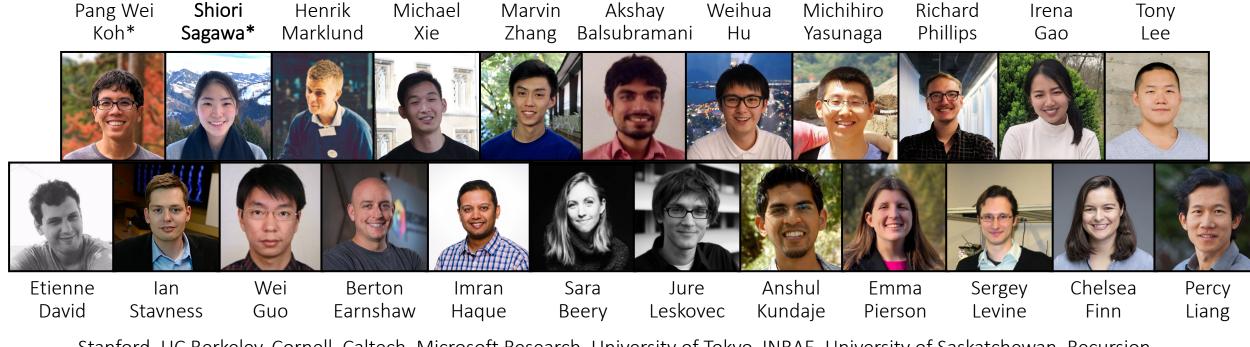


A Benchmark of in-the-Wild Distribution Shifts



Stanford, UC Berkeley, Cornell, Caltech, Microsoft Research, University of Tokyo, INRAE, University of Saskatchewan, Recursion

Standard assumption in machine learning

Train
data
distribution

Test
data
distribution

Models perform well

Distribution shifts can cause models to fail

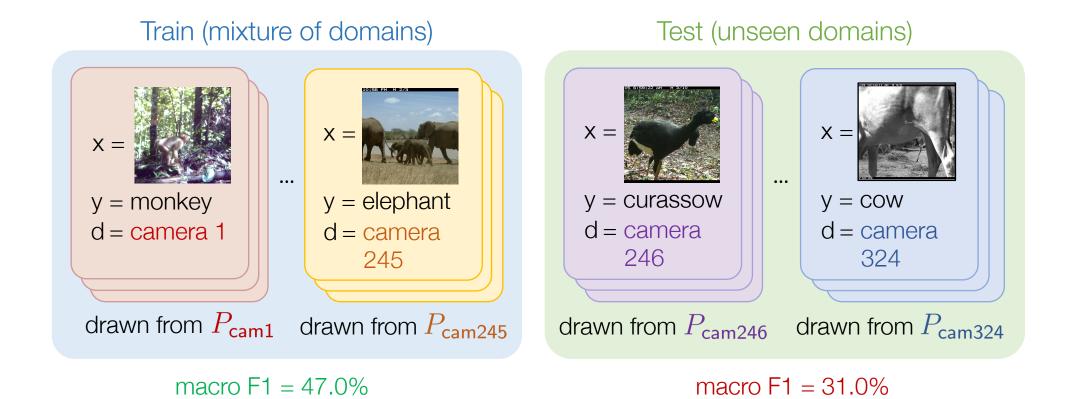
Train
data
distribution



Test
data
distribution

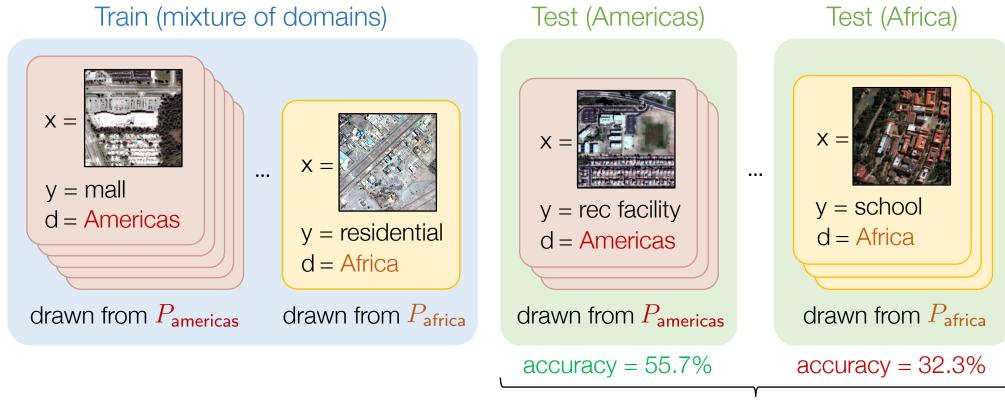
Model performance degrades

Shift to unseen cameras in animal classification for wildlife conservation



domain generalization: the goal is to generalize to unseen domains

Shift across regions in land use classification on satellite imagery



worst-region accuracy = 32.3%

subpopulation shift: the goal is to perform well on many subpopulations of the training distribution

