# **Machine learning**
# for **everyone**

Gabriel Vigliensoni-Martin
Jeronimo Barbosa

# **Learning machines**
# for **everyone**

# Machine learning

- What is **learning**?
    - Memorizing vs learning
- Machine learning
    - Science of getting computers to act **without being explicitly programmed**
    - Study of algorithms that **learn from examples** and experiences **instead of hard-coded rules**
- Machine learning **tasks**
    - **Classification**: output is discrete categories
    - **Regression**: output is a real-value number

# Machine learning

http://www.gestaltu.com/2015/10/apples-and-oranges-a-random-portfolio-case-study.html/

# Machine learning

- How to **write code to tell the difference** between (classify) an orange and an apple?
  - Take an **input** image, do some **analysis**, and **output** the types of fruit
  - Writing **lots of manual rules**
    - Count how many **green pixels** there are in the image and compare that to the number of **red pixels**? The **ratio** should give a **hint about the type of fruit.**
    - **Works fine for simple images**, but the world is messy and rules start to break. What about red apples? Or other fruits?
    - Colours, edges, shapes, guessing textures, …
  - New problem may imply **a new set of rules**!

# Machine learning

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# Machine learning

- We need an **algorithm** that **can figure out the rules** for us!
- For this, we **train a classifier** (a function that takes some data and assign a label to it as output)
- One big distinctions in machine learning: **supervised learning** versus **unsupervised learning**

# Machine learning

## Supervised learning

- Supervised learning approaches **use examples of the problem** you want to solve
- These methods create a classifier by **finding patterns in these examples**

# Machine learning
## Supervised learning

https://previews.123rf.com/images/lestertair/lestertair1506/lestertair150600264/41403024-background-fresh-fruit-apples-oranges-lemons-Stock-Photo.jpg

# Machine learning
## Supervised learning

- **Supervised learning steps** based on features:
    - **collect training data** (examples of the problem we want to solve)
    - **take some measurements**. In the context of machine learning these measurements are called **features** (e.g., go to an orchard and measure the weight, shape, and texture of fruits, and then label them)
    - put all training data into a table, **the more training data the better the classifier** (model)
    - **train the classifier with this data**. There are many training methods, but the inputs and outputs are always the same

# Machine learning

## Supervised learning

- A **classifier** can be seen as **a box of rules**, and so the **training algorithm** is the **procedure to learn those rules**
- It does so by **finding patterns in the training data**
- For example, it may notice that oranges tend to weigh more, and so it creates a rule saying the more heavy the fruit is the more likely it is an orange

# Machine learning

## Supervised learning

- This procedure is the same for a new problem. **By changing the training data we can create a new classifier**. There is no need of writing new rules!
- Questions
    - How much training data is needed?
    - How is the optimization achieved?
    - What makes a good feature?
- **“all models are wrong, but some are useful.”** (George E. P. Box)
- The goal of ML is never to make “perfect” guesses, because ML deals in domains where there is no such thing
- **The goal of ML is to make guesses that are good enough to be useful**

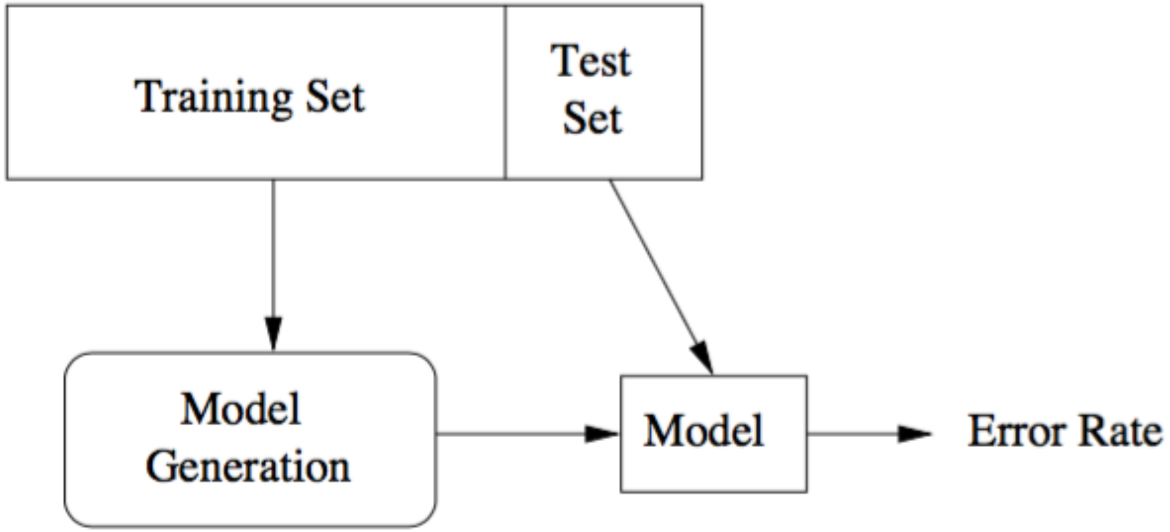
# Machine learning
## Unsupervised learning

- In **unsupervised learning** there is **no such thing such a class label**
- We provide a set of **training examples** that **we believe contains internal patterns**
- We leave it to the system to **discover those patterns on its own**

# Machine learning

## Training and testing architecture

- The purpose of creating a model or classifier is not to classify the training set, but to classify the data **whose class we do not know**
- We want to create models **that are generalizable**

