THE UNIVERSITY OF BRITISH COLUMBIA

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

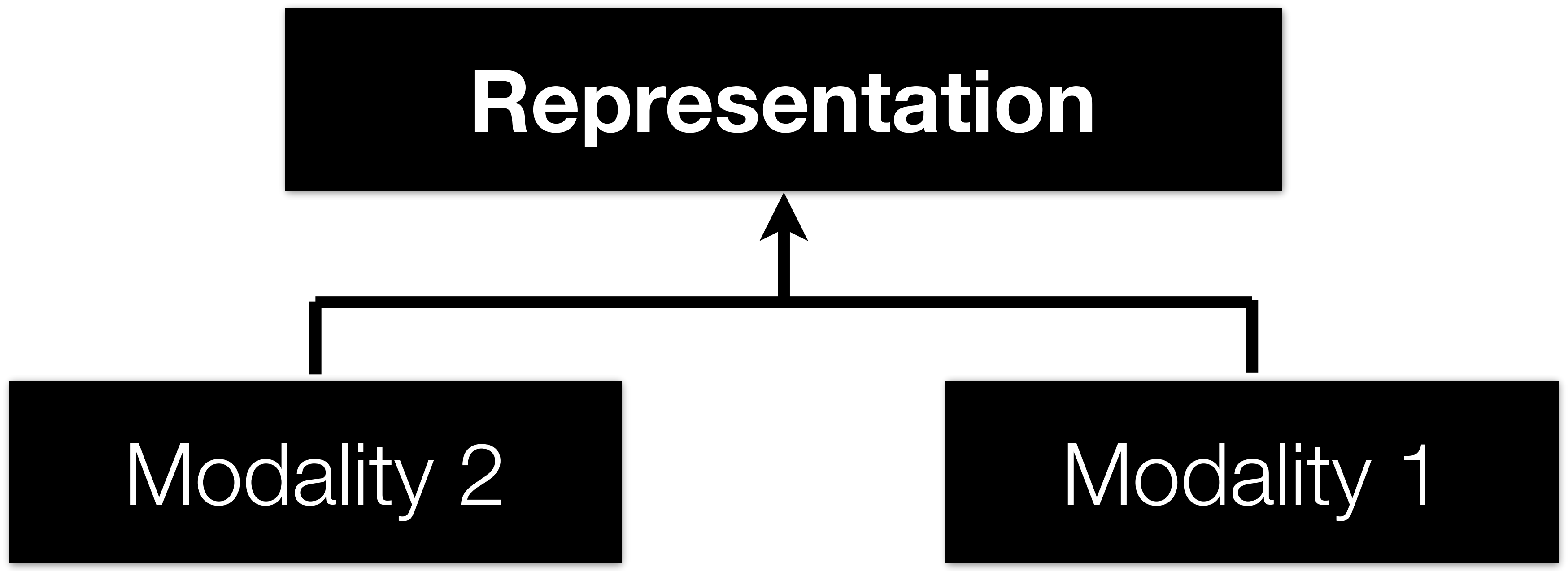
Lecture 10: Coordinated Representations and Joint Embeddings

Course **Logistics**

- **Assignment 3** due Wednesday
- Paper presentation assignments are done, will post later in the week

Multimodal Representation Types

Joint representations:



— Simplest version: modality concatenation (early fusion)

— Can be learned supervised or unsupervised

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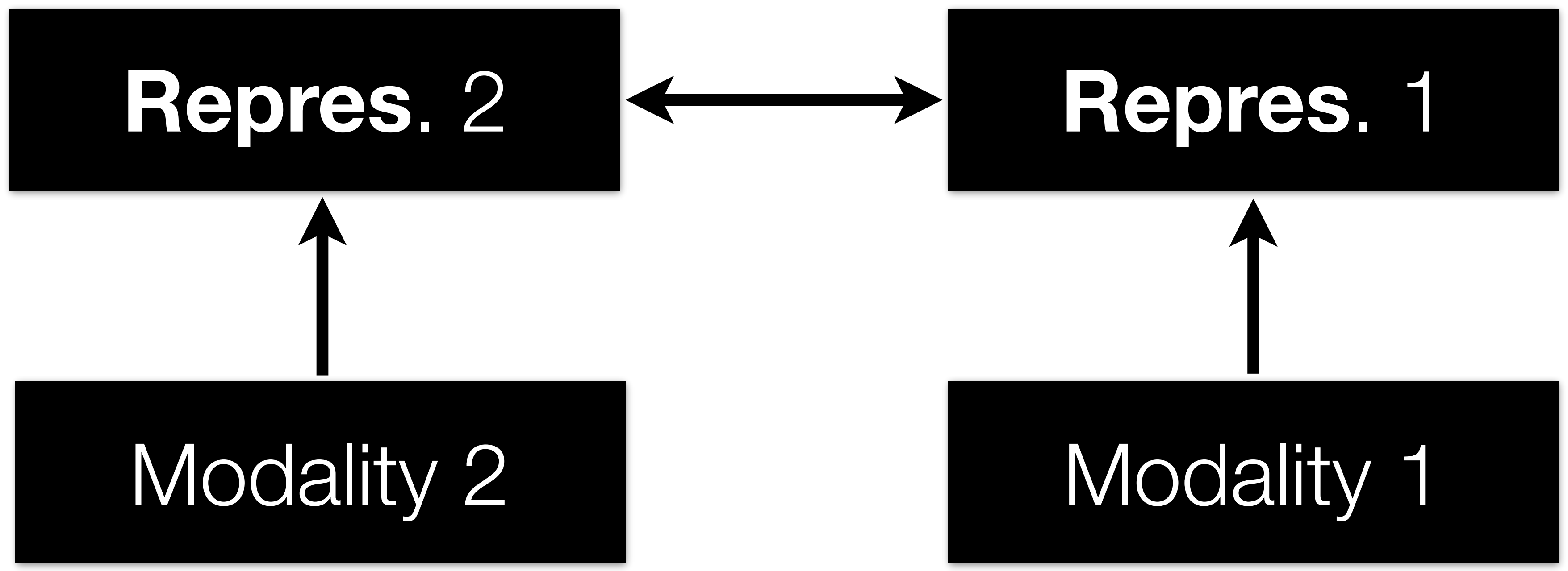

— Similarity-based methods (e.g., cosine distance)

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

— CCA (unsupervised), joint embeddings (supervised)

*slide from Louis-Philippe Morency

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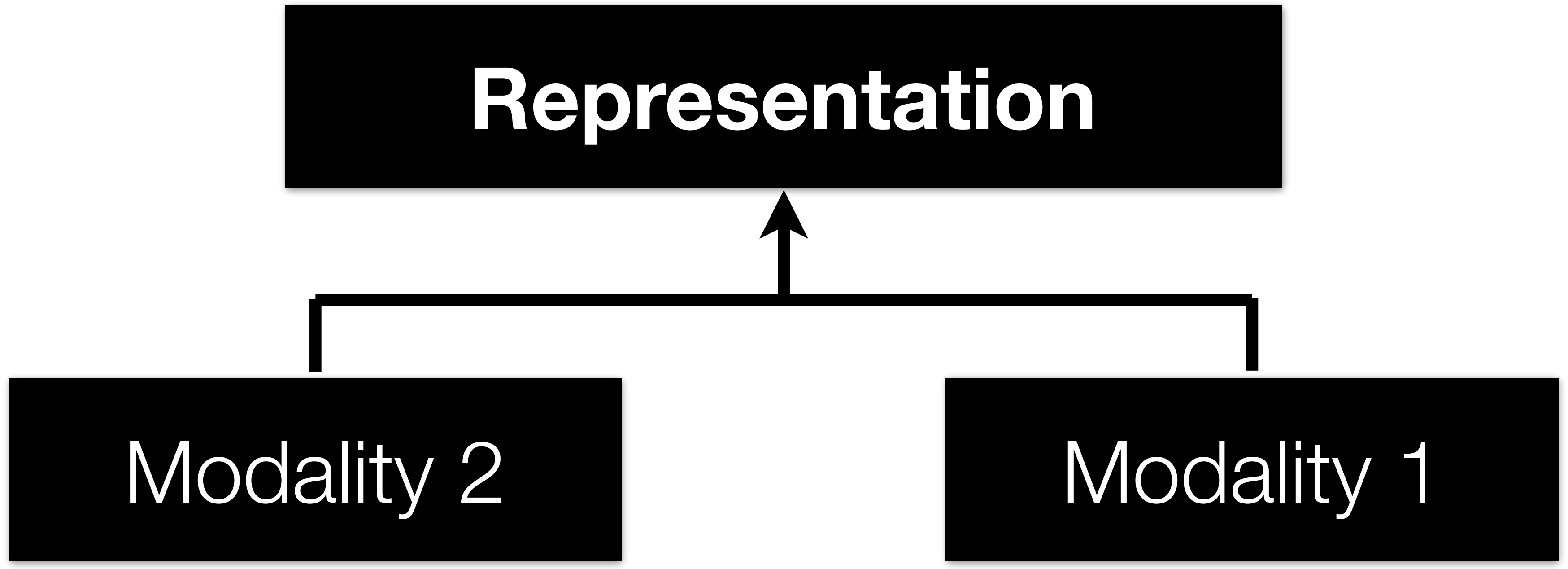

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Joint Representation: Deep Multimodal Autoencoders

[Ngiam et al., 2011]

Each modality can be pre-trained

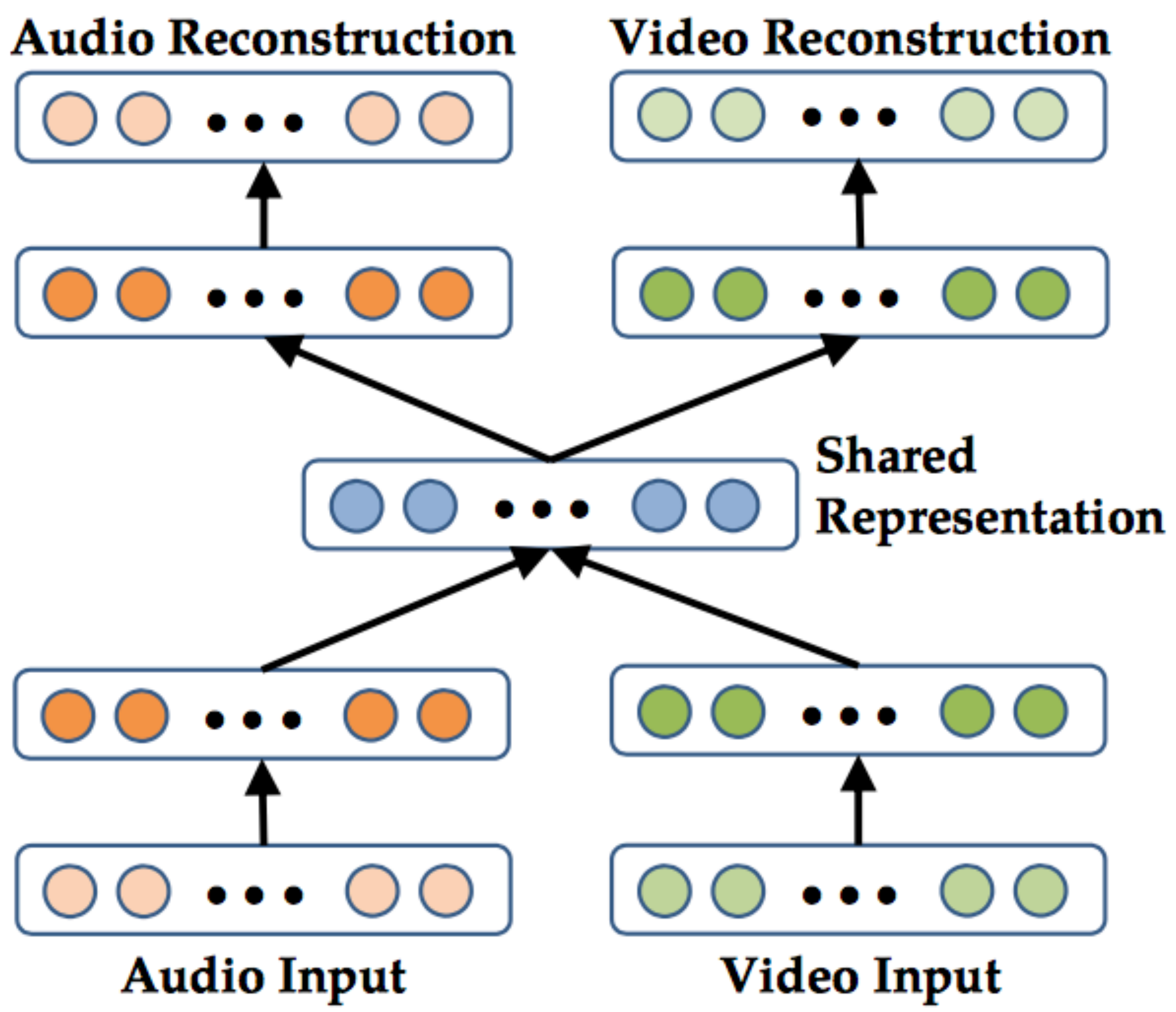
— using denoising autoencoder

To train the model, reconstruct both modalities using

— both Audio & Video

— just Audio

— just Video



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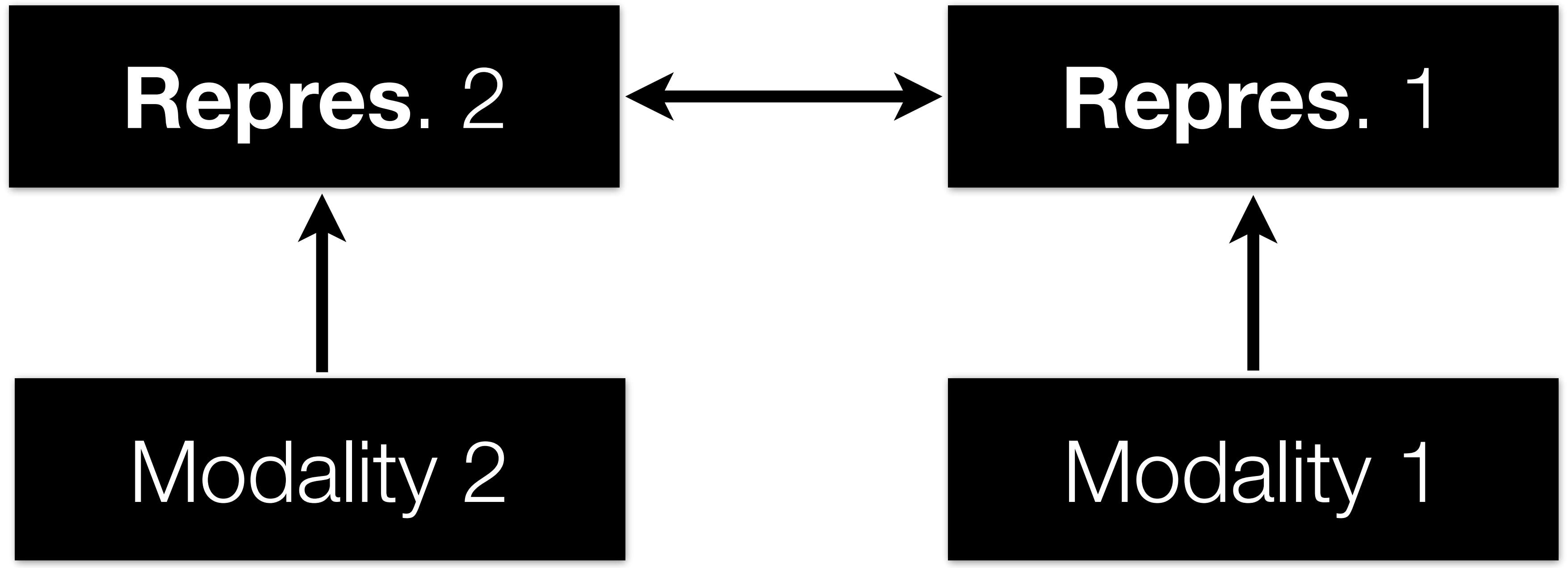

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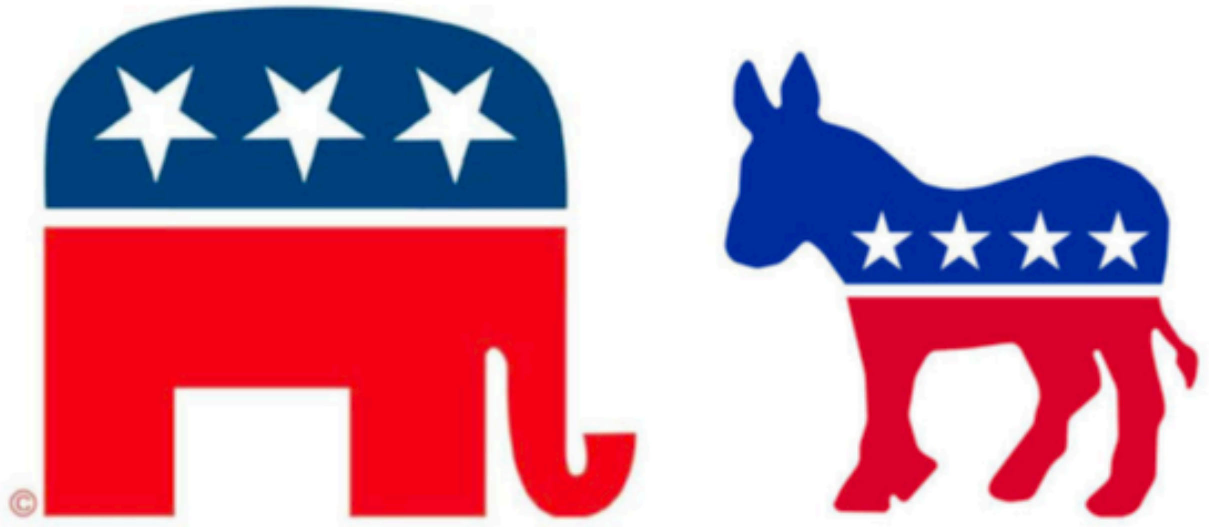
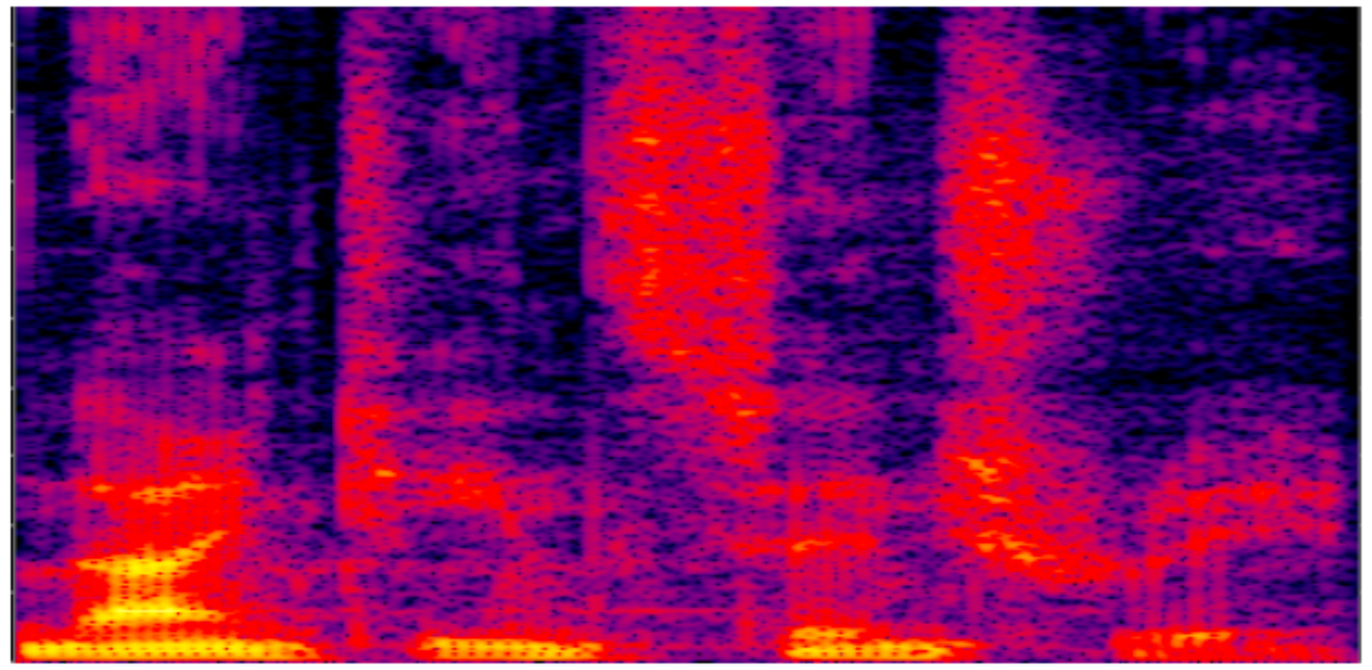
Data with **Multiple Views**

$x_1^{(i)}$	$x_2^{(i)}$
 demographic properties	 responses to survey
 audio features at time i	 video features at time i

*slide from Andrew, Arora, Bilmes, Livescu

Correlated Representations

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

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

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Finding correlated representations can be **useful** for

- Gaining insights into the data
- Detecting of asynchrony in test data
- Removing noise uncorrelated across views
- Translation or retrieval across views

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Has been **applied widely** to problems in computer vision, speech, NLP, medicine, chemometrics, metrology, neurology, etc.

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CCA: Canonical Correlation Analysis

Classical technique to find **linear** correlated representations, i.e.,

$$f_1(\mathbf{x}_1) = \mathbf{W}_1^T \mathbf{x}_1 \qquad \mathbf{W}_1 \in \mathbb{R}^{d_1 \times k}$$

where

$$f_2(\mathbf{x}_2) = \mathbf{W}_2^T \mathbf{x}_2 \qquad \mathbf{W}_2 \in \mathbb{R}^{d_2 \times k}$$

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The first columns $(\mathbf{w}_{1,:1}, \mathbf{w}_{2,:1})$ of the matrices $\mathbf{W}_1$ and $\mathbf{W}_2$ are found to maximize the **correlation of the projections**:

$$(\mathbf{w}_{1,:1}, \mathbf{w}_{2,:1}) = \arg\max \mathbf{corr}(\mathbf{w}_{1,:1}^T \mathbf{X}_1, \mathbf{w}_{2,:1}^T \mathbf{X}_2)$$

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Subsequent pairs are constrained to be **uncorrelated with previous components** (i.e., for $j < i$)

$$\mathbf{corr}(\mathbf{w}_{1,:i}^T \mathbf{X}_1, \mathbf{w}_{1,:j}^T \mathbf{X}_1) = \mathbf{corr}(\mathbf{w}_{2,:i}^T \mathbf{X}_2, \mathbf{w}_{2,:j}^T \mathbf{X}_2) = 0$$

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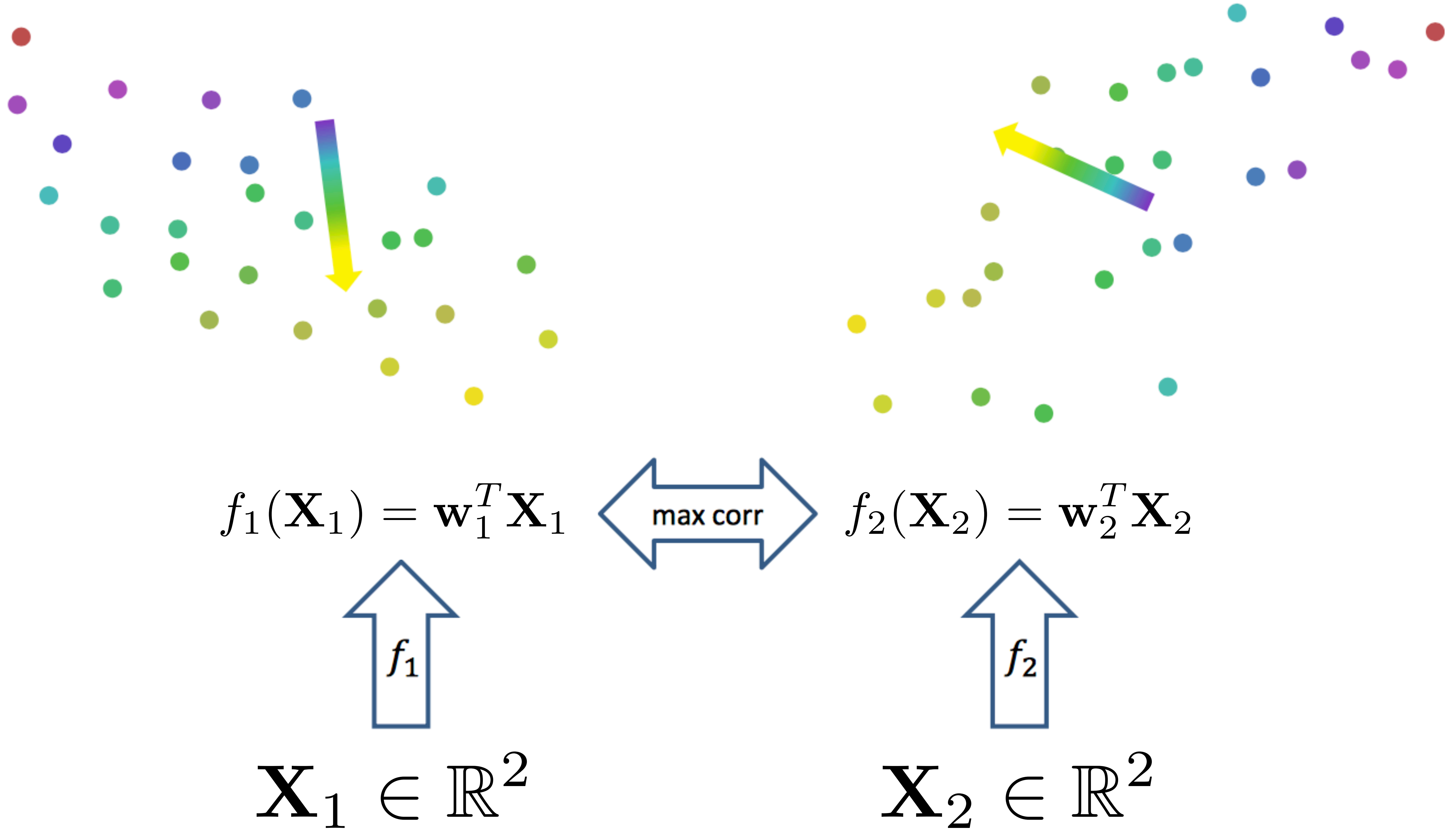
CCA Illustration



Two views of each instance have the same color

*slide from Andrew, Arora, Bilmes, Livescu

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$$\Sigma_{11} = \frac{1}{N-1}\sum_{i=1}^{N}(\mathbf{x}_1^{(i)} - \bar{\mathbf{x}}_1)(\mathbf{x}_1^{(i)} - \bar{\mathbf{x}}_1)^T + r_1\mathbf{I}$$

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4. The optimal projection matrices are: $\mathbf{W}_1^* = \Sigma_{11}^{-1/2}\mathbf{U}_k$

$$\mathbf{W}_2^* = \Sigma_{11}^{-1/2}\mathbf{V}_k$$

where $\mathbf{U}_k$ is the first k columns of $\mathbf{U}$.

*slide from Andrew, Arora, Bilmes, Livescu

KCCA: Kernel CCA

There maybe **non-linear** functions $f_1(\mathbf{x}_1), f_2(\mathbf{x}_2)$ that produce more highly correlated (better) representations than linear projections

Kernel CCA is a principal method for finding such function

— Learns functions from any reproducing kernel Hilbert space

— May use different kernels for each view

Using **RBF** (Gaussian) kernel in KCCA is akin to finding sets of instances that form clusters in both views

*slide from Andrew, Arora, Bilmes, Livescu

KCCA vs. CCA

Pros:

— More complex function space of KCCA can yield dramatically higher correlations

Cons:

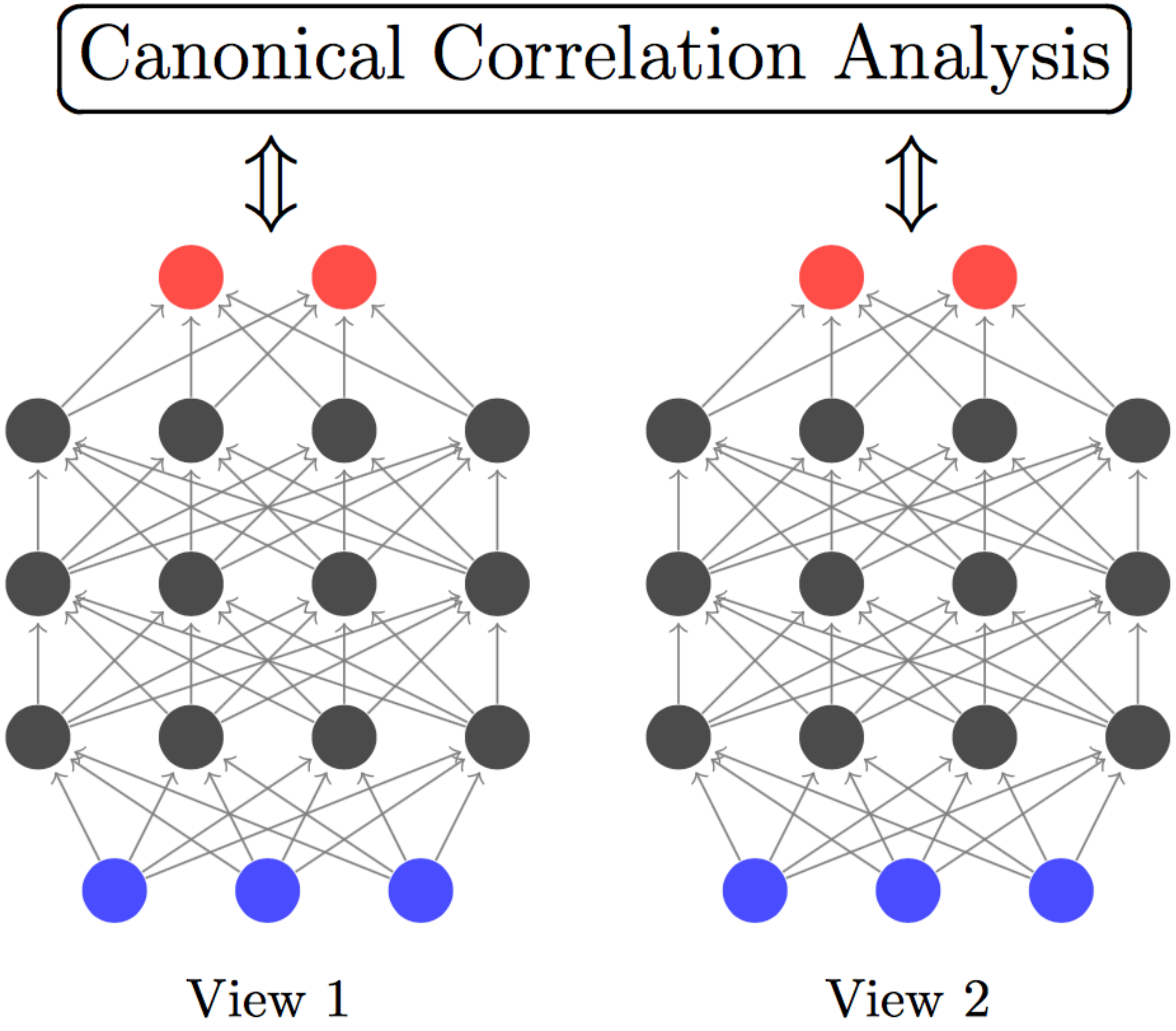
— KCCA is slower to train

— For KCCA training set must be stored and referenced at test time

— KCCA model is more difficult to interpret

*slide from Andrew, Arora, Bilmes, Livescu

Deep CCA



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Benefits of Deep CCA

Pros:

— Better suited for natural, real-world data

— **Parametric model**

  — The training set can be disregarded once the model is learned

  — Computational speed at test time is fast

*slide from Andrew, Arora, Bilmes, Livescu

Deep CCA: Training

Training a Deep CCA model:

1. **Pretrain** the layers of **each side** individually

2. **Jointly fine-tune** all parameters to maximize the total correlation of the output layers. Requires computing correlation gradient:
   - Forward propagate activations on both sides.
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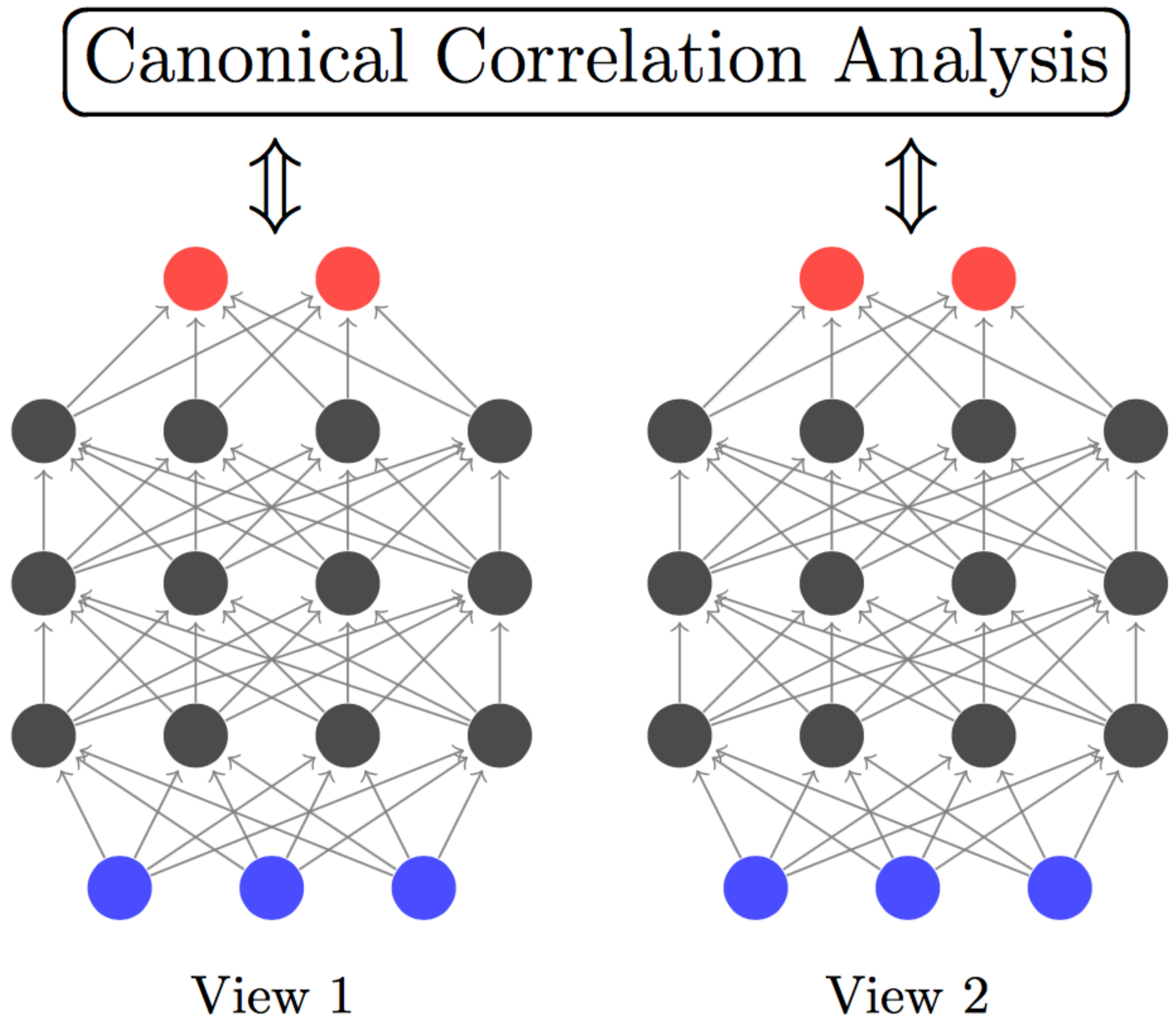

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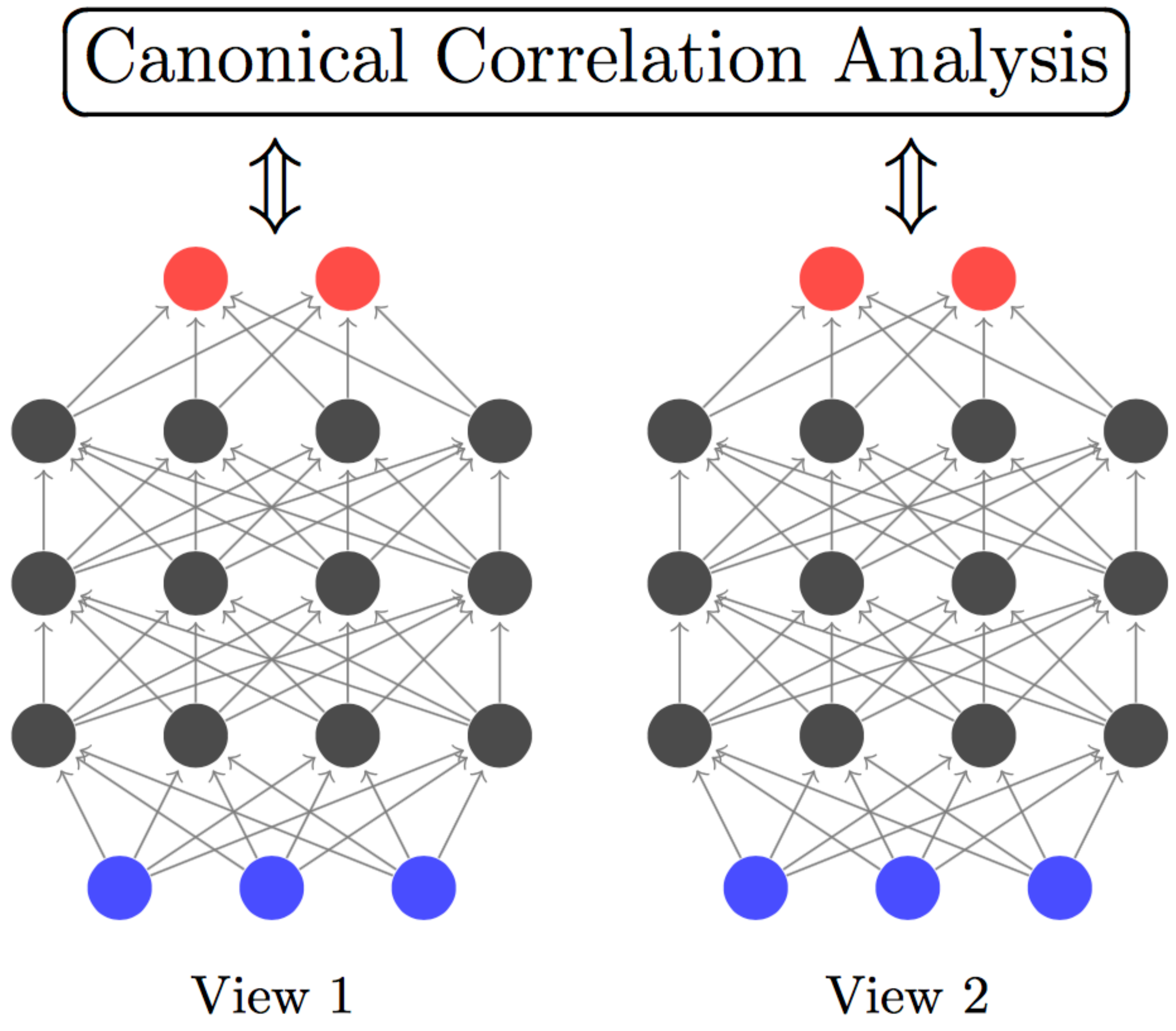

Correlation is a population objective, so instead of one instance (or minibatch) training, requires L-BFGS second-order method (with full-batch)

*slide from Andrew, Arora, Bilmes, Livescu

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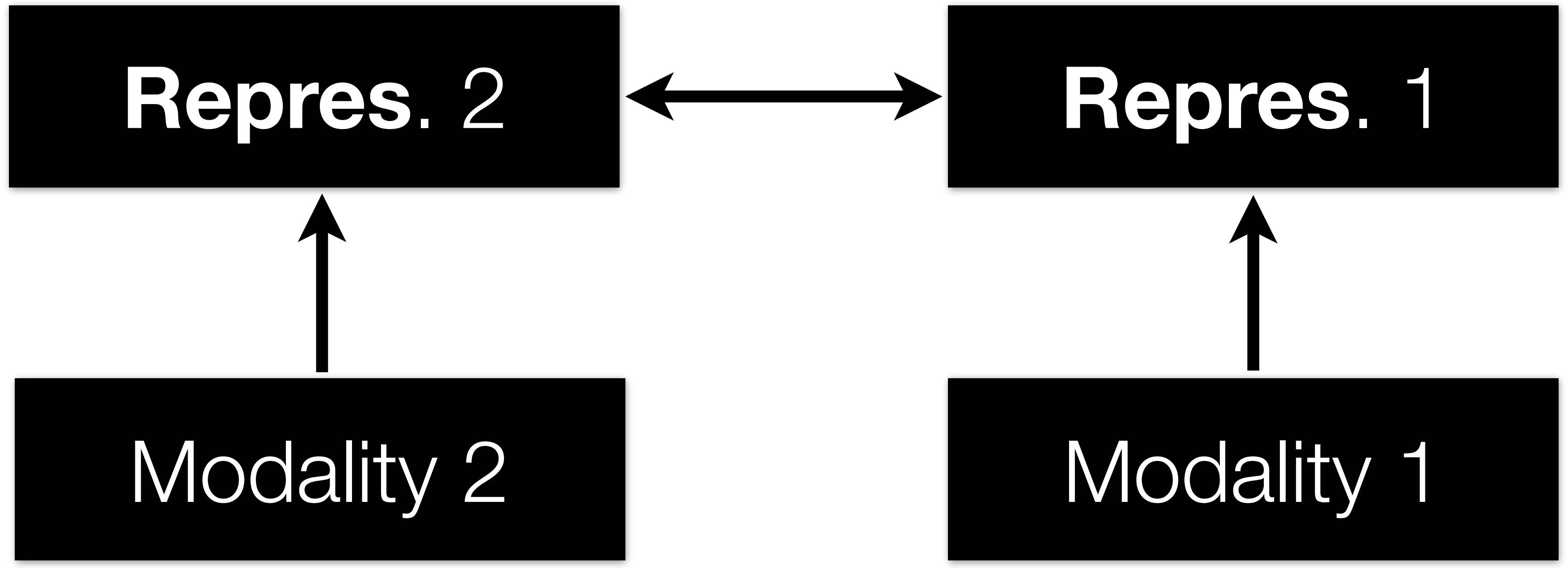

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Correlated Representations vs. **Joint Embeddings**

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

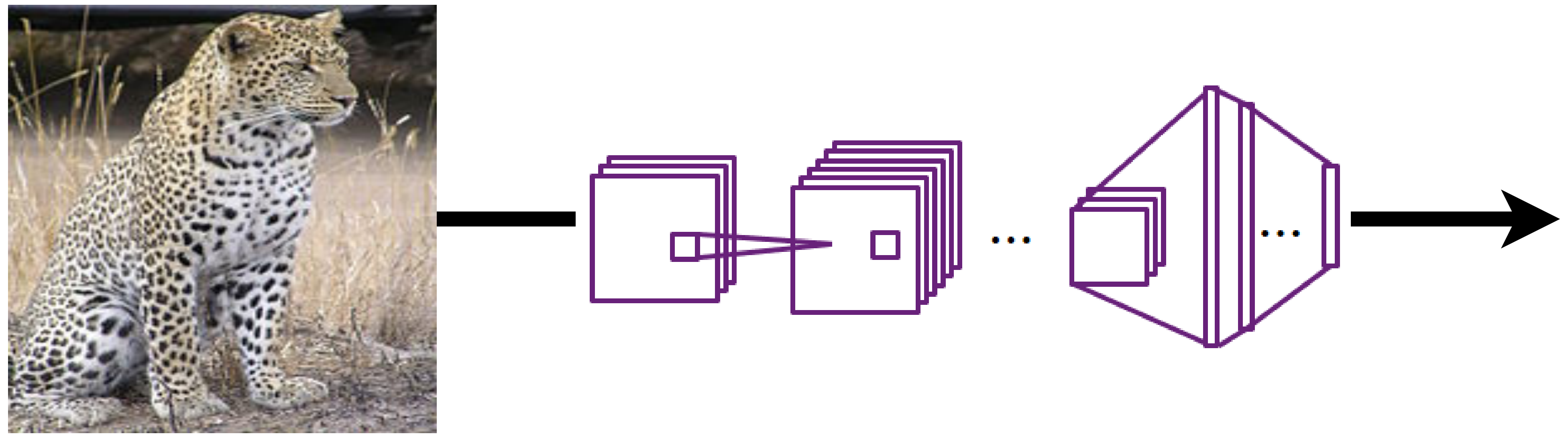
$$min_{f_1, f_2} D\left(f_1(\mathbf{x}_1^{(i)}), f_2(\mathbf{x}_2^{(i)})\right)$$

