Dynamic Routing Between Capsules

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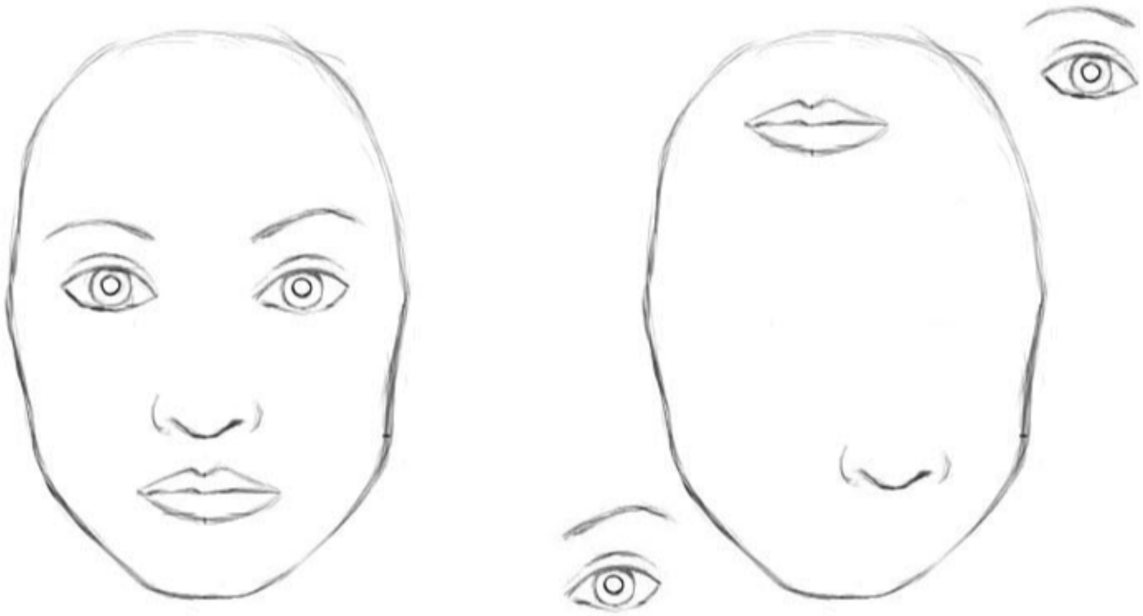
Presentation Architecture

1. Problems with CNNs
2. Motivation and Intuition
3. Network Architecture
    - Capsules
    - Dynamic Routing
4. Experimental Results
5. Critique

Drawbacks of Convolutional Neural Networks

- Translational invariance; no spatial hierarchies between objects
- “The pooling operation used in convolutional neural networks is a big mistake and the fact that it works so well is a disaster.”- Hinton
- Overlapping Segments



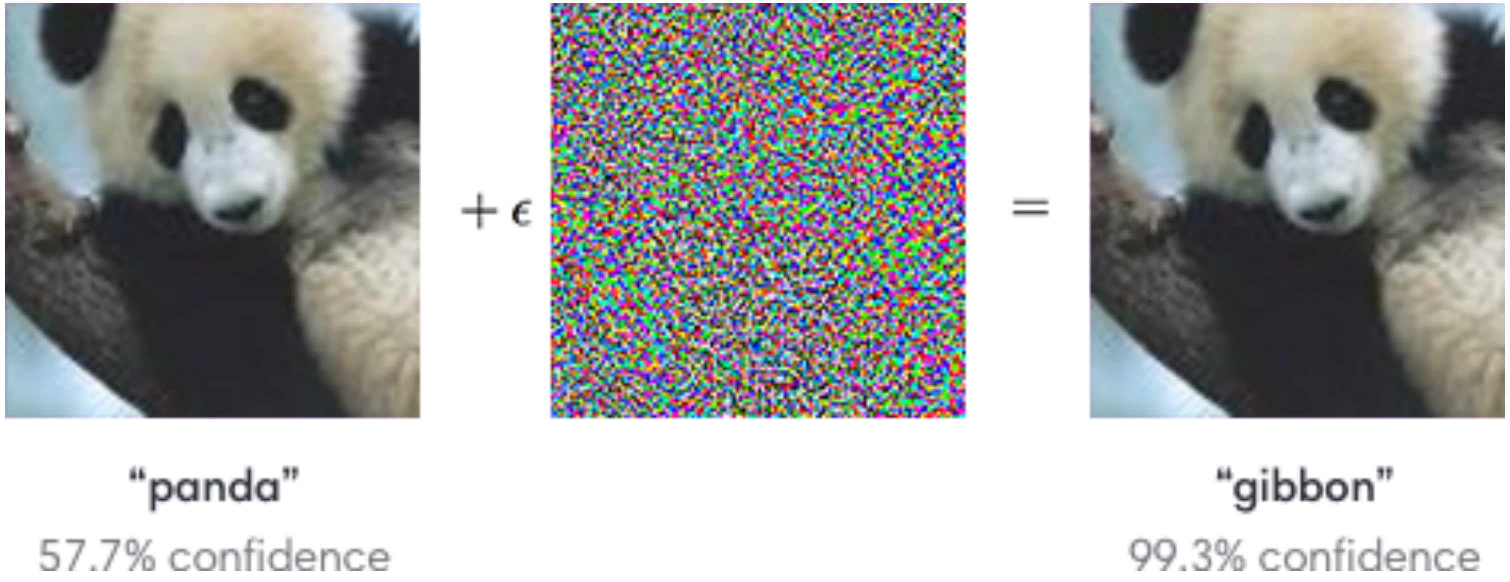
Drawbacks of Convolutional Neural Networks

