Inferring Concept Prerequisite Relations from Online Educational Resources

PREREQ

Sudeshna Roy¹ Meghana Madhyastha³ Sheril Lawrence³ Vaibhav Rajan² IAAI 2019

¹VideoKen

³IIIT-B, India (*authors were intern at VideoKen)

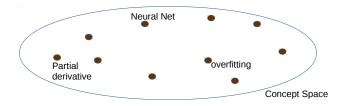
²National University of Singapore

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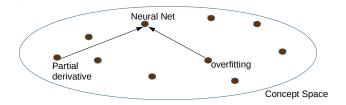
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- 2. PREREQ Algorithm
- 3. Experiments
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Introduction

Motivation



Motivation

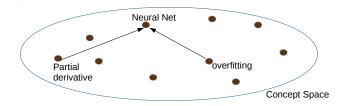


Motivation

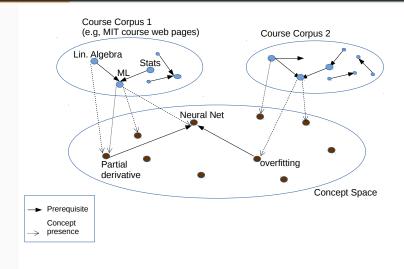
Concept Prerequisite plays a fundamental role in the following applications,

- · Personalized online education
- · Reading list generation
- · Automatic curriculum planning
- · Automatic evaluation of curriculum

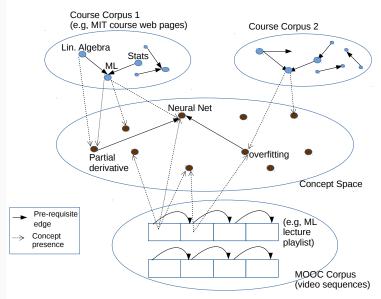
Problem Statement



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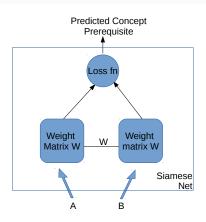
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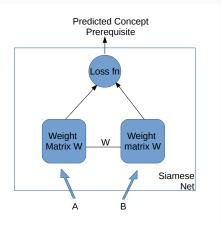
[1] CPR-Recover (EAAI '17), [3] MOOC-RF (ACL '17)

PREREQ Algorithm

Our Approach

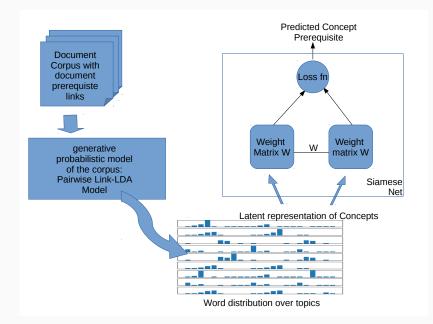


Our Approach

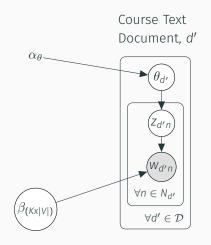


Problem: We do not have enough annotated data

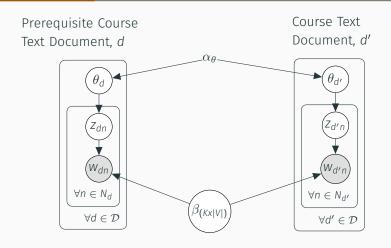
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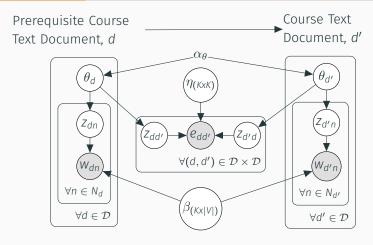
Concept Representation: Pairwise-link LDA



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Concept Representation: Pairwise-link LDA

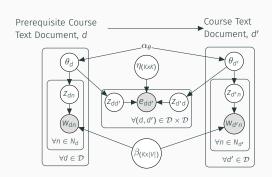


Observed prerequisite relation, $e_{dd'} \sim Bernoulli(.|\eta_{Z_{dd'},Z_{d'd}})$

Pairwise-link LDA: Discriminatory Signal

Given, *V* is the vocabulary of *n*-grams concepts and *K* be number of topics,

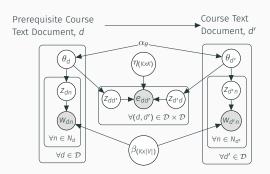
- $\beta_{K \times |V|}$, the word distribution over topics
- $\eta_{K \times K}$, the asymmetric relationship between each pair of topics.



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- $\beta_{K \times |V|}$, the word distribution over topics
- $\eta_{K \times K}$, the asymmetric relationship between each pair of topics.
- Using (β and η), we may predict $c_s \rightarrow c_t$ as $\beta_{c_s}^T \eta \beta_{c_t}$. Later mentioned as **Pairwise LDA**.



