Practical recommendations

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Contents

Contents

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This state of affairs can of course be a problem in domains where security is important, such as clinical applications.

General recommendations

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- Only at the end: test!

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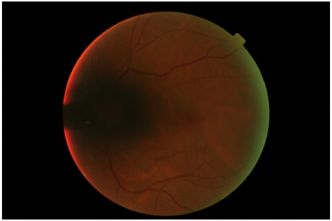
- Familiarize yourself with the data (input and output images)
- Choose the right representation for your images. Resolution? What labels?

Example: eye fundus image quality

Good quality



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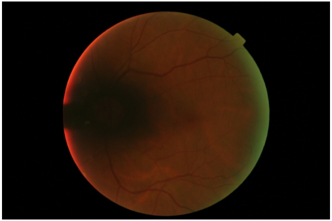

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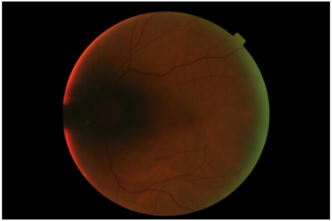

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- First solution: regression (center of macula position)
- Second solution: predict macula mask

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Performance evaluation

- Choose the right metrics and try to use a loss function that is as close as possible to these metrics
- Define an objective

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Building the data sets

- Gather your images in order to build a data set that conveniently represents your problem
- How many images do you need?
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Is database constitution the main step?

- In practical, real-world applications, this is becoming the most time-consuming step
- If the data set does not conveniently represent your problem you will run into difficulties

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(This anecdote might be a urban legend, but nevertheless is a good illustration of the problems one might run into during database preparation)

What quality is needed for the ground-truth?

- Deep learning models tend to be robust with respect to ground-truth errors
- In the case of segmentation, you do not need a pixel-precision high quality segmentation

Preprocessing

- Standard statistical preprocessing: not always useful, and sometimes problematic, when applied to images. It is often enough to divide by 255!
- Use other preprocessing only if really necessary.

Data augmentation

- Geometrical transformations: similarities
- Elastic transformations
- Specific methods: articulated objects, . . .

Example: plankton classification

Plankton classification: hundred classes - a few dozen examples per class.

Data augmentation:

- Geometric transformations
- Detect joints and simulate their functioning

Credits: Kaggle plankton classification challenge (https://www.kaggle.com)

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- A transfer learning method with real data will probably be necessary
- Your test data, of course, should be real

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It is interesting to note that the rate of publication of new architectures tends to decrease.

Contents

Optimizing your model

- Choose an optimizer
- Use regularization (L_1, L_2, dropout, noise layer ...)
- Add batch normalization if convergence is difficult

Hyperparameters tuning

Your options are:

- Manual tuning: works well if the number of parameter is small and the experience of the developer/researcher high
- Automatic tuning (grid search, random search): computationally time-consuming

Computing power

DL became feasible in practice thanks to the use of Graphical Processing Units (GPU). Beyond theoretical research on the subject, to work with DL you need specific hardware:

- CPUs: with many of them, and using libraries that allow parallelization, this could be a solution - in practice, it is seldom done.
- GPUs: this is the most common solution adopted for deep learning. In practice, you need many of them. Note that you can either buy them or rent them online.
- TPU: Tensor Processing Units are integrated circuits specifically developed by Google for deep learning.

Computing power

- DL research and development is extremely computationally time-consuming.
- However, a simple CPU is enough in most cases for running a given, already optimized, model.

References I