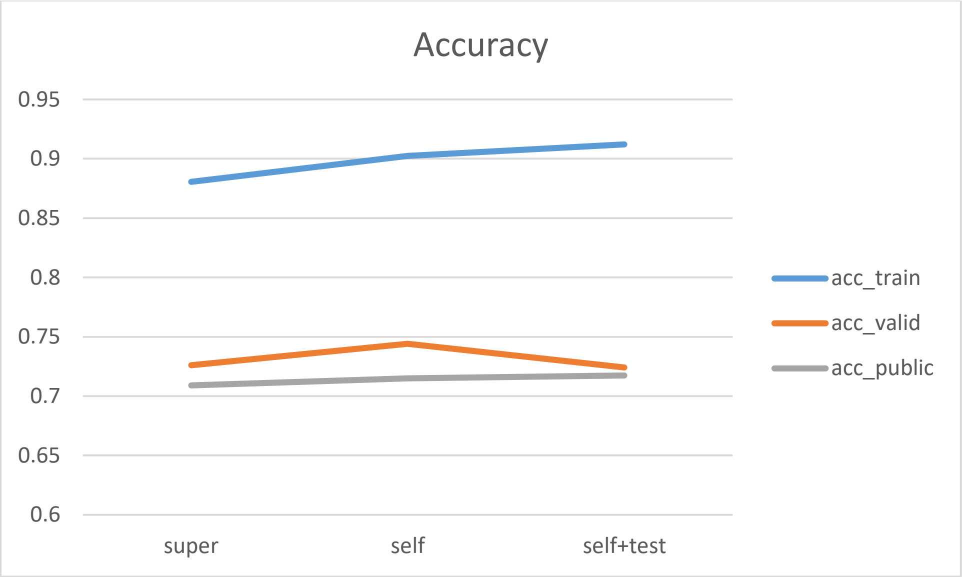
acc_train	acc_valid	acc_public
0.8175	0.2480	0.2322

d. Description

Batch size	32	Optimizer	Adam
Epoch	200	Training set	4500
Data augment	Apply	Validation set	500

D. Compare and analysis

a. Accuracy



Note： 使用 self-learning 可以有效提升 accuracy

Note： 將 testing data 放入，若預測不準確，可能會讓 testing data 上面的表現變差

b. Bad performance of auto-encoder

方法(2)反而會導致效果變差，可能的原因是，剛開始利用 auto-encoder 分群時沒有做好，導致 training 時使用到錯誤的 label。