

A Prototypical Signature Approach for Writer-Independent Offline Signature Verification

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ÉCOLE DE TECHNOLOGIE SUPÉRIEURE (ÉTS) - UNIVERSITÉ DU QUÉBEC, MONTREAL, CANADA

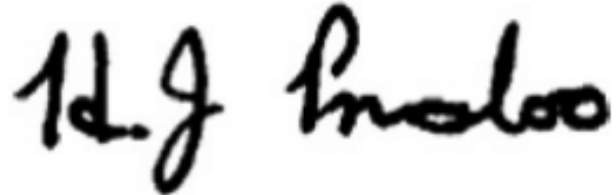
ICPR 2026

The Main Goal: Detecting Skilled Forgery

Signatures



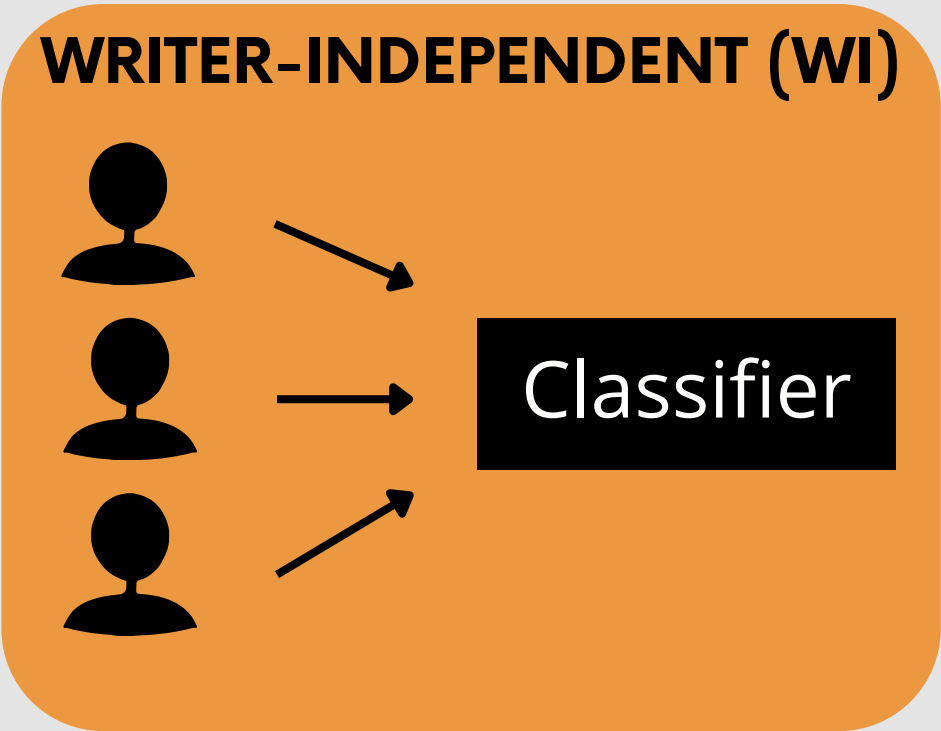
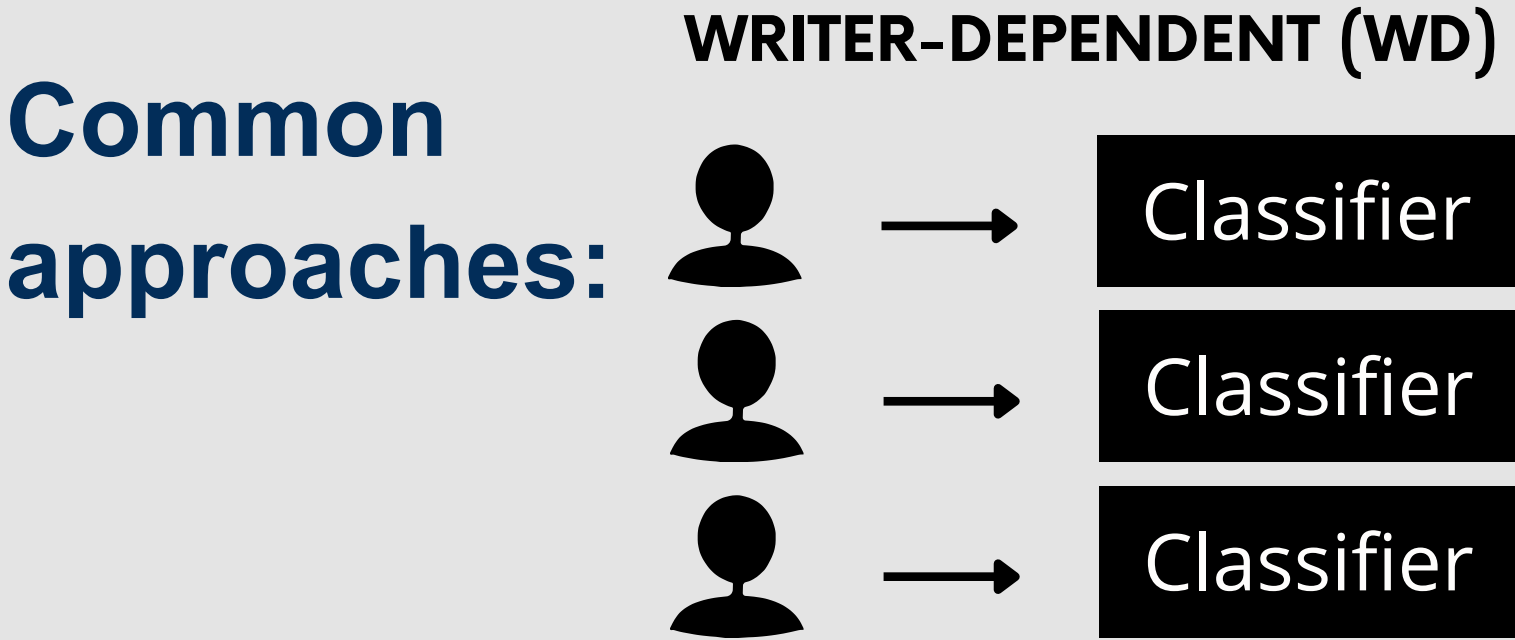
GENUINE



RANDOM FORGERY



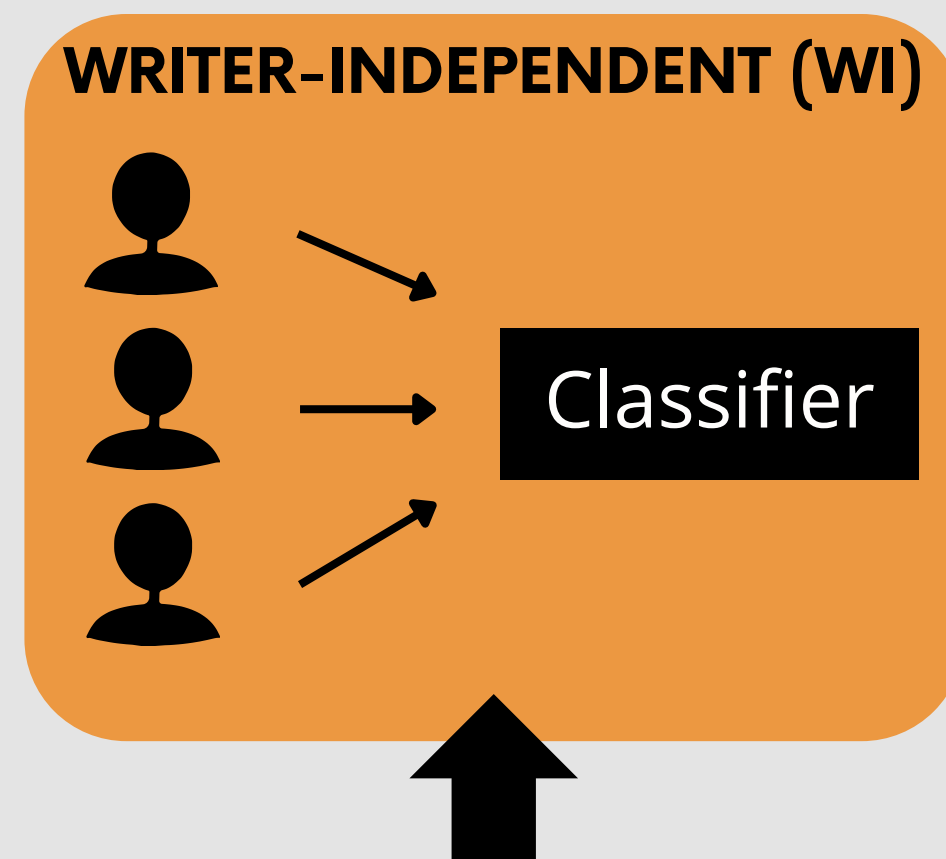
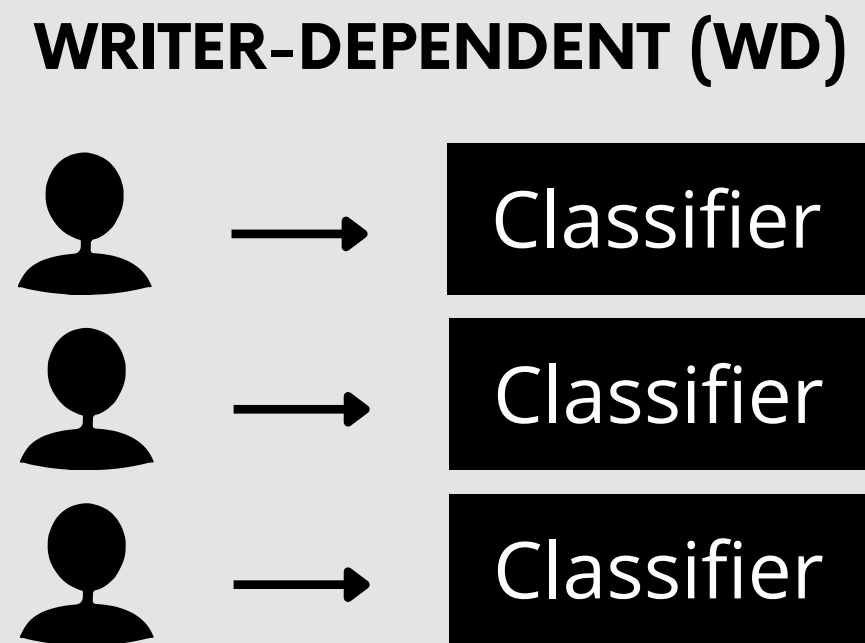
SKILLED FORGERY



The Main Goal: Detecting Skilled Forgery



Common approaches:



TRAINING WITH DISSIMILARITIES:

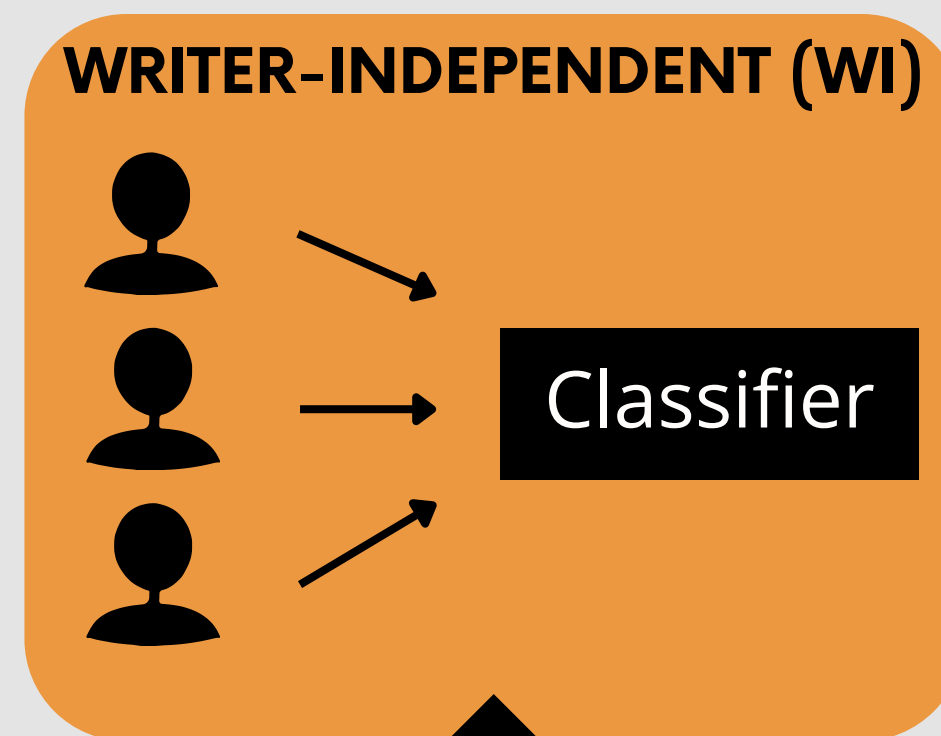
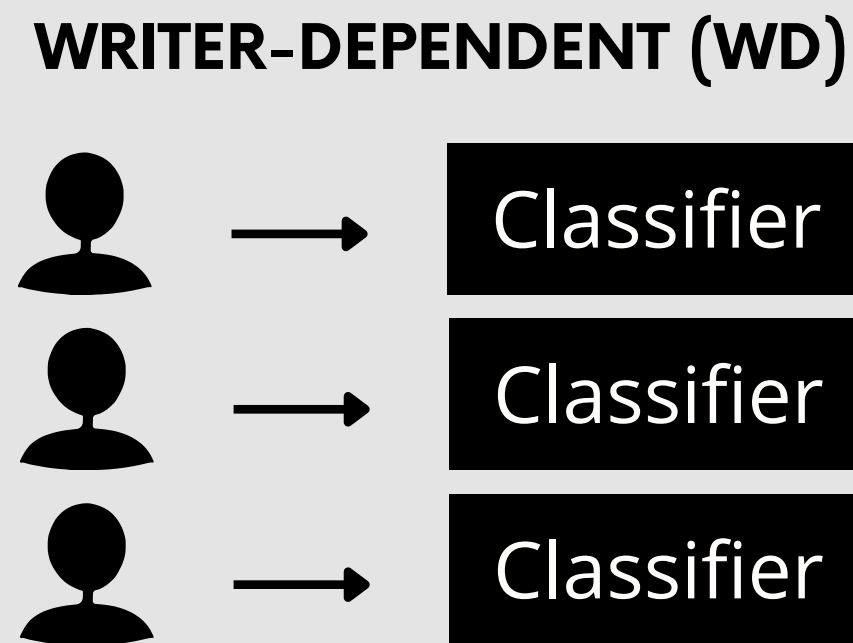
GENUINE/GENUINE GENUINE/FORGERY

+ -

The Main Goal: Detecting Skilled Forgery



Common approaches:

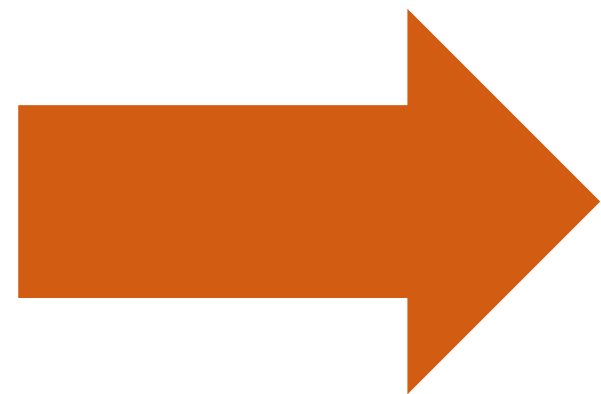
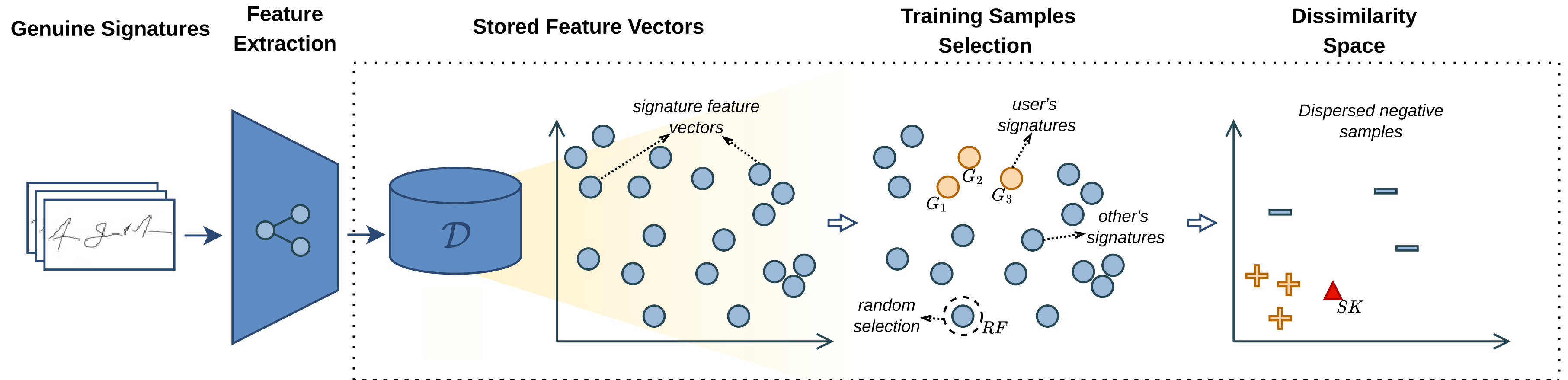


Challenge: Skilled forgeries are usually **not** available during training.

TRAINING WITH DISSIMILARITIES:

GENUINE/GENUINE + GENUINE/FORGERY -

The Status Quo: Relying on Random Forgery



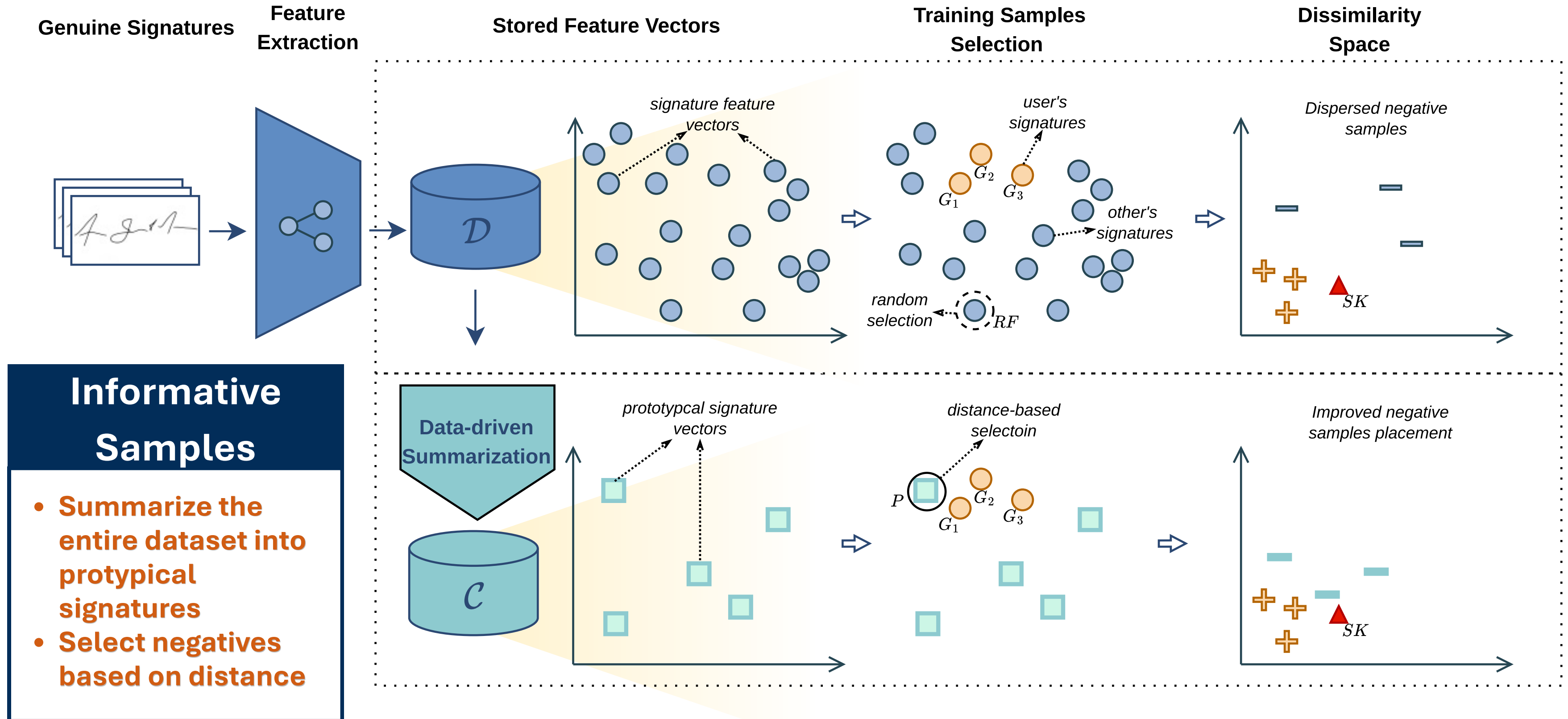
Poor Localization

Random forgeries are widely scattered across the feature space.

