# Chen Data Science & AI for Neuroscience Summer School

TIANQIAO & CHRISSY CHEN INSTITUTE

Caltech

# Introduction to Machine Learning

Sabera Talukder

# What is machine learning?

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*Deep learning is when the model you use to solve your task is a deep neural network.

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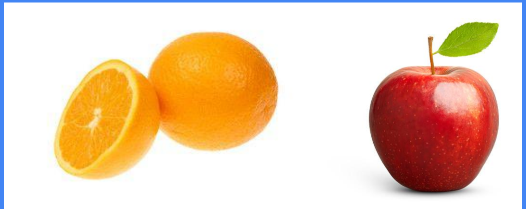
## Classification



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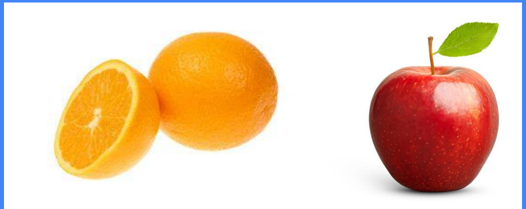

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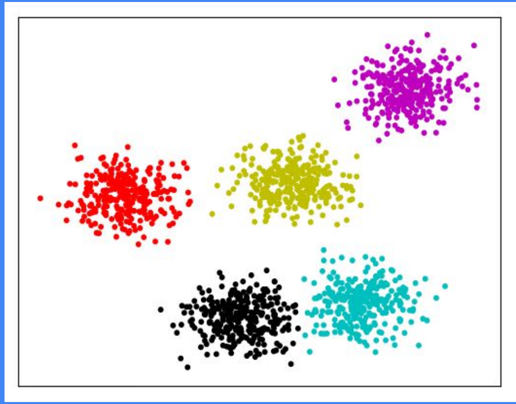

What signals in my dataset are similar or different?

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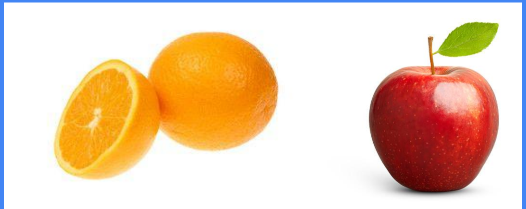

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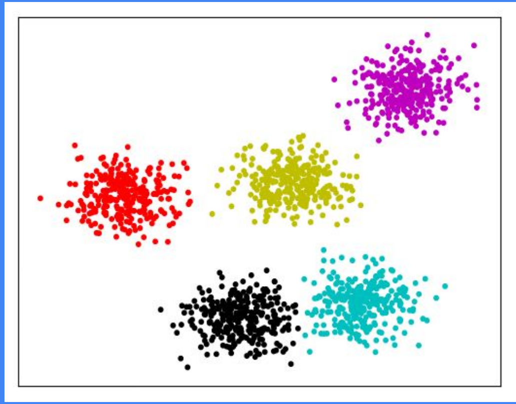

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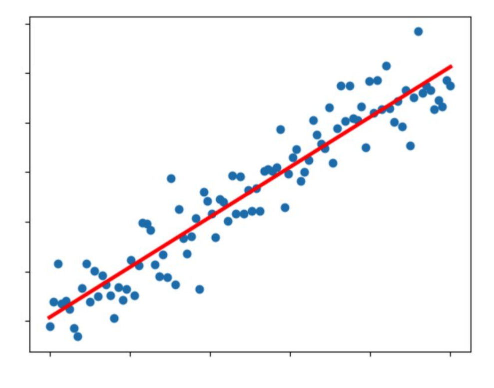
## Regression



What function describes the relationship between a house’s price and square footage?

# Previous Topics

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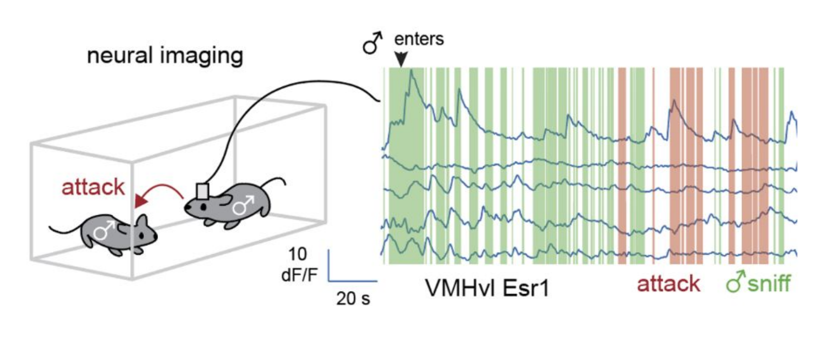
- Can we predict mouse attack behavior from linear combinations of neuron values?



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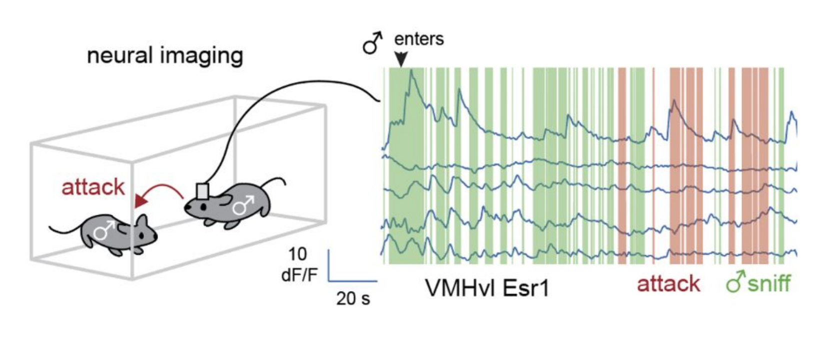

