Implementing neural networks with tensorflow report

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February 28, 2017

Abstract

The aim of this project is to create a virtual Texas Hold'em player by using a convolutional neural network, based on the paper "Poker-CNN: a pattern learning strategy for making draws and bets in poker games" [1] by Yakovenko, Nikolai et. al. The aim is to imitate human poker-playing behaviour, including bluffing, as close as possible - a task where current, non neural network based poker bots usually fail.

1 Introduction

Unlike other games such as chess or checkers, poker provides an especially challenging task for computer players (bots). That is because poker contains a very "human" component aside from its set of rules: the bidding, raising, the bluffing. Where other games only provide a reward upon successfully winning them, the reward itself is a key element of the poker turn structure. Furthermore, since Texas Hold'em poker can be played with up to 9 people at a regular game, the state space grows to an enormous size. All these factors lead to the fact that current bot implementations usually are rather weak. Confronted with a human player, these bots have the huge disadvantage of being predictable: They often show repetitive behaviour and are bad at bluffing [CITATION NEEDED, genaue player anfhren]. Due to these barriers, the team of Yakovenko, Nikolai et. al. developed a CNN based approach that aims at surpassing the current implementations and even competing with human tournament players [1]. As their data source, they used simple bots to generate a large training and validation set. Learning only from the successful games, the CNN should afterwards be easily able to surpass the weak bots.

2 Poker-CNN: A Pattern Learning Strategy for Making Draws and Bets in Poker Games

2.1 The original paper

In the paper "A Pattern Learning Strategy for Making Draws and Bets in Poker Games"[1] the authors propose a convolutional neural network, which should be adaptable for all poker variants under the hypothesize that poker games can be described as a pattern matching problem. The poker network learns through iterative self-play and improves using the results of its previous actions for training. The main challenges for a data driven approach like this one, is to find a good representation of the game (which can be adapted to several poker games) and to arrive at a sophisticated result using self-generated, imperfect data.

In order to solve the first challenge, the authors introduce a unified representation of poker games. To encode the game state into a form which can be used in a convolutional network the game information is described in different matrices. There are 13 ranks of poker[1] cards and 4 different suits[2], so each card is represented in a 4 x 13 sparse binary matrix, where only one element is non zero. To capture the full hand information a further layer is added, the sum of the previous layers. The advantages in doing so are: a large input builds a good base for a CNN and the full hand representations makes it easier to model common poker patterns, "without game specific card sorting or suit isomorphisms

[1] 2,3,4, ..., J,Q,K,A

[2] club, diamond, heart, spade

(e.g. AsKd is essentially the same as KhAc)".[1] Because poker is not only expressed in cards, context information need to be passed to the CNN as well. For example the number of chips in the pot is represented as a numerical coded 4x13 matrix, where the minmal amount is coded similar to the smallest poker card and the maximal amount[3] is encoded as a binary matrix (entails only ones). A binary 4x13 matrix (two-player games) is used to represent the position, hence it entails whether the system is first to bet. Further layers are added, which are not relevant for Texas Hold'em. Each matrix is finally zero padded to a 17x17 matrix to ease the convolutions and max pooling. The whole Yx17x17 tensor is used as input. In section 2.2 we discuss our extended representation for Texas Hold'em no Limit Cash Game.

Different poker games usually consist of either betting or draw actions, in rare cases there are both type of actions.

Draw actions are defined as actions in which the player has the option to replace one or more of his cards with a new drawn card. The task for a neural network concerning draws is to estimate the return of every possible card replacement and select the one with the highest output. Yakovenko, Nikolai et. al. employed Monte Carlo Sampling to first generate 250000 poker hands and simulate the expected outcome for each possible draw, for each of these hands.

While the 250000 hands are encoded into the input tensor, the expected outcome will serve as label. The authors did train three different networks: a fully connected neural network, a convolutional layer with a filter size of 5x5 and a convolutional neural network with the filter size of 3x3. The latter one outperformed the other two, hence we used this one as basis. Further details of the network will be discussed in section 3.

Betting actions on the other hand are defined as action in which the player evaluates the win chance of his current hand and places a corresponding amount of chips. If he sees no winning chance at all he can quit the round in which he also loses his already placed bets. Important to notice is that players don't has to be honest about his hand and may raise (bet a higher amount of chips than the previous players) regardless in order to bluff the other players into folding. Due to this fact there is often not "one" right move. Players often vary their actions although their cards might be similar.

