



Fixed Simplex Coordinates for Angular Margin Loss in CapsNet

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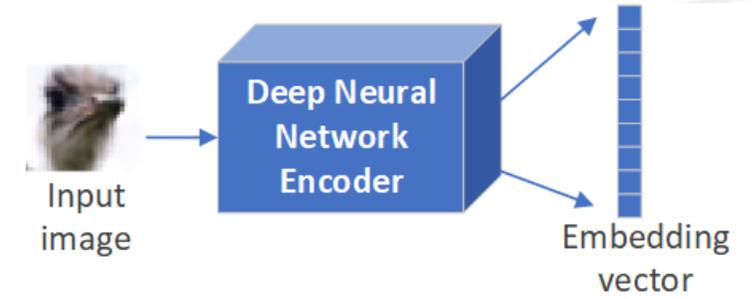
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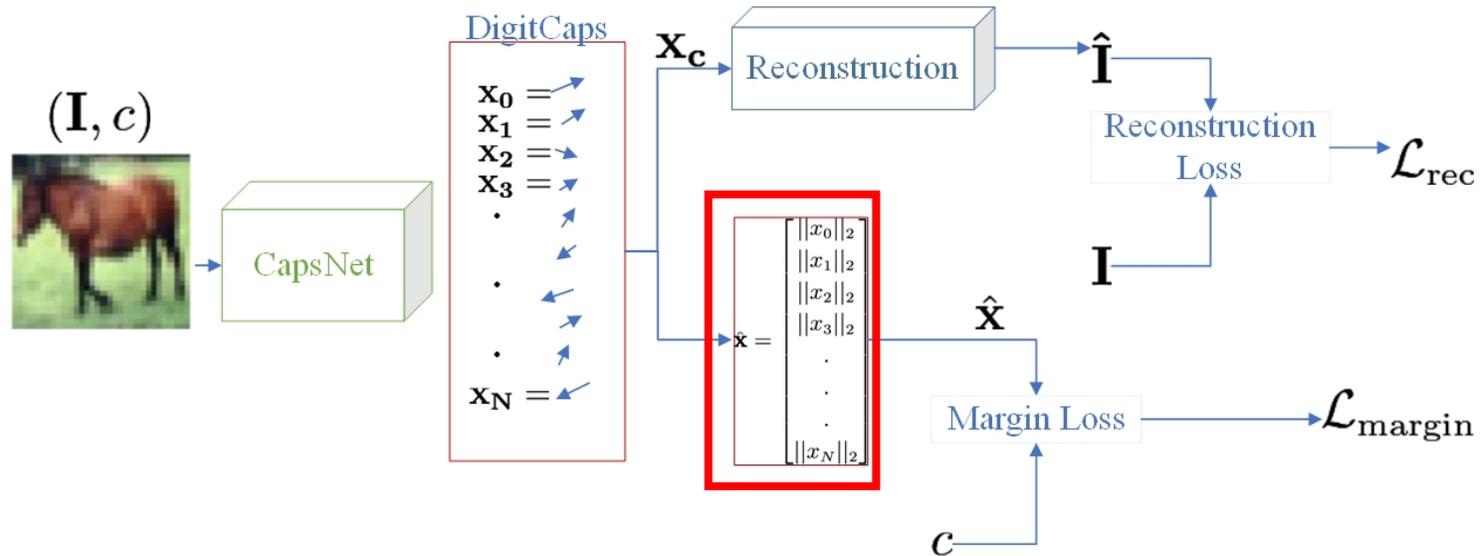
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Image embedding and CapsNet

- An **embedding**: is a mapping of a discrete (categorical) variable to a vector of continuous numbers
- **Neural network embeddings**: reduce the dimensionality of categorical variables and meaningfully represent categories in the transformed space
- **CNN-driven approach**: we can obtain images embedding by taking the **intermediate output** (before the classification layer) of a considered architecture

