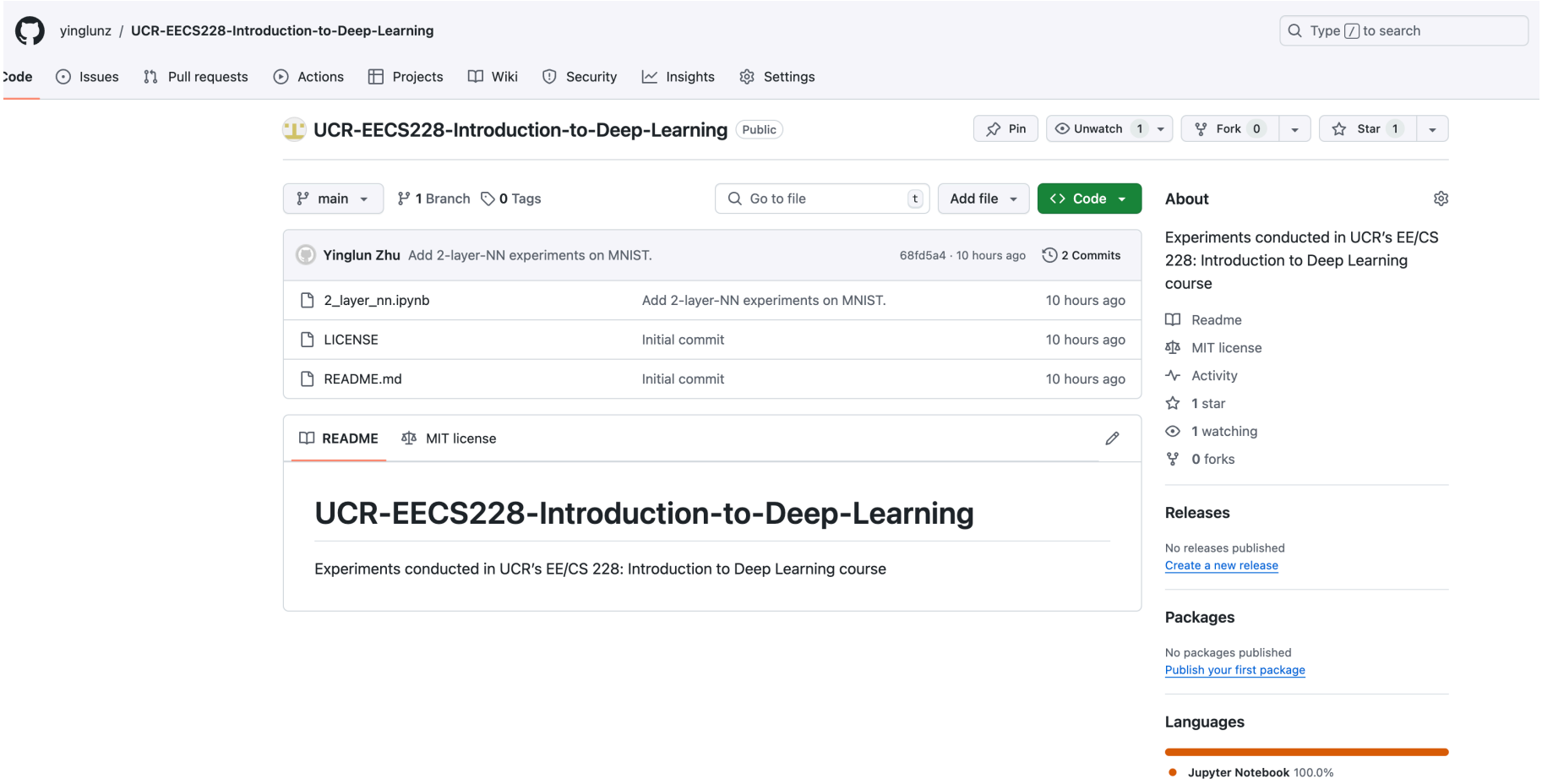
Intro to Deep Learning

Lecture 4: Project and Backpropagation

Experiments Files



https://github.com/yinglunz/UCR-EECS228-Introduction-to-Deep-Learning

Course Project

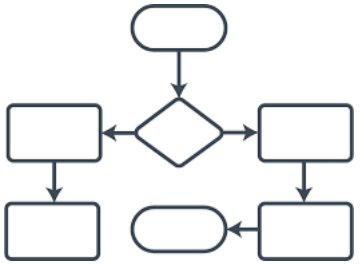
Expectations

1. A project topic
   - reasonably complex but not too complex
2. Study it in detail
   - Identify challenges
   - Connection to prior art
   - Try different solutions
3. Demonstration
   - Empirical results
   - Something to show off

Show your work, and you should get your credit!

Project Proposal

- 1-page proposal Due: Feb 13
- Describes the idea and its feasibility
  - which problem, which dataset, why deep learning
- Suggestion: Add a workflow chart



- Decompose the work
  - Justify each group member will contribute

Project Report Format

- Should resemble an academic paper
- Expected length:
  - Between 6 to 8 pages (not including references)
  - NeurIPS format
  - https://neurips.cc/Conferences/2023/PaperInformation/StyleFiles
- Example Structure:
  - Introduction and Summary of Contribution
  - Discussion of Prior art
  - Proposed method
  - Experiments (e.g. from your demo)
  - Discussion & future plans: How would you improve?

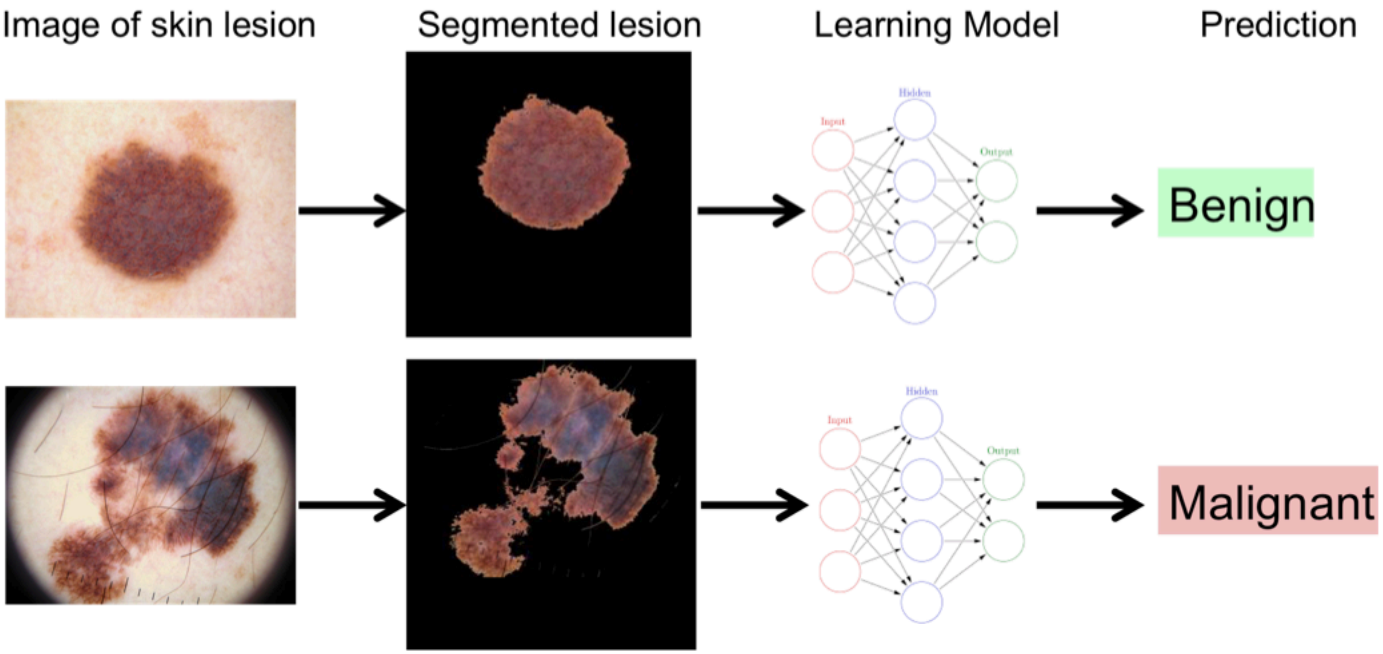
Topics in Deep Learning

Many deep learning research and applications

Project Resources

- Data: https://www.kaggle.com/
- Models: https://huggingface.co/
- Papers: https://arxiv.org/
- Code: https://github.com/

Computer Vision



Example project from Stanford's class:
https://web.stanford.edu/~kalouche/cs229.html

Computer Vision

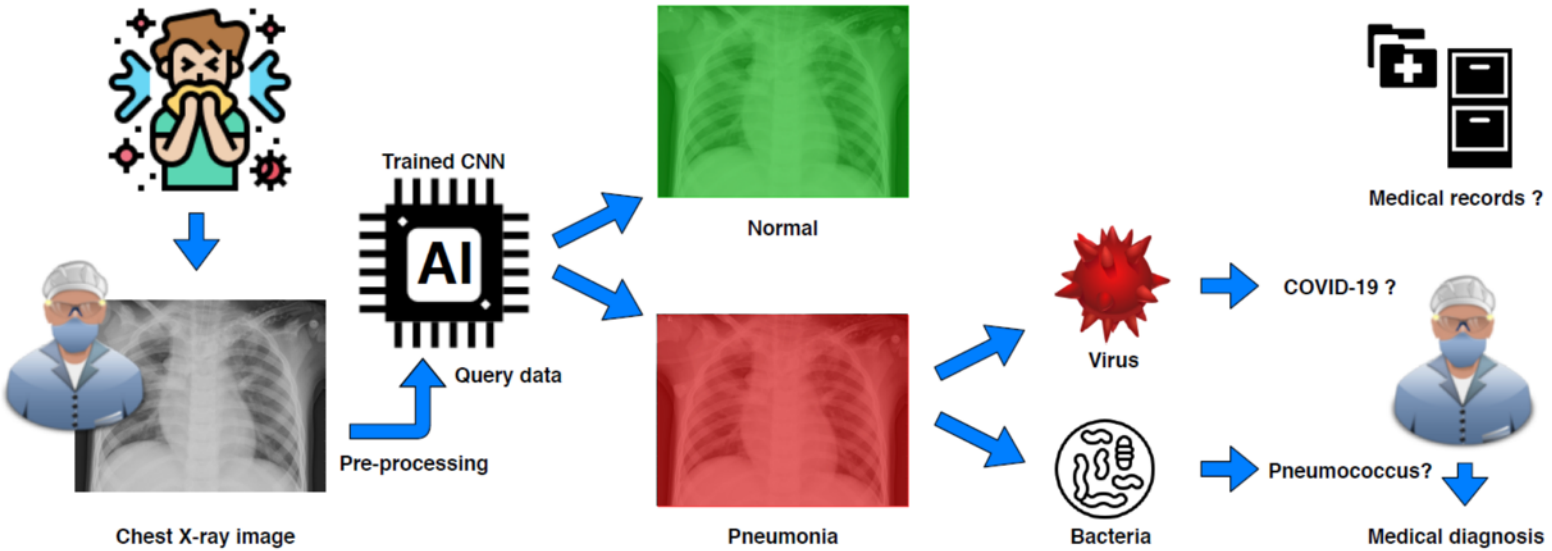
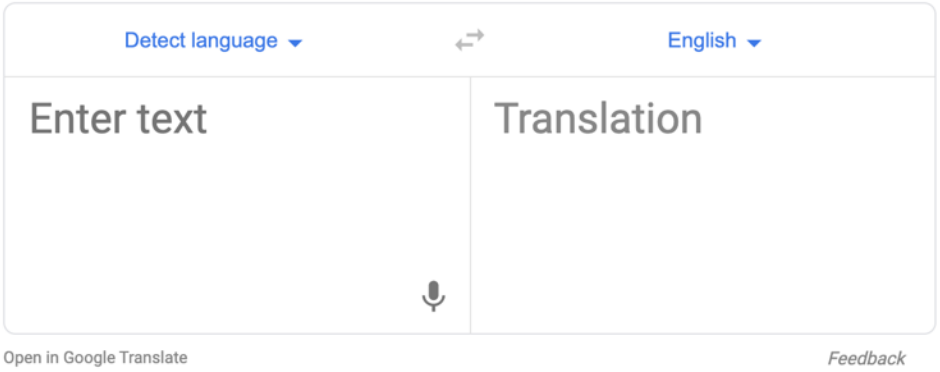
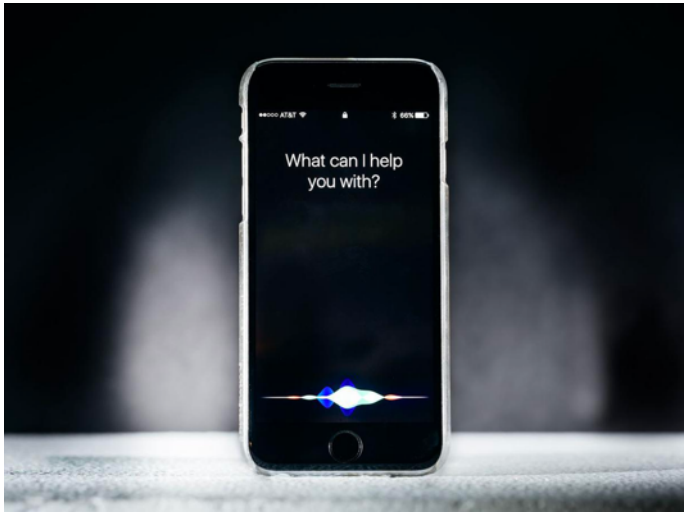


