Construction and Visualization of Concept Prerequisite Graphs for E-Learning

by
Mehmet Cem Aytekin

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CONSTRUCTION AND VISUALIZATION OF CONCEPT PREREQUISITE GRAPHS FOR E-LEARNING

APPROVED BY:

Prof. Dr. Yücel Saygın ....
(Thesis Supervisor)

Assoc. Prof. Dr. Hüsnü Yenigün ....

Asst. Prof. Dr. Tevfik Aytekin ....

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Mehmet Cem Aytekin

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Thesis Supervisor: Yücel SAYGIN

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Abstract

The growth of internet technologies in the last decade allowed the knowledge to spread out very fast across the globe. Users began educating themselves with huge amounts of online material on the internet. Today many academic institutions offer publicly available courses where students all around the world can join and benefit from them.

The abundance of online material from many different resources created an unorganized content in which it is likely for the learners to get lost. Furthermore, some concepts may require knowledge from other concepts and the learner may not be aware of those prerequisite relations between the concepts, therefore, she may have difficulties in understanding them.

In our work, we propose a methodology for calculating prerequisite scores among text-based educational material. We choose Wikipedia articles to work with since it is a large encyclopedia containing huge amounts of information on lots of different concepts. Furthermore, from a given set of concepts with their corresponding Wikipedia articles, we calculate each concept's prerequisite score towards other concepts and build a prerequisite concept graph for the learner. We believe that our graph model will guide the students in their studies and enhance their learning experience.

ÇEVRİMİÇİ EĞİTİM İÇİN KAVRAM ÖNKOŞUL HARİTALARININ OLUŞTURULMASI VE GÖRSELLEŞTİRİLMESİ

Mehmet Cem Aytekin

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Özet

Son on yılda internet teknolojilerinin hızlı gelişimi bilginin dünyanın her yerine çok kolay bir şekilde yayılmasına izin vermiştir. İnternet ortamındaki bilgi bolluğu sayesinde kullanıcılar kendilerini geliştirmeye fırsat bulmuştur. Günümüzde bir çok akademik kurum herkesin kullanımına açık dersler sunmaya başlamış ve dünyanın bir çok yerinden öğrenciler bunlara katılıp yararlanma imkanı elde etmiştir.

Neredeyse her konuyla ilgili bir çok farklı kaynaktan yapılan paylaşımlar her ne kadar öğrenciler için bir avantaj gibi gözükse de tüm bu bilgi yığını, öğrenilmek istenilen konunun internette düzensiz ve karmaşık bir şekilde sunulmasına yol açmıştır. Bu yüzden öğrencinin ilgili olduğu konuyu öğrenmeye çalışırken tüm bu karmaşa içinde kaybolması olasıdır. Daha da önemlisi, öğrenilmek istenen konu bir çok teknik kavram gerektirebilir ve bu kavramlardan bazıları, diğer kavramları anlamak için ön koşul olabilir. Bu durumda öğrenci konuyu öğrenmeye hangi kavramlardan başlamalı bilemeyebilir ve dolayısıyla bütün konuyu kavramakta zorluk yaşar.

Bu temel problemden yola çıkarak çalışmamızda, öncelikli olarak iki farklı kavramı anlatan yazılı akademik dökümanın arasında olabilmesi muhtemel önkoşul ilişkisini sayısal olarak ifade etmeye çalışıyoruz. Kavramlarla ilgili yazılı dökümanları hemen hemen her konudan bilgi içeren ve çok büyük bir çevrimci ansiklopedi olan Wikipedia'dan makale olarak alıyoruz. Bununla beraber, konuyla ilgili öğrenilmek istenilen kavram-

lar, Wikipedia makale karşılıkları ile verilirse tüm bu kavramların birbiri ile olan önkoşul ilişkilerini hesaplayıp bunlardan bir önkoşul kavram haritası oluşturarak öğrenciye sunuyoruz. Oluşturduğumuz haritanın yeni bir konuyu çevrimci öğrenmek isteyen bir kimseye öğrenme sürecinde faydalı olmasını umuyoruz.

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Chapter 1

Introduction

Online learning has grown exponentially during the first decade of the twenty-first century due to the rapid advancements in internet technologies. Many large colleges and universities began putting their course materials on the internet and making it publicly available to everyone who is interested in learning a particular subject. There are also a number of growing online encyclopedias, especially Wikipedia which is the largest and most popular general reference work on the World Wide Web with more than 300.000 active users and thousands of contributors from all around the world [1].

The abundance of online technical material on the internet accelerated the process of reaching out to specific information. However, this simplicity has also brought certain disadvantages along with it.

The major challenge for the learner is to be able to choose the right resources among a huge amount of online materials. The particular concept she is trying to learn may require some background knowledge, in that case, the learner should be able to identify the other concepts that are necessary to understand that particular concept and start studying them first.

Another challenge is the lack of a generalization mechanism in the huge concept pool. The concepts may belong to very specific areas and may contain very detailed information which in return prevents the learner from being able to look at those concepts at a broader level. It is always helpful for the learner when the discussed content is presented in an organized way. For instance, in a book, we have chapters, sections, and sub-sections so whenever we refer to a specific concept in a book, we have an idea of where we are in the global context.

The last difficulty is the variety in the learning process itself. Even if two different learners have the same level of background, their learning styles may be different. Some people may learn better with visual material whereas some may learn better with text-based material. Hence the learner also needs to be able to recognize her learning style and choose the right kind of online resource accordingly.

What should one know first before trying to learn a new concept? The answer to that question relies on the notion *prerequisite*. As defined in the Cambridge dictionary [2], a prerequisite is something that must exist or happen before something else can exist or happen. In this thesis, a prerequisite defines a relationship among two concepts A and B. We define it as a score between [-1 and 1] where the sign indicates the direction of this relationship and the score gives us the strength of the prerequisite.

Our work aims to build a complete weighted graph structure out of all the prerequisite scores between concept pairs. More technically, given a set of concepts $C = \{C_1, C_2, ..., C_k\}$ we want to build a score matrix S

$$S = \begin{pmatrix} s_{11} & \cdots & s_{1k} \\ \vdots & \vdots & \vdots \\ s_{k1} & \cdots & s_{kk} \end{pmatrix}$$

where s_{ij} is the prerequisite score between the i^{th} and j^{th} concept.

Using the concept list C and the score matrix S, we construct our graph where nodes in the graph represent the concepts in the list C and the elements of the matrix S represent the directed weighted edges among nodes.

The constructed graph is then presented to the learner where she sees all the concepts and their degree of prerequisite relations with each other by looking at the nodes and the directed edges of the graph. If the learner wants to master a specific target topic c_t but she is not sure whether that topic c_t requires some knowledge from the other concepts in the concept list C, she can first look at the prerequisite concepts for the target topic by following the incoming edges to c_t in the graph and master them first in order to completely understand the concept c_t. If these concepts are also not familiar to her, then the learner can go back once more and repeat the above procedure recursively until arriving at the concepts in the graph that she feels hundred percent confident about. Beginning from those known concepts, the learner can this time go forward and start studying the prerequisite concepts along the way until she reaches the target concept c_t. Finally, with enough knowledge gained along the way, the learner can master the concept c_t and move on.

Furthermore, when we analyze the constructed graph, we observe natural clusters within the structure. It is expected to have this sort of disconnected components in the graph since any unrelated concept pair will likely to have zero prerequisite score in between. It is also possible to conclude that the concepts in the naturally formed clusters are related to each other to some degree, therefore, we have a grouping. These clusters can be thought of as first level generalizations of the concepts in the given concept set. Treating each cluster as a one level generalized concept, their inter-prerequisite scores can again be calculated which yields second level generalized clusters. This procedure can go on until we are left with one cluster which represents the highest level of generalization.

1.1 Overview of the Methodology and Contributions

Calculating a score for a prerequisite relationship between two concepts is not a straightforward task. In general, an online educational material revolves around the main concept and is presented to the user in various forms such as text, audio, image or a video. In this thesis, a concept is represented by a Wikipedia article, which may be considered as a text-based online educational material. When we refer to concepts A and B, we need to fetch the corresponding articles A and B from Wikipedia. Since Wikipedia is a vast encyclopedia, it is often possible to find the corresponding articles easily. Furthermore, Wikipedia offers its Wikipedia library to developers which makes it easy to query any article and get detailed information about it.

Our initial work starts by exploring which properties of the two Wikipedia articles A and B can give us information about the prerequisite relationship between them and we determine several important features that we will explain in detail in Chapter 3.1. Moreover, after discovering the relevant features, we apply a standard supervised machine learning technique to determine the weights of these discovered features. The data-set that is used in the weight learning process is the famous university course data-set first introduced by Liang et al. 2017 in [3] where 1008 Computer Science topics are listed and labeled according to their prerequisite relation by the domain experts.

After having learned the features and their corresponding weights, our model becomes ready to assess the prerequisite relation of a concept pair A and B, and gives a score to them between -1 and 1 where -1 means A is a complete prerequisite of B and 1 means B is a complete prerequisite of A and anything in between shows the degree of their relationship.

Although the score prediction part of the system makes our approach a regression type of solution, it is also possible to use the system as a classifier such that if the score of a pair A and B is above 0, then concept B is a prerequisite of A, if 0, then there is no prerequisite relation and if below 0, then A is a prerequisite of B.

To test the performance of our system, we make use of the classification property of our system and ask it to classify the different concept pair instances from different labeled data sets and report the classification accuracies. We also choose prerequisite pairs from different domains and show that although our method is trained with computer science topics, it performs still well in other fields as well.

Finally, on the same data-set, we perform two other prerequisite calculation methods which are similar to ours and make comparisons of our approach with those approaches.

