Final report

Project for course Deep Learning
University of Helsinki
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Chosen dataset: Images

Final F1-score of the group's model evaluated against our own test set: 0.759

Final predictions: Predictions on actual test set using the final model

Short description of the final model and training process

Model: Resnet-152

Our best-performing model was a deep pretrained convolutional neural network with residual connections. We froze all layers but the final layer, which we replaced with our own 2048->14 fully connected layer, which we trained. Our final F1-score on own test data was 0.78 (micro averaging).

Our final model is constructed so that we first trained for 25 epochs on our train data. We then continued training the model on our validation data and test data for 1 epoch each. Evaluation of model performance is done before the last two epochs.

Preprocessing

- Read in images and labels so that we could attach a one-hot encoded vector of labels to each image
- Also used **images with no labels** (n=9824 out of 20000)
- Used **train-validation-test split** of 0.6-0.2-0.2
- **Normalized images** using the means and stds of the RGB channels computed over the given image set
- **Random data augmentation** applied to train set images only: we used random horizontal flipping, rotation, colorjitter, grayscaling and perspective changes
- Calculated **pos_weights** (to be used with BCEWithLogitsLoss) for all labels to compensate the label imbalance

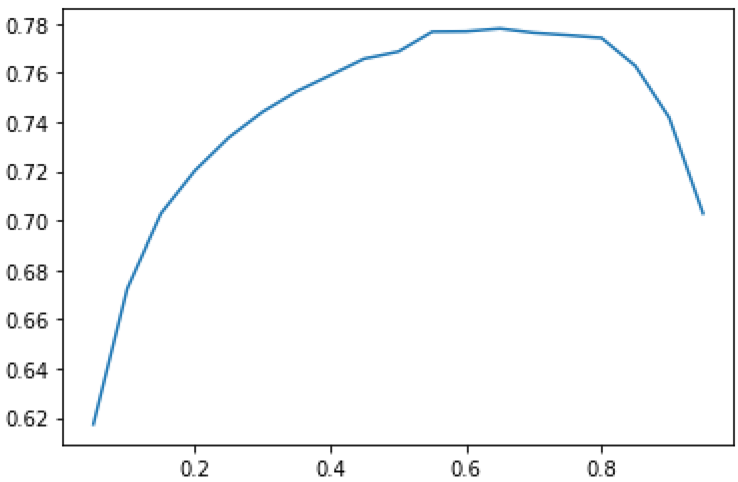
Training

- BCEWithLogitsLoss as the **loss function**. We Used the pos_weight parameter to control the label imbalance in the training data.
- Stochastic gradient descent as the **training algorithm**
- **Batch size** 64
- **Learning rate**: using one-cycle-policy

- **25 epochs**: the validation accuracy had leveled off at this point and the validation loss was already rising, so we opted for early stopping after 25 epochs
- During training, we evaluated the prediction accuracy on the validation set using the **threshold** 0.75 (for the probability of the an individual label to attach that label on the image). The training-phase threshold does not have direct effect on the training (only on our evaluation of how the model is doing and when we should opt for early stopping).

Evaluation

- We used **f1 scores** to evaluate models with **'micro' averaging**, where each sample-class pair is given an equal contribution to the overall metric. We also considered the 'macro' averaging, which could have been appropriate if the label frequencies in the test set would have been different from training data. But our understanding was that the test set would be similar to the training set also in this aspect (and 'micro' seemed to be used in the test_eval.py script), so we stuck with 'micro'.
- **Thresholds.** We searched for the optimal threshold by scanning the from 0.05 to 1.0 with 0.05 steps and chose the threshold that led to maximum validation f1 score. Our model gave best results with the threshold of 0.65, but the thresholds in the range 0.55-0.80 all had f1 scores very close to each other in the range 0.774-0.778.



Threshold search for the final model, resnet-152

Fighting imbalanced data

Some of the labels (e.g. *people*) were very common in the training data, some (e.g. *baby* and *river*) very rare. Our approach to working with the label imbalance was using the pos_weights option of the BCEWithLogitsLoss loss function. We calculated pos_weights (using the function calculate_label_statistics present in notebook 8 but removed from the final notebook 20) with the formula pos_weights = negative_label_count / positive_label_count for each label. So for e.g. label *baby* the pos_weight was 19905/95 = 209.526. In this case, the loss would act as if the dataset contained 95 * 209.526 = 19 905 positive samples (each mistake with a positive sample would get a very large weight with regard to gradient updates). Additional information on the pos_weights is available in the loss function's documentation.

