CVPR LONG BEACH CALIFORNIA June 16-20, 2019

Center for Research in Computer Vision
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Capsule Networks: A Survey

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CVPR Tutorial

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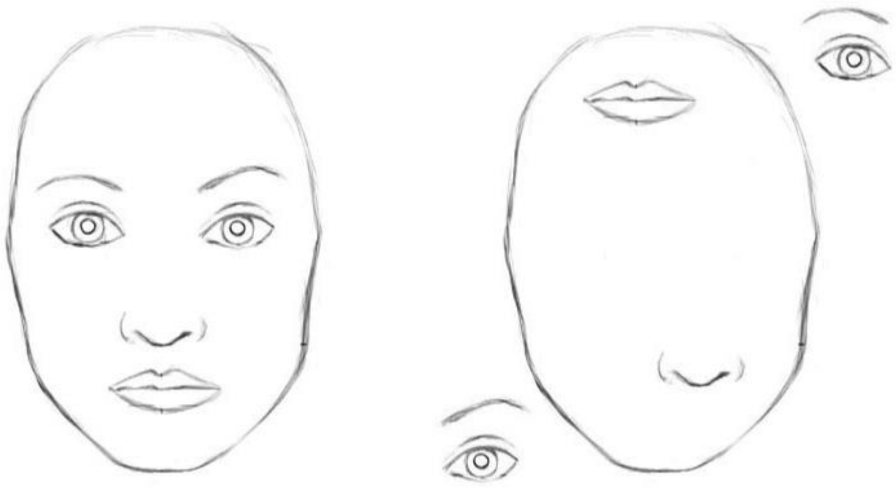
Outline

- Introduction
- CapsNet
- EM routing
- Application[3D point cloud]

Introduction

- Motivation[CNN drawbacks]
  - *Internal data representation of a convolutional neural network does not take into account important spatial hierarchies between simple and complex objects.*



CNN:
neuron [scalar]
activation

CapsNet:
capsule [vector/matrix]
activation and state

Introduction

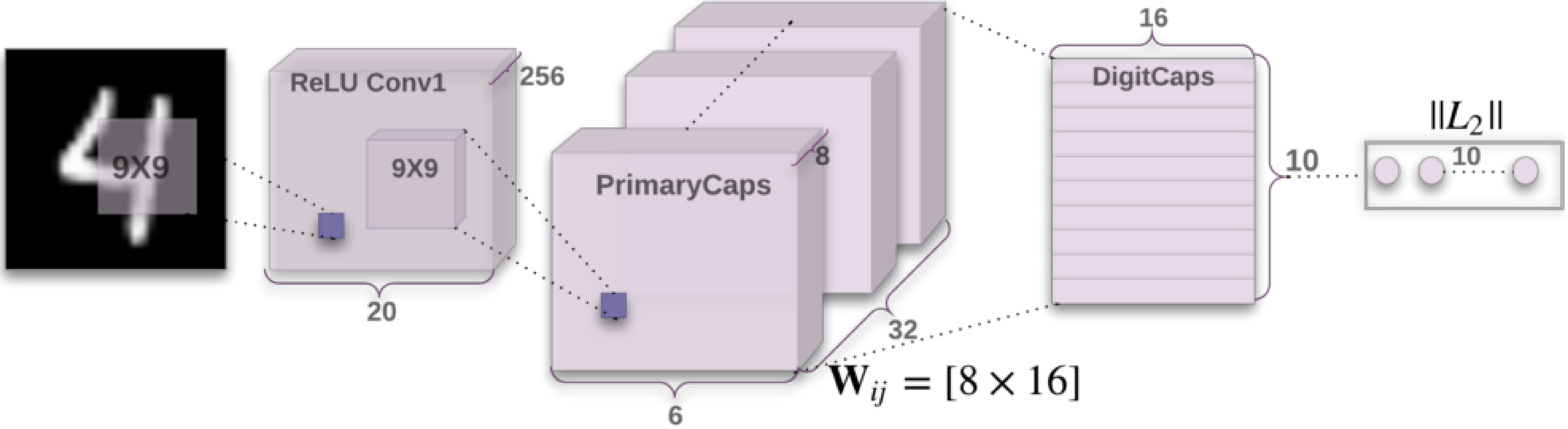
- Motivation
  - *Hinton: "The pooling operation used in convolutional neural networks is a big mistake and the fact that it works so well is a disaster."*

CNN:
- max pooling
- average pooling

CapsNet:
- dynamic routing(routing by agreement)
- EM routing

Introduction

- Motivation
  - Inverse rendering



CapsNet

- What is capsule?
  Capsules encapsulate all important information about the state of the feature they are detecting in **vector** form.

