TEXT MINING

L12. CONCLUSIONS

SUZAN VERBERNE 2021

Universiteit Leiden

TODAY'S LECTURE

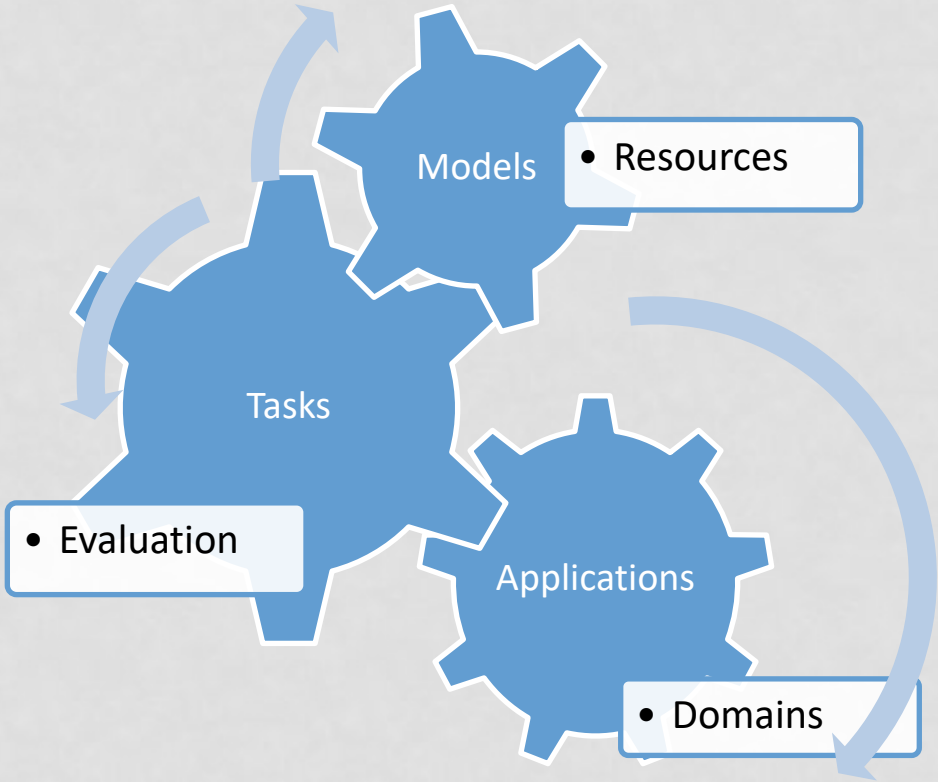
- Course summary
  - Tasks
    - and evaluation
  - Models
    - and resources
  - Applications
    - and domains
- Exercises to practice for the exam
- Schedule of tests (exam/assignment)

