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Idea

The main component of AlphaStar/ MiniAlphaStar

1. Preparation and Initialization
   - The definition of observation and action
   - The architecture of network
   - Collect training data from replays
   - Train model from supervised learning(behavior cloning)
2. Two-player zero-sum games
   - How to choose an opponent (Priority fictitious self play)
   - RL algorithm (impala upgo and some auxiliary task)
   - Sparse reward (human pseudo reward)

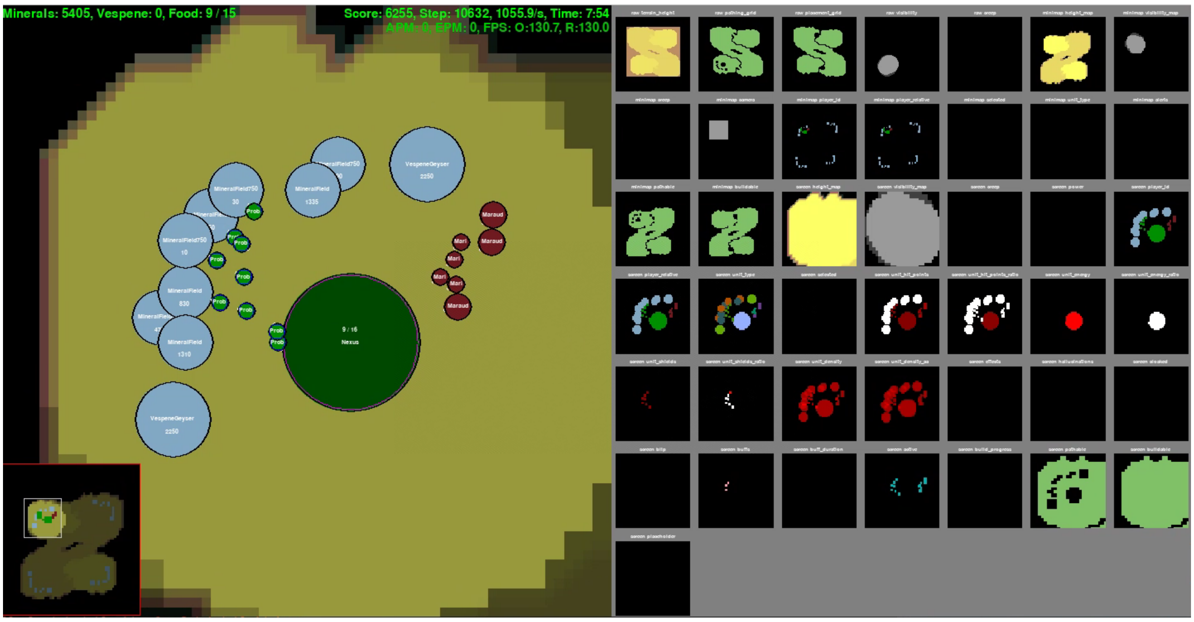
Introduction

暴雪星际争霸开源项目提供了不同版本的可以在Linux上运行的游戏引擎，以及人类对战的录像

deepmind pysc2提供了对应的gym风格的api调用

env introduction

```python
interface = AgentInterfaceFormat(
    Dimensions(64, 64),
    rgb_dimensions=None  # only windows support rgb_dimensions
    )

players = [
    Agent(Race.protoss, 'TestAgent'),
    Bot(Race.terran, Difficulty.easy)
]
with SC2Env(map_name="Simple64", players=players,
agent_interface_format=interface, visualize=True, version="4.10.0") as env:
    obs = env.reset()
    while obs[0].step_type != StepType.LAST:
        obs = env.step([FunctionCall(0, [])]) # (action_type, [queue,
selected_units, target_units, target location])
```



[video]