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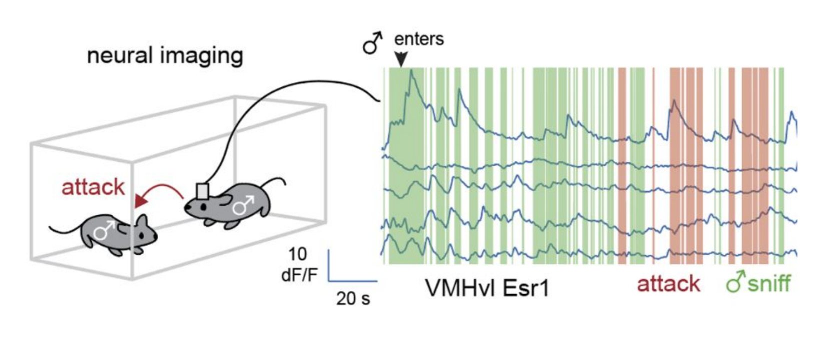
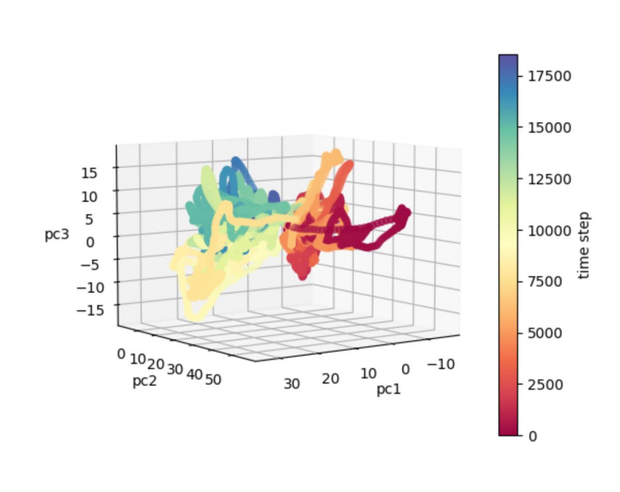



- Can we use principal components analysis to learn a “simple” yet rich representation of high-dimensional neural time-series data?



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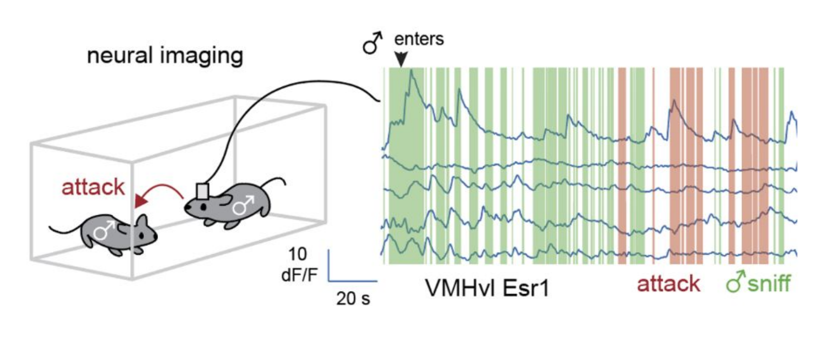
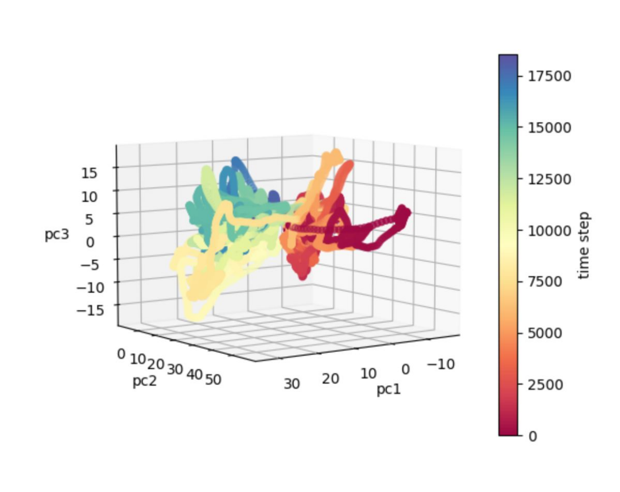



- Can we use principal components analysis to learn a “simple” yet rich representation of high-dimensional neural time-series data? (unsupervised representation learning)



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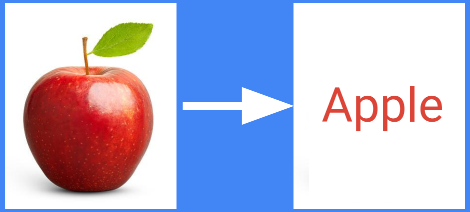


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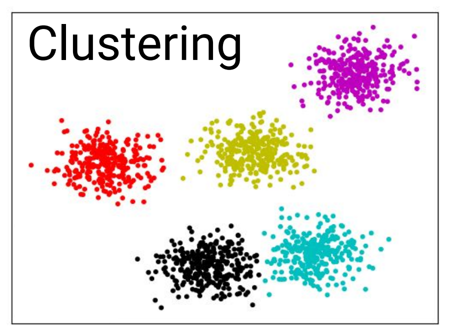

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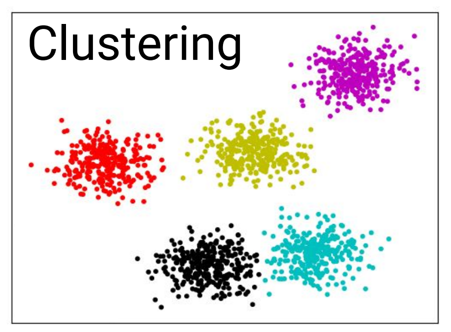


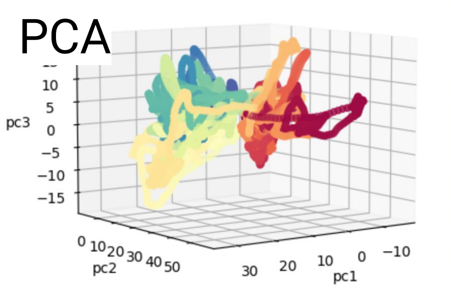

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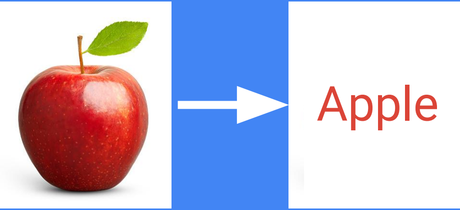


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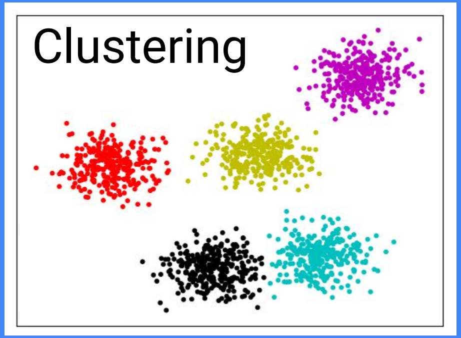


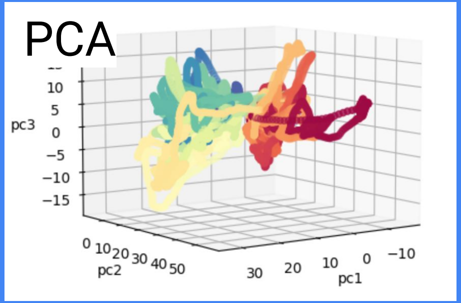


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Learn patterns from the data using the data itself as a label.