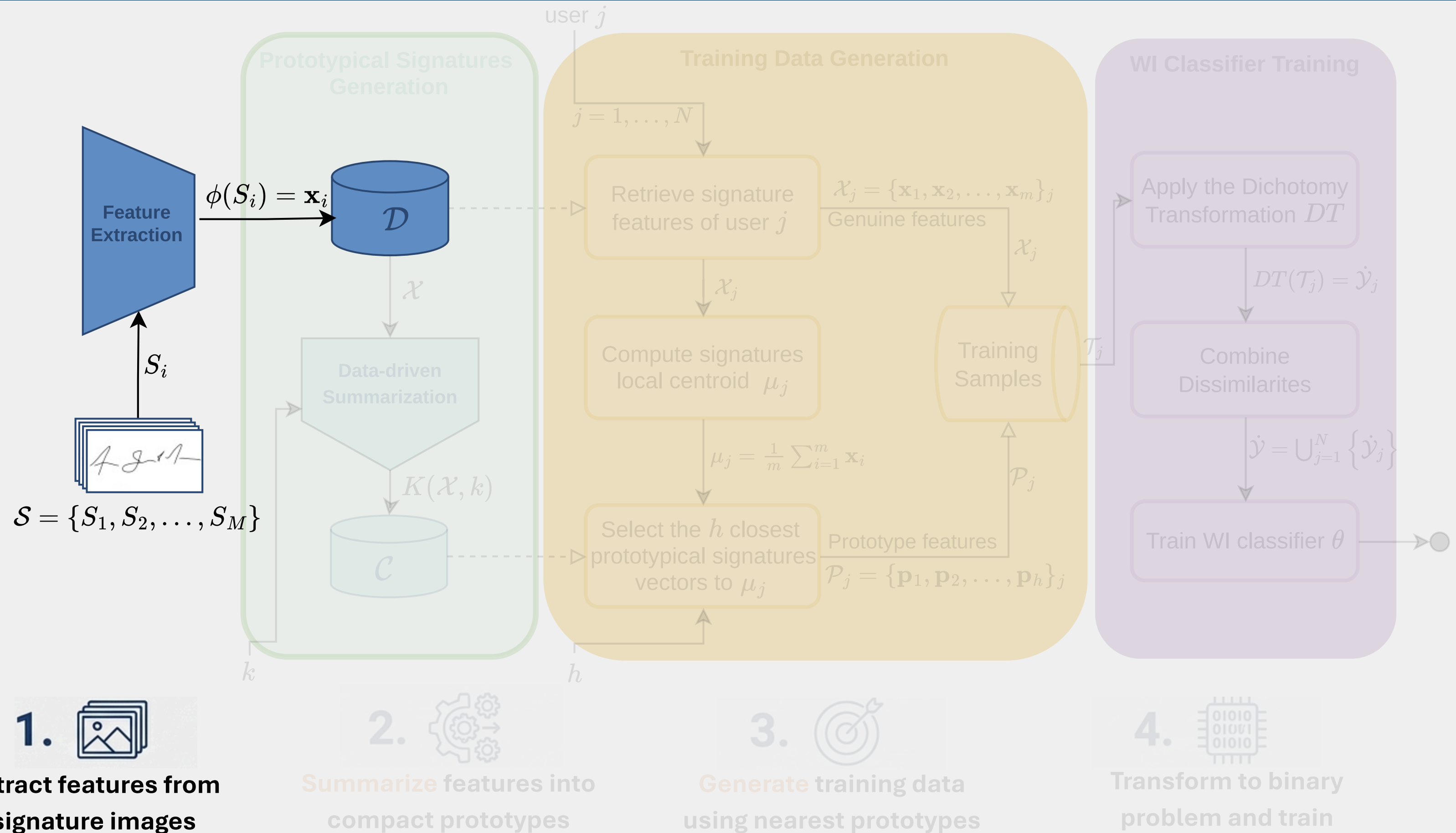
Limited Approximation

Fails to provide the proximity-based characteristics of skilled forgeries.

