딥러닝 세미나 Season #7

Zero-Shot Learning by Convex Combination of Semantic Embeddings

2014, ICLR, M. Norouzi et al.

https://arxiv.org/pdf/1312.5650.pdf

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10가지 클래스를 분류하는 image classifier 에 대해 생각해보자

- Introduction
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- ConSE:
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- Result

10가지 클래스를 분류하는 image classifier 에 대해 생각해보자

이미지를 처리해야 하므로

ResNet, VGG, Inception 등을 이용하면 되겠지?

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학습에 이용할 데이터셋은

10가지 클래스에 대한 이미지를 각각 준비하면 되겠다

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이제 학습을 돌려보자!

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이제 클래스를 좀더 세분화해서

10,000가지 클래스를 분류하는 image classifier 에 대해 생각해보자

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게다가 열심히 학습했던 10가지 클래스 분류 모델은

재활용이 안되네 ㅠㅠ

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정리하자면, n-way classification 문제에서 n이 아주 클 경우에는 기존 기계학습 방법을 그대로 적용하기 어려움

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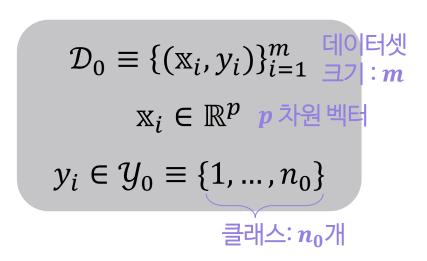
그래서

이미지의 semantic embedding을 이용하는 방법이 나옴

바로 Zero-Shot Learning

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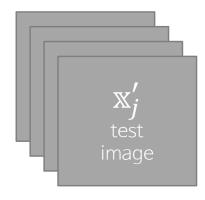




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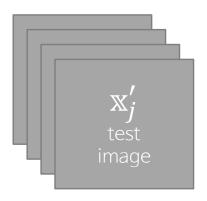
$$\mathcal{D}_0 \equiv \{(\mathbf{x}_i, y_i)\}_{i=1}^m \stackrel{ ext{diolety}}{ ext{diolety}}: m$$
 $\mathbf{x}_i \in \mathbb{R}^p$ p 차원 벡터 $y_i \in \mathcal{Y}_0 \equiv \{1, ..., n_0\}$ 클래스: n_0 개



$$\mathcal{D}_1 \equiv \left\{ (\mathbf{x}_j', y_j')
ight\}_{j=1}^{m'}$$
 데이터셋 크기 $: m'$ $\mathbf{x}_j' \in \mathbb{R}^p$ p 차원 벡터 $y_j' \in \mathcal{Y}_1 \equiv \{n_0+1, ..., n_0+n_1\}$ 클래스 $: n_1$ 개

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〈 제로샷 러닝의 목적 〉

 \mathcal{D}_0 으로 학습한 classifier가

 \mathcal{D}_1 에도 잘 적용되도록 하는 것

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 $y_0 \cap y_1 = \emptyset$ 이므로 다른 정보가 주어지지 않으면 **불가능**

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〈제로샷 러닝의 목적〉

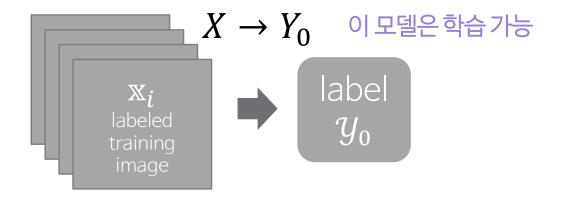
 \mathcal{D}_0 으로 학습한 *classifier*가

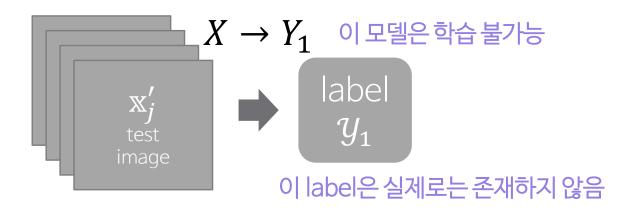
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모든 label y ($1 \le y \le n_0 + n_1$) 에 대해서 semantic embedding $s(y) \in \mathcal{S} \equiv \mathbb{R}^q \quad q$ 차원 벡터 가 존재하면 가능

