

Web of Slides: Automatic Linking of Lecture Slides to Facilitate Navigation

Sahiti Labhishetty*
sahiti12@illinois.edu, UIUC

Bhavya*
bhavya2@illinois.edu, UIUC

Kevin Pei*
kspei2@illinois.edu, UIUC

Assma Boughoula
boughou1@illinois.edu, UIUC

Chengxiang Zhai
czhai@illinois.edu, UIUC

ABSTRACT

Lecture slides covering many topics are becoming increasingly available online, but they are scattered, making it a challenge for anyone to instantly access all slides relevant to a learning context. To address this challenge, we propose to create links between those scattered slides to form a Web of Slides (WOS). Using the sequential nature of slides, we present preliminary results of studying how to automatically create a basic link based on similarity of slides as an initial step toward the vision of WOS. We also explore interesting future research directions using different link types and the unique features of slides.

Author Keywords

Slides; Link probabilities; MOOC

INTRODUCTION

With the growth of online education, especially MOOCs, or Massive Open Online Courses, a large number of slides are being put online. The vast amounts of online slides cover many topics and are very useful resources for learners. For example, a student taking a course might come across unfamiliar topics that are covered in detail by other courses and thus would benefit from immediate access to those other relevant slides. Moreover, learners who have a hard time grasping a topic might also look for alternative explanations of the same topic in the slides of another lecture. Unfortunately, those slides are scattered in many isolated files, making it a challenge for learners to instantly get access to relevant slides.

To address this challenge, we propose to create links between these scattered slides to form a Web of Slides (WOS). Just as the hyperlinks connecting many web pages enable users to easily navigate the Web, we envision that the links created between slides would also enable students to easily navigate between relevant slides from different sources on the WOS. The units to be linked can vary from slides to smaller units

such as phrases or text segments inside a slide, and many different types of links can potentially be created. The final Web of Slides would operate similarly to the World Wide Web, where links connect otherwise isolated information.

The hyperlinks on the Web are mostly created manually by people; similarly, slide links can also be manually created. However, such an approach is labor-intensive, and cannot scale up to link all slides available online. In this paper, we study how to automatically create such links. As a first step in studying this new problem, we focus on one basic link, the similarity-based link, which connects slides that are similar. We explore and evaluate multiple methods for automatically generating such links. Our preliminary experimental results show that standard information retrieval techniques work reasonably well, but accuracy can be further improved by leveraging the semantic cohesion of adjacent slides. We also create a user interface similar to PowerPoint but with similarity-based links generated using our best performing method. We show the utility of WOS using a user experiment where students evaluate the user interface. In the future, we hope to further study how to automatically create all kinds of links and further evaluate the educational benefit of this technology.

THE WEB OF SLIDES VISION

Our vision of the WOS follows the general vision of linking educational content, which has been studied in several previous works [3, 4, 5, 1]. Some previous work aims to leverage the general semantic web technology to link (often heterogeneous) data objects¹. The WOS focuses on integrating the same type of objects; lecture slides. By focusing on homogeneous objects, we can obtain deeper semantic integration of objects. WOS is closer to some existing work that also attempts to integrate the same type of content (e.g. integration of lecture scripts [5, 1] and lecture videos [6]).

While on the surface, focusing only on slides appears to be restrictive, it has two significant benefits. First, slides are a unique kind of educational resource that have broad coverage of all kinds of topics and also have a uniform format. This makes it possible to leverage an existing application such as PowerPoint to support navigation over the entire WOS. Once we have the technology to link slides, the same application system can be used to support navigation over scattered slides for all courses, quickly generating broad application impact. The

*These authors contributed equally

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the owner/author(s).

L@S '19 June 24–25, 2019, Chicago, IL, USA

© 2019 Copyright held by the owner/author(s).

ACM ISBN 978-1-4503-6804-9/19/06.

