Music Learning with Massive Open Online Courses (MOOCs)
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Chapter 4. Social Flow in Social MOOCs

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Abstract. Flow theory is a way to explain how humans can be self-motivated and reach a state of high focus and intense, very effective learning. Usually this theory is merely descriptive but recently it has also been operationalized and used as the basis for building autonomous agents. This paper examines how such an operationalization can be incorporated in computer-supported learning environments such as MOOCs. It also expands the notion of flow to take into account 'social flow' occurring in a group of learners, such as a sports team or a small Jazz ensemble. We discuss how this kind of social flow can be induced, what the benefits are, and how it is relevant for building learning communities through web and social media.

Keywords. Flow, Social Flow, Autotelic principle, MOOCs, online learning, distance-education, social MOOCs.

1. Introduction

What is the best way to teach and learn? Whole libraries have been filled with theoretical treatises, many educational experiments have been performed (e.g. by Freynet, Malaguzzi, Steiner, Froebel, etc.), and a wide variety of national policies have been formulated and implemented. This rich landscape of educational theory and practice can be organised according to several dimensions. One important distinction is in terms of structured teaching versus open-ended learning environments, and a second one in terms of external versus internal motivation.

Structured vs. open-ended learning

The *structured teaching* approach assumes that teaching must rely on a carefully planned process that is then followed step-by-step by the learner. It is often practiced in state-wide education systems which are based on top-down fully planned national educational curricula where all learners of a certain age go through the same steps. The curricula define what has to be learned, which handbooks must be followed, how courses are to be prepared by the teachers, which exercises must be carried out. The outcome is carefully monitored through standardised, often nationally administered exams. In this scheme, teachers are often reduced to executioners of centrally designed plans and learners are viewed as uniform absorbers of knowledge. The teacher is also the source of authority, challenging the students and handing out reward and punishment. Although structured learning usually takes place in a classroom, the learner is individually evaluated and supposed to master the material by personal study.

Structured teaching has dominated the European educational landscape since the start of national curricula in the 19th century, and it is practiced world-wide. It is also widely used for continued education. Structured teaching works well for certain domains of knowledge. It has important advantages in terms of quality control, uniform training of teachers, and job recruitment - because it is clear what a diploma stands for. On the other hand, it is not very well adapted to the current generation of restless students, which are not only confronted with a massive amount of information to learn from, but also with a bombardment of multi-media materials, delivered through social media such as Facebook or Twitter, that encourage very short and rapidly shifting attention spans. It is also not very well adapted to types of expertise that require a great dosis of creativity, such as Jazz improvisation or advanced programming. Nevertheless, today's MOOCs mostly follow such a highly structured pedagogy, with a fixed lesson-plan that presents small chunks of knowledge or methods to students, and provides regular tests to check whether the student has mastered the material.

An *open-ended learning* approach is regularly proposed as an alternative that would lead to greater motivation and direct participation of students, and hence to a more enjoyable learning experience and continued curiosity. In this approach, the students are presented with a rich learning environment and a library of challenges they can tackle. They must seek out themselves the knowledge and resources needed to cope with a challenge and they often need to collaborate with others to solve tasks.

An example of this approach has been practiced the past decades in the Reggio Emilia schoolsystem. Young children work in small teams on projects and have a wide range of tools and materials at their disposal. The projects require learning many skills (drawing, writing, calculation) but these skills are acquired within the context of the project, and teachers act as organizers and tutors [21]. The LOGO environment designed by Seymour Papert is another example implementing the same philosophy, later used as the foundation for the Lego Mindstorms electronics kit. LOGO provides programming primitives and an intuitive model of computation, straightforward enough to make sense to children [10]. Although LOGO can be used in a traditional classroom setting with a rigid lesson plan, Papert's original goal was to create a learning environment in which children could autonomously seek out challenges and gradually discover solutions and build up skill.

Hackatons work along the same principles. There is a target domain to be learned (for example, programming apps for a smart phone) and students work together in groups with a more knowledgable guide on hand but without a strict lesson plan. Within the domain of music, a small Jazz band is another good example of an open-ended learning environment [7], [9]. Band members learn from each other and by playing with more experienced players. They are challenged by performance before an audience.

A final example is a well-functioning team of ph.D students working together under the guidance of a professor. They tackle together challenging problems, exchange knowledge, acquire new skills together or seek outside knowledge.

