Autonomous Semantic Structuring of Lecture Topics
Synthesis of Knowledge Models

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Abstract: Students attending lectures in universities suffer from a weak structural awareness on lecture content. According to learning theories, structural awareness is a relevant factor to association and comprehension of new learning inputs. We synthesize semantic structures from non annotated lecture slides using Topic Modeling algorithms to identify relevant terms and relate them in force-directed graphs. The synthesized graphs provide a structural overview on the topic distribution and relations of non annotated sequential lecture slides.

1 INTRODUCTION

University teachers, aka lecturers, use lectures to teach facts and concepts to students. From the perspective of the teacher, in the preparation phase the relevant information of a lecture is analyzed, reduced and sequenced into learning units and taught in a way that is comparable to leading a path through a constrained area of knowledge. During a study a student learns from many different lectures or knowledge units. Some of these units reference each other, some are partially overlapping or describe common topics from different perspectives. An ideal situation would be given, if the students identifies and understands the key concepts plus their relations and their hierarchy or topology. However, reality often leads to different situations: Even if the teacher usually is preparing a lecture via sequencing the important facts of an overall topic in a logical order, in quite a lot cases, lectures are evolutionary grown over time. This results in a situation, where the key concepts of a lecture are somewhat hidden in the text. From the perspective of the teacher, this is not so bad, as the overall picture shall not be influenced. However, in exams, we were able to observe that students often miss important items or misinterpret items. The situation grows even worse, when students were asked to detect relations between different topics, i.e. different lectures in different semesters. This seems to be a cognitive step which is not directly supported in current lecture formats. On the teacher's side, an interconnection of the topics or areas of study is seldom taking place. This results in a situation where students are usually missing the overall picture.

To develop a solution, i.e. to develop support mechanisms and tools to support the student's knowledge construction in lectures, we have to take a look at learning psychology. Learning theories such as cognitivism describe the inner effects of processing lecture information inputs by using cognitive models (lernpsychologie.net, 2016). To understand, how processes of knowledge construction could potentially take place, we made several investigations together with our students.

Our work started a while ago, when we developed a tool for extracting knowledge from lectures with the goal to support student's annotation of lectures and for giving support for learning (Nicolay et al., 2015). To support our claim that understanding of the main concepts and their interrelation is the key to understanding the lecture in a first step and to understanding the overall picture in a study direction as a second step, we investigated student's intuitive method of knowledge construction.

Our main study took place last semester, where we made a structured investigation with a first grade master course with 20 students from different departments. They were organized in teams of two to four (mixed male and female). They got a free choice of material (either digital or not), and free choice of most important topics. Their task was to identify areas of knowledge and relations in self designed knowledge

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management structures. We asked students, how they identify key words, how they relate and organize them and how they identify clusters or areas of topics. They had to show and explain the results, e.g. in form of a poster or slides. Additional to keywords, relations and clusters, they have to show us in a next step, which system they use (e.g. mindmap, tables, other graphs or trees). More information about this part of our study and the related insights is described in section 2. After we got insight to the student's ideas of organizing lecture knowledge, we applied this to our tool described in section 3.1 and 3.2. We added a mathematical algorithm to visualize the results using force-directed graphs described in section 4 allowing further inference of insights described in section 5.

2 STUDENT'S INTUITIVE MANAGEMENT OF KNOWLEDGE

We asked students how they process or recap the past study course. Therefore we had 20 students from different fields of study, such as mathematics, ship building, teacher training and computer science. All students recently finished their bachelors level and attended some first master lectures. The Age of the students where between 24 and 31. We asked the students to invent a concept, with which they can manage and organize their experience of past courses. They developed several different semantic knowledge structures consisting of keywords and relations. Hereby, we did not find significant differences between male and female students. The following paragraphs summarize the outcomes in particular areas.

Students identified relevant topics and keywords in two ways. First, the memorization of most relevant terms, second the identification of keywords using past lecture material. The results of both techniques where almost equal. While the memorized terms show a tendency to specializations on interesting and for the individual student relevant aspects, the topics identified by lecture material showed a broader coverage of the study course and reflected the characteristics of the curriculum. All groups defined different hierarchies between terms. We identified two main levels and call them: *Thematic area* terms for higher more general terms and *technical terms* for lower and more specific terms. Students used thematic area terms to group the more specific technical terms in domains.

