THE ROBOTICS INSTITUTE

Carnegie Mellon University

CLEAR

Challenge of Continual LEArning on Real-World Imagery

CVPR 2022 VPLOW Workshop Challenge Track

Organizers: Zhiqiu Lin, Siqi Zeng, Jia Shi, Shihao Shen

Visual perception systems need to cope with **changing environments**..

A self-driving car

Pittsburgh

New cities?

Miami

Domino's car (2013)

New car models?

2013

2023

Domino's car (2023?)

But vision benchmarks **stay the same over time**..

ImageNet (2010)

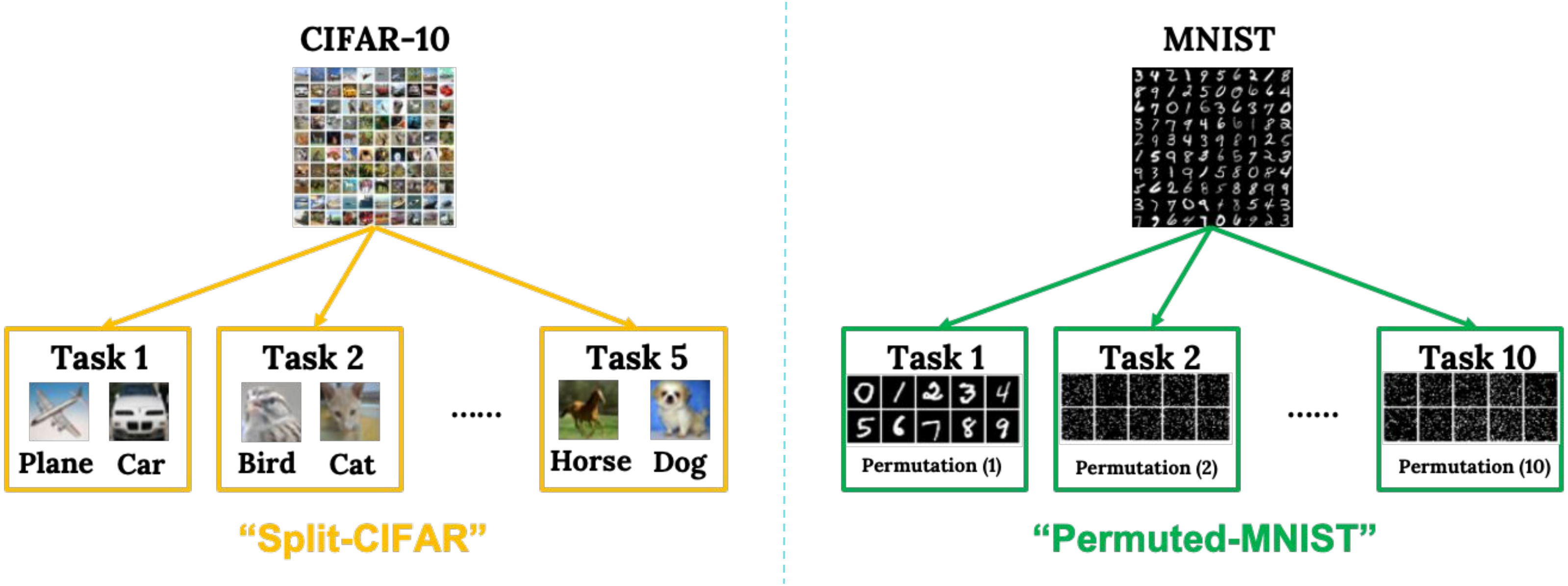
same as in 2010

COCO (2015)

same as in 2015

2010 2014 2018 2022

Prior works simulates changing environments via **continual/lifelong learning** benchmarks



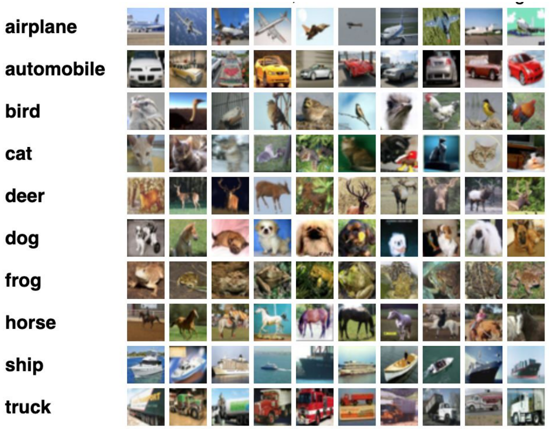
! **Issue: Extreme distributions shifts between tasks..**

Real-world distributions shifts are **smooth**, such as computer make and models.

💡 **Idea: To collect a benchmark with natural distribution shifts!**

CLEAR: Continual LEArning with Real-world Imagery

→ First CL benchmark for open-world vision



[1]

CIFAR10 (2009)

Superclass	Classes
aquatic mammals	beaver, dolphin, otter, seal, whale
fish	aquarium fish, flatfish, ray, shark, trout
flowers	orchids, poppies, roses, sunflowers, tulips
food containers	bottles, bowls, cans, cups, plates
fruit and vegetables	apples, mushrooms, oranges, pears, sweet peppers
household electrical devices	clock, computer keyboard, lamp, telephone, television
household furniture	bed, chair, couch, table, wardrobe
insects	bee, beetle, butterfly, caterpillar, cockroach
large carnivores	bear, leopard, lion, tiger, wolf
large man-made outdoor things	bridge, castle, house, road, skyscraper
large natural outdoor scenes	cloud, forest, mountain, plain, sea
large omnivores and herbivores	camel, cattle, chimpanzee, elephant, kangaroo
medium-sized mammals	fox, porcupine, possum, raccoon, skunk
non-insect invertebrates	crab, lobster, snail, spider, worm
people	baby, boy, girl, man, woman
reptiles	crocodile, dinosaur, lizard, snake, turtle
small mammals	hamster, mouse, rabbit, shrew, squirrel
trees	maple, oak, palm, pine, willow
vehicles 1	bicycle, bus, motorcycle, pickup truck, train
vehicles 2	lawn-mower, rocket, streetcar, tank, tractor

[1]

CIFAR100 (2009)

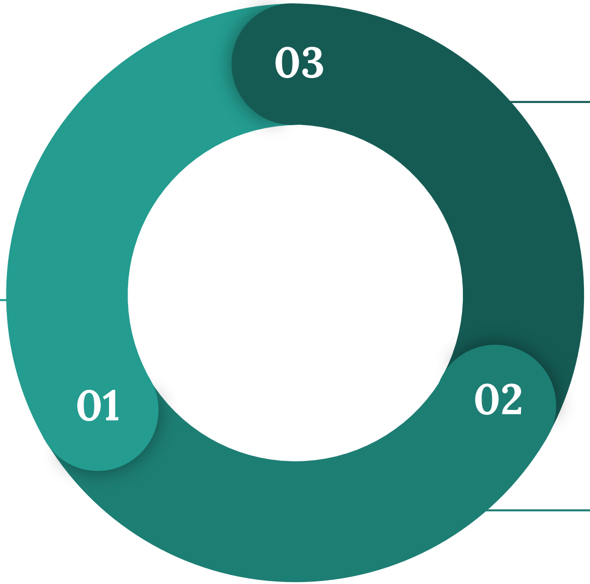
How about CLEAR10 / CLEAR100 for Real-World Continual Learning?

