CS 598CM: ML for Compilers and Architecture

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Brief Announcements

- **Paper Reviews:** hotCRP access
- **Paper Presentations:** Meet the week before, use Piazza or email to schedule
- **Piazza:** on-line discussions of papers; let's be active!
- **COVID19:** If you feel sick, please stay at home.

Recap

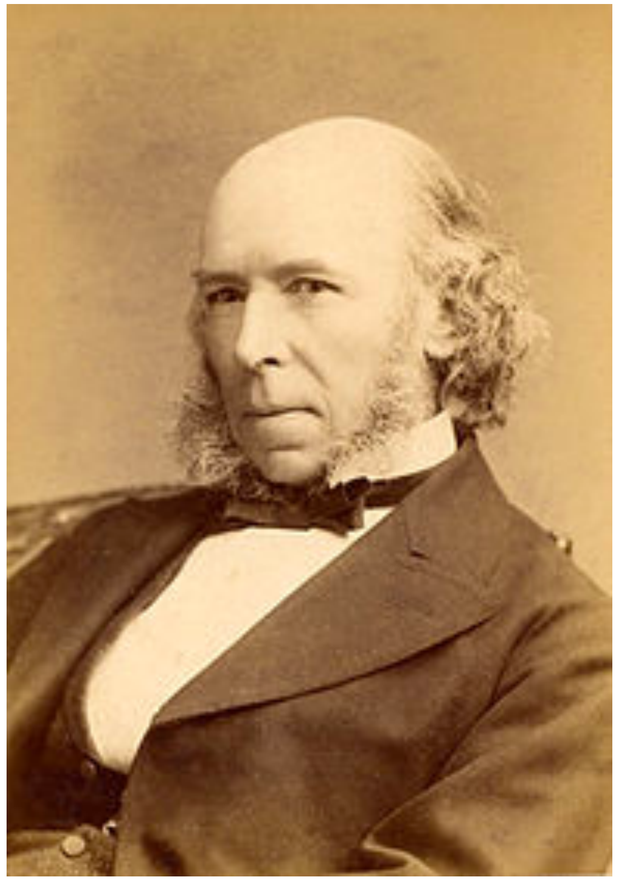
- Neural Networks Primer
  - Perceptrons
  - Multilayer perceptrons
  - Convolutional Neural Networks
  - Recurrent Neural Networks
  - Graph Neural Networks
  - Transformers

Lecture 6:
ML Techniques + Auto-tuning

Genetic Algorithms

Survival of the Fittest

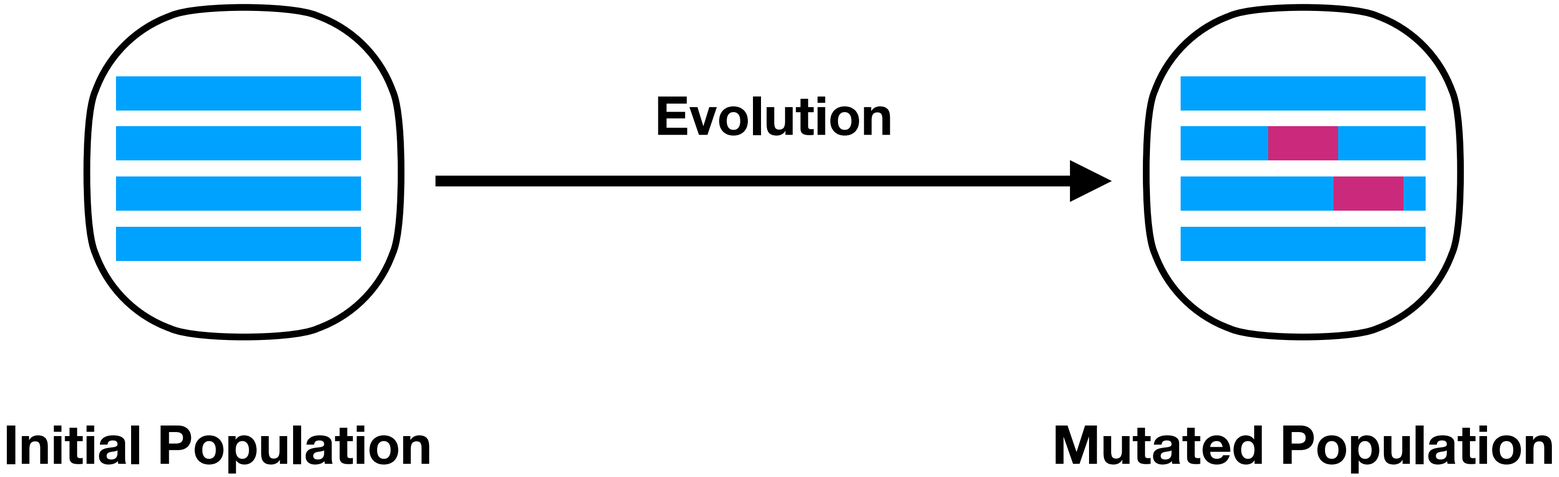
“Survival of the form that will leave the most copies of itself in successive generations."



