What Teachers Can Learn from Machine Learning

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1. Introduction

- In some application areas e.g., in the control of many mechanical systems:
 - we know the equations
 - that describe how the state of the system will change under different controls.
- In such situations, selecting the best control becomes a precise optimization problem.
- This problem may be difficult to solve, but at least its formulation in precise.
- In many other application areas:
 - we do *not* have equations
 - that would have enabled us to predict the results of different actions.
- Teaching is definitely one of such situations.

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- In such situations, we need to rely on the experience:
 - people tried different actions in different circumstances and
 - got different results.
- Some of this experience have been processed and summarized formally or informally by experts.
- The resulting expert knowledge often formulated in fuzzy terms is indeed very helpful.
- However, the amount of experience related to teaching is limited.
- On the one hand, billions of people are being taught all the time, true.



- On the other hand, interesting conclusions can be made about the effect of different actions:
 - only when we try different actions, and
 - not many such experiments are being performed.
- It is relatively easy to try different ways of controlling a mechanical system:
 - in some cases, a new idea will lead to a better control,
 - in other cases, it will lead to a worse control, but no big harm is done.
- Education is different.
- You do not want to try untested ideas, ideas that may turn out to make situation worse, on real students.



- The situation in education is even worse than in medicine:
 - there, at least, we can try on animals first, but
 - teaching animals is too limited to be useful.
- As a result, the amount of actual teaching experience that we can use to improve teaching is indeed limited.
- But there is another source of teaching and learning experience numerous application of machine learning.
- In machine learning, many different algorithms and ideas have been tried.
- It is now reasonably clear what worked and what did not.
- So why not utilize this experience?

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- Yes, machine learning is different from teaching a human being:
 - however, a model plane tested in a wind tunnel is also different from the actual plane, but
 - we can still use the wind tunnel experience when designing the actual planes.
- Let us see how we can use the experience of machine learning to improve our teaching.



6. First Idea: Take into Account that There Are Very Wrong and Somewhat Wrong Answers

- In teaching, we usually distinguish between correct and wrong answers.
- This is especially true in teaching arithmetic or other simple mathematical skills.
- The answer that $5 \times 5 = 55$ is as wrong as the answer that $5 \times 5 = 26$.
- Both answers will lead to 0 points.
- The overall grade on a homework or on a test is based on the number of correct answers.
- This may sound reasonable since this is what most teachers have been doing for millennia.
- However, this is not what the state-of-the-art machine learning algorithms like deep learning recommend.



7. First Idea (cont-d)

- At the initial stages of learning, we may not get any correct answers.
- However, the algorithms distinguish between:
 - answers which are closer to the correct ones and
 - answers which are further away from the correct answers.
- In other words, they distinguish between:
 - answers which are somewhat wrong and
 - answers which are very wrong.



8. First Idea (cont-d)

- Crudely speaking:
 - answers which are only somewhat wrong still get some points,
 - i.e., in precise terms, contribute to the value of the corresponding objective function,
 - while answers which are very wrong contribute much less.
- This idea has shown to work in education too.
- The big question is:
 - how to gauge the difference,
 - i.e., in fuzzy terms, what membership function to select for the corr. "degree of correctness".



9. First Idea (cont-d)

- In the past:
 - in effect, the Euclidean distance between the correct and actual answers was used,
 - i.e., equivalently, the sum of the squares of the differences.
- It turned out that other measures such as Kullback-Leibler relative entropy – lead to better learning.
- This is an area where human expertise may help.



10. Historical Comment

- Two of us (OK and VK) are originally from the former Soviet Union.
- So we are familiar with the differences between more and less serious mistakes.
- In one of Lenin's polemic papers that we had to study, he confesses that he also makes serious mistakes,
 - sometimes even mistakes similar to claiming that 2 plus 2 is 5, but
 - when his opponents make mistakes, their mistakes are often like claiming that 2 plus 2 is a candle.



