Generating Handwritten Character Clones from an Incomplete Seed Character Set using Collaborative Filtering

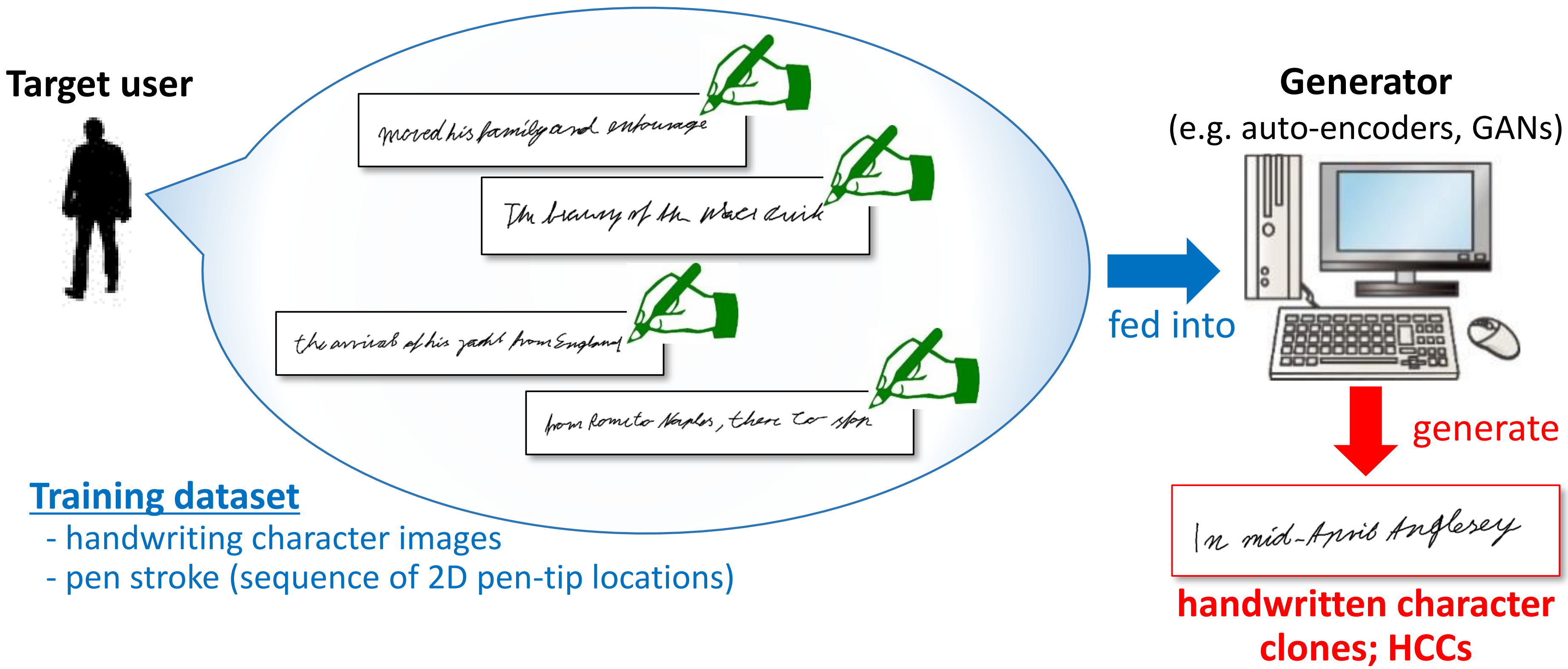
Kazuaki Nakamura, Eiji Miyazaki,
Naoko Nitta, and Noboru Babaguchi

Osaka University, Japan

on 6th Aug. 2018, at ICFHR2018

Research Background

- **Handwriting generation**
  - generate synthetic (or clone) images of handwritten characters resembling a target user's actual handwriting.

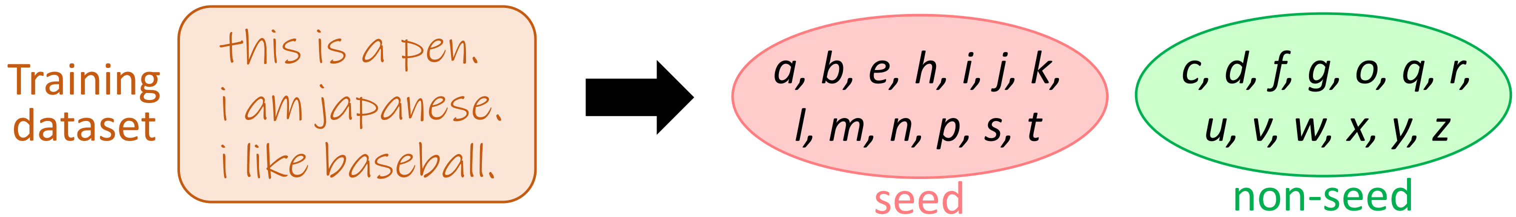


Automatically generated HCCs

- are applicable to communication tools (especially for hand-impaired people).
- serve a large scale dataset for handwriting recognition, faked signature detection, etc.

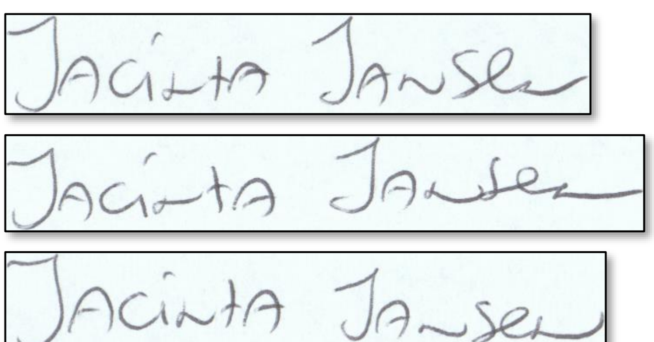
Requirements in Practice

- **Incomplete seed character set**
  - ***Seed characters***: characters whose image(s) is in the training dataset



  - Seed characters are usually limited because it is difficult to collect a lot of images from the target user.
    - It is not rare that at most one or zero image is available per character, especially in the case of Asian languages

- **Within-person variety**
  - Images of humans' actual handwriting differ from each other even if the same writer writes the same character.