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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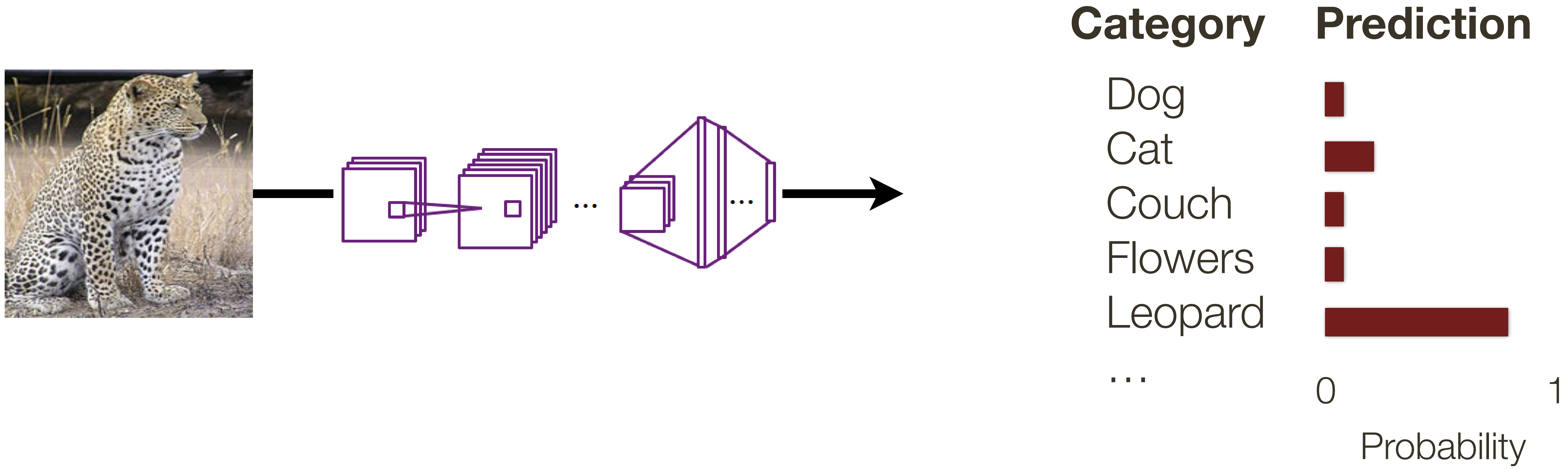

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Discriminative Embeddings

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

$\mathbb{R}^d$

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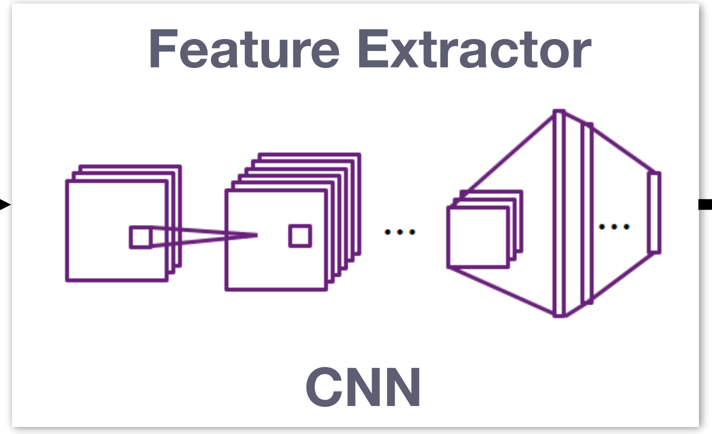
Image Embedding

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

I_i



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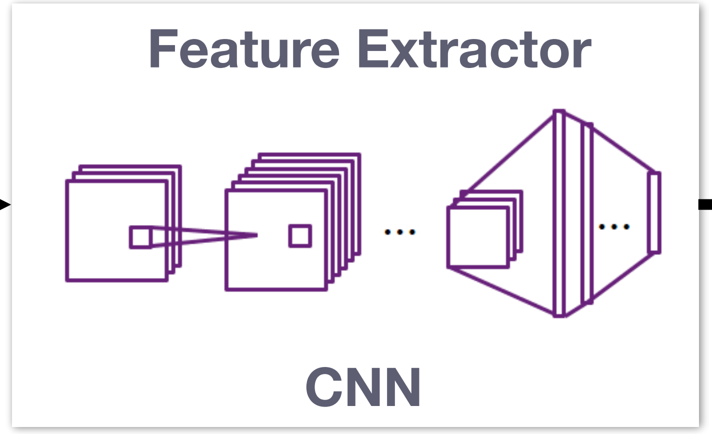

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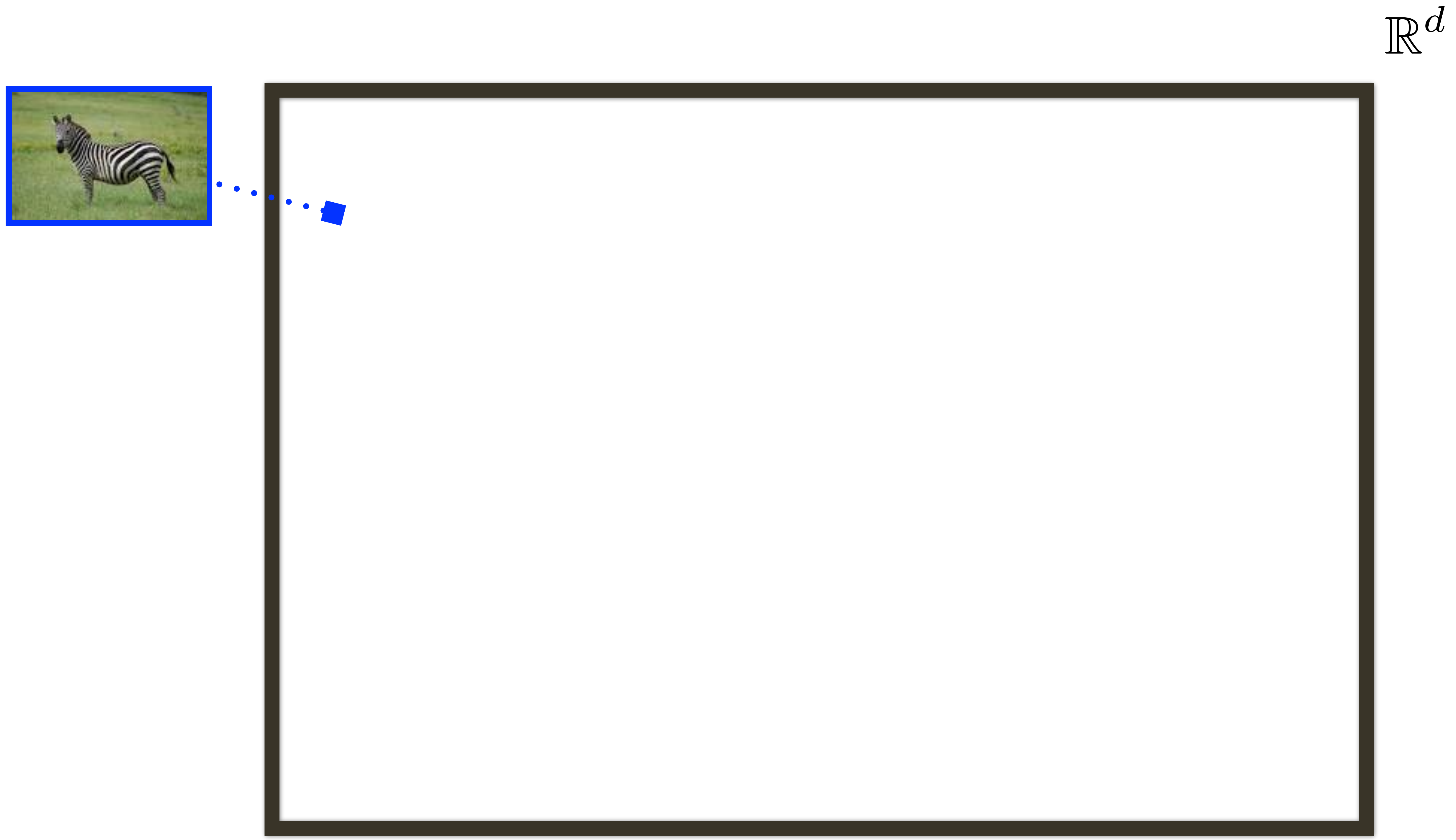

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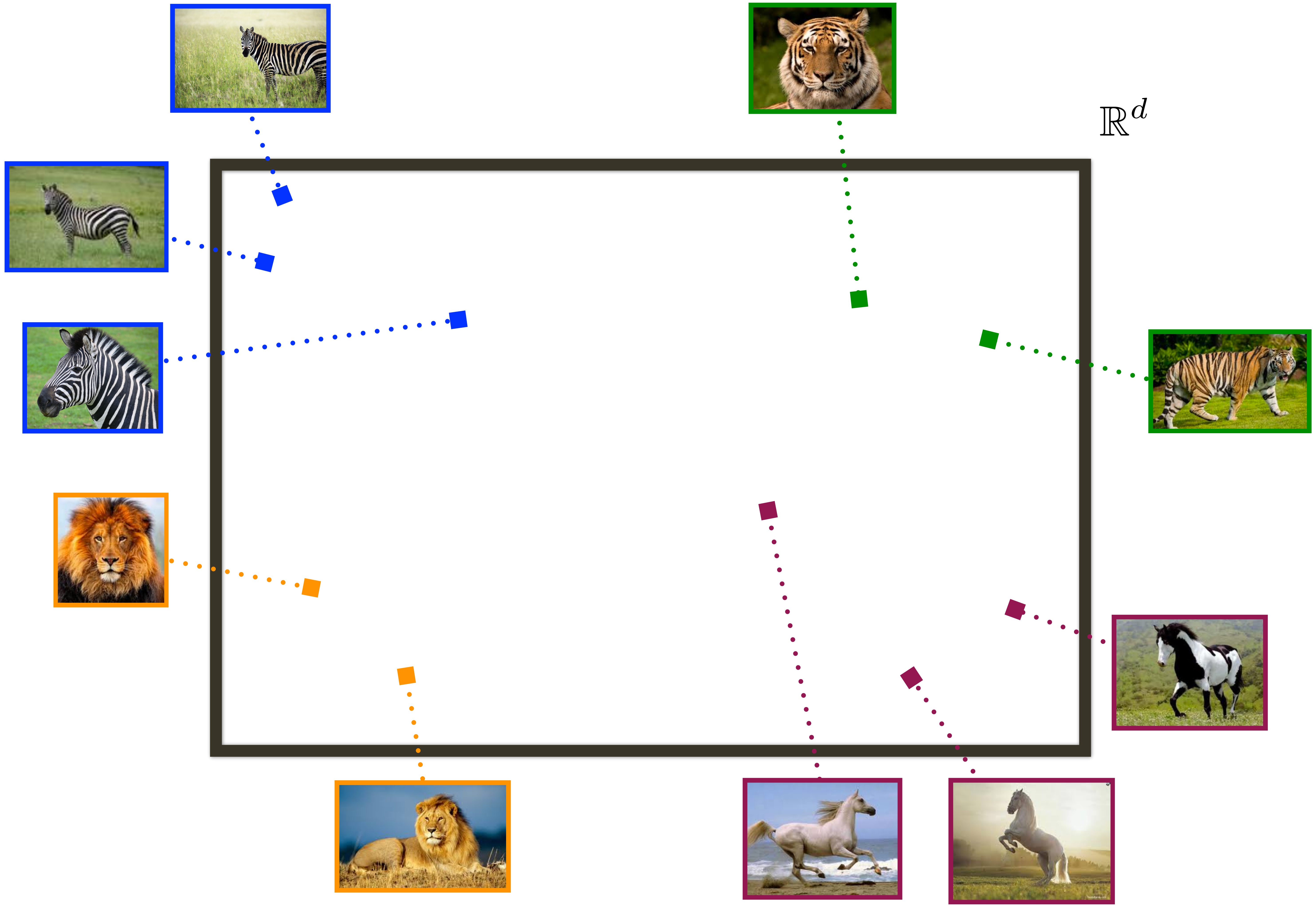

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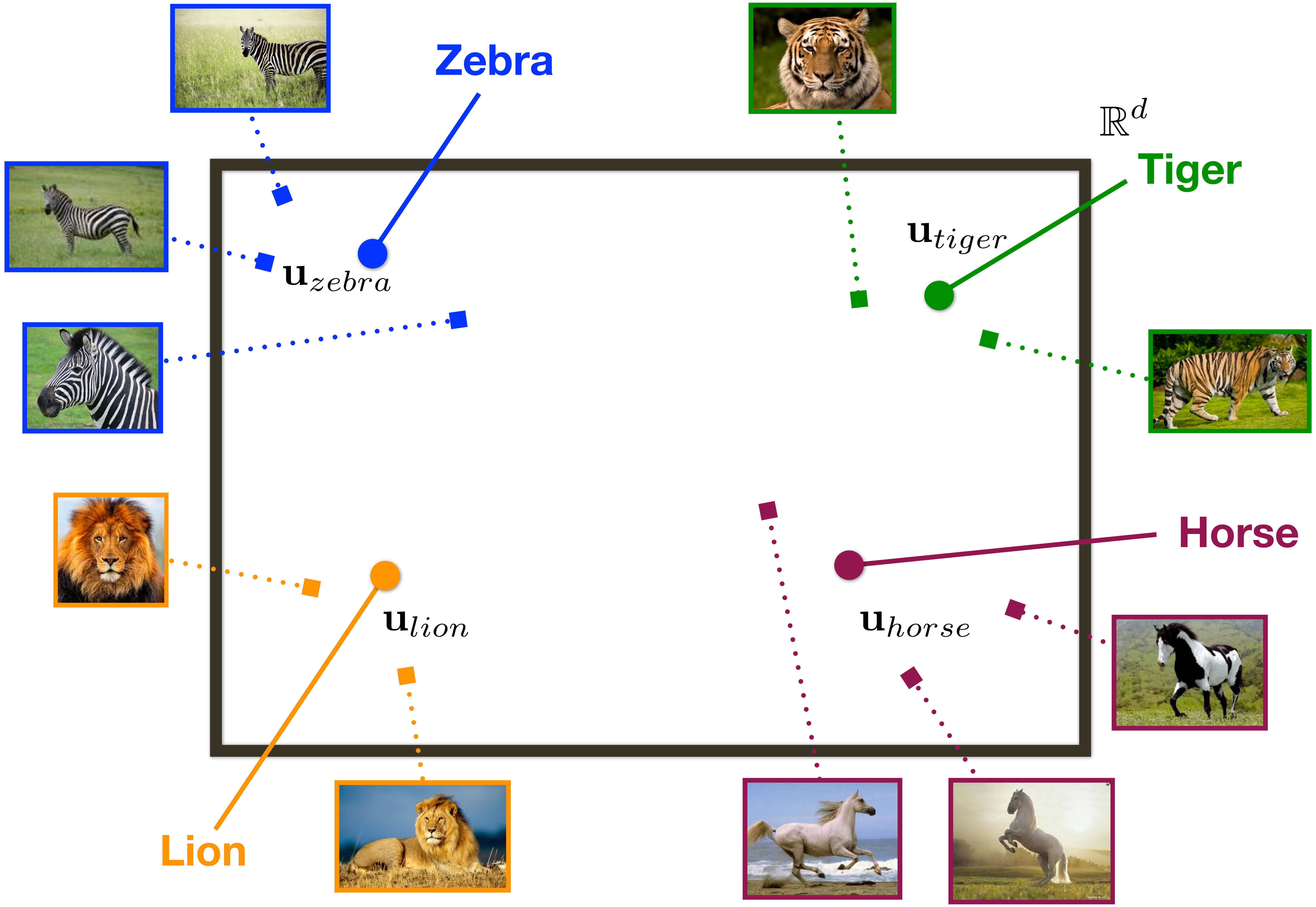

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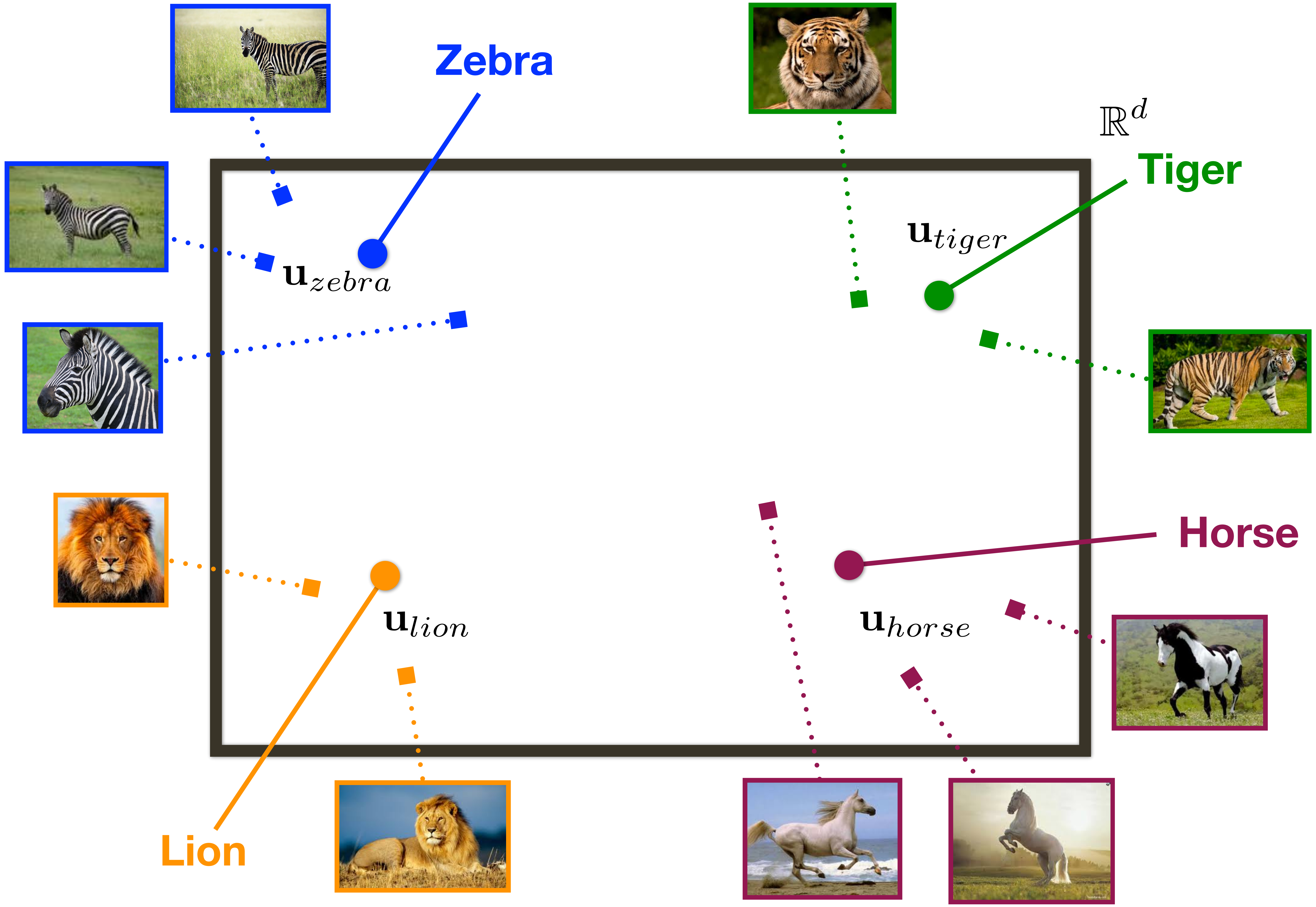
Similarity in Embedding Space

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



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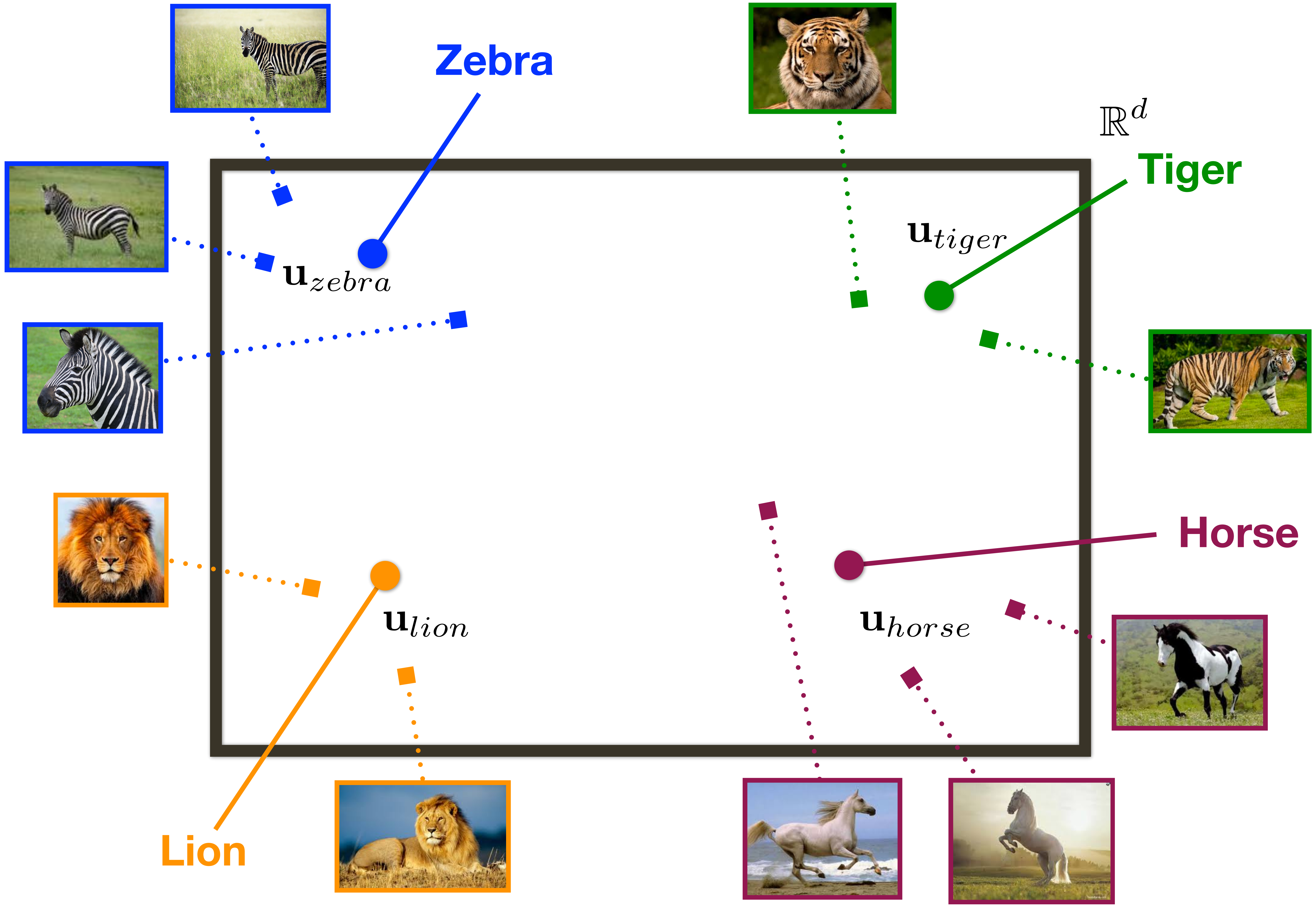

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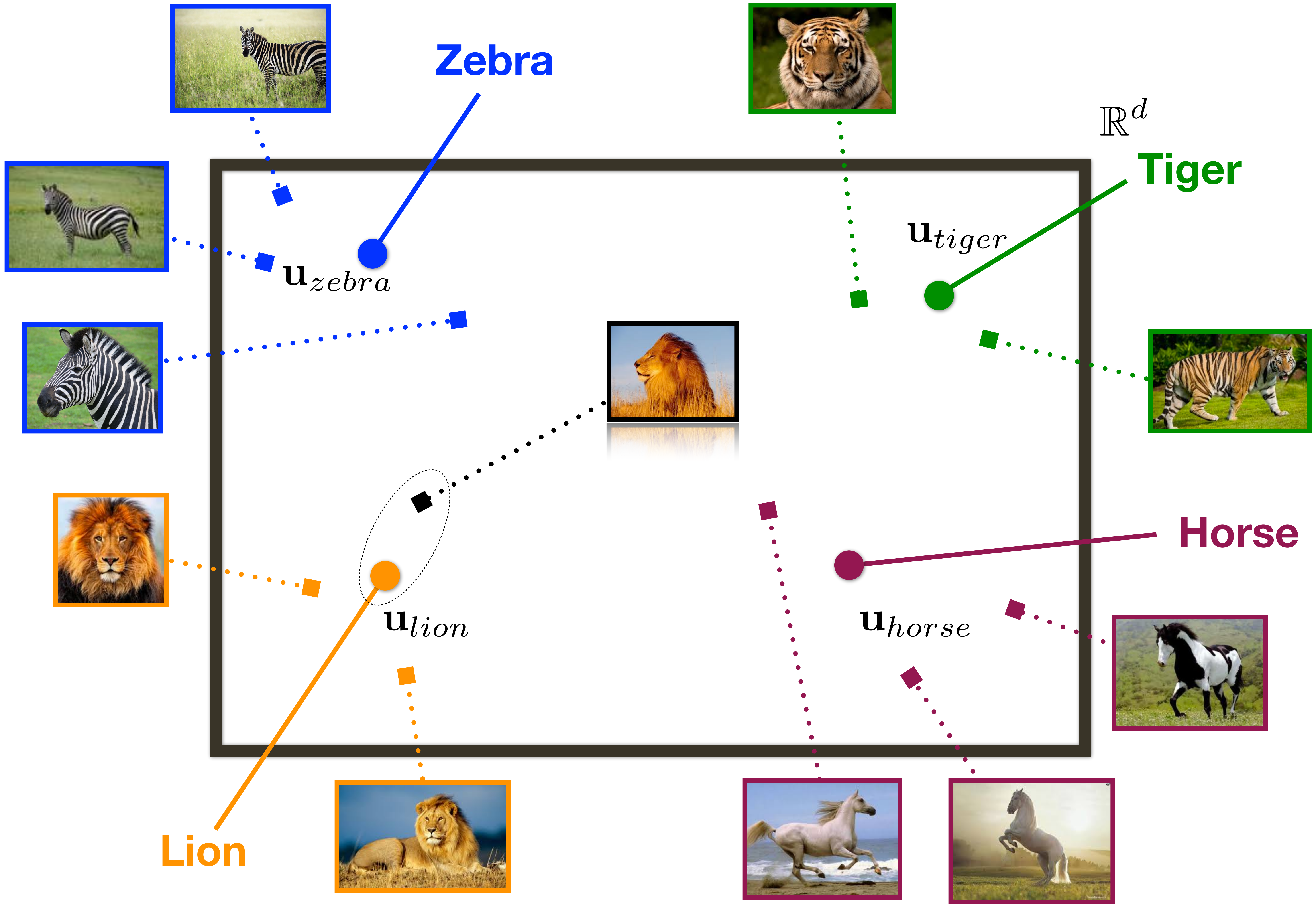
Image Categorization / Annotation

which object category does image belong to?



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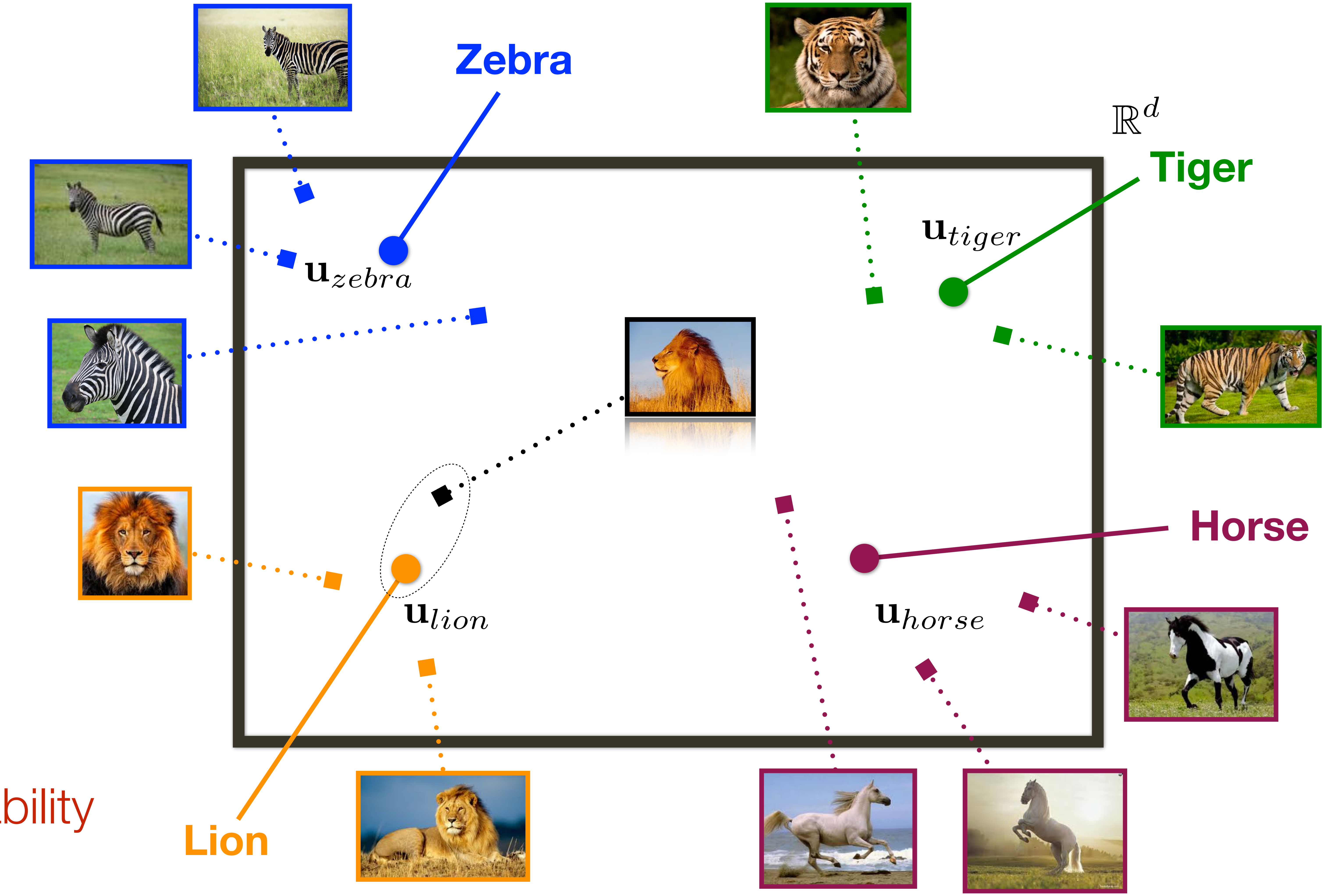
Distance can be interpreted as probability



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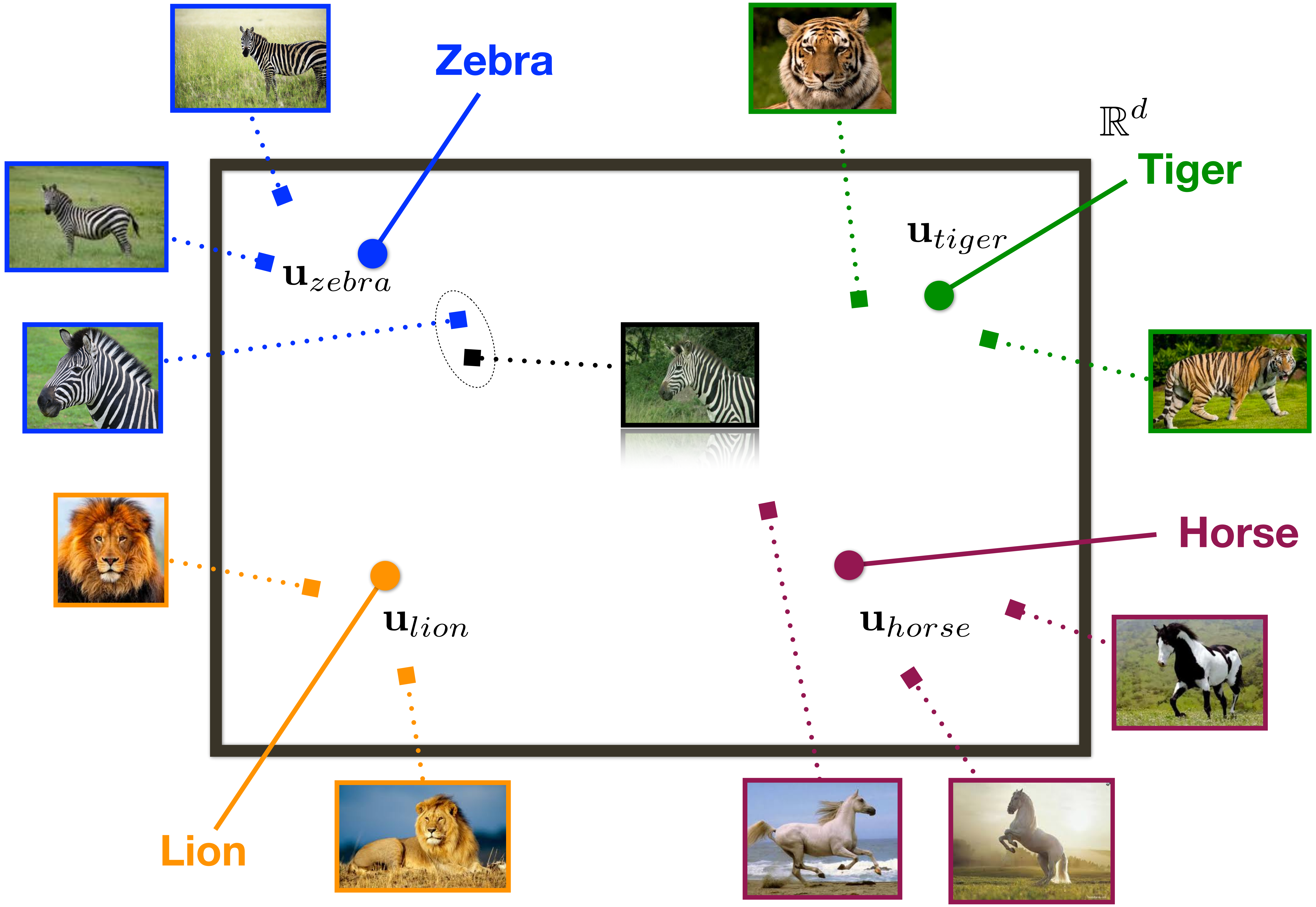
Search by Image

most similar image to a query?



Discriminative Embeddings

Search by Label

most representative image for a label?

Image Embedding

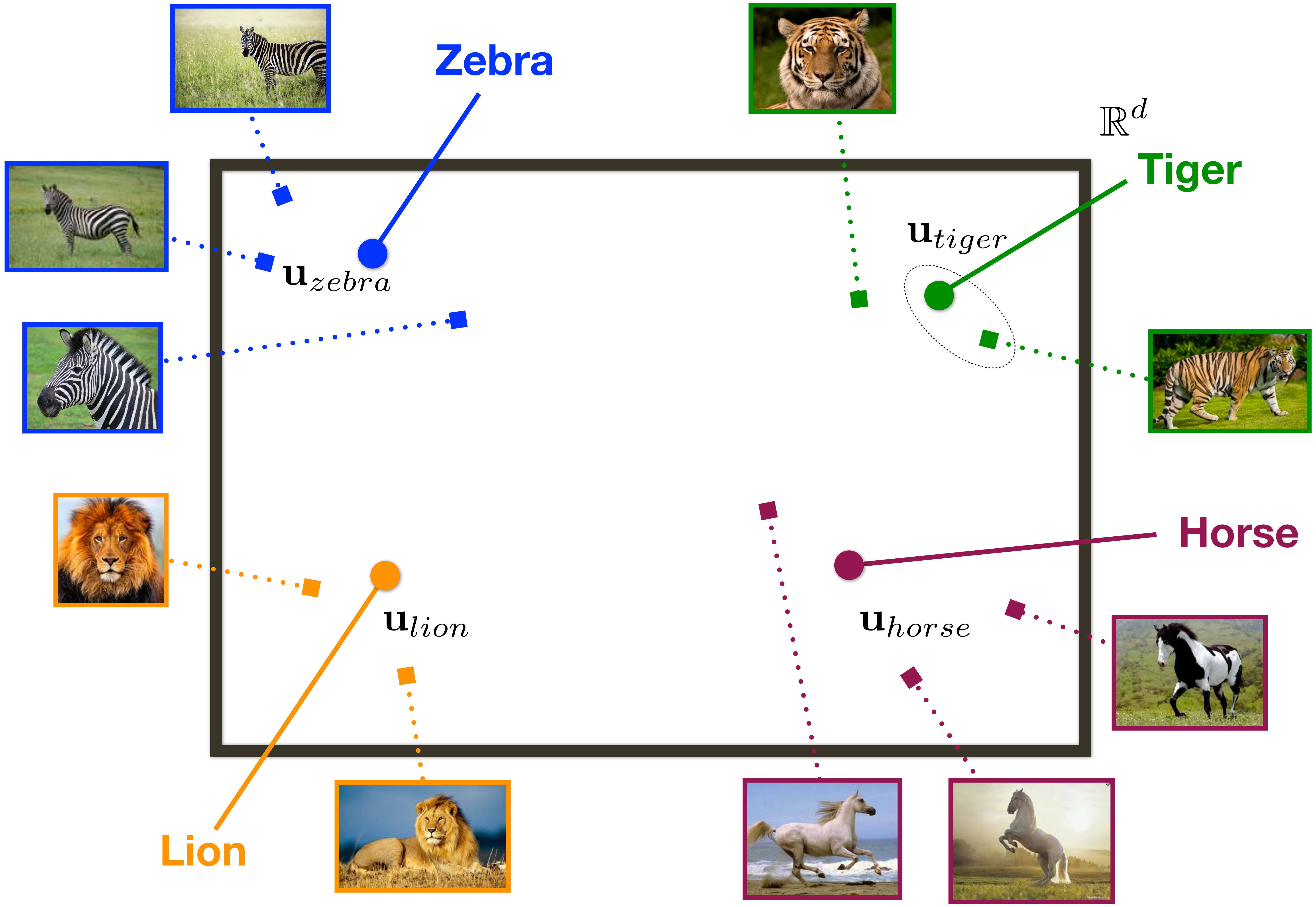
$$\Psi(I_i) = \mathbf{W} \cdot CNN(I_i; \mathbf{\Theta}) \colon \mathbb{R}^D \rightarrow \mathbb{R}^d$$

Label Embedding

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

Similarity in Embedding Space

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



Discriminative Embeddings

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

Image Embedding

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

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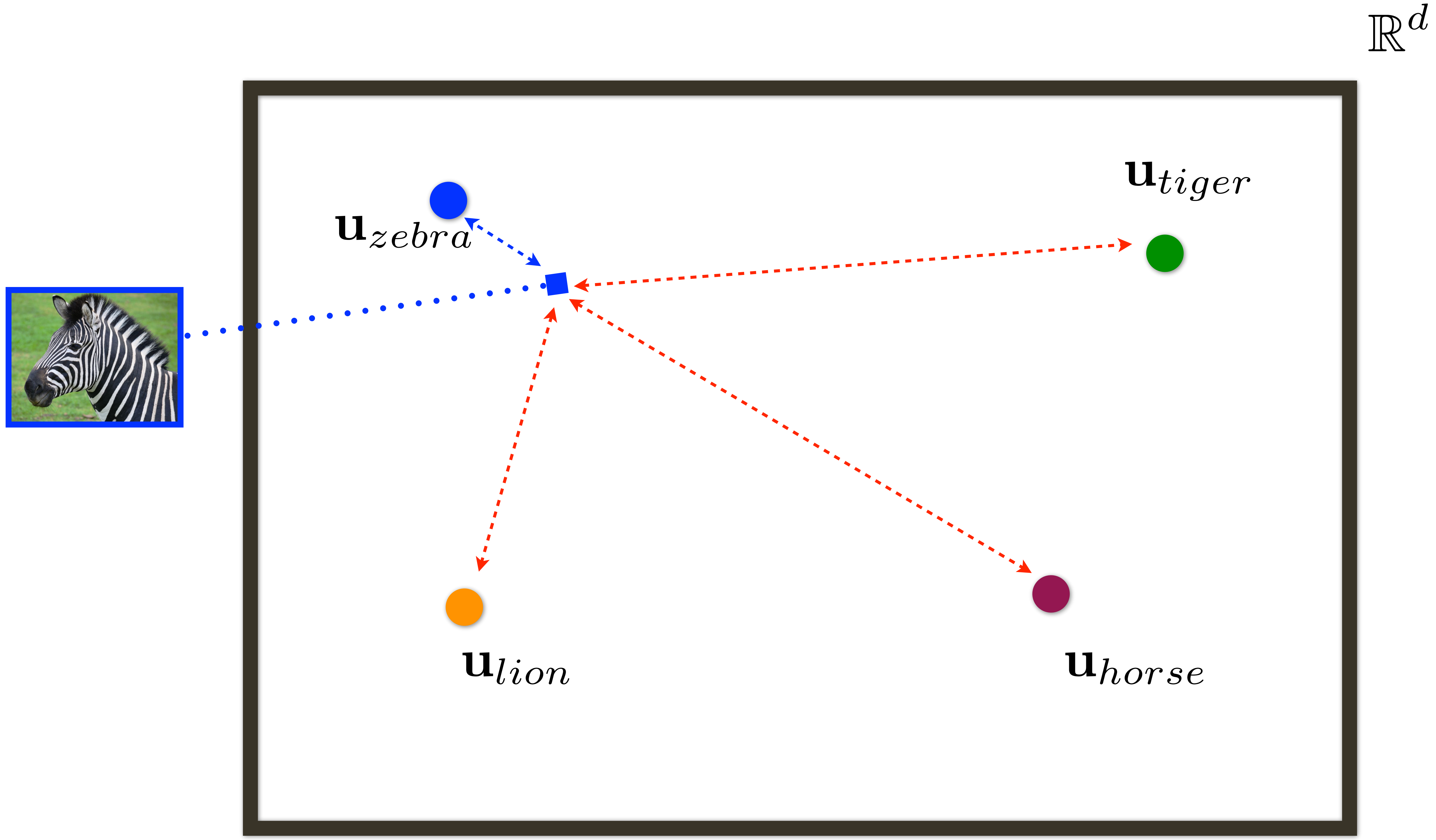
$$\Psi_L(word_i) = \mathbf{u}_i : \{1, ..., L\} \to \mathbb{R}^d$$



Similarity in Embedding Space

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

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?

