The Benefits of Balance

From Information Projections to Variance Reduction

NeurIPS 2024

Team

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Learning Transferable Visual Models From Natural Language Supervision

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Girish Sastry [1] Amanda Askell [1] Pamela Mishkin [1] Jack Clark [1] Gretchen Krueger [1] Ilya Sutskever [1]

Unsupervised Learning of Visual Features by Contrasting Cluster Assignments

Mathilde Caron[1,2] Ishan Misra[2] Julien Mairal[1]
Priya Goyal[2] Piotr Bojanowski[2] Armand Joulin[2]
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SELF-LABELLING VIA SIMULTANEOUS CL
AND REPRESENTATION LEARNING

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Visual Geometry Group
ots.ox.ac.uk

DEMYSTIFYING CLIP DATA

Hu Xu[1] Saining Xie[2] Xiaoqing Ellen Tan[1] Po-Yao Huang[1] Russell Howes[1] Vasu Sharma[1]
Shang-Wen Li[1] Gargi Ghosh[1] Luke Zettlemoyer[1,3] Christoph Feichtenhofer[1]
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DINOv2: Learning Robust Visual Features without Supervision

Maxime Oquab**, Timothée Darcet**, Théo Moutakanni**,
iec*, Vasil Khalidov*, Pierre Fernandez, Daniel Haziza,
Nouby, Mahmoud Assran, Nicolas Ballas, Wojciech Galuba,
Huang, Shang-Wen Li, Ishan Misra, Michael Rabbat,
l Synnaeve, Hu Xu, Hervé Jegou, Julien Mairal[1],
tut*, Armand Joulin*, Piotr Bojanowski*
Meta AI Research [1]Inria
core team **equal contribution

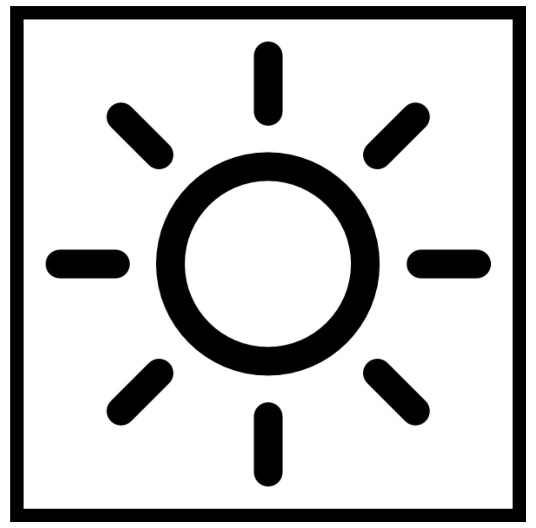
DATACOMP:
In search of the next generation of multimodal datasets

adre*[2], Gabriel Ilharco*[1], Alex Fang*[1], Jonathan Hayase[1],
nis[5], Thao Nguyen[1], Ryan Marten[7,9], Mitchell Wortsman[1],
eyu Zhang[1], Eyal Orgad[3], Rahim Entezari[10], Giannis Daras[5],
Vivek Ramanujan[1], Yonatan Bitton[11], Kalyani Marathe[1],
Stephen Mussmann[1], Richard Vencu[6], Mehdi Cherti[6,8], Ranjay Krishna[1],
Pang Wei Koh[1,12], Olga Saukh[10], Alexander Ratner[1,13], Shuran Song[2],
Hannaneh Hajishirzi[1,7], Ali Farhadi[1], Romain Beaumont[6],
Sewoong Oh[1], Alex Dimakis[5], Jenia Jitsev[6,8],
Yair Carmon[3], Vaishaal Shankar[4], Ludwig Schmidt[1,6,7]

