# HW5 (3)

May 1, 2019

```
In [1]: import numpy as np
        import pandas as pd
        import keras

        # plots
        import matplotlib.pyplot as plt
        import seaborn as sns
        %matplotlib inline

        # processing & model selection
        from keras.preprocessing import image
        from keras.utils import to_categorical
        from sklearn.utils import resample
        from sklearn.model_selection import GridSearchCV, train_test_split, StratifiedShuffleSp

        # models
        from keras import regularizers
        from keras.models import Sequential, Model
        from keras.layers import Dense, Activation, BatchNormalization, Dropout, Input, add, Co
        from keras.wrappers.scikit_learn import KerasClassifier

        # other
        import warnings
        warnings.filterwarnings('ignore')
        np.random.seed(42)

        # task3 data loading
        import fnmatch
        from glob2 import glob
        import cv2
```

```
Using TensorFlow backend.
```

# 1 Homework 5

## 1.1 Task 1

The first task is to run a multilayer perceptron with two hidden layers and relu activations, using the Keras Sequential Interface. We also tune for regularization strength and number of hidden units.

Importing the data:

```
In [2]: df = sns.load_dataset('iris')
        df.head()
```

```
Out[2]:    sepal_length  sepal_width  petal_length  petal_width species
        0           5.1          3.5           1.4          0.2  setosa
        1           4.9          3.0           1.4          0.2  setosa
        2           4.7          3.2           1.3          0.2  setosa
        3           4.6          3.1           1.5          0.2  setosa
        4           5.0          3.6           1.4          0.2  setosa
```

Map the target variable:

```
In [3]: print(df.species.unique())
```

```
['setosa' 'versicolor' 'virginica']
```

```
In [0]: mapping = {'setosa': 0, 'versicolor': 1, 'virginica': 2}
        df.species.replace(mapping, inplace = True)
```

Split our dataset into training and test sets.

```
In [0]: X_train, X_test, y_train, y_test = train_test_split(df.drop('species', axis=1), df.spe
```

Encode the target:

```
In [0]: num_species = len(df['species'].unique())

        y_train = to_categorical(y_train, num_species)
        y_test = to_categorical(y_test, num_species)
```

Make our model:

```
In [7]: X_train.shape
```

```
Out[7]: (120, 4)
```

```
In [0]: def make_model(hidden_size, reg_strength, optimizer='adam'):
            """
            Create the model to pass to the Keras Classifier
            """
```

```
    model = Sequential([
        Dense(hidden_size, input_shape=(4,), activation='relu',   # first layer
              kernel_regularizer=regularizers.l2(reg_strength)),
        Dense(hidden_size, activation='relu',                      # second layer
              kernel_regularizer=regularizers.l2(reg_strength)),
        Dense(3, activation='softmax')                             # output layer
    ])

    # compile the above model
    model.compile(optimizer=optimizer, loss='categorical_crossentropy', metrics=['accu

    return model
```

Before proceeding any further, we should initialize the cross-validation method to be used in the grid search later on.

```
In [0]: sss = StratifiedShuffleSplit(n_splits=3, test_size=0.2, random_state=42)
```

```
In [10]: clf = KerasClassifier(make_model, epochs=10, verbose=0)

         param_grid = {'hidden_size': [32, 64, 128],
                       'reg_strength': np.logspace(-3, -1, 5)}

         grid = GridSearchCV(clf, param_grid=param_grid, cv=sss, n_jobs=-1)
         grid.fit(X_train, y_train)
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/framework/op_
Instructions for updating:
Colocations handled automatically by placer.
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/ops/math_ops.
Instructions for updating:
Use tf.cast instead.
```

```
Out[10]: GridSearchCV(cv=StratifiedShuffleSplit(n_splits=3, random_state=42, test_size=0.2,
                     train_size=None),
                error_score='raise-deprecating',
                estimator=<keras.wrappers.scikit_learn.KerasClassifier object at 0x7fc5af1445c
                fit_params=None, iid='warn', n_jobs=-1,
                param_grid={'hidden_size': [32, 64, 128], 'reg_strength': array([0.001   , 0.00
                pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
                scoring=None, verbose=0)
```

```
In [11]: print('Best score: {}'.format(np.round(grid.best_score_, 2)))
         print('Best params: {}'.format(grid.best_params_))
```

```
Best score: 0.92
Best params: {'hidden_size': 128, 'reg_strength': 0.001}
```

```
In [12]: score = grid.score(X_test, y_test)
         print('Test score: {}'.format(np.round(score, 2)))
```

```
Test score: 0.97
```

