# Reinforcement Learning

## Building a Complete RL System

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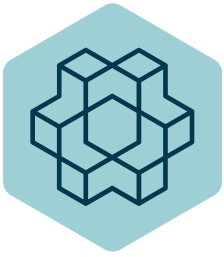
THE UNIVERSITY of EDINBURGH
informatics

# Lecture Outline

- What is Gym?
- How to implement your own environment?
- How to implement a RL algorithm?
- How to evaluate your results?
- Demonstration

# OpenAI Gym

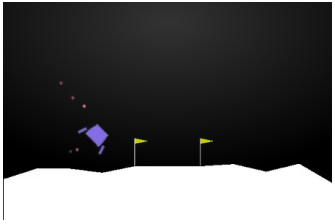
# What is Gym? (Brockman et al., 2016)

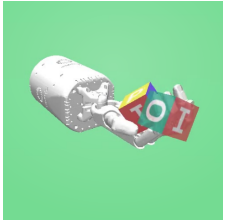


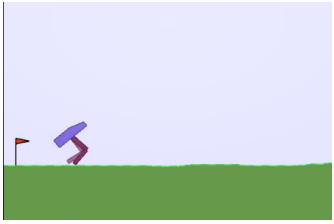
- Open source interface for sequential decision processes
- Developed and maintained by OpenAI Research Lab
- Collection of RL environments
- Standardised interface for RL environments

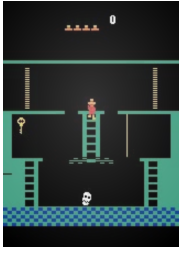
```
pip install gym
```

# Lots of Interesting Environments! (Brockman et al., 2016)

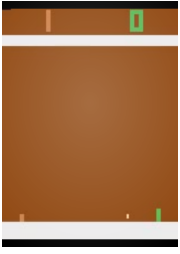




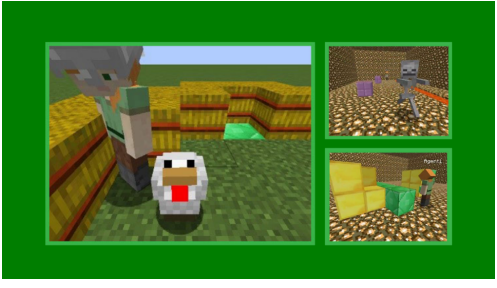






# And many more... (Vinyals et al., 2017; Johnson et al., 2016; Kauten, 2018)

# Gym Interface

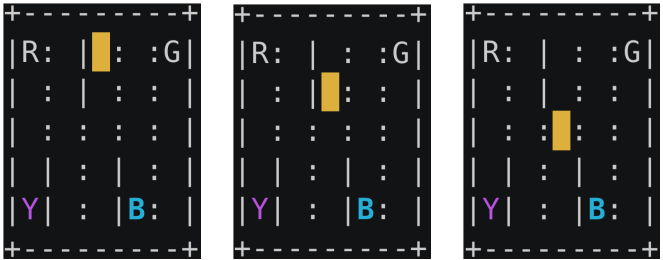
- `gym.make(<environment_name>)` $\longrightarrow$ gym environment
  Create a gym environment
- `env.reset()` $\longrightarrow$ observation
  Resets environment for a new episode
- `env.step(action)` $\longrightarrow$ observation, reward, done, info
  Take an action and observe new information
- `env.render()`
  Render a visualisation of the current environmental state
- `env.close()`
  Close created environment

# Gym Example Snippet

## Gym control flow

```
env = gym.make('CartPole-v0')
obs = env.reset()
done = False
while not done:
    env.render()
    action = agent.choose_action(obs)
    next_obs, reward, done, info = env.step(action)
    obs = next_obs
env.close()
```

# Example: Taxi-v3 Environment




- Gridworld with $5 \times 5$ map
- `R, G, Y, B` - locations
  B - passenger
  Y - destination
  - taxi