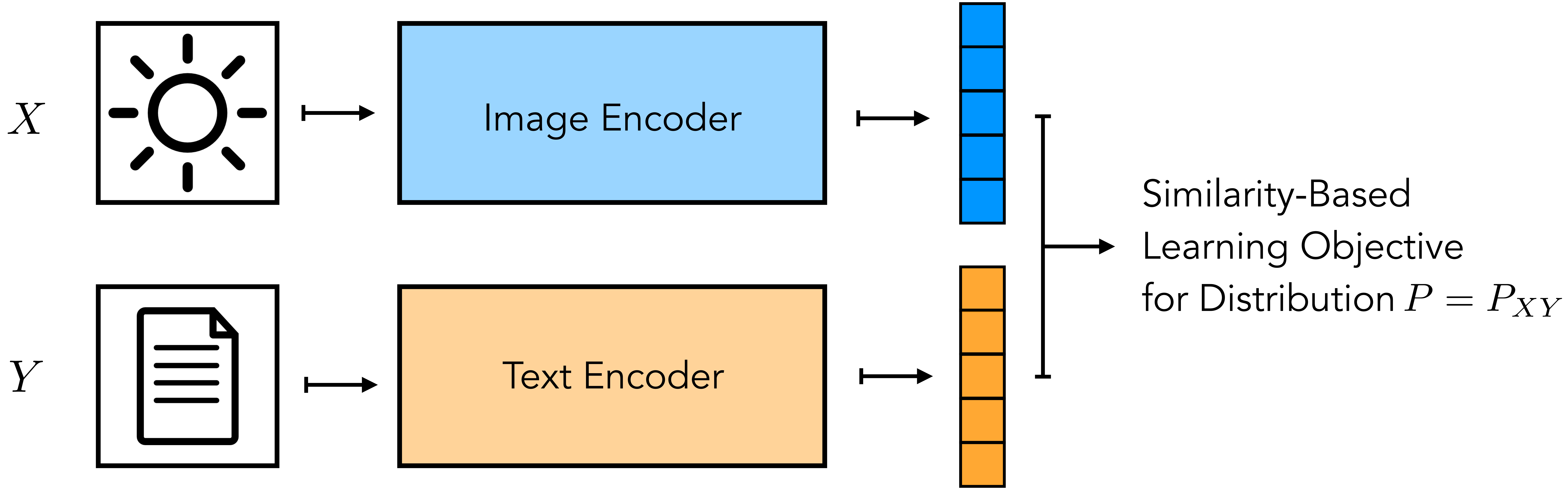
Discriminative clustering with representation learning with any ratio of labeled to unlabeled data

