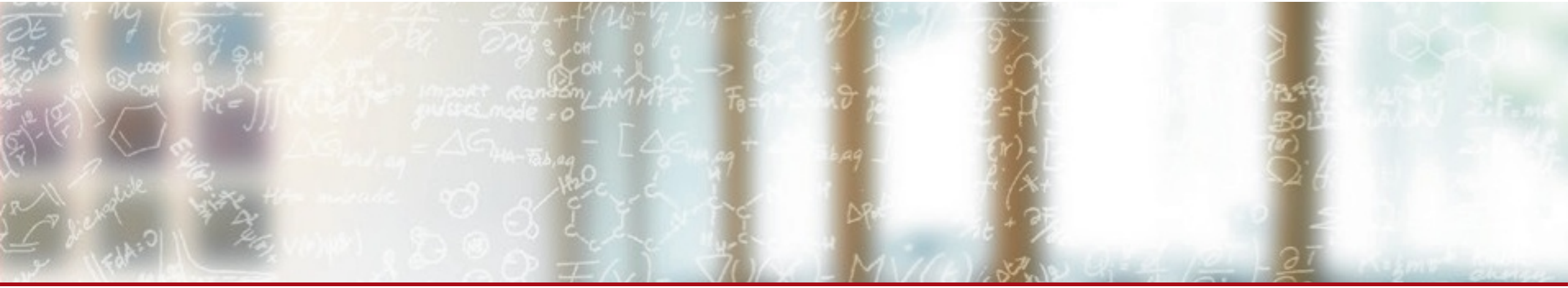
CSCS
Centro Svizzero di Calcolo Scientifico
Swiss National Supercomputing Centre

