Building Deep Reinforcement Learning Applications on Apache Spark with Analytics Zoo using BigDL

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Agenda

Analytics Zoo overview

Reinforcement learning overview

Reinforcement learning with Analytics zoo

future directions

Analytics Zoo

- ***Analytics + AI Platform for Apache Spark and BigDL***
  - Open source, Scala/Python, Spark 1.6 and 2.X

Analytics Zoo	High level API, Industry pipelines, App demo & Util
BigDL	MKL, Tensors, Layers, optim Methods, all-reduce
Apache Spark	RDD, DataFrame, Scala/Python

https://github.com/intel-analytics/analytics-zoo

Analytics Zoo

High level pipeline APIs

nnframes: Spark DataFrames and ML Pipelines for DL

Keras-style API

autograd: custom layer/loss using auto differentiation

Transfer learning

Analytics Zoo

Built-in deep learning pipelines & models

Object detection: API and pre-trained SSD and Faster-RCNN

Image classification: API and pre-trained VGG, Inception, ResNet, MobileNet, etc.

Text classification API with CNN, LSTM and GRU

Recommendation API with NCF, Wide and Deep etc.

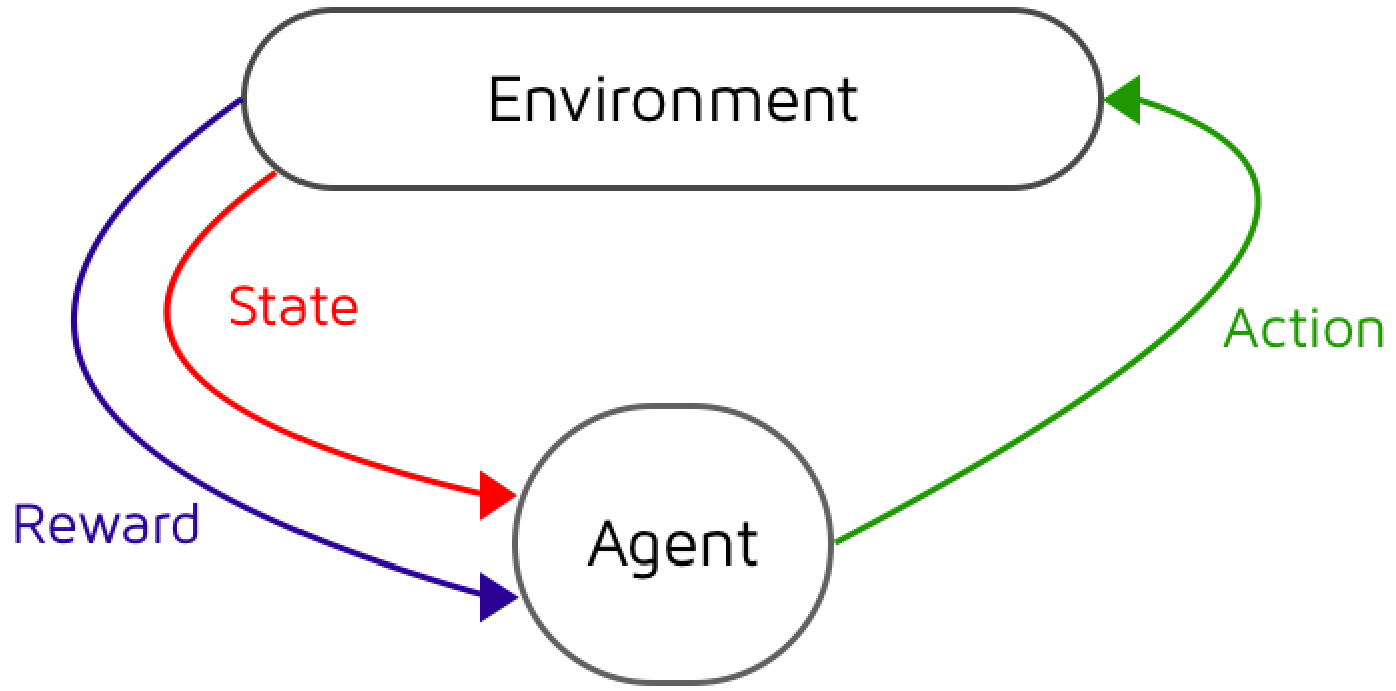
Analytics Zoo

End-to-end reference use cases

- reinforcement learning
- anomaly detection
- sentiment analysis
- fraud detection
- image augmentation
- object detection
- variational autoencoder
- …

Reinforcement Learning (RL)

