CS 1671 / CS 2071 / ISSP 2071
Human Language Technologies

Session 13: Neural networks part 1, project peer group feedback

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Assessments

- Project proposal is due **this Fri Feb 27**
- Homework 2 is due Mar 17
    - Implement a logistic regression classifier to detect if someone is lying in the 'Diplomacy' game

Midterm OMET feedback: what helps learning

6 responses out of 52 students (11.5%)

- Varied activities in class
  - Top Hat
  - Examples in slides
  - In-class coding examples
- Homework

Midterm OMET feedback: what could be improved

- In-class coding examples
  - Hands-on coding instead of walkthroughs
  - More assistance with Python concepts
  - Too much content in class, though good to look back on
  - More notebooks
  - ***Change: Working through code with classmates + walkthrough***
- Quizzes are weighted too much
  - ***Change: Adding an extra credit quiz***
- Recording lectures so can process the content later on
  - ***Change: Will record lectures on Zoom, make them available***
- More application examples

Learning objectives: neural networks part 1, project peer group feedback

- Explain the **fundamental parts of neural networks**
- Describe **non-linear activation functions**
- Explain how **feedforward neural networks can act as classifiers**
- Project peer group feedback

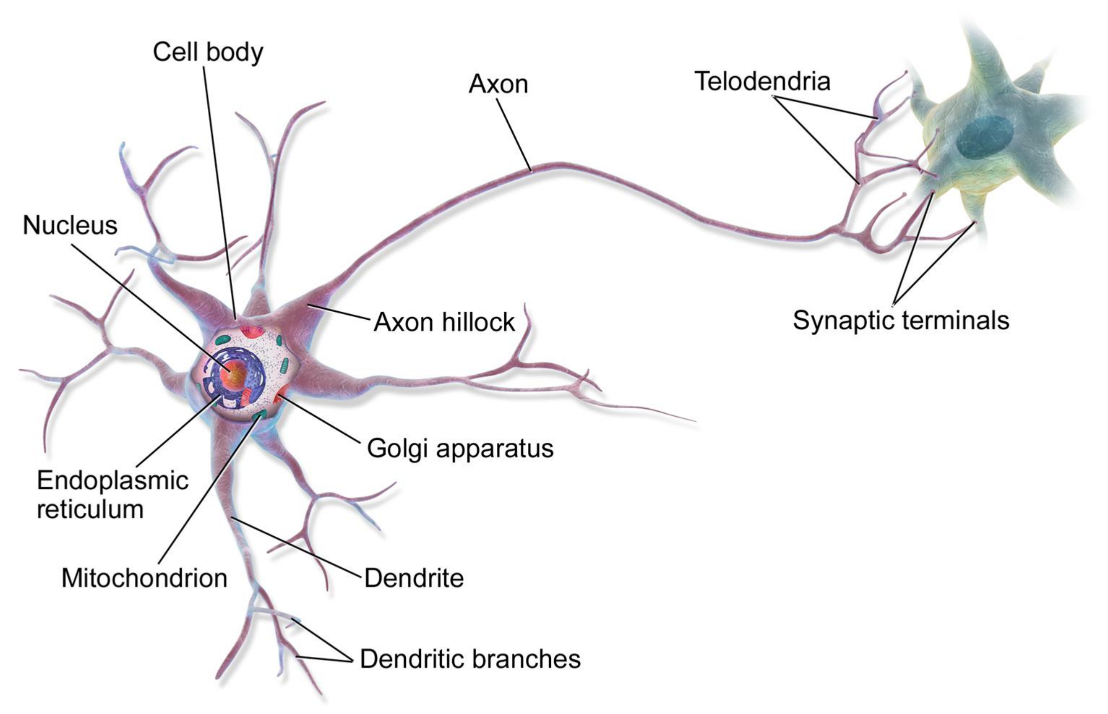
Why neural networks?

- Powerful classifiers for supervised learning
- At the heart of state-of-the-art machine learning systems in computer vision and NLP
- Large language models, search engines, speech recognition, ad and content recommendation systems

Pittsburgh Business Times

Neural network fundamentals

This is in your brain



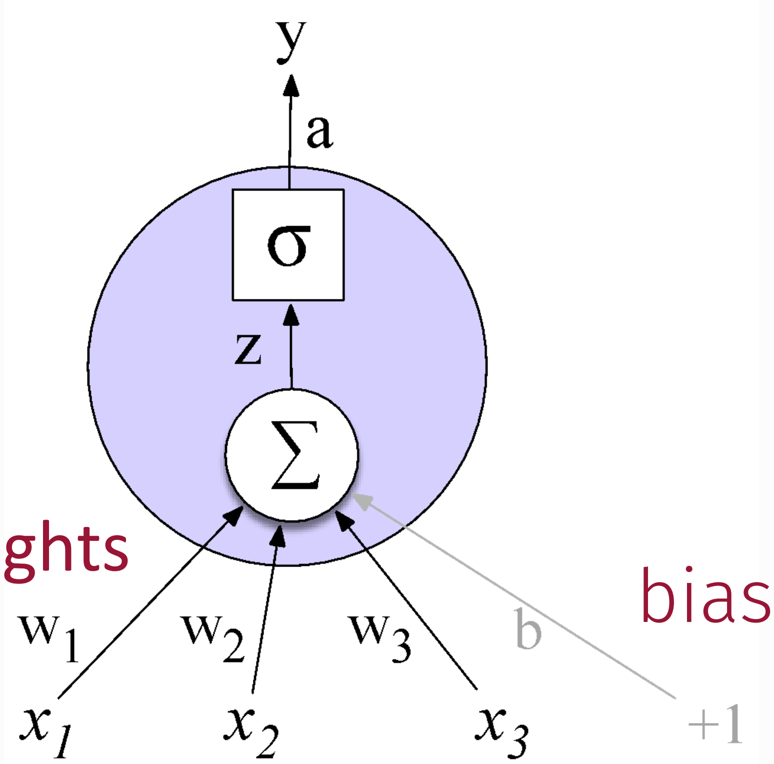
Neural network unit: This is not in your brain

