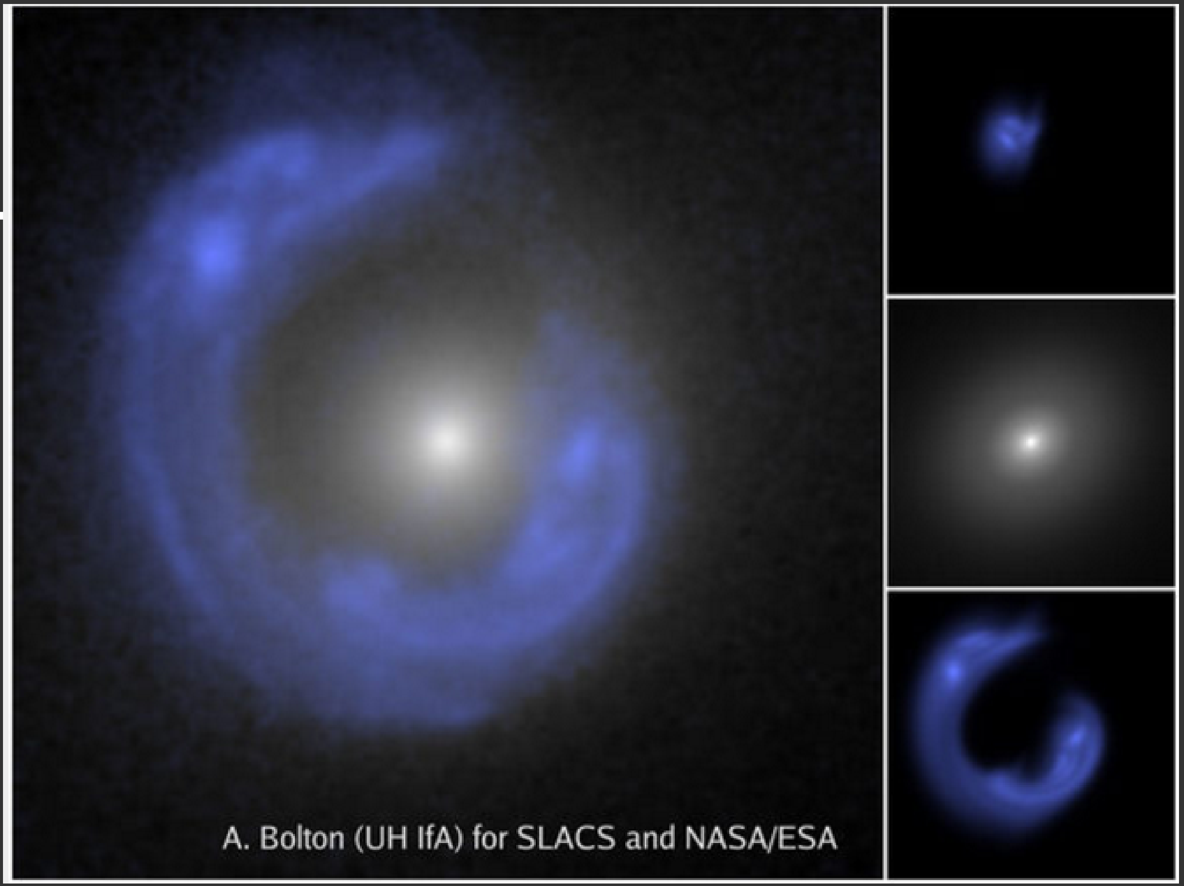
Strong Lensing analysis using Deep Neural Networks



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Motivation:

- Strong galaxy-galaxy lensing
  - Details of matter density profiles, evolution
  - Constrain cosmological constants

- Strong Lensing detection
  - Visual inspection
  - Automated codes using
    - Morphology
    - Machine learning

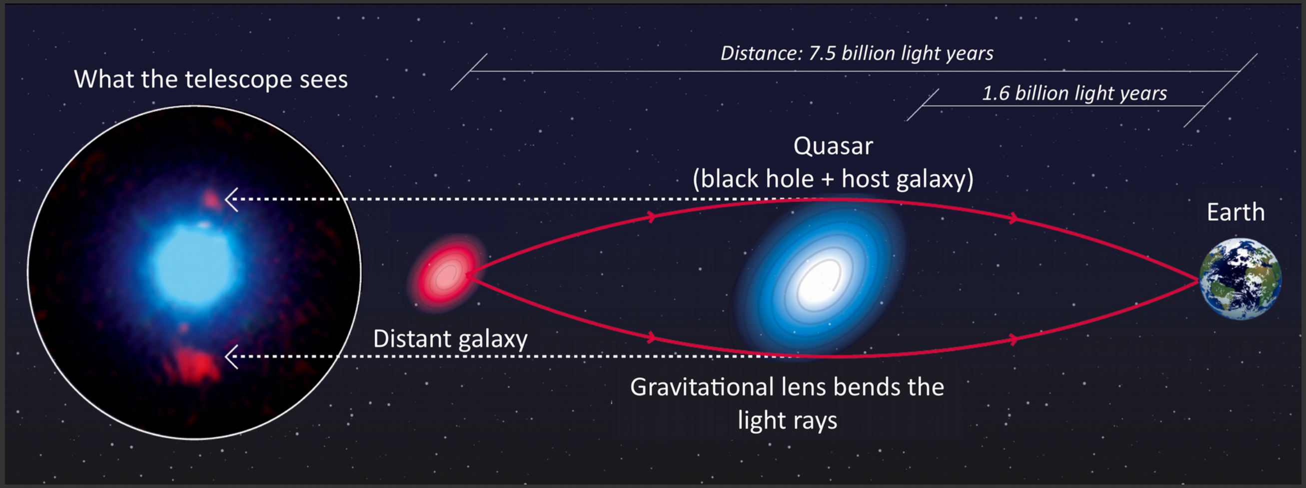
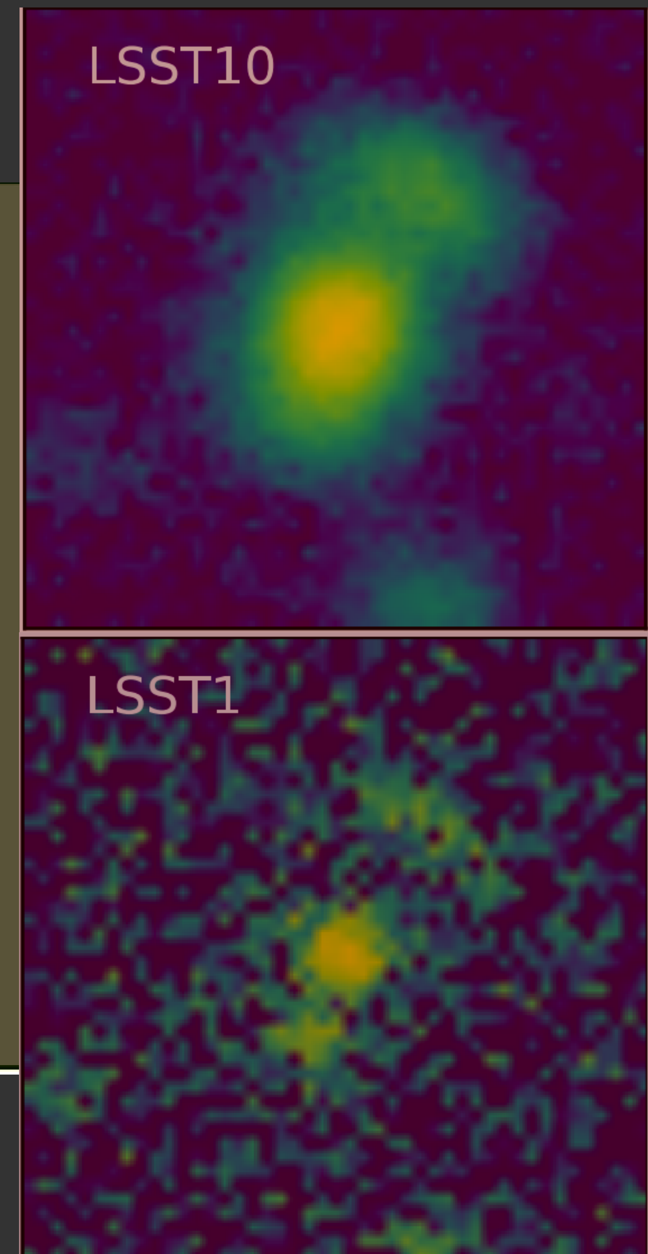


