AlphaGo board implementation

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In this assignment, I implemented a Go board with alphago-compatible game states according to the guide by Zhijun Sheng on medium.com.

Output Screenshots

```
Board state before move 25 by Player.black:

*-----*

9 | . o . . . . . . . . |

8 | . o . . . . . . . . |

7 | . . . . . . . . . . |

5 | . . . . . . . . . . . |

4 | o x . . . . o . . . . |

2 | . . . . . . . . . . . . |

1 | 1 | . . o o . . . . x |

*-----*

A B C D E F G H I

(I, 1) is an eye.

Turn 25 Player.black (x) places at (H, 5)
```

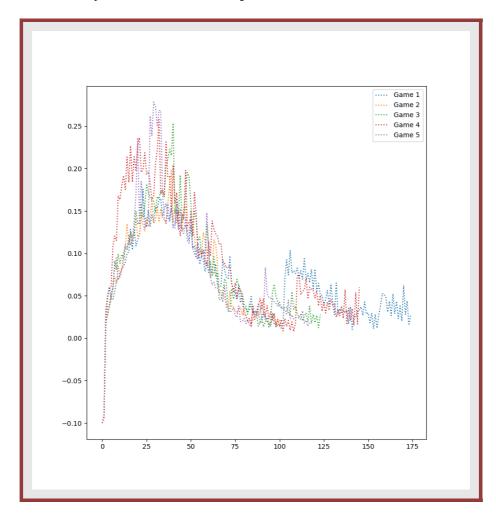
Early stages of a bot-vs-bot game

Board		st	at	te	ь	f	ore	= r	nov	/e	49	95	ьі	J F	Pla	aye	r	ь.	l a	ck	
19		X	×	X	0	0			0	0	0	0		×	×	×	×	X	X	×	Ī
18		×	×	0	0	×	0	0	0		0	0	0	×	X	×		×	×	×	1
17		×	×	×	×	×	X	X		0	0	0	X	X	X		X	×	X	×	1
16		x-		×		×	0	0	0	0	X	x	X		X	X	×	x	×	×	T
15 I		0	×	×	X	×	0			0	X		X	X	×	×	×	X	×	×	. 1
14			×	×	0	0	0	0	b	0	X	X	×	X		×	×		×		1
13		0+	0		0		0		0		0	0	X	X	X	X		X	×	×	ü
12		0	×	×	0		0	0	0	0		0	×	X	X	X	×	×	×	×	Ī
11				×	×		0				0	×	×		X	x	×	X	×		1
10			0	×	0	0	0			0	×	×	0	X	X	X	×	X	×	×	1
9 1		0	×	×			0		0			0		X	×	X	×	×	×	×	ï
8 1		×	×	0	0	0	0	0		0	0	0	×	X	×	X	×	×	×	×	ī
7.1		×	×	×	0	0		0		0	×	×	×	X	×	×	X	×	×	×	1
6 1			×	×	X	0	0	0	0	0	0	×		×	×	×	X		×		1
5 1		×	×	×	X		0		0	0	X	X.	X	X		×	×	X	×	X	4
4 1		×	×		×	X	0	0	X	0	X		X		X	X	X	X	X	X	1
3			×	×	X				X	X	X	×	X	X	X	X	X	X	X	X	. 1
2		×	×	X	X	0	X	X	X	X	X		×	X	X	X		X	X	X	1
1			×		X	×	X		X	X		X	X	X		X	X	X	X		ı
	E —	-						-			-		-		-	-		-	-		
		А	В	C	D	Е	F	G	Н	1	J	K	L	М	И	О	P		R	S	

Final state of a bot game on a 19x19 board.

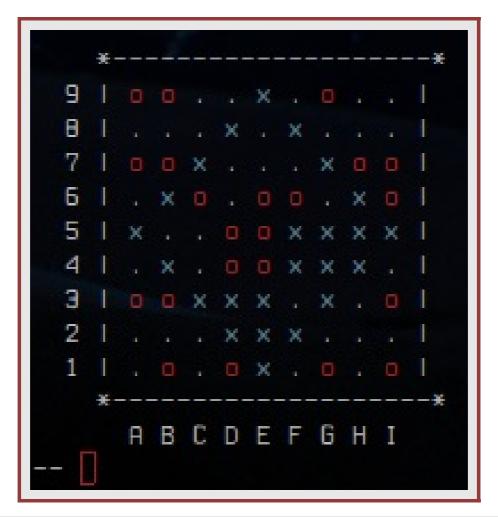
Even with zobrist hashes, the combinatorial explosion of conditions that needed to be checked on each move slowed 19x19 bot games to a halt on my machine, so most of my testing involved 9x9 boards.

