

Multinomial Logistic Regression

CSC 461: Machine Learning

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Logistic regression

- ▶ Binary classification
 - ✓ uses a **logistic function** (type of sigmoid function)
 - ✓ models **probability** of output in terms of input
- ▶ What if we want $k > 2$ classes?
 - ✓ can try one-vs-all
 - ✓ learn a binary classifier per class; relabel training data with samples of that class as positive and all other as negatives; predict using the highest score from all classifiers
 - ✓ can try one-vs-one
 - ✓ learn $k(k-1)/2$ binary classifiers; each learns to distinguish between two classes; predict using a voting scheme

Issues with OvA or OvO

- ▶ Class imbalance
- ▶ Scale of scores may differ from classifier to classifier
- ▶ Computational cost (both train and predict)

MNIST

- ▶ The MNIST database is a large database of handwritten digits

- ✓ contains 60,000 training images and 10,000 testing images

- ✓ convolutional neural networks, manages to get an error rate of 0.23%

- ✓ original paper reports an error rate of 0.8% with SVMs



<http://yann.lecun.com/exdb/mnist/>

https://en.wikipedia.org/wiki/MNIST_database

Basics of multiclass classification

▸ Data instance

✓ in general, $x \in \mathcal{X}, \mathcal{X} = \mathbb{R}^d$

✓ $y \in \mathcal{Y}, \mathcal{Y} = \{1, 2, \dots, C\}$

▸ Hypothesis

✓ each hypothesis g is a classifier

$$g : \mathcal{X} \mapsto \mathcal{Y}, g \in \mathcal{H}$$

From binary to k classes

▸ Binary logistic regression:

$$P(y = +1 \mid \mathbf{x}; \mathbf{w}) = \frac{1}{1 + e^{-\mathbf{w}^T \mathbf{x}}} = \frac{e^{\mathbf{w}^T \mathbf{x}}}{e^{\mathbf{w}^T \mathbf{x}} + 1}$$

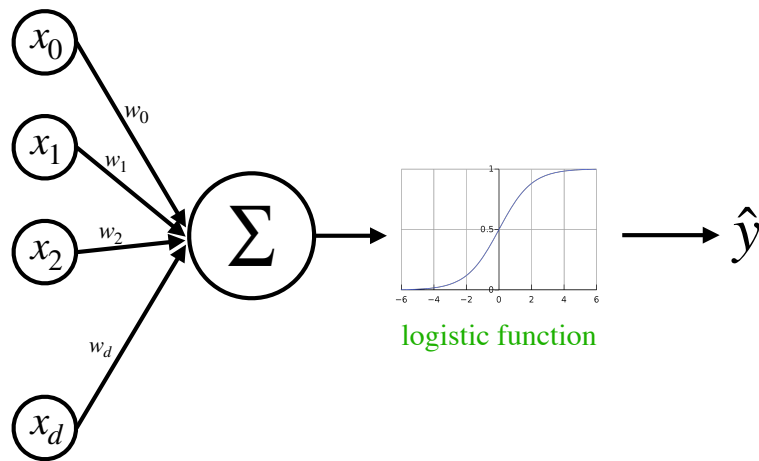
▸ Can be extended to:

$$P(y = c \mid \mathbf{x}; \mathbf{W}) = \frac{e^{\mathbf{w}_c^T \mathbf{x}}}{\sum_{k=1}^C e^{\mathbf{w}_k^T \mathbf{x}}}$$

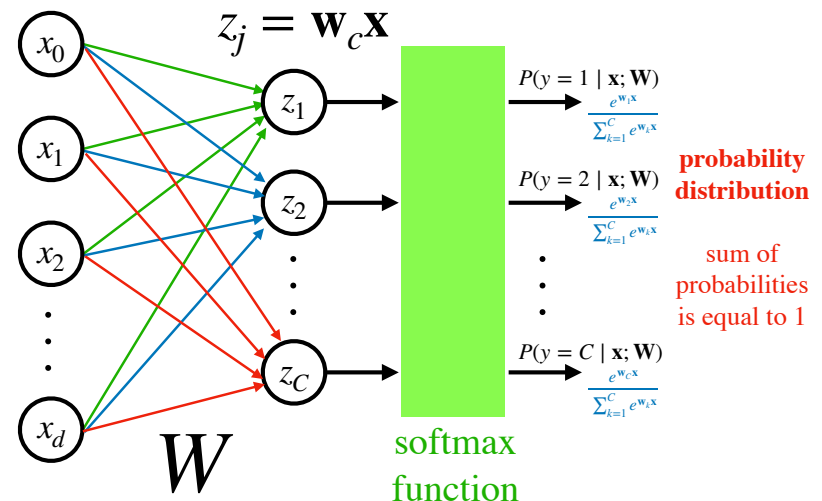
\mathbf{w}_c is the row vector c from \mathbf{W}

$\mathbf{W}_{C \times d+1}$ is a matrix where every row is a “class” weight vector

Logistic regression (binary classification)



Multinomial logistic regression



Example

- What is the value of $\text{softmax}(\mathbf{z})$, given that $\mathbf{z}^T = [-10, 10, 5, 4.3, 7]$?