While students put a lot work on the specification, and definition on keywords, they neglected the specification of the relations. Students intuitively defined relations to denote inheritance dependencies between area keywords and technical terms. Procedural descriptions between keywords as used in *Concept Maps* defined in (Cañas et al., 2004) where not used. Students relate terms by declarative *Associations*. To map learning resources, they link learning materials as *Occurrences* to *Topics*. This intuitive approach is very similar to the concept of *Topic Maps* defined in (Marius et al., 2008).

For a cognitive description of relations between important keywords, students needed to handle many thematic areas and cross references on technical terms. We identified two main approaches to layout identified keywords.

The first approach shown in figure 1 defined several thematic areas. These area keywords then where surrounded by technical terms mapped to these areas. At a first glance, the first approach was similar to *Mindmaps*. But students noted hierarchy of an Mindmaps did lack in decentralization and a clean cross referencing of dependencies between more than one thematic areas and a single technical terms.

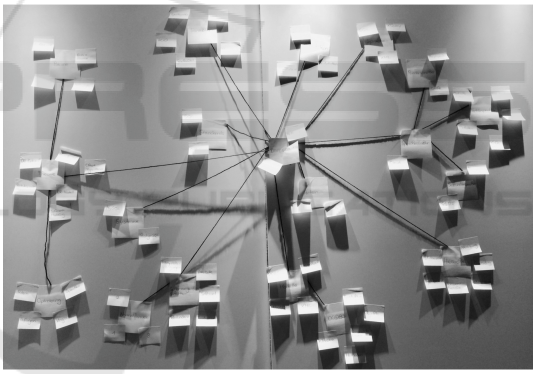


Figure 1: Example of student's analog Mindmap approach to organize learned knowledge (S. Brossmann, T. Auge).

The second approach shown in figure 2, provided an interesting way to deal with cross referencing of keywords. Students used dark colored sticker to denote thematic area keywords. In the middle is the general thematic area. Matching this general thematic area there are more specialized thematic areas placed equally spaced around it. The all technical terms were placed with a rule in mind: The level of dependency of a technical term to a thematic area is described by its distance. That means technical terms in the middle of the circle did not have a specified affiliation and specialized techinal terms are placed in the areas in the corresponding thematic area. The result is that words with an affiliation to thematic areas built a lobe from the center of the circle to the thematic area keyword.

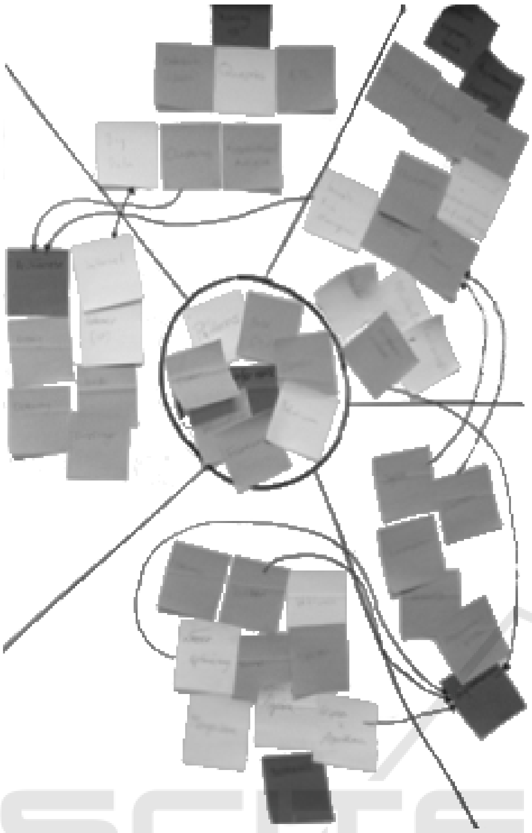


Figure 2: Example of a student's analog approach to organize learned knowledge (J. Abel, S. Arth, T.Baudis, K. Klohs).

Students claimed that the structure of a lecture is not visible to a listener during lectures. Difficulties arise in the identification of relevant topics, inference of relations between topics, relations between topics and lecture material as well as relations between lectures themselves. Information in lectures are not presented in a structured way but in a sequences of little annotated lecture slides. An option would be to provide a structured, semantic overview about lecture topics on an high abstraction level. This overview, given by the lecturer, could be used by the students to follow the structure and relations of topics during a lecture while individually adding received stimuli and associations to the provided skeleton.

