AutoGPart: Intermediate Supervision Search for Generalizable 3D Part Segmentation

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Abstract

Training a generalizable 3D part segmentation network is quite challenging but of great importance in real-world applications. To tackle this problem, some works design task-specific solutions by translating human understanding of the task to machine’s learning process, which faces the risk of missing the optimal strategy since machines do not necessarily understand in the exact human way. Others try to use conventional task-agnostic approaches designed for domain generalization problems with no task prior knowledge considered. To solve the above issues, we propose AutoGPart, a generic method enabling training generalizable 3D part segmentation networks with the task prior considered. AutoGPart builds a supervision space with geometric prior knowledge encoded, and lets the machine to search for the optimal supervisions from the space for a specific segmentation task automatically. Extensive experiments on three generalizable 3D part segmentation tasks are conducted to demonstrate the effectiveness and versatility of AutoGPart. We demonstrate that the performance of segmentation networks using simple backbones can be significantly improved when trained with supervisions searched by our method.

1. Introduction

Humans parse objects into parts for a deeper understanding of semantics, functionality, mobility as well as the fabrication process. It is natural to consider equipping machines with such part-level understanding. Over the past few years, there has been an increasing interest in 3D part segmentation tasks to support various applications [14, 23, 32, 46] in vision, graphics, and robotics. Thanks to the availability of large-scale 3D part datasets [32, 48] and the development of 3D deep learning techniques, these methods achieve impressive part segmentation results when a test shape comes from the same distribution as the training set. However, they usually suffer from a huge performance drop when it comes to parsing 3D shapes from a novel distribution, e.g. from a different semantic category.

In this work, we focus on generalizable 3D part segmentation tasks. The goal is to learn the essence of parts on some training sets and to be able to generalize well to shapes from novel distributions. A main challenge comes from the versatile cues defining parts. Shape parts can be defined via many cues like geometric primitive fitting [14, 23, 46], rigid motions [12, 13, 47], and semantic prior [27, 29, 32]. The same shape can be segmented into different parts based upon different cues for the seek of various applications. Therefore for a specific application, other than understanding input shapes, a network also needs to figure out the exact cues defining parts from the training data. This is where it becomes tricky. Some of these cues are more salient than others, making them easier to be captured. When these cues heavily correlate with the real part cue in the training domain, they could easily become shortcut features [7,8,15] biasing the network and hindering the generalizability, as observed in [29].

To cope with the above challenges, existing works usually focus on a specific type of parts and incorporate part-type priors towards generalizable 3D part segmentation. For example, a modularized design has been adopted to explicitly extract motion flow and the rigid
motion of local patches so that generalizable motion-based part segmentation can be achieved in [47]. Similarly, the networks are guided explicitly to extract primitive parameters in order to segment primitive parts in [23, 46]. Finding such explicit part type priors requires a deep understanding of the target task, which might not always be available. Even after a huge amount of trial-and-errors in expert designs, such approaches are still not guaranteed to fully grasp the essence of parts. This is because human understandings might not align well with the way that machines prefer to follow [6, 18, 52].

Another line of works from the machine learning community studies generic domain generalization algorithms to help a network handle out-of-distribution samples. However, without considering any geometric prior which is important for part segmentation tasks, they fail to improve crucial parts of the model but merely focus on generic regularization strategies such as making gradients of 3D part segmentation networks via automatically present a generic method to improve the generalizability of 3D part segmentation networks via automatically discovered intermediate supervisions and the method is suitable for different part definitions. 2) We design a parametric model to depict the distribution of useful intermediate supervisions with geometric prior encoded. 3) We propose an automatic search algorithm to find the proper intermediate supervision given a specific part segmentation task.

2. Related Work

Domain Generalization. As an important technique to handle out-of-distribution scenarios, existing domain generalization approaches can be categorized into four streams: 1) learning domain invariant features from multiple source domains aiming to minimize the difference between source domains [22, 25, 33], meta-learning [20, 21], and other model-agnostic strategies [30]; 2) data augmentation algorithms to simulate domain shift [55]; 3) ensemble learning techniques that train domain-specific models and uses their ensemble for inference [45, 55]; 4) automated machine learning (AutoML) techniques that aim to automatically search for data augmentation [4, 24] or neural architecture [1, 2] which can achieve optimal generalization performance. Different from previous AutoML strategies, we propose to search for geometric and part-aware features for intermediate supervisions. Such features are invariant across shapes from different distributions, indicating the superiority of our method to improve the generalizability of the network.

