Introduction to Machine Learning

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Chamblee Charter High School

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The application of algorithms which learn automatically through experience.

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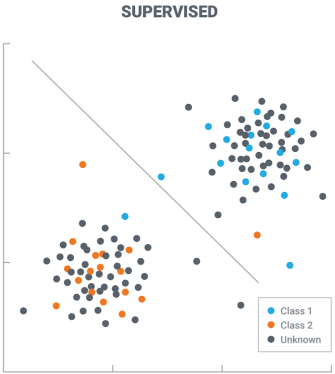
- Although it sometimes seems like we don't know much about how ML algorithms pick out specific features, a lot is known experimentally and there still is a strong mathematical foundation behind it.
- However, the field is still catching up with regard to understanding why models learn the way they do.

1. What is ML?
2. Types of ML Algorithms
3. Core Concepts of ML
4. Neural Nets
5. Backpropagation
6. Example
7. Conclusion

- Supervised Learning



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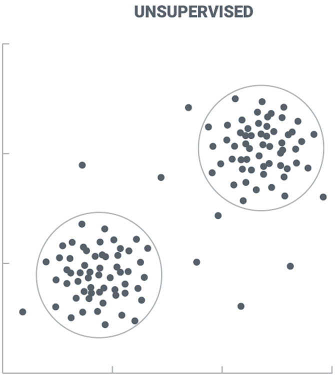

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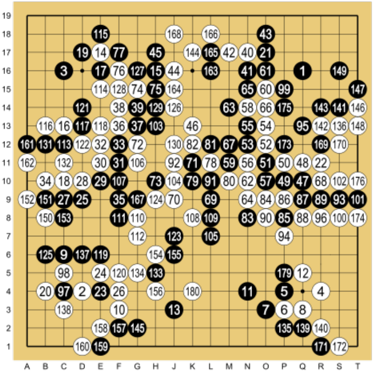

Lee Sedol (W) vs AlphaGo (B) - Game 4
177 at 51 178 at 57

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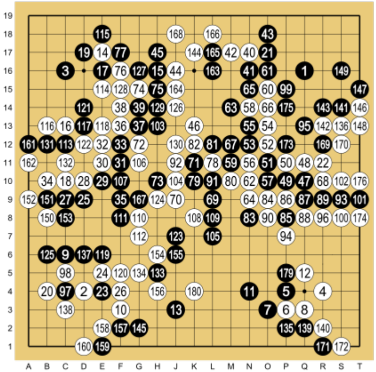

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- Supervised Learning
- Unsupervised Learning
- Reinforcement Leaning
- Move 37 and 78!
- We are going to focus on supervised learning for the remainder of this presentation

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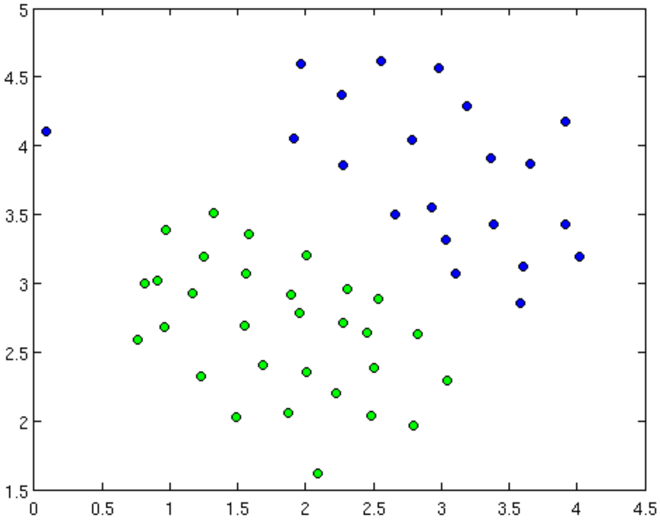
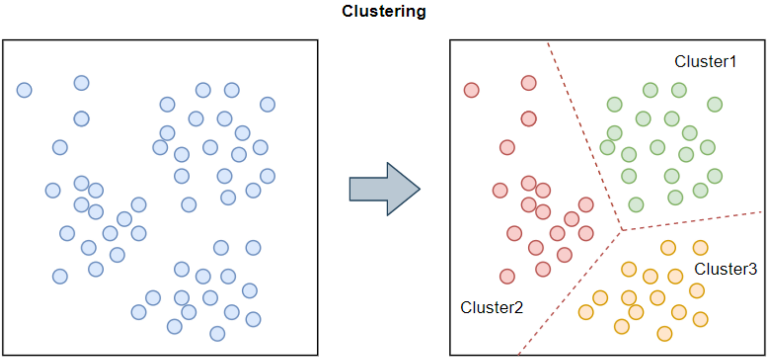
Label