Output value

Non-linear transform

Weighted sum

Input layer



The Variables in Our Very Important Formula

- $\mathbf{x}$ A vector of features of n dimensions (like number of positive sentiment words, length of document, etc.)
- $\mathbf{w}$ A vector of weights of n dimensions specifying how discriminative each feature is
- b A scalar bias term that shifts z
- z The raw score
- y A random variable (e.g., $y = 1$ means positive sentiment and $y = 0$ means negative sentiment

Slide adapted from David Mortensen

The Fundamentals

The fundamental equation that describes a unit of a neural network should look very familiar:

$$z = b + \sum_i w_i x_i \tag{1}$$

Which we will represent as

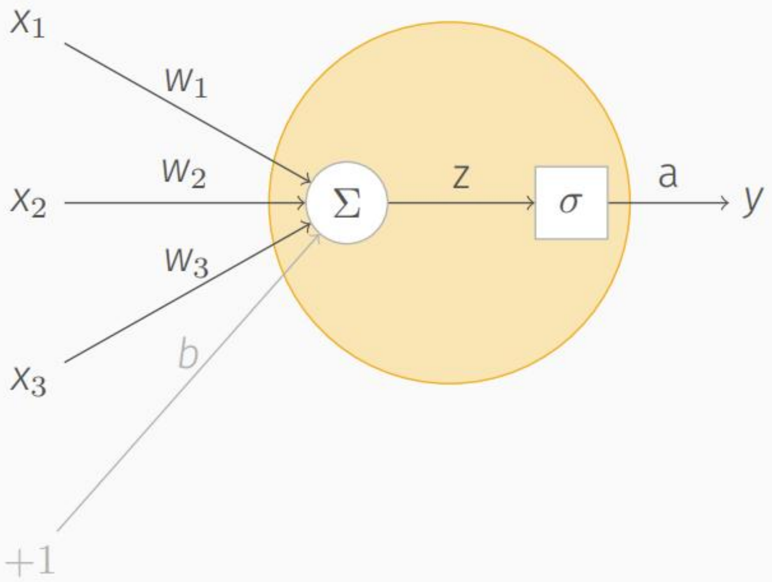
$$z = \mathbf{w} \cdot \mathbf{x} + b \tag{2}$$

But we do not use z directly. Instead, we pass it through a non-linear function, like the sigmoid function:

$$y = \sigma(z) = \frac{1}{1 + e^{-z}} \tag{3}$$

(which has some nice properties even though, in practice, we will prefer other functions like tanh and ReLU).

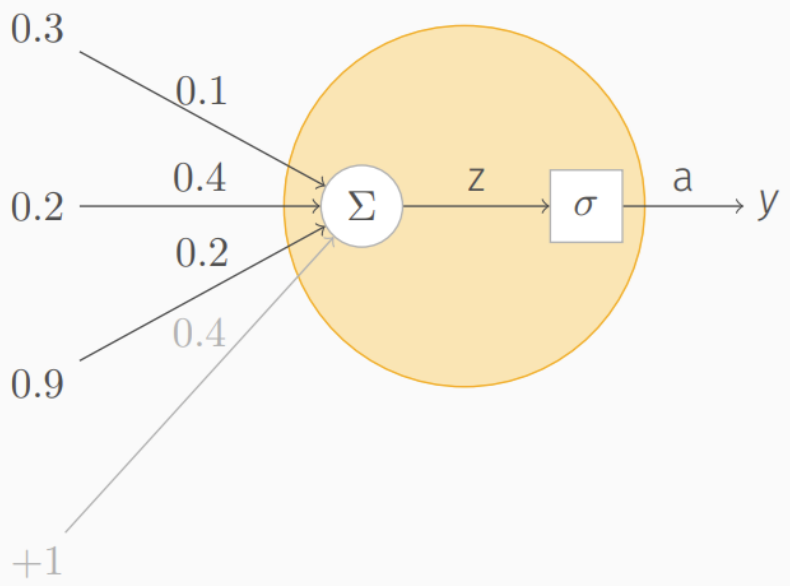
A Unit Illustrated



Take, for example, a scenario in which our unit has the weights [0.1, 0.4, 0.2] and the bias term 0.4 and the input vector x has the values [0.3, 0.2, 0.9].

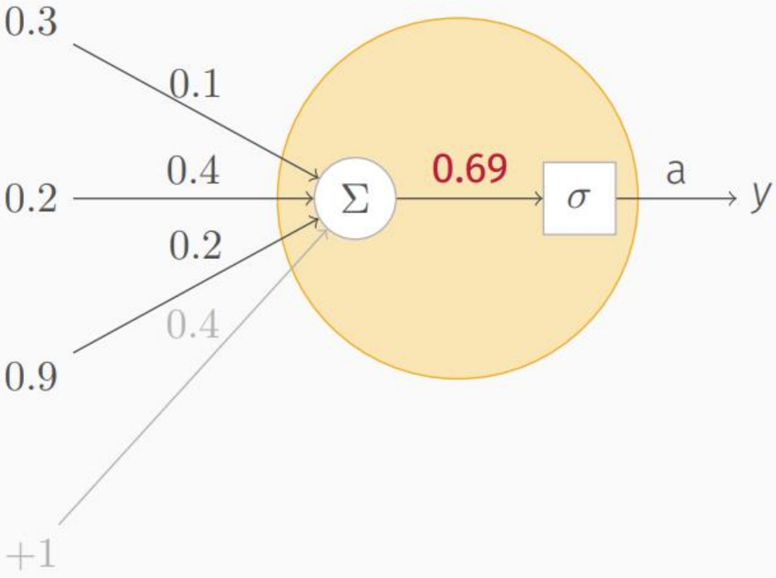
Slide adapted from David Mortensen

Filling in the Input Values and Weights



Slide adapted from David Mortensen

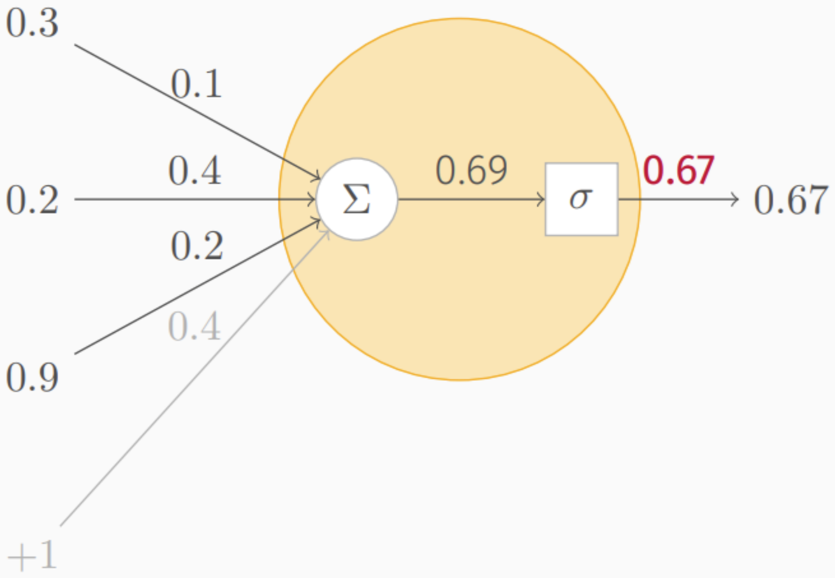
Multiplying the Input Values and Weights and Summing Them (with the Bias Term)