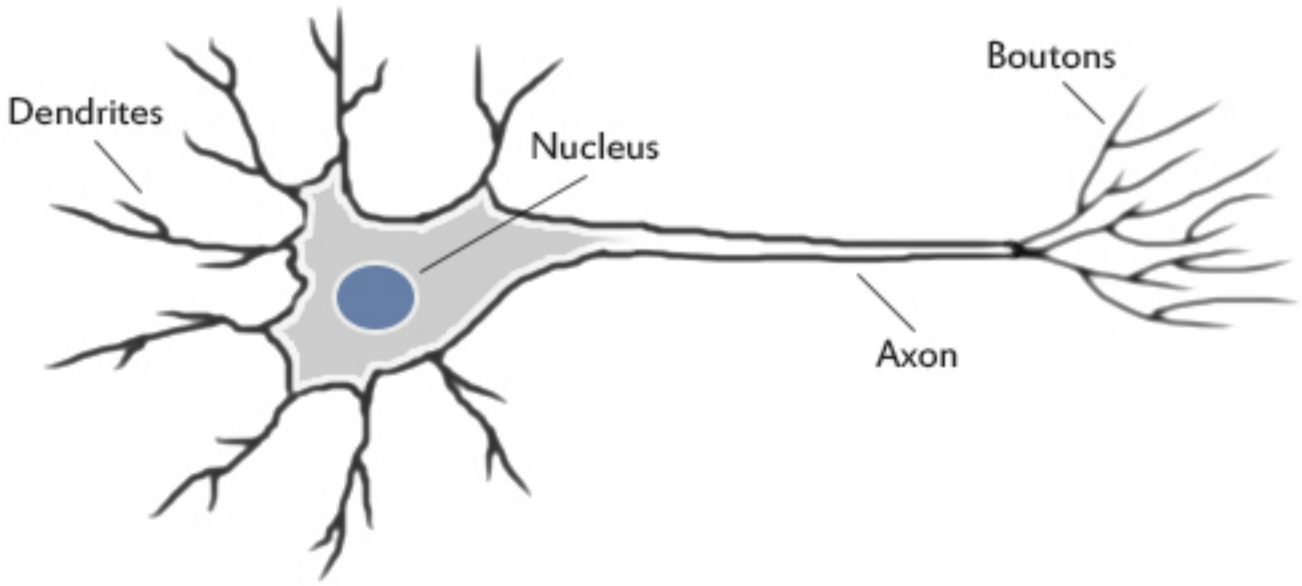



Leskovec, Jurij, Anand Rajaraman, and Jeffrey D. Ullman. 2014. *Mining of Massive Datasets*. 2nd ed. Cambridge, United Kingdom: Cambridge University Press.

# Wrongness

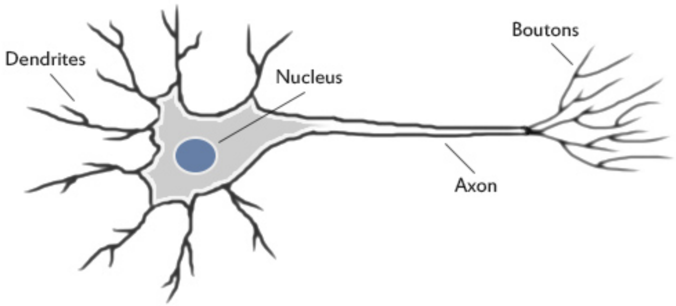
- The **error rate** is known as the **cost function** (a.k.a., loss function or error)