ETH zürich



Deep Learning at Scale

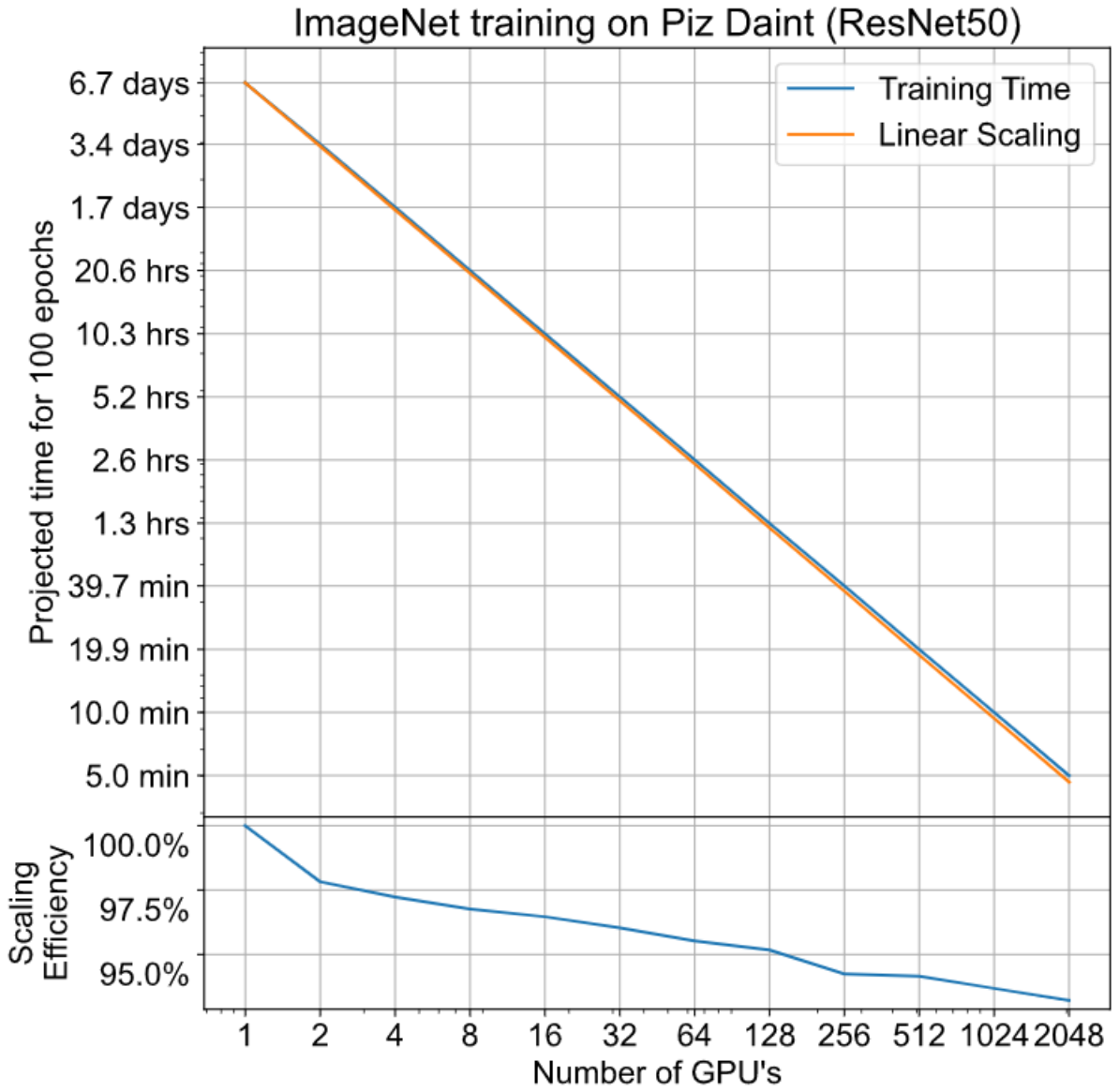
CSCS Summer School 2021

Henrique Mendonça and Rafael Sarmiento, CSCS

30 July 2021

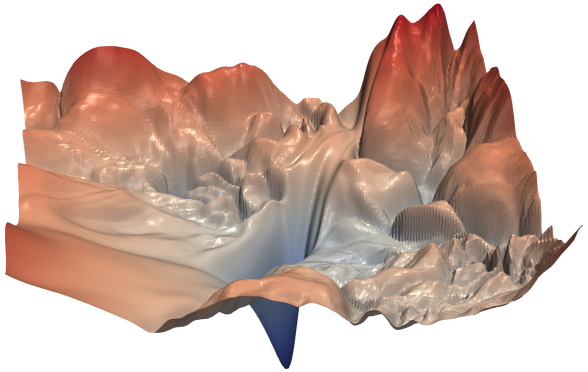
Deep Learning at Scale

- Motivation
    1. Speed:
        - Fast experimentation
        - Fail fast, try new ideas



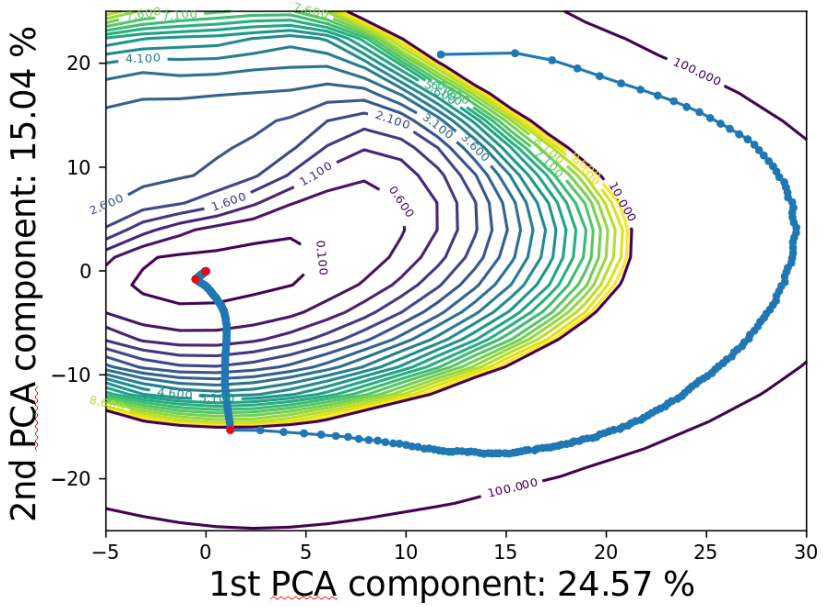
Motivation

- 2. Quality:
  - Allows SGD with larger batch sizes, less noise
  - Search a large hyper-parameter space

