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Activation Subspaces for Out-of-Distribution Detection

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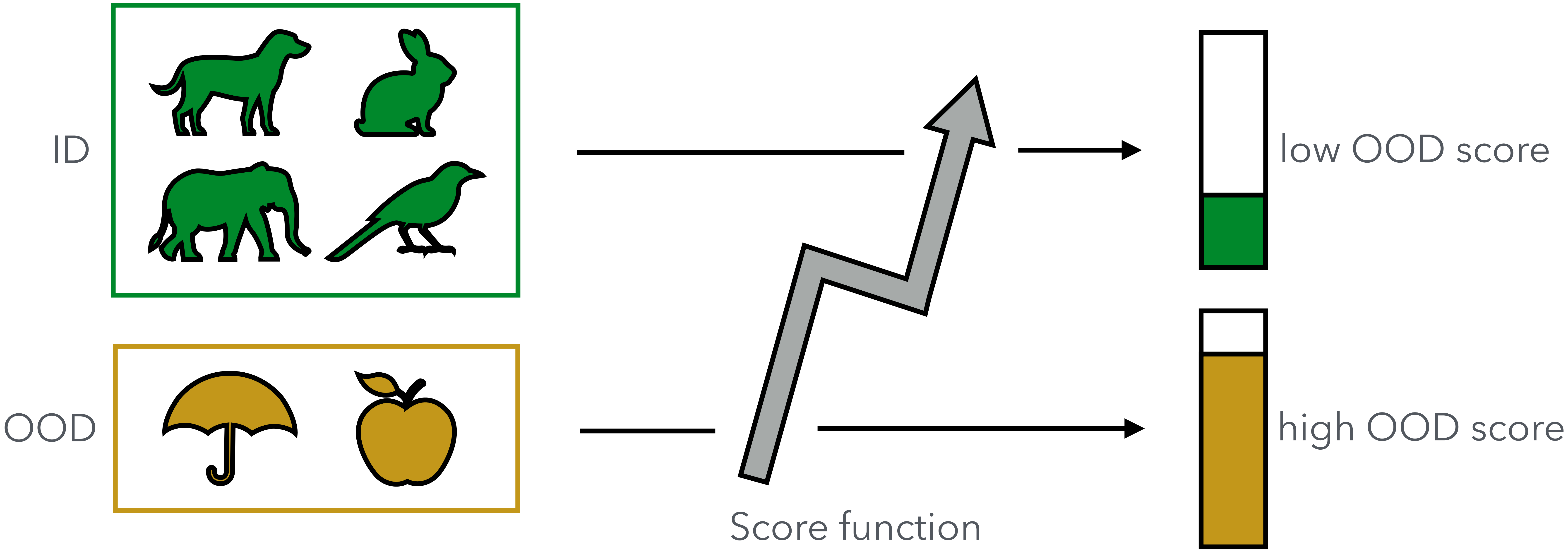
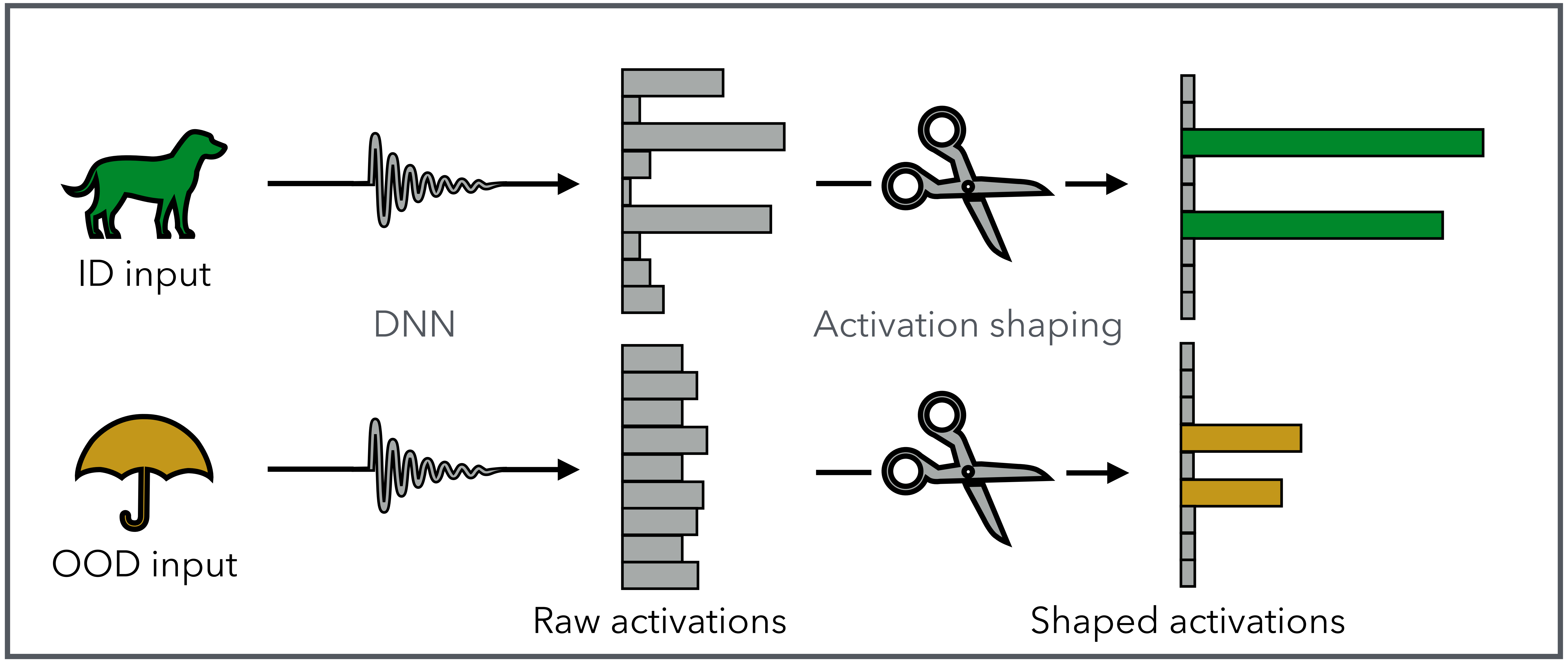
OOD Detection



