ClusterGNN: Cluster-based Coarse-to-Fine Graph Neural Network for Efficient Feature Matching

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Abstract

Graph Neural Networks (GNNs) with attention have been successfully applied for learning visual feature matching. However, current methods learn with complete graphs, resulting in a quadratic complexity in the number of features. Motivated by a prior observation that self- and cross- attention matrices converge to a sparse representation, we propose ClusterGNN, an attentional GNN architecture which operates on clusters for learning the feature matching task. Using a progressive clustering module we adaptively divide keypoints into different subgraphs to reduce redundant connectivity, and employ a coarse-to-fine paradigm for mitigating miss-classification within images. Our approach yields a 59.7% reduction in runtime and 58.4% reduction in memory consumption for dense detection, compared to current state-of-the-art GNN-based matching, while achieving a competitive performance on various computer vision tasks.

1. Introduction

Finding correspondences between images is an essential task for many computer vision applications such as Simultaneous Localization and Mapping (SLAM) [14, 20], Structure-from-Motion (SfM) [32, 43] and camera pose estimation [48]. Given a pair of images, correspondences can be established through point-to-point feature matching. Classical pipelines typically obtain correspondences with a nearest neighbor (NN) search of feature descriptors and reject outliers based on their match score or using a mutual NN check. Such methods focus only on the local similarity between feature descriptors while ignoring geometric information and the global receptive field.

Recent works [5, 30, 35] have proposed to learn the task of feature matching using graph neural networks (GNNs) and attention. In SuperGlue [30], Transformer [40] based GNNs are applied on the complete graph of keypoints within (intra graph) and between (inter graph) images. Each node is represented with an encoded keypoint descriptor and updated using self- and cross- multi-head attention, while alternating between the intra- and inter- complete graphs, respectively. Learning complete graphs with attention suffers from a computational and memory complexity which is quadratic in N, where N is the number of keypoints. However, keypoints typically show a strong correlation with just a small number of points (sparse adjacency matrix). Furthermore, in the context of feature matching, a large portion of keypoints are non-repeatable and irrelevant for matching. A complete graph representation is thus redundant and results in wasteful attention-based message passing.

Efforts to reduce the quadratic complexity of attention mainly focused on self-attention. For example, reducing the attention dimension by splitting the input sequence into local windows [23] or by approximating attention with kernels [8]. However, these works are less suitable for fea-
ture matching, where we are required to perform self- and cross- attention on features within and between images, respectively. Inspired by the Routing Transformer [27], we propose a coarse-to-fine cluster-based GNN to learn the feature matching task with a lower redundancy and computational complexity. We extract query and key features of keypoints across images to classify the points with strong correlation into the same cluster and establish local graphs using points from the same category. Each point interacts only with points in the same local graph resulting with a sparser attention computation (Fig. 1). Since clustering keypoints across images may lead to an erroneous grouping within images, we take a coarse-to-fine approach and first divide the points into a small number of major clusters which are gradually divided into multiple smaller clusters. We evaluate our method on multiple tasks, namely: relative pose estimation, homography estimation and visual localization. Our model achieves state-of-the-art accuracy across tasks, with a significant improvement in efficiency for dense detection (59.7% and 58.4% reduction in runtime and memory, respectively).

In summary, our contributions are as follows:

1. We present a learnable, coarse-to-fine clustering method to establish local graphs for feature matching, which reduces the spread of redundant information and makes message passing more effective.

2. We introduce the ClusterGNN architecture, an attentional GNN for learning the feature matching task using gradually forming clusters, approximating attention on complete graphs.

3. The proposed ClusterGNN method achieves state-of-the-art results on various tasks, with a significant reduction in runtime and memory consumption on dense detection (59.7% and 58.4%, respectively) compared to the current leading feature matching method (SuperGlue).

2. Related Work

Visual Feature matching. Matching features between a pair of images is used in different computer vision applications, such as visual localization and relative pose estimation. In classical pipelines, keypoints are first detected and described using hand-crafted methods such as SIFT [18] and ORB [28]. The nearest neighbor of each descriptor is obtained based on Euclidean distances, followed by filtering of incorrect matches using mutual consistency check, Lowe’s ratio test [18], matching scores and neighborhood consensus.

