Capsule Networks

By Modar Alfadly

(October 2nd, 2018)

Papers

- Sabour, Sara, Nicholas Frosst, and Geoffrey E. Hinton.
  "Dynamic routing between capsules."
  Advances in Neural Information Processing Systems (2017)

- Hinton, Geoffrey E., Sara Sabour, and Nicholas Frosst.
  "Matrix capsules with EM routing."
  International Conference on Learning Representations (2018).

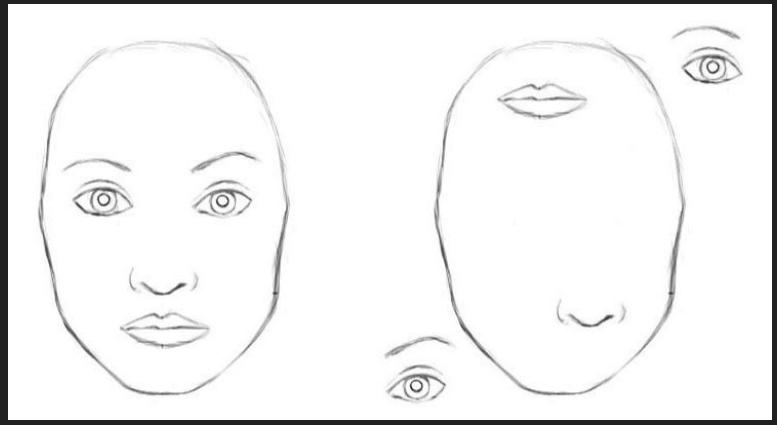
Motivation

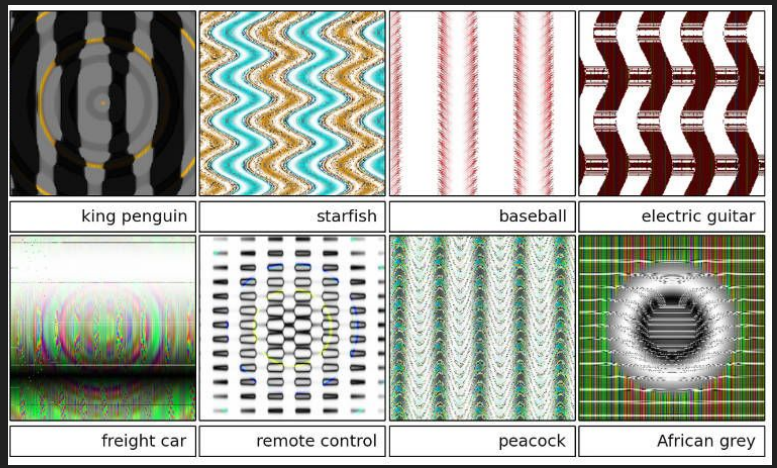
Why Convolutional Neural Networks (CNNs)?

- Spatial coherence of images
- Translation invariance
- Hierarchy of features

So, what is wrong with CNNs?

- Pooling layers
- Objects relationships
- Part-whole relationships



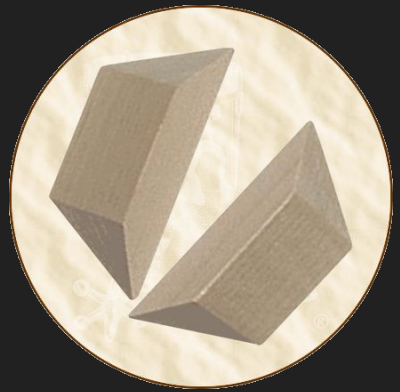


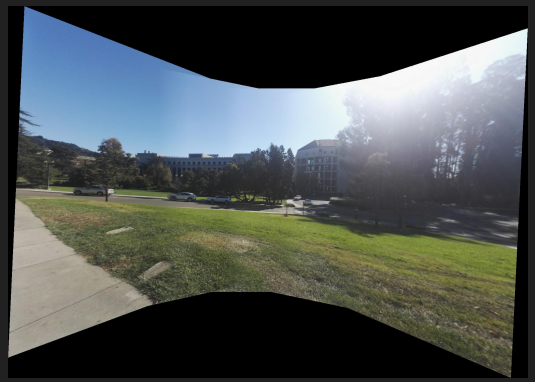
Motivation

What is wrong with pooling? [~40 minutes of Hinton's talk]