The value that we are predicting. Denoted as y

Labeled Data Example



Unlabeled Data Example



Problems in Machine Learning

- Classification (Supervised)
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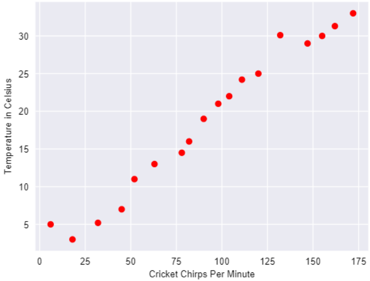
- Regression (Supervised)
  - What is the estimated price of the house?
  - How much will this flight cost?
  - What score will they get on the test?

Linear Regression Explained

- Linear regression is the modeling of the relationship between two variables.



Graphs courtesy of Google.

Linear Regression Explained

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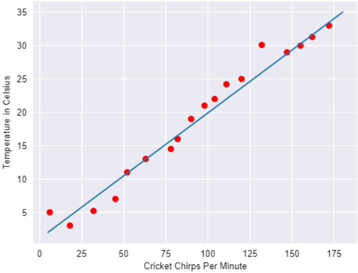
- Here, the regression line, sometimes also called the *Least Squares Regression Line* (LSRL) seems to fit the data pretty well.



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- Since data is never perfect, we try and create the "line of best fit." Or in other words, closest to all of the points.
- It allows us to make predictions about for a given x what the y would be.
- There are some fairly easy to use statistical methods for finding these lines. So... that concludes my presentation then!

But Wait!

This becomes much more complicated in N-dimensions

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- This is called *gradient descent*. But we will talk about this in a bit.

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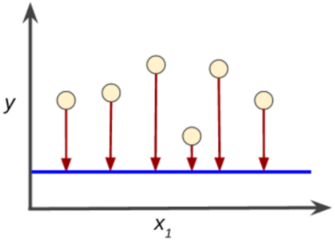

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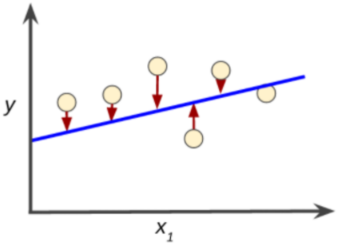

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- But we don't want loss to be $-\infty$! We want loss to be 0.

A New Loss Equation

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Mean Squared Error (MSE)

MSE is the average squared loss per example over the entire dataset. It is represented by the equation:

$$MSE = \frac{1}{N} \sum_{(x,y) \in D} (y - \lambda(x))^2$$

- This equation is only for one feature, x, but predictions often take into account many other features.

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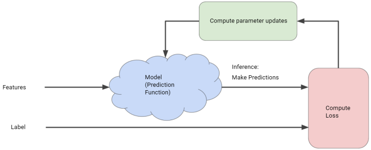

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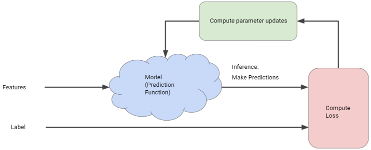

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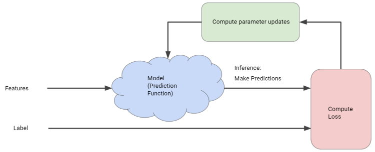

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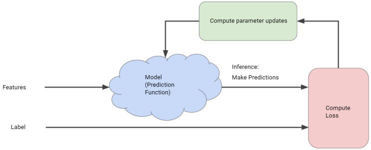
- But how do we know how to tweak the model?



