AAAI-16
PHOENIX, ARIZONA USA

Knowledge Transfer with Interactive Learning of Semantic Relationships

Feb. 15, 2016

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We Can Recognize This

Image courtesy by http://www.4pawshuddersfield.com

We Can Recognize This Too

Image courtesy by https://en.wikipedia.org/wiki/List_of_birds_of_South_Carolina

And We Can Easily Infer What This Is

[1] J. Feldman, "**The structure of perceptual categories**," **Journal of Mathematical Psychology 1997**
[2] J. Tenenbaum, "**Bayesian modeling of human concept learning**", **NIPS 1999**
[3] T. Tommasi et al, "Safety in Numbers: Learning Categories from Few Examples with Multi Model Knowledge Transfer", **CVPR 2010**
[4] Qi et al, "Towards Cross-Category Knowledge Propagation for Learning Visual Concepts", **CVPR 2011**
[5] B. Lake, R. Salakhutdinov, J. Tenenbaum, "Human-level concept learning through probabilistic program induction", **Science 2015**

Image courtesy by http://www.hypertomb.com/dirds/

Knowing Some Categories Allows Recognition of Others

If we know these categories well

We may recognize a bird-dog better[1]

Image courtesy by Google

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Learning Semantic Relationship in Metric

- To improve the classification accuracy of ***rarely seen*** object category in metric learning framework

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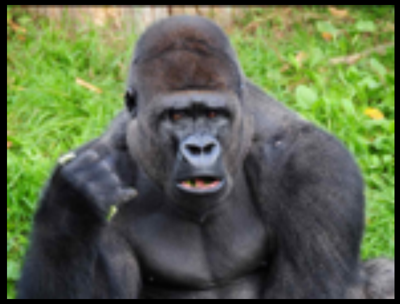
Target category

What Relationship?

- **A** is more similar to **B** than **C**

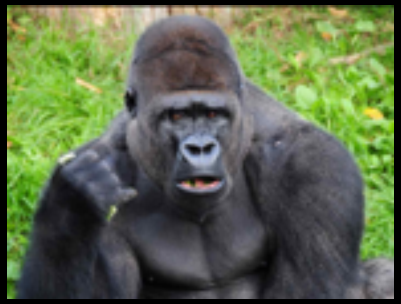


Chimpanzee is more similar to **Gorilla** than **Deer**

What Relationship?

Target category   Anchor categories

- A is more similar to B than C



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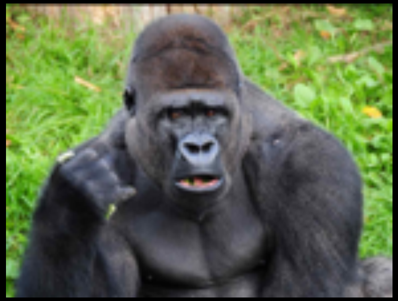

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How to obtain the relationships?

Creating Relational Knowledge Base

- is expensive

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  - Exponentially many (N^3) knowledges

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    - ➡ Ambiguous relative similarity

Creating Relational Knowledge Base

- is expensive
  - Exponentially many (N^3) knowledges
  - Difficult to answer
    ➡ Ambiguous relative similarity
  - Every relationship is not equally useful
    ➡ Some are more useful, some are less or useless

Ambiguous Relationship

- Who is more similar to Ironman?

Image courtesy by Disney and Toei Company

Ambiguous Relationship

- Who is more similar to Ironman?

Power ranger?

Image courtesy by Disney and Toei Company

Ambiguous Relationship

- Who is more similar to Ironman?

Power ranger?

Tony Stark?

Image courtesy by Disney and Toei Company

Not Every Relationship is Equally Useful for Classification

Classifier for prettiness

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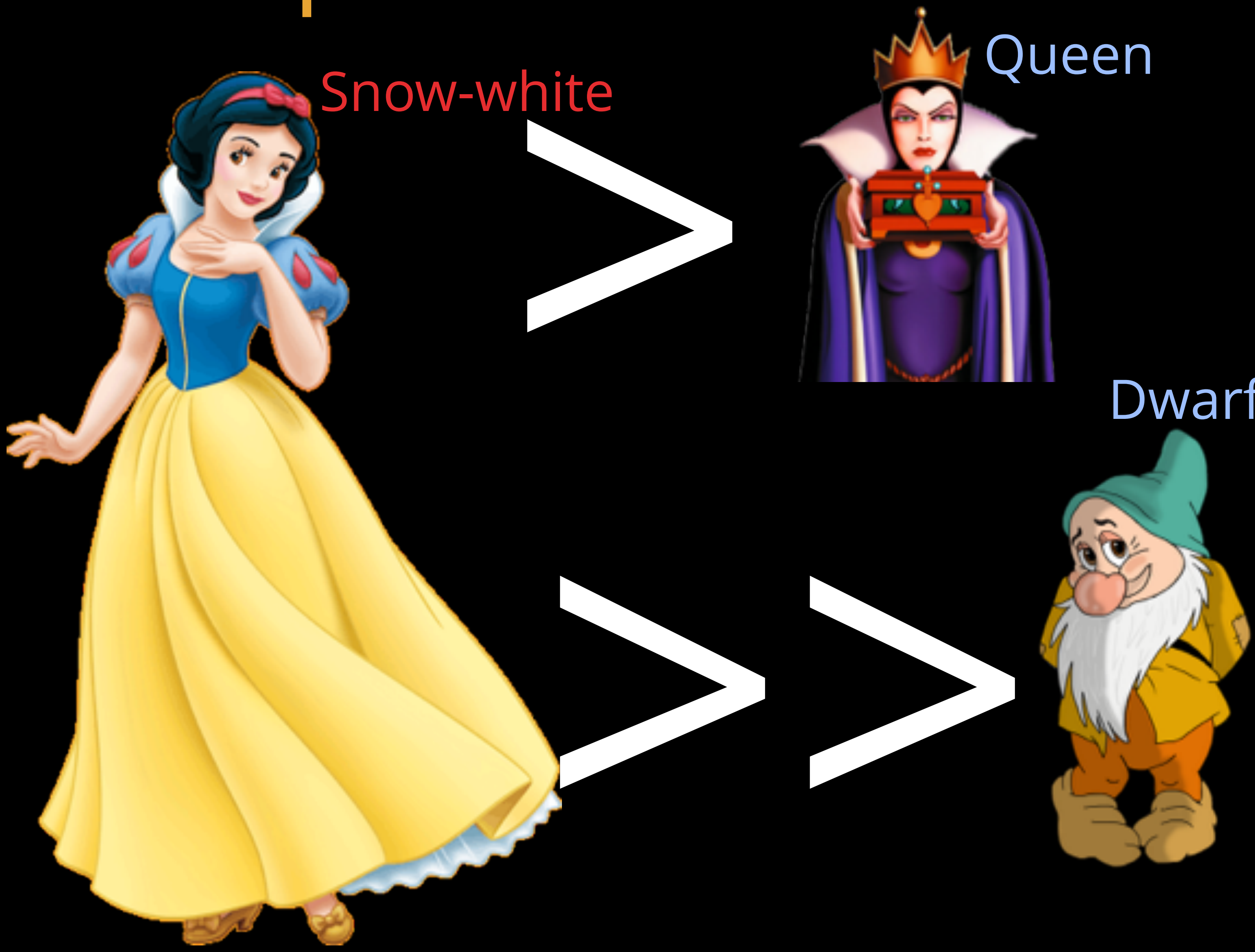
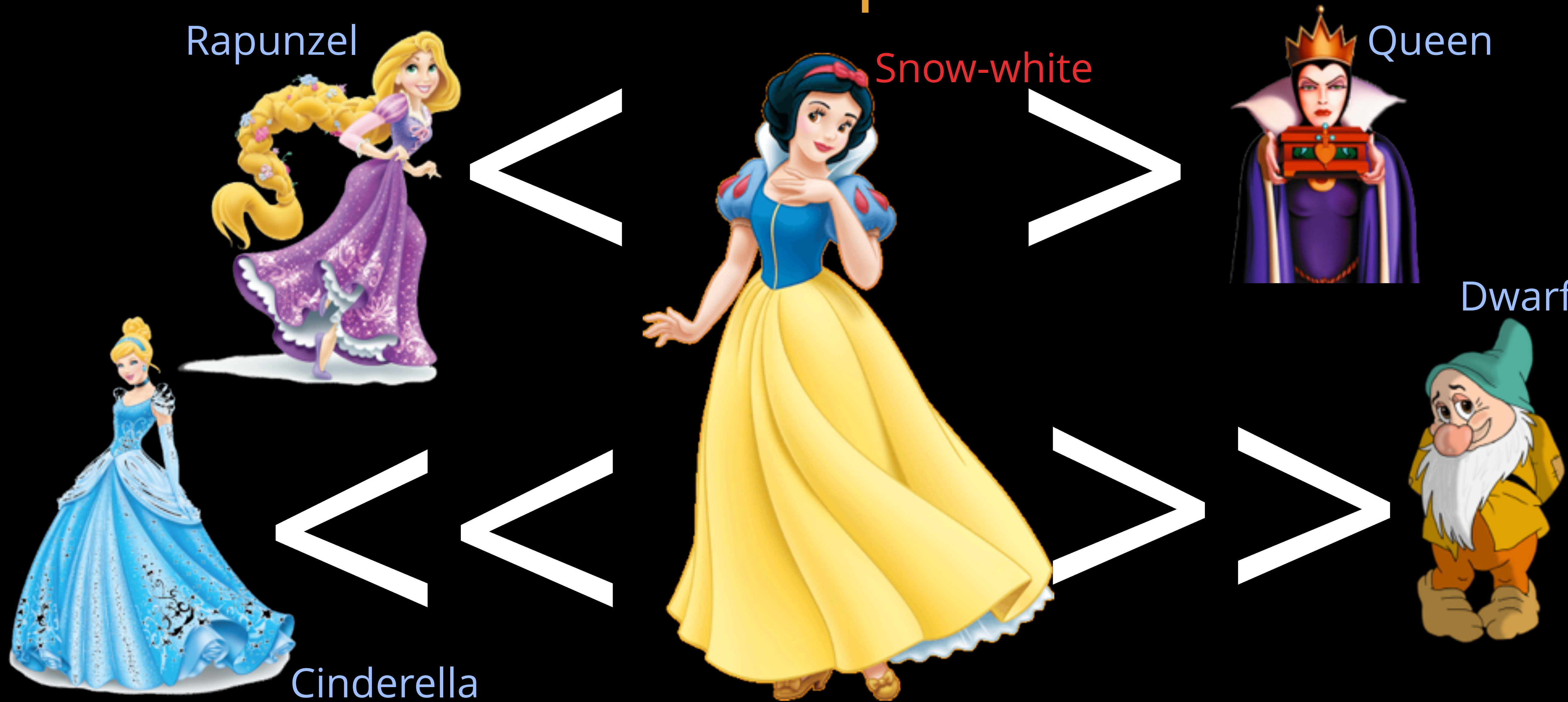


Snow-white is prettier than the Queen rather than the Seven dwarfs?

Image courtesy by Disney

Not Every Relationship is Equally Useful for Classification

Classifier for prettiness

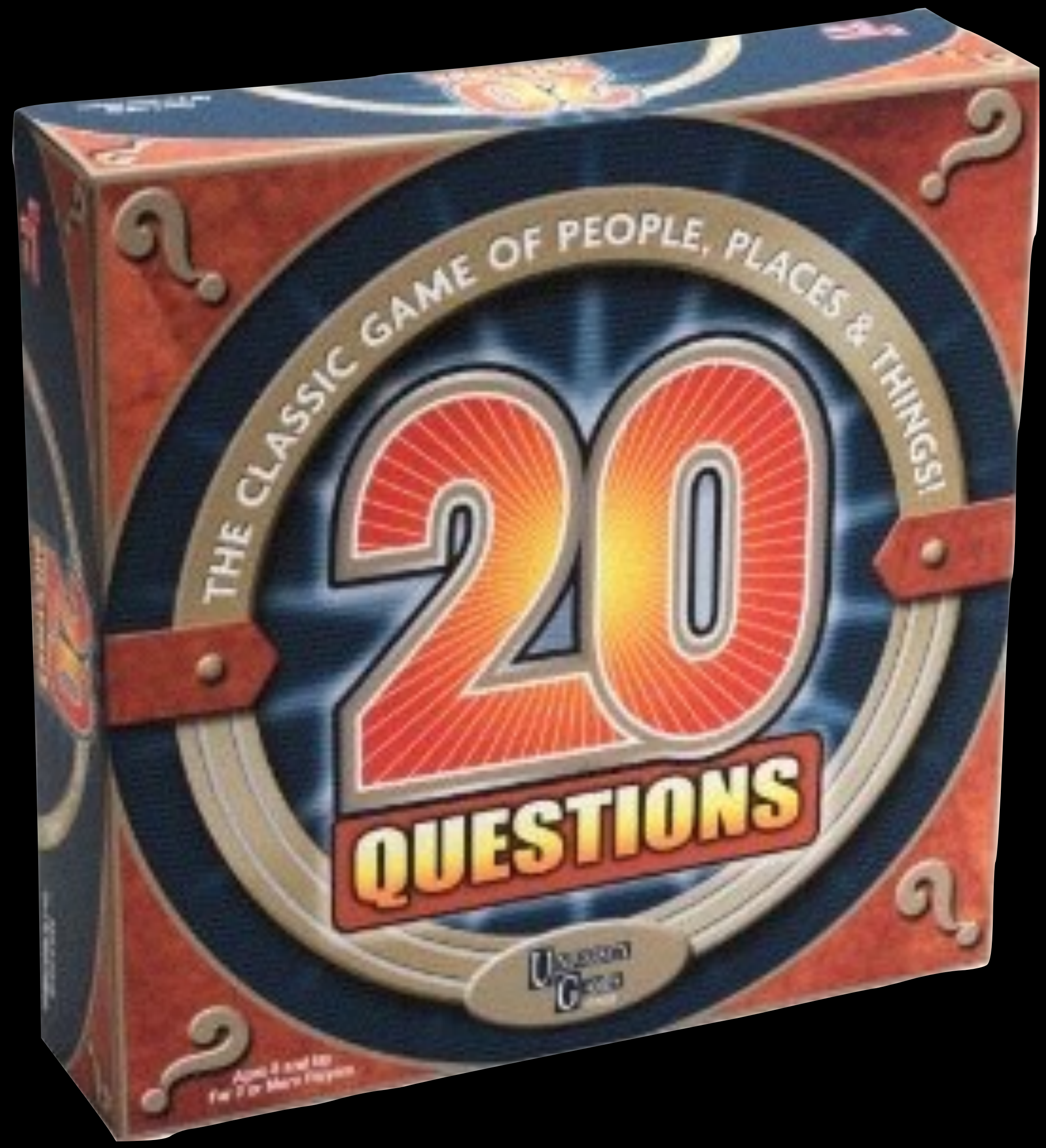


Snow-white is prettier than the Queen rather than the Seven dwarfs?

Snow-white is prettier than Rapunzel rather than Cinderella?

