Slide-recommendation System: A Strategy for Integrating Instructional Feedback into Online Exercise Sessions

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Abstract: A structured learning behavior needs an understanding of the learning environment, the feedback it returns, and comprehension of the task requirements. However, as observed in the activity logs of our SQLValidator, students spend most time doing trial-and-error until they came to the correct answer.While most students resort to consulting their colleagues, few eventually acquire a comprehension of the rules of the SQL language. However, with instructional feedback in form of a recommendation, we could reduce the time penalty of ineffective engagement. To this end, we have extended our SQLValidator with a recommendation subsystem that provides automatic instructional feedback during online exercise sessions. We show that a mapping between SQL exercises, lecture slides, and respective cosine similarity can be used for providing useful recommendations. The performance of our prototype reaches a precision value of 0.767 and an $F_{\beta=0.5}$ value of 0.505 which justifies our strategy of aiding students with lecture slide recommendation.

1 INTRODUCTION

The beauty of traditional task exercise sessions is the on-hand availability of instructors to provide guidance, corrections to tasks, and immediate feedback to questions that arise in the course of learning. However, owing to new regulations that require online dispensation of lectures and corresponding exercises, the use of online tools and platforms, such as Moodle (Costello, 2013), Blackboard (Machado and Tao, 2007), and the SQLValidator (Obionwu et al., 2021), for lecture administration, and collaborative learning (Obionwu et al., 2022) is the new standard. This switch to online learning platforms, while making learning flexible, mostly erases direct instructional feedback, which is necessary for computer science and engineering-related disciplines. Moreover, for learners that are new to programming languages like the structured query language, SQL, absence of instructional feedback results in a trial and error-based form of learning engagement which results in a high count of easily avoidable errors and an inconvenient time penalty that leads to frustration. Thus, instructional feedback is necessary to aid novice students in bringing their task engagement behavior into conformity with the rules of SQL. Ergo, we integrated automatic recommendations into the exercise task engagement workflow. Hence, student need not get frustrated as the feedback is persistent, automatic, and efficient compared to traditional settings. Our implementation relies on content-based filtering since the pedagogical aspects of the database concepts course, corresponding exercise tasks, and student's proficiency levels are already known (Charu, 2016). Hence, feedback provided to students are enriched with recommendations that point to sections of our lecture material containing SQL topics, and sample queries necessary to successfully solve the exercise task in question. Compared to related efforts at student SQL learning engagement improvement, optimization, and skill acquisition, our method:

- provides meaningful instructional feedback during individual online exercise sessions.
- fosters SQL skill acquisition by linking SQL theory with corresponding exercise tasks.

In the following, we first present related work. In Section 3, we present the conceptual idea of our following implementation in Section 4. We evaluate our implementation in Section 5 and discuss challenges in Section 6. Finally, in Section 7, we conclude our work.

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2 RELATED WORK

Several systems were developed to foster SQL learning. An educational tool developed by Arizona State University enables the students to learn about relational query languages by letting the students solve their homework assignments using their tool (Dietrich, 1993). However, the students receive their feedback directly from the interpreter, and thus we assume the feedback to be too technical to be understood by class participants with minor knowledge about SQL. In comparison, our recommendation point's students to the lecture material that explains the correct usage of SQL concepts, thus reduces the time penalty of the trial and error pattern. Another tool that supports students at learning SQL is the SQL-Tutor developed by the University of Canterbury (Mitrović, 1998) and used at many universities around the globe. The tool prompts students to solve SQL-related exercises and, while doing so, it provides different stages of feedback to the students. The feedback although is restricted to the task at hand and is not utilizing the learning materials of the course. Another tool, the SQL Tester (Kleerekoper and Schofield, 2018), is an online assessment tool based on a 50-minute test that comprises ten questions. These questions are based on a table with different categories of SQL concepts. There is no limit to the number of trials that a student can attempt the test. However, the students only received the regular error messages from the RDBMS as feedback. We are not aware of any research that is trying to improve the SQL learning experience by automatically connecting exercises to the material of the lecture. In general, no techniques have been proposed to improve SQL learning experience by integrating our method of instructional feedback.