In Chapter 3, we look at the idea of the concept maps which attempt to capture the concepts and their relationships among them in a given educational material. Elaborating on this idea, we specialize our focus on a specific type of relationship, namely the prerequisite relationship and discuss the ways to identify it by giving references to the existing literature. In Chapter 3, we explain how we calculate the prerequisite relationships and build a graph from the given concepts in detail. We also discuss the ways to generalize the given concepts and rebuilding graphs in different hierarchical levels. In Chapter 4 we analyze the performance of our system on different data-sets from different domains and report the results in detail. We also try to understand the weak and strong sides of our algorithm. In Chapter 5 we describe the limits of our algorithm and we suggest possible ways to overcome them. We explain how the students can benefit from our system and how it can be further developed for online learning.

Chapter 2

Related Work

The search for a visual representation of knowledge has long been an occupation for the researchers in computer science. One of the successfully adapted and widely used technique for this task is concept mapping [4]. It attempts to capture the subjects in the context as concepts, draws them with a special symbol, tries to name their inter-relationships and links them one to another with arrows. Concept maps are especially useful in the field of education and facilitate the learning process of the students.

The idea of a concept map comes with its challenges and part of those challenges have been an inspiration for our work. The main challenge is the need for an expert when building a concept map. In theory, the expert should be able to list all the relevant concepts and be able to define their relationships with each other in a given context. However, the context may be complex and the relation between the concepts may not be obvious. Moreover, each context requires a different concept map and no expert in the world has enough knowledge to combine those maps together to build a universal concept map. This major problem then raises the question: Can it be possible to automate the process of concept map creation?

The first challenge in the automation process is the extraction of subjects or namely concepts in the given context. The second challenge is to define the relationship between the two concepts. Considering the relationship as an interaction between two subjects, there may be huge amounts of possible relations between a concept pair (A, B) such that concept A can be a part of concept B, or it can be a prerequisite of B or it can simply be the detailed version of B, etc. These two major difficulties have been the focus points of the researchers who wanted to build automatic or semi-automatic concept maps.

In the search for a semi automatic concept map creation, one tool that grabbed the attention in the area is TextStorm and its extension Clouds [5], [6]. When the context is given as a text document, TextStorm identifies the subject, object, and verb by parsing each sentence in the document. The subject becomes the first concept; the object becomes the second concept, and the verb defines their relationship. From there on, TextStorm takes the candidate concepts and relationships and feeds them into Clouds. After getting input from TextStorm, Clouds asks questions to domain expert about the concept-verb-concept structures it formed and it attempts to generalize its knowledge by using inductive logic and outputs a concept map in the end. One good example to understand the generalization process is given in the paper as follows [7]: If it is observed that: *produce* (apple tree; apple) *produce* (pear tree; pear) and from the domain knowledge, it is known that *isa* (pear tree; tree) *isa* (apple tree; tree) *isa* (pear; fruit) *isa* (apple; fruit) a generalization is deduced *produce* (tree; fruit).

Other approaches to capture relevant concepts are based on converting the text documents into vector representations by using standard approaches such as Bag of Words and TFIDF weighting [8], [9]. After turning documents into vectors, the term-document matrix is constructed where the rows correspond to terms and columns correspond to documents. Then by applying Latent semantic analysis technique, it is possible to cluster the documents that share similar words [10]. One can then look at the most referenced word in each document cluster and come up with a list of words representing the main concepts in all the documents. If the context is considered as a set of documents then the above approach is one way of doing concept extraction in a large textual resource. However, these series of techniques do not solve the problem of defining the relationships among the concepts. They only attempt to provide a solution for the first challenge mentioned at the beginning of this chapter.

The string-searching algorithms such as AhoCorasick algorithm [11] use pre-defined dictionaries to deal with concept extraction problem. Given a specific context, the expert can predetermine the necessary concepts and build a dictionary out of them so that whenever the system receives a text resource about that particular context, it can quickly identify the relevant concepts in it by looking at the dictionary. Having concepts in advance, several association measures from information theory and statistics such as pointwise mutual information [12] are proposed in the literature to quantify the relatedness of the relevant concepts appearing in the same text resource.

Om P. Damani took Pointwise Mutual Information (PMI) technique as a base and then developed the significant co-occurence idea to discover the meaningful associations among concepts both at document and corpus level [13] [14]. The main idea in PMI is that to have a meaningful association score, the probability of observing concepts A and B together should be high and the probability of observing them individually should be low in a given text. A new probability function is defined for calculating the joint probabilities of concept A and B appearing in close ranges and the results of these probabilities are used to determine whether their co-occurence shows any statistical significance or not.

It is important to state that although co-occurence indicates a relatedness between two concepts, it does not imply causality and still it does not define what type of relationship exists between two concepts.

In this thesis, we concentrate on a specific type of relationship, namely the prerequisite relationship between two concepts. Moreover, we also assumed that the concepts are pre-defined by the expert.

Tseng et al. proposed an interesting way of automatic concept map creation in 2005 by considering the prerequisite relationships among concepts [15]. They proposed a Two-Phase Concept Map Construction (TP-CMC) algorithm to automatically construct a concept map of a course by historical testing records. The test record contents were known in advance and the authors assumed that concepts asked in some test A are prerequisites of some other concepts in test B, if lots of students have either high or low scores in both tests. By matching a group of concepts as the prerequisites of other concepts, they formed a concept map where the nodes are the individual concepts and the weighted directed edges are the prerequisite strengths together with the prerequisite directions. A similar approach is used by Yang et al. where they analyzed course prerequisites from different university databases to learn a directed universal concept graph, and they used the induced graph to predict unobserved prerequisite relations among a broader range of courses [16].

The other idea for determining a prerequisite relationship is to treat each concept as a possible Wikipedia article and calculate prerequisite scores for the articles. To the best of our knowledge, this idea was first mentioned by Talukdar and W. Cohen [17]. They mention the nice properties of Wikipedia in textual analysis such as the densely linked structure of the site, its standardized format, and information available about how documents are used by the Wikipedia community.

The idea of using Wikipedia articles for determining prerequisite relation between concepts is further analyzed by Liang et al.[18]. They defined a metric called reference distance (RefD) which takes two Wikipedia articles as inputs and outputs a prerequisite score between 1 and -1 where the sign indicates the direction of the prerequisite and the score demonstrates the strength of the prerequisite.

The articles in Wikipedia have hyperlinks. The domain specific terms that are important in understanding the article are underlined with blue color by the editors. Whenever the reader is unfamiliar with the underlined term, she can move to the article that explains it by clicking on it.

These hyperlinks that are in some article A, are considered as related to A. Chen Liang et al. called these hyperlinks inside A, as the concept space of A [18]. The observation is that given two articles A and B, if most of the concepts in concept space of A refer to article B, this may indicate B is a prerequisite of A since in order to understand the related concepts of A we have to know concept B in advance. The vica versa is also valid.

The reference distance calculation is based on this above observation. Given two articles A and B, the ratio of concepts referring to B to the number of concepts in concept space A yields a score between 0 and 1. This score can be interpreted as how much B is a prerequisite of A. Applying the same logic, the ratio of concepts referring to A to the number of concepts in concept space B again yields a score between 0 and 1. This second score can be interpreted as how much A is a prerequisite of B. Finally, the difference between these two scores gives us a number between -1 and 1 which constitutes the reference distance score.

Elaborating on this method, we discovered that it is possible to add more features to RefD formula due to the abundant information available for the articles in Wikipedia.

We observed that only considering the concept spaces of articles A and B are not enough and we should also consider the references in the articles themselves. Moreover, it is also important how many times A itself referenced B or vica versa. These considerations are not taken into account in plain RefD calculation.

It is also possible to read the summary of the articles in Wikipedia. We concluded that if the concept A refers to the concept B in its summary, then this concept of B must be valuable for A since the summaries are short and only the most important aspects of the concepts are presented to the user. Therefore we also included the summary reference count into the refD formula.

Furthermore, we know that not every feature about an article is at the same importance when calculating a prerequisite score, so with the help of the existing labeled prerequisite data-sets, we approximated the weights of those features by applying machine learning techniques. Details of these techniques and the stages of the whole procedure are discussed in Chapter 3.

Chapter 3

Methodology and Problem Definition

In this chapter, we explain and discuss in detail how we construct the prerequisite graph from a given set of concepts. Our algorithm has three main stages:

- Stage 1: Prerequisite score calculation between two concepts,
- Stage 2: Building a graph out of the prerequisite scores calculated in the first stage
- Stage 3: Clustering and generalizing the given concepts by using the hierarchical property of our graph.

The process in the first stage has four major steps. We first start by defining our score function and objective then we move to the data preparation part and explain which type of data we use and how we determine the relevant features. After that, we reach to learning part where we determine the weights of the features by supervised learning. We finally interpret our results on the test data and finish the first stage in our algorithm. The second stage has two major steps. At the first step we calculate each concept's prerequisite score with the other concepts in the list and we build a prerequisite score matrix. At the second step we make simplifications on the score matrix and then turn it into a graph model. Finally, in the third stage, we show different levels of concept generalizations on the graph.

3.1 Prerequisite Score Calculation

In order to give a score for given concepts, we should define a mathematical function f and describe all its properties in detail.

3.1.1 Definition of the Score Function

The arguments: Our function takes two concept names as inputs. In order for these arguments to be valid, these two concepts should have their corresponding articles in Wikipedia with the same name.

The output: Function outputs a score between -1 and 1.

Asymmetry: Given concept names A and B, $f(A, B) + f(B, A) = 0$.

Irreflexivity:$f(A, A) = 0$.