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

Image Embedding

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

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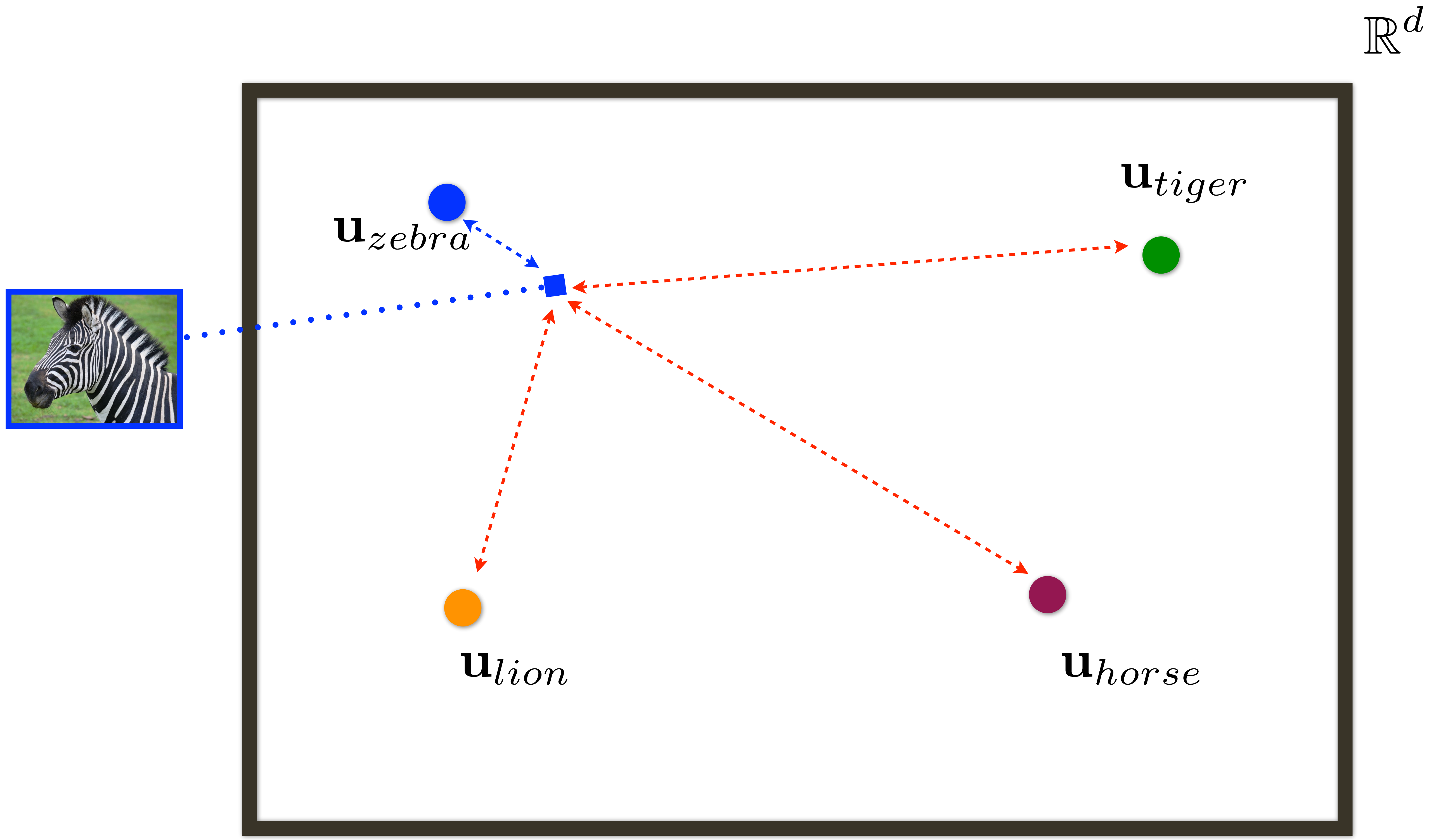

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Objective Function:

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

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Discriminative Embeddings

Image Embedding

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

Label Embedding

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

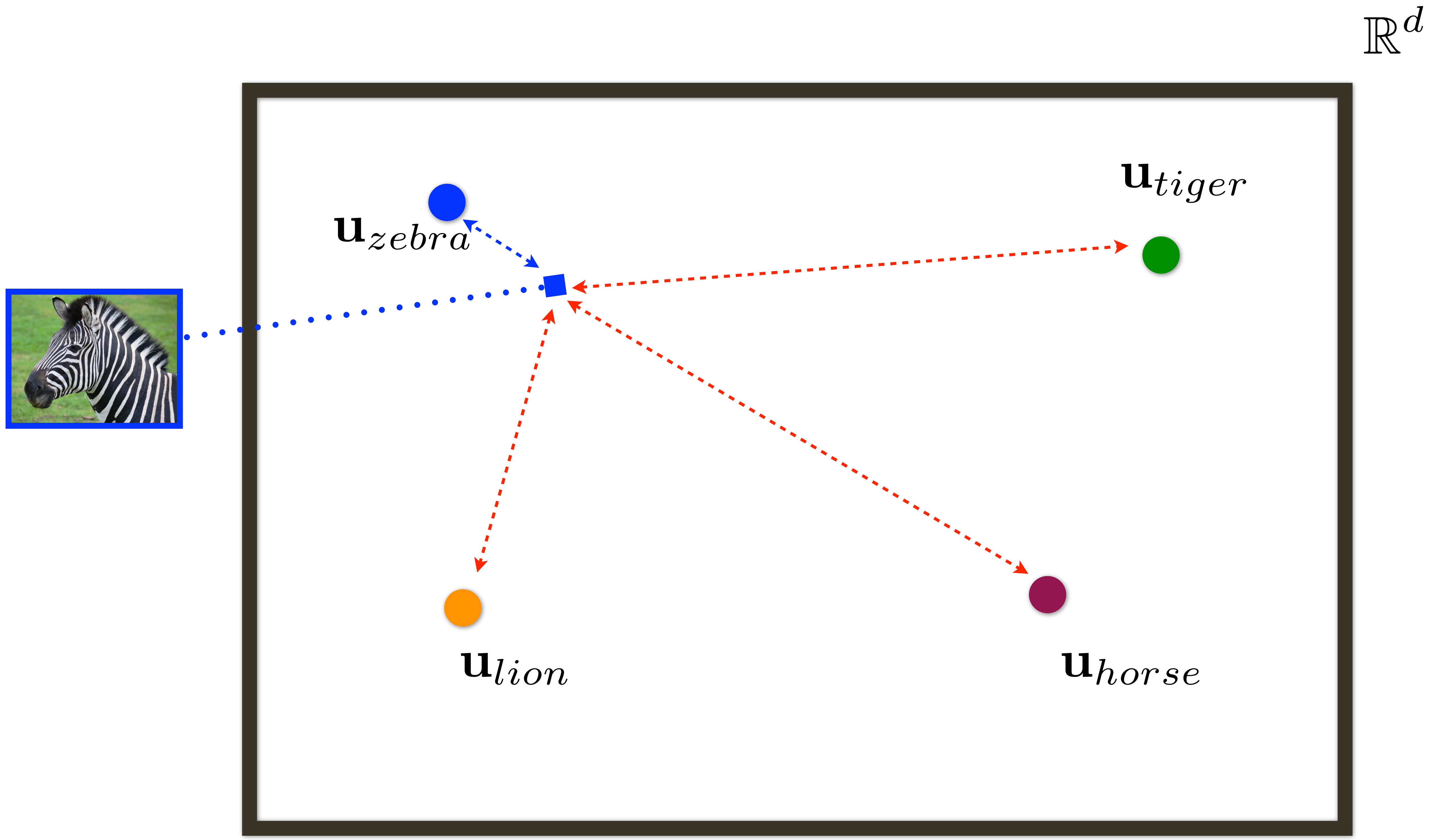
Similarity in Embedding Space

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

Objective Function:

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

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

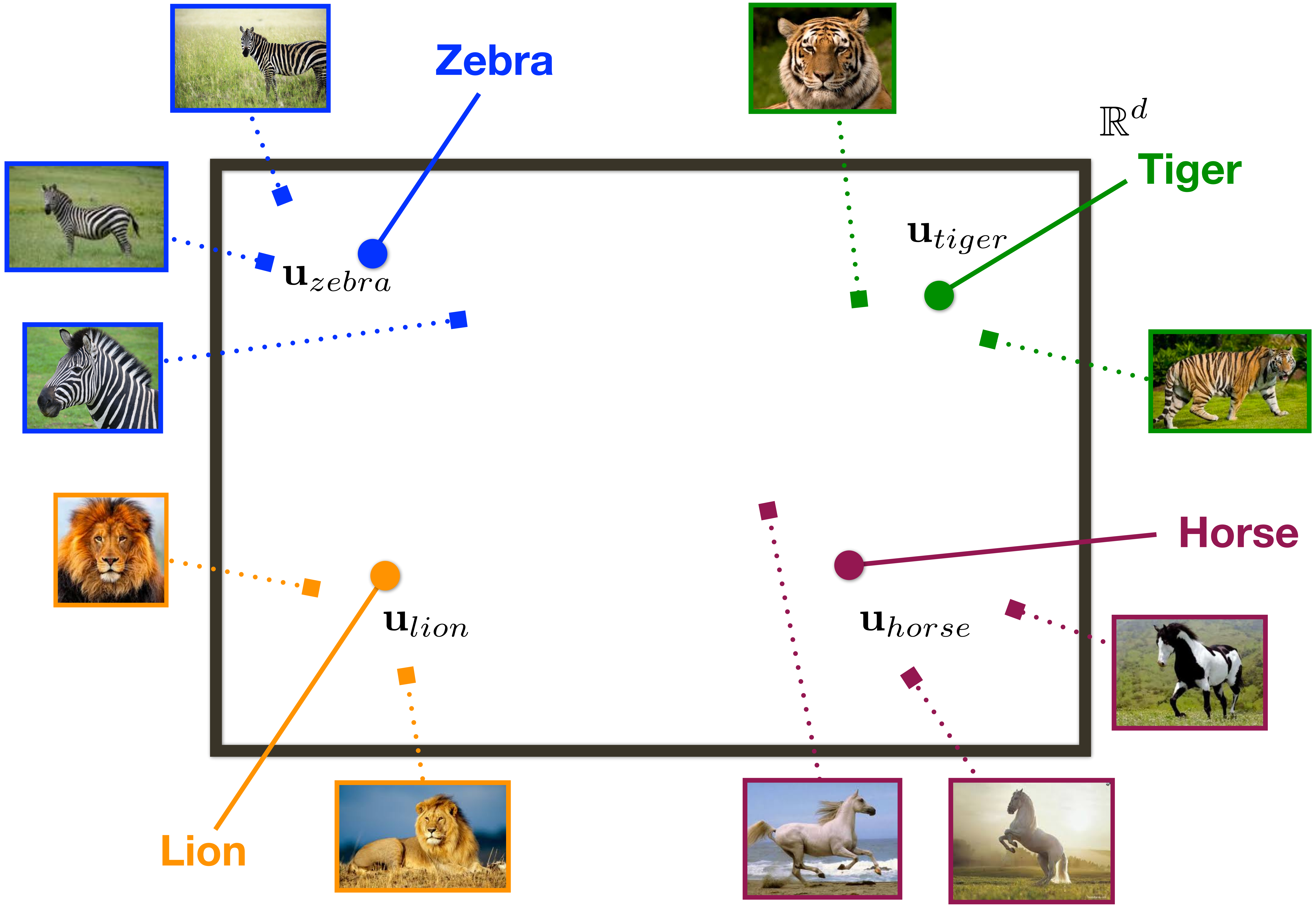


[Bengio *et al.*,, NIPS'10]

[Weinberger, Chapelle, NIPS'09]

Discriminative Embeddings

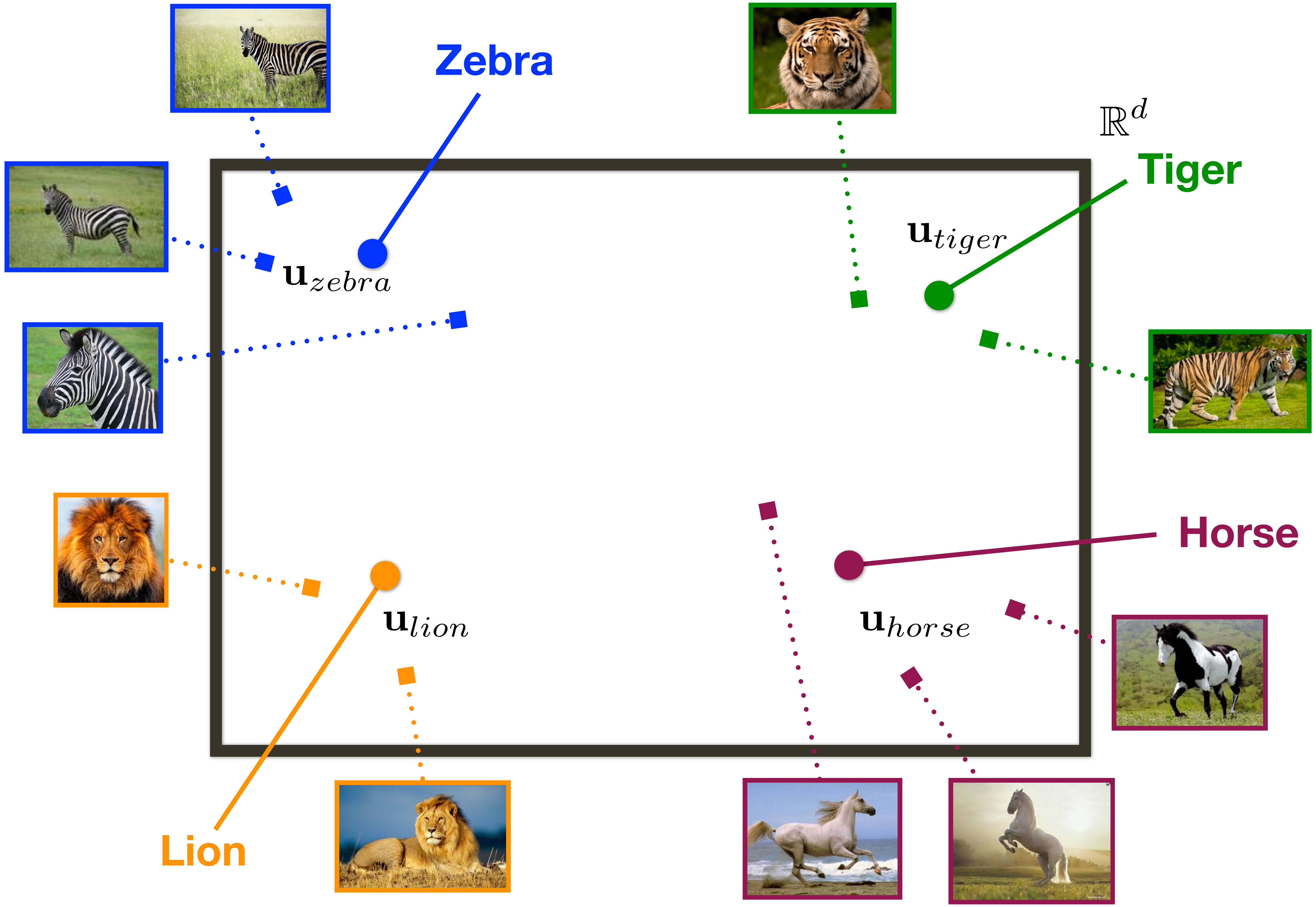
This is a very **convenient model**



Discriminative Embeddings

This is a very **convenient model**

Inducing semantics on the embedding space



Semantic Embeddings

Why adding **semantics is useful**?

— Allows for transference of knowledge from classes that have a lot of data to those that have few (or no labeled instances)

— Can serve as additional regularization, so can be more efficient for learning.

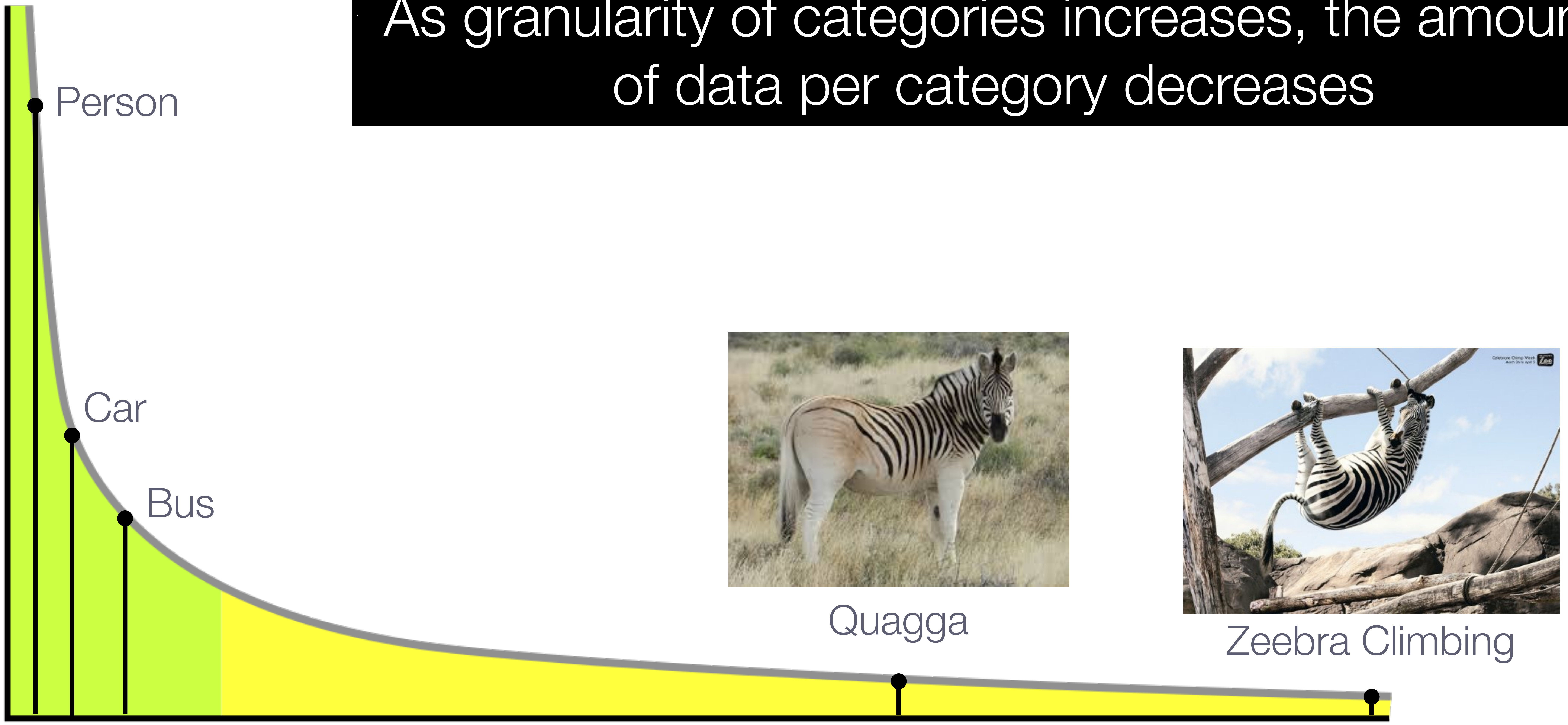
Long Tail of Categories

Few most frequent categories contain most of the samples, most of the categories contain few samples

Long Tail of Categories

Few most frequent categories contain most of the samples, most of the categories contain few samples

As granularity of categories increases, the amount of data per category decreases



Inspiration from Human Structured Semantics

[Hwang et al., 2014]

Truck

Inspiration from Human Structured Semantics

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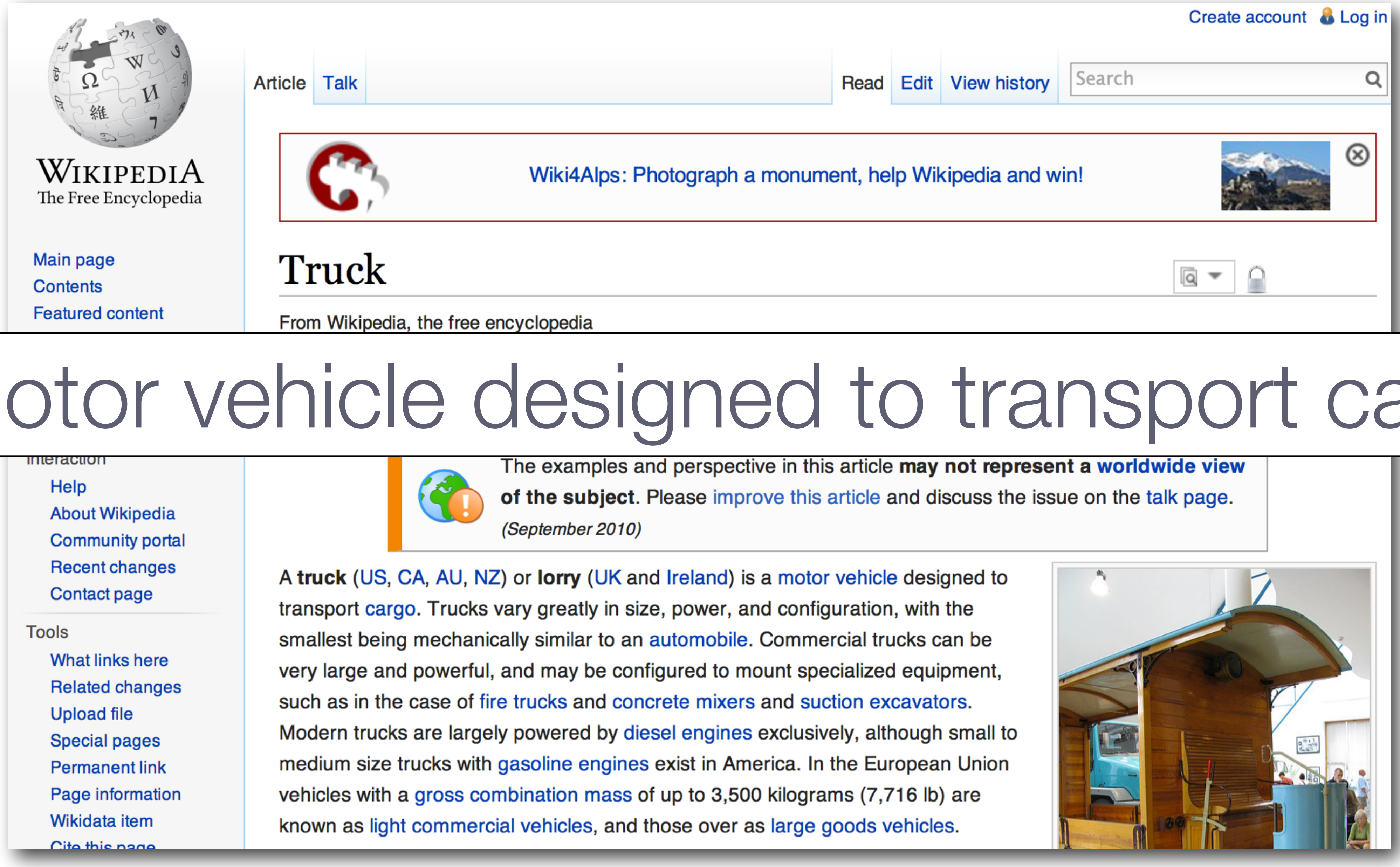
Truck

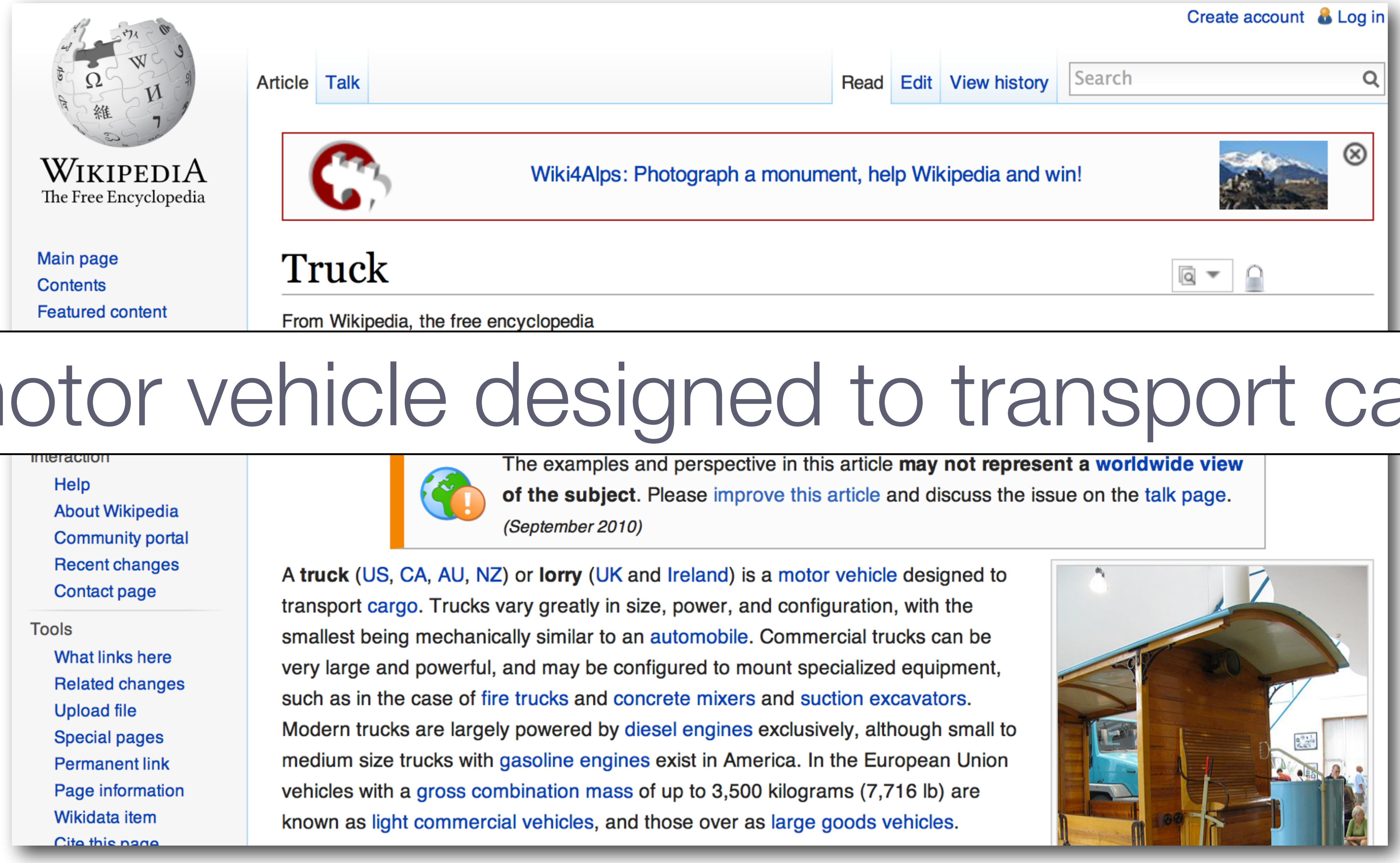


motor vehicle designed to transport cargo

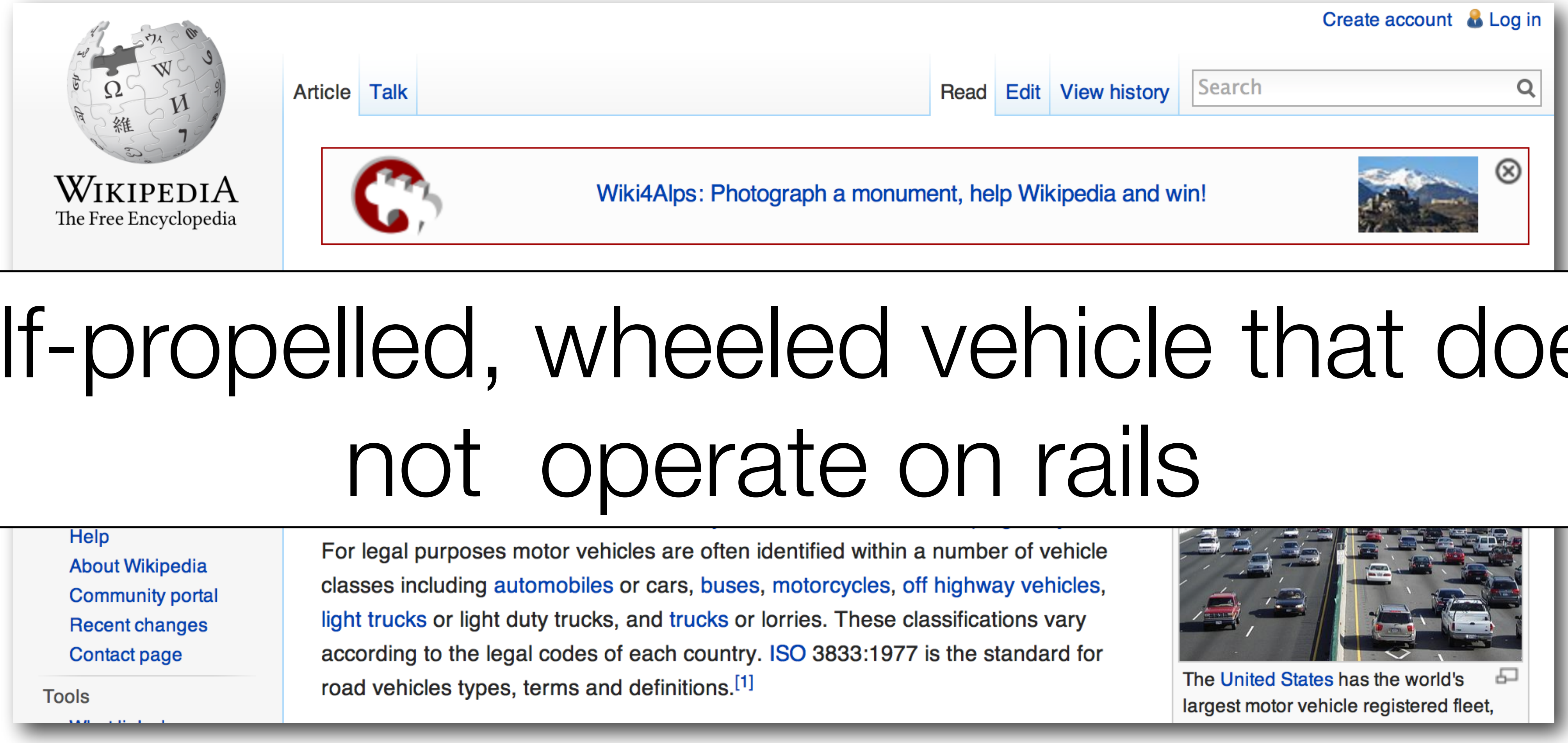
Inspiration from Human Structured Semantics

[Hwang et al., 2014]

Truck



motor vehicle designed to transport cargo

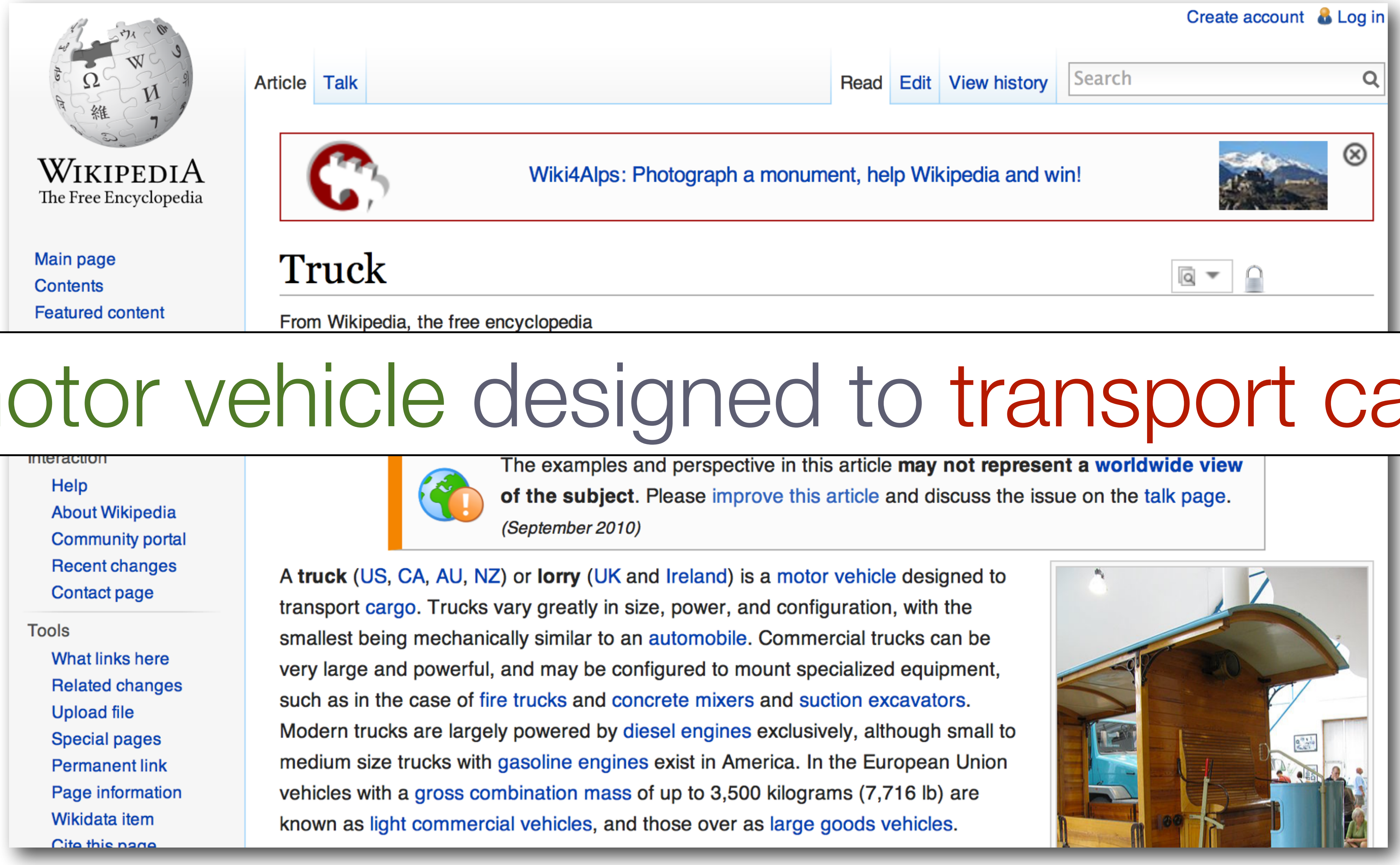


self-propelled, wheeled vehicle that does not operate on rails

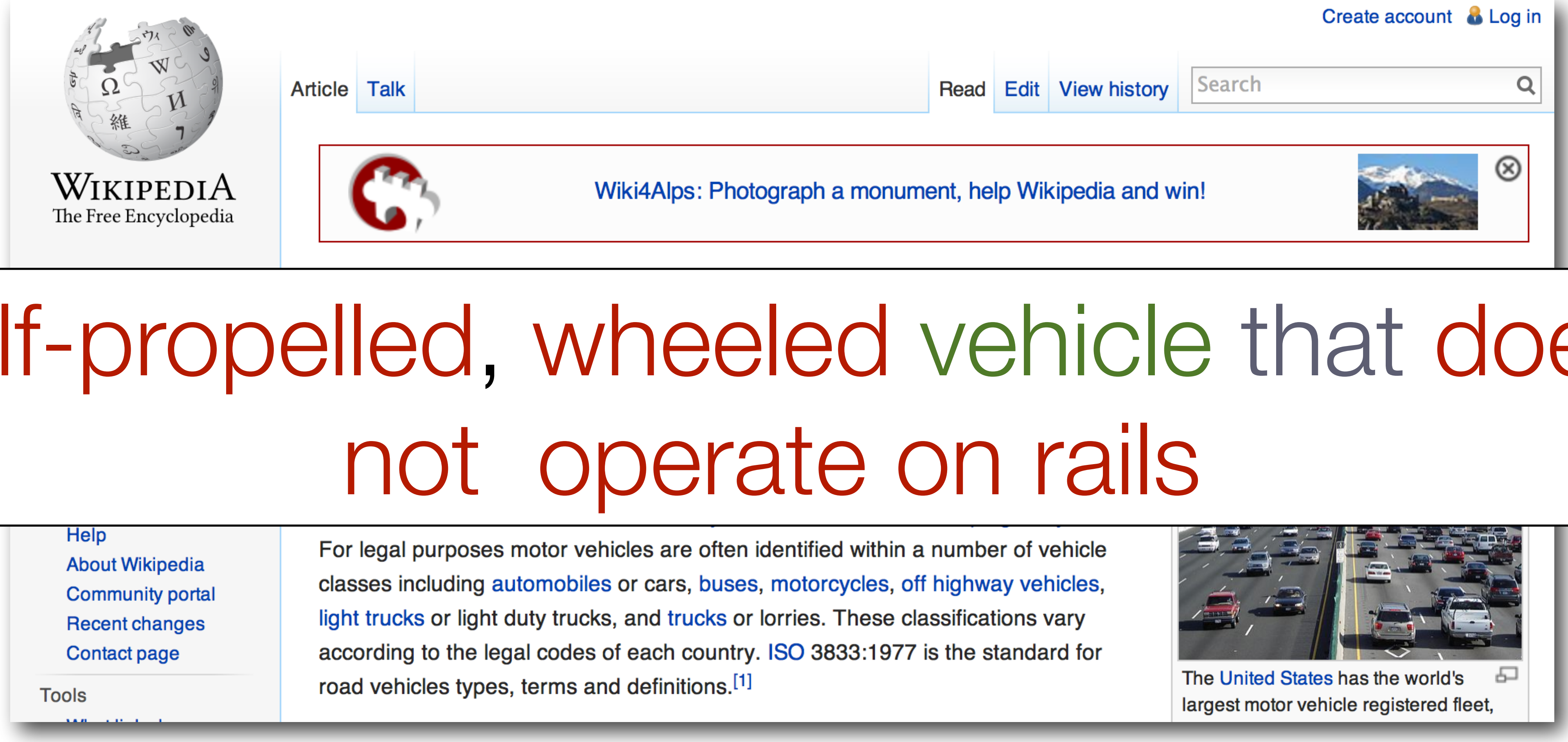
Inspiration from Human Structured Semantics

[Hwang et al., 2014]

Truck



motor vehicle designed to transport cargo



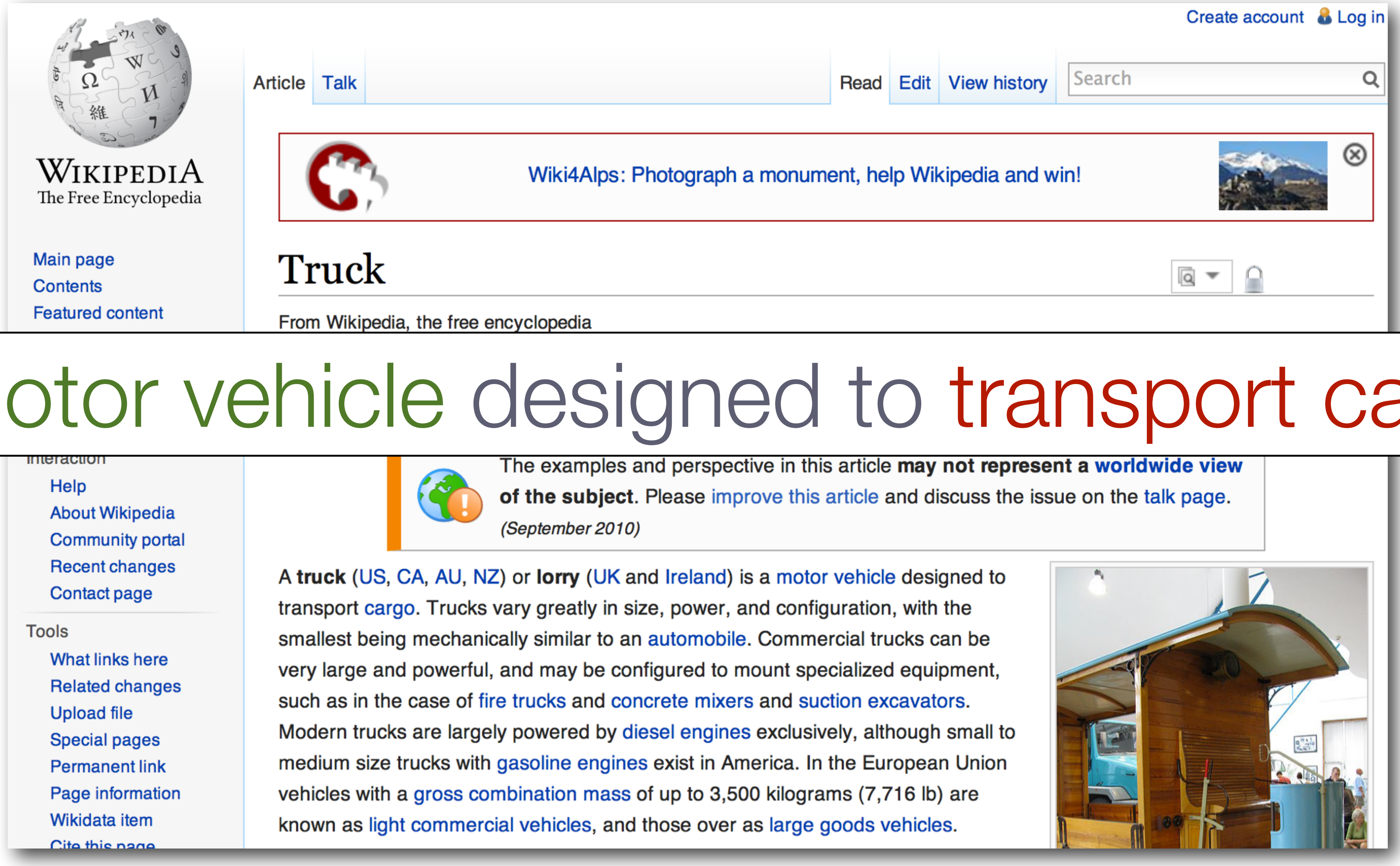
self-propelled, wheeled vehicle that does not operate on rails

Inspiration from Human Structured Semantics

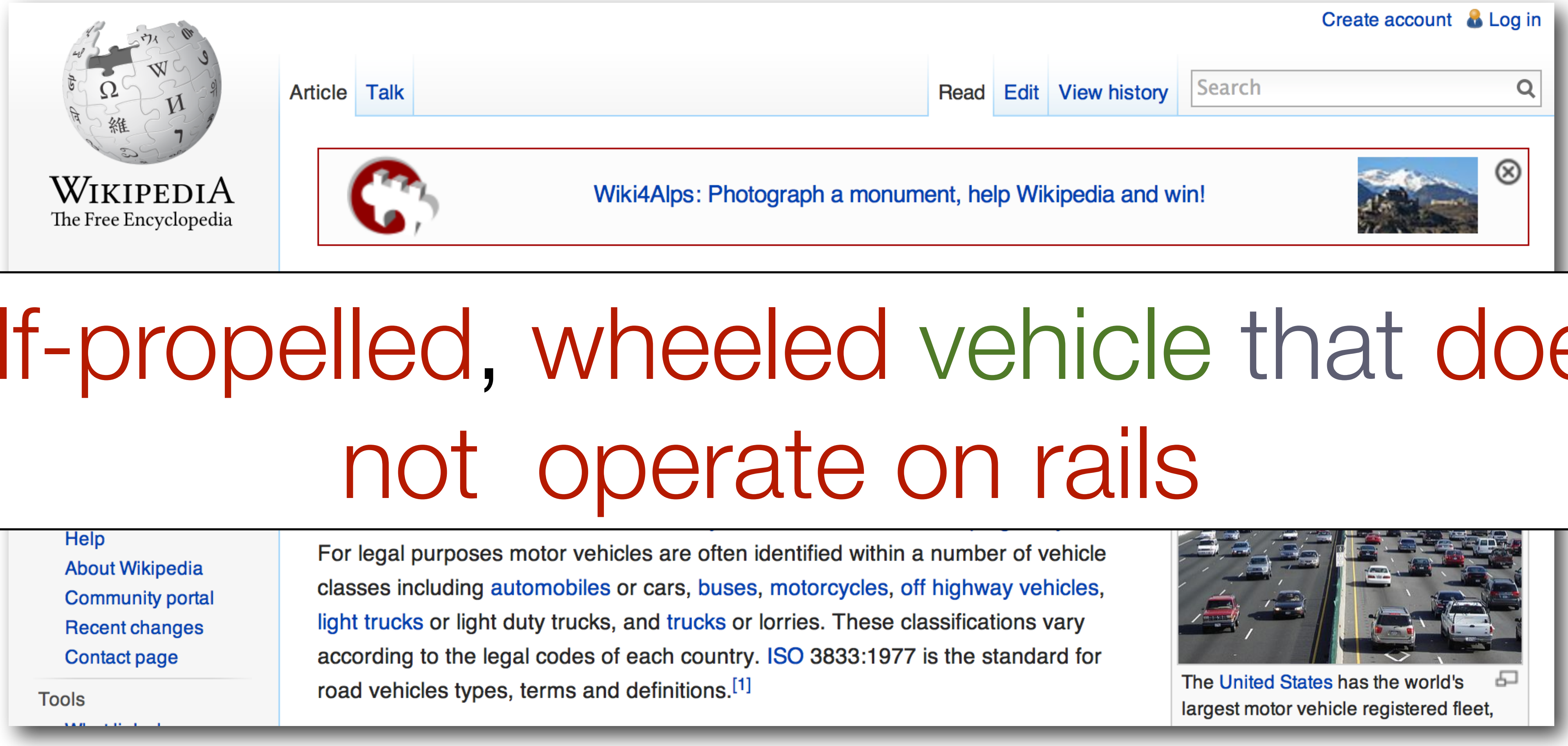
[Hwang et al., 2014]