Final code structure

Functions

- Data loading
- Models
- Training and evaluation functions
- Visualization functions
- Prediction functions

Training

- Set variables for data loading and training
- Create and save / load dataloaders from disk
- Select model
- Train a model or load an existing model from disk

Prediction evaluation and visualization

- Visualization
- Predict and evaluate using our own test data
- Add our validation and test data and evaluate
- Predict and evaluate using actual test data

Model selection

As SGD is known to generalize better [1] than its adaptive variations, we decided to use SGD for optimization. The optimization was done using SGD with Momentum and SGD with Nesterov Momentum.

It was quite clear from the beginning that we would need transfer learning to achieve any notable results. But to test our pipeline and to get some kind of baselines we started with one and two layer feedforward neural networks. As suspected these did not give very good results. We also tested a simple CNN and more complex CNN (similar to VGG16) and tried to train these without much success. But now we knew that our pipeline worked and we could switch to pretrained models, which will be described next.

We started with a model that is easy to understand, known to be robust and perform rather well. So the first model gave us some notable results was ***VGG16***. Training was performed manually, using plain SGD with Momentum. After some initial fuzzing around we noticed that 0.01 was the learning rate to use. The model was trained for several epochs and after the validation F1 -score stopped increasing, the learning rate was decreased and more training was performed. After many trial-and-errors training periods we managed to get the validation F1 -score to around 0.71. However, the training score never got very high and it was obvious that we are not overfitting yet.

For ***VGG16*** we retrained all the layers but replaced the fully connected layers with two layers of our own: 4096->2048 and 2048->14 with ReLUs between.

As a side note: we also tested a batch normalized version of ***VGG16*** but for some unknown reason it did not reach as high F1 -score as the plain ***VGG16*** that we had already trained. This was bit surprising, as we thought that in theory a batch normalized network should perform at least as well as without batch normalization.

After establishing a well working learning rate it was time to drop the manual labor: we adopted One Cycle Policy [2]. This gave us the opportunity to use the learning rate that had been proven to work (0.01) and use that as a max learning rate for One Cycle Policy. For momentum we used a base of 0.5 and a max value to 0.95. We tested both normal Momentum and Nesterov Momentum, which of the latter was used to train our more advanced models. At this point we still did not overfit.

After not yet overfitting it was time to move to more modern networks. We started with ***ResNet-34*** which did not perform very well. The same thing happened with ***ResNet-50***, so we tuned up again and switched to ***ResNet-101***. After training it for 20 epochs we reached a training and validation F1 -scores of 0.94 and 0.71 respectively. Finally, ***ResNet-101*** was the first model that started to overfit!

For ***ResNet*** models we just replaced the fully connected layers with a direct mapping to our label space of 14 outputs. For example, with ***ResNet-34/50*** we used a linear layer with 512 inputs and 14 outputs, and with ***ResNet-101/152*** we used a linear layer with 2048 input and 14 outputs.

Now that we had our model overfitting, it was time to start fighting the overfitting. As everybody knows the best way to fight overfitting is to get more data! However, the competition rules required us to train with the given data. Also, as we were using pretrained models it was not possible to add any more regularization to the model. So the next step was to perform data augmentation to get more training data. We tested numerous data augmenting policies. After some testing we ended up using our custom data augmentation policy: we modified existing PyTorch code to create a new policy that randomly (with a given probability) selects transformations from a given list. The list consisted of horizontal flips, rotations, color jitter adjustments, turning images into grayscale, and changing of perspective.

After adding the data augmentation to the pipeline the model stopped overfitting, as expected. So it was time to turn to a bigger model! Just tuning up and using a pretrained ResNet model proved to be efficient when we managed to train the ***ResNet-152*** model to a validation F1 -score of about 0.78. The training accuracy was around 0.88 so we were not overfitting that bad and there could have been chances for improvement. However, we decided to stick with this model.

The final touches we did was to train our model with the validation and testing data that we had for our own purposes: the data do not include any training examples that our model is going to be evaluated against, and also the data included training examples that the model had not seen before, so there was a learning possibility for the model!