Existing datasets don't focus on real-world shifts

synthetic perturbations

Colored MNIST (Kim et al., 2018)











ImageNet-C (Hendrycks et al., 2019)



Waterbirds (Sagawa et al., 2020)







+ rotated MNIST and CIFAR-10 Stylized ImageNet (Geirhos et al., 2018) the Backgrounds Challenge (Xiao et al., 2020) disparate data splits

photo

sketch















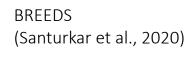












+ ObjectNet (Barbu et al., 2019) NICO (He et al., 2020) DeepFashion-Remixed (Hendrycks et al., 2020)

WILDS: A benchmark for robustness to distribution shifts



A suite of 10 datasets with...

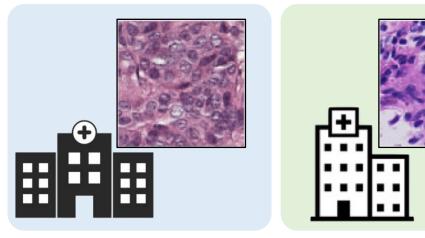


Real-world distribution shifts

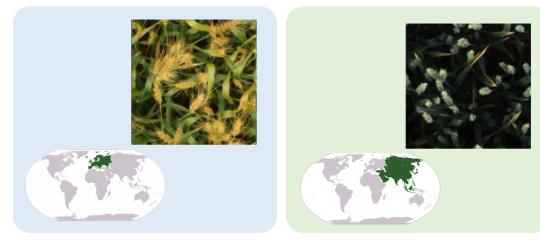


Diverse applications

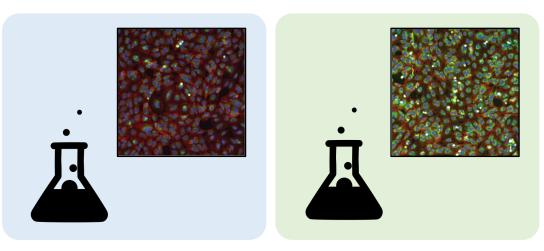
Talking to domain experts → lots of real-world distribution shifts!



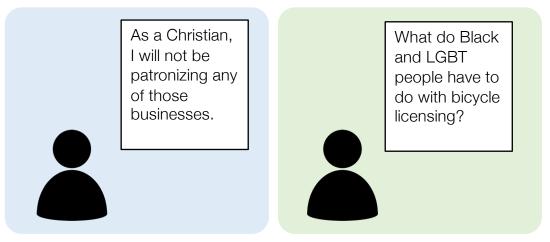
shifts across hospitals in histopathology