All of them have the similar characteristics but are slightly different from each other

Goal

- **Goal:** To propose a HCC generation method
  - that can achieve the *within-person variety*

    Not a single HCC but its distribution should be created.

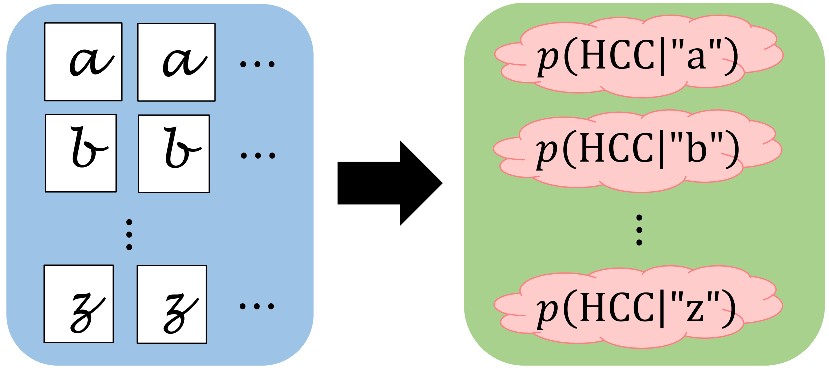
  - based on the *incomplete seed character set*

    At most one or zero image is available per character
    as a training data.

Related Work

- **(Conventional) HCC generation** [1, 2]

INPUT
A lot of images
for each character

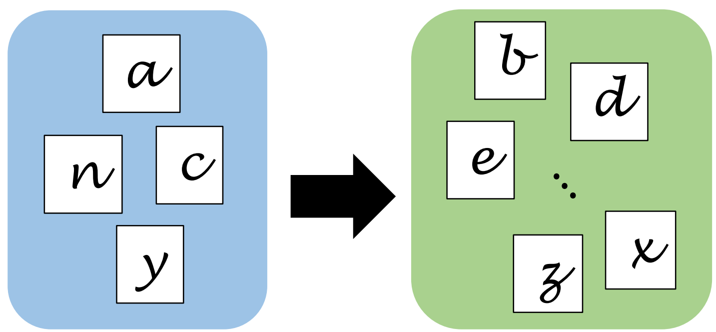


OUTPUT
HCC distribution
for each character

☒Incomplete seed character set **☑within-person variety**

- **Font generation** [3, 4, 5]

INPUT
A few images of
several seed characters
written in a certain style



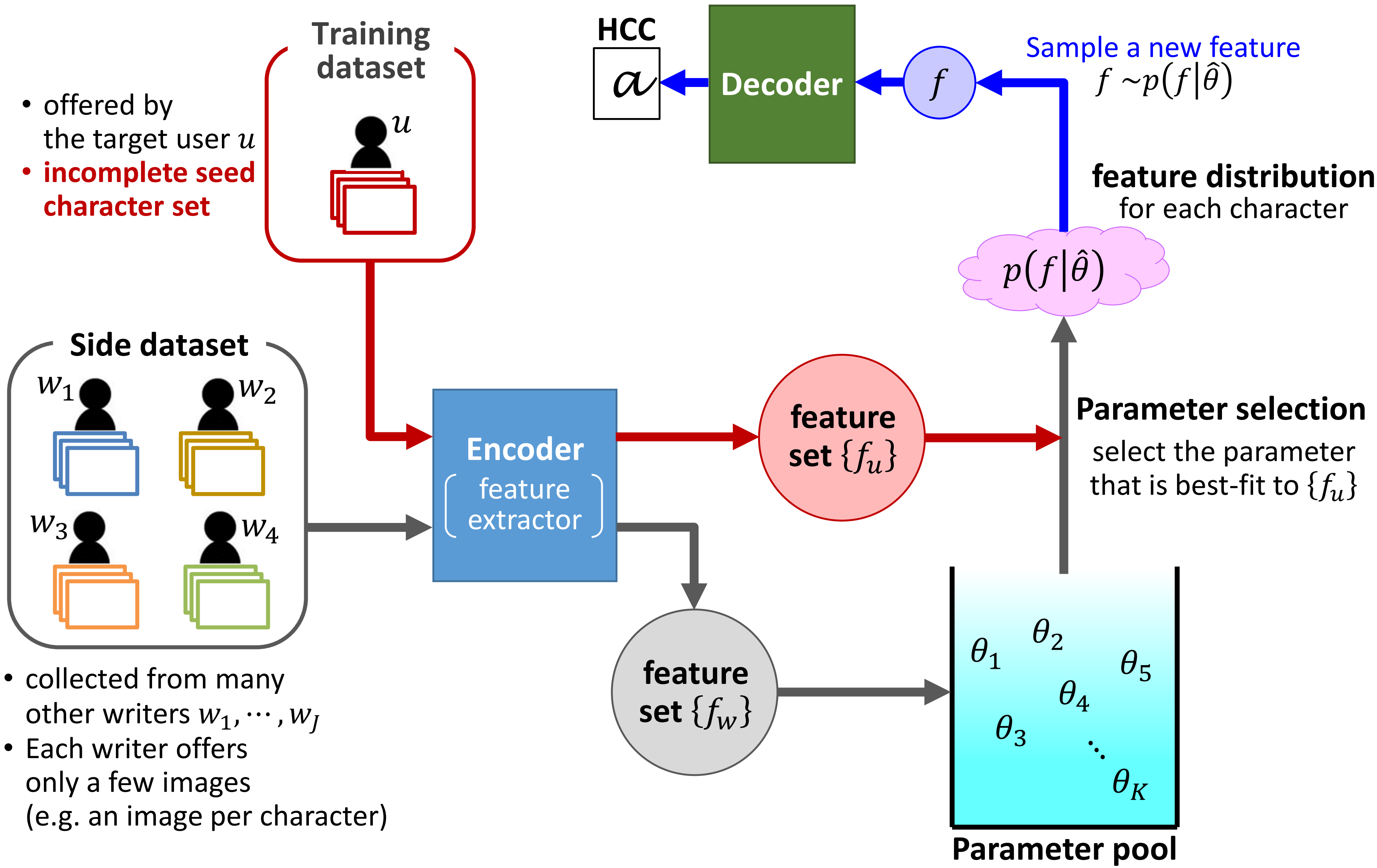
OUTPUT
Images of
the other characters
that seems to be written
in the same style