CNN Prediction: Kitten

CNN Prediction: Guinea Pig

Adversarial Examples

- Demonstrates the lack of robustness in CNNs
- Security threat, and demonstrates that CNNs may not be learning in the way we desire



Motivation for CapsuleNets

- Intuition similar to rendering in computer graphics
- Explicit representation of pose relationships to induce rotational invariance

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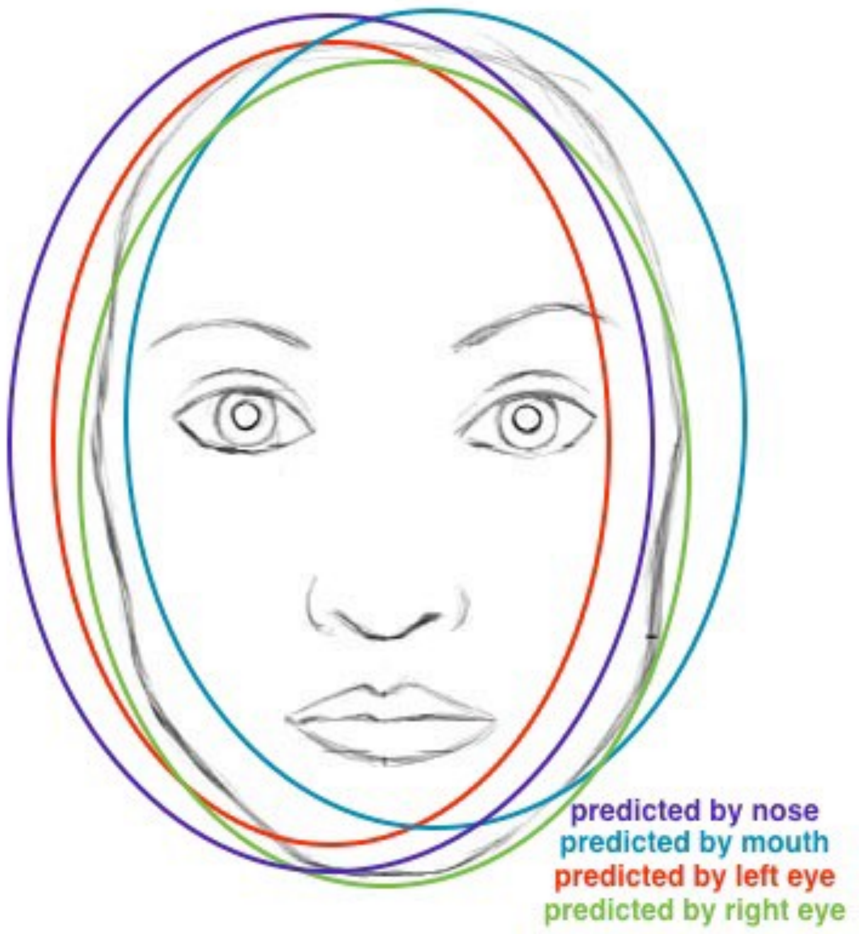
What are Capsules?

- Vector representations of the state of a detected feature
- Low level capsules communicate to infer information of higher level features



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Notation

- Squash

$$\mathbf{v}_j = \frac{||\mathbf{s}||^2}{1 + ||\mathbf{s}||^2} \frac{\mathbf{s}_j}{||\mathbf{s}_j||}$$