In recent years, deep learning methods have been employed for improving different aspects of the feature matching pipeline. Learning-based feature detectors and descriptors such as SuperPoint [10], ASLFeat [19] and R2D2 [25], were proposed for learning more robust, discriminative and repeatable representations of keypoints. Other methods focused instead on the matching and filtering tasks [30, 36, 44]. A significant improvement in matching accuracy was recently achieved by SuperGlue [30], an attentional GNN architecture, which establishes complete graphs over keypoints within and between images and update their representations with an attention-based message passing. Albeit, since the runtime and memory complexity of attention is quadratic in the number of nodes, operating on the complete graph does not scale well. This in turns limits usability of SuperGlue, especially when matching a large number of points. In this work, we build on the success of SuperGlue and propose a sparser alternative to reduce the propagation of redundant messages, achieving a significant decrease in runtime and memory while preserving matching performance.

Efficient Attention. The attention mechanism was popularized through the Transformer architecture [40], achieving state-of-the-art results across different natural language processing and computer vision tasks [4, 11, 12]. In the context of attentional GNNs, Transformers can be viewed a graph-like model operating on the complete graph of tokens, which are updated using self- and cross- attention [15, 41]. Since Transformers (and attentional GNNs operating on complete graphs) are hampered by the quadratic complexity of attention in the sequence length (number of nodes), different methods were recently proposed to sparsify connections or linearize the attention complexity.

In [5], a small set of reliable nodes are established as seeds to reduce the cost of attention. In [6, 22, 23], data independent or fixed sparsity patterns were proposed to bound temporal dependencies, such as local or strided attention. Drawing inspiration from CNN networks, those works suggested to apply attention within a fixed local neighborhood, which bounds the complexity, but limits the ability to establish long range interactions. In the context of feature matching, such methods may degrade performance since the distribution of keypoints is not regular, and the two matched images may have large scale and viewing angle differences. Other approaches [2, 7, 42] proposed to approximate attention by either lowering the sequence dimension through pooling or lowering the attention matrix dimension using low-rank methods. Such approximations, however, include assumptions which are less appropriate for feature matching.

Inspired by content-based sparse attention [16, 27], which use data-driven sparse attention [16, 27], which use data-driven sparse attention to cluster tokens and operate within clusters, we propose a learned clustering module, which utilizes k-means to construct sub-graphs in a coarse-to-fine module, and passes messages within each local clus-
Figure 2. **The ClusterGNN architecture.** Our model is composed of three components. A Complete Graph Initialization Module (Section 3.3.1) first constructs and updates complete inter- and intra-graphs with attentional GNN layers. In order to leverage on the inherent sparsity of keypoint attention maps, a ClusterGNN Module (Section 3.3.2), learns to hierarchically partition the joint complete graph into smaller sub-graphs before applying attention-base updates. Finally, a Matching Module (Section 3.3.3), establishes the matching probability matrix using dot product and the Dual Softmax operator. A learnable dustbin is further appended to account for non-matching keypoints.

3. Method

3.1. Problem Definition

Given an image pair \((I_a, I_b)\) and extracted keypoints \((K_a, K_b)\) with corresponding confidence scores \((C_a, C_b)\) and descriptors \((D_a, D_b)\), the feature matching problem is defined as pairing keypoints which match in real-world coordinates:

\[
M_{a,b} = \{(i,j) | \| T_a(K_a(i)) - T_b(K_b(j)) \| \leq \epsilon \}
\]

(1)

where \(T_x\) represents the function which transfer pixel coordinates to world coordinates. In practice, \(T_x\) is usually obtained by homography matrix estimation based on predicted matches. When faced with large differences between camera views and long-term environmental changes, traditional methods which rely on NN search often produce wrong matches. Recent GNN-based methods apply attention in an iterative manner to remove matching-unrelated environmental noise and learn global geometric distribution information in order to achieve optimal matching and increase matching robustness.

3.2. Motivation

Existing works [30, 35] which learn the feature matching task with attention-based GNNs, use densely connected graphs. However, as shown in Fig.3a, a large portion of keypoints are non-repeatable and irrelevant for feature matching. In addition, the respective self- and cross- attention matrices tend to converge to sparse matrices (visualized in Fig.3b), where most of the attention values are distributed around zero (Fig.3c). Therefore, it is important to design a sparse structure for efficient feature matching.

