

Machine Learning for Natural Language Processing

Task Specific Modelling of Text

Session 3

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Course Outline

- ① The Why and What of Natural Language Processing
- ② Representing text with vectors
- ③ Task specific Modeling of Text
- ④ Neural Natural Language Processing
- ⑤ Language Modelling
- ⑥ NLP in the "real-world"

Lecture 2 recap

How to represent text into vectors ?

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- Feature based approach for word representation (e.g. Wordnet)
- Distributional approach using co-occurrence statistics

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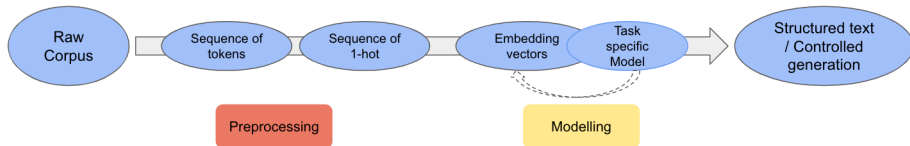
How to represent text into vectors ?

- Feature based approach for word representation (e.g. Wordnet)
- Distributional approach using co-occurrence statistics
- Continuous representation with the word2vec Skip-Gram Model
 - Embedding matrices
 - Predicting context words with focus words
 - Trained with Negative Sampling using Stochastic Gradient Descent
- Evaluating word vectors

Lecture Outline

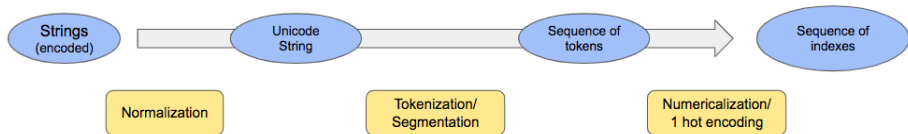
- Pre-processing (encoding, tokenization)
- Two sequence labelling tasks : POS tagging, NER
- Sequence Labelling: Sentiment Analysis
- Sequence Generation (lecture 5)

Standart NLP pipeline



Preprocessing

Preprocessing pipeline



Preprocessing

- Encoding
- Tokenization: Word and Sentence Segmentation

What is Encoding ?

At the beginning of any NLP problems is a collection of **strings**

NB : encoding is at play in **every computer programs** that handle strings !

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Reminder: a string is *data type* used to **represent** text

Definition: The process of **encoding** converts information from a source into **symbols** for **communication** or **storage**.

In other words, the way strings are stored in the memory of the computer is called the **encoding**

NB : encoding is at play in **every computer programs** that handle strings !

Encoding properties

A good encoding algorithm should have the following properties:

- Encode any string in memory (in bits)
- Universal

e.g: should be able to share string across computers and still have the same rendering

UTF-8 : the current global encoding standard

- **Unicode**: a universal table that maps any character to a *code point*
e.g : "Hello" → U+0048 U+0065 U+006C U+006C U+006F
- **Encoding**: a way to store any code-point to a sequence of bits.

UTF-8 : the current global encoding standard

- **Unicode:** a universal table that maps any character to a *code point*
e.g : "Hello" → U+0048 U+0065 U+006C U+006C U+006F
- **Encoding:** a way to store any code-point to a sequence of bits.

Definition UTF-8 (8-bit Unicode Transformation Format) is a variable width character encoding capable of encoding all 1,112,064 valid code points in Unicode using one to four 8-bit bytes. It is the standard in the internet.

Guideline: Everytime you face some encoding problem/bugs, make sure everything is correctly encoded in UTF-8. If it is not, convert it to UTF-8.

Preprocessing

- Encoding
- Tokenization: Word and Sentence Segmentation

Text segmentation

Definition: Text Segmentation is the process of splitting raw (encoded) text (i.e. list of characters) into units of interest.

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Two level of segmentation (usually) required :

- Split raw text into **modelling units** (ex: sentence, paragraph, 1000 characters...)
- Split modelling units into sequence of **basic units** (referred as **tokens**) (e.g: words, word-pieces, characters, ...)