- RL is for Decision-making

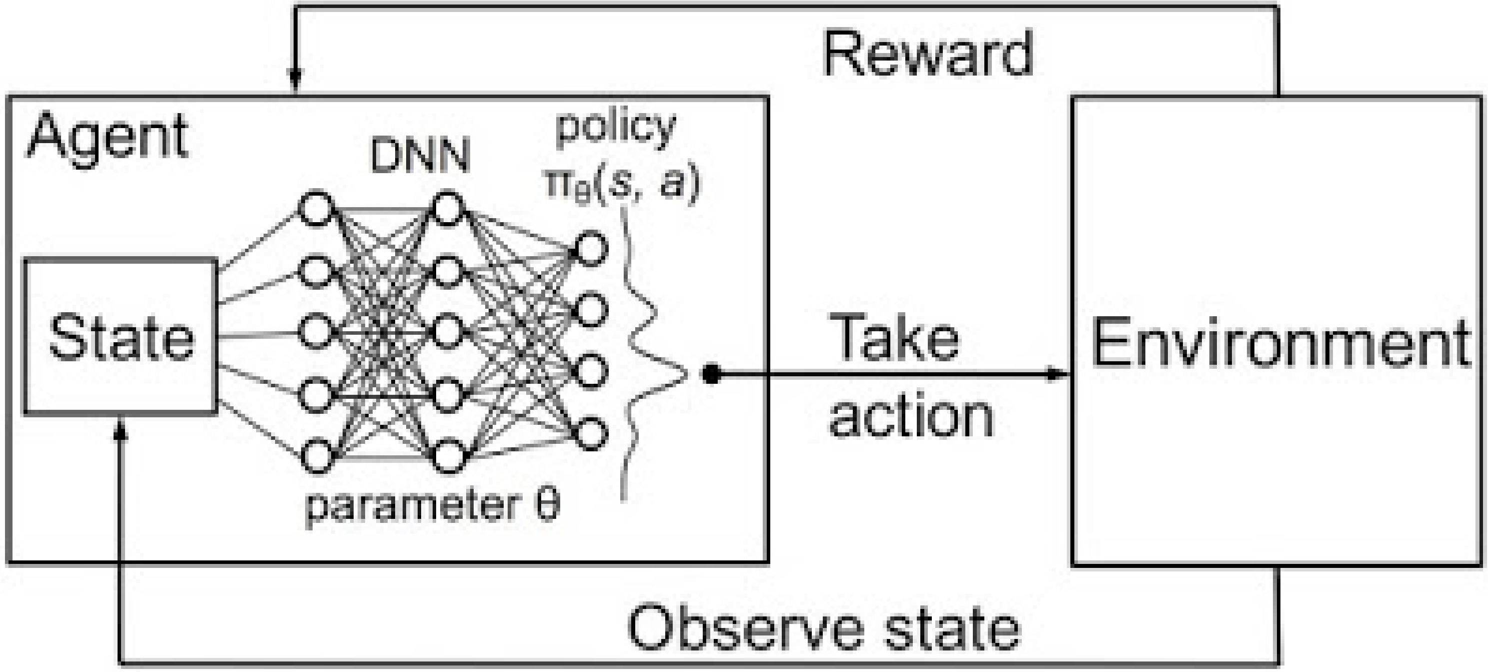


Examples of RL applications

- Play: Atari, poker, Go, ...
- Interact with users: recommend, Healthcare, chatbot, personalize, ..
- Control: auto-driving, robotics, finance, …

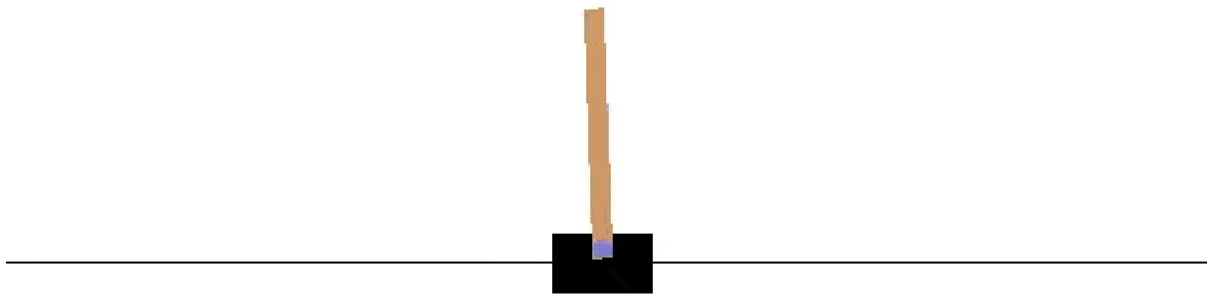
Deep Reinforcement Learning (DRL)

Agents take actions (a) in state (s) and receives rewards (R)
Goal is to find the policy (π) that maximized future rewards



http://people.csail.mit.edu/hongzi/content/publications/DeepRM-HotNets16.pdf

Cartpole



Observation

Type: Box(4)

Num	Observation	Min	Max
0	Cart Position	-2.4	2.4
1	Cart Velocity	-Inf	Inf
2	Pole Angle	~ -41.8°	~ 41.8°
3	Pole Velocity At Tip	-Inf	Inf

Actions

Type: Discrete(2)