☑Incomplete seed character set **☒within-person variety**

[1] T. S. Haines et al.: “My Text in Your Handwriting,” ACM Trans. on Graphics, Vol.35, No.3, 2016.
[2] A. Graves: “Generating Sequences With Recurrent Neural Networks,” arXiv preprint, arXiv:1308.0850, 2013.
[3] D. G. Balreira et al.: “Handwriting Synthesis from Public Fonts,” in Proc. of 30th SIBGRAPI Conf. on Graphics, Patterns and Images (SIBGRAPI), pp.246--253, 2017.
[4] J. W. Lin et al.: “Complete Font Generation of Chinese Characters in Personal Handwriting Style,” in Proc. of 34th IEEE Int'l Performance Computing and Communications Conf. (IPCCC), pp.1--5, 2015.
[5] Z. Lian et al.: “Automatic Generation of Large-Scale Handwriting Fonts via Style Learning,” in Proc. of SIGGRAPH ASIA 2016 Technical Briefs, 2016.

Overview

- Character-wise HCC generation
- Offline (using only images)



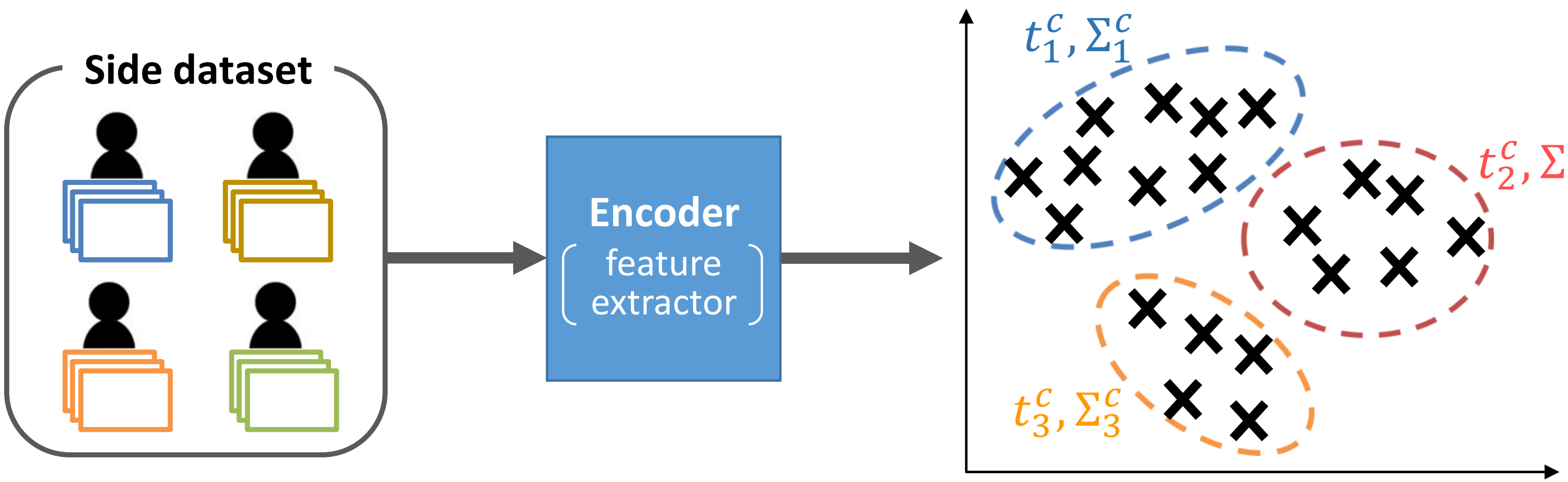
Parameter Pool Construction

Hypothesis

- It is not rare that the shapes of two writer's handwriting are very similar for some characters. IOW, there are a lot of writer-pairs whose handwriting shapes are similar for some characters.