Charles Darwin

Genetic Algorithms

- Find the set of genes (parameters settings) that are the fittest (optimizes an objective) using genetic evolution.



Genetic Algorithms

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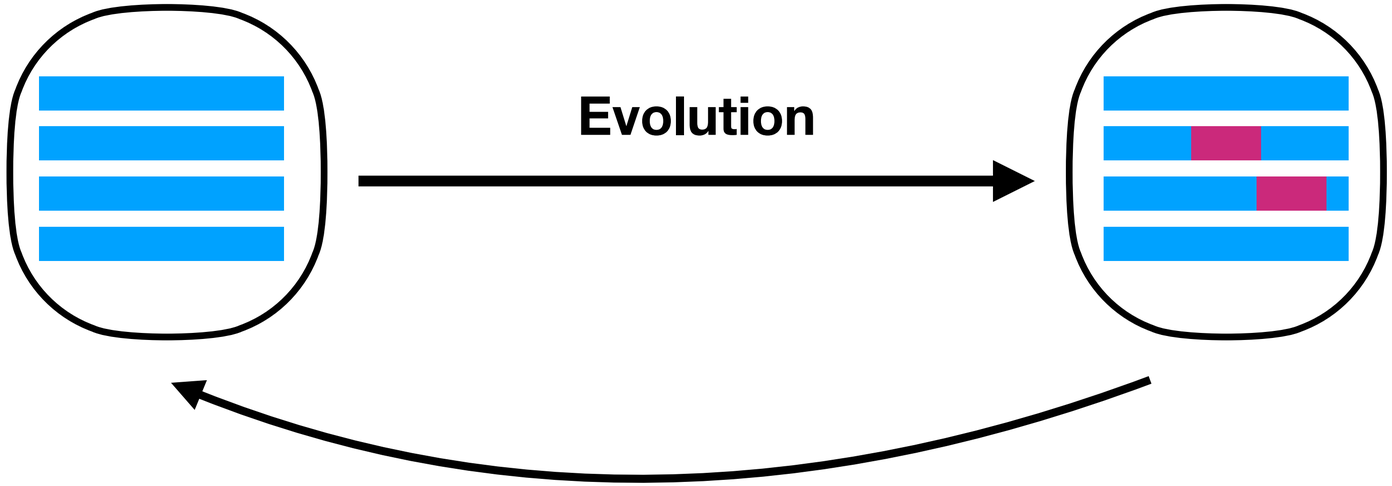
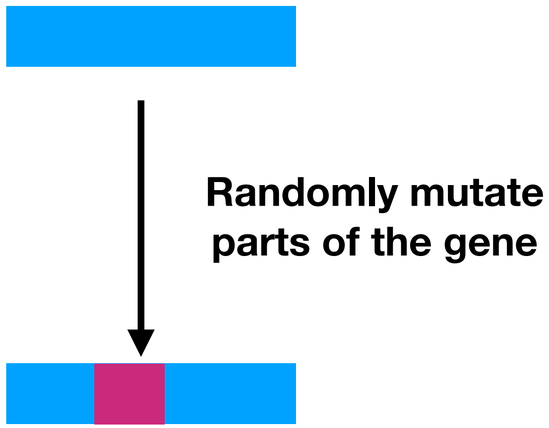


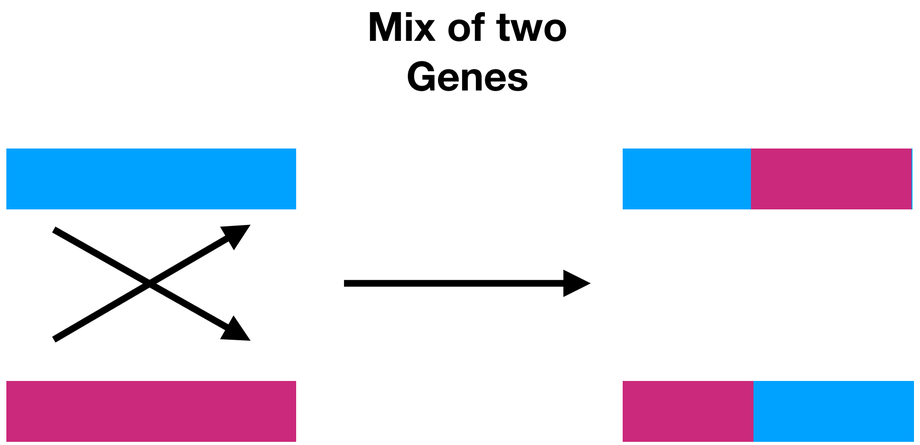
Repeat until budget exhausted or population meets convergence criteria