Open-ended learning environments are 'learner-centered'. Each student carves out his or her own path and cooperation with others plays a very important role. There is usually a tutor but that is not even necessary. The advantage is that students are more motivated because they learn by doing and understand the relevance of the study material. It works best with good students that can move at their own pace, and have already mastered basic study material. For example, you cannot participate in a Jazz ensemble without prior music theory and competence on the instrument. On the other hand, external quality control becomes more difficult, the role of the teacher has to be much more proactive, and students may show big knowledge gaps because they may not have encountered a basic method or technique yet - although they have acquired the skills to fill those gaps autonomously.

Several researchers are currently exploring in how far open-ended learner-centered environments can be created using the web and social media, characteristic of MOOCs [30], [19]. They thus try to build *social MOOCs* [27], going back to the original idea of a MOOC, namely a platform to foster communities of learners [23].

These social MOOCs do not follow a strict lesson plan but provide a framework with the following basic components:

1. Materials and challenges to stimulate students. For example, a library of Jazz standards against which students can practice their improvisation skills [17].
2. Ways to share engagement with these learning materials, for example, by uploading improvisations performed by the learner. [19].
3. Facilities for giving peer commentary. For example, by attaching praise or criticism to a short stretch of uploaded music. [30]

On top of these facilities various elements are added to enhance the learning experience, for example:

1. Apps that provide automatic feedback to the individual, e.g. analyzing whether classical compositional rules have been violated [2], or whether the improviser is playing ‘on the beat’ [19].
2. Mechanisms to track opinion dynamics, e.g. using techniques of sentiment analysis, or network structure (who is interacting with whom) [13].

External vs. Self-Motivation

Another related dimension for categorizing the landscape of learning and education is in terms of the mechanisms that are available for fostering motivation. The high drop-out rate of current MOOCs and the large student failure in traditional instructional teaching shows that motivation is a critical factor that must be addressed. Here an important distiction can be made between external versus internal or self-motivation.

External motivation is based on reward and punishment. The reward can take the form of praise, higher marks, recognition by teachers and peers, fame, promotion, monetary benefit. Punishment can be in the form of low grades, public shaming, lack of recognition, demotion, rejection by peers. Instructional teaching, particularly in its extreme forms proposed by Skinner, is entirely based on the assumption that reward and punishment has to lie at the heart of education, not only to shape the knowledge students have to learn - because it provides positive and negative examples - but also to motivate them.

Internal motivation is entirely intrinsic to the learner. Several possible motors for internal motivation have been proposed (see the review in: [1]). One is based on the notion of curiosity [16], whereby the learner is driven by the desire to increase his or her success in predicting how the world behaves. Another possible motor for internal motivation is based on the notion of flow [20]. Flow is a state where humans obtain a strong focus on a particular task, losing awareness of all aspects of the environment which are not relevant for the task, feel great enjoyment, and achieve a high sense of creativity [5]. Concentration can be maintained for a very long time and no physiological effort is felt (although heavy fatigue may set in later). One of the most important characteristics of the flow state, is that the individual becomes *autotelic*, where 'auto-' means "self" and 'telos' means "goal". There is no need for external rewards.

As pointed out first by Cskiszentmihalyi [4], flow is observed in children at play, in athletes, artisans, artists, scientists but just as well people carrying out mundane looking jobs. They all go to great length to excel and push the boundaries of their knowledge and skills. Practitioners are said to reach a state of flow or optimal experience which not only pushes forward their competence but also provides tremendous enjoyment so that they seek the same experience again in the future. Most importantly, they see their activity as meaningful and the hard effort required for learning hence becomes meaningful as well. There is no doubt that this state of flow is reached by many musicians, including amateur musicians, and that this is the main reason why they go to great lengths to master their instrument or engage in music theory, a rather dry subject in itself.

Most humans operate both with internal and external motivation, and some people are more apt to experience and hence seek flow than others. But there is a consensus that the high emphasis on external reward in the structured learning environments dominating current educational systems is leading to a large number of negative side effects, among them: shallow knowledge acquisition, just enough to pass grades, and not in the least, a lack of long-term motivation [12]. Many people report that their desire to learn an instrument was stifled in an early stage by teachers who applied a reward and punishment methodology - occasionally associated with physical violence. The experience of flow is encouraged in open-ended learning environments, indeed it is a crucial ingredient of such learning environments because it is the major organizing principle, determining when and why learners are autonomously seeking what knowledge or skill to acquire, and the major motivational principle, because the teacher (or an assessment board) is no longer the source of authority handling out punishment.

