Automated Design — Using Machine Learning to Design Structures

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Why Automate?

Total automated building design would involve feeding a computer program a relatively small number of parameters, then letting it automatically design both the architecture and structure of a building.

Automation of design could lead to enormous benefits:

- Orders of magnitude faster than designing by hand.
- Increased productivity from rapid prototyping of structures.
- More optimised design by designing more structures in a given time frame.
- Greater quality reducing the likelihood of errors.

Background

Automation in design has been a long sought after goal. Bathurst (1965) was one of the first to propose the concept, writing early software which could select members given the loading.

Although methods have evolved significantly since, research has stalled as no methods have yet been presented which can automate design for buildings which are not rectangular or rectilinear.

Current methods are limited in that they must be programmed by a human engineer, this would make designing rules to cope with every feasible structural or architectural form a formidable task.

However if a method could be developed which could decompose arbitrary floorplans into rectangular segments, then current methods could be used to design an entire structure. To solve this I proposed to use a neural network based approach.

Neural networks were designed to mimic biological brains using a mathematical representation which could be simulated in a machine. Unlike a normal algorithm which has to have rules programmed in, methods exist to get a neural network to learn automatically from solved examples, called training data. This automates the rule designing process.

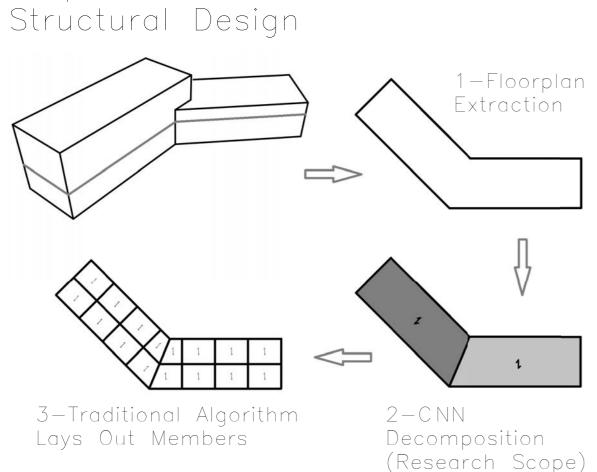
In addition recent advances in the field have lead to them generalising better. This means that it can predict outputs for inputs it has never seen before. In theory this means only a small number of floorplans would have to be shown for the network to predict accurate results.