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Loss Minimization and Gradient Descent

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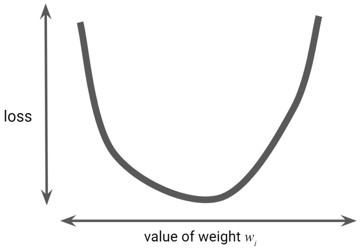

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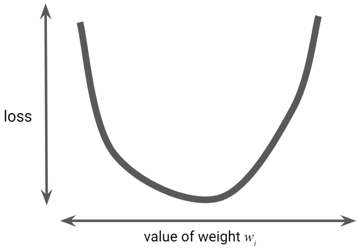

Loss Minimization and Gradient Descent

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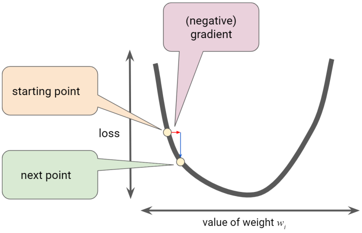
- All we need to do is estimate the derivative at that point and move to the lower side.



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- Looking at, and updating weights based off of a randomly selected single example is called **stochastic gradient descent (SGD)**.
- However this often is too extreme and yields noisy results. A combination approach is instead taken.

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- We also are able to control the number of **epochs**, or the number of full passes through the data, as well as the number of **steps per epoch** which is the number of batches before an epoch is considered complete.

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- Does this relate to ML?
- Nope! Just something interesting that I wanted to share.

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- For example, in classification problems, **accuracy** alone can be misleading and one should also keep track of the F_1 score for example.
- We will get to see an example of loss going down soon!

Training, Validation, and Overfitting

- **Overfitting** is what happens when the model fits the training data too much and then starts to make incorrect predictions.

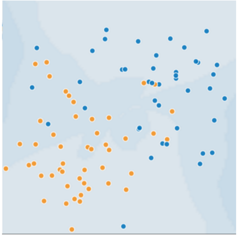

Figure 1. Sick (blue) and healthy (orange) trees.

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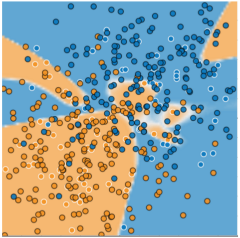

Figure 3. The model did a bad job predicting new data.

Training, Validation, and Overfitting

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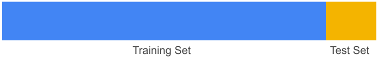
- To determine how well the model is able to predict data that it wasn't trained on, we split the dataset into a **training** and a **validation** set.



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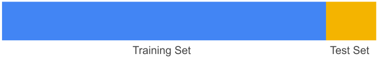
- 80% training data and 20% validation data.



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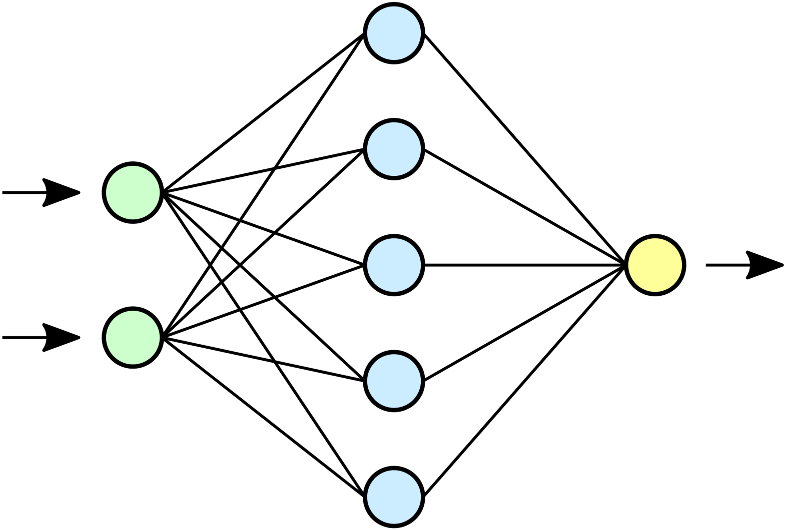
- Now that we have a *basic* understanding of machine learning, we can start to harness its power.
- However, I will have to limit the scope even more, so we are only going to focus on feed forward networks. We can also briefly talk about how convolutional neural networks work at the end if there is interest.

