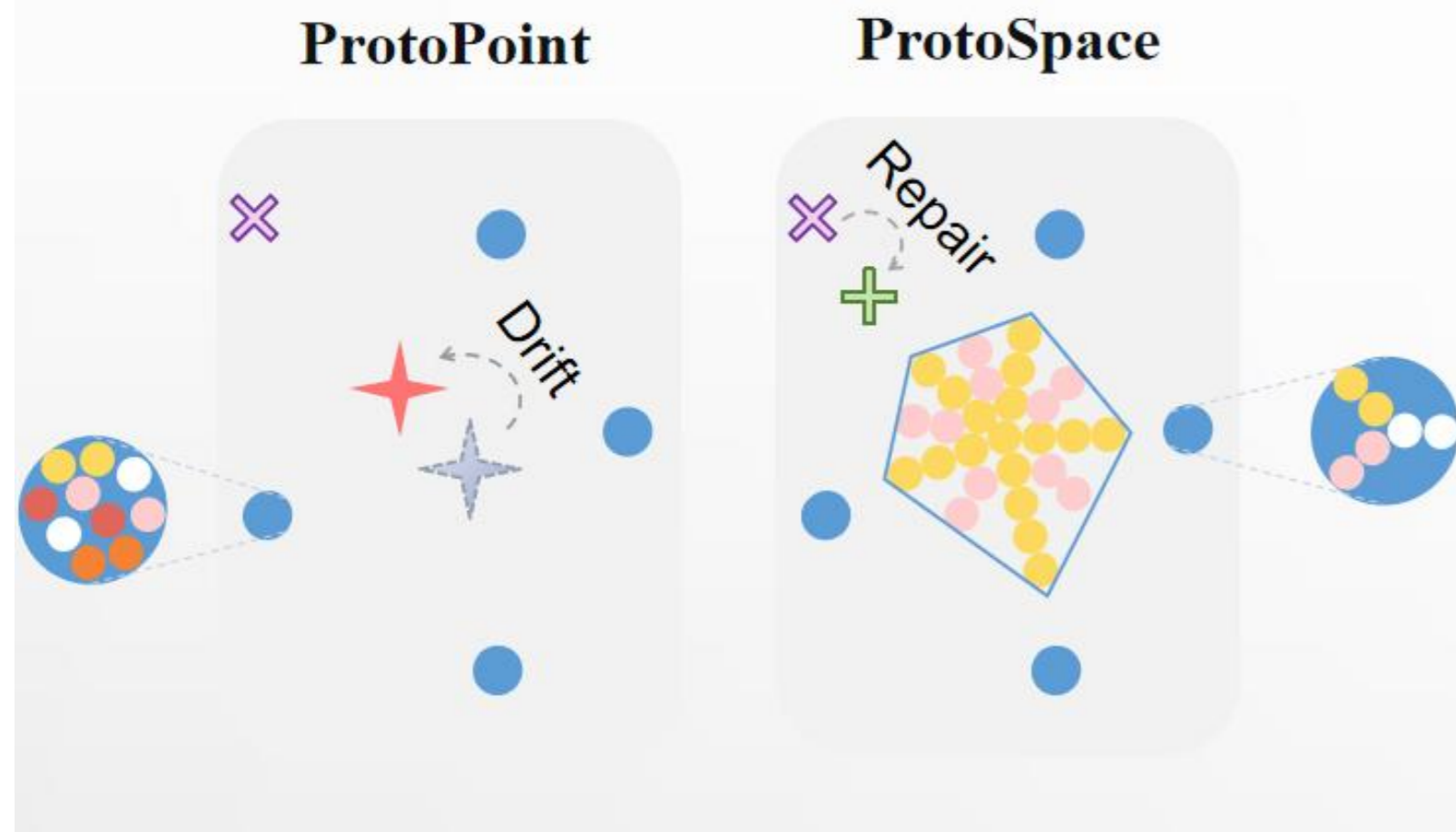


DDSF: Robust Few-Shot Learning via Disentangled Subspaces with Determinantal Point Process

