IMAGE ANALYSIS FOR DISASTER RECOVERY, A DATAKIND REPORT FOR THE WORLD BANK GFDRR

KRISHNA BHOGAONKER & PATRICK DOUPE

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ABSTRACT

We discuss how the World Bank can use machine learning and satellite images to improve disaster relief efforts. We include a review of image analysis with convolutional neural networks. These networks are illustrated with code examples using the Keras deep learning library.

1 INTRODUCTION

The review of deep learning [1].

1.1 Terms of reference or questions to be answered

1.2 Main recommendations

2 FRAMEWORKS

If we present methods, it would be good to introduce frameworks up front.

2.1 Keras

```python
from keras.layers import Input
from keras.layers import Dense
from keras.models import Model

# This returns a tensor
inputs = Input(shape=(10,))
predictions = Dense(1, activation='softmax')(inputs)
model = Model(inputs=inputs, outputs=predictions)
model.compile(optimizer='rmsprop',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
# starts training
model.fit(data, labels)
```

2.2 Tensorflow, PyTorch, Caffe, MXNet, etc.

Links to sites and blog articles

3 METHODS

3.1 Why convolutional neural networks

1. Pixels are not independent of one another 2. With pictures, only relative position matters [Spatially stationary statistics] 3. Much fewer neurons.

Results of image analysis

3.1.1 *If you understand VGG-net, you're 80 per cent there*

VGG net is super simple and easy to explain.

4 LITERATURE

4.1 Image classification

LeNet
Krizhevsky ImageNet [2]

- Used dropout to prevent overfitting

- We start to go deep: 5 convolutional layers

- Got best results to that date on a hard problem

VGG Net [3]

- Increased depth (16–19 layers) with smaller filters

- First/Second places at ImageNet2014

- Widely used as a base :: need references.

ResNet [4]

- Residual learning framework

- Degradation became an issue with deep models. This makes no sense, you could just have a shallower model with identity mappings. So residual networks contain the identity mapping.

- Crazy large :: 152 layers but with lower 'complexity'

- Then state of the art.

4.2 Object detection

Using regression to do this [5]
RCNN [6, 7]
Faster RCNN [8]
Mask RCNN [9]
R-FCN [10]
YOLO [11]
SSD [12]

4.3 Image segmentation

First fully convnet segmenter [13]
Some more [14, 15]

4.4 Analysis with satellite images

Mexico [16] (There are two WB co-authors)
Poverty mapping [17]
Population [18, 19]
Private sector [20, 21]

5 SATELLITE DATA

5.1 Free sources

LANDSAT, Sentinel,
Quasi free: Bing

5.2 Expensive sources

Digital Globe, Planet Labs, Own drone data

5.3 Labelled data

6 EXAMPLES

6.1 Building detection

7 RECOMMENDATIONS

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