Learning a Deep Embedding Model for Zero-Shot Learning

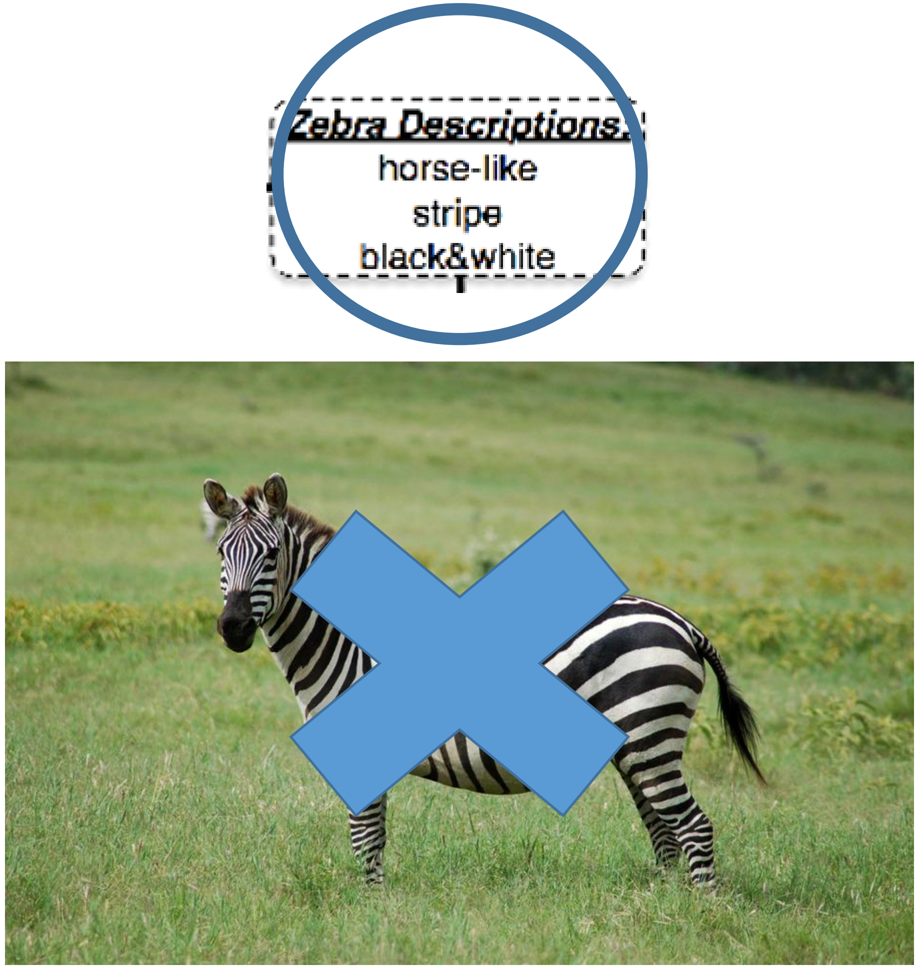
CVPR, 2017

장두수

Zero-Shot Learning?

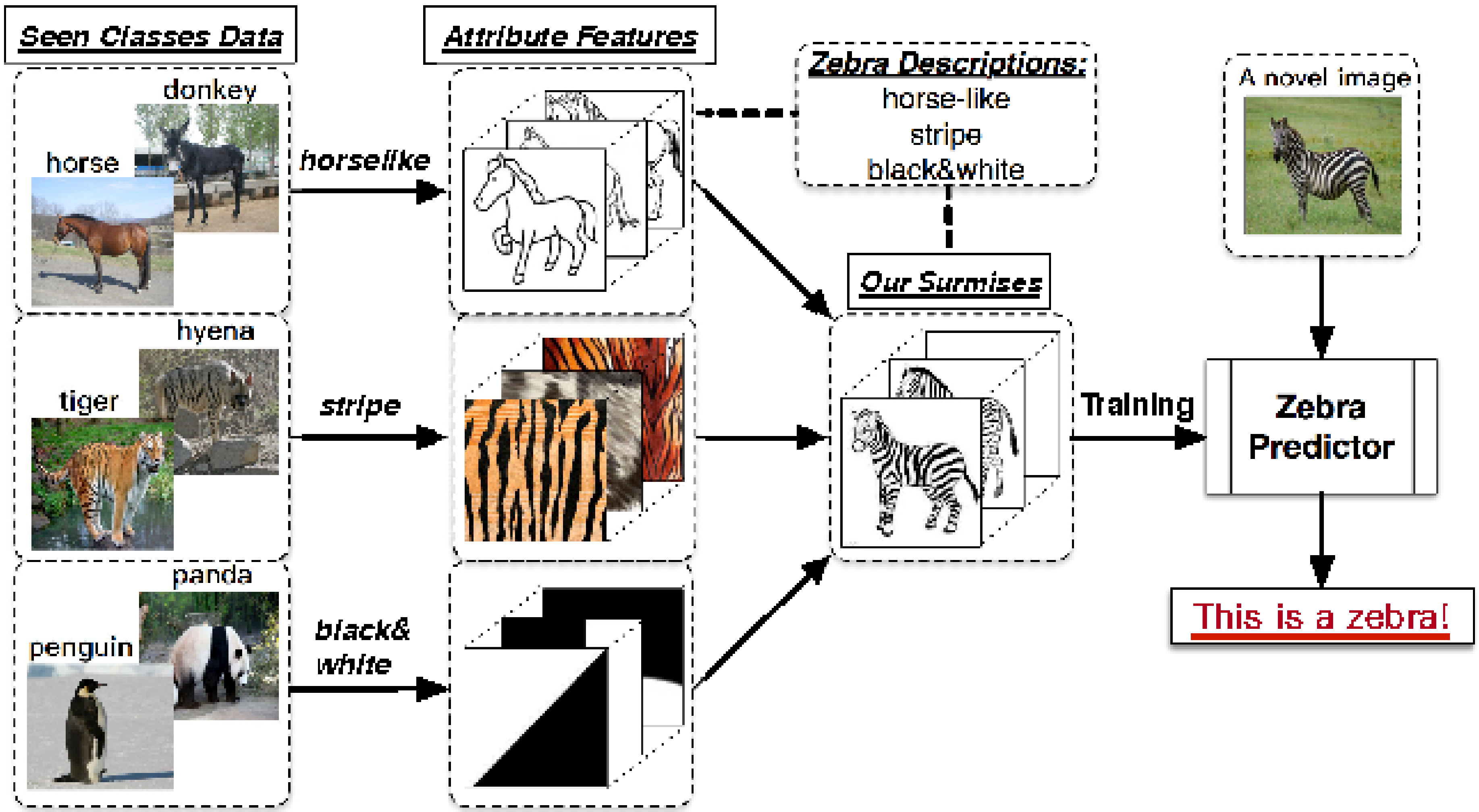
Image는 본적 없음, 근데 뭔지는 들어봄

말(seen class)



얼룩말(unseen class)

Zero-Shot Learning?



Zero-Shot Learning?