The present paper pursues the question how the concept of flow can help to build more exciting and effective MOOCs, tackling in particular the problem of student motivation and scaffolding of complexity in tackling knowledge. First we discuss models of flow in individuals so that we can identify the requirements of a learning environment inducing flow. Next we turn to flow in groups. I characterize the notion of 'social flow' and discuss its relevance for the creation of social MOOCs.

2. Models of flow

Most of the work on flow and self-motivation in psychology is of a descriptive nature, taking an observer's point of view and using questionnaires and experience-sampling methods [14]. The main application area is counseling towards achieving well-balanced personalities or more productive work places [22]. However there has also been some work on building artificial 'autotelic agents' which incorporate the kind of mechanisms assumed to be necessary for flow as computational components in (robotic) agents that learn autonomously by interaction with their environment and others [25] [26].

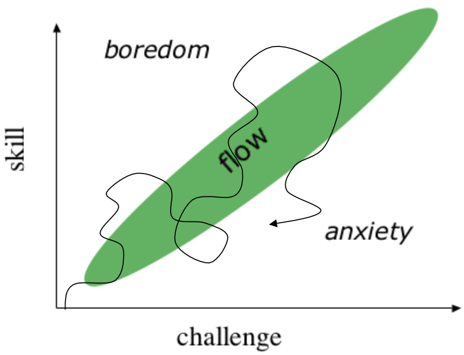

Figure 1. Flow diagram displaying development of a single individual. The x-axis shows the degree of challenge of tasks being considered and the y-axis the skill level of the individual. The flow state occurs when the two are balanced. When the challenge is too high for the skill, anxiety sets in. When the challenge is too low, the subject experiences boredom. During development a person navigates around the flow regime, regulating the challenge level of tasks he or she takes on while skills build up due to learning or decrease due to lack of practice.

2.1. Descriptive models

The key idea to come out of empirical research on optimal experience, already stated by Cskiszentmihalyi [4], is that there are a number of critical characteristics of flow. The first set of characteristics are preconditions for reaching flow:

1. There must be a clarity of goals. The individual has to be entirely focused on trying to achieve a particular challenge and the resources are available to carry out the necessary subtasks.
2. The goal is set by the individual, so that there is a sense of control. When the goals are beyond reach, the individual must be allowed to change goals, decreasing the challenge.
3. There must be clear feedback on how well the individual is doing, i.e. whether actions make significant steps towards the goal.
4. There must be a balance of challenge and skill, as captured in the famous flow diagram (see Figure 1). The task should fit well with available skills to avoid anxiety but also challenging enough to avoid boredom.

The second set of characteristics relate to the subjective experience while being in the flow state:

1. Awareness and action are merging, so that time seems to disappear.
2. There is a high concentration.
3. Solutions to problems come spontaneously and rapidly.
4. There is no concern or worry about anything else.
5. The activity is felt as intrinsically rewarding and therefore repeated.

More recent literature sees flow more as a process, in two ways. First, the flow state itself is dynamic: there are various preconditions, it takes a certain amount of time to get into it, and there is a phase of winding down with consequences for future behavior [11]. Second, the challenge/skill landscape is constantly shifting [26]. Skill builds up during the exercising of a task, so that a task which was a big challenge at some point may no longer be so and therefore may become boring. On the other hand, skill may decrease when not exercised, forcing the learner back to earlier challenge levels. This is a common experience of musicians, who have mastered a particular piece after a lot of hard work but then find that they have to go through a tedious (and less motivating) learning process again when they have not practised this piece for a while.

2.2. *Autotelic Agents*

Complementary to descriptive models, there have been efforts the past decade to develop agent-based models of flow [24]. 'Agent-based' means, that we think about the cognitive mechanisms, context, and social interactions that are required for the flow state to occur, and proposals are validated using computer simulations or experiments with robotic agents [25]. This objective requires a significant change in perspective because both challenge and skill are not parameters that are under direct control. It is often difficult for a learner to know in advance how challenging a particular task will be and skill cannot simply be increased at will, it requires practice, possibly with tasks that are less challenging.

