Chapter 4
Massive Numbers, Diverse Learning

Abstract MOOCs provide education for millions of people worldwide. Though it is not clear whether everyone can learn in a MOOC. Building on the typology of MOOC participants introduced is in Chap. 3, and we explore the claim that MOOCs are for everyone. We trace the different reasons people participate in MOOCs and the ways they learn. MOOCs tend to be designed for people who are already able to learn as active, autonomous learners. Those with low confidence may be inactive. However, even learners who are confident and able to regulate their learning experience difficulties if they don't comply with the expectations of the course designers or their peers. For example, if a learner chooses to learn by observing others, rather than contributing, this behaviour can be perceived negatively by tutors and by peers. This indicates that MOOCs sustain the traditional hierarchy between the educators (those that create MOOCs and technology systems) and the learners (those who use these courses and systems). Although this hierarchy is not always visible, since it is embedded within the algorithms and analytics that power MOOC tools and platforms.

4.1 Learning in MOOCs; What Does It Mean?

MOOCs have massive number of learners with diverse intentions and characteristics. Yet, little is known about how and why they engage in MOOCs. Research on learning in MOOCs tends to focus on MOOC designs, the data trails of learners and the semantic traces they leave in discussion forums (Gasevic et al. 2014). These studies tell little about the cognitive and affective factors that influence the reasons that learners study, their learning strategies, why they drop in and out of courses and whether they have learnt. Few researchers examining learning in MOOCs have taken a holistic view of learners' experiences, for example, by gathering learners' stories and listening to them describe their motivations, experiences and feelings about learning in a MOOC. Yet an all-inclusive view is needed to allow critical analysis that positions learning and technology within broader organisational, political, economic and social contexts in order to explore how it can foster, support and counteract issues of empowerment, equality and democratisation (Selwyn 2010).

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This chapter is informed by a programme of research overseen by one of the authors which was based around conversations with 88 learners in three different MOOCs (see Littlejohn et al. 2016; Milligan and Littlejohn 2016; Milligan et al. 2013). This research was motivated by the claim that MOOCs are opening up education, which is underscored by the assumption that MOOC learners are able to self-regulate their own learning. Our findings questioned this claim, highlighting that MOOCs open up education principally for people who are already able to learn. Our findings contest the belief that MOOCs challenge existing models and paradigms of education. In fact our research illustrates that MOOCs are, in some ways, reinforcing traditional patterns and behaviours in both learning and learners. The pluralism that characterises the need for learners to be able to learn actively in MOOCs and the limited ability of many MOOC learners to self-regulate their learning makes any attempt to discuss MOOCs in a unified manner challenging. Furthermore, the absence of strong, extant theoretical frameworks for conceptualising learning in a digital age further limits the academic scholarship in this area.

Building on the typology of learners presented at the end of Chap. 3, this chapter re-examines the potential to reconceptualise learning and learners in MOOCs, while simultaneously questioning how much of this reconceptualisation is current reality, versus a desired future vision. The pluralism present in the structure and purpose of individual MOOCs is matched by the multiplicity of stances and approaches adopted in this chapter. While, to the academic purist, moving between different theoretical framings in a single chapter may be criticised, we argue that this multiple framing aligns perfectly with the diverse frameworks governing the approaches to learning in individual MOOCs and diversity of backgrounds, motivations and behaviours of MOOC learners.

MOOCs frequently are positioned as re-operationalising traditional concepts in education, representing a new approach to instruction and learning (Fischer 2014). In Chap. 2 we characterised how the MOOC platform providers, along with their university partners, have emphasised a re-orientation of learning through open access to courses that are free of charge, use learning materials created by elite faculty and facilitate interaction with thousands of other learners. At the same time, those who use the 'connectivist' approach to MOOCs argue that the idea of learning in an open and autonomous network changes the educational paradigm (Downes 2012). While this is undoubtedly true in some cases, the degree to which they are re-operationalising and reconceptualising the learning process requires careful consideration. MOOCs hold an uncertain space where they appear simultaneously to challenge traditional approaches and paradigms, while continuing to draw on and replicate existing educational and learning models.

To explore this tension between novelty and continuity in MOOCs, we draw upon Illeris' (2007) fundamental processes of learning framework as a lens for examining the nature of learning. More particularly learning framework can be used for considering the positioning of the individual learner in relation to their broader MOOC experience. Illeris suggests that at its most basic, learning requires two simultaneously occurring processes: (1) external interaction between the learner and their social, cultural and material environment(s), where their activities and actions are situated; and (2) the internal, psychological process of acquisition and elaboration, where new stimuli are connected with prior learning. These internal processes are mediated through the individual, arising from the interplay between the incentives influencing and structuring an individual's behaviour, and engagement with content and learning activities.

Put more simply, to understand any learning, it is necessary to consider how an individual learner draws upon his or her existing cognitive frameworks, personal ontologies and social capital to navigate the experiences, resources, tools and spaces made available to them. How is the learner and his or her learning activity situated within their broader contexts of action?

Illeris (2007) states all learning involves three dimensions: cognitive (knowledge and skills), affective (feelings and motivation) and social (communication and co-operation), which are embedded in the learning context (in this case the MOOC). Thus, Illeris' model combines the internal psychological stance of the individual, with the socially mediated dimensions of the learning process.

