# Machine learning

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# Why is learning important?

- So far we have assumed we know how the world works
  - Rules of queens puzzle
  - Rules of chess
  - Knowledge base of logical facts
  - Actions' preconditions and effects
  - Probabilities in Bayesian networks, MDPs, POMDPs, …
  - Rewards in MDPs
- At that point "just" need to solve/optimize
- In the real world this information is often not immediately available
- AI needs to be able to learn from experience

# Different kinds of learning…

- Supervised learning:
  - Someone gives us examples and the right answer (*label*) for those examples
  - We have to predict the right answer for unseen examples
- Unsupervised learning:
  - We see examples but get no feedback (no labels)
  - We need to find patterns in the data
- Semi-supervised learning:
  - Small amount of labeled data, large amount of unlabeled data
- Reinforcement learning:
  - We take actions and get rewards
  - Have to learn how to get high rewards

# Example of supervised learning: classification

- We lend money to people
- We have to predict whether they will pay us back or not
- People have various (say, binary) features:
  - do we know their Address? do they have a Criminal record? high Income? Educated? Old? Unemployed?
- We see examples: (Y = paid back, N = not)

  +a, -c, +i, +e, +o, +u: Y

  -a, +c, -i, +e, -o, -u: N

  +a, -c, +i, -e, -o, -u: Y

  -a, -c, +i, +e, -o, -u: Y

  -a, +c, +i, -e, -o, -u: N

  -a, -c, +i, -e, -o, +u: Y

  +a, -c, -i, -e, +o, -u: N

  +a, +c, +i, -e, +o, -u: N
- Next person is +a, -c, +i, -e, +o, -u. Will we get paid back?

