Self-Supervision based Task-Specific Image Collection Summarization

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Abstract Successful applications of deep learning (DL) require a large amount of annotated data. This often restricts the benefits of employing DL to businesses and individuals with large budgets for data-collection and computation. Summarization offers a possible solution by creating much smaller representative datasets that can allow real-time deep learning and analysis of big data and thus democratize the use of DL. In the proposed work, our aim is to explore a novel approach to task-specific image corpus summarization using semantic information and self-supervision. Our method uses a classification-based Wasserstein generative adversarial network (CLSWGAN) as a feature generating network. The model also leverages rotational invariance as self-supervision and classification on another task. All these objectives are added on features from resnet34 to make it discriminative and robust. The model then generates a summary at inference time by using K-means clustering in the semantic embedding space. Thus, another main advantage of this model is that it does not need to be retrained each time to obtain summaries of different lengths which is an issue with current end-to-end models. We also test our model efficacy by means of rigorous experiments both qualitatively and quantitatively.

Keywords Deep Learning · Multimedia · Task-Specific Image Summarization · Generative Adversarial Networks · k-Means Clustering · semantics · Self Supervision

1 Introduction

There has been a huge success in applications of deep learning methods for tasks in computer vision and multimedia [18][13][10]. Much of it can be attributed to the availability of accurately labeled training data. This has resulted in the growth of interest in semi-supervised learning or zero-shot learning frameworks [2][9]. While these methods are attracting interest they have their limitations. The challenges that need to be overcome for making applications of deep learning more ubiquitous are: to circumvent the need for label annotations to train models for each task, the requirement of large amounts of data to train classifiers of reasonably good accuracy, and the computational complexities of the model. Therefore, summarization of a large corpus of image data is becoming more and more relevant for the scaling of deep learning algorithms to make them more ubiquitous and real-time. Summarization creates new representative datasets for real-time deep learning. Image corpus summarization has remained a long-standing challenge in the area of computer vision research. Unlike text, event, or video there is no strong temporal relationship between the set of images in a dataset. This subtlety results in significant differences regarding how image summarization must be approached.

In general for summarization, the key challenges are to rigorously define different attributes of a good summary. How to identify redundancy and ensure that all
the parts of source data find an equitable representation in the summarized data in context of an primary objective. Also, how to qualitatively and quantitatively evaluate a summary i.e. distinguish a good and bad summary. Summary of an image corpus can be both qualitatively and quantitatively analyzed based on factor of relevance i.e. how relevant is a particular image to our task for which summary is being built and also on the factor of diversity, that all the images that are distinct are included in the summary i.e. coverage. Overall for generic summarization, a summary should cover all the aspects of data set and must not contain any redundancy. The models for image collection summarization similar to any other automatic summarization problem can be categorized into the following: simultaneous and iterative based on their training routines.

In unsupervised iterative summarization, it is a challenging task is to create a model that summarizes by looking at a small set of images in multiple iterations. Collections are diverse and the order might not have any temporal sequence or correlation within the images. A way to inherently identify how important a image is in set of images is critical. Immediate applications of automatic image corpus summarization can be to summarize datasets and collection of images in settings where manual review is not possible. Recent applications also include finding the representative set of best images among a burst of images captured during an event. It is also a sub-domain of event summarization. Another very important application is while training machine learning algorithms and in ensuring their fairness. Usually massive datasets are scaled down to train networks, this scaling can generate bias if sampled dataset is not accurate summary of the data. While video summarization has been well explored for efficient browsing, image corpus summarization has received far less attention.

We can train machine learning models for different applications using smaller and precise data sets built as a summary of huge data sets. Summarization of data set can help train models without trading-off much on accuracy as the diversity of data will be maintained. Datasets can be summarized with less amount of annotations by first training on annotated data and then drawing inference on entire dataset. This can help reduce annotation cost, a issue that is of paramount significance in training of deep learning models. We propose a self supervised model as it gives us added leverage to exploit and select images based on the representation of their feature vector maps from the learning representations of the model on a particular task. Therefore, the main contributions of the paper are the following:

- To propose a novel task-specific image corpus summarization model.
- Proposed model is unsupervised and uses self supervision objective to extract an unbiased features from the network.
- The features then leverage the task-specific information from the model combined with the representation of unbiased features and then cluster those features to find out the summary by picking up images closest to the centroids of the clusters.
- The method also infuses the semantic information into summarization objective by using class-labels as attributes for the given task annotations.
- We prove the efficacy of method by several qualitative and quantitative experiments.

