

# Font Representation Learning via Paired-glyph Matching

Junho Cho<sup>1,2</sup>, Kyuewang Lee<sup>1</sup>, Jin Young Choi<sup>1</sup>

Department of ECE, ASRI, Seoul National University<sup>1</sup>

Samsung Advanced Institute of Technology, Samsung Electronics<sup>2</sup>



## Introduction

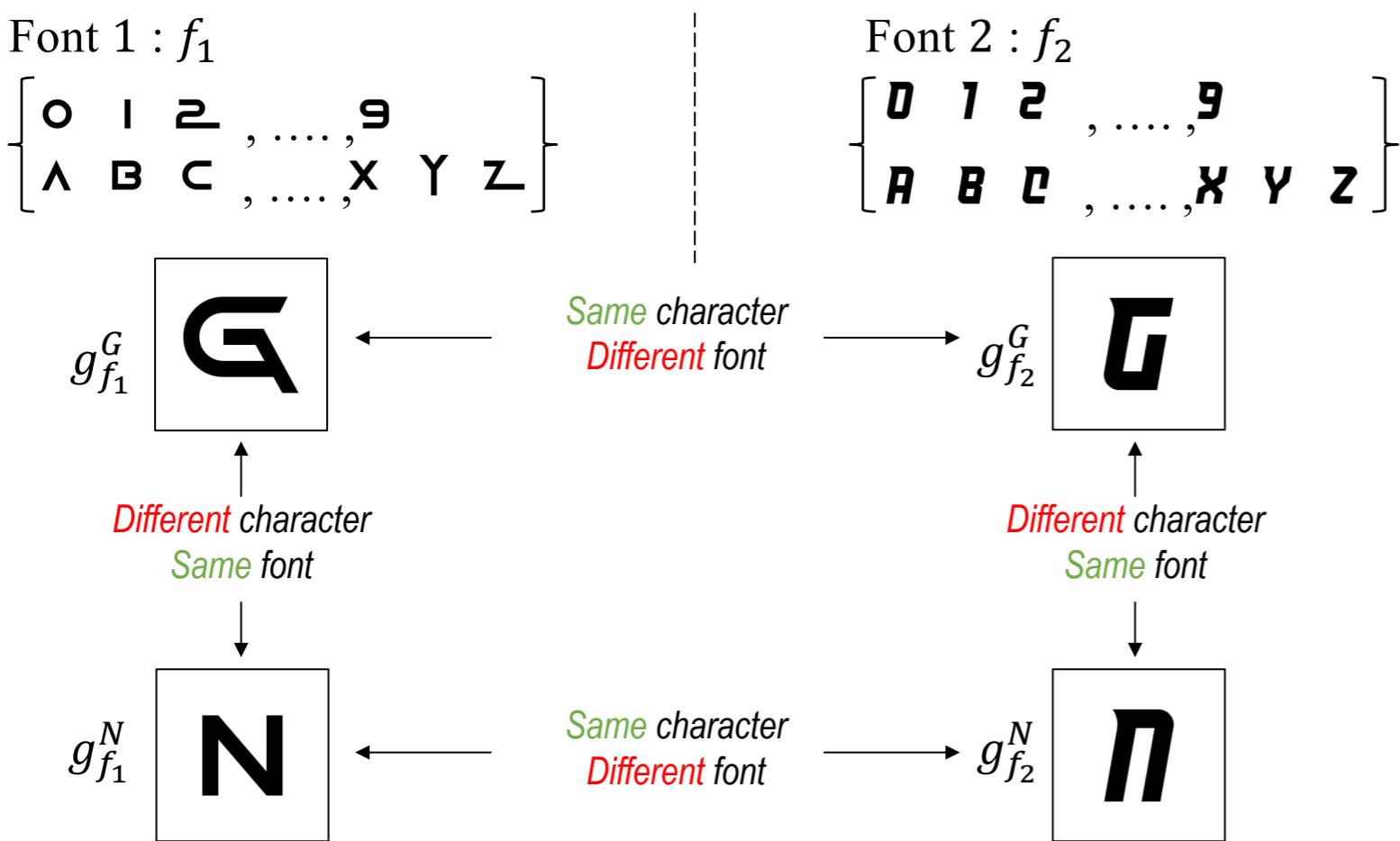
Abadi MT Condensed Light  
**Albertus Extra Bold**  
 Albertus Medium  
 Antique Olive  
 Arial  
**Arial Black**  
 Arial MT  
 Arial Narrow  
**BAAZOOKA**  
 Book Antiqua  
 Book Old Style  
**Boulder**  
 Calisto MT  
**Calligrapher**  
 Century Gothic  
 Century Schoolbook



