Multiple Heads are Better than One:
Few-shot Font Generation with Multiple Localized Experts

Song Park[1]   Sanghyuk Chun[2, 3]   Junbum Cha[3]   Bado Lee[3]   Hyunjung Shim[1*]

[1] School of Integrated Technology, Yonsei University   [2] NAVER AI Lab   [3] NAVER CLOVA

Abstract

A few-shot font generation (FFG) method has to satisfy two objectives: the generated images should preserve the underlying global structure of the target character and present the diverse local reference style. Existing FFG methods aim to disentangle content and style either by extracting a universal representation style or extracting multiple component-wise style representations. However, previous methods either fail to capture diverse local styles or cannot be generalized to a character with unseen components, e.g., unseen language systems. To mitigate the issues, we propose a novel FFG method, named Multiple Localized Experts Few-shot Font Generation Network (MX-Font). MX-Font extracts multiple style features not explicitly conditioned on component labels, but automatically by multiple experts to represent different local concepts, e.g., left-side sub-glyph. Owing to the multiple experts, MX-Font can capture diverse local concepts and show the generalizability to unseen languages. During training, we utilize component labels as weak supervision to guide each expert to be specialized for different local concepts. We formulate the component assign problem to each expert as the graph matching problem, and solve it by the Hungarian algorithm. We also employ the independence loss and the content-style adversarial loss to impose the content-style disentanglement. In our experiments, MX-Font outperforms previous state-of-the-art FFG methods in the Chinese generation and cross-lingual, e.g., Chinese to Korean, generation. Source code is available at https://github.com/clovaai/mxfont.

1. Introduction

A few-shot font generation task (FFG) [35, 45, 9, 34, 4, 5, 31] aims to generate a new font library using only a few reference glyphs, *e.g.*, less than 10 glyph images, without additional model fine-tuning at the test time. FFG is espe-
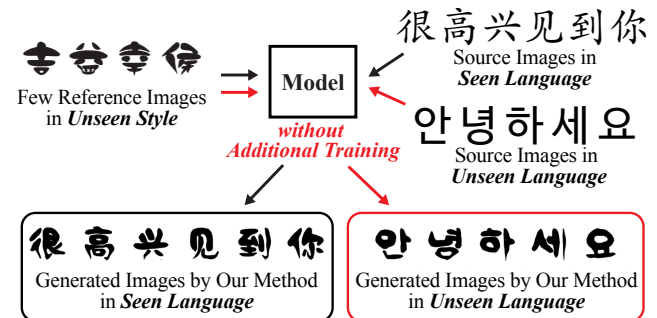
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*Hyunjung Shim is a corresponding author.

Figure 1. **Cross-lingual few-shot font generation results by MX-Font.** With only four references, the proposed method, MX-Font, can generate a high quality font library. Furthermore, we first show the effectiveness of the proposed method on the *zero-shot cross-lingual* few-shot generation task, *i.e.*, generating unseen Korean glyphs using the Chinese font generation model.

cially a desirable task when designing a new font library for glyph-rich scripts, *e.g.*, Chinese ($>$ 50K glyphs), Korean ($\approx$ 11K glyphs), or Thai ($\approx$ 11K glyphs). It is because the traditional font design process is very labor-intensive due to the complex characteristics of the font domain. Another real-world scenario of FFG is to extend an existing font design to different language systems. For example, an international multi-media content, such as a video game or movie designed with a creative font, is required to re-design coherent style fonts for different languages.

A high-quality font design is obliged to satisfy two objectives. First, the generated glyph should maintain all the detailed structure of the target character, particularly important for glyph-rich scripts with highly complex structure. For example, even very small damages on a local component of a Chinese glyph can hurt the meaning of the target character. As another objective, a generated glyph should have a diverse local style of the reference glyphs, *e.g.*, serifness, strokes, thickness, or size. To achieve both objectives, existing methods formulate FFG by disentangling the content information and the style information from the given glyphs [35, 45, 9, 4, 31]. They combine the content features from the source glyph and the style features from the refer-
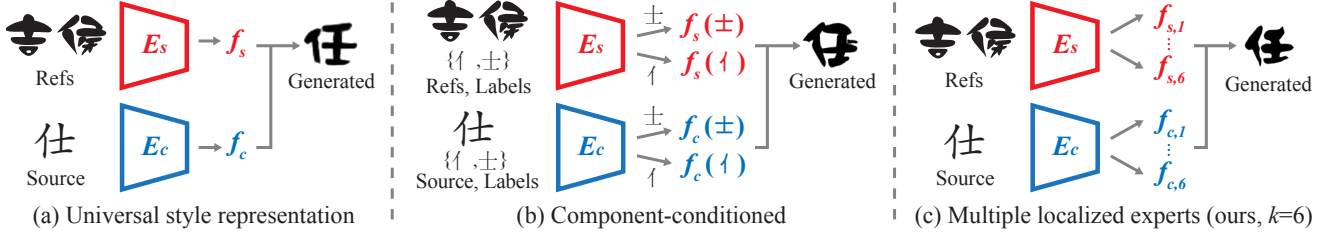
Figure 2. **Comparison of FFG methods.** Three different groups of FFG are shown. All methods combine style representation f_s from a few reference glyphs (Refs) by a style encoder (E_s) and content representation f_c from a source glyph (Source) by a content encoder (E_c). (a) Universal style representation methods extract only a single style feature for each font. (b) Component-conditioned methods extract component conditioned style features to capture diverse local styles (c) Multiple localized experts method (ours) generates multiple local features without an explicit condition, but attends different local information of the complex input glyph. The generated images in (a), (b) and (c) are synthesized by AGIS-Net [9], LF-Font [31] and MX-Font, respectively.