In order to learn over sparse graphs and reduce redundancy, we extract query and key features of keypoints to classify strongly correlated points into the same cluster (Fig.3d). The points in each cluster are used to build a small sub-graph. Using attention, we can then pass information and update keypoints representation within each local sub-graph. Due to different descriptor statistics between images, direct classification may cause points from the same image to be wrongly classified into the same cluster. In order to address this problem, we propose a cluster-based coarse-to-fine paradigm and apply attentional GNN layers within clusters for learning feature matching between two sets of feature points and their associated descriptors.

3.3. Network Architecture

Similarly to [30], our method first applies a Complete Graph Initialization Module (Section 3.3.1), which constructs complete graphs over encoded keypoints and descriptors within and between images (intra- and inter-graphs respectively), and updates them using attention. Instead of learning multiple attentional GNN layers over these complete graphs, we design a ClusterGNN module (Section 3.3.2), which learns to hierarchically partition the complete graph into smaller sub-graphs, and then applies the attention update mechanism within these graphs. Fi-
nally, the matching probability between keypoints is computed with a Matching Module (Section 3.3.3), based on the dot product of updated feature representations and the Dual-Softmax operator [26, 35]. An overview of our proposed method is shown in Fig. 2.

3.3.1 Complete Graph Initialization Module

Given input keypoints $\mathcal{K}$, confidence scores $\mathcal{C}$ and local descriptors $\mathcal{D}$, we generate a joint representation as in [30] by adding descriptors and encoded keypoints and confidence scores. We then construct complete intra (within images) and inter (between images) graphs over the keypoints in $(\mathcal{I}_a, \mathcal{I}_b)$ and apply multi-head attention as in [40] and [30] for updating node representation. This construction and initialization process can be expressed as follows:

$$
\begin{align*}
D^0_a, D^0_b &= CA(SA(KE(\mathcal{I}_a)), SA(KE(\mathcal{I}_b))), \\
D^i_a, D^i_b &= CA(SA(D^{i-1}_a), SA(D^{i-1}_b)), \\
KE(\mathcal{I}_x) &= D_x + MLP(K_x + C_x),
\end{align*}
$$

where $SA/CA$ stands for self/cross attention (introduced below), $KE$ is the keypoint encoding layer, and $\oplus$ denotes the concatenation operator. For two input feature sets $(\mathcal{F}_a, \mathcal{F}_b)$, we implement attention-based GNNs to pass and aggregate messages between nodes, as follows:

$$
\begin{align*}
CA(\mathcal{F}_a, \mathcal{F}_b) &= \mathcal{F}_{a,b} + MLP(\mathcal{F}_{a,b} \oplus Att(\mathcal{F}_{a,b}, \mathcal{F}_{b,a})), \\
Att(\mathcal{F}_a, \mathcal{F}_b) &= softMax \left( \frac{Q_a K_b^T}{\sqrt{\text{dim}}} \right) V_b, \\
(Q_x, K_x, V_x) &= \text{Linear}(Q_x K_x V_x) \mathcal{F}_x, x \in \{a, b\}, \\
SA(\mathcal{F}_x) &= CA(\mathcal{F}_x, \mathcal{F}_x), x \in \{a, b\}.
\end{align*}
$$

In practice, we use multi-head attention [40] to improve the expressivity. In addition, all MLP operators are followed with batch normalization and ReLU before the last layer.

3.3.2 Cluster GNN Module

Cluster-based Sparse Attention. The computational bottleneck of the attentional GNNs (Equation 3) is due to the matrix multiplication operation between the query and the key matrices. However, since keypoints are likely to be correlated to only a small number of points (Fig. 3b), it is desirable to operate over local sub-graphs (where the corresponding matrices are much smaller). The Cluster-GNN module implements a cluster-based sparse attention to approximate self- and cross-attention over complete graphs, as follows:

$$
\begin{align*}
\hat{\text{Att}}(\mathcal{F}) &= M \cdot softMax \left( \frac{Q K^T}{\sqrt{\text{dim}}} \right) \tilde{V}, \\
\mathcal{F} &= \mathcal{F}_a \cup \mathcal{F}_b, \\
\tilde{Q} &= Q_a \cup Q_b, \tilde{K} = K_a \cup K_b, \tilde{V} = V_a \cup V_b
\end{align*}
$$

