

Classifying Help Seeking Behaviour in Online Communities

Sebastian Cross, Zak Waters, Kirsty Kitto, Guido Zuccon

Queensland University of Technology (QUT)

Brisbane, Australia

[kirsty.kitto,g.zuccon]@qut.edu.au

ABSTRACT

While help seeking has been extensively studied using self report survey data and models, there is a lack of content analysis techniques that can be directly applied to classify help seeking behaviour. In this preliminary work we propose a coding scheme which is then applied to an open dataset that we have created by carefully selecting sub groups from two popular discussion sites (Reddit and StackExchange). We then explore the possibility for automatically classifying help seeking behaviour using machine learning models. A preliminary model provides good initial results, suggesting that it may indeed be possible to construct student support systems that build off of an accurate classifier.

CCS CONCEPTS

•Computing methodologies → Supervised learning by classification; •Information systems → Personalization; •Applied computing → E-learning;

KEYWORDS

help seeking; content analysis; machine learning; open data

ACM Reference format:

Sebastian Cross, Zak Waters, Kirsty Kitto, Guido Zuccon. 2016. Classifying Help Seeking Behaviour in Online Communities. In *Proceedings of LAK '17*,

March 13 - 17, 2017, Vancouver, BC, Canada, 5 pages.

DOI: <http://dx.doi.org/10.1145/3027385.3027442>

1 INTRODUCTION

Self-regulated learning (SRL) appears to be a key indicator of student success. SRL has been associated with improved academic outcomes, engagement and motivation, as well as with constructive autonomy [28]. Two decades of research has provided us with a wide range of definitions [21, 29] and models [3, 23, 27], which serve to highlight the importance of helping people to learn how to initiate a wide variety of meta-cognitive, cognitive, affective, and motivational behaviours to achieve their learning goals [15]. This has demonstrated that self regulated learners have an ability to plan, organize, self-instruct, and self-evaluate which is essential to achieving long term success [29].

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

LAK '17,

© 2017 Copyright held by the owner/author(s). Publication rights licensed to ACM. 978-1-4503-4870-6/17/03...\$15.00

DOI: <http://dx.doi.org/10.1145/3027385.3027442>

SRL is particularly important in online learning environments, especially as they scale up to Massive Open Online Courses (MOOCs) [15, 16]. Within this overarching context, help seeking forms an important part of the SRL process [1, 13]. Here, we briefly discuss help seeking before proposing a scheme for content analysis.

Help Seeking behaviour. Richardson et al. [24] defined help seeking as the “tendency to seek help from instructors and friends when experiencing academic difficulties”, but this definition misses an important further possibility; people can seek help from general communities of practice where they do not necessarily have an instructor or a friend. For example, learners frequently coalesce around topics of interest in sites such as StackExchange and Reddit, asking for help and often receiving it in a very timely manner. For this reason, we will adopt the definition provided by Kizilcec et al. [15], which extends this basic definition to include the possibility that a help seeker might consult external help and resources.

It becomes critically important that learners develop a sophisticated approach to seeking help when they are studying in self directed online learning environments; they must be able to self-diagnose as requiring help, and then understand how to find it. For decades collaborative learning environments have been proposed as a way to encourage learners to learn from each other, providing necessary help along the way [6, 25]. Today, the vast majority of Learning Management Systems (LMSs) feature discussion fora and other environments (e.g., instant messaging services) that enable students to seek help in a variety of ways. However, it is precisely the people who most need help who tend not to possess the skills necessary to find it in a timely manner. Students can lack understanding of the topic [17, 18], not know how to ask a question [4], and some students suffer from help seeking threat. This can translate into a lack self-esteem, or a fear of social embarrassment [14], a problem that has been shown to disproportionately affect certain groups. Similarly, anxiety has been found to anti-correlate with appropriate help seeking behaviour [9].