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Two distinct approaches:

- Linguistically informed
e.g. word, sentence segmentation...
- Statistically informed
e.g. frequent sub-words (wordpieces, sentencepieces...)

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NB: Text Segmentation algorithms are task and model dependant

Tokenization

Tokenization is a broad (vague) term which simply refers to the process of splitting raw text into sequences of tokens.

Therefore, It can refer to word segmentation, wordpieces segmentation, character splitting...

NB: In its most usual meaning, tokenization refers to word segmentation.

Preprocessing : Word Segmentation

- First step for most NLP application: **text segmentation**
- e.g: Given a string $\mathbf{x}_{1:T}$:
predict for each position if end of word and sentence
- Can be framed as **a character level task**

input: une industrie métallurgique existait.
output: IIEIIIIIIIIIEIIIIIIIIIIIEIIIIIIIIIEE

- Easy task for most languages and not too noisy text
- Can be very complex in some cases (Chinese, User-Generated Content...)

Segmentation: Annotated data

- Can be trained/evaluated on Universal Dependency data (60+ languages)¹:

```
text =...  une industrie métallurgique existait.  
18  une            DET      19  det      -  
19  industrie      NOUN     21  nsubj   -  
20  métallurgique ADJ      19  amod    -  
21  existait       VERB     4   ccomp   SpaceAfterNo  
22  .              PUNCT    4   punct   -
```

¹<https://universaldependencies.org/>

Word Segmentation: a complex task (UGC² example)

- How to segment UGC text? e.g :

```
text = J'vais regarder teen wolf :)) @kino13...!!!  
1 J'  
2 vais  
3 regarder  
4 teen  
5 wolf  
15 :))  
16 @kino13  
17 ...  
18 !!!
```

²User Generated Content

Sentence Segmentation: a complex task

How to segment transcribed French speech ?

e.g : euh il y avait donc une euh jeune fille qui regardait dans une boutique apparemment une pâtisserie qui semblait avoir faim qui a profité de ce que le livreur s' éloigne pour euh voler un une baguette euh a rencontré donc Charlot à ce moment -là lui est rentrée dedans euh dans la confusion donc une euh une passante a dénoncé la jeune fille au livreur qui a couru après la jeune fille euh les policiers sont arrivés en raison du du du vacarme je p je pense (Gerdes)

Sentence Segmentation: a complex task (speech text example)

How to segment transcribed French speech ?

e.g : *euh il y avait donc une euh jeune fille qui regardait dans une boutique apparemment une pâtisserie qui semblait avoir faim qui a profité de ce que le livreur s' éloigne pour euh voler un une baguette euh a rencontré donc Charlot à ce moment -là lui est rentrée dedans **END** euh dans la confusion donc une euh une passante a dénoncé la jeune fille au livreur qui a couru après la jeune fille euh **END** les policiers sont arrivés en raison du du du vacarme je p je pense (Gerdes)*

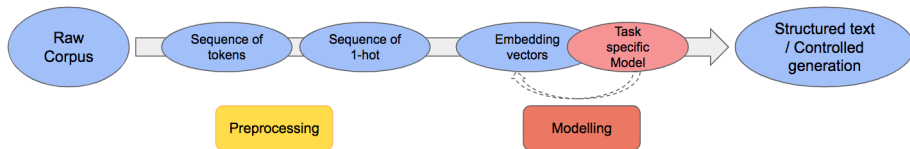
Segmentation

How to approach segmentation ?

- Easy cases: Define set of rules (e.g. using regex)
- Complex cases: Build a character-level sequence labelling model using annotated data

Modelling

Standart NLP pipeline



Sequence Modelling

Modelling Framework

- Rule-based approach (e.g. defining regex for extraction and rules for handling ambiguity)
- **Statistical approach**
- Neural approach (lectures 4 and 5)

Type of tasks

- Sequence Labelling (lecture 3)
- Sequence Classification (lecture 3)
- Sequence Generation (lecture 5)
- Topic Models (lecture 6)

Sequence Labelling

Definition: Sequence Labelling is a type of task that involves the assignment of **a label/tag** to **each element** of a sequence.