Num	Action
0	Push cart to the left
1	Push cart to the right

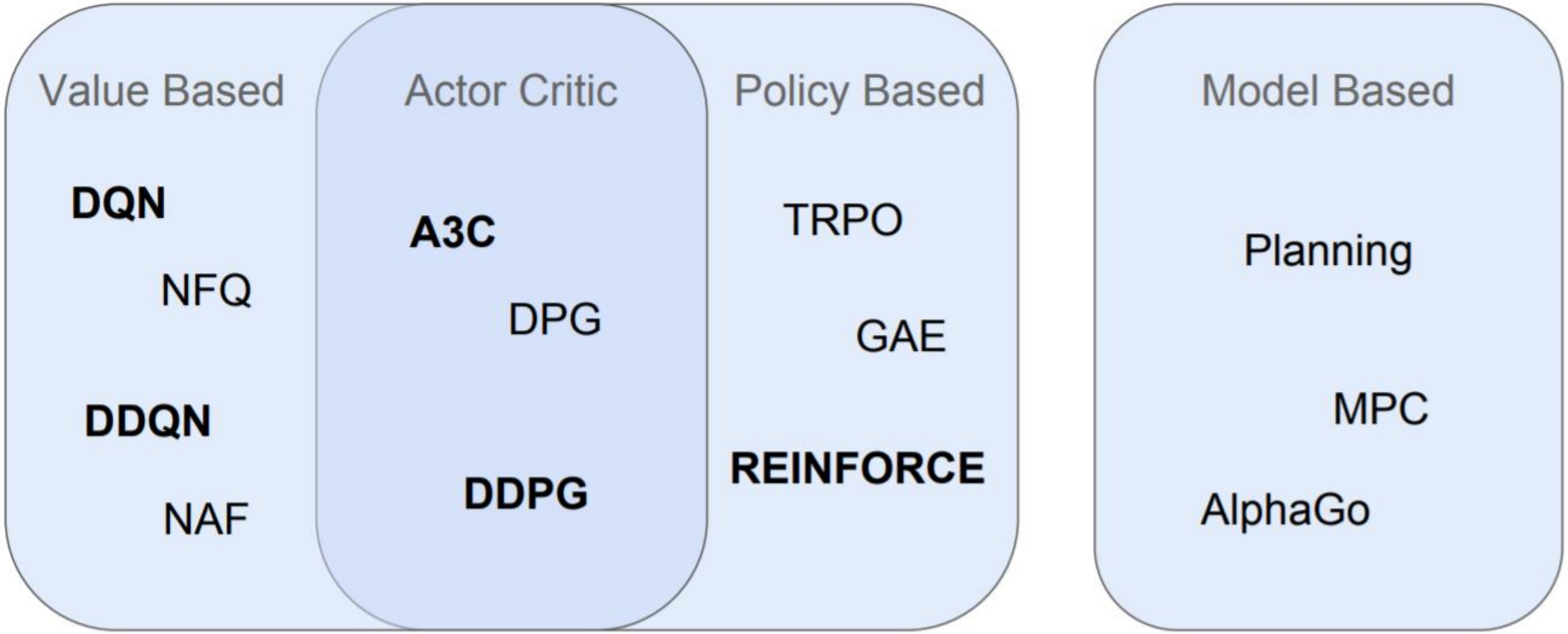
Reward

Reward is 1 for every step taken,

Approaches to Reinforcement Learning

- Value-based RL
  - Estimate the optimal value function Q*(S,A)
  - Output of the Neural network is the value for Q(S, A)
- Policy-based RL
  - Search directly for the optimal policy π*
  - Output of the neural network is the probability of each action.
- Model-based RL

DRL algo



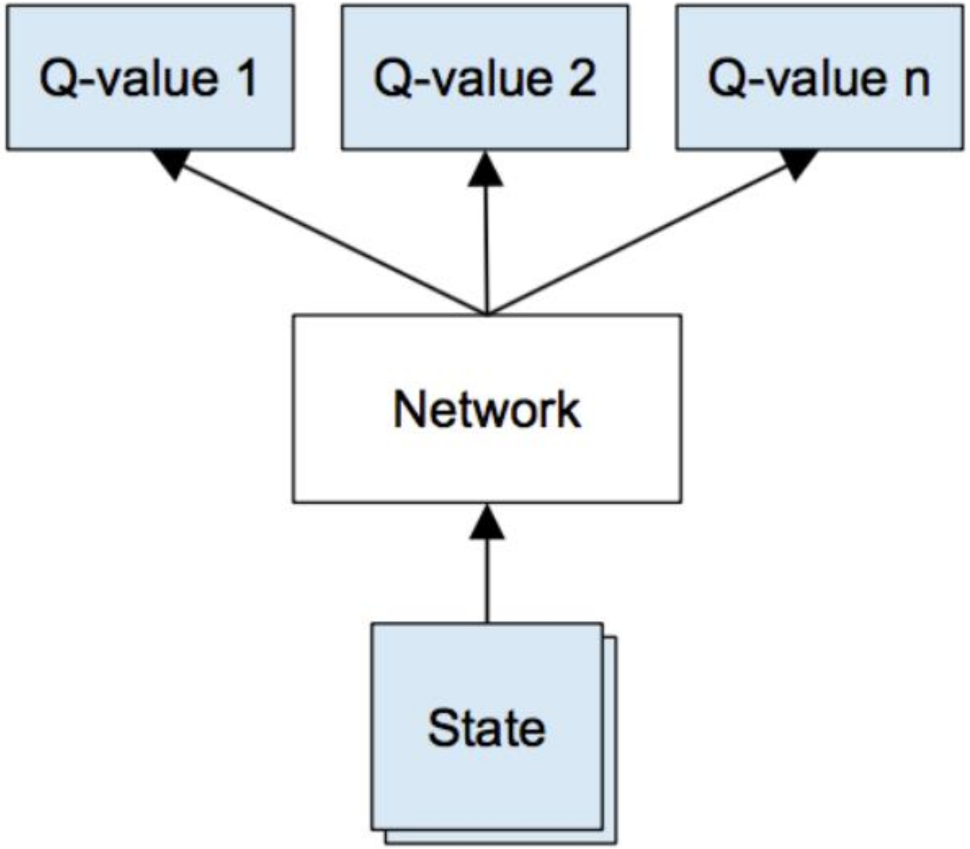
Value Based
DQN
NFQ
DDQN
NAF
Actor Critic
A3C
DPG
DDPG
Policy Based
TRPO
GAE
REINFORCE
Model Based
Planning
MPC
AlphaGo

