# Synthesizing Image with High-Quality Segmentation Mask by Prompting Large Vision Model

Tuyen Tran
Applied AI Institute, Deakin University
t.tran@deakin.edu.au

## Abstract

*This paper presents a novel pipeline to generate high-quality segmentation masks for synthetic datasets produced by a text-to-image generative model. In contrast to previous approaches that directly apply a threshold on the attention map extracted during generation process, we leverage this map to prompt a large vision model. We extract a set of candidate point prompts from the attention maps and then select a subset that maximizes diversity within the candidate set. These selected points prompt the vision model, yielding fine-grained segmentation masks. To validate our method, we trained segmentation models on synthetic datasets and evaluated them on real datasets, including PASCAL VOC and MSCOCO. Both qualitative and quantitative results demonstrate the superior quality of segmentation masks produced by our method compared to other thresholding baseline approaches.*

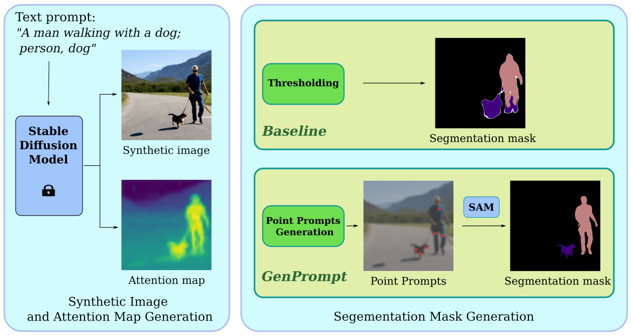


Figure 1. Prior approaches applying a threshold on the attention map yield coarse, low-quality segmentation masks. In contrast, we suggests using the attention map to generate prompts for a promptable vision model (e.g., SAM). To this end, we propose the GenPrompt algorithm, which generates points (marked in red circles) for prompting the segmentation model, resulting in high-quality masks.

## 1. Introduction

The development of generative models like Stable Diffusion (SD) has unlocked the potential of using synthetic data to train Artificial Intelligence (AI) systems, offering advantages in scalability and accessibility. While SD model can effectively produce photorealistic dataset with great diversity, it remain challenging to get high quality segmentation mask, where we need the annotation at pixel level. Simply applying a pre-trained segmentation model to synthetic images is not a valid option, because the goal is to generate a synthetic dataset across various domains, potentially beyond the seen categories of the pre-trained model[1].

One pioneering research is Diffumask [14], where they demonstrated the potential of extracting text-guided cross-attention information in SD model for localizing class-specific regions within synthetic images. To convert the resulting cross-attention maps into usable annotation masks, they employed AffinityNet [1] to estimate an adaptive threshold for each class present in the synthetic image. Another work, Dataset Diffusion [12] proposed to refine the cross-attention map by multiplying it with a power of the self-attention map. They then empirically select a fixed threshold to transform the refined attention map into a segmentation label mask. While Diffumask and Dataset Diffusion illustrate the feasibility of generating semantic masks through attention maps, producing high-quality segmentation masks remains challenging due to the difficulty in determining the optimal threshold for each specific case.

To address this challenge, we propose a different strategy of prompting a large vision model. Instead of applying a threshold to the cross-attention map, we use this map to generate point prompts for a promptable vision model. This approach, requiring only a small number of high-certainty prompt points, significantly improves segmentation performance. Additionally, the promptable model can generate segmentation masks for arbitrary image areas based on given prompts, without relying on specific categories. This fulfills

[1] Synthetic data generation also holds promise for tackling tasks with objectless regions of interest, like satellite imagery segmentation [2] or partial object segmentation [10], as explored in [12].

the task's requirements for domain-agnostic image generation. We specifically employ the Segment Anything Model (SAM) [8], known as one of the most effective promptable models for segmentation task.

