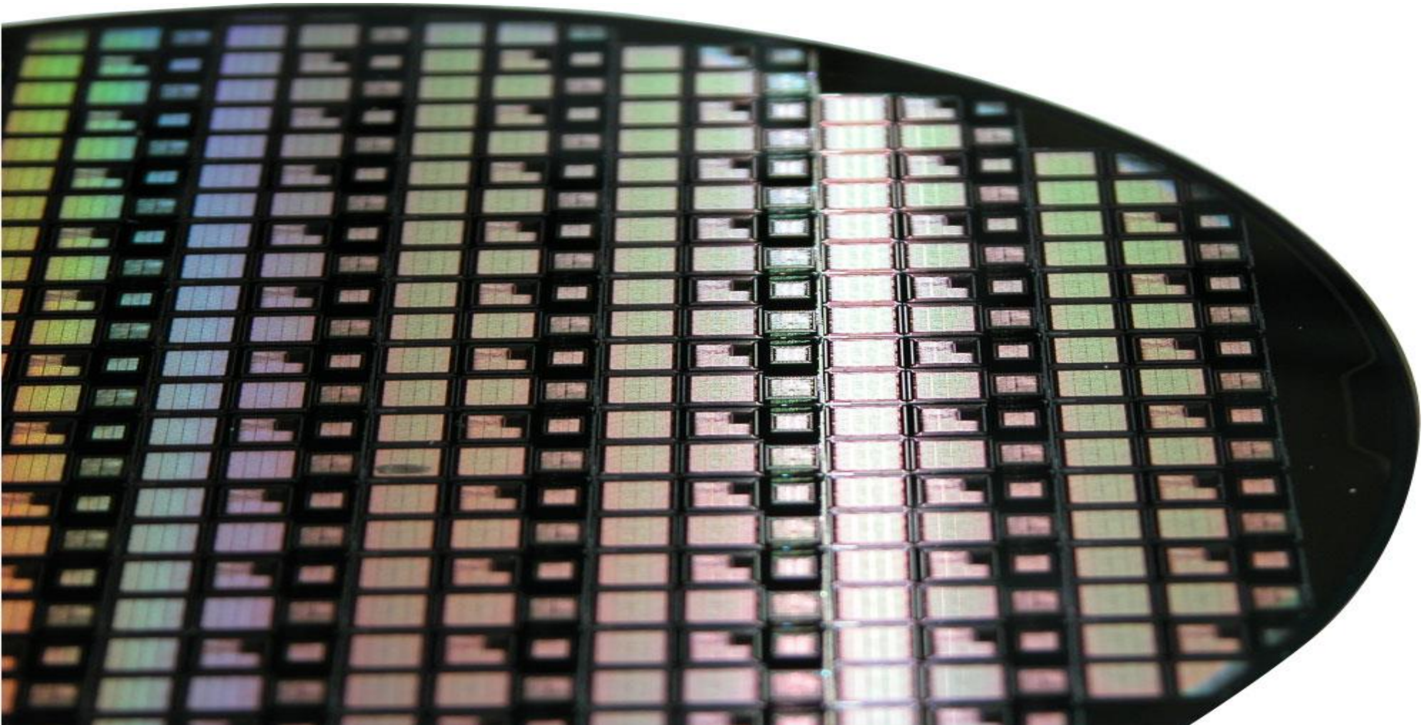
Compressing Subject-specific Brain-Computer Interface Models into One Model by Superposition in Hyperdimensional Space



22 April 2020

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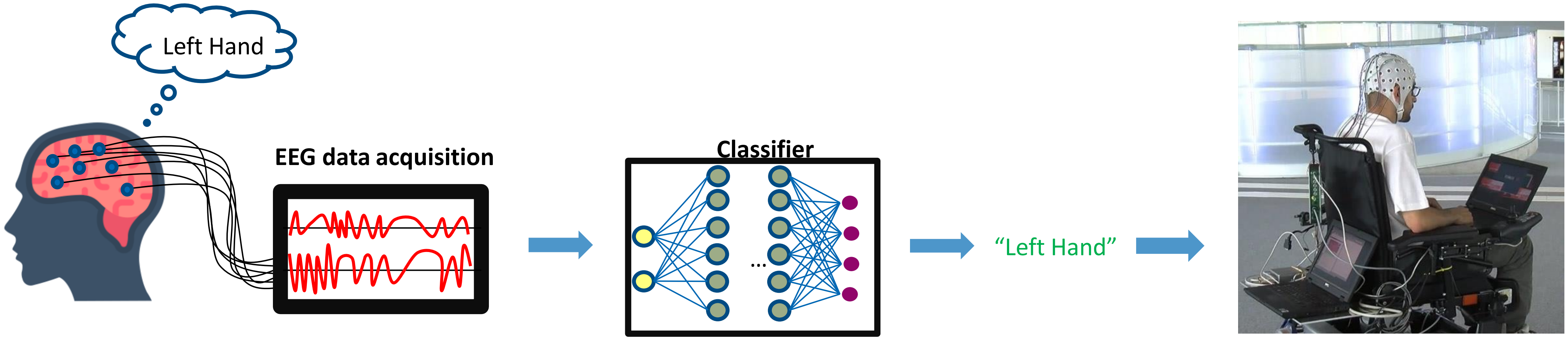
Towards wearable embedded Motor-Imagery Brain – Computer Interfaces (MI-BCIs)



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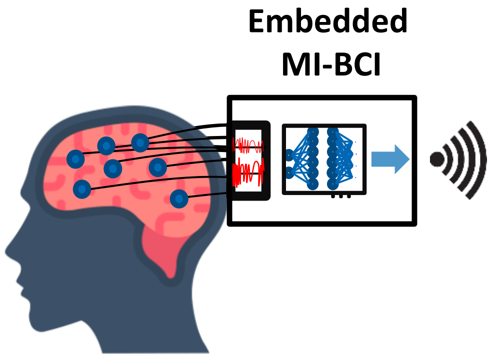
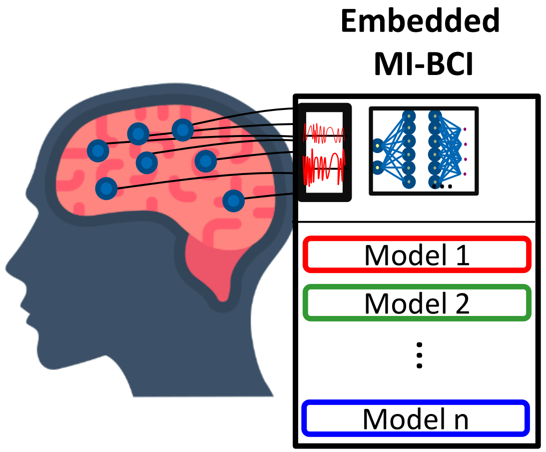


Why embedded embedded MI-BCI?

- User comfort
- Latency
- Security & privacy
- Long-term usability

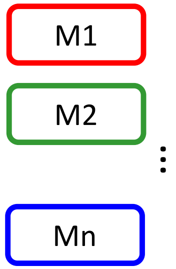
Subject-specific models pose a challenge for embedded MI-BCIs

- MI-Brain signals are highly subject dependent
  $\Rightarrow$Need to train subject-specific models
- Store **multiple subject-specific models on device**
  - Device for multiple subjects
  - Model selection on unseen subjects
- We need to reduce memory footprint!