We consider it important that Learning Analytics (LA) starts to develop methods for studying help seeking behaviour at scale. It is likely that recommendation systems can be built that would help to support a subset of students who have not yet learned to seek help effectively, or who suffer from help seeking threat. If categories of help seeking behaviour could be automatically detected in online fora then it would become possible to construct tools that could scaffold students towards more SRL patterns of behaviour. Even more interestingly, if we can automate the detection of help providing behaviour then students could potentially be rewarded for providing this invaluable service to their peers. Rewards do not have to relate just to summative assessment: sites such as StackExchange work on reputation, where the kudos of a help provider is increased as they provide more relevant help. (Although Howley has cautioned that up voting can be counter productive in an educational context [11].)

This paper provides an exploratory step towards an overarching goal of automating the detection of help seeking and providing behaviour in online discussion transcripts.

Models of help seeking. A number of models of help seeking have been created but as Howley has observed [11], they tend to be very similar. One example was proposed by Gall [20] whose model of help seeking focuses on five specific steps: i) Awareness of need for help. ii) Decision to seek help. iii) Identification of potential helpers. iv) Employment of strategies to elicit help. v) Reaction to help seeking attempts. These steps are then implemented by the help seeker using different strategies. Non verbal strategies are indirect, and consist of the student placing themselves in the proximity of a likely help provider. Gall does not discuss the case, but in a modern online context, a non verbal strategy would involve lurking in a discussion forum, and passively waiting for a post that resolved the problem. Verbal strategies can be implemented in a wider range of formats. The direct help seeker might simply ask for help with a direct question. However, verbal help seekers may also apply indirect strategies, perhaps by implying that a task is hard, or that they cannot do something. They may also ask for information about a problem, rather than directly asking for assistance and expecting an answer. Sometimes a power relationship is leveraged, e.g., they might remind an instructor of an obligation to provide help.

Models such as these will prove essential in constructing a tool that can automate the provisioning of help to students who are identified as requiring assistance. However, we first require a way in which to understand help seeking behaviour *per se*.

Qualitative studies of help seeking. A number of different papers have studied help seeking using qualitative surveys. Usually a help seeking construct is defined and then studied together with other educational factors (e.g., there is a help seeking subscale a part of the MLSQ [22]). Help seeking behaviour is then often correlated with educational outcomes (e.g., GPA [24]). Intriguingly, the recent work of Kizilcec et al. [15] demonstrates a negative relation between help seeking behaviour and goal attainment in MOOCS, a result that appears to contradict the work of Richardson et al., which demonstrates a positive correlation for help seeking behaviour and GPA [24]. However, as these methods use self-reporting to establish their correlations their conclusions are fraught, and can be critically questioned [7]. It is important that we start to correlate survey data with behavioural data obtained from learning communities — are students *actually* seeking help in the way that they claim in surveys? To answer these questions, it will be necessary to develop a coding scheme that can be used to classify help seeking behaviour in online discussion fora, code a variety of datasets and then attempt to correlate survey responses with actual patterns of behaviour.

Coding text for help seeking behaviour. Despite the apparent need to cross-correlate self report data with observed student behaviour, few content analysis schemes have been developed for the problem of classifying help seeking behaviour. One scheme exists for the classification of collaborative learning [5]. It is broken up into five main behaviour categories and associated sub categories: Planning (Group skills, Organising Work, Initiating Activities); Contributing (Help Giving, Feedback Giving, Exchanging Resources, Sharing Knowledge, Challenging Others and Explaining or Elaborating); Seeking Input (Help Seeking, Feedback Seeking and Advocating

Effort); Reflection/Monitoring (Monitoring Group Effort and Reflecting on Medium); and Social Interaction (Social Interaction). This is a good first step, however, its roots in a schema for collaborative learning makes it difficult to apply to our scenario. Many of the behaviours in the contributing categories overlap which makes coding unnecessarily complex. Furthermore, this scheme does code for achieving resolution (when an answer is provided to the help seeker). For this reason, we decided to develop a new specific scheme.