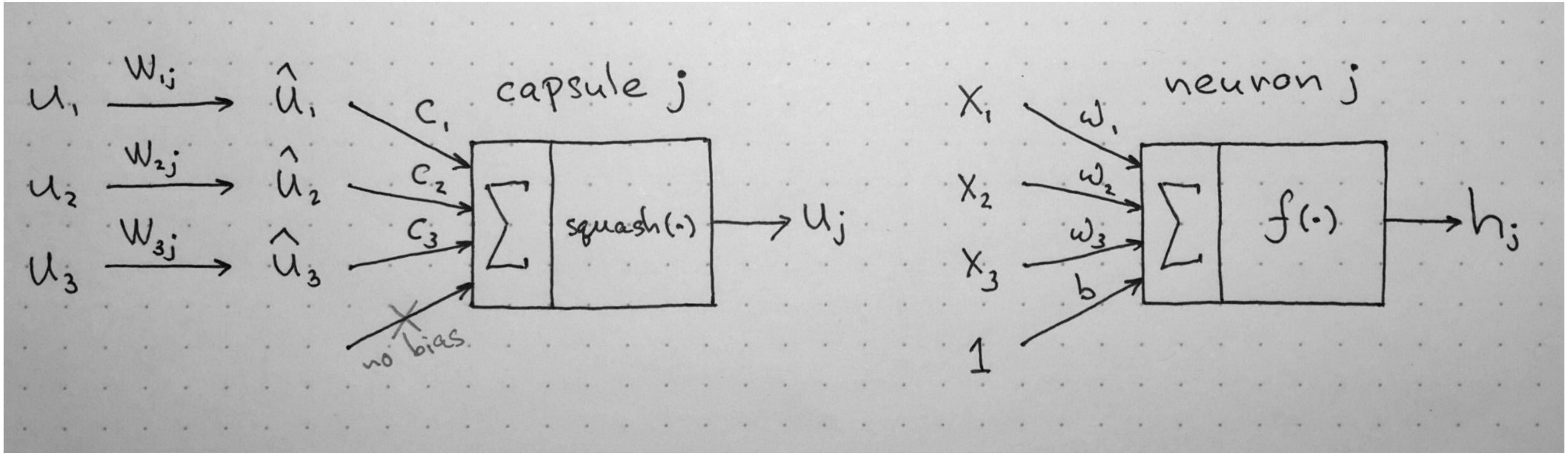
- Coupling coefficients

$$c_{ij} = \frac{\exp(b_{ij})}{\sum_k \exp(b_{ik})}$$

- Capsule Operations

$$\mathbf{s}_j = \sum_i c_{ij} \hat{\mathbf{u}}_{j|i}, \hat{\mathbf{u}}_{j|i}, = \mathbf{W}_{ij} \mathbf{u}_i$$

Capsules vs. Neurons



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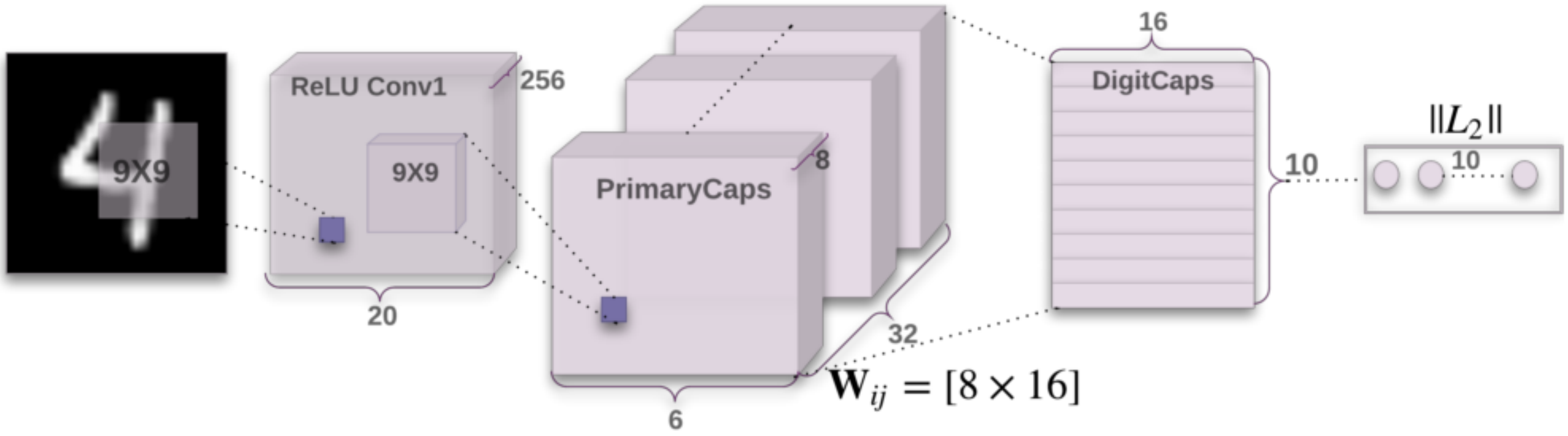
Architecture

1. Encoder
2. Loss Function
3. Decoder
4. Dynamic Routing/Training

Encoder



9X9
ReLU Conv1
9X9
256
20
PrimaryCaps
8
6
32
$\mathbf{W}_{ij} = [8 \times 16]$
16
DigitCaps
10
$\|L_2\|$
10

