Could Neurolecturing Address the Limitations of Live and Recorded Lectures?

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ABSTRACT

Lectures are a common teaching method in higher education. However, they have many serious limitations, including boredom, attendance, short attention span, low knowledge transmission and the passivity of students. This paper suggests how a combination of electroencephalography (EEG) and eye-tracking technology could address some of these limitations – an approach that I have called neurolecturing. Neurolecturing could measure students' attention, learning and cognitive load and provide real time feedback to students and lecturers. It could also play a role in the flipped classroom and artificial intelligence tutoring.

1. Introduction

There is a long tradition of teaching through lectures in higher education. The lecturer verbalizes the knowledge and students listen and take notes. Ideally at the end of the lecture the students will have assimilated the information that is contained in the lecture. Originally lectures were delivered by reading to the audience. They have now metamorphosed into multimedia PowerPoint presentations and many are delivered online (live or recorded) to remote campuses.

Lectures are a popular teaching method because they are *scalable*: a live lecture can be delivered to thousands of people; an online lecture to millions. Other forms of teaching, such as one-to-one tutorials and group work, can only be delivered to small numbers of people. One reason why scalability is important is that many university courses teach specialized knowledge that is held by a limited number of people. Specialized courses can be supported in seminars and labs by non-specialized staff, but their core content has to be delivered by experts in the field, and lectures enable this to be done to a large group. The scalability of lectures also saves money. It takes one hour of staff time to deliver a lecture to 200 students; it takes ten hours of staff time

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to deliver seminars to 200 students with a class size of 20.

While lectures are standard practice in universities, they have serious limitations as a teaching method (see Section 2). While alternative teaching methods can be more effective (see Section 3), they are often not scalable and have their own problems.

In market research people are increasingly using a combination of electroencephalography (EEG)[1] and eye-tracking to measure how people respond to adverts and products (Hannaford 2013). This paper explores whether EEG and eye-tracking could be used to increase the effectiveness of lectures – an approach that I have called 'neurolecturing'.

The first part of the paper discusses the problems with lectures, including boredom, attendance, short attention span, low knowledge transmission and the passivity of students. Section 3 examines alternatives to lectures, such as group work, the flipped classroom and problem-based learning. I then propose a new solution, which uses a combination of EEG and eye-tracking to measure students' attention, learning and cognitive load. This data could be used in a variety of ways to enhance learning. Finally Section 5 examines potential objections to neurolecturing and the appendix discusses the technology and likely costs.

2. Limitations of Lectures

Lectures are a popular method for teaching large numbers of students. However, they have a number of serious limitations.

Boredom

Lectures are often boring. Academics are not trained entertainers and there is a limit to how exciting some topics can be – many students would rather watch TV than listen to a programming lecture.[2]

Attendance

When lecturers make their slides available online there is little perceived benefit to attending a lecture. In my own courses at least 25% of students do not regularly attend lectures and this figure is often higher. Even if lectures were an effective teaching method, they do not benefit all students.

[1] EEG measures brain activity by placing electrodes on the scalp. It has good temporal resolution and low spatial resolution (up to 300 electrodes).

[2] There used to be a competition at Leeds University for the most boring lecture (Rawlinson 2015).

Attention Span

It is often claimed that people have a ten minutes attention span. However, this figure is controversial and there is not much evidence to back it up (Wilson and Korn 2007). Even if the ten minutes figure was true, students drift in and out – they do not completely shut down ten minutes into the lecture. So although the total amount of attention in a lecture is likely to be more than ten minutes, it is reasonable to conclude that students do not attend to everything that is said in a fifty minute lecture.

Passive Learning

In a lecture, students are mostly passive recipients of knowledge from the teacher. However, experiments have shown that active learning is a more effective way of acquiring knowledge (Held and Hein 1963; Kohler and Fiss 1964; Voss et al. 2011).[3] More active teaching methods have been shown to reduce failures, increase examination scores and increase the long-term retention of information (Deslauriers et al. 2011; Freeman et al. 2014; Miller et al. 2013). The only exception to this trend is an older study by Bligh (2000), who claims that there is no significant difference between lecturing and other teaching methods.