Therefore, to understand the nature of learning in MOOCs, it is necessary to consider how the internal drive to learn is transformed into learning opportunities through an individual's engagement with the socio-cultural and socio-technical contexts of practice. In these contexts learning is distributed across the individual, other people, resources, technology and physical contexts (Cobb and Bower 1999; Greeno et al. 1996; Pea 1997; Putnam and Borko 1997). Learning is embedded within the individual's cognition, influenced and shaped by their personal histories, as well as situated in the environmental, social and technological contexts in which the individual operates. Learning is explored through individual learners' interactions with online systems, with other people and with (online and offline) information resources (Abeer and Miri 2014). Therefore, learners are influenced by their own cognition and experiences, their social surroundings and both the digital and physical contexts in which the learning is embedded.

Eraut (1994) suggests that learning does not occur when an individual encounters an idea or information, but rather through new input or use. It is through being enacted that an idea gets reinterpreted and acquires new meaning, which is specific to the individual and their context. This moves beyond the learning as acquisition metaphor (Hakkarainen and Paavola 2007; Sfard 1998) to the conceptualisation of learning as construction (Piaget 1964). Hakkarainen and Paavola (2007) suggest that in this conception:

> Learning is seen as analogous to innovative inquiry through which new ideas, tools and practices to support intelligent action are created and the knowledge being developed is significantly enriched or changed during the process.

Learning, therefore, occurs within the internal, psychological setting of the individual (thinking) as well as through the actions of an individual, (behaviour), which are situated within a particular environmental context (Illeris 2007).

This reading of learning in MOOCs is in contrast to much of the literature, which characterises MOOCs as de-contextualised learning experiences. MOOC platform providers view MOOCs as contained courses supported by distributed and fragmented technology tools, rather than as a holistic learning journey that brings together all the experiences and contexts each individual learner engages within (Ebben and Murphy 2014). To more fully understand the nature of the learning experience it is necessary to situate the MOOC, the learning opportunities it provides, and individual learners within the multiple ecosystems in which they interact.

From this perspective, learning is not prescriptive or predefined by a set of objectives. While the curriculum and learning outcomes of a particular MOOC may guide the discourse and activities of the learners, the specific knowledge and concepts that are learnt will emerge through the activities and actions of the learners, and will, therefore, be influenced by a myriad of factors (Milligan et al. 2013; Williams et al. 2011). These factors encompass the understanding and experience the learner brings to the course, including their motivation and level of confidence, the knowledge of other learners, the course design, and the temporal and geographic contexts in which the MOOC and its learners are situated.

4.2 Individual-Level Factors

A number of studies have sought to identify the individual-level factors that influence successful learning in MOOCs. A learner's geographic location affects not only accessibility to MOOCs, but also their interest in topics (Liyanagunawardena et al. 2013), with demographic information positioned as a mediating factor to explain behaviour in a MOOC (Skrypnyk et al. 2015). Confidence, prior experience and motivation (Littlejohn et al. 2016; Milligan et al. 2013), and a learner's occupation (de Waard et al. 2011; Hood et al. 2015; Wang and Baker 2015) further have been found to mediate engagement. A relationship between learners' goals and their learning outcomes has also been identified (Kop et al. 2011; Littlejohn et al. 2016), while there is also evidence that a learners' prior education experience influence their retention in a MOOC (Emanuel 2013; Koller et al. 2013; Rayyan et al. 2013).

Some of these individual-level factors identified in the literature are associated with the norms and expectations of how learners behave in education. Other factors, raised in Chap. 3, are focused around the role of motivations, incentives and self-regulation in determining how a learner engages within the learning environment.

4.3 The Environment

Learning is enabled in part through an individual's participation within their context of practice, as well as through interaction and engagement with the resources (material and human) available in that context (Lave and Wenger 1991). The learning process and resultant knowledge is shaped by the context(s) in which knowledge is acquired and used. Nonaka and Toyama (2003) utilise the concept of *ba*, to explain the specific context, encompassing both spatial and temporal dimensions, in which learning takes place and knowledge is created. *Ba* is a shared space for emerging relationships composed of physical (classroom, office, etc.), virtual (digital tools, platforms) and mental (concepts, ideas, shared knowledge) dimensions.

The environment is not a single, static entity but rather is comprised of multiple complex systems, which come together to inform and shape the ways in which a learner engages with learning opportunities and resources. Barron (2006), in her work on learning ecologies, describes the importance of understanding the multiple environments in which technology-enabled learning occurs:

> Understanding how learning to use technology is distributed among multiple settings and resources is an increasingly important goal. The questions of how, when, and why adolescents choose to learn are particularly salient now, as there has been a rapid increase in access to information and to novel kinds of technologically mediated learning environments such as online special interest groups, tutorials, or games.
>
> It has become easier for those with computer access to find resources and activities that can support their learning in their own terms. However, there are also widespread concerns about equity. Although physical access to computing tools is becoming less of an issue, there are still stark differences among children and adolescents in access to learning opportunities that will help position them to use computers in ways that can promote their own development. In addition, there is the related concern that we convince a more diverse set of people to pursue advanced knowledge that will position them to work in technological design fields. (p. 194)

Barron goes on to explain that:

> The survey responses indicated that often learning was distributed over several settings and across many types of resources. More experienced students accessed a greater number of resources both in and out of school. Individual differences in the range and types of learning resources utilized were found even when physical access to computers and to the Internet were the same, suggesting that differences were due to variations in interest or resourcefulness. The results also suggested critical interdependencies between contexts. (2006, p. 196).

