EE3-25: Deep Learning

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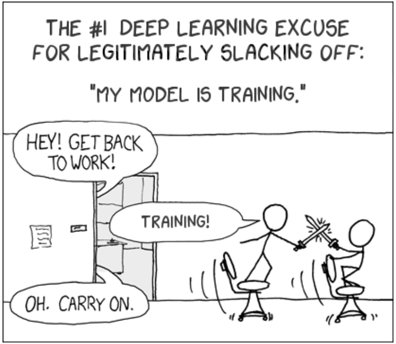


Course Information

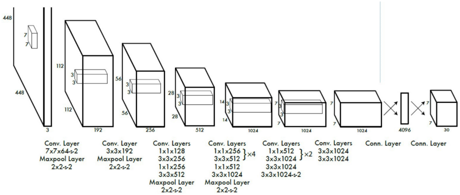
- Dr Krystian Mikolajczyk
  - Room 1015
  - Office hour: Friday 17:00pm-18:00pm
  - Email: k.mikolajczyk@imperial.ac.uk
- Dr Carlo Ciliberto
  - Room 1005
  - Office hour: Friday 17:00pm-18:00pm
  - Email: c.ciliberto@imperial.ac.uk
- GTAs
  - Axel Barroso Laguna
  - Adrian Lopez Rodriguez
  - Office hour: Tuesday 17:00pm-18:00pm

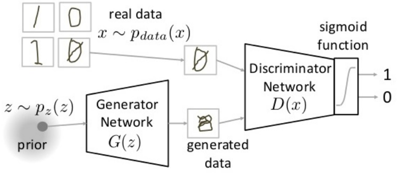
Goal

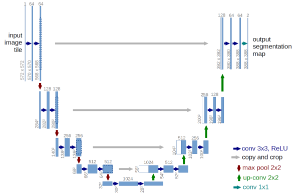
- To introduce fundamental principles, theory and approaches for learning with deep neural networks.
- To offer practical course on implementing and experimenting with deep learning.
- Part of a course on machine learning and related topics:
  - EE3-10 (Autumn): Maths for Signals and Systems
  - EE3-23 (Autumn): Machine Learning
  - EE3-25 (Spring): Deep Learning
  - EE3-08 (Spring): Advance Signal Processing
  - EE4-68 (Autumn): Pattern Recognition
  - EE4-62 (Spring): Selected Topics in Computer Vision
  - EE4 (Spring): Final Year Project

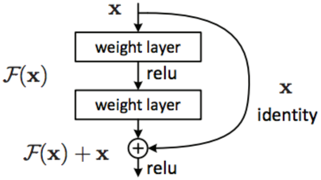
Goal

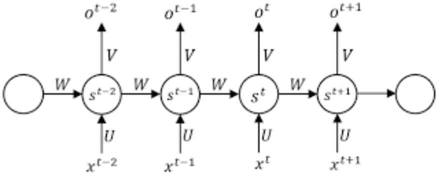
- Learn to apply different types of networks in various DL tasks











Course Information

- Lectures: Friday 3-5pm (403)
  - Lecture notes available on the lecture day (at latest)
  - Book: *Deep Learning*, Ian Goodfellow, Yoshua Bengio & Aaron Courville, 2016. MIT Press, http://www.deeplearningbook.org
  - https://towardsdatascience.com
- Weekly practical exercises
  - Self studying on your PC
  - Colab - online python environment with Keras and TensorFlow backend
  - Lab sessions (Lab 305, Tuesday 17:00, 28/01, 4/02)
- Coursework (100%)
  - Work: online exercises from DL github, experiments and reports
  - Assessment: 2 page interim report 20%, Deadline: 13 Feb 2020 (23:59), via Blackboard
  - Assessment: 4 page final report 80%, Deadline: 19 March 2020 (23:59), via Blackboard

Lectures by Dr Krystian Mikolajczyk

- Part 1: Introduction to deep learning
- Part 2: Convolutional Neural Networks (CNN)
- Part 3: Network Training
- Part 4: CNN architectures
- Part 5: Recurrent Neural Networks

Lectures by Dr Carlo Ciliberto

- Part 6: Representation Learning and Autoencoders
- Part 7: GANs & friends
- Part 8: Metalearning
- Part 9: Reinforcement Learning I
- Part 10: Reinforcement Learning II