DOI: <https://doi.org/10.1145/3330430.3333668>

¹<http://linkeddata.org/>

generality of the technology would be a significant advantage over previous work linking course content or videos. Second, working on slides allows us to establish very specific semantic links at the level of concepts, pushing the links down to the lowest level of units in education. Because slides are usually created to cover one specific topic, slides can be thought of as a basic unit of information. Linking together slides enables users to find desired information at a much finer-grained level than linking together lectures. A sample of the Web of slides vision is shown in Figure 1.

A Wide Variety of Links: A Web of slides would potentially be composed of many different types of links. For example, a “prerequisite” link, which links a slide to slides containing information prerequisite to understanding its content. A “related” link can also be formed between slides with similar content; such a link can be used by students to obtain alternate explanations and perspectives of the same concept. For example, as shown in Figure 1, the two slides explaining *Expectation Maximization(EM)* in different courses are linked by a “Related” link. Another type of link is “Application Scenario,” pointing to applications of a slide’s topic. For example, *EM* is used in *PLSA*, so there can be an “Application Scenario” link as shown in Figure 1. Such a link will be especially useful when the applications are not taught in that specific course.

More fine grained links can be formed based on phrases within a slide. Phrases can be entire bullet points or phrases within a bullet point. A fine-grained “Explanation” link can be formed between a phrase and a slide which has its explanation, similar to a “prerequisite” link but at a finer level. For example, as shown in Figure 1, the slide explaining “Expectation Maximization” contains the phrase “Gaussian parameter” which is not explained in detail in that lecture, but can be linked to slides in other lectures where it is. Such a link is useful for learners to understand a basic concept quickly while trying to learn a main concept. Another phrase-level link is an “Advanced concept” link. If a concept or phrase is not explained further in the lecture but is not a basic concept necessary to understand the slide’s content, an “advanced concept” link can be formed. It links the phrase to another slide which explains it in detail. This link will be useful when a student wants to learn particular concepts in more depth.

Phrase-level linking is similar to creating links between web pages through anchor text. By treating a slide as a document, we should be able to apply existing methods developed for linking web pages to linking slides. Compared with linking regular text documents such as web pages, linking slides is often more challenging because slides generally have less content and contain images and formulae, which are harder to analyze than text. However, we can also identify some unique characteristics of slides that can be leveraged to facilitate linking. For example, one unique feature is the structure of a slide. A slide title is more informative compared to a document title and often summarizes the content. Bullet points clearly define a context for the phrases within each bullet. Each bullet point can be considered as discussing a specific concept within the slide’s topic and a link can be formed for each bullet. The hierarchical structure of bullet points can also be leveraged for

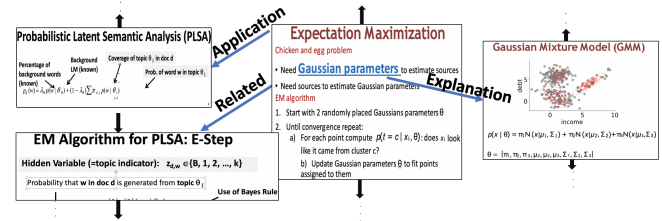


Figure 1: Sample links in a Web of Slides. Blue arrows represent different types of links between slides across courses. Black arrows denote sequential flow of slides in a lecture.

forming these links. Another unique feature is that slides are sequential. This natural sequential information can be leveraged to create approximate labels used for training supervised models and for evaluation[5]. Another deviation from a typical web of documents is that a web of slides is made to improve the learning experience. This poses some constraints on the number of links and the location of links on the slides.

Navigating the WOS: Once all slides are linked together, any user would be able to navigate the WOS flexibly by following different kinds of links. A major benefit of focusing on slides is that it is possible to build an application system similar to PowerPoint to be used as a “universal” browser of slides that everyone can use to browse any part of the WOS. With such a WOS browser, phrase-level links can be displayed as hyperlinks as shown in Figure 1. The slide-level links can be displayed similarly to a “See also” section on Wikipedia.