3D Part Segmentation. Mobility-based part segmentation, primitive fitting, and semantic-based part segmentation are three important and representative 3D part segmentation tasks, on which we conduct experiments to prove the effectiveness and versatility of AutoGPart. 1) Mobility-based part segmentation aims to parse articulated input objects into rigidly moving parts. A number of previous works have devoted into it based on traditional techniques such as clustering and co-segmentation [41, 50], or deep 3D neural networks [13, 47]. 2) Primitive fitting addresses the task of clustering input points and fitting them with geometric primitives. Standard solutions include RANSAC [37], region growing [31], supervised learning [14, 23, 46] and unsupervised learning [5, 40]. Recently, [23] proposes an end-to-end neural network that takes point clouds as input and predicts a varying number of primitives. [46] further uses hybrid feature representations to separate points of different primitives. 3) Semantic-based part segmentation detects and delineates each distinct object of interest. Conventional approaches rely on manual design on geometric constraints, including K-means [38], graph cuts [9] and spectral clustering [26]. As for learning-based methods [34, 49], although they achieve state-of-the-art performance on seen categories, it is hard for them to parse shapes from unseen categories due to category-variant information that is easy to take.
than real cues defining parts [29]. Different from previous task-specific methods that employ sophisticated frameworks and delicately designed supervisions, we demonstrate that simple learning frameworks equipped with the intermediate supervisions searched from AutoGPart can achieve comparable or even better performance than existing task-specific designs on the three tasks.

**Auxiliary Supervision.** Adding auxiliary supervisions is a common strategy to regularize the learning process for performance improvement. Among them, weight decay is a widely used technique [17, 28]. Besides, multi-task learning [3, 11, 36, 51] trains a network to solve multiple tasks by sharing parameters between different tasks, where the interested branches acquire benefits from other branches. Deeply Supervise [19] and Inception [39] explore how to add auxiliary supervisions on hidden layers to improve the quality of learned low-level features [53, 54]; LabelEnc [10] proposes a new label encoding function that maps ground-truth labels to the latent embedding space to add intermediate supervisions. In this work, we automatically select proper intermediate supervisions for generalizable 3D part segmentation networks. It can be viewed as an approach that utilizes auxiliary supervisions to improve the network’s generalizability.

### 3. Method

We present AutoGPart, a technique to improve the cross-domain generalizability of a supervised 3D part segmentation network by automatically finding useful intermediate supervisions for the network. Then at training time, supervisions found by AutoGPart are introduced in addition to the segmentation supervision to alleviate the influence of shortcut features [7] and capture real part cues that are invariant across different shapes distributions. The resulting network can better generalize to shapes from novel distributions without any additional cost at inference time. Figure 2 shows an example where AutoGPart is plugged into an end-to-end network for primitive segmentation.

To automatically find such supervisions, we design a parametric supervision feature space with geometric prior knowledge encoded (a parametric intermediate supervision model, Sec. 3.1). To adapt the model for a specific segmentation network, we optimize its parameters via a “propose, evaluate, update” strategy (Sec. 3.2). After that, a greedy search strategy is utilized to select the optimal supervisions from the optimized model (Sec. 3.3).

#### 3.1. Parametric Modeling for the Supervision Space

Based on the observation that many previous generalizable 3D part segmentation works guide part feature learning via intermediate supervisions calculated from per-point geometric features and ground-truth part labels, we assume that being aware of some of such features can help the network learn real part cues. We propose to automatically search for proper part-aware supervision features for each type of part and add intermediate supervisions to encourage the segmentation network to leverage those features. We then move on to introduce the structural model for supervision features and further the supervision space.

**Structural model for supervision features.** We define the possible supervision features as the outcome of a tree-structured operation flow (an operation tree) taking geometric features and ground-truth part labels as input. It is inspired by the calculation process of hand-crafted part-aware geometric features (e.g. rotation matrix, cylinder axis [23], etc.).

