13_svhn_object_detection

September 29, 2021

1 Object Detection with Street View House Numbers

This notebook illustrates how to build a deep CNN using Keras' functional API to generate multiple outputs: one to predict how many digits are present, and five for the value of each in the order they appear.

1.1 Imports & Settings

[1]:
```
%matplotlib inline
from pathlib import Path
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.metrics import confusion_matrix

import tensorflow as tf
from tensorflow.keras.models import Model
from tensorflow.keras.applications.vgg16 import VGG16
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping
from tensorflow.keras.layers import (Flatten,
                                     Dense,
                                     BatchNormalization,
                                     Activation,
                                     Concatenate)
from tensorflow.keras import backend as K
from matplotlib.ticker import FuncFormatter
```

[2]:
```
gpu_devices = tf.config.experimental.list_physical_devices('GPU')
if gpu_devices:
    print('Using GPU')
    tf.config.experimental.set_memory_growth(gpu_devices[0], True)
else:
    print('Using CPU')
```

```
Using CPU
```

[3]:
```python
sns.set_style('whitegrid')
```

[4]:
```python
data_path = Path('images', 'svhn')
```

[5]:
```python
results_path = Path('results', 'svhn')
if not results_path.exists():
    results_path.mkdir()
```

1.1.1 Settings

[6]:
```python
IMG_SIZE = 32
IMG_SHAPE = (IMG_SIZE, IMG_SIZE, 3)
SEQ_LENGTH = 4
N_CLASSES = 11
```

1.2 Load Data

[7]:
```python
X_train = np.load(data_path / 'X_train.npy')
y_train = np.load(data_path / 'y_train.npy')
```

Removing the rare cases of 5-digit house numbers.

[8]:
```python
X_train = X_train[y_train[:, 0] < 5]
y_train = y_train[y_train[:, 0] < 5, :5]
y_train[:, 0] -= 1
```

[9]:
```python
X_test = np.load(data_path / 'X_test.npy')
y_test = np.load(data_path / 'y_test.npy')
```

[10]:
```python
X_test = X_test[y_test[:, 0] < 5]
y_test = y_test[y_test[:, 0] < 5, :5]
y_test[:, 0] -= 1
```

[11]:
```python
pd.DataFrame(y_train).nunique()
```

[11]:
```
0     4
1    10
2    11
3    11
4    11
dtype: int64
```

[12]:
```python
y_train.shape
```

[12]:
```
(33392, 5)
```

1.3 Best Architecture

Multi-digit Number Recognition from Street View Imagery using Deep Convolutional Neural Networks, Goodfellow, et al, 2014

[13]:
```
digit_pos = {1: [4, 14], 2: [14, 25], 3: [25, 36], 4: [36, 47]}
```

[14]:
```
def weighted_accuracy(y_true, y_pred):
    n_digits_pred = K.argmax(y_pred[:, :SEQ_LENGTH], axis=1)

    digit_preds = {}
    for digit, (start, end) in digit_pos.items():
        digit_preds[digit] = K.argmax(y_pred[:, start:end], axis=1)
    preds = tf.dtypes.cast(tf.stack((n_digits_pred,
                                     digit_preds[1],
                                     digit_preds[2],
                                     digit_preds[3],
                                     digit_preds[4]), axis=1), tf.float32)

    return K.mean(K.sum(tf.dtypes.cast(K.equal(y_true, preds), tf.int64),␣
 ↪axis=1) / 5)
```

[15]:
```
def weighted_entropy(y_true, y_pred):
    cce = tf.keras.losses.SparseCategoricalCrossentropy()
    n_digits = y_pred[:, :SEQ_LENGTH]

    digits = {}
    for digit, (start, end) in digit_pos.items():
        digits[digit] = y_pred[:, start:end]
    return (cce(y_true[:, 0], n_digits) +
            cce(y_true[:, 1], digits[1]) +
            cce(y_true[:, 2], digits[2]) +
            cce(y_true[:, 3], digits[3]) +
            cce(y_true[:, 4], digits[4])) / 5
```