shifts across regions in wheat head detection



shifts across batches in cell imaging experiments

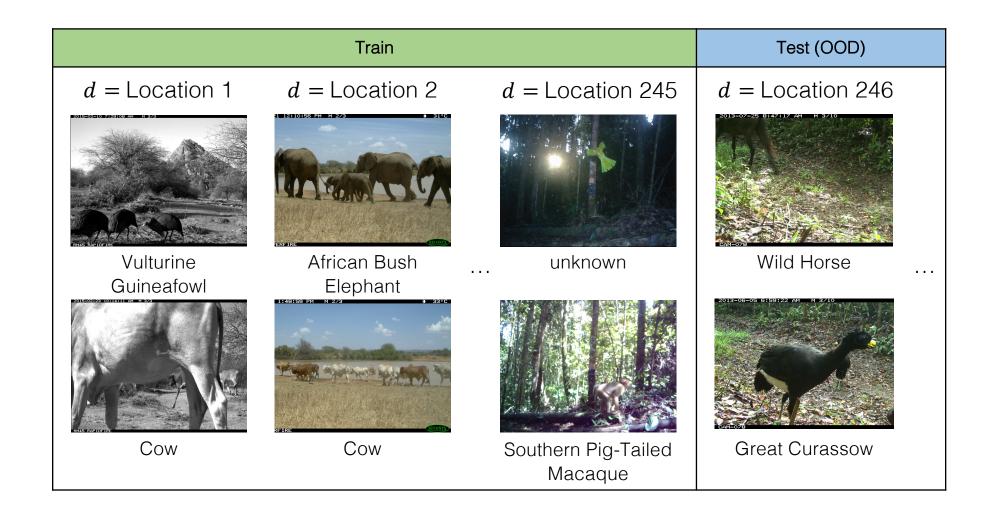


shifts across demographics in toxic comment detection

		Doi	main generalizati	ion		Subpopulation shift	Doma	in generalizatior	n + subpopulatio	on shift
Dataset	iWildCam	Camelyon17	RxRx1	OGB-MolPCBA	GlobalWheat	CivilComments	FMoW	PovertyMap	Amazon	Py150
Input (x)	photo	tissue slide	cell image	molecular graph	wheat image	online comment	t satellite image	satellite image	product review	code
Prediction (y)	animal species	tumor	perturbed gene	bioassays	wheat head bbo	x toxicity	land use	asset wealth	sentiment	autocomplete
Domain (d)	camera	hospital	batch	scaffold	location, time	demographic	time, region	location	user	git repository
Train example				N HN		What do Black and LGBT people have to do with bicycle licensing?			Overall a solid package that has a good quality of construction for the price.	import numpy as np norm=np
Test example				HO N S O HN		As a Christian, I will not be patronizing any of those businesses.			I *loved* my French press, it's so perfect and came with all this fun stuff!	<pre>import subprocess as sp p=sp.Popen() stdout=p</pre>
Adapted from	Beery et al. 2020	Bandi et al. 2018	Taylor et al. 2019	Hu et al. 2020	David et al. 2021	Borkan et al. 2019	Christie et al. 2018	Yeh et al. 2020	Ni et al. 2019	Raychev et al. 2016

		Do	main generalizat	ion		Subpopulation shift	n + subpopulatio	n shift		
Dataset	iWildCam	Camelyon17	RxRx1	OGB-MolPCBA	GlobalWheat	CivilComments	FMoW	PovertyMap	Amazon	Py150
Input (x)	photo	tissue slide	cell image	molecular graph	wheat image	online comment	t satellite image	satellite image	product review	code
Prediction (y)	animal species	tumor	perturbed gene	bioassays	wheat bbox	toxicity	land use	asset wealth	sentiment	autocomplete
Domain (d)	camera	hospital	batch	scaffold	location, time	demographic	time, region	location	user	git repository
Train example	50 Ed. 11-2/2			N HN		What do Black and LGBT people have to do with bicycle licensing?			Overall a solid package that has a good quality of construction for the price.	import numpy as np norm=np
Test example	and the second s			HO N S		As a Christian, I will not be patronizing any of those businesses.			I *loved* my French press, it's so perfect and came with all this fun stuff!	<pre>import subprocess as sp p=sp.Popen() stdout=p</pre>
Adapted from	Beery et al. 2020	Bandi et al. 2018	Taylor et al. 2019	Hu et al. 2020	David et al. 2021	Borkan et al. 2019	Christie et al. 2018	Yeh et al. 2020	Ni et al. 2019	Raychev et al. 2016

iWildCam: shifts across cameras in animal classification



		Dor	nain generalizat	ion		Subpopulation shift	Doma	in generalizatior	+ subpopulation	on shift
Dataset	iWildCam	Camelyon17	RxRx1	OGB-MolPCBA	GlobalWheat	CivilComments	FMoW	PovertyMap	Amazon	Py150
Input (x)	photo	tissue slide	cell image	molecular graph	wheat image	online comment	t satellite image	satellite image	product review	code
Prediction (y)	animal species	tumor	perturbed gene	bioassays	wheat bbox	toxicity	land use	asset wealth	sentiment	autocomplete
Domain (d)	camera	hospital	batch	scaffold	location, time	demographic	time, region	location	user	git repository
Train example	99.PH H-229			N HN		What do Black and LGBT people have to do with bicycle licensing?			Overall a solid package that has a good quality of construction for the price.	import numpy as np norm=np
Test example	ST HIGH STANK			HO N S		As a Christian, I will not be patronizing any of those businesses.			I *loved* my French press, it's so perfect and came with all this fun stuff!	<pre>import subprocess as sp p=sp.Popen() stdout=p</pre>
Adapted from	Beery et al. 2020	Bandi et al. 2018	Taylor et al. 2019	Hu et al. 2020	David et al. 2021	Borkan et al. 2019	Christie et al. 2018	Yeh et al. 2020	Ni et al. 2019	Raychev et al. 2016