### 1.2 Task 2

Train a multilayer perceptron (fully connected) on the Fashion MNIST dataset. 1. Use 10000 samples from the training set for model selection and to compute learning curves (accuracy vs epochs). 2. Compare the following models and plot their learning curves: - Vanilla Model - Model using dropout - Model using batch normalization and residual connections (but no dropout)

```
In [13]: # loading the data
         (X_train, y_train), (X_test, y_test) = keras.datasets.fashion_mnist.load_data()
```

```
Downloading data from http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-labels-i
32768/29515 [==================================] - 0s 9us/step
Downloading data from http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-images-i
26427392/26421880 [==============================] - 4s 0us/step
Downloading data from http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-labels-id
8192/5148 [==============================================] - 0s 0us/step
Downloading data from http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-images-id
4423680/4422102 [===============================] - 2s 1us/step
```

```
In [14]: print('Training size: {}, Test size: {}'.format(X_train.shape[0],X_test.shape[0]))
         print('Each image has a shape of: {}x{}'.format(X_train.shape[1], X_train.shape[2]))
```

```
Training size: 60000, Test size: 10000
Each image has a shape of: 28x28
```

Before proceeding with the modeling, we have to process our data accordingly.

```
In [0]: # reshape X and cast to float
        X_train = X_train.reshape(60000, 784); X_test = X_test.reshape(10000, 784)
        X_train = X_train.astype('float32'); X_test = X_test.astype('float32')

        # scale X
        X_train /= 255; X_test /= 255

        # encode the target accordingly
        n_classes = len(np.unique(y_train))
        y_train = to_categorical(y_train, n_classes); y_test = to_categorical(y_test, n_classe
```

We also have to get a stratified sample of size 10000 from the training set for model selection.

```
In [0]: X, X_valid, y, y_valid = train_test_split(X_train, y_train, stratify=y_train, random_s
```

```
In [0]: # sss = StratifiedShuffleSplit(n_splits=1, test_size=1/6, random_state=6)
        # for a, b in sss.split(X_train, y_train):
        #     X_sample, y_sample = X_train[b], y_train[b]
```

### 1.2.1 Parameter Tuning

```
In [0]: sss = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=410)
```

**Vanilla Model**

We start off by tuning our vanilla model. Vanilla models are typically used to describe simple networks with 1 layer, so we'll only look at optimizing the number of hidden units in this case.

```
In [0]: def make_model(hidden_size):
            """
            Create the model to pass to the Keras Classifier
            """

            model = Sequential([
                Dense(hidden_size, input_shape=(784,), activation='relu'), # first layer
                Dense(10, activation='softmax')                            # output layer
            ])

            # compile the above model
            model.compile(optimizer='adam', loss='categorical_crossentropy',
                          metrics=['accuracy'])

            return model
```

```
In [0]: clf = KerasClassifier(make_model, epochs=10, verbose=0)

        param_grid = {'hidden_size': [256, 512]}

        grid = GridSearchCV(clf, param_grid=param_grid, cv=sss, n_jobs=-1).fit(X, y)
```

```
In [21]: print('VANILLA MODEL TUNING:')
         print('Best Score: {}'.format(np.round(grid.best_score_, 2)))
         print('Best Hidden Size: {}'.format(grid.best_params_['hidden_size']))
```

```
VANILLA MODEL TUNING:
Best Score: 0.88
Best Hidden Size: 512
```

```
In [0]: vanilla = grid.best_estimator_
        history_vanilla = vanilla.fit(X, y, epochs=10, validation_data=(X_valid, y_valid))
```

**Bigger Model w/ Dropout**

We can now proceed with tuning our bigger model with dropout.

```
In [0]: def make_model(hidden_size, hidden_layers, dp_p):
            """
            Create the model to pass to the Keras Classifier
            """
```

```python
    model = Sequential()

    # input layer
    model.add(Dense(hidden_size, input_shape=(784,), activation='relu'))
    model.add(Dropout(dp_p))

    # add as many layers as needed
    for i in range(hidden_layers):
        model.add(Dense(hidden_size, activation='relu'))
        model.add(Dropout(dp_p))

    # output layer
    model.add(Dense(10, activation='softmax'))


    # compile the above model
    model.compile(optimizer='adam', loss='categorical_crossentropy',
                  metrics=['accuracy'])

    return model
```

In [24]:
```python
clf = KerasClassifier(make_model, epochs=10, verbose=0)

param_grid = {'hidden_size': [256, 512],
              'hidden_layers': [1,2,3],
              'dp_p': np.linspace(0.25, 0.75, 3)}

grid = GridSearchCV(clf, param_grid=param_grid, cv=sss, n_jobs=-1).fit(X, y)
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - keep_prob`.
```

In [25]:
```python
print('DROPOUT MODEL TUNING:')
print('Best Score: {}'.format(np.round(grid.best_score_, 2)))
print('Best Hidden Size: {}'.format(grid.best_params_['hidden_size']))
print('Best Number of Hidden Layers: {}'.format(grid.best_params_['hidden_layers']))
print('Best Dropout Prob: {}'.format(grid.best_params_['dp_p']))
```

```
DROPOUT MODEL TUNING:
Best Score: 0.88
Best Hidden Size: 512
Best Number of Hidden Layers: 1
Best Dropout Prob: 0.25
```