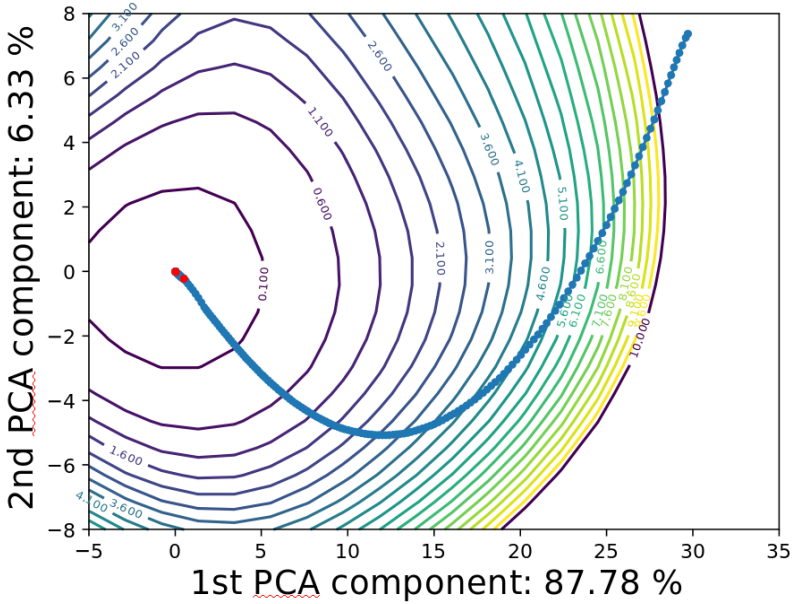


Visualizing the Loss Landscape of Neural Nets
https://arxiv.org/pdf/1712.09913.pdf

Batch size 128

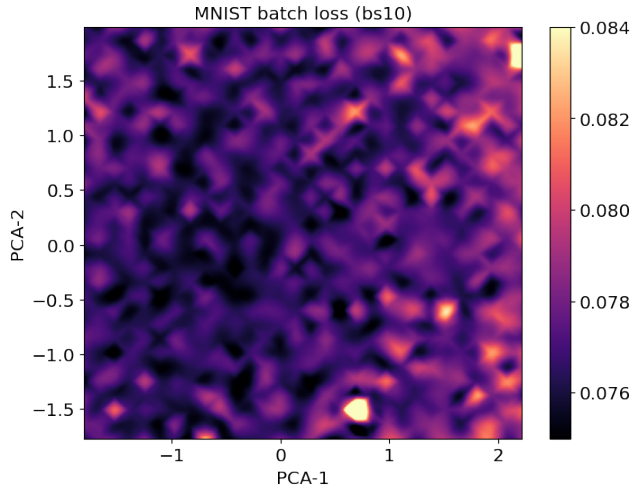


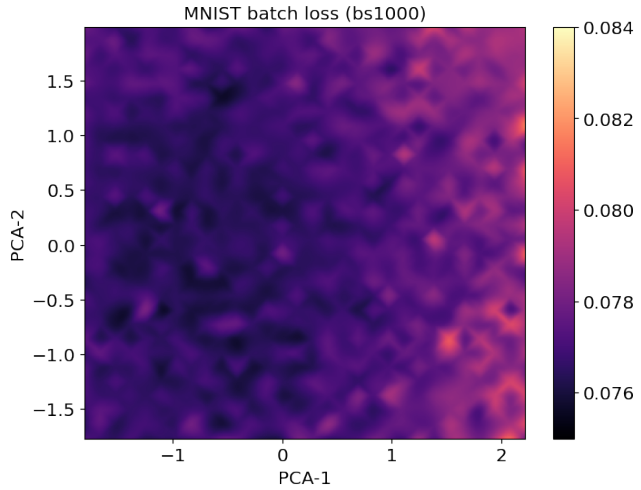
Batch size 8192



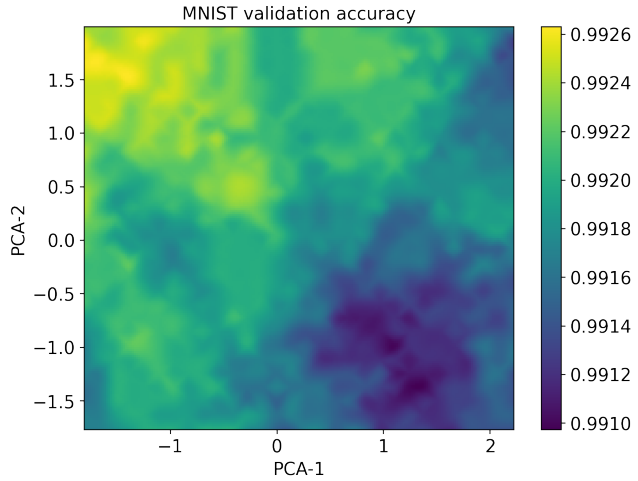
Motivation

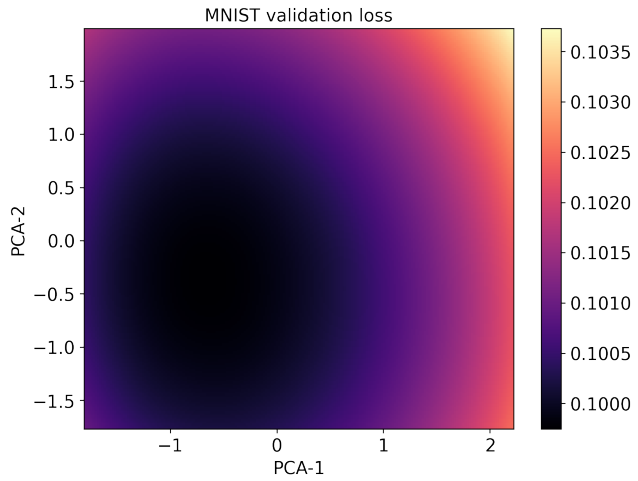
- Training:





- Validation:





Deep Learning at Scale

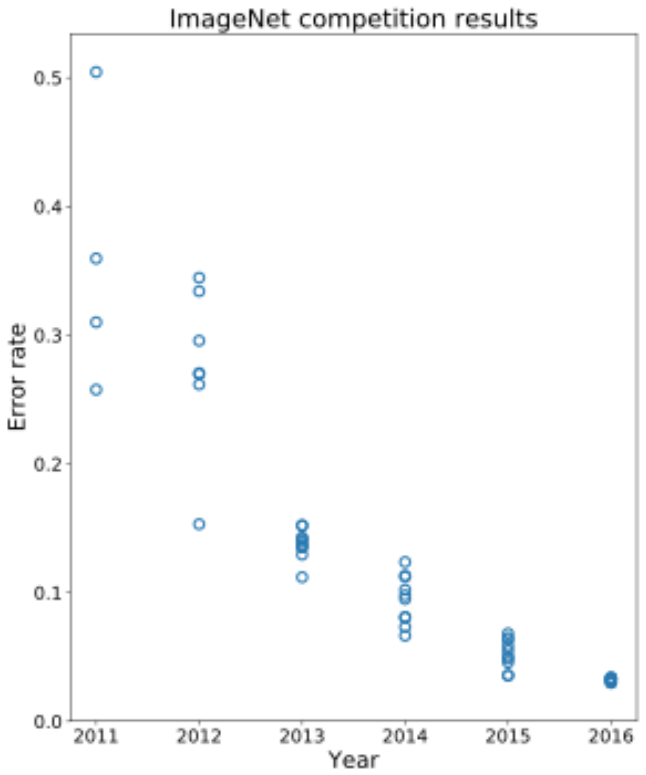
- Motivation

  1. Speed:
     - Fast experimentation
     - Fail fast, try new ideas
  2. Quality:
     - Allows SGD with larger batch sizes, less noise
     - Search a large hyper-parameter space
  3. Potential:
     - Train models larger than memory (not covered in this course)

       e.g. GPT-3 175 billion parameters won‘t fit in any available accelerator

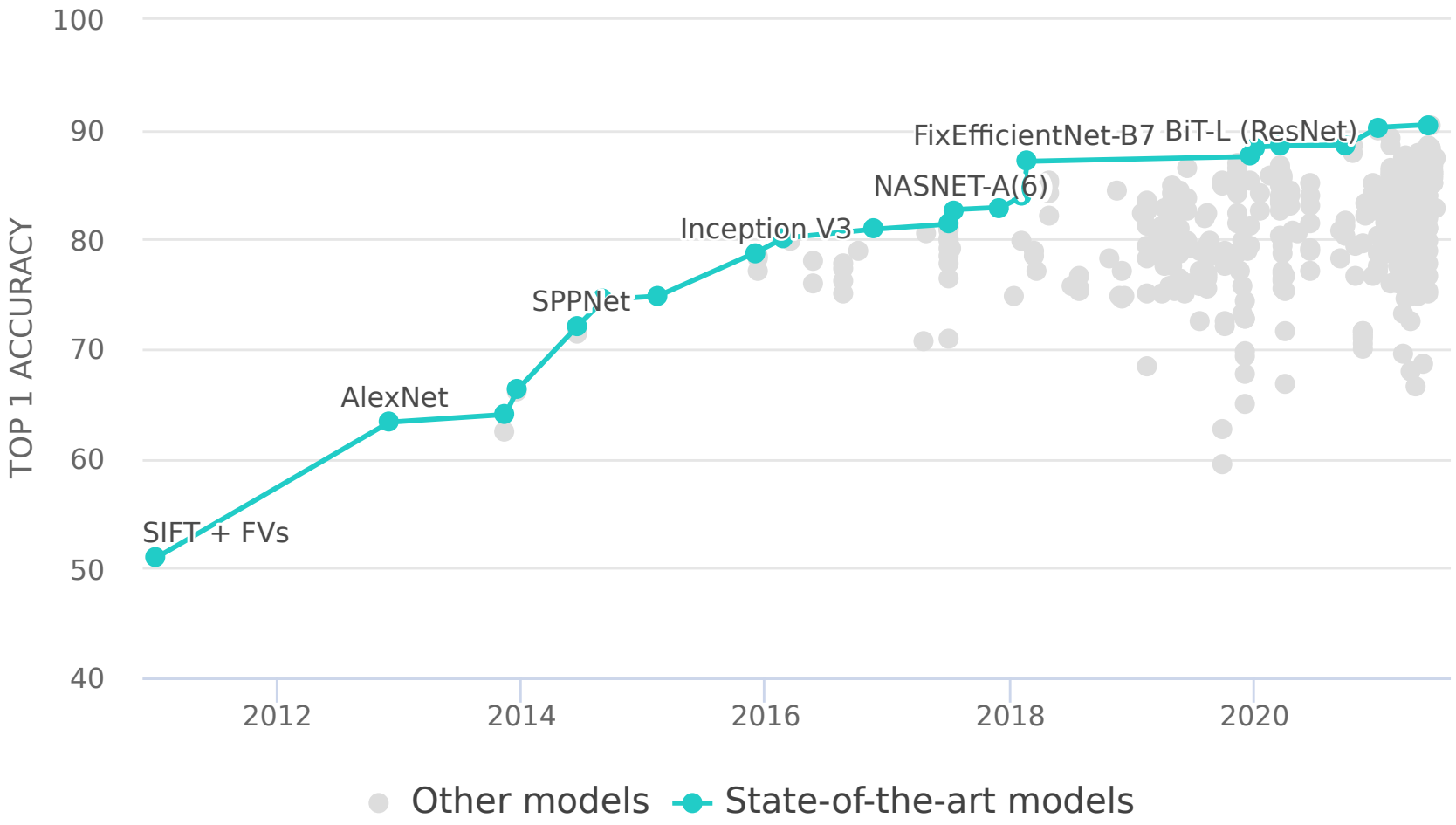
ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