Examples

- 1. Simple DQN to demo API and train with Spark RDD.

- 2. Distributed REINFORCE

Q-network



https://ai.intel.com/demystifying-deep-reinforcement-learning/

Bellman Equation

- Optimal value maximises over all decisions. Informally:

$$
\begin{aligned}
Q^*(s, a) &= r_{t+1} + \gamma \max_{a_{t+1}} r_{t+2} + \gamma^2 \max_{a_{t+2}} r_{t+3} + \ldots \\
&= r_{t+1} + \gamma \max_{a_{t+1}} Q^*(s_{t+1}, a_{t+1})
\end{aligned}
$$

- Value iteration algorithms solve the Bellman equation

$$
Q_{i+1}(s, a) = \mathbb{E}_{s'}\left[r + \gamma \max_{a'} Q_i(s', a') \mid s, a \right]
$$

http://www0.cs.ucl.ac.uk/staff/d.silver/web/Resources_files/deep_rl.pdf

DQN critical routines

```
for e in range(EPISODES):
    state = env.reset()
    state = np.reshape(state, [1, state_size])
    for time in range(500):
        action = agent.act(state)       ε-greedy action selection
        next_state, reward, done, _ = env.step(action)
        reward = reward if not done else -10
        next_state = np.reshape(next_state, [1, state_size])
        agent.remember(state, action, reward, next_state, done)
        state = next_state
        if len(agent.memory) > batch_size:
            agent.replay(batch_size)
```