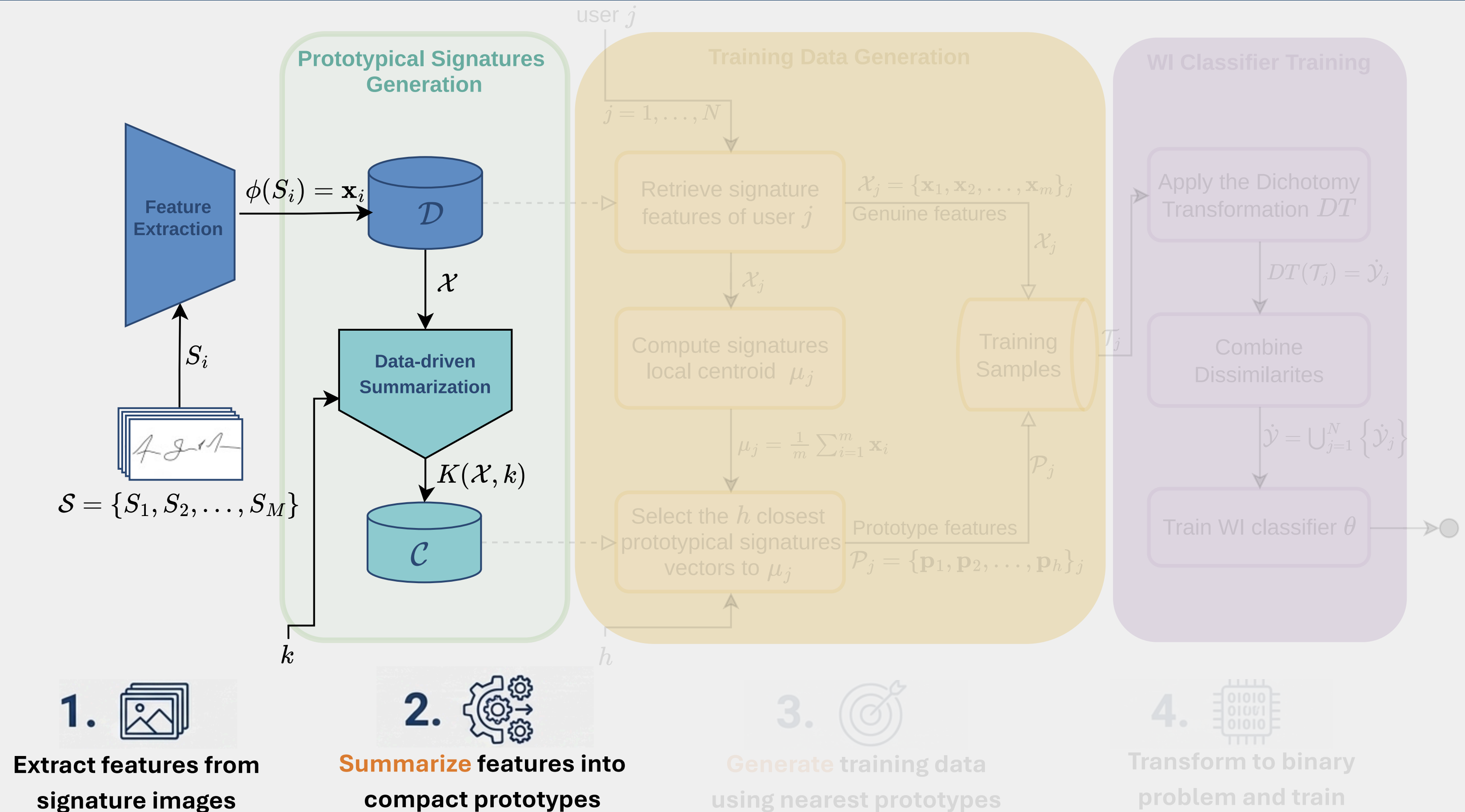
Our Approach: Prototypical Signatures



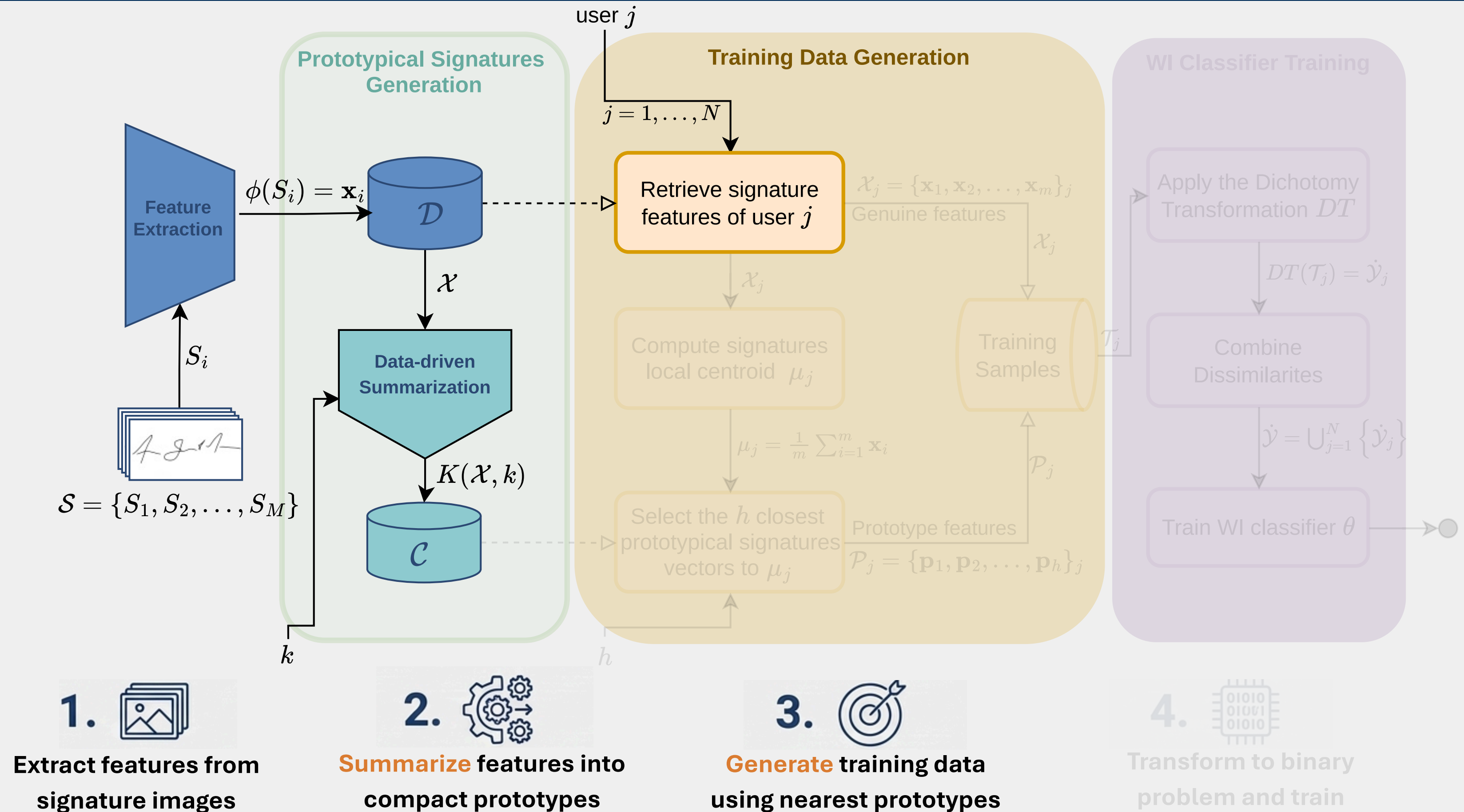
The Proposed Method



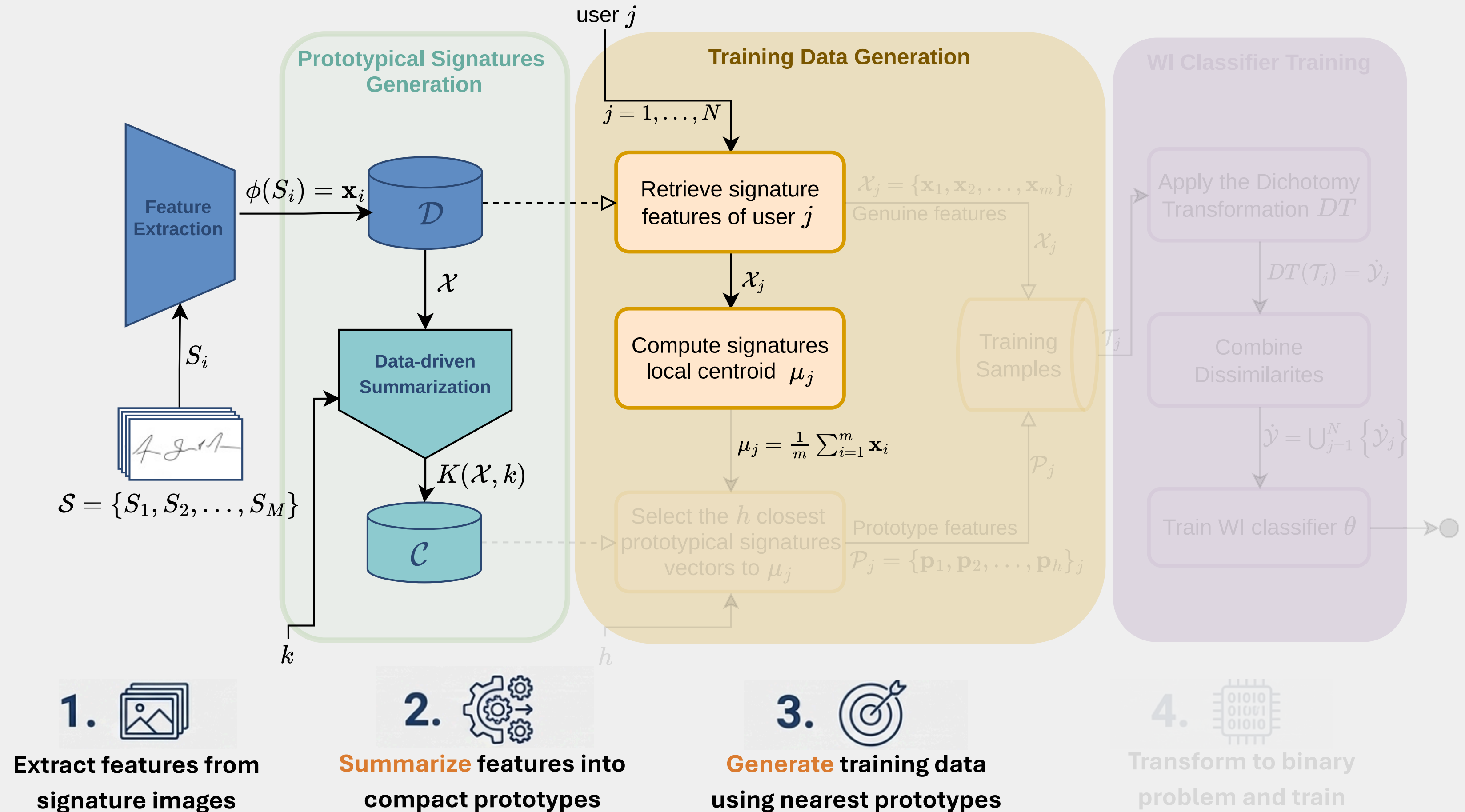
The Proposed Method



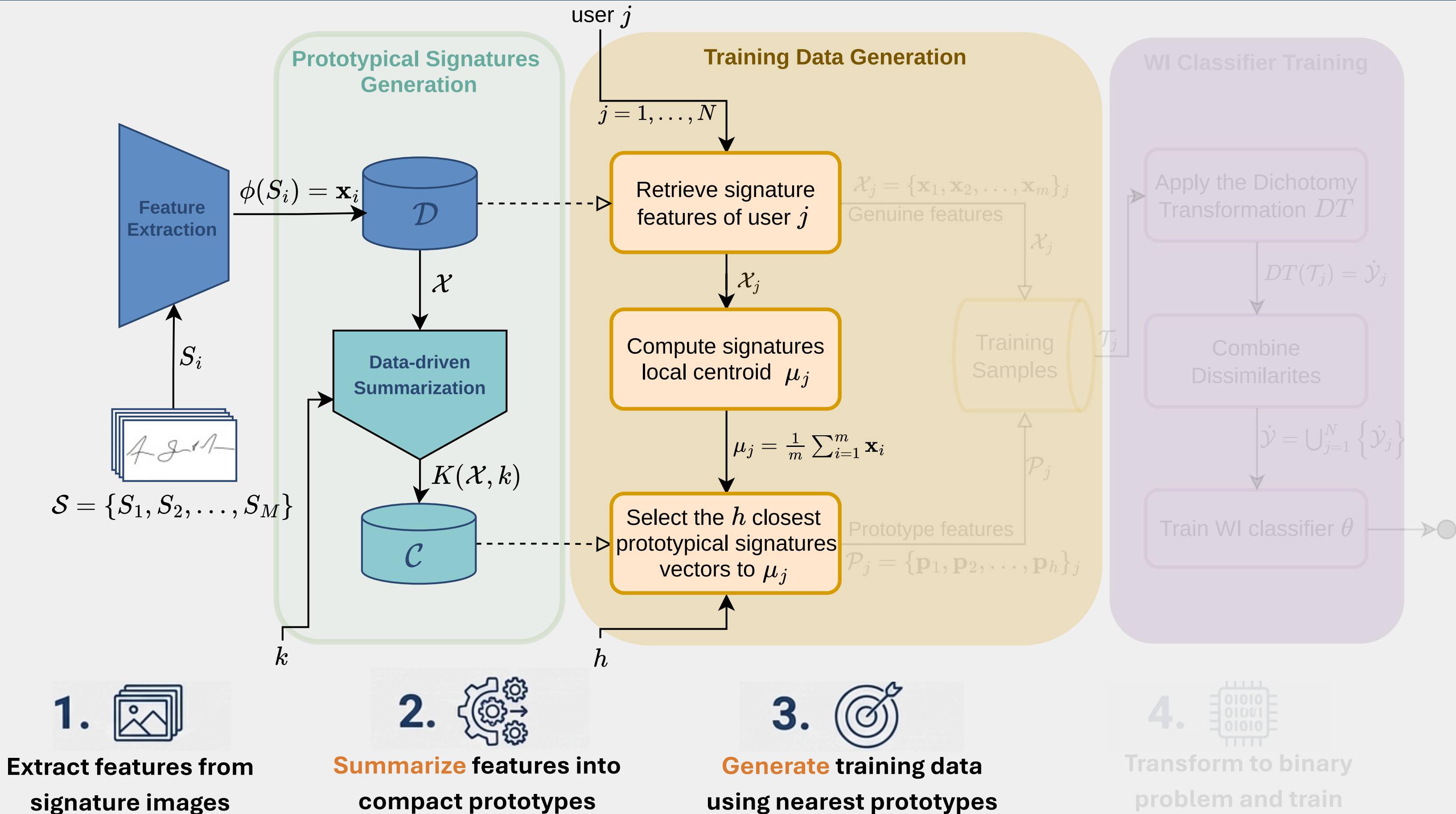
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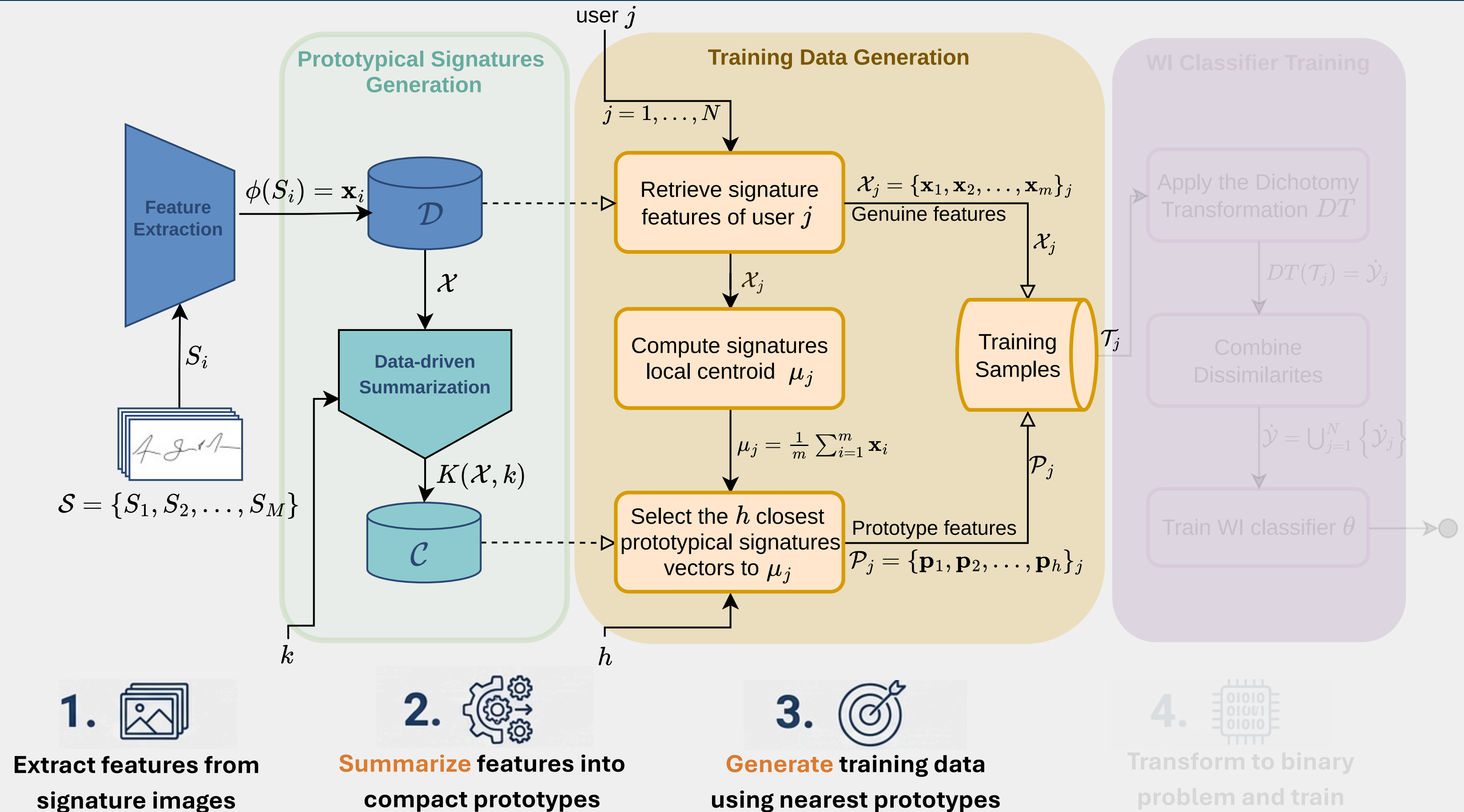
The Proposed Method