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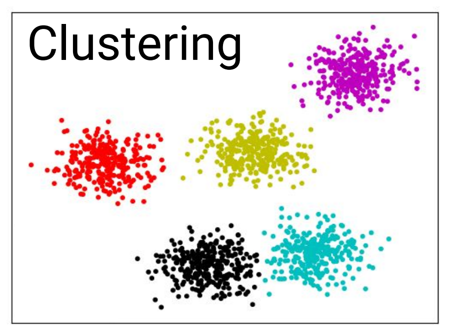


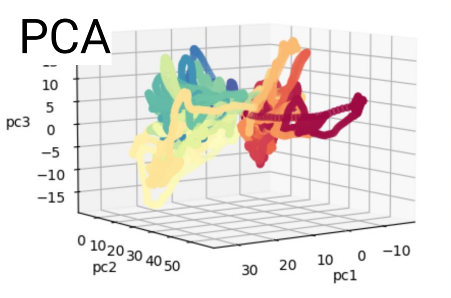


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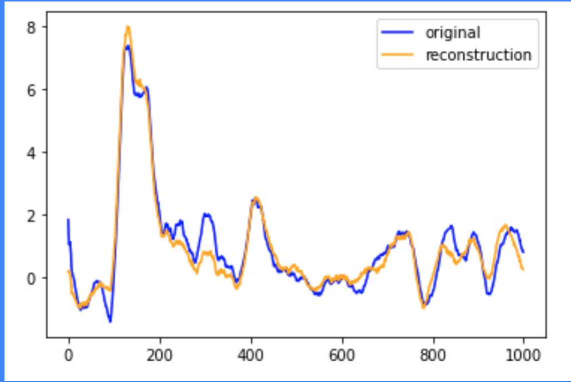

All of the learning paradigms utilize features in the data to accomplish their task.

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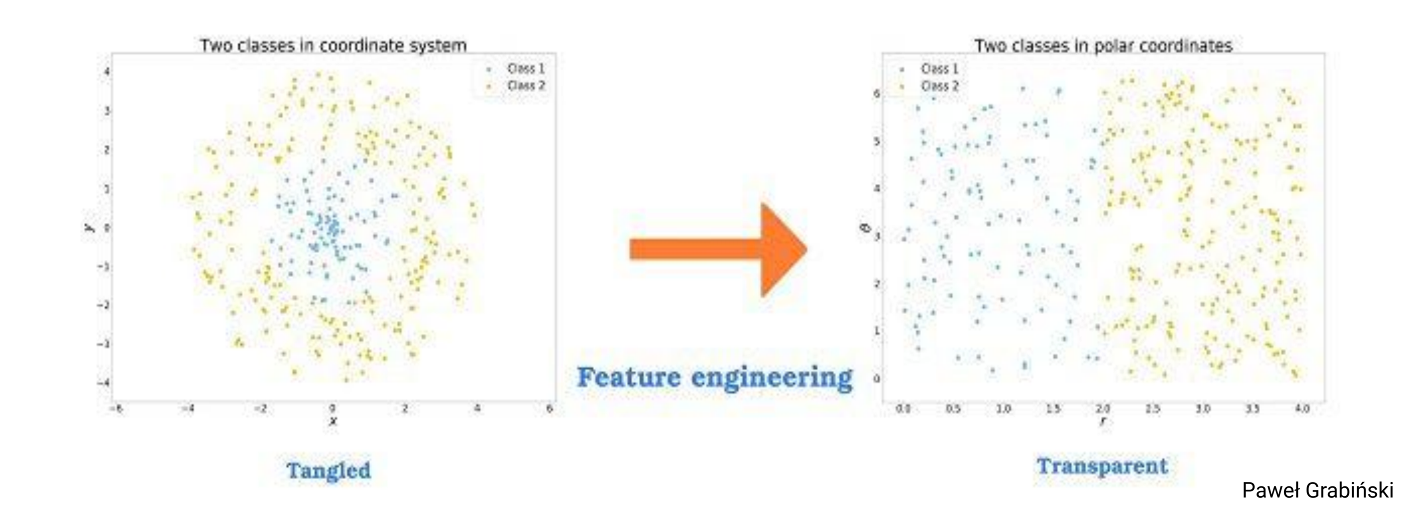


