Dopamine

A Research Framework for Deep Reinforcement Learning

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Where I’m from

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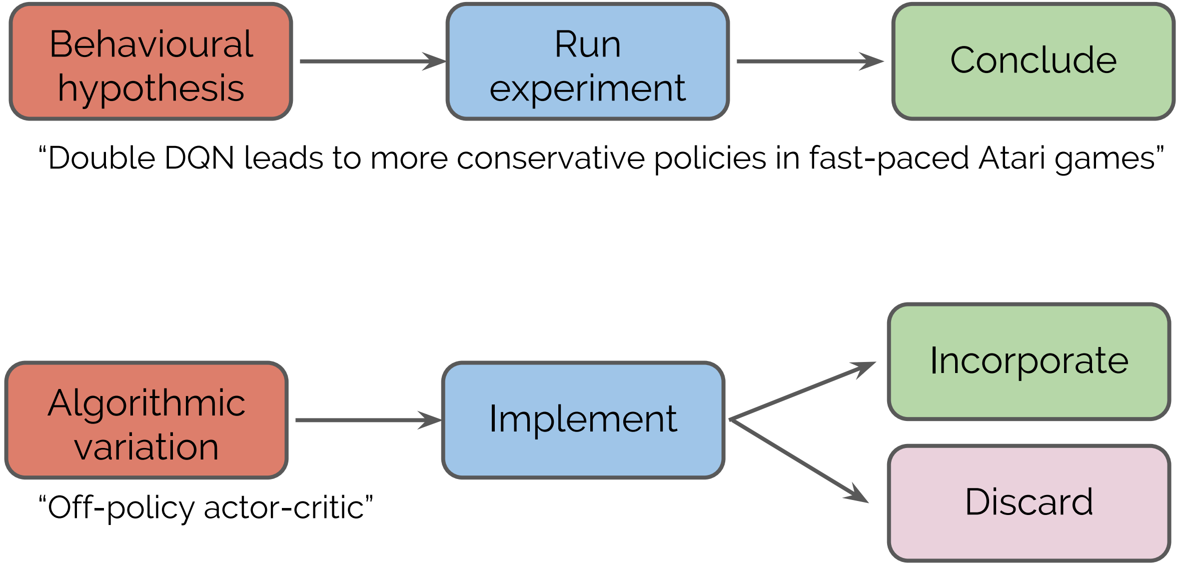
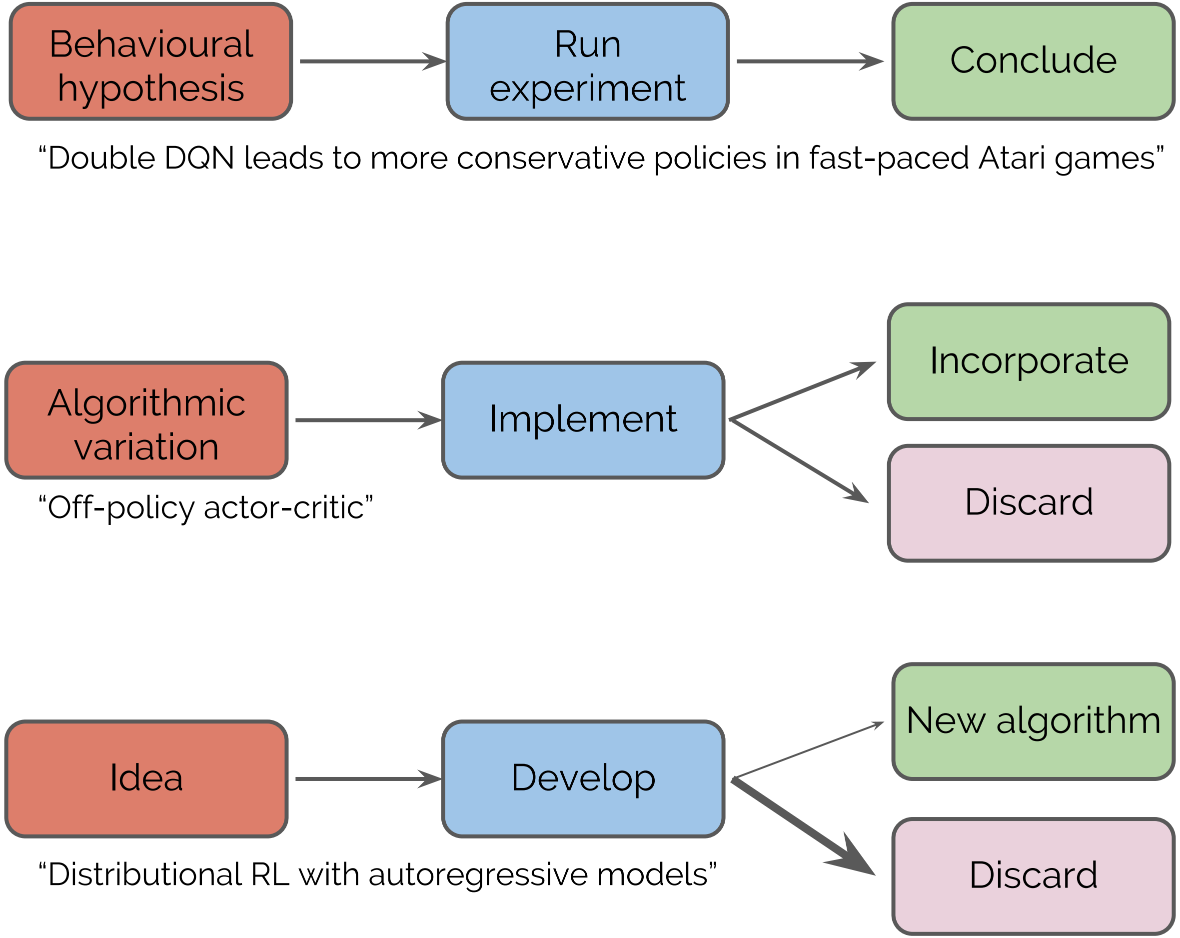
Main message