"The pooling operation used in CNNs is a big mistake
and the fact that it works so well is a disaster" -Geoffrey Hinton

- Bad fit to the psychology of shape perception
  We assign intrinsic coordinate frames to objects (think homography)





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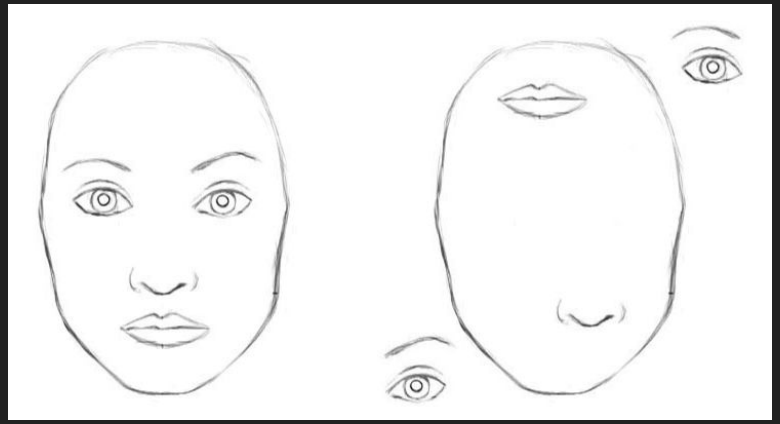
What is wrong with pooling? [~40 minutes of Hinton's talk]

- It gives us invariance where we want equivariance
  Small translations are fine but big ones are not (place-coded vs rate-coded)



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What is wrong with pooling? [~40 minutes of Hinton's talk]

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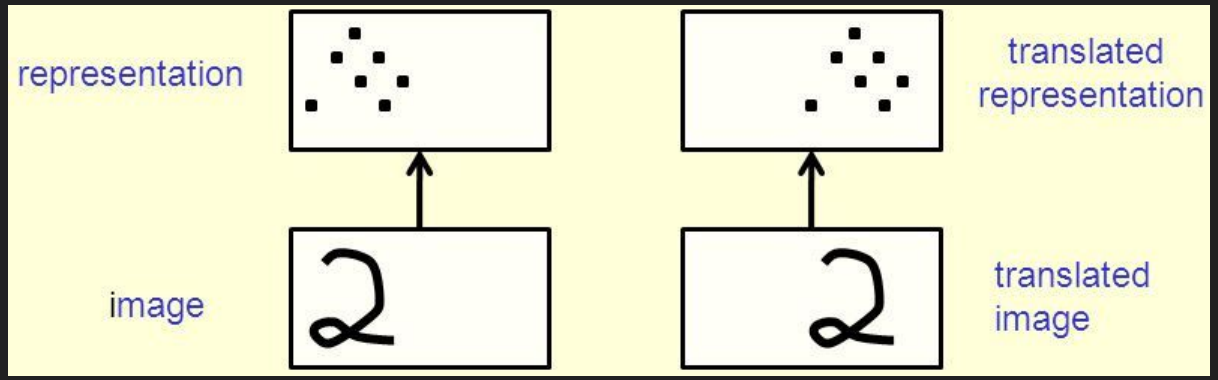
  Translated pixels should be processed by the same neurons (or Capsules)



