Idea Analytics & code along: Intro to different techniques for data mining

Managing Innovation - Master in Innovation Management and Business Development - Spring 2022

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Outline

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Data*
Data
Data science
Type of Data
KDD
Normalization
Big Data?
Human-in-the-Loop Models
Example
Trend Reservoirs
Techniques
Text analytics
Word counts
Word distributions
Vector space model
Sentiment analysis
Non-negative Matrix Factorization
Classification
EDA
Neural embeddings
Feedback
Data feedback
Collaboration feedback

Data Access

https://cloud.sdu.dk/

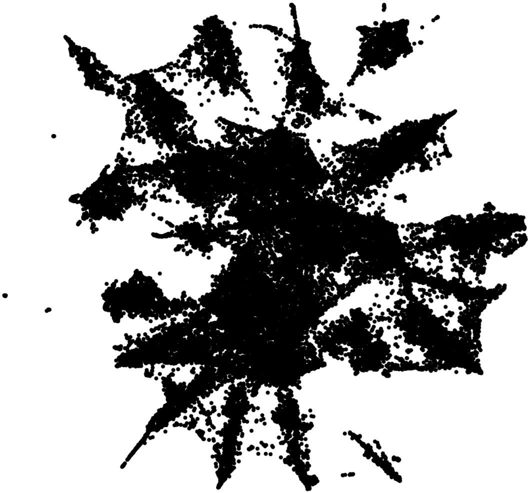
Communication

chcaa@cas.au.dk

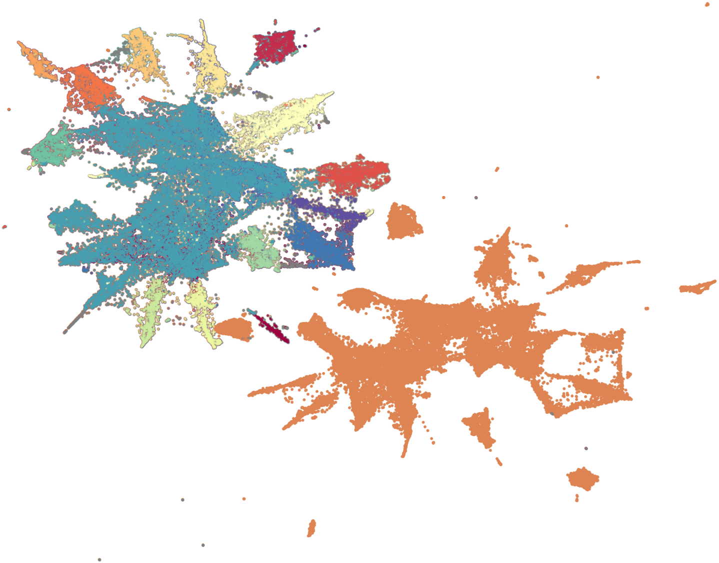
Add subject: [Group <your group number>] <description>

Example: You want to submit group 5's requirements:

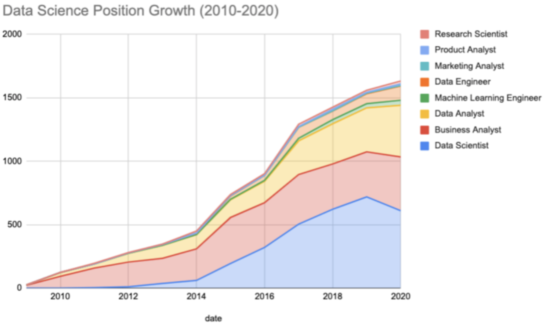
- list the group's requirements, e.g., 'estimate the effect of comment tone on number of votes'
- add '[Group 5] requirements' to the subject line
- submit to chcaa@cas.au.dk



JSTOR Data For Research, $n = 43,802$, $\sim$ 400m words, Eng*, Fr, Ger.



Why does this matter?



With the rise of Big Data, we have seen a rapid increase in data-related positions, source: Stephanie Glen (2021) ‘Data Science Job Market Shrinking? Not So Fast’

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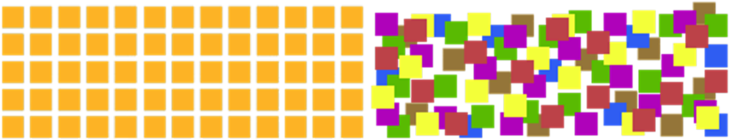
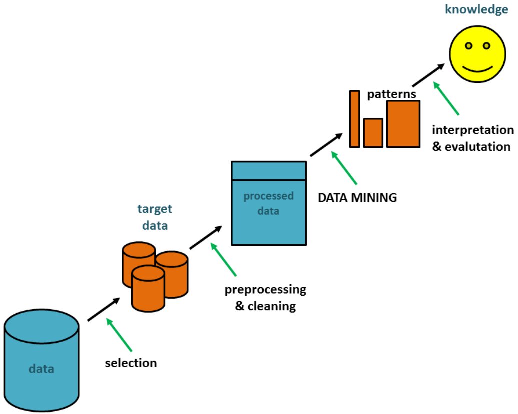
Type of Data



Structured versus unstructured data.