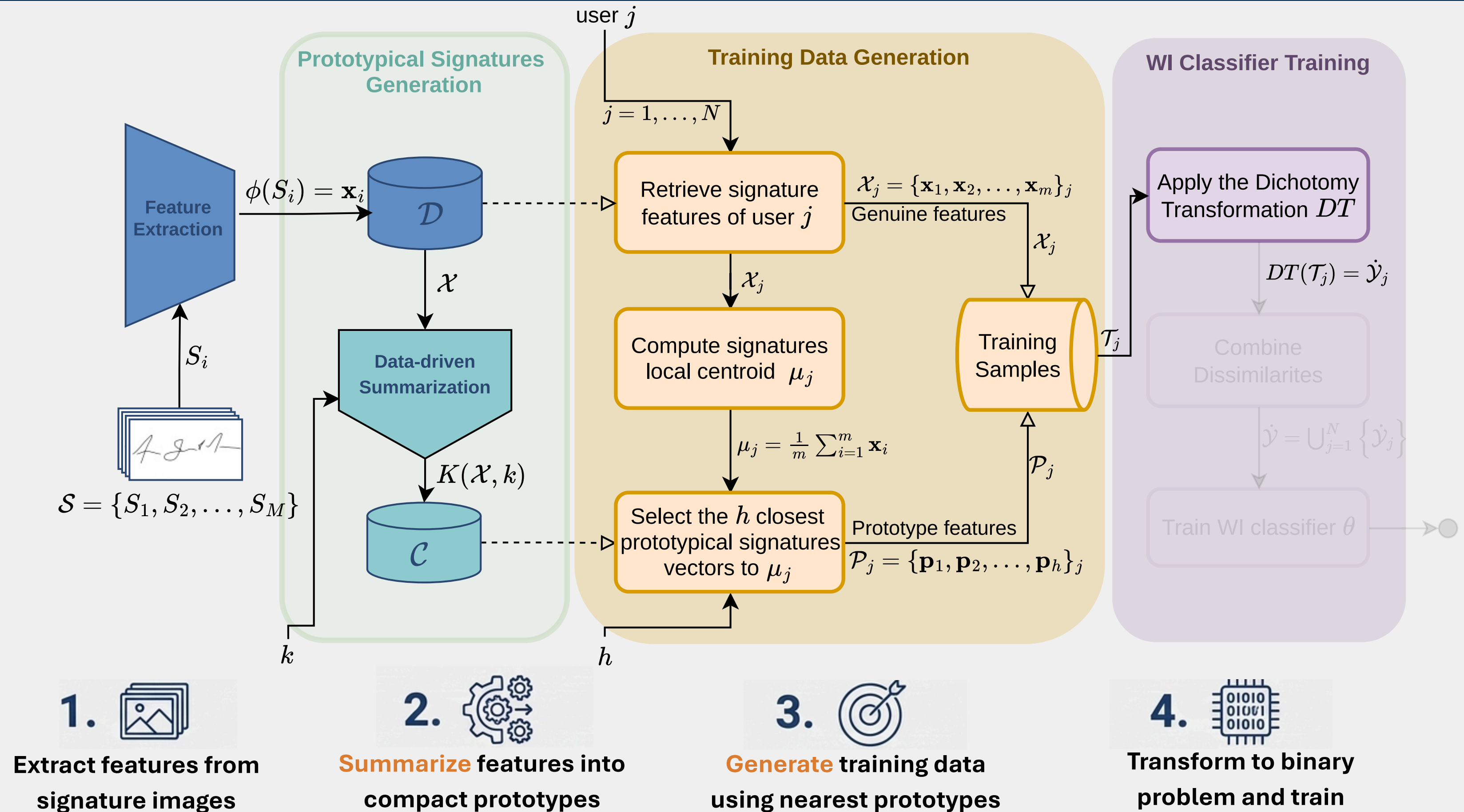
The Proposed Method



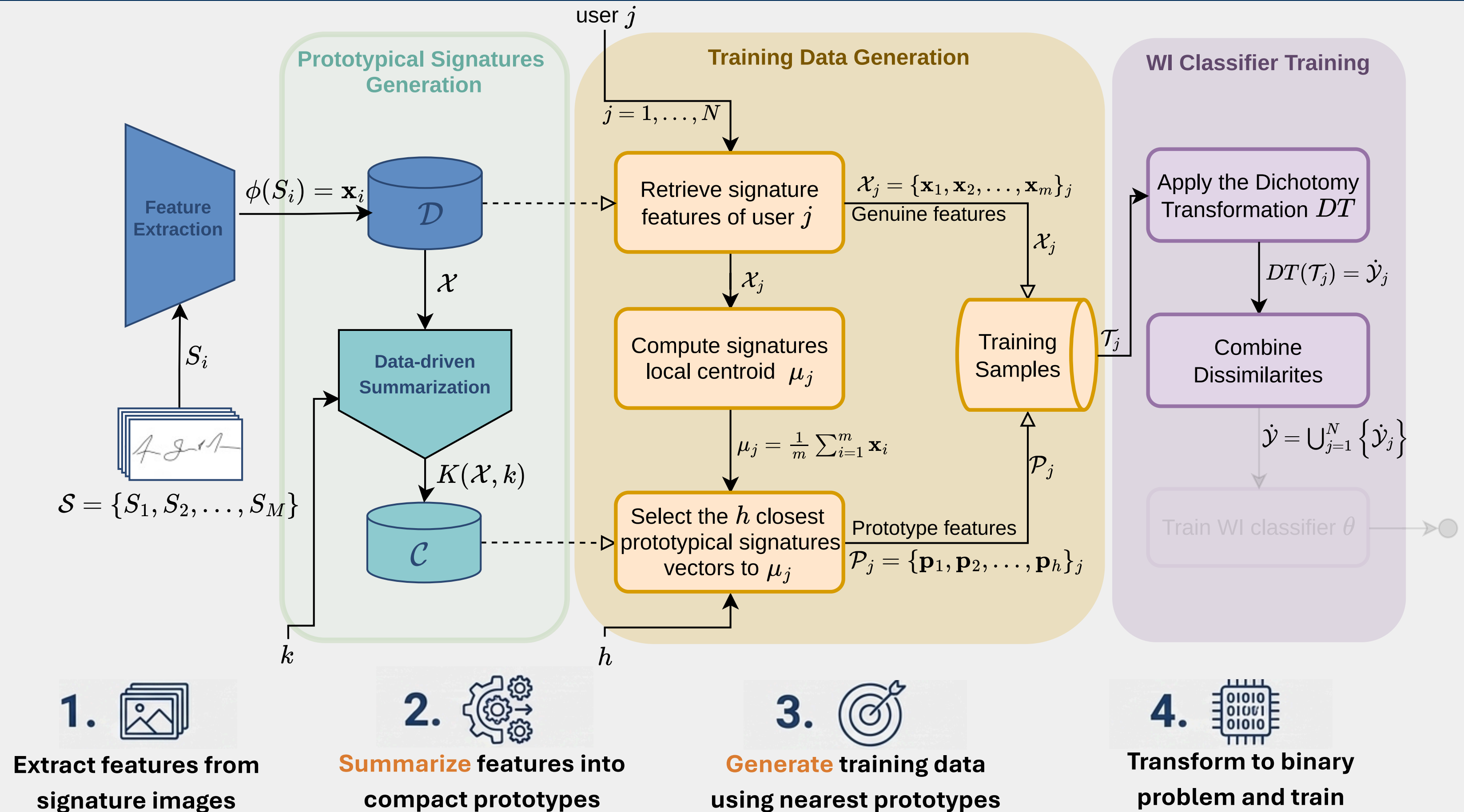
The Proposed Method



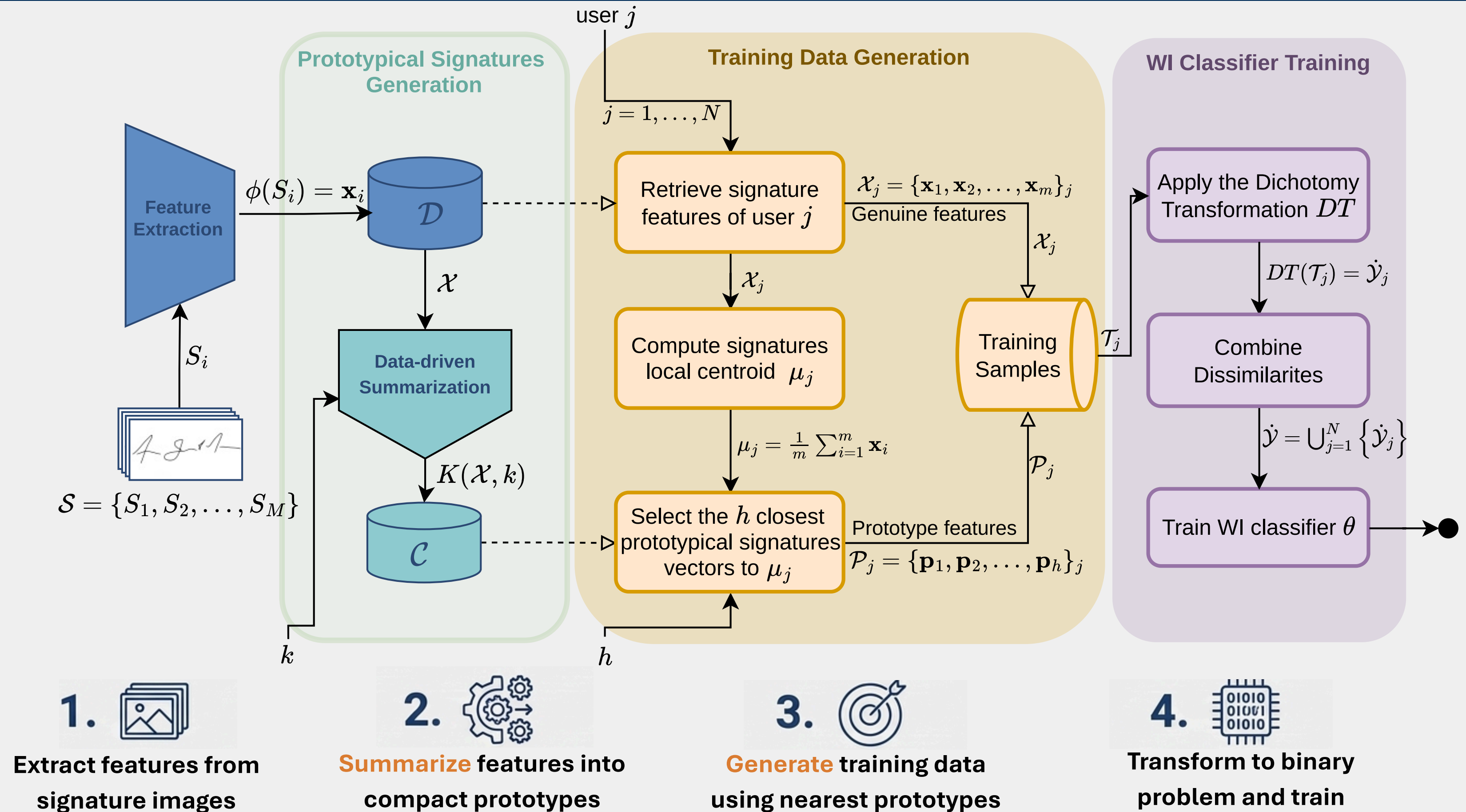
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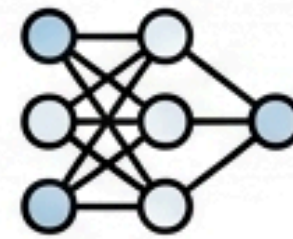


Experimental Setup



Datasets

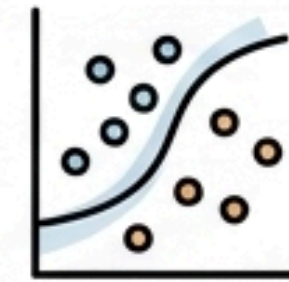
- **CEDAR**
 - 55 users | 24 genuine | 24 forgeries
- **MCYT-75**
 - 75 users | 15 genuine | 15 forgeries
- **GPDS Synthetic**
 - 10000 users | 24 genuine | 24 forgeries



Feature Extraction

Different backbones, 7 models

- **AlexNet**
 - SigNet-S trained on GPDS-S (Viana, et al., 2023)
 - Continual SigNet (Viana, et al., 2024)
- **ResNet**
 - ResNet18: GEOM + BT (Tsourounis et al., 2025)
 - ResNet18: GEOM + BC (Tsourounis et al., 2025)
 - ResNet18: GEOM + TCE (Tsourounis et al., 2025)
 - Continual ResNet152 (Viana, et al., 2024)
- **Vision Transformer (ViT)**
 - Continual ViT (Viana, et al., 2024)



Classifiers

- **SVM-RBF**
 - Standard, computationally heavy baseline
- **SVM-Linear (SGD)**
 - Trained via primal formulation using SGD.

Evaluation Metric: Equal Error Rate (EER)

Experimental Setup



Datasets

Data Segmentation

Dataset	Development set $\mathcal{D}$		Exploitation set $\mathcal{E}$	
	Users	ID range	Users	ID range
CEDAR [11]	27	1–27	28	28–55
MCYT-75 [15]	37	1–37	38	38–75
GPDS Synthetic [7]	581	301–881	300	1–300

