

# Spec-Driven CTLE Model Synthesis through Reinforcement Learning

Presenter: Daniel Wu, [danielw@xilinx.com](mailto:danielw@xilinx.com)



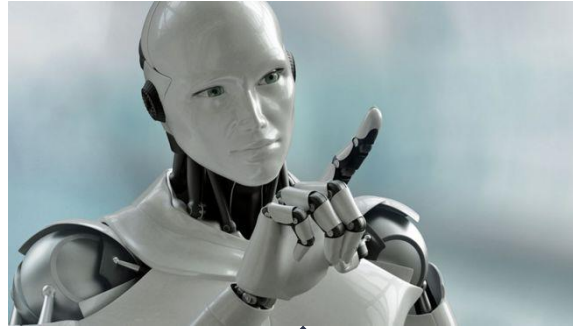
# Agenda

- **Introduction to Reinforcement Learning**
  - Application Examples
- **Synthesis of CTLE Modeling**
- **Spec-Driven w/ Reinforcement Learning**
- **Examples**
- **Summary**



# Introduction of Enforcement Learning

Agent



Observation  
(state:  $s_i$ )

Next state ( $s_{i+1}$ )

Reward ( $r_i$ )

Action ( $a_i$ )

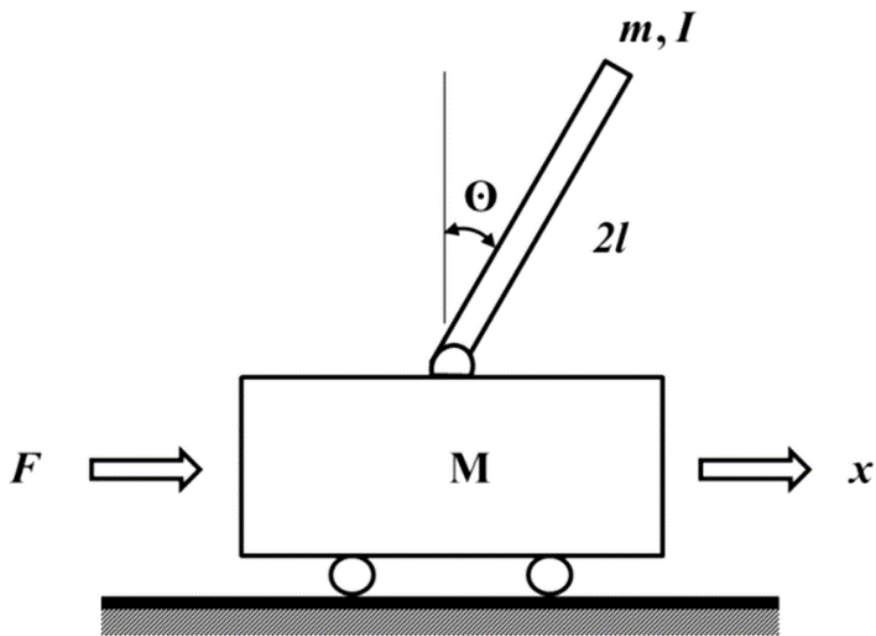


Environment

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# Introduction of Enforcement Learning

## Application Example: Cart-Pole Problem



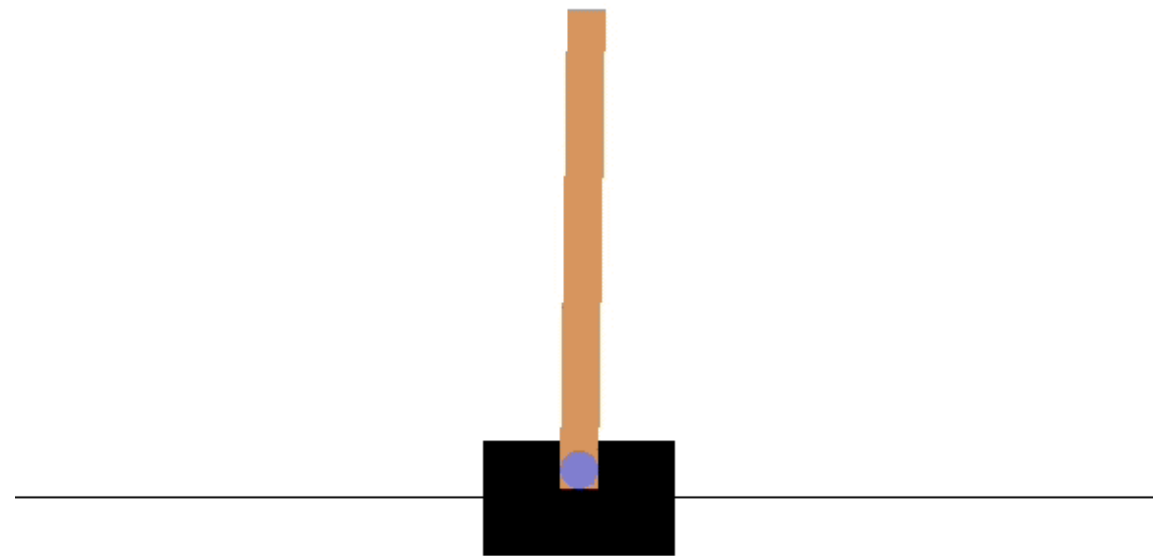
Objective: Balance a pole on top of a movable cart