Modeling is further complicated because a particular task usually requires a wide variety of components. For example, playing a particular piano piece fluently may be hampered by lack of skills in sight reading, unfamiliarity with the tonality of the piece, unusual chords or arpeggios, or simply lack of practice to move fingers fast enough. Each of these skills has its own requirements and a learner may have reached uneven levels of skills.

The Steels flow model [24] has been applied both to robot behavior acquisition [25] and language learning [26] and has recently been reimplemented by Cornudella et al. [3]. It assumes that an autotelic agent has a set of self-developing components, all necessary to solve a complex task within a particular situational context. The components have input-output relations with each other and may be organized in a hierarchy.

Each self-developing component has the following elements (see Figure 2):

- *Goal*: The component performs some mapping from inputs to outputs.
- *Knowledge*: The mapping is established through an algorithm (which may have critical parameters), a neural network, a set of production rules, or any other kind of computational device.
- *Feedback*: The component receives a feedback signal how well the mapping was established, coming from other components that make use of the result, or from an external source.
- *Learning*: Each component has a learning mechanism which is responsible for learning the knowledge needed for establishing the mapping. Any kind of learning mechanism can be employed.
- *Performance:* The component is able to track how well it has established a mapping.
- *Challenge level* The component is able to determine the level of challenge of the input and has at any point in time a particular challenge level as target. The challenge consists of a number of aspects and is represented as a feature vector with values between 0.0 and 1.0. Inputs whose challenge level surpass the challenge level set by the component are ignored, leading to overall failure in the task be-

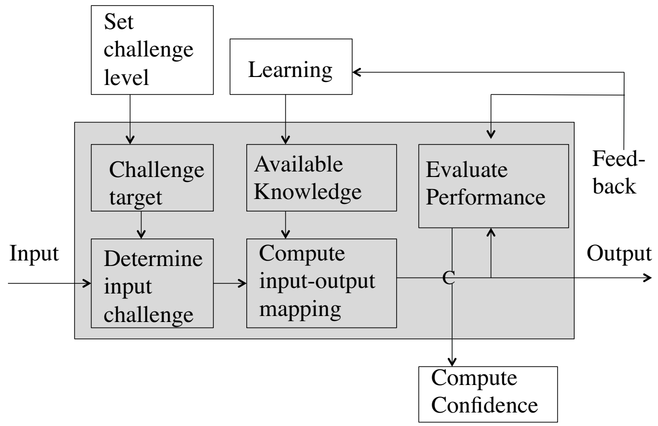

Figure 2. A self-developing component is able to compute a mapping between input and output, but it has additional machinery to determine whether the input is within the given targeted challenge, to learn the mapping and evaluate performance based on feedback, and compute confidence over time.

cause other components relying on it will receive no input. In principle a self-developing component should include an additional mechanism to learn which aspects of the input are important and how they can be calculated but this point has not been worked out further in the models developed so far.

- *Confidence*: The component has a way to track in how far it masters its goal. It is based on average performance over a window of time for a given challenge level.

The objective of a component is to reach steady performance for the targeted challenge level. Because usually some form of learning is required, it may take a while before this point is reached. When there is steady performance and hence high confidence, the challenge level can be increased. When feedback persistently generates a lot of failures, the challenge level is decreased to build first enough expertise to attempt a higher challenge level later.

Consider by way of example the task of sight reading and performing a piece of music. Human learners typically spend years before they fully master this task, gradually scaling up the difficulty with many hours of practice required. Suppose we want to build an autotelic agent that goes through the same developmental process. For example, imagine a robot that tries to ‘read’ a score using a camera and plays the notes on a saxophone. Two components are needed: the ‘sight reading component’ decides which note needs to be played and the ‘note production component’ produces the needed physical movements to play the note.

Let us just focus on the first component: deciding which note to be played. It needs the following elements:

- *Goal*: The input is a score and the output is a stream of instructions to the motor component that controls manipulation of the instrument.
- *Knowledge*: The component needs to visually recognize the pitch of each note on the staff, taking into account sharps or flats, the key, and the tuning of the instrument.