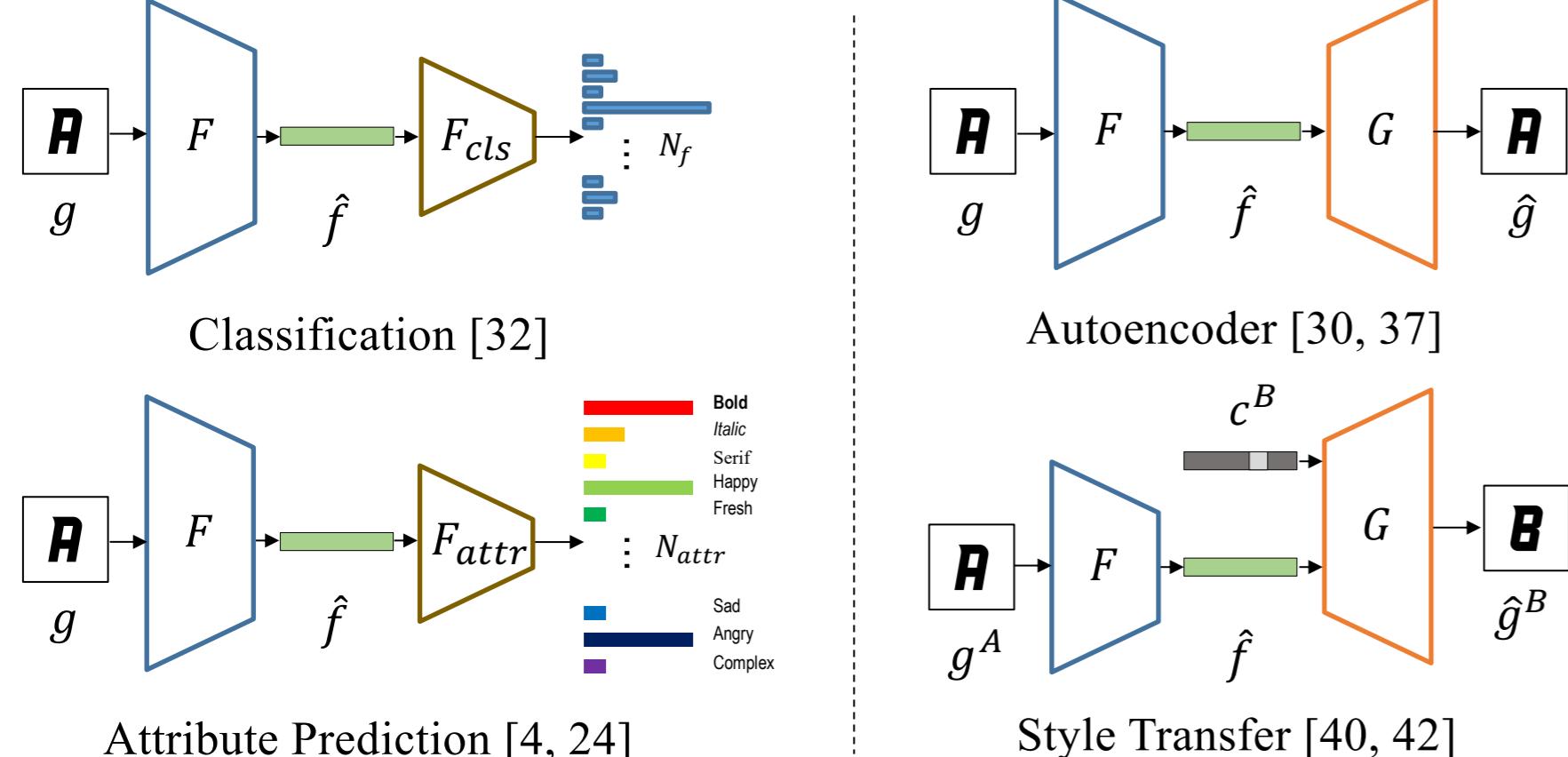
We aim to learn **font representation** to explore vast font styles.

