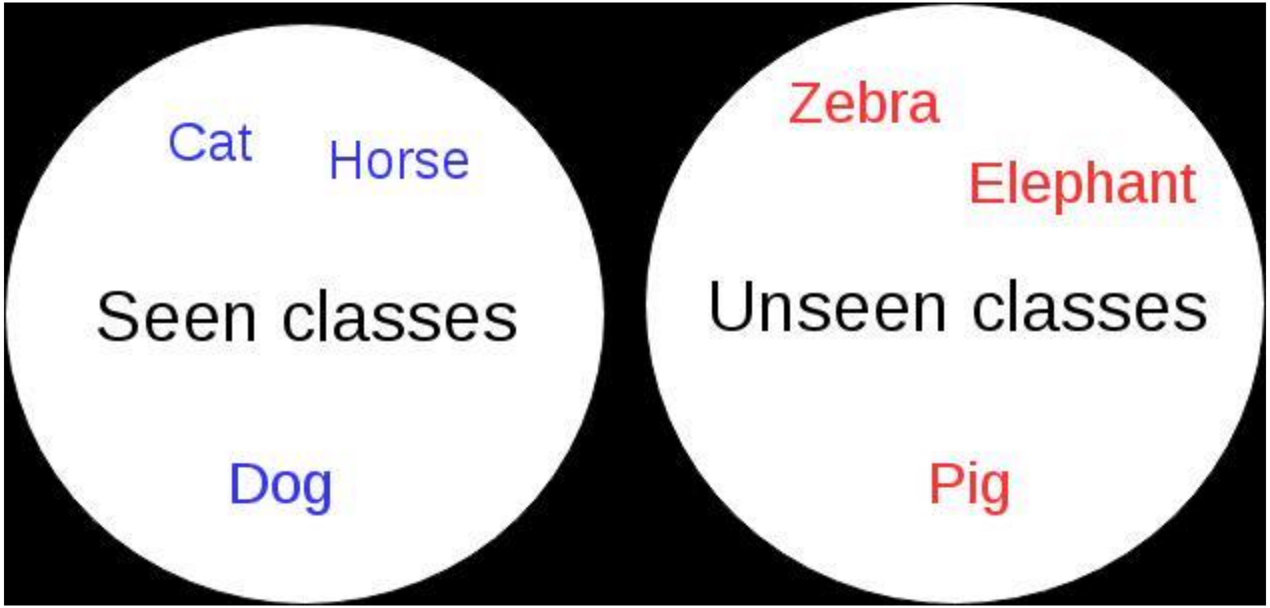
Latent Embeddings for Zero-shot Classification

Yongqin Xian, Zeynep Akata, Gaurav Sharma, Quynh Nguyen, Matthias Hein, Bernt Schiele;
The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016

