Using Subjective Logic to Divide Learners into Groups

Thomas Largillier
Normandy University
thomas.largillier@unicaen.fr

Abstract

Massive Open Online Courses (MOOC) appeared fairly recently in distance education. Unlike traditional e-learning classes, they are intended for an unlimited number of participants and successful ones can gather hundreds of thousands of participants. Basically they consist on a video class per week that the learners can watch when it is most fitting for them. It is a very useful tool for learners who wish to learn at their own pace. One of the biggest problems facing MOOCs is the high drop ratio. Indeed even for the very successful ones it is common to see only 10% of the participants following the class until the end. As shown in previous studies on online learning, collaboration between the participants is an effective way to solve this problem. This paper introduces a group partitioning scheme based on subjective logic operators that intends to satisfy the learners by reforming successful alliances and splitting unfulfilling ones.

I. Introduction

MOOCs appeared fairly recently in distance education and have already attracted a lot of attention and generated a huge interest in the scientific community [10].

Unlike traditional e-learning classes, they are intended for an unlimited number of participants who can subscribe without any geographic restriction. This implies that the learners participating in MOOCs can number in hundreds of thousands with close to a hundred different nationalities for the most successful ones. The participants are also very diverse in ages and educational background.

In MOOCs, some material, usually videos and documents, are made available to the learners at fixed points in time and the learners have a predefined time period to watch/read the material before turning in an assignment to make sure they have assimilated the content of the material. This time period is usually one or two weeks. Also the learners are encouraged to use collaborative tools such as forums, blogs, online shared storage, *etc.* to interact with each other.

The main problem faced by MOOCs is their really high drop ratio. Even the most successful ones have a completion rate around 10%. This drop ratio is usually estimated using the percentage of learners who turn their assignment in. Some studies shown that learners can feel isolated in a MOOC and overwhelmed by the amount of information available on collaborative platforms. Especially learners whose mother tongue is not the one the class is teached in.

In this paper, we propose to solve this problem by "forcing" learners to interact with a subset of other learners through group assignments. In order to do this, we introduce a model to partition learners in order to maximise the probability of success of all the assembled groups. We also propose an algorithm that computes such a partition.

II. Related Work

Despite them being fairly recent, MOOCs have been studied a lot. Mackness *et al* conducted a study [7] on one of the first ever MOOC to happen in 2008. The authors discovered that learners like the autonomy they have in a MOOC environment, but they also really appreciate the interactions/connections between the learners since a lot of them felt really isolated during this class.

The first MOOC proposed on the edX platform[1] was extensively studied by Breslow *et al* in [1]. This MOOC was launched in 2012 and regrouped more than 155, 000 learners. One of the objectives of the study was to identify the factors that lead to the success of a learner for this class. The only positive correlation they got was with the interaction factor. Learners that completed the class interacted more with other learners. This study is still undergoing.

The problem of partitioning learners into small groups in order to optimize their progression has been extensively studied. Most of the work done concerns learners in a classroom of a "classical" e-learning environment. Few people consider the case where there are hundreds of thousands of learners spread across the globe.

Oakley et al. propose, in [9], a team formation method. Their objective is to group students with diverse ability levels and common blocks of time to meet outside classes. Groups are put together by the teacher who uses forms filled by the students. Learners will be assigned roles in their group. These roles will evolve so that the learners can see different aspects of the collaboration.

The Felder-Silverman classification [3] has been used by Martin *et al.* in [8] to group students and adapt e-learning material to learners. Their system for grouping learners uses the students' profile obtained via the Index of Learning Styles questionnaire. The idea is then to group together both reflexive and active learners to produce more efficient groups. This system needs to be studied further since it is not clear what should happen to well-balanced learners and if a student learning style in a group is not influenced by the rest of the group.

[1] https://www.edx.org

Katherine Deibel implemented in a class the method above as well as the latent jigsaw method and describe her results in [2]. The feedback she got from her students was really positive. The learners really appreciated to work in groups as they felt it helped them to learn more efficiently by being confronted with different ideas.