miniAlphaStar interface

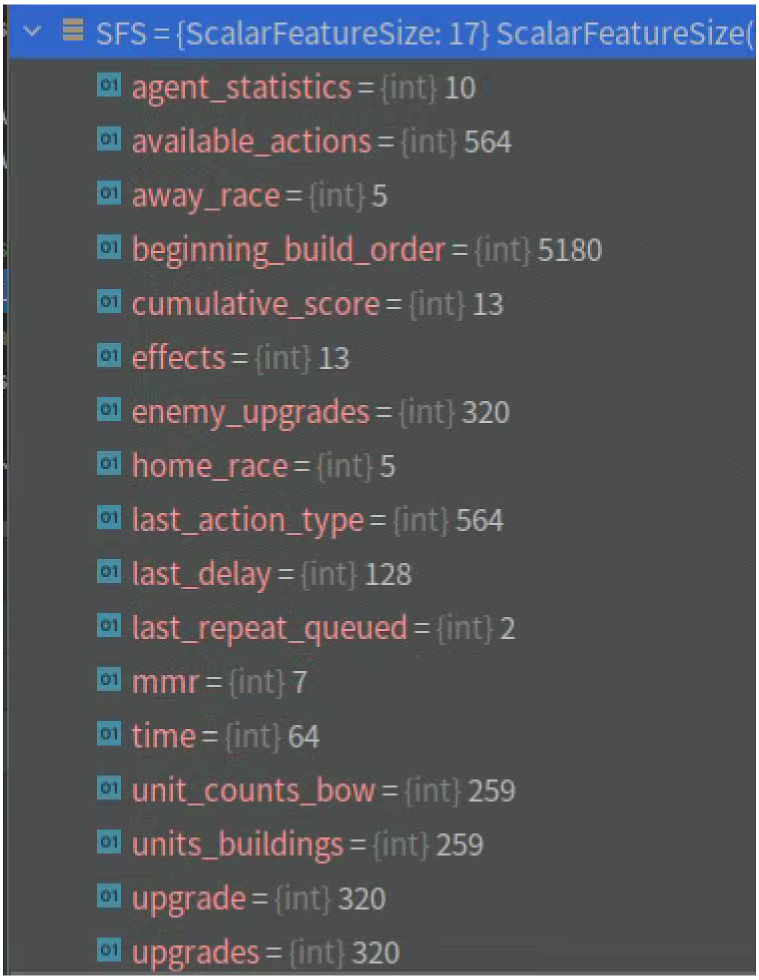
```python
interface = AgentInterfaceFormat(
    Dimensions(64, 64),
    rgb_dimensions=None,  # only windows support rgb_dimensions
    use_raw_units=True, #地图上的所有单位的信息，无迷雾
    use_raw_actions=True, #使用定义的函数调用，不是鼠标键盘操作
    use_camera_position=False, #不考虑移动摄像头的操作
    )
```

实际上是blog版本的AlphaStar，早期AlphaStar的版本

Observation

- 调用env.step得到的observation
- observation有3类属性，分别为scalar feature, entity feature 和 spatial feature