As the number of valid moves decreases in the late game, the combinatorial possibilities diminish, causing move frequency to speed back up. The following figure shows the interval of time between moves by each bot with respect to the total number of moves.



Turn time interval wrt move count

I also implemented a human-vs-bot version of the Go game according to the guide. The following is a sample of a game where I tried to claim the entire center of the board (despite the fact this is very inadvisable when playing Go for victory).



Analysis of AlphaGo architecture and comparison to human gameplay

Original implementations of AlphaGo by Google's DeepMind team were initially trained on human gameplay data before being transitioned to learn by playing against itself. The model is a residual convolutional network which uses a 19x19x17 binary matrix with a 19x19 board state matrix for each of the players, a 7-state feature map for each player's history, and an additional 19x19 grid containing a uniform bit indicating the turn.

The output feature vector of the network is used to generate a value representation - a float between zero and 1 - predicting the likelihood of winning the game given the current state, and a policy vector which evaluates the quality of all available moves.

After each real stone placement, the Monte-Carlo tree search component of AlphaGo selects several of the highest-probability moves from the policy vector and repeats the process of evaluating each of the options until ~1,600 hypothetical game states have been tried.

Ultimately, the network chooses the move that optimizes the future value representation.

AlphaGo is especially effective against humans for a few reasons. First, Go is a perfect information game (each player has instant knowledge of the entire game state at every stage, which enables the network to fully simulate future game states without the influence of free uncertain parameters. Additionally, Go is a heavily combinatorial game, with more than 2.081E170 valid game states (for reference, chess has roughly 4.5E46 valid games states). In games like this, humans rely heavily on tradition and heuristics. AlphaGo, on the other hand, is simply able to evaluate vastly more future game states than humans are capable of. Even in early game stages when humans are playing standard opening moves, AlphaGo is known to make stone placement decisions that humans would rarely consider, and which impact the short-term future states of the game in ways that seem unpredictable to human players. For example, the latest iteration of AlphaGo (AlphaGo Zero) was trained entirely using gameplay against itself - no human data whatsoever. Initially, it rediscovered openings (like 4/5 and 3/3) commonly used by humans, but ultimately diverged from these and discovered abstract and highly state-sensitive openings that humans rarely if ever used, but which were shockingly more effective.

