Predicting the dynamics of 2d objects with a deep residual network

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Abstract

We investigate how a residual network can learn to predict the dynamics of interacting shapes purely as an image-to-image regression task.

With a simple 2d physics simulator, we generate short sequences composed of rectangles put in motion by applying a pulling force at a point picked at random. The network is trained with a quadratic loss to predict the image of the resulting configuration, given the image of the starting configuration and an image indicating the point of grasping.

Experiments show that the network learns to predict accurately the resulting image, which implies in particular that (1) it segments rectangles as distinct components, (2) it infers which one contains the grasping point, (3) it models properly the dynamic of a single rectangle, including the torque, (4) it detects and handles collisions to some extent, and (5) it re-synthesizes properly the entire scene with displaced rectangles.

1 Problem definition

We implemented a simple 2d physics simulator to generate short sequences of interacting shapes. The simulation is quite crude but still includes an elastic collision model, a proper torque model, and (strong) fluid frictions.

As illustrated with a few examples on Figure 1, each sequence is composed of grayscale images of resolution $64 \times 64$, and is created as follows: We dispatch 10 rectangles

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of fixed size at random in the unit square, so that they do not overlap. Then we pick at random a point uniformly in the union of the rectangle interiors, and we apply there a constant force pulling upward for a constant time delay. This moves the grasped rectangle upward and may induce collisions with other rectangles, and make them move. The borders of the square area are impenetrable, hence rectangles grabbed near the top may have their motion constrained accordingly.

While the grasping point location is randomized for every sequence, the characteristics of the force and its duration are common to all the sequences.

![Diagram](image)

Figure 1: Each row corresponds to one sequence of our data-set. It is composed of six gray-scale images of size 64 × 64: the “grasping point image”, followed by five frames. In each sequence, the rectangle originally containing the grasping point is pulled upward and moves accordingly. It may collide with and push other rectangles. We show several frames of each sequence for clarity here, but use only the two leftmost images \((S_n, G_n)\) and the rightmost one \(R_n\) from each sequence in our experiments, in which we try to predict the latter from the former.

As illustrated on Figure 1, from each generated sequence we produce three images: \(G_n, S_n, R_n\) which correspond, respectively, to the grasping point image (all white, with a dot at the location of the grasp, as shown in the leftmost column of Figure 1), the starting configuration, which is the first image of the sequence, and the resulting configuration, which is the last image of the sequence.
2 Network and training

We train a residual network (He et al., 2015) with 18 layer and 16 channels to predict $R_n$, given $G_n$ and $S_n$ as input.

To ease the reading of long compositions of mappings, given two mappings $f$ and $g$, let $f \circ g$ stand for $g \circ f$.

2.1 Structure of the network

Our network follows the classical structure of the residual networks, and chains several identical modules of two convolutional layers. We define

- $C^f_{c,d}$ a standard convolution layer (LeCun et al., 1998) with filters of size $f \times f$, padding of $(f - 1)/2$ to maintain the map size, $c$ channels as input and $d$ channels as output,
- $\mathcal{R}$ a ReLU rectifier layer (Glorot et al., 2011),
- $\mathcal{B}$ a batch-normalization layer (Ioffe and Szegedy, 2015),
- $\mathcal{I}$ the identity layer, and
- $\mathcal{M} = (C^f_{q,q} \circ \mathcal{B} \circ \mathcal{R} \circ C^f_{q,q} + \mathcal{I}) \circ \mathcal{B} \circ \mathcal{R}$ a two-layer resnet module (He et al., 2015) with the second batch normalization and non-linearity applied after summing the identity.

The structure of the full network is

$$\Psi = C^f_{2,q} \circ \mathcal{B} \circ \mathcal{R} \circ \underbrace{\mathcal{M} \circ \ldots \circ \mathcal{M}}_{\times D} \circ C^f_{q,1}$$

with convolution filters of size $f \times f$ with $f = 5$, $q = 16$ channels in the internal encoding, and $D = 8$ resnet modules, each with two layers. It has a total of 104,417 parameters, which is roughly $f^2 \times q^2 \times 2D$.

2.2 Loss, initialization and training

We minimize the quadratic loss between the predicted and target training images,

$$L = \sum_n \|\Psi(S_n, G_n) - R_n\|_2^2$$

and train with 32,768 samples. We use a standard stochastic gradient descent, randomizing the training set ordering for every epoch, using mini-batches of size 128, and a constant learning rate of 0.1.
The initialization of the weights is the standard Torch rule, which for the convolution
layers is a centered uniform distribution of width twice the inverse of the square root
of the number of weights (i.e. total number of filter coefficients), and for the batch
normalization picks the target standard deviation uniformly in [0, 1] and sets the
target mean to zero.

We did not tune the network structure, all the results obtained here are with the first
attempt. A run with half the channels (i.e. \( q = 8 \)) shows that it degrades noticeably
the performance.

3 Results

![Loss vs Number of epochs](image)

Figure 2: Train and validation losses during training.

We implemented the simulator in C++ and the network processing and perfor-
mance evaluation in the Torch framework (Collobert et al., 2011). The network
implementation is given in appendix A.

