Image Aesthetics Assessment Using Graph Attention Network

Koustav Ghosal¹², Aljosa Smolic¹
¹School of Computer Science and Statistics, Trinity College Dublin
²Accenture Labs
{ghosal,k, smolica}@tcd.ie

Abstract—Aspect ratio and spatial layout are two of the principal factors influencing the aesthetic value of a photograph. However, incorporating these into the traditional convolution-based frameworks for the task of image aesthetics assessment is problematic. The aspect ratio of the photographs gets distorted while they are resized/cropped to a fixed dimension to facilitate training batch sampling. On the other hand, the convolutional filters process information locally and are limited in their ability to model the global spatial layout of a photograph. In this work, we present a two-stage framework based on graph neural networks and address both these problems jointly. First, we propose a feature-graph representation in which the input image is modelled as a graph, maintaining its original aspect ratio and resolution. Second, we propose a graph neural network architecture that takes this feature-graph and captures the semantic relationship between different regions of the input image using visual attention. Our experiments show that the proposed framework advances the state-of-the-art results in aesthetic score regression on the Aesthetic Visual Analysis (AVA) benchmark. Our code is publicly available for comparisons and further explorations.

I. INTRODUCTION

Image Aesthetics Assessment refers to the task of predicting a score or rating of an image based on its aesthetic value. In photography, the aesthetic value of an image is influenced by several independent and correlated factors. For example, apart from the content, a photograph may look pleasing or dull for the photographer’s choice of colour balance, exposure levels, sharpness, content layout, crop etc. In the past, non-deep learning or feature-based attempts tried to identify and encode these factors and define a generic model for image aesthetics [1], [2], [3], [4], [5], [6]. Because of the ambiguous and overlapping nature of aesthetic properties, the task was quite complex and ill-posed. But in recent years, deep learning based data-driven approaches have proven quite effective [7], [8], [9], [10], [11]. Due to the availability of the large scale Aesthetic Visual Analysis (AVA) [12] dataset and the rapid improvements in convolutional neural network (CNN) architectures, the current state-of-the-art (SoA) methods outperform the classical approaches by a wide margin. However, most deep learning-based methods face two primary challenges — aspect ratio awareness and image layout understanding.

Aspect ratio i.e. the ratio of the height and width of the photograph plays a crucial role in image aesthetics. For example a portrait shot or selfie may look better in a 1 : 1 ratio but a 16 : 9 frame may be better suited for a wide landscape or architectural shot. But in a standard CNN set up, the inputs have to be scaled or cropped to a uniform size in order to facilitate mini-batch sampling. This pre-processing step results in distortion or loss of information and subsequently introduces an undesirable bias in the learned features. Lu et al. [9] proposed a solution by sampling multiple crops from the input and aggregating them and thereby roughly approximating the entire image. Several other multi-crop based strategies have followed [13], [14]. The problem with these multi-crop approaches is computational cost and also their sensitivity towards the crop sampling and aggregation strategy. A different approach is to use a dynamic receptive field for the input and use an adaptive or average pooling layer at a later stage in the network [11], [7]. While this approach allows to use an arbitrary sized input in its original resolution, the pooling operators nevertheless map it to a fixed size at the feature-level and thus discard the aspect ratio.

The second challenge i.e. image layout understanding refers to capturing the spatial relations of the important visual elements of a photograph. The placement of the different objects within a frame is a key factor in photographic composition and there are several principles such as symmetry, The Rule of Thirds, framing etc. that photographers exploit to add aesthetic value to their images. Standard CNNs by design, have local receptive fields to achieve translation-invariance and are limited in their ability to perform global relational reasoning [15]. Towards this Lu et al. [8] proposed a two column local-global approach in which the local column processed crops and the global column processed a warped version of the entire image. But it lacked aspect ratio understanding as discussed before. Ma et al. [10] used an object detector to find salient regions in the image and them fused the coordinates with the main network. But apart from computational overhead due to the subnet, the number of objects for every image was experimentally set to five, which is not true for all images.