The rest of this paper is structured as follows: Section 2 presents a comprehensive review of the approaches found in the bibliography related to image collection summarization in similar scopes. Then, Section 3 details the methodology considered in the study. Which includes the architecture of the model, types of losses used and the algorithm.Datasets used for evaluation along with the evaluation metrics are reported in Section 4, which is also devoted to analyse the obtained results on different tasks and discusses about the underlying relevance diversity trade off. Visualization results are discussed in Section 5, which show the efficacy of the algorithm. Section 6 does a review about motivation and efficacy of task specific loss which was first proposed in [29]. Finally, conclusions and future lines of work are presented in Section 7.

2 Related Works

Summarization in case for videos has received more recent attention than image corpus, text or event summarization. Deep learning based models for video summarization using long short term memory(LSTM) and their variants for unsupervised setting have shown how to exploit temporal sequences in videos using LSTMs. LSTMs with application of reinforcement learning show how temporal sequences can be modelled in form of states, not only with respect to time but also within the framework of reinforcement learning by making diversity representative awards.

J Camero et. al [4] gives a multi-kernel clustering approach for the image summarization task. Many of the works use clustering in on way or another [32,27]. Some other approaches involve graph methods, similarity methods or neural network based methods such
as self organizing maps. Simon et. al in [27] consider task of scene summarization, which deals with problem of concisely depicting a scene that is creating a visual summary for a given interest point. Images in a summary must not be totally identical to each other. This concept is referred as diversity or dispersion the property is also known as orthogonality. It can also be noted that Simon et. al in [27] give a concept of “likelihood” where image representing a set of images in summary must have similarity to that set of images. Yang et. al [38] formulate image summarization as an optimization problem. The authors apply a dictionary learning approach based of SIFT-Bag of Words model for creating the summary. Sebastian et. al in [34], pose a detailed analysis of submodular functions and try to solve problem of image summarization using sub modular functions. Similar to these in [35], Wang et al propose an optimization based on L2 distances between points in a hyper sphere. They also use L1 regularization for promoting sparsity as an approach to find diverse representatives on the hyper sphere.

Sebastian et. al in [34] also propose a novel evaluation metric V-ROUGE based on recall inspired by ROUGE a evaluation metric extensively used in document summarization community. Recently deep learning based approach has been experimented. In one of the seminal works around image summarization done by Jain et. al in [30], importance of intent for the task was highlighted. Also in [30], Jain el. al describe about the effective image summarization and how intent and coverage play an important role in it. In many of the recent deep learning architecture developments, even in case of video summarization tend to ignore its relevance.

Subramanyam et. al in [29] propose a novel end to end deep learning based architecture for iterative summarization of image corpus. They also proposed new techniques for evaluation of summaries quantitatively using Gini Coefficient and the idea of classification accuracy to test the information capturing capabilities of summary along with Reconstruction Error. Our work uses several evaluation metrics as proposed in their work. The precision and recall metrics define quantitatively how good a summary is only when they are provided with user annotated summary. This limits the scope to data sets where such meta data is available. Secondly, this also adds an issue to annotate the ground truth with relevance to a particular task for which summary is desired. As it is possible that with change of task, the images needed in summary may change. Therefore a need for standard to compare different algorithms and approaches on particular dataset and fixed set of evaluation metrics needs to be established. However, our contributions differ from the recent deep learning methods for both image and video summarization [29][33][40][39] since we need not re-train our model to obtain summaries of different length.

3 Research Methodology

Out network comprises of two main components: a Deep learning network and clustering. The features are extracted from the images using an Resnet-34 backbone [18], pre-trained on Image-Net [8]. Which is denoted by \( F : \mathbb{R}^{d_1 \times d_2} \rightarrow \mathbb{R}^{d_{feat}} \). The generator \( G \) in our model is conditioned on attributes \( W(y) \) of a class \( y \) to generate sample from prior distribution. After training, we obtain feature embedding of images in the semantic space by inferencing from the model. Then features are clustered using \( k \) means where number of clusters is \( k = \sigma n \). Where the \( n \) is the number of images present in the whole dataset and the \( \sigma \) is the fraction images to be selected in the summary. The image corresponding to the feature embedding nearest to the centroid of the cluster is selected as the representative image of that cluster and is selected in the summary.