		Do	main generalizat	ion		Subpopulation shift	Doma	in generalizatior	n + subpopulatio	on shift
Dataset	iWildCam	Camelyon17	RxRx1	OGB-MolPCBA	GlobalWheat	CivilComments	FMoW	PovertyMap	Amazon	Py150
Input (x)	photo	tissue slide	cell image	molecular graph	wheat image	online commen	t satellite image	satellite image	product review	code
Prediction (y)	animal species	tumor	perturbed gene	bioassays	wheat bbox	toxicity	land use	asset wealth	sentiment	autocomplete
Domain (d)	camera	hospital	batch	scaffold	location, time	demographic	time, region	location	user	git repository
Train example	91.81 8.273			N HN		What do Black and LGBT people have to do with bicycle licensing?			Overall a solid package that has a good quality of construction for the price.	import numpy as np norm=np
Test example	SPECIAL SECTION AND ASSESSMENT OF THE SECTION ASSESSMENT OF THE SECTIO			HO		As a Christian, I will not be patronizing any of those businesses.			I *loved* my French press, it's so perfect and came with all this fun stuff!	<pre>import subprocess as sp p=sp.Popen() stdout=p</pre>
Adapted from	Beery et al. 2020	Bandi et al. 2018	Taylor et al. 2019	Hu et al. 2020	David et al. 2021	Borkan et al. 2019	Christie et al. 2018	Yeh et al. 2020	Ni et al. 2019	Raychev et al. 2016

		Doi	nain generalizati	ion		Subpopulation shift	Doma	in generalization	ı + subpopulatio	on shift
Dataset	iWildCam	Camelyon17	RxRx1	OGB-MolPCBA	GlobalWheat	CivilComments	FMoW	PovertyMap	Amazon	Py150
Input (x)	photo	tissue slide	cell image	molecular graph	wheat image	online commen	t satellite image	satellite image	product review	code
Prediction (y)	animal species	tumor	perturbed gene	bioassays	wheat bbox	toxicity	land use	asset wealth	sentiment	autocomplete
Domain (d)	camera	hospital	batch	scaffold	location, time	demographic	time, region	location	user	git repository
Train example	9 H H 222			N HN		What do Black and LGBT people have to do with bicycle licensing?			Overall a solid package that has a good quality of construction for the price.	import numpy as np norm=np
Test example	THE STATE OF THE S			HO N S		As a Christian, I will not be patronizing any of those businesses.			I *loved* my French press, it's so perfect and came with all this fun stuff!	<pre>import subprocess as sp p=sp.Popen() stdout=p</pre>
Adapted from	Beery et al. 2020	Bandi et al. 2018	Taylor et al. 2019	Hu et al. 2020	David et al. 2021	Borkan et al. 2019	Christie et al. 2018	Yeh et al. 2020	Ni et al. 2019	Raychev et al. 2016

		Do	main generalizat	ion		Subpopulation shift	n + subpopulatio	on shift		
Dataset	iWildCam	Camelyon17	RxRx1	OGB-MolPCBA	GlobalWheat	CivilComments	FMoW	PovertyMap	Amazon	Py150
Input (x)	photo	tissue slide	cell image	molecular graph	wheat image	online comment	satellite image	satellite image	product review	code
Prediction (y)	animal species	tumor	perturbed gene	e bioassays	wheat bbox	toxicity	land use	asset wealth	sentiment	autocomplete
Domain (d)	camera	hospital	batch	scaffold	location, time	demographic	time, region	location	user	git repository
Train example	0 8 8 1 1 2 2 2			HIN		What do Black and LGBT people have to do with bicycle licensing?			Overall a solid package that has a good quality of construction for the price.	import numpy as np norm=np
Test example	STREET AND AND ADDRESS OF THE ADDRES			HO N S S S S S S S S S S S S S S S S S S		As a Christian, I will not be patronizing any of those businesses.			I *loved* my French press, it's so perfect and came with all this fun stuff!	<pre>import subprocess as sp p=sp.Popen() stdout=p</pre>
Adapted from	Beery et al. 2020	Bandi et al. 2018	Taylor et al. 2019	Hu et al. 2020	David et al. 2021	Borkan et al. 2019	Christie et al. 2018	Yeh et al. 2020	Ni et al. 2019	Raychev et al. 2016