A Network



Parts of a Network

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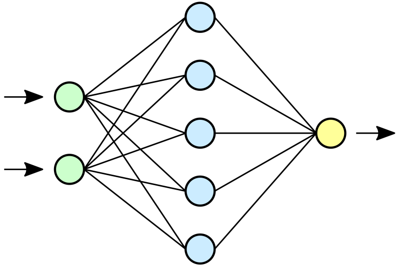

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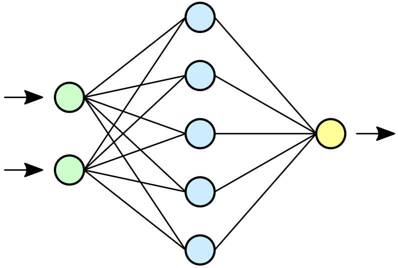

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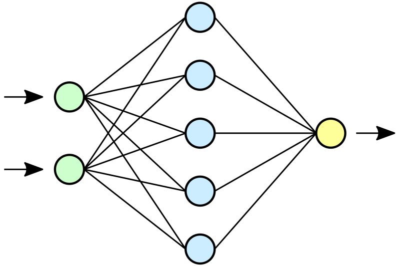

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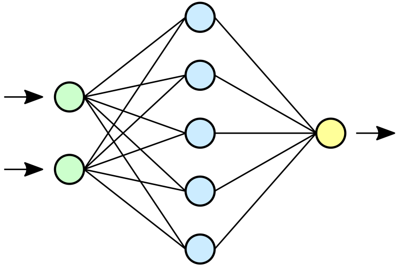
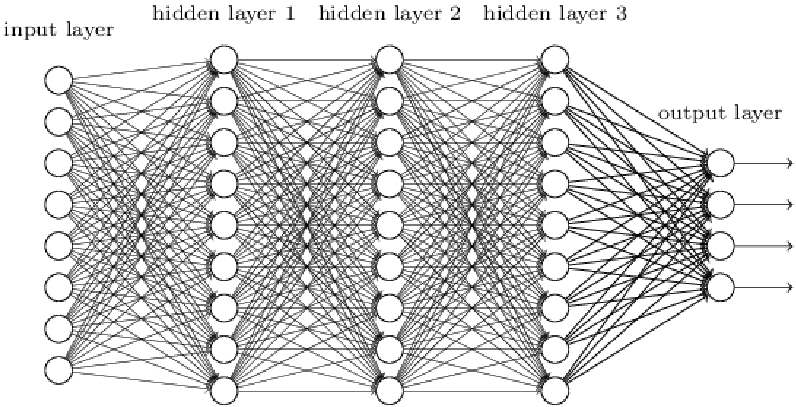
- Note: Non-linear transformations can happen between input and hidden as well as hidden and output.