Parallelize the neural network training

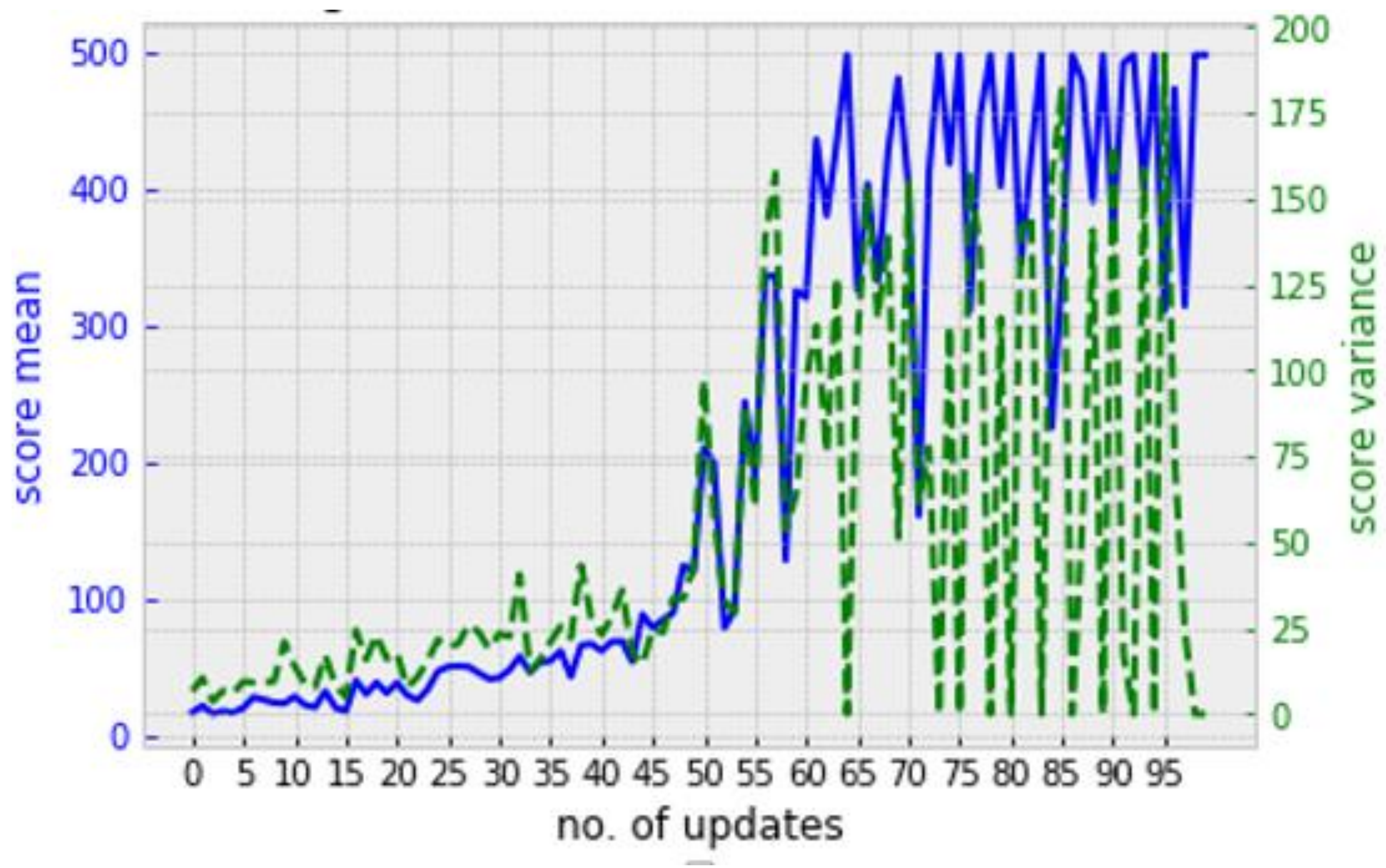
```
def replay(self, batch_size):
    X_batch = np.array([0,0,0,0])
    y_batch = np.array([0,0])
    minibatch = random.sample(self.memory, batch_size)      experience replay
    for state, action, reward, next_state, done in minibatch:
        target = reward
        if not done:
            target = (reward + self.gamma *
                      np.amax(self.model.predict_local(next_state)[0]))
        target_f = self.model.predict_local(state)
        target_f[0][action] = target
        X_batch = np.vstack((X_batch, state))
        y_batch = np.vstack((y_batch, target_f))

    rdd_sample = to_RDD(X_batch,y_batch)
    self.model.fit(rdd_sample, None, nb_epoch=10, batch_size=batch_size)
```

Analytics Zoo Keras-style Model

```
def _build_model(self):
    # Neural Net for Deep-Q learning Model
    model = Sequential()
    model.add(Dense(24, input_dim=self.state_size, activation='relu'))
    model.add(Dense(24, activation='relu'))
    model.add(Dense(self.action_size, activation='linear'))
    model.compile(loss='mse',
                  optimizer=Adam(learningrate=self.learning_rate))
    return model
```

Vanilla DQN



score mean
score variance
no. of updates
0
100
200
300
400
500
0
25
50
75
100
125
150
175
200
0 5 10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85 90 95

Policy gradients

- In Policy Gradients, we usually use a neural network (or other function approximators) to directly model the action probabilities.

- we tweak the parameters θ of the neural network so that "good" actions will be sampled more likely in the future.

