Machine Learning

Making A Computer Look Like It's Thinking

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BU Summer Challenge

July 17th, 2025

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  - Randomness is inherent here, our algorithm will sometimes be wrong but we want it to be right more than just randomly guessing

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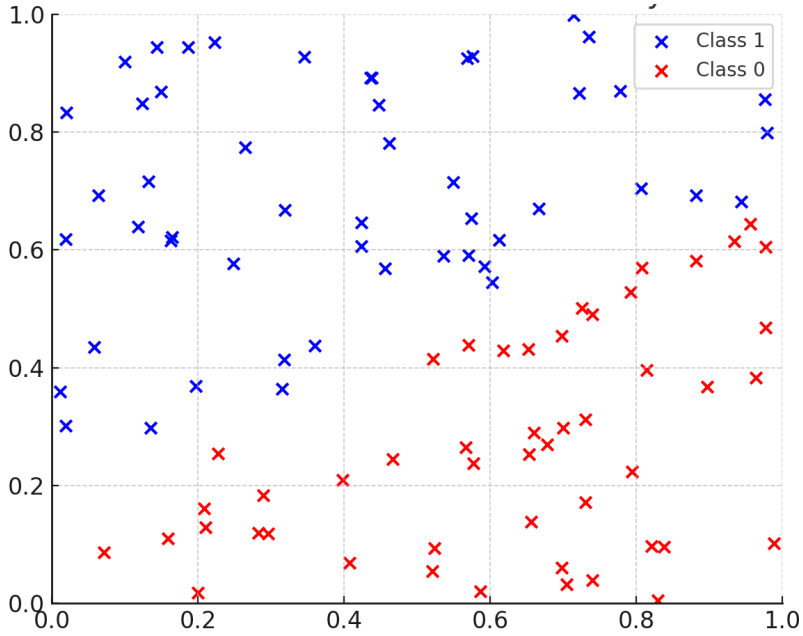

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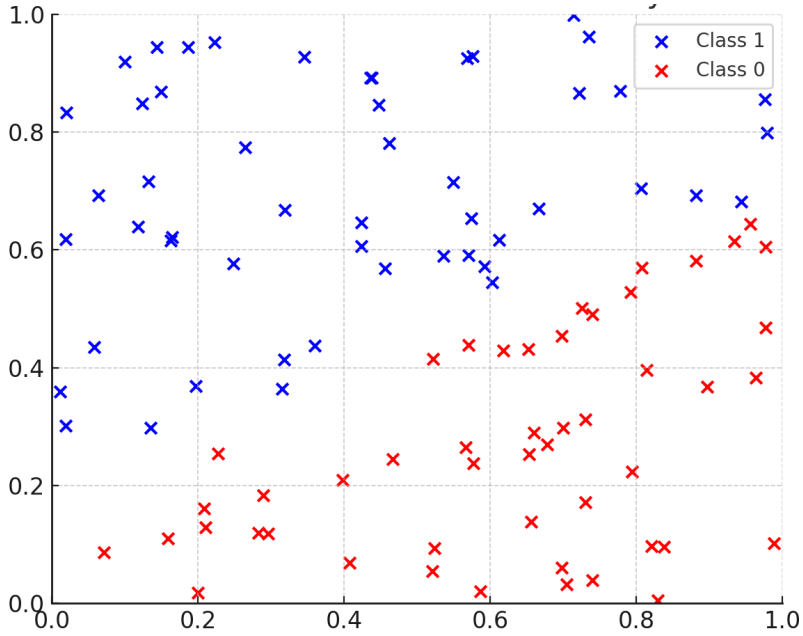