Good supervision features could bridge the gap between input point cloud geometry and the output segmentation labels while avoiding shortcuts. And it is crucial to consider how to use ground-truth labels in order to generate such **part-aware and geometrically-discriminative** supervision features. To compute a possible intermediate supervision, instead of treating ground-truth labels as additional input feature vectors, we pre-encode these labels by transferring geometric features of each point to part-aware features. We then use such part-aware features as input to an operation tree directly.

An operation tree transforms input features by operators for the output intermediate supervision feature. Such operators include grouping operators (e.g. sum, SVD\(^1\), etc.) that summarize a feature set into a point-level feature, point-level unary operators (e.g. square, double, etc.), and binary operators (e.g. add, minus, etc.) that encourage feature communications to enlarge and diversify the supervision space. We further introduce some fixed operator-type combinations named operation cells such as a unary operator followed by a grouping operator. They are high-frequent operation combinations in the computing process of hand-crafted geometric features [23, 47].

An operation tree is then constructed by connecting operation cells.

**Supervision feature space.** The supervision feature space consists of all valid operation trees. We set the maximum height of an operation tree to three, thus the supervision feature space is spanned by all possible tree structures and sub-structures of cells in it (Figure 3). To measure the generalization benefit of each supervision feature and to optimize the space toward the optimal intermediate supervisions for a segmentation network, a parametric distribution model \(M_T(\cdot|\theta)\) is constructed to depict the operation tree space. The subscription \(T\) here indicates

\(^1\) Singular Value Decompose.
that it is constructed based on prior knowledge of the task set \( \mathcal{T} \). \( \theta \) denotes parameters introduced in the distribution model. In practice, a marginal distribution is introduced for the grouping operator of the root cell. Then, conditional distributions are introduced for children operators and leaf part-aware features conditioned on their parents.

### 3.2. Learning Task-Conditioned Supervision Distribution

To optimize the distribution parameters \( \theta \) for a segmentation network, we adopt a “propose, evaluate and update” strategy.

**Supervision proposal.** Since a supervision feature is modeled by its generation process in our model, an operation tree depicting the generation of a supervision feature is sampled from the parametric model \( \mathcal{M}_T(\cdot|\theta) \) to generate a supervision feature. After that, the input part-aware geometric feature matrices are passed through the sampled operation tree to generate the corresponding supervision feature \( s \). Then the ground-truth intermediate supervision feature \( g_i^{gt} \) for each point \( i \) is calculated by passing its input features through \( s \).

**Supervision evaluation.** The cross-domain generalization ability of the proposed supervision feature is estimated under a simulated domain-shift setting. Firstly, the training domain is split into different sub-domains. After that, the OOD performance of the sampled supervision feature is estimated by the average generalization error calculated on all of those train-validation splits created by learning one sub-domain out for validation. The network is trained together with the proposed supervision \( s \) and the segmentation task-related supervision to evaluate the generalization benefit of \( s \).

**Supervision space optimization.** The parameter \( \theta \) is updated by the probability density value of the generated supervision \( (\mathcal{M}_T(s|\theta)) \) and its estimated generalization score. The updating strategy is derived from the REINFORCE [44] algorithm. Simply updating parameters of conditional distributions involved in the generation process of \( s \) via REINFORCE equals to updating the joint distribution by REINFORCE.

### 3.3. Greedy Supervision Selection

Though we can select a single supervision feature from the supervision model after the optimization (e.g. the feature with the highest probability), we wish to select multiple features to use for better generalizability enhancement.

To be more specific, we adopt a greedy search strategy to select several supervisions (one to three, in our practice) to use further for the segmentation network. The greedy search aims to choose an optimal supervision set step-by-step. It starts from a set containing single supervisions sampled from the optimized supervision space. The generalization ability of such supervision features are then estimated. After that, supervisions with
top performance are kept and further used to construct a set containing two supervision pairs. Similarly, the performance of supervision combinations are estimated with a new set constructed by coupling top supervisions in each following step. Finally, the supervision combination achieved the best performance is then selected to use further.

4. Experiments

We evaluate the effectiveness of the proposed AutoGPart in searching for suitable intermediate supervisions and improving the domain generalization ability of a segmentation network on three 3D part segmentation tasks: mobility-based part segmentation [13, 47], primitive fitting [14, 23, 46] and semantic-based part segmentation [29].