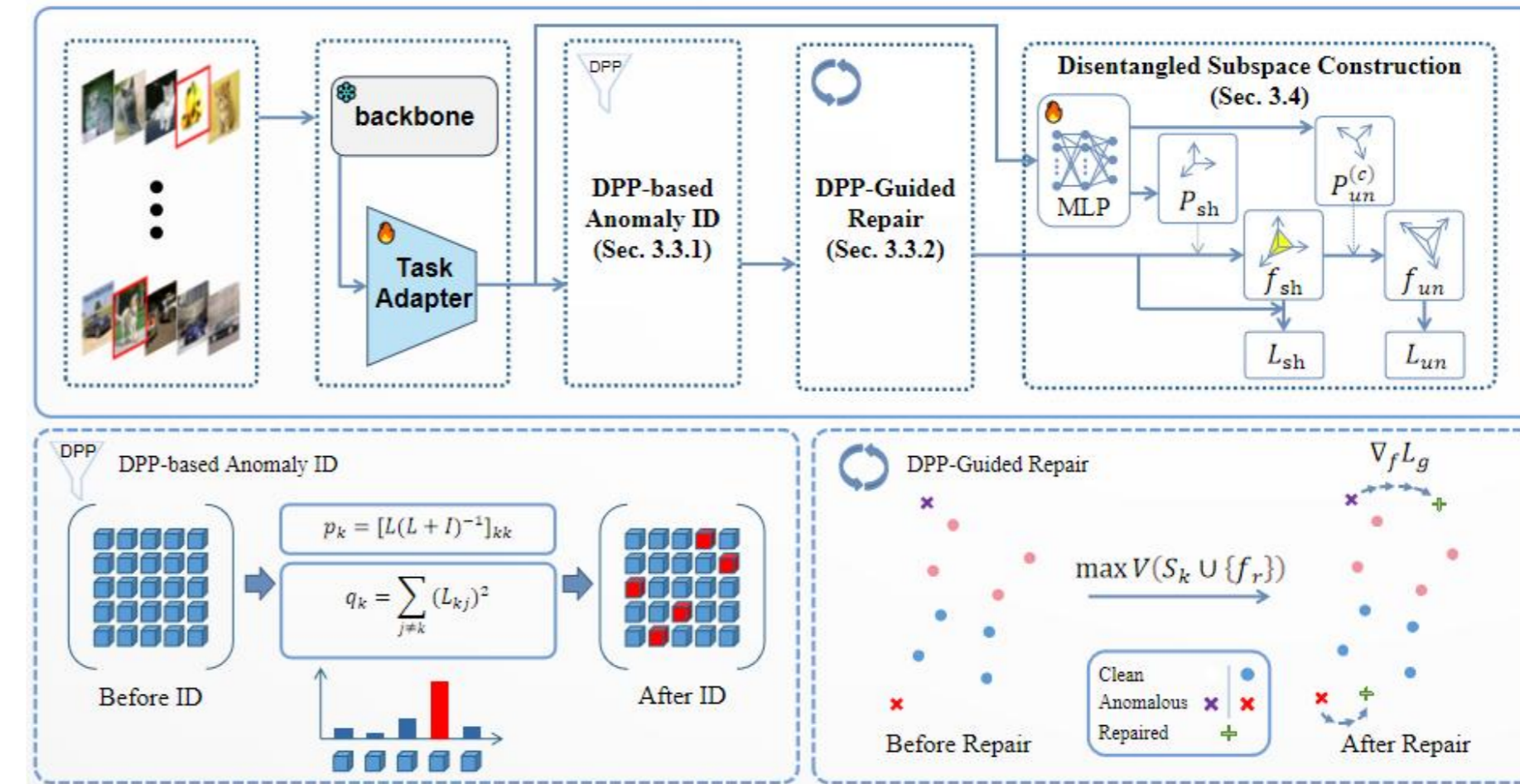
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Introduction



The performance of mean-based prototypical methods in few-shot learning is frequently compromised by noise and hard positives, where entangled feature representations cause prototype instability. We present a novel “Filter Repair-Expand” framework grounded in Determinantal Point Process (DPP) theory. The method leverages DPP as its core logic, employing it to estimate sample confidence to filter anomalous samples from the initial set, guide a diffusion process via volume-maximization to enhance the sample representation, and subsequently maximize the volume of synergistic disentangled subspaces, constructing robust and diverse prototype subspaces. Experimental results establish new state-of-the-art performance on multiple benchmarks, demonstrating significant gains in few shot learning robustness.