In this work, we address both these problems jointly, using graph neural networks (GNN) [16]. GNNs have two key advantages over CNNs. First, they are designed to work for arbitrary sized graphs. Secondly, they are able to capture both local and non-local dependencies between nodes efficiently, using neural message passing [17]. Based on this, we propose a strategy in which arbitrary sized images are represented as arbitrary graphs and then we develop a framework leveraging

https://github.com/koustav123/aesthetics_assessment_using_graphs.git
(a) Feature Graph Construction: In the first stage of the proposed pipeline, features \((D \times W \times H)\) are extracted from the input image using a CNN, pre-trained on ImageNet. Instead of pooling to a fixed dimension, we split the features along \(D\) and construct a graph having a set of \((W \times H)\) nodes, \(V \in \mathbb{R}^D\). A certain node in the feature graph corresponds to a certain neighbourhood in the input image (colour coded) and thus this representation preserves the spatial layout of the input. On the other hand, the structure and size of the graph captures the aspect ratio and resolution of the original image (e.g. for an input size \(3 \times 200 \times 168\), the downsampled feature size is \(D \times 4 \times 3\) and therefore the graph has 12 nodes).

(b) Score regression using Graph Attention Network: In the second stage, the high-dimensional input graph is first encoded to a compact representation and then passed to the GNN which performs global relational reasoning using three message passing and a pooling layer. The output is passed to a decoder which maps the features to the score. More details on the architecture are provided in the supplementary material.

Fig. 1. The proposed two-stage pipeline

the power of GNNs and address the two problems discussed above.

Specifically, there are two distinct stages in our pipeline — (a) Feature Graph Construction (Fig. 1a) (b) Score Regression Using GNN (Fig. 1b). (a) First, an ImageNet-trained CNN-based feature extractor computes features from an input image in its original aspect ratio and resolution. The features across different layers are concatenated along the depth dimension thereby capturing both the high and low level details from the image. Next, a feature graph is constructed from the concatenated maps such that the aspect ratio and the spatial relations of the input image are encoded in the structure of the graph. For example, as can be seen in Fig 1a, for an input with feature dimensions \((D \times 4 \times 3)\), \(D\) being feature depth, the resulting feature graph is a set of 12 nodes, \(V \in \mathbb{R}^D\). The position of a node \(v_i\) corresponds to a certain region in the image. (b) In the next stage, a mini-batch of graphs is sampled from the disk and fed to a GNN based framework for aesthetic score regression. The architecture consists of an encoder, an attention based graph-convolution block and a decoder. The encoder maps the high dimensional sparse graph to a compact representation. The encoded feature-graph is fed to the graph convolution layers which performs spatial reasoning using message passing and pooling. Finally, it is passed to a decoder for predicting the scores.

Apart from maintaining the aspect-ratio and layout information, the proposed feature-graph representation has other advantages. Aesthetic quality is influenced by factors such as high frequency components (texture, sharpness etc.) and the low frequency elements (patterns, shapes etc.). On one hand, while cropping the image preserves the original high frequencies, a part of the low frequency information such as patterns and shapes is lost. On the other hand, resizing the entire input does a better job at preserving the ‘global’ components but distorts and blurs the image [8]. We avoid this typical ‘catch-22’ situation by extracting features from the entire input in its original resolution. Moreover, by concatenating features from the different layers of the CNN we are able to encode diverse information across the frequency spectrum [7]. We do not pool or resize the CNN features to a fixed dimension at any stage of the pipeline and thus the feature graph representation encodes rich visual information, aspect ratio and layout, simultaneously.