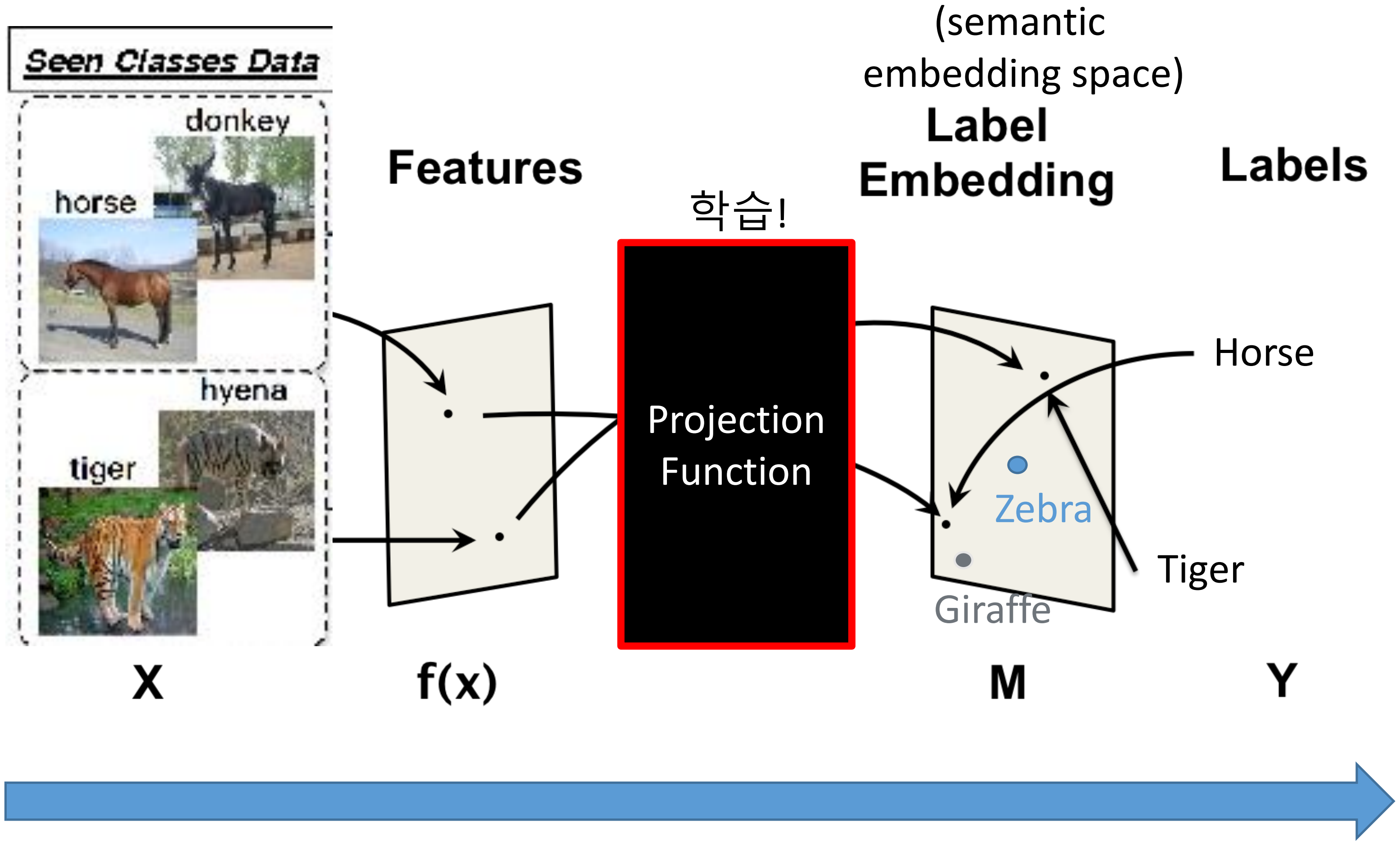
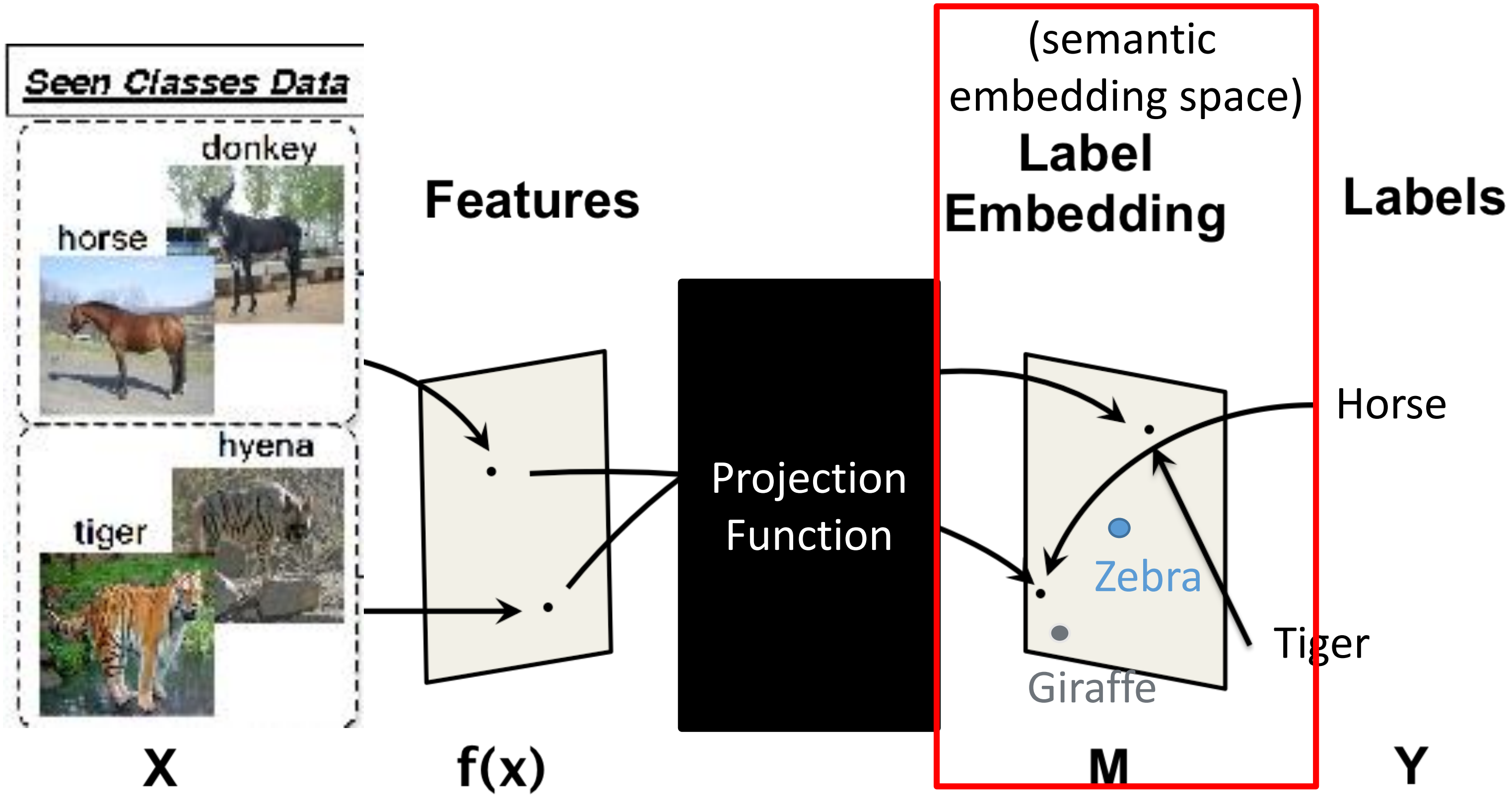
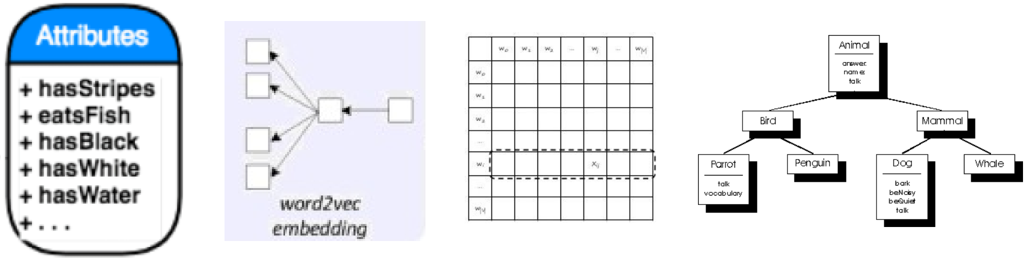


image-to-semantic

Zero-Shot Learning?