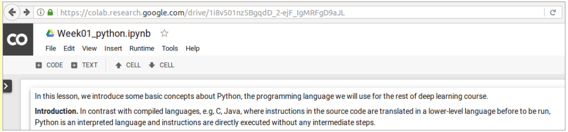
Practical Experiments & Coursework

https://github.com/MatchLab-Imperial/deep-learning-course

- Week 2-3
  - Introduction to Python and some frameworks (NumPy, Pandas, etc..)
  - Introduction to Keras
- Week 4-6
  - Fundamentals of deep learning: handling different type of data (text, image, audio, etc), feedforward of artificial neural networks, introduction to last generation of CNN architectures (VGG, Inception, ResNet, UNets etc...)
- Week 7-10
  - Advanced deep learning: LSTM sequence modelling, Generative Adversarial Networks, Neural style transfer (CycleGan, Pix2Pix), Reinforcement Learning.

Practical Experiments & Coursework

- Environment: Colaboratory *[1,2]
  - Repository: `https://github.com/MatchLab-Imperial/deep-learning-course`
  - Jupyter notebook environment which requires not setup and supported from most major browsers, e.g, Chrome and Firefox.
  - Code is run in virtual machines with free GPU.
  - Files are stored securely in your own Google Drive account.
  - Supports developing Python applications using popular deep learning libraries, e.g, **Keras**, Tensorflow, Pytorch.



*[1] https://colab.research.google.com/notebooks/welcome.ipynb

*[2] https://medium.com/deep-learning-turkey/google-colab-free-gpu-tutorial-e113627b9f5d

Practical Experiments & Coursework

- Format: Jupyter [*3]
  - Notebooks are documents produced by the Jupyter Notebook Apps, e.g., Colaboratory, containing both python code and rich text elements (paragraph, equations, figures, links, etc. . .)

In [0]:
```python
N=5
start_val = 0# pick an element for the code to plot the following N**2 values
fig, axes = plt.subplots(N,N)
for row in range(N):
  for col in range(N):
    idx = start_val+row+N*col

    im = np.concatenate((np.clip(X_test_noise[idx], 0, 1), np.clip(pred[idx], 0, 1)), 1)
    axes[row,col].imshow(im)
    y_target = int(y_train[idx])
    axes[row,col].set_xticks([])
    axes[row,col].set_yticks([])
```

[*3] https://jupyter-notebook-beginner-guide.readthedocs.io/en/latest/what_is_jupyter.html

Practical Experiments & Coursework

- Deep Learning Framework: Keras [*4]
  - modular, minimalist framework, especially good for beginners
  - along with Colab environment allows to set a neural network and start prototyping in no time.

[*4] https://pypi.org/project/Keras/

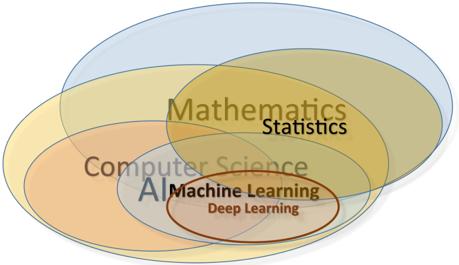
Communication/Interaction

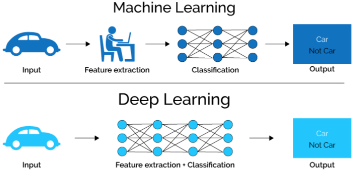
- BlackBoard Q&A forum
- Open Office hour, Lecturers and GTAs (humans)
- Emails - risk of getting missed, otherwise will be copied to Q&A forum anyway

Deep Learning

Deep Learning

- AI, Machine Intelligence
  - Intelligent agents with perception and actions to achieve goals
- Machine Learning
  - Ability to learn: Data $\longrightarrow$ Hypothesis
- Deep Learning
  - Ability to learn data representation (features) and predictors





ML Summary

Goal

Learning with generalisation

Machine Learning Revision

- Components of Learning
- ML Tasks
- Types of learning
- Types of data
- Learning setup
- Error/Loss Measures
- Perceptron
- Neural Networks
- Gradient descent
- Backpropagation
- Learning curves
- Regularization