Evaluation metrics (`F1-score`, `Precision`, `Recall`) for each model evaluated against our own test set are listed below under heading 'Evaluation of different approaches'.

Evaluation of different approaches

Below are listed the results (`F1-score`, `Precision`, `Recall`) of running the `test_eval.py` script for each trained model against our own test set (20% of the initial data). In the results we list also `Ratio of F1` for each model. We used `Ratio of F1` as a measure of overfitting and it was computed as a ratio of training and validation F1-scores after epoch 25.

All the models have been trained on our own training set (60% of the initial data). The models are trained for 25 epochs using a batch size of 64. For all models we use `BCEWithLogitsLoss` loss function, `SGD` optimizer and `OneCycle` scheduler (documented in detail above).

Results for models that utilize data augmentation techniques.

Model	F1-score	Precision	Recall	Ratio of F1	Training time
Feed forward 1-layer	0.245	0.191	0.341	0.881	22min 57s
Feed forward 2-layer	0.269	0.206	0.387	0.989	24min 9s
Convolutional	0.145	0.118	0.186	0.879	26min 55s
Plain ResNet-152	0.180	0.126	0.317	-	-

Results for models that utilize transfer learning and data augmentation techniques.

Model	F1-score	Precision	Recall	Ratio of F1	Training time
VGG16	0.700	0.626	0.794	1.014	27min 29s
VGG16 with BN	0.669	0.565	0.820	0.967	27min 44s
ResNet-34	0.726	0.684	0.774	1.137	27min 36s
ResNet-50	0.749	0.727	0.773	1.161	29min 29s
ResNet-101	0.745	0.718	0.773	1.168	36min 57s
ResNet-152	0.759	0.729	0.791	1.161	42min 22s

Results for models that utilize transfer learning (without data augmentation).

Model	F1-score	Precision	Recall	Ratio of F1	Training time
ResNet-50 no aug	0.751	0.783	0.722	1.350	14min 4s
ResNet-50 no aug with dropout	0.760	0.783	0.739	1.344	13min 51s

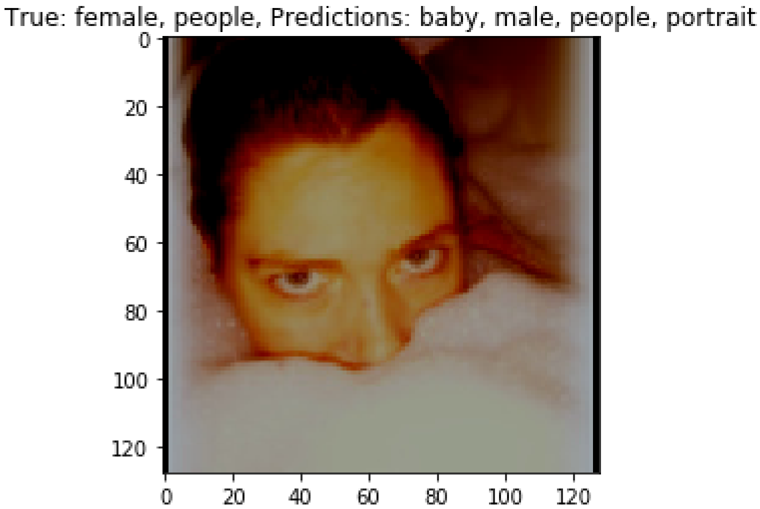
Other notes

- Labels in the training set are not all independent. E.g male, female and baby photos are very often also people photos. It's important to train the model with all labels for a certain image so that it can learn from these dependencies.