3.1.2 Input Format and Feature Selection

Having found the corresponding Wikipedia articles for the concepts A and B, three features are analyzed by our function. The first feature is RefD score for the articles A and B. (Detail about RefD score is in Related Work). This score computes how much of the neighbour concepts of A refer to concept B. If most of the neighbours of concept A refer to B, this indicates a possible prerequisite relationship from B to A. The second feature is the number of reference different count in the articles A and B themselves. For example, if the concept A itself refers to B 15 times in its article and concept B refers to concept A 3 times in its own article then the number of reference different count is +12 which again indicates a possible strong prerequisite relationship from B to A. The last feature is the summary reference difference count which is the same procedure as in the second feature calculation case but this time instead of analyzing the articles themselves, we analyze their summaries and come up with a third feature score.

Let's symbolize RefD score of articles A and B as $f1$, reference difference count of the article themselves as $f2$ and summary reference difference count as $f3$.

Note again that features $f1$, $f2$ and $f3$ for the concepts A and B are calculated as follows:

let $nrAB$ be the number of references to A in article B and let $nrBA$ be the number of references to B in article A.

let $snrAB$ be the number of references to A in summary of the article B and let $snrBA$ be the number of references to B in summary of the article A.

$f1 = \frac{\text{number of neighbour concepts that refer to B}}{\text{number of neighbour concepts of A}}$

$f2 = nrBA - nrAB$

$f3 = snrBA - snrAB$

Each of these features also has some undetermined weights in prerequisite score calculation $w1$, $w2$, $w3$ and we have a threshold $w0$.

To be able to fulfill the desired properties of the prerequisite function that we defined above, we first define a new variable $p1$ which indicates how much of a concept B is prerequisite of the concept A as follows:

$$p1 = \frac{e^{w0+w1*f1+w2*f2+w3*f3}}{1+e^{w0+w1*f1+w2*f2+w3*f3}}$$

By taking advantage of the property of the sigmoid function we guarantee that $p1$ is in the range of 0 and 1.

To be able to indicate how much of a concept A is a prerequisite of B, we use the same features and weights but this time the features are calculated as follows:

$f1' = \frac{\text{number of neighbour concepts that refer to A}}{\text{number of neighbour concepts of B}}$

$f2 = nrAB - nrBA$

$f3 = snrAB - snrBA$

We then define a second variable $p2$ which is:

$$p2 = \frac{e^{w0+w1*f1'+w2*f2'+w3*f3'}}{1+e^{w0+w1*f1'+w2*f2'+w3*f3'}}$$

By again taking advantage of the property of the sigmoid function we guarantee that $p2$ is also in the range of 0 and 1.

Finally, we define the output of our function as $p1 - p2$ which is guaranteed to be between -1 and 1. The function also has the asymmetry and irreflexivity properties which ensure that when the arguments are given in reverse order, the score is the same but negative and when the two same arguments are given, the score is zero.

3.1.3 Weight Learning

We apply supervised learning to determine the weights of the features. For the training, we use the university course data-set where 1008 Computer Science topics are listed and labeled according to their prerequisite relation by the domain experts [3].

Our algorithm first calculates a score indicating how much concept B is a prerequisite of A and outputs a score between 0 and 1, then it calculates a second score indicating how much concept B is a prerequisite of A where it again outputs a score between 0 and 1 and finally it gives the difference.

Initially, each concept pair (A, B) in the existing training data is listed in a format where concept B is a prerequisite of A. We label this information as 1. However, since A is not a prerequisite of B, we should also label this information as 0. Ideally, for each concept pair (A, B) our algorithm should give 1 for how much B is a prerequisite of A and it should give 0 for how much A is a prerequisite of B and it should output a positive score of 1 in the end by taking the difference between these two scores. Therefore each concept pair (A, B) in the training data is actually two instances for the learner where one instance is prerequisite information from B to A which should be labeled as 1 and the second instance is a prerequisite information from A to B which should be labeled as 0. The visual demonstration of the training data can be seen in the Figure 3.1.

For each prerequisite direction either from A to B or B to A, we are given three features and we need to make a prediction between 0 and 1. A suitable machine learning approach for this task is logistic regression, therefore, we apply it to come up with the best weights that would describe the prerequisite relations for all the pairs in the training data.

It is important to note that our classification accuracy and the training/test accuracy in logistic regression is different. To clarify this explanation it is best to look at a particular example:
Imagine that for a given concept pair (A, B) in the training data, the prerequisite relation from B to A is calculated as 0.4. Logistic regression classifies this as class 0 since it is less than 0.5 (more probable class) and it looks like we have a wrong classification because its true label is 1. Imagine also the prerequisite relation from A to B is calculated as 0.3. It is classified as 0 and it is the true label. It seems like out of 2 examples we have only labeled one of them correctly but our classifier sees the (A, B) pair as a single example and it calculates the difference of the two scores and in that case, it is 0.4 - 0.3 = 0.1. Since 0.1 is a positive score it concludes that B is a prerequisite of A therefore we have a correct classification for the concept pair (A, B).

After training our logistic regression model according to our training data, we determine our weights to be: $w1$=0.8778, $w2$=0.0536 $w3$=0.9713 and $w0$=-0.1541. This finding suggests that the most important feature in the prerequisite calculation is the summary reference count, second is the RefD score and the last one is the article reference count. $w0$ can be thought of as a threshold value and it is found to be -0.1541 by our model.

The final structure of our prerequisite function f is as follows:

3.1.4 Testing the Scoring Function

The prerequisite score function that we formulated can be used either as a regressor or a classifier. When used as a regressor, it predicts the strength of the prerequisite relation between the concepts A and B by outputting a score between -1 and 1 and when used as a classifier, it simply interprets the positive values as B being a prerequisite of A and the negative values as A being a prerequisite of B.

To test the performance, we use the function as a classifier to determine the accuracy in the test data.

We use 3 different test sets. We also test by using refD as a single feature and

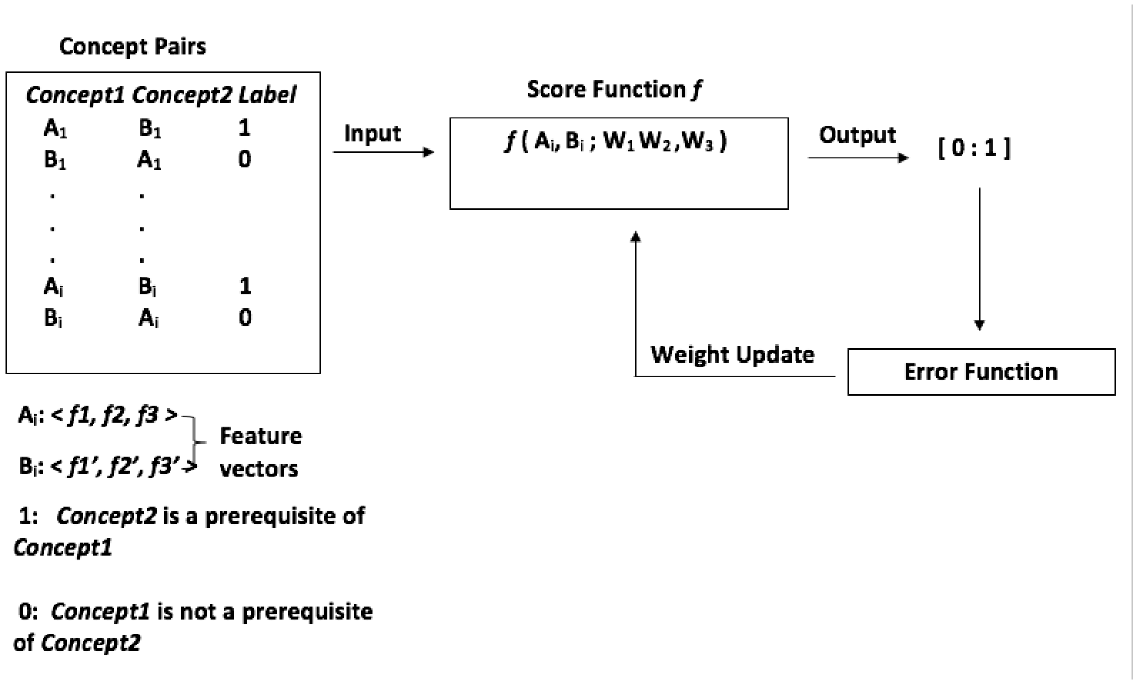


Figure 3.1: Weight Learning of our Score Function

Algorithm 1 Working principle of the score function f.

Input: Two concepts A and B each represented as three dimensional feature vectors.

Output: Prerequisite score between -1 and 1.

function SCOREPREQFUNCTION(A, B)

$f1, f2, f3 \leftarrow$ getFeaturesforA(A,B) $\triangleright$ we need information from concept B as well to determine the features of A.

$f1', f2', f3' \leftarrow$ getFeaturesforB(A,B) $\triangleright$ we need information from concept A as well to determine the features of B.

raw score 1 $\leftarrow 0.8778 * f1 + 0.0536 * f2 + 0.9713 * f3 - 0.1541$

p1 $\leftarrow$ math.exp(raw score 1)/(math.exp(raw score 1)+1)

raw score 2 $\leftarrow 0.8778 * f1' + 0.0536 * f2' + 0.9713 * f3' - 0.1541$

score $\leftarrow p1 - p2$

return score

end function

make comparisons. The results obtained for this part will be explained in detail in Chapter 4.

3.2 Graph Formation

Now that it is possible to calculate a prerequisite score for any concept A and B which have their corresponding articles in Wikipedia, we can go back to our initial goal of determining the prerequisite relations for a given set of concepts and then visualize this information by forming a graph out of it.