# Classification…

- We want some hypothesis h that predicts whether we will be paid back

  +a, -c, +i, +e, +o, +u: Y

  -a, +c, -i, +e, -o, -u: N

  +a, -c, +i, -e, -o, -u: Y

  -a, -c, +i, +e, -o, -u: Y

  -a, +c, +i, -e, -o, -u: N

  -a, -c, +i, -e, -o, +u: Y

  +a, -c, -i, -e, +o, -u: N

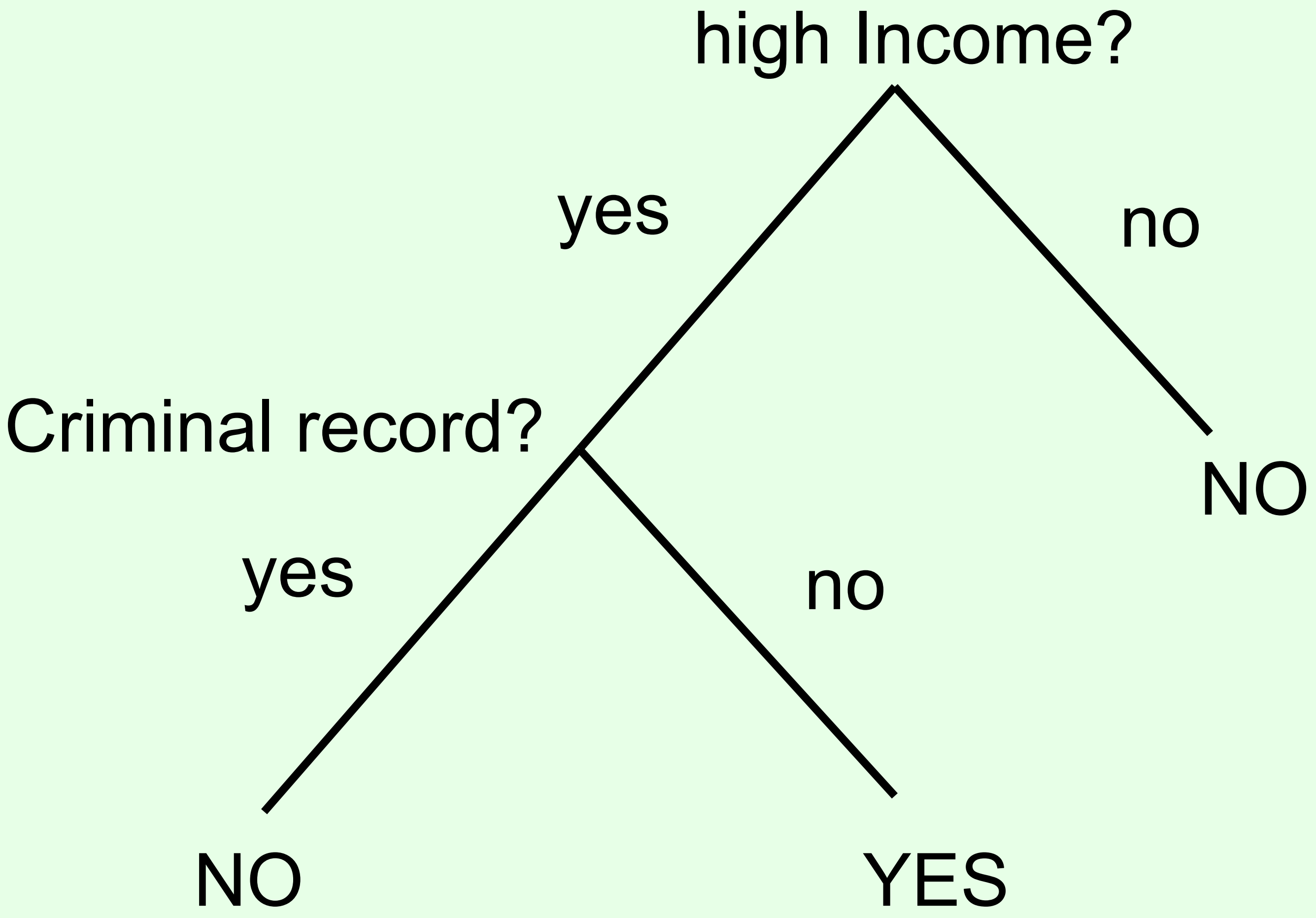
  +a, +c, +i, -e, +o, -u: N

- Lots of possible hypotheses: will be paid back if…
  – Income is high *(wrong on 2 occasions in training data)*
  – Income is high and no Criminal record *(always right in training data)*
  – (Address is known AND ((NOT Old) OR Unemployed)) OR ((NOT Address is known) AND (NOT Criminal Record)) *(always right in training data)*
- Which one seems best?  Anything better?