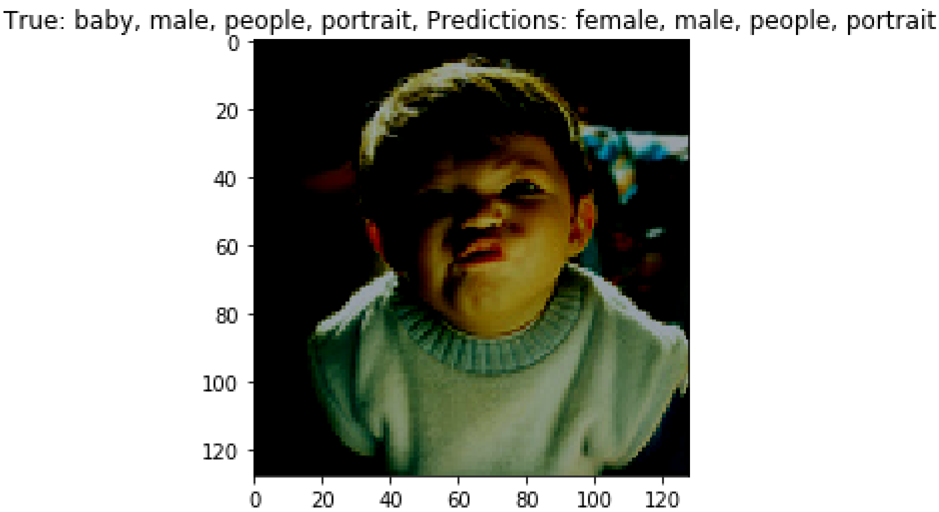
Error analysis

The labels with the lowest f1 scores were river (0.33), sea (0.54) and baby (0.65), but this is not surpising as the labels in question had the least training examples (120, 173, and 95 respectively). The precision and recall components were quite close to each other for all other classes but *sea* (precision 0.70, recall 0.43), which would suggest that using class-specific thresholds would not give any significant improvement for any classes but perhaps sea. For sea, the precision score is higher than the recall score, so lowering the threshold might improve the performance.

Error types and representative examples

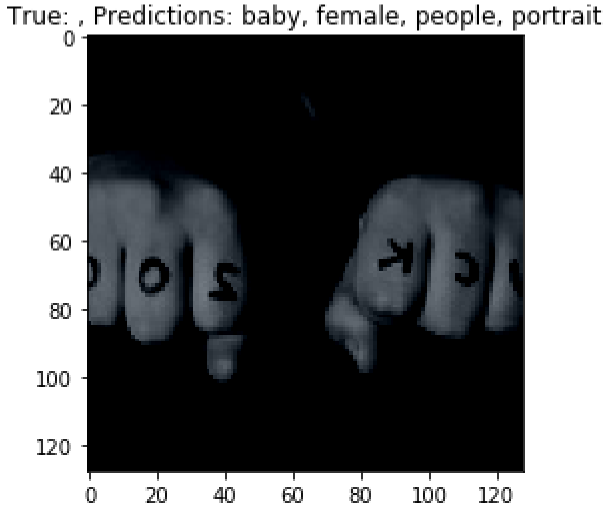


- **Can't make difference between labels male and female.** Discriminating between males and females is in some cases very hard (for the network, but also for human observers) as the appearance of males and females is in some cases almost identical. The f1 score of people (0.88) was much higher than for female (0.75) and male (0.67). This error is hard to improve on.

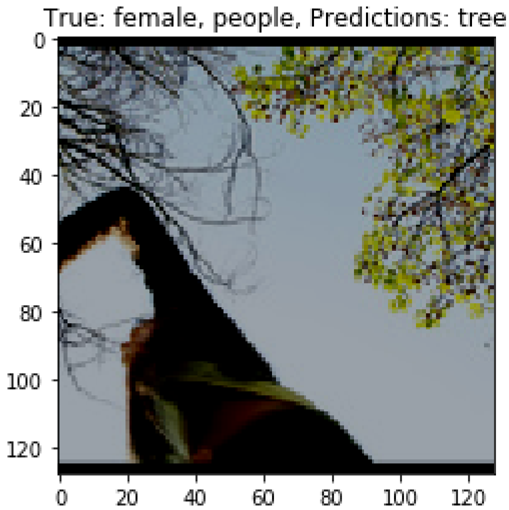


- **Same person is male and female.** In some cases the model thinks the same person is both male and female. This is an error that a human observer would likely not make: people are almost never *both* sexes. And this is something the network should be able to learn (but that might be hard to learn for a convolutional network like ours).

