CLIP Paper Explained Easily in 3 Levels of Detail

🤔 And the key points to remember

Jeffrey Boschman · Follow

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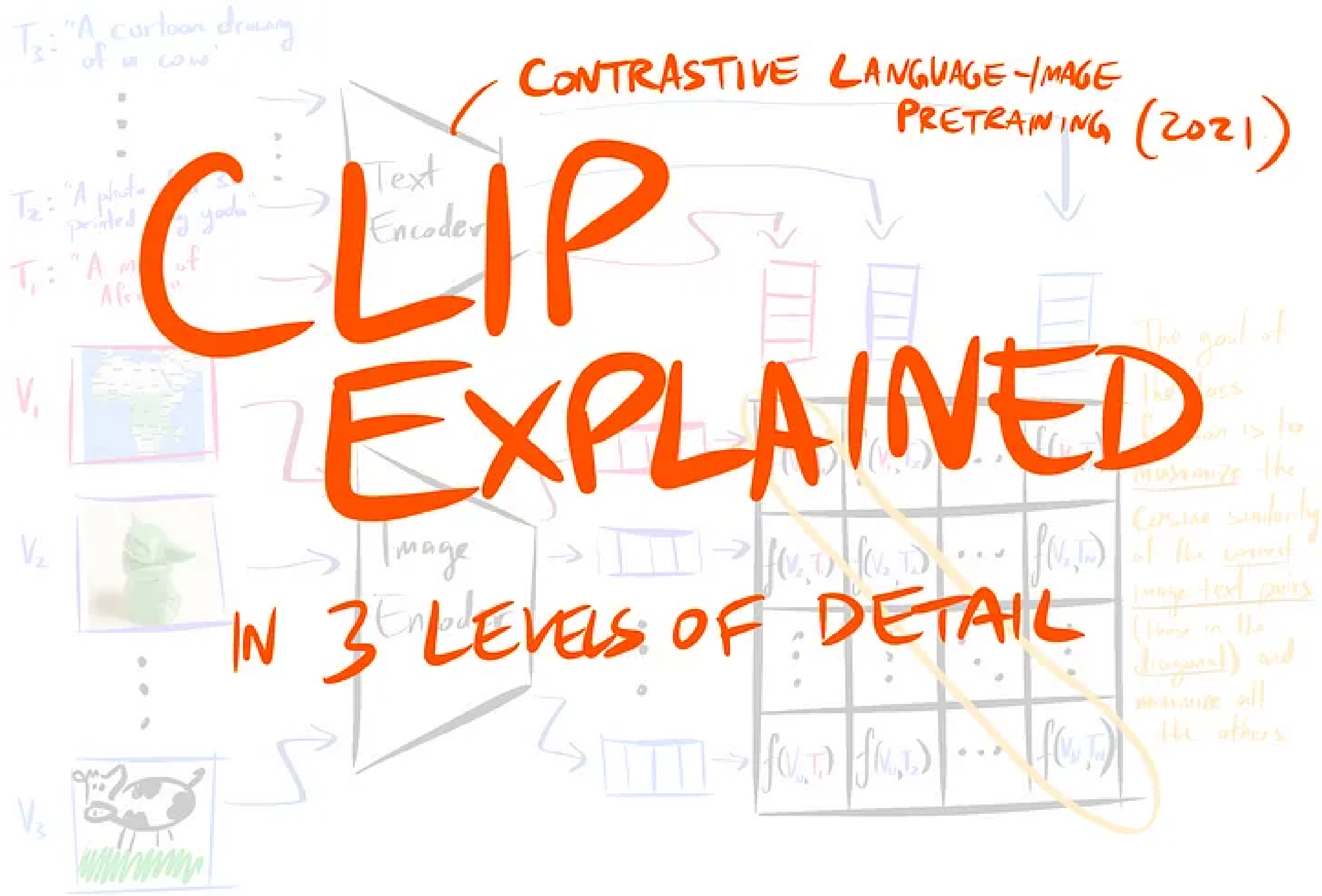


Can you answer these questions easily?

1. CLIP is a pre-trained model for telling you how well a given ___ and a given ___ fit together.

2. In training CLIP, the similarity scores of the correct image-text pairs are found on the ___ of the similarity score matrix for the current batch.