Image credits: F. Courbin, S. G. Djorgovski, G. Meylan, et al., Caltech / EPFL / WMKO

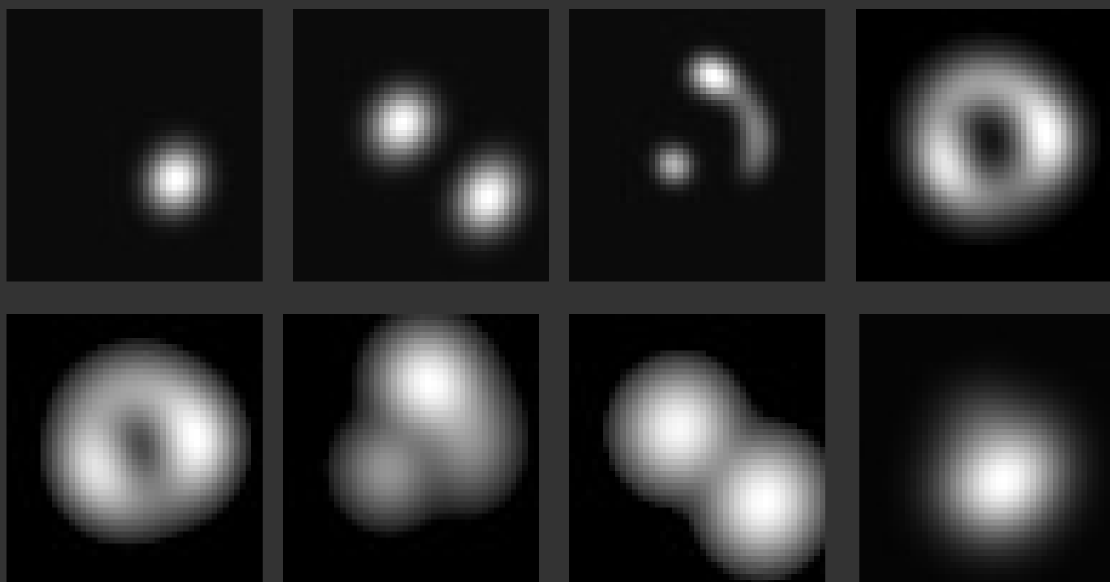
- Expected number of galaxy-galaxy strong lenses (eg. Collett 2015)
    - DES: 2,400
    - LSST: 120,000
    - Euclid: 170,000

Mock telescope images: (Avestruz et. al. 2017)

- Present:
  - HST: high res, low noise
- Future:
  - LSST: low res, 6 bands
  - Euclid: high res, gray-scale



Simulated images (From Nan Li)