Experimental Setup



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(a) Development set ($\mathcal{D}$).

Dissimilarities Generation

Method	Negative class <i>Distance between:</i>	Positive class <i>Pairwise distance of:</i>
Standard	6 random forgeries and 11 genuine signatures for each user	12 genuine signatures for each user
Summarization	6 prototypical signatures and 11 genuine signatures for each user	

Summarization is performed via k-means clustering

Experimental Setup



Datasets

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(b) Exploitation set ($\mathcal{E}$).

Data	Reference set	Claimed set
CEDAR	$r \in \{1, 2, 3, 5, 10, 12\}$	10 genuine, 10 random, 10 skilled
GPDS-S	$r \in \{1, 2, 3, 5, 10, 12\}$	10 genuine, 10 random, 10 skilled
MCYT	$r \in \{1, 2, 3, 5, 10\}$	5 genuine, 5 random, 5 skilled

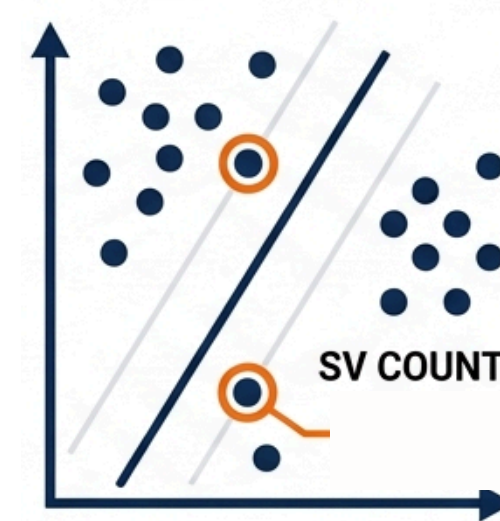
Summarization is performed via k-means clustering

Experimental Setup



Training and testing time (in seconds):

Measures the total time required for model training and prediction.



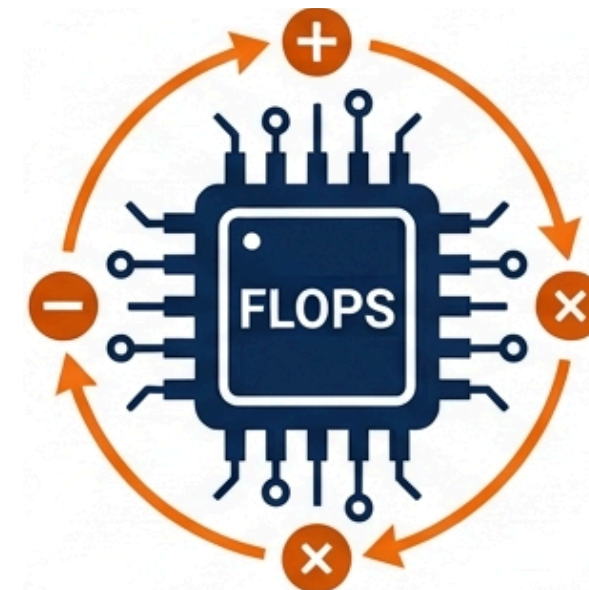
Number of support vectors (SV):

Indicates model complexity, since more support vectors generally increase memory and prediction cost.



Model size (in megabytes):

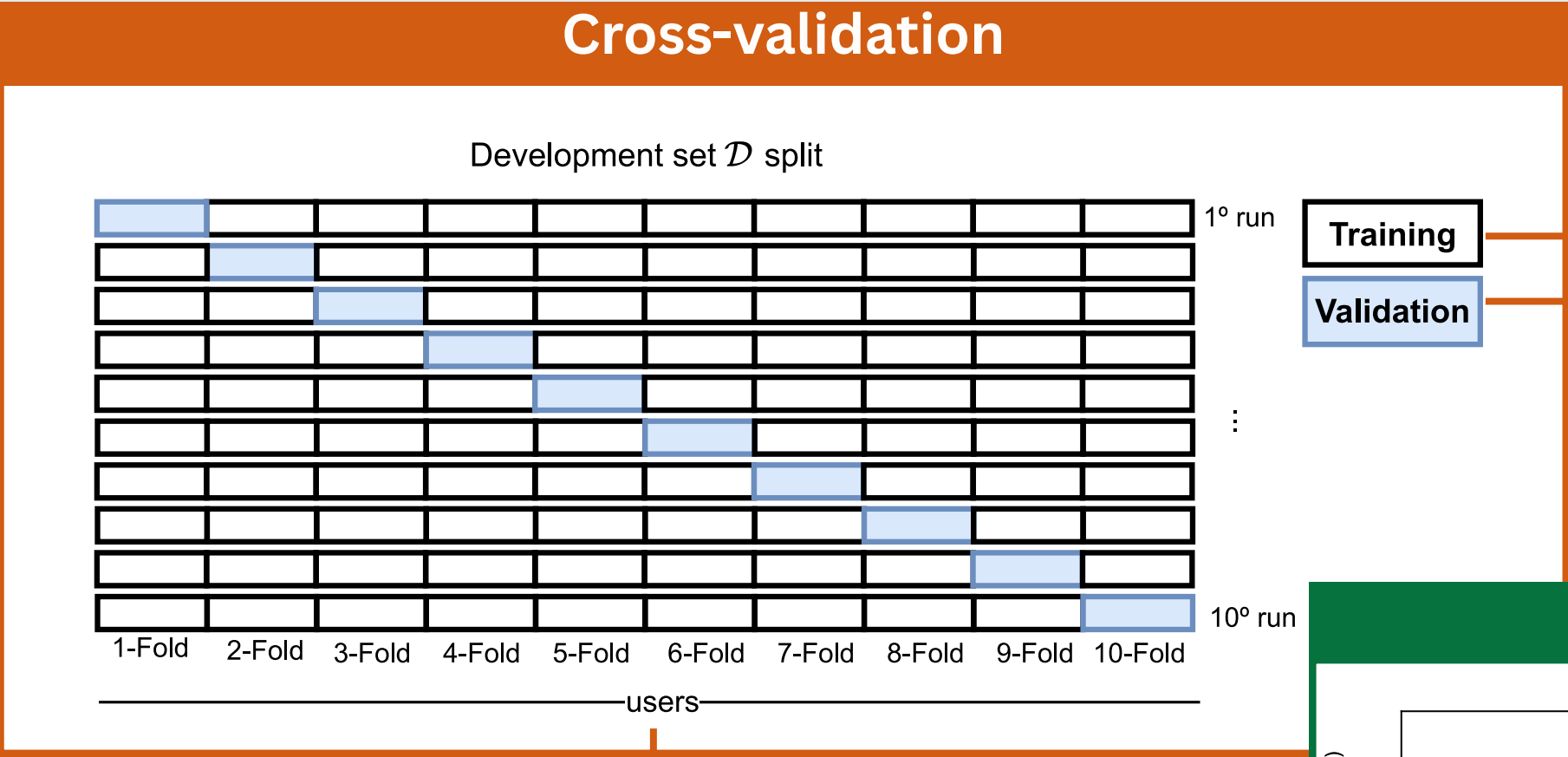
Evaluates the trained model's total storage.