Fig. 1: Global workflow using deep learning for **automatic detection of infection towards supporting COVID-19 screening** from chest X-ray images. In a COVID-19 epidemic context, a detected viral pneumonia can particularly presume a COVID-19 infection.

Paper: https://arxiv.org/pdf/2004.03399.pdf

Natural Language Processing





Neural machine translation: https://github.com/tensorflow/nmt

Pretrained language models: https://github.com/google-research/bert

Natural Language Processing

Application: Image to Sentence

"man in black shirt is playing guitar."

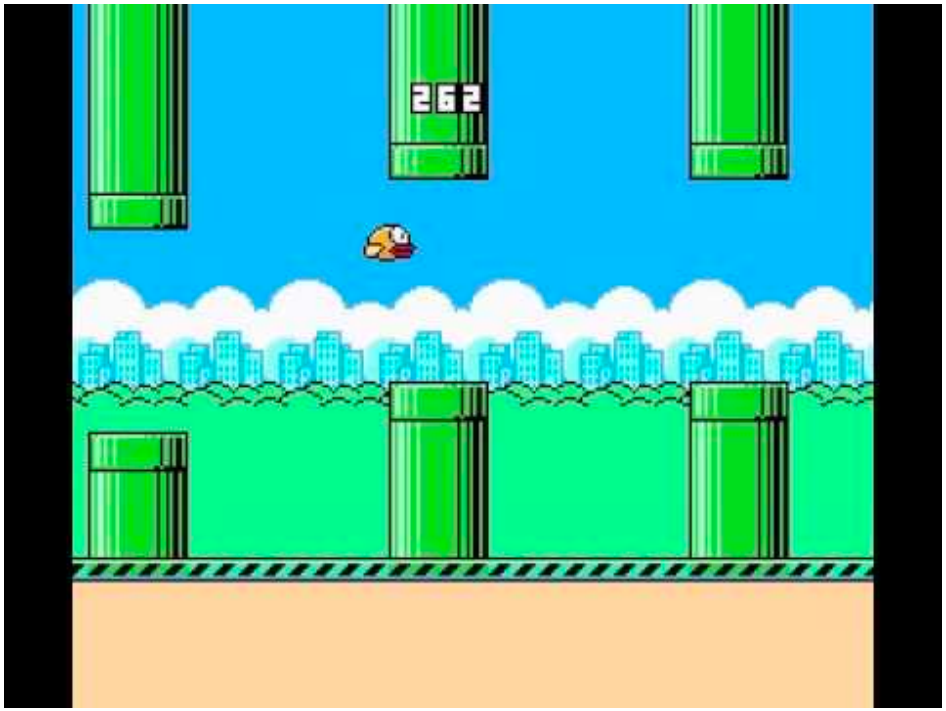
"construction worker in orange safety vest is working on road."

"two young girls are playing with lego toy."

Deep Reinforcement Learning

Q: How can we make optimal **decision** in uncertain environments?

Deep Reinforcement Learning

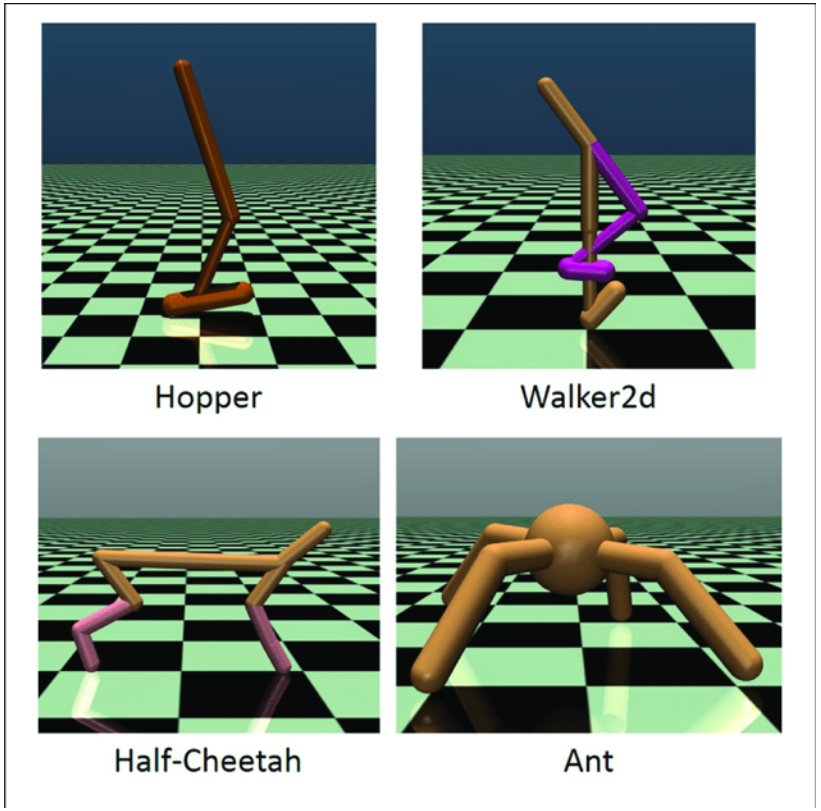


https://github.com/yenchenlin/DeepLearningFlappyBird

Deep Reinforcement Learning

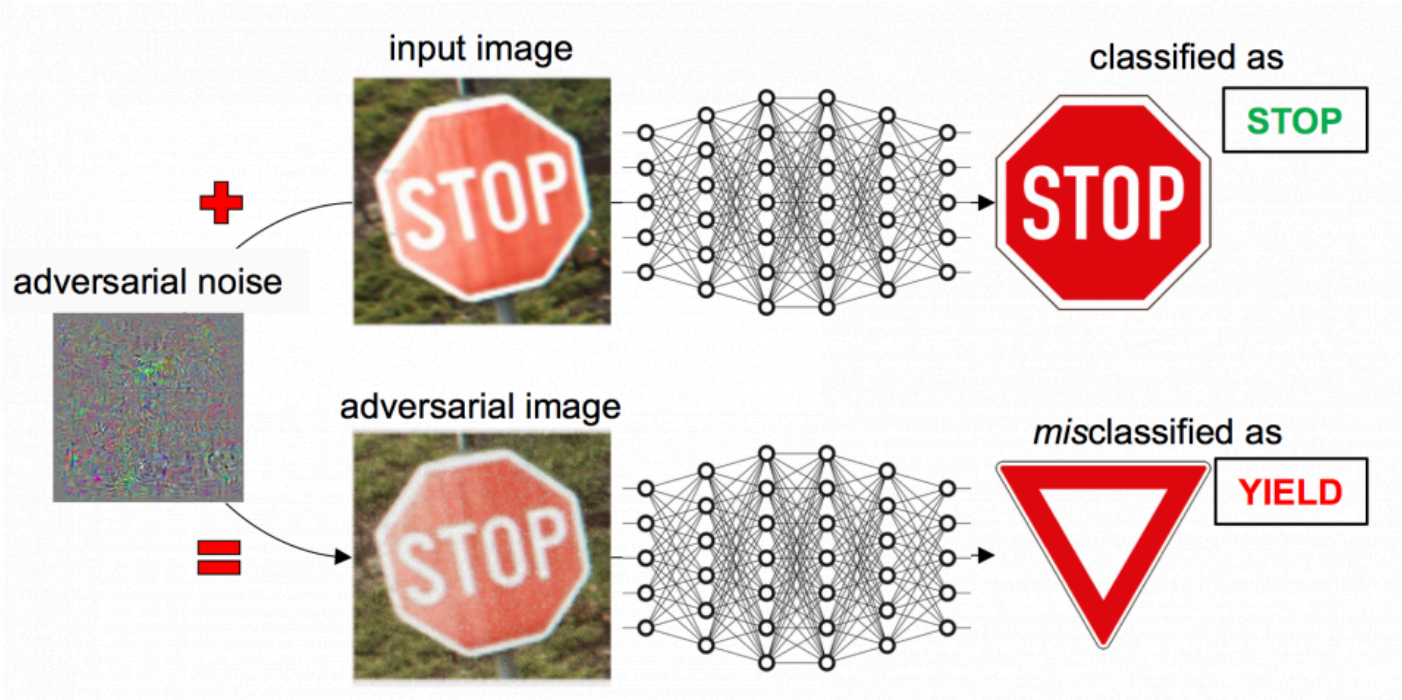
Simulation environments:

- OpenAI Gym
- MuJoCo

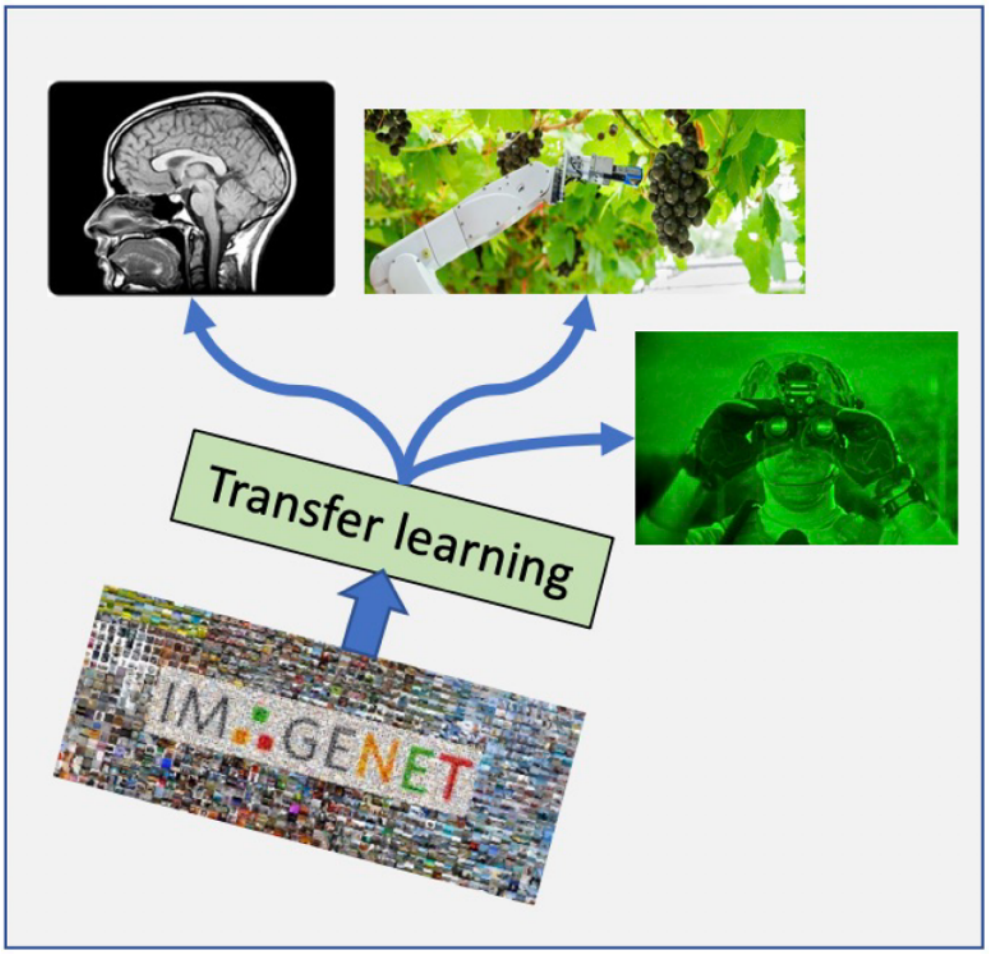


Adversarial Learning

- Can we mess with an ML model?



Learning New Tasks

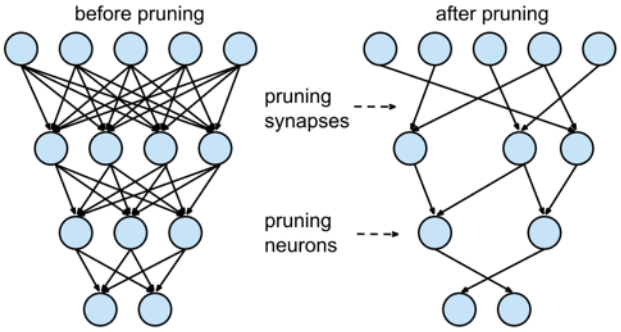


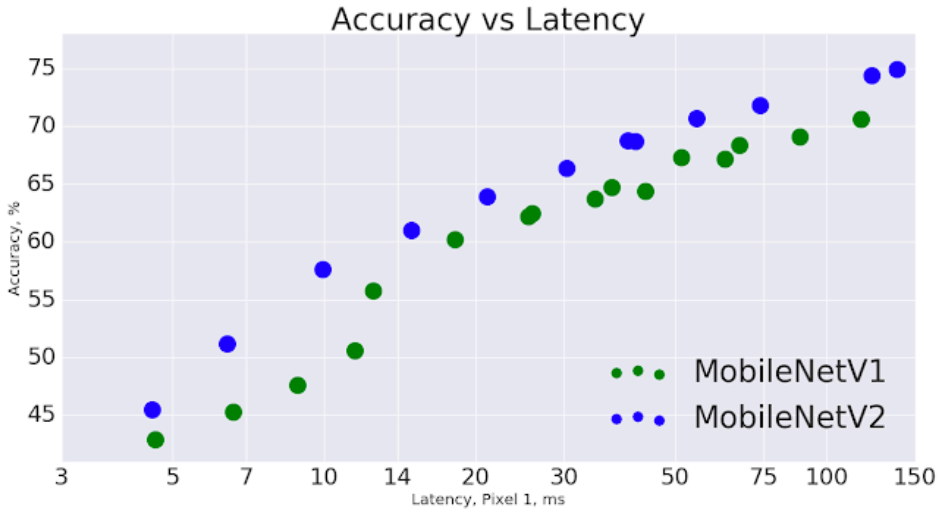
Related keywords:

- Meta-learning
- Domain adaptation
- Multi-task learning

Mobile Friendly ML

Q: Can we fit deep networks in a smartwatch?





Generative Modeling

Open-source models

- Facebook's Llama, Stanford Alpaca, StableDiffusion

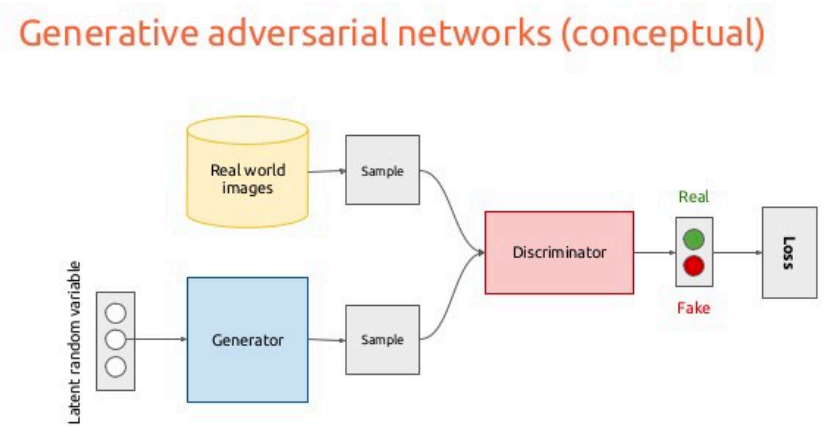
Accessing SOTA models through APIs

- ChatGPT, Gemini

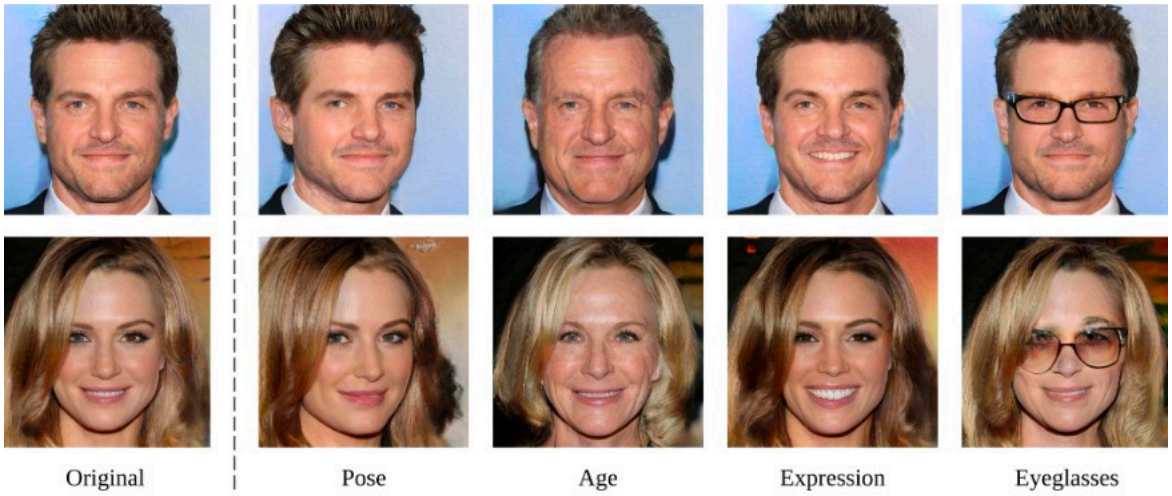
Chaining Language Model Outputs for Autonomous Agents

- ✓ https://github.com/Torantulino/Auto-GPT
- ✓ https://github.com/hwchase17/langchain

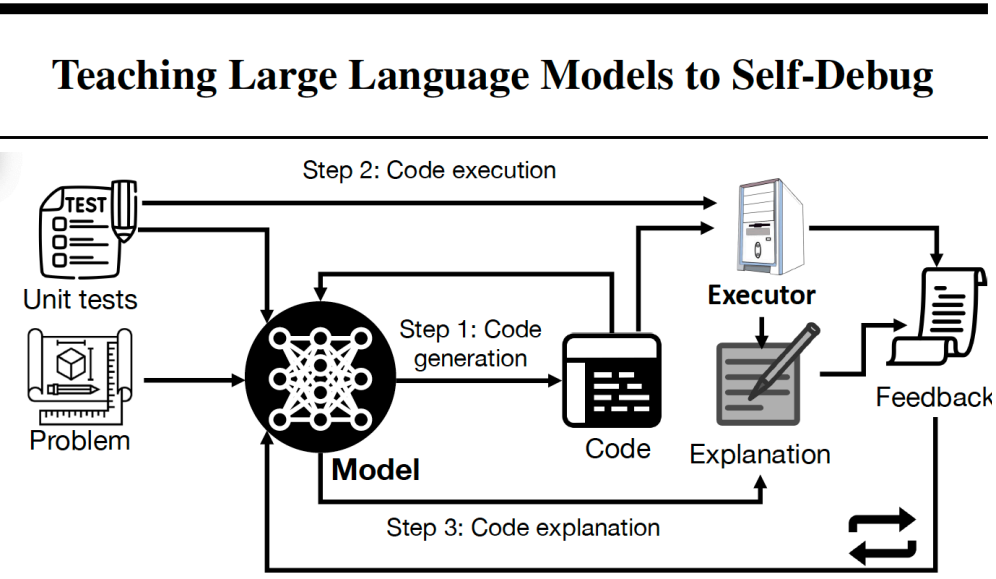
Generative Models



Q: Can we learn to generate fake stuff?