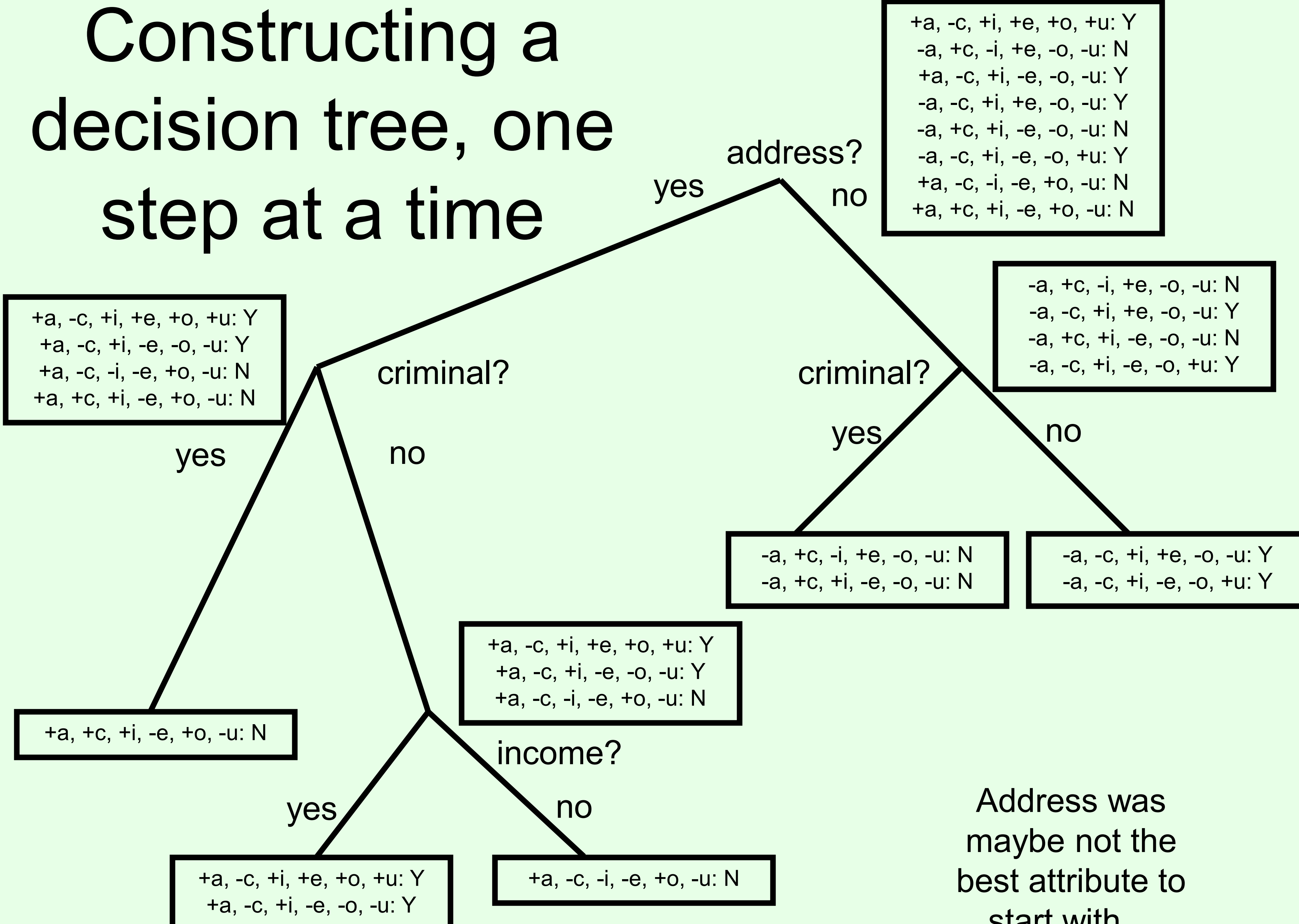
# Occam's Razor

- Occam's razor: *simpler hypotheses tend to generalize to future data better*
- Intuition: given limited training data,
  - it is likely that there is some complicated hypothesis that is not actually good but that happens to perform well on the training data
  - it is less likely that there is a simple hypothesis that is not actually good but that happens to perform well on the training data
    - There are fewer simple hypotheses
- Computational learning theory studies this in much more depth

