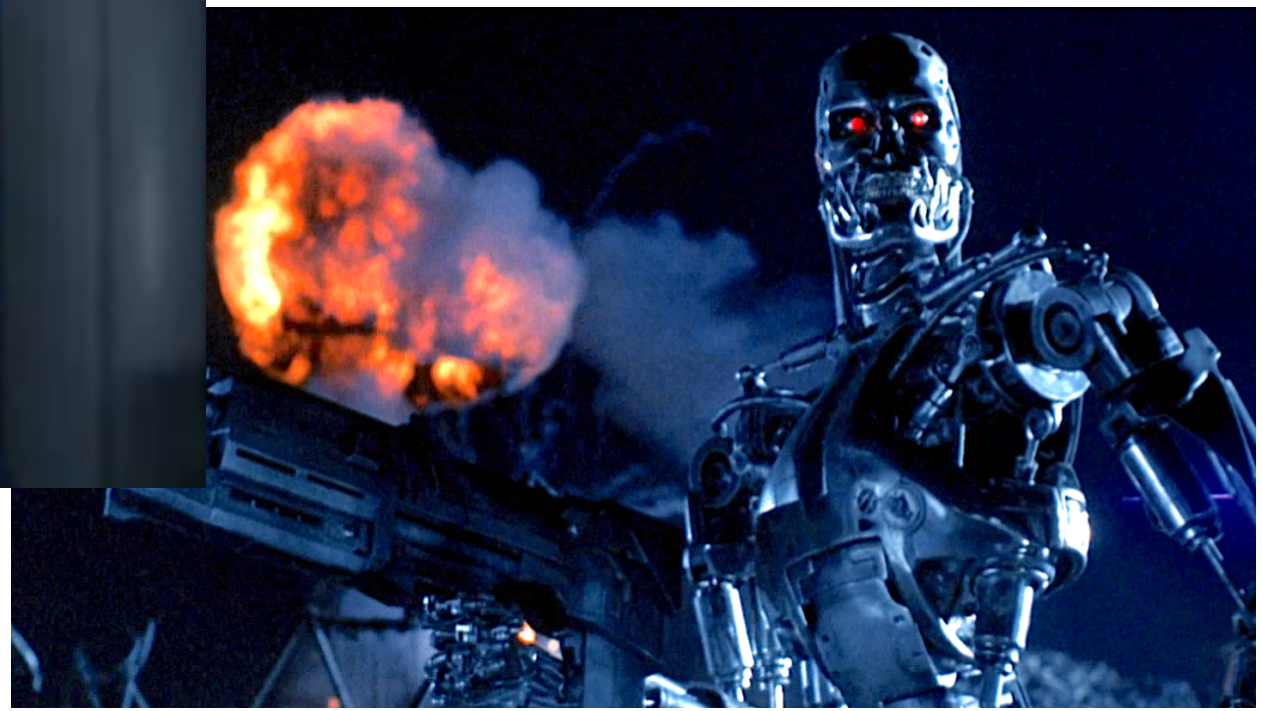
Ethics: The Alignment Problem

How do we harness artificial intelligence for the good of humanity?

The problem we think about: Skynet



Some Problems Are Already Here

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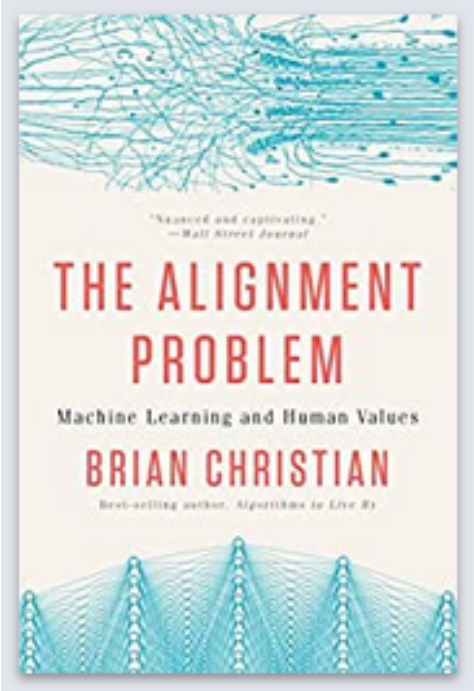