State (Observation): angle, angular speed, position, horizontal velocity

Action: horizontal force applied on the cart

Reward: +1 at each time step if the pole is upright

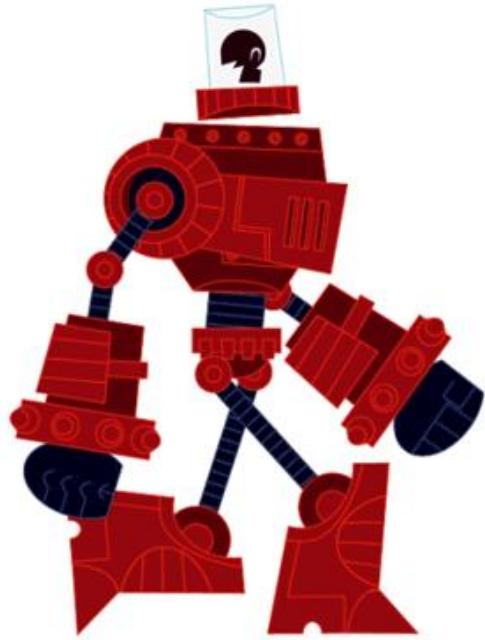
[http://cs231n.stanford.edu/slides/2017/cs231n\\_2017\\_lecture14.pdf](http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture14.pdf)



<https://keon.io/deep-q-learning/>

# Introduction of Enforcement Learning

## Application Example: Robot Locomotion



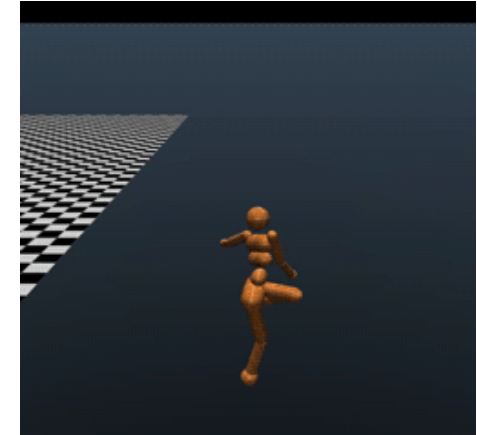
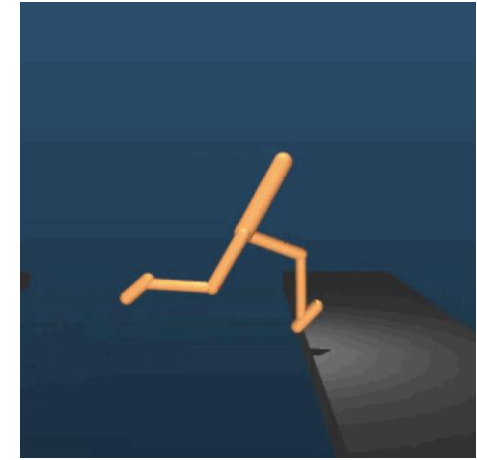
Objective: Make the robot move forward

State (Observation): Angle and position of the joints

Action: Torques applied on joints

Reward: +1 at each time step upright & forward movement

[http://cs231n.stanford.edu/slides/2017/cs231n\\_2017\\_lecture14.pdf](http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture14.pdf)



# Introduction of Enforcement Learning

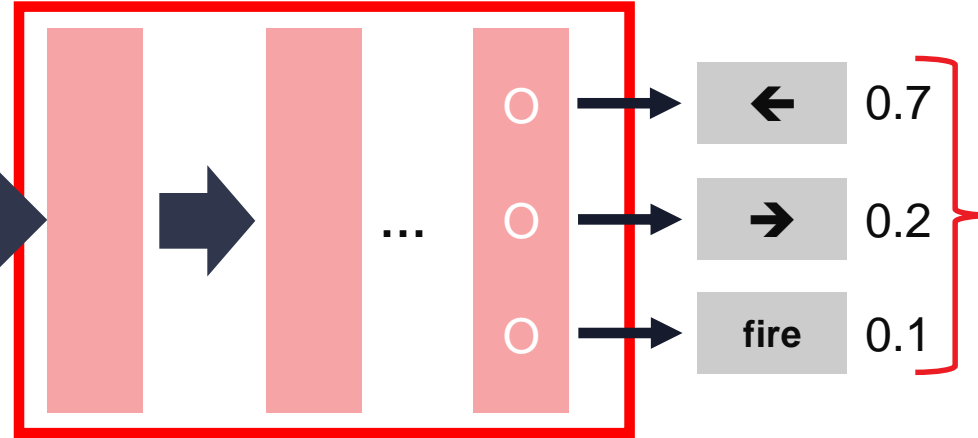
Application Examples: Atari, Space Invader, and etc.

