EDAN96
Applied Machine Learning
Lecture 8: Classification Techniques and Neural Networks

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Content

Overview and practice of some neural network architectures:

- Datasets
- Input formatting
- Feedforward networks

We will use:

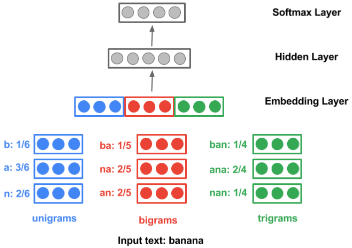
- PyTorch, `https://pytorch.org`, a powerful API to design and train network, and
- scikit-learn, `https://scikit-learn.org/stable/`, a general purpose machine-learning toolkit.

Goal of the Lecture

Describe a language detector: Given a string predict the language:

- *Bonjour* –> French
- *Guten Tag* –> German

Follow the complete compact language detector (CLD3)
`https://github.com/google/cld3`



You will implement it during the fourth lab

Dataset Exploration

When dealing with a dataset, the first step is to explore it.
All machine-learning experiments should start with it.
Such a step is called *exploratory data analysis* (EDA)
It consists of measuring:

- the size of the dataset (observations)
- the number of classes, number of observations per class
- the mean and standard deviation of the variables
- the domain of categorical classes
- number of missing values, etc.

EDA and Visualization

Many EDAs show results on graphics

Many examples on `https://www.kaggle.com/`, for instance `https://www.kaggle.com/code/imoore/intro-to-exploratory-data-analysis-eda-in-python` and `https://www.kaggle.com/code/ekami66/detailed-exploratory-data-analysis-with-python`

The Tatoeba Dataset

- A language detector (lab 4) is a kind of categorization
- Categorization is by far the most popular application of machine learning
- See here for the datasets: `https://huggingface.co/tasks`, `https://archive.ics.uci.edu/ml/datasets.php`
- As dataset to train CLD3, we will use Tatoeba `https://tatoeba.org/`

Code Example

Experiment: An elementary EDA Jupyter Notebook:
`https://github.com/pnugues/edan96/blob/main/programs/5-tatoeba_eda_select.ipynb`

Dataset Formatting

When training a model, a common practice is to split the dataset in three sets:

1. Train, validation (also called development), and test sets
2. Already done in many datasets, see `https://huggingface.co/datasets`
3. Otherwise do it. You will have to do it for CLD3

This partitioning is essential to measure overfit when training.
Identical test sets give means to compare results and performance of systems (see scientific papers).

Code Example

Experiment: An elementary EDA Jupyter Notebook:
https://github.com/pnugues/edan96/blob/main/programs/5-tatoeba_eda_select.ipynb

Input Formatting

Starting from observations, we format the input to use it as input to a classifier

This step is also called the vectorization: Turn the input into numerical vectors

Digitization: We will assume all our data is in digital format

Numerical input: We already have vectors or tensors to represent our data. We have to standardize them

Categorical or text input: Linear classifiers do not accept this: We have to encode the symbols as vectors, using one-hot encoding (also called indicator vector or function)

- **Hashing:** One-hot encoding may result in very large vectors, millions of parameters, when dealing with text. We can reduce their size with hashing techniques

Embeddings: One-hot encoding is a sparse representation. We can design network architectures to produce smaller (dim=100) and dense vectors

Standardization

Most algorithms in classification do not work well if the parameters have widely differing ranges:

1. Parameter 1: $[10,000,000; 20,000,000]$
2. Parameter 2: $[-0.01; 0.002]$

Before training a model, we must standardize the data.

Two options:

1. Remove the mean and divide by the standard deviation with respect to columns:

$$\boxed{x_{i,j_{std}} = \frac{x_{i,j} - \bar{x}_{.,j}}{\sigma_{x_{.,j}}}.}$$

2. Norm the rows to 1:

$$\boxed{x_{i,j_{norm}} = \frac{x_{i,j}}{\sqrt{\sum_{k=0}^{n-1} x_{i,k}^2}}.}$$

Fisher's Iris Dataset (1936)