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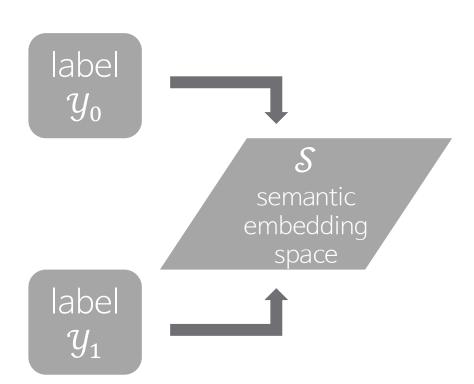




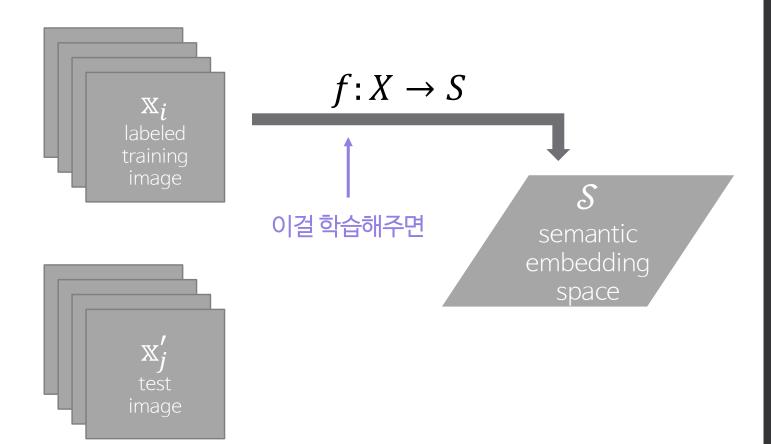
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Word2Vec

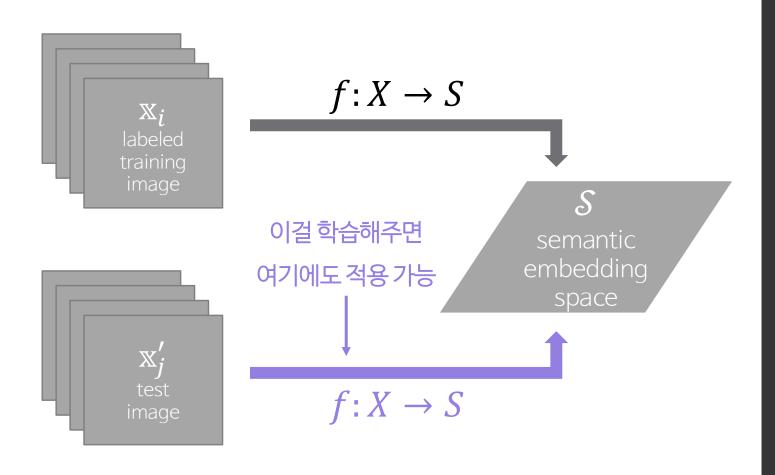
단어의 의미가 비슷하면 semantic embedding space 상의 벡터 좌표도 비슷하도록 학습함



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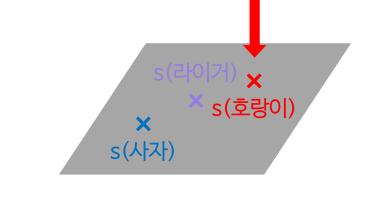
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예를 들어 '호랑이'와 '사자' 이미지를 학습했을 경우

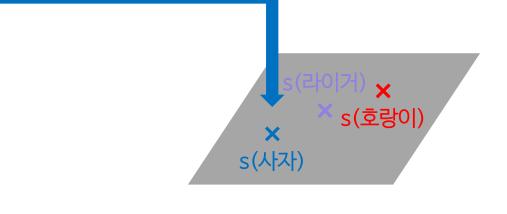




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embeddings

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Zero-shot

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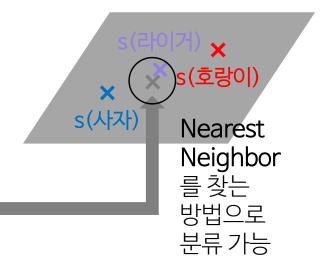