Therefore, to fully understand the learning that occurs in a MOOC it is necessary to understand both the individual learner, as well as how the learner is situated in and navigates the multiple spaces, contexts and settings in which they and their learning are situated and the materials and resources on which they draw.

4.4 Analysing the Norms of Behaviour

As Chap. 3 investigated, identifying a single 'norm' of behaviour or type of engagement in a MOOC is impossible. MOOCs, at least in theory, are positioned to endow learners with the flexibility to determine and chart their own individual learning journeys. Consequently, learning cannot be understood without deep engagement with the experiences of individual learners. That is, learning is inseparable from the personal histories and experiences, beliefs, and motivations of individual learners as well as their broader socio-cultural context and the relationship between the MOOC and their offline contexts. It is difficult to know whether someone has learned unless all of these factors are taken into account. Narrative accounts of learning provide the sorts of qualitative data needed to understand whether a learner is learning. However, these data are difficult to analyse and draw conclusions from.

To get around this problem and simplify analyses of learning in MOOCs, there has been an emphasis on identifying digital trace data that can be analysed to monitor academic performance. The greater the number of learners who provide data, the larger the potential to analyse data in meaningful ways and provide scaffolds and supports for learners.

Learning analytics usually is designed around one or more of the following:

- *early alert systems* that predict the likelihood of a learner falling behind or dropping out of a course;
- *visualisation systems* that provide dashboards to tutors and learners illustrating progress in relation to a pathway pre-prescribed by the tutor or in relation to the learner's position within a network of peers and tutors;
- *recommender systems* that endorse resources, people or future pathways;
- *adaptive learning systems* that aim to personalize the resources, people or future pathways the learner accesses, depending on their demographics or progress.

Early alert systems are based on predictive analytics that predetermine the learner's likelihood of achieving a 'success' measure, by comparing the learner's data to those of other students. For example, systems have been developed to analyse contributions to discussion forums and use these data to predict the likelihood of a learner dropping out (Muñoz-Merino et al. 2015; Skrypnyk et al. 2015; Vu et al. 2015). Learners' engagement and progression in a MOOC has been linked with a learner's prior education level (Rayyan et al. 2013). Jiang et al (2014) found factors related to a learner's behaviour in week 1 of a MOOC to be early alert indicators that signal whether or not a student would complete the MOOC. These factors included the number of assessments completed by the learner and the score from quizzes within the MOOC. Other early alert indicators link time management in a MOOC and retention (Balakrishnan and Cooetzee 2013). Retention rates have been correlated with a lighter workload, higher autonomy and more flexible assessments; the highest levels of perseverance were connected to autonomy, high levels of learning support and scaffolding activities (Skrypnyk et al. 2015).

Visualisation systems include Social Network Analysis techniques that use the learner's position within a learning network as an indicator of his or her connectedness, assuming a relationship between the learner's position in a learning network associated with a MOOC and the likelihood of them leaving the course (Yang et al. 2014). The learner's position within this network may be strengthened through interactions with peers and tutors using social media tools such as blogging and microblogging tools or by linking with others through discussion threads (ibid.). Other visualisation methods combine learning characteristics data with cognitive and behavioural data. For example Buckingham–Shum and Deakin–Crick (2012) link data on student's ability to self-direct their learning with assessment data to feedback to learners how they might amend their learning in ways that allow them to achieve success. Other, similar systems use recommendations, for example advocating that learners with a similar profile took a specific course of action (e.g. reading a text or engaging in a supplementary course) to achieve success.

Recommender systems offer MOOC learners all kinds of guidance, including advice about the next MOOC they select, or the likelihood of successful completion of a course. These recommendations are based on different kinds of data gathered from the learner and analysed against previous data from earlier rounds of the course. For example Skrypnyk et al. (2015) reported how analysis of learners' demographics and cultural groupings allowed personalised recommendations to students about the actions they could take to scaffold their learning. Emerging analytics systems are gathering a wider range of data, including affective data that indicate how learners feel about their learning. These data allow for more influential recommendations and adaptations of learning resources.

Adaptable systems include MOOCs where content is tailored and personalised for each student (Tabba and Medouri 2013). Some techniques adapt the learning design of a course, depending on the data (Mor et al. 2015). Other systems use semantic analysis of online discussions in MOOCs to allow adaptation. Gillani et al. (2014) examined the strategies of hundreds of learners as they engaged in online discussions. Using complex network analysis techniques, they identified a number of 'significant interaction networks' embedded within discussion forums. Although these interaction networks can support learning, they are vulnerable to breaking down. MOOC providers are capitalising on these analytics techniques to structure discussion forums so that students who join the course late are as able as the early cohorts to form lasting bonds and get integrated into the cohort of students taking the course.