Dopamine is a research framework for fast prototyping of reinforcement learning algorithms.

It aims to fill the need for a small, easily grokked codebase in which users can freely experiment with wild ideas [speculative research].

“Double DQN leads to more conservative policies in fast-paced Atari games”


Behavioural hypothesis
Run experiment
Conclude
“Double DQN leads to more conservative policies in fast-paced Atari games”
Algorithmic variation
Implement
Incorporate
Discard
“Off-policy actor-critic”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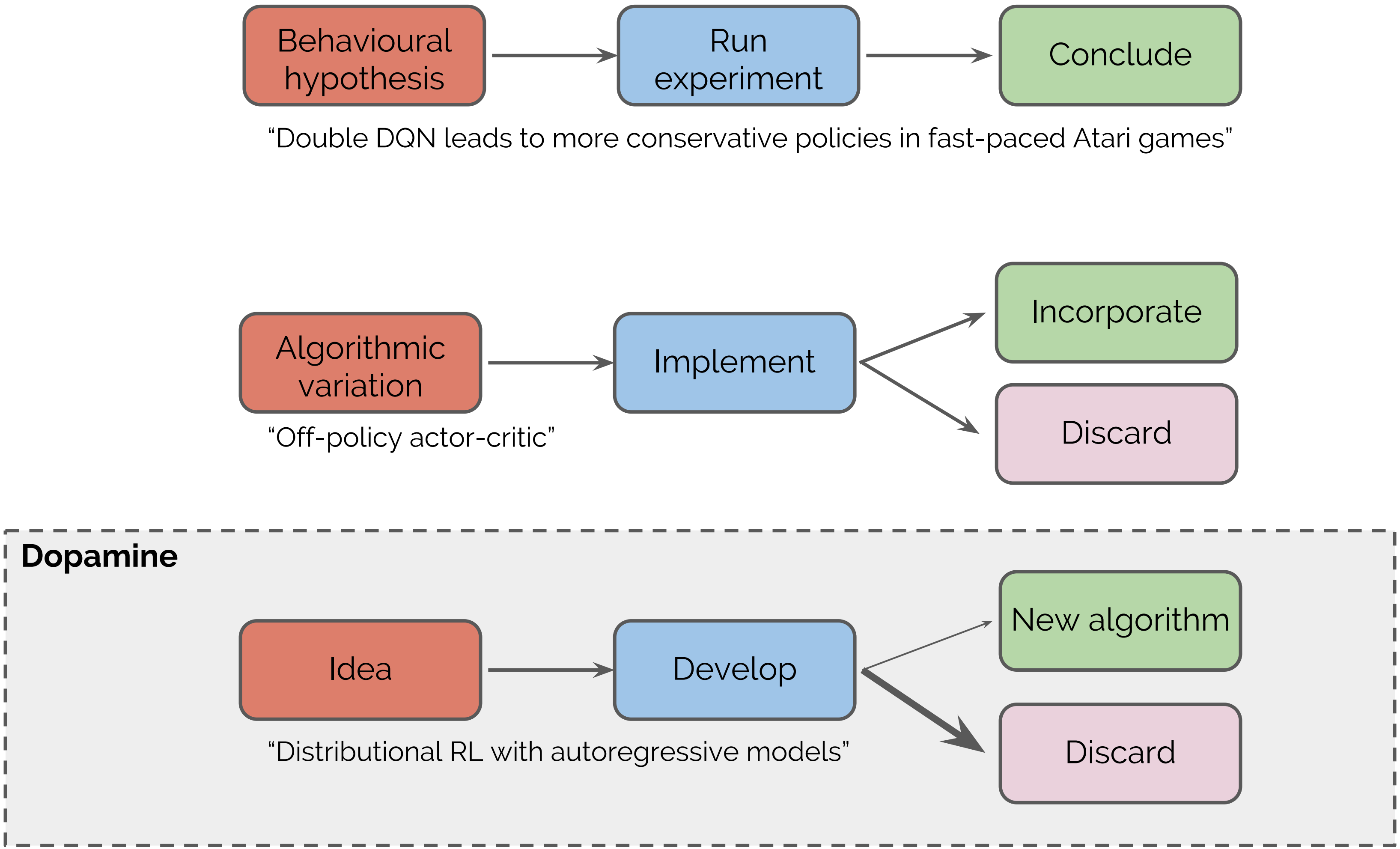
Idea
Develop
New algorithm
Discard
"Distributional RL with autoregressive models"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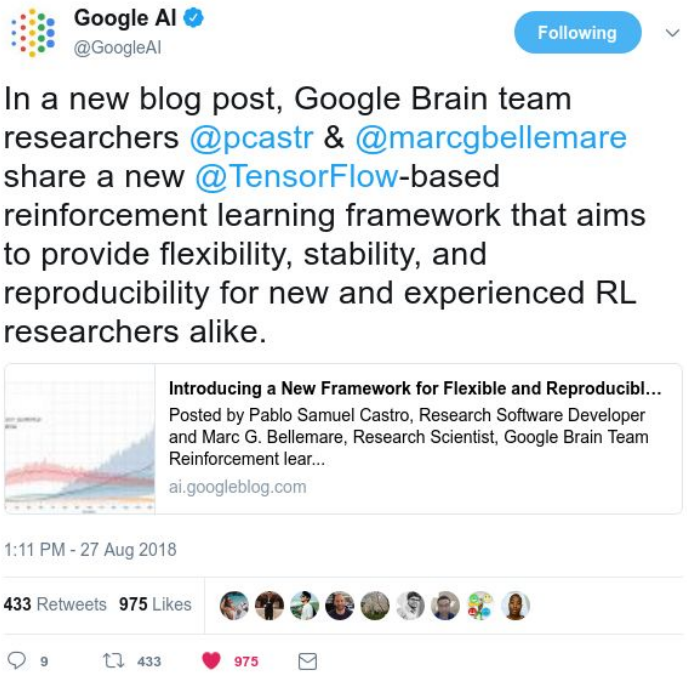
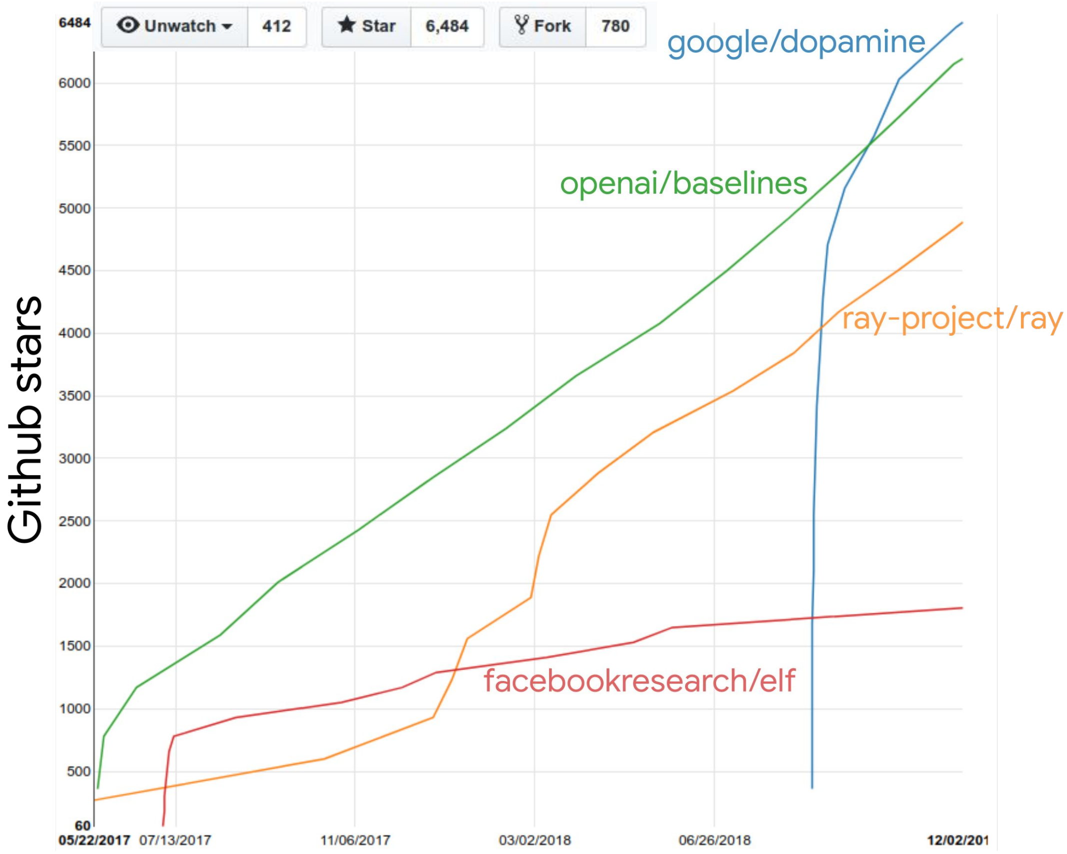
Launch stats