Self-debugging language models



C++

```
int remainder_7_large_numbers ( string num ) {
  int series [ ] = {
    1, 3, 2, - 1, - 3, - 2 };
    int series_index = 0;
    int result = 0;
    for ( int i = num . size ( ) - 1;
    i >= 0; i -- ) {
      int digit = num [ i ] - '0';
      result += digit * series [
      series_index ];
      series_index = ( series_index +
      1 ) % 6;
      result %= 7;
    }
    if ( result < 0 ) result = (
    result + 7 ) % 7;
    return result;
  }
```

Original Python

```
def remainder_7_large_numbers(num):
    series = [1, 3, 2, -1, -3, -2]
    series_index = 0
    result = 0
    for i in range((len(num) - 1), -1,
     -1):
        digit = (num[i] - '0')
        result += (digit * series[
        series_index])
        series_index = ((series_index
        + 1) % 6)
        result %= 7
    if (result < 0):
        result = ((result + 7) % 7)
    return result
```

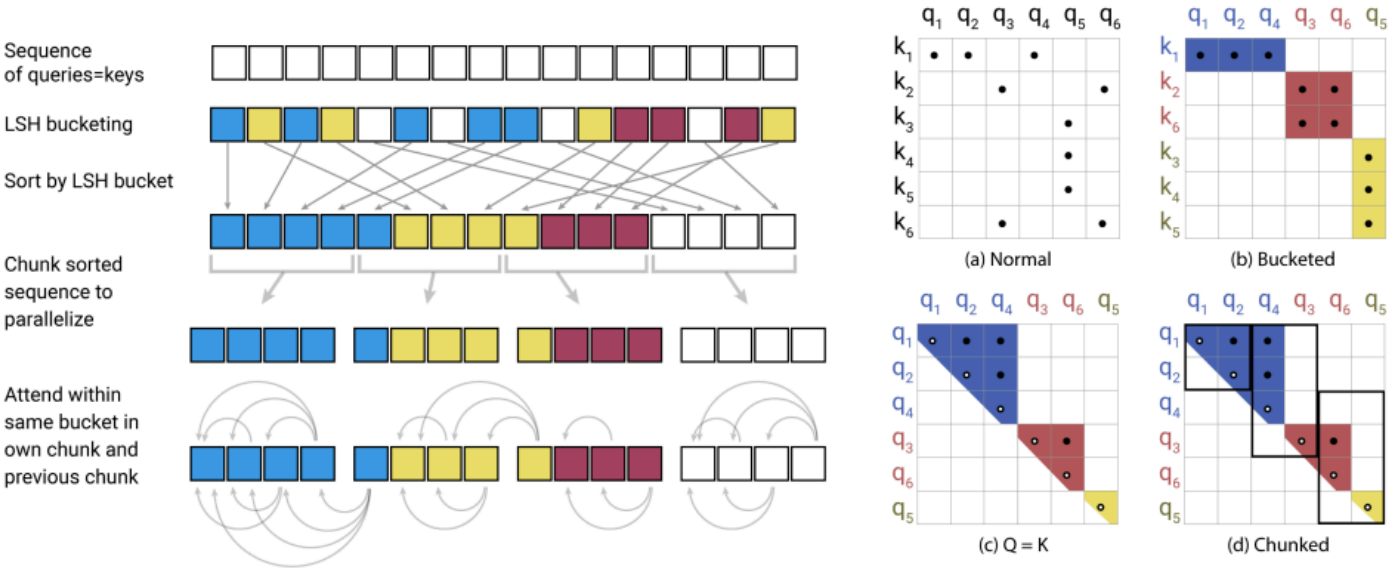
Self-debugging with UT feedback

```
The Python translation does not do the same thing as the C++ code. These are
the results of one failed unit test that tests whether the Python translation's
 outputs match the C++ program's outputs:
Failed: assert remainder_7_large_numbers('K') == 6
Actual Result: Python runtime error: Traceback (most recent call last):
  File <filename>, line 29, in <module>
    print(remainder_7_large_numbers('K') )
  File <filename>, line 22, in remainder_7_large_numbers
    digit = (num[i] - '0')
TypeError: unsupported operand type(s) for -: 'str' and 'str'
Correct the Python translation.
```

```
def remainder_7_large_numbers(num):
    series = [1, 3, 2, -1, -3, -2]
    series_index = 0
    result = 0
    for i in range((len(num) - 1), -1, -1):
        digit = (ord(num[i]) - ord('0'))
        result += (digit * series[series_index])
        series_index = ((series_index + 1) % 6)
        result %= 7
    if (result < 0):
        result = ((result + 7) % 7)
    return result
```


Figure 9: An example where SELF-DEBUGGING with unit test feedback fixes the code translation error, while the simple feedback fails.

Efficient Attention Computation



Reduce computation from $O(n^2)$ to $O(n)$

The Learning Problem

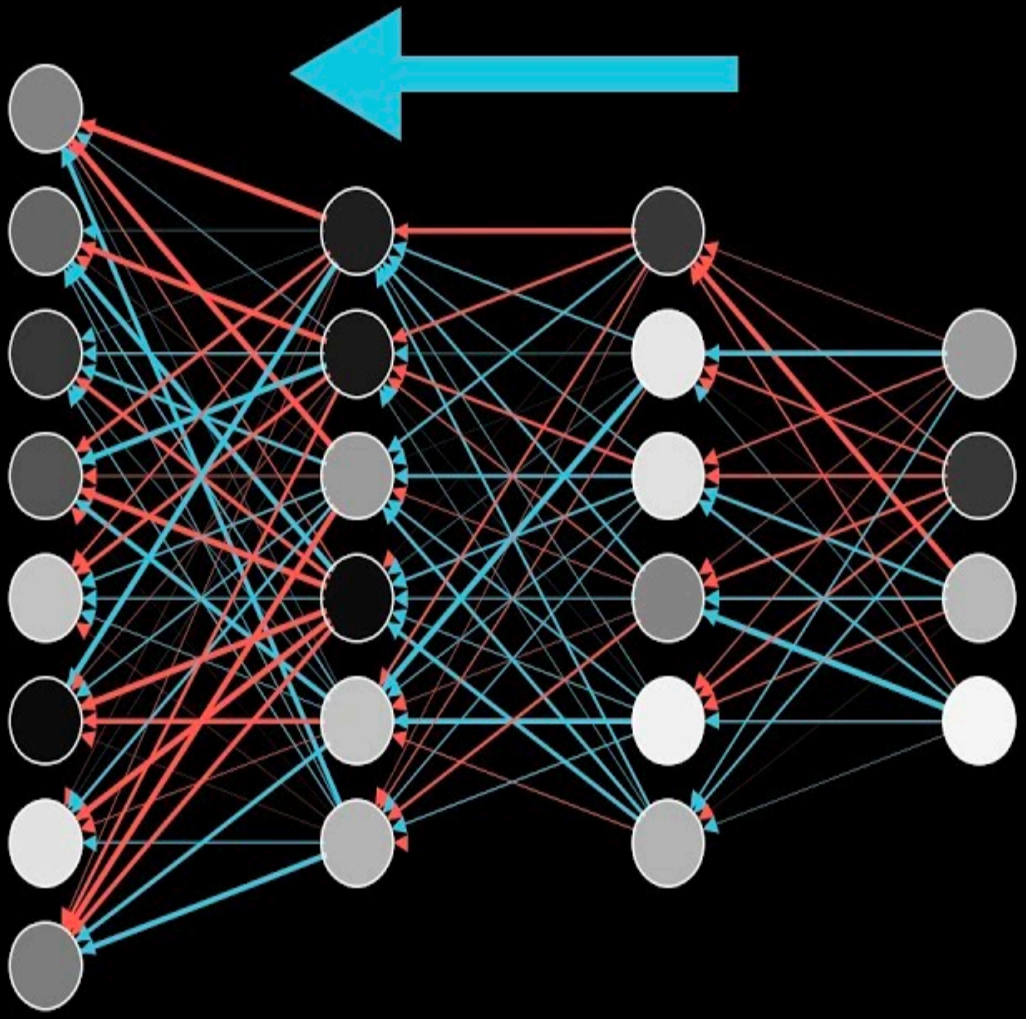
1. Data: $\left(x_i, y_i\right)_{i=1}^{n},\ x_i \in \mathbb{R}^d, y_i \in \mathbb{R}^K$
2. Model: neural networks with trainable weight matrices $W_1, W_2, \cdots, W_L, W_{\text{out}}$
3. Loss function depending on the task

Last lecture

4. Optimization

This lecture

Backpropagation



Chain Rule

- Suppose $x \rightarrow u \rightarrow y$
- Then $\dfrac{dy}{dx} = \dfrac{dy}{du}\dfrac{du}{dx}$

Recall Stochastic Gradient Descent

1. Pick example (x, y)
2. Pick ML model $f_w(\,.\,)$ with weights w
3. Pick loss function ℓ to minimize (e.g. squared)
4. Optimization becomes:

$$\mathscr{L}(w) = l\big(y, f_w(x)\big)$$

5. Gradient via chain rule

$$\nabla \mathscr{L}(w) = \ell'(y, f_w(x)) \times \nabla f_w(x)$$

Derivative of Loss

Gradient of Model

HOW?

Loss Functions

- Square loss: $\ell(y, f(x)) = \frac{1}{2}\big(f(x) - y\big)^2$

$$\ell'(y, f(x)) = \big(f(x) - y\big)$$

- Cross entropy loss

$$\ell\big(y, f(x)\big) = -\sum_{i \in [k]} y_i \log(p_i), \quad \text{where} \quad p_i = \frac{e^{f_i(x)}}{\sum_{j=1}^{n} e^{f_j(x)}}$$

Break

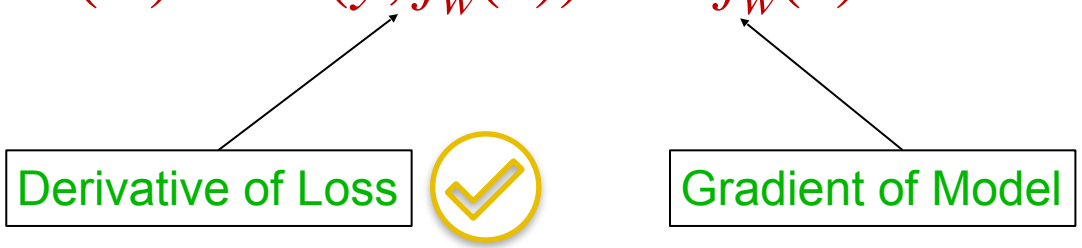
Recall Stochastic Gradient Descent

1. Pick example (x, y)
2. Pick ML model $f_w(\,.\,)$ with weights w
3. Pick loss function ℓ to minimize (e.g. squared)
4. Optimization becomes:

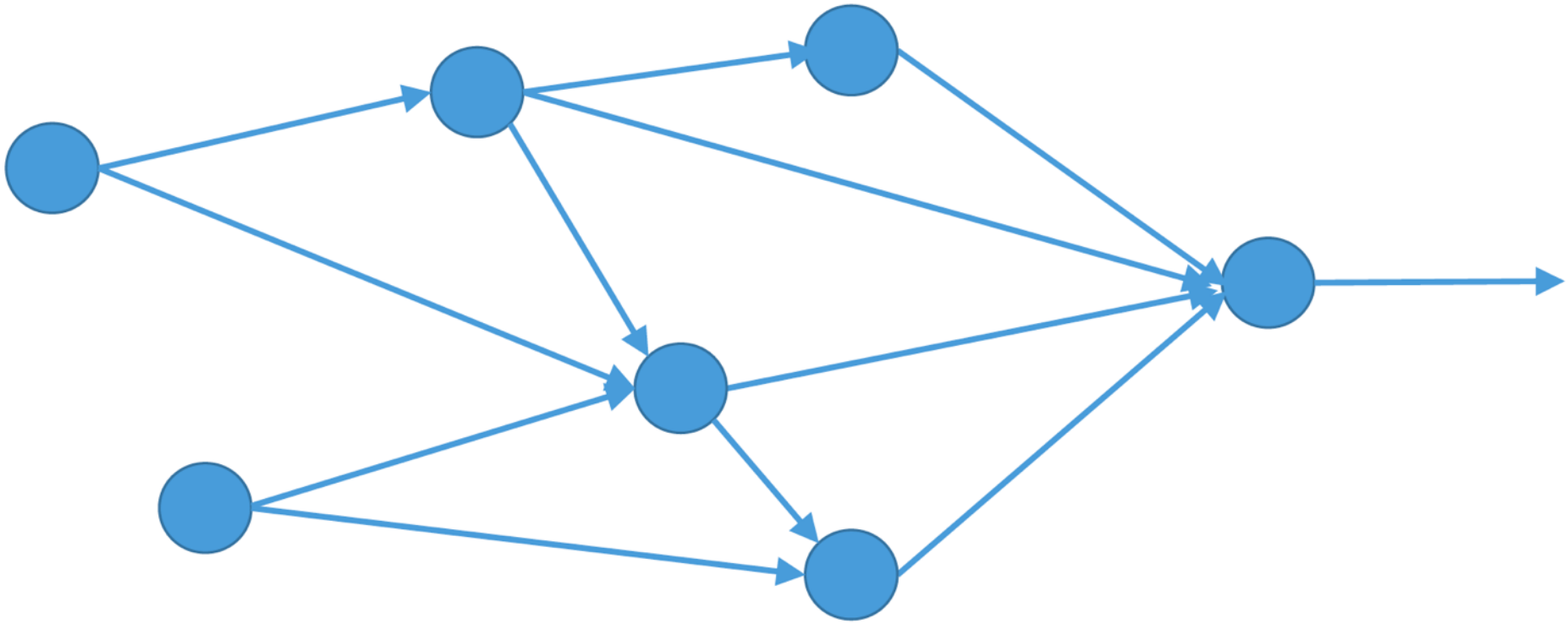
$$\mathscr{L}(w) = l\big(y, f_w(x)\big)$$