We will focus on two sequence labelling tasks:

- Part-of-Speech Tagging (POS)
- Name Entity Recognition (NER)

Part of Speech Tagging (POS tagging)

Input: *Cette exposition nous apprend que dès le XIIe siècle , à Dammarie-sur-Saulx , entre autres sites , une industrie métallurgique existait .*

Output: Cette/DET exposition/NOUN nous/PRON apprend/VERB
que/SCONJ dès/ADP le/DET XIIe/ADJ siècle/NOUN ,/PUNCT à/ADP
Dammarie-sur-Saulx/PROPN ,/PUNCT entre/ADP autres/ADJ sites/NOUN
,/PUNCT une/DET industrie/NOUN métallurgique/ADJ existait/VERB
./PUNCT

Part of speeches

- Part of speech: **morphosyntactic categories** (not semantic)
 - Syntactic function: how words are composed together
 - Morphological properties: how words are formed (e.g. prefix/suffix)
- Divided into two broad categories:
- **Closed class**: new words rarely appear. e.g. conjunction or pronouns
- **Open class**: new words often appear. e.g. nouns or verbs

Part of speeches: open classes

- **Noun:** word to describe thing, people, concept, entity, etc. Can occur with adjective and determiners, can be the subject of sentence, can be marked for plural with -s

dog, apple, robot

- **Verb:** word to describe action, process, state of being, etc. Can be inflected to mark tense, voice, or aspect

eat, run, drive

- **Adjective:** word to describe property or quality, etc. Modify a noun or noun phrase.

big, blue, good

- **Adverb:** word to express place, time, frequency, etc. Diverse class, modify verbs, adjectives, adverbs, whole phrases or sentences.

quickly, often, sometimes

Part of speeches: closed classes

- **Auxiliary verbs:** add information to a clause or sentence, such as tense, voice, aspect, etc. Usually modify a verb.

be, have

- **Conjunction:** join two nouns, phrases, or clauses.

and, or, if

- **Pronouns:** shorthand to refer to noun phrase, person, entity, etc.

she, him, who

- **Determiners:** add information to a noun or noun phrase. Often appear at the beginning of noun phrase

a, the, any

Part of speech tagging

- Why hard? **ambiguity**:

Time flies like an arrow

- [N V Adp Det N] or [N N V Det N]?
- But also easy? most frequent tag baseline: \sim **88%** for English
- Want to capture local information (*like* can be a verb or preposition) and context information (V often follows N).

Named Entity Recognition (NER)

- Detect and classify named entities in text.

Input: During World War II, Turing worked for the Government Code and Cypher School at Bletchley Park.

Output: During World War II, [Turing]_{PER} worked for the [Government Code and Cypher School]_{ORG} at [Bletchley Park]_{LOC}.

- Standard tag set: PER, ORG, LOC
- Sometimes: TIME, MONEY, ...
- For other applications, names of products, books, molecules, etc.

Named Entity Recognition (NER)

- Framed as sequence labelling using **BIO** tag scheme
- Using BIO makes NER a token level task
- B for beginning of entity, I for inside entity, O for other

During/O World/O War/O II/O ,/O Turing/B-PER worked/O for/O
the/O Government/B-ORG Code/I-ORG and/I-ORG Cypher/I-ORG
School/I-ORG at/O Bletchley/B-LOC Park/I-LOC

- Why BIO? adjacent entities: *[United States] [Department of State]*

United States Department of State
/B-ORG /I-ORG /B-ORG /I-ORG /I-ORG

- Sometimes BILOU: L for last, U for unit

Sequence classification model

Let $(Y_t, X_t)_{t \in \{1, \dots, n\}}$ be our observed sequence of labels and tokens

