Adversarially Diversified Rehearsal Memory (ADRM): Mitigating Memory Overfitting Challenge in Continual Learning

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I. Introduction
II. Related Work
III. Problem Statement
IV. Our Work: Adversarially Diversified Rehearsal Memory
V. Results and Baselines
    1. Evaluation Against Common Corruptions
    2. Evaluation Against Common Adversarial Attacks
    3. t-SNE Visualization of Latent Features Distributions in CL
    4. Features Similarity Metrics: A Central Kernel Alignment Analysis
    5. Visualization of CL Model's Features in Input Space
VI. Conclusion

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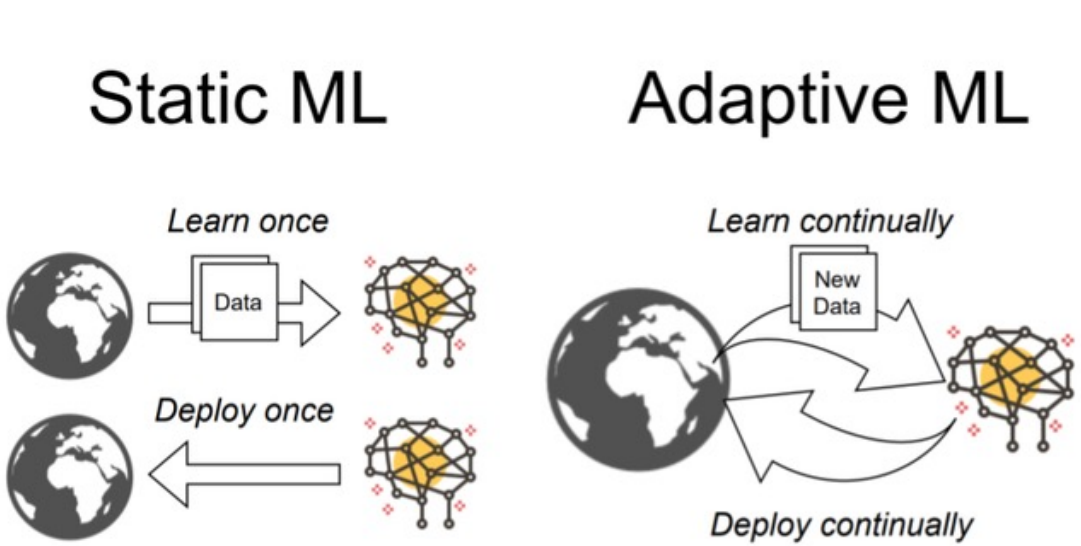
Deep Learning – The Promise

- Deep Learning (DL)/Artificial Intelligence (AI) models have achieved or even surpassed human-level accuracy in several areas, including computer vision and pattern recognition.

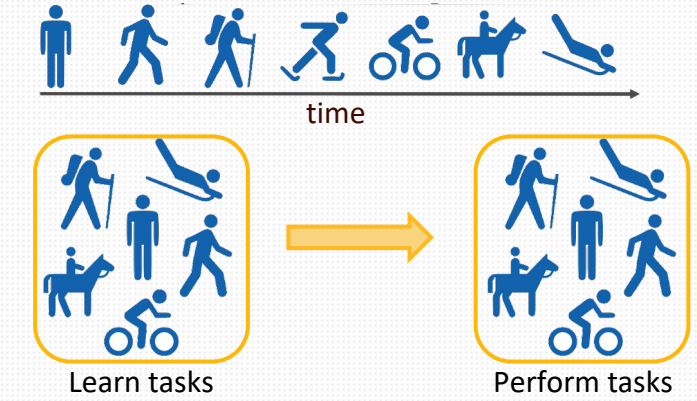
The World is Non-Stationary [5]

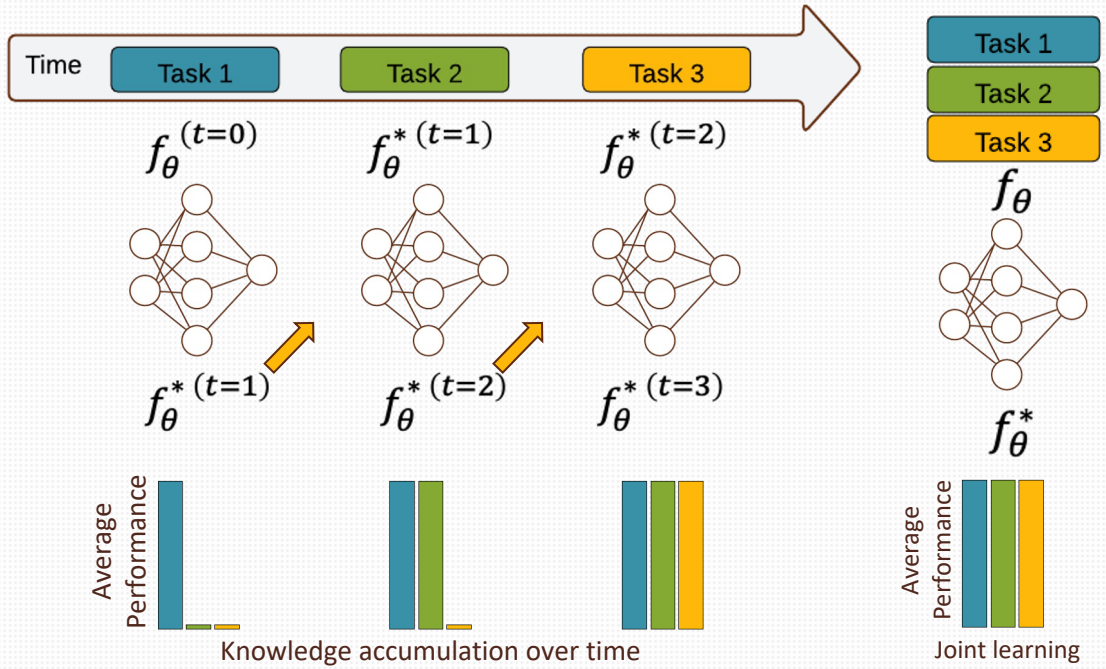


https://medium.com/gooroo-official/if-youre-not-learning-you-re-dying-b2b4d54eace4 | https://senicessm.live/product_details/47625942.html

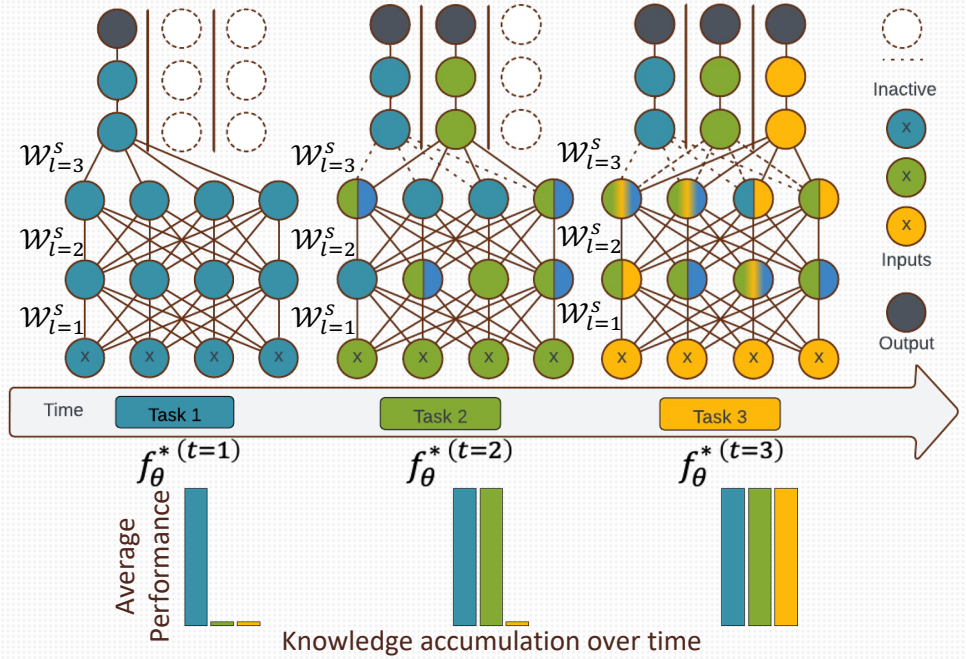
Continual Learning (CL)

- Learning tasks over time[1].
  - The tasks can be any classification or segmentation.
- Offline learning [1, 2].
  - Learn all tasks simultaneously.





Task Incremental Learning [2]