↓

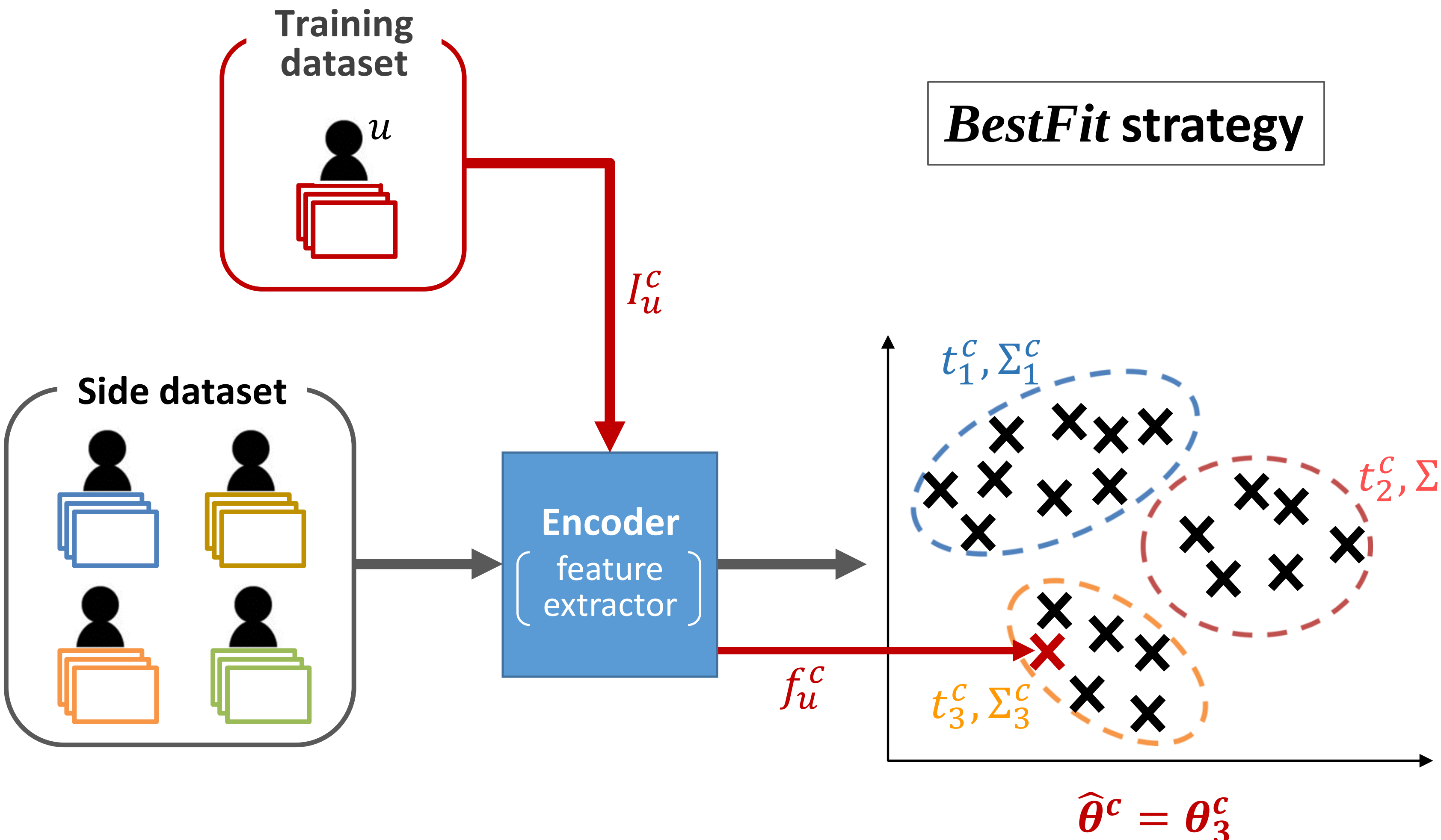
Not only the average shape but also the shape distribution of their handwriting would be similar.



Separately perform the following procedure for each character c:

1. Extract a feature for each handwriting image in the side dataset
2. Cluster a set of the extracted features
3. Compute the mean t_k^c and the covariance Σ_k^c for each cluster k ➡ $\theta_k = (t_k^c, \Sigma_k^c)$

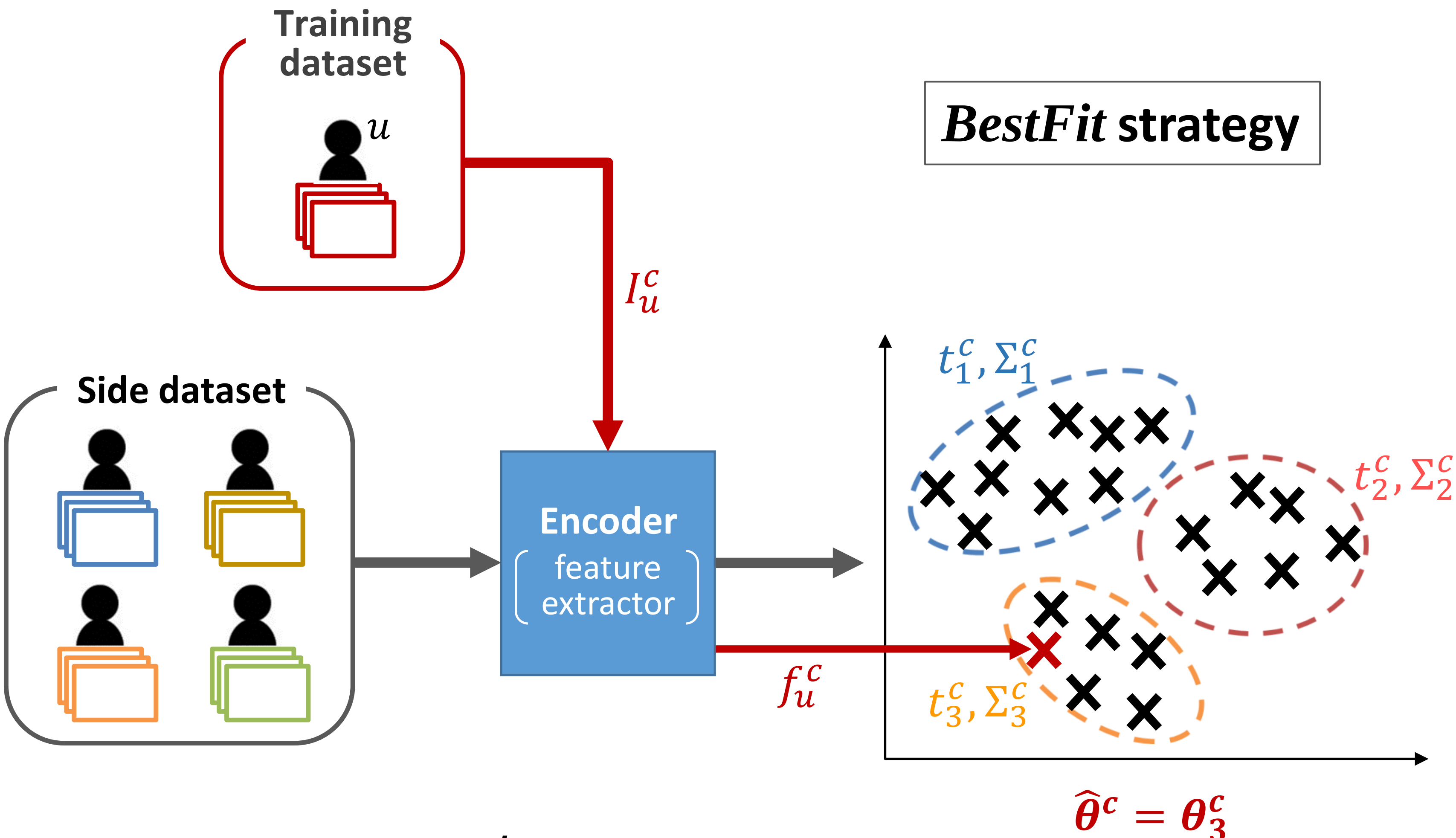
Parameter Selection for Seeds



For a seed character c,

- use the target user's actual handwriting image I_u^c .
- select the parameter that is best-fit to I_u^c .