If not, keep reading! (see answers at the bottom of this post)

One Sentence Summary

CLIP is a *pretrained* model for telling you how well a given *image* and a given *text* fit together.

One Minute Summary

CLIP, which stands for Contrastive Language-Image Pre-training, is a model for telling you how well a given image and a given text caption fit together.

In *training*, it tries to *maximize* the "cosine similarity" between *correct* image-caption vector pairs, and *minimize* the similarity scores between all *incorrect* pairs.

In *inference*, it calculates the similarity scores between the vector of a *single image* with a *bunch of possible caption* vectors, and picks the caption with the highest similarity.

Note that CLIP is *not* a *caption generation* model, it can only tell you if some existing text caption fits well with an existing image or not.

Five Minute Summary

CLIP is a pre-trained model for telling you how well a given image and a given text caption fit together, introduced by the paper "Learning Transferrable Visual Models from Natural Language Supervision" (2021) from OpenAI. It was ***trained contrastively*** on a huge amount (400 million) of web scraped data of image-caption pairs (one of the first models to do this). It is useful because this pre-trained model can be used for a lot of downstream tasks; instead of just associating an image with a class label out of a set of class labels, it can ***associate an image with*** a text caption containing ***any words from the English language***.

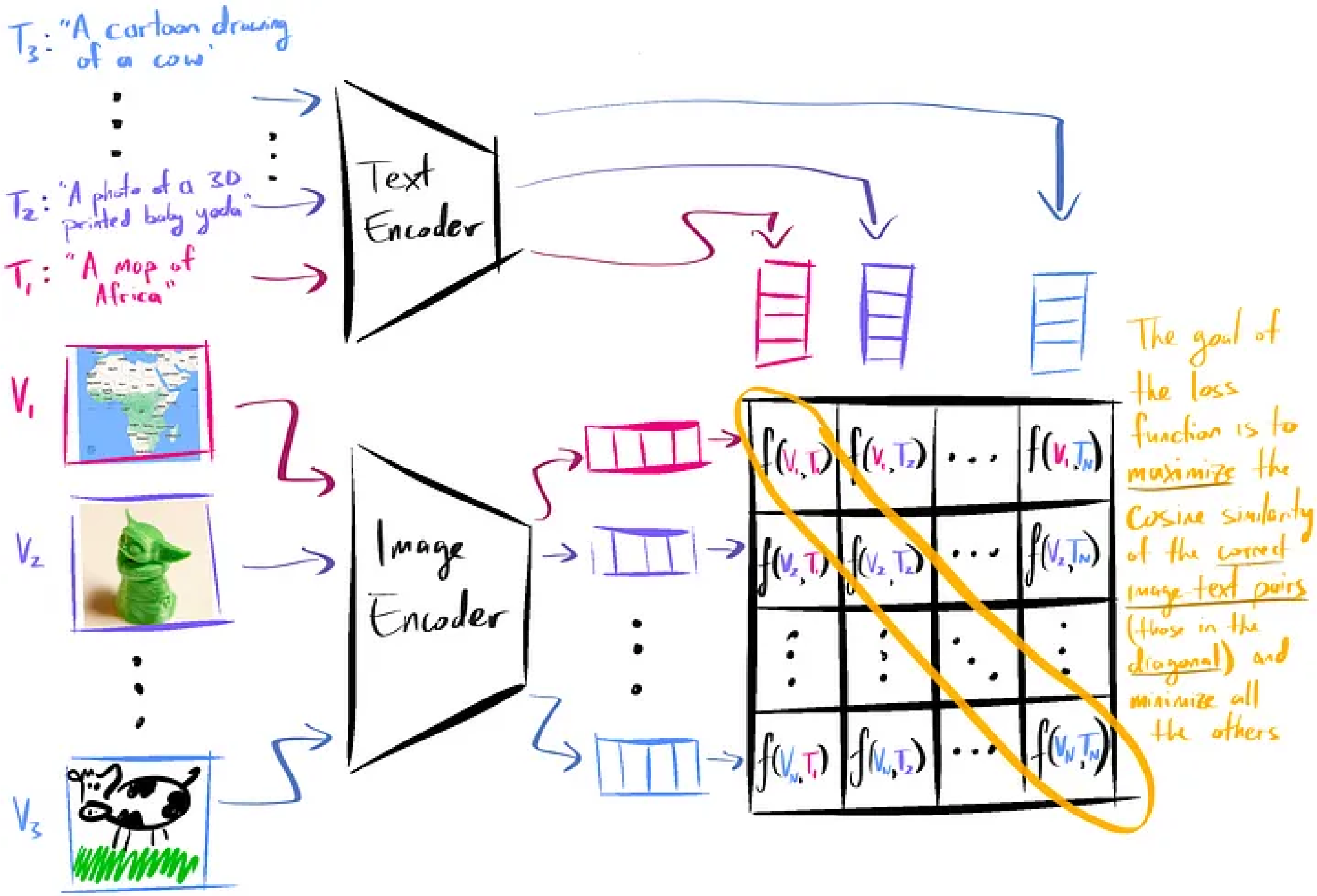
🏋️ Training

Input: A bunch of image-caption(text) pairs (all encoded to be vectors).

Output: The "cosine similarity" scores between *all* the image vector and caption vector combinations.

Objective function: A contrastive function that will modify the weights of the model such that correct image-caption pairs get a high similarity score, and incorrect pairs get low similarity scores.

