NLP Programming Tutorial 10 - Neural Networks

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Prediction Problems

Given x, predict y

Example we will use:

- Given an introductory sentence from Wikipedia
- Predict whether the article is about a person

Given		Predict
Gonso was a Sanron sect priest (754-827) in the late Nara and early Heian periods.	→	Yes!
Shichikuzan Chigogataki Fudomyoo is a historical site located at Magura, Maizuru City, Kyoto Prefecture.	→	No!

- This is binary classification (of course!)

Linear Classifiers

$$y = \text{sign}(\mathbf{w} \cdot \boldsymbol{\varphi}(x)) = \text{sign}\left(\sum_{i=1}^{I} w_i \cdot \varphi_i(x)\right)$$

- x: the input
- **φ(x)**: vector of feature functions $\{\varphi_1(x), \varphi_2(x), \ldots, \varphi_I(x)\}$
- **w**: the weight vector $\{w_1, w_2, \ldots, w_I\}$
- y: the prediction, +1 if "yes", -1 if "no"
  - (sign(v) is +1 if v >= 0, -1 otherwise)

Example Feature Functions: Unigram Features

- Equal to “number of times a particular word appears”

x = A site , located in Maizuru , Kyoto

$\varphi_{\text{unigram “A”}}(x) = 1$ $\varphi_{\text{unigram “site”}}(x) = 1$ $\varphi_{\text{unigram “,”}}(x) = 2$

$\varphi_{\text{unigram “located”}}(x) = 1$ $\varphi_{\text{unigram “in”}}(x) = 1$

$\varphi_{\text{unigram “Maizuru”}}(x) = 1$ $\varphi_{\text{unigram “Kyoto”}}(x) = 1$

$\varphi_{\text{unigram “the”}}(x) = 0$ $\varphi_{\text{unigram “temple”}}(x) = 0$

…

The rest are all 0

- For convenience, we use feature names ($\varphi_{\text{unigram “A”}}$) instead of feature indexes (φ_1)

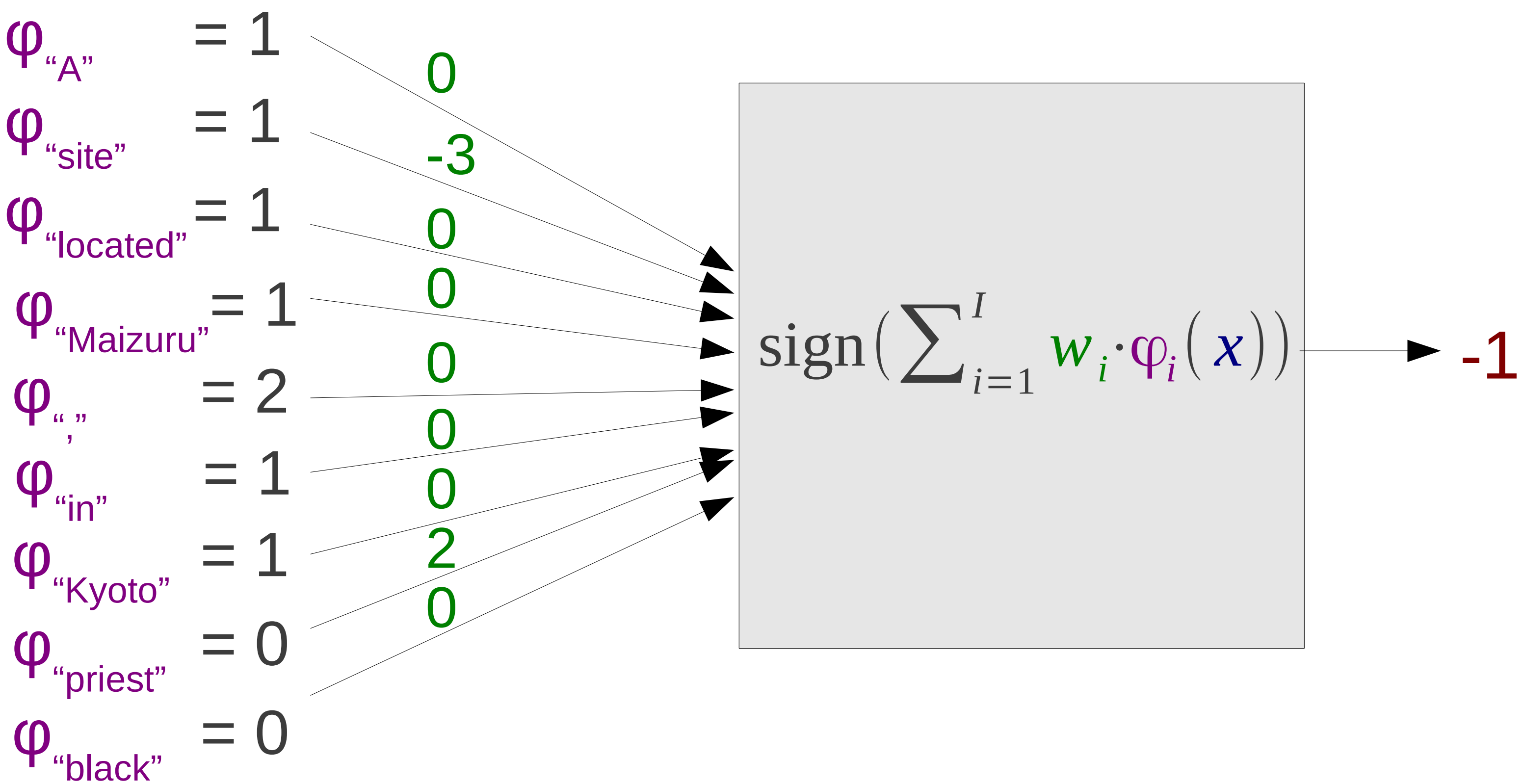
Calculating the Weighted Sum

x = A site , located in Maizuru , Kyoto

$$
\begin{array}{lllll}
\varphi_{\text{unigram “A”}}(x) = 1 & & w_{\text{unigram “a”}} = 0 & & 0 \; + \\
\varphi_{\text{unigram “site”}}(x) = 1 & & w_{\text{unigram “site”}} = -3 & & -3 \; + \\
\varphi_{\text{unigram “located”}}(x) = 1 & & w_{\text{unigram “located”}} = 0 & & 0 \; + \\
\varphi_{\text{unigram “Maizuru”}}(x) = 1 & & w_{\text{unigram “Maizuru”}} = 0 & & 0 \; + \\
\varphi_{\text{unigram “,”}}(x) = 2 & * & w_{\text{unigram “,”}} = 0 & = & 0 \; + \\
\varphi_{\text{unigram “in”}}(x) = 1 & & w_{\text{unigram “in”}} = 0 & & 0 \; + \\
\varphi_{\text{unigram “Kyoto”}}(x) = 1 & & w_{\text{unigram “Kyoto”}} = 0 & & 0 \; + \\
\varphi_{\text{unigram “priest”}}(x) = 0 & & w_{\text{unigram “priest”}} = 2 & & 0 \; + \\
\varphi_{\text{unigram “black”}}(x) = 0 & & w_{\text{unigram “black”}} = 0 & & 0 \; + \\
& \ldots & & & \ldots \\
& & & & = \\
& & & & -3 \rightarrow \text{No!}
\end{array}
$$