Evolution

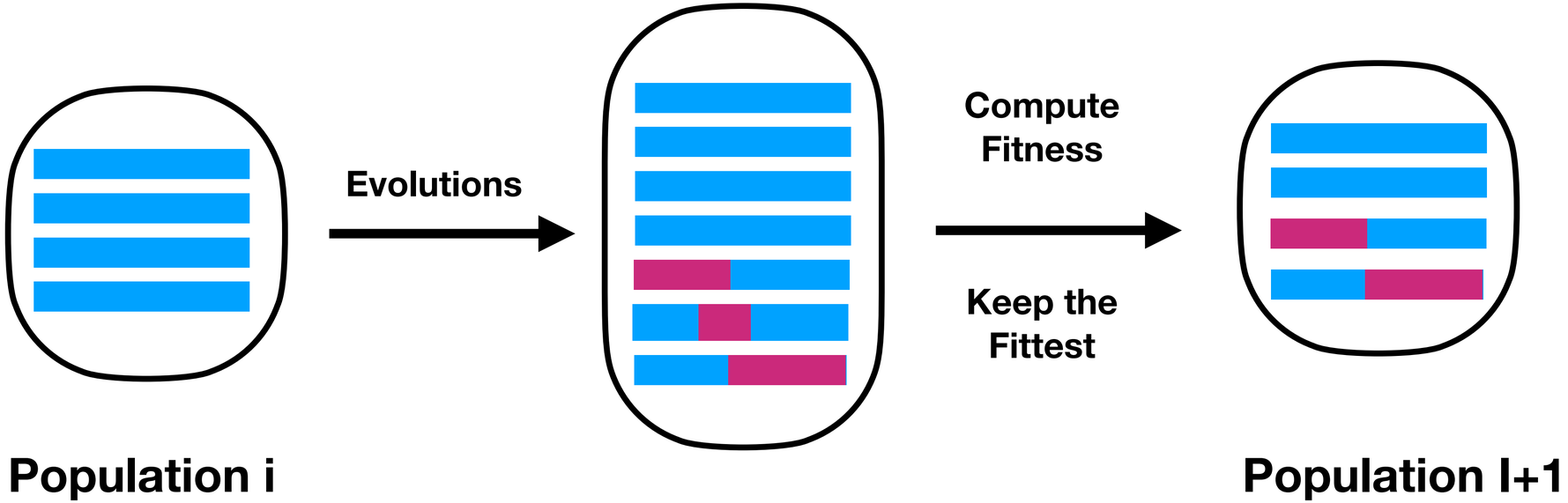
Mutations



Crossovers

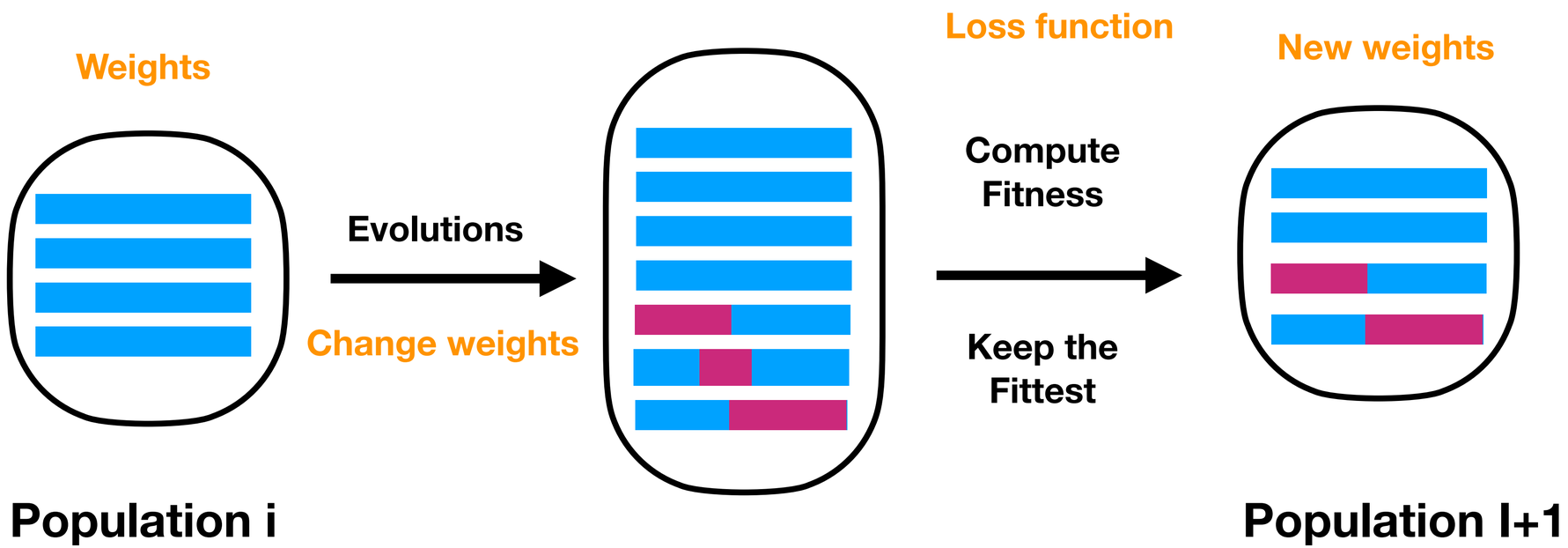


Evolution


Evolutions
