

# Deep Learning predicts Loto Numbers

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## Abstract

Google's AI beats a top player at a game of Go. This news arrived on the 27th of January symbolizes a revolution in the machine learning community. Has deep learning any limit? To test those limits, we applied it to what we thought was an impossible problem: the lottery. The goal is to predict the next draw with regard to the past. With respect to existing models, deep learning gave very impressive results. It is able to capture an underlying structure of the problem and the results are very conclusive. We leave you this paper to contemplate the possibilities behind deep learning. Has the loto problem been solved? The answer is yes.

Deep Learning has proven its ability to solve many different problems from handwriting and speech recognition to computer vision. The structure of the algorithms is based on a reproduction of the human brain, which is known to be the most powerful engine. It is able to capture the latent structure in any dataset as a human being could and the results seem somehow magical for someone who is not familiar with this class of algorithms. The main purpose of this paper is to test its limits. After a great success in Go, the next step is simply to test whether deep learning is able to deal with randomness. It looks feasible because *God does not play dice*, see [Einstein, 1933]. Go is indeed a pure combinatorial problem and it may merely be reduced to a computational and optimization task. Randomness is conceptually more interesting and cannot be reduced to few dimensions: a higher dimensional model is required.

We propose in this article a new model to predict lottery numbers by using the past as training set. The paper is organized as follows: In section 1, we present the problem and general considerations about deep learning. The model is presented in section 2 and the results are in section 3. The remarkable performances call for a discussion which is in section 4. We conclude by describing our future works.

## 1 Background

### 1.1 Lottery

Loto is a famous and widespread game involving randomness. The first lotteries are not clearly established but it is mentioned in [*Holy Bible*, 50] and the Han dynasty used it to finance the construction of the Great Wall of China. The lottery principle is very easy: people buy a ticket which corresponds to a combination bet over a general set of numbers. A draw is eventually done at a fixed date and time. The gains are related to how the combination matches the draw and the jackpot is won if the combination is correct.

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In this study, we focus on the Mega Millions Lottery, which is the biggest lotto in the world. It started as the *Big Game* and was renamed in 2003. In our study, we used the data from after the change. 5 balls are drawn between 1 to 75 without replacement and a last ball (the **Mega Ball**) is drawn between 1 to 15.

The mathematical study of lottery is as old as mathematics. The first attempts concerned the calculations of the odds. It is crucial in order to design the lottery. Even Leonard Euler worked on that subject and these studies led to the Theory of Probability done by Kolmogorov [Kolmogorov, 1933]. Few works try to solve the much more difficult problem which of predicting the draws. A recent paper [Claus et al., 2011] investigates the behavior of the players by an economic perspective and gives interesting insights to a better play. However, it would be more useful to get the true numbers. Some esoteric authors tried various methods such as alchemy or hypnosis but the results are, by definition, erratic because they are not based on scientific methods. Those controversial methods are often used by economic forecasters to predict GDP.

## 1.2 Deep Learning

Deep learning is a particular field in Machine Learning that is driven by an abstract representation of reality. The structure is close to those of the famous neural networks: the idea is to mimic the human brain, which is known to be very efficient in learning. A large number of layers with non-linear processes between them are used: the deeper the network is, the more complex structures it can capture. The first machine learning algorithms appeared in the 1950s and their development is clearly related to computational-power improvements.

Predicting Loto numbers is a supervised task: the collected data, in the present case based on the past draws, are used as inputs. The model is a neural network whose parameters are tuned according to the data during the training phase. Training is often difficult in neural networks, due to vanishing or exploding gradients. This is the main problem in these algorithms. At each pass over the data, the parameters are optimized and, after convergence, the validation set is used to compute the validation error.

## 2 Model

The features retained are firstly, at each draw time, the quarterly GDP, the quarterly unemployment rate, the American President (Obama or not), the day, the month and the year. To this, we added the number of times each number was drawn during all past draws and the cross presence matrix defined as the number of times every pair of numbers appeared together. For the number of times each number was drawn and the cross presence matrix, they were set to zero for the first draw and then were incremented at each step.

The neural network implemented is represented figure 1. We distinguished the cross-presence matrix and the other inputs. We applied convolutional layers to the cross-presence matrix. Then, using residual learning, we added the intermediate result to the output of the convolutional layers. This is concatenated with all other features (quarterly GDP, unemployment rate, American president, day, month, yea, and number of times every number was seen) and acts as an input to a first dense layer. A second dense layer leads to the final prediction. A non-linear sigmoid is used to predict the presence or not of the lotto number. For instance, on figure 1, the 2 and 46 are two numbers (out of the six numbers) that are predicted given the input.