Loss Function

CapsNet Loss Function

calculated for correct DigitCap | **calculated for incorrect DigitCaps**

loss term for one DigitCap

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

L2 norm

L2 norm

1 when correct DigitCap, 0 when incorrect

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

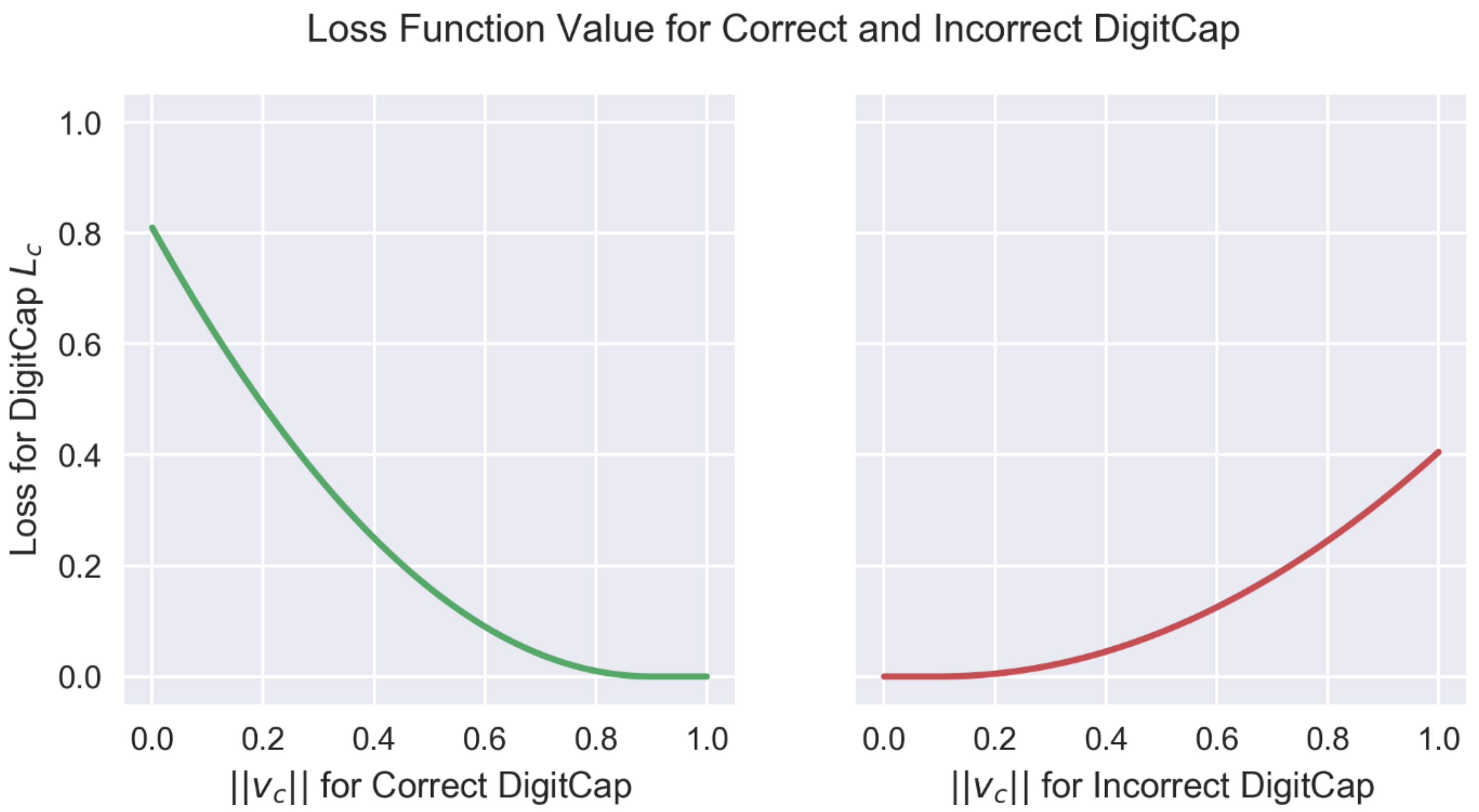
0.5 constant used for numerical stability

1 when incorrect DigitCap, 0 when correct

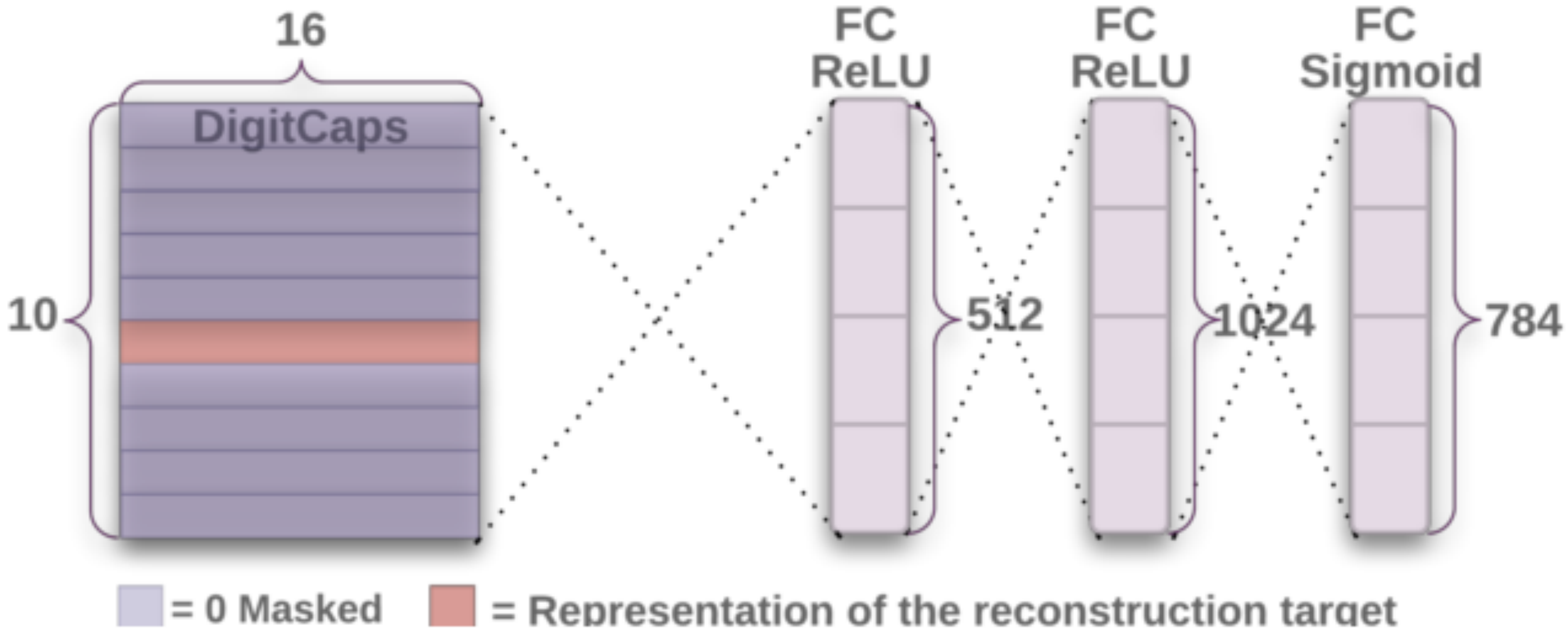
zero loss when incorrect prediction with probability less than 0.1, non-zero otherwise