		Do	main generalizat	ion		Subpopulation shift	Doma	n + subpopulation shift		
Dataset	iWildCam	Camelyon17	RxRx1	OGB-MolPCBA	GlobalWheat	CivilComments	FMoW	PovertyMap	Amazon	Py150
Input (x)	photo	tissue slide	cell image	molecular graph	wheat image	online comment	satellite image	satellite image	product review	code
Prediction (y)	animal species	tumor	perturbed gene	bioassays	wheat bbox	toxicity	land use	asset wealth	sentiment	autocomplete
Domain (d)	camera	hospital	batch	scaffold	location, time	demographic	time, region	location	user	git repository
Train example	01.FE H 2/2			N HN HN		What do Black and LGBT people have to do with bicycle licensing?			Overall a solid package that has a good quality of construction for the price.	import numpy as np norm=np
Test example	SOUTH STORY			HO N S		As a Christian, I will not be patronizing any of those businesses.			I *loved* my French press, it's so perfect and came with all this fun stuff!	<pre>import subprocess as sp p=sp.Popen() stdout=p</pre>
Adapted from	Beery et al. 2020	Bandi et al. 2018	Taylor et al. 2019	Hu et al. 2020	David et al. 2021	Borkan et al. 2019	Christie et al. 2018	Yeh et al. 2020	Ni et al. 2019	Raychev et al. 2016

		Do	main generalizat	ion		Subpopulation shift	Doma	in generalization	n + subpopulatio	on shift
Dataset	iWildCam	Camelyon17	RxRx1	OGB-MolPCBA	GlobalWheat	CivilComments	FMoW	PovertyMap	Amazon	Py150
Input (x)	photo	tissue slide	cell image	molecular graph	wheat image	online comment	satellite image	satellite image	product review	code
Prediction (y)	animal species	tumor	perturbed gene	bioassays	wheat bbox	toxicity	land use	asset wealth	sentiment	autocomplete
Domain (d)	camera	hospital	batch	scaffold	location, time	demographic	time, region	location	user	git repository
Train example	00 FH H 222			N HN		What do Black and LGBT people have to do with bicycle licensing?			Overall a solid package that has a good quality of construction for the price.	import numpy as np norm=np
Test example	SO CHAIL SE VICE			HO N S		As a Christian, I will not be patronizing any of those businesses.			I *loved* my French press, it's so perfect and came with all this fun stuff!	<pre>import subprocess as sp p=sp.Popen() stdout=p</pre>
Adapted from	Beery et al. 2020	Bandi et al. 2018	Taylor et al. 2019	Hu et al. 2020	David et al. 2021	Borkan et al. 2019	Christie et al. 2018	Yeh et al. 2020	Ni et al. 2019	Raychev et al. 2016

FMoW: hybrid shift across time and region

		Train		7	est
Satellite Image (x)					
Year / Region (d)	2002 / Americas	2009 / Africa	2012 / Europe	2016 / Americas	2017 / Africa
Building / Land Type (y)	shopping mall	multi-unit residential	road bridge	recreational facility	educational institution

		Do	main generalizat	ion		Subpopulation shift	Doma	in generalizatior	+ subpopulation	on shift
Dataset	iWildCam	Camelyon17	RxRx1	OGB-MolPCBA	GlobalWheat	CivilComments	FMoW	PovertyMap	Amazon	Py150
Input (x)	photo	tissue slide	cell image	molecular graph	wheat image	online commen	t satellite image	satellite image	product review	code
Prediction (y)	animal species	tumor	perturbed gene	bioassays	wheat bbox	toxicity	land use	asset wealth	sentiment	autocomplete
Domain (d)	camera	hospital	batch	scaffold	location, time	demographic	time, region	location	user	git repository
Train example	9F.HE 11:222			N HN HN		What do Black and LGBT people have to do with bicycle licensing?			Overall a solid package that has a good quality of construction for the price.	import numpy as np norm=np
Test example				HO N S		As a Christian, I will not be patronizing any of those businesses.			I *loved* my French press, it's so perfect and came with all this fun stuff!	<pre>import subprocess as sp p=sp.Popen() stdout=p</pre>
Adapted from	Beery et al. 2020	Bandi et al. 2018	Taylor et al. 2019	Hu et al. 2020	David et al. 2021	Borkan et al. 2019	Christie et al. 2018	Yeh et al. 2020	Ni et al. 2019	Raychev et al. 2016