ence glyphs to generate a glyph with the reference style. Due to the complex nature of the font domain, the major challenge of FFG is to correctly disentangle the global content structure and the diverse local styles. However, as shown in our experiments, we observe that existing methods are insufficient to capture diverse local styles or to preserve the global structures of unseen language systems.

We categorize existing FFG methods into *universal style representation methods* (USR) [35, 45, 28, 9] and *component-conditioned methods* (CC) [4, 31]. USR methods extract only a single style representation for each style – see Figure 2 (a). As glyph images are highly complex, these methods often fail to capture diverse local styles. To address the issue, CC methods utilize *compositionality*; a character can be decomposed into a number of sub-characters, or *components* – see Figure 2 (b). They explicitly extract component-conditioned features, beneficial to preserve the local component information. Despite their promising performances, their encoder is tightly coupled with specific component labels of the target language domain, which hinders processing the glyphs with unseen components or conducting a cross-lingual font generation.

In this paper, we propose a novel few-shot font generation method, named **M**ultiple Localized e**X**perts Few-shot **Font** Generation Network (MX-Font), capturing multiple local styles, but not limited to a specific language system. MX-Font has a multi-headed encoder, named *multiple localized experts*. Each localized expert is specialized for different local sub-concepts from the given complex glyph image. Unlike component-conditioned methods, our experts are not explicitly mapped to a specific component, but each expert implicitly learns different local concepts by weak supervision *i.e.* component and style classifiers. To prevent that different experts learn the same local component, we formulate the component label allocation problem as a matching problem, optimally solved by the Hungarian algorithm [23] (Figure 4). We also employ the *independence loss* and the *content-style adversarial loss* to enforce the content-style disentanglement by each localized expert. Interestingly, with only weak component-wise supervision (*i.e.* image-level not pixel-level labels), we observe that each localized expert is specialized for different local areas, *e.g.*, attending the left-side of the image (Figure 7). While we inherit the advantage of component-conditioned methods [4, 31] by introducing the multiple local features, our method is not limited to a specific language by removing the explicit component dependency in extracting features. Consequently, MX-Font outperforms the state-of-the-art FFG in two scenarios: *in-domain transfer scenario*, training and tested on the same language, and *zero-shot cross-lingual transfer scenario*, training and tested on different languages. Our ablation and model analysis support that the proposed modules and optimization objectives are important to capture multiple diverse local concepts.

2. Related Works

Style transfer and image-to-image translation. FFG can be viewed as a task that transfers reference font style to target glyph. However, style transfer methods [11, 16, 25, 29, 26, 39] regard the texture as a style while in FFG, a style is often defined by a local shape, *e.g.*, stroke, size, or serif-ness. On the other hand, image-to-image translation (I2I) methods [18, 48, 6, 27, 40, 7] learn the mapping between domains from the data instead of defining the style. For example, FUNIT [28] aims to translate an image to the given reference style while preserving the content. Many FFG methods, thus, are based on I2I framework.

Many-shot font generation methods. Early font generation methods, such as zi2zi [36], aim to train the mapping between different font styles. A number of font generation methods [19, 10, 17, 37] first learn the mapping function, and fine-tune the mapping function for many reference glyphs, *e.g.* 775 [19]. Despite their remarkable performances, their scenario is not practical because collecting hundreds of glyphs with a coherent style is too expensive. In this paper, we aim to generate an unseen font library without any expensive fine-tuning and collecting a large number of reference glyphs for a new style.
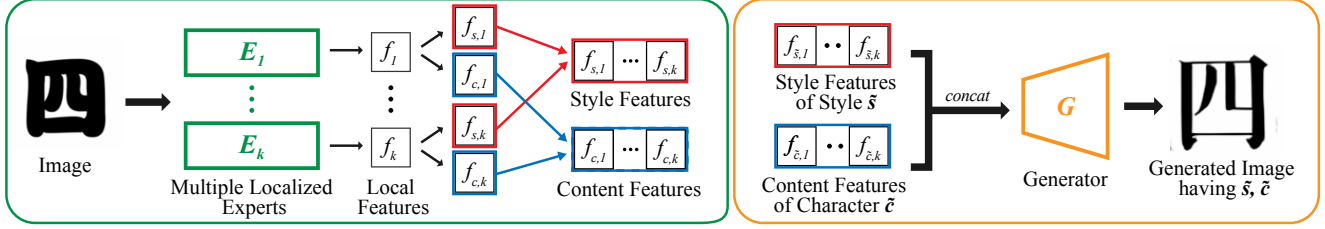
Figure 3. **Overview of MX-Font.** The *multiple localized experts* (green box) consist of k experts. E_i (i-th expert) encodes the input image to the local feature f_i. The style and content features $f_{s,i}$, $f_{c,i}$ are computed from f_i. The yellow box shows how the generator G generates the target image. When k style features representing the target style $\widetilde{s}$ and k content features representing the target style $\widetilde{c}$ are given, the target glyph having style $\widetilde{s}$ and character $\widetilde{c}$ is generated by passing the element-wisely concatenated style and content features to the G.