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

Loss Function

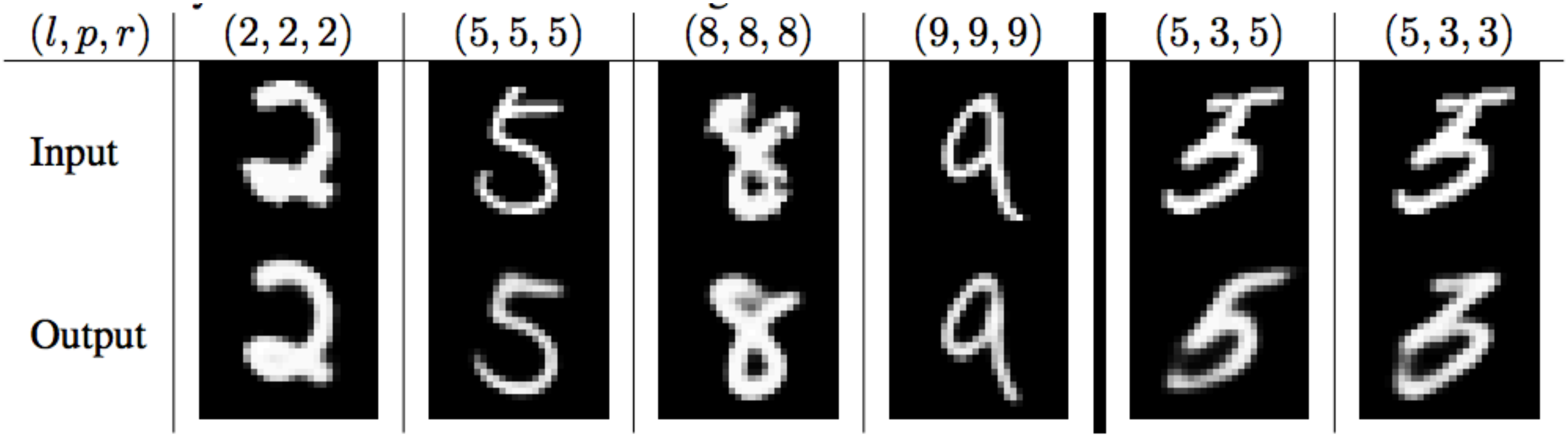


Decoder



16
DigitCaps
10
FC
ReLU
512
FC
ReLU
1024
FC
Sigmoid
784
= 0 Masked
= Representation of the reconstruction target

Decoder

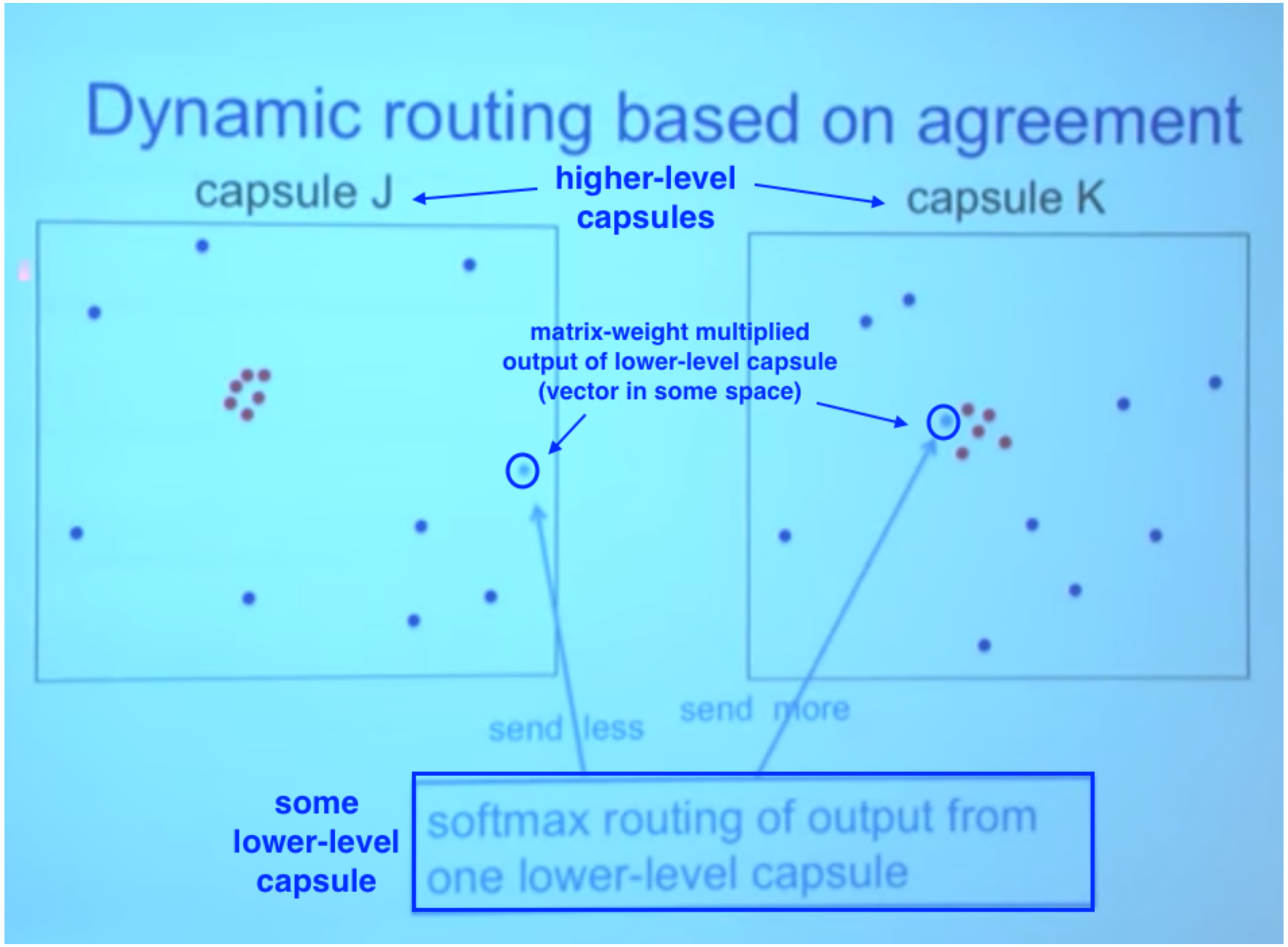


Dynamic Routing

Procedure 1 Routing algorithm.

