A More Robust Way of Teaching Reinforcement Learning and Decision Making

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Abstract

We propose a new way of teaching reinforcement learning and decision making that is designed be an improvement to traditional academic teaching. We use a three-step approach to delivering a complete learning experience in a way that engages the student and allows them to grasp the concepts regardless of their skill level. We present a specific way of teaching the content, a new and fully configured coding platform, a set of hands-on exercises and a group of recommended next steps for deeper learning.

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Repository: https://www.github.com/mimoralea/applied-reinforcement-learning

Short Presentation: https://youtu.be/ltjS5ktziLQ

Long Presentation: https://youtu.be/1WjNj_JmFaE

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1 Introduction

Reinforcement Learning and Decision Making is a complex subject. Being the focus of research of a variety of fields including artificial intelligence, psychology, machine learning, operations research, control theory, animal and human neuroscience, economics, and ethology, it is expected that the vast amount of available information could become counterproductive. Beginners often find themselves lost while trying to grasp the key concepts that are truly vital for understanding. Additionally, reinforcement learning and decision making, being a relatively new field, is often taught by world-class researchers that frequently unintentionally omit explaining core concepts that might seem too basic [1], but are as well fundamental. This creates a gap of knowledge that, if left unfilled, causes trouble for learning the more advanced topics. This present a challenge for sparking interest and keeping students engaged throughout their learning experience. If the content is not delivered correctly, the students can quickly feel confused, lost and disengaged, and when that happens learning stops.

2 Sparking Curiosity

Fortunately, since reinforcement learning and decision making is studied by fields like animal and human neuroscience, ethology, and psychology[2], often the concepts can be taught on an intuitive level. Recent studies in neuroscience have shown that emotions and cognition are interrelated[3]. By keeping the readings approachable we allow students to connect to the narratives at different levels. The notion of learning by interacting with an environment should be easy to understand to all of us as this is one of the ways we learn.

We leverage this fact and use a strategy to keep readers engaged on the material.

2.1 Using Simple And Direct Language

One of the important things to we accomplished is to use simple and direct language throughout the documents. This keeps the reader engaged regardless of their reinforcement learning knowledge level.

We carefully select words and examples that bring the concepts to a common sense understanding so that all students can follow the initial readings.

2.2 Keeping A Single Narrative

Additionally, and what was perhaps the most difficult part, we keep a single narrative throughout the sequence of concepts being presented. The intention here is to allow students to continue reading and use the understanding they accumulated in previous lessons to understand the following. Similar to what the direct instruction paradigm[4] encourages, we provide with the structure and sequence on how the concepts will be presented.

The more simplistic approach is to select concepts from the entire body of reinforcement learning and decision making and use different lessons to present different material. However, the problem with this approach is that it does not help the student get the full picture and the connection with other topics. The effort to present concepts in logical sequence, although complex to define initially, not only feel a more natural way to present beginners, but it helps beginners stay engaged in the material.

2.3 Showing Concepts And Their Complement

Finally, in order to spark and maintain students' curisity on, we show the full spectrum of a single concept. Even if just defining the opposite, we still make an effort to mention it and briefly explain it. Often things in life have a complementary side that when combined better show the qualities of each other. For example, explaining deterministic actions is interesting all by itself, but you could gain a much better understanding if I explained them along side stochastic actions. This approach is also known as Compare and Contrast, and the literature suggests that teaching comparative thinking strengthens student learning[5].

We paid close attention to show concepts and their complements in every lesson. The expectation is that this would help the students have a better sense of the full range of possibilities on any given point, keeping them this way engaged as concepts get progressively more and more complex.

3 Removing Friction

Once the students' curiosity has been sparked and intuition is engaged, a convenient way to interact with the concepts should be presented. The friction of getting hands-on experience is one of the most difficult barriers to break for beginners, but once this is past, the student can much better understand the concepts.

We worked on three different important points to fully remove the friction beginners have when first getting into reinforcement learning.

3.1 Setting Up A Convenient Environment

One of the most remarkable accomplishments on this project is the creation of a fully configured reinforcement learning platform to use OpenAI Gym [7] environments on Jupyter Notebooks inside of Docker containers.

Besides technicalities, having a ready-to-go environment that can help students be ready to go within 20 min wait time for the first run after copy-paste of provided commands is wonderful. After that initial setup it takes less than 1 min every subsequent run. This allows the student to put very little time configuring and battling with packages and configuration scripts that do not add knowledge in reinforcement learning concentrating that way all the effort on things that trully matter.

3.2 Providing With Boilerplate Code

Moreover, we supplement the notebooks with abundant boilerplate code. Graphs and visualization functions that very likely aid in the learning process [6], binaries creating web requests in the background to show videos of carefully selected agent episodes are some of the examples of code provided to the students.