Few-shot font generation methods. Existing FFG methods aims to disentangle font-specific style and content information from the given glyphs [45, 34, 1, 9, 35, 24]. We categorize existing FFG methods into two different groups. The universal style representation (USR) methods, such as EMD [45], AGIS-Net [9], synthesize a glyph by combining the style vector extracted from the reference set, and the content vector extracted from the source glyph. MX-Font employs multiple styles, not relying on the font specific loss design, *e.g.*, the local texture refinement loss by AGIS-Net. USR methods show limited performances in capturing localized styles and content structures. To address the issue, *component-conditioned methods* such as DM-Font [4], LF-Font [31], remarkably improve the stylization performance by employing localized style representation, where the font style is described multiple localized styles instead of a single universal style. However, these methods require explicit component labels for the target character even at the test time. This property limits practical usages such as cross-lingual font generation. Our method inherits the advantages from component-guided multiple style representations, but does not require the explicit labels at the test time.

3. Method

We introduce a novel few-shot font generation method, named Multiple Localized Experts Few-shot Font Generation Network (MX-Font). MX-Font has a multi-headed encoder (*multiple localized experts*), where i-th head (or expert E_i) encodes a glyph image x into a local feature $f_i = E_i(x)$ (§3.1). We induce each expert E_i to attend different local concepts, guided by a set of component labels U_c for the given character c (§3.2). From f_i, we compute local content and style features $f_{c,i}$, $f_{s,i}$ (§3.3). We generate a glyph $\widetilde{x}$ with a character label $\widetilde{c}$ and a style label $\widetilde{s}$ by combining expert-wise features $f_{\widetilde{c},i}$ and $f_{\widetilde{s},i}$, from the source glyph and the reference glyph, respectively. (§3.5).

3.1. Model architecture

Our method consists of three modules; 1) k-headed encoder, or localized experts E_i, 2) a generator G, and 3) style

and component feature classifiers Cls_s and Cls_u. We illustrate the overview of our method in Figure 3 and Figure 5. We provide the details of the building blocks in Appendix.

The green box in Figure 3 shows how the *multiple localized experts* works. The **localized expert** E_i encodes a glyph image x into a local feature $f_i = E_i(x) \in \mathbb{R}^{d \times w \times h}$, where d is a feature dimension, and $\{w, h\}$ are spatial dimensions. By multiplying two linear weights $W_{i,c}, W_{i,s} \in \mathbb{R}^{d \times d}$ to f_i, a local content feature $f_{c,i} = W_{i,c}^\top f_i$ and a local style feature $f_{s,i} = W_{i,s}^\top f_i$ are computed. Here, our localized experts are not supervised by component labels to obtain k local features $f_1, \ldots, f_k$; our local features are not component-specific features. We set the number of the localized experts, k, to 6 in our experiments if not specified.

We employ two **feature classifiers**, Cls_s and Cls_u to supervise $f_{s,i}$ and $f_{c,i}$, which serve as weak supervision for f_i. The classifiers are trained to predict the style (or component) labels, thereby E_i receives the feedback from the Cls_s and Cls_u that $f_{s,i}$ and $f_{c,i}$ should preserve label information. These classifiers are only used during training but independent to the model inference itself. Following the previous methods [4, 31], we use font library labels for style labels y_s, and the component labels U_c for content labels y_c. The example of component labels is illustrated in Figure 4. The same decomposition rule used by LF-Font [31] is adopted. While previous methods only use the style (or content) classifier to train style (or content), we additionally utilize them for the content and style disentanglement by introducing the content-style adversarial loss.

The **generator** G synthesizes a glyph image $\widetilde{x}$ by combining content and style features: $\widetilde{x} = G((f_{s,1} \circ f_{c,1}), \ldots, (f_{s,k} \circ f_{c,k}))$, where $\circ$ denotes a concatenation.