Knowledge Discovery in Data(bases)



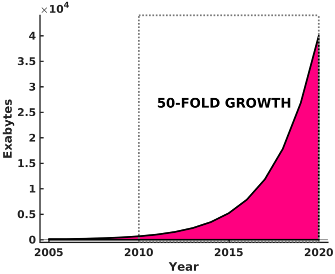
Data Normalization

We normalize natural language data in order to increase our signal/reduce the randomness

- Removal of duplicate whitespaces and punctuation.
- Casefolding.
- Removal or substitution of special characters/emojis (e.g.: remove hashtags).
- Substitution of contractions (very common in English; e.g.: 'I'm'→'I am').
- Transform word numerals into numbers (eg.: 'twenty three'→'23').
- Substitution of values for their type (e.g.: '50DKK'→'MONEY').
- Acronym normalization (e.g.: 'DK'→'Denmark') and abbreviation normalization (e.g.: 'btw'→'by the way').
- Normalize date formats, social security numbers or other data that have a standard format.
- Spell correction
- Removal of gender/time/grade variation with Stemming or Lemmatization.
- Substitution of rare words for more common synonyms.
- Stop word removal (∼ dimensionality reduction technique).

> *Big Data* are not necessarily enough data to solve your problem.

- wrong data
- lack precision/low detection rate
- problem complexity
- (too many data)



revise question OR collect more data OR **enrich existing data**

Human-in-the-Loop Models

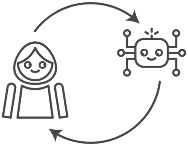
as task complexity increases, a need for (operational approaches to) leveraging human intelligence in the development of learning algorithms has become apparent

Type	Human Involvement	Resources	Relevance
Out-of-the-loop	not required	low	low
On-the-loop	checking	medium	medium↓
In-the-loop	required	high	medium↑

WHEN

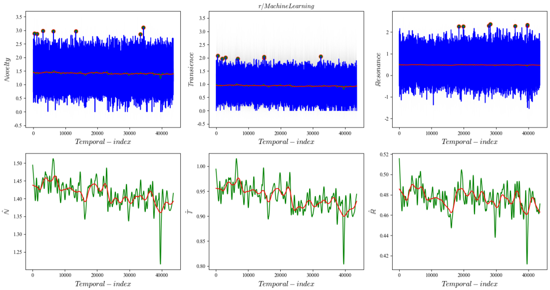
- algorithms are not understanding the input
- data input is interpreted incorrectly
- algorithms do not know how to perform the task
- to make models more accurate
- cost of errors is too high in development
- data is rare or not available

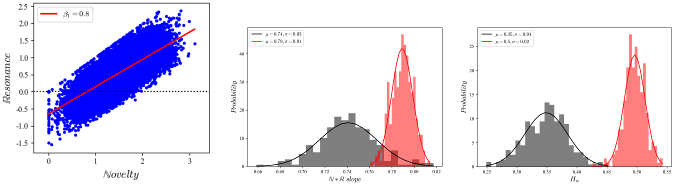
THEN



HITL Models

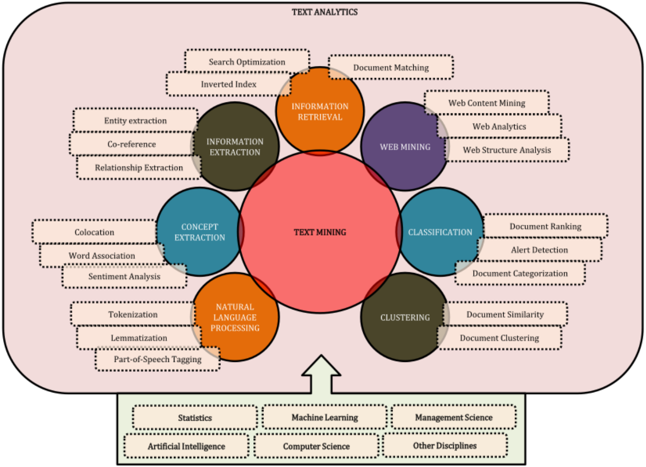
Trend Reservoirs in Social Media





trend reservoirs (i.e., social media signals that display high trend potential) can be identified by their relationship between novel and resonant behavior, and their minimal persistence.