Earlier, we indicated that learning is inseparable from the learner's personal experiences, beliefs and motivations, but data around these factors is difficult to measure and analyse. As a shortcut measure, it is sometimes assumed that 'learning' is synonymous with active engagement in a MOOC and with retention, completion and certification (see, for example Hew 2014). An example is a study by Colvin et al. (2014) analysed learning in the 8.MReV Mechanics ReView MOOC, offered on the EdX platform from June to August 2013. The course, an introduction to Newtonian Mechanics, was run in parallel with an on-campus course at MIT. The MOOC version of the course substituted face-to-face lectures with video lectures and textbooks with digital texts, and was open to anyone who met a number of prerequisites. The course design was structured around weekly video lectures to help students engage with task-based problem. The learning gains of 1080 students were evaluated by analysing the results of pre- and post-tests through normalised gain and item response theory. The learning gains for these students were comparable with those in the on-campus class, and 95% achieved the MOOC certificate. However, unlike the campus-based course, most of the MOOC students (almost 16,000 of the 17,000 people registered for the MOOC) did not complete the course and achieve the certificate.

This example illustrates that as technology advances, MOOC providers need to rethink MOOC models, and the role that tracking can play in them. Gathering data is likely to be more streamlined into online learning and those data that are easiest to measure are often used more prominently in analyses. However, one issue to consider is whether the right data is being gathered (Gašević et al. 2015).

At times the application of analytics overlooks the fact that technology is socially constructed and negotiated, rather than imbued with predetermined characteristics (Gašević et al. 2015). Poor application of analytics may promote a narrow view of desired outcomes and norms of behaviour in a MOOC which belie the fluidity and flexibility of the learning opportunities that MOOCs can offer.

Over-reliance on learning analytics for understanding and measuring learning may lead to what Biesta (2009) has termed ‘normative validity’. That is:

> The question whether we are indeed measuring what we value, or whether we are just measuring what we can easily measure and thus end up valuing what we [can] measure. (p. 35)

There is a danger that, by missing the learner’s context, that analytics systems may oversimplify how we understand learning. There are three key problems. First systems may focus on data that are easily measured—retention, completion and certification, rather than what cannot be easily measured—learner motivations, goals, self-regulation and agency—but are nevertheless critically important to learning. Second, those who code the algorithms that underpin analytics may not be concerned with the wider questions of the learner’s context and consequences for their learning decisions (Morozov 2014). The Joint Committee of the European Supervisory Authorities has undertaken a consultation on big data and the financial profiling of customers, emphasising that the algorithms that are used in big data analytics must be shown to be unbiased, otherwise the benefits of analysis will be diminished (ESA 2016).

While learning analytics provide the potential to personalise the learning experiences and opportunities of learners in MOOCs, the extent to which they can currently do this is questionable. Selwyn (2016) suggests that rather than personalising the learning experience, analytics instead is reinforcing mass customization of education through large systems. He explains:

> Many personalised, bespoke learning systems are concerned primarily with delivering predetermined content to students, albeit in different sequences and various forms of presentation. (p. 72)

Learning analytics in MOOCs may “personalise” the learning but this “personalisation” is not to the individual needs or goals of the learner but rather to the behavioural norms and desired outcomes of the MOOC provider. The learner’s behaviours are being adjusted to maximise the outcomes for the course providers, rather than the learning being optimised to meet the learner’s needs and objectives. This is because the assumptions that underpin the analytics may be based on the MOOC provider’s requirements, rather than the learners’s aspirations.

Algorithms are developed by coders to analyse data in a meaningful way. These can be helpful in understanding data, but inevitably are shaped by underpinning assumptions and biases. Data gathered and analysed by algorithms are limited by the expertise and assumptions held by those people who write the code (Williamson

2015). If the coders do not appreciate the underlying assumptions of their codes, then the data the algorithms analyse can be compromised. According to Boyd and Crawford (2011):

> As computational scientists have started engaging in acts of social science, there is a tendency to claim their work as the business of facts and not interpretation. A model may be mathematically sound, an experiment may seem valid, but as soon as a researcher seeks to understand what it means, the process of interpretation has begun. This is not to say that all interpretations are created equal, but rather that not all numbers are neutral.

Researchers such as Williamson (2015) warn that these biases may result in a hierarchy between those that create MOOC systems and those who use these courses and systems, such that empowered 'producers' of technical systems indirectly can overly influence and exploit the student consumers of the systems. To aim for equality, we need to engage with and interpret the qualitative narratives of individual MOOC learners.

4.5 Qualitative Narratives and Learners' Stories

> Inequalities persist even for those people who do get to take part. In particular, experiences and outcomes of education differ considerably according to who someone is – what is often referred to as 'inequalities of participation'. (Selwyn 2016, p. 31).

Engaging with the qualitative narratives of individual MOOC participants enables a richer perspective of what it means to learn in a MOOC. An example of a MOOC where we have gathered narratives of how learners have learned is *Introduction to Data Science* (https://www.coursera.org/course/datasci). This MOOC was offered in 2014 by the University of Washington on the Coursera platform. The course was designed for people with a moderate level of programming experience. Over 8 weeks, 50,000 learners, from 197 countries participated in the course.

The course homepage, illustrated in Fig. 4.1, provided information about the course aims and instructional design.

To achieve the course aims, learners were expected to engage in a number programming activities, supplemented by educational materials including video lectures (Fig. 4.2).

