THE UNIVERSITY OF BRITISH COLUMBIA

Topics in AI (CPSC 532S):
Multimodal Learning with Vision, Language and Sound

Lecture 14: Unsupervised Learning, Autoencoders [Part 3]

Logistics

— **Project pitches** next week (**November 1** & **3**)

9 groups per class (~8 minutes / group, 5-6 min presentation + questions)

— Project proposals are **NOT** due next week (due **November 15th**)

— **Assignment 4** — Remember you only need to do 1 PART

Final **Project** (40% of grade total)

- Group project (groups of 3 are encouraged, but fewer maybe possible)
- Groups are self-formed, you will not be assigned to a group
- You need to come up with a project proposal and then work on the project as a group (each person in the group gets the same grade for the project)
- Project needs to be **research** oriented (not simply implementing an existing paper); you can use code of existing paper as a starting point though

Project proposal + class presentation: 15%
Project + final presentation (during finals week): 25%

Correlated Representations vs. **Joint Embeddings**

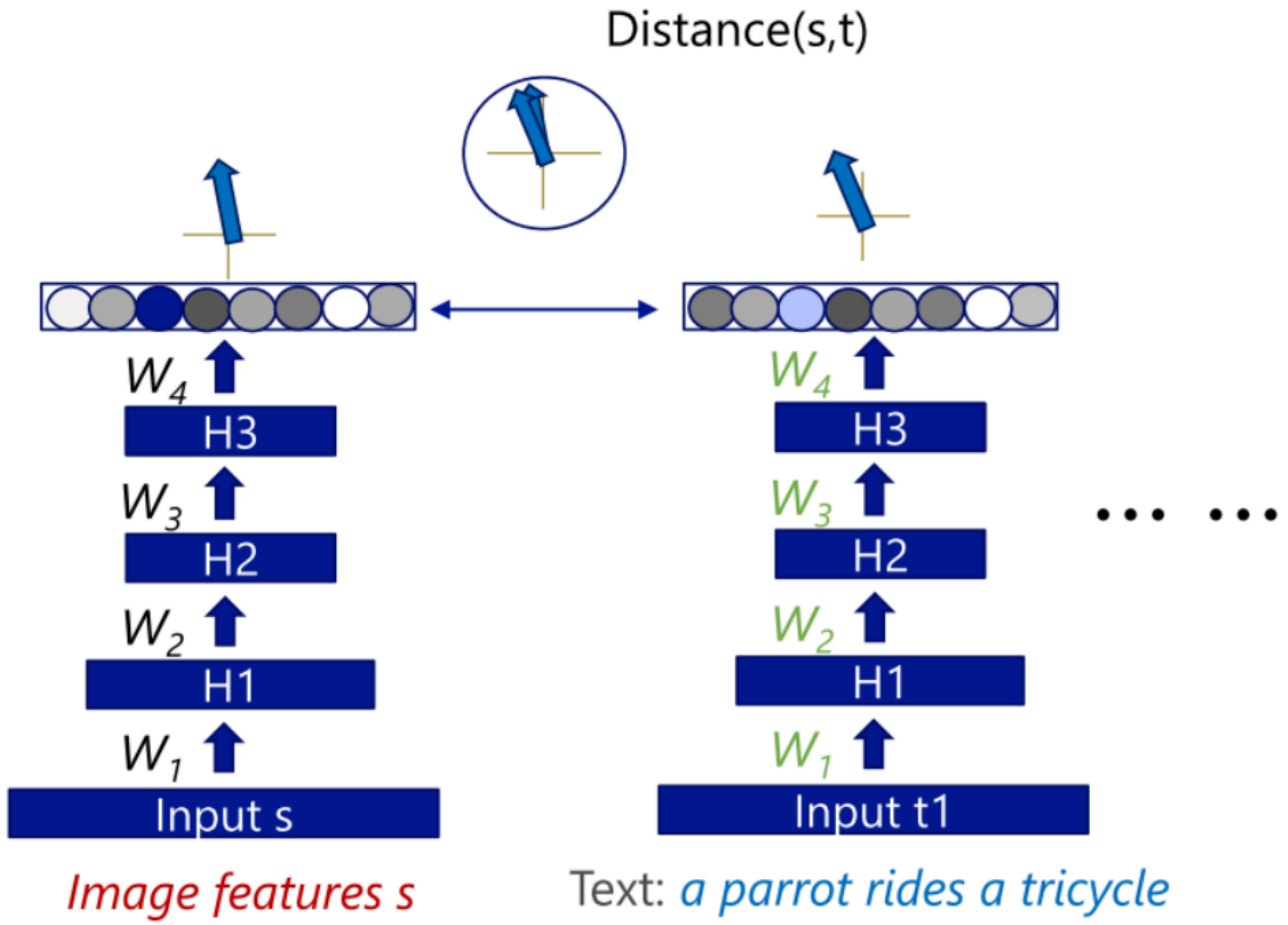
Correlated Representations: Find representations $f_1(\mathbf{x}_1), f_2(\mathbf{x}_2)$ for each view that maximize correlation:

$$\mathbf{corr}(f_1(\mathbf{x}_1), f_2(\mathbf{x}_2)) = \frac{\mathbf{cov}(f_1(\mathbf{x}_1), f_2(\mathbf{x}_2))}{\sqrt{\mathbf{var}(f_1(\mathbf{x}_1)) \cdot \mathbf{var}(f_2(\mathbf{x}_2))}}$$

Joint Embeddings: Models that minimize distance between ground truth pairs of samples:

$$min_{f_1, f_2} D\left(f_1(\mathbf{x}_1^{(i)}), f_2(\mathbf{x}_2^{(i)})\right)$$

Joint **Embeddings**



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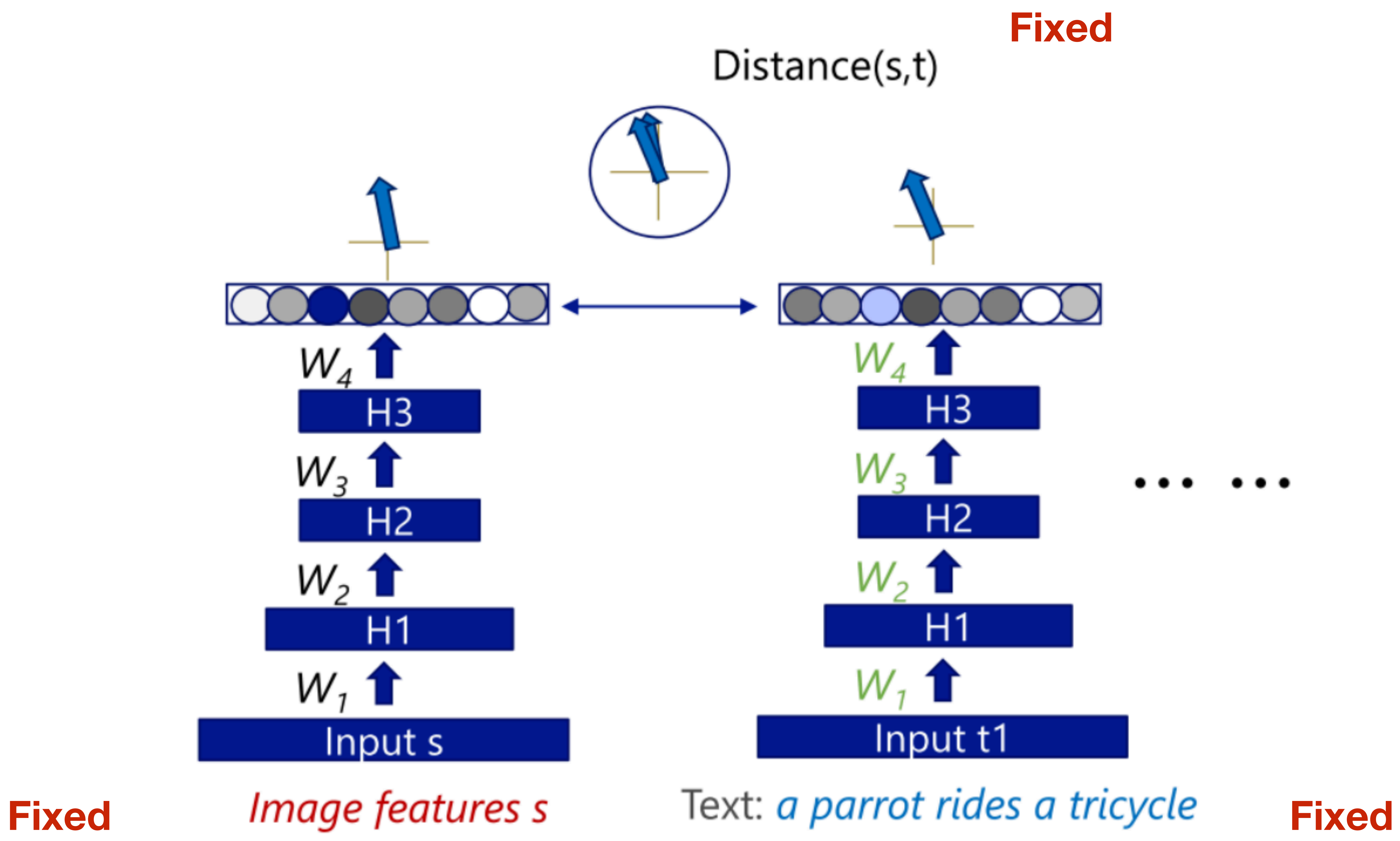
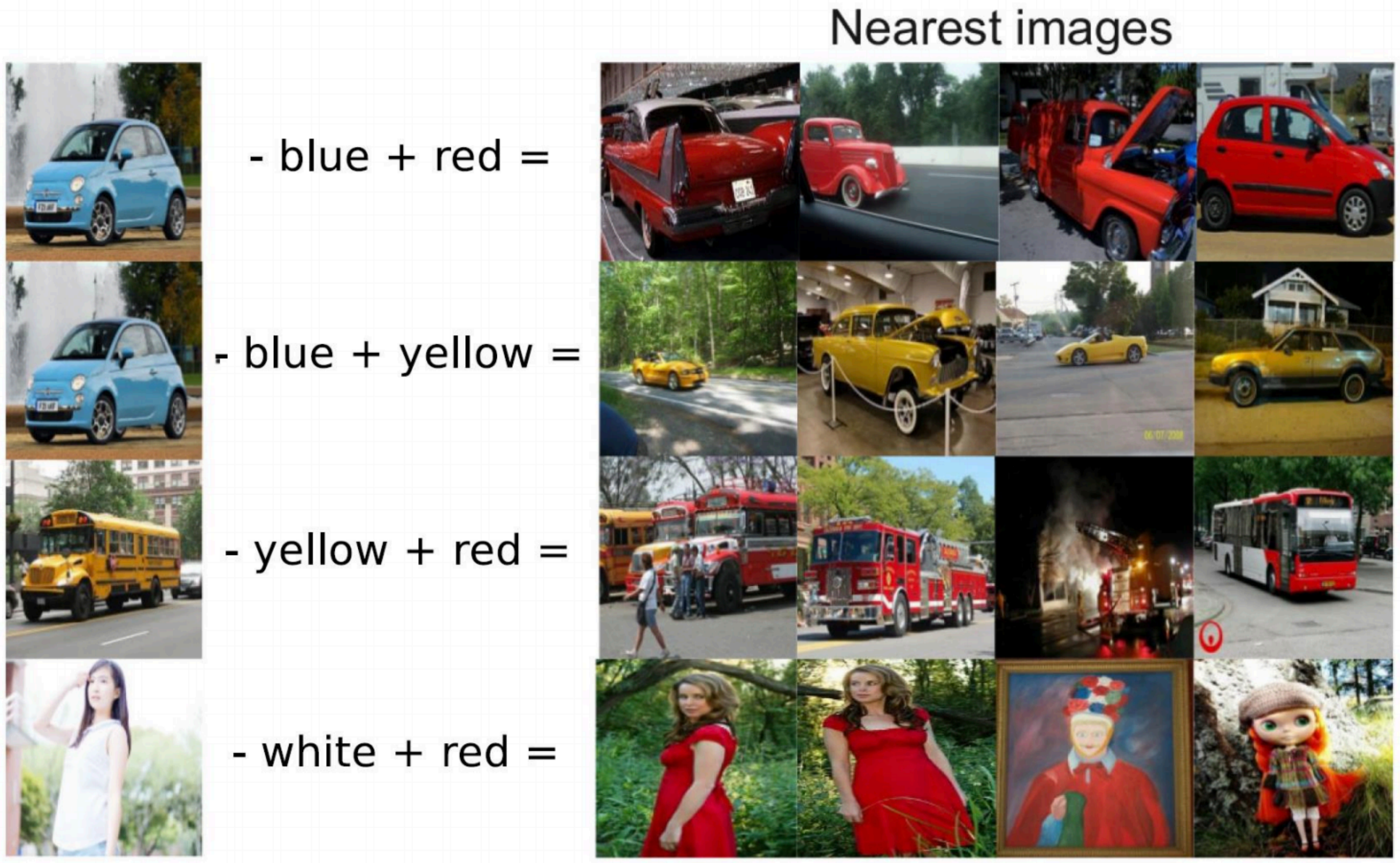
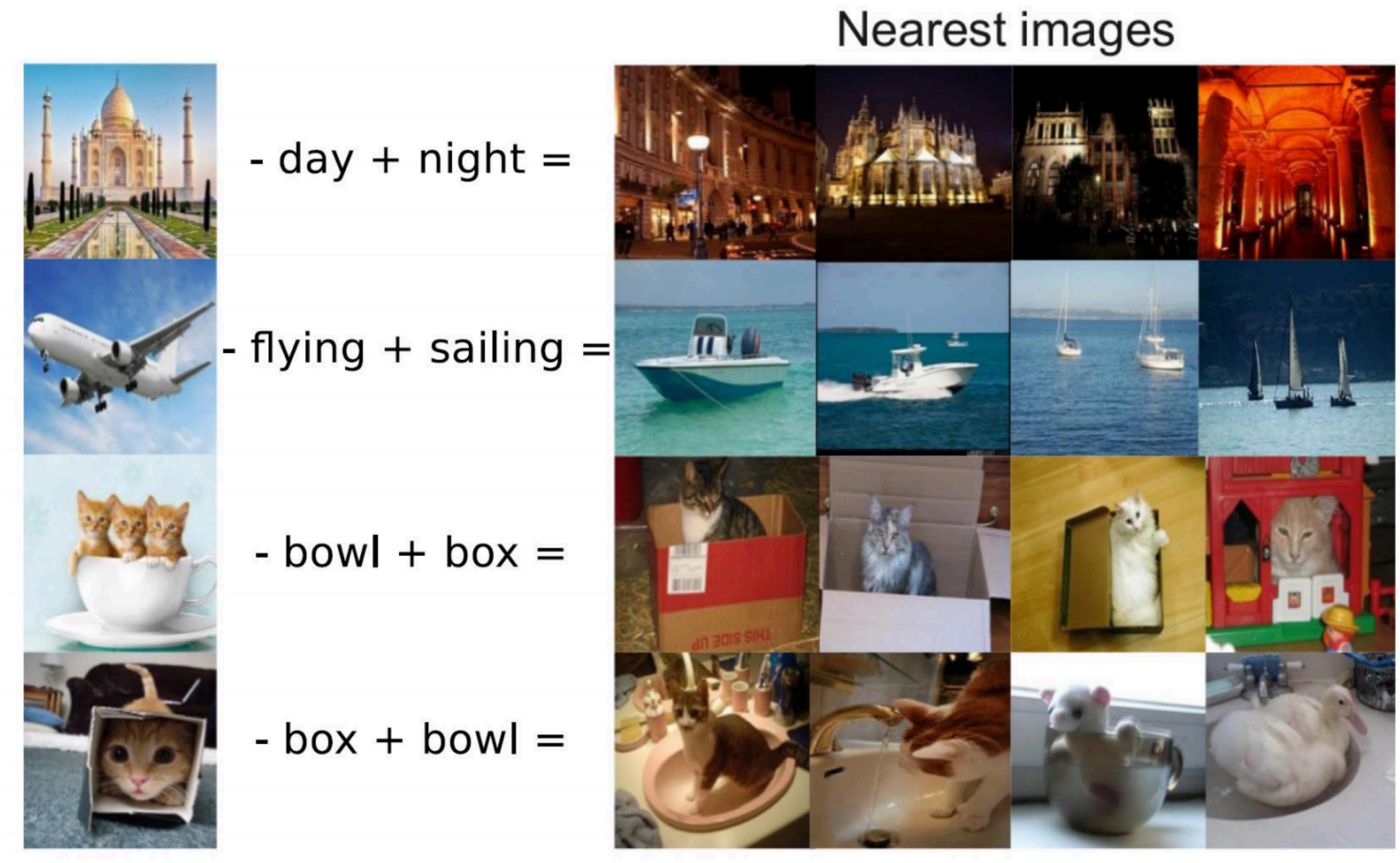


Joint **Embeddings**



[Kiros et al., Unifying Visual-Semantic Embeddings with Multimodal Neural Language Models, 2014]

Joint **Embeddings**



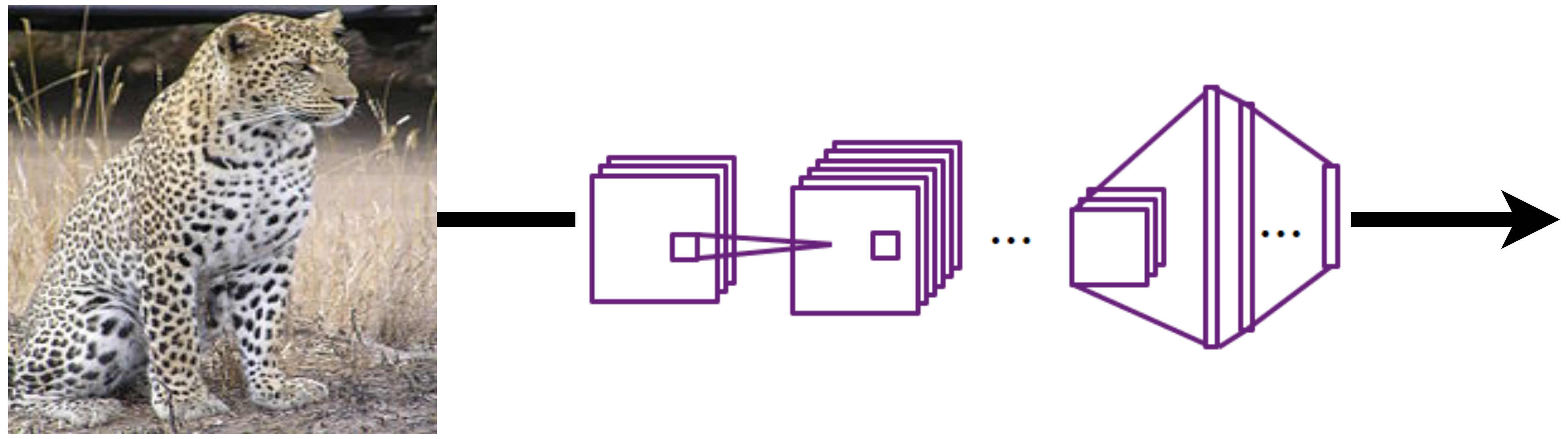
[Kiros et al., Unifying Visual-Semantic Embeddings with Multimodal Neural Language Models, 2014]

Object **Classification**

Category	Prediction
Dog	No
Cat	No
Couch	No
Flowers	No
Leopard	**Yes**
…	…

Problem: For each image predict which category it belongs to out of a fixed set

Object **Classification**



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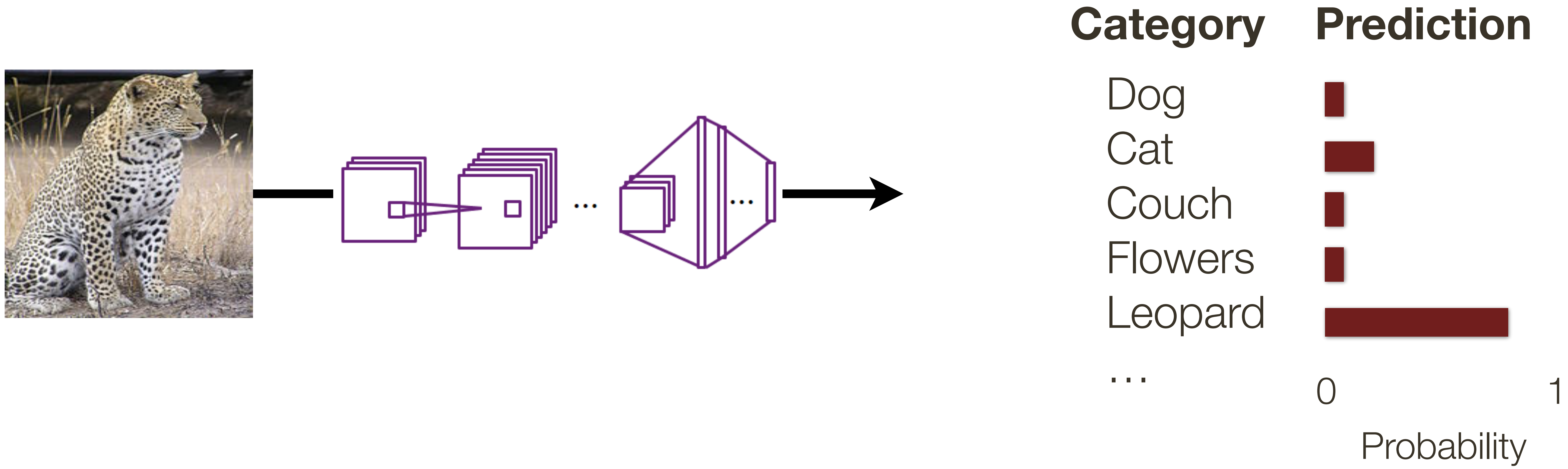

Problem: For each image predict which category it belongs to out of a fixed set

Discriminative Embeddings

Images and **class labels** are embedded into the same space

$\mathbb{R}^d$

Discriminative Embeddings

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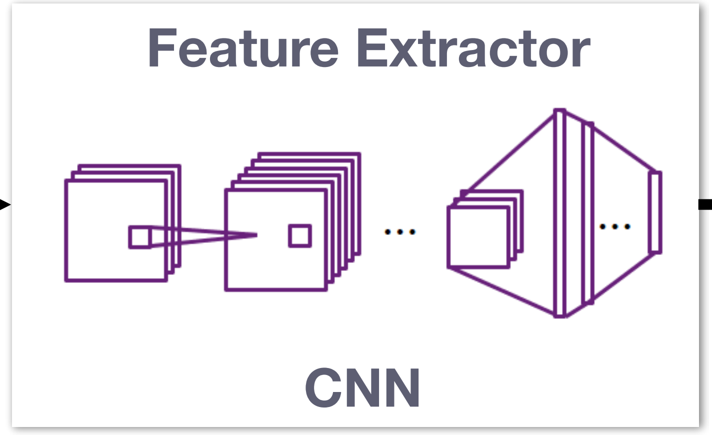
Image Embedding

$$\Psi(I_i) = \mathbf{W} \cdot CNN(I_i; \mathbf{\Theta}) \colon \mathbb{R}^D \rightarrow \mathbb{R}^d$$

$\mathbb{R}^d$

I_i

$\rightarrow$



$CNN(I_i; \mathbf{\Theta})$

$\rightarrow \Psi_I(I_i)$

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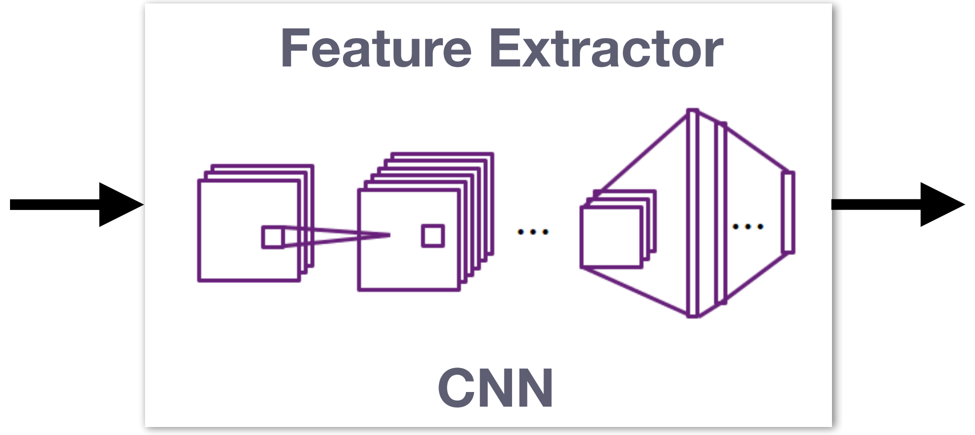

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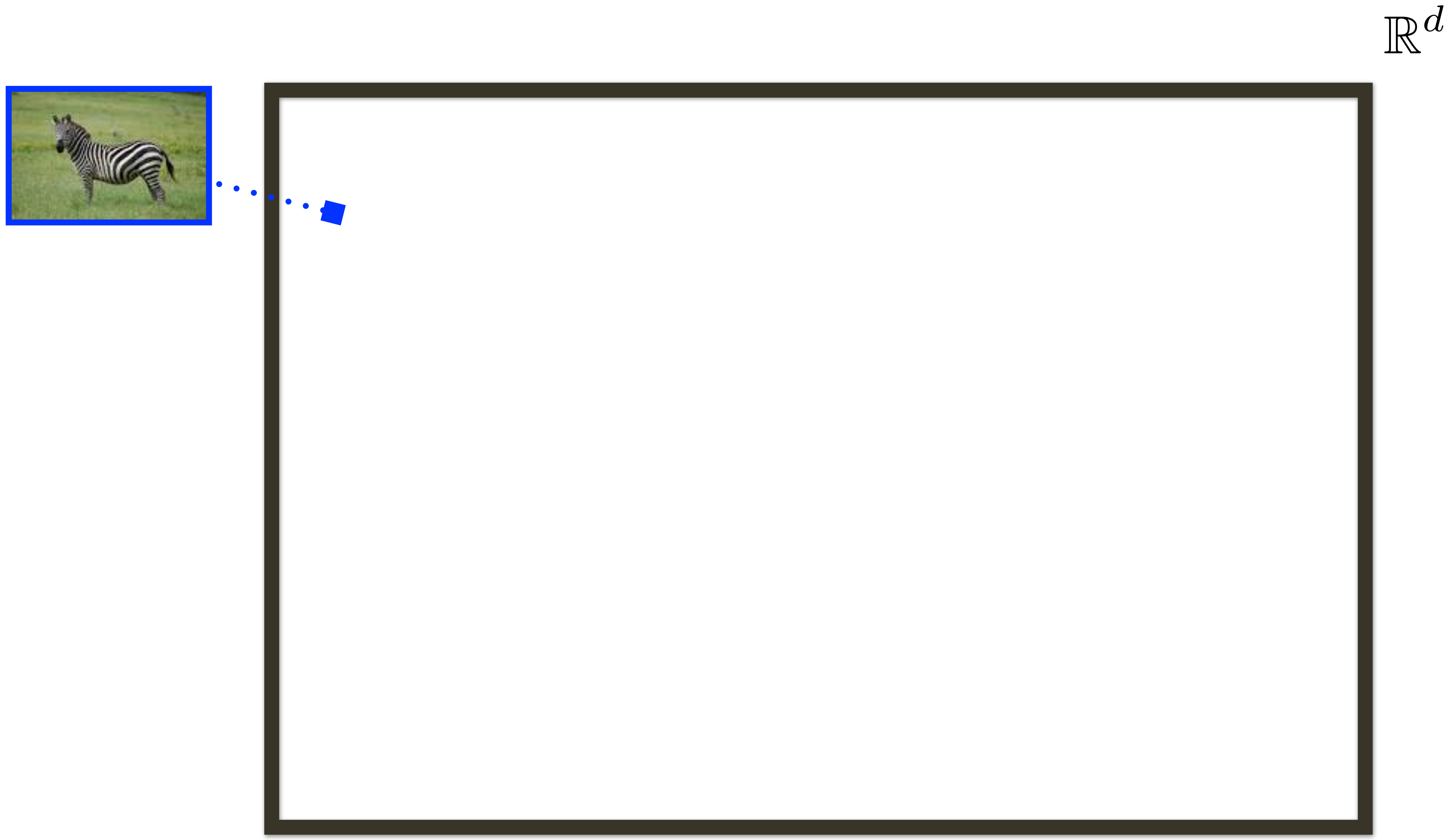