3.2.1 Prerequisite Matrix

Given a set of concepts $C = \{C_1, C_2, ..., C_k\}$ We calculate each concept's prerequisite score with respect to the rest of the concepts and form the score matrix S.

$$S = \begin{pmatrix} s_{11} & \cdots & s_{1k} \\ \vdots & \vdots & \vdots \\ s_{k1} & \cdots & s_{kk} \end{pmatrix}$$

where s_{ij} is the prerequisite score between the i^{th} and j^{th} concept.

Diagonal elements of the matrix are zero since the concept's prerequisite relationship with itself is zero. Moreover $s_{ij} = -s_{ji}$ because of the asymmetric property of our function.

3.2.2 Matrix Filtering and Graph Building

The constructed score matrix needs to be turned into a graph for a visual representation to the user and we explain the process in this subsection.

We use a graph database to store the concepts and their prerequisite information. A graph database is a database that uses graph structures for semantic queries with nodes, edges, and properties to represent and store data [19]. We choose Neo4j as the graph database management system which is developed by Neo4 Inc. According to DB-Engines ranking [20], it is the most popular graph database. It has its own querying language called Cypher Query Language which is easy to understand and use and which also makes it possible to do complex graph operations in a few lines of codes. Moreover, any software written in any computer programming language can query the database using the Cypher Query Language through a transactional HTTP endpoint, or through the binary "bolt" protocol [21].

In our work, we treat each concept as a node in the graph and when we get the concept set C, we construct a node for every element in C. Then to be able to define the directed weighted edges we use the score matrix S.

Initially, the process seems rather straightforward and one can draw a weighted edge from concept i to j if there is a positive score s_{ij} and from j to i if there is a negative score s_{ij}. However, there are some issues to consider. The first issue is the possible cycles in the graph. If concept A is a prerequisite of B, if concept B is a prerequisite of C and if concept C is a prerequisite of A then the learner will be stuck in a loop in the graph and never proceed to the other concepts. To overcome this issue, we propose the following sparsification method:

For every concept c_i in the concept list C, we look at the highest absolute value score $s_{ij}*$ by examining the i'th row of the score matrix S. This score demonstrates the most powerful prerequisite relation for the concept c_i. We only draw an edge from the concept c_i to concept c_j* or vica versa according to the sign of the score and discard the other scores in the i'th row of the matrix. We repeat the same procedure until there are no more concepts left in the concept list C.

This approach ensures an acyclic property in the graph. To prove this let's analyze a simple case with three concepts A, B, and C with the random scores x, y, z. Imagine a score matrix S as follows:

$$S = \begin{pmatrix} 0 & x & z \\ -x & 0 & y \\ -z & -y & 0 \end{pmatrix}$$

In order for a cycle, there has to be an edge from A to B meaning $|x| > |z|$, from B

to C meaning $|y| > |x|$ and from C to A meaning $|z| > |y|$.

However, since $|z| > |y|$ and $|y| > |x|$, the statement $|z| > |x|$ should also be true. This contradicts with the assumption of $|x| > |z|$ in the beginning so we are sure that we don't have any cycles in the graph.

We should note that this algorithm only prevents cycle formation in the graph and other cases such as one concept being a prerequisite for multiple concepts or multiple concepts being prerequisite for a single concept is still possible.

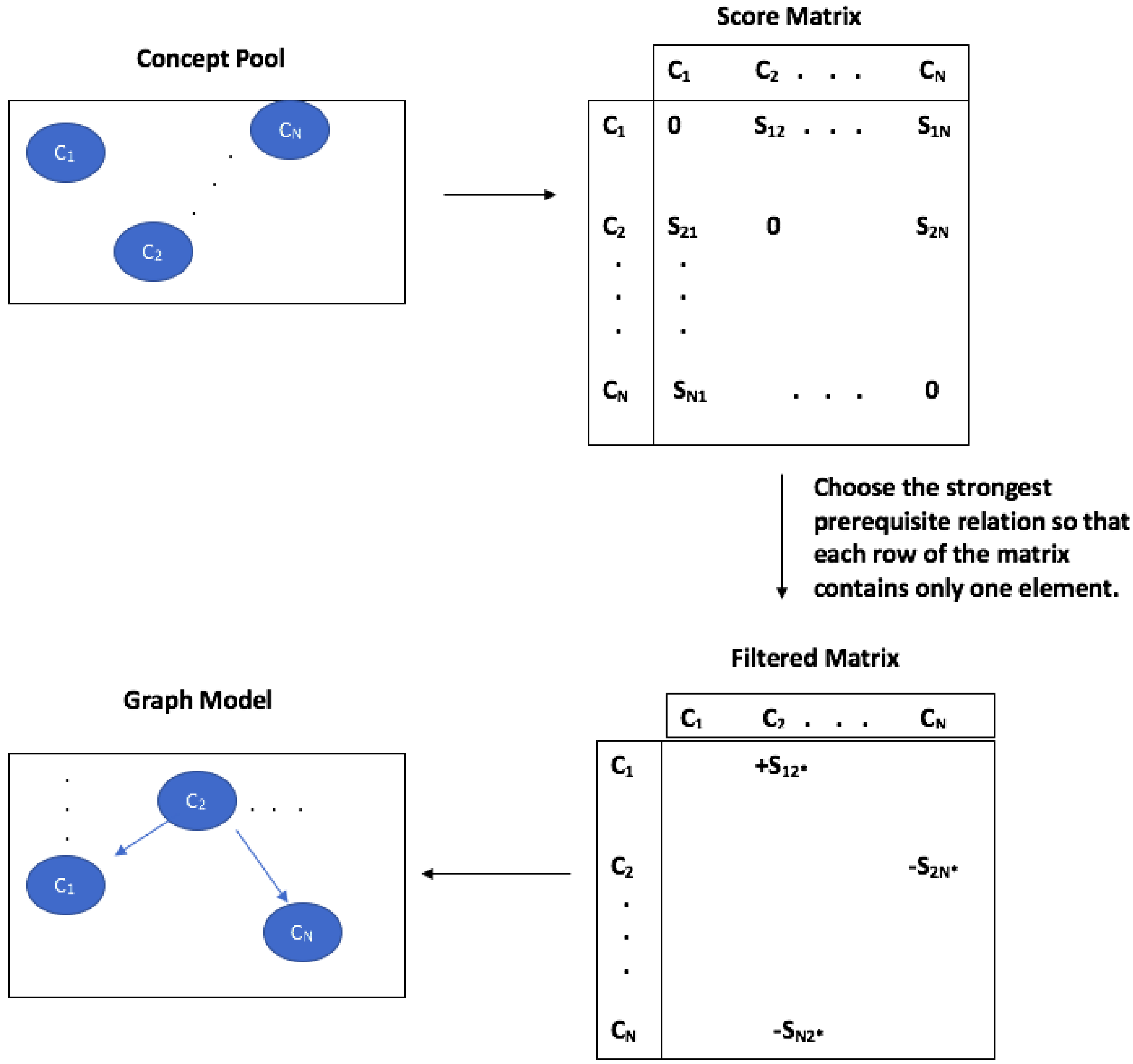


Figure 3.2: Forming the Graph Model

Algorithm 2 Graph construction algorithm

Input: List of concepts L

Output: Prerequisite concept graph G.

function BUILDSCOREMATRIX(L)

  $S \leftarrow$ createEmptyMatrix(size(L)) ▷ creating an empty matrix with size LXL

  $i \leftarrow$ size(L)

  $j \leftarrow$ size(L)

  for iteration 0 to i **do**

    for iteration 0 to j **do**

      $S[i][j] \leftarrow$ scorePreqFunction(L(i),L(j)) ▷ filling the score matrix

    end for

  end for

  return S

end function

function BUILDGRAPH(L,S)

  for concept c in L **do**

    createNode(c) ▷ Create a node in the graph database

  end for

  $i \leftarrow$ size(L)

  $j \leftarrow$ size(L)

  for iteration 0 to i **do**

    $temp \leftarrow$ createEmptyList(size(L))

    for iteration 0 to j **do**

      $temp \leftarrow S[i][j]$ ▷ assign the scores in the same row to the list temp.

    end for

    $value, index \leftarrow$ getHighestAbsoluteValue($temp$) ▷ consider only the concept which has the highest absolute prerequisite score.

    createEdge($L(i)$,$L(index)$,$value$) ▷ Create a weighted directed edge between these two nodes. Direction is decided according to the sign of the value.

  end for

end function

3.3 Different Levels of Generalizations in the Graph

Often times we observe disconnected components in the graph since not every concept is a prerequisite of another concept or some prerequisite relations are simply eliminated since they are not the strongest relations for that particular concept.

These disconnected components are the natural clusters within the graph which may be seen as the higher level representations of the detailed content-specific concepts. One observation that we make from the high-school physics data-set is that concepts such as Velocity, Acceleration and Angular Velocity form one cluster in the graph which in fact belong to the topic of motion at a higher level.