  Vector: length & orientation

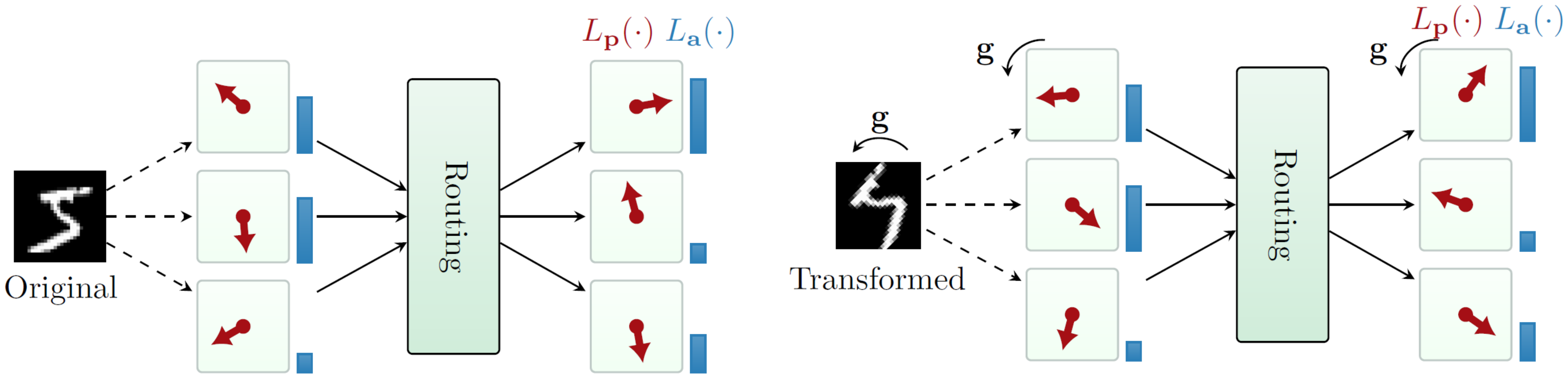
  想要达到的效果:

  when detected feature moves around the image or its state somehow changes, the probability still stays the same (length of vector does not change), but its orientation changes.

  [invariance & variance]

Generic routing by agreement

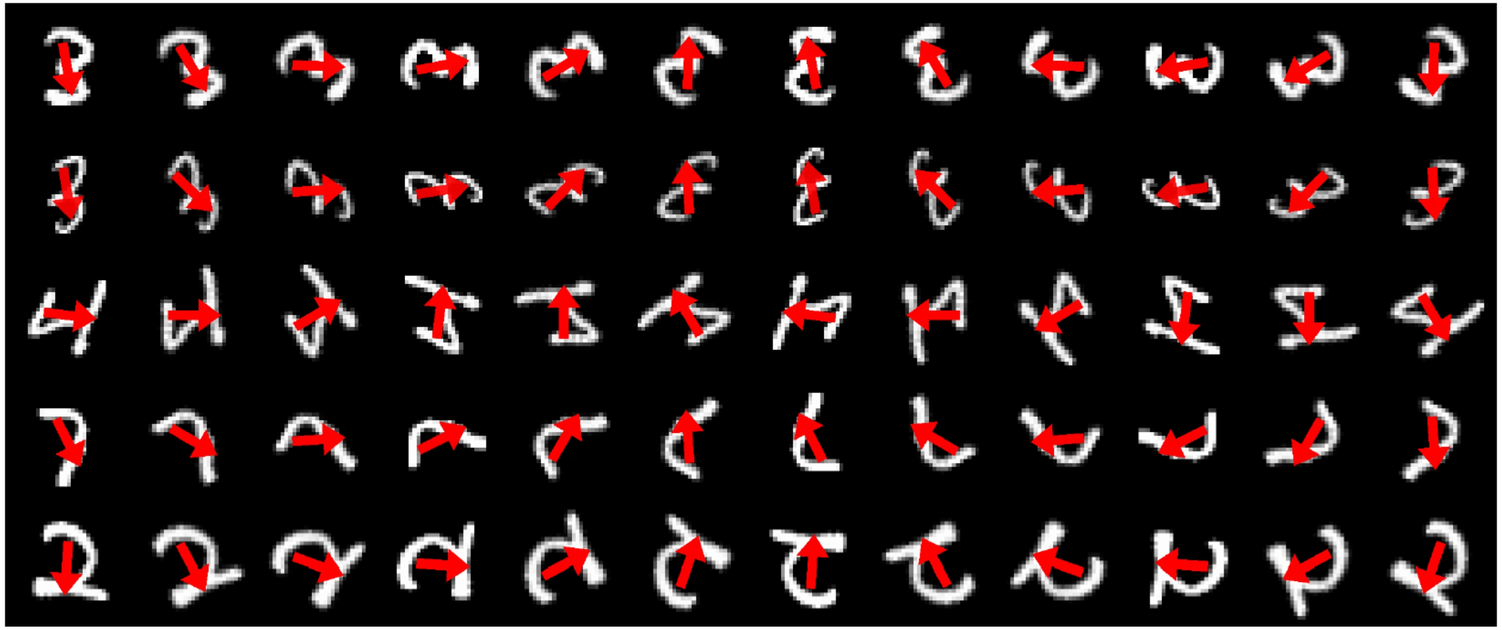
- Equivalance and invariance [5]



