# Hill-Climbing

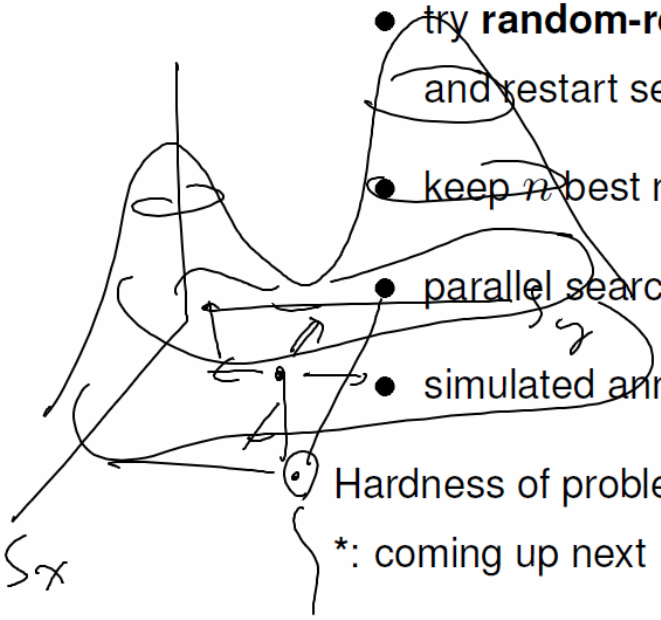
- no queue, keep only the best node
- greedy, no back-tracking
- good for domains where **all nodes are solutions**:
  - goal is to **improve** quality of the solution
  - optimization problems
- note that it is different from greedy best-first search that uses the heuristic function, which keeps a node list

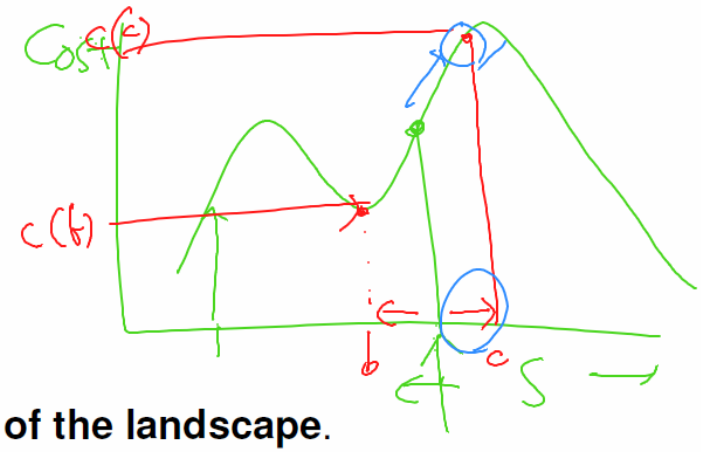
These nodes

# Hill-Climbing Strategies

Problems of local maxima, plateau, and ridges:

- try **random-restart**: move to a random location in the landscape and restart search from there
- keep $n$ best nodes (beam search)
- parallel search
- simulated annealing *



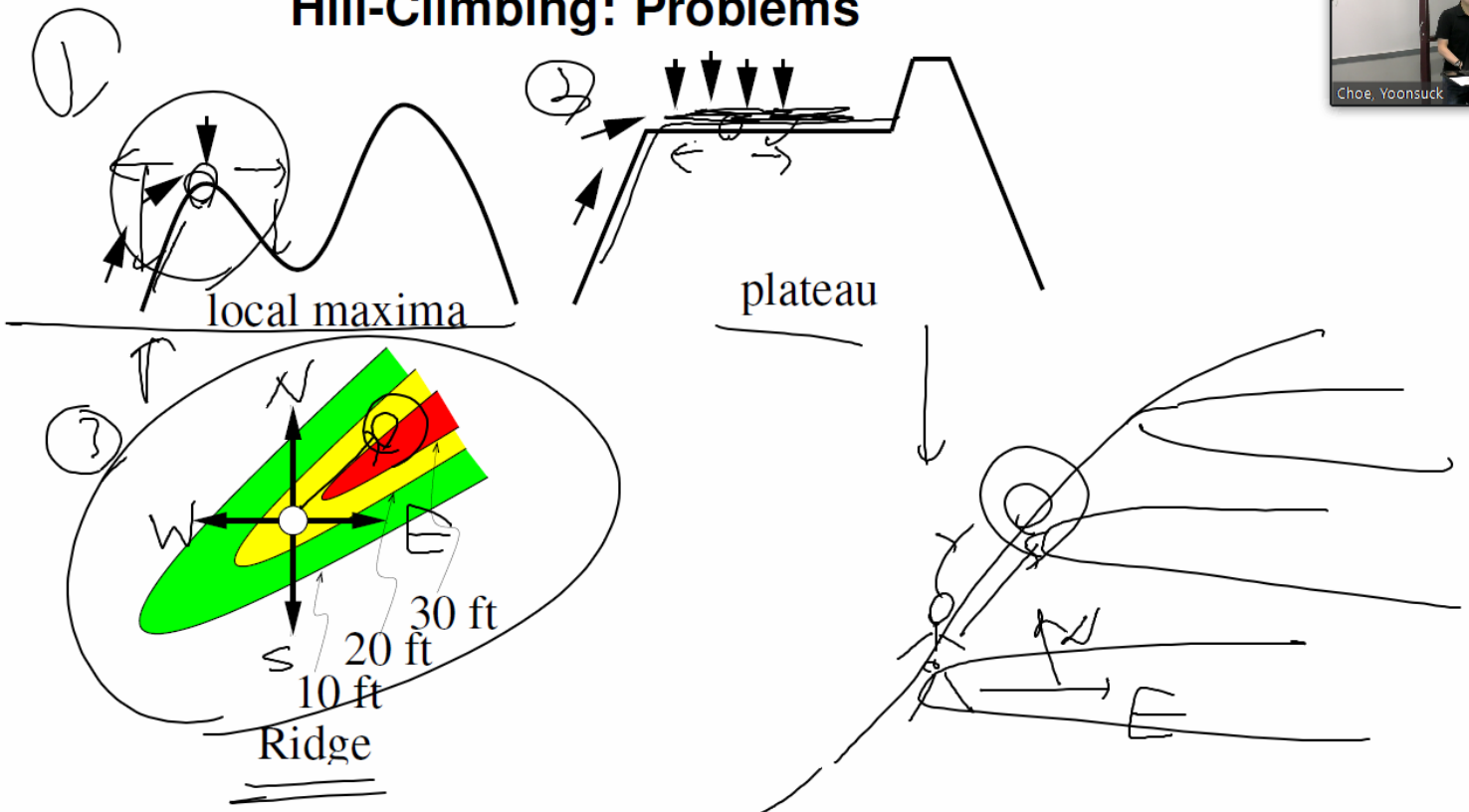



Hardness of problem depends on the **shape of the landscape**.

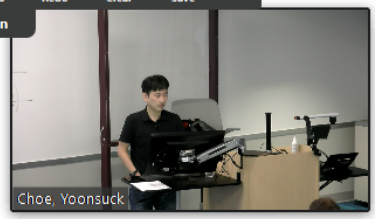
*: coming up next

$a = (a_x, a_y)$

# Hill-Climbing: Problems




- Possible solution: **simulated annealing** – gradually decrease randomness of move to attain globally optimal solution (more on this next week).

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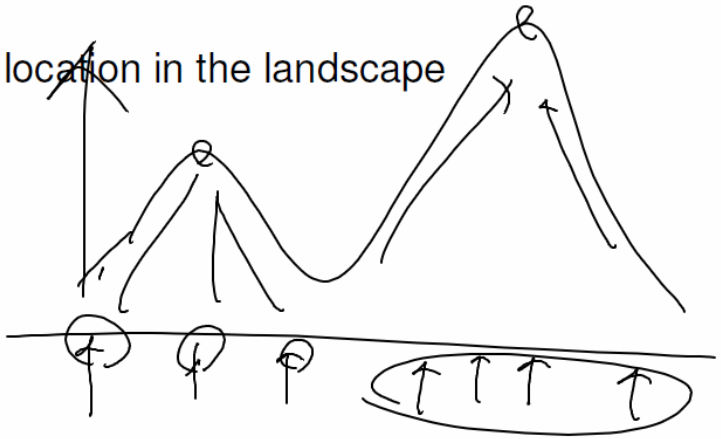
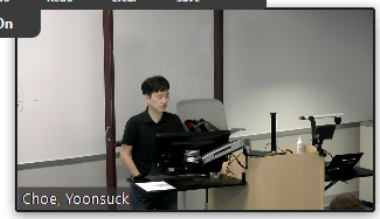


Hardness of problem depends on the **shape of the landscape**.

*: coming up next

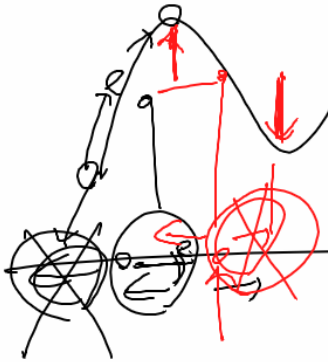
Then you can do this paddle as such and the final solution is it's called simulated the kneeling




# Simulated Annealing: Overview

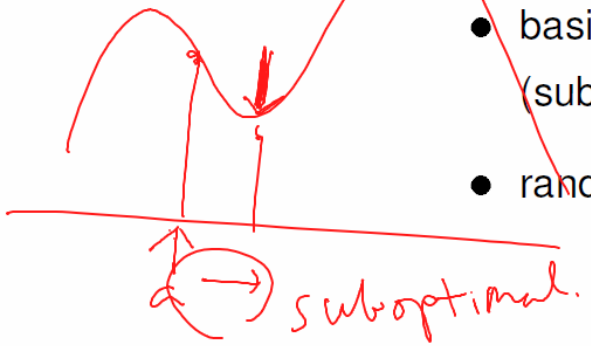
Annealing:

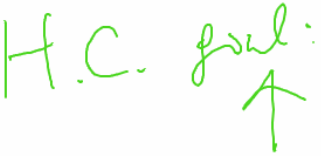
- heating metal to a high-temperature (making it a liquid) and then allowing to cool slowly (into a solid); this relieves internal stresses and results in a more stable, lower-energy state in the solid.
- at high temperature, atoms move actively (large distances with greater randomness), but as temperature is lowered, they become more static.

