Notes on Spatial Transformer Networks

> *New method for incorporating spatial attention in neural networks*

Articles

- Torch article 'The power of Spatial Transformer Networks'
    - my notes
- Deep Learning Paper Implementations: Spatial Transformer Networks - Part I
    - my notes
- Deep Learning Paper Implementations: Spatial Transformer Networks - Part II
    - my notes

Power of STNs

- code examples are in Lua
- Main takeaway was that they were able to beat a really complicated model:

Pipeline	IDSIA (2011)	Moodstocks (2015)
Augmentations	Yes	No
Jittering	Yes	No
Network	~90M weights	~20M weights
Accuracy	**99.46%**	**99.61%**
Architecture/Ensemble	25 networks	1 network
Model	3 CONV, 2 FC layers each	3 CONV, 2 FC, 2 ST layers

About GTSRB dataset

- German Traffic Sign Recognition Benchmark (available here)
- 43 categories | 39,209 train samples | 12,630 test ones

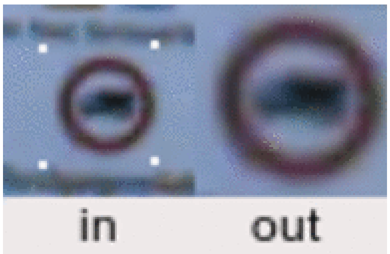
GIFs

> The transformations can be easily visualized since the STN module is inserted right after the input layer and before the first hidden layer.

Runtime visualization of transformations performed by STN

- left : input image
- right : transformed image produced by the Spatial Transformer
- bottom : counter representing training steps (0 = before training, 10/10 = end of epoch 1)
- white dots : corners of the part of the image that is sampled

Input with geometric noise



- Input image contains scale and positional variability
- Yet, Spatial Transformer's output remains almost static
- The transformer simplifies the task for the rest of the network as it learns to forward only the interesting part of the input and removes geometric noise

Article part I notes

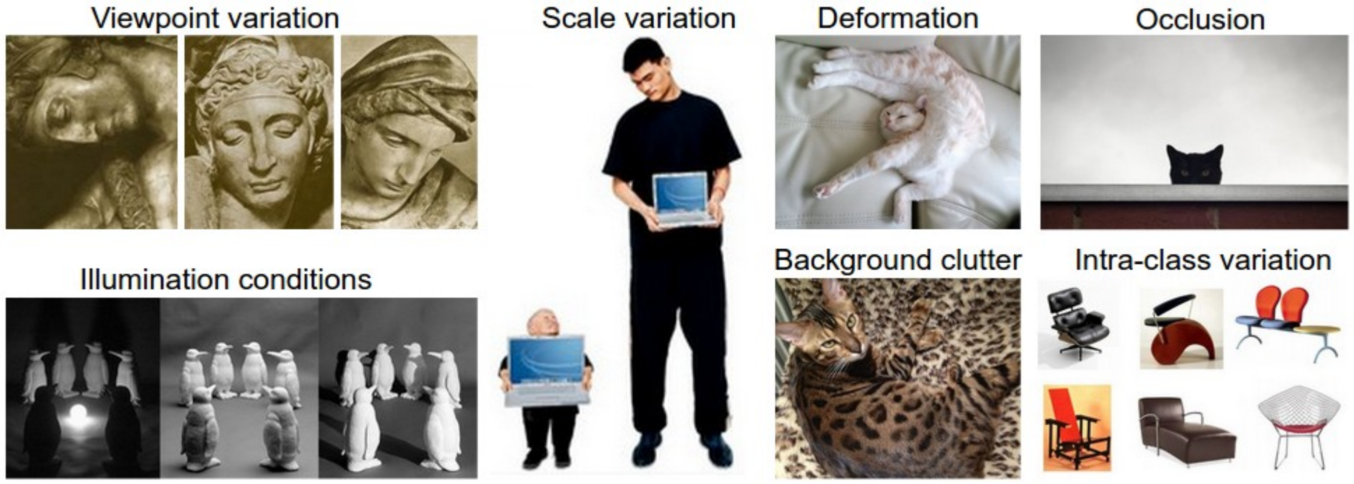
Article part II notes

> Goal: a system robust to input variations like scale variation, viewpoint variation, deformation (*non rigid bodies can be deformed and twisted in unusual shapes*), etc.