Image courtesy by Disney

Our Approach:
Ask A Few Useful Questions



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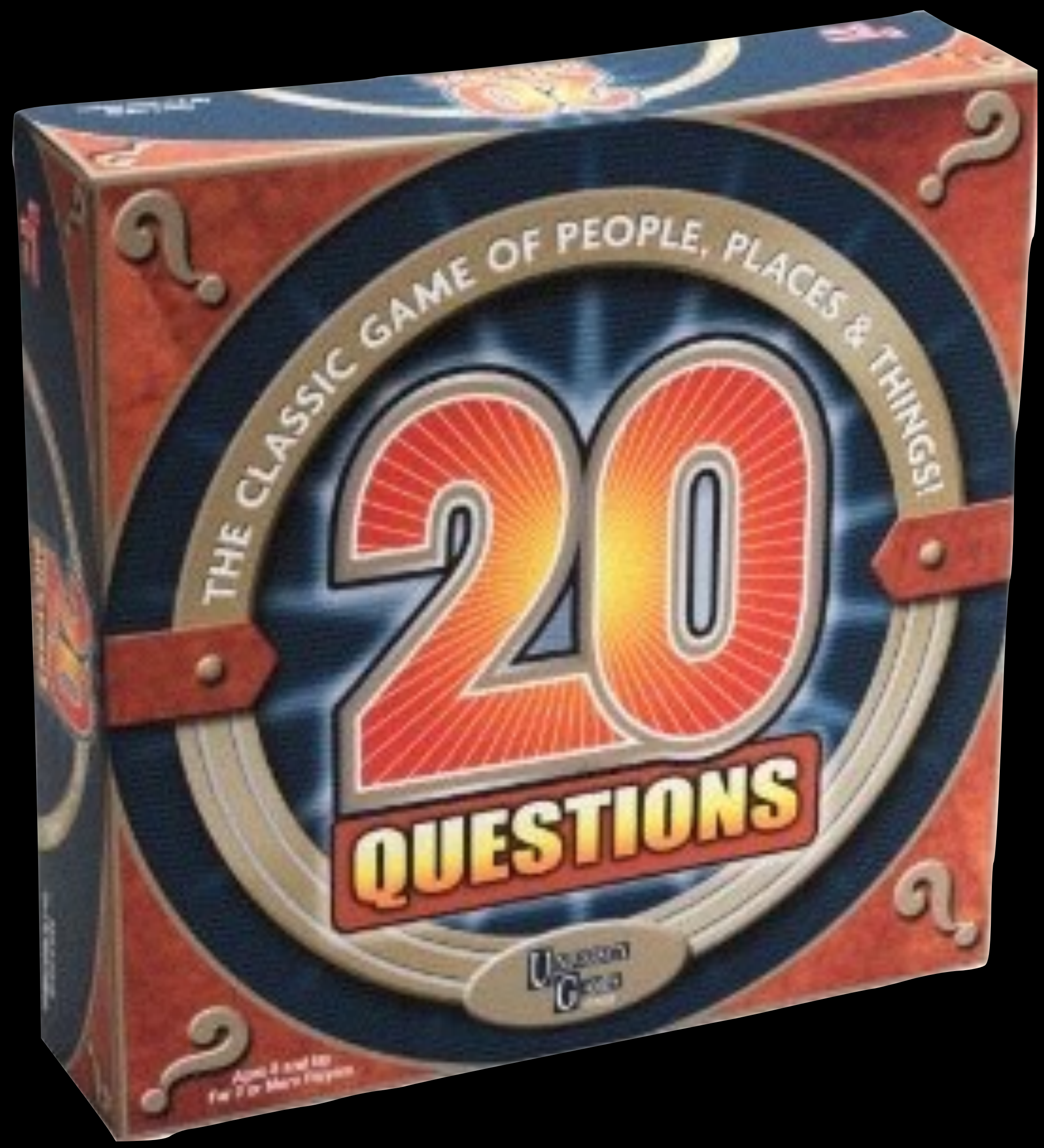


Ask most useful questions in interactions

We Propose

- To learn a semantic space for target categories with constraints of semantic distance from the anchor categories

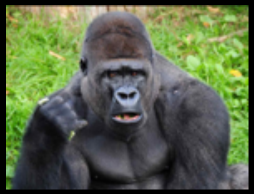
- Target category: one to improve the classification
  - with few samples

- Anchor category: one to transfer knowledge from
  - with more samples

We Propose

- To learn a semantic space for target categories with constraints of semantic distance from the anchor categories

- Example:


  - Chimpanzee is more similar to Gorilla than Deer?



  - Collie is more similar to Dalmatian than Giraffe?

Learning Classification Embeddings

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Training images of Anchor Categories

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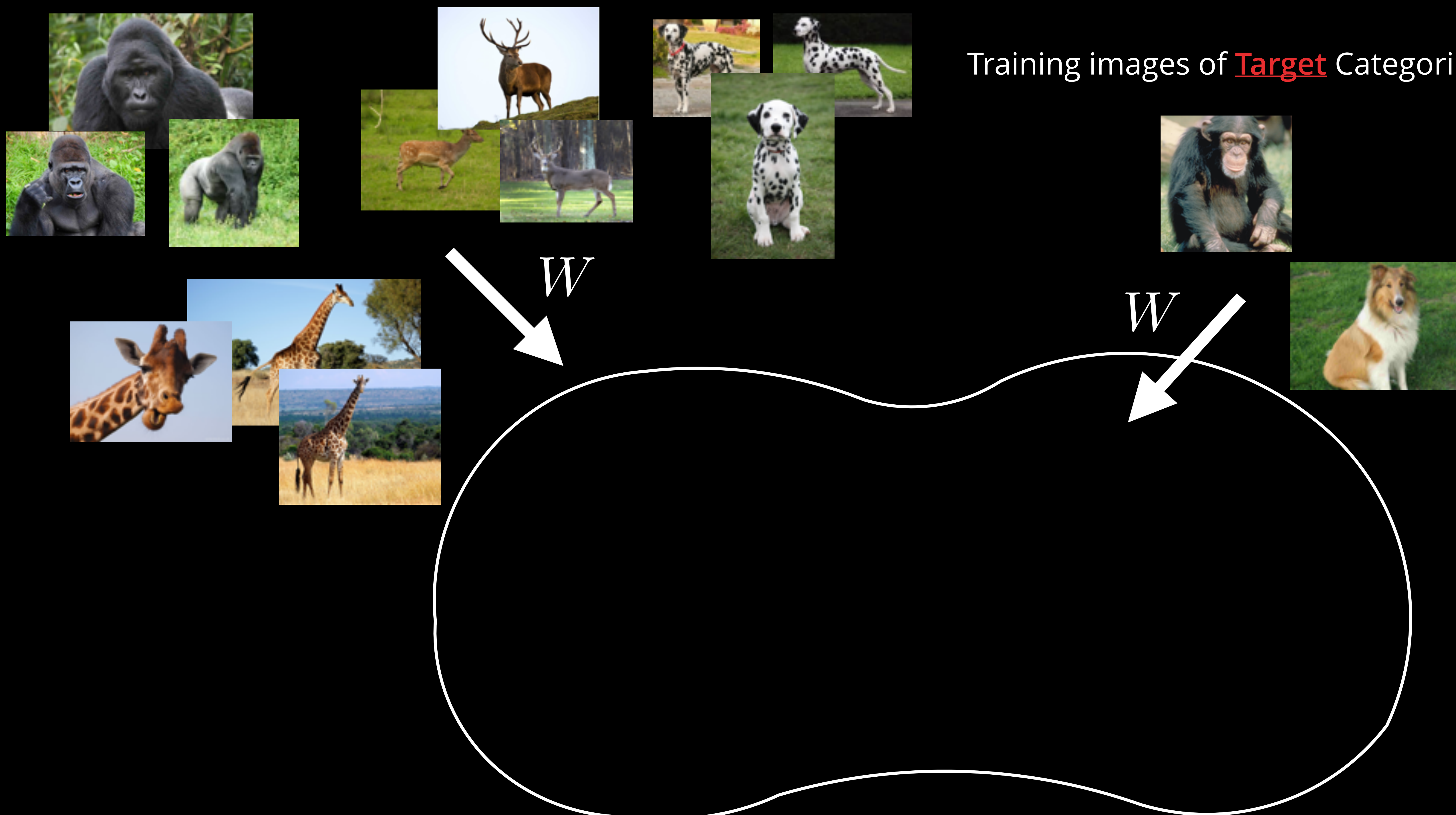
Training images of **Anchor** Categories

Training images of **Target** Categories

Learning Classification Embeddings

Training images of Anchor Categories



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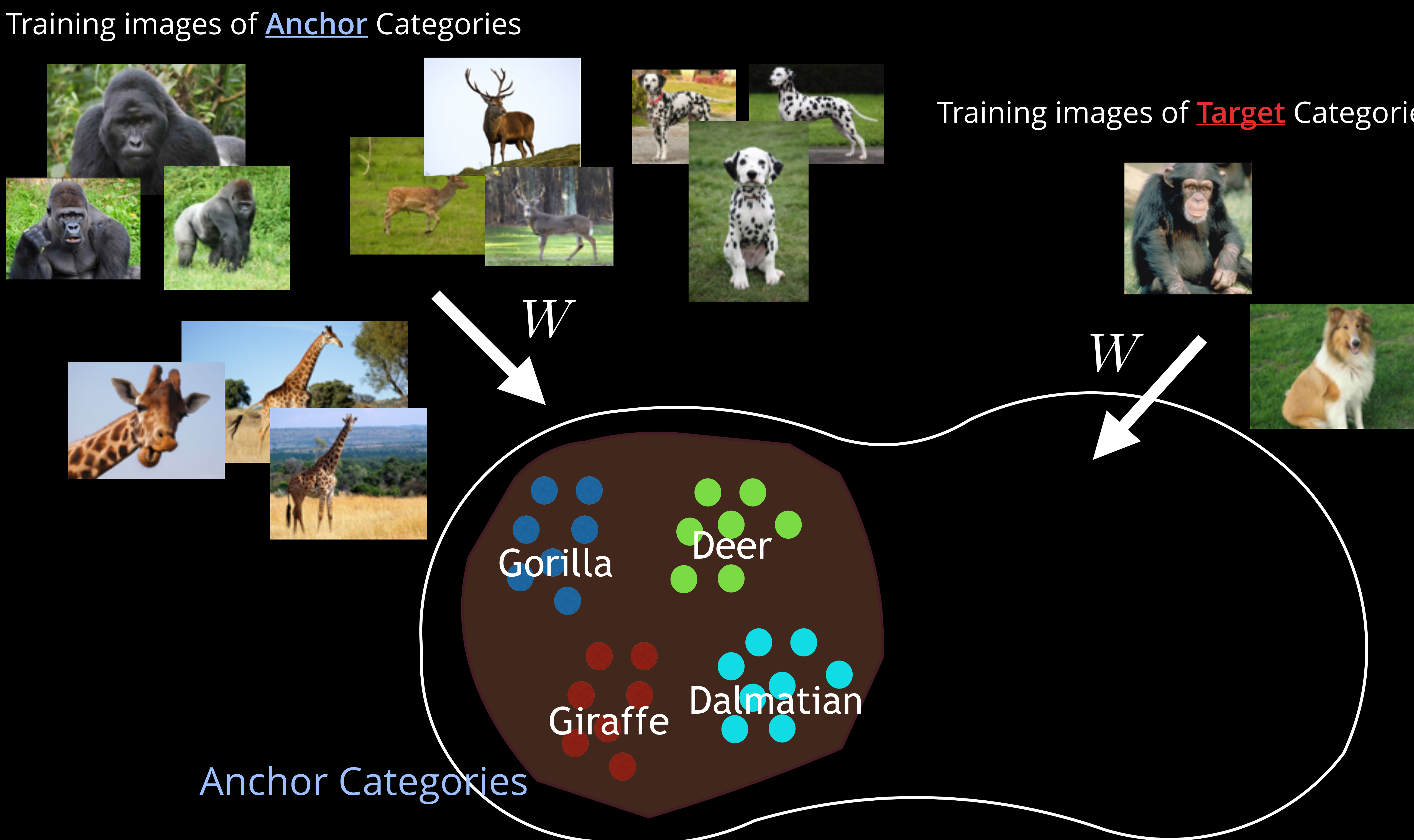

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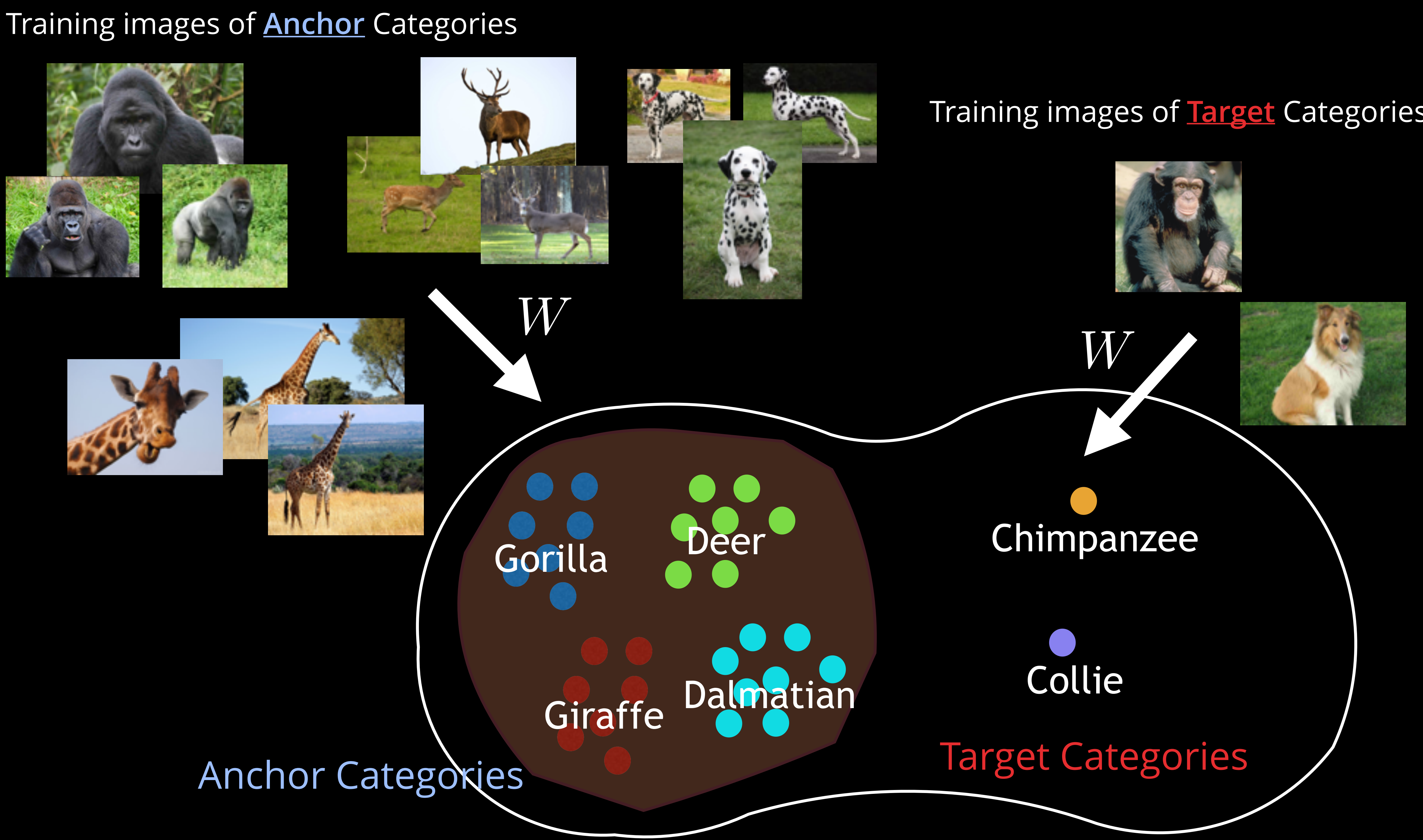