Compute
Fitness
Keep the
Fittest
Population i
Population I+1

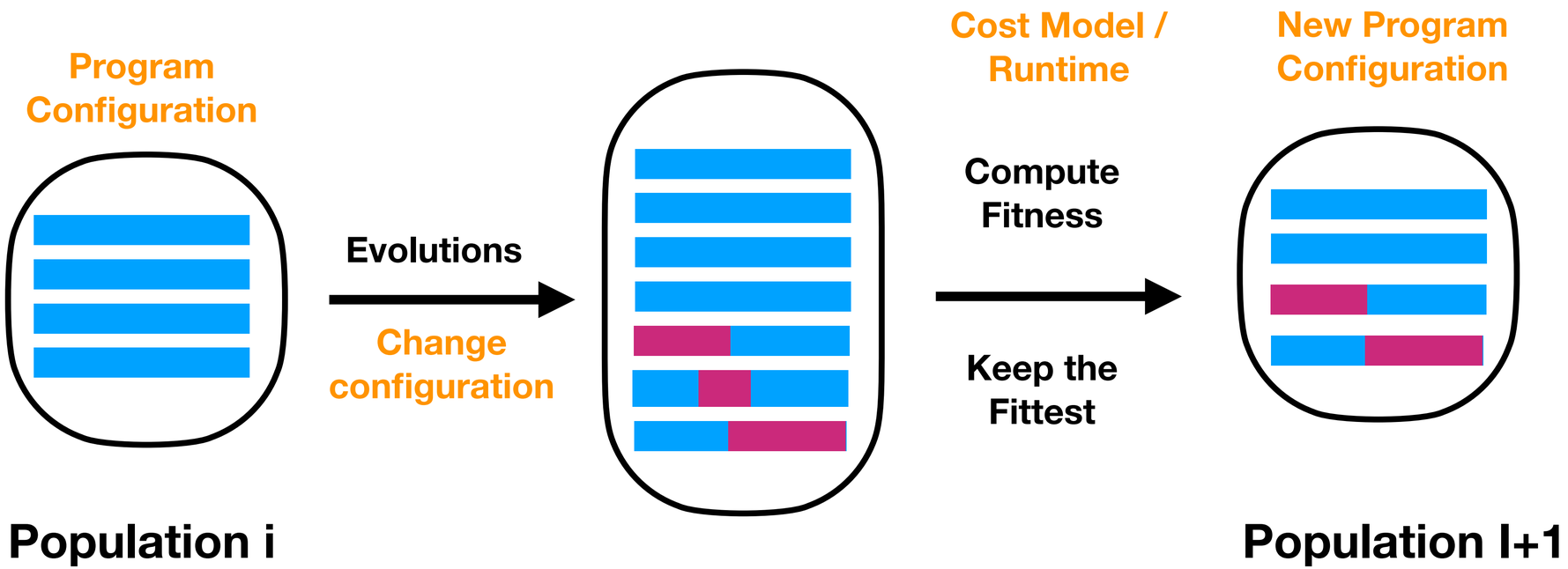
Can we train NNs using GAs?

YES!