In [0]:
```python
dropout = grid.best_estimator_
history_dropout = dropout.fit(X, y, epochs=10, validation_data=(X_valid, y_valid))
```

**Residual Batch Model**

Moving on to our final model for this task - we introduce batch normalization and residual connections.

```
In [0]: inputs = Input(shape=(784,))                    # input

        x1 = Dense(256, activation='relu')(inputs)    # first layer: 256 units

        x2 = Dense(256, activation='relu')(x1)        # second layer: 256 units
        x2 = BatchNormalization()(x2)                 # batch normalization
        x2 = add([x1, x2])                            # residual connection

        x3 = Dense(256, activation='relu')(x2)        # third layer: 256 units
        x3 = BatchNormalization()(x3)                 # batch normalization
        x3 = add([x2, x3])                            # residual connection

        x4 = Dense(128, activation='relu')(x3)        # fourth layer: 128 units
        x4 = BatchNormalization()(x4)                 # batch normalization

        preds = Dense(10, activation='softmax')(x4)

        resbatch = Model(inputs=inputs, outputs=preds)
```

```
In [0]: resbatch.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy
        history_resbatch = resbatch.fit(X, y, epochs=10, validation_data=(X_valid, y_valid), ve
```

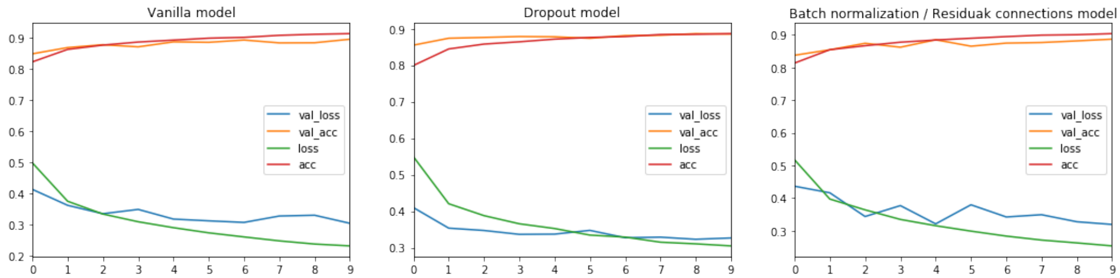
```
In [29]: for k, h in {'vanilla': history_vanilla,
                      'dropout': history_dropout,
                      'resbatch': history_resbatch}.items():
              print(k.upper() + ' RESULTS:')
              print('Training Accuracy: {}'.format(np.round(h.history['acc'][-1], 2)))
              print('Validation Accuracy: {}'.format(np.round(h.history['val_acc'][-1], 2)))
```

```
VANILLA RESULTS:
Training Accuracy: 0.91
Validation Accuracy: 0.9
DROPOUT RESULTS:
Training Accuracy: 0.89
Validation Accuracy: 0.89
RESBATCH RESULTS:
Training Accuracy: 0.9
Validation Accuracy: 0.89
```

### 1.2.2 Learning Curves

```
In [30]: fig, ax = plt.subplots(1,3, figsize=(18, 4))
         pd.DataFrame(history_vanilla.history).plot(ax=ax[0])
         ax[0].set_title("Vanilla model")
```

```
pd.DataFrame(history_dropout.history).plot(ax=ax[1])
ax[1].set_title("Dropout model")
pd.DataFrame(history_resbatch.history).plot(ax=ax[2])
ax[2].set_title("Batch normalization / Residuak connections model")
plt.show()
```




## 1.3 Task 3

Before proceeding, we should get the data. We have downloaded the dataset onto a Google Drive, where we can unzip the file and load the images.

```
In [3]: from google.colab import drive
        drive.mount('/content/drive', force_remount=True)
```

```
Mounted at /content/drive
```

```
In [0]: # unzip the new zip file and store all its files into our images directory
        !unzip -q -o drive/'My Drive'/'AML HW5'/IDC_regular_ps50_idx5.zip -d images
```

```
In [0]: # load the images
        imagePatches = glob('images/**/*.png', recursive=True)

        # seperate our two classes
        class0 = fnmatch.filter(imagePatches, '*class0.png')
        class1 = fnmatch.filter(imagePatches, '*class1.png')

        # create our target variable
        y = []
        for img in imagePatches:
            if img in class0:
                y.append(0)
            elif img in class1:
                y.append(1)
```

We turn the images and the target into a dataframe so we can see the class proportions and create a test set.