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  We assign intrinsic coordinate frames to objects (think homography)
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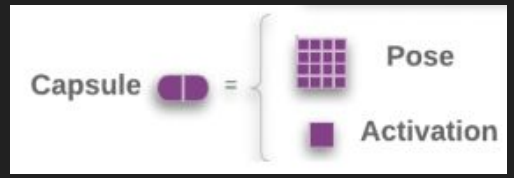
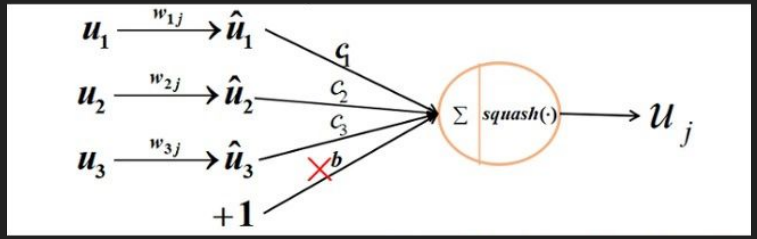
  Small translations are fine but big ones are not (place-coded vs rate-coded)
- It fails to use the underlying linear structure (Inverse Graphics)
- It is a poor way to do dynamic routing:
  Translated pixels should be processed by the same neurons (or capsules)

What is a Capsule?

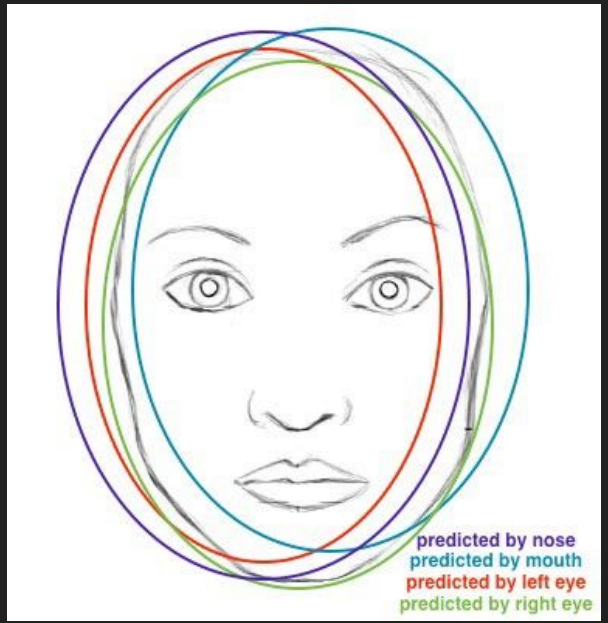
- Capsules encode features as vectors that contain the pose and the activation, so, instead of scalar neurons, now we have vectors
- By applying learned viewpoint invariant projection, on the capsules of a certain layer we are projecting these capsules/features to the coordinate frame of the next layer (low to high)
- The projected capsules are then weighted using dynamic routing
- Finally, a non-linear activation function is applied to the weighted sum





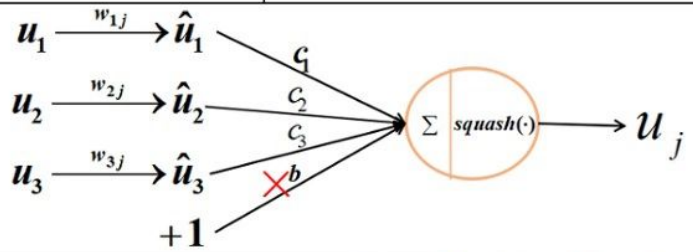
What is a Capsule?

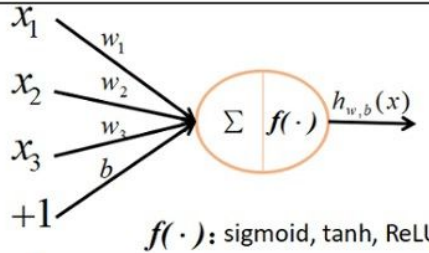
For example, lower capsules can be part detectors (eye, mouth, nose) and higher ones can be whole detectors (face)



Capsule vs Neurons

		capsule	vs.	traditional neuron
Input from low-level neuron/capsule		vector($\boldsymbol{u}_i$)		scalar(x_i)
Operation	Affine Transformation	$\hat{u}_{j\|i} = W_{ij} u_i$ (Eq. 2)		–
	Weighting	$s_j = \sum_i c_{ij} \hat{u}_{j\|i}$ (Eq. 2)		$a_j = \sum_{i=1}^{3} W_i x_i + b$
	Sum			
	Non-linearity activation fun	$v_j = \frac{\|s_j\|^2}{1+\|s_j\|^2} \frac{s_j}{\|s_j\|}$ (Eq. 1)		$h_{w,b}(x) = f(a_j)$
output		vector(v_i)		scalar(h)





Capsule = New Version Neuron!
vector in, vector out VS. scalar in, scalar out

Dynamic Routing (A modern Hough transform)

A chance of 1 in a million for two 6 dimensional vectors to agree on every dimension within 10%.