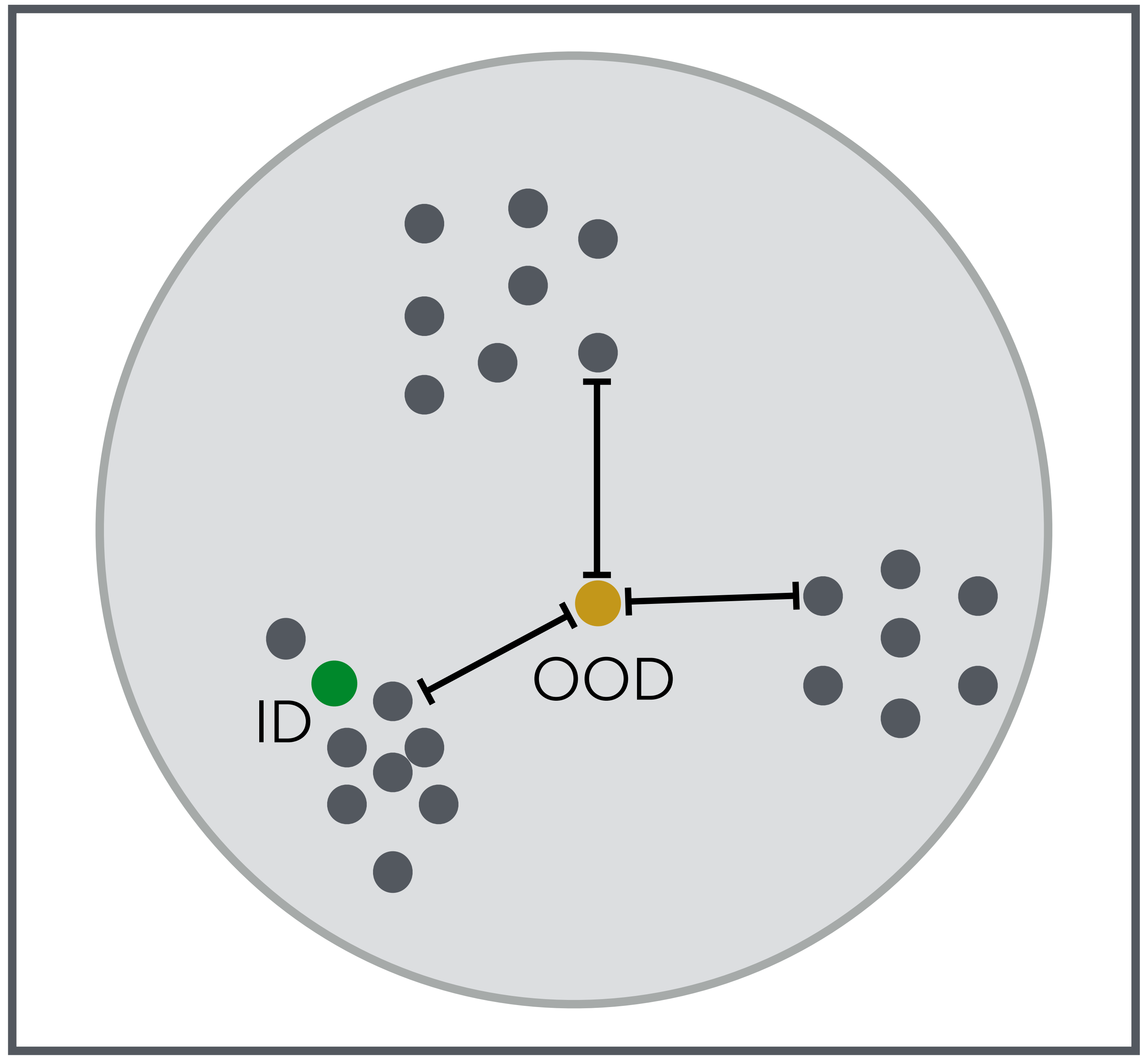
- ***ID (in-distribution)*** inputs belong to the training distribution.
- ***OOD (out-of-distribution)*** inputs deviate from the predefined class taxonomy [1].

[1] Hendrycks et al. A baseline for detecting misclassified and out-of-distribution examples in neural networks. In ICLR, 2017.