A Deep Neural Network Example



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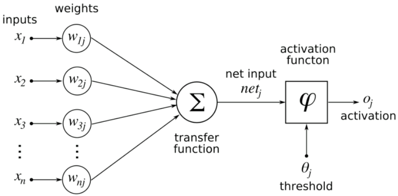

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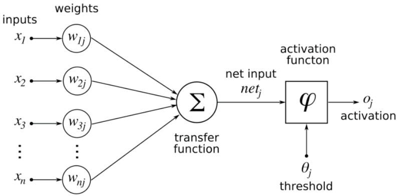

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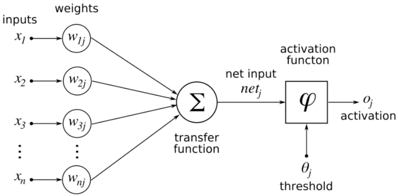
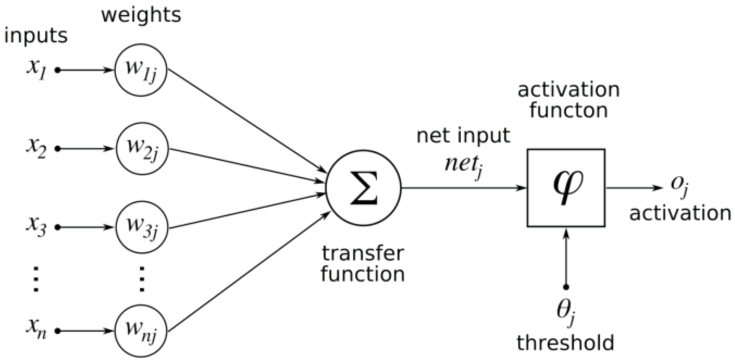


A Closer Look look at a Neuron



$$f(x_1, x_2, x_3, ..., x_n) = a(\sum_{0}^{n} x_i w_i + b)$$

where a is an activation function

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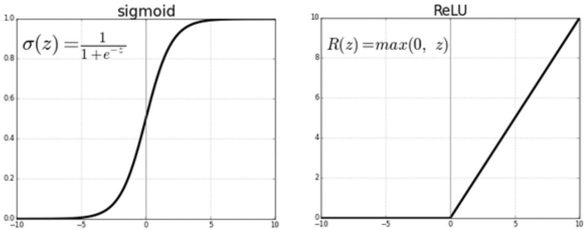
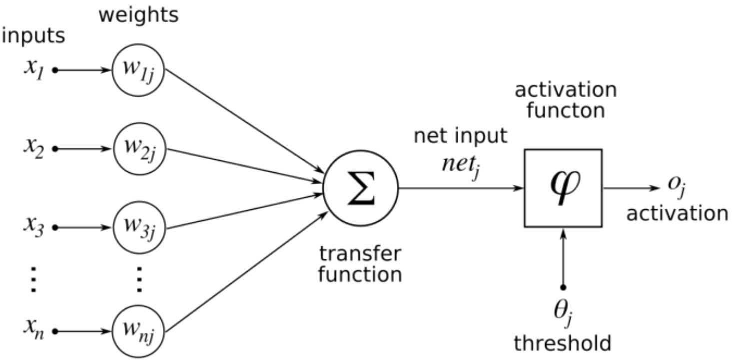


Looking Back At the Diagram



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Backpropagation

- We saw that it seemed relatively trivial to update the weights on a single node.
- But what about if there are multiple nodes? How about if there are multiple hidden layers?
- Well, you probably guessed it from the title of this frame but the answer is **backpropagation** (RMSprop also would suffice, however that is less common).

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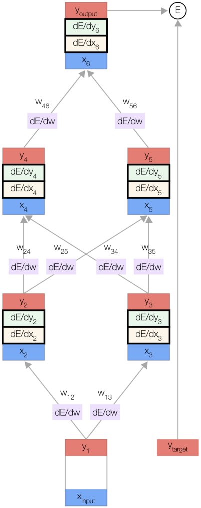
- Well, backpropagation is an algorithm which allows one to calculate the gradient (∇) of the loss function for each weight.
- Now let's take a look at the math behind backpropagation (backprop).

Backpropagation Explained

- The first step to backpropagation is in fact forward propagation.