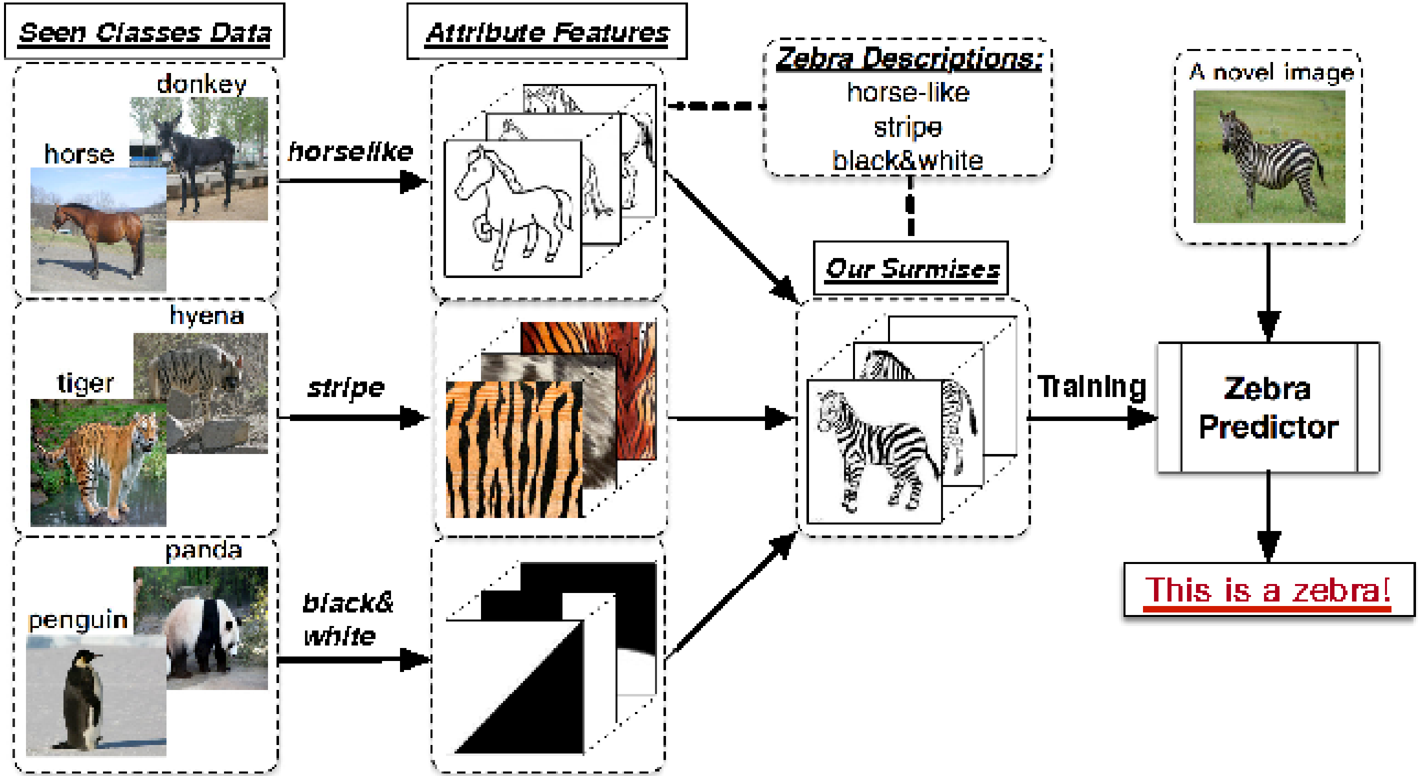
Latent Embeddings for Zero-shot Classification

- Zero-shot Learning?
  - 목표



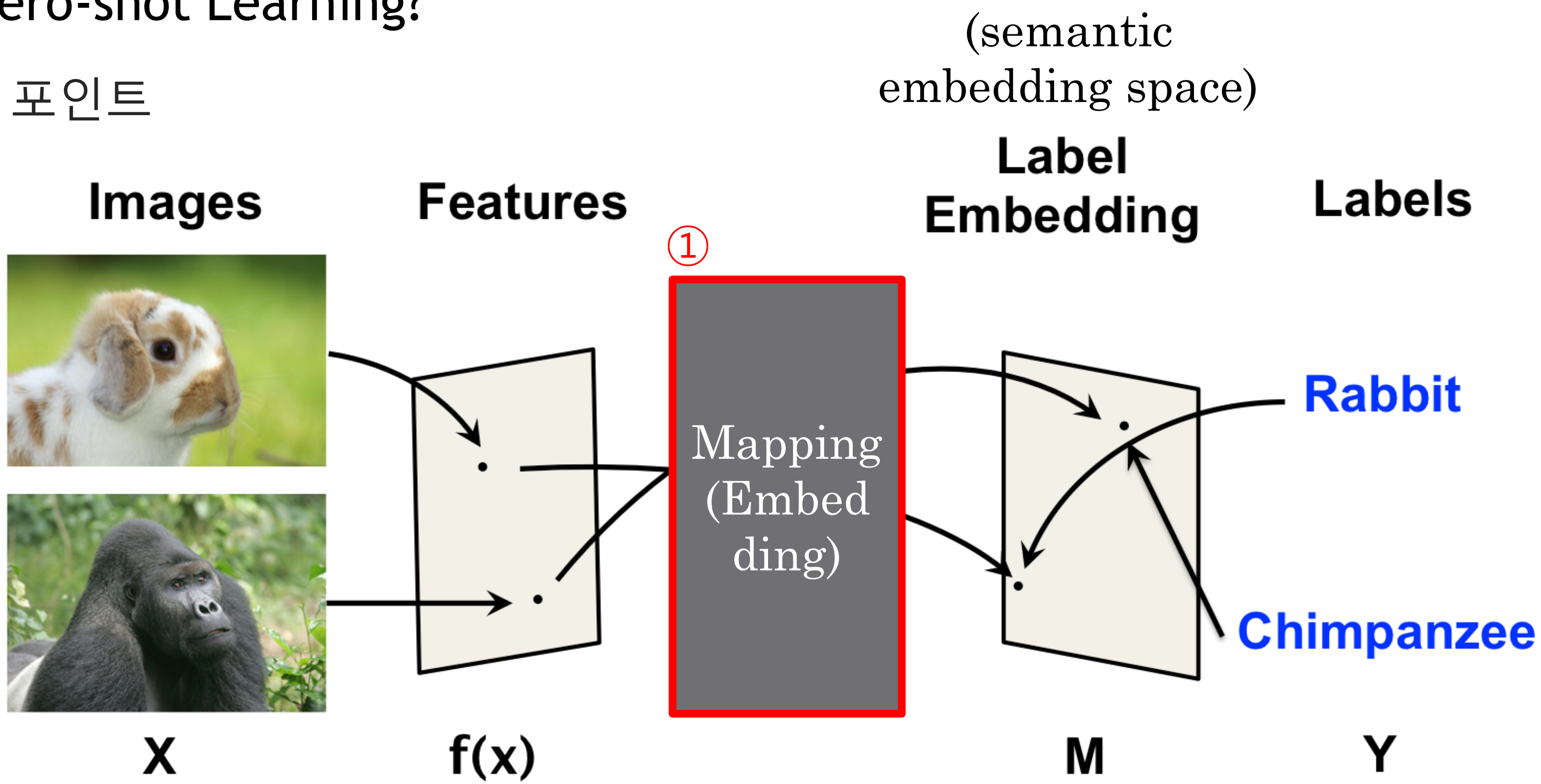
labeled -> 학습!　　　unlabeled -> 예측!