The source code of the simulator and the residual network to replicate the experiments
is available under the GPL-3.0 open-source license at

https://gitlab.idiap.ch/francois.fleuret/dyncnn/

As shown on Figure 2, the loss decreases regularly, with no over-fitting. It is still
going down after 2,000 epochs, which takes slightly less than 30 hours on a NVIDIA
GTX 1080 graphic card, using cuda toolkit 8.0, and cudnn 5.1.
3.1 Prediction

The resulting network makes an accurate prediction of the final configuration. We provide on Figure 3 five examples selected to illustrate the strengths and weaknesses of the prediction, and on Figure 4 some examples taken according to the ranks of their individual losses to get a better intuition of the overall performance.

We observe that the network:

- detects the grasped rectangle, and moves it while keeping the other ones undisturbed if there is no collision.
- models translation and torque.
- propagates to some extent the dynamics when collisions occur (Figure 3(d)).
- models the hard borders around the area, although with some deformations (Figure 3(b)).
- implements the synthesis of the perturbed scene, which involves in particular the segmentation of the moving vs. non-moving parts, and synthesis of edges at multiple orientations.

Figure 4 gives a better understanding of the overall performance of the network on 1,024 test sequences. The six examples (a)-(f) shown in the top half are those with the highest losses, hence are the worst mistakes of the network, and the six bottom examples (g)-(l) correspond to the ones ranked in the middle.

It is remarkable that the worst mistakes correspond to complicated cases even for a human, where the predicted motion would have been correct for a minimal variation of the starting conditions (e.g. Figure 4(a), and (b)), or involves a chain of collisions (e.g. Figure 4(c), (d), (e), and (f))

3.2 Inner representation

To shade a light on the processing occurring in the network, we represent on Figure 5 for two examples the processing from top to bottom as the activations of the input layer, ReLU layers after each resnet module, and output layer.

The top row contains two activation maps corresponding to the two input channels, respectively the starting configuration $S_n$ and the grasping point $G_n$, the bottom row contains a single map, corresponding to the network’s output $\Psi(S_n, G_n)$. The 9 other rows correspond to the ReLU layer situated after the initial convolution layer $\mathcal{C}^f_{2,q}$ that converts the 2 input channels to the $q$ internal channels, followed by the ReLU layers placed at the output of each of the $D = 8$ resnet modules $\mathcal{M}$. The 16 columns in this 9 rows correspond to the $q = 16$ channels for the internal coding.
For clarity, we highlight the pixels in the two bottom rows proportionally to the difference with the starting configuration. See § 3.1 for discussion.

We observe a homogeneity “per channel”, which translates here to “per column”. This is probably because the resnet architecture favors processing near the identity, which results in gradual changes through layers, and discourages the shuffling of information across channels.

As we can see, an important part of the computation aims at segmenting the grasped rectangle (channels 11 and 15), segmenting the moving rectangles (channels 4 and 5), and removing the moving parts (channels 1, 10, and 16).
Figure 4: Examples from a random set of 1024 test examples, selected according to their loss. Examples (a)-(f) are the worst regarding loss, (g)-(l) are median. The ranks (from worst to best) and $L^2$ losses are provided above each example. As in Figure 3, the four images in each example correspond from top to bottom to $F_n$, $G_n$, $S_n$ and $\Psi(S_n, G_n)$. For clarity, we highlight the pixels in the two bottom rows proportionally to the difference with the starting configuration. See §3.1 for discussion.
Figure 5: Activations in the input, internal ReLU, and output layers. See § 3.2 for discussion.
A Torch network structure

nn.Sequential {
  [input -> (1) -> (2) -> (3) -> (4) -> (5) -> output]
  (1): nn.SpatialConvolution(2 -> 16, 5x5, 1,1, 2,2)
  (2): nn.SpatialBatchNormalization
  (3): nn.ReLU
  (4): nn.Sequential {
    [input -> (1) -> (2) -> (3) -> (4) -> (5) -> (6) -> (7) -> (8)
      -> (9) -> (10) -> (11) -> (12) -> (13) -> (14) -> (15) -> (16)
      -> (17) -> (18) -> (19) -> (20) -> (21) -> (22) -> (23) -> (24)
      -> (25) -> (26) -> (27) -> (28) -> (29) -> (30) -> (31) -> (32)
      -> output]
    (1): nn.ConcatTable {
      [input
       |'-> (1): nn.Sequential {
         [input -> (1) -> (2) -> (3) -> (4) -> output]
         |(1): nn.SpatialConvolution(16 -> 16, 5x5, 1,1, 2,2)
         |(2): nn.SpatialBatchNormalization
         |(3): nn.ReLU
         |(4): nn.SpatialConvolution(16 -> 16, 5x5, 1,1, 2,2)
       |
     } -> (2): nn.Identity
     ... -> output
    }
    (2): nn.CAddTable
    (3): nn.SpatialBatchNormalization
    (4): nn.ReLU

    /... repeated 7 more times .../

  }
  (5): nn.SpatialConvolution(16 -> 1, 5x5, 1,1, 2,2)
}
References

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