- *Feedback*: Given current technology, feedback can easily be provided by an automatic system that compares the produced note with the desired note, for example based on a rendering of the same note on a synthetizer.
- *Learning*: Associations need to be acquired between the visually perceived position of a note on a staff and the tone to be produced. Practise leads to more accurate and faster retrieval of this relation.
- *Performance*: Performance is determined by the speed with which the note is identified and whether it is the correct note when played.
- *Challenge level*: Challenge decomposes into a number of parameters, such as the distances between the notes (shorter distances are usually easier), how common the interval is (e.g. a third is usually easier than a sixth), the key (C-major with no sharps or flats is easier than C#-major which has seven sharps), the speed ('largo' is easier than 'presto').
- *Confidence*: This measure computes in how far the component masters its goal. It is based on average performance over a window of time for a given challenge level.

An autotelic agent either receives inputs from the environment without being able to control their challenge level, in which case he just ignores cases that cannot be handled or handles a situation only partly (e.g. an instrumentalist may skip ornamentations that require very fast finger movements). Alternatively, when an agent can control which situations he will handle (e.g. the instrumentalist can choose which scores to try) he can use a prior evaluation of the challenge level of the situation and choose those that fit with the targeted challenge level.

When there is a set of such self-developing components that are interrelated in the sense that one provides input to the next one, the agent is confronted with a multi-dimensional control problem through which he has to navigate, increasing or decreasing the challenge levels until stable performance is reached, and then climbing up by selected increases of the challenge levels of individual components. For example, the production of tone and the fingering of the instrument needs to be mastered at the same time as reading scores. Even if sight reading is fast enough, the instrumentalist might still not be able to fluently play the notes within the required tempo.

Occasionally the agent might get stuck in a loop that traps further growth: when challenge is decreased it leads to increased performance, but then increasing the challenge again leads (even after a period of learning) back to decreased performance. This signals that an additional or different component must be recruited for the task or that some other learning strategy is needed by one of the existing components.

An autotelic agent is striving towards two states: (i) to stay within the 'flow' regime, in the sense of having a consist performance which means that there is a balance between challenge levels and skill, and (ii) to achieve, in the longer term, a steady increase in challenge levels, while maintaining adequate performance. Note that this is clearly an intrinsic motivational system. There is no external agency that supplies the reward or scaffolds the external environmental conditions.

Optimizing a multi-dimensional system is known to be a notoriously difficult problem. It is faced, for example, by roboticists that have to control a humanoid robot with a large number of degrees of freedom. Many techniques exist for dealing with it. In the original Steels model [24], this issue is approached by introducing two different phases: a learning phase and a shake-up phase. During the learning phase, all challenge parameters are kept fixed and the agent is exercising knowledge or learning new knowledge. This phase lasts until there is a high confidence level. In the shake-up phase, the challenge parameters are changed. There are two possibilities:

- Performance is consistently low, leading to low confidence in task achievement (anxiety). In this case one or more challenge parameters need to be lowered, typically the ones that were increased most recently.
- Performance is consistently high, leading to high confidence in task achievement (boredom). In this case, some of the challenge parameters need to be increased.

It is quite often the case that performance is decreasing rapidly after the increase of challenge parameters, which requires the agent to take action sooner. The choice which challenge parameter in which component is to be changed is difficult and heuristics need to be employed to avoid combinatorial explosions. For example if component X depends on input from component Y, whereby Y has a high performance but X consistently fails, then one of the challenge parameters of Y can be decreased in order to allow X to catch up. Concretely, if sight reading itself is already smoothly working for complex scores but the instrument is not yet sufficiently mastered, then the targeted complexity of the scores should be of a lower challenge level, until the note production component catches up. There is no doubt that a good learner employs powerful heuristics like this, helping to choose when and how to simplify the problems he or she tackles, and when and for which aspect of the task the challenge level should be increased.

3. Social Flow

Most of the literature on flow focuses on how a single individual can reach a flow state and what beneficial effects this can have. But music and many other human activities often take place in a group and there is a widely shared belief that a group is more than the sum of its individual members. It has its own ‘flow dynamics’ influencing the selection of tasks and the availability of knowledge to share. A special case of social flow occurs when the ‘group’ is very small, consisting for example only of a learner and a tutor, or a child and her two parents.

There are two ways in which inter-individual dynamics enhances learning.

1. Some members in the group may have a higher skill level than others and are therefore able to solve a more challenging task, possibly explaining on the way how a solution can be reached. This can help to pull less knowledgable members towards a higher level of expertise and acts as a role model of what can be achieved by others. A tutor is a special case of this, but this situation can also occur in a group of peers.