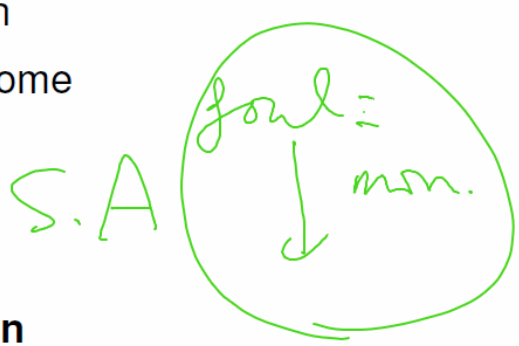


Simulated annealing is similar:

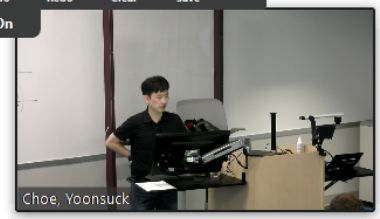
- basically, hill-climbing with randomness that allows going **down** (suboptimal) as well as the desired **up** (optimal)
- randomness (as temperature) is reduced over time





As I mentioned, you can flip it either way, and does that the same thing

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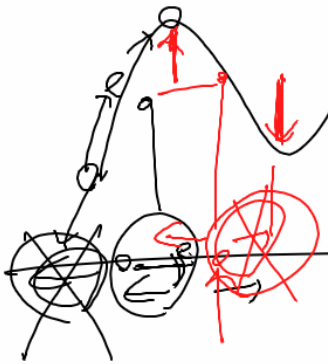

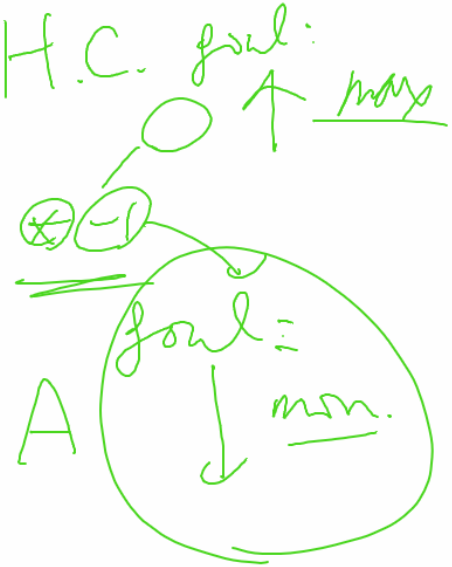


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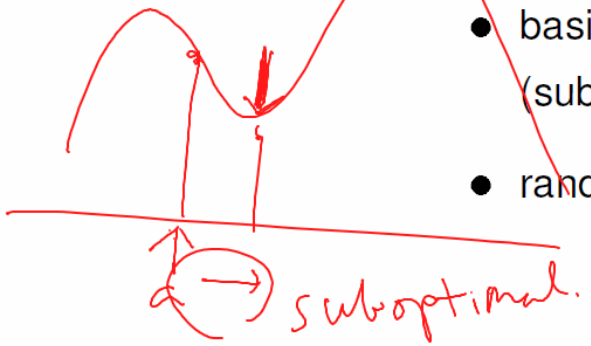
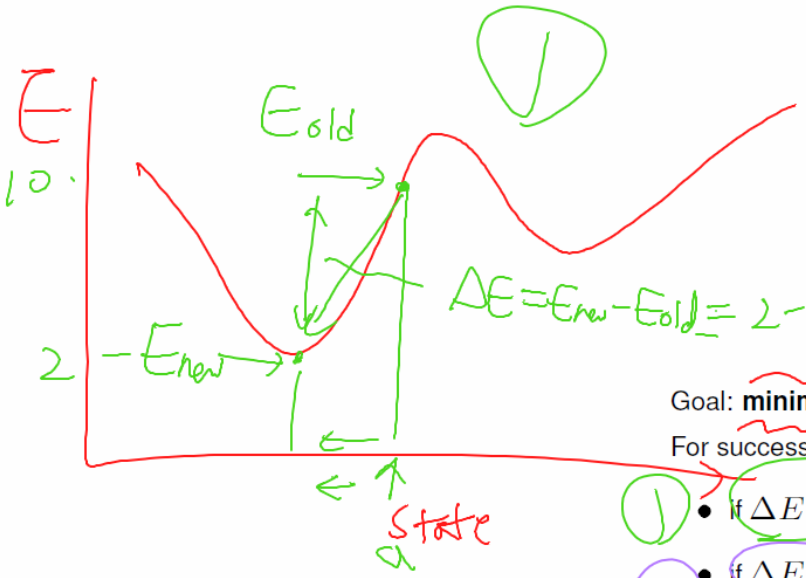
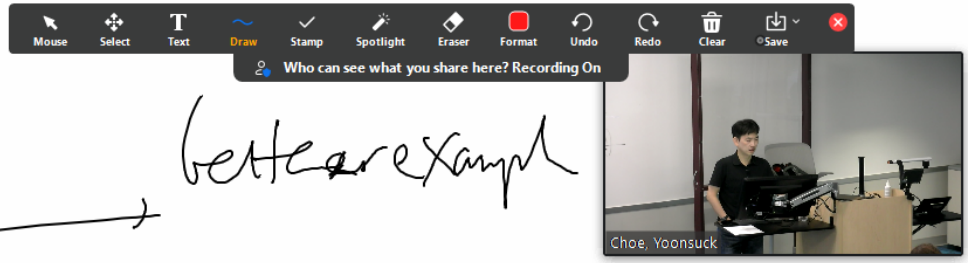



You can make it into this minimization goal. Niceization can be turned into minimization by just multiplying the objective function or the cost is




better example

## Simulated Annealing (SA)

Goal: **minimize** the energy $E$, as in statistical thermodynamics.

For successors of the current node,

1. if $\Delta E \leq 0$ (desired), the move is accepted
2. if $\Delta E > 0$ (undesired), the move is accepted with probability $P(\Delta E) = e^{-\frac{\Delta E}{kT}}$, where $k$ is the Boltzmann constant and $T$ is temperature.
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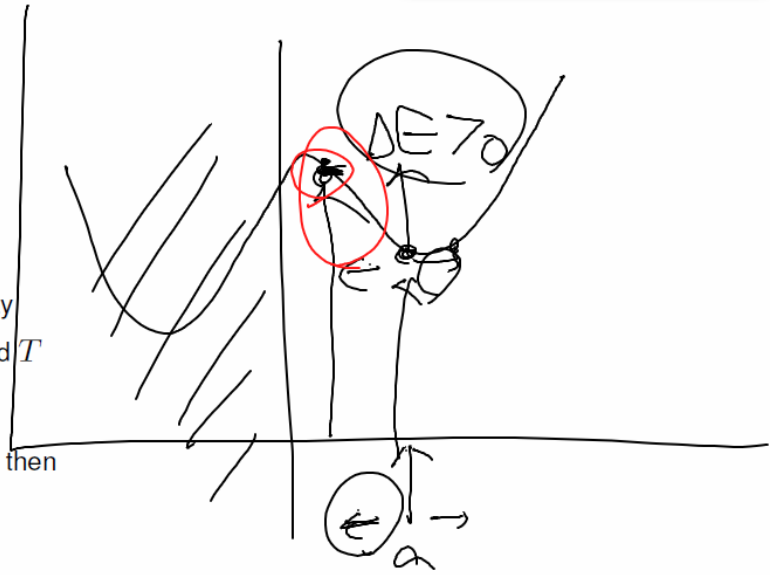
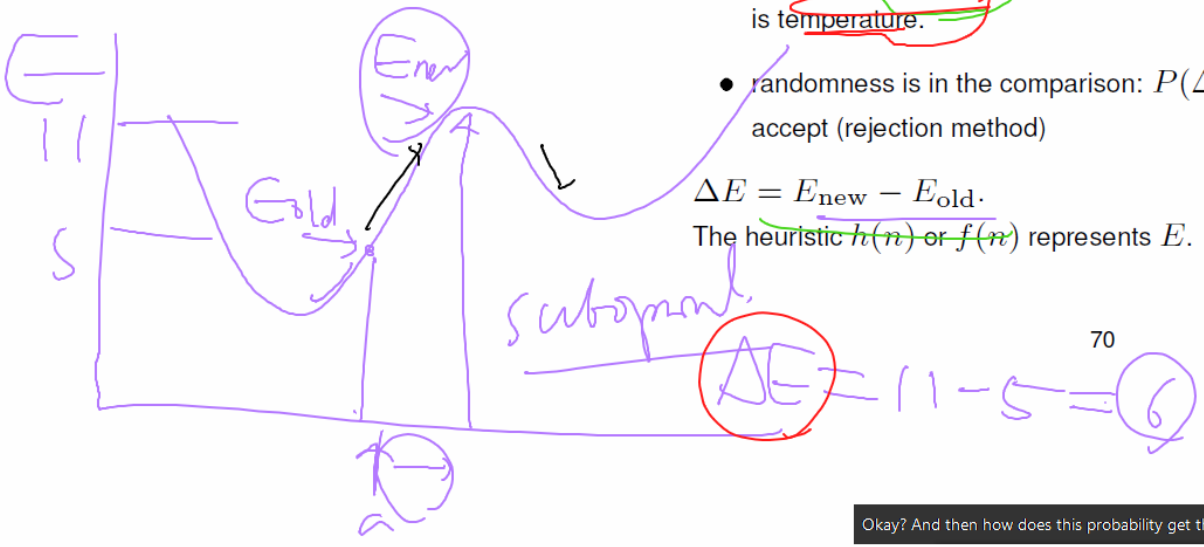