Pixels

NN as actor



or



Probability of taking the action

Objective: Complete the game with highest score

State (Observation): Raw pixel inputs of the game state

Action: Game controls e.g. left, right, and/or fire

Reward: Score increase at each time step

[http://speech.ee.ntu.edu.tw/~tlkagk/courses ML17\\_2.html](http://speech.ee.ntu.edu.tw/~tlkagk/courses ML17_2.html)

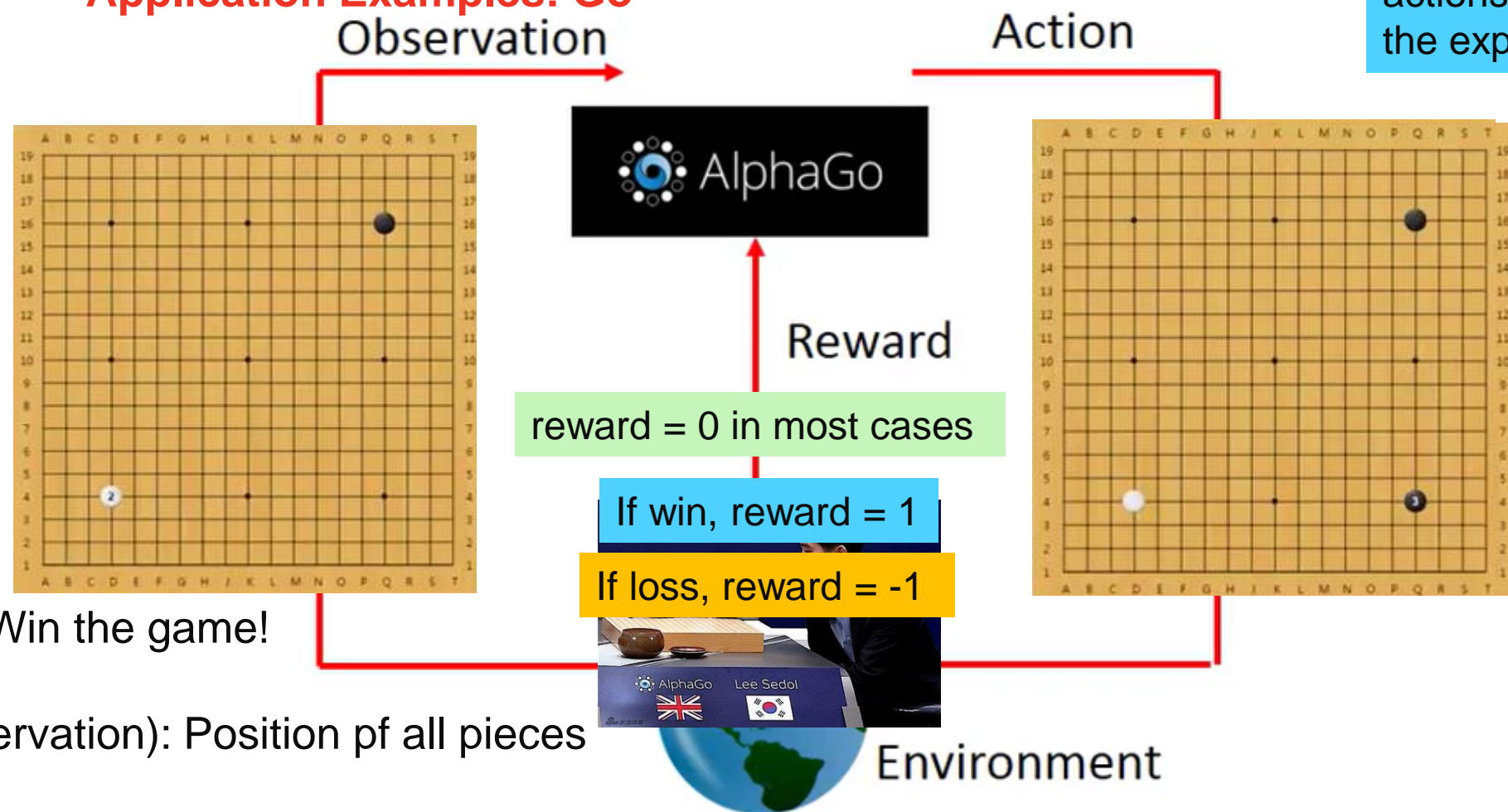
26 Feb 2015, vol 518



# Introduction of Enforcement Learning

## Application Examples: Go

Agent learn to take actions to maximize the expected reward.



Objective: Win the game!