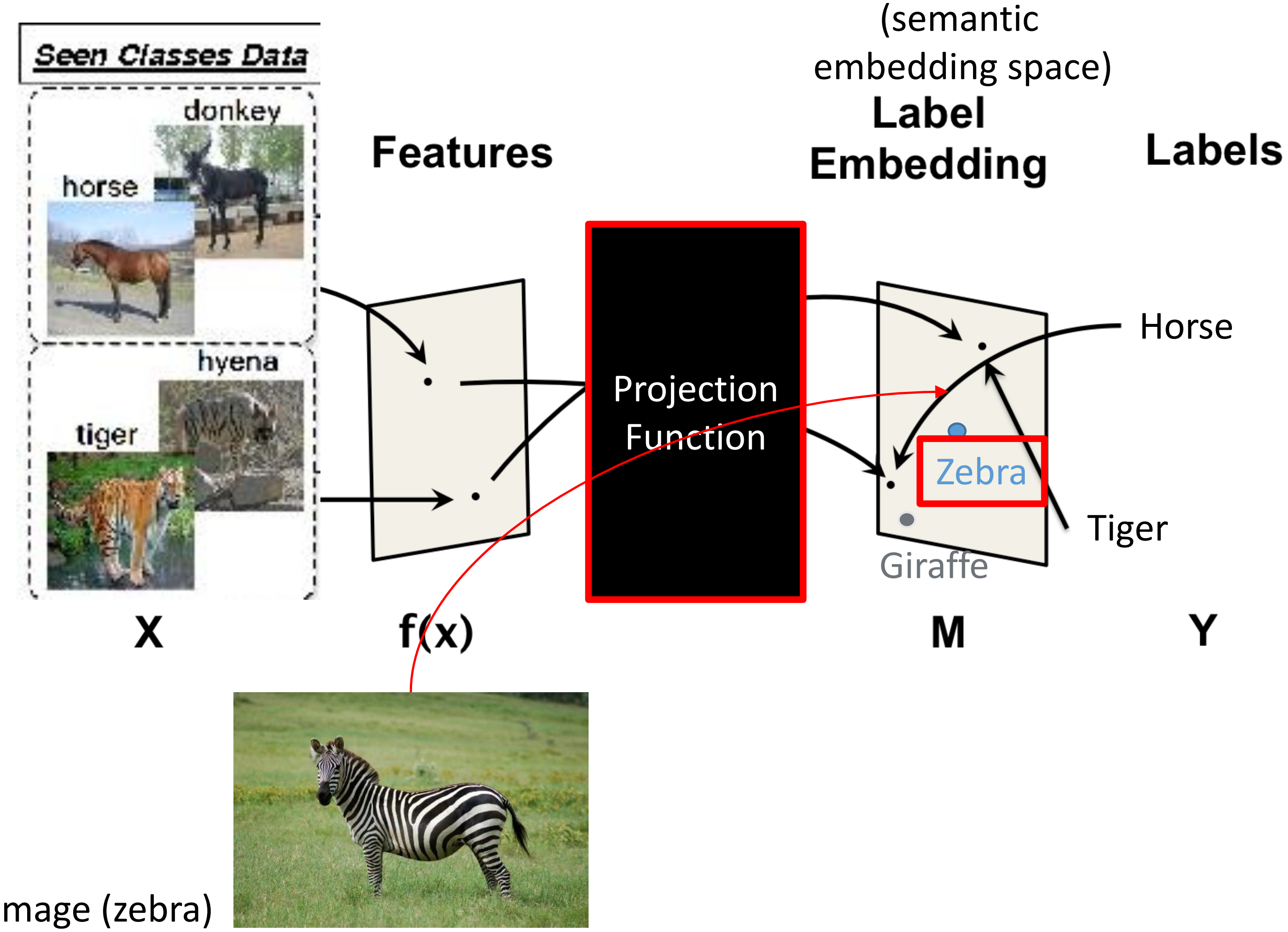
attribute vector

word2vec

GloVe

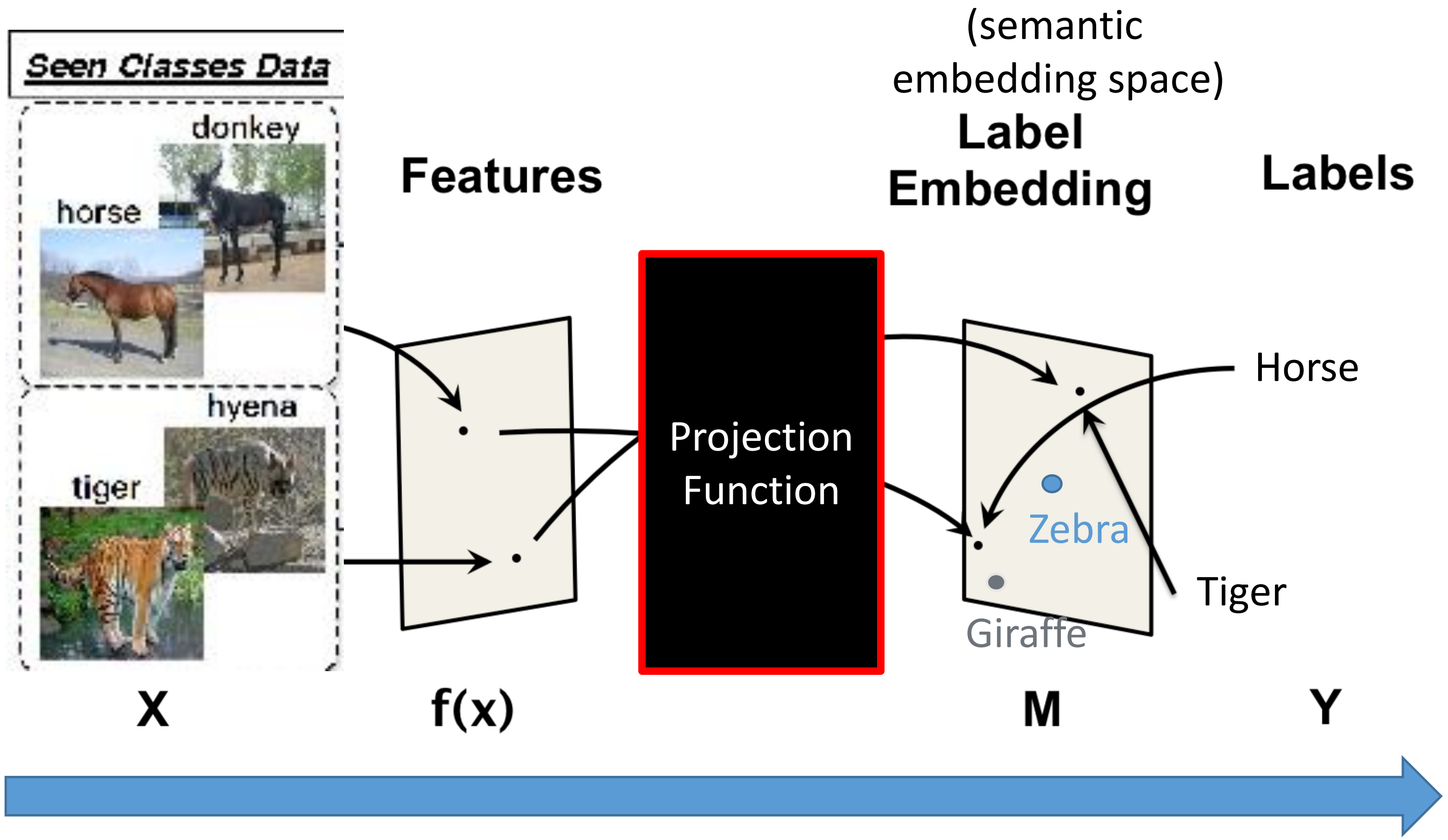
hierarchy

Zero-Shot Learning?