Okay? And then how does this probability get the term

You are screen sharing
Stop Share

$\Delta E > 0$

## Temperature and $P(\Delta E) < \text{rand}(0, 1)$

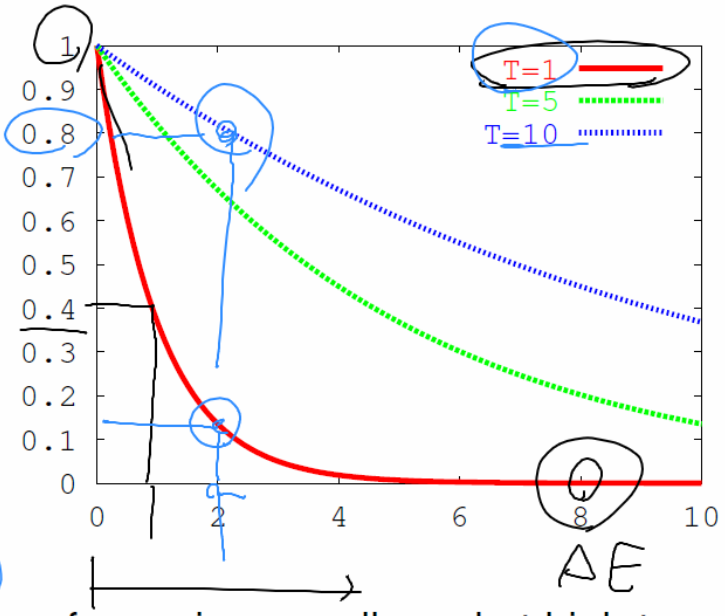
1 a $\Delta E = 8$ ≈ 0.0

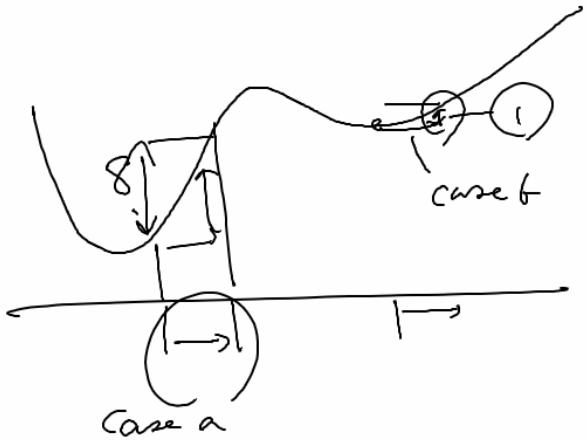
b $\Delta E = 1$ ≈ 0.4

2 $\Delta E = 2$.

a $T = 1$ $p \approx 0.15$

b $T = 10$ $p \approx 0.8$

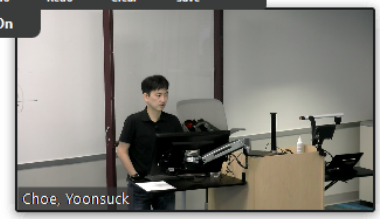


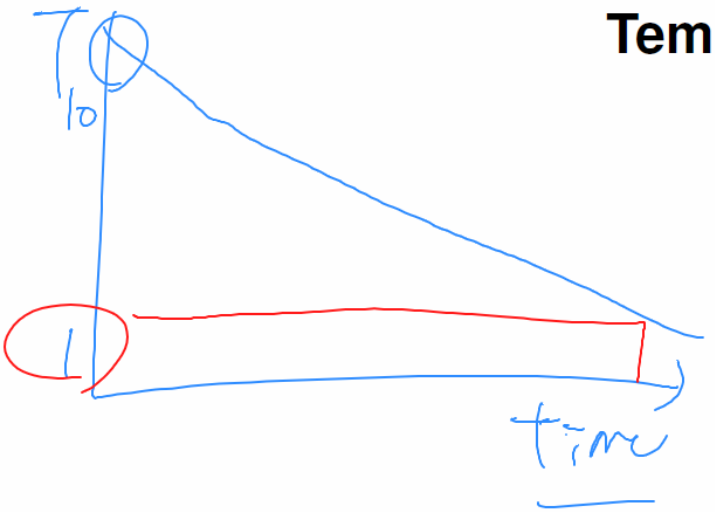

Downward moves of any size are allowed at high temperature, but at low temperature, only small downward moves are allowed.

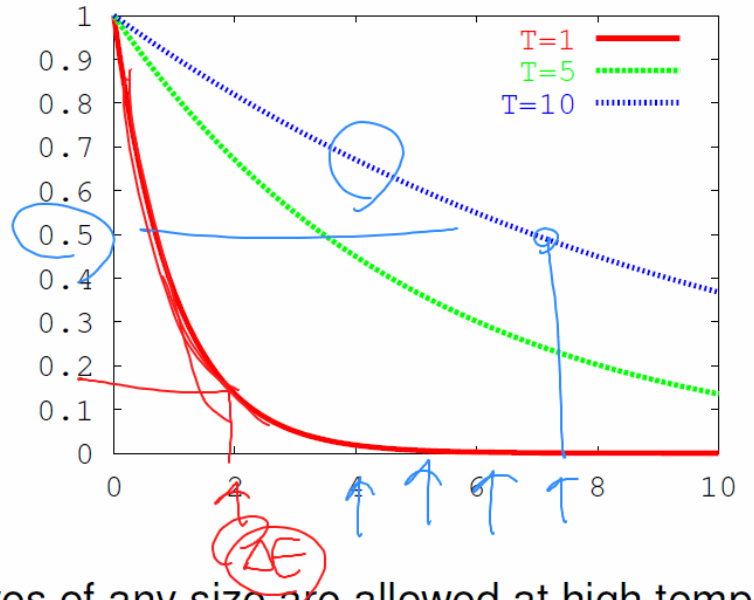
- Higher temperature $T \rightarrow$ higher probability of suboptimal move
- Lower $\Delta E \rightarrow$ higher probability of suboptimal move

chance of accepting that move which is suboptimal with the Delta e is very low, then there's a higher chance of accept accepting the sub optimal move




# Temperature and $P(\Delta E) < \text{rand}(0, 1)$

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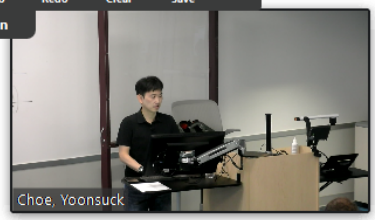
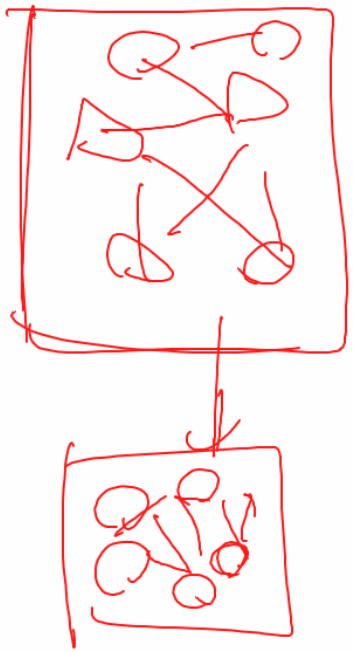



# Simulated Annealing Applications



- VLSI wire routing and placement
- Various scheduling optimization tasks
- Traffic control
- Neural network training
- etc.

And and also this this kind of concept has been used in training neural networks

# $IDA^*$

**function** $IDA^*$(*problem*)

*root* ← Make-Node(Initial-State(*problem*))

*f-limit* ← f-Cost(*root*)

**loop do**

*solution, f-limit* ← DFS-Contour(*root, f-limit*)

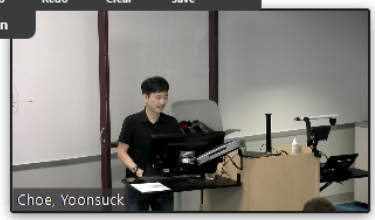
**if** *solution* != NULL **then return** *solution*

**if** *f-limit* == $\infty$ **then return** *failure*

**end loop**

Basically, iterative deepening depth-first-search with depth defined as the $f$-cost ($f = g + n$):

So if you go very, very deep, then basically, this cool spec you to this kind of request to call would be your memory footprint