← Noiseless single

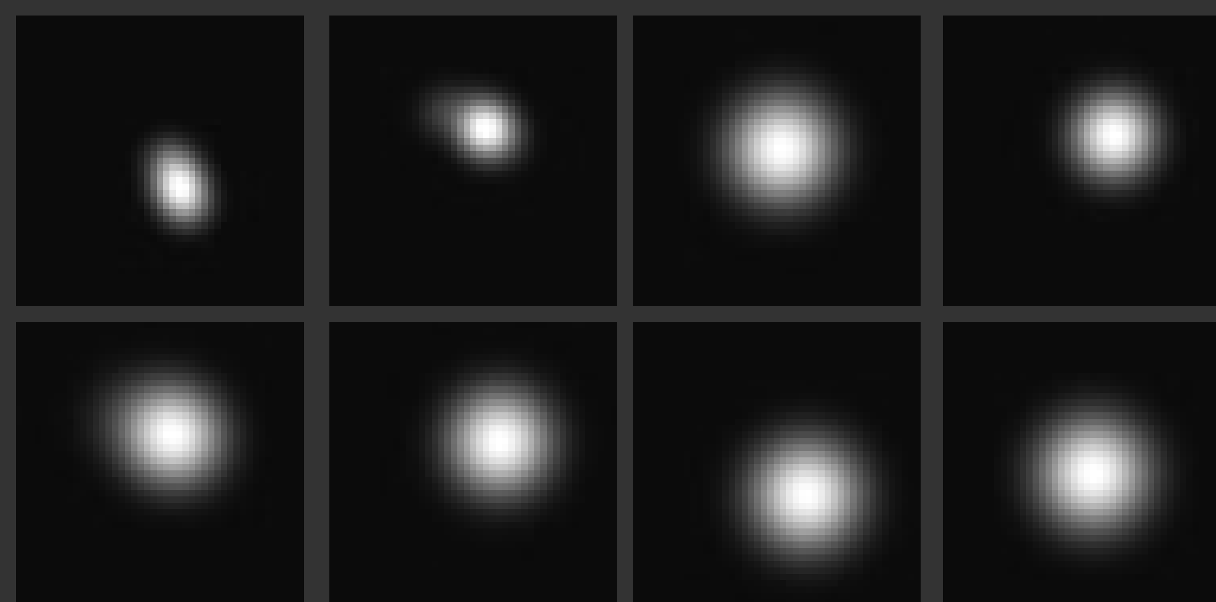
← Lensed

← Noiseless stack

Noiseless single →

Unlensed →

Noiseless stack →

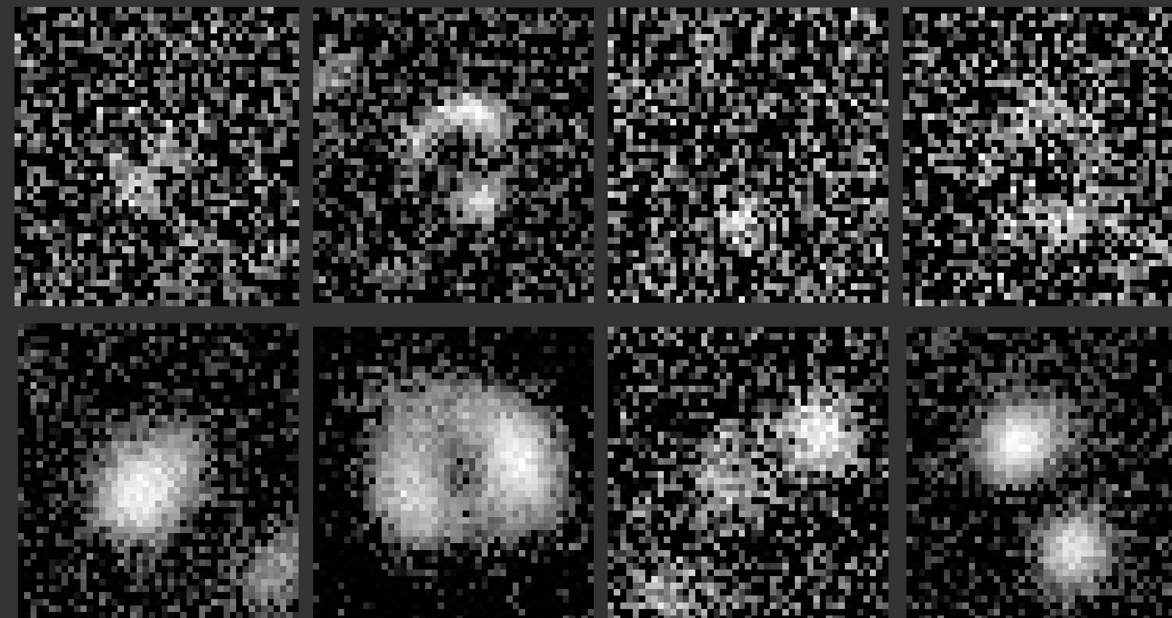


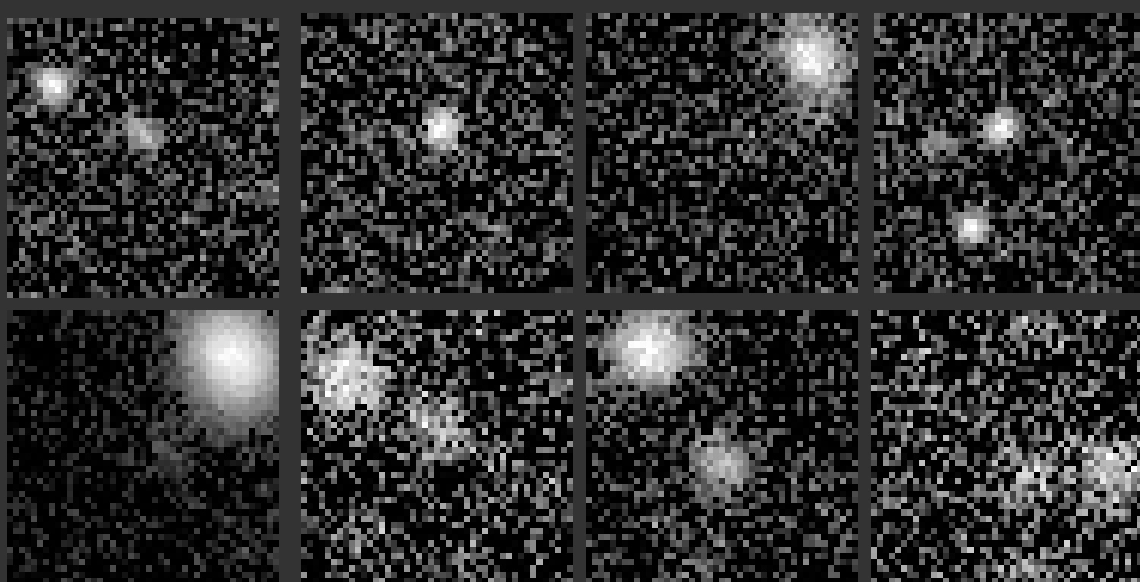
Noisy data for training: 8,000 each, 45x45 pixels (0.18 arcsec/pixel)