Implementation screenshots

```
from gogame.goboard import GameState, Move
from gogame gotypes import Player, Point
from gogame.agent.naive import RandomBot
from gogame.utils import start_bots_game, update_times
freq = .1
timefile = "/home/krttd/uah/22.s/cs430/hw3/turn_times.pkl"
capture_sequence = [
   Move.play(Point(row=5, col=10)),
   Move.play(Point(row=6, col=10)),
   Move.play(Point(row=5, col=11)),
   Move.play(Point(row=6, col=11)),
   Move.play(Point(row=5, col=9)),
   Move.play(Point(row=1, col=1)),
   Move play(Point(row=6, col=12)),
   Move.play(Point(row=2, col=1)),
   Move.play(Point(row=7, col=10)),
   Move.play(Point(row=3, col=1)),
   Move.play(Point(row=7, col=11)),
   Move.play(Point(row=4, col=1))]
if __name__=="__main__":
   for i in range(5):
      times = start_bots_game(
           board_size=size,
           update_freq=freq,
         bot_a=RandomBot(size),
           bot_b=RandomBot(size),
       update_times(times, timefile)
```

```
from gogame.agent.naive import RandomBot
from gogame.goboard import GameState, Move
from gogame.gotypes import Player
from gogame.utils import print_board, print_move, point_from_coords
def start_game():
    board_size = 9
    game = GameState.new_game(board_size)
    bot = RandomBot(board_size)
   while not game.is_over():
print(chr(27)+"[2J")
       print_board(game.board, False)
       if game.next_player == Player.black:
         human_move = input("-- ")
           point = point_from_coords(human_move.strip())
           move = Move.play(point)
          move = bot.get_move(game)
       print_move(game.next_player, move, c)
        game = game.apply_move(move)
    start_game()
```

```
self._grid = {}
self._hash = zobrist.EMPTY_BOARD
     return self._nrows
def get_col_count(self);
def put_stone(self, player, point, real_move):
    # Make sure the provided point is unoccupied and on
     assert self.is_on_grid(point)
assert self._grid.get(point) is None
     adjacent_opposite_color = []
      for neighbor in point.neighbors():
          if not self.is_on_grid(neighbor):
          neighbor_string = self._grid.get(neighbor)
if neighbor_string is None:
               liberties.append(neighbor)
          elif neighbor_string.color == player:
               if neighbor_string not in adjacent_same_color:
                   adjacent_same_color.append(neighbor_string)
              if neighbor_string not in adjacent_opposite_color:
    adjacent_opposite_color.append(neighbor_string)
     new_string = GoString(player, [point], liberties)
          new_string = new_string.merged_with(same_color_string)
     for new_string_point in new_string.stones:
     self._grid(new_string_point) = new_string
self._hash ^= zobrist.HRSH_CODE(point, player)
     for other_color_string in adjacent_opposite_color:
    replacement = other_color_string.without_liberty(point)
               self._replace_string(replacement)
              self._remove_string(other_color_string, real_move)
          other_color_string.remove_liberty(point)
def _replace_string(self, new_string):
    """ Replace an entire former string with a new one. """
```

```
def __init__(self, board, next_player, previous, last_move):
    self.next_player = next_player
    self.previous_state = previous
    self.last_move = last_move
   if self.previous_state is None:
       self.previous_states = frozenset()
        self.previous_states = frozenset(previous.previous_states |
               {(previous.next_player, previous.board.zobrist_hash())})
def new_game(cls, board_size):
       board_size = (board_size, board_size)
   board = Board(*board_size)
    return GameState(board, Player.black, None, None)
def apply_move(self, move):
       next_board = copy.deepcopy(self.board)
        next_board.put_stone(self.next_player)
      move.point, real_move=True)

If the next move doesn't invalid
        next_board = self.board
    return GameState(next_board, self.next_player.opponent, self, move)
def is_over(self):
    if self.last_move is None:
       return True
    second_last_move = self.previous_state.last_move
    if second_last_move is None:
    return self.last_move.is_pass and second_last_move.is_pass
    if self.is_over(): return False
if move.is_pass or move.is_resign:
    return self.board.get_stone(move.point) is None \
            and not self.does_move_violate_ko(self.next_player, move)
def is_move_self_capture(self, player, move):
    if not move.is_play: return False
   next_board = copy.deepcopy(self.board)
    new_string = next_board.get_go_string(move.point)
    return not new_string.num_liberties
```

```
@property
def situation(self):
    """ Return a tuple wrapping the player and the board state """
    return (self.next_player, self.board)

def does_move_violate_kb(self, player, move):
    """ Determine if a move sequence has been repeated """
    if not move.is_play: return False
    next_board = copy.deepcopy(self.board)
    next_board.put_stone(player, move.point, real_move=False)
    next_sit = (player.opponent, next_board.zobrist_hash())
    return next_sit in self.previous_states
```

```
ass Move():
    """ Class representing all possible game actions """
   def __init__(self, point=None, is_pass=False, is_resign=False):
    assert (point is not None) ^ is_pass ^ is_resign
       self.is_play = self.point is not None
       self.is_pass = is_pass
       self.is_resign = is_resign
   @classmethod
def play(cls, point):
       return Move(point=point)
   @classmethod
   def pass_turn(cls):
        pass_turn(cis):
""" Return a pass move. """
        resign(Cls):
""" Return a resignation move. """
return Move(is_resign=True)
   def resign(cls):
       return Move(is_resign=True)
class Board():
   def __init__(self, row_count, col_count):
       self._nrows = row_count
       self._grid = {}
self._hash = zobrist.EMPTY_BOARD
   def get_row_count(self):
   def get_col_count(self):
```