Parent Category + Attributes

Truck



motor vehicle designed to transport cargo



self-propelled, wheeled vehicle that does not operate on rails

Unified Semantic Embedding

Adding regularization from **ontology / taxonomy** over labels

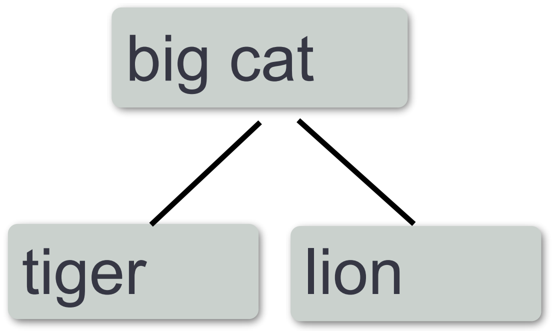
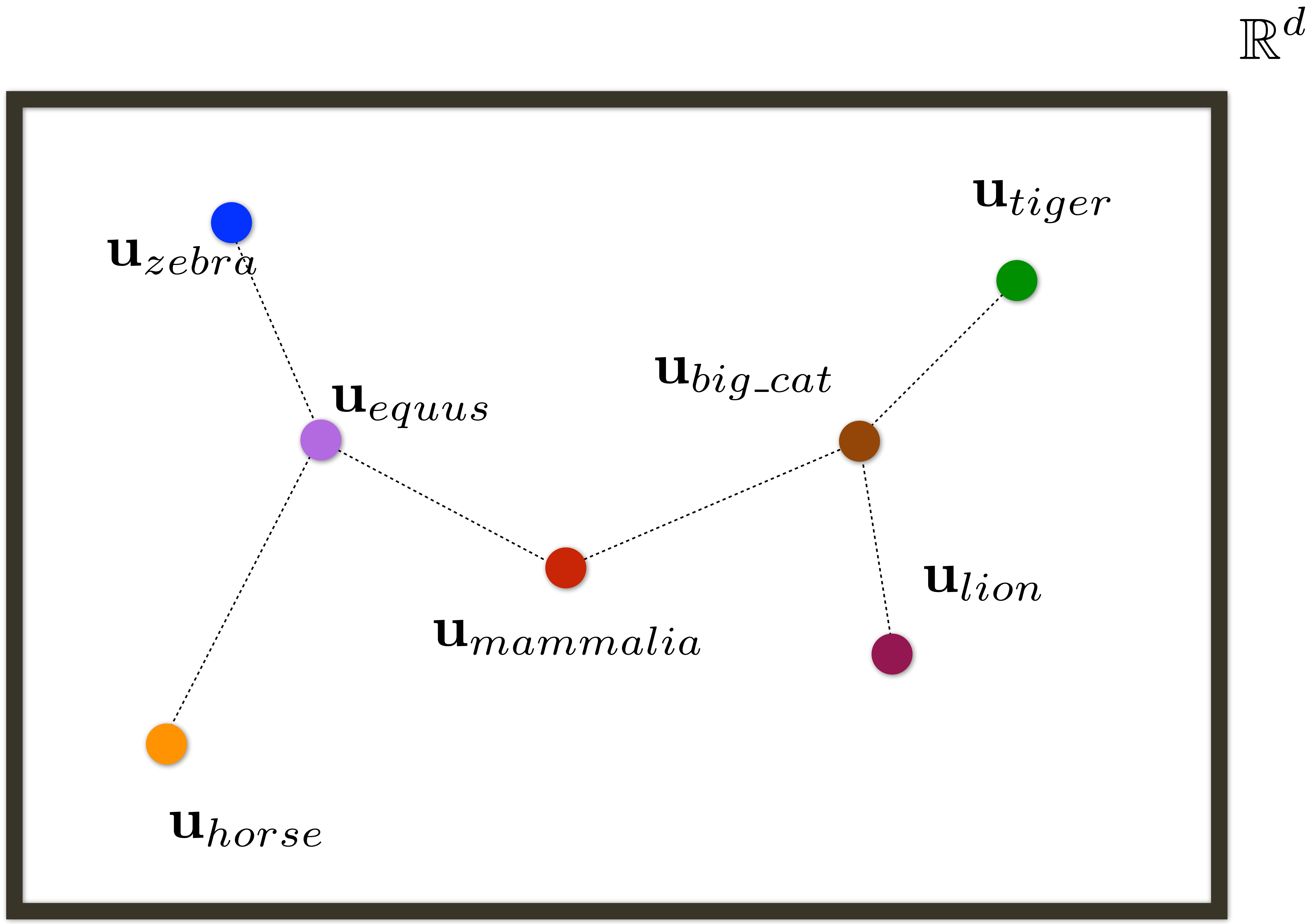


Image Embedding

$$\Psi_I(I_i) = \mathbf{W} \cdot CNN(I_i) : \mathbb{R}^D \rightarrow \mathbb{R}^d$$

Label Embedding

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



Similarity in Embedding Space

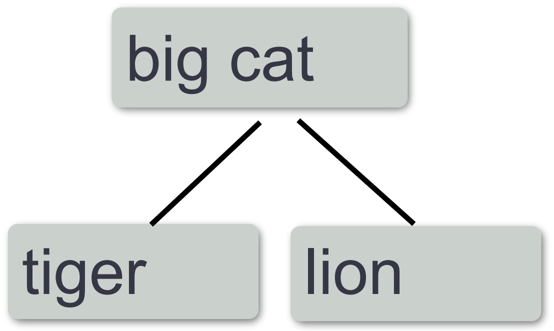
$$D(\mathbf{u}, \mathbf{u}') = ||\mathbf{u} - \mathbf{u}'||_2^2$$

Objective Function:

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

Unified Semantic Embedding

Adding regularization from **ontology / taxonomy** over labels



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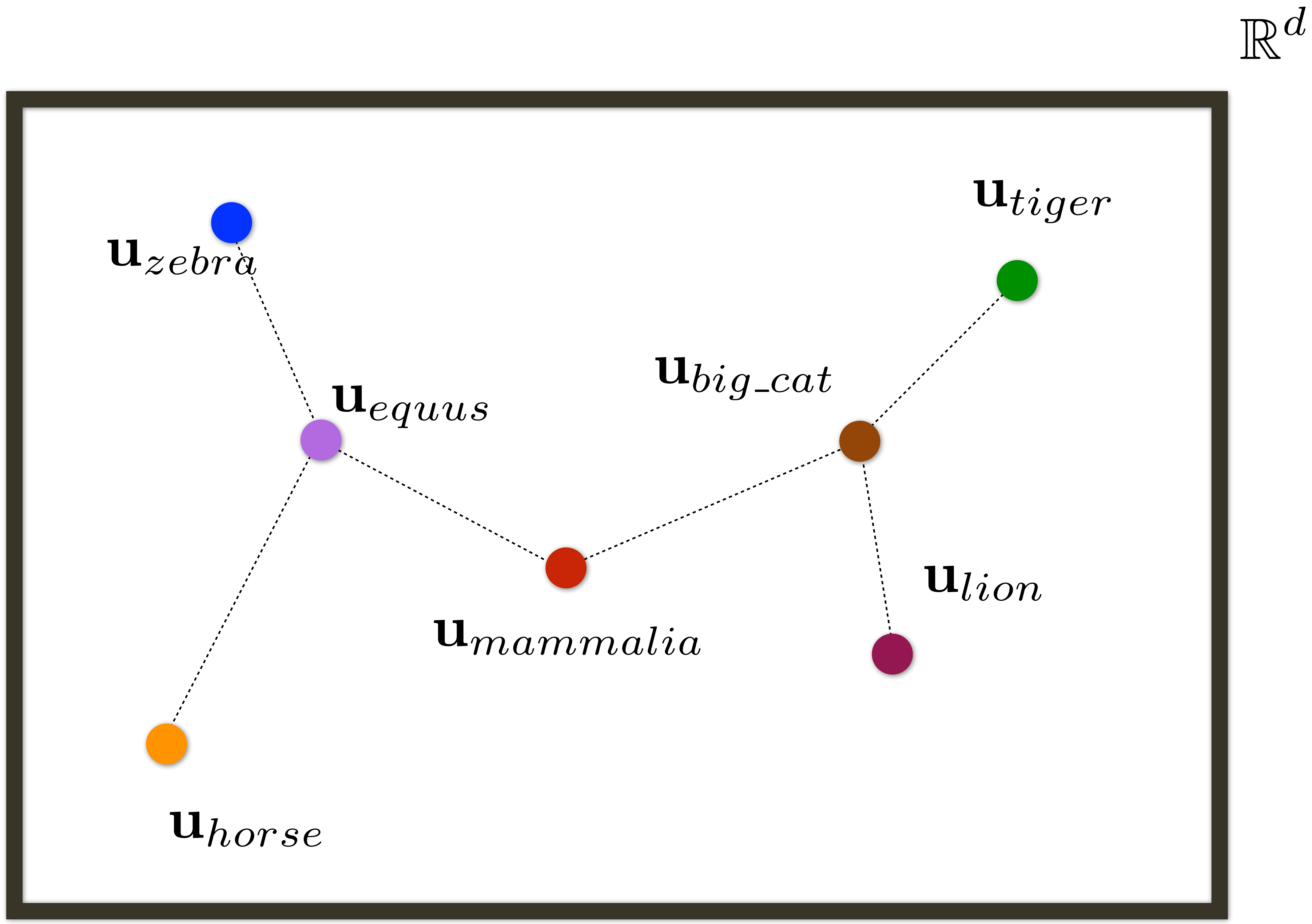

Similarity in Embedding Space

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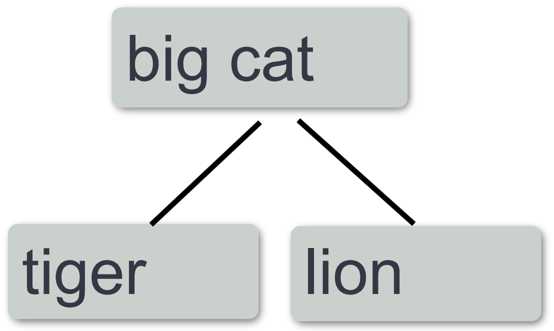
Objective Function:

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

Unified Semantic Embedding

Adding regularization from **ontology / taxonomy** over labels



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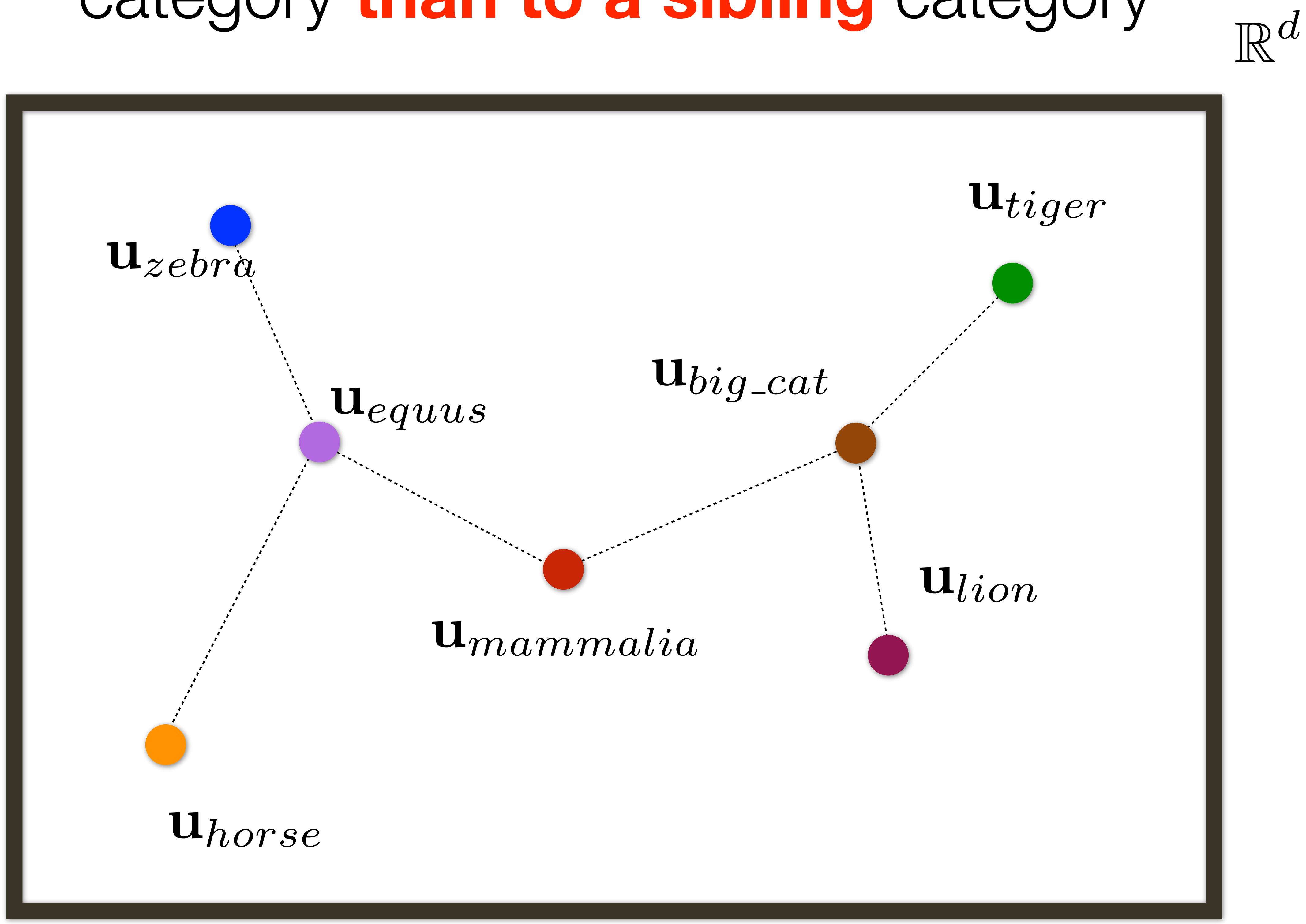
Label Embedding

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

Similarity in Embedding Space

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

Each sample is **closer to the parent** category **than to a sibling** category



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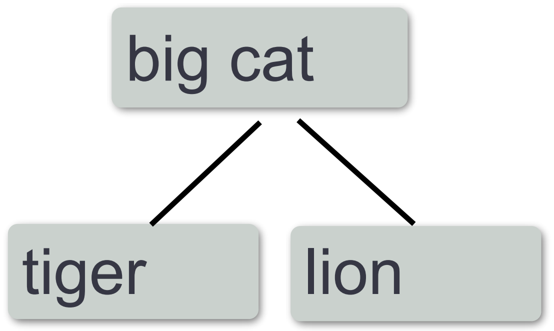
$$\min_{\mathbf{W},\mathbf{U},\mathbf{B}} \sum_i^N \mathcal{L}_C(\mathbf{W},\mathbf{U},I_i,y_i) + \underline{\mathcal{L}_S(\mathbf{W},\mathbf{U},I_i,y_i)} + \mathcal{L}_A(\mathbf{W},\mathbf{U},I_i,y_i) + \mathcal{R}(\mathbf{U},\mathcal{B}) + \lambda_1||\mathbf{W}||_F^2 + \lambda_2||\mathbf{U}||_F^2$$

Unified Semantic Embedding

Adding regularization from **ontology / taxonomy** over labels



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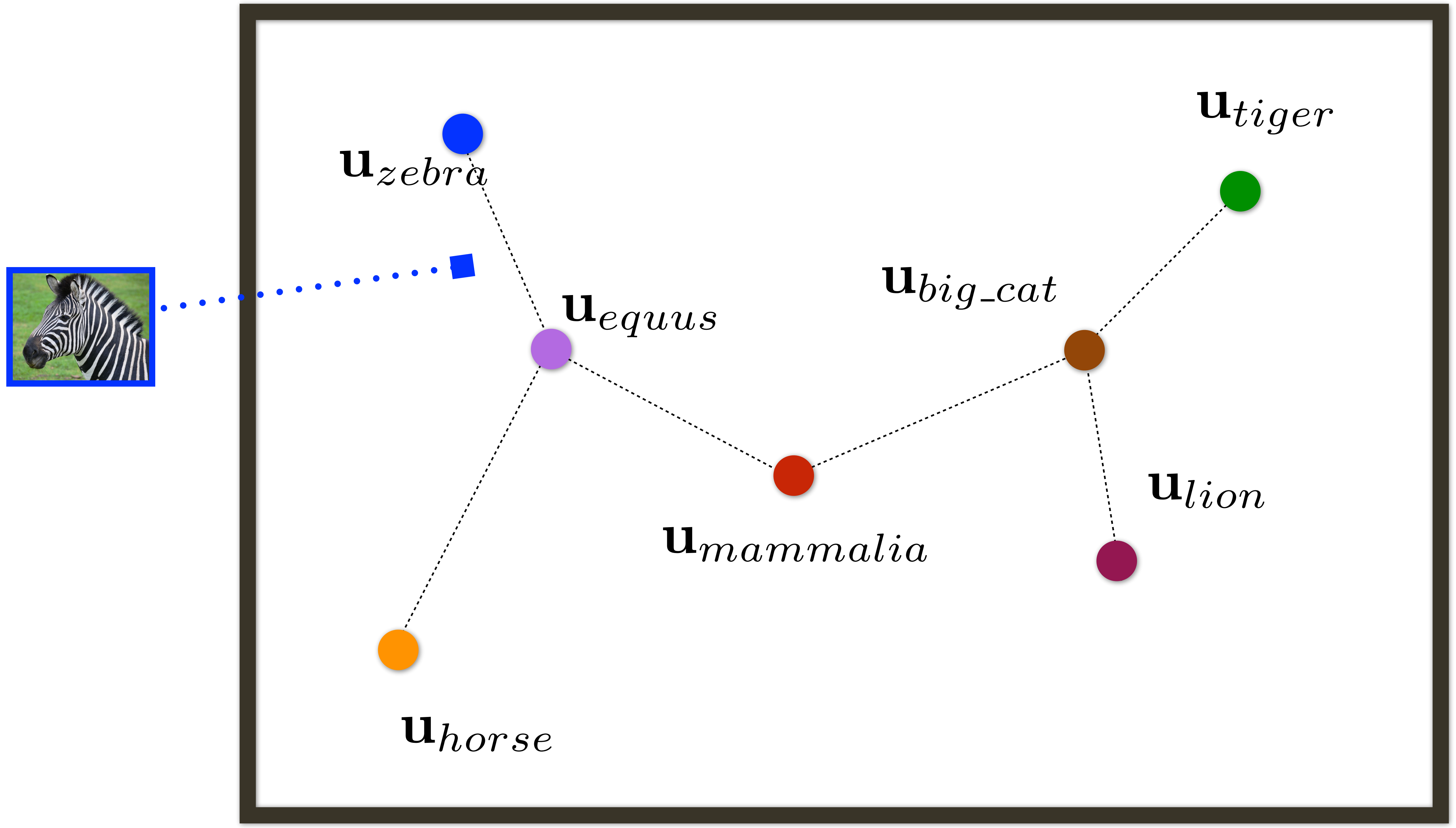
Each sample is **closer to the parent** category **than to a sibling** category

$\mathbb{R}^d$



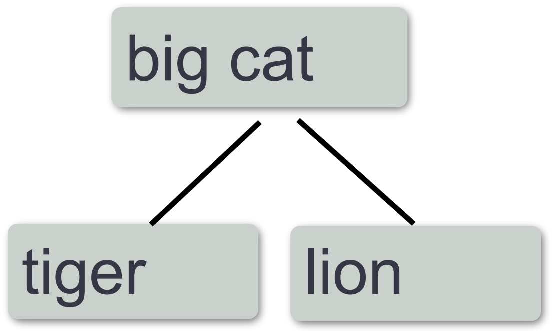
Similarity in Embedding Space

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

Objective Function:

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

Unified Semantic Embedding



Adding regularization from **ontology / taxonomy** over labels

Image Embedding

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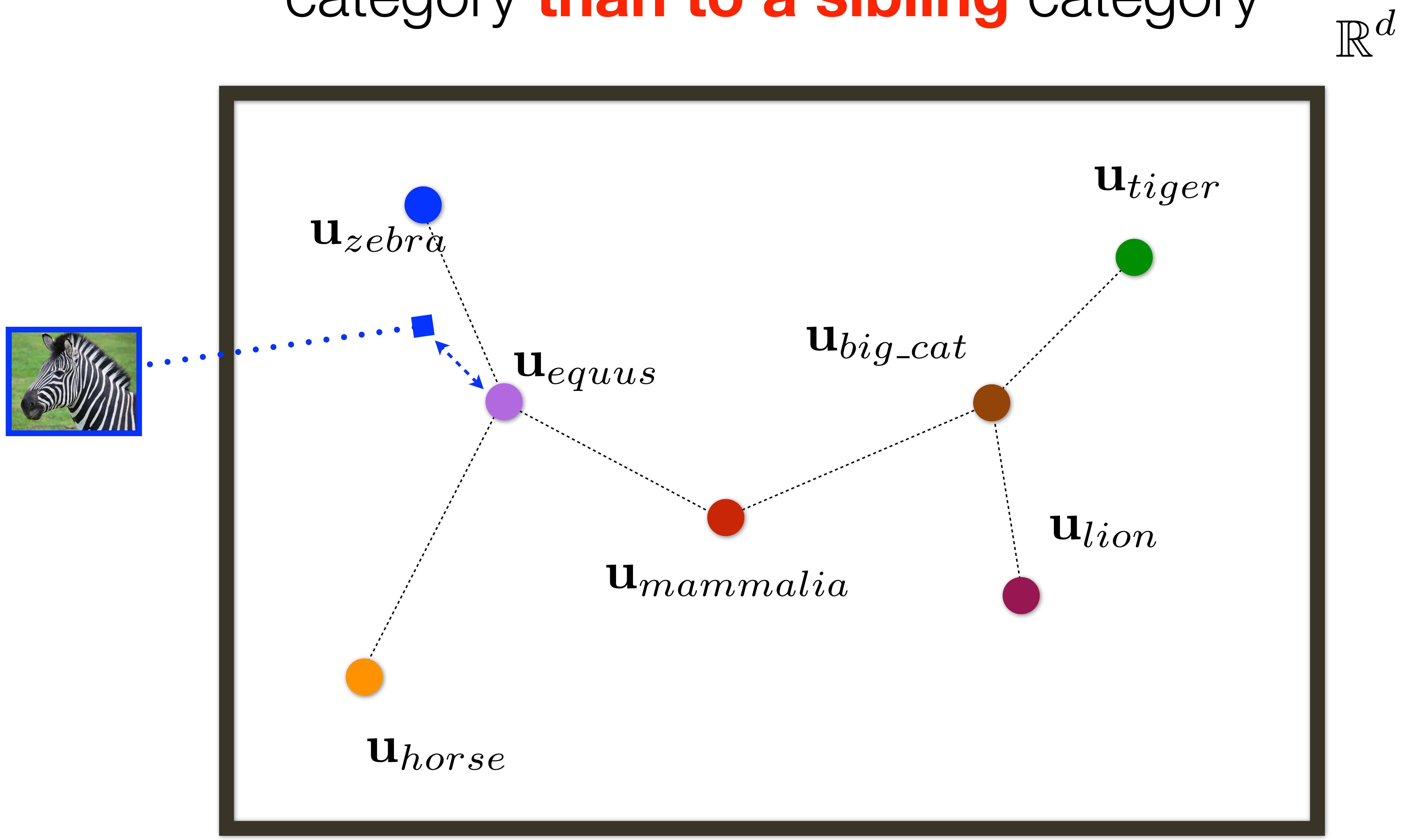
Each sample is **closer to the parent** category **than to a sibling** category



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Unified Semantic Embedding

Adding regularization from **ontology / taxonomy** over labels

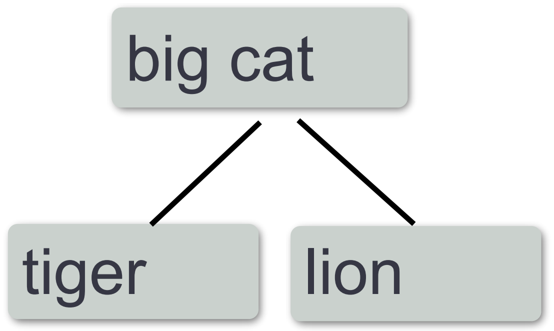

Image Embedding

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Label Embedding

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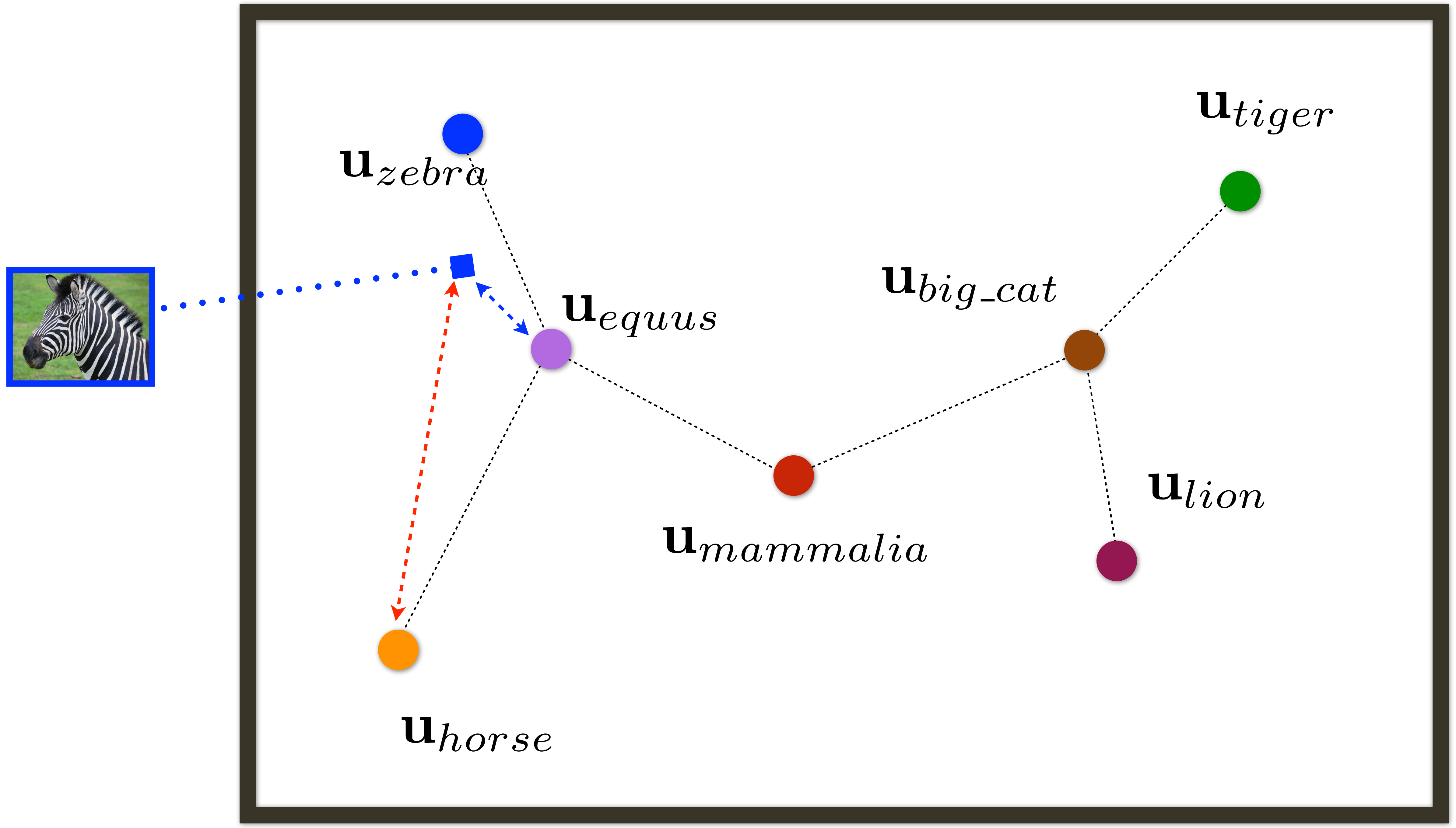
Each sample is **closer to the parent** category **than to a sibling** category

$\mathbb{R}^d$



Similarity in Embedding Space

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Objective Function:

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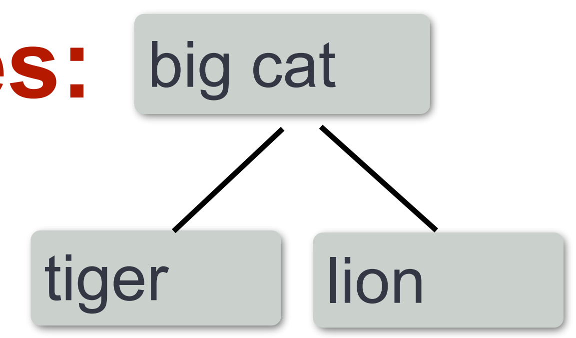
Unified Semantic Embedding

Adding regularization from **ontology / taxonomy** over labels

Taxonomies:



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Label Embedding

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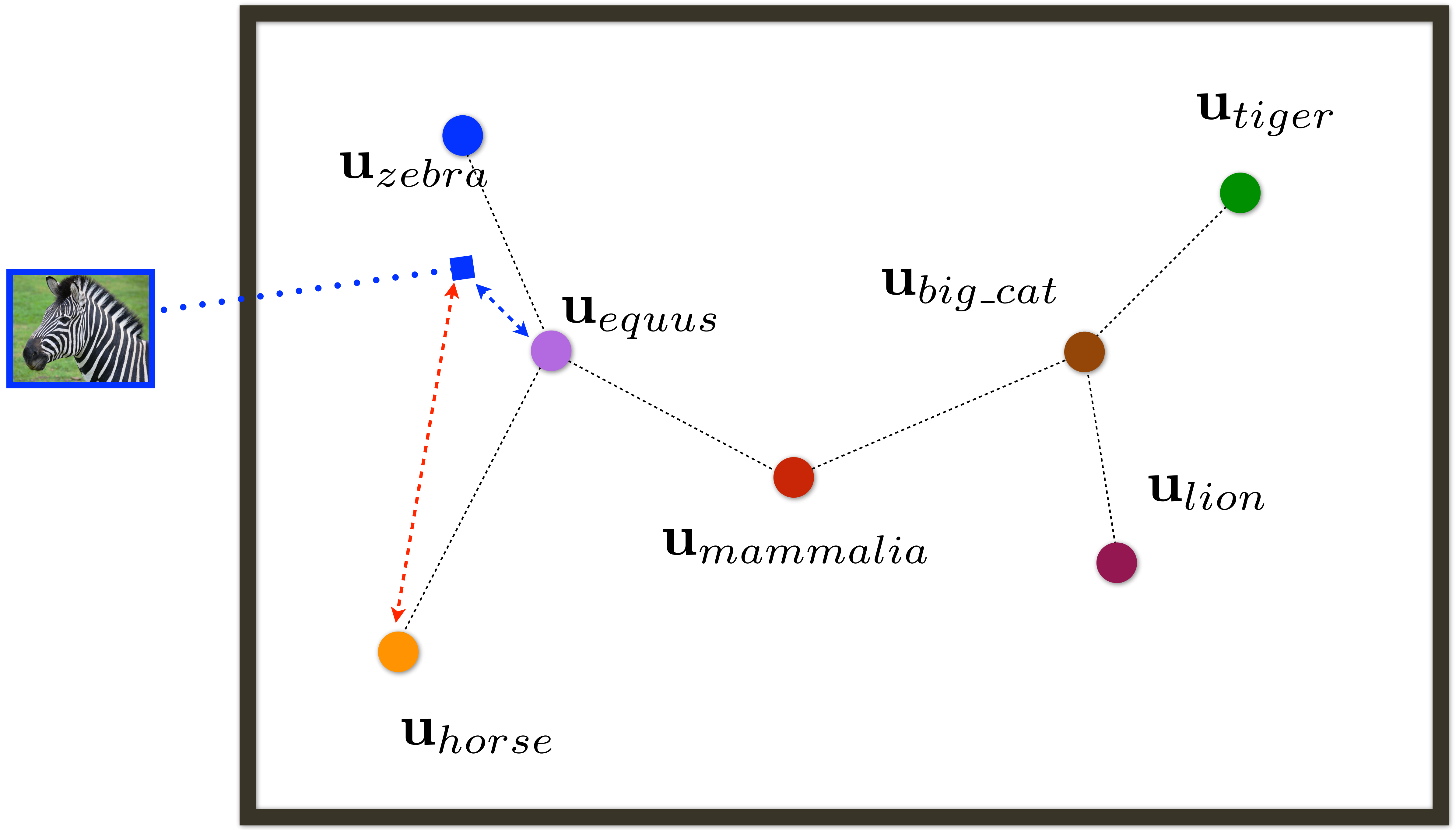
$$\mathcal{L}_S(\boldsymbol{W}, \boldsymbol{U}, \boldsymbol{x}_i, y_i) = \sum_{s \in \mathcal{P}_{y_i}} \sum_{c \in \mathcal{S}_s} [1 + \|\boldsymbol{W}\boldsymbol{x}_i - \boldsymbol{u}_s\|_2^2 - \|\boldsymbol{W}\boldsymbol{x}_i - \boldsymbol{u}_c\|_2^2]_+$$



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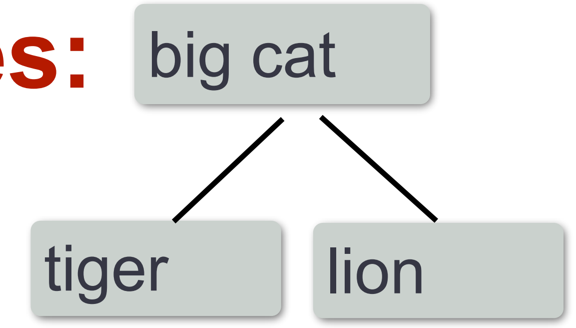
Unified Semantic Embedding

Adding regularization from **ontology / taxonomy** over labels

Taxonomies:



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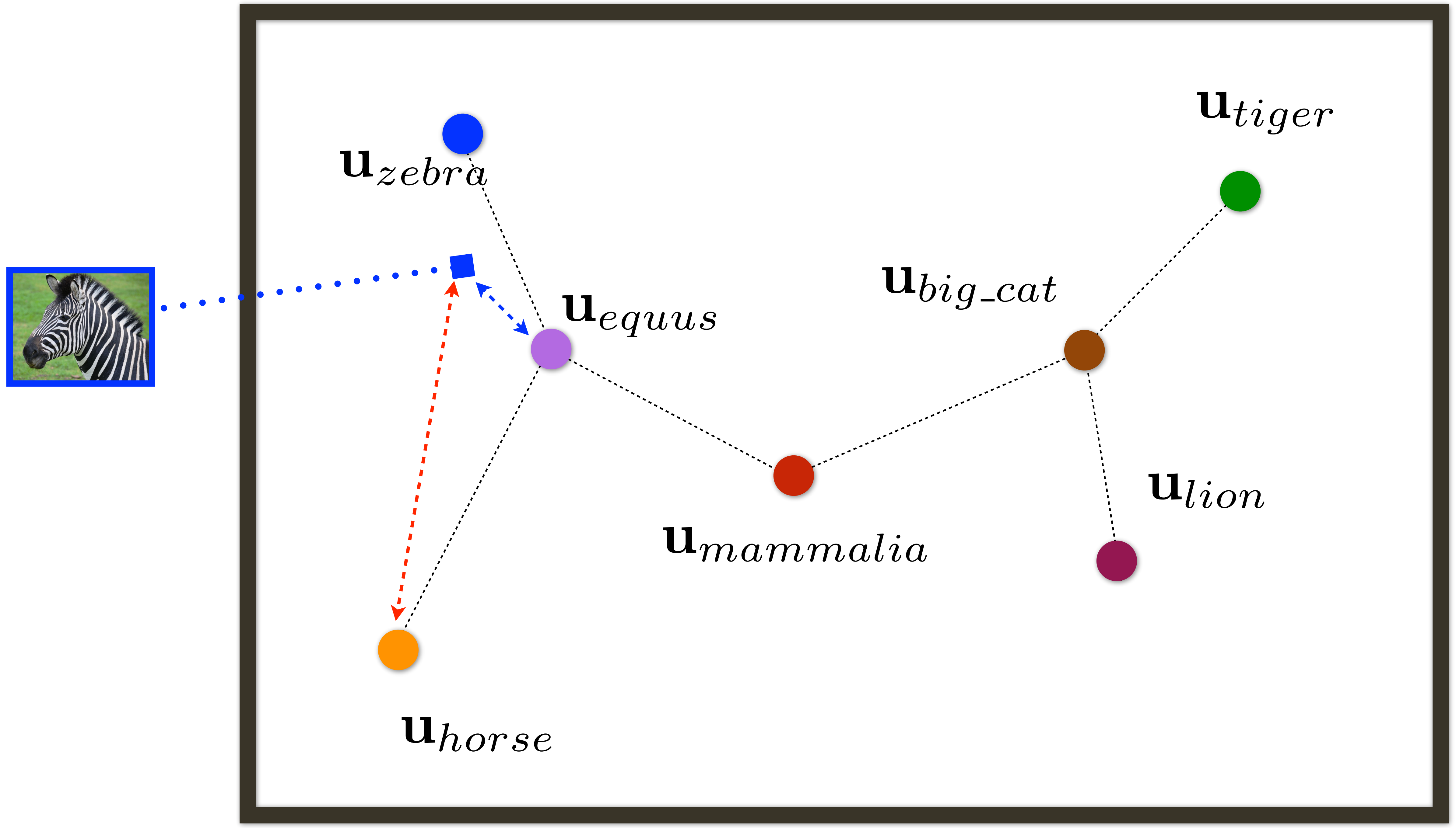

Similarity in Embedding Space

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Objective Function:

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Unified Semantic Embedding

Attributes : has(zebra, Stripes)

Attributes embedded as (basis) **vectors** in the semantic space

Image Embedding

$$\Psi_I(I_i) = \mathbf{W} \cdot CNN(I_i) : \mathbb{R}^D \rightarrow \mathbb{R}^d$$

Label Embedding

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

Attribute Embedding

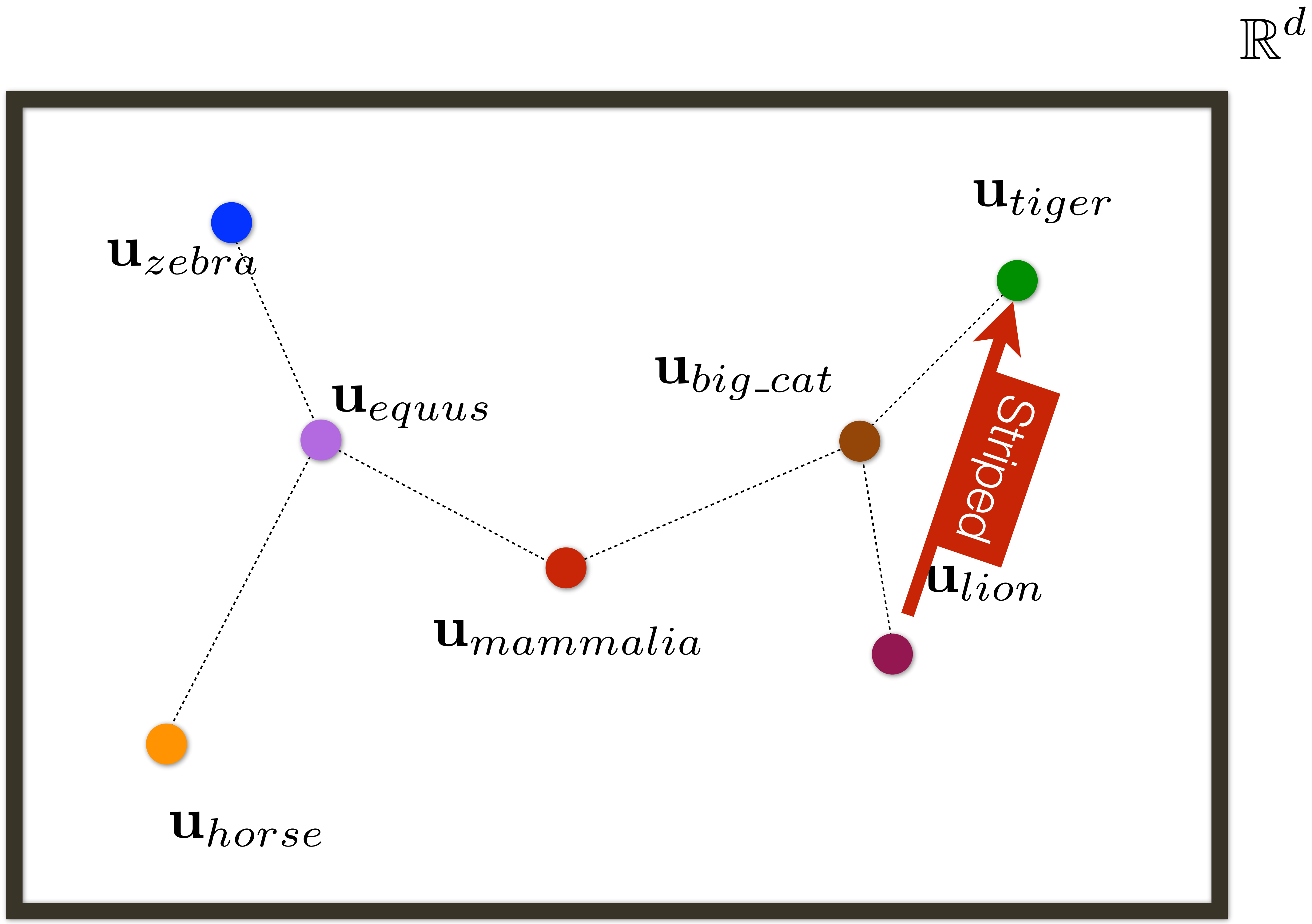
$$\Psi_A(attr_i) = \mathbf{a}_i \ : \{1, ..., A\} \rightarrow \mathbb{R}^d, s.t. \ ||\mathbf{a}_i||^2 \leq 1$$

Similarity in Embedding Space

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

Objective Function:

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



Unified Semantic Embedding

[Hwang et al., 2014]

$$\mathcal{R}(\boldsymbol{U}, \boldsymbol{B}) = \sum_{c}^{C} \|\boldsymbol{u}_c - \boldsymbol{u}_p - \boldsymbol{U}^A \boldsymbol{\beta}_c\|_2^2 + \gamma_2 \|\boldsymbol{\beta}_c + \boldsymbol{\beta}_o\|_2^2.$$

each category is a parent + sparse subset of attribute bases

Image Embedding

$$\Psi_I(I_i) = \mathbf{W} \cdot CNN(I_i) : \mathbb{R}^D \rightarrow \mathbb{R}^d$$

Label Embedding

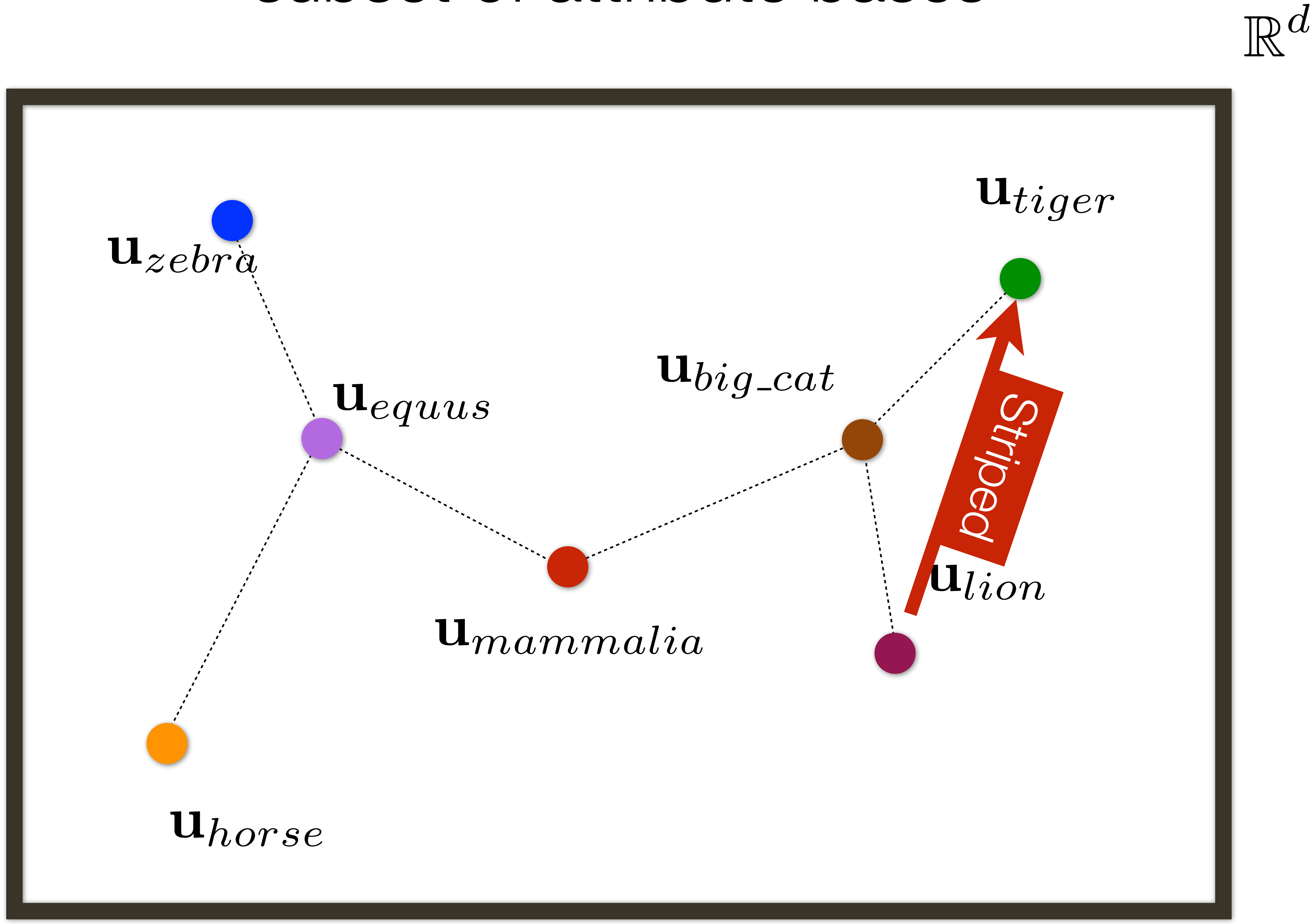
$$\Psi_L(word_i) = \mathbf{u}_i : \{1, ..., L\} \rightarrow \mathbb{R}^d$$