Text Analytics



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Word counts

words are (one of) the basic units of meaning

most TM techniques rely on word frequencies, that is, we tokenize a text at the word level and count the number of tokens for each type

I am Daniel
I am Sam
Sam I am
That Sam-I-am
That Sam-I-am!
I do not like
that Sam-I-am
...

'I' 'am' 'Daniel' 'I'
'am' 'Sam' 'Sam' 'I'
'am' 'That' 'Sam' 'I'
'am' 'That' 'Sam' 'I'
'am' 'I' 'do' 'not' 'like'
'that' 'Sam' 'I' 'am' ...

a	1	59	0.073
am	1	16	0.02
and	1	24	0.03
anywhere	1	1	0.001
anywhere	1	7	0.009
...			
you	1	34	0.042
total	55	804	1.0

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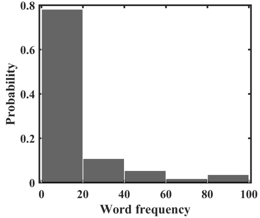
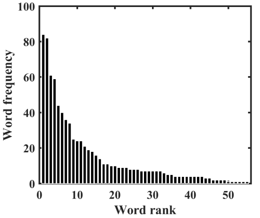
Word Distributions





Most words are infrequent, but a few words are very frequent

'i' 'not' 'them' 'a' 'like' 'in' 'do' 'you' 'would'

Model a text as a distribution over words. Some words are more likely than other.

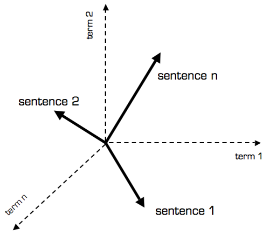
Often times we are looking at the mid-range (not too likely and not too unlikely).

Vector Space Model

any collection of *m* documents can be represented in the vector space model by a document-term matrix of *m* documents and *n* terms

a vector space model is a basic modeling mechanism for a word- or document-space (whether we look at rows or columns)

- a document vector with only one word is collinear to the vocabulary word axis
- a document vector that does not contain a specific word is orthogonal/perpendicular to the word axis
- two documents are identical if they contain the same words in a different order (BOW assumption)



Document space ↘ $\quad$ Term vector space ←

$$
\begin{array}{c|ccccc|}
 & t_1 & t_2 & t_3 & \dots & t_n \\
\hline
D_1 & a_{11} & a_{12} & a_{13} & \dots & a_{1n} \\
D_2 & a_{21} & a_{22} & a_{23} & \dots & a_{2n} \\
D_3 & a_{31} & a_{32} & a_{33} & \dots & a_{3n} \\
\dots & & & & & \\
D_m & a_{m1} & a_{m2} & a_{m3} & \dots & a_{mn} \\
\hline
Q & b_1 & b_2 & b_3 & \dots & b_n
\end{array}
$$

You can use the 'words' as predictors $x_1, x_2, \dots x_m$ in:

$$Y_i = f(X_i, \beta) + \epsilon_i$$

but it can result in an underdetermined system

Sentiment Analysis

- we can use a dictionary to extract cognitive and affective keywords from a collection of documents and apply a sentiment function

```
'Did Crooked Hillary help disgusting (check out sex tape and past) Alicia M become a U.S. citizen
so she could use her in the debate?'

Positive sex, citizen
Negative crooked, hillary, disgusting, out
Sentiment Score (2+1) + (-2-1-3-1) = -4
Sentiment Polarity Negative
Overall Score Sum of all sentence scores
```

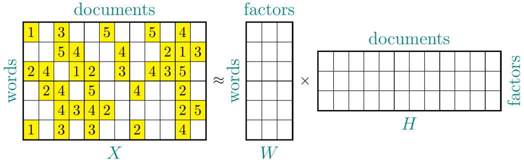
- a sentiment vector is a vector of keyword frequencies weighted by sentiment scores

> You can avoid the underdetermined system and use the overall 'sentiment' as predictor in: $Y_i = f(X_i, \beta) + \epsilon_i$

Matrix decomposition of *TD* matrix

For bag-of-words representation X w. documents in columns and words in rows, such that each entry X_{ij} is the ith word in the jth column, we solve

$$\underset{W,H}{\operatorname{argmin}} \parallel X - WH \parallel_F^2 \quad s.t.\ W, H \geq 0$$