[16]:
```
vgg16 = VGG16(input_shape=IMG_SHAPE, include_top=False, weights='imagenet')
vgg16.trainable = False
x = vgg16.output
x = Flatten()(x)
x = BatchNormalization()(x)
x = Dense(256)(x)
x = BatchNormalization()(x)
x = Activation('relu')(x)
x = Dense(128)(x)
x = BatchNormalization()(x)
x = Activation('relu')(x)
n_digits = Dense(SEQ_LENGTH, activation='softmax', name='n_digits')(x)
digit1 = Dense(N_CLASSES-1, activation='softmax', name='d1')(x)
```

```
digit2 = Dense(N_CLASSES, activation='softmax', name='d2')(x)
digit3 = Dense(N_CLASSES, activation='softmax', name='d3')(x)
digit4 = Dense(N_CLASSES, activation='softmax', name='d4')(x)
predictions = Concatenate()([n_digits, digit1, digit2, digit3, digit4])

model = Model(inputs=vgg16.input, outputs=predictions)
```

[17]:
```
model.compile(optimizer='adam',
              loss=weighted_entropy,
              metrics=[weighted_accuracy])
```

As a result, the model produces five distinct outputs that we can evaluate.

1.4 Define Callbacks

[18]:
```
svhn_path = (results_path / 'svhn.weights.best.hdf5').as_posix()
checkpointer = ModelCheckpoint(filepath=svhn_path,
                               verbose=1,
                               monitor='val_weighted_accuracy',
                               save_best_only=True)
```

[19]:
```
early_stopping = EarlyStopping(monitor='val_weighted_accuracy',
                               patience=5)
```