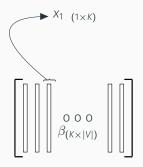
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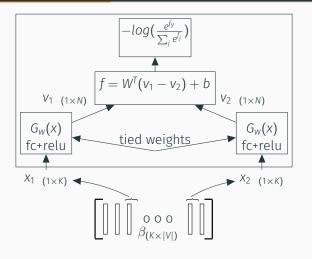
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- Using (β and η), we may predict $c_s \rightarrow c_t$ as $\beta_{c_s}^T \eta \beta_{c_t}$. Later mentioned as **Pairwise LDA**.
- Using two different measures that use topics of the learned model, statistical hypothesis testings show that, topics have enough signal to discriminate between related and unrelated documents.

Concept Representation

Represent each concept as distribution over topics, from the learned Pairwise-link LDA model.



Relationship Prediction: Siamese Network



K = number of topics, V = vocabulary $y \in \{0,1\}$ is the label of the corresponding ordered pair

Experiments

Datasets for Evaluation

Dataset	Number	Number	Number of	Number of	
	of Course/	of Course	Concepts	Concept	
	Lecture	Prerequisite		Prerequisite	
	Document	Edges		Pairs	
University	654	861	365	1008	
Course					
Dataset [1]					
NPTEL	382	1445	345	1008	
MOOC					
Dataset ¹					

¹http://nptel.ac.in/

^[1] Recovering Concept Prerequisite Relations from University Course Dependencies, EAAI 2017

Experimental Settings

- · Results are presented over 5-fold cross validation
- Evaluation metrics, Precision = $\frac{True\ positive}{True\ positive+False\ positive}$, Recall = $\frac{True\ positive}{True\ positive+False\ negative}$ and, F-measure = $2\times\frac{Precision.Recall}{Precision+Recall}$ Also,

Precision@K = $\frac{\sum_{i=1}^{K} rel(i)}{K}$, where rel(.) is a binary indicator of presence of the concept pair (c_s, c_t) in the ground truth

Code and Datasets, https://github.com/suderoy/PREREQ-IAAI-19

Experiments

We did three sets of experiments,

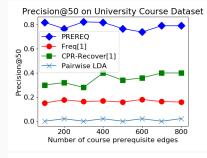
- Performance evaluation against the baseline methods
- · Effect of training data size
- Effectiveness of the learned representation

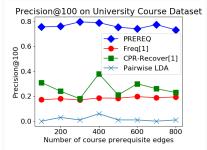
Performance Evaluation

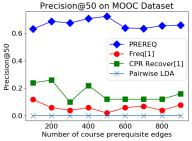
Dataset	University Course Dataset[1]			NPTEL MOOC Dataset		
Method	Precision	Recall	F-score	Precision	Recall	F-score
PREREQ	46.76	91.64	59.68	55.60	75.74	60.73
Pairwise LDA	98.27	16.42	28.14	48.43	10.47	17.22
CPR-Recover[1]	16.66	46.51	24.54	17.18	52.97	25.94
MOOC-RF[3]	43.70	53.43	50.95	59.74	56.48	58.07

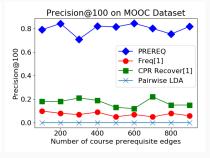
- [1] Recovering Concept Prerequisite Relations from University Course Dependencies, EAAI 2017
- [3] Prerequisite Relation Learning for Concepts in MOOCs, ACL 2017

Evaluation: Precision@K over 5-fold cross validation

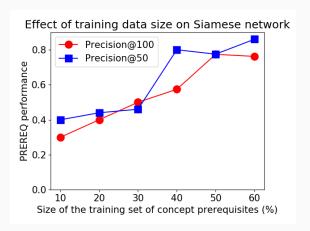






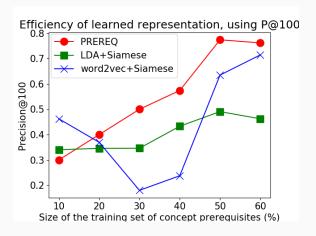


Effect of Training Data Size



Effect of training data size, averaged over multiple random train-test splits.

Efficacy of the Learned Representation

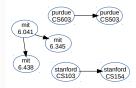


Comparison between different Concept Representations, averaged over multiple random train-test splits.