where $M = \{m_{ij}\}$ is the cluster matrix. $m_{ij} = 1$ when $query_{ij}$ (the $i$th query vector of $\mathcal{F}$) and $key_{ij}$ (the $j$th key vector of $\mathcal{F}$) belong to the same cluster. Note that with this formulation, we no longer distinguish between features from different images (like the self/cross attention in Section 3.3.1), and directly operate on their union. While other works also apply the K-NN or top-k operators to determine the index matrix $M$, they do not apply well to cross-attention in matching tasks.

Learnable Hierarchical Clustering. The key to our clustering method is the definition of cluster centers and the discrepancy function. We note that the attention map itself provides a means for measuring similarity, where the attention weights between two features are determined according to their query and key vectors, as follows:

$$
\alpha_{i,j} = \frac{\exp(query_{ij} \cdot key_{ij})}{\sum_k \exp(query_{ij} \cdot key_{jk})}
$$

Since the query and key vectors are different linear projections derived from the input features (Eq. 3), $\alpha_{i,j} \neq \alpha_{j,i}$ is satisfied in most cases. Thus, instead of directly clustering...
the feature vectors, we propose to cluster the union space of the query and key vectors in order to get a better sparse approximation.

Given \( k \) known cluster vectors \( \{ c_i \} \) and features \( \{ f_j \mid f_j \in Q \cup K \} \), the discrepancy function is defined as follows:

\[
\text{dis}(c_i, f_j) = 1 - \frac{c_i \cdot f_j}{\| c_i \| \| f_j \|},
\]

(7)

Using this function, we assign each feature with a cluster center index \( c_{id} \) based on its closest cluster and construct the cluster Matrix \( M \) in Equation 5. Note that, in practice, \( M \) does not need to be calculated explicitly.

During the training process, we initialize clusters centers with the k-means algorithm, and update them as follows:

\[
c_i = \beta c_i + (1 - \beta) \left( \sum_{c_{id} = i} f_j \right)
\]

(8)

where \( \beta \) is a weight to balance the old and new value of \( c \), which is set to 0.99. During test time, the trained cluster centers are directly used to cluster the input features, thus avoiding the iterative process used in traditional clustering algorithms.

By using hierarchical clustering, we reduce the theoretical complexity of attention from \( O(n^2) \) to \( O(n^2 k) \), where \( n \) is the number of features and \( k \) is the number of clusters. Since \( k \) controls the tradeoff between the quality of approximation (better for small values of \( k \)) and the amount of calculations (smaller for large values of \( k \)), its value should be set with consideration. In theory, the best balance between clustering semantics and computational complexity can be reached when we set cluster number \( k = \sqrt{n} \) [27]. However, the input features processed in [27] come from the same image and share similar statistics. For the image matching problem, the input features are keypoint descriptors extracted from two images, which may present significant style differences. Directly using the fixed \( \sqrt{n} \) as the number of clusters can thus lead to over-segmentation, so that each cluster only contains features from the same image. In order to mitigate this behavior we apply ClusterGNN with an increasing number of clusters, realizing a coarse-to-fine semantic clustering (Fig. 4). We further carry an ablation study to guide the choice of \( k \) and evaluate its effect.

### 3.3.3 Matching Module

We establish a matching confidence matrix \( C \), by applying the dot product operator between the features computed with the ClusterGNN module, \( \{ F^a(i), i = 1, 2, ..., n \} \) and \( \{ F^b(i), i = 1, 2, ..., m \} \):

\[
C = \{ C_{i,j} = F^a(i) \cdot F^b(j) \}
\]

(9)

We further add an extra learnable dustbin channel on both row and column of the confidence matrix \( \tilde{C} \) in order to detect keypoints that are not matched. We adopt the Dual-softmax operator [26, 35] for computing the matching probability matrix \( P \), by applying the log-softmax operator on both the row and column dimensions of \( \tilde{C} \), as follows:

\[
P_{i,j} = \text{logSoftMax}(\tilde{C}_{i,})_j + \text{logSoftMax}(\tilde{C}_{i,})_i.
\]

(10)

At test time, we predict the matches using the argmax operator and a mutual check mechanism.