unseen image (zebra)

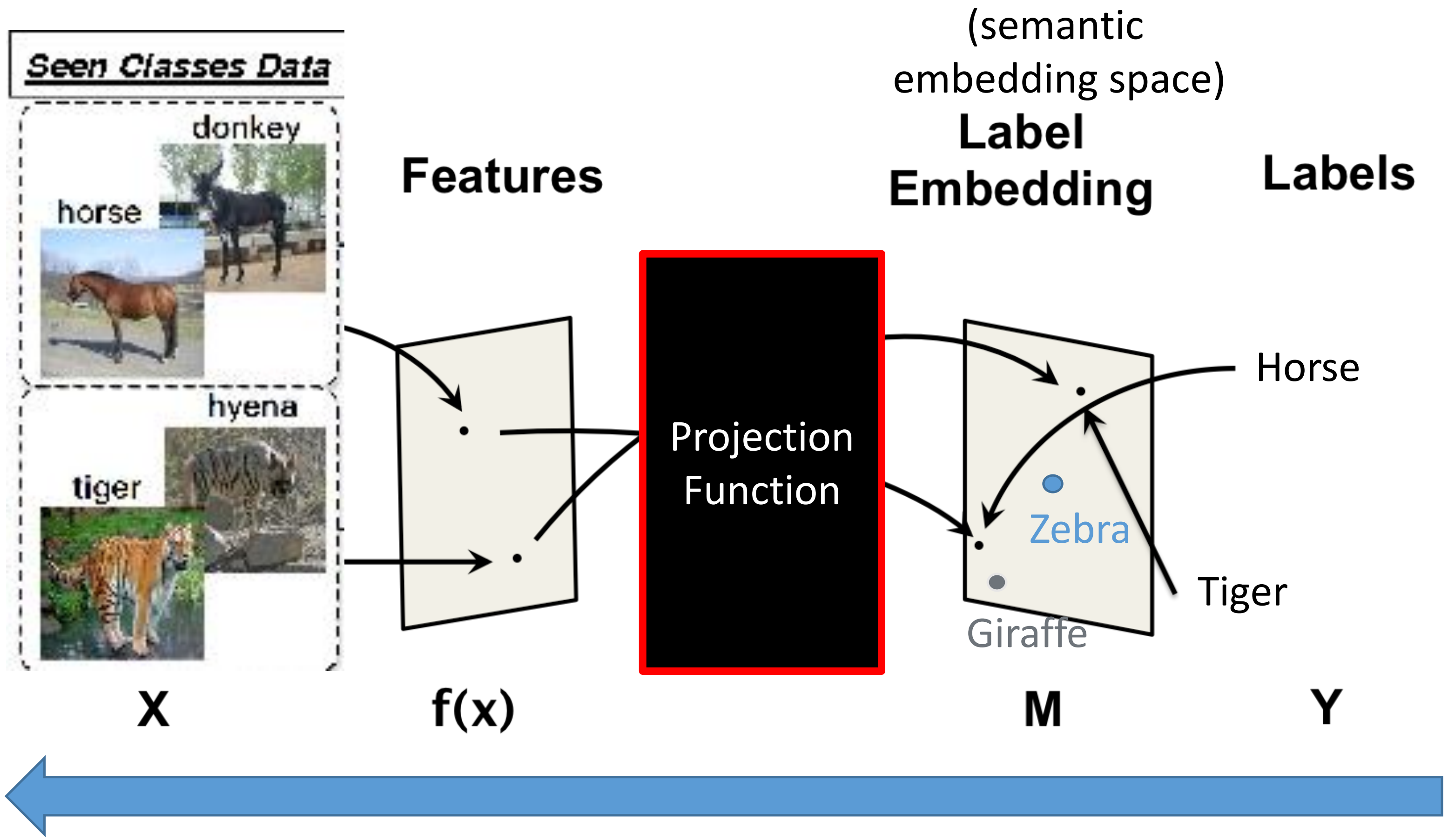
Introduction



기존 visual-to-semantic embedding

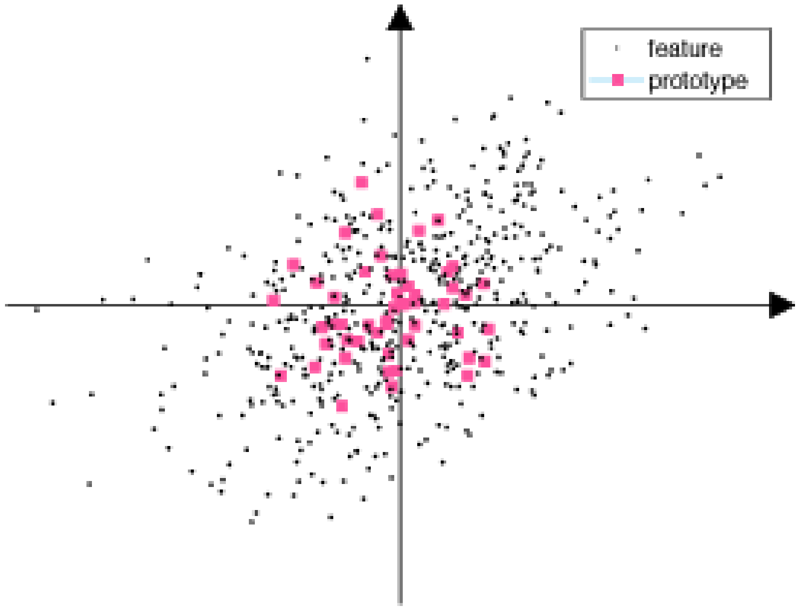
- NN search
    - high dimensional embedding space
    - Less prototypes(labels)
- hubness problem! (특정 prototype에만 편중되어 projection 되는 현상)