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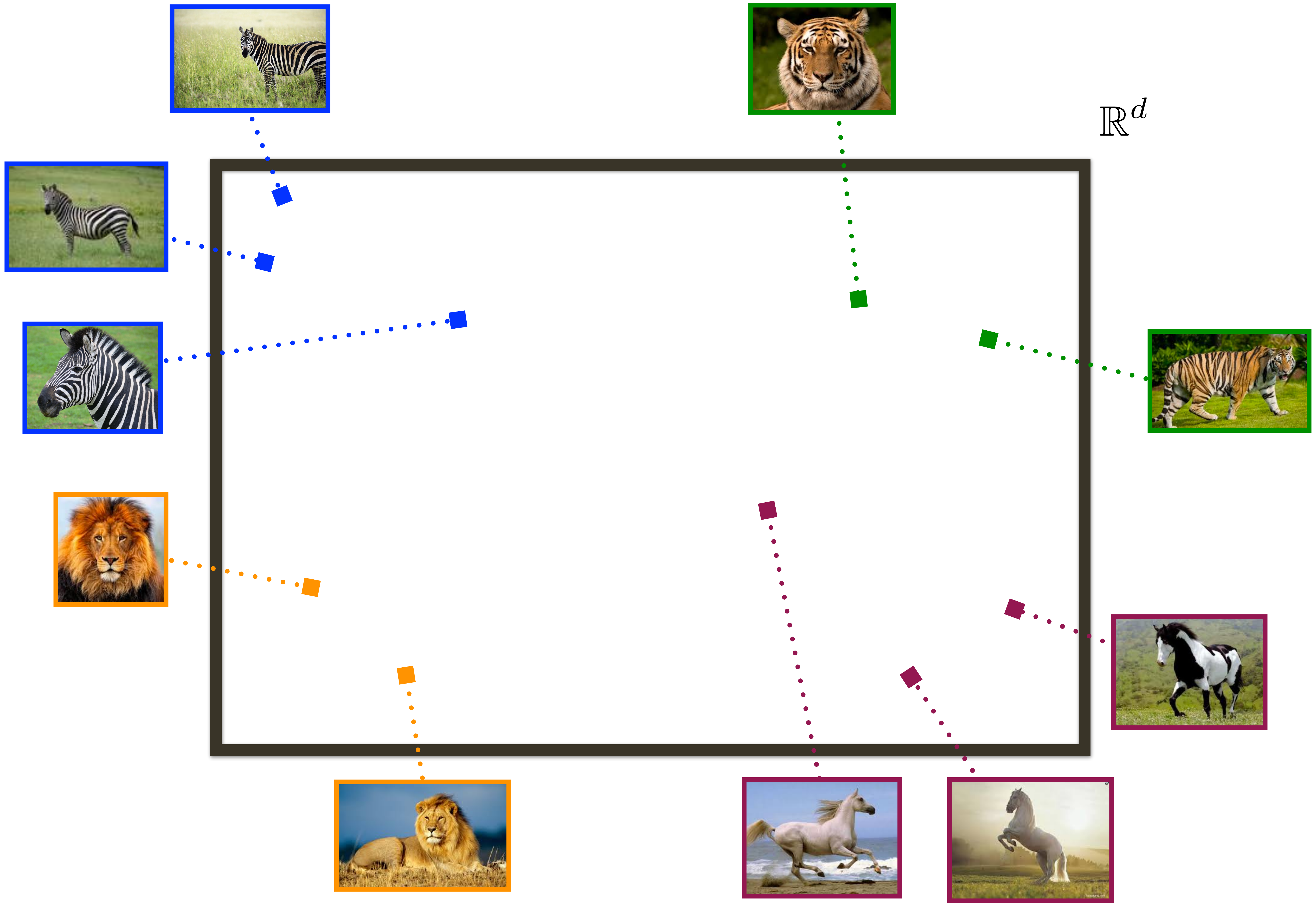

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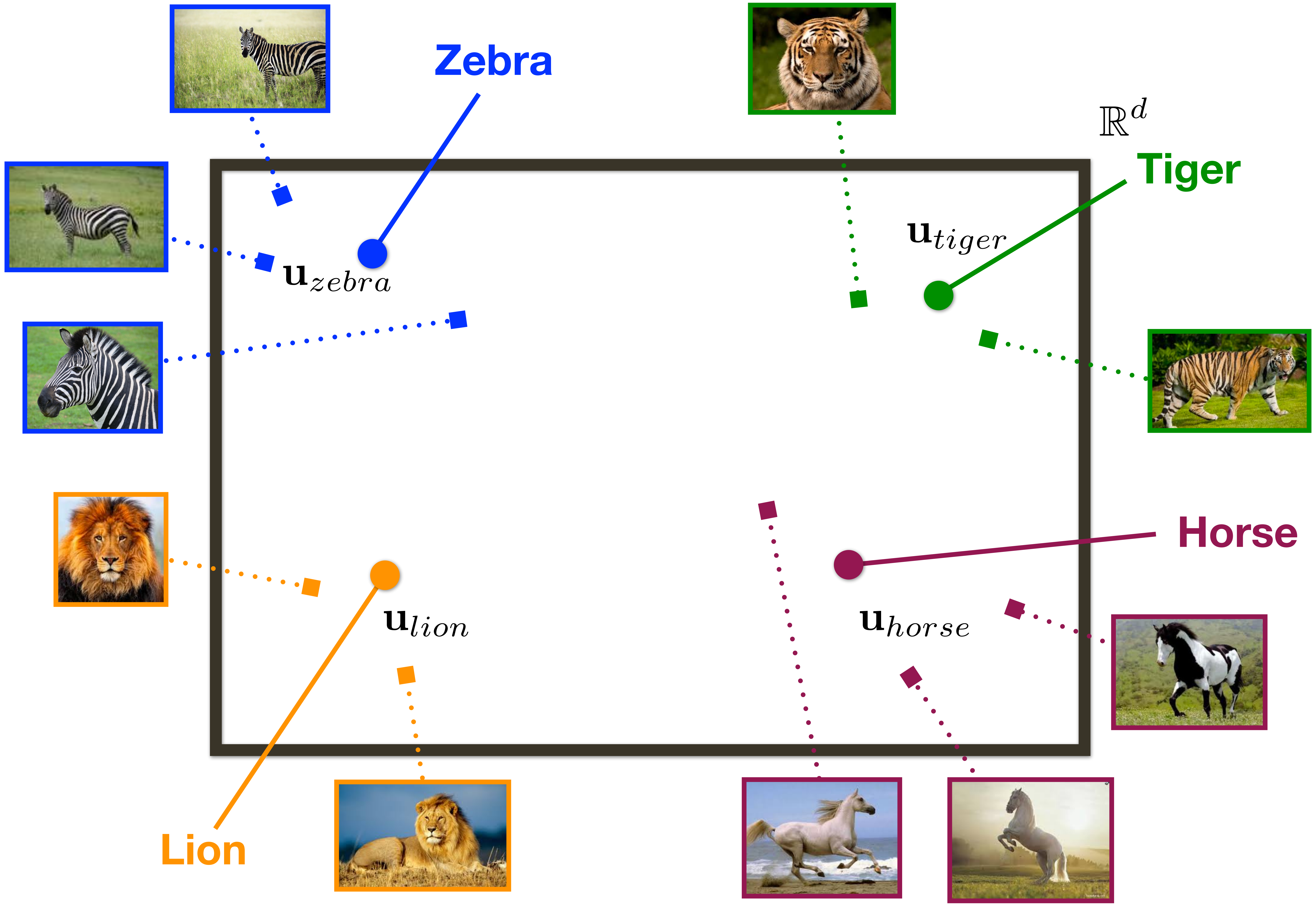

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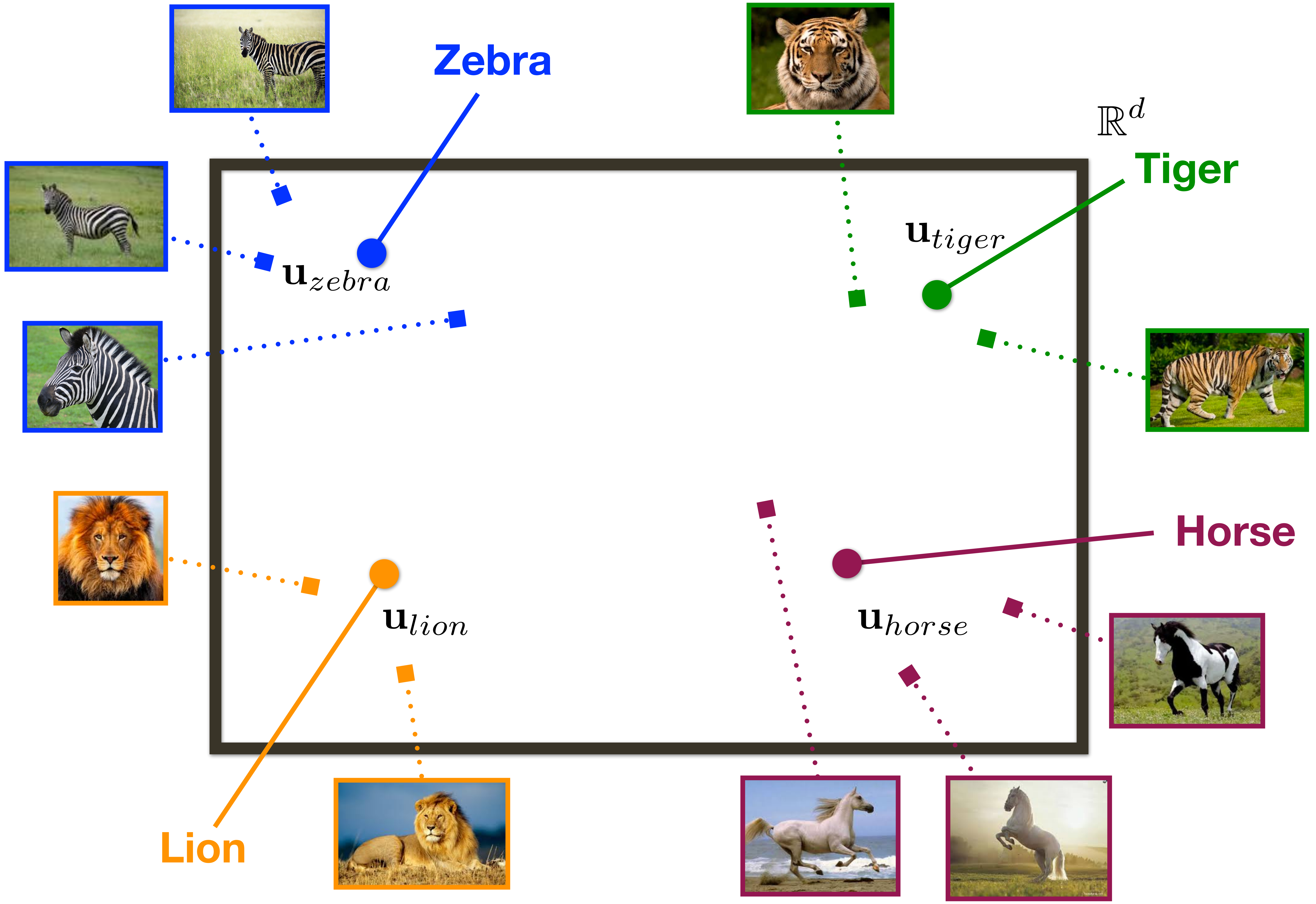

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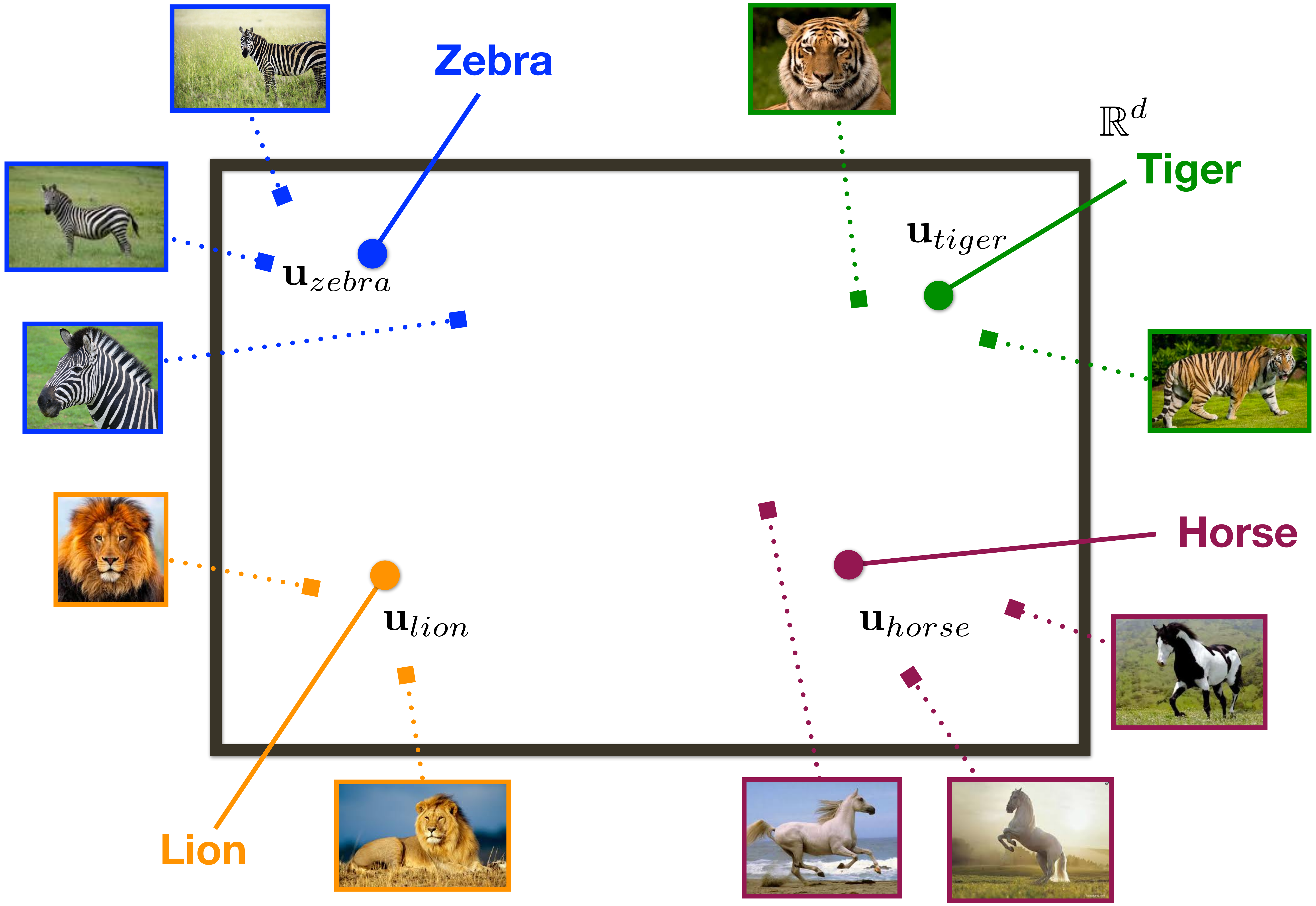

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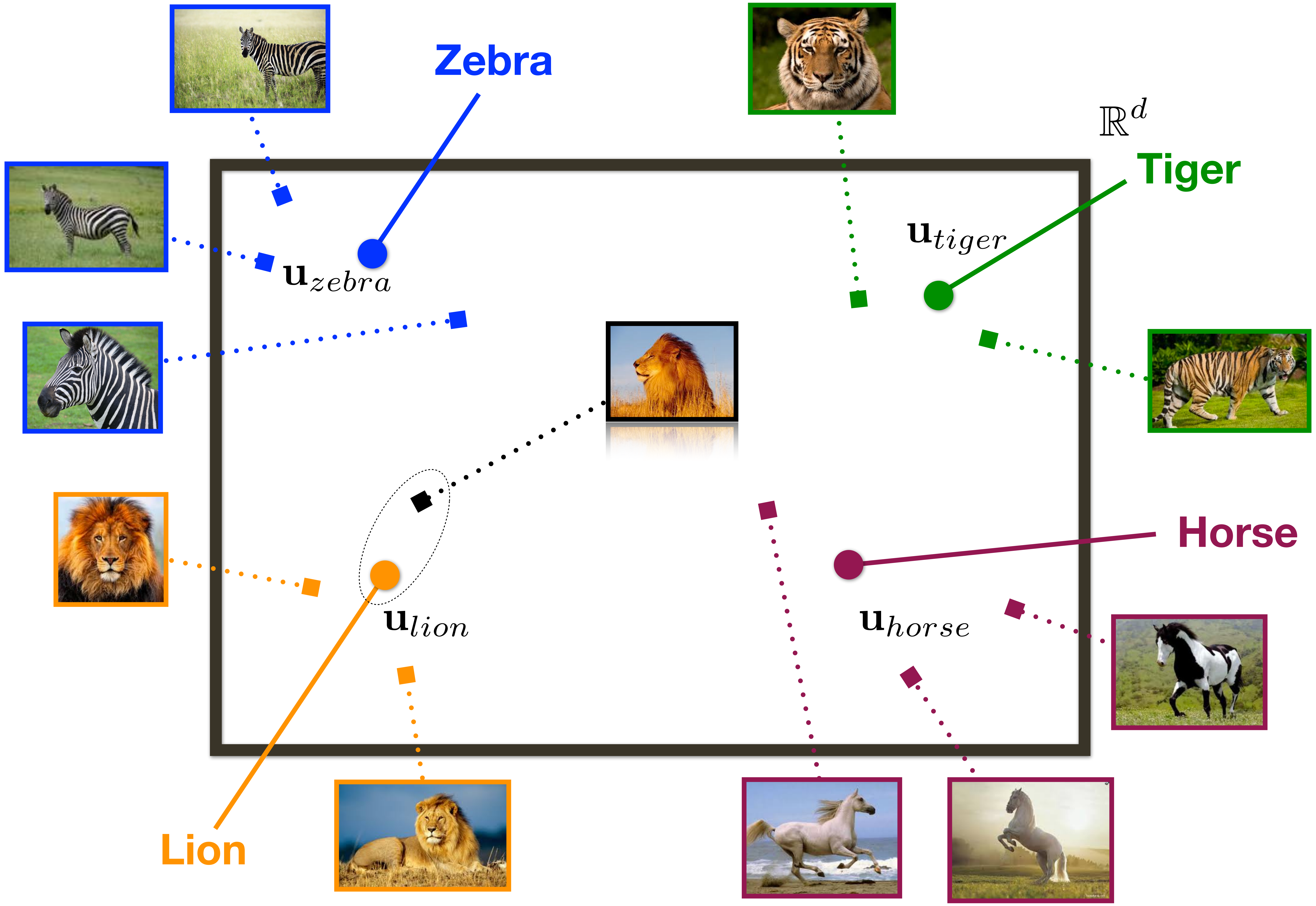
Image Categorization / Annotation

which object category does image belong to?



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Distance can be interpreted as probability

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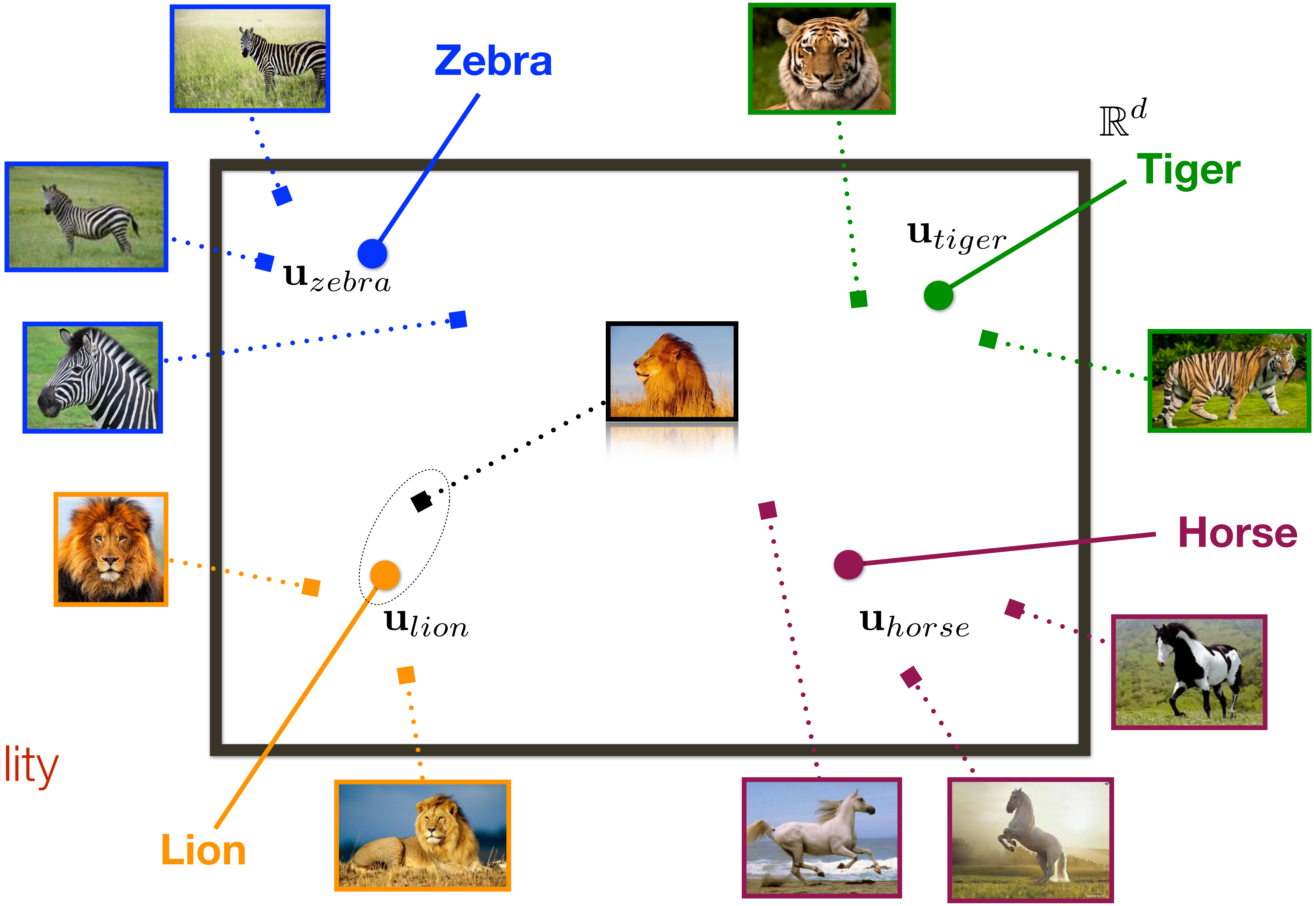

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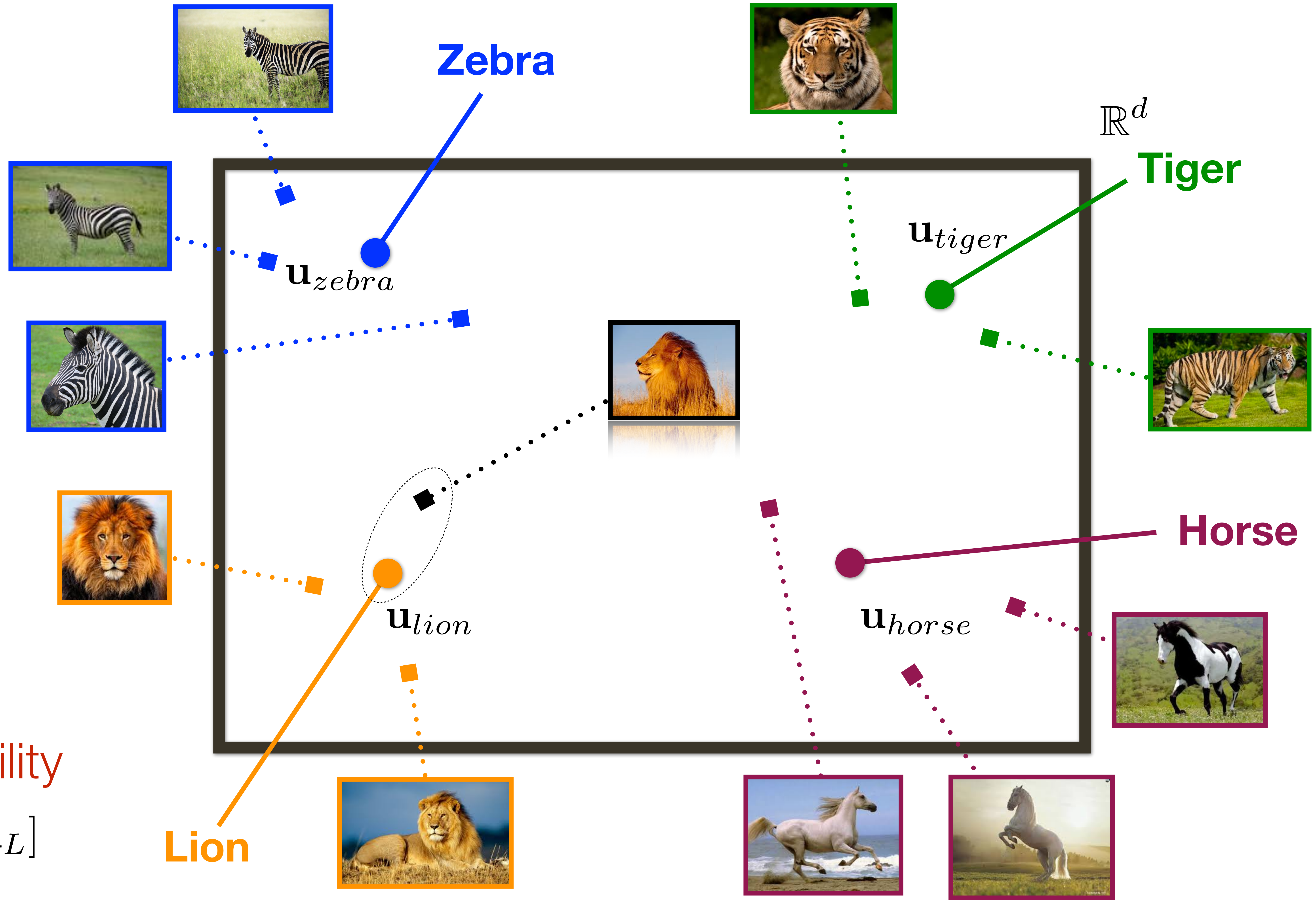
Similarity in Embedding Space

$$D(\mathbf{u}_i, \mathbf{u}') = \mathbf{u}_i \cdot \mathbf{u}'$$

Distance can be interpreted as probability

$$\text{Softmax}(\mathbf{U}\mathbf{u}'), \quad where\ \mathbf{U} = [\mathbf{u}_1, \mathbf{u}_2, \cdots, \mathbf{u}_L]$$



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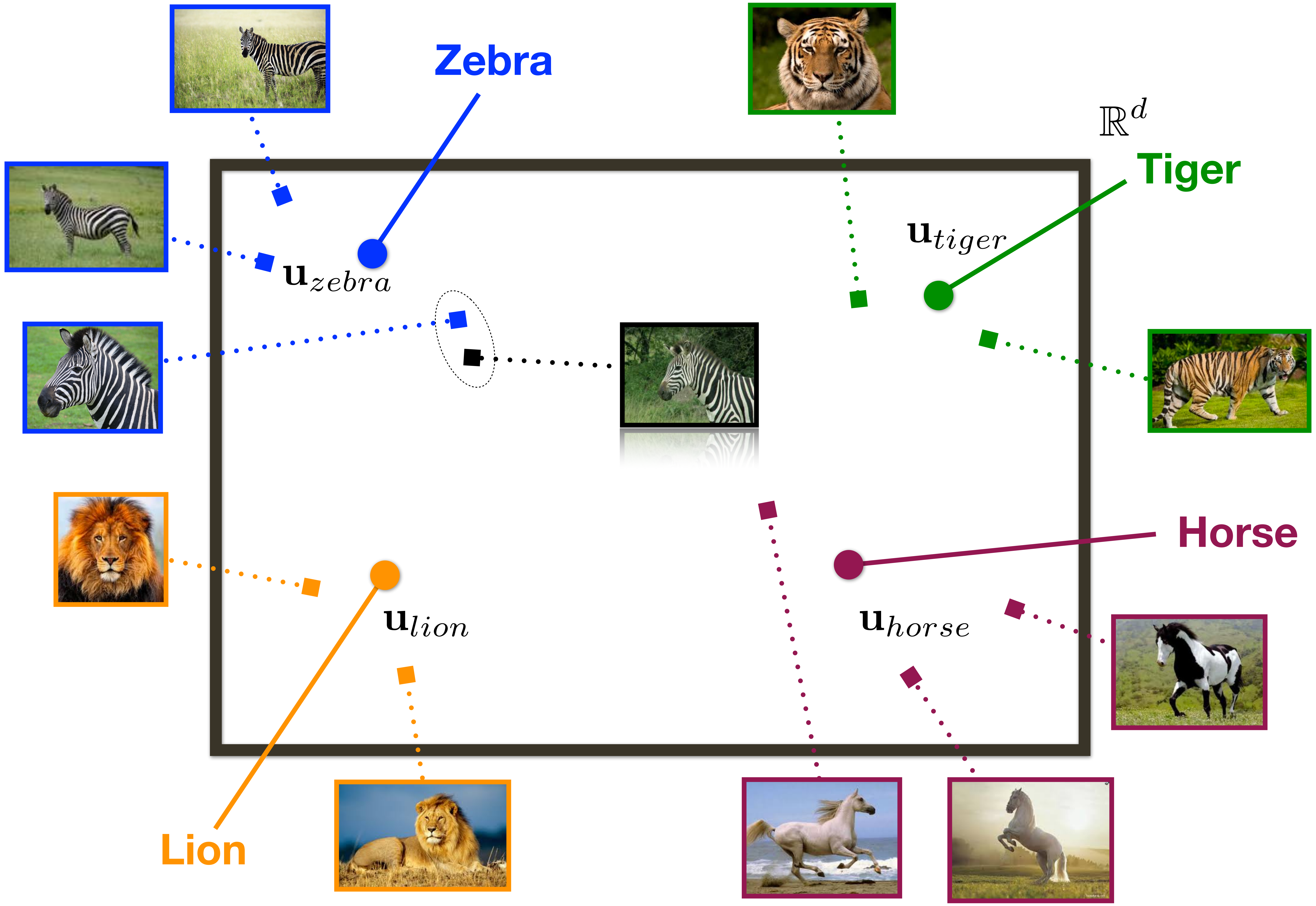
Search by Image

most similar image to a query?