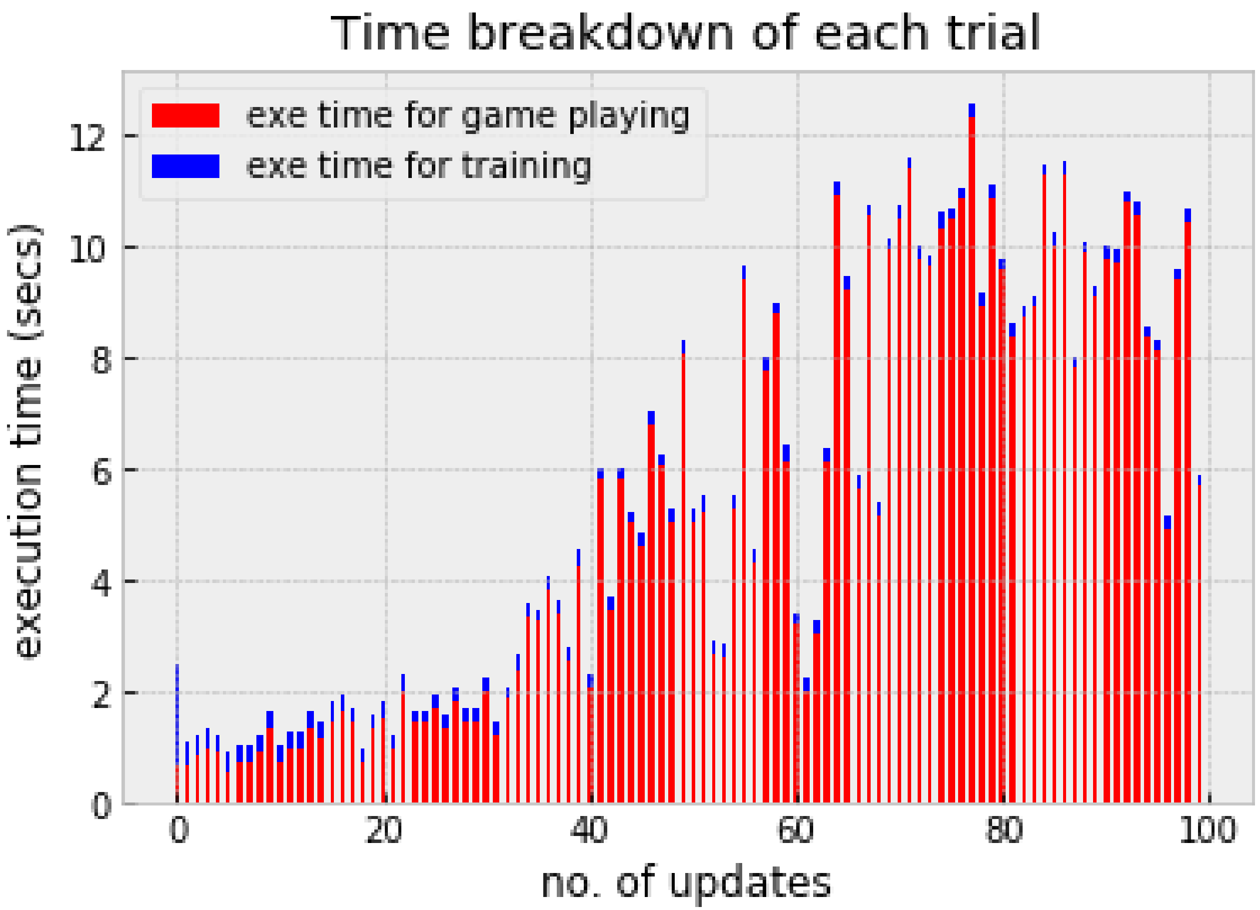
$$\nabla_\theta E[R_t] = E[\nabla_\theta log P(a) R_t]$$

REINFORCE

function REINFORCE
    Initialise θ arbitrarily
    for each episode $\{s_1, a_1, r_2, ..., s_{T-1}, a_{T-1}, r_T\} \sim \pi_\theta$ **do**
        for $t = 1$ to $T - 1$ **do**
            $\theta \leftarrow \theta + \alpha \nabla_\theta \log \pi_\theta(s_t, a_t) v_t$
        end for
    end for
    return θ
end function

Time breakdown

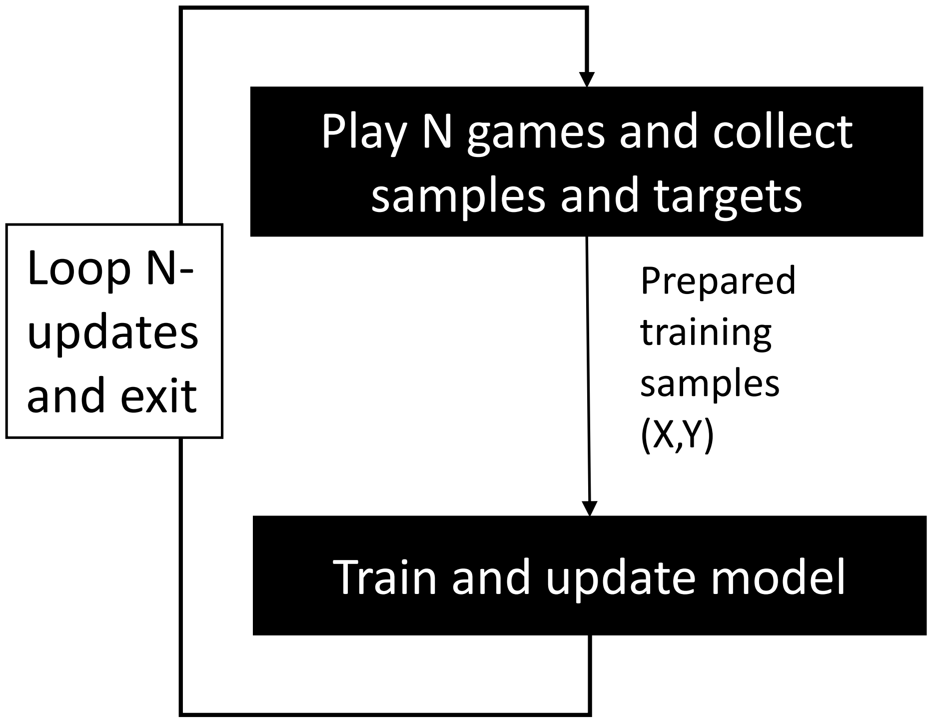
- Game playing takes the most time in each iteration