11. Historical Comment (cont-d)

- Another Russian example is related to the distinction between serious errors and measurement errors.
- Quantitatively, the main difference is that the measurement errors are usually very small.
- In English, in both cases, the same word "error" is used, which sometimes confuses the general public.
- In Russian, these two concepts are described by two different words:
 - "oshibka" for a serious error and
 - Bible-motivated "pogreshnost" (literally meaning "small (not so severe) sin") for measurement error.



12. Second Idea: Asking Why-Questions, Not Just Checking Where Answers are Correct

- At present, as we have mentioned:
 - the most efficient machine learning techniques are neural networks,
 - in their current form of deep neural networks.
- Originally, the most widely used neural networks were 3-layer ones.
- There, there are only two processing layers, one of which is linear.
- During training, there is a learning error, the difference between:
 - the value that we want the network to learn, and
 - the value that the trained-so-far network produces.

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- In a 3-layer network, this difference practically directly changes the state of the neurons.
- In such networks:
 - if we want to know why a certain value was produced by the network,
 - we can easily understand that by using the parameters of these neurons.
- To be more precise, based on the inputs x_1, \ldots, x_n , we first compute the values

$$y_k = s_0 \left(\sum_{i=1}^n w_{ki} \cdot x_i - w_{k0} \right).$$



- Here:
 - the function $s_0(z)$ is a non-linear function called activation function, and
 - the parameters w_{ki} describes the state of each neuron.
- Once the value y_k are computed, we compute the final result $y = \sum_{k=1}^{K} W_k \cdot y_k W_0$.
- It turned out that deep neural networks with many layers learn better.
- In such networks:
 - if we try to trace why a given value was produced,
 - we can easily trace it only to the previous layer.

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- Of course:
 - to explain why the corresponding values were produced on this layer,
 - we need to go one more layer back, etc.
- How can this be used for actual teaching?
- Traditional assessment:
 - when we check the student's knowledge by making sure that they give us correct answers,
 - is similar to the traditional neural network case.



- A natural analog of the deep learning would be:
 - not only to check the answer, but
 - also to go deeper, to ask why the student obtained this answer,
 - i.e., what thinking and what methods he/she used and why, etc.
- This is definitely more time-consuming.
- This is similar to the fact that:
 - deep learning requires much more computational resources
 - than the traditional neural networks.
- However, this will hopefully lead to better learning.

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Historical Comment

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- This way, we will know, e.g., why the student answered that 5 times 5 is 55.
- Maybe he/she make an honest arithmetic mistake.
- Maybe this student under a false impression that:
 - similar to the notation *ab* for multiplication,
 - to compute a product, we need to place the multiplied numbers together.



- This idea also fits well with our Russian experience.
- This time, it fits with the experience of oral exams for math department classes:
 - once you successfully prove a theorem which usually means using other previously studied theorems,
 - the professor who takes this exam would often ask to prove these auxiliary theorems,
 - then to prove the theorems used in their proof, etc.,
 - all the way to the basics (or, sometimes, to a gap in the student's knowledge).



19. Relation to Explainability

- So far, we have described what we can borrow from successes of deep learning.
- However, we can also learn from problems of deep learning.
- One of such problems is the lack of explainability.
- This problem is similar to what we have when assessing student's knowledge:
 - we see their results which are not always correct,
 - however we do not understand why.
- If we explicitly ask the why-questions, we will understand the reason for these mistakes.
- This will help teach the correct way to students.



- Traditional neural networks used the so-called sigmoid activation function $s_0(z) = \frac{1}{1 + \exp(-z)}$.
- This formula was borrowed, by the way, from biological neurons.
- In deep learning, learning becomes much better if we use the *rectified linear* activation function:

$$s_0(z) = \max(0, z).$$

- What is the difference?
- With the sigmoid, we take into account both negative (z < 0) and positive (z > 0) inputs.