- Launched on August 27th to a very a positive reception



Launch stats

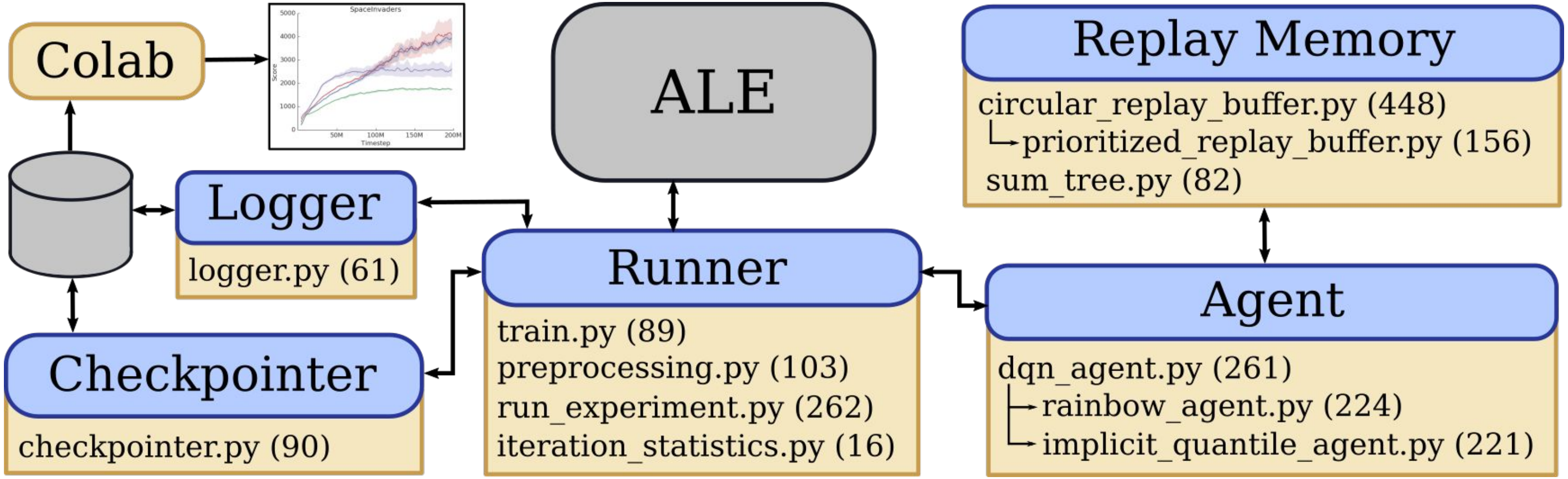


Launch stats

Code Stats

- 12 python files (excluding tests)
  - A little over 2000 lines in total
- 98% code coverage
- Initial offering:
  - Atari environment (ALE)
  - 4 agents: DQN, C51, Rainbow, IQN
- Tensorboard integration

Code Design


Colab
ALE
Replay Memory
circular_replay_buffer.py (448)
prioritized_replay_buffer.py (156)
sum_tree.py (82)
Logger
logger.py (61)
Runner
train.py (89)
preprocessing.py (103)
run_experiment.py (262)
iteration_statistics.py (16)
Agent
dqn_agent.py (261)
rainbow_agent.py (224)
implicit_quantile_agent.py (221)
Checkpointer
checkpointer.py (90)

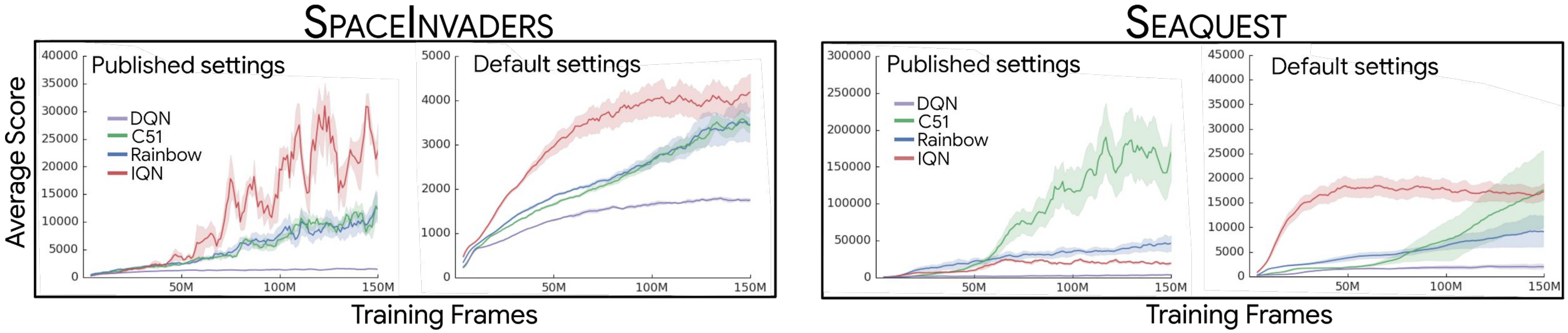
Code details

- Code is well-documented
- We ran 5 independent runs for all 4 agents on all 60 games
- We provide:
  - TensorFlow checkpoints for each of these runs
  - pickle files to easily visualize in colab (or anywhere)
  - Tensorboard event files
  - JSON files with data for plotting
- Colabs for extra documentation and instruction