- Zero-shot Learning?
  - 개념적으로는..



Latent Embeddings for Zero-shot Classification

- Zero-shot Learning?
  - 포인트



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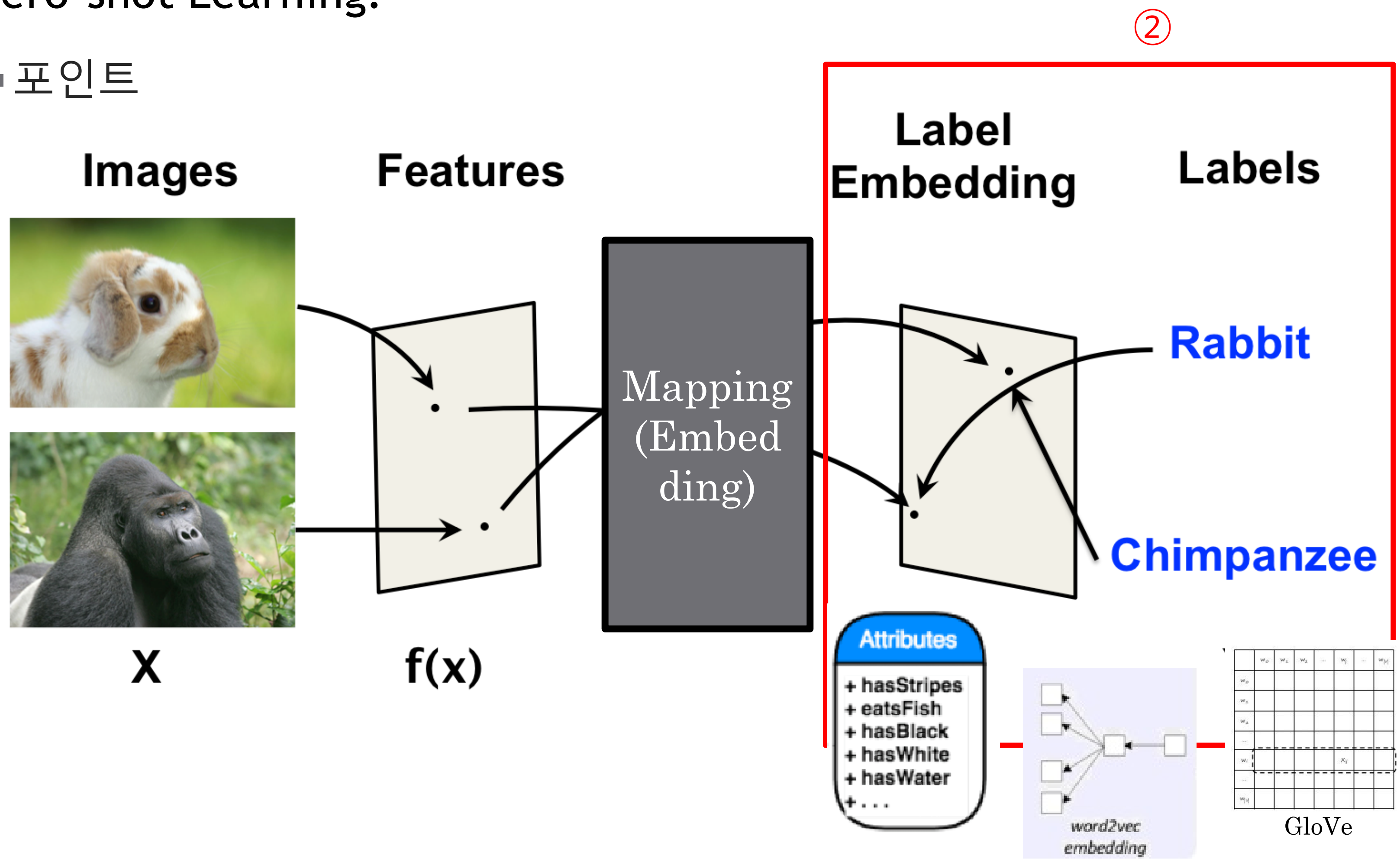