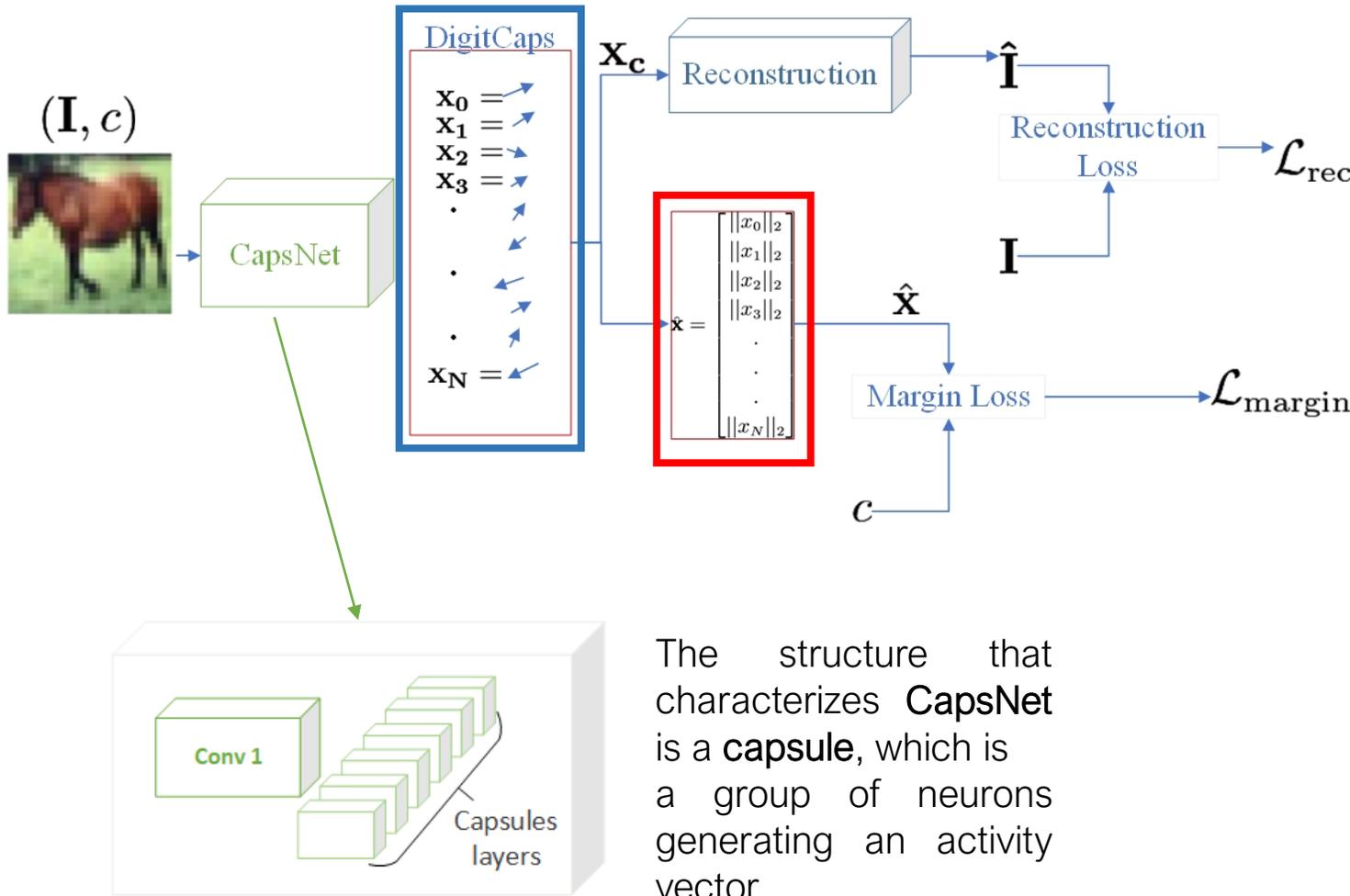


What if we apply CapsNet as Deep Neural Network encoder to extract the embedding?



We identify in the **magnitude of DigitCaps** the **Embedding** of input image

CapsNet overview



DigitCaps is a matrix $X \in R^{N \times D}$, N d -dimensional vectors from capsules

N is the number of classes

The **image embedding** is $\hat{x} = [\|x_0\|_2 \cdots \|x_N\|_2]$: the magnitude of each row (classes) of the matrix X

$$\hat{x}$$

- Maintains all the information from the digits of each capsule
- Provides a **discriminative embedding** based on the predicted class

The structure that characterizes CapsNet is a **capsule**, which is a group of neurons generating an activity vector

PolyCapsNet: CapsNet with maximal discriminativity

We want to train our model to enhance the intra-class compactness and inter-class discrepancy among images

Angular margin loss:

reduces the geodesic distance between the image embedding (\hat{x}) and the vector centroid (w_c) of the corresponding class c

The image embedding (\hat{x})