3.2. Learning multiple localized experts with weak local component supervision

Our intuition is that extracting different localized features can help each local feature to represent the detailed local structure and fine-grained local style in a complex glyph image. We utilize the compositionality of the font domain to inherit the advantages of component-conditioned
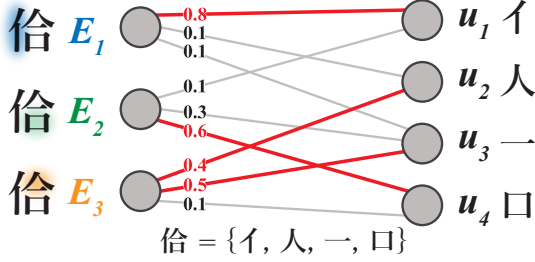
Figure 4. **An example of localized experts.** The number of experts k is three (E_1, E_2, E_3), and the number of target component labels m is four ($u_1, \ldots, u_4$). An edge between an expert E_i and a component u_j means the prediction probability of u_j by E_i using the component classifier Cls_u. Our goal is to find a set of edges that maximizes the sum of predictions, where the number of the selected edges are upper bounded by $\max(k, m) = 4$ in this example. The red edges illustrate the optimal solution.

methods [4, 31]. Meanwhile, we intentionally remove the explicit component dependency of the feature extractor for achieving generalizability, which is the weakness of previous methods. Here, we employ a multi-headed feature extractor, named *multiple localized experts*, where each expert can be specialized for different local concepts. A naïve solution is to utilize explicit local supervision, *i.e.*, the pixel-level annotation for each sub-glyph, unable to obtain due to expensive annotation cost. As an alternative, a strong machine annotator can be utilized to obtain local supervision [41], but training a strong model, such as the self-trained EfficientNet L2 with 300M images [38], for the font domain is another challenge that is out of our scope.

Utilizing the compositionality, we have the weak component-level labels for the given glyph image, *i.e.*, what components the image has but without the knowledge where they are, similar to the multiple instance learning scenario [30, 47]. Then, we let each expert attend on different local concepts by guiding each expert with the component and style classifiers. Ideally, when the number of components m is same as the number of experts, k, we expect the k predictions by experts are same as the component labels, and the summation of their prediction confidences is maximized. When $k < m$, we expect the predictions by each expert are "plausible" by considering top-k predictions.

To visualize the role of each expert, we illustrate an example in Figure 4. Presuming three multiple experts, they can learn different local concepts such as the left-side (blue), the right-bottom-side (green), and the right-upper-side (yellow), respectively. Given a glyph composed of four components, the feature from each expert can predict one (E_1, E_2) or two (E_3) labels as shown in the figure. Because we do not want that an expert is explicitly assigned to a component label, *e.g.*, strictly mapping "人" component to E_1, we solve an automatic allocation algorithm, finding the optimal expert-component matching as shown in Figure 4.

Specifically, we formulate the component allocation problem as the Weighted Bipartite B-Matching problem, which can be optimally solved by the Hungarian algorithm [23].

From a given glyph image x, each expert E_i extracts the content feature $f_{c,i}$. Then, the component feature classifier Cls_u takes $f_{c,i}$ as input and produces the prediction probability $p_i = Cls_u(f_{c,i})$, where $p_i = [p_{i0}, \ldots, p_{im}]$ and p_{ij} is the confidence scalar value of the component j. Let $U_c = \{u_1^c, \ldots, u_m^c\}$ be a set of component labels of the given character c, and m be the number of the components. We introduce an allocation variable w_{ij}, where $w_{ij} = 1$ if the component j is assigned to E_i, and $w_{ij} = 0$ otherwise. We optimize the binary variables w_{ij} to maximize the summation over the selected prediction probability such that the number of total allocations is $\max(k, m)$. Now, we formulate the component allocation problem as:

$$\max_{w_{ij} \in \{0,1\} | i=1\ldots k, j \in U_c} \sum_{i=1}^{k} \sum_{j \in U_c} w_{ij} p_{ij},$$

$$\text{s.t.} \quad \sum_{i=1}^{k} w_{ij} \geq 1 \text{ for } \forall j, \quad \sum_{j \in U_c} w_{ij} \geq 1 \text{ for } \forall i, \quad (1)$$

$$\sum_{i=1}^{k} \sum_{j \in U_c} w_{ij} = \max(k, m),$$

where (1) can be reformulated to the Weighted Bipartite B-Matching (WBM) problem, and can be solved by the Hungarian algorithm in a polynomial time $O((m + k)^3)$. We describe the connection between (1) and WBM in the Appendix. Now, using the estimated variables w_{ij} in (1), we optimize auxiliary component classification loss $\mathcal{L}_{cls,c}$ with the cross entropy loss (CE) as follows:

$$\mathcal{L}_{cls,c,i}(f_{c,i}, U_c) = \sum_{j \in U_c} w_{ij} \text{CE}(Cls_u(f_{c,i}), j). \quad (2)$$

Here, we expect that each localized expert is specialized for a specific local concept so that it facilitates the content-style disentanglement. Because the feedback from (2) encourages the local features to be better separated into the style and content features, we expect that each expert automatically attends local concepts. We empirically observe that each expert is involved to different local areas without explicit pixel-level supervision (Figure 7).