[5] Lenssen, Jan Eric, Matthias Fey, and Pascal Libuschewski. "Group equivariant capsule networks." Advances in Neural Information Processing Systems. 2018.

Equivariance and Invariance

- Variation in pose vector



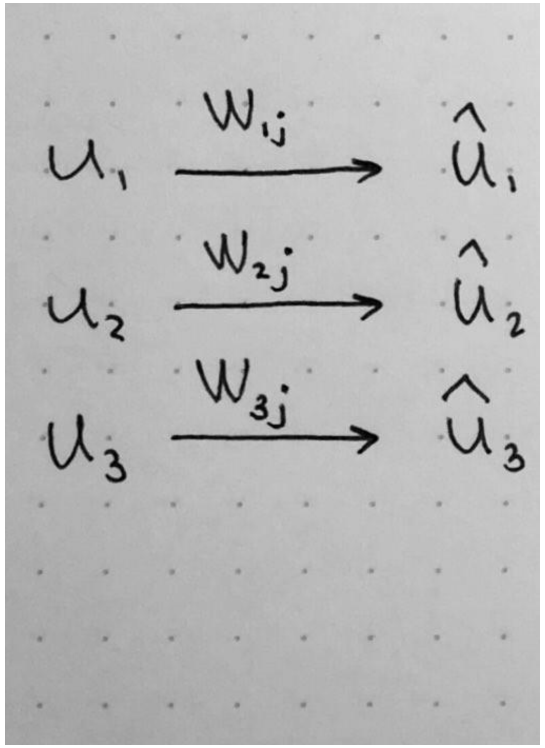
[5] Lenssen, Jan Eric, Matthias Fey, and Pascal Libuschewski. "Group equivariant capsule networks.“ Advances in Neural Information Processing Systems. 2018.

CapsNet

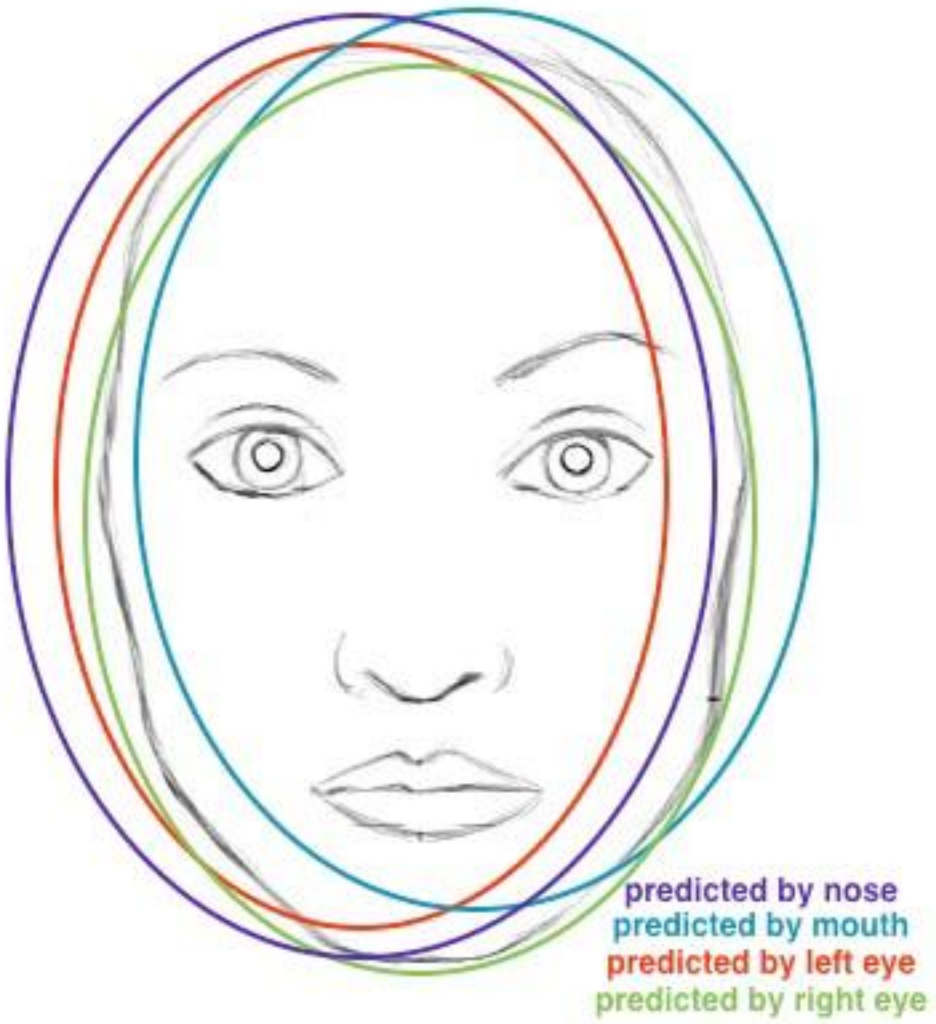
- How capsule works
  1. matrix multiplication of input vectors
  2. scalar weighting of input vectors
  3. sum of weighted input vectors
  4. vector-to-vector nonlinearity