For each task, we set a default segmentation network to evaluate AutoGPart on, which is a point-cloud processing backbone for representation learning followed by a classification-based segmentation module to propose segmentations. Two backbones are used in experiments, namely PointNet++ [35] and DGCNN [43]. We denote such two segmentation networks as “PointNet++” and “DGCNN” directly for simplicity. For each task, we demonstrate that a simple 3D point-cloud segmentation network trained with intermediate supervisions searched by AutoGPart and segmentation task-related supervisions is able to perform better than task-specific models proposed in previous works as well as networks trained by generic domain generalization strategies.

4.1. Mobility-based Part Segmentation

Datasets. Three datasets are used in the task: training dataset, auxiliary training dataset that is only used in the supervision search stage to help simulate domain-shift, and the out-of-domain (OOD) test dataset. The training dataset is created from [48], containing 15,776 shapes from 16 categories. The auxiliary training dataset is created from PartNet [32], containing 5,662 shapes from 4 categories different from those used in the training dataset. The test dataset used is the same as the one used in [47], which is created from [13], containing 875 shapes covering 175 objects from 23 categories.

Experimental settings. We evaluate the effectiveness of AutoGPart on both PointNet++ and DGCNN. Metric used for this task is Segmentation Mean IoU (MIoU). To apply AutoGPart on this task, we add a flow estimation module ahead of the segmentation network. We compare our method with both task-specific baselines [41, 47, 50], and task-agnostic methods [20, 55]. Deep Part Induction [47] is trained on the same training dataset using the same settings as those used for our models. All learning-based models use only one forward flow estimation and segmentation proposal pass with no iteration between them.

Experimental results. The performance of AutoGPart and baseline models are summarized in Table 1. Based on the table, we can make the following observations: 1) AutoGPart can find useful intermediate supervisions that can significantly improve the generalization ability of both PointNet++ and DGCNN (e.g. 4.9% absolute MIoU improvement on OOD-test set for PointNet++). This can verify the effectiveness of adding intermediate supervisions to boost the generalization ability of segmentation networks and the ability of AutoGPart to find such supervisions. 2) AutoGPart can outperform all task-specific models by a large margin, including traditional methods (e.g. JLinkage clustering) and learning based strategies such as Deep Part Induction. This may echo the proposed assumption that hand-crafted supervisions may not be optimal ones for the task due to the misalignment between human knowledge and machine understanding. 3) AutoGPart can outperform all task-agnostic strategies when using the same point-cloud processing backbone. A possible reason is that geometric prior knowledge which is quite useful to solve the task inherently is carefully considered in the design of AutoGPart, while task-agnostic strategies are not aware of such prior knowledge.

4.2. Primitive Fitting

Dataset. Dataset used in this task is the same as the one used in [23]. However, instead of using the provided data splitting method directly, we re-split the dataset into 4 subsets according to shapes such that it is more suitable to test the cross-domain generalization ability of a model. Three subsets out of them, containing 13,528 shapes in total, are used for training, including the supervision search stage and regular training stage for supervision evaluation.

| Method             | In-dist. | Out-of-dist. |
|--------------------|----------|--------------|
| PointNet++         | 86.4     | 61.0         |
| DGCNN [43]         | 88.3     | 68.1         |
| MixStyle_PN++ [55] | 86.6     | 63.4         |
| MixStyle_DGCNN [55]| 83.1     | 69.5         |
| Meta-learning_PN++ [20] | 71.3 | 63.4 |
| Meta-learning_DGCNN [20] | 76.5 | 69.4 |
| JLC [50]           | N/A      | 67.3         |
| SC [41]            | N/A      | 69.4         |
| Deep Part Induction [47] | 84.8 | 64.4 |
| AutoGPart_PN++     | 87.2     | 66.5         |
| AutoGPart_DGCNN    | 83.1     | 73.8         |
Experimental settings. We evaluate the effectiveness of AutoGPart on both PointNet++ and DGCNN. Metric used for this task is MIoU. We compare our method with both task-specific baselines [23, 46] and task-agnostic methods [20, 30, 55].

