

# Lecture reviews — Week 07

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# Week 7 keypoints

- ▶ supervised/unsupervised
- ▶ preprocessing is key
- ▶ baseline methods:
  - ▶ classification: Naive Bayes, (Logistic regression,) KNN
  - ▶ clustering: K-means, dendrograms
  - ▶ dim. reduction: PCA, UMAP
- ▶ don't forget evaluation keypoints (see lesson 2)

# Week 7 – study case

a abacus abbey --- cat ..... mouse ..... zulu 6324  
 zygomatig

$D_1$  : 37 0 0 ... 10 ... 12 ... 0 0

Some financial company offers you to work on  
 “*fraud detection using Natural Language Technology applied to client documents*”.

- ① Some preliminary work has already been performed by a former intern who created document vectors based on an indexing set of 6'324 terms and reduced them to vectors of size 100 using PCA.

Reviewing his/her work and report, you found a graph related to the corresponding singular values.

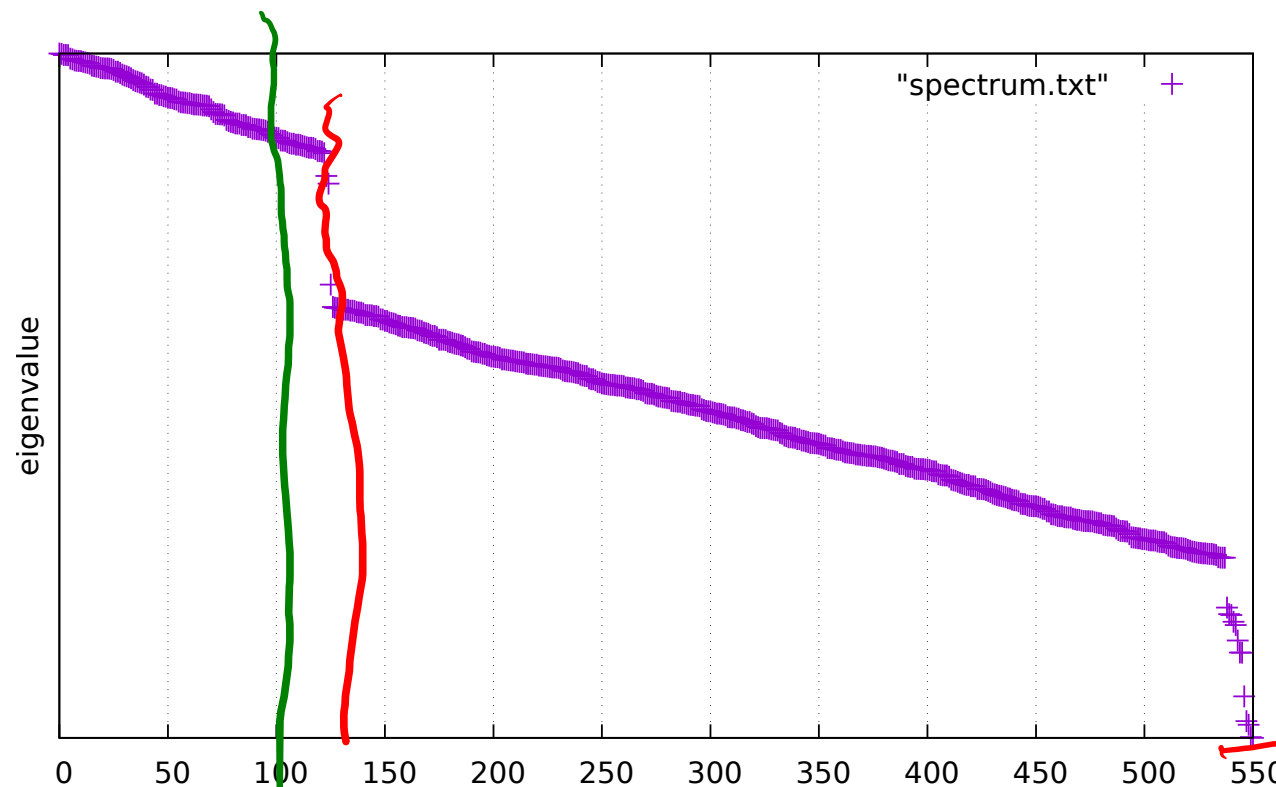
Next slide shows a (rescaled) zoom on the first 550 left-most points in that graph.