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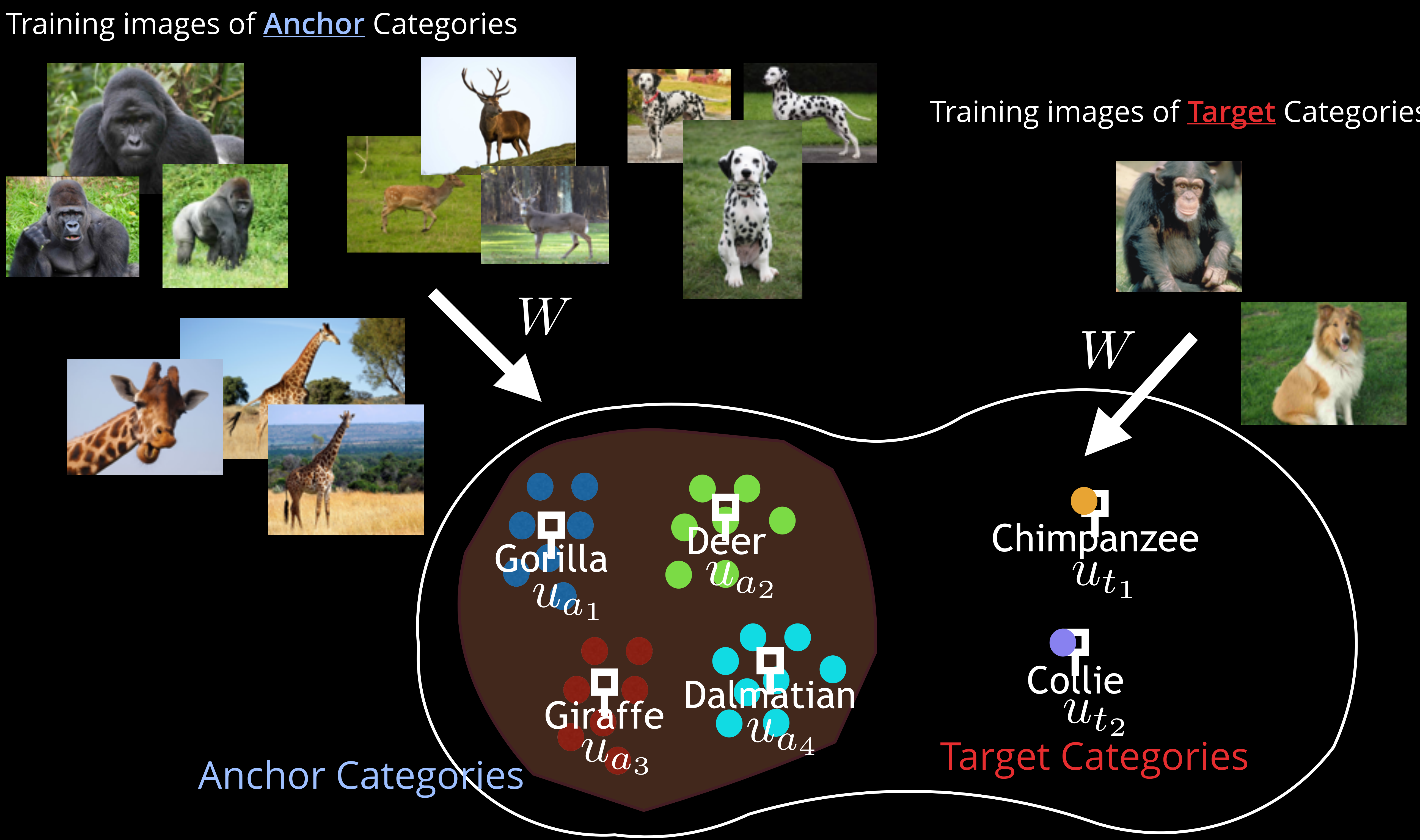
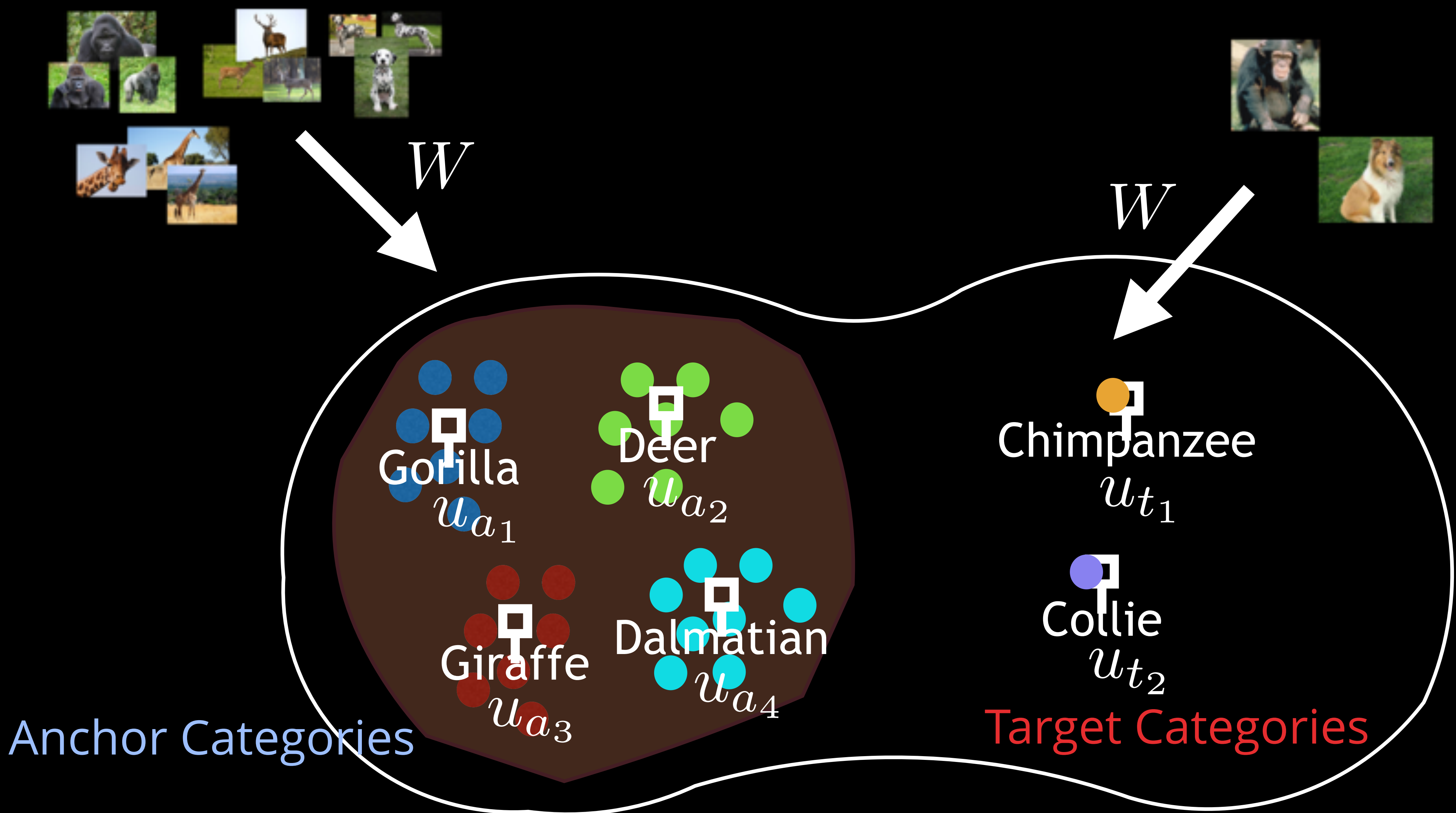


Refine Classification Embedding by Relational Semantics



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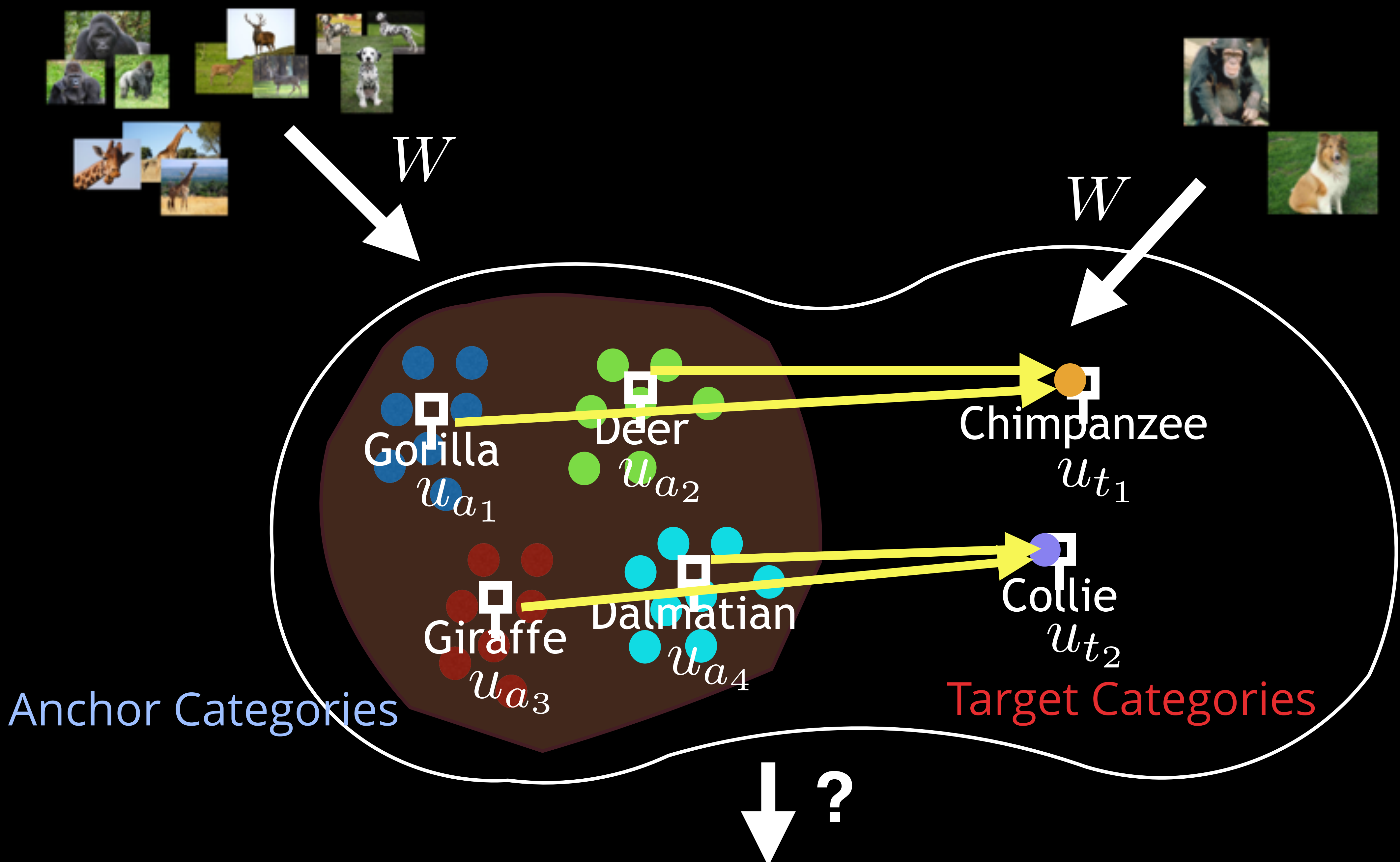

- Is Chimpanzee more similar to Gorilla than Deer?
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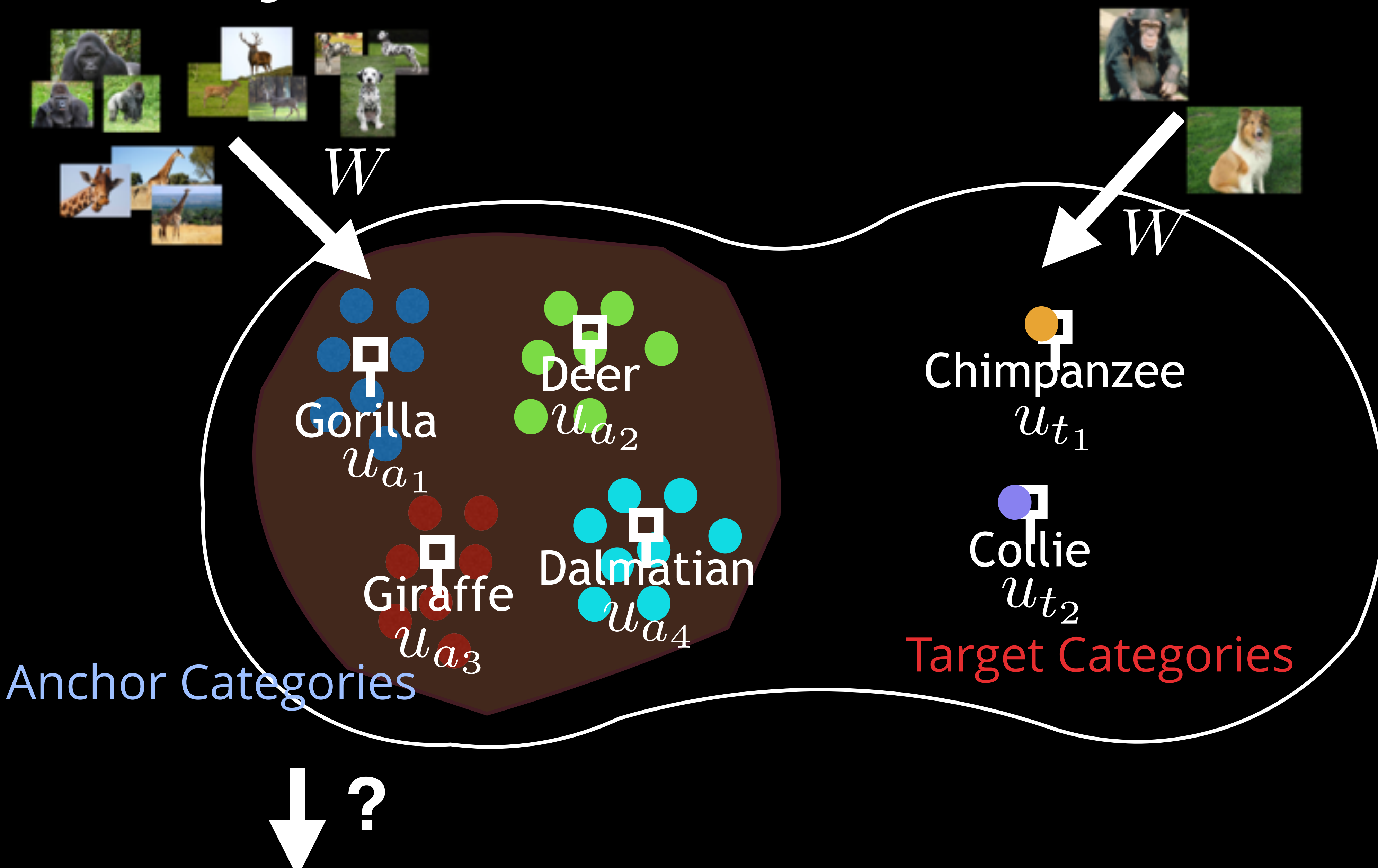
Learning Classification Embedding by Relational Semantics Feedback