CapsNet

1. matrix multiplication of input vectors



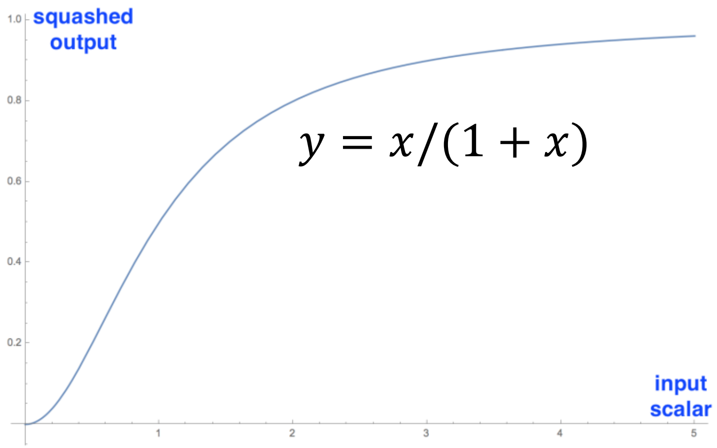
$\hat{u_i}$: predict vectors
u_i: output of last layer capsules



CapsNet

2. Scalar Weighting of Input Vectors
   Question: How to determine the weights/coefficients?
   Answer: Dynamic routing
3. Sum of Weighted Input Vectors
4. “Squash”: Novel Vector-to-Vector Nonlinearity

$$\mathbf{v}_j = \underbrace{\boxed{\frac{\|\mathbf{s}_j\|^2}{1+\|\mathbf{s}_j\|^2}}}_{\text{additional “squashing”}} \underbrace{\boxed{\frac{\mathbf{s}_j}{\|\mathbf{s}_j\|}}}_{\text{unit scaling}}$$



CapsNet

- Dynamic routing

  "*Lower level capsule will send its input to the higher level capsule that "agrees" with its input. This is the essence of the dynamic routing algorithm.*" – routing by agreement

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: $\mathbf{c}_i \leftarrow \mathtt{softmax}(\mathbf{b}_i)$ ▷ `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 $(l+1)$: $\mathbf{v}_j \leftarrow \mathtt{squash}(\mathbf{s}_j)$ ▷ `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 $\mathbf{v}_j$

CapsNet

- Dynamic routing questions
  - What is agreement?
  - Softmax along which axis? [My experiment result]