5. Gradient via chain rule

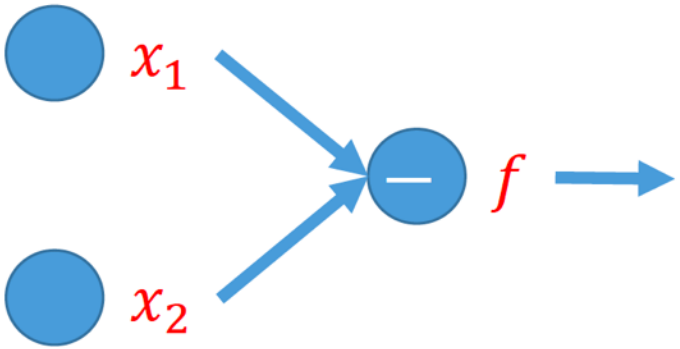
$$\nabla \mathscr{L}(w) = \ell'(y, f_w(x)) \times \nabla f_w(x)$$



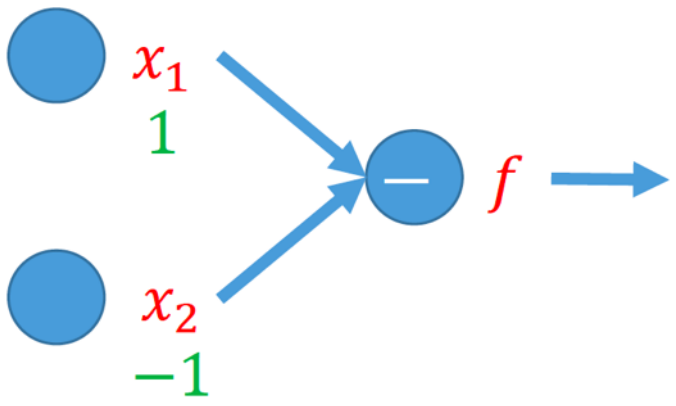
How to differentiate a neural net?



Answer: *Backpropagate*

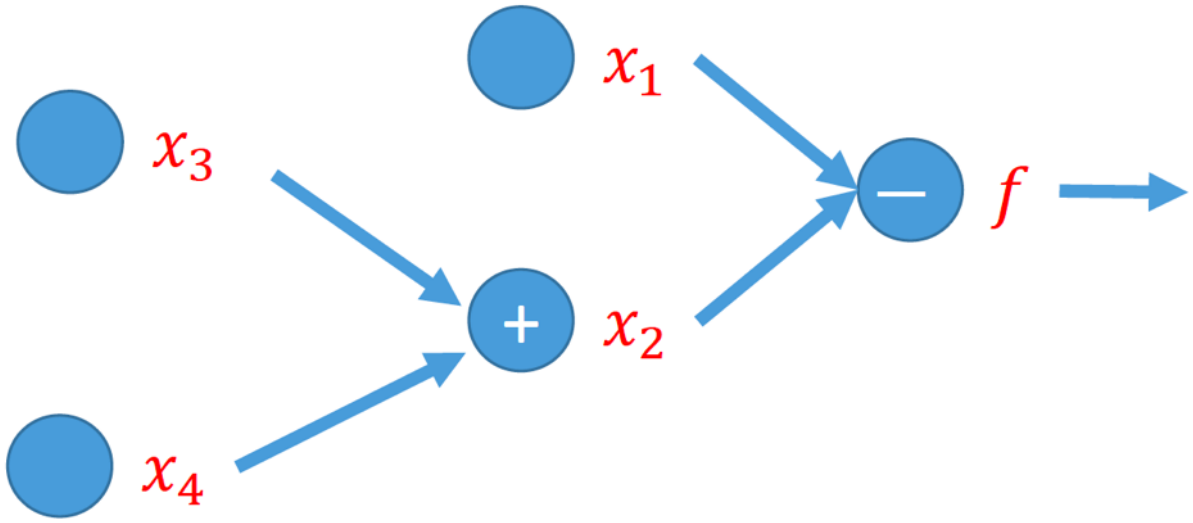


Function: $f = x_1 - x_2$

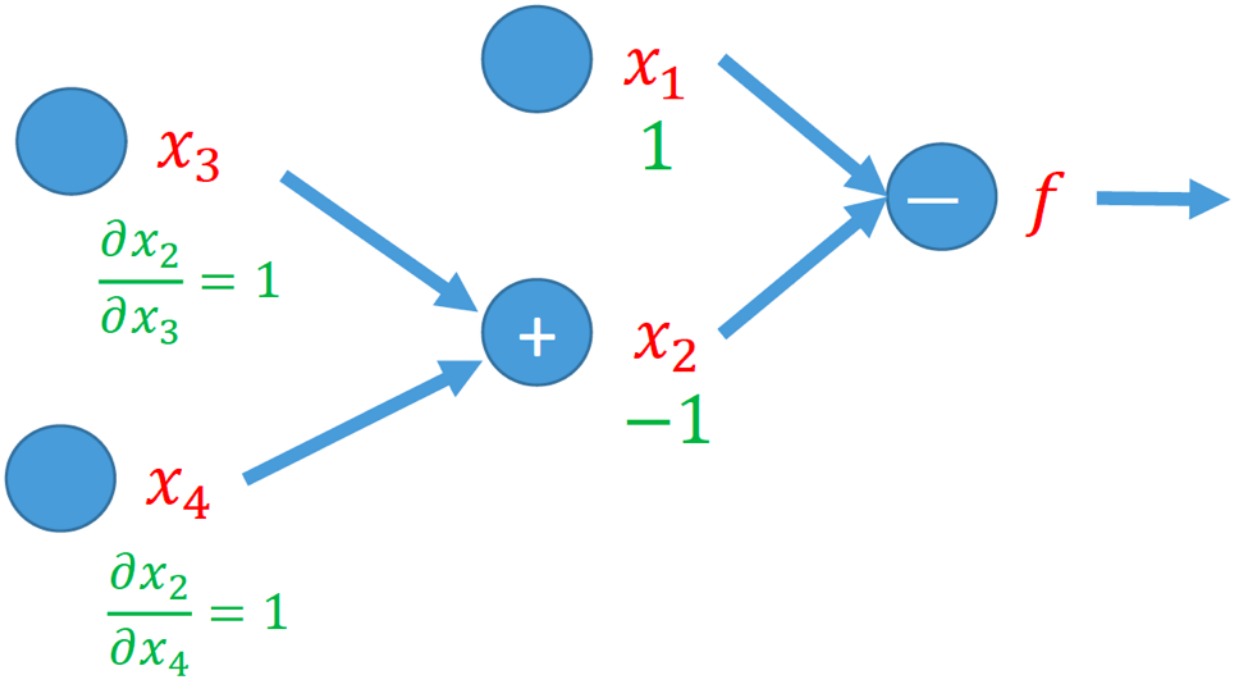


Function: $f = x_1 - x_2$

Gradient: $\frac{\partial f}{\partial x_1} = 1, \frac{\partial f}{\partial x_2} = -1$