Vygotsky’s notion of the *zone of proximal development* conceptualizes this type of learning situation (Figure 3) [29]. He groups task challenges into three zones. The inner region are problems that the learner can solve comfortably, the middle zone are problems that the learner can solve when aided by a more knowledgable tutor or peer who can scaffold the problem by solving subproblems which the learner cannot solve yet, by drawing attention to aspects of the problem to which the learner is not yet sensitive, or by supplying information needed. The third zone is entirely out of reach.

Vygotsky’s conceptualization is often brought in relation to the flow model (Figure 1) by equating the zone of proximal development with the flow region in which challenge

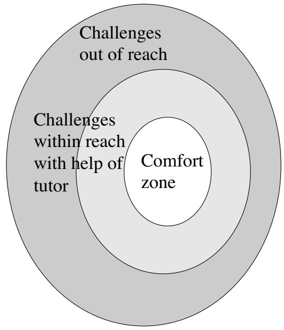

Figure 3. Vygotsky's conceptualization of learning guided by a tutor involves a zone of challenges between comfort (possibly leading to boredom), a zone with problems out of reach (possibly leading to anxiety), and a region where a tutor can scaffold the situation to allow the learner to discover solutions.

and skill is balanced, although this seems to be too much of a simplification. First of all, the flow model does not address tutoring situations but the optimal experience of an individual, and second, the zone of proximal development is not the region of comfort where there is a strict balance between challenge and skill, but rather the region where skill is insufficient, but thanks to scaffolding the learner moves towards the flow region.

2. The members of a group can often solve problems together which no single individual is able to solve. A group can then be viewed as a single autotelic agent with multiple components which solve specific subtasks. Because the members of the group have to cooperate, their challenge levels must be compatible. For example, a jazz ensemble has different players each contributing with their own instrument and having different functions (rhythm section, harmonic background, melodic lines). The problem is the same as between the components of a single agent, namely how to ensure that the challenge levels of the different components are compatible with each other. The group can only thrive and move up in challenge when the different players have roughly equal levels of competence. Humans spontaneously will lower complexity of their behavior for others, e.g. a mother uses 'motherese' to scale down the complexity of her language in order to create input that the child can master, a pianist may simplify the chord structure so that the beginning improviser hears more clearly the harmonic structure of the piece.

The autotelic model has been operationalized and used in various experiments in which robots acquire more complex behavior (which is the case of one autotelic agent against the environment that he needs to scaffold himself) or more complex language (in which you have multiple agents that have to coordinate their challenge levels to allow everybody to catch up).

An example of the kind of results obtained is shown in figure 4 from [26], which contains more details. The experiment concerns a population of 10 agents trying to create a common language. Challenge levels relate to the complexity of the meanings that agents try to express, moving from single predicates to relations. Initially they use a lexical strategy, that allows them to invent and learn words from others, but they are able to recruit a grammatical strategy if needed. Task success is here equal to communicative success in the language game. The size of the lexicon first overshoots and then agents align. Communicative success gets higher and higher and confidence builds.

Next challenge levels are being increased by agents (around interaction 4000) and there is an immediate significant drop in performance. Agents try at first to invent more

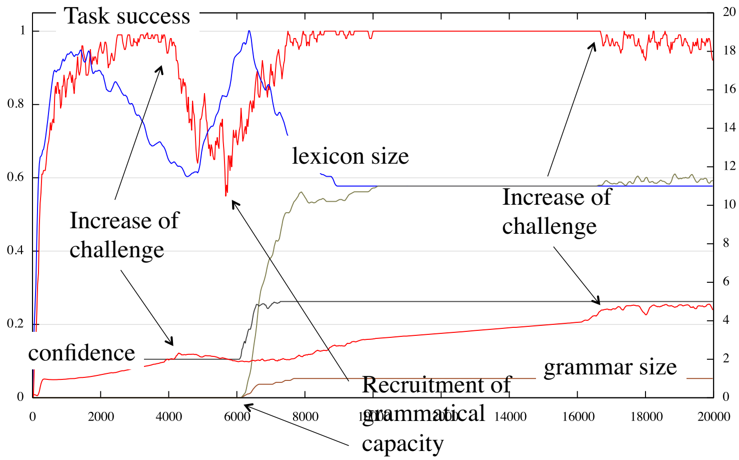

Figure 4. Experiment with social flow in a population of agents self-organizing a language. The x-axis shows the number of interactions between agents and the y-axis various observed measures: Task success, which is the running average of succeeded communications, lexicon size which gives the average size of the lexicon of all agents in the population, grammar size which gives the average number of constructions, average confidence of the agents, and some other measures not relevant for the present discussion.

words, but relief only comes when recruiting a grammatical strategy. As agents invent and share grammatical constructions, success goes back up, until a new cycle of challenge increase becomes feasible (around interaction 16000).

