

Step 3: Domain-Specific Fine-Tuning

General-purpose models lack the specialized "vocabulary" for academic text. To create a more discriminative embedding space, we fine-tune a pre-trained model on our course data using **deep metric learning**.

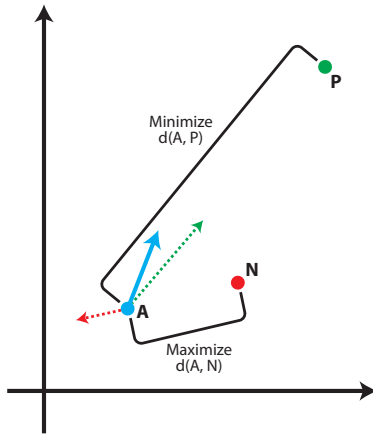
Learning Objective: The Triplet Loss

We train the model using a **Triplet Loss** function, which teaches the model to understand nuanced similarity by operating on triplets of courses [2, 1]:

- An **Anchor** course (A)
- A **Positive**, equivalent course (P)
- A **Negative**, non-equivalent course (N)

The goal is to adjust the embedding space such that the distance between the Anchor and Positive is smaller than the distance between the Anchor and Negative, enforced by a margin (α):

$$L(A, P, N) = \max(d(A, P) - d(A, N) + \alpha, 0)$$



Automating Course Articulation

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Introduction

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