Introduction

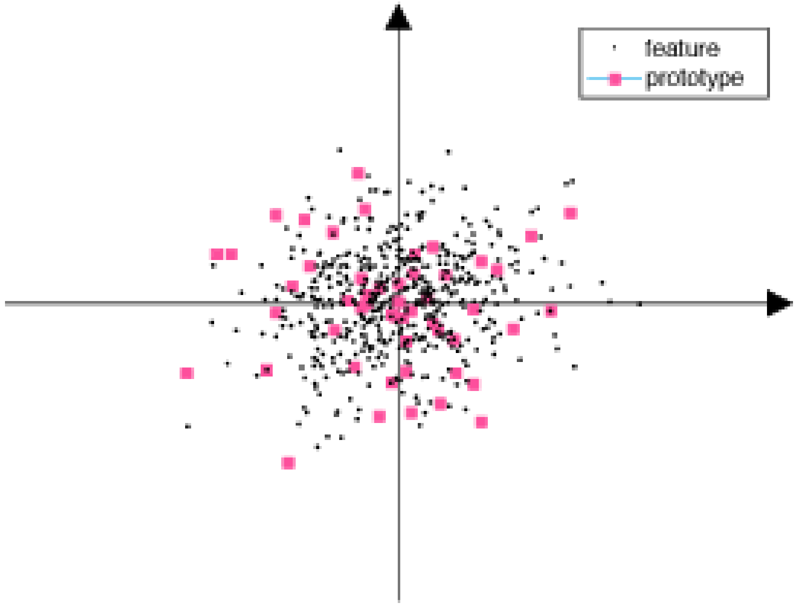


1. semantic-to-image embedding

Introduction

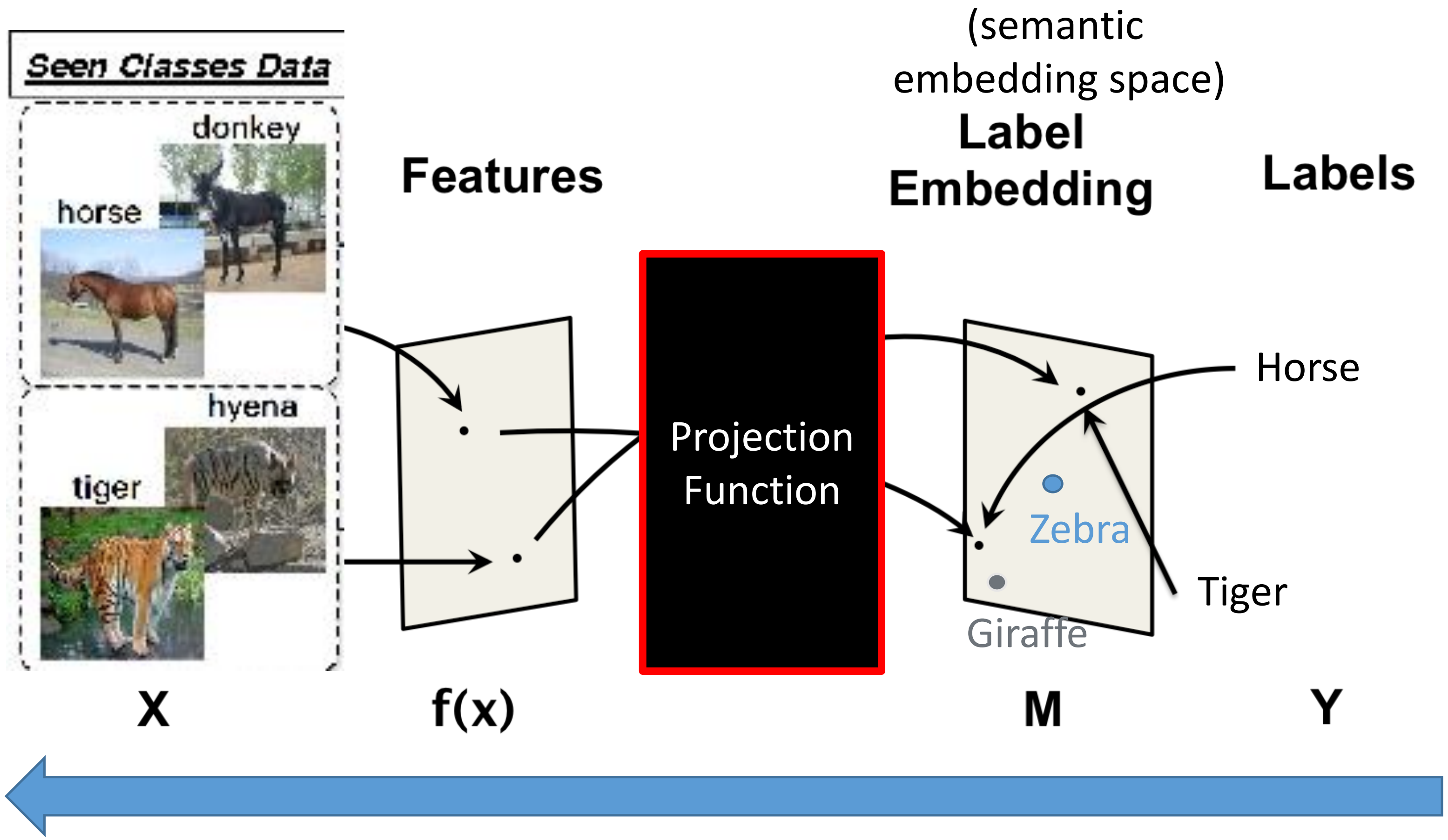


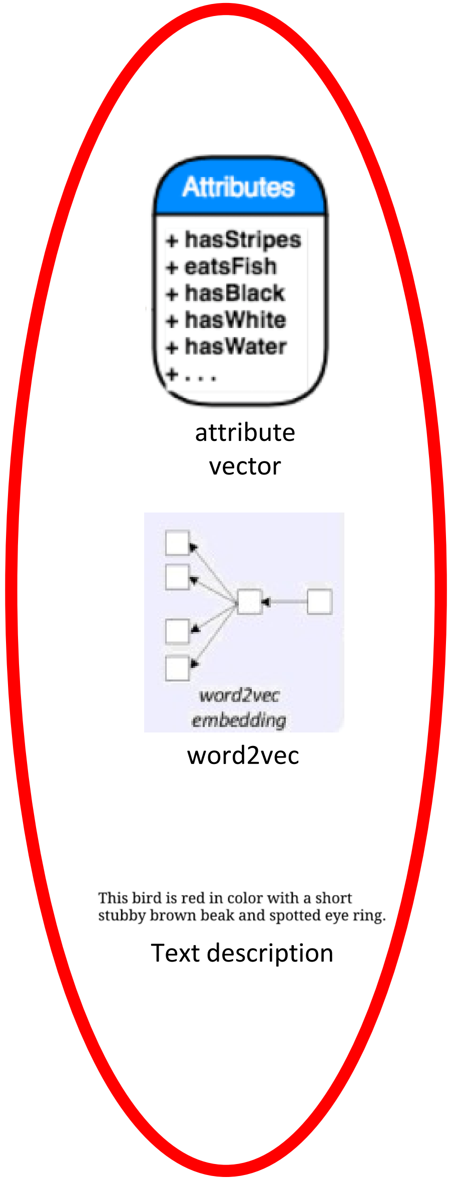
(a) S → V



(b) V → S

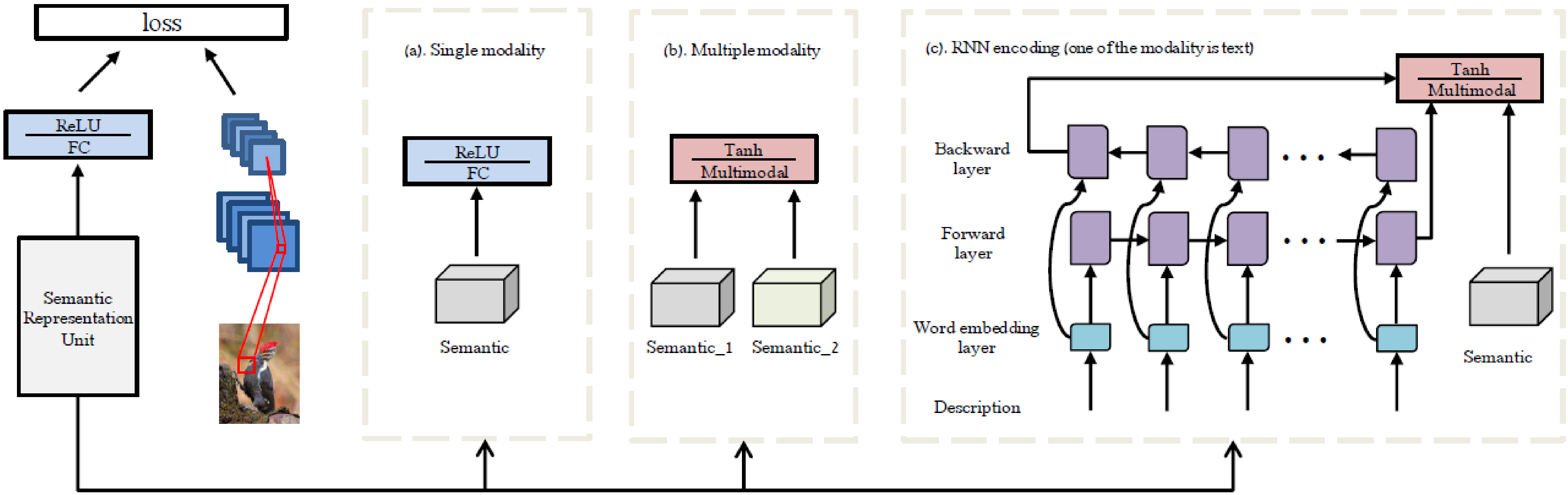
Introduction





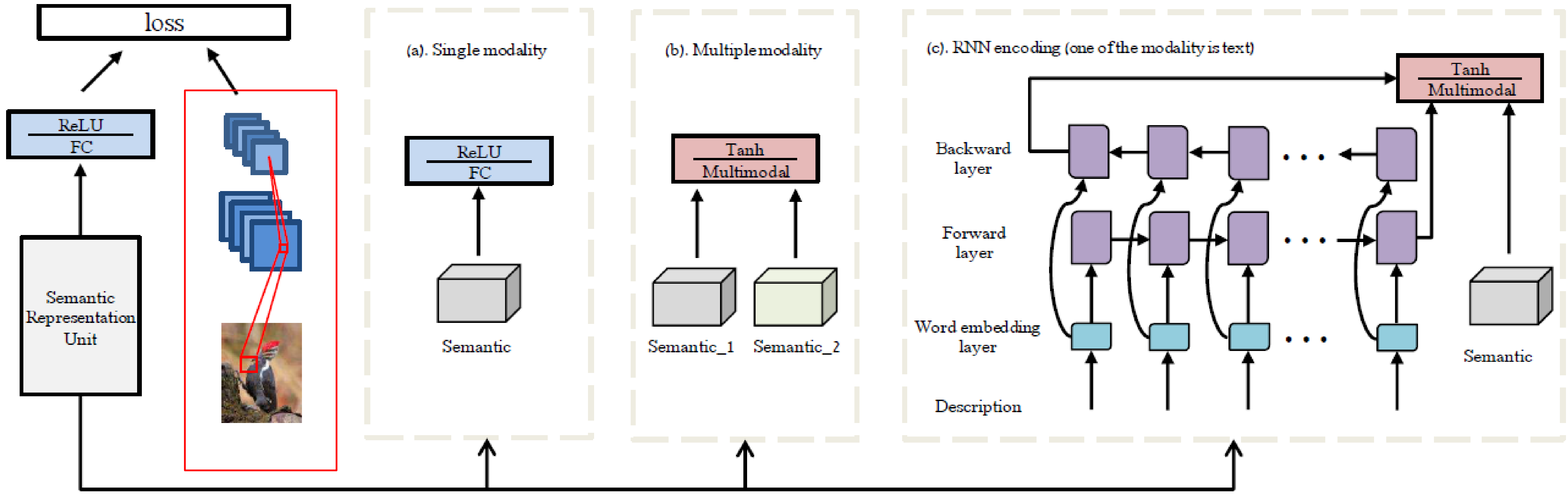
2. Multi –modality fusion method
- **Combine multiple semantic** representation
- Enables **end-to-end learning** of the semantic space representation