1.5 Train Transfer Model

[20]:
```
epochs = 50
```

[21]:
```
result = model.fit(x=X_train,
                   y=y_train,
                   validation_split=.1,
                   batch_size=32,
                   epochs=epochs,
                   verbose=1,
                   callbacks=[checkpointer, early_stopping])
```

```
Epoch 1/50
940/940 [==============================] - ETA: 0s - loss: 1.0570 -
weighted_accuracy: 0.6429
Epoch 00001: val_weighted_accuracy improved from -inf to 0.67796, saving model
to results/svhn/cnn.weights.best.hdf5
940/940 [==============================] - 10s 11ms/step - loss: 1.0570 -
weighted_accuracy: 0.6429 - val_loss: 0.9570 - val_weighted_accuracy: 0.6780
Epoch 2/50
939/940 [============================>.] - ETA: 0s - loss: 0.9246 -
weighted_accuracy: 0.6835
Epoch 00002: val_weighted_accuracy improved from 0.67796 to 0.68603, saving
```

```
model to results/svhn/cnn.weights.best.hdf5
940/940 [==============================] - 10s 11ms/step - loss: 0.9247 -
weighted_accuracy: 0.6834 - val_loss: 0.9284 - val_weighted_accuracy: 0.6860
Epoch 3/50
937/940 [============================>.] - ETA: 0s - loss: 0.8844 -
weighted_accuracy: 0.6978
Epoch 00003: val_weighted_accuracy improved from 0.68603 to 0.69097, saving
model to results/svhn/cnn.weights.best.hdf5
940/940 [==============================] - 10s 11ms/step - loss: 0.8843 -
weighted_accuracy: 0.6979 - val_loss: 0.9175 - val_weighted_accuracy: 0.6910
Epoch 4/50
939/940 [============================>.] - ETA: 0s - loss: 0.8490 -
weighted_accuracy: 0.7088
Epoch 00004: val_weighted_accuracy improved from 0.69097 to 0.69671, saving
model to results/svhn/cnn.weights.best.hdf5
940/940 [==============================] - 10s 11ms/step - loss: 0.8490 -
weighted_accuracy: 0.7088 - val_loss: 0.9014 - val_weighted_accuracy: 0.6967
Epoch 5/50
936/940 [============================>.] - ETA: 0s - loss: 0.8199 -
weighted_accuracy: 0.7196
Epoch 00005: val_weighted_accuracy improved from 0.69671 to 0.69742, saving
model to results/svhn/cnn.weights.best.hdf5
940/940 [==============================] - 10s 11ms/step - loss: 0.8200 -
weighted_accuracy: 0.7194 - val_loss: 0.9036 - val_weighted_accuracy: 0.6974
Epoch 6/50
935/940 [============================>.] - ETA: 0s - loss: 0.7952 -
weighted_accuracy: 0.7266
Epoch 00006: val_weighted_accuracy improved from 0.69742 to 0.69829, saving
model to results/svhn/cnn.weights.best.hdf5
940/940 [==============================] - 10s 11ms/step - loss: 0.7952 -
weighted_accuracy: 0.7266 - val_loss: 0.9069 - val_weighted_accuracy: 0.6983
Epoch 7/50
935/940 [============================>.] - ETA: 0s - loss: 0.7745 -
weighted_accuracy: 0.7347
Epoch 00007: val_weighted_accuracy improved from 0.69829 to 0.70073, saving
model to results/svhn/cnn.weights.best.hdf5
940/940 [==============================] - 10s 11ms/step - loss: 0.7745 -
weighted_accuracy: 0.7347 - val_loss: 0.9127 - val_weighted_accuracy: 0.7007
Epoch 8/50
937/940 [============================>.] - ETA: 0s - loss: 0.7568 -
weighted_accuracy: 0.7397
Epoch 00008: val_weighted_accuracy did not improve from 0.70073
940/940 [==============================] - 10s 11ms/step - loss: 0.7569 -
weighted_accuracy: 0.7396 - val_loss: 0.9234 - val_weighted_accuracy: 0.6983
Epoch 9/50
939/940 [============================>.] - ETA: 0s - loss: 0.7378 -
weighted_accuracy: 0.7452
Epoch 00009: val_weighted_accuracy did not improve from 0.70073
```

```
940/940 [==============================] - 10s 11ms/step - loss: 0.7379 -
weighted_accuracy: 0.7450 - val_loss: 0.9311 - val_weighted_accuracy: 0.6971
Epoch 10/50
938/940 [============================>.] - ETA: 0s - loss: 0.7192 -
weighted_accuracy: 0.7521
Epoch 00010: val_weighted_accuracy did not improve from 0.70073
940/940 [==============================] - 10s 11ms/step - loss: 0.7193 -
weighted_accuracy: 0.7520 - val_loss: 0.9380 - val_weighted_accuracy: 0.6958
Epoch 11/50
937/940 [============================>.] - ETA: 0s - loss: 0.7066 -
weighted_accuracy: 0.7557
Epoch 00011: val_weighted_accuracy did not improve from 0.70073
940/940 [==============================] - 10s 11ms/step - loss: 0.7070 -
weighted_accuracy: 0.7554 - val_loss: 0.9588 - val_weighted_accuracy: 0.6966
Epoch 12/50
937/940 [============================>.] - ETA: 0s - loss: 0.6923 -
weighted_accuracy: 0.7615
Epoch 00012: val_weighted_accuracy did not improve from 0.70073
940/940 [==============================] - 10s 11ms/step - loss: 0.6925 -
weighted_accuracy: 0.7612 - val_loss: 0.9697 - val_weighted_accuracy: 0.6980
```

1.5.1 Evaluate Results

[22]:
```
metrics = pd.DataFrame(result.history)
initial_epochs = len(metrics)
```

[23]:
```
y_pred = model.predict(X_test, verbose=1)
```

```
409/409 [==============================] - 3s 7ms/step
```

[24]:
```
n_digits = y_pred[:, :SEQ_LENGTH]
digits = {}
for digit, (start, end) in digit_pos.items():
    digits[digit] = y_pred[:, start:end]
```

[25]:
```
(y_test[:, 0] == np.argmax(n_digits, axis=1)).sum()/len(n_digits)
```

[25]:
```
0.829710699525486
```

[27]:
```
confusion_matrix(y_true=y_test[:, 0], y_pred=np.argmax(n_digits, axis=1))
```