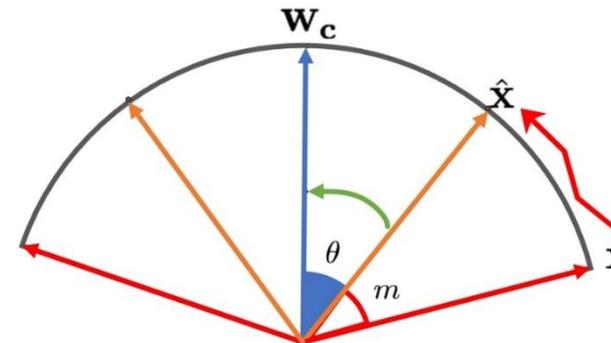
Softmax Function

$$L_1 = -\frac{1}{K} \sum_{i=1}^K \log \frac{e^{w_{c_i}^T \hat{x}_i + b_i}}{\sum_{j=1}^N e^{w_j^T \hat{x}_i + b_j}}$$

K : number of input samples

$W \in R^{d \times N}$: responsible of projecting the input embedding to the class space

Does not encourage the similarity among intra-class samples and the diversity among inter-class samples



$$w_{c_i}^T \hat{x}_i = \|w_{c_i}\| \|\hat{x}_i\| \cos \theta_j \quad b = 0 \quad \text{where } w_c \in W$$

$$L_{\text{angle}} = -\frac{1}{K} \sum_{i=1}^K \log \frac{e^{s(\cos(\theta_c+m))}}{e^{s(\cos(\theta_c+m))} + \sum_{j=1, j \neq c}^N e^{s(\cos(\theta_j+m))}}$$

$$w_c \in W$$

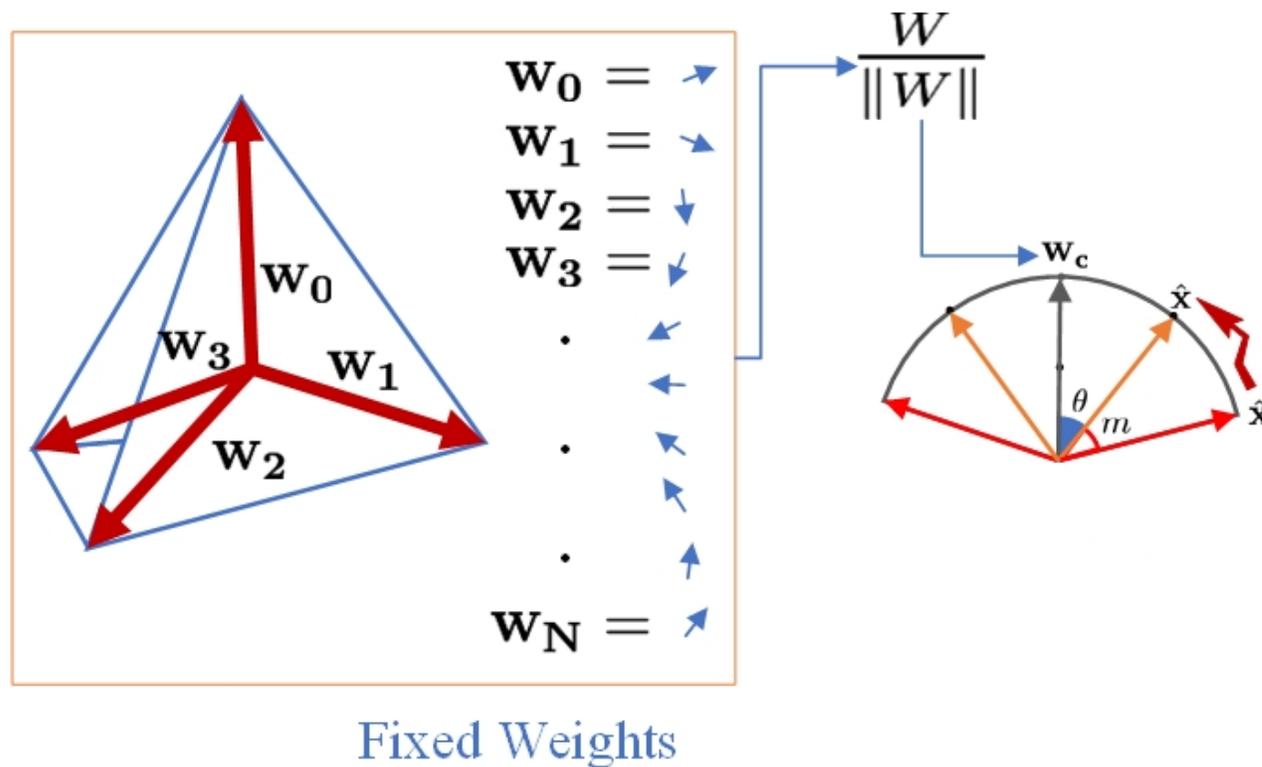
The angular margin loss introduces the need for a weight matrix W to represent the class centroids described in an hyperspherical space of definition