DQN gin-config

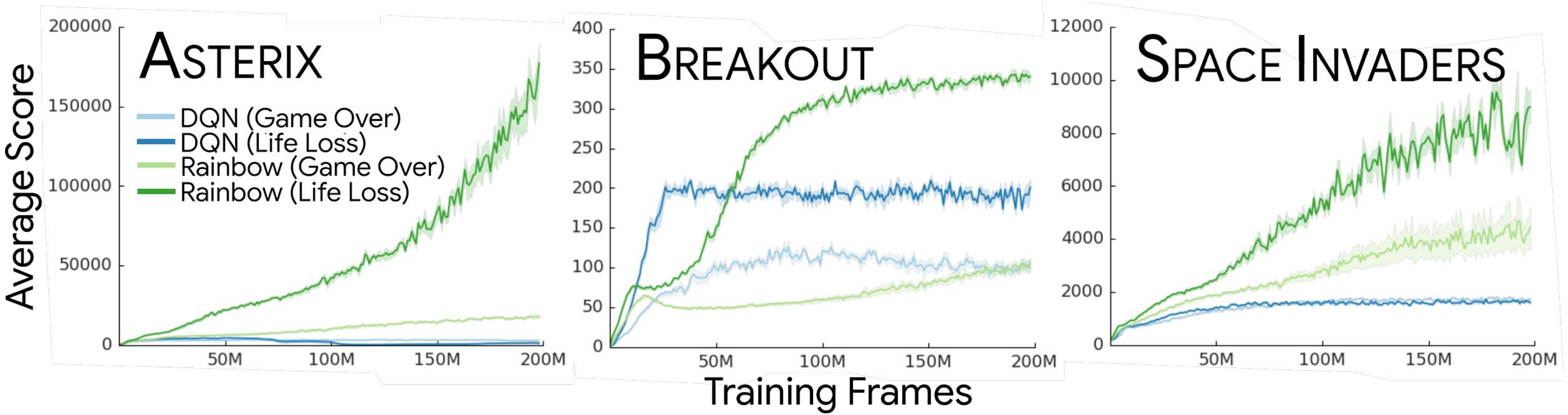
```
DQNAgent.gamma = 0.99
DQNAgent.update_horizon = 1
DQNAgent.min_replay_history = 20000  # agent steps
DQNAgent.update_period = 4
DQNAgent.target_update_period = 8000  # agent steps
DQNAgent.epsilon_train = 0.01
DQNAgent.epsilon_eval = 0.001
DQNAgent.epsilon_decay_period = 250000  # agent steps
DQNAgent.tf_device = '/gpu:0'  # use '/cpu:*' for non-GPU version
DQNAgent.optimizer = @tf.train.RMSPropOptimizer()

tf.train.RMSPropOptimizer.learning_rate = 0.00025
tf.train.RMSPropOptimizer.decay = 0.95
tf.train.RMSPropOptimizer.momentum = 0.0
tf.train.RMSPropOptimizer.epsilon = 0.00001
tf.train.RMSPropOptimizer.centered = True

Runner.game_name = 'Pong'
Runner.sticky_actions = True
Runner.num_iterations = 200
Runner.training_steps = 250000  # agent steps
Runner.evaluation_steps = 125000  # agent steps
Runner.max_steps_per_episode = 27000  # agent steps

WrappedReplayBuffer.replay_capacity = 1000000
WrappedReplayBuffer.batch_size = 32
```

Comparison with published settings



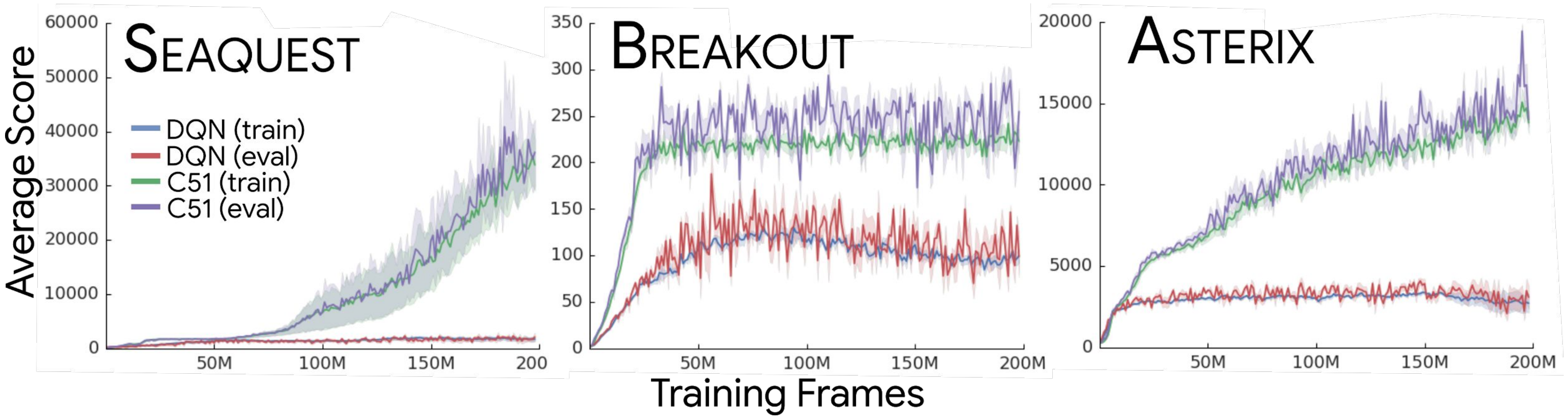
Episode ends: LifeLoss vs GameOver

```
AtariPreprocessing.terminal_on_life_loss = True
```