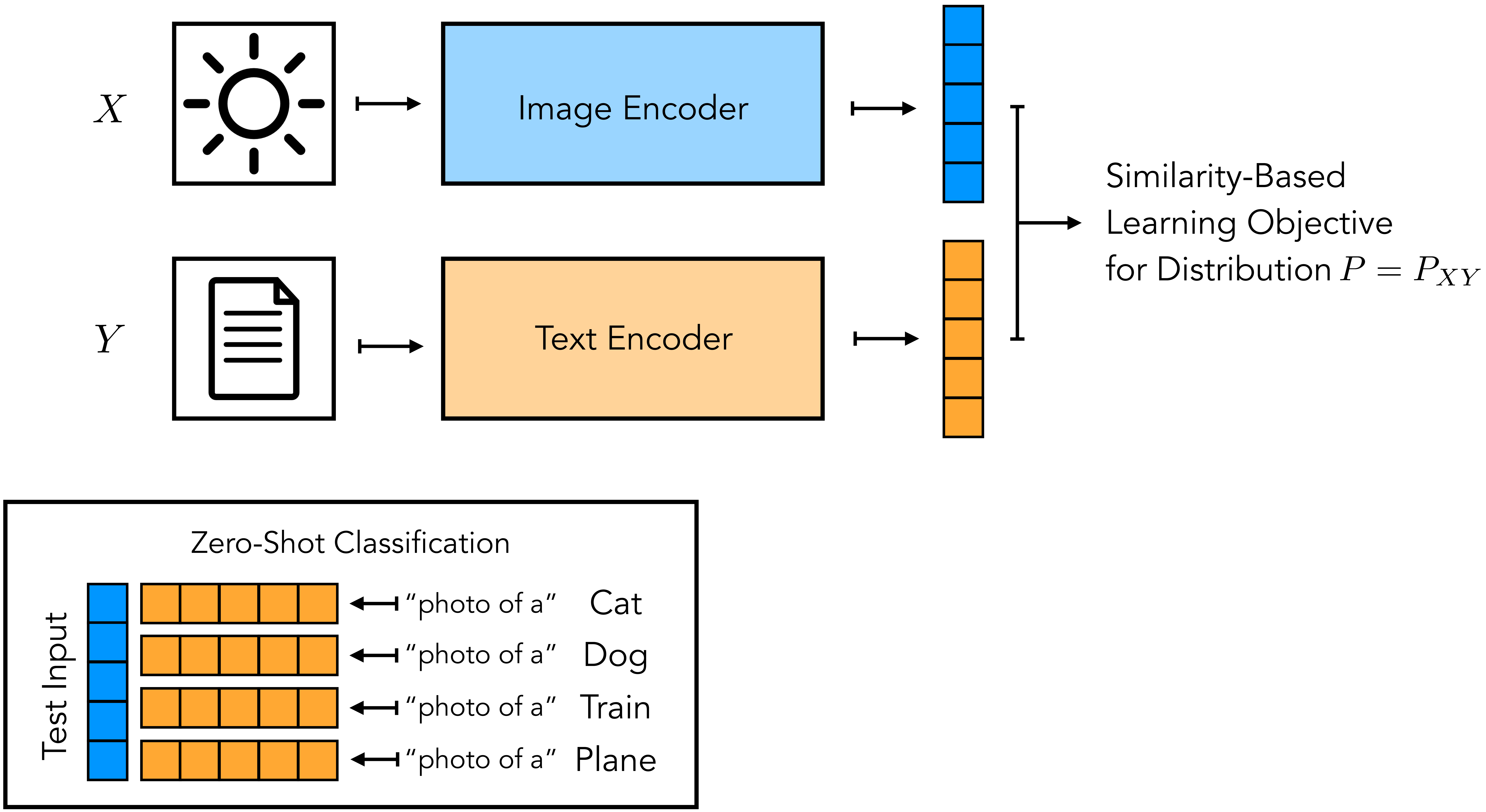
Corinne Jones[1] · Vincent Roulet[2] · Zaid Harchaoui[2]