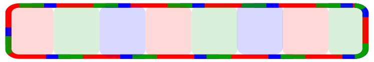


Global Model

Quantization



Superposition

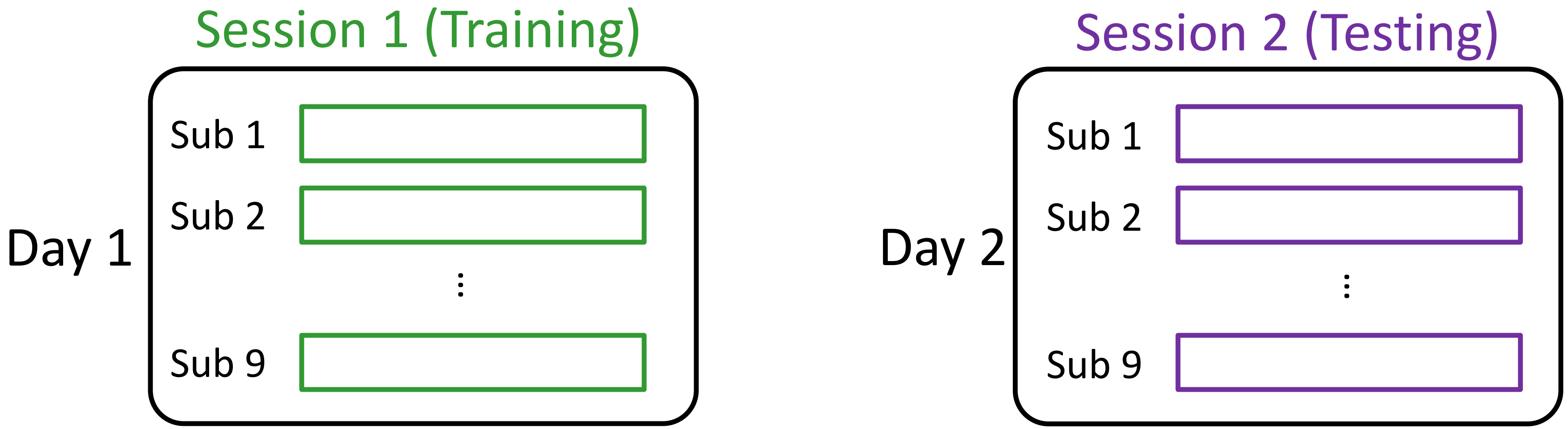


This Work: Model compression by **hyperdimensional superposition**

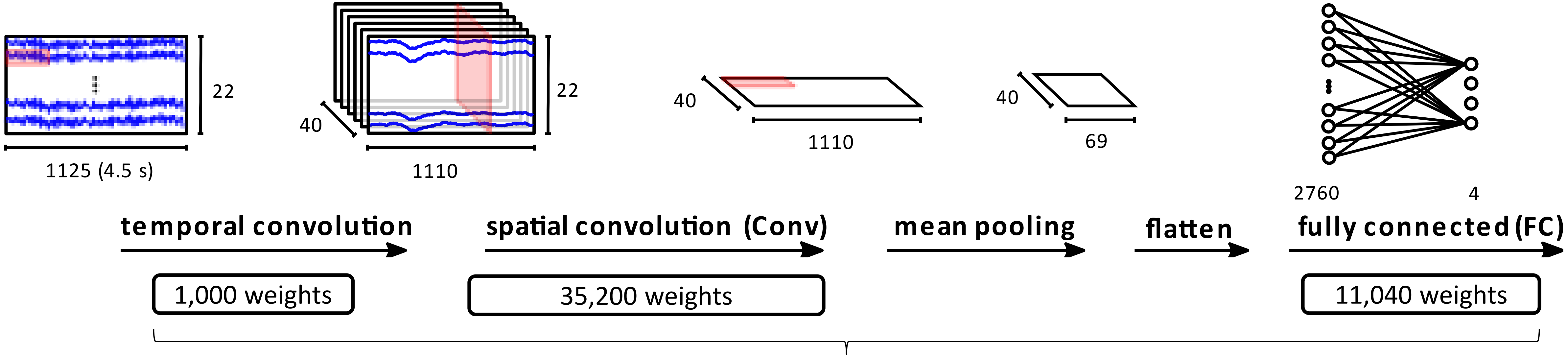
- Compress subject-specific CNN models with **superposition**
- Novel **retraining method** to counteract compression noise
- Compress two compact SoA CNNs by **up to 3x with slightly better accuracy**
  - Shallow ConvNet **+1.46%**
  - EEGNet +**2.41%**

The BCI competition IV-2a dataset is still a big challenge

- **9 subjects**
- 2 sessions per subject: training and test set
- 288 trials per session and subject
- 4 different MI tasks initiated by visual cue
  - Left hand/right hand/feet/tongue
- 22 EEG channels sampled with 250 Hz



Shallow Convnet[1] is a **light-weight** and **accurate** CNN for MI classification



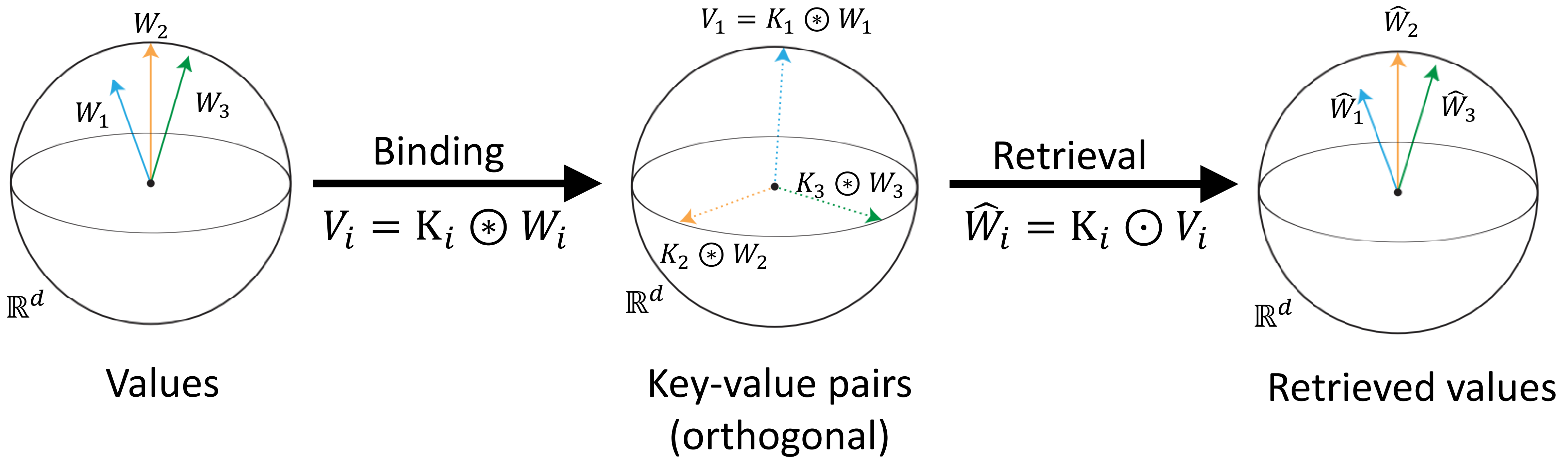
47,240 weights

One model per subject (sub-spec)

74.3% on 4-class MI

[1] Schirrmeister et al. , "Deep learning with convolutional neural networks for EEG decoding and visualization," Human Brain Mapping 2017

Orthogonalization by key-value binding in hyperdimensional space



Orthogonalized key-value pairs are **superimposed and retrieved** in hyperdimensional space

1) Superimpose multiple key-value pairs

$$\boxed{S = \sum_i K_i \circledast W_i}$$

$W \in \mathbb{R}^d$ – value

$K \in \mathbb{R}^d, K \sim N(0, \frac{1}{d}\boldsymbol{I}_d)$ – key

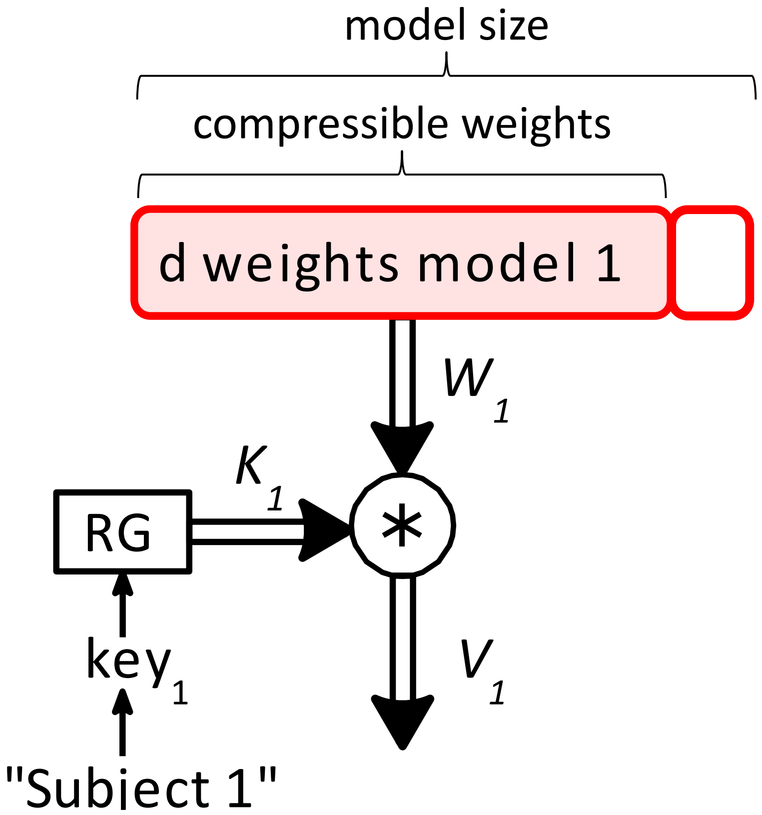
$\circledast$ – circular convolution

$\odot$ – circular correlation

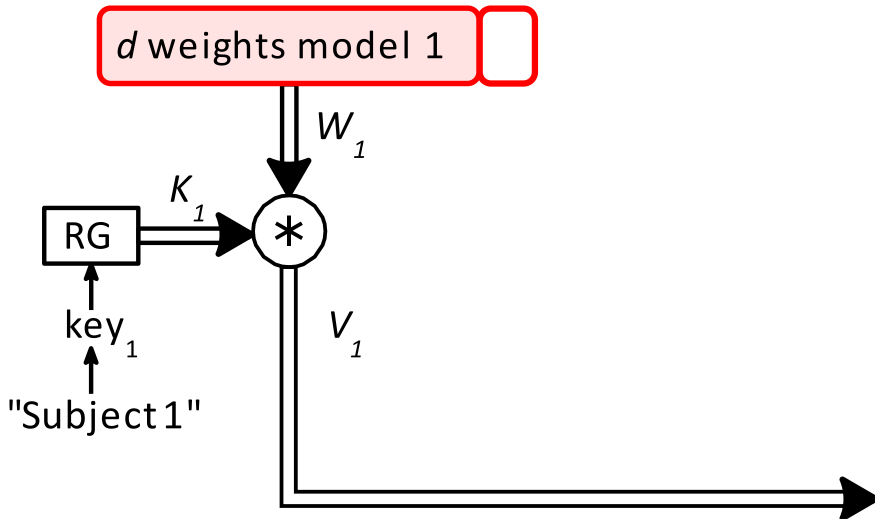
2) Retrieve values

$$\boxed{\widehat{W_k} = K_k \odot S = K_k \odot K_k \circledast W_k + \sum_{i \neq k} K_k \odot K_i \circledast W_i = W_k + n}$$