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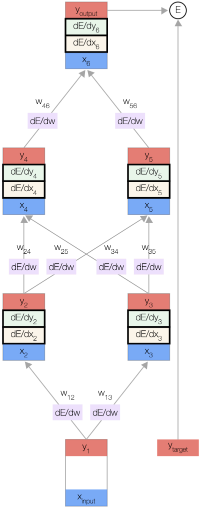
- If you recall, this means applying the formula of each neuron: $N(\mathbf{x}) = a(\sum_0^n \mathbf{x}_i w_i + b)$



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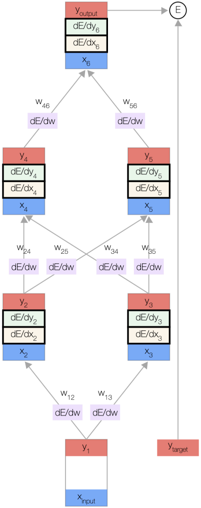
- The first step to backpropagation is in fact forward propagation.
- If you recall, this means applying the formula of each neuron: $N(\mathbf{x}) = a(\sum_0^n \mathbf{x}_i w_i + b)$
- Then we feed that value into all of the next neurons and repeat!



Backpropagation Explained

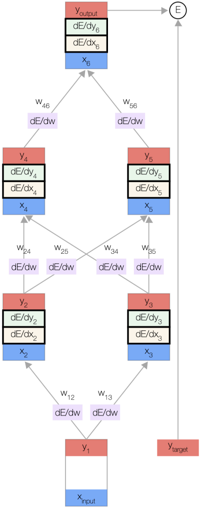
Now, we want to calculate the derivative of the error with respect to each specific weight. We will do this by first defining the function for error:

$$E = \frac{1}{2}(y_{output} - y_{target})^2$$

We can then take the derivative of the error yielding:

$$\frac{\partial E}{\partial y_{output}} = y_{output} - y_{target}$$

Remember the power rule! From now on we will refer to this as $\frac{\partial E}{\partial y}$.



Backpropagation Explained

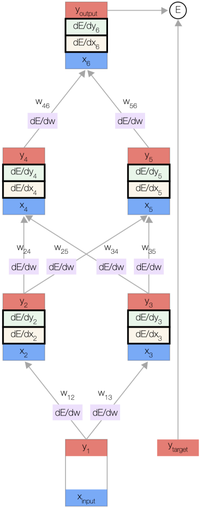
We can now recall the chain rule $\frac{d}{dx}\left[f(g(x))\right] = f'(g(x))g'(x)$ in order to get the derivative of E with respect to x. This would allow us to get closer to the weight because if we recall the equation for a neuron:

$$N(\mathbf{x}) = \sigma(\sum \mathbf{x}_i w_i + b)$$

Therefore, to get $\frac{\partial E}{\partial x}$ we can say:

$$\frac{\partial E}{\partial \mathbf{x}} = \frac{dy}{d\mathbf{x}} \cdot \frac{\partial E}{\partial y}$$

So what function do we pass all the output through for the neuron? (i.e. function for $\frac{dy}{d\mathbf{x}}$)

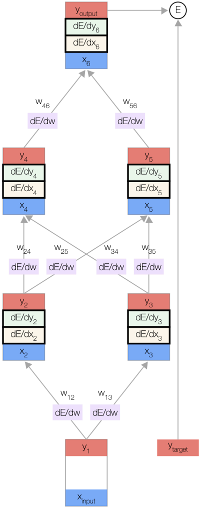


Backpropagation Explained

The activation function! You may have noticed that I replaced a with σ. That is because in this example we are going to assume that the activation function in this layer is a sigmoid function. Thus:

$$\frac{\partial E}{\partial \mathbf{x}} = \frac{dy}{d\mathbf{x}} \cdot \frac{\partial E}{\partial y} = \frac{d\sigma}{d\mathbf{x}} \cdot \frac{\partial E}{\partial y}$$

Bonus: Why did I use sigmoid instead of ReLU for this example?