3.1 Problem Formulation

Summarization can be approached in two different ways as a subset selection problem or as an optimization problem. Given a collection of \( n \) images \( X = \{X_1, \ldots, X_n\} \) we aim to find a subset \( S \) such that \( S \subset X \) and \( |S| < n \), while preserving relevance and diversity.

3.2 Learning Framework

In our algorithm, we first extract features of the images \( X = \{X_1, X_2, \ldots, X_n\} \) using resnet34 [18]. Let these features be \( x = \{x_t: t = 1 \ldots n\} \). \( X = \{X_1, X_2, \ldots, X_n\} \) is the set of images that are reconstructed from the feature representation \( x \). The decoder module converts images from features as follows \( \hat{X}_i = D(x_i) \) which is then used by \( L_{constr} \) to train the model.

The discriminator in the GAN, \( D' \) distinguishes between features \( x \) and \( x' \) as real and fake. In principle, GAN in the model is similar to generative adversarial networks presented in DC-GANs and face-GANs[17]. A
important question to be addressed is that why are the images with feature vectors nearest to centroids being picked as a part of summary. Without loss of generality, while summarizing the dataset in general we do not know what is the perfect length of the summary that should be kept which maximizes the diversity and has least redundancy. Therefore, we employ summary selection as an inference problem rather than train the model on weakly related task end to end. Our training focuses on creating such semantic space that meaningfully embeds the dataset so it can be summarized. Then, for a given $k = \sigma \times n$ we pick the image nearest to centroid. For a cluster, the average distance of the centroid from every other image is minimum. Therefore, centroid serves as the best approximation for every image. Hence, we pick the image nearest to centroid as the representative image of that cluster. Here $k$ is a hyper parameter that needs to be searched for by observing the average distance of elements in the cluster to their centroids [20][33]. The advantages of this method is that to obtain models of different summary length it doesn’t need to be retrained. Moreover, our model can also be easily extended to generate zero-shot summaries, since the embedding space is semantically meaningful.

3.3 Semantic Initialization

We use the class labels as an semantic attribute. We use pretrained Glove vectors [24] of 50 dimensions to encode the class labels as attributes which are denoted as $W$. This embeds the features into the semantic space. This information also helps us condition the generator using attribute $W(y)$ of a class $y$ as prior to generate more relevant features in CLSWGAN. The CLSWGAN has been discussed in greater detail in further parts of this section.

3.4 Reconstruction Loss $\mathcal{L}_{re}$

$\mathcal{L}_{re}$ is used to make a summary that captures all relevant frames. It has been used in many of previous works in both image and video summarization [39][23]. If original set of images can be reconstructed using the their deep features respectively it would mean that the network has been able to reduce the dimensionality of the problem without sacrificing much on the information present in the image. Then summary can be generated on a tractable set of feature vector representations rather than images themselves. Feature representation encodes relevant information and makes the clustering robust to negative examples where a mere pixel shift between a pair of similar images would have landed them far in hyper-dimension space while clustering based on their euclidean distances.

$$\mathcal{L}_{re} = \left\| \sum_{t=1}^{n} (X_t - \hat{X}_t) \right\|$$  

(1)

Where $X_t$ is image in dataset, $\hat{X}_t$ is reconstructed from the generator and $n$ is number of images in dataset.