X

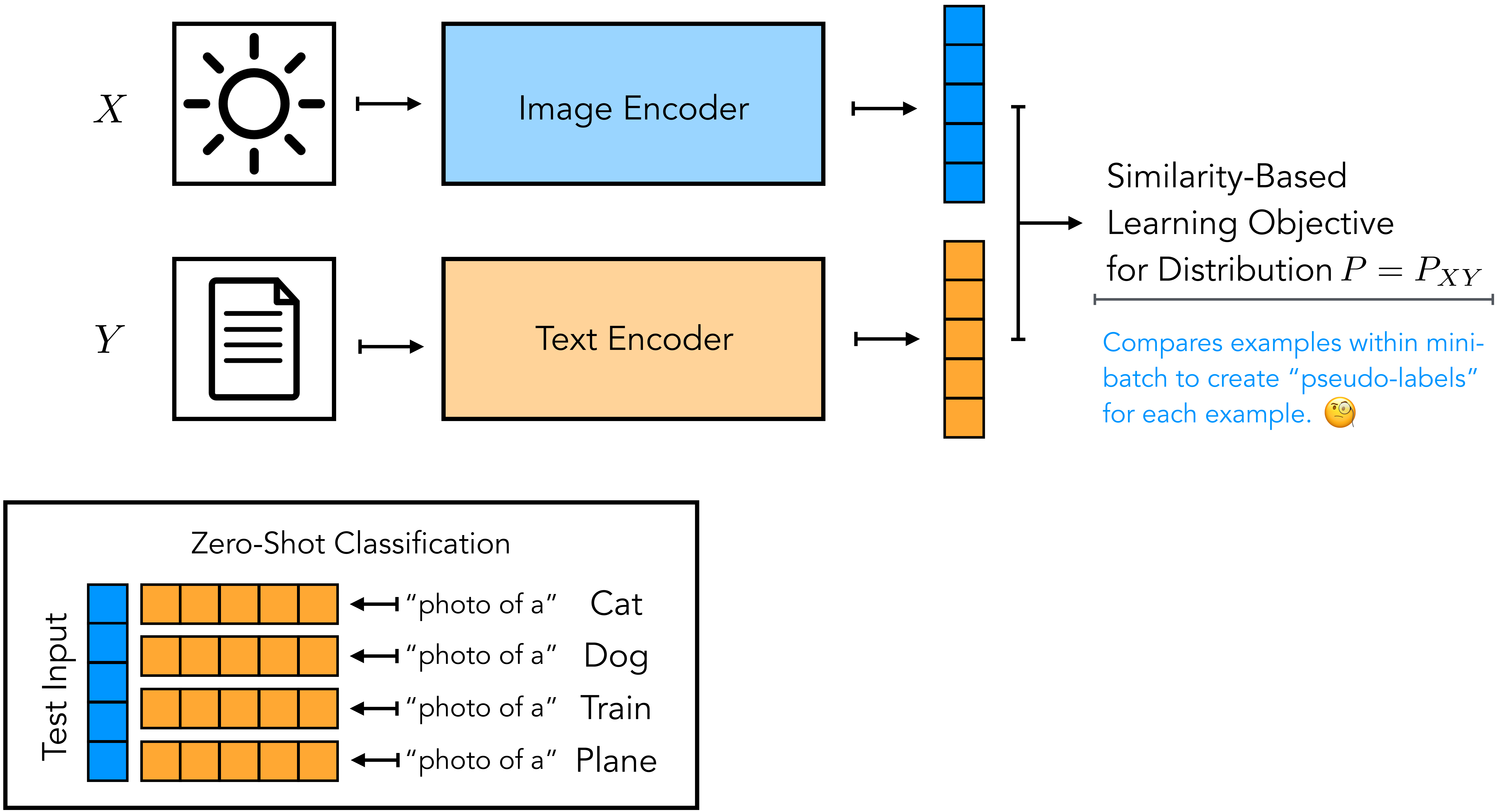


Y


X
Image Encoder
Y
Text Encoder
Similarity-Based
Learning Objective
for Distribution $P = P_{XY}$



X
Image Encoder
Y
Text Encoder
Similarity-Based
Learning Objective
for Distribution $P = P_{XY}$
Zero-Shot Classification
Test Input
"photo of a" Cat
"photo of a" Dog
"photo of a" Train
"photo of a" Plane