Attribute Embedding

$$\Psi_A(attr_i) = \mathbf{a}_i : \{1, ..., A\} \rightarrow \mathbb{R}^d, s.t. ||\mathbf{a}_i||^2 \leq 1$$

Similarity in Embedding Space

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



Objective Function:

$$\min_{\mathbf{W},\mathbf{U},\mathbf{B}} \sum_{i}^{N} \mathcal{L}_C(\mathbf{W}, \mathbf{U}, I_i, y_i) + \mathcal{L}_S(\mathbf{W}, \mathbf{U}, I_i, y_i) + \mathcal{L}_A(\mathbf{W}, \mathbf{U}, I_i, y_i) + \underline{\mathcal{R}(\mathbf{U}, \mathcal{B})} + \lambda_1 ||\mathbf{W}||_F^2 + \lambda_2 ||\mathbf{U}||_F^2$$

Unified Semantic Embedding

[Hwang et al., 2014]

Image Embedding

$$\Psi_I(I_i) = \mathbf{W} \cdot CNN(I_i) : \mathbb{R}^D \rightarrow \mathbb{R}^d$$

Label Embedding

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

Attribute Embedding

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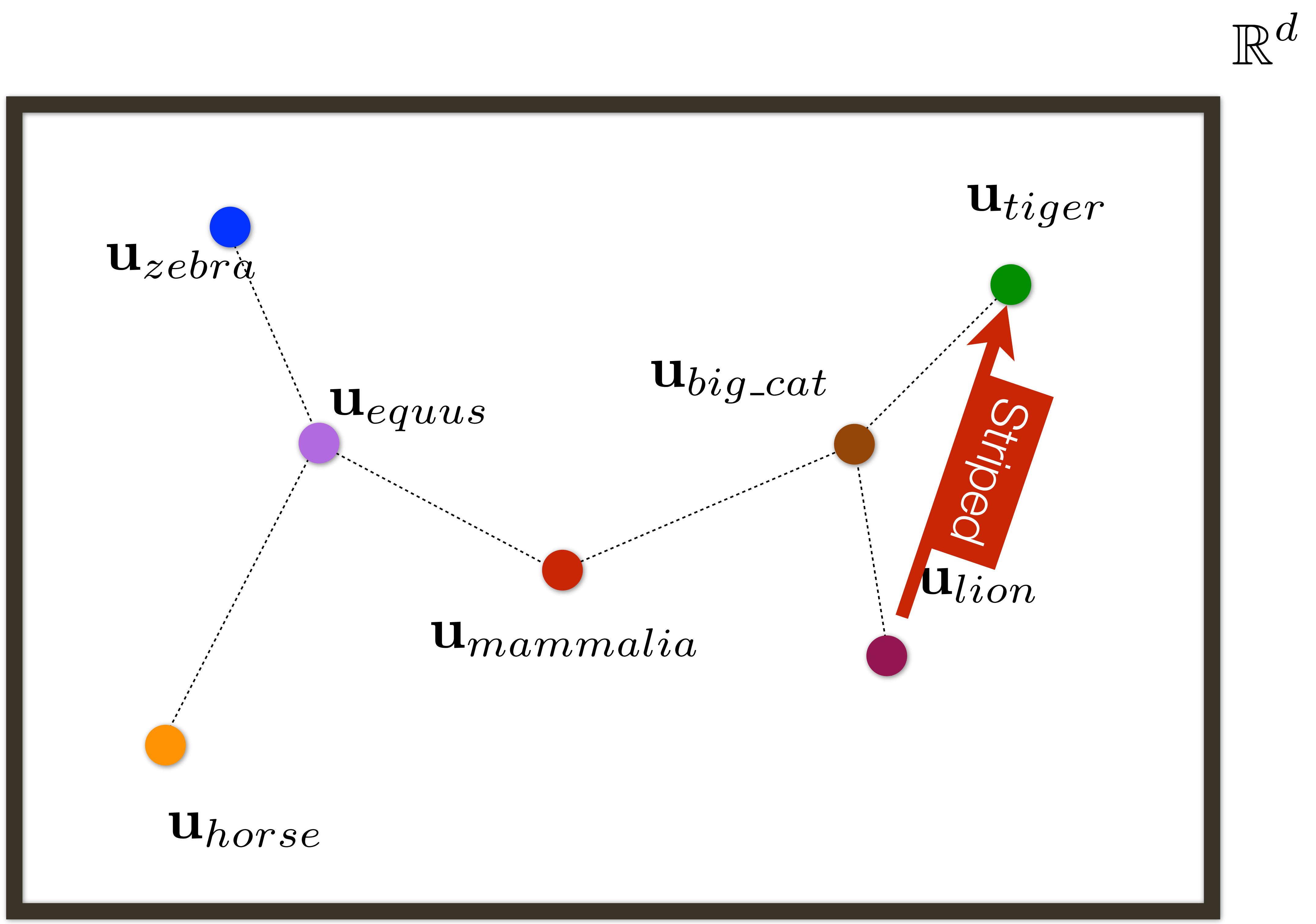
$$D(\mathbf{u}, \mathbf{u}') = ||\mathbf{u} - \mathbf{u}'||_2^2$$

Objective Function:

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

Alternating optimization



Experiments: Animals with Attributes (AwA) Dataset

Labeled Images

30,475 Images

50 Animal Classes

Semantic Attributes

black
white
blue
brown
gray
orange
red
yellow
patches

...

paws
longlegs
longneck
tail
chew teeth
meat teeth
buck teeth
horns
claws
tusks

85 Attributes

[Lampert, Nickisch, Harmeling, CVPR'09]

Experiments: Animals with Attributes (AwA) Dataset

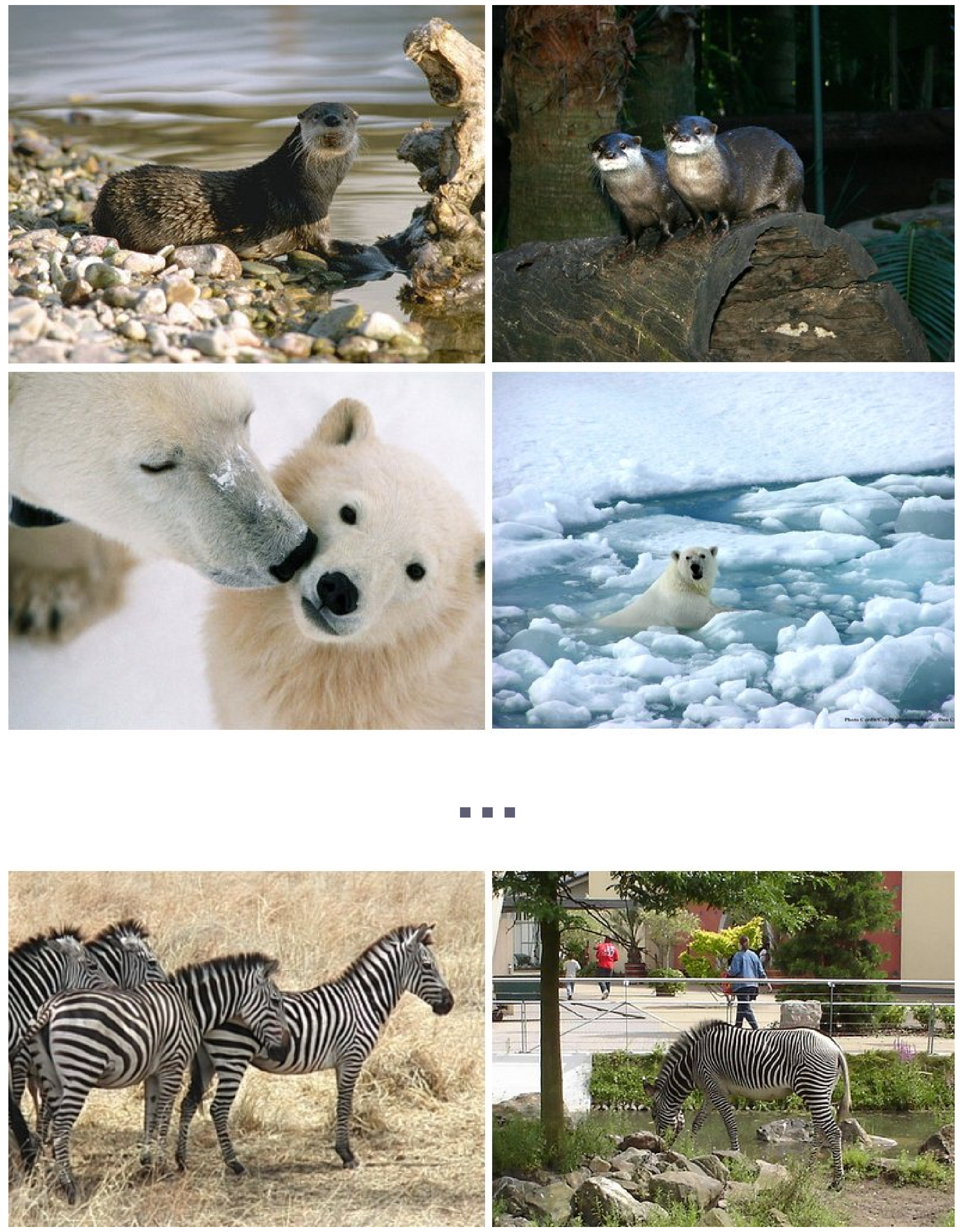
Labeled Images

Otter

Polar Bear

...

Zebra



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horns
claws
tusks

85 Attributes

Class Ontology

WordNet
A lexical database for English

50 Animal Classes are Leaves

[Lampert, Nickisch, Harmeling, CVPR'09]

Experiments: Animals with Attributes (AwA) Dataset

(we assume no association between classes and attributes)

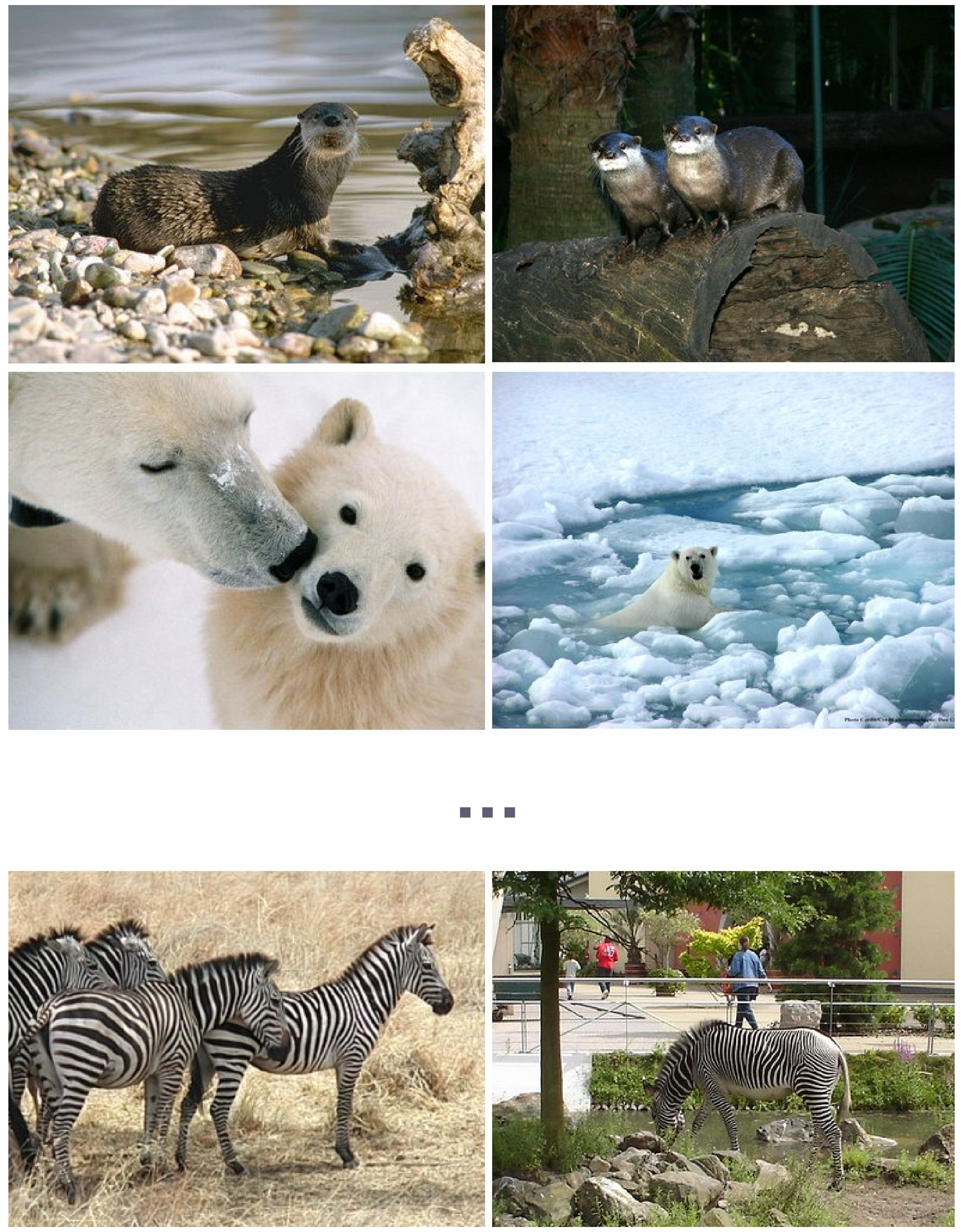
Labeled Images

Otter

Polar Bear

...

Zebra



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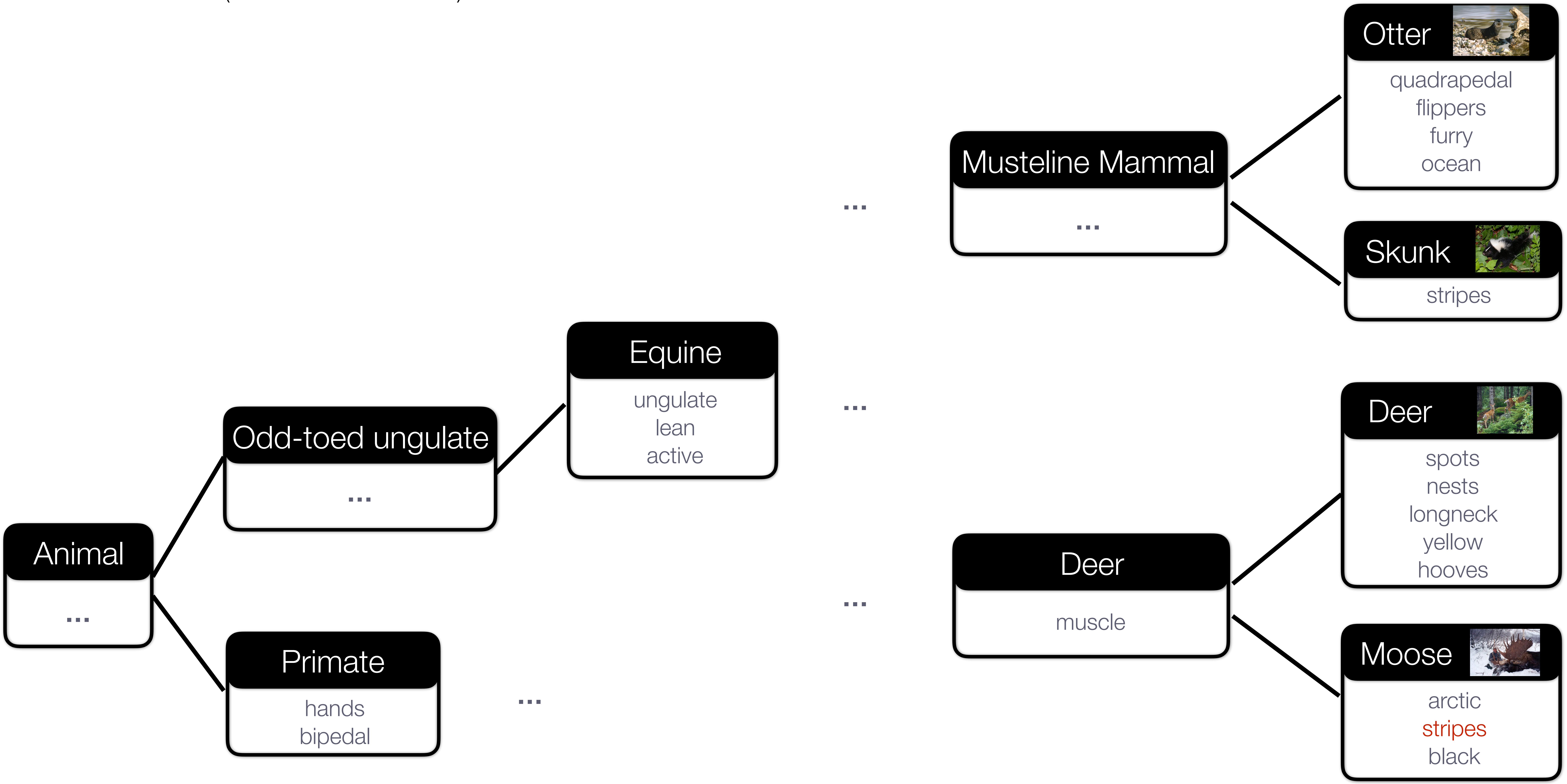
[Lampert, Nickisch, Harmeling, CVPR'09]

Experiments

[Hwang et al., 2014]

Results with AWA (with latent attributes)



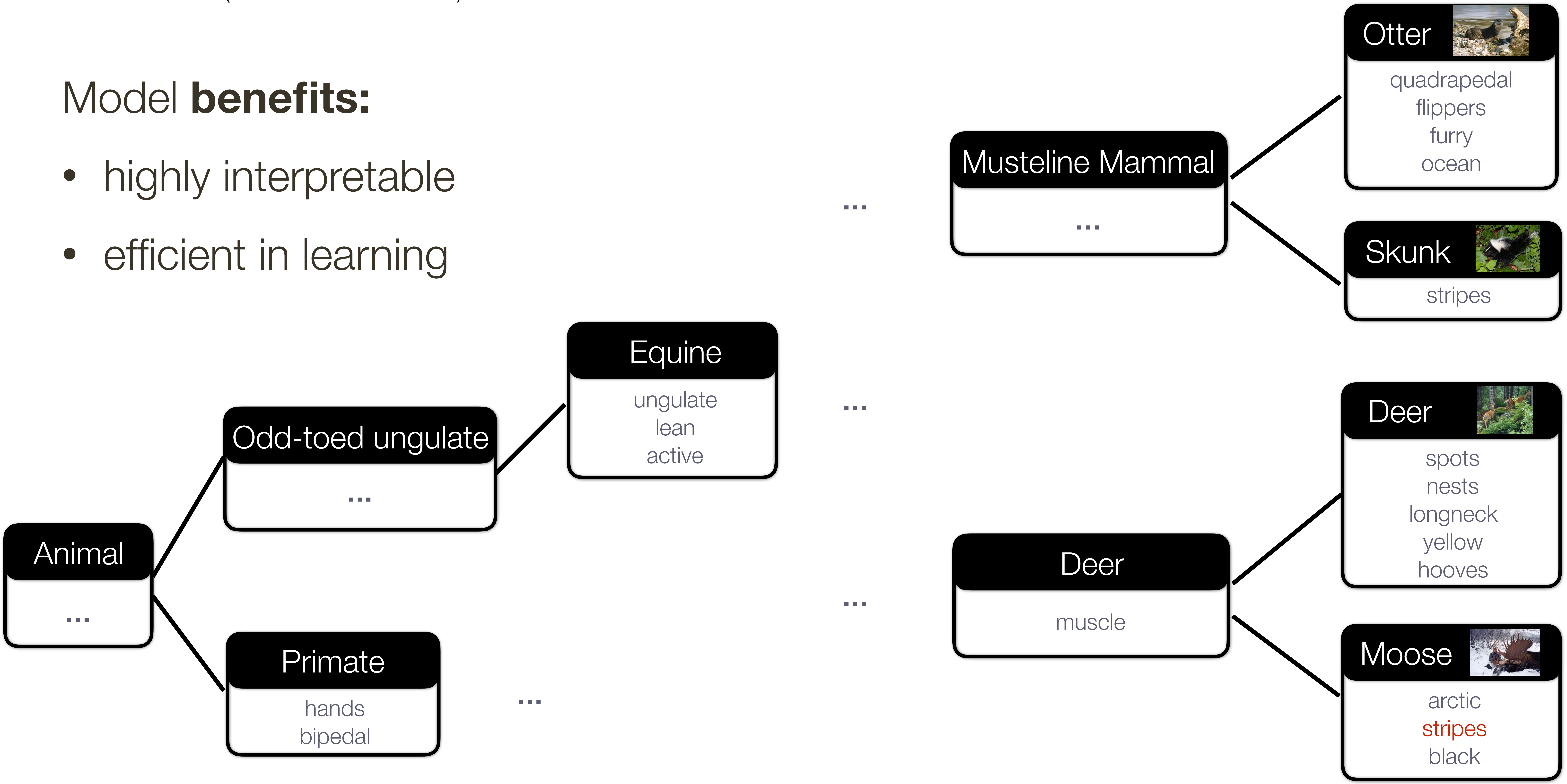
Experiments

[Hwang et al., 2014]

Results with AWA (with latent attributes)

Model **benefits:**

- highly interpretable
- efficient in learning



Experiments

Results with AWA (with latent attributes)

[Hwang et al., 2014]

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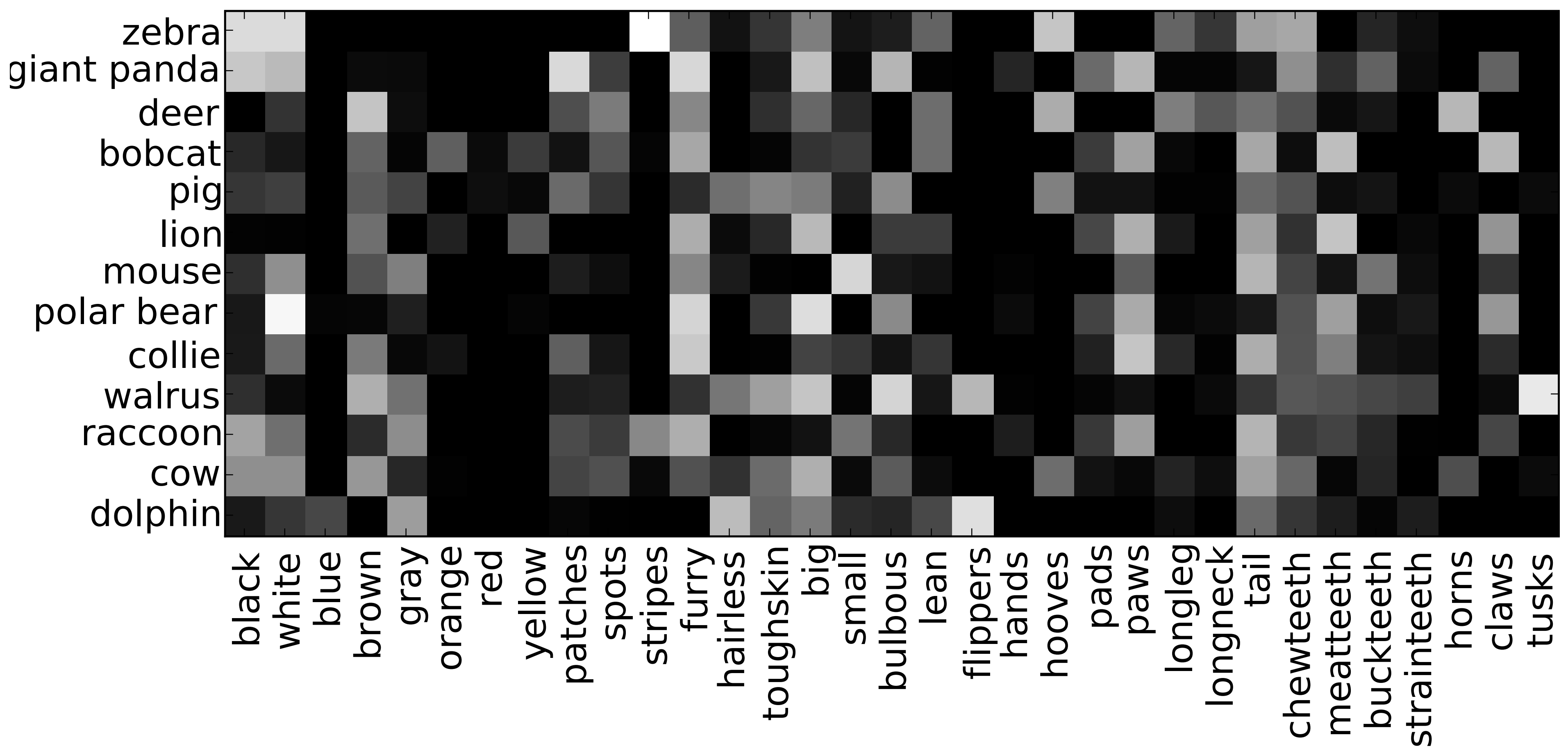
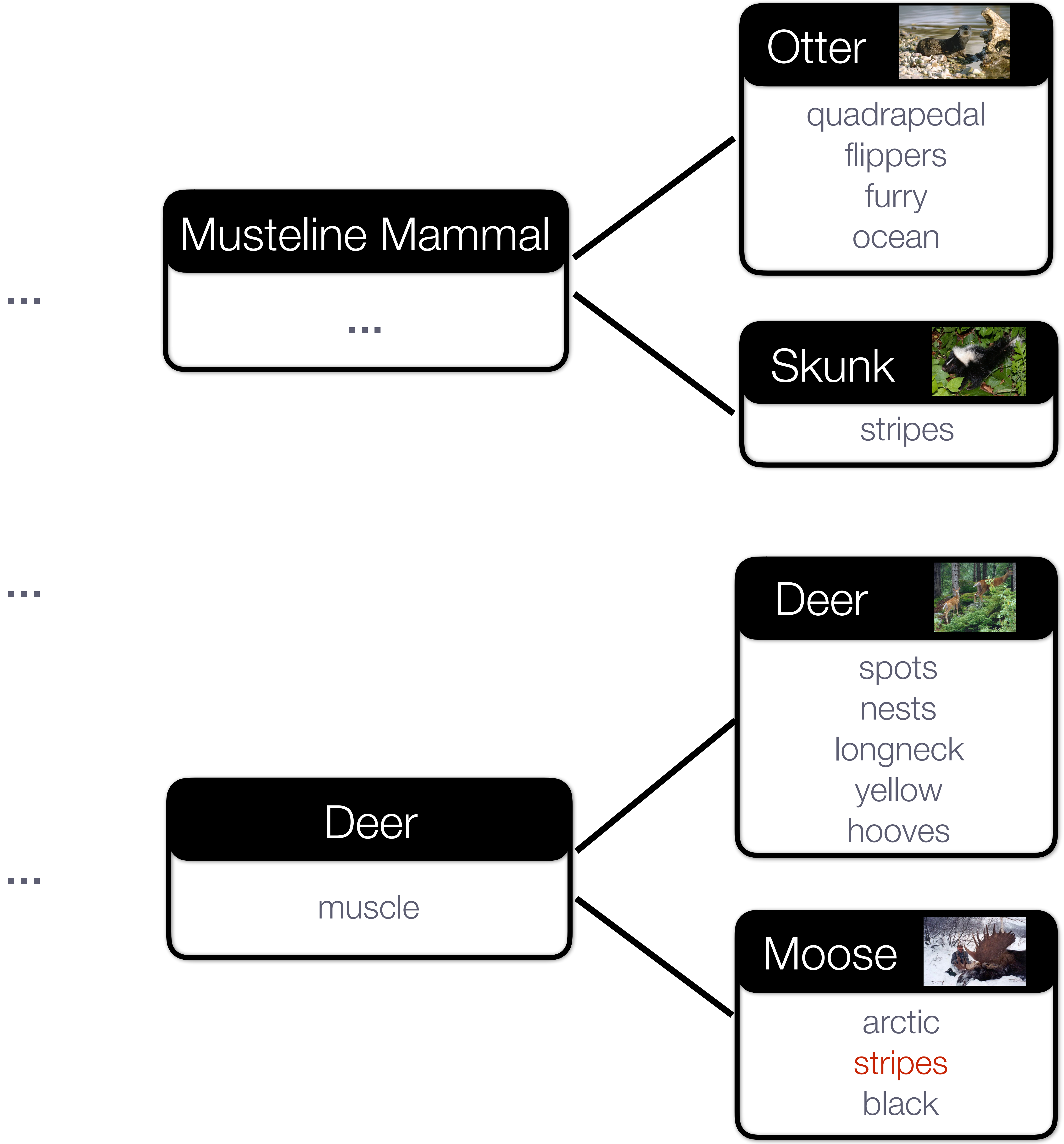


alternative attribute-based representations



Experiments

[Hwang et al., 2014]

Results with AWA (with latent attributes)

	Method	Flat hit @ k (%) 1	Flat hit @ k (%) 2	Flat hit @ k (%) 5	Hierarchical precision @ k (%) 2	Hierarchical precision @ k (%) 5
No semantics	Ridge Regression	38.39 ± 1.48	48.61 ± 1.29	62.12 ± 1.20	38.51 ± 0.61	41.73 ± 0.54
	NCM **[1]**	43.49 ± 1.23	57.45 ± 0.91	75.48 ± 0.58	45.25 ± 0.52	50.32 ± 0.47
	LME	44.76 ± 1.77	58.08 ± 2.05	75.11 ± 1.48	44.84 ± 0.98	49.87 ± 0.39
Implicit semantics	LMTE **[2]**	38.92 ± 1.12	49.97 ± 1.16	63.35 ± 1.38	38.67 ± 0.46	41.72 ± 0.45
	ALE **[3]**	36.40 ± 1.03	50.43 ± 1.92	70.25 ± 1.97	42.52 ± 1.17	52.46 ± 0.37
	HLE **[3]**	33.56 ± 1.64	45.93 ± 2.56	64.66 ± 1.77	46.11 ± 2.65	$\mathbf{56.79 \pm 2.05}$
	AHLE **[3]**	38.01 ± 1.69	52.07 ± 1.19	71.53 ± 1.41	44.43 ± 0.66	54.39 ± 0.55
Explicit semantics	LME-MTL-S	45.03 ± 1.32	57.73 ± 1.75	74.43 ± 1.26	46.05 ± 0.89	51.08 ± 0.36
	LME-MTL-A	45.55 ± 1.71	58.60 ± 1.76	74.97 ± 1.15	44.23 ± 0.95	48.52 ± 0.29
USE	USE-No Reg.	45.93 ± 1.76	59.37 ± 1.32	74.97 ± 1.15	47.13 ± 0.62	51.04 ± 0.46
	USE-Reg.	$\mathbf{46.42 \pm 1.33}$	$\mathbf{59.54 \pm 0.73}$	$\mathbf{76.62 \pm 1.45}$	$\mathbf{47.39 \pm 0.82}$	53.35 ± 0.30

Variants of our Unified Semantic Embedding (**USE**) model:

- **Ontology**
- **Attributes**
- **Parent + Sparse Attributes**

[1] Mensink, Varbeek, Perronnin, Csurka Chapelle, TPAMI'13

[2] Weinberger, Chapelle, NIPS'09

[3] Akata, Perronnin, Harchaoui, Schmid, CVPR'13

Experiments

[Hwang et al., 2014]

Results with AWA (with latent attributes)

	Method	1
No semantics	Ridge Regression NCM [1] LME	38.93
Implicit semantics	LMTE [2] ALE [3] HLE [3] AHLE [3]	
Explicit semantics	LME-MTL-S LME-MTL-A	
USE	USE-No Reg.	44.87 (+5.9%)
	USE-Reg.	**49.87** (+5.0%)

Variants of our Unified Semantic Embedding (**USE**) model:

- Ontology
- Attributes
- Parent + Sparse Attributes

with **2 samples/category**

[1] Mensink, Varbeek, Perronnin, Csurka Chapelle, TPAMI'13

[2] Weinberger, Chapelle, NIPS'09

[3] Akata, Perronnin, Harchaoui, Schmid, CVPR'13

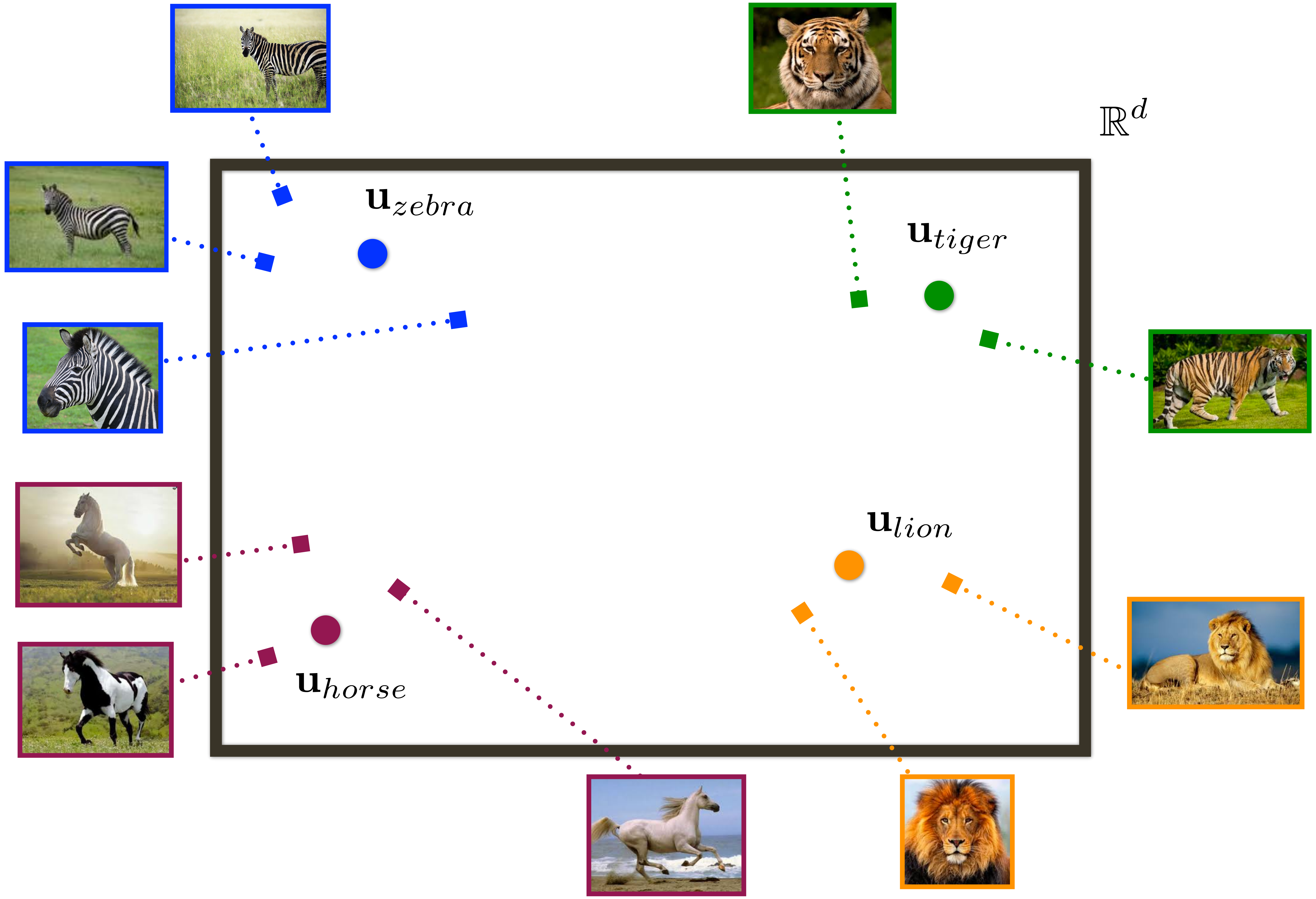
Semantic Embeddings

Image Embedding

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

Label Embedding

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



word2vec: Unsupervised Word Embedding

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

Label Embedding

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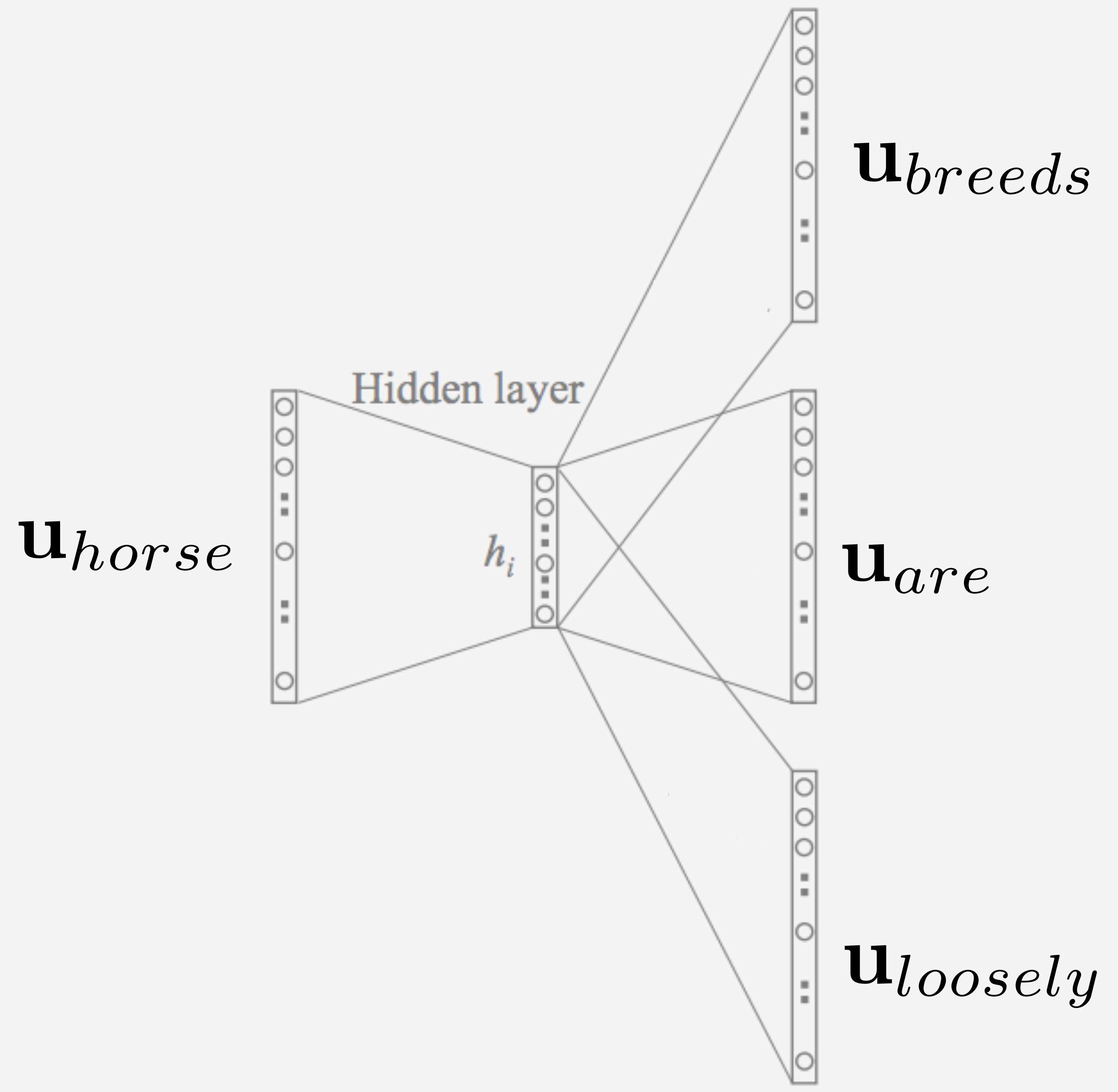
word2vec: Unsupervised Word Embedding

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

Label Embedding

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

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

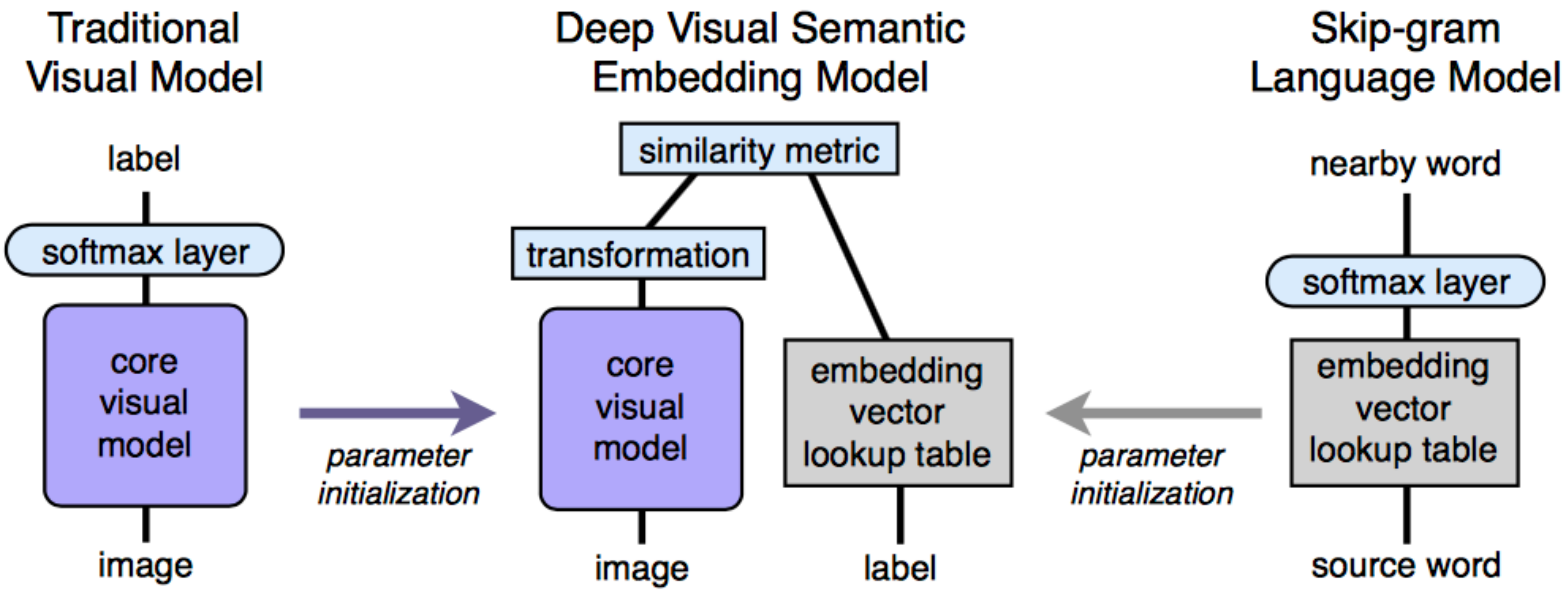


Skip-gram Model: unsupervised semantic representation for words

[Mikolov, Sutskever, Chen, Corrado, Dean, NIPS'13]

