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

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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

2 FRAMEWORKS

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

2.1 Keras

```
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

Pixels are not independent of one another
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

Krizhevsky ImageNet [2]
VGG Net [3]
ResNet [4]

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

Tough.

REFERENCES

[1] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. Deep learning. *nature*, 521(7553):436, 2015.

[2] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In F. Pereira, C. J. C. Burges, L. Bottou, and K. Q. Weinberger, editors, *Advances in Neural Information Processing Systems 25*, pages 1097–1105. Curran Associates, Inc., 2012.

[3] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *CoRR*, abs/1409.1556, 2014.

[4] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.

[5] Christian Szegedy, Alexander Toshev, and Dumitru Erhan. Deep neural networks for object detection. In C. J. C. Burges, L. Bottou, M. Welling, Z. Ghahramani, and K. Q. Weinberger, editors, *Advances in Neural Information Processing Systems 26*, pages 2553–2561. Curran Associates, Inc., 2013.

[6] Ross Girshick, Jeff Donahue, Trevor Darrell, and Jitendra Malik. Rich feature hierarchies for accurate object detection and semantic segmentation. In *Proceedings of the 2014 IEEE Conference on Computer Vision and Pattern Recognition*, CVPR '14, pages 580–587, Washington, DC, USA, 2014. IEEE Computer Society.

[7] R. Girshick. Fast r-cnn. In *2015 IEEE International Conference on Computer Vision (ICCV)*, pages 1440–1448, Dec 2015.

[8] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. *IEEE Trans. Pattern Anal. Mach. Intell.*, 39(6):1137–1149, June 2017.

[9] K. He, G. Gkioxari, P. Dollár, and R. Girshick. Mask r-cnn. In *2017 IEEE International Conference on Computer Vision (ICCV)*, pages 2980–2988, Oct 2017.

[10] Jifeng Dai, Yi Li, Kaiming He, and Jian Sun. R-fcn: Object detection via region-based fully convolutional networks. In D. D. Lee, M. Sugiyama, U. V. Luxburg, I. Guyon, and R. Garnett, editors, *Advances in Neural Information Processing Systems 29*, pages 379–387. Curran Associates, Inc., 2016.

[11] Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi. You only look once: Unified, real-time object detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 779–788, 2016.

[12] Wei Liu, Dragomir Anguelov, Dumitru Erhan, Christian Szegedy, Scott Reed, Cheng-Yang Fu, and Alexander C Berg. Ssd: Single shot multibox detector. In *European conference on computer vision*, pages 21–37. Springer, 2016.

[13] Jonathan Long, Evan Shelhamer, and Trevor Darrell. Fully convolutional networks for semantic segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3431–3440, 2015.

[14] L. C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille. Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 40(4):834–848, April 2018.

[15] Pedro O Pinheiro, Ronan Collobert, and Piotr Dollar. Learning to segment object candidates. In C. Cortes, N. D. Lawrence, D. D. Lee, M. Sugiyama, and R. Garnett, editors, *Advances in Neural Information Processing Systems 28*, pages 1990–1998. Curran Associates, Inc., 2015.

[16] Boris Babenko, Jonathan Hersh, David Newhouse, Anusha Ramakrishnan, and Tom Swartz. Poverty mapping using convolutional neural networks trained on high and medium resolution satellite images, with an application in mexico. *arXiv preprint arXiv:1711.06323*, 2017.

[17] Neal Jean, Marshall Burke, Michael Xie, W. Matthew Davis, David B. Lobell, and Stefano Ermon. Combining satellite imagery and machine learning to predict poverty. *Science*, 353(6301):790–794, 2016.

[18] Patrick Doupe, Emilie Bruzelius, James Faghmous, and Samuel G. Ruchman. Equitable development through deep learning: The case of sub-national population density estimation. In

Proceedings of the 7th Annual Symposium on Computing for Development, ACM DEV '16, pages 6:1–6:10, New York, NY, USA, 2016. ACM.

[19] Caleb Robinson, Fred Hohman, and Bistra Dilkina. A deep learning approach for population estimation from satellite imagery. In *Proceedings of the 1st ACM SIGSPATIAL Workshop on Geospatial Humanities*, GeoHumanities'17, pages 47–54, New York, NY, USA, 2017. ACM.

[20] Tobias Tiecke Andreas Gros. Connecting the world with better maps. https://code.facebook.com/posts/1676452492623525/connecting-the-world-with-better-maps/, 2016. [Online; accessed 19-May-2018].

[21] Emma Kennedy. AI companies spot a business opportunity in space. http://money.cnn.com/2018/04/06/technology/business/geospatial-analytics-satellite/index.html, 2018. [Online; accessed 19-May-2018].