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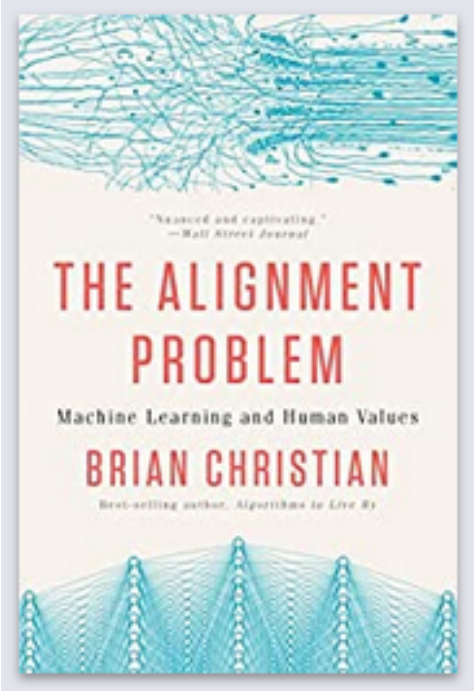

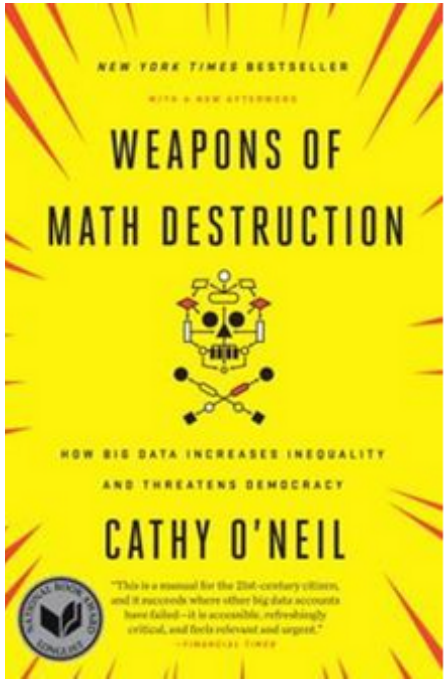

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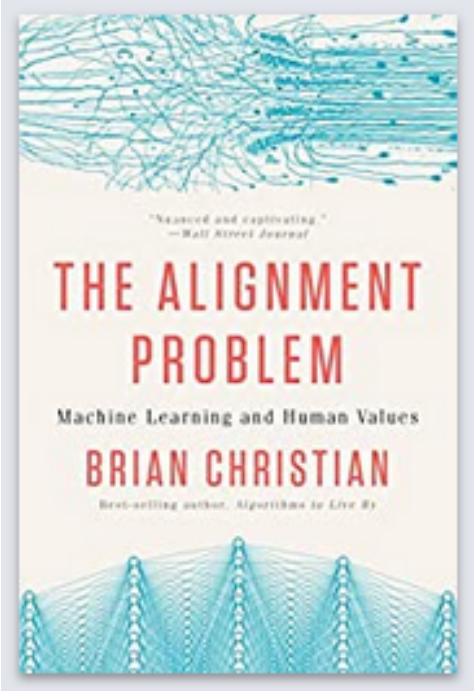

