**Comparative Study To Solve Text Categorization**

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# Abstract

In the last decade, **D**eep **L**earning (**DL**) has demonstrated outstanding performance in the field of computer vision beating indisputably traditional methods, thanks to the GPU performance leapfrog and the huge amount of labeled datasets. A bit more recently, DL also went into the **N**atural **L**anguage **P**rocessing (**NLP**) field battle to solve common NLP problems like text classification and translation, with very promising perspectives and results: in particular, word embedding and **R**ecurrent/**C**onvolutional **N**eural **N**etwork (**RNN/CNN**) architectures provide efficient technical responses to NLP challenge.

**POSOS** French startup has submitted a data challenge for which I took the opportunity to verify humbly whether DL is a suitable solution compared to traditional techniques, for a beginner like me having very few experiences on NLP/DL area and low-end hardware system (DL has the bad reputation to be numerically intensive…).

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# Statement of the Problem

It’s plainly exhibited at ENS school web site ([link](https://challengedata.ens.fr/en/challenge/33/predict_the_expected_answer.html)) and it consists in classifying into **51** intents, drug related questions written in natural language (French to be precise). **POSOS** claimed to get good modeling result with 86% accuracy by utilizing DL: they don’t provide any details on the DL architecture nor any engineering clues except the possibility to extract some relevant information procured by the French drug administration (**ANSM**).

The target categories (question intent) have been intentionally anonymized into indices from 0 to 50: hiding their respective semantic is probably aimed to avoid the usage of topic-specific (and so biased) procedures. Training dataset contains only ~8000 questions: it’s pretty short to produce a good learning outcome. Moreover, the text suffers from many types of anomalies (misspelling, grammatical incorrectness, familiar acronym, …) and employs specific medical vocabulary (drug name like “mirtazapine”, …): it makes the NLP challenge harder to handle.

Here’s an example of misspelled sentence: “8 jrs avant la fin de ma plaquette d'evepar j'ai eu des saignement~~s~~ et des douleurs au bas ventre et au bas du dos dois je m'inquiéter»

# Project Motivation

The purpose of this study is to compare and the pro and cons between DL and non-DL approaches from different perspectives:

model accuracy/performance

operational aspect (tooling, hardware requirement, ...)

engineering level of difficulty to find the good hyper-parameter, architecture and processing logic

In fact, these aspects are somehow inter-related: typically, model accuracy may be unexpectedly suboptimal due to operational reasons (memory shortage to complete the processing job, …).

The idea is not to get a fined-tuned model with DL or other techniques, but an attempt to explore comparatively the end to end methodology to tackle a text classification problem with 2 distinct technologies.

“Traditional techniques” refer to any ML algorithms which don’t rely on neural network theory (eg: Word2Vec is excluded): to quote some of them, Hidden Markov Model, XGBoost, SVM, logistic regression and PCA are eligible.

Conversely, DL option should rely uniquely on neural network but it can as well benefit from “neutral” text preprocessing (feature enrichment with external source, stemming, stopWords, …) for fairness sake.

# ML Workbench Environment

All experiments have been written in Python in the popular Jupyter environment: the notebooks are accessible publicly as a github project whose details are provided in the annex section. I had made use of many python packages to satisfy various requirements:

data manipulation and visualization: pandas, numpy and matplotlib

text processing (stemming, stopWords, …): NLTK, standard regex and spellChecker (built from github)

ML algorithms (XGBoost, PCA, t-SNE): sklearn and XGBoost

DL framework: Keras + Tensorflow

Most of packages have been installed as is, except for XGBoost I recompiled locally from its github source code to get the GPU accelerated version which is not shipped officially.

In addition to the above runtime packages, this project also takes advantage of public resource or pretrained models (NLTK corpus, FastText word embedding model, ….).

ML jobs had been initially executed with an old MacBook Pro whose chipset was damaged by the heating caused by the overnight DL train, then with a many CPU core/low-end GPU PC workstation.

I finally paid a GPU boosted Amazon instance: even if the GPU/CPU resource is not utilized, the data storage is charged permanently making the overall cost very high (5$/h) during 2 full days.