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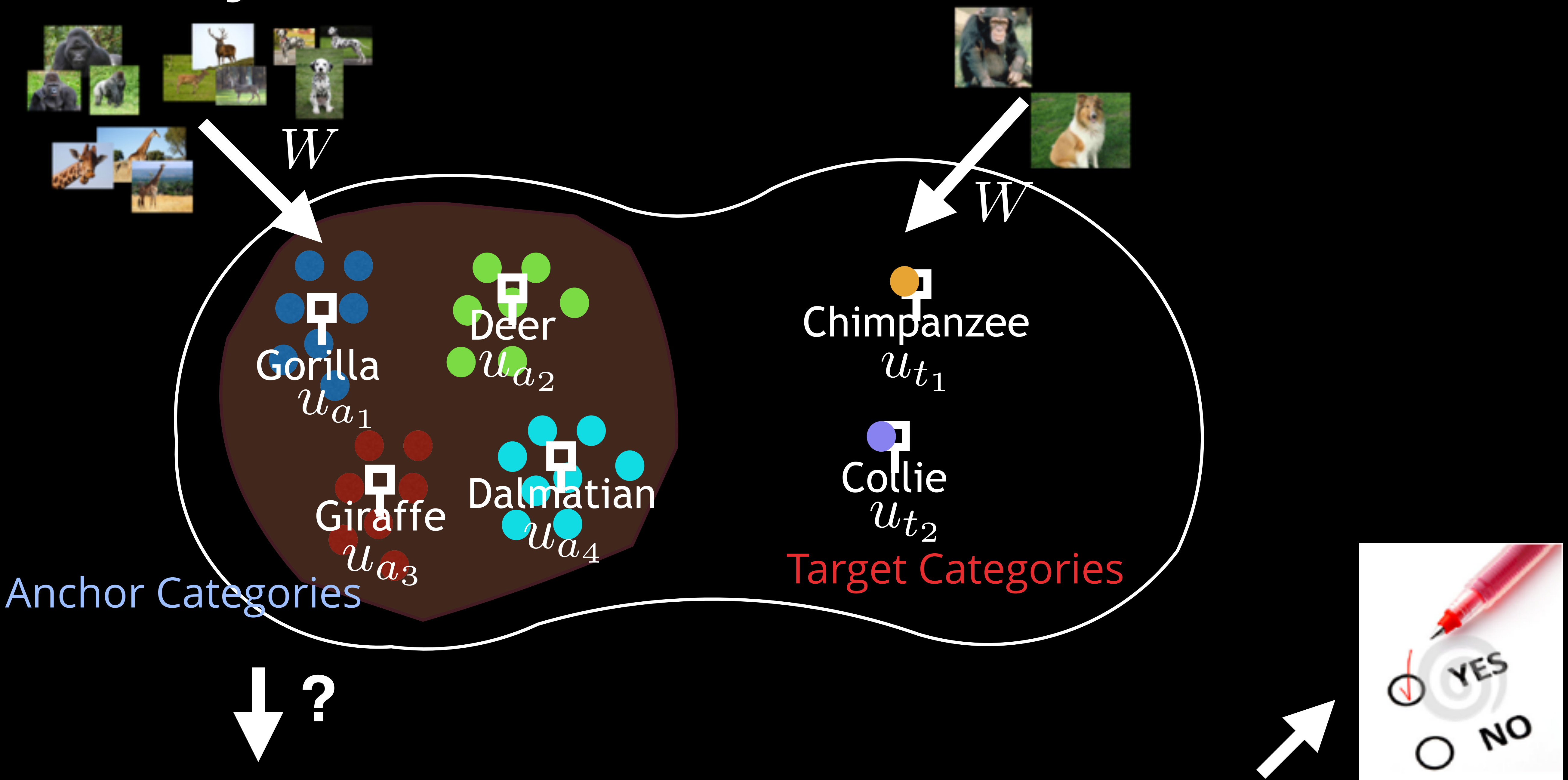

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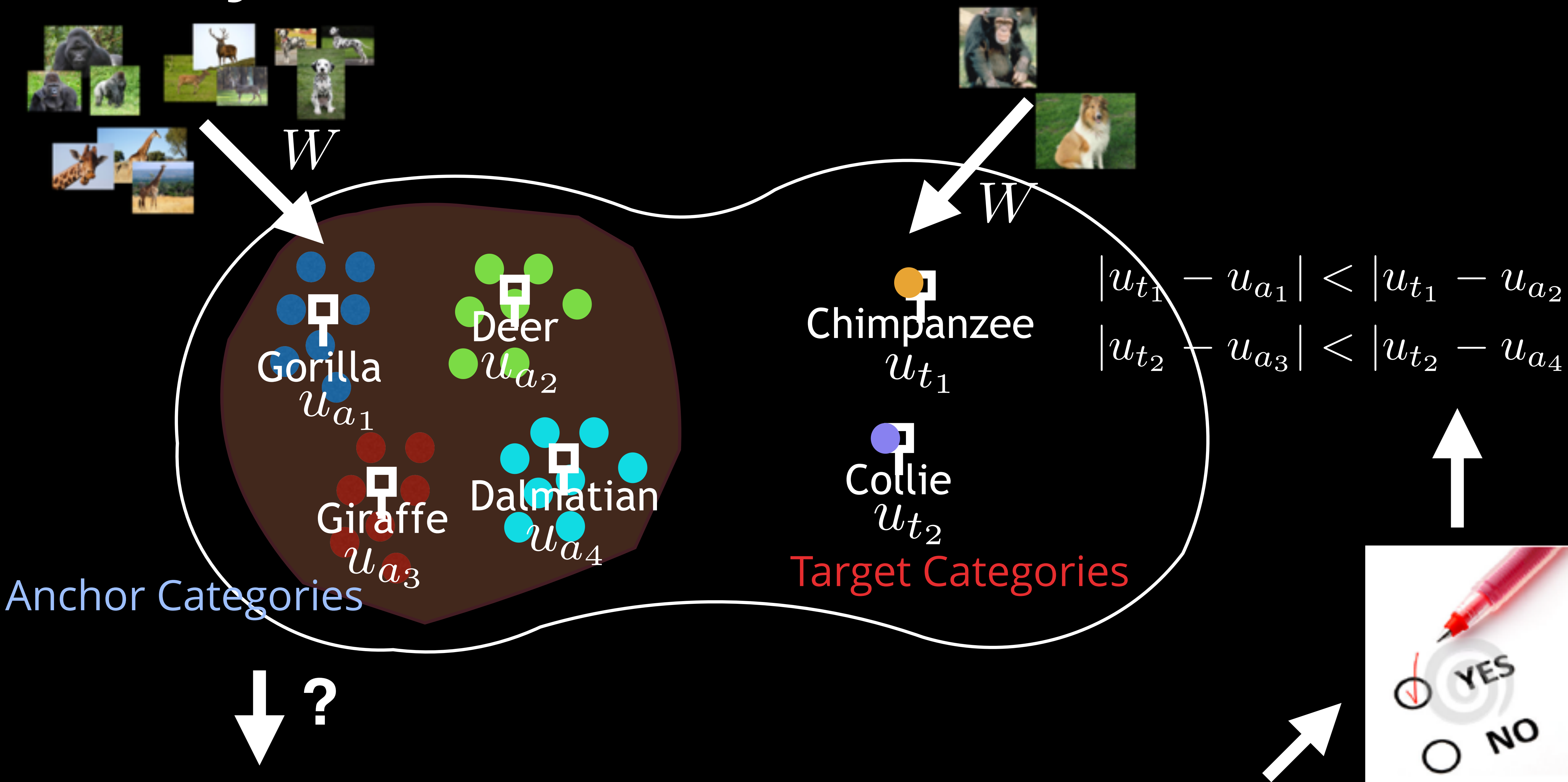

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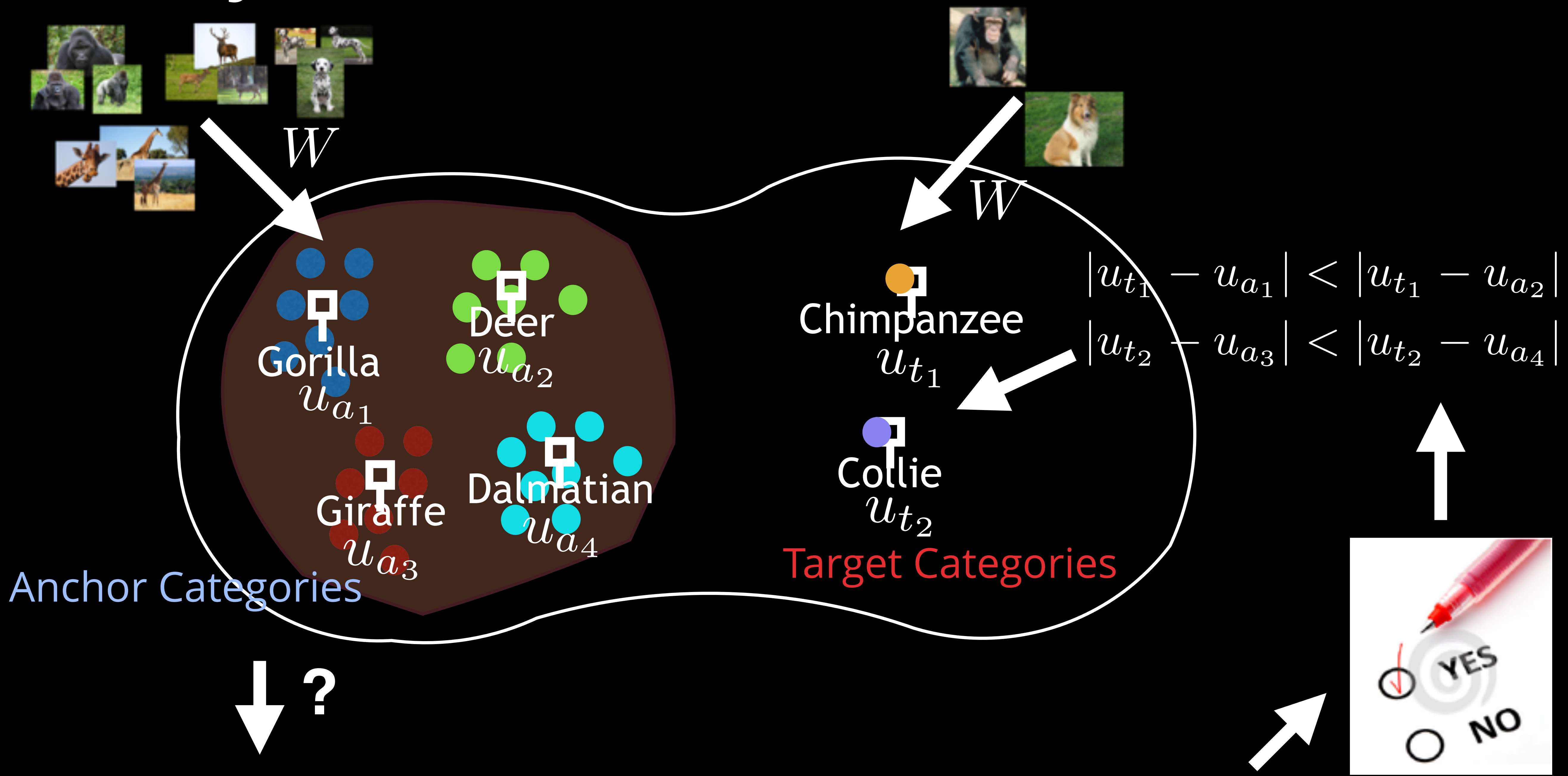

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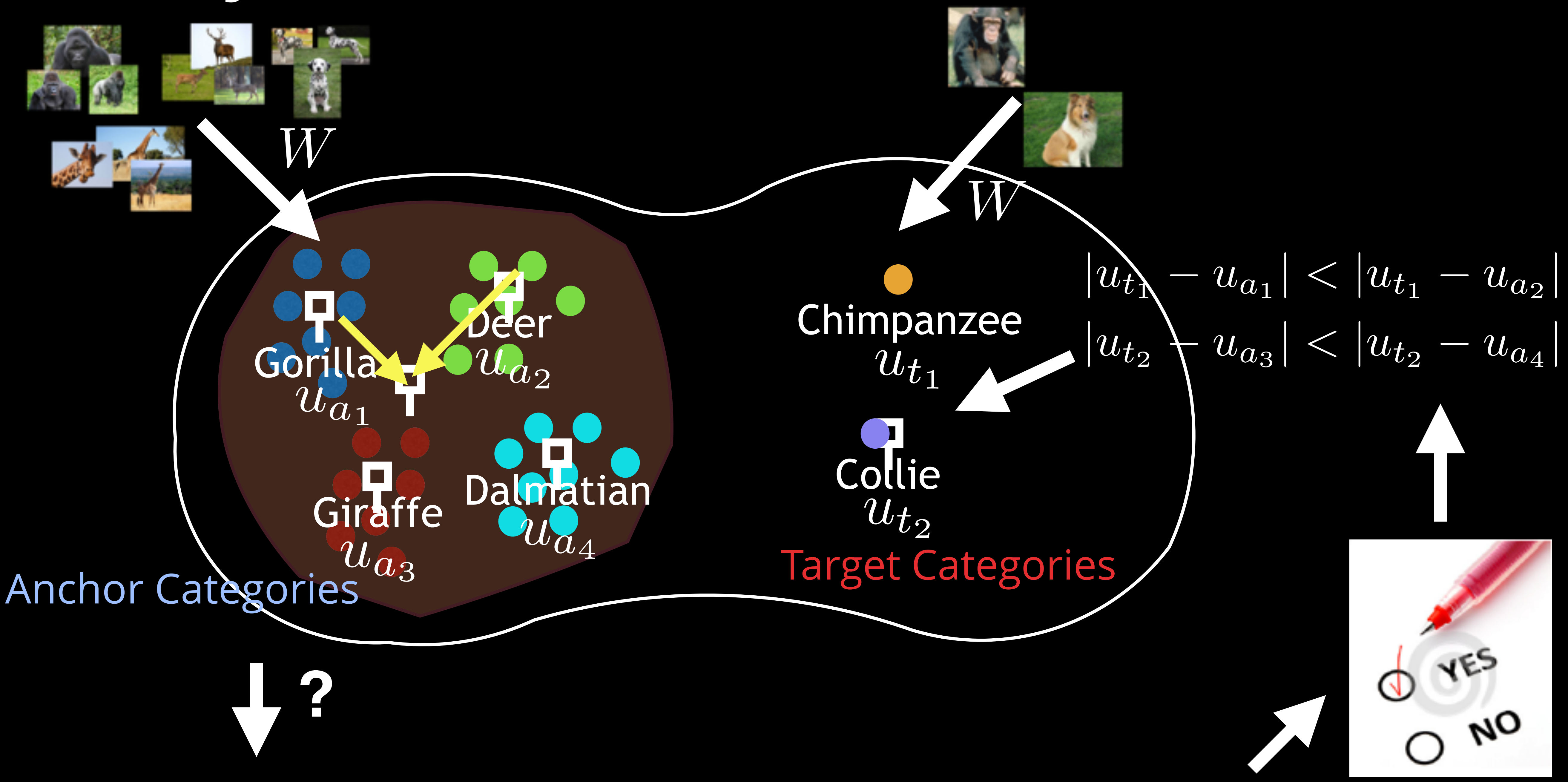