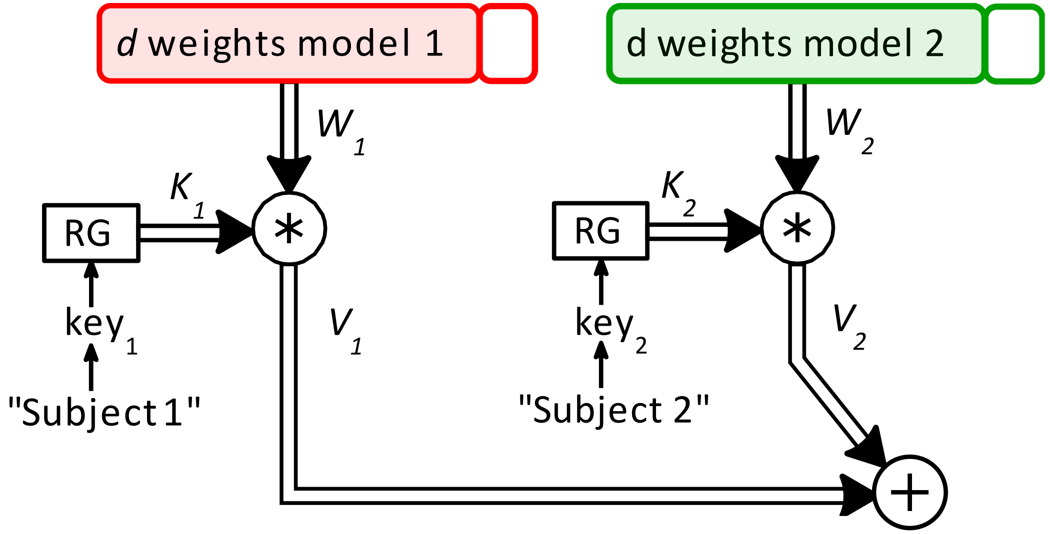
Key-weight binding of compressible weights



Superposition of key-value pairs **reduces the memory footprint** while staying in **same dimensionality**



Superposition of key-value pairs **reduces the memory footprint** while staying in **same dimensionality**



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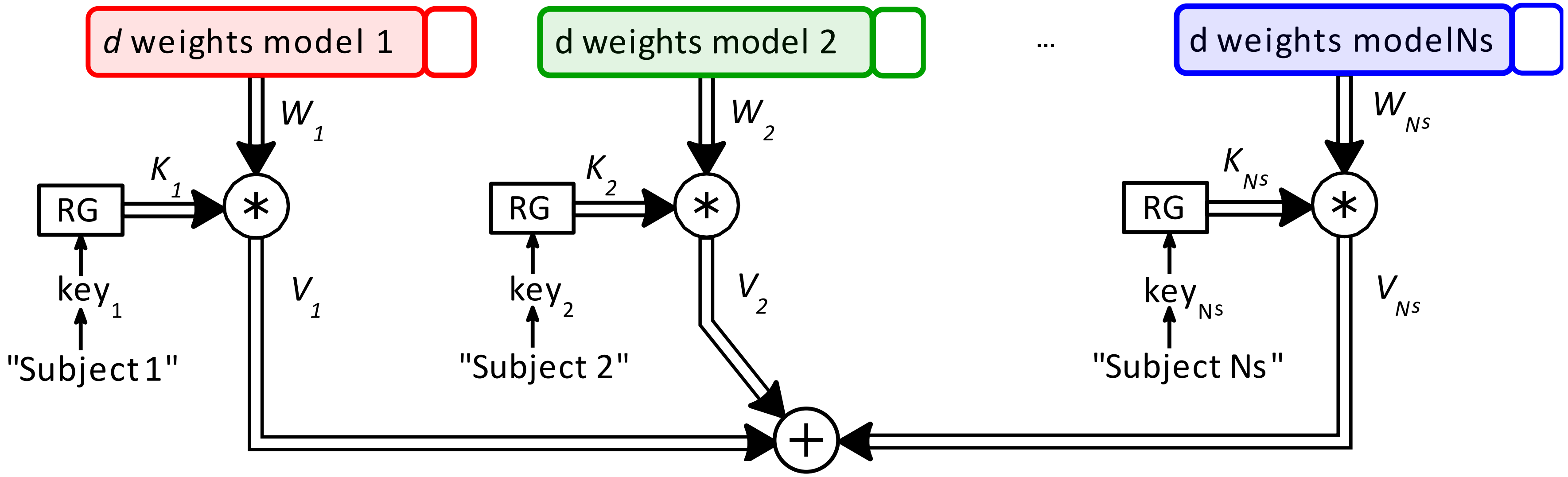