'라이거'라는 label은 학습되지 않았지만 분류할 수 있게 됨





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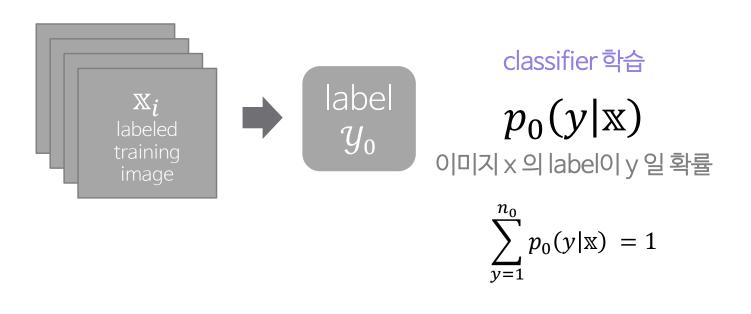
기존 제로샷은

f: *X* → *S* 를 **직접** 학습하지만

이 논문에서 제안하는 모델(ConSE)은 $f: X \to S$ 를 간접적으로 학습함

오히려 classic machine learning 처럼 기존 classifier를 그대로 가져다 이용

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$$\widehat{y_0}(\mathbf{x}, 1) \equiv \underset{y \in \mathcal{Y}_0}{\operatorname{argmax}} \, p_0(y|\mathbf{x})$$

most likely training label

(즉, 이 classifier는 x의 label을 이 label로 판단할 것이다)

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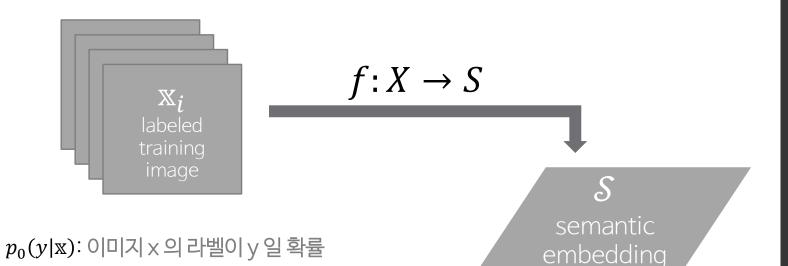


$$\widehat{y_0}(x,t)$$

tth most likely training label

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 $\widehat{y_0}(\mathbf{x},t)$: t^{th} most likely training label



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space

$$f(\mathbf{x}) = \frac{1}{Z} \sum_{t=1}^{T} p(\widehat{y_0}(\mathbf{x}, t) | \mathbf{x}) \cdot s(\widehat{y_0}(\mathbf{x}, t))$$

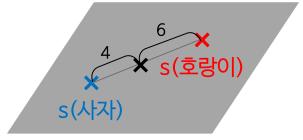
'라이거' 이미지를 classifier에 넣었을 때 각 label일 확률





y	У		
$\widehat{y_0}(x,1)$	사자	0.6	
$\widehat{y_0}(x,2)$	호랑이	0.4	

$$f(x) = 0.6 \cdot s('사자') + 0.4 \cdot s('호랑이')$$
 $\approx s('라이거')$



$$f(\mathbf{x}) = \frac{1}{Z} \sum_{t=1}^{I} p(\widehat{y_0}(\mathbf{x}, t) | \mathbf{x}) \cdot s(\widehat{y_0}(\mathbf{x}, t))$$

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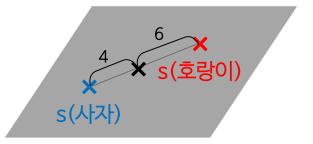
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cosine similarity

$$\widehat{y_1}(\mathbf{x}, 1) \equiv \underset{y' \in \mathcal{Y}_1}{\operatorname{argmax}} \cos(f(\mathbf{x}), s(y'))$$

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Test Image	Softmax Baseline [7]	DeViSE [6]	ConSE (10)
	wig fur coat Saluki, gazelle hound Afghan hound, Afghan stole	water spaniel tea gown bridal gown, wedding gown spaniel tights, leotards	business suit dress, frock hairpiece, false hair, postiche swimsuit, swimwear, bathing suit kit, outfit
	ostrich, Struthio camelus black stork, Ciconia nigra vulture crane peacock	heron owl, bird of Minerva, bird of night hawk bird of prey, raptor, raptorial bird finch	ratite, ratite bird, flightless bird peafowl, bird of Juno common spoonbill New World vulture, cathartid Greek partridge, rock partridge
	sea lion plane, carpenter's plane cowboy boot loggerhead, loggerhead turtle goose	elephant turtle turtleneck, turtle, polo-neck flip-flop, thong handcart, pushcart, cart, go-cart	California sea lion Steller sea lion Australian sea lion South American sea lion eared seal
O SEATTLE	hamster broccoli Pomeranian capuchin, ringtail weasel	golden hamster, Syrian hamster rhesus, rhesus monkey pipe shaker American mink, Mustela vison	golden hamster, Syrian hamster rodent, gnawer Eurasian hamster rhesus, rhesus monkey rabbit, coney, cony