Lensed →

Noisy single →

Noisy stack →





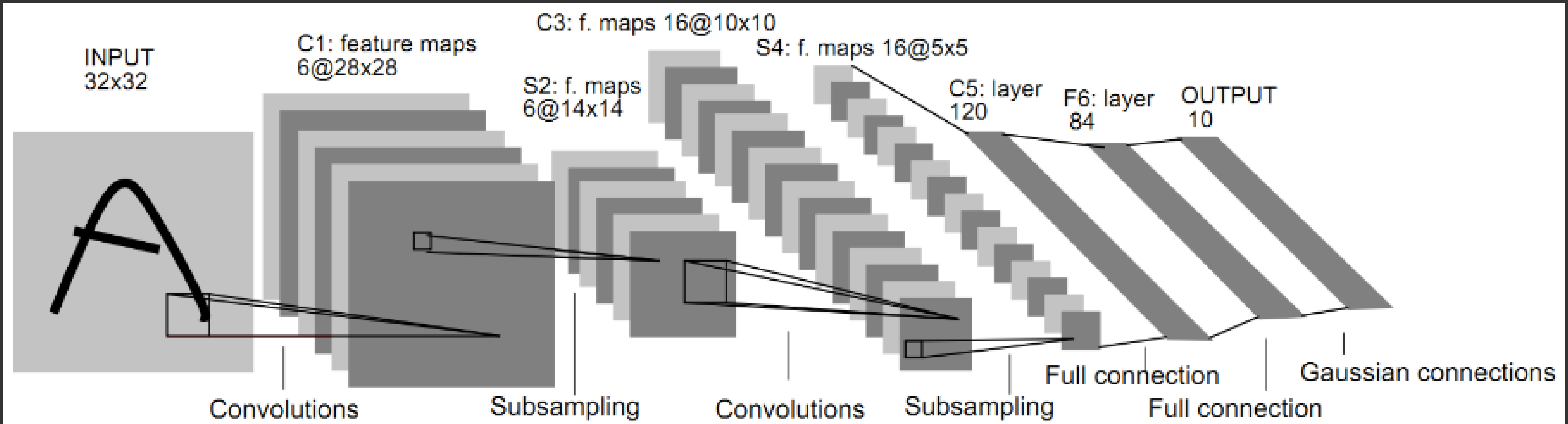
← Noisy single

← Unlensed

← Noisy stack

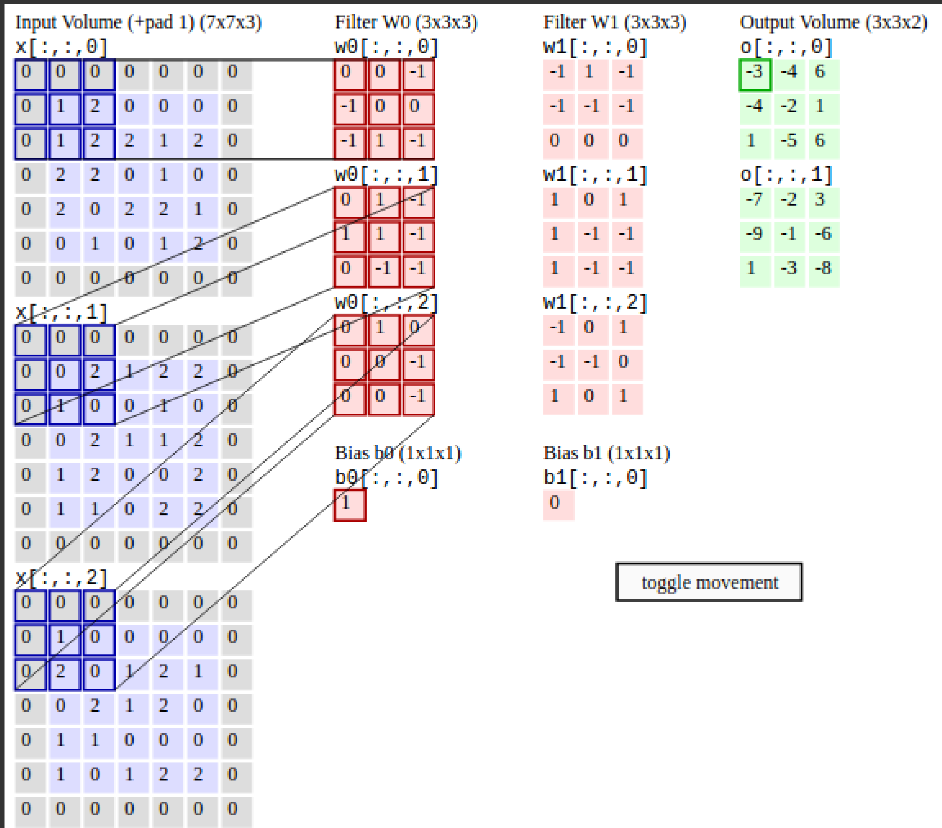
Convolutional neural networks (CNNs/ConvNets)

- Been around since early 1990s;
  - Recently became mainstream due to GPUs. Surpassed human ability ~ 2015
- Applied in new image recognition systems, language processing, AlphaGo
- Lensing images study:
  - Petrillo et. al. 2017 (Kilo Degree Survey)
  - Lanusse et. al. 2017 (CMU-DeepLens)



LeNet, 1998

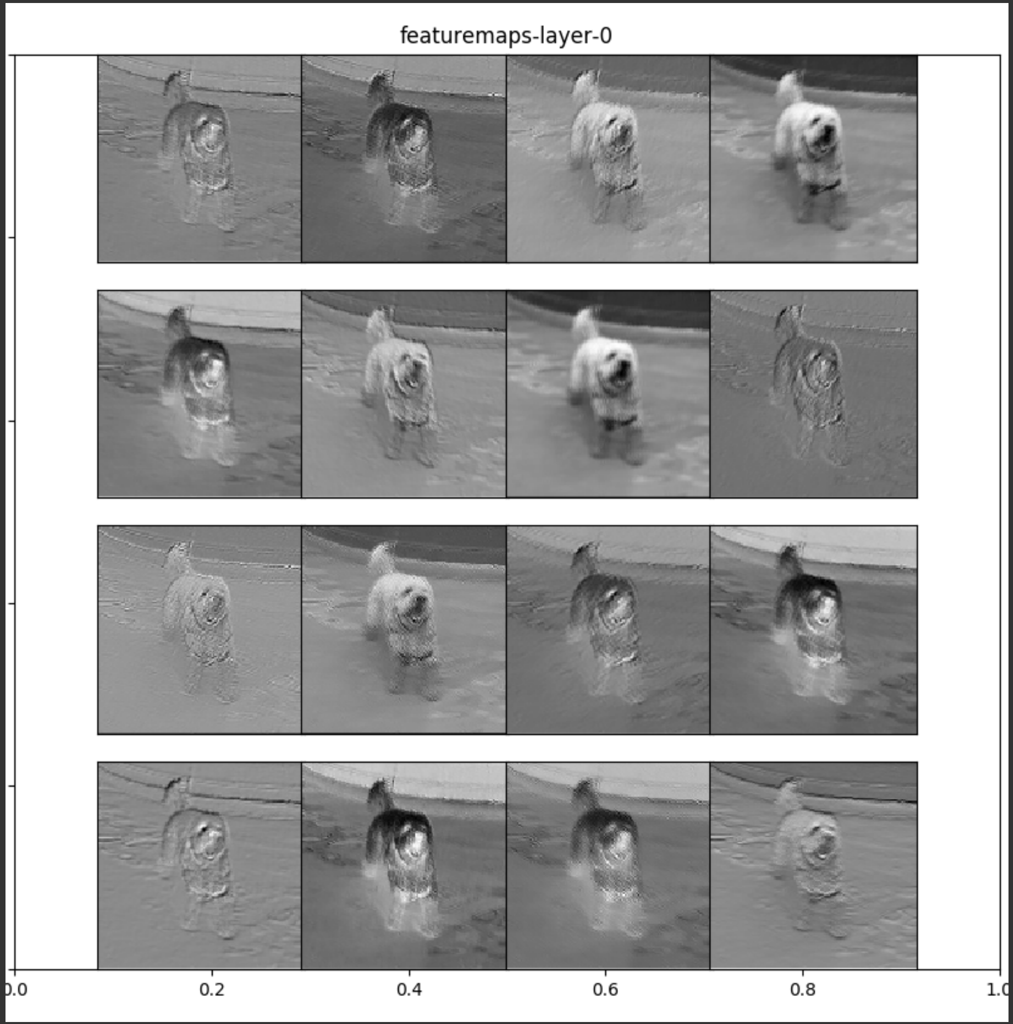
Convolution layer



http://cs231n.github.io/convolutional-networks/

- Filters/kernels of various types
  - Stride through every image
  - Pick up features, which are used as inputs for activation