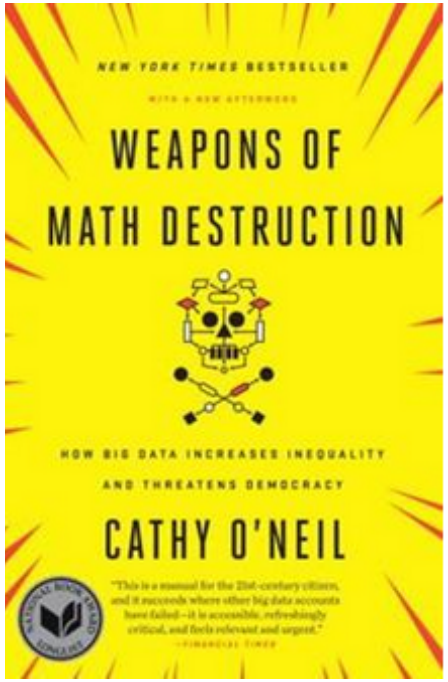

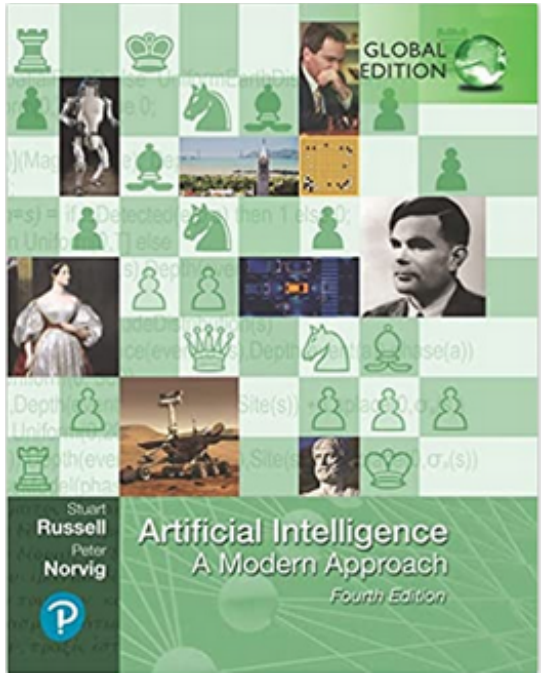

Two Categories

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Immediate Problems

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Long-Term Problems

Two Categories

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- Weak AI

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- Subtle Challenges

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Long-Term Problems

- Strong AI
- Existential Threats

Immediate Problem: Bias in Data

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word2vec

300-dimensional embedding trained just
based on hiding words from phrases

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Czech + currency = koruna
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doctor – man + woman
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`doctor - man + woman` = nurse

Immediate Problem: Difficulty removing information from Data

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- date of birth + gender + zip code = % uniquely identified

Immediate Problem: Difficulty removing information from Data

- date of birth + gender + zip code = 87% uniquely identified

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COMPAS: predicting recidivism

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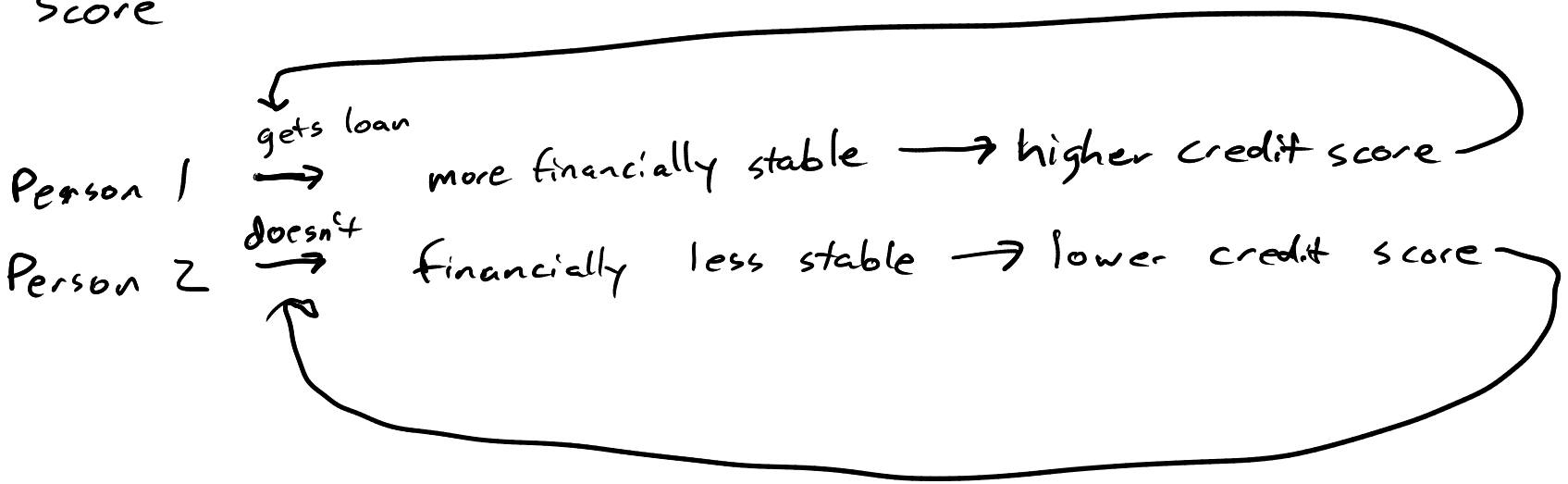
Suggested possible solution in AIMA:

"Equal Impact": assigning utility

Immediate Problem: Decision Feedback Loops

Lender: Lend to people who have highest prob. making payments on time

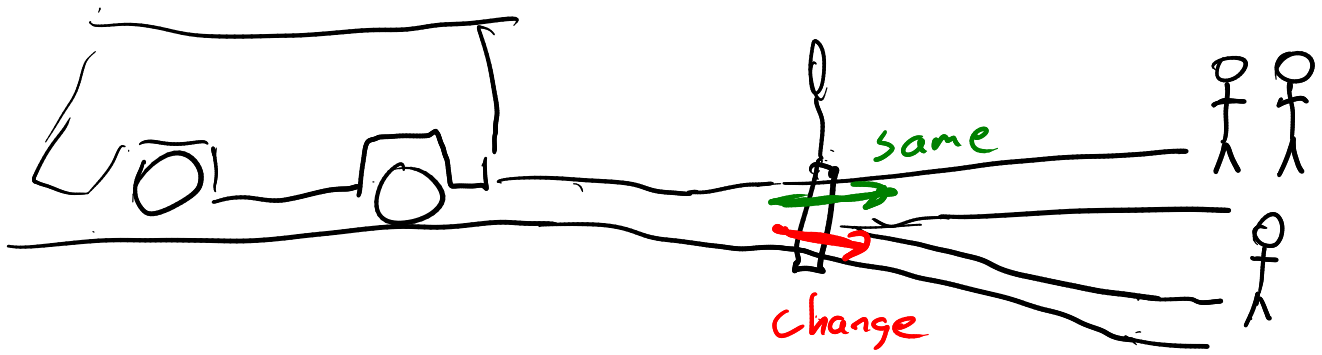
Credit Score



Immediate Problem: Employment

- Bank Tellers / ATM
  - 1900: >40% in agriculture 2000: <2%
    - Differences:
      - AI can do interesting things
      - Pace of Change
        - 100 years vs 10 years
      - Zero-marginal cost of replication
        - 10% better farmer → 20% more income
        - 10% better AI engineer → 1000% more income ←
      - Less cost for adoption
- Employment
  1. production of goods ← X
  2. income ←
  3. sense of purpose, accomplishment, social integration ←

Values: Trolley Problems



Transparency / Trust
- Releasing system specification
- Automated explanation

IEEE P7001

Standard for transparency in autonomous systems

Reward Shaping

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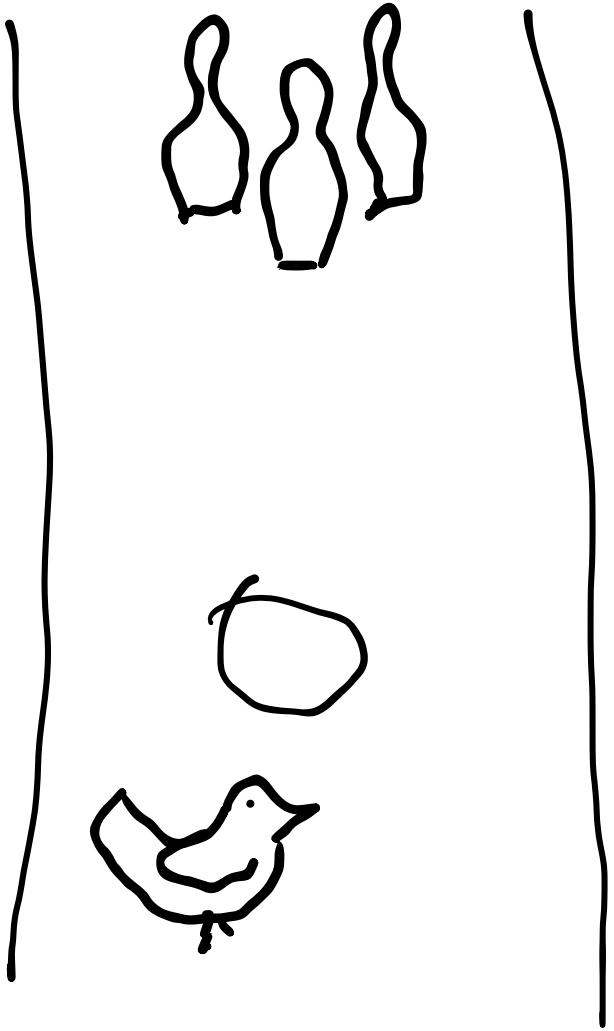
B. F. Skinner