Learner interactions were enabled through sharing data science examples (see Fig. 4.3), uploading assignments, engaging in online discussions within the MOOC platform as well as collaboration through other social media sites, including OpenStack, an online site commonly used by computer scientists to share codes and discuss coding problems. Through creating and sharing computer codes, the learners independently structured informal learning and combined this with the formal learning activities within the MOOC. This ability to personalise learning outcomes was important for professional learners who wanted to align their learning in the MOOC with their job.

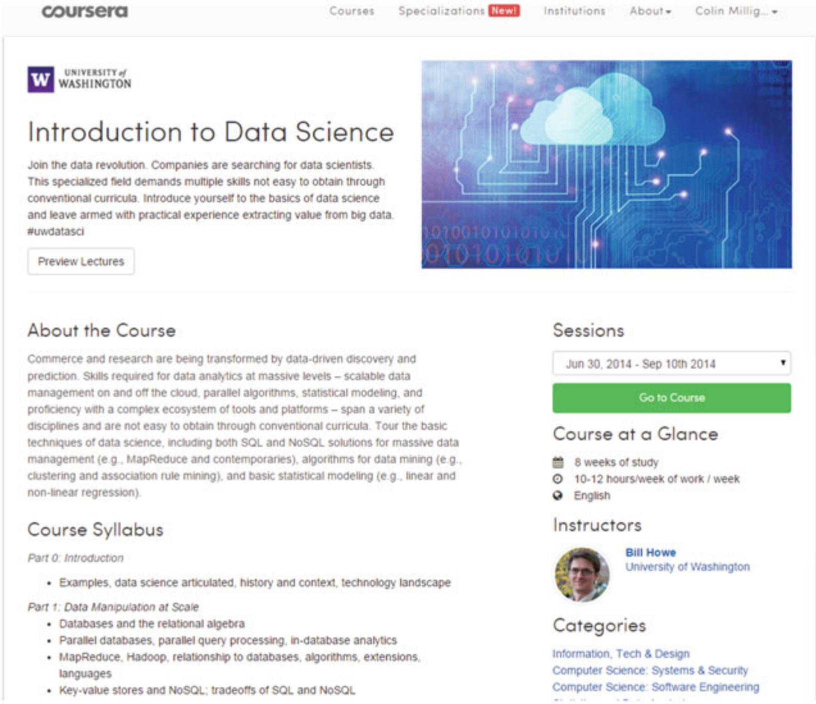

Fig. 4.1 IDS MOOC Introduction Page

Below are the narrative stories of the four types of MOOC learner outlined in the typology in Chap. 3. These portraits are drawn from the stories of actual learners, who participated in the Introduction to Data Science MOOC. These narratives are part of a larger study examining the self-regulated learning of 788 participants in the MOOC (https://www.coursera.org/specializations/data-science). Quantitative data was collected through a survey posted on the course message board. Participants who completed the survey were invited to participate in an interview to explore their experiences. 32 learners were interviewed via Skype. Their narrative accounts of being a MOOC learner demonstrate the diversity of motivations, goals, learning behaviours and perspectives of the participants.