Table I

Iris setosa				*Iris versicolor*				*Iris virginica*			
Sepal length	Sepal width	Petal length	Petal width	Sepal length	Sepal width	Petal length	Petal width	Sepal length	Sepal width	Petal length	Petal width
5·1	3·5	1·4	0·2	7·0	3·2	4·7	1·4	6·3	3·3	6·0	2·5
4·9	3·0	1·4	0·2	6·4	3·2	4·5	1·5	5·8	2·7	5·1	1·9
4·7	3·2	1·3	0·2	6·9	3·1	4·9	1·5	7·1	3·0	5·9	2·1
4·6	3·1	1·5	0·2	5·5	2·3	4·0	1·3	6·3	2·9	5·6	1·8
5·0	3·6	1·4	0·2	6·5	2·8	4·6	1·5	6·5	3·0	5·8	2·2
5·4	3·9	1·7	0·4	5·7	2·8	4·5	1·3	7·6	3·0	6·6	2·1
4·6	3·4	1·4	0·3	6·3	3·3	4·7	1·6	4·9	2·5	4·5	1·7
5·0	3·4	1·5	0·2	4·9	2·4	3·3	1·0	7·3	2·9	6·3	1·8
4·4	2·9	1·4	0·2	6·6	2·9	4·6	1·3	6·7	2·5	5·8	1·8
4·9	3·1	1·5	0·1	5·2	2·7	3·9	1·4	7·2	3·6	6·1	2·5
5·4	3·7	1·5	0·2	5·0	2·0	3·5	1·0	6·5	3·2	5·1	2·0
4·8	3·4	1·6	0·2	5·9	3·0	4·2	1·5	6·4	2·7	5·3	1·9
4·8	3·0	1·4	0·1	6·0	2·2	4·0	1·0	6·8	3·0	5·5	2·1
4·3	3·0	1·1	0·1	6·1	2·9	4·7	1·4	5·7	2·5	5·0	2·0
5·8	4·0	1·2	0·2	5·6	2·9	3·6	1·3	5·8	2·8	5·1	2·4
5·7	4·4	1·5	0·4	6·7	3·1	4·4	1·4	6·4	3·2	5·3	2·3
5·4	3·9	1·3	0·4	5·6	3·0	4·5	1·5	6·5	3·0	5·5	1·8
5·1	3·5	1·4	0·3	5·8	2·7	4·1	1·0	7·7	3·8	6·7	2·2
5·7	3·8	1·7	0·3	6·2	2·2	4·5	1·5	7·7	2·6	6·9	2·3
5·1	3·8	1·5	0·3	5·6	2·5	3·9	1·1	6·0	2·2	5·0	1·5
5·4	3·4	1·7	0·2	5·9	3·2	4·8	1·8	6·9	3·2	5·7	2·3
5·1	3·7	1·5	0·4	6·1	2·8	4·0	1·3	5·6	2·8	4·9	2·0

Code Example

Experiment: sklearn and its cancer dataset with a Jupyter Notebook:
`https://github.com/pnugues/edan96/blob/main/programs/6-standardization.ipynb`

Categorical Values

Linear classifiers only understand numbers

A collection of two documents D1 and D2:

> D1: Chrysler plans new investments in Latin America.
>
> D2: Chrysler plans major investments in Mexico.

How to represent these words or these documents?

Categorical Values: One-hot encoding

Let us suppose we want to predict the parts of speech of the words, for instance *plans* in:

Input:	Chrysler	*plans*	major	investments	in	Mexico
Output:	PNoun	Verb	Adjective	Noun	Prep.	PNoun

One-hot encoding:

1. Assigns a unique index to each symbol. The number of indices corresponds to the number of symbols:
   ```
   {'Chrysler': 1, 'in': 2, 'investments': 3,
   'major': 4, 'Mexico': 5, 'plans': 6}
   ```
2. Represent a symbol of index i by a vector $\mathbf{x} = (x_1, x_2, ..., x_n)$, where n is the largest index and all the coordinates are 0, except $x_i = 1$
   ```
   'Chrysler':    (1, 0, 0, 0, 0, 0)
   'in':          (0, 1, 0, 0, 0, 0)
   'investments': (0, 0, 1, 0, 0, 0)
   ...
   ```

Categorical Values: Multi-hot encoding

A collection of two documents D1 and D2:

D1: Chrysler plans new investments in Latin America.

D2: Chrysler plans major investments in Mexico.

Multi-hot encoding (also called a bag-of-words representation):

1. Creates a index of all the symbols (words) in all the documents
2. For each document, creates a set of its symbols (word)
3. Represents a document by a vector of 0s and 1s. $x_i = 1$ if the word of index i is in the document, or 0 otherwise.

D.	america	chrysler	in	investments	latin	major	mexico	new	plans
1	1	1	1	1	1	0	0	1	1
2	0	1	1	1	0	1	1	0	1

Hashing

One-hot encoding leads to very large dimensions as there are billions of different words.