Components of learning

- Theory
  - ML problem formulation
  - Errors, loss and bounds
- Predictors and Learners
  - Linear and non linear
  - SVM
  - **Neural Networks**
- Learning frameworks
  - Supervised
  - Reinforcement learning

Domain $\mathcal{D}$ (test/out-of-sample)

Data $\mathbf{x} \in \mathcal{D}$

Target outputs $\mathbf{y} \in \mathcal{Y}$

Target function $f : \mathcal{X} \to \mathcal{Y}$

Experience $\mathcal{X}$ (observations/train/in-sample)

$\mathbf{x} \in \mathcal{X} \subset \mathcal{D}$

$(\mathbf{x}_1, y_1), (\mathbf{x}_n, y_n), \ldots, (\mathbf{x}_n, y_n)$

with generalisation!

Learners

Expertise

Predictors, Models

Hypothesis $g : \mathcal{X} \to \mathcal{Y}$

Learning

Hypothesis class

$\mathcal{H} \subset \{h : \mathcal{X} \to \mathcal{Y}\}$

Learning algorithm

Goal $g \approx f$

Error $g \approx f$

$\{l : (g, \mathcal{Y}) \to \mathbb{R}^+\}$

$\hat{l}[g(\mathbf{w}, \mathbf{x}), f(\mathbf{x})] \in \mathbb{R}^+$

$\widehat{R}_n = \frac{1}{n} \sum_{i=1}^{n} \hat{l}[g(\mathbf{w}, \mathbf{x}), f(\mathbf{x})]$

Error Measures/Loss Functions

- How to quantify $h \approx f$?
- Usually pointwise error: $\ell : \mathcal{Y} \times \mathcal{Y} \to \mathbb{R}$

$$\ell(h(\mathbf{x}), f(\mathbf{x}))$$

Defined by the user for the ML task!

- Examples:

squared error $L2$ $\quad \ell(\hat{y}, y) = (\hat{y} - y)^2$ (regression)

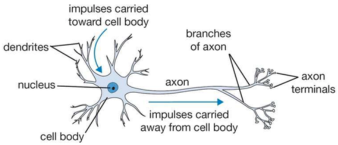
binary error $\quad \ell(\hat{y}, y) = \mathbb{I}(\hat{y} \neq y)$ (classification)

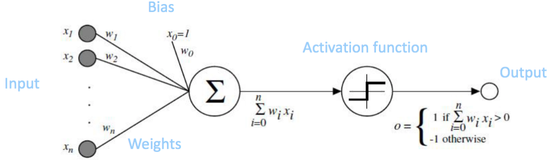
cross-entropy error $\quad \ell(\hat{y}, y) = \log\left(1 + e^{-y_i \mathbf{w}^\top \mathbf{x}_i}\right)$ (see logistic regression)

- Training error: $\widehat{R}_n(h) = \frac{1}{n} \sum_{i=1}^{n} \ell(h(\mathbf{x}_i), y_i)$
- Test error: $R(h) = \mathbb{E}\left[\ell(h(\mathbf{x}), y)\right]$

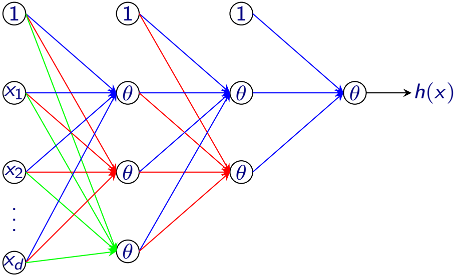
Neural Network: Perceptron

- Binary class perceptron
  - biologically inspired model of a single neuron

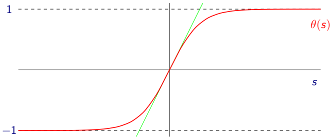




Neural Network



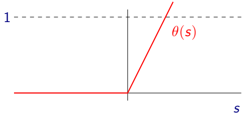
Linear vs. Non-linear activation function $\theta(s)$

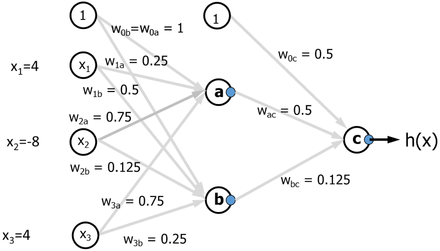


if $\theta(s) = s$ then $h(x) = \mathbf{w}_L^\top W_{L-1} W_{L-2} \dots W_1 \mathbf{x} = \mathbf{w}_*^\top \mathbf{x}$

Neural Network Forward Pass (inference)

- Input $\mathbf{x} = (4, -8, 4)$
- Non linear activation ReLU $\theta(s) = s_+ = \max\{0, s\}$.