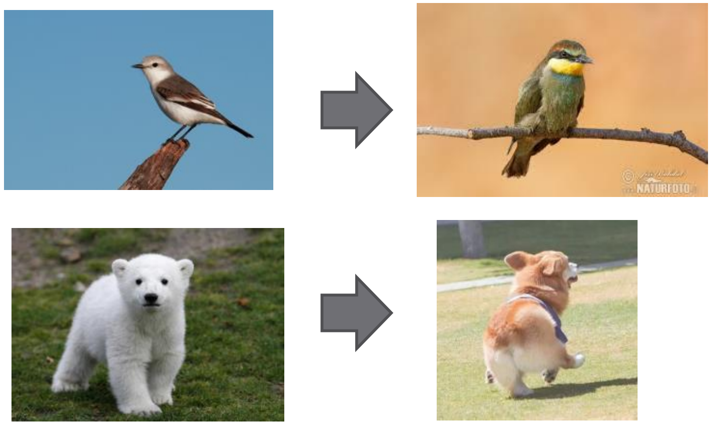
Latent Embeddings for Zero-shot Classification

- Zero-shot Learning?
  - ZSL 기본 모델의 가정(한계점?)

1. 관련성이 높은 seen 과 unseen class는 이미지에 비슷한 feature를 포함

2. 그런 class들의 label은 semantic embedding space 내 비슷한 위치에 있을 것

   (이건 현재로선 어쩔수 없음)