In the next sections we describe our approach to analyze sequential lecture material and synthesize the identified structures shown in figure 1 and 2.

3 AUTOMATIC EXAMINATION OF LECTURE'S TOPIC AREAS AND SEMANTIC STRUCTURES

This section describes our system derived from two parts: First, a system based on a former approach to extract semantic topics from non annotated lecture slides described in detail in (Nicolay et al., 2016). Second, the identification of relations and semantic structures between topics, keywords etc.

3.1 Inference of Topics from Lecture Slides

To synthesize a model that approximates a lecturer's intended taught knowledge structure after attending a lecture, we analyze the text on presented lecture slides. We found in (Nicolay et al., 2016) that the text on lecture slides allows us to identify semantic topics or thematic areas during a lecture. Further steps will include a synchronized transcription of the lecturers verbally explanations during a lecture. The following paragraphs provides a short overview about the used algorithms.

Preparation of Text and Vocabulary. To prepare and clean up the text on lecture slides, we implemented a set of filters described below. To identify semantic topics from unstructured text, we used the statistic topic modeling algorithm *Latent Dirichlet Allocation* (LDA) introduced by Blei (Blei et al., 2003) implemented using the *Markov-Chain-Monte-Carlo* (MCMC) *Gibbs Sampling* algorithm (Griffiths and Steyvers, 2004).

At first, we describe the implemented a set of filters. The system extracts all text without special characters from the slides of a lecture and splits the text into single words. Then the system removes grammatical deviations having a minor impact to semantic meaning, such as a stemming (Yoshiki Shibukawa, 2015) and unifies all words to lowercase. Additionally, it removes stopwords (Porter et al., 2015), short words with less than 3 letters, numbers, and words with a high occurrence on many different slides (e.g. repeating footers). Then all words are added to an word-slide adjacency matrix. Using the filters the average number of different words (or rank of matrix) is reduced by 25 percent.

Common lecture slides consist of a low amount of text. As shown in (Wallach et al., 2009) the use of *Dirichlet Priors* introduced by LDA improves the quality and convergence of inference on texts with a lower number of words considerably. Nevertheless, we looked into ways of interpreting layout information and structure on lecture slides to improve the inference with additional meta information. First to be published results show, analyzing outline slides that contain meaningful headings of a lecture, indicate number and order of thematic areas. Further, correlating size of words and importance added as weight function to the Gibbs implementation improves the separation between topics and their word distributions.

On the other hand, arrangement of text on lecture slides is not easy to understand for automatic algorithms. Factors such as layout templates, images and aesthetics influence the position of words on a slide. Here LDA supports a ”bag of words assumption” and does not infer information from the position of words within a text. As stated in (Blei, 2012, S.82) this would be a disadvantage for synthesizing natural speech, but is appropriate for semantic analysis.

Identifying Topics with Latent Dirichlet Allocation. In our approach LDA infers a fixed number of topics $T = t_1, t_2, ..., t_k$ from a set of slides S. As mentioned above, we keep the separation of lecture information into separate slides. The filtered, relevant subset of occurring words is V. LDA provides a discrete distribution $\theta(s)$ denoting the proportion of every topic $t \in T$ on slide $s \in S$. Every topic t is defined by a discrete distribution $\beta(t)$ over the probability of occurrence of every word $w \in V$. Both, the possible random values of $\theta(s)$ and $\beta(t)$ sum to one.

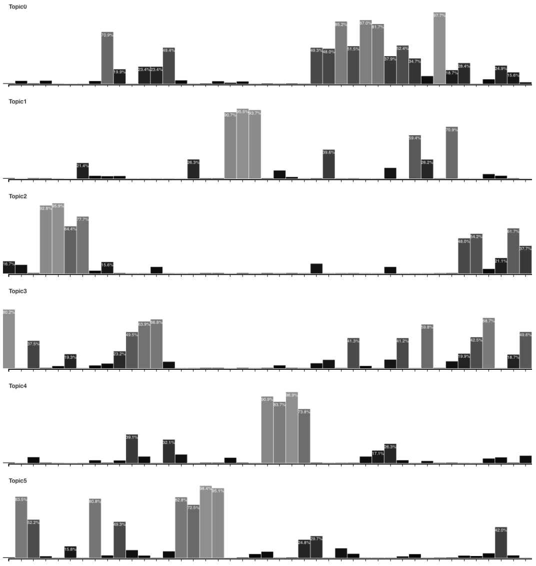
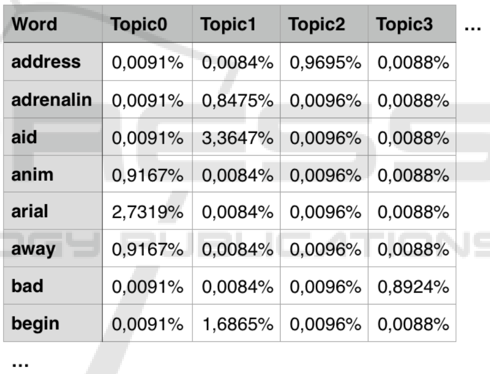