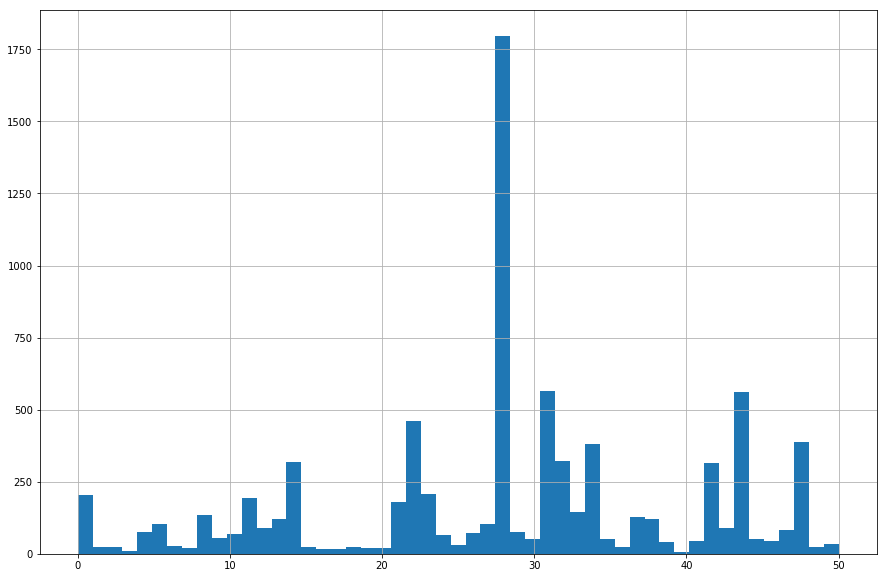
At the very end, the best money saving option was to buy a PC gamer machine with mid-range Nvidia GPU card to carry out the computing workload: I noticed a huge speed improvement at training time.

# Data Exploration

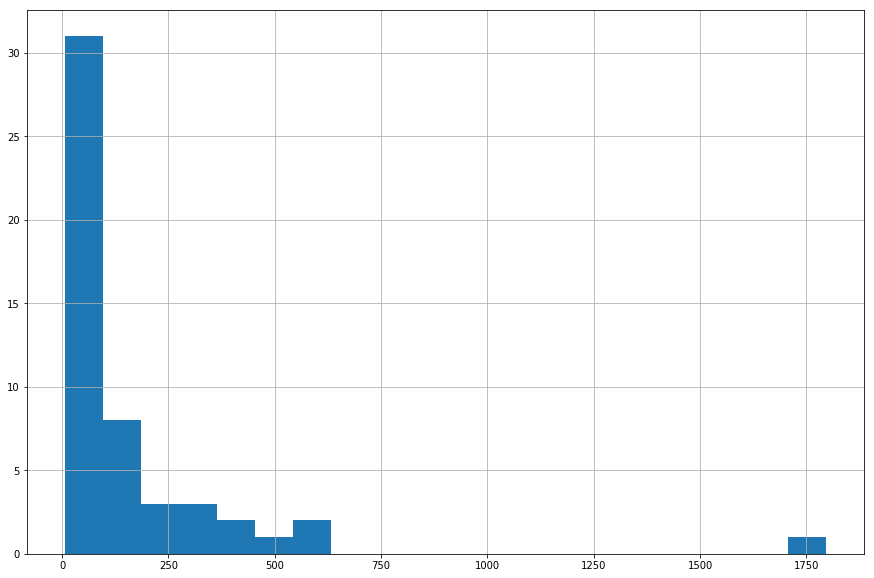
## Data Distribution

Here’s the target distribution on training dataset revealing that it’s pretty imbalanced with a peak at intention=28.

Target distribution (number of classes = 51)



Most of labels are associated to pretty small number of samples: half of classes have less than 100 rows.



Regardless of the ML algorithms and smart feature engineering, achieving a good enough classification rate is really tricky considering the small training size and imbalanced distribution.

Let’s try to guess intuitively the hidden semantic of the most frequent labels:

**first mode**: intention=28

It looks like to be related to questions on drug side effects and somehow the contraindications



**second mode**: intention=31

it concerns questions on symptom-drug adequacy/efficiency



**multi-topic class**: intention=39

the commonality across text samples seems to the presence of multiple question mark tokens (counting it may be a good option to predict mult-topic label)



The painpoint of the text classification problem is to find a way to estimate the intent similarity between 2 questions written in a natural language.

Let’s focus on 2 questions having the same label (symptom-drug adequacy):

“épilepsie et havlane?”