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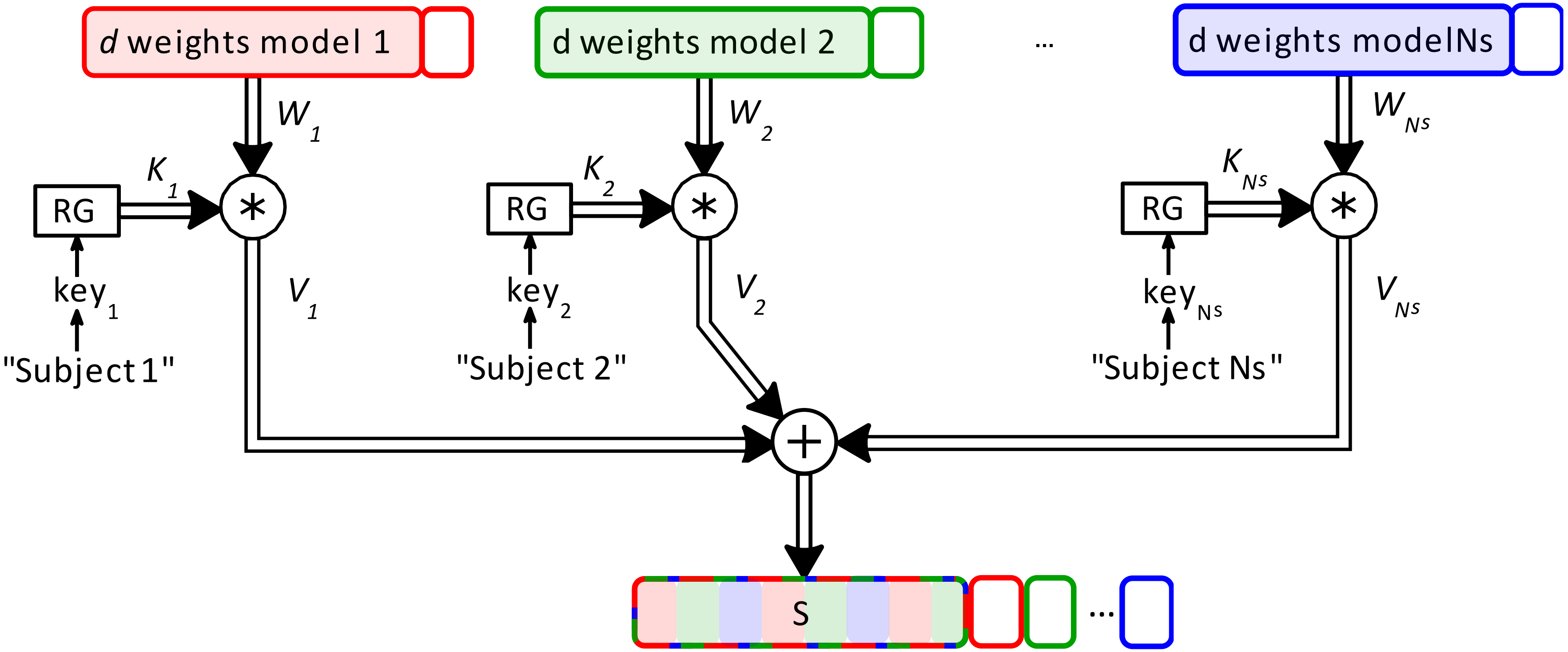
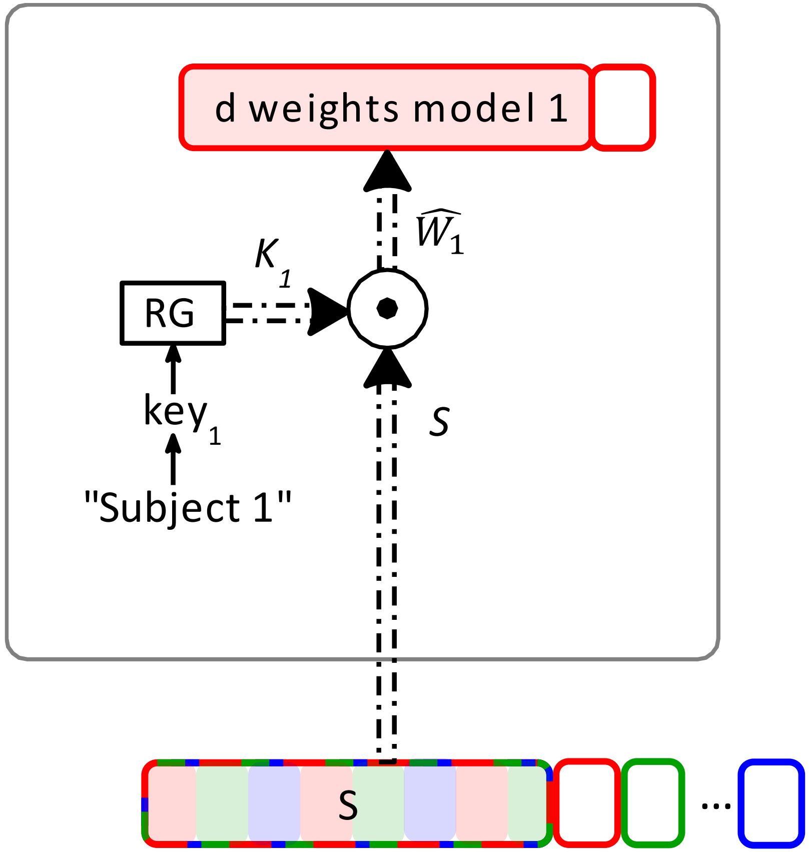
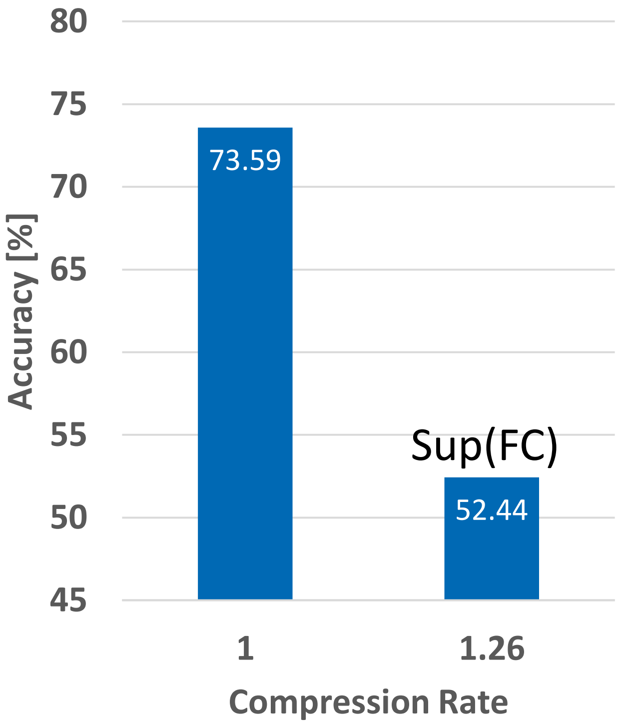


$$\text{Compression Rate} = \frac{Ns}{Ns(1-r)+r}$$

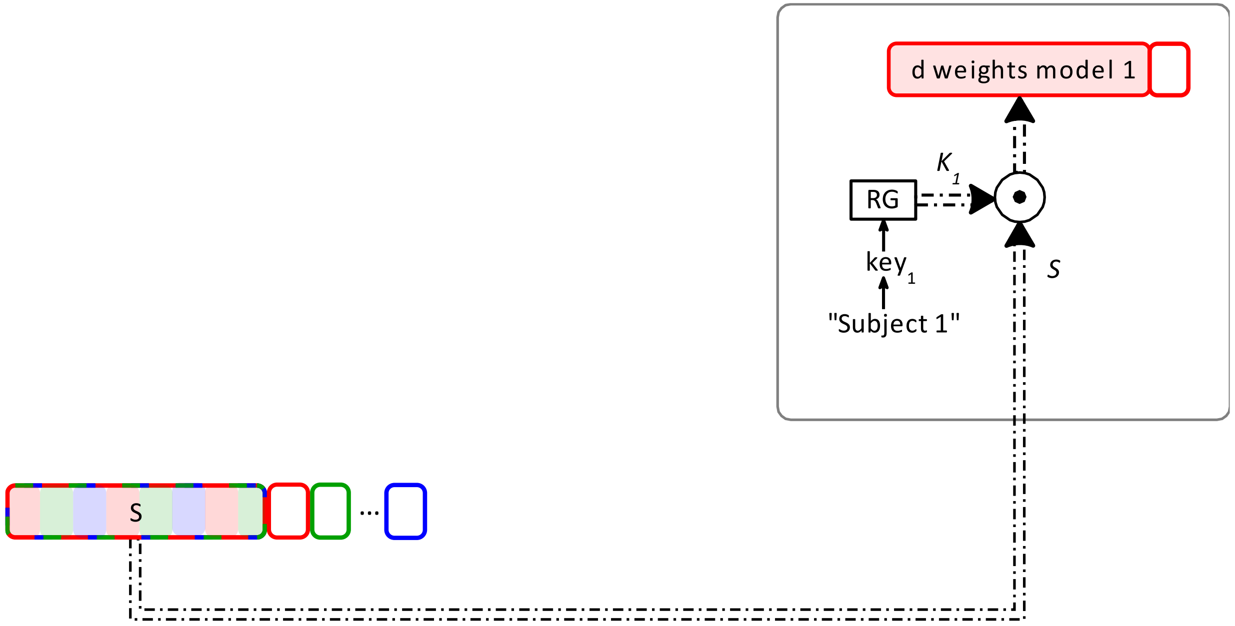
$$r := \frac{d}{\text{model size}}$$

Approximate retrieval from compressed representation yields **huge accuracy loss**