Among them, HPNet [46] adopts a clustering-based two-stage segmentation network for feature learning and segmentation proposal. Based on the observation that the high performance achieved by HPNet is largely powered by its clustering-based segmentation module and the synergies between the added supervisions and the clustering module, we conduct the following two experiments to fairly compare AutoGPart with HPNet, since the classification-based segmentation module used in default settings of AutoGPart is not that representative compared with Mean-Shift clustering used in HPNet: 1) Plug AutoGPart in HPNet’s first learning stage to evaluate the effectiveness of AutoGPart in finding useful features that can regularize this learning stage. 2) Replace the clustering-based segmentation proposal module used in HPNet with a classification-based module to compare the effectiveness of supervisions introduced in HPNet and those searched by AutoGPart under a same segmentation network. Resulted models are denoted as “AutoGPart_{HPNet}” and “HPNet*” respectively in Table 2.

Experimental results. The performance of AutoGPart and other baseline models are summarized in Table 2. We can make the following observations from Table 2: 1) AutoGPart can find useful intermediate supervisions to improve the generalization ability of a simple segmentation network for the primitive fitting task using either PointNet++ or DGCNN as the backbone, similar with that observed for mobility-based part segmentation task. 2) For models using classification-based segmentation modules, AutoGPart can boost a simple segmentation network’s performance better than all task-specific models such as SPFN. A possible reason is that the added supervisions, though believed useful by human to help the network learn a correct solution inherently, may not align well with the way preferred by machines to solve the task. Thus, those hand-crafted supervisions may not be effective enough to train a generalizable network. Besides, networks may even use shortcut features to optimize those supervisions. For models using clustering-based segmentation modules, AutoGPart_{HPNet} can achieve better generalization performance than HPNet by adding some intermediate supervisions in its first learning stage. It is probably because that the added supervisions searched by AutoGPart can help the network use more real cues to learn per-point features in this stage. 3) AutoGPart can help better improve the generalization ability of 3D part segmentation networks compared with task-agnostic methods.

The absolute improvement that AutoGPart adds on HPNet is not as significant as PointNet++ or DGCNN, for which we want to emphasize two points as follows: 1) The high performance achieved by HPNet is largely benefit from the clustering-based segmentation module (i.e. 69.6% MIoU on OOD-test set achieved by HPNet* v.s. 79.5% achieved by HPNet). However, such a segmentation proposal process is quite time-consuming, where about 40 hours are needed to segment all test shapes, while a classification-based one only needs no more than 40 seconds. 2) For classification-based segmentation networks, intermediate supervisions searched by AutoGPart are clearly better than that used in HPNet.
by comparing the performance of AutoGPart$_{DGCNN}$ with HPNet* (i.e. 73.4% vs. 69.6% MIoU on OOD-test set). The significant effectiveness of AutoGPart in improving the generalization ability of an end-to-end trained model is of larger practical value.

### 4.3. Semantic-based Part Segmentation

**Dataset.** We use the same dataset provided by [29] as well as the train-test data splitting strategy stated in the paper.

**Experimental Settings.** The evaluation metric used in this task is the Mean Recall value, the same as the one used in [29]. Values reported in Table 3 are the average Mean Recall scores over all test categories. We compare AutoGPart with four task-specific methods [16, 29, 42, 49], and two task-agnostic approaches [20, 55].

**Experimental results.** The performance of AutoGPart and other baseline models are summarized in Table 3. Different from the above two tasks, where the criterion about segmenting a shape is obvious such as rigid motions, it is not that clear what part cues are useful for this task, meaning not enough prior knowledge to guide a learning-based network’s design. Thus, the role of ground-truth geometric features is not that important in the previous task-specific designs [29, 42, 49]. However, their resulting models tend to perform not that well when parsing shapes from novel categories, as shown in Table 3, probably due to the influence of shortcut features. However, our method can help improve the generalization ability of a simple segmentation network to a level comparable to the two-stage learning-based method [29] as well as traditional segmentation methods such as WCSeg [16]. It demonstrates the usefulness of ground-truth part-aware features in providing real cues for a generalizable segmentation network. And also indicates the superiority of AutoGPart to find such useful features for a task where human prior knowledge is not that available or hard to be translated to guide a network’s learning process.