[1] https://www.cs.toronto.edu/~kriz/cifar.html

Highlights

Natural Distribution Shift Over A Decade

CLEAR captures real distribution shifts of Internet images from 2004 to 2014 in YFCC100M.



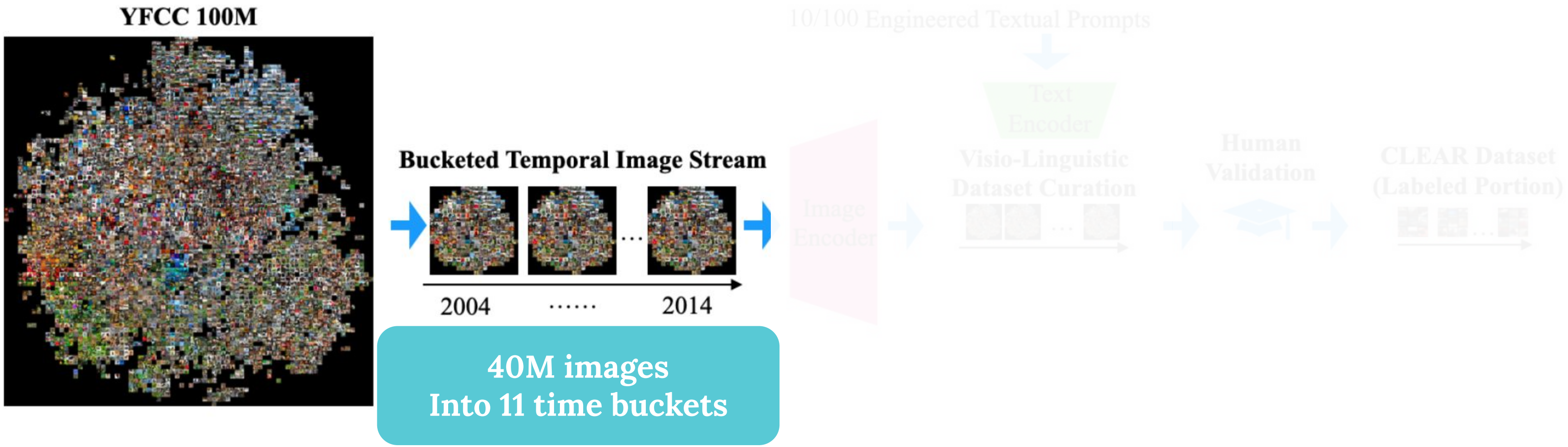
Assets For Future CL Research

Unlabeled data
→ continual unsupervised learning
Metadata
→ continual multimodal learning
Instruction set
→ dataset curation/transparency

Efficient & Faithful Dataset Curation

To avoid working with massive data in YFCC, we create an efficient semi-automated visio-linguistic dataset curation pipeline followed by human verification.

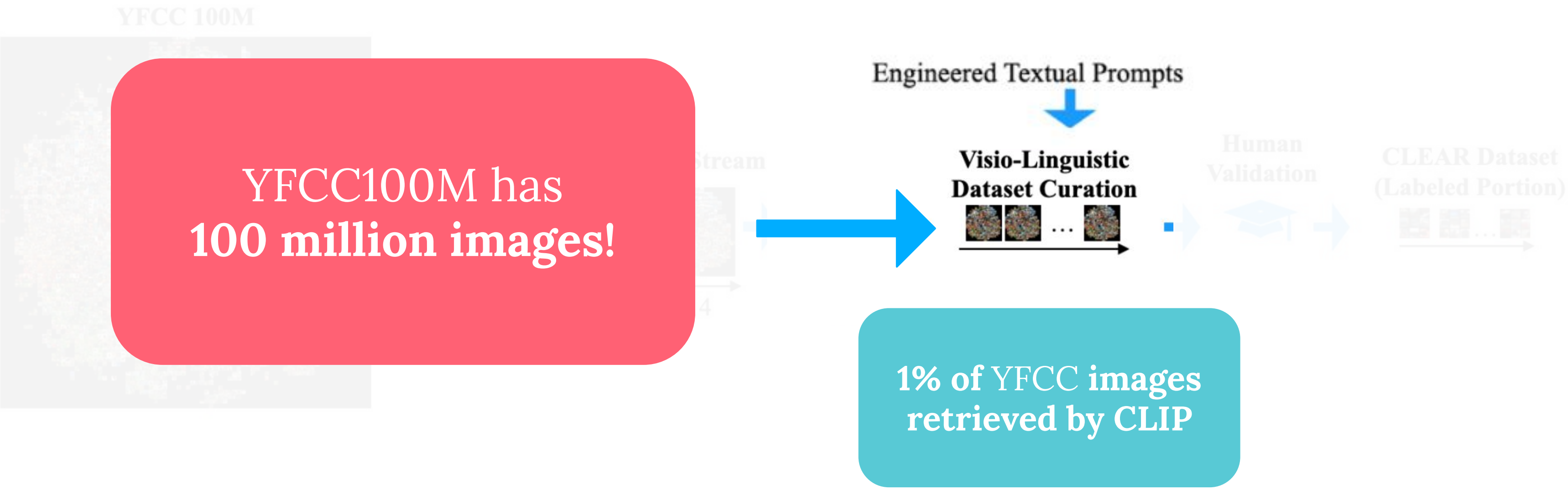
We start from **Flickr YFCC100M** with **timestamped images from 2004 to 2014.**



We split the temporal image stream into 11 buckets:
→ 0th bucket reserved for unsupervised pretraining
→ 1st - 10th buckets with annotation for continual classification