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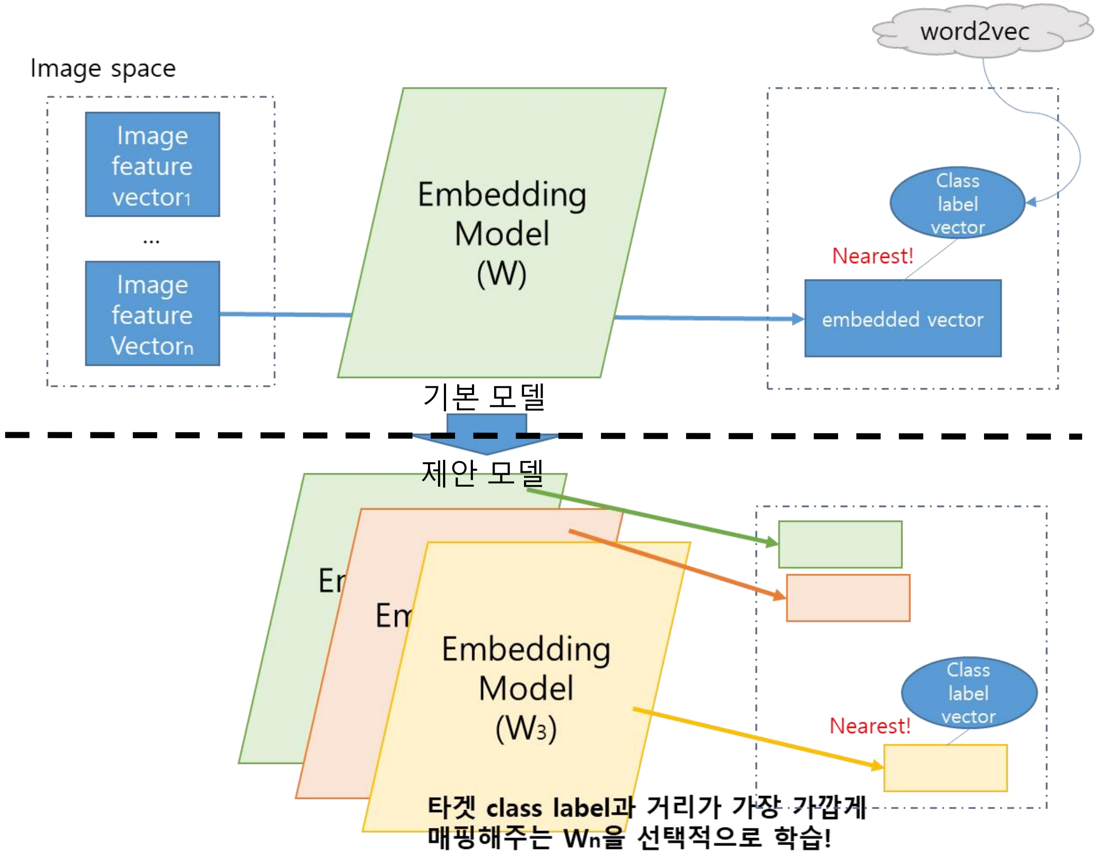

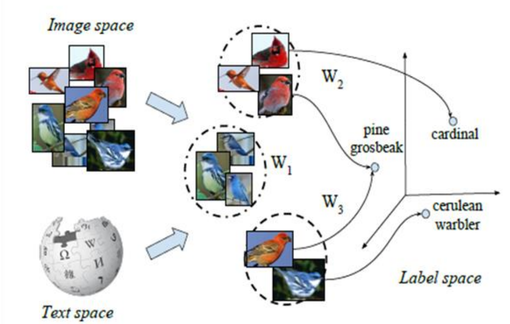

Figure 1: LatEm learns multiple W_i's that maximize the compatibility between the input embedding (image, text space) and the output embedding (label space) of all training examples. The different W_i's may capture different visual characteristics of objects, i.e. color, beak shape etc. and allow distribution of the complexity among them, enabling the model to do better classification.

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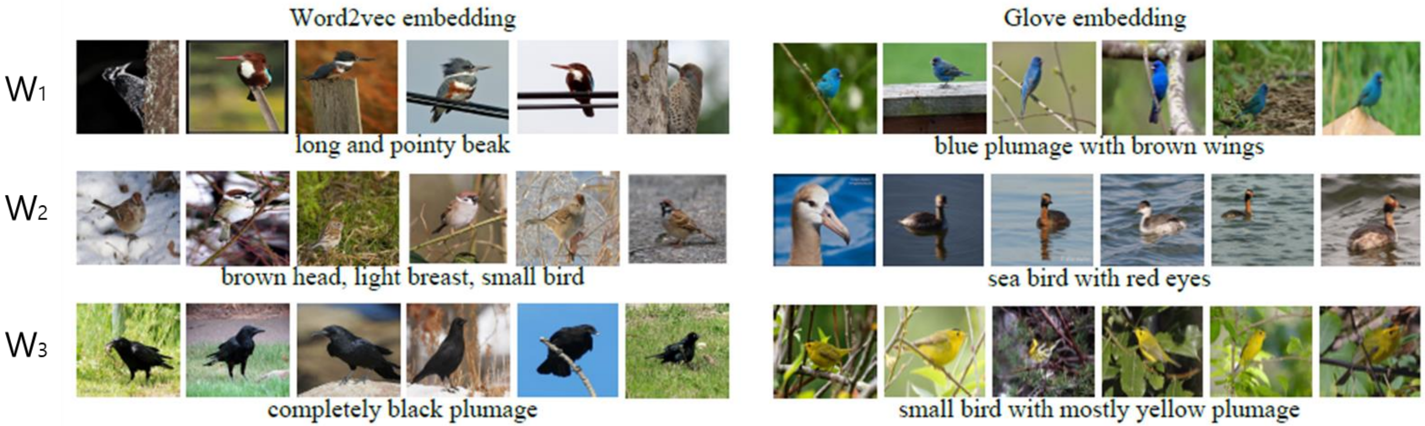