Convolution →



Other layers

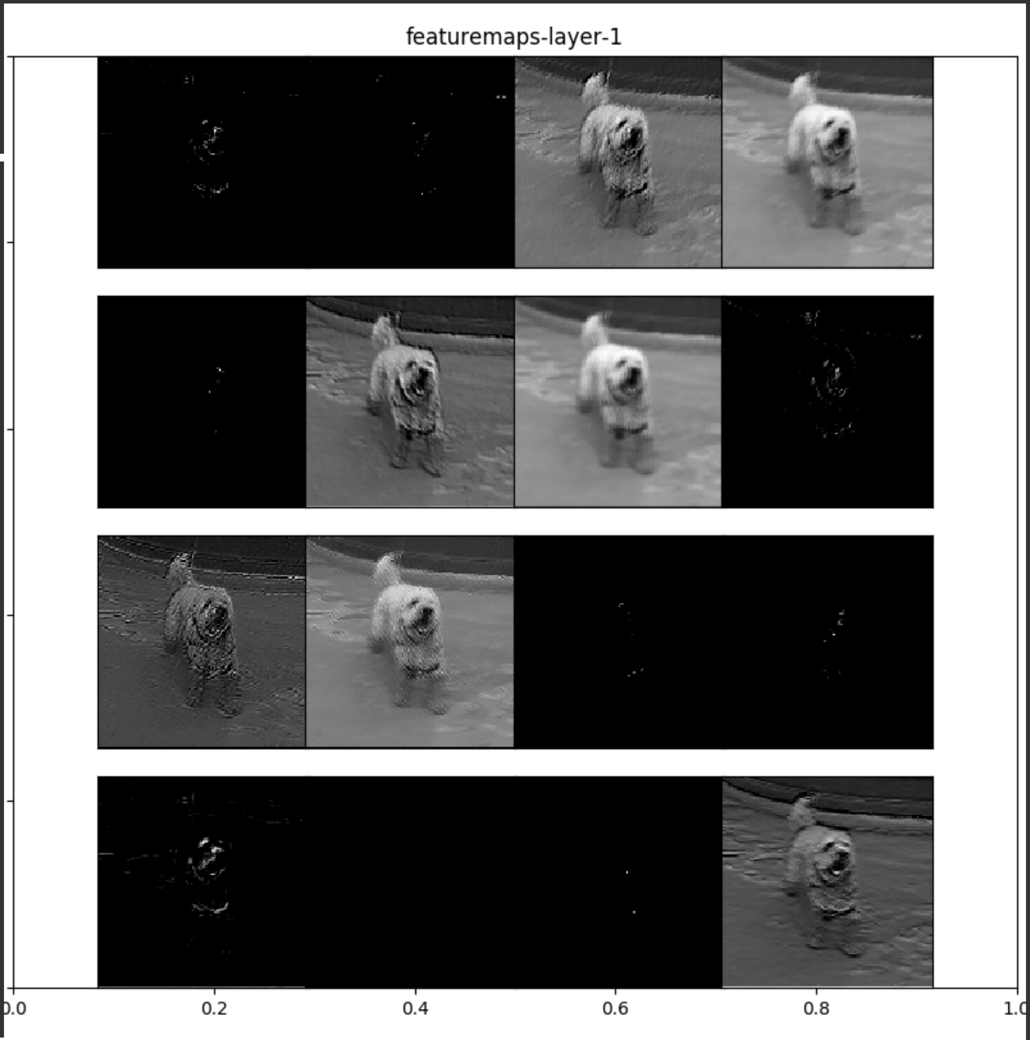
- Activation layer
  - Introduces non-linearity
  - Activation function: f(x) = max(0, x) applied to all the values of input array

- Pooling layer

- Dropout layer

- Dense layer
  - Fully connected layer that checks correlation between input and output
  - Generally around the final layers