3 CONCEPTUAL FRAMEWORK

Several systems have been developed to facilitate SQL skill acquisition. SQLValidator (Obionwu et al., 2021) is one of such web-based tools.It is an integral part of the database courses held is our faculty, and encompasses exercises, questionnaires, and tests to assess students' SQL programming skills. In the next subsection, we describe the Concept of analyzing the lecture's slides

3.1 Analyzing the Lecture's Slides

Being that our aim is to support students in solving SQL exercises by recommending slides from the lecture that relates to the exercise they engage with, we restrict the analysis of the lecture slides to the chapters that contain SQL query-related information required in the exercises. Ergo, the lecture slide analysis workflow consists of the following activity blocks: slide conversion, preprocessing, keyword recognition, and keyword analysis as shown in Figure 1. These activities are briefly described in the subsections below.

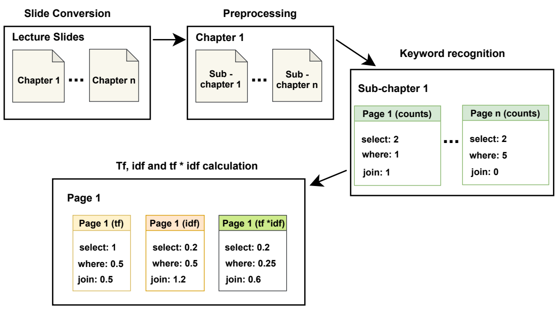


Figure 1: Lecture slide analysis workflow.

3.1.1 Slide Conversion & Preprocessing

The objective of the slide conversion step is the extraction of relevant information from lecture slides. To achieve this, we first convert a selected chapter from PDF file format into a string format, enabling us to further examine the textual contents of the chapter. From here, we transit to the preprocessing activity as shown in Figure 1. The objective of the preprocessing stage is to clean the string data from the slide conversion step (Famili et al., 1997; Nadkarni et al., 2011). To execute the preprocessing step, the strings are normalized and tokenized, splitting the normalized strings into individual word stems. After this process, the stop words are removed. Also at this stage, further separation into subchapters, and partitioning into pages are done as shown in Figure 1.

3.1.2 Keyword Recognition

This task aims to detect a slide's topic designation. Thus, the subchapters are broken down into pages, and their contents are parsed, and stored for further analysis. Then, for each page, the number of occurring SQL keywords is counted. A list of relevant keywords is predefined for this event. A sample list of detected keywords is shown in the keyword recognition block. We observed that the frequency of the keyword in a page is insufficient for deriving the slide's designation, as some keywords like the "SELECT" occur too often. Hence, we further perform keyword analysis. Requisite for keyword analysis is the computation of term frequency tf of a term, which can easily be done by taking a count of all occurrences of a keyword in a document (Manning et al., 2008).

We further observed that larger documents are more likely to repeat terms, which results in higher tf values in comparison to smaller pages. To eliminate the effect of page length, we employ the maximum tf normalization technique (Leskovec et al., 2014).

3.1.3 Keyword Analysis

Having evaluated, and normalized the term frequency, we discriminate the pages from each other based on term occurrences using a heuristic approach, inverse document frequency, (idf). The mere occurrence of a term in a document gives little or no insight into the document with respect to its topic. When a term appears seldom in the collection but occurs frequently in a specific document, this term provides a hint about how to distinguish the observed document from other documents of the collection. The idf value for each term t_i is calculated by dividing the corpus (number of documents), N, by the number of documents in which the term n_i appears and applying the logarithm, The term frequency multiplied with the result of the formula below equals the tf*idf value.