On their part, GNNs too have several benefits. They can be trained efficiently with mini-batches of arbitrarily sized graphs i.e. each element in the batch can have a different structure. Traditional convolutional frameworks followed by fully connected layers (CNN-FC) require the samples of a batch to have the same dimensions and thus lack this advantage. Additionally, graph convolutions are capable of capturing long range dependencies unlike the traditional CNNs which have local receptive fields. Thus, the proposed GNN block
efficiently utilizes unique properties stored in each feature-graph and learns robust features for the target task. In this work, instead of using the traditional message passing [16] for graph convolutions, we use multi-headed self-attention [18], where nodes are combined selectively based on the image layout and content. We discuss more about this in Sec.III.

Contributions: Essentially, we utilize the rich representational power of CNNs for modelling appearance while exploiting GNNs for a better semantic understanding. We evaluate our idea on the AVA dataset, which is the largest publicly available widely used benchmark for image aesthetics and advance the SoA results for aesthetics score regression. The summary of our contributions is as follows:

1) We propose a novel graph-based, aspect-ratio aware representation for CNN features extracted from images in their original resolution.
2) We propose a GNN based framework using visual attention which is both aspect ratio preserving and layout aware.
3) We advance the SoA results for aesthetics score regression on the AVA dataset.

We believe that the novelty of this work is two-fold. Firstly, handling arbitrary aspect ratio and global layout are two "fundamental but antagonistic problems" in image aesthetics and traditional CNNs struggle to find a suitable trade-off. We show that these two problems can be addressed jointly and efficiently using GNNs. We are not aware of any previous work that has managed to capture the global layout without transforming the input for batch processing. Secondly, we propose a novel network architecture, tailor-made for this particular application. In addition to the graph convolution layers, our network has an encoder, decoder, normalization layers and multi headed pooling layer. Our final framework was carefully designed and optimized for the task after rigorous hyperparameter tuning.

This paper is organized as follows. In Sec. II we discuss relevant research, in Sec. III we discuss our contributions in detail, in Sec. IV we discuss the evaluation metrics and baselines used and report our results.

II. RELATED WORK

Feature-based aesthetics assessment: Early methods, i.e., those of pre-deep learning era, used to focus on hand-coded feature-driven techniques by explicitly modelling popular attributes like The Rule of Thirds, colour harmony, exposure, etc. [1], [2], [3]. Similarly, [4], [5], [19] proposed features by combining object and scene information with appearance-based factors such as luminance, colourfulness, etc. Alongside aesthetic score prediction, [20] developed a calibration technique to identify the factors that influence the overall score. [21] use textual comments as auxiliary information to improve aesthetics assessment.

Data-driven aesthetics assessment: The release of the large-scale benchmark, the AVA dataset [12] and the developments in neural network architectures over the years have resulted in a lot of interest and improvements in this domain. As mentioned in Sec.I, the crux of most deep learning-based approaches has been to improve prediction by addressing the aspect-ratio awareness and holistic layout understanding [8], [9], [10], [13], [22], [11]. Strategy wise, these approaches adopt crop-based [8], [9], [10], attention-based [13] and adaptive receptive field-based [11] techniques. On the contrary, graph-based approaches are recently becoming popular [22], [23]. The majority of these methods pose the problem as binary classification and compare using accuracy. The good and bad labels are obtained by thresholding the ground-truth scores. However, the problems with a classification accuracy based approach are the label imbalance in the AVA dataset, the arbitrary choice of the threshold and its inability to capture the relative aesthetic ranks of photographs. Most recent methods [24], [7], [25], [23] deal with these problems by posing it as a mean opinion score (MOS) regression task. In [24], the authors propose a Earth Mover distance (EMD) based new differentiable metric to compare the regressed MOS with ground truth opinion. [7] propose a multi-layer feature pooling strategy and an inception based architecture. [25] uses spatial attention maps for layout understanding. In addition to score regression or classification, other variants of the problem such as attribute classification [19], [9], [26], [27], photograph ranking [28] and aesthetic captioning [29], [30] have also been explored.