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Text Encoder
Similarity-Based
Learning Objective
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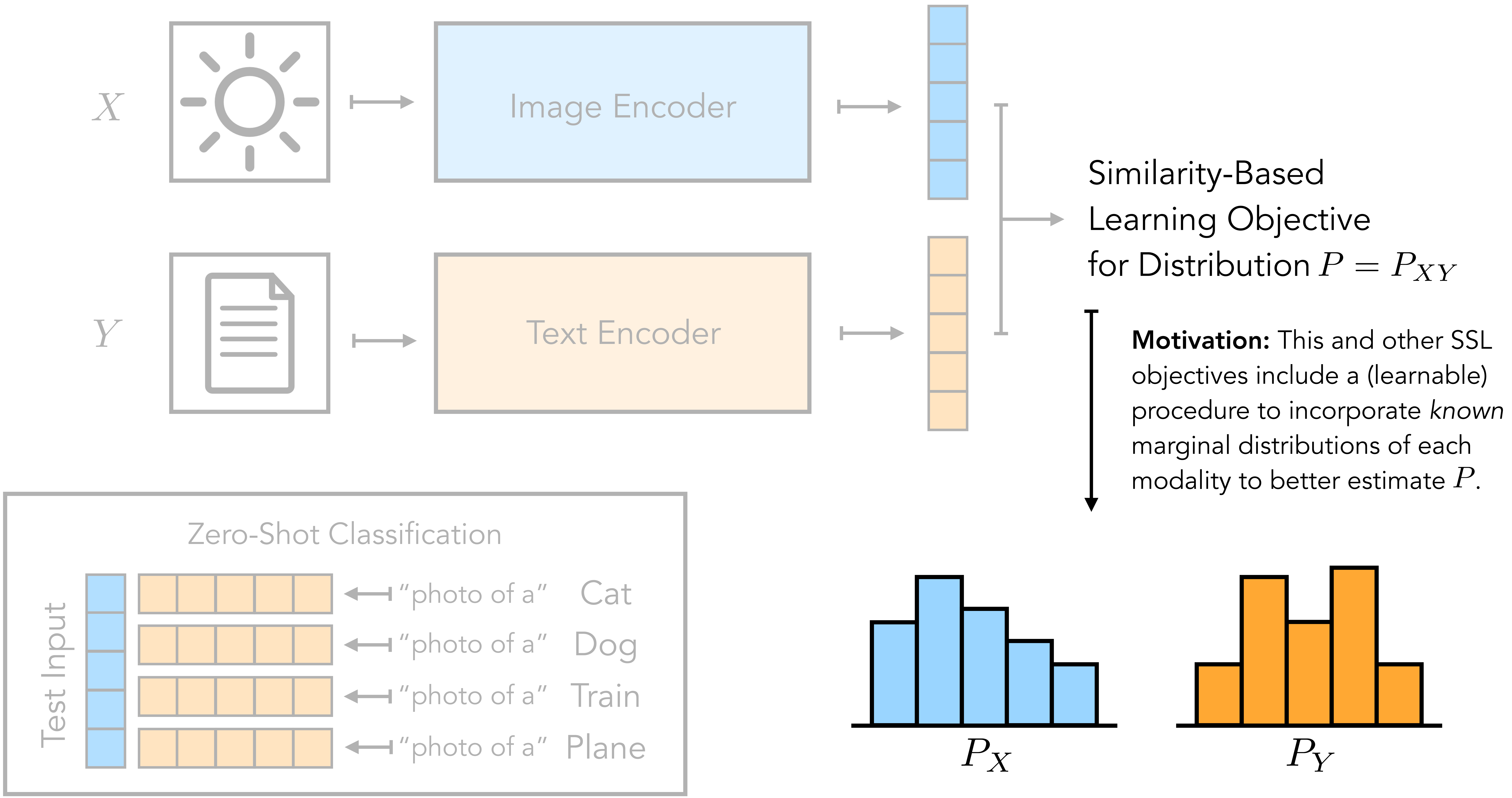
Compares examples within mini-batch to create "pseudo-labels" for each example.
Zero-Shot Classification
Test Input
"photo of a" Cat
"photo of a" Dog
"photo of a" Train
"photo of a" Plane



X
Image Encoder
Y
Text Encoder
Similarity-Based Learning Objective for Distribution $P = P_{XY}$
Motivation: This and other SSL objectives include a (learnable) procedure to incorporate *known* marginal distributions of each modality to better estimate P.
Zero-Shot Classification
Test Input
"photo of a" Cat
"photo of a" Dog
"photo of a" Train
"photo of a" Plane
P_X
P_Y

Problem Setting

Data from **unknown** joint probability distribution.

$$(X_1, Y_1), \ldots, (X_n, Y_n) \sim P$$

Access to **known** marginal distributions.