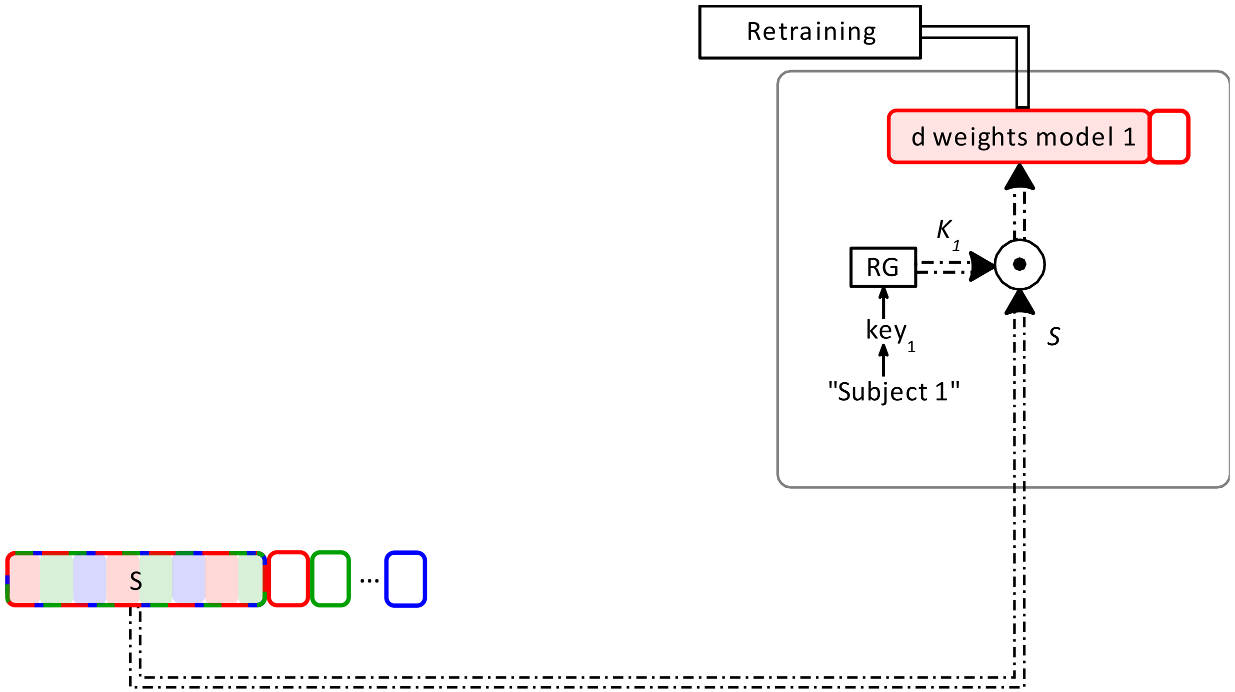




Iterative Retraining



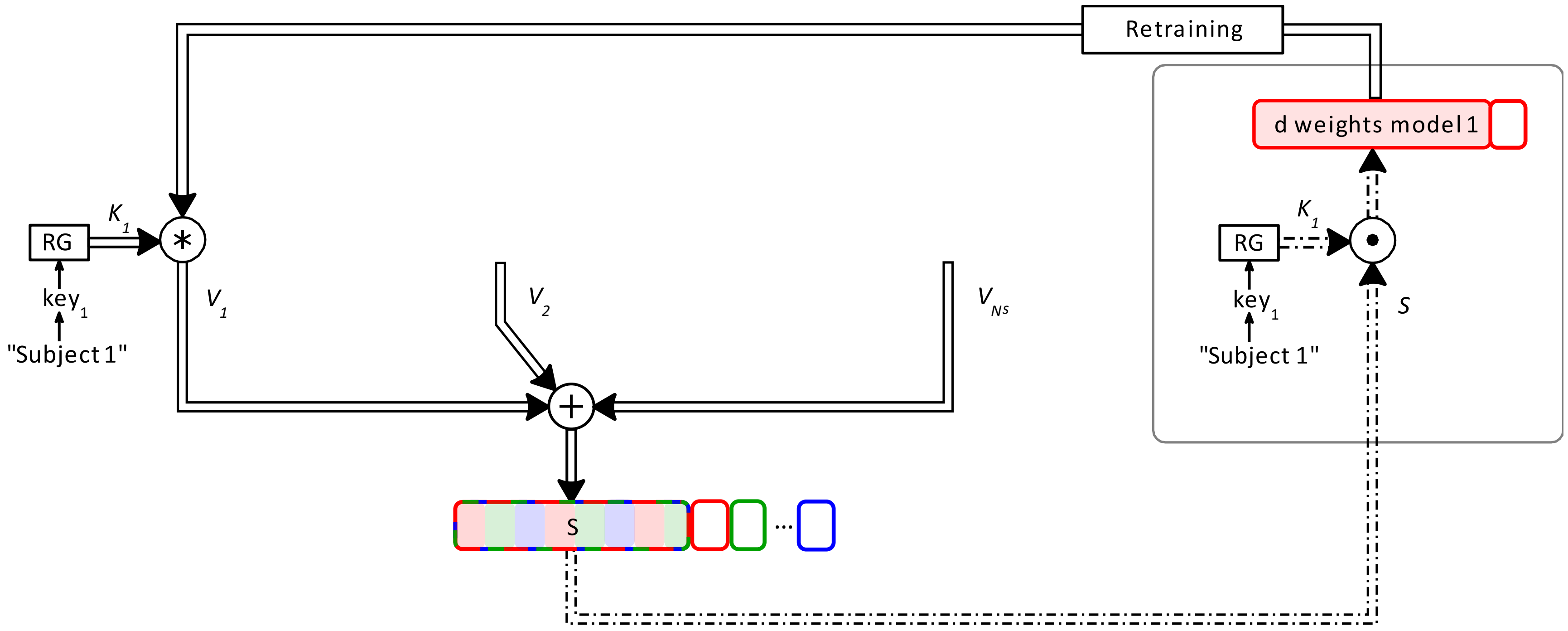
Iterative Retraining



for *i* =1:Ns

1) Retrieve weights for subject *i*
2) Retrain model for subject *i*
3) *Update compressed representation*

Iterative Retraining



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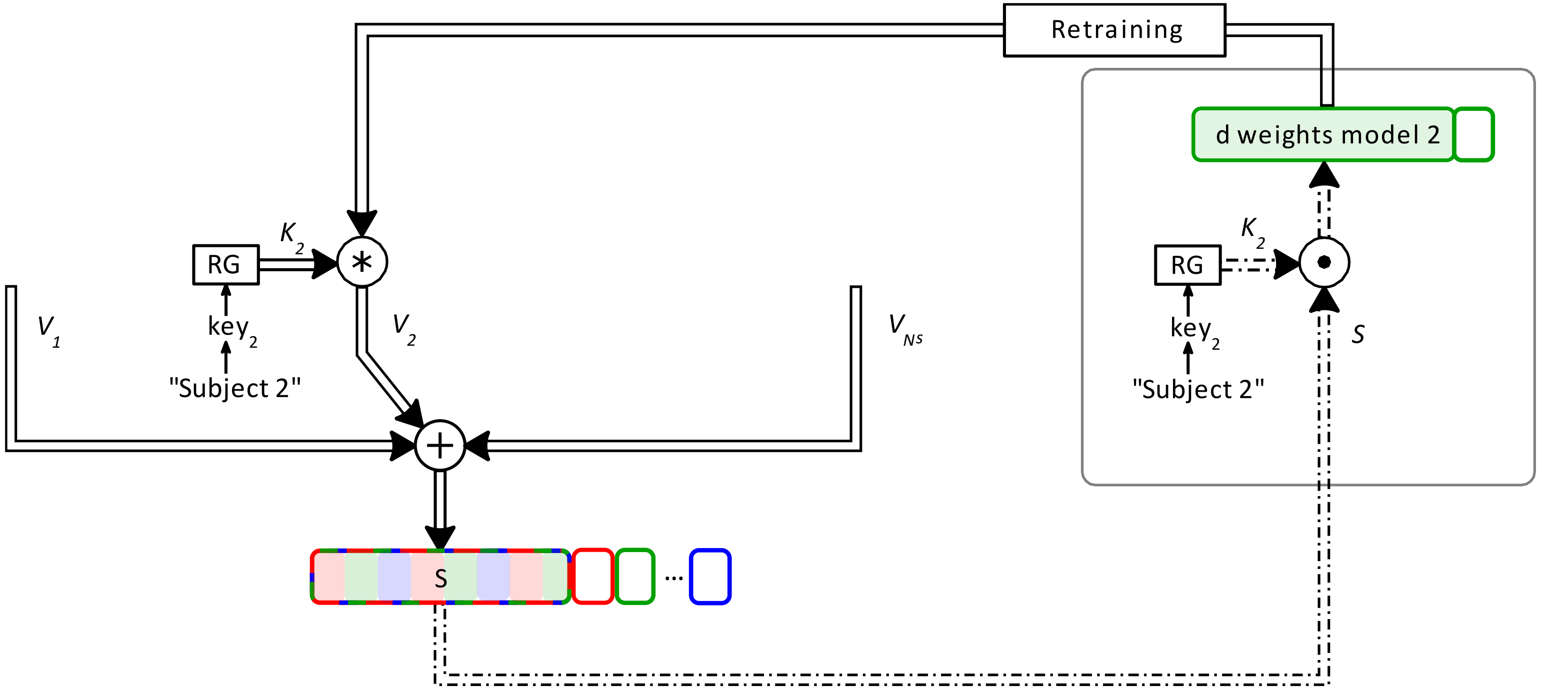