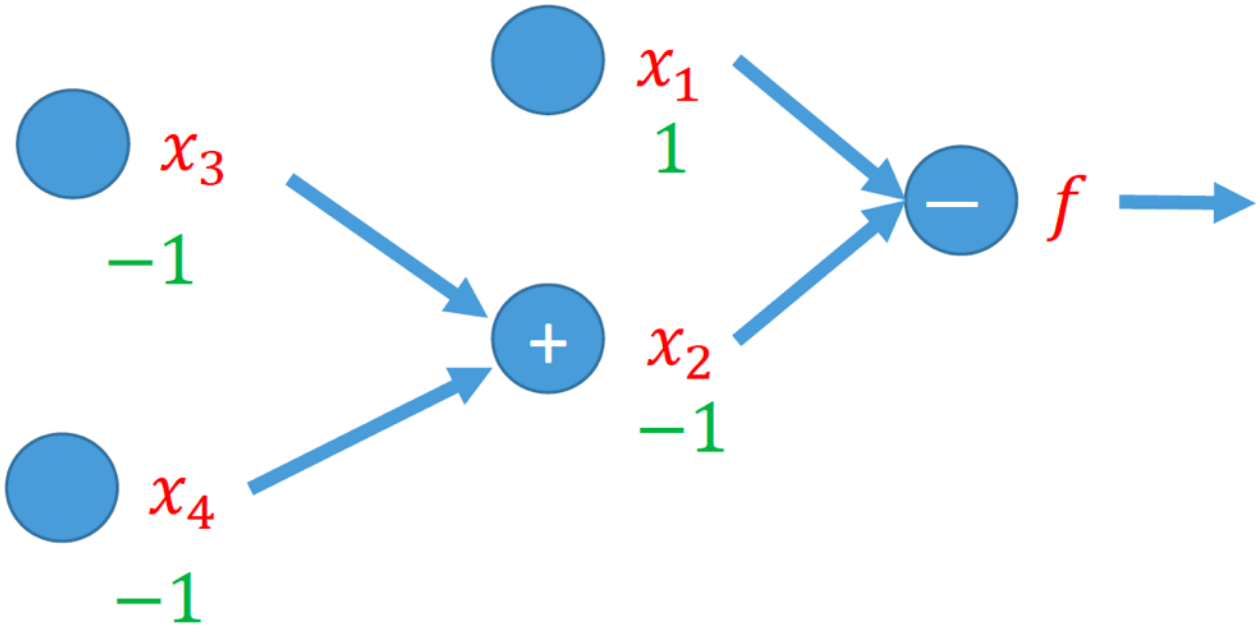


Function: $f = x_1 - x_2 = x_1 - (x_3 + x_4)$



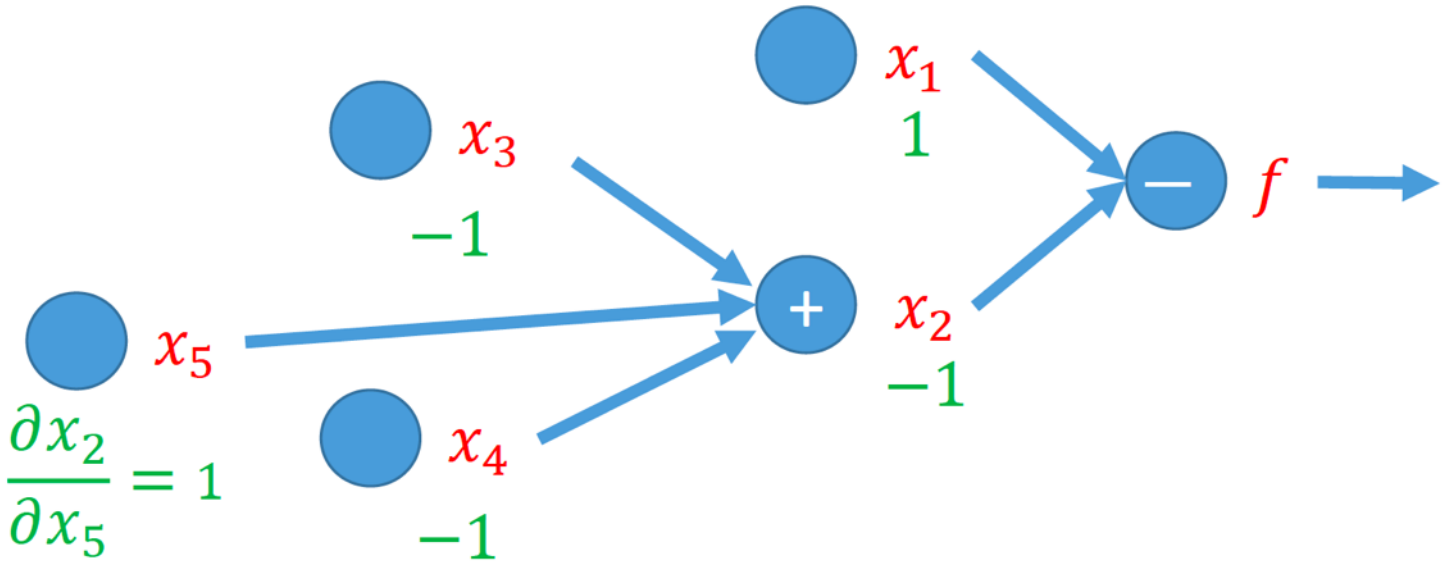
Function: $f = x_1 - x_2 = x_1 - (x_3 + x_4)$

Gradient: $\frac{\partial x_2}{\partial x_3} = 1, \frac{\partial x_2}{\partial x_4} = 1$. What about $\frac{\partial f}{\partial x_3}$?



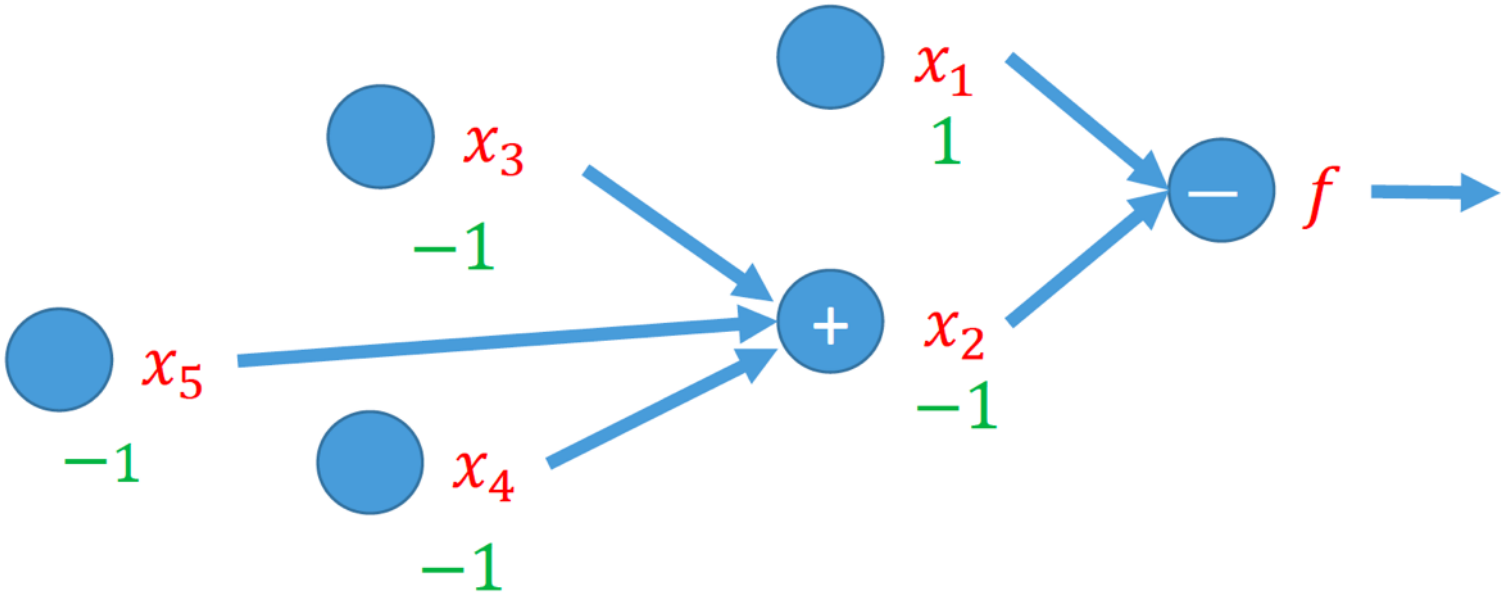
Function: $f = x_1 - x_2 = x_1 - (x_3 + x_4)$

Gradient: $\frac{\partial f}{\partial x_3} = \frac{\partial f}{\partial x_2}\frac{\partial x_2}{\partial x_3} = -1$



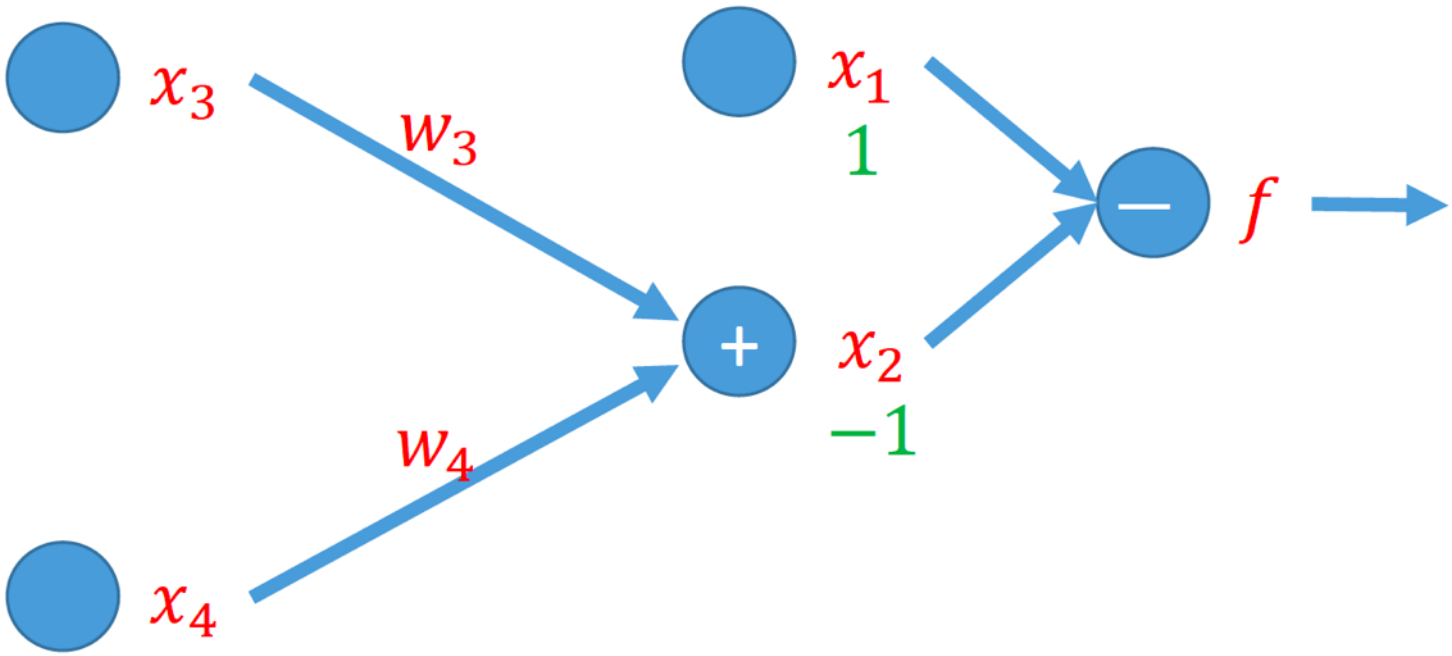
Function: $f = x_1 - x_2 = x_1 - (x_3 + x_5 + x_4)$

Gradient: $\frac{\partial x_2}{\partial x_5} = 1$

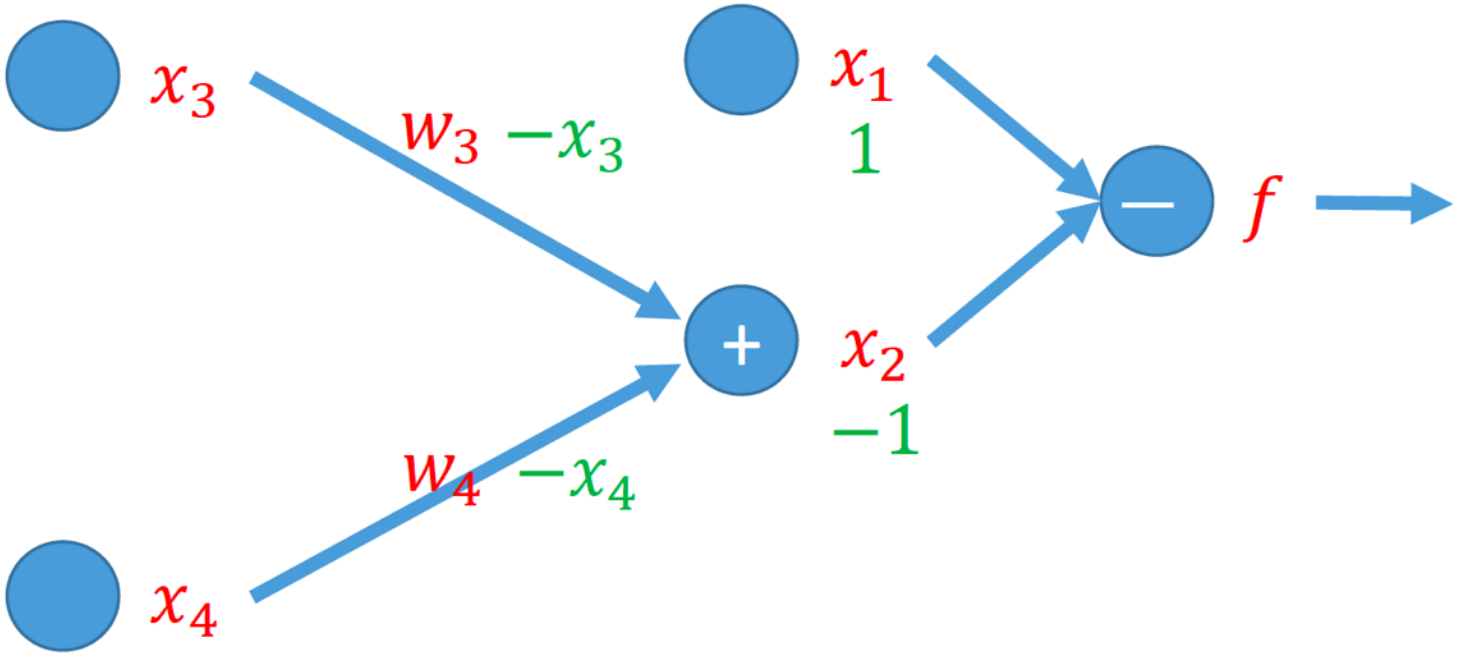


Function: $f = x_1 - x_2 = x_1 - (x_3 + x_5 + x_4)$

Gradient: $\frac{\partial f}{\partial x_5} = \frac{\partial f}{\partial x_2}\frac{\partial x_2}{\partial x_5} = 1$