Methodology



Two main branches

Methodology

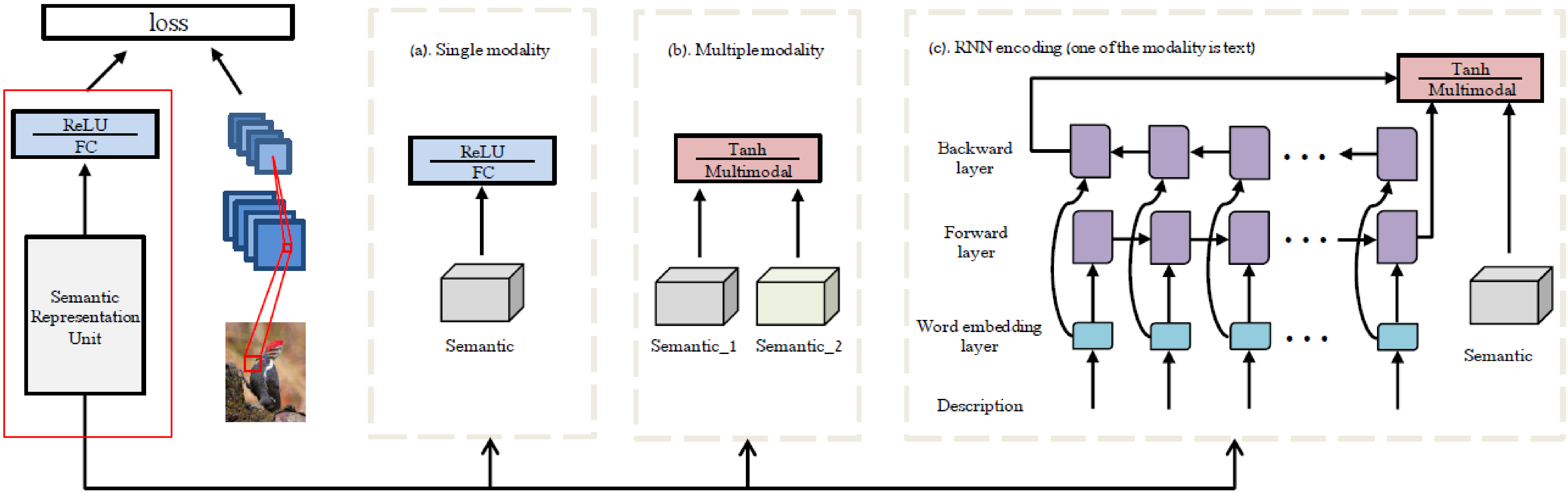


Two main branches

1. Visual encoding

- CNN subnet
- Input : image
- Output : *D*-dim feature vector

Methodology

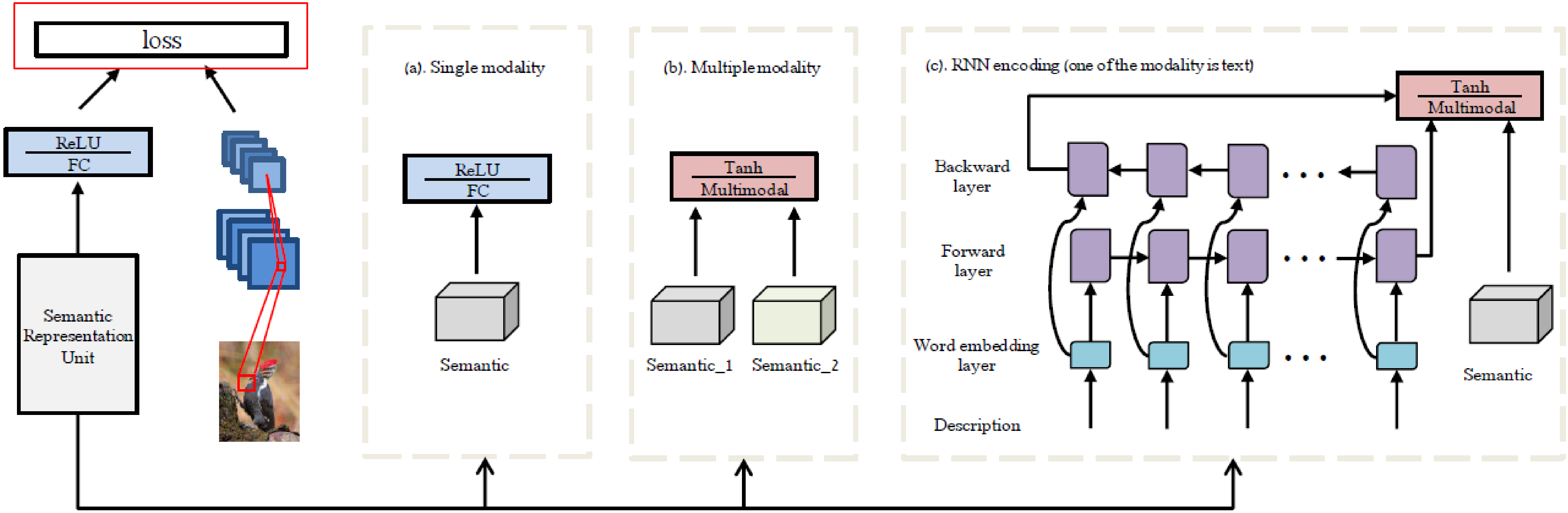


Two main branches

2. Semantic encoding

- Two fully connected layers (ReLU)
- Input : *L*-dim semantic representation vector
- Output : *D*-dim semantic embedding vector