Wessner *et al.* introduces in [11] a tool to regroup students participating in a e-learning platform. This tool is based on the "Intended Points of Cooperation" (IPC). These IPCs are used by the teacher to assemble groups. The grouping can also be done automatically to regroup people that have reached the same learning stage.

Giemza *et al* proposed in [4] an android application called Meet2Learn for university freshmen to help them connect with other student and join learning groups associated with courses. Within this application students can create, look for and join learning groups. Here, the grouping is done manually by each student that wishes to join a group.

Largillier *et al*, in [6], proposed a model to recommend the best fitted group for any learner in an online environment using information from previous collaborations. Their method estimate the expected performance of any group that might be assembled and select the one with the highest expected performance using a greedy algorithm. They do not aim to solve the problem we are concerned with in this paper but the model presented in this paper presents some similarities since it is also used previous collaborations to partition the set of learners to build future efficient collaborations.

In the next section we present a model and an algorithm to efficiently partition a set of learners into small groups in order to maximise the overall success probability of the partition. The model we use is similar to the one in [6] since they are both based on previous collaborations to infer the performance of new ones. Here we try to solve a more general problem since we want to find an optimal partition of the learners instead of the best fitted group to assemble around one learner. Also the model presented in this paper does not use the result of the previous collaborations but the willingness of the learners to work again with people they previously collaboratd with and therefore use an asymetric notion.

III. Method

In this section we present a new modeling for the group formation problem that uses subjective logic to decide which groups should be formed. I will briefly introduce subjective logic and the relevant related information before presenting the proposed modeling of the problem.

I. Subjective Logic

Subjective logic is extensively described by Josang in [5]. It was developed as an extension of the probabilistic logic. The founding principles of subjective are that opinions always belong to an observer and nobody can be certain of everything as expressed by Josang: "*A fundamental aspect of the human condition is that nobody can ever determine with absolute certainty whether a proposition about the world is true or false. In addition, whenever the truth of a proposition is expressed, it is always done by an individual, and it can never be considered to represent a general and objective belief. These philosophical ideas are directly reflected in the mathematical formalism and belief representation of subjective logic.*"

In subjective logic, an opinion is noted as ω_X^A where A is the owner of the opinion and X is the target frame over which the opinion is expressed. Opinions in subjective logic are triplets,

$$\omega_X^A = (u_X^A, \overrightarrow{b}_X^A, \overrightarrow{a}_X^A)$$

where $u_X^A \in [0,1]$ represent the uncertainty of the opinion, $\overrightarrow{b}_X^A$ is the belief vector over the element of the target frame X and $\overrightarrow{a}_X^A$ is the base rate vector.

Whenever it is clear from the context or non essential we will remove the notation corresponding to the owner of the opinion.

Let X be a set, we will note $\mathcal{R}(X) = 2X \setminus \{X, \emptyset\}$ the reduced power set of X.

These values and vectors are such that

$$\forall x_i \in \mathcal{R}(X), \overrightarrow{b}_{\mathcal{R}(X)}(x_i) \in [0,1]$$

$$u_{\mathcal{R}(X)} + \sum_{x_i \in \mathcal{R}(X)} \overrightarrow{b}_{\mathcal{R}(X)}(x_i) = 1$$

$$\forall x_i \in X, \overrightarrow{a}_X(x_i) \in [0,1] \wedge \sum_{x_i \in X} \overrightarrow{a}_X(x_i) = 1$$

The base rate is used as the "intuitive" value when the uncertainty is total, it represents the basic opinion in absence of any knowledge.

In order to aggregate opinions of several on an element of $\mathcal{R}(X)$ we will use the belief constraint operator defined in [5]. This operator is associative and commutative and can be computed in polynomial time for a consta nt number of opinions.

II. Modeling the problem

Let $\mathcal{L}$ denote the set of all learners. The target frame of our opinions will be the reduced power set of our learners.

Each user $l \in \mathcal{L}$ maintains a list of users she wants to collaborate again with noted OK_l together with a list of users she doesn't want to collaborate with again in the future noted NOK_l. Both sets are empty at the beginnning of the process.

In order to influence the future formation of groups we will bias the base rate of users in favor of other learners the current one wish to work again with.

