Text Classification and Neural Networks

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Overview

1. Text Classification
2. Logistic Regression
3. Evaluation
4. Neural Networks
5. Extras

Text Classification

Task definition

- We are given a **training set** $\{X, Y\}$ of data pairs (x, y), where x is a text document and y is the class the document belongs to.
- Each $y \in \mathcal{Y}$, where $\mathcal{Y} = \{c_1, c_2, \ldots, c_k\}$ are the distinct (finite and enumerable) classes we have. If $|\mathcal{Y}| = k = 2$, we have a binary classification task.
- Using a *learning method*, our goal is to learn a **classifier**, or a classification function γ that maps documents to classes:

$$\gamma : \mathcal{X} \to \mathcal{Y}$$

- The fact that we use annotated data to learn makes this a form of *supervised learning*. Note that a “document” can be anything really: words, text sequences, longer texts.

Examples

task	x	$\mathcal{Y}$
language ID	text	{english, mandarin, greek, ...}
spam classification	email	{spam, not spam}
authorship attribution	text	{jk rowling, james joyce, ...}
genre classification	novel	{detective, romance, gothic, ...}
sentiment analysis	text	{postive, negative, neutral, mixed}

Credit: David Bamman (UC Berkeley).

Text representation

Our text documents X can be **represented** in many ways:

- Pre-computed features (e.g., the length of the document or the average length of the words it contains).
- A selection of words (e.g., only stopwords for language detection).
- Words in isolation (so called “bag of words”, or unigram model).
- Conjunctions of words (e.g., bigrams).
- Higher-order features (e.g., PoS).
- Word embeddings.

Logistic Regression

Logistic regression

- Our goal is, given a document represented with a feature vector $\boldsymbol{x}$ and classes $c \in \mathcal{Y}$, to learn a classifier discriminating the right class for $\boldsymbol{x}$:

$$\hat{p}(y = c|\boldsymbol{x})$$

- Let us start with a binary classifier and two classes, thus $\mathcal{Y} = \{0, 1\}$.
- We need to estimate $\hat{p}(y = 1|\boldsymbol{x})$, and $\hat{p}(y = 0|\boldsymbol{x}) = 1 - \hat{p}(y = 1|\boldsymbol{x})$ will follow suit.
- Logistic regression uses two components for this: a **linear model** of the inputs and the **Sigmoid (or logistic) function**. So, it is like the perceptron but with a different classification function.

Sigmoid (or logistic) function

- Let us consider the set of features $x_1, x_2, \ldots, x_d$ we used to represent our input document $\boldsymbol{x}$. We add $x_0 = 1$ to model the intercept, and create a linear model with them:

$$z = \sum_{j=0}^{d} w_j x_j = \boldsymbol{w} \cdot \boldsymbol{x}$$

- To create a probability distribution, we pass z through the Sigmoid $\sigma(z)$:

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

- The Sigmoid squeezes z within 0 and 1 and is always positive.

Sigmoid (or logistic) function

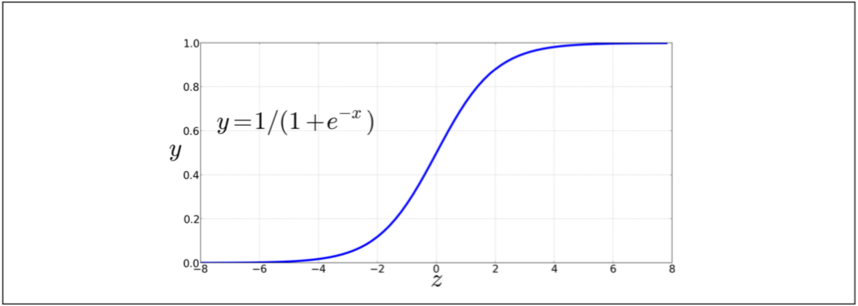


Figure 5.1 The sigmoid function $y = \frac{1}{1+e^{-z}}$ takes a real value and maps it to the range $[0, 1]$. Because it is nearly linear around 0 but has a sharp slope toward the ends, it tends to squash outlier values toward 0 or 1.

¿¿

Credit: M&J, Ch. 5.

