Topic Analysis of Textbooks Using AI

Coby Simmons

Utrecht University

cobysimmons01@gmail.com

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- enable enhanced learning experiences via learning object classification, automatic index creation, content personalisation, etc.

Overview

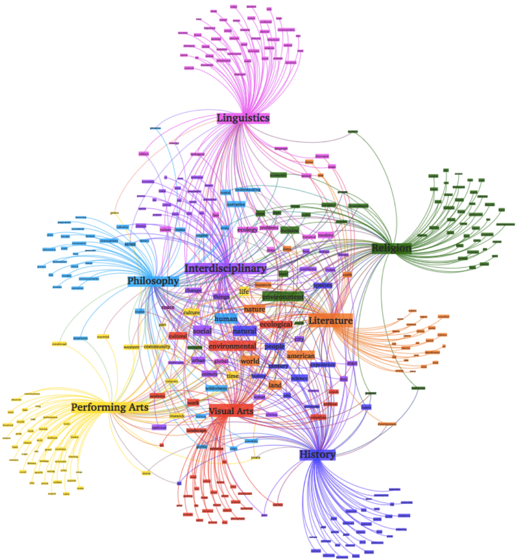
Previous Research

Modelling of textbooks

- proposal for an intelligent online learning experience: "Intextbooks"
  (Alpizar-Chacon, Hart, et al. 2020)
- extraction of knowledge models from PDF textbooks; encoding as TEI[1] files
  (Alpizar-Chacon and Sosnovsky 2020; Alpizar-Chacon and Sosnovsky 2021)
- semantic linking and enrichment of glossary & index
  (Alpizar-Chacon and Sosnovsky 2019; Alpizar-Chacon and Sosnovsky 2022)

[1] `https://tei-c.org/`

Modelling Topics



Term Frequency-Inverse Document Frequency (TF-IDF)

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- for a term t in a document d in a corpus of size N, the TF-IDF is

$$tf_{t,d} \times \log \frac{N}{df_t}$$

  where $tf_{t,d}$ is the frequency of t in d and df_t is the number of documents containing t.
- (see Spärck Jones 1972)

Latent Dirichlet Allocation

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- faces a number of challenges:
  - need to set the number of topics as a parameter
  - struggles with topics that are tangential or overlapping

    (Ajinaja et al. 2023)

Embedding Models

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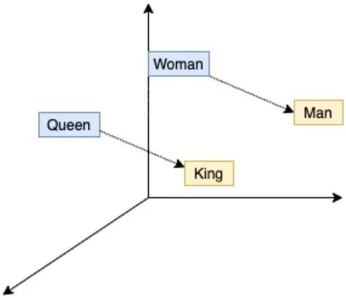

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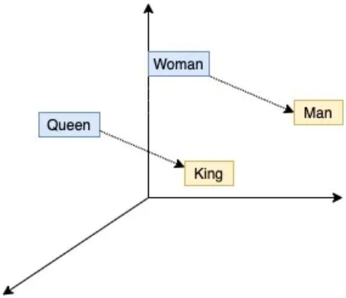

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- Doc2Vec extends Word2Vec to entire documents and outperforms LDA in textbook content linkage tasks (Thaker, Brusilovsky, and He 2018)

Bidirectional Encoder Representations from Transformers (BERT)

- uses two unsupervised tasks for pre-training:
  - masked token prediction
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- effectively used for automatic keyword extraction from textbooks

  (Pozzi, Alpizar-Chacon, and Sosnovsky 2023)

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  (Bengio, Simard, and Frasconi 1994)
- Long Short-Term Memory (LSTM) networks introduced to overcome this limitation
  (Hochreiter and Schmidhuber 1997)

Semantic Similarity

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- can be measured through cosine similarity S_C, where documents are represented by n-dimensional vectors, $\mathbf{a}$ and $\mathbf{b}$,

$$S_C(\mathbf{a}, \mathbf{b}) := \cos(\theta) = \frac{\mathbf{a} \cdot \mathbf{b}}{\|\mathbf{a}\| \|\mathbf{b}\|}$$

Linking Multiple Textbooks

- **Topic Aggregation:** Only compute the topic vectors for the sections at lowest level in the hierarchy, and for higher levels, aggregate topic vectors by taking a weighted average of sub-topic vectors.