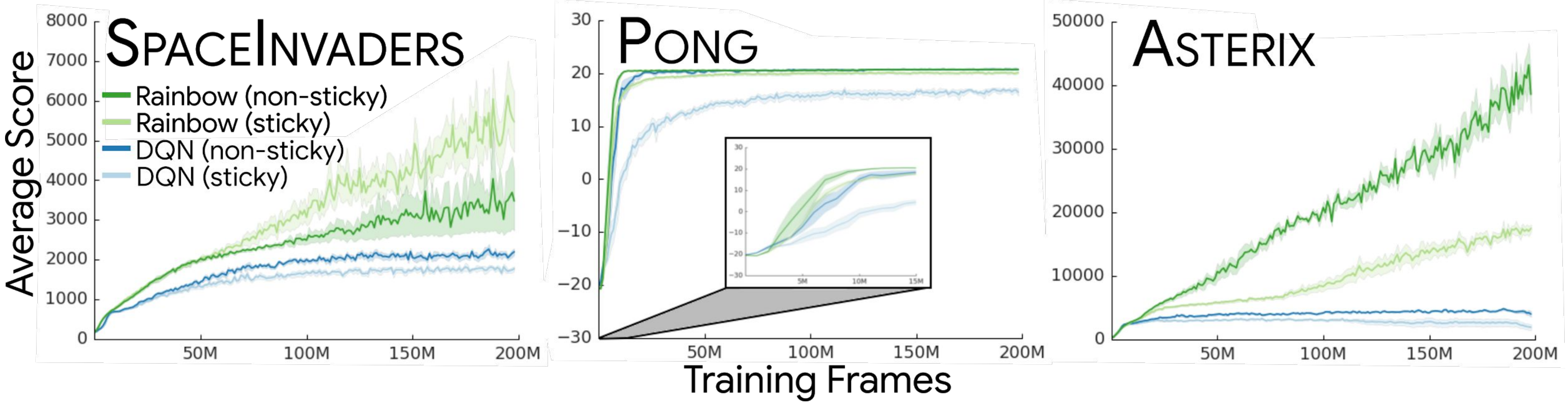
[Machado et al., *Revisiting the Arcade Learning Environment: Evaluation Protocols and Open Problems for General Agents*, Journal of Artificial Intelligence Research, 2018.]()

Train vs Eval curves



Sticky vs non-sticky actions

$$A_t = \begin{cases} a, & \text{with prob. } 1-\varsigma, \\ a_{t-1}, & \text{with prob. } \varsigma. \end{cases}$$




```
Runner.sticky_actions = False
```

New agent based on DQN

```python
# @title Create an agent based on DQN, but choosing actions randomly.

LOG_PATH = os.path.join(BASE_PATH, 'random_dqn', GAME)

class MyRandomDQNAgent(dqn_agent.DQNAgent):
  def __init__(self, sess, num_actions):
    """This maintains all the DQN default argument values."""
    super(MyRandomDQNAgent, self).__init__(sess, num_actions)

  def step(self, reward, observation):
    """Calls the step function of the parent class, but returns a random action.
    """
    _ = super(MyRandomDQNAgent, self).step(reward, observation)
    return np.random.randint(self.num_actions)

def create_random_dqn_agent(sess, environment, summary_writer=None):
  """The Runner class will expect a function of this type to create an agent."""
  return MyRandomDQNAgent(sess, num_actions=environment.action_space.n)

# Create the runner class with this agent. We use very small numbers of steps
# to terminate quickly, as this is mostly meant for demonstrating how one can
# use the framework. We also explicitly terminate after 110 iterations (instead
# of the standard 200) to demonstrate the plotting of partial runs.
random_dqn_runner = run_experiment.Runner(LOG_PATH,
                                          create_random_dqn_agent,
                                          game_name=GAME,
                                          num_iterations=200,
                                          training_steps=10,
                                          evaluation_steps=10,
                                          max_steps_per_episode=100)
```