While a basic slide navigator would only need to support navigation over static links and let a user decide which link to follow, a more intelligent navigator can also infer a user’s current interests or preferences based on observed user actions (e.g., browsing patterns and preferred paths in browsing). All “prospective slides” linked to the current slide can then be re-ranked based on their likelihood of satisfying the user’s current preferences. Moreover, the intelligent WOS browser can also go beyond static links to generate dynamic virtual links while a user is viewing a slide by recommending highly relevant slides that may not necessarily have been pre-linked to the current slide. To provide a user with complete support for navigating the WOS, the browser can further allow a user to enter any keyword query to direct the browser where to go on the WOS, and respond to such a query by showing a ranked list of matching slides returned by a WOS search engine. For example, if a student does not find a useful link on a slide, they can make a query to obtain relevant slides. These results can be regarded as temporary “virtual” links to the target slide.

Static and dynamic links can evolve together: the structure of static links can be used to obtain better dynamic links and the context of dynamic links can be used to create new static links. Our vision of the WOS includes both static and dynamic links as well as a universal browser integrated with a WOS search engine that can leverage advanced information retrieval and machine learning techniques to learn from user interactions and dynamically optimize the navigation of every user.

LINKING SLIDES BASED ON SIMILARITY

As the first step towards realizing the WOS vision, we focus on studying how to automatically create links between slides based on their similarity. Computationally, the problem is to take a set of slides from one or more lectures and score each pair of slides with a probability that the two slides have similar content, then create a link if the probability is high enough. Note that while the pictures on a slide might be useful, we only consider the textual content of a slide in this work.

Similarity Measures as Features

To determine link probability, we use different text similarity measures as features for our supervised methods. We study different techniques to represent slide content and use them to compute similarity.

TF-IDF Similarity: We compute TF-IDF vectors for each slide by combining their title, content, and transcript if available. Similarity between slides is computed using cosine similarity between document vectors.

Word Embedding Based Similarity: We computed similarity using pretrained GloVe embeddings and Word2Vec embeddings. We then compute the embedding of a slide as the average of all of its word embeddings and use cosine similarity between slide embedding as our similarity measure.

Topic Model Based Similarity: We use LDA and BTM[7] for topic modeling. LDA uses document-word co-occurrences whereas BTM uses word-word co-occurrences. The similarity between two slides is proportional to the inverse of the KL-divergence of the topic distributions of the slides.

Pseudo Labels

Given any lecture, the slides are sequential in nature. The adjacent slides should be more coherent than the non-adjacent slides as they are positioned in a sequence while explaining the topic. We approximate this coherence to similarity. If the model can predict high link probability between neighbouring slides, then there can be more confidence that the other slides that are predicted with high link probability are also similar. This can be further understood using the following simulation: imagine a scenario wherein the sequential slides in a lecture are actually scattered in a random order. In this case, the actual sequence of slides observed in the lecture can act as a good approximation of similarity. For our methods, we consider slides within a window size of 2 to be adjacent and all other slides to be non-adjacent.

Logistic Regression and Feed Forward Network

Using the pseudo labels, we trained two types of classification models. The first is a logistic regression model. The second is a feed forward neural network with a single hidden layer with a ReLU activation function and a linear layer which outputs a single value. The models output the probability of a link between each pair of slides. Our goal is to see whether neural networks would be able to learn a non-linear combination of these features that performs better than the linear combination in logistic regression. The input for both models are feature representations. We use the similarity measures described earlier as features.

EXPERIMENTAL SETUP

Dataset: We trained and evaluated our methodology using all available slides and lecture transcripts for 4 courses on

Coursera related to data mining and information retrieval: Bayesian Methods in Machine Learning, Cluster Analysis, CS410: Text Information Systems, and Language Processing. Lecture transcripts are available for all of these courses. For each slide, we extracted the slide title, the content of the slide, and the part of the lecture transcript which corresponded to the slide. We were able to map parts of the lecture transcripts to the corresponding slides in 124 out of the 189 lectures.