Methods

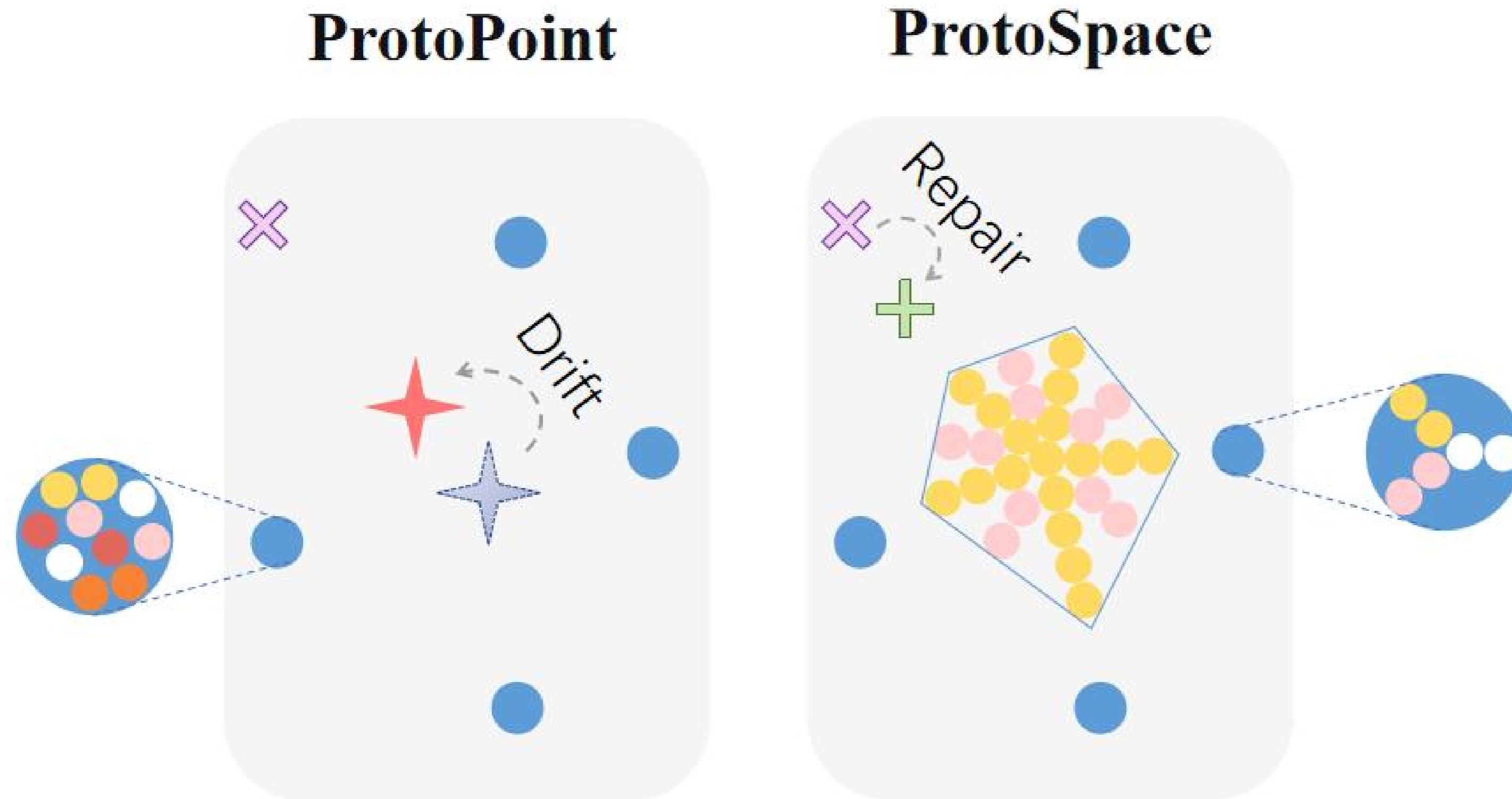


- Probabilistic Anomaly Identification (Filter)
- DPP-Guided Feature Optimization (Repair)
- Disentangled Subspace Construction (Expand)

Discussion & Conclusions

- Introduces a "Filter-Repair-Expand" paradigm to address representation instability from corrupted data.
- Synergistically uses DPP to identify anomalies, guide diffusion-based repair, and maximize disentangled subspace volume.
- Transforms high-interference samples into effective features, overcoming the information destruction and representation confusion of prior methods.
- Significantly outperforms existing methods across noise benchmarks, setting a new robustness standard in Few-Shot Learning.