Automating the detection of help seeking behaviour. Q&A systems are increasingly being used in education [8, 12, 26], but many rely on large amounts of curated or structured data. Moreover, they cannot tell whether the students require help in advance of a direct question, and so miss crucial potential intervention points. We adopt a different stance here. If it is possible to hand code a dataset for help seeking behaviour, then an obvious question presents; can we automate this coding process using Machine Learning? As was discussed above, automating the detection of help seeking behaviour would enable the construction of tools that could help students to become more self directed in their learning.

2 APPROACH

Rather than generating another closed dataset based upon real student data extracted from a LMS or MOOC, a core contribution of this work is the ongoing creation of an open dataset that can be used and extended by other research groups. We have started by carefully selecting a subset of online discussion fora from two already released open datasets. *Reddit* (www.reddit.com) is a content aggregation and discussion website that is split up into a number of subsections covering a wide range of topics. These subsections are called SubReddits, and hundreds are generated daily by the Reddit user base. The data examined from Reddit was obtained from www.kaggle.com and consists of all user generated activity from May 2015. The user base of Reddit is a mix between users who have made a name for themselves as well as users who make temporary accounts to remain anonymous, which potentially allows users to post more freely (and sometimes more abusively) than might be expected in a more traditional online learning environment. We chose to use the */r/askhistorians* SubReddit in this study, because it is a strong learning community offering a set of free flowing questions and answers that appear similar in structure to an inquiry based LMS discussion forum. This dataset was released under the API terms of Reddit allowing for non-commercial use.

Stack Exchange (www.stackexchange.com) is a question answering (QA) platform that covers 160 topics, from coding and mathematics, to typography, language and science fiction. It is made up of many different communities, and these can contain sub communities of their own. The site has released a dataset which can be found at <https://archive.org/details/stackexchange>. This dataset consists of all user-contributed content (i.e. posts, comments, upvotes, downvotes, marked resolved, etc.) for the website. In this study we selected the *english.stackexchange.com/* topic because (i) most of its members are identified and so we expect it to have better behaviour than some communities (ii) it contains few ideological arguments or humorous posts, and (iii) questions are frequently marked as resolved in this community, providing an extra corroborating data point. This dataset

Table 1: The qualitative coding scheme developed for labelling help seeking in online communities.

| Main Label | Sub-label | Code | Details |
|--------------------|------------------------------|------|---|
| Help Seeking | Direct Question | DQ | Direct question being asked. Indicative features: question marks; five w's (who, what, where, when, why); how; does. Example: <i>"Is there a pronoun I can use as a gender-neutral pronoun?"</i> |
| | Implied Help Seeking | IS | Validation seeking ("I was wondering", "... am I wrong?", "... Right?") and Indirect questions. Example: <i>"I'd love to find some area I could investigate on my own over the summer."</i> |
| Help Providing | Sharing Knowledge | SK | User sharing their knowledge on the current topic, can be a reply to a help seeking post or the elaboration of a previously given help providing post. Example: <i>Singular they enjoys a long history of usage in English and can be used here: "Each student should save their questions until the end."</i> |
| | Exchanging Resources | ER | Providing resources as part of an answer. Linking to websites, references, books... Example: <i>"Take a look at The Girls of Atomic City: The Untold Story of the Women Who Helped Win World War II."</i> |
| | Feedback or Validation Given | FG | Providing feedback or validation on a user's work/response/opinion can be given even when validation is not sought. Example: <i>"Yes, that is correct."</i> |
| Clarification | Asking for Clarification | AC | Asking for clarification in reference to a post. Example: <i>"Can you please explain why you have no love for zir?"</i> |
| | Giving Clarification | GC | Providing clarification or elaboration in relation to a previous post. Example: <i>"I like zir but I reserve it (in my idiolect) for known persons of determinate gender who are neither male nor female."</i> |
| Resolution | Help Received | HR | An explicit textual indication that help was received. Example: <i>"Loved your answer :, Thanks"</i> |
| Social Interaction | Unrelated | USI | Unrelated social interaction, random statement that is not related to a topic. Example: <i>"You're so lucky - imagine, in German there is a female form for every profession and such (something like actor and actress), and we fight on the proper gender to use."</i> |
| | Abusive | ASI | Abusive, overly critical or inappropriate language and attitude. Example: <i>"You are an idiot."</i> |
| | Trolling | TSI | Unnecessary and intentionally provocative statements. Example: <i>"Hitler did nothing wrong."</i> |