$$z = x_1 w_1 + x_2 w_2 + x_3 w_3 + b = 0.1(0.3) + 0.4(0.2) + 0.2(0.9) + 0.4 = 0.69 \tag{4}$$

Slide adapted from David Mortensen

Applying the Activation Function (Sigmoid)



$$y = \sigma(0.69) = \frac{1}{1 + e^{-0.69}} = 0.67 \qquad (5)$$

Slide adapted from David Mortensen

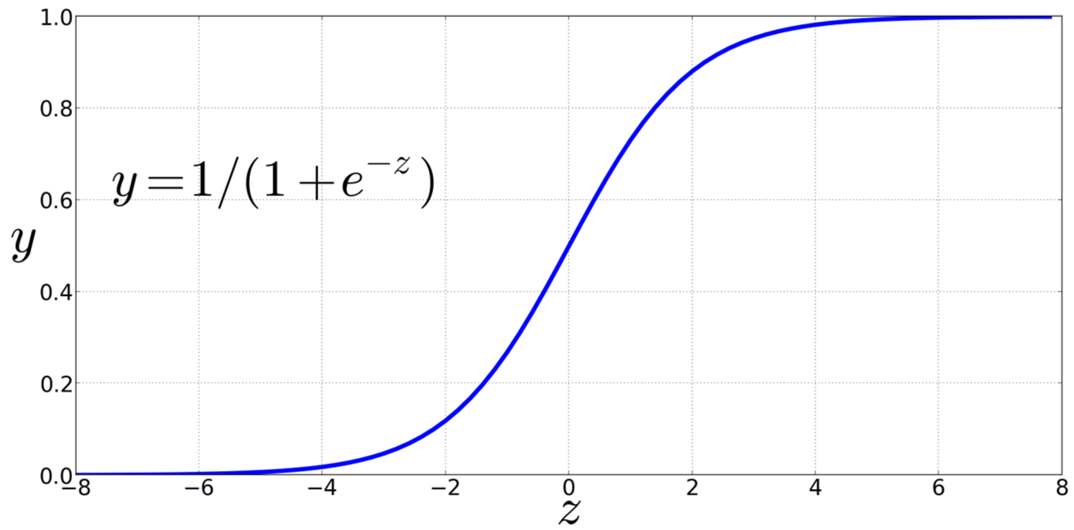
Non-linear activation functions

Non-Linear Activation Functions

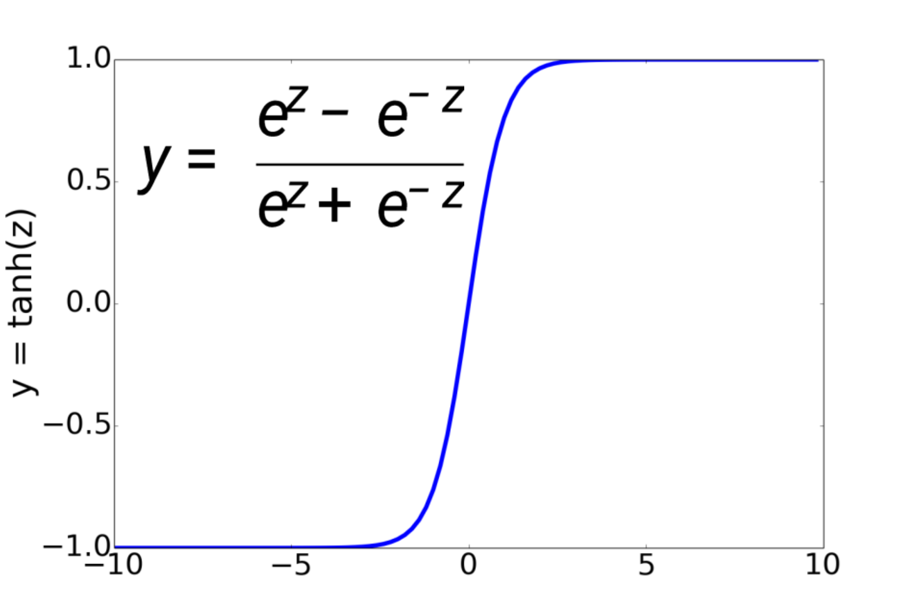
We're already seen the sigmoid for logistic regression:

Sigmoid

$$y = \sigma(z) = \frac{1}{1 + e^{-z}}$$

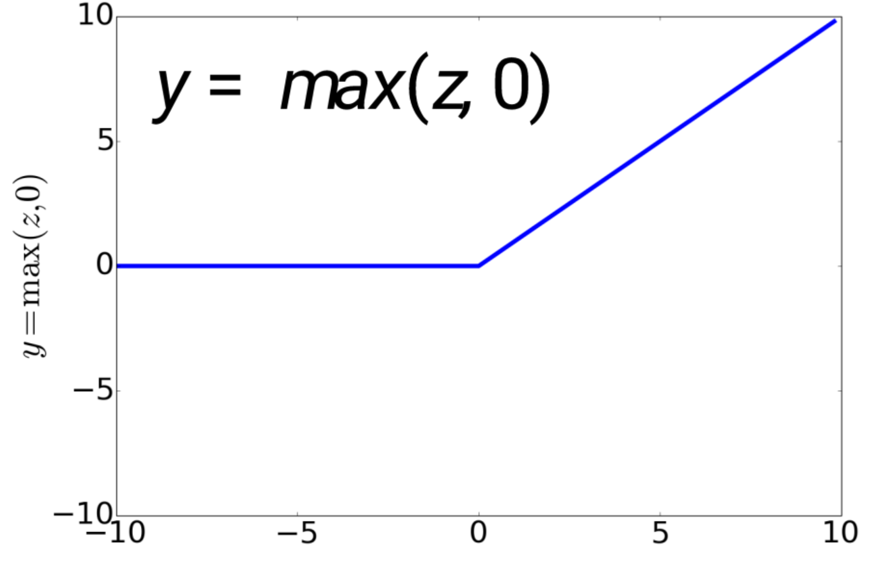


Nonlinear activation functions besides sigmoid



tanh

Most common:



ReLU
Rectified Linear

Slide adapted from Jurafsky & Martin

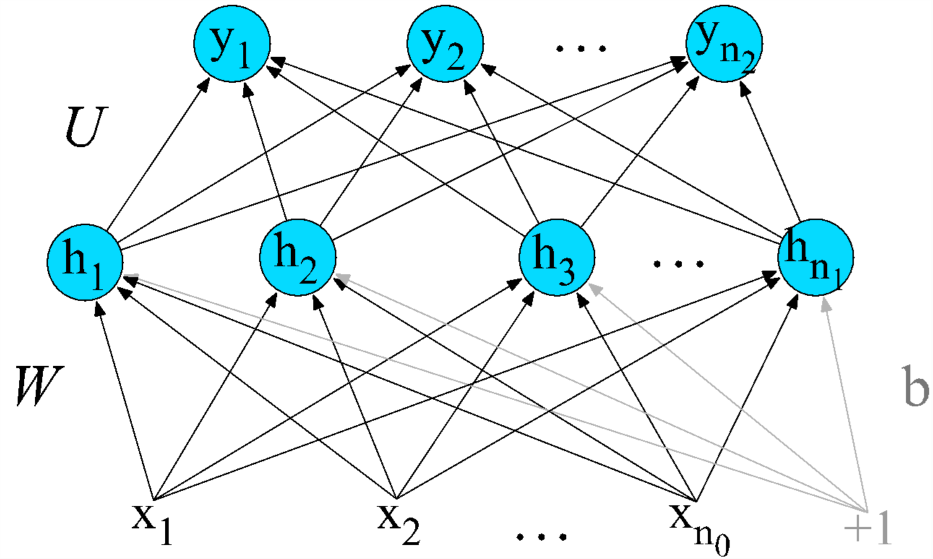
Feedforward neural networks

Adding multiple units to a neural network increases its power to learn patterns in data. **Feedforward Neural Nets (FFNNs or MLPs)**

Slide adapted from David Mortensen

Feedforward Neural Networks

Can also be called **multi-layer perceptrons** (or **MLPs**) for historical reasons



Slide adapted from Jurafsky & Martin

The simplest FFNN is just binary logistic regression (INPUT LAYER = feature vector)

Slide adapted from David Mortensen

Binary Logistic Regression as a 1-layer Network

(we don't count the input layer in counting layers!)

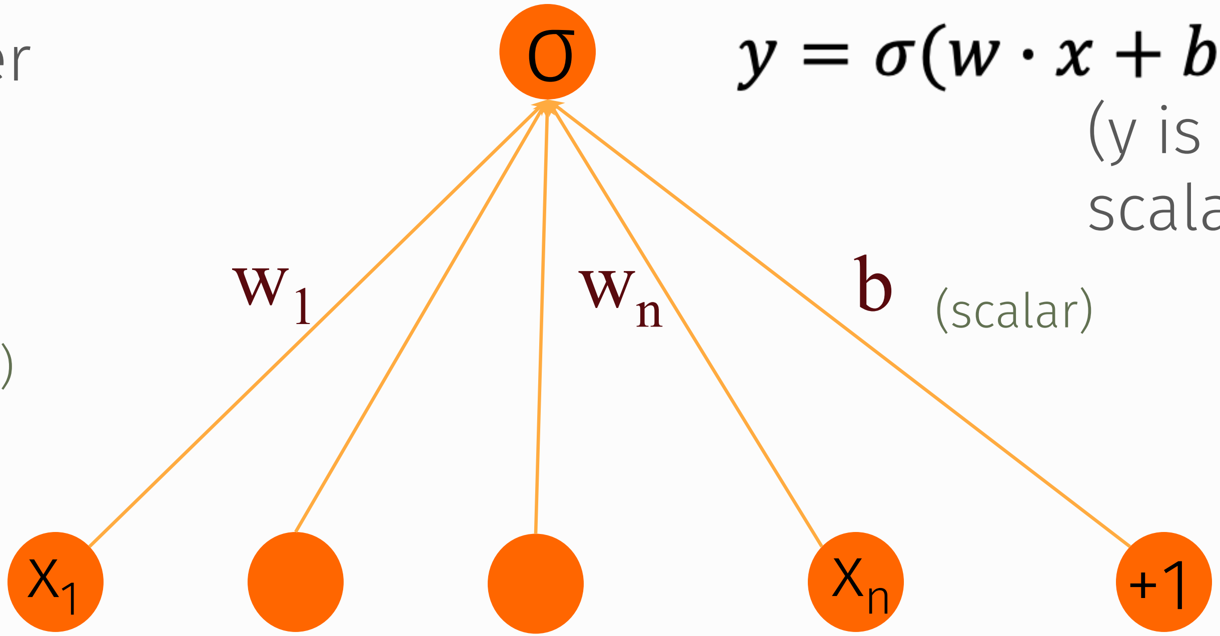
Output layer
(σ node)

$$y = \sigma(w \cdot x + b)$$

(y is a scalar)

w

(vector)