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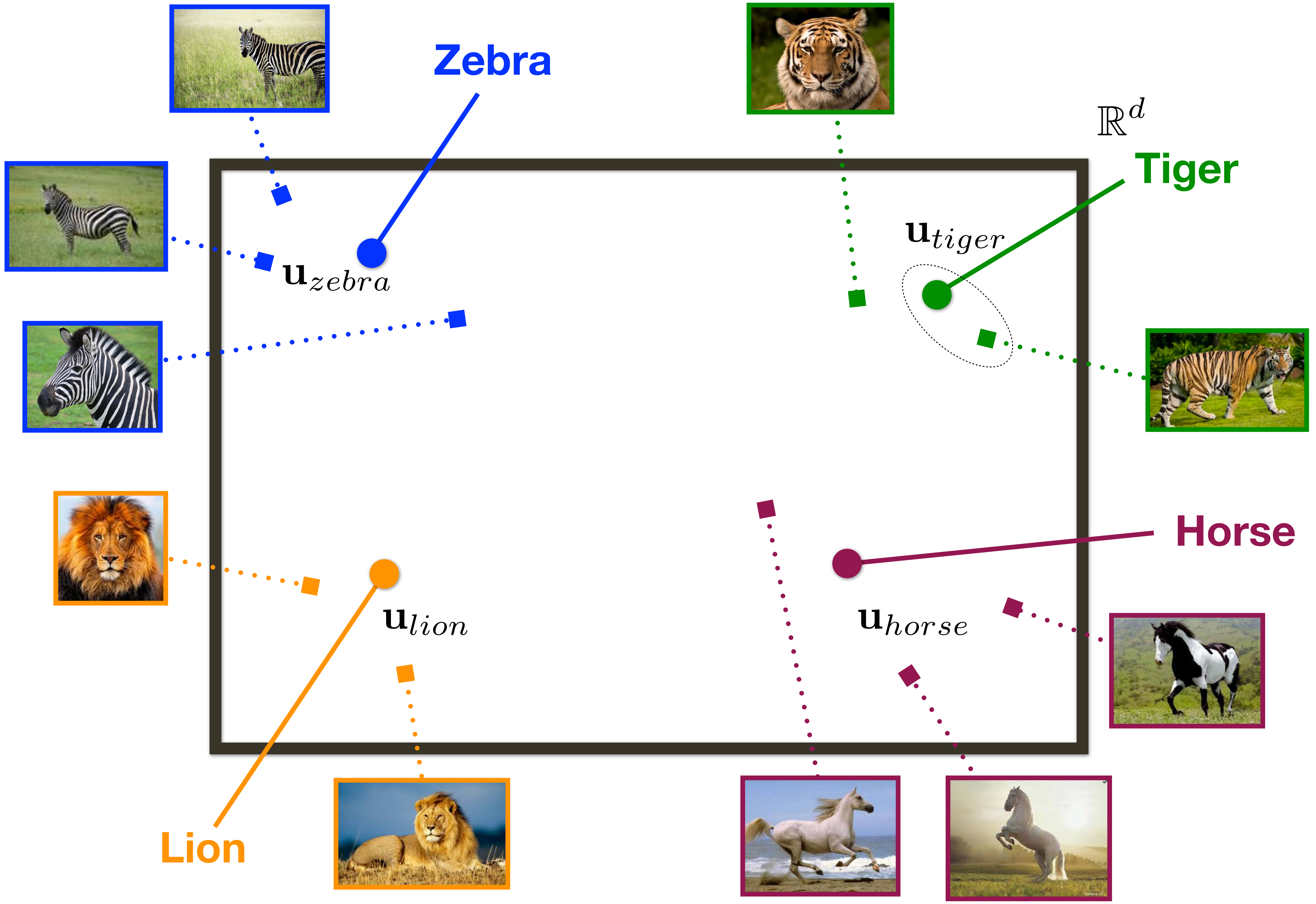
Search by Label

most representative image for a label?



Discriminative Embeddings

$$\mathcal{L}_C(\mathbf{W}, \mathbf{U}, I_i, y_i) = \sum [1 + \underline{D(\Psi(I_i), \mathbf{u}_{y_i})} - \underline{D(\Psi(I_i), \mathbf{u}_{y_c})}]$$

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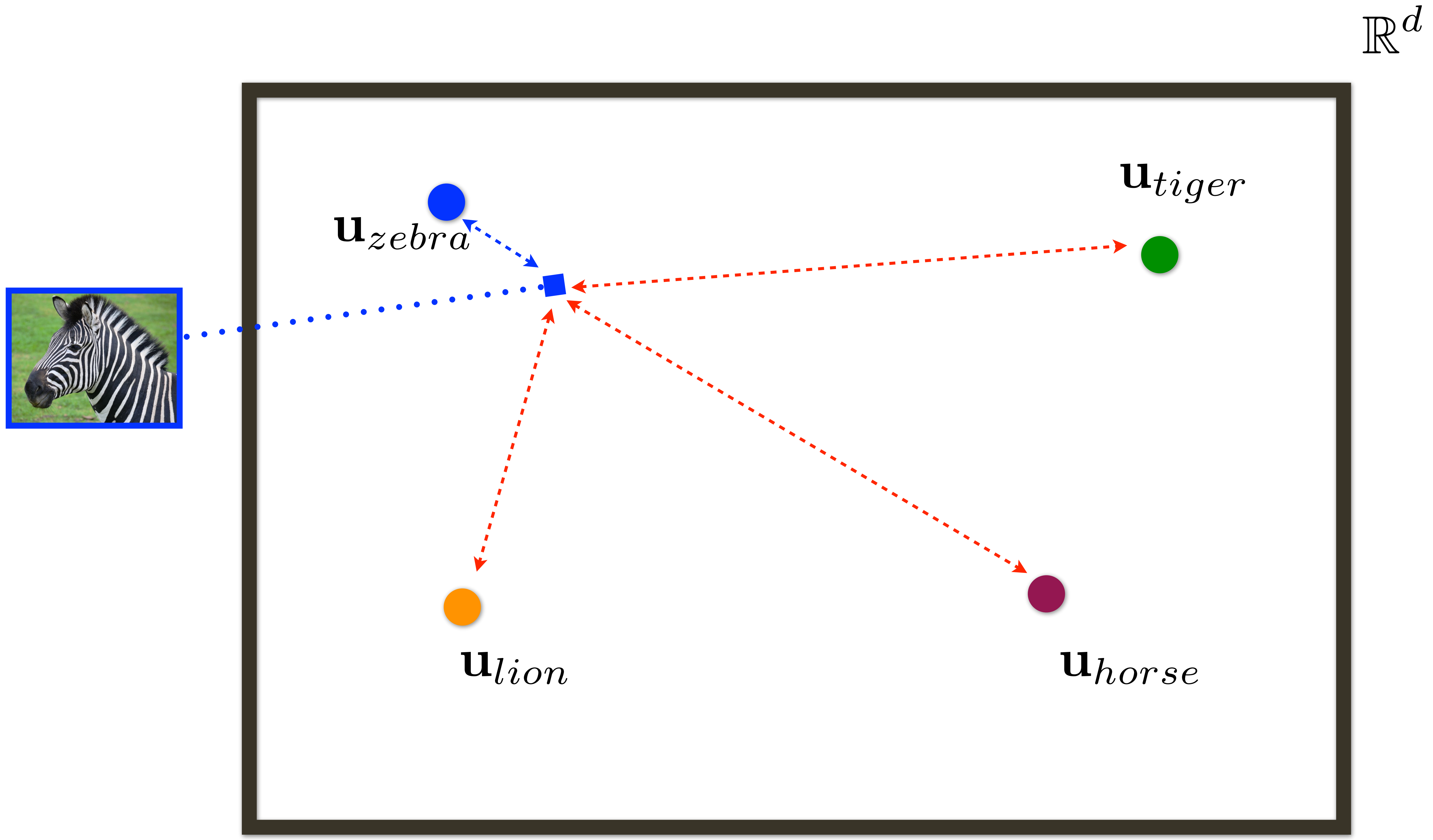

Similarity in Embedding Space

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Objective Function:

$$\min_{\mathbf{W}, \mathbf{U}} \sum_i^N \mathcal{L}_C(\mathbf{W}, \mathbf{U}, I_i, y_i) + \lambda_1 ||\mathbf{W}||_F^2 + \lambda_2 ||\mathbf{U}||_F^2$$

[Bengio *et al.*,, NIPS'10]

[Weinberger, Chapelle, NIPS'09]

Discriminative Embeddings

Why not minimize distance directly?

$$\mathcal{L}_C(\mathbf{W}, \mathbf{U}, I_i, y_i) = \sum [1 + D(\Psi(I_i), \mathbf{u}_{y_i}) - D(\Psi(I_i), \mathbf{u}_{y_c})]$$

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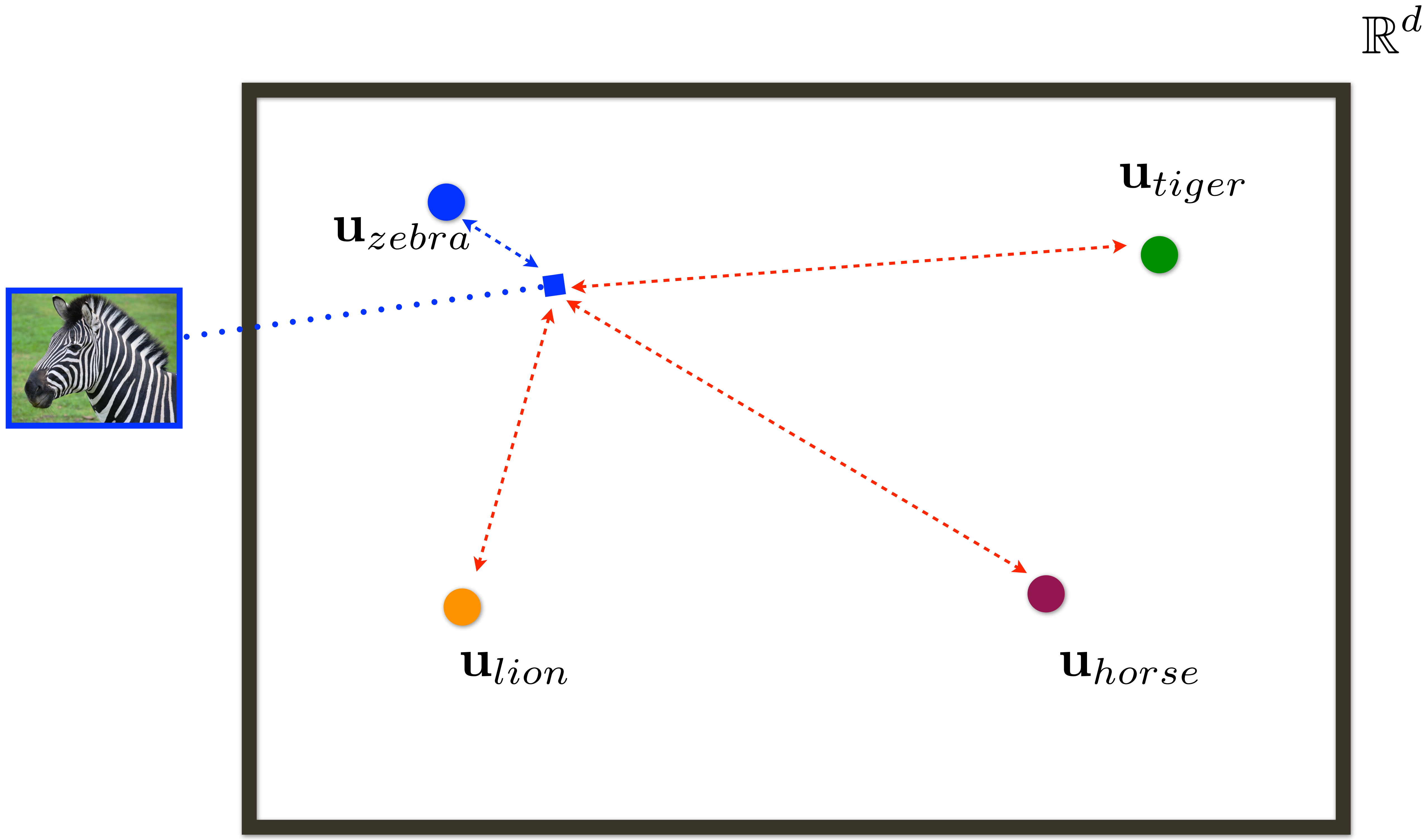

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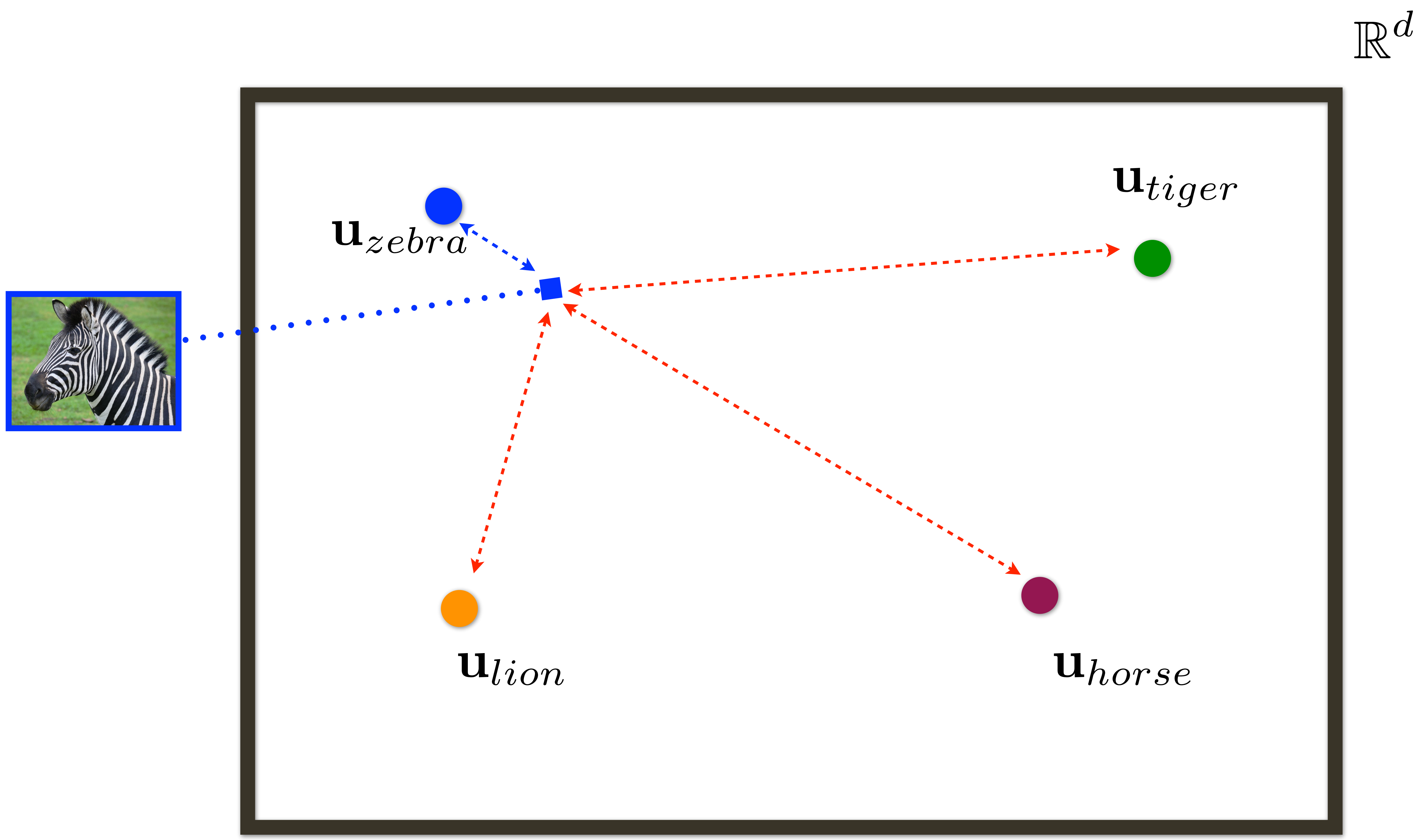
$$\mathcal{L}_C(\mathbf{W}, \mathbf{U}, I_i, y_i) = \sum max\{0, \alpha - \underline{D(\Psi(I_i), \mathbf{u}_{y_i})} + \underline{D(\Psi(I_i), \mathbf{u}_{y_c})}\}$$



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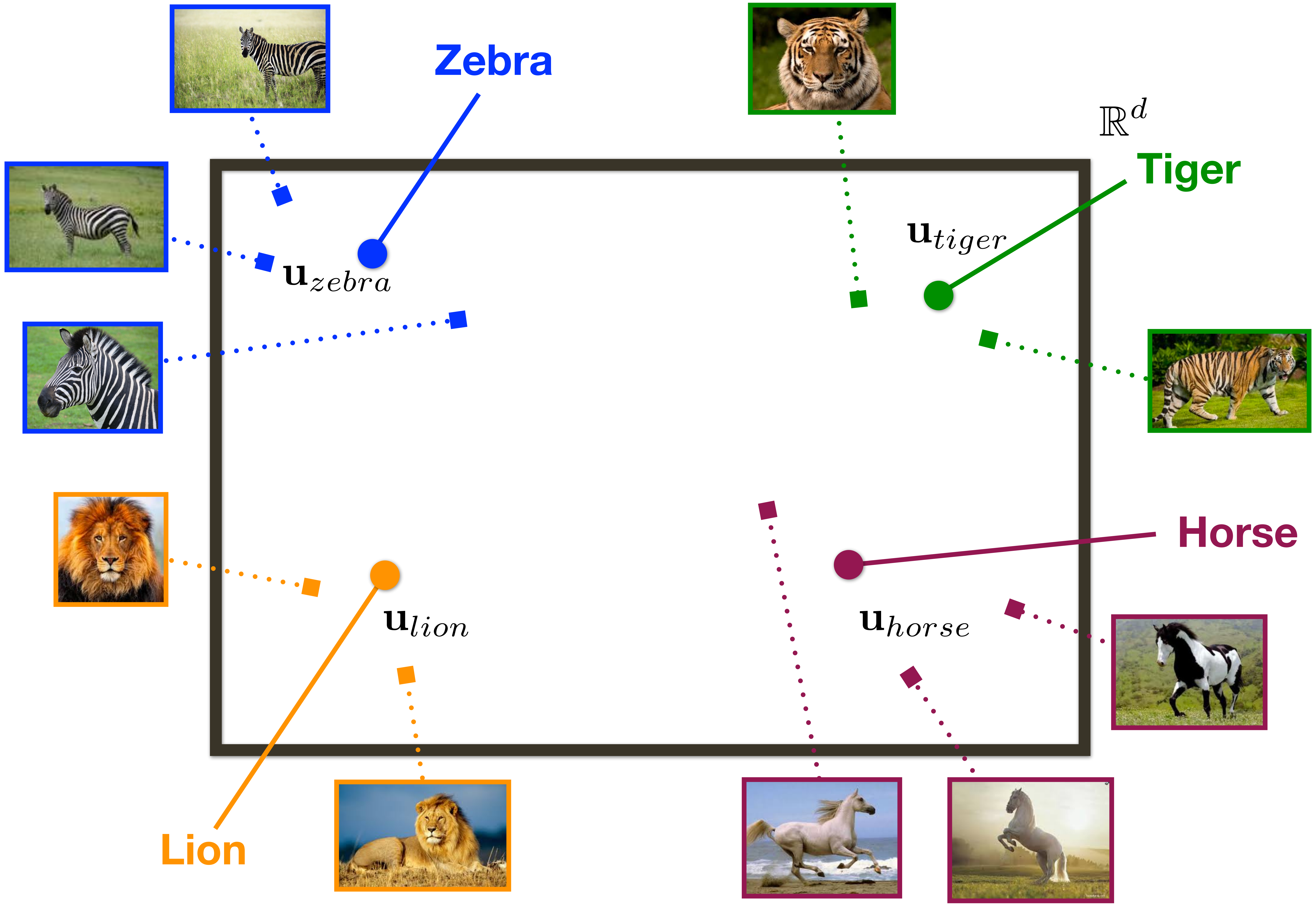
Discriminative Embeddings

This is a very **convenient model**



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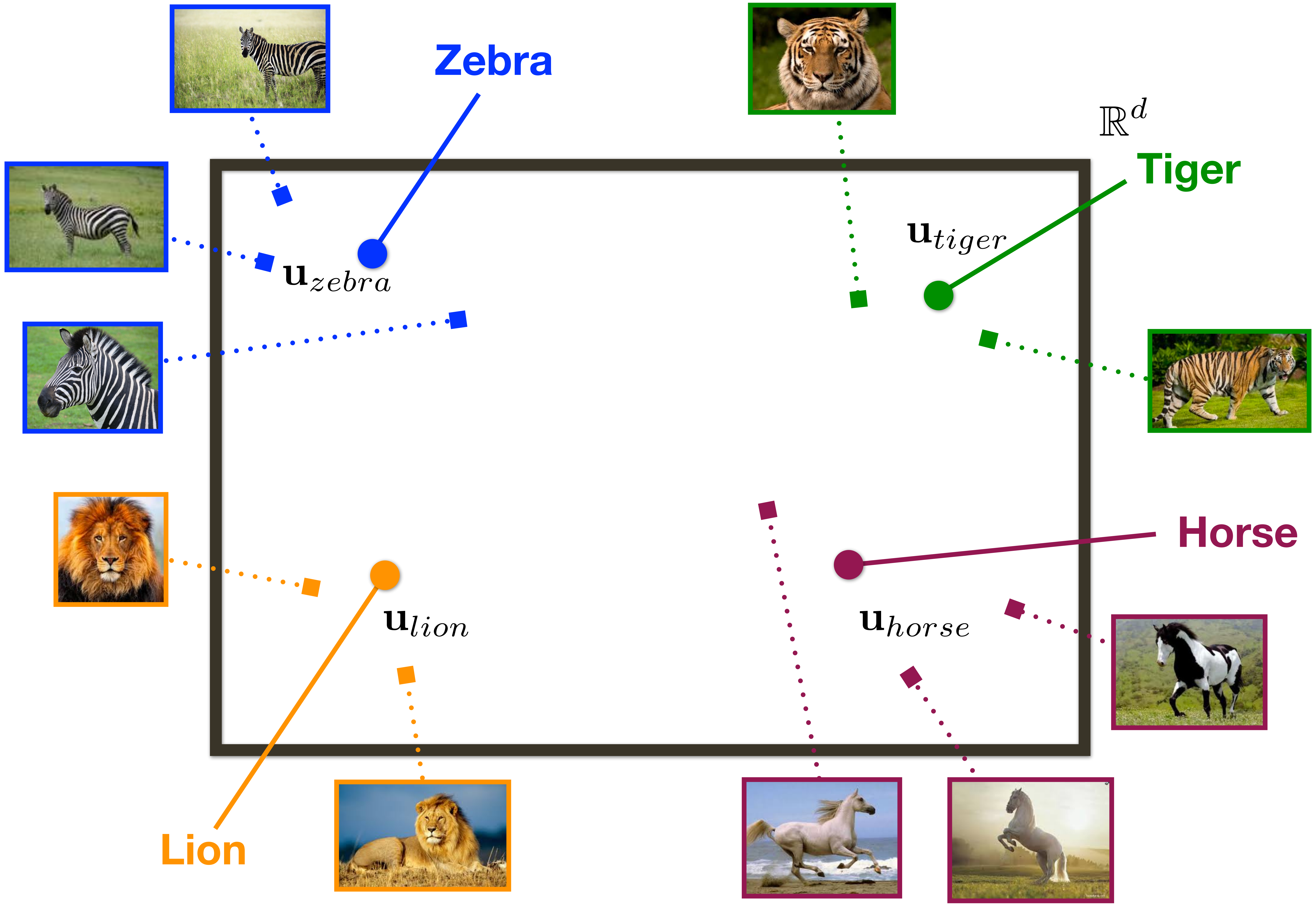
Inducing semantics on the embedding space