Related Work



Activation Shaping

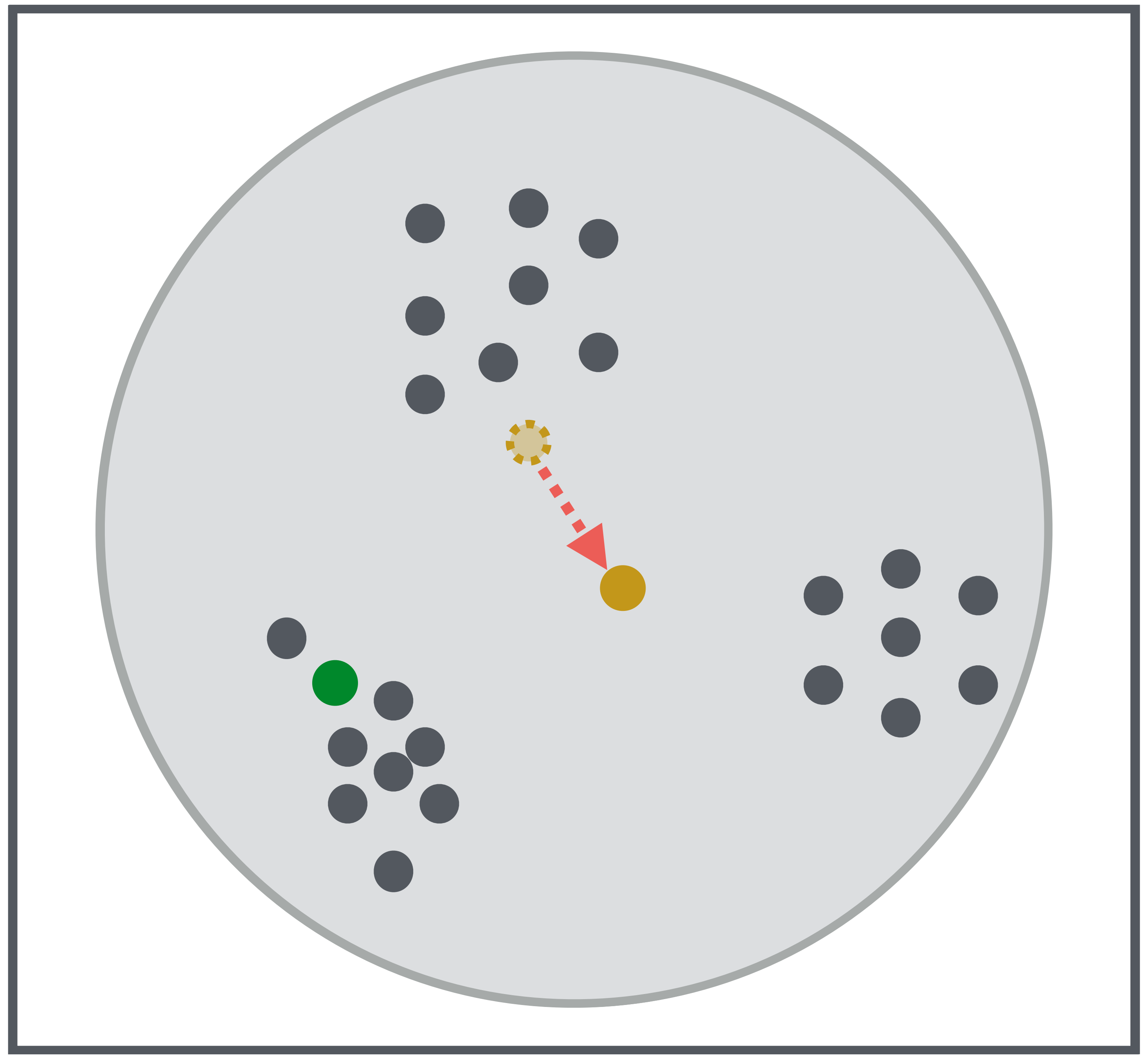


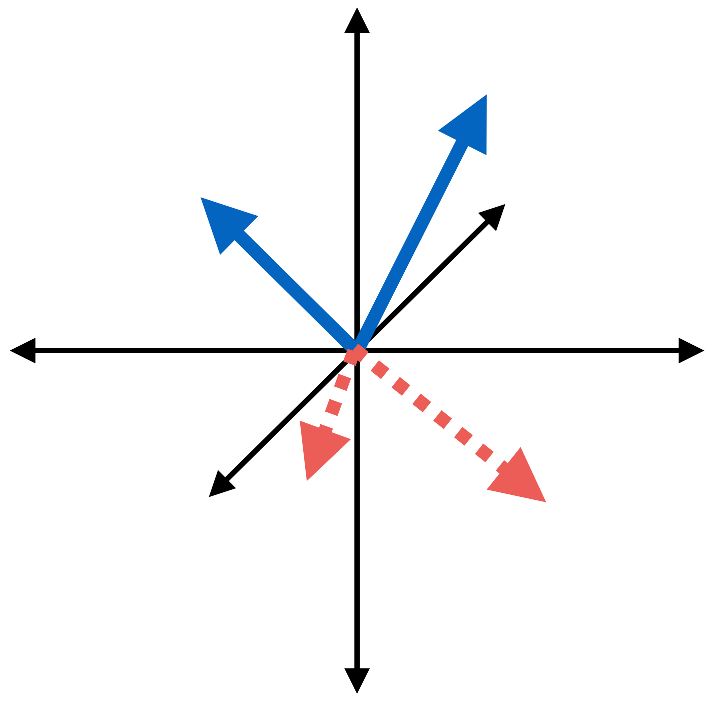
Distance-based

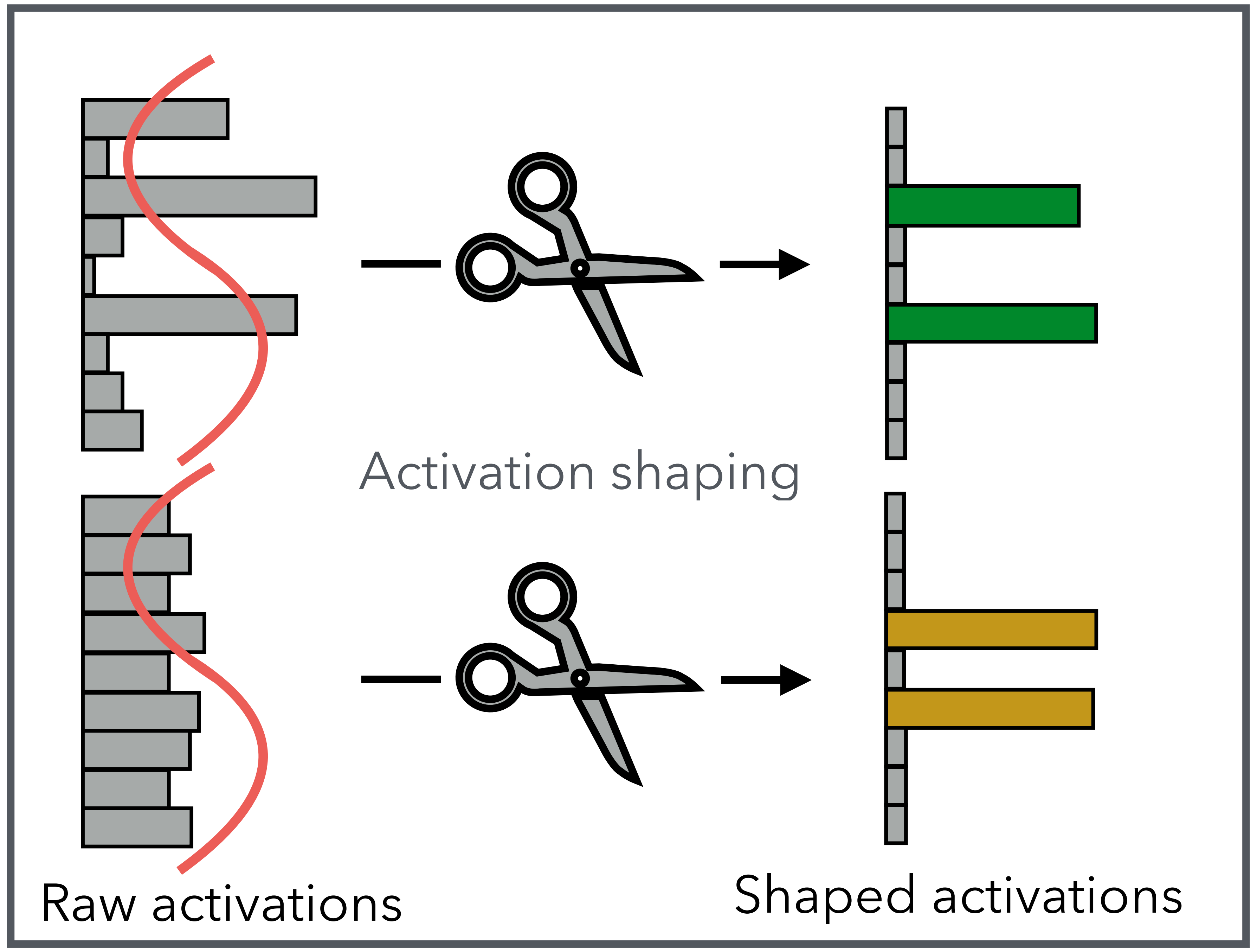
- ***Activation shaping*** methods prune or scale the activation channels [1].
- ***Distance-based methods*** utilize the position of the activations [2, 3].

[1] Djurisic et al. Extremely simple activation shaping for out-of-distribution detection. In ICLR, 2023.
[2] Park et al. Nearest neighbor guidance for out-of-distribution detection. In ICCV, 2023.
[3] Sun et al. Out-of-distribution detection with deep nearest neighbors. In ICML, 2022.

Motivation







- OOD inputs can produce activations that ***highly align*** with the class vectors.
- ***Insignificant*** directions can be useful for OOD detection.
- To identify the insignificant directions, we examine the ***right singular vectors*** of the weight matrix.

- The insignificant directions can interfere with the ***decisive information*** on activations.