The inverse document frequency assigns a weight to each keyword based on the number of pages the keyword appears in. The keyword recognition block in Figure 1 shows the idf values for the three keywords WHERE, SELECT, and JOIN. The WHERE keyword appears less often than the SELECT clause, and the JOIN keyword among these three keywords is least often featured in the slides. Thus, in the lower part showing the calculations, the JOIN keyword receives a weight of 1.2 while the WHERE and SELECT clauses receive an idf value of 0.5, and 0.2 respectively. Next, we proceed to multiply the tf and idf values for each keyword to compute the tf*idf value.

The Tf*idf (*term frequency times inverse document frequency*) is used as a term weighting system to calculate a weighing which translates to the influence that a keyword has on a page. Figure 1 shows the JOIN keyword to have the highest tf*idf value with 0.6 compared to 0.25 for the WHERE clause and 0.2 for the select keyword (Ramos et al., 2003; Wu et al., 2008). Thus, we estimate the topic of the page to be mostly about joins. As a result, we can use these tf*idf values for the typical SQL keywords to extract the topic of a slide that can be compared to the topic of the SQL exercise task. This process, Figure 1. is repeated for the lecture slide.

3.2 Comparing Slides and Exercises

Having processed respective slides and SQL exercises, Section 3.1, into a comparable format, we use the cosine similarity between the lecture slides and SQL exercises as a comparison metric. A depiction of this process for a hypothetical Exercise 1 is shown in Figure 2. It consists of the following steps: merging of previous analysis, computation of cosine similarity, and mapping of exercises to pages with the highest cosine similarity.

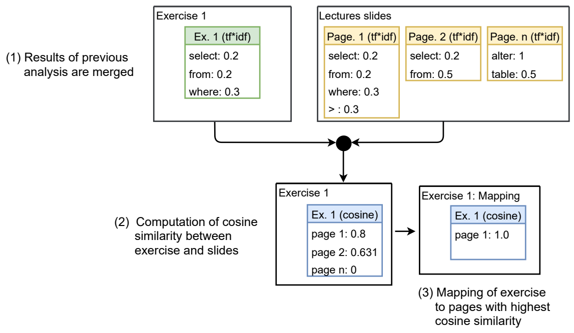


Figure 2: Concept of combining the analysis results for the lecture slides and SQL exercises.

In the merge stage, the slides and exercise analysis are merged into a list during the first step of the comparison process. Thus, for each exercise, we now have access to the tf*idf values from every page with respect to this exercise. Figure 2 shows the mapping between Exercise 1, and each page alongside the result of their keyword analysis. Having performed the merging, we evaluate the cosine similarity, i.e.,the angle between two-word vectors (Sidorov et al., 2014). In our use case, the word vectors consist of keywords recognized from a query or lecture slide. A low angle between those vectors means that the content of the vectors is similar, while a high angle expresses dissimilar content. An advantage of using the cosine angle as a similarity metric is that the length of the vectors is not relevant. As a result, the cosine similarity for each page of the lecture is calculated in regard to Exercise 1. The result shows that Page 1 has the highest cosine similarity of 0.8 followed by Page 2 with 0.631, and Page n with 0. The page with the best cosine value, in this case, Page 1, is then selected to be mapped to Exercise 1, and hence recommended to students having a problem with Exercise 1.

4 KEYWORD AND JOIN RECOGNITION

Keywords, being a vital part of our system as they are used every time we search for the occurrence of certain SQL keywords, we implemented a tool to create a customary keyword lists that contain specific SQL keywords selected by the administrator. For example, there are SQL keywords available in our implementation, such as CONCAT, that are currently not mentioned in the lecture. Since this could also change in the future, our implementation already supports a wide variety of keywords. We now show the process of mapping slides to exercises by walking through a recommendation for Exercise *E* that is about the update operation:

Update wine set vintage = vintage +1
Where color = ’red’;

The keyword analysis for Exercise *E* is displayed in Table 1 with WHERE and UPDATE recognized once and the equality sign twice. The idf values reveal that the UPDATE keyword is the rarest keyword of these three with an idf of 1.82 compared to 0.301 for the WHERE keyword and 0.519 for the equality sign. A tf*idf value of 0.91 is assigned to the UPDATE statement, which means that it is the most important SQL keyword for the Exercise *E*.