Figure 3: Intensity of 6 different topics $t \in T$ to the slides $s \in S$ used during a lecture.

To get an impression of the result, figure 3 shows the inferred distribution of six topics over a set of 43 lecture slides on *Learning Theories* at the *University of Rostock*. The Bars in this figure lying above each other, show the proportion of every topic to a slide $\theta(s)$. The topics *Topic0* to *Topic5* are, as a result of the sampling algorithm automatically named and only defined by their probability of occurrence of semantically relevant words $\beta(t)$, showing as *Adjacency Matrix* indicated in figure 4. A MCMC sampling algorithm uses a high number of randomly generated samples the initial distribution of topics on every lecture slide and corrects the topics by a high number of iterations fitting steps. The essence is, that the algorithm does not include knowledge about lecture slides being next to each other. However, figure 3 shows a meaningful distribution of topics during a lecture. Nearby slides tend to share the same topic. Furthermore, topics show the trend to fade in and fade out during a lecture. In conclusion, results on real data indicate a well known pedagogical distribution of topics on a sequence of lecture slides.



Word	Topic0	Topic1	Topic2	Topic3	...
address	0,0091%	0,0084%	0,9695%	0,0088%	
adrenalin	0,0091%	0,8475%	0,0096%	0,0088%	
aid	0,0091%	3,3647%	0,0096%	0,0088%	
anim	0,9167%	0,0084%	0,0096%	0,0088%	
arial	2,7319%	0,0084%	0,0096%	0,0088%	
away	0,9167%	0,0084%	0,0096%	0,0088%	
bad	0,0091%	0,0084%	0,0096%	0,8924%	
begin	0,0091%	1,6865%	0,0096%	0,0088%	
...					

Figure 4: An excerpt of $\beta(t)$. The probability of occurrences of vocabulary words $w \in V$ on lecture topics $t \in T$.

3.2 Relating Slides by Topics

In section 3.1, we explained our approach to identify single topics in lecture slides. In (Nicolay et al., 2016), we described a first approach to connect slides with each other that share the same topics. Identified connections, based on common topics, are meaningful. Figure 5 shows, nearby slides have a higher proportion of shared topics. Only a few cross references bridge the chord diagram. Accordingly only a few slides, lying far apart in a lecture, have high proportions to a common topic.

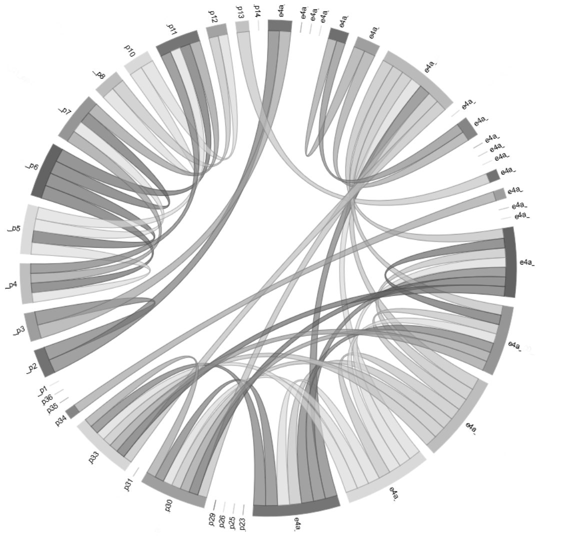


Figure 5: Relations between slides of a talk based on joined topic assignments. Slides are arranged clockwise at the outer ring of the graph. Lines indicate a shared topic of over 65% for connected slides. (Nicolay et al., 2016).