Procedure 1 Routing algorithm.

procedure ROUTING($\hat{\boldsymbol{u}}_{j|i}, r, l$)
  for all capsule i in layer l and capsule j in layer $(l+1)$: $b_{ij} \leftarrow 0$.
  for r iterations **do**
    for all capsule i in layer l: $\mathbf{c}_i \leftarrow \texttt{softmax}(\mathbf{b}_i)$ ▷ `softmax` computes Eq. 3
    for all capsule j in layer $(l+1)$: $\mathbf{s}_j \leftarrow \sum_i c_{ij} \hat{\mathbf{u}}_{j|i}$
    for all capsule j in layer $(l+1)$: $\mathbf{v}_j \leftarrow \texttt{squash}(\mathbf{s}_j)$ ▷ `squash` computes Eq. 1
    for all capsule i in layer l and capsule j in layer $(l+1)$: $b_{ij} \leftarrow b_{ij} + \hat{\mathbf{u}}_{j|i}.\mathbf{v}_j$
  return $\mathbf{v}_j$

The number of iterations is r and 3 is found to be good in practice (more overfits)

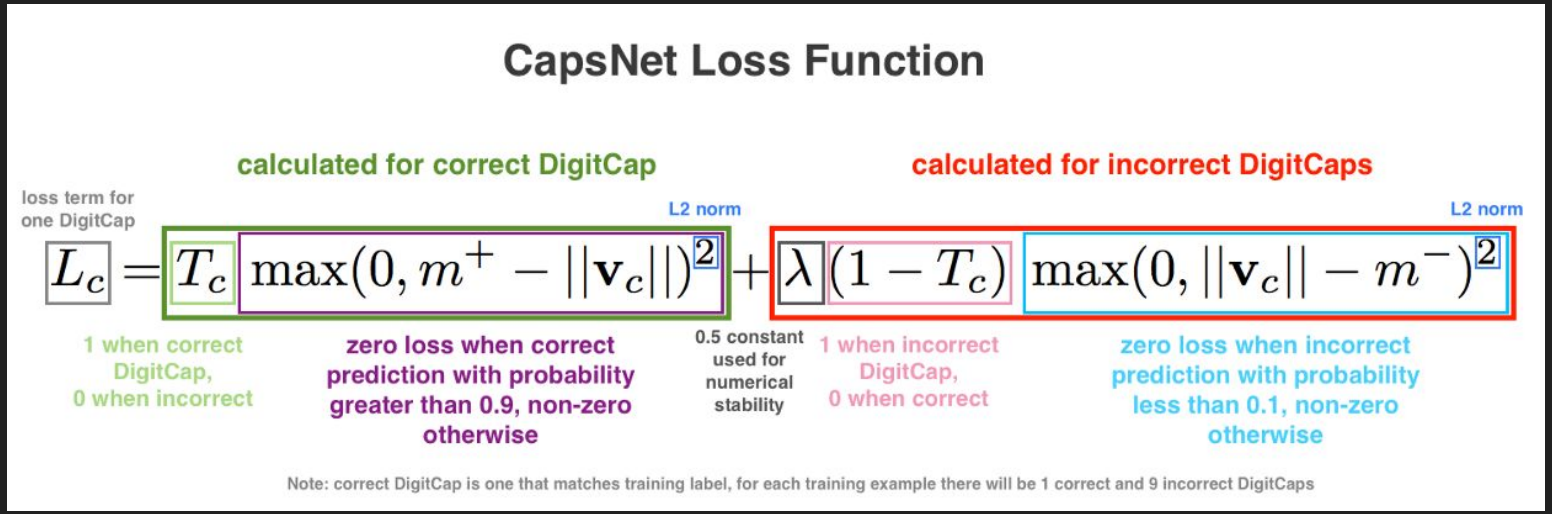
Dynamic Routing (A modern Hough transform)