COURSE SUMMARY

Universiteit Leiden

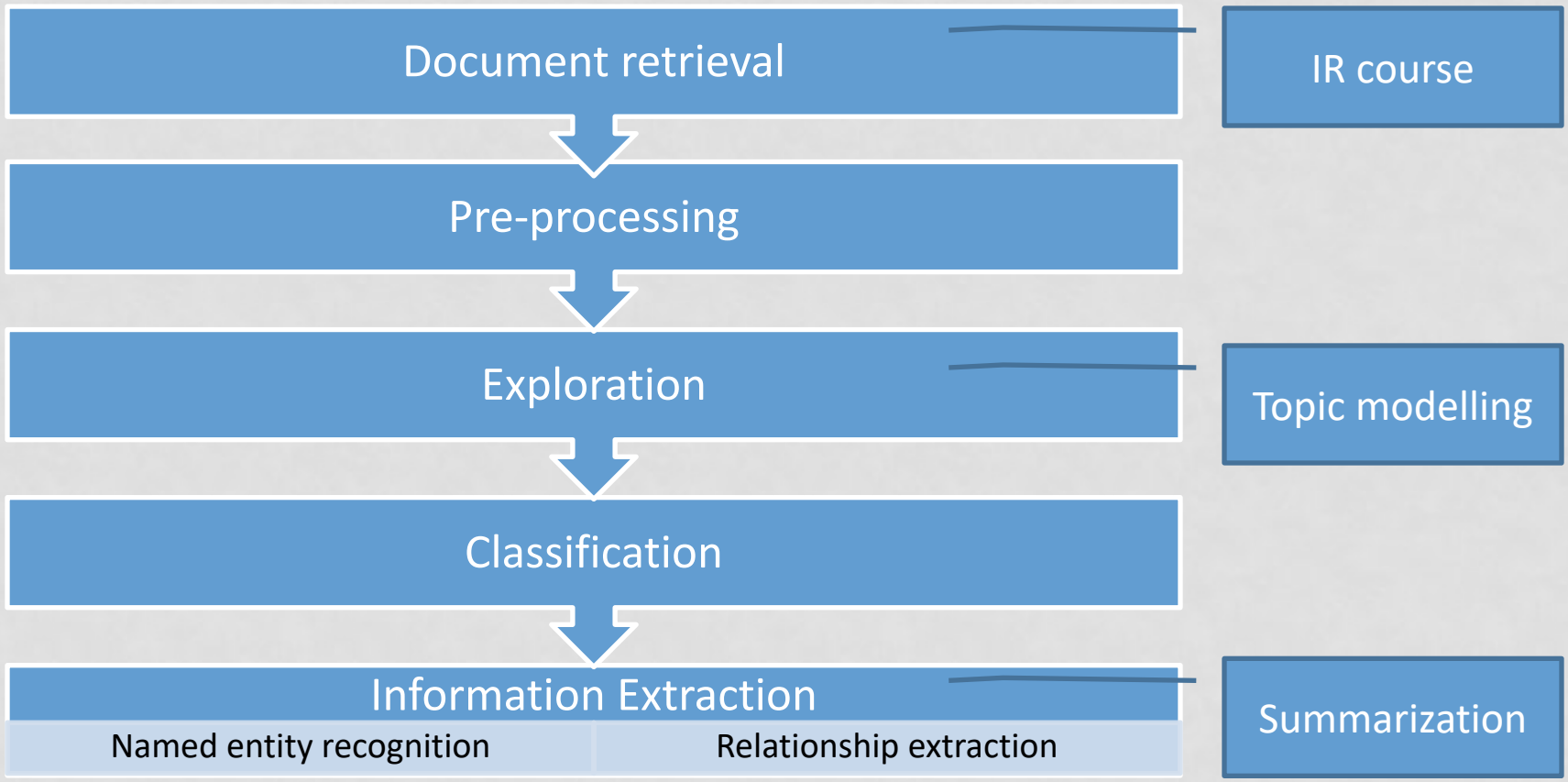
Suzan Verberne 2021

MODELS, TASKS, APPLICATIONS



TASKS

TASKS IN THE TM PIPELINE



PRE-PROCESSING

Cleaning

- PDF/docx/HTML to text
- Language filtering
- Encoding issues
- Regex patterns
- Spelling correction

Minimal edit distance

Linguistic pipeline

- Tokenization
- Stop word removal
- Lemmatization/stemming
- POS-tagging

CLASSIFICATION

- Multi-class vs multi-label
- Feature selection
- Term weighting: tf-idf

INFORMATION EXTRACTION

- Named entity recognition
  - Segmentaton & classification
  - Sequence labelling task with IOB-labels
  - Rule-based, feature-based, neural-network based
  - Help of dictionaries

- Relation extraction
  - Co-occurrences, patterns, classification
  - Distant supervision

SUMMARIZATION

- Extractive: sentence classification
- Abstractive: sequence-to-sequence (compare with translation)