Paweł Grabiński

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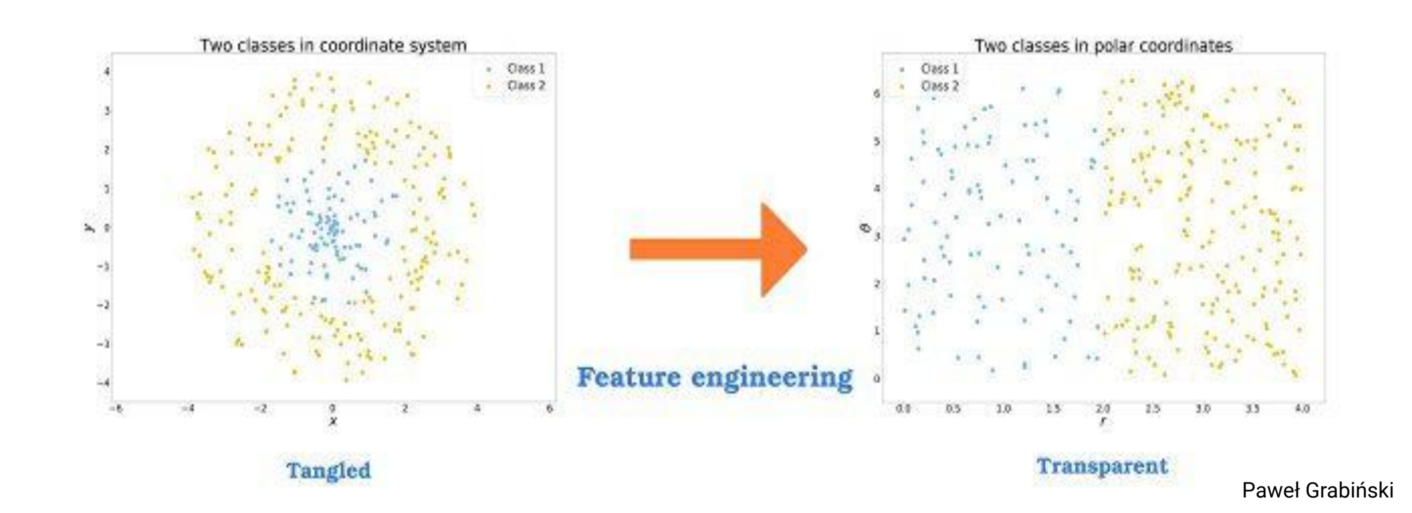


Other times we let our algorithms learn the important features in our data (aka representation learning).

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Ideally your representation is useful for solving many tasks & interpretable (can be very challenging).

Now that we know a little bit more about types of learning & data representations, the let’s jump into the components of learning!

# Example: Supervised Learning

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$$\boxed{\{x_i, y_i\}_{i=1}^{N}}$$

Data

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$$\boxed{\{x_i, y_i\}_{i=1}^{N}} \longrightarrow \boxed{\hat{y} = f_\theta(x)}$$

Data Model

# Example: Supervised Learning

$$\boxed{\{x_i, y_i\}_{i=1}^{N}} \longrightarrow \boxed{\hat{y} = f_\theta(x)} \longrightarrow \boxed{\ell = \mathcal{L}(y, \hat{y})}$$

Data | Model | Loss

# Example: Supervised Learning

$$\underbrace{\boxed{\{x_i, y_i\}_{i=1}^N}}_{\text{Data}} \longrightarrow \underbrace{\boxed{\hat{y} = f_\theta(x)}}_{\text{Model}} \longrightarrow \underbrace{\boxed{\ell = \mathcal{L}(y, \hat{y})}}_{\text{Loss}}$$

Use loss to update
model parameters
$\theta$ ("learning")

# A little bit more on models!

# Models are successful when they exploit domain knowledge in the data

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Convolutional Neural Networks → Images

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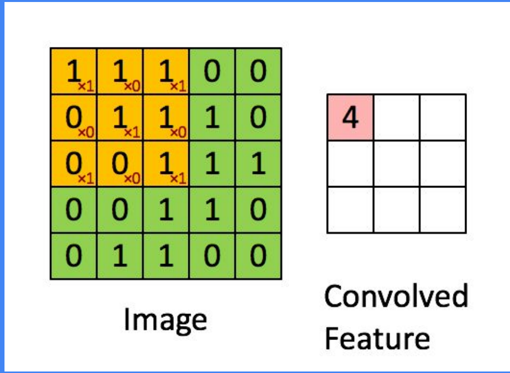

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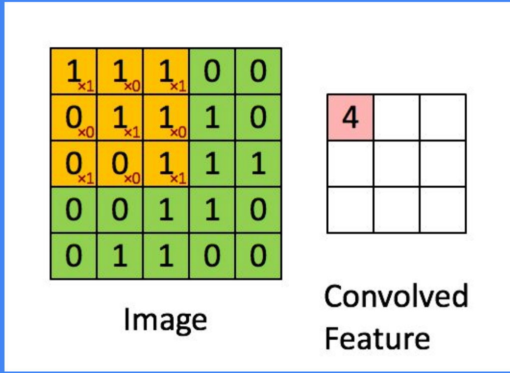


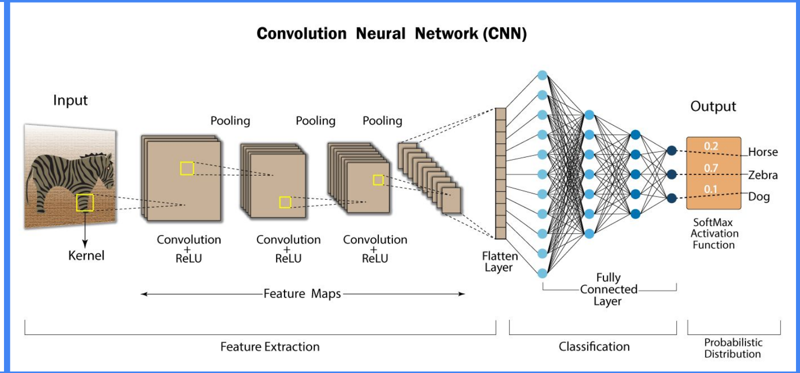

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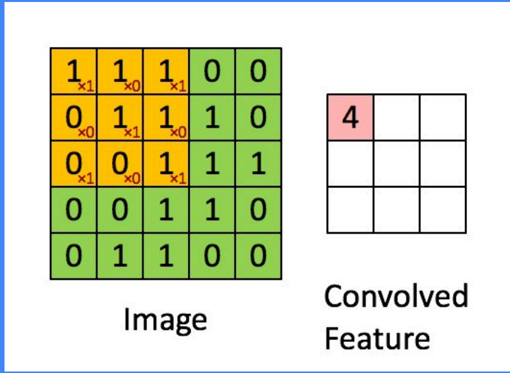