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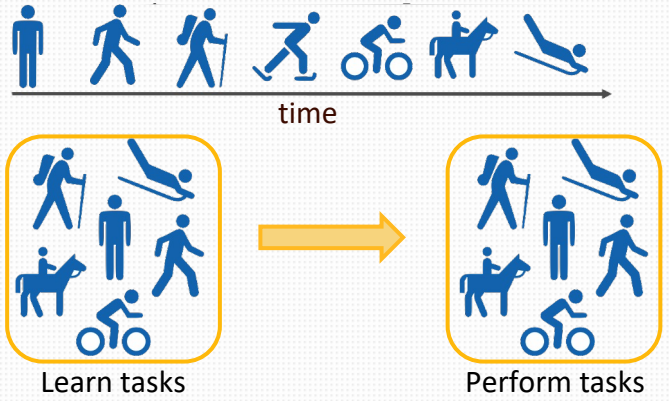
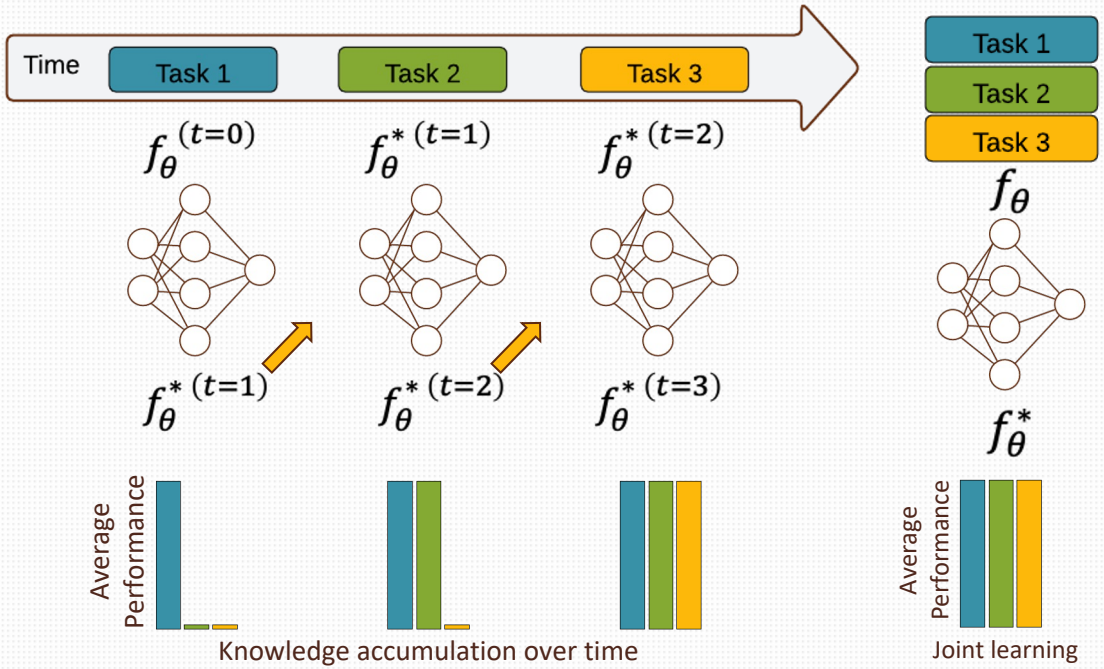
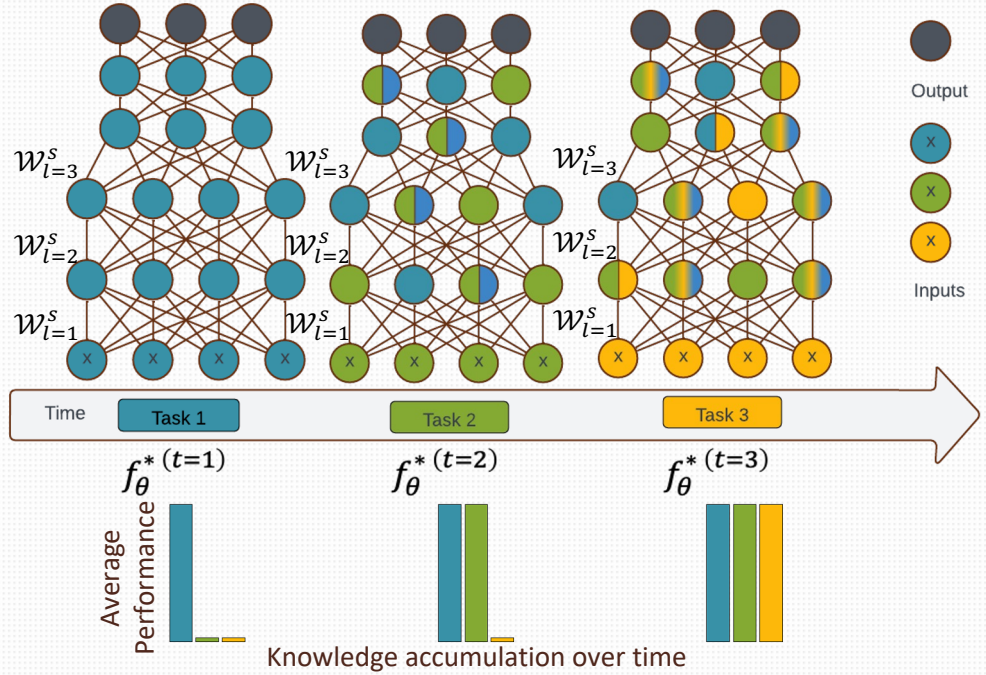




Domain Incremental Learning [2]



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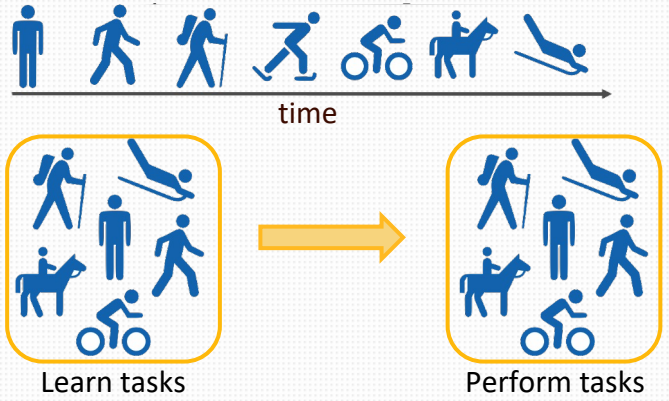
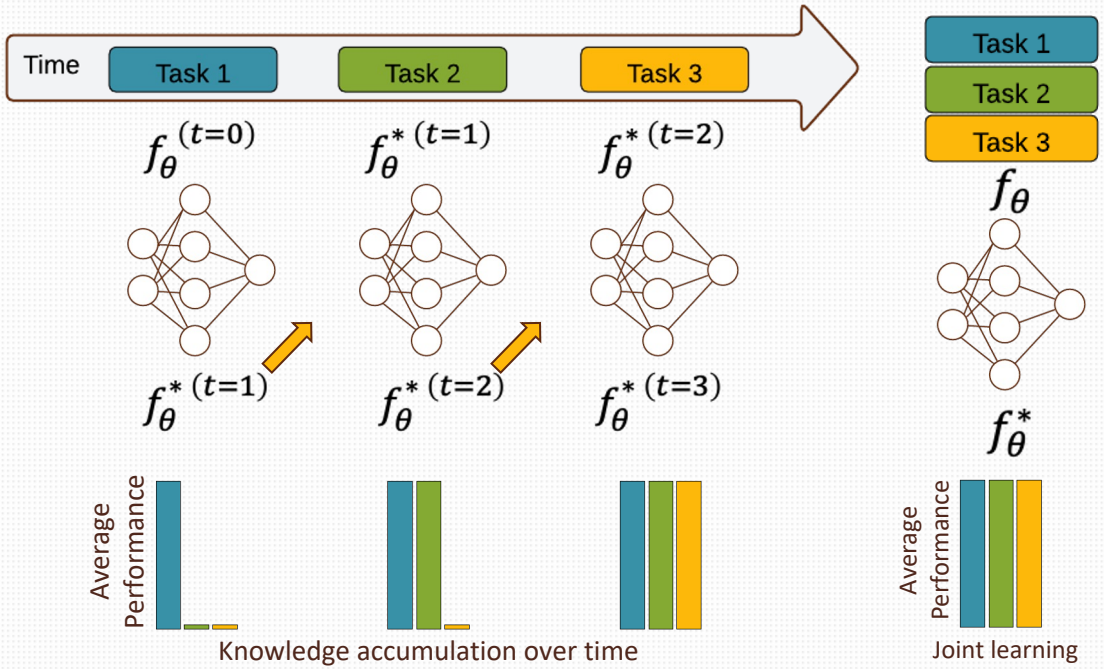
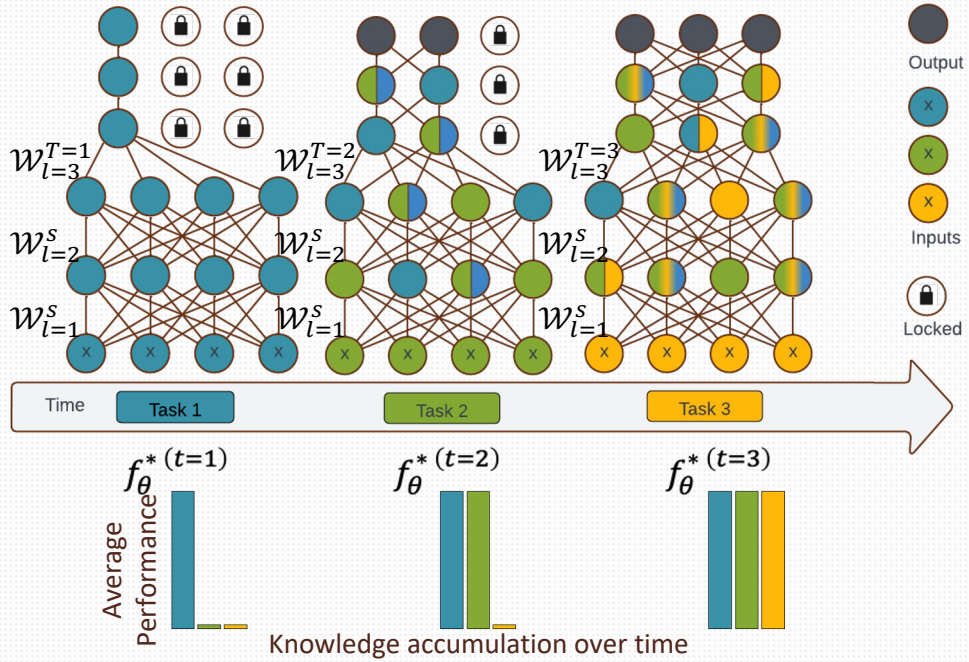