→

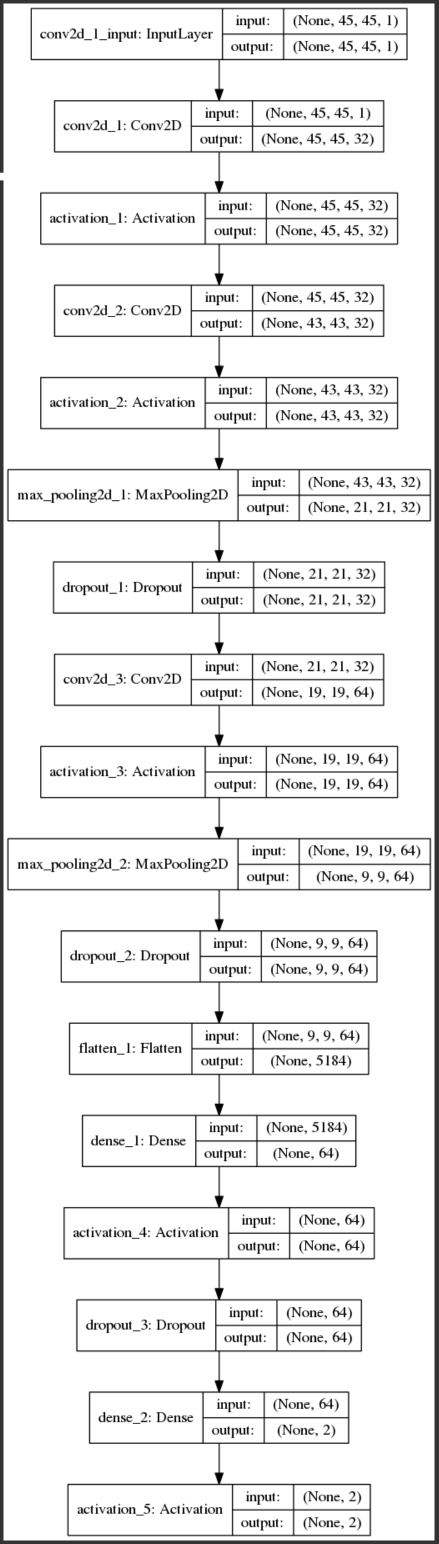


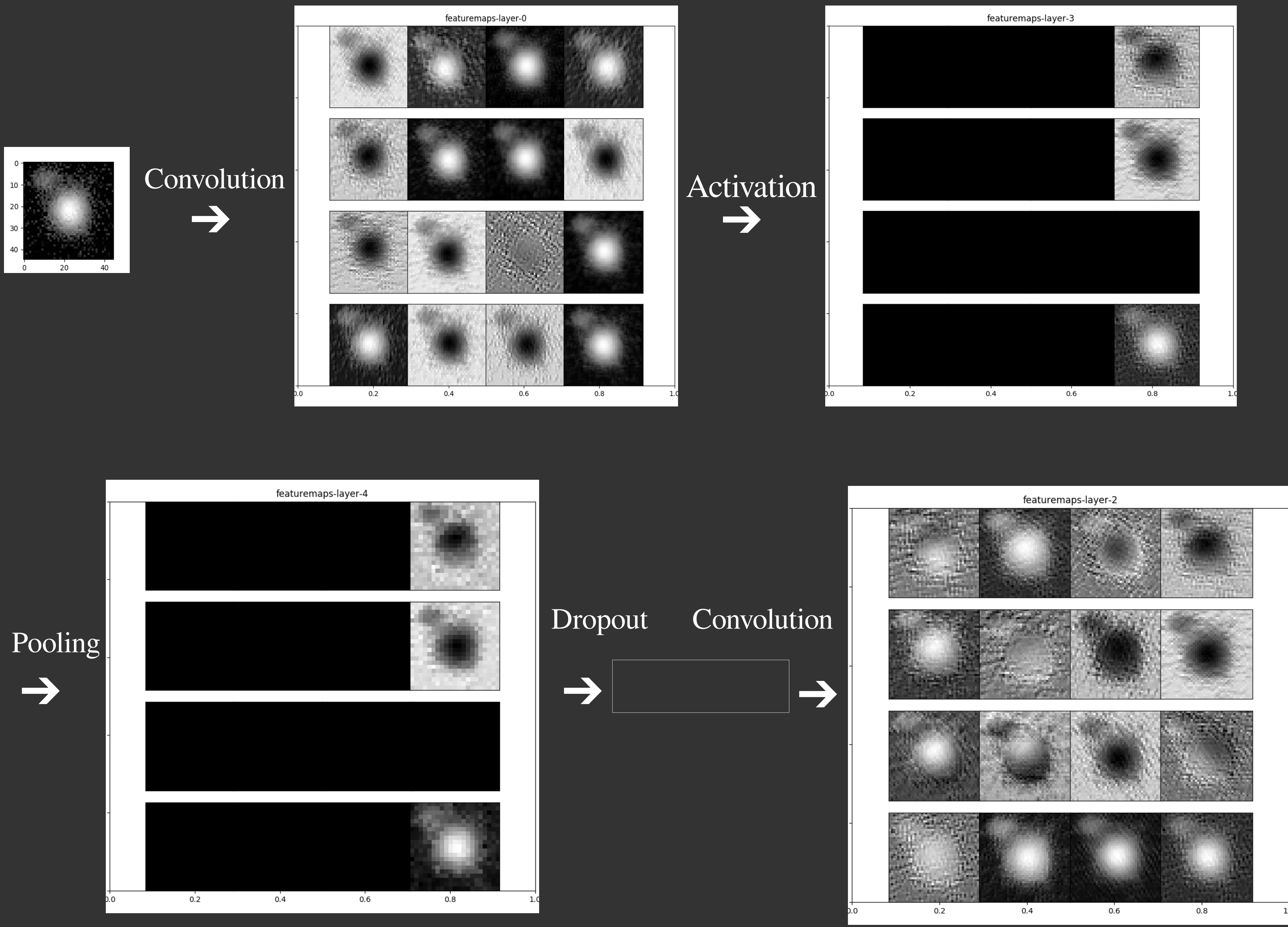
- Backpropagation
  - End of every epoch, predicted labels are checked against real labels, and loss (error) is calculated.

  - We try to minimize this error in the next epoch, by updating weights

Our SL detection framework

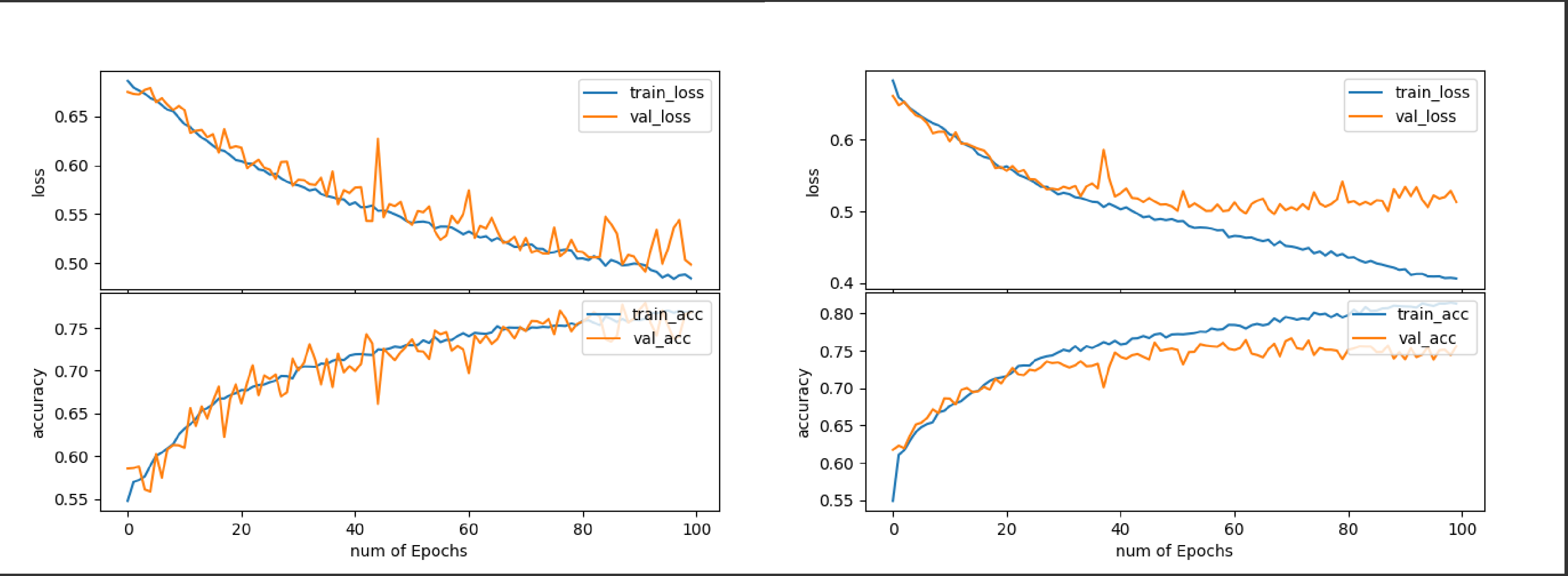
- Our network currently has 17 layers.
  - **Input image [45x45]** → Conv → Actv → Conv → Act → Pool → Drop → Conv → Actv → Pool → Drop → Flat → Dense → Actv → Drop → Dense → Actv → **Output label [Prob(lensed), 1-Prob(lensed)]**
  - Can be made deeper or wider
- Lots of parameters to optimize: order of 10^6
- Hyper-parameters to choose ~ 10 to 15
  - Learning rate, decay rate
  - Number of epochs
  - Batch size
  - Dropout percentage
  - Back-propagation optimizers (SGD, RMSprop)
  - Loss functions




Convolution
featuremaps-layer-0
Activation
featuremaps-layer-3
Pooling
featuremaps-layer-4
Dropout
Convolution
featuremaps-layer-2