“mon medecin me soigne pour une rhino pharingite et m'a prescrit du amoxicilline comme anti biotique. Est-ce vraiment pour cette indication?”

The writing style differ significantly: on one hand, a very concise expression putting the symptom entity and the drug entity in an adversarial fashion, on the other, the question is more detailed with one sentence to set up the context/fact and the second one to raise the concrete question of adequacy between the 2 entities mentioned previously.

This typically illustrates the stylish complexity and diversity of the human language to convey an idea and more particularly a high level topic!

Moreover, notice that certain questions are lexically and syntactically incorrect: words are misspelled especially when dealing with drug product names which are unfamiliar for most of non-professional persons.

To have a glimpse on the classification difficulty, it’s common to perform some visualizations of the feature space distribution.

The multi-sentence question text is basically converted into of bag of words which is vectorized with TF-IDF transformation. Each question is then represented as a data point within the global vocabulary space. To make such data points humanly observable, a dimension reduction of these features is needed at the cost of some approximations: we will use both linear/fast PCA dimension reduction technique and non-linear/slow t-SNE. The data point color is determined by the associate target class.

**PCA-reduced feature space**



**t-SNE-reduced feature space**



Both shapes are very different but as suspected, we can observe intuitively from both visualizations that the decision boundaries are unclear in the original feature space, just by considering the occurrence of words. To get a chance to obtain a better classification performance, it’s obvious that the raw text needs to be encoded more smartly into a suitable space where the semantic proximity between documents is prevailing.

## Text Anatomy Analysis

Todo

Vocab / misspelling

Statistics on text structure (sentence, …)

Context then question

Interesting entities: drug name, quantity, time, what/when/…

# General NLP Architecture

Text classification is a common but non-trivial NLP topic going through the following main steps:



This is the general NLP text classifier framework/guidance but for practical reasons, some processing steps are skipped or significantly simplified to fit the project timeframe but also because of the lack of French language support.

In fact, here’s the concrete pipeline I built per technical scenario:



Each processing unit will be described more precisely in the next sections.

The overall modeling procedure should capture the sequential nature of the text to exploit efficiently the contextual information: typically, the feature representation should preserve the word/symbol order and the classification process should be based on **sequence modeling**.

Text Preprocessing *(common trunk)*



It’s all about operations on the raw text to make it more reliable/workable in order to extract relevant characteristics. It falls into 3 categories:

tokenization which breaks down the sentence into a sequence of atomic word

spelling correction which fixes as far as possible words which are misspelled

lexical and grammar tagging which basically decorates the text tokens with metadata

text cleansing and normalization which simplify the sentence composition

## Tokenization

This operation is very common and it doesn’t raise significant issue: I simply use the python string split() function. I tokenized the whole document regardless of the sentence split with punctuation like “.”,”:”,”;”, “!” and “?”.

## Spelling correction(Syntactical processing)

I assumed as misspelled all words which don’t belong to any trustworthy vocabularies, also known as **OOV** (Out Of Vocabulary) word.

I retained 3 reference vocabularies in the following priority order:

vocabulary from the word embedding model used downstream in the processing pipeline

indeed, it’s very important to avoid random vectorization on OOV words

Custom vocabulary to capture the specific drug domain, typically on drug product and active ingredient entities where misspelling is frequent. It has been built from the public RCP (Résumé des Caractéristiques du Produit) repository supplied by ANSM.

Predefined general purpose vocabulary from the github python project pysspellchecker <https://github.com/barrust/pyspellchecker>

Spelling correction basis is to find from a set of reliable vocabularies, the closer word candidate from **Levenhstein** distance standpoint: this distance measures the minimum number of character level operations (change, remove, add) required to map 2 words.

I defined an arbitrary threshold to accept the closest word as a fix on the misspelled word: the ratio between the number of atomic operations and the total number of characters should be under 25%.

I applied this correction method with the last 2 vocabularies: the first vocabulary layer only filters out the recognized words, the unfixed words at the second layer are then passed to the third layer.

Here’s the python output showing the fix on more than 400 drug product names with a reasonable error rate (~ 15%):



For the active ingredient, only 25 fixes have been detected.



The general vocabulary fixes up 430 words with relative high error rate (~25%): as accent encoding is badly handled by pyspellchecker module, I fixed it manually afterwards.



At the very end, it remains 583 unfixed words over an intial2108 unknown words (25%): that corresponds to hard cases where the word is unexpectedly a concatenation of multiple word or transcribed phonetically.



Below diagram illustrates the different python notebooks (parallelogram in yellow) necessary to fix word misspelling: the blue folder represents the file consumed or produced by the python processing unit.

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## Lexical and Grammar Tagging

**NER** is a NLP process to tag text token with predefined semantical categories (location, person, quantity, …), enabling to count entities as explanatory feature. Typically, distinct drug product counting may be a discriminating feature to predict labels corresponding to question on drug interaction.



**POS (Part Of Speech)** tagging is a process to markup text tokens with lexical categories (noun, adjective, verb, …), enabling typically to compute tag frequency distribution as explanatory feature.



**Dependency parsing** is a more sophisticated process than POS tagging to discover the grammatical dependencies between words within a sentence. It produces an annotated dependency tree which reveals the nature of the interaction between the words.



I finally didn’t employ these advanced tagging methods because French language is not well supported by most of NLP packages (Spacy, Standorf NLP or NLTK). The only basic NER I put in place is to locate the drug name or active ingredient entities based on the list of words extracted from the RCP repository: such entities are central and their identification within the sentence will be used later on to create additional features.

## Text Cleansing and Normalization

I implemented some ad-hoc cleansing/normalization rules based on regular expression to tackle special characters, repetitive number, punctuation characters or usual acronyms.



In a second time, for regular words, stopWords eliminates semantically irrelevant and frequent tokens whereas stemming/lemmatization reduces the morphological variants into their etymological root.

For this job, I utilized the NLTK package: this process simplifies gracefully the phrase structure but at the expense of its lexical and grammar correctness.

The stemming/lemmatization preprocessing is counterproductive to word embedding model learnt from corpora which haven’t been stemmed or lemmatized as prerequisite: they are mutually incompatible. For DL scenario, I made use of word embedding excluding de facto this root normalization.

# Classical Technique

## Abstract

**HMM** (Hidden Markov Model) is a probabilistic and transitional graph modeling which is actually suitable to tackle sequential structure like sentence. Typically, it’s capable to learn on text corpus and predict POS tags: some experiments have been conducted to address text categorization problem with quite good result. When looking at HMM python implementation, there’s no strong and active community working on it.

The arguable fallback is to use instead non-parametric statistical inference method like SVM, decision true and so on, with the significant downside to lose the native support of sequence modeling. To compensate slightly such discarding, the feature extraction/enrichment would include some handmade tricks trying to grasp some contextual information from the word sequence.

## Feature Enrichment

This step adds a-priori extra features which may discriminate the label much more than the original features: they can be calculated from the text or can originate from external sources**.**

I incorporated above basic statistics giving insights on the text structure and composition:

count of sentences

count of words

distinct count of drug name entities

distinct count of active ingredient entities

count of question marks (typically to identify specifically multi-intent label)

individual count of interrogative pronoun entities (one column per pronoun: quand, qui, quoi, ou, comment, pourquoi, combien, quel(s|le,..)

distinct count of time entities (eg: jours, après midi, soir, année, 12h, mardi, samedi, temps....)

distinct count of quantity entities (eg: 5mg, 10ml, ...)

count of association entities (eg: et, avec, ou, ...)

distance between interrogative pronoun and drug name entities

distance between active ingredient and drug name entities

distance between quantity and drug name entities

distance between time and drug name entities

distance between question marks and drug name entities

They are either **count-based or distance-based statistics**: distance variant is intended to catch native the word context by measuring the relative distance between key entities. This computation needs to put in place the domain-based (list of distinct values) or custom regular expression NER (Named Entity Recognition) to identify the key entities in consideration.

An extra calculated column is added to the train data frame per statistics as below:



If the text sample has identified drug product entities, it’s valuable to extend the primary feature vector with relevant information related to these drug products.

I illustrate below a specialized **knowledge sub graph** centered around the drug product entities with some interesting relationships to other entities (quantity, human body part , …).



Indeed, such related entities characterize well the drug product and they can improve the detection of the commonality between texts sharing same target label: for instance, a drug product class (eg: antidepressant family) may raise particular questions.

Unfortunately, this knowledge graph is not available publicly and should be built by our own: the ANSM provides online the full description of the drug usage indication in HTML format. Such resource can feed a learning system to extract above salient related entities.

I didn’t implement this information extraction from ANSM source because it’s a huge workload which is incompatible with the project scope.

## Feature Representation

The document (composed of sentences) should be converted into numerical vector because most of ML classifiers can only cope with numeric values and they don’t care about symbol and semantic conveyed by the text entity.

First basic solution is the **BOW** (Bag Of Words) representation where each word of the vocabulary is defined in column and the text in row: the cell value stores the word frequency.

I didn’t consider **n-gram** document representation because as specified earlier, the classical technique scenario doesn’t employ sequence modeling like HMM which is able to treat n-gram structure.

The problem of the **BOW** representation is that rare term which in general discriminates well the document are under estimated in regards with commonly used but irrelevant terms (eg: generic verb, …).

**TF-IDF** (**T**erm **F**requency **I**nverted **D**ocument **F**requency) overcomes this pitfall by overweighting terms which are identified as rare for a given corpus.

The shortcoming is that such vectorization generates a very high dimensional space depending on the vocabulary size. We fall into the well-known **curse of dimensionality** where data distribution is extremely sparse making classification task inefficient when training size is too short.

The space dimension should be reduced consequently:

stop words and stemming processes already reduce upfront the vocabulary size

I applied the **PCA** (Principal Component Analysis) linear dimension reduction which keeps the top eigen vectors capturing the maximum of the data distribution variance: PCA is a process which is totally semantic unaware in contrary to word embedding I will tackle later on

TF-IDF application and PCA reduction produce a low dimensional numerical vector per document as below:



## Classification Modeling

The classifier takes as input a feature space combining the reduced BOW representation and the handcrafted statistics:



I bet on the **XGBoost** classifier delivering excellent accuracy in a reasonable time (it’s multi-thread friendly): XGBoost is based on boosting ensemble technique combining sequentially weak classifiers (in general decision tree) where at each iteration, the weighting on incorrected classified observations is increased to enforce the next classifier to focus its attention on feature sub space with high error.

XGBoost comes up with many hyper-parameters to tune: an inappropriate selection usually leads to suboptimal model.

I followed the standard methodology and best practices:

find out the optimal hyper-parameters by testing different selective combinations. I retained the one delivering the best accuracy on unseen dataset (validation) with **cross validation** enable as training is very small

fit the final model with the above fixed hyper-parameters on the whole training and assess the generalization error on test

Here’s the learning pipeline for the classical technique track:



I focused my attention on the following parameters which are the most instrumental to the final accuracy:

**max\_depth**

this parameter drives the decision tree complexity to partition the feature space

a low value usually prevents from overfitting and favor the weak learner synergy

I tested empirically 3 values: 4 , 6, 8

**min\_child\_weight**

under the threshold, the learner stops splitting and generates a leaf node

it controls as well the tree complexity and consequently the overfitting

I tested empirically 3 values: 2, 5, 10

**n\_estimators**

this parameter sets the maximum number of stacked trees

I fixed it empirically to 100

**learning\_rate (eta)**

it controls an important parameter of the gradient descent optimizer

I tested empirically 2 values: 0.05, 0.1

**cross validation fold**

cross validation ensures a more reliable generalization error indicator which is not biased by a particular split (test set). It’s valuable typically in imbalanced label or small dataset situation (it’s the data challenge case)

I fixed it empirically to 4

Other parameters settings rely on the XGBoost defaulting to avoid excessive processing time caused by the grid search combinatory explosion: by crossing max\_depth, min\_child\_weight, learner rate and cross validation fold, it represents 72 (3x3x4x2) learning units to reveal the optimal parameter values.

For the final model fit, I set up the early stopping parameter to 10, in order to control overfitting.

## Result Analysis

todo

# Deep Learning Technique

## Abstract

DL is commonly recognized as an universal estimator capable of fulfilling any sort of learning requirements from feature representation to the predictive modeling within a single neural network. The key strength of this all-in-one learning is that the loss optimization to find out the best modeling parameters (weights, …) operates consistently across all functional layers regardless of their respective purpose (embedding, decision making, …). In contrast, with traditional method, feature representation and classification are 2 sub tasks which are engineered/optimized separately.

I specifically looked at its sequence modeling capacity carried by 2 architecture types:

* **RNN** (Recurrent Neural Network with **LSTM** (Long Short Term Memory) unit
* **CNN** (Convolutional Neural Network)

The hybrid option mixing up CNN and RNN is not considered here for simplicity sake even if some practitioners claim that it’s a winning combination to get cutting edge performance.

Furthermore, DL also provides a very good support of word embedding which can be combined nicely with above architectures as upstream layer.

## Feature Enrichment

I intentionally excluded extra features to verify how a DL sequence modeling can give some good results without manual contributions (statistics on text, …).

## Feature Representation

### Sequential representation

As the predictive modeling layer is sequence aware, the text representation should be **n-gram** where n is the number of words to keep: if the number of words is insufficient, it’s necessary to apply a padding to get at the end a fixed sequence length for all documents.

As observed in the “Data Exploration” section, lengthy document usually starts with the description of the question context and ends up with concrete question (eg: “Je suis suivi par un médecin … Qu’est ce que c’est recommandé?”). It would make sense as the document can be truncated due to the fixed sequence length constraint to keep the n-th last words and not the n-th first words to not lose the question part.

In short, each document is shaped as a fixed\_sequence\_length x vocabulary\_size matrix: again, vocabulary size can be huge leading to inappropriate high dimensional feature space and a dimension reduction is mandatory.

### Word embedding

#### Text corpus

Instead of applying a generic PCA, a better alternative is the popular **word embedding**: it’s an unsupervised method which learns from a very large text corpora to optimize a lower dimensional vector representation where words sharing similar context (within a sentence) are close to each other. The wonder of this dimension reduction is that vector proximity is governed by semantic similarity.

Word embedding is implemented in a DL flavor (Word2Vec or FastText) and in a non-DL way too (GloVe project) with nearly similar performance.

The question now is to determine the **text corpus** used to build this embedding model:

consume directly model tediously pre-trained by the GAFA companies

such model is based on very large general purpose vocabulary but probably miss domain specific vocabulary (our study case in fact)

build a custom embedding from the POSOS corpus

it overcomes the domain specific vocabulary lack (drug product name, …) but it’s not complete and robust enough considering the small training dataset with many misspelling/incorrectness in the text.

Perform a model transfer from GAFA base with specific vocabulary coming from POSOS corpus

In practice, this ideal solution is undoable because it’s required corporate level hardware to rebuild a merge embedding model combining general and specific vocabulary

I finally experimented the custom and general embedding models (transferred model is out of scope). For the general embedding option, I opted for the 300-dimensional **FastText** model which is gracefully available in French language.

In conclusion, the training dataset is represented as a n x k x v numerical matrix where:

* n is the number of observation (document)
* k embedded space dimension
* v fixed sequence length

I decided empirically to set fixed sequence length to the word count means observed in POSOS train dataset.

#### OOV handling stratregy

Embedding layer can only deal with word which exists in its vocabulary: if the learnt corpus and the corpus to vectorize are dissimilar, OOV is potentially frequent. The common practice is to encode unknown words into a random embedded vector with the risk to generate noisy feature representation.

A more elegant alternative is to merely project such unknown words into its **hypernym** entity (having a type-of relationship with the concerned word) guaranteeing a semantic proximity in the embedded space for entities of the same class/hypernym:

* all drug product entities (eg: Xanax, Abboticine) is replaced by ‘médicament’
* all active ingredients (eg: Acabavir) is replaced by ‘médicament’

To not totally lose the subtle distinction between entities sharing the same class, I added a very small stochastic variation vector based on the entity name so that all ‘Xanax’ entities have exactly the same vector and are also close to ‘Paracétemol’ entities.



## DNN Architecture

I setup a test with DNN (Dense Neural Network) which is not a sequence modeler, as a comparison baseline for the more sophisticated architectures like RNN and CNN. It would give a gut feeling on the performance gain with sequence awareness in the modeling procedure.

Moreover, the embedding layer is built from the POSOS corpus to define again a comparison baseline to measure the gain (or loss) when opting for general purpose corpus.

## CNN Architecture

In **C**omputer **V**ision (**CV**), convolution operation is well known to be efficient to extract the high level representation of an image by passing a sliding window filter and computing consequently an average value for each filter position as output. These convoluted values are then activated with usual non-linear function and down-sampled thanks to the pooling layer. This pixel-wise processing is inspired by how the visual cortex analyzes the signal sent by the eye receptors.

Surprisingly, such biological inspiration also works well to grasp the high level structure of word sequence in NLP. The convolution operates in a 1-dimensional array (word sequence) instead of 2D (pixel matrix) in CV. The sequential filter enforces the neural network to focus its attention on local context which establishes connection between words.

Some research studies demonstrate that convolution is powerful enough to cover embedding requirements making FastText contribution useless. Nevertheless, I preferred to keep going with an embedding layer relying on a proven algorithm (FastText) associated with a convolution layer specialized to extract the high level representation of the text.

In short, here’s the neural network layout:

word embedding layer as explained in the Feature Representation section

a series of 1-dimensional convolutional and pooling layers

The best practice recommends building many convolutional layers with different filter sizes and/or strides

I used Relu (Rectified linear unit) activation function after the convolution operation and the popular maxpooling

a series of dense layer plus dropout layer

last dense layer with softmax as activation function

CUDNNLTSM

## RNN Architecture

In a classical neural network, we assume that all inputs of a node are independent to each other but it’s not applicable in NLP because text is composed of an ordered sequence of words (inputs) which are inter-related.

Recurrent neural network architecture tries to leverage this sequential information with a particular layout where each layer at the i-th position is fed with the i-th element of the input sequence and the output of the direct preceding layer: each layer captures somehow the hidden state (memory) of the preceding sub sequence of inputs (words).

RNN can be **bi-directional** (instead of forward only) where the i-th layer also depends on the computational output of the direct successor (i+1 th position).



*(source: Wikipedia)*

In practice, the simple layer computational unit (“h” blue box in above diagram) exhibits inability to catch long term dependencies to distant input x(t-n) where n is significant high, due to the vanishing gradient problem.

The **LSTM** (**L**ong **S**hort **T**erm **M**emory) cell unit has been invented to bypass this long-tailed sequential dependency we typically observe in multi-sentence text analysis where the context may be specified upfront far from the concerned word.



*(source: Wikipedia)*

This processing unit adds a secondary flow (upper stream) to update gradually the memory (cell state denoted as C(t)) with contributions controlled by several input gates (shown at the bottom).

The final architecture looks like below:

word embedding layer as explained in the Feature Representation section

bi-directional LSTM layer with dropout (for learning regularization)

dense layer with softmax as activation function

Bi-directional?

## Implementation and Execution

I coded all DL experiments with **Keras** as a frontline API on top of Tensorflow engine: Keras provides a very comprehensive and easy-to-use API hiding the Tensforflow verbosity.

Here’s an example of Keras code where the layers are built in a very concise manner thanks to helper object like Convolution2D, Activaction and so forth.

model = Sequential()

model.add(Convolution2D(32, kernel\_size=(3, 3),padding='same',input\_shape=(3 , 100, 100)))

model.add(Activation('relu'))

model.add(Convolution2D(64, (3, 3)))

model.add(Activation('relu'))

model.add(MaxPooling2D(pool\_size=(2, 2)))

model.add(Dropout(0.25))

In general, the model performance depends importantly on the selection of the hyper-parameter values: as the DL training is really slow even with the aid of GPU boosting, I was not able to test a lot of hyper-parameter selections and I proceeded with default or best guess values at the risk to be far from the optimum point.



**Common Setup**

GPU enable config

**Doc2Vec based Implementation**

## Result Analysis

Nb params to optimize vs nb observation (overfitting) => show error estimation vs validation evolution

# Comparison Study

Graph to summarize candidate (XGBoost / RNN / CNN / Custom embedding

## Implementation/Engineering

## Model Accuracy

Focus on dominant class error

# Improvement Tracks

## Text PreProcessing

To combat the training size shortage impose by the data challenge, one option to enrich the former dataset is to complement it with other medication questions from public forum like the one hosted by doctissimo.fr. These extra observations are unlabeled (the 51 target classes are anonymized) and so cannot be used as regular dataset for the supervised training. Nevertheless, it can be consumed to complement gracefully the text corpus for all unsupervised learnings (eg: Word2Vec) to strengthen the modeling result. Such trick is also applicable for unlabeled test dataset of the challenge.

## Classical Technique

## Deep Learning Technique

Building a **custom** **embedding model** from text corpora which are specific to the data challenge domain is a real plus: indeed, the generic FastText model has been trained on clean corpora writing in an elevated literary style by professionals (Wikipedia, newspaper, …) whereas the POSOS text style is much more familiar as questions are mostly raised by uninitiated people.

As POSOS training size is not sufficient, it can be completed with other unlabeled drug question sources (eg: doctissimo.fr forum, …): just to remind that embedding is an unsupervised learning process requiring no exhaustive manual labeling.

Another improvement possibility is to refine the proposed **imputation** that replaces words unknown from the embedding model standpoint, by its named entity (hypernym). Typically, train our own NER (Named Entity Recognition) on French general/domain-specific corpora combination with NLTK package: the trick here is to take advantage of the English NER model provided by Stanford NLP active community and the English-to-French word translation, in order to get for free the global standard label on French corpora.

ANSM source of information on drug product is poorly exploited: I only extracted vocabulary on drug product names and active ingredients to identify such entities into the text because it’s straight-forward (ANSM public dataset contains a drug product name and active ingredients columns). Other relevant named entities (adverse effect, target body part, drug category, …) should be learnt from the ANSM corpus with manual entity labeling.

For the handcrafted features to characterize the text, thanks to a more complete entity identification (adverse effect, body part, quantity, …) , it would be possible to compute more count-based statistics on entity and even introduce selective entity distance to capture indirectly the word sequential distribution.

For the classification modeling layer, there’s room for improvement as well. Due to lack of time and computing resource shortage, no extensive hyper-parameters search has been performed mainly in the DL sub project: we know for sure that parameter optimization is crucial to achieve good results.

I intentionally separated the DL and non-DL techniques in order to make an academic comparison study but in practice, the state-of-art in ML competition is to build heterogeneous and complex predictive pipeline involving a variety of algorithms and technologies, by sticking to the ensemble learning principle. The DL architecture may be reinforced with handcrafted features utilized in the non-DL approach. In the same vein, CNN and RNN architectures are tested separately but they can be combined nicely into a single neural network to obtain the best of breed learning system.

# Conclusion

In this present paper, I describe a walkthrough return of experience on text classification problem in a **DL (D**eep **L**earning) and non-DL fashion (a.k.a. traditional method). The goal of the study is to have a fair idea on the pro and cons between above approaches from a practical standpoint on a real use case.

The non-DL scenario enrolling notably the favorite XGBoost classifier delivers poor modeling performance (X % accuracy in cross validation) mainly due to its inability to leverage natively the sequential context from the text structure: this solution is furthermore penalized by the absence of pre-trained French word embedding model based on non-DL principle (eg: GloVe matrix factorization) and not surprisingly, the handcrafted statistics on text don’t improve at all the final accuracy. Nevertheless, its implementation and execution are pretty straight/simple accommodating with mid-range CPU.

DL option with RNN/LSTM architecture outperforms the non-DL candidate in term of accuracy (X % on validation set), partly thanks to the available pre-trained FastText embedding model and its sequential structure awareness. The counterpart is that DL algorithm is hungry of GPU and badly runs on standard machine configuration: on top of that, elaborating an appropriate architecture (operation composition) and tuning the hyper parameters (activation function, dropout rate, …) demand some strong practical engineering experiences to achieve good enough performance.

In addition to the probable suboptimal ML procedure I had built so far, the low accuracy on validation can also be justified by the learning materials: indeed, the training set is really too small (~8000) with regards to the 51 labels and most of the texts are written in an everyday language style with plenty of abbreviations and misspellings.

Even if the comparison is totally unfair/biased, Deep Learning turns out to be the most efficient ML technique in NLP task solving: it’s presently a very active research topic within the ML community as DL expressiveness/capacity are unbound similarly to the brain plasticity.

This short study with non-conclusive performance result, has the educational benefit to make me practice on a large spectrum of domains that a data science should master: from the data analysis to experimental result debriefing, unsupervised (word embedding) vs supervised (classifier), experiment implementation and execution (GPU activation, python programming, AWS computing infrastructure, …), text pre processing techniques, concept of sequence modeling, Deep learning architecture variety and general best practice on classification task (cross validation, early stopping, …).

# Annex

## Github project

The project is available fromthe public github repository at the following URL:

<https://github.com/jhuu32/CES>

It contains Jupyter notebooks allowing to reproduce all learning experiments mentioned in this report: the only missing artifact is the FastText embedding model which is too large to be pushed into github (2Gb), but the README.md gives the necessary information to download it.

Here’s the high level project source tree



## References

todo