Table 1: Keyword analysis for exercise *E*.

keywords	count	tf	idf	tf-idf
Where	1	0.5	0.301	0.151
Update	1	0.5	1.82	0.91
=	2	1	0.519	0.519

Table 2: Keyword analysis of the recommended page to exercise *E*.

Chp: 2, Page: 34, Cosine: 0.984				
keywords	count	tf	idf	tf-idf
where	1	0.5	0.507	0.254
update	2	1	1.109	1.109
in	1	0.5	0.273	0.137
=	2	1	0.556	0.556
as	1	0.5	0.316	0.158

Our system declares the 34th page of the second chapter as the most similar slide of the lecture. The keyword analysis for this slide is shown in Table 2 with the keywords WHERE, IN, AS recognized once and UPDATE and equality sign twice. The cosine similarity between Exercise *E* and the recommended page with 0.984 is close to one, which resembles a high similarity.Compared to keyword recognition, the recognition of joins needs a more sophisticated effort because joins in SQL can either be created with the JOIN keyword or by the usage of the WHERE keyword. In case of a join in the form of the WHERE keyword, simply counting the number of keywords would lead to an increase of recognized equality signs and WHERE keywords, but a JOIN would not be recognized. We have implemented a way to recognize those disguised joins in our implementation. An example of a join formulated by using the WHERE keyword in ***Query 4*** below

select Name, Vintage, PRODUCER.Vineyard

Table 3: Keyword analysis of the recommended page to exercise *E*.

keywords	where	update	in	=	as
Count	1	1	1	1	1

Table 4: Method to recognize joins in the WHERE clause.

1	$ join_stack = [ ] ;
2	array_push ($ join_stack , ’ where ’ , ’ ’ , ’=’ , ’ n . ’) ;
3	foreach ($uni_gram as $ index =¿ $ entry) :
4	if (preg_match ($ join_stack [0] , $ entry) != false)
5	if (sizeof ($ join_stack) ¿ 1) array_shift ($ join_stack) ;
6	else {
7	array_shift ($ joins_tack) ;
8	array_push ($ join_stack , ’where ’ , ’’ , ’=’ , ’’)
9	$ join_counter++;
10	}
11	end foreach ;
12	return $ join_counter ;

Table 5: Keyword recognition of page 21 from chapter six after enabling join detection.

keywords	select	from	join
Count	1	1	1

from WINES, PRODUCER
where WINES.Vineyard = PRODUCER.Vineyard;

The keyword analysis of the above query is displayed in Table 3. The SQL keywords SELECT, FROM, WHERE and = are recognized once. The desired behavior would be to recognize the keywords SELECT, FROM and JOIN once each.

Table 4 shows the conceptual implementation of the join recognition. We employ an array $\$join\_stack$ that stores the elements ’where’, ’.’, ’=’, ’.’ in this exact order. In Line 3, the content of a page is read in as one-liners. For each word, we test if this word is equal to the first element in the $\$join\_stack$. If the word is equal to the first element, we remove it from the stack. This will be repeated until the stack is empty, indicating that each keyword necessary to describe a join has been found, and therefore we increment the $\$join\_counter$ variable. The $\$join\_stack$ is being filled again with keywords, and we resume the join detection until every word of the page has been read in. In the end, we return the number of detected joins stored in the $\$join\_counter$ variable of Line 12.

Considering ***Query 4***, we can now correctly declare the recognized keywords in Table 5. There is one JOIN keyword detected, while the WHERE and equality sign disappeared.

5 EVALUATION

Since our objective is the integration of automatic instructional feedback into online exercise sessions, we resorted to adding the recommendation feature to our exercise administration tool, SQLValidator. This required the analysis of our lecture slides, and SQL exercise tasks. The keyword list has a significant influence on the mapping between slides and exercises. Thus, based on the performance, we collated a list of relevant keywords from a pool of SQL keywords containing 58 elements.