3.5 Loss of Conditional WGAN $\mathcal{L}_{CLSWGAN}$

Inspired from [36], we train the feature generating wasserstein generative adversarial network (WGAN) such that
it is able to distinguish between the real $X$ and fake $x'$ feature representations. The CLSWGAN $L_{CLSWGAN}$ has two components generator $G : z \times W \to x'$ and discriminator $D' : x \times y \to \mathcal{R}$ is thus defined as:

$$L_{WGAN} = E[D'(x, y)] - E[D'(x', y)] - \lambda E[\|\nabla_{\hat{x}} D'(\hat{x}, y)\|_2 - 1]^2$$

where $x' = G(z, W(y))$ and $\hat{x} = \alpha x + (1 - \alpha)x'$ where $\alpha \sim U(0, 1)$. Then,

$$L_{CLSWGAN} = L_{WGAN} + \gamma L_{CE}(x', y)$$

Where $L_{CE}$ is the standard cross-entropy loss and $\gamma$ is an hyper-parameter.

### 3.6 Task Specific Loss $L_{task}$

In this paper, we use self supervision and classification jointly to create a task specific loss term. We merge the classification and self-supervision rotational invariance objective together to create a task specific loss as follows.

$$L_{focal} = -\sum_{k=1}^{K} (1 - p_k)^\gamma \log(p_k)$$

$$L_{self} = -\sum_{k=1}^{4} \log(p'_k)$$

$$L_{task} = L_{self} + \frac{L_{focal}}{\beta}$$

Where $p_k = W(k).F_1(x)$ and $p' = F_2(x)$ are the respective probabilities of feature vector belonging to a class $y$ and to a rotation $\phi = [0, 90, 270, 360]$ The images are passed from a network for classification which also shares its backbone weights across all classifiers, we use Resnet34 as backbone [18]. The backbone acts as a multi-task network that does encoding of the image for self supervision task and its classification [1]. Multi-task learning has shown better results for training in several tasks [25, 6]. It is also important to note that for a particular task $\beta$ is likely to control the degree to which the outliers are included along with the inliers. Training in task-specific fashion will ensure that the images that are given same label by the pretrained classifier for a given task will have similar features during summarization for that task as well. As mentioned in the earlier discussion, a suitable value of $k$ can be chosen to further tune the number of outliers present in the summary.

### 3.7 Inference

After the model has been trained the images are passed through the backbone and classifier $F$ in order to embed them into the semantic space. Then the model does clustering of the feature vector embeddings to obtain $\sigma \times n$ images as the summary. In order to obtain the summary following selection criteria is employed, where $C_i$ denotes the $i^{th}$ cluster and $\hat{x}_i$ is the feature vector corresponding to the centroid:

$$S = \{x_i \mid \forall i \in \{1 \ldots \sigma \times n\}\}$$

$$x_i = \min_{j \in \{1 \ldots |C_i|\}} ||x_j - \hat{x}_i||^2$$

### 3.8 Training the model

We discuss the different loss functions and training part of the algorithm in this section. The parameters of model are $w_F, w_{F_1}, w_{F_2}, w_D, W, W'(D')$ for the encoder, decoder i.e. generator and classifier i.e. discriminator. The training of our model is defined by following losses Loss of CLSWGAN $L_{CLSWGAN}$. Reconstruction loss $L_{reconstruct}$, self supervision loss $L_{self}$ and focal loss $L_{focal}$. Similar to usual training GAN models in adversarial manner. The objective is iteratively achieved by:

1. for learning $\{w_F\}$, minimize $L_{re} + L_{CLSWGAN} + L_{self} + L_{focal}$
2. for learning $\{w_{F_1}\}$, minimize $L_{focal}$
3. for learning $\{w_{F_2}\}$, minimize $L_{self}$
4. for learning $\{w_D\}$, minimize $L_{re}$
5. for learning $\{w_{D'}\}$, maximize $L_{CLSWGAN}$
6. for learning $\{w_G\}$, minimize $L_{CLSWGAN}$

**Algorithm 1 Training the model**

1. function Update Params \(\triangleright\) where input is the feature vector sequence and output is learned parameters $w_F, w_{F_1}, w_{F_2}, w_D, w_{D'}$
2. for max number of iterations do
3. \quad $X \leftarrow$ Mini Batch Of Images
4. \quad $x \leftarrow F(X)$ \(\triangleright\) Feature vector
5. \quad $z \sim N(0, 1)$
6. \quad $x' \leftarrow G(z, W(y))$
7. \quad $w_F = w_F - \nabla(L_{re} + L_{task} + L_{CLSWGAN})$
8. \quad $w_{F_1} = w_{F_1} - \nabla(L_{focal})$
9. \quad $w_{F_2} = w_{F_2} - \nabla(L_{self})$
10. \quad $w_D = w_D - \nabla(L_{re})$
11. \quad $w_{D'} = w_{D'} - \nabla(L_{CLSWGAN})$
12. \quad $w_G = w_G - \nabla(L_{CLSWGAN})$
4 Results Analysis