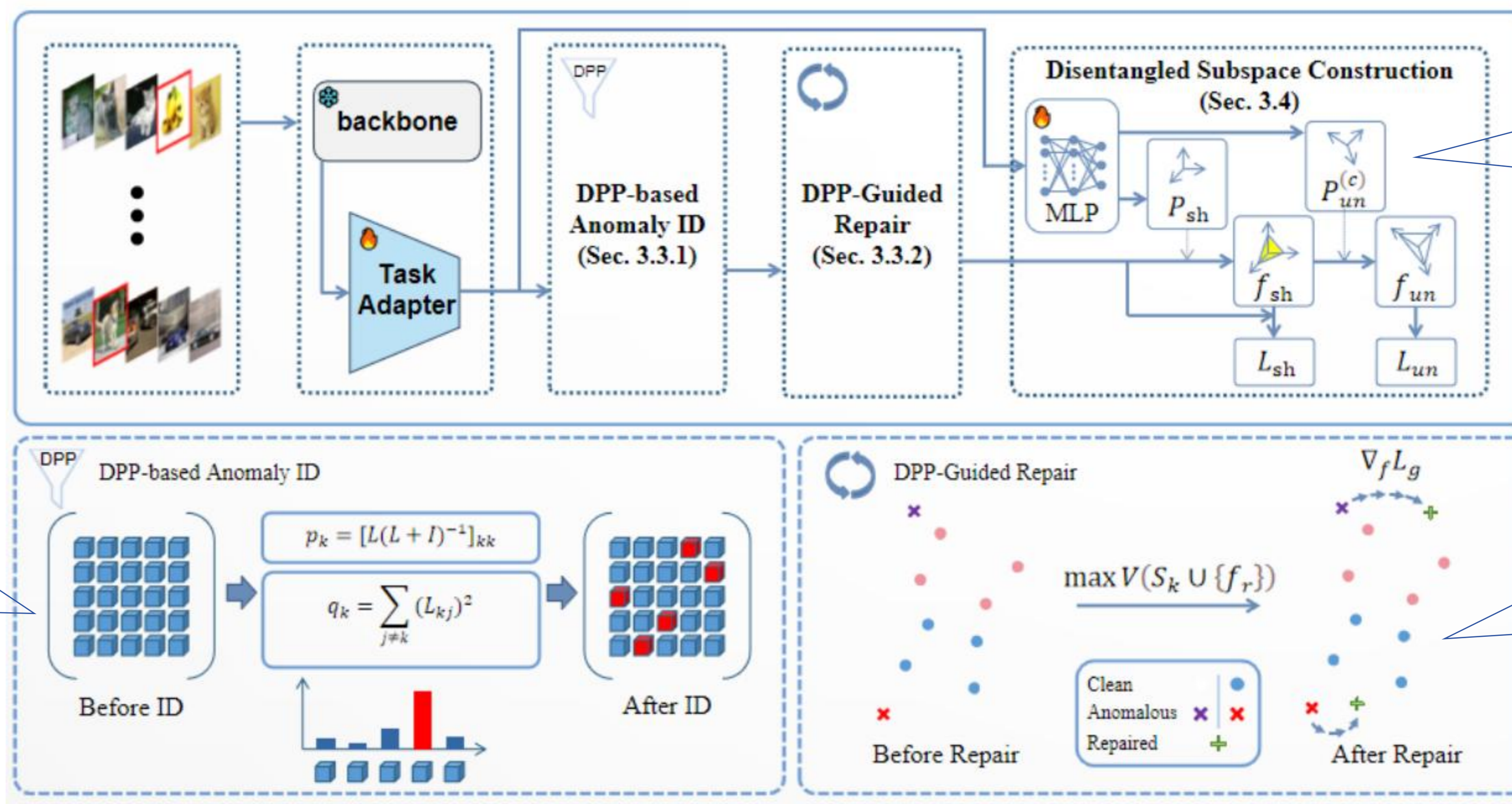
Introduction



- Mean-based prototypical methods in few-shot learning (FSL) are heavily compromised by real-world noise and out-of-distribution (OOD) samples.
- Information Destruction: Current "Filter-Compress" strategies indiscriminately discard hard positives along with true noise.
- Representation Confusion: Point prototypes confound high-variance shared background features with low-variance unique discriminative features.