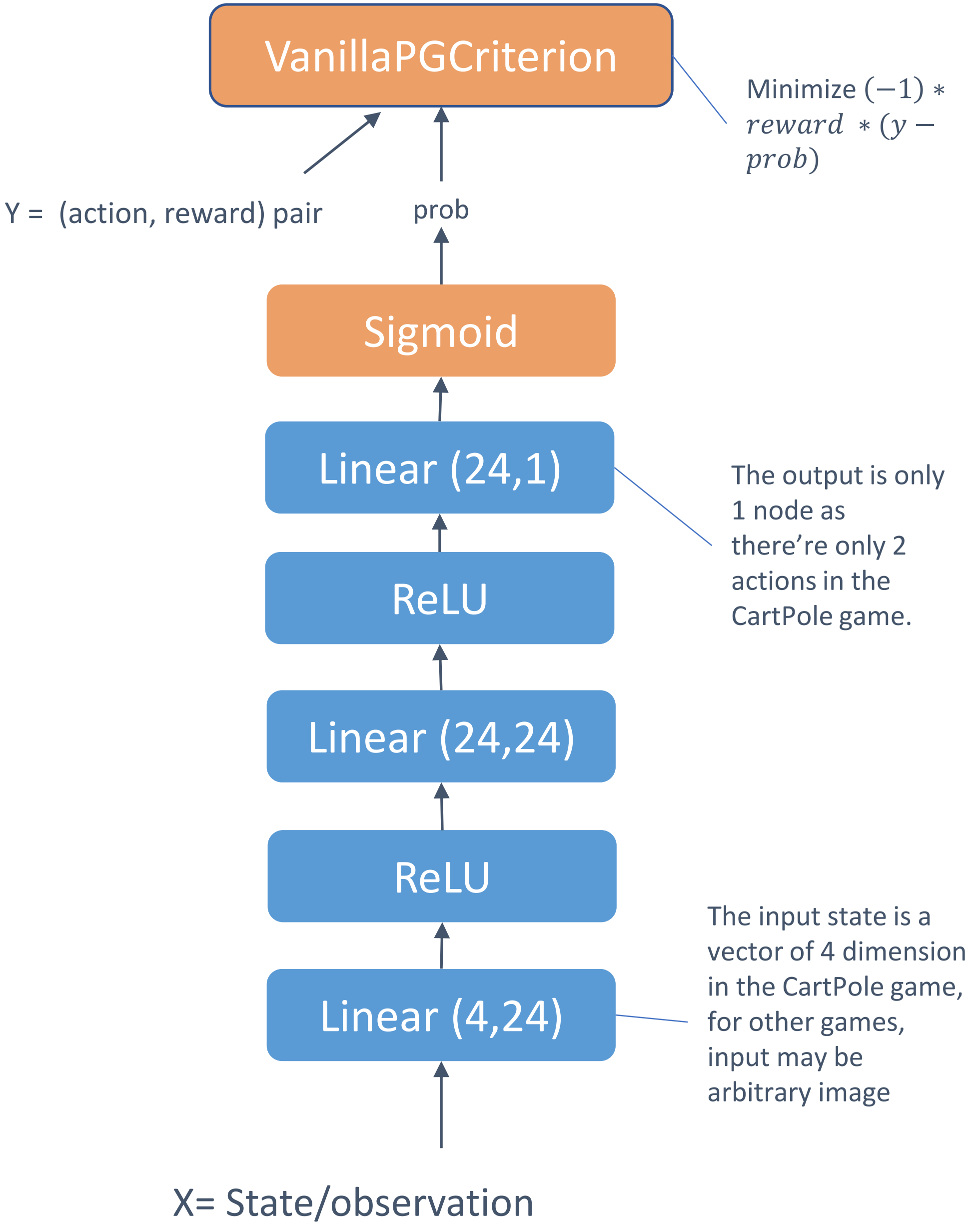
Distributed REINFORCE

```
# create and cache several agents on each partition as specified by parallelism
# and cache it
with DistributedAgents(sc, create_agent=create_agent, parallelism=parallelism) as a:
    agents = a.agents # a.agents is a RDD[Agent]
    optimizer = None
    num_trajs_per_part = int(math.ceil(15.0 / parallelism))
    mean_std = []
    for i in range(60):
        with SampledTrajs(sc, agents, model, num_trajs_per_part=num_trajs_per_part) as trajs:
            trajs = trajs.samples \ # samples is a RDD[Trajectory]
                .map(lambda traj: (traj.data["observations"],
                                   traj.data["actions"],
                                   traj.data["rewards"]))
```