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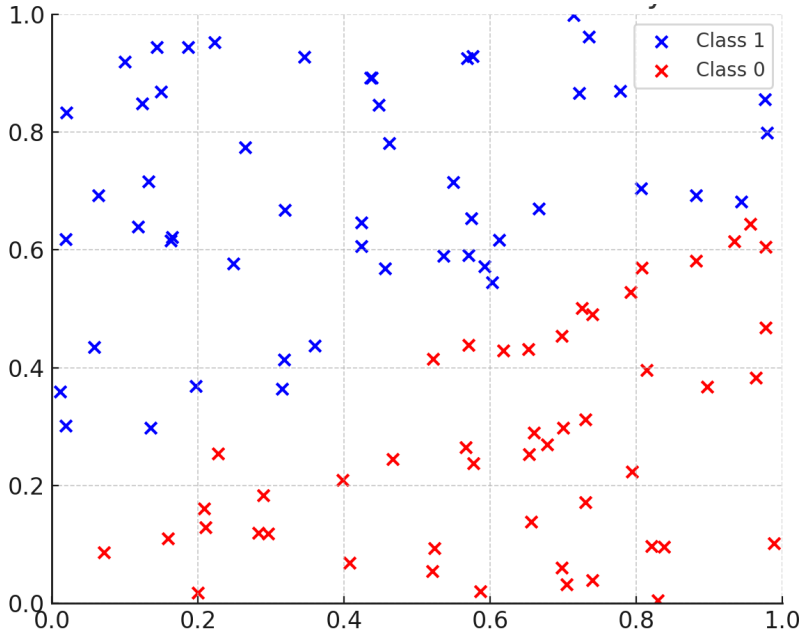

- Given a new point, how should we decide whether it should be red/blue?
- We can draw trying drawing a line that's separating the bulk of the red and blue:

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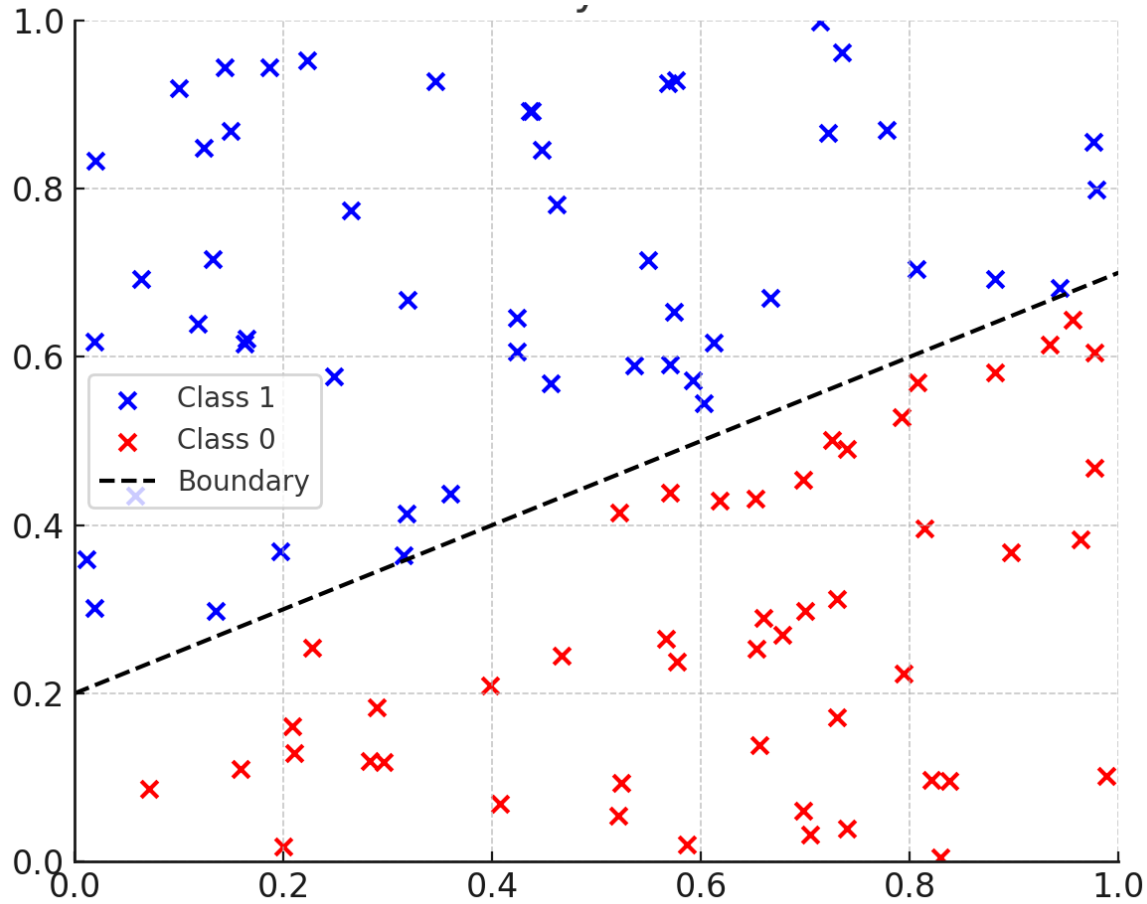