Knowledge Retention

Experimental studies have suggested that lectures are a poor way to transmit knowledge. For example, Scerbo (1992) found that students recognized 70% of lecture material immediately after it was delivered, but could only recall 50%. A study by Kaplan and Pascoe (1977) found that around 70% of lecture material was retained after six weeks. Other studies have shown that students retain 40–46% of the material (Wilson and Korn 2007) and it has even been claimed that students retain as little as 5% (Miller 2008).[4]

3. Common Methods for Addressing the Limitations of Lectures

A number of teaching methods are often used to address the limitations of lectures.

[3] While the importance of active learning is often stressed, it is possible to learn passively and even unconsciously (Dell'Acqua and Grainger 1999, Merikle and Daneman 1996). However, material that is learnt passively and/or unconsciously is less likely to be consciously recalled. At best it produces a sense of familiarity with the topic, not something that can be consciously recalled in an exam.

[4] It could be argued that lecture material might be passively learnt and later produce a sense of familiarity that could be reinforced and consciously assimilated in other exercises, such as group work or practical exercises. This would be harder to measure, except possibly in multiple choice tests, where you would expect above chance guessing. However, it could be argued that a sense of familiarity does not justify the time and effort spent on lectures by the teacher and students.

Problem-based learning

In this approach students learn by solving problems. The teachers provide detailed learning resources and the students find their own solutions with the teacher's support (Kilroy 2004). This encourages students to find solutions for themselves and frees up staff time for supporting students. This approach is typically applied in small groups and it requires staff with expertise in the problems that are set, so it is difficult to implement with more specialized courses that have a substantial knowledge component. For example, few staff would have enough expertise on machine learning to help students with problems set on this topic. The students also need a substantial amount of background knowledge before they can start to solve problems and this approach will only work when all of the resources for solving the problems are readily available to students, which might not be the case for more specialized courses.

Group Work

Teachers often use group exercises to break up lectures and reset attention. While group work can be a good way of consolidating knowledge, it can be difficult to stop students from talking about irrelevant things. With lectures to large audiences little or no effective support to the groups can be given, and it can be difficult to refocus the class on the lecture material. It is also questionable whether a lecture with group exercises is more effective than a continuous lecture in which students' attention fluctuates in a cyclical way.

Flipped classroom

In the flipped classroom live lectures are replaced with recorded lectures that are distributed online. This frees up class time for exercises that consolidate the lecture material and students can watch the videos multiple times until they have fully understood them (Bergmann and Sams 2012). The flipped classroom promotes active learning and students have easy access to all of the course contents, instead of just the slides. Recorded lectures are not limited by the timetable, so they can be broken up into chunks that focus on specific topics.

The flipped classroom is not a perfect replacement for live lectures. One problem is that it creates more work for the lecturer (recording lectures and preparing extra class time). When a module has more than 20 students it can also increase the staff teaching hours. For example, if a lecture to 100 students is replaced by five seminars, then there are four extra hours of teaching per week. Another disadvantage of the flipped classroom is that it creates more work for the students, who have to watch the lectures in their own time, and there are no opportunities for asking questions as the lecture unfolds. The most serious disadvantage is that it can be difficult to persuade students to watch the lectures, which devalues the seminars that consolidate the lecture material. Studies have shown that 70% of students do not do preparatory reading before class (Clump et al. 2004; Stelzer et al. 2009), and it is likely that similar numbers will fail to watch the video before the seminar in a flipped classroom. While this problem can be avoided (Mok 2014) or partly addressed by short quizzes (Heiner et al. 2014) and learning contracts (Stephenson and Laycock 2013) it is likely to be a significant issue when there are many unmotivated students.

Tutoring in Small Groups

In small groups the teacher can measure students' level of attention by monitoring their eye movements and they can easily check whether students understand what they are being taught. In an ideal world all knowledge would be transmitted in tutorials with 1-2 students. However, this approach requires a lot of staff time, which makes it impractical on courses with large numbers of students.

Some of these teaching methods place unrealistic demands on staff time and in some areas of higher education only a limited number of experts are available to teach a given field. We need more scalable ways of increasing the effectiveness of live or recorded lectures.

4. Neurolecturing

This section suggests how EEG and eye-tracking technology could be used to address the limitations of live and recorded lectures.