- First large scale image dataset
  - 14,197,122 images
  - Manually annotated to 21,841 WordNet synsets
  - High class imbalance
- 2012 subset with 1000 classes
  - 1,281,166 images
  - 50,000 images for validation
  - AlexNet greatly outperforms traditional ML methods
- Made deep learning popular
  - Large pretrained models allowed *transfer-learning* to other domains



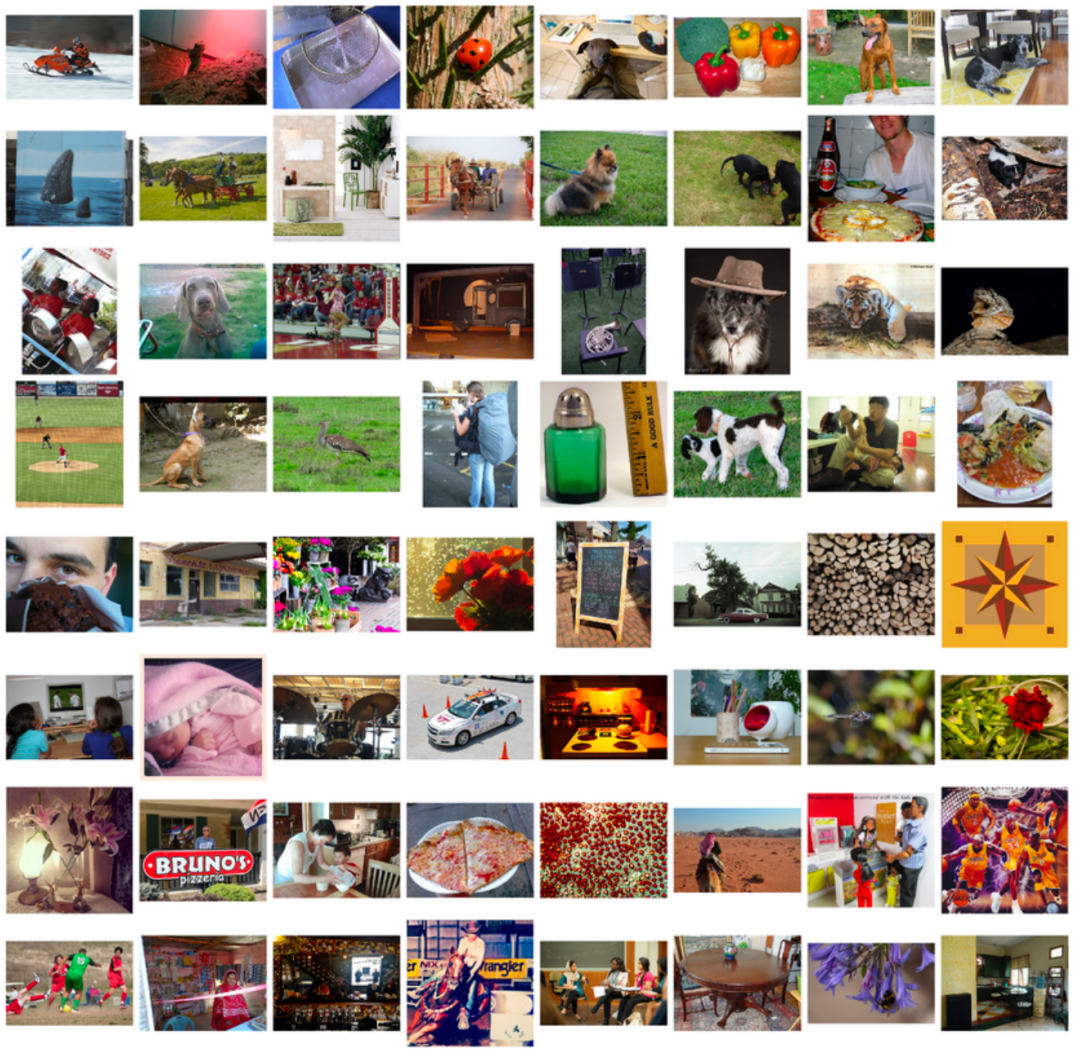
Top5-Accuracy error: https://en.wikipedia.org/wiki/ImageNet