Why aren't we using GAs? **Completely Random; Inefficient**

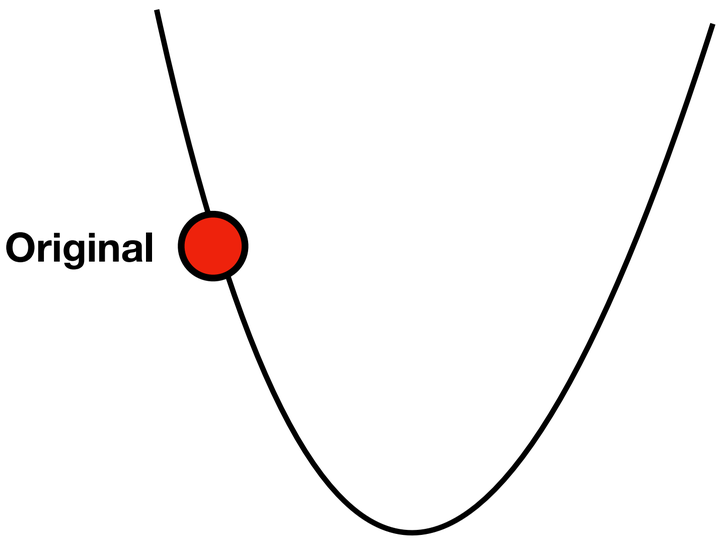
Performance Tuning



Simulated Annealing

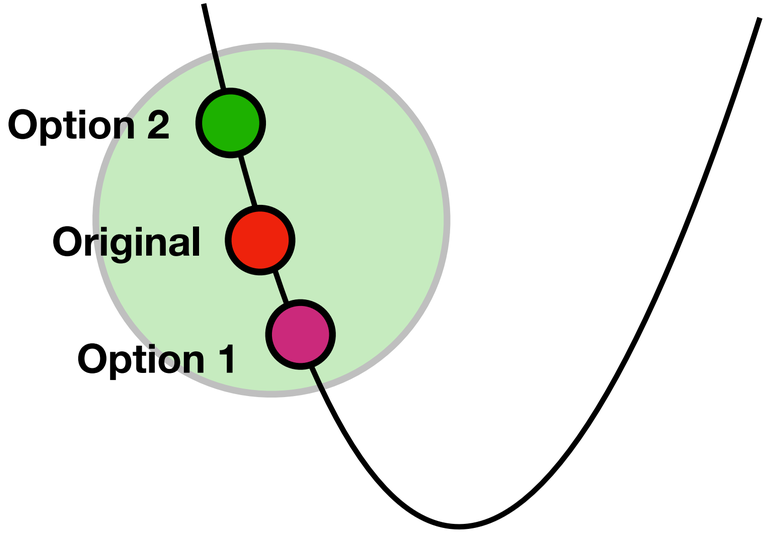
- Optimization algorithm / meta-heuristic
- Similar to the general genetic algorithm structure
- Basic idea => Propose a solution (initial weights) and propose other solutions (new weights) and accept them based on a calculated probability

Simulated Annealing



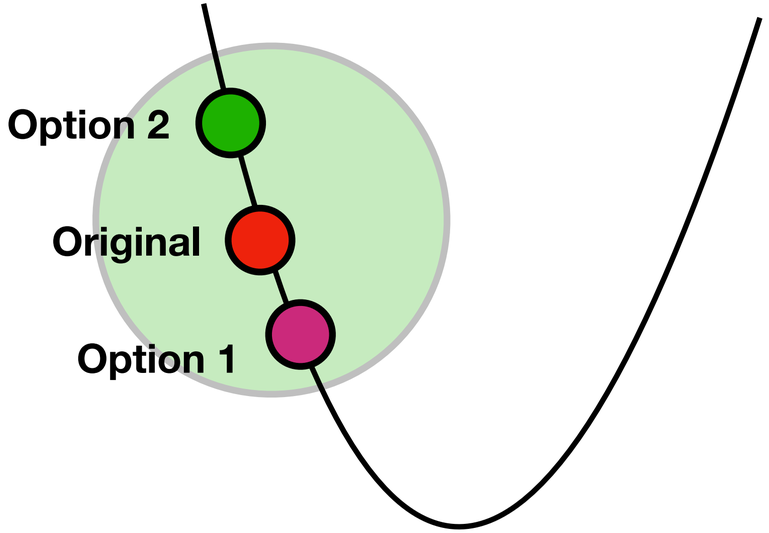
- **Select an initial solution**

Simulated Annealing



- **Select an initial solution**
- **Select solution within a small neighborhood**

Simulated Annealing



Should we accept

Option 1? Yes

Option 2? Maybe

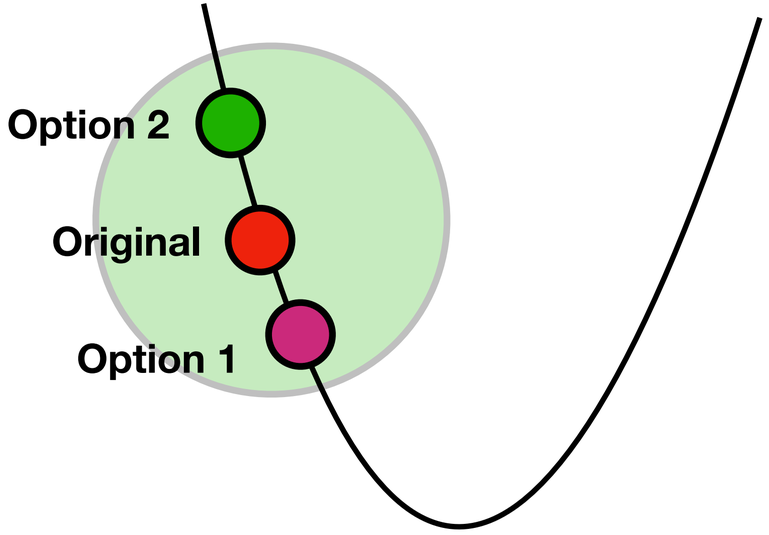
- **Select an initial solution**
- **Select another solution within a small neighborhood**
- **Accept the new solution with probability P**

$$P = \begin{cases} 1 & if \Delta c \leq 0 \\ e^{-\Delta c / t} & if \Delta c > 0 \end{cases}$$

t - temperature (hyperparameter)

ΔC **- Cost difference**

Simulated Annealing



- Select an initial solution
- Until Convergence
  - Change temperature
  - Select another solution within a small neighborhood
  - Accept the new solution with probability P

$$P = \begin{cases} 1 & if \Delta c \leq 0 \\ e^{-\Delta c / t} & if \Delta c > 0 \end{cases}$$

t - temperature (hyperparameter)

ΔC - Cost difference

Acceptance Probability

$$P = \begin{cases} 1 & if \Delta c \leq 0 \\ e^{-\Delta c / t} & if \Delta c > 0 \end{cases}$$