Table 2: A comparison of the category counts of sentences in Stack Exchange and Reddit. Bracketed numbers denote percentages.

| | DQ | IS | SK | ER | FG | AC | GC | HR | USI | ASI | TSI |
|----------------|-------------|------------|--------------|-------------|-------------|-----------|------------|------------|-------------|-----------|------------|
| Reddit | 197 (.0905) | 35 (.0157) | 1408 (.6475) | 176 (.0817) | 138 (.0642) | 4 (.0018) | 20 (.0092) | 37 (.0175) | 139 (.0646) | 5 (.0023) | 2 (.0009) |
| Stack Exchange | 474 (.1244) | 86 (.0257) | 2676 (.7023) | 154 (.0404) | 110 (.0288) | 5 (.0013) | 10 (.0026) | 54 (.0141) | 239 (.0627) | 0 | 29 (.0005) |

is released under a CC BY-SA 3.0 licence. Only the posts made in May 2015 were used to maintain consistency across the datasets.

While not formal LMSs, we consider Reddit and Stack Exchange to be excellent proxies for online collaborative learning. Indeed, many students in the formal education system make use of one or the other of these two sites as a core component of their Personal Learning Networks [19] to seek help with formal coursework and generally find out information or debate issues. Thus, the decision to make use of data from these sites is not just pragmatic, such open fora play an increasingly critical role in learning, and it is important that we develop solutions for them too. Both datasets have different affordances. For example, Stack Exchange provides a more structured learning environment driven by direct questions and attempts to answer them. Additionally, reputation (in the form of up votes and down votes) can be awarded by any registered member for both questions and answers, and the original question asker can mark a specific answer as having solved their question. These features mean that Stack Exchange is very much geared towards high quality questions and answers. In contrast, the Reddit dataset provides a more untamed structure that lends itself to more social interaction and back and forth banter. Although posts can be marked up or down, users are not represented on the site with reputation scores, which creates a less punishing environment for low quality answers/replies.

The datasets were processed to allow for the labelling and classification of the data. Both were split from paragraphs into sentences using NLTK's [2] `nltk.tokenize` function. No attempt was made

to correct for poor grammar or punctuation in an attempt to keep our approach as replicable as possible. After this process, we had extracted 2156 sentences from the Reddit dataset and 3810 sentences from the Stack Exchange dataset for further processing. This step involved removing all XML tags, along with all comments that were marked as deleted. For both datasets, all hyperlinks were converted to a standard indicator (URL) format using regex so that they were recognised accordingly during feature extraction. Reddit data preprocessing included an extra step where automated comments generated by bots, which tend to mimic help providing behaviour, were deleted.

2.1 Qualitative Coding

We have created a coding scheme for help seeking and providing behaviour (see Table 1) that combines the initial work of Curtis and Lawson [5] and Gall [20], and extends it. Our scheme was developed with an underlying intent to code data at a sentence level rather than at a paragraph level, in an attempt to provide a more accurate representation of the behaviour being expressed. This can be very complex, with individual posts expressing many different sentiments. In order to encourage replicability between coders, our schema assumed no context (i.e. was based on the behaviour presented within specific sentences). While the majority of the current coding was completed by one person, a test of Inter-Rater Reliability (IRR) was carried out. Two coders worked to achieve an IRR Cohen's kappa value of 0.766 on a test set of 200 sentences,

after working to achieve full agreement on a previous subset of 600 classifications. Further incremental reliability tests will be performed to ensure dataset integrity as the dataset grows.