Logistic regression

- Applied to our binary classification task, we have that:

$$\hat{p}(y=1|\boldsymbol{x}) = \sigma(z_{\boldsymbol{x}}) = \frac{1}{1+e^{-\boldsymbol{w}\cdot\boldsymbol{x}}}$$

$$\hat{p}(y=0|\boldsymbol{x}) = 1-\sigma(z_{\boldsymbol{x}}) = \frac{e^{-\boldsymbol{w}\cdot\boldsymbol{x}}}{1+e^{-\boldsymbol{w}\cdot\boldsymbol{x}}}$$

- Then, we just need to use a **decision boundary** to assign the class given the estimated probabilities:

$$\hat{y} = \begin{cases} 1 \text{ if } \hat{p}(y=1|\boldsymbol{x}) > 0.5 \\ 0 \text{ otherwise} \end{cases}$$

- **So, we have defined out data and task, and have a model. What do we miss?**

Logistic regression: Cross-entropy

- We need a loss function. Let us use MLE to find one.
- We have that $p(y|\boldsymbol{x})$ follows a Bernoulli distribution given that we only have two discrete outcomes $(0, 1)$, hence:

$$p(y|\boldsymbol{x}) = \hat{y}^y(1-\hat{y})^{1-y}$$

- As usual, let us move to log space and add a minus to switch to a minimization problem (note we work with a single data point $(\boldsymbol{x}, y)$ for now):

$$\begin{aligned} -logp(y|\boldsymbol{x}) &= -log\left[\hat{y}^y(1-\hat{y})^{1-y}\right] \\ &= -\left[ylog\hat{y} + (1-y)log(1-\hat{y})\right] \end{aligned}$$

- Let us now plug-in the Sigmoid and call it the loss:

$$\mathcal{L}_{\boldsymbol{x}}(\boldsymbol{w}) = -\left[ylog\sigma(\boldsymbol{wx}) + (1-y)log(1-\sigma(\boldsymbol{wx}))\right]$$

Logistic regression: Cross-entropy

- Let us now plug-in the Sigmoid and call it the loss:

$$\mathcal{L}_{\boldsymbol{x}}(\boldsymbol{w}) = -\big[y log \sigma(\boldsymbol{wx}) + (1-y) log(1-\sigma(\boldsymbol{wx}))\big]$$

- The loss on the whole dataset is going to be (note we are already in log space thus we can sum):

$$\mathcal{L}(\boldsymbol{w}) = -\frac{1}{N}\sum_{i=1}^{N}\big[y_i log \sigma(\boldsymbol{wx}_i) + (1-y_i) log(1-\sigma(\boldsymbol{wx}_i))\big]$$

- To this we can, as usual, attach regularization:

$$\mathcal{L}_{L_2}(\boldsymbol{w}) = \mathcal{L}(\boldsymbol{w}) + \frac{\lambda}{2}||\boldsymbol{w}||^2$$

Logistic regression: Optimization via SGD

- The last missing bit is how to find good parameters $\boldsymbol{w}$: we can use SGD.
- It turns out that the derivative for one data point $\boldsymbol{x}$ is (w.o. regularization):

$$\frac{\partial \mathcal{L}_{\boldsymbol{x}}(\boldsymbol{w})}{\partial \boldsymbol{w}_j} = \big[\sigma(\boldsymbol{w}\boldsymbol{x}) - y\big]\boldsymbol{x}_j$$

- For multiple data points, we just sum (w.o. regularization), and with this we are good to go for SGD:

$$\frac{\partial \mathcal{L}(\boldsymbol{w})}{\partial \boldsymbol{w}_j} = \sum_{i=1}^{N} \big[\sigma(\boldsymbol{w}\boldsymbol{x}_i) - y_i\big]\boldsymbol{x}_{ij}$$

- *Full derivation as an extra, below.*

Notes

Notes

Evaluation

Data splitting

	training	development	testing
size	80%	10%	10%
purpose	training models	model selection; hyperparameter tuning	evaluation; never look at it until the very end

Credit: David Bamman (UC Berkeley).

Accuracy and baselines

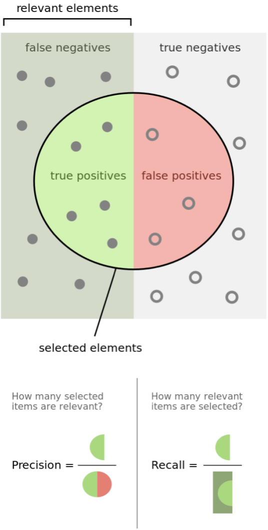
- **Accuracy** is the fraction of correctly predicted data points over the total. It can be calculated on any dataset split: train, development and test. Very good starting point.
- **Baseline**: important to have one. It can be a random classifier (i.e., flip a coin for a binary classifier), or a fast and reasonable model (e.g., logistic regression with TF-IDF features).