Parameter Selection for Non-seeds



For a non-seed character c',

- there are no images of the target user's actual handwriting.
- ***BestFit*** strategy cannot be used.

Parameter Selection for Non-seeds

- **For a non-seed character c', employ collaborative filtering (CF).**
- To perform CF, first construct a writer-character matrix Φ.
  - Estimate the best-fit parameters for not only the target user but also the other writers.
  - $\phi_{jm} \in \{1,2,\cdots,K\}$: ID of the best-fit parameter of j-th writer's feature distribution for m-th character

Seed characters

non-seed character

$\Phi =$

	c_1	c_2	$\cdots$	c_m	$\cdots$	c_M
w_1	ϕ_{11}	ϕ_{12}	$\cdots$	ϕ_{1m}	$\cdots$	ϕ_{1M}
w_2	ϕ_{21}	ϕ_{22}	$\cdots$	ϕ_{2m}	$\cdots$	ϕ_{2M}
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$
w_J	ϕ_{J1}	ϕ_{J2}	$\cdots$	ϕ_{Jm}	$\cdots$	ϕ_{JM}
u	$\phi_{u,1}$	$\phi_{u,2}$	$\cdots$	?	$\cdots$	$\phi_{u,M}$

other writers

target user

writer-character matrix

$\phi_{u,1}, \phi_{u,2}, \phi_{u,M}$: known (estimated by *Best-Fit* strategy)

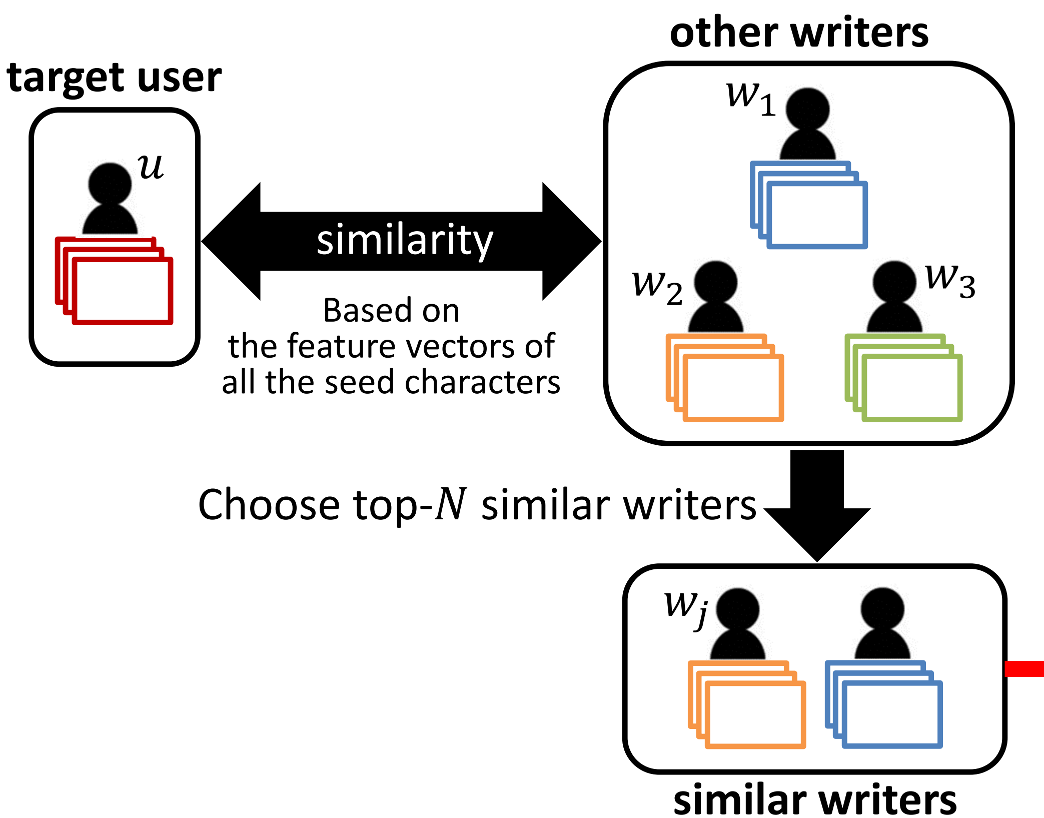
$\phi_{u,m}$: unknown $\longrightarrow$ try to estimate it by collaborative filtering!

Collaborative Filtering

- **User-based collaborative Filtering (*UserCF*)**

Hypothesis

If the feature distributions of two writers are similar with each other for some characters, their distributions for another character also tend to be similar.

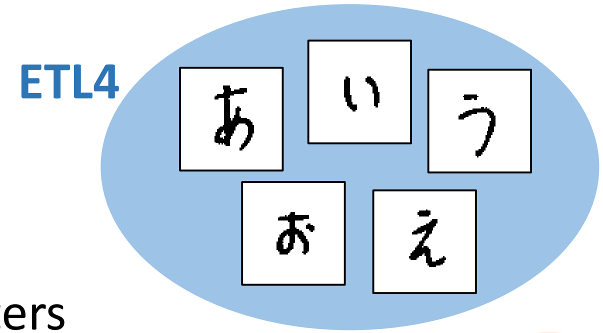


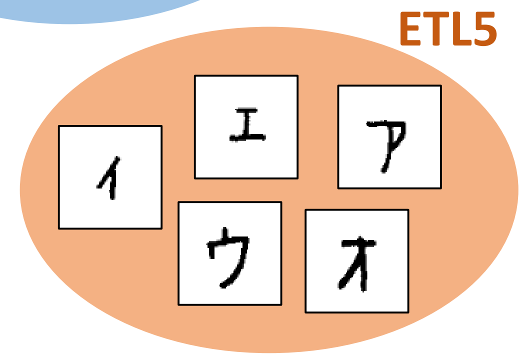
	c_1	c_2	c_3	c_4
w_1	ϕ_{11}	ϕ_{12}	k	ϕ_{14}
w_2	ϕ_{21}	ϕ_{22}	k	ϕ_{24}
w_3	ϕ_{31}	ϕ_{32}	ϕ_{33}	ϕ_{34}
u	$\phi_{u,1}$	$\phi_{u,2}$	k	$\phi_{u,4}$

similar writers

[Majority voting] For each w_j, vote the similarity score $\mathrm{sim}(u, w_j)$ for ϕ_{j3}-th parameter