The remaining challenge is to generate a suitable set of point prompts for producing high-quality segmentation masks. We explored various approaches and found that maximizing the distance between points is the most effective strategy. Figure 1 illustrates an overview of our approach. In contrast to the thresholding methods described in [12, 14], we utilize the attention map to generate point prompts for SAM. Specifically, we propose GenPrompt, an algorithm that generates point prompts with maximum diversity. The diversity score we use is the mean harmonic distance between points, which encourages the selected points to be far apart and evenly distributed over the target area. To evaluate the effectiveness of our proposed method, we train two deep learning models, DeepLabV3 [3] and Mask2Former [4] on the generated dataset to and evaluate them on the validation sets of PASCAL VOC [7] and COCO [11]. Both quantitative and qualitative results indicate the effectiveness of our approach compared to the thresholding baselines.

## 2. Methodology

### 2.1. Attention map generation

The pipeline overview is illustrated in Figure 2. Following the procedures described in [12, 14], we harness the SD model to generate images and their attention maps (probability maps) from textual input. First, text encoder in SD encodes the text prompt to embedding $e \in \mathbb{R}^{\ell \times d_e}$, where $\ell$ represents the text length and and $d_e$ denotes its dimension. We use the same text prompt $\tilde{S} = [S; C]$ as in [12], where $S$ is an image caption and $C = [\mathtt{c}_1; \mathtt{c}_2; ...; \mathtt{c}_M]$ represents $M$ class objects in an image. For example, the prompt in Figure 2 is: *"A man walking with a dog; person, dog"*. The embedding $e$ guides the denoising process over $T$ step of the SD. During these steps, the SD transform the initial latent state $z_T = \mathcal{N}(0,1)$ into the final latent state $z_0$ residing in $\mathbb{R}^{H \times W \times d}$, where $H$, $W$ and $d$ represent size of $z_0$. In each step $t$, the transformation of $z_t$ to $z_{t-1}$ occurs across $L$ layers of self- and cross-attention within the UNet framework. For each layer $\ell$ and time step $t$, we extract the self-attention map:

$$A_S^{\ell,t} = \text{Softmax}\left(\frac{Q_z K_z^\top}{\sqrt{d_\ell}}\right) \in [0,1]^{HW \times HW}, \quad (1)$$

where $Q_z$, $K_z$ are query, key of $z_t$ obtained from linear transformation, and $d_\ell$ is the feature length at layer $\ell$. Intuitively, the extracted self-attention maps illustrate the pairwise correlations among each positions within the latent variable $z_t$. Similarly, the cross-attention maps represent how each specific location in the image space correlates with each word token of the text embedding. Because we focus on the relationship between each image region and its class label, rather than the entire sentence, we use the text prompt containing only the class label names $C$. Note that this prompt is solely used for the extraction of cross-attention map, with the original text prompt $\tilde{S}$ for image generation remaining unaltered. For example, the text used to extract the cross attention map in Figure 2 is: *["person", "dog"]*. The resulting cross-attention map at time step $t$ of layer $\ell$ and is expressed as:

$$A_C^{\ell,t} = \text{Softmax}\left(\frac{Q_z K_e^\top}{\sqrt{d_l}}\right) \in [0,1]^{HW \times M}. \quad (2)$$

The aggregated self-attention and cross-attention maps are derived by averaging all maps over layers and timesteps:

$$A_S = \frac{1}{L \cdot T} \sum_{(\ell=1,t=1)}^{(L,T)} A_S^{\ell,t}, \; A_C = \frac{1}{L \cdot T} \sum_{(\ell=1,t=1)}^{(L,T)} A_C^{\ell,t}. \quad (3)$$

Finally, we follow [12] to obtain the probability map $P$ by exponentiating the attention map $A_S$ to the power of $r$ before multiplying it by with $A_C$ :

$$P = (A_S)^r \cdot A_C \in [0,1]^{HW \times M}. \quad (4)$$

The probability map $P$ can be equivalently presented as set $\{p_{ij}^m\}$, where $i$ from 1 to $W$, $j$ from 1 to $H$ and $m$ from 1 to $M$. Each element $p_{ij}^m$ represents *the confidence score that the pixel at position $(i,j)$ in the generated image belongs to the class $m$*. However, the probability map $P$ is still coarse-grained, so we propose to use it only for generating point prompts in the next step.

