INF554 - Team TVRPZ

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École polytechnique

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Plan

- Basic features, citations graph and first predictive model
 - First features
 - Graph-based features
 - First predictive model
- Solving the overfitting issue
- 3 Final model and parameters tuning

Raw data & data exploration

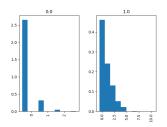


Figure 1: Overlap between titles

Figure 2: Temporal difference

- Raw data: date, title, authors, journal, abstract
- Features: difference between dates, overlap between titles, authors in common...

Abstract embedding

How to use the abstract?

- Overlapping words between articles
- Embedding: a representation of text in high dimensional vector space

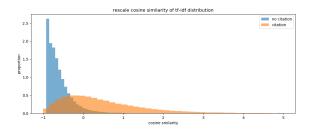


Figure 3: Tf-idf cosine similarity

The graph of documents

Nodes: documents, edges: citations



D the adjacency matrix of the graph:

- DD^T: number of common neighbors
- DD^TD: quoted simultaneously

Compute the degrees: $d_{in}(s), d_{in}(t), d_{out}(s), d_{out}(t)$

First neural network

Score with SVM classifier trained on 5% of the dataset: 96,52 %

 $\rightarrow \mbox{Computed features are meaningful}$

Multi Layer Perceptron

- 1 hidden layer of 16 perceptrons
- Trained on 5% of the dataset
- Accuracy: 97,01% on kaggle

Bad results with all the data

To improve predictions: train over a larger part of the dataset

- Good results on our validation dataset
- Very poor results on kaggle (around 85%)...

Plan

- Basic features, citations graph and first predictive mode
- 2 Solving the overfitting issue
 - Change the model
 - Deeper data exploration
 - Random forests
- 3 Final model and parameters tuning

Autoencoder

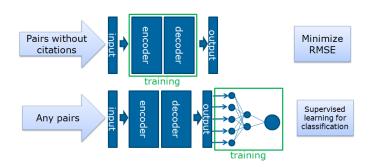


Figure 4: Autoencoder pipeline

- No overfitting thanks to compressed information
- Accuracy: 95,24% on kaggle

degree in source distribution

Distributions

10-4

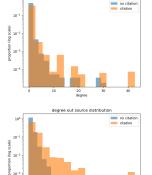


Figure 5: Source degrees

7.5 10.0 12.5 15.0

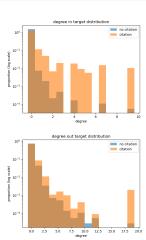


Figure 6: Target degrees

Correlations

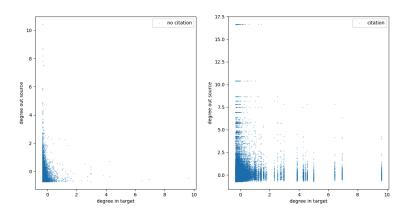


Figure 7: Correlation between source degree out and target degree in

Decision Tree analysis



Figure 8: Decision Tree understanding of the data

3 features: DDtD, year, tf-idf and 95.62% accuracy

Change the model Deeper data exploration Random forests

Random forest results

Random forest on basic features: 77.9% Random forest on all features:

- 99.7% on validation
- 80.1% on Kaggle
- \Rightarrow Is our validation set correct ?

Change the model
Deeper data exploration
Random forests

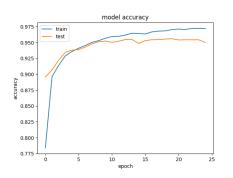
Data splitting issue



Figure 9: Initial data split

The results are already in the training data!

Data splitting issue



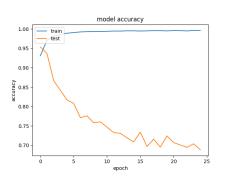


Figure 10: No overfit on few data (5%)

Figure 11: Overfit with more data (70%)

Data splitting issue



Figure 12: Initial data split

The results are already in the training data!



Figure 13: Final data split

It's now safe to learn.

Random Forest analysis

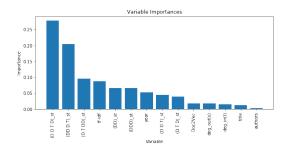


Figure 14: Features importance in a random forest

Well performing forest (96.59% accuracy)

⇒ Add new features: abstract and authors graph

Random Forest analysis

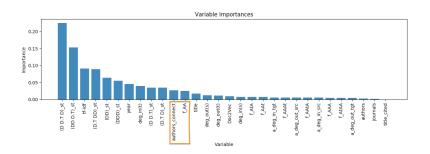


Figure 15: Features importance in our best random forest

High performing forest (97,11% accuracy)

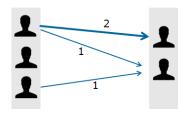
Plan

- Basic features, citations graph and first predictive mode
- Solving the overfitting issue
- Final model and parameters tuning
 - Enriching the data
 - Parameters tuning
 - Final results

The graph of authors

Build a citation network for the authors

- Nodes: authors, edges: number of citations
- Multiple authors for each paper



$$author_connection = \sum_{s \in S} \sum_{t \in T} A_{st}$$

Convolution Network for abstract embedding

Idea: convert abstract into features maps, train CNN on these maps and collect intermediate layer output to reuse as features in the final model.

Input data:

- Word embedding: word2vec
- Abstract embedding: array of word2vec vectors

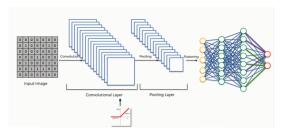


Figure 16: Structure of a CNN

Convolution Network for abstract embedding

Results of the CNN: too much overfitting

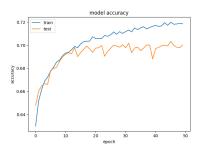


Figure 17: CNN model accuracy showing overfitting

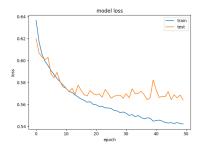


Figure 18: CNN model loss showing overfitting

Overfit vs. Regularization

How to reduce overfitting directly in the neural network?

- Dropout
- Regularization
- Batch size

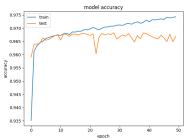


Figure 19: Model accuracy without regularization

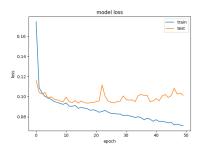


Figure 20: Model loss without regularization

Overfit vs. Regularization

- Dropout: add dropout layers between each dense layer
- Regularization: l₂-regularization
- Batch size: increase size

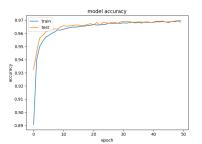


Figure 21: Model accuracy with regularization

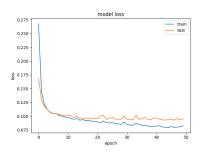


Figure 22: Model loss with regularization

Best results

38	_	ugfdd908	9	0.97035	7	6d
39	▼ 16	Pumpkin	9 9	0.97035	22	2d
40	▼ 14	TVRPZ	<u>R</u> A	0.97010	28	3d
41	A 1	MBS	9 9	0.96986	23	2d
42	▼ 2	BDC	B 🕽 C	0.96961	17	4d
43	A 1	Navy		0.96955	10	2d