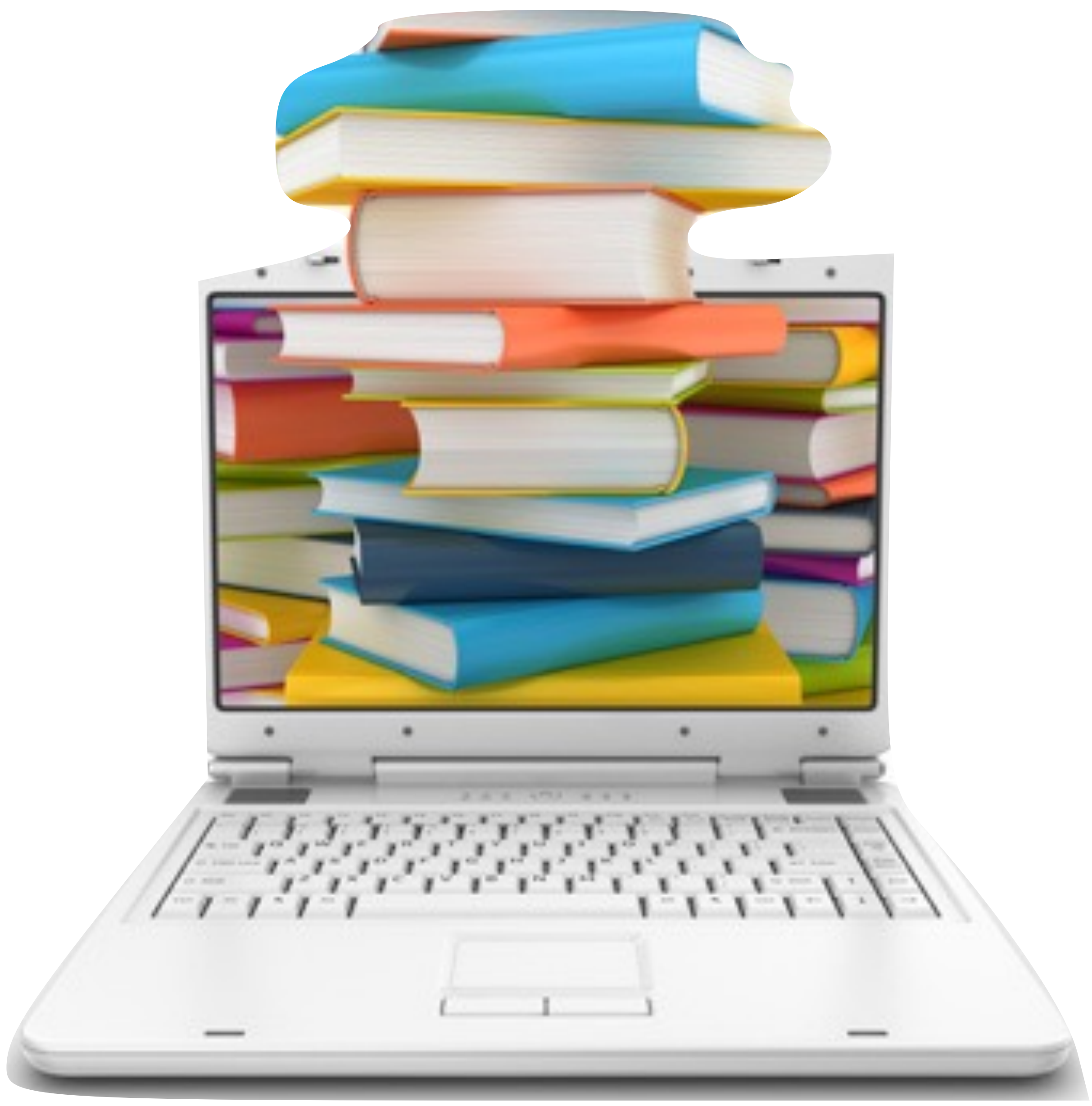


word2vec: Unsupervised Word Embedding

Distributional Semantics Hypothesis: words that are used and occur in the same context tend to have similar meaning

Label Embedding

$$\Psi_L(word_i) = \mathbf{u}_i : \{1, ..., L\} \rightarrow \mathbb{R}^d$$



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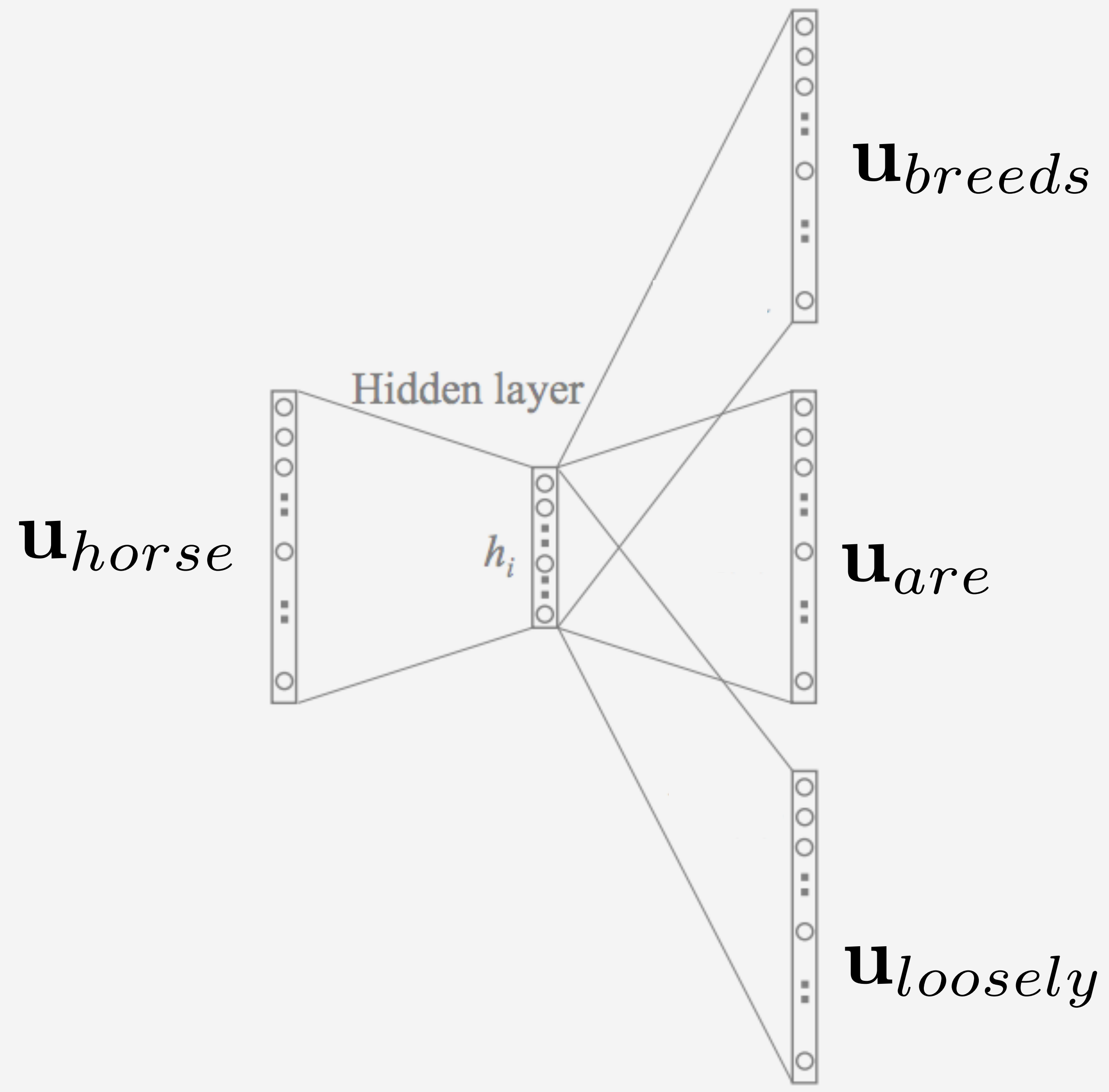
$L = 310,000$

e.g., Horse breeds are loosely divided into three categories



Skip-gram Model: unsupervised semantic representation for words

(trained from 7 billion word linguistic corpus)

Semi-supervised **Vocabulary Informed** Learning

[Fu et al., 2016]

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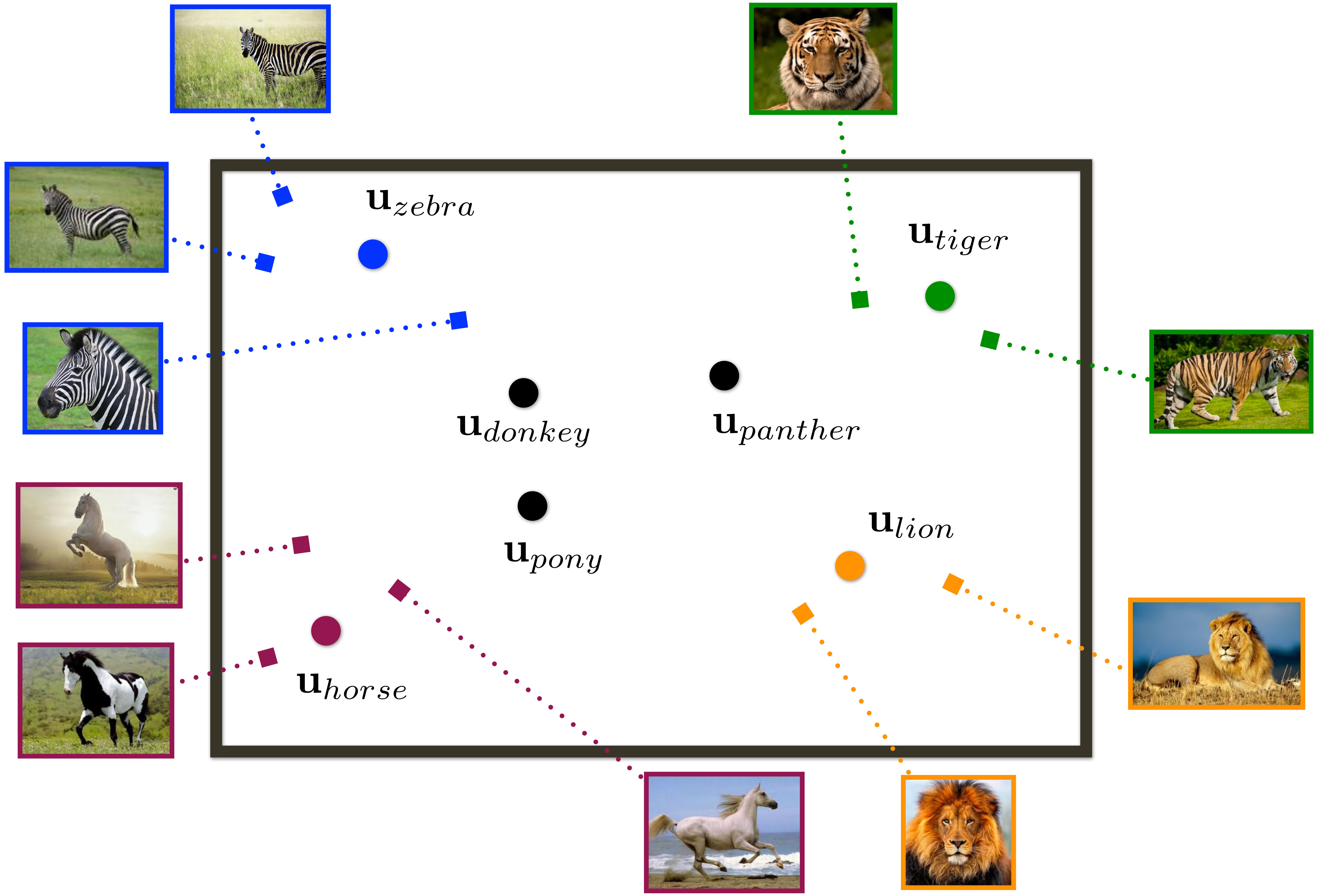

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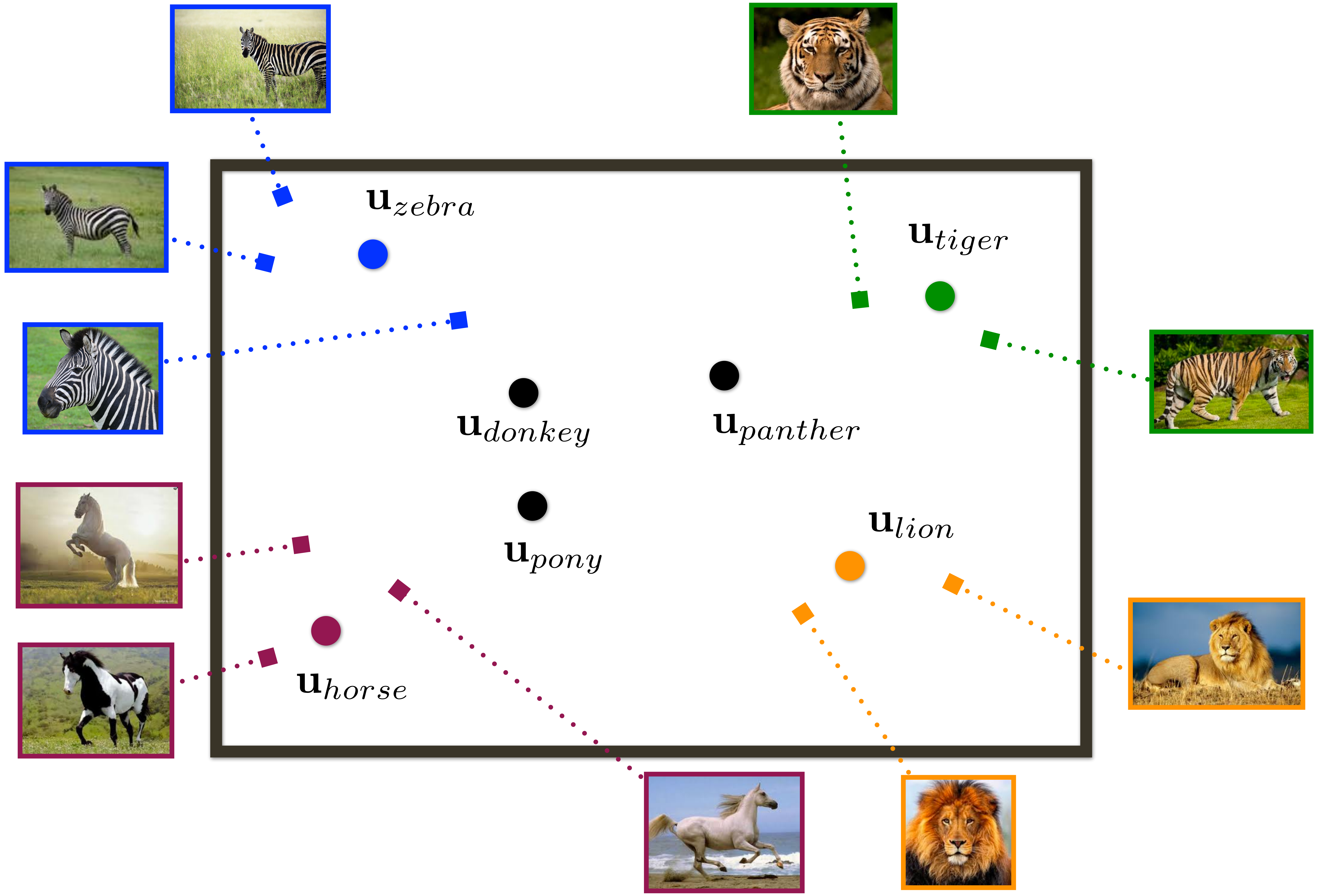

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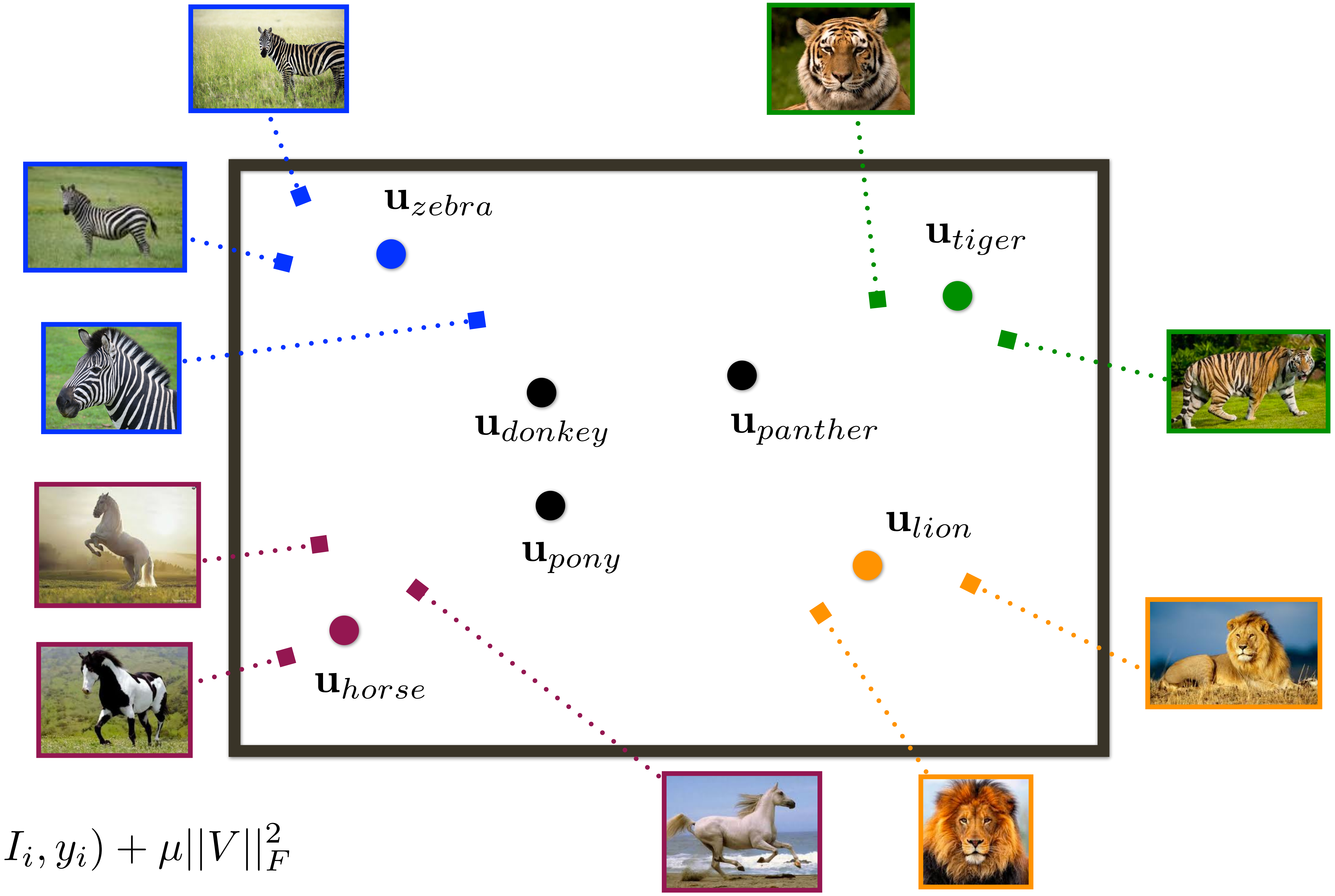

Similarity in Embedding Space

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Objective Function:

$$\min_{\mathbf{W}} \sum_{i}^{N} \mathcal{L}_C(\mathbf{W}, \mathbf{V}, I_i, y_i) + \mathcal{L}_R(\mathbf{W}, \mathbf{V}, I_i, y_i) + \mu ||V||_F^2$$

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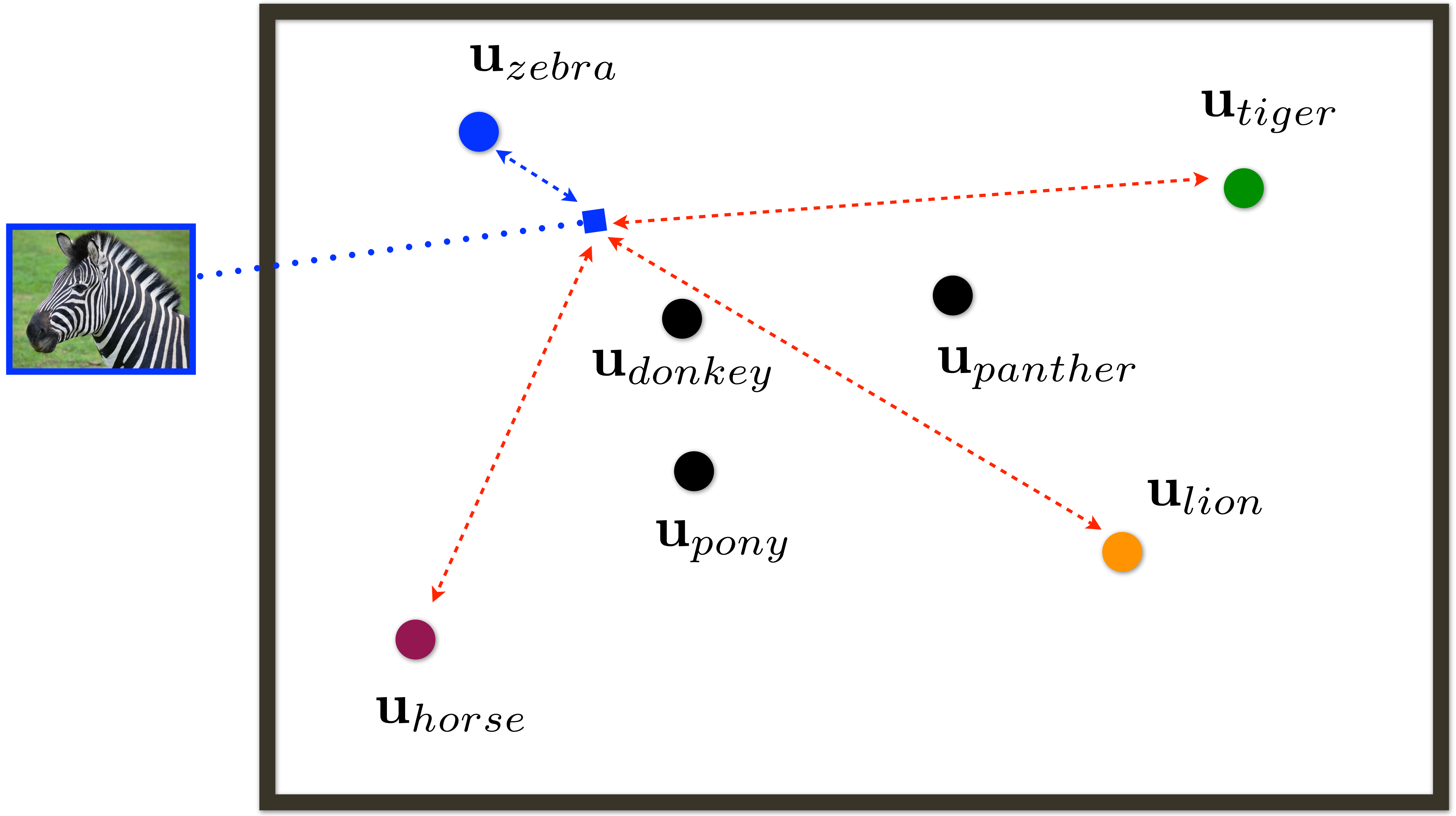

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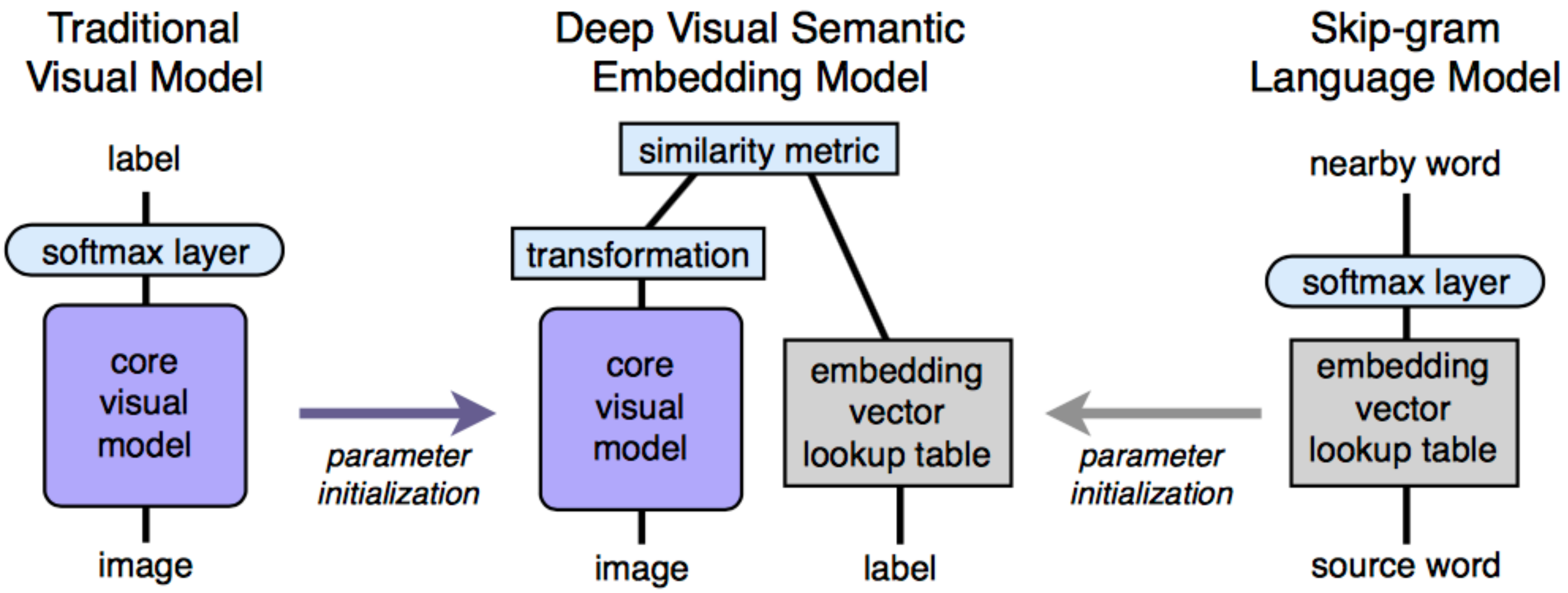
Intuition

DeViSE: A Deep Visual-Semantic Embedding Model

[Frome et al., 2013]



$$loss(image, label) = \sum_{j \neq label} \max[0, margin - \vec{t}_{label} M \vec{v}(image) + \vec{t}_j M \vec{v}(image)]$$

DeViSE: A Deep Visual-Semantic Embedding Model

[Frome et al., 2013]

Supervised Results

Model type	dim	Flat hit@k (%)				Hierarchical precision@k			
		1	2	5	10	2	5	10	20
Softmax baseline	N/A	**55.6**	**67.4**	**78.5**	**85.0**	0.452	0.342	0.313	0.319
DeViSE	500	53.2	65.2	76.7	83.3	0.447	**0.352**	**0.331**	**0.341**
	1000	54.9	66.9	78.4	**85.0**	**0.454**	0.351	0.325	0.331
Random embeddings	500	52.4	63.9	74.8	80.6	0.428	0.315	0.271	0.248
	1000	50.5	62.2	74.2	81.5	0.418	0.318	0.290	0.292
Chance	N/A	0.1	0.2	0.5	1.0	0.007	0.013	0.022	0.042

Zero-shot Results

Model	200 labels	1000 labels
DeViSE	31.8%	9.0%
Mensink et al. 2012 [12]	35.7%	1.9%
Rohrbach et al. 2011 [17]	34.8%	-

Semi-supervised **Vocabulary Informed** Learning

[Fu et al., 2016]

Image Embedding

$$\Psi(I_i) = \mathbf{W} \cdot CNN(I_i; \mathbf{\Theta}) \colon \mathbb{R}^D \to \mathbb{R}^d$$