4.1 Data set

The approach is evaluated on following datasets: CIFAR-10 and CIFAR-100 [22], Animals with attributes 2 (AwA2) [37], VOC2012 [11] and diversity 2016 [19]. CIFAR-10 consists of 60,000 32x32 images belonging to 10 classes with same images per class. There are 50,000 training and 10,000 test images. CIFAR-100 consists of similar 60,000 32x32 images with 600 images per class. The classes are divided into 20 super-classes with 5 classes per super-class. AwA2 is another data set used for classification purposes. It contains 37322 images of 50 animal classes. Visual Object Classes (VOC 2012) is another image classification data set with 20 classes and 11,530 images. While diversity 2016 contains the images with corresponding ground truth images for task of diversity in image retrieval. Images are ranked according to their importance within a class in ground truth annotations. There are 20821 images of multiple classes with each class containing 300 images. The classes correspond to events such as balloon festival, Buckingham guard change or sports like surfing etc.

4.2 Performance Evaluation

Regarding evaluation metrics there have been multiple attempts to understand summaries both quantitatively and qualitatively. Still there exists a need for gold standard both in terms of data set with annotated summaries and evaluation of summaries generated for data sets with only meta data being image labels. Like previous works in video summarization [31] [23] where key frame annotations are given.

4.2.1 Precision and Recall

Precision and Recall can be used for evaluation of summaries of data sets with ground truths. Precision is the ratio of number of correct classifications to summary length and recall is the ratio of number of correct classifications to size of ground truth. The F-score is harmonic mean of precision and recall. Here, Pr refers to precision and Re refers to recall. Let, \( N_s \) be set of images in the summary, for our model \( |N_s| = \sigma n \) and \( N_{gt} \) refer to the set of annotated images present in the ground truth. Then precision and recall can be calculated as follows:

\[
Pr = \frac{N_s \cap N_{gt}}{N_s} \quad (5)
\]

\[
Re = \frac{N_s \cap N_{gt}}{N_{gt}} \quad (6)
\]

\[
F-score = \frac{2 \times Pr \times Re}{Pr + Re} \quad (7)
\]

In table 1 we try to compare the f-scores for different values of \( \sigma \) to find out how the efficacy of our model varies with respect to the length of the summary. We also try to compare our image summarization model against the two state of art video summarization techniques run on diversity 2016 dataset. We give the comparison for the two available techniques based on their open source implementation [23] [40]. The three rows for each method correspond to the precision, recall and f-scores for different summary lengths given particular method. It can be observed that when methods made for video summarization are transferred to image summarization they perform relatively poorer on F-scores consistently across all the values of \( \sigma \). This is partly because a lot of temporal sequence exists in videos. Video summarization architectures are designed to learn and exploit such sequences. Whereas, in the case of image datasets when no such temporal sequence may exist it is very likely that network might learn or fine tune itself on absurd parameters which can in turn hurt its performance. In table where F-scores are reported vs the sparsity loss hyper-parameter \( \sigma \). They peak out in range \( 0.3 < \sigma < 0.5 \). The scores drop sharply outside this range as \( \sigma \) tends to 0 or 1. Precision value goes down with \( \sigma \) going from 0 to 1 because the size of summary increases and the recall goes up for same reasons.

4.2.2 Gini Coefficients

There is need of evaluation metrics used when datasets without ground truth are summarized. To measure the diversity of our summary on data sets with only meta data available as image labels we use gini-index [16] [20]. A metric often used in economics to define diversity of income levels in a country. In [29], authors propose use of gini coefficient for evaluation of diversity in the summarization tasks by means of understanding the representation of elements from each class in the constituent summary, which is also referred to as completeness of the summary or its coverage capacity. Gini index is defined using a differentiable cumulative distribution function \( f(x) \) which has mean \( \rho \), and is zero for all negative values of \( x \),

\[
Gini = 1 - \frac{1}{\rho} \int_0^\infty (1 - f(x))^2 \ dx \quad (8)
\]
In practice, we compute an approximation to the given integral using the trapezoid rule for calculation of Gini Coefficients.