ImageNet Large Scale Visual Recognition Challenge (ILSVRC)



https://paperswithcode.com/sota/image-classification-on-imagenet

ImageNet Large Scale Visual Recognition Challenge (ILSVRC)



{0: 'tench, Tinca tinca',
 1: 'goldfish, Carassius auratus',
 2: 'great white shark, white shark, man-eater, man-eating shark, Carcharodon carcharias',
 3: 'tiger shark, Galeocerdo cuvieri',
 4: 'hammerhead, hammerhead shark',
 5: 'electric ray, crampfish, numbfish, torpedo',
 6: 'stingray',
 7: 'cock',
 8: 'hen',
 9: 'ostrich, Struthio camelus',
 10: 'brambling, Fringilla montifringilla',
 11: 'goldfinch, Carduelis carduelis',
 12: 'house finch, linnet, Carpodacus mexicanus',
[...]
152-269: 117 DOG BREEDS
[...]
 988: 'acorn',
 989: 'hip, rose hip, rosehip',
 990: 'buckeye, horse chestnut, conker',
 991: 'coral fungus',
 992: 'agaric',
 993: 'gyromitra',
 994: 'stinkhorn, carrion fungus',
 995: 'earthstar',
 996: 'hen-of-the-woods, hen of the woods, Polyporus frondosus, Grifola frondosa',
 997: 'bolete',
 998: 'ear, spike, capitulum',
 999: 'toilet tissue'}

Storage Access: TF Records

- Accessing millions of small files concurrently can be challenging
  - Disk and Network drives work better with larger files
- TF Records
  - Can pack several images and metadata serially on each file
  - Can read image by image without loading the whole file to memory

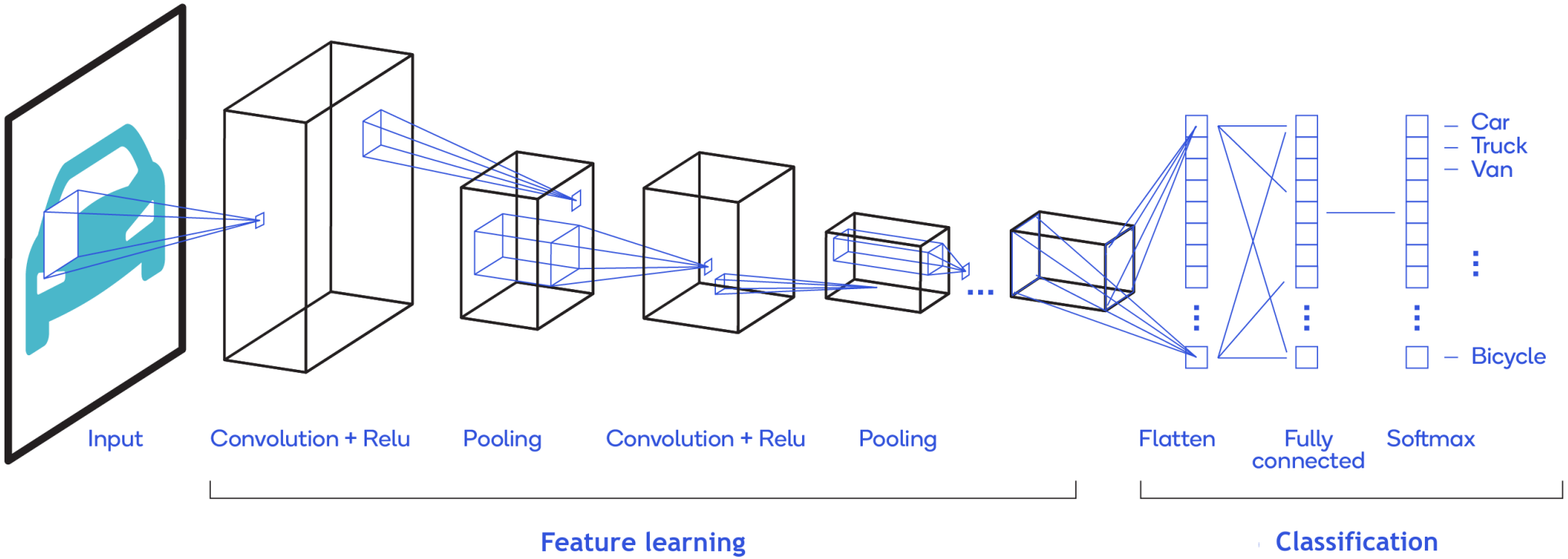
```
features = {
        'filename': tf.train.Feature(bytes_list = tf.train.BytesList(value = [bytes(filename, 'utf-8') ])),
        'Image shapes': tf.train.Feature(int64_list = tf.train.Int64List(value = [img_shape[0], img_shape[1]])),
        'image': tf.train.Feature(bytes_list = tf.train.BytesList(value = [image])),
        'label': tf.train.Feature(bytes_list = tf.train.BytesList(value = [label])),
        ...
}

record = [{'image': […], 'label': 123},  {'image': […], 'label': 42},  {'image': […], 'label': 789},  ...]
```