This allows the students to interact only with bits of code that are directly related with reinforcement learning and be able to safely ignore other bits.

3.3 Asking For Minimal Effort

Then, we proceed to ask students to put just enough effort to get them engage. The hands-on interaction with the notebooks are designed for beginner to get started with reinforcement learning. Perhaps, these students have not seen reinforcement learning or even machine learning code in action before. Therefore, in addition to all of the boilerplate material already mentioned, we also provide with most of the common algorithms on each of the notebooks and only ask the students to complete small sections that would make the core algorithms work more effectively.

The idea is that after they have contact with reinforcement learning code, they will have more confidence when interacting with more advanced problems and projects during the OMSCS course.

4 Showing Options

Lastly, connecting to intuition and getting hands-on experience will be futile unless the students have a new interest of exploring the field by themselves. This is the most important aspect of our project, we believe education is about motivation. The role of an instructor is merly to spark students curisity and help them find the path to their own realization.

Therefore, at this point we hope to have awaken the students' interest to explore this marvelous field. Now, showing the path for further learning is a final and very important step.

4.1 Assigning Relevant Readings

To help the students better navigate the field of reinforcement learning, we provide with "Further Reading" sections in every single lesson, and a single final section of "Recommended Books" at the end of the project. The fact that we teach the concepts in an direct and simple language is by no means an indication that academic material can be skipped. Actually, the way we present the material should be seen just as a *primer*, helping the concepts later presented come together more naturally, and absorbed more quickly.

4.2 Watching Academic Lectures

Next, we will hope students go on watching academic lectures afterwards. To have world-class experts in the field of reinforcement learning teaching concepts they are so familiar with and have been studying and working for so many is necessary. For this reason, we added a "Recommended Courses" sections for students to continue the search and learning on their own.

4.3 Completing Homework and Projects

Finally, we would hope that many of the students using these materials are the same students either planning to enroll for the OMSCS course or just enrolled. The OMSCS course, after a brief explanation of core concepts, shows very advanced concepts very rapidly. In addition, there are specially designed homework and project assignments so that the students get a solid grasp of reinforcement learning.

Completing the coursework would certainly put the students in the driving seat making them owners of their destiny and letting them pick wisely what reinforcement learning area to explore next.

5 Future Work

No work is perfect and neither is this one. However, for the ~2 months of effort put into it, I think the progress that has been made is incredible. We started with an aggresive proposal and delivered most of it. We kept progress steady, but flexible enough to adapt along the way while still completing core components. The lessons, the container, the notebooks, the assigned readings, the recommended courses, all provide with a solid foundation for the deep understanding of reinforcement learning and decision making.

It is this foundation that can now make further progress easier to achieve. After opening this work to the community during the summer semester, we hope to receive help to make this project better going forward.

5.1 Additional Notebooks

One of the important future work is the addition of notebooks. We had the chance to complete 7 notebooks, but while trying to rush in some final work, we noticed the quality of the later notebooks was seriously degrading the quality of the project. Instead, we opted for improving the quality of previous notebooks and leaving the newer projects out of this release.

This creates an opportunity for adding those notebooks that were removed and improving them considerably. Also, the addition of new notebooks would be of great benefit as well.

5.2 Effectiveness Evaluation

A more difficult future work would be to find a way to measure the effectiveness of this material. Ideally, an Educational Technology student can take on the task to research whether the strategy presented here actually improves student performance. It would be interesting to gather and study this kind of feedback.

5.3 Request For Feedback

Finally, one of the next steps we will be taking on is to release this project on different places. First, to previous students on the Slack channel of the Georgia Tech Study Group organization. These folks are now veterans of our course and would be a great source of feedback. Second, we will release to the OpenAI community in an attempt to get a very diverse group to look and provide with feedback. The expectation is that this feedback will be followed at times with actual changes in the form of GitHub pull requests. This, and only this, would make this the project we initially envisioned.

6 Conclusion

In this paper, we proposed a more robust way of teaching reinforcement learning and decision making. We presented a series of lessons taught on a very specific format, we delivered a fully-configured coding environment for the development of reinforcement learning agents and algorithms, we provided with boilerplate code and a series of notebooks to assist with hands-on experimentation, and we supplemented this with more academic readings, and lectures.

We sincerely hope this project will be useful to lots of people interested in learning the ins and outs of reinforcement learning and decision making. And, in fact, the project recently helped an OMSCS Reinforcement Learning and Decision Making student find his way around the complex topic of function approximation in reinforcement learning. The potential, however, is bigger and the path for improvement obvious in some cases. Our desire is to see this work continue to grow into a more mature and effective way of teaching this amazing field.

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