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%	-

Semantic Embeddings

Image Embedding

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

Label Embedding

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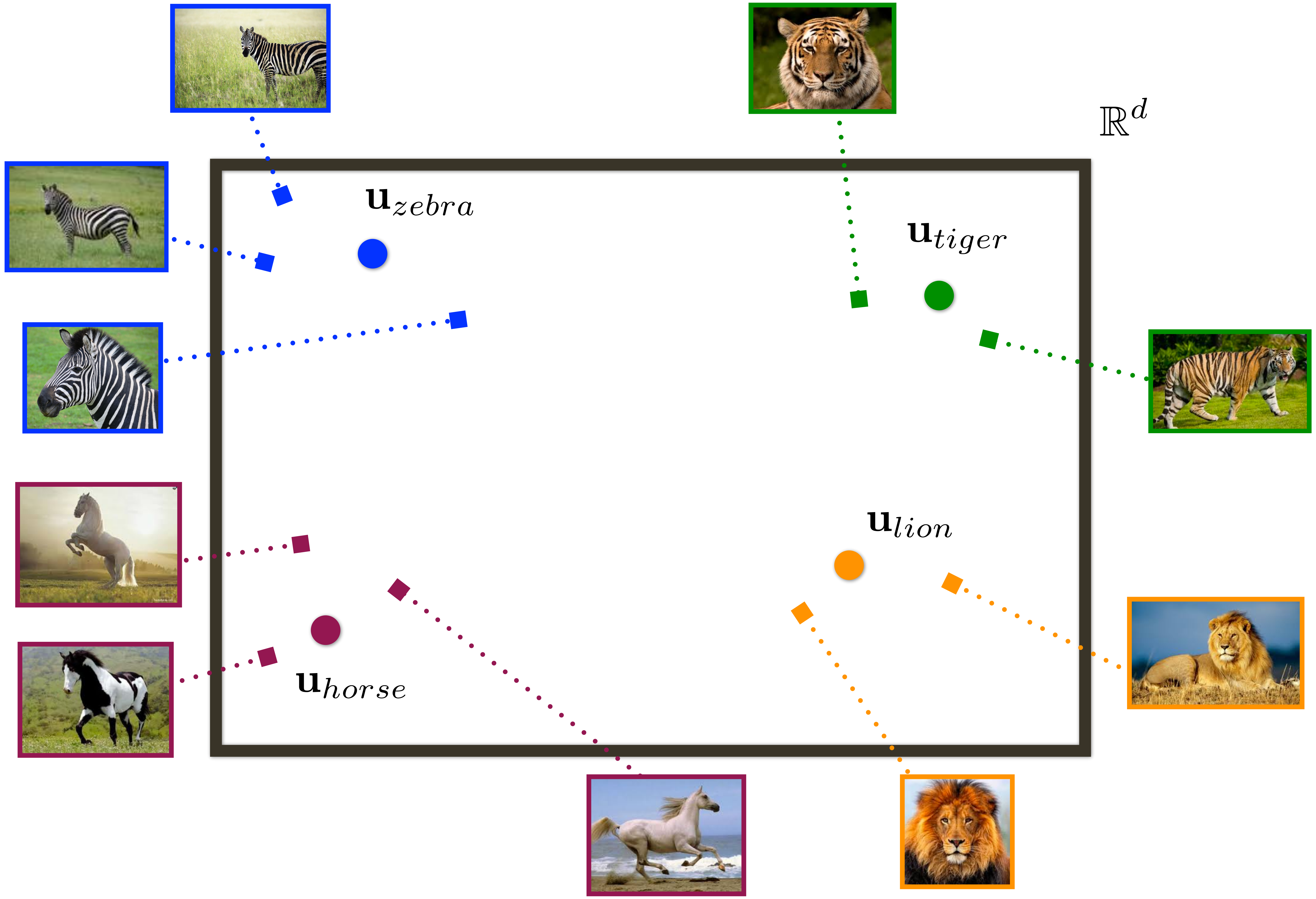


word2vec: Unsupervised Word Embedding

[Fu et al., 2016]

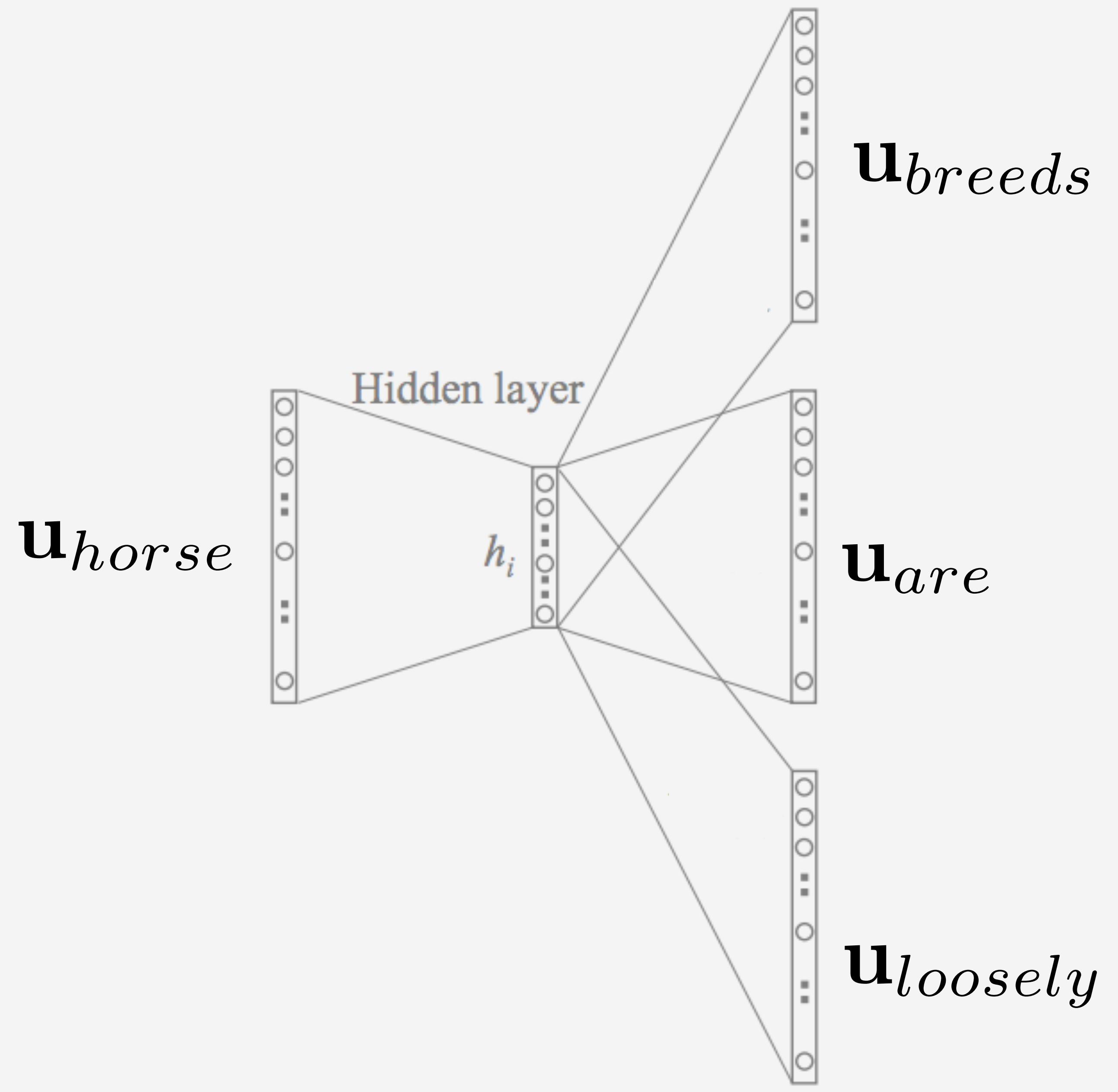
Distributional Semantics Hypothesis: words that are used and occur in the same context tend to have similar meaning

Label Embedding

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

$L = 310,000$

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]

Image Embedding

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

Label Embedding

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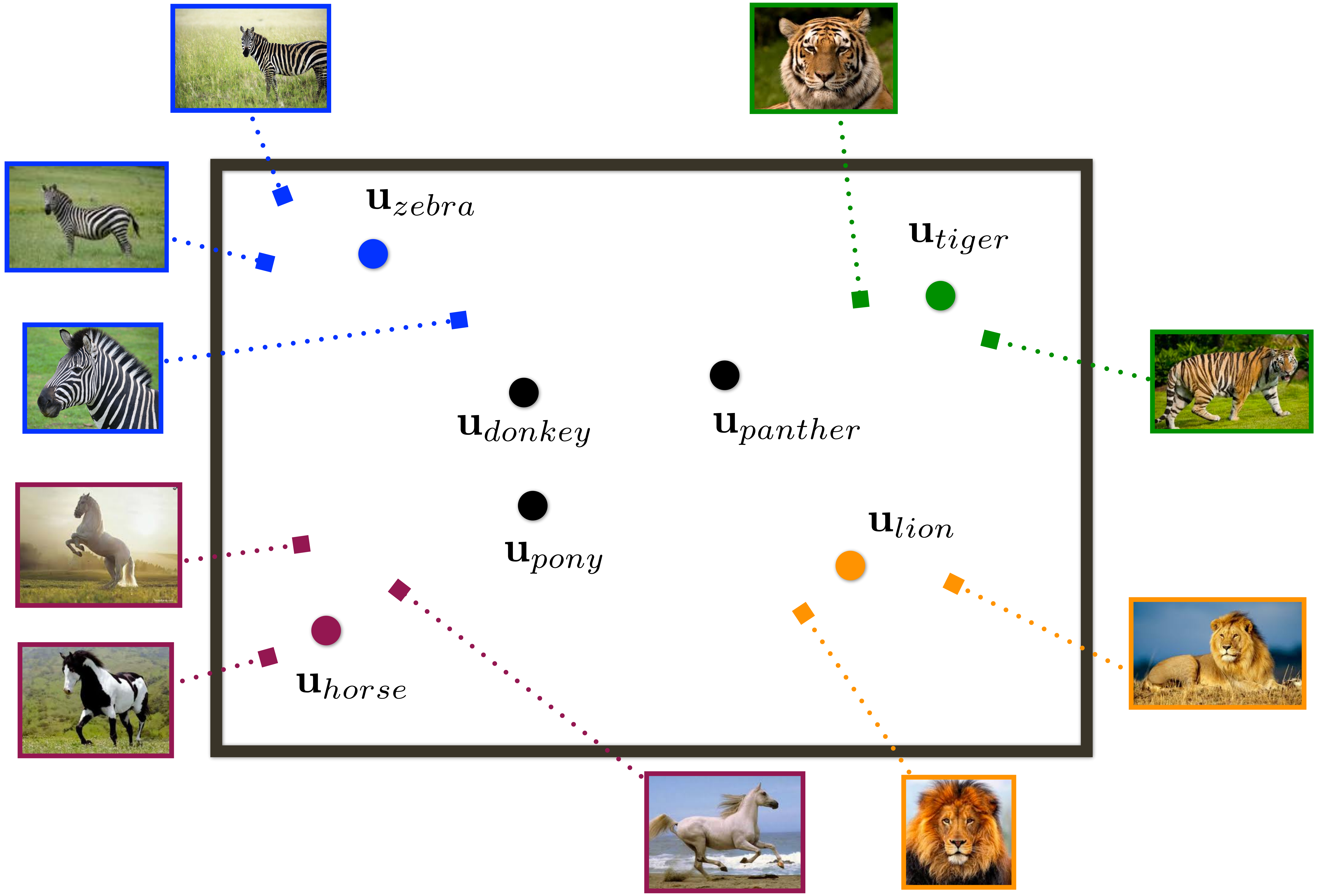

Semi-supervised **Vocabulary Informed** Learning

[Fu et al., 2016]

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

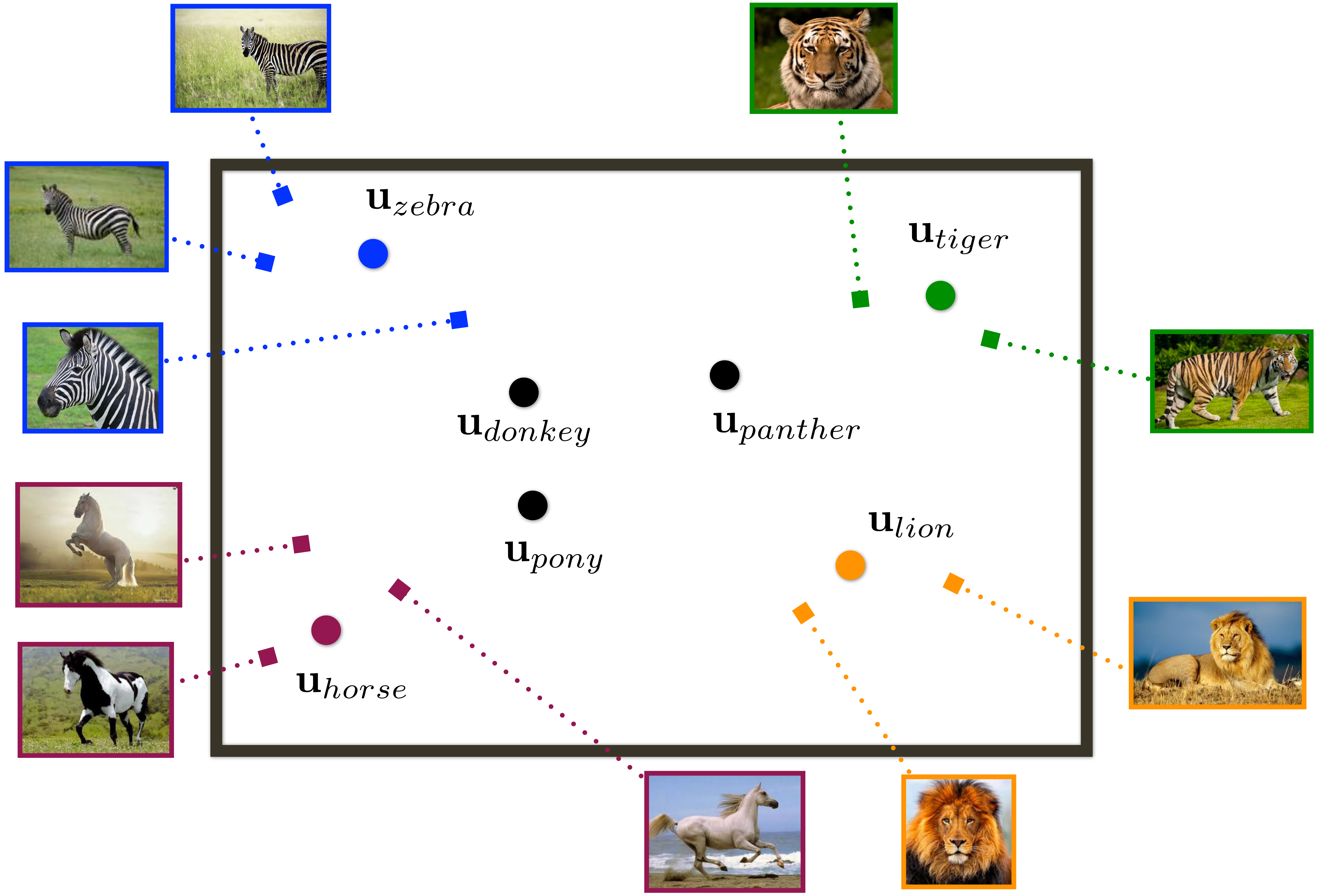
Label Embedding

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

$L = 310,000$

Similarity in Embedding Space

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



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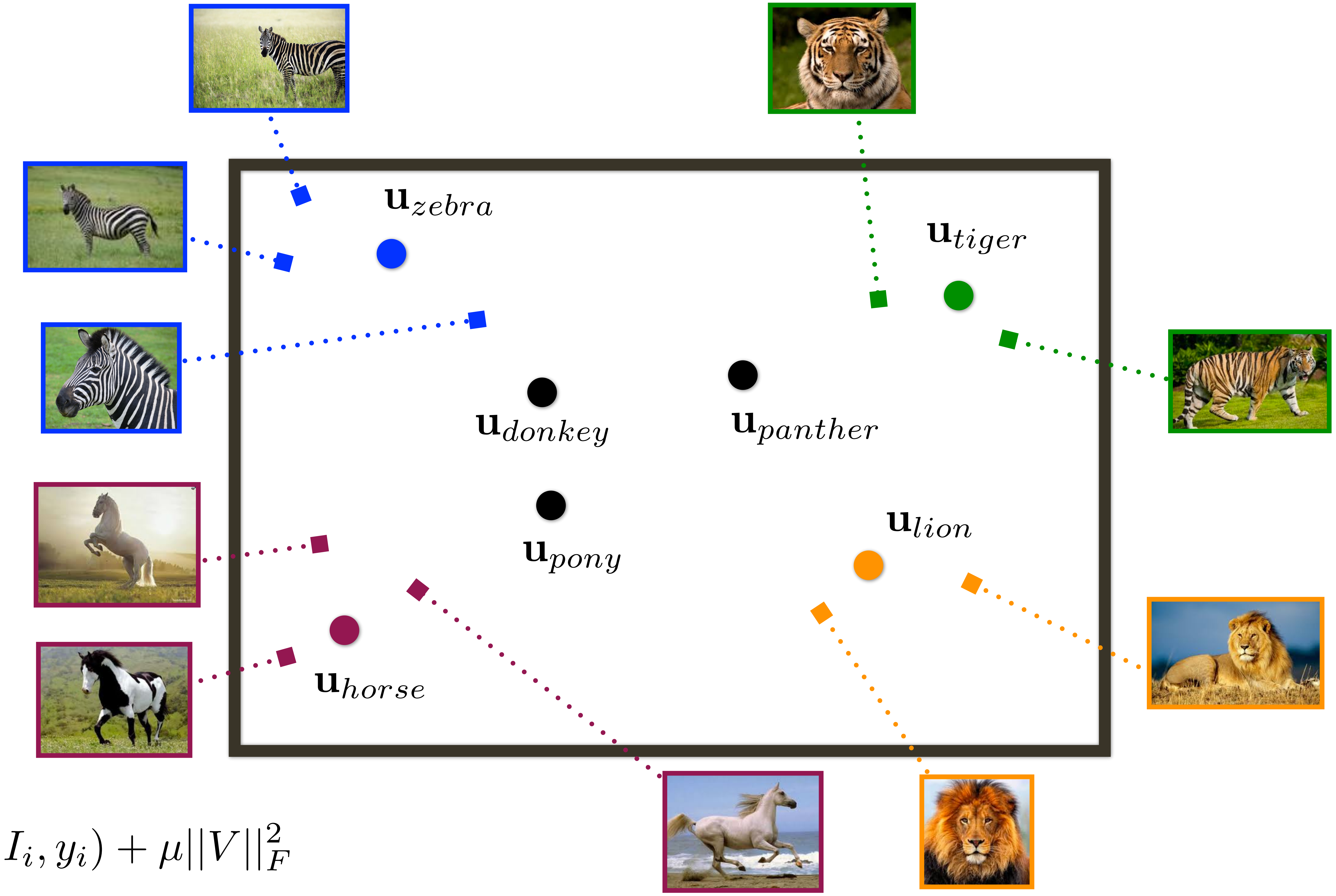
Similarity in Embedding Space

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

Objective Function:

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



Semi-supervised **Vocabulary Informed** Learning

[Fu et al., 2016]

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

Image Embedding

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

Label Embedding

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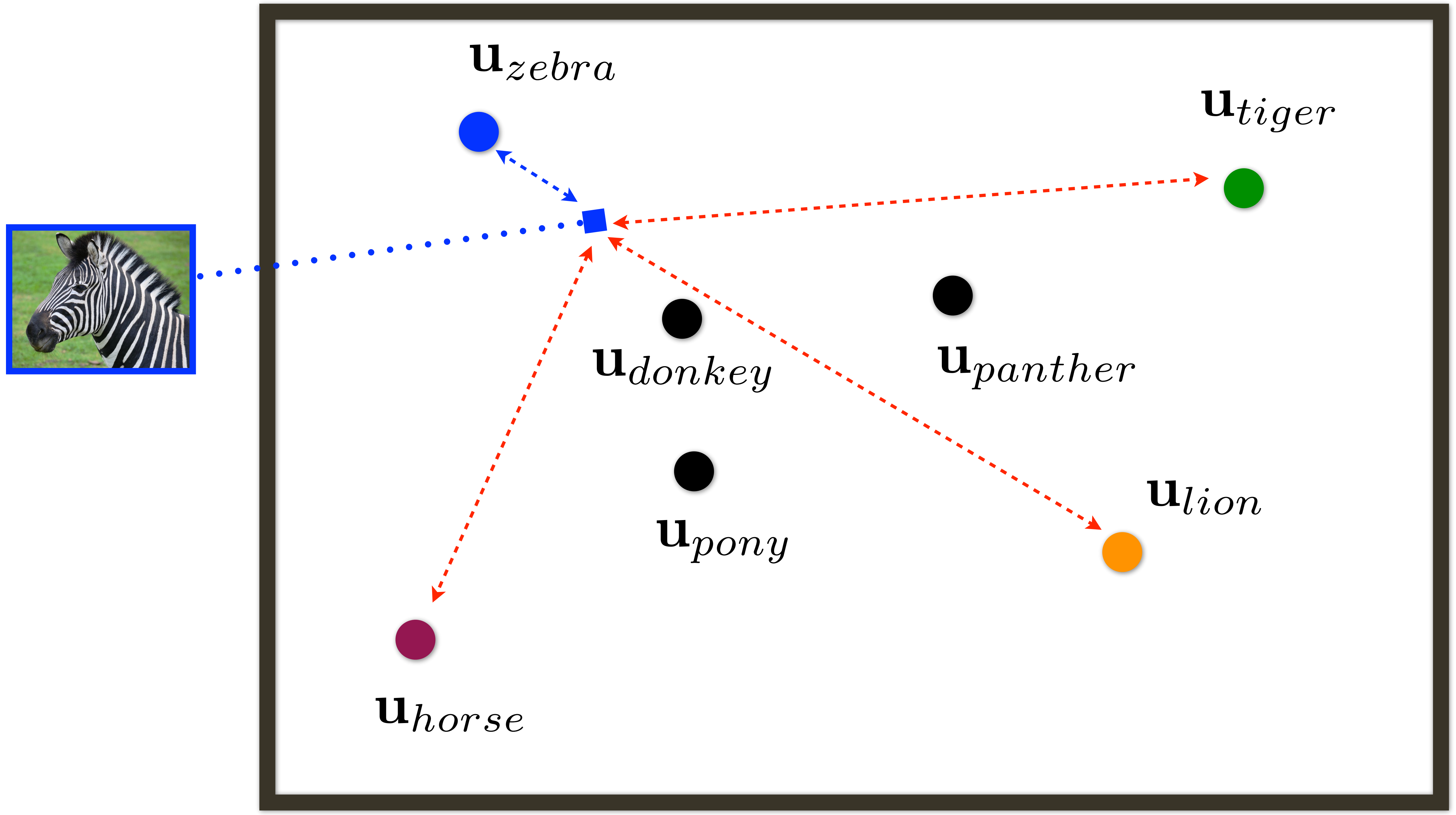

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Image Embedding

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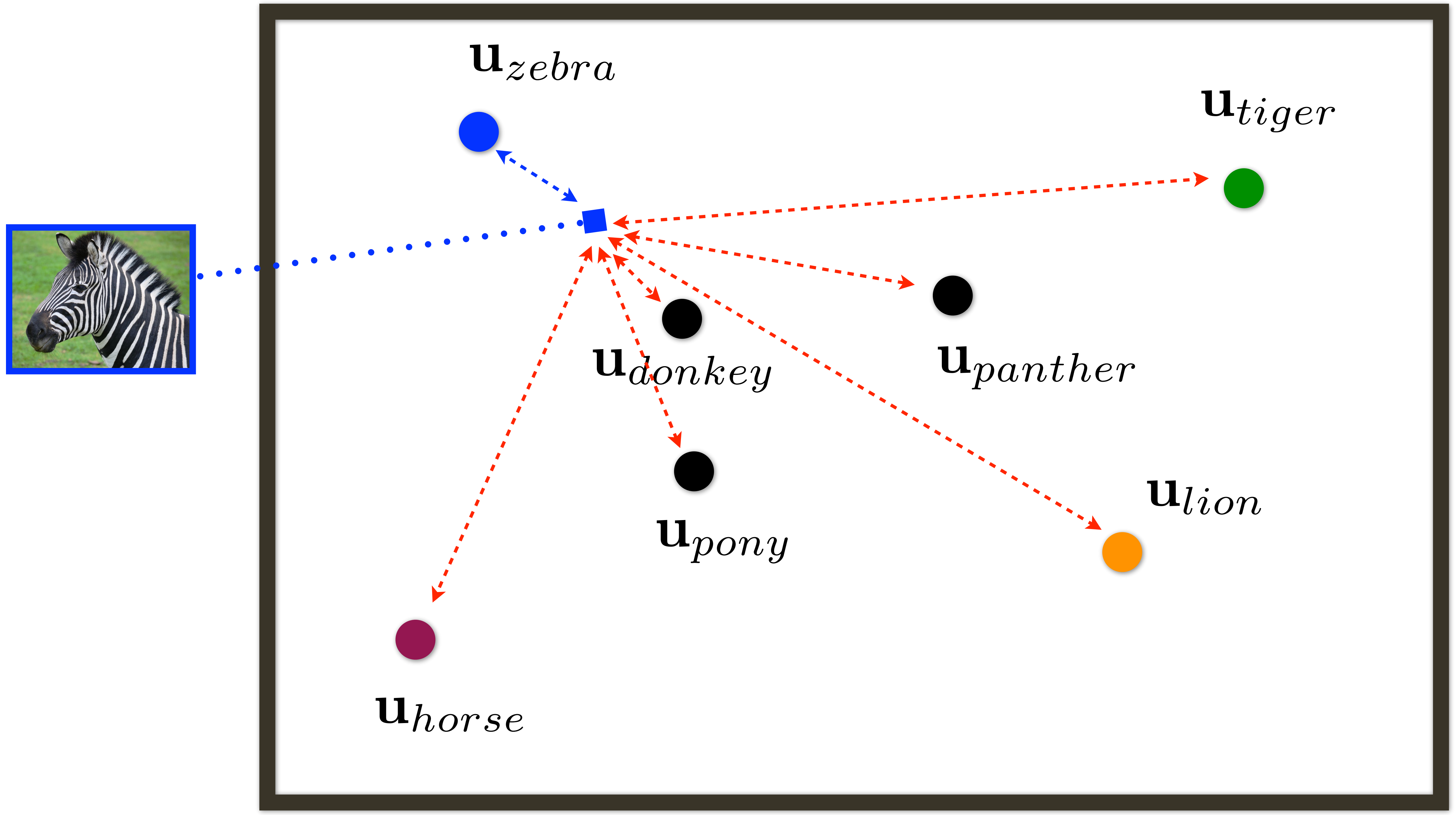
$L = 310,000$



Similarity in Embedding Space

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

Objective Function:

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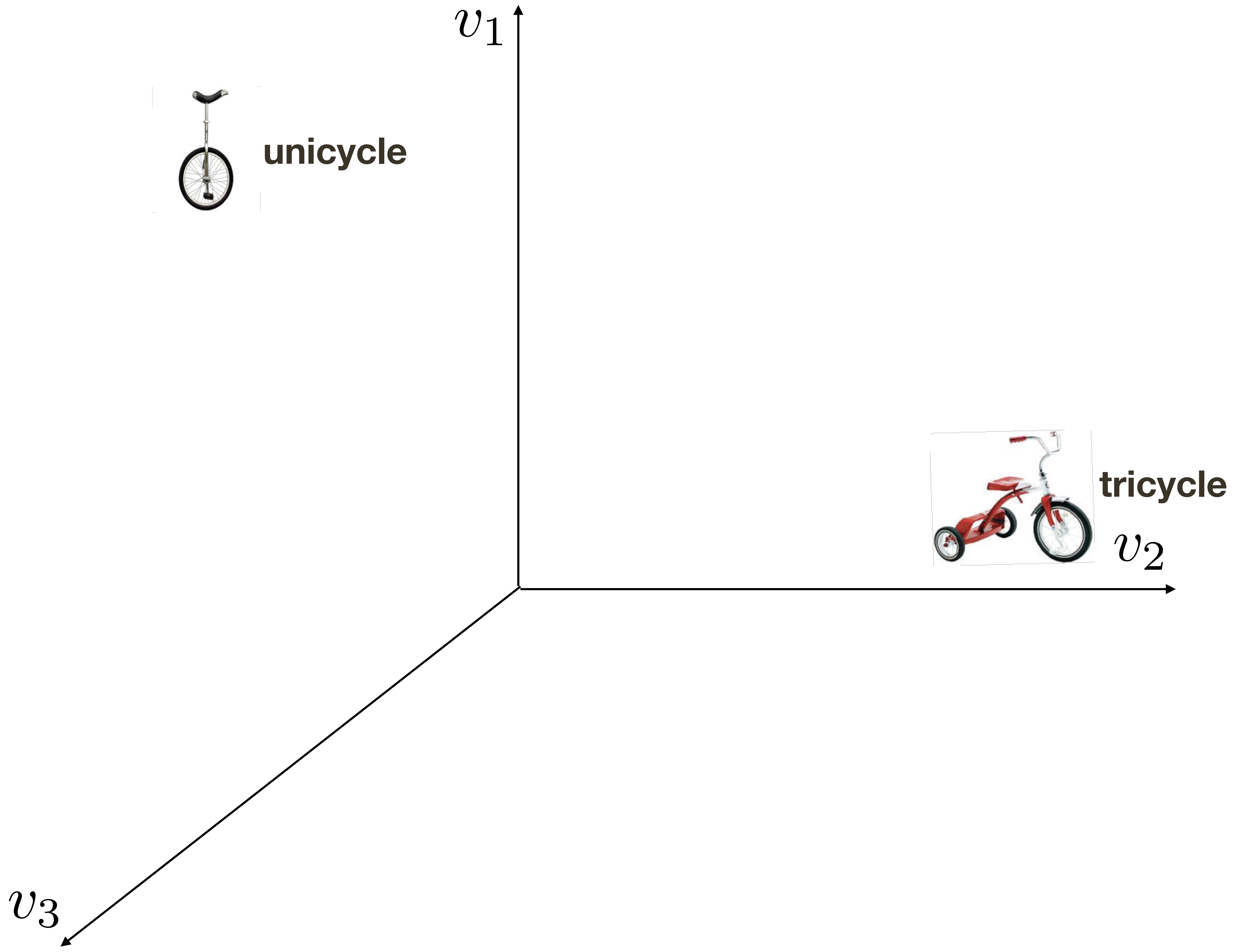
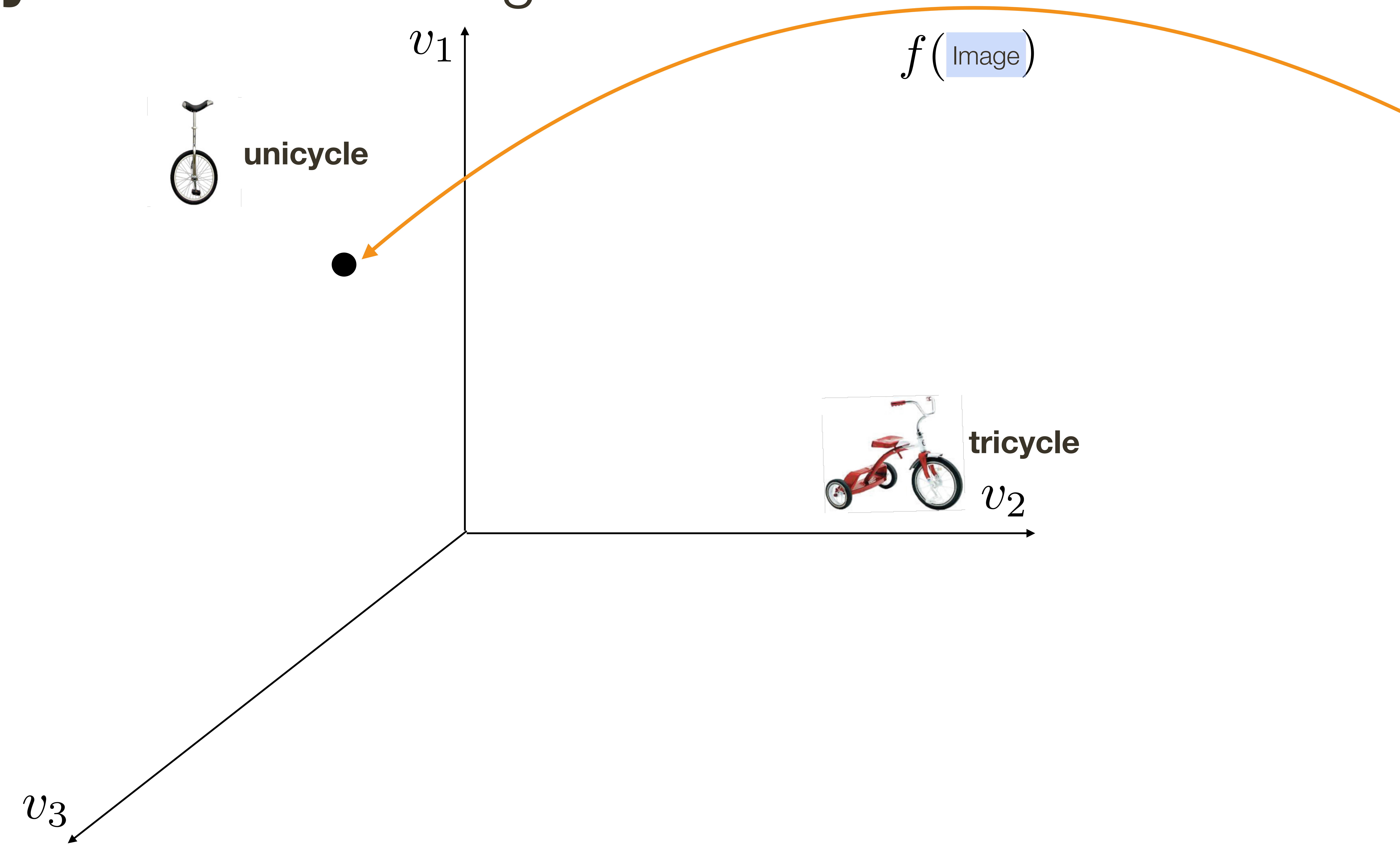
Vocabulary Informed Recognition

[Fu et al., 2016]



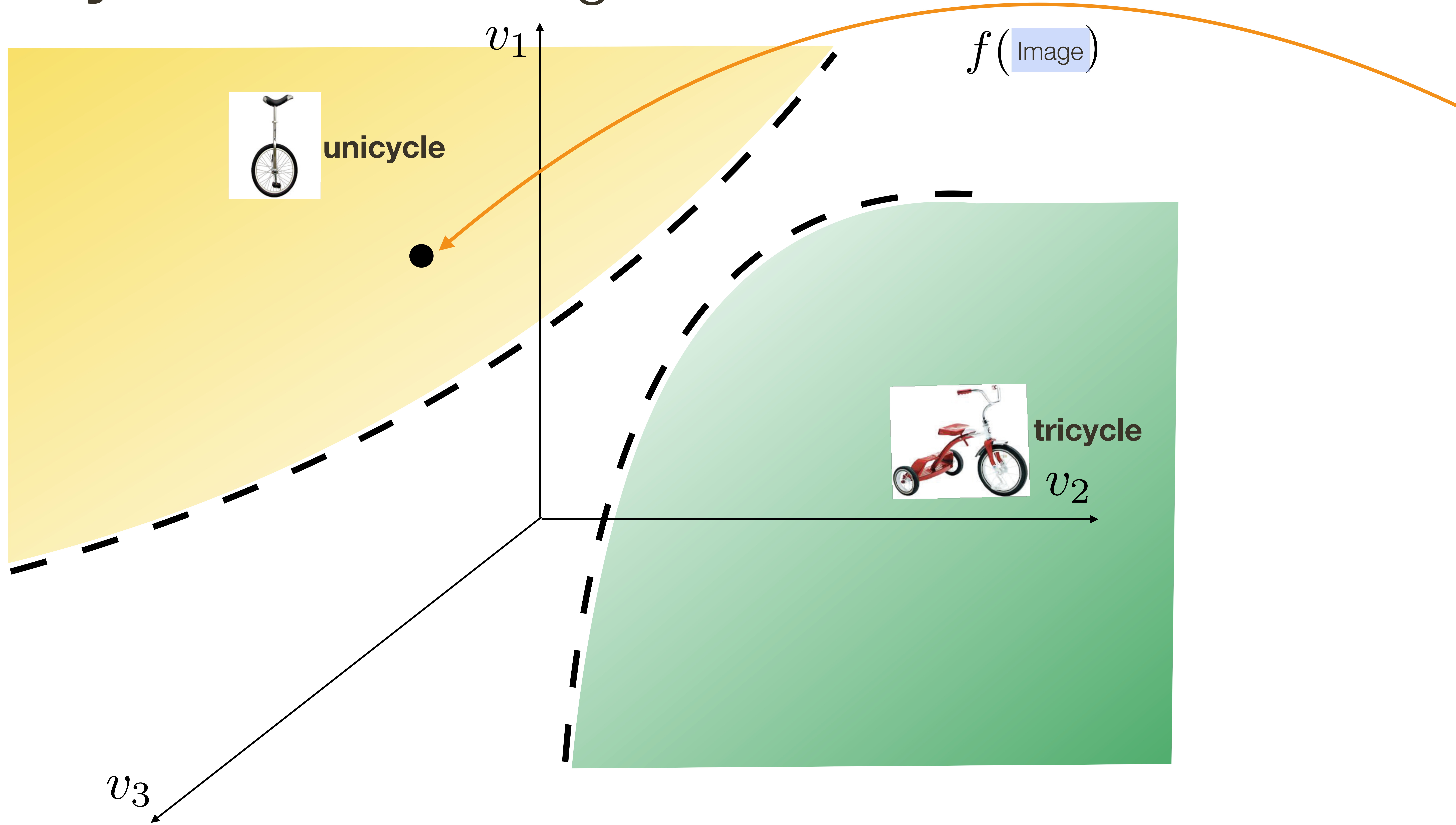
Vocabulary Informed Recognition

[Fu et al., 2016]



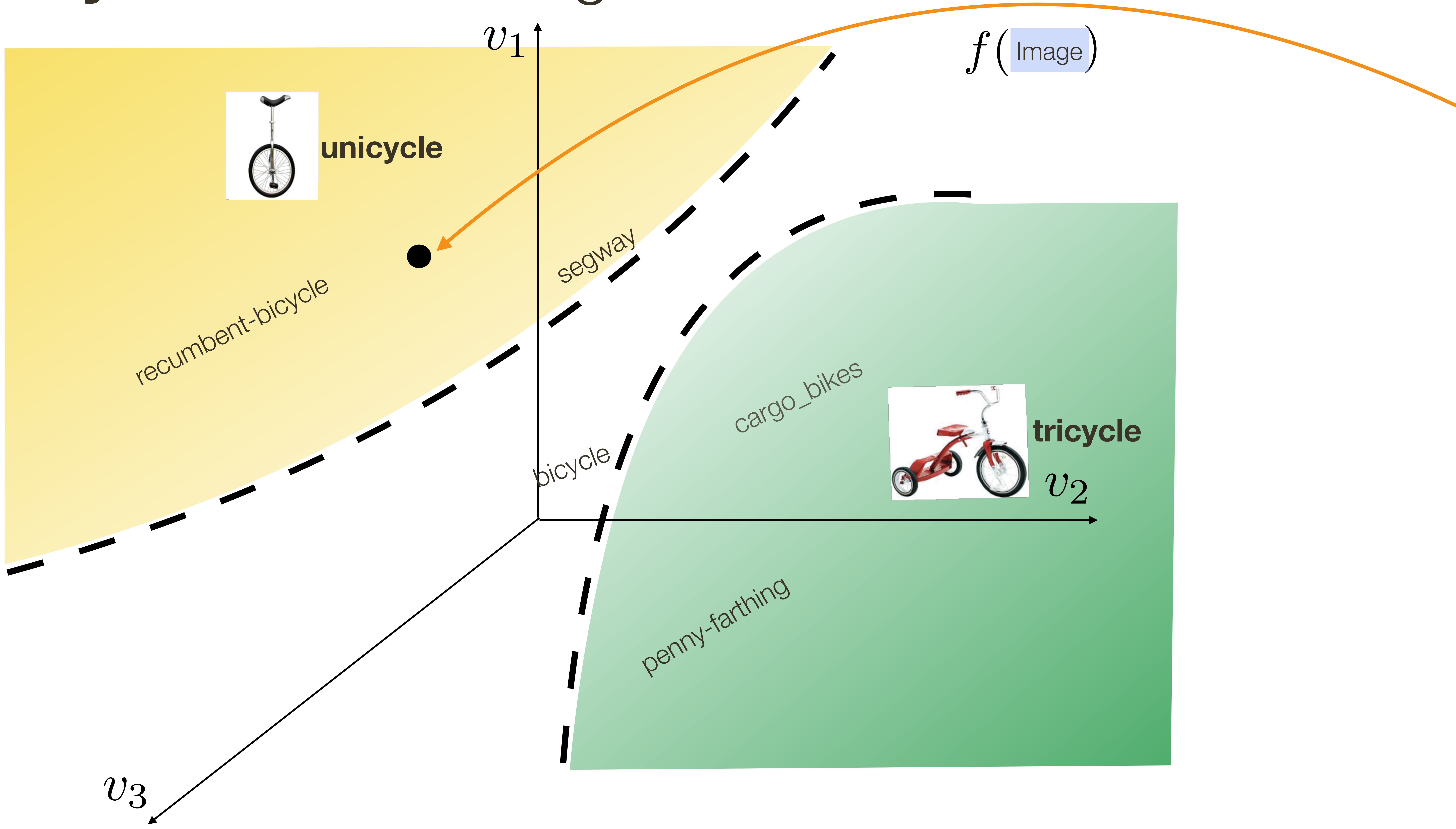
Vocabulary Informed Recognition

[Fu et al., 2016]



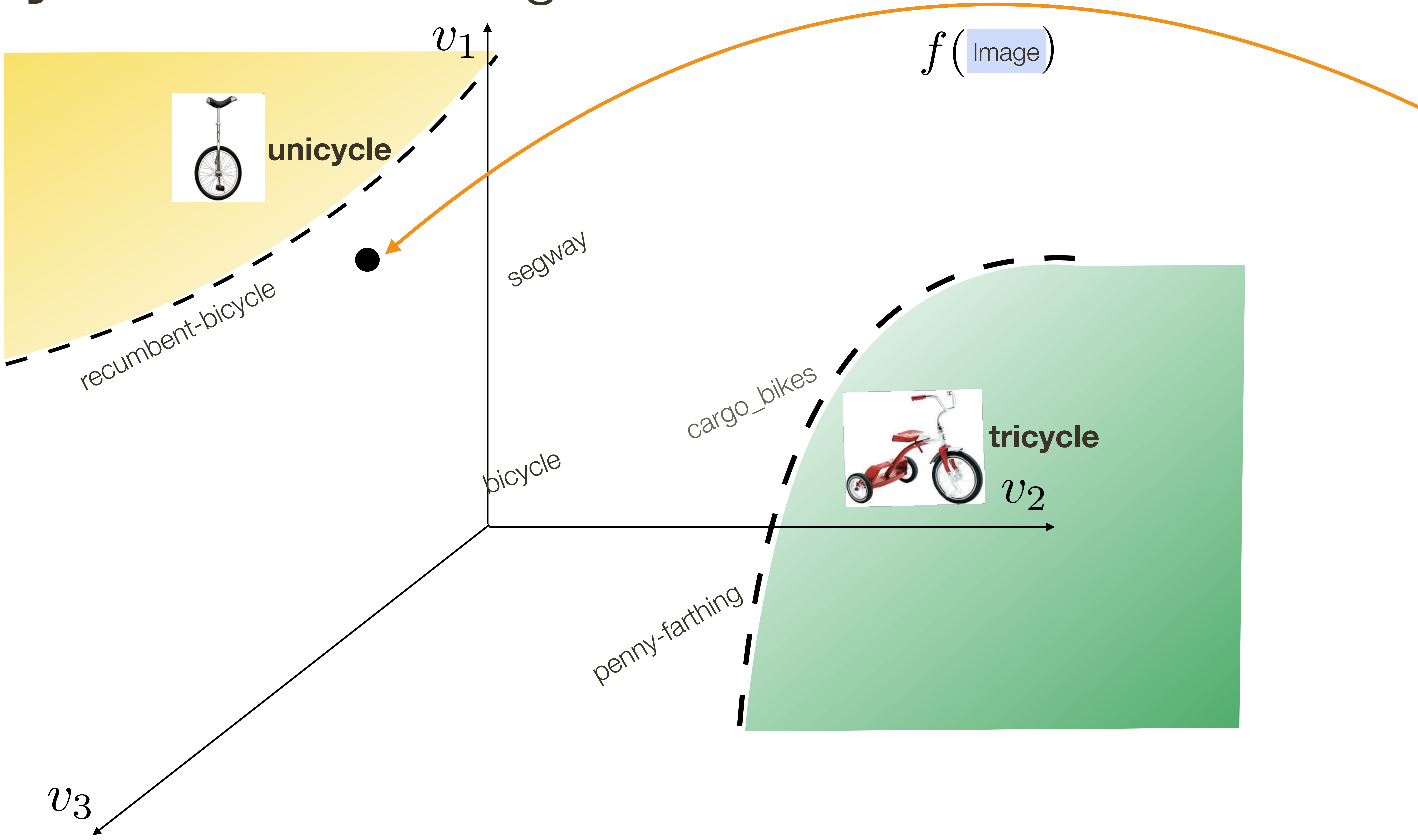
Vocabulary Informed Recognition

[Fu et al., 2016]



Vocabulary Informed Recognition

[Fu et al., 2016]



Experiments: Datasets

[Fu et al., 2016]

Animals with Attributes

Otter

Polar Bear

...