## Preliminary

- A glyph ( $g$ ) is an image form of a character that has a specific style in a font.
- A font ( $f$ ) is a matching style set of glyphs.



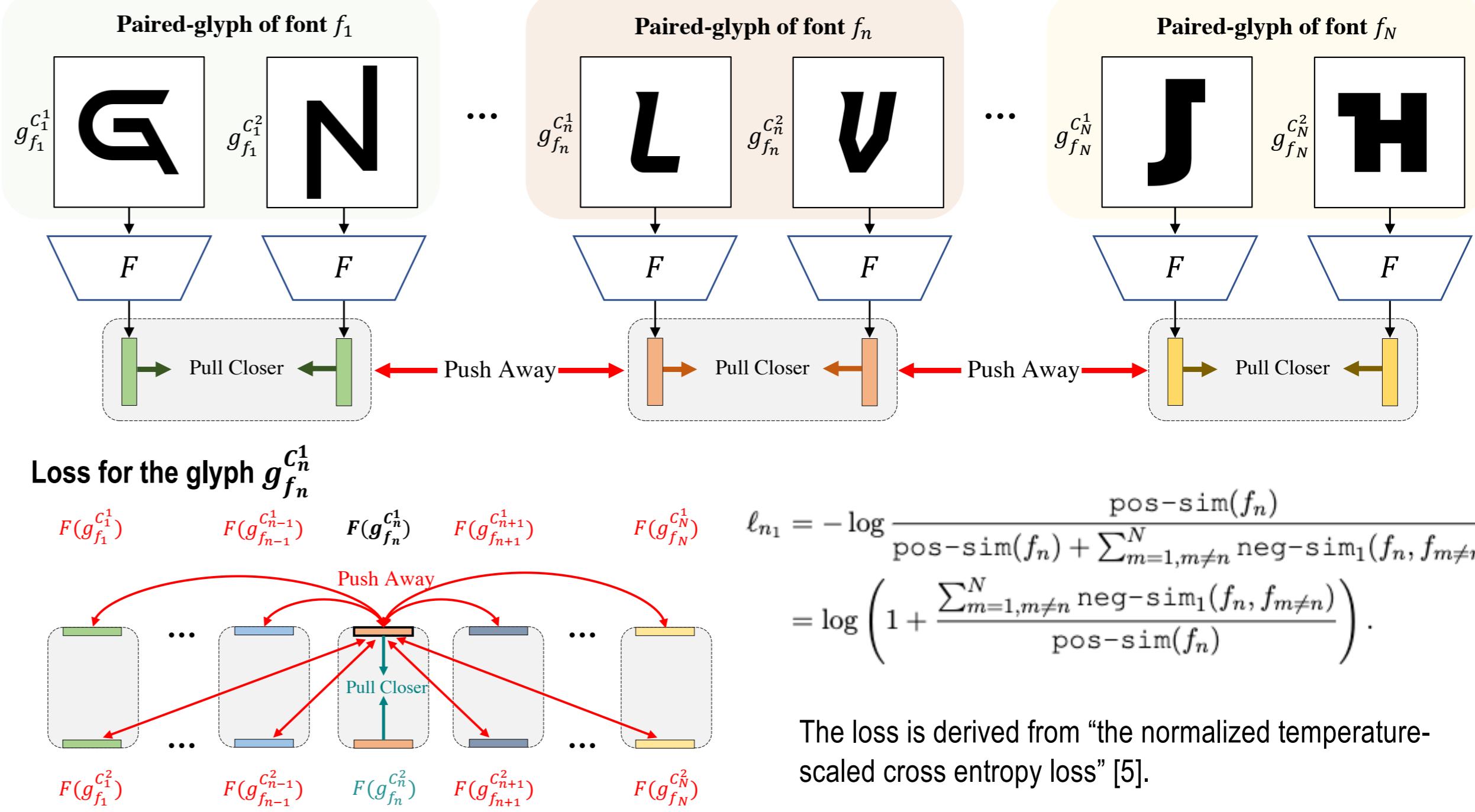
## Previous Method



## Reference

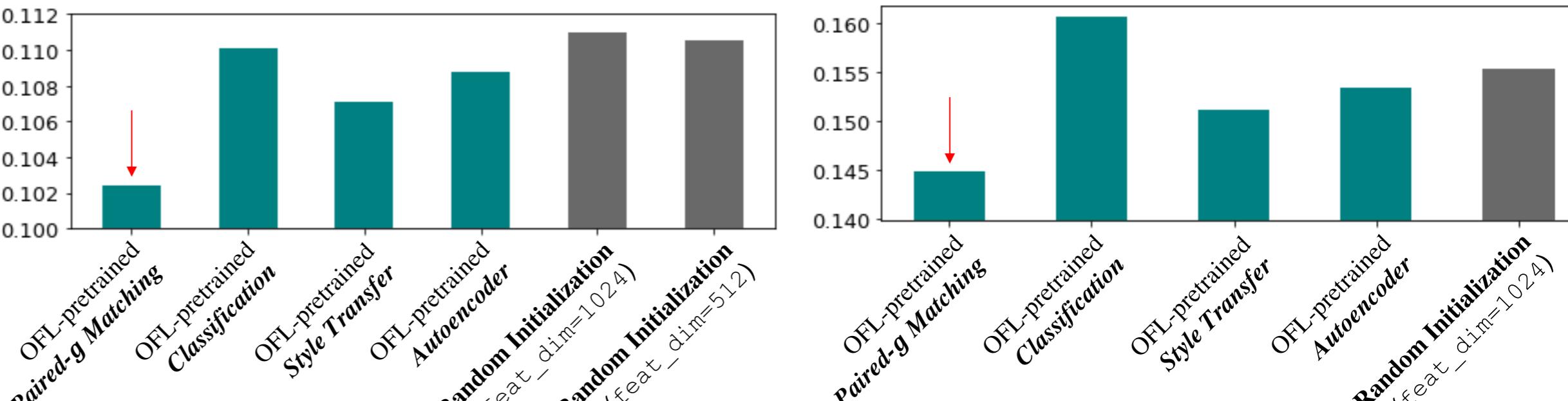
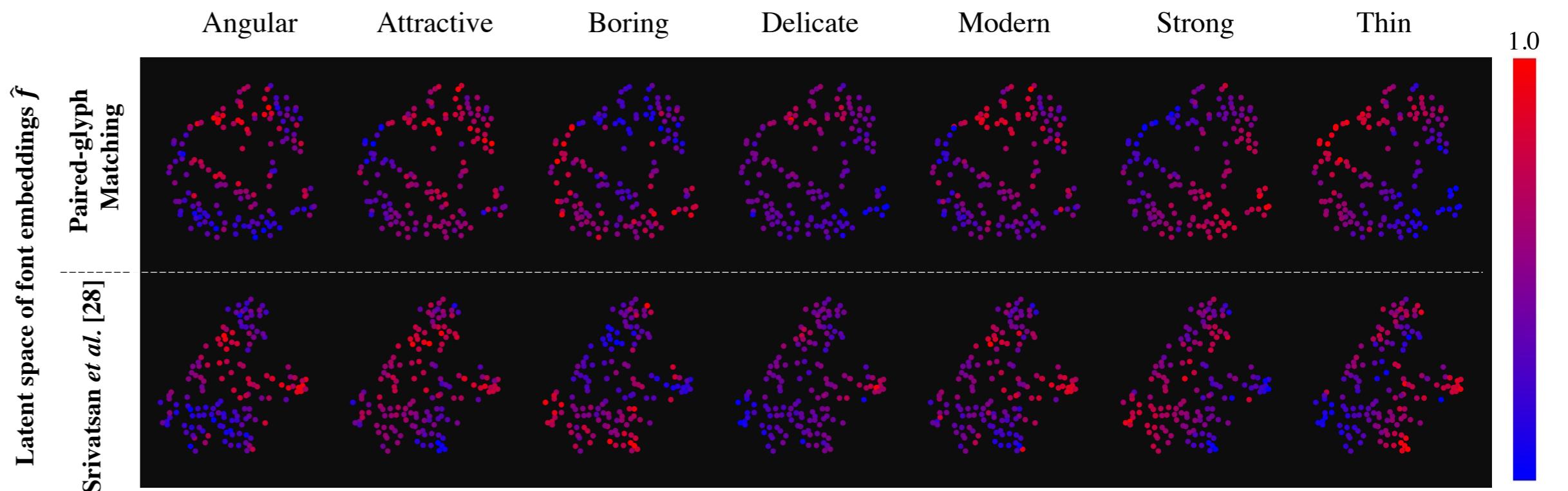