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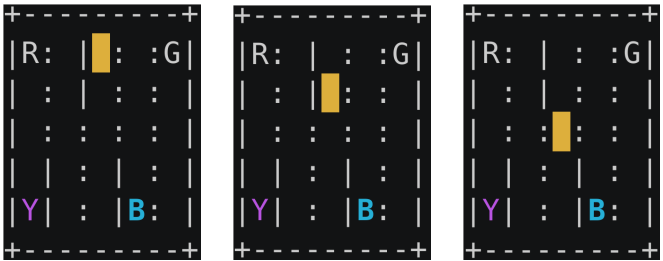


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- Observations $\in [0, 499]$ including taxi row and col, pass. and dest. index

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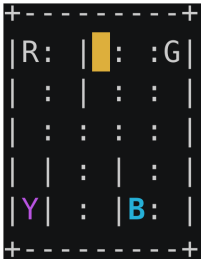


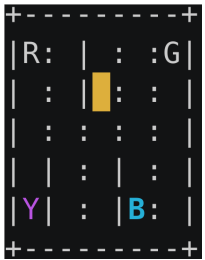


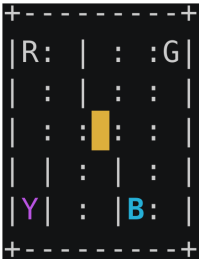


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- Actions:
  `South`, `North`, `East`, `West`, `Pick`, `Drop`

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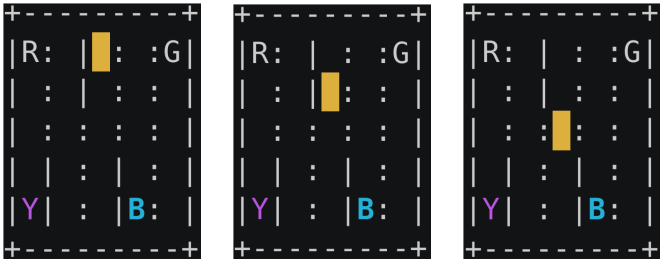


- Goal: Pickup passenger and drop it off at destination
- Reward: $+20$ for successful delivery, $-1$ at each timestep, $-10$ for illegal move
- Challenge: navigate gridworld

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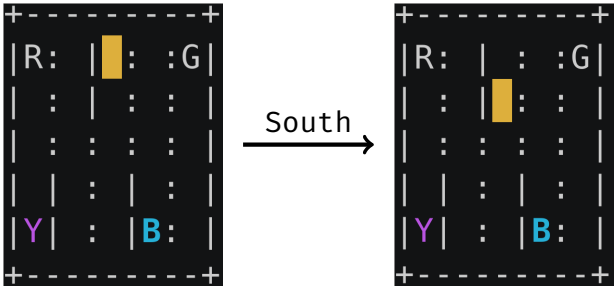
# Taxi Environment Step I



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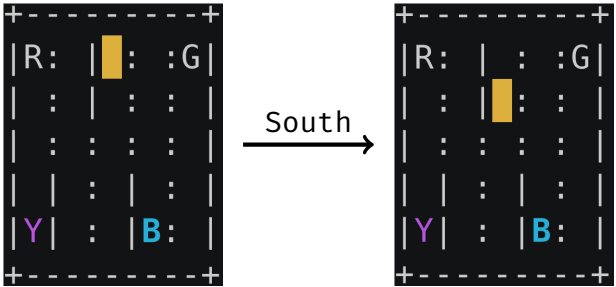
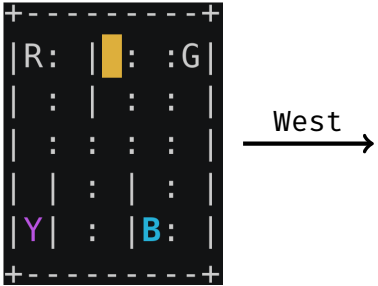