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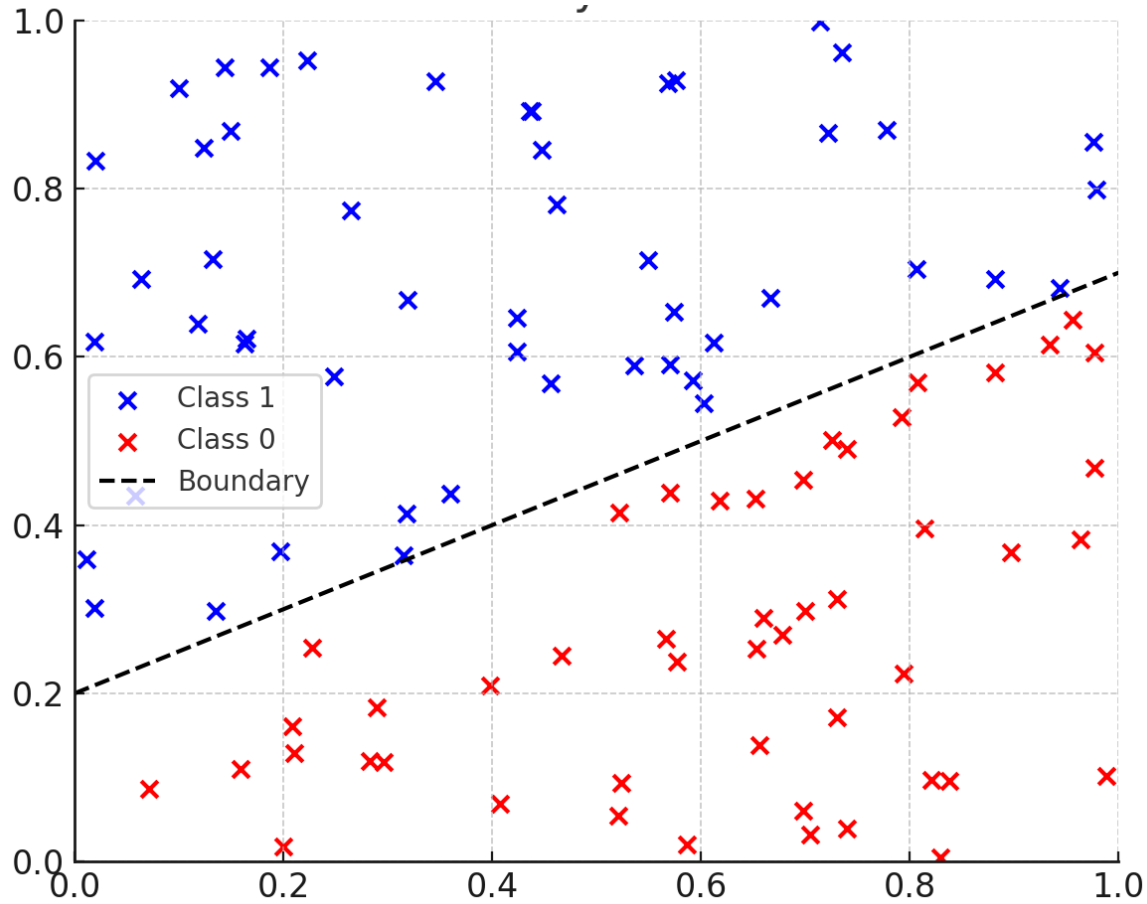