$$\boxed{\mathbf{l} = \mathbf{W}\mathbf{a}}$$

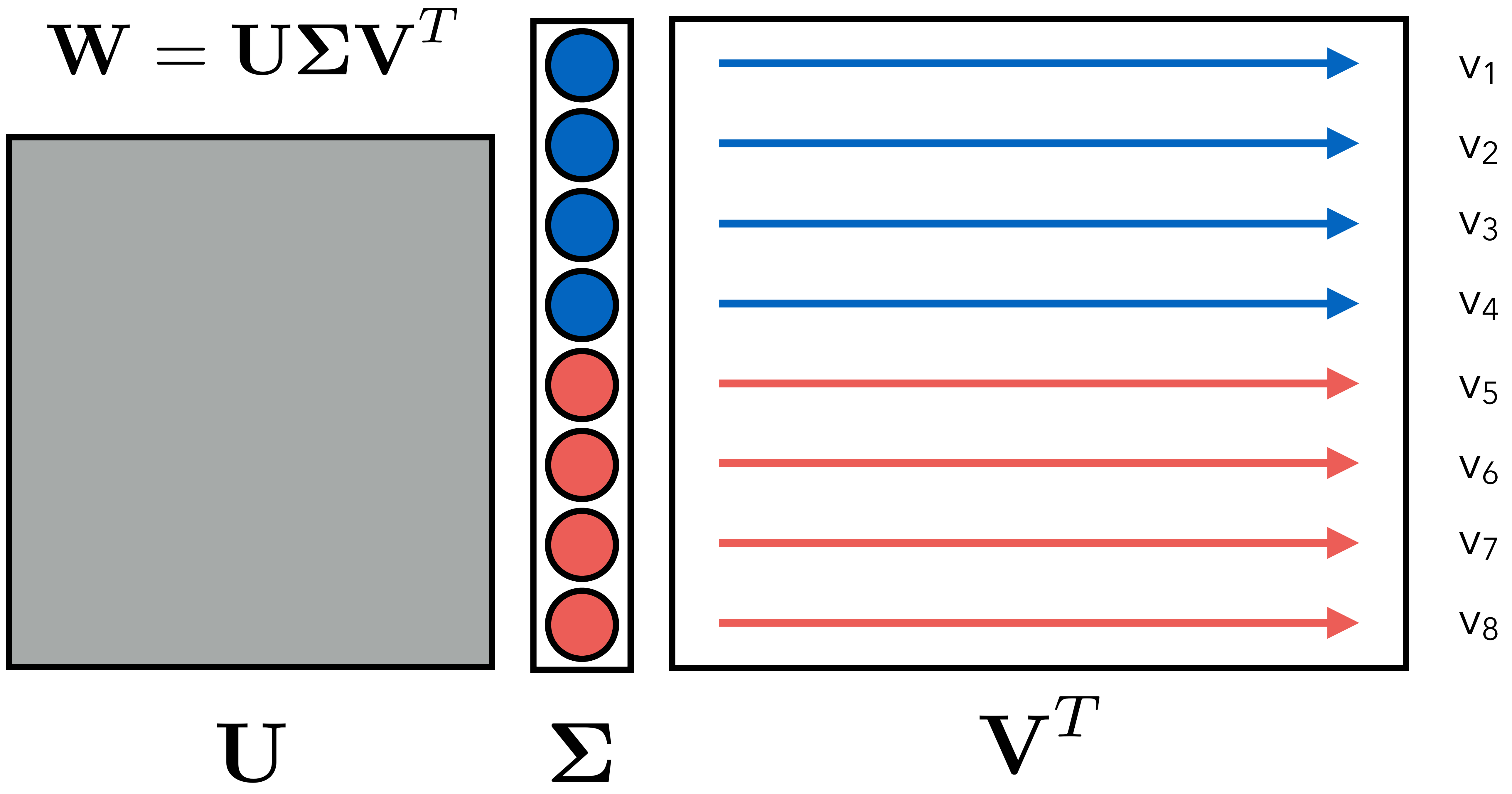
linear classification head (penultimate later)

logits

activation

weight matrix

Activation Subspaces



Decisive Subspace

$$\overleftarrow{\mathbf{V}}^T = \begin{cases} \mathbf{v}_i^T & \text{if } i \leq k \\ \mathbf{0}^T & \text{otherwise} \end{cases},$$

$$\overleftarrow{\mathbf{a}} = \overleftarrow{\mathbf{V}}\overleftarrow{\mathbf{V}}^T\mathbf{a}$$

Insignificant Subspace

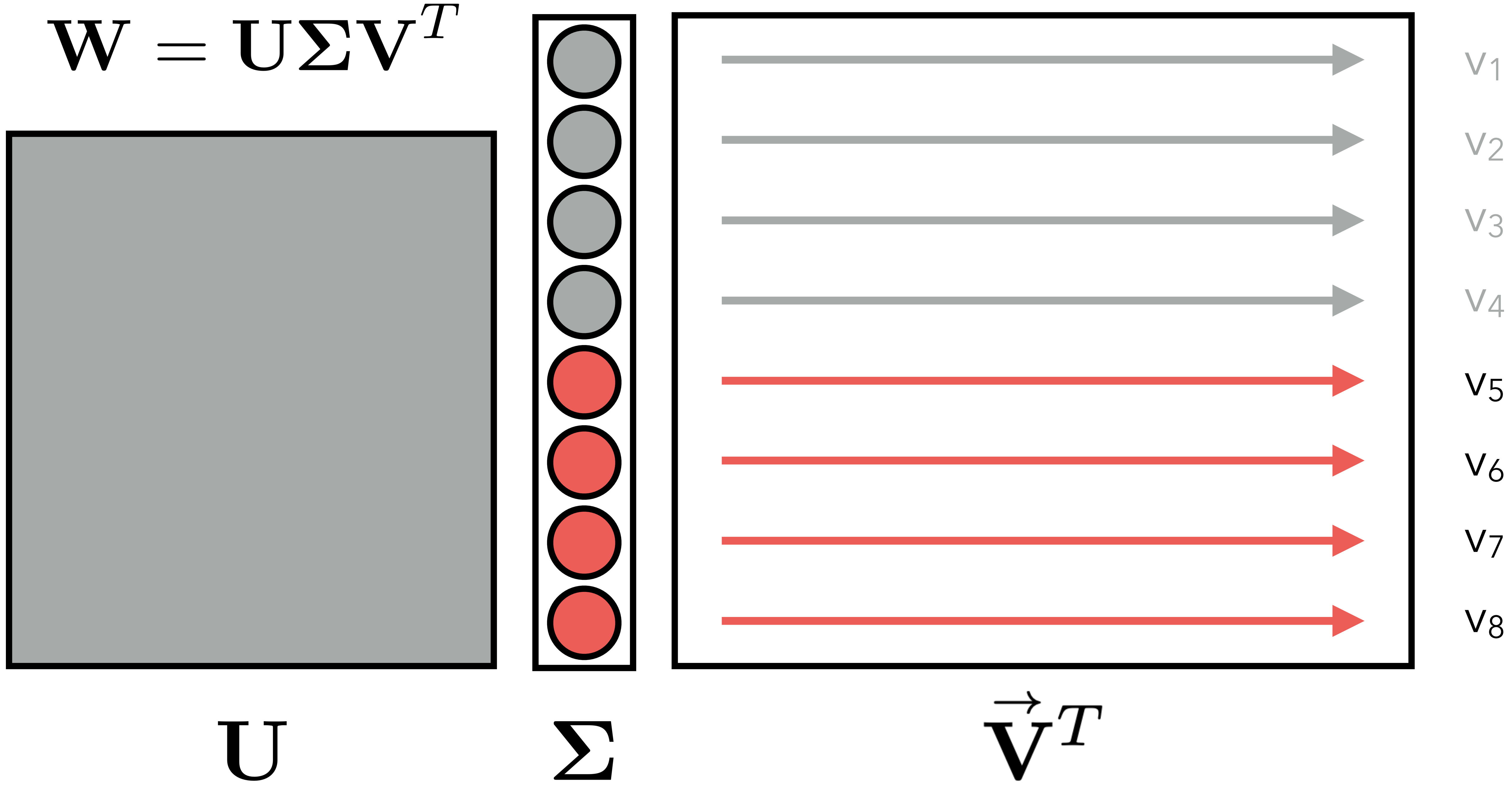
$$\overrightarrow{\mathbf{V}}^T = \begin{cases} \mathbf{0}^T & \text{if } i \leq k \\ \mathbf{v}_i^T & \text{otherwise} \end{cases},$$