Visual Concepts in CLEAR10 and CLEAR100

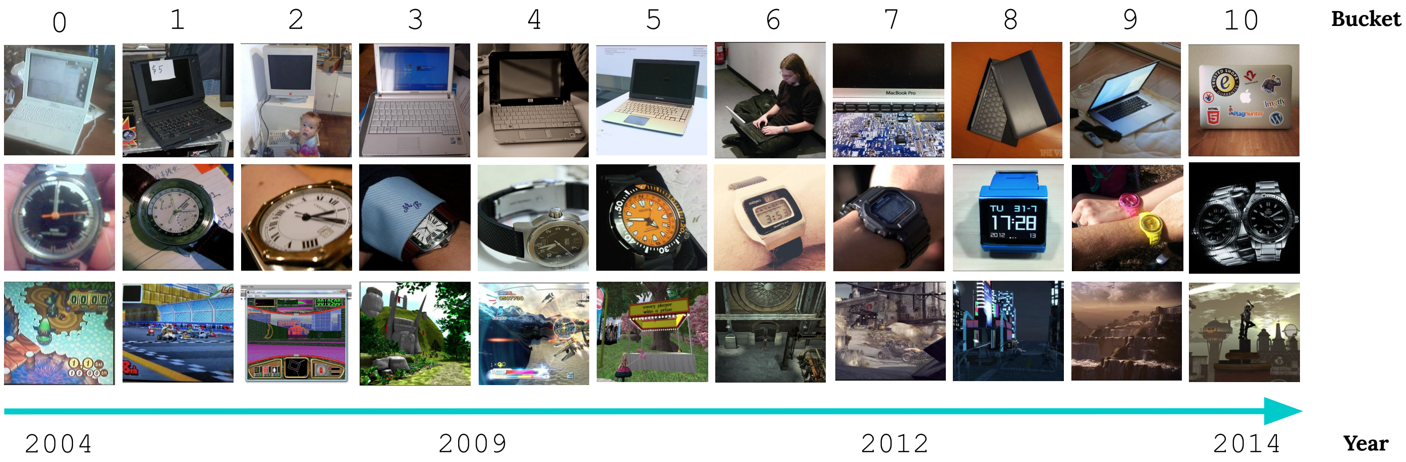
We propose **a visio-linguistic approach** utilizing **OpenAI's pretrained CLIP model** to **automatically retrieve images** of particular visual concepts.



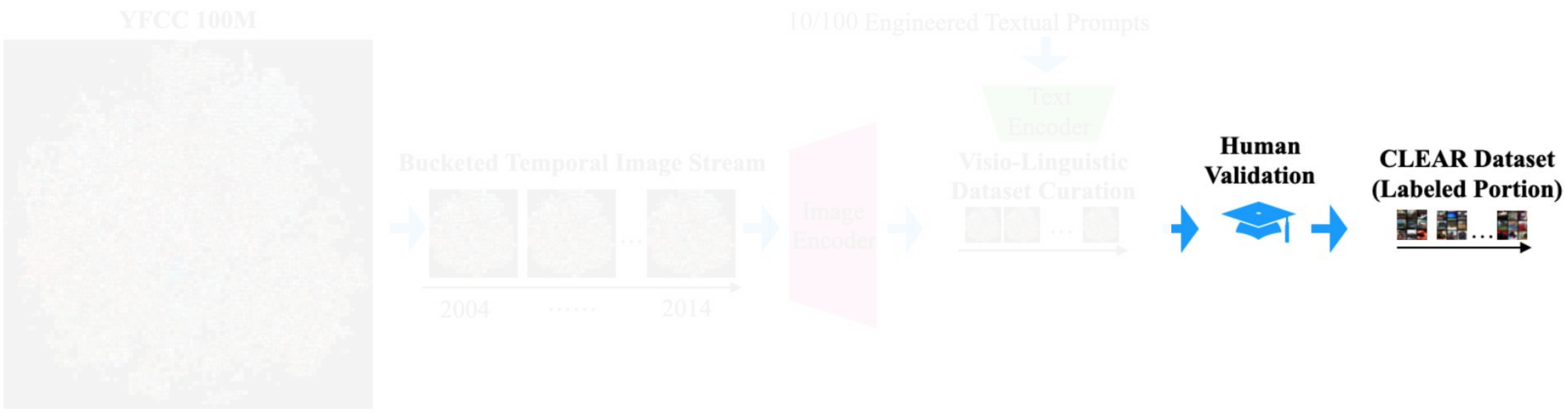
A Snapshot of CLEAR

Natural Temporal Evolution

CLIP Prompt	Visual Concept
laptop, computer	computer
a photo of watch	watch
a screenshot of video game	video game