`nobs, r, done, _ = env.step(a)`:

$\texttt{o} = 45 \xrightarrow{\texttt{a=0 (South)}} \langle \texttt{nobs} = 154,\ \texttt{r} = -1,\ \texttt{done} = \texttt{False} \rangle$

# Taxi Environment Step II



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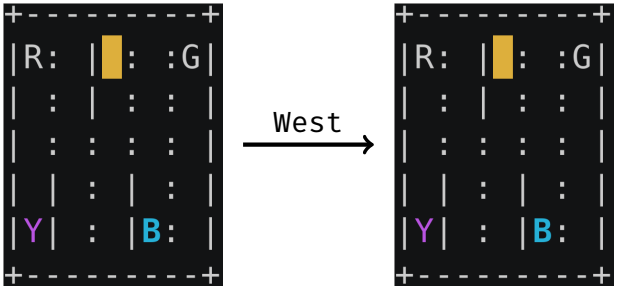
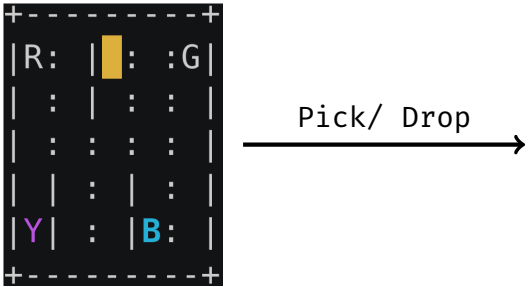



`nobs, r, done, _ = env.step(a)`:

$\texttt{o} = 45 \xrightarrow{\texttt{a=3 (West)}} \langle \texttt{nobs} = 45,\ \texttt{r} = -1,\ \texttt{done} = \texttt{False} \rangle$

# Taxi Environment Step III



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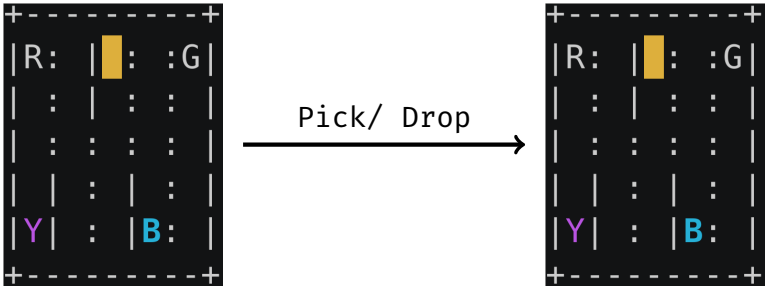


`nobs, r, done, _ = env.step(a)`:

$o = 45 \xrightarrow{a=4/5\ \text{(Pick/ Drop)}} \langle \texttt{nobs} = 45,\ \texttt{r} = -10,\ \texttt{done} = \texttt{False} \rangle$

# Implement your RL Agent

# Recap: SARSA

**On-Policy TD Control: Sarsa**

$\longrightarrow$ learn $q_\pi$ and improve $\pi$ while following $\pi$

**Updates:** $Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \left[R_{t+1} + \gamma Q(S_{t+1}, A_{t+1}) - Q(S_t, A_t)\right]$

**Exploration:** $\epsilon$-soft policy $\pi$

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**Exploration:** $\epsilon$-soft policy $\pi$

Initialize $Q(s,a), \forall s \in \mathcal{S}, a \in \mathcal{A}(s)$, arbitrarily, and $Q(\textit{terminal-state}, \cdot) = 0$
Repeat (for each episode):
  Initialize $S$
  Choose $A$ from $S$ using policy derived from $Q$ (e.g., $\varepsilon$-greedy)
  Repeat (for each step of episode):
    Take action $A$, observe $R$, $S'$
    Choose $A'$ from $S'$ using policy derived from $Q$ (e.g., $\varepsilon$-greedy)
    $Q(S,A) \leftarrow Q(S,A) + \alpha[R + \gamma Q(S', A') - Q(S,A)]$
    $S \leftarrow S'$; $A \leftarrow A'$;
  until $S$ is terminal