Note — during training, the model requires that a huge batch of image-text pairs is fed at once (e.g., 20,000 pairs). That way, each batch contains 20,000*20,000 = 400,000,000 possible pairs, with only 20,000 being correct pairs. For efficient processing, the similarity scores of all possible pairs are computed at once to yield a 20,000 by 20,000 matrix, with the values in the ***diagonal*** being the similarity scores for the ***correct image-text pairs***. That way, the objective function can have the goal to maximize the scores in the diagonal and minimize all the scores not in the diagonal. See the figure below.



Overview of how CLIP works during training.

🤔 Inference

Inputs: the vector for a single image, and the vectors for a bunch of different possible text captions.

Output: the similarity scores of the single image to all the different text captions.

Goal: select the text which has the highest similarity with the image.

Note — the authors used this strategy to use CLIP for ***classification*** inference on the ImageNet dataset. They turned the label of each ImageNet class into a sentence, and used these sentences as the possible captions for a given image. For example, instead of using the ImageNet label "cat", they created a sentence like "A photo of a cat" because this is the type of text that CLIP is used to. Then they compared a given ImageNet image with the set of sentences that correspond to the different classes, and picked the sentence

The paper says they have ***high zero-shot performance*** — this is because even though the model might not have been trained on any examples of the classes in the ImageNet dataset, it still performs well because it could kind of figure out what the words of the classes mean and associate that with the images.

Other Notes

Although CLIP itself is not a caption generator model, the pre-trained CLIP model can be used to calculate similarity scores between images and captions, which could therefore be useful ***as part of*** caption generator models.

Answers to questions at the beginning

1. *Image, text (or caption)*
2. *Diagonal*

Links

- https://www.youtube.com/watch?v=dh8Rxhf7cLU — this YouTube video does a great job explaining the main points of CLIP visually.
- https://openai.com/research/clip — This is the official post about CLIP from OpenAI, which contains links to the paper and code.

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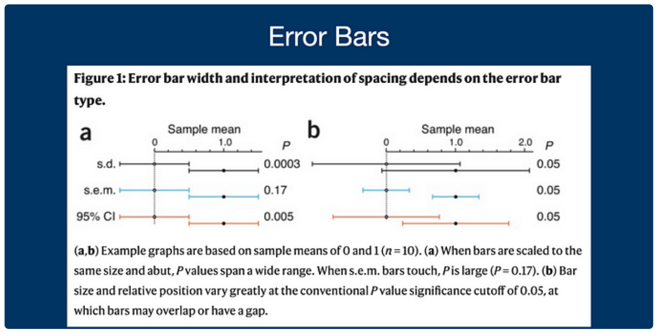