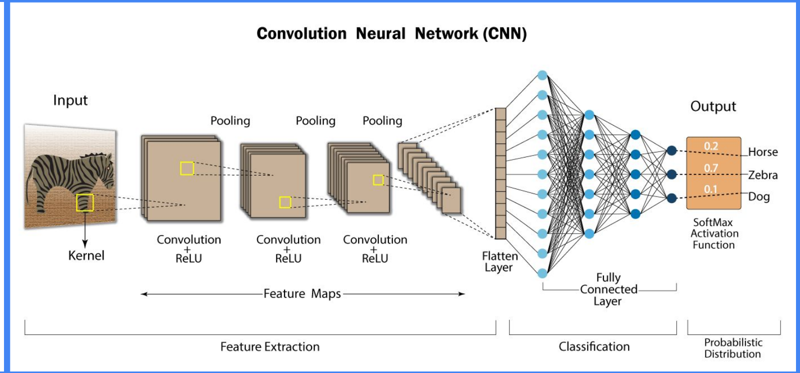


## Recurrent Neural Networks → Sequences

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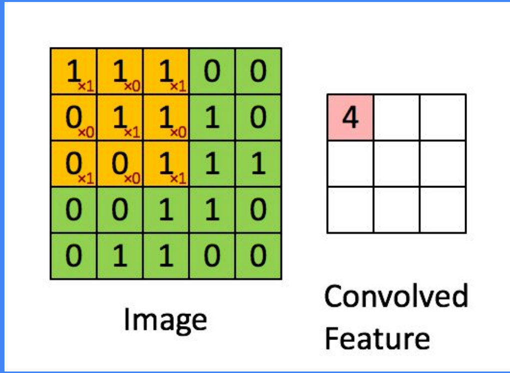


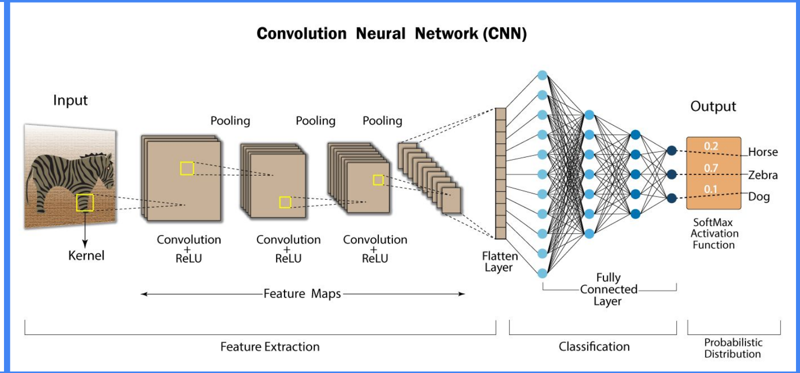


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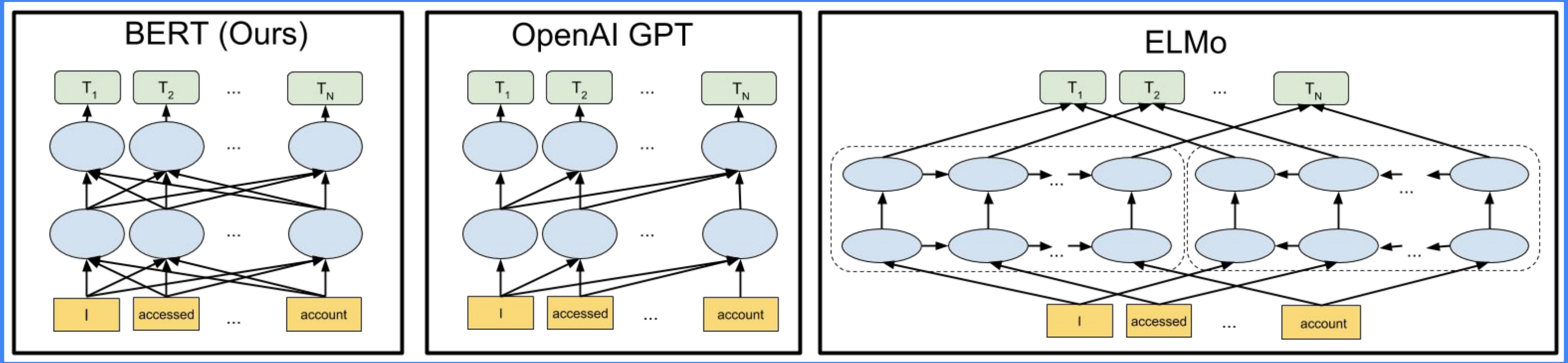

What are some examples of neuroscience domain knowledge that we could bake into our models?

# A little bit more on losses (with an example)!

We’re going to explore losses in the context of *parametric models* (models where all information is represented within its parameters).

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Q: For fixed data, what are the best parameters to explain the data?

# Ex: 3-Parameter Sinusoidal Model

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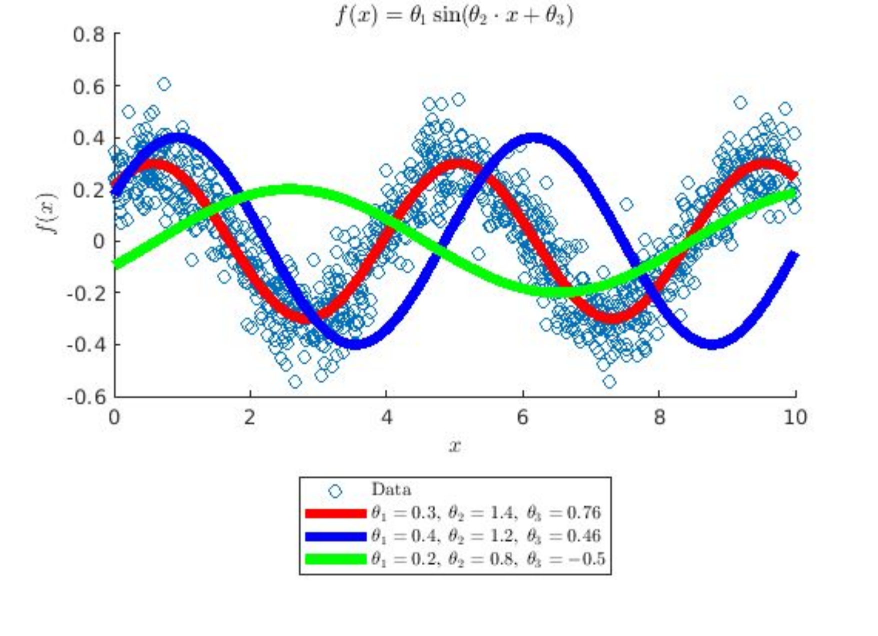


The data are the blue dots. We generated them by sampling from the red line and adding noise.