Expectation-Maximization (EM) procedure

$$\text{score} = \sum_i \log p(\mathbf{x}_i | \textit{unifom-gauss-mixutre}) - \sum_i \log p(\mathbf{x}_i | \textit{uniform})$$

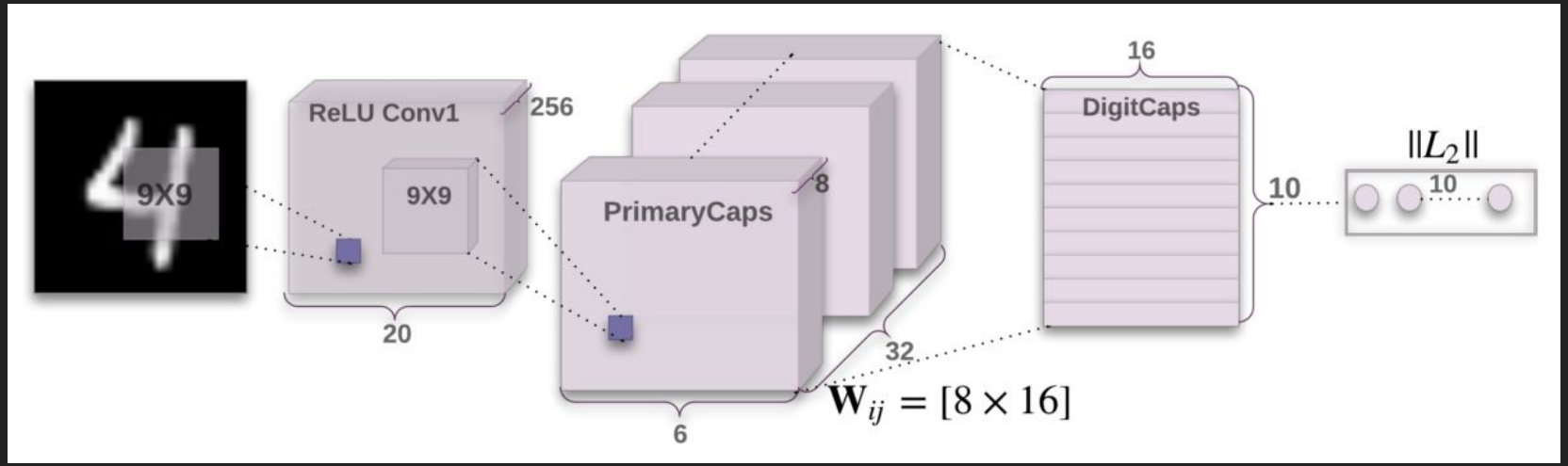
Loss function

Spread loss (similar to hinge loss)