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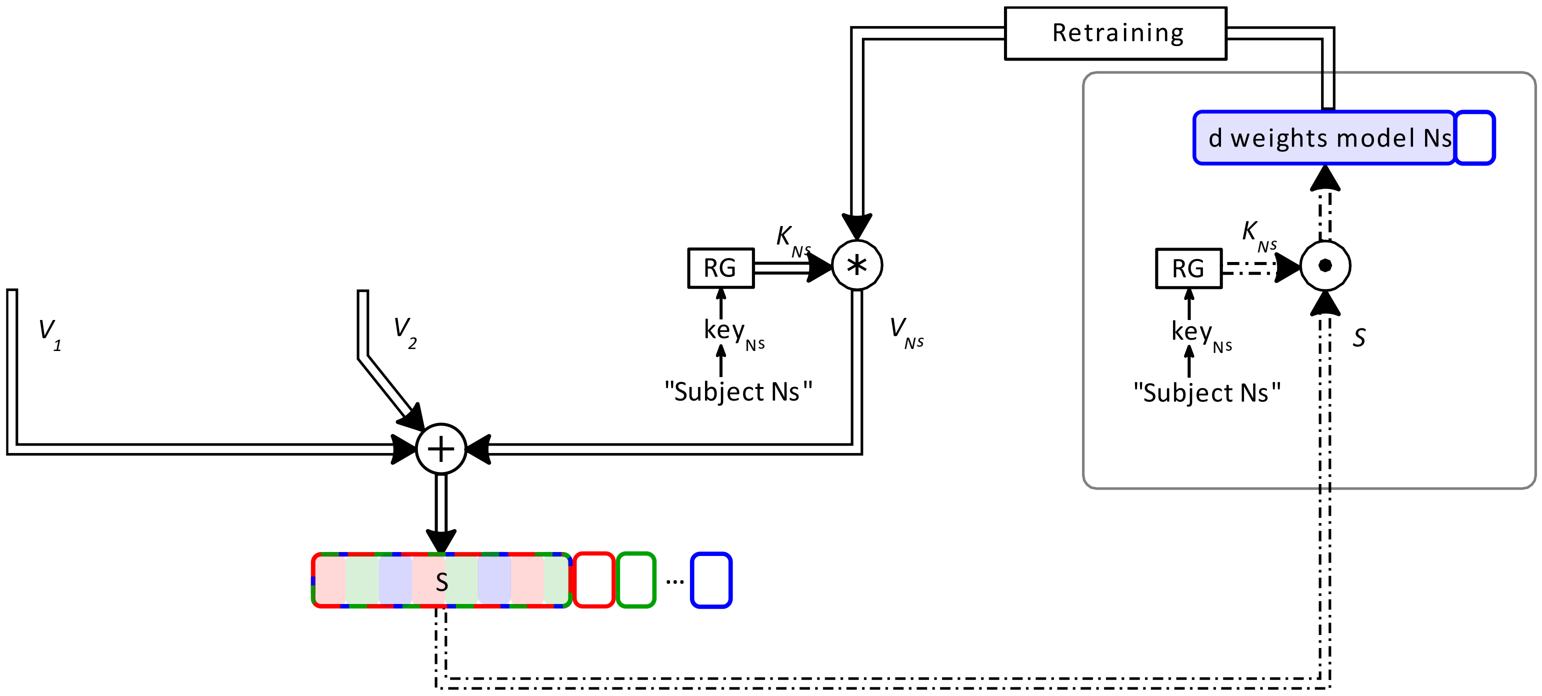
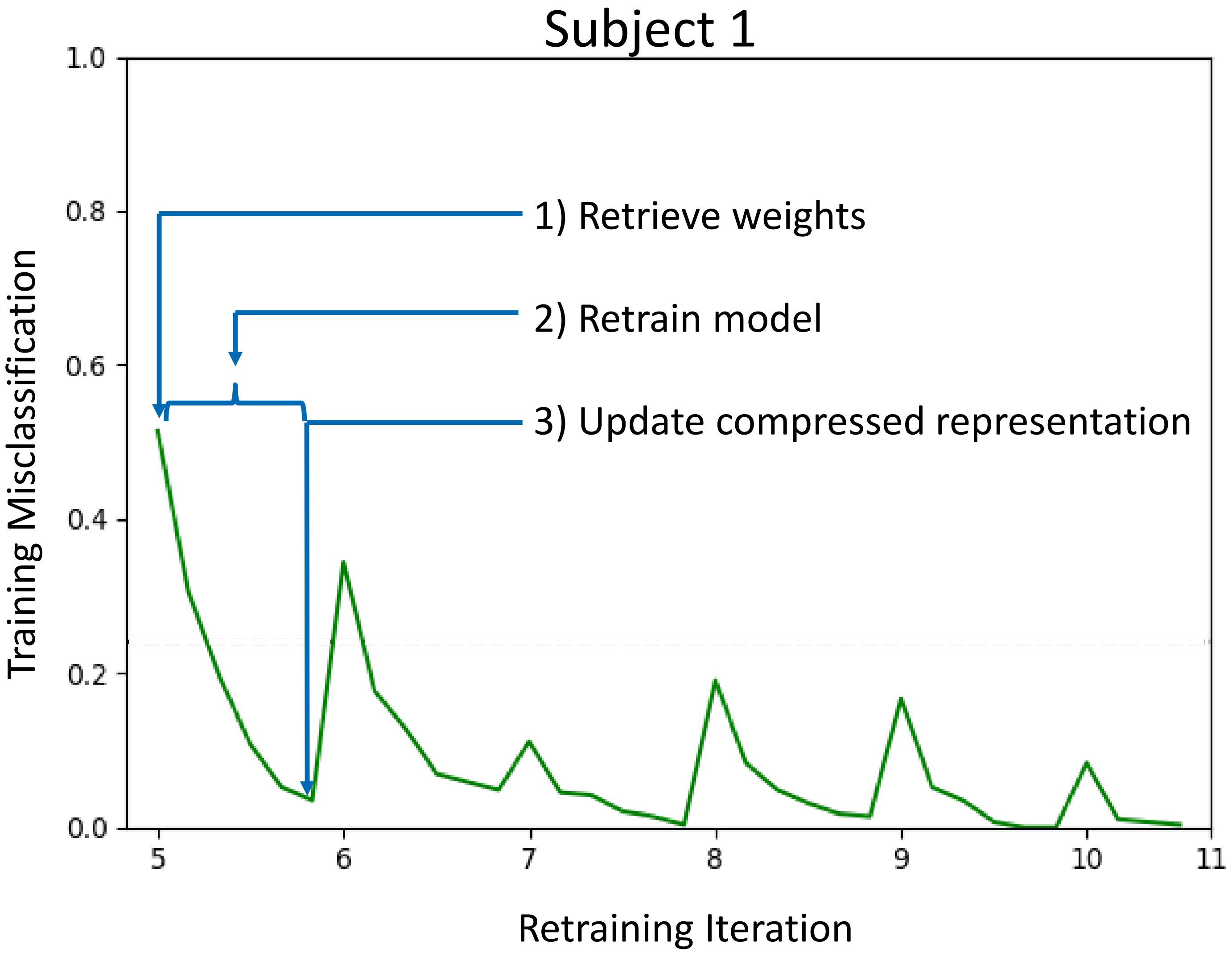


for i =1:Ns

1) Retrieve weights for subject i
2) Retrain model for subject i
3) Update compressed representation

Retraining recovers the performance on **training set**



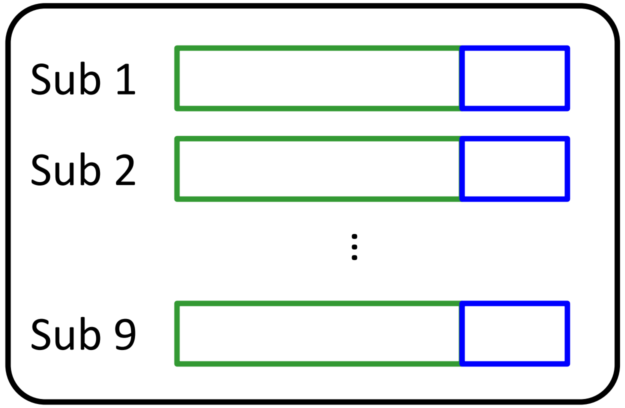
Randomized subject ordering and hyperparameter selection improve iterative retraining

- Randomized subject ordering

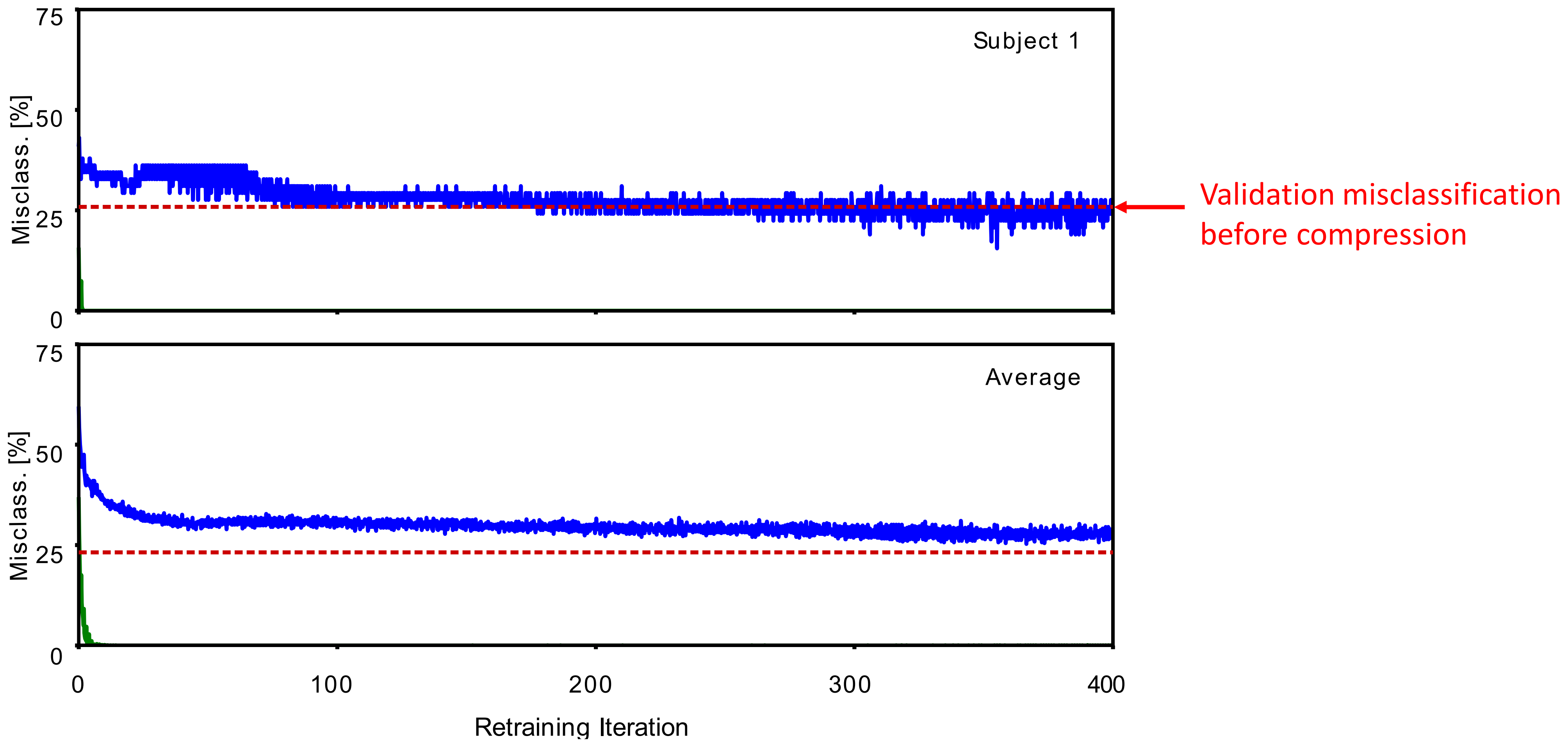
  $\Rightarrow$Change subject order after every retraining iteration