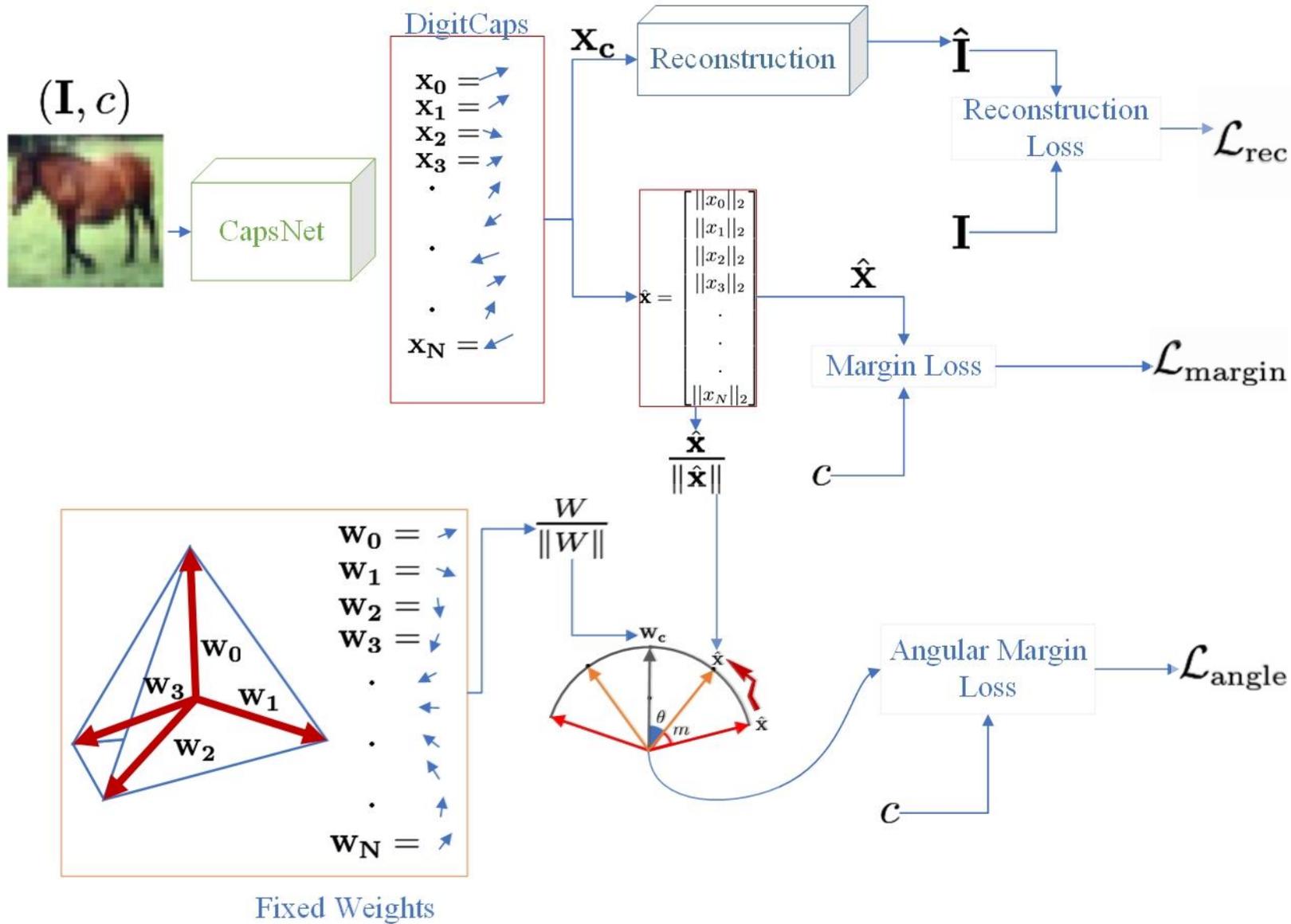
Fixed Classifier:

- Guaranteeing stationarity of the embedding

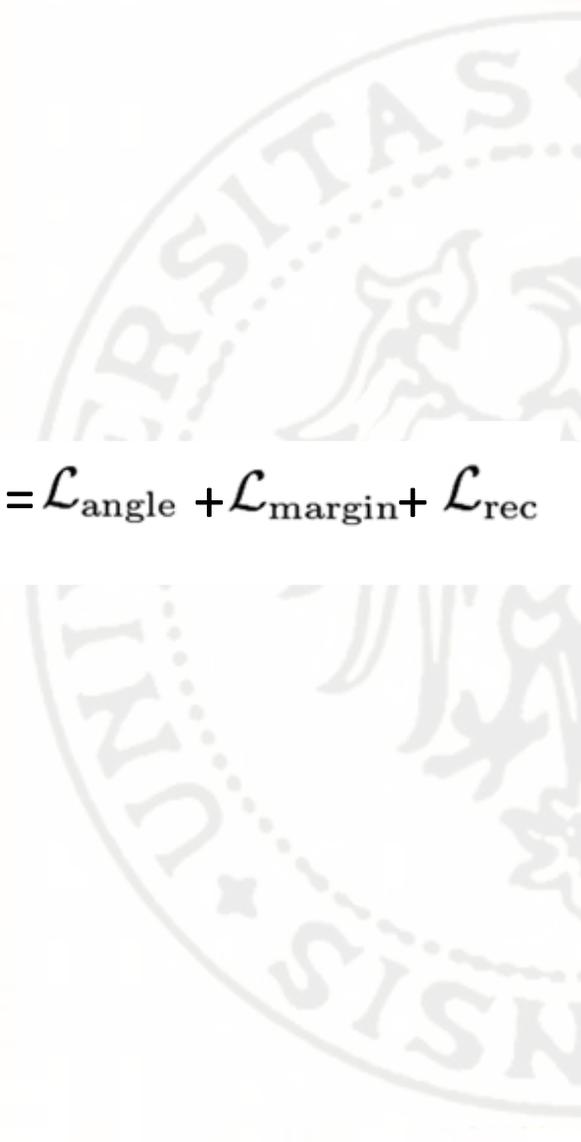
Polytopes (geometric object with "flat" sides):

- Define weight matrix
- Maximal discriminability representation





$$\mathcal{L} = \mathcal{L}_{angle} + \mathcal{L}_{margin} + \mathcal{L}_{rec}$$

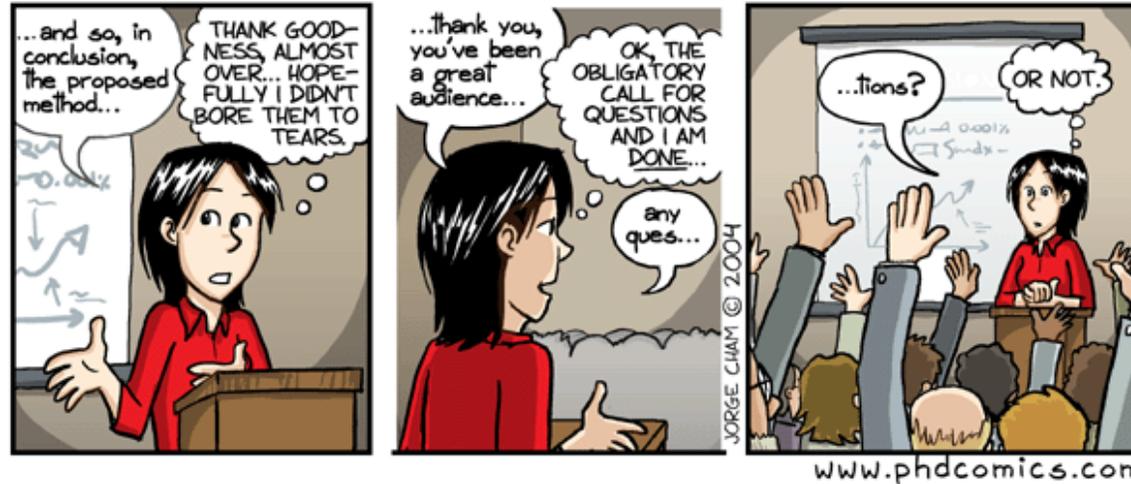


Loss function	MNIST	CIFAR10	SmallNorb
$\mathcal{L}_{\text{margin}}$	99.33%	72.84%	66.98%
$\mathcal{L}_{\text{margin}} + \mathcal{L}_{\text{rec}}$	99.37%	73.11%	64.62%
$\mathcal{L}_{\text{angle}}$	99.30%	70.61%	77.29%
$\mathcal{L}_{\text{angle}} + \mathcal{L}_{\text{rec}}$	99.14%	68.97%	66.25%
$\mathcal{L}_{\text{angle}} + \mathcal{L}_{\text{margin}}$	99.39%	68.96%	78.41%
$\mathcal{L}_{\text{angle}} + \mathcal{L}_{\text{margin}} + \mathcal{L}_{\text{rec}}$	99.39%	71.61%	81.44%

What if we use a learnable W matrix?

Classifier	MNIST	CIFAR10	SmallNorb
Fixed W with Simplex	99.39%	71.61%	81.44%
Learnable W	98.75%	50.38%	57.28%

Thank you for listening to this presentation!



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