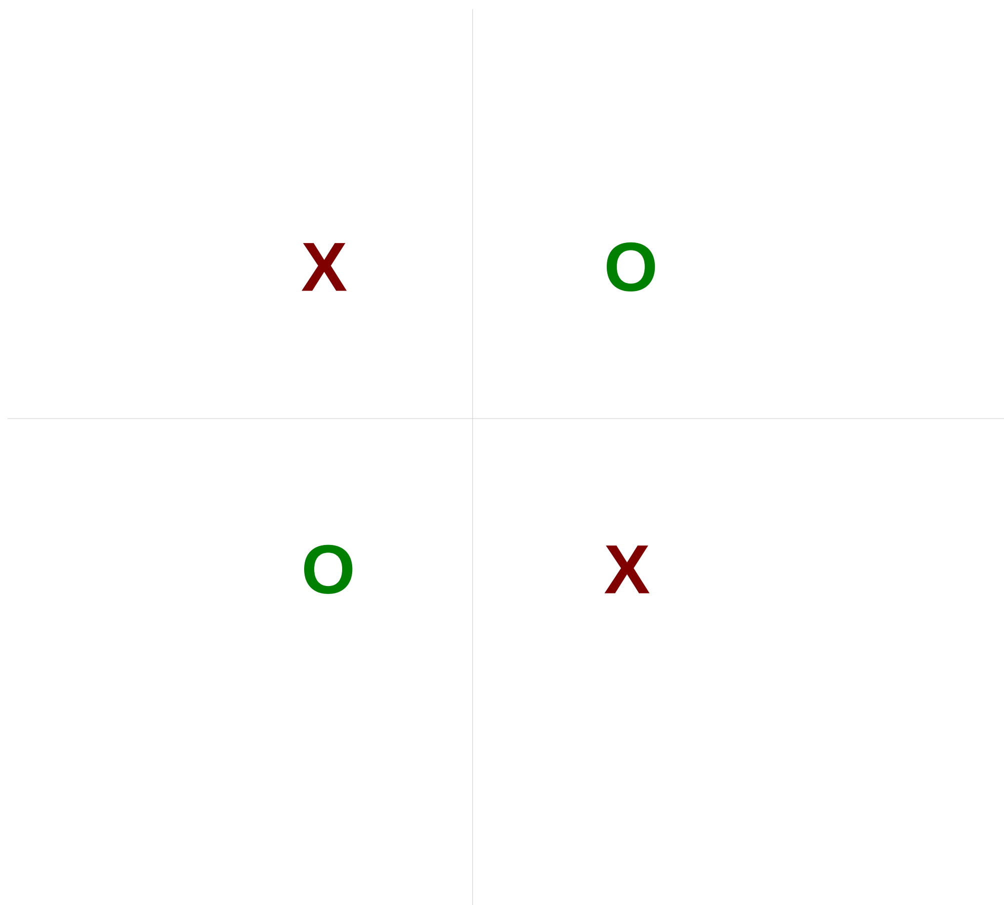
The Perceptron

- Think of it as a "machine" to calculate a weighted sum



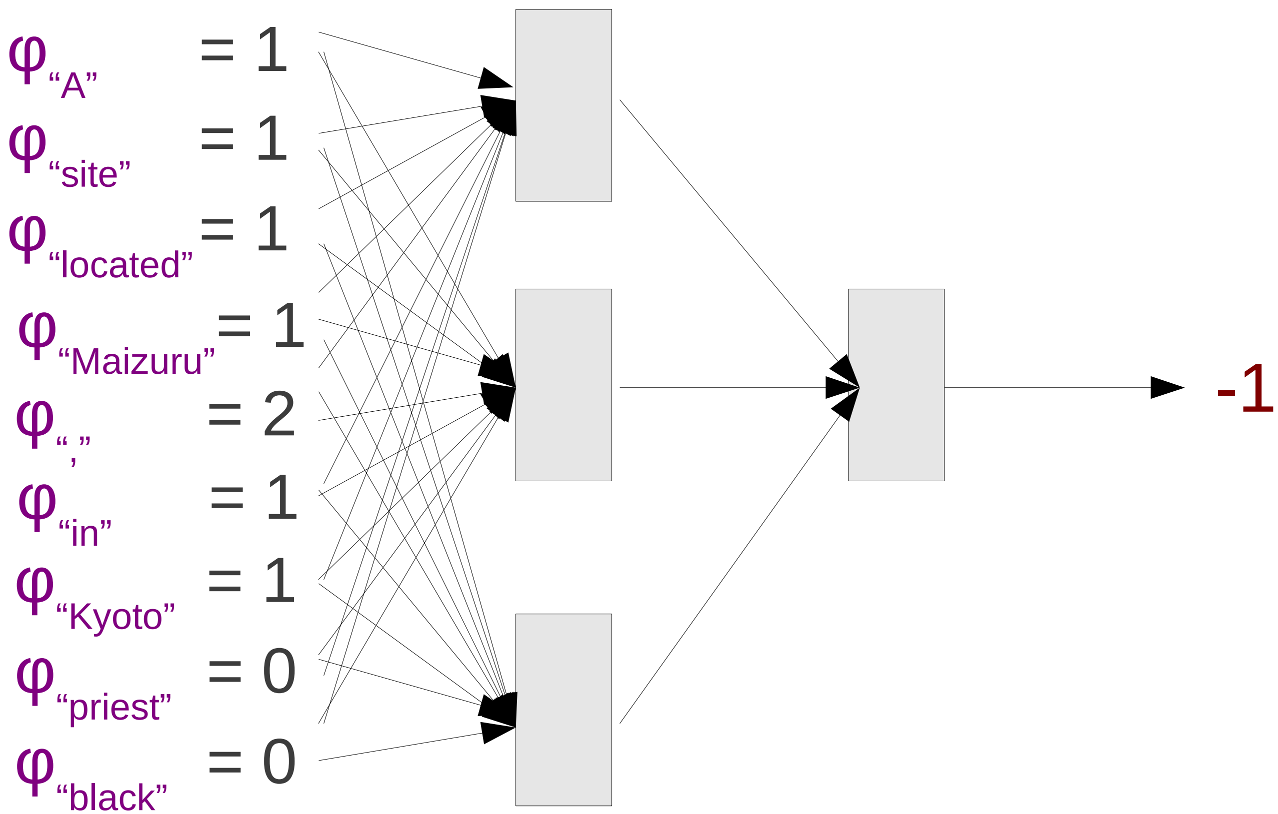
Problem: Linear Constraint

- Perceptron cannot achieve high accuracy on non-linear functions



Neural Networks

- Neural networks connect multiple perceptrons together

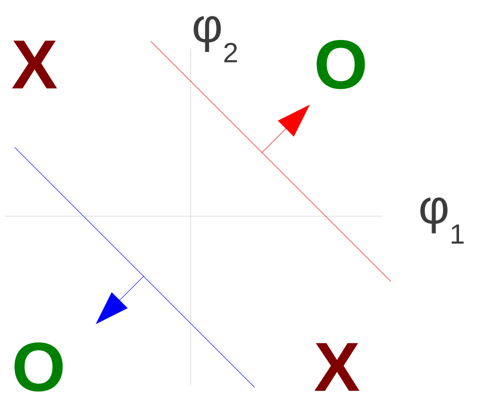


- Motivation: Can express non-linear functions

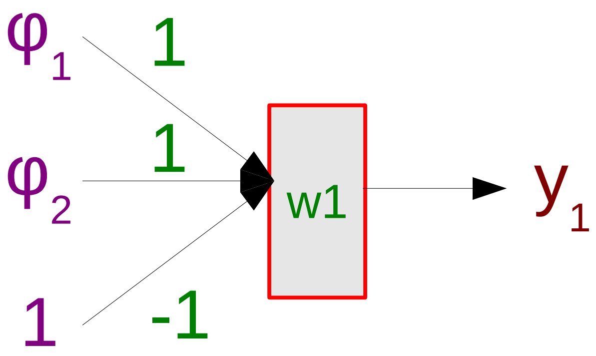
Example:

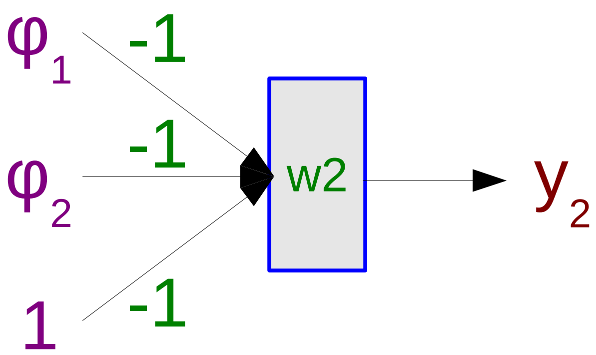
- Build two classifiers:

$\varphi(x_1) = \{-1, 1\}$ $\varphi(x_2) = \{1, 1\}$



$\varphi(x_3) = \{-1, -1\}$ $\varphi(x_4) = \{1, -1\}$



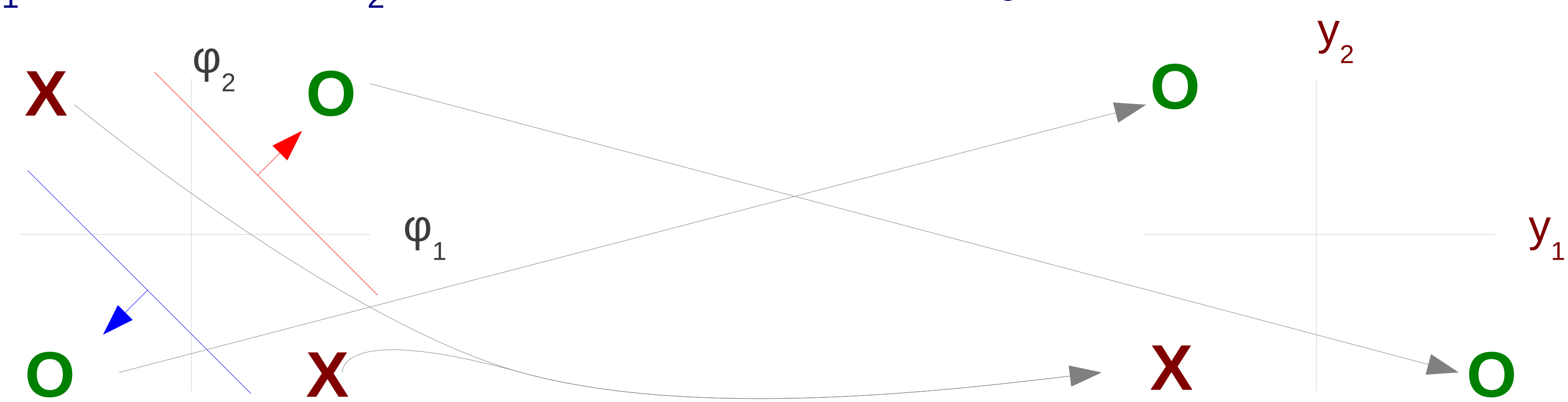


Example:

- These classifiers map the points to a new space

$\varphi(x_1) = \{-1, 1\}$ $\varphi(x_2) = \{1, 1\}$

$y(x_3) = \{-1, 1\}$



$\varphi(x_3) = \{-1, -1\}$ $\varphi(x_4) = \{1, -1\}$

$y(x_1) = \{-1, -1\}$ $y(x_2) = \{1, -1\}$

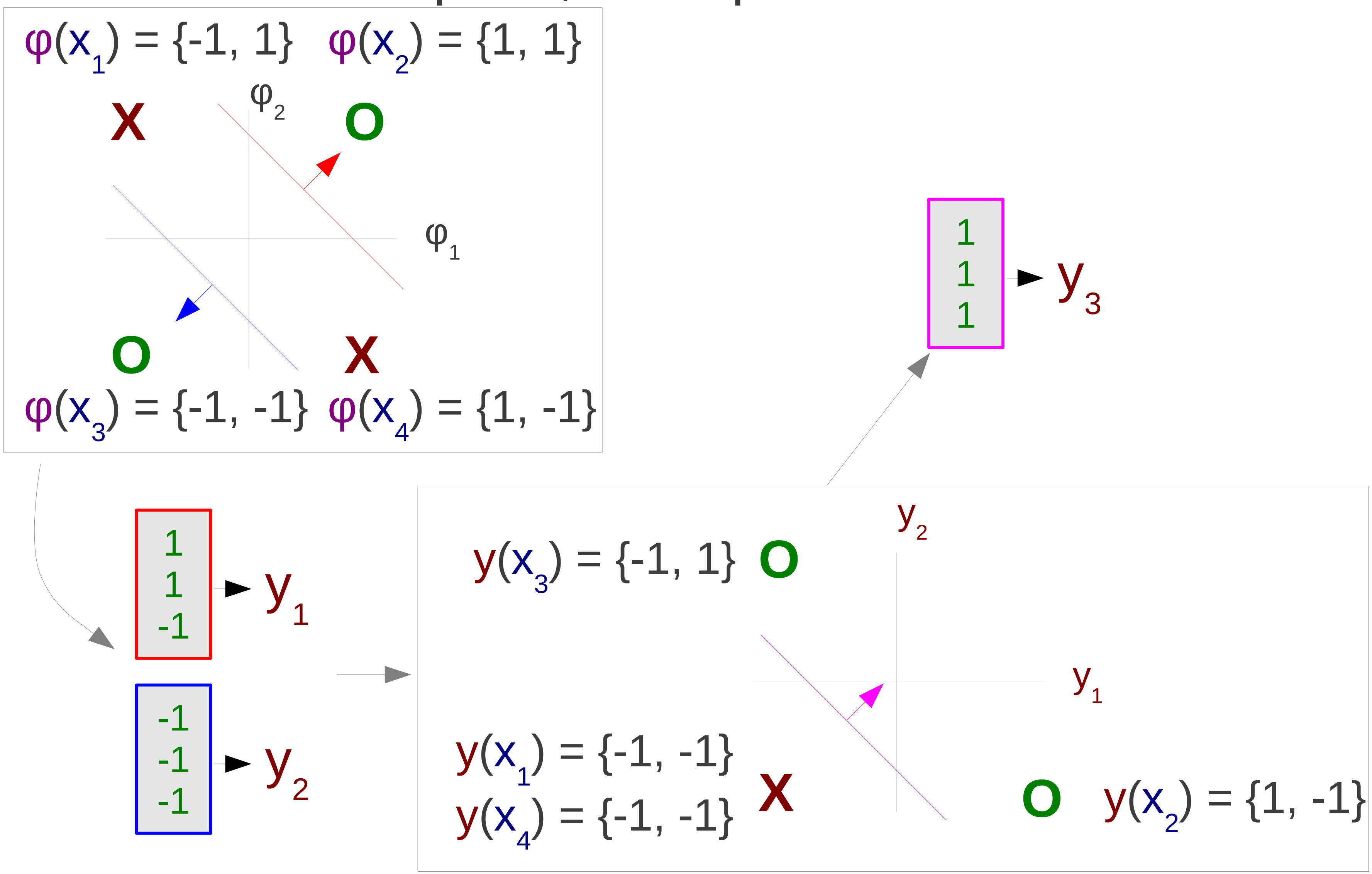
$y(x_4) = \{-1, -1\}$

1
1
-1
→ y_1

-1
-1
-1
→ y_2

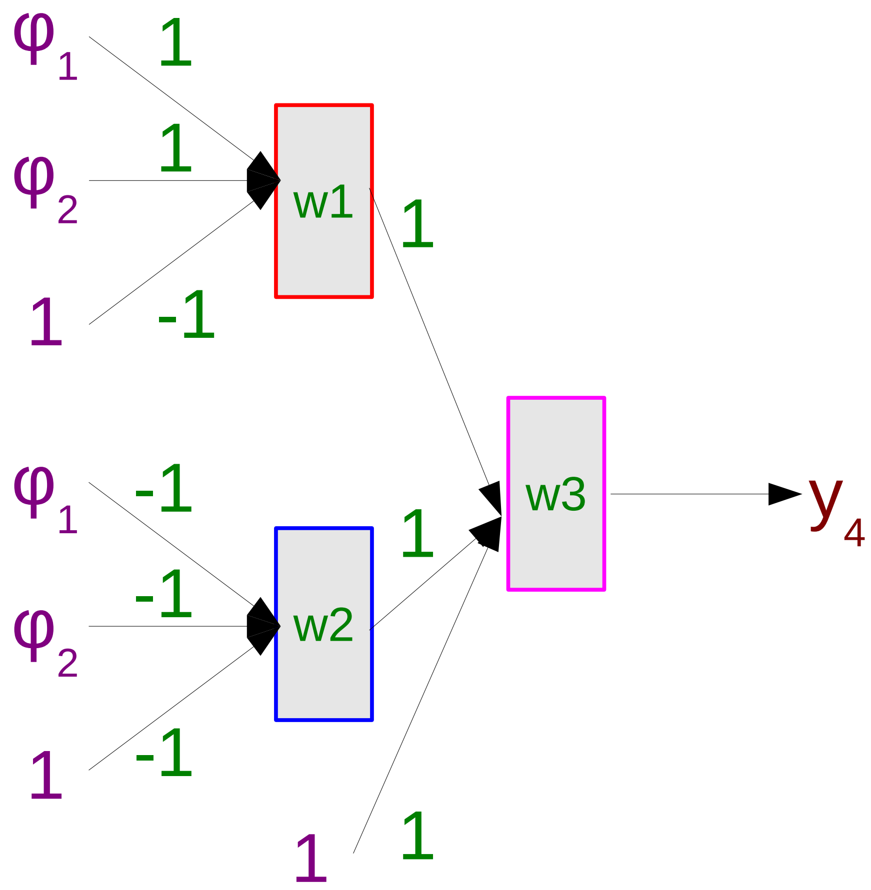
Example:

- In the new space, examples are classifiable!



Example:

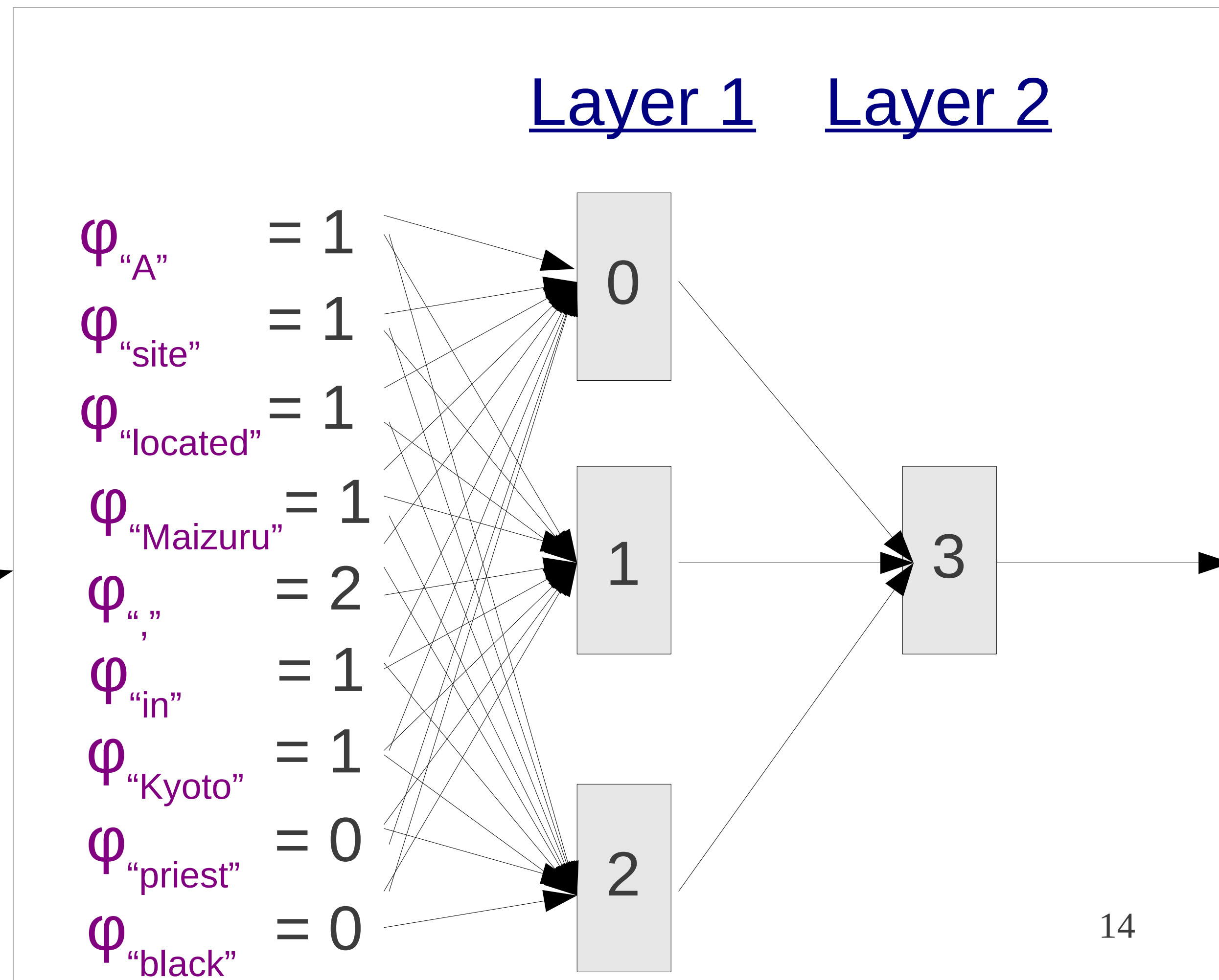
- Final neural network:



Representing a Neural Network

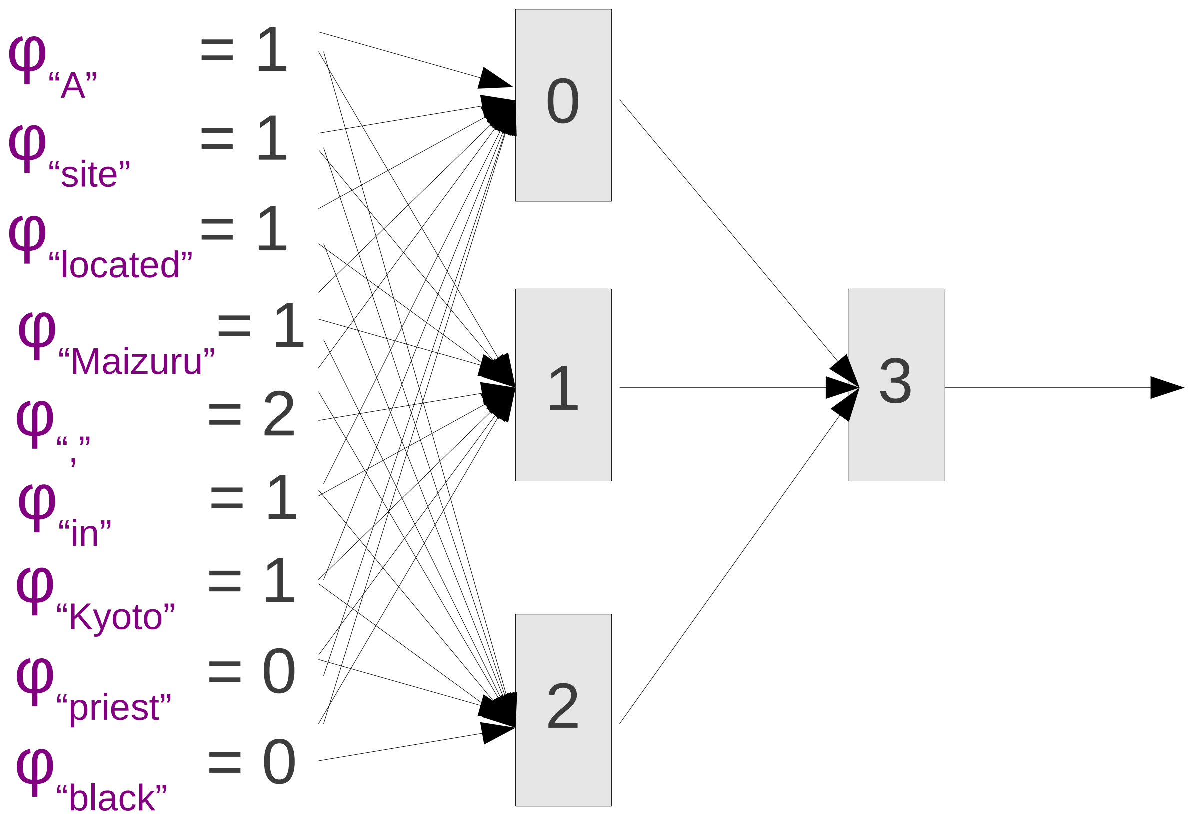
- Assume network is fully connected and in layers
- Each perceptron:
  - A layer ID
  - A weight vector

network = [
    (1, w_0),
    (1, w_1),
    (1, w_2),
    (2, w_3)
]



Neural Network Prediction Process

- Predict one perceptron at a time using previous layer



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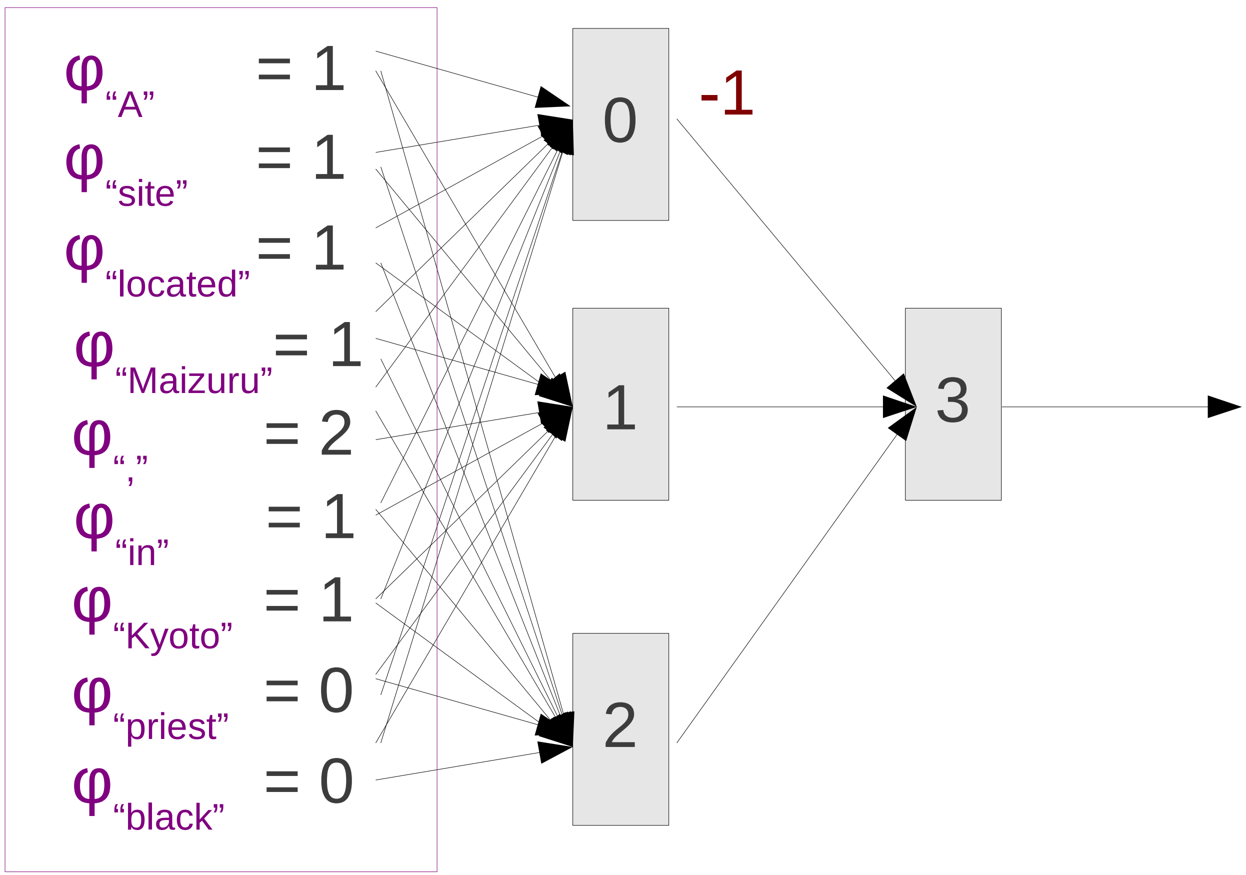