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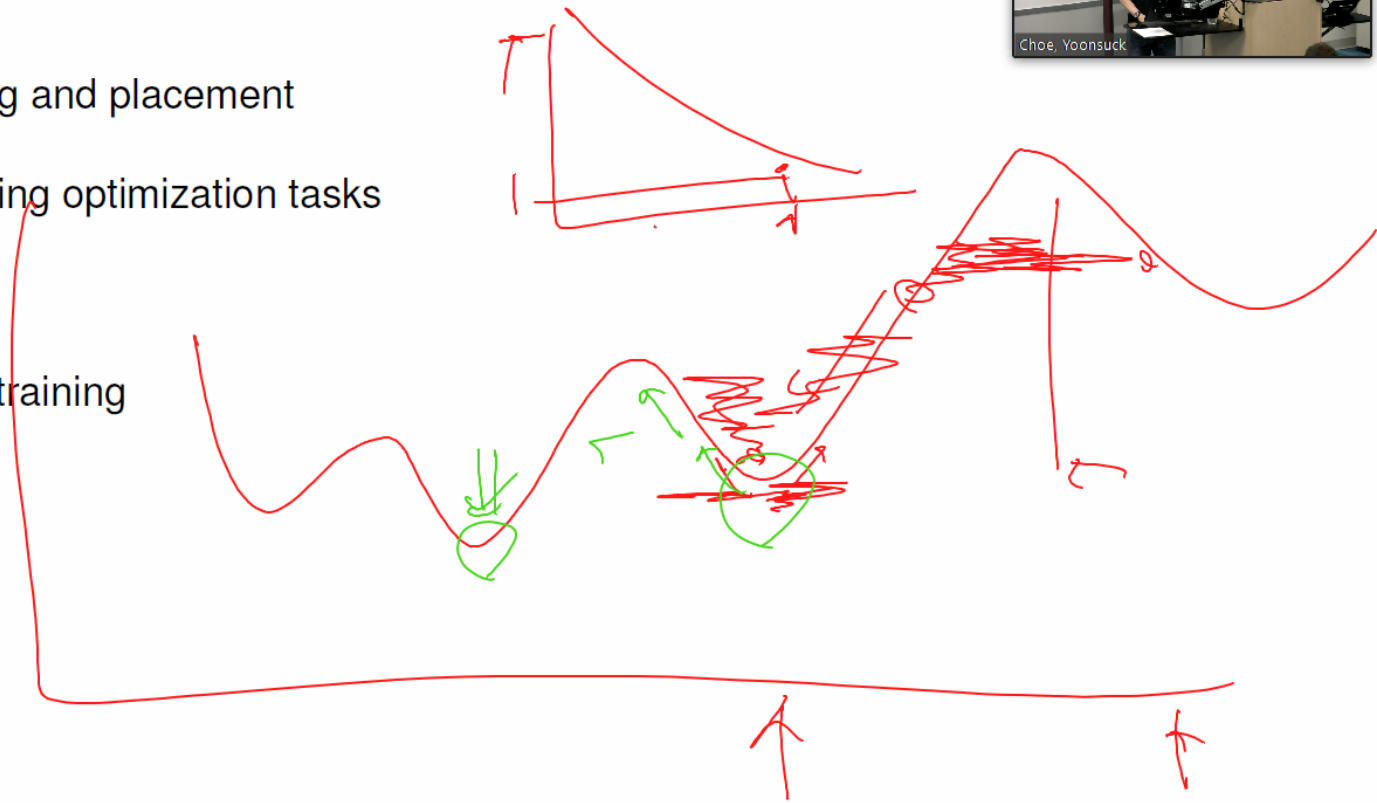
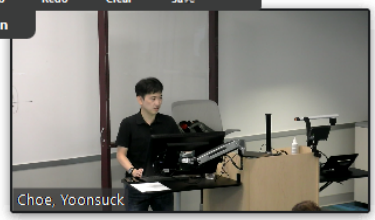


Yeah. Well, I guess it depends depends on manufacturing right

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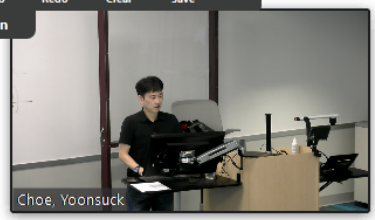


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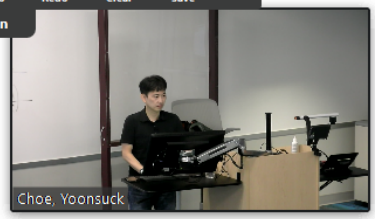
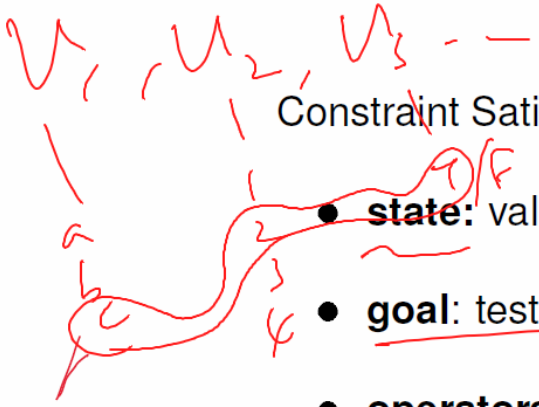


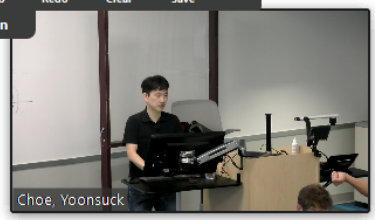

# Constraint Satisfaction Search



Constraint Satisfaction Problem (CSP):

- **state:** values of a set of **variables**
- **goal**: test if a set of constraints are met
- **operators**: set values of variables
- general search can be used, but specialized solvers for CSP work better

So all these constraints are met. The operators are basically the act of setting a particular value to the particular

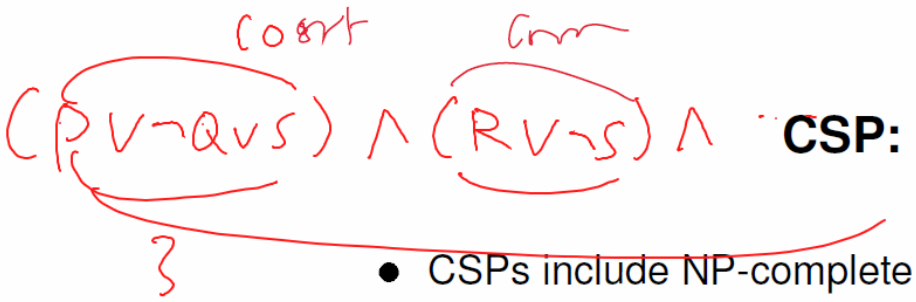


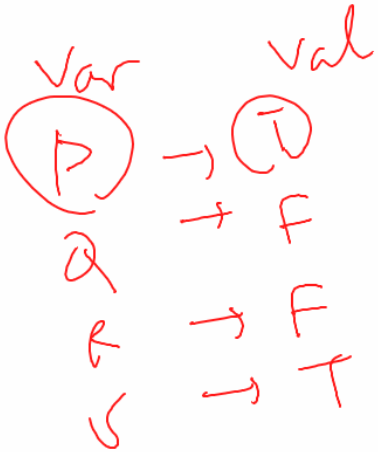

# Constraints

- Unary, binary, and higher order constraints: how many variables should simultaneously meet the constraint
- Absolute constraints vs. preference constraints
- Variables are defined in a certain **domain**, which determines the possible set of values, either discrete or continuous.

This is part of a much more complex problem called **constrained optimization problems** in operations research consisting of cost function (either minimize or maximize) and several constraints. Problems can be linear, nonlinear, convex, nonconvex, etc. Straight-forward solutions exist for a limited subclass of these (for example, for linear programming problems can be solved by the simplex method).

But this is a little bit too detailed



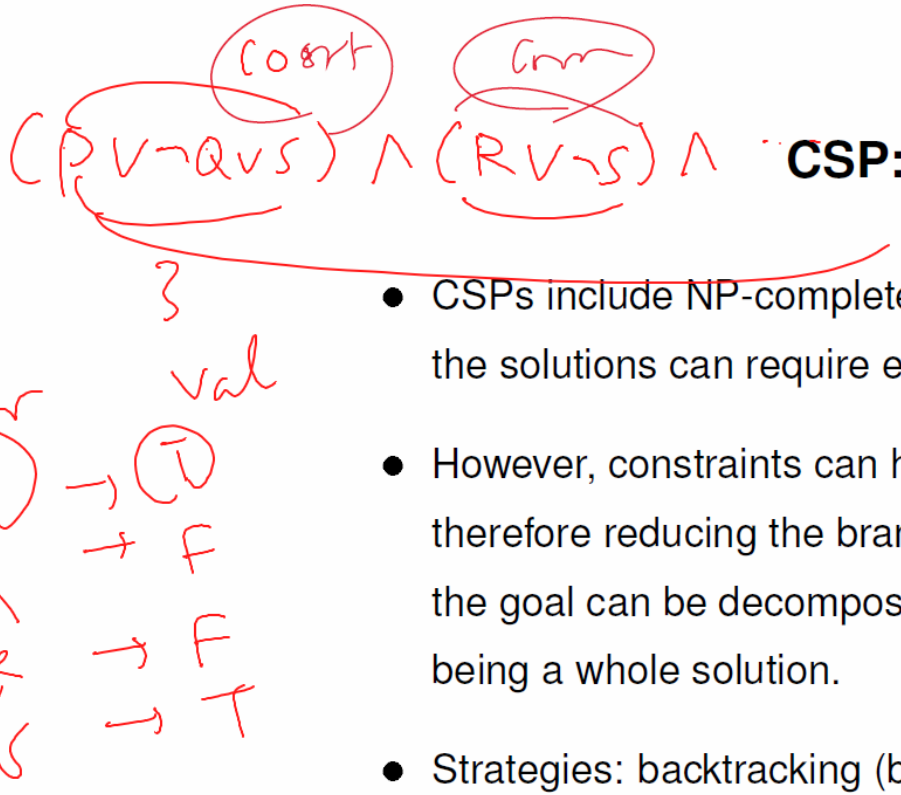




# CSP: continued

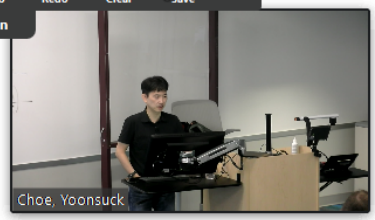
- CSPs include NP-complete problems such as 3-SAT, thus finding the solutions can require exponential time.
- However, constraints can help narrow down the possible options, therefore reducing the branching factor. This is because in CSP, the goal can be decomposed into several constraints, rather than being a whole solution.
- Strategies: backtracking (back up when constraint is violated), forward checking (do not expand further if look-ahead returns a constraint violation). Forward checking is often faster and simple to implement.



