Supplementary Material for Scene Graphs for Interpretable Video Anomaly Classification

Nicholas F. Y. Chen, Zhiyuan Du, Khin Hua Ng
DSO National Laboratories
Singapore
{cfangyew,dzhiyuan,nkhinhua}@dso.org.sg

1 Feature Selection with Mutual Information

To investigate the discriminative nature of the triplets, we used mutual information (MI) for the NB classifier, which calculates information shared between two random variables. Two MI schemes are conceived: MI-Labels and MI-Class. MI-Class is calculated between a random variable representing all anomaly labels and each triplet. MI-Labels is calculated between each anomaly activity label and the triplets, thus each triplet will have a different MI value for each anomalous activity label. In both schemes, the triplets are ranked and the top γ percentile of the ranked features are selected ($\gamma = (0, 1)$). MI-Labels is conceived to extract out features that can be more associative with respect to specific labels but may not be associative to all of the anomaly labels. The features selected for MI-Labels are the union of the top γ percentile of each different feature set generated for their respective anomaly class. Note that for the same γ, the cardinality of the feature sets selected from MI-Class and MI-Labels may be different.

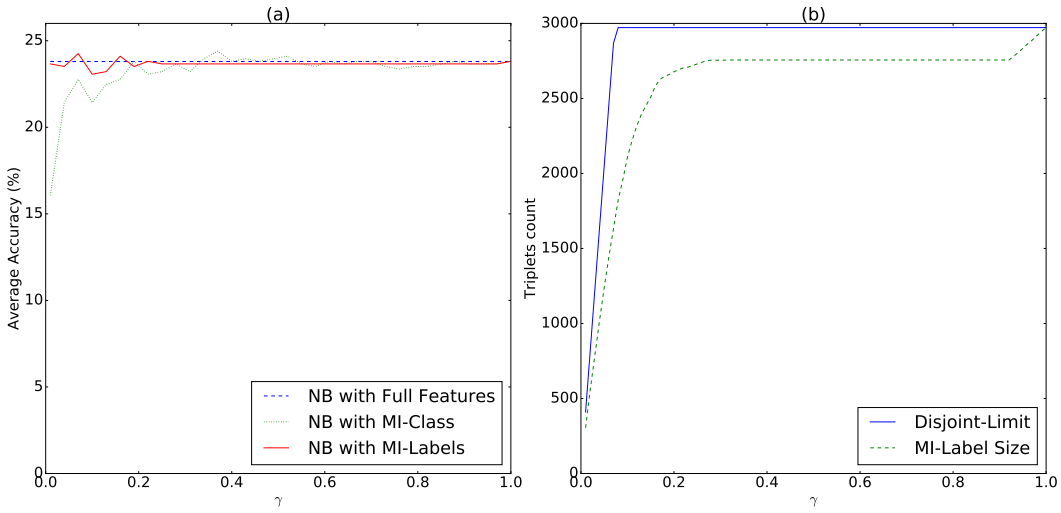

Figure 1: (Best viewed in color.) (a) Average accuracy as a function of γ. The original NB(V) result is shown to serve as a baseline. (b) The cardinality of union over MI-Labels as a function of γ.

Figure 1a shows the result of using MI to select discriminative features. Compared to the NB baseline where all features are used, trimming the feature space can improve the accuracy, but not significantly. Additionally, it also shows that many triplets are spurious features. This is shown again in Fig. 1a where MI-Class requires only the top 36% ($\gamma = 0.36$) to be stably competitive with the NB

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baseline. From the NB model's standpoint, the spurious features either contribute equal likelihood to all anomaly labels, or they are independent relative to most of the anomaly labels. Using MI-Labels, the top 1% ($\gamma = 0.01$) of triplets in each anomaly class is enough to be competitive with the baseline. At $\gamma = 0.01$, the cardinality of the union over MI-Label triplets sets is 305. This is less than the disjoint limit (see Fig. 1b), defined as the upper bound of cardinality if all triplet sets are distinct from each other, indicating that even at the top 1% some triplets are shared across some anomaly labels. Using the same number of top features in MI-Class set ($\gamma \approx 0.1$) yields 21.4% average accuracy, indicating that MI-Labels do extract out triplets that help discriminate specific anomaly classes.