2.2 Exploratory Automation

Two classifiers were used in an exploratory study aiming to automate the classification of help seeking and help providing behaviours within online discussions. We used (i) a Support Vector Machine (SVM), and (ii) a Random Forest (RF) model, as both perform well on feature rich high dimensional tasks. These models were implemented using the <http://scikit-learn.org/> Python libraries. The features extracted for this classification task were primarily lexical; we implemented a basic approach utilising: (i) word N-grams; and (ii) simple question counts. We utilised groupings of words due to the hypothesis that similar HS behaviours may be associated with clusters of words and their contexts. One example of such a case could be the words “*is this*”, which might indicate the poster is asking a question or otherwise seeking help. Our second exploratory feature seeks to incorporate the amount of inquiry contained in a post by counting the usage of question marks. We used two validation methods common for classification tasks: 10-fold cross validation; and a training/testing split (of 75% and 25% respectively), which was used in the generation of confusion matrices to enable further exploration of the results.

2.3 Results

The breakdown of help seeking behaviour for our two online communities is shown in Table 2. We admit to a certain amount of surprise that Stack Exchange and Reddit both appear to have a similar help seeking profile for the communities chosen. This similarity possibly arises from the specific communities chosen for preliminary analysis, and extending the dataset to other communities will be required before any conclusions can be drawn. It is unsurprising that few abusive and trolling behaviours were found in this dataset; as previously mentioned, both communities were chosen for their integrity and high moderation. Table 3 provides performance metrics for the two classification models, obtained using 10 fold cross validation. When we consider the simplicity of the feature set specified in Section 2.2, it is surprising that such high values were obtained.

The confusion matrix in Table 4 provides an explanation, showing an obvious over classification of SK behaviour and precision losses because of false positives. Table 5 shows the Gini importance (GI) value (the higher the GI, the more important in reducing classification uncertainty or miss classification), for the 5 most prevalent features in the random forest model, for both the full dataset (FULL) and the most common categories. As expected, the most valued features are those that relate to under represented behaviours. For example, the ‘url’ feature can often co-occur with a request for information (where someone points to a url as an example of something they are not sure about). Features such as ‘yes’ often co-occur with FG behaviour, where a help provider agrees with a help seeker. Finally, features such as ‘does’ can often occur in DQ behaviour, at the start of a question. Some features are less obvious, for example the feature ‘islam’, which relates to the ER behaviour, and is due to a specificity of the dataset, where many of the comments discussed religion and users would provide Islamic text as sources.

Table 3: Performance metrics for 3 different datasets.

| | | Precision | Recall | F-Value | Accuracy |
|-----------------------|-----|-----------|--------|---------|----------|
| Reddit | SVM | 0.667 | 0.752 | 0.665 | 0.752 |
| | RF | 0.728 | 0.739 | 0.677 | 0.742 |
| Stack Exchange | SVM | 0.622 | 0.742 | 0.658 | 0.742 |
| | RF | 0.765 | 0.787 | 0.762 | 0.791 |
| Combined | SVM | 0.624 | 0.687 | 0.595 | 0.687 |
| | RF | 0.725 | 0.742 | 0.698 | 0.751 |

Table 4: Confusion Matrix for Entire Dataset using RF.

| | DQ | IS | SK | ER | FG | AC | GC | HR | USI | ASI | TSI | Precision |
|----------|-------|-------|-------|-------|------|-----|----|-------|-------|-----|-----|-----------|
| DQ(164) | 101 | 0 | 59 | 0 | 0 | 0 | 0 | 0 | 4 | 0 | 0 | 61.58 |
| IS(39) | 1 | 9 | 29 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 23.07 |
| SK(1130) | 16 | 4 | 1017 | 5 | 29 | 0 | 2 | 3 | 54 | 0 | 0 | 90 |
| ER(55) | 1 | 0 | 29 | 17 | 0 | 0 | 0 | 0 | 8 | 0 | 0 | 30.90 |
| FG(20) | 1 | 0 | 14 | 0 | 1 | 0 | 0 | 0 | 4 | 0 | 0 | 5 |
| AC(2) | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| GC(0) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | N/A |
| HR(18) | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 15 | 1 | 0 | 0 | 83.33 |
| USI(68) | 2 | 0 | 36 | 0 | 1 | 0 | 0 | 0 | 29 | 0 | 0 | 42.64 |
| ASI(0) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | N/A |
| TSI(0) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | N/A |
| Recall | 82.78 | 69.23 | 85.67 | 77.27 | 3.22 | N/A | 0 | 83.33 | 28.71 | N/A | N/A | |