We additionally formulate the independence between each expert by the Hilbert-Schmidt Independence Criterion [13] which has been used in practice for statistical testing [13, 14], feature similarity measurement [22], and model regularization [32, 42, 2]. HSIC is zero if and only if two inputs are independent of each other. Since HSIC is non-negative, the independence criterion can be achieved by minimizing HSIC. Under this regime, we use HSIC and
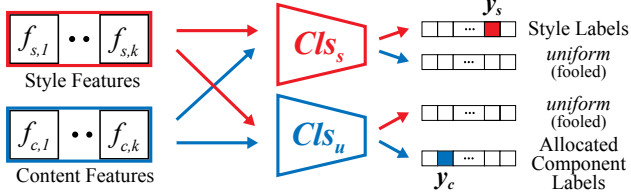
Figure 5. **Feature classifiers.** Two feature classifiers, Cls_s and Cls_u are used during the training. Cls_s classifies the style features to their style label y_s while Cls_u predicts the *uniform* probability from them. Similarly, Cls_u classifies the content features to their allocated component labels y_u while Cls_s is fooled by them. The details are described in § 3.2 and § 3.3.

lead the local feature f_i extracted by E_i independent to the other local features $f_{i'}$ as follows:

$$\mathcal{L}_{\text{indp exp},i} = \sum_{i'=1, i' \neq i}^{k} \text{HSIC}(f_i, f_{i'}). \quad (3)$$

We leave the detailed HSIC formulation is in Appendix.

3.3. Content and style disentanglement

To achieve perfect content and style disentanglement, the style (or content) features should include the style (or content) domain information but exclude the content (or style) domain information. We employ two objective functions for this: *content-style adversarial loss* and *independent loss*.

The **content-style adversarial loss**, motivated by the domain adversarial network [8], enforces the extracted features for style (or content) to be useless to classify content (or style). Thus, a style feature $f_{s,i}$ is trained to satisfy (1) correctly classify a style label y_s by the style classifier Cls_s with the cross entropy loss (CE) and (2) fooling the content labels predicted by the component classifier Cls_u. Specifically, we maximize the entropy (H) of the predicted probability to enforce the uniform prediction. Formally, we define our objective function for a style feature $f_{s,i}$ as follows:

$$\mathcal{L}_{s,i}(f_{s,i}, y_s) = \text{CE}(Cls_s(f_{s,i}), y_s) - H(Cls_u(f_{s,i})). \quad (4)$$

We define the loss for a content feature $f_{c,i}$ ($\mathcal{L}_{c,i}$) by $\mathcal{L}_{cls,c,i}$ (2) instead of CE of y_c as follows:

$$\mathcal{L}_{c,i}(f_{c,i}, U_c) = \mathcal{L}_{cls,c,i}(f_{c,i}, U_c) - H(Cls_s(f_{c,i})). \quad (5)$$

We also employ HSIC between content and style local features, $f_{c,i}$ and $f_{s,i}$ for disentangling content and style:

$$\mathcal{L}_{\text{indp},i} = \text{HSIC}(f_{s,i}, f_{c,i}). \quad (6)$$

3.4. Training

We train our model to synthesize a glyph image from the given content and style labels using the Chinese font dataset (details in §4.2). More specifically, we construct a

mini-batch, where n glyphs share the same content label y_c (from random styles), and n glyphs share the same style label y_s (from random contents). Then, we let the model generate a glyph with the content label y_c and the style label y_s. In our experiments, we set $n = 3$ and synthesize 8 different glyphs in parallel, *i.e.*, the mini-batch size is 24.

We employ a discriminator module D and the generative adversarial loss [12] to achieve high-quality visual samples. In particular, we use the hinge generative adversarial loss $\mathcal{L}_{adv}$ [43], feature matching loss $\mathcal{L}_{fm}$, and pixel-level reconstruction loss $\mathcal{L}_{recon}$ by following the previous high fidelity GANs, *e.g.*, BigGAN [3], and state-of-the-art font generation methods, *e.g.*, DM-Font [4] or LF-Font [31]. The details of each objective function are in Appendix.

Now we describe our full objective function. The entire model is trained in an end-to-end manner with the weighted sum of all losses, including (3), (4), (5), and (6).

$$\mathcal{L}_D = \mathcal{L}_{adv}^D, \quad \mathcal{L}_G = \mathcal{L}_{adv}^G + \lambda_{recon}\mathcal{L}_{recon} + \mathcal{L}_{fm}$$
$$\mathcal{L}_{exp} = \sum_{i=1}^{k} [\mathcal{L}_{s,i} + \mathcal{L}_{c,i} + \mathcal{L}_{\text{indp},i} + \mathcal{L}_{\text{indp exp},i}] \quad (7)$$

As conventional GAN training, we alternatively update $\mathcal{L}_D$, $\mathcal{L}_G$, and $\mathcal{L}_{exp}$. The control parameter λ_{recon} is set to 0.1 in our experiments. We use Adam optimizer [21], and run the optimizer for 650k iterations. We additionally provide the detailed training settings in the Appendix.