So these are the variables. These are the values. And basically these are the constraints



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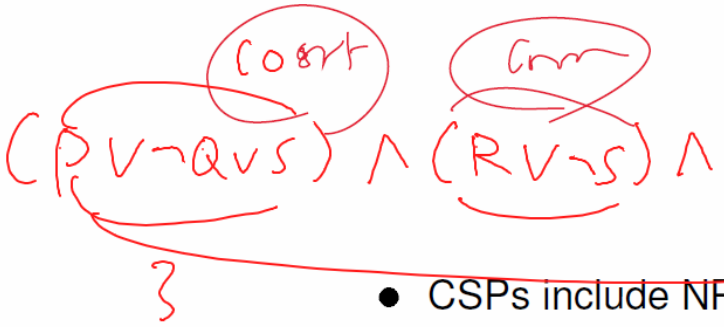
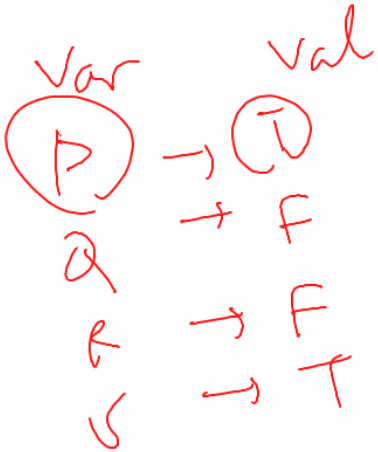
So in practice, it can be done more

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So in practice, it can be done much more efficiently, and there are several strategies like backtracking, or for checking, as you assign these values to the


# Heuristics for Constraint Satisfaction Problems

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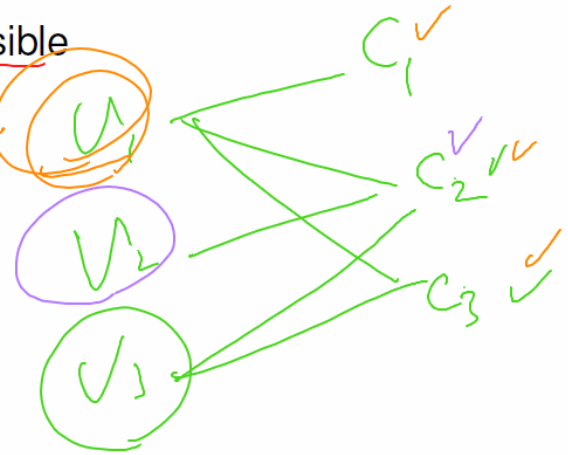

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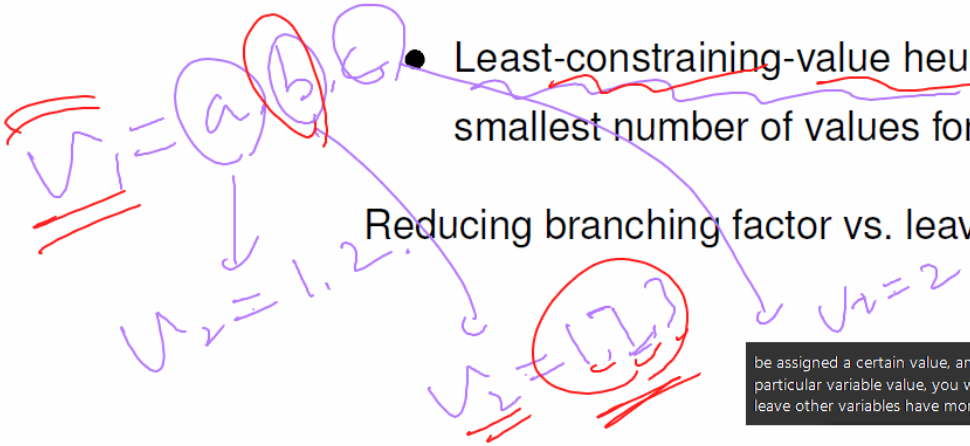
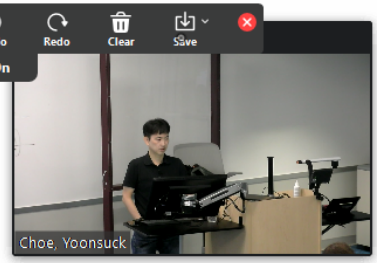
Reducing branching factor vs. leaving freedom for future choices.



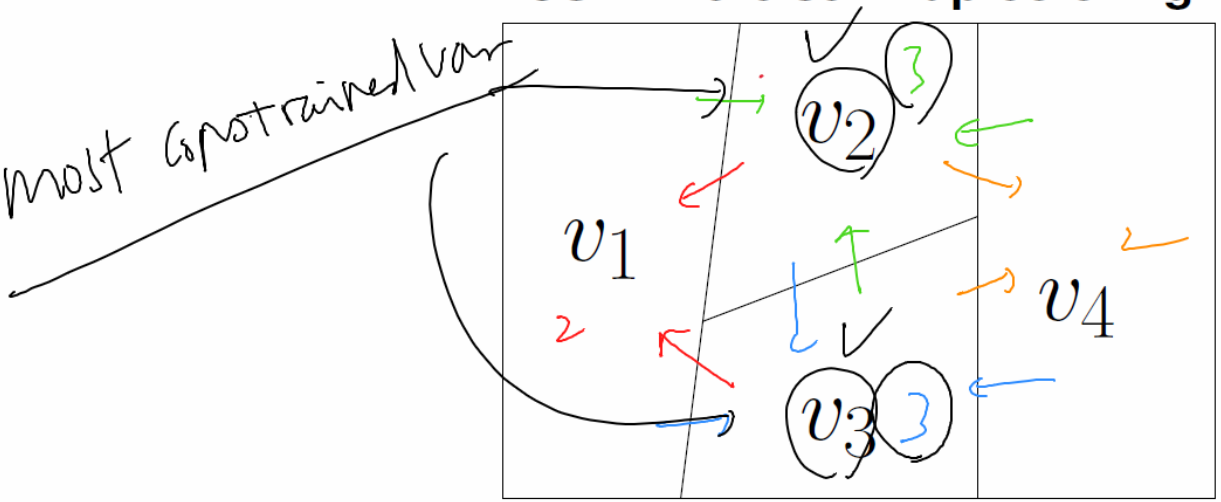
be assigned a certain value, and in trying to pick a particular variable value, you want to pick the one that will leave other variables have more choice

Values = R, G, B






# CSP Exercise: Map coloring

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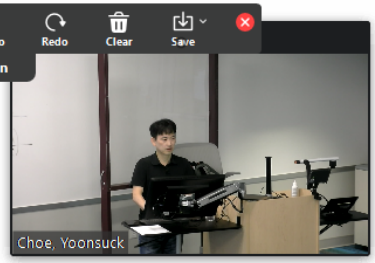



# DFS-Contour(*root, f-limit*)

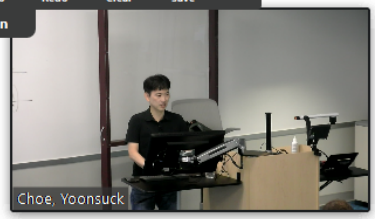
**function** DFS-Contour (**root, f-limit**): returns **solution, f-limit**

Find solution from node **root**, within the $f$-cost limit of **f-limit**. DFS-Contour returns **solution sequence** and **new $f$-cost limit**.

- if $f$-cost(**root**) $>$ **f-limit**, return **null solution** and the $f$-cost(**root**).
- if **root** is a goal node, return solution and its $f$-cost(**root**).
- **recursively call** on all successors, and find successor with minimum $f$-cost. Return its solution and its $f$-cost.

Similar to the recursive implementation of DFS.

That. So that was the Dfs control function which we see that there is this recursive call

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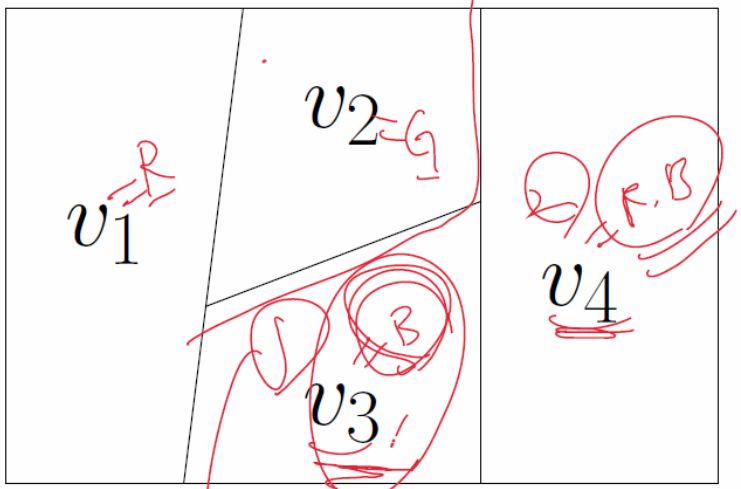


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Most constraining variable

$V_2$ or $V_3$

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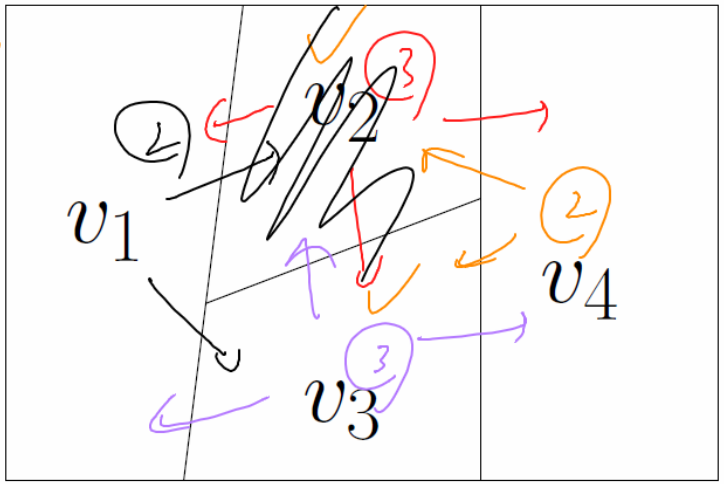