Label Embedding

$$\Psi_L(word_i) = \mathbf{u}_i : \{1, ..., L\} \to \mathbb{R}^d$$

$L = 310,000$

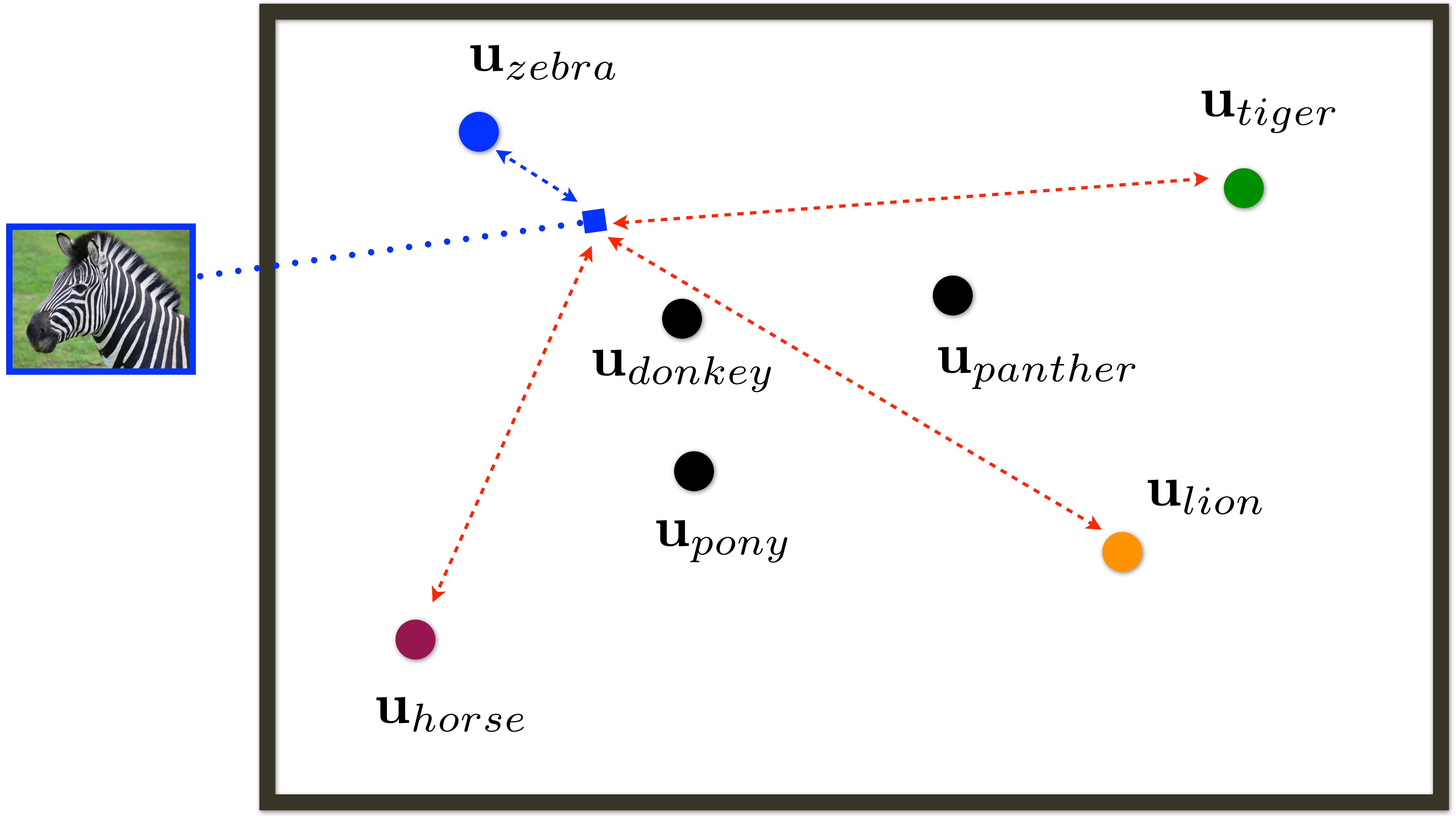
Similarity in Embedding Space

$$D(\mathbf{u}, \mathbf{u}') = ||\mathbf{u} - \mathbf{u}'||_2^2$$

Objective Function:

$$\min_{\mathbf{W}} \sum_i^N \mathcal{L}_C(\mathbf{W}, \mathbf{V}, I_i, y_i) + \mathcal{L}_R(\mathbf{W}, \mathbf{V}, I_i, y_i) + \mu||V||_F^2$$

$$\mathcal{L}_C(\mathbf{W}, \mathbf{U}, \mathbf{x}_i, y_i) = \sum [1 + D(\mathbf{W}\mathbf{x}_i, \mathbf{u}_{y_i}) - D(\mathbf{W}\mathbf{x}_i, \mathbf{u}_c)]$$



Semi-supervised **Vocabulary Informed** Learning

[Fu et al., 2016]

$$\mathcal{L}_C(\mathbf{W},\mathbf{U},\mathbf{x}_i,y_i) = \sum [1 + \underline{D(\mathbf{W}\mathbf{x}_i,\mathbf{u}_{y_i})} - \underline{D(\mathbf{W}\mathbf{x}_i,\mathbf{u}_c)}]$$

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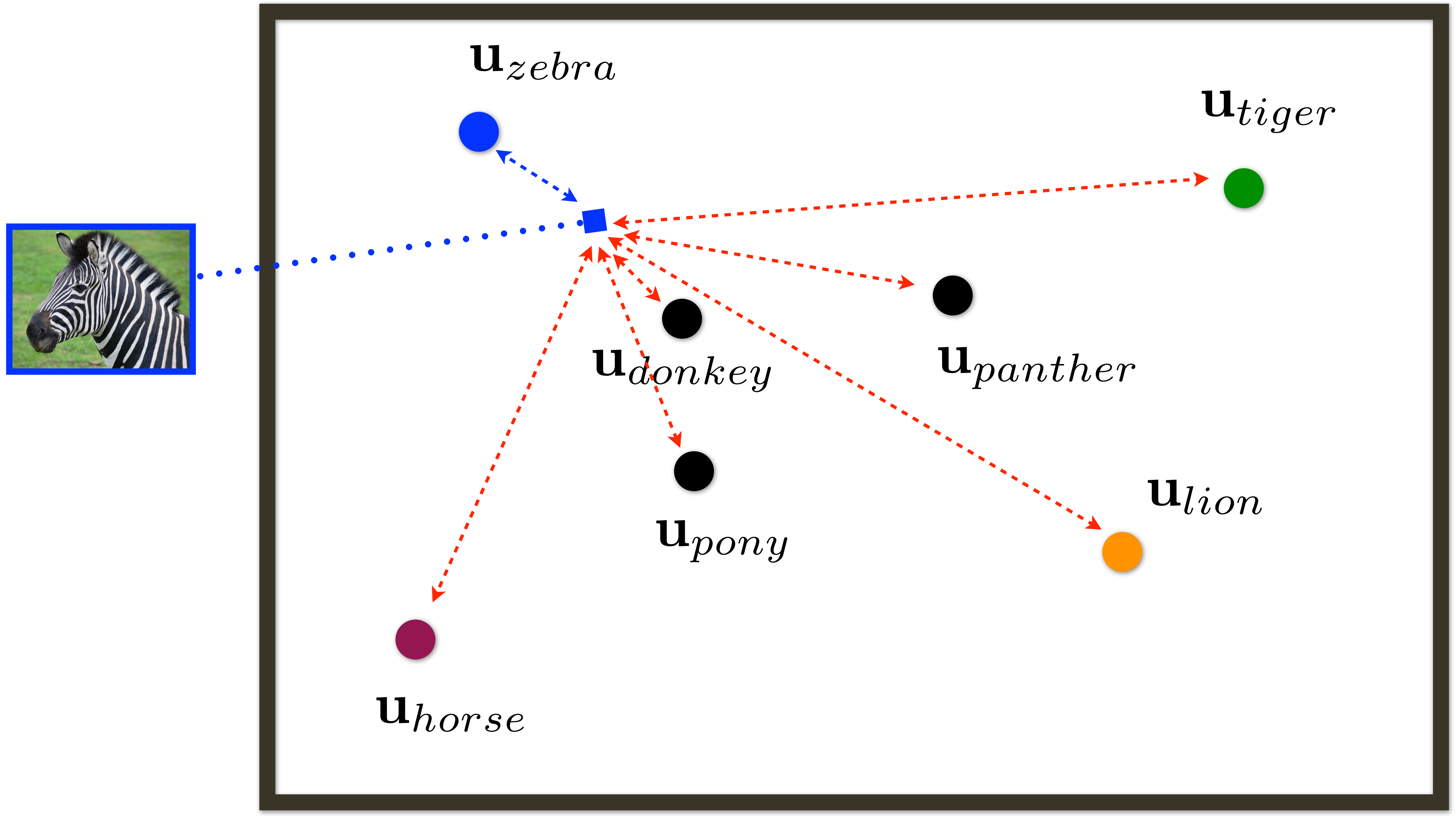

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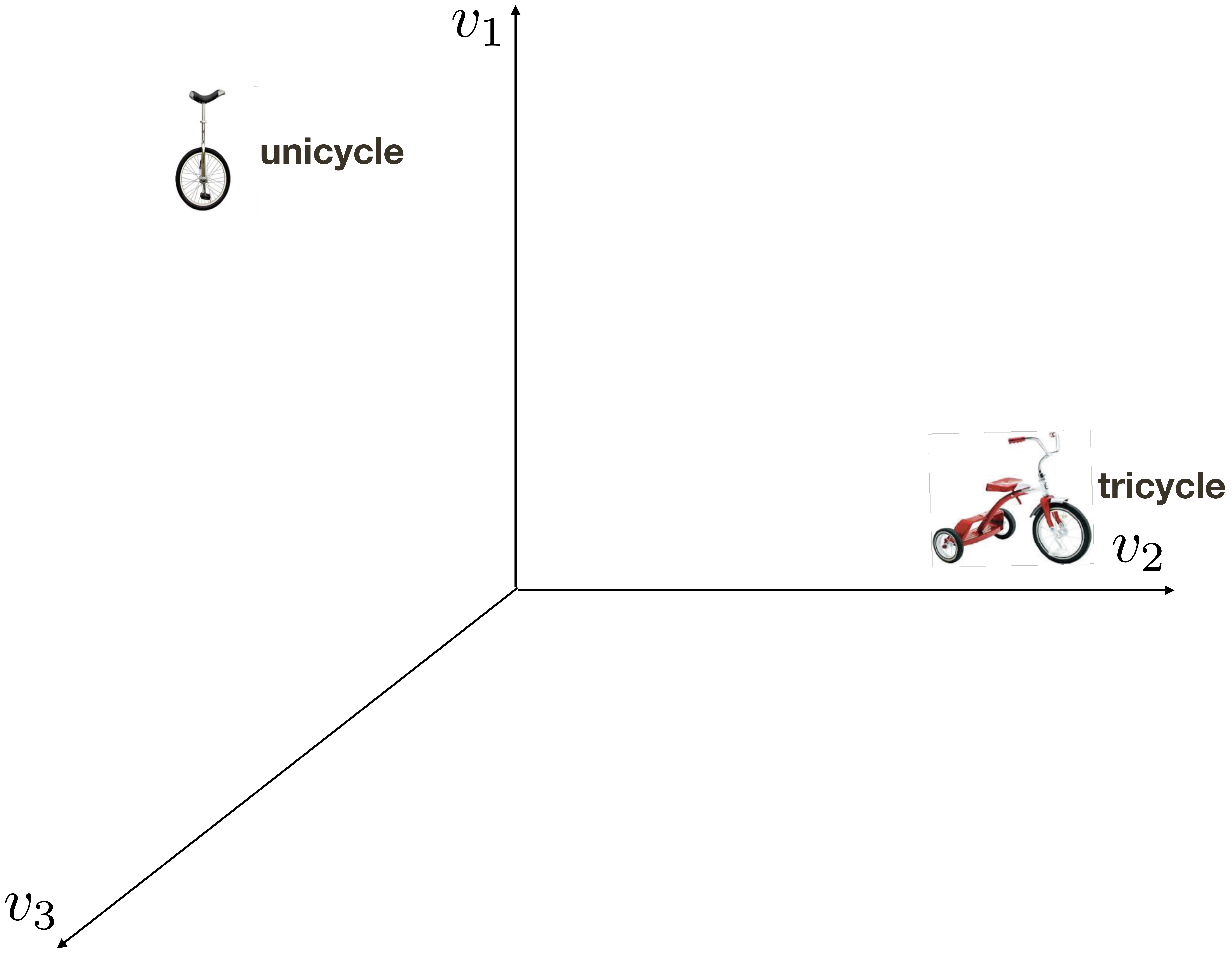
Vocabulary Informed Recognition

[Fu et al., 2016]



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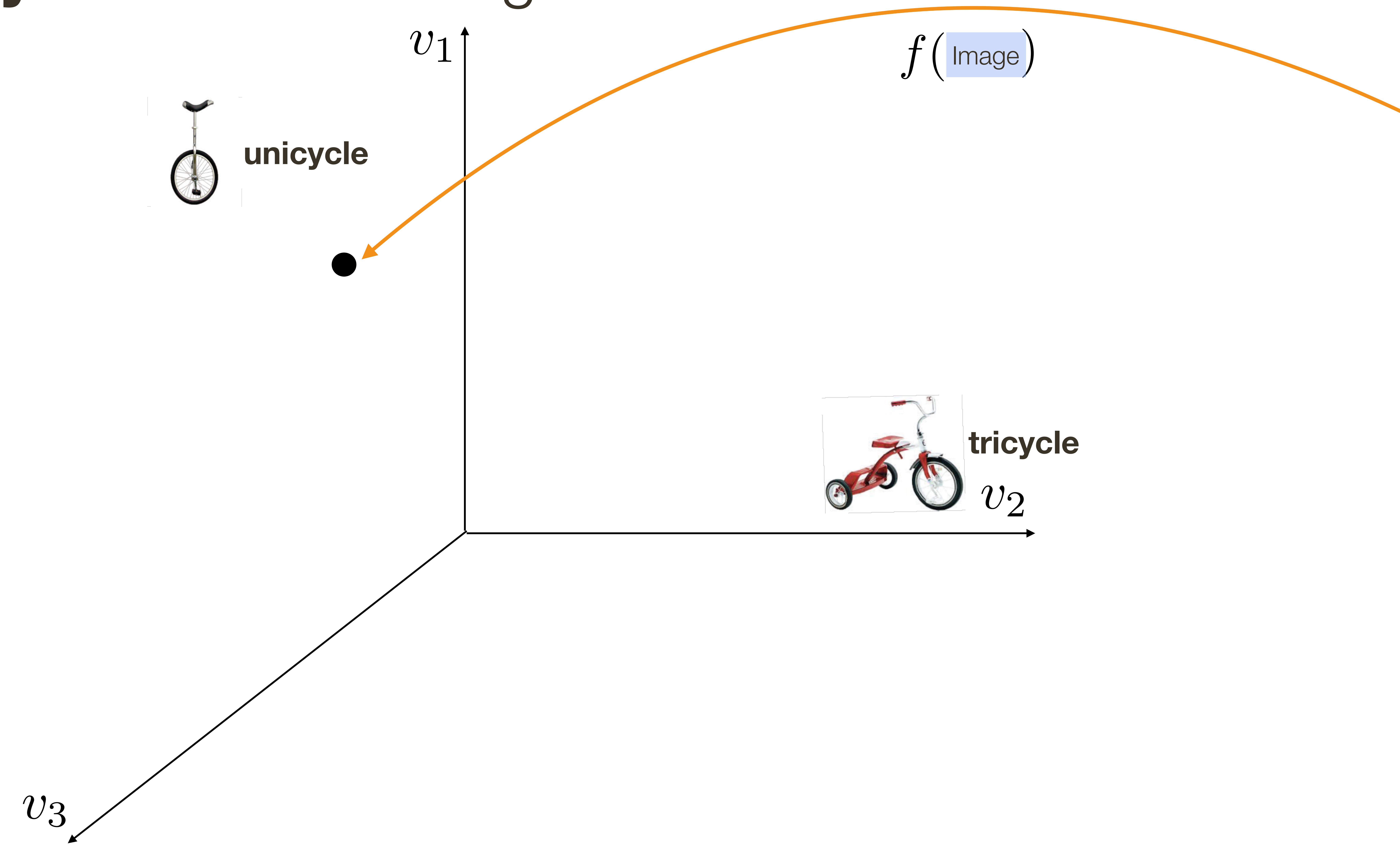

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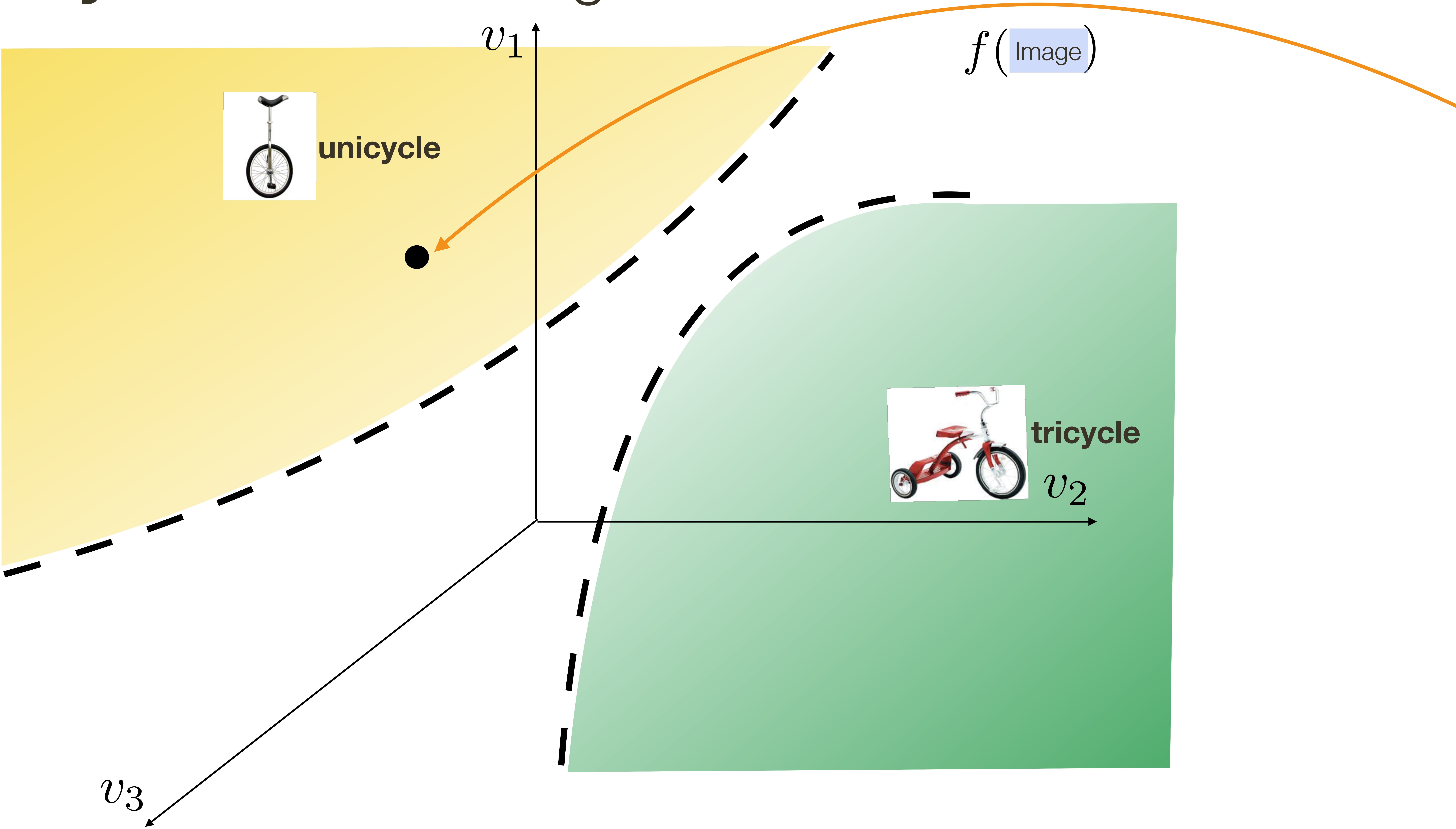

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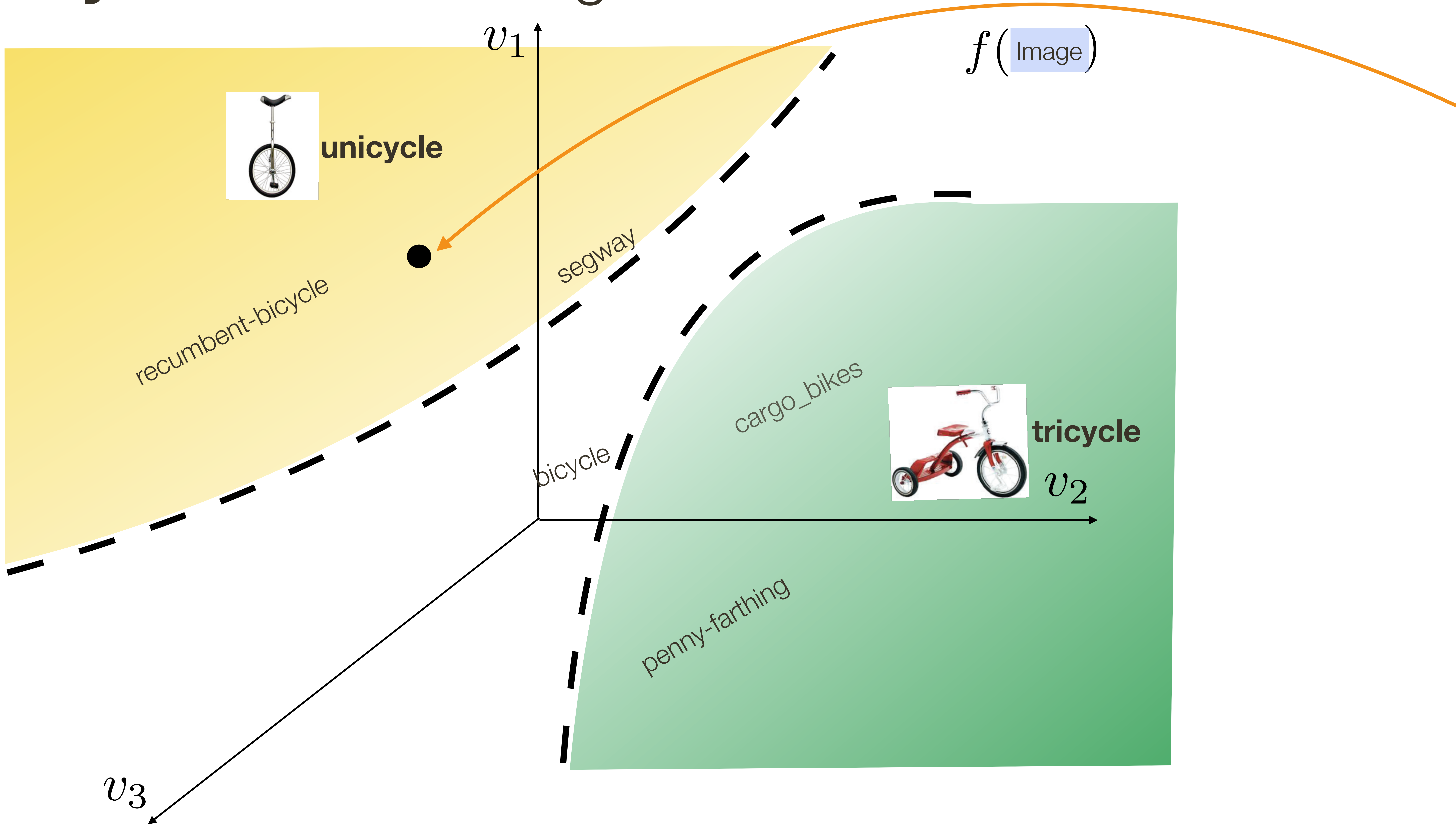

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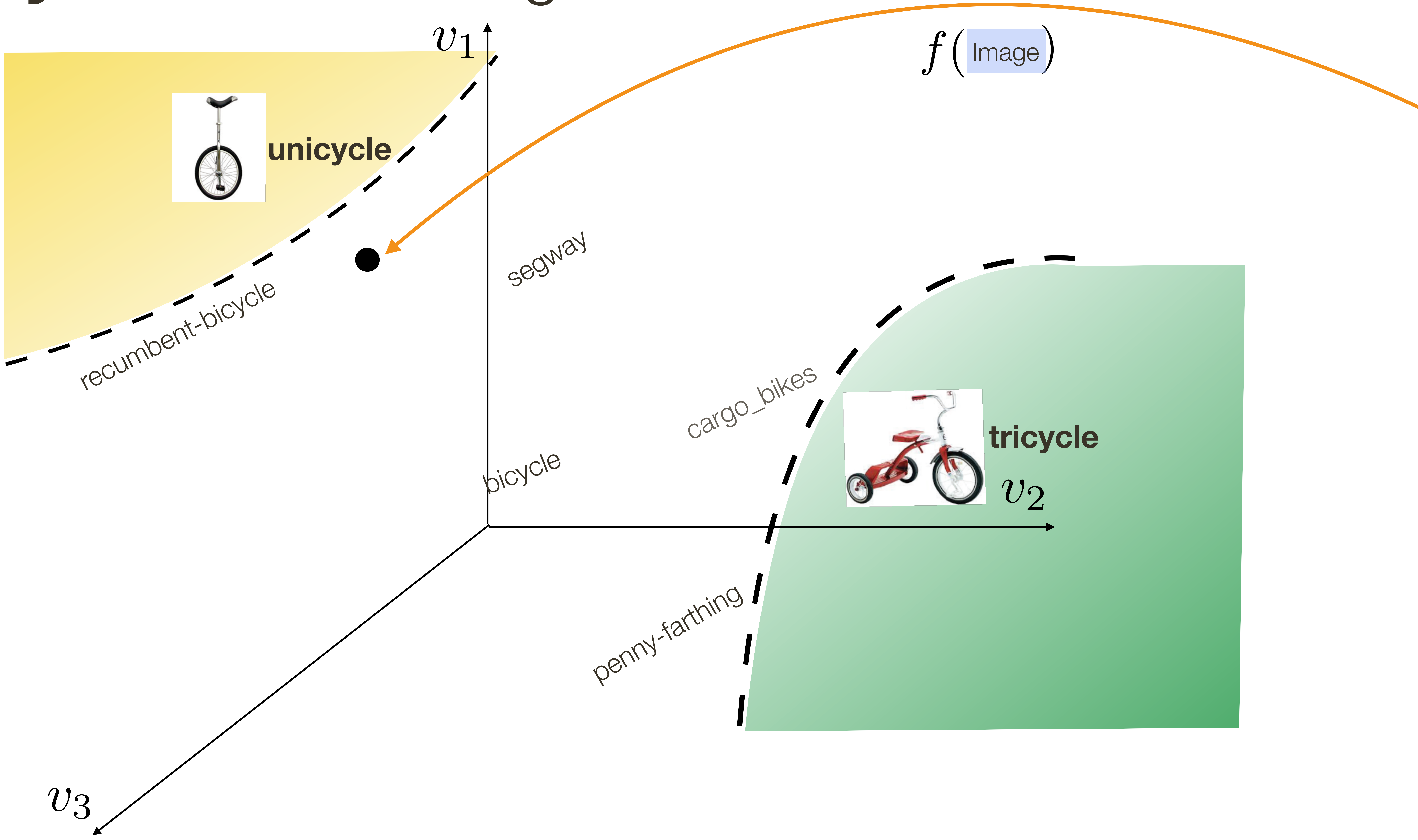

Zero-shot Results

[Fu et al., 2016]

Results with AWA

Method	Features	Accuracy
SS-Voc: full instances	$\text{CNN}_{\text{OverFeat}}$	78.3
Akata *et al*. CVPR 2015	$\text{CNN}_{\text{GoogLeNet}}$	73.9
TMV-BLP (Fu *et al*. ECCV 2014)	$\text{CNN}_{\text{OverFeat}}$	69.9
AMP (SR+SE) (Fu *et al*. CVPR 2015)	$\text{CNN}_{\text{OverFeat}}$	66.0
DAP (Lampert *et al*. TPAMI 2013)	$\text{CNN}_{\text{VGG19}}$	57.5
PST (Rohrbach *et al*. NIPS 2013)	$\text{CNN}_{\text{OverFeat}}$	53.2
DS (Rohrbach *et al*. CVPR 2010)	$\text{CNN}_{\text{OverFeat}}$	52.7
IAP (Lampert *et al*. TPAMI 2013)	$\text{CNN}_{\text{OverFeat}}$	44.5
HEX (Deng *et al*. ECCV 2014)	$\text{CNN}_{\text{DECAF}}$	44.2

+4.4%

Zero-shot Results

[Fu et al., 2016]

Results with AWA

3.3% of training data

Method	Features	Accuracy
SS-Voc: full instances	$\text{CNN}_{\text{OverFeat}}$	78.3
800 instances (20 inst*40 class);	$\text{CNN}_{\text{OverFeat}}$	74.4
Akata *et al*. CVPR 2015	$\text{CNN}_{\text{GoogLeNet}}$	73.9
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AMP (SR+SE) (Fu *et al*. CVPR 2015)	$\text{CNN}_{\text{OverFeat}}$	66.0
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+0.5%

Zero-shot Results

[Fu et al., 2016]

Results with AWA

0.82% of training data

Method	Features	Accuracy
SS-Voc: full instances	$CNN_{OverFeat}$	78.3
800 instances (20 inst*40 class);	$CNN_{OverFeat}$	74.4
200 instances (5 inst*40 class);	$CNN_{OverFeat}$	68.9
Akata *et al*. CVPR 2015	$CNN_{GoogLeNet}$	73.9
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Weakly-supervised **Visual Grounding** of Phrases

[Xiao et al., 2017]

Given **image-sentence pairs** learn how to **localize** arbitrary language phrase or sentence in new images

The man at bat readies to swing at the pitch while the umpire looks on.

A large bus sitting next to a very tall building.