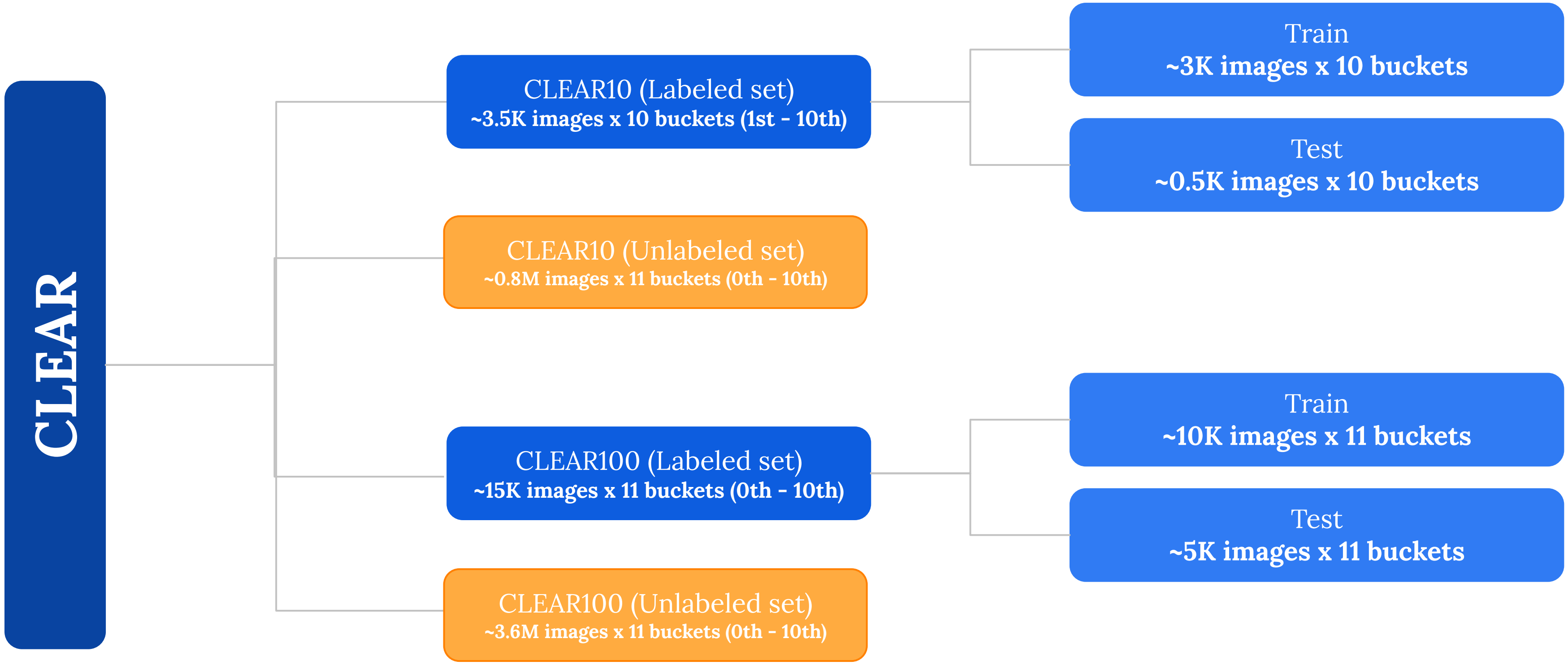


CLIP generated labels are **verified by human** to ensure the label quality.

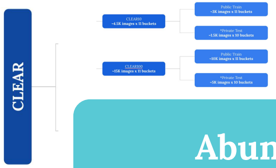


→ **crowd-sourced & professional labeling service for human validation**
→ **high-quality labels!**

Data Statistics



Assets for Future CL Research

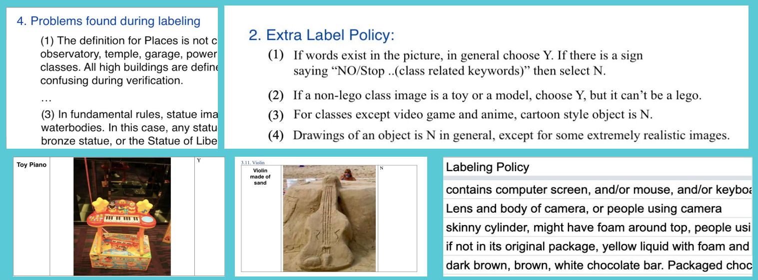


Abundant Unlabeled Images

→ unsupervised continual learning

Metadata
Time/Location/Social Media Hashtag/Text Description/…

→ multimodal learning



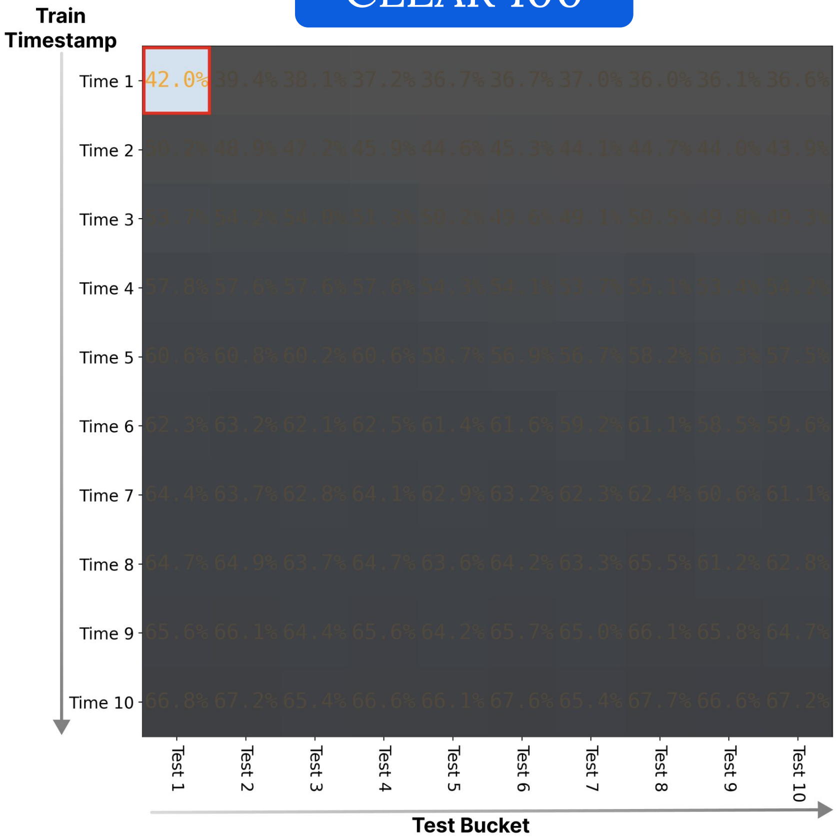
200+ Pages of Instruction Set & Corner Cases

→ dataset curation/transparency

CLEAR

→ Simulating Real-World Continual Learning

CLEAR 100

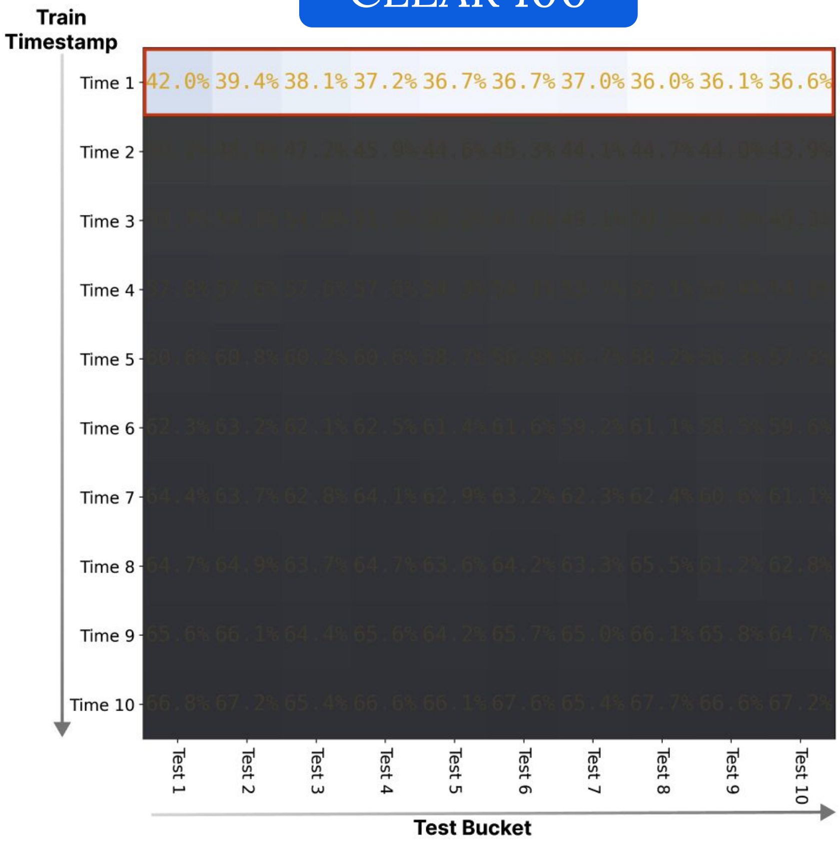


Train on 1st, test on 1st Acc = 42.0%

Standard classification model (ResNet18) can achieve reasonable test accuracy on 1st bucket..