- Hyperparameter selection
  - 5-fold cross-validation **on training set**
  - Find best hyperparameters
    - Batch size
    - Number of epochs per iteration
    - Learning rate
    - Number of retraining iterations

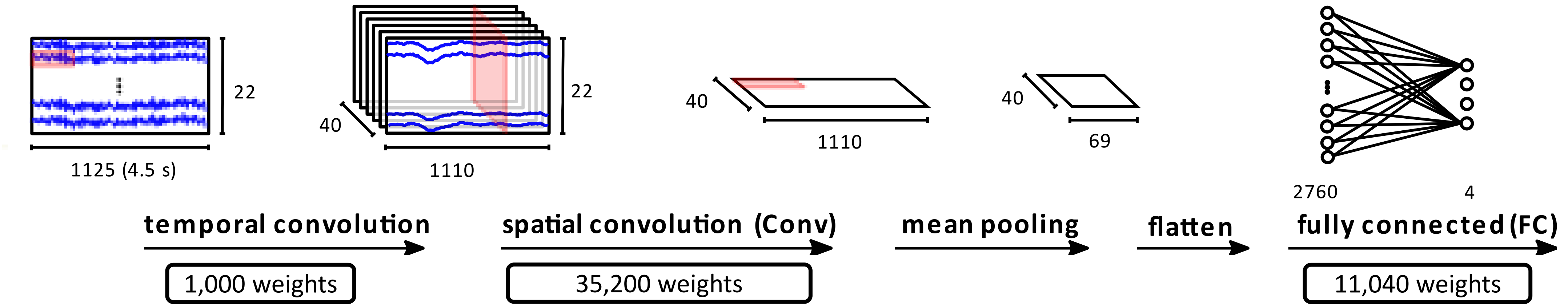
Session 1 (Training & Validation)

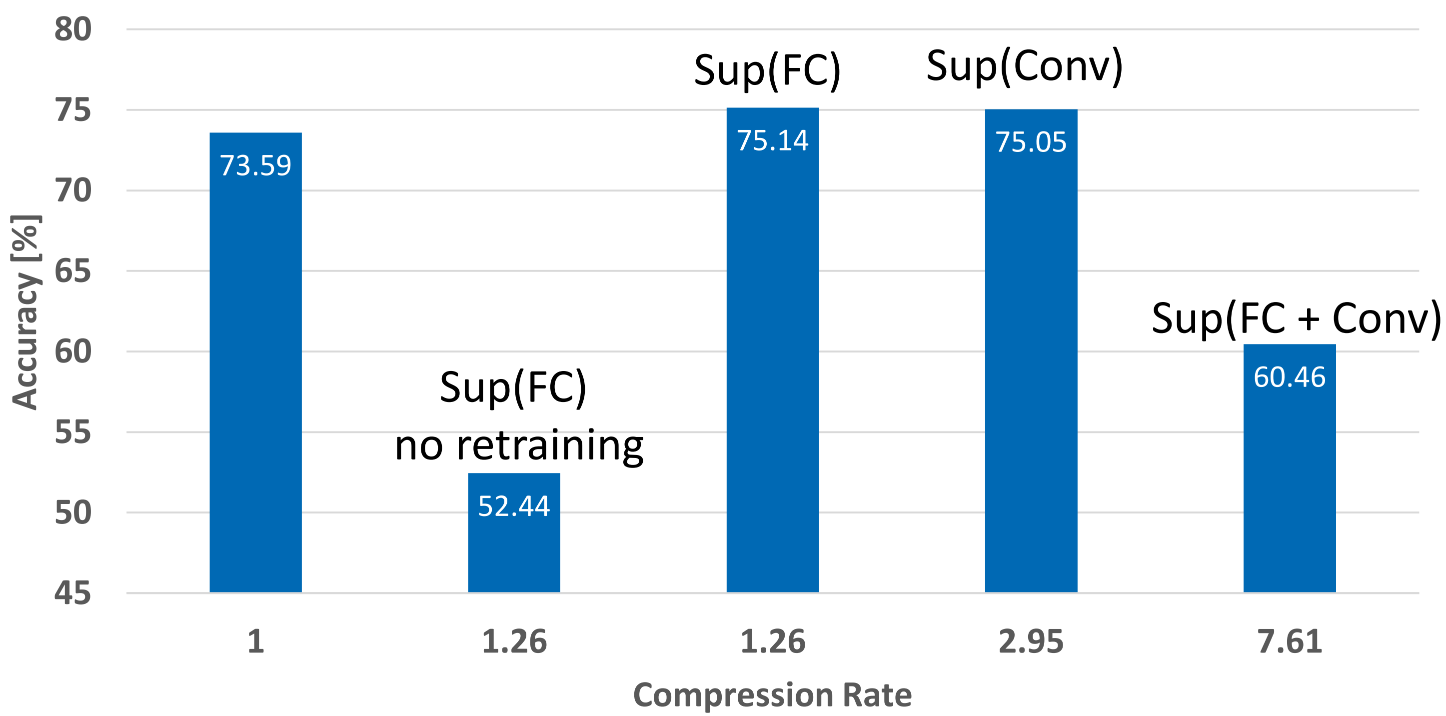


Retraining recovers the misclassification on **validation set**

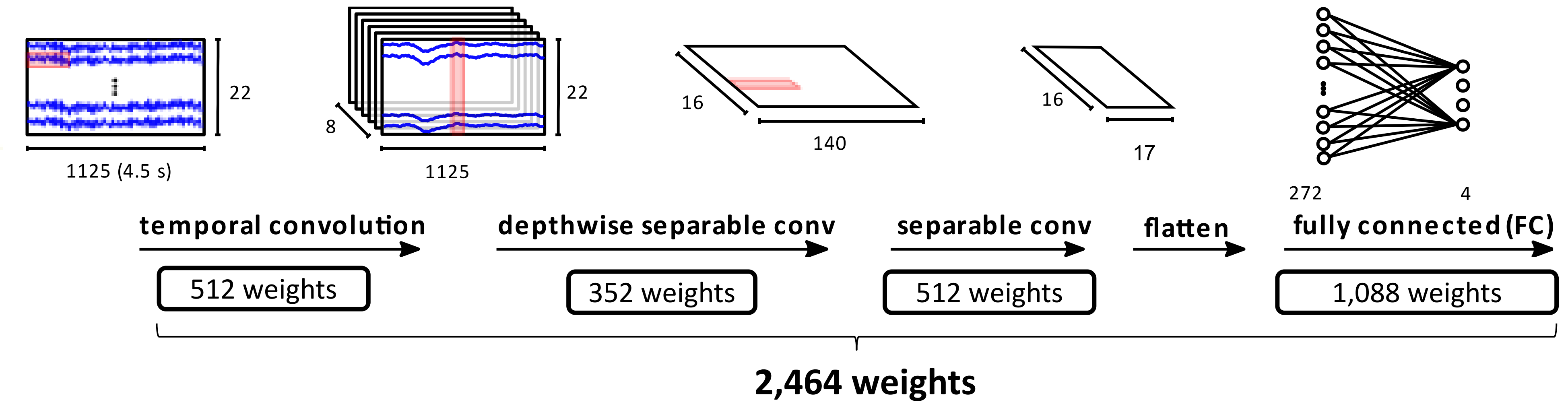


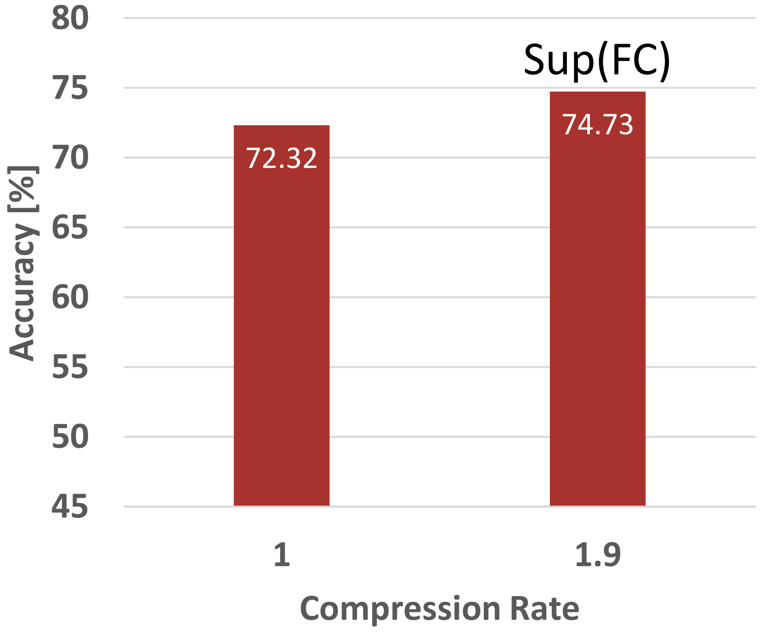
With **retraining** we compress FC or Conv layer with **no accuracy loss**