### 3.4 Loss

The ground truth matches set \( M \) and non-matching keypoints set \( (M_{a,}, M_{b,}) \) are supervised with the cross projection error (less than 3 pixels for matches and more than 5
pixels for non-matches). The matching loss $L_m$ is defined as:

$$L_m = -|M| \sum_{(i,j) \in M} P_{ij} - |M_a| \sum_{i \in M_a} P_{i,m+1} - |M_b| \sum_{j \in M_b} P_{n+1,j}$$  \hspace{1cm} (11)

In order to achieve a better clustering effect and enable semi-supervision, we further introduce a clustering loss: $L_c$:

$$L_c^t = \sum_{i,j} \|c_i^t - f_j^t\|.$$  \hspace{1cm} (12)

Our total loss consists of the matching loss $L_m$ and the clustering losses $L_c^t$ computed across different clustering stages:

$$L = L_m + \gamma \sum_{t \in \{1, 2, \ldots, L\}} L_c^t,$$  \hspace{1cm} (13)

where $\gamma$ is set to 0.1 for balancing the two losses, $t$ indicates the clustering stage and $L$ is the total number of stages.

### 3.5. Implementation Details

We train our model on the MegaDepth dataset [17], a large outdoor dataset, including 1M internet images from 196 different locations and sparse 3D models computed with COLMAP [32]. It also uses multi-view stereo to generate depth maps. We select training image pairs as in [13,21], based on the overlap rate from the SfM co-visibility and resize images so that the larger edge is of size 1600.

Our model is optimized using Adam with an initial learning rate of $1 \times 10^{-3}$. We implement attention with a four heads multi-head attention throughout. Our Graph Initialization module consists of three stacked self/cross attention GNN layers. In order to reduce the GPU memory cost, we further chunk query vectors into four parts for this module. Our Cluster GNN module involves four stages with a different number of clusters, set as $\{16, 32, 64, 128\}$, respectively, where each stage consists of two cluster-based GNN attention layer.

### 4. Experiments

Feature matching is a challenging task due to different factors such as occlusions, illumination and weather changes. We evaluate ClusterGNN on three different tasks, which heavily rely on feature matching, namely: pose estimation, homography estimation and visual localization.

We compare our method with NN-search, SGMNet [5] and SuperGlue [30], using both hand crafted features (SIFT [18]) and learning-based features (ASLFeat [19] and SuperPoint [10]). For SGMNet, we retrain it ASLFeat using the official training code. For SuperGlue, since the official training code is not available and since its public model (denoted as SuperGlue*) was trained on MegaDepth [17], Oxford and Paris datasets [24]), we retrain it with different features following the training method described in the SuperGlue paper. We report both our own implementation and the official results reported in the SuperGlue paper. We also provide analysis of computation and memory efficiency. All the reported experiments were run on a Tesla P-100 GPU with 16GB memory.

#### 4.1. Pose Estimation

We use the YFCC100M [38] dataset to evaluate the performance of ClusterGNN on the pose estimation task. This dataset provides a sparse reconstruction from SfM [21,32,33] and ground truth poses. Following [3,30,44,45], we report the AUC of pose errors at different thresholds ($5^\circ, 10^\circ, 20^\circ$), where the pose errors are computed by the maximum angular differences between estimated results and ground truth in rotation and translation. For pose estimation, we use RANSAC as a post-processing tool to compute the essential matrix from predicted matches.

As shown in Table 1, ClusterGNN outperforms other methods with ASLFeat. When using SuperPoint, our method outperforms our re-implemented SuperGlue and SGMNet, with a slight degradation compared to the official version. When using SIFT, our method outperforms SuperGlue, with a slight degradation compared to SGMNet. These results demonstrate the approximation and denoising abilities of ClusterGNN. Qualitative inspection (Fig. 5), further shows that ClusterGNN detects a larger number of true matches compared to other methods, resulting in an improved pose estimation.