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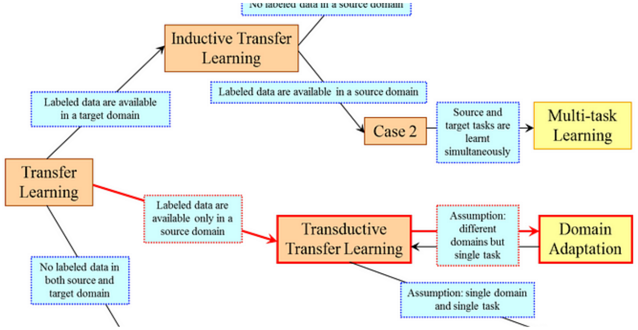

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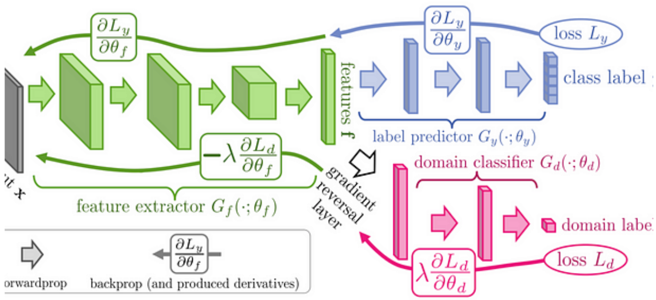

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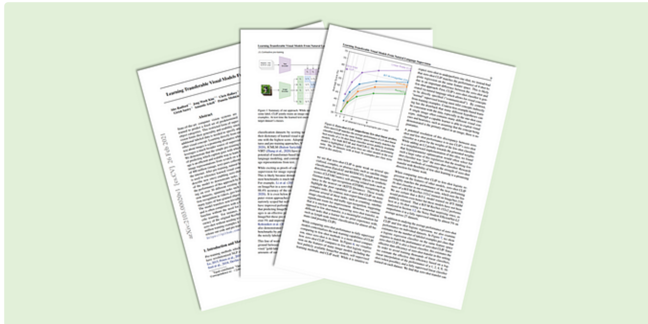

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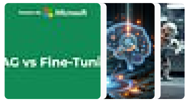

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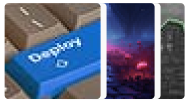

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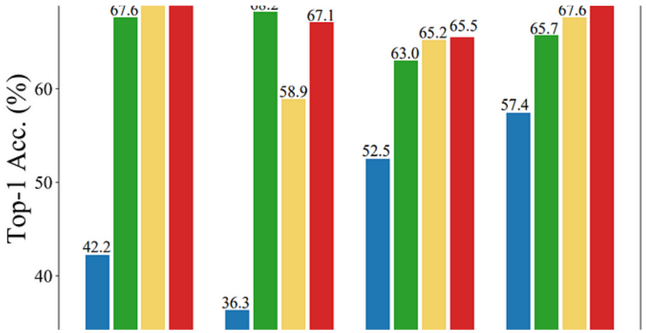

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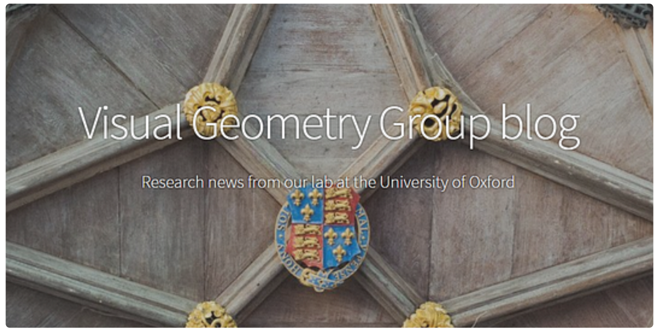

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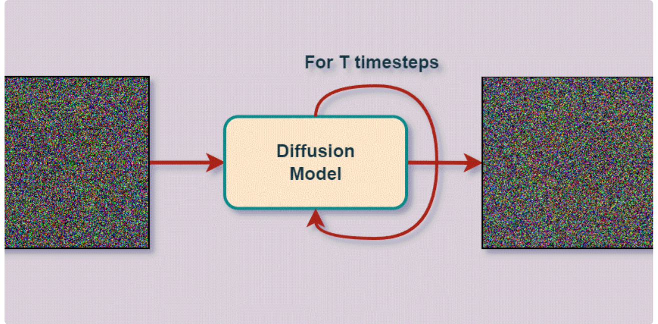

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