Our goal is to learn the distribution

$$P(Y_1, \dots, Y_T \mid X_1, \dots, X_T)$$

From a probabilistic perspective: Two approaches

- Generative modelling: $p(X, Y)$ (and Bayes' rule)
- Discriminative modelling: $p(Y|X)$

Discriminative modeling

- Naive solution: formulate as n independent classification problems
- Given features \mathbf{x}_t representing word t and its context:
- Learn a linear classifier with logistic regression to predict label y_t .
- Examples of features:
 - previous word x_{t-1} and/or next word x_{t+1}
 - pair of word (x_{t-1}, x_t) or (x_t, x_{t+1})
- **Limitation:** does not take into account previous/next predictions
- Solution: condition the prediction of y_t on y_{t-1}

Maximum entropy Markov models

- Our goal is to learn the distribution

$$P(Y_1, \dots, Y_T \mid X_1, \dots, X_T)$$

- Using the chain rule, we can factorize as

$$P(Y_{1:T} \mid X_{1:T}) = \prod_{t=1}^T P(Y_t \mid Y_{1:t-1}, X_{1:T})$$

- Then, use Markov independence assumption:

$$P(Y_t \mid Y_{1:t-1}, X_{1:T}) = P(Y_t \mid Y_{t-1}, X_{1:T})$$

- Use a (log) linear model to parametrize this distribution.

Maximum entropy Markov models

- We introduce feature vector $\Phi(\mathbf{x}, t, y_t, y_{t-1})$ and get

$$p(y_t \mid y_{t-1}, \mathbf{x}) = \frac{\exp(\mathbf{w}^\top \Phi(\mathbf{x}, t, y_{t-1}, y_t))}{\sum_{k \in \mathcal{Y}} \exp(\mathbf{w}^\top \Phi(\mathbf{x}, t, y_{t-1}, k))}$$

- This is a regular log linear model:
each class probability is a "learnt" (w) linear combination of feature extracted from x, y_{t-1}, y_t
- The parameters \mathbf{w} are learned using (stochastic) gradient descent
- The training data corresponds to $(\mathbf{x}_{1:T}, t, y_{t-1}, y_t)$
- Then, we have a model of

$$p(y_1, \dots, y_T \mid x_1, \dots, x_T).$$

Maximum Entropy Markov Models (MEMMs): inference

- Given trained model and input \mathbf{x} ,
how to compute most probable sequence of labels?

- Naive solution: greedy decoding
- For $t = 1, \dots, T$:

$$y_t = \operatorname{argmax}_k p(k \mid y_{t-1}, \mathbf{x}_{1:T})$$

- **Limitation:** what if

$$p(i \mid y_t) = p(j \mid y_t) + \varepsilon$$

but

$$\max_k p(k \mid i) \ll \max_k p(k \mid j)$$

→ Not making use of future predictions for inferring current state leads to performance drops

Maximum entropy Markov models: inference

- Compute most probable sequence using **Viterbi algorithm**
- We define:

$$s(t, k) = \max_{\substack{\mathbf{y}_{1:t} \\ y_t=k}} p(\mathbf{y}_{1:t} \mid \mathbf{x})$$

- Then, we have

$$\begin{aligned} s(t, k) &= \max_{\substack{\mathbf{y}_{1:t} \\ y_t=k}} p(k \mid y_{t-1}, \mathbf{x}) p(\mathbf{y}_{1:t-1} \mid \mathbf{x}) \\ &= \max_j \max_{\substack{\mathbf{y}_{1:t-1} \\ y_{t-1}=j}} p(k \mid y_{t-1}, \mathbf{x}) p(\mathbf{y}_{1:t-1} \mid \mathbf{x}) \\ &= \max_j \max_{\substack{\mathbf{y}_{1:t-1} \\ y_{t-1}=j}} p(k \mid j, \mathbf{x}) p(\mathbf{y}_{1:t-1} \mid \mathbf{x}) \\ &= \max_j p(k \mid j, \mathbf{x}) \max_{\substack{\mathbf{y}_{1:t-1} \\ y_{t-1}=j}} p(\mathbf{y}_{1:t-1} \mid \mathbf{x}) \\ &= \max_j p(k \mid j, \mathbf{x}) s(t-1, j) \end{aligned}$$