Precision and recall

Given a binary classifier:

- **True positive**: a data point correctly predicted to be 1.
- **True negative**: a data point correctly predicted to be 0.
- **False positive**: a data point incorrectly predicted to be 1.
- **False negative**: a data point incorrectly predicted to be 0.

Precision and recall



Credit: Wikipedia.

F-measure and accuracy reloaded

- F-measure (harmonic mean of precision and recall):

$$F = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

- Accuracy:

$$A = \frac{tp + tn}{tp + tn + fp + fn}$$

Parameters and hyperparameters

Parameters whose values are *learned*

Hyperparameters whose values are *chosen*

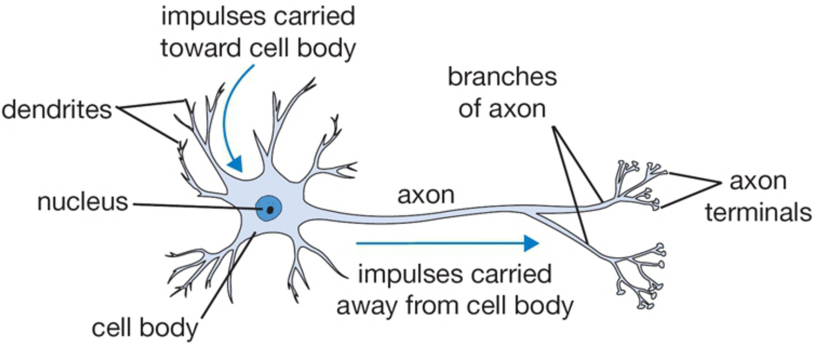
Feature	β
the	0.01
and	0.03
bravest	1.4
love	3.1
loved	1.2
genius	0.5
BIAS	-0.1

Hyperparameter	value
minimum word frequency	5
max vocab size	10000
lowercase	TRUE
regularization strength	1.0

Credit: David Bamman (UC Berkeley).

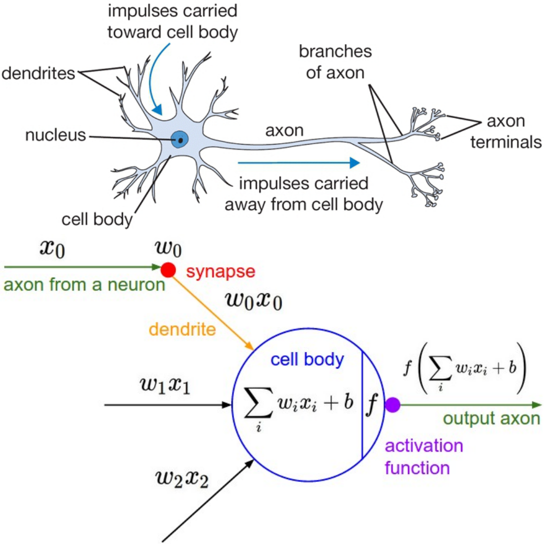
Neural Networks

A single neuron



Credit: Andrej Karpathy via Stanford's CS231N.

A single neuron



Credit: Andrej Karpathy via Stanford's CS231N.

Logistic regression as a neural network

Following the notation in the previous slide, we have:

- $\boldsymbol{x} = \langle x_0, x_1, x_2, \ldots, x_d \rangle$ is our input representation.
- We aggregate the features $\boldsymbol{x}$ into a linear combination using weights $\boldsymbol{w}$. We also include the bias term b into the matrix by adding an appropriate dimension fixed at 1 to $\boldsymbol{x}$, so that we can use matrix notation:

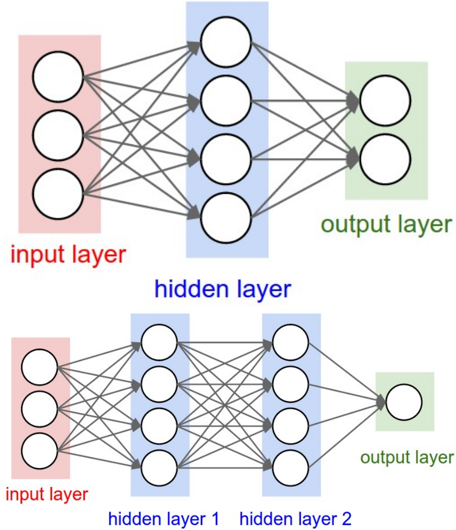
$$z = \sum_{i=0}^{d} w_i x_i = \boldsymbol{w} \cdot \boldsymbol{x}$$

- We pass z through an activation function, in this case the sigmoid:

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

- **Linear models are a single neuron**. *Question: what is the activation function for linear regression?*

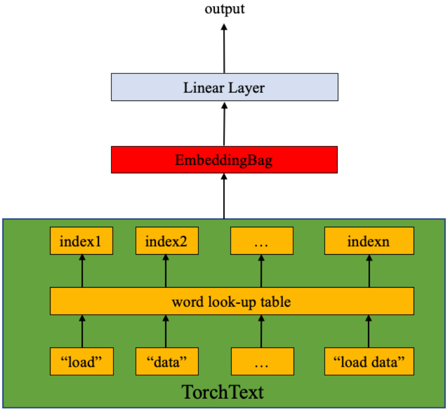
From single layer to multi-layer



Credit: Andrej Karpathy via Stanford's CS231N.

Using embeddings as features

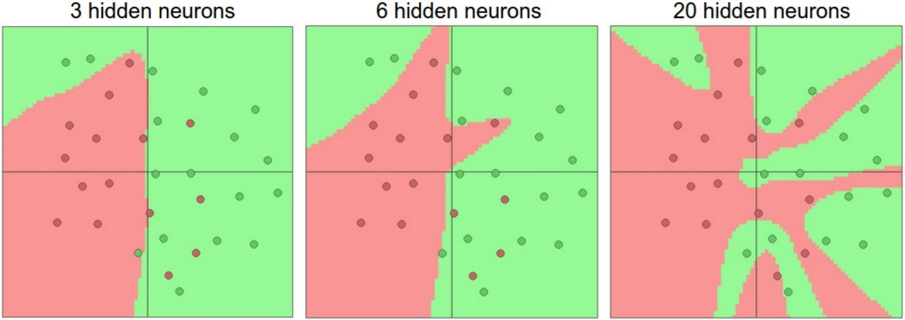
Neural networks are **modular**: we can piece them together into advanced architectures. For example, we can use embeddings to represent our input (either training them or using pre-trained ones). *More on this in the lab.*



Credit: TorchText.

Why do we need non-linearities?

Multiple layers and **non-linear functions** (such as the sigmoid) allow us to fit complex decision boundaries.



Credit: Andrej Karpathy via Stanford's CS231N.

How do we train neural networks?

- Key idea: use a smart way to apply SGD, called **backpropagation**.
- Backpropagation combines using the chain rule to calculate local derivatives (called gradients) with the re-use of pre-computed operations to speed the computation up.
- *More on this in the external materials for the course.*

Neural networks practicalities

Training neural networks entails a lot more than stacking up layers. Several topics require practical and theoretical knowledge beyond this course:

- Weight initialization
- Regularization (e.g., via dropout)
- Which non-linearities to use
- Which loss functions to use
- How to monitor and adjust the learning process (e.g., optimizers and learning rates) to avoid dying neurons and overfitting

Notes

Notes

Extras

Full derivation for logistic regression

- First, we need some notable derivatives:

$$
\begin{aligned}
\frac{\partial log(x)}{\partial x} &= \frac{1}{x} \\
\frac{\partial \sigma(x)}{\partial x} &= \sigma(x)(1-\sigma(x)) \\
\frac{\partial f(g(x))}{\partial x} &= \frac{\partial f}{\partial g} \cdot \frac{\partial g}{\partial x} \rightarrow \text{chain rule}
\end{aligned}
$$

Full derivation for logistic regression

- Then:

$$\begin{aligned}
\frac{\partial \mathcal{L}_{\boldsymbol{x}}(\boldsymbol{w})}{\partial w_j} &= -\partial\Big[y log \sigma(\boldsymbol{wx}) + (1-y) log(1-\sigma(\boldsymbol{wx}))\Big] \\
&= -\Big[\partial y log \sigma(\boldsymbol{wx}) + \partial(1-y) log(1-\sigma(\boldsymbol{wx}))\Big] \\
&= -\frac{y}{\sigma(\boldsymbol{wx})}\partial\sigma(\boldsymbol{wx}) - \frac{1-y}{1-\sigma(\boldsymbol{wx})}\partial(1-\sigma(\boldsymbol{wx})) \rightarrow \text{chain rule} \\
&= -\Big[\frac{y}{\sigma(\boldsymbol{wx})} - \frac{1-y}{1-\sigma(\boldsymbol{wx})}\Big]\partial\sigma(\boldsymbol{wx}) \rightarrow \text{re-arrange}
\end{aligned}$$

