

PUNE INSTITUTE OF COMPUTER TECHNOLOGY

DHANKAWADI, PUNE – 43

**UG SEMINAR ABSTRACT**

Academic Year: 2021-22

**DEPARTMENT: COMPUTER ENGINEERING**

**Seminar On:** Self supervised learning in images

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**Roll No.**

1. Name of The Topic: Mutual Information maximization for representation learning in images.

2. Topic wise contents: 1.Introduction

2.Literature Survey

3.Dependence of results on MI

4.Analyzing Alternative factors affecting MI

5.Conclusion

3. References Used:

1. Michael Tschannen, Josip Djolonga, Paul K. Rubenstein, Sylvain Gelly, Mario Lucic. ON MUTUAL INFORMATION MAXIMIZATION FOR REPRESENTATION LEARNING. ICLR, 2020
2. Sherjil Ozair, Corey Lynch, Yoshua Bengio, Aaron van den Oord, Sergey Levine, and Pierre Sermanet. Wasserstein dependency measure for representation learning. In Advances in Neural Information Processing Systems, 2019.
3. Alexander Kolesnikov, Xiaohua Zhai, and Lucas Beyer. Revisiting self-supervised visual representation learning. International Conference on Computer Vision, 2019.
4. Sanjeev Arora, Hrishikesh Khandeparkar, Mikhail Khodak, Orestis Plevrakis, and Nikunj Saunshi. A theoretical analysis of contrastive unsupervised representation learning. In International Conference on Machine Learning, 2019.

Date: 12/04/2021



Student

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REMARKS BY UG SEMINAR CO-ORDINATOR:

Date: 12/04/2021

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UG Seminar Coordinator

**Abstract:** Many recent methods self-supervised representation learning train feature extractors by maximizing an estimate of the mutual information (MI) between different views of the data. In this literature survey we discuss and provide evidence to analyze the extent to which maximizing Mutual Information (MI) between vectors has an effect on training feature extractors. They take 2 images, pass it through particular feature extractors and get 2 independent 2D-vectors for each of the images respectively. Following this MI is calculated using a predefined formula between these 2 vectors, using one among a variety of estimators (InfoNCE, InfoMAX, etc). The primary task is to maximize this MI. After noting down initial results they discuss if employing a better MI formula is the only way in which we could get better feature extractors. The authors go on to prove that the success of these methods cannot be attributed to the properties of MI alone, and that they strongly depend on the inductive bias in both the choice of feature extractor architectures, the parametrization of the employed MI estimators, the estimators and critics employed. This paper is to prove that maximization of mutual information, and focusing on improving solely that is not a necessary and/or sufficient condition for beating current SOTA results. It is further suggested that the use of triplet technique, in which we use representation of images, could help reduce the MI factor between similar images and increase it for distinct ones. It also suggests that while all of this is true we must continue to pursue better formulae to find MI as although it isn't solely responsible for the performance of our experiment but it does play a vital role in it.

**Keywords:** Self-supervised learning, Unsupervised representation, Mutual Information, InfoMAX, InfoNCE, pretrained models.

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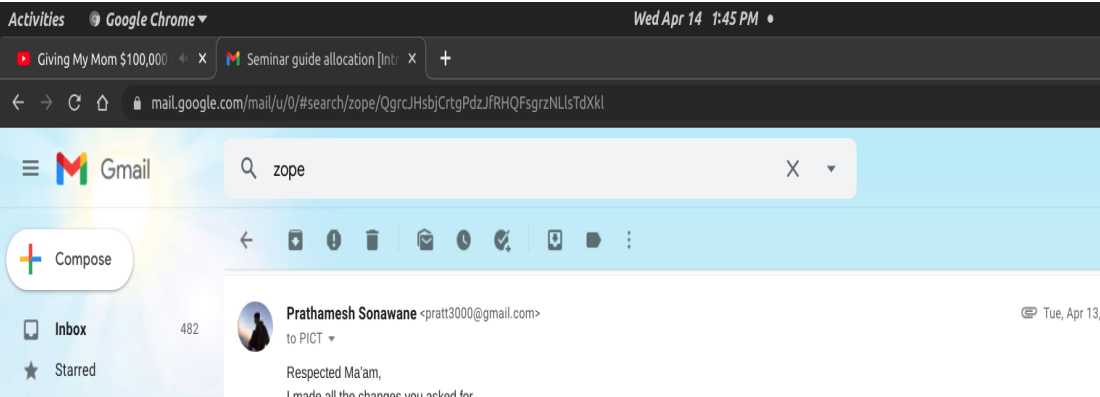
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( Prof.                      )



Approval