2.4 Discussion

At first glance, standard supervised learning techniques appear to perform surprisingly well in the identification of key help seeking and help providing behaviours using a very simple feature set. However, it appears that both SVM and RF classifiers are fixating upon the Seeking Knowledge (SK) category. This is to be expected, as SK dominates these two datasets, a phenomenon that is to be expected given the affordances of the Stack Exchange and Reddit subcommunities that we have chosen; both are very much sites set up for those who are seeking knowledge. This means that the precision and recall for SK is remarkably high, but only at the expense of low recall for many other categories of behaviour in the dataset.

This pattern of behaviour is also reflected in the dominant features of FULL vs SK shown in Table 5, which largely overlap. The RF appears to be the better performing algorithm with the current feature set. This may be attributed to the ability of RF models to withstand overfitting, by averaging the results of multiple decision trees.

3 FUTURE WORK

The schema presented in Table 1 is preliminary and may need to be modified as it is applied to a wider range of online educational environments. This will be a priority for the future. Within the current schema, the distribution of data for both the Reddit and Stack Exchange datasets discussed in this paper shows a very direct approach to help seeking. We anticipate that more implied help seeking could be found in other online environments, but this remains to be tested in future work. We will also seek to compare our results with student survey data, enabling the exploration of actual help seeking behaviour as exhibited by students in an online forum when compared to their self-report data. We are surprised to find little work on this topic, and this paper is one small step towards that end goal. Our dataset is released under a CC BY-SA 4.0 license, and is currently available at <https://github.com/CognitiveEcosystemsLab/OpenEducationalData>. It is essential that the LA community develops more open and shareable datasets for baseline comparisons between groups, and this work is a step in that direction. We will continue to develop and extend this dataset. It is currently hand coded for help seeking behaviour

Table 5: Top 5 features and Gini importance for the full dataset (FULL), as well as the five most dominant categories in the schema.

| Class | Features (Gini importance) | | | | |
|-------|----------------------------|------------------|---------------------|----------------------------|---------------------|
| FULL | url (0.0413) | thanks (0.0178) | deleted (0.0106) | thank (0.0096) | does (0.0025) |
| SK | url (0.0385) | thanks (0.0157) | thank (0.0092) | deleted (0.0091) | welcome (0.0027) |
| DQ | does (0.0039) | correct (0.0037) | express (0.0026) | vague (0.0025) | enlighten (0.0025) |
| ER | url (0.1356) | islam (0.0058) | url did (0.0049) | oxford university (0.0049) | url url (0.0045) |
| FG | yes (0.0057) | respond (0.0042) | haven read (0.0039) | didn actually (0.0039) | good point (0.0037) |
| USI | deleted (0.0559) | welcome (0.0124) | elu (0.0095) | congrats (0.0062) | hi (0.0052) |

according to the scheme discussed in Section 2.1, but will gradually be extended with other educationally relevant coding schemas applied to the same data (e.g., Cognitive Presence [10]). As it is further extended and refined, we anticipate that this dataset could emerge as a baseline comparison data source for the LA community. We are also interested in more complex features of help seeking and providing behaviour, such as cognition indicators derived from text. It will be interesting to investigate how platform specific features such as post quality can be applied to ML under the lens of our framework. For example, what features correlate with meta-data such as up/down-votes (in the case of Reddit), and the marking of a post as resolving a question (StackExchange) of particular help seeking categories? Extracting these features would enable them to be used in datasets that do not contain such metadata.

