Machine Learning Project - Hand-To-Age (H_2A)

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MSc Health Data Analytics & Machine Learning

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Project description

Data

Data source: Radiology Society of North America(RSNA) and Radiology Informatics Committee (RIC). Available in Kaggle. Images gathered by several

Dataset: 12,621 images of individuals aged between 1 month and 19 years (228 months) old. Gender and age available for all fo them.

Context: Images gathered for the Pediatric Bone Age ML Challenge.

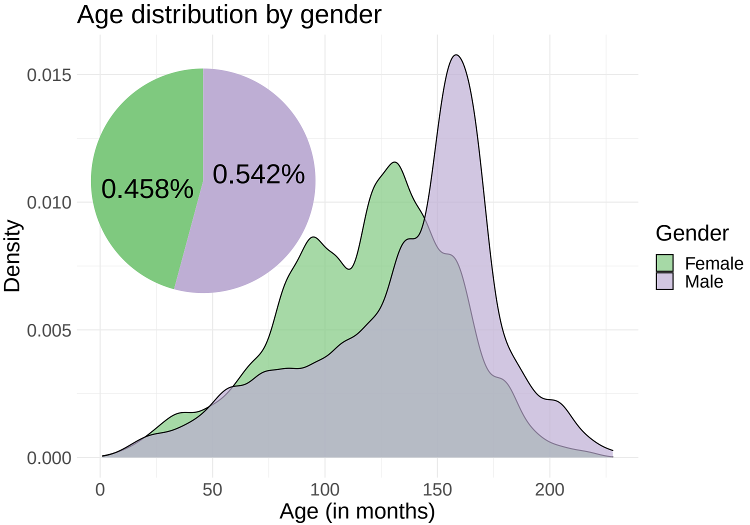
Aim(s) of my study

Supervised question #1: *How close can we estimate age from images only?*

Supervised question #2: *Can gender be derived from the image?*

Unsupervised question: *Can clustering algorithm accurately group together individuals by gender*

Population statistics



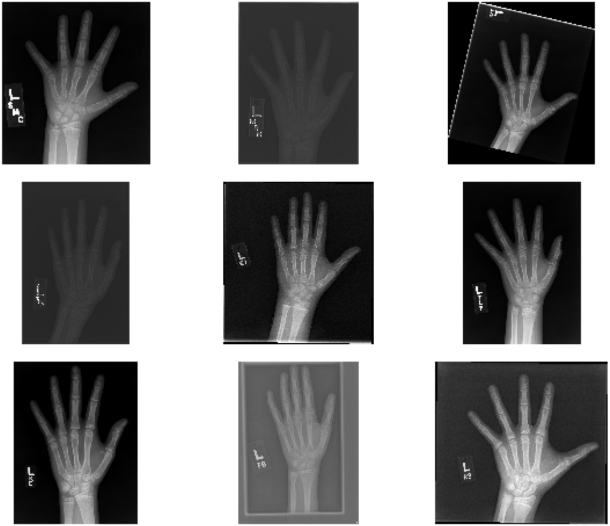
The images

X-ray images of each individuals' hand (one or two - information not available)

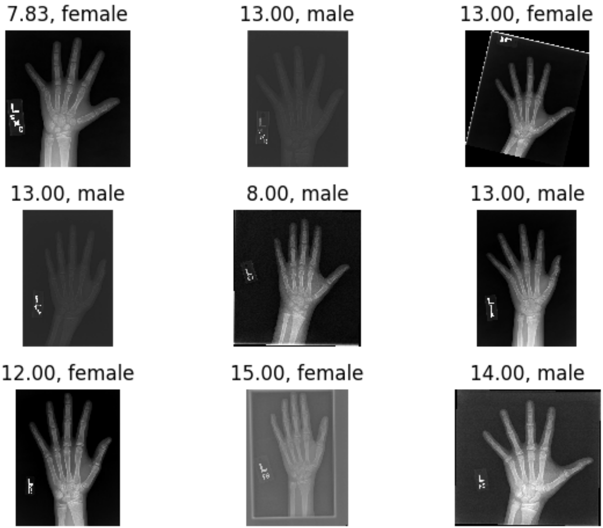
- Difficulties:
  - Varying resolution (plot)
  - Varying contrast
  - Varying exposure
  - Some scanned and some digital images
- Advantages:
  - Standardised medical images

Let's have a look at some pictures!

Raw Images



Raw Images


7.83, female
13.00, male
13.00, female
13.00, male
8.00, male
13.00, male
12.00, female
15.00, female
14.00, male

Methods: Deep Learning for Computer Vision

Data processing

Data split

10,000 Images for training, 2611 for testing/validation, no cross-validation because of computational cost and large amount of training data.