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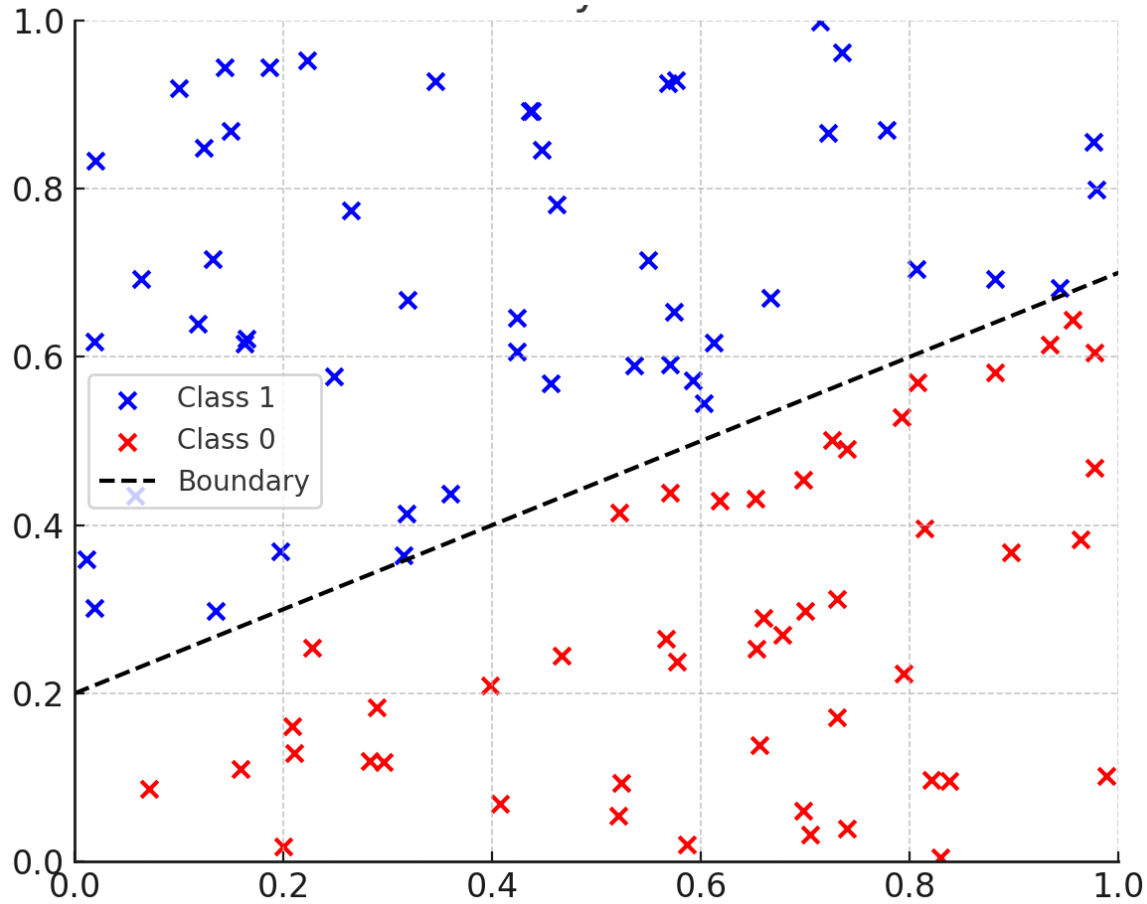

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- How do we judge how good a line is?

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- We repeat this many times until we get a good prediction

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  - It will then randomly predict the next word based on the probability

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- Tech companies, investors, influencers, etc. are overselling LLMs as "AI" in order to make money