Treating each cluster as a single node that generalizes some concepts at a higher level, we can in fact again use our algorithm to calculate a new score matrix S and construct a new graph which contains higher level concepts. The procedure for doing that is rather straightforward and performed as follows:

Algorithm 3 Graph generalization algorithm

Input: Graph G and Score matrix S.
Output: New graph G' which is the one level higher version of the old graph G .
$Clusters \leftarrow$ findClustersInGraph(G) ▷ $Clusters$ is a two dimensional list where each element contains the concept names that are in the same cluster.
function CLUSTERLEVELPREREQUISITESCORE(G_1, G_2)
  $sum \leftarrow 0$.
  $i \leftarrow$ size(G_1) ▷ G_1 is a list containing concepts in same cluster.
  $j \leftarrow$ size(G_2) ▷ G_2 is a list containing concepts in same cluster.
  for iteration 0 to i **do**
    $temp \leftarrow$ empty list.
    for iteration 0 to j **do**
      $weight \leftarrow$ getWeight($G_1(i)$,$G_2(j)$)
      $temp \leftarrow weight$
    end for
    $value \leftarrow$ getHighestAbsoluteValue($temp$)
    $sum \leftarrow sum + value$
  end for
  return $sum/size(G_1)$
end function
$L' \leftarrow$ assignLabels($Clusters$) ▷ Each cluster is in new list L'.
function BUILDHIGHLEVELSCOREMATRIX(L')
  $S' \leftarrow$ createEmptyMatrix(size(L')) ▷ Empty matrix with size $L'XL'$
  i, $j \leftarrow$ size(L')
  for iteration 0 to i **do**
    for iteration 0 to j **do**
      $S'[i][j] \leftarrow$ clusterLevelPrerequisiteScore($L'(i)$,$L'(j)$)
    end for
  end for
  return S'
end function
$G' \leftarrow$ buildGraph(L',S') ▷ The graph building function in Section 3.2.2

We have step by step explained our algorithms in three stages. In Chapter 4 we go over them once more by giving various examples from different stages and report our results in detail. We will be also analyzing our model's performance on different data-sets and discuss its weak and strong aspects.

Chapter 4

Implementation, Experiments, and Evaluation

In this chapter, we talk about experimental results performed to test our methodology. We explain our methodology in three stages just like we did in Chapter 3 and we support our algorithm's capabilities and efficiency at each stage by showing results obtained from different data-sets. There are three main different test data-sets:

1. An existing data-set that contains computer science topics labeled according to their prerequisite relationship.
2. A custom prepared data-set that includes database management system concepts.
3. High school physics concepts data-set that is again formed by us with the help of the existing online materials on the internet.

4.1 Prerequisite Score Accuracy

We first start our algorithm by constructing a function which computes a prerequisite score between -1 and 1 for two given concepts. The working principle of this function was explained in detail in Chapter 3 but it is important to make some remarks again so that what we are evaluating in this section becomes clear. Our function can both serve as a classifier and as a regressor. In this section, we demonstrate its power in classification on various data-sets. Given two concepts A and B it can give either a positive or a negative score where positive means B is a prerequisite of A and negative means A is a prerequisite of B. If the score is exactly 0 then they are classified as NONE.

Before moving into the results, it is important to talk about the data-set format as well. The first test data-set is taken from [3]. It contains 154 pairs of computer science topics. All these concepts have corresponding articles in Wikipedia. For each pair (A, B) we are given the knowledge that A is a prerequisite of B. If our function outputs a positive score it means it correctly classifies the given instance and if it gives a negative score it means it misclassifies the given instance. Moreover, since we also know the scores of our function for the test data-set, it is possible to calculate the error margin in the classification. In theory, we assume all the instances in the test data-sets are a full prerequisite of each other meaning that they should have a score of 1 if they are listed in a format of B is a prerequisite of A and -1 if they are listed as A is a prerequisite of B. We use the word in theory because in reality a concept is not always absolutely a prerequisite for another concept and rather it has a certain degree of prerequisite relation with it.

There is also another question on our mind before running the experiment on this data-sets. Since the function is trained with concepts from computer science, we want to know whether the domain similarity in the first data-sets adds any advantage to our function.

The function's classification performance is also compared with the sole refD function developed by Chen Liang and his team in 2015 [18]. This refD function as we described earlier, was the starting point for us in determining a score function and we improved its performance by adding two new features and by learning the weights of these features with logistic regression on an existing training data.

Out of 154 concept pair instances, 126 of them are correctly classified, and we obtained an accuracy of % 81 in the first data-sets. We then tested the sole refD method on the same test data but this time only 97 concept pair instances are correctly classified and the classification accuracy remained at % 63. Our method outperformed refD by labeling % 18 more of the instances correctly. We analyzed the misclassified examples after the experiment and tried to identify the cause of this wrong classifications. One example pair from the first data-sets is Robotics and Robots. Our function states that robotics is a prerequisite for understanding robots but it is labeled other way around in the data-sets. This is rather an arguable instance and one can say to understand the robots we should study robotics or one can again say we should have knowledge about the term robot to study robotics. The other issue is the difference in the level of the concepts, for instance, if one concept is programming language and the other concept is C++, since C++ is a programming language it is not very accurate to look for a prerequisite relationship among these concepts because they rather have an *isa* relationship which is something different than what we are interested in..

By keeping the controversial instances in mind, we prepare our own data-sets which we believe is clearer than the other existing prerequisite data-sets. We first choose the domain to be high school physics concepts. There are two main reasons for choosing this domain. One is that like we stated above, we wanted to have a different area than computer science and secondly; it seemed easy to capture the prerequisite relations in physics. For instance, if we look at the definition of the concept *Acceleration*: the rate of change of velocity of an object with respect to time [22], one can easily understand that she has to first understand the concept *Velocity*. It is also possible to look at the formulas for certain concepts in physics and state that the components of the formula for the given concept may be the prerequisites of it.

Our custom high school physics data-sets contains 82 concept pair instances. Out of 82 instances, 60 of them are labeled correctly with our function by reaching an accuracy of %73 while with the refD method only 46 of them are labeled correctly with an accuracy of %56.

Lastly, we move to our final data-sets which contains concepts from the database management system course. It is again a custom data-sets that is prepared by us. There are two main motives for choosing this course. Firstly in the former computer science topics data-sets, the concepts are not domain-specific and rather in general.

In this data-sets, we want to see the performance of the classifier when the concepts are in micro-level meaning that they are content-specific and short. Secondly, we are familiar with the course since my thesis advisor Yücel Saygın is the professor of this course in our university and his expertise contributed to the data-sets preparation.

Out of 50 database concept pairs, 33 of them are classified correctly with %66 accuracy and with refD method 27 of them are classified correctly with an accuracy of %54. The accuracy decreased but this was expected since there is a limited amount of information in Wikipedia about these detailed micro concepts.

4.2 Graph Formation

This is the second stage of our algorithm. Now for a given set of concepts C with length k, we are interested in forming $n \times n$ score matrix S where an element of the matrix s_{ij} is the prerequisite score between the concept i and concept j.

After forming score matrix S we are interested in turning this matrix into a graph structure in Neo4j where nodes in the graph represent the concepts and the directed weighted edges represent the strength and the direction of the prerequisite relations between concepts.

4.2.1 Complexity of the Algorithm

For a given set C with length n, we have to calculate each concept's prerequisite score with the other concepts in the set, therefore, constructing the score matrix requires n^2 operations. This complexity can be reduced to half by knowing the fact that $s_{ij} = -s_{ji}$ and $s_{ii} = 0$ in the score matrix S.

The main bottleneck for the algorithm is not the complexity of the calculations but rather the requests sent back and forth to the Wikipedia API. Each prerequisite score calculation for a concept pair (A, B) approximately takes 10 - 15 seconds because of the connection overhead. There may be several approaches to overcome this problem one is to parallelize the requests with multi-threaded programming. Another approach is to dump Wikipedia articles into the local machine in advance to speed up the matrix formation process. Our length of the concept sets never exceeded 100, so we did not have much trouble because of this overhead.

4.2.2 Physics data-sets

We first start with a set of 30 physics concepts and build their prerequisite graph.