4 CONCLUSION

While help seeking has attracted much interest over the decades, far less work has been completed on the content analysis of help seeking transcripts. This paper is a preliminary step in that direction, providing a coding scheme and exploring how it can be applied to the analysis of online community discourse. Two basic feature sets (n-grams and question counting) for automating the detection of this behaviour have proven to be of interest. Much work remains to be completed, but this paper has provided a proof of concept that help seeking behaviour can be automatically detected in online discourse. This is a promising development for the provisioning of personalised just-in-time solutions to students in online environments.

REFERENCES

- [1] Vincent Alevan, Ido Roll, Bruce M McLaren, and Kenneth R Koedinger. 2010. Automated, unobtrusive, action-by-action assessment of self-regulation during learning with an intelligent tutoring system. *Educational Psychologist* 45, 4 (2010), 224–233.
- [2] Steven Bird, Ewan Klein, and Edward Loper. 2009. *Natural language processing with Python*. "O'Reilly Media, Inc."
- [3] Monique Boekaerts. 1997. Self-regulated learning: A new concept embraced by researchers, policy makers, educators, teachers, and students. *Learning and instruction* 7, 2 (1997), 161–186.
- [4] Ikseon Choi, Susan M. Land, and Alfred J. Turgeon. 2005. Scaffolding peer-questioning strategies to facilitate metacognition during online small group discussion. *Instructional Science* 33 (2005), 483–511. DOI: <http://dx.doi.org/10.1007/s11251-005-1277-4>
- [5] David D. Curtis and Michael J. Lawson. 2001. Exploring collaborative online learning. *Journal of Asynchronous Learning Networks* 5, 1 (2001), 21–34. DOI: <http://dx.doi.org/10.1016/j.jass.2007.08.004>
- [6] Pierre Dillenbourg. 1999. What do you mean by 'collaborative learning'? *Collaborative-learning: Cognitive and Computational Approaches*. 1 (1999), 1–19. DOI: <http://dx.doi.org/10.1.1.167.4896>
- [7] Stewart I Donaldson and Elisa J Grant-Vallone. 2002. Understanding self-report bias in organizational behavior research. *Journal of Business and Psychology* 17, 2 (2002), 245–260.
- [8] Donghui Feng, Erin Shaw, Jihie Kim, and Eduard Hovy. 2006. An intelligent discussion-bot for answering student queries in threaded discussions. In *Proceedings of the 11th international conference on Intelligent user interfaces*. ACM, 171–177.
- [9] Adrian Furnham, Tomas Chamorro-Premuzic, and Fiona McDougall. 2002. Personality, cognitive ability, and beliefs about intelligence as predictors of academic performance. *Learning and Individual Differences* 14 (2002), 49–66. DOI: <http://dx.doi.org/10.1016/j.lindif.2003.08.002>
- [10] D. Randy Garrison, Terry Anderson, and Walter Archer. 2001. Critical thinking, cognitive presence, and computer conferencing in distance education. *American Journal of distance education* 15, 1 (2001), 7–23.
- [11] Iris Howley. 2015. *Leveraging Educational Technology to Overcome Social Obstacles to Help Seeking*. Ph.D. Dissertation. Carnegie Mellon University.
- [12] Jason C Hung, Ching-Sheng Wang, Che-Yu Yang, Mao-Shuen Chiu, and George Yee. 2005. Applying word sense disambiguation to question answering system for e-learning. In *19th International Conference on Advanced Information Networking and Applications (AINA'05) Volume 1 (AINA papers)*, Vol. 1. IEEE, 157–162.
- [13] Stuart Karabenick. 2001. Help seeking in large college classes: Who, why, and from whom. *The annual meeting of the American Educational Research Association* (2001).