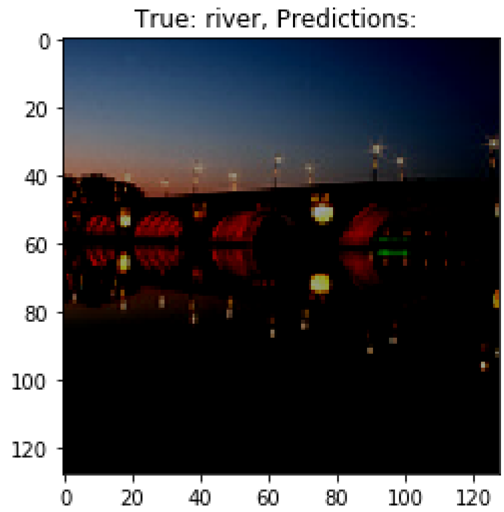
- **Difference between baby and a small child is fuzzy.** The label baby (f1 0.65) was quite difficult for the model: the easy part in identifying babies was presumably identifying them as humans and the difficulty was drawing the line between baby and child (a small human that is no longer a baby). This line is fuzzy for human observers also, so the tags will most likely be somewhat incoherent. The example above is labeled as a baby, but many human observers would say "He's not a baby anymore!".

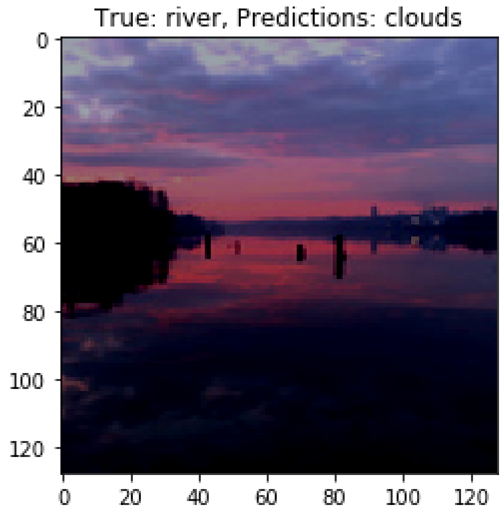


- **Untypical images of parts.** Is a picture of knuckles (of a person) a picture of a person? This relation of a part to the whole is ambiguous for human labelers, so the labeler of the sample image has decided not to label it as people or male even though the picture surely displays a part of a human, most likely a male. The model could learn to associate pictures of parts with the label of the whole if it had enough systematically labeled training data. Here the problem has most likely been that scarceness of these atypical images of parts and the unsystematic labeling by humans (as there might not be a consensus how to treat the part images).

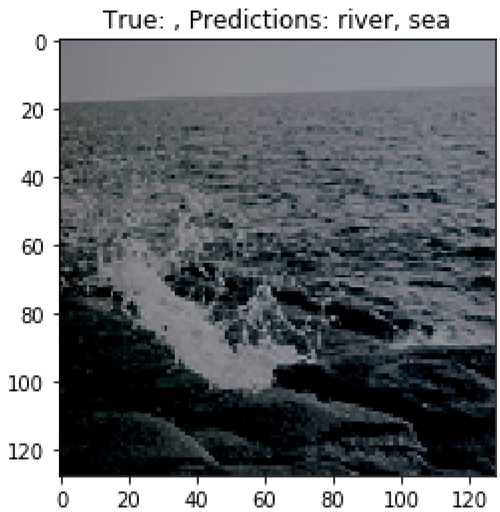


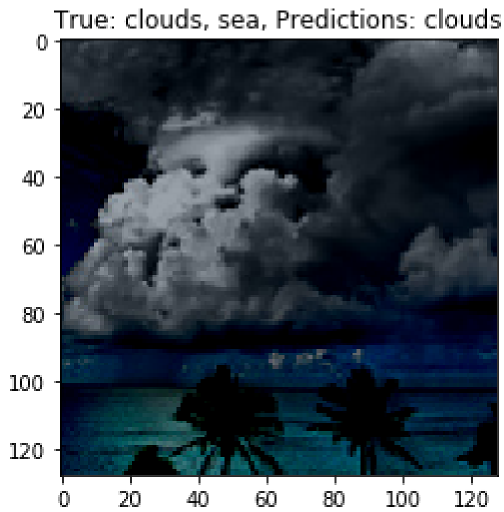
- **Main subject of the image.** Sometimes the image has some objects in the foreground and some objects in the background. Is the image an image about only the foreground objects or also about the background objects? Some human labelers might be inclined to label only the foreground objects and disregard the background objects as unessential. This sample definitely depicts a tree, but the main object is a human in the foreground.