Graph Neural Networks: Graph Neural Nets (GNN) have recently become popular in computer vision due to their ability to process irregularly structured data and non-local information. Existing GNN literature can be broadly classified into spectral [31], [16], [32], [33] and non-spectral approaches [17], [34], [18], [35], [36], [37]. While the spectral methods operate in the Fourier domain, the non-spectral methods are suited for the spatial domain and have endless applications such as molecular property prediction [17], [35], 3D shape estimation from point clouds [34], etc. Typically in a GNN, rich representations are learnt from an input graph by sharing information among neighbouring nodes. Several solutions have been proposed to handle the arbitrary graphs with a different degree for each node. For example, [36] learns weights for each degree and [37] samples a fixed-sized neighbourhood and aggregates them. [18] use self-attention to select nodes based on relative importance.

Our approach is similar to [22], [23] in the sense that they use graphs too. But, both use fixed sized inputs and additionally, [22] pose this as a classification problem. Our method on the other hand, is capable of handling arbitrary sized images and optimized for regression. Our feature extractor backbone is inspired from [7]. But, unlike their pooled approach, we preserve the aspect ratio and spatial layout of the input images. Also, we use a GNN block instead of fully connected layers as the regression head.

III. PIPELINE

In this section we present the details of the proposed pipeline. First we elaborate on our two main contributions. In Sec.III-A, we discuss the proposed feature-graph construction
and in Sec.III-B, we present the theory and architectural details of our GNN block and in Sec.III-C we state the training procedure.

A. Feature Graph Construction

The first stage of our pipeline can be roughly divided into two sub-stages: feature extraction and graph construction.

Feature Extraction We chose Inception-Resnet [38] architecture as the backbone network for extracting robust visual features. The choice is motivated from previous works [24], [7] which have demonstrated that Inception networks perform better for regression as compared to other popular choices such as ResNet [39] or DenseNet [40]. Following [7], we use pre-trained ImageNet [41] weights directly and did not notice any significant difference from fine-tuning the backbone on AVA dataset. This is probably due to the fact that although they are tuned for object recognition, these weights capture generic visual properties as also observed in several other tasks such as segmentation [42], style-transfer [43], captioning [29] etc.

Generally, in an Inception block [44], input feature maps are handled by different filter sizes (e.g. $1 \times 1, 3 \times 3, 5 \times 5$), in parallel and then concatenated before passing it to the next layer. The multiple receptive fields let the network process the input at different scales. Inception-Resnet consists of 43 such blocks with residual connections. We collect the feature maps after each inception block, resize them to a size of $4 \times 3$ and feature maps from all the previous 43 inception blocks are resized accordingly and concatenated resulting in a feature size of $16928 \times 4 \times 3$. As discussed in Sec I, extracting multi-level features helps in capturing a wider range of image frequencies and has been tried before for image aesthetics in [7], [45], [19].

Graph Construction Once the multi-level features are extracted from an input, constructing the feature-graph $G(V, E)$ is straightforward, where $V, E$ represents the set of nodes and edges, respectively. The feature map $F(I) \in \mathbb{R}^{D \times W \times H}$ is split along $D$ i.e. the depth dimension into a set of node vectors $V \in \mathbb{R}^D$ as shown in Fig. 1a. Note, that for Inception-Resnet, $D = 16928$ and $\|V\| = W \times H$ e.g. 12 for Fig 1a. We construct a complete graph i.e. each node is connected with an undirected edge to every other node without self loops and therefore $\|E\| = \frac{W \times H}{2}$. Stating formally,

$$G(V, E) \leftarrow \bigoplus_{i=1}^{L} \mathcal{T}[f_i(I)]$$

where, $\bigoplus$ denotes concatenation, $L$ stands for the number of layers in the feature extractor, $f_i(I) \in \mathbb{R}^{d_i \times w_i \times h_i}$ represents feature at layer $i$ and $\mathcal{T}$ is a resize operation.

The proposed feature-graph representation has three important properties. First, unlike the traditional CNN-FC pipelines, we avoid pooling the features from all images to a fixed size.

