Multi-Label Image Classification with Deep Learning

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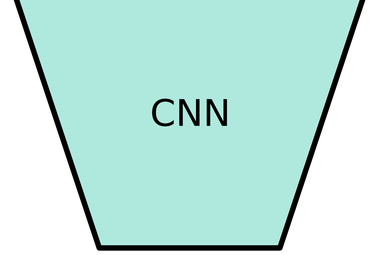
Problem

1. Given a satellite **image**,

2. Apply a **Convolutional Neural Network** (CNN),



3. To obtain **multiplelabels,**

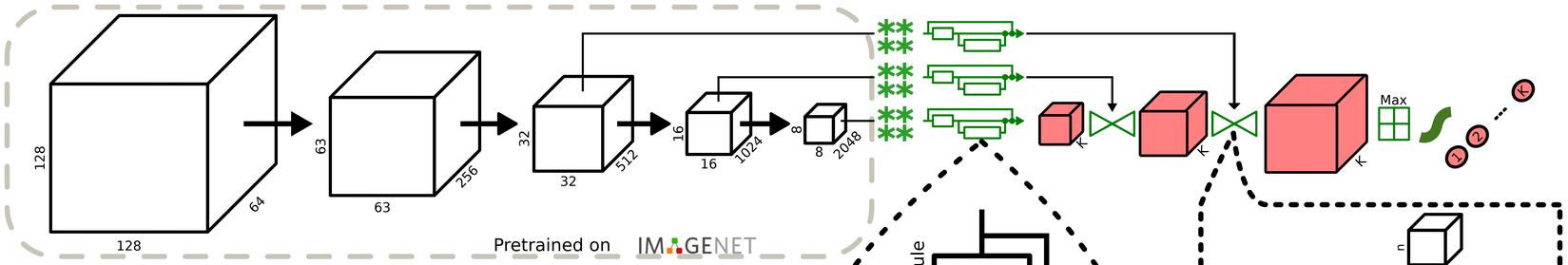
4. Which maximise the **F_2-score**,

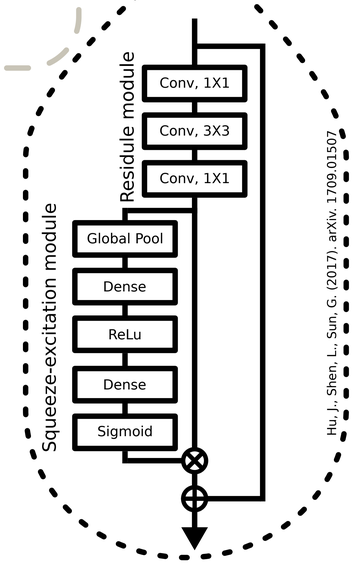
$$F_\beta = (1+\beta^2)\frac{precision \cdot recall}{\beta^2 \cdot precision + recall}, \beta = 2$$

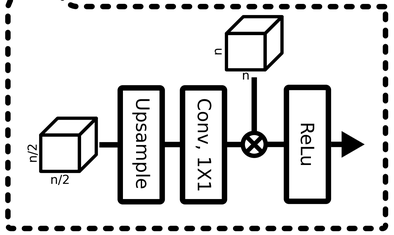
[1] Lin, T., Dollar, P., Girshick, R., He, K., Hariharan, B., Belongie, S. Feature Pyramid Networks for Object Detection. In CVPR, 2017.
[2] Zhu, F., Li, H., Ouyang, W., Yu, N. and Wang, X. (2017). Learning Spatial Regularization with Image-level Supervisions for Multi-label Image Classification. arXiv. 1702.05891.
[3] Wang, H.-D., Zhang, T. and Wu, J. (2017). The Monkeytyping Solution to the YouTube-8m Video Understanding Challenge. arXiv. 1706.05150.
[4] Gong, Y., Jia, Y., Leung, T., Toshev, A., Ioffe, S. Deep Convolutional ranking for multilabel image annotation. (2013). arXiv. 1312.4894.
[5] Li, Y., Song, Y., Luo, J. Improving Pairwise Ranking for Multi-label Image Classification. In CoRR, 2017.