In [0]:
```
images_df = pd.DataFrame()
images_df['images'] = imagePatches
images_df['y'] = y
```

In [7]:
```
images_df.groupby('y').size()
```

Out[7]:
```
y
0    198738
1     78786
dtype: int64
```

Given the imbalanced proportions of our dataset, we implement downsampling.

In [0]:
```
images_0 = images_df[images_df.y == 0]  # all our images w/ class 0
images_1 = images_df[images_df.y == 1]  # all our images w/ class 1

# downsample the majority class (0)
images_0 = resample(images_0, replace=False, n_samples=images_1.shape[0], random_state=
# images_1 = resample(images_1, replace=False, n_samples=100000, random_state=42)

df = pd.concat([images_0, images_1])    # join the two back together
```

In [9]:
```
df.head(3)
```

Out[9]:
```
                                                   images  y
21948   images/10268/0/10268_idx5_x3501_y1101_class0.png  0
83757    images/14211/0/14211_idx5_x701_y2101_class0.png  0
181091   images/13616/0/13616_idx5_x1551_y701_class0.png  0
```

In [0]:
```
df = df.sample(frac=1).reset_index(drop=True)
```

We can now process our images:

In [0]:
```
y = df.y
X = np.asarray([cv2.resize(cv2.imread(img), (50,50)) for img in df.images])
```

We create a test set and encode/process our data accordingly:

In [0]:
```
# encode the target accordingly
n_classes = len(np.unique(y))                 # number of classes in our target
y = to_categorical(y, n_classes)              # encode training

# cast X to float and scale
X = X.astype('float32')
X /= 255
```

Now that our data is ready, we can proceed with our tasks.

**3.1**: A model without residual connections.

**3.2**: Augment the data. How much has this improved the original model?

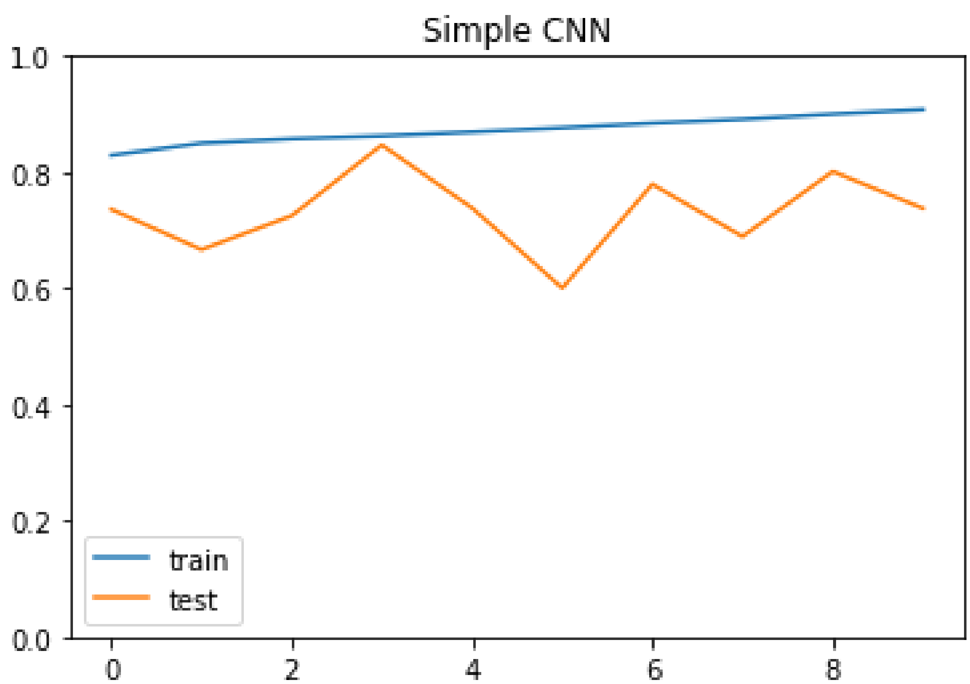
**3.3**: Build a deeper model using residual connections. Show that you can build a deep model that would not be able to learn without the residual connections.

