

# FeTrIL: Feature Translation for Exemplar-Free Class-Incremental Learning

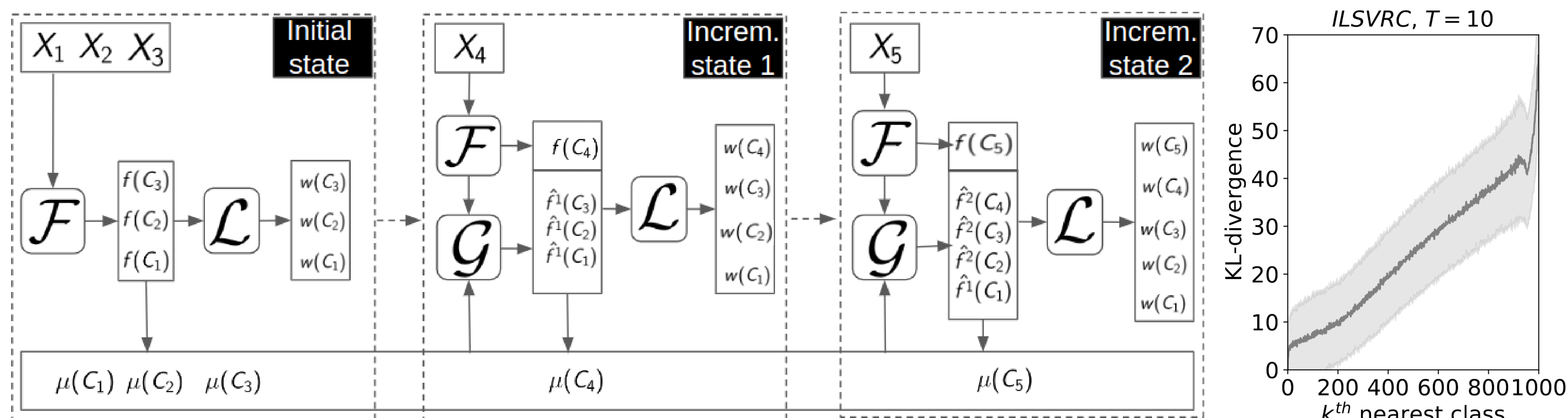


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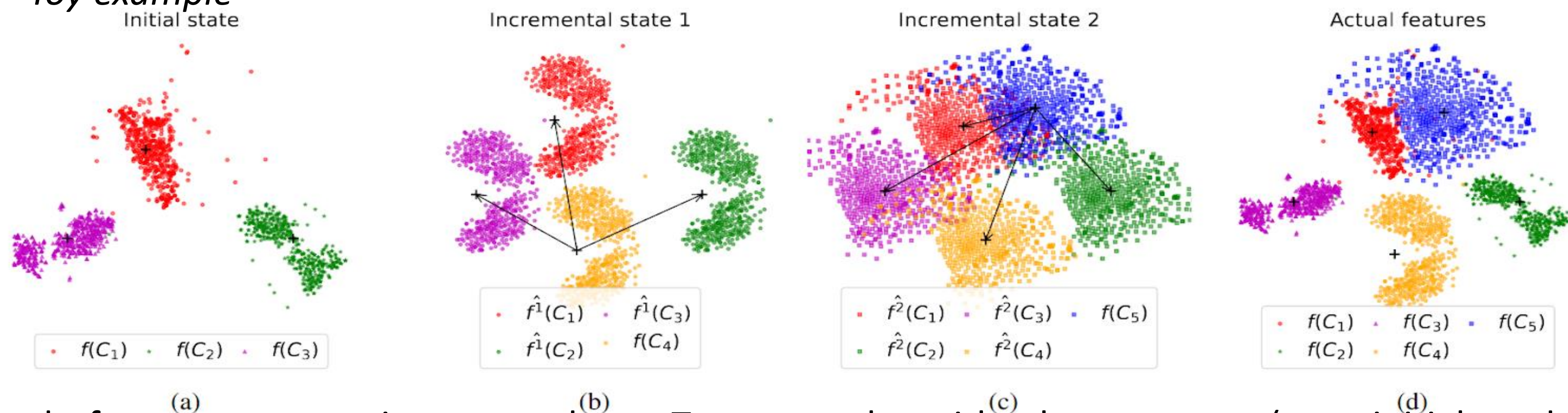
## Motivation & directions

- Class-Incremental Learning: data arrives sequentially (e.g.  $[C_0, C_1, \dots, C_9]$ , then  $[C_{10}, C_{11}, \dots, C_{19}]$ , etc.)
- Exemplar-Free: No possibility to store previously seen data (i.e. no rehearsal memory)
- Generation via geometric translation of pseudo features for past classes in each new state



FeTrIL overview. Average KL-divergence between distributions, depending on their neighboring rank.

## Toy example



Pseudo-features generation procedure. Toy example with three states (one initial and two incremental) in (a), (b) and (c). (d) provides the actual features of all four classes

Results	CIFAR-100				TinyImageNet				ImageNet-Subset				ImageNet		
	T=5	T=10	T=20	T=60	T=5	T=10	T=20	T=100	T=5	T=10	T=20	T=60	T=5	T=10	T=20
DeeSIL (ECCVW'18)	60.0	50.6	38.1	x	49.8	43.9	34.1	x	67.9	60.1	50.5	x	61.9	54.6	45.8
PASS (CVPR'21)	63.8	61.8	58.1	x	49.6	47.3	42.1	x	64.4	61.8	51.3	x	-	-	-
IL2A (NeurIPS'21)	<u>66.0</u>	60.3	57.9	x	47.3	44.7	40.0	x	-	-	-	x	-	-	-
SSRE (CVPR'21)	65.9	<u>65.0</u>	<b>61.7</b>	x	50.4	48.9	48.2	x	-	67.7	-	x	-	-	-
FeTrIL <sub>fc</sub>	64.7	63.4	57.4	<u>50.8</u>	<u>52.9</u>	<u>51.7</u>	<u>49.7</u>	<u>41.9</u>	<u>69.6</u>	<u>68.9</u>	<u>62.5</u>	<u>58.9</u>	<u>65.6</u>	<u>64.4</u>	<u>63.4</u>
FeTrIL	<b>66.3</b>	<b>65.2</b>	<u>61.5</u>	<b>59.8</b>	<b>54.8</b>	<b>53.1</b>	<b>52.2</b>	<b>50.2</b>	<b>72.2</b>	<b>71.2</b>	<b>67.1</b>	<b>65.4</b>	<b>66.1</b>	<b>65.0</b>	<b>63.8</b>

Benchmark of FeTrIL against the state-of-the-art methods that have results. We notice, in bold, that although FeTrIL is very simple, it is really performing. It should also be noted that in the case of one-class incremental learning FeTrIL works and is also very efficient and not very sensitive to catastrophic forgetting.

## Conclusion

FeTrIL advantages:

- Embeddable since it has low requirements in terms of computation and memory
- Much simpler and more effective than mainstream distillation-based methods
- Usable for one-class incremental steps
- Performance close to that of exemplar-based methods

FeTrIL limitations:

- Dependent on the domain shift between the initial fixed model and subsequent data
- Initial classes are favored over the rest since the fixed model is trained with them
- The pseudo-feature generator could be learned for a more refined representation of past classes