Illustration

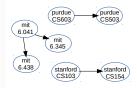
<u>Illustration</u>

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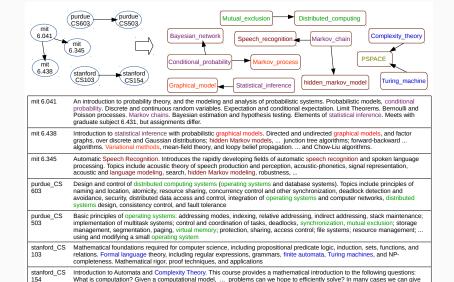
naming and location, atomicity, resource sharing, concurrency control and other synchronization, deadlock detection and	
processing. Topics include acoustic theory of speech production and perception, acoustic-phonetics, signal representation, acoustic and language modeling, search, hidden Markov modeling, robustness, Design and control of distributed computing systems (operating systems and database systems). Topics include principles of laming and location, atomicity, resource sharing, concurrency control and other synchronization, deadlock detection and	
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Basic principles of operating systems: addressing modes, indexing, relative addressing, indirect addressing, stack maintenance; implementation of multitask systems; control and coordination of tasks, deadlocks, synchronization, mutual exclusion; storage management, segmentation, paging, virtual memory, protection, sharing, access control; file systems; resource management; sing and modifying a small operating system	
Mathematical foundations required for computer science, including propositional predicate logic, induction, sets, functions, and relations. Formal language theory, including regular expressions, grammars, finite automata, Turing machines, and NP-completeness. Mathematical rigor, proof techniques, and applications	
introduction to Automata and Complexity Theory. This course provides a mathematical introduction to the following questions: What is computation? Given a computational model, problems can we hope to efficiently solve? In many cases we can give completely ingorous ariswers, able to classify computational problems in terms of their computational complexity (Is the problem regular? Not regular? Decidable? Recognizable? Neither? Solvable in P? NP-complete? PSPACE-complete?, etc.) echnology, such as the Church-Turing Thesis and the P versus NP problem.	
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Illustration



An introduction to probability theory, and the modeling and analysis of probabilistic systems. Probabilistic models, conditional probability. Discrete and continuous random variables. Expectation and conditional expectation. Limit Theorems. Bernoulli and Poisson processes. Markov chains. Bayesian estimation and hypothesis testing. Elements of statistical inference. Meets with graduate subject 6.431, but assignments differ.			
Introduction to statistical inference with probabilistic <mark>graphical models.</mark> Directed and undirected graphical models, and factor graphs, ower discrete and Gaussian distributions; hidden Markov models, junction tree algorithms; howard-backward algorithms. Variational methods, mean-field theory, and loopy belief propagation and Chow-Liu algorithms.			
Automatic Speech Recognition. Introduces the rapidly developing fields of automatic speech recognition and spoken language processing. Topics include acoustic theory of speech production and perception, acoustic-phonetics, signal representation, acoustic and language modeling, search, hidden Markov modeling, robustness,			
Design and control of distributed computing systems (operating systems and database systems). Topics include principles of naming and location, atomicity, resource sharing, concurrency control and other synchronization, deadlock detection and avoidance, security, distributed data access and control, integration of operating systems and computer networks, distributed systems design, consistency control, and fault tolerance			
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Demo

A Demo

Conclusion

Summary

Model PREREQ obtains concept representations through the Pairwise-Link LDA model, followed by, Siamese net based classifier to identify prerequisite relations.

Generic PREREQ can learn effectively from course webpages as well as unlabeled video playlists, using minimal training data.

Utility PREREQ can effectively utlize the large course corpora and MOOCs to solve a fundamental problem, essential for online educational technology applications.

References



C. Liang, J. Ye, Z. Wu, B. Pursel, and C. L. Giles.

Recovering concept prerequisite relations from university course dependencies.

In AAAI, 2017.



R. M. Nallapati, A. Ahmed, E. P. Xing, and W. W. Cohen. Joint latent topic models for text and citations. In ACM SIGKDD, 2008.



L. Pan, C. Li, J. Li, and J. Tang.

Prerequisite relation learning for concepts in moocs.

In ACL, volume 1, pages 1447–1456, 2017.

Pairwise Link-LDA: Generative Process

```
For each document d \in \mathcal{D}
      \theta_d \sim \text{Dirichlet}(.|\alpha)
      For each w_n \in d
             z_n \sim Multinomial(.|\theta_d)
             w_n \sim Multinomial(.|\beta_{z_n})
For each document pair (d, d')
      z_{dd'} \sim Multinomial(.|\theta_d)
      z_{d'd} \sim Multinomial(.|\theta_{d'})
      e_{dd'} \sim \text{Bernoulli}(.|\eta_{Z_{dd'},Z_{d'd}})
```

Topics in Related and Unrelated Documents

 E_D be the set of document pairs (d_i, d_j) such that there is a prerequisite relation between d_i and d_j in either direction. $\overline{E_D}$ be the set of document pairs (d_i, d_j) such that there is no prerequisite relation between d_i and d_j in either direction.

- Jaccard Index $\frac{\theta_i \cap \theta_j}{\theta_i \cup \theta_j}$ is significantly different between document pairs in the sets E_D and $\overline{E_D}$, using the University Course dataset[1], p-value: 1.54901e-51.
- Kullback-Leibler divergence $D_{KL}(\theta_i||\theta_j)$ between topics in the document pairs are significantly different between document sets E_D and $\overline{E_D}$, using the University Course dataset, p-value: 5.14549e-31.
- The tests suggest that inferred topics have discriminatory signal at the document level.