Non-negative matrix factorization of *TD* matrix X

WH is a low-rank approximation of the data (++fewer factors than documents and words) and each document is the weighted sum of columns in W, "document factors" $\sim$ themes or topics

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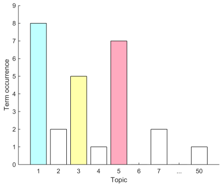

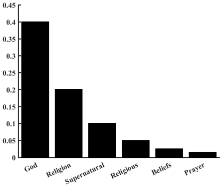

Document representation from NMF

ABSTRACT—*We present two studies aimed at resolving experimentally whether religion increases prosocial behavior in the anonymous dictator game. Subjects allocated more money to anonymous strangers when God concepts were implicitly activated than when neutral or no concepts were activated. This effect was at least as large as that obtained when concepts associated with secular moral institutions were primed. A trait measure of self-reported religiosity did not seem to be associated with prosocial behavior. We discuss different possible mechanisms that may underlie this effect, focusing on the hypotheses that the religious prime had an ideomotor effect on generosity or that it activated a felt presence of supernatural watchers. We then discuss implications for theories positing religion as a facilitator of the emergence of early large-scale societies of cooperators.*

Many theorists have suggested that the cognitive availability of omniscient and omnipresent supernatural agents has had a dramatic impact on the development of large-scale human societies. The imagined presence of such agents, along with emotional ritual and costly commitment to the social group they govern, may have been the major development that allowed genetically unrelated individuals to interact in cooperative ways (e.g., Atran & Norenzayan, 2004; Irons, 1991; Sosis & Ruffle, 2004). The research reported in this article experimentally investigated this link between two broad classes of culturally widespread phenomena of interest to social science—religious beliefs and cooperative behavior among unrelated strangers.

Although anecdotes documenting religion's prosocial and antisocial effects abound, the empirical literature has produced mixed results regarding religion's role in prosocial behavior.

[redacted]

Sosis and Ruffle (2004) examined levels of generosity in an experimental cooperative pool game in religious and secular kibbutzim in Israel and found higher levels of cooperation in the religious ones, and the highest levels among religious men who engaged in daily communal prayer. Batson and his colleagues (Batson et al., 1989; Batson, Schoenrade, & Ventis, 1993) have shown that although religious people report more explicit willingness to care for others than do nonreligious people, controlled laboratory measures of altruistic behavior often fail to corroborate this difference. Furthermore, when studies demonstrate that helpfulness is higher among more devoted people, this finding is typically better explained by egoistic motives such as seeking praise or avoiding guilt, rather than by higher levels of compassion or by a stronger motivation to benefit other people.

However insightful these findings are, research on religion and prosocial behavior has been limited by its overwhelming reliance on correlational designs. If religiosity and prosocial behavior are found to be correlated, it is just as likely that having a prosocial disposition causes one to be religious, or that some third variable such as guilt proneness or dispositional empathy causes both cooperative behavior and religiosity, as that religious beliefs somehow cause prosocial behavior. Only rarely have studies induced supernatural beliefs to examine them as a causal factor. Bering (2003, 2006) inhibited 3-year-old children's tendencies to cheat (i.e., open a "forbidden box") by telling them that an invisible agent ("Princess Alice") was in the room with them. In a different study, college students who were casually told that the ghost of a dead graduate student had been spotted in their private testing room were less willing to cheat on a computerized spatial-reasoning task than were those told nothing (Bering, McLeod, & Shackelford, 2005). These studies suggest that explicit thoughts of supernatural agents curb cheating behavior.

In the research reported here, we examined the effect of God concepts specifically on selfish and prosocial behavior. Our research design was novel in two ways. First, we introduced an

Original document

You can use the 'topics' as predictors $x_1, x_2, ... x_n$ in $Y_i = f(X_i, \beta) + \epsilon_i$ where $n < m$ for word-based regression

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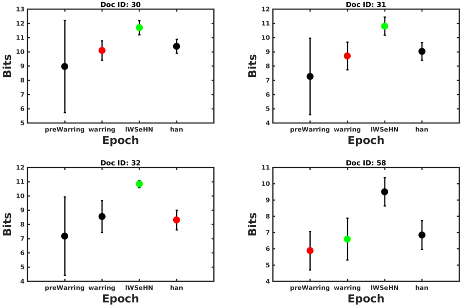
Text Classification

- Given labeled data, a classification algorithm will output a solution that categorizes new examples → associate labels with subsets of the data (c.f., logistic regression)
- data (features) with class values (∼ labeled data), excellent opportunity to make use of metadata (e.g., reviews scores, evaluations &c)



Source classification of Chinese historical documents

Naive Bayes

A simple and very popular probability learning model that can be implemented very efficiently

The probability of a document d being in class c, $P(c \mid d)$ is computed as:

$$P(c \mid d) \propto P(c) \prod_{i=1}^{m} P(t_i \mid c) \quad (1)$$

and the class of a document d is then computed as:

$$c_{MAP} = arg\ max_{c \in \{c_1, c_2\}} P(c \mid d) \quad (2)$$

Naive assumption that the presence/absence of a feature is completely independent of other features.