### 2.2. GenPrompt: Generating Point Prompts with Maximum Diversity

#### Objective of the GenPrompt Algorithm

Prompt selection strategy greatly effects on the segmentation quality, which is illustrated in Figure 3. Using a single point with the highest certainty can lead to ambiguities for the SAM model. Selecting multiple points with the highest certainty does not improve much, as these points are likely close to each other, making it difficult for SAM to segment the entire object. Randomly selecting a set of points can result in selecting points that are too close together or have low certainty, which can damage the segmentation quality. Based on these observations, we suggest two criteria for a good set of point prompts. First, all points in the set should have high certainty to ensure they belong precisely to the target object. Second, these points should be sufficiently far apart to evenly distribute across the entire object. Our findings align with [6], who concluded that prompt points

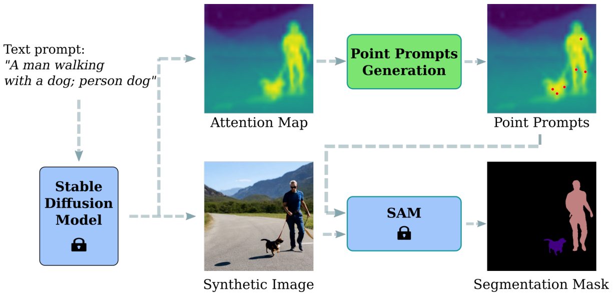
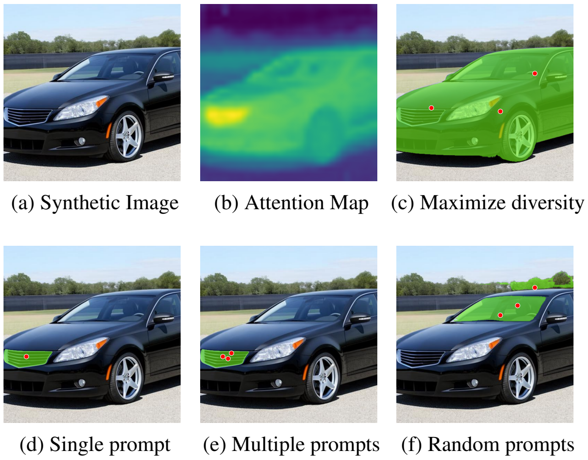


Figure 2. **Pipeline for the Synthetic Image and Segmentation Mask Generation:** In the first stage, we use the SD model to generate a synthetic image and attention map based on a given text prompt (Section 2.1). The attention map is then used in the second stage for prompt generation. Here, we introduce an algorithm to generate point prompts (marked in red circles) that maximize diversity within the candidate set (Section 2.2). These points are used to prompt the SAM model, producing the final segmentation mask.



(a) Synthetic Image (b) Attention Map (c) Maximize diversity

(d) Single prompt (e) Multiple prompts (f) Random prompts

Figure 3. Comparing segmentation results of different strategies to generate point prompts from an input attention map.

with maximum distance yield the best segmentation quality. With this intuition, we formulate the point prompts generation problem as the Maximum Diversity Problem (MDP)[9], aiming to select a subset of elements from a larger set to maximize the diversity score among them. We define the diversity score as the harmonic mean of the distances between points, encouraging even distribution over the object and preventing points from being too close together. Formally, let $M$ represent the number of objects in the image, and $P$ be the certainty map derived from Equation 4. Since a pixel location is exclusive to a single object, we obtain initial coarse probability map for class $m$ by executing argmax operation along the class dimension of $P$:

$$\hat{p}^m_{ij} = \begin{cases} p^m_{ij} & \text{if } m = \arg\max_\eta (p^\eta_{ij}) \\ 0 & \text{otherwise} \end{cases}. \tag{5}$$

We define $\mathcal{C}^m$ as a set of candidate point $(i,j)$ taken from $P$ such as for each point $(i,j) \in \mathcal{C}^m$, the associated element $\hat{p}^m_{ij} > 0$:

$$\mathcal{C}^m = \{(i,j) \mid \hat{p}^m_{ij} > 0 \text{ , and } 1 \le i \le W, 1 \le j \le H\}. \tag{6}$$