EEG is a low cost non-invasive method for monitoring brain activity through electrodes that are placed on the scalp. It is a very rough measure, so it cannot be used to read a person's thoughts.[5] However, it can be used to measure:

- Sleeping/waking states (Šušmáková 2004).
- Real and imagined motor movements (Alomari and Al Kamha 2013; Loboda et al. 2014).
- Learning (Mazher et al. 2015; Walter et al. 2011).[6]
- Cognitive load (Berka et al. 2007; Das et al. 2013).

[5] Functional Magnetic Resonance Imaging (fMRI) can be used to reconstruct the videos people are watching (Nishimoto et al. 2011) and their dreams (Horikawa et al. 2013).

[6] Learning is narrowly defined in these experiments as the assimilation of new information. For example, Walter et al. (2011) measured subjects' EEG when they were reading theorems and watching comic strips about angular geometry.

- Attention (Chen et al. 2015; Hamadicharef et al. 2009; Landau et al. 2007; Li et al. 2012; 2013).
- Mental fatigue (Shen et al. 2008).

Eye-tracking systems use a camera mounted on glasses or in front of the user to monitor what subjects are paying attention to and how they are interpreting a scene. While EEG could be used for neurolecturing by itself, a combination of EEG and eye-tracking would provide more accurate data about how subjects are responding to a lecture.

In a neurolecturing class students would be issued with EEG headsets and eye-tracking glasses.[7] As they watched a live or recorded lecture their data would be processed into the following measurements:

- *Attention score*. The extent to which they are attending to the lecture material.
- *Cognitive load*. How hard the students are working to process the lecture material.
- *Learning*: Whether their brains are storing the lecture material.

Figure 1 illustrates how these measurements could change during a lecture.

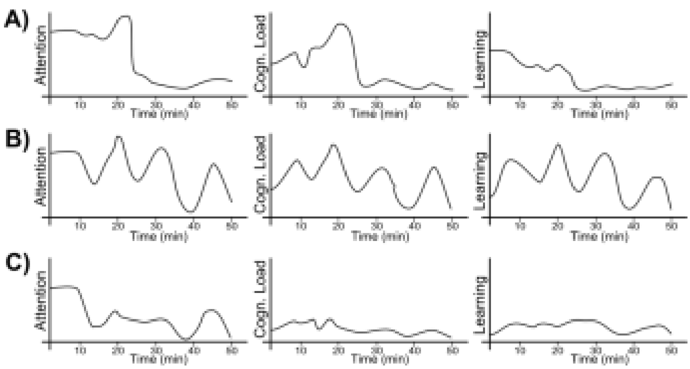

Figure 1. Illustration of how students' attention, cognitive load and learning could change during a 50 minute lecture. A) This student's attention and cognitive load increase at 20 minutes when more challenging material is introduced. They don't understand it, give up and cease to pay attention for the rest of the lecture. B) The lecture material is within this student's zone of proximal development and their attention cycles regularly along with their cognitive load and learning. C) This student is familiar with most of the material. They pay little attention, learn little and have a low cognitive load.

[7] EEG and eye-tracking hardware is discussed in the appendix.

These measurements could be used to improve teaching quality in lectures in the following ways.

Neurofeedback to Students

Research has shown that people can change their brain activity when their EEG data is displayed to them in real time (neurofeedback). This can help them to improve their attention span, psychomotor skills, memory, intelligence, mood and creativity (Gruzelier 2014a; Gruzelier 2014b). Neurolecturing could deliver these benefits by displaying the measurements of learning, attention and cognitive load to the students, either on their headsets or using augmented reality. A vibration or sound could alert them when these measures fell below a threshold.[8] This would be a form of behaviourist learning (Skinner 1938) in which students are trained to put their brains into beneficial states. Eventually they would learn to control their brains without equipment - a transferable skill that could benefit them throughout life.[9]

There is also evidence that neurofeedback can be used to induce brain states that are beneficial for memory consolidation (Reiner et al. 2014). This opens up the possibility of a lecture that has periods of knowledge delivery followed by periods in which students use neurofeedback to put their brains into a memory consolidation state.