Furthermore, to evaluate the usefulness of a mapping between slides and exercises, a ground truth is required. Thus, we manually labeled the SQL exercises so for each exercise there is a stored selection of recommendable lecture slides. The decision of which slides shall be recommended for a particular exercise might be a topic of discussion. Depending on the experts' view, the selection of suitable slides can be either flexible or strict. As a result, the evaluation is greatly influenced by the experts' labeling. We mitigate this problem by using multiple experts in the labeling process instead of a single expert.

5.1 Performance Measures

We will evaluate the performance of our implementation by computing several performance metrics.These are the standard performance metrics (Sokolova and Lapalme, 2009; Bradley et al., 2006; Alvarez, 2002):
Accuracy: the fraction of slides correctly predicted as being recommendable plus the number of slides that were correctly not recommended to the students,
Precision: an estimate of the exactness of the recommendation,
Recall: an estimate how many slides that are labeled as positive were recommended to the students,
F-measure: a combination of precision and recall. We also use the F_β, which enables us to put more emphasis on one of the metrics, and therefore we chose to weigh the precision value higher. Therefore, we chose 0.5 for our β parameter.

5.2 Baseline Evaluation

The baseline evaluation of our system derives a mapping between slides, and SQL exercises by purely computing the cosine similarity without using any additional parameters. Only the preferred way of calculating the idf values has to be selected. Using the baseline approach means that only the slide with the highest cosine similarity will be selected for recommendation. If multiple slides are sharing the best cosine value, then they are recommended. The confusion matrix of the baseline approach using the idf$_{sub}$ computation is shown in Table 6. In our implementation, there are 180 slides, and 66 SQL exercises resulting in 11.880 entries in the confusion matrix. Out of the 70 entries predicted as positive, 38 were positive. There are 11.810 entries in the column predicted negative with 178 counted as false negative and 11632 as actually negative. The table cell of true negative entries is of interest to us since it contains a little more than 98% of all entries. This imbalance of instance distribution is expected because there are 180 possible recommendations for each exercise but usually, only a few slides for each exercise are labeled as recommendable. Suppose there is an exercise for which we selected three pages as appropriate. If our implementation recommended a random slide for this exercise, which turns out to be inappropriate for this exercise, there would still be 176 slides correctly classified as not recommendable and, hence, 176 entries are added to the true negative cell. This effect is reinforced by using the baseline approach, since the recommendation is restricted to only recommend the pages with the highest cosine value, further decreasing the number of slides that are recommended. Furthermore, the idf value of a keyword can also be calculated by considering, for all available pages, the number of occurrences of the keyword. Thus, we will refer to the subchapter-wise idf calculation as idf$_{sub}$, and the collection-wise idf values will be referred to as idf$_{col}$. The result for the baseline approach in combination with the idf$_{col}$ calculation is shown in Table 7. The idf variation is barely visible because the idf$_{col}$ method predicts 66 instances as positive, compared to 70 positive predictions in the idf$_{sub}$ computation. The difference in negative predictions is also negligible, with 11.810 negative predictions in Table 6 and 11.814 in Table 7.

Table 6: Confusion matrix of baseline approach with idf$_{sub}$.

	pred. pos.	pred neg.
actual pos.	38 (TP)	178 (FN)
acutal neg.	32 (FP)	11632 (TN)
total	70	11.810

Table 7: Confusion matrix of baseline approach with idf$_{col}$.

	pred. pos.	pred neg.
actual pos.	38 (TP)	178 (FN)
acutal neg.	28 (FP)	11636 (TN)
toal	66	11.814

Table 8: Performance metrics for baseline approach.