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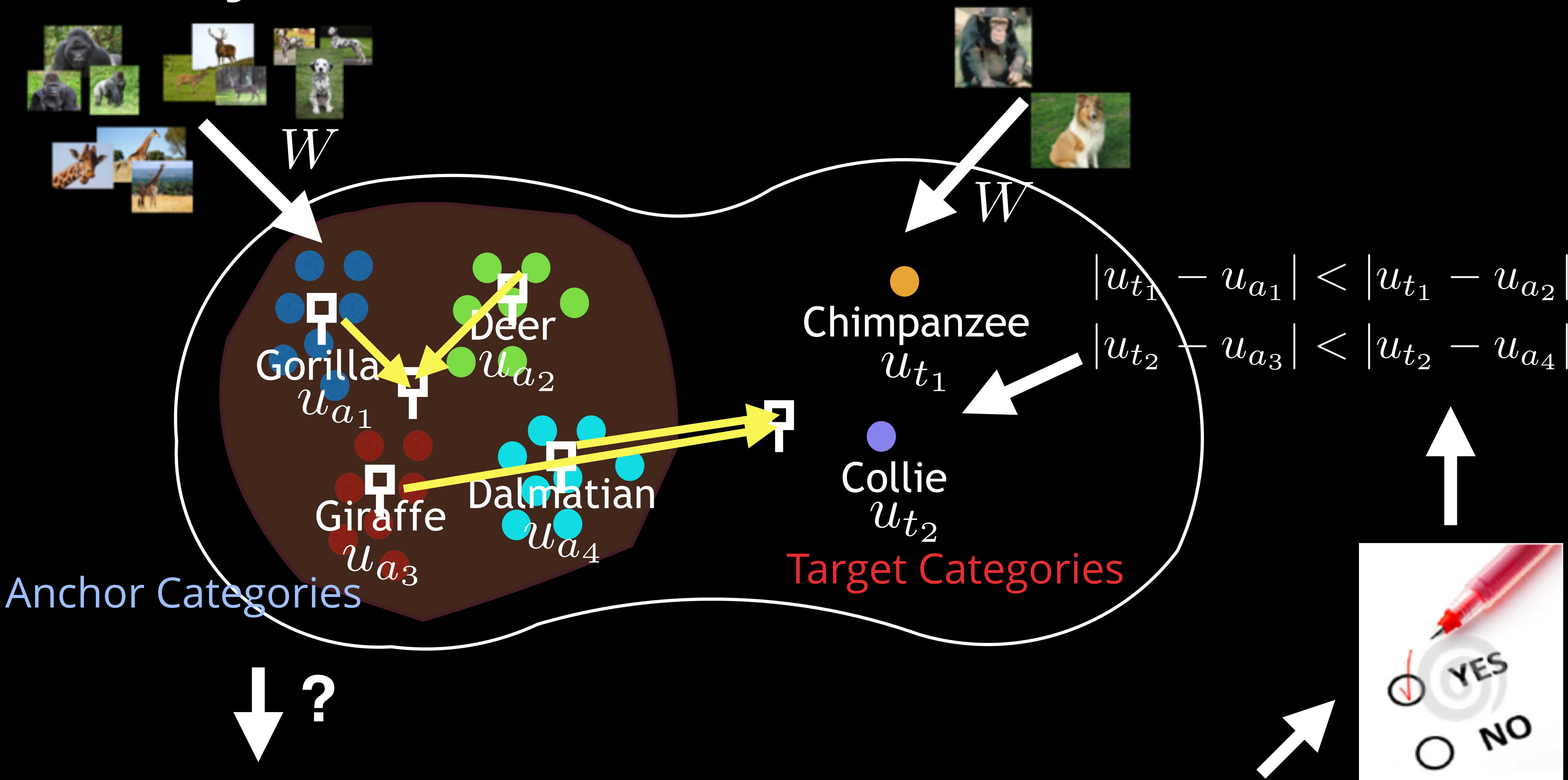

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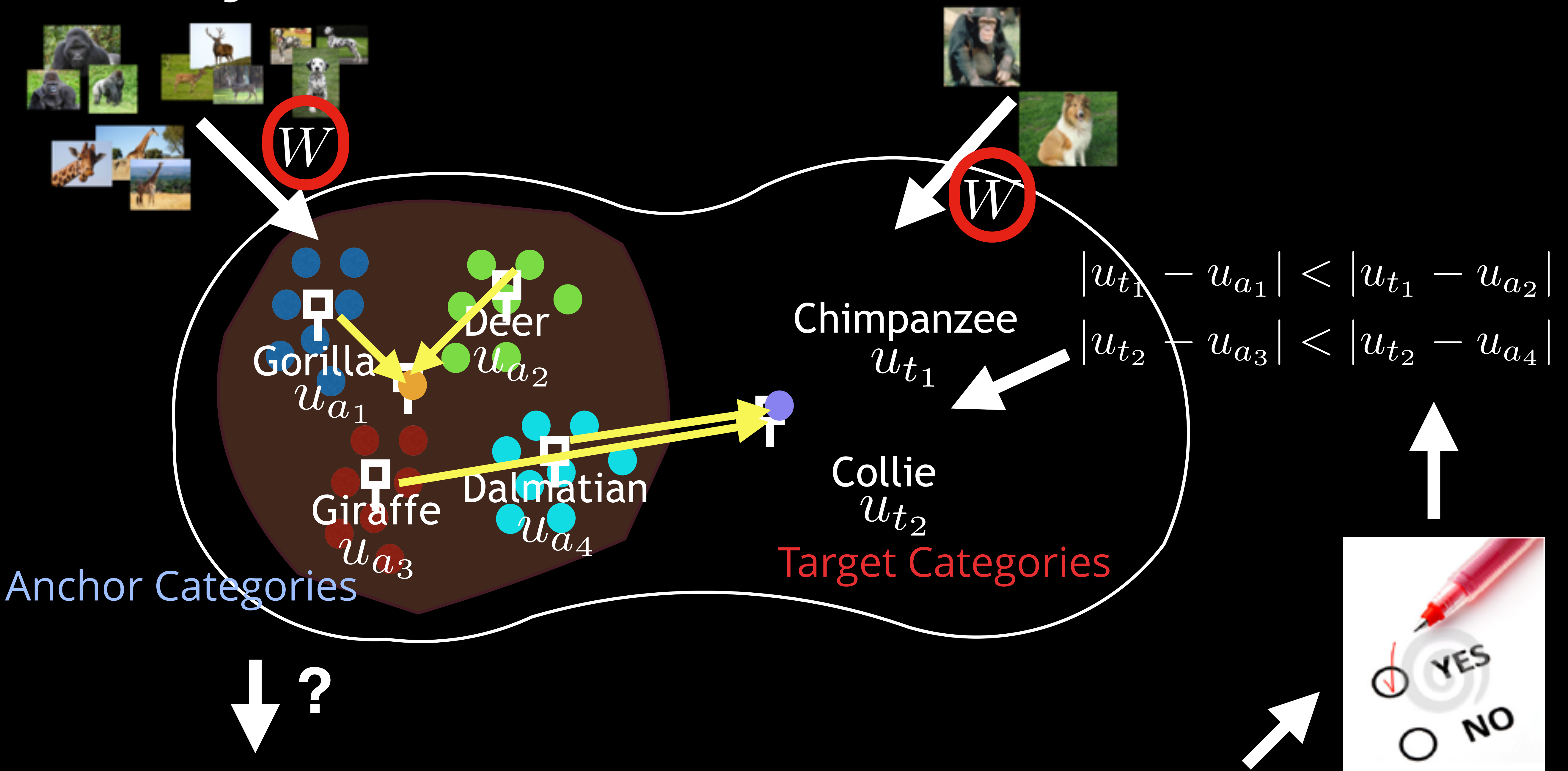

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Relationship Transferred Metric Learning (RTML)

- Embed both visual feature and label entities
  - First on the **Anchor** categories only

$$\min_{\boldsymbol{W}^A,\boldsymbol{U}^A} \sum_{i=1}^{N^A} \sum_{c \in \mathcal{C}^A} \mathcal{L}\left(\boldsymbol{W}^A, \boldsymbol{x}_i, \boldsymbol{u}_c\right) + \lambda_1 \|\boldsymbol{W}^A\|_F^2 + \lambda_2 \|\boldsymbol{U}^A\|_F^2,$$

$$\text{s.t. } \mathcal{L}(\boldsymbol{W}^A, \boldsymbol{x}_i, \boldsymbol{u}_c) =$$

$$\max\left(\|\boldsymbol{W}^A \boldsymbol{x}_i - \boldsymbol{u}_{y_i}\|_2^2 - \|\boldsymbol{W}^A \boldsymbol{x}_i - \boldsymbol{u}_c\|_2^2 + 1, 0\right), \forall i, \forall c \neq y_i$$

- W: subspace mapper, U: label embeddings,

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Large margin embedding[1] on Anchor Categories

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Relationship Transferred Metric Learning (RTML)

- Learn target category label prototypes and update W

$$
\begin{aligned}
&\min_{\boldsymbol{W}^T,\boldsymbol{U}^T} \sum_{i=1}^{N^T} \sum_{c \in \mathcal{C}^T} \mathcal{L}\left(\boldsymbol{W}^T, \boldsymbol{x}_i, \boldsymbol{u}_c\right) + \lambda_1 \|\boldsymbol{W}^T\|_F^2 + \lambda_2 \|\boldsymbol{U}\|_F^2 \\
&\qquad + \lambda_3 \|\boldsymbol{W}^T - \boldsymbol{W}^A\|_F^2 + \gamma \sum_j \Omega\left(R_j, \boldsymbol{U}\right), \\
&\text{s.t. } \mathcal{L}(\boldsymbol{W}^T, \boldsymbol{x}_i, \boldsymbol{u}_c) = \max\left(\|\boldsymbol{W}^T\boldsymbol{x}_i - \boldsymbol{u}_{y_i}\|_2^2 - \|\boldsymbol{W}^T\boldsymbol{x}_i - \boldsymbol{u}_c\|_2^2 + 1, 0\right), \\
&\qquad \forall i, \forall c \neq y_i,\ R_j \subset \mathcal{R}
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- W: subspace mapper, U: label embeddings, Ω: semantic relational constraints

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Large margin embedding[1] on <u>Target</u> Categories

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Bound to W^A

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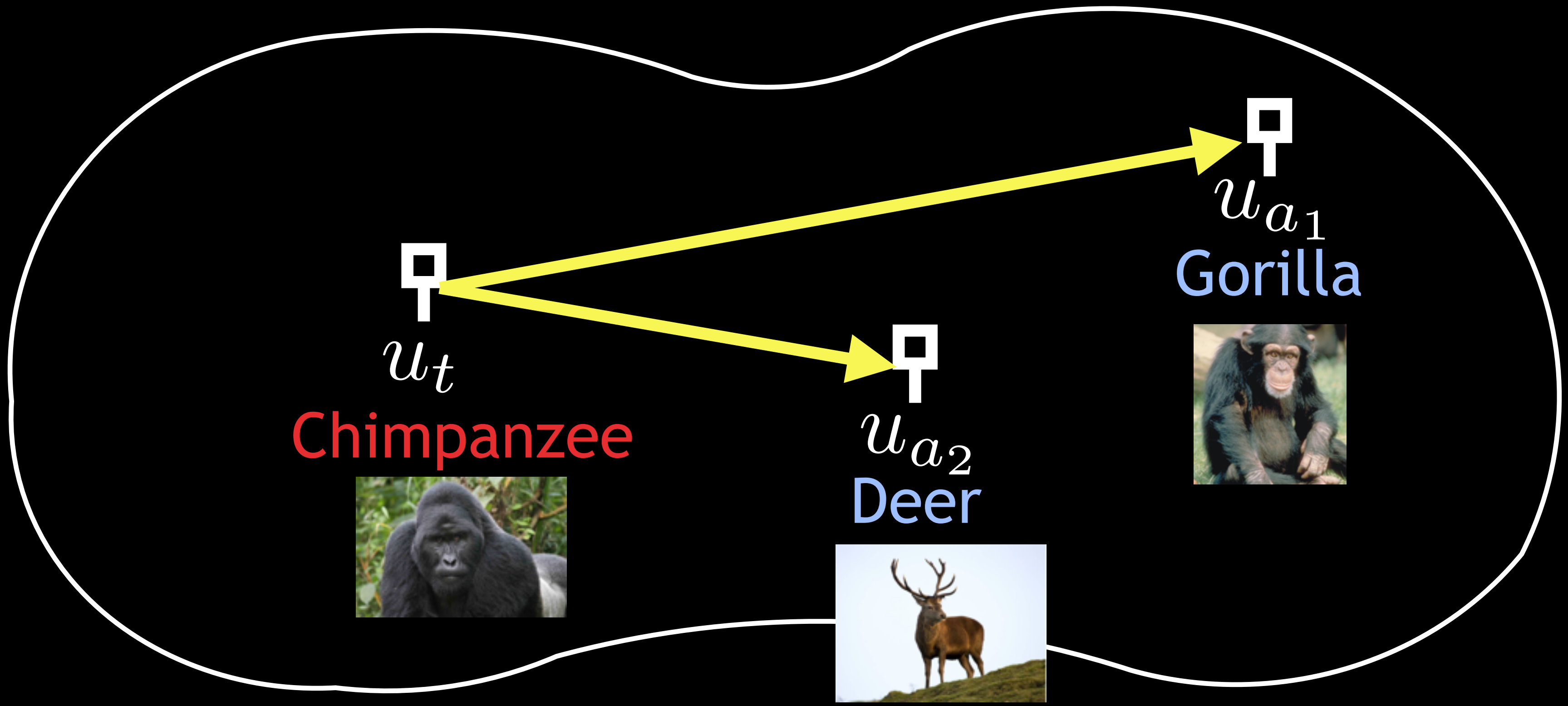
Semantic Relational Constraints



- u_t should be closer to u_{a1} than u_{a2}

$$\|u_{a_1} - u_t\|_2^2 < \|u_{a_2} - u_t\|_2^2$$

$$\rightarrow \quad \min_{U} \max\left(1 - \frac{\|\boldsymbol{u}_{a_2} - \boldsymbol{u}_t\|_2^2}{\|\boldsymbol{u}_{a_1} - \boldsymbol{u}_t\|_2^2}, 0\right).$$

Semantic Relational Constraints

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- Neither convex nor differentiable
  - So, relax by a way of [1]:

$$\gamma \sum_{j} \Omega\left(R_j, U\right) = \sigma_1 h_\rho \left(\|u_{a_1} - u_t\|_2^2 - \|u_{a_2} - u_t\|_2^2 \right)$$

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Semantic Relational Constraints

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Objective function now becomes convex

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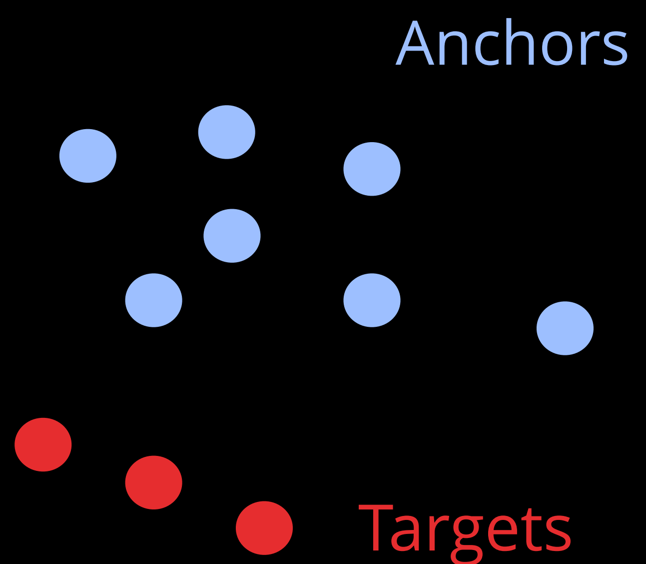
Questions in What Order?