$$(P_X, P_Y)$$

Goal: estimate the parameter:

$$P(h) = \mathbb{E}_{(X,Y)\sim P}\left[h(X, Y)\right]$$

and characterize how the marginals improve upon

$$P_n(h) = \frac{1}{n}\sum_{i=1}^{n} h(X_i, Y_i)$$

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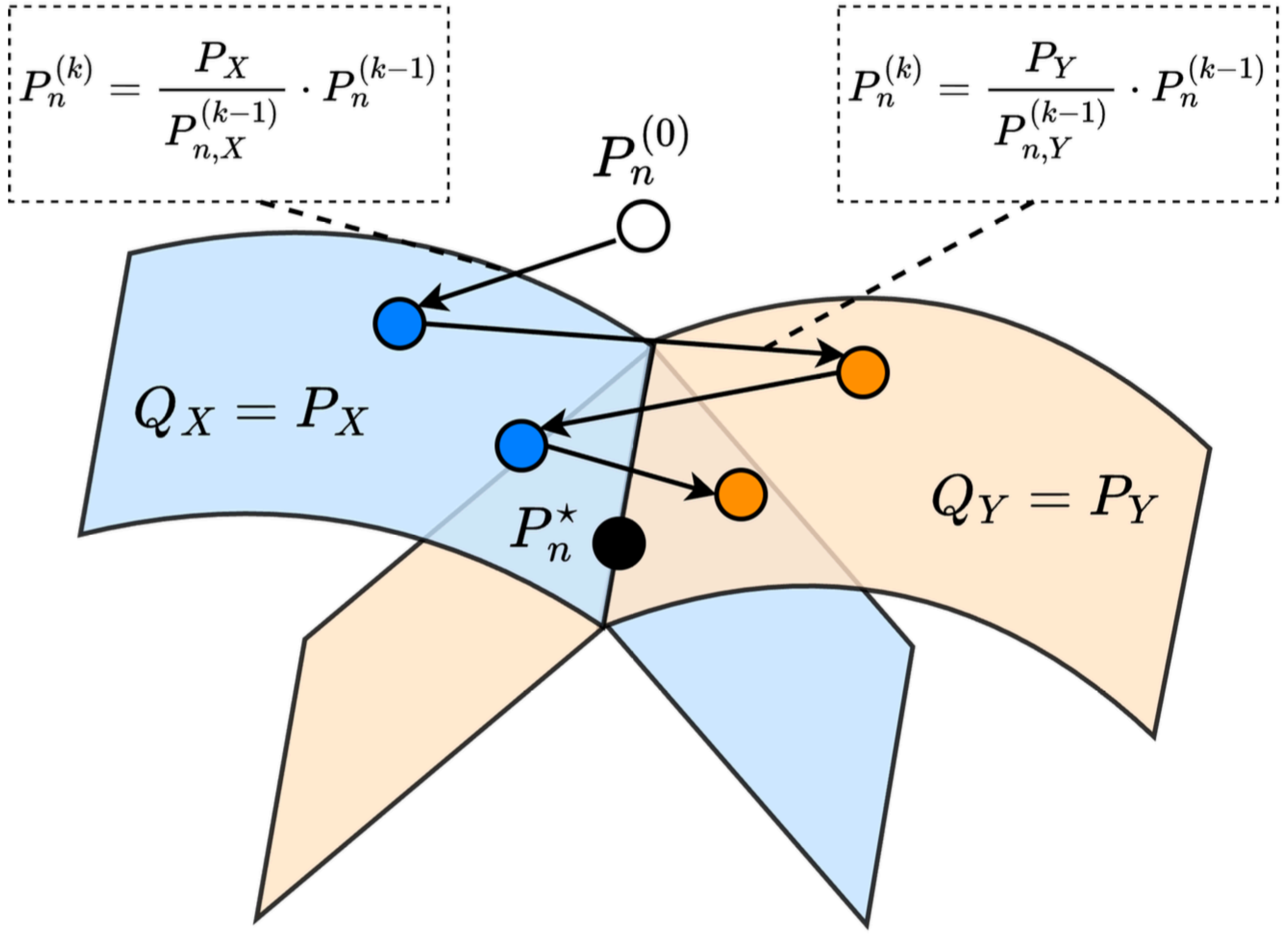
Data Balancing