Metric	Accuracy	Precision	Recall	F-Measure	$F_{\beta=0.5}$
value$_{sub}$	0.982	0.543	0.176	0.266	0.383
value$_{col}$	0.983	0.576	00.176	0.27	0.396

Table 8 shows the performance metrics with respect to the confusion matrices from Table 6 and 7. The accuracy of both idf calculations is rather high, with 0.982 using idf$_{sub}$ and 0.983 using idf$_{col}$. This is mostly due to the previously described fact that most of the pages are correctly classified as true negative. The precision value of idf$_{sub}$ is slightly lower than the precision for idf$_{col}$ method with 0.576. That means slightly more than half of our baseline's recommendations are correct recommendations. Each of the remaining metrics recall, F-measure and $F_{\beta=0.5}$ are rather similar for both idf computations. The recall value for both methods is 0.176 which implies that around 17% of the slides classified as recommendable are selected by our system. The F-measure, which is influenced by the precision and recall metrics equally, reaches 0.266 with the idf$_{sub}$ and 0.27 with the idf$_{col}$. The most important metric in our use case is the $F_{\beta=0.5}$ which equates to 0.383 for the idf$_{sub}$ calculation and 0.396 for the idf$_{col}$. The performance metrics of the collection-wise idf approach are slightly better than the subchapter-wise idf. Therefore, we focus on the collection-wise idf calculation technique in the remainder because the peak performance will be achieved by using idf$_{col}$. Hence, by the baseline approach, we mean the baseline approach using the collection-wise idf from now on. In the following sections, we will improve the recommendation performance by utilizing our already introduced optimizations of join detection, clustering of keywords and minimal cosine values.

5.3 Detecting Joins

The join detection has a beneficial effect on the false negative and true negative predictions, although they profited percentage-wise significantly less compared to the positive predictions. Table 9 shows the confusion matrix of our join detection alongside the rate of change compared to the baseline approach using collection-wise idf values. Applying the join detection yields a positive effect on the classification results. The number of true positive predictions increased by 15.8% while the number of false-positive predictions decreased by 21.4%. The performance metrics of the baseline approach with and without join detection are shown in Table 10. Each of the performance metrics increased with the activated join detection. The accuracy value increased almost negligible from 0.983 to 0.984. The recall and F-measure improved more with 0.176 to 0.204 and 0.27 to 0.312 respectively. Especially noteworthy is the increase in the precision value from 0.576 to 0.667 through enabling the join detection.

Table 9: Results of activated join detection compared with baseline approach.

idf$_{col}$	pred. pos.	pred neg.
actual pos.	44 ↑ 15.8%	172 ↓ 3.4%
acutal neg.	22 ↓ 21.4%	11642 ↑ 0.052%
total	66 ±0	11.814 ±0

Table 10: Performance with and without join detection.

Metric	Accuracy	Precision	Recall	F-Measure	$F_{\beta=0.5}$
¬(join detection)	0.983	0.576	0.176	0.27	0.396
join detection	0.984	0.667	0.204	0.312	0.459

5.4 Clustering Keywords

To improve our slide recommendation, we analyzed our data set and identify specific keywords that need to be clustered. This cluster consists of the keywords $<,>=$, and SELECT. This process of choosing suitable keywords is manual. Table 11 depicts the confusion matrix for this clustering approach. The clustering leads to 4.6% more true positive predictions, while the false positive recommendations were lowered by 9.1%. The performance metrics are displayed in Table 12 alongside the comparison to the former best approach without cluster usage, but with join detection. The application of the cluster causes the accuracy to increase from 0.983 to 0.984. More notably, the precision rises from 0.667 to 0.697. The recall value increases slightly from 0.204 to 0.213. The improvement of both the recall and precision values causes the F$_\beta$ value to increase from 0.459 to 0.479. Especially, the improved precision and F$_\beta$ metrics imply that the clustering of keywords enables our system to recommend useful slides to the students.