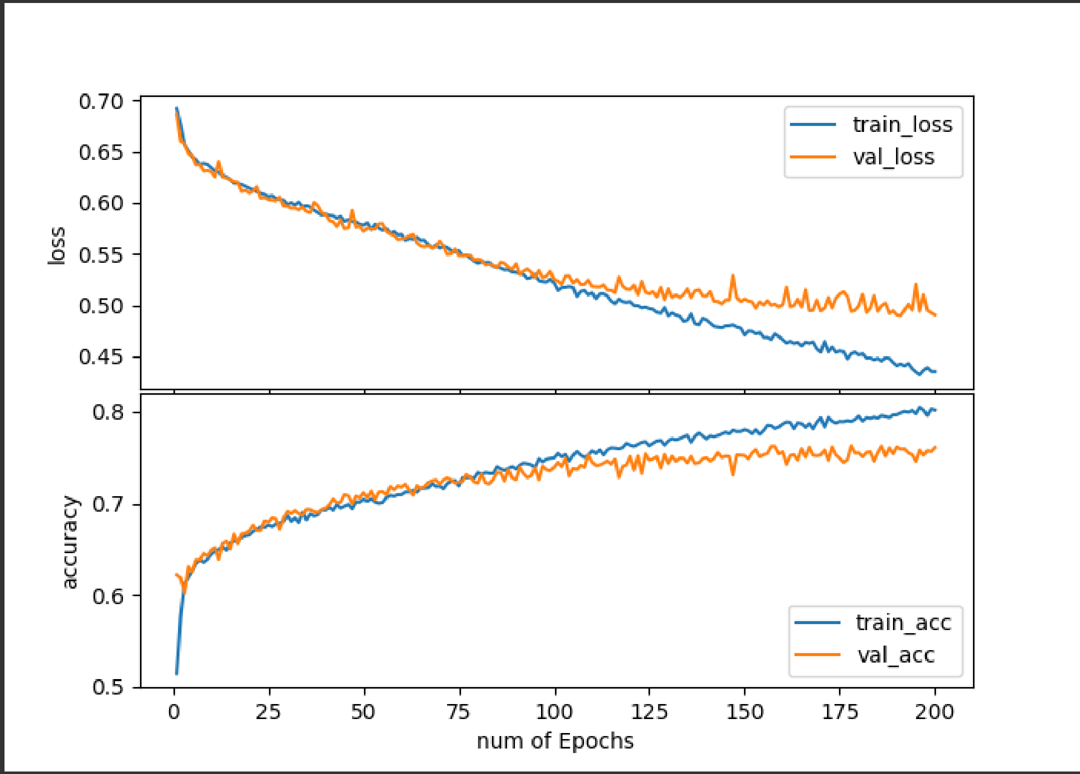
Hyper-parameters fine-tuning

- No quick rule to find the best hyper-parameters
  - Sweep across all ranges, or choose randomly
- Monitor a few values during training and decide from there:
  - Loss, Validation loss – how good are the weights
  - Accuracy, Validation accuracy – how accurate is the model



Sample training

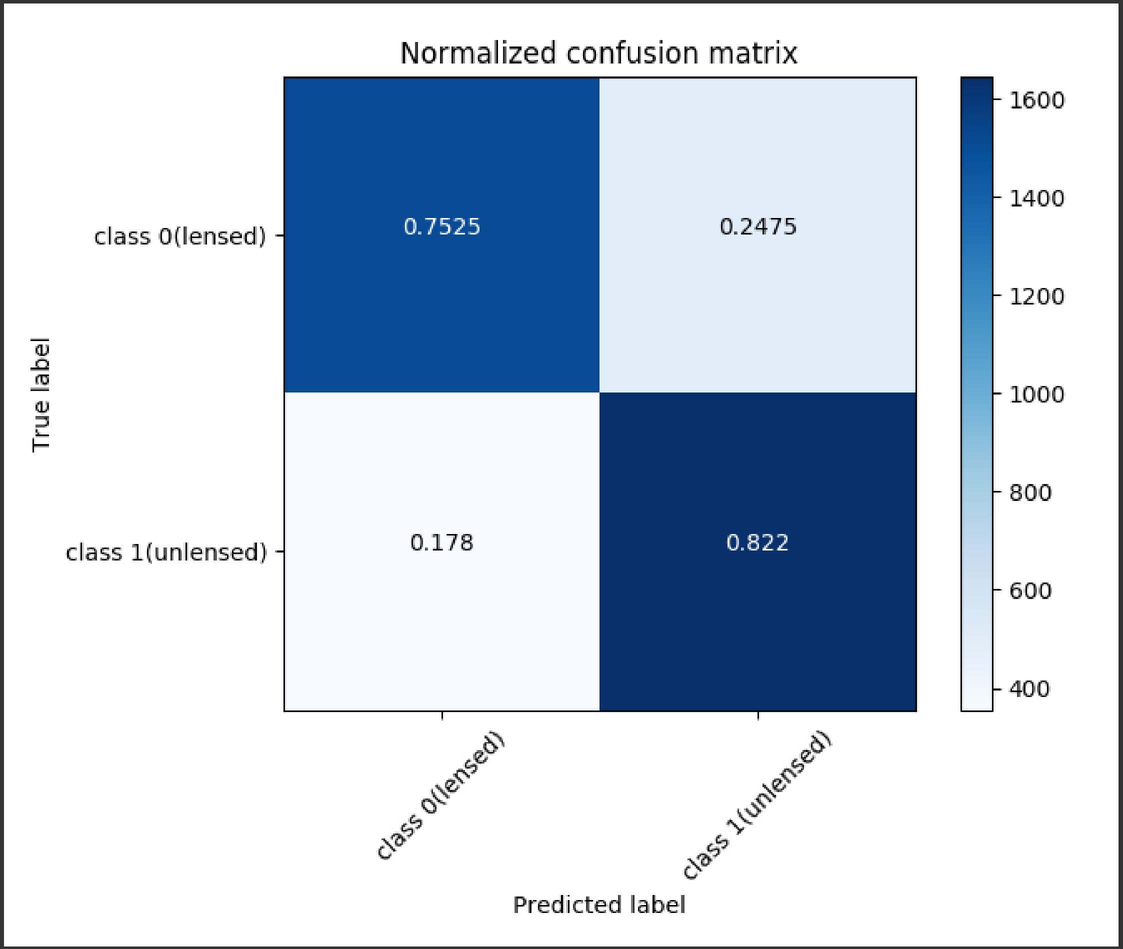
- Loss decreases, accuracy increases with epochs
- Deviation of validation loss/accuracy after 100 epochs
- Hyper-parameters
  - Learning rate: 0.001
  - Decay rate: 0.01
  - Total epochs: 200
  - Batch size: 32



- 80 per cent accuracy in 30 mins on 1 Intel-Haswell node with 16 CPU cores (Cori)
- About the same time on NVIDIA GeForce GT 755M with 384 cores.

