

Machine Learning

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After this session you will be able to:

- Describe the main intuitions behind Machine Learning
- Discuss and illustrate possible real applications of Machine Learning in a high-level manner

- You have 5 minutes to come up with a definition for "Machine Learning" (You can use Google if you've never ever heard about it)

What is Machine Learning?

- “Machine Learning, field of study that gives computers the ability to learn without being explicitly programmed” - Arthur Samuel.



Machine Learning: Humans vs Machines

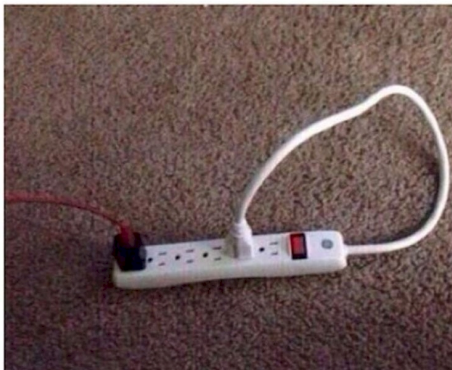
- Humans: Smart



Machine Learning: Humans vs Machines

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Why won't my power strip turn on?
I have everything plugged in. 😡



- Well, most of the time.

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- Humans are slow and computers are blindingly fast.

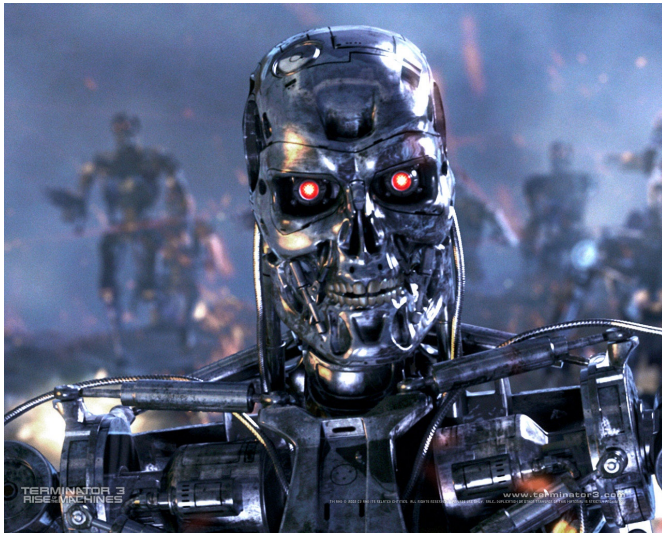


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- Humans are slow and computers are blindingly fast.
- So, what if we could give a bit of human intelligence to the computer?



The end of the world!



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A more rigorous definition of Machine Learning

- “Well-posed Learning Problem: A computer program is said to learn from experience E with respect to some task T and some performance measure P , if its performance on T , as measured by P , improves with experience E .” - Tom Mitchell



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- Lot of big words!



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- Lot of big words!
- However, if you think about it, that’s exactly what we humans do.



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- Usually we do it little by little, moving the “knobs” of the learning model, in a clever way that makes the error go down
- Pro tip: Usually you do want some error because many times that’s the difference between learning (good) and memorizing (bad)

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- The idea was to improve their ratings prediction engine by 10%
- Prize: 10 million dollars.
- The core question was, how to predict the rating a user is going to give to certain movie after watching it?
- Answer: Machine Learning.



Netflix: A possible solution

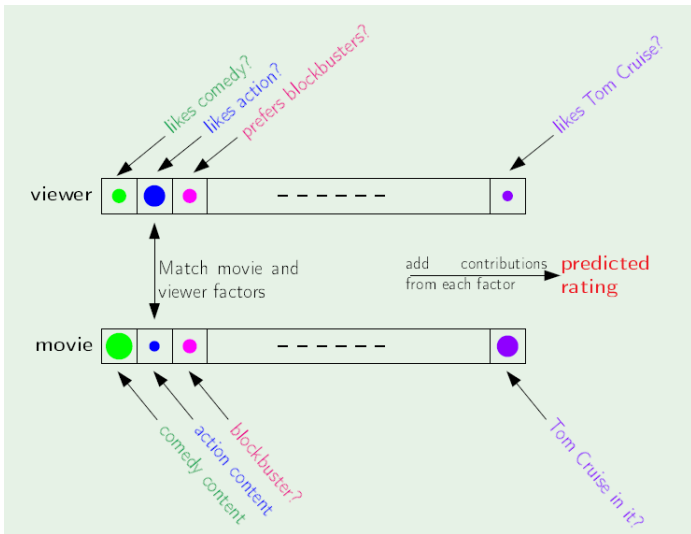


Figure: Source: Abu-Mostafa, Magdon-Ismail, Hsuan-Tien. Learning from Data.

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- In all fairness, this is just one type of learning, there are more. But let's not get ahead of ourselves.

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- You tell me one!



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- Machine Learning is all about discovering relationships
- By lots of repetition, the computer learns from its mistakes and tries to minimize them
- And by minimizing the error, it gradually learns to approximate the right answer
- In order to do Machine Learning, we need...DATA
- I really really wish my linear algebra and calculus teachers had mentioned that those things were useful for ML. Cool stuff after all.

Thank you very much!

Questions?