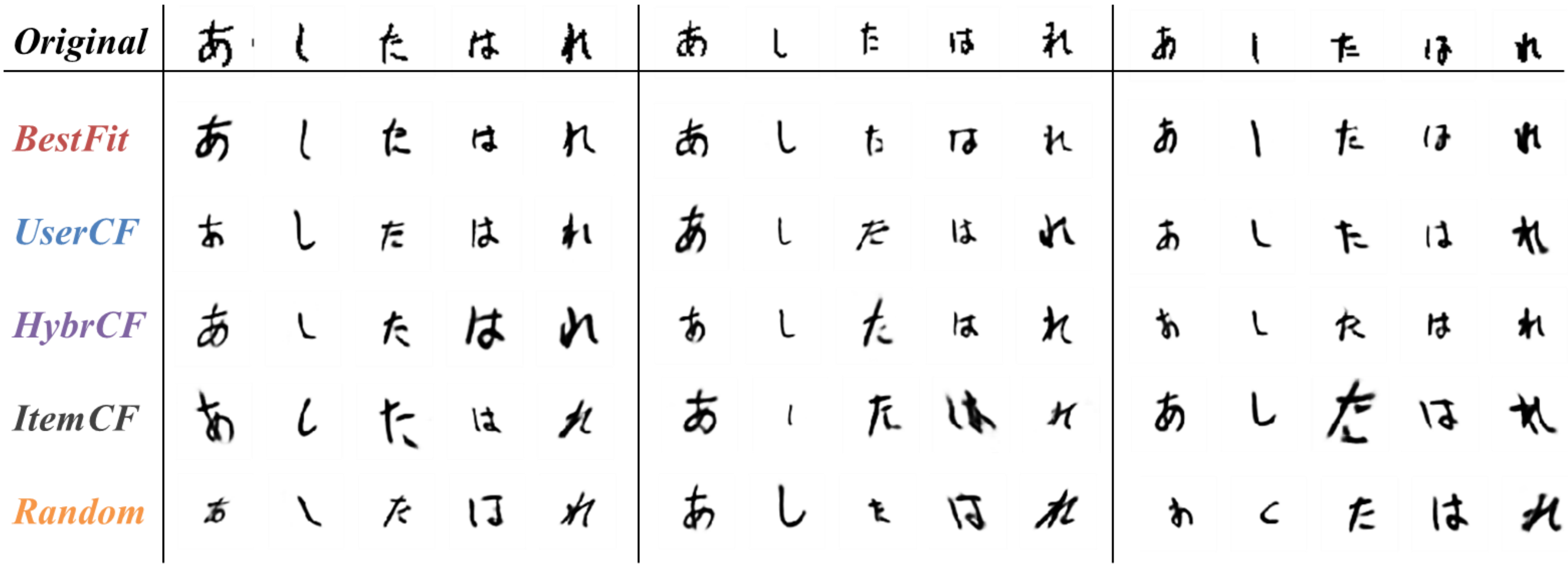
Experiment

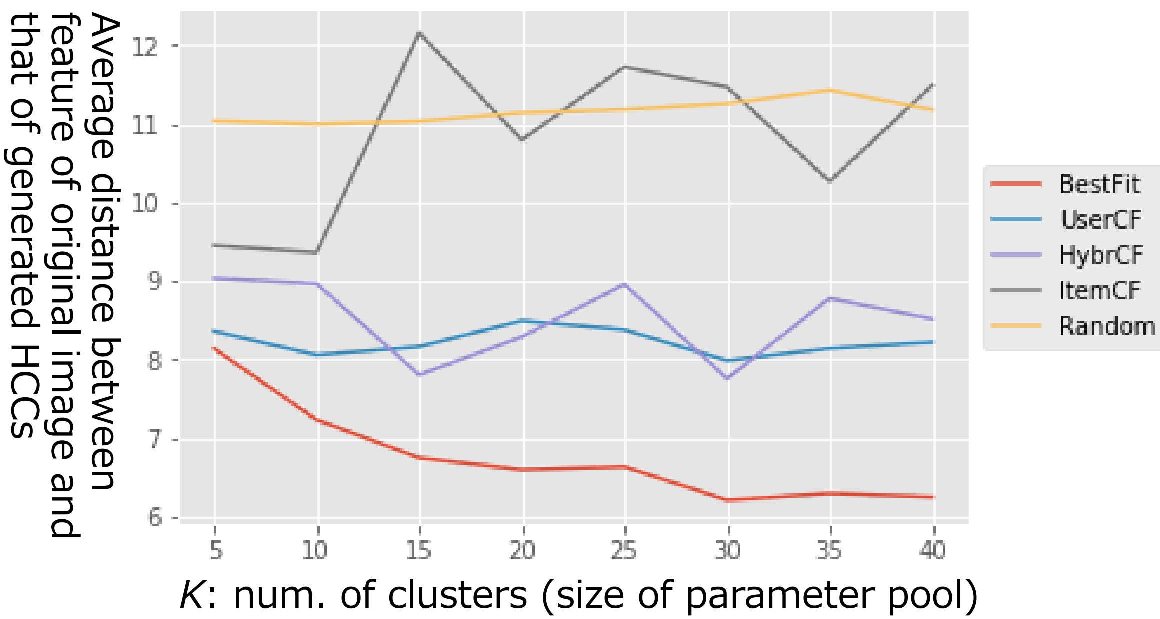




- **Dataset**
  - ETL4: a set of Japanese *Hiragana* Characters
    - 48 characters, 120 writers, 48*120=5760 images
  - ETL5: a set of Japanese *Katakana* Characters
    - 48 characters, 208 writers, 48*204=9984 images
- **Setting**
  - Randomly select 3 writers as “target user”, i.e., u,
    and regard the remaining writers as “other writers”, i.e., $\{w_j\}$.
  - Generate the following 5 characters, regarding the other 43 characters as seed.
    - *Hiragana*: **あ** (a), **し** (shi), **た** (ta), **は** (ha), **れ** (re)
    - *Katakana*: **ア** (a), **シ** (shi), **タ** (ta), **ハ** (ha), **レ** (re)
  - Encoder & Decoder: Variational Autoencoder