Figure 2: Top images ranked by the matrices using word2vec and glove on CUB dataset, each row corresponds to different matrix in the model. Qualitative examples support our intuition – each latent variable captures certain visual aspects of the bird. Note that, while the images may not belong to the same fine-grained class, they share common visual properties.

dom to treat different types of images differently. Let us consider a fixed class $\hat{\mathbf{y}}$ and two substantially visually different types of images $\mathbf{x}_1, \mathbf{x}_2$, e.g. the same bird flying and swimming. In SJE [2] these images will be mapped to the class embedding space with a single mapping $W^\top \mathbf{x}_1, W^\top \mathbf{x}_2$. On the other hand, LatEm will have learned two different matrices for the mapping i.e. $W_1^\top \mathbf{x}_1, W_2^\top \mathbf{x}_2$. While in the former case a single W has to map two visually, and hence numerically, very different vectors (close) to the same point, in the latent case such two different map-

Latent Embeddings for Zero-shot Classification

- Objective
  - Compatibility function F (수치값)
    - K : the number of W, W: embedding matrix
    - x : image feature vector, y : label vector

$$F(\mathbf{x}, \mathbf{y}) = \max_{1 \le i \le K} \mathbf{x}^\top W_i \mathbf{y}.$$

  - Loss function

$$L(\mathbf{x}_n, \mathbf{y}_n) = \sum_{\mathbf{y} \in \mathcal{Y}} \max\{0, \Delta(\mathbf{y}_n, \mathbf{y}) + F(\mathbf{x}_n, \mathbf{y}) - F(\mathbf{x}_n, \mathbf{y}_n)\} \quad (6)$$

where $\Delta(\mathbf{y}, \mathbf{y}_n) = 1$ if $\mathbf{y} \neq \mathbf{y}_n$ and 0 otherwise. This ranking-based loss function has been previously used in [12, 38] such that the model is trained to produce a higher compatibility between the image embedding and the class embedding of the correct label than between the image embedding and class embedding of other labels.

Latent Embeddings for Zero-shot Classification

- Optimization

Algorithm 1 SGD optimization for LatEm

$\mathcal{T} = \{(\mathbf{x}, \mathbf{y}) | \mathbf{x} \in \mathbb{R}^{d_x}, \mathbf{y} \in \mathbb{R}^{d_y}\}$

for all $t = 1$ to T **do** epochs

  for all $n = 1$ to $|\mathcal{T}|$ **do** training set

    Draw $(\mathbf{x}_n, \mathbf{y}_n) \in \mathcal{T}$ and $\mathbf{y} \in \mathcal{Y} \setminus \{\mathbf{y}_n\}$ 비교 대상(정답이 아닌) label 선택

    if $F(\mathbf{x}_n, \mathbf{y}) + 1 > F(\mathbf{x}_n, \mathbf{y}_n)$ **then** L(xn,yn) > 0

      $i^* \leftarrow \underset{1 \leq k \leq K}{\arg\max}\, \mathbf{x}_n^\top W_k \mathbf{y}$

      $j^* \leftarrow \underset{1 \leq k \leq K}{\arg\max}\, \mathbf{x}_n^\top W_k \mathbf{y}_n$

현재 image feature가 각 class label에
가장 큰 영향을 주는 W를 선택

      if $i^* = j^*$ **then**

        $W_{i^*}^{t+1} \leftarrow W_{i^*}^t - \eta_t \mathbf{x}_n (\mathbf{y} - \mathbf{y}_n)^\top$ 그 W가 같으면 정답은 가까워지게 정답
아닌건 멀어지게 학습

      end if

      if $i^* \neq j^*$ **then**

        $W_{i^*}^{t+1} \leftarrow W_{i^*}^t - \eta_t \mathbf{x}_n \mathbf{y}^\top$

        $W_{j^*}^{t+1} \leftarrow W_{j^*}^t + \eta_t \mathbf{x}_n \mathbf{y}_n^\top$ 그 W가 다르면 각각 학습

      end if

    end if

  end for

end for

Latent Embeddings for Zero-shot Classification

	Total		train+val		test	
	imgs	cls	imgs	cls	imgs	cls
CUB	11786	200	8855	150	2931	50
AWA	30473	50	24293	40	6180	10
Dogs	19499	113	14681	85	4818	28