*Numbers are top-1 accuracy

CLEAR 100

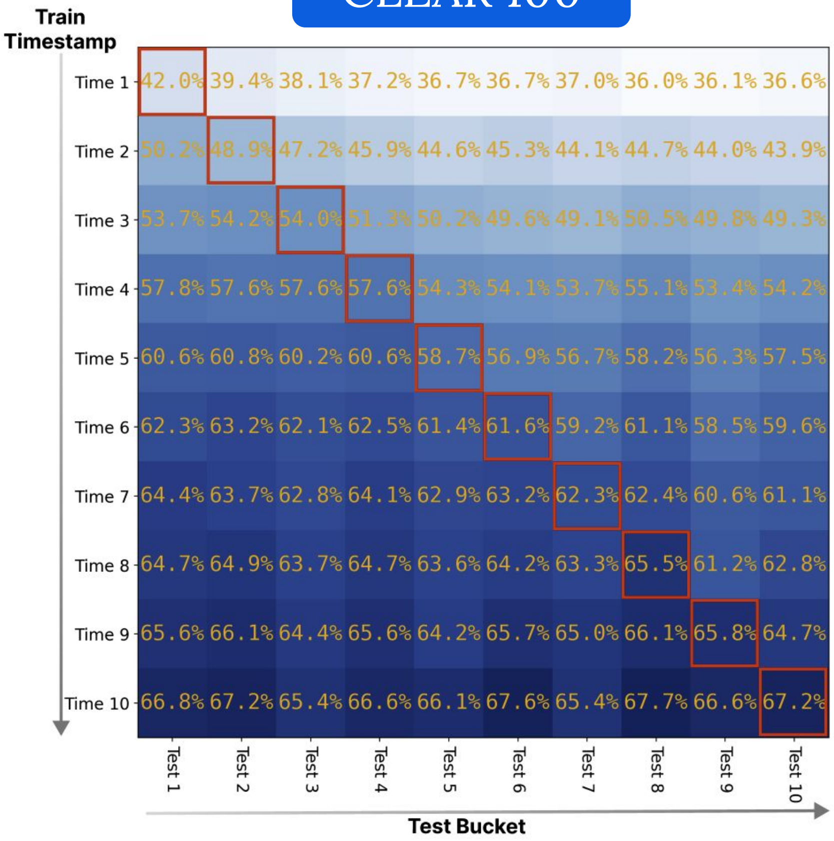


Train on 1st, test on 1st Acc = 42.0% .. **Train on 1st, test on 2nd Acc = 39.4%** …… **Train on 1st, test on 10th Acc = 36.6%**

Without continual learning, performance suffers by 5.4% (from 42.0% to 36.6%) over time..