➤ We propose a "Filter-Repair-Expand" paradigm grounded in Determinantal Point Process (DPP) to construct robust disentangled subspaces instead of fragile point prototypes.

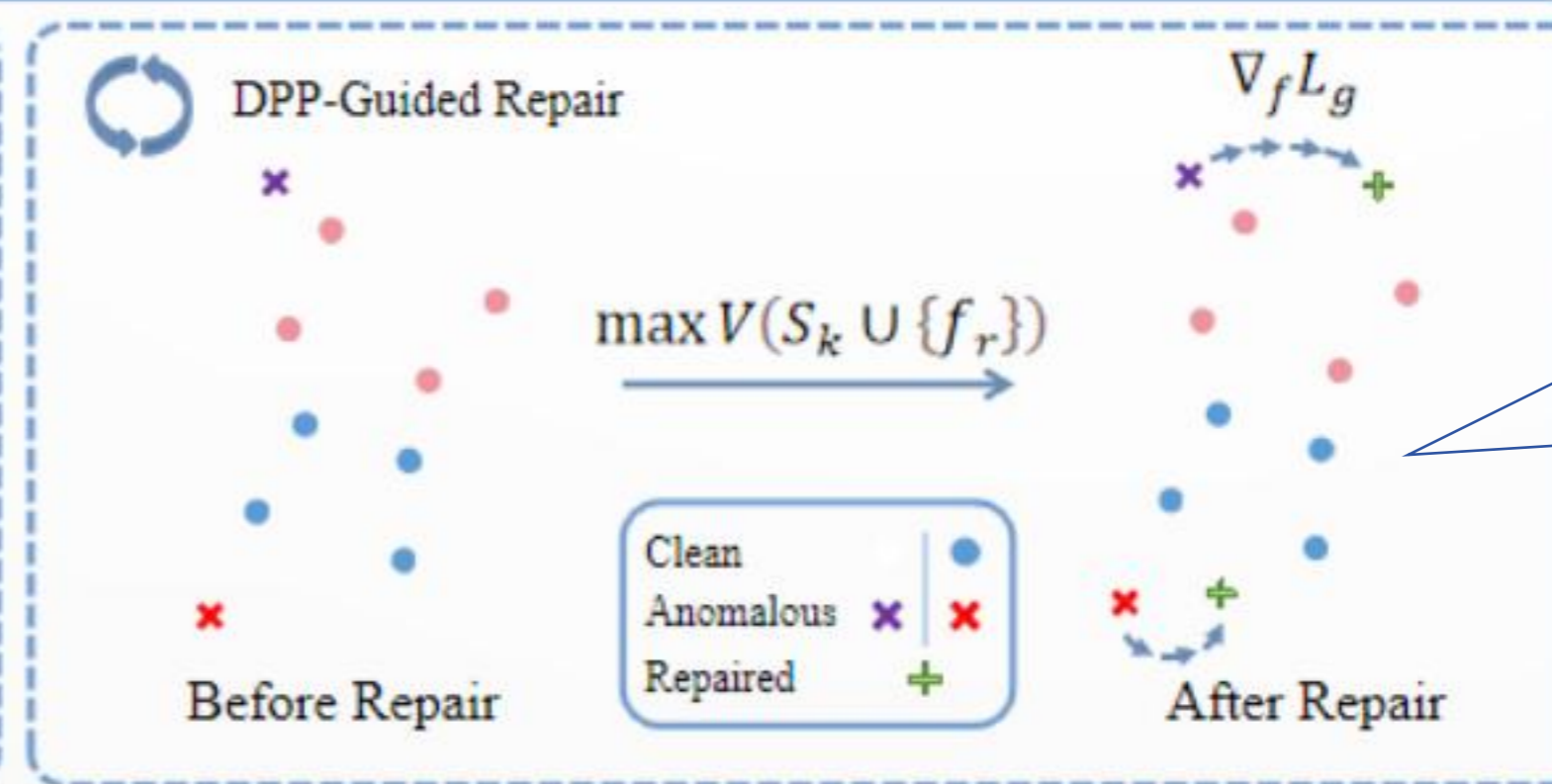
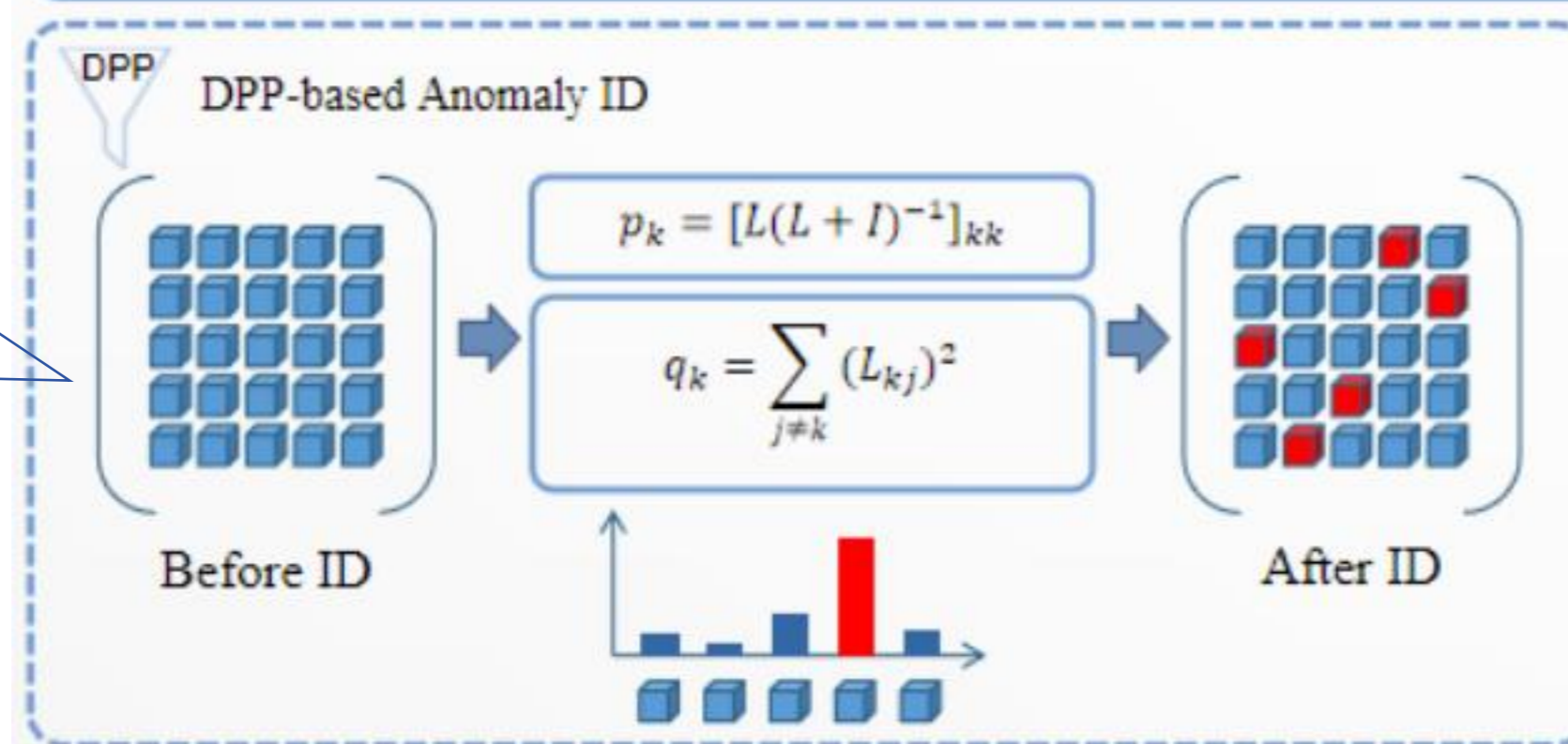
Methodology



1. Filter Probabilistic Anomaly Identification

3. Expand Disentangled Subspace Construction

2. Repair DPP-Guided Feature Optimization



Experiments: Main Results

Table 1. Main SOTA Comparison on OOD-polluted Meta-Dataset. We compare our DDSF against standard baselines and recent state-of-the-art methods. All results are mean accuracy (%). Our method outperforms all competitors, especially in the direct comparison on the same SwinT backbone.