The output loss chosen was the categorical cross-entropy between predictions and targets. For

one data point  $k$ , the categorical cross-entropy is:

$$H^k(p_k, q_k) = - \sum_{n=1}^N p_k(n) \log(q_k(n)) \quad (1)$$

With  $N$  being the number of categories (number of possible numbers, 75),  $p_k$ , the target distribution and  $q_k$  the prediction from the neural network. To obtain the overall categorical cross-entropy, we average over all data points. The optimizer used was Adam. We split the set of observations into a training set of 892 draws and a validation set of 315 draws.

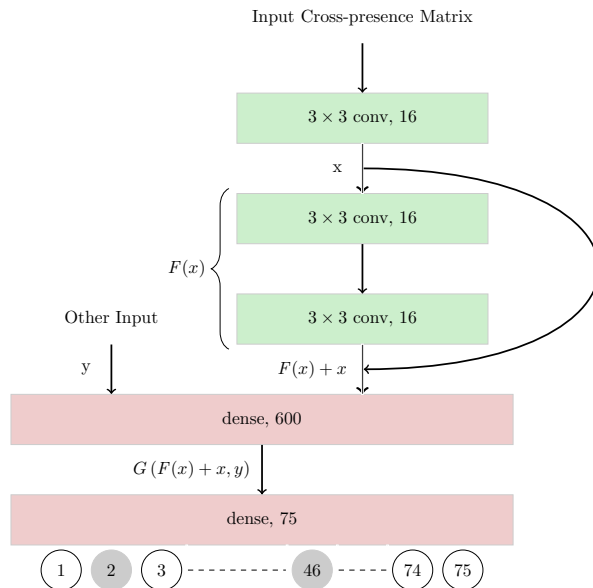


Figure 1: Deep Neural Network model

### 3 Results

The results are plotted figure 2. The graph on the left is the error on the training set. To check for overfitting, we also calculated the error on the validation set. On both sets, the error goes down substantially, dividing the initial error by 5. This is the proof that it is capturing an unidentified structure underlying the data. We would like to emphasize this point: even though the neural network in my brain can not identify the underlying structure of the data, the liberties given to the deep neural network give the possibility to learn a larger class of functions which explains how this model could capture an understanding of lotto when the human brain can only interpret it, at best, as randomness. Moreover, the algorithm converges quickly after only a few iterations showing the efficiency of the neural network.

### 4 Discussion

Following the logic of the results, this leads to a new understanding of the concept of randomness. Where the human brain essentially understands randomness, a powerful model from the neural

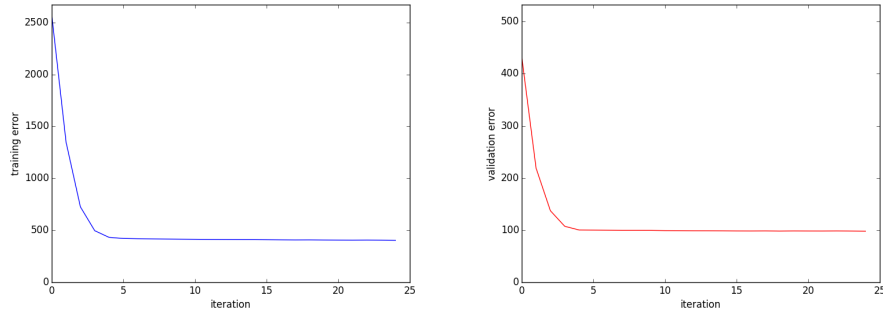


Figure 2: Validation and Training error

network framework captures a non-random structure. The human brain, as a physical system, has limits and the deep learning framework also. What we showed here is that the human brain limits are contained strictly within the deep learning limits which leads to whole new possibilities on our understanding of the world and to all the remaining unanswered questions.

The next step is to use this model on a tougher issue. Across many, we would like to apply this model to understand whether Schrödinger cat is actually alive or dead, see for more explanations [Schrödinger, 1935].

## 5 Conclusion

For a large-scale proof of concept, we predicted the numbers that will be drawn on the 11<sup>th</sup> of April, these will be 1, 9, 13, 14, 63, and the mega number will be 7. And we can conclude on the existence of God.

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