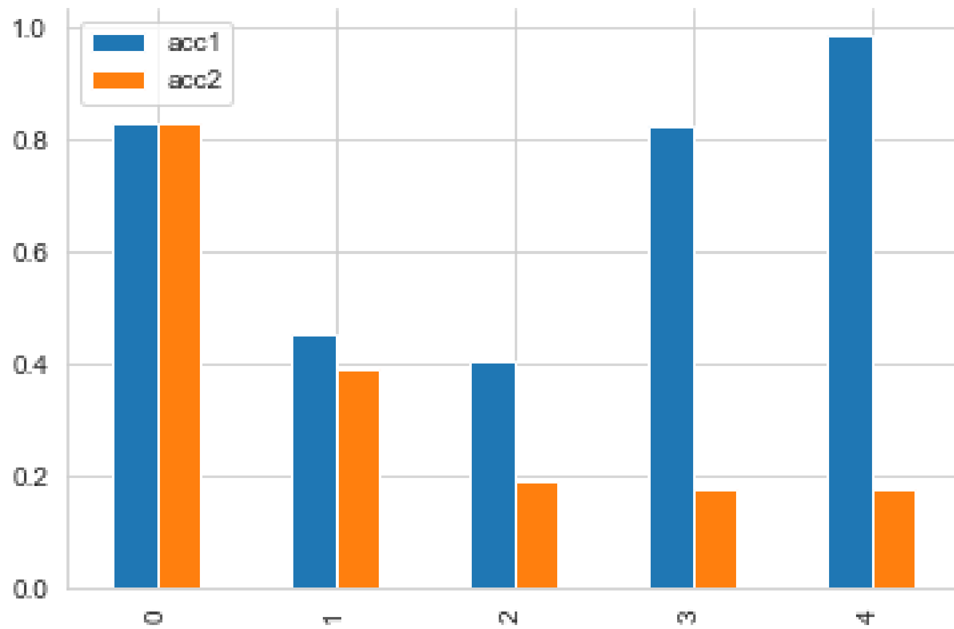
[27]:
```
array([[1907,  559,   16,    1],
       [ 347, 7257,  739,   13],
       [  12,  357, 1606,  106],
       [   0,    3,   72,   71]])
```

```
[28]: accuracy = np.zeros_like(y_test)
accuracy[:, 0] = (y_test[:, 0] == np.argmax(n_digits, axis=1))
for i in range(1, 5):
    accuracy[:, i] = (y_test[:, i] == np.argmax(digits[i], axis=1))
```

```
[29]: acc_by_output = {}
for i in range(5):
    acc_by_output[i] = accuracy[:, i].sum()/accuracy[:, i].shape[0]
```

```
[30]: acc_up_to_out = {}
for i in range(1, 6):
    r = accuracy[:, :i].all(1)
    acc_up_to_out[i-1] = r.sum()/r.shape[0]
```

```
[31]: pd.DataFrame({'acc1': acc_by_output, 'acc2': acc_up_to_out}).plot.bar()
sns.despine();
```



1.6 Fine Tune VGG16 weights

[32]:
```python
vgg16.trainable = True
# Fine-tune from this layer onwards
start_fine_tuning_at = 1

# Freeze all the layers before the `fine_tune_at` layer
for layer in vgg16.layers[:start_fine_tuning_at]:
    layer.trainable =  False
```

[33]:
```python
model.compile(optimizer='adam',
              loss=weighted_entropy,
              metrics=[weighted_accuracy])
```

[34]:
```python
fine_tune_epochs = 50
total_epochs = initial_epochs + fine_tune_epochs
```