[Lin, Maire, Belongie, Hays, Perona, Ramanan, Dollar, Zitnick, ECCV'14]

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a table

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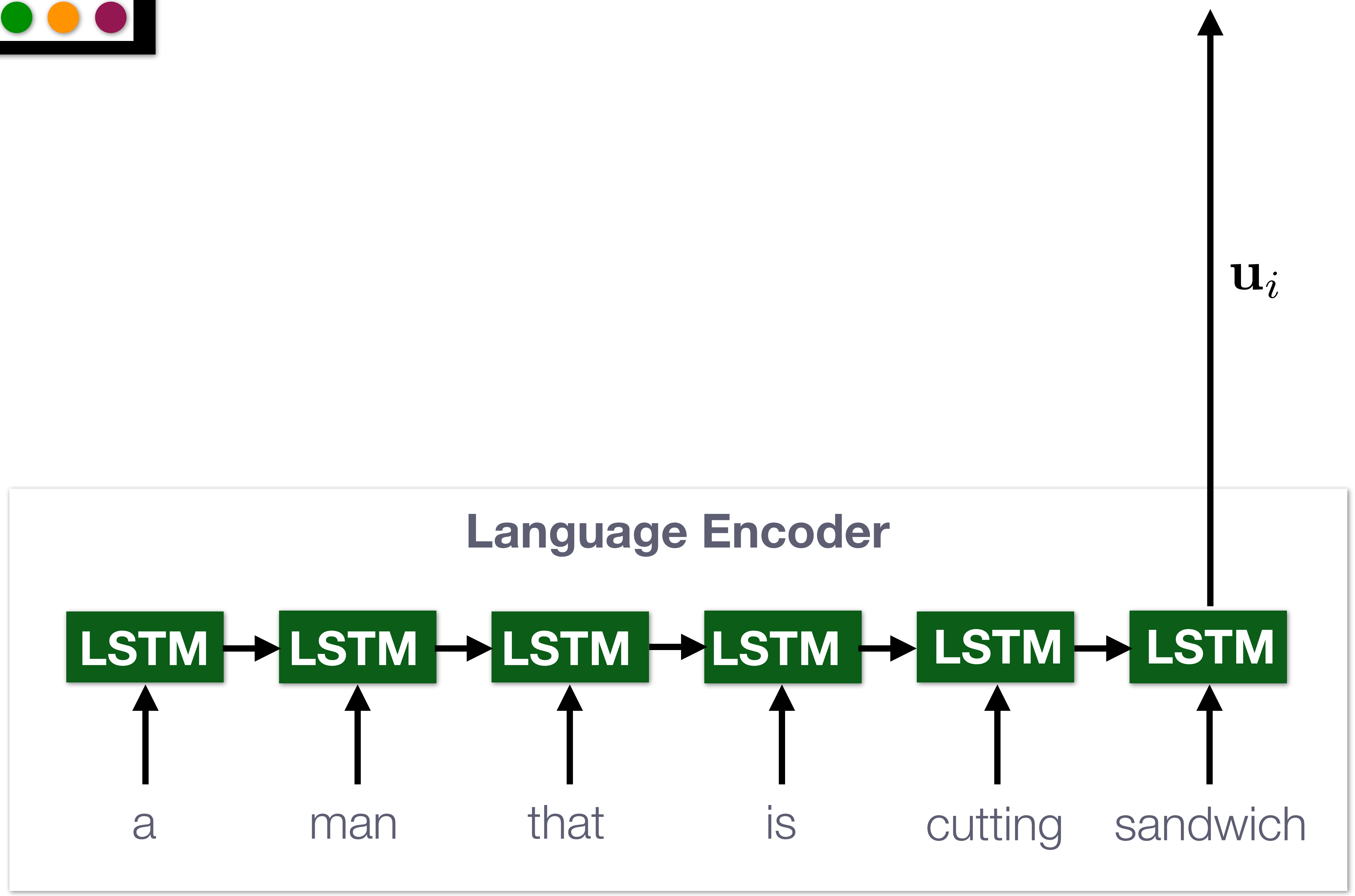

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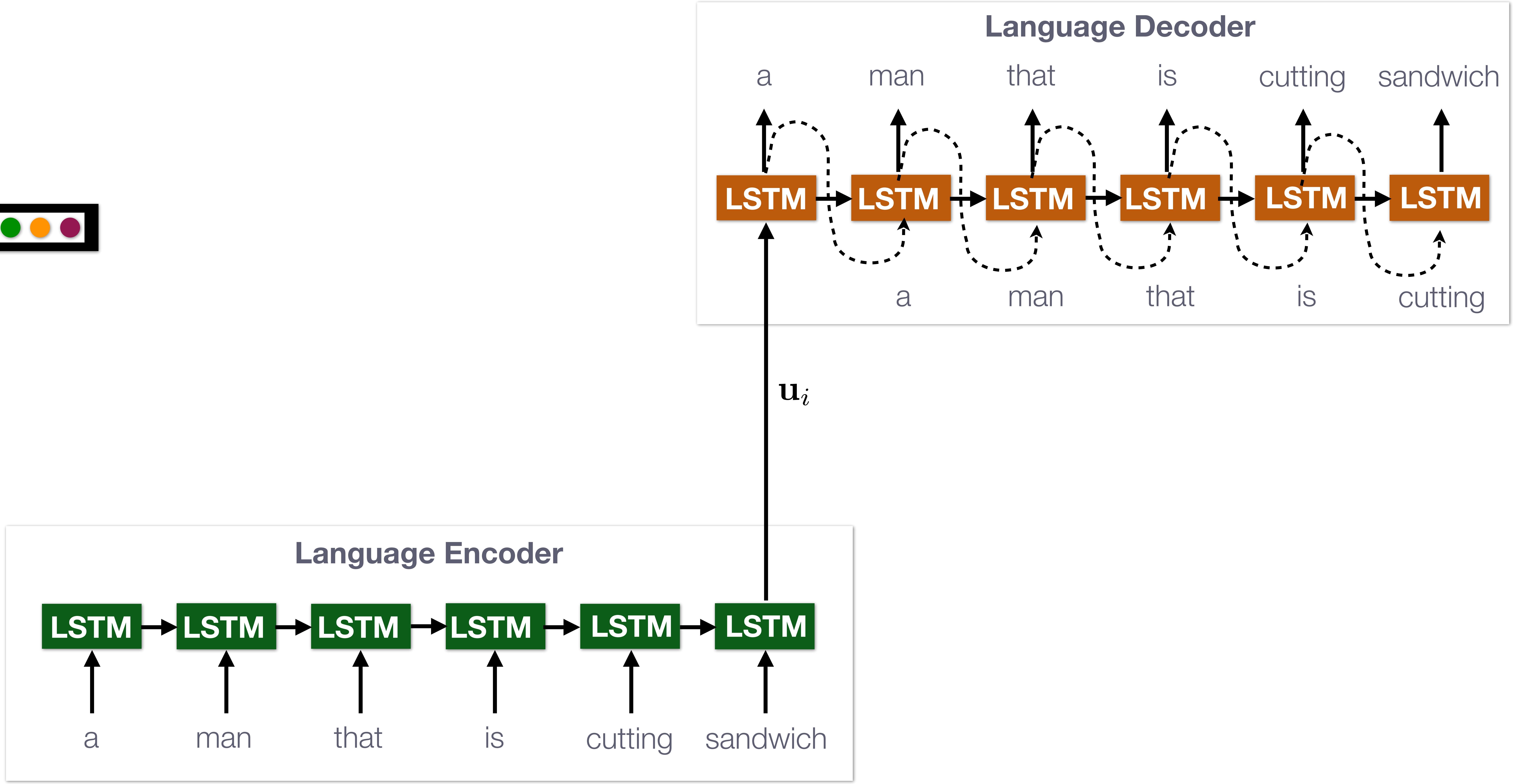

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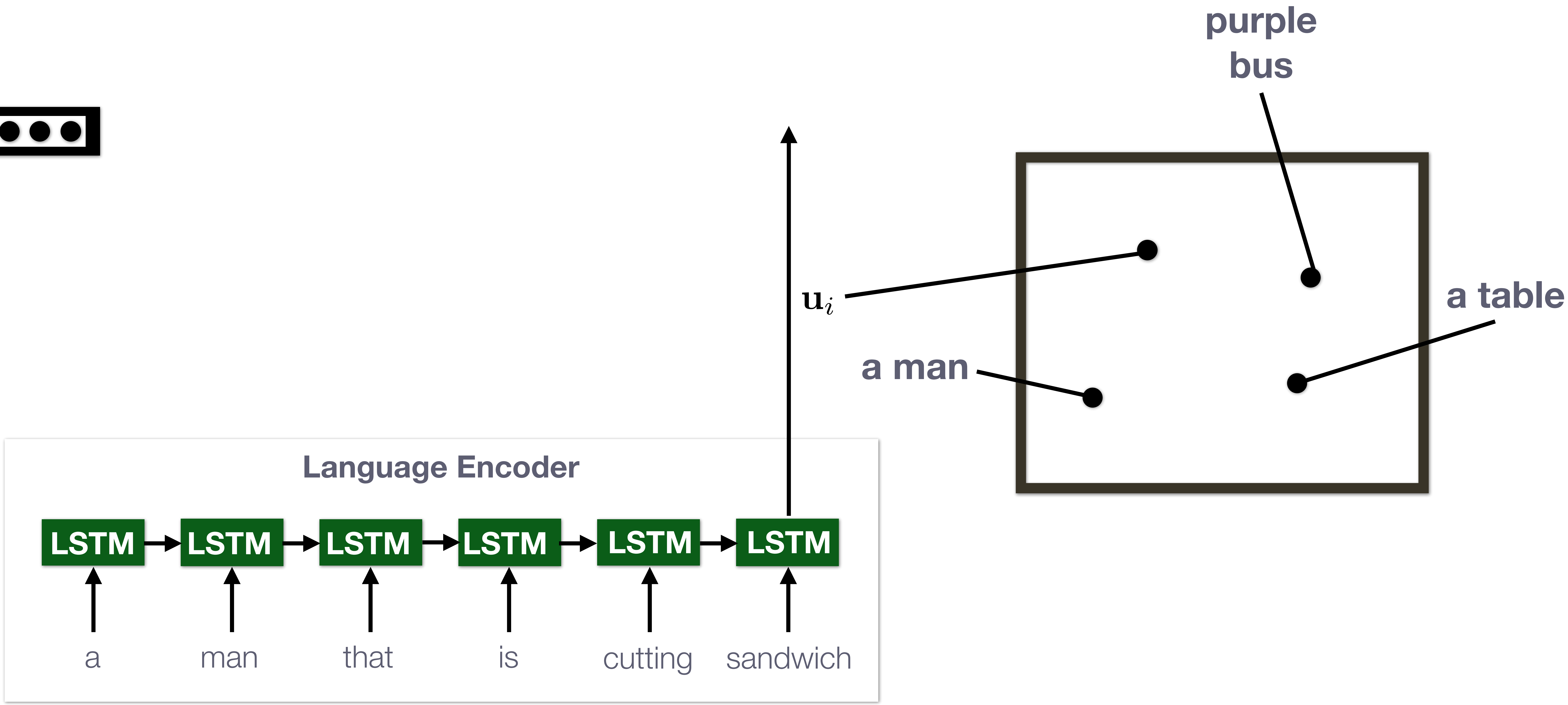

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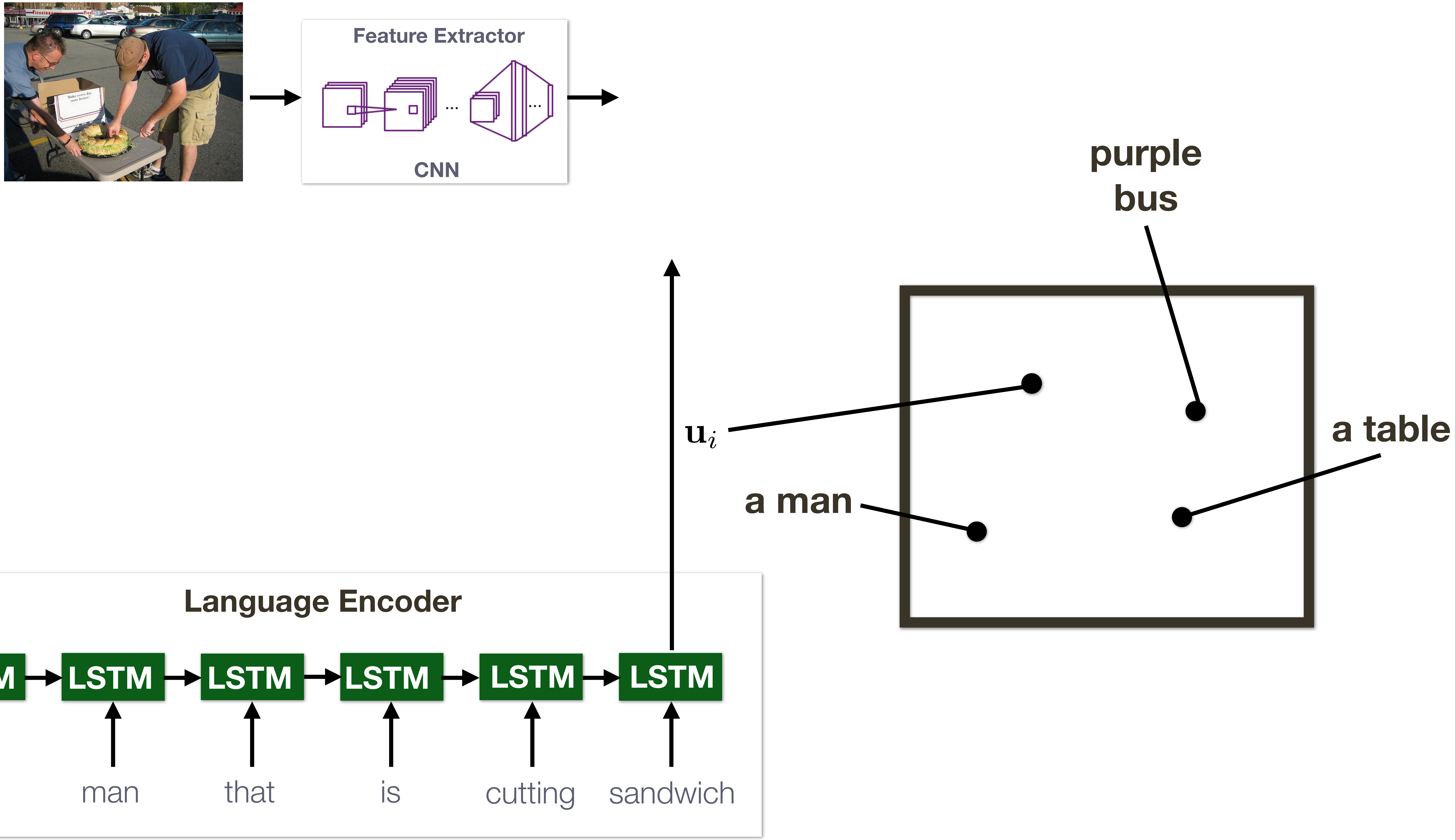

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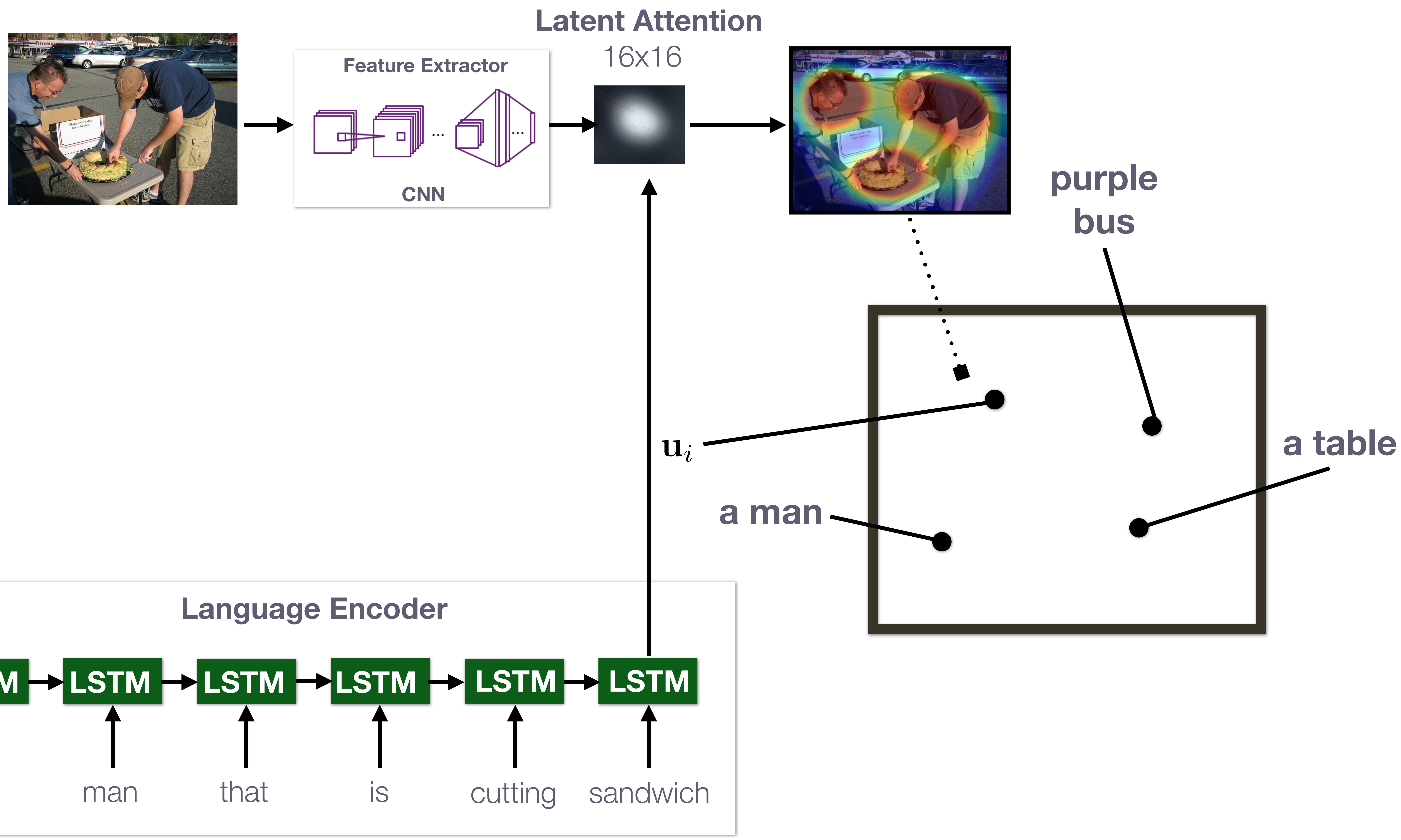

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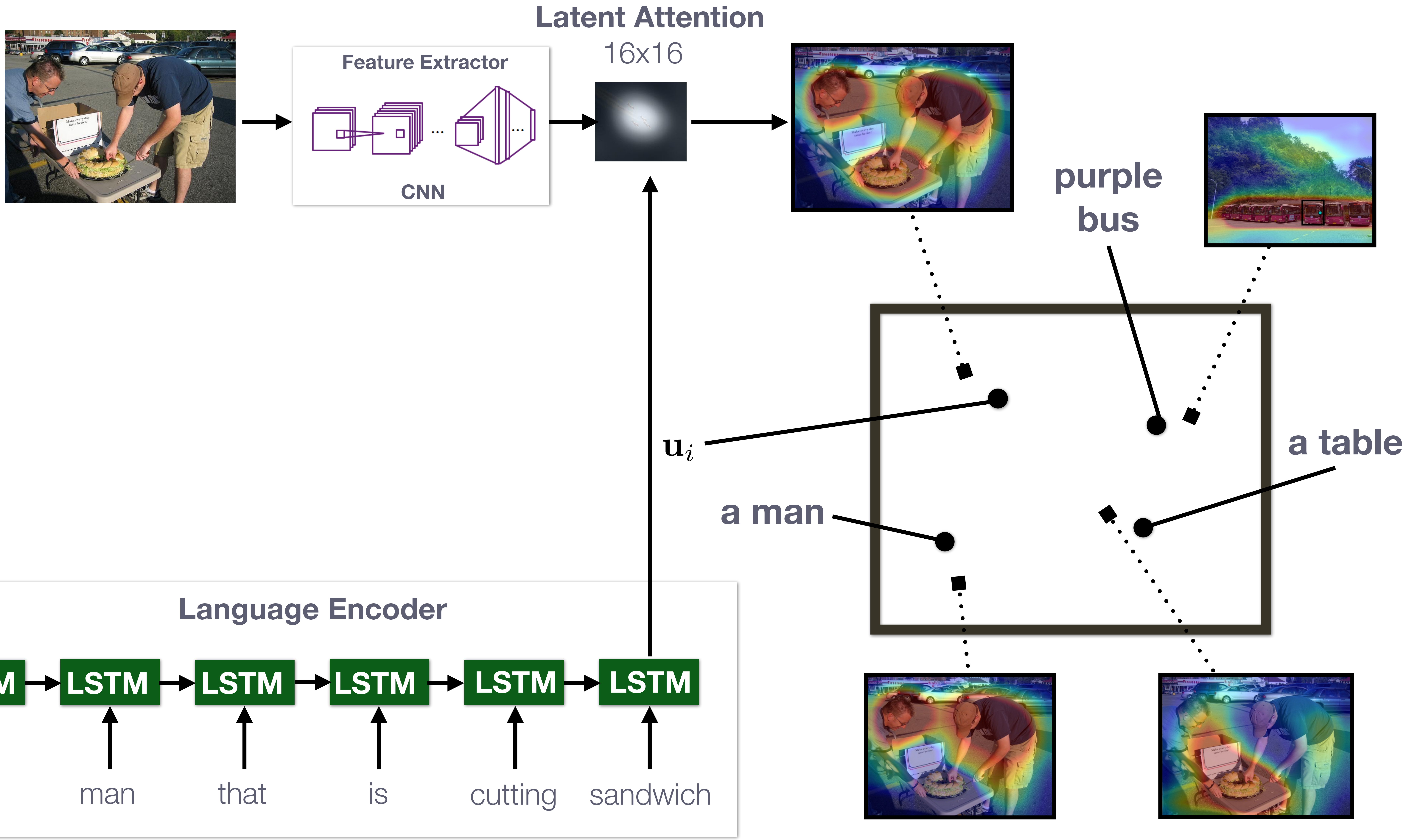

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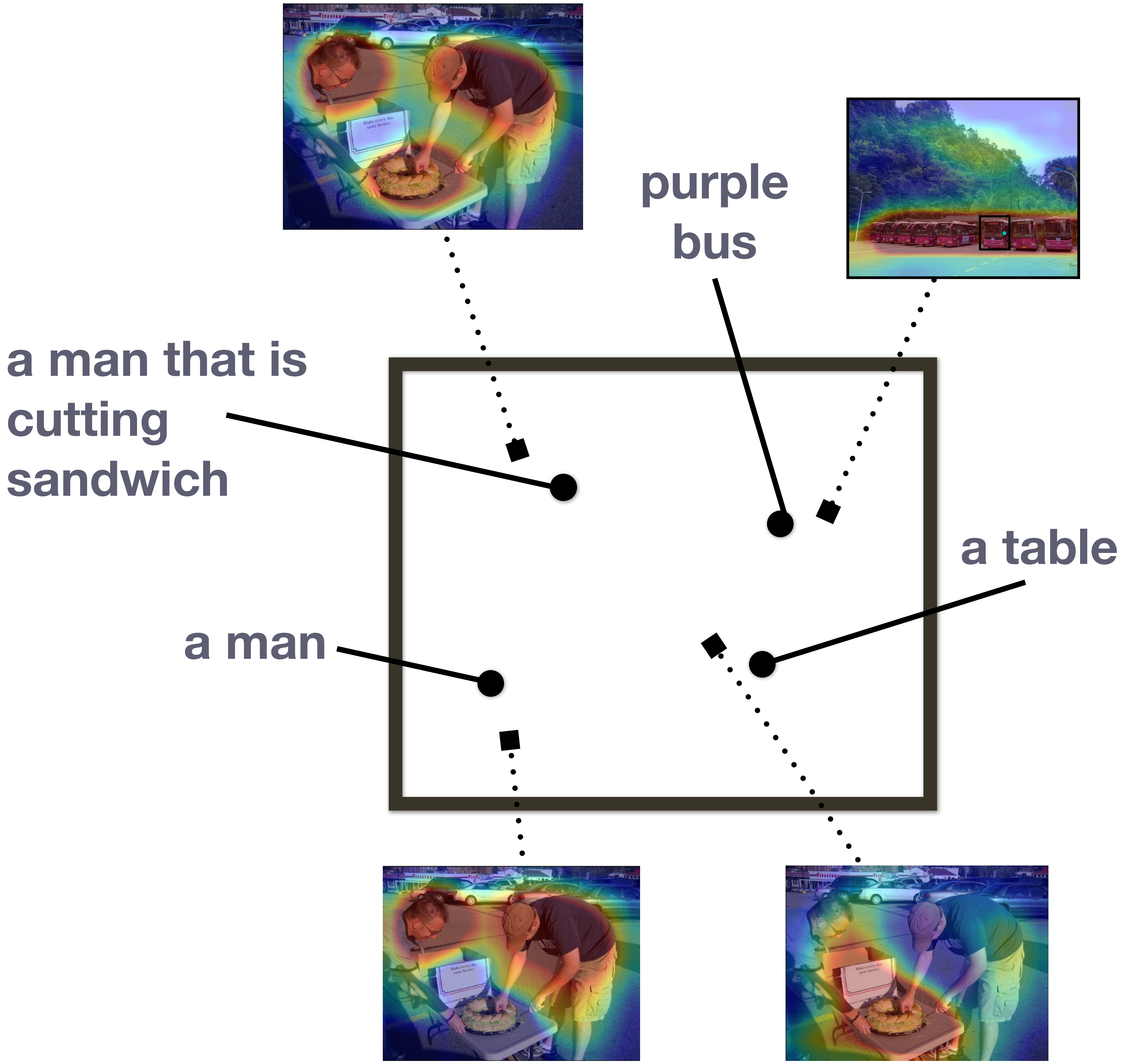

Combination of previous discriminative similarity and **linguistic regularization**

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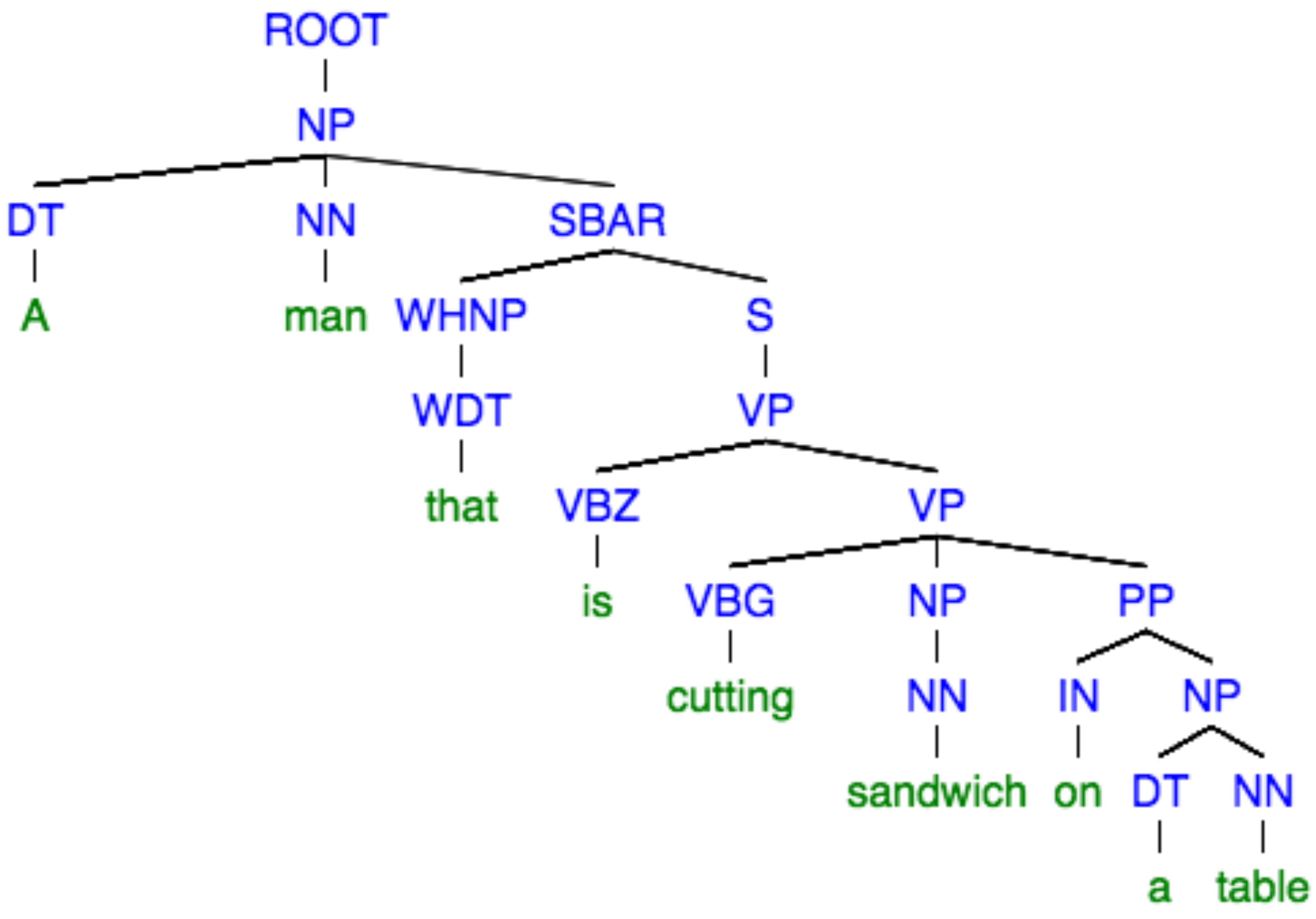