In the Tatoeba experiment (see notebook), the number of unigrams, bigrams, and trigrams is (4844, 88471, 294472)

A solution is to hash the symbols and use the remainder of a division (modulo) as index

```
>>> hash('abc')
-6712881850779232724
>>> hash('abc') % 100
76   # Always less than 100
```

Hashing:

1. Reduces the vectors size and makes it manageable
2. Creates conflicts: two symbols can have the same hash numbers
3. Is usable in classification

Code Example

Experiment: hashing CLD3 n-grams Jupyter Notebook:
https://github.com/pnugues/edan96/blob/main/programs/7-ngram_hashing.ipynb

Reproducible Hash Codes

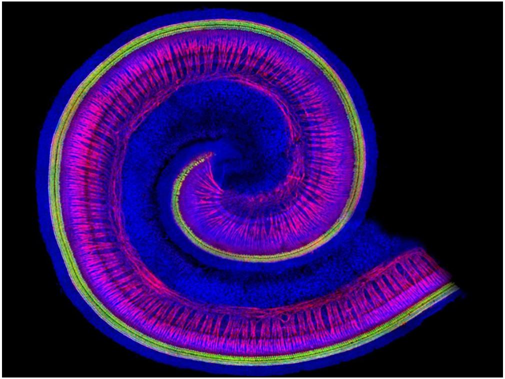
```
def reproducible_hash(string):
    """
    reproducible hash on any string

    Arguments:
       string: python string object

    Returns:
       signed int64
    """

    # We are using MD5 for speed not security.
    h = hashlib.md5(string.encode("utf-8"),
                    usedforsecurity=False)
    return int.from_bytes(h.digest()[0:8], 'big', signed=True)
```

Neural Networks



A photomicrograph showing the classic view of the snail-shaped cochlea with hair cells stained green and neurons showing reddish-purple. [Decibel Therapeutics (`https://www.decibeltx.com`)]. Source: `https://www.genengnews.com/insights/targeting-the-inner-ear/`

Logistic Regression as a Neural Network

= single-layer neural network with a linear combination of inputs followed by a sigmoid activation function.

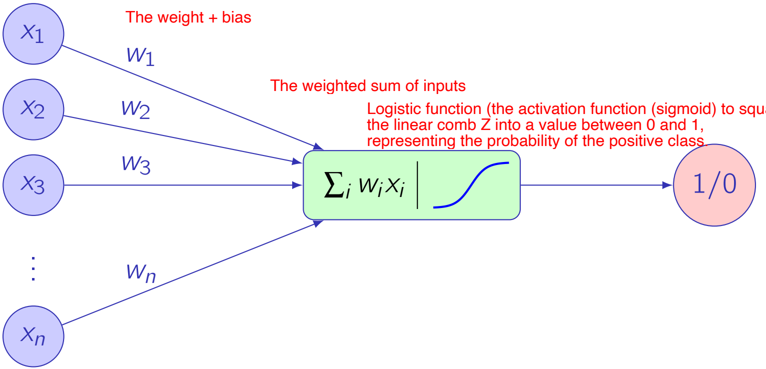
Input features

The weight represents the strength of the connection between ihe input and output.

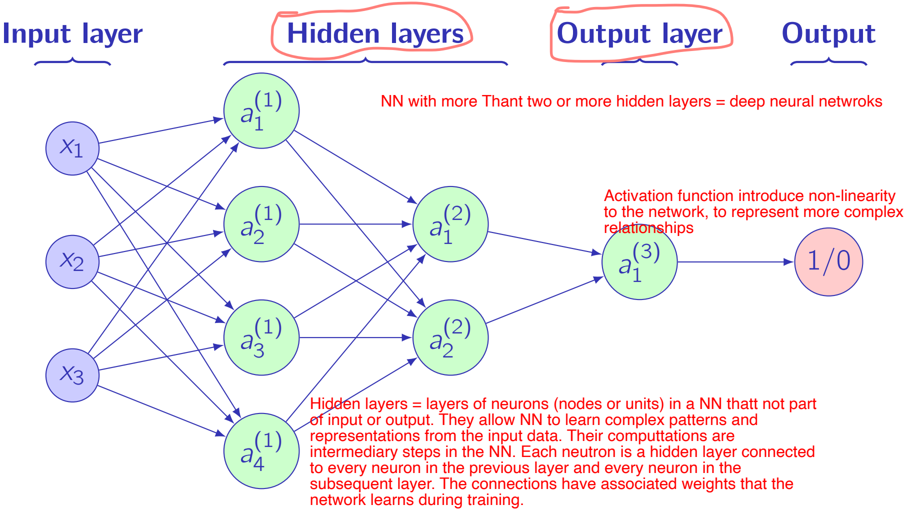
The weight + bias

The weighted sum of inputs

Logistic function (the activation function (sigmoid) to squash the linear comb Z into a value between 0 and 1, representing the probability of the positive class.