[35]:
```python
result_fine_tune = model.fit(x=X_train,
                              y=y_train,
                              validation_split=.1,
                              batch_size=32,
                              epochs=total_epochs,
                              initial_epoch=history.epoch[-1],
                              callbacks=[early_stopping])
```

```
Epoch 12/62
940/940 [==============================] - 28s 30ms/step - loss: 1.1122 -
weighted_accuracy: 0.6255 - val_loss: 1.4838 - val_weighted_accuracy: 0.5645
Epoch 13/62
940/940 [==============================] - 27s 29ms/step - loss: 0.7990 -
weighted_accuracy: 0.7213 - val_loss: 0.7274 - val_weighted_accuracy: 0.7598
Epoch 14/62
940/940 [==============================] - 28s 29ms/step - loss: 0.5737 -
weighted_accuracy: 0.8069 - val_loss: 0.6773 - val_weighted_accuracy: 0.8038
Epoch 15/62
940/940 [==============================] - 27s 29ms/step - loss: 0.4478 -
weighted_accuracy: 0.8533 - val_loss: 0.5126 - val_weighted_accuracy: 0.8332
Epoch 16/62
940/940 [==============================] - 27s 29ms/step - loss: 0.3589 -
weighted_accuracy: 0.8841 - val_loss: 0.3812 - val_weighted_accuracy: 0.8817
Epoch 17/62
940/940 [==============================] - 27s 29ms/step - loss: 0.3012 -
weighted_accuracy: 0.9045 - val_loss: 0.5555 - val_weighted_accuracy: 0.8590
Epoch 18/62
940/940 [==============================] - 27s 29ms/step - loss: 0.2549 -
weighted_accuracy: 0.9193 - val_loss: 0.3523 - val_weighted_accuracy: 0.8995
Epoch 19/62
940/940 [==============================] - 28s 30ms/step - loss: 0.3463 -
weighted_accuracy: 0.8900 - val_loss: 4.3139 - val_weighted_accuracy: 0.4720
```

```
Epoch 20/62
940/940 [==============================] - 27s 29ms/step - loss: 0.2846 -
weighted_accuracy: 0.9100 - val_loss: 0.3679 - val_weighted_accuracy: 0.8956
Epoch 21/62
940/940 [==============================] - 27s 29ms/step - loss: 0.1913 -
weighted_accuracy: 0.9411 - val_loss: 0.2391 - val_weighted_accuracy: 0.9345
Epoch 22/62
940/940 [==============================] - 28s 29ms/step - loss: 0.1625 -
weighted_accuracy: 0.9497 - val_loss: 0.2586 - val_weighted_accuracy: 0.9305
Epoch 23/62
940/940 [==============================] - 27s 29ms/step - loss: 0.1505 -
weighted_accuracy: 0.9532 - val_loss: 0.2329 - val_weighted_accuracy: 0.9360
Epoch 24/62
940/940 [==============================] - 28s 30ms/step - loss: 0.1301 -
weighted_accuracy: 0.9591 - val_loss: 0.3306 - val_weighted_accuracy: 0.9168
Epoch 25/62
940/940 [==============================] - 27s 29ms/step - loss: 0.1247 -
weighted_accuracy: 0.9609 - val_loss: 0.2463 - val_weighted_accuracy: 0.9360
Epoch 26/62
940/940 [==============================] - 27s 29ms/step - loss: 0.1177 -
weighted_accuracy: 0.9629 - val_loss: 0.2444 - val_weighted_accuracy: 0.9374
Epoch 27/62
940/940 [==============================] - 28s 30ms/step - loss: 0.1076 -
weighted_accuracy: 0.9660 - val_loss: 0.2647 - val_weighted_accuracy: 0.9308
Epoch 28/62
940/940 [==============================] - 27s 29ms/step - loss: 0.0974 -
weighted_accuracy: 0.9691 - val_loss: 0.2547 - val_weighted_accuracy: 0.9346
Epoch 29/62
940/940 [==============================] - 28s 29ms/step - loss: 0.0928 -
weighted_accuracy: 0.9710 - val_loss: 0.2480 - val_weighted_accuracy: 0.9382
Epoch 30/62
940/940 [==============================] - 27s 29ms/step - loss: 0.0844 -
weighted_accuracy: 0.9733 - val_loss: 0.2474 - val_weighted_accuracy: 0.9392
Epoch 31/62
940/940 [==============================] - 27s 29ms/step - loss: 0.0791 -
weighted_accuracy: 0.9750 - val_loss: 0.2747 - val_weighted_accuracy: 0.9322
Epoch 32/62
940/940 [==============================] - 28s 29ms/step - loss: 0.0727 -
weighted_accuracy: 0.9767 - val_loss: 0.2443 - val_weighted_accuracy: 0.9415
Epoch 33/62
940/940 [==============================] - 27s 29ms/step - loss: 0.0697 -
weighted_accuracy: 0.9777 - val_loss: 0.3545 - val_weighted_accuracy: 0.9268
Epoch 34/62
940/940 [==============================] - 27s 29ms/step - loss: 0.0672 -
weighted_accuracy: 0.9786 - val_loss: 0.2289 - val_weighted_accuracy: 0.9473
Epoch 35/62
940/940 [==============================] - 28s 29ms/step - loss: 0.0666 -
weighted_accuracy: 0.9792 - val_loss: 0.2312 - val_weighted_accuracy: 0.9500
```

```
Epoch 36/62
940/940 [==============================] - 27s 29ms/step - loss: 0.0538 -
weighted_accuracy: 0.9827 - val_loss: 0.2671 - val_weighted_accuracy: 0.9453
Epoch 37/62
940/940 [==============================] - 28s 30ms/step - loss: 0.0544 -
weighted_accuracy: 0.9824 - val_loss: 0.2291 - val_weighted_accuracy: 0.9481
Epoch 38/62
940/940 [==============================] - 27s 29ms/step - loss: 0.0641 -
weighted_accuracy: 0.9801 - val_loss: 0.2299 - val_weighted_accuracy: 0.9500
Epoch 39/62
940/940 [==============================] - 27s 29ms/step - loss: 0.0427 -
weighted_accuracy: 0.9868 - val_loss: 0.2624 - val_weighted_accuracy: 0.9452
Epoch 40/62
940/940 [==============================] - 28s 29ms/step - loss: 0.0445 -
weighted_accuracy: 0.9859 - val_loss: 0.2670 - val_weighted_accuracy: 0.9512
Epoch 41/62
940/940 [==============================] - 27s 29ms/step - loss: 0.0458 -
weighted_accuracy: 0.9854 - val_loss: 0.2708 - val_weighted_accuracy: 0.9504
Epoch 42/62
940/940 [==============================] - 27s 29ms/step - loss: 0.0413 -
weighted_accuracy: 0.9869 - val_loss: 0.2706 - val_weighted_accuracy: 0.9498
Epoch 43/62
940/940 [==============================] - 27s 29ms/step - loss: 0.0421 -
weighted_accuracy: 0.9869 - val_loss: 0.2810 - val_weighted_accuracy: 0.9481
Epoch 44/62
940/940 [==============================] - 27s 29ms/step - loss: 0.0385 -
weighted_accuracy: 0.9876 - val_loss: 0.3396 - val_weighted_accuracy: 0.9430
Epoch 45/62
940/940 [==============================] - 28s 29ms/step - loss: 0.0410 -
weighted_accuracy: 0.9871 - val_loss: 0.2367 - val_weighted_accuracy: 0.9486
```