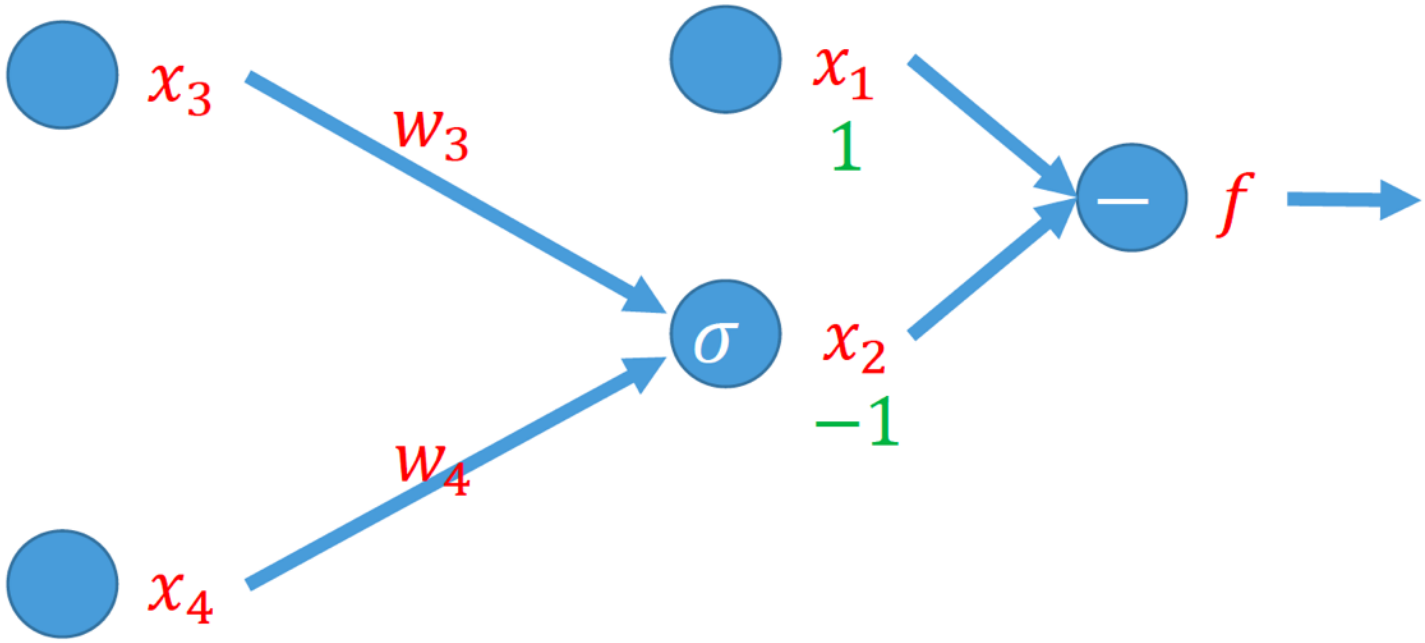


Function: $f = x_1 - x_2 = x_1 - (w_3 x_3 + w_4 x_4)$

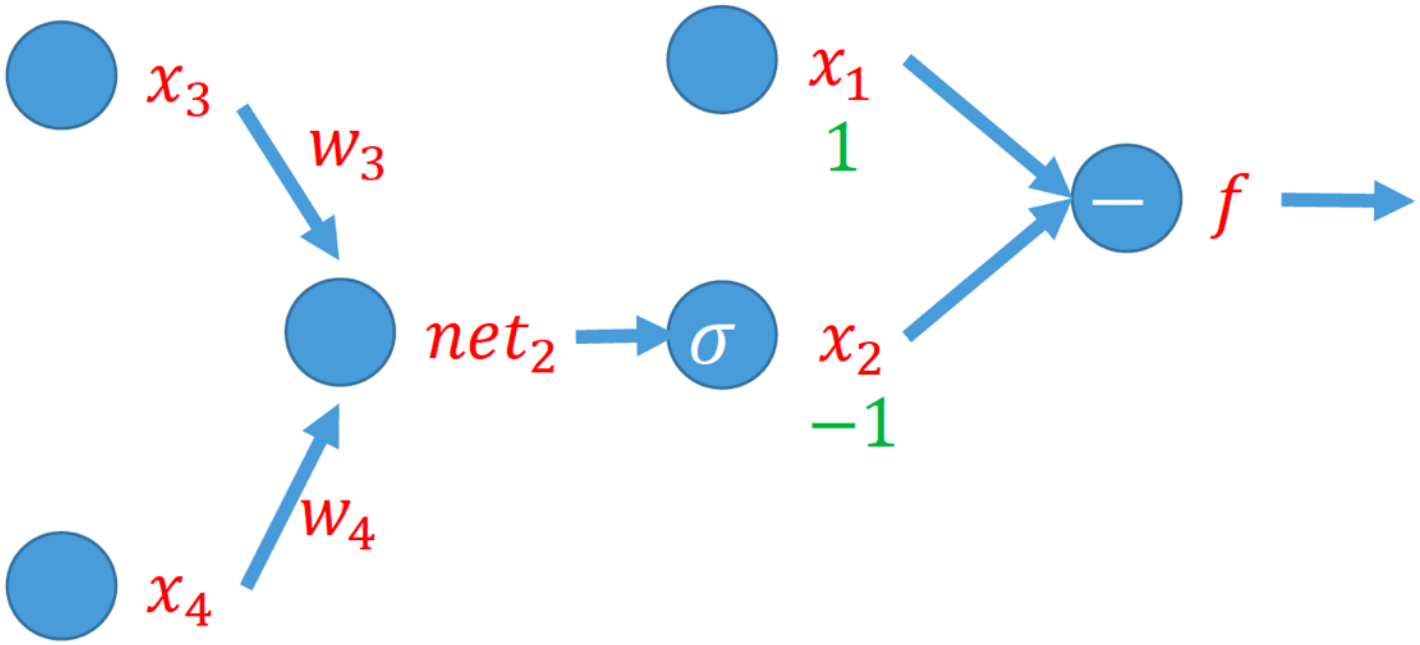


Function: $f = x_1 - x_2 = x_1 - (w_3 x_3 + w_4 x_4)$

Gradient: $\frac{\partial f}{\partial w_3} = \frac{\partial f}{\partial x_2}\frac{\partial x_2}{\partial w_3} = -1 \times x_3 = -x_3$

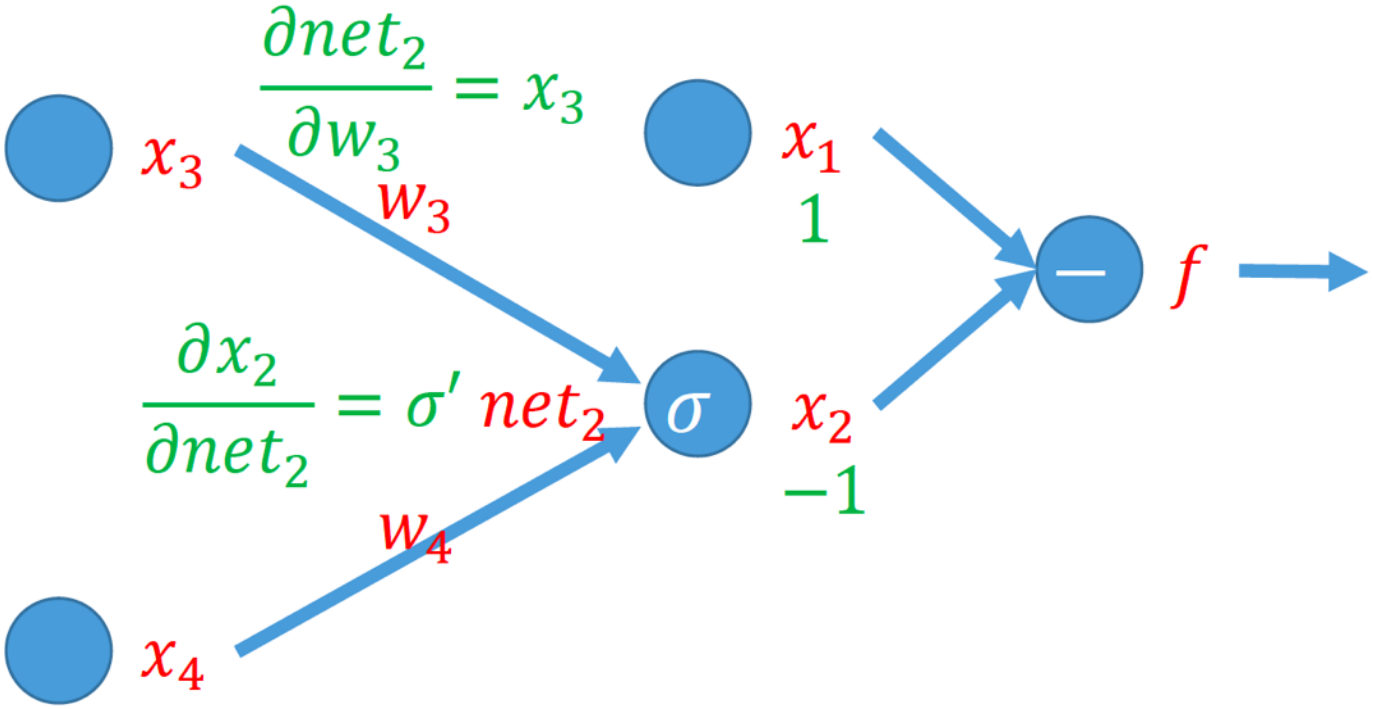


Function: $f = x_1 - x_2 = x_1 - \sigma(w_3 x_3 + w_4 x_4)$



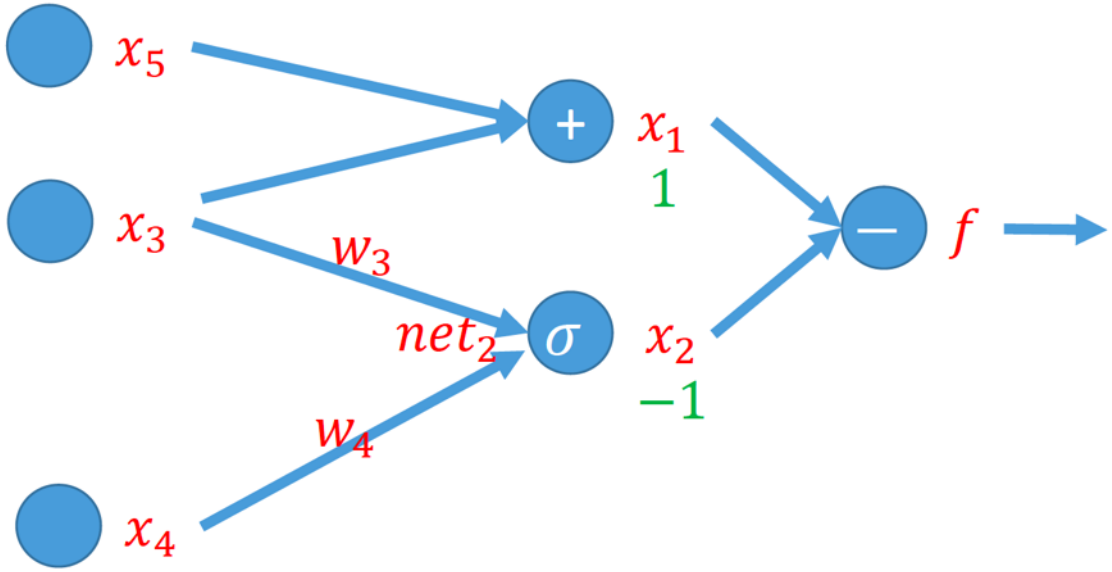
Function: $f = x_1 - x_2 = x_1 - \sigma(w_3 x_3 + w_4 x_4)$