3.5. Few-shot generation

When the source and a few reference glyphs are given, MX-Font extract the content features from the source glyphs and the style features from the reference glyphs. Assume we have n_r number of reference glyphs $x_1^r, \ldots, x_{n_r}^r$ with a coherent style y_{s^r}. First, our multiple experts $\{E_1, \ldots, E_k\}$ extract localized style feature $[f_{s^r,i}^1, \ldots, f_{s^r,i}^{n^r}]$ for $i = 1 \ldots k$ from the reference glyphs. Then, we take an average over the localized features to represent a style representation, *i.e.*, $f_{s^r,i} = \frac{1}{n^r} \sum_{j=1}^{n^r} f_{s^r,i}^j$ for $i = 1 \ldots k$. Finally, the style representation is combined with the content representation extracted from the known source glyph to generate unseen style glyph.

4. Experiments

In this section, we describe the evaluation protocols, and experimental settings. We extend previous FFG benchmarks to unseen language domain to measure the generalizability of a model. MX-Font is compared with four FFG methods on the proposed extended FFG benchmark via both the qualitative and quantitative evaluations. Experimental results demonstrate that MX-Font outperforms existing methods in the most of evaluation metrics. The ablation and analysis study helps understand the role and effects of our multiple experts and objective functions.

4.1. Comparison methods

Universial style representation methods. EMD [45] adopts content and style encoders that extract universal content and style features from a few reference glyphs. **AGIS-Net** [9] proposes the local texture refinement loss to handle unbalance between the number of positive and negative samples. **FUNIT** [28] is not directly proposed for FFG task, but we employ the modified version of FUNIT as our comparison method following previous works [4, 31].

Component-conditioned methods. DM-Font [4] learns two embedding codebooks (or the dual-memory) conditioned by explicit component labels. When the target character contains a component either unseen during training or not in the reference set, DM-Font is unable to generate a glyph. As these drawbacks are impossible to be fixed with only minor modifications, we do not compare DM-Font to MX-Font. **LF-Font** [31] relaxes the restriction of DM-Font by estimating missing component features via factorization module. Although LF-Font is still not applicable to generate a character with unseen components, we slightly modify LF-Font (as described in the Appendix) and compare the modified version with other methods.

4.2. Evaluation protocols

To show the generalizability to the unseen language systems, we propose an extended FFG scenario; training a FFG model on a language system and evaluating the model on the other language system. In this paper, we first train FFG models on the Chinese font dataset, and evaluate them on both Chinese generation (*in-domain transfer scenario*) and Korean generation (*zero-shot cross-lingual scenario*).

Dataset. We use the same Chinese font dataset collected by Park *et al.* [31] for training. The dataset contains 3.1M Chinese glyph images with 467 different styles, and 19,514 characters are covered. We also use the same decomposition rule as Park *et al.* [31] to extract component labels. We exclude 28 fonts, and 214 Chinese characters from the training set, and use them to evaluation. For the Korean FFG evaluation, we use the same test characters with Cha *et al.* [4], 245 characters. To sum up, we evaluate the methods by using 28 font styles with 214 Chinese and 245 Korean characters.

Evaluation metrics. Due to the style of the font domain is defined by a local fine-grained shape, *e.g.*, stroke, size, or serif-ness, measuring the visual quality with a unified metric is a challenging problem. A typical challenge is the multiplicity of the font styles; because the font style is defined locally, there could be multiple plausible glyphs satisfying our objectives. However, we only have one "ground truth" glyphs in the test dataset. Furthermore, for the Korean generation task with Chinese references, we even do not have "ground truth" Korean glyphs with the reference styles. Thus, we need to employ evaluation metrics that does not require ground truth, and can evaluate plausibility of the given samples. We therefore use four different evaluation metrics to measure the visual quality in various viewpoints.

Following previous works [4, 31], we train evaluation classifiers for character labels (content-aware) and font labels (style-aware). Note that these classifiers are only used for evaluation, and trained separately to the FFG models. We train three classifiers, the style classifier and the content classifier on the Chinese test fonts, and the content classifier on the Korean test characters. The details of the evaluation classifiers are in Appendix. We measure the **classification accuracies** for style and content labels. We also report the accuracy when both classifiers are correctly predicted.