State (Observation): Position of all pieces

Action: Where to put the next piece down

Reward: 1 if win at the end of the game, 0 otherwise

28 Jan 2016, vol 529



# Agenda

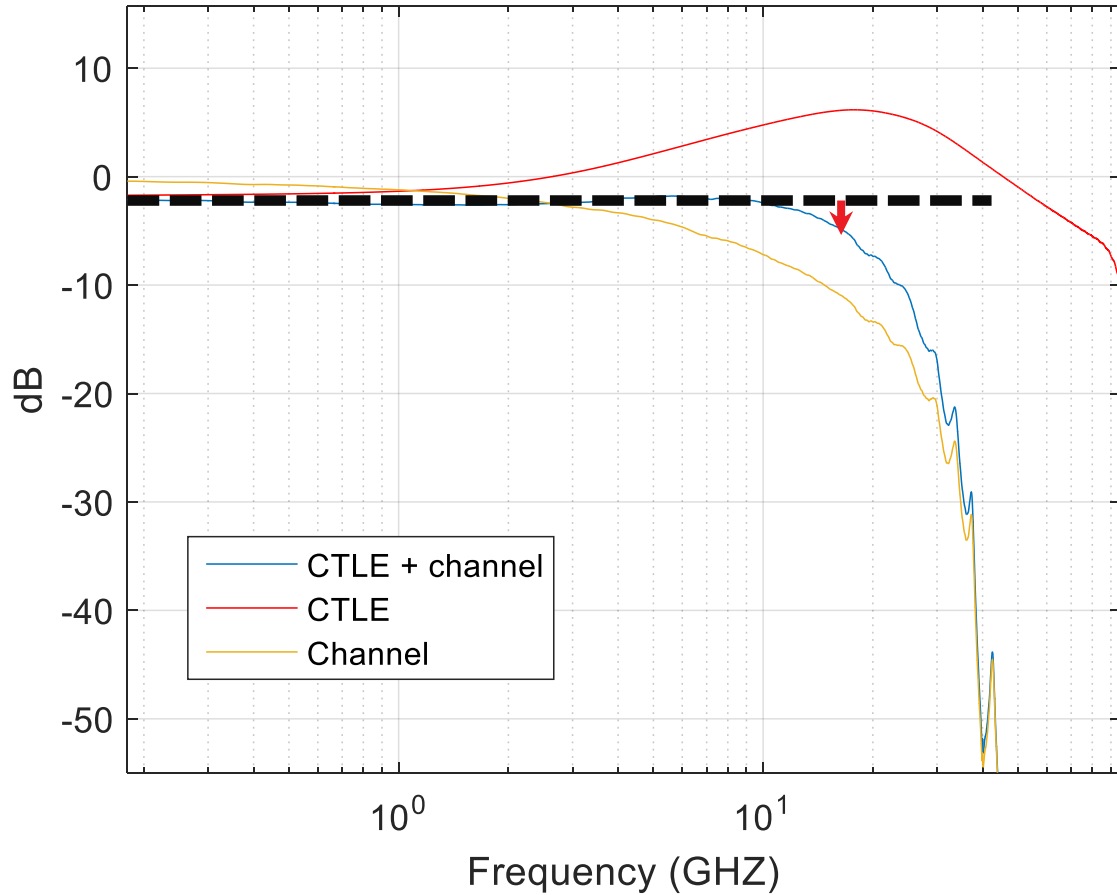
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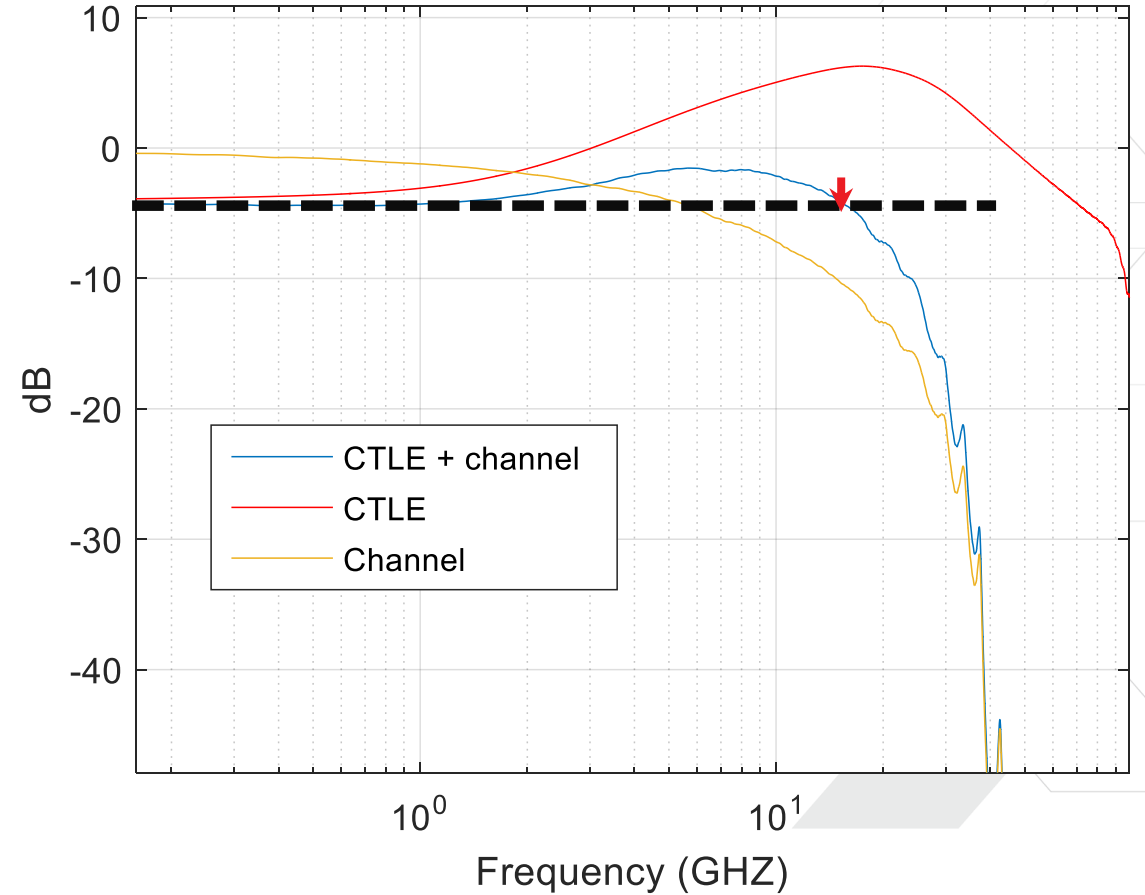