$D_N$

# Week 7 – study case

$$\frac{\lambda_i}{\sum \lambda_i}$$

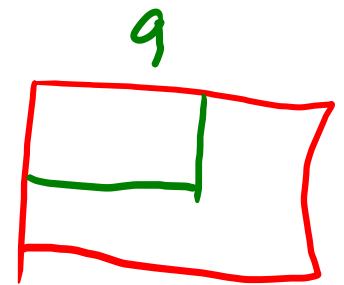
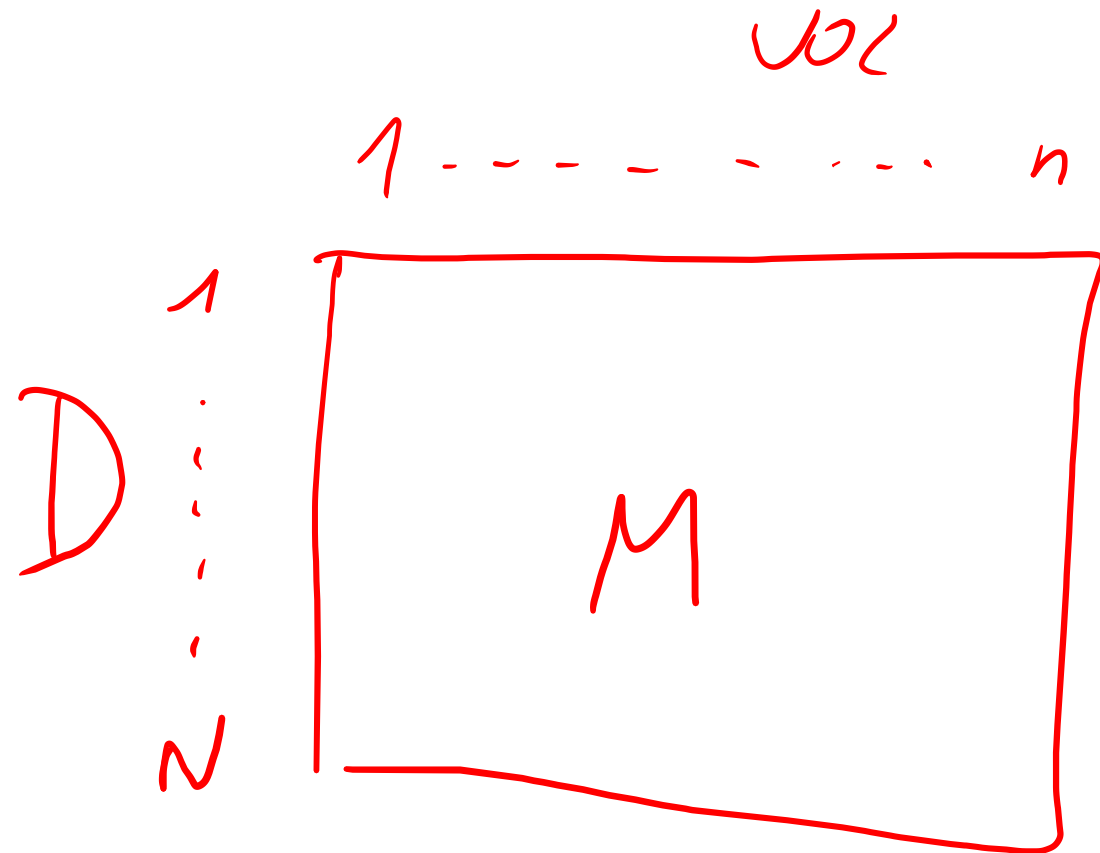
$\lambda_i$



9 130

6324

- a) What is the abscissa (x-value, horizontal axis) of the right-most point in the original complete graph (not reported here)?
- b) What do you think about the intern's methodology for selecting the dimension of the vector space? Would you have performed differently? If yes, how?



$$MM^t \rightarrow$$

$$U \Lambda V^t$$

The equation shows three matrices:  $U$ ,  $\Lambda$ , and  $V^t$ . Below each matrix is a green number 9, indicating that each matrix is 9x9.

# Week 7 – study case

features  $f_i$   
↑  
vector  
document after PCA: dim 130

② Before considering more sophisticated Deep-Learning methods, you wisely decide to start with a simple baseline, namely a Naive Bayes model (on the former representation).

$P(\text{fraud})$

a) Based on your former answer, what is the input of the Naive Bayes module? What is the output? → fraud / not fraud

$P(f_i | \text{fraud})$

← What are the parameters? What is needed for training such a model?

+ same with  $\neg \text{fraud}$

b) Concretely, what probability should be computed as an output from the (very simple excerpt of) client document:

*My salary is about 10'000 CHF and I don't pay any tax.*

1) preprocessing?

2) project → vector  $f_i$  130

3) classify :  $P(\text{fraud}) \cdot \prod_{i=1}^{130} P(f_i | \text{fraud})$

same for  $\neg \text{fraud}$ .

# Week 7 – study case

- ③ From your first analysis of the baseline results, you realize that single tokens do not adequately capture dependencies that clearly appear at the syntactic level (for instance the one between “*don’t*” and “*pay*” in the former example). Using some syntactic parser, you are able to transform the former example sentence

$P(\text{-fraud})$

*My salary is about 10'000 CHF and I don't pay any tax.*

into:

$P(\text{!}_i | \text{-fraud})$

*SALARY-10K-RANGE/not\_pay/tax*  $\text{!}_i$

- a) What probability would then be computed as the resulting output by the Naive Bayes model in such a case?
- b) Compared to former Naive Bayes model, what is the main fundamental reason why you can reasonably expect the results to be better?

$$P(c) \cdot \prod_{i=1}^3 P(\text{!}_i | c)$$

$c \in \{\text{fraud}, \neg \text{fraud}\}$