#### 4.4. Qualitative Evaluation

We visualize the segmentation results of “AutoGPart$_{HPNet}$” and “HPNet” in Table 2 on the Primitive Fitting task for an intuitive comparison and understanding w.r.t. the network’s generalization ability on OOD shapes. Figure 4 shows that AutoGPart$_{HPNet}$ can achieve better segmentation performance on shapes from a novel distribution, i.e., having a relatively large primitive-type distribution gap from that of training shapes. A possible reason is that the added intermediate supervisions in the first stage of HPNet can help the model learn per-point features relying more on real part cues, thus less sensitive to the primitive type of each part as well as the primitive-type distribution of the shape.

Besides, we draw an intermediate supervision feature searched from our designed supervision space in Figure 6 for an intuitive understanding towards the property of our searched feature. It can be seen that the searched feature is not only discriminative across different parts, but also changes continuously within one part. Such property may make it be more friendly for the network learning real part cues avoiding shortcut features that only exist in shapes from training distributions.

**5. Ablation Study**

In our method, we construct an intermediate supervision space and search for useful supervisions from it to increase the generalizability of a segmentation network. In this section, we ablate our method by replacing some crucial designs with other possible alternatives to analyze the effect of those parts.
Table 4. Ablation study w.r.t. reward function design and supervision space design. For abbreviations used, “Arch.” refers to “Architecture”; “PN++” denotes “PointNet++”; In/Out-of-dist. refers to In/Out-of-distribution performance.

| Ablation | Arch. | In-dist. | Out-of-dist. |
|----------|-------|---------|--------------|
| /        | PN++  | 87.2    | **66.5**     |
| −Cross Validation |     | 85.6    | 64.6         |
| −Gap     |       | 90.6    | 64.9         |
| Less operators |      | 87.5    | 63.1         |
| Less unary operators | | 86.8    | 64.1         |
| Less binary operators | | 83.0    | 65.1         |
| Less tree height |   | 82.1    | 63.5         |
| /        | DGCNN | 83.1    | **73.8**     |
| −Cross Validation |     | 84.5    | 73.1         |
| −Gap     |       | 89.4    | 70.4         |
| Less operators |      | 92.1    | 70.6         |
| Less unary operators | | 89.3    | 69.5         |
| Less binary operators | | 89.7    | 71.6         |
| Less tree height |   | 89.4    | 71.8         |

**Reward function design.** In AutoGPart, we adopt the average generalization gap over all train-validation splits as the reward value to estimate the effectiveness of the selected supervision on improving the model’s generalization ability. The intuition is that the cross-validating the generalization gap of the searched supervision feature could probably give its generalizability a better estimation. In Table 4, we validate the superiority of the designed reward function by replacing it with 1) generalization gap on a single split (denoted as “−Cross validation”), and 2) average performance on validation sets over all splits (denoted as “−Gap”).

**Supervision space design.** In our method, we use a large supervision feature space to increase the diversity of features in it and also to enable the model a high freedom to select its preferred features by itself at the same time. To demonstrate its benefit, we downsize the supervision space by downsizing the input part-aware geometric feature set, the unary operator set and the binary operator set respectively and then evaluate the effectiveness of the searched supervisions. Experimental results prove the superiority of using a large supervision space (see Table 4).

**Supervision selection strategy.** In our method, we use a greedy search-like strategy to select supervision features for future use based on the intuition that such a strategy can help us find a good supervision feature combination from the optimized space. To demonstrate the effectiveness of the greedy supervision selection strategy used in our method, we try to ablate it and consider the following two alternatives: 1) Select top $K (1 \leq K \leq 3)$ features from the supervision feature set ordered by the probability density value. Results are summarized in Table 5. 2) Choose features from the optimized distributions randomly. Ten random features are sampled and their results are summarized in Figure 5.

Figure 5. Ablation study w.r.t. supervision selection strategy. Ten supervision features are randomly selected from the optimized distributions and evaluated. Left for PointNet++ and right for DGCNN.

6. Discussion and Conclusion

In this paper, we propose to automatically search for proper intermediate supervisions for generalizable 3D part segmentation networks. Although experimental results can prove the effectiveness and versatility of AutoGPart to some extend, there are still many directions worth exploring by the community in the future: 1) Search intermediate supervisions and the backbone’s structure at the same time. Synergies between backbone architecture and intermediate supervisions may be found since different backbones may prefer different features. 2) How to add intermediate supervisions. Directly predicting a ground-truth feature may not be suitable for each feature. Moreover, synergies between supervisions features and how to supervise the network to learn such features may be discovered.
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