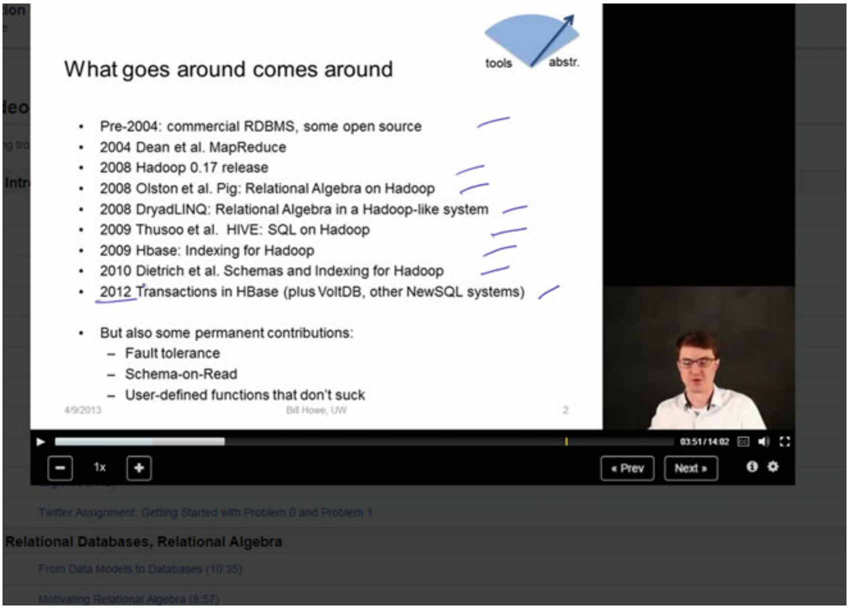

Fig. 4.2 IDS MOOC Video Lecture

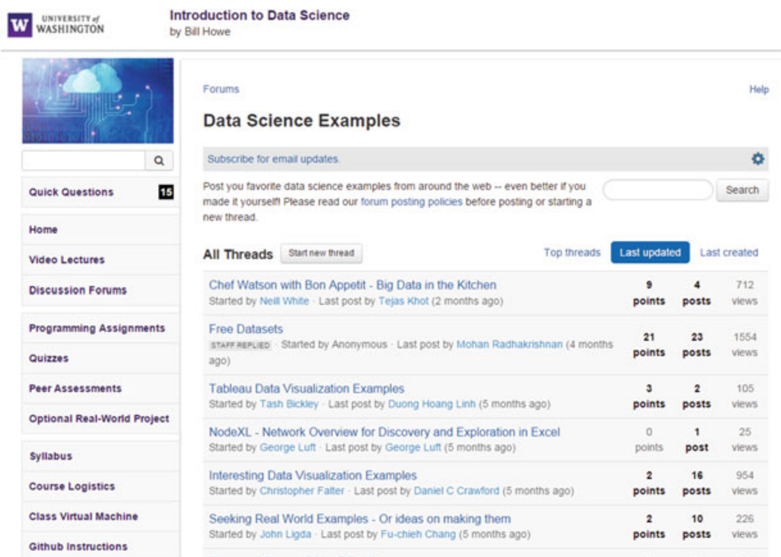

Fig. 4.3 IDS MOOC Forum for sharing coding examples

The invisible agent

It's very important for me to improve my knowledge base because I want to ensure that I am keeping up to date with the latest ideas and thinking. The MOOC is related to my profession. But I did it, not because I had to, but because I was interested in expanding my knowledge and my skill set.

I'm a fairly independent learner and feel like I am good at knowing what I need to do in order to learn the content and skills that I want to learn. I have the strength of quickly being able to tackle the problem and search for results on Internet sites, you know Google, forums and things like that. So, I think I have that strength where I can quickly just go ahead. And I did this in the MOOC. I didn't tend to go through all of the activities or watch all of the videos. I just picked and chose the content and activities that I thought were going to help me the most. I also was very happy to go and find the information elsewhere.

When I need to learn something, I will usually try to do it myself, usually with the help of Google and textbooks rather than to seek out another person or to find a formal training opportunity. I have used those kinds of 3 avenues. I rely a lot on academic literature for things of a technical nature and I also buy a lot of books. So, I buy a lot of programming books, a lot of statistical, data science and data mining book.

I guess one thing is I am optimistic, so it means I'll try a lot of things and I kind of enjoy doing new things and that makes it I guess kind of easy for me to go out on a limb and do a whole bunch of different things and see how it goes. I'm pretty decent at…basically I work reasonably well without the interaction of other people. I didn't particularly use the direction of other people during my regular university classes or regular school classes and I don't particularly need it now. So, I guess it could be considered a strength, I don't really need to depend on other people for it.

The socialiser

The MOOC is more of a personal curiosity than a real work requirement. I'm doing it for myself. Work know that I'm doing it, but it's not a recommended thing on the company, so I'm doing it out of interest.

I think that the way I wanted to approach the MOOC was just to follow what interested me, and not worry too much about trying to keep a complete overview of the area. I wanted to find appropriate tools, and tools that can be used in a timely manner. I still completed a couple of the assignments, but I wasn't that worried that I didn't keep going right to the end. To be honest the assignment is not the best benchmark to measure your learning, it is one form of measurement, but it's not a huge one because a lot of times the assignment is just a subset of what you do. Your peers are your best reflection actually.

So, if you have someone who is doing the same thing and you talk to him or her every day, then that's the best thing actually.

I would say I now very rarely watch lectures. I will look through the slides and I will read the transcripts that are provided, the subtitles, as a high-speed way to look over the material. Then, if it isn't obvious from those two, I'll go to the lecture and only then. But I've found it a much more effective way of learning for me. I had realised that the discussion aspects were among those that suited me best because, as I saw it, I could read a book and get the same content or at least I could get equivalent content, I could watch YouTube videos and the same kind of thing. The things that were really different were the motivation from doing things with a group of people and the chance to talk things out about issues. In my personal experience, being able to talk things out has been really useful to me. So that's probably the predominant way I learn in MOOCs now.

The "conventional" learner

I was aiming to get a certificate of completion and to get a passing distinction grade out of the class. I took the course very seriously from the beginning and this meant that I planned to watch all the videos and go through all the assignments. I have at least completed all the compulsory assignments.

I've taken several MOOCs and I would say that I'm at the point now where I am very familiar with the platform and how to learn on a MOOC, at least in terms of what works for me. So I can tackle courses very efficiently when I'm doing them as a student. First of all I watch lectures and after that I try to answer all the quizzes and questions, and after that I go to programme assignments.

If there is a quiz which actually makes you think it generally drives you to read more things, to discuss with your friends and generally helps you build your knowledge a lot.

I made a little Excel spreadsheet with the key dates. So, for example, I knew an assignment had to be handed in on a certain day or I knew a quiz had to be handed in on a certain day, or I knew a course project had to be handed in on a certain date. So then I guess I sort of kept track of what lectures I'd need to have covered before I could answer those questions and I kept that in mind. So I kind of planned my way through it, so I didn't miss any of the hard deadlines.

I think that the forums are very important because all the classmates could have the same problems that I have and I think the forums are very important for all the courses. When I'm working on a quiz or an assessment I like to go into the discussion forums. And it's the collaboration around the assessments *that I will get involved with on the forums. This is the type of collaboration on the discussion forums that I will get involved in.*

The cautious student

We've got a bit contract with the health service and that's coming to an end now, so they're trying to move all out skills into a different area, so we've been encouraged to learn a new database technology like NoSQL, analytics and so this course just fitted that learning requirement. I hadn't done any professional learning for a couple of years, although I always feel I try and learn every day if possible, but I hadn't done a course with coursework for at least 5 or 6 years.