Due to this, the number of nodes in the graph is a function of $W$ and $H$ and hence proportional to the input resolution and aspect ratio, which is unique to each image. Second, the spatial layout of the input is preserved as shown in Fig 1a, where a certain region of the input (coloured boxes) corresponds to a specific node in the graph. Third, by constructing a complete graph, we ensure that the long range dependencies of the input are captured by graph convolution layers in the next stage. The problem with CNN-FC frameworks while capturing long range or ‘global’ dependencies has recently gained significant attention and is an active area of research [15], [46], [47]. The issue is particularly important in the case of image aesthetics as photographic composition often involves ‘globally’ aligning subjects within the frame in a certain way such as The Rule of Thirds.

B. Score Regression using GNN

In this section, we discuss the second stage of our pipeline where the input is a feature-graph and the output is the aesthetic score distribution as illustrated in Fig 1b. Graph-regression tasks such as ours can broadly be divided into two stages [17] — (a) Message Passing: Each node updates itself by exchanging information within its neighbourhood and the output, which is also a graph with the same structure, encodes the complex correlations between the different nodes. (b) Readout: The nodes of the encoded graph are combined using a function, which maps an arbitrary number of tensors to a fixed-sized vector, which is generally mapped to the desired output using a fully connected network. In the following sections, we describe the details of these two stages in our framework.

(a) Message Passing with Self-Attention Given an input graph $G(V, E)$, the traditional message passing [16] in GNNs is formally stated as follows:

$$v_i' = \sum_{j \in N_i} \mathcal{W}v_j$$

where, $N_i$ is the neighbourhood of node $v_i$, $v_i'$ is the updated node and $\mathcal{W}$ is a shared learnable weight matrix. It is similar to traditional convolutions except there, $N_i$ is a fixed grid and its size is equal to the receptive field of the filter. Eq 2, can be formalized as a GPU trainable matrix operation $V' = \mathcal{W}AV$, where $A$ is the adjacency matrix that stores the neighbourhood information. A problem with the traditional message passing is that while updating a node, it assigns equal weights to its neighbours. This is undesirable for image aesthetics since certain areas of the image may drive the composition more than the rest (such as the eyes in a portrait) and it is important that this relationship is efficiently encoded.

To this end, Veličković et al. [18] extended the traditional message passing algorithm using self-attention and proposed graph attention networks (GAT). Eq 2, for GAT is modified to:

$$v_i' = \sum_{j \in N_i} \alpha_{ij} \mathcal{W}v_j$$

$^3\mathcal{T}$ is aspect ratio preserving and an optional step for faster training without a significant difference in performance.
where the attention coefficient $\alpha_{ij}$ captures the effect of $v_j$ on $v_i$. The form of attention used in this work follows [18] which can be formally stated as:

$$\alpha_{ij} = \frac{\exp(g(v_i, v_j))}{\sum_{k \in \mathcal{N}_i} \exp(g(v_i, v_k))}$$

(4)

Eq 4, is a softmax over $g(v_i, v_j)$, where $g$ is a neural network of the form:

$$g(v_i, v_j) = \text{LeakyReLU} \left( \mathcal{U}v_i \oplus \mathcal{U}v_j \right)$$

(5)

where $\mathcal{U}$ is a shared linear transformation, typically another neural network, applied to each node. In practice to increase stability during training, instead of a single $\alpha_{ij}$, multiple attention heads are concatenated together and the final form of message passing (modified from Eq 3) used is:

$$v_i' = \bigoplus_{k=1}^K \left( \sum_{j \in \mathcal{N}_i} \alpha_{ij}^k \mathcal{M}^k v_j \right)$$

(6)

where $K$ is the number of attention heads. Unlike in Eq 2 where a node treats all its neighbours equally, in Eq. 6, neighbours are attended selectively based on the weight $\alpha_{ij}$, which is in fact a function of $v_i$ and $v_j$. Essentially, modelling the input as feature graph preserves its aspect-ratio and resolution whereas using self-attention lets us encode the global correlations of the input effectively. Note, that the output of this layer which is passed to the next block, is an encoded feature-graph with the same structure as the input.

