POSOS: Predict the expected answer

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Introduction

Drug misuse could be responsible for more than 144,000 hospitalizations every year in France!

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People often ask questions about the drugs they use. How to accurately understand the underlying intent? (contraindication, side effects,...)

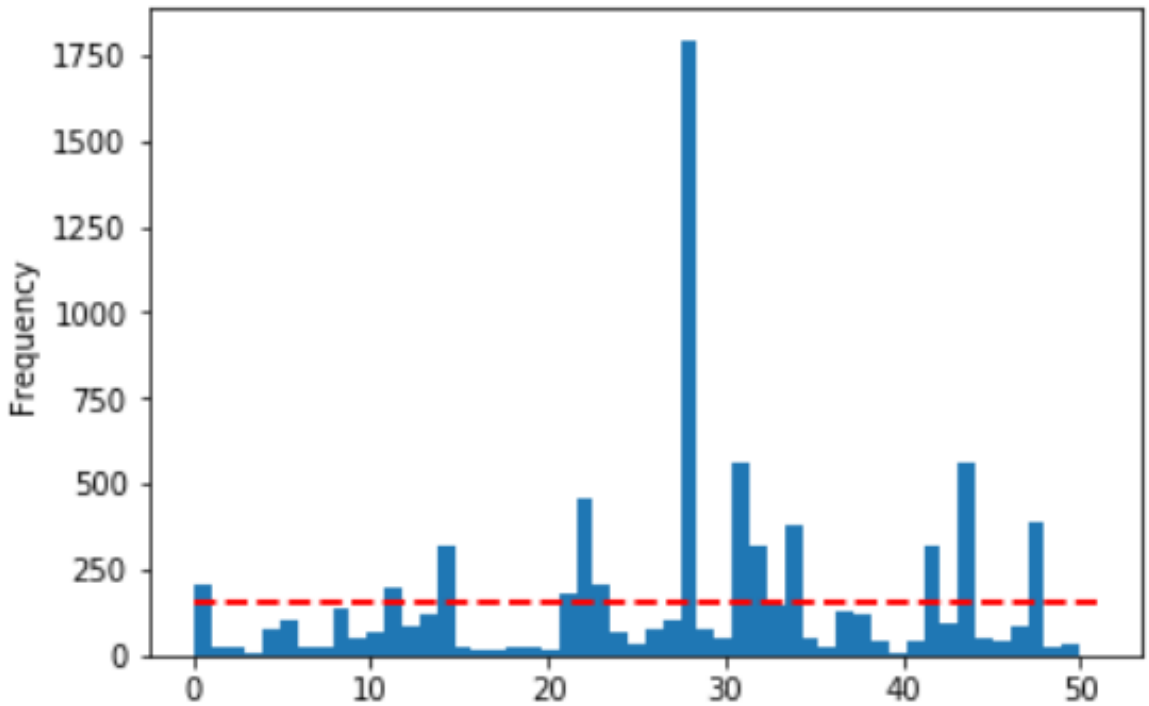
Introduction

Goal: predict the intent associated to a given question among 51 possible categories

Dataset

- 10,063 questions: 8028 for training, 2035 for testing.
- Training set divided in two splits: 80% training, 20% validation

Class Imbalance



Class 28 accounts for 22% while +30 classes account for <1% each

Dealing with Drug Names

"Par quoi remplacer Aerius et Doliprane ?" :

- "Par quoi remplacer Aerius et Doliprane ?" + [2]

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- "Par quoi remplacer Aerius et Doliprane ?" + [2]
- "Par quoi remplacer <MED> et <MED> ?"
- "Par quoi remplacer <MED0> et <MED1> ?"

Bag of Words

the dog is on the table

TF-IDF

Issue of BoW: some words will be over-represented thus disturb the statistics of rarer but discriminative words

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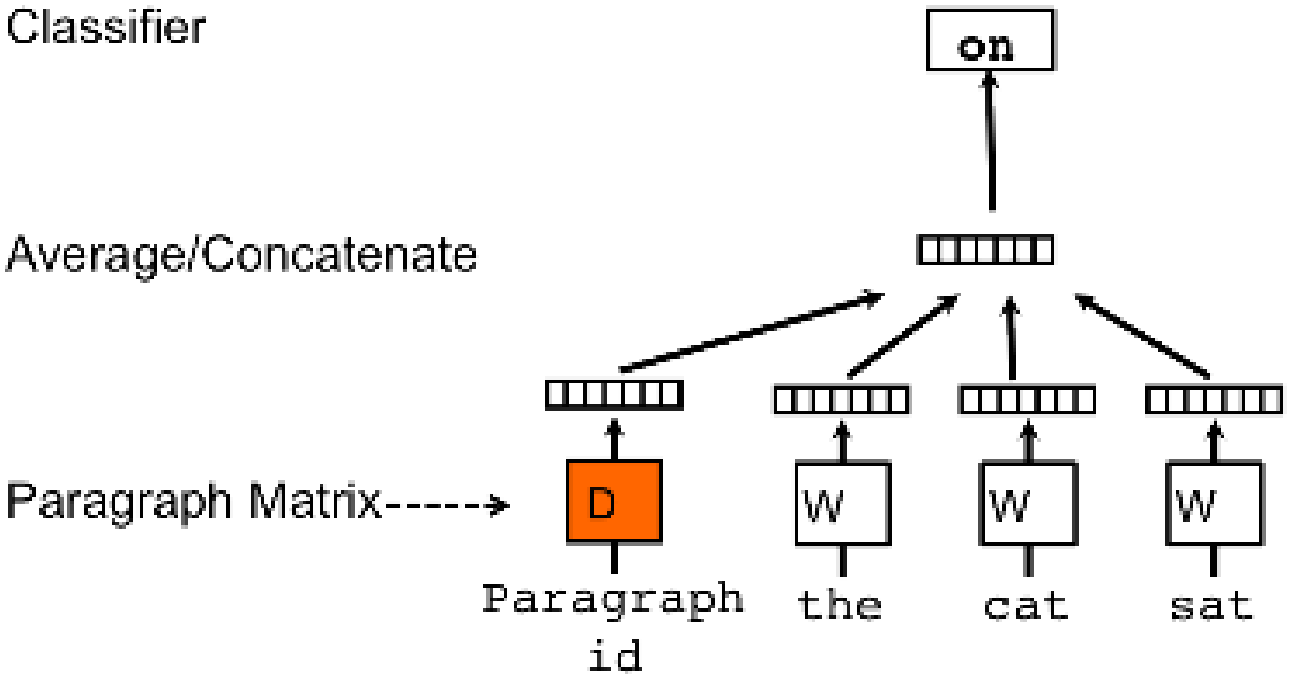
Reweighing scheme:

$$\begin{aligned} \text{tf-idf}(t, d) &= \text{tf}(t, d) \times \text{idf}(t) \\ &= f_{t,d} \times \log\left(\frac{N}{n_t}\right) \end{aligned}$$

Doc2Vec [Le and Mikolov, 2014]



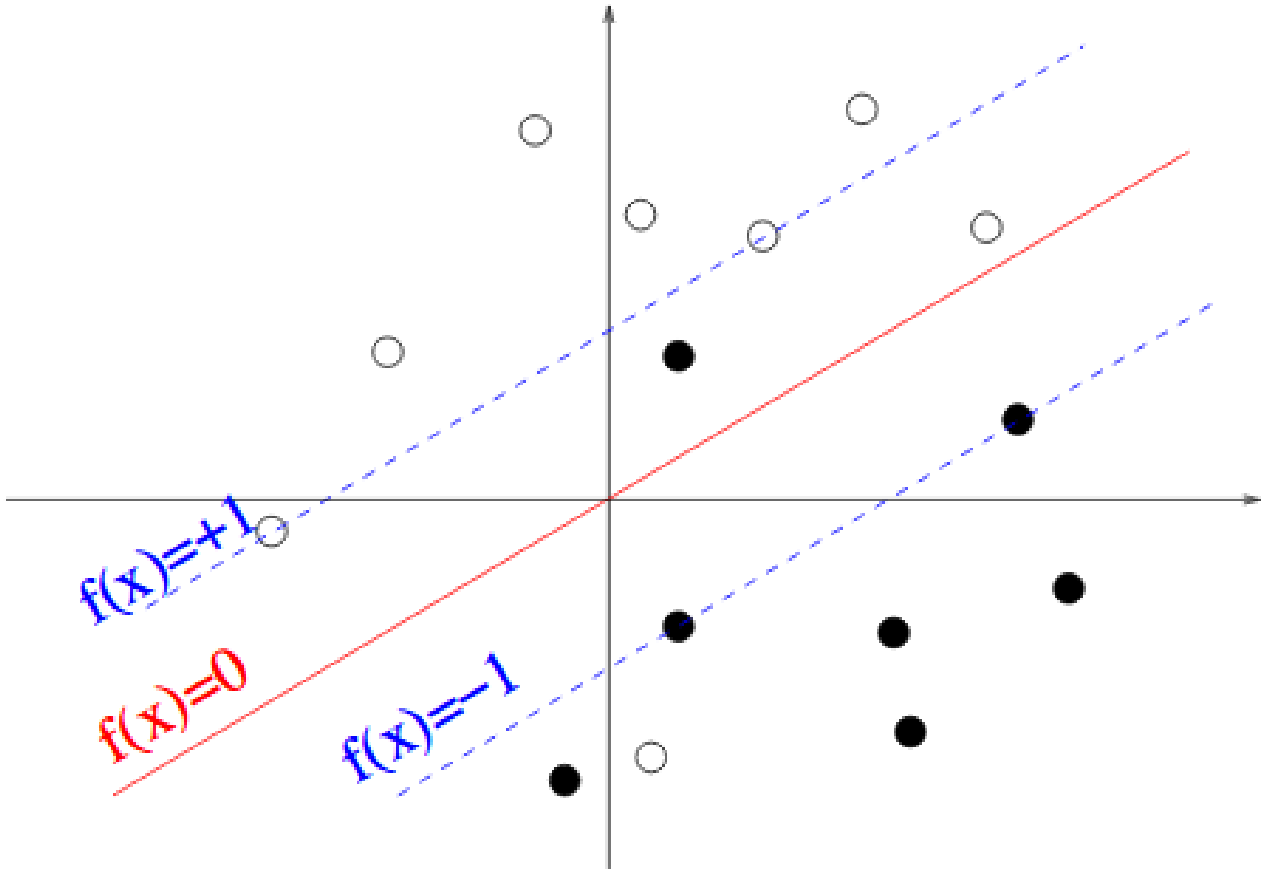
Support Vector Machine [Cortes and Vapnik, 1995]

Idea: (i) map input data $\mathbf{x}$ into a higher dimensional space where the data become separable

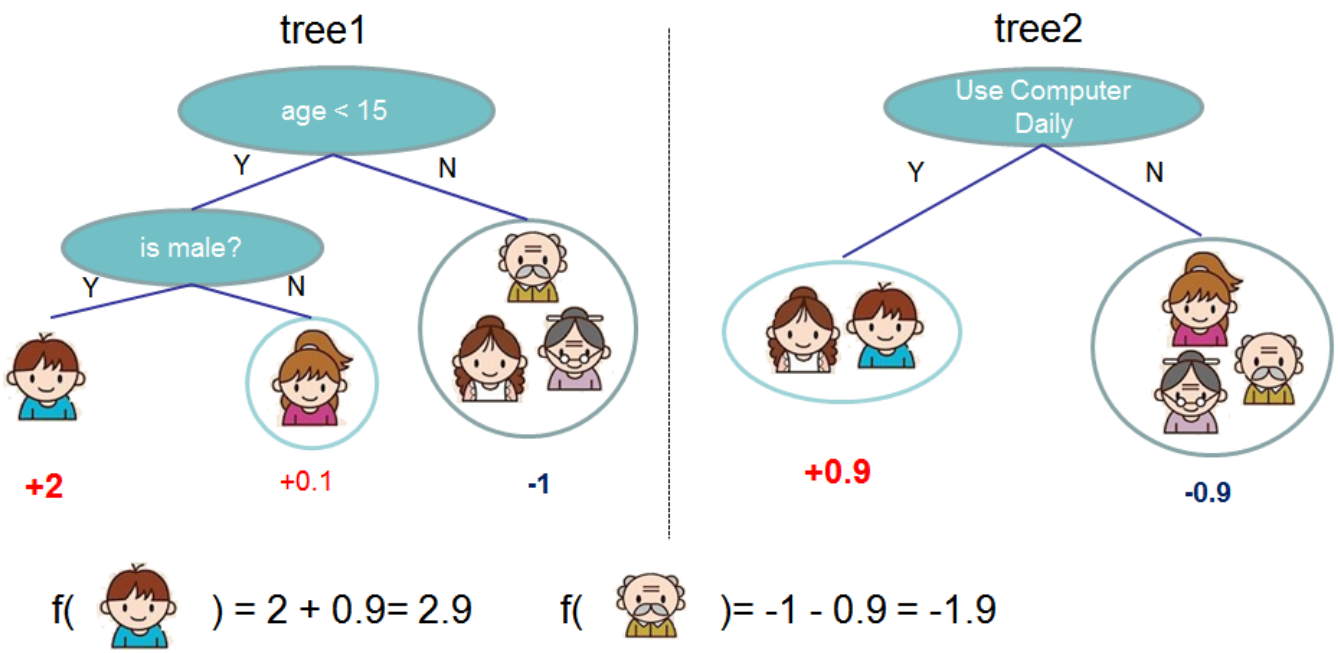
$$\phi : \mathbf{x} \rightarrow \phi(\mathbf{x}) \in \mathcal{H}$$

Support Vector Machine [Cortes and Vapnik, 1995]

(ii) use large margin classifier

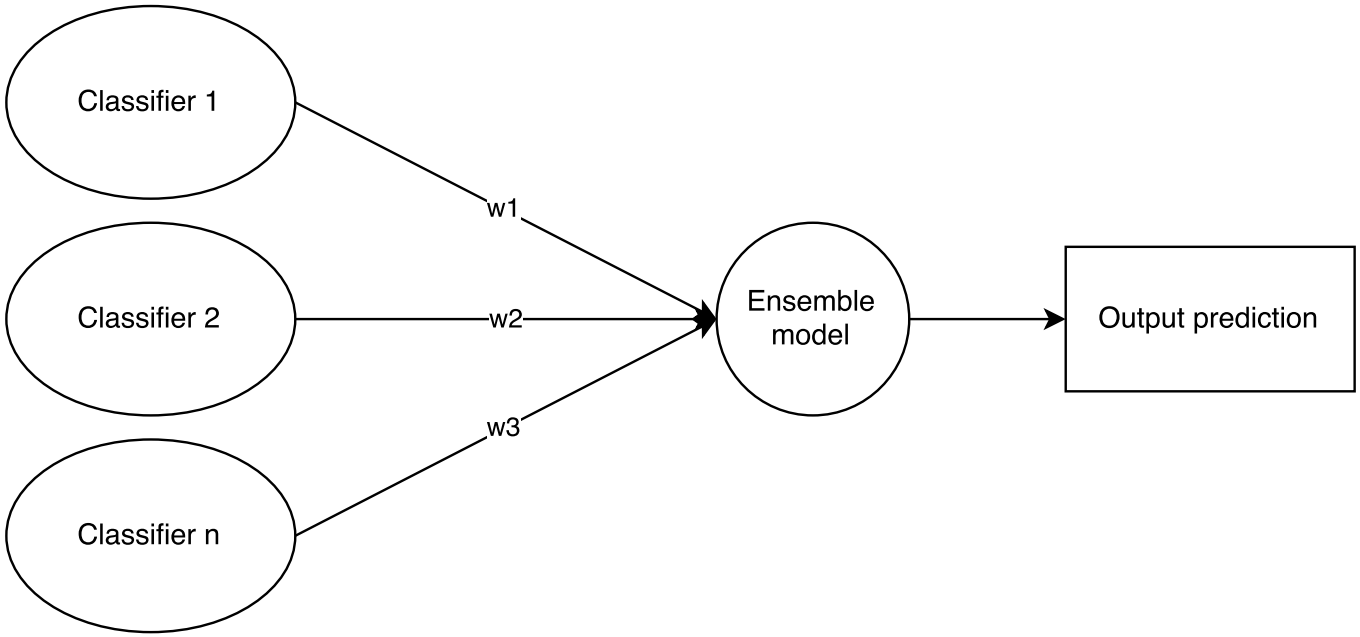


Xgboost [Chen and Guestrin, 2016]



Ensembling

Taking advantage of different models to boost prediction accuracy

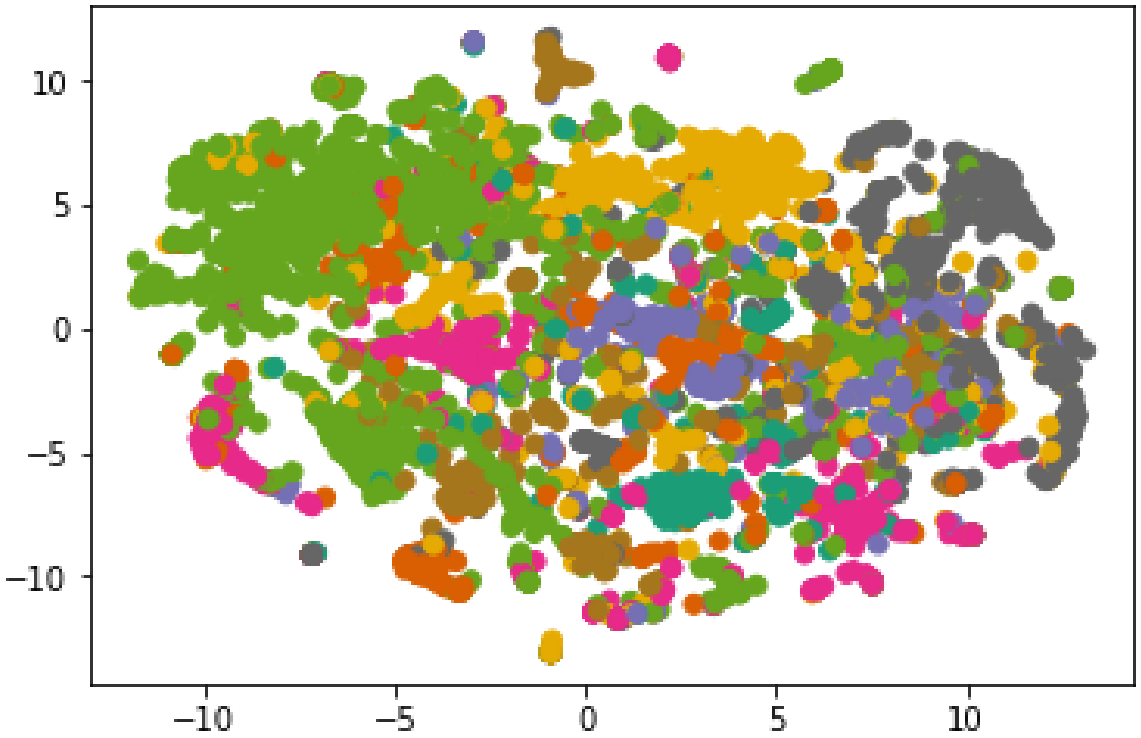


Quantitative Experiments

tf-idf	Doc2Vec	SVM	XGB	train	val
✓		✓		99.41	65.91
✓			✓	94.11	60.50
✓		✓	✓	99.37	**66.71**
	✓	✓		84.28	51.84
	✓		✓	98.65	50.18
	✓	✓	✓	93.98	52.03

Accuracy of 68.60% (8/19) on the test set with tf-idf and SVM/XBF ensemble

Qualitative Experiments



T-SNE representation of the 50-dimensional Doc2Vec embedding of the training split.

Conclusion

- Improve spelling normalization with e.g. noisy channel approaches [Kernighan et al., 1990]

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- Drug embedding by looking at the co-occurrence matrix
- Exploring CNN and RNN as a powerful way to learn the features

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