Logistic Regression and Feed Forward Network Implementation:

Using all four courses, we have 2388 slides in total. We used four-fifths of the slides for training(1911) and the rest for testing(477). For each slide in the training set, we chose its adjacent slides to make positive pairs and randomly chose non-adjacent slides for negative pairs such that there will be 200 pairs in total per slide. In total we have 382200 pairs for training and 95400 pairs for our test set.

Evaluation Measures: As the adjacent slides are only an approximate gold-standard, measuring the sensitivity of ranking these slides in top k may not be meaningful, since a model can also predict other semantically related slides that can potentially form a useful link with high link probability, but are not adjacent (and thus would be counted as incorrect). Thus, the commonly used measures such as Precision, MRR and MAP [8] may not be a reasonable measure. In our setting, the Recall measure would be more robust and thus more appropriate. Therefore, we compute recall for the ranked results. For each slide, we measure the Recall@10 and Recall@20 against its adjacent slides and then compute the average recall on the whole dataset. Additionally, we believe that transcripts provide additional context to slides and thus expect slides mapped to their transcripts to have higher recall. Thus, we separately report our results on slides with lecture transcripts.

EXPERIMENTAL RESULTS

We compare the results of different methods in Table 1. We

Method	All Slides		Slides with Lecture Transcripts	
	k=10	k=20	k=10	k=20
TF-IDF	0.5059	0.5927	0.5130	0.6155
Logistic regression	0.5419	0.6219	0.5540	0.6476
Feed forward network	0.5472	0.6287	0.5495	0.6516

Table 1: Average Recall@k computed for all slides (total 2388) and slides successfully mapped to lecture transcripts (total 1075) with k=10 and k=20.

observe that the baseline of TF-IDF based similarity is outperformed by supervised methods indicating that the proposed idea of using adjacent slides to create pseudo labels and using other similarity measures as features are effective. We also observe that the performance of both Logistic regression and the Feed forward network are similar, indicating that non-linear combinations of features do not provide an advantage over a simpler combination of features in logistic regression. The feed forward network performs best of all methods.

We compute the recall for two cases. One with *All slides* where all the slides are considered and the other with *Slides with Lecture transcripts* where only the slides with lecture transcripts are considered. Because slides with lecture transcripts have

more content and therefore more context, we expect to have higher performance on them. We observe that all methods perform better on *Slides with Lecture transcripts*.

Re-ranking Results For a given slide, its adjacent slides often have high link probability. As these links are not very useful, we created a ranking algorithm based on Maximal Marginal Relevance(MMR)[2]. For each slide, we omit any slides that are in the same lecture as the current slide. Each subsequent result then has a new ranking score that takes into account both its link probability and distance from all slides that have already been returned. The link probability and distance are both given weight 0.5. The distance of the next slide s_2 from the set of already selected slides($results$) is computed as follows:

$$distance(s_2|results) = \frac{\sum_{s' \in results} 1 - link(s'|s_2)}{|results|}$$

Where $link(s'|s_2)$ is link probability of the pair (s', s_2) .

For any slide that is in a different lecture from all results returned thus far, we set $distance(s_2|results)$ equal to 1. We also use a threshold(0.03) such that when the overall score is below the threshold, we stop adding to the results list.

USER EVALUATION

In order to assess the quality of the links we formed and their utility for learners, we created a UI and gathered user feedback on our tool. The UI allowed users to view slides sequentially, similar to PowerPoint, and also provided a way for users to access slides related to the current slide. The related slides are based on the re-ranking algorithm with similarity score greater than the threshold(0.03). A search bar was also provided for users to type queries for specific concepts. The list of courses and the lectures in the course are given as two drop-down menus in the navigation bar.