### 3.1 Simple Model

```
In [13]: input_shape = (50, 50, 3)
         simple = Sequential()

                                                                        ### Layer 1 ###
         simple.add(Conv2D(32, (2, 2), activation='relu',               # Convolutional L
                          input_shape=input_shape))
         simple.add(BatchNormalization())                               # Batch Norm.
         simple.add(MaxPooling2D(pool_size=(2, 2)))                     # Pooling Layer

                                                                        ### Layer 2 ###
         simple.add(Conv2D(32, (2, 2), activation='relu'))              # Conv. Layer
         simple.add(BatchNormalization())                               # Batch Norm.
         simple.add(MaxPooling2D(pool_size=(2, 2)))                     # Pooling Layer

                                                                        ### Layer 3 ###
         simple.add(Flatten())                                          # Flatten the data
         simple.add(Dense(128, activation='relu'))                      # 64 units dense

         simple.add(Dense(2, activation='softmax'))                     ### Output ###

         simple.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/framework/op_
Instructions for updating:
Colocations handled automatically by placer.


In [14]: history_simple = simple.fit(X, y, batch_size=128, epochs=10, verbose=1,
                                     validation_split=0.1)

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/ops/math_ops.
Instructions for updating:
Use tf.cast instead.
Train on 141814 samples, validate on 15758 samples
Epoch 1/10
141814/141814 [==============================] - 21s 145us/step - loss: 0.4027 - acc: 0.8292 -
Epoch 2/10
141814/141814 [==============================] - 17s 121us/step - loss: 0.3528 - acc: 0.8502 -
Epoch 3/10
141814/141814 [==============================] - 17s 121us/step - loss: 0.3371 - acc: 0.8576 -
Epoch 4/10
141814/141814 [==============================] - 18s 124us/step - loss: 0.3245 - acc: 0.8627 -
Epoch 5/10
141814/141814 [==============================] - 17s 121us/step - loss: 0.3112 - acc: 0.8694 -
Epoch 6/10
141814/141814 [==============================] - 17s 122us/step - loss: 0.2958 - acc: 0.8767 -
Epoch 7/10
```

```
141814/141814 [==============================] - 17s 122us/step - loss: 0.2799 - acc: 0.8847 -
Epoch 8/10
141814/141814 [==============================] - 18s 125us/step - loss: 0.2619 - acc: 0.8914 -
Epoch 9/10
141814/141814 [==============================] - 18s 124us/step - loss: 0.2435 - acc: 0.9003 -
Epoch 10/10
141814/141814 [==============================] - 17s 122us/step - loss: 0.2255 - acc: 0.9081 -
```

```
In [29]: plt.plot(history_simple.history['acc'], label='train')
         plt.plot(history_simple.history['val_acc'], label='test')
         plt.title("Simple CNN")
         plt.legend()
         plt.ylim(0,1)
         plt.show()
```




```
In [16]: print('Training Accuracy: {}'.format(np.round(history_simple.history['acc'][-1], 2)))
         print('Validation Accuracy: {}'.format(np.round(history_simple.history['val_acc'][-1]
```

```
Training Accuracy: 0.91
Validation Accuracy: 0.74
```

As we can see, our model has a good training accuracy, but appears to overfit a little. The validation accuracy in particular fluctuates a lot.

**3.2 Augmenting the data** We're now going to try data augmentation to improve the results of the same CNN - this technique will likely lead our network to overfit less. Here are the options we have:

- Mirroring
- Rotations
- Translations
- Scaling (zooming in/out)

When taking a look at the data, it makes sense to apply all these transformations to the images we have, since they don't have a "normalized" size, orientation, etc. If we were working on the digits dataset, it wouldn't make sense to apply rotations for instance, but here we don't have that problem and we can apply pretty much what we want, since a quick look at the images tells us that they don't seem to be standardized in their scale, orientation, centering, etc.