4 MAPPING OF TOPICS AND KEYWORDS

To fulfill the requirements indicated by the student models described in section 2, we need to order technical terms to thematic areas by relations based on affiliations. Therefore, we decided to interpret affiliations of technical keywords to thematic areas as forces and examined two force-directed approaches. First, the circular approach. We place area thematic keywords around technical terms, as seen in figure 2. Second, an extension of student's Mindmap approach by proximity concepts of the circular approach.

To graphically depict the results of LDA, we used forced-directed graph models. Identified abstract topics T were interpreted as abstract thematic clusters. Their centers are shown as white points. The elements of the filtered vocabulary V denote the unfiltered set of technical terms indicated by smaller gray points. The distribution $\beta(t)$ defines the proportion of every technical keyword $w \in V$ to every topic $t \in T$.

While the sets of technical keywords and thematic areas are defined, we need to convert $\beta(t)$ (the knowledge of affiliation of technical terms to thematic areas) to positions indicating proximity to thematic areas. Therefore we built a force-directed graph containing vertices $K = T \cup V$ and edges $E = (w,t) \in \beta(t)$. The edges are weighted by the level of proportion defined in $\beta(t)$. Forces on the graph are denoted by the weight of edges as an attraction strength factor, a repulsion strength between two vertices and a gravity to the center. The learning resources (not shown in the following graphs) can be related to thematic areas by $\theta(s)$ outlined in figure 3. Both figures 6 and 7 represents the network as a graph drawing, with different success.

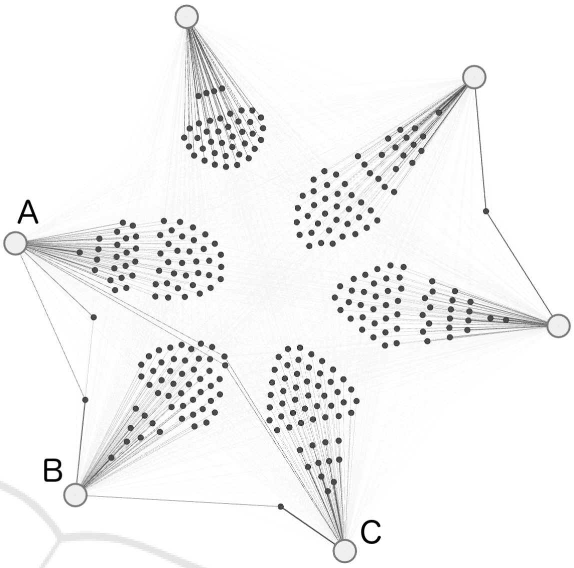


Figure 6: The first result on an force-directed graph of the LDA results. The 6 topics (white points) placed on the outer circle, words (dark points) oriented as lobes to their affiliated topics. Forces (edges) are determined by proportions defined in $\beta(t)$. We reduced visibility of weak connections.

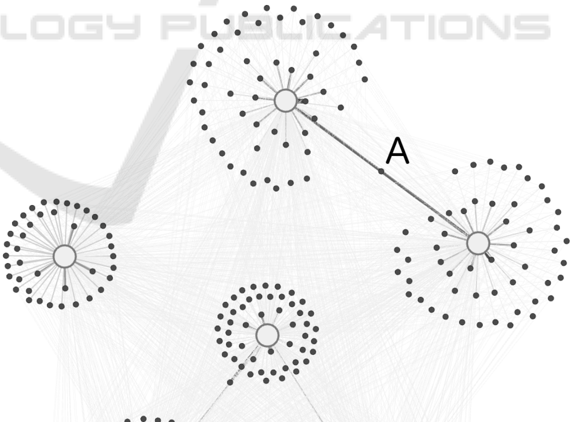


Figure 7: The second result on a force-directed graph of the LDA results. The words (dark points) are organized around their most affiliated topics. Forces are determined by proportions $\beta(t)$. We reduced visibility of weak connections.

The different arrangement result in different force models. Figure 6 shows *ForceAtlas* algorithm, figure 7 shows *ForceAtlas 2*. Both algorithms (described in (Jacomy et al., 2014)) are implemented for the open-source tool Gephi (v. 0.9.1) (Bastian et al., 2009), a software to visualize and manipulate networks. ForceAtlas2 is developed by combining existing techniques as an improvement and extension of the ForceAtlas algorithm. It simulates a physical system with mutual repulsion of the nodes and attraction towards their inzident edges. The lower based energy model is inspired by real life: Forces of nodes depends on the distance between the interacting entities.