(b) **Readout with Soft-Attention** Our readout function is based on the soft-attention based global pooling layer [49] (GATP), which takes the arbitrarily-structured encoded graph and generates a fixed-sized embedding. It is formally stated as follows:

$$g_{\text{pool}} = \sum_{n=1}^{\|\mathcal{G}\|} \text{softmax} \left( h_{\text{gate}}(v_n) \right) \odot v_n$$

(7)

where $h_{\text{gate}}$ is a neural network that generates the attention mask and $g_{\text{pool}}$ is the pooled graph. We extend this to a multi-headed approach, as in the previous section as follows:

$$g_{\text{pool}} = \frac{1}{K} \sum_{k=1}^K \sum_{n=1}^{\|\mathcal{G}\|} \text{softmax} \left( h_{\text{gate}}^k(v_n) \right) \odot v_n$$

(8)

where $K$ different attention heads $h_{\text{gate}}^k$ are learnt. Note, that unlike Eq 6, the output from the $K$ attention heads are averaged instead of concatenation.

**Architecture:** The final architecture used for the task as illustrated in Fig. 1b consists of an encoder, the message passing layer, readout layer and a decoder. The encoder is a fully-connected layer followed by ReLU activation and batch-normalization. The encoder maps the high-dimensional feature-graph to a more compact latent representation which is fed to the graph layers. The message passing layer in the graph block consists of three graph attention layers [18] with the shared linear transformation $\mathcal{U} = \text{Linear}(2048,64)$ and $16$ attention heads. Each layer is preceded by a dropout regularizer and followed by a ReLU activation and GraphSizeNorm layer [50]. The GraphSizeNorm Layer normalizes the node features by the graph size i.e. $G_{\text{norm}} = \frac{G}{\|G\|}$. This is followed by the readout or pooling layer with 16 attention heads and a fully connected encoder $h_{\text{gate}} = \text{Linear}(2048,1)$. Finally, a decoder takes the output of the pooling layer and maps it to the score distribution. It consists of two fully connected layers with a ReLU activation, batch-norm, preceded by a dropout. We implemented the entire framework using PyTorch [51] and PyTorch-Geometric [52].

C. Training

We train the network using the traditional mean-squared-error loss between the normalized histogram of scores ($1 \times 10$) and the network output. We use the ADAM optimizer [53] with default PyTorch parameters. The starting learning rate is set to 1e-4 which is reduced every epoch by a factor $(1 - \frac{e}{E})^\lambda$, where $e$ and $E$ are the current and the total number of epochs, respectively. $\lambda$ and $E$ is experimentally determined as 2.5 and 30, respectively. We followed an augmentation strategy similar to [7] to add regularization. Four corner crops each covering 85% of the image and with the original aspect ratio were extracted and flipped giving eight different representations. During training, one random augmentation was chosen and during inference the scores were averaged. Using a batch size of 64 on a Nvidia RTX 2080-Ti 11 GB GPU, training a model until convergence takes about 9 hours.

IV. EXPERIMENTS

**Dataset and metric** We evaluate our approach using the AVA dataset, which is a collection of 230,000 training and 20,000 test images. The images were uploaded by photographers for competitions hosted on www.dpchallenge.com and rated by the community on a scale of 10. The ground-truth annotations for AVA are provided as a 10-bin histogram of scores. The final score is obtained as a weighted average of the histogram. We optimize our framework for the task using the Pearson (PLCC) and Spearman (SRCC) Rank Correlation Coefficients for the ablation study and comparison with the current SoA [24], [7], [25], [23]. These metrics are superior to binary classification accuracy in terms of correlation with human ratings and their capacity to handle label imbalance $^4$.