- Ones improving the accuracy the most
  - Score the questions by expected accuracy improvement

- How to obtain the scores



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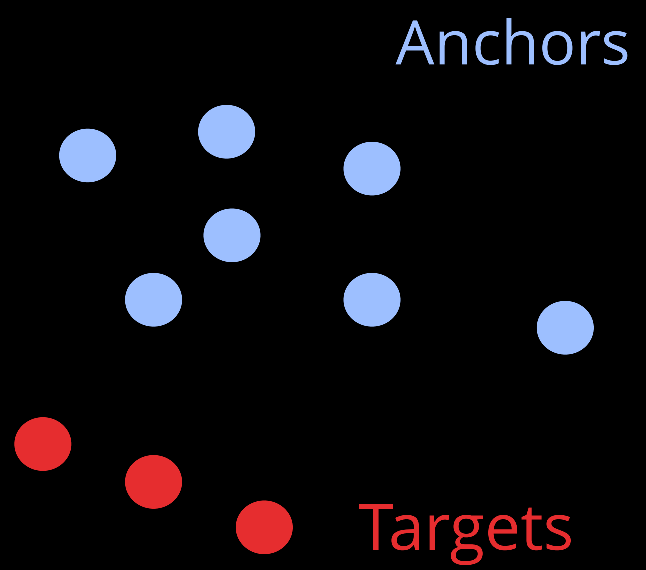

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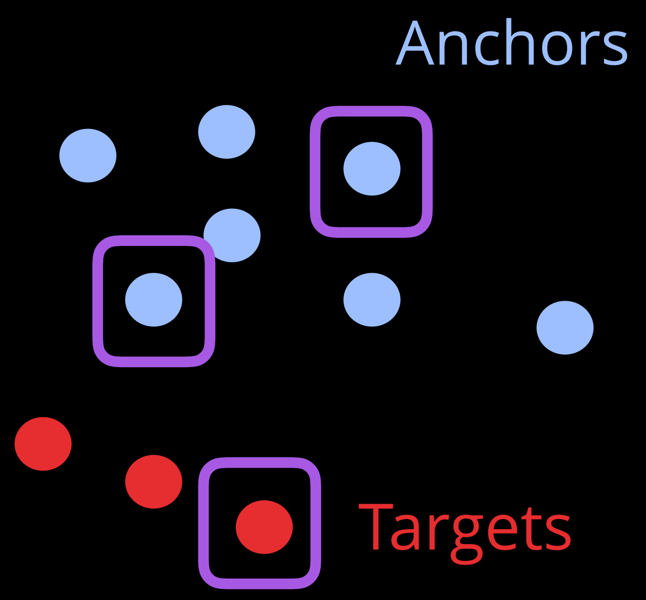

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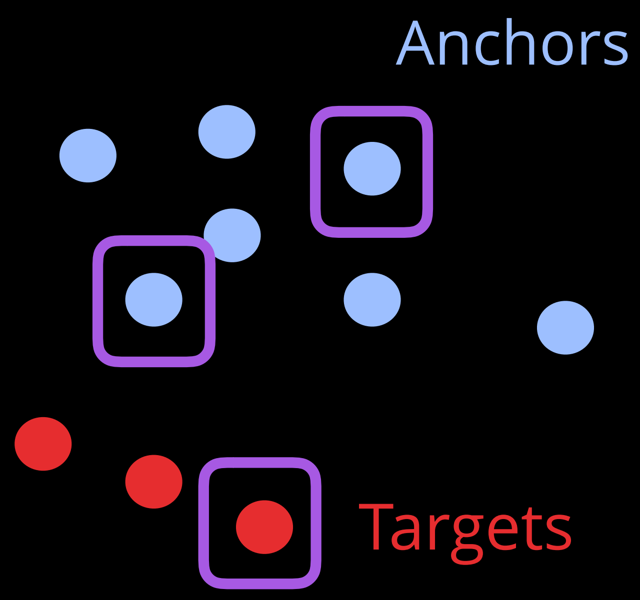

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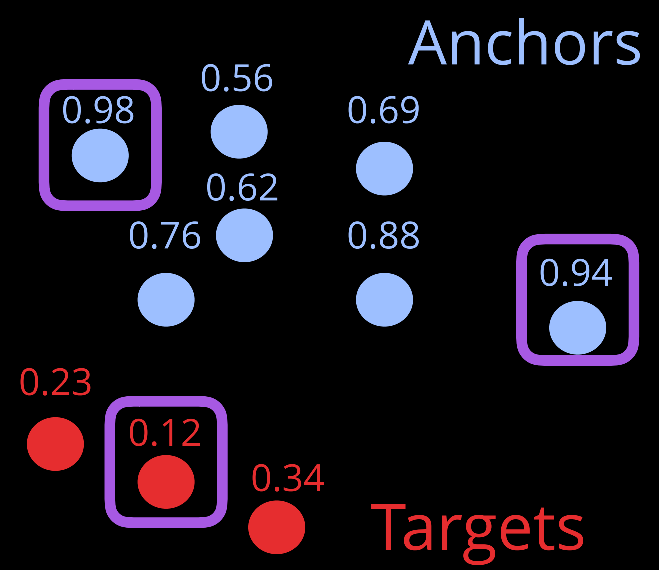

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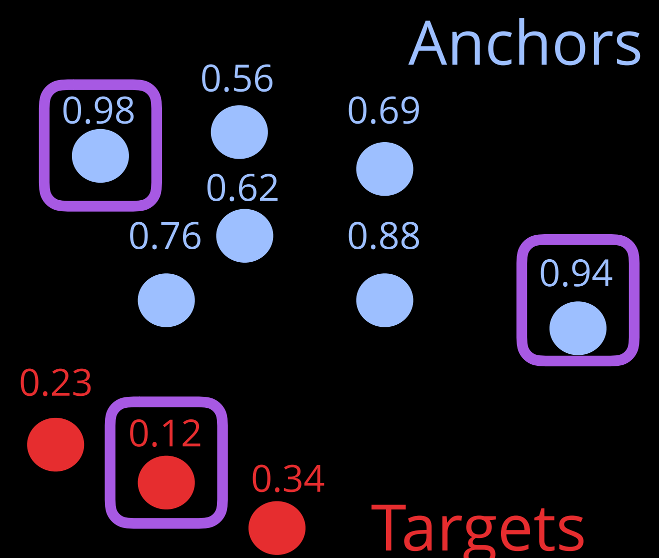

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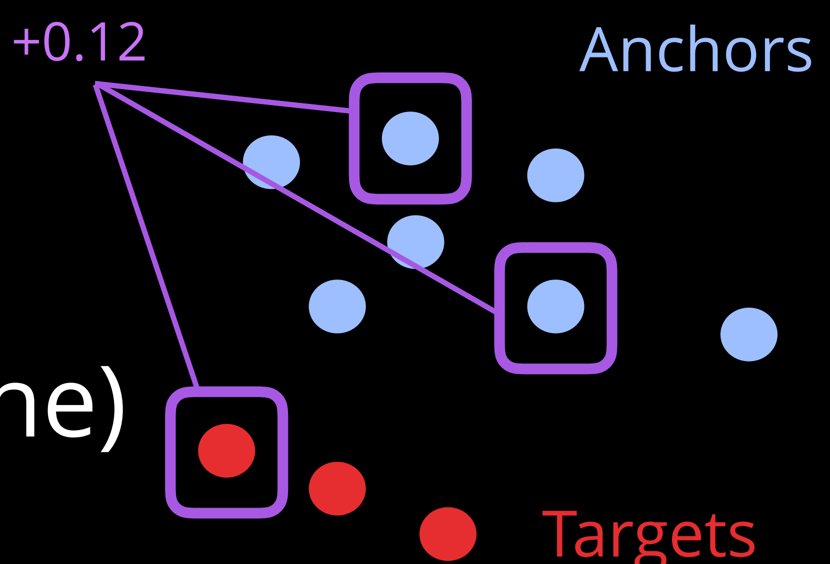

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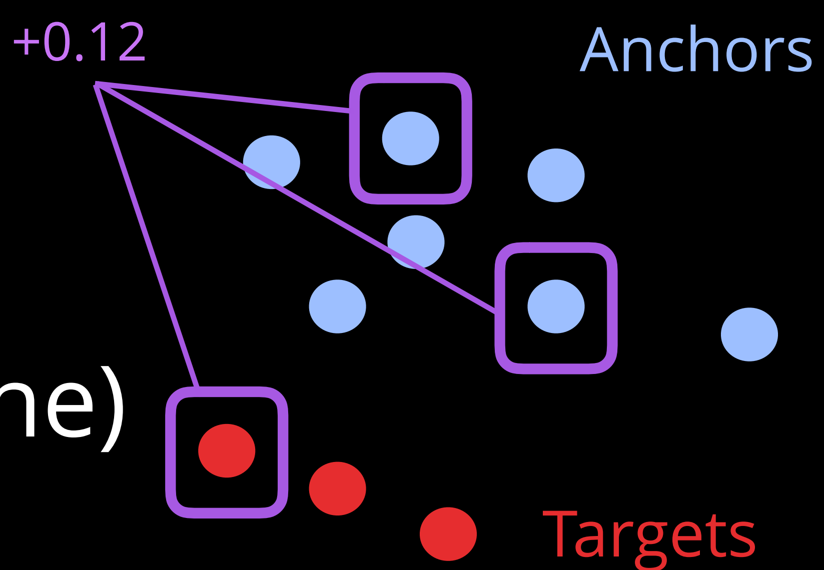


- How to obtain the scores
  1. No scores - Random (baseline)
  2. Training accuracy (entropy)
  3. Accuracy improvement on a validation set
  4. Linear regression: predict the accuracy improvement on the validation set

Experiments

Datasets

- Animals with Attributes (AwA)[1]
  - 50 animal classes (30,475 images)
  - 10 target classes (2,5,10 training/class)
  - 40 anchor classes (30 training/class)
- ImageNet-50[2]
  - 50 object classes (70,380 images)
  - 10 target classes (2,5,10 training/class)
  - 40 anchor classes (30 training/class)

[1] C. H. Lampert, H. Nickisch, and S. Harmeling. "Learning To Detect Unseen Object Classes by Between-Class Attribute Transfer". CVPR, 2009
[2] S. J. Hwang, "Analogy-preserving Semantic Embedding for Visual Object Categorization," ICML 2013

Questions Generated At Iterations

- Top ranked query for 'persian-cat' at each iteration

# Iteration	Positively answered query at its highest rank
1	$\lvert \text{fox} - \text{persian cat} \rvert < \lvert \text{blue whale} - \text{persian cat} \rvert$

Questions Generated At Iterations

- Top ranked query for 'persian-cat' at each iteration

# Iteration	Positively answered query at its highest rank
1	|fox - persian cat| < |blue whale - persian cat|
2	|grizzly bear - persian cat| < |horse - persian cat|

Questions Generated At Iterations

- Top ranked query for ‘persian-cat’ at each iteration

# Iteration	Positively answered query at its highest rank
1	|fox - persian cat| < |blue whale - persian cat|
2	|grizzly bear - persian cat| < |horse - persian cat|
3	|dalmatian - persian cat| < |beaver - persian cat|

Questions Generated At Iterations

- Top ranked query for 'persian-cat' at each iteration

# Iteration	Positively answered query at its highest rank
1	|fox - persian cat| < |blue whale - persian cat|
2	|grizzly bear - persian cat| < |horse - persian cat|
3	|dalmatian - persian cat| < |beaver - persian cat|
4	|dalmatian - persian cat| < |german shepherd - persian cat|

Questions Generated At Iterations

- Top ranked query for 'persian-cat' at each iteration

# Iteration	Positively answered query at its highest rank
1	$\lvert$fox - persian cat$\rvert$ < $\lvert$blue whale - persian cat$\rvert$
2	$\lvert$grizzly bear - persian cat$\rvert$ < $\lvert$horse - persian cat$\rvert$
3	$\lvert$dalmatian - persian cat$\rvert$ < $\lvert$beaver - persian cat$\rvert$
4	$\lvert$dalmatian - persian cat$\rvert$ < $\lvert$german shepherd - persian cat$\rvert$

As interactions continue, top ranked query becomes semantically more meaningful.

Qualitative Results

Persian Cat

Nearest

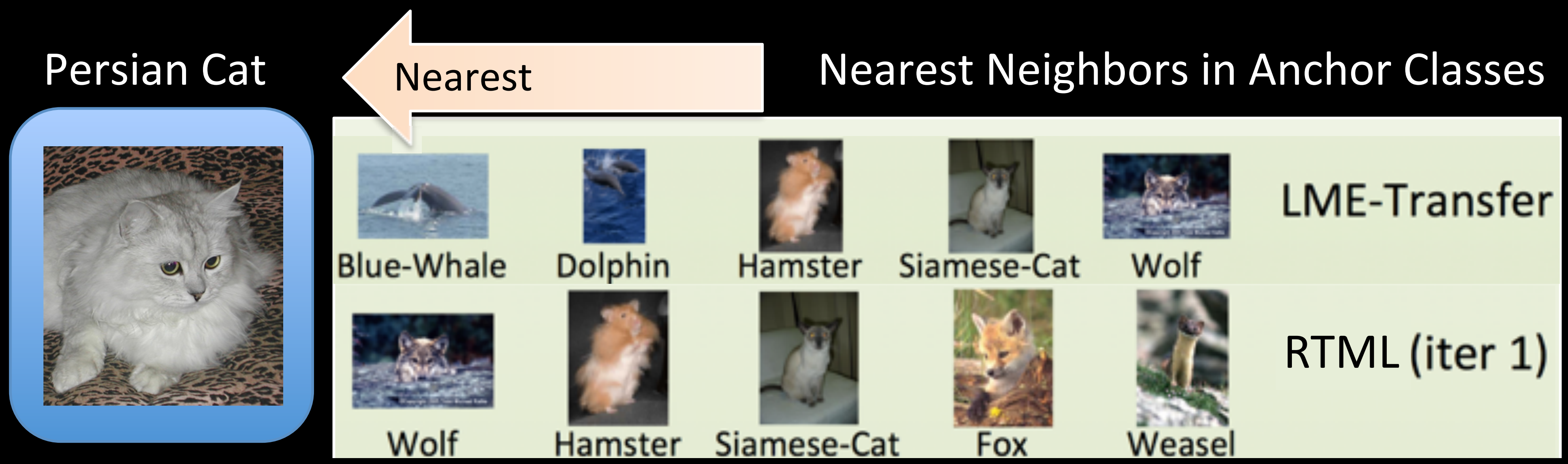
Nearest Neighbors in Anchor Classes

As iterations proceed, nearest neighbors become more semantically meaningful

Qualitative Results

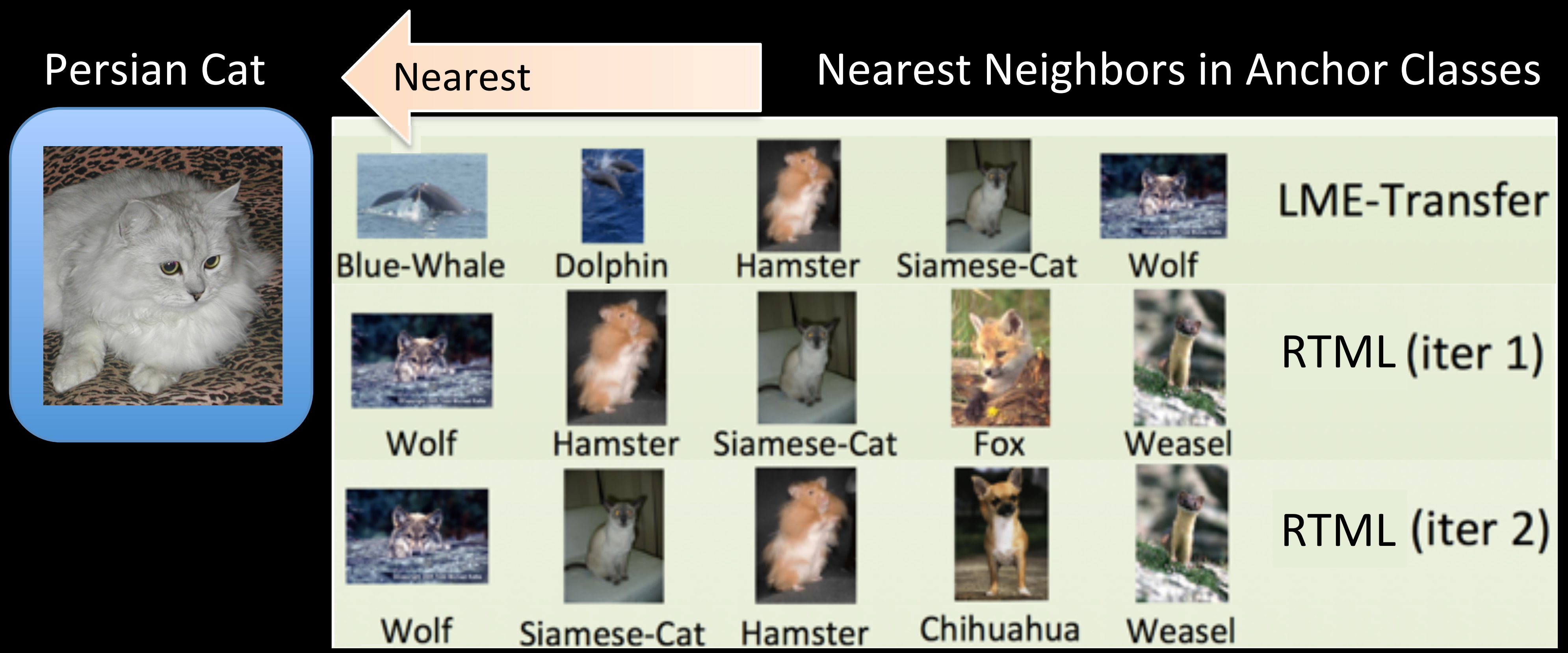
As iterations proceed, nearest neighbors become more semantically meaningful