Scalar Feature



- beginning_build_order reshape 为 20*259，即考虑前20个building的建造顺序

Entity Feature

observation 的 raw_units 字段， 每个unit的属性如下：

- 最大entity的个数设置为512，将少于512的padding到512, 每个entity的维度为1856

Spatial Feature

obs.feature_minimap

- 增加4个feature图 表示每个位置是否有unit，最多有4个unit

action

action type head

564 action type

delay head

delay 表示下一次执行动作要经过多少帧，即delay帧之后才会执行下一个动作，而当前动作是立刻执行的，没有delay的。 delay最大值为128

queue head

当前动作是否排队

selected units head

最多选择12个units

target units head

目标target只有1个

target location head

目标位置

Transform replays to data

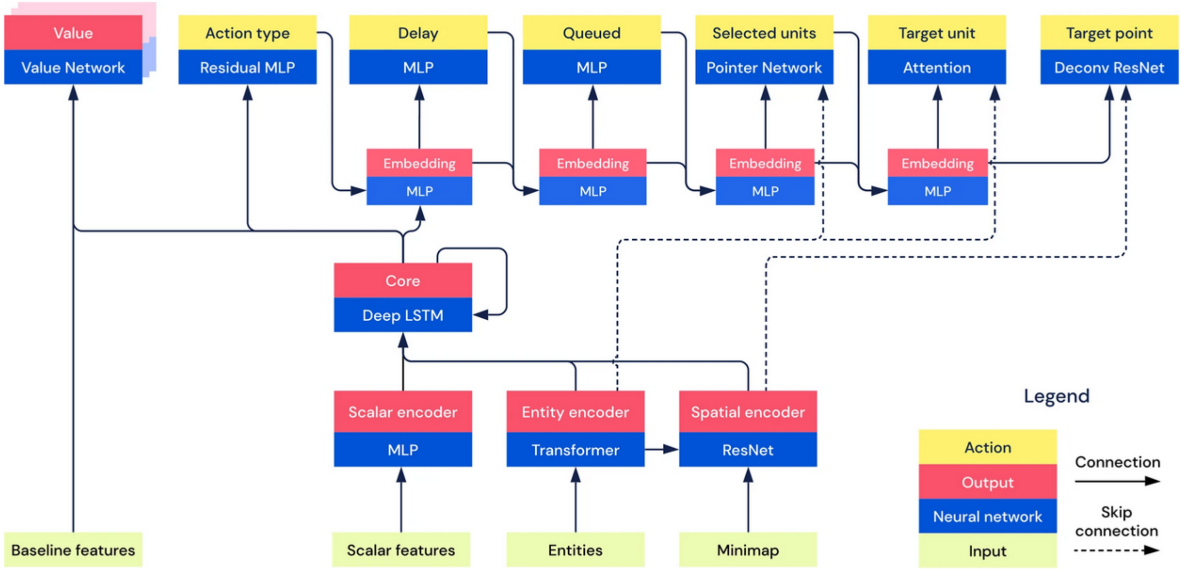
```
# build game controller
controllor = build_controller()

for replay_file in replay_files_dir:
    # get replay_info
    replay_info = controller.replay_info(replay_file)

    # 如果对战一方为虫族，并且虫族获胜，则提起此数据
    is_valid = judge_protoss_win(relpay_info)
    if not is_valid:
        continue

    #开始播放replays
    env = controller.start_replay(replay_file)
    o, done = env.reset()

    obs_list = [o]
    action_list = [function_call("no_op",[])] # action type, [queue,
selected_units, target_units, target_location]
    last_delay_list = []

    steps = 0
    while not done:
        if o.actions.type != "no_op":
            #将人类的观测o转变为agent的观测obs
            obs_list.append(transform_obs(o))
            action_list.append(o.actions[0])
            last_delay_list.append(steps-sum(last_delay_list))

         o, done = env.step()
         steps += 1

    save(obs_list, action_list, last_delay_list)
```

details

- 不考虑human interface 的camera move动作
- 每个时刻人类有多个action , 只选择第一个action
- delay的含义为过去delay之后，才执行下一个action, 中间的帧全部no_op

Supervised Learning

Model



- mathematic model

$$p(a|s) = p(a_1, a_2, a_3, a_4, a_5, a_6|s) = p(a_1|s)p(a_2|s, a_1)p(a_3|s, a_1, a_2)p(a_4|s, a_1, a_2, a_3)\cdots$$

```python
class Model(nn.Module):
    def __init__(self):
        # build encoder
        self.scalar_encoder = ScalarEncoder()
        self.entity_encoder = EntityEncoder()
        self.spatial_encoder = SpatialEncoder()

        #lstm core
        self.core = Core()

        #build action heads
        self.action_type_head = ActionTypeHead()
        self.delay_head = DelayHead()
        self.queue_head = QueueHead()
        self.selected_units_head = SelectedUnitsHead()
        self.target_unit_head = TargetUnitHead()
        self.location_head = LocationHead()

        # build all baselines
        self.winloss_baseline = Baseline(baseline_type='winloss')
        self.build_order_baseline = Baseline(baseline_type='build_order')
        self.built_units_baseline = Baseline(baseline_type='built_units')
        self.upgrades_baseline = Baseline(baseline_type='upgrades')
        self.effects_baseline = Baseline(baseline_type='effects')
```

- details 见ppt

training

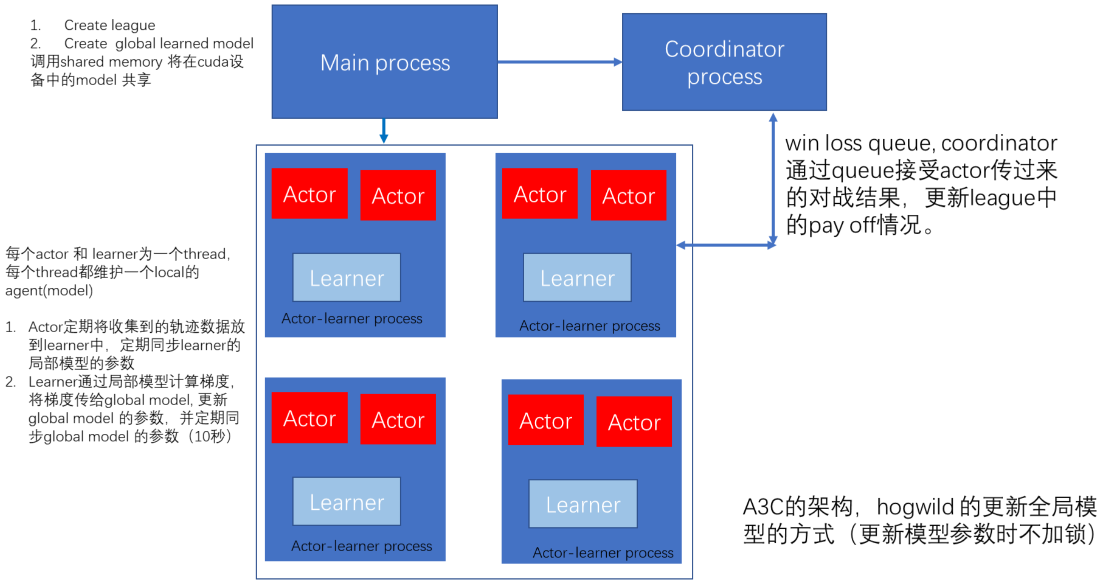
```
model = Model()
optimizer = Adam(model.parameters(), lr=1e-4)

# 对于每个replay 提取到的s1,a1,s2,a2,...,sn,an, 构建长度为4的滑动窗口, 即截断长度大于4的序列
dataloader = build_dataloader()

for feature, labels in dataloader:
    # feature: batch_size * 4 * 1056596
    # labels: batch_size * 4* 11446
    state = transform_feature(feature)
    logits = model(state)
    loss = criterion(logits, label)
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

Evaluate

[video]

RL

- 整体架构为impala/ A3C 算法



Actor

- 随机采样一个replay, 记录replay中的build order, built units, upgrades, effect信息，作为pseudo reward的依据