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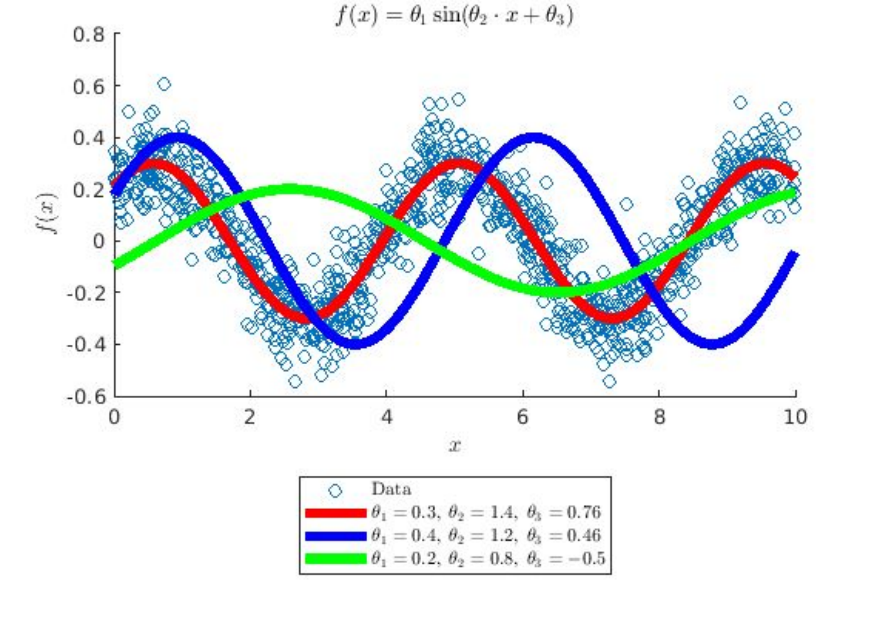


The data stays fixed, "learning" this model means picking the three parameter values.

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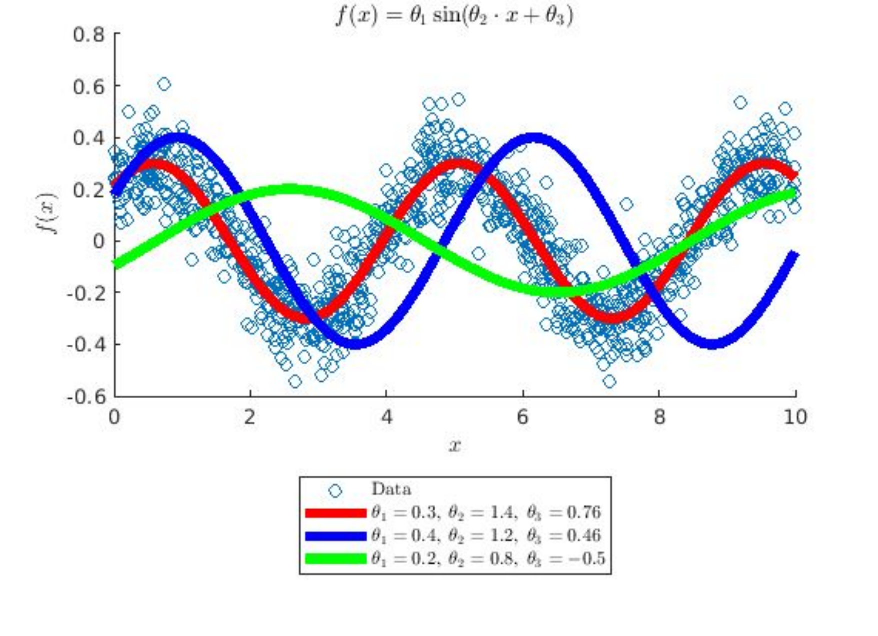


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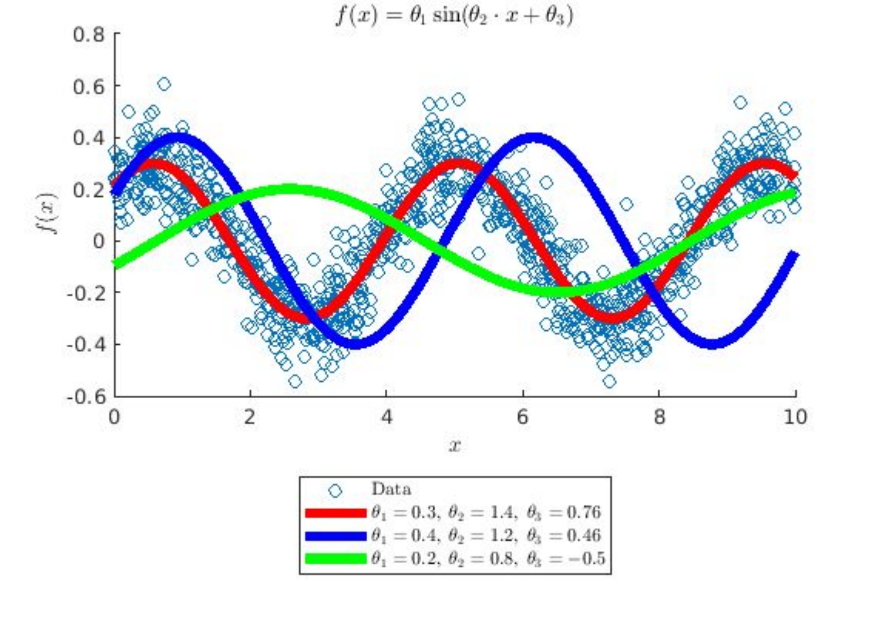


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Q: How do we pick them?
A: Gradient descent.