Methodology



Embedding loss

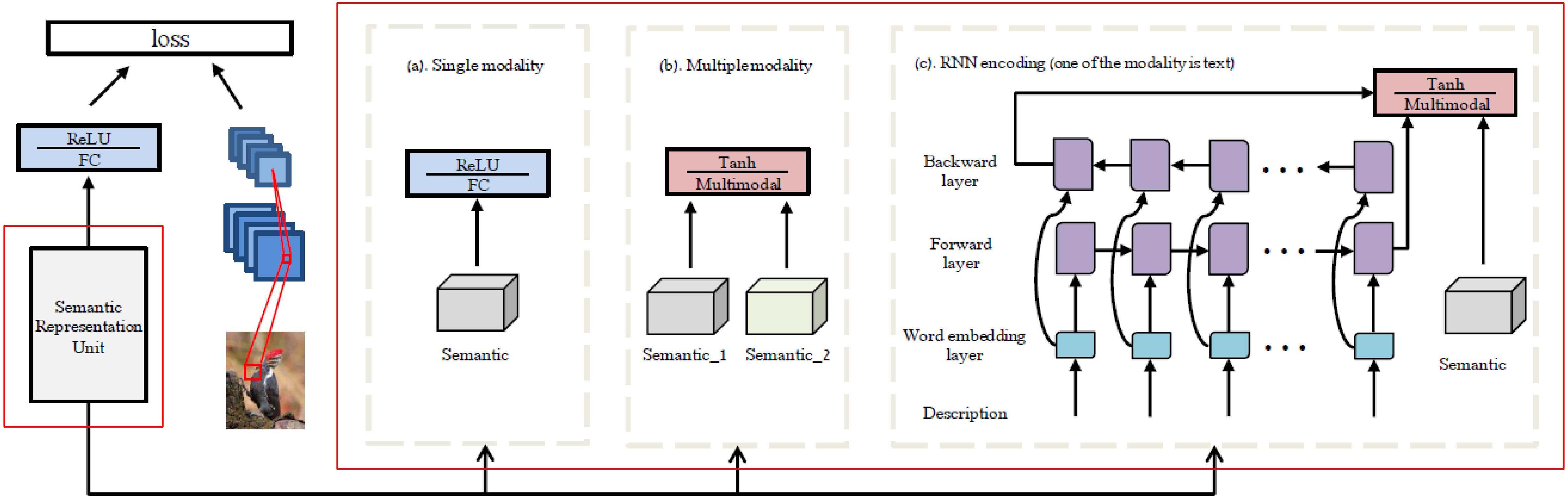
$$\mathcal{L}(\mathbf{W}_1, \mathbf{W}_2) = \frac{1}{N}\sum_{i=1}^{N} ||\phi(\mathbf{I}_i) - f_1(\mathbf{W}_2 f_1(\mathbf{W}_1 \mathbf{y}_i^u))||^2$$

$$+\lambda(||\mathbf{W}_1||^2 + ||\mathbf{W}_2||^2)$$

parameter regularization loss

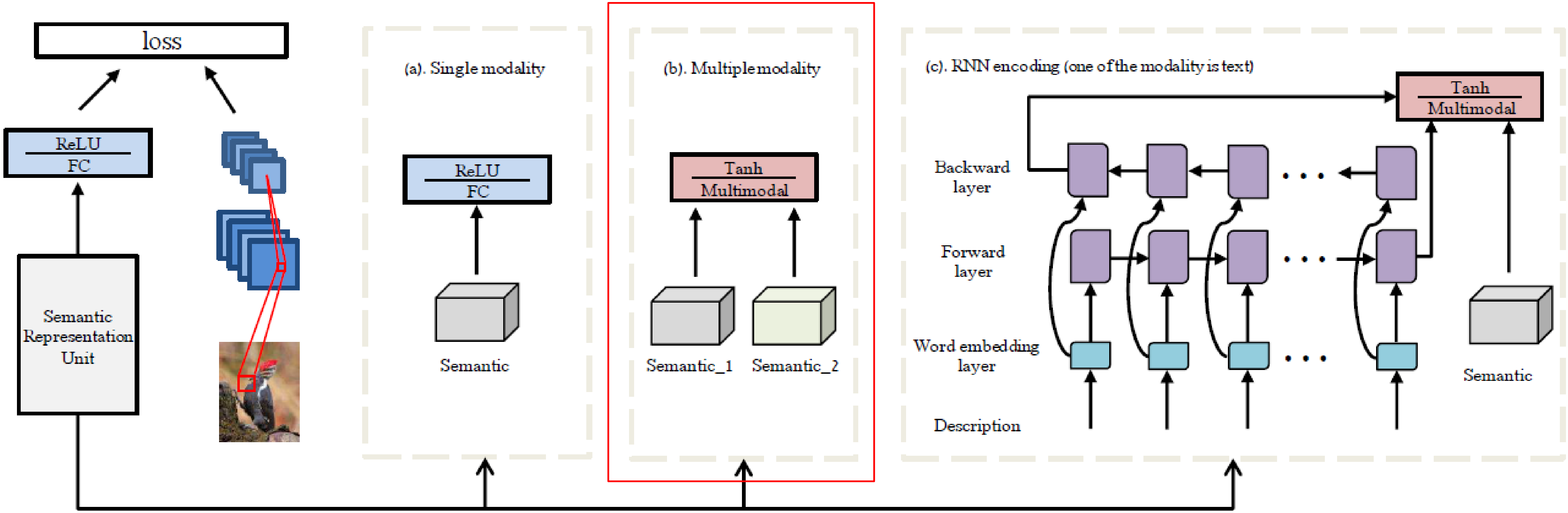
W1 : 1st FC layer weights (L x M)
W2 : 2nd FC layer weights (M x D)
ϕ(Ii) : image feature vector
f1 : ReLU
y : semantic representation vector