procedure ROUTING($\hat{\mathbf{u}}_{j|i}$, 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 $\mathbf{v}_j$

Dynamic Routing Intuition



MNIST Experiments

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**

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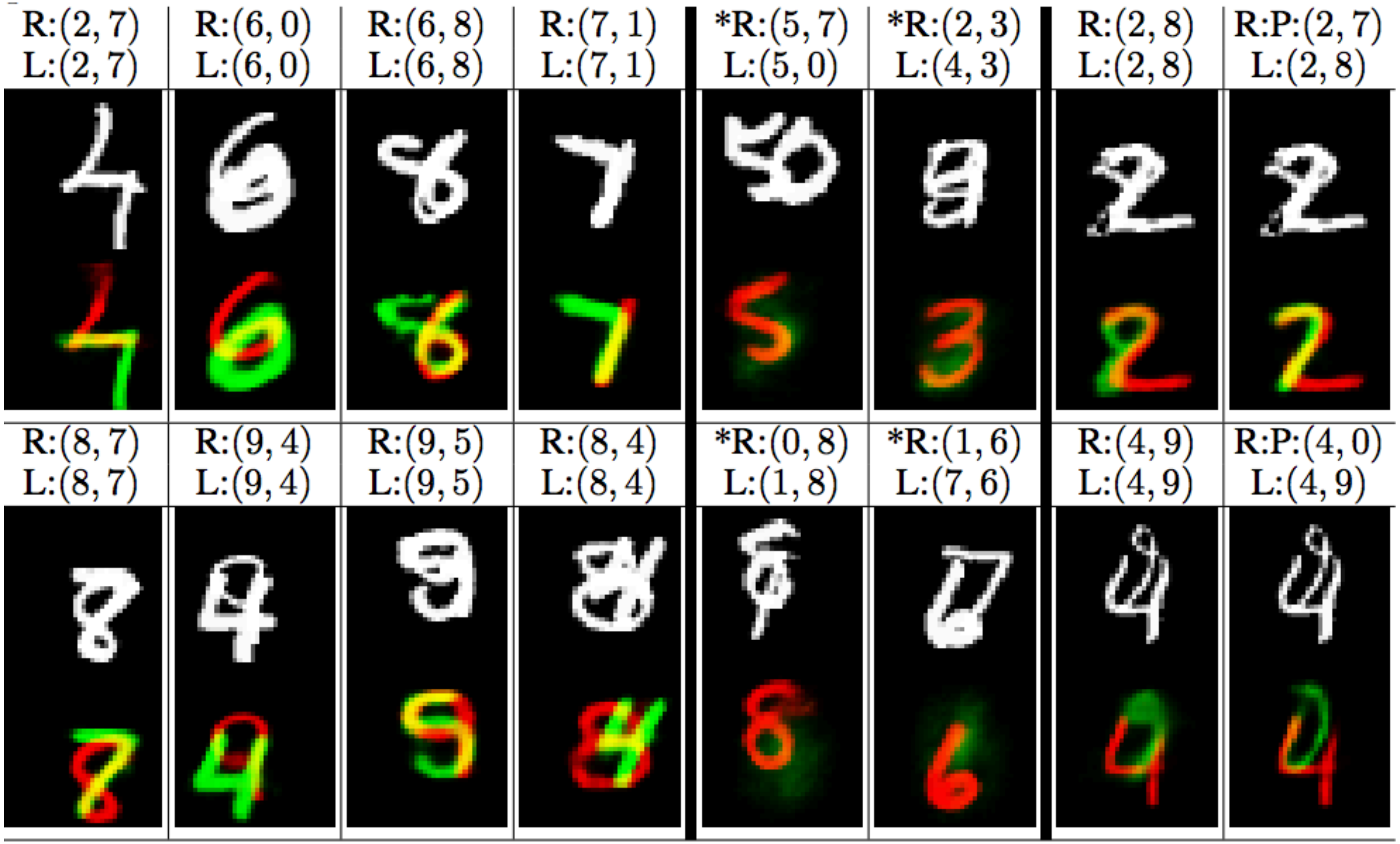
DigiCaps Representations in MNIST