[36]:
```
metrics_tuned = metrics.append(pd.DataFrame(result_fine_tune.history),␣
↪ignore_index=True)
```

[37]:
```
metrics_tuned.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 46 entries, 0 to 45
Data columns (total 4 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   loss                   46 non-null     float64
 1   weighted_accuracy      46 non-null     float64
 2   val_loss               46 non-null     float64
 3   val_weighted_accuracy  46 non-null     float64
dtypes: float64(4)
memory usage: 1.6 KB
```

[38]:

```
fig, axes = plt.subplots(ncols=2, figsize=(15, 4))
metrics_tuned[['loss', 'val_loss']].plot(ax=axes[1], title='Cross-Entropy Loss')
metrics_tuned[['weighted_accuracy', 'val_weighted_accuracy']].plot(ax=axes[0], title=f'Accuracy (Best: {metrics_tuned.val_weighted_accuracy.max():.2%})')
axes[0].yaxis.set_major_formatter(FuncFormatter(lambda y, _: '{:.0%}'.format(y)))
axes[0].set_ylabel('Accuracy')
axes[1].set_ylabel('Loss')
for ax in axes:
    ax.axvline(14, ls='--', lw=1, c='k')
    ax.legend(['Training', 'Validation', 'Start Fine Tuning'])
    ax.set_xlabel('Epoch')
fig.tight_layout()
fig.savefig(results_path / 'transfer_learning_svhn');
```