Maximum entropy Markov models: inference

- Given a sequence of tokens $\mathbf{x}_{1:T}$ and parameters of the model.
- Initialization: $\forall k, s(1, k) = p(k \mid \text{Start}, \mathbf{x}_{1:T})$
- For $t = 2, \dots, T$:

$$s(t, k) = \max_j p(k \mid j, \mathbf{x}_{1:T}) \times s(t-1, j)$$

- return $\max_k s(T, k)$
- Complexity of algorithm: $O(dT|\mathcal{Y}|^2)$, where d is number of features.

Features for sequence tagging

- We need to define $\Phi(\mathbf{x}, t, y_{t-1}, y_t)$

- Transition features (similar to HMM):

$$\delta(y_{t-1} = \text{Noun}, y_t = \text{Verb})$$

- Emission features (similar to HMM):

$$\delta(x_t = \text{eating}, y_t = \text{Verb})$$

- But also (impossible in HMM):

$$\delta(x_{t-1} = \text{the}, x_t = \text{flies}, y_t = \text{Noun})$$

- Or:

$$\delta(x_t = \text{flies}, y_{t-1} = \text{Det}, y_t = \text{Noun})$$

Features for POS tagging or NER

Word features

- Prefix and suffix: *un-*, *-ing*, *-ed*, ...
- Word shape: Capitalization, ContainsDigit, DD/DD/DDDD, ...
- Gazetteers: list of named entities

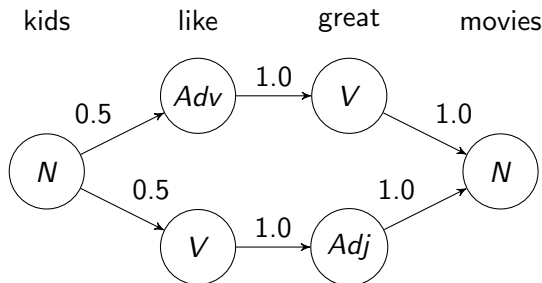
Context features

- Word before and after
- Tag before and after

Nowadays

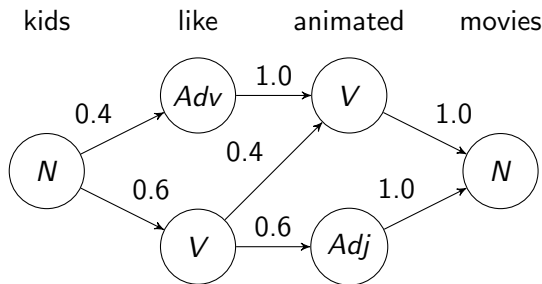
- Most word features replaced by pre-trained word vectors
- Most context features can be replaced by neural network

Label bias problem



- We have $p(V \mid Adv, \text{great}) = 1$, because we've always observed verbs after adverbs in training data
- Both paths have equal probabilities, states with single outgoing transition ignore observation!
- Because local normalization
- Because MEMM only **condition** on observation

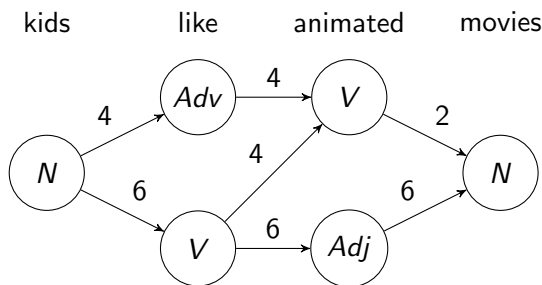
Label bias problem



- Locally, we have: N, V, Adj, N
- But most probably: N, Adv, V, N
- Locally normalized models: favor state with low transition entropy!
- (This could even happen with HMM)

Label bias problem

- Solution? Global normalization!