Feedback to Lecturer

Constructivism plausibly claims that students assimilate new knowledge on the basis of what they already know (Fosnot 2005). But this is virtually impossible to apply to a large mixed ability class. Neurolecturing can address this problem by displaying each student's attention, learning and cognitive load to the teacher, who can use it control the pace of a live lecture and fine tune individual student's learning. For example, when the average attention dropped below a threshold the lecturer could slow down, recapitulate, switch to a group exercise or start a period of memory consolidation. After the lecture the teacher could review the data from individual students, identify people who were struggling and suggest resources that would help them to assimilate difficult concepts. More challenging material could be directed to students with a low cognitive load. In

[8] The threshold could be dynamically set for each student by measuring their maximum and minimum attention, cognitive load and learning. The threshold could then be set to half way between the maximum and minimum and the alert could be generated when attention, cognitive load and learning fell below the threshold for 60 seconds (for example). The maximum and minimum values could be recalculated over time.

[9] Futurelab (2009) discuss the potential role of neurofeedback in education in more detail.

this way constructivism could become a practical teaching method in which the lecturer could identify the zones of proximal development (Vygotsky 1978) and threshold concepts for each student (see Figure 1). The students' data could also help lecturers to evaluate new course material and it could be taken into account by teaching observations.

Artificial Intelligence (AI) Tutoring
People are already experimenting with delivering parts of a course with computer programs known as chatbots (McFarland 2016). These chatbots could use the measurements of attention, learning and cognitive load to control the amount and complexity of material that they present to the student. This would keep the material within the student's zone of proximal development and the chatbot could introduce novel exercises or periods of memory consolidation when the student's attention dropped.

Support for Students with Attention Deficits
Neurolecturing could help teachers identify students with attention deficit disorders so that they can be given extra support.[10] It has been shown that neurofeedback is an effective treatment for ADHD (Arns et al. 2014), so an appropriately designed neurolecturing program could benefit students with attention deficits without the need to explicitly identify them.

Allocation of Course Marks
Neurolecturing can accurately measure how much students pay attention to live and recorded lectures. Since attending *to* the lecture (and not just attending the lecture) is beneficial to students, this could be used to allocate a proportion of the grade for the course. This would work particularly well with the flipped classroom since students could pause the video and watch it multiple times until they had attended to everything in the lecture. This mark could only be available if the students watched the video prior to the seminar in which the material was consolidated. EEG biometrics could be used to prevent students from getting other people to watch the videos for them (Gui et al. 2014; Mandic and Palaniappan 2007; Mohammadi et al. 2006; Poulos et al. 2002; Ruiz-Blondet et al. 2016).

A prototype of a neurolecturing system has been developed by Li et al.

[10] This would not be a formal clinical diagnosis. The teacher could identify students that were struggling to attend to lectures and have a conversation with them about this issue. Extra support could be given and they could be directed to see a doctor if this seemed appropriate.

(2009; 2012), who created a study website and recorded the EEG of students as they interacted with the website. Other neurolecturing systems have been built by Liu et al. (2013) and Chen et al. (2015), who showed that EEG could be an effective way of monitoring attention during e-learning. A system that uses EEG and eye-tracking technology to identify distraction during reading has also been developed by Rodrigue et al. (2015). The hardware and software for neurolecturing are covered in the appendix.

5. Potential Objections to Neurolecturing

Some people might think that neurolecturing reads minds and invades privacy. However, as I explained earlier, EEG and eye-tracking cannot be used to read people's minds – they only obtain information that is already accessible to the lecturer, such as level of attention, eye direction and cognitive load. In one-to-one tutorials teachers often use this information. But a single teacher cannot process this information from 200 students in a live or recorded lecture. Neurolecturing enables teachers to use data that they already have access to on a larger scale.

Other people might feel that neurolecturing degrades the relationship between students and teachers. However, I am only suggesting that neurolecturing could improve situations in which students are passively receiving information – not laboratory sessions or seminars in which they are solving problems and actively engaging with their teachers and peers. There are also ethical issues surrounding the storage and use of neurolecturing data, which would have to be treated in the same way as other personal data.

A full debate about the benefits and limitations of neurolecturing will only be possible when it has been systematically tested. Neurolecturing should be discarded if it is not a significant improvement on existing teaching methods. But if it is accurate[11] and effective, then it can be argued that it would be wrong *not* to use this technology. People's heart rate and EEG are monitored in hospital so that they can be given the best treatment. If neurolecturing can be used to teach more effectively, then it would be wrong to refuse access to it. Future generations might judge that universities without neurolecturing facilities are poorly equipped.