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	# Candidate			<u>Flat hit@k (%)</u>			
Test Label Set	Labels	Model	1	2	5	10	20
		DeViSE	6.0	10.0	18.1	26.4	36.4
2 hons	1,589	ConSE(1)	9.3	14.4	23.7	30.8	38.7
2-hops	1, 569	ConSE(10)	9.4	15.1	24.7	32.7	41.8
		ConSE(1000)	9.2	14.8	24.1	32.1	41.1
		DeViSE	0.8	-2.7	7.9	14.2	$-2\overline{2}.\overline{7}$
2-hops (+1K)	1,589	ConSE(1)	0.2	7.1	17.2	24.0	31.8
2-110ps (<u>+1K)</u>	+1000	ConSE(10)	0.3	6.2	17.0	24.9	33.5
		ConSE(1000)	0.3	6.2	16.7	24.5	32.9
	7,860	DeViSE	1.7	2.9	5.3	8.2	12.5
3-hops		ConSE(1)	2.6	4.2	7.3	10.8	14.8
3-nops		ConSE(10)	2.7	4.4	7.8	11.5	16.1
		ConSE(1000)	2.6	4.3	7.6	11.3	15.7
		DeViSE	0.5	1.4	3.4	5.9	9.7
3-hops (+1K)	7,860	ConSE(1)	0.2	2.4	5.9	9.3	13.4
3-110ps (+1K)	+1000	ConSE(10)	0.2	2.2	5.9	9.7	14.3
		ConSE(1000)	0.2	2.2	5.8	9.5	14.0
		DeViSE	0.8	1.4	2.5	3.9	6.0
ImageNet 2011 21K	20,841	ConSE(1)	1.3	2.1	3.6	5.4	7.6
imagenet 2011 21K	20, 641	ConSE(10)	1.4	2.2	3.9	5.8	8.3
		ConSE(1000)	1.3	2.1	3.8	5.6	8.1
		DeViSE	0.3	0.8	1.9	$\overline{3.2}$	5.3
ImageNet 2011 21K (+1K)	20,841	ConSE(1)	0.1	1.2	3.0	4.8	7.0
imagenet 2011 21K (+1K)	+1000	ConSE(10)	0.2	1.2	3.0	5.0	7.5
		ConSE(1000)	0.2	1.2	3.0	4.9	7.3

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		Hierarchical precision@k					
Test Label Set	Model	1	2	5	10	20	
2 hong	DeViSE	0.06	0.152	0.192	0.217	0.233	
2-hops	ConSE(10)	0.094	0.214	0.247	0.269	0.284	
	Softmax baseline	0	0.236	0.181	0.174	0.179	
2-hops (+1K)	DeViSE	0.008	0.204	0.196	0.201	0.214	
	ConSE(10)	0.003	0.234	0.254	0.260	0.271	
2 hons	DeViSE	0.017	0.037	0.191	0.214	0.236	
3-hops	ConSE(10)	0.027	0.053	0.202	0.224	0.247	
	Softmax baseline	0	0.053	0.157	0.143	0.130	
3-hops (+1K)	DeViSE	0.005	0.053	0.192	0.201	0.214	
	ConSE(10)	0.002	0.061	0.211	0.225	0.240	
ImageNet 2011 21K	DeViSE	0.008	0.017	0.072	0.085	0.096	
	ConSE(10)	0.014	0.025	0.078	0.092	0.104	
	Softmax baseline	0	0.023	0.071	0.069	0.065	
ImageNet 2011 21K (+1K)	DeViSE	0.003	0.025	0.083	0.092	0.101	
	ConSE(10)	0.002	0.029	0.086	0.097	0.105	

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		Hierarchical precision@k					
Test Label Set	Model	1	2	5	10	20	
	Softmax baseline	0.556	0.452	0.342	0.313	0.319	
	DeViSE	0.532	0.447	0.352	0.331	0.341	
ImageNet 2011 1K	ConSE (1)	0.551	0.422	0.32	0.297	0.313	
	ConSE (10)	0.543	0.447	0.348	0.322	0.337	
	ConSE (1000)	0.539	0.442	0.344	0.319	0.335	

		Flat hit@ k (%)				
Test Label Set	Model	1	2	5	10	
	Softmax baseline	55.6	67.4	78.5	85.0	
	DeViSE	53.2	65.2	76.7	83.3	
ImageNet 2011 1K	ConSE (1)	55.1	57.7	60.9	63.5	
	ConSE (10)	54.3	61.9	68.0	71.6	
	ConSE (1000)	53.9	61.1	67.0	70.6	

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