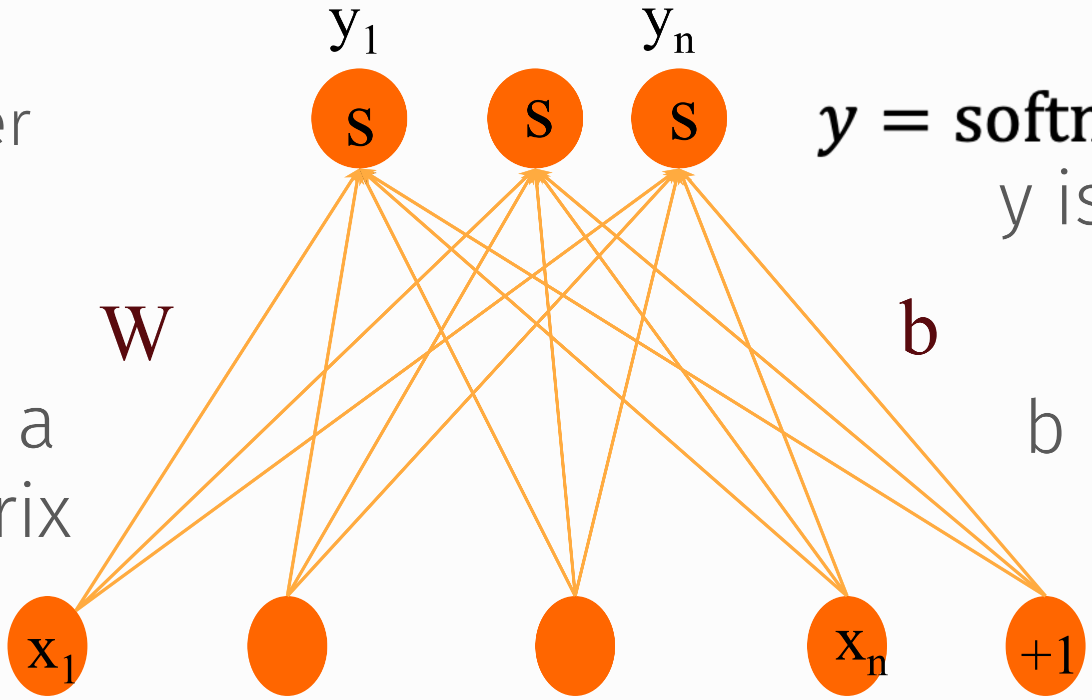
Input layer
vector x

Slide adapted from Jurafsky & Martin

Multinomial Logistic Regression as a 1-layer Network

Fully connected single layer network

Output layer (softmax nodes)



$$y = \text{softmax}(Wx + b)$$

y is a vector

W is a matrix

b is a vector

Input layer scalars

Slide adapted from Jurafsky & Martin

The real power comes when multiple layers are added

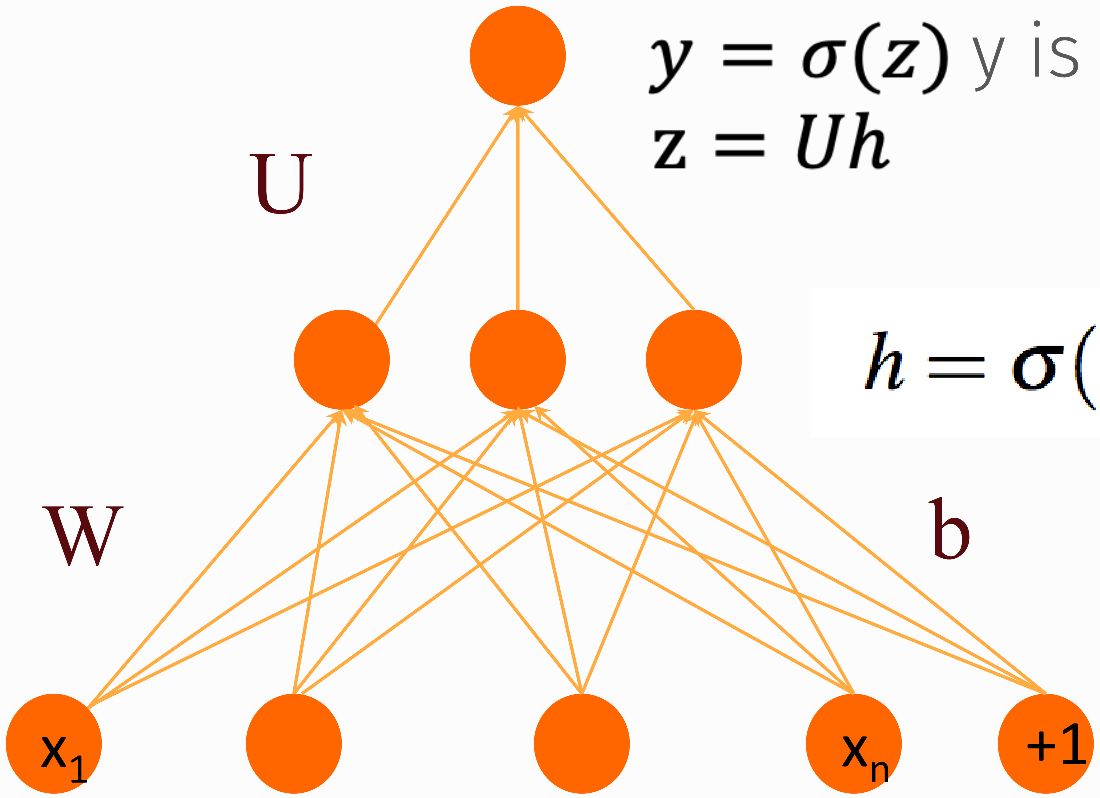
Slide adapted from David Mortensen

Two-Layer Network with scalar output

Output layer
(σ node)

hidden units
(σ node)

Input layer
(vector)