*Numbers are top-1 accuracy

CLEAR 100



Train on 1st,
test on 1st
Acc = 42.0%

Train on 1st,
test on 2nd
Acc = 39.4%

Train on 1st,
test on 10th
Acc = 36.6%

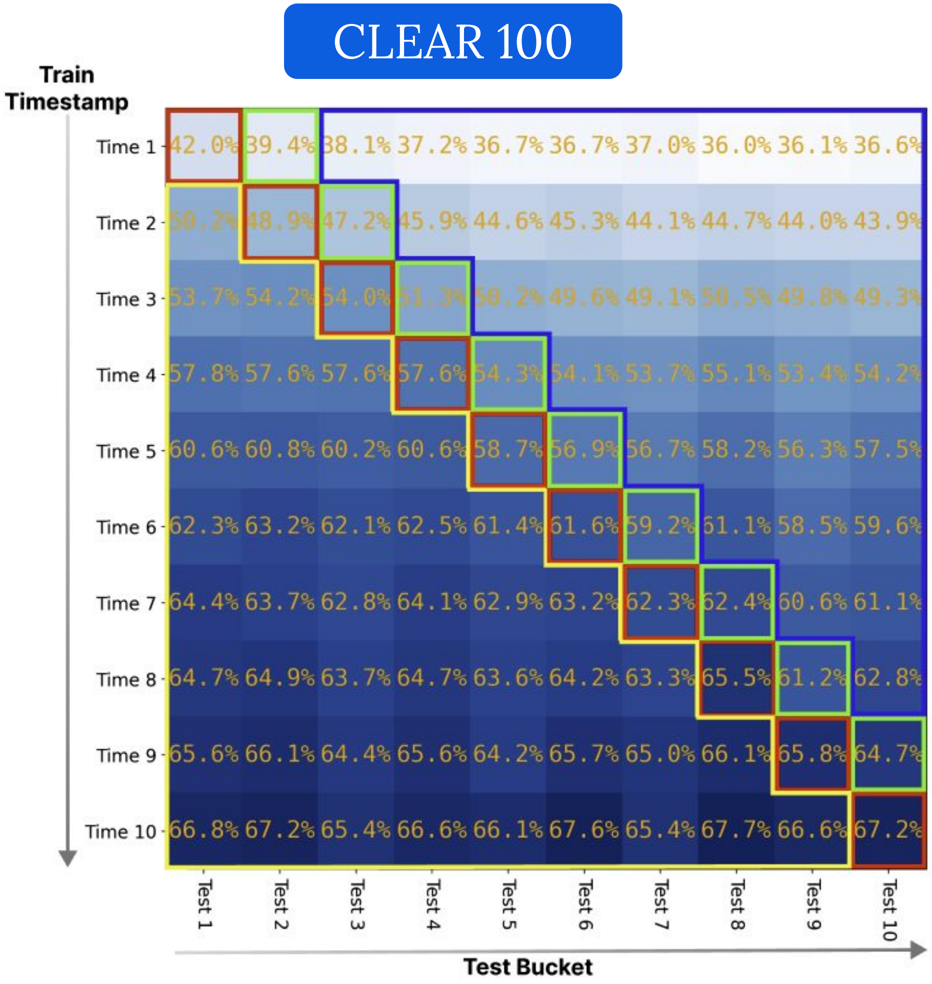
Train on [1+2],
test on 2nd
Acc = 48.9%

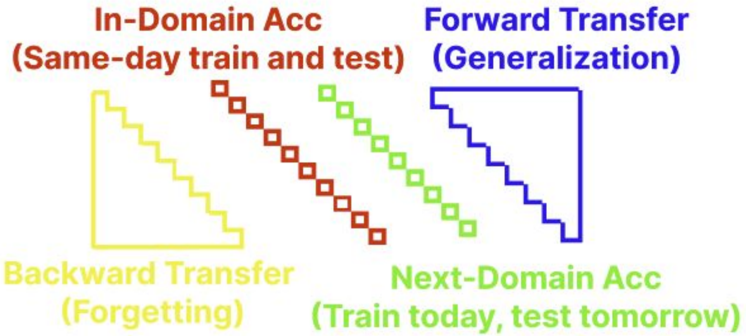
Train on
[1:10],
test on 10th
Acc = 67.2%

Continual learning helps – simply “finetuning” on accumulated data boosts on average 20% accuracy!

*darker color is higher accuracy

Metrics to quantify CL performances..





Next-Domain Acc is more realistic than **In-Domain Acc** due to time delay between **data arrival** and **model deployment**

*Caveat: Forward Transfer is in fact defined as the entire upper trig of matrix (including the superdiagonal). We apologize if this figure causes any confusion.

CLEAR 100

Train Timestamp / Test Bucket

Train Timestamp	Test 1	Test 2	Test 3	Test 4	Test 5	Test 6	Test 7	Test 8	Test 9	Test 10
Time 1	42.0%	39.4%	38.1%	37.2%	36.7%	36.7%	37.0%	36.0%	36.1%	36.6%
Time 2	50.2%	48.9%	47.2%	45.9%	44.6%	45.3%	44.1%	44.7%	44.0%	43.9%
Time 3	53.7%	54.2%	54.0%	51.3%	50.2%	49.6%	49.1%	50.5%	49.8%	49.3%
Time 4	57.8%	57.6%	57.6%	57.6%	54.3%	54.1%	53.7%	55.1%	53.4%	54.2%
Time 5	60.6%	60.8%	60.2%	60.6%	58.7%	56.9%	56.7%	58.2%	56.3%	57.5%
Time 6	62.3%	63.2%	62.1%	62.5%	61.4%	61.6%	59.2%	61.1%	58.5%	59.6%
Time 7	64.4%	63.7%	62.8%	64.1%	62.9%	63.2%	62.3%	62.4%	60.6%	61.1%
Time 8	64.7%	64.9%	63.7%	64.7%	63.6%	64.2%	63.3%	65.5%	61.2%	62.8%
Time 9	65.6%	66.1%	64.4%	65.6%	64.2%	65.7%	65.0%	66.1%	65.8%	64.7%
Time 10	66.8%	67.2%	65.4%	66.6%	66.1%	67.6%	65.4%	67.7%	66.6%	67.2%

Backward Transfer = 63.1%
(Forgetting)

In-Domain Acc = 58.4%
(Same-day train and test)

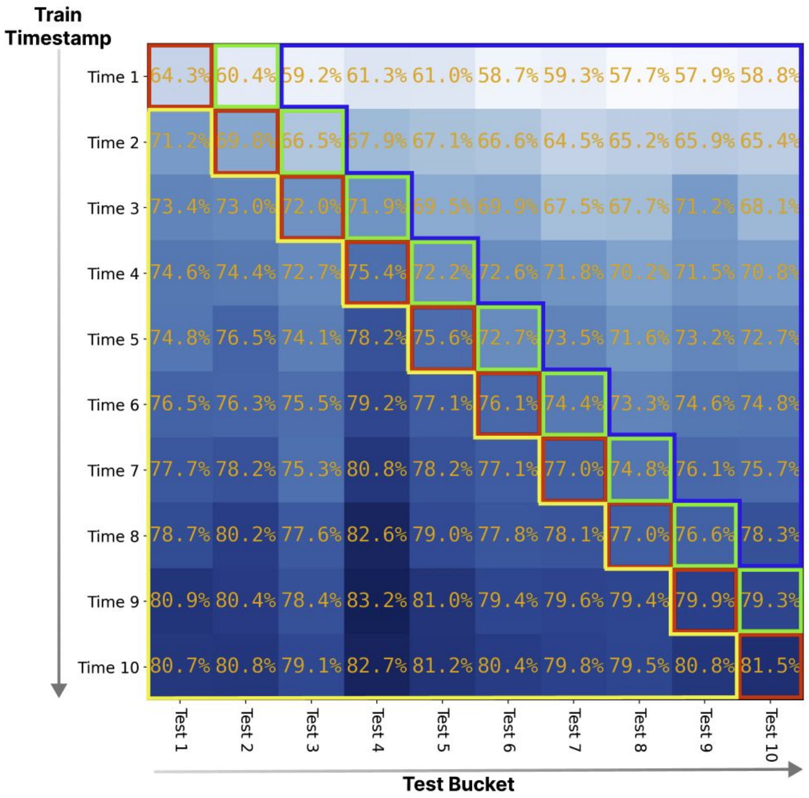
Next-Domain Acc = 55.2%
(Train today, test tomorrow)

Forward Transfer = 50.3%
(Generalization)

Next-Domain Acc / Forward Transfer are more challenging than **In-Domain Acc / Backward Transfer**, leaving large room for improvement.

*Caveat: Forward Transfer is in fact defined as the entire upper trig of matrix (including the superdiagonal). We apologize if this figure causes any confusion.

CLEAR 10



Backward Transfer = 78.9%
(Forgetting)

In-Domain Acc = 74.9%
(Same-day train and test)

Next-Domain Acc = 72.1%
(Train today, test tomorrow)

Forward Transfer = 68.9%
(Generalization)

Same trends hold for CLEAR10!

Though CLEAR10 performance is on average **15%** higher than CLEAR100 as it is a simpler task.

*Caveat: Forward Transfer is in fact defined as the entire upper trig of matrix (including the superdiagonal). We apologize if this figure causes any confusion.