- [14] Stuart Karabenick. 2003. Seeking help in large college classes: A person-centered approach. *Contemporary Educational Psychology* 28 (2003), 37–58. DOI: [http://dx.doi.org/10.1016/S0361-476X\(02\)00012-7](http://dx.doi.org/10.1016/S0361-476X(02)00012-7) arXiv: [S0361-476X\(02\)00012-7](http://arxiv.org/abs/S0361-476X(02)00012-7)
- [15] René Kizilcec, Mar Pérez-Sanagustín, and Jorge Maldonado. 2017. Self-regulated learning strategies predict learner behavior and goal attainment in Massive Open Online Courses. *Computers & Education* 104 (2017), 18–33.
- [16] Allison Littlejohn, Nina Hood, Colin Milligan, and Paige Mustain. 2016. Learning in MOOCs: Motivations and self-regulated learning in MOOCs. *The Internet and Higher Education* 29 (2016), 40–48.
- [17] Hans Van Der Meij. 1990. Question Asking : To Know That You Do Not Know Is Not Enough. 82, 3 (1990), 505–512.
- [18] Naomi Miyake and Donald a. Norman. 1979. To ask a question, one must know enough to know what is not known. *Journal of Verbal Learning and Verbal Behavior* 18 (1979), 357–364. DOI: [http://dx.doi.org/10.1016/S0022-5371\(79\)90200-7](http://dx.doi.org/10.1016/S0022-5371(79)90200-7)
- [19] Jonathan Mott. 2010. Envisioning the post-LMS era: The open learning network. *Educause Quarterly* 33, 1 (2010), 1–9.
- [20] Sharon Nelson Le-Gall. 1981. Help-seeking: An understudied problem-solving skill in children. *Developmental Review* 1 (1981), 224–246. DOI: [http://dx.doi.org/10.1016/0273-2297\(81\)90019-8](http://dx.doi.org/10.1016/0273-2297(81)90019-8) arXiv: [0273-2297/81/030224-23](http://arxiv.org/abs/0273-2297/81/030224-23)
- [21] Paul Pintrich. 1999. The role of motivation in promoting and sustaining self-regulated learning. *International Journal of Educational Research* 31, 6 (1999), 459–470. DOI: [http://dx.doi.org/10.1016/S0883-0355\(99\)00015-4](http://dx.doi.org/10.1016/S0883-0355(99)00015-4)
- [22] Paul Pintrich and Elisabeth De Groot. 1990. Motivational and self-regulated learning components of classroom academic performance. *Journal of educational psychology* 82, 1 (1990), 33.
- [23] Minna Puustinen and Lea Pulkkinen. 2001. Models of self-regulated learning: A review. *Scandinavian Journal of Educational Research* 45, 3 (2001), 269–286.
- [24] Michelle Richardson, Charles Abraham, and Rod Bond. 2012. Psychological correlates of university students' academic performance: a systematic review and meta-analysis. *Psychological bulletin* 138, 2 (2012), 353.
- [25] Piet Van den Bossche, Wim Gijssels, Mien Segers, and Paul A. Kirschner. 2006. Social and cognitive factors driving teamwork in collaborative learning environments team learning beliefs and behaviors. *Small group research* 37, 5 (2006), 490–521.
- [26] Chun-Chia Wang, Jason Hung, Che-Yu Yang, and Timothy Shih. 2006. An application of question answering system for collaborative learning. In *26th IEEE International Conference on Distributed Computing Systems Workshops (ICDCSW'06)*. IEEE, 49–49.
- [27] P Hadwin Winne and Allyson F Hadwin. 1998. Studying as self-regulated learning. *Metacognition in educational theory and practice* 93 (1998), 27–30.
- [28] Barry J. Zimmerman. 2002. Becoming a Self-Regulated Learner: An Overview. *Theory Into Practice* 41, August (2002), 64–70. DOI: <http://dx.doi.org/10.1207/s15430421tip4102>
- [29] Barry J. Zimmerman and Manuel Martinez-Pons. 1988. Construct validation of a strategy model of student self-regulated learning. *Journal of Educational Psychology* 80, January (1988), 284–290. DOI: <http://dx.doi.org/10.1037/0022-0663.80.3.284>