

VRNN 2018 - Predicting legal chess moves

”Chess is the struggle against the error.”

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Abstract

One of the recent problems that gained a lot of attention in Deep Learning field was playing Go and Chess at the professional level. The models for those problems are assigning the probability of the win for certain moves and positions where the moves are generated deterministically. In our work we are checking if it is possible to learn a CNN network the rules of chess providing only image of the board before and after the move. We test two different models architectures: single CNN model which processes two input images as one concatenated; and Siamese CNN model which takes two images separately, extracts features and combines them together predicting the result. Those two approaches achieve $\sim 90\%$ on training set and $\sim 86\%$ on validation set.

1. Introduction

Recent achievements in Deep Learning allowed researchers to beat top players in Go and Chess using Deep Learning models[3]. To learn such a model authors have used techniques like Reinforcement Learning and Deep Convolutional Neural Networks to predict win percentages for given positions. Those models rely on deterministic move generation and known encoding of position.

In our work we wanted to change the perspective of playing Chess. We wanted our model to learn Chess rules without prior definition of what they are and what is the purpose of the game. This is exactly what people, who did not see games like Chess or Go before, do when they see two other players playing those games – they try to understand the possibilities, rules and purpose of the game just by looking at how the players move.

We believe that this problem is super important. If model can learn the rules of Chess, maybe it also can learn the rules

of the world. Long standing question about single formula describing the world could be solved by CNN. It is still long way ahead of us but we believe we can make it and our work is first step towards this achievement.

2. Related work

We have struggled to find any papers or work done in this area. All the papers we have found, are targeting learning model to evaluate positions but not how to play the game. In end-to-end chess playing paper [1] authors discuss a model to not only evaluate positions but also determining if the move is correct. We have used the key insights from the paper to improve our models architectures. Another paper about predicting Chess moves [2] provided us a lot of useful information about using and not using different types of layers in our models.

3. Data

Chess is deterministic game and the moves as well as positions can be easily generated and encoded.

Data used in our experiments was generated using python chess library¹ which allowed to save given position as images which then we converted into numpy arrays². We have created framework for generating random data with different outputs which were necessary for different types of models we have tested. The data was generated from random plays as well as positions and moves from book games³. We have combined these two sources into datasets on which our models were trained and tested. This way we wanted prevent our model from overfitting on specific types of plays. Illegal moves were created randomly but putting

¹<https://github.com/niklasf/python-chess>

²<http://www.numpy.org>

³<https://www.ficsgames.org/download.html>

pieces in empty spaces on currently processed chess board. The ratio of legal and illegal moves was around 50–50.

To train the models we have generated around 15 datasets with different random vs book games ratio each of them containing about 5'000 moves. In total we gained about 70'000 moves to train on.

4. Methods

In our approach, we tried two different type of CNN models.

4.1. Single CNN model

One of the first models we trained is CNN model which consists of couple convolution layers followed by the fully connected layers⁴. The model, as an input, was feeded with concatenated images: before and after move. In this model we wanted to check if convolution layers can extract more features having more information.

4.2. Siamese CNN model

Siamese CNN model consists of two identical CNN networks which output was then concatenated and passed to the fully connected layers⁵. This model was feeded with two inputs: image before and after move. Our understanding was that the model should independently extract features of each of the image and in the output have some kind of encoding which then was feeded to fully connected layers.

4.3. Deterministic encoding

In our last method we tried to see what accuracy can we achieve if we pass encoding of the chess board to fully connected layer without need of extracting features by convolution layers. This experiment was to see what is the bottleneck: too shallow representation of features extracted by convolution layers or fully connected layers. A term deterministic encoding means a chess board, encoded as $\{0, 1\}$ vector of length 768 – there are 12 different pieces (number of colors * number of pieces) each of them can occupy one of 64 positions.

4.4. Color vs gray scale

In the beginning, we used colorful images (3 channels). We suspected that the networks could have been learning specific features depending on color. We then started generating images in gray scale (1 channel). Unfortunately, we did not observe any improvement and thus came to conclusion that our convolution layers must have been generalizing quite well.

⁴Single model architecture: http://students.mimuw.edu.pl/~jm360338/vrnn2018/model_single.png

⁵Dual model architecture: http://students.mimuw.edu.pl/~jm360338/vrnn2018/model_dual.png

5. Experiments

In the experiments we have tried different approaches for different types of models. In both types of models as well as deterministic encoding we achieved $\sim 86\%$ on validation set.

Interestingly, the deterministic encoding had similar accuracy as the other models what suggest that convolution layers did a great job in extracting features and the bottleneck in the accuracy was caused by fully connected layers. Worth noting is the fact, that thanks to the compact encoding representation, we were able to train a network on a much bigger dataset of roughly 200'000 moves. However we observed that it did not have significant impact on results, as final accuracy reached $\sim 87\%$. With this information we tried to implement different set of fully connected layers but without further success. We decided to not go further with this part of a project, as this is out of the course's scope.

5.1. Method comparison

Method	Dataset size	No. epochs	Accuracy
Single	15'000	10'000	50%
Siamese	70'000	4'000	86.2%
Single gray scale	10C	21C	87%
Deterministic encoding	200'000	10'000	87%

6. Conclusions

At the very beginning of the project, its goal was to solve a problem of pattern recognition and logical reasoning based on rules of Chess. We did not accomplish any significant results taking into consideration solely the given task. However, our experiments turned out to be successful in terms of image recognition problem.

Our project contributed to show that logical reasoning is a hard problem even if it is limited to very specific use case. It shows that well crafted convolution neural network successfully extracts desired features from images, even when a loss function describes abstract concept, like legality of chess move, rather than simple idea like a class of an object on an image. The image recognition overhead is relatively small (~ 1 -2 percentage points), compared to perfect representation of deterministic encoding.

There are plenty of opportunities for further work. They include, but are not limited to:

- testing proposed solutions on better hardware and much larger datasets, as we provide a convenient way to generate almost unlimited dataset,

- evaluating our CNN solution with better designed neural network for logical reasoning part.

References

- [1] E. David, N. S. Netanyahu, and L. Wolf. Deepchess: End-to-end deep neural network for automatic learning in chess. *CoRR*, abs/1711.09667, 2017.
- [2] B. Oshri. Predicting moves in chess using convolutional neural networks. 2015.
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