$y = \sigma(z)$ y is a scalar

$z = Uh$

$h = \sigma(Wx + b)$

Could be
ReLU
or tanh

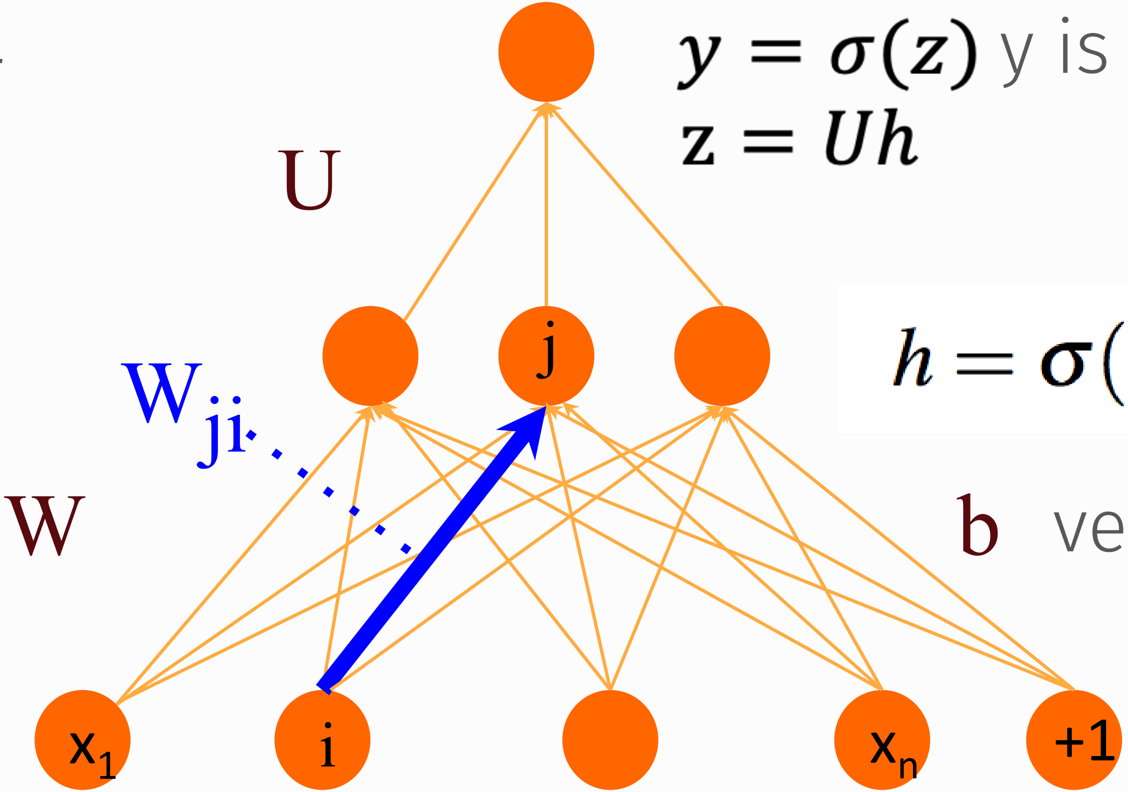
Slide adapted from Jurafsky & Martin

Two-Layer Network with scalar output

Output layer
(σ node)

hidden units
(σ node)

Input layer
(vector)



$y = \sigma(z)$ y is a scalar

$z = Uh$

$h = \sigma(Wx + b)$

b vector

Slide adapted from Jurafsky & Martin

Two-Layer Network with scalar output

Output layer
(σ node)

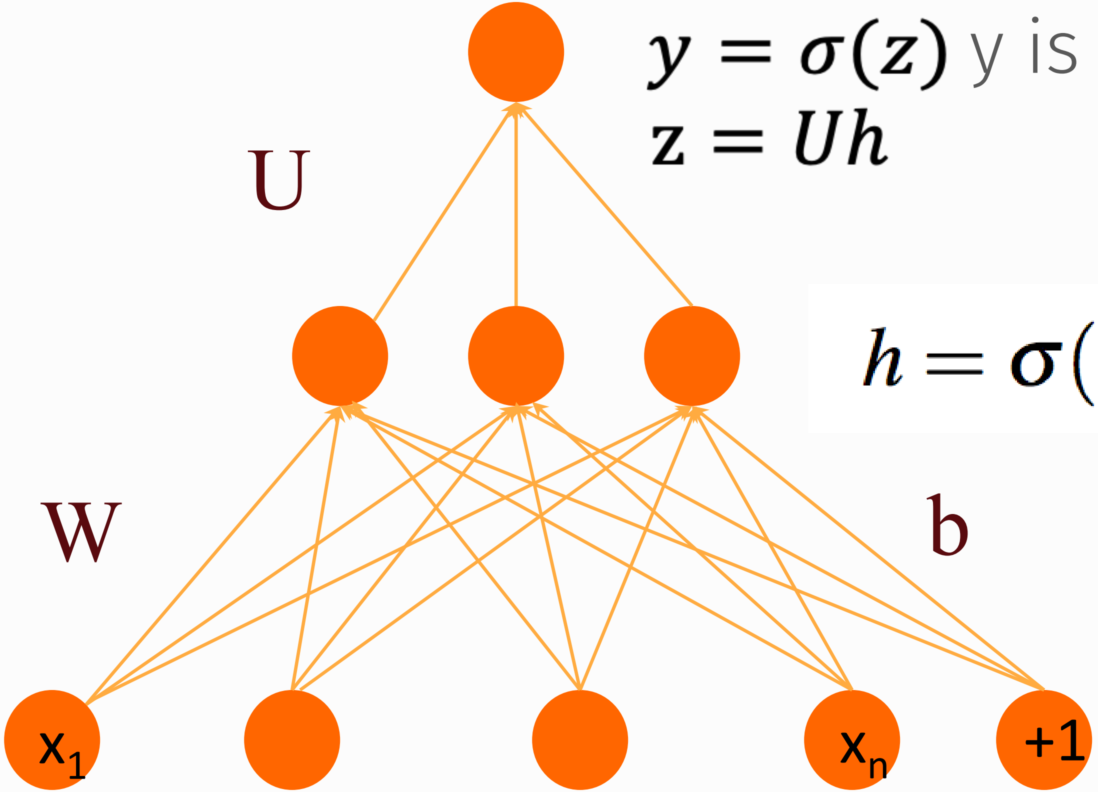
$y = \sigma(z)$ y is a scalar
$z = Uh$

hidden units
(σ node)

$h = \sigma(Wx + b)$

Could be
ReLU
Or tanh

Input layer
(vector)