Training and testing FLOPs

(floating-point operations):
Quantifies the computational cost for training and prediction.

Defining the summarization hyperparameter k



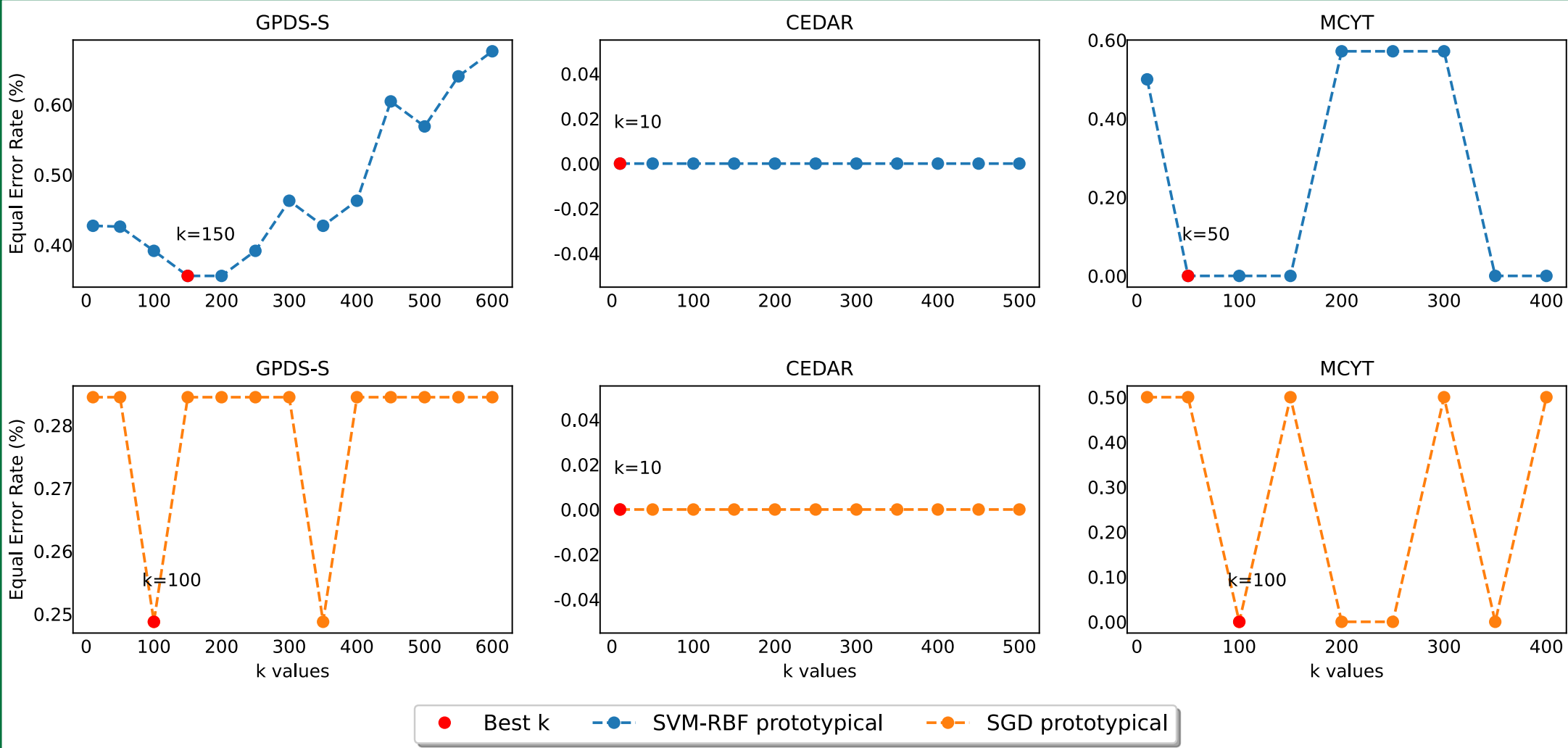
Only Genuine Signatures

- Genuine and prototypical signatures
- Genuine and random forgeries

Disjoint subsets of users

The Summarization Method
k-means, with k-values
raging from 10 to 600

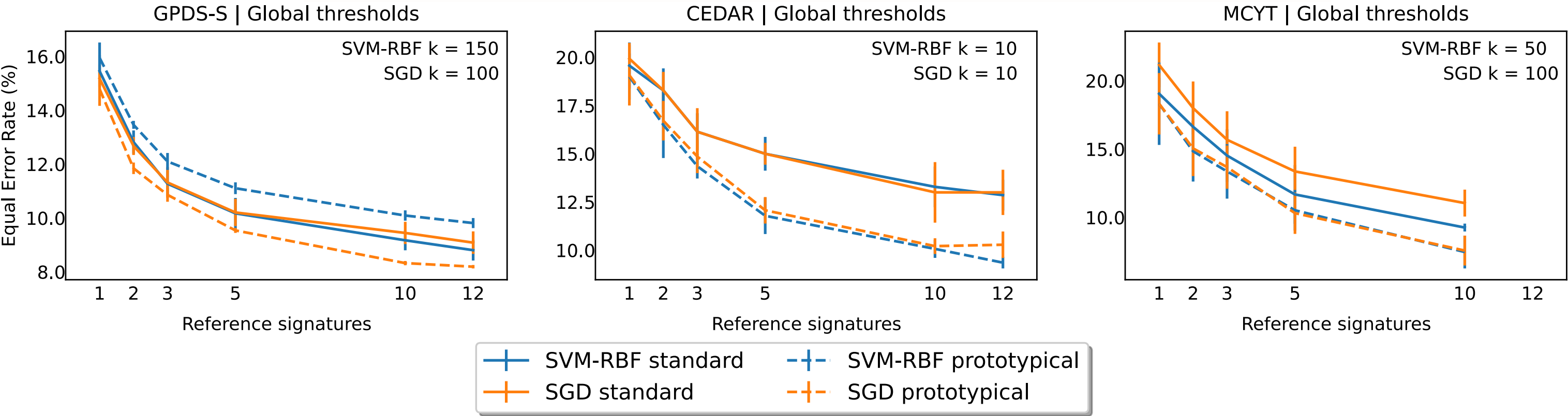
Best k value on each dataset



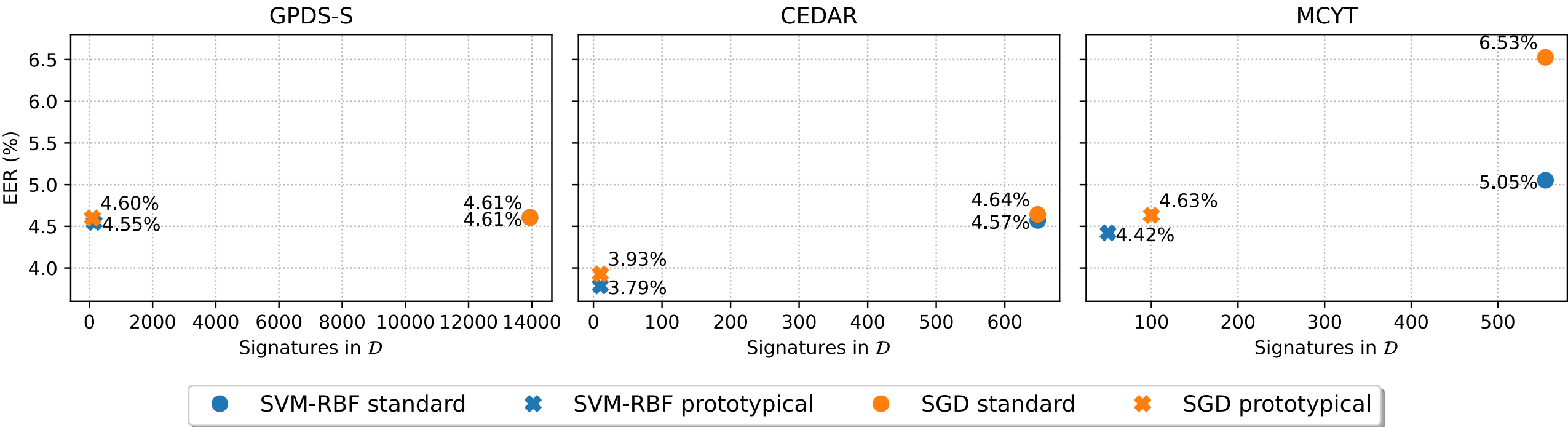
Performance with Prototypical Signatures

Lower or
Comparable
EER

Skilled forgery detection under global thresholds.