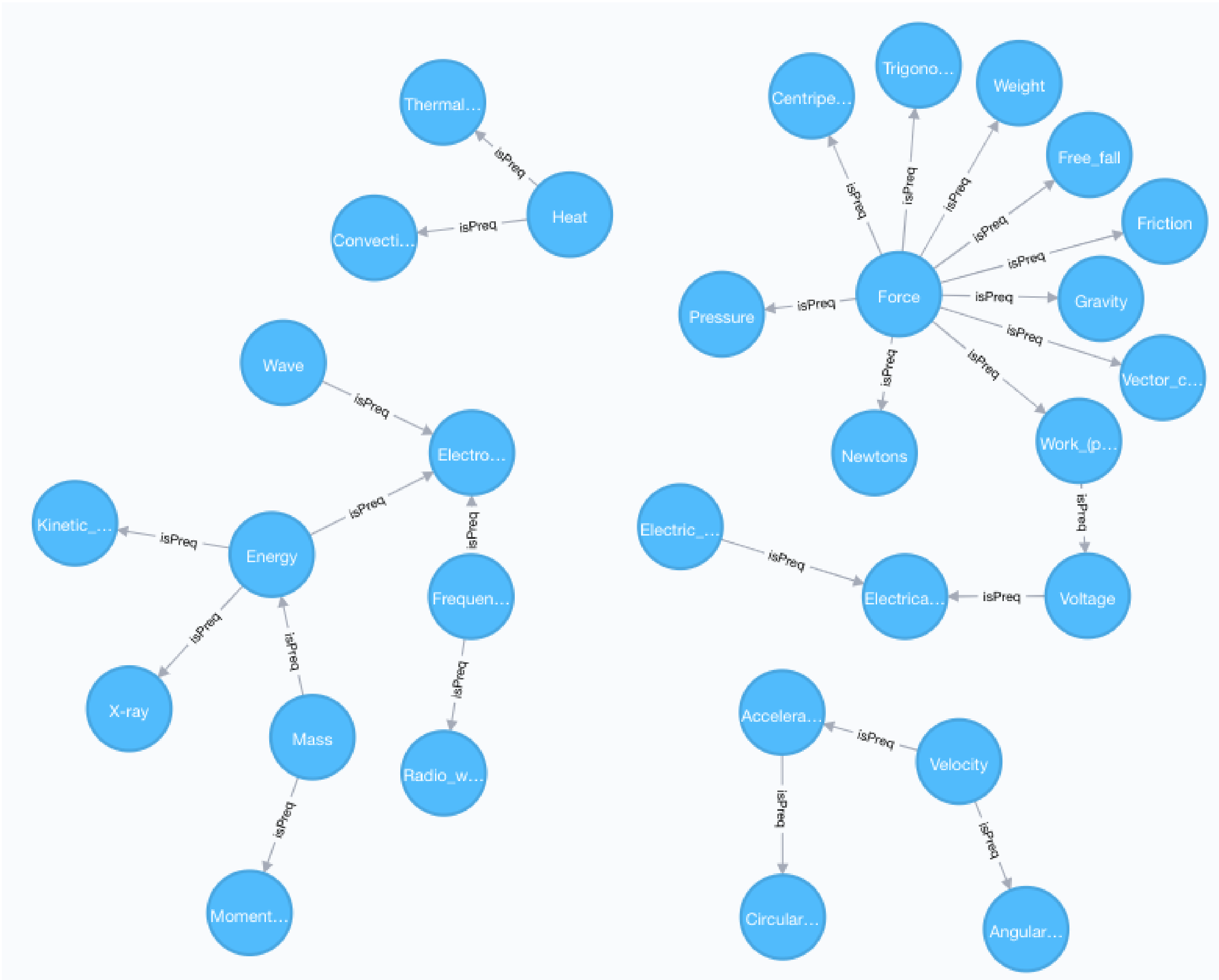
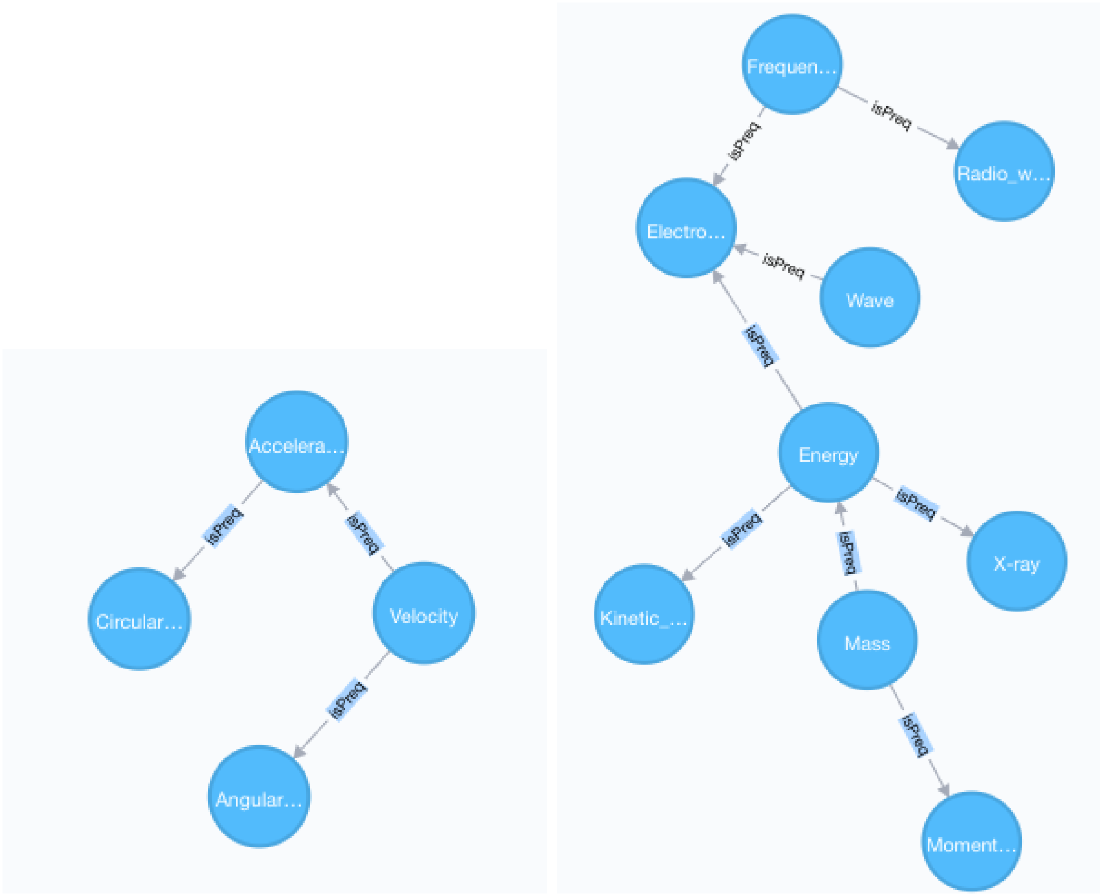


Figure 4.1: General View of the Graph

The Figure 4.1 is the general view of the graph. We see four different clusters indicating those 30 concepts can be gathered around in four different categories. In the following figures, we zoom into the clusters and look at some individual prerequisite relationships found between concepts.

We see four concepts in the first cluster. We observe that *Velocity* is a prerequisite



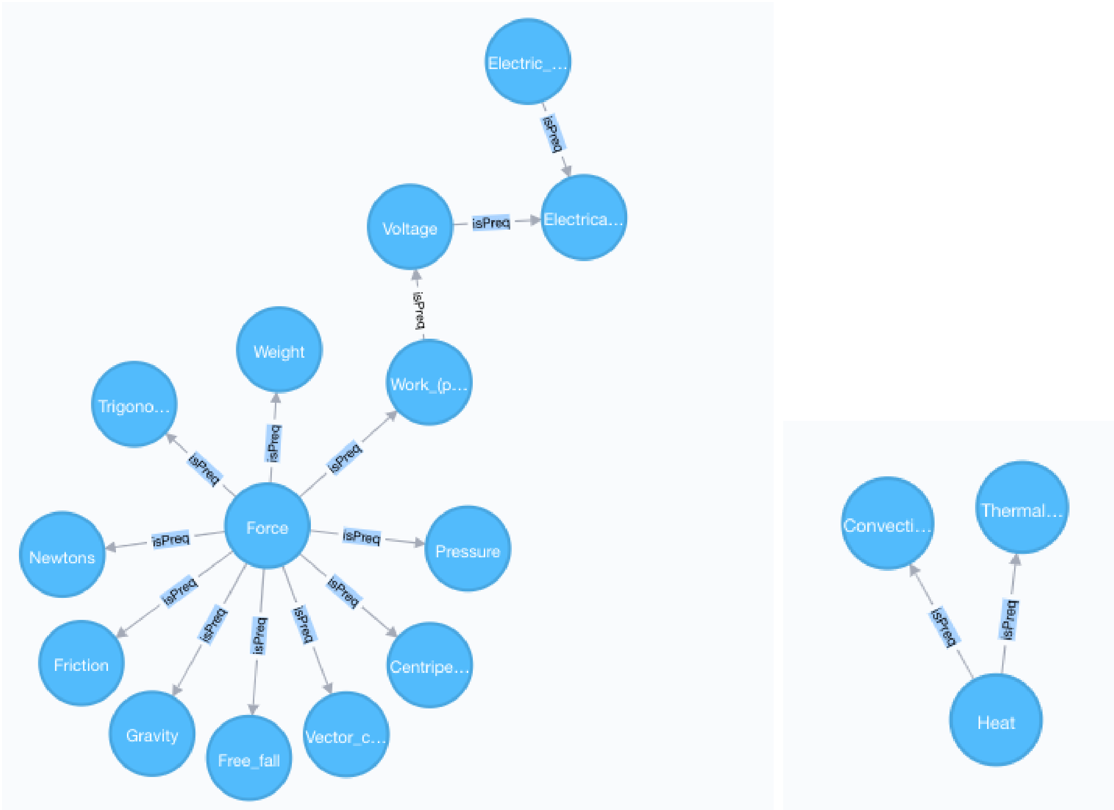
(a) Cluster 1 (b) Cluster 2

Figure 4.2: View of Cluster 1 and Cluster 2

for *Acceleration* and *Angular velocity*, and *Acceleration* is a prerequisite for *Circular motion*. Although not shown in Figure 4.2, it is possible to click the edges in the graph database and see the weights of each edge. The concepts in this cluster belong to a topic of *motion* at a higher level.

The second cluster has nine concepts inside. We observe that *Mass* becomes a prerequisite for *Energy* and *Momentum*. It makes sense as both of these concepts include mass in their formulas and if one does not know what mass is then she can not understand those concepts as well. *Electromagnetic radiation* requires knowledge of the concepts *Wave*, *Frequency*, and *Energy*. These concepts in this cluster may belong to a topic of *electromagnetic waves* at a higher level.

In cluster 3, we see that *Force* is at the core of all concepts. Almost every concept requires knowledge from *Force*. *Gravity*, *Friction*, *Weight* and *Pressure* has the strongest prerequisite relationships with *Force* than the other concepts in the cluster.



(a) Cluster 3 (b) Cluster 4

Figure 4.3: View of Cluster 3 and Cluster 4

We should note that although for a given concept c_i we only draw an edge to its strongest prerequisite (or from its prerequisite to c_i), we still don't put a universal threshold for the concepts in the graph. For example, an irrelevant concept may have a prerequisite relation to some concept of A with weight 0.01 in the list and it may have zero prerequisite relationship with the others. In that case, that concept's strongest prerequisite relation score is still 0.01 and we draw an edge for that relation. Our graph database provides an interface to any application-level service, therefore, it is possible to query the prerequisite scores of any concept pair in the graph. Furthermore, applications using our graph database can put their own thresholds if they want to filter out the weak prerequisite relations in the graph. For instance, application A can state that the prerequisite scores below 0.5 will not be considered as meaningful relations or application B can take this threshold up to 0.8 etc. If the graph were to be constructed by a human expert, she would separate the concepts *Voltage*, *Electrical current* and *Electrical resistance* but our algorithm found a bridge concept *Work* which connects these clusters together. Indeed the definition of the change in voltage is equal to the work per unit charge [23] and one should be familiar with concept *Work* before studying concept *Voltage*. The last cluster has three concepts inside and we see that concept *Heat* is a prerequisite for the concepts *Convection* and *Thermal conduction* which is an expected result.