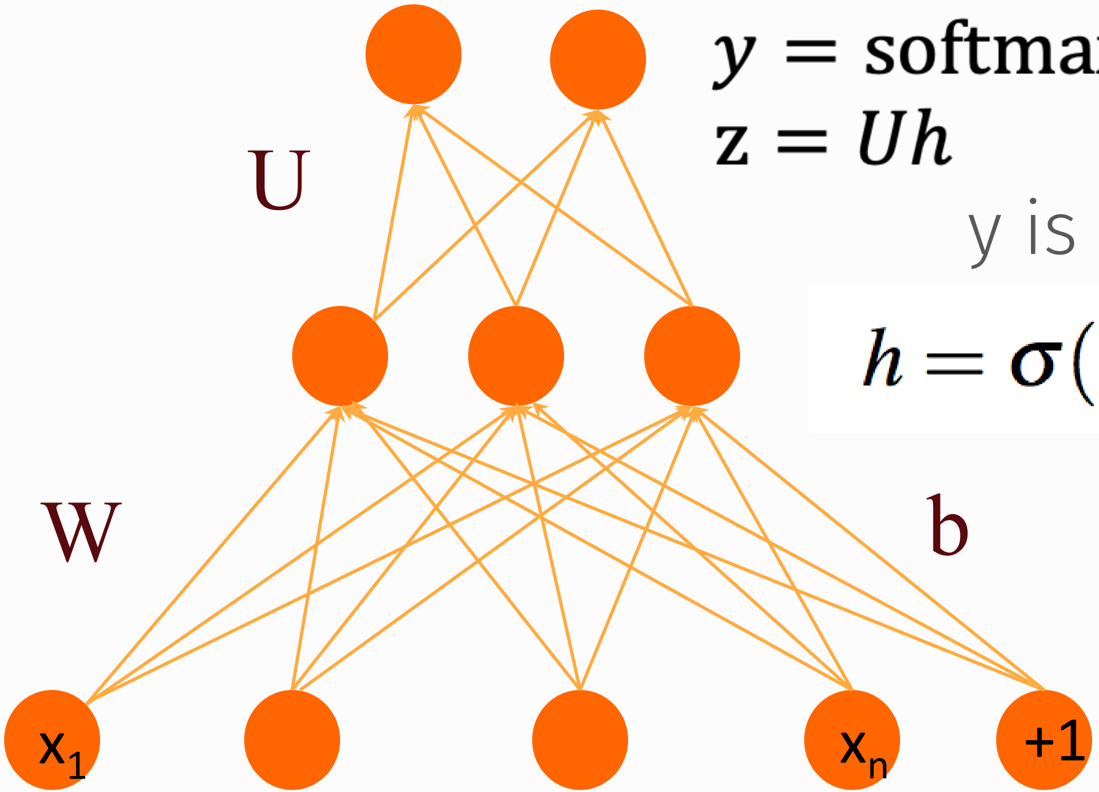
Slide adapted from Jurafsky & Martin

Two-Layer Network with softmax output

Output layer (σ node)

hidden units (σ node)

Input layer (vector)