Method	Backbone	0% Noise	10% Noise	30% Noise	50% Noise	70% Noise
TSA (2022) [20]	URL	75.5	71.4	64.4	56.0	36.7
eTT (2022) [47]	DINO	80.9	76.7	67.5	50.4	38.1
full-FT	MoCo	73.0	66.9	62.8	54.1	34.8
full-FT	CLIP	75.3	70.1	64.9	54.0	35.7
full-FT	DeiT	82.5	78.0	75.4	63.8	43.2
AM3 (2019) [46]	ResNet-12	74.1	68.4	62.5	50.8	33.7
FGFL (2023) [6]	ResNet-12	80.1	74.8	69.9	55.8	36.7
MetaDiff (2024) [49]	ResNet-12	74.5	69.2	63.5	51.5	34.1
SemFew (2024) [51]	ResNet-12	81.5	78.6	73.5	61.0	44.9
SemFew-Trans (2024) [51]	SwinT	81.9	77.2	71.2	57.9	40.6
FedFSL-CFRD (2025) [44]	ResNet-12	65.0	60.6	56.8	50.8	42.5
ECER-FSL (2025) [24]	ResNet-12	84.4	78.1	73.3	61.2	42.8
ECER-FSL (2025) [24]	Visformer-T	85.2	79.8	74.3	62.8	43.8
LDC (2025) [19]	CLIP	85.2	79.2	74.2	64.3	44.6
full-FT	SwinT	81.3	75.4	70.7	58.5	41.1
DETA++ (2025) [53]	SwinT	86.5	80.9	77.3	64.2	47.0
Ours (DDSF)	SwinT	91.9 (± 0.43)	89.9 (± 0.50)	85.3 (± 0.65)	75.9 (± 0.88)	61.6 (± 1.09)

Table 2. Performance of our DDSF framework across various backbone architectures. All results are reported on the OOD-polluted Meta-Dataset under 0% and 30% noise levels.

Backbone	0% Noise	30% Noise
Swin-T [26]	91.9 (± 0.43)	85.3 (± 0.65)
ViT-B/32 (CLIP) [33]	93.1 (± 0.31)	86.1 (± 0.55)
ViT-S (DINO) [3]	90.0 (± 0.53)	84.2 (± 0.71)
ConvNeXt-B [27]	90.4 (± 0.52)	83.9 (± 0.61)
ResNet-50 [11]	89.1 (± 0.49)	82.2 (± 0.76)

Experiments: Ablation and Robustness

Table 3. Component-additive ablation study of the DDSF framework. We analyze the contribution of each module defined in Sec 3.3.1 (Filter) and Sec 3.4 (Expand). Models (A-E) serve as the baseline pipeline, while the full model (F) additionally integrates the DPP-based volume loss (\mathcal{L}_{un}). Accuracy (%) is reported on 0% (clean) and 30% (noisy) settings.

Idx	Components					Accuracy (%)	
	Filter (p_k)	Filter (q_k)	Filter (s_k)	Repair (DPP)	Expand (\mathcal{L}_{un})	0% Noise	30% Noise
(A)	×	×	×	×	×	84.4	77.1
(B)	✓	×	×	×	×	86.3	79.4
(C)	×	✓	×	×	×	86.2	79.5
(D)	×	×	✓	×	×	87.3	80.7
(E)	×	×	✓	✓	×	89.9	83.4
(F)	×	×	✓	✓	✓	91.9	85.3