- *Exercise: plug-in the derivative of the Sigmoid and re-arrange yourself to reach:*

$$\ldots = \big[\sigma(\boldsymbol{wx} - y)\big] x_j$$

Full derivation for logistic regression

- In case you were wondering:

$$
\begin{aligned}
\frac{\partial \sigma(x)}{\partial x} &= \partial \frac{1}{1+e^{-x}} \\
&= \partial [1+e^{-x}]^{-1} \\
&= \frac{e^{-x}}{1+e^{-x}} \frac{1}{1+e^{-x}} \\
&= \frac{(1+e^{-x})-1}{1+e^{-x}} \sigma(x) \\
&= \sigma(x)(1-\sigma(x))
\end{aligned}
$$

- *Exercise, derive*:

$$
\frac{\partial log \sigma(x)}{\partial x} = \sigma(-x)
$$

Why MSE and cross-entropy?

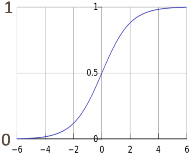
- It turns out that, given some standard assumptions on our models, using those two losses corresponds to doing Maximum Likelihood Estimation. See `https://www.expunctis.com/2019/01/27/Loss-functions.html`.
- If you are curious about the information theory underpinning cross-entropy, read this: `http://colah.github.io/posts/2015-09-Visual-Information`.

NN activation functions

Several non-linear activation functions have been proposed. A good default options is ReLU.

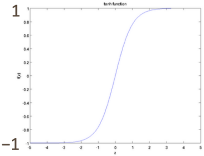
logistic ("sigmoid")

$$f(z) = \frac{1}{1+\exp(-z)}.$$



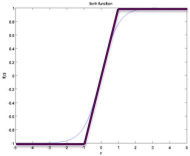
tanh

$$f(z) = \tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}},$$



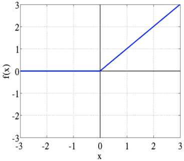
hard tanh

$$\mathrm{HardTanh}(x) = \begin{cases} -1 & \text{if } x < -1 \\ x & \text{if } -1 <= x <= 1 \\ 1 & \text{if } x > 1 \end{cases}$$



ReLU (Rectified Linear Unit)

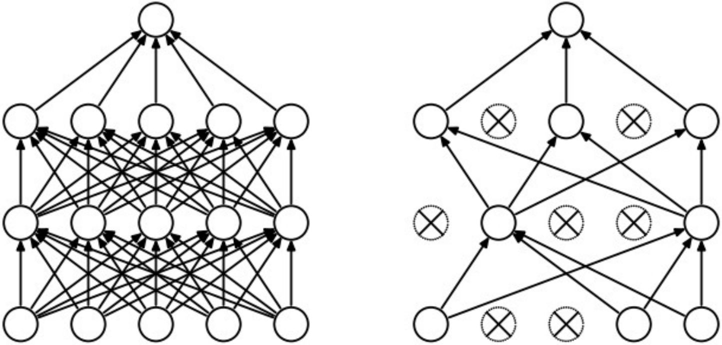
$$\mathrm{rect}(z) = \max(z, 0)$$



Credit: Stanford CS224N.

NN regularization via dropout

Dropout's idea is to mask a random set of neuron connections at training time, in order to compel the network to learn redundant paths and avoid overfitting.

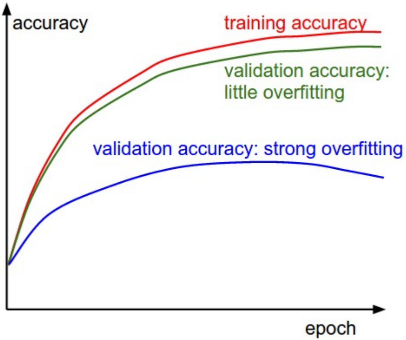


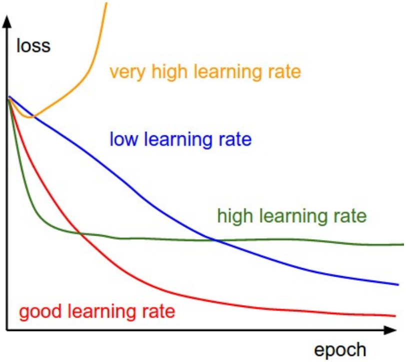
(a) Standard Neural Net (b) After applying dropout.

Credit: Srivastava et al.
https://www.cs.toronto.edu/~hinton/absps/JMLRdropout.pdf.

NN under/overfitting and learning rates

Two illustrations on how to spot correct learning behaviour.





Credit: Andrej Karpathy via Stanford's CS231N.