Change	Temperature	Acceptance Probability
0.2	0.9	0.8007
0.4	0.9	0.6412
0.6	0.9	0.5134
0.8	0.9	0.4111

Sample acceptance probabilities given the a temperature of 0.9

Change	Temperature	Acceptance Probability
0.2	0.1	0.1353
0.4	0.1	0.0183
0.6	0.1	0.0025
0.8	0.1	0.0003

Sample acceptance probabilities given the a temperature of 0.1

t $\uparrow$

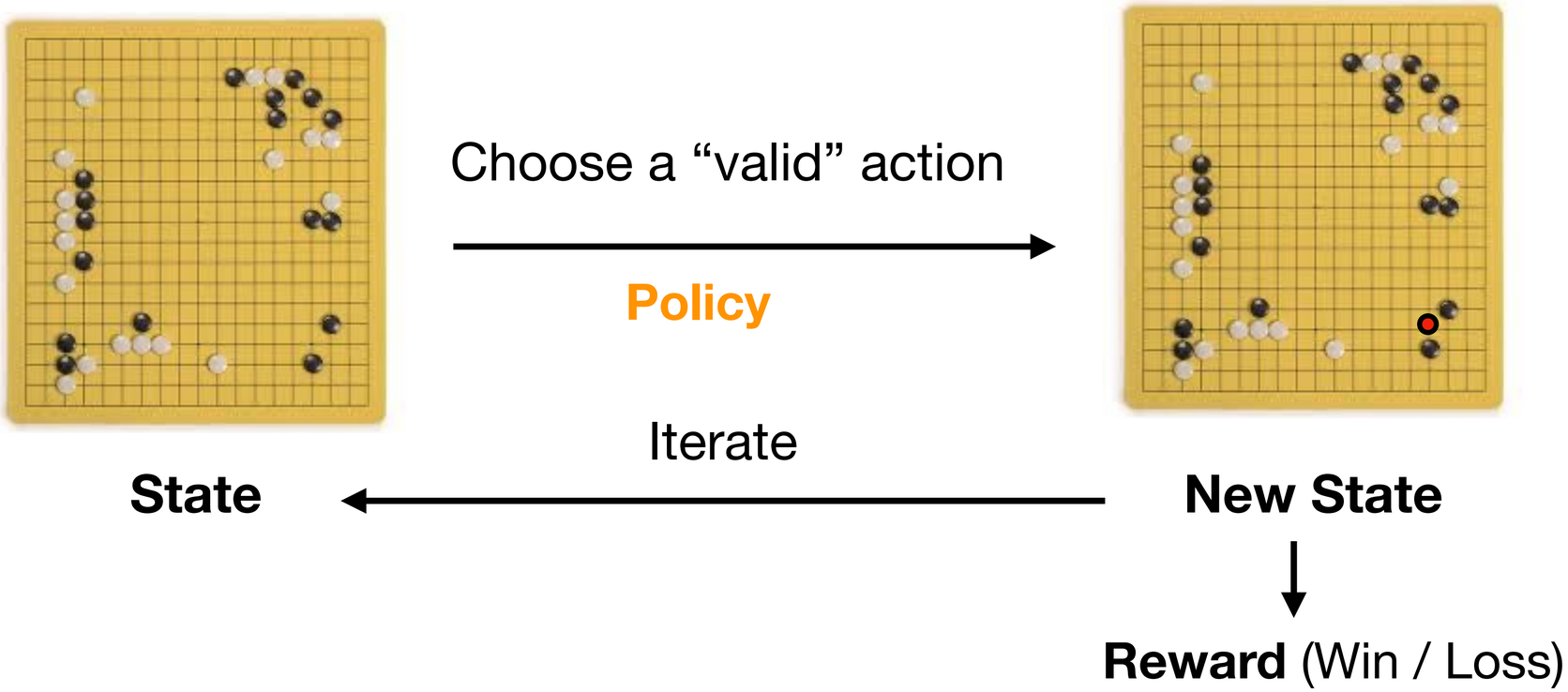
ΔC $\downarrow$

Acceptance probability increases

How should be change t across iterations?

Start high (exploration) and decrease (exploitation)

Sequential Decision Making



Markov Decision Process (MDP)

Vectorization as a MDP

```
a[1] = b[1] + c[1]
a[2] = b[2] + c[2]
a[3] = a[1] + c[3]
a[4] = a[2] + c[4]
a[5] = b[5] * c[5]
```