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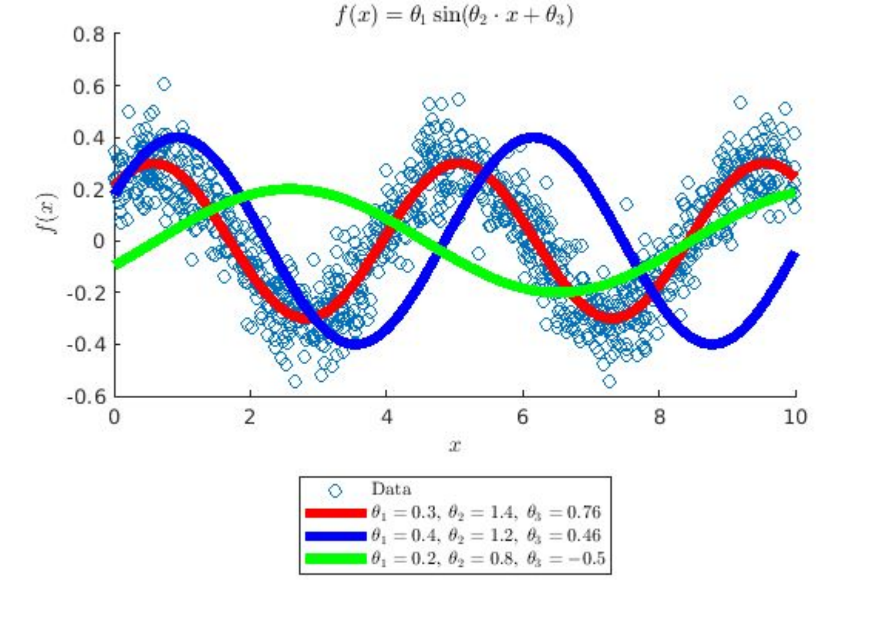


Loss Values (MSE)

$$\ell = \frac{1}{N} \sum_{i=1}^{N} \|y_i - f_\theta(x_i)\|^2$$

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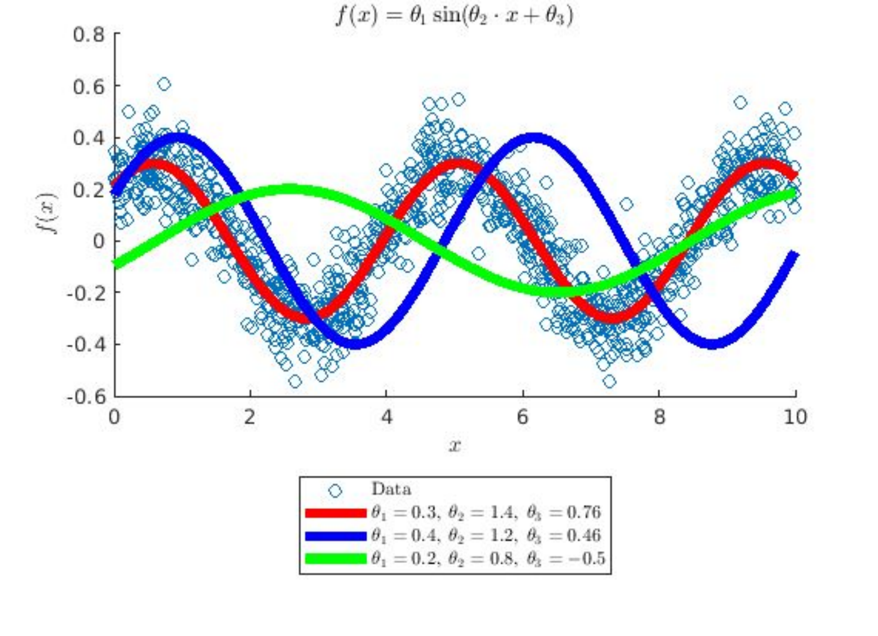


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$$\ell_1 = 0.01$$

$$\ell_2 = 0.11$$

$$\ell_3 = 0.08$$

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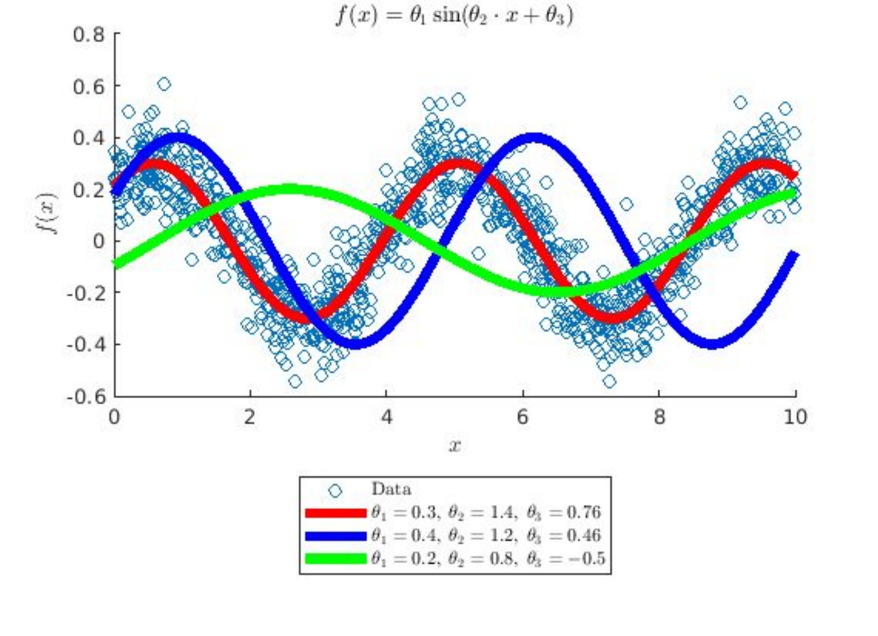



## Loss Gradient Values

$$\nabla_\theta \ell = \frac{1}{N} \sum_{i=1}^{N} -2(y_i - f_\theta(x_i)) \begin{bmatrix} \sin(\theta_2 \cdot x_i + \theta_3) \\ \theta_1 \cdot x_i \cdot \cos(\theta_2 \cdot x_i + \theta_3) \\ \theta_1 \cdot \cos(\theta_2 \cdot x_i + \theta_3) \end{bmatrix}$$