    99.60 v.s. 99.37 on MNIST

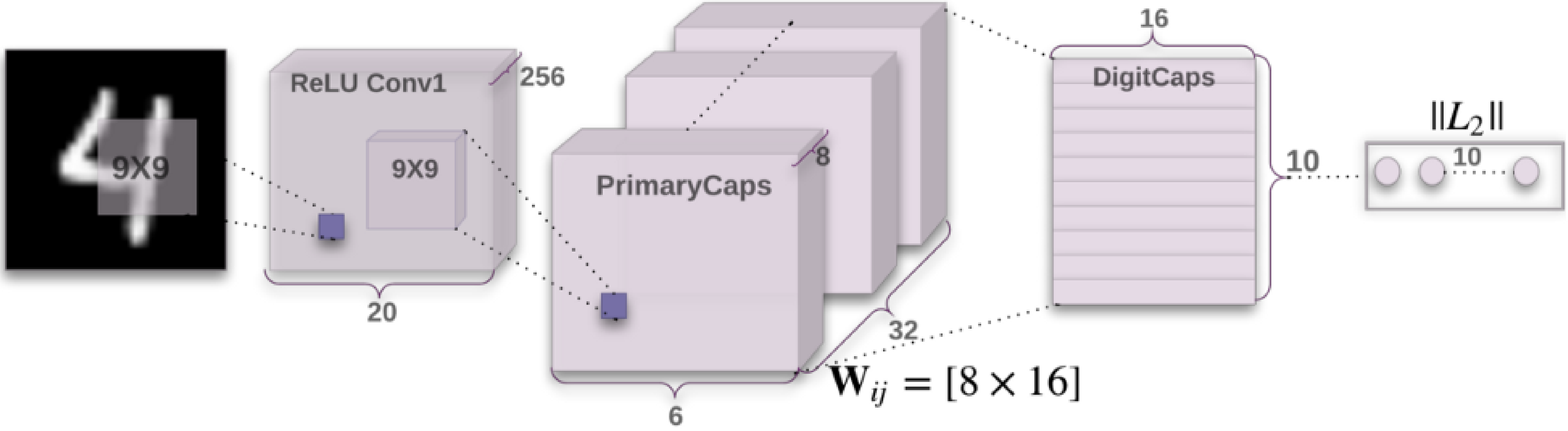
  - How many iterations to use?
    - two many iterations: overfit
    - suggestion: 3
  - Trainable parameters?
    W_{ij}, C_{ij}

CapsNet

- Network architecture
  - Encoder
  - Decoder[regularization]

CapsNet

- Part I. Encoder



CapsNet

- Part I. Encoder

CapsNet Loss Function

calculated for correct DigitCap

calculated for incorrect DigitCaps

loss term for one DigitCap

L2 norm

L2 norm

$$\boxed{L_c} = \boxed{\boxed{T_c}\ \boxed{\max(0, m^+ - ||\mathbf{v}_c||)^{\boxed{2}}}} + \boxed{\boxed{\lambda}\ \boxed{(1 - T_c)}\ \boxed{\max(0, ||\mathbf{v}_c|| - m^-)^{\boxed{2}}}}$$

1 when correct DigitCap, 0 when incorrect

zero loss when correct prediction with probability greater than 0.9, non-zero otherwise

0.5 constant used for numerical stability

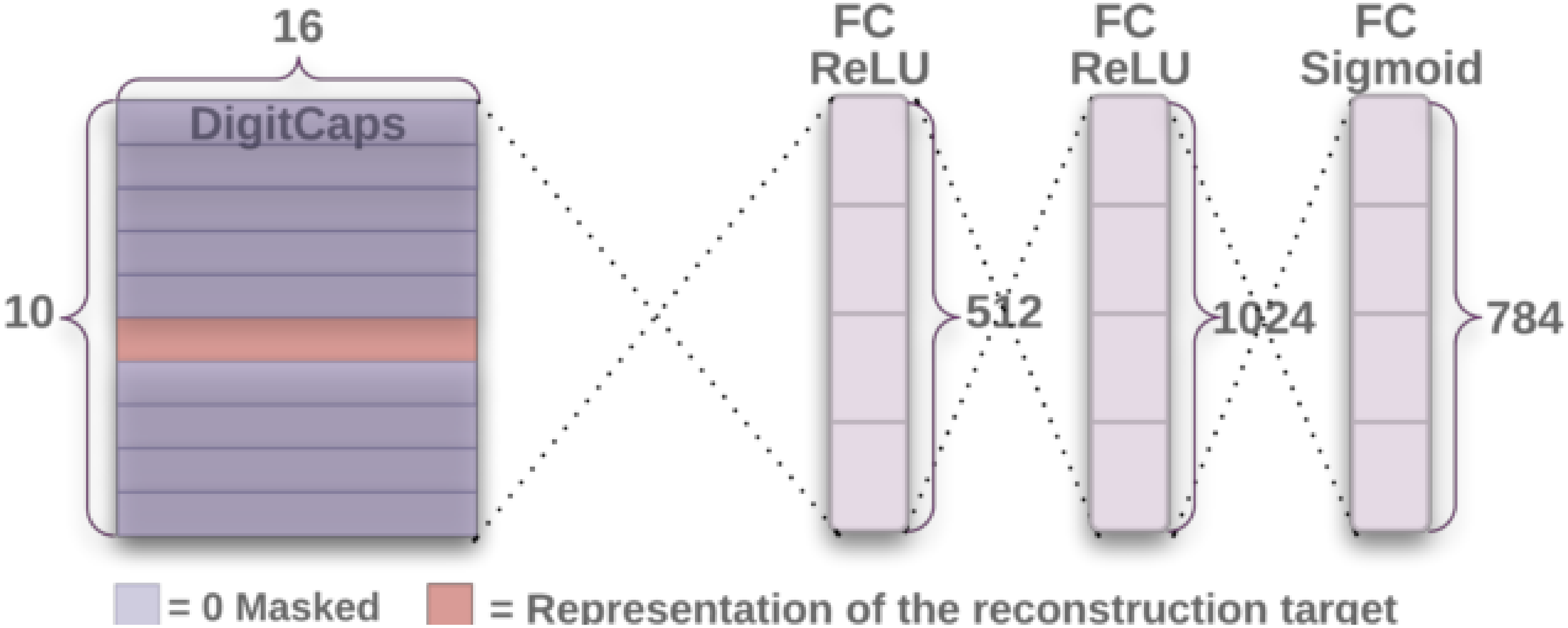
1 when incorrect DigitCap, 0 when correct