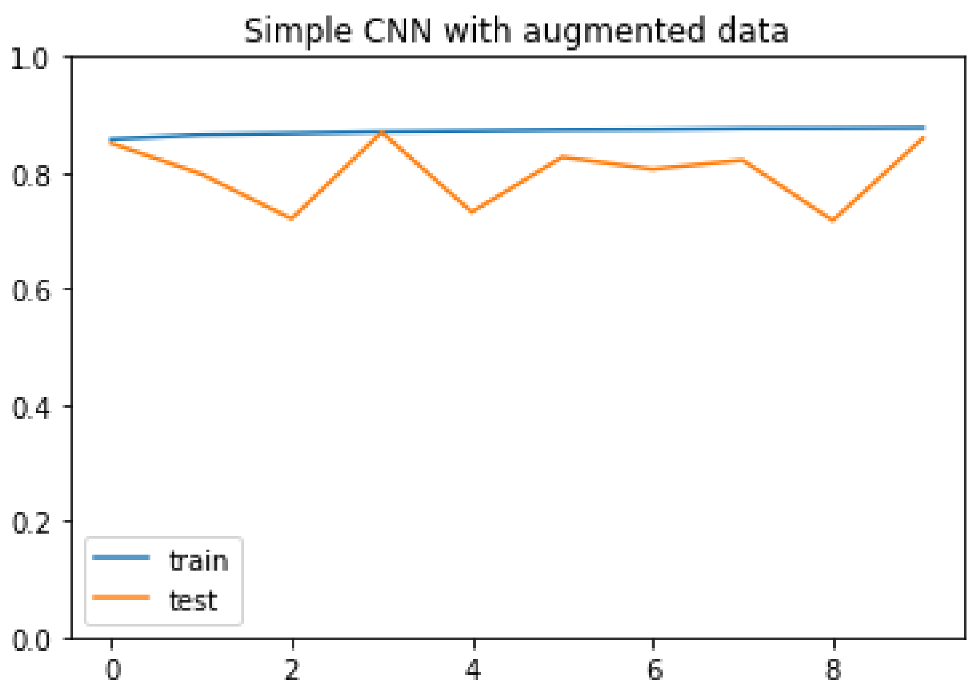
We're going to do what's called "online" data augmentation, i.e. data augmentation "on the fly", whenever we train a batch. Otherwise, the dataset we'd create would be way too large.

```
In [17]: data_aug = image.ImageDataGenerator(
                horizontal_flip=True,                           ## Mirroring (horizontal)
                vertical_flip=True,                             ## Mirroring (vertical)
                rotation_range=90,                              ## Rotation
                width_shift_range=0.2,                          ## Translation (horizontal)
                height_shift_range=0.2,                         ## Translation (vertical)
                zoom_range=[1,2],                               ## Zooming in
                validation_split=0.1
                )

         train_generator = data_aug.flow(X, y, batch_size=128, subset='training')
         val_generator = data_aug.flow(X, y, batch_size=128, subset='validation')

         history_aug = simple.fit_generator(train_generator,
                                  steps_per_epoch=len(train_generator)*4,
                                  # We choose to get 4 times as much data on
                                  # each epoch
                                  epochs=10, verbose=1,
                                  validation_data=val_generator,
                                  validation_steps=len(val_generator))
```

```
Epoch 1/10
4432/4432 [==============================] - 424s 96ms/step - loss: 0.3368 - acc: 0.8577 - val_
Epoch 2/10
4432/4432 [==============================] - 422s 95ms/step - loss: 0.3216 - acc: 0.8653 - val_
Epoch 3/10
4432/4432 [==============================] - 423s 96ms/step - loss: 0.3152 - acc: 0.8679 - val_
Epoch 4/10
4432/4432 [==============================] - 422s 95ms/step - loss: 0.3100 - acc: 0.8707 - val_
Epoch 5/10
4432/4432 [==============================] - 420s 95ms/step - loss: 0.3064 - acc: 0.8721 - val_
Epoch 6/10
```

```
4432/4432 [==============================] - 416s 94ms/step - loss: 0.3028 - acc: 0.8738 - val_
Epoch 7/10
4432/4432 [==============================] - 416s 94ms/step - loss: 0.3006 - acc: 0.8745 - val_
Epoch 8/10
4432/4432 [==============================] - 416s 94ms/step - loss: 0.2972 - acc: 0.8762 - val_
Epoch 9/10
4432/4432 [==============================] - 415s 94ms/step - loss: 0.2957 - acc: 0.8765 - val_
Epoch 10/10
4432/4432 [==============================] - 427s 96ms/step - loss: 0.2936 - acc: 0.8774 - val_
```

In [28]:
```python
plt.plot(history_aug.history['acc'], label='train')
plt.plot(history_aug.history['val_acc'], label='test')
plt.title("Simple CNN with augmented data")
plt.legend()
plt.ylim(0,1)
plt.show()
```




In [19]:
```python
print('Training Accuracy: {}'.format(np.round(history_aug.history['acc'][-1], 2)))
print('Validation Accuracy: {}'.format(np.round(history_aug.history['val_acc'][-1], 2
```

```
Training Accuracy: 0.88
Validation Accuracy: 0.86
```

At the expense of a much increased training time, we can see that the same model with augmented data does a little bit better in terms of validation accuracy. The plot also show us that the validation accuracy fluctuates less and generally stays higher. The final accuracy numbers tell us that we indeed overfit less, as the training accuracy has decreased and the validation accuracy is much increased.