TF Records

- Demo Notebook
  - Decode TF records
  - Encode

Convolutional Neural Networks

- Exploits translational equivariance on natural images
- Large filters can be decomposed into smaller ones



Convolutional Neural Networks

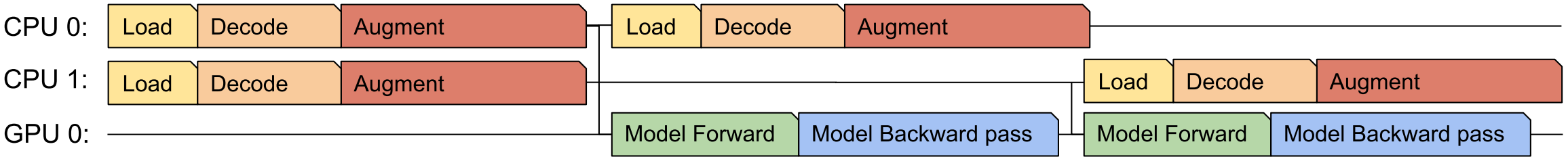
- Practice Notebook
  - 01_imagenet-conv.ipynb

Data Augmentation on CNN‘s

- Convolutional layers are invariant to translation (spatial shift)
  - But not to rotations
  - Only to certain degree to color and luminosity shift

- Data Augmentation is yet another form of regularization
  - Can be as important as model architecture
  - Extensive literature, and several open source libraries
  - **Generally done on CPU in the background**
    - Some GPU implementations are also available
  - Augmentation can be used as a platform for self-supervised learning