utils code

```
# Maps each player to their stone character
stone_to_char = {
    None: ',
    Player.black:Fore.BLUE+'x'+Fore.WHITE,
    Player.white:Fore.RED+'o'+Fore.WHITE,
    Player.white:Fore.RED+'o'+Fore.WHITE,
    }
}

# Print the current board state. Rssymes board is square
def print_board(board, clear_on_move=True):
    cols = [chr(ord('@')+n) for n in range(l,board.get_row_count()+i);
    if clear_on_move: print(chr(??)+"[2J'])
    print(4*' '* '* 'cboard.get_col_count()+i)* '--'+"*')
for i in range(board.get_row_count(), @, -1):
    line = []
    for j in-range(l, board.get_col_count()+i):
        stone = board.get_stone(Point(i,j))
        line.append(stone_to_char[stone]+")
    print(f(':3) i (', 'join(line))!")
    print(4*' '+'*'+(board.get_col_count()+i)*'--'+"*")
print(6*' '+' 'join(cols))

# Print this player and their move
def print_move(player, move, turn):
    "" print string describing the next move .""

if move.is_pass: move_str = "passes this turn"
    elif move.ls_resign: move_str = "rasses this turn"
    elif move.ls_resign: move_str = "rasses this turn"
    elif move.ls_resign: move_str = "rasses this turn"
    elif move.ls_resign: move_str = "cast_ns"
    else: move_str = f'(move_point.col_letter()), (move_point.row))"
    print(f'Turn (turn) (player) ((stone_to_char[player])) places at (move_str)")

def update_times(turn_times, timefile):
    with open(timeffile, "rb") as timefp:
    times = pkl.load(timefp)
    times.append(turn_times)
    with open(timeffile, "ub") as timefp:
        pkl.dump(times, timefp)
```

```
rom .gotypes import Player, Point
_all__ = ['HASH_CODE', 'EMPTY_BOARD']
    (Point(row=1, col=1), Player.white): 5059206809261739078, (Point(row=1, col=2), Player.black): 5006050773891761297,
    (Point(row=1, col=2), Player.white): 5259041124309758012,
    (Point(row=1, col=3), Player.black): 477898242865825586,
    (Point(row=1, col=3), Player.white): 5584287647338898939, (Point(row=1, col=4), Player.black): 5894800554688549930,
    (Point(row=1, col=4), Player.white): 3537721230578135479, (Point(row=1, col=5), Player.black): 4276519715013619409, (Point(row=1, col=5), Player.white): 2299044865014256982,
    (Point(row=1, col=5), Player.black): 5537841095575436401,
    (Point(row=1, col=6), Player.white): 4933952713071908042, (Point(row=1, col=7), Player.black): 5391828484223924812,
    (Point(row=1, col=8), Player black): 4588415496171865816, (Point(row=1, col=8), Player white): 447972796156814551, (Point(row=1, col=9), Player black): 8234134455318916159,
    (Point(row=1, col=9), Player.white): 0560110109950989353,
    (Point(row=1, col=10), Player.black): 5729324340188812510, (Point(row=1, col=10), Player.white): 4147802528503838558,
    (Point(row=1, col=11), Player.black): 842466009992063129, (Point(row=1, col=11), Player.white): 83930962983764159, (Point(row=1, col=12), Player.black): 6098825418620661069,
    (Point(row=1, col=12), Player.white): 3758778469821183445, (Point(row=1, col=13), Player.black): 4486425757899855554, (Point(row=1, col=13), Player.white): 2982368772862751228,
    (Point(row=1, col=14), Player.black): 7979598031999474789, (Point(row=1, col=14), Player.white): 7909158663214286314, (Point(row=1, col=15), Player.black): 3109297293426772277, (Point(row=1, col=15), Player.white): 4449806350897963898,
    (Point(row=1, col=16), Player.black): 6659405935430007340, (Point(row=1, col=16), Player.white): 691150618054807320,
    (Point(row=1, col=17), Player.black): 4360404964072595876,
    (Point(row=1, col=17), Player.white): 3578928140360233120, (Point(row=1, col=18), Player.black): 887213122545822875, (Point(row=1, col=18), Player.white): 4319259250687696416,
    (Point(row=1, col=19), Player.black): 9123139402105021339, (Point(row=1, col=19), Player.white): 4726219459777586225,
    (Point(row=2, col=1), Player.black): 416153434590373417,
    (Point(row=2, col=1), Player.white): 8910670344132932378, (Point(row=2, col=2), Player.black): 4661950264302637053, (Point(row=2, col=2), Player.white): 7553068695651571216,
    (Point(row=2, col=3), Player.black): 7567347697021677886,
    (Point(row=2, col=3), Player.white): 515641553151291071, (Point(row=2, col=4), Player.black): 4844278315241465689,
    (Point(row=2, col=4), Player.white): 1503432405700872709,
    (Point(row=2, col=5), Player.black): 7851888194925528288, (Point(row=2, col=5), Player.white): 3576544879862918919,
    (Point(row=2, col=5), Player.black): 1313084040348167561,
    (Point(row=2, col=6), Player.white): 3425209199765721605, (Point(row=2, col=7), Player.black): 2802188139385482073,
    (Point(row=2, col=7), Player.white): 8506417616825360340,
    (Point(row=2, col=8), Player.black): 580850731873902171, (Point(row=2, col=8), Player.white): 8680698093383335843,
    (Point(row=2, col=9), Player.black): 3617607699978684931,
     (Point(row=2, col=10), Player.black): 4784491323483384969,
    (Point(row=2, col=10), Player.white): 5317263329063746477,
     (Point(row=2, col=11), Player.black): 349987563015686602,
     (Point(row=2, col=11), Player.white):
```