Image processing

- Rescaled and Center Cropped Images:
- Centering and scaling features (pixel values)
- Contrast adjustment

Image processing & Feature engineering (1/3)

Large disparity in image resolution therefore need to make all images same size. Default for many network architectures is 224x224 so that is our choice! Could be increased for likely better results at higher computational cost

Image processing & Feature engineering (2/3)

It is widely recommended to normalise the inputs of a neural networks as this will speed up training by gradient descent. Several forms of normalisation: Instance Normalisation(IN) and Batch Normalisation(BN):

- IN: Center and scale each image w.r.t. its mean and standard deviation.
- BN: Center and scale each image w.r.t. the whole batch of images mean and standard deviation

  The (instance) normalization process allows to remove instance-specific contrast information from the content image (see Smith 2015)

Image processing & Feature engineering

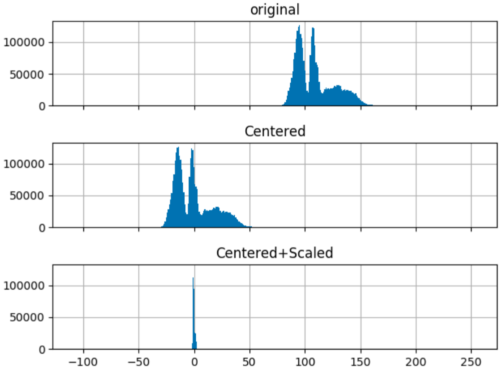
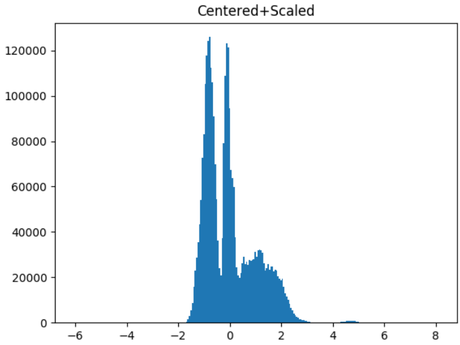


Image processing & Feature engineering



Network of choice: ResNet

Hyperparameter tuning

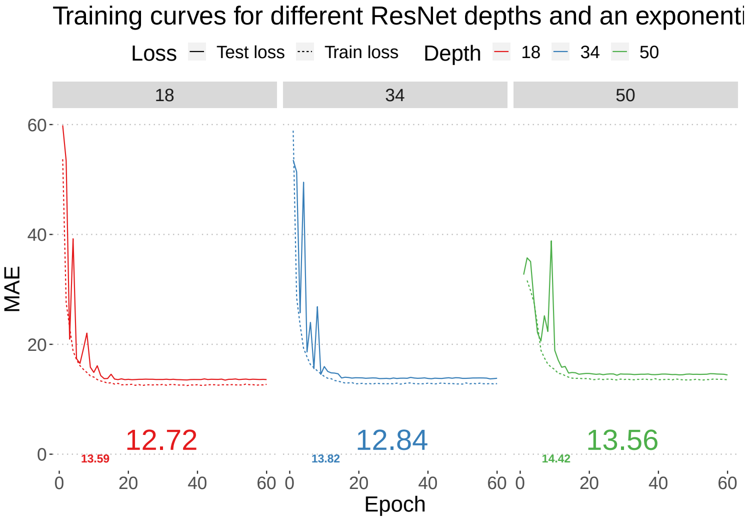
- Learning rate α
- Optimizer: **SGD**, Adam
- Learning rate scheduler: StepLR, Exponential LR, ReduceONPlateauLR, **CyclicLR**, **OneCycle Policy**
- Image normalisation: batch vs instance
- Networks' depth (# of layers): 18, 34 and 50 layer-deep ResNets
- Regularisation: L2-regularisation

Exponentially growing possibilites

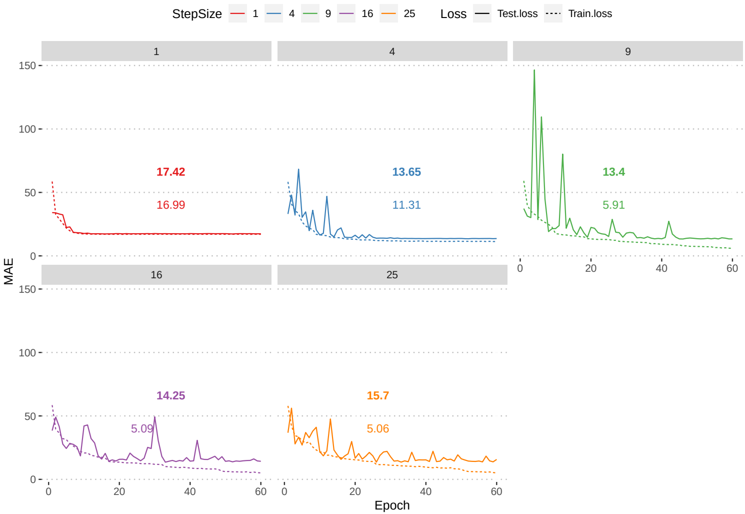
The 'Caviar' approach: training many many models with different hyperparameters, seeing which one does best. I tried:

- Varying ResNet Depth: 18, 34, 50 layers.
  - IN, $\alpha = 1$,ExponentialLR schedule, $\gamma = 0.7$, ADAM optimizer, no weight decay
- Changing LR schedule: ReduceOnPlateau, StepLR with different γ (0.1 and 0.5) and stepsize (1,4,9,16,25).
- **Moving into smarter ideas:** CyclicLR, LR Range finder and One cycle policy.