In the case of Texas Hold'em limited Poker, which was used in the paper as trainings example, the player has 5 betting actions:

Check - bet nothing, but keep playing), which is only possible if their are no bets in this round so far

Bet - start to actually put something in the pot

Raise - set a higher amount of chips than the previous players

Call - match the bet of the previous players

Fold - give up the current hand

Due to this different options the expected outcome can not simply be estimated by Monte Carlo sampling. Thus for each training hand several epochs of this hand were simulated using simple heuristic bots, which adjusted their

[3] 4*13*minimal amount (small blind), everything higher than this is encoded identical

winning chance according to the previously simulated allin probabilities. Once again the expected outcome of this simulation was used as label for the respective hand. Overall 500000 hands were used for training.

As a result the CNN was finally able to outperform the bot used for training and was even competetive against a human expert.

2.2 Input adaption for (regular) Texas Hold'em

Texas Hold'em Poker is one of the most popular poker variants existing and hence we wanted to examine how the CNN would be able to perform when trained on it. In fact Yakovenko, Nikolai et. al. already implemented Texas Hold'em as training data set, but they used a simplified version.

Our initial goal was to implement the CNN on training data containing the game states of (regular) "9 player Texas Hold'em no Limit (cash-game)". The main difference hereby aside from the player count is that in limited poker the player may only bet and raise a fixed amount.

In general Texas Hold'em consists of 4 betting rounds. At first each player gets 2 cards, known as hole cards and the first betting round begins. Afterwards 3 community cards (the flop) are drawn which are visible for everyone and constitute the current hand of each player together with their respective hole cards. The next betting round starts and the game continues with the drawing of a single community card and the following betting round which will be repeated once more (the turn and river). The 5 best cards out of this 7 constitutute the hand of each player and determines the winner.

Instead of using a 4x13 matrix for each indivudal card we used one matrix for each round. Thus the first 4x13 matrix has two elements different than zero, the second one has 3 and the others have one, respectively. Hence the network shouldn't differentiate between the sequence of cards entailed in one round (e.g. 5s5c is identically to 5c5s). The layer containing all cards information (the sum of the previous 7) will be kept. Furthermore using one binary matrix as input is no longer sufficient. A 9x9 matrix will be used instead, where each row despite one will be zero. The row filled with ones marks the position (who is first to bet). Another 9x9 matrix entails information about the state of the other players, if the respective row is 1 they are still active and didn't fold yet. Additional to the numerical coded amount of chips in the pot a second similarly coded matrix containing the amount of chips placed in the current betting round is needed. We assume that a really competetive Player would need more information but assumed that this would increase the learning phase. The final representation is a 9x17x17 tensor, summarized in Table 1.

3 The CNN architecture

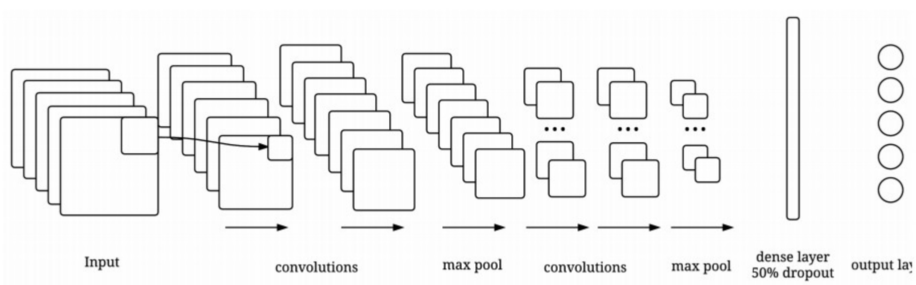
The convolutional neural network that was used within this project has an architecture similar to the original CNN from the paper[1]. The input data is

Feature	Num. of matrices	Description
xCards	4	Hole cards (Individual private cards)
	1	All cards together
xPosition	1	Player first to bet
xActivePlayers	1	Players active (did not fold)
xPotSize	1	Number of chips in the round
xRoundSize	1	Number of chips added in this phase

Table 1: Features used as inputs for Texas Hold'em no Limit Poker

formatted as a 17x17x9 3-dimensional tensor, including all blablablubb [Wie zum Geier sieht denn nun unser Format eig. aus?]

Figure 1: Network structure



Bibliography

[1] Yakovenko, Nikolai, et al., *Poker-CNN: a pattern learning strategy for making draws and bets in poker games.*, arXiv preprint arXiv:1509.06731 (2015).