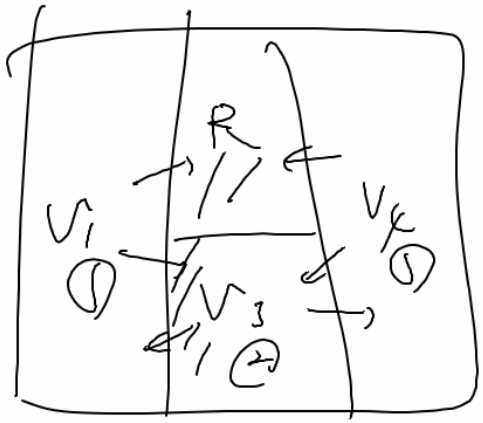


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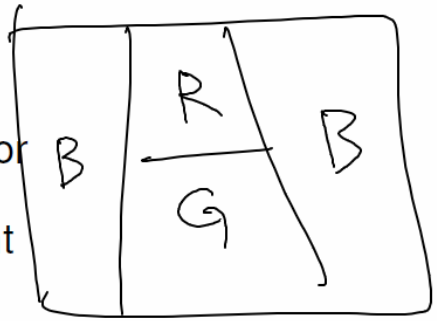


It doesn't matter then. Now we can quickly feel that the rest out blue and blue blue


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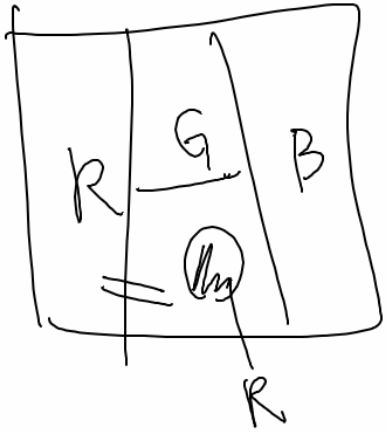


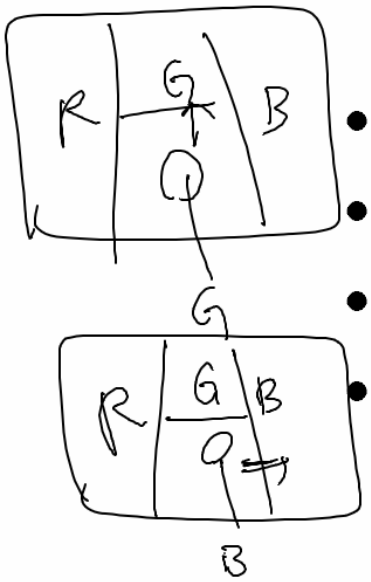


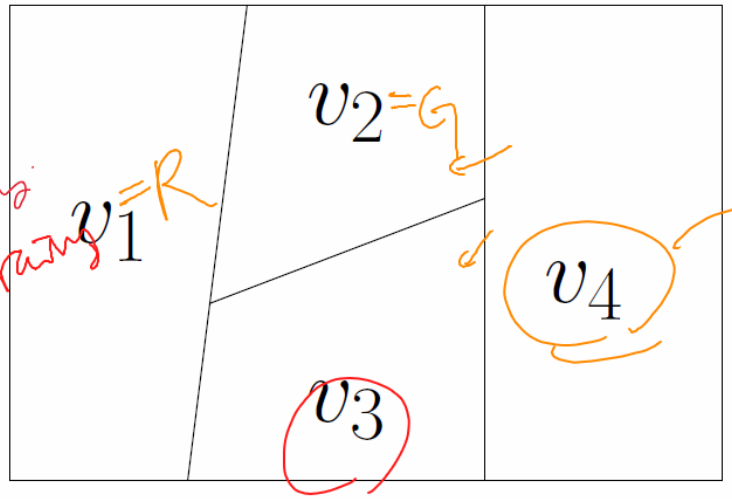


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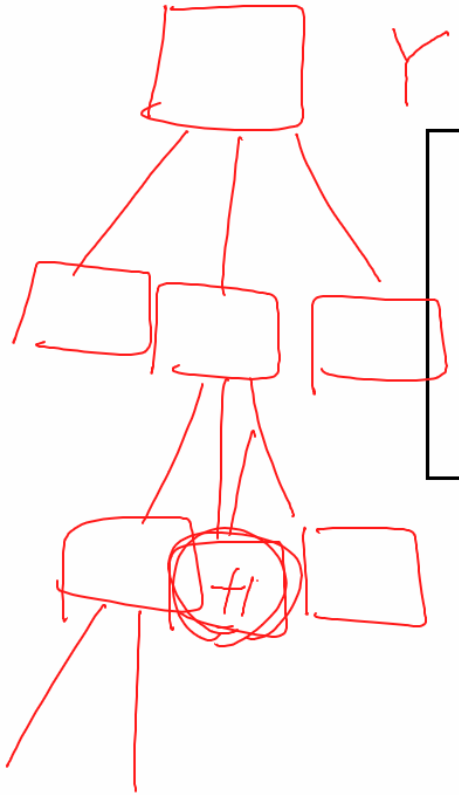
You stick, and the least constrained value heuristic, and these are for again, variable selection and value. assignment

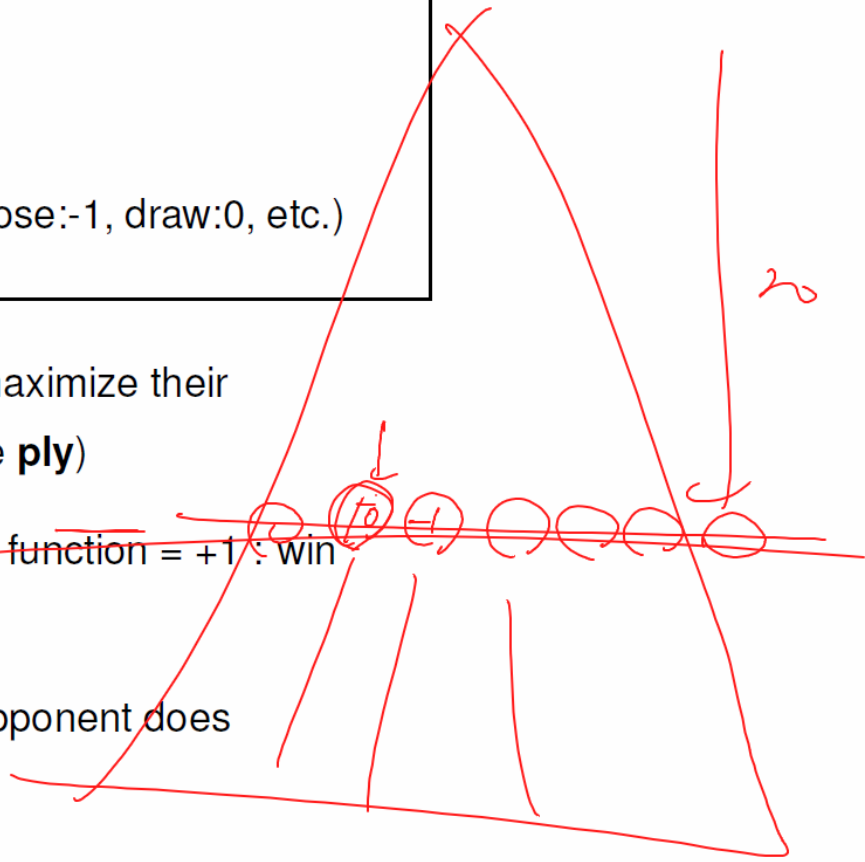
# Two-Person Perfect Information Game

**initial state**: initial position and who goes first

**operators**: legal moves

**terminal test**: game over?

**utility function**: outcome (first player win:+1, lose:-1, draw:0, etc.)



- two players (**MAX** and **MIN**) taking turns to maximize their chances of winning (each turn generates one **ply**)
- one player's victory is another's defeat (utility function = +1 : win for MAX, loss for MIN)
- need a **strategy** to win no matter what the opponent does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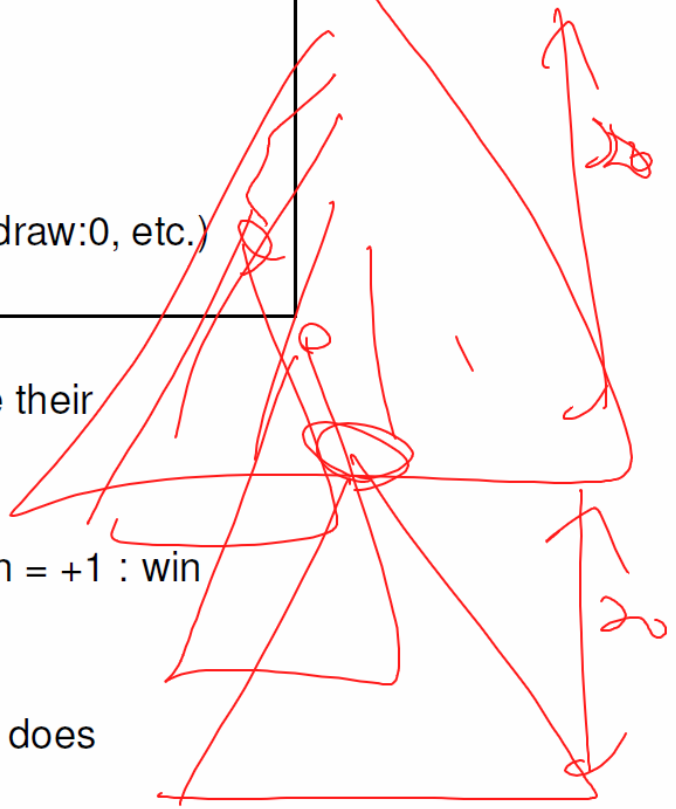
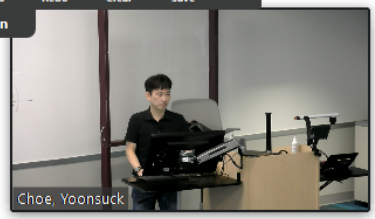