		Doi	main generalizat	ion		Subpopulation shift	Doma	in generalizatio	n + subpopulatio	on shift
Dataset	iWildCam	Camelyon17	RxRx1	OGB-MolPCBA	GlobalWheat	CivilComments	FMoW	PovertyMap	Amazon	Py150
Input (x)	photo	tissue slide	cell image	molecular graph	wheat image	online comment	t satellite image	satellite image	product review	code
Prediction (y)	animal species	tumor	perturbed gene	bioassays	wheat bbox	toxicity	land use	asset wealth	sentiment	autocomplete
Domain (d)	camera	hospital	batch	scaffold	location, time	demographic	time, region	location	user	git repository
Train example	97.84			N HN		What do Black and LGBT people have to do with bicycle licensing?			Overall a solid package that has a good quality of construction for the price.	import numpy as np norm=np
Test example				HO N S		As a Christian, I will not be patronizing any of those businesses.			I *loved* my French press, it's so perfect and came with all this fun stuff!	<pre>import subprocess as sp p=sp.Popen() stdout=p</pre>
Adapted from	Beery et al. 2020	Bandi et al. 2018	Taylor et al. 2019	Hu et al. 2020	David et al. 2021	Borkan et al. 2019	Christie et al. 2018	Yeh et al. 2020	Ni et al. 2019	Raychev et al. 2016

		Do	main generalizat	ion		Subpopulation shift	Doma	in generalizatior	n + subpopulatio	on shift
Dataset	iWildCam	Camelyon17	RxRx1	OGB-MolPCBA	GlobalWheat	CivilComments	FMoW	PovertyMap	Amazon	Py150
Input (x)	photo	tissue slide	cell image	molecular graph	wheat image	online commen	t satellite image	satellite image	product review	code
Prediction (y)	animal species	tumor	perturbed gene	bioassays	wheat bbox	toxicity	land use	asset wealth	sentiment	autocomplete
Domain (d)	camera	hospital	batch	scaffold	location, time	demographic	time, region	location	user	git repository
Train example	93.PH H 2/2			N HN		What do Black and LGBT people have to do with bicycle licensing?			Overall a solid package that has a good quality of construction for the price.	import numpy as np norm=np
Test example	31010			HO N S		As a Christian, I will not be patronizing any of those businesses.			I *loved* my French press, it's so perfect and came with all this fun stuff!	<pre>import subprocess as sp p=sp.Popen() stdout=p</pre>
Adapted from	Beery et al. 2020	Bandi et al. 2018	Taylor et al. 2019	Hu et al. 2020	David et al. 2021	Borkan et al. 2019	Christie et al. 2018	Yeh et al. 2020	Ni et al. 2019	Raychev et al. 2016

Criteria for selecting datasets



Real-world distribution shifts

Criteria for selecting datasets



Real-world distribution shifts



Potential leverage

- Training data consists of multiple domains
- All points annotated with domain and other metadata

Criteria for selecting datasets



Real-world distribution shifts



Potential leverage



Large performance drops

Large gaps between ID and OOD performance

- Evaluated standard models (e.g., ResNet) trained using ERM on metrics chosen for each application
- Out-of-distribution: WILDS default splits
- In-distribution: performance without distribution shift (on held-out set)

Large gaps between ID and OOD performance

- Evaluated standard models (e.g., ResNet) trained using ERM on metrics chosen for each application
- Out-of-distribution: WILDS default splits
- In-distribution: performance without distribution shift (on held-out set)

Dataset	Metric	In-distribution	Out-of-distribution	Gap	
IWILDCAM2020-WILDS	Macro F1	47.0	31.0	16.0	
CAMELYON17-WILDS	Average accuracy	93.2	70.3	22.9	
RXRX1-WILDS	Average accuracy	39.8	29.9	9.9	
OGB-MOLPCBA	Average AP	34.4	27.2	7.2	
GLOBALWHEAT-WILDS	Average domain accuracy	64.8	48.4	16.4	large gaps
CIVILCOMMENTS-WILDS	Worst-group accuracy	92.2	56.0	36.2	
FMoW-WILDS	Worst-region accuracy	48.6	32.3	16.3	
POVERTYMAP-WILDS	Worst-U/R Pearson R	0.60	0.45	0.15	
AMAZON-WILDS	10th percentile accuracy	71.9	53.8	18.1	
Py150-wilds	Method/class accuracy	75.4	67.9	7.5	

Existing algorithms do not close ID-OOD gaps

- Benchmarked representative algorithms for domain generalization and subpopulation shifts
 - Domain generalization: CORAL (Sun and Saenko, 2016), IRM (Arjovsky et al., 2019)
 - Subpopulation shift: Group DRO (Sagawa et al., 2020)