Auxiliary: 40 Animal Classes (annotated)

Target: 10 Animal Classes (**NO** annotation)

[Lampert, Nickisch, Harmeling CVPR'09]

ImageNet

Auxiliary: 1,000 General Classes (annotated)

Target: 360 General Classes (**NO** annotation)

[Deng *et al.*, CVPR'09]

Experiments: Settings

[Fu et al., 2016]

AwA/ImageNet	No. Testing Classes			No. Testing Words	
	Auxiliary	Target	Total	Vocabulary	Chance(%)
SUPERVISED	✓		40/1000	40/1000	2.5/0.1
ZERO-SHOT		✓	10/360	10/360	10/0.28
OPEN-SET	✓	✓	50/1360	310K/310K	3.2E-04

The tasks are only separated in **evaluation**;
We train **one unified model** for all the settings

Experiments: Settings

[Fu et al., 2016]

Training

Otter

Polar Bear

Donkey

Poney

Panther

310, 000

Testing

Supervised

Experiments: Settings

[Fu et al., 2016]

Training

Otter

Polar Bear

Donkey

Poney

Panther

310, 000

Testing

Supervised

Zero-shot

Experiments: Settings

[Fu et al., 2016]

Training

Otter

Polar Bear

Donkey

Poney

Panther

$310,000$

Testing

Open-set

Experiments: Settings

[Fu et al., 2016]

AwA/ImageNet	No. Testing Classes			No. Testing Words	
	Auxiliary	Target	Total	Vocabulary	Chance(%)
SUPERVISED	✓		40/1000	40/1000	2.5/0.1
ZERO-SHOT		✓	**10**/360	**10**/360	**10**/0.28
OPEN-SET	✓	✓	50/1360	310K/310K	3.2E-04

The tasks are only separated in **evaluation**;
We train **one unified model** for all the settings

Zero-shot Results

[Fu et al., 2016]

Results with AWA

Method	Features	Accuracy
SS-Voc: full instances	$CNN_{OverFeat}$	78.3
Akata *et al*. CVPR 2015	$CNN_{GoogLeNet}$	73.9
TMV-BLP (Fu *et al*. ECCV 2014)	$CNN_{OverFeat}$	69.9
AMP (SR+SE) (Fu *et al*. CVPR 2015)	$CNN_{OverFeat}$	66.0
DAP (Lampert *et al*. TPAMI 2013)	CNN_{VGG19}	57.5
PST (Rohrbach *et al*. NIPS 2013)	$CNN_{OverFeat}$	53.2
DS (Rohrbach *et al*. CVPR 2010)	$CNN_{OverFeat}$	52.7
IAP (Lampert *et al.* TPAMI 2013)	$CNN_{OverFeat}$	44.5
HEX (Deng *et al*. ECCV 2014)	CNN_{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	$CNN_{OverFeat}$	78.3
SS-Voc: 800 instances (20 inst*40 class);	$CNN_{OverFeat}$	74.4
Akata *et al*. CVPR 2015	$CNN_{GoogLeNet}$	73.9
TMV-BLP (Fu *et al*. ECCV 2014)	$CNN_{OverFeat}$	69.9
AMP (SR+SE) (Fu *et al*. CVPR 2015)	$CNN_{OverFeat}$	66.0
DAP (Lampert *et al*. TPAMI 2013)	CNN_{VGG19}	57.5
PST (Rohrbach *et al*. NIPS 2013)	$CNN_{OverFeat}$	53.2
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IAP (Lampert *et al.* TPAMI 2013)	$CNN_{OverFeat}$	44.5
HEX (Deng *et al*. ECCV 2014)	CNN_{DECAF}	44.2

+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
TMV-BLP (Fu *et al*. ECCV 2014)	$CNN_{OverFeat}$	69.9
AMP (SR+SE) (Fu *et al*. CVPR 2015)	$CNN_{OverFeat}$	66.0
DAP (Lampert *et al*. TPAMI 2013)	CNN_{VGG19}	57.5
PST (Rohrbach *et al*. NIPS 2013)	$CNN_{OverFeat}$	53.2
DS (Rohrbach *et al*. CVPR 2010)	$CNN_{OverFeat}$	52.7
IAP (Lampert *et al.* TPAMI 2013)	$CNN_{OverFeat}$	44.5
HEX (Deng *et al*. ECCV 2014)	CNN_{DECAF}	44.2

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.

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Label Embedding

$$\Psi_L(phrase_i) = \mathbf{u}_i$$

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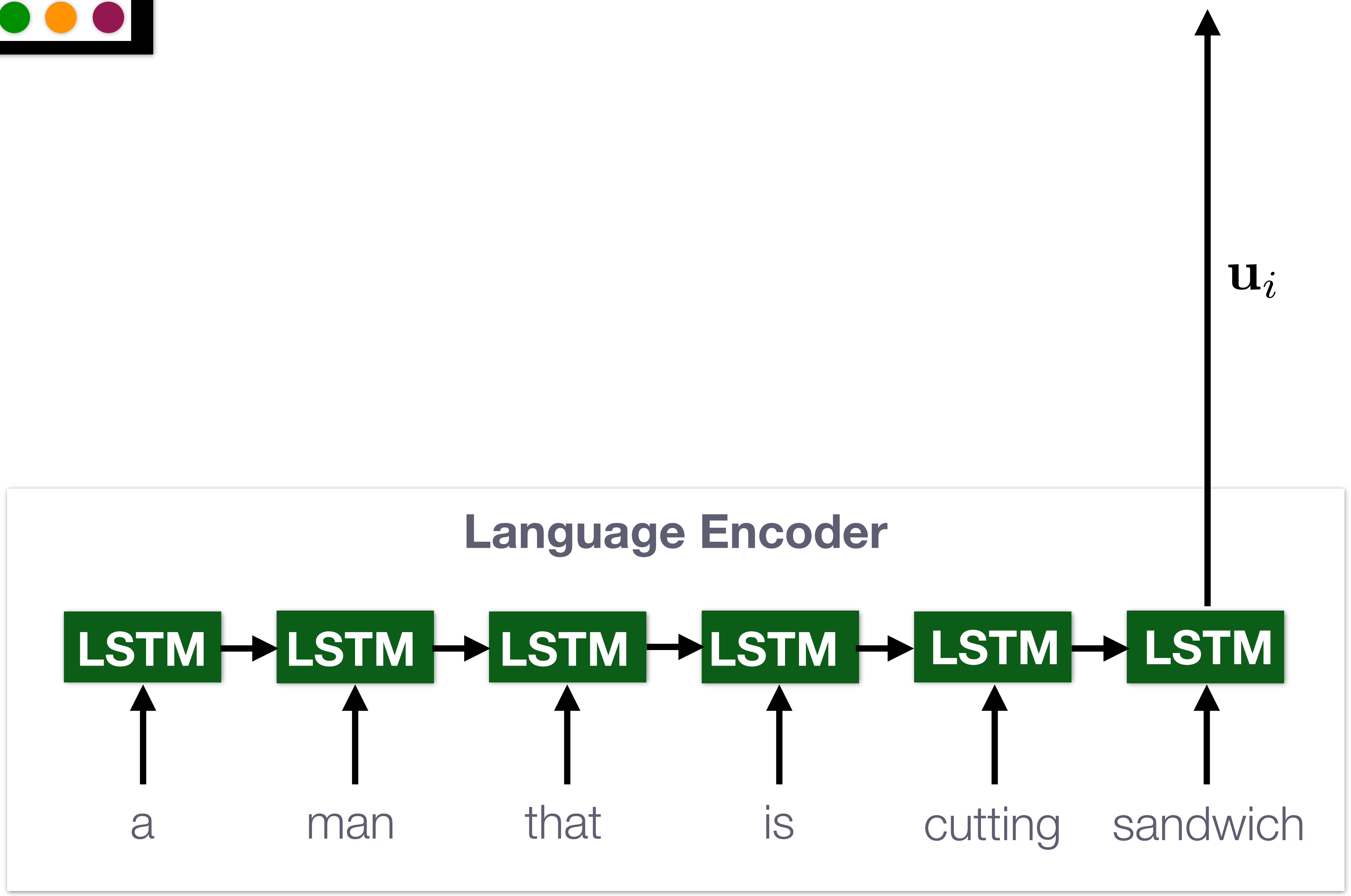

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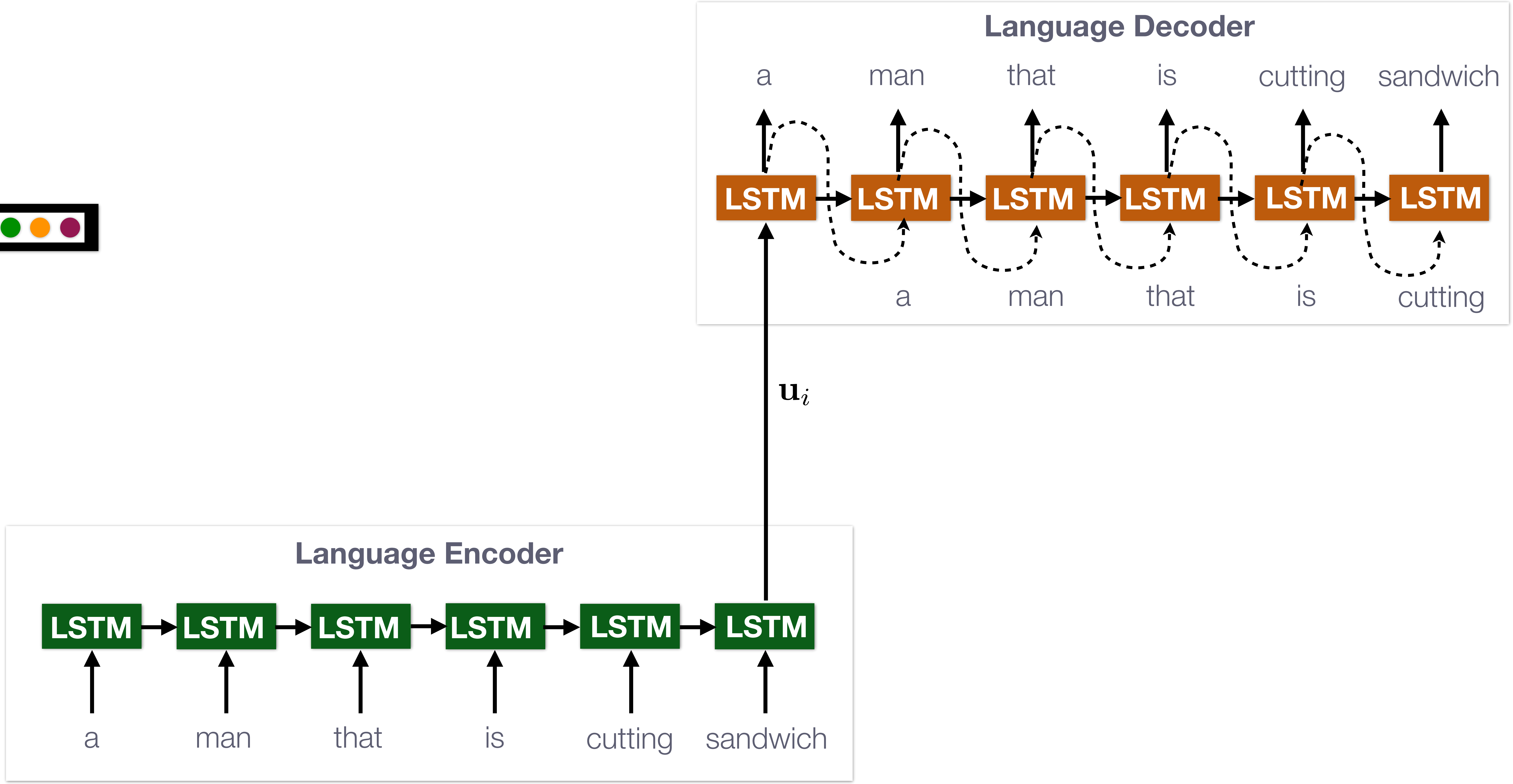

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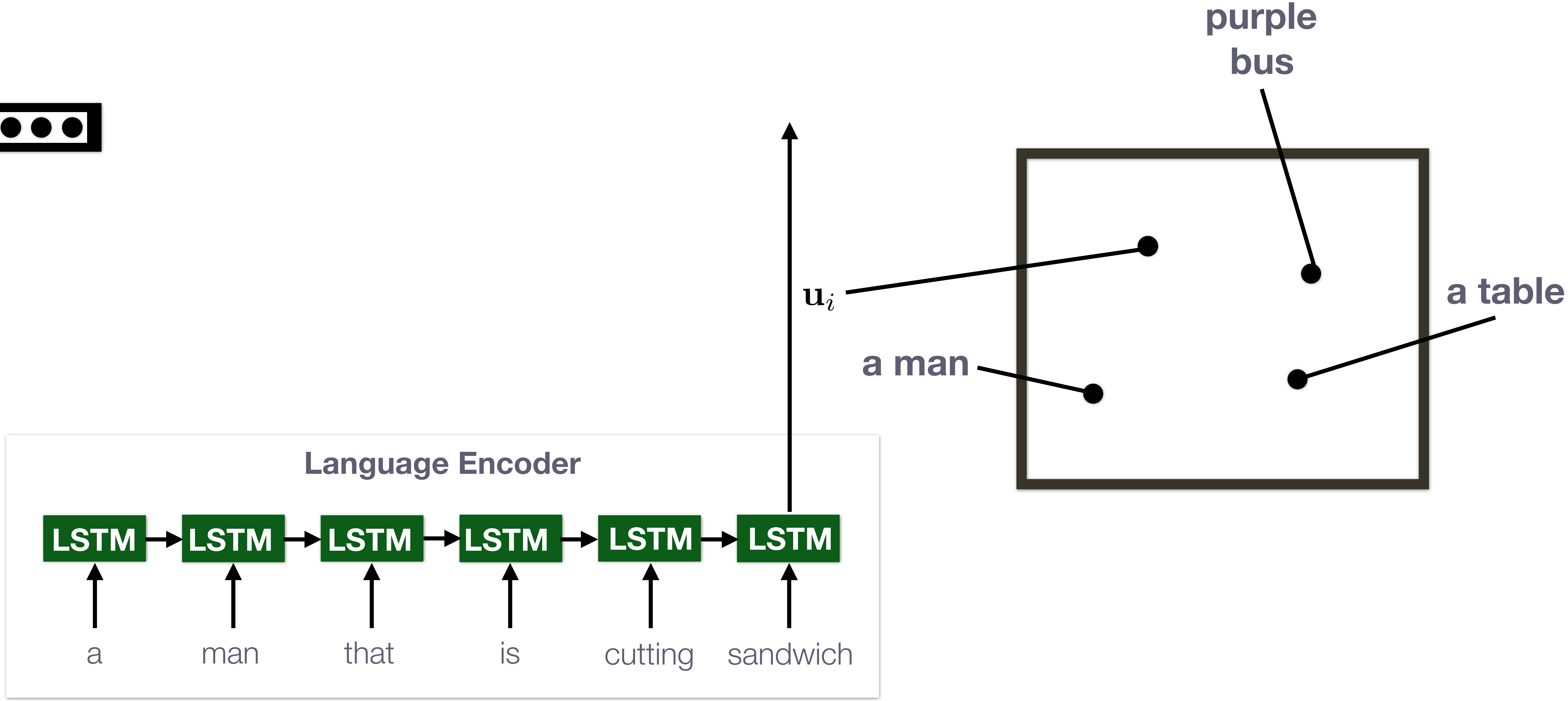
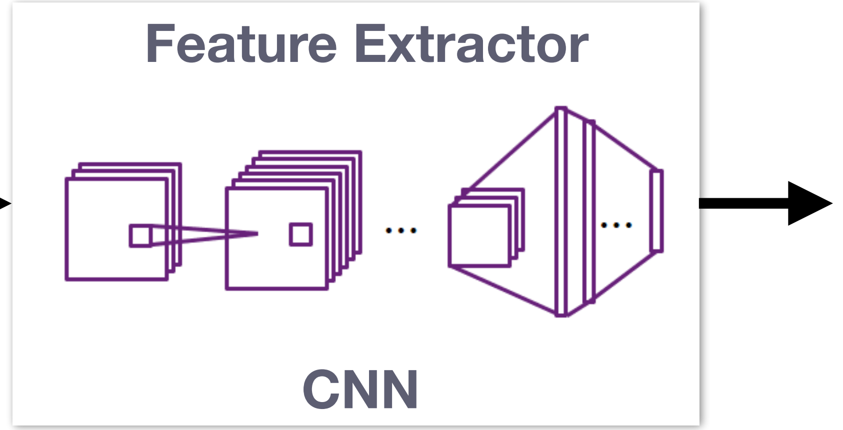


Weakly-supervised **Visual Grounding** of Phrases [Xiao et al., 2017]

Image Embedding

$$\Psi(I_i) = \mathbf{W} \cdot CNN(I_i; \mathbf{\Theta})$$



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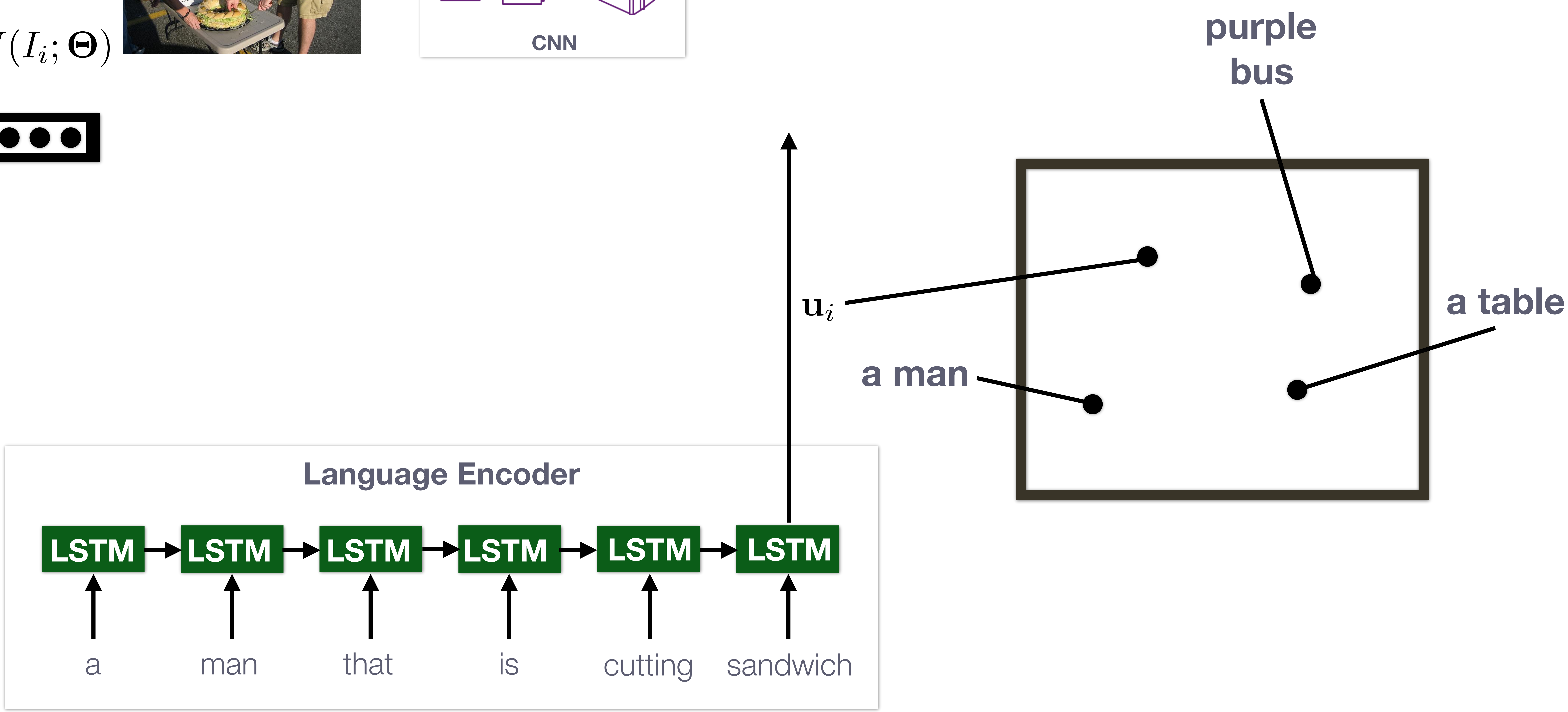

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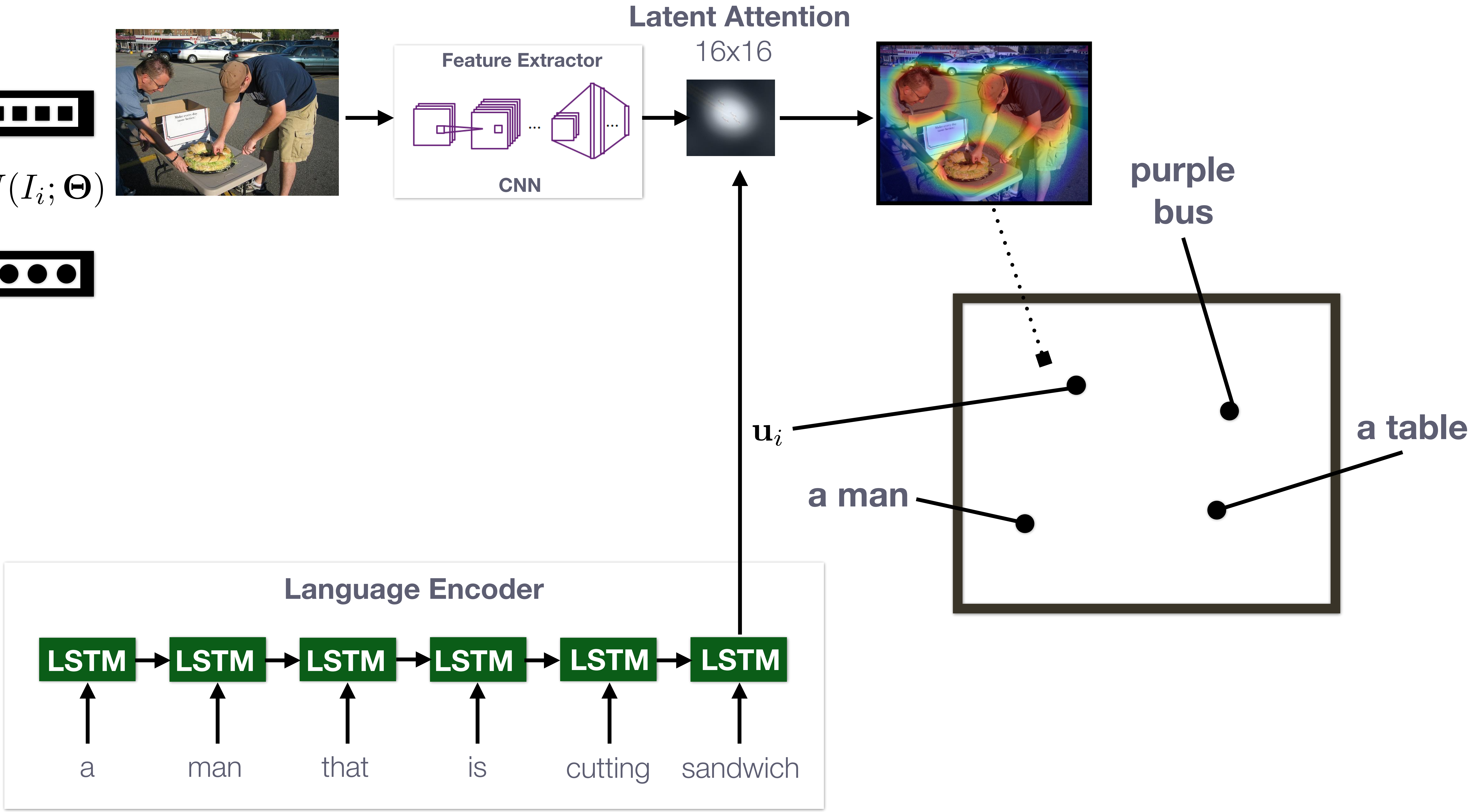

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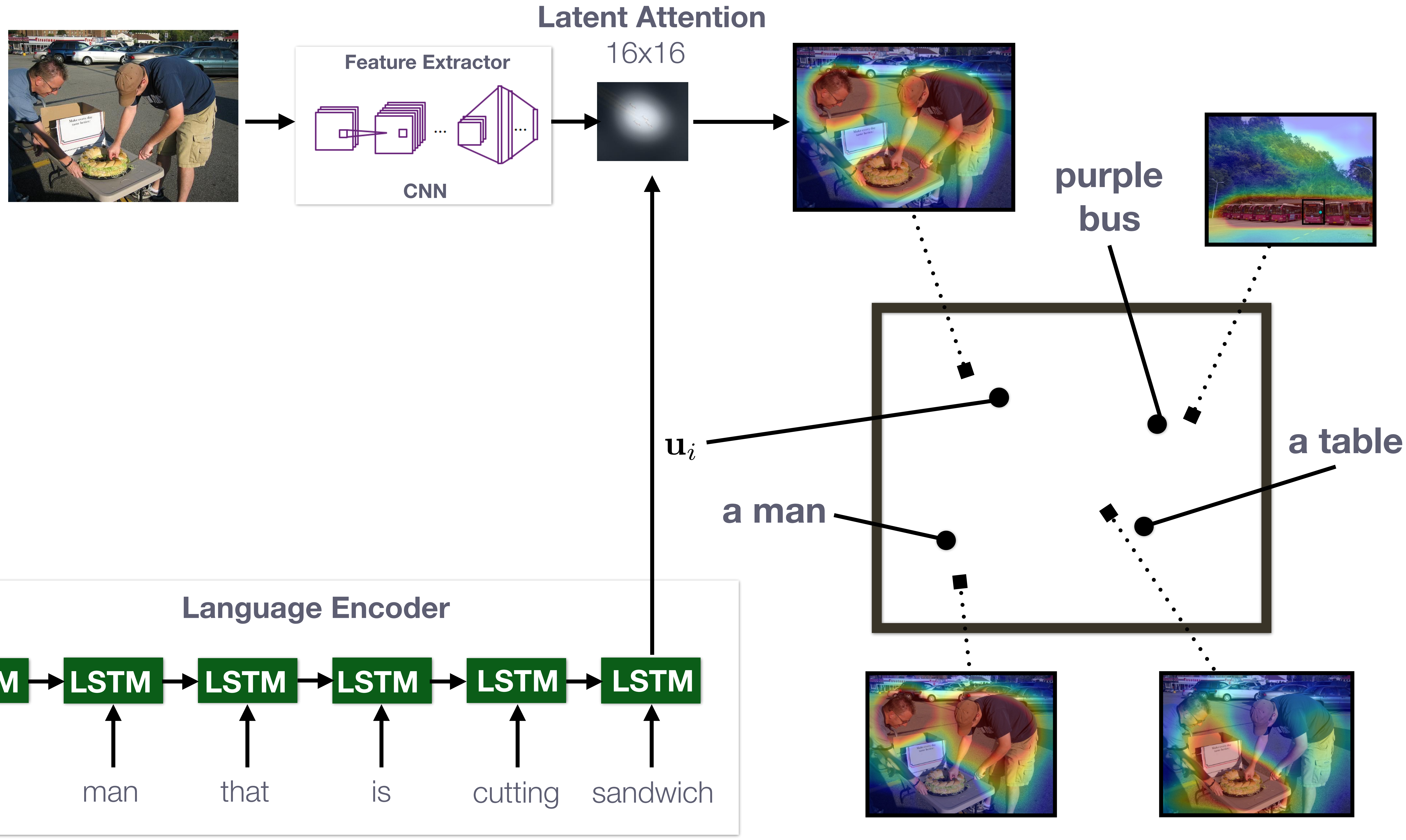

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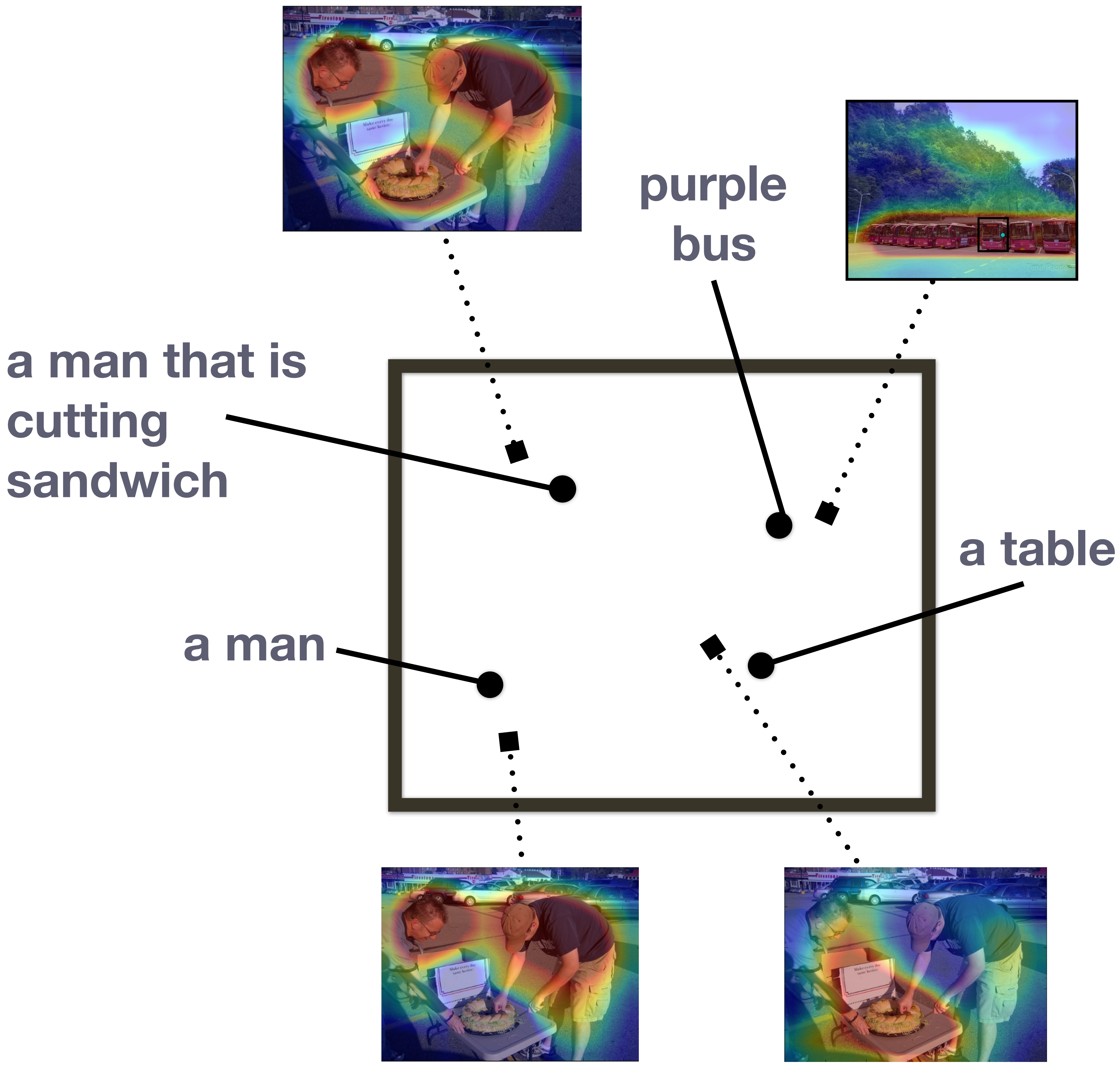
Similarity in Embedding Space

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

Objective Function:



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

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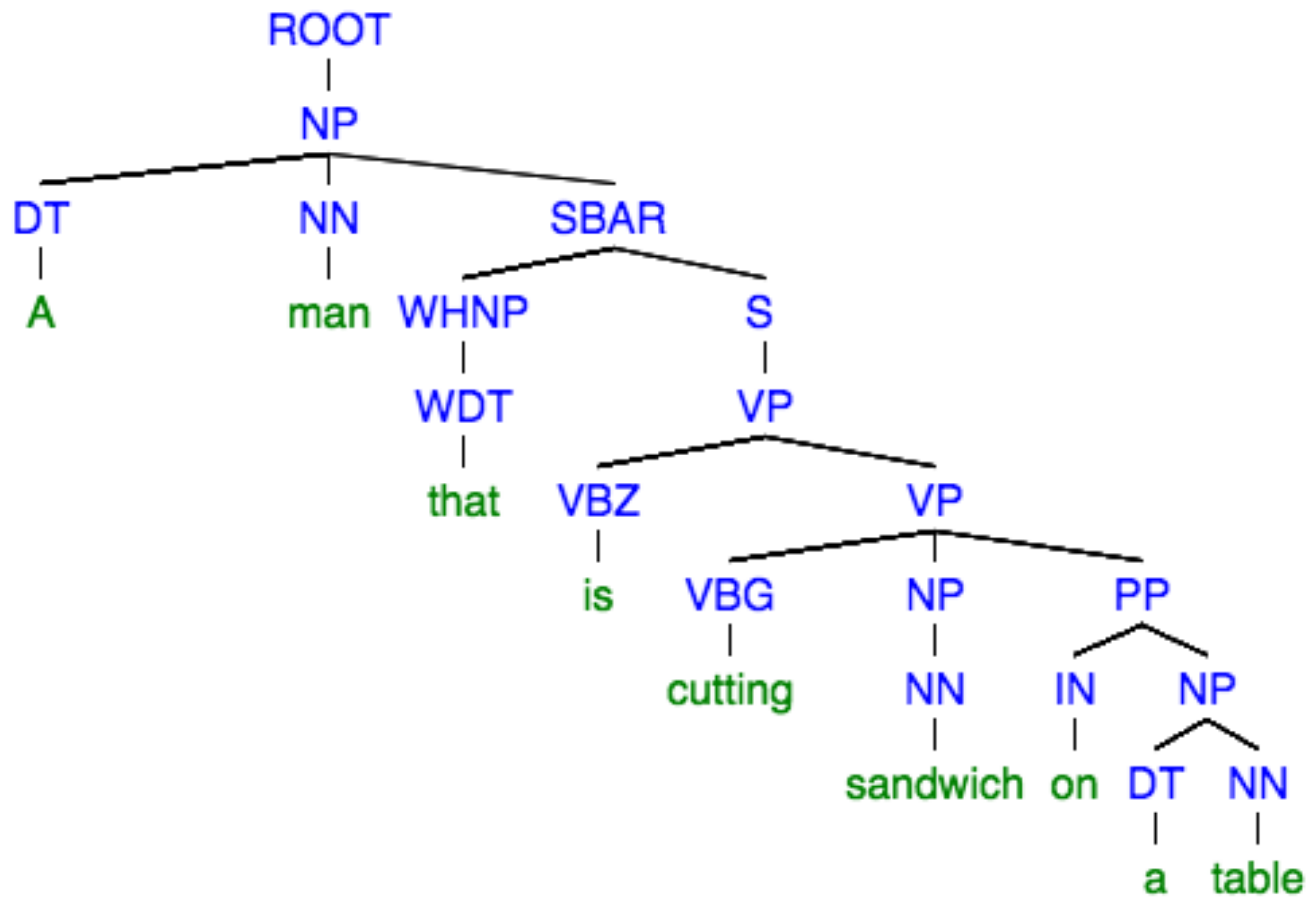

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[Xiao et al., 2017]

For **noun phrases**:

- **siblings** should have **disjoint** masks

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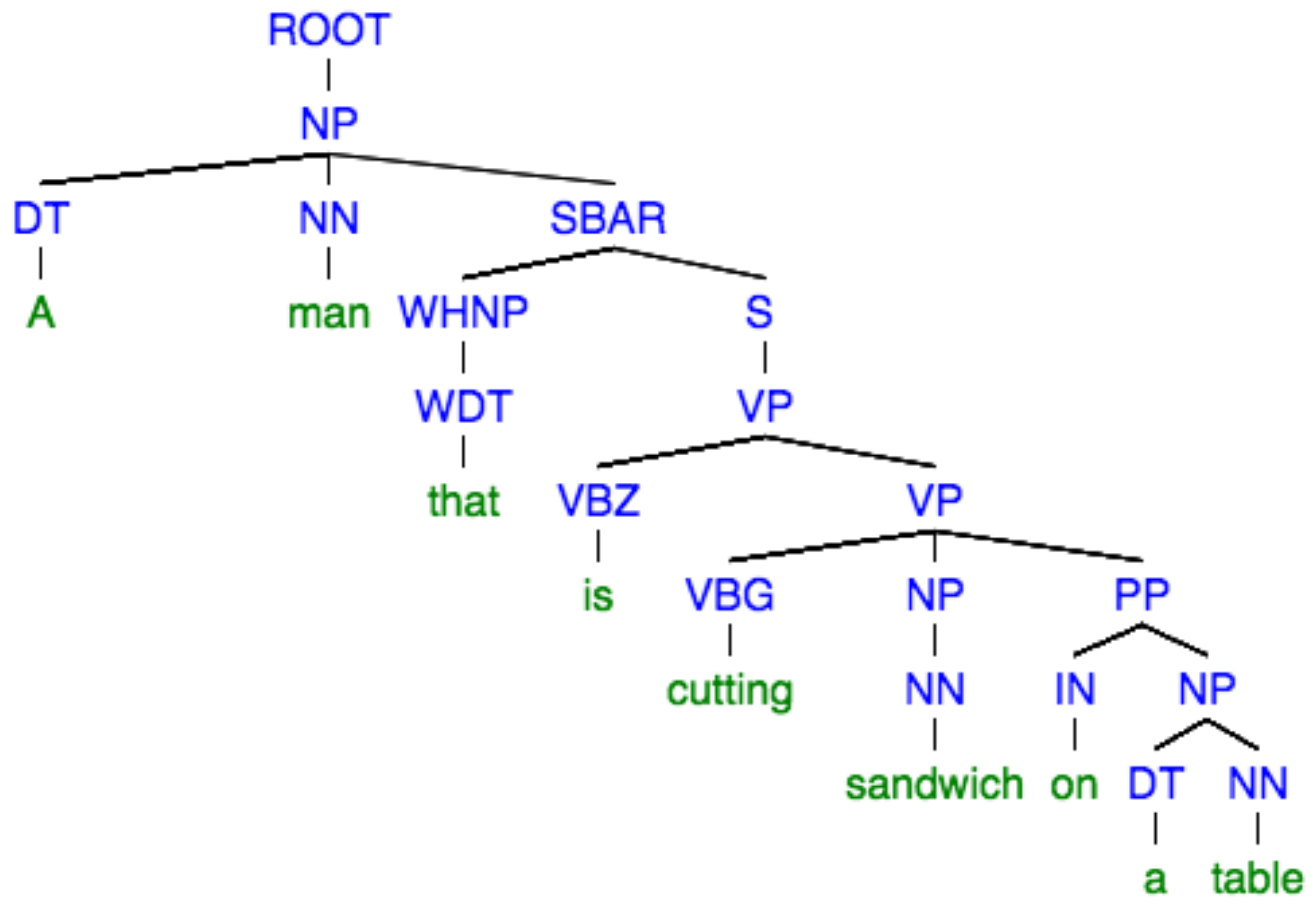

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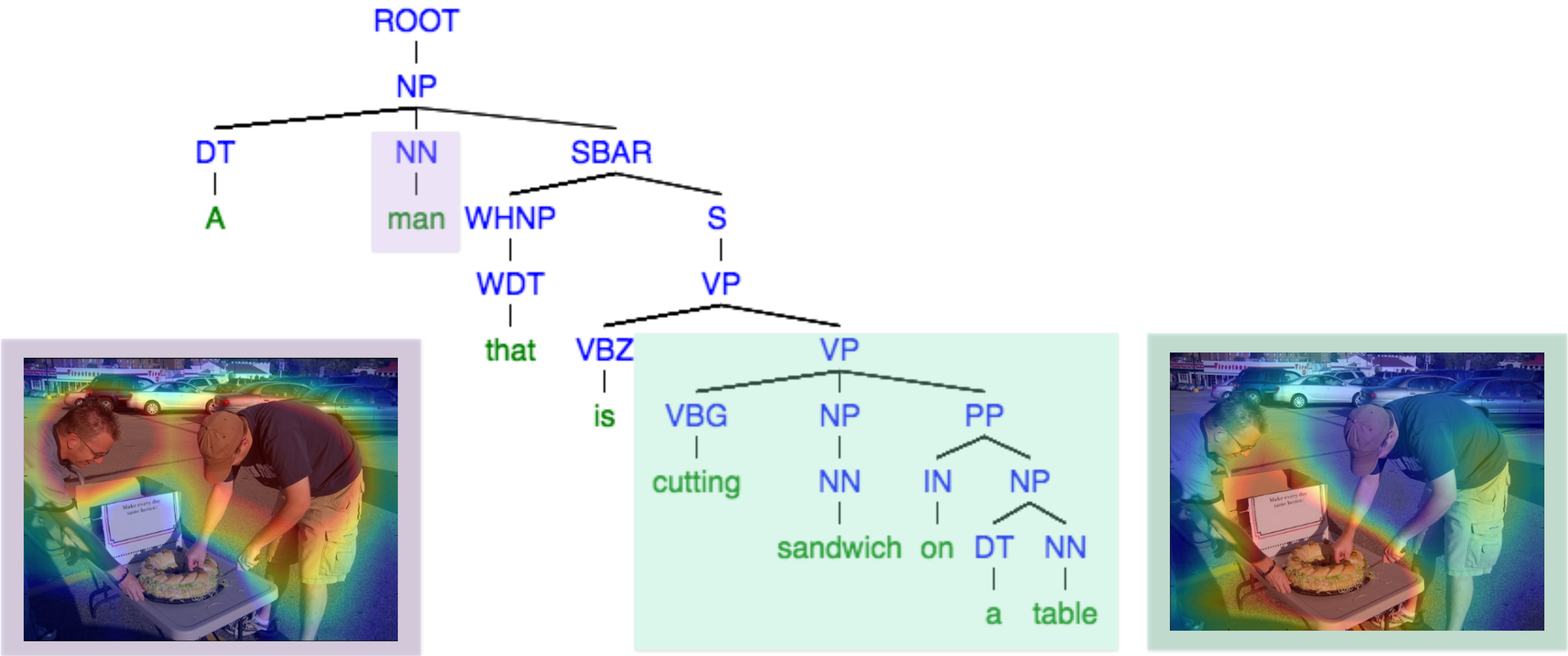

Combination of previous discriminative similarity and **linguistic regularization**

Weakly-supervised **Visual Grounding** of Phrases

[Xiao et al., 2017]

For **noun phrases**:

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

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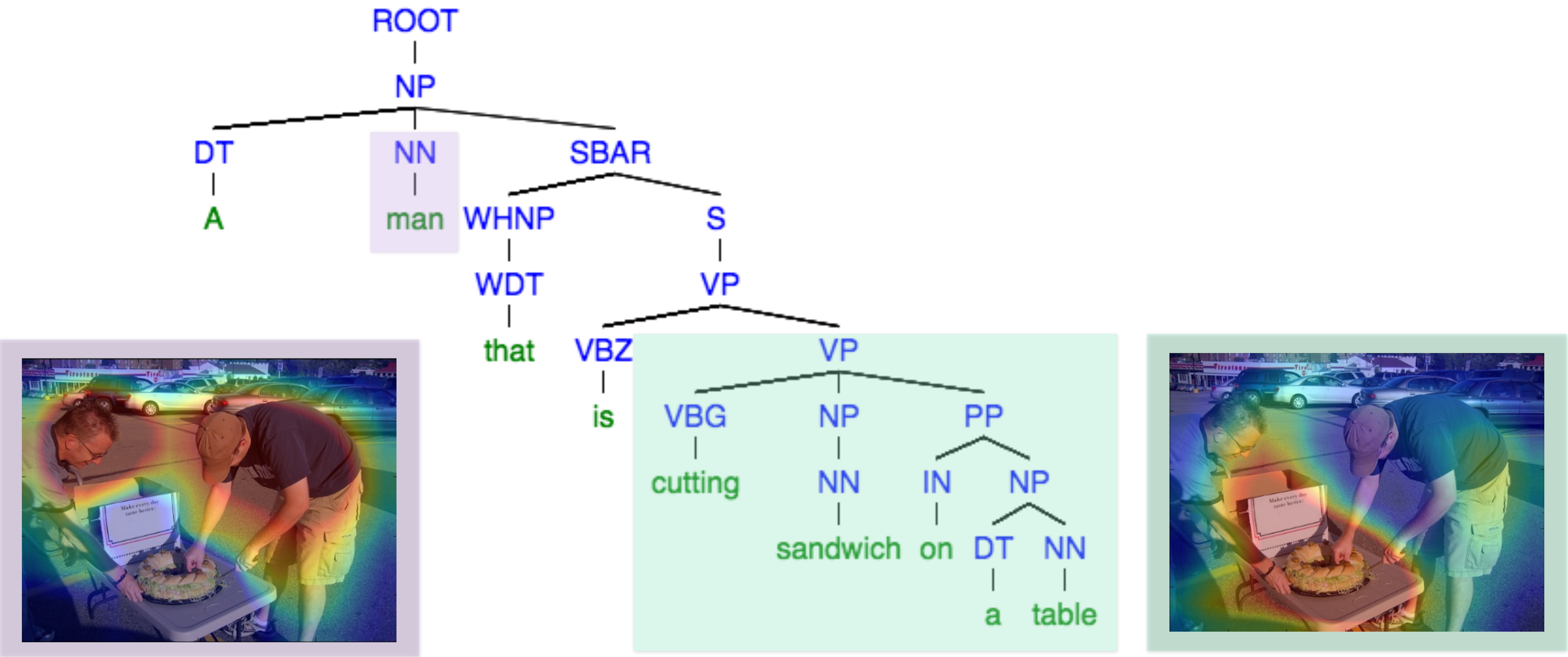