- Here most probable sequence: N, V, Adj, N .
- If path contains one very unlikely transition: can be strongly penalized

Conditional Random Fields

Conditional Random Fields

- Discriminative model of \mathbf{y} given \mathbf{x} :

$$p(y_1, \dots, y_T \mid x_1, \dots, x_T) = \frac{\exp(\mathbf{w}^\top \Phi(\mathbf{y}, \mathbf{x}))}{\sum_{\mathbf{z} \in \mathcal{Y}^T} \exp(\mathbf{w}^\top \Phi(\mathbf{z}, \mathbf{x}))}$$

- One large log linear model: **normalize over all sequences!**
- $\Phi(\mathbf{y}, \mathbf{x})$: feature vector for the pair of the whole sequences \mathbf{x} and \mathbf{y}
- Normalization factor has exponential number of sequences: \rightarrow How to compute this efficiently?

Conditional Random Fields

- Main idea: restrict the feature vector to decompose as

$$\Phi(\mathbf{y}, \mathbf{x}) = \sum_{t=1}^T \phi(\mathbf{x}, t, y_{t-1}, y_t)$$

- Example of feature vector $\phi(\mathbf{x}, t, y_{t-1}, y_t)$:

$$\phi_r(y_{t-1}, y_t) + \phi_e(x_t, y_t)$$

- This means that transition score: independent of position/input
- Association score between label and input: only local
- Most common extension: ϕ_e can depend on whole \mathbf{x}

Conditional Random Fields

- Using previous decomposition, efficient inference:

$$\begin{aligned}\operatorname{argmax} p(\mathbf{y} \mid \mathbf{x}) &= \operatorname{argmax} \frac{\exp(\mathbf{w}^\top \Phi(\mathbf{y}, \mathbf{x}))}{\sum_{\mathbf{z}} \exp(\mathbf{w}^\top \Phi(\mathbf{z}, \mathbf{x}))} \\ &= \operatorname{argmax} \exp(\mathbf{w}^\top \Phi(\mathbf{y}, \mathbf{x})) \\ &= \operatorname{argmax} \mathbf{w}^\top \Phi(\mathbf{y}, \mathbf{x}) \\ &= \operatorname{argmax} \sum_t \mathbf{w}^\top \phi(\mathbf{x}, t, y_{t-1}, y_t)\end{aligned}$$

- Again, we can use Viterbi to compute the argmax!

Conditional Random Fields: inference

- We introduce

$$\begin{aligned}s(t, k) &= \max_{\substack{\mathbf{y}_{1:t} \\ y_t=k}} \mathbf{w}^\top \Phi(\mathbf{y}_{1:t}, \mathbf{x}) \\ &= \max_{\substack{\mathbf{y}_{1:t} \\ y_t=k}} \mathbf{w}^\top \phi(\mathbf{x}, t, y_{t-1}, y_t) + \mathbf{w}^\top \Phi(\mathbf{y}_{1:t-1}, \mathbf{x}) \\ &= \max_j \max_{\substack{\mathbf{y}_{1:t-1} \\ y_{t-1}=j}} \mathbf{w}^\top \phi(\mathbf{x}, t, j, k) + \mathbf{w}^\top \Phi(\mathbf{y}_{1:t-1}, \mathbf{x}) \\ &= \max_j \mathbf{w}^\top \phi(\mathbf{x}, t, j, k) + \max_{\substack{\mathbf{y}_{1:t-1} \\ y_{t-1}=j}} \mathbf{w}^\top \Phi(\mathbf{y}_{1:t-1}, \mathbf{x}) \\ &= \max_j \mathbf{w}^\top \phi(\mathbf{x}, t, j, k) + s(t-1, j)\end{aligned}$$