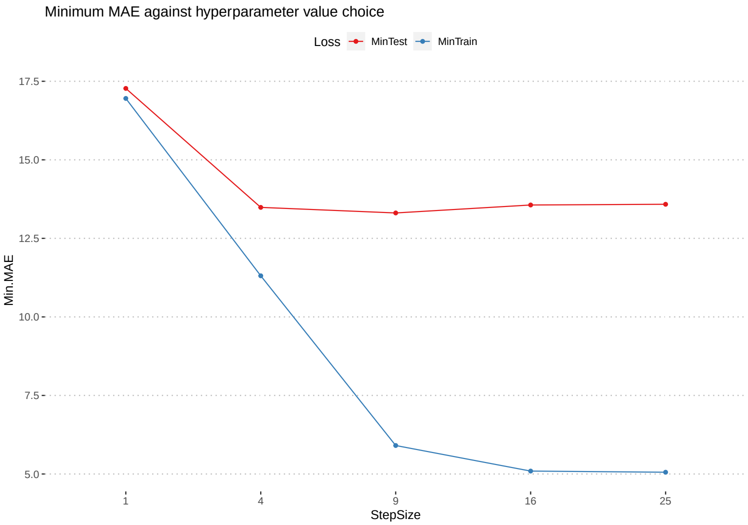
Results 1, varying depth



Results 2, varying LR scheduler

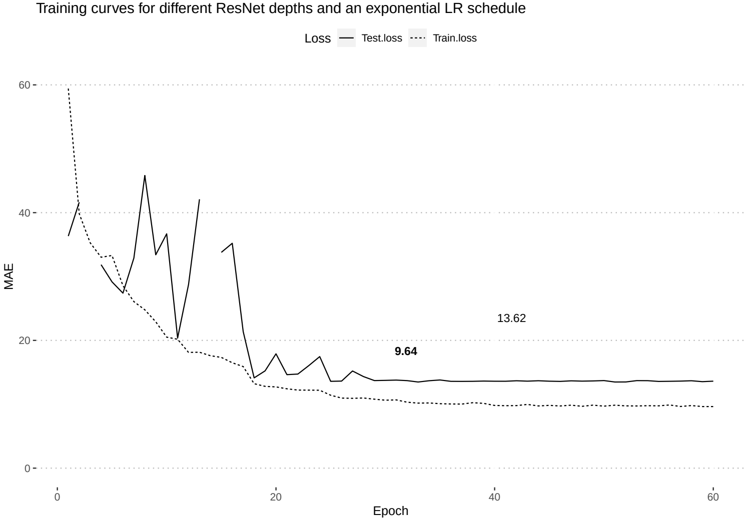


Exploring the bias-variance tradoff



Instead of fixed learning rate changes, reduce on pleateau

Goign for a slightly smarter choice



Challenging conventional wisdom

Cyclic Learning Rates and One-Cycle Policy

Leslie Smith challenged conventional wisdon on deep learning optimisation when he presented his work on Cyclic Learning Rates and the One cycle policy, as well as a method to efficiently find a reasonable learning rate for an application (LR range test) (See Smith (2015), Smith and Topin (2017))

Unsupervised Learning

Umap and K-means

Results

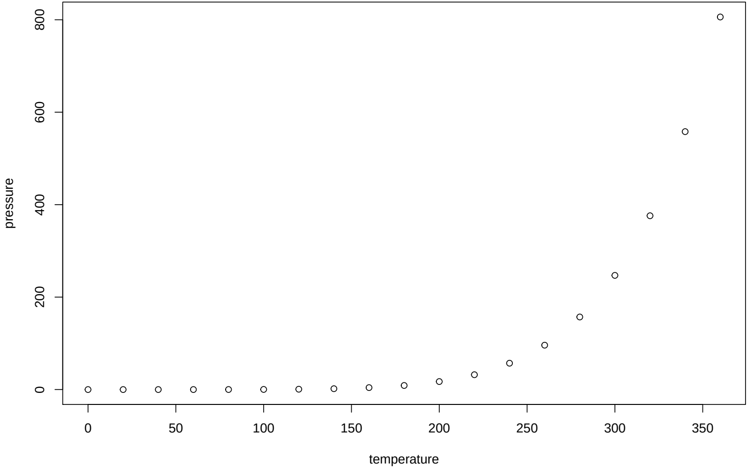
Slide with R Output

POTATO

```r
summary(cars)
```

```
##      speed           dist       
##  Min.   : 4.0   Min.   :  2.00  
##  1st Qu.:12.0   1st Qu.: 26.00  
##  Median :15.0   Median : 36.00  
##  Mean   :15.4   Mean   : 42.98  
##  3rd Qu.:19.0   3rd Qu.: 56.00  
##  Max.   :25.0   Max.   :120.00  
```

Slide with Plot



Smith, Leslie N. 2015. "Cyclical Learning Rates for Training Neural Networks." *Proceedings - 2017 IEEE Winter Conference on Applications of Computer Vision, WACV 2017*. Institute of Electrical; Electronics Engineers Inc., 464–72.