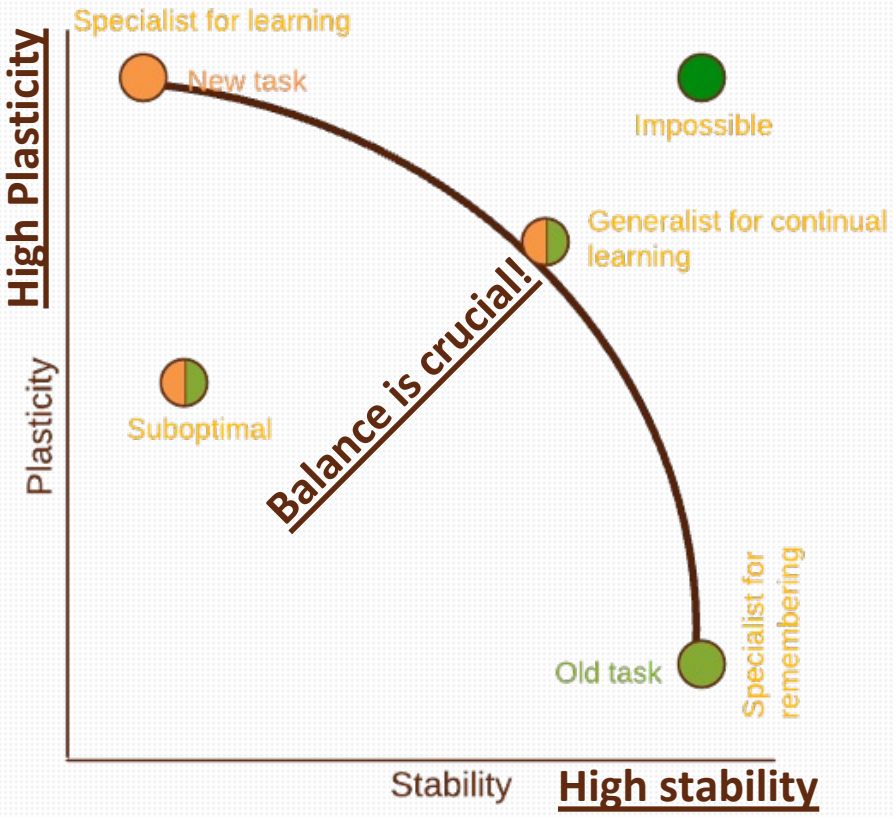


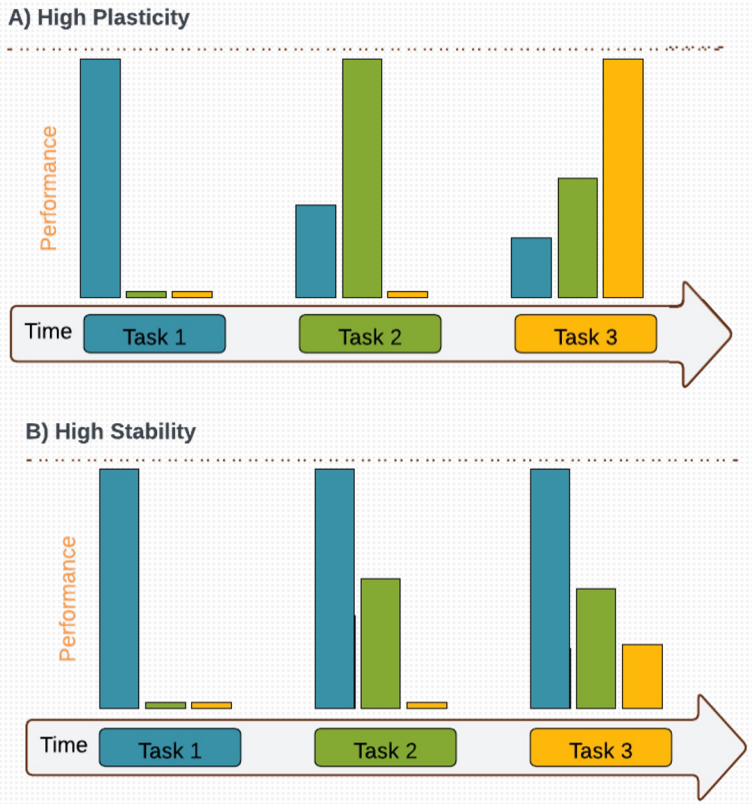
Class Incremental Learning [2]



The Challenges Stopping CL

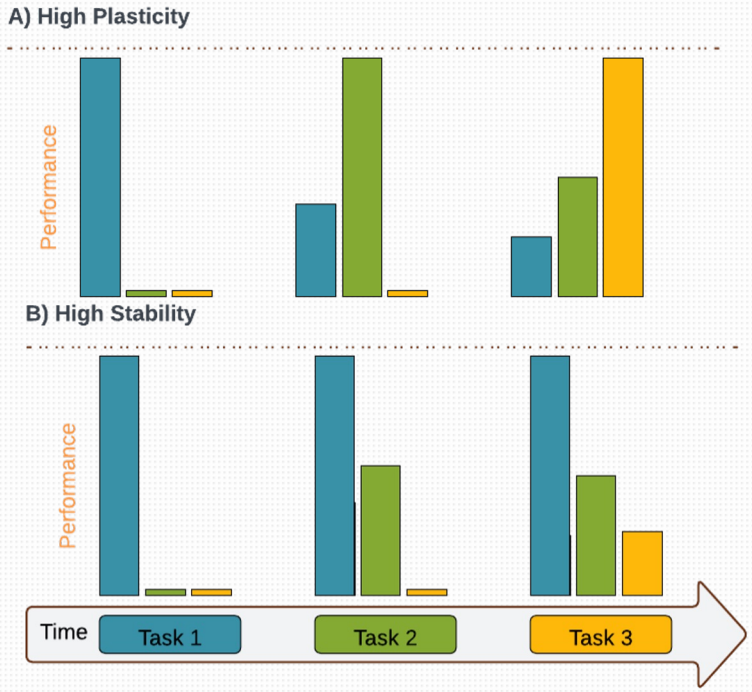
- Plasticity-stability dilemma [3].
  - The plasticity-stability dilemma is a fundamental challenge in both neuroscience and deep learning design.





The Challenges Stopping CL (Continued)

- Plasticity-stability dilemma [3].
  - Plasticity:
    - Easily learn and adapt to new experiences.
    - Enables good adaptation.
  - Stability:
    - Ability to retain previously learned experiences.
    - Ensures proficiency in solving old tasks.
- Catastrophic forgetting [4].
  - If a system is too plastic, it risks overriding old knowledge (aka catastrophic forgetting)
  - A phenomenon where a model forgets previously learned knowledge after acquiring new knowledge.



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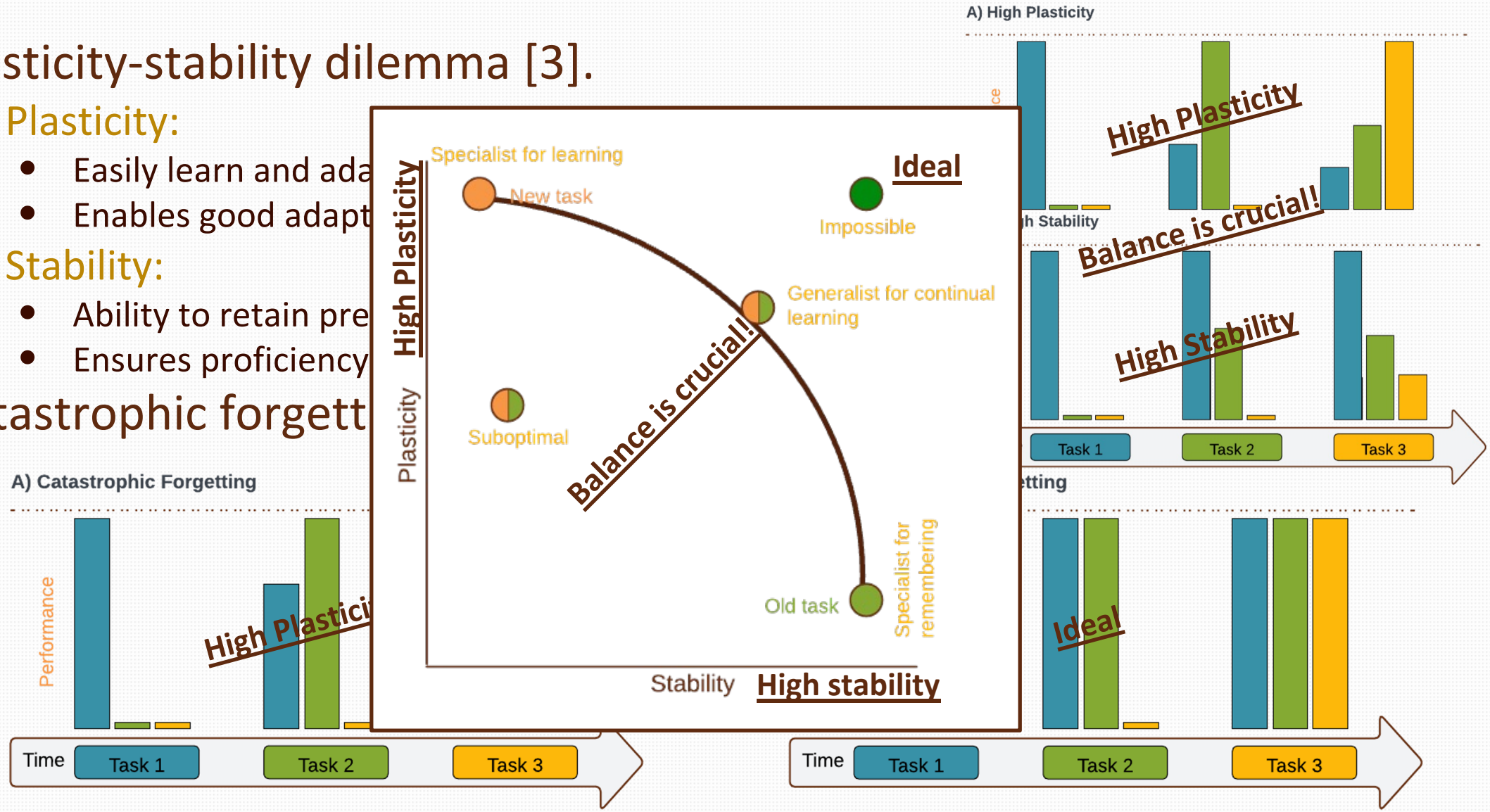