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21. Third Idea: Let Us Be Positive (cont-d)

- In contrast, if we use the rectified linear activation function:
 - we completely ignore negative signals and
 - we only take positive ones into account.
- How can we use this idea in teaching?
- Naturally ignore negative feeling and emotions and concentrate only on positive ones.
- This idea is in perfect accordance with the psychologists' ideas of the power of positive thinking.
- It is worth noticing that:
 - while at present, the function $s_0(z) = \max(0, z)$ is largely associated with deep learning,
 - this function was known and used much much earlier.

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22. Third Idea: Let Us Be Positive (cont-d)

- The function $s_0(z) = \max(0, z)$ describes a *diode*, an electronic device used to transform:
 - the highly oscillating amplitude-modulated signal
 - into the original lower-frequency signal e.g., corresponding to radio-transmitted speech.
- For teaching, the idea to avoid sometimes observed fast-mood-oscillation is also good.
- Such mood oscillations create too much stress and thus, hinder the students' learning.



23. Fourth Idea: Making Learning More Robust

- One of the main challenges of deep learning is that it is often not robust:
 - a minor change to a picture of a cat a change invisible to a human eye,
 - can cause the neural network to confidently classify this picture as a dog.
- To avoid such mistakes, a natural idea is to train the network:
 - not only on the original examples,
 - but also on modified versions of these examples.
- A similar idea can be helpful in teaching.
- For example, in school math, students often learn the "rules" when to use which arithmetic operation.



24. Fourth Idea (cont-d)

- For example, they learn that "all" means addition.
- In general, it does mean addition.
- However, what happens sometimes is that:
 - they uncritically use this rule all the time,
 - even when "all" means something else.
- To avoid such false uses, it is important:
 - in addition to standard word problems,
 - to train students on modified versions of these problems,
 - where the formulation of the problem is reworded in different ways.



25. Fifth Idea: Averaging

- Yes another idea of deep learning is "averaging".
- It means that:
 - instead of using the whole neural network to learn,
 - we divide it into subnetworks.
- Each of these subnetworks learns the same or even different patterns.
- Then these different learning results are combined ("averaged").
- A natural application to teaching is that:
 - instead of the teacher teaching the same material to the whole class,
 - students are divided into groups.



26. Fifth Idea: Averaging (cont-d)

- Groups learn by themselves with the teacher's help.
- Then all groups get back together and learn from each other.
- Learning is never absolutely even.
- So for each topic, one of the groups learned better.
- Thus all the groups have something to teach to each other, again with the teacher's help.



27. What Else?

- So far, we have listed several features of deep learning for which it is clear how we can use them in teaching.
- There are, of course, many other features and challenges, and how to use them is not yet clear.
- For example, one of the big challenges of deep learning is a possible bias.
- Indeed, a neural network simply learns from real-life examples.
- Some real-life examples are biased; e.g.:
 - there is still bias against women in some areas,
 - there is bias against people of certain race or ethnicity in some places.
- As a result, the neural network will (and had), unfortunately, learn some of this bias.

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28. What Else (cont-d)

- Many related ideas have been proposed and are researched
- However, it is not absolutely clear how to avoid this bias.
- It is also not clear how to apply these ideas in teaching
 where there definitely is bias.
- Some Computer Science departments have a bias against students from community colleges.
- For some not-yet-perfect community colleges, this may be a justified concern; however:
 - when extrapolated to all community colleges, including ones that provide good-quality education,
 - this becomes a bias.



29. What Else (cont-d)

- There is sometimes bias against students who are not native speakers of English.
- These students may know math well and are very skilled in programming.
- However, many of them have trouble with word problems, especially problems that deal with:
 - American realia like baseball
 - or details of the American complicated election system.
- It would be great to see how we can use:
 - anti-bias techniques which are currently actively developed in AI
 - against bias in teaching.

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30. What Else (cont-d)

• And, of course, all the above qualitative ideas need to be developed into more quantitative solutions.

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