My primary goal is not to learn, but to complete the course so I can get certified statement of accomplishment. So I definitely set out to watch all the videos and the content provided and try to solve all the assignments, although not necessarily to take part in the additional optional assignments. I am motivated by the reward of getting a certificate. But my learning strengths? I don't think I have anything particular on this one. I always think if I start something then I finish it. So I just want to keep this up.

I'm a designer so I find picking up a new thing is not that difficult, but it takes time to really be good at it, to be comfortable with it. Some of the assignments were quite a challenging task for me and I had to spend 3 days on one of the assignments. It took me quite a bit of time. Sometimes it's hard for me to gauge how much I've understood.

I watched the lectures and then I did the assignments and if I found something that I didn't know, but it was really specific to the language, let's say Python function names, then I Googled. I didn't talk to anyone. I occasionally went onto the forum to read, but I didn't ask questions on the forum. I mean it was mostly general chit chat, but if I had a problem I'd do a search on it and then it's just a matter of looking through all the responses, trying to find answers to problems.

4.6 Making Sense of the Learner Stories

One of the most impenetrable features of a MOOC is the variability in the degree to which learners engage in the course. Analysis of publically available data on MOOCs shows a positive correlation between course length and total number enrolments, but a negative correlation between course length and completion (Jordan 2014). However, as learner stories one and two above demonstrate, not completing is not synonymous with not learning.

At the same time completion, or at least engaging with all of the content and participating in learning activities, is not necessarily indicative of learning or of the learner's ability to participate in a MOOC. As learner story four (the cautious student) illustrated, this individual was less concerned with learning, and, indeed, at many stages struggled to regulate their learning behaviour and actions to maximise their experience. Instead, this learner was motivated by a need, imposed by their workplace, to undertake professional development.

The potential perils of MOOCs and online learning, and their inability to adequately support the learning of all students is identified by Selwyn (2016) who contended:

> The assumption that all individuals can navigate their own pathways through digital education opportunities implies a corresponding withdrawal of expert direction, guidance and support. While offering an alternative to the perceived paternalism of organised education provision, this approach does bump up against the widely held belief in education that learning is a social endeavour that is best supported by more knowledgeable others. (p. 73)

Selwyn highlights two themes that emerged from the learner stories narrated above. The first theme is that individuals are able to adequately regulate their learning behaviours and actions, and the second theme is the level of social engagement and interaction that occurs in a MOOC.

Stories one, two and three portrayed learners who demonstrated relatively high levels of self-regulation during their engagement in the MOOC. All three were able to shape their learning in order to reach their desired goals. The variation in their engagement during the MOOC reflected how the course was situated within the individual contexts and interests of each learner. These three learners were able to employ a range of learning behaviours and to pursue different pathways, in order to meet their different goals and outcomes. They had the skills necessary to actively and very deliberately determine the nature of their engagement, aligning their behaviours with their course goals and personal ambitions.

Some MOOC providers have recognised this need to provide variation in engagement and have designed courses to crowdsource data in areas of contemporary social interest. For example, three MOOCs from the University of Edinburgh (UK) used this strategy. A MOOC on Behavioural Economics invited learners to participate in an analysis of European dietary choices; a group of astrobiologists created an international community of people interested in research into life on other planets; and, in 2014 during the run-up to the Scottish Independence referendum, a group of political science academics ran a number of opinion polls during the MOOC 'Toward Scottish Independence? Understanding the Referendum'. These opinion and data gathering activities helped to sustain engagement throughout each MOOC. There were signs of reduced engagement, although the rate of reducing activity within these MOOCs over time was less striking than in many other MOOCs. Though it is difficult to link sustained learner engagement with the MOOC activities, or their connection with current affairs and events outside the MOOC.

Selwyn (2016) identified the absence of socialisation in much online learning. MOOCs allow opportunities for massive numbers of learners to develop through mutual forms of engagement. However, there is evidence that many MOOC learners do most of their learning on their own (see, for example Littlejohn et al. 2016; Alario-Hoyos et al. 2014). Yet learners' behaviour may be similar whether the MOOC is run as a live event (in-session, instructor-led with the opportunity to earn a certificate) or as an archived course (standalone materials, self-directed course with minimal instructional support and peer student presence, no deadlines, no peer-assessment, and no opportunity to earn credit) (Campbell et al. 2014). Even when there are many people learning at the same time, learners may choose to work on their own, rather than taking the opportunity to learn with other people. One reason may be because the course design offers few opportunities to interact with other people (Margaryan et al. 2015).

MOOC learners find ways to organise themselves, finding ways to create opportunities for interaction. In some MOOCs students plan collaboration and interaction via social media (e.g. Facebook, WhatsApp, etc.) or with colleagues, family and friends (Lin et al. 2015). Other learners organise face-to-face meet-ups in locations around the world (Lin et al. 2015; Vale and Littlejohn 2014).