So, By the way, I mean the on the on the past to this you've been you'll be exploring these different alternatives right

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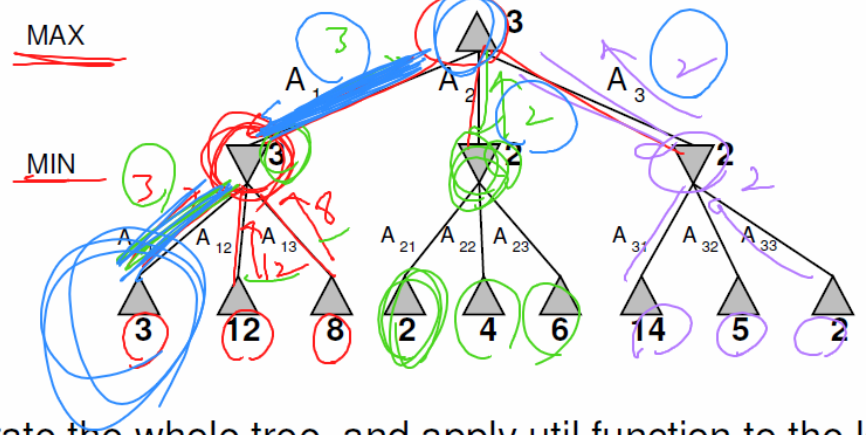
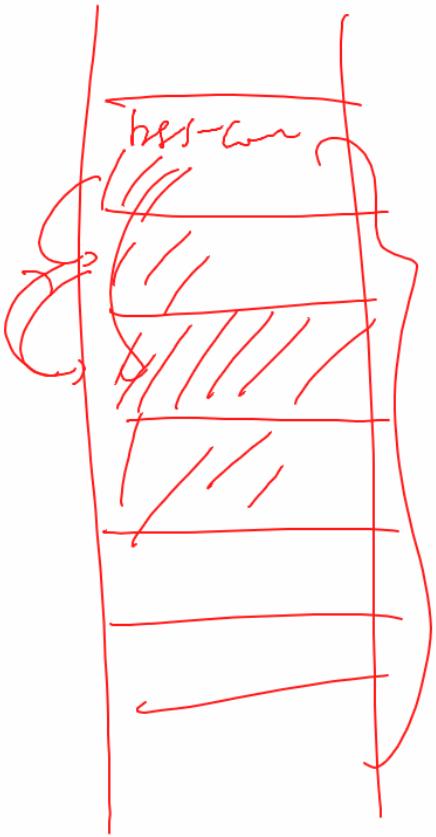
# Minimax: Strategy for Two-Person Perfect Info Games



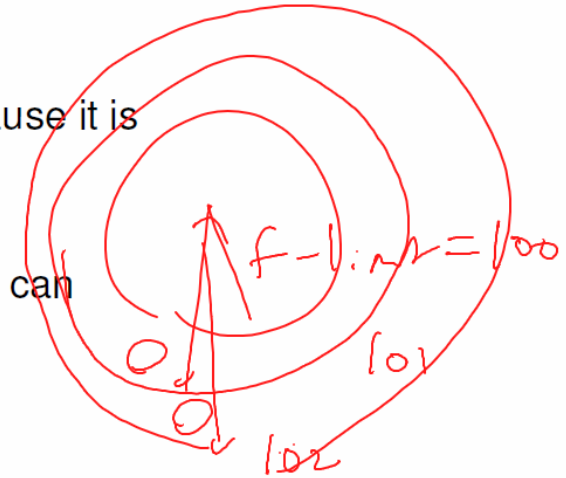

- generate the whole tree, and apply util function to the leaves
- go back upward assigning utility value to each node
- at MIN node, assign **min(successors' utility)**
- at MAX node, assign **max(successors' utility)**
- **assumption**: the opponent acts optimally

Okay, So here, there, the assumption is that you're pulling X. optimally

# $IDA^*$: Evaluation



- complete and optimal (with same restrictions as in $A^*$)
- space: proportional to longest path that it explores (because it is depth first!)
- time: dependent on the number of different values $h(n)$ can assume.



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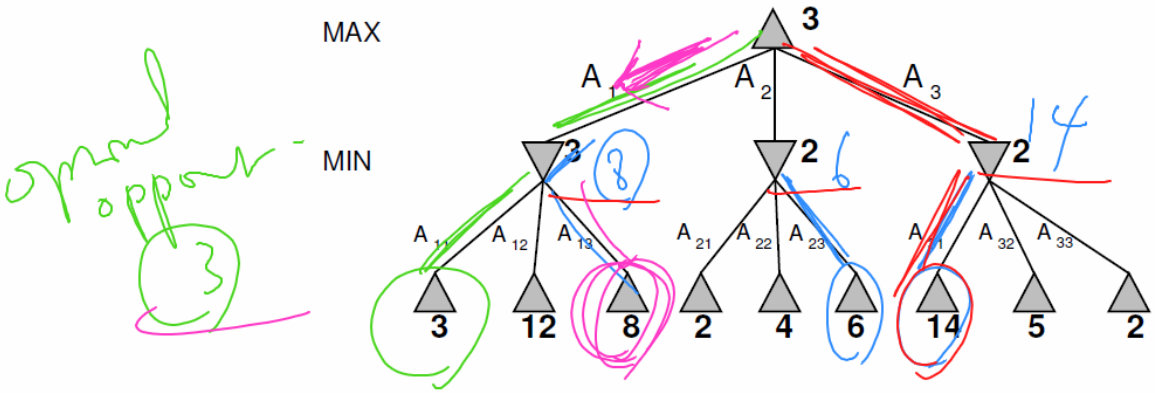


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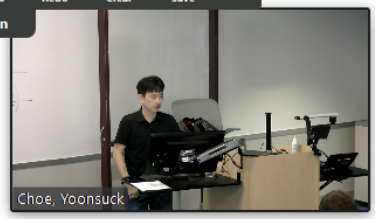


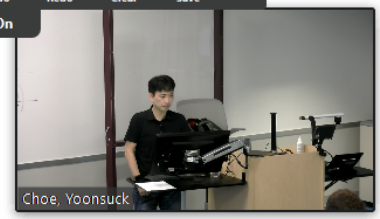

# $IDA^*$: Time Complexity

Depends on the heuristics:

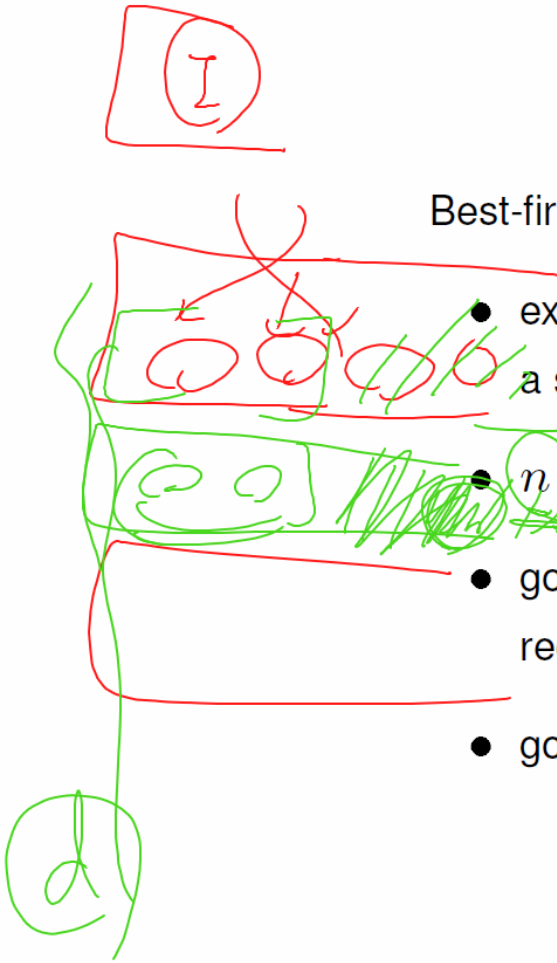
- small number of possible heuristic function values $\rightarrow$ small number of $f$-contours to explore $\rightarrow$ becomes similar to $\mathrm{A}^*$
- complex problems: each $f$-contour only contain one new node

  if $\mathrm{A}^*$ expands $N$ nodes,
  $IDA^*$ expands
  $1 + 2 + .. + N = \frac{N(N+1)}{2} = O(N^2)$
- a possible solution is to have a **fixed** increment $\epsilon$ for the $f$-limit $\rightarrow$ solution will be suboptimal for at most $\epsilon$ ($\epsilon$-admissible)

But the optimality will only suffer by that




# Other Methods: Beam Search



Best-first search with a fixed limited branching factor

- expand the first $n$ nodes with the best Eval-Fn value, where $n$ is a small number.
- $n$ is called the **width of the beam**
- good for domains with continuous time functions (like speech recognition)
- good for domains with huge branching factor (like above)