# Synthesis of CTLE Model

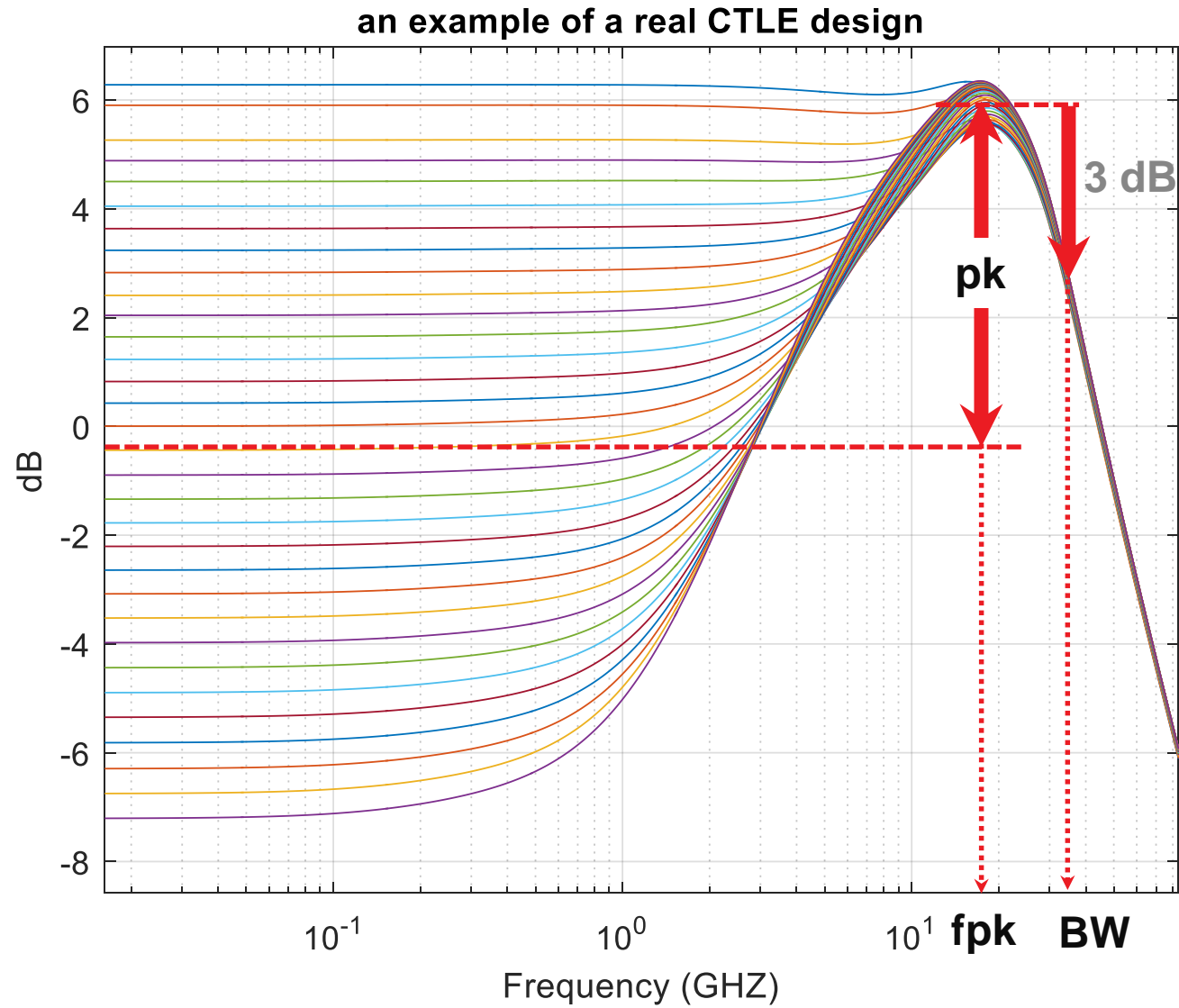
(a) optimally equalized system



(b) over equalized system



# CTLE Spec



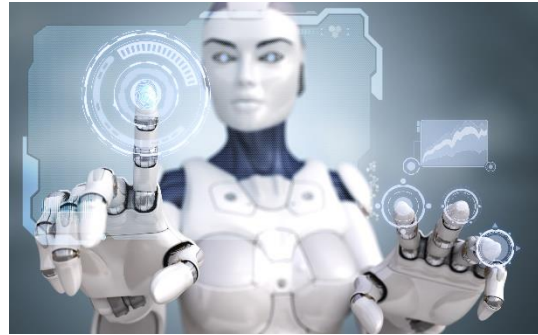
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# Spec-driven Modeling w/ Reinforcement Learning