4.2.3 Database Management System Concepts

In the second experiment, we give a set of 45 database management system concepts to our system. The general overview of the graph is presented in Figure 4.4

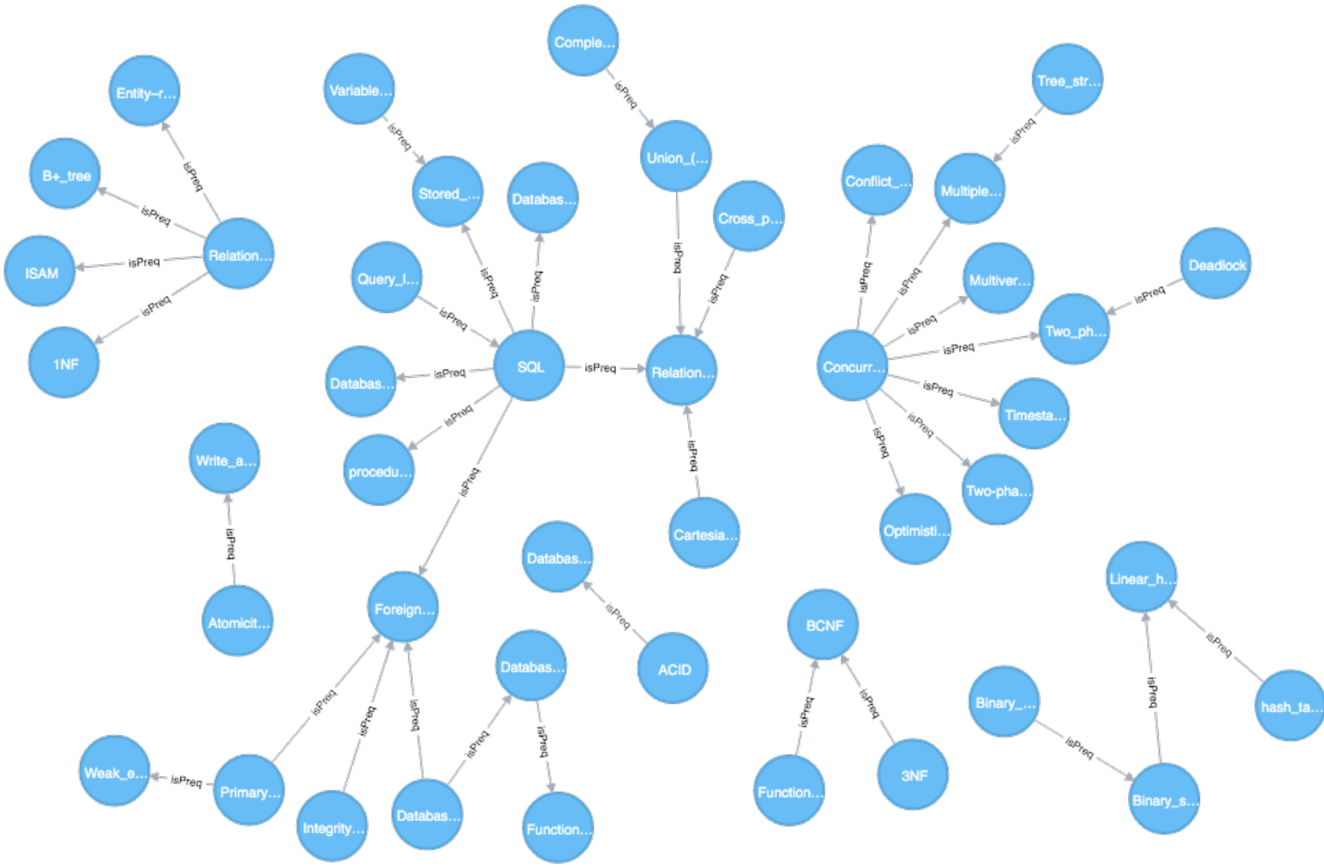


Figure 4.4: General View of the Graph

We observe again that similar concepts are gathered in the same clusters. There are six clusters, representing the topics of relational databases, concurrency control, data structures, database normalization, database recovery, and database indexing.

We test some individual concept pair's prerequisite scores by sending queries to our graph database to see if our graph is giving correct information or not.

```
MATCH (n)-[r:isPreq]->(m) where n.title="Primary_key"
and m.title="Foreign_key"
return r.weight as weight
```

We get a return value as : "weight" 0.999759287115

Indeed concept *Primary key* is a prerequisite of *Foreign key* and we get a value very close to 1. It is important to note that weights are always positive and we understand the direction of the prerequisite by looking at the direction of the arrow or if we are writing a query, we specify it in the *MATCH* statement with the symbols $(n) - [r : isPreq] - > (m)$ where n and m are the concepts we are questioning, r is the type of the relation and $- >$ symbol is the direction of this relation.

Here are some strong prerequisite relationships captured by our methodology in the graph :

Table 4.1: Prerequisite Scores

Concept A	Concept B	Weight	Direction
Primary Key	Foreign Key	0.99	$- >$
Concurrency Control	Conflict Serializability	0.85	$- >$
3NF	BCNF	0.80	$- >$
SQL	Query Language	0.74	$< -$
Hash Table	Linear Hashing	0.97	$- >$

We hope that this graph becomes a helpful tool for the students who are interested in learning database management course. Although not implemented in this experiment, the Wikipedia links of the corresponding articles can easily be inserted inside the nodes so that the learner can immediately find the article and start studying.

4.3 Graph Generalization

In this section we refer again to the physics data-sets that is explained in Section 4.2.2. When we formed our graph for the 30 high school physics concepts, we observed four different clusters each representing a different topic in the given context. We denote each cluster with the C_a, C_b, C_c, and C_d. C_a has the concepts regarding the topics of *Heat* and *Heat transfer*, C_b has the concepts regarding the topic of *Motion* C_c has the concepts of *Energy* and *Electromagnetic waves*, and C_d has the concepts of *Force* and *Electricity.* Below you can see each cluster with its concepts :

$Cluster\ a = \{Heat, Convection, Thermal\ conduction\}$
$Cluster\ b = \{Circular\ motion, Angular\ velocity, Velocity, Acceleration\}$
$Cluster\ c = \{Kinetic\ energy, Radio\ Wave, Momentum, X\text{–}ray, Energy, Wave,$
$Frequency, Electromagnetic\ radiation, Mass\}$
$Cluster\ d = \{Trigonometry, Electrical\ resistance, Newton's\ laws\ of\ motion, Force,$
$Vector\ calculus, Friction, Pressure, Weight, Centripetal\ force, Free\ fall, Voltage,$
$Electric\ current, Gravity, Work\}$

According to the algorithm provided in Section 3.3 we should calculate each cluster's prerequisite relation with other cluster and form the new prerequisite matrix S'. After the calculations we find the new matrix S' to be :

$$S' = \begin{pmatrix} 0 & 0.014 & 0.989 & 0.460 \\ -0.005 & 0 & -0.210 & 0.080 \\ -0.184 & 0.263 & 0 & -0.170 \\ -0.150 & 0.312 & 0.148 & 0 \end{pmatrix}$$

Where the rows and the columns of the matrix are aligned according to order C_a, C_b, C_c, and C_d.

One thing to note is that in the new matrix S' we don't have the $s'_{ij} = -s'_{ji}$ property anymore because each cluster's score with the other cluster is divided into its cluster size. In order to state a valid prerequisite relationship between any cluster i and j, we seek the condition that if $s'_{ij} > 0$ then $s'_{ji} < 0$ or vica versa meaning that both clusters should agree about the direction of the prerequisite relationship or else they will be discarded. Assuming that a cluster pair agrees on the direction of the relationship, to be able to calculate their score we perform the operation $\|(s'_{ij} - s'_{ji})\|/2$ to come up with the final weight score.

Continuing with our example, we analyze the new score matrix S' and at each row, we pick the highest absolute value.

For the cluster C_a, the highest absolute value in its row is 0.989, therefore, C_c is a prerequisite of C_a and we should draw an edge from C_c to C_a. For the cluster C_b, the highest value in its row is -0.21 hence C_b is a prerequisite of C_c and we should draw an edge from C_b to C_c. For the third row, we observe that C_c's strongest prerequisite is C_b and we again draw an edge from C_b to C_c. For the last row we observe that C_b should be a prerequisite of C_d with the highest value being $s'_{db} = 0.312$. However, $s'_{bd} = 0.08$ is also positive meaning that there is not a clear agreement between the direction of the prerequisite relationship, therefore, we leave cluster d out.

We calculate the weights as: :
$\|(-0.210 - (0.263))\|/2 = 0.473$ for the edge E_{bc}.
$\|(0.989 - (-0.184))\|/2 = 0.586$ for the edge E_{ca}

Now the second level graph is formed as shown in Figure 4.5 :

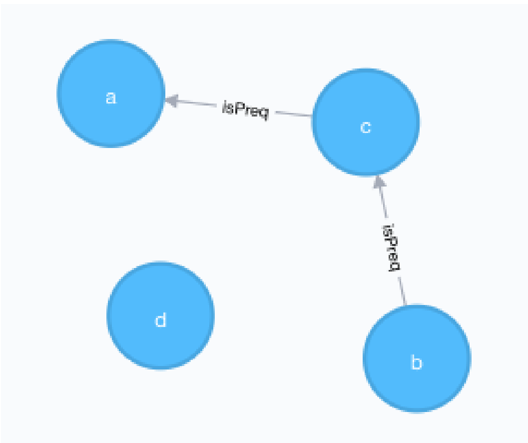


Figure 4.5: Second Level Physics Graph

Observing Figure 4.5 we conclude that topic speed and motion (C_b) is a prerequisite for the topic energy and electromagnetic waves (C_c) and the topic energy and electromagnetic waves is a prerequisite for understanding the topic heat and heat transfer (C_a).