zero loss when incorrect prediction with probability less than 0.1, non-zero otherwise

Note: correct DigitCap is one that matches training label, for each training example there will be 1 correct and 9 incorrect DigitCaps

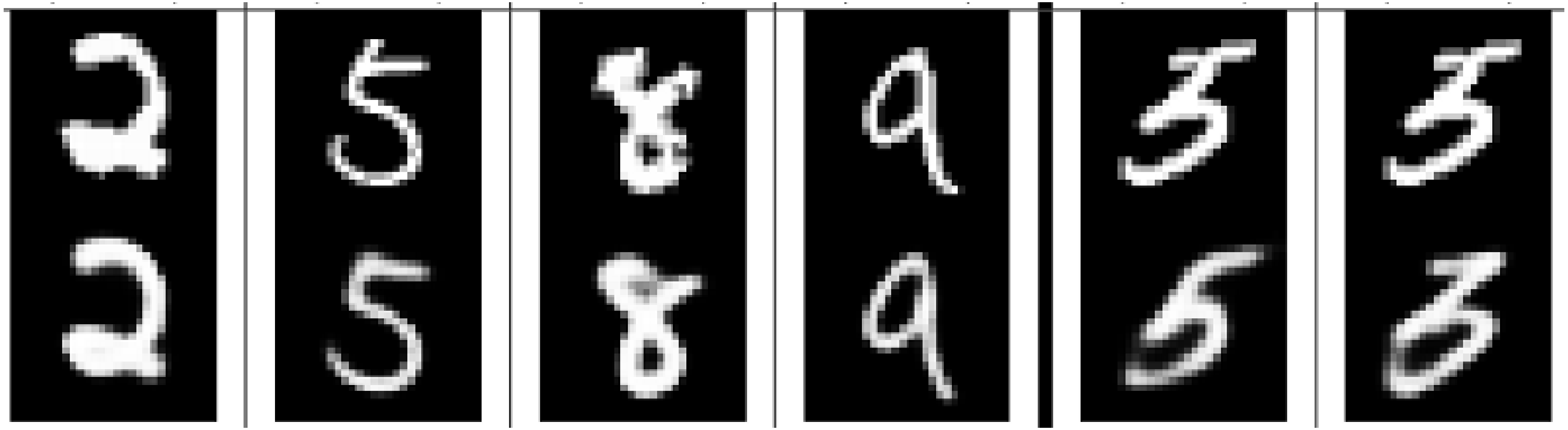
CapsNet

- Part II. Decoder



CapsNet

- Part II. Decoder

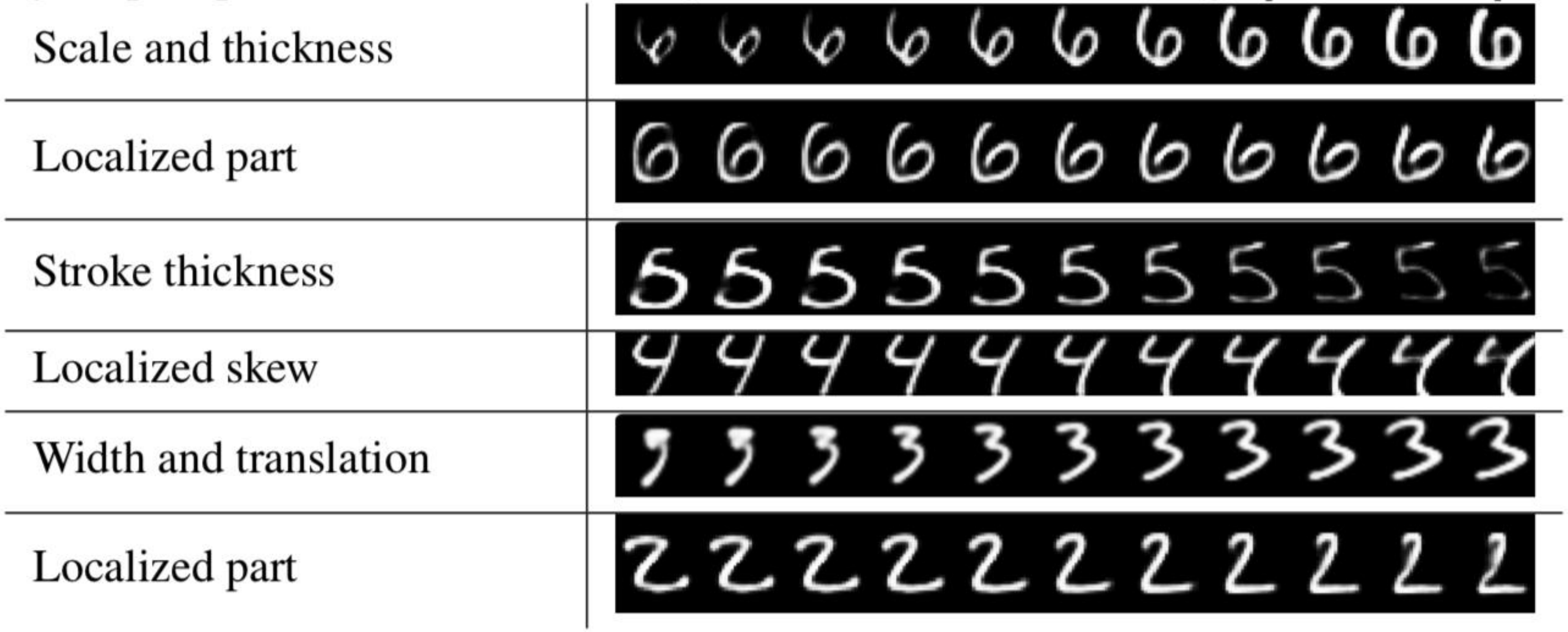


Question: why a decoder is necessary?
Loss: MSE

CapsNet Experiments

- What the individual dimensions of a capsule represent

Figure 4: Dimension perturbations. Each row shows the reconstruction when one of the 16 dimensions in the DigitCaps representation is tweaked by intervals of 0.05 in the range $[-0.25, 0.25]$.