**3.3 Deeper model** Here is our deeper model with residual connections. The architecture is inspired by resnet.

```
In [0]: inputs = Input(shape = (50, 50, 3))

                                                                ### First layer ###
        x1 = Conv2D(32, (3, 3), activation='relu')(inputs)      # Conv Layer
        x2 = BatchNormalization()(x1)                           # Batch Norm.
        x4 = MaxPooling2D(pool_size=(2, 2))(x2)                 # Pooling Layer


        x5 = Conv2D(32, (3, 3), padding='same',
                   activation='relu')(x4)                       # Conv Layer
        x6 = BatchNormalization()(x5)                           # Batch Norm.

        x8 = Conv2D(32, (3, 3), padding='same',
                   activation='relu')(x6)                       # Conv Layer
        x9 = BatchNormalization()(x8)                           # Batch Norm.

        x11 = add([x4, x9])                                     # Residual connection

        x12 = Conv2D(32, (3, 3), padding='same',
                    activation='relu')(x11)                     # Conv Layer
        x13 = BatchNormalization()(x12)                         # Batch Norm.

        x15 = Conv2D(32, (3, 3), padding='same',
                    activation='relu')(x13)                     # Conv Layer
        x16 = BatchNormalization()(x15)                         # Batch Norm.

        x80 = add([x11, x16])                                   # Residual connection

        x99 = Conv2D(32, (3, 3), padding='same',
                    activation='relu')(x80)                     # Conv Layer
        x98 = BatchNormalization()(x99)                         # Batch Norm.

        x97 = Conv2D(32, (3, 3), padding='same',
                    activation='relu')(x98)                     # Conv Layer
        x96 = BatchNormalization()(x97)                         # Batch Norm.

        x18 = add([x80, x96])                                   # Residual connection

        x19 = Conv2D(64, (3, 3), padding='same',
```

```python
              activation='relu')(x18)                        # Conv Layer
x20 = BatchNormalization()(x19)                              # Batch Norm.

x22 = Conv2D(64, (3, 3), padding='same',
              activation='relu')(x20)                        # Conv Layer
x23 = BatchNormalization()(x22)                              # Batch Norm.

x26 = Conv2D(64, (3, 3), padding='same',
              activation='relu')(x23)                        # Conv Layer
x27 = BatchNormalization()(x26)                              # Batch Norm.

x28 = add([x27, x20])                                        # Residual connection

x29 = Conv2D(64, (3, 3), padding='same',
              activation='relu')(x28)                        # Conv Layer
x30 = BatchNormalization()(x29)                              # Batch Norm.

x31 = Conv2D(64, (3, 3), padding='same',
              activation='relu')(x30)                        # Conv Layer
x32 = BatchNormalization()(x31)                              # Batch Norm.

x40 = add([x32, x28])                                        # Residual connection

x41 = Conv2D(64, (3, 3), padding='same',
              activation='relu')(x40)                        # Conv Layer
x42 = BatchNormalization()(x41)                              # Batch Norm.

x43 = Conv2D(64, (3, 3), padding='same',
              activation='relu')(x42)                        # Conv Layer
x44 = BatchNormalization()(x43)                              # Batch Norm.

x45 = add([x44, x40])                                        # Residual connection

x46 = Conv2D(64, (3, 3), padding='same',
              activation='relu')(x45)                        # Conv Layer
x47 = BatchNormalization()(x46)                              # Batch Norm.

x48 = Conv2D(64, (3, 3), padding='same',
              activation='relu')(x47)                        # Conv Layer
x49 = BatchNormalization()(x48)                              # Batch Norm.

x33 = add([x45, x49])                                        # Residual connection

                                                             ### Last layer ###
x34 = Flatten()(x33)                                         # Flatten the data
x35 = Dense(64, activation='relu')(x34)                      # 64 units dense

preds = Dense(2, activation='softmax')(x35)                  ### Output ###
```

```
deep_res = Model(inputs=inputs, outputs=preds)
deep_res.compile(optimizer='adam', loss='categorical_crossentropy',
             metrics=['accuracy'])
```

And here is the same model without residual connections.

```
In [0]: input_shape = (50, 50, 3)
        deep_nores = Sequential()

                                                                ### Layer 1 ###
        deep_nores.add(Conv2D(32, (3, 3), activation='relu',    # Convolutional L
                       input_shape=input_shape, padding='same'))
        deep_nores.add(BatchNormalization())                    # Batch Norm.
        deep_nores.add(MaxPooling2D(pool_size=(2, 2)))          # Pooling Layer

        for i in range(6):                                      ### Layers 2-7 ###
          deep_nores.add(Conv2D(32, (3, 3), activation='relu',
                           padding='same'))                     # Conv. Layer
          deep_nores.add(BatchNormalization())                  # Batch Norm.

        for i in range(9):                                      ### Layers 8-16 ###
          deep_nores.add(Conv2D(32, (3, 3), activation='relu',
                           padding='same'))                     # Conv. Layer
          deep_nores.add(BatchNormalization())                  # Batch Norm.

                                                                ### Layer 17 ###
        deep_nores.add(Flatten())                               # Flatten the data
        deep_nores.add(Dense(64, activation='relu'))            # 64 units dense

        deep_nores.add(Dense(2, activation='softmax'))          ### Output ###

        deep_nores.compile(optimizer='adam', loss='categorical_crossentropy',
                         metrics=['accuracy'])
```

Let's now train them.

```
In [45]: history_res = deep_res.fit(X, y, batch_size=128, epochs=10, verbose=1,
                                validation_split=0.1)

Train on 141814 samples, validate on 15758 samples
Epoch 1/10
141814/141814 [==============================] - 110s 779us/step - loss: 0.4136 - acc: 0.8314 -
Epoch 2/10
141814/141814 [==============================] - 103s 726us/step - loss: 0.3477 - acc: 0.8540 -
Epoch 3/10
141814/141814 [==============================] - 103s 726us/step - loss: 0.3315 - acc: 0.8606 -
Epoch 4/10
141814/141814 [==============================] - 103s 724us/step - loss: 0.3180 - acc: 0.8671 -
```