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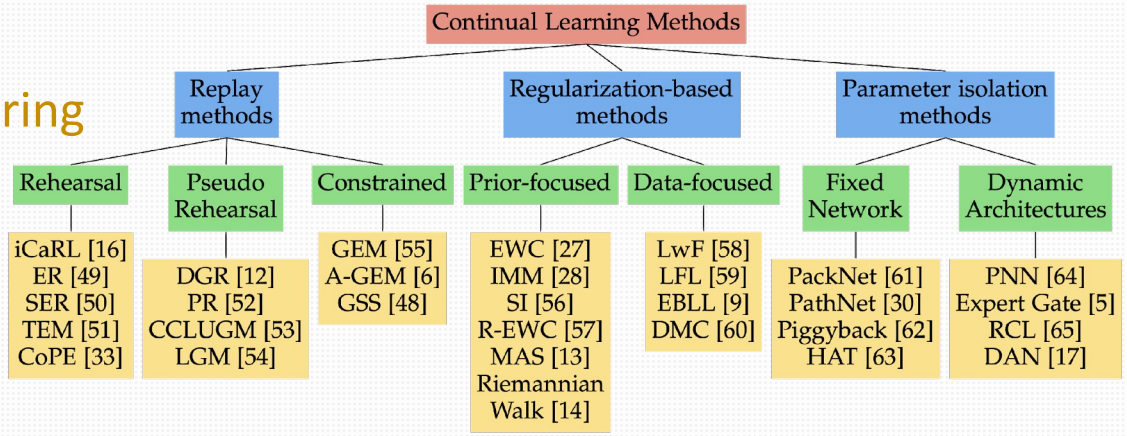
Related Work

1. Rehearsal-based Approaches [1, 5]
   - Store a subset of the old data and rehearse it during the learning of the subsequent tasks.
2. Regularization-based Approaches [1, 5]
   - Penalize (important) parameter updates.
3. Architectural-based Approaches [1, 5]
   - Increase the model capacity for every new task.
   - Explicitly identify important parameters for each task.
4. Knowledge Distillation-based Approaches [1, 5]
   - Take inspiration from the Knowledge Distillation.
   - Use the previous task model as a teacher.
5. Dataset Distillation-based Approaches [1, 5]
   - Create representative subsets that can be rehearsed during the learning of the subsequent tasks.
6. Brain-inspired Approaches [1, 5]
   - Incorporate inspiration from neuroscience in designing the CL
7. Hybrid Approaches [1, 5]
   - Combine multiple approaches to create more robust solutions against catastrophic forgetting.



Taxonomy of CL approaches [1]

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Problem Statement

- Rehearsal-based approaches are widely adopted to mitigate catastrophic forgetting in CL models.
- However, these approaches suffer from rehearsal memory overfitting, where the CL model becomes overly specialized on a limited set of memory samples, resulting in catastrophic forgetting.
- Leading to a progressive decay in the effectiveness of the rehearsal memory, ultimately causing the model to forget previously learned tasks.
- **Question!**
  - Can rehearsal memory be diversified to prevent rehearsal memory overfitting in the CL model?

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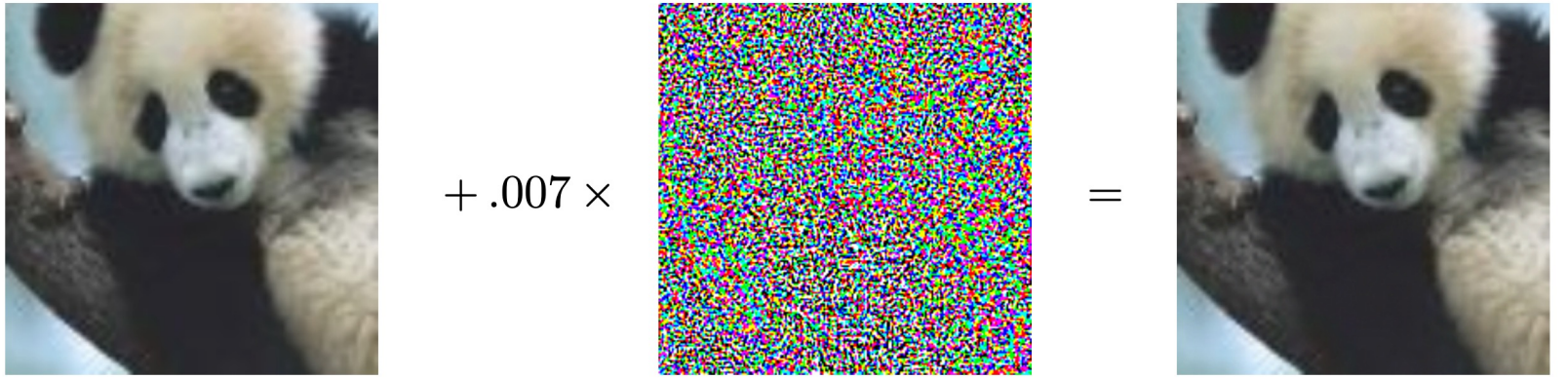
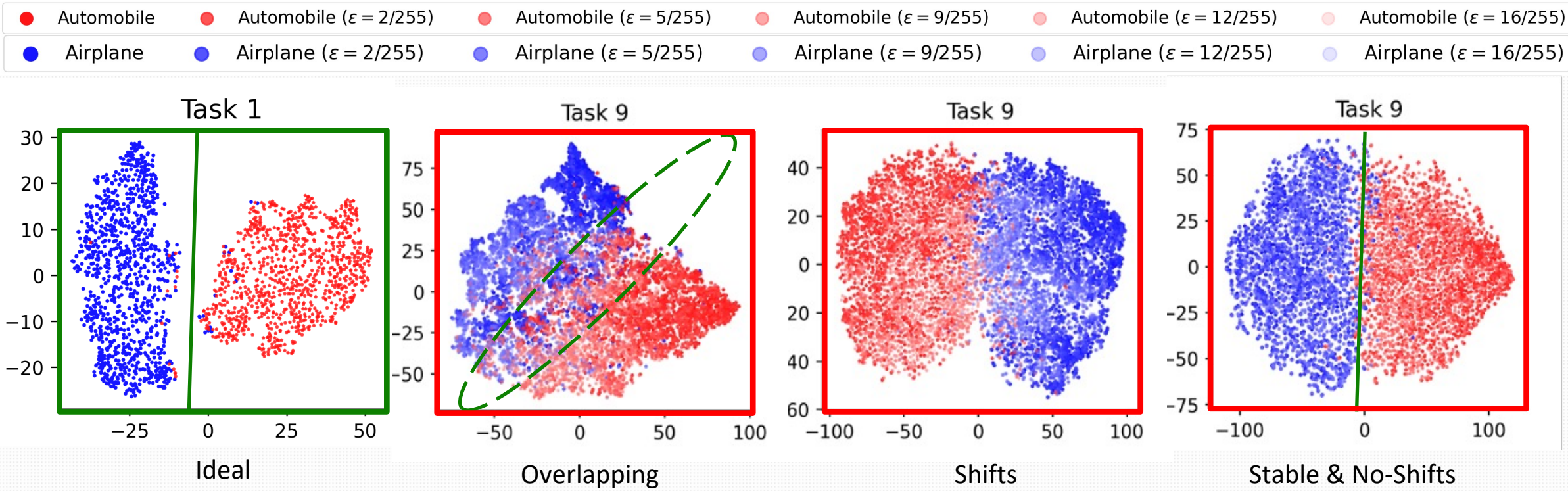
Adversarial Attacks (Quick Refresher)

- Fast Gradient Sign Method (FGSM) [10]

$$x_{adv} = x + \epsilon * sign(\Delta_x \, J(\theta, x, y))$$



Idea Illustration: Adversarially Diversified Rehearsal Memory



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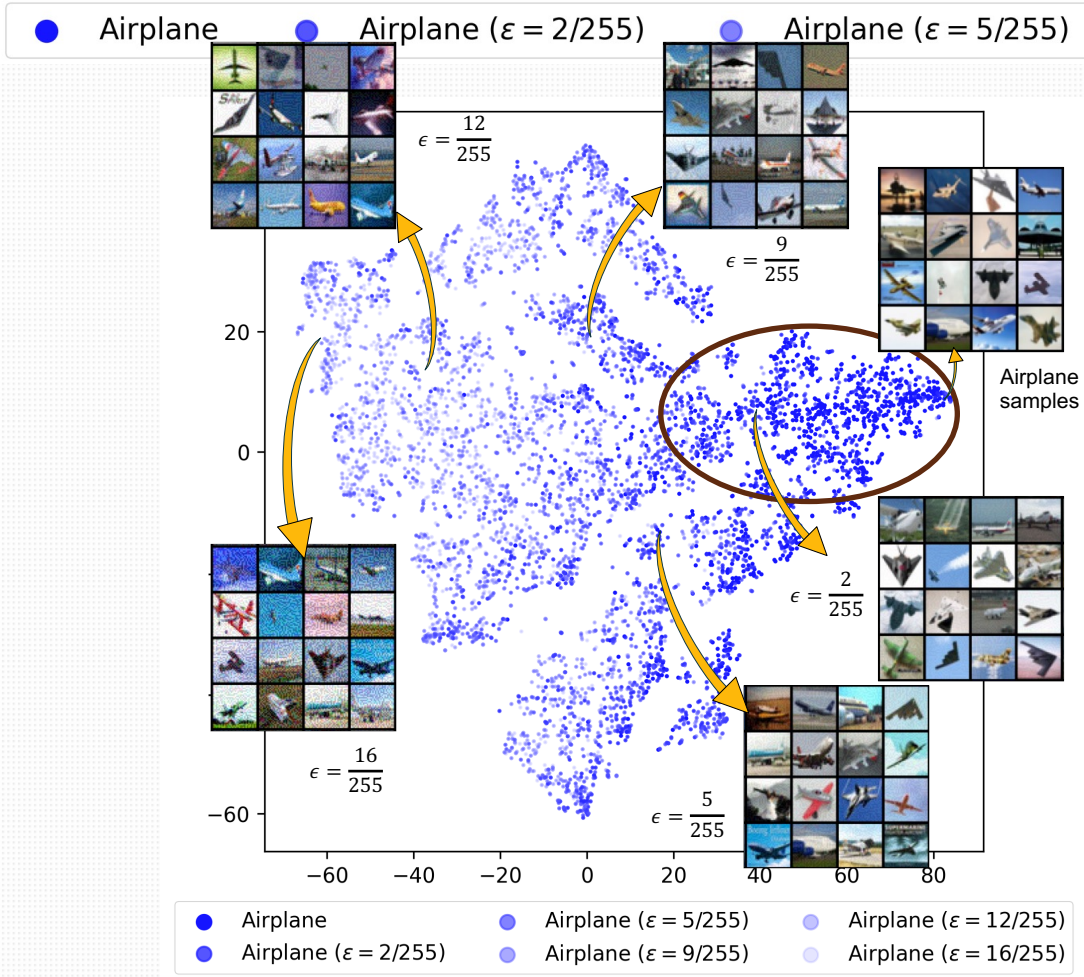
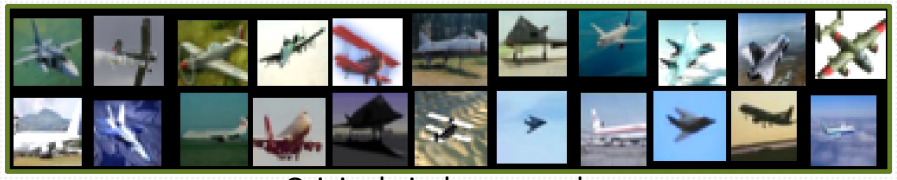
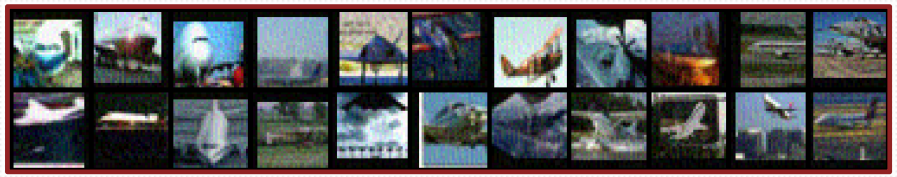