# SARSA Agent Class Structure

- **`__init__`** Initialise agent and Q-table as dictionary mapping `(obs, act) -> q-val`
- **`act`**: Epsilon-soft policy
- **`learn`**: Update Q-table given new experience

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \left[ R_{t+1} + \gamma Q(S_{t+1}, A_{t+1}) - Q(S_t, A_t) \right]$$

- **`schedule_hyperparameters`**: Update hyperparameters given training progress

# And now in Code ... act

## Epsilon-soft Action Selection

```
def act(self, obs):
    act_vals = [self.q_table[(obs, act)] for act in range(self.
    n_acts)]
    max_val = max(act_vals)
    max_acts = [idx for idx, act_val in enumerate(act_vals) if
    act_val == max_val]

    if random.random() < self.epsilon:
        return random.randint(0, self.n_acts - 1)
    else:
        return random.choice(max_acts)
```

# And now in Code ... learn

SARSA Q-Update

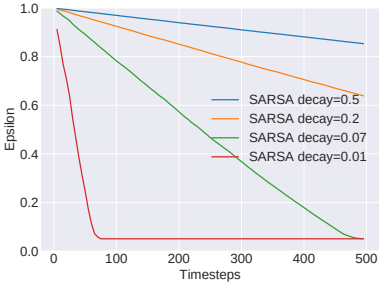
```
def learn(self, obs, action, reward, n_obs, n_action, done):
    target_value = reward + self.gamma * (1 - done) * self.
  q_table[(n_obs, n_action)]
    self.q_table[(obs, action)] += self.alpha * (
        target_value - self.q_table[(obs, action)]
    )
    return self.q_table[(obs, action)]
```

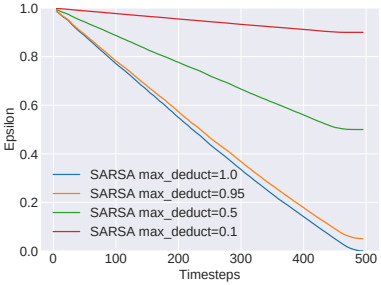
$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \left[R_{t+1} + \gamma Q(S_{t+1}, A_{t+1}) - Q(S_t, A_t)\right]$$

# And now in Code … schedule_hyperparameters

## SARSA $\epsilon$-Scheduling

```
def schedule_hyperparameters(self, timestep, max_timestep):
    max_deduct, decay = 0.95, 0.07
    self.epsilon = 1.0 - (min(1.0, timestep/(decay *
 max_timestep))) * max_deduct
```



# Evaluate your Results

# Why do We Evaluate in the First Place?

- It gives our approach credibility
- Empirical evaluation is no proof, but can give strong indication about the strengths and limitations of an approach (when done right!)

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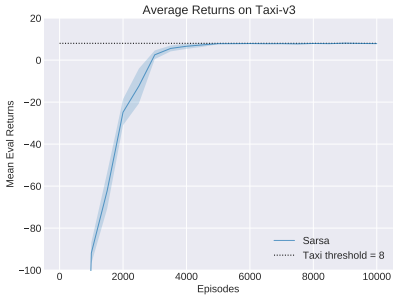
How to do it *right*?

# What to Evaluate?

## Evaluation Returns

- Plot mean returns over multiple runs
- Visualise standard deviation or variance



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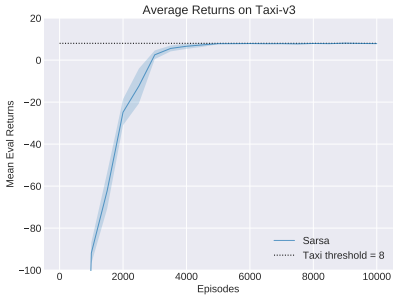


Which returns do we plot?