III. Algorithm

Our proposed algorithm has three separated phases. In the first phase, each learner will build a list of groups she wish to part of together with a mesure of desire to see these groups assembled. In a second phase we aggregate for each group the desire of all its members to see it assembled. At last we build a partition using a greedy algorithm based on the aggregated mesure we obtained on the previous step.

Building groups Each learner l will compute a list of groups, $groups_l$, she will consider to be part of. Each group $g \in groups_l$ is such that

$$g \cap OK_l \neq \emptyset \quad (1)$$

$$g \cap NOK_l = \emptyset \quad (2)$$

Eq. 1 only applies when $OK_l \neq \emptyset$. The base rate of these groups is simply the sum of the base rates of its members.

As for the belief in each group, let $b = 1 - u_l$ be the available belief for learner l and let $p_l = \min(|OK_l|, k)$ and $\forall i \in [1, p_]], g_l^i = \{g | g \cap OK_l| = i\}$.

$$b(G_l^i) = b \cdot \frac{2 \cdot i}{p \cdot (p+1)}$$

This belief is then uniformly distributed amongst each group, *i.e.*

$$\forall i \in [1, p], \forall g \in G_l^i \overrightarrow{b}(g) = \frac{b(G_l^i)}{|G_l^i|}$$

Aggregating opinions It is then possible to use the belief constraint operator to compute the the aggregated desire of its member to see it assembled. This operator is used to compute the consensual opinion of several observers on a particular focus element of the target set. It will help separate groups that are happy to work together from those whose only a fraction of the users wish to see it assembled.

During this phase we also remove all groups g where at least one learner do not wish to see assembled, *i.e.* $\exists l \in g \quad s.t. \quad g \cap NOK_l \neq \emptyset$. Since a learner l might wish to work again with another leaner m but not the other way around.

Partitioning learners We then compute a partition of the learners using a greedy algorithm that iteratively select the group with the highest belief and adding it to the partition. When a group is selected we then remove all candidate groups that can no longer be assembled because at least one of their members has already been picked to be part of another group. We repeat this step until the partition is complete and every learner appears in the partition.

Input: a learner set $\mathcal{L}$, an integer k
Output: a partition p of $\mathcal{L}$ in groups of size k

1. **foreach** $l \in \mathcal{L}$:
   $groups_l \leftarrow builg\_groups_k(l)$
2. $G \leftarrow aggregate(\bigcup_{l \in \mathcal{L}} groups_l)$
3. $p \leftarrow \emptyset$
4. **while** p is not complete:
   $g_{\max} \leftarrow argmax_{g \in G}(E[g])$
   $G \leftarrow G \setminus \{g | g \in G \wedge g_{\max} \cap g \neq \emptyset\}$
   $p \leftarrow p \cup \{g_{\max}\}$
5. **return** p

Figure 1: *Partition method*

The whole process is presented in Fig. 1. The presented solution in this paper use a greedy algorithm but any other optimization technique might be used instead to build the partition.

Updating values After the assignment are done by the groups we update for each learner l its OK_l and NOK_l sets based on her feedback. The feedback can be obtained through asking each learner if they wish to see the group they were part of be assembled in the future and use this information for all the members in the group or by asking the learner is she wish to work again with each learner that were part of the group.

The later kind of feedback is much more precise since if the group worked fine for except one or two members that did nothing this finer granularity can help get a more precise understanding of which connections inside the group where really effective. Keep in mind that the assembled groups are of a reasonable size, $k \in [2, 5]$ usually.

When a learner l is added to the NOK_m set of another learner m her base rate is simply set to 0 and its value is uniformly distributed among all other learners that do not belong to the NOK_m set.

When a learner is added to another leaner l set Ok_l it reduces the uncertainty of leaner l of a value α . Since she has found a good match she has gain knowledge about her future collaborations. This will give a higher belief to the future groups l will select to work with. The precise value of uncertainty decrease might depend on several criteria like the duration of the class and the time that can reasonably spent searching an optimal group for the learner l.