t-SNE visualization showing the dispersion of 'airplane' class features under increasing adversarial perturbations



Original airplane samples

Correctly classified adversarially diversified airplane samples



Incorrectly classified adversarially diversified airplane samples

Adversarially Diversified Rehearsal Memory (ADRM)

- Rehearsal-Based Continual Learning

$$\min_{\theta \in \Theta} \left[\mathbb{E}_{(x_t, y_t) \sim \mathcal{D}_t} \overbrace{\mathcal{L}(\theta, x_t, y_t)}^{\text{Current task}} + \mathbb{E}_{(x_m, y_m) \sim \mathcal{M}_t} \overbrace{\mathcal{L}(\theta, x_m, y_m)}^{\text{Memory}} \right]$$

- Aims to increase the complexity of memory samples using FGSM [10]

$$x_{diversified} = x_m + \epsilon \,.\, sign(\nabla_{x_m} J(\theta,\ x_m,\ y_m))$$

- Benefits of ADRM:
  - Prevents rehearsal memory overfitting.
  - Maintains the effectiveness of rehearsal memory samples.
  - Enables CL models to learn new tasks without performance degradation.

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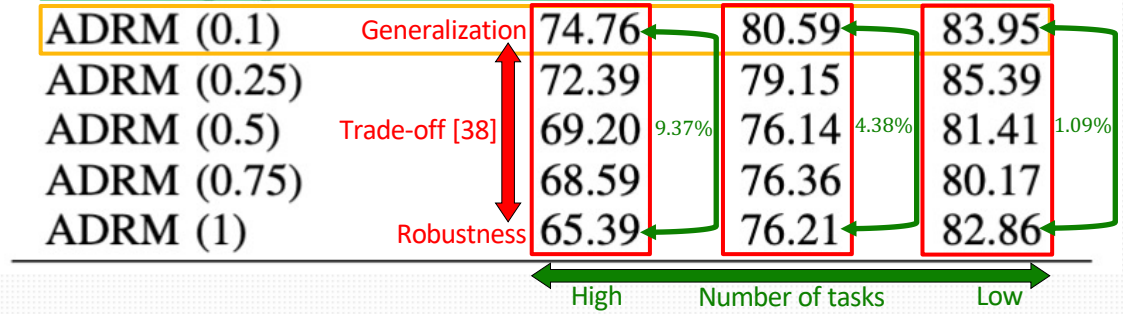
Results and Baselines

- The ADRM outperforms several established CL approaches and achieves comparable results to state-of-the-art CL approaches.
- ADRM, when rehearsed with 10% adversarially diversified memory, demonstrates superior performance over variants incorporating 25%, 50%, 75%, and 100% diversified memory.
- The 10% adversarially diversified memory suggests that a minimal level of adversarial diversification, can prevent the rehearsal memory overfitting in CL.

CL Methods	Split-CIFAR10		
	9 steps	5 steps	2 steps
Joint		94.8	
Fine-tune	11.11	18.54	45.31
Experience Replay [6]	67.62	75.97	80.26
iCaRL [33]	69.25	74.85	79.98
BiC [26]	53.11	71.01	86.57
PODNet [34]	72.41	76.96	87.64
WA [25]	75.56	81.67	85.34
DER [35]	74.33	78.14	82.57
SimpleCIL [27]	52.67	54.54	75.01
FOSTER [36]	74.61	80.40	83.89
FETRIL [37]	65.26	67.51	84.52
MEMO [38]	80.60	85.93	87.81
ADRM (0.1)	74.76	80.59	83.95
ADRM (0.25)	72.39	79.15	85.39
ADRM (0.5)	69.20	76.14	81.41
ADRM (0.75)	68.59	76.36	80.17
ADRM (1)	65.39	76.21	82.86



Comparative performance of CL methods on the Split-CIFAR10 dataset over 9 steps, 5 steps, and 2 steps.

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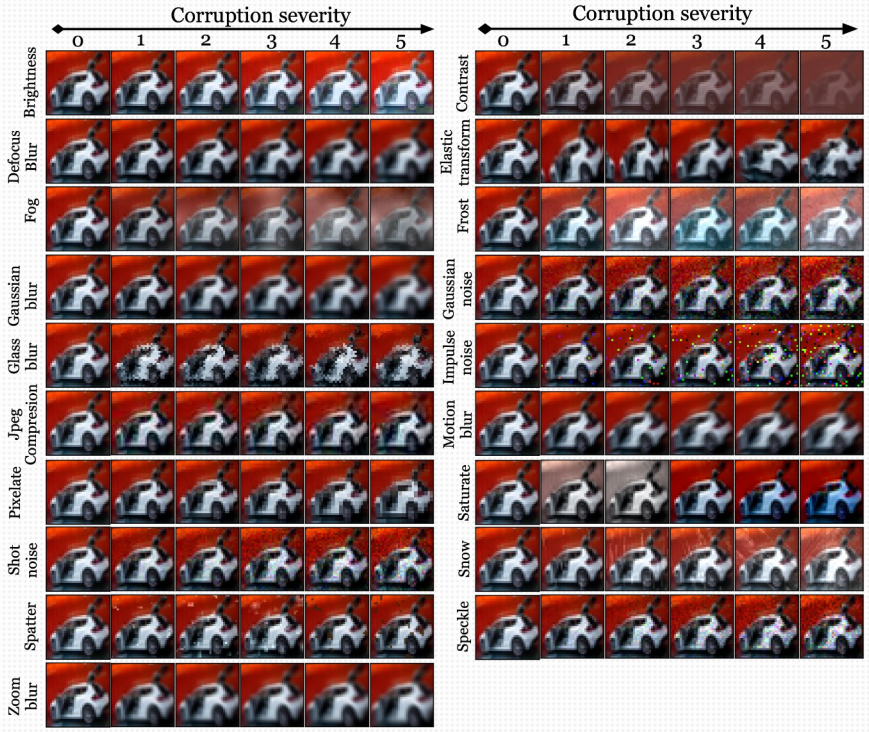
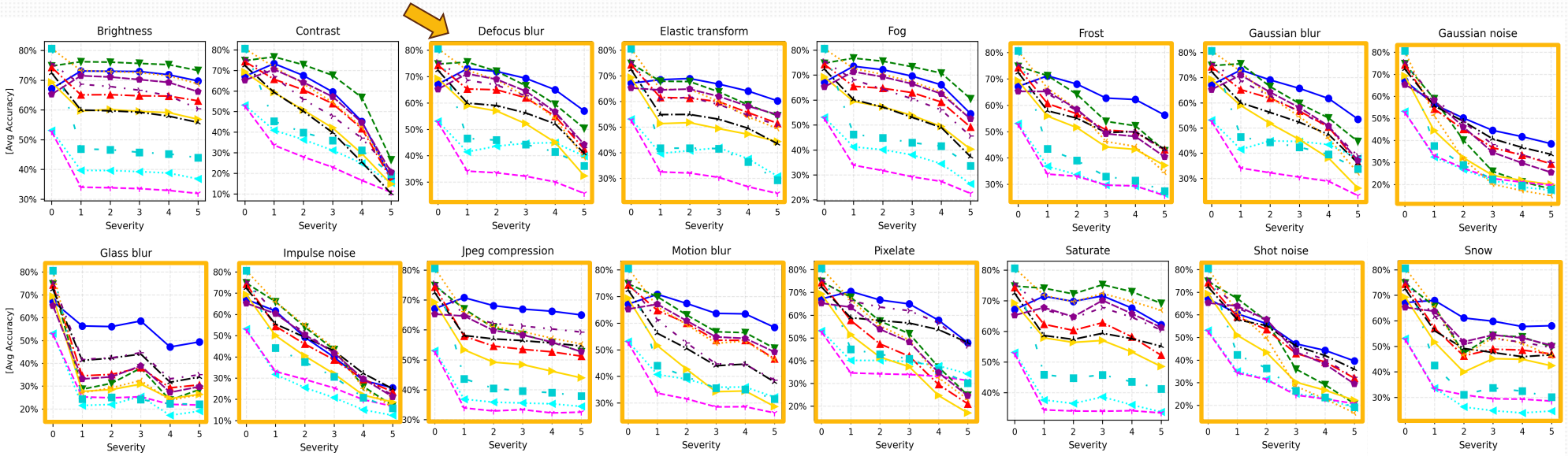
CIFAR10-C (Corrupted) Dataset