Methodology



Semantic representation unit
= semantic representation + 1st FC and ReLU

Methodology



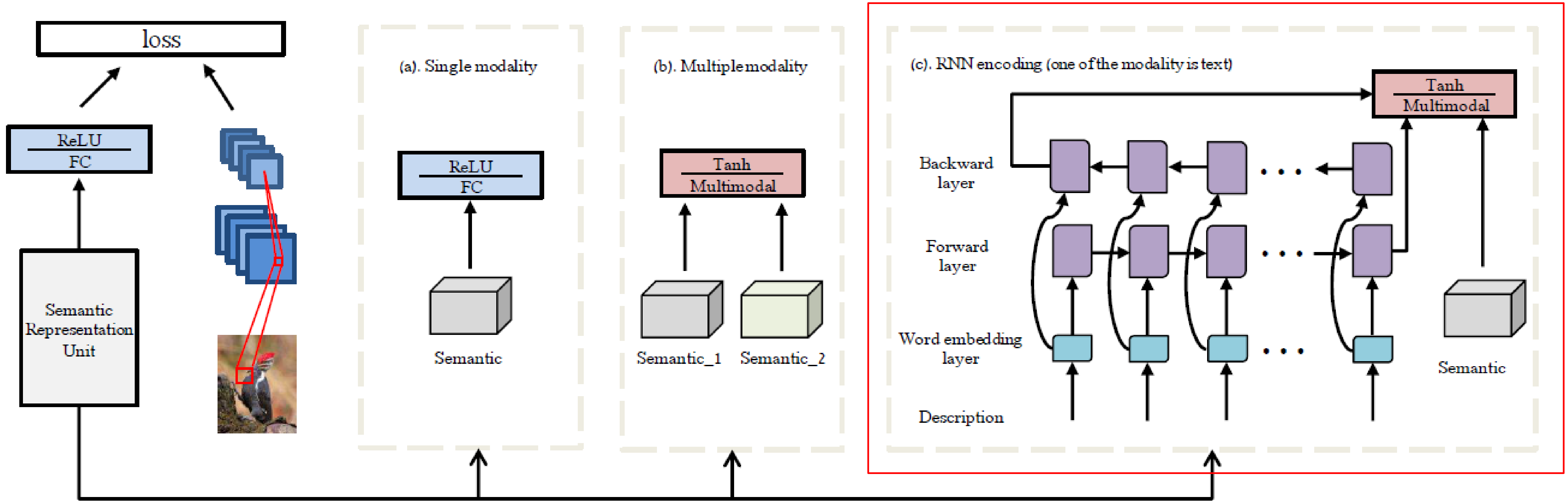
(b) multi-modality

- e.g. an attribute vector and a word vector

$$f_2(\mathbf{W}_1^{(1)} \cdot \mathbf{y}_i^{u_1} + \mathbf{W}_1^{(2)} \cdot \mathbf{y}_i^{u_2})$$

- f2 : element-wise scaled tanh

Methodology



(c) Bi-LSTM encoder for text description

$$f(\mathbf{W}_{\overrightarrow{\mathrm{h}}} \cdot \overrightarrow{\mathrm{h}} + \mathbf{W}_{\overleftarrow{\mathrm{h}}} \cdot \overleftarrow{\mathrm{h}})$$

- f : f1, ReLU (single) , f2, tanh (multiple)

Experiment

1. AWA and CUB

- AWA : 40 training classes, 10 test classes
    - 1000 dim word vec
    - 85 dim attribute vec

- CUB : 150 training classes, 50 test classes
    - 312 dim attribute vec
    - 10 descriptions per image

- CNN subnet : Inception-V2, 1024 dim

Model	F	SS	AwA	CUB
AMP [14]	F_O	A+W	66.0	-
SJE [2]	F_G	A	66.7	50.1
SJE [2]	F_G	A+W	73.9	51.7
ESZSL [37]	F_G	A	76.3	47.2
SSE-ReLU [47]	F_V	A	76.3	30.4
JLSE [48]	F_V	A	80.5	42.1
SS-Voc [13]	F_O	A/W	78.3/68.9	-
SynC-struct [4]	F_G	A	72.9	54.5
SEC-ML [3]	F_V	A	77.3	43.3
DeViSE [10]	N_G	A/W	56.7/50.4	33.5
Socher *et al.* [43]	N_G	A/W	60.8/50.3	39.6
MTMDL [46]	N_G	A/W	63.7/55.3	32.3
Ba *et al.* [24]	N_G	A/W	69.3/58.7	34.0
DS-SJE [34]	N_G	A/D	-	50.4/**56.8**
Ours	N_G	A/W(D)	**86.7/78.8**	**58.3**/53.5
Ours	N_G	A+W(D)	**88.1**	**59.0**

Experiment

1. ImageNet
- ILSVRC 2010 1K : 800 train, 200 test

- ILSVRC 2012/2010 : 1000 train(2012)
  360 test (2010, disjoint)

- Train word vectors on 4.6M Wikipedia corpus

- Alexnet

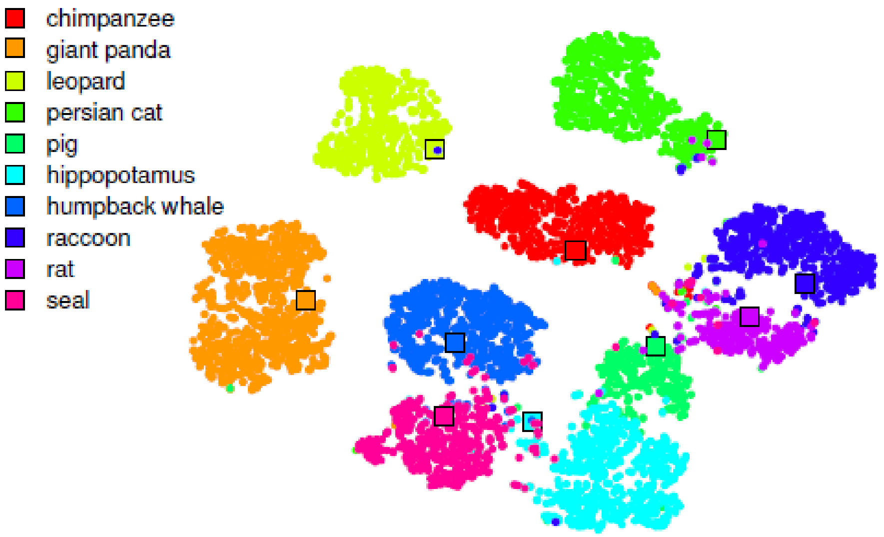
Model	**hit@5**
ConSE [31]	28.5
DeViSE [10]	31.8
Mensink *et al.* [27]	35.7
Rohrbach [36]	34.8
PST [35]	34.0
AMP [14]	41.0
Ours	**46.7**
Gaussian Embedding [30]	45.7
PDDM [18]	48.2
Ours	**60.7**

ILSVRC 2010

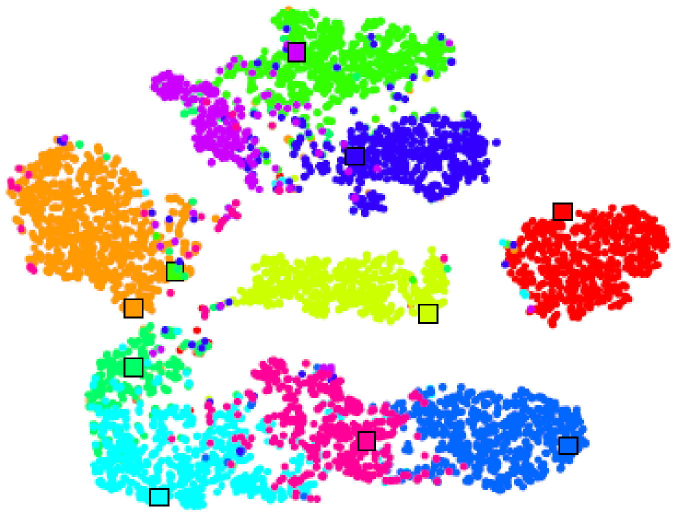
Model	**hit@1**	**hit@5**
ConSE [31]	7.8	15.5
DeViSE [10]	5.2	12.8
AMP [14]	6.1	13.1
SS-Voc [13]	9.5	16.8
Ours	**11.0**	**25.7**

ILSVRC 2012/2010

Experiment



(a) S → V



(b) V → S

N_1 **skewness**	**AwA**	**CUB**
Visual → Semantic	0.4162	8.2697
Semantic → Visual	**-0.4834**	**2.2594**

Model	**AwA**	**CUB**
Linear regression (V → S)	54.0	40.7
Linear regression (S → V)	74.8	45.7
Ours	**86.7**	**58.3**

$$(N_k skewness) = \frac{\sum_{i=1}^{l}(N_k(i) - E[N_k])^3/l}{Var[N_k]^{\frac{3}{2}}}$$

Loss	**Visual → Semantic**	**Semantic → Visual**
Least square loss	60.6	**86.7**
Hinge loss	57.7	72.8