Now the second graph can be further divided into two new clusters C_1 and C_2. In C_1 there are former clusters C_a, C_b, C_c and in C_2 there is only C_d. It is possible to re-do the procedure above to determine if there is any prerequisite relationship between the clusters by observing the matrix S'. Since C_1 has only the topic C_d, the element with the largest absolute value in the last row of S' will determine the prerequisite score from C_2 to C_1 which is 0.312. For calculating a score from C_1 to C_2, we consider each elements (C_a, C_b, C_c) prerequisite score with C_d which are 0.460, 0.08 and -0.17 respectively. Summing these values up and dividing them to the size of C_2 yields a score of 0.123. Since both of these scores are positive we conclude that they do not agree on the direction of the prerequisite relationship and we do not assign a prerequisite relation between the clusters.

Although not considered in our methodology, if the user wants to force prerequisite relationships between clusters and does not want to see any left out clusters in the graph she can do the following: If cluster c_i and c_j have both negative scores s_{ij} and s_{ji}, it implies that cluster c_i is a prerequisite of c_j and cluster c_j is a prerequisite of c_i. In that case, we can simply pick the cluster which has the score with the maximum absolute value and draw an edge from that cluster to the other cluster. We can calculate the weight score as $\|(s'_{ij} - s'_{ji})\|/2$. If cluster c_i and c_j have both positive scores s_{ij} and s_{ji}, this time it implies that cluster c_j is a prerequisite for cluster c_i and cluster c_i is a prerequisite for cluster c_j. In that case, we can pick the cluster which has the score with the maximum absolute value and draw an edge from that cluster to the other cluster. The weight determination is same in both cases with the operation $\|(s'_{ij} - s'_{ji})\|/2$. This approach creates an alternative graph that does not contain any disconnected components.

When we perform this alternative algorithm to our example in the second level graph, C_b is a prerequisite for C_d with a score of 0.312 and cluster C_d is a prerequisite for C_b with a score of 0.08. We consider the score with the highest absolute value which is 0.312, therefore, we conclude that C_b is a prerequisite for cluster C_d. We calculate the weight as $\|(0.312 - 0.08))\|/2 = 0.116$ and we conclude that C_b is a prerequisite for cluster C_d with a prerequisite score of 0.116. Our alternative second level graph is shown in Figure 4.6.

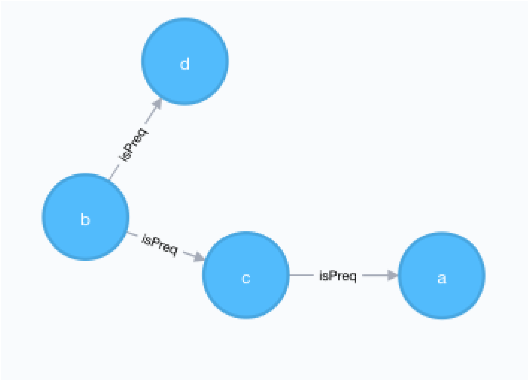


Figure 4.6: Second Level Alternative Physics Graph

In our alternative graph, the learner can have two preferences. If she wants to master concepts regarding heat and heat transfer (C_a) she first needs to master the concepts of motion (C_b) and then master the concepts of energy and electromagnetic waves (C_c) and then start learning topic C_a. Alternatively, if the learner wants to master the whole context (all of the topics in high school physics) she should start with topic C_b, then she can study topics C_c and C_d and then she can study the topic C_a to finish the given graph.

The constructed graph is aimed to serve the learner as a tool to facilitate her learning process. The graph can be enriched in many ways and we believe it has the potential to increase student performance in lots of different courses. These ideas and possible future applications of these prerequisite concept graphs are discussed in Chapter 5.

Chapter 5

Conclusion and Future Work

In the quest of finding an organized representation of the huge unstructured online learning materials, we believe that the concept prerequisite graphs constructed through our methodology will guide the learners in their learning process. We also provide an extendable framework on top of which many more innovative ideas can be developed.

The prerequisite score calculations are currently based on the articles on Wikipedia. We use three main features in prerequisite score calculation but there can be other important features that may contribute to prerequisite scores as well. For instance, one can also include the reference position of the concept in the article as a new feature or one can consider the size of the article when calculating the reference feature and so on. With the addition of the right features, we think the classification performance of our system may be further increased.

We choose to seek the concepts in Wikipedia because of its useful properties that we mentioned throughout the thesis but it is also possible to incorporate knowledge from other resources to calculate prerequisite scores. Those resources can be video as well as text-based.

In the graph construction algorithm, we always include a concept's strongest prerequisite in order to avoid possible cycle formations. However, there may be an alternative algorithm where not only the strongest prerequisite but also multiple strongest prerequisites may be used while still preserving the acyclic property of the graph. In Section 4.2.2 we mention a universal threshold that each prerequisite score needs to pass. In our work, we don't have this kind of threshold. However, with various experiments on large data-sets it may be helpful to come up with such a threshold which can guarantee that there are no weak prerequisite relations in the graph.

Besides the algorithmic part, if we go back to our initial objective of enhancing student learning experience there can be several components in the graph that may help the students. For example, a questioning component may be added to the graph. Each node in the graph may be enriched with multiple questions regarding its concept. If the student wants to move on to another concept that the current concept is a prerequisite of, she may have to correctly answer the questions of that concept so that we understand that the student fully grasped the content in that topic. Since each node is, in fact, a Wikipedia article, the nodes can also include links to these articles. Furthermore, for the same topic there can be multiple different resources so that if a student does not understand the article, she may move to the alternative resources.

Once the graph is formed, it is stored in a graph database and it can be implemented as a web service to other systems. An intelligent adaptive learning management system may use this database to present learning paths to students according to their objectives. By keeping track of each student's profile and the past data, the intelligent system can change the weights of the edges if it thinks there are other alternative prerequisite relations based on the student data it has.

The domain invariant property of the algorithm makes the system a useful learning tool not just for computer science, and physics courses but for other courses from other domains. We believe that especially the students studying courses that require lots of reading and domain- specific terminologies such as biology or literature will benefit most from our system.

Appendix A

Tabular results of evaluations on each data-set

Table A.1: Evaluations on physics data-set with a threshold value of 0.8.

Concept1	Concept2	Prerequisite Score
Mass	Energy	-0.991872536275
Mass	Momentum	-0.948114245534
Mass	Kinetic energy	-0.963246383255
Mass	Convection	-0.971735686337
Velocity	Force	-0.982055478863
Velocity	Acceleration	-0.975253748977
Velocity	Momentum	-0.911654216016
Velocity	Circular motion	-0.855230213027
Velocity	Angular velocity	-0.999999999054
Velocity	Work (physics)	-0.850958772409
Force	Gravity	-0.998362023493
Force	Weight	-0.999834071543
Force	Friction	-0.999844596391
Force	Circular motion	-0.906887422963
Force	Centripetal force	-0.999723106557
Force	Newtons laws of motion	-0.992735971457

Table A.2: Evaluations on physics data-set with a threshold value of 0.8.

Concept1	Concept2	Prerequisite Score
Force	Work (physics)	-0.999915440679
Force	Free fall	-0.954538589358
Force	Pressure	-0.988458568502
Acceleration	Circular motion	-0.972457410798
Energy	Friction	-0.99901259911
Energy	Heat	-0.999996465462
Energy	Thermal conduction	-0.997922157957
Energy	Kinetic energy	-0.99999601306
Energy	Electromagnetic radiation	-0.99999728113
Energy	X-ray	-0.921038883094
Energy	Wave	-0.916567809217
Gravity	Free fall	-0.938609274061
Friction	Work (physics)	0.800898909263
Friction	Kinetic energy	0.88966442389
Heat	Thermal conduction	-0.999998584781
Heat	Work (physics)	0.999889373899
Heat	Convection	-0.999999795139
Frequency	Electromagnetic radiation	-0.999920774246
Work (physics)	Voltage	-0.821566035606
Electromagnetic radiation	Wave	0.995985341382

Table A.3: Evaluations on database management systems data-set with a threshold value of 0.5.

Concept1	Concept2	Prerequisite Score
Entity relationship model	Relational database	0.574905971913
Database design	Foreign key	-0.917743478419
Database design	Database normalization	-0.810222201105
Primary key	Foreign key	-0.999759287115
Primary key	Weak entity	-0.99643657114
Foreign key	SQL	0.933692406412
Foreign key	Weak entity	-0.821307950347
Foreign key	Stored procedure	0.529595722782
SQL	Query language	0.74519392494
SQL	Stored procedure	-0.846331854774
1NF	Relational database	0.808997494714
3NF	BCNF	-0.801929651851
ACID	Database transaction	-0.515820232241
Atomicity (database systems)	Write ahead logging	-0.530019702361
BCNF	Functional dependency	0.794670233574
Concurrency control	Conflict serializability	-0.852474283314
Concurrency control	Multiversion concurrency control	-0.978476116184
Concurrency control	Optimistic concurrency control	-0.989795078295
Concurrency control	Timestamp-based concurrency control	-0.822766390581
Concurrency control	Two phase locking	-0.555309700087
Database normalization	Functional dependency	-0.538208598348
Database normalization	Relational database	0.557931828985
Functional dependency	Relational database	0.523605637531
Hash table	Linear hashing	-0.975295097481
Weak entity	Relational database	0.558951593337

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