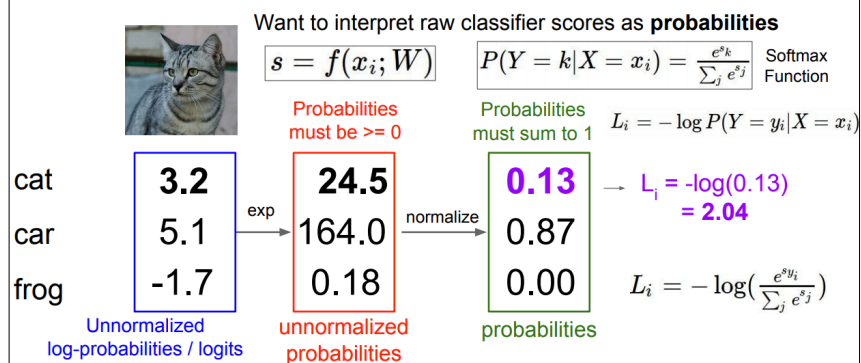
Multinomial logistic regression

- Use the **softmax function** for activation
- Predict the label with the highest probability score (**forward pass**)

$$\hat{y} = \arg \max_c P(y = c \mid \mathbf{x}; \mathbf{W})$$

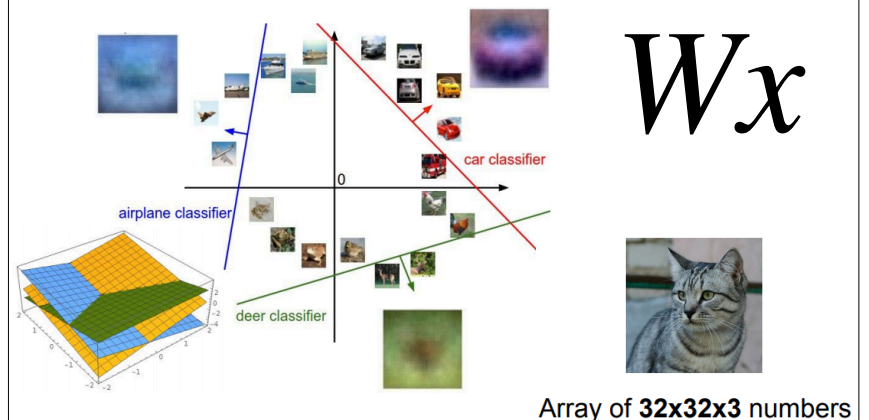
- How to learn the weights?
 - need to define a **Loss Function** ... then apply **gradient descent**
 - loss function can be derived using **MLE** (similar to binary logistic regression)

Softmax and the loss function



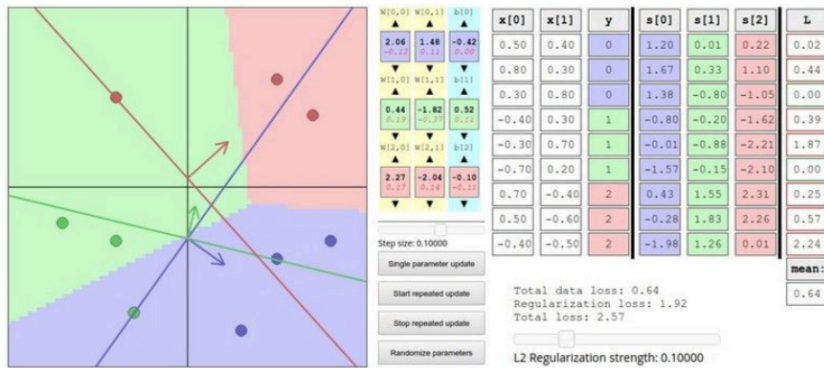
http://vision.stanford.edu/teaching/cs231n/slides/2019/cs231n_2019_lecture03.pdf

Geometric interpretation



http://vision.stanford.edu/teaching/cs231n/slides/2019/cs231n_2019_lecture02.pdf

Interactive web demo



<http://vision.stanford.edu/teaching/cs231n-demos/linear-classify/>