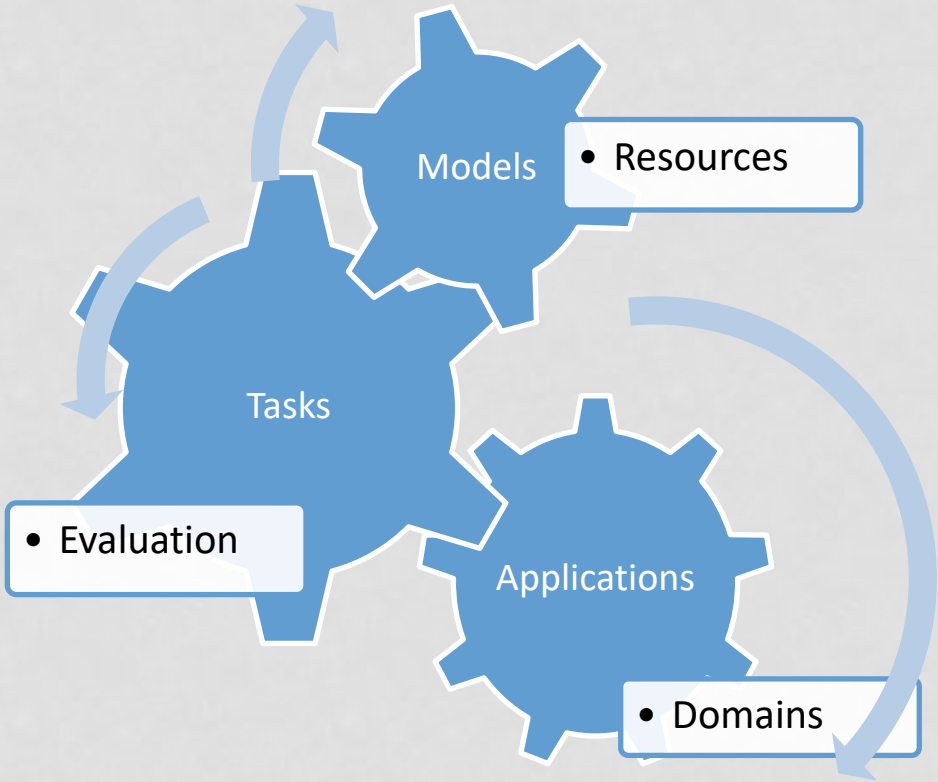
- Challenges:
  - Training data (ground truth, humans disagree)
  - Evaluation

EVALUATION

- Intrinsic: comparison against ground truth (=human) for task
  - Metrics:
    - Accuracy
    - Precision, recall, F1
    - ROUGE for summarization
  - Train-test split to prevent overfitting, or cross validation
    - Hyperparameter tuning on train-tune-set, or cross validation (GridSearchCV)

- Extrinsic: effectiveness in context

MODELS, TASKS, APPLICATIONS



MODELS

MODELS

- Neural language models (embeddings)
  - Traditional: word2vec (a NN with 1 hidden layer) and others
  - Transformer-based: BERT
- Goal: from high-dimensional sparse vectors (10,000s) to lower-dimensional (~100-800) dense vectors
- Pre-trained as a word/sentence prediction task
  - = Language modelling
- The hidden layer has the dimensionality of the embeddings

Distributional hypothesis

MODELS

- Classification
  - Vector space model, bag of words
  - Dimensionality reduction
  - Machine learning methods
    - Naïve Bayes (probabilistic)
    - Support Vector Machines (vector space)
    - Feedforward neural networks (compare with logistic regression, multi-node, multi-layer)
    - Transformer models (BERT)

MODELS

- Sequence labelling
  - Conditional Random Fields
  - Recurrent Neural Networks / Bi-LSTMs
  - Transformer models: BERT

- Sequence-to-sequence
  - Encoder-decoder models
  - Transformer models

TRANSFER LEARNING

- Pre-trained neural language models allow for transfer learning
- Inductive transfer learning: transfer the knowledge from pretrained language models to any text mining task
  - Fine-tuning
- Current state-of-the-art for many text mining tasks