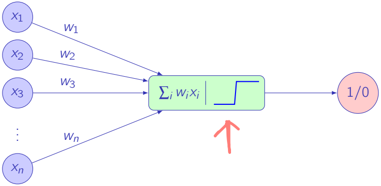


Neural Networks

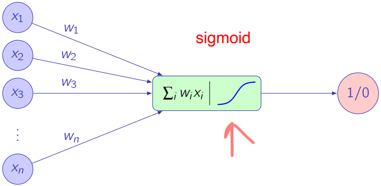


Activation Functions

The perceptron



Logistic regression



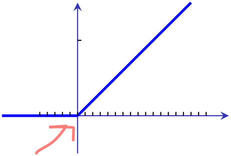
Activation Functions

Non-linear activation function

Rectified linear unit (ReLU), where

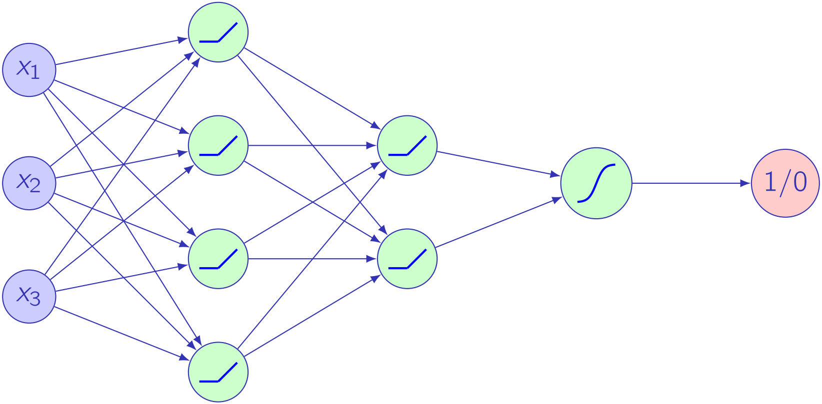
The maximum of 0 and input x.

$$reLU(x) = \max(0, x).$$



Helps mitigate vanishing gradient problem, which can occur in activation functions like sigmoid.
Gradients become very small during back propagation leading to slow or stalled learning.

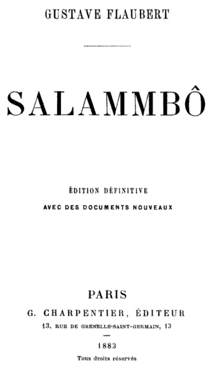
Neural Networks with Hidden Layers



A Text Dataset: *Salammbô*

A corpus is a collection – a body – of texts.

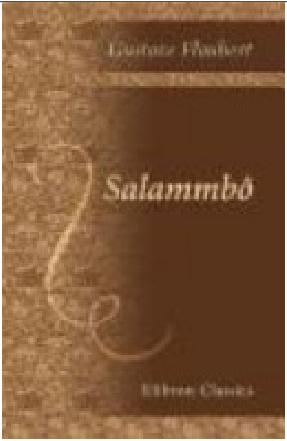
French original	English translation


GUSTAVE FLAUBERT

SALAMMBÔ

ÉDITION DÉFINITIVE
AVEC DES DOCUMENTS NOUVEAUX

PARIS
G. CHARPENTIER, ÉDITEUR
13, RUE DE GRENELLE-SAINT-GERMAIN, 13
1883
Tous droits réservés



Classification Dataset

Dataset for binary classification: *Salammbô* in French (1) and English (0)

	# char.	# A	class (y)	# char.	# A	class (y)
Chapter 1	36,961	2,503	1	35,680	2,217	0
Chapter 2	43,621	2,992	1	42,514	2,761	0
Chapter 3	15,694	1,042	1	15,162	990	0
Chapter 4	36,231	2,487	1	35,298	2,274	0
Chapter 5	29,945	2,014	1	29,800	1,865	0
Chapter 6	40,588	2,805	1	40,255	2,606	0
Chapter 7	75,255	5,062	1	74,532	4,805	0
Chapter 8	37,709	2,643	1	37,464	2,396	0
Chapter 9	30,899	2,126	1	31,030	1,993	0
Chapter 10	25,486	1,784	1	24,843	1,627	0
Chapter 11	37,497	2,641	1	36,172	2,375	0
Chapter 12	40,398	2,766	1	39,552	2,560	0
Chapter 13	74,105	5,047	1	72,545	4,597	0
Chapter 14	76,725	5,312	1	75,352	4,871	0
Chapter 15	18,317	1,215	1	18,031	1,119	0

Code Example

Experiment: Jupyter Notebook:
https://github.com/pnugues/edan96/blob/main/programs/10-Salammbo_multi_torch-2022.ipynb