CLEAR 10

Method	Evaluation Metrics			
	In-domain Acc	Next-domain Acc	Backward Transfer	Forward Transfer
Continual Finetuning	$74.9\% \pm .3\%$	$72.1\% \pm .2\%$	$78.1\% \pm .2\%$	$68.9\% \pm .1\%$
EWC (Elastic Weight Consolidation)	$76.6\% \pm .2\%$	$74.3\% \pm .6\%$	$76.5\% \pm .4\%$	$71.1\% \pm .6\%$
SI (Synaptic Intelligence)	$76.0\% \pm .2\%$	$73.6\% \pm .2\%$	$76.0\% \pm .5\%$	$71.0\% \pm .4\%$
LwF (Learning w/o Forgetting)	$77.8\% \pm .3\%$	$75.7\% \pm .3\%$	$79.6\% \pm .3\%$	$72.5\% \pm .3\%$
CWR	$69.5\% \pm .2\%$	$67.8\% \pm .3\%$	$68.8\% \pm .3\%$	$66.6\% \pm .3\%$
GDumb	$66.0\% \pm .4\%$	$64.3\% \pm .5\%$	$68.9\% \pm .4\%$	$61.4\% \pm .5\%$
ER (Experience Replay)	$77.3\% \pm .1\%$	$75.6\% \pm .3\%$	$79.3\% \pm .1\%$	$72.4\% \pm .2\%$
A-GEM (Gradient Episodic Memory)	$76.2\% \pm .3\%$	$73.6\% \pm .2\%$	$75.8\% \pm .2\%$	$70.2\% \pm .2\%$

Avalanche

Similar Performances!

Classic CL algorithms (Avalanche-based implementation), originally designed to combat forgetting, perform only marginally better or about the same as simple continual finetuning on CLEAR Benchmark.

CLEAR is now publicly available on Avalanche (a snapshot of the API)

Avalanche

v0.2.0

Search docs

AVALANCHE API

- Benchmarks module
  - avalanche.benchmarks
- Evaluation module
- Logging module
- Models module
- Training module

Benchmarks based on the CLEAR dataset.

`CLEAR` (*[, data_name, evaluation_protocol, ...])	Creates a Domain-Incremental benchmark for CLEAR 10 & 100 with 10 & 100 illustrative classes and an n+1

Benchmarks for learning from pretrained models or multi-agent continual learning scenarios. Based on the Ex-Model paper. Pretrained models are downloaded automatically.

`ExMLMNIST` ([scenario, run_id])	ExML scenario on MNIST data.
`ExMLCoRE50` ([scenario, run_id])	ExML scenario on CoRE50.
`ExMLCIFAR10` ([scenario, run_id])	ExML scenario on CIFAR10.

Datasets

The **datasets** sub-module provides PyTorch dataset implementations for datasets missing from the torchvision/audio/* libraries. These datasets can also be used in a standalone way!

`CORe50Dataset` (root, ~pathlib.Path]] = None, *)	CORe50 Pytorch Dataset
`CUB200` (root, ~pathlib.Path]] = None, *[, ...])	Basic CUB200 PathsDataset to be used as a standard PyTorch Dataset.

Try it out!

CLEAR

→ Summary of CVPR 2022 Challenge

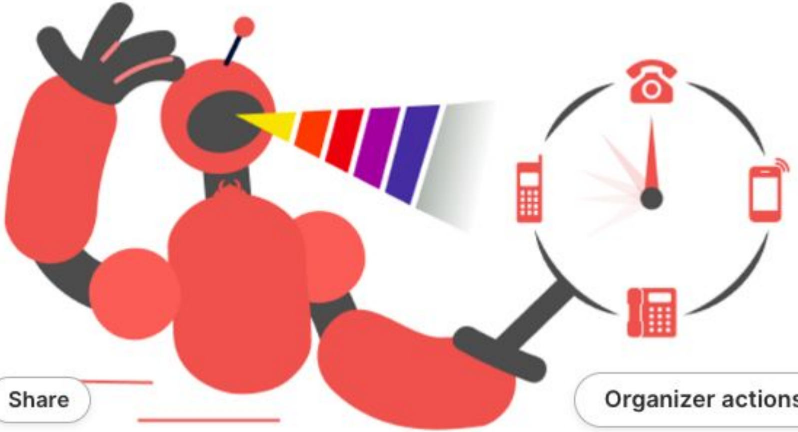
Stage 1: Completed | Stage 2: Completed

CVPR 2022 CLEAR Challenge

CVPR 2022 Workshop Challenge on CLEAR: Continual LEArning on Real-world Imagery

$1500 Cash Prize Pool

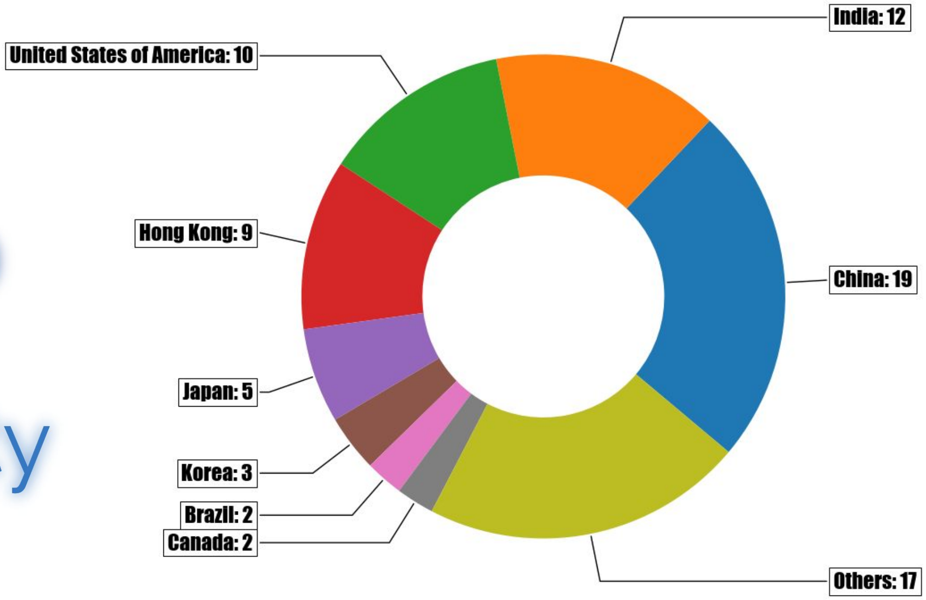
By Carnegie Mellon University 5482 79 15 547 5 Share