For each category $m$, our objective is to find a subset $\mathcal{S}^m = \{(i_1,j_1),(i_2,j_2),\ldots,(i_K,j_K)\}$ containing $K$ points selected from $\mathcal{C}^m$ to maximize $H(\mathcal{S}^m)$ as the harmonic mean of distance among the points in $S^m$. The optimization problem could be defined as:

$$\max_{\mathcal{S}^m} H(\mathcal{S}^m) = \left( \frac{1}{\Omega} \sum_{a=1}^{K-1} \sum_{b=a+1}^{K} \frac{1}{d\left((i_a,j_a),(i_b,j_b)\right)} \right)^{-1}, \tag{7}$$

subject to:

$$\mid \mathcal{S}^m \mid = K \text{ and } \mathcal{S}^m \subseteq \mathcal{C}^m.$$

In Equation 7, $d\left((i_a,j_a),(i_b,j_b)\right)$ is the Euclidean distance between points $(i_a,j_a)$ and $(i_b,j_b)$, and is given by:

$$d\left((i_a,j_a),(i_b,j_b)\right) = \sqrt{(i_a - i_b)^2 + (j_a - j_b)^2}, \tag{8}$$

and $\Omega$ is defined as the total number of unique pairs in $\mathcal{S}^m$, which is equal to $\frac{K(K-1)}{2}$.

### Procedure of the GenPrompt Algorithm

The MDP is NP-hard, implying that there is no known polynomial-time algorithm for its efficient solution [9]. However, an optimal solution is not necessary because a set of high-certainty points reasonably far apart can already yield high-quality segmentation results with the SAM model. Therefore, we use a Random Sampling approach with uncertainty awareness to find a satisfactory solution. Formally, we firstly initialize the max diversity score $D_{\text{max}} = 0$ and the selected subset $\mathcal{S}_{\text{sel}} = \emptyset$ then repeat the iteration $N$ time. For each iteration $n$, where $n = 1, 2, ..N$, we sample $K$ high-certainty elements to form the subset $\mathcal{S}_{\text{tmp}}$ from the candidate prompt points $\mathcal{C}^m$:

$$\mathcal{S}_{\text{tmp}} = \{(i_k,j_k)\}_{k=1}^{K} \subseteq \{(i_e,j_e) \in \mathcal{C}^m \mid \hat{p}_{i_e j_e} > \alpha\}, \tag{9}$$

where $\alpha$ is a threshold certainty to guarantee the selected point belong to specific target object. Then, the diversity score is calculate using function $H(.)$ defined in Equation 7:

$$D_{\text{tmp}} = H(\mathcal{S}_{\text{tmp}}). \tag{10}$$

If $D_{\text{tmp}}$ exceeds the previous iteration's $D_{\text{max}}$ , we update $D_{\text{max}} = D_{\text{tmp}}$ and $\mathcal{S}_{\text{sel}} = \mathcal{S}_{\text{tmp}}$, accordingly. This iterative process continues until reaching the maximum iteration $N$. Once the $S_{\text{sel}}$ with the highest diversity score is obtained, it is assigned to $\mathcal{S}^m$ as the set of augmented point prompts for object $m$. This procedure is repeated for all $M$ objects in the

| Training set | Model | VOC<br>*(mIOU)* | COCO<br>*(mIOU)* |
|---|---|---|---|
| Real Data | DeepLabV3, R50 | 77.4 | 48.9 |
|  | DeepLabV3, R101 | 79.9 | 54.9 |
|  | Mask2Former, R50 | 77.3 | 57.8 |
| DiffuMask [14] | Mask2Former, R50 | 57.4 | - |
| Dataset Diffusion [12] | DeepLabV3, R50 | 61.6 | 32.4 |
|  | DeepLabV3, R101 | 64.8 | 34.2 |
|  | Mask2Former, R50 | 60.2 | 31.0 |
| GenPrompt | DeepLabV3, R50 | 65.1 | 35.2 |
|  | DeepLabV3, R101 | 68.3 | 36.1 |
|  | Mask2Former, R50 | 64.0 | 33.8 |

Table 1. Semantic segmentation performance of DeepLabV3 and Mask2Former models trained on different dataset.

image to derive the final set of point prompts $\mathcal{S}$ (please refer to the pseudocode 1 in the Supplementary Material). Finally, the set of point prompts $\mathcal{S}$, along with the originally generated image $I$, are used as inputs to generate the segmentation mask $I_{\text{mask}}$ using the SAM.

# 3. Experiments

## 3.1. Experimental setup

**Baselines:** We compare against two recent works: Dataset Diffusion [12] and DiffuMask [14].

**Model and dataset:** Following [12, 14], we evaluate the generated dataset's quality by training standard segmentation models, DeepLabv3 and Mask2Former on $40k$ images for VOC dataset [7] and $80k$ images for COCO dataset [11].

## 3.2. Quantitative results

Table 1 compares the semantic segmentation performance of the DeepLabV3 and Mask2Former models when trained on real datasets and synthetic datasets generated through various methods. The GenPrompt approach, which leverages prompting techniques, clearly outperform thresholding approaches, with gains of 6.6 mIOU over DiffuMask and 3.8 mIOU over Dataset Diffusion on the VOC dataset. Although GenPrompt demonstrates encouraging capabilities, a substantial performance gap of over 10 mIOU remains between our synthetic datasets and real datasets. This gap is partly attributed to the limitations of the SD model for generating complex scenes from text prompts, as discussed in [12]. Additionally, the efficacy of our approach relies on the precision of initial attention maps to enable effective prompt selection. Without sufficiently precise attention maps, our approach may struggle to achieve high-quality annotations.

## 3.3. Qualitative results

Figure 4 displays qualitative results, comparing our method to the baseline Dataset Diffusion [12]. Object masks are color-coded to match the object names in the caption.

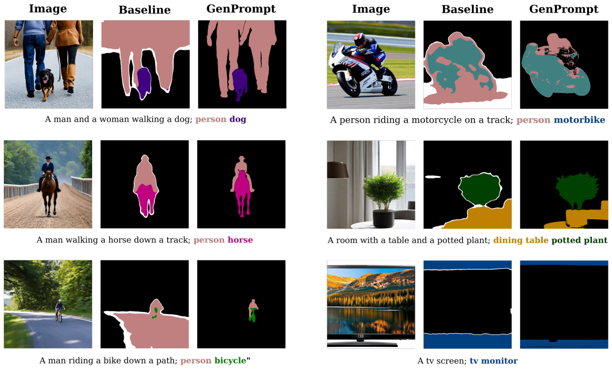


Image
Baseline
GenPrompt
A man and a woman walking a dog; person dog
A man walking a horse down a track; person horse
A man riding a bike down a path; person bicycle"
Image
Baseline
GenPrompt
A person riding a motorcycle on a track; person motorbike
A room with a table and a potted plant; dining table potted plant
A tv screen; tv monitor

(a) Successful Cases.

(b) Failure Cases.

Figure 4. **Qualitative analysis of GenPrompt algorithm:** Figure (a) shows successful cases. With sufficiently accurate attention maps, our method could produce fine-grained segmentation annotation (Row 1). Our approach also effectively handles challenging scenarios from the baseline method [12], such as closely intertwined objects (Row 2) or small objects (Row 3). Figure (b) analyzes failure cases, where poor-quality attention maps can result in selecting incorrect prompt points, decreasing segmentation mask quality (Row 1, 2). A notable error occurs in Row 3, where the TV and background are misclassified, leading to an erroneous segmentation mask despite the potential for fine-grained segmentation.

Figure 4a presents some successful cases. As shown, our method yields segmentation masks with significantly higher precision compared to baseline outputs. GenPrompt reaches optimal capability in cases where the initial probability maps can reasonably approximate visual characteristics of the intended objects.

We also demonstrate limitations of our method in Figure 4b. When the attention map fails to provide an accurate candidate set, our method may not perform optimally, leading to incorrect data annotations. This impacts the training of the segmentation model, explaining why although our method can produce more precise segmentation masks in many cases, the gain in quantitative results is reasonable and still exits a notable gap compared to training on real data.

# 4. Conclusion

In this work, we introduce GenPrompt, an algorithm that utilizes the extracted attention map to generate prompts for synthetic dataset generation in segmentation tasks. By using prompting technique, our work can yields substantially more accurate mask annotations compared to the thresholding baselines. This enhanced performance is accomplished without compromising the critical requirement of generating images in diverse domains. We hope our proposed framework, supported by detailed analysis, will facilitate further exploration in this promising research direction.

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