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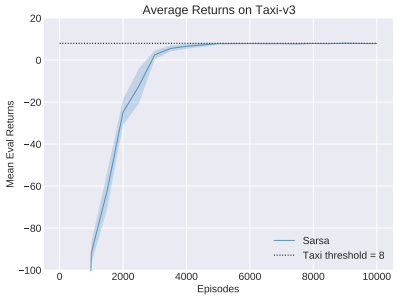


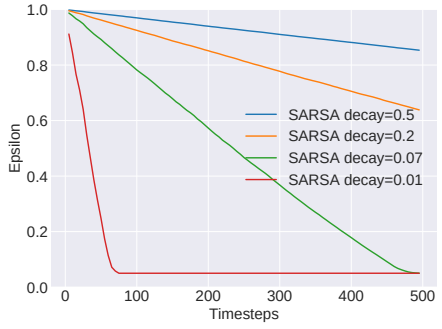

## Which returns do we plot?

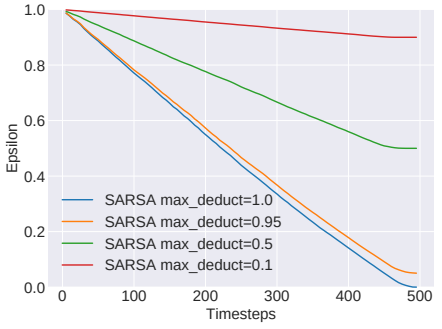
- Execute multiple evaluation runs with $\epsilon = 0$ at fixed intervals
- Evaluation does not involve any learning!

# Keep Track of Everything!

## Hyperparameters

- Track hyperparameters, here $\epsilon$-decay
- Try various values in a grid- or random-search and find good configuration



# SARSA Gridsearch over Learning Rate $\alpha$ for Taxi-v3

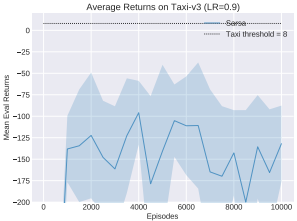



Figure 1: $\alpha = 0.9$

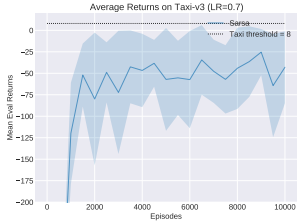



Figure 3: $\alpha = 0.7$

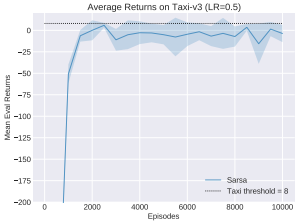



Figure 5: $\alpha = 0.5$


Figure 2: $\alpha = 0.3$

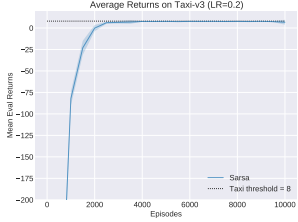



Figure 4: $\alpha = 0.2$


Figure 6: $\alpha = 0.1$

# SARSA Learning Rate $\alpha$ Gridsearch Overview

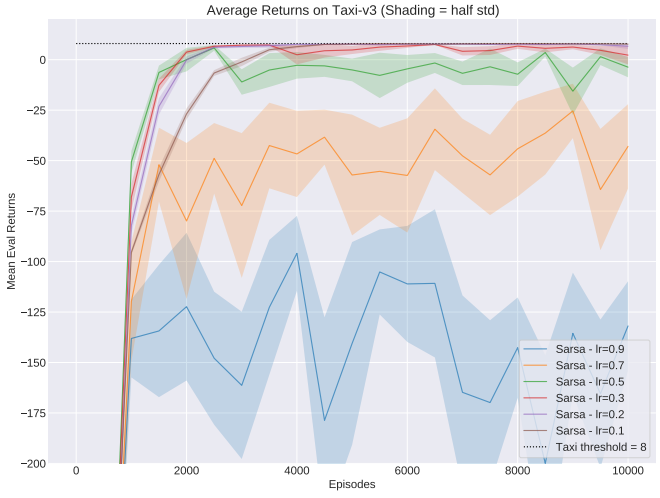



**Figure 7:** Gridsearch overview over learning rate $\alpha$ with half standard deviation as shading

# Common Pitfalls (1)

”But it worked last time!”