State

Choose a “valid” action

{a[3],a[4]}

{a[1],a[2],a[3],a[4]}

Iterate

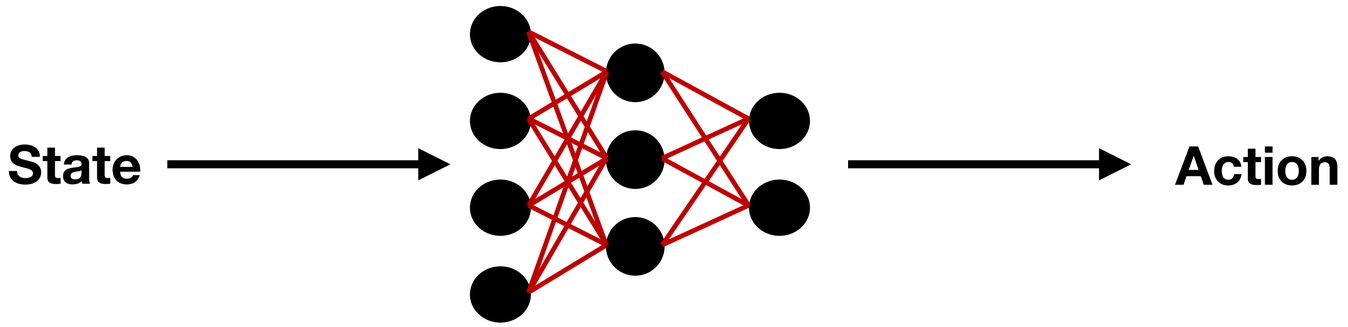
```
a[1:2] = b[1:2] + c[1:2]
a[3:4] = a[1:2] + c[3:4]
a[5]   = b[5]   * c[5]
```

New State

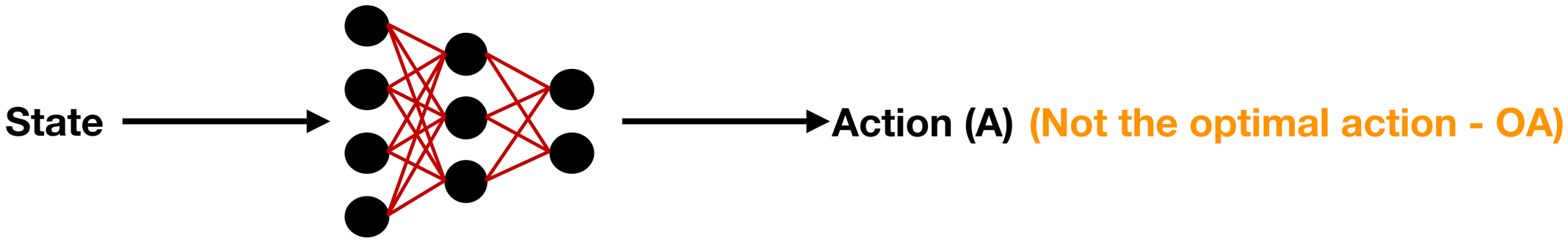
Reward (Speed of execution)

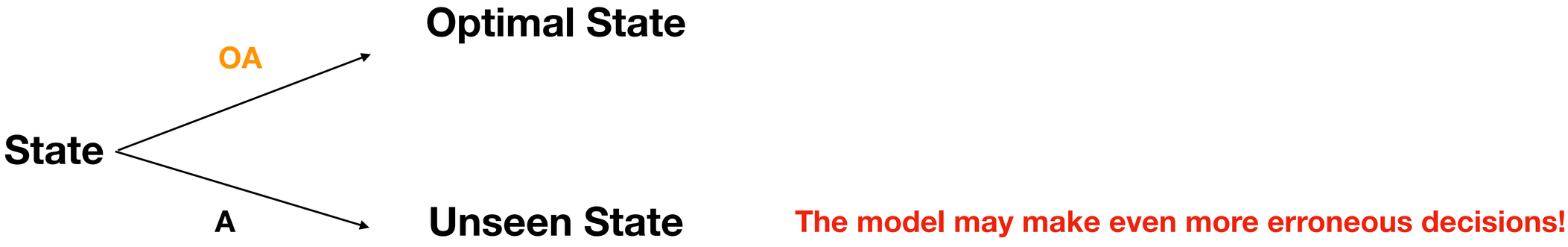
Imitation Learning

- Collect a dataset of (state, action) pairs from an oracle
- Essentially supervised learning on those collected experiences



What if the model makes a mistake?