There has been a lot of work on operationalizing motivational theories based on reward and punishment, but these experiments show that it is also possible to operationalize autotelic principles and incorporate them in artificial agents. This field is in its infancy and many further experiments have to be done, for example to discover heuristics for navigating in a multi-component autotelic system. These operationalization will help to better understand the flow phenomenon and base learning environments on this theory of motivation.

4. Implications for MOOCs

The first experiments exploring flow for creating more exciting learning environments were conducted by François Pachet [18]. Pachet proposed to create 'mirrors' for a learner that reflect back his or her knowledge or skill, for example, playing back the chord sequences that the learner already knows, as a stimulus to then entrench existing knowledge or be a basis for building further on it. Pachet's 'Continuator' is a music system that acquires the statistical properties of musical input introduced through a keyboard and then mirrors this with its own output which consists of variations on the learned patterns. This activity generates a lot of excitement, even in young children. The system learns continuously and therefore players try to elicit more complex behavior by becoming more sophisticated themselves. Pachet's 'flow machine' (in the sense of machines that help to generate flow) tell us something about why humans become excited and what features a system needs to have in order to elicit excitement.

Another approach, illustrated by the (artificial) counterpoint tutor described later in this book [2], assumes that the learner is an autotelic agent and that the tutor must help to scaffold tasks and inputs and steer the learner through the search space of challenge levels. The (artificial) tutor achieves this by modeling the student at a very detailed level, and this allows him to come up with exercises that are within his or her Zone of Proximal Development.

More general, embedding autotelic principles in a (social) MOOC learning environment requires the following:

1. The system should generate clear goals in the form of tangible problems to be solved. In the case of music, these goals could be: generating an improvisational line on top of an existing accompaniment for a Jazz standard, writing a 4 part choral piece given a melody, interpret a Chopin prelude on the piano.
2. The learner must be able to select a goal to pursue, among a set of possible goals, and also the specific situation that is to be tackled (e.g. which melody will be harmonized). This goal should be compatible with his or her skill level. This implies that learners must either be given an indication of the challenge level required for a particular task (e.g. how hard is it to play along or improvise for a particular Jazz standard in the database) or they must be encouraged to build up skill for determining the challenge level themselves (e.g. by inspecting the score).
3. Learners must have a way to gauge how well they are doing, ideally in ways that do not kill the enjoyment of engaging in the task, in other words, not by separate tests, but by tracking performance during the execution of the task, if possible automatically. So feedback is of crucial importance and many of the mechanisms discussed in this book (e.g. testing the quality of a Jazz improvisation based on tracking how many notes are within the scale, what shifts occur with respect to the beats, whether melodic continuity is preserved, etc. [19]) are entirely relevant. In the case of a social MOOC, learners must be able to get an idea of the performance level of others so that they can choose peers with which to jointly solve a task (e.g. jointly engage in an improvisation).
4. The learning environment must not only track performance to regulate the challenge level of proposed tasks, but also make a model of the learner in order to present appropriate possible goals, related to the skill level of the learner.

Of course many school curricula and MOOCs already have such elements, such as continuous testing, scaffolding of course material, etc., and teachers will naturally attempt to personalize student tasks - although testing is usually uniform. The key difference is that a flow-based learning environment gives more control to the learner who can thus carve out his or her own individual trajectory to balance challenge and skill.

5. Conclusions

Flow theory is a welcome complement to the reward-and-punishment theory that underlies a lot of learning theories and teaching systems. It leads to greater long-term motivation, curiosity about the subject, and a more balanced feeling of well-being. More work is needed to understand the cognitive mechanisms and features of the task context that help the induction of flow, and these can be of great value in creating computer-based learning environments, including MOOCs that are more personalized to the individual student and present material and exercises adapted to move from the student's comfort zone to the Zone of Proximal Development. Particularly in the case of social MOOCs, flow theory points to certain characteristics that could in many cases be easily added to currently available systems, to make it easier for learners to have more enjoyable and effective learning experiences.

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