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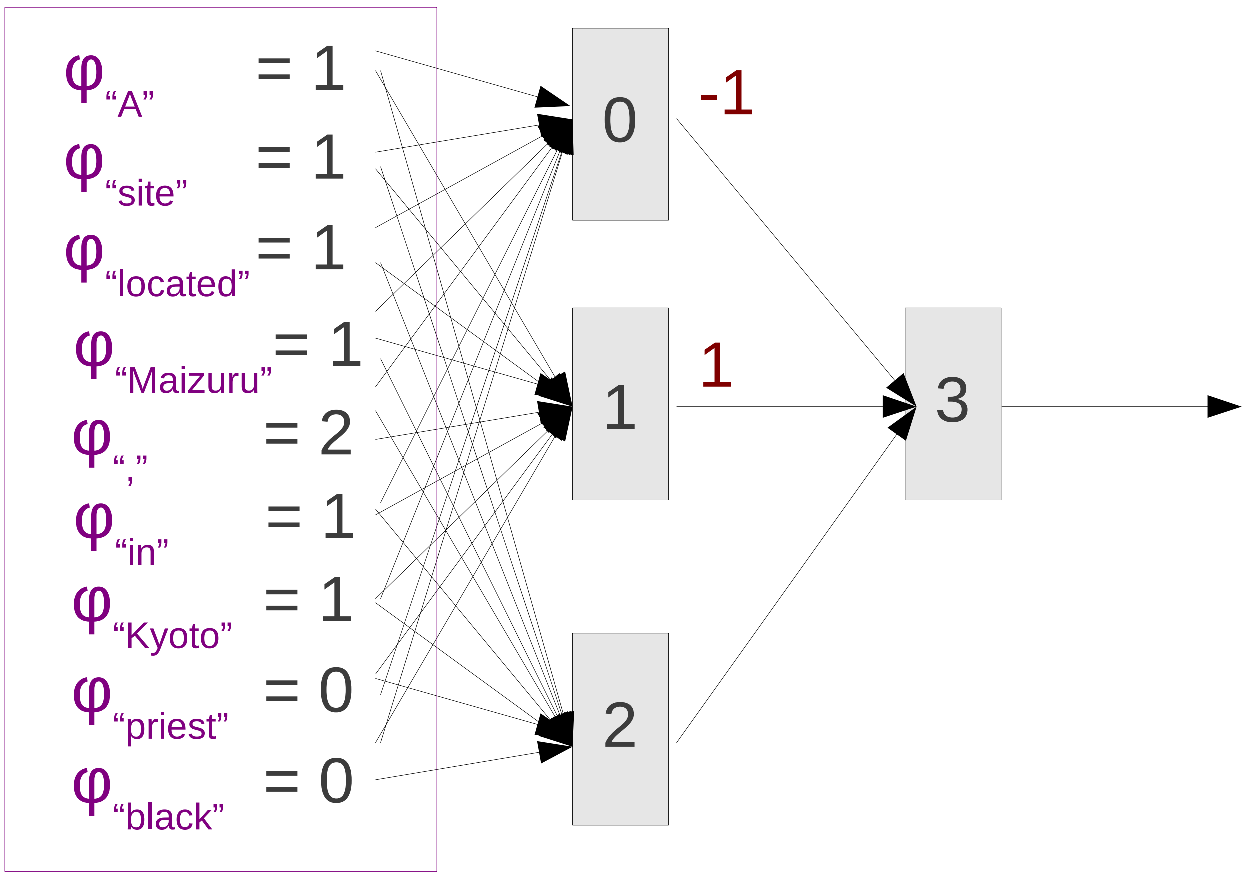

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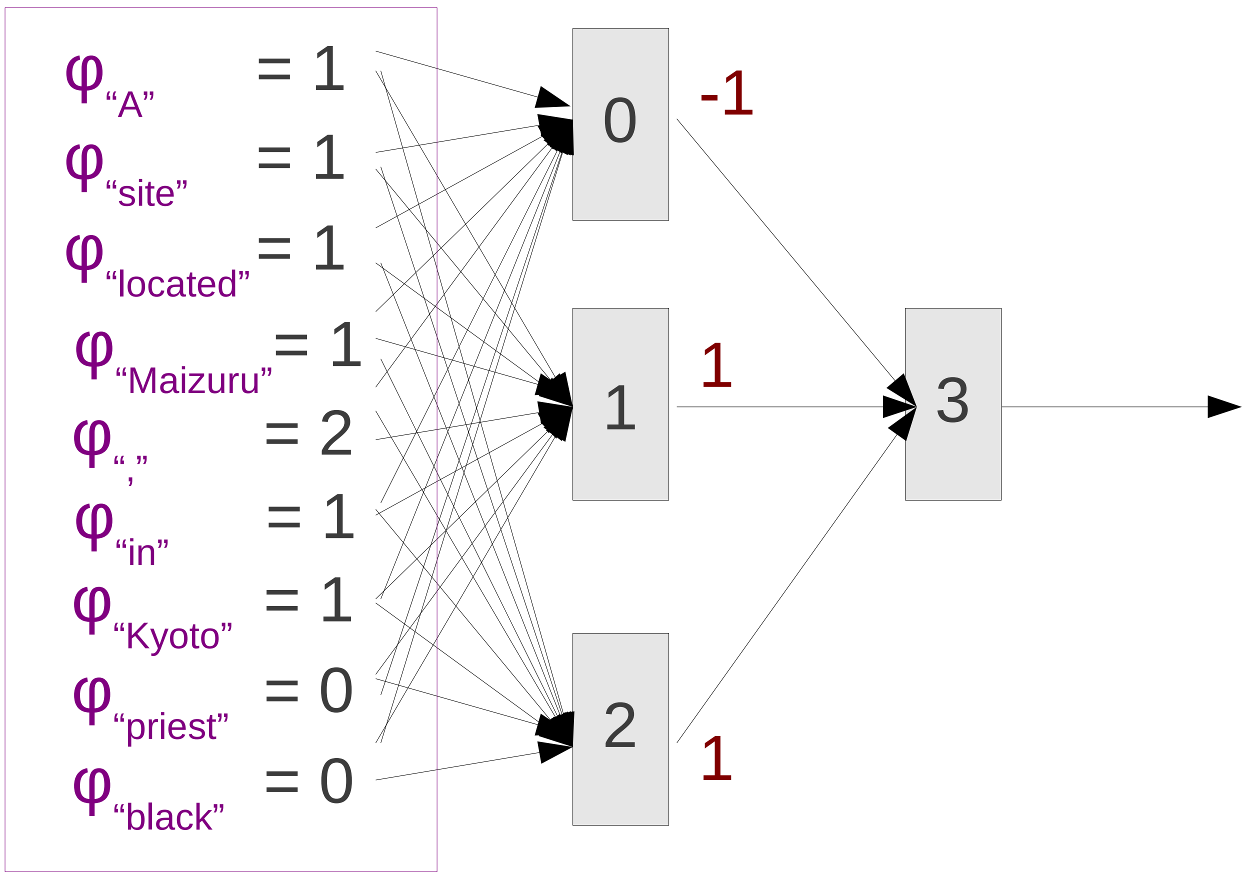