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**”But it worked last time!”**

- It’s not enough to make it work once!
- Meaningful evaluation achieves consistent performance over multiple randomised runs
- Most RL algorithms have random components (e.g. $\epsilon$-greedy policies)

# Common Pifalls (2) (Henderson, 2018; Colas et al., 2019)

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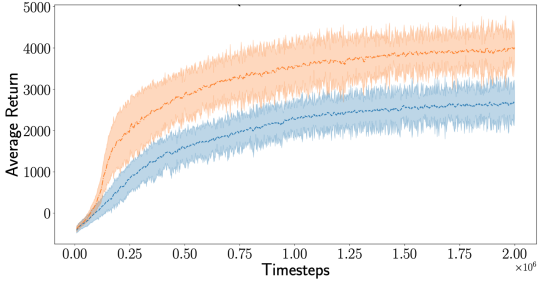

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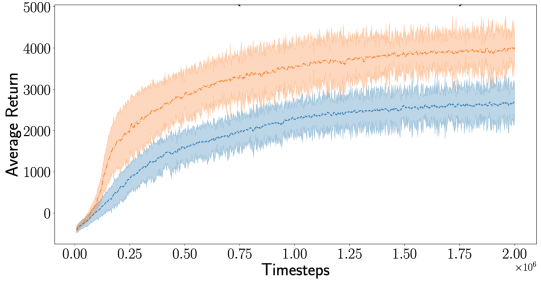
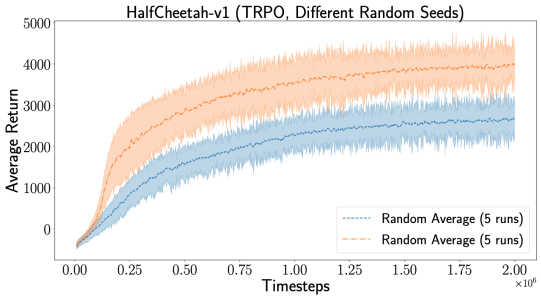



Which one is better?

# Common Pifalls (2) (Henderson, 2018; Colas et al., 2019)

Is plotting the mean return, even with variance, enough?

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It's actually the same method!

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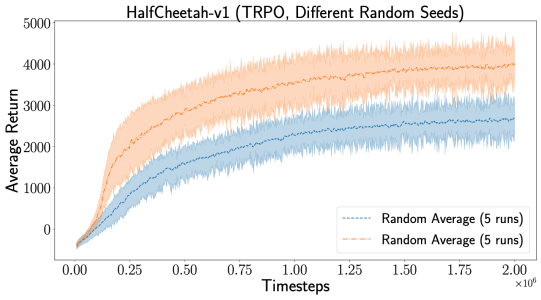


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Apparently, it's not enough! $\longrightarrow$ Statistical hypothesis testing (Colas et al., 2019)

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**Rein in the four horsemen of irreproducibility**

Dorothy Bishop describes how threats to reproducibility, recognized but unaddressed for decades, might finally be brought under control.

Dorothy Bishop

# Demonstration

All code is available at

https://github.com/uoe-agents/RL2021_Building-a-Complete-RL-System_Demonstration

## References

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Colas, C., Sigaud, O., and Oudeyer, P.-Y. (2019). A Hitchhiker's Guide to Statistical Comparisons of Reinforcement Learning Algorithms. *arXiv preprint arXiv:1904.06979*.

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# Reading ii

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Any questions about this lecture or the demonstration?