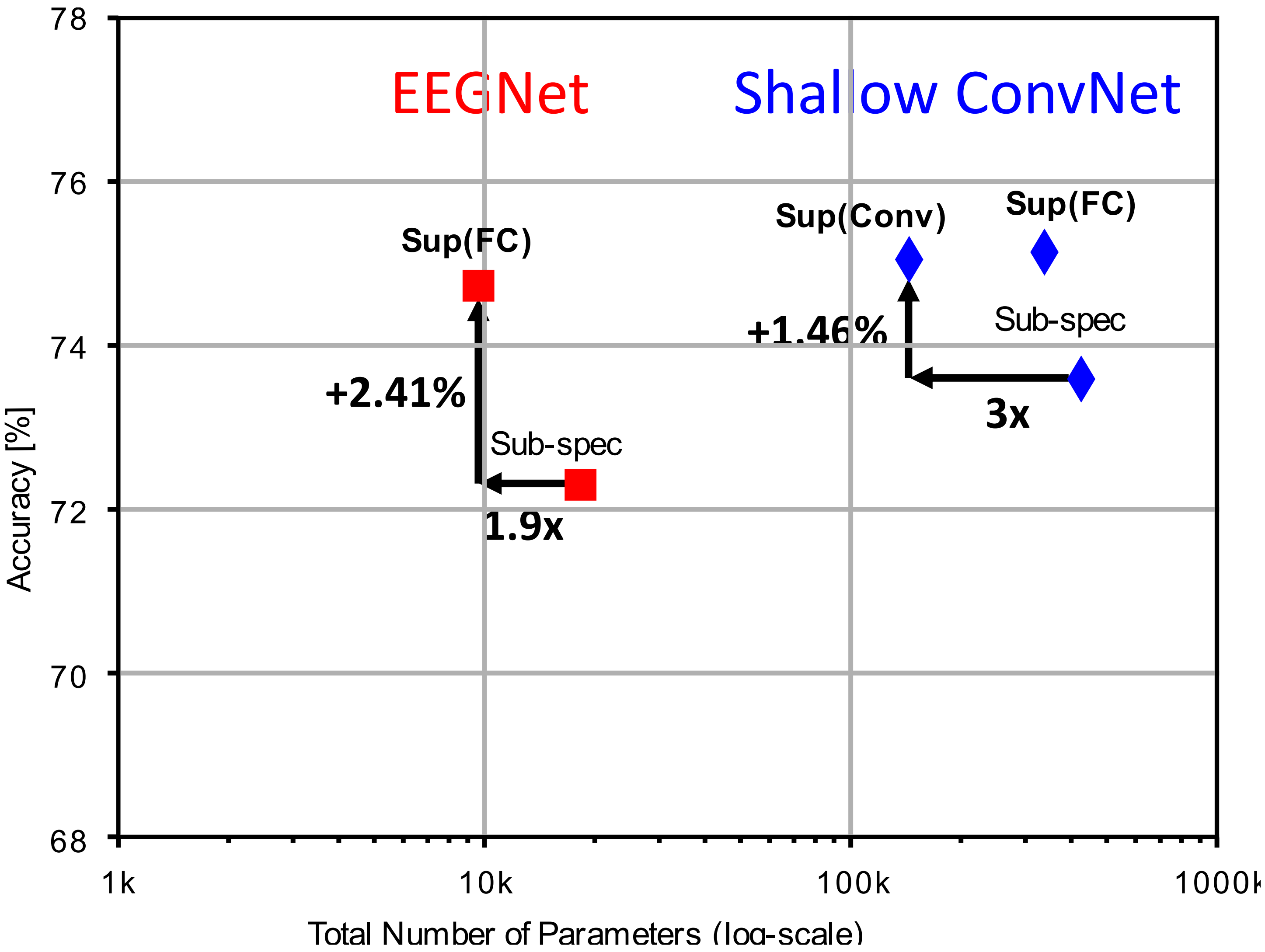


Superposition even compresses tiny EEGNet





Our compression **improves** both **Shallow ConvNet and EEGNet**



Conclusion

- Hyperdimensional superposition compresses already compact MI-BCI CNN models
- **Iterative retraining** recovers loss
- Compress two SoA light-weight networks
  - **Shallow ConvNet** (47k weights) by **3x at 1.46%** higher accuracy
  - **EEGNet** (2.5k weights) by **1.9x at 2.41%** higher accuracy
- Code is available!

https://github.com/MHersche/bci-model-superpos

ETH zürich

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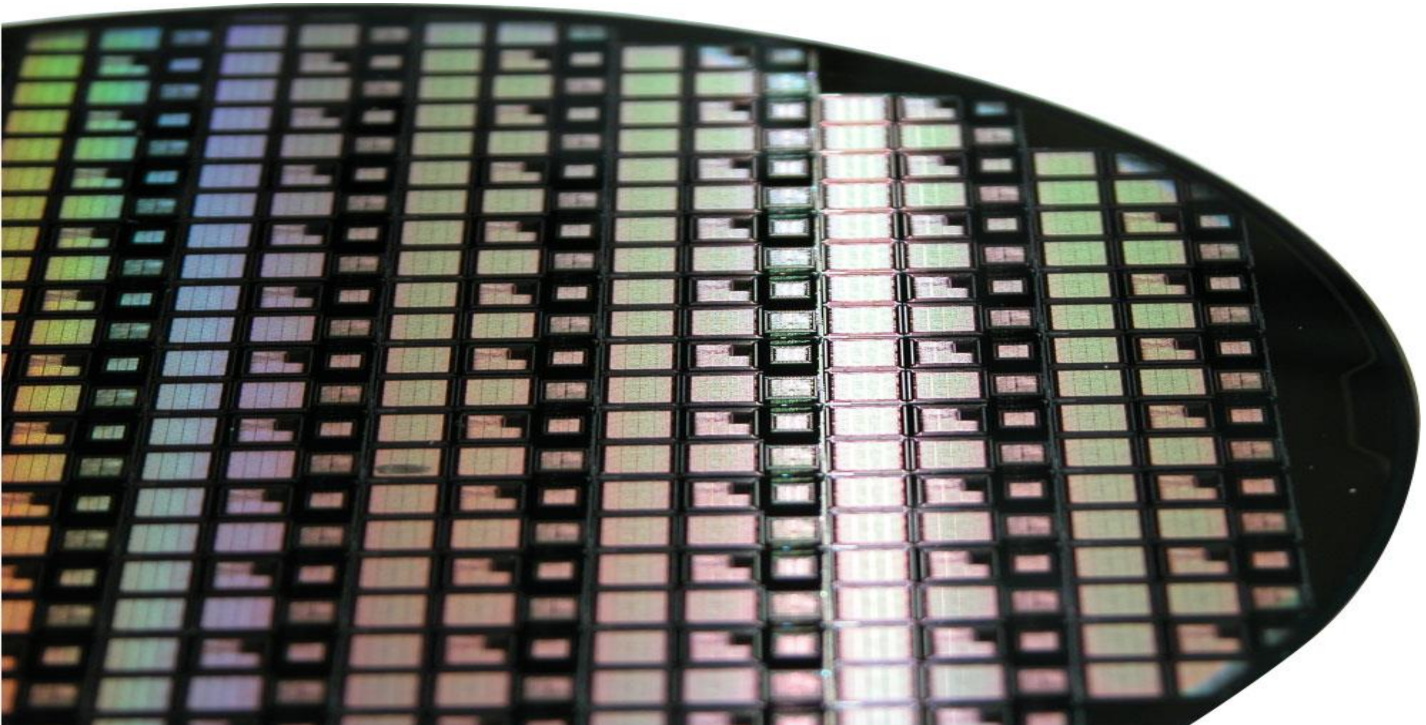

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