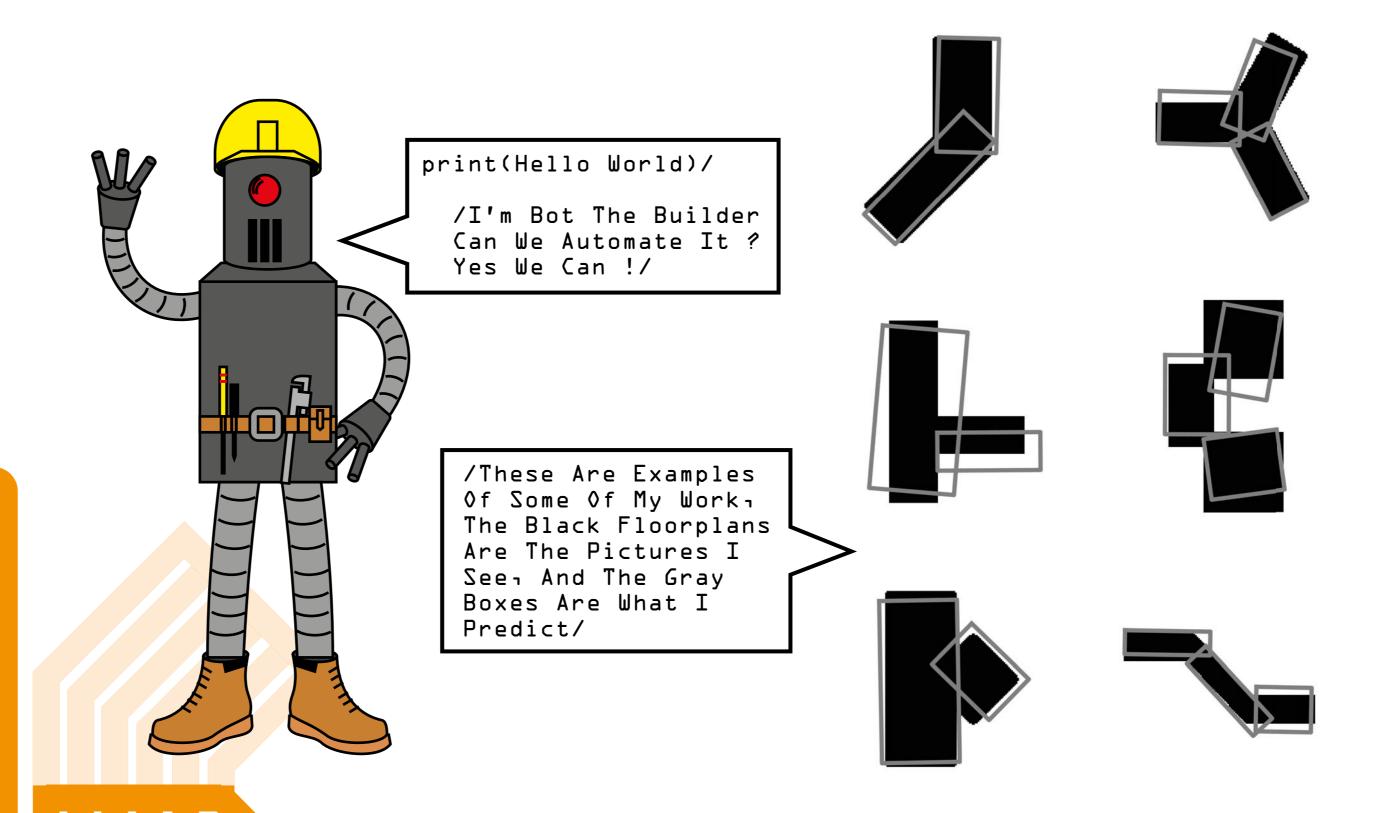
The goal of decomposing floor plans can be framed as an image recognition problem, attempting to classify boxes within an image of a floorplan. A specific type of neural network called a Convolutional Neural Network has been designed specifically for this task, hence this is the type used.

Goal

The objective of the research was to use a CNN (Convolutional Neural Network) to decompose images of arbitrary floorplans into a set of appropriate boxes, specifically outputting the size, location and rotation of these boxes.