Scale and thickness	
Localized part	
Stroke thickness	
Localized skew	
Width and translation	
Localized part	

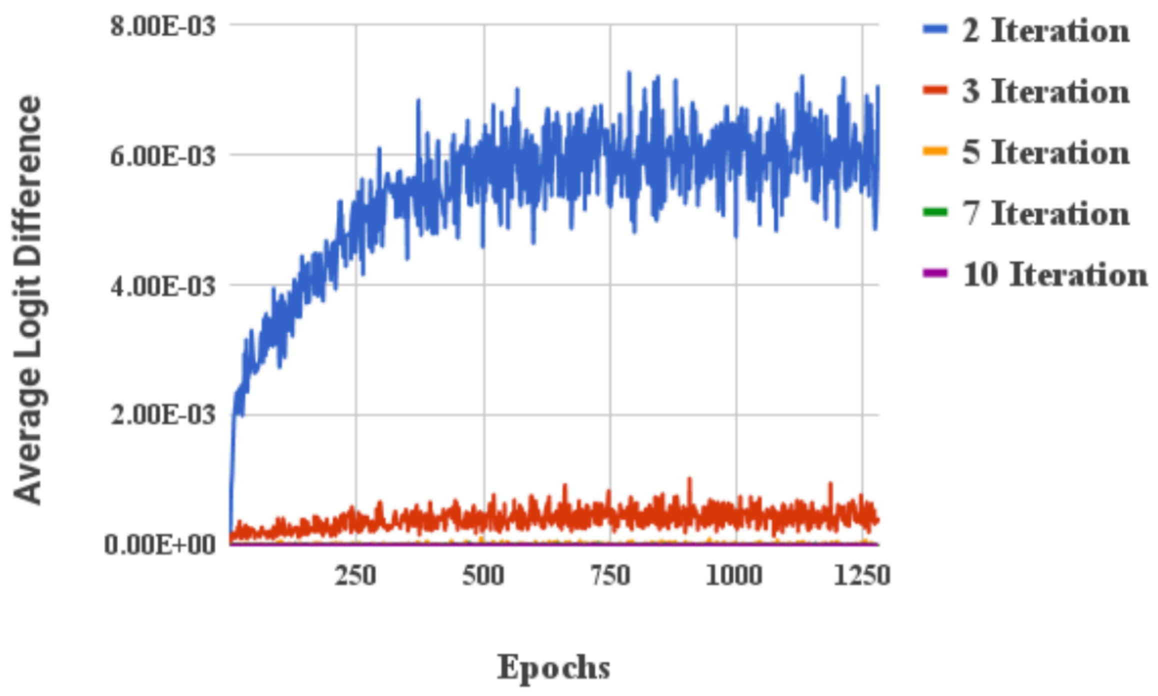
MultiMNIST



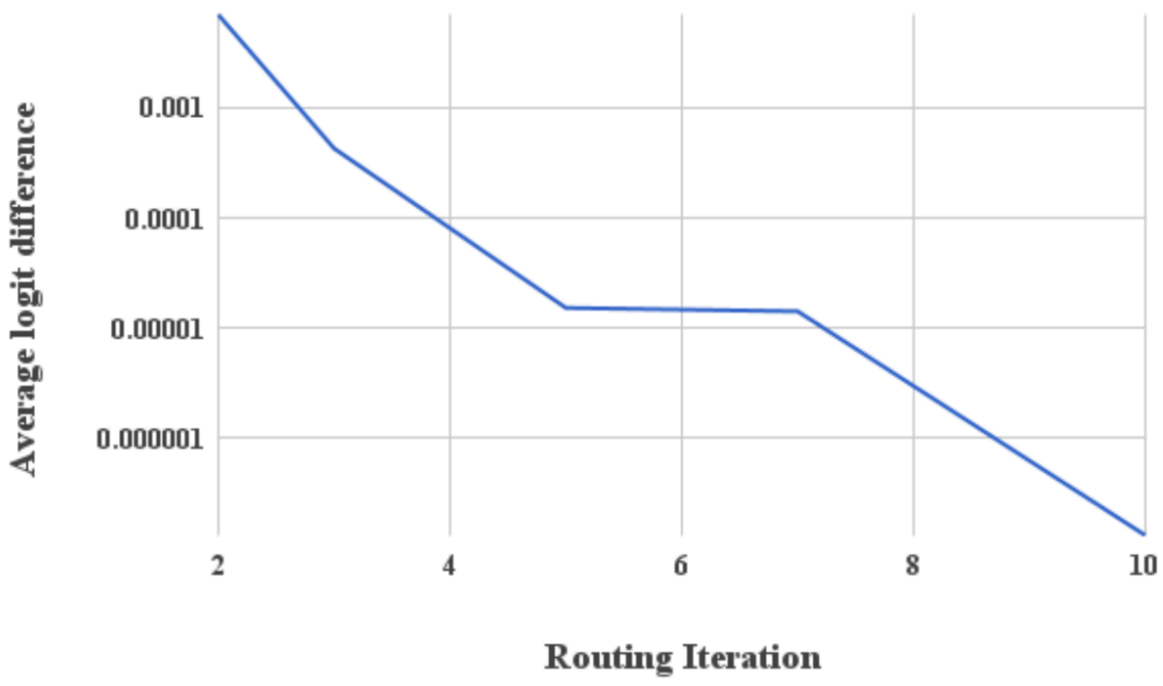
R:(2, 7)
L:(2, 7)
R:(6, 0)
L:(6, 0)
R:(6, 8)
L:(6, 8)
R:(7, 1)
L:(7, 1)
*R:(5, 7)
L:(5, 0)
*R:(2, 3)
L:(4, 3)
R:(2, 8)
L:(2, 8)
R:P:(2, 7)
L:(2, 8)
R:(8, 7)
L:(8, 7)
R:(9, 4)
L:(9, 4)
R:(9, 5)
L:(9, 5)
R:(8, 4)
L:(8, 4)
*R:(0, 8)
L:(1, 8)
*R:(1, 6)
L:(7, 6)
R:(4, 9)
L:(4, 9)
R:P:(4, 0)
L:(4, 9)