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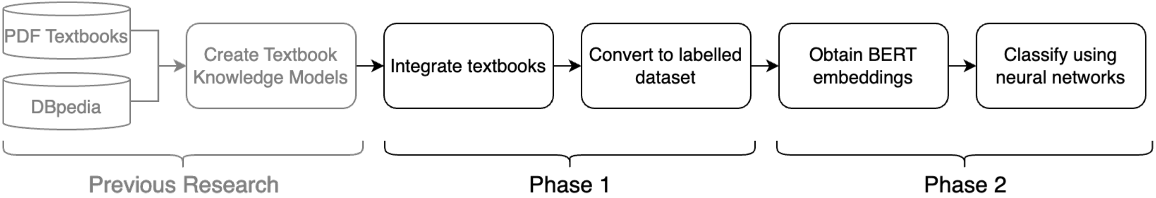
- **Re-Indexing:** Compute the topic vector for every section by considering a section's 'document' to be the content of the section and all it's sub-sections.
- (see Guerra, Sosnovsky, and Brusilovsky 2013)

Methodology

Methodology

Architecture for topic representation and classification



Dataset Generation (Phase 1)

Base Textbook

Other Textbooks

Dataset Generation (Phase 1)

- use multiple attributes for each section
  - header
  - content
  - concept names, definitions, concept subjects
- quick, inexpensive way to generate dataset of sections and their topics

Dataset Generation (Phase 1) – Strategies

- TF-IDF
- Doc2Vec
- Clustering
- Ensemble Modelling
  - combination of TF-IDF and clustering
- TF-IDF & Doc2Vec Hybrid Approach
  - first check for matches using TF-IDF, then use Doc2Vec for uncertain matches
- Iterative Learning
  - recompute section's vector after each match

Topic Classification (Phase 2)

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- RNNs are trained to classify sections into topics

Evaluation

Evaluation – Dataset Generation (Phase 1)

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- evaluate performance using manual mapping generated by experts
- false positives can have a greater cost than false negatives
  $\implies$ precision more important than recall for this task
- therefore, use the F_β score with $\beta = 0.5$

Evaluation – Dataset Generation (Phase 1)

Table: Summary of results for all textbook integration methods

name	precision	recall	F_1	F_β
Hybrid Model	**0.8333**	0.3169	0.4592	**0.6285**
Doc2Vec	0.5714	**0.3944**	**0.4667**	0.5243
TF-IDF	0.5926	0.3380	0.4305	0.5150
Ensemble	0.4632	0.3099	0.3713	0.4215
Clustering	0.0260	0.0282	0.0270	0.0264

more detailed results available at GitHub repository:
`https://github.com/CobySim01/textbook-topic-analysis`

Evaluation – Topic Classification (Phase 2)

- expert dataset
  - 14 class labels
  - 216 data points
- small dataset
  - 32 class labels
  - 352 data points
- large generated dataset
  - 329 class labels
  - 2371 data points

Evaluation – Topic Classification (Phase 2)

Table: Summary of cross-validation performance for each dataset

dataset	concepts	accuracy		precision		recall		F_1	
		model	baseline	model	baseline	model	baseline	model	baseline
expert	true	**0.59**	0.13	**0.67**	0.07	**0.59**	0.13	0.61	0.08
expert	false	0.41	0.13	0.50	0.09	0.41	0.13	0.44	0.09
small	true	0.35	0.05	0.48	0.03	0.35	0.05	0.53	0.04
small	false	0.45	0.05	0.64	0.03	0.45	0.05	**0.62**	0.04
large	true	0.26	0.00	0.56	0.00	0.26	0.00	0.40	0.00
large	false	0.24	0.00	0.57	0.00	0.24	0.00	0.37	0.00

Discussion

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- quality issues with generated dataset limit the performance of topic classification

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- quality issues with generated dataset limit the performance of topic classification
- pre-trained model from Hugging Face is not fully tailored to our needs
- classes are too broad, since top-level sections are used

Key Takeaways

- a wide variety of research into this area already exists

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- a wide variety of research into this area already exists
- we propose a novel architecture to develop a domain-dependent and fine-grained topic model
- initial results justify further research and investments to improve the architecture

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Table: Selected parameters for each dataset

dataset	concepts	model type	batch size	dropout rate	units
expert	true	SimpleRNN	128	0.40	125
expert	false	LSTM	128	0.40	200
small	true	SimpleRNN	32	0.90	100
small	false	SimpleRNN	64	0.90	100
large	true	SimpleRNN	64	0.90	125
large	false	SimpleRNN	64	0.90	100