$$\overrightarrow{\mathbf{a}} = \overrightarrow{\mathbf{V}}\overrightarrow{\mathbf{V}}^T\mathbf{a}$$

- ***Decisive Subspace:*** Directions corresponding to high singular values.
    - Contributes ***maximally*** to the final classifier output.
- **Insignificant Subspace:** Directions corresponding to low singular values.
    - Contributes ***minimally*** to the final classifier output.

Insignificant Component

$$\mathbf{W} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T$$



Insignificant Subspace

$$\vec{\mathbf{V}}^T = \begin{cases} \mathbf{0}^T & \text{if } i \le k \\ \mathbf{v}_i^T & \text{otherwise} \end{cases},$$

$$\vec{\mathbf{a}} = \vec{\mathbf{V}}\vec{\mathbf{V}}^T\mathbf{a}$$

$$\vec{S} = -\log\left(1 - \frac{1}{N}\sum_{i=1}^{N} \text{cos\_sim}(\vec{\mathbf{a}}^{(i)}, \vec{\mathbf{a}})\right)$$

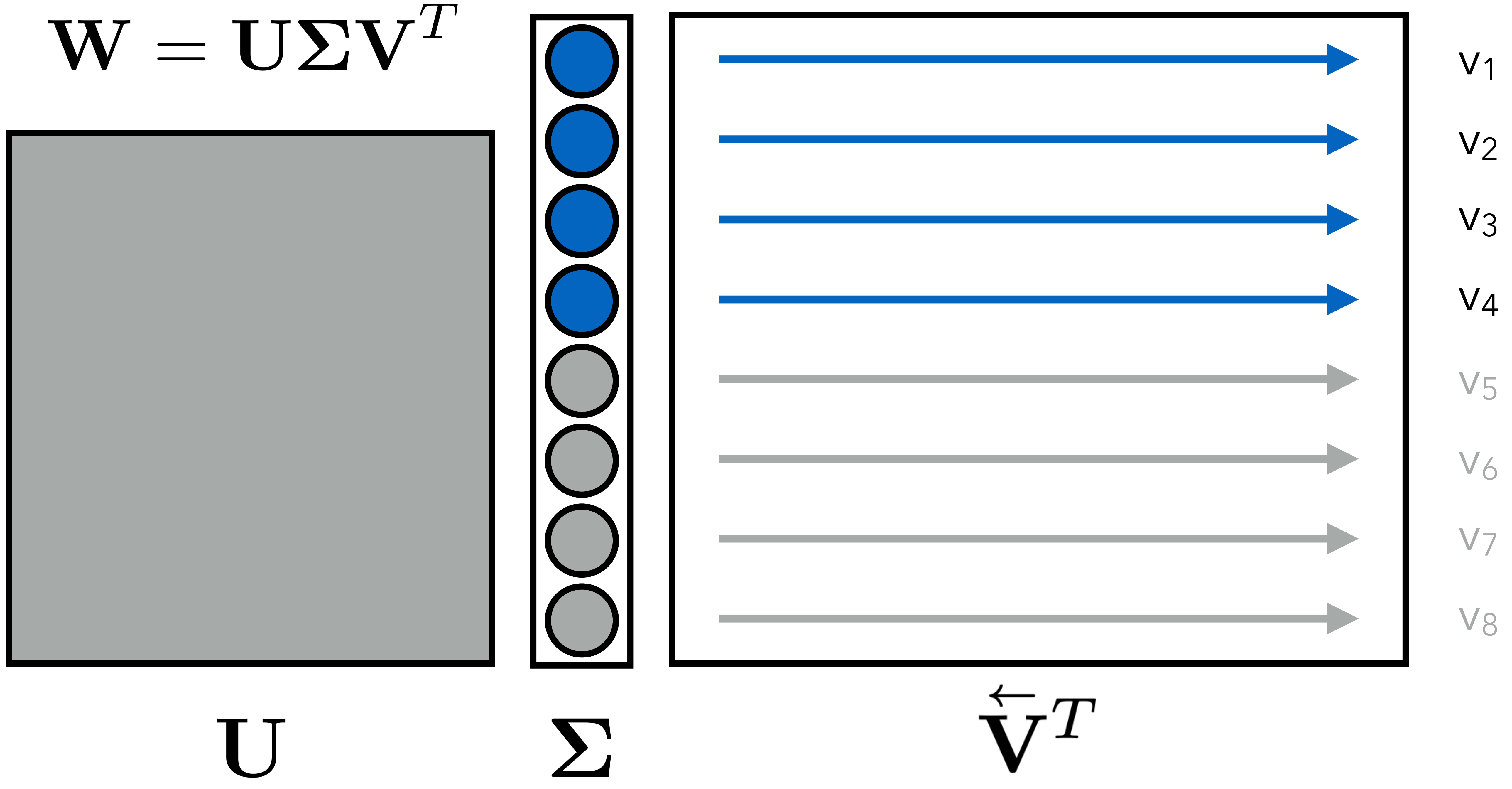
Key Observation

- The ***insignificant component*** yields powerful features, akin to a random neural network [1, 2], that is discriminative for OOD detection!
- $\vec{S}$: The ***average cosine similarity*** to nearest neighbors from the training data.