The improved performance due to the clustering is due to two more mappings between exercises and slides that are now done correctly. One of the exercises for which the prototype found the correct recommendation will be referred to as task E:

SELECT job, MIN** (ALLsalary) **AS min_salary
FROM employee
GROUP BY job;

The keyword analysis for task E yields the results shown in Table 13 with the recognized keywords SELECT, GROUP BY, GROUP, AS, MIN, and ALL. The MIN and ALL keywords have the highest tf*idf value with 1.217 assigned to it and therefore they are the most important keywords for this exercise.

The recommendation before clustering is incor-

Table 11: Confusion matrix of cluster application.

	pred. pos.	pred neg.
actual pos.	46 ↑ 4.6%	170 ↓ 1.2%
acutal neg.	20 ↓ 9.1%	11644 ↑ 0.02%
total	66 ±0	11.814 ±0

Table 12: Performance with and without clustering.

Metric	Accuracy	Precision	Recall	F-Measure	$F_{\beta=0.5}$
¬cluster	0.984	0.667	0.204	0.312	0.459
cluster	0.984	0.697	0.213	0.326	0.479

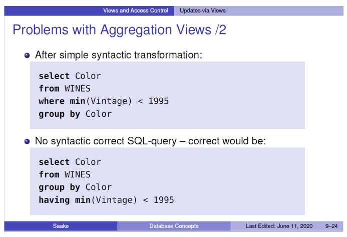
Table 13: Keyword analysis for task E from our system.

Chapter: 9, Page: 24, Cosine: 0.625						
keywords	select	group by	group	as	min	all
count	1	1	1	1	1	1
tf	1	1	1	1	1	1
idf by	0.087	1.121	1.121	0.405	1.217	1.217
tf*idf	0.087	1.121	1.121	0.405	1.217	1.217

rect, since the recommended page is not helpful to the students. The chosen page is the twenty-fourth page of the ninth chapter ”Views and Access Control”. Page 24 contains information about the problems with aggregation views, although task E does not feature any information about views. Hence, the recommendation of page 24 is not useful for students that are challenged by task E. Table 14 displays the keyword analysis for page 24. The keywords WHERE and HAVING were recognized once, and the keywords SELECT, GROUP BY, <, MIN, GROUP twice. The highest tf*idf values are reached by the keywords MIN at 1.556 and < with 1.352.

The recommendation to task E should contain information as to how the GROUP BY keyword can be used to aggregate data. Instead of recommending page 24 of the ninth chapter, the independent labelers chose page 61 of the sixth chapter, displayed in Figure 4 as a good fit for task E since it visualizes the process of using the GROUP BY clause.

The keyword analysis for our desired recommendation is shown in Table 15. Page 61 contains the three SQL keywords AND, GROUP BY and GROUP once with the GROUP BY keyword reaching a tf*idf of 1.109 and the GROUP clause following at 1.051. The comparison between Table 14 and Table 15 shows that the cosine similarity of page 61 with 0.625 is lower than the cosine value of 0.682 from the current recommendation. In order to change the recommendation from page 24 to page 61, we need to influence the cosine similarity between task E and the slides by creating a suitable cluster.


Views and Access Control | Updates via Views

Problems with Aggregation Views /2

- After simple syntactic transformation:

```
select Color
from WINES
where min(Vintage) < 1995
group by Color
```

- No syntactic correct SQL-query – correct would be:

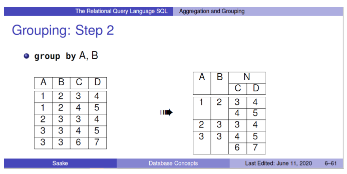
```
select Color
from WINES
group by Color
having min(Vintage) < 1995
```

Saake | Database Concepts | Last Edited: June 11, 2020 | 9–24

Figure 3: Incorrect recommendation of page 24 from chapter nine to task E before clustering.

Table 14: Keyword analysis of the incorrectly referred page 24 from chapter nine.