We conduct a **user study** for quantifying the subjective quality. The participants are asked to pick the three best results, considering the style, the content, and the most preferred considering both the style and the content. All 28 test styles with 10 characters are shown to the participants. For each test style, we show Chinese and Korean samples separately to the users. *I.e.*, a participant picks $28 \times 3 \times 2 = 168$ results. We collect the responses from 57 native Korean speakers, highly educated with the Chinese script. User study samples are in the Appendix.

We also report LPIPS [44] to measure the dissimilarity between the generated images and their corresponding ground truth images. Frechét inception distance (FID) [15] between the generated images and real images are computed by the style and content classifiers and their harmonic mean is reported (FID(H)). The details are in Appendix.

4.3. Experimental results

Quantitative evaluation. Table 1 shows the FFG performances by MX-Font and competitors. The reported values are the average of 50 different experiments, where four reference images per style are used for font generation in each experiment. In the table, we observe that MX-Font outperforms other methods in the both in-domain transfer scenario and zero-shot cross-lingual generation scenario with the most of evaluation metrics. Especially, MX-Font remarkably outperforms other methods in the cross-lingual task. In the in-domain transfer scenario, ours exceeds others in the classification accuracies and the user study. We observe that MX-Font perform worse than others in the Chinese FID, where FID is known to sensitive to noisy or blur images, regardless of the image quality itself [33]. Our method shows the remarkably better performances in more reliable evaluation, user study in all criterions.

Qualitative evaluation. We illustrated the generated samples in Figure 6. We show four reference images to extract each style in the top row, and the source images in the second row where each source image is used to extract the content. In the green box in Figure 6, we observe that AGIS-Net often fails to reflect the reference style precisely and generate local details. FUNIT generally shows similar trends with

		Acc (S) %	Acc (C) %	Acc (B) %	User (S) %	User (C) %	User (B) %	LPIPS ↓	FID (H) ↓
CN → CN	EMD (CVPR'18)	6.6	51.3	4.6	0.7	0.1	0.3	0.212	79.7
	AGIS-Net (TOG'19)	25.5	**99.5**	25.4	22.4	**34.2**	26.8	0.124	19.2
	FUNIT (ICCV'19)	34.0	94.6	31.8	22.9	21.6	22.2	0.147	19.2
	LF-Font (AAAI'21)	58.7	96.9	57.0	19.5	12.3	15.6	**0.119**	**14.8**
	MX-Font (proposed)	**78.9**	**99.5**	**78.7**	**34.5**	31.8	**35.2**	0.120	21.8
KR → CN	EMD (CVPR'18)	4.6	15.4	0.8	0.8	0.1	0.1	-	150.1
	AGIS-Net (TOG'19)	13.3	32.1	3.1	1.8	0.6	0.6	-	146.5
	FUNIT (ICCV'19)	11.3	66.4	6.6	12.0	17.3	9.1	-	176.0
	LF-Font (AAAI'21)	47.6	28.7	12.8	10.6	0.7	1.0	-	148.7
	MX-Font (proposed)	**66.3**	**75.9**	**50.0**	**74.6**	**81.3**	**89.2**	-	**84.1**

Table 1. **Performance comparison on few-shot font generation scenario.** The performances of five few-shot font generation methods with four reference images are compared. We report accuracy measured by style-aware (Acc (S)) and content-aware (Acc (C)) classifiers and accuracy considering both the style and content labels (Acc (B)). The summarized results of the user study are also reported. The User preference on considering style (User (S)), content (User (C)), both of them (User (B)) are shown. LPIPS shows a perceptual dissimilarity between the ground truth and the generated glyphs. The harmonic mean (H) of style-aware and content-aware FID is also reported. Note that the FIDs are computed differently in two FFG scenarios. All numbers are average of 50 runs with different reference glyphs.

Figure 6. **Generated Samples.** The generated images by five different models are shown. We also provide the reference and the source images used for the generation in the top two rows. The available ground truth images (GT) are shown in the bottom row. We highlight the samples that reveal the drawback of each model with colored boxes; green for AGIS-Net, red for FUNIT, and yellow for LF-Font.

AGIS-Net, while FUNIT often produces shattered glyphs when the target glyph and the source glyph have significantly different structures (red box). At a glance, LF-Font seems to capture the detailed local styles well. However, it often misses important detailed local component such as dot and stroke, as shown in the yellow box. Comparing to other methods, MX-Font synthesizes the better detailed structures both in content and style, owing to the strong representation power of locally specialized experts. The advantage of MX-Font is highlighted in the cross-lingual FFG. All existing models often generate unrecognizable characters under the cross-lingual scenario. Nevertheless, MX-Font preserves both the detailed local style and content and generates the plausible and recognizable images consistently. Such a noticeable gap in visual quality explains the large performance leap of MX-Font in the user study.
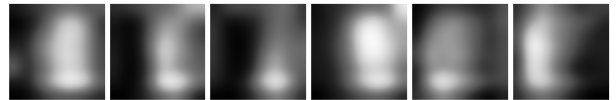

Figure 7. **Each localized expert attends different local areas.** The variance of Class Activation Maps (CAMs) for each expert are shown. The brighter regions indicate the larger values.

k	Acc (S) ↑	Acc (C) ↑	Acc (B) ↑	LPIPS ↓
1	72.2	98.7	71.4	0.133
2	79.0	99.3	78.5	0.128
4	78.3	99.5	78.0	0.125
6	78.9	**99.5**	**78.7**	**0.120**
8	75.5	99.5	75.2	0.123

Table 2. **Impact of the number of experts** k. The models with different number of heads are compared on in-domain Chinese transfer benchmark. We used $k = 6$ for all experiments.