Solution

The proposed solution is a CNN architecture that follows the hourglass shape proven to be very effective in object detection and segmentation tasks. It can be built on top of any popular CNN for classification - we use ResNet 50. Its main advantage is that it can classify concepts relating to small parts of an image by utilising convolutional feature maps, , of multiple resolutions. The feature maps for each chosen scale is first transformed by a dilated convolution, , so that there is a channel for each label, while maintaining a larger field of perception. Then it is sent through Squeeze-Excitation (SE) residual module, , which is able to model interdependencies between channels - important to exploit spatial relations between labels. The output is merged with an upsampled version of a smaller, already processed, feature map in . The final feature maps are pooled globally, , and then transformed by a sigmoid activation, , so that the class scores, , are in [0,1] but not sum to 1. The network is trained by optimising the label-wise binary cross-entropy.







How to ...

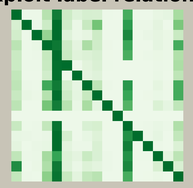
Detect small objects?

We make use of multiple feature maps of different scale to make predictions. Novel in multi-label image classification, popular in object detection and segmentation, e.g. [1]

Exploit spatial relations?

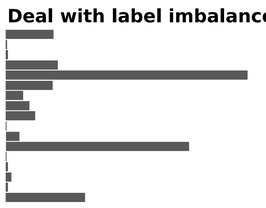
We use the SE-residual module on learned label attention maps. Inter-channel dependencies are learned, therefore spatial! Similar to, [2].

Exploit label relations?



Feature map output from SE-module is passed on to next scale prediction. Since, the maps are pixel-wise class scores, the model is effectively learning label relations. See Chaining, [3].

Deal with label imbalance?

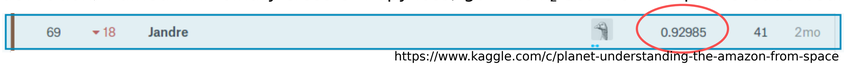


Assign higher weights to infrequent labels or use a more robust loss function. [4] used a pairwise rank loss.
We want to try stratified mini-batch sampling for better gradient approx. during training.
Another challenge is threshold selection. Either by grid search or by learning, as in [5].

Results

Results are work in progress. These are preliminary and baseline results.

On the *Planet: Understanding the Amazon from Space*, Kaggle competition our baseline model (ResNet50 with an added residual block with K filters, global average pooling and sigmoid activation, trained with binary cross-entropy loss) got this F_2-score on the public leaderboard:



https://www.kaggle.com/c/planet-understanding-the-amazon-from-space

The winning score was 0.9333 (out of 938 competitors). Our results are acceptable since it is a single model solution, compared to large ensembles of models used by the winners.

... to come

> Implementation and evaluation of stratified mini-batch sampling.

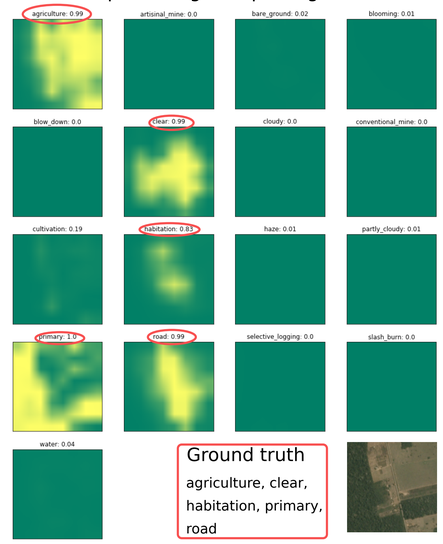
> Evaluate the effectiveness of adding lower level feature maps to make predictions.

> Evaluate proposed network on more datasets, such as MSCOCO and VOC2007*.

*requires big GPU.

Examples

The advantage of global pooling as prediction layer - get approximate localisation of labels for free. These are the most discriminative parts in an image and are the activations from the last feature map before global pooling.



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