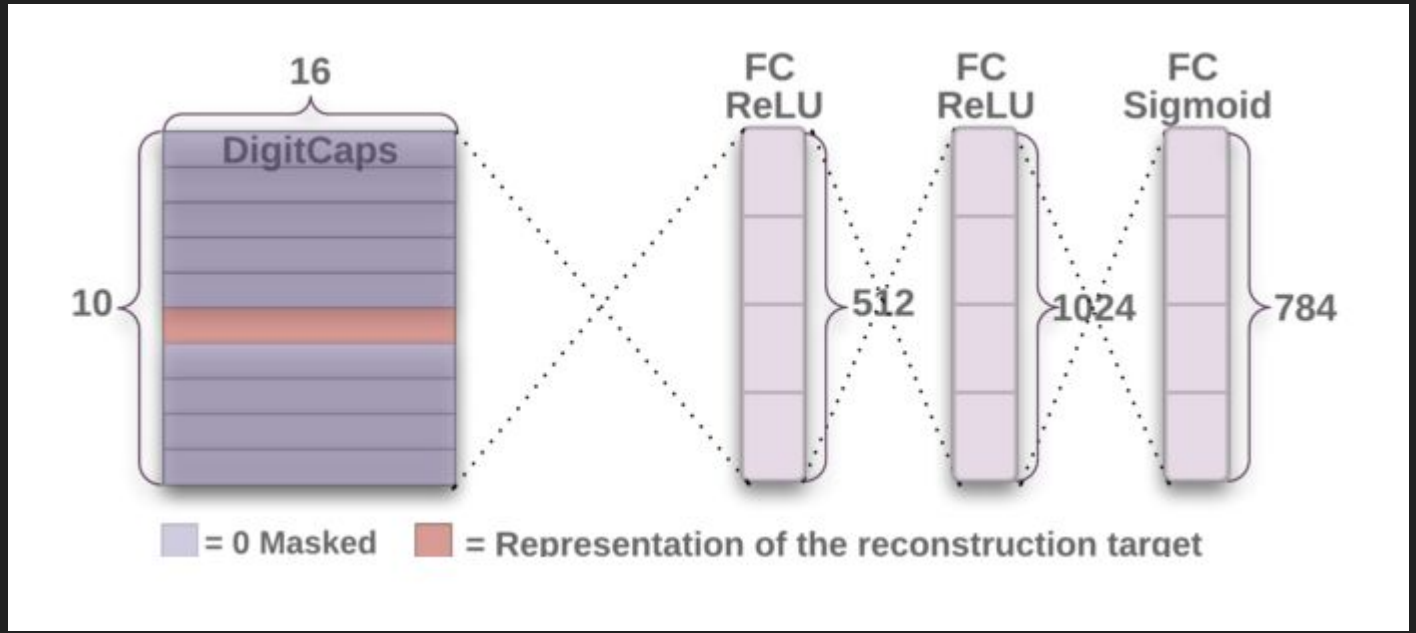
Architecture

Encoder Part

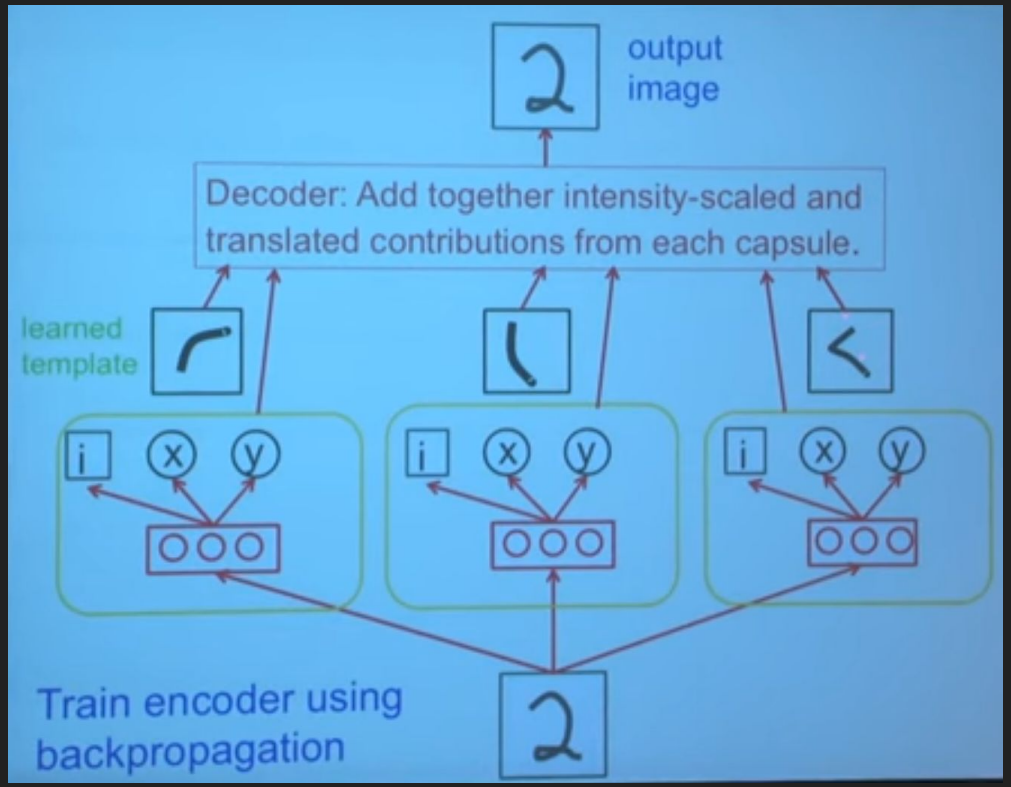


Architecture

Decoder Part



Proof of Concept on MNIST



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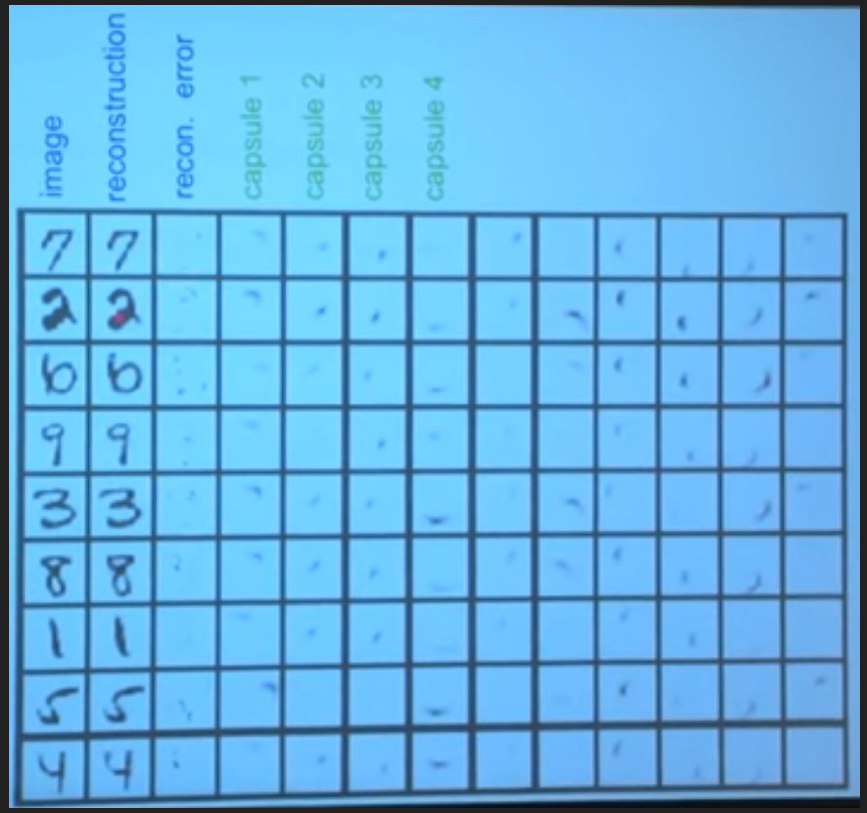

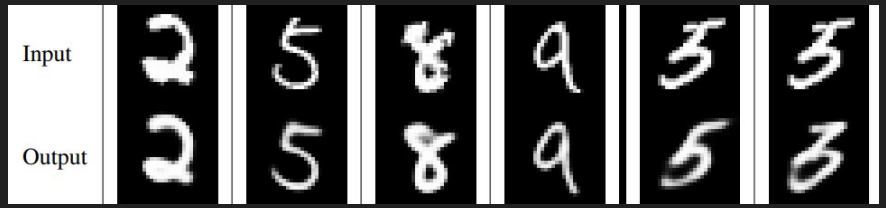

Thank You!

See the list of references

1. Dynamic routing between capsules [NIPS17]
2. Matrix capsules with EM routing [ICLR18]
3. What is wrong with ConvNets? [Video]
4. Does the brain do inverse graphics? [Video]
5. Nice series of blogs by Max Pechyonkin
6. Compilation of CapsNets references
7. PyTorch Tutorial by Dulat Yerzat [Code]