Number of Routing Iterations

(a) During training.

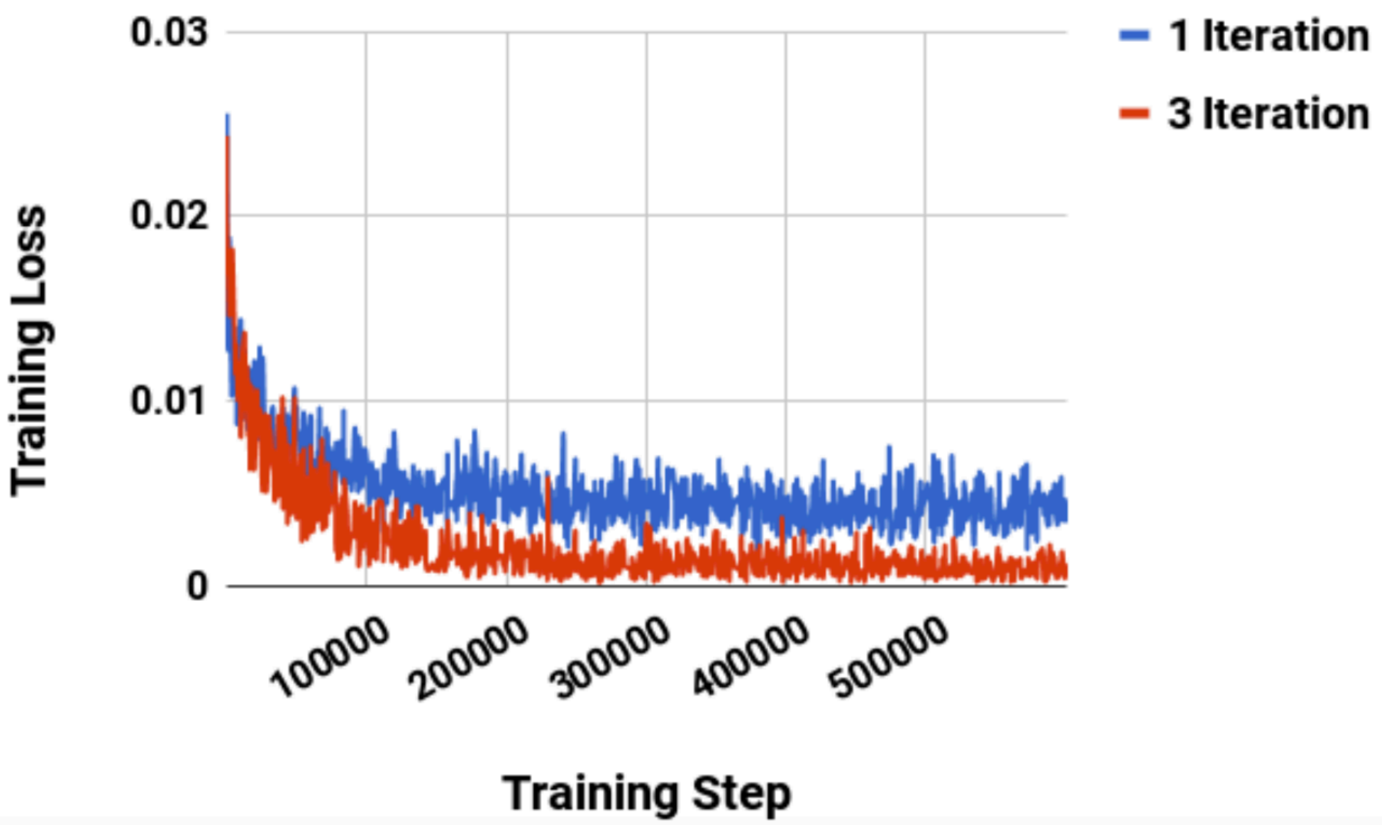


(b) Log scale of final differences.



Number of Routing Iterations

Overfitting Observed in CIFAR 10 Experiment



Critique

- Novel Approach, will lead to a new wave of research
- Resolves shortcomings of CNNs but currently underwhelming
- May require more domain knowledge of specific problems unlike CNNs
- Incredibly slow training for number of parameters (exponential number of iterations for routing training as number of capsule layers increase)
- Interesting concept which may change the landscape of CV