Rescale rows and columns by the desired marginals.

$$P_n^{(0)} = P_n = \frac{1}{n}\sum_{i=1}^{n} \delta_{(X_i, Y_i)}$$

$$P_n^{(k)} = \begin{cases} \frac{P_X}{P_{n,X}^{(k-1)}} \cdot P_n^{(k-1)} & k \text{ odd} \\ \frac{P_Y}{P_{n,Y}^{(k-1)}} \cdot P_n^{(k-1)} & k \text{ even} \end{cases}$$



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1. How does the balanced distribution improve upon the empirical measure **theoretically**?
2. What are the **practical** implications for SSL objectives such as CLIP?

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Theorem. The iterates of balancing satisfy

$$\mathbb{E}_P \left| P_n^{(k)}(h) - P(h) \right|^2 = \frac{\sigma_k^2}{n} + \tilde{O}\left(\frac{k^6}{n^{3/2}}\right) \to \frac{\sigma_0^2 - \sigma_{\text{gap}}^2}{n}$$

Novel recursion formula for estimation error that is of independent interest (OT, data-centric ML, etc.)

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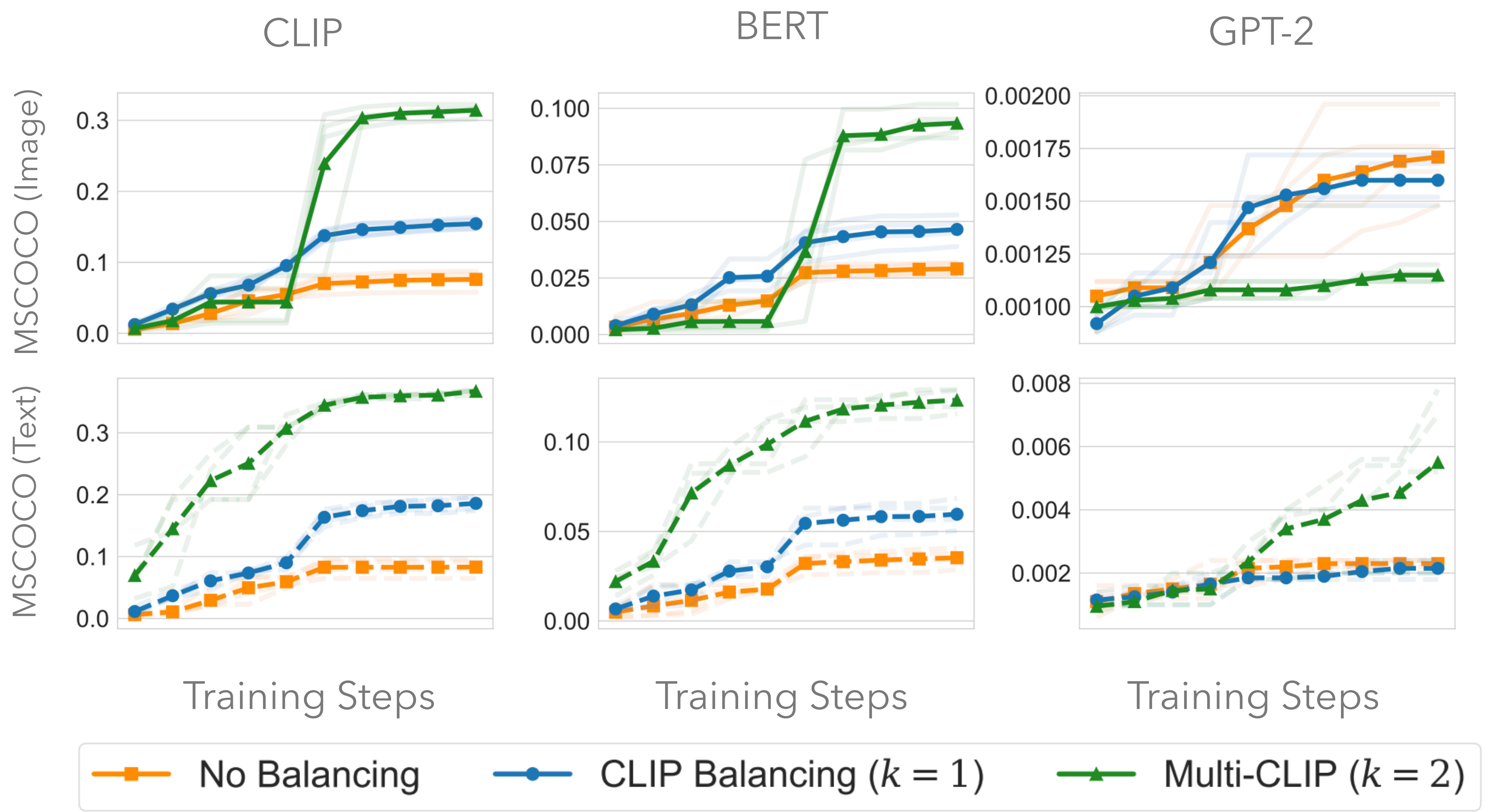
Balancing mini-batches to improve the stability of the CLIP training objective.