Agent



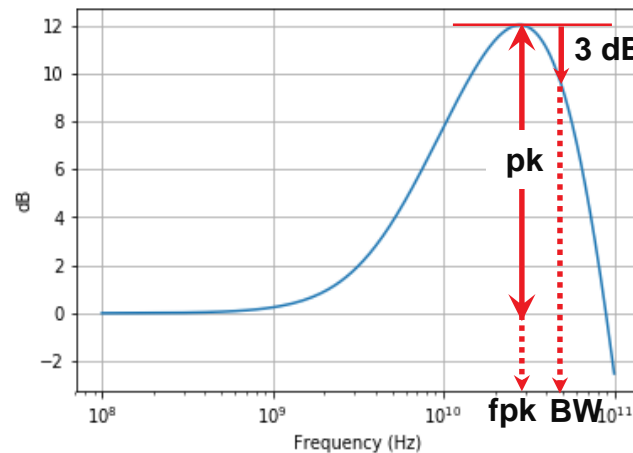
Reward ( $r_i$ )

$$Dist_i = (f\_pk_i - f\_pk_{spec})^2 + \beta_i(pk_i - pk_{spec})^2$$

$$\begin{cases} Dist_i < Dist_{i-1} : \mathbf{reward} = +2 \\ \text{else} & : \mathbf{reward} = -2 \end{cases}$$

$$\begin{cases} |f\_pk_i - f\_pk_{spec}| < tol : \beta_i = \beta_{i-1}/2 \\ \text{else} & : \beta_i = 2\beta_i \end{cases}$$

$$\begin{cases} BW_i < BW_{spec} : \mathbf{reward} = +1 \\ \text{else} & : \mathbf{reward} = -1 \end{cases}$$



Environment

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Action:  $a_i$

```
[incZ1,      decZ1,      incP1,      incP1,      incP1, incP2,
 incZ1P1,    decZ1P1,    incZ2P1, decZ2P2, incP1P2, decP1P2,
 incZ1P1P2, decZ1P1P2,
 mvUP,      mvDN,      mvPUP,   mvPDN,
 incZ1decP2, incP1decZ1]
```

state:  $s_i$   
 $[(s\_fpk_i, s\_pk_i), s\_bw_i]$

Next state:  $s_{i+1}$   
 $[(s\_fpk_{i+1}, s\_pk_{i+1}), s\_bw_{i+1}]$

# Bellman Equation

$$Q(s_t, a_t) = r(s_t) + \gamma \max(Q(s_{t+1}, a_{t+1}))$$

r: reward of each action

Q: Total reward of full course

a: Action

s: State

$\gamma$ : Decay factor

Objective: Tune the CTLE performance into user-defined specs

State (Observation): CTLE's  $[(f_{pk}, pk), BW]$

Action: Maximized the total reward (Q) from the action table of each iteration

Reward: +3 or +1 if the distance to specs are shorter, vice versa.



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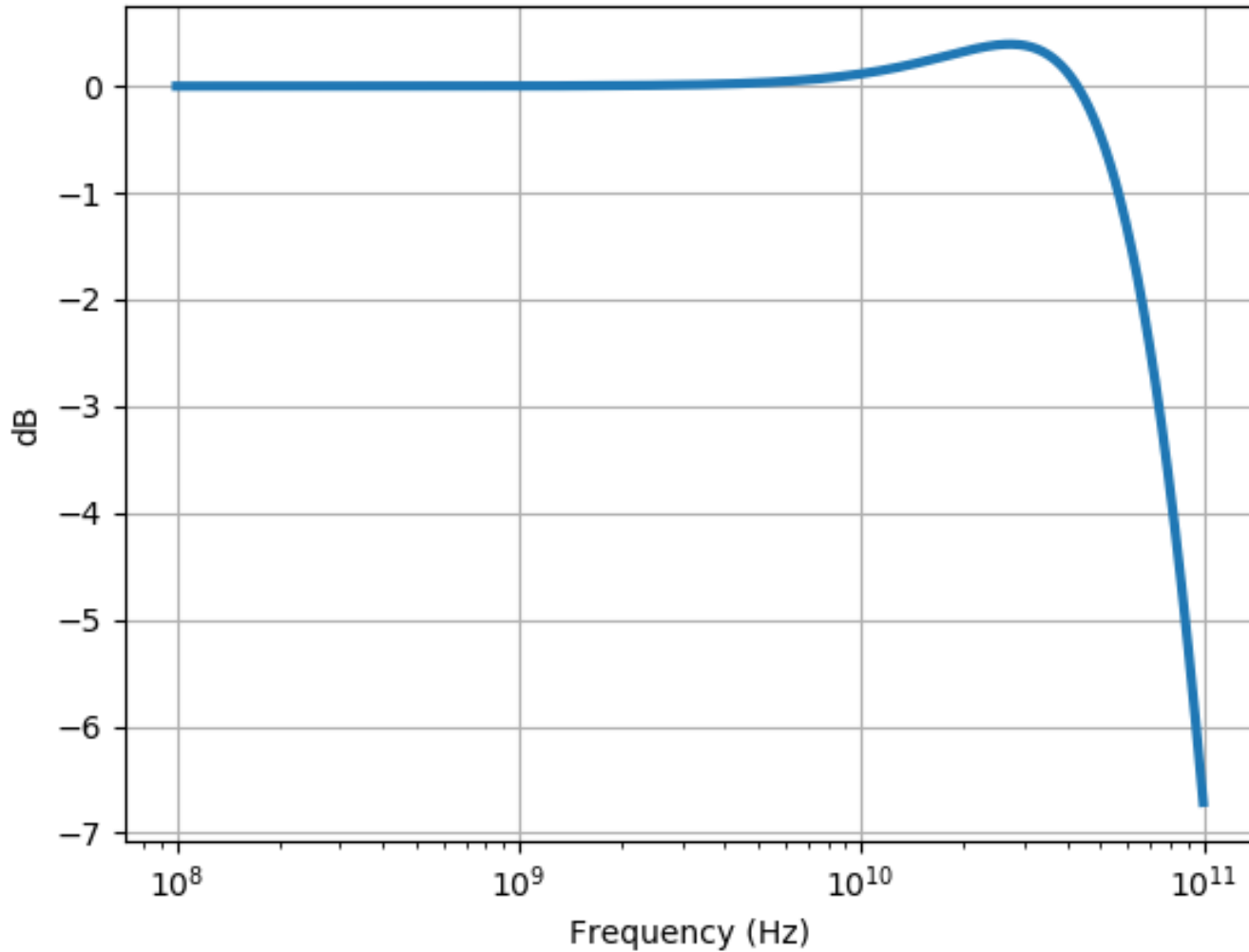