Now for the data sets only with labels as meta data we try to plot gini-indexes as a comparison between randomly picked images from data set, images picked corresponding to centers of K-means image clusters and gini index for images from summary are plotted in Fig.2 for different data sets. There is observed difference that our model is more diverse and shows lower gini index than the summary from clustering images directly. The summary is more diverse throughout the number of images present in summary with multiple data sets as lower the value of gini index more is diversity.

4.2.3 Classification Accuracy

In order to evaluate whether the summary is a good representation of original, we perform the following experiment. We first fine-tune on original datasets an inception v3 model which is pre-trained on imagenet and compute the accuracy. The results are reported in Table 2. Since our goal is to test the goodness of summary, we only run the model for few epochs attaining a decent accuracy, though stat of art accuracy may be achieved by using more epochs. Further, we do not use any image augmentation techniques in the experiments. We observe that the accuracy achieved using summary itself is comparable to its original counterpart. In addition, with data augmentation, the accuracy may boost up and be significantly close to original case. Since our goal is to be able to essentially differentiate in the efficacy of summaries, absolute values of accuracy do not hold much significance. However, it can be concluded that the training using summary uses only 10% of original data, while the trade-off in accuracy is reasonable it can be relevant application of summarization to use summaries to fine tune models/prototype and test deep learning architectures.

4.3 Relevance and Diversity Trade-off

In table 3 we show the number of images of each class in the VOC2012 dataset, and their respective ratios to the total number of images in the dataset. In Table 3 the summary of the VOC2012 dataset with a $\sigma = 0.05$ and $\beta = 1.4$ is given. The value of $\beta$ was chosen empirically as the one which gave the least reconstruction error and the highest classification accuracy, and thus, can be said to have a balance between the number of outliers and inliers in the summary. It is evident from the table that our model trains in a way so that the percentage of images selected from each class is inline
Table 2: Classification accuracy for different datasets

| Class       | bicycle | motorbike | bird | airplane | horse | car | tv-monitor | train | chair | cat |
|-------------|---------|-----------|------|----------|-------|-----|------------|-------|-------|-----|
| No. of images | 390     | 395       | 669  | 604      | 421   | 700 | 376        | 470   | 491   | 946 |
| Ratio       | 0.0262  | 0.0262    | 0.0443 | 0.0400  | 0.0279| 0.0463 | 0.0249   | 0.0311 | 0.0325 | 0.0626 |
| No. of outliers | 143     | 130       | 26   | 24       | 140   | 156 | 122        | 51    | 281   | 55  |
| Ratio of outliers | 0.0421  | 0.0382    | 0.0076 | 0.0071  | 0.0414| 0.0459 | 0.0359   | 0.0150 | 0.0826 | 0.016 |

Table 3: The number of images of each class for the VOC full dataset (15104 images) and their proportion in dataset. Also the Outliers (3400 images) on loss threshold of 0.1, and their ratio Similarly Number of images of a class in summary (790 images) at \( \sigma = 0.05 \) and \( \beta = 1.4 \) and their ratio to the total number of images in summary. Reconstruction Loss = 0.410. Classification Accuracy = 68.36. Summary at \( \sigma = 0.05 \) and \( \beta = 0.5 \), and their ratio. Reconstruction Loss = 0.452. Classification Accuracy = 65.85

with the number of images of that class present in the complete dataset. For example, from table 3 we see that 2.58% of the dataset contains images of the class bicycle, and in the summary 2.41% of images are of the class bicycle, which is quite close to the initial composition. Similarly, for the person class, 40.02% images in the dataset and 40.01% images in the summary are present. Thus, we can say that the relevant information in an image corpus is maintained by our model by maintaining the composition of different classes in the summary. Thus, we can say that by minimizing the sparsity loss, regularize the composition of images of different classes in the summary and by minimizing the reconstruction loss, we ensure the most relevant images are included in this composition.