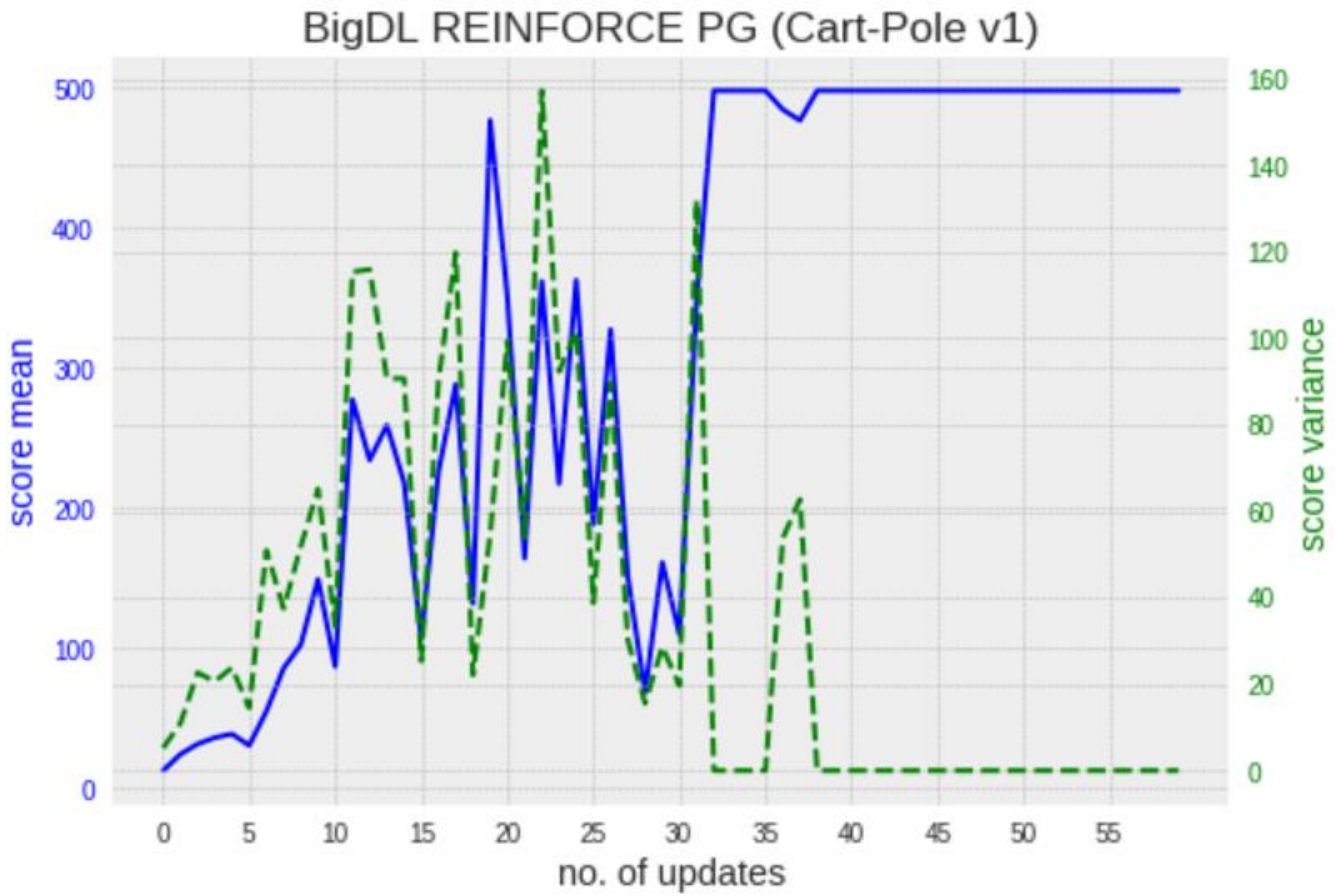
REINFORCE algorithm



Overflow of a PG program

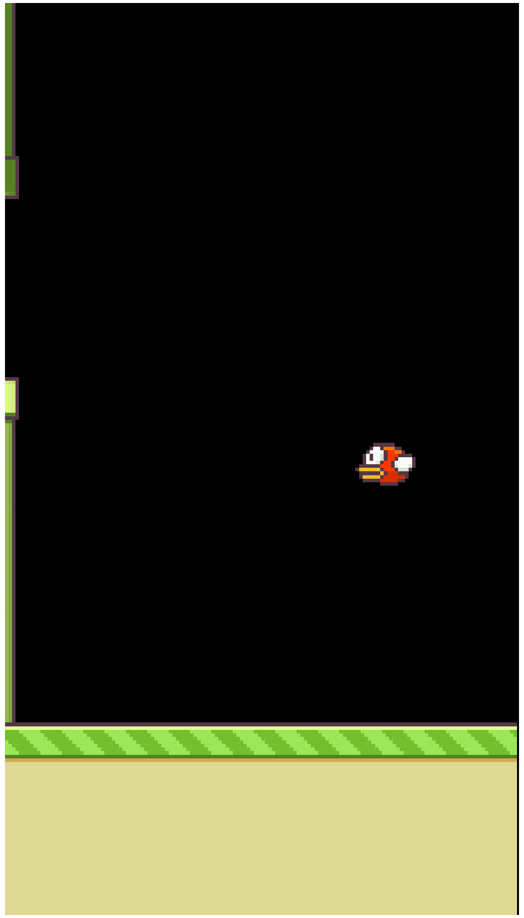


Distributed REINFORCE



Other RL algorithms

- Flappy bird with DQN
- Discrete and continuous PPO
- A2C (in roadmap)



Q & A

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Thanks Shane Huang and Yang Wang for working on RL implementations.