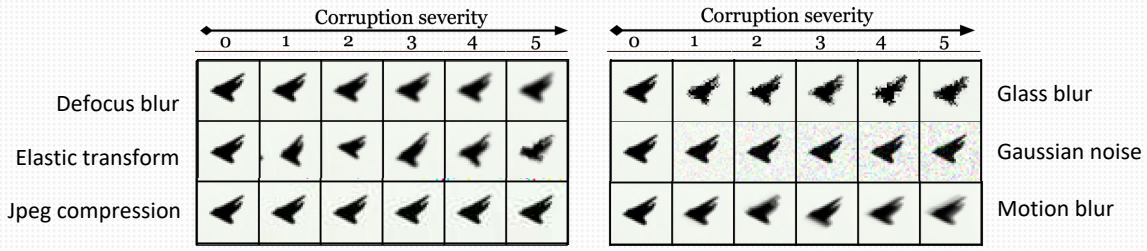
- The CIFAR10-C dataset is a variant of the original CIFAR10 dataset, characterized by the inclusion of corrupted images designed to challenge and evaluate the robustness of models [21].
  - Corrupted images are generated by applying nineteen different types of corruption, such as brightness, fog, and others.
  - We used the CIFAR-10-C dataset to evaluate the robustness and catastrophic forgetting for all benchmark CL models.



Evaluating Against Common Corruptions

- CIFAR10-C (Corrupted) is a variant of the original CIFAR10 dataset that contains corrupted images [6, 21].
- The ADRM model performed relatively best (in 15 out of 19 cases) in various noisy conditions.





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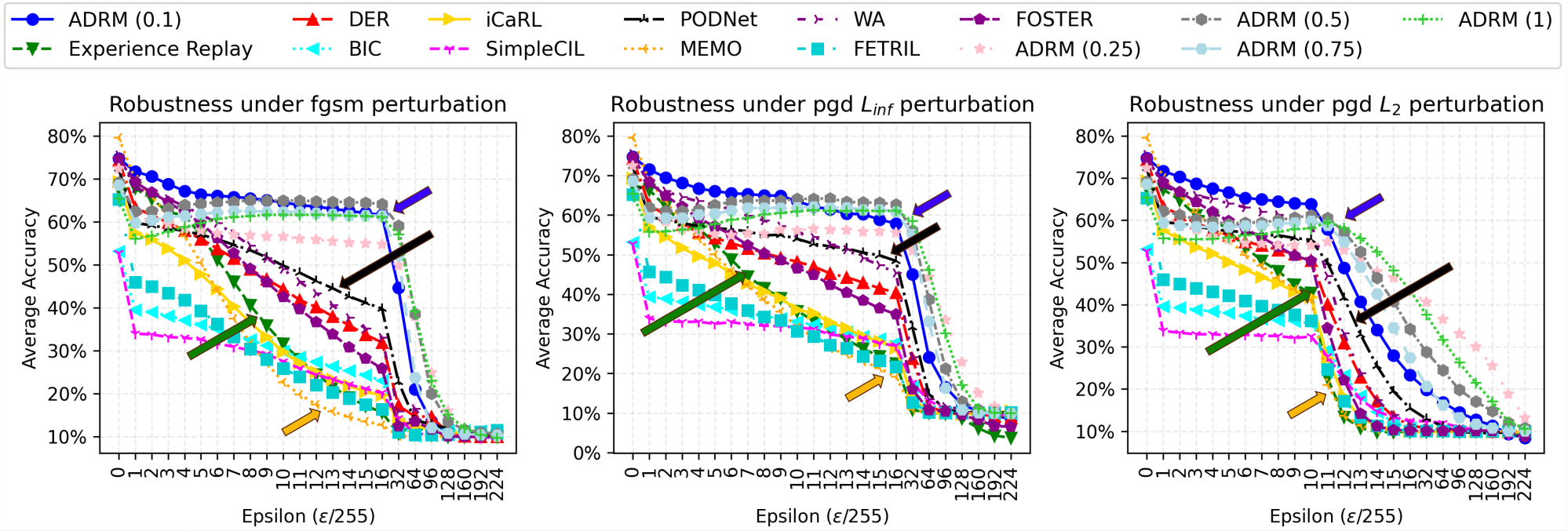
Evaluating Against Adversarial Attacks

- All ADRM variants experienced less catastrophic forgetting in adversarial conditions.



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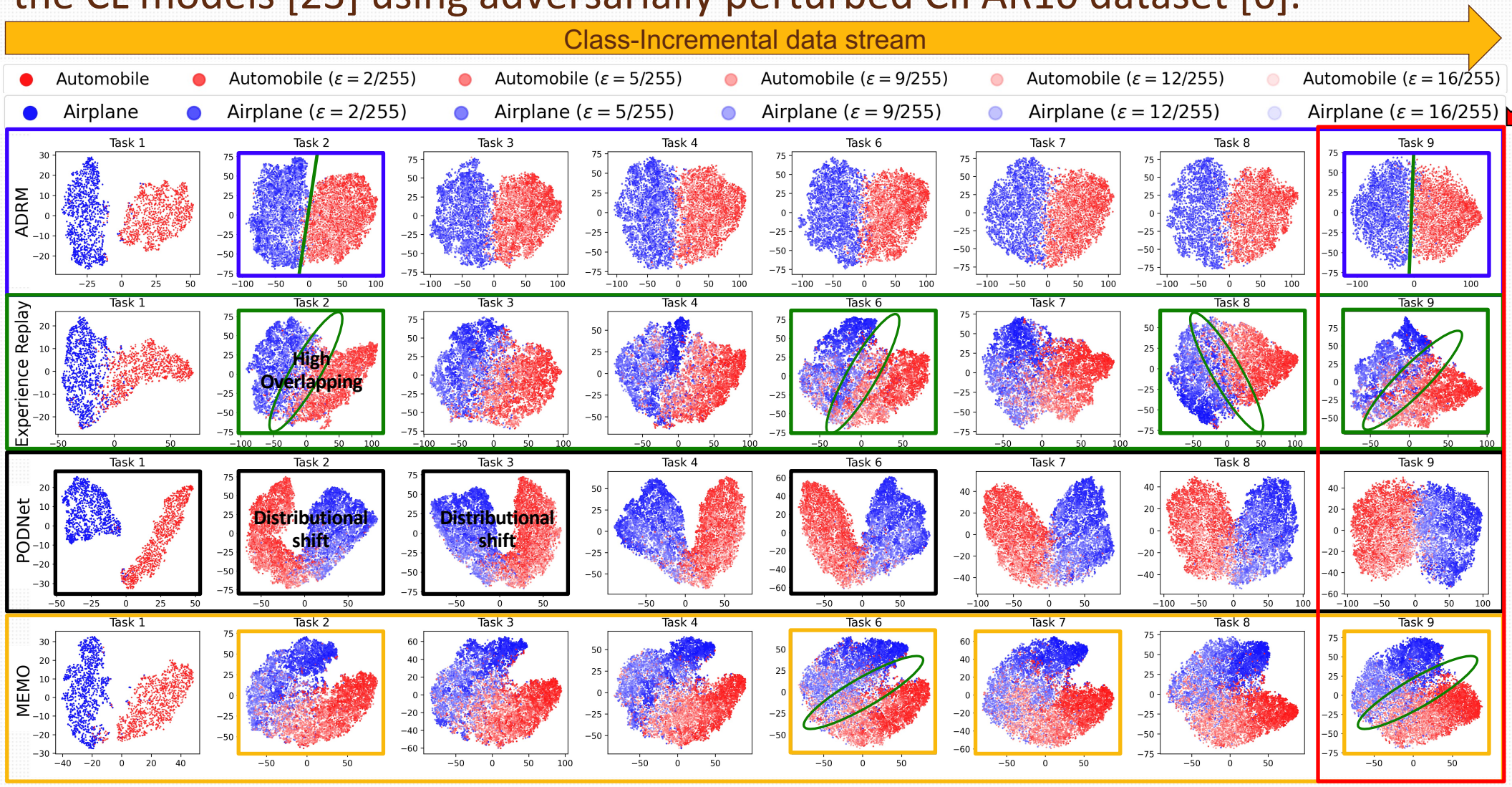
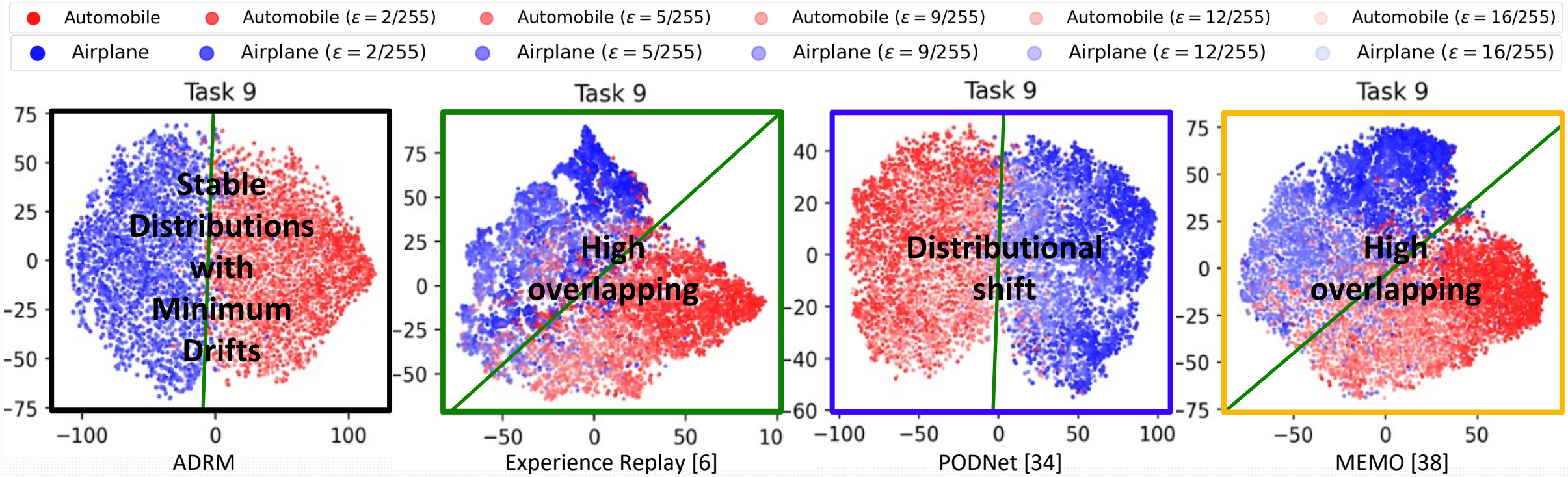
t-SNE Visualization of Latent Feature Distributions in CL

- We utilized t-SNE to visualize the distributions of latent features at the logit layer of the CL models [23] using adversarially perturbed CIFAR10 dataset [6].



t-SNE Visualization of Latent Feature Distributions in CL (Continued)

- Visualization of the learned latent feature distributions for airplanes and automobiles (from the adversarially perturbed CIFAR10 dataset [6]) at the logit layer of CL models [23].