- Using simple ϕ :

$$s(t, k) = \max_j \mathbf{w}^\top \phi_r(j, k) + \mathbf{w}^\top \phi_e(x_t, k) + s(t-1, j)$$

Conditional Random Fields: inference

- Given an input \mathbf{x} and a trained model \mathbf{w}
- Initialization: $s(1, k) = \mathbf{w}^\top \phi(\mathbf{x}, 1, \text{Start}, k)$
- For $t = 2, \dots, T$:

$$s(t, k) = \max_j s(t-1, j) + \mathbf{w}^\top \phi(x, t, j, k)$$

- Return $\max_k s(T, k)$.

Sequence Modelling

Type of tasks

- Sequence Labelling
- Sequence Classification
- Sequence Generation (lecture 5)
- Topic Models (lecture 6)

A sequence classification task : Sentiment Analysis

Input: Brilliant and moving performances by Tom Courtenay and Peter Finch.³

Output: Positive

Annotation scheme

Sentiment labels: {Neutral, Negative, Positive}, {Negative, Positive}, {0,...,5}...

³IMDB dataset (Pos,Neg) (2)

Sequence Classification: a bag-of-words approach

Let $(W_1, \dots, W_T)_i$ be the input sequence, Y_i the label, let X be a pretrained word embedding matrix ($X \in \mathbb{R}^{V \times d}$).

- X_{w_1}, \dots, X_{w_T} the embedded sequence
- Compute a sentence vector representation with $s = \frac{1}{T} \sum_j X_{w_j} (\in \mathbb{R}^d)$
- Train a logistic regression on $\{s_i, y_i\}_{1 \dots n}$

"Bag-of-words" because we do not model the tokens positions in the sequence.

Evaluation

Evaluating classification tasks

- **Classification tasks** (token level like sequence labelling, or sequence level like sequence classification) are evaluated with *confusion matrix-based metrics*⁴.
- Define class(es) of interest as *Positive*
- Count Correct Prediction (True Positive/Negative) and Incorrect Prediction (False Positive Prediction and False Negative)
- Aggregate those numbers with statistics: Accuracy, F1⁵

Example:

- POS tagging: Accuracy
- NER: F1 score with regard to the name entities
- Sentiment Classification: F1 score (usually)

4

⁵https://en.wikipedia.org/wiki/F1_score

Evaluating classification tasks

Confusion Matrix

		Prediction		
Observations	total	P	N	
		TP: True Positive	FN: False Negative	P'
		FP: False Positive	TN: True Negative	N'

Evaluation metrics for Classification

$$Accuracy = \frac{TP + TN}{P + N}$$

$$Precision = \frac{TP}{P'} \text{ and } Recall = \frac{TP}{P}$$

$$F1 = hmean(Precision, Recall) = \left(\frac{Precision^{-1} + Recall^{-1}}{2} \right)^{-1}$$

- Accuracy is relevant if the classes are balanced and if no specific care should be given to the performance on a specific class
- Otherwise: F1-score (or more generally ROC curve based scores) should be used

The Modelling Challenge

All NLP tasks require a sequence model i.e an estimation of

$$P(t_1, \dots, t_n | x_1, \dots, x_n)$$

So far, we have studied one solution (e.g. MEMMs):

- ① Modelling in terms of probability the problem
- ② Making assumption on the distribution to simplify the joint distribution
- ③ Estimate it with data

In lecture 4, we will study how Deep Learning brings a more powerful solution for this problem

Lecture Summary

- Preprocessing (encoding, segmentation)
- Modelling sequence tagging tasks (such as POS or NER) with MEMMS and CRF model
- Modelling Sentiment Analysis with a *bag-of-words* model
- Evaluation

References I

- Armand Joulin & Edouard Graves, ENSAE ML for NLP, 2019
- [Gerdes] Gerdes, Kim; Kahane, S. Y. C. E. A. C. M. C. French spoken treebank. In *github.com/UniversalDependencies/UD_French – Spoken*.
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