Similarity in Embedding Space

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- **parents** should be **union of**

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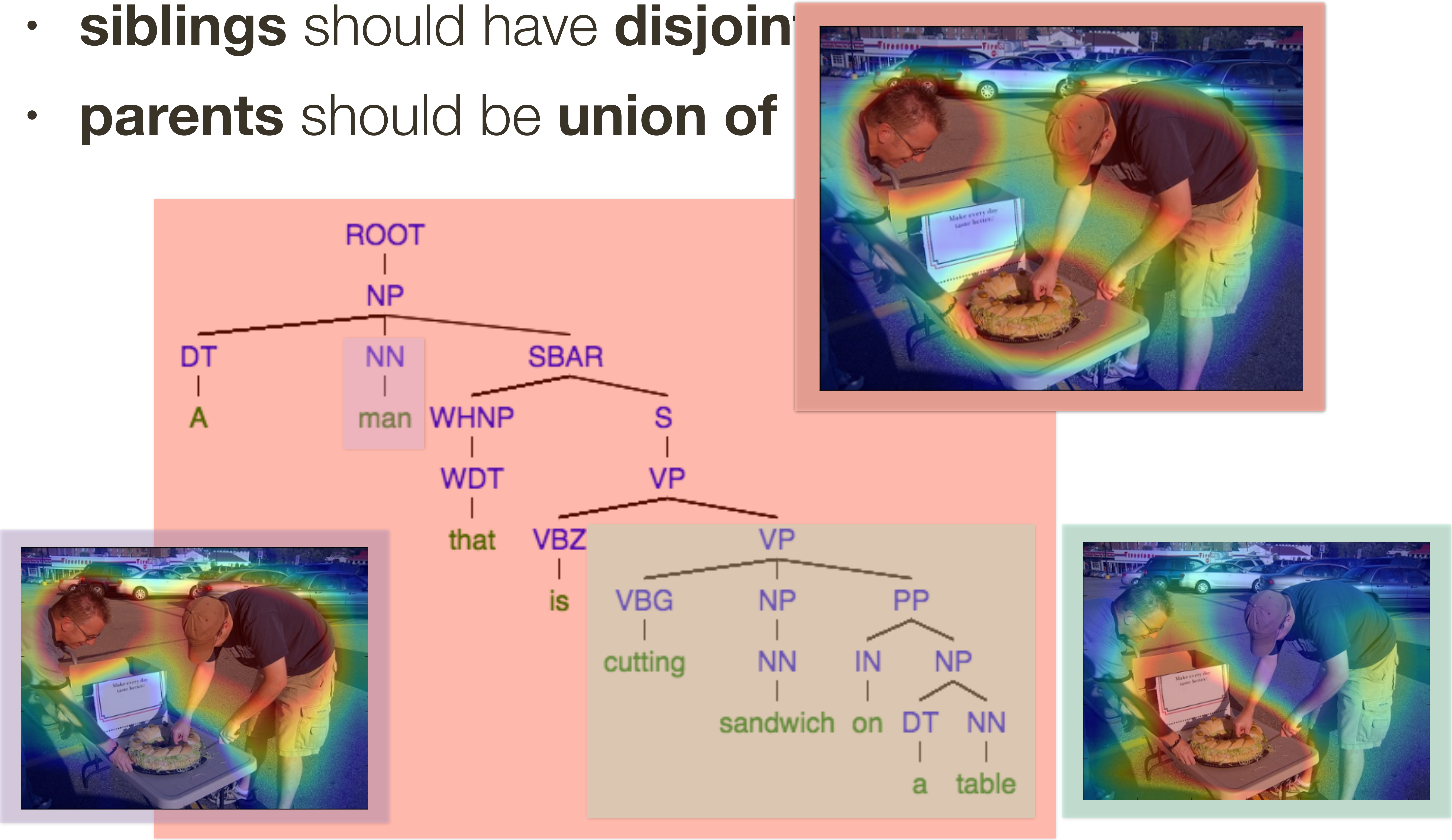

Combination of previous discriminative similarity and **linguistic regularization**

Qualitative **Results**

[Xiao et al., 2017]

Input:

guy in green t-shirt holding skateboard

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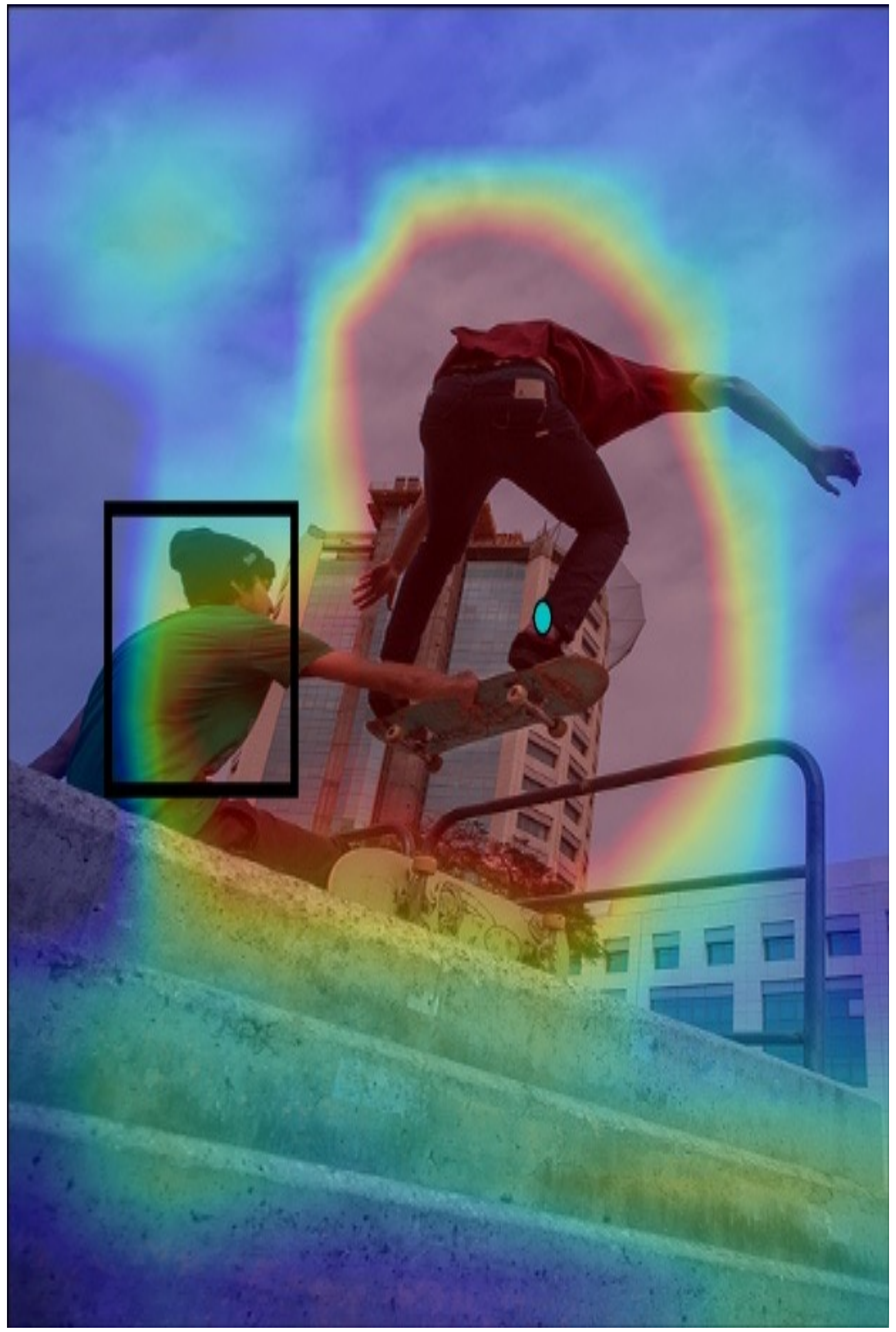
NO linguistic constraints



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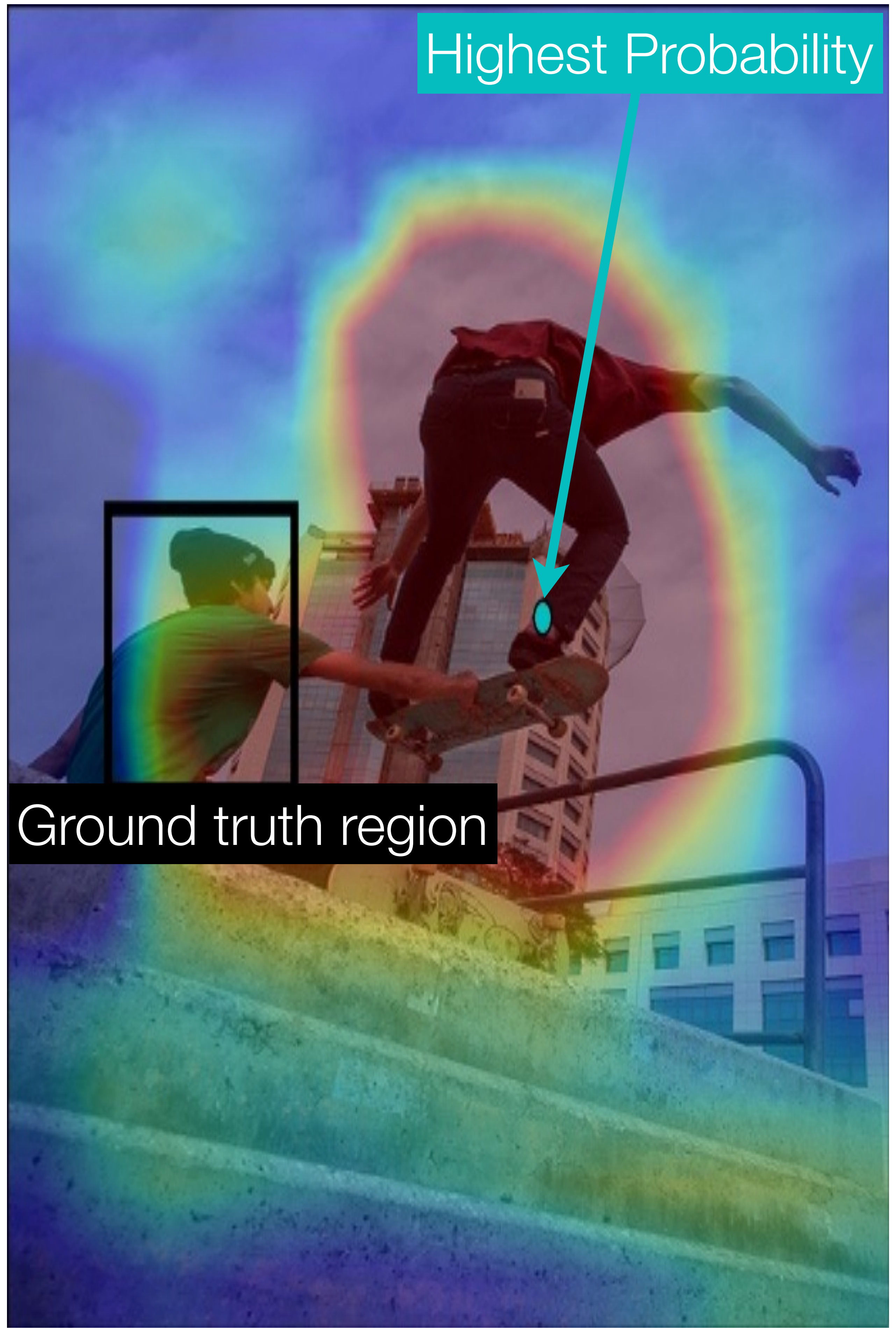

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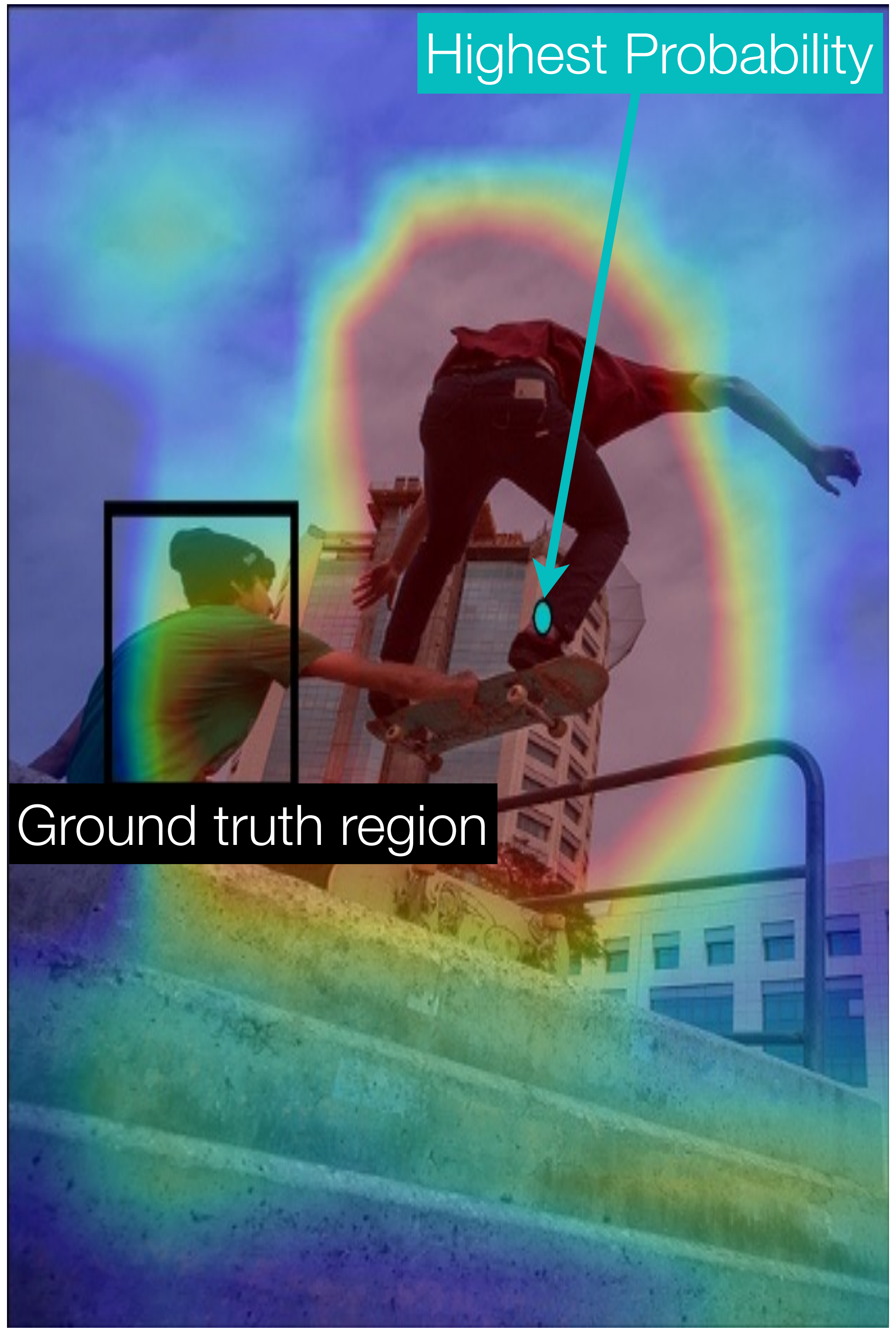
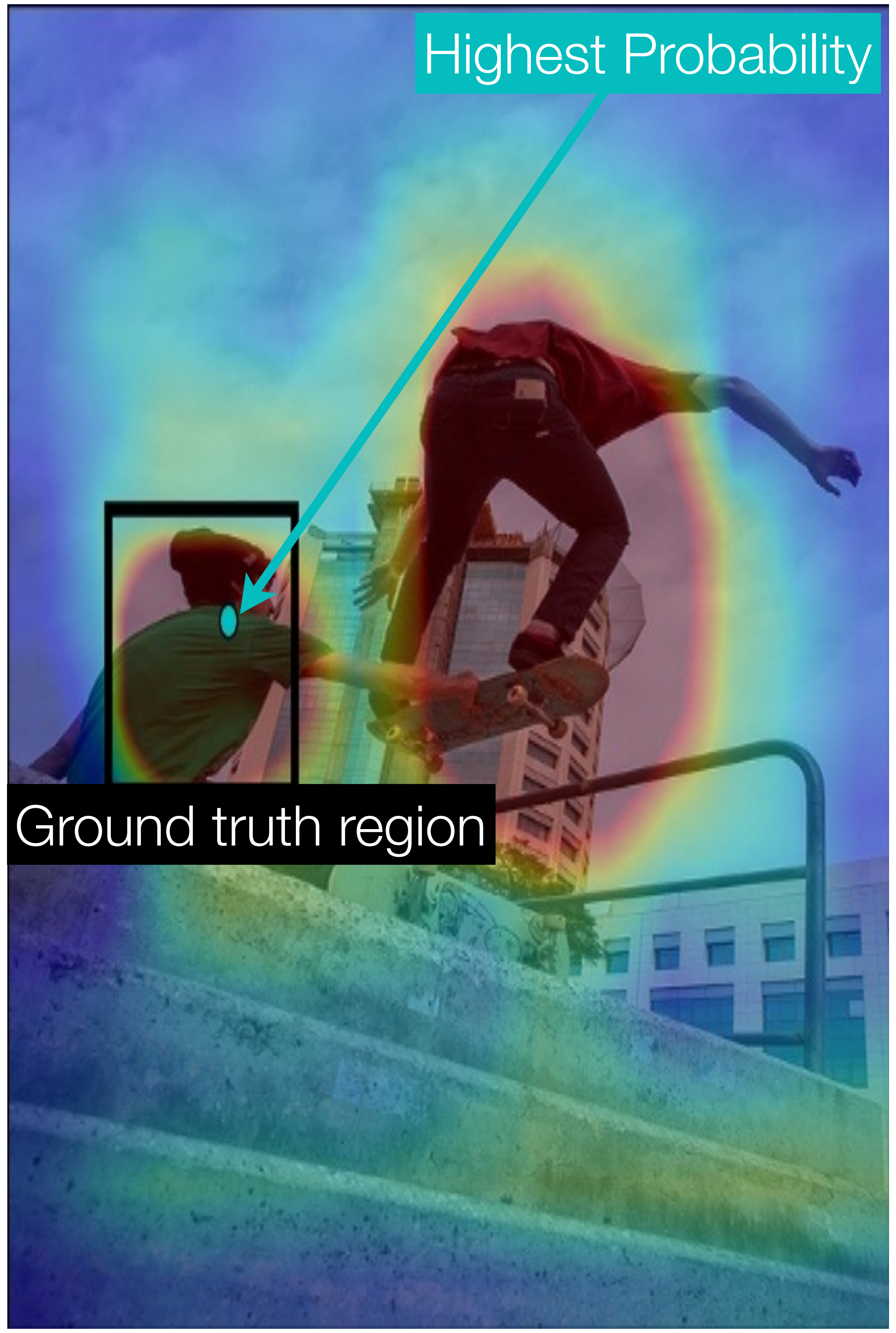


Our Model



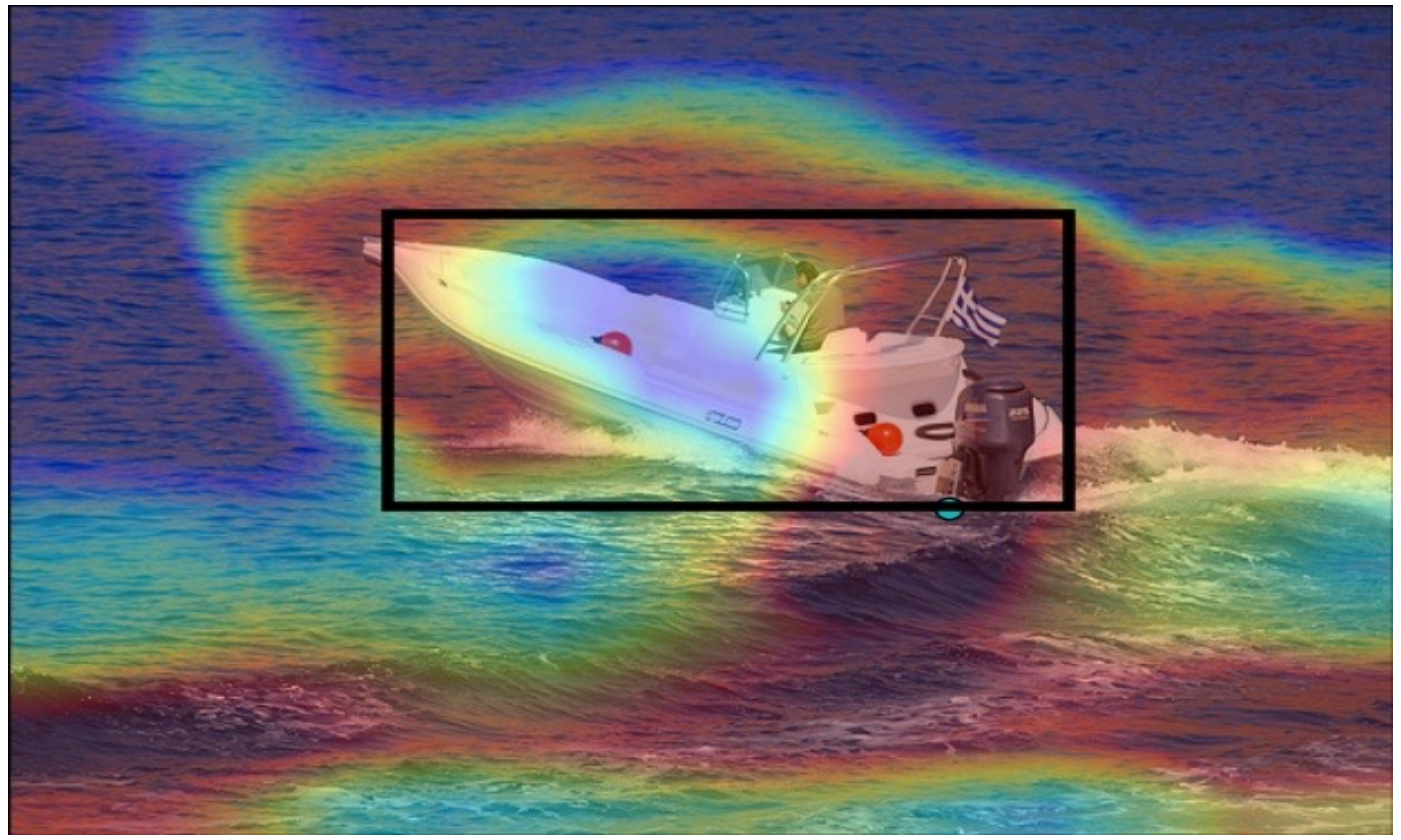
Qualitative **Results**

[Xiao et al., 2017]

Input:

a person driving a boat

NO linguistic constraints



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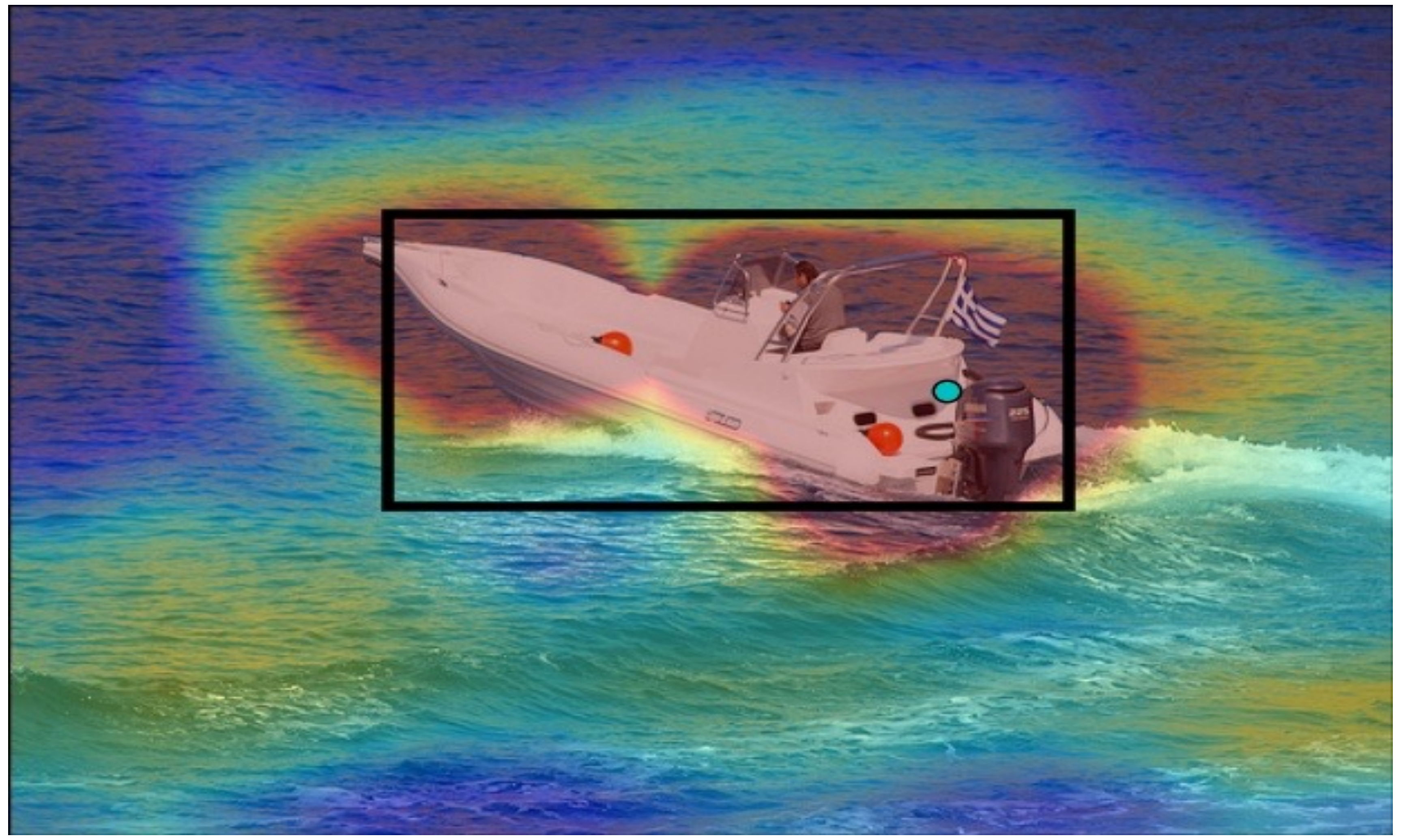
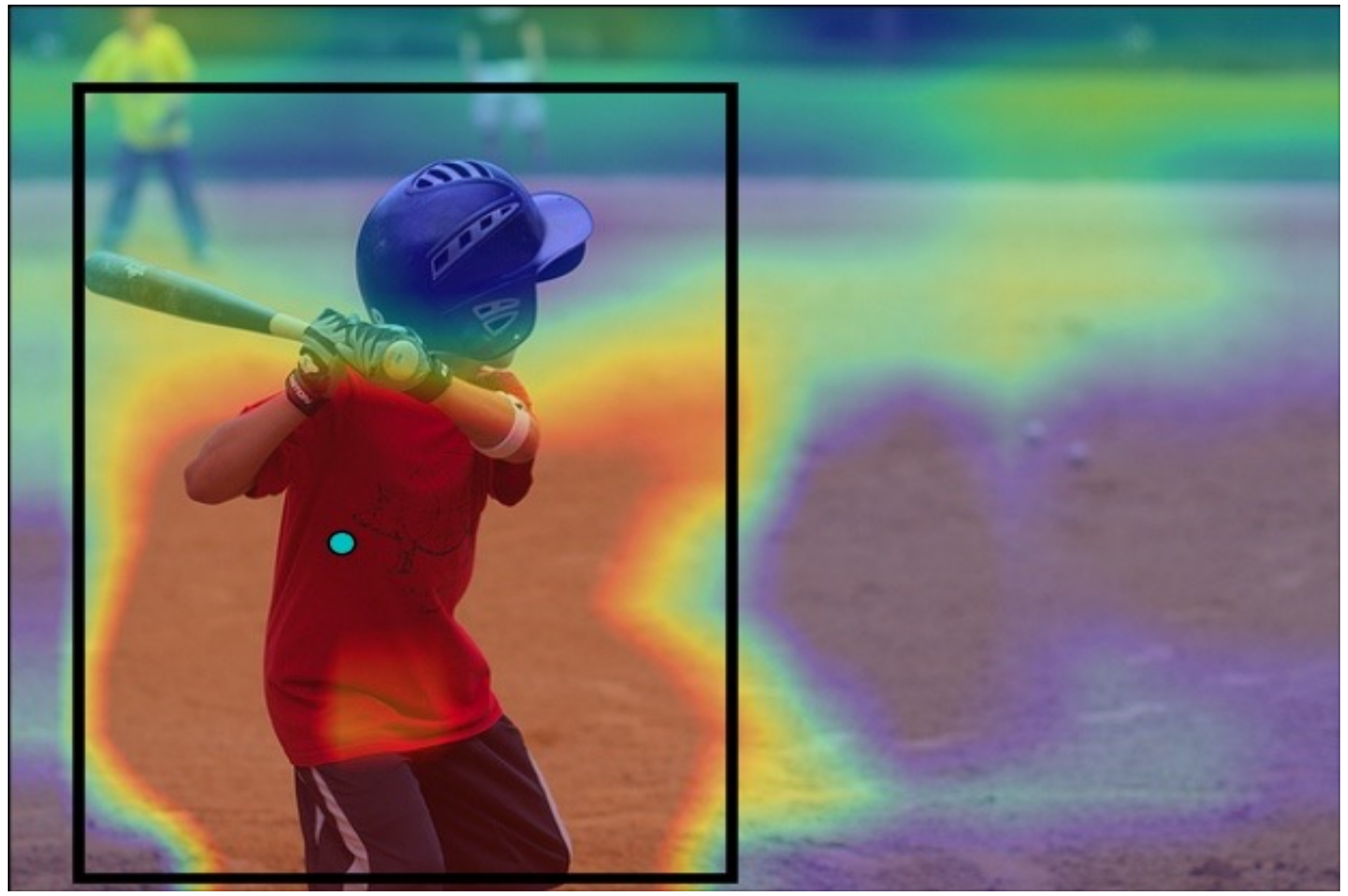


Qualitative **Results**

Input:

a child wearing black protective helmet

NO linguistic constraints [Xiao et al., 2017]



Our Model

Quantitative Results

[Xiao et al., 2017]

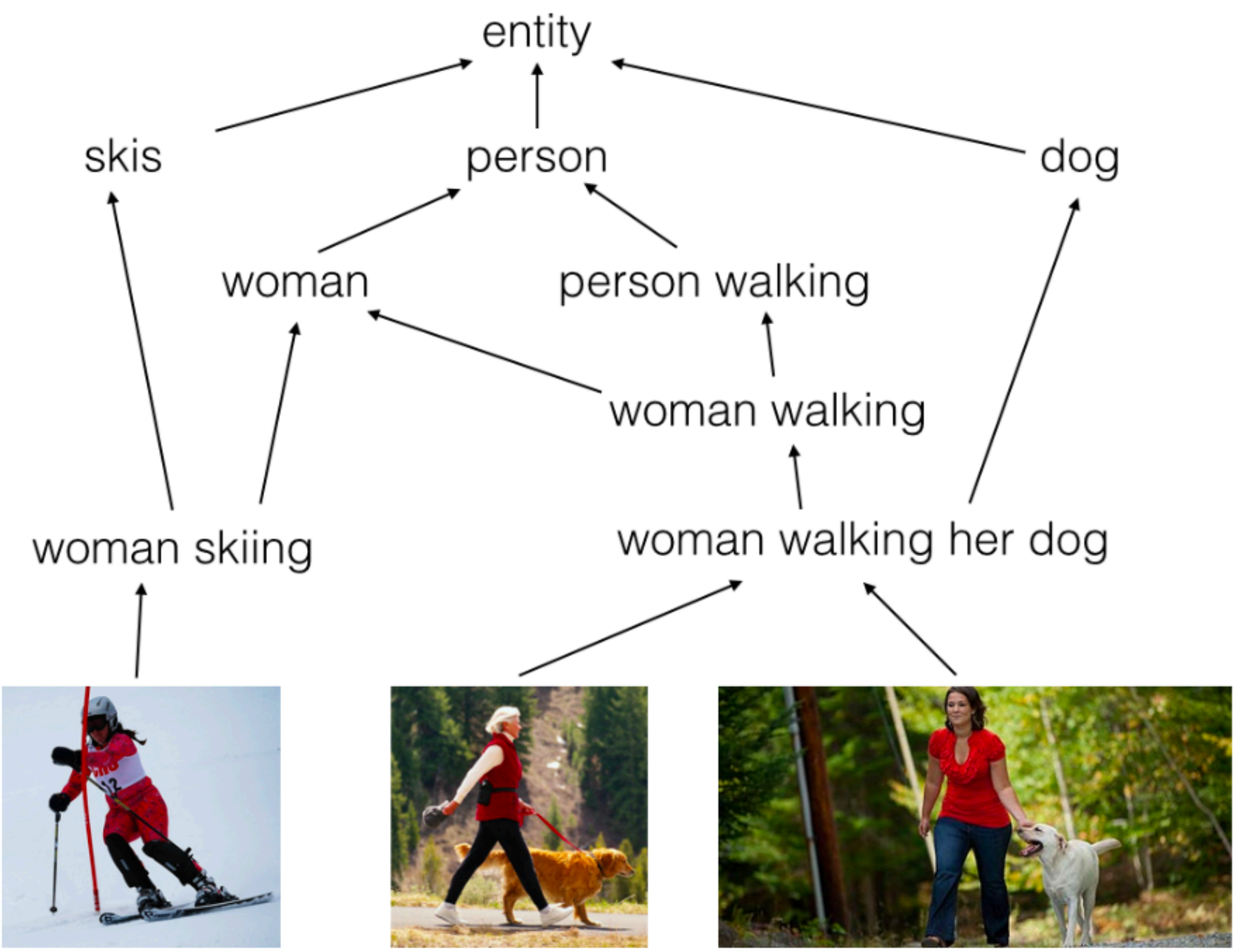
Segmentation performance on COCO dataset

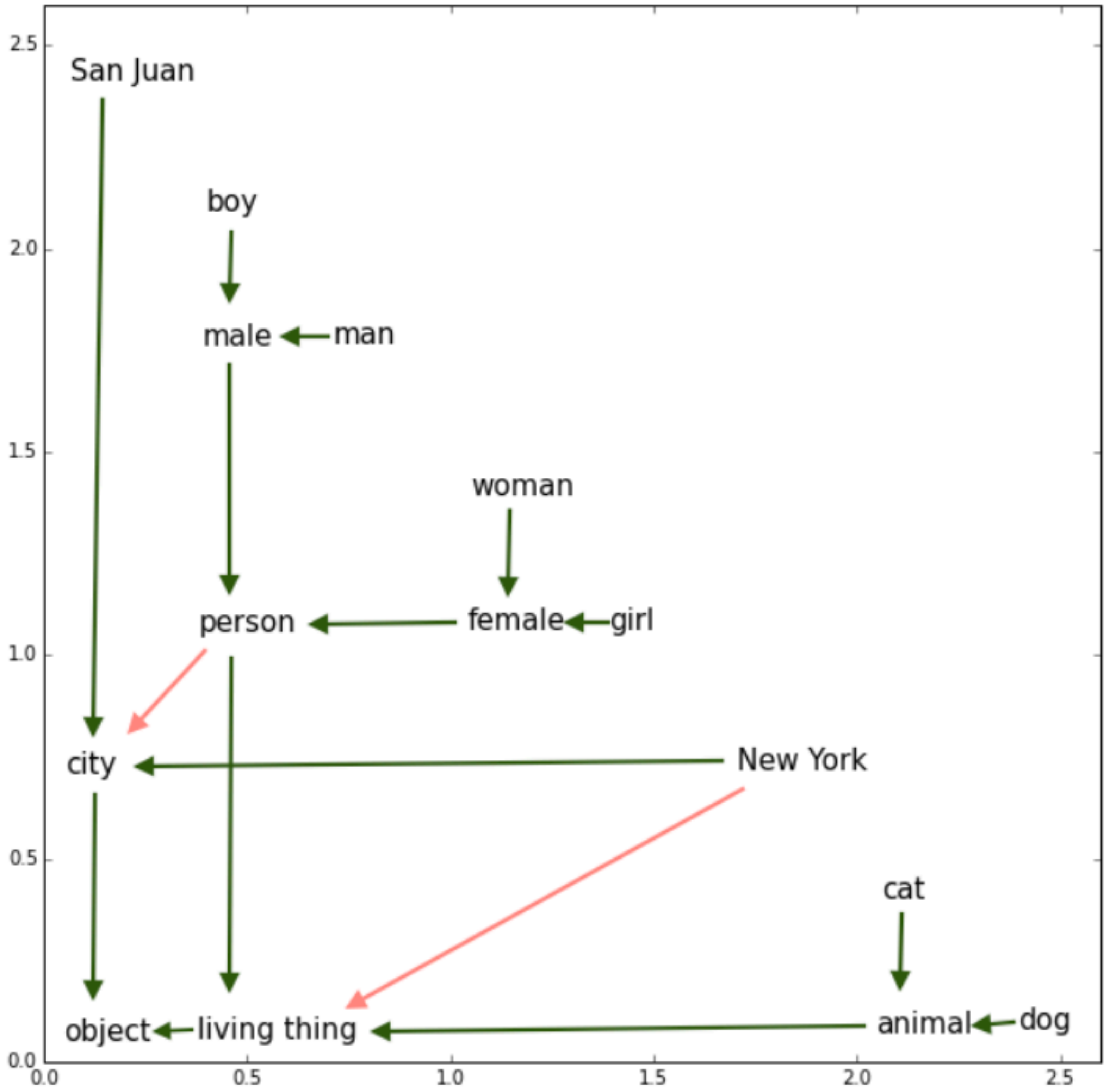
[Lin, Maire, Belongie, Hays, Perona, Ramanan, Dollar, Zitnick, ECCV'14]

	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

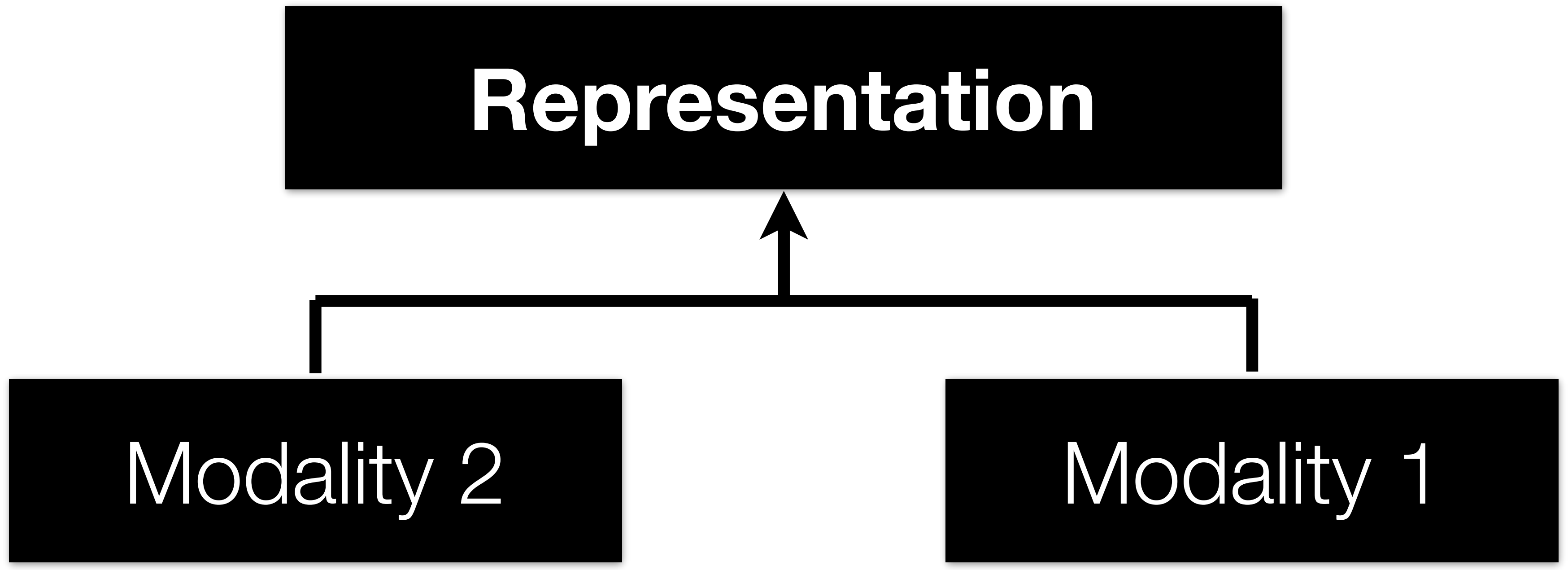
[Vendrov et al., 2016]





Multimodal Representation Types

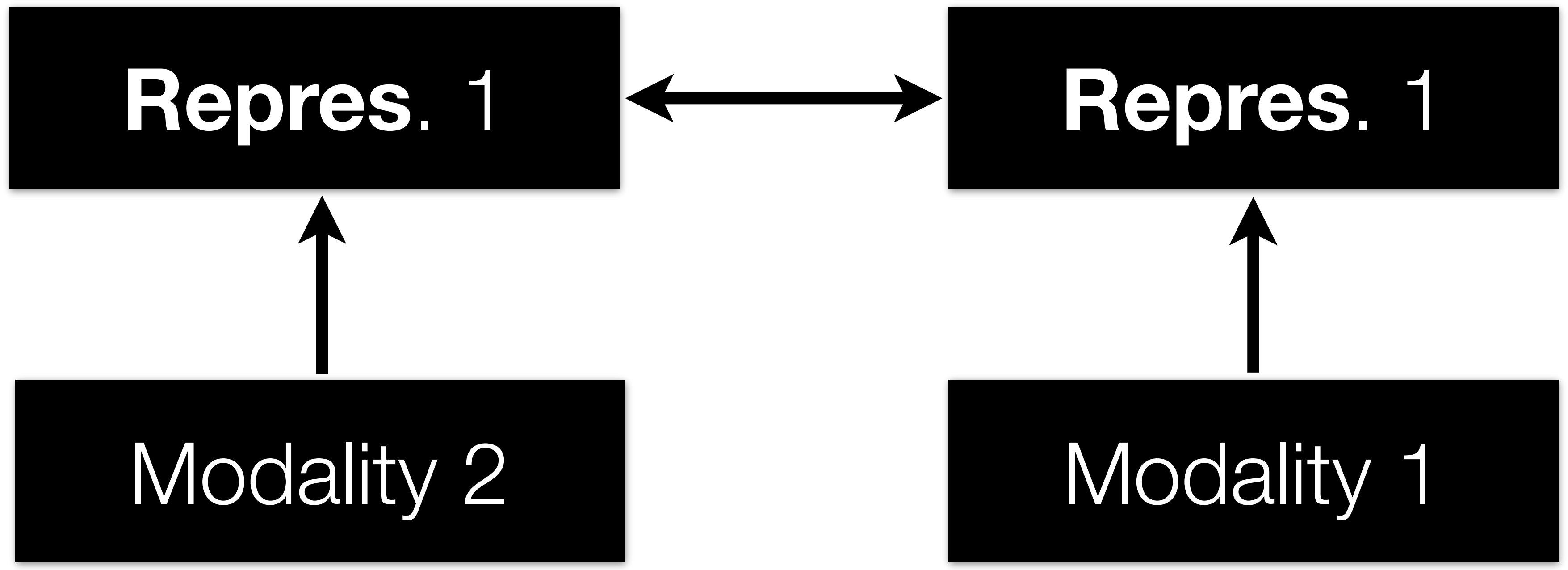
Joint representations:



— 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