Pigeon-guided bombs, 1943

Reward Shaping



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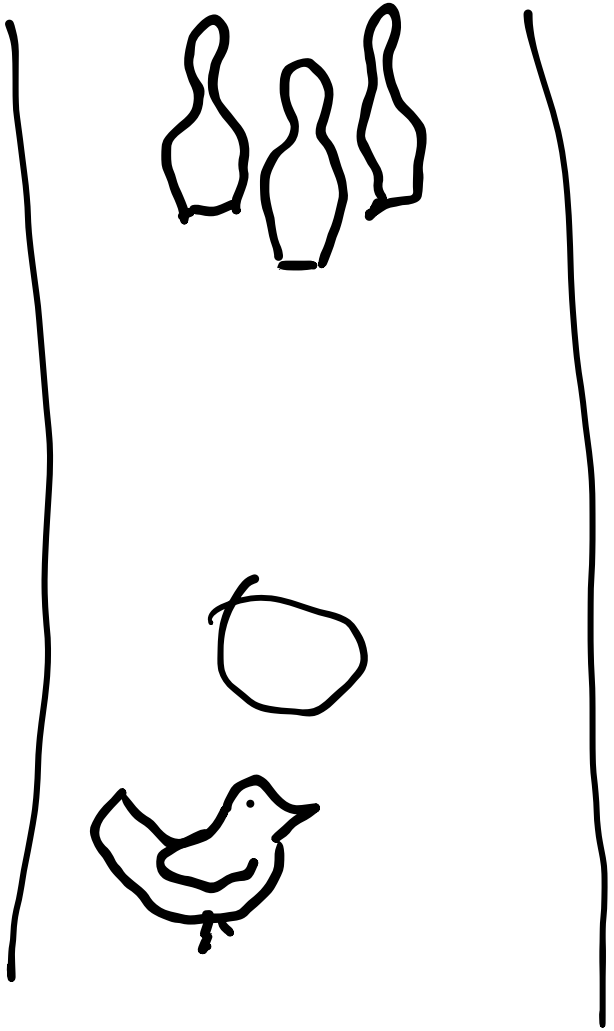

B. F. Skinner

Pigeon-guided bombs, 1943

> We decided to reinforce any response which had the slightest resemblance to a swipe—perhaps, at first, merely the behavior of looking at the ball—and then to select responses which more closely approximated the final form. The result amazed us. In a few minutes, the ball was caroming off the walls of the box as if the pigeon had been a champion squash player.

https://www.youtube.com/watch?v=tlOIHko8ySg

Reward Shaping

"As a general rule, it is better to design performance measures according to what one actually wants in the environment, rather than according to how one thinks the agent should behave." - Stuart Russell

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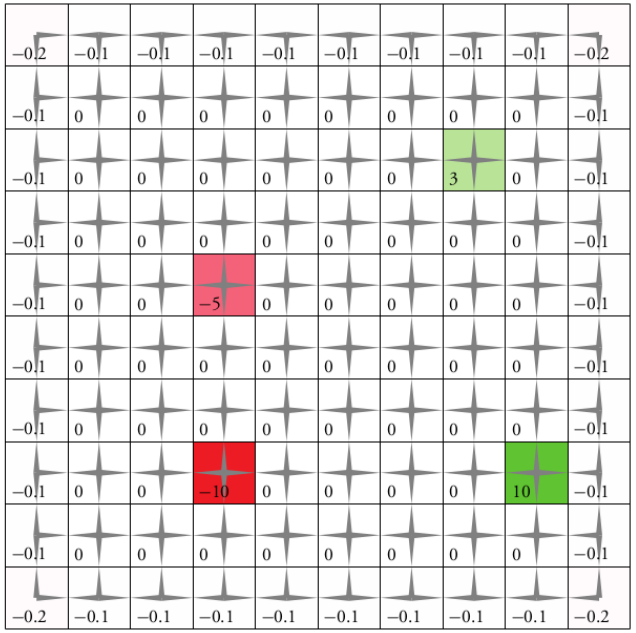