Source	呼 和 字 最 副 富 努 多
Ours (k=1)	呼 和 字 最 副 富 努 多
Ours (k=6)	呼 和 字 最 副 富 努 多
GT	呼 和 字 最 副 富 努 多

Figure 8. **Generated samples of the models having different number of heads (k).** The samples generated with four reference glyphs by the single-headed model and multi-headed model are shown. We highlight the defects in red dotted circles that appeared in the images generated by the single-expert model.

4.4. Analyses

Learned local concepts by different experts. We show the local concepts learned by each expert by visualizing where each expert attends on. We extract the Class Activation Maps (CAMs) [46] of the training samples using the component classifier Cls_u on each local feature. Then, we visualize the variance of CAMs in Figure 7. In Figure 7, the region with bright intensity than the surrounding indicates the region where each expert pays more attention. Interestingly, without any explicit pixel-level annotation, our localized experts attend different local areas of the images. These maps support that each expert of MX-Font tends to cover different local areas of the input image. Summarizing, these experimental studies demonstrate that *multiple localized experts* capture different local areas of the input image as we intend, and employing *multiple localized experts* helps us to enhance the quality of generated images by preserving the local details during the style-content disentanglement.

Multiple experts vs. single expert. We compare the performances of the single expert model ($k = 1$) with our multiple experts model ($k = 6$) on benchmark in-domain transfer scenario. The results are shown in Table 2 and Fig 8. We observe that the multi-headed model performs better than a single-headed one. We also observe that the generated images by the single-headed model fails to preserve the local structures delicately, *e.g.* important strokes are missing, while the multi-headed model captures local details well. More analyses on different k are in the Appendix.

Character vs. Components. We replace the component supervision (multiple image-level sub-concepts) to the character supervision (single image-level label). Table 3 shows that utilizing character supervision incurs a mode collapse. We speculate that two reasons caused the collapse, (1) the number of characters ($\approx 19k$) is too large to learn, while the number of components is reasonably small (371), and (2) our best allocation problem prevents the experts from collapsing into the same values, while the character supervised model has no restriction to learn different concepts.

	Acc (S) ↑	Acc (C) ↑	Acc (B) ↑	LPIPS ↓
Ours (Cls_u)	78.9	99.5	78.7	0.120
Ours (Cls_c)	94.8	0.04	0.04	0.214

Table 3. **Comparing the component classifier and the character classifier as weak supervision.** We compare two auxiliary classifiers as content supervision. Ours (Cls_u) denotes MX-Font using the component classifier and Ours (Cls_c) denotes the model replaced the component classifier to the character classifier.

$\mathcal{L}_{indp,i}$	$\mathcal{H}_{c,s}$	$\mathcal{L}_{c,s}$	Acc (S)	Acc (C)	Acc (B)
✔	✔	✔	**59.0**	**95.9**	**56.8**
✘	✔	✔	52.0	95.8	50.0
✘	✘	✔	51.6	95.5	49.4
✘	✘	✘	27.8	89.1	24.7
LF-Font [31]			38.5	95.2	36.5

Table 4. **Impact of loss functions.** We compare models by ablating the proposed object functions trained and tested on Korean-handwriting dataset. The results show that the content-style adversarial loss $\mathcal{L}_{c,s}$ and the maximizing entropy term $\mathcal{H}_{c,s}$ and independent loss $\mathcal{L}_{indp,i}$ are all important components.

Loss ablations. In Table 4, We investigate the effect of our loss function design by the models trained and tested on Korean handwritten dataset (details in Appendix). The table shows that all the proposed loss functions for the style-content disentanglement are effective to the performances.

5. Conclusion

We propose a novel few-shot font generation method, namely MX-Font. Our goal is to achieve both the rich representation for the local details and the generalizability to the unseen component and language. To this end, MX-Font employ *multi-headed encoder*, trained by weak local component supervision, *i.e.* style and content feature classifiers. Based on interactions between these *feature classifiers* and localized experts, MX-Font learns to disentangle the style and content successfully by developing localized features. Finally, the proposed model generates the plausible font images, which preserve both local detailed style of the reference images and precise characters of the source images. Experimental results show that MX-Font outperforms existing methods in in-domain transfer scenario and zero-shot cross-lingual transfer scenario; especially large performance leap in the cross-lingual scenario.

Acknowledgements

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