$$y = \text{softmax}(z)$$
$$z = Uh$$

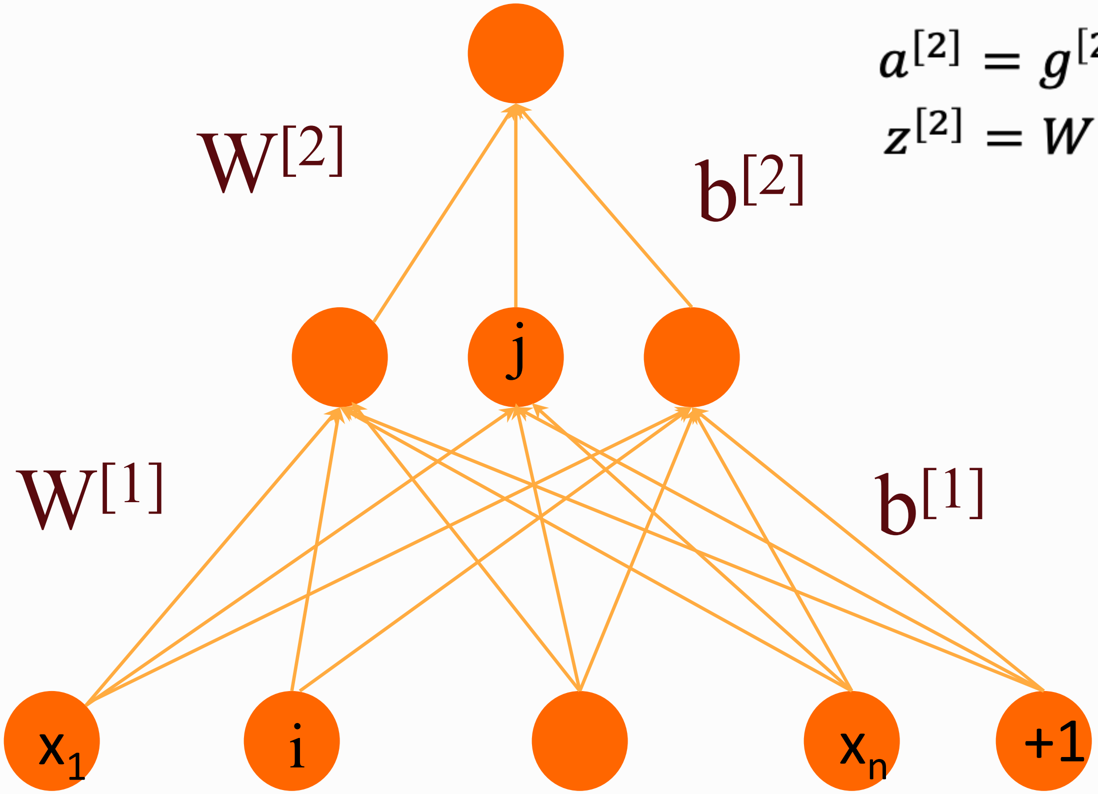
y is a vector

$$h = \sigma(Wx + b)$$

Could be
ReLU
Or tanh

Slide adapted from Jurafsky & Martin

Multi-layer Notation



$y = a^{[2]}$

$a^{[2]} = g^{[2]}(z^{[2]})$ sigmoid or softmax

$z^{[2]} = W^{[2]}a^{[1]} + b^{[2]}$

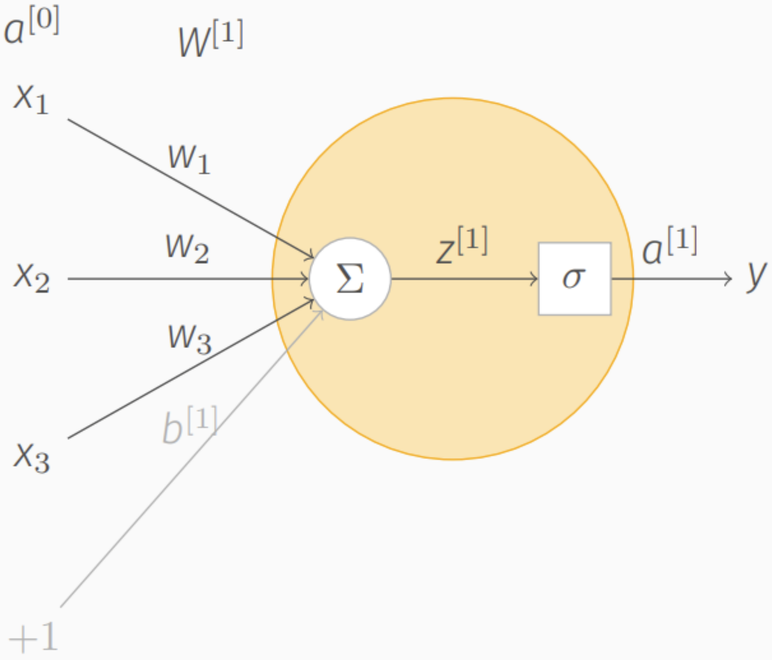
$a^{[1]} = g^{[1]}(z^{[1]})$ ReLU

$z^{[1]} = W^{[1]}a^{[0]} + b^{[1]}$

$a^{[0]}$

Slide adapted from Jurafsky & Martin

A Forward Pass in Terms of Multi-Layer Notation



for each $i \in 1..n$ **do**

$\quad z^{[i]} \leftarrow W^{[i]} a^{[i-1]} + b^{[i]}$

$\quad a^{[i]} \leftarrow g^{[i]}(z^{[i]})$

end for

$\hat{y} \leftarrow a^{[n]}$

Slide credit: David Mortensen

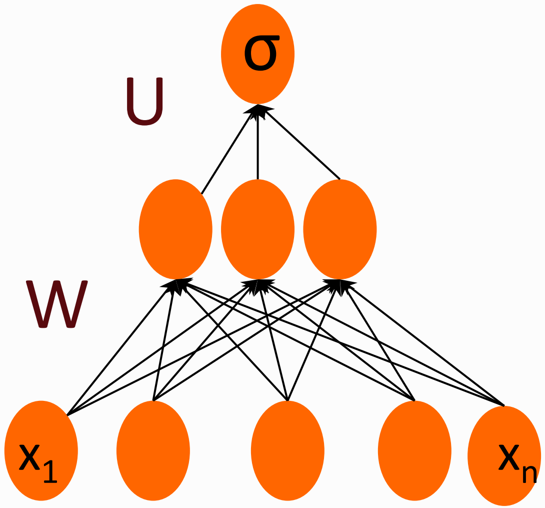
Feedforward neural nets as classifiers

Classification: Sentiment Analysis

We could do exactly what we did with logistic regression

Input layer are binary features as before

Output layer is 0 or 1



Slide adapted from Jurafsky & Martin

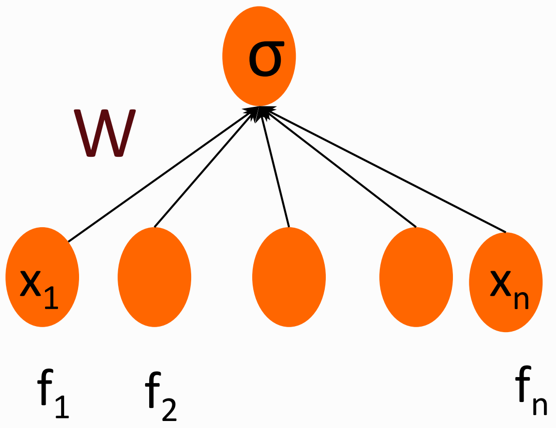
Sentiment Features

Var	Definition
x_1	count(positive lexicon) $\in$ doc)
x_2	count(negative lexicon) $\in$ doc)
x_3	$\begin{cases} 1 & \text{if "no"} \in \text{doc} \\ 0 & \text{otherwise} \end{cases}$
x_4	count(1st and 2nd pronouns $\in$ doc)
x_5	$\begin{cases} 1 & \text{if "!"} \in \text{doc} \\ 0 & \text{otherwise} \end{cases}$
x_6	log(word count of doc)

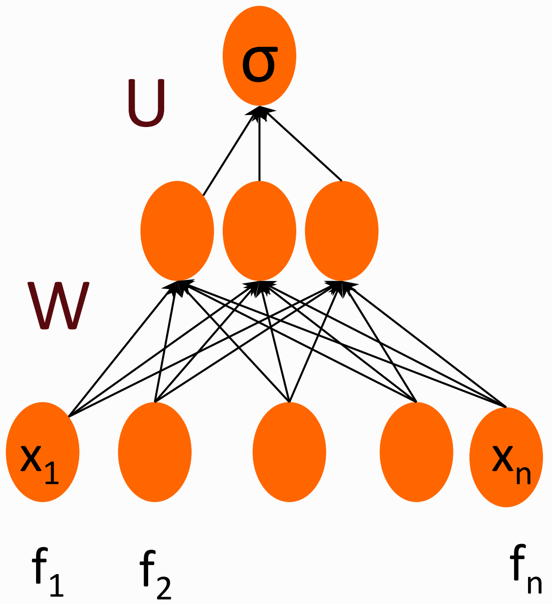
Slide adapted from Jurafsky & Martin

Feedforward nets for simple classification

Logistic Regression



2-layer feedforward network



Just adding a hidden layer to logistic regression

- allows the network to use non-linear interactions between features
- which may (or may not) improve performance.

Slide adapted from Jurafsky & Martin

Conclusion: neural networks part 1

- Neural networks are machine learning systems with “layers” of weighted sums and nonlinear functions
  - Take a vector representing a datapoint as input (feature vector)
  - Produce probabilities over labels (from a softmax) as output
- “Activation functions” are nonlinear functions that enable neural networks to model complex, nonlinear relationships between input and output
  - ReLU, sigmoid, tanh

Project peer group feedback

Project peer group feedback

1. Find another group to work with. Decide which project group will go first as the presenting group
2. Present an overview of your project: 5 min
3. Other group asks clarifying questions
4. Presenting group asks for any advice or guidance from the other group on lingering questions about the project proposal
5. Switch groups (the other group becomes the presenting group) when Michael says