The position of a node can't be interpreted on its own, it has to be compared to the other nodes in the graph drawing. However, using ForceAtlas 2, the distance, edge weight and degree plays an important role for positioning the nodes. In the classical case, the attraction is linearly based on the distances

$$F(n_1, n_2) = d(n_1, n_2).$$

The edge weight influences the attraction multiplicatively

$$F(n_1, n_2) = w(e)^{\delta} \cdot d(n_1, n_2)$$

with weight $w(e)$ of the edge e and edge weight influence parameter δ ($\delta = 0$: weights are ignored, $\delta = 1$: attraction is proportional to the weight, $\delta \geq 2$: strong influences of the weights). And node degree is important for the dissuade hubs:

$$F(n_1, n_2) = \frac{d(n_1, n_2)}{deg(n_1) + 1}.$$

Here grant authorities (nodes with a high degree) get a more central position than hubs (nodes with a small degree). Whereas in the use of ForceAtlas, hubs are pushed at the periphery and authorities more central.

5 INTERPRETATION OF SYNTHESIZED FORCE-DIRECTED SEMANTIC NETWORKS

Looking into the interpretation of results, the circular arrangement, approximates the student's model from figure 2. The force graph builds out a good visualization of lobe based on pure LDA data. In figure 6, most of the words lie in a topic's lobe. The distance to a topic node identify the attraction to the corresponding topic. The bigger the radius, the stronger the affinity by other topics. On the first look, the interpretation of keywords and their level of affiliation to specific topics seems straight forward. However, 6 shows words belonging to two not-adjazent topics (*A* and *C*), are likely to be pulled into the wrong topic's lobe (*B*). Furthermore, words oriented to the center of the graph, either have no strong affiliation to one of the topics, or have a strong affiliation to opposite oriented topics. This issues leads to misleading interpretations of affiliation.

In the case of the representation in figure 7, combining aspects of Mindmap and proximity, the position of the thematic area nodes is arranged by avoiding foreign keywords. Each word is assigned unambiguously to the topic based on the strongest affiliation. Words in the inner circle indicate a high attraction to its topic; the larger the radius, the weaker the affinity. Words that almost equally fit into multiple thematic areas keywords as shown in figure 7 at *A* and *B* are highlighted by their corresponding strong edges. The more equal the affiliation to both topics is, the more both topics share a keywords by pulling it out of the corresponding circles. This representation supports a more clear identification of thematic areas and corresponding terminal keywords.

6 CONCLUSION AND FURTHER WORK

In this paper we have synthesized a student's intuitive model from a non annotated sequence of lecture slides. We visualized semantic structures using a force-directed graph drawing algorithms.

The possible application for teaching and learning are manifold. While the structure itself provides an overview about the semantic structure of a curriculum, it serves as an semantic index on learning material. The proportional assignment of learning resources to thematic areas support a semantic selection of appropriate learning material across different lectures.

As one aspect, we improve the visualization of these results. To limit complexity, we need to filter the view to show only currently relevant information and resources. Based on a student's currently marked content, the structure needs to be dynamically reorganized to accent relevant technical terms and intertopic relations. Our goal is to automatically synthesize an assistive map showing the completed path of learning content as well as relevant relations between current and past learning resources.

Another aspect is described in (Wittrock, 1989). Learning is a process of associating input stimuli to structures of internal knowledge. The structure synthesized in this work, provides a step towards visualizing and organizing an associative grid out of non annotated, sequential learning material. On the one hand, it improves the structural awareness of students, on the other hand the structure can be enhanced by students during the processing of stimuli perceived in the lecture. The observation of student's annotation of lecture content described as coding in (Lee et al., 2008) enables an observation of student's processing of knowledge. Adding a semantic meta structure to non annotated lecture material enables an observation of student's coding in connection to lecture topics and relations.

Our next operative goals are to reduce the number of words in our representation. We need to identify relevant parameters, such as average importance, inter topic relations and layout information, such as size of text to weight identified technical terms by relevance.

Further, we look into time dynamics of these networks. Students and lecture structures develop over time. New keywords and relation appear during a curriculum. David Blei introduces dynamic topic models in (Blei and Lafferty, 2006). These concepts allow an observation of appearing new topics and distribution of words over time. These changes lead to movements in the force graph over time, providing insights in a lectures teaching and later student's learning process and progress.

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