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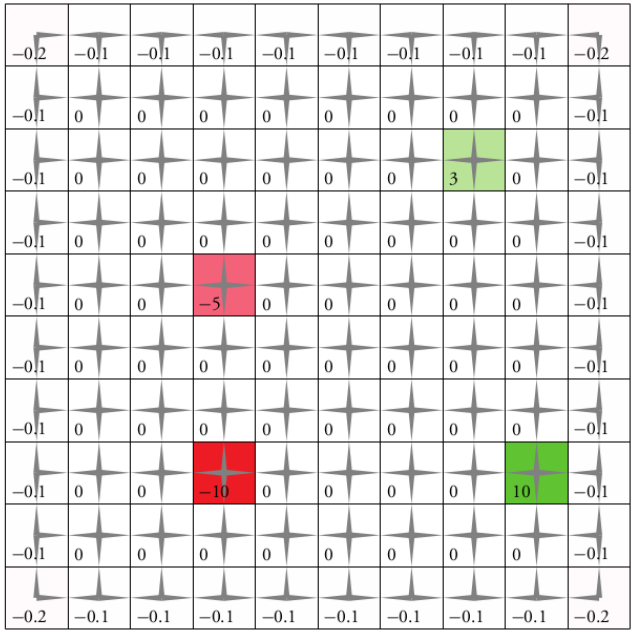
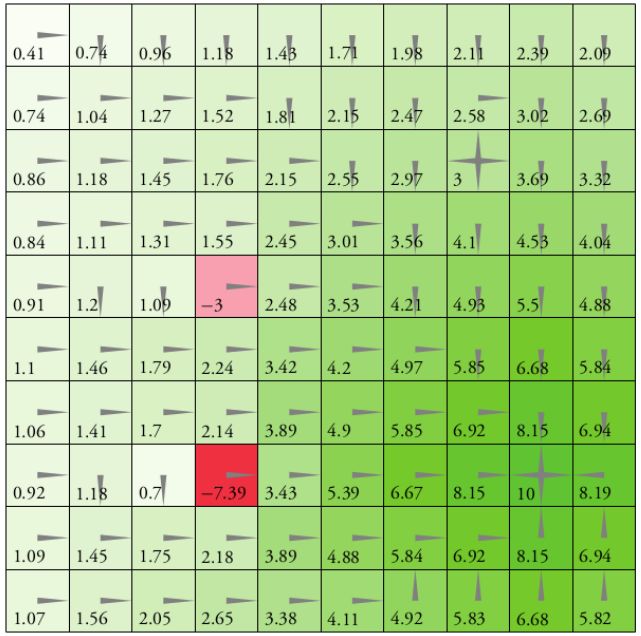


Value



Reward Shaping

Potential-Based Reward Shaping

$F(s') - \gamma F(s'')$

- $R(s, a, s') += F(s) - \gamma F(s')$ ← will not change optimal policies
- any other transformation may yield sub optimal policies unless further assumptions are made about the underlying MDP

Long-Term Problems

Defining Reward Functions is Hard

Hypothetical Examples:

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- Acme paper clip research division

Defining Reward Functions is Hard

Hypothetical Examples:

- Acme paper clip research division
- Asimov's laws
  - A robot may not injure a human being or, through inaction, allow a human being to come to harm.
  - A robot must obey the orders given it by human beings except where such orders would conflict with the First Law.
  - A robot must protect its own existence as long as such protection does not conflict with the First or Second Law.

Gorilla Problem: Super-Human Intelligence