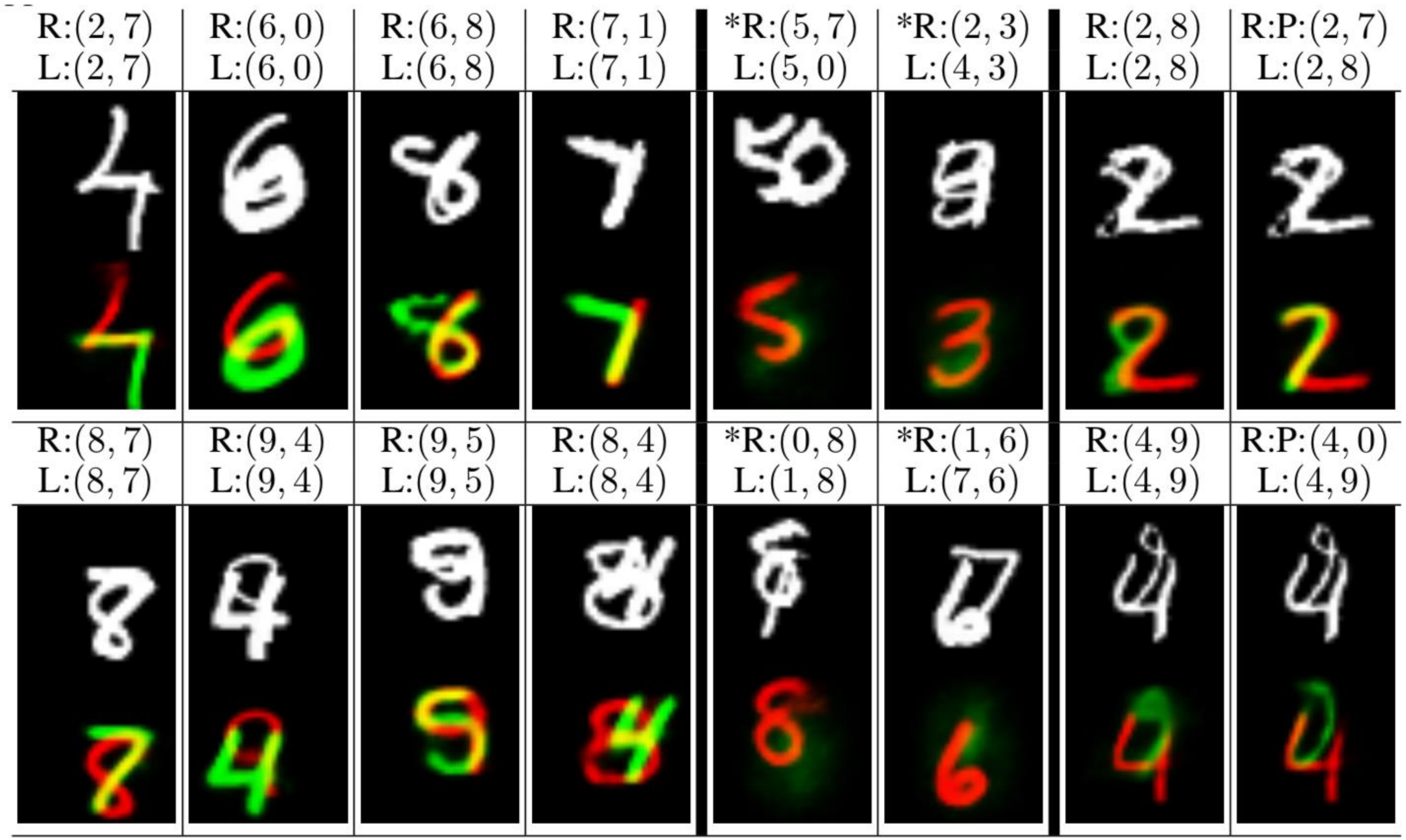


CapsNet Experiments

- Robustness to Affine Transformations
  - SOTA CNN:
    99.22 % -> 66 %
  - CapsNet:
    99.23% -> 79%

CapsNet Experiments

- Segmenting highly overlapping digits[MultiMNIST]



CapsNet Experiments

- Overall

Table 1: CapsNet classification test accuracy. The MNIST average and standard deviation results are reported from 3 trials.

Method	Routing	Reconstruction	MNIST (%)	MultiMNIST (%)
Baseline	-	-	0.39	8.1
CapsNet	1	no	$0.34_{\pm 0.032}$	-