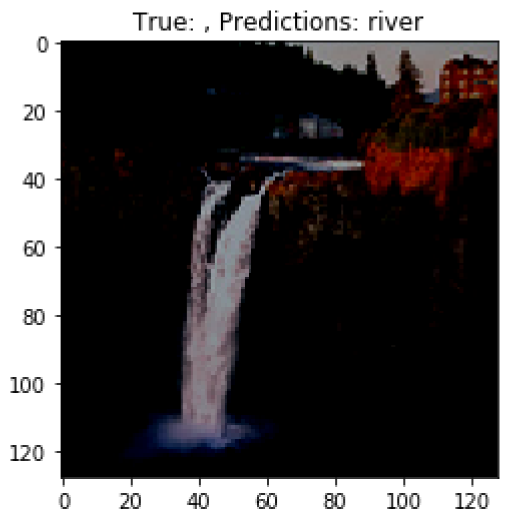


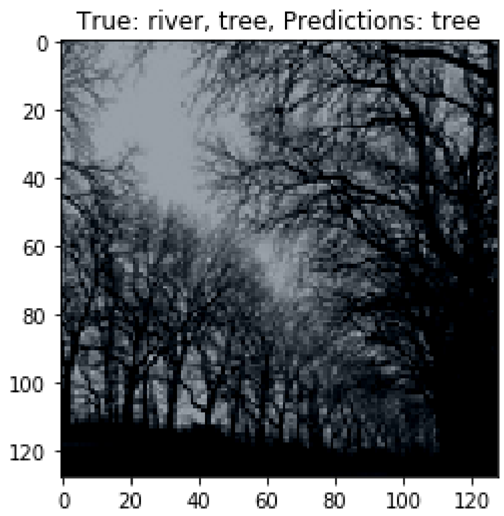
- **Difficult labels: river**. The label 'river' is difficult for both the model and a human. Labeling 'water' would be a bit easier, but if there is water in the picture, is it a part of a river or a part of a lake or a sea? This is ambiguous also for humans. In some cases *domain knowledge* does give the answer (as in one of the samples above): if there is a bridge over water with lamps on it, it's almost always a river flowing underneath. With enough training data, the model could learn this.





- **Difficult labels: sea**. The label 'sea' is difficult for both the model and a human for the same reasons as 'river': there is water, but is it a river, lake, a sea or an ocean? It is hard to improve on this error, as the concepts are hard to tell apart in 2-dimensional pictures of parts of the bodies of water. *Color* is also an important feature here: the seas are pretty much always blue. In theory a deep resnet model with residual connections should be able to exploit the color aspect of the image, so maybe more training data could improve this.





- **Obviously wrong labels**. The labels have been given by humans (on Amazon mechanical turk or some other similar service). Humans make mistakes. So sometimes the model predicts something that seems more right than the ground truth. The only way to improve this is to get better quality training data.

Per label performance

To assess our model's per-label performance we computed a by-label classification report on our own testset (20% of the given dataset):

```
              precision    recall  f1-score   support

           0       0.54      0.67      0.60        21
           1       0.68      0.75      0.71        72
           2       0.66      0.81      0.73        58
           3       0.67      0.85      0.75       200
           4       0.69      0.74      0.71        94
           5       0.69      0.75      0.72       631
           6       0.71      0.80      0.75       145
           7       0.60      0.69      0.64       595
           8       0.55      0.69      0.62       118
           9       0.88      0.84      0.86      1262
          10       0.77      0.86      0.81       644
          11       0.33      0.48      0.39        27
          12       0.52      0.68      0.59        37
          13       0.63      0.72      0.67        93

   micro avg       0.73      0.79      0.76      3997
   macro avg       0.64      0.74      0.68      3997
weighted avg       0.74      0.79      0.76      3997
 samples avg       0.37      0.38      0.37      3997
```

We also evaluated our model's by-label performance by plotting a confusion matrix of the classification report data. In the confusion matrix we also assess our model's performance on non-labelled images.

Possibilities for further improvement

- **Ensemble methods** could provide improved results. We considered using 3 of our top models and implementing a per-label majority voting ensemble. This was however left at the idea level and not implemented within this project.

References

1 - Wilson A. et al., The Marginal Value of Adaptive Gradient Methods in Machine Learning, http://papers.nips.cc/paper/7003-the-marginal-value-of-adaptive-gradient-methods-in-machine-learning.pdf

2 - Smith L., Super-Convergence: Very Fast Training of Neural Networks Using Large Learning Rates, https://arxiv.org/pdf/1708.07120.pdf