UNIVERSITY

LEVEL's Degree in COURSE

LEVEL's Degree Thesis

TITLE

Supervisors

Prof. NAME SURNAME

Prof. NAME SURNAME

Prof. NAME SURNAME

Candidate

NAME SURNAME

MONTH YEAR

Summary

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Acknowledgements

ACKNOWLEDGMENTS

"HI"
Goofy, Google by Google

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Acronyms

AI
: artificial intelligence

Chapter 1

Hello

[Hi 1, Goofy]
$\mathrm{kg\,s^{-1}}$

Figure 1.1: Hi

1.1 Extremely long name with manual linebreak which otherwise would not fit the page

1. A

2. B

3. C

Figure 1.2: HI

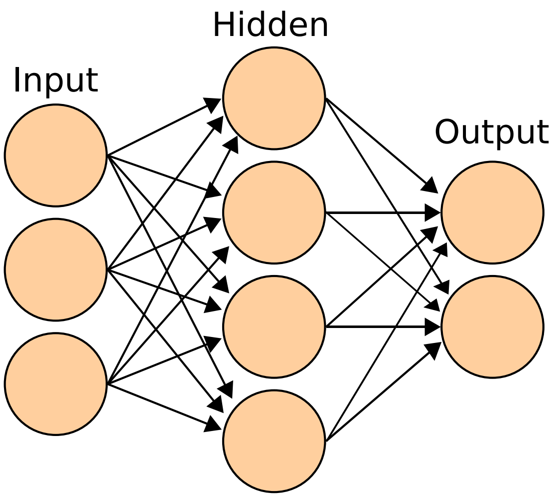

Figure 1.3: SVG

ReLU	$f(x) = \begin{cases} 0 & \text{for } x \leq 0 \\ x & \text{for } x > 0 \end{cases}$
Softmax	$f_i(\vec{x}) = \frac{e^{x_i}}{\sum_{j=1}^{J} e^{x_j}} i = 1, ..., J$
tanh	$f(x) = \tanh(x) = \frac{(e^x - e^{-x})}{(e^x + e^{-x})}$

Table 1.1: Examples of activation functions, operating either element-wise or vector-wise, depending on the function

$$output = f_{activation}\left(\sum_{\#neurons} input_i + bias\right) \tag{1.1}$$

- A
- B
- C

Algorithm 1 Adam optimizer algorithm. All operations are element-wise, even powers. Good values for the constants are $\alpha = 0.001, \beta_1 = 0.9, \beta_2 = 0.999, \epsilon = 10^{-8}$. ϵ is needed to guarantee numerical stability.

procedure ADAM($\alpha, \beta_1, \beta_2, f, \theta_0$)
▷ α is the stepsize
▷ $\beta_1, \beta_2 \in [0, 1)$ are the exponential decay rates for the moment estimates
▷ $f(\theta)$ is the objective function to optimize
▷ θ_0 is the initial vector of parameters which will be optimized
▷ Initialization
$m_0 \leftarrow 0$ ▷ First moment estimate vector set to 0
$v_0 \leftarrow 0$ ▷ Second moment estimate vector set to 0
$t \leftarrow 0$ ▷ Timestep set to 0
▷ Execution
while θ_t not converged **do**
$t \leftarrow t + 1$ ▷ Update timestep
▷ Gradients are computed w.r.t the parameters to optimize
▷ using the value of the objective function
▷ at the previous timestep
$g_t \leftarrow \nabla_\theta f(\theta_{t-1})$
▷ Update of first-moment and second-moment estimates using
▷ previous value and new gradients, biased
$m_t \leftarrow \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t$
$v_t \leftarrow \beta_2 \cdot v_{t-1} + (1 - \beta_2) \cdot g_t^2$
▷ Bias-correction of estimates
$\hat{m}_t \leftarrow \frac{m_t}{1 - \beta_1^t}$
$\hat{v}_t \leftarrow \frac{v_t}{1 - \beta_2^t}$
$\theta_t \leftarrow \theta_{t-1} - \alpha \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$ ▷ Update parameters
end while
return θ_t ▷ Optimized parameters are returned
end procedure

MSE / L2 Loss / Quadratic Loss	$\frac{\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2}{N}$
(Binary) Cross Entropy (average reduction on higher dimensions)	$\frac{\sum_{i=1}^{N}\sum_{j=1}^{C}\hat{y}_i \log\left(y_{i,j}\right)}{N}$
Categorical Cross Entropy (sum reduction on higher dimensions)	$-\sum_{i=1}^{N}\hat{y}_i + \log\left(\sum_{i=1}^{N}\sum_{j=1}^{C} y_{i,j}\right)$

Table 1.2: y is the output of the network, N is the batch size multiplied by the number of outputs (e.g. pixels), C is the number of classes and $\hat{y}$ is the correct output.

Appendix A

Galileo

```python
import os
os.system("echo 1")
```

$\mathcal{O}(n \log n)$

`numpy`

Bibliography

[1] S. Zhang, C. Zhu, J. K. O. Sin, and P. K. T. Mok. «A Novel Ultrathin Elevated Channel Low-temperature Poly-Si TFT». In: 20 (Nov. 1999), pp. 569–571 (cit. on p. 1).