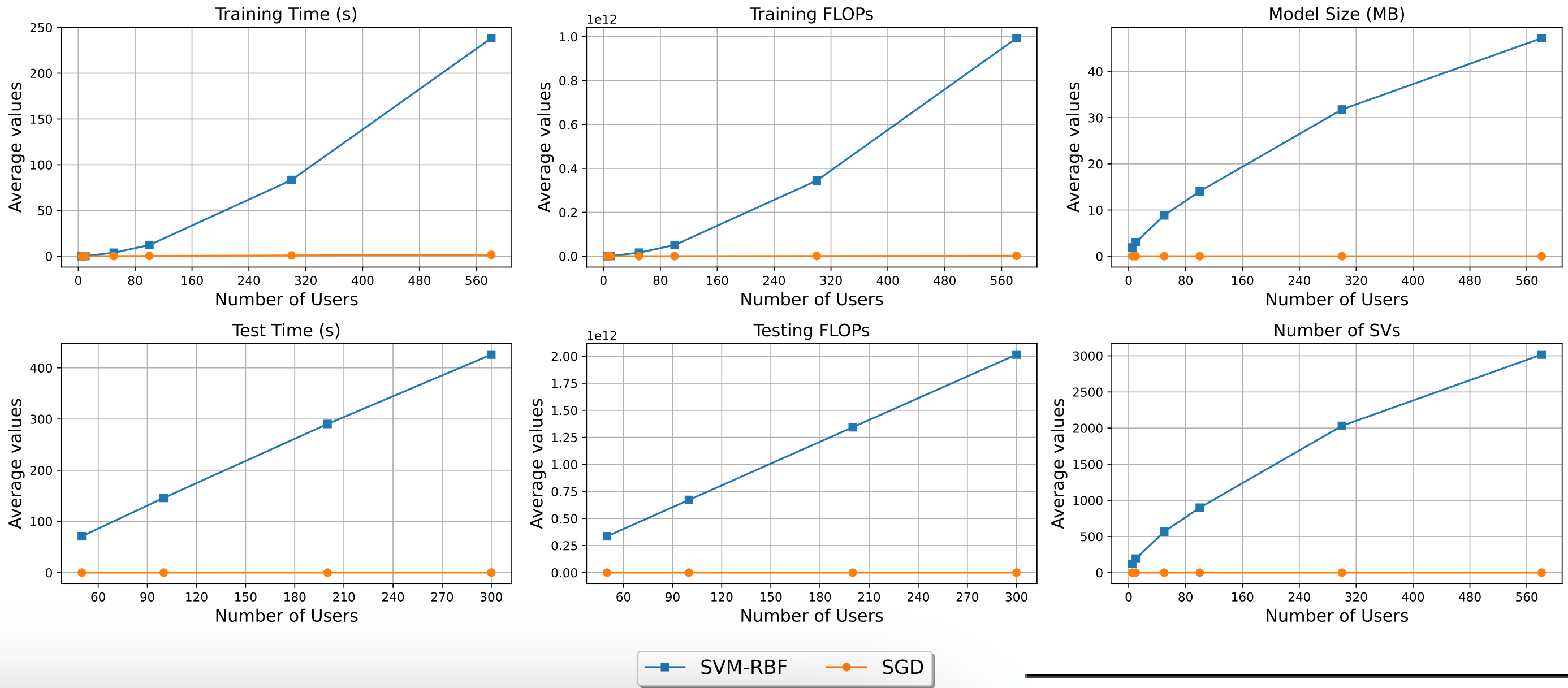


EER under user-specific thresholds vs. development set size.



Reduced
Development Set
Size

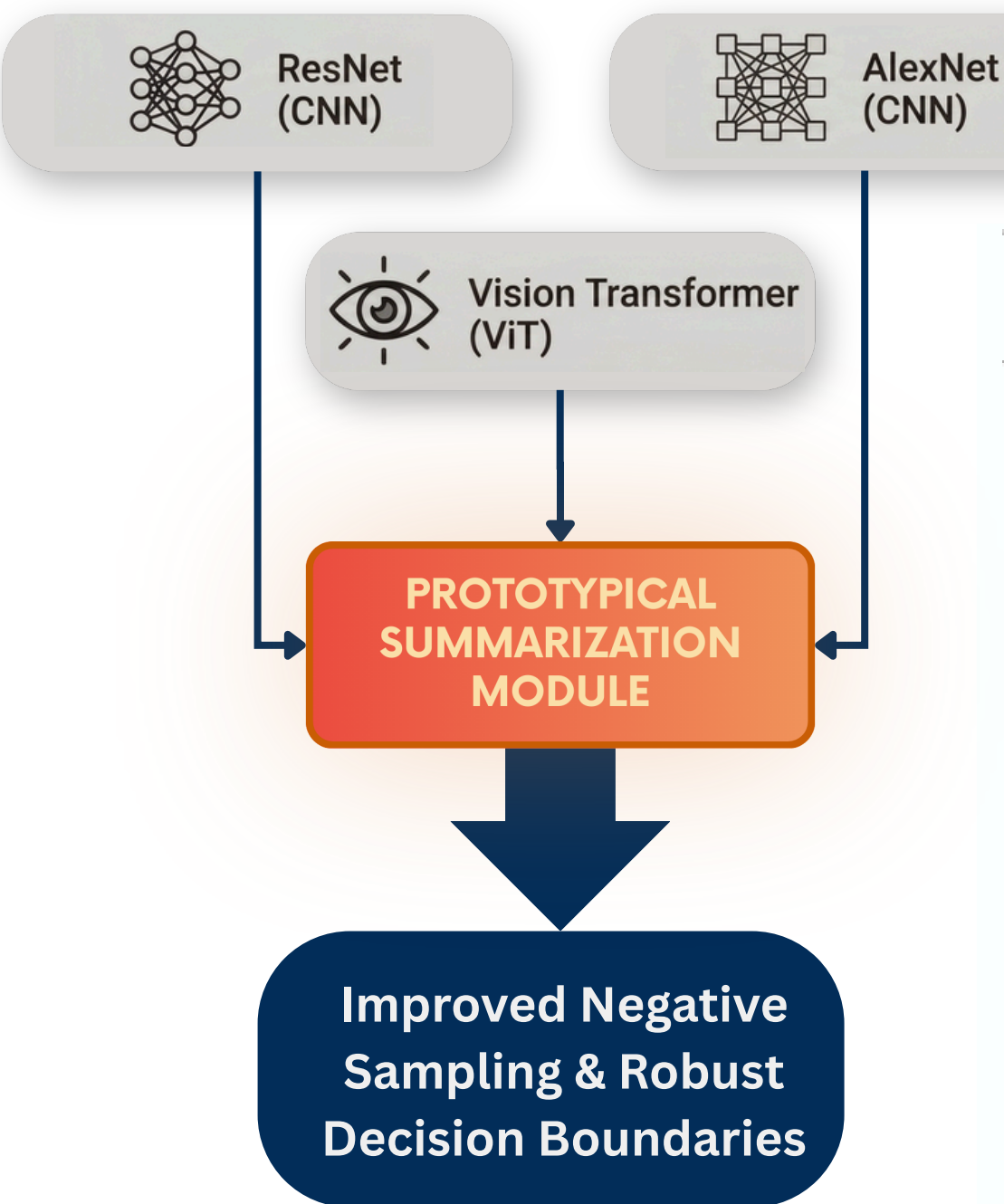
Computational Complexity



≈150× faster training
≈3,900× faster inference
>5,000× smaller model
≈18 million× fewer inference FLOPs

Metric	SVM-RBF	SVM-Linear (SGD)
Training Time (s)	238.31	1.59
Testing Time (s)	425.95	0.11
Model Size (KB)	47,205.95	8.91
Number of SVs	3017	0
Training FLOPs	9.93×10^{11}	1.88×10^9
Testing FLOPs	2.02×10^{12}	1.10×10^5

A Backbone Agnostic Approach



EER under user-specific thresholds.
Results demonstrating statistical equivalence are highlighted.

Dataset	Model	$EER_{user} (\%)$		p-value	% in ROPE	95% HDI
		Standard	Prototypical			
CEDAR	ResNet18 CL + KD: GEOM with BC	2.39 ± 0.48	1.93 ± 0.43	0.04	100.0	−0.009 – 0.000
	ResNet18 CL + KD: GEOM with BT	1.29 ± 0.46	1.29 ± 0.83	1.00	99.3	−0.009 – 0.009
	ResNet18 CL + KD: GEOM with TCE	1.43 ± 0.53	1.93 ± 0.74	0.20	98.5	−0.004 – 0.014
	Continual ResNet152	2.64 ± 0.68	2.93 ± 0.76	0.16	99.0	−0.007 – 0.012
	Continual SigNet	2.61 ± 0.42	2.39 ± 0.60	0.53	99.7	−0.010 – 0.006
	Continual ViT	3.14 ± 0.75	3.18 ± 0.44	0.91	99.9	−0.007 – 0.008
GPDS-S	Continual ResNet152	4.02 ± 0.32	4.21 ± 0.28	0.09	100.0	−0.001 – 0.004
	Continual SigNet	4.18 ± 0.31	4.55 ± 0.20	0.02	100.0	0.001 – 0.007
	Continual ViT	5.69 ± 0.34	7.65 ± 0.44	0.00	3.0	0.015 – 0.025
MCYT	ResNet18 CL + KD: GEOM with BC	4.16 ± 0.89	5.42 ± 1.27	0.02	66.9	0.002 – 0.024
	ResNet18 CL + KD: GEOM with BT	4.32 ± 1.45	3.95 ± 1.34	0.59	91.6	−0.015 – 0.013
	ResNet18 CL + KD: GEOM with TCE	4.26 ± 0.83	5.68 ± 1.28	0.00	58.4	0.005 – 0.023
	Continual ResNet152	3.53 ± 1.45	4.84 ± 0.77	0.06	61.0	−0.001 – 0.027
	Continual SigNet	2.68 ± 1.12	3.11 ± 0.95	0.47	93.9	−0.009 – 0.014
	Continual ViT	6.32 ± 1.37	9.63 ± 2.05	0.00	1.5	0.017 – 0.049

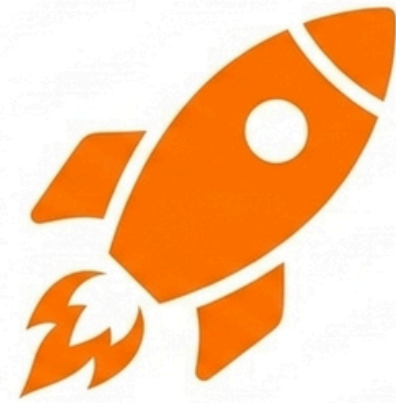
- Frequentist: Shapiro–Wilk for normality → paired t-test or Wilcoxon signed-rank → p-values (alpha=0.05)
- Bayesian: 95% HDI vs. ROPE [−0.015, 0.015] → equivalence if HDI $\subset$ ROPE

Main Contributions



Informative Negative Samples

Prototypical signatures provide superior approximation of skilled forgeries compared to random forgeries sampling.



Massive Scalability

Achieved >98% data reduction. Enables the use of Linear SVMs, dropping computational memory and FLOP costs by orders of magnitude.



Backbone-Agnostic

Acts as a universal, plug-and-play module that integrates seamlessly with any existing or future feature extraction architecture.

Future Works

- Alternative clustering methods
- Adaptive learning of prototypical signatures

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- rafael.menelau-cruz@etsmtl.ca

Pages:

- https://github.com/kdmoura/proto_hsv
- <https://www.etsmtl.ca/en/labs/livia>
- <https://www.etsmtl.ca/>



THANK YOU!