And the rest you want to discard. The choice of this can be critical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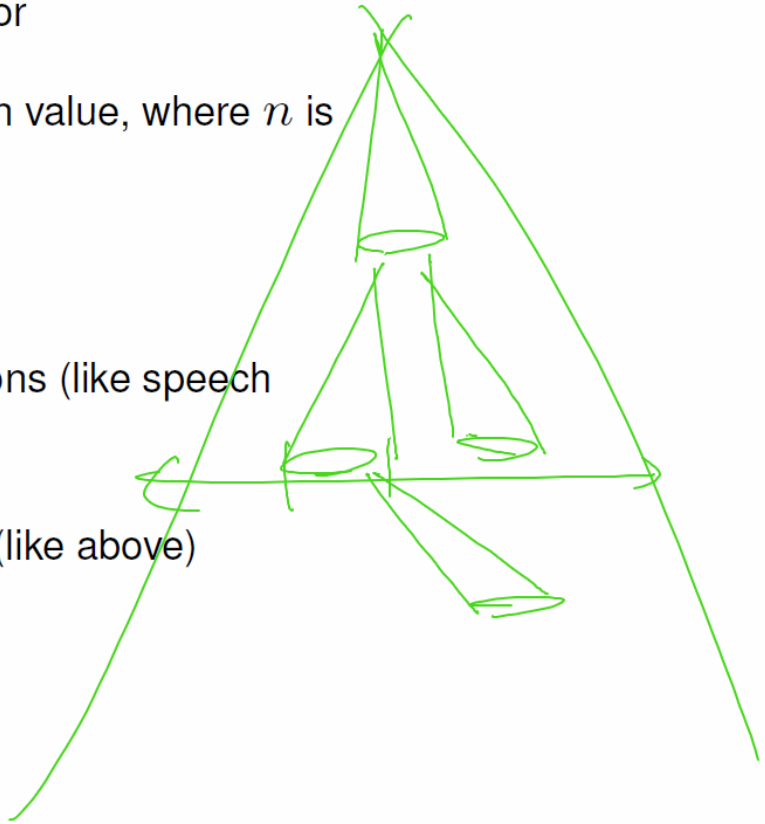
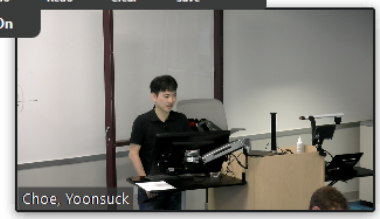
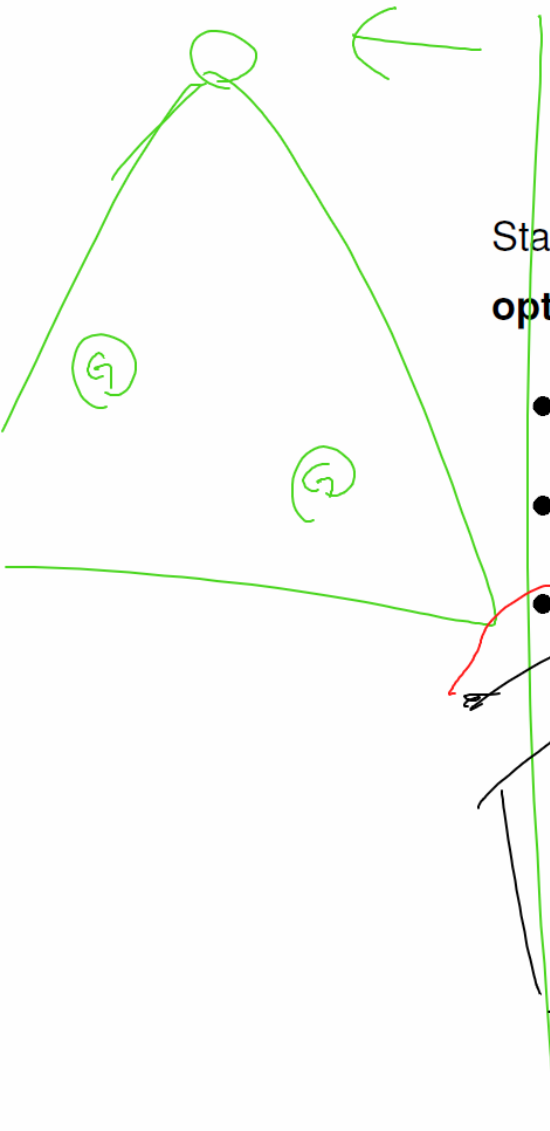


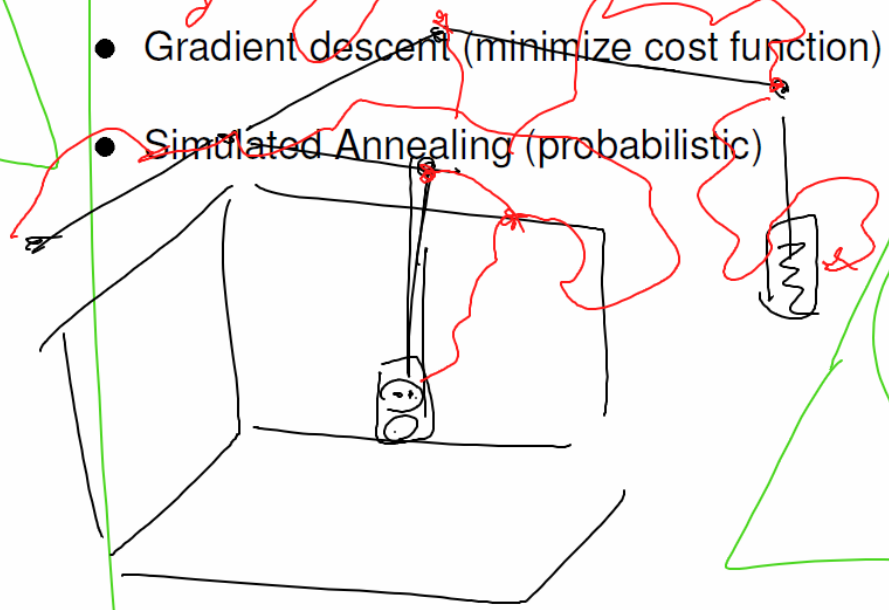


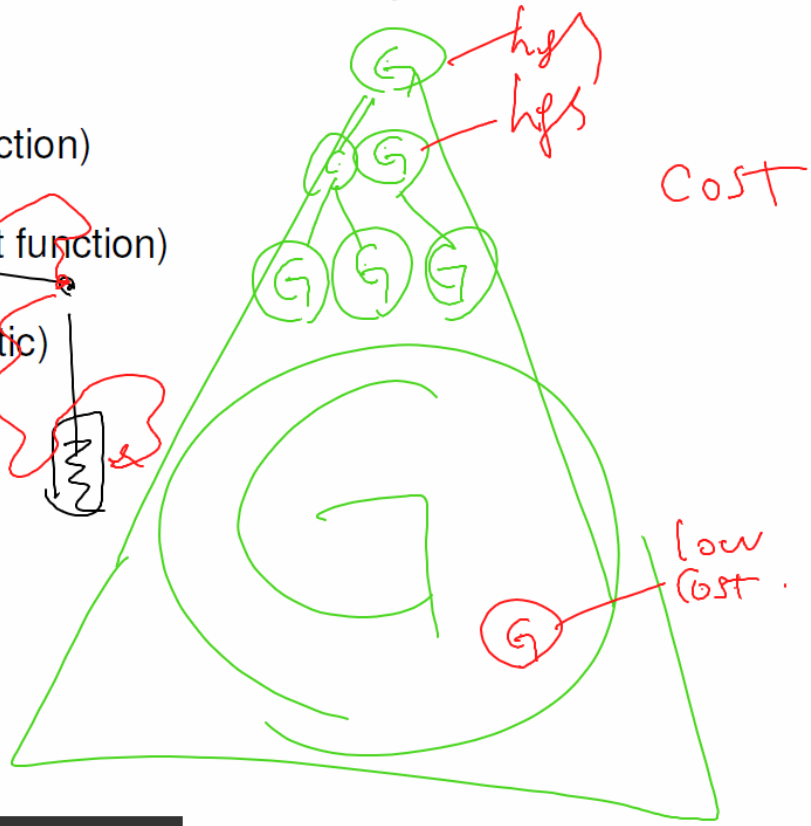

# Iterative Improvement Algorithms

Start with a complete configuration (all variable values assigned, and **optimal**), and **gradually improve** it.

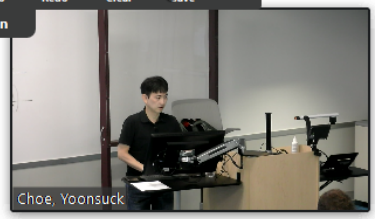
- Hill-climbing (maximize cost function)
- Gradient descent (minimize cost function)
- Simulated Annealing (probabilistic)








Come on right, that's another solution what is it not optimal and probably

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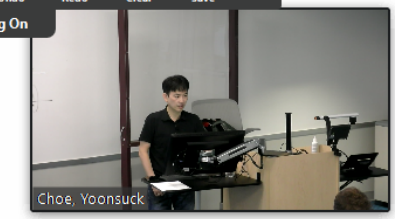
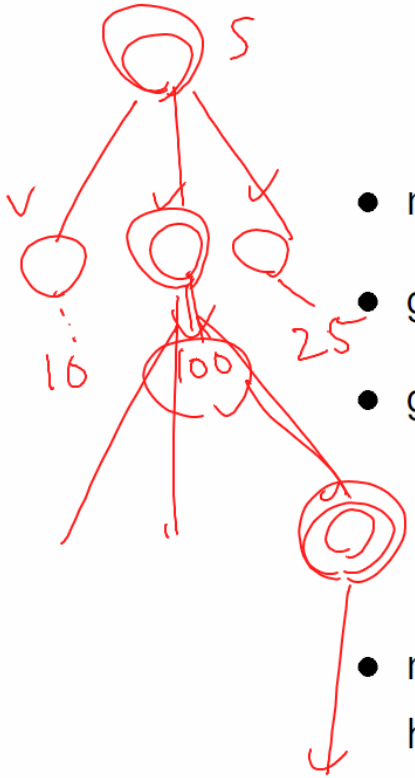
$$ income $$ energy

So maximize and minimize that just the the flip side of the coin




# Hill-Climbing




- no queue, keep only the best node
- greedy, no back-tracking
- good for domains where **all nodes are solutions**:
  - goal is to **improve** quality of the solution
  - optimization problems
- note that it is different from greedy best-first search that uses the heuristic function, which keeps a node list