Proposed Method of Automated Structural Design



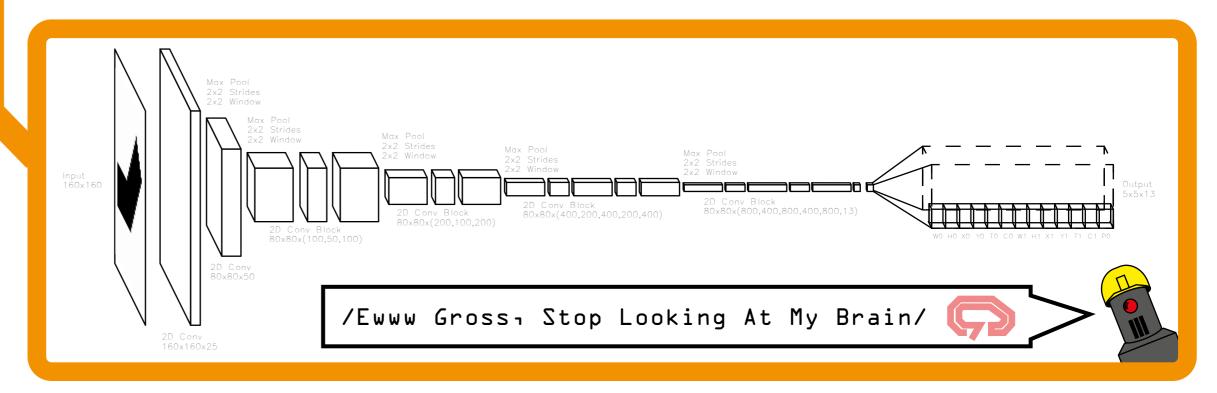


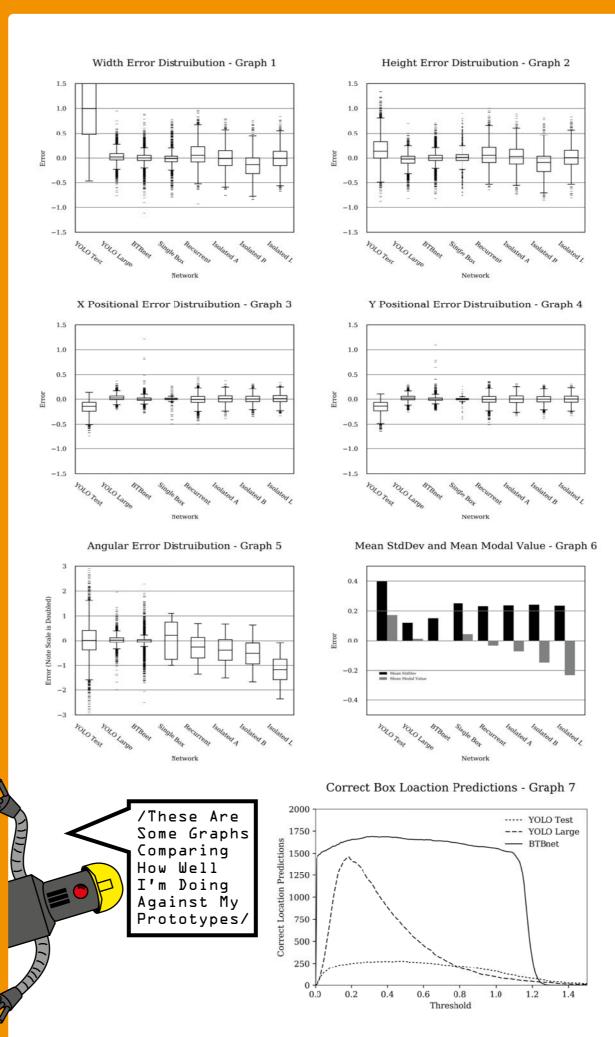
Conclusions and Recommendations

BTBnet performs well, robustly predicting boxes given arbitrary floorplans. Importantly it behaves often as human engineer might, certainly showing potential. However it is still not predicting with enough accuracy (only 47.5% correct) to be commercially useful. In order to become robust enough to be used improvements would have to be made.

One of the biggest improvements would be to increase the input resolution from 160x160 pixels, though simple, the dimensionality increase requires significantly more processing power for training. In addition the recommendations made in the subsequent YOLO papers could be implemented.

The network has further problems not related to accuracy. At the moment it is only capable of designing buildings with uniform floorplans in the vertical direction, and only decomposes into rectangles. The current method offers a simple solution to the second problem as it can be quickly modified to predict additional shapes. However the first problem would require the network to be expanded to read 3D input data.





Method and Results

A series of CNNs were developed each improving on the last ultimately leading to the final BTBnet.

The networks were all trained using automatically generated data, presenting an image of a specified number of superimposed boxes as the input, and the location, size and rotation as the output.

The bootstrapped data ought to represent a very wide range of potential floorplans.

Single Box Network

To asses the feasibility of the method, I created an initial CNN which predicted the location of a single box. This network proved to be successful.

Recurrent Networks

In order to predict multiple boxes a slightly different approach was taken. A Recurrent Convolution Neural Network using a Long Short—Term Memory layer was designed. The idea was that this would remember the first box predicted, then sequentially predict the next and so forth. In reality the network performed badly. This lead to the development of isolated layers of the network to determine the issue. After significant research it was discovered that the networks were predicting averaged boxes of all presented boxes, due to the way the training was Although this could have been remedied a different approach was taken.

YOLO Based Networks

By slightly reformulating the problem I realised that networks presented in existing literature which located bounding boxes in images, could be used to solve the research goal. I sought initially to use the YOLO network (J. Redmon S. D., 2016), this not only simultaneously predicts multiple images and hence bounding boxes, unlike the sequential recurrent network, but also uses data in a very similar way to my previous networks. I modified the YOLO network to work using the specific data presented, and modified the loss function to include a term for box rotation. Two initial YOLO based networks evolved ultimately into the final BTB net presented, which I modified further from the original YOLO network. BTB net robustly predicts the location of multiple rectangles given an input image of a floor plan.