Dataset	Setting	ERM	CORAL	IRM	Group DRO
IWILDCAM2020-WILDS	Domain gen.	31.0 (1.3)	32.8 (0.1)	15.1 (4.9)	23.9 (2.1)
CAMELYON17-WILDS	Domain gen.	70.3 (6.4)	59.5 (7.7)	64.2 (8.1)	68.4 (7.3)
RXRX1-WILDS	Domain gen.	29.9 (0.4)	28.4 (0.3)	8.2 (1.1)	23.0 (0.3)
OGB-MOLPCBA	Domain gen.	27.2 (0.3)	17.9 (0.5)	15.6 (0.3)	22.4 (0.6)
GLOBALWHEAT-WILDS	Domain gen.	49.2 (1.5)	_	_	46.1 (1.6)

Existing algorithms do not close ID-OOD gaps

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 - Subpopulation shift: Group DRO (Sagawa et al., 2020)

Dataset	Setting	Setting ERM		IRM	Group DRO
IWILDCAM2020-WILDS	Domain gen.	31.0 (1.3)	32.8 (0.1)	15.1 (4.9)	23.9 (2.1)
CAMELYON17-WILDS	Domain gen.	70.3 (6.4)	59.5 (7.7)	64.2 (8.1)	68.4 (7.3)
RxRx1-wilds	Domain gen.	29.9 (0.4)	28.4 (0.3)	8.2 (1.1)	23.0 (0.3)
OGB-MOLPCBA	Domain gen.	27.2 (0.3)	17.9 (0.5)	15.6 (0.3)	22.4 (0.6)
GLOBALWHEAT-WILDS	Domain gen.	49.2 (1.5)	_	_	46.1 (1.6)
CIVILCOMMENTS-WILDS	Subpop. shift	56.0 (3.6)	65.6 (1.3)	66.3 (2.1)	70.0 (2.0)

Existing algorithms do not close ID-OOD gaps

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Dataset Setting		ERM	CORAL	IRM	Group DRO
IWILDCAM2020-WILDS	Domain gen.	31.0 (1.3)	32.8 (0.1)	15.1 (4.9)	23.9 (2.1)
CAMELYON17-WILDS	Domain gen.	70.3 (6.4)	59.5 (7.7)	64.2 (8.1)	68.4 (7.3)
RxRx1-wilds	Domain gen.	29.9 (0.4)	28.4 (0.3)	8.2 (1.1)	23.0 (0.3)
OGB-MOLPCBA	Domain gen.	27.2 (0.3)	17.9 (0.5)	15.6 (0.3)	22.4 (0.6)
GLOBALWHEAT-WILDS	Domain gen.	49.2 (1.5)	_	_	46.1 (1.6)
CIVILCOMMENTS-WILDS	Subpop. shift	56.0 (3.6)	65.6 (1.3)	66.3 (2.1)	70.0 (2.0)
FMoW-wilds	Hybrid	32.3 (1.3)	31.7 (1.2)	30.0 (1.4)	30.8 (0.8)
POVERTYMAP-WILDS	Hybrid	0.45 (0.06)	0.44 (0.06)	0.43 (0.07)	0.39 (0.06)
AMAZON-WILDS	Hybrid	53.8 (0.8)	52.9 (0.8)	52.4 (0.8)	53.3 (0.0)
PY150-WILDS	Hybrid	67.9 (0.1)	65.9 (0.1)	64.3 (0.2)	65.9 (0.1)

No improvements over ERM!

These real-world shifts are still an open problem

WILDS leaderboard

wilds.stanford.edu



Algorithm	Contact	FMoW	PovertyMap	iWildCam	Camelyon17	OGB-MoIPCBA	Amazon	CivilComments	Py150
		Worst-Region Acc	Rural Pearson r	Macro F1	Avg Acc	Avg Precision	10% Acc	Worst-Group Acc	Method/Class Acc
ERM	WILDS	32.8 (0.45)	0.46 (0.07)	31.0 (1.3)	70.3 (6.4)	27.2 (0.3)	53.8 (0.8)	56.0 (3.6)	67.9 (0.1)
CORAL	WILDS	31.0 (0.35)	0.44 (0.07)	32.8 (0.1)	59.5 (7.7)	17.9 (0.5)	52.9 (0.8)	65.6 (1.3)	65.9 (0.1)
IRM	WILDS	33.5 (1.35)	0.48 (0.04)	15.1 (4.9)	64.2 (8.1)	15.6 (0.3)	52.4 (0.8)	66.3 (2.1)	64.3 (0.2)
Group DRO	WILDS	31.4 (2.1)	0.4 (0.08)	23.9 (2.1)	68.4 (7.3)	22.4 (0.6)	53.3 (0.0)	70.0 (2.0)	65.9 (0.1)