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Weakly-supervised **Visual Grounding** of Phrases

[Xiao et al., 2017]

For **noun phrases**:

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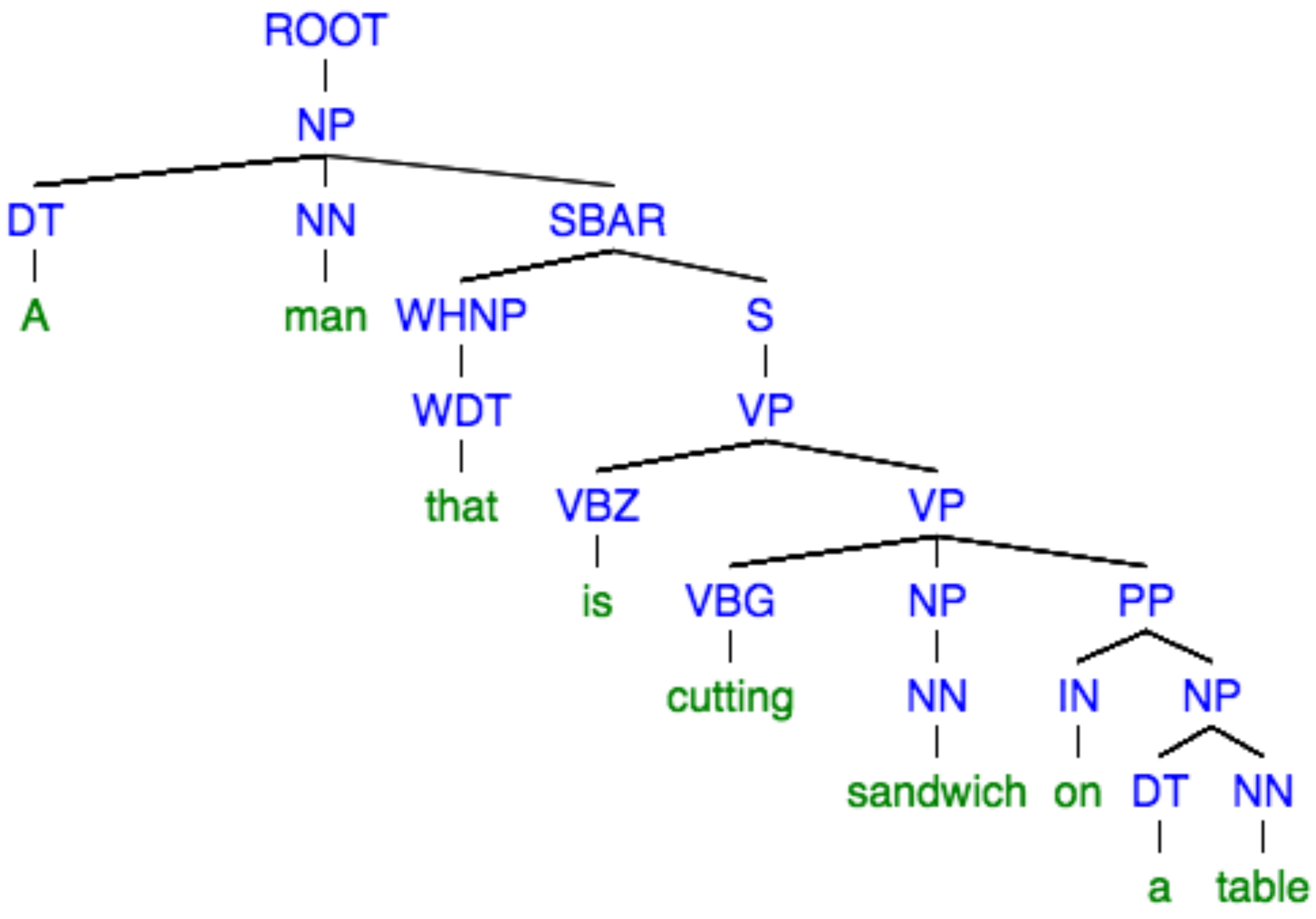

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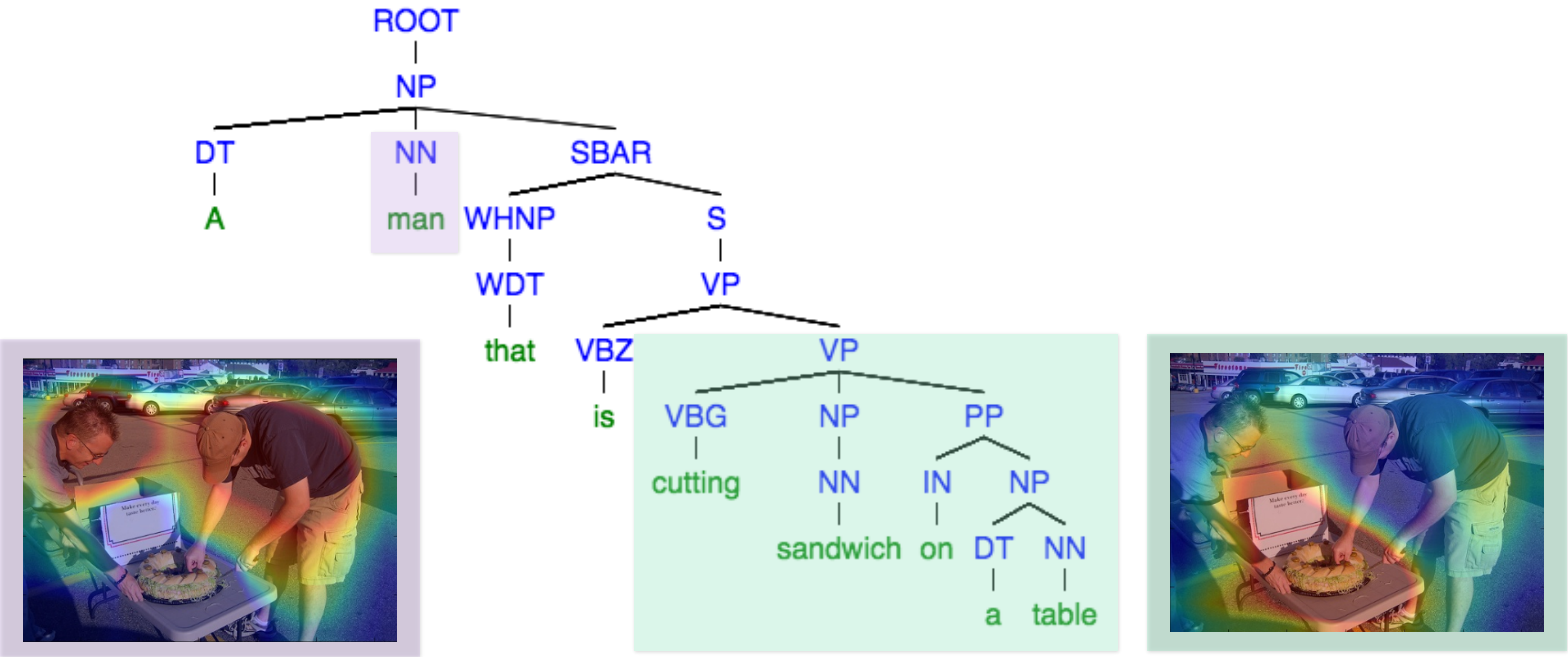

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For **noun phrases**:

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- **parents** should be **union of children** masks

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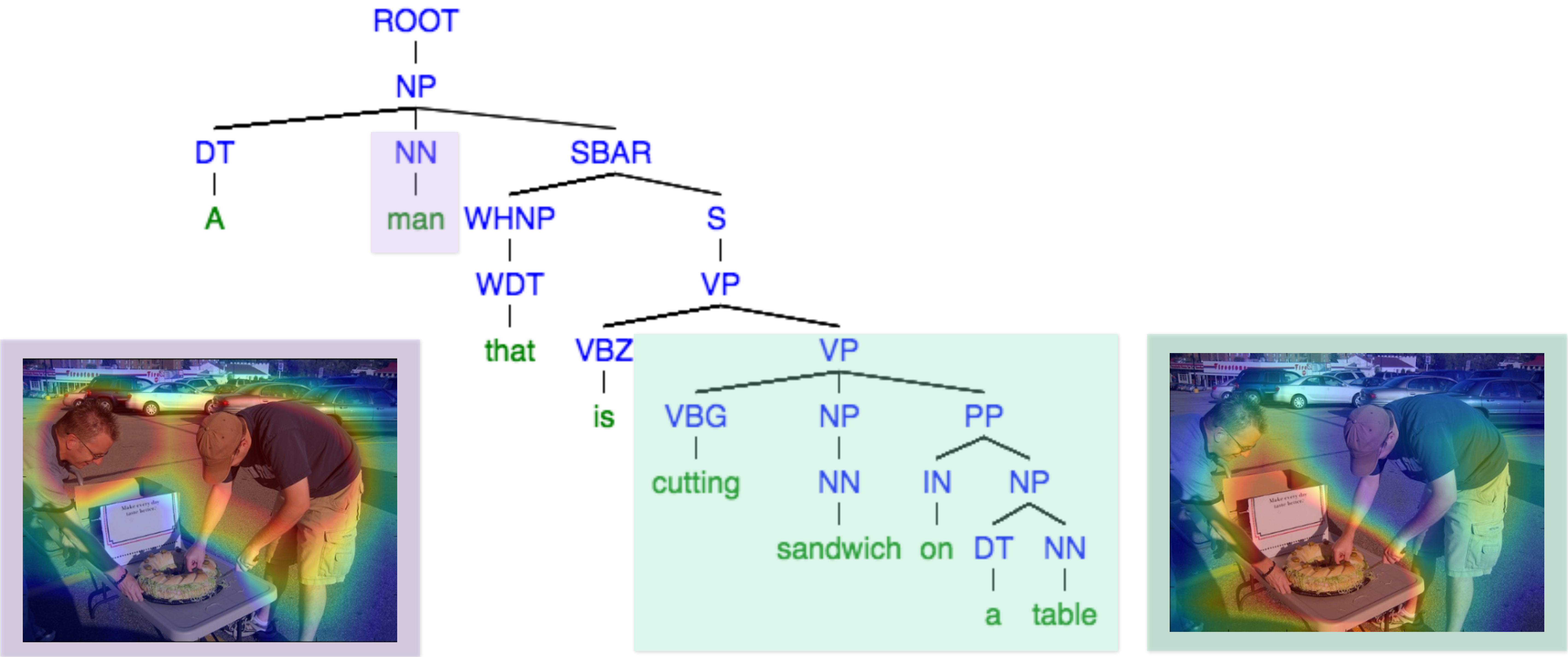

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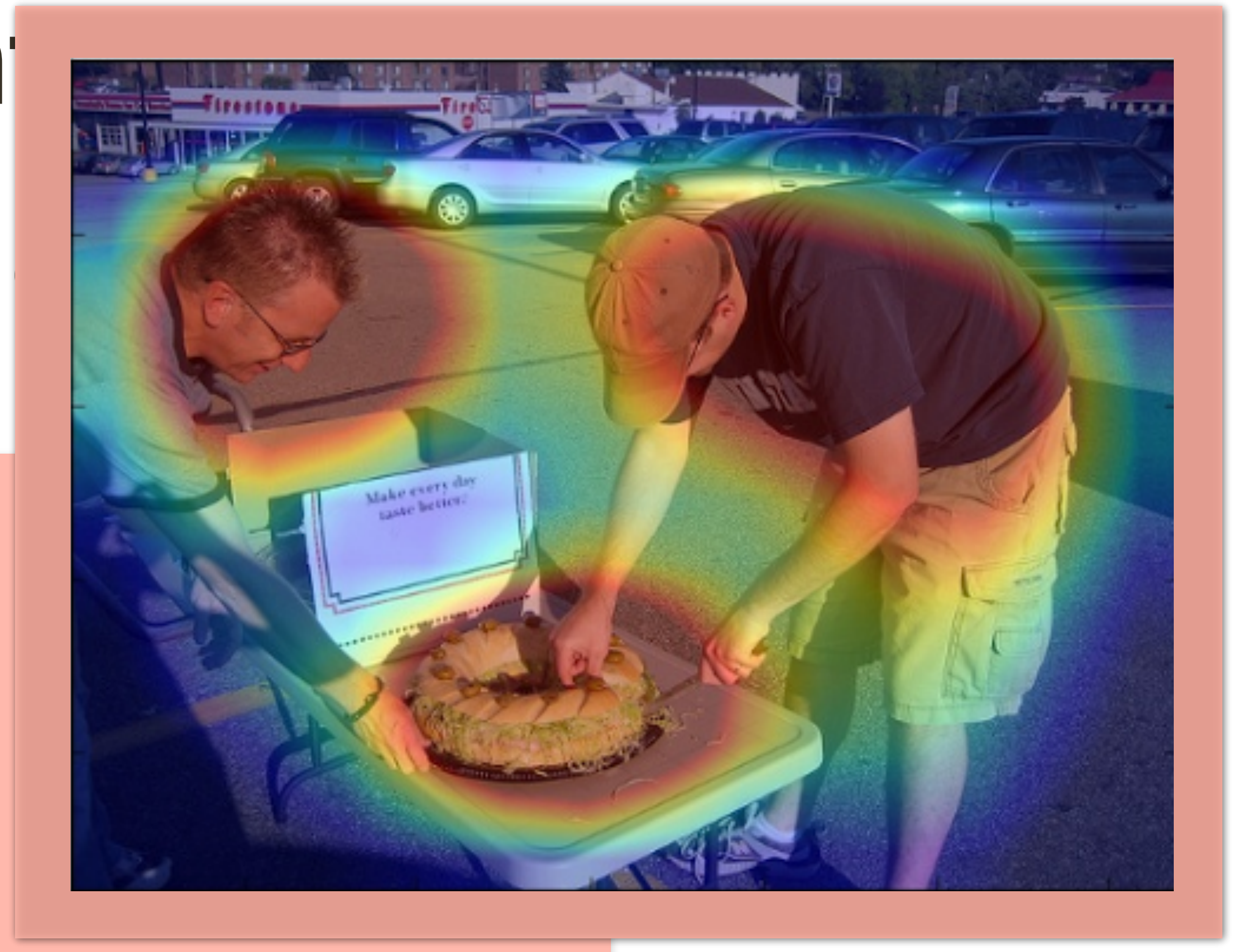
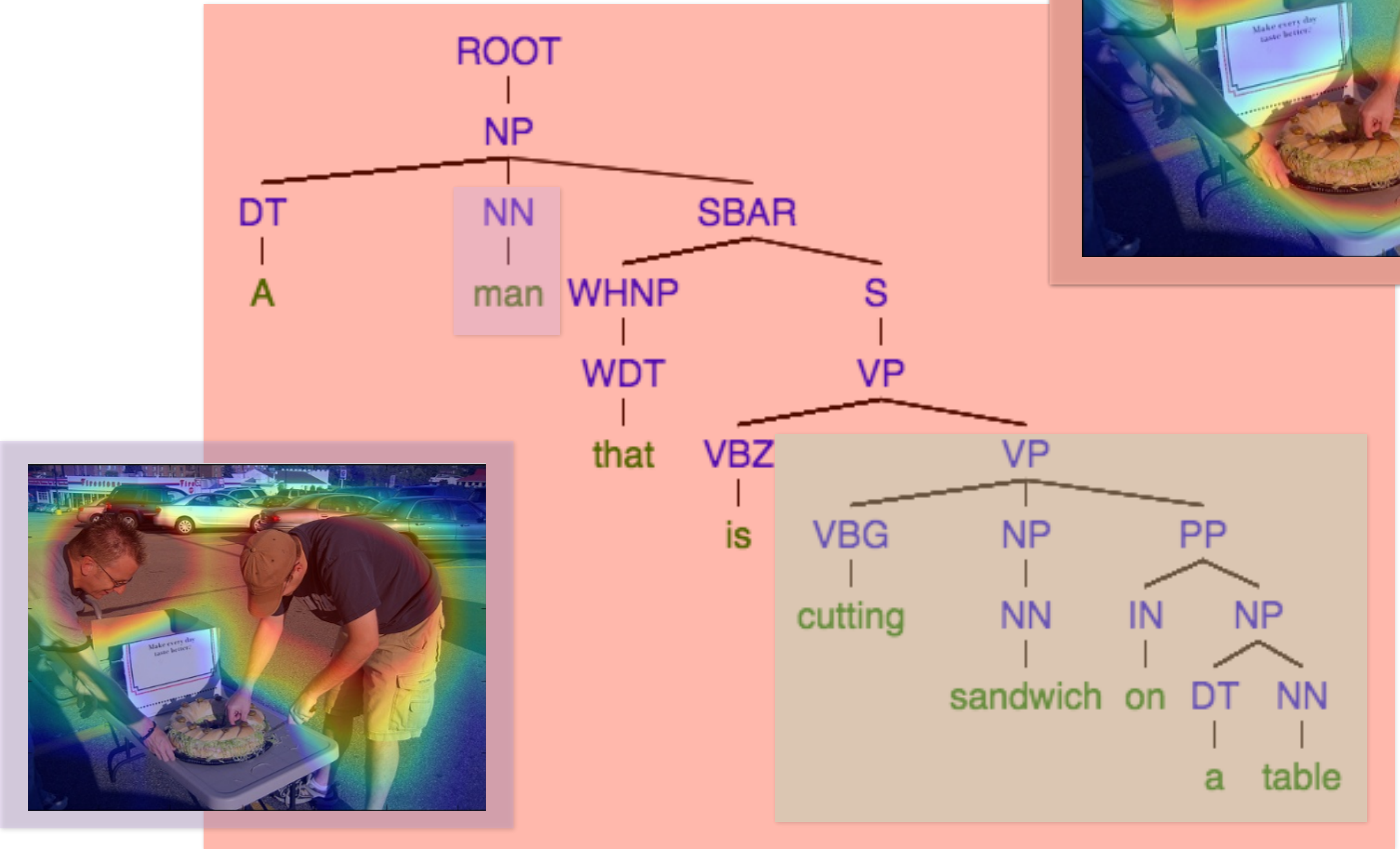
Objective Function:

For **noun phrases**:

- **siblings** should have **disjoin**
- **parents** should be **union of**





Combination of previous discriminative similarity and **linguistic regularization**

Qualitative **Results**

[Xiao et al., 2017]

Input:

guy in green t-shirt holding skateboard

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NO linguistic constraints

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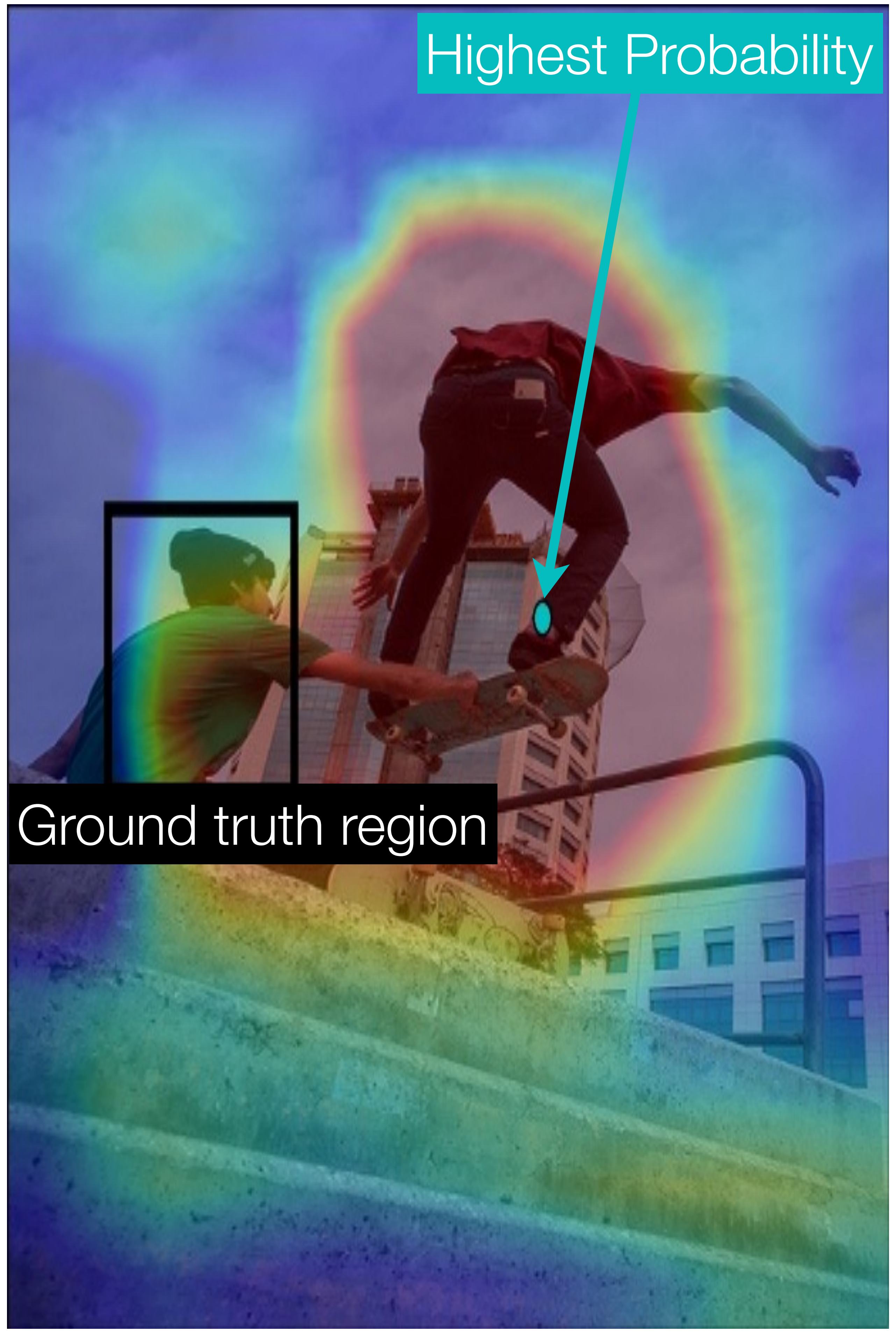

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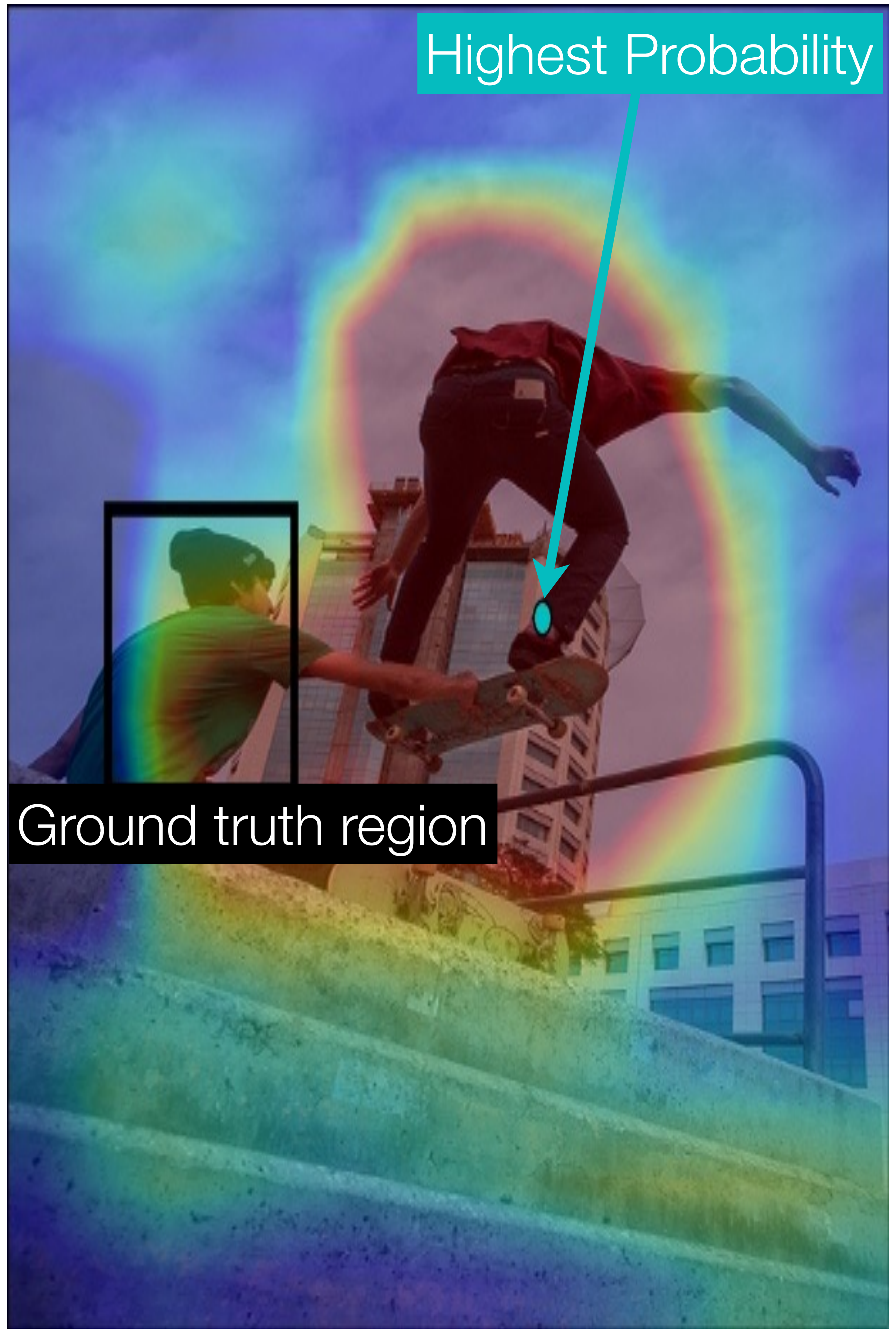
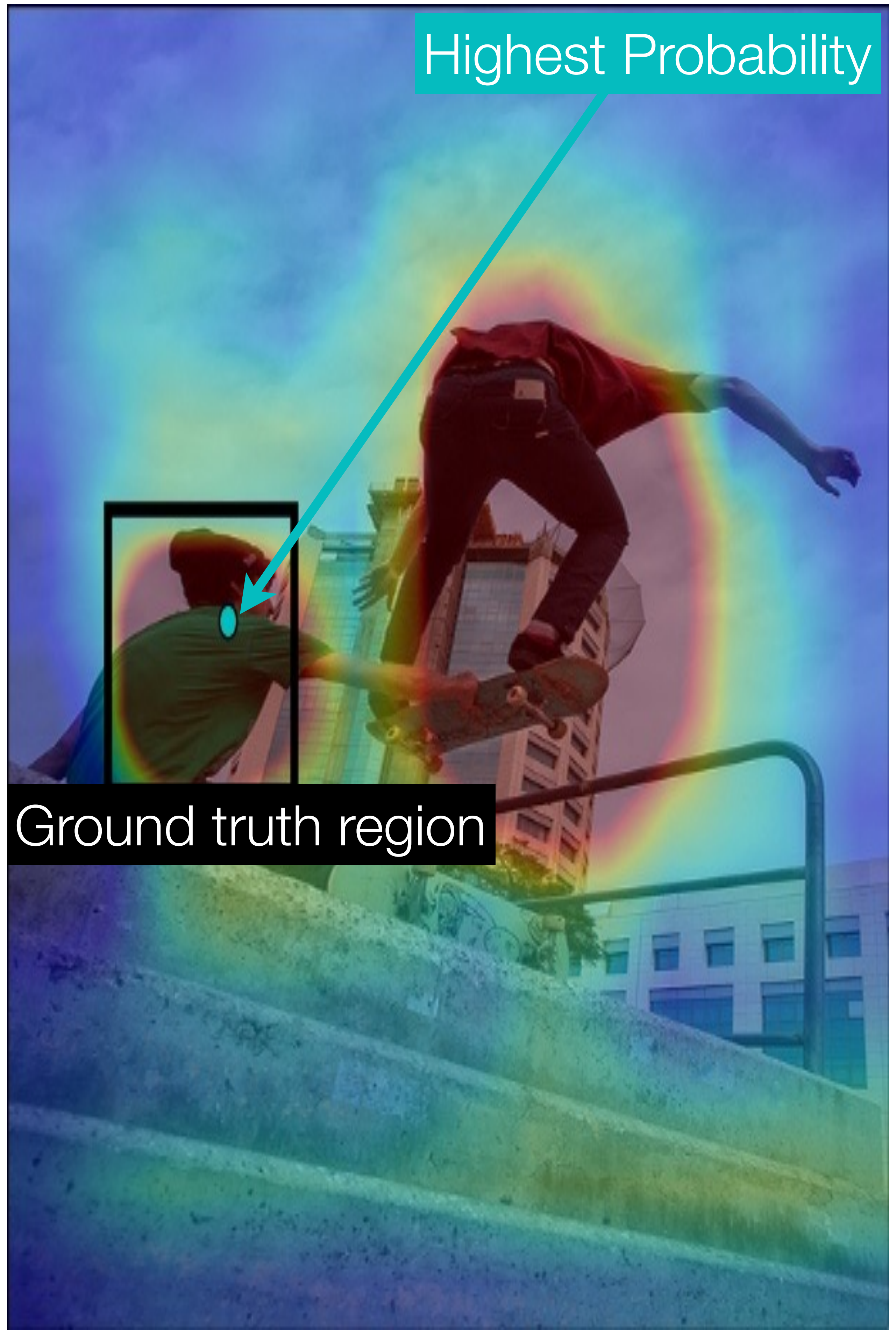