Let $net_2 = w_3 x_3 + w_4 x_4$

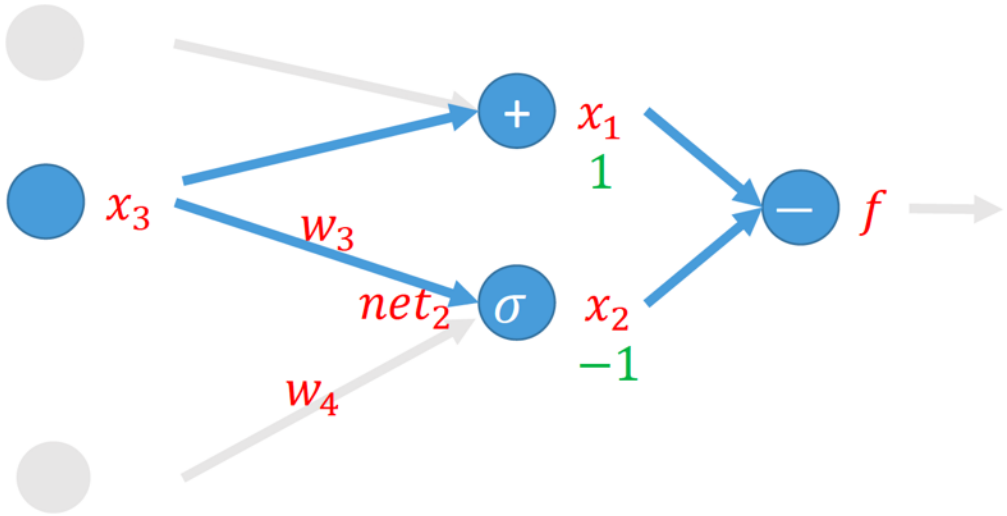


Function: $f = x_1 - x_2 = x_1 - \sigma(w_3 x_3 + w_4 x_4)$

Gradient: $\frac{\partial f}{\partial w_3} = \frac{\partial f}{\partial x_2}\frac{\partial x_2}{\partial net_2}\frac{\partial net_2}{\partial w_3} = -1 \times \sigma' \times x_3 = -\sigma' x_3$



Function $f = x_1 - x_2 = (x_3 + x_5) - \sigma(w_3 x_3 + w_4 x_4)$

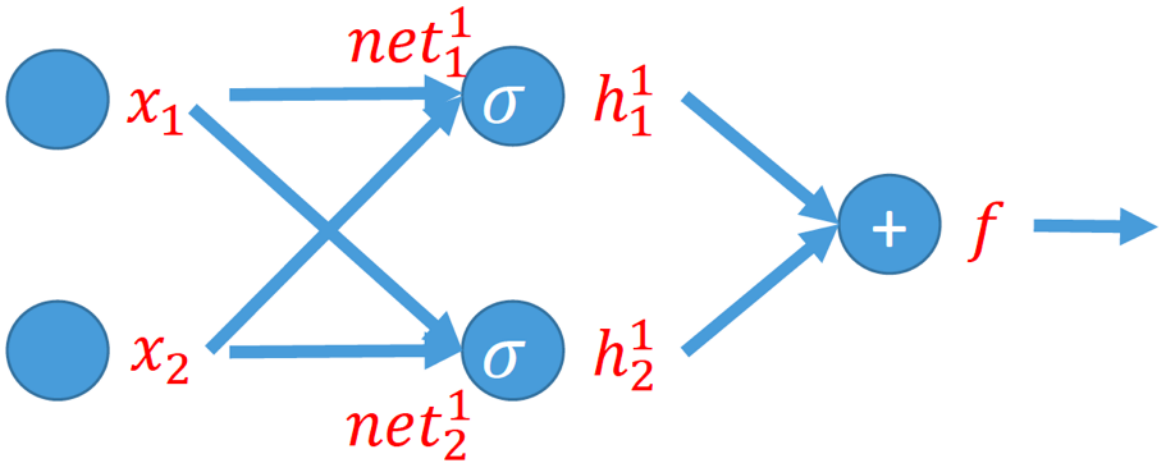


Function: $f = x_1 - x_2 = (x_3 + x_5) - \sigma(w_3 x_3 + w_4 x_4)$

Gradient: $\frac{\partial f}{\partial x_3} = \frac{\partial f}{\partial x_2}\frac{\partial x_2}{\partial net_2}\frac{\partial net_2}{\partial x_3} + \frac{\partial f}{\partial x_1}\frac{\partial x_1}{\partial x_3} = -1 \times \sigma' \times w_3 + 1 \times 1 = -\sigma' w_3 + 1$

Summary

- Forward to compute f
- Backward to compute the gradients



Activation Functions

- ReLU $\mathrm{ReLU}(x) = \max\{x, 0\}$

$$\mathrm{ReLU}'(x) = \begin{cases} 0, & x \leq 0 \\ 1, & x > 0 \end{cases}$$

Sub-gradient used at $x = 0$

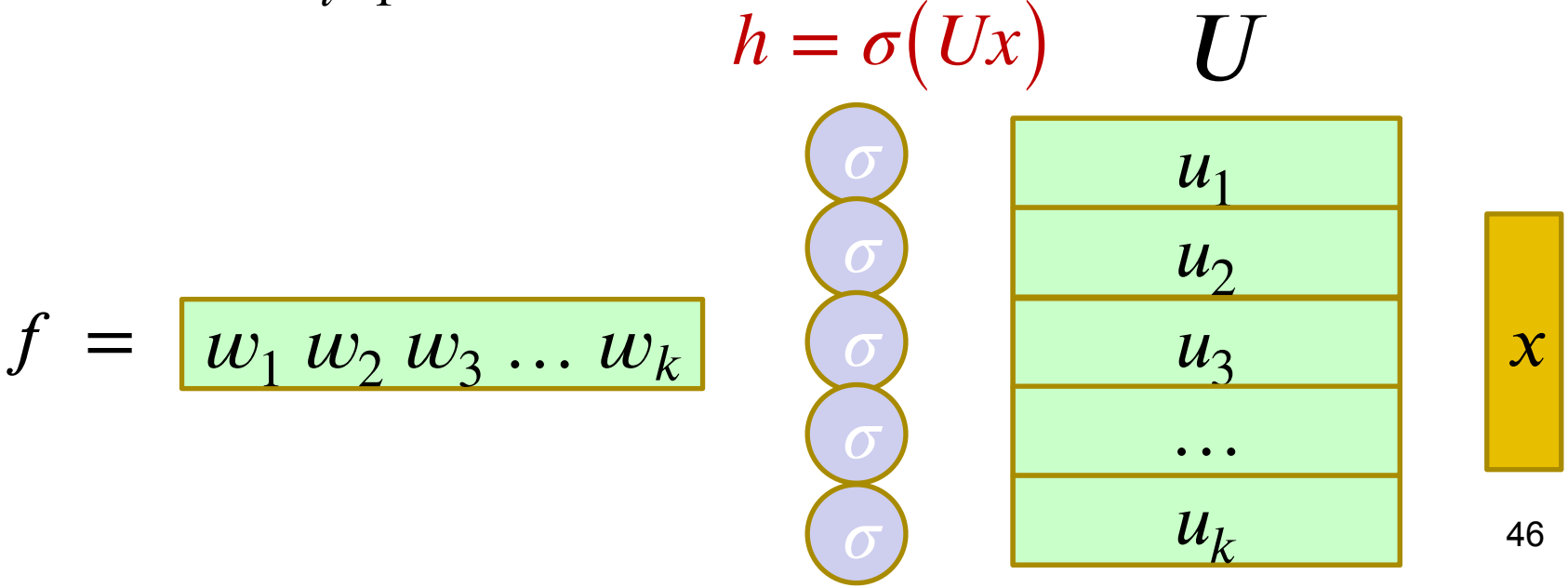
- Sigmoid $\sigma(x) = \dfrac{1}{1 + e^{-x}}$

$$\sigma'(x) = \sigma(x) \cdot \big(1 - \sigma(x)\big)$$

- $\tanh(x) = \dfrac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$

One-hidden layer network

- $f_\theta(x) = w^\top \sigma(Ux)$ where $\theta = (w, U)$
- $f_\theta(x) = \sum_{i=1}^{k} w_i \, \sigma(u_i^\top x)$



One-hidden layer network

- $f_\theta(x) = \sum_{i=1}^{k} w_i \sigma(u_i^\top x)$
- $\nabla f_\theta(x) = \left(\frac{\partial f}{\partial w}, \frac{\partial f}{\partial U} \right)$
- $\frac{\partial f}{\partial w} = h = \sigma(Ux)$
- $\frac{\partial f}{\partial U} = ?$

One-hidden layer network

- $$\frac{\partial f}{\partial u_i} = \frac{\partial w_i \sigma\left(u_i^\top x\right)}{\partial u_i} = w_i \sigma'\left(u_i^\top x\right) x$$

Overall size $k \times d$

$$\frac{\partial f}{\partial U} = \left(w \odot \sigma'(Ux)\right) x^\top$$

$k \times 1$ vector with entries $w_i \sigma'\left(u_i^T x\right)$

$1 \times d$ input features

$\odot$ is Hadamard product (entry-wise multiplication)

One-hidden layer network

- $\dfrac{\partial f}{\partial w} = \sigma\big(Ux\big)$
- $\dfrac{\partial f}{\partial U} = \big(w \odot \sigma'(Ux)\big)x^\top$

- Consider $\mathscr{L}(\theta) = \dfrac{1}{2}\Big(w^\top \sigma(Ux) - y\Big)^2$

$$\frac{\partial \mathscr{L}}{\partial w} = \Big(w^\top \sigma(Ux) - y\Big)\,\sigma(Ux)$$

$$\frac{\partial \mathscr{L}}{\partial w} = \Big(w^\top \sigma(Ux) - y\Big)\,\big(w \odot \sigma'(Ux)\big)x^\top$$

Training a one-hidden layer net

Initialize w_0, U_0

Learning rate $\eta > 0$, duration END

for $0 \leq t \leq \text{END} - 1$

1. Randomly pick example (x, y) from training data
2. Update weights
   - $w_{t+1} = w_t - \eta \left(w^\top \sigma(Ux) - y \right) \sigma(Ux)$
   - $U_{t+1} = U_t - \eta \left(w^\top \sigma(Ux) - y \right) \left(w \odot \sigma'(Ux) \right) x^\top$

Return final model $\theta_{\text{FINAL}} = \left(w_{\text{END}}, U_{\text{END}} \right)$

Acknowledgements

- A lot of content from online resources
  - Yingyu Liang's slides https://www.cs.princeton.edu/courses/archive/spring16/cos495/
  - Goodfellow's slides https://www.deeplearningbook.org/