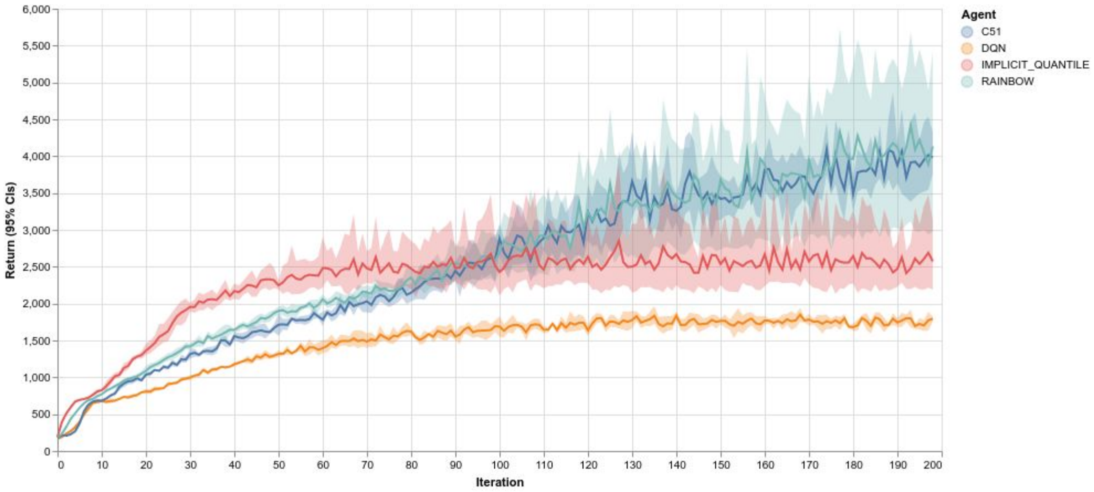
New agent from scratch

```
class StickyAgent(object):
  """This agent randomly selects an action and sticks to it. It will change
  actions with probability switch_prob."""
  def __init__(self, sess, num_actions, switch_prob=0.1):
    self._sess = sess
    self._num_actions = num_actions
    self._switch_prob = switch_prob
    self._last_action = np.random.randint(num_actions)
    self.eval_mode = False

  def _choose_action(self):
    if np.random.random() <= self._switch_prob:
      self._last_action = np.random.randint(self._num_actions)
    return self._last_action

  def bundle_and_checkpoint(self, unused_checkpoint_dir, unused_iteration):
    pass

  def unbundle(self, unused_checkpoint_dir, unused_checkpoint_version,
               unused_data):
    pass

  def begin_episode(self, unused_observation):
    return self._choose_action()

  def end_episode(self, unused_reward):
    pass

  def step(self, reward, observation):
    return self._choose_action()

def create_sticky_agent(sess, environment, summary_writer=None):
  """The Runner class will expect a function of this type to create an agent."""
  return StickyAgent(sess, num_actions=environment.action_space.n,
                     switch_prob=0.2)

sticky_runner = run_experiment.Runner(LOG_PATH,
                                      create_sticky_agent,
                                      game_name=GAME,
                                      num_iterations=200,
                                      training_steps=10,
                                      evaluation_steps=10,
                                      max_steps_per_episode=100)
```

Baselines plots

spaceinvaders

spaceinvaders



Save as SVG Save as PNG View Source Open in Vega Editor

Common requests

- Non-Atari gym environments (Cartpole, Acrobot, etc.)
    - very soon!
- Policy gradient methods
- Distributed training
- Visualizations

¡Gracias!
github.com/google/dopamine

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