- **Compared methods**
  - ***BestFit***: using all of the 48 characters as seed (complete seed character set)
  - ***UserCF***
  - ***ItemCF*** : item-based collaborative filtering
  - ***HybrCF***: the method combining ***UserCF*** and ***ItemCF***
  - ***Random***: randomly selecting a parameter from the pool

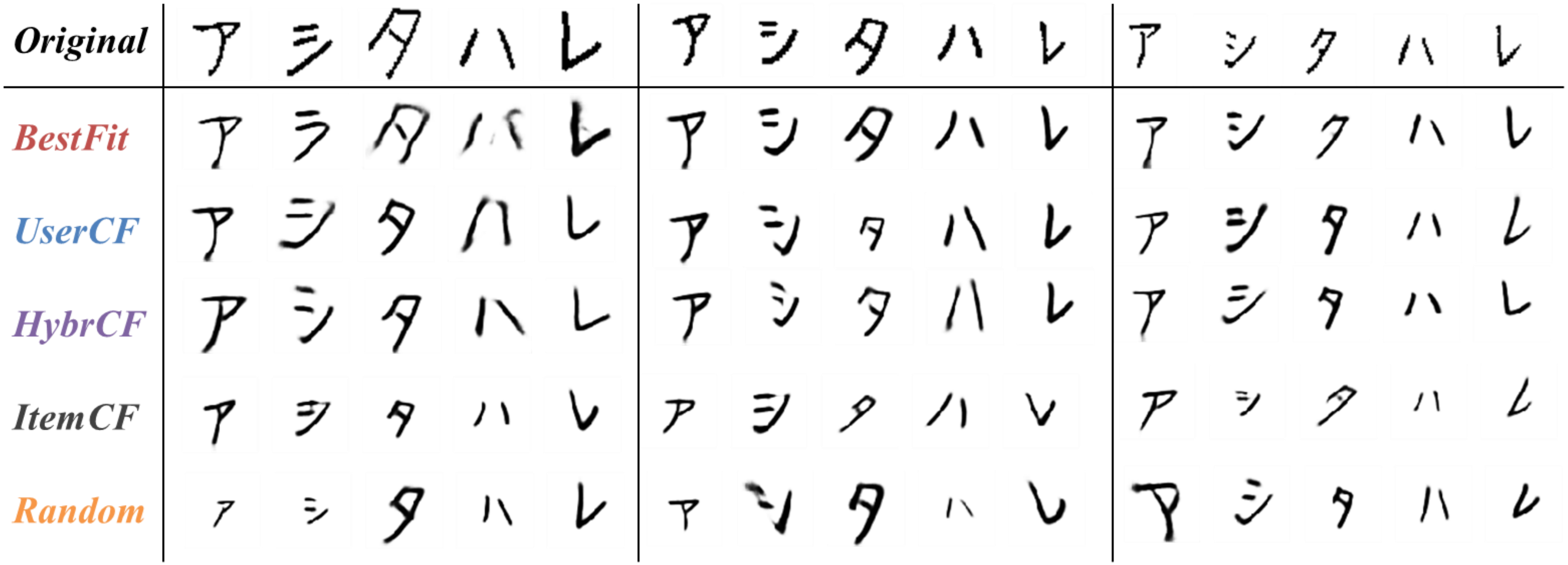
Result (*Hiragana* in ETL4, *K*=40)

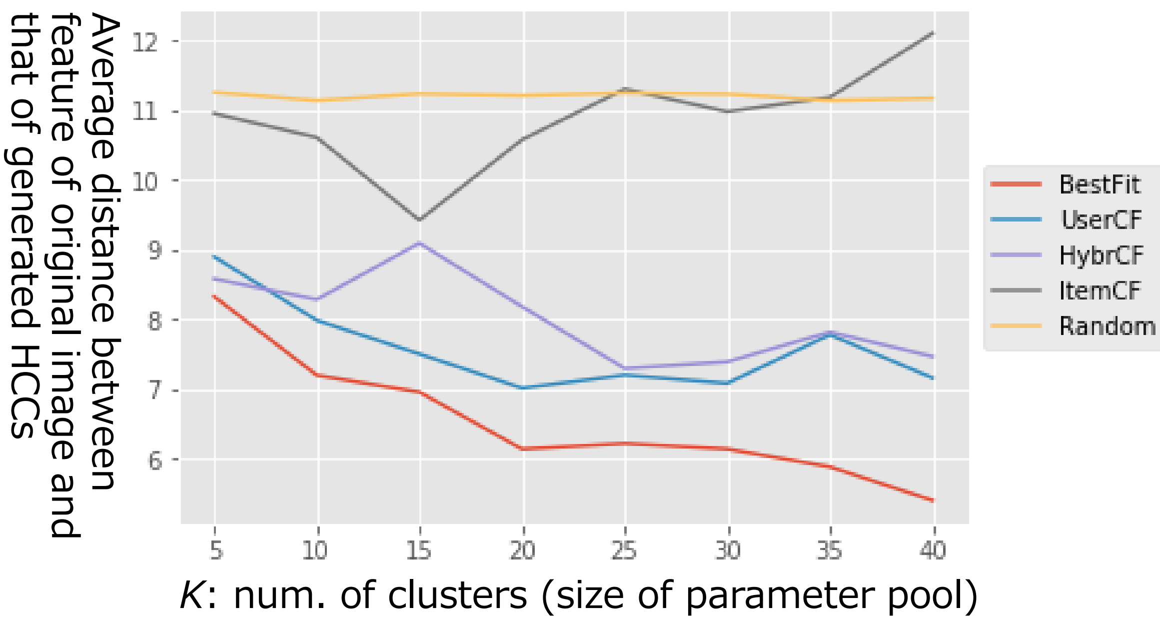




- ***BestFit*** can generate HCCs quite similar with ***Original***.
- ***UserCF*** and ***HybrCF*** can also generate good HCCs.
- The performance of ***ItemCF*** is almost same with that of ***Random***.
  - Co-occurrence probability *L* becomes statistically unreliable with large *K*.