A desirable system (note from cs231n):

- A classification system must be invariant of the following variations in images, while retaining sensitivity to inter-class (inside one class) variations
  - **Viewpoint variation**; A single instance of an object can be oriented in many ways with respect to the camera.

- **Scale variation**: Visual classes often exhibit variation in their size (size in the real world, not only in terms of their extent in the image).
- **Deformation**: Many objects of interest are not rigid bodies and can be deformed in extreme ways.
- **Occlusion**: The objects of interest can be occluded. Sometimes only a small portion of an object (as little as few pixels) could be visible.
- **Illumination conditions**: The effects of illumination are drastic on the pixel level.
- **Background clutter**: The objects of interest may blend into their environment, making them hard to identify.
- **Intra-class variation**: The classes of interest can often be relatively broad, such as chair. There are many different types of these objects, each with their own appearance.



Some spatial invariance of pooling layers

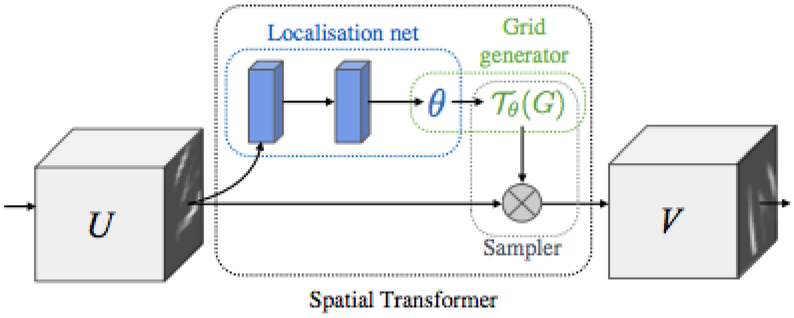
- CNNs add translation invariance (i know this)
- But how about other forms of invariance?
  - Pooling layer add limited spatial invariance:
  - Pooling is local and predefined
  - *The main takeaway is that ConvNets are not invariant to relatively large input distortions. This limitation is due to having only a restricted, pre-defined pooling mechanism for dealing with spatial variation of the data.*

STNs

3 Defining properties of STNs:

- Modular: STNs can be inserted anywhere in existing architectures
- Differentiable: can be trained with backprop
- Dynamic: as opposed to pooling layers which are predefined, STNs perform active spatial transformations

STN module:



Localization Net

> Learns and spits out parameters θ of affine transformation

Defined as follows:

- Input: feature map U of shape (H, W, C)
- Output: transformation matrix θ of shape (6,)
- Architecture: FCN or CNN

The localization network learns and outputs more an more accurate thetas

Grid Generator

- First, creates normalized meshgrid of the same size as the input image U of shape (H, W).
  - the meshgrid is a set of indices (x^t, y^t) that cover the whole input feature map (t for target coordinates in the output feature map).

> Don't really understand the sections *Parameterised Sampling Grid* and *Differentible Image Sampling* (will return to this after reading part 1)

Resources

Papers

- Original STN (*Jaderberg, Simonyan, Zisserman, Kavukcuoglu*)
  - Spatial Transformer Networks
  - STN experiment videos
- RNN-STN model
  - Recurrent Spatial Transformer networks

Code

1. (Lasagne) Spatial transformer layer documentation
2. (Lasagne) github implementation
3. (tensorflow) Spatial Transformer
   - Uses this @skaae code as reference. Which is the same code as 2 (on lasagne github)
   - Local: `~/development/spatial-transformer-tensorflow`
4. (Lasagne) static notebook example of using a transformer in a model

5. (Lasagne) Recurrent transformer implementation unofficial

- Lasagne uses Theano

Other links I need to look at still

- https://pytorch.org/tutorials/intermediate/spatial_transformer_tutorial.html
- https://medium.com/@kushagrabh13/spatial-transformer-networks-ebc3cc1da52d
- https://medium.com/@shanlins/spatial-transformer-networks-stn-and-its-implementation-2638d58d41f8
- https://towardsdatascience.com/review-stn-spatial-transformer-network-image-classification-d3cbd98a70aa