[11] EEG can be a noisy signal (for example, the study by Liu et al. (2013) had a classification accuracy of 77%), which would raise issues f the attention score was used to allocate marks. This problem can be partly overcome by combining EEG with eye-tracking (Rodrigue et al. 2015) and the accuracy could be further increased by adding other signals, such as galvanic skin response, heart rate and facial expression.

6. Conclusions

Lectures are a widely used teaching method. But they have a number of problems, such as boredom, attendance, attention span, passivity and low knowledge transmission. While there are alternative teaching methods, these are mostly complementary to lectures and the specialized knowledge that is required to teach some courses means that live or recorded lectures are likely to be part of the curriculum for a long time to come.

In this paper I have suggested how the technology that is currently revolutionizing market research could lead to major improvements in how we teach and learn. Some people might find the idea of neurolecturing ethically objectionable. However, in a world in which students are paying their own fees and often working to support themselves, many students will want to learn in the most efficient way possible. If neurolecturing is shown to increase the rate of transmission of knowledge and enhance creativity, memory and attention, then it is likely that many students will request that this technology is used on their courses. As the hardware for brain monitoring and eye-tracking gets cheaper, it is likely that neurolecturing will be tried in the classroom. If it has clear demonstrable benefits, it could become a mainstream teaching method in fifty years.

Appendix: The Development of Neurolecturing Technology

The EEG headsets that are used in scientific experiments provide high resolution data (~300 channels), but they are expensive. A more realistic approach for neurolecturing would be to use consumer-grade EEG devices, such as the NeuroSky MindWave headsets (£112),[12] the EMOTIV headsets, which are available in 14 channel or 5 channel models (£550 / £205),[13] or EEG earphones, which are likely to retail for less than £100 (Strickland 2016). It is also possible to build EEG headsets from scratch.[14]

Professional eye-tracking glasses can be expensive (~£10,000).[15] Eye-tracking bars that mount on the desk or screen can be obtained for less than

[12] NeuroSky EEG headsets: http://neurosky.com/biosensors/eeg-sensor/biosensors/.
[13] EMOTIV EEG headsets: http://emotiv.com/.
[14] Information and equipment for DIY EEG headsets: http://openbci.com/. A hacker-oriented guide to building an EEG headset is available here: http://www.instructables.com/id/DIY-EEG-and-ECG-Circuit/.
[15] For example, the Tobii Pro glasses: http://www.tobiipro.com.

£140 and Pupil Labs have developed a sophisticated system that can be printed and assembled at home.[16] A number of websites explain how to build cheap eye-tracking hardware.[17]

Neurofeedback to the students could be done cheaply and simply with LEDs mounted on the eye-tracking glasses. Or it could be displayed in augmented reality (AR) using the student's mobile phone mounted in a Google Cardboard headset.[18] The Oculus Rift (£400) is a higher quality and more expensive AR option.[19]

The neurolecturing software would have to integrate the eye tracking and EEG data and display it to the students and lecturer in real time. Software and toolboxes for EEG analysis and eye tracking can be downloaded for free – for example, BCILAB,[20] Brainstorm[21] and openEyes[22] – which could be adapted for the neurolecturing environment.

Taken together, the hardware can be obtained or made for less than £200 per set. The main cost for a pilot study would be the development of the software that integrates everything together. It is likely to take 3-6 months for an experienced programmer to integrate the software and hardware into a working neurolecturing system.[23]

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[17] DIY eye-tracking systems: http://www.instructables.com/id/The-EyeWriter-20 and http://hackaday.com/2013/02/12/build-an-eye-tracking-headset-for-90.
[18] Google Cardboard virtual reality headset that works with mobile phone: https://vr.google.com/intl/en_uk/cardboard/.
[19] Oculus Rift virtual reality headsets: www.oculus.com.
[20] BICLAB EEG toolbox: http://sccn.ucsd.edu/wiki/BCILAB.
[21] BrainStorm EEG data analysis application: http://neuroimage.usc.edu/brainstorm/.
[22] openEyes toolkit for eye tracking: http://thirtysixthspan.com/openEyes/.
[23] A laboratory with eye-tracking technology was installed by Andrew Duchowski at Clemson University: http://www.gazept.com/2015/01/eye-tracking-in-the-classroom-with-gazepoint/.

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