Not just for "distribution shift researchers": Distribution shifts are unavoidable in many ML applications

WILDS package (pip install wilds)

```
Standardized datasets and data loaders
```

Defaults and baselines

Easy evaluation

```
>>> from wilds.datasets.iwildcam dataset import IWildCamDataset
>>> from wilds.common.data loaders import get train loader
>>> dataset = get dataset(dataset="iwildcam", download=True)
>>> train data = dataset.get subset("train")
>>> train_loader = get_train_loader("standard", train_data,
                                    batch size=16)
>>> for x, y true, metadata in train loader:
        [Train a model using your algorithm; we provide defaults]
>>> dataset.eval(y_pred, y_true, metadata)
{ 'macro_recall': 0.66, ...}
```

Other distribution shifts beyond WILDS

 Many other real-world shifts, but challenging to find suitable datasets



Demographic shifts in automatic speech recognition (ASR)

Difficulty finding training data on natural speech with enough demographic diversity



Time and hospital shifts in medicine

Datasets with those shifts also involve *concept drifts* due to changes in label definition, clinical procedures, etc.

Other distribution shifts beyond WILDS

Other datasets had no substantial ID-OOD gap



Day vs. night shift in autonomous driving (BDD100K)

No substantial performance drop if training set is sufficiently diverse



Demographic fairness in weapon possession prediction (SQF)

Substantial disparities across races, but due to biased data instead of the distribution shift

Surveys: fairness, healthcare, genomics, speech, NLP, robotics, education **Additional examples**: cell type shift in genomics, shifts in review datasets

Many open questions



Datasets and shifts

 How can we construct benchmarks for the many applications and shifts for which we don't have suitable datasets?



Theoretical frameworks

 How can we characterize and categorize all of these different shifts?



Algorithms

 How can we train models that are robust due to real-world shifts? (e.g., by incorporating domain annotations and metadata, or using prior knowledge?)



A Benchmark of in-the-Wild Distribution Shifts

Code, paper, leaderboard, and contact info at https://wilds.stanford.edu

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Based on datasets from...

- P. Bandi, O. Geessink, Q. Manson, M. V. Dijk, M. Balkenhol, M. Hermsen, B. E. Bejnordi, B. Lee, K. Paeng, A. Zhong, et al. From detection of individual metastases to classification of lymph node status at the patient level: the CAMELYON17 challenge. *IEEE Transactions on Medical Imaging*, 2018.
- S. Beery, E. Cole, and A. Gjoka. The iWildCam 2020 competition dataset. arXiv, 2020.
- D. Borkan, L. Dixon, J. Sorensen, N. Thain, and L. Vasserman. Nuanced metrics for measuring unintended bias with real data for text classification. WWW, 2019.
- G. Christie, N. Fendley, J. Wilson, and R. Mukherjee. Functional map of the world. CVPR, 2018.
- E. David, S. Madec, P. Sadeghi-Tehran, H. Aasen, B. Zheng, S. Liu, N. Kirchgessner, G. Ishikawa, K. Nagasawa, M.A. Badhon, and C. Pozniak. Global Wheat Head Detection (GWHD) dataset: a large and diverse dataset of high-resolution RGB-labelled images to develop and benchmark wheat head detection methods. *Plant Phenomics*, 2020.
- W. Hu, M. Fey, M. Zitnik, Y. Dong, H. Ren, B. Liu, M. Catasta, and J. Leskovec. Open Graph Benchmark: Datasets for Machine Learning on Graphs. NeurIPS, 2020.
- J. Ni, J. Li, and J. McAuley. Justifying recommendations using distantly-labeled reviews and fine- grained aspects. *EMNLP*, 2019.
- C. Yeh, A. Perez, A. Driscoll, G. Azzari, Z. Tang, D. Lobell, S. Ermon, and M. Burke. Using publicly available satellite imagery and deep learning to understand economic well-being in Africa. *Nature Communications*, 2020.
- V. Raychev, P. Bielik and M. Vechev. Probabilistic Model for Code with Decision Trees. OOPSLA, 2016.
- J. Taylor, B. Earnshaw, B. Mabey, M. Victors, and J. Yosinski. RxRx1: An Image Set for Cellular Morphological Variation Across Many Experimental Batches. ICLR, 2019.

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