```

env = create_env()
obs = env.reset()

while not obs.is_final:
    state = agent.preprocess(obs)
    action_function_call, action, action_logits = agent.model(state)
```

```
    #计算teacher_logits 为损失的一部分
    teacher_logits = teacher.model(state, action) # 要将action传入，因为计算logit的过程有采样的过程，将采样的过程代替为agent的action

    #与环境交互
    next_obs = env.step(action_function_call,step_mul=action.delay) #执行delay步

    #得到输赢的稀疏奖励，只有结束的时候才为1，大部分时间为0
    reward = next_obs.reward
    # 也可以通过obs中的cummulative score字段计算一个得分,与采集资源和造兵有关，代替win loss的 sparse reward

    #计算agent建造建筑的顺序
    play_bo = calculate(next_obs)
    #此时可以同时开一个replay, 计算人类玩家的build order 两者的编辑距离为奖励

    trajectories.append((state, obs, action, action_logits, teacher_logits,player_bo, last_action))

    if len(trajectories) >= 8:
        learner.trajectories.append(trajectories)

    obs = next_obs

    if time_to_sync:
        agent.model.load_state_dict(learner.model.state_dict())
```

Learner

- **actor loss**: vtrace
- **critic loss**: td lambda (并不重采样，起到正则化的作用)
- **upgo loss**: imitation一个比当前policy更优的策略
- **KL loss**: 与teacher policy 的 KL divergence
- **entropy loss**: 增大当前policy 的 entropy

notes: 每个action head单独计算再累加， a-c loss 对5种奖励都计算，upgo loss 只对win loss reward 计算

```
trajectories: List[List[Tuple]] # traj1, traj2, traj3, 每条轨迹的长度为8

#计算每个state对应action的logits,每个action有六个logits,为action type, delay, queue, select_units, target_unit, target_location
# 每个state有5个baseline, 为winloss, build_order, built_units, upgrades, effects
#每个时刻learner使用的hidden state为action的hidden state
target_logits, baselines = agent.unroll(trajectories) #shape (nums * batch_size * seq_length)

loss =0

for baseline in baselines: #Tensor(batch_size*seq_length)
    #根据trajectories 中存储的人类数据计算每个baseline对应的奖励
    rewards = compute_pseudoreward(trajectories, baseline.name)
```

```
    #计算truncated-td-lambda-loss， lambda = 0.8
    loss_baseline = td_lambda_loss(baseline, rewards)
    loss += loss_baseline
    #计算vtrace loss
    for filed in action_fields: # action_fileds = (type, delay, queue, 
selected_units, target units, target_location)
        # trajectories 中算出对应field的mask, clipped_ratio 中 c=1
        target_log_prob, clipped_ratio = get_log_prob(target_logits, field, 
trajectories)

        weighted_advantage = vtrace_advantage(clipped_ratio, rewards, baseline)

        loss_field = -target_log_prob * weighted_advantage * mask # 可能这个field
不存在
        loss += loss_field