**Ablation study:** Here, we investigate the effects of the different components of our pipeline. Specifically, we study the effects of the encoder-decoder and the benefits of using attention in the graph layers over the conventional message passing and readout layers. For that, we define the following baselines:

$^4$We provide a detailed discussion on this and comparison with the classification-based approaches [12], [9], [54], [55], [11], [10], [22] using accuracy and balanced accuracy in the supplementary material.
(a) **Avg-Pool-FC**: This is the most basic network where the Inc-ResNet features are average pooled and trained using a single fully-connected (FC) layer (16928 x 1).

(b) **Avg-Pool-ED**: The FC layer from Avg-Pool-FC is replaced by the encoder-decoder blocks.

(c) **GCN-GMP**: Instead of average pooling, the feature-graph representation is introduced. We use the traditional message passing [16] without attention and global mean pooling or averaging for the readout. The encoder-decoder is identical as the previous baseline.

(d) **GAT×1-GMP**: We replace the traditional message passing of GCN-GMP with Eq.6 (1 layer).

(e) **GAT×1-GATP**: The readout function from GAT×1-GMP is replaced by Eq.8.

(f) **GAT×3-GATP**: We add 2 more layers of message passing to GAT×1-GATP. This is our final framework with all the different components discussed in Section III.

In Table I, we compare the performance of these different baselines. We notice that Avg-Pool-FC has the lowest scores, which is expected as it preserves neither the aspect ratio nor the layout. Avg-Pool-ED performs slightly better, probably because the encoder-decoder layers provide additional non-linearity. The performance improves in GCN-GMP, where the proposed feature-graph representation is introduced. Note, that even this simple graph baseline performs better than MLSP (Pool-3FC)[7], the current SoA for score regression (in Table II). The superiority of GCN-GMP over the pooling-based underpins the hypothesis that aspect-ratio and layout information are crucial for IAA which is otherwise lost due to pooling or resizing. On the other hand in GAT×1-GMP, attention based message passing utilizes this information more efficiently by focusing on important regions. The performance improves more in GAT×1-GATP by replacing the readout block with the soft-attention based pooling. Finally, we add two more layers to the message passing block and this completes the proposed framework GAT×3-GATP.

As we added more layers, we noticed overfitting and to handle that, we introduced dropout regularization before each new block. We also noticed that the performance was quite sensitive to the parameters of the normalization layers (both graph and batch normalization). The number of attention heads and the encoded graph size also mattered. All these hyperparameters were determined experimentally and we encourage the readers to check the code for more details (link in the abstract).

**Comparison with the state-of-the-art**: In Table II, we compare our approach with the previous score-regression benchmarks. We chose three different baselines from NIMA [24]. The baselines use different feature-extractors. We chose two different architectures proposed in MLSP [7]. We also select [25], [23], which are (to the best of our knowledge) the most recent works on score regression. We notice that our method outperforms the rest in terms of all the metrics. It can also be observed that both [7] and our method outperform [24], [25], [23] by a large margin. This is probably due to the fact that both methods extract features at their original resolution whereas the others use some mode of cropping or warping to achieve a uniform input size. Our results underpin the claim that seeing the image in their original resolution is beneficial, which is also pointed by [7]. On the other hand, we perform better than [7]. We argue that the improvement is primarily due to the aspect-ratio aware representation and a better layout understanding by virtue of using graph networks.

In summary, our experiments suggest that the improvement observed is due to the combination of the rich information stored in the feature graph and its efficient utilization by the GAT×3-GATP framework.

### V. Conclusion

In this work, we address two central challenges in deep-learning based image aesthetics assessment: aspect ratio and spatial layout understanding. Earlier methods have tried to address these problems independently. We, for the first time, address these jointly, by combining the complementary representational powers of CNNs and GNNs, enhanced by visual attention. For future studies, it may be interesting to explore more advanced graph architectures or better global-relational reasoning abilities using more sophisticated feature extractors.

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