Less-experienced learners may find it challenging to understand how to engage in a MOOC (Milligan et al. 2013), particularly where there is no overall course summary or well-defined structure to scaffold their learning (Kop et al. 2011). In the learner stories above, learner four struggled to determine his own learning journey and consequently used the predefined, linear course structure to scaffold his learning. In cases where MOOCs lack a clear structure or predefined learning journey, community and peer support become more important. Learners who are unable to chart their own learning pathways may rely on others to help scaffold their learning. They might follow other learners' pathways and actions, or seek advice as to their next steps. However, not all learners feel comfortable engaging socially or collaboratively in a MOOC setting (Milligan and Littlejohn 2016). Therefore, the student experience is likely to be different depending on each individual's prior learning experience.

Research has found that learner discussions and interactions on a MOOC tend to be characterised by decreasing participation over time (Jordan 2014). There is evidence that some conversations are restricted because the students have limited experience and knowledge to drive forward analysis of key concepts (Sinha et al. 2014). People sometimes post their own perceptions and anecdotal evidence, which may lead to the development of surface, rather than deep, analysis and dialogue. Generally, MOOC learners have limited opportunities for one-to-one dialogue with people who have more expertise or with tutors, particularly when the ratio of tutors to students is thousands to one. Yet it is this sort of engagement with an expert that might help to sustain interaction.

Another characteristic of discussion forums is that people with similar interests and knowledge may work together, giving rise to a phenomenon termed 'homophily'. On the one hand, learning with people of similar interests and ability can be beneficial (Wegerif 1998). On the other hand, homophily can lead to a narrowing of knowledge and ideas, which can lead to high levels of activity and engagement within a MOOC, leading to narrow knowledge development (Sinha et al. 2014).

Gillani and Eynon (2014) examined tens of thousands of comments in MOOC discussion forums across a range of MOOCs. Their findings indicated that learners may participate in discussions without completing assignments (like learner two in the narratives above). They further detected declining participation in the discussion forum over time. Over time the discussion participants formed small groups, with 20% of the participants contributing to 90% of the overall discussion. The motivations for participating in the discussion varied, depending on the course and the learner, and ranged from seeking help to contributing ideas.

These types of interactions are indicative of critical peer-supported learning processes. Where learners are not supported directly in a MOOC by tutors or experts, peer support becomes more crucial. Peer learning is supported by a number of technologies, both within the course on the MOOC platform and outside the course boundary, via learners' self-selected digital tools, such as Facebook and Twitter, and also in non-digital settings (Kellogg et al. 2014; Shen and Kuo 2015; Sinha et al. 2014).

Sentiment analysis of a student's contributions to a social media site or forum is being investigated by Rosé and colleagues to support deeper analysis of affective factors influencing learning (see, for example Yang et al. 2014). Learners may learn more effectively when they are happy or when they feel challenged, though these characteristics are likely to be tightly bound to the learner, rather than being general factors (Boekaerts 1993). There is a view that using data analytics to gather information about learners' characteristics and motivations can help to design more attractive courses and promote engagement, which may lead to better retention, engagement and learning (Rienties and Rivers 2014).

What makes these measurements difficult is that these characteristics and motivations extend beyond the boundaries of the MOOC; a learner may elect to drop out of a MOOC because of a competing priority in her life. This situation emphasises first the importance of gathering a broad range of data that enables engagement with learner stories and narratives to complement the use of data analytics, and second, that data associated with learners are dynamic and change over time—a learner may intent to complete a MOOC then change her mind.

The fourth learner story illustrated above highlights the less empowered and agentic MOOC learner. Learners who tend towards the fourth learner story typically have less experience in self-directing their own learning and in deliberately modifying their learning behaviours and actions in order to learn in the ways that are most relevant to them. This type of learner might benefit from engaging in regulatory activities, such as *planning* what they will do in the MOOC, *monitoring* and *controlling* these activities, and *self-reflecting and evaluating* their own learning (Milligan et al. 2012). However, this chapter has illustrated that, given the apparent inability to fully understand the nature of learning occurring through quantitative measures alone, and the complexity of gathering and analysing qualitative data, designing high quality, responsive learning on MOOCs is highly challenging.

MOOCs need to accommodate learners with—at certain times—opposed intentions, motivations and goals. The learners themselves come with very different learning approaches, prior experiences and confidence in managing and directing their own learning. Learners further are seeking significant variety in levels of social interaction and engagement in a MOOC. Given this diversity, understanding what makes a 'good' or 'high quality' MOOC is an incredibly challenging question to answer. Chapter 5 attempts to unpack the complexities around notions of quality in MOOCs.

4.7 Concluding Thoughts

The diversity of learners engaging with MOOCs has been well documented. And there is a growing body of research exploring the learning implications associated with this diversity. What we have attempted to argue in this chapter is the need to ensure that this diversity is understood in a holistic, contextually mediated way. This requires a move beyond current limits of quantitative data and learning analytics. Learning is a deeply personal, context-dependent (which of course includes a social dimension) undertaking. In order to fully appreciate the diversity of learning and learners in MOOCs, it is necessary to engage with the qualitative learning stories of individual learners. While the quest to open up access to massive numbers of learners is a noble task, the reality is that deep learning will only be successful when each individual learner is supported to engage in the learning process. This centrality of the individual learner in discussions about quality in MOOCs, will be explored in greater detail in Chap. 5.

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