Outliers are images which are difficult to classify. There could be many reasons behind an image being an outlier, one being, its diversity. For example, consider an image containing a number of pets, say, a cat, a dog, a rabbit, and a horse. Now, no matter which one of the four labels is given to such an image, it will be an outlier, as the cross-entropy loss of such an image would be high because the probability that it belongs any of the remaining classes would be significant. Thus, we say that in order to ensure diversity, outliers must be present in the summary. In our paper, we show how task-specific loss is responsible for incorporating the outliers in the summary, and the affects of varying \( \beta \) on the number of outliers included in the summary.

For table 3 we calculate the number of outliers in each class of the VOC2012 dataset using a loss threshold of 0.1 i.e. all images having a cross-entropy loss greater than 0.1 were considered to be outliers. A truly diverse summary must have a composition similar to
this class, mostly containing the outliers of different classes, the values in table 3 are calculated in the same way as table 3 except this time, $\beta$ is taken to be a small value equal to 0.5. In the paper, we show that small values of $\beta$ ensure the presence of a greater number of outliers in the summary. Here, we see that how small values of $\beta$ lead to loss of relevant information from the summary by scaling up the affect of the task-specific loss, and leading the composition of the summary to be similar to the one only made up of outliers.

For example, consider the class, dining-table. It’s balanced composition, the one with the most appropriate number of outliers and inliers, in table 3 shows that 2.78% of the summary must comprise of the images of this class. But, when the $\beta$ is lowered, its composition from table 3 shows that 4.27% of summary contains the images of this class. Thus, we see that by taking a significant affect of the task-specific with a lower value of $\beta$ leads the composition of the summary to be similar to the composed of only outliers, as in table 3.

5 Visualization

5.1 t-SNE

We give the t-SNE visualization plots for different experiments conducted on the AWA2, VOC2012 and diversity 2016 data sets. For Diversity 2016, we generate image-embedded t-SNE plots for ground truth with top 20 ranked images from each class i.e. 1400 images in Figure 6(a) and top 50 ranked images from each class i.e. 3500 images in Figure 6(c). We also give the corresponding set of 1400 and 3500 images generated by our model in Figure 6(b) and Figure 6(d). For these figures, we have highlighted some of the images which were selected by our model, and were also present in the ground truth summary. Further, t-SNE scatter plots as in figure 6(a), 6(b), 6(a) and 6(b) show how the summary generated from our models in more sparse and avoids clusters, as compared to the randomly generated summary.

5.2 Qualitative Ground Truth Comparison

For qualitative assessment of the model proposed in this paper a comparison on diversity dataset was done. Where images were ranked according to their relevancy and diversity in a search result for a particular keyword which in turn was the class of those images. For every class we chose to keep the number of clusters 6. So the $K = 6 \times 70$ that is number of clusters in each class times the number of classes. In Figure 6 we show the top-6 results in the diversity dataset vs the 6 images selected from clustering by our model. There is intersection between images in the ground truth and the images selected by summary.

5.3 Tile Visualization

Due to lack of a standard dataset for task of generic summarization we thought of a novel method to qualitatively identify the efficacy of model. The qualitative visualization is done on a single image rather than a dataset where the image is broken into patches of size 32 pixels (tiny images). These tiny images are then fed forward to the model to generate feature vectors which are then clustered by the model. Depending upon the length of the summary, the number of tiny images are selected. In Figure 7 we use the famous lenna image commonly used in image processing research and break it into tiny block images of size $32 \times 32$, then clustered for different $\sigma$. Within the Figure 7 it can be observed that the model tends to discard the background and keeps most relevant and diverse information blocks as the size of summary continues to decrease. The eyes and the blocks containing hair are not so similar in their feature representations as compared to two adjacent blocks in the background. The trade-off between relevance and diversity suggests that for some values of $\sigma$ minimum redundancy and high diversity can be simultaneously achieved. Decreasing the $\sigma$ further will cause the important parts of the dataset/image to be discarded and keeping the $\sigma$ too high would mean keeping redundancy. The efficacy can be observed by comparison with randomly picked blocks which do not consider the relevance and diversity of a block. While a randomly generated summary will be most effused because of the random nature but it is likely to neglect the relevance of a block absolutely which can be seen in case of all 10%, 30% and 50% of the blocks picked randomly.