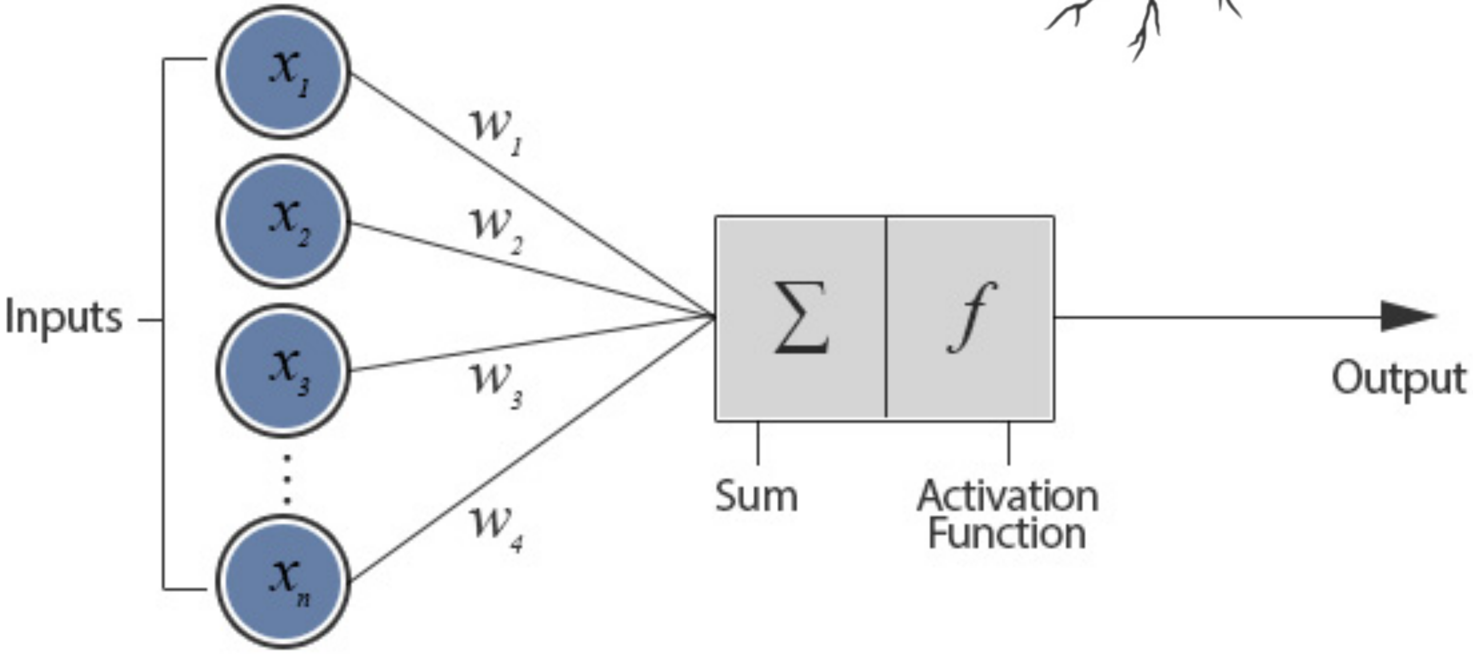
# Neuron




http://www.theprojectspot.com/tutorial-post/introduction-to-artificial-neural-networks-part-1/7

# Artificial Neuron



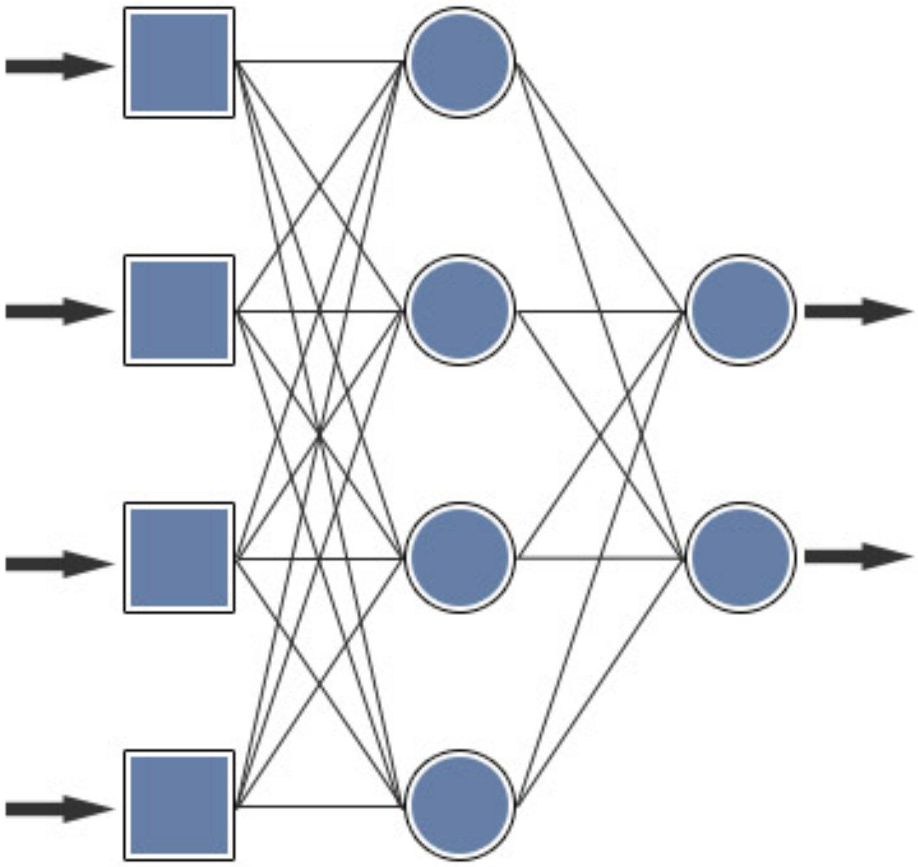

weight vector

$$y = \sum_i w_i x_i = \mathbf{w}^\mathbf{T}\mathbf{x}$$

input vector

http://www.theprojectspot.com/tutorial-post/introduction-to-artificial-neural-networks-part-1/7