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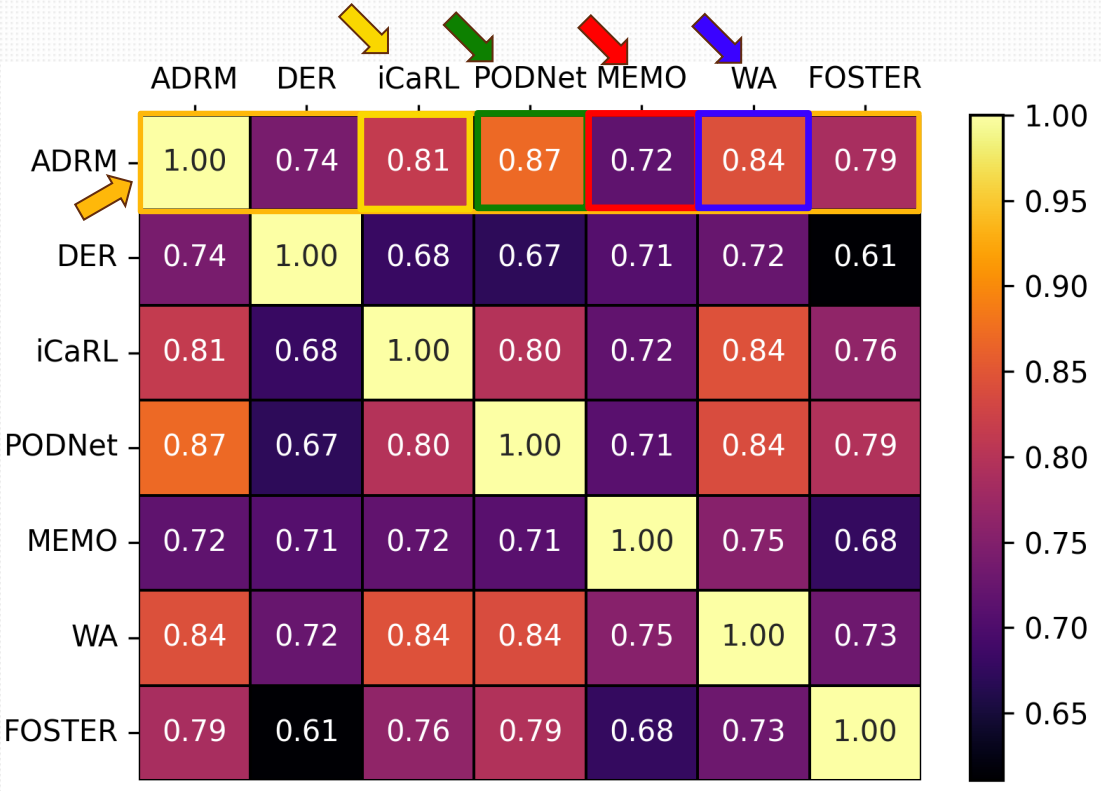
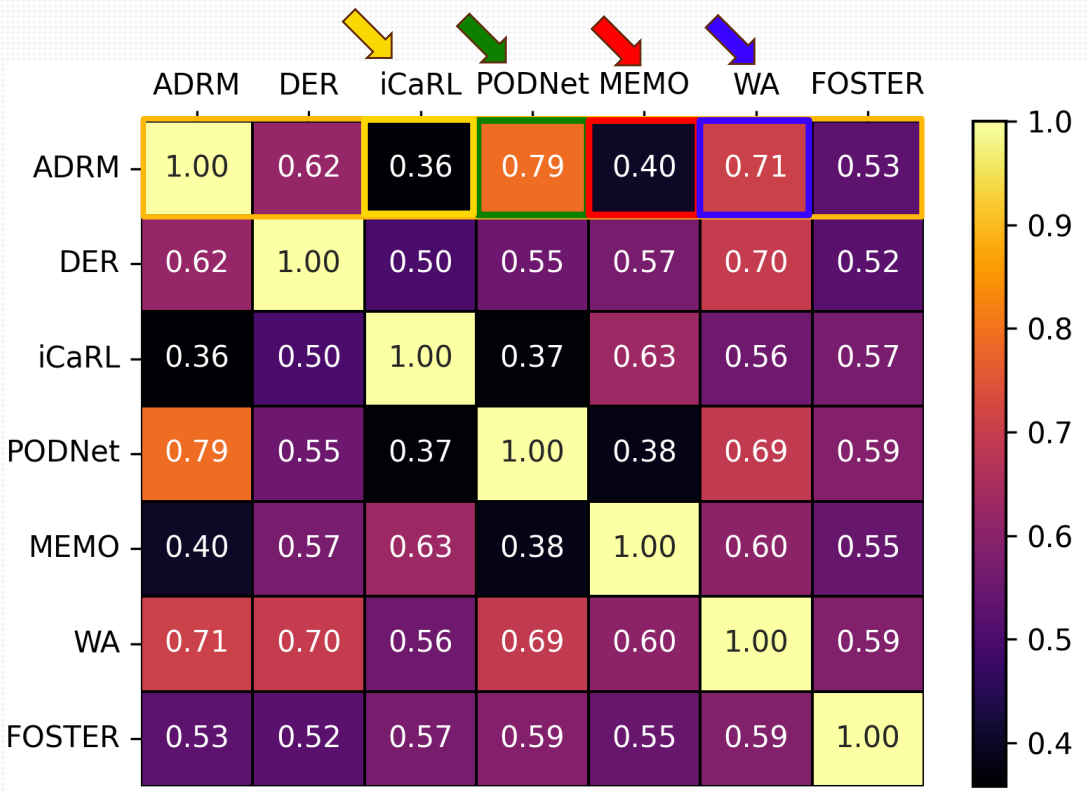
Features Similarity Matrices: A Central Kernel Alignment Analysis [24]

- The CL models displayed higher feature similarities (Central Kernel Alignment [24]) to ADRM on Standard CIFAR10 but differed in feature similarities on adversarially perturbed CIFAR10 [6].



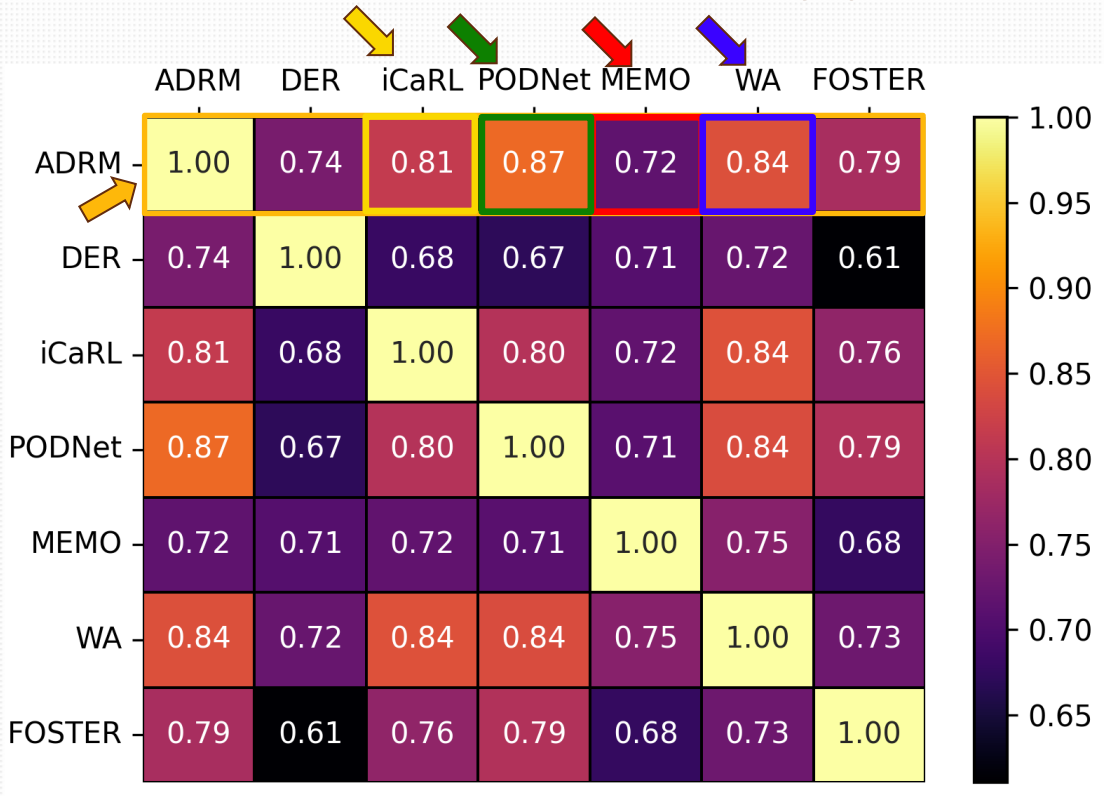
a) Feature Similarity on Standard CIFAR10



b) Feature Similarity on adversarial perturbed CIFAR10

Features Similarity Matrices: A Central Kernel Alignment Analysis [24]

- The CL models displayed higher feature similarities (Central Kernel Alignment [24]) to ADRM on Standard CIFAR10 but differed in feature similarities on adversarially perturbed CIFAR10 [6].