6 Review of Task Specific Loss $L_{\text{task}}$

The aim of task-specific loss is to generate a task-specific summary, in other words, the task-specific loss must be able to generate a summary in cognizance of the intent by which the summary is being produced. The intent is embedded into the objective by means of a pre-trained network that is used and the pre-trained loss that is followed by that network. Although many diversity regularization losses like Detrimental Point Processes or Repelling Regularization Losses try to achieve diversity. But most of the diversity regularization works in
an unsupervised fashion to help select images with high visual diversity by selecting points that are sufficiently distant in feature space representation. Repelling regularization works in a way that it repels the selection of images that are near to each other in the feature space. But there should be a priority in terms of the selection of images from feature space where images of multiple labels cluster together in the dataset. Since diversity regularization techniques mentioned above are unsupervised it is less likely that they would take care of such scenarios where an outlier of a particular class rests within the cluster of inliers of another class. For the use case of task specific summarization, it is necessary that such outliers do get picked in general along with ensuring similar high visual diversity. As task-specific loss leverages labels it is able to distinguish between images from a class that is present within a cluster of images of other class as outliers. It can be observed in the t-

Fig. 3: Karaparthy style t-SNE plot for Diversity2016 of our model in comparison to ground truth. The red boundaries highlight the images which are common to both summary and ground truth. Top-20 and Top-50 images selected from each of 70 classes to make ground truth of 1400 and 3500 images in (a) and (c) respectively. While (b) and (d) represent the summary of 1400 and 3500 images generated by our model. Please zoom in for better visualization.

Fig. 4: The above figure talks about the t-SNE plots for VOC data set Fig:(a) is a randomly generated summary for VOC dataset at 5%. Fig(b) and Fig(c) is the summary for VOC dataset, 5% and 10% of images selected from dataset by our model respectively. Fig:(d) is t-SNE for full voc dataset. Different colors represent different classes. Please zoom in for better visualization.

Fig. 5: The above figure talks about the t-SNE plots for AWA data set with Fig:(a) is a randomly generated summary for AWA dataset at 5%. Fig(b) and Fig(c) is the summary for dataset at 5% and 10% of images selected from dataset by our model. The Fig:(d) is t-SNE for full AwA dataset. Different colors represent different classes. Please zoom in for better visualization.
Fig. 6: Comparison of the clouds and Tour-de France class images selected by our model ranked using ground truth vs top-6 images in ground truth for diversity 2016 dataset.

Fig. 7: Tile visuals on leena: Model Summary (Fig a-d) for different values of $\sigma$ and randomly generated summary (Fig e-g). The figure shows a qualitative comparison of how proposed model is able to capture global semantics and is therefore able to preserve saliency of image.

SNE visualization scatter plots for example in Figure 4(b) in the top right corner within selected images of a particular class i.e. cat we can find an outlier image of the person being selected. The same can be observed in Figure 5(b) for example in the bottom left corner where images from giant panda have selected outliers from other classes are also selected.

7 Conclusion and Future Works

In this work, we propose an unsupervised model to summarize a large collection of images. The classification results attained by training a deep network on a summary only and on the original dataset are close and show a similar trend. Thus, the model can also be used for a quick analysis of various models without needing to train on the entire dataset. Moreover, image summarization can also be used to curate more precise data sets for given tasks. Summarization of data sets can be performed and accuracy achieved on summaries can be used to find out the small scale data sets for quicker training of models. In case the labels are not available, the technique can be used to summarize and retains a fraction of data, which can be relatively convenient to annotate. Further, one can perform different tasks on this data before scaling up the model as well as other processing on the original data.

The image collection summarization models can be fine-tuned and used for the other tasks. For example similar idea to Figure 4 can perform saliency detection or attention, that it keeps only important parts in an image for small summary lengths i.e low values of $\sigma$. Also if the discarded information can be estimated using the remaining summary. The reconstruction would act as the compressed image from lossy compression. There is also scope in exploring the design of much better healthcare and diagnosis systems using summarization. Summarized data from weakly related tasks can provide much better learning representations when augmented with the fewer data available for medical imaging tasks.

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12 A. Singh et al.

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