Our Model



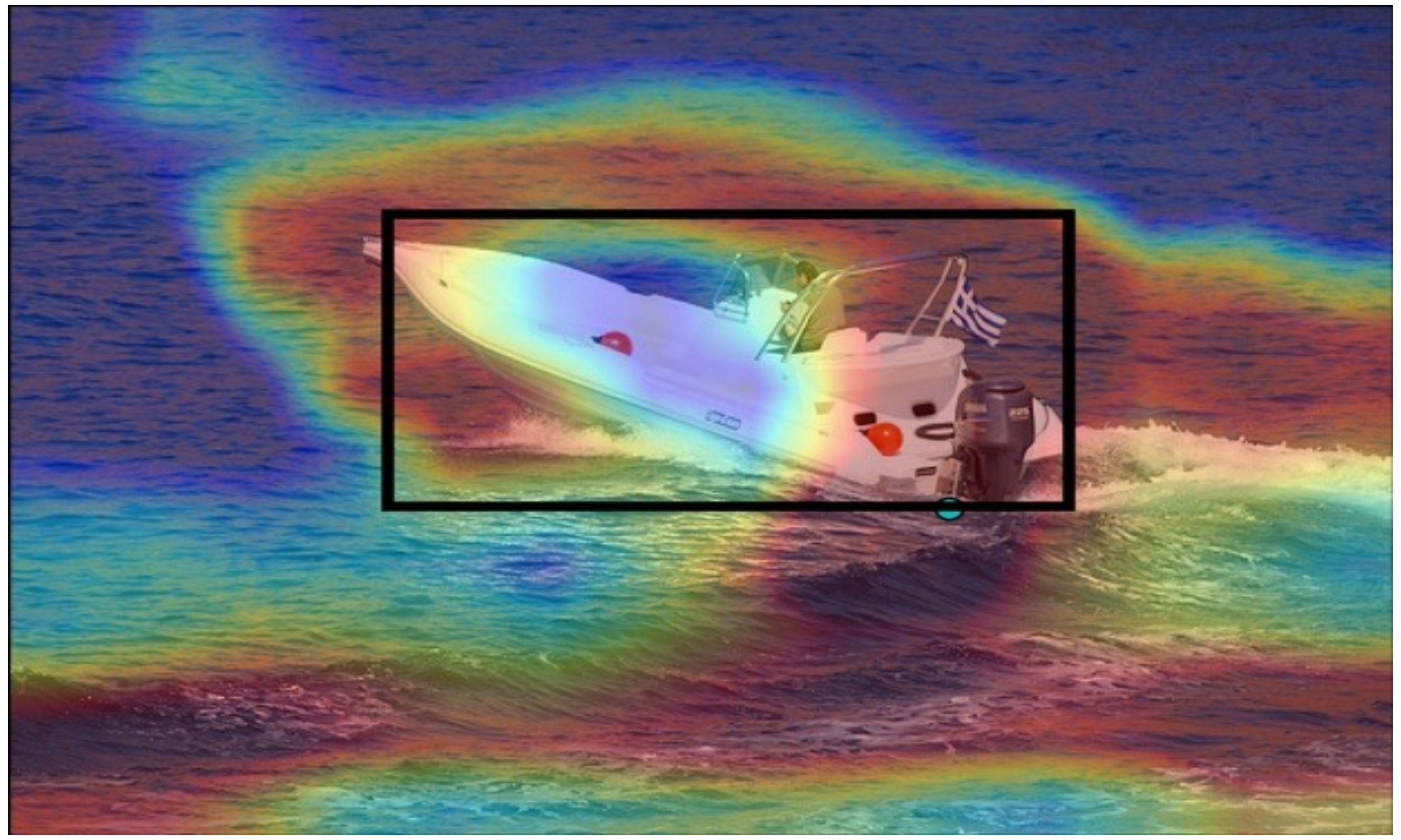
Qualitative **Results**

[Xiao et al., 2017]

Input:

a person driving a boat

NO linguistic constraints



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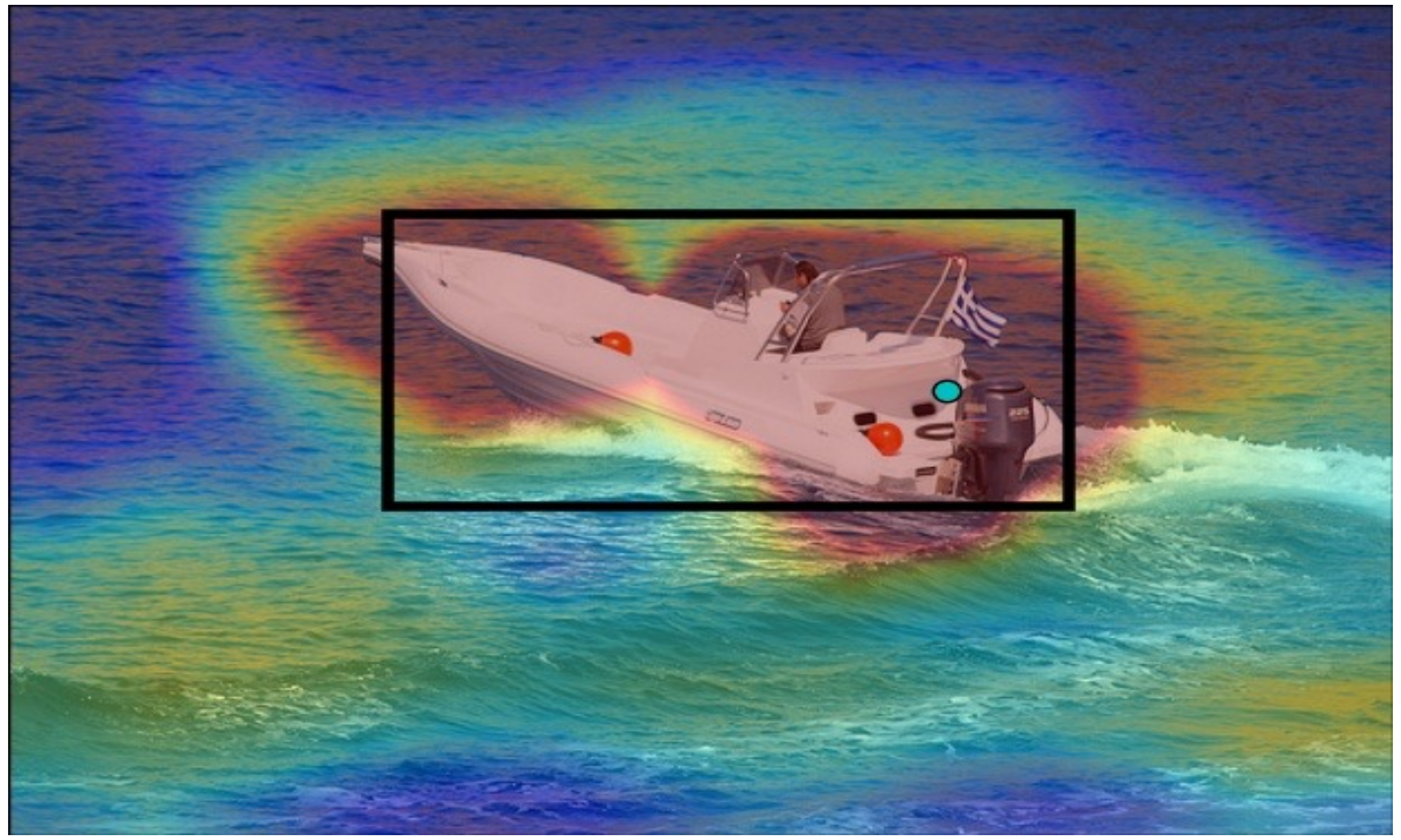
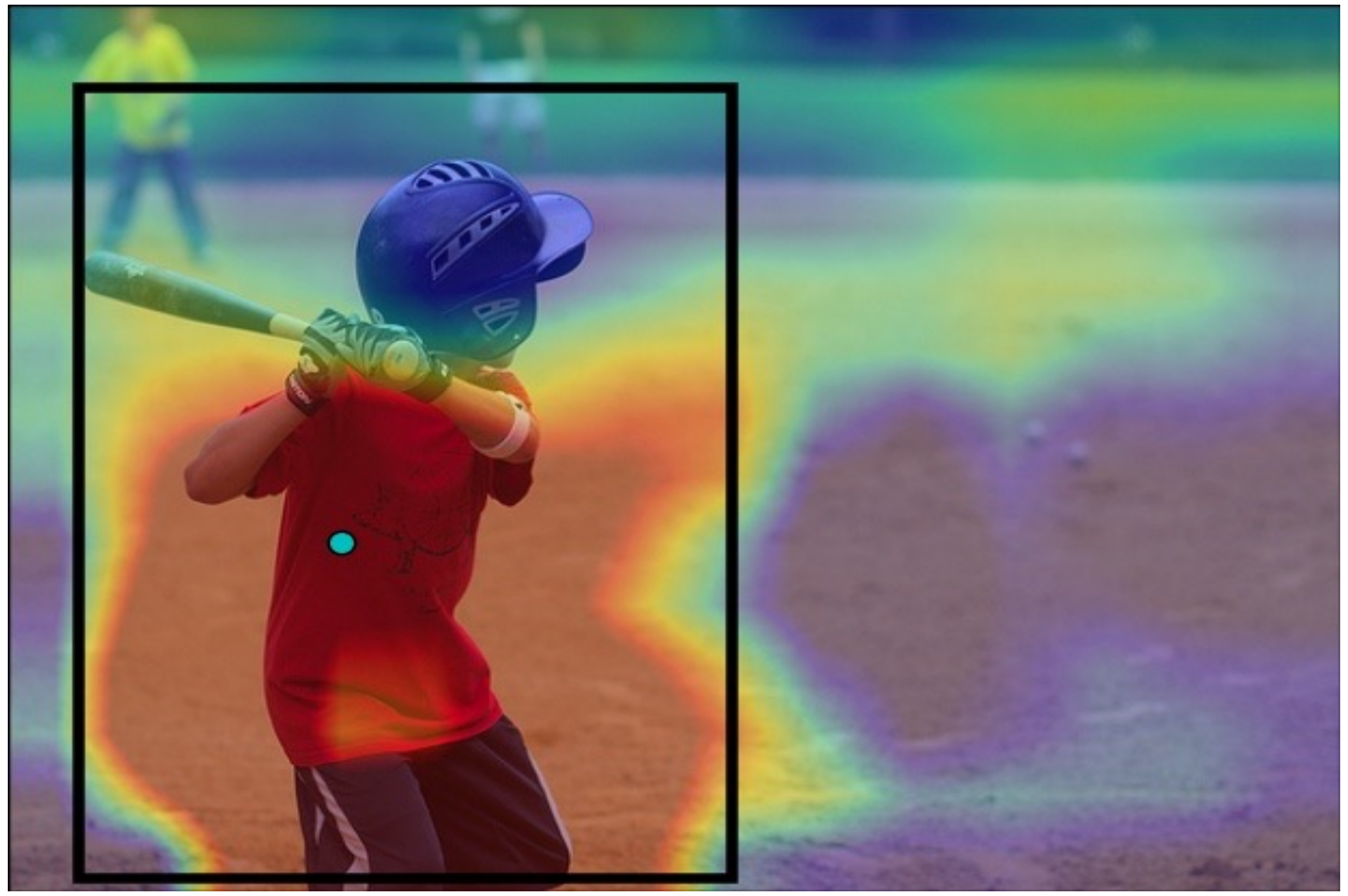


Qualitative **Results**

Input:

a child wearing black protective helmet

NO linguistic constraints [Xiao et al., 2017]



Our Model

Quantitative Results

[Xiao et al., 2017]

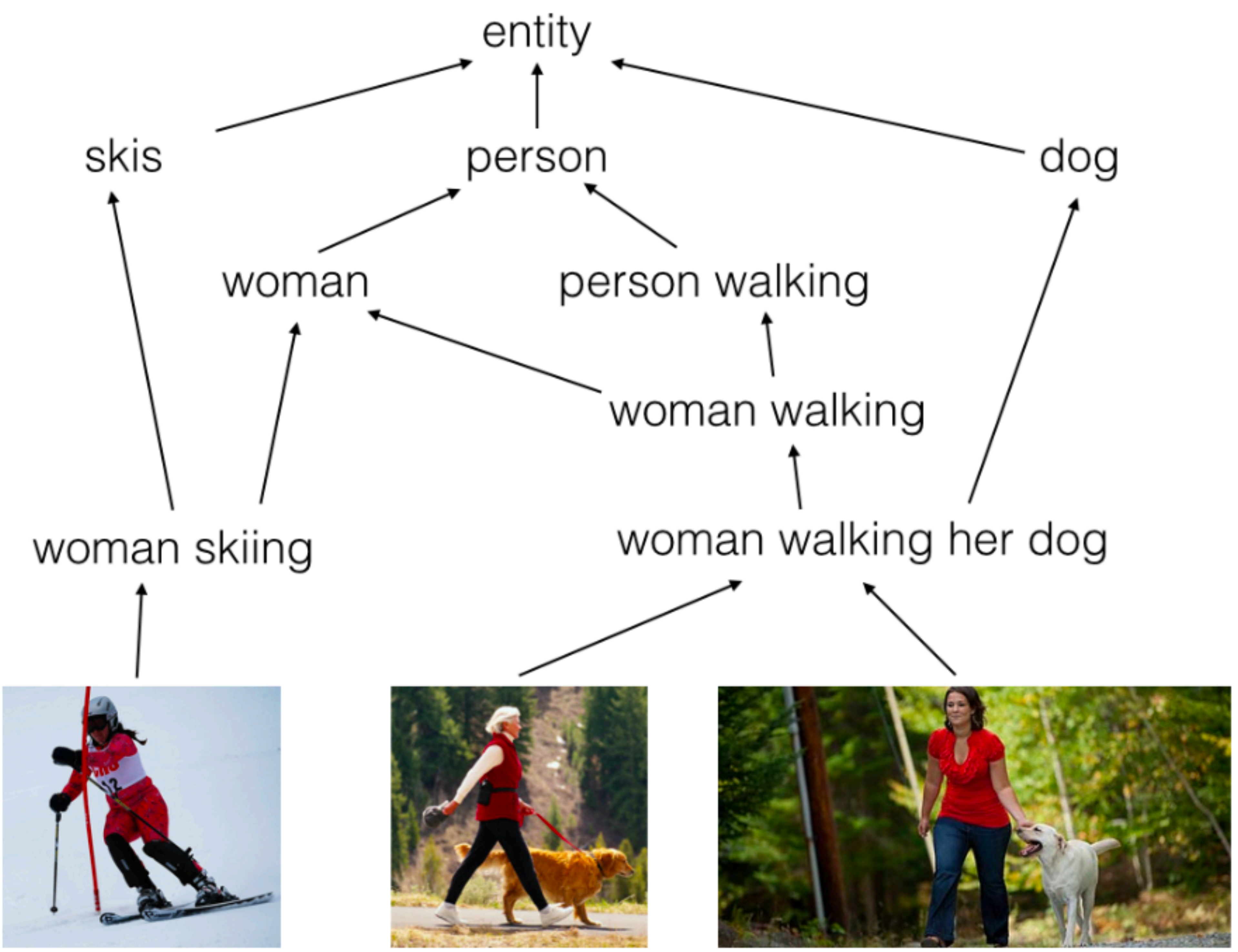
Segmentation performance on COCO dataset

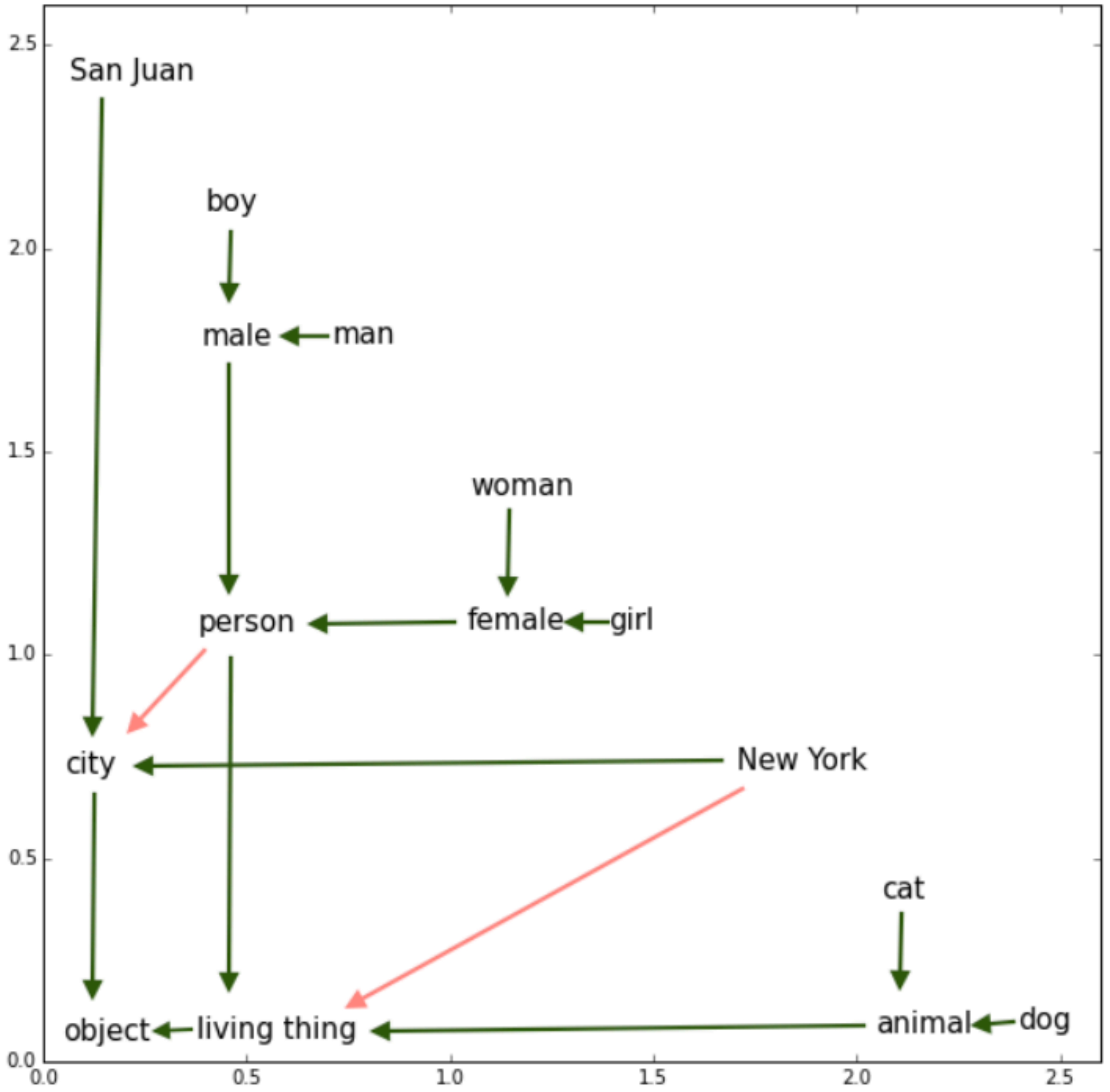
[Lin, Maire, Belongie, Hays, Perona, Ramanan, Dollar, Zitnick, ECCV'14]

	IoU@0.3	IoU@0.4	IoU@0.5	Avg mAP
Non-strcutred	0.302	0.199	0.110	0.203
Parent-Child	0.327	0.213	0.118	0.219
Sibling	0.316	0.203	0.114	0.211
Ours	**0.347**	**0.246**	**0.159**	**0.251**

Order Embeddings

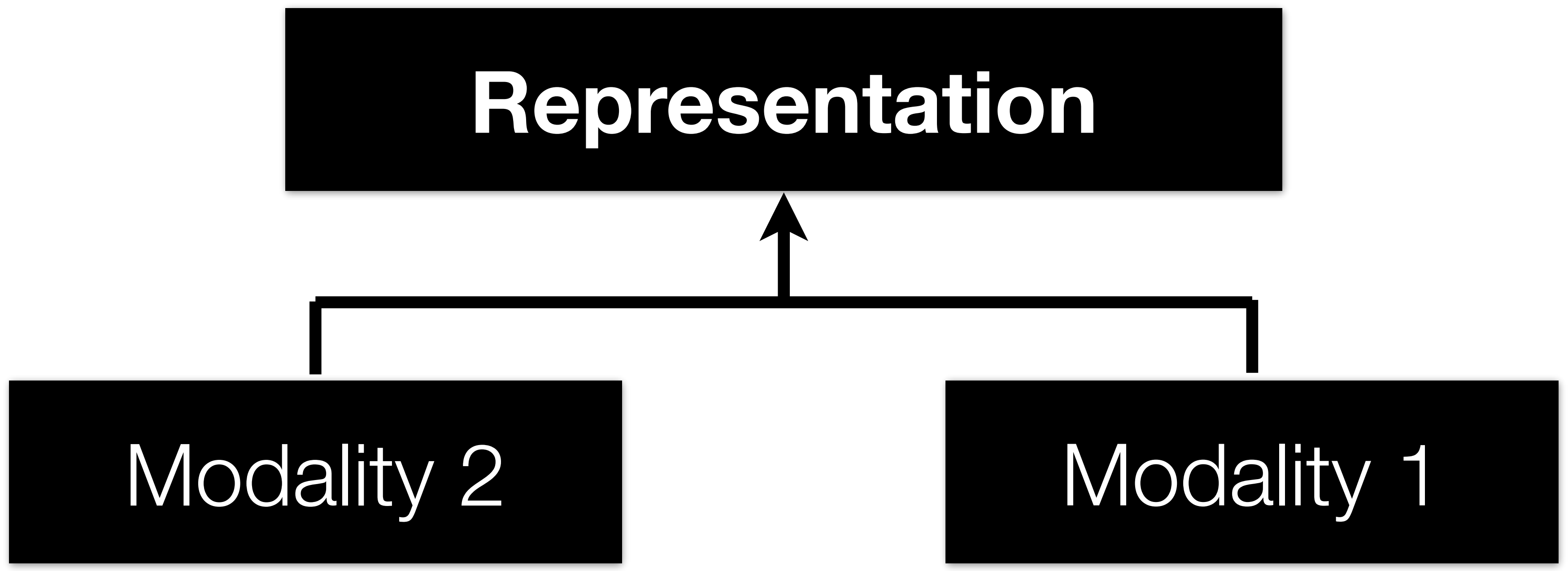
[Vendrov et al., 2016]





Multimodal Representation Types

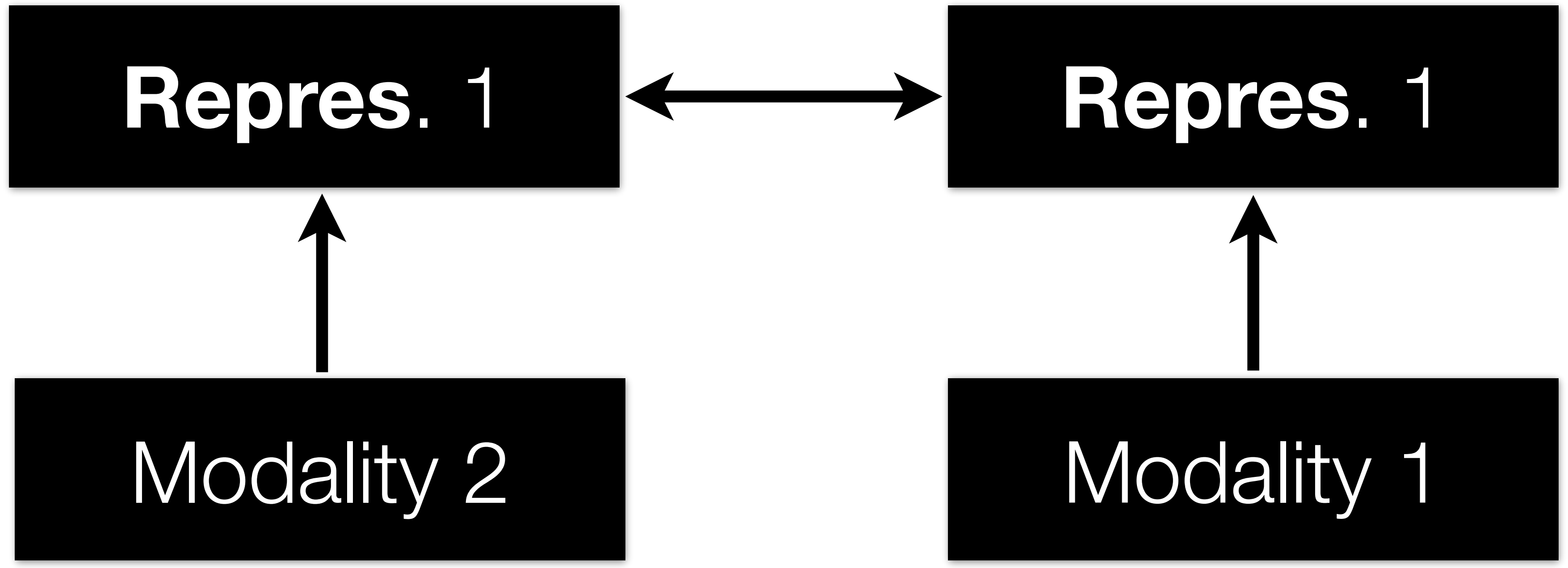
Joint representations:



— Simplest version: modality concatenation (early fusion)

— Can be learned supervised or unsupervised

Coordinated representations:



— Similarity-based methods (e.g., cosine distance)

— Structure constraints (e.g., orthogonality, sparseness)

— CCA (unsupervised), joint embeddings (supervised)

*slide from Louis-Philippe Morency

Final Words …

Joint representations

- Project modalities to the same space
- Use when all the modalities are present during test time
- Suitable for multi-model fusion

Coordinated representations

- Project modalities to their own coordinated spaces
- Use when only one of the modalities is present during test-time
- Suitable for multimodal translation
- Good for multimodal retrieval

*slide from Louis-Philippe Morency