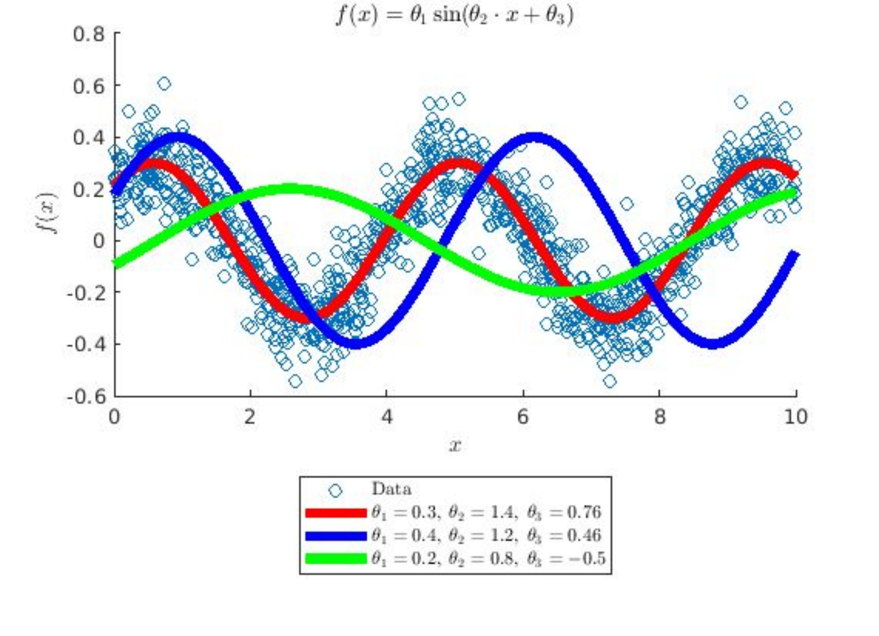
$$\nabla_\theta \ell_1 = \begin{bmatrix} -0.0033 \\ 0.0074 \\ 0.0016 \end{bmatrix}$$

$$\nabla_\theta \ell_2 = \begin{bmatrix} 0.33 \\ -0.66 \\ -0.11 \end{bmatrix}$$

$$\nabla_\theta \ell_3 = \begin{bmatrix} 0.19 \\ 0.049 \\ -0.0004 \end{bmatrix}$$

Element i of the gradient vector is how much the loss changes when changing θi

# Takeaway 1: Gradient values for red model are very small, because it's good!

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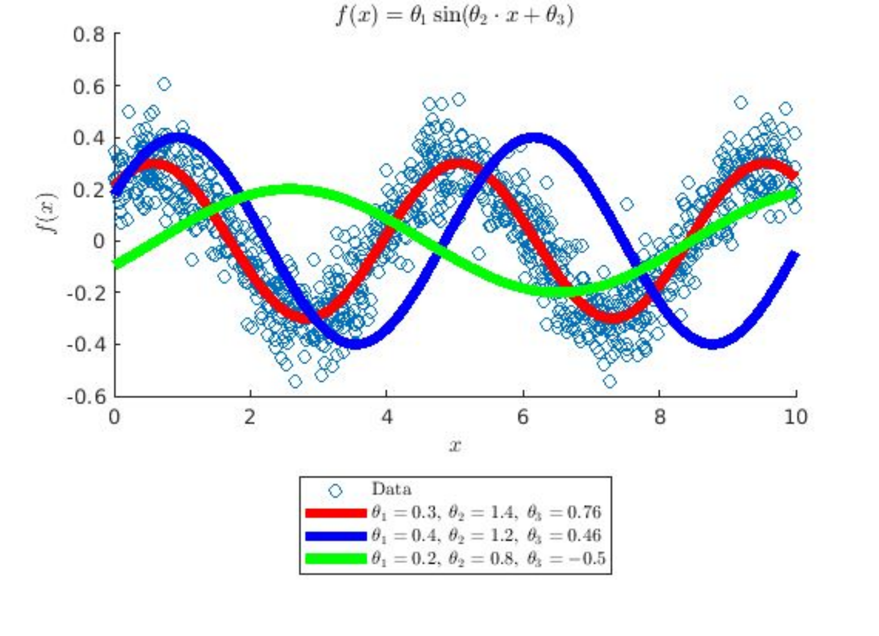
# Takeaway 2: Blue and Green models are bad, so the loss changes a lot when we perturb the parameter values.

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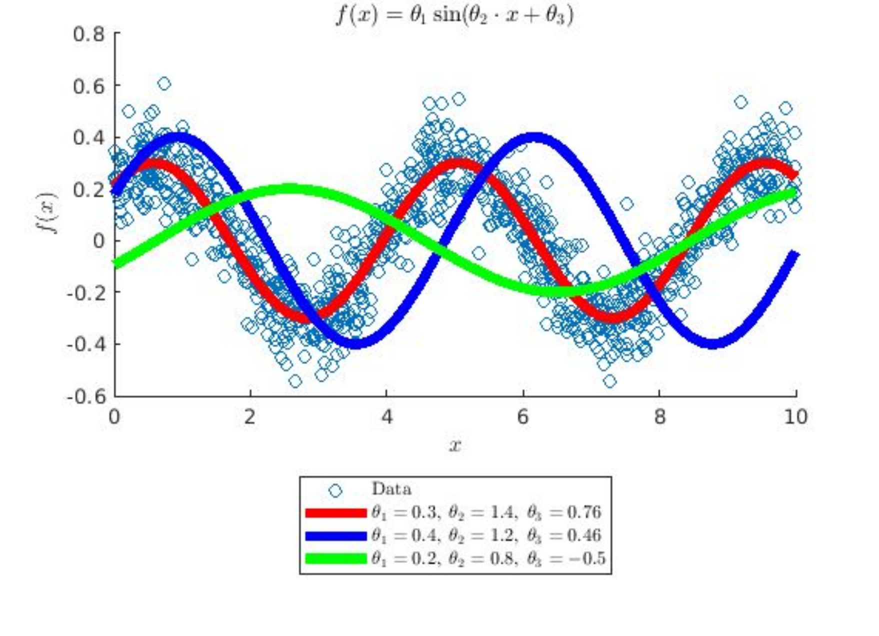
Takeaway 3: Gradient information is LOCAL. The third element of the green gradient is very small but that doesn't mean the parameter values are good. It just means that with the current parameters values, changing θ3 slightly isn't really going to change the loss that much.

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The model family we choose is important! No linear model would ever fit the data well in this regression problem.

We must choose a sufficiently expressive parametric family.

Gradient Descent is the easiest way to optimize our learning objective.

It is a method that changes the weights of your model so you can approach a local minimum.