Table 1: The statistics of the three datasets used. CUB and Dog are fine-grained datasets whereas AWA is a more general concept dataset.

Latent Embeddings for Zero-shot Classification

- Epochs : 150
- Learning rate : 0.1, 0.001, 0.01 (CUB, AWA, DOG, respectively)

	CUB		AWA		Dogs	
	SJE	LatEm	SJE	LatEm	SJE	LatEm
att	**50.1**	45.5	66.7	**71.9**	N/A	N/A
w2v	28.4	**31.8**	51.2	**61.1**	19.6	**22.6**
glo	24.2	**32.5**	58.8	**62.9**	17.8	**20.9**
hie	20.6	**24.2**	51.2	**57.5**	24.3	**25.2**

Table 2: Comparison of Latent Embeddings (LatEm) method with the state-of-the-art SJE [2] method. We report average per-class Top-1 accuracy on unseen classes. We use the same data partitioning, same image features and same class embeddings as SJE [2]. We cross-validate the K for LatEm.

Latent Embeddings for Zero-shot Classification

- Model Selection
  - Cross-validation
    - data split을 다르게 해서 validation 단계에서 가장 좋은 성능을 나타내는 W의 개수(K) 선택
    - K = {2, 4, 6, 8, 10} 으로 각각 돌려봄
  - Pruning
    - 성능을 유지하며 더 빠르게 학습시키게 하기 위한 선택 방법
    - 학습 5번 돌 때 5프로 미만으로 선택된 W를 제거
    - 16개로 시작해서 pruning 수행

Latent Embeddings for Zero-shot Classification

	CUB		AWA		Dogs	
	PR	CV	PR	CV	PR	CV
att	3	4	7	2	N/A	N/A
w2v	8	10	8	4	6	8
glo	6	10	7	6	9	4
hie	8	2	7	2	11	10

	CUB		AWA		Dogs	
	PR	CV	PR	CV	PR	CV
att	43.8	**45.6**	63.2	**72.5**	N/A	N/A
w2v	**33.9**	33.1	48.9	**52.3**	**25.0**	24.5
glo	**31.5**	30.7	**51.6**	50.7	18.8	**20.2**
hie	**23.8**	**23.7**	45.5	**46.2**	25.2	**25.6**

Table 5: (Left) Number of matrices selected (on the original split) and (right) average per-class top-1 accuracy on unseen classes (averaged over five splits). PR: proposed model learnt with pruning, CV: with cross validation.

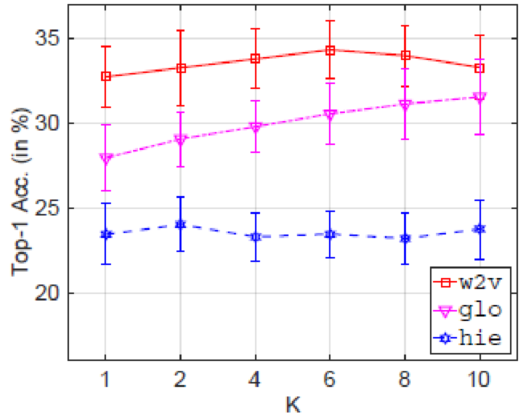

Figure 3: Effect of latent variable K, with unsupervised class embeddings (on CUB dataset with five splits).

Latent Embeddings for Zero-shot Classification

Dataset : Caltech-UCSD Birds**(CUB)**
training set (seen)
label – 100 classes
images – 5894 images

test set (unseen)
label – 50 classes
images – 2931 images

epoch : 150
learning rate : 0.1

class embedding	average per-class Top-1 accuracy(%)
attributes	**38.2**
word2vec (wikipedia)	**27.8**
glove (wikipedia)	**25.7**
hierarchies (WordNet)	**17.0**

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