Data Augmentation

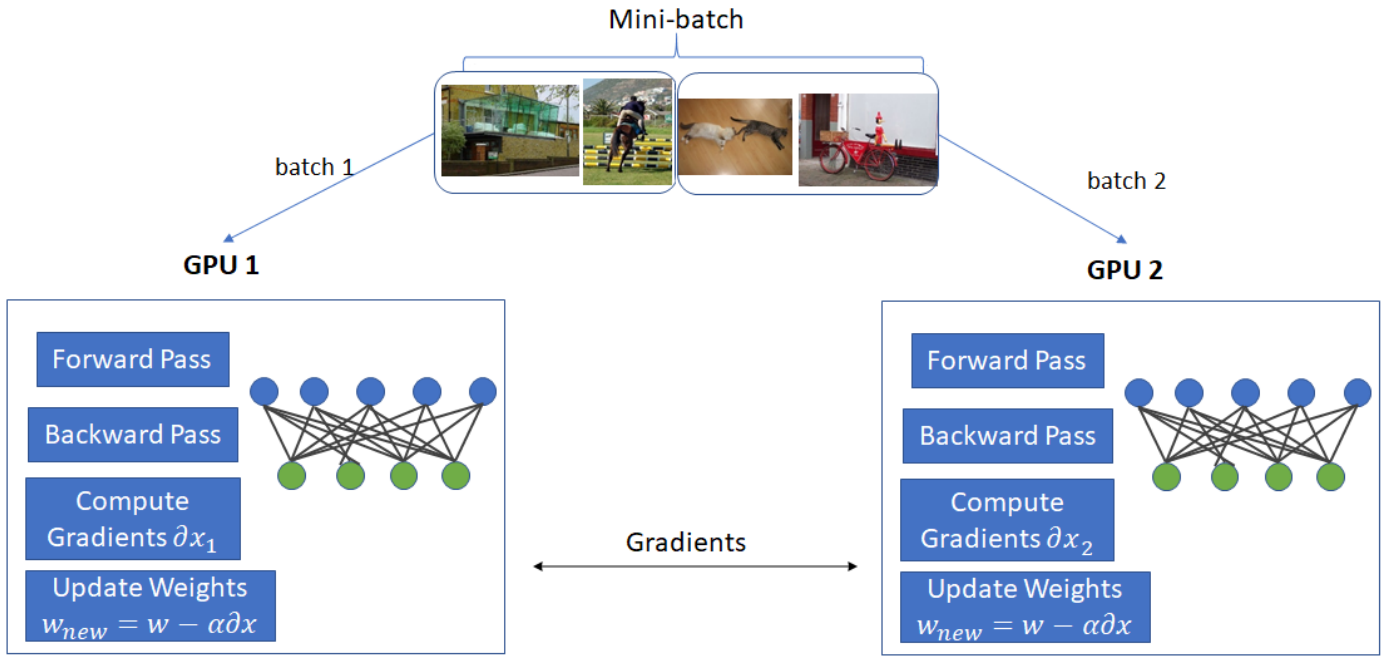


Data Augmentation

- Practice Notebooks
  - 02_imagenet_tfa.ipynb
  - 02b_imagenet_albumentations.ipynb
  - 03_imagenet.ipynb

Deep Learning at Scale

- Data parallelism
  - Sharded data-loader
    - 1/N of the data on each Nth node
  - Gradient synchronization
    - AllReduce gradients



Deep Learning at Scale

- Practice Notebook
  - 04_tf-data-shard.ipynb
  - 05_dist-imagenet.ipynb

Batch Norm Synchronization

- Exponential Moving Average per channel

$$x_i^* = \frac{x_i - \mu}{\sigma + \epsilon}$$

$$y_i = \gamma x_i^* + \beta$$

$$\mu = (1-\alpha)\mu + \alpha\mu_B \qquad \mu_B = \frac{1}{n}\sum_i^n x_i$$

$$\sigma^2 = (1-\alpha)\sigma^2 + \alpha\sigma_B^2 \qquad \sigma_B^2 = \frac{1}{n}\sum_i^n (x_i - \mu)^2$$

- SyncBatchNormalization Layer
  - Synchronizes all statistics during forward pass
  - AllReduce across BN layers may induce additional latency

Batch Norm Synchronization

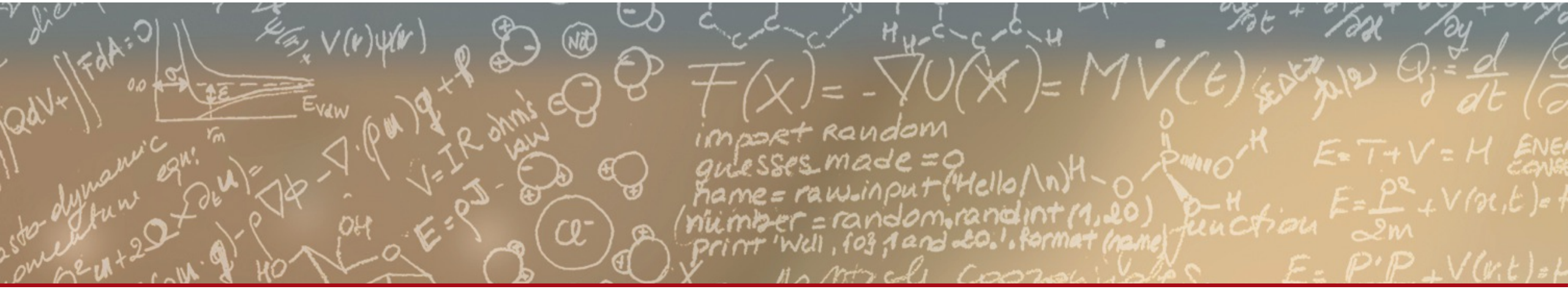
- Demo Notebook
  - 06_bn-sync.ipynb

Machine Learning Engineering - Good Practices

- Unit-test model, data pipeline and loss functions
  - Integration test: overfit to subset of data
  - Test checkpoints
- Use reliable metrics and validation split

- Reuse code, data and models
  - Transfer-learning when possible

- Hyper-parameter search (including data augmentation and LR scheduling)
  - Only then run architecture search



Thank you for your attention.