Chapter: 9, Page: 24, Cosine: 0.625							
keywords	select	where	group by	group	having	<	min
count	2	1	2	2	1	2	2
tf	1	0.5	1	1	0.5	1	1
idf by	0.347	0.484	1.109	1.051	1.301	1.352	1.556
tf*idf	0.347	0.242	1.109	1.051	0.651	1.352	1.556


The Relational Query Language SQL | Aggregation and Grouping

Grouping: Step 2

- group by A, B

A	B	C	D
1	2	3	4
1	2	4	5
2	3	3	4
3	3	4	5
3	3	6	7

A	B	N	
		C	D
1	2	3	4
		4	5
2	3	3	4
3	3	4	5
		6	7

Saake | Database Concepts | Last Edited: June 11, 2020 | 6–61

Figure 4: Page 61 of the sixth chapter, which should be chosen for recommendation.

Page 24 contains the < and SELECT keywords, with the SELECT clause being also shared with task E. We have a cluster in use that contains the SELECT and < statements and thus changes the tf*idf values of page 24. The performance evaluation of page 24 is shown in 16 with the SELECT keyword having a tf*idf value at 1.352 instead of 0.347. The increased tf*idf value causes the similarity between task E and page 24 to shrink, and thus the new cosine value equals 0.625. The cosine similarity of page 61 does not change in respect to task E because our desired recommendation does not share any keywords with the cluster. The unchanged similarity of 0.64 is sufficient in order to be chosen for recommendation in task E, since the former cosine value of page 24 decreased. Our cluster contains three keywords in total, with the >= clause not being mentioned yet. In our research, we observed a performance decrease when using a cluster that only contains the SELECT and < keywords. We believe that using the cluster without the >=yields a side effect to the other exercises, which is why we chose to include >= in our cluster.

6 DISCUSSION

The evaluation shows that we achieved our goals at providing a method to optimize student learning engagement during online SQL exercise task engagement. However, there are still challenges with SQL keywords which are regularly used in the English language. Some SQL keywords such as AND, IN or AS

Table 15: Keyword analysis for page 61 from chapter six.

Chapter: 6, Page: 61, Cosine: 0.64				
keywords	count	tf	idf	tf*idf
group by	1	1	1.109	1.109
group	1	1	1.051	1.051
and	2	1	0.499	0.499

Table 16: Keyword analysis for page 24 from chapter nine after clustering.

Chapter: 9, Page: 24, Cosine: 0.625							
keywords	select	where	group by	group	having	!	min
count	2	1	2	2	1	2	2
tf	1	0.5	1	1	0.5	1	1
idf by	0.347	0.484	1.109	1.051	1.301	1.352	1.556
tf*idf	0.347	0.242	1.109	1.051	0.651	1.352	1.556

are regularly used in the English language without any SQL context. Since the lecture slides are written in English, problems arise when counting the number of times these keywords are used in a SQL environment. This is challenging for our recommendation process if the encountered keyword rarely appears in the corpus, as it would receive a high idf weight, leading to a great influence in deciding the topic of the page. In the case of a page populated with many SQL keywords, the negative effect of one incorrectly recognized keyword might be mitigated by the tf*idf values of the other keywords. If the page only has a few keywords, it might happen that a word like IN or AND not used in any SQL context will mislead the recommendation process for this page.

7 CONCLUSION

This research is aimed at improving students' performance by reducing the unsystematic trial-and-error behavior during online SQL exercises task engagement in our SQLValidator. To this end, we have implemented a strategy in which suitable slides from lecture materials are mapped to respective SQL exercise tasks and are recommended to students in the form of hints during exercise task engagement. We have described, evaluated, and further optimized our strategy via join detection and clustering. Our implementation as shown in the evaluation section reaches a precision value of 0.767 and $F_{\beta=0.5}$ value of 0.505 thus justifying our strategy. The next stage in this recommendation system track is the impact assessment of the recommendation on students' engagement and SQL skill acquisition. Students tend to share solution codes. While solution distribution among students cannot be stopped as it is also a part of learning. A future direction is the implementation of a plagiarism discouragement feature.

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