# Examples: what if brute force?

```
for p1 in np.arange(1e9, 50e9, 3e8): # 164
    for p2 in np.arange(10e9, 100e9, 3e8): # 300
        for p3 in np.arange(10e9, 100e9, 3e8): # 300
            for p4 in np.arange(10e9, 100e9, 3e8): # 300
                for p5 in np.arange(10e9, 100e9, 3e8): # 300
                    for z in np.arange(1e9, 10e9, 3e8): # 30
                        freq, Hs = evalH([z], [2*np.pi*p1, 2*np.pi*p2, 2*np.pi*p3, 2*np.pi*p4, 2*np.pi*p5], 1)
                        (fpk, pk), bw = findpeak_bw(freq, Hs)
                        Xc = np.abs(fpk - peak_freq)/1e9
                        Yc = np.abs(pk - peak)
                        current_dist = Xc*Xc + Yc*Yc
                        if current_dist < dist:
                            dist = current_dist
                            opt_pz = [z, [p1, p2, p3, p4, p5]]
```

$164 * 300 * 300 * 300 * 300 * 30 \sim 40$  Tera cases!

# Examples: EL with a small $pk_{spec} = 0.1 \text{ dB}$



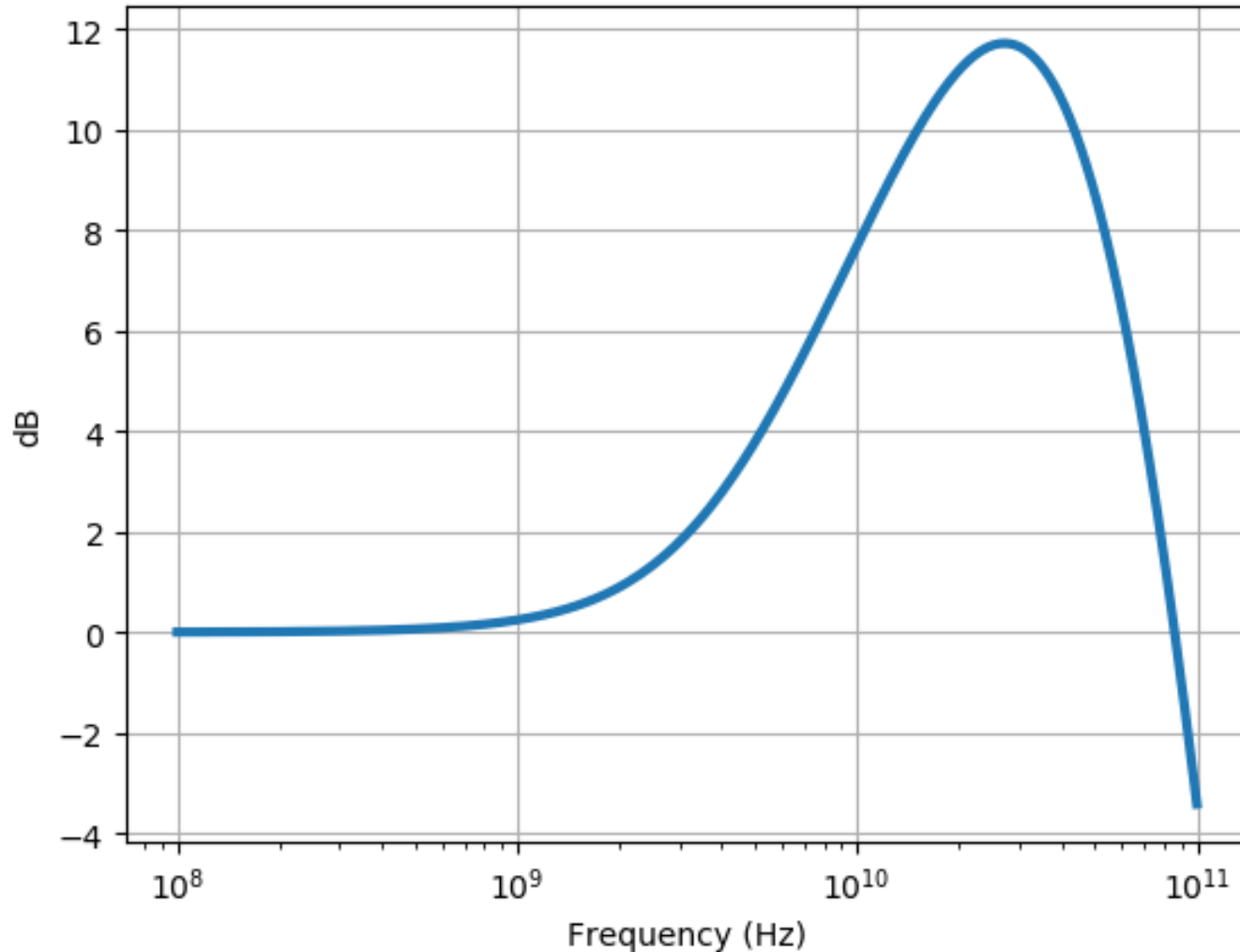