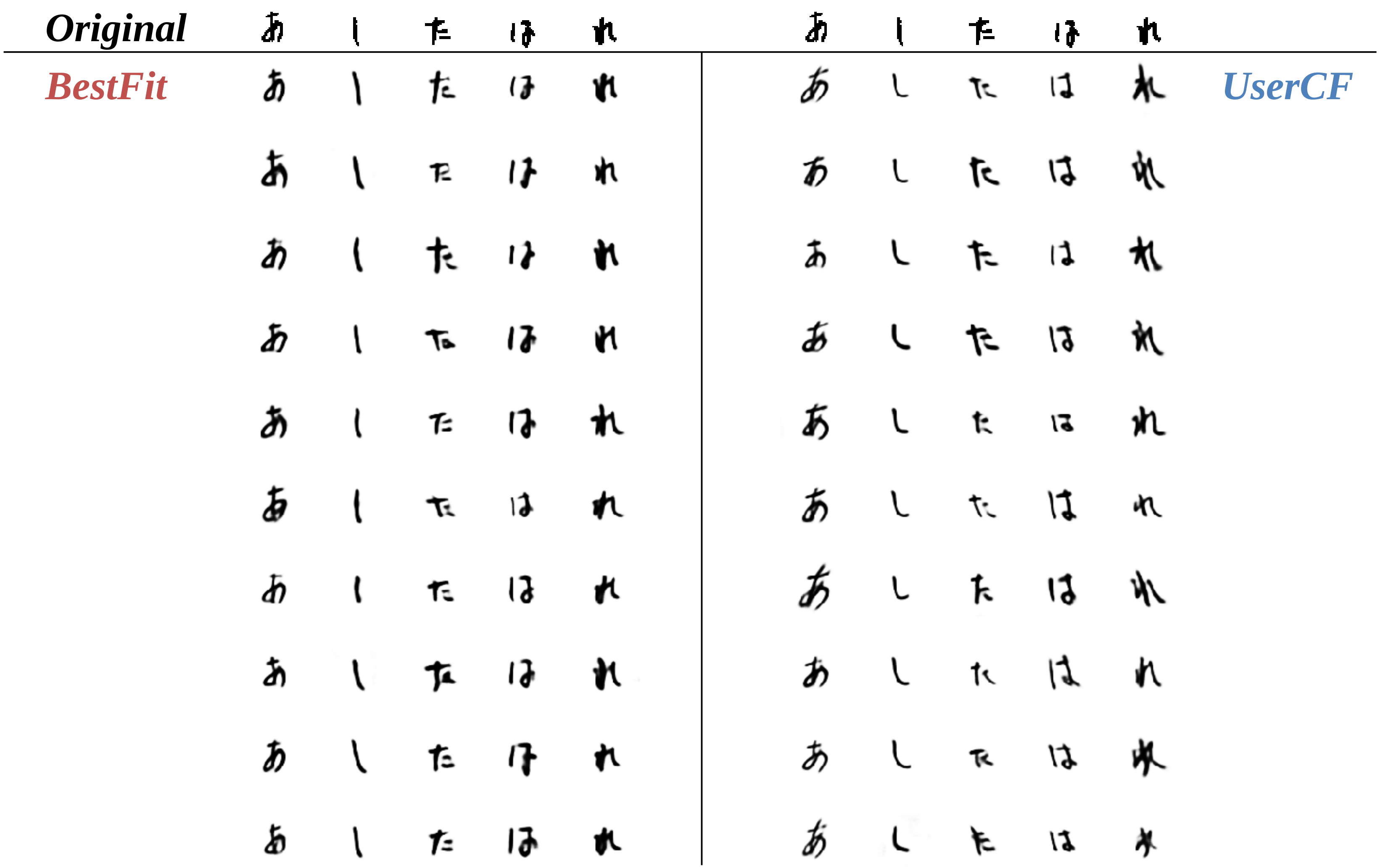
Result (*Katakana* in ETL5, *K*=40)





- Similar result was obtained.
  - HCCs generated by ***BestFit*** are quite similar with Original.
  - ***UserCF*** and ***HybrCF*** also generate good HCCs
  - ***ItemCF*** did not work well.
- ***UserCF* is more suitable to the HCC generation task.**

Several Examples of HCC (ETL4)



- HCCs generated by ***BestFit*** slightly differ from each other while keeping the similar shape with ***original***.
- This is also the case with ***UserCF***.

➡ **within-person variety**

Several Examples of HCC (ETL5)

- HCCs generated by ***BestFit*** slightly differ from each other while keeping the similar shape with ***original***.
- This is also the case with ***UserCF***.

➡ **within-person variety**

Conclusion

- **Proposal:** A method for generating HCCs from a limited size of training data
  - The target writer only offers at most one or zero image per character, i.e., an incomplete seed character set.
  - To achieve within-person variety, the feature distribution of the target user's handwriting is estimated for each character.
- **Idea:**
  - For seed characters: *BestFit* strategy
  - For non-seed characters: Collaborative Filtering (*UserCF*)
- **Result:**
  - Examined the proposed method with a dataset of Japanese characters
  - *UserCF* can generate good HCCs with a certain level of within-person variety