Neural Network Prediction Process

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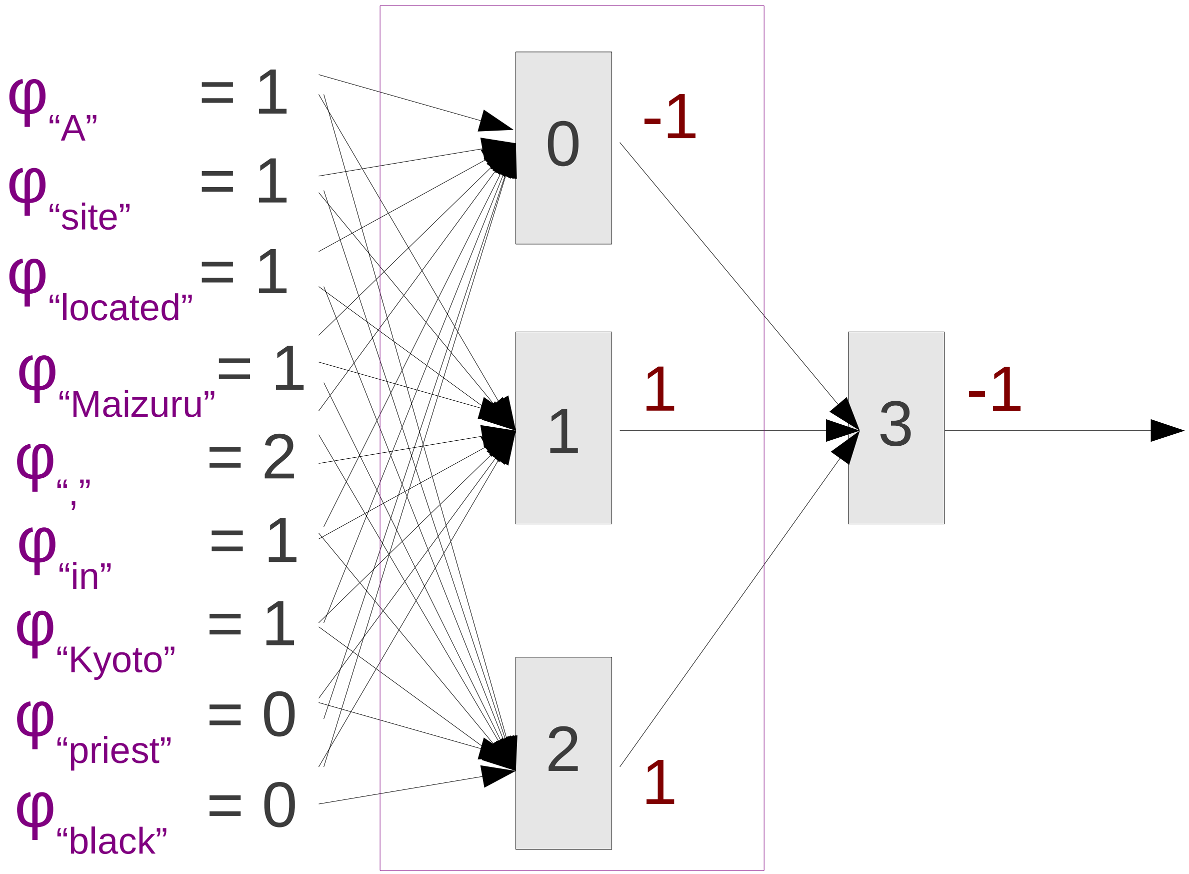


Review:
Pseudo-code for Perceptron Predicton

```
PREDICT_ONE(w, phi)
    score = 0
    for each name, value in phi          # score = w*φ(x)
        if name exists in w
            score += value * w[name]
    if score >= 0
        return 1
    else
        return -1
```

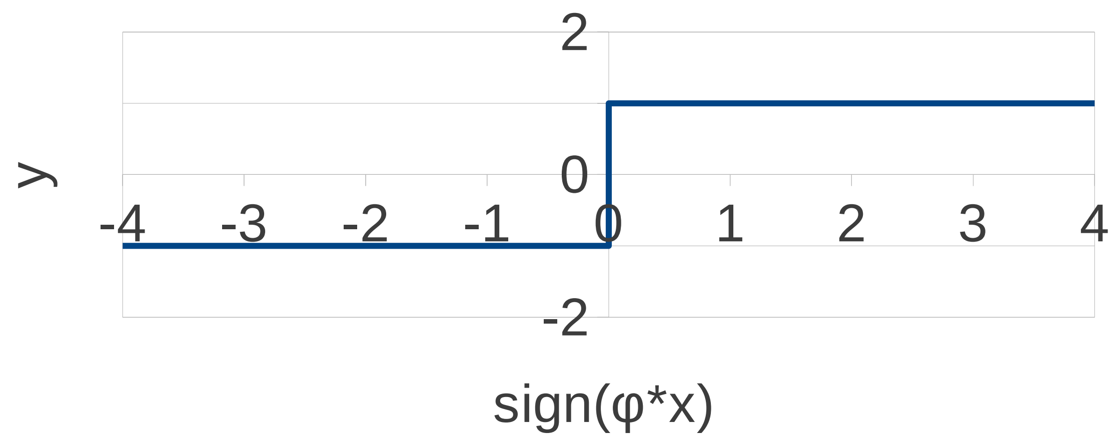
Pseudo-Code for NN Prediction

```
PREDICT_NN(network, phi)
    y = [ phi, {}, {} … ] # activations for each layer
    for each node i:
        layer, weight = network[i]
        # predict the answer with the previous perceptron
        answer = PREDICT_ONE(weight, y[layer-1])
        # save this answer as a feature for the next layer
        y[layer][i] = answer
    return the answer for the last perceptron
```

Neural Network Activation Functions

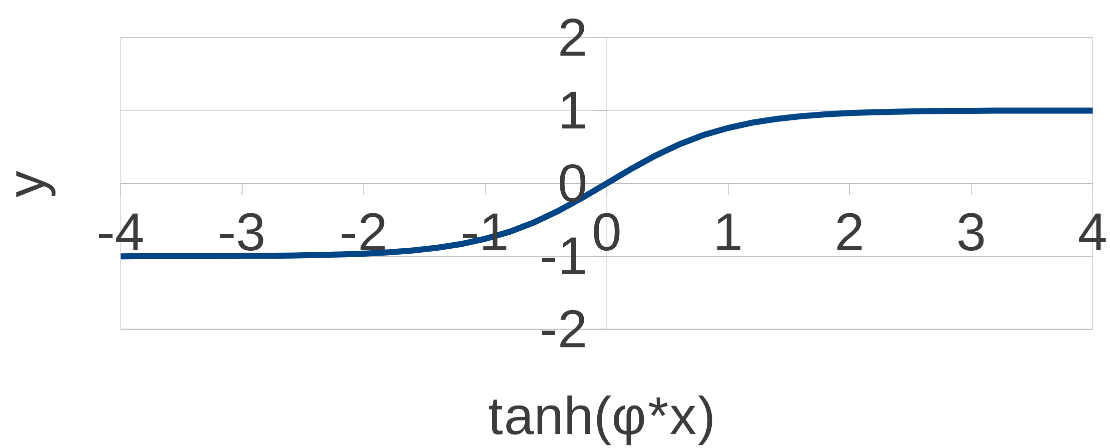
- Previously described NN uses step function

$$y = \text{sign}(w \cdot \varphi(x))$$



- Step function is not differentiable → use tanh

$$y = \tanh(w \cdot \varphi(x))$$



Python:
from math import tanh
tanh(x)