- $f = \max(0, \sum_i w_i x_i)$
- $f_a = \max(0, 1 + 0.25 \cdot 4 + 0.75 \cdot (-8) + 0.75 \cdot 4) = 0$
- $f_b = \max(0, 1 + 0.5 \cdot 4 + 0.125 \cdot (-8) + 0.25 \cdot 4) = 3$
- $f_c = h(\mathbf{x}) = \max(0, 0.5 + 0.5 \cdot 0 + 0.125 \cdot 3) = 0.875$
- Ground truth $y = 2$
- Error $\widehat{R}_n(\mathbf{w}_t) = (y - h(\mathbf{x}))^2 = (2 - 0.875)^2 \approx 1.27$

Learning Setup with $\mathbf{x} \sim P$ and $P(y|\mathbf{x})$

- Input: $\mathbf{x} \in \mathcal{X}$
- Output: $y \in \mathcal{Y}$
- Data: $(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \ldots, (\mathbf{x}_n, y_n) \sim P$ (P is the joint distribution of $(\mathbf{x}, y)$)

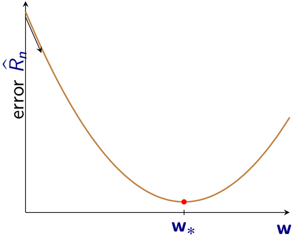
Learning

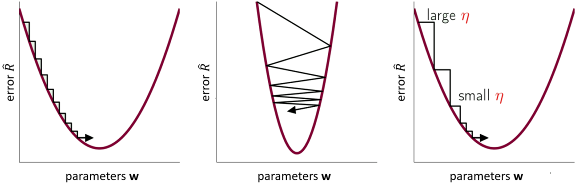
- Hypothesis class: $\mathcal{H} \subset \{h(\mathbf{w}) : \mathcal{X} \to \mathcal{Y}, w \in \mathbb{R}\}$
- Loss function: $\ell : \mathcal{Y} \times \mathcal{Y} \to \mathbb{R}^+$
- Find $\mathbf{w}^* \in \mathbb{R}^{\|\mathbf{w}\|}$ such that $g \approx P(y|\mathbf{x})$

$$\mathbf{w}^* = \operatorname*{argmin}_{\mathbf{w}} \left\{ R(\mathbf{w}) = \mathbb{E}\left[\ell(h(\mathbf{wx}), y)\right] \right\}$$

Gradient descent

- General method for non-linear optimization: $\mathbf{w}_{t+1} = \mathbf{w}_t + \eta \mathbf{v}$
- Direction $\mathbf{v}$: starting from $\mathbf{w}_t$, step along the steepest slope
  - $\mathbf{v} = -\frac{\nabla \widehat{R}_n(\mathbf{w}_t)}{\|\nabla \widehat{R}_n(\mathbf{w}_t)\|}$ is a unit vector.
- Step size η: how quickly find the minimum
  - η is a scalar.





η is small $\qquad$ η too large $\qquad$ variable η

Heuristic: step size should increase with the slope $\mathbf{w}_{t+1} = \mathbf{w}_t + \Delta \mathbf{w}$

$$\Delta \mathbf{w} = -\eta \nabla \widehat{R}_n(\mathbf{w}_t) \text{ (with } \eta \text{ redefined)}$$

Neural Network Backpropagation (training)