Number of Iteration = 1567

$[(f_{pk}, pk), BW] = [(27.3e9, 0.39), 71.1e9]$

Elapsed time is 73 sec



# Examples: EL with large $pk_{spec} = 12 \text{ dB}$

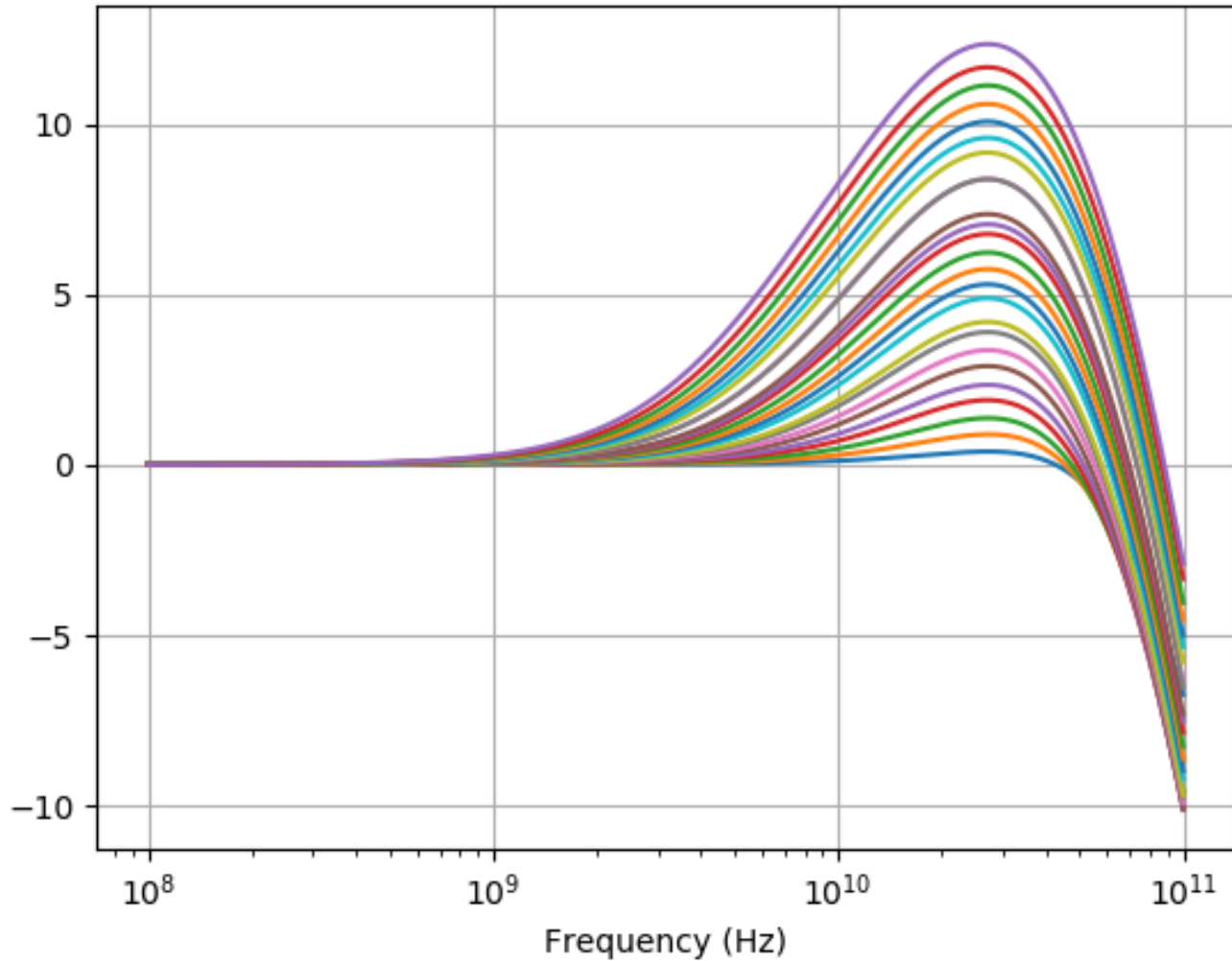


Number of Iteration = 258

$[(f_{pk}, pk), BW] = [(27.1e9, 11.7), 50.1e9]$

Elapsed time is 13 sec

# Examples: EL with 24 $pk_{spec}$ swept



Elapsed time is 493.6 sec

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# Summary

- **Reinforcement Learning had been used in many areas and showing its capabilities outperforming human being such as “video games” and “go”.**
- **Spec-driven reinforcement learning provide a solution to design the architecture spec of CTLE.**
  - **It is not abnormal to model CTLE with one zero and five poles.**
  - **It is impractical to do the exhaustive search for the locations of zero and poles to fit the CTLE into specs.**
- **A few examples have been demonstrated here in this paper to show the efficiency of find the design parameters of CTLE.**