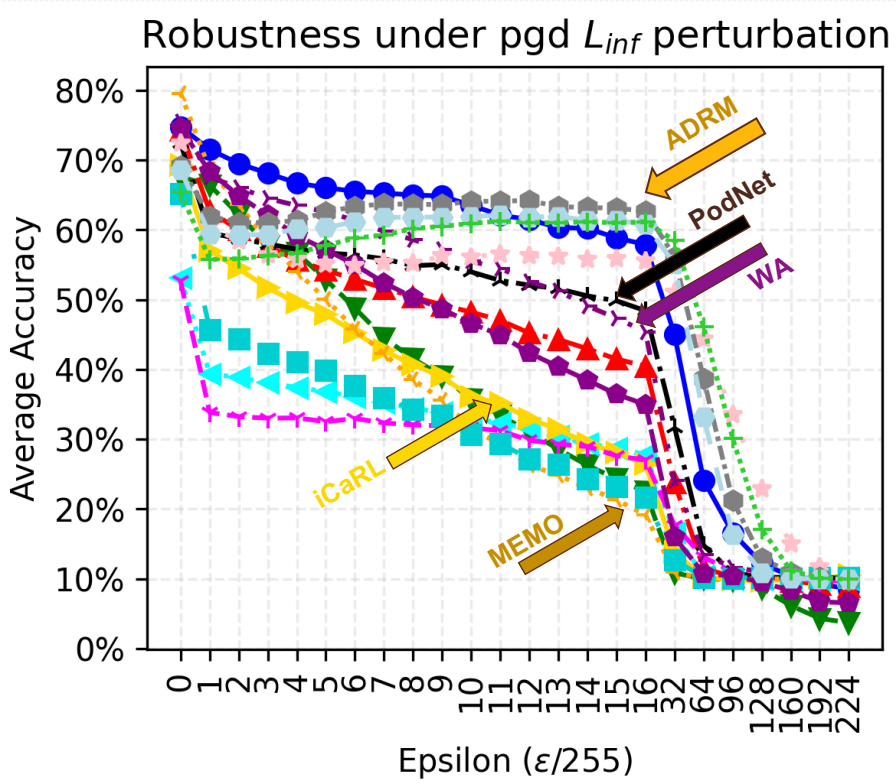
a) Feature Similarity on Standard CIFAR10

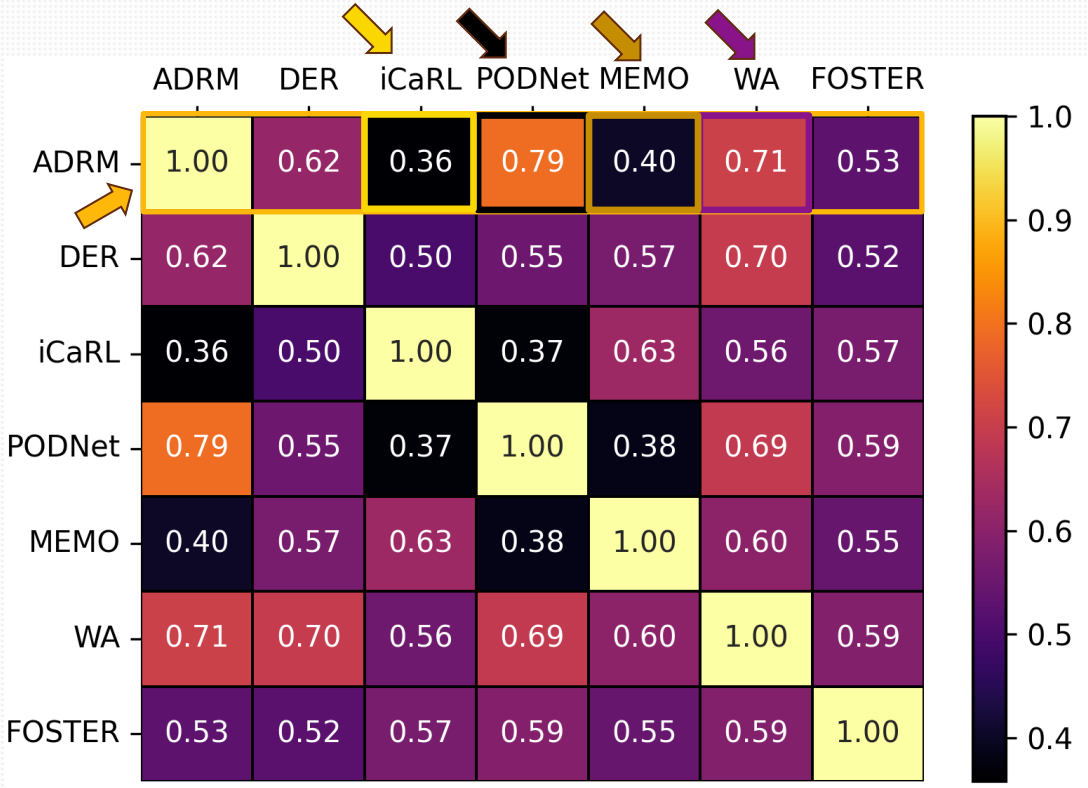
CL Methods	Split-CIFAR10		
	9 steps	5 steps	2 steps
Joint		94.8	
Fine-tune	11.11	18.54	45.31
Experience Replay [6]	67.62	75.97	80.26
iCaRL [33]	69.25	74.85	79.98
BiC [26]	53.11	71.01	86.57
PODNet [34]	72.41	76.96	87.64
WA [25]	75.56	81.67	85.34
DER [35]	74.33	78.14	82.57
SimpleCIL [27]	52.67	54.54	75.01
FOSTER [36]	74.61	80.40	83.89
FETRIL [37]	65.26	67.51	84.52
MEMO [38]	80.60	85.93	87.81
ADRM (0.1)	74.76	80.59	83.95
ADRM (0.25)	72.39	79.15	85.39
ADRM (0.5)	69.20	76.14	81.41
ADRM (0.75)	68.59	76.36	80.17
ADRM (1)	65.39	76.21	82.86

Comparative performance of CL methods on the Split-CIFAR10 dataset over 9 steps, 5 steps, and 2 steps.

Features Similarity Matrices: A Central Kernel Alignment Analysis [24]

- The CL models displayed higher feature similarities (Central Kernel Alignment [24]) to ADRM on Standard CIFAR10 but differed in feature similarities on adversarially perturbed CIFAR10 [6].





b) Feature Similarity on adversarial perturbed CIFAR10

Outline

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II. Related Work
III. Problem Statement
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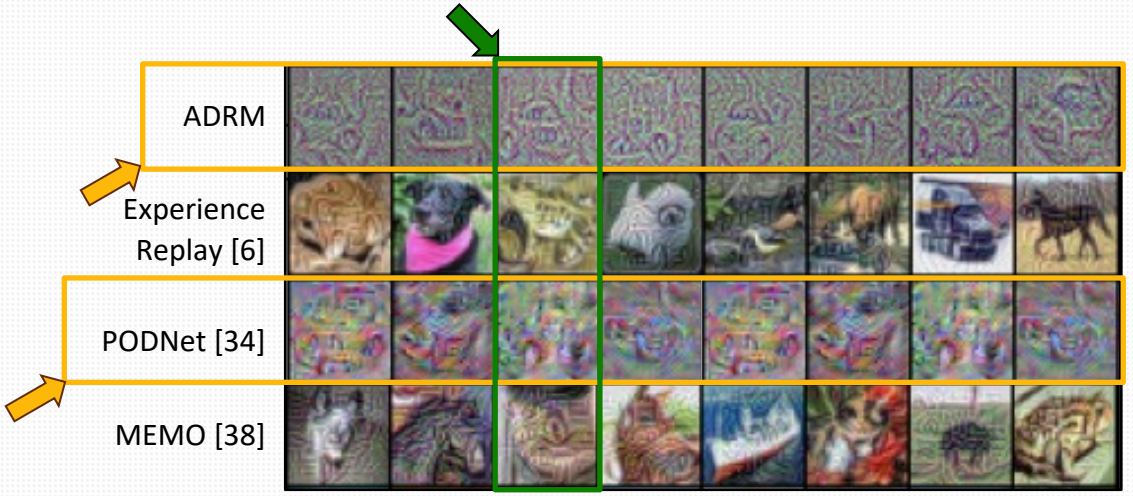
V. Results and Baselines
    1. Evaluation Against Common Corruptions
    2. Evaluation Against Common Adversarial Attacks
    3. t-SNE Visualization of Latent Features Distributions in CL
    4. Features Similarity Metrics: A Central Kernel Alignment Analysis
    5. Visualization of CL Model's Features in Input Space
VI. Conclusion

Visualization of CL Models' Features for Automobile (Car) Class in Input Space

- The features visualization for the CL model $f^*_{\theta_t}$ is performed by solving the below:

$$\min_{x_r} \| f^*_{\theta_t}(x_r) - f^*_{\theta_t}(x) \|_2^2, \quad x_r \sim D$$

- ADRM learned the salient features of the object as compared to the others CL models.



a) Visualization of disentangled features for car class in input space

Outline

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Conclusions

- Rehearsal memory can be diversified to prevent rehearsal memory overfitting in the CL models.

- Rehearsal memory diversification increases the complexity of the memory samples and prevents memory overfitting,
  - Resulting in:
    - Maintaining the effectiveness of memory samples throughout learning
    - Reduced catastrophic forgetting

- Our Code is publicly available at https://github.com/hikmatkhan/ADRM

Acknowledgment

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Adversarially Diversified Rehearsal Memory (ADRM): Mitigating Memory Overfitting Challenge in Continual Learning

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