#Upgo Loss: imitate past good experience
# G(t) = r(t) + G(t+1) if r(t+1) + V(t+2) > V(t+1) else  r(t) + V(t+1)
# idea: 如果behaviour policy比当前好，使用behaviour policy, 如果 current policy 比
behaviour policy好，使用current policy
# 也就意味着G(t) 可以看成是一个比current policy更好的策略。
# 对每个field 单独求，也要乘clipped ratio。
loss_upgo = sum_upgo_loss(target_logits, trajectories, winloss_baseline, 
winloss_rewards)

loss += loss_upgo

# KL loss, 每个filed单独求
loss += KL_loss(target_logits, trajectories.teacher_logits)

#entropy loss
loss += entropy_loss(target_logits, trajectories)

#optimize loss
```

TD λ

考虑策略π产生的轨迹$s_0, a_0, r_0, s_1, a_1, r_1, s_2, a_2, r_2, \ldots, s_n, a_n, r_n$, 设0时刻$n$-step的值函数$V_0^n$估计为 $r_0 + \gamma r_1 + \gamma^2 r_2 + \cdots + \gamma^n V_n$， 设$\delta_t = r_t + \gamma V_{t+1} - V_t$, 则:

$$V_0^n - V_0 = \sum_{t=0}^{n-1} \gamma^t \delta_t$$

TD-λ即对于长度为n轨迹，考虑$V_0^1, V_0^2, V_0^3 \ldots, V_0^n$整合起来对$V_0$估计，具体来说给$V_0^i$一个权重，正比于$\lambda^i$,即:

$$
\begin{aligned}
V_0^{td-\lambda} - V_0 &= (1-\lambda)\sum_{i=1}^{n-1}\lambda^{i-1}V_0^i + \lambda^{n-1}V_0^n \\
&= (1-\lambda)\sum_{i=1}^{n-1}\lambda^{i-1}\sum_{t=0}^{i-1}\gamma^t\delta_t + \lambda^{n-1}\sum_{t=0}^{n-1}\gamma^t\delta_t \\
&= (1-\lambda)\sum_{t=0}^{n-2}\gamma^t\delta_t\sum_{i=t+1}^{n-1}\lambda^{i-1} + \lambda^{n-1}\sum_{t=0}^{n-1}\gamma^t\delta_t \\
&= (1-\lambda)\sum_{t=0}^{n-2}\gamma^t\delta_t\frac{\lambda^t(1-\lambda^{n-1-t})}{1-\lambda} + \lambda^{n-1}\sum_{t=0}^{n-1}\gamma^t\delta_t \\
&= \sum_{t=0}^{n-2}\gamma^t\delta_t(\lambda^t-\lambda^{n-1}) + \lambda^{n-1}\sum_{t=0}^{n-1}\gamma^t\delta_t \\
&= \sum_{t=0}^{n-1}\gamma^t\lambda^t\delta_t
\end{aligned}
$$

Vtrace

Vtrace

Upgo

设当前网络为$\pi_\theta(a|s)$, 值为$V_\theta(s)$，behavior policy 为$\pi_b(a|s)$， 注意behavior policy 可能有多个，不唯一，基于behavior policy产生的trajectories为$s_1, a_1, r_1, s_2, a_2, r_2, \ldots, s_n, a_n, r_n$, UPGO 定义：

$$
G_t = \begin{cases} r_t + G_{t+1} & \text{if } r_{t+1} + V_\theta(s_{t+2}) > V_\theta(s_{t+1}) \\ r_t + V_\theta\left(s_{t+1}\right) & \text{otherwise} \end{cases}
$$

并优化

$$
\sum_t \frac{\pi_\theta(a_t|s_t)}{\pi_b(a_t|s_t)} \cdot (G_t - V_\theta(s_t)) \cdot ln\pi_\theta(a_t|s_t)
$$

定义这样一个新的policy:

$$
\pi_{new}(a|s) = \begin{cases} 1 & \text{if } s, a \text{ in trajectories and } Q_\theta(a|s) > V_\theta(s) \\ \pi_\theta(a|s) & \text{otherwise} \end{cases}
$$

显然，π_{new}是π_θ的一个improvement，并且$Q_{new}(a_t|s_t) >= E(G_t)$, 所以，$G_t$可以看成是$Q_{new}(a_t|s_t)$一个比较估计。

根据soft q-learning 和 policy gradient 的关系可知，优化

$$
E_{s,a\in\pi_\theta}\left(ln\pi_\theta(a|s)[Q_{new}(a|s) - V_\theta(s)]\right)
$$

等价于优化

$$
E_{s,a\in\pi_\theta}(Q_{new}(a|s) - Q_\theta(a|s))
$$