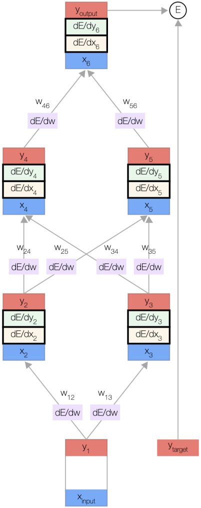
Backpropagation Explained

Now, we have $\frac{\partial E}{\partial \mathbf{x}}$, but we want $\frac{\partial E}{\partial w_{ij}}$. Luckily, we can call on our old friend chain rule to help us out again. Therefore:

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial \mathbf{x}}{\partial w_{ij}} \cdot \frac{\partial E}{\partial \mathbf{x}}$$

But what is $\frac{\partial \mathbf{x}}{\partial w_{ij}}$? Well lets recall that the neuron with respect to the inside (ignoring the activation function since we are using the chain rule) is just $(\sum \mathbf{x}_i \cdot w_i) + b$. Therefore, removing the *constant* b:

$$\frac{\partial \mathbf{x}}{\partial w_{ij}} = \frac{\partial}{\partial w_{ij}} \left(\sum \mathbf{x}_i w_i\right) = \mathbf{x}$$



Backpropagation Explained

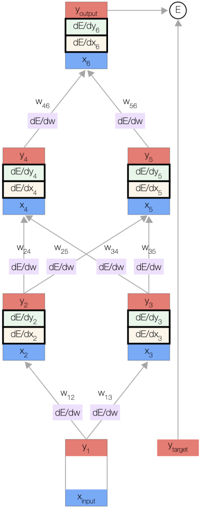
Thus,

$$\frac{\partial E}{\partial w_{ij}} = \mathbf{x}\frac{\partial E}{\partial \mathbf{x}}$$

We can now get the derivative of the error with respect to the previous output (and then we can repeat!)

$$\frac{\partial E}{\partial y^{(L-1)}} = \sum \frac{\partial \mathbf{x}_i}{\partial y_i} \cdot \frac{\partial E}{\partial \mathbf{x}_j} = \sum w_{ij} \frac{\partial E}{\partial \mathbf{x}_j}$$

The gradient for the biases are calculated similarly.

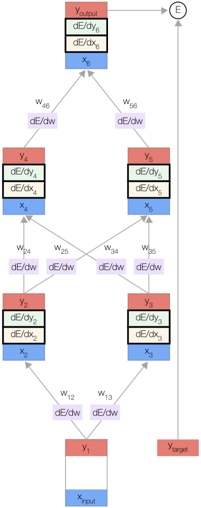


Backpropagation Summary

If we combine all the work from previous slides, we get:

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial y} \cdot \frac{\partial y}{\partial \mathbf{x}} \cdot \frac{\partial \mathbf{x}}{\partial w_{ij}}$$

Don't worry if this seems confusing. Backpropagation is one of the hardest parts of machine learning.



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- The final value(s) in the output layer then constitutes the prediction
- **Backpropagation** then updates all of the weights based on **loss** (often MSE) which is known as **Stochastic Gradient Descent**.

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- The example code we are going to work with is going to be in python.
- If you are not familiar with python, or any other programming language, this portion may be a little hard to follow but I will try to do my best to make this understandable.

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- You can also find and modify this notebook here: `https://github.com/Owen-Oertell/introToMLConcretePrediction`.

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- When you need to read the csv, you will want to put in the URL for the data here: `https://bit.ly/3AJE02X`.

1. What is ML?
2. Types of ML Algorithms
3. Core Concepts of ML
4. Neural Nets
5. Backpropagation
6. Example
7. Conclusion

Going Forward: What I Didn't Cover

- ML is a vast field and today we didn't even come close to scratching the surface. So, where next? (not in order)
  - Techniques for preventing overfitting.
  - Feature crossing for weirder non-linear data.
  - Encoding of Qualitative data (One-Hot Vectors)
  - Classification
  - Regularization
  - Convolutional Neural Networks (CNNs)
  - Optimization
  - Reinforcement Learning
  - Anomaly Detection

Where to start learning more? Check out the Machine Learning Crash Course by Google. It contains what was covered in this presentation and much more!

FIN.