IV. Discussion

The first question regarding this method one should ask is "is it tractable on real life data?". For each user, the method has to handle a polynomial ($\mathcal{O}(n^k)$) groups at most and all operations on those groups are poynomial as well.

Sorting all the groups created by all the users requires $\mathcal{O}(n^{k+1} \cdot \log(n^{k+1}))$ operations.

At last constructing the partition is linear in the total number of considered groups which is $\mathcal{O}(n^{k+1})$.

The update phase runs in time linear in the number of users since each user interacts with a constant number $k-1$ of other users.

Therefore the all process runs in polynomial time which is often considered as tractable on regular sized instances. For a class with a few thousands students, this method is undeniably tractable and can be used weekly to construct more and more efficient groups. It will be interesting to run this method and larger instances of the problems as some real life MOOCs can reach several hundreds of thounsands of users. This might be problematic even if one can have a couple of days to compute an efficient partition.

This limitation can be circumvent in practice because it is unlikely that a learner can collaborate with any other learner in the same class. For example it makes sense to divide learners into subgroups corresponding to time zone or the mother tongue so they can actually interact with one another in a more direct way.

V. Conclusion & Future Work

In this paper I presented a method to efficiently partition a group of learner in order to maximize the probability that the groups will turn their assignment in and therefore helping learners to keep a high level of motivation through meaningful interactions with other learners. This is a very important problem for MOOCs. The proposed method rely on a sound theoretical background, the subjective logic. Subjective logic is particularly fit for this kind of problems since it helps capture the personal opinions of learners and aggregating them in a simple yet robust manner.

This method requires a very small investment for the learners, *i.e.* they need to rate the interactions they had with the other learners on previous assignments in order to be part a great team in the future.

This method still need to be tested in a real MOOC to assert that users are willing to give this simple feedback in order to improve their overall experience of online learning and also to mesure the impact of teamwork on demotivation. One should also look closely at how to most efficiently set the uncertainty decrease during the updating phase of the method. This should be carefully observed during a real life experiment.

References

[1] Lori Breslow, David E Pritchard, Jennifer DeBoer, Glenda S Stump, Andrew D Ho, and DT Seaton. Studying learning in the worldwide classroom: Research into edxs first mooc. *Research & Practice in Assessment*, 8:13–25, 2013.

[2] Katherine Deibel. Team formation methods for increasing interaction during in-class group work. In *Proceedings of the 10th annual SIGCSE conference on Innovation and technology in computer science education*, ITiCSE '05, pages 291–295, New York, NY, USA, 2005. ACM.

[3] R.M. Felder and L.K. Silverman. Learning and teaching styles in engineering education. *Engineering education*, 78(7):674–681, 1988.

[4] Adam GIEMZA, Sven MANSKE, and H Ulrich HOPPE. Supporting the formation of informal learning groups in a heterogeneous information environment.

[5] Audun Jøsang. Subjective logic. *Book Draft*, 2011.

[6] Thomas Largillier and Julita Vassileva. Using collective trust for group formation. In *Collaboration and Technology*, pages 137–144. Springer, 2012.

[7] Jenny Mackness, Sui Mak, and Roy Williams. The ideals and reality of participating in a MOOC. In *Networked Learing Conference*, pages 266–275. University of Lancaster, 2010.

[8] Estefania Martin and Pedro Paredes. Using learning styles for dynamic group formation in adaptive collaborative hypermedia systems. In *In Proceedings of the First International Workshop on Adaptive Hypermedia and Collaborative Web-based Systems (AHCW 2004) (2004) 188-198 available at http://www.ii.uam.es/rcarro/AHCW04/MartinParedes.pdf.*

[9] B. Oakley, R.M. Felder, R. Brent, and I. Elhajj. Turning student groups into effective teams. *Journal of Student Centered Learning*, 2(1):9–34, 2004.

[10] Laura Pappano. The year of the mooc. *The New York Times*, 2(12):2012, 2012.

[11] Martin Wessner and Hans-Rüdiger Pfister. Group formation in computer-supported collaborative learning. In *Proceedings of the 2001 International ACM SIGGROUP Conference on Supporting Group Work*, GROUP '01, pages 24–31, New York, NY, USA, 2001. ACM.