Qualitative Results



As iterations proceed, nearest neighbors become more semantically meaningful

Qualitative Results



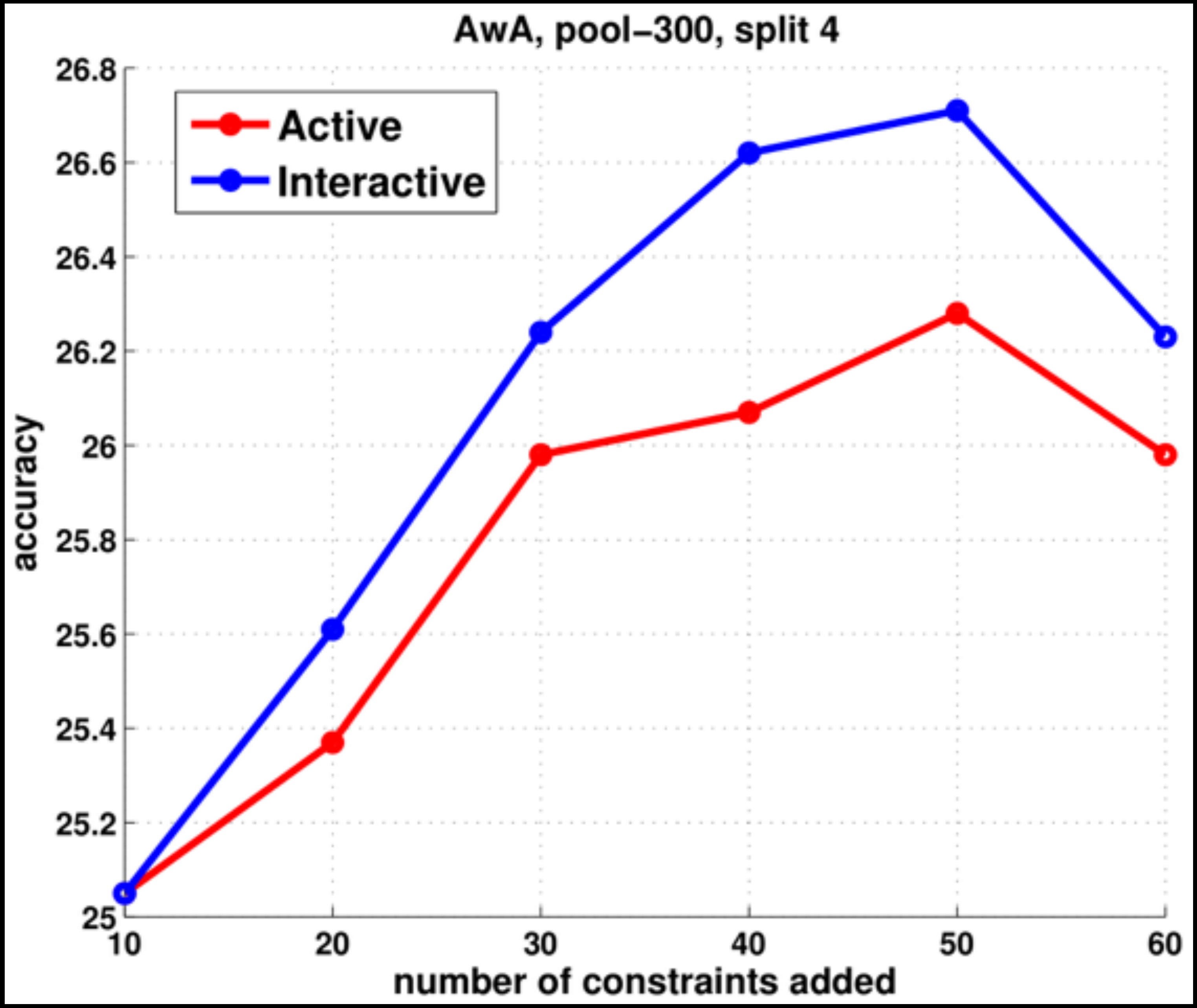
As iterations proceed, nearest neighbors become more semantically meaningful

Qualitative Results

As iterations proceed, nearest neighbors become more semantically meaningful

Reduced Number of Questions

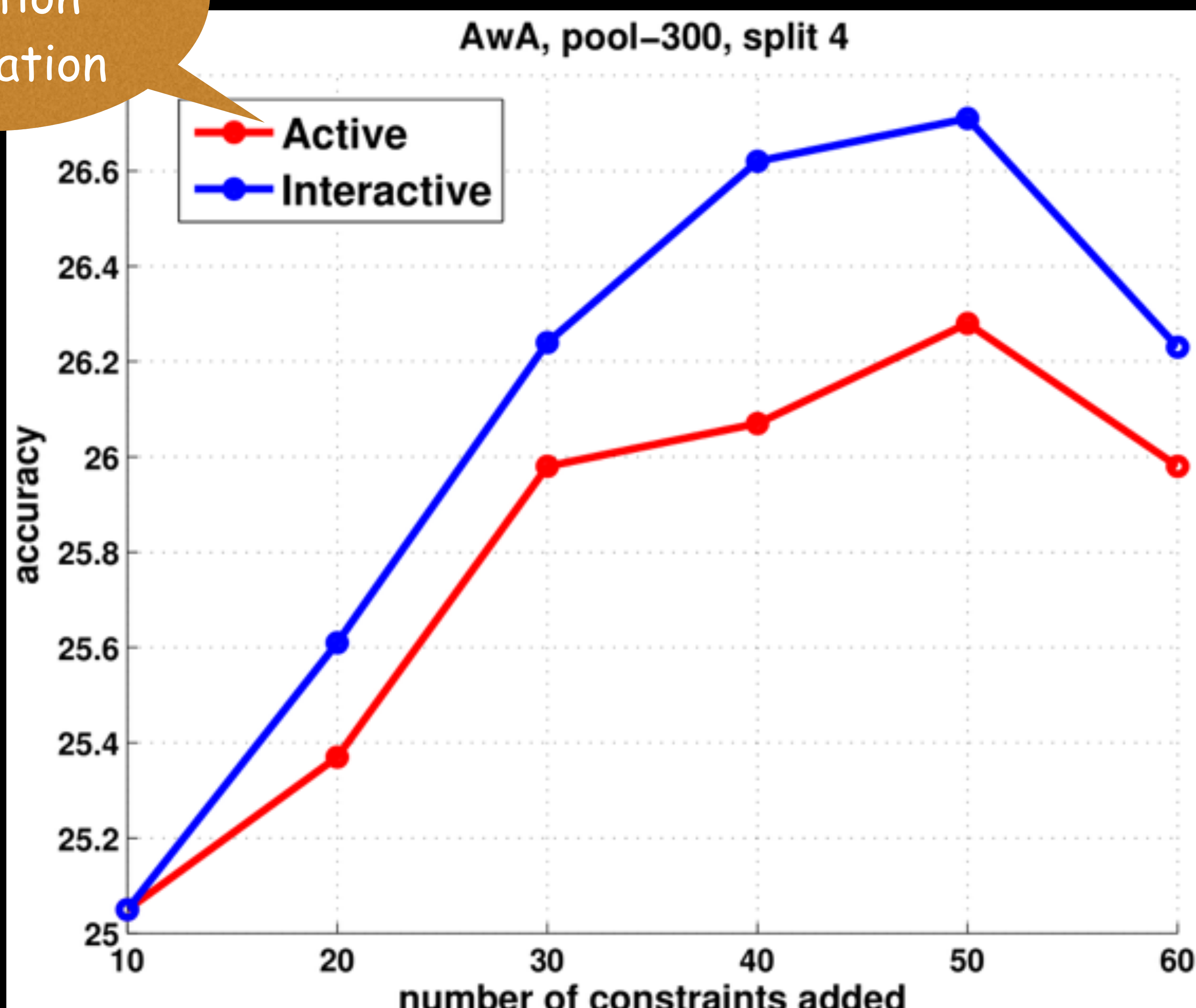
- Answer to better questions at every iteration
  - improve accuracy faster



Reduced Number of Questions

- Answer to better questions at every iteration
  prove accuracy faster

batchmode
question
generation

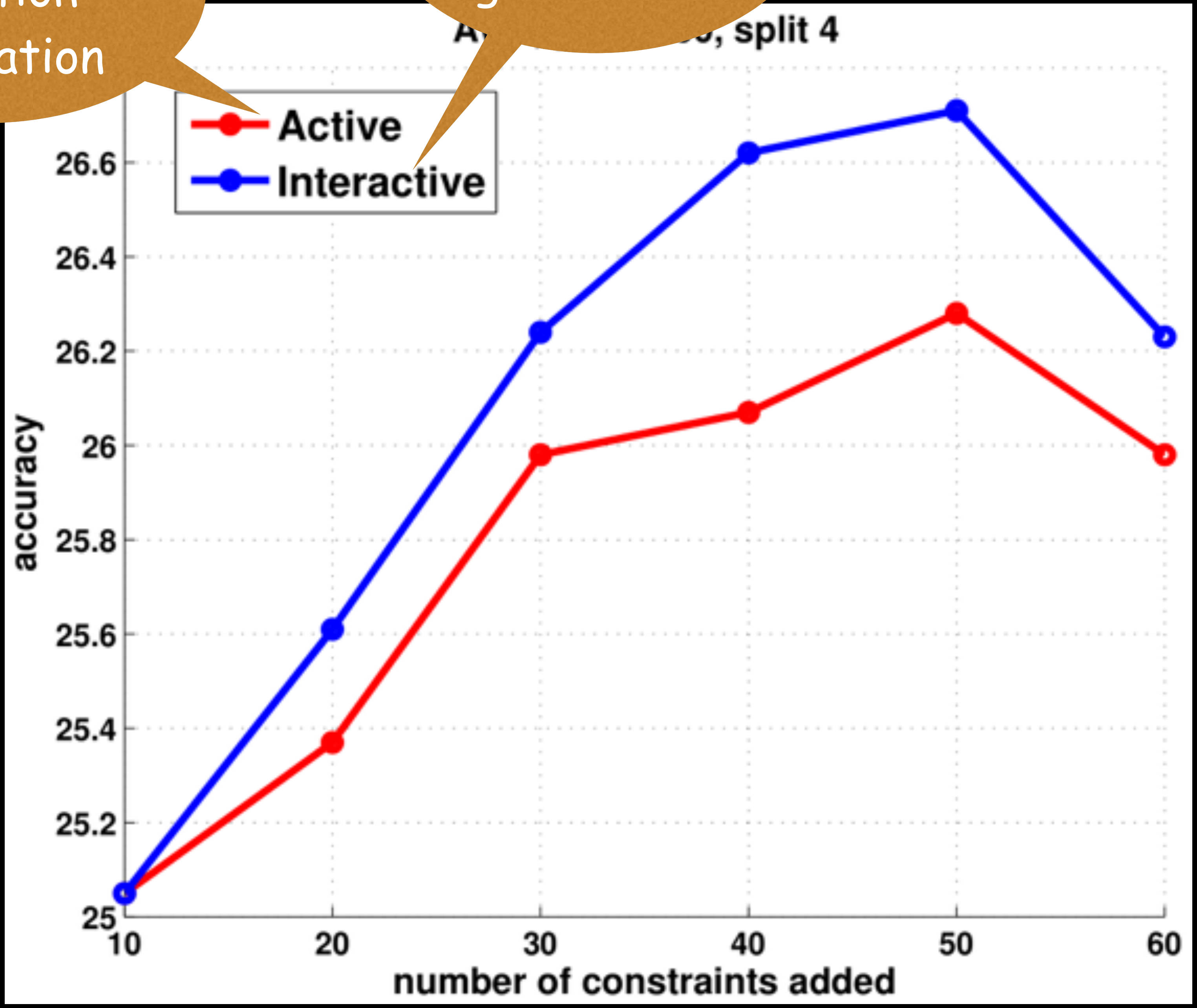


Reduced Number of Questions

- Answer to be… uestions at every iteration
- …rove a… er

batchmode question generation

Interactive question generation



Reduced Number of Questions

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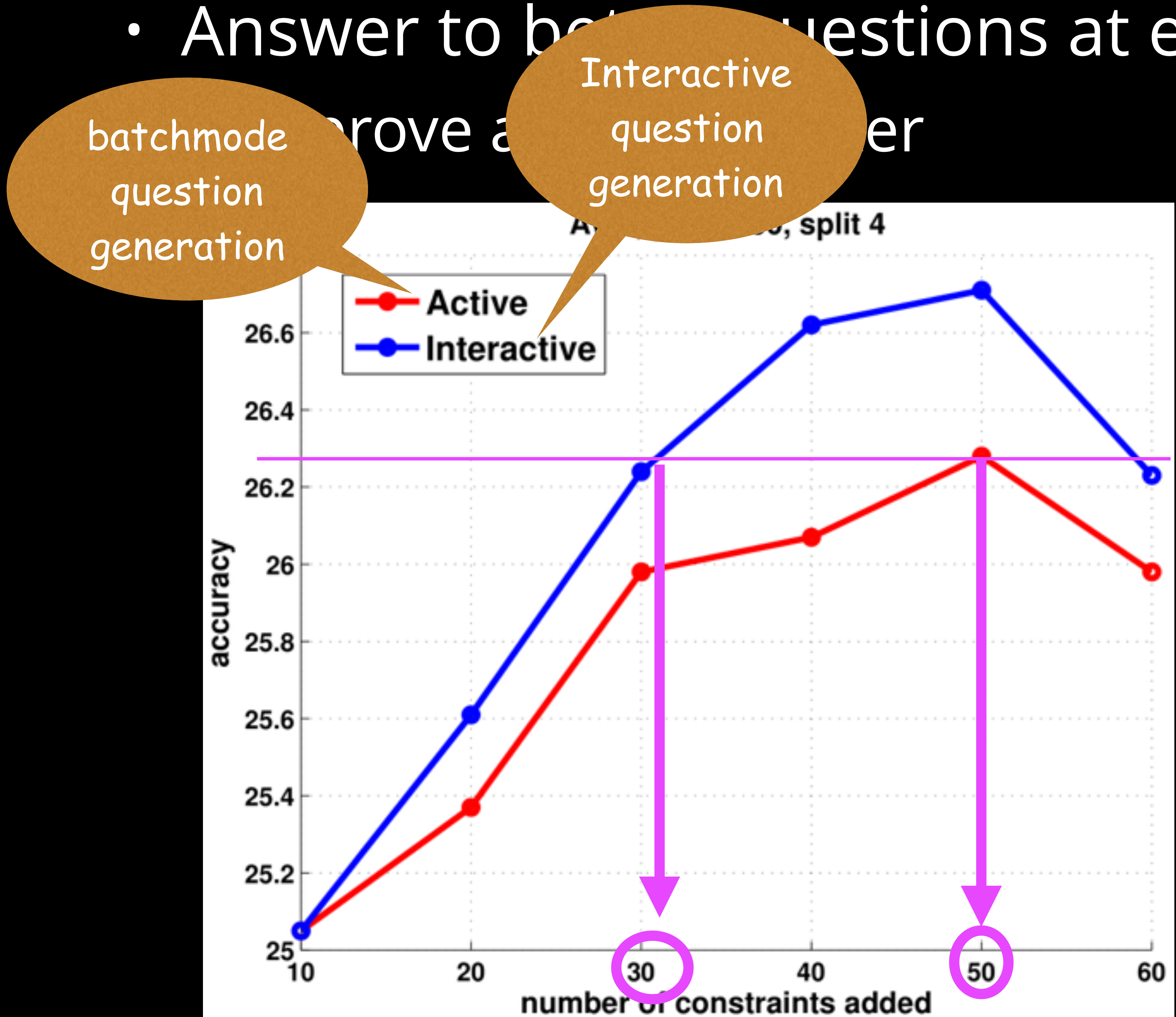