Using a balanced objective increases zero-shot retrieval (recall) across datasets and embedding architectures.



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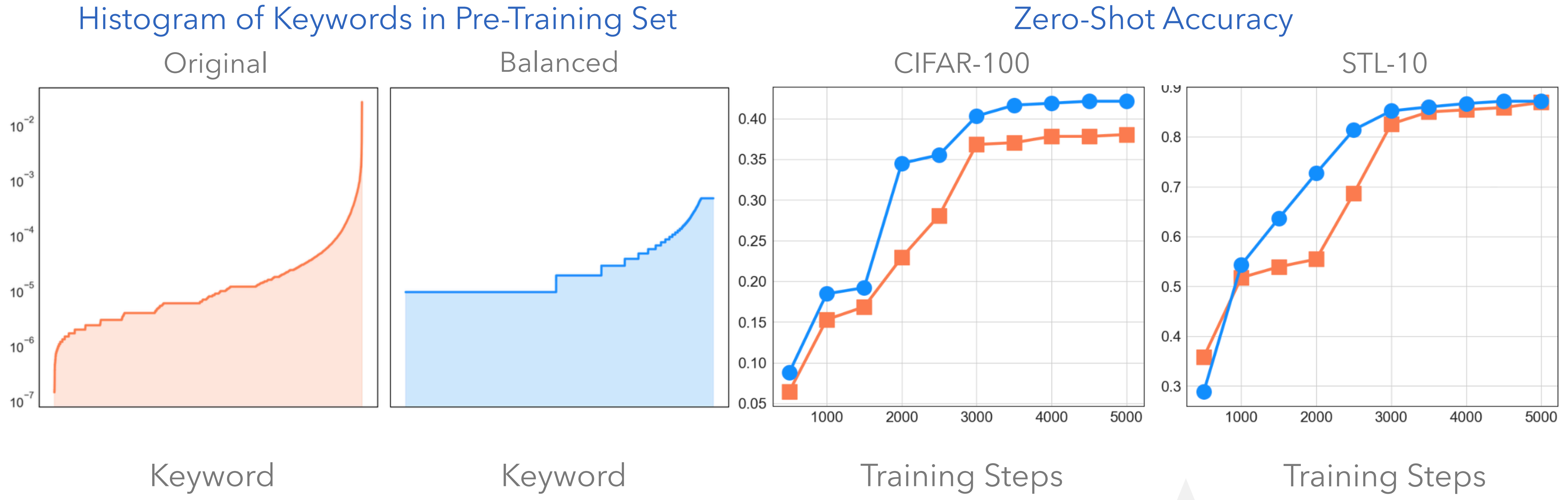
CLIP models trained on the balanced pre-training set improve over those trained on the original.



Balancing at scale improves performance on zero-shot classification.

Problem Setting

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Thank you!