#### 4.2. Homography Estimation

We evaluate our method on the homography estimation task using the HPathes dataset [1]. HPathes consist of 52 sequences that exhibit large illumination changes and 56 sequences under significant viewpoint changes. We follow the setup proposed in Patch2Pix [47], and report the percentage of correctly estimated homographies whose average corner error distance is below 1/3/5 pixels. For all compared methods, we apply the OpenCV RANSAC toolbox to estimate homography matrix. The local keypoints of SuperPoint [10] and ASLFeat [19] are both tested in detail. To make a fair comparison, we choose 4k keypoints for all methods and use the same hyper-parameters.

As shown in Table 2, ClusterGNN achieves competitive performance with a slight improvement compared to SuperGlue and SGMNet.

#### 4.3. Visual localization

Visual localization is one of the most important applications of feature matching and its performance heavily relies on the matching quality. Given a query image, visual
The comparison of NN, Superglue, SGMNet and ClusterGNN on YFCC100M dataset with ASLFeat [19]. The number of keypoints is 2048. The red color indicates outliers and green color indicates inliers. ClusterGNN obtains more correct matches.

Table 1. Pose estimation using the YFCC100M dataset. We compare different matching methods (NN, SuperGlue, SGMNet and ClusterGNN) across different keypoint extraction methods (SIFT, ASLFeat and SuperPoint). We report the AUC of pose errors at different thresholds (Section 4.1). Superglue∗ indicates the officially released model. The best performance is highlighted in bold.

Table 2. Homography Estimation on Hpatches. We report the percentage of correctly estimated homographies under different corner error distances.

4.4. Efficiency

Improving the processing efficiency and GPU memory requirements, while maintaining or improving matching performance is the main motivation for developing ClusterGNN. In this section, we compare the runtime and memory of our method with SGMNet and SuperGlue.

Fig. 6a and 6b, report the time and memory consumption for different numbers of detected keypoints on a Tesla P-100 GPU with 16GB memory. Specifically, we test both run
The comparison of memory board of Long-Term Visual Localization Benchmark [39]. The evaluation metrics are defined according to the percentage of correctly localized queries under different thresholds. The evaluation metrics are refer to the leaderboard of Long-Term Visual Localization Benchmark (v1.0).

Table 3. Indoor Localization Results (InLoc Dataset). We report the percentage of correctly localized queries under different thresholds. The evaluation metrics are defined according to the leader board of Long-Term Visual Localization Benchmark [39].

Table 4. Indoor Localization Results (Aachen Day-Night Benchmark(v1.0)). The evaluation metrics are refer to the leader board of Long-Term Visual Localization Benchmark [39].

Figure 6. Efficiency Comparison. We report the time and memory consumption with an increasing number of input keypoints.

4.5. Ablation Study

We conduct ablation studies on the YFCC100M dataset using ASLFeat [19] for detecting keypoints and the same experimental setting as in Section 4.1. Our ablation focuses on the effect of fixing or varying the number of clusters and on the operator used for generating the matching probability matrix.

Fixed vs. Varying Number of Clusters. Our ClusterGNN strategy gradually decreases the size of clusters while increasing their number due to the tradeoff between over segmentation and efficiency. In this experiment we evaluate the effect of fixing the number of clusters versus our choice to gradually increase it. Table 5 shows the results of fixing the number of cluster to \{16, 32, 64, 128\} versus the results of our varying strategy. ClusterGNN with a fixed number of cluster suffers from significant drop in performance.

Sinkhorn vs Dual Softmax. Superglue [30] uses a differential iterative optimal transport, namely Sinkhorn [9,34], to solve the matching confidence. In our work, we adopt non-iterative dual-softmax [26] operator for efficiency. As shown in Table 6, dual-softmax achieves competitive performance compared with Sinkhorn.

5. Conclusion

In this work, we have addressed the quadratic complexity of GNN methods for feature matching. The proposed method, named ClusterGNN, leverages on the inherent sparsity of self- and cross- attention between keypoints in the complete graph and dynamically constructs local subgraphs through a learned coarse-to-fine clustering. Extensive evaluation on several computer vision tasks demonstrates the effectiveness of our approach, achieving a competitive performance while reducing runtime and memory by 59.7% and 58.4%, respectively.

Table 5. The effect of fixing or varying the number of clusters. We report pose accuracy under different thresholds based on YFCC100M using 2K keypoints.

Table 6. The effect of different operators for computing matching probability. We report pose accuracy, processing time and GPU memory for the YFCC100M dataset using 2K keypoints.
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