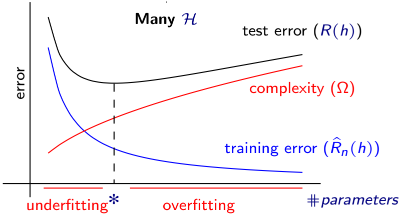
Backpropagation

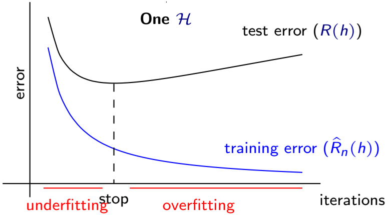
- Intialize all weights $w_{ij}^{(l)}$ at random
- for $t = 1, 2, \ldots$ do
  - Pick a data point (x_k, y_k)
  - **Forward:** Compute all $x_j^{(l)}$
  - **Backward:** Compute all $\delta_j^{(l)}$
  - **Update:** $w_{ij}^{(l)} \leftarrow w_{ij}^{(l)} - \eta_t x_i^{(l-1)} \delta_j^{(l)}$
    - ⋆ single point (SGD), minibatch, batch
- Return final weights $w_{ij}^{(l)}$

Learning from noisy data

Overfitting

- Fitting to noise instead of the underlying target function/distribution.
- Occurs when $\widehat{R}_n(h) \downarrow \quad R(h) \uparrow$, moving away from the target function.





Remember n matters too!

Noise types: stochastic $(N \sim \mathcal{N}(0, \sigma^2))$, deterministic (complexity)

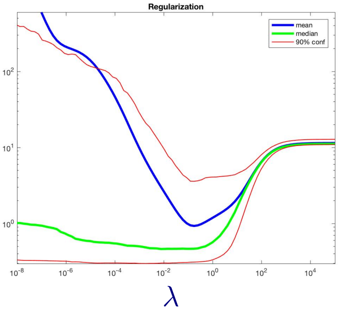
deterministic noise	$\uparrow$	overfitting	$\uparrow$
stochastic noise	$\uparrow$	overfitting	$\uparrow$
number of data points	$\uparrow$	overfitting	$\downarrow$

Regularisation

Regularised Loss (Augmented Error)

$$\mathcal{L}_n(h) = \widehat{R}(h) + \lambda \underbrace{\Omega(h)}_{overfit\ \ penalty}$$

- $\Omega(h)$ – regulariser with parameter λ
  - $\|\mathbf{w}\|_2^2$: L2
  - $\|\mathbf{w}\|_1$: L1
  - $\|\mathbf{w}\|_1 + \|\mathbf{w}\|_2^2$: elastic net
  - $\mathbf{w}^\top \Gamma^\top \Gamma \mathbf{w}$: Tikhonov



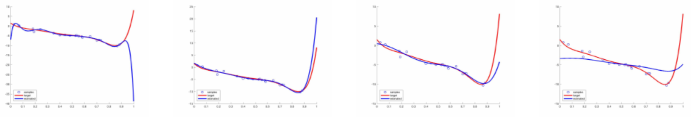
Occam's razor: Simpler is usually better

Regularize towards smoother, simpler functions. Why?

Because noise is not smooth!

Regularized Loss Minimization

$\lambda = 0$ $\quad$ $\lambda = 0.0001$ $\quad$ $\lambda = 1$ $\quad$ $\lambda = 100$



overfitting $\longrightarrow$ $\longrightarrow$ underfitting

Regularized Loss Minimization (RLM)

- Hypothesis class $\mathcal{H} = \cup_i(\mathcal{H}_i, \lambda_i)$, with $i \in \mathbb{N}$ e.g. $\lambda_i \in \{0.0001, 0.001, \ldots\}$
- Augmented error:

$$\mathcal{L}_{\bar{k}}(\mathbf{w}, \lambda) = \widehat{R}_{\bar{k}}(\mathbf{w}) + \lambda\Omega(\mathbf{w}) \qquad \text{e.g. } \Omega(\mathbf{w}) \in \{\|\mathbf{w}\|_2^2, \|\mathbf{w}\|_1, \|\mathbf{w}\|_2^2 + \|\mathbf{w}\|_1, \ldots\}$$

- RLM solution:
  - for all i, **train** on $\mathcal{D}_{\bar{k}}$: $\quad g(\mathbf{w}_{\lambda_i}) = \operatorname{argmin}_{\mathbf{w}} \mathcal{L}_{\bar{k}}(\mathbf{w}, \lambda_i)$
  - from all i, **select** on $\mathcal{D}_k$: $\quad g(\mathbf{w}_{\lambda *}) = \operatorname{argmin}_{\lambda_i} \check{R}_k(g(\mathbf{w}_{\lambda_i}))$

Summary

- Organization of DL course
- Exercises and coursework
- Revision of fundamentals of Machine Learning