[1] Ulyanov et al. Deep image prior. In CVPR, 2018.
[2] Can et al. A random CNN sees objects: One inductive bias of CNN and its applications. In AAAI, 2022.

Decisive Component

$$\mathbf{W} = \mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^T$$



Decisive Subspace

$$\overleftarrow{\mathbf{V}}^T = \begin{cases} \mathbf{v}_i^T & \text{if } i \leq k \\ \mathbf{0}^T & \text{otherwise} \end{cases},$$

$$\overleftarrow{\mathbf{a}} = \overleftarrow{\mathbf{V}}\overleftarrow{\mathbf{V}}^T\mathbf{a}$$

$$\overleftarrow{S} = -E\left(\mathbf{U}\boldsymbol{\Sigma}\overleftarrow{\mathbf{V}}^T\Phi(\overleftarrow{\mathbf{a}})\right)$$

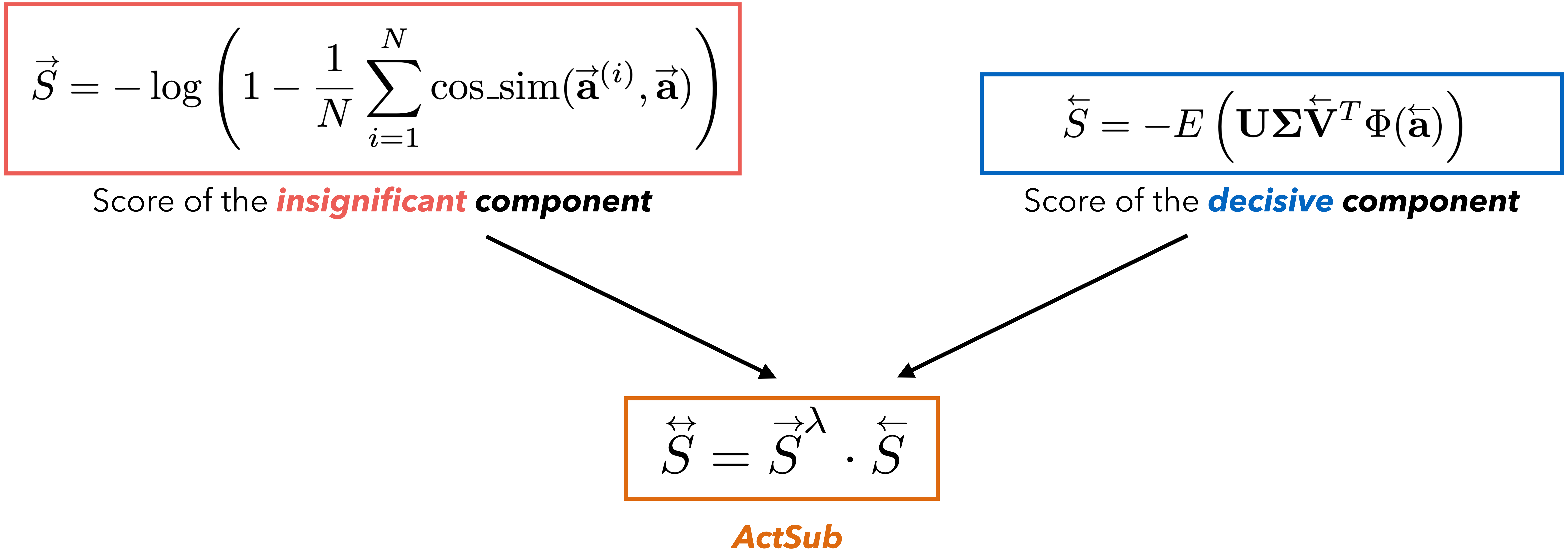
activation shaping

Key Observation

- Activation shaping methods profit from considering the ***decisive component***, as the insignificant component can cause interference.
- $\overleftarrow{S}$: The ***energy function*** [1] on logits from the shaped activation.

[1] Liu et al. Energy-based out-of-distribution detection. In NeurIPS, 2020.

ActSub



$$\vec{S} = -\log\left(1 - \frac{1}{N}\sum_{i=1}^{N} \text{cos\_sim}(\vec{\mathbf{a}}^{(i)}, \vec{\mathbf{a}})\right)$$

Score of the ***insignificant*** ***component***

$$\overleftarrow{S} = -E\left(\mathbf{U}\mathbf{\Sigma}\overleftarrow{\mathbf{V}}^{T}\Phi(\overleftarrow{\mathbf{a}})\right)$$