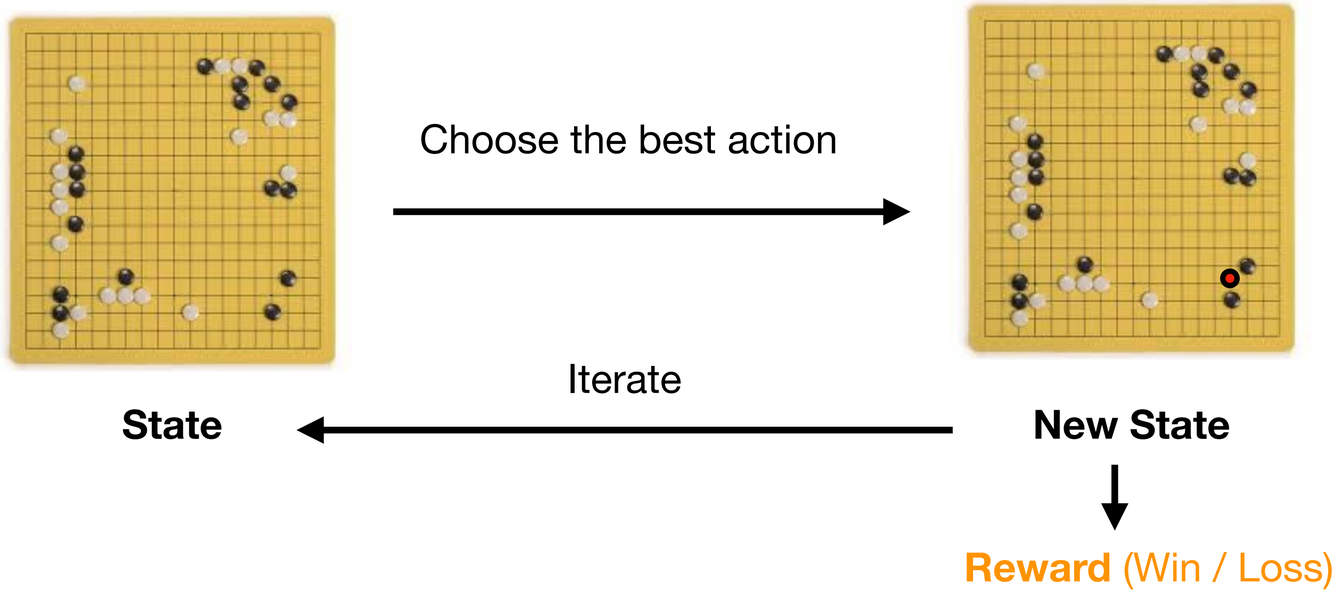




DAgger algorithm gives a solution (Ross et. al)!

Reinforcement Learning

- No oracle, but we have access to the reward
- Devise a mechanism to take the best action that would maximize the total reward
- Not greedy; but tries to maximize the total reward for the entire episode



Different RL algorithms

- Directly learn the policy function (policy gradient techniques)
- Learn the value function (Q-learning)
- Hybrid (Actor-critic models)

http://rail.eecs.berkeley.edu/deeprlcourse/

https://nanjiang.cs.illinois.edu/cs498/

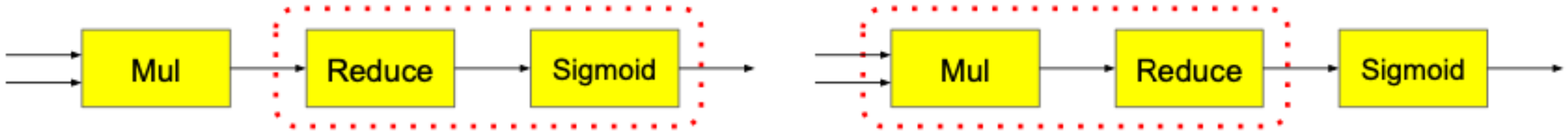
Auto-tuning

- Automatically find the best program or program configuration in an optimization space according to some metric

Exhaustive Search
Genetic Algorithms
Simulated Annealing
Reinforcement Learning

Examples of auto-tuning

- Normally we just do **parameter tuning**
  - Loop unrolling (unroll factor)
  - Compiler Flags (binary vector)
  - Operator fusion, layout selection, tile-size selection in DL stacks (how?)



Fusion?

Halide

Halide auto-tuner: Generate Program Constructs as well; not just parameter tuning

```
Func blur_3x3(Func input) {
  Func blur_x, blur_y;
  Var x, y, xi, yi;

  // The algorithm - no storage or order
  blur_x(x, y) = (input(x-1, y) + input(x, y) + input(x+1, y))/3;
  blur_y(x, y) = (blur_x(x, y-1) + blur_x(x, y) + blur_x(x, y+1))/3;

  // The schedule - defines order, locality; implies storage
  blur_y.tile(x, y, xi, yi, 256, 32)
        .vectorize(xi, 8).parallel(y);
  blur_x.compute_at(blur_y, x).vectorize(x, 8);

  return blur_y;
}
```

```
blur_x.compute_at(blur_y, x)
      .vectorize(x, 4);
blur_y.tile(x, y, xi, yi, 8, 8)
      .parallel(y)
      .vectorize(xi, 4);
```

```
blur_x.store_root()
      .compute_at(blur_y, y)
      .split(x, x, xi, 8)
      .vectorize(xi, 4).parallel(x);
blur_y.split(x, x, xi, 8)
      .vectorize(xi, 4).parallel(x);
```

```
blur_x.store_at(blur_y, y)
      .compute_at(blur_y, yi)
      .vectorize(x, 4);
blur_y.split(y, y, yi, 8)
      .vectorize(x, 4)
      .parallel(y);
```

Agenda for Auto-tuning

- **Empirical Autotuning:** ATLAS
- **Exposing Choices:** Petabricks
- **Autotuning Techniques:** Bliss (Bayesian Optimization)
- **Frameworks:** OpenTuner
- **Scaling Up:** GPTune
- **Diverse Workloads:** GSwitch (graphs)
- **ML in compilers:** Presentation from a Google Research Scientist

Paper Reading

- Try to read evaluation, contributions and motivating examples first
- Then go into details of the paper
- Focus on high-level ideas and not on the implementation in your summary

Any Questions?