CapsNet	1	yes	$0.29_{\pm 0.011}$	7.5
CapsNet	3	no	$0.35_{\pm 0.036}$	-
CapsNet	3	yes	$\mathbf{0.25}_{\pm 0.005}$	**5.2**

Dynamic vs EM routing

- Both are iterative
- Dynamic
  - Squash function
  - Cosine similarity
- EM
  - Existence probability
  - Distribution

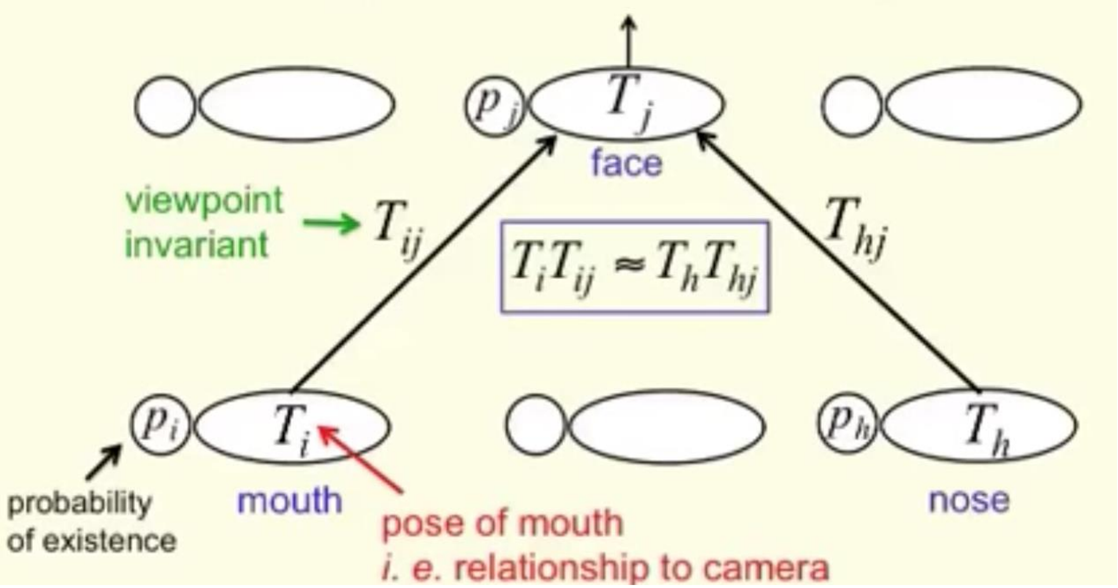


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Image source: https://jhui.github.io

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Applications

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