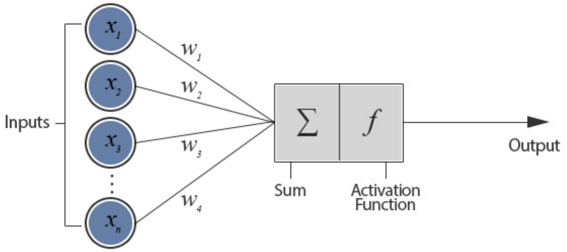
# Neural Networks



Input
layer

Hidden
layer

Output
layer

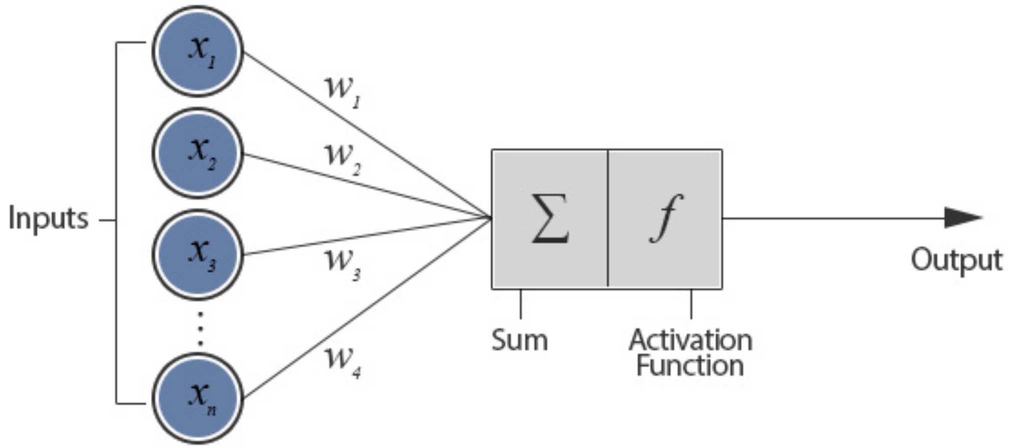



http://www.theprojectspot.com/tutorial-post/introduction-to-artificial-neural-networks-part-1/7

# Iterative optimization

- How to **learn the weights** of a neuron?
- By using a **learning algorithm**
    - learning turns to be a **numerical optimization of weight** parameters
    - The actual output values **get closer** to the target values **in each iteration**
    - Many quite **different sets of weights may work** well

# Learning as iterative optimization




weight vector

$$y = \sum_i w_i x_i = \mathbf{w}^{\mathbf{T}}\mathbf{x}$$

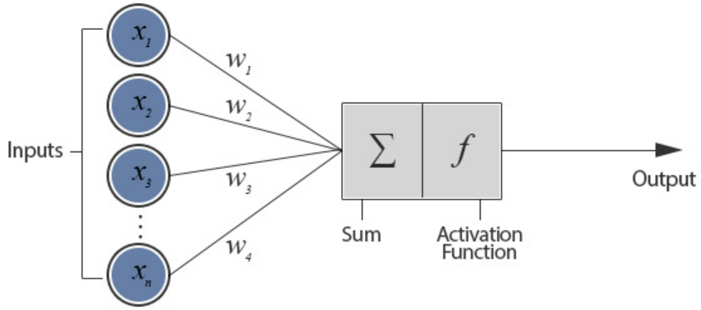
input vector

- Simplest example: linear neuron with error measure
  - A linear neuron has a real-valued output that is a weighted sum of its inputs
- The aim of the learning is **to minimize the error summed over all training cases**

# Learning as iterative optimization

- **Toy example** to illustrate the iterative method:
  - Each day you get lunch at the cafeteria
    - Diet consists of **protein**, **salad**, and **carbohydrate**
    - You get **several portions** of each
  - The cashier only tells you the **total price of the meal**
  - After a few days, you ought to be able to **figure out what the price is for each portion** of each kind of food based on all previous examples

# Learning as iterative optimization




$$price = x_{protein} w_{protein} + x_{carbo} w_{carbo} + x_{salad} w_{salad}$$

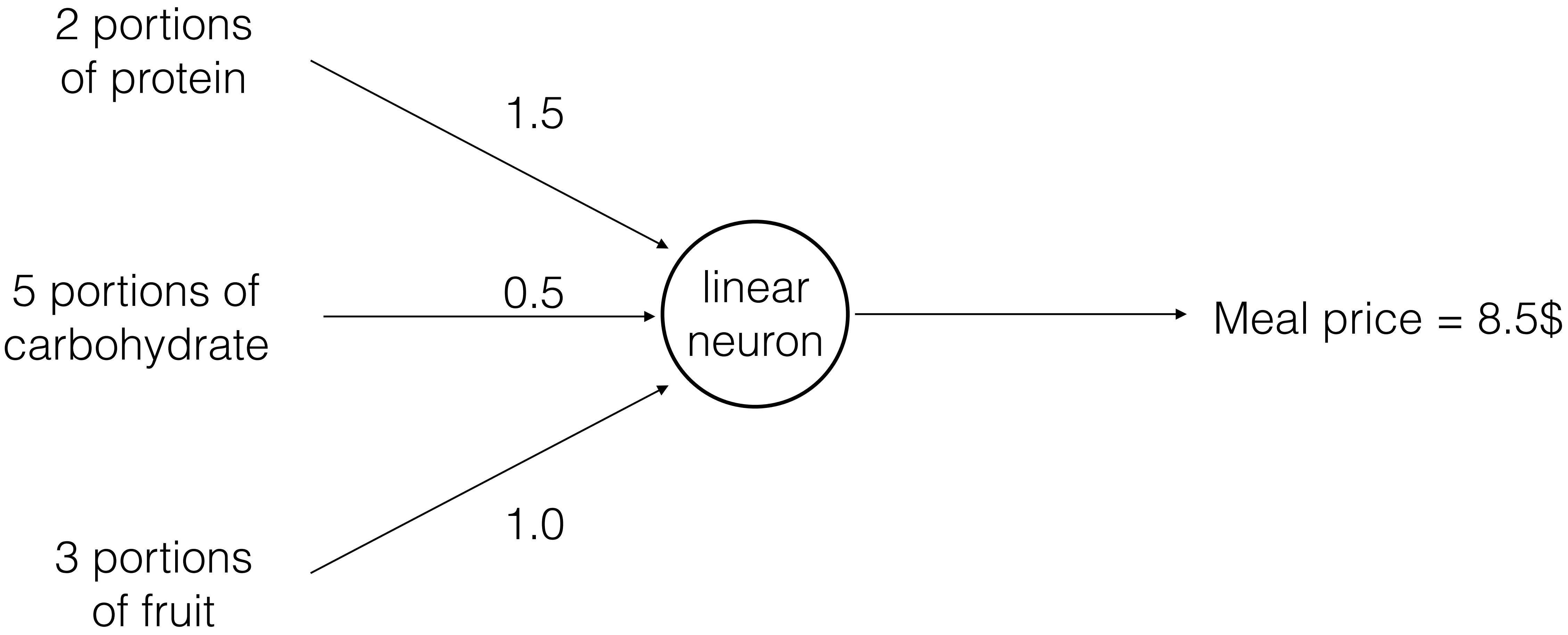
- The prices of the portions are like the weights of a linear neuron