Organizer actions

39 Days, **79** Participants, **15** Teams, **547** Submissions

Composition



CLEAR10 Leaderboard

Δ	#	Participants	Weighted Average Score	Next-Domain	In-Domain	BwT	FwT
●	01	shennong3	0.905	0.901	0.912	0.923	0.885
▲	02	BOE_AIoT_CTO	0.895	0.891	0.904	0.915	0.871
▼	03	AI_PRIME	0.889	0.885	0.896	0.911	0.864
●	04	Lge	0.867	0.859	0.879	0.895	0.833
●	05	unist-miil	0.728	0.711	0.748	0.781	0.670
●	06	try	0.677	0.654	0.705	0.728	0.619
		Baseline clear10_naive_streaming_resnet18, script at https://github.com/ContinualAI/avalanche/blob/master/examples/clear.py	0.663	0.649	0.698	0.685	0.618
●	07	chen_sun	0.644	0.630	0.680	0.671	0.593

>20% Jump from baseline

CLEAR100 Leaderboard

Δ	#	Participants	Weighted Average Score	Next-Domain Accuracy	In-Domain Accuracy	Backward Transfer	Forward Transfer
	01	shennong3	0.9146	0.9125	0.9199	0.9340	0.8920
	02	AI_PRIME	0.9124	0.9077	0.9178	0.9379	0.8863
▲	03	BOE_AIoT_CTO	0.8873	0.8829	0.8960	0.9074	0.8630
▼	04	Lge	0.8606	0.8536	0.8696	0.8965	0.8229
	05	unist-miil	0.6216	0.6078	0.6329	0.6890	0.5568
	06	chen_sun	0.5455	0.5363	0.5704	0.5689	0.5065
		Baseline Baseline clear100_naive_streaming_resnet18, script at https://github.com/ContinualAI/avalanche/blob/master/examples/clear.py	0.4935	0.4810	0.5220	0.5342	0.4367

>40% Jump

The Most Promising Strategies on CLEAR

- Experience Replay to utilize both current and previous buckets' data
- Strong Data Augmentation (e.g. AutoAug, CutMix, Mixup)
- Enhancing Generalization via
  - Sharpness Aware Minimization
  - Supervised Contrastive Loss
  - Unsupervised Domain Generalization
  - Meta Learning
  - Larger Backbone for Over-Parameterization

Winners

1st Place -- $1000
Xinkai Guo, Bo Ke, Sunan He, Ruizhi Qiao
Tencent, YouTu Lab

"Bucket-Aware Sampling Strategy for Efficient Replay"

2nd Place -- $300
Jiawei Dong, Mengwen Du, Shuo Wang
AI Prime

"Comprehensive Studies on Sampling, Architecture and Augmentation Strategies"

3rd Place -- $100
Xiaojun Tang, Pan Zhong, Tingting Wang, Yuzhou Peng
BOE Technology Group

"Adaptive Loss for Better Model Generalization in Real World"

4th Place -- $100
Ge Liu
Shanghai Jiao Tong University

"Improving Model Generalization by Contrasting Features across Domains"

Innovation Prize
Solang Kim, Jin Hyuk Lim, Sung Whan Yoon
Ulsan National Institute of Science and Technology

"Domain Generalization & Meta Learning for Robustness against Distribution Shifts"

CLEAR

→ Invited Team Presentation: 1st Place

Bucket-Aware Sampling Strategy for Efficient Replay

In Workshop Visual Perception and learning in an Open World at CVPR2022

Team: shennong3

Members: Xinkai Gao, Bo Ke, Sunan He, Ruizhi Qiao

Affiliation: Tencent Youtu Lab

CLEAR

→ Lessons Learned & Future Directions

Lessons we learned in this competition

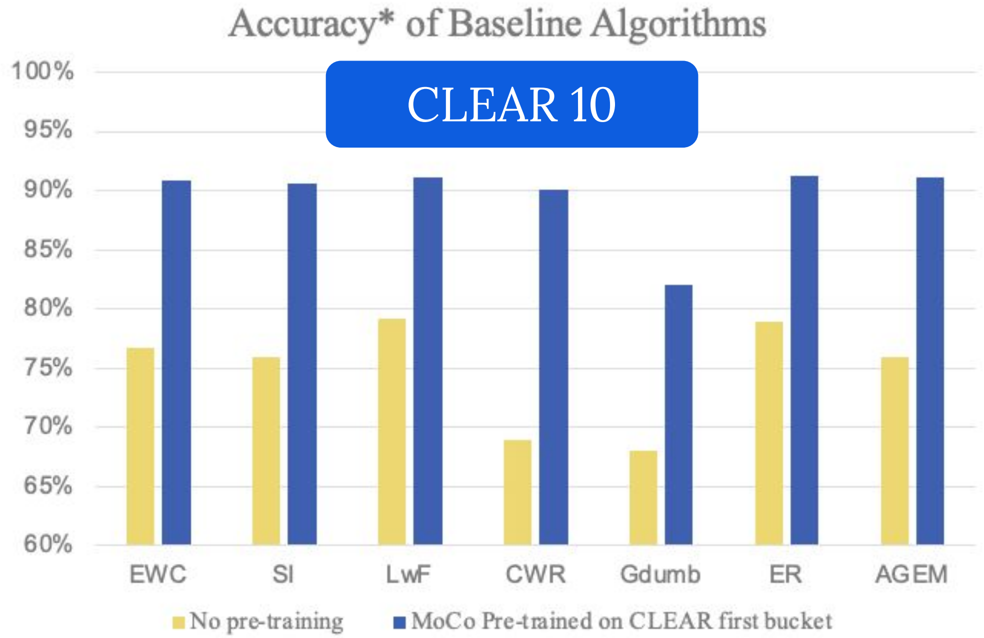
- Lesson 1: Sampling matters for efficient learning
- Lesson 2: Augmentation improves generalization in CL
- Lesson 3: Generalization is the bottleneck for real-world CL

Future Step: Generalization Bottleneck for Real-World CL

Next-Domain Acc /**Forward Transfer** are more challenging than **In-Domain Acc** /**Backward Transfer**, suggesting the **generalization bottleneck** for real-world CL.

Domain generalization/domain adaptation/meta learning could be promising research directions.

Future Direction: Continual Unsupervised Learning



We use an unsupervised MoCo V2 model pretrained on **CLEAR's 0th bucket** of unlabeled data, and this simple pre-training steps boosts on average **15%** for all baseline methods.

It could be promising to perform **continual unsupervised learning**, using the unlabeled data of 1st-10th buckets.

Future Direction: ImageNet-scale Real-world CL Benchmark

for real-world CL?

We are trying to expand CLEAR to an ImageNet-scale benchmark!

Stay tuned!

Thank You!