Evaluation of the tool was done by CS410 students at UIUC. The students were asked to learn the concepts in the slide just as they would while preparing for a quiz and navigate through related slides if they found them relevant. As they are familiar with CS410, a set of lectures from the course were provided as starting points. They were instructed to use the tool for at least 20 minutes. A total of 89 students participated in the evaluation. We logged and analyzed their click-through rates. For this analysis, we considered three kinds of clicks: the “next” button, “prev” button, and “related links”. We found that 14.97% percent of user clicks belong to “related link”. From all “related link” clicks, it was observed that 34.84% of the time user clicked the top ranked link and 65.43% percent of the time it was one of the top three links.

At the end of their exploration, they were asked to fill a survey with questions about the tool. When asked *How useful is this tool compared to other tools for viewing slides you’ve used before?*, 16.9% said “very useful”, 30.3% said “useful”, 29.2% said “somewhat useful”, 20.2% said “not very useful”, and 3.4% said “not useful at all”. When asked *How useful is the set of related links?*, 4.2% responded “very useful”, 38.2% responded “useful”, 33.7% responded “somewhat useful”, and 23.6 responded “not very useful”. The survey results and the user click logs indicate that the set of suggested related

links are relevant and useful. We conclude from this that it is possible to use state of the art IR and ML methods to generate reasonably accurate links between slides. The results also indicate that this tool more useful than other tools for viewing slides for learning therefore indicate the utility of the WOS.

CONCLUSION

We present our vision of linking slides from scattered sources to form a Web of Slides (WOS), which would enable many learners to get access to all relevant slides in a learning context similar to how the hyperlinks on web pages help people access information on the Web. As an initial step in realizing the vision, we studied how to automatically create similarity-based links between slides. Because we do not rely on any hand-labeled data, expanding this Web of Slides will not require any additional effort from the instructors or designers of MOOCs. We hope that our work will open up an interesting new direction in developing intelligent education infrastructures with both plenty of new research problems and great opportunities for building useful application systems.

ACKNOWLEDGEMENTS

This material is in part based upon work supported in part by the National Science Foundation under grant number 1801652.

REFERENCES

1. Rakesh Agrawal, Maria Christoforaki, Sreenivas Gollapudi, Anitha Kannan, Krishnam Kenthapadi, and Adith Swaminathan. 2014. Mining videos from the web for electronic textbooks. In *ICFCA*. Springer, 219–234.
2. Jaime Carbonell and Jade Goldstein. 1998. The use of MMR, diversity-based reranking for reordering documents and producing summaries. In *Proceedings of ACM SIGIR 1998*. ACM, 335–336.
3. K. M. Hover and M. Muhlhauser. 2014. LOOCs – Linked Open Online Courses: A Vision. In *2014 IEEE 14th ICAIT*.
4. Nelson Piedra, Janneth Alexandra Chicaiza, Jorge López, and Edmundo Tovar. 2014. An Architecture based on Linked Data technologies for the Integration and reuse of OER in MOOCs Context. *Open Praxis* 6, 2 (2014), 171–187.
5. Sheng-syun Shen, Hung-yi Lee, Shang-wen Li, Victor Zue, and Lin-shan Lee. 2015. Structuring lectures in massive open online courses (moocs) for efficient learning by linking similar sections and predicting prerequisites. In *16th Annual Conference of the ISCA*.
6. Vedran Vukotić, Christian Raymond, and Guillaume Gravier. 2018. A Crossmodal Approach to Multimodal Fusion in Video Hyperlinking. *IEEE MultiMedia* 25, 2 (2018), 11–23.
7. Xiaohui Yan, Jiafeng Guo, Yanyan Lan, and Xueqi Cheng. 2013. A biterm topic model for short texts. In *Proceedings of WWW 2013*. ACM, 1445–1456.
8. ChengXiang Zhai and Sean Massung. 2016. *Text data management and analysis: a practical introduction to information retrieval and text mining*. Morgan & Claypool.