$$\mathbf{w} = (w_{protein}, w_{carbo}, w_{salad})$$

- Let's suppose that the **true weights** that the cashier using to figure out the price, are **1.5$** for a portion of **protein**, **0.5$** for a portion of **carbohydrate**, and **1.0$** for a portion of **salad**
- We **start with guesses** for these prices and then **we adjust the guesses slightly**, so that we agree better with what the cashier says

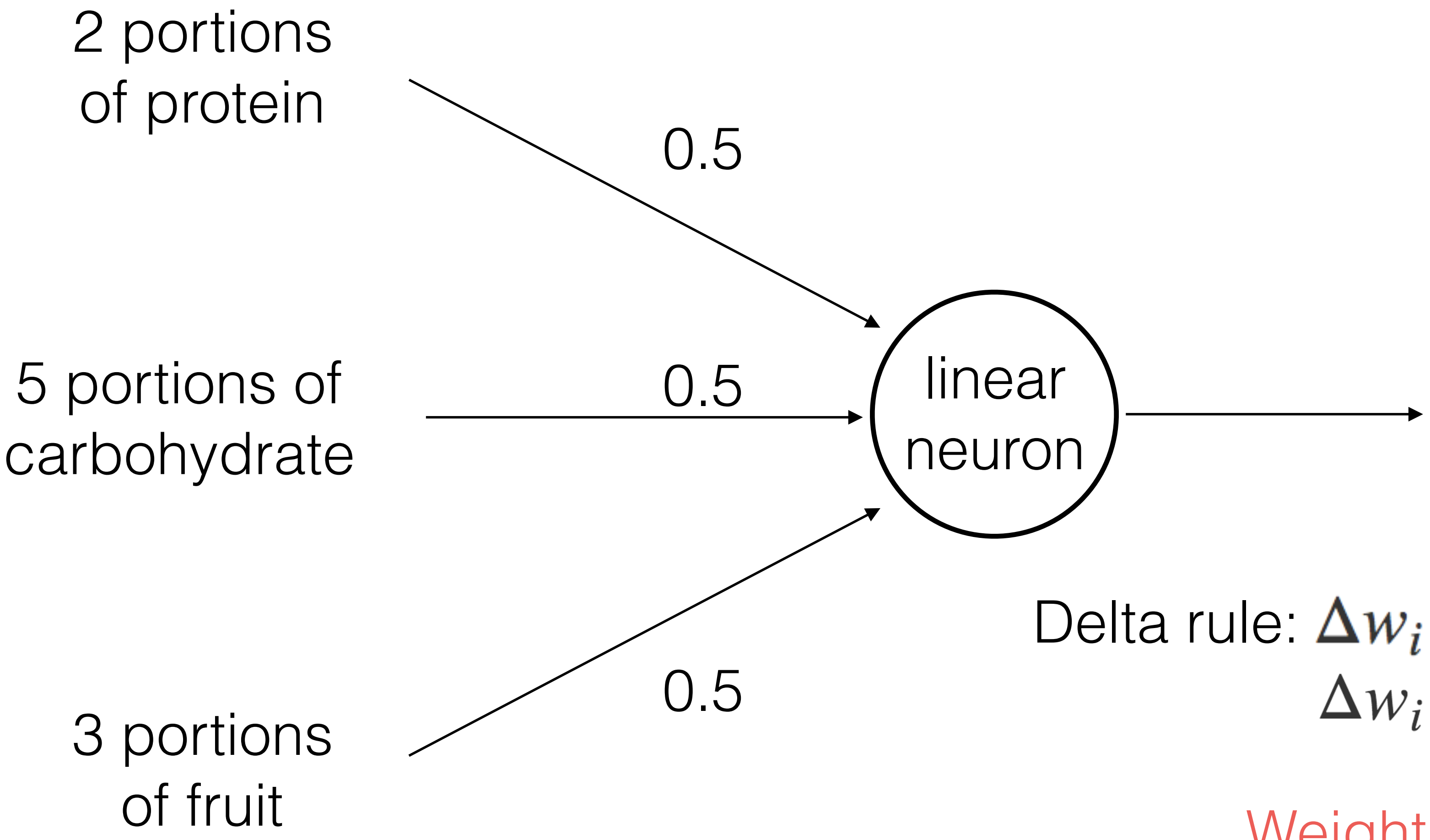
# Learning as iterative optimization

True weights used by the cashier



# Learning as iterative optimization

Starting with guesses




Actual price = 8.5$
Computed price = 5.0$
Residual error = 3.5

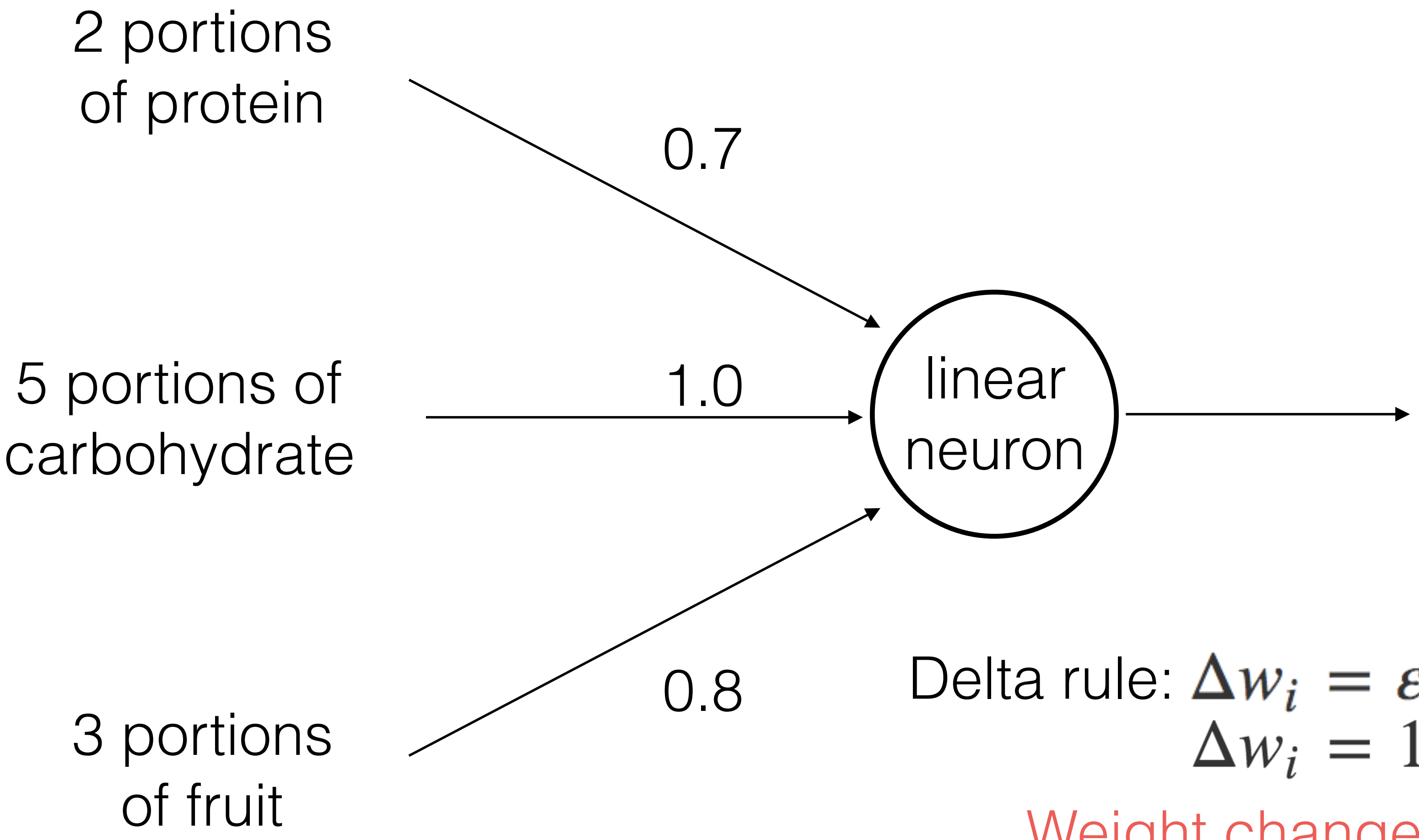
Delta rule: $\Delta w_i = \varepsilon\, x_i(t - y)$

$$\Delta w_i = 1/35\ x_i\ 3.5 = 0.1\ x_i$$

Weight changes: (0.2, 0.5, 0.3)
New weights: (0.7, 1.0, 0.8)