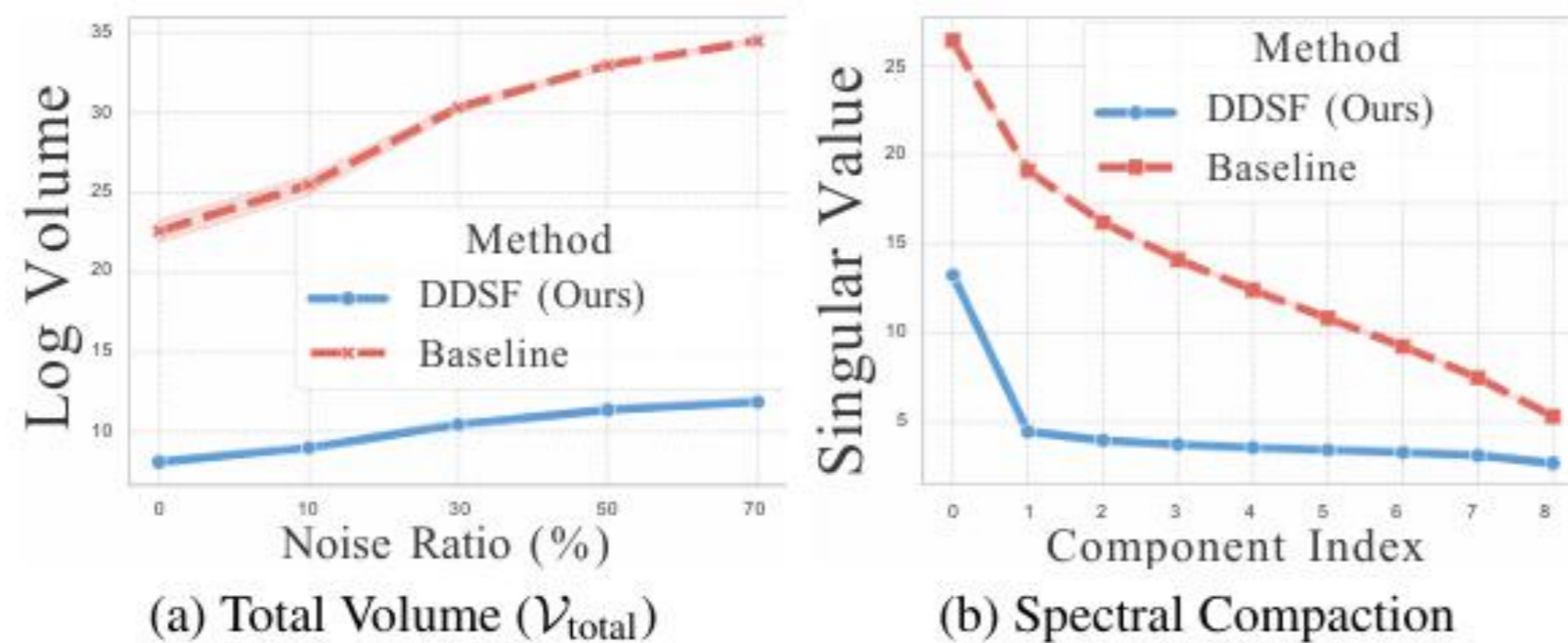


Figure 3. Ablation analysis of the feature space. (a) Log Volume: DDSF’s purified feature volume remains low and stable against noise, unlike the baseline. (b) Spectral Compaction: DDSF’s singular values decay sharply, indicating successful purification and compaction of shared/noise variance.

Table 4. Performance vs. 30% OOD and 30% SLS Noise (SwinT).

Method	Noise Type	Accuracy (ACC, %)
DETA++ [53]	OOD Noise	77.3
	SLS Noise	75.1
Ours (DDSF)	OOD Noise	85.3
	SLS Noise	83.2

Conclusion

- 1 Synergistically leverages Determinantal Point Process (DPP) theory to perform probabilistic anomaly identification, guide a diffusion-based repair, and maximize the volume of disentangled, class-specific subspaces.
- 2 Transforms high-interference samples into effective features to construct robust prototype subspaces.
- 3 Successfully resolves both the information destruction and representation confusion that limit prior methods.
- 4 Proposes DDSF, a robust framework introducing the "Filter-Repair-Expand" paradigm to address representation instability caused by corrupted data.
- 5 Extensive experiments across multiple noise benchmarks demonstrate that DDSF significantly outperforms state-of-the-art methods.
- 6 Establishes new standards for robustness in Few-Shot Learning (FSL).