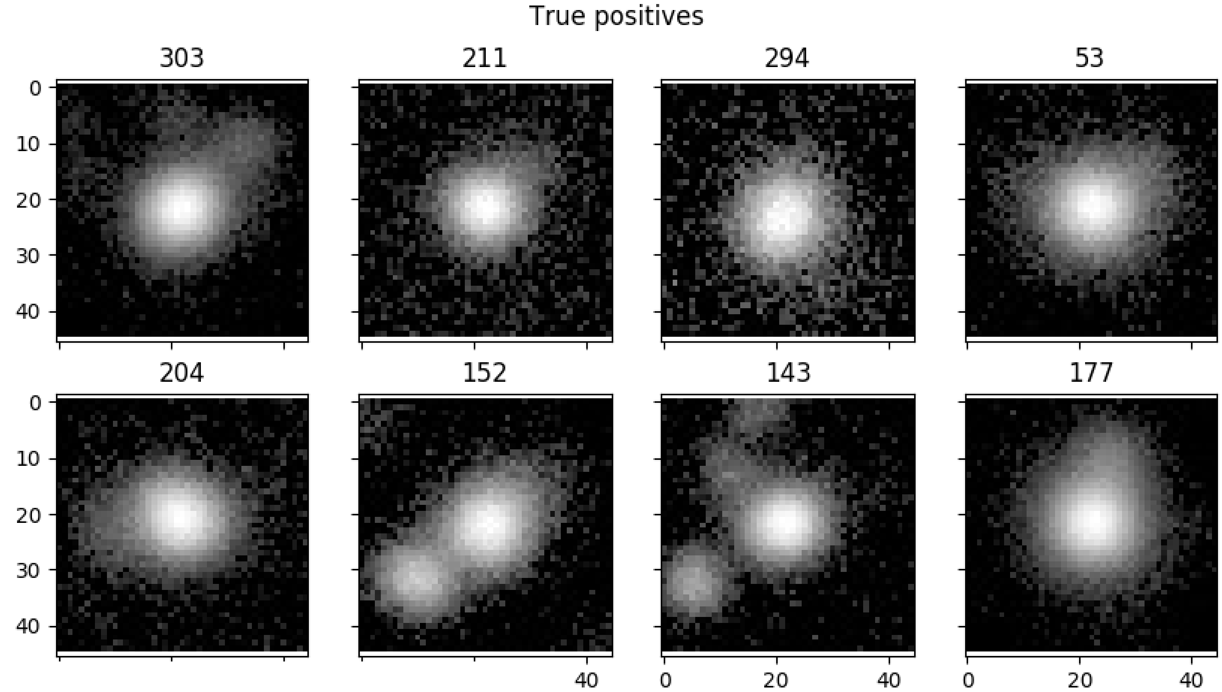
Testing data:

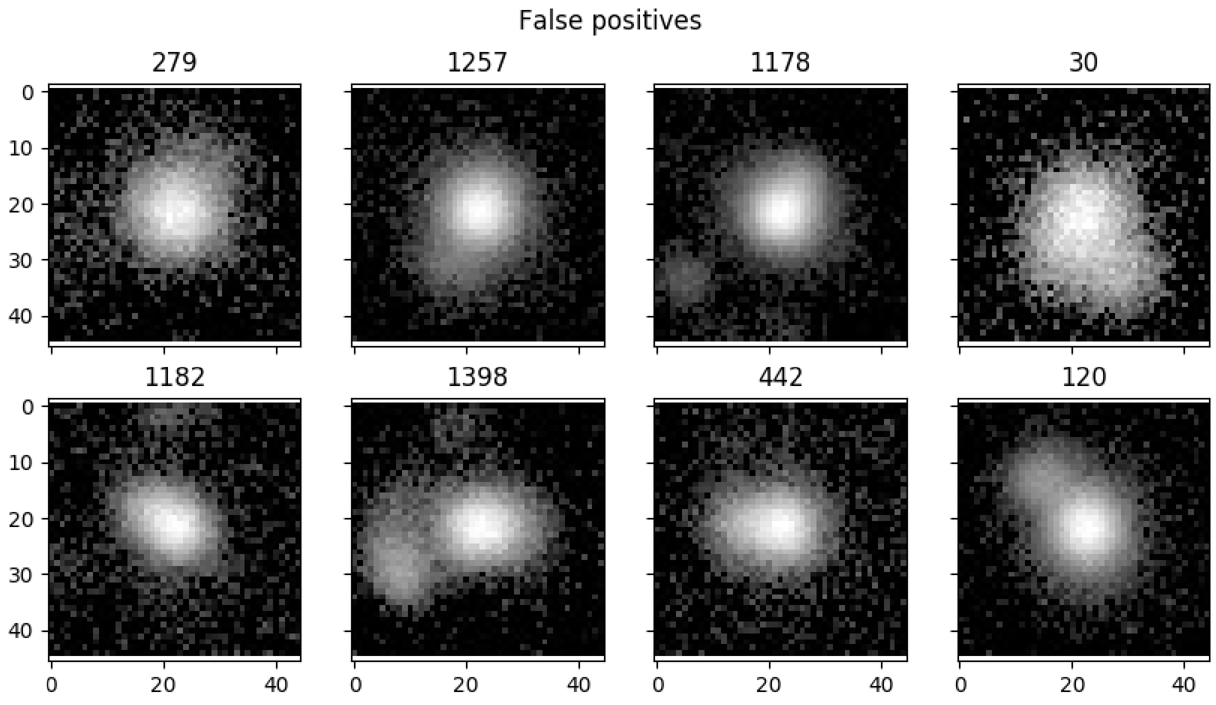
- Using the fully trained model, with optimized weights
- Testing on completely new data
- Classification time: $O(10^{-3})$ seconds per image
- Confusion matrix: probabilities of correct and incorrect classifications.



Preliminary testing results: True and False positives

Correct classifications →





← Incorrect classifications

Summary and future plans

- We’ve reached 80-90 percent accuracy within 200 epochs.
  - Around 75-82 percent accuracy on new images
  - Lot of improvements can be made:
    - Data augmentation
    - Better hyper-parameter sweeps
    - Deeper architectures can be trained using the state-of-the-art GPUs at Argonne.

- Quantitative analysis of strong lensing
  - Can we constrain properties of the lens using simulation-trained ConvNets?
  - Currently we are working on regression problems

Questions?

https://xkcd.com/1838/

References

- https://github.com/hep-cce/ml_classification_studies
- http://cs231n.github.io/convolutional-networks/
- CMU DeepLens: Deep Learning For Automatic Image-based Galaxy-Galaxy Strong Lens Finding, Lanusse et. al. 2017 (arXiv: 1703.02642)
- Finding Strong Gravitational Lenses in the Kilo Degree Survey with Convolutional Neural Networks, Petrillo et. al. 2017 (arXiv: 1702.07675)
- Automated Lensing Learner - I: An Automated Strong Lensing Identification Pipeline, Avestruz et. al. 2017 (arXiv: 1704.02322)
- The population of galaxy-galaxy strong lenses in forthcoming optical imaging surveys, Collett (arXiv: 1507.02657)