Score of the ***decisive*** ***component***

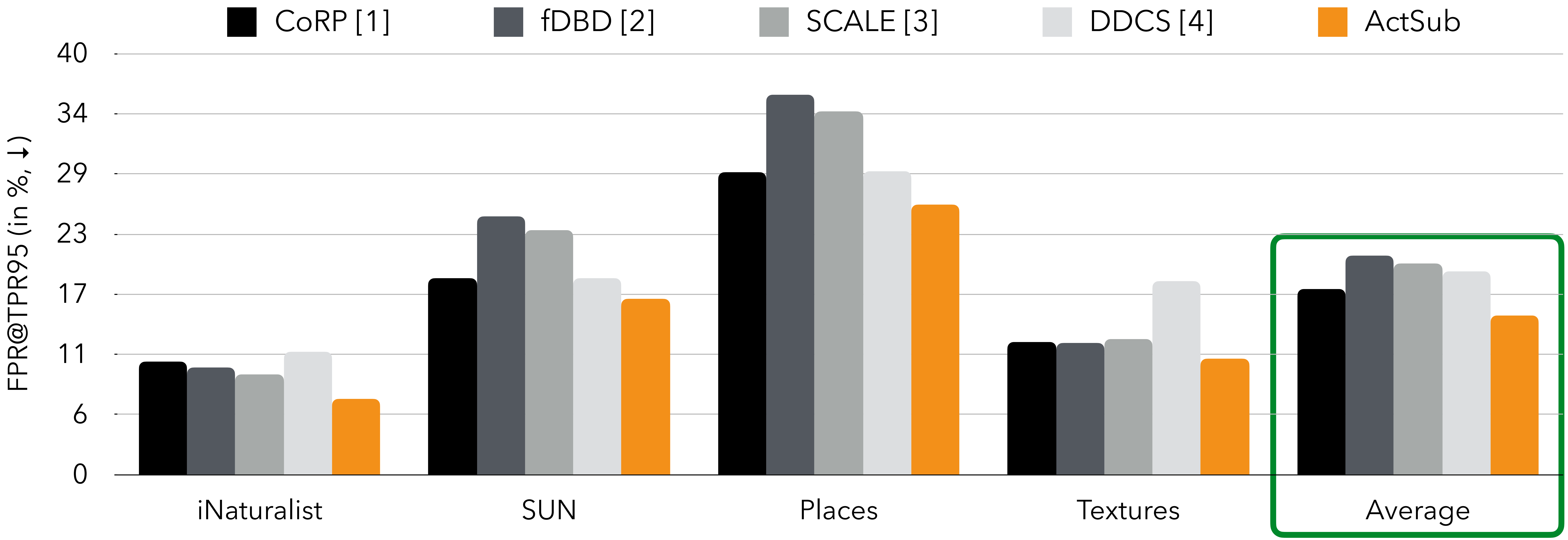
$$\overleftrightarrow{S} = \vec{S}^{\lambda} \cdot \overleftarrow{S}$$

ActSub

- We utilize the discriminative information from both components to define our final score function ***ActSub*****.**

Experiments

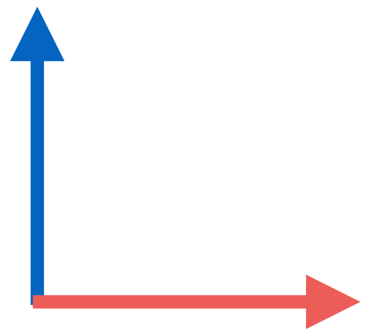
Model: ResNet-50 ID: ImageNet-1K OOD: iNaturalist, SUN, Places, Textures



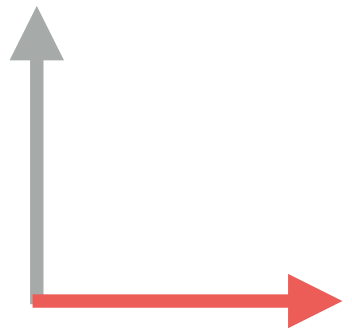
- With the complementary effect of both subspaces, ***ActSub*** achieves SoTA results.
- Note: For distance-based methods CoRP [1] and fDBD [2], we consider the strongest reported variant with an activation shaping method.

[1] Fang et al. Kernel PCA for out-of-distribution detection. In NeurIPS, 2024.
[2] Liu et al. Fast decision boundary based out-of-distribution detector. In ICML, 2024.
[3] Yan et al. Discriminability-driven channel selection for out-of-distribution detection. In CVPR, 2024.
[4] Xu et al. Scaling for training time and post-hoc out-of-distribution detection enhancement. In ICLR, 2024.

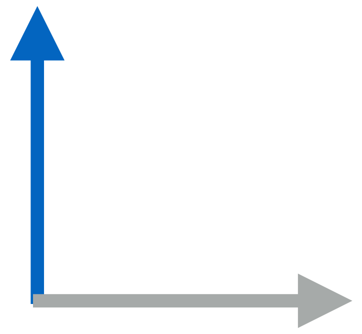
Conclusion



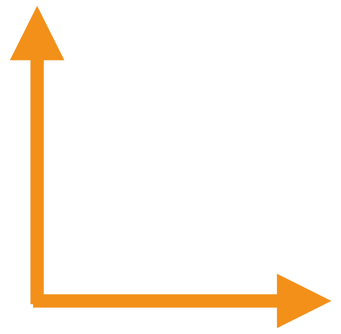
- We define ***two orthogonal subspaces*** of the activation space based on their contribution to the classifier output.



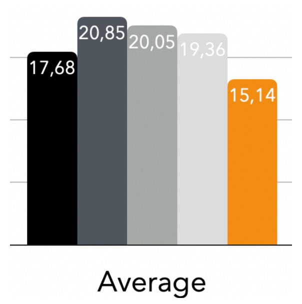
- The ***insignificant component*** yields powerful features untainted by the classification task, discriminative for OOD Detection.



- Selectively applying activation shaping to ***decisive component*** mitigates the channel-wise interference on activations.



- We define ***ActSub*** by combining discriminative information from both subspaces.



- With the complementary effect of the subspaces, ***ActSub*** achieves SoTA results.

https://github.com/visinf/actsub/

https://arxiv.org/abs/2508.21695

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visual inference

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