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batchmode
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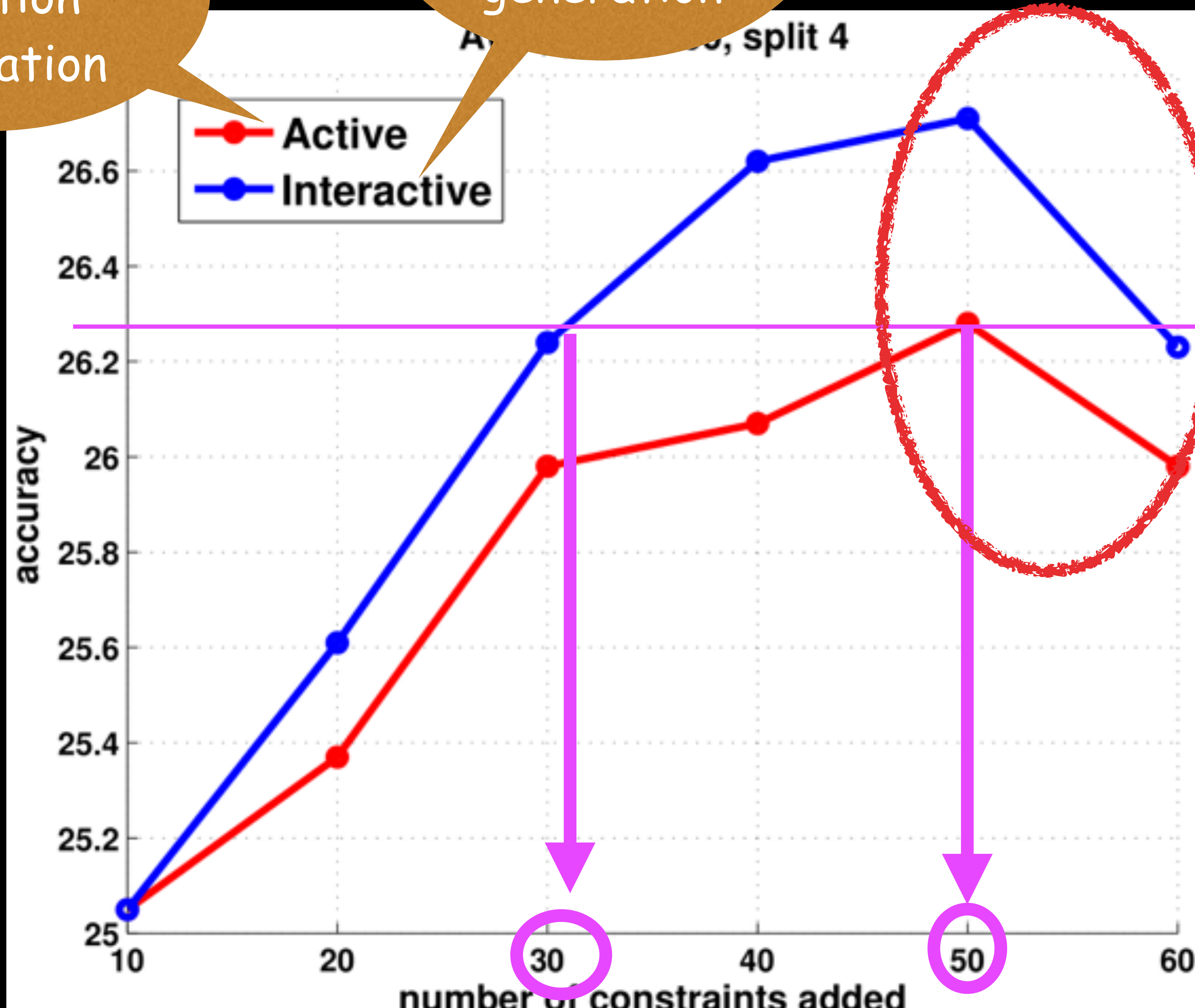

Reduced Number of Questions

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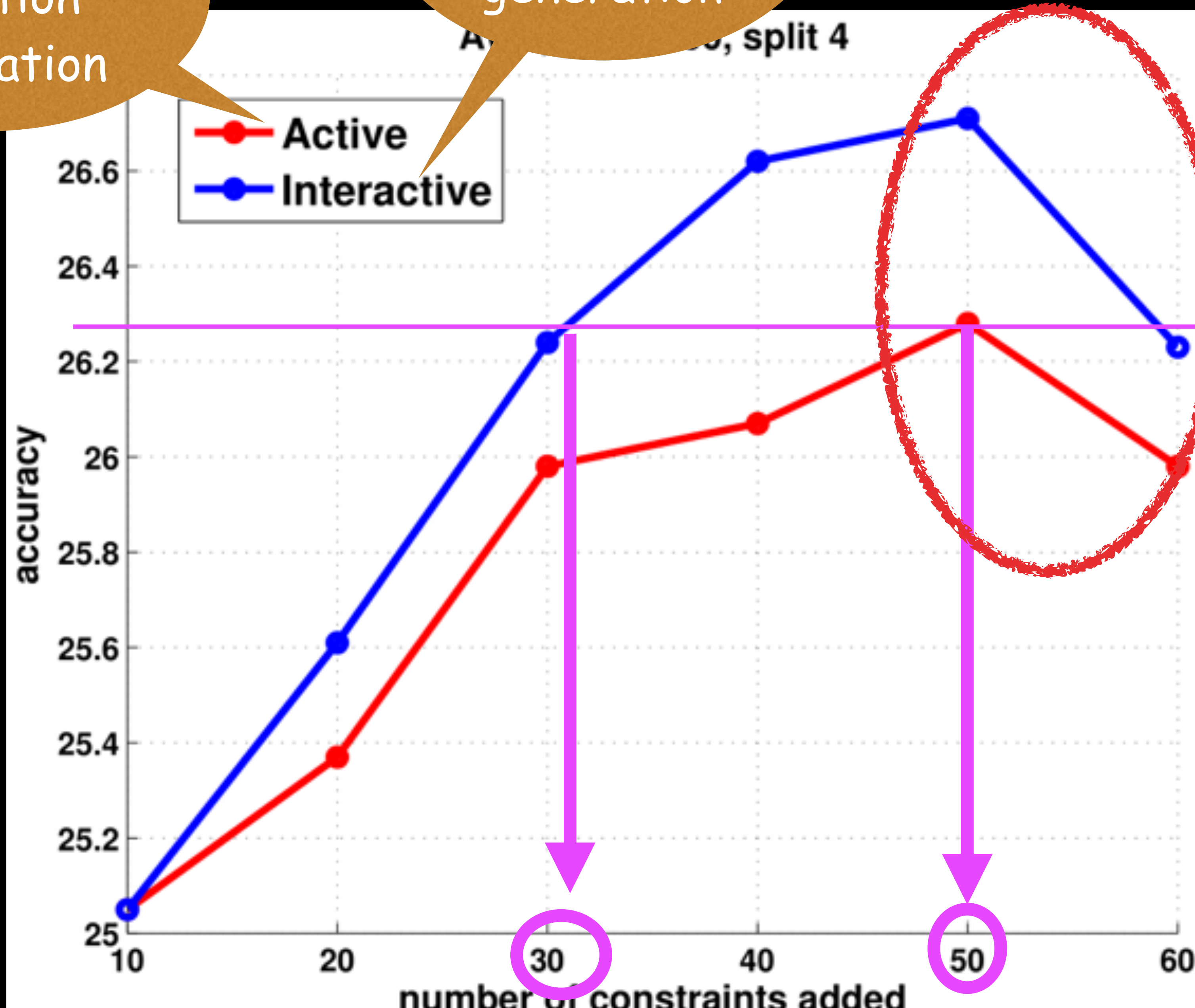
batchmode question generation

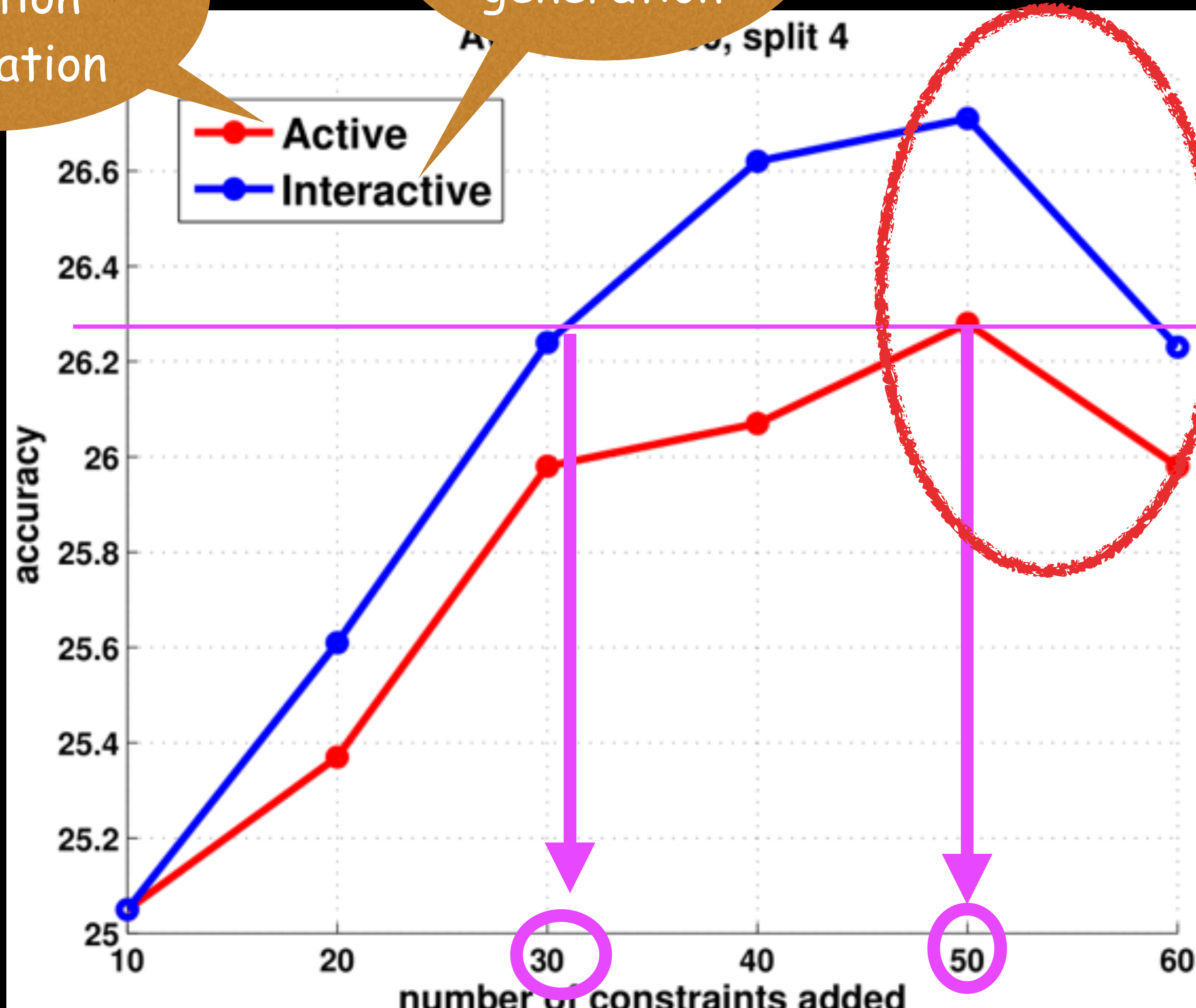
Interactive question generation



When to stop?

Reduced Number of Questions

- Answer to be uestions at every iteration
  prove a er



When to stop?

: start to decrease in two consecutive iterations

By Different Query Selection Criteria

# samples/class	2	5	10
Animals with Attribute			
LME	22.51±2.48	29.85±1.90	34.52±1.33
LME-Transfer	24.59±2.23	32.17±1.53	35.39±1.67
Random	24.75±2.11	31.32±1.31	35.96±1.66
Entropy	24.96±2.24	31.81±1.27	35.92±1.91
Active-Regression	25.43±1.90	32.49±1.58	36.18±0.88
Active	26.62±1.67	32.42±1.45	36.40±1.33
Interactive	**27.24±1.82**	**33.31±1.28**	**36.46±1.60**
Interactive-UB	28.57±1.85	33.61±2.15	36.86±1.83
ImangeNet-50			
LME	23.20±2.97	28.22±2.43	34.67±1.62
LME-Transfer	23.47±2.66	28.78±2.05	34.94±1.03
Random	24.23±1.92	28.72±2.26	34.74±2.26
Entropy	24.60±2.80	28.88±2.43	35.64±0.99
Active-Regression	23.34±2.76	28.99±2.34	35.49±0.89
Active	24.35±2.42	28.55±2.07	35.60±1.01
Interactive	**24.95±2.20**	**29.08±1.88**	**35.62±1.01**
Interactive-UB	25.15±2.13	29.23±1.85	35.95±1.53

Classification Accuracy (%) for Comparing Quality of Scoring Function

By Different Query Selection Criteria

Baseline

Proposed

# samples/class	2	5	10
Animals with Attribute			
LME	22.51±2.48	29.85±1.90	34.52±1.33
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Classification Accuracy (%) for Comparing Quality of Scoring Function

Summary

- Propose an efficient and interactive strategy for collecting category relationship semantics
- Embedding semantic regularization into a classification model ensures the model to be semantically more meaningful over iterations
- Improve classification accuracy with **small** number of human verifications

Q/A

Thank you!

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Summary

- Propose an efficient and interactive strategy for collecting category relationship semantics
- Embedding semantic regularization into a classification model ensures the model to be semantically more meaningful over iterations
- Improve classification accuracy with **<u>small</u>** number of human verifications