# Learning as iterative optimization

First iteration




Actual price = 8.5$

Computed price = 8.8$

Residual error = -0.3

Delta rule: $\Delta w_i = \varepsilon \, x_i (t - y)$

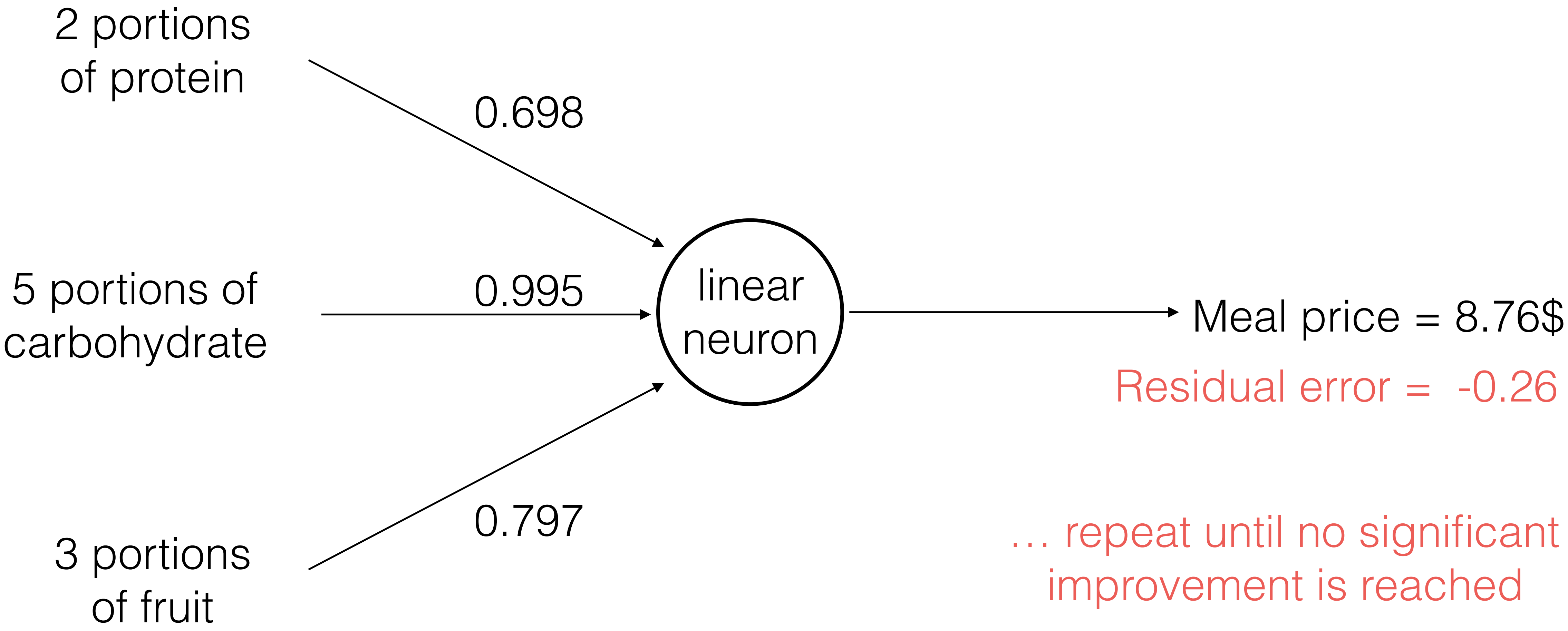
$$\Delta w_i = 1/35 \; x_i \; (-0.3) = -0.001 \; x_i$$

Weight changes: (-0.002, -0.005, -0.003)

New weights: (0.698, 0.995, 0.797)