# Decision trees

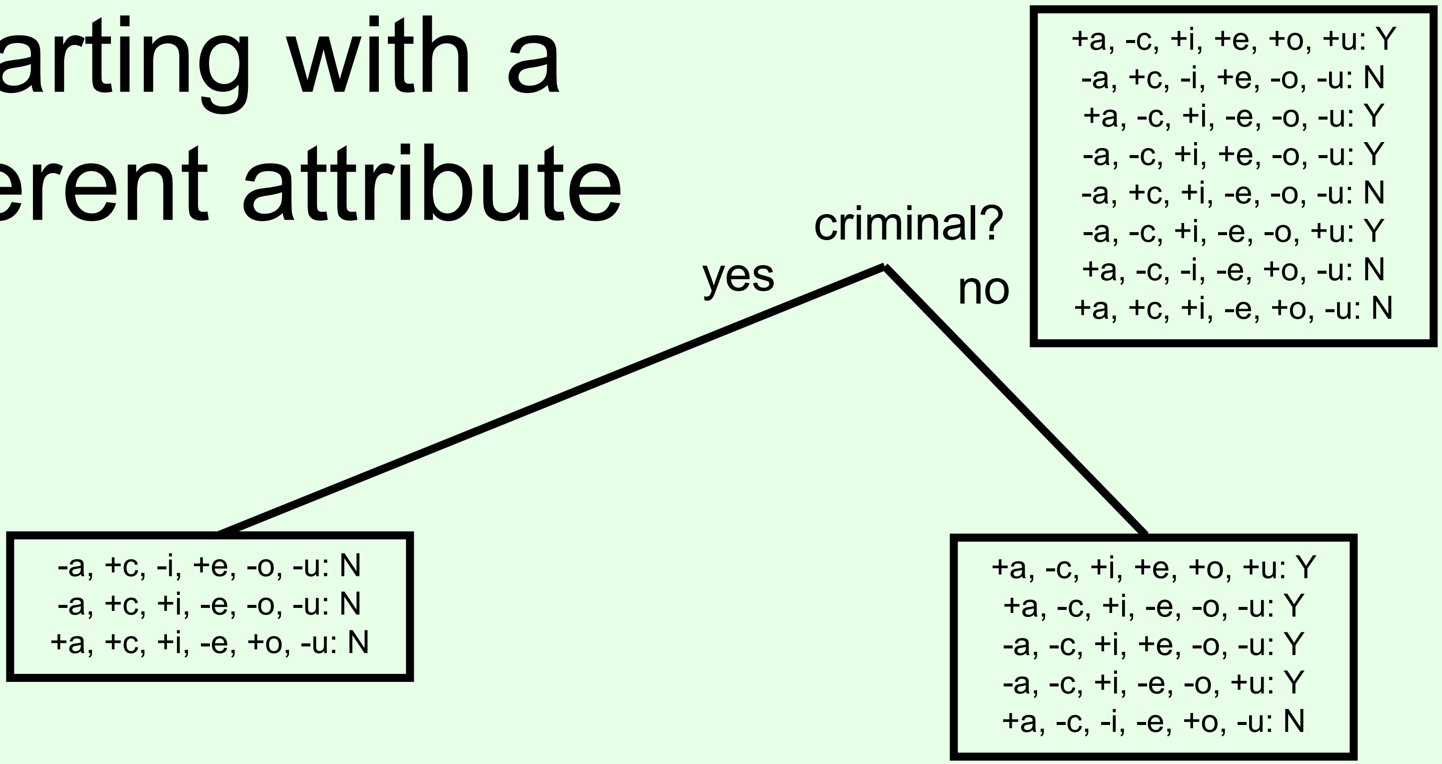


# Constructing a decision tree, one step at a time




Address was maybe not the best attribute to start with…

# Starting with a different attribute




- Seems like a much better starting point than address
  - Each node almost completely uniform
  - Almost completely predicts whether we will be paid back

# Different approach: nearest neighbor(s)

- Next person is -a, +c, -i, +e, -o, +u. Will we get paid back?
- Nearest neighbor: simply look at most similar example in the training data, see what happened there

  +a, -c, +i, +e, +o, +u: Y *(distance 4)*

  -a, +c, -i, +e, -o, -u: N *(distance 1)*

  +a, -c, +i, -e, -o, -u: Y *(distance 5)*

  -a, -c, +i, +e, -o, -u: Y *(distance 3)*

  -a, +c, +i, -e, -o, -u: N *(distance 3)*

  -a, -c, +i, -e, -o, +u: Y *(distance 3)*

  +a, -c, -i, -e, +o, -u: N *(distance 5)*

  +a, +c, +i, -e, +o, -u: N *(distance 5)*

- Nearest neighbor is second, so predict N
- k nearest neighbors: look at k nearest neighbors, take a vote
  - E.g., 5 nearest neighbors have 3 Ys, 2Ns, so predict Y

# Another approach: perceptrons

- Place a weight on every attribute, indicating how important that attribute is (and in which direction it affects things)
- E.g., $w_a = 1$, $w_c = -5$, $w_i = 4$, $w_e = 1$, $w_o = 0$, $w_u = -1$

  +a, -c, +i, +e, +o, +u: Y *(score 1+4+1+0-1 = 5)*

  -a, +c, -i, +e, -o, -u: N *(score -5+1=-4)*

  +a, -c, +i, -e, -o, -u: Y *(score 1+4=5)*

  -a, -c, +i, +e, -o, -u: Y *(score 4+1=5)*

  -a, +c, +i, -e, -o, -u: N *(score -5+4=-1)*

  -a, -c, +i, -e, -o, +u: Y *(score 4-1=3)*

  +a, -c, -i, -e, +o, -u: N *(score 1+0=1)*

  +a, +c, +i, -e, +o, -u: N *(score 1-5+4+0=0)*
- Need to set some threshold above which we predict to be paid back (say, 2)
- May care about combinations of things (nonlinearity) – generalization: neural networks

# Reinforcement learning

- There are three routes you can take to work: A, B, C
- The times you took A, it took: 10, 60, 30 minutes
- The times you took B, it took: 32, 31, 34 minutes
- The time you took C, it took 50 minutes
- What should you do next?
- Exploration vs. exploitation tradeoff
  - Exploration: try to explore underexplored options
  - Exploitation: stick with options that look best now
- Reinforcement learning usually studied in MDPs
  - Take action, observe reward and new state

# Bayesian approach to learning

- Assume we have a prior distribution over the long term behavior of A
  - With probability .6, A is a “fast route” which:
    - With prob. .25, takes 20 minutes
    - With prob. .5, takes 30 minutes
    - With prob. .25, takes 40 minutes
  - With probability .4, A is a “slow route” which:
    - With prob. .25, takes 30 minutes
    - With prob. .5, takes 40 minutes
    - With prob. .25, takes 50 minutes
- We travel on A once and see it takes 30 minutes
- P(A is fast | observation) = P(observation | A is fast)*P(A is fast) / P(observation) = .5*.6/(.5*.6+.25*.4) = .3/(.3+.1) = .75
- Convenient approach for decision theory, game theory

# Learning in game theory

- Like 2/3 of average game
- Very tricky because other agents learn at the same time
- From one agent's perspective, the environment is changing
  - Taking the average of past observations may not be good idea