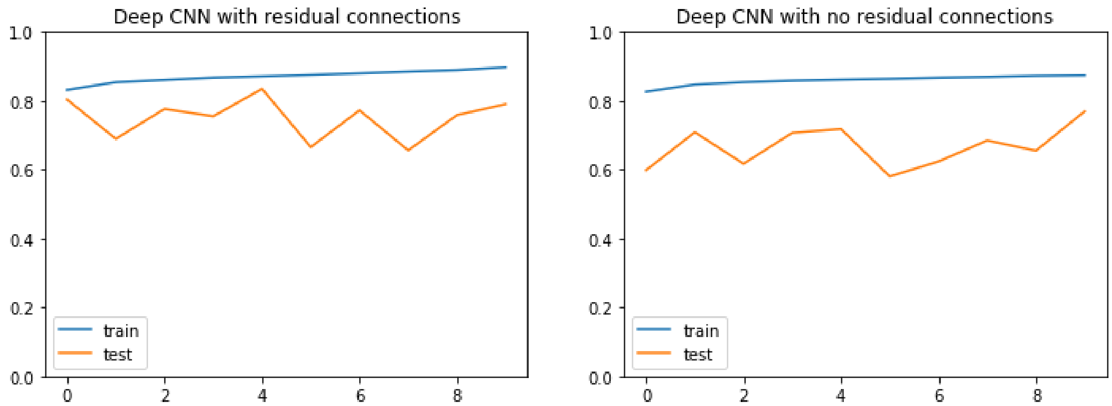
```
Epoch 5/10
141814/141814 [==============================] - 103s 725us/step - loss: 0.3100 - acc: 0.8710 -
Epoch 6/10
141814/141814 [==============================] - 103s 724us/step - loss: 0.2989 - acc: 0.8752 -
Epoch 7/10
141814/141814 [==============================] - 103s 725us/step - loss: 0.2867 - acc: 0.8798 -
Epoch 8/10
141814/141814 [==============================] - 103s 726us/step - loss: 0.2739 - acc: 0.8846 -
Epoch 9/10
141814/141814 [==============================] - 103s 724us/step - loss: 0.2615 - acc: 0.8888 -
Epoch 10/10
141814/141814 [==============================] - 103s 726us/step - loss: 0.2410 - acc: 0.8970 -
```

```
In [46]: history_nores = deep_nores.fit(X, y, batch_size=128, epochs=10, verbose=1,
                                        validation_split=0.1)
```

```
Train on 141814 samples, validate on 15758 samples
Epoch 1/10
141814/141814 [==============================] - 78s 549us/step - loss: 0.4050 - acc: 0.8263 -
Epoch 2/10
141814/141814 [==============================] - 71s 497us/step - loss: 0.3597 - acc: 0.8471 -
Epoch 3/10
141814/141814 [==============================] - 70s 496us/step - loss: 0.3447 - acc: 0.8542 -
Epoch 4/10
141814/141814 [==============================] - 71s 499us/step - loss: 0.3364 - acc: 0.8586 -
Epoch 5/10
141814/141814 [==============================] - 71s 499us/step - loss: 0.3318 - acc: 0.8614 -
Epoch 6/10
141814/141814 [==============================] - 70s 497us/step - loss: 0.3253 - acc: 0.8638 -
Epoch 7/10
141814/141814 [==============================] - 71s 498us/step - loss: 0.3199 - acc: 0.8669 -
Epoch 8/10
141814/141814 [==============================] - 71s 498us/step - loss: 0.3140 - acc: 0.8693 -
Epoch 9/10
141814/141814 [==============================] - 71s 498us/step - loss: 0.3082 - acc: 0.8726 -
Epoch 10/10
141814/141814 [==============================] - 71s 498us/step - loss: 0.3025 - acc: 0.8742 -
```

```
In [47]: fig, ax = plt.subplots(1,2, figsize=(12, 4))
         ax[0].plot(history_res.history['acc'], label='train')
         ax[0].plot(history_res.history['val_acc'], label='test')
         ax[0].set_title("Deep CNN with residual connections")
         ax[0].set_ylim(0,1)
         ax[0].legend()

         ax[1].plot(history_nores.history['acc'], label='train')
```

```
ax[1].plot(history_nores.history['val_acc'], label='test')
ax[1].set_title("Deep CNN with no residual connections")
ax[1].set_ylim(0,1)
ax[1].legend()
plt.show()
```




As we can see, removing the residual connections makes the performance decrease - although not by much. We expect the difference in performance to be even higher with an even deeper model.