Learning a Perceptron w/ tanh

- First, calculate the error:

$$\delta = y' - y$$

correct tag system output

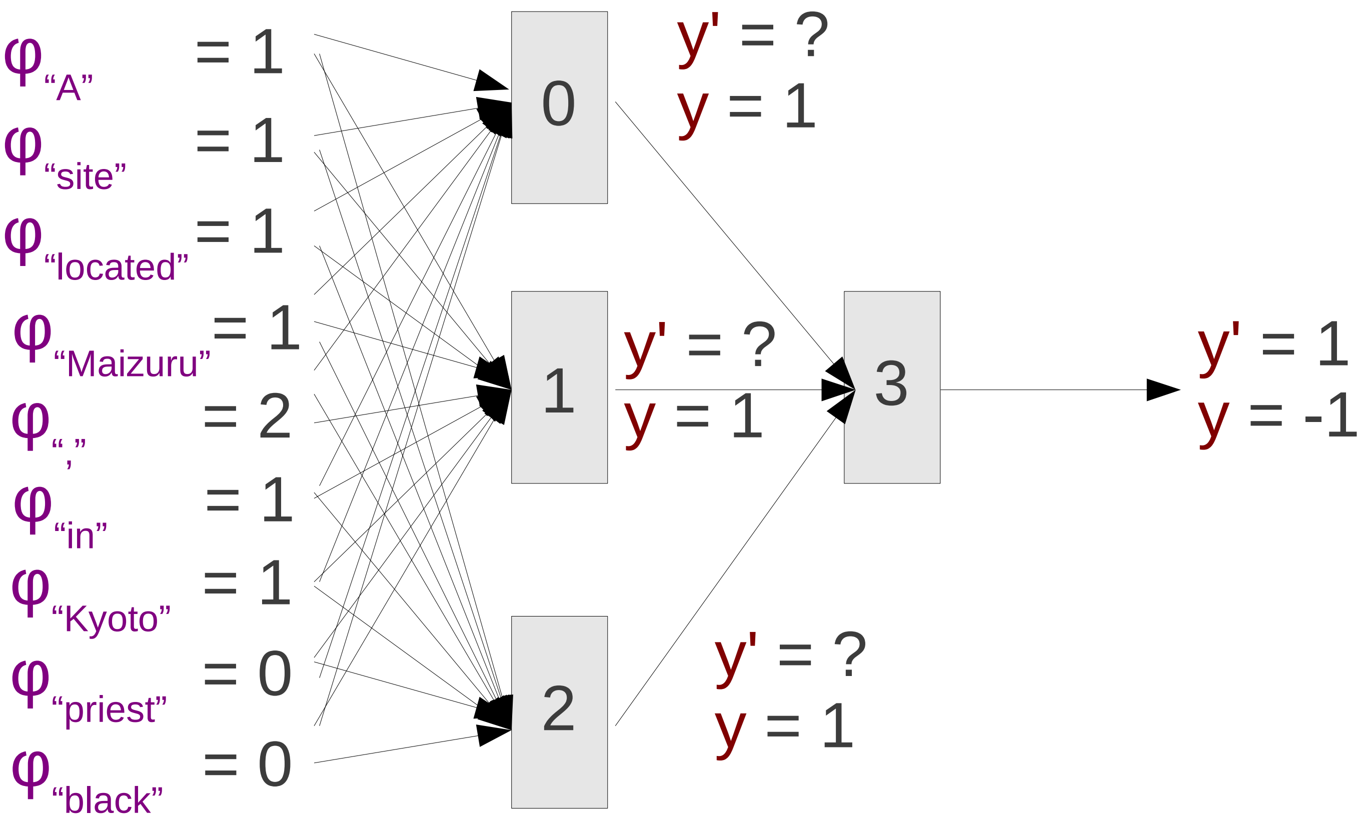
- Update each weight with:

$$\boldsymbol{w} \leftarrow \boldsymbol{w} + \lambda \cdot \delta \cdot \varphi(x)$$

- Where λ is the learning rate
- (For step function perceptron δ = -2 or +2, λ = 1/2)

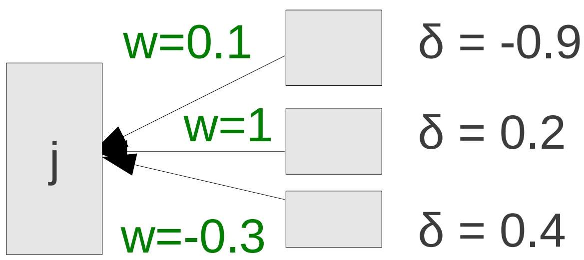
Problem: Don't Know Correct Answer!

- For NNs, only know correct tag for last layer



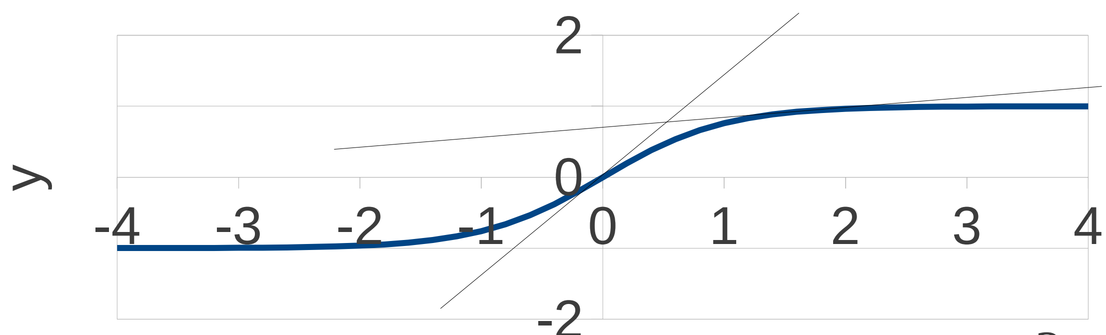
Answer: Back-Propogation

- Pass error backwards along the network



$$\sum_i \delta_i w_{j,i}$$

- Also consider gradient of tanh



$$d\tanh(\varphi(x)*w)=1-(\varphi(x)*w)^2=1-y_j^2$$

- Combine:

$$\delta_j=(1-y_j^2)\sum_i \delta_i w_{j,i}$$

Back Propagation Code

```
UPDATE_NN(network, phi, y')
    create array δ
    calculate y using PREDICT_NN
    for each node j in reverse order:
        if j is the last node
            δ_j = y' – y_j
        else
            δ_j = (1 – y_j^2) Σ_i δ_i w_j,i
    for each node j:
        layer, w = network[j]
        for each name, val in y[layer-1]:
            w[name] += λ * δ_j * val
```

Training process

```
create network
randomize network weights
for I iterations
    for each labeled pair x, y in the data
        phi = CREATE_FEATURES(x)
        UPDATE_NN(w, phi, y)
```

- For previous perceptron, we initialized weights to zero
- In NN: randomly initialize weights
  (so not all perceptrons are identical)

Exercise

Exercise (1)

- Write two programs
  - train-nn: Creates a neural network model
  - test-nn: Reads a neural network model
- Test train-nn
  - Input: test/03-train-input.txt
  - Use one iteration, one hidden layer, two hidden nodes
  - Calculate updates by hand and make sure they are correct

Exercise (2)

- Train a model on data/titles-en-train.labeled
- Predict the labels of data/titles-en-test.word
- Grade your answers
  - script/grade-prediction.py data-en/titles-en-test.labeled your_answer
- Compare:
  - With a single perceptron/SVM classifiers
  - With different neural network structures

Thank You!