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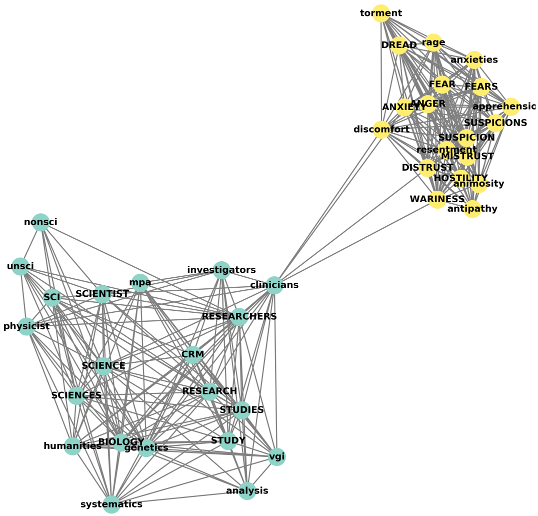
Exploratory analysis with Deep Neural Nets



Sparse query graph for MISTRUST and SCIENCE

Distributed word representation

For a discrete input $w_0, w_1, \ldots, w_n$, we train a simple feedforward network such that

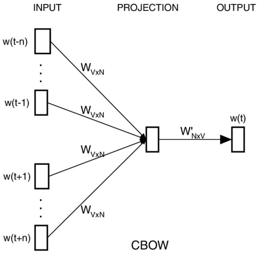
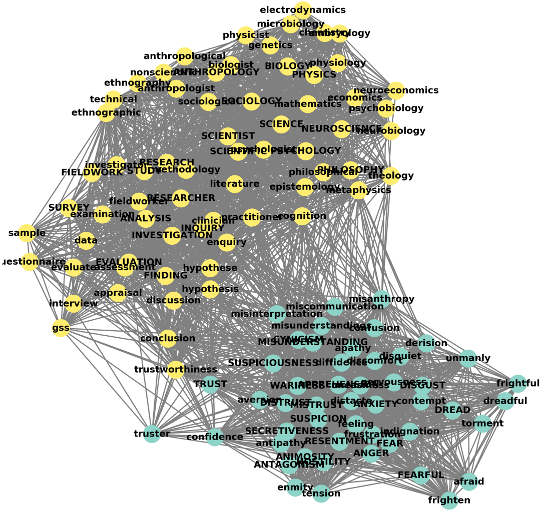


Figure 1: CBOW architecture for learning neural embeddings at the word level

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-n\leq j\leq n}\log p(w_t|w_{t+j}), \quad j\neq 0$$

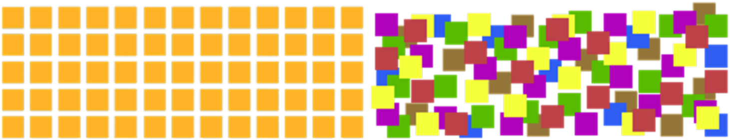
Semantic similarity between any two word embeddings, A and B, can then be measured as their angular similarity

$$1-\frac{\cos^{-1}\left(\frac{A\cdot B}{\|A\|\|B\|}\right)}{\pi}$$



Dense query graph for MISTRUST and SCIENCE

Data



most solutions were focused on structured data - low effort.

- you never have enough data!

  no effect, property of the data or ‘in the eye of the beholder’
  all data come with limitations
  understand your data (e.g., visualization: look for unusual patterns)
  the data are never as assumed (e.g., latent groups are the rule)

- utilize unstructured data

  annotate, enrich and augment...

- dynamics matter!

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Collaboration

- interdisciplinary collaboration is *costly...*

  requires a common frame of reference
  psychology and information systems are good matches

- *you will often have to make decisions on weak evidence*

  you are probably more qualified to make the call

- *predictive accuracy is not the only performance metric...*

  inspect and test for biases

Thank you for your attention

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slides: http://knielbo.github.io/files/kln_mginno.pdf

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