# Learning as iterative optimization

### Second iteration



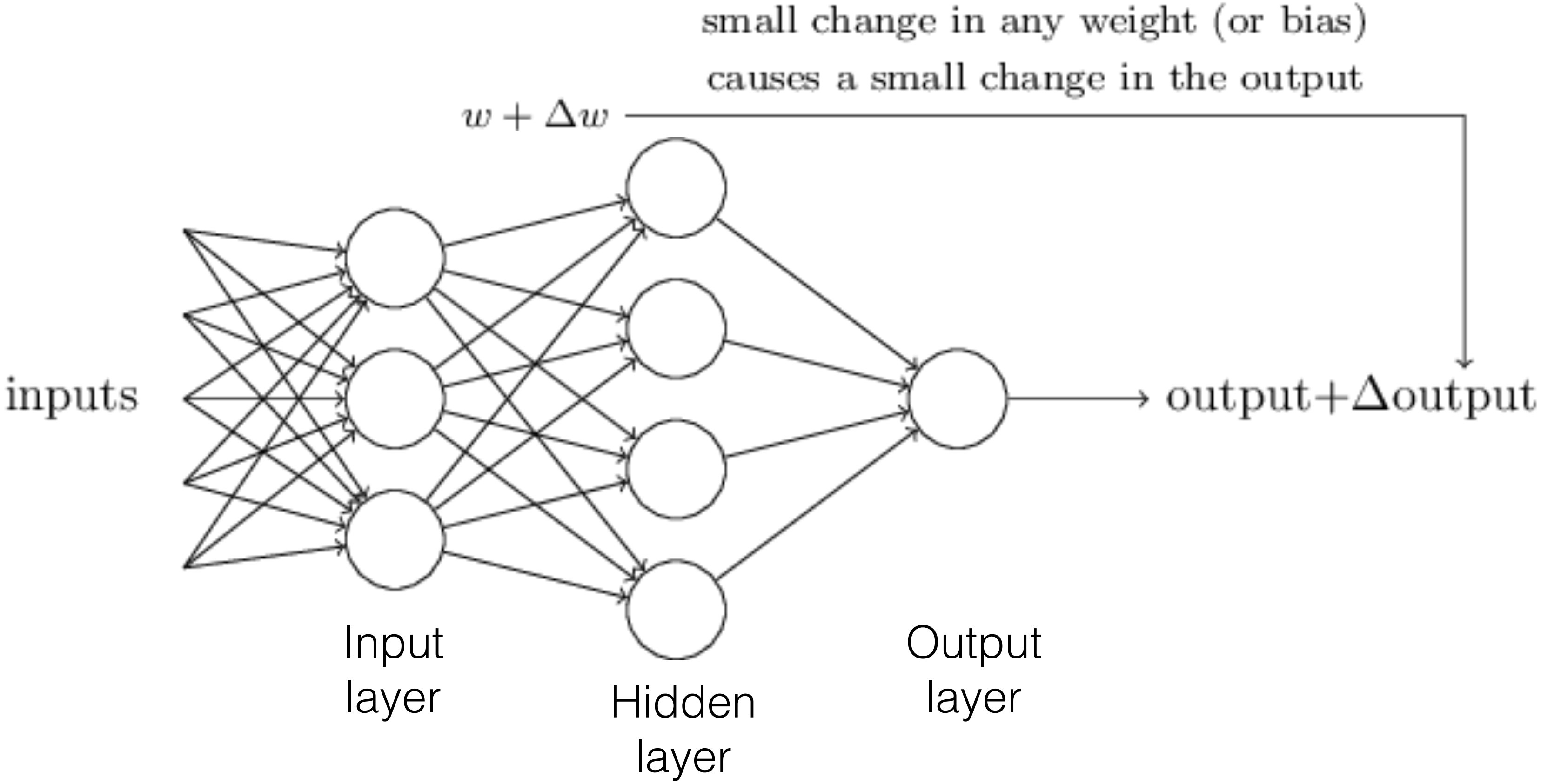

… repeat until no significant improvement is reached

# Learning as iterative optimization

- But the delta rule is **applied to all training cases**, not just one, and so the **weights are learnt from all training cases**

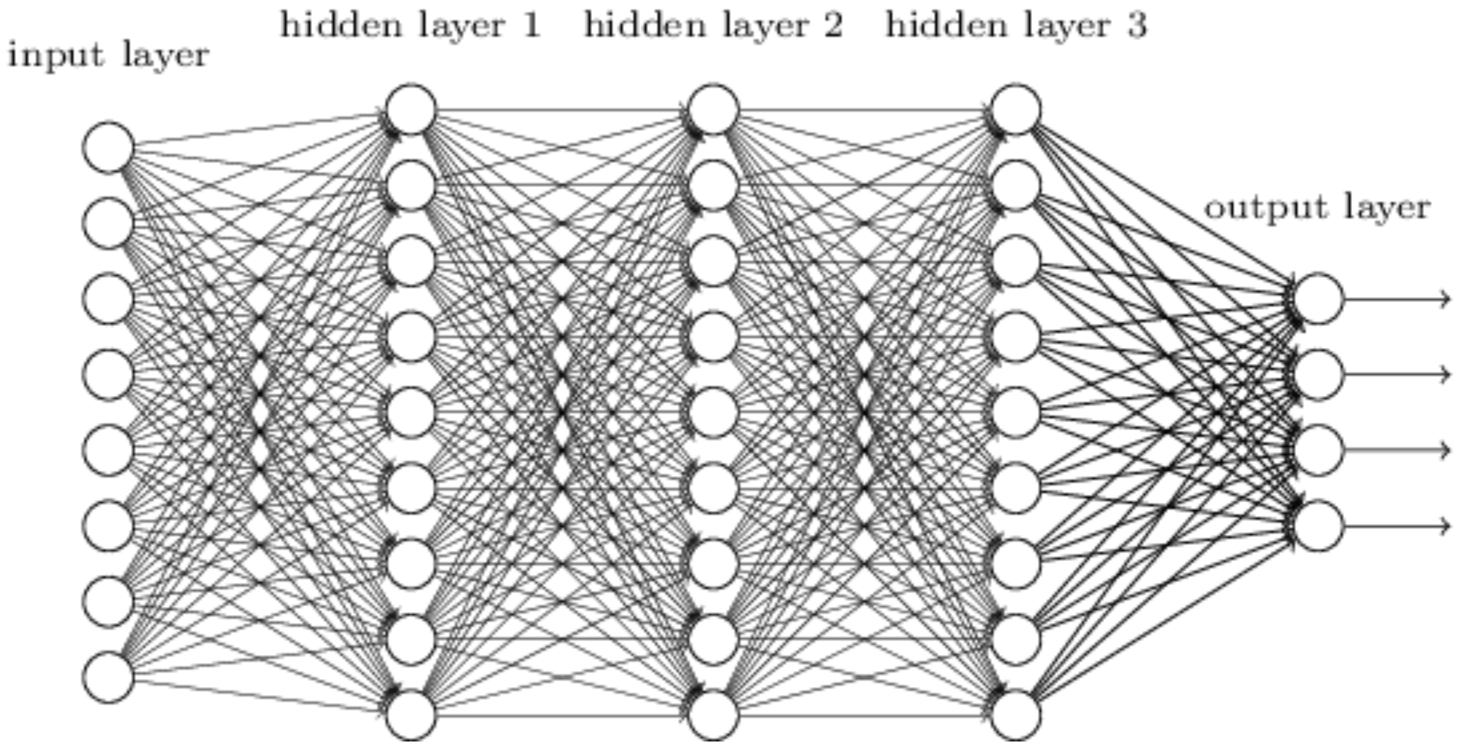
$$\Delta w_i = \sum_n \varepsilon\, x_i^n\, (t^n - y^n)$$

# Neural Networks




http://neuralnetworksanddeeplearning.com/chap1.html

# Deep Neural Networks




http://stats.stackexchange.com/questions/234891/difference-between-convolution-neural-network-and-deep-learning/235265

# Deep Neural Networks

## Tensorflow online example

- Tensorflow playground

# ML benchmark datasets

- UCI ML Repository
- Deep Learning datasets
  - MNIST online (benchmark) (human performance)
  - CIFAR10 online (benchmark)

Thanks!

# Derivative work

- Google’s Deep dream generator
- Neural network "art"
- SONY CSL Research Flow Machines
- Daddy's car
- Mr. Shadow

Rebecca Fiebrink's "Machine Learning for Artists and Musicians" online course on Kadenze:

https://www.kadenze.com/courses/machine-learning-for-musicians-and-artists/info