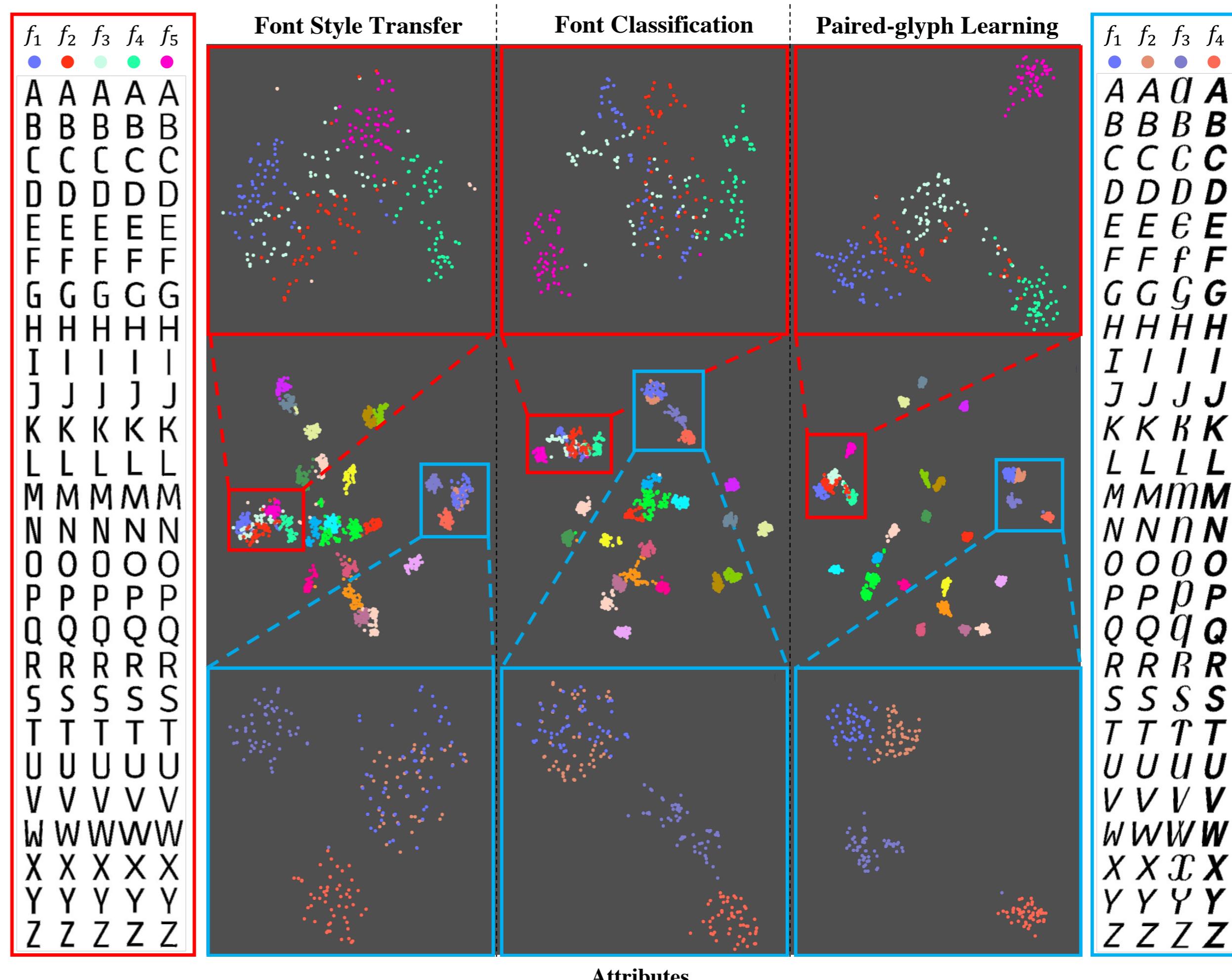
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## Proposed Method



The loss is derived from “the normalized temperature-scaled cross entropy loss” [5].

## Result



Performance evaluation (MACC and Font attribute prediction) on the Capitals64 dataset. Font attribute prediction is evaluated on O'Donovan dataset with  $L_1$  error.

Image L1-error measured in (a) font style transfer and (b) font generation with the OFL dataset pretrained and random initialization.



Perception and Intelligence Laboratory

Seoul National University