RESOURCES

- Labeled data
  - For training and evaluating task-specific models
  - Typically small (1000s of examples, or even 100s)
  - Supervised learning
  - How to obtain labelled data:
    - Benchmark data
    - Existing expert labels
    - User-generated content
    - Data annotation (crowdsourcing)

Inter-rater agreement (Cohen's Kappa)

RESOURCES

- Unlabeled data
  - For pre-training language models (language modelling = word prediction/sentence prediction)
  - General vs domain-specific
  - Typically large (Millions of words)

RESOURCES

- Dictionaries (gazetteers)
- Ontologies / taxonomies
- General domain (names, places) or specific domain (e.g. bio)

Controlled vocabulary

APPLICATIONS

APPLICATIONS

- Sentiment analysis
  - Classification / ordinal regression / linear regression
  - Extraction: aspect-based sentiment analysis (E,A,S,H,C)
- Argument mining
  - Sentence classification (classifying argument components into different types such as claims and premises)
  - Structure identification focuses (linking arguments or argument components)

APPLICATIONS

- CV-vacancy matching
  - Extracting the structure of a CV
  - Extracting structured fields (e.g. name, education) from a CV
  - Mapping words with similar meaning (e.g. function titles) between CV and vacancy

DOMAINS

- Social media analytics (classification, extraction, sentiment)
- E-commerce (sentiment classification/extraction, ontologies)
- Biomedical text mining (classification/retrieval, extraction)
  - Clinical applications (EHRs)
- Humanities, historical documents (pre-processing, classification/retrieval, extraction)

EXERCISES

EXERCISES

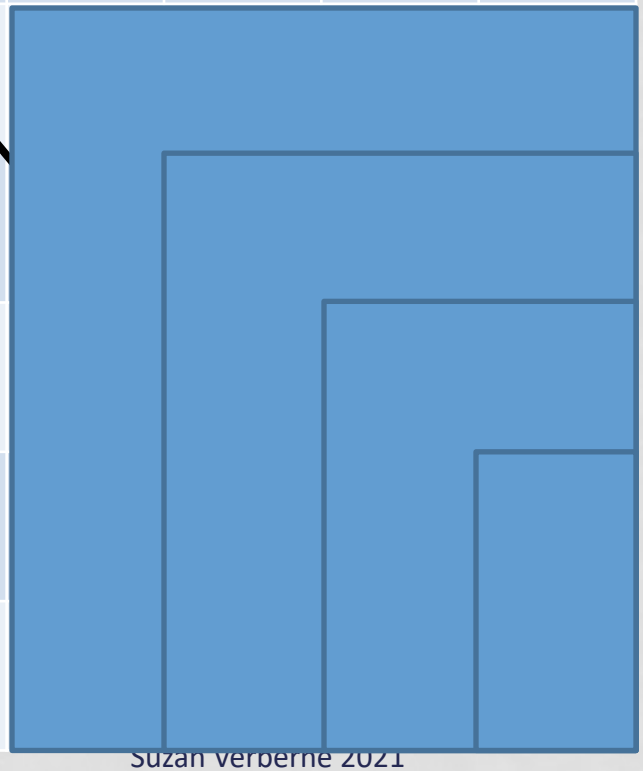
- Minimal edit distance
- Tf-idf
- Naïve Bayes
- Inter-rater agreement
- Precision and recall

MINIMAL EDIT DISTANCE

- Compute the Levenshtein distance between ‘where’ and ‘hear’. Show your computation.

MINIMAL EDIT DISTANCE

		H	E	A	R
	0	1	2	3	4
W	1				
H	2				
E	3				
R	4				
E	5				



MINIMAL EDIT DISTANCE

cost	operation	input	output
1	delete	w	
0	(copy)	h	h
0	(copy)	e	e
1	substitute	r	a
1	substitute	e	r
Total: 3			

TF-IDF

- We have a collection of 100,000 movie scripts.
  a. The term *Elsa* occurs in 10 scripts. What is the inverse document frequency for *Elsa*? Show your computation.
  b. We have a film script *s* in which *Elsa* occurs 2 times. What is the tf-idf weight for *Elsa* in *s*?

TF-IDF

a. idf = $\log_{10}(100{,}000/10) = \log_{10}(10{,}000) = 4$

b. tf = $1 + \log_{10}(2) \approx 1.3$
tf*idf = 1.3*4 = 5.2

NAÏVE BAYES

- Consider this toy training set for a text classification task with Naïve Bayes:

Doc id	Content	Class
1	make our garden grow	relevant
2	we make the best of it	not relevant
3	together we can grow	not relevant
4	we make the best plans	not relevant

Doc id	Content	Class
1	make our garden grow	relevant
2	we make the best of it	not relevant
3	together we can grow	not relevant
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a. What is the prior probability of the 'relevant' class?

b. What is the vocabulary size of the training set? Assume that we do not remove stop words.

c. Estimate *P('make', not relevant)* using the maximum likelihood estimate on the train set.

d. Why is add-one smoothing needed when we estimate the probability of an unseen document? Provide an example test document given the toy training set for which add-one smoothing is needed.

Doc id	Content	Class
1	make our garden grow	relevant
2	we make the best of it	not relevant
3	together we can grow	not relevant
4	we make the best plans	not relevant

a. 1/4

b. 12

c. (2+1)/(15+12)

d. Because a word in the test document that does not occur in the training set will have a zero probability and the multiplication of zero probabilities will lead to a combined probability of zero; a correct example would be any text with a word that does not occur in training set.

INTER-RATER AGREEMENT

- Compute Cohen's Kappa for this agreement table. Show your computation. (You can keep the last fraction of your computation as it is, without estimating the decimal numbers.)

Agreement table		Annotator 2		
		Positive	Negative	Neutral
Annotator 1	Positive	25	10	5
	Negative	0	25	15
	Neutral	5	5	10

INTER-RATER AGREEMENT

Agreement table		Annotator 2			
		Positive	Negative	Neutral	
	Positive	25	10	5	**40**
	Negative	0	25	15	**40**
	Neutral	5	5	10	**20**
		30	**40**	**30**	**100**

Pr(a)	60 / 100	0.6
Pr(e,pos)	40 / 100 * 30 / 100	0.12
Pr(e,neg)	40 / 100 * 40 /100	0.16
Pr(e,neut)	30 / 100 * 20 / 100	0.06
Pr(e)	(sum of the 3 rows above)	0.34
kappa	(0.6 - 0.34) / (1 - 0.34) = 0.26 / 0.66	

PRECISION AND RECALL

- Consider the following output table of an automatic classifier for 10 documents. Compute (please show the fractions):

a. the recall for the A class

b. the precision for the A class

doc id	class assigned by classifier	ground truth class
1	A	C
2	A	A
3	B	B
4	B	A
5	C	C
6	A	A
7	D	A
8	A	D
9	B	B
10	C	A

PRECISION AND RECALL

- Consider the following output table of an automatic classifier for 10 documents. Compute (please show the fractions):

a. Recall(A) = 2/5

b. Precision(A) = 2/4

doc id	class assigned by classifier	ground truth class
1	A	C
2	A	A
3	B	B
4	B	A
5	C	C
6	A	A
7	D	A
8	A	D
9	B	B
10	C	A

CONCLUSIONS

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HOMEWORK

- Work on the final assignment

- Prepare for the exam
  - Exam Text mining, Thursday January 13, 10.15 – 13.15
    - (Students with a provision card get an addition 30 minutes)
  - Location: GORL / 04/5
  - The exam is closed book, individual

- Practice materials are on Brightspace

THANK YOU

- Thank you